

Seasonal decomposition and climatic factors with morbidity malaria incidence in Banjar district, Indonesia

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ABSTRACT

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Malaria is a serious health problem in Indonesia, and it is important to understand the disease. Climatic factors play an important role in malaria transmission. Understanding the characteristics of this disease will benefit the health monitoring system and provide ways to address this problem. This study aimed to determine the effect of climatic factors with morbidity malaria incidence in Banjar district, Indonesia. Malaria case data (2015–2022) were obtained from the Banjar Health Office, South Kalimantan province, while climate data were obtained from the Meteorology, Climatology, and Geophysics Agency. A multivariable linear regression model was developed to analyze the relationship between climate factors and malaria cases, and a forecasting model was used to analyze trends over time. Our findings show that malaria cases peak twice a year in November–January and April–May. Rainfall and wind speed—both maximum and average—were identified as key climatic variables impacting malaria incidence. These findings suggest that local health authorities can utilize climatic data to forecast malaria trends and implement timely interventions before transmission peaks.

Keywords: malaria; rainfall; wind speed; forecasting

1. INTRODUCTION

Malaria is a disease caused by *Plasmodium* parasites and transmitted by mosquitoes, which act as vectors. Humans contract the disease through the bites of infected *Anopheles* mosquito (Tainchum et al., 2015; Sugiarto et al., 2016). Currently, five *Plasmodium* species are known to infect humans (Basu & Sahi, 2017; Varo et al., 2020). Early

diagnosis and effective treatment of malaria are essential for reducing disease burden, preventing death and contributing to the decrease in transmission rates. The World Health Organization (WHO) recommends microscopy or rapid diagnostic tests for malaria diagnosis (Ohrt et al., 2015; WHO, 2018). Prompt diagnosis enables clinicians to differentiate malarial from non-malarial fevers and to administer appropriate therapy.

Vector control is an important component of malaria prevention and elimination strategy (Ridha et al., 2021). Effective vector control can reduce disease transmission and prevent new infections. Common interventions include the use of insecticide-treated nets (ITN), and indoor residual spraying. However, the main challenges for these interventions is the emergence of insecticide resistance among *Anopheles* mosquitoes (Alout et al., 2017). Additional challenges to ITN effectiveness highlighted in the latest World Malaria Report include insufficient access, loss of net due to wear and tear exceeding replacement rates, and behavioral changes in mosquitoes, such as increased biting before people go to bed and resting outside to avoid insecticide exposure (WHO, 2022).

Malaria elimination is defined as the interruption of local transmission of a specific malaria parasites in a defined geographic area as a result of deliberate activities. (Li et al., 2019). There were 249 million cases of malaria in 2022 compared to 244 million in 2021, according to the most recent World Malaria Report. The number of malaria fatalities was estimated at 608,000 in 2022, a slight decrease from 610,000 in 2021. The African Region continues to bear a disproportionate share of the global malaria burden. In 2022, this region accounted for 94% of all malaria cases and 95% of deaths. Children under the age of five accounted for 78% of the malaria deaths in the region. In the world, Nigeria (26.8%), the Democratic Republic of the Congo (12.3%), Uganda (5.1%), and Mozambique (4.2%) accounted for slightly more than half of the malaria fatalities. Nine countries—the Maldives (2015), Sri Lanka (2016), Kyrgyzstan (2016), Paraguay (2018), Uzbekistan (2018), Argentina (2019), Algeria (2019), China (2021), and El Salvador (2021)—have been certified malaria-free since 2015. This declaration was made by the Director General of WHO certification (WHO, 2022). According to data from the Indonesian Ministry of Health, 415,140 cases of malaria are expected in Indonesia in 2022. Comparing this figure to the 304,607 instances from the prior year, there has been a 36.29% increase (Sugiarto et al., 2022). The goal of Indonesia is to eradicate malaria by 2030. The ability to identify malaria cases in the population early will determine whether Indonesia can become a malaria-free nation by 2030 (Sitohang et al., 2018).

Although Banjar Regency, a malaria-endemic area in South Kalimantan, has achieved elimination status, local transmission persists. Malaria cases are thought to be linked to deforestation which is the habitat of the *Anopheles* mosquito (Barros & Honório, 2015). Distribution vectors can be influenced by meteorological variables such as temperature and precipitation (Alimi et al., 2015; Salahi-Moghaddam et al., 2017). The connection between climatic conditions and malaria is examined in the 2023 World Malaria Report. The behavior and survival of the *Anopheles* mosquito, which transmits malaria, can be influenced by temperature, humidity, and rainfall (Ayanlade et al., 2022; Villena et al., 2022). Severe weather conditions, such as heat waves and floods, can directly affect the burden and spread of disease. For instance, malaria incidence increased fivefold in Pakistan in 2022, as a result of catastrophic floods (Vohra et al., 2023). Findings on the influence of climate on *Anopheles* breeding were also observed in Sabah, Malaysia. *Anopheles* mosquitoes thrive in warm climates, especially equatorial regions, including Indonesia (Ramdzan, et al., 2020). Other studies in Java

and northern Sumatra, Indonesia, also explain that climate factors and human migration affect malaria transmission (Rejeki et al., 2018; Fahmi et al., 2022). Climate factor poses a significant threat to progress against malaria, particularly in susceptible regions. Sustainable and resilient malaria responses are more important than ever, as are urgent steps to limit and mitigate the effects of global warming (Mbouna et al., 2023). In addition to environmental factors, risk factors for malaria also include individual factors, such as sleeping without mosquito nets and unprotected houses (Grigg et al., 2017). Information on factors causing malaria in Banjar district is still very limited. Behavioral factors, vector mosquitoes and their breeding habitat, as well as climatic factors, are still unknown. In this study, the researchers focused on the relationship between climatic factors and transmission trends of falciparum and vivax malaria. Therefore, a better understanding of the trend of malaria transmission in Banjar will help determine a more effective and sustainable vector control strategy. The purpose of this study was to determine the relationship between climatic factors with morbidity malaria incidence in Banjar district, Indonesia.

2. MATERIALS AND METHODS

2.1 Study location

Banjar Regency is located in 3°19'45"S and 114°48'52"E. It is divided into 20 sub-districts with 290 villages. The elevation of the regency ranges from 0 to 1,878 m above sea level (ASL). This altitude is one of the factors that determine the location of residents' activities, so height is also used to determine the boundaries of business land areas, where 35% are at an altitude of 0–7 m ASL, 55.54% are at an altitude of 300 m ASL, the remaining 9.45 % more than 300 m ASL (Figure 1).

2.2 Data collection

This study used secondary data from two main sources. First, monthly, laboratory-confirmed malaria case data for Banjar district from 2015 to 2022 were obtained from the Banjar Health Office. These records were aggregated from initial reports submitted by Public Health Centers (PHCs) and hospitals in Banjar district. Second, corresponding monthly climate data (temperature, humidity, rainfall, and wind speed) were obtained from the Class II Meteorological Station Syamsudin Noor in Banjarmasin.

2.3 Statistical analysis

Data was cleaned and formatted using R software with the R statistical language version 4.3.2 used for analysis. All charts and tables are also created in R Studio (version 4.3.2) (Kronthaler & Zöllner, 2021).

Measuring the strength of the linear relationship between 2 variables in this study used the Spearman correlation coefficient, which is relatively robust to the appearance of outliers in the data. The calculation of the Spearman correlation coefficient also does not require the fulfillment of the assumption of data normality in its calculation. The Spearman coefficient is a Pearson correlation coefficient that uses the ranked value of the data in its calculation, instead of the actual data. The correlation coefficient (symbolized by r) has a range

the relationship is concluded to be weak if the correlation coefficient is close to 0. correlation coefficient.

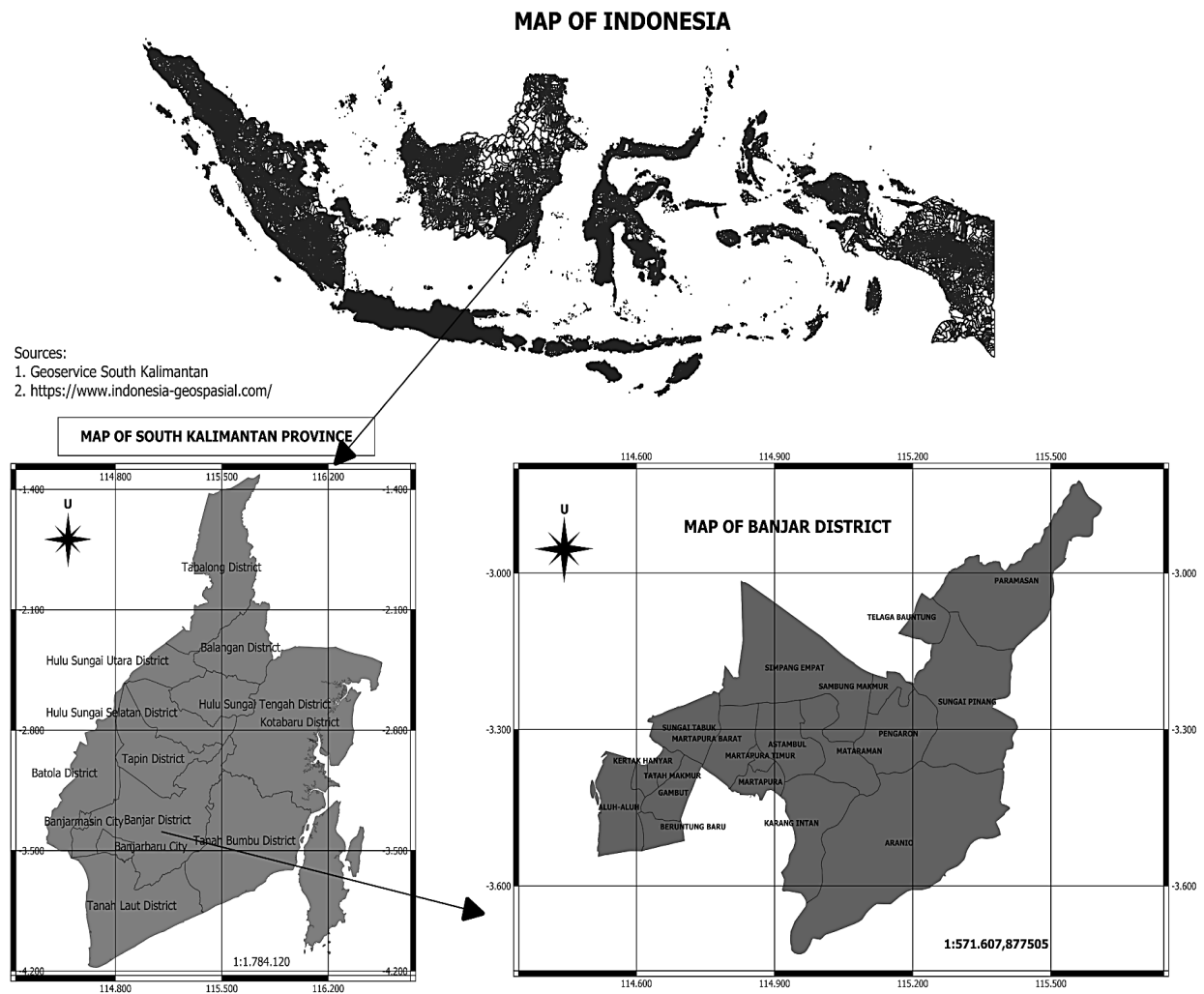


Figure 1. Map of Banjar district, Indonesia

3. RESULTS

Malaria cases have been known to occur mostly in the productive age range of 15–54 years, with as many as 684 cases over 8 years, while the least common age range is 0–9 years (6 cases). Based on gender, males outnumbered females, with 683 and 38 cases, respectively. Based on the type of *Plasmodium*, *P. vivax* (270 cases) was more common than *P. falciparum* (240 cases). The number of cases increased from 2015 to 2017 before showing a decreasing trend through 2022 (Table 1).

While malaria cases were reported every month, a notable increase occurred at the beginning of the year. The same pattern occurs for *P. falciparum* and *P. vivax* in January–February, then the cases increase again in April (Figure 2).

The decomposition analysis results indicate a significant decrease trend for the *P. falciparum* (Figure 3)

and *P. vivax* (Figure 4) cases. Furthermore, for both illnesses, the decomposition analysis reveals a distinct seasonal trend. *P. vivax* infections showed a bimodal seasonal pattern (February and October), while *P. falciparum* infections showed two peaks in January and June every year.

Table 2 provides the results of the Spearman correlation computation between pairs of variables in this study. Based on the correlation coefficient, the variables significantly associated with malaria incidence were rainfall ($r = 0.226114, p = 0.02675$) and wind speed, both maximum wind speed ($r = 0.3129837, p = 0.001904$) and average wind speed ($r = 0.3435171, p = 0.0006112$). Although the results of the correlation coefficient show a relatively weak relationship, the significance test results show that the correlation is statistically significant ($p < 0.05$).

Table 1. Malaria case distribution in Banjar district, Indonesia, 2015–2022

Years	Age (years)				Gender		Type of <i>Plasmodium</i>			Total
	0–9	10–14	15–54	> 54	Male	Female	<i>P. falciparum</i>	<i>P. vivax</i>	mix	
2015	2	2	174	1	168	11	56	62	61	179
2016	2	6	159	9	166	10	66	62	48	176
2017	1	6	175	3	175	10	67	67	51	185
2018	1	3	115	0	112	7	29	51	37	117
2019	0	1	34	0	35	0	13	17	5	35
2020	0	0	15	0	15	0	2	7	6	15
2021	0	0	1	0	1	0	0	1	0	1
2022	0	0	11	0	11	0	7	3	1	11
Total	6	18	684	13	683	38	240	270	209	719

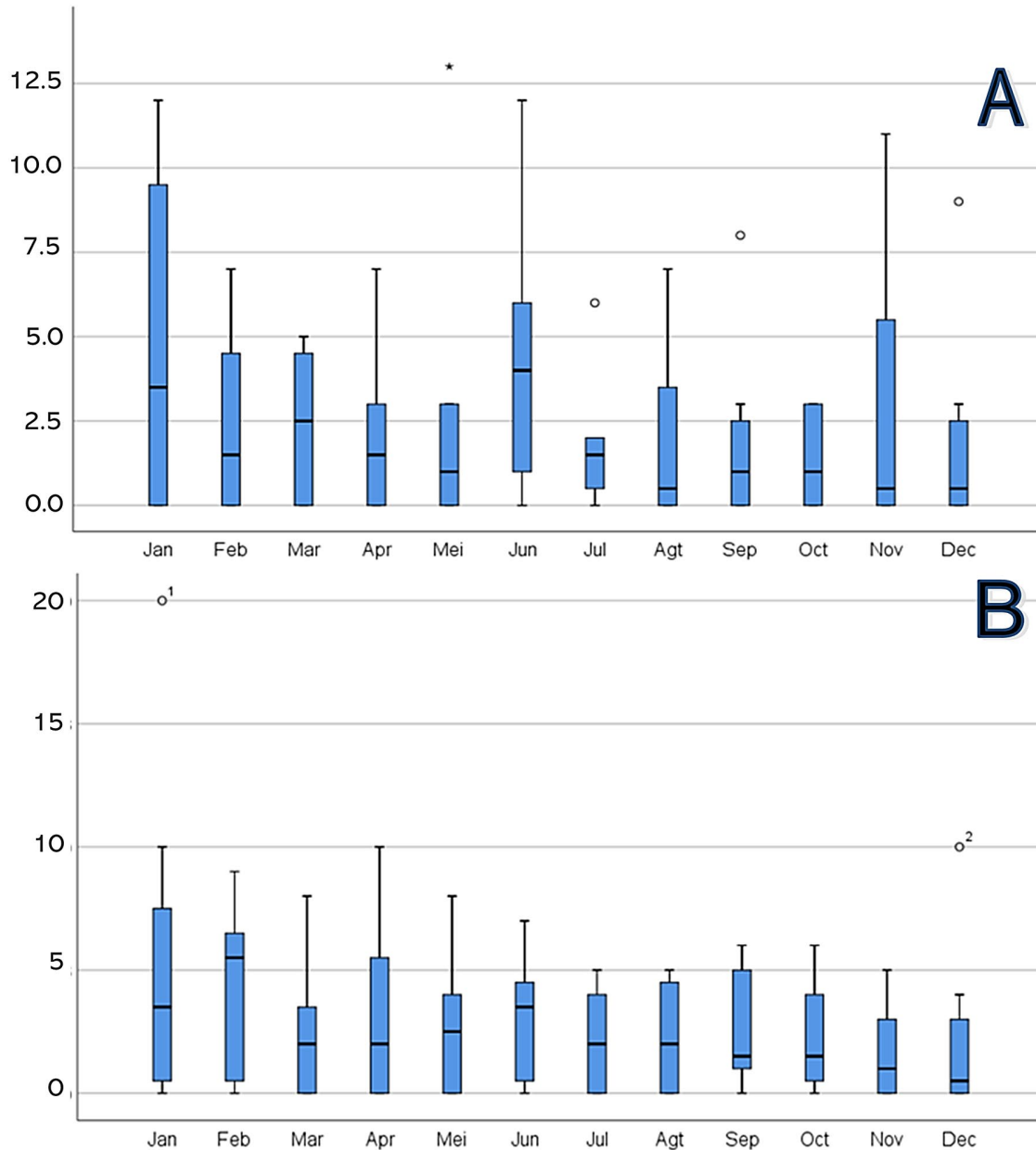


Figure 2. Box plots of monthly malaria cases; (A) *Plasmodium falciparum*, (B) *Plasmodium vivax* from 2015–2022 in Banjar district, Indonesia

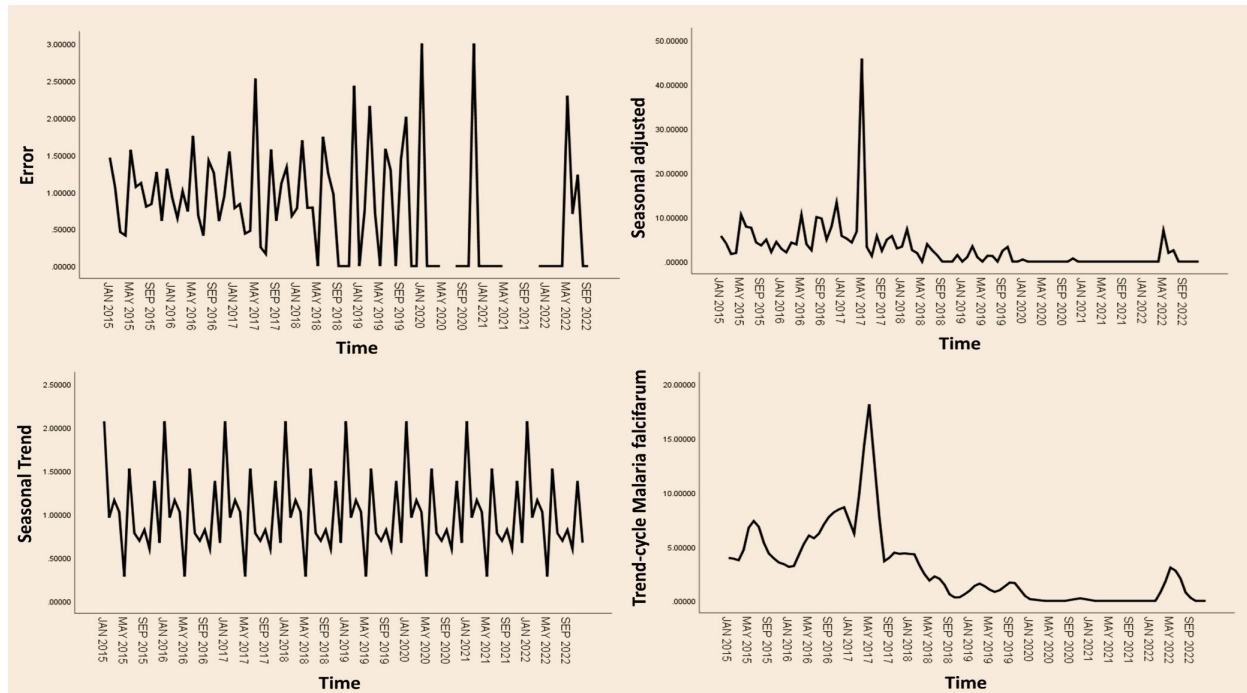


Figure 3. Seasonal decomposition of monthly *P. falciparum* (2015–2022), Banjar district, Indonesia

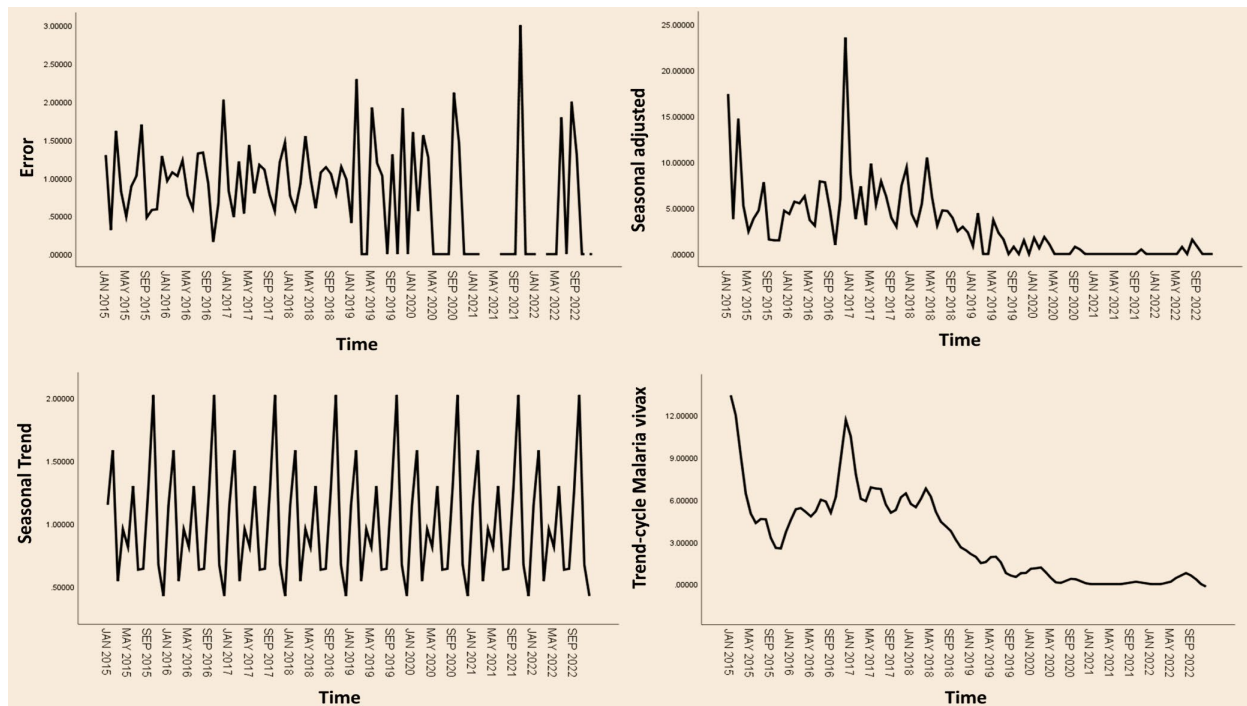


Figure 4. Seasonal decomposition of monthly *P. vivax* (2015–2022), Banjar district, Indonesia

Furthermore, the influence of the two variables was identified based on lags 1–5 using Pearson correlation. This lag selection is based on the assumption that the cycle of mosquito breeding and subsequent transmission to humans occur over a 1- to 5-month interval. Table 3 presents the results of the correlation calculation at lags 1 to 5. The maximum wind speed and average wind speed variables generally have an effect on each lag in the

emergence of malaria cases. While the rainfall variable affects malaria cases in lags 3, 4, and 5. This is possible because of the transmission process which consists of several steps, namely from mosquitoes biting humans and getting infected, mosquitoes breeding, and then mosquitoes transmitting to other humans through bites. This process is assumed to occur within 3 to 5 months.

Table 2. Spearman's coefficient of rank correlation between two variables

Variable	Measure	Variable				
		T _{min}	T _{max}	Rainfall	Max wind	Ave wind
Malaria	Correlation	-0.03858	0.121963	0.226114	0.3129837	0.3435171
	p-value	0.709	0.2365	0.02675*	0.001904**	0.0006112**
T _{min}	Correlation		-0.22225	0.261045	-0.19973	-0.2854941
	p-value		0.0295*	0.0102*	0.05106	0.004809**
T _{max}	Correlation			-0.54661	0.4972721	0.4613712
	p-value			$8.47 \times 10^{-9**}$	$2.55 \times 10^{-7**}$	$2.234 \times 10^{-6**}$
Rainfall	Correlation				-0.06494988	-0.099335
	p-value				0.5295	0.3356
Max Wind	Correlation					0.8912286
	p-value					$2.2 \times 10^{-16**}$

a Italicized entry denotes the largest value of correlation coefficient and significance with *p < 0.05; and **p < 0.01; All significance levels are assessed at $\alpha < 0.05$

Table 3. Spearman correlation between each variable and malaria cases at lags 1–5

Lag	Measure	Variable				
		T _{min}	T _{max}	Rainfall	Max wind	Ave wind
1	Correlation	-0.04847944	0.136228	0.1971724	0.3077369	0.3538178
	p-value	0.6408	0.1881	0.05547	0.002416**	0.0004357**
2	Correlation	-0.06215119	0.1268863	0.2023692	0.2914982	0.3576386
	p-value	0.5518	0.223	0.05046	0.004364**	0.0004019**
3	Correlation	-0.06125919	0.09457405	0.2119751	0.2674682	0.3568877
	p-value	0.5575	0.3646	0.04026*	0.009156**	0.0004142**
4	Correlation	-0.03946537	0.0550245	0.22673	0.260095	0.3550822
	p-value	0.7088	0.6024	0.02975*	0.01228*	0.0005144**
5	Correlation	-0.002739212	0.03608223	0.2384855	0.2492881	0.3510052
	p-value	0.9794	0.7342	0.0082**	0.01718*	0.0006465**

4. DISCUSSION

The province of South Kalimantan has the greatest malaria load, with 719 cases reported in Banjar throughout the seven years from 2015 to 2022. We found a consistent rise in the prevalence of malaria in Banjar throughout January and February based on data spanning seven years. This is consistent with research conducted in Chimoio, Mozambique, which discovered that January marks the start of the rainy season and that the frequency of malaria increased by 20.1% between 2006 and 2014 (Ferraio et al., 2018). Malaria infections peaked in January and April, according to another study conducted in Malaysia (Naserrudin et al., 2022). In addition, Zayed reported that the *Anopheles* mosquito population peaks in January (Zayed et al., 2023). Since all of the aforementioned locations are in the tropical zone, almost all malaria cases occur over the same time frame (Akpan et al., 2019).

The high malaria rate in Banjar is most likely due to recent demographic changes. As the largest district in South Kalimantan, Banjar is the center of education and the main destination for job seekers coming from various regions in South Kalimantan. Banjar Regency is also known as a coal and diamond mining area, but due to lack of supervision and regulation, many post-mining reclamation activities are not carried out, especially for illegal miners. In 2015–2018, reforestation activities were carried out to

close the former mining area. This activity is allegedly the cause of the increased incidence of malaria in the area because it is still close to the forest area. The forest and water area of Banjar is 252,024 km², almost 50% of the total area of 468,800 km². This concurs with a study in Thailand that showed an association between malaria morbidity and environmental factors and land use (forest area) (Kaewpitoon et al., 2015).

This is known because many officers affected by malaria work as volunteer tree planters. The location far from the city causes volunteers to spend the night in the forest, which is a risk factor for malaria transmission. Forest ecosystems can support the spread of malaria, which will significantly increase the global burden of the disease (Kweka et al., 2016; Tucker Lima et al., 2017). Almost half of the malaria risk is estimated to occur in communities living in forest areas (Kar et al., 2014; Ranjha & Sharma, 2021). This is in accordance with the geographical conditions of Banjar district, which are forests and wetland areas that support the breeding of malaria vectors.

The findings of this study indicate that temperature, rainfall, wind velocity max and average wind speed influence the incidence of malaria. High rainfall can increase the number of puddles, which serve as breeding sites for *Anopheles* mosquitoes. An increase in *Anopheles* breeding sites can lead to a larger mosquito population, thereby increasing the risk of malaria transmission. There

will be a greater chance of malaria transmission if there are more *Anopheles* mosquitoes. Elevated temperatures have the potential to impact mosquito metabolism, leading to an increase in the frequency of human bites. Conversely, a rise in temperature can abbreviate the sporogony cycle for *Plasmodium* (Arsin, 2012), thus increasing the potential for Malaria transmission to humans. High humidity causes mosquitoes to become more active and bite more often, thereby increasing the transmission of malaria.

The investigation's findings aligned with a Thai study, that demonstrated a correlation between malaria incidence and rainfall (Kotepui & Kotepui, 2018). Rainfall may have an impact on vector populations during both the larval and adult stages, according to a previous experimental investigation. Droughts typically lead to a decrease in the number and quality of vector breeding sites, which in turn affects vector populations and the transmission of malaria because *Anopheles* mosquitoes lay their eggs in tiny, naturally occurring pools of clean water (Gage et al., 2008).

The density of *An. gambiae* in the East African forested highlands was found to have a quadratic linear connection with the mean temperature of the preceding month and the amount of rainfall two months prior (Kelly-Hope et al., 2009; Agyekum et al., 2021). Another study conducted in the same area revealed that potential evaporation and the rainfall-to-rainfall ratio played a significant role in the population growth of *An. gambiae* and *An. arabiensis* (Lyons et al., 2013). The same vectors investigated in the Gambia experienced a peak in population following the rainy season when humidity rose, and a rapid increase in population at the conclusion of the dry season (Obala et al., 2012). Forest trees typically increase the amount of moisture in the air through evaporation and contribute to lowering temperatures, which raises rainfall. Rain improves the habitat and damp environment that vectors live in, which lengthens their lifespan and accelerates the development of malaria (Vantaux et al., 2021).

The most significant variables influencing geographic distribution and transmission of malaria are elevation and climate change. The bionomics of malaria vectors, which in turn affects the intensity of malaria transmission, can be influenced by meteorological factors such as temperature, humidity, and rainfall (Caminade et al., 2014). Conflicting evidence has been found in several research linking the spread of malaria to climate change (Mordecai et al., 2020; Parihar et al., 2022).

Studies in Southeast Asia show that temperature is an important factor in analyzing the relationship between malaria cases, with *Anopheles* mosquitoes and *Plasmodium* parasites dependent on optimal temperatures between 21–27°C. Research in Koh Chang, Thailand (2001–2011) showed a positive correlation between maximum and average temperatures and malaria cases (Ninphanomchai et al., 2014). Research in Indonesia using Poisson and negative binomial models showed maximum and minimum temperatures had a significant influence on monthly malaria cases with negative and positive directions, although not significant at $\alpha \leq 0.05$ in the final model (Rejeki et al., 2018). Another study in Bukit Manoreh concluded that most malaria cases occur during the rainy season, between August and February. The majority of malaria cases occur at temperatures ranging from 25.0°C – 26.5°C (Rejeki et al., 2019). It was discovered that the yearly average temperature negatively impact malaria cases, indicating that temperatures outside of the ideal range can lower the

number of cases of malaria in East Nusa Tenggara, Indonesia (Mau et al., 2020). A study conducted in Vietnam (Manh et al., 2011) and Thailand (Mercado et al., 2019), highlight that the influence of temperature varies depending on topographic factors and local conditions, with some regions showing opposite interactions. Other factors also influence the variation in malaria cases, although temperature remains a critical determinant.

In addition, higher altitude is also a determining factor in the incidence and spread of malaria. As altitude increases, temperature decreases and vice versa, which in turn affects the dynamics of infection spread. In addition, climate-induced geographical changes in *Anopheles* mosquitoes favor the spread of malaria in previously malaria-free areas, leading to uneven disease distribution (Dabaro et al., 2021). Climate impacts vary across agroecological regions. Therefore, malaria prediction models employing meteorological data vary from place to place, so one model cannot be applied to all geographic regions. This inconsistency in prediction is due to variations in risk factors for malaria prevalence (Pinchoff et al., 2015).

Although the frequency of malaria has declined in previous decades, especially from 2019–2022, which showed a significant decline. However, this raises the question of whether other factors, such as the Covid-19 pandemic, contributed to this decrease. COVID-19 in 2019–2021 resulted in restrictions on activities in the community so malaria cases dropped significantly. But in 2022, malaria began to rise to 11 cases. This is likely due to increased health services with human mobility still not maximized. To accomplish the elimination target within the allotted time, it is imperative to make efficient and effective use of currently available treatments, as well as to allocate and mobilize sufficient resources and employ alternative and complementary control methods and techniques.

The average community mobility of South Kalimantan Province's population was 10.21% between March 22, 2020, and December 31, 2021, according to data from Google Covid-19 Community Mobility Reports. From January 1, 2021, to December 31, 2021, the average community mobility decreased to 2.5% (Google LLC, 2021). This makes people have limited mobility and spend more of their activities at home. The most common malaria vectors found in South Kalimantan are *An. tessellatus* and *An. vagus* species. Both species are zoophilic mosquito species that are found outside the home, so the risk of malaria transmission is greater outside the home. Transmission is greater outside the home (Indriyati et al., 2017).

A limitation of this study is the exclusion of other meteorological parameters such as relative humidity and average temperature that may influence malaria morbidity interventions due to unavailable data. Such data could be used in future studies in other areas.

5. CONCLUSION

We observed that the highest incidence of malaria in Banjar increased in January and February. In this study, the researchers found that variables that have a major influence on the emergence of malaria cases are rainfall ($r = 0.226$, $p = 0.026$) and wind speed, both maximum wind speed ($r = 0.313$, $p = 0.002$) and average wind speed ($r = 0.343$, $p = 0.0006$). The growing threat of climate change necessitates the development of sustainable and

resilient malaria control strategies that are integrated with climate change mitigation efforts. Our findings are expected to improve our understanding of malaria prevalence, particularly in Banjar. This information is expected to help public health institutions improve malaria prevention and control efforts in the future.

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AUTHOR CONTRIBUTIONS

M.R.R. conceptualized the study, designed the methodology, conducted data analysis, and drafted the original manuscript. R.Y. contributed to data collection, validation of results, and manuscript review. T.W.A.G. assisted in data interpretation and contributed to the revision of the manuscript. D.S.S. provided methodological guidance and critically reviewed the manuscript for important intellectual content. H.H.D.L. supervised the research process and contributed to manuscript editing and final approval. All authors have read and approved the final version of the manuscript.

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