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Determinants of Malaria in Indonesia

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Table of Contents

Zusammenfassung 4
Summary 7
List of abbreviations 9
Comprehensive Summary 11
1.1 An introduction with reference to the overall research question 11
1.2 A presentation of the manuscripts respectively the publications 12
1.3 Discussion of the results obtained and their relevance with regards to the research question. 16
Overview of the manuscripts and publications accepted for release 21
The manuscripts/publications 23
Presentation of the personal contribution regarding manuscripts/publications 24
Publication #1 Spatial modelling of malaria cases associated with environmental factors in South Sumatra, Indonesia 25
Publication #2 Does livestock protect from malaria or facilitate malaria prevalence? A cross-sectional study in endemic rural areas of Indonesia 41
Publication #3 Social Determinants of Malaria in an Endemic Area of Indonesia 53
Bibliography 65
An Annex 71
Additional file 1 71
Additional file 2 74
Additional file 3 77
Additional file 4 83
Acknowledgements 86
Curriculum Vitae 89
Schriftliche Erklärung 92

Zusammenfassung

Malaria ist eine Umweltkrankheit, die nicht nur von den physischen und biologischen Umweltfaktoren, sondern auch von soziokulturellen Faktoren beeinflusst wird. Einige Faktoren, die eine mit der Krankheit verbundene hohe Morbiditätsrate verursachen, umfassen den Klimawandel, die geografische Umgebung, sozioökonomische Umstände, und das menschliche Verhalten. Weitere Risikofaktoren sind das Vorhandensein von Tieren, Wohnbedingungen mit schlechten sanitären Einrichtungen, fehlende Hygienepraktiken und unzureichende Gesundheitsdienste in Endemiegebieten. Die Bemühungen zur Beseitigung von Malaria und zur Beseitigung von Vektoren sind seit Jahrzehnten Gegenstand zahlreicher Tagungen und Initiativen im Bereich der öffentlichen Gesundheit. In Indonesien ist Malaria nach wie vor eine der Hauptursachen für Morbidität und Mortalität. Das Ziel dieser Studie ist es, die multiplen Determinanten von Malaria in den endemischen Gebieten Indonesiens zu analysieren, die mit soziodemografischen als auch physischen Umgebungen korrelieren. Wir teilen diese Forschung in drei Teilstudien auf, um ein Vorstellungsmodell zu entwickeln, das die Determinanten für Malaria in Indonesien umfassend beschreibt.

Diese Dissertation folgt einer Querschnittsdesignstudie. Die Forschungsdaten dieser Dissertation stammen aus vier Quellen: routinemäßige Berichterstattung über Malaria aus der Gesundheits-Provinz in Süd-Sumatra; die nationalen Grundlagenforschungsdaten (IDN-Akronym: Riskesdas); Klimadaten aus der Klimatologie-Agentur Meteorologie, Klimatologie und Geophysik (IDN-Akronym: BMKG); Geodaten von Geospatial Information Agency (IDN-Akronym: BIG). In dieser Studie wurde ein ganzheitlicher Ansatz verfolgt, der die folgenden univariaten, binär-logistische Regressionsanalyse, und multivariate-logistische Regressionsanalyse, um eine Modellierungsdeterminante von Malaria zu etablieren. Darüber hinaus haben wir beide Modelle, die geographisch gewichtete Regression (GWR) und die Methode der kleinsten Quadrate (OLS) verglichen. Wir verwendeten folgende statistische Programme für die Datenverarbeitung, Analyse, Visualisierung und die Entwicklung der Modelle: Statistisches Paket für die Sozialwissenschaften (SPSS), Stata, Aeronautical Reconnaissance Coverage Geographisches Informationssystem (ArcGIS) und Geographisch gewichtete Regression 4 (GWR4).

Die Prävalenz von Malaria variiert in Abhängigkeit von der lokalen Umgebung und diese Varianz wird durch die örtlich unterschiedliche physische Umgebung verursacht. Es zeigte sich in dieser Studie zudem, dass die Determinanten für Malaria in lokalen Regionen unterschiedlich waren. Wir folgern, dass ländliche Gebiete mit einem hohen Prozentsatz von Haushalten mit Nutz- und Haustieren einhöhere Malaria-Prävalenz aufwiesen als der nationale Durchschnitt in Indonesien. Darüber hinaus weist die Studie darauf hin, dass soziodemografische Variablen der Teilnehmer (z.B. Geschlecht, Alter, Bildungsgrad, Kenntnis der Zugänglichkeit und Nutzung von Gesundheitsdiensten, Maßnahmen zum Schutz vor Mückenstichen, und Wohnzustand der Studienteilnehmer) mit der Malariaprävalenz in endemischen Provinzen in Indonesien zusammenhängen.

In Süd-Sumatra, Indonesien sind die unabhängigen Variablen Höhe, Entfernung vom Wald und Niederschlag im globalen OLS Modell signifikant mit Malariafällen assoziiert. Das ergänzende GWR Modell zeigte schlüssig, daß die Ursache der Malariafälle auf der dörflichen Ebene erheblich variiert. Daher ist es für den Entscheidungsträger, d.h. die Regierung, sehr wichtig, ein tiefergehendes Verständnis der regionalen und ökologischen Faktoren zu entwickeln, welche die bestätigten Malariafälle beeinflussen. Auf Grundlage der vorliegenden Ergebnisse empfehlen wir die Entwicklung nachhaltiger regionaler Malariakontrollprogramme, welche Anreize für die Beseitigung von Malaria schaffen, und insbesondere auf Dorfebene. Das Vorhandensein von bestimmten Tieren stellt einen Hauptrisikofaktor für Malaria im ländlichen Indonesien dar und muß in Bekämpfungsstrategien berücksichtigt werden. Hier empfehlen wir insbesondere für das Untersuchungsgebiet einen One Health Approach mit Integriertem Vector Management (IVM), beispielsweise die simultane Umsetzung von insektizidbehandelten Bettnetzen (ITN) und insektizidbehandelten Nutztieren (ITL). Darüber hinaus sind auch soziodemografische Faktoren, zum Beispiel die gesundheitliche Versorgung für die lokale und regionale Malaria-Prävalenz wichtig.
Wir empfehlen den Ausbau von Bildung und öffentlichen Informationsmöglichkeiten und eine verbesserte Zugänglichkeit bzw. Nutzung der Gesundheitsfürsorge, um das Wissen und das Bewusstsein der Dorfbewohner bezüglich der Reduktion von *Anopheles* Stechmücken zu fördern. Wir empfehlen den Ausbau von Bildung und öffentlichen Informationsmöglichkeiten und eine verbesserte Zugänglichkeit bzw. Nutzung der

Gesundheitsfürsorge, um das Wissen und das Bewusstsein der Dorfbewohner bezüglich der Reduktion von Anopheles Stechmücken zu fördern.
Diese Forschungsarbeit zeigt, dass es einen Zusammenhang zwischen soziodemografischen Faktoren gibt, welche die Malaria-Prävalenz beeinflussen. Die unterschiedlichen Beziehungen zwischen Malaria und den soziodemografischen Faktoren, die die Krankheit beeinflussen können schliessen Merkmale der Teilnehmer ein. Diese Forschung stellt Faktoren dar, die verwaltet werden können und die Beseitigung der Malaria begünstigen würden. Dazu gehören eine Reihe von Präventionsverhalten auf individueller Ebene und die Nutzung der Netzwerke von primären Gesundheitszentren auf Gemeindeebene. Diese Studie legt nahe, dass die Verbesserung der Verfügbarkeit einer Vielzahl von Gesundheitseinrichtungen in endemischen Gebieten, insbesondere Informationen zu ihren Diensten und des Zugangs zu diesen wesentlich ist.

Schlüsselwörter: Geographisch gewichtete Regression (GWR), Methode der kleinsten Quadrate (OLS), Akaike Information Criterion (AIC), physikalische Umwelt, lokalKlima, Sumatra, Regenfälle, Elevation, Entfernung zum Wasser, Ländliches Gebiet, Vieh, Zooprophylaxe, Zoopotenzierung, Multivariate-logistische Regressionsanalyse, Malaria-prävalenz, Soziale Gesundheitsdeterminanten, Sozialepidemiologie und Gesundheitsdienste der Gemeinschaft.

Summary

Malaria is an environmental disease, influenced not only by physical and biological environmental factors but also by socio-cultural ones. These factors affect each other, and, in turn, cause the disease in endemic areas. Some factors that cause the high morbidity rate associated with the disease include climate change, physical environment that varies geographically, socio-economic circumstances, and human behaviour in the affected areas. Other risk factors include housing conditions and poor sanitation, lack of hygiene practices, and inadequate health services in endemic areas. Efforts to eliminate malaria have been a topic at various public health meetings for decades. However, in Indonesia, malaria continues to be one of the leading causes of morbidity and mortality. The research aimed to analyse and model the critical variables associated with malaria in endemic areas of Indonesia. So, this included relationships between malaria and both socio-demographic variables and physical environments. The research is in **three parts**, adding value to a model that determines malaria in Indonesia.

This dissertation follows a cross-sectional design survey. The research data in this PhD dissertation is drawn from four sources: routine reporting of malaria from provincial health departments in South Sumatra; the national basic health research data (IDN acronym: Riskesdas); climate data from the Meteorology, Climatology, and Geophysics Climatological Agency (IDN acronym: BMKG); spatial data from Geospatial Information Agency (IDN acronym: BIG). This study takes a holistic approach, integrating the following univariate, bivariate, and multivariable logistic regressions, to establish a modelling determinant of malaria. Additionally, the researchers compared the performance of both Geographically Weighted Regression (GWR) and Ordinary Least Square (OLS). It also used some statistical analysis software tools for data processing, analysis, visualisation, and the development of the model as follows: Statistical Package for the Social Sciences (SPSS), Stata, Aeronautical Reconnaissance Coverage Geographic Information System (ArcGIS) 10.3, and GWR 4.0 version 4.0.90 for Windows.

The prevalence of malaria varied according to the local area, which, in turn, was related to the local physical environment that varied geographically. The determinants for malaria cases varied locally and regionally as well. Rural areas with a high percentage of households keeping livestock/pets showed a higher proportion of malaria prevalence than the national average. Other socio-demographic risk factors included gender, age, occupation, knowledge about healthcare, protection against mosquito bites, and condition of dwellings. This study reveals that the independent variables - "rainfall", "altitude", and "distance from mosquito resting sites in the forest," in global OLS analysis- are significantly associated with malaria cases in South Sumatra, Indonesia.

On the other hand, in the GWR analysis, the determinants of malaria cases at the village level vary geographically. Therefore, it is essential for the decision maker, the government, to acquire a more in-depth understanding of region-specific, ecological factors that influence confirmed malaria cases. The findings lead to the recommendation for developing sustainable regional malaria control programs and incentivising malaria elimination efforts, particularly at the village level. In another setting, the research led to the conclusion that the presence of mid-sized livestock comprised a significant risk factor for contracting malaria in rural Indonesia. The recommendation, especially for the study area, is to employ integrated vector management (IVM), for example, the simultaneous implementation of insecticide-treated bed nets (ITNs) and insecticide-treated livestock (ITL). Other factors such as socio-demographic and use of health care facilities were also crucial as they related to malaria prevalence. Further, the research leads to the recommendation for increased education and increased promotion and utilisation of the health care framework to promote knowledge and awareness of villagers on how to protect themselves from Anopheles bites. Finally, improving information concerning the availability of health care services and access to various health facilities in endemic areas is essential.

Keywords: Geographically weighted regression (GWR), ordinary least squares (OLS), Akaike information criterion (AIC), physical environment, local climate, Sumatra, rainfall, elevation, distance to water, rural area, livestock, zooprophylaxis, zoopotentation, multivariable analysis, malaria prevalence, social health determinants, social epidemiology, and community health services.

List of abbreviations

An.	:	Anopheles
ANC	:	Antenatal care
ANOVA	:	Analysis of variance
AOR	:	Adjusted odds ratio
API	:	Annual parasite incidence (number of slides positive for parasite × 1000/total population)
ArcGIS	:	Aeronautical Reconnaissance Coverage Geographic Information System
Balitbangkes	:	Badan Penelitian dan Pengembangan Kesehatan (National Institute for Health Research and Development)
BIG	:	The Geospatial Information Agency (IDN acronym: BIG)
BMKG	:	Meteorology, Climatology, and Geophysics Climatological Agency
BPS	:	Central Agency on Statistics (IDN acronym: BPS)
CI	:	Confidence interval
CV	:	Cross validation
DEM	:	Digital elevation model
DOF	:	Degrees of Freedom
GRDP	:	Gross regional domestic product
GWR	:	Geographically weighted regression
HDI	:	Health Development Index
IDN	:	Indonesia
IRS	:	Indoor residual spraying reduction
ITL	:	Insecticide-treated livestock
ITNs	:	Insecticide-treated bed nets
IVM	:	Integrated Vector management
LLINs	:	Long-lasting insecticidal net
MDGs	:	Millennium development goals
MoH	:	Ministry of Health
MP	:	Malaria prevalence
NAD	:	Nanggroe Aceh Darussalam
NIHRD	:	The national institute for health research and development

NMCP	:	National malaria control programme
NMTDP	:	National Medium-Term Development Plan (IDN acronym:RPJMN)
NTB	:	West Nusa Tenggara
NTT	:	East Nusa Tenggara
OLS	:	Least squares regression
OR	:	Odds ratio / unadjusted odds ratio
P	:	*Plasmodium*
PHCs	:	Primary health centres
Polindes	:	Pos bersalin desa (village maternity clinic)
Poskesdes	:	Pos kesehatan desa (village health post)
Posyandu	:	Pos pelayanan terpadu (integrated health post)
Puskesmas	:	Pusat kesehatan masyarakat (primary health care centre)
Pv	:	P-values
RDTs	:	Rapid diagnostic tests
Riskesdas	:	Riset kesehatan dasar (Basic Health Research)
Ristekdikti	:	Ministry of Research, Technology and Higher Education (IDN acronym:Ristekdikti)
SPSS	:	Statistical Package for the Social Sciences
Susenas	:	the National Socioeconomic Survey (Indonesia acronym: Susenas)
Svy	:	Survey
UNICEF	:	United nations children’s fund
VBDs	:	Vector-borne diseases
VIF	:	Variance inflation factor
WGS84	:	the World Geodetic System 1984
WHO	:	World Health Organization

Comprehensive Summary

1.1 An introduction with reference to the overall research question

Malaria, as a vector-borne disease is still a public health problem in the world, including in Indonesia.[1]. More than 80% of the deaths related to the *Plasmodium vivax* pathogen are in Ethiopia, India, Indonesia, and Pakistan. Although *Plasmodium vivax* infection is generally related to severe disease and death, the specific risks are uncertain[2]. Malaria is endemic in nine of the 11 countries of South-East Asia Region, accounting for approximately 70% of the burden outside the WHO African Region[3]. Almost 63% of the cases are due to *P. falciparum*. Indonesia accounted for 16% of the reported cases, and 30% of malaria deaths in 2016. Instead, 85% of estimated vivax malaria cases occurred in just five countries, including in Indonesia [3]. There are more than 3.3 million people at potential risk of malaria, who live in regions of high malaria transmission when the world changes the paradigm of the Millennium Development Goals (MDGs) to the Sustainable Development Goals (SDGs), it is crucial that the fight against malaria keep on [4]. Malaria elimination policy included in the MDGs target in 2015, and also contained in the Decree of the Minister of Health of the Republic of Indonesia, as well as in the national medium-term development plan (NMTDP) 2010-2014 with the target of reaching the annual parasite incidence (API) of 2015 is 1 ‰. National Strategic of Ministry of Health 2015 – 2019: number of districts with API < 1 per 1,000 (under MoH monitoring). The emphasis on health development is done through preventive and curative approaches by improving public health to reduce malaria morbidity[5]. Currently, as in medium-term development plan of 2015-2019 has a target enhanced control of communicable and non-communicable diseases. Numbers of districts/cities that are succeeded in eliminating malaria from initial status is 212 of districts/cities in 2013 to achieve target 300 of districts/cities in 2019 [6]. The Indonesian government has set a national goal for Indonesia to be malaria-free by 2030 [1,7,8]. However, malaria is still one of the leading causes of morbidity and mortality in Indonesia [9]. The National Malaria Eradication Program of 1959-1968; which we called of KOPEM (Komando Operasi Pembasmian Malaria, the Malaria Eradication Operation Command) was set up in 1962 by the first Presiden Indonesia, who initiated malaria control efforts, and Indonesia has set the year 2030 as a deadline for the elimination of malaria in the archipelago [10,11]. However, malaria remains a public health problem in Indonesia despite various attempts being made for its elimination, including its discovery and management, infection prevention, surveillance

performance, availability of logistics and follow-up plans. There, 15 provinces with malaria prevalence higher than the national average. Each region has different geographical conditions, causing differences between the areas of malaria cases. The national prevalence of malaria (based on the diagnosis of health professional and respondent complaints) was 2.85% in 2007 and malaria prevalence in 2013 was 6.0 % [12,13]. Besides, malaria is a serious disease and a threat to life in South Sumatra Province, Indonesia. Some studies show the complexity of causes for malaria prevalence [14, 15, 16, 17]. Its target coincides with the level of malaria endemicity and the strength of the health infrastructure [18]. The country shows nationwide a continuously decreasing incidence of malaria, but at the district level, the situation is more complex[16]. For example, the regional deadline for malaria elimination for the island of Java was the end of 2015[7]. Some areas have shown efforts to eliminate malaria [7,19]. Furthermore, the Purworejo Region, a malaria-endemic zone in Java with an API of 0.05 per 1,000 resident in 2009, wants to introduce this elimination phase[7]. To achieving malaria elimination, good evidence is needed concerning the relationship between malaria and environmental risk factors.

1.2 A presentation of the manuscripts respectively the publications

This present study explores some risk factors that influence malaria in Indonesia. Furthermore, this dissertation **divided into three studies** to get comprehensive information regarding determinants malaria in an endemic area in Indonesia, which evidence-based. An increased understanding of the dynamics of transmission of *falciparum* and *vivax* malaria could suggest improvements for malaria control efforts [20]. As an example, China has experienced noticeable changes in climate over the past 100 years, and modelling shows that the potential impact of climate change on the transmission of mosquito-borne infectious diseases poses a risk to Chinese populations[21]. Henceforth, malaria transmission is also affected by changes in meteorological conditions which influence the biology of the parasite and its vector [22]. There are a large number of factors that affect potential susceptibility to malaria that involves social, demographic and geographic dimensions[23]. The principal factors associated with malaria prevalence include environmental, socio-demographic and behavioural ones[24]. Infection with malaria parasites is directly dependent on mosquitoes and human characteristics. Environmental variables such as "altitude", and "land cover" are predicted to affect malaria[25]. Besides, the "rainfall", and "temperature" can predict the risk of malaria transmission and modify the breeding site of Anopheles. The regions with having a significant "precipitation" and

higher "temperatures" are expected to possess a higher prevalence of malaria because this condition supports the breeding of many Anopheline species and reproduction of parasites in mosquitoes[26]. The analysis of the spatial malaria epidemiology can describe a geographical distribution of the prevalence of the disease. To analyse the elements of geographical influence (a risk factor for spatial epidemiology of malaria), so, a modelling approach can be used to uncover the relationship with malaria prevalence [27,28]. At its simplest, maps can identify the location of cases of malaria. There are issues to be overcome with the production of charts and analysis of data [29]. First, modelling can be used to map disease distribution and attempt to uncover underlying patterns. Second, is to analyse the spatial relationships between the variables: disease and critical factors). It is usually done at a regional level by aggregating local level data. Finally, general clustering is done to identify areas of unusual incidence [29]. Also, the presence of livestock in a rural area, and socio-demographic factors (gender, age, education, and job), the behaviour of participants (using insecticide-treated mosquito nets) influence malaria prevalence [30]. In Indonesia, the presence of livestock in households is common with 39.4% of households raise poultry, 11.6% raise medium-sized, 9.0% raise large-sized animals and 12.5% raise animals such as dogs, cats, or rabbits. Of the families who raise livestock, around 10-20% raise them in house[12]. Since malaria had been early acknowledged as being transmitted by zoophilic vectors, zooprophylaxis is used to prevent disease, but also zoopotentation has been observed. While the existence of livestock as a variable of interest for malaria risk has been widely accepted, the other outcomes of small-to-medium-sized studies are still highly debated. For example, Franco *et al.* (2014) stated that there was controversy over research on the presence of livestock, although based this was based on studies investigating. The presence of animals as a protection against malaria in countries such as New Guinea, Papua and Sri Lanka.

On the contrary, cattle have been proven to be a risk factor for malaria in several countries, such as Pakistan, Philippines and Ethiopia [31]. Habtewold *et al.* (2001) analysed the habits of *An. arabiensis and An. quadriannulatus* are known as a low proportion of human blood meal occurrence [32]. In this study, based on the Riskesdas questionnaire, the animal domestic categorised are livestock, pets, and poultry. The term livestock includes here large-sized animals (cattle, horses, buffaloes), medium-sized animals (goats, sheep, pigs). Additionally, poultry, such as chicken and ducks, and pets, such as dogs, cats and rabbits, are included in the term of *pets* [12]. The proportion of households who raise livestock

indoors is lower in urban areas than in the countryside [12]. The present study investigates if the prevalence of malaria is higher amongst participants who raise cattle in rural malaria endemic areas. Indeed, malaria is a global health challenge and is an increasing concern, especially in the endemic provinces in Indonesia. Further explanatory variables are the accessibility to and utilisation of health services, environmental sanitation as well as the quality of drinking water, primary water source, distance to drinking water, wastewater disposal associated with malaria prevalence. However, the extent to which the explanatory variables influence malaria prevalence remains poorly understood. A range of environmental risks, socio-demographic, behaviour, and structural factors have been implicated affect malaria prevalence. This study used data from the large-scale survey Riskesdas to explore the accessibility and utilised of healthcare facilities such as a public hospital or government hospitals; private hospitals; primary health care (PHC) and investigated their connection with malaria prevalence. In addition, healthcare facilities others are clinics or doctor practices, midwife practices or maternity hospital; and integrated health posts (Posyandu). The participants were also asked for utilised and access healthcare of rural health posts (Poskesdes) and rural clinics (Polindes). Next to these potential explanatory variables for malaria prevalence, environmental sanitation like and preventative behaviour against mosquito bites by using mosquito repellent, or insecticide sprays, anti-malaria drugs, and housing conditions were investigated.

The present study aimed to analyses multiple potential determinants of malaria in Indonesia. Data collection described the local physical environment, presence of livestock in a rural area and socioeconomic data not only from regular health reporting in the endemic area but also from large-scale surveys in Indonesia 2007 and 2013, respectively. The data were integrated and analysed utilising an epidemiological modelling approach.

The specific objective of this research was divided into three studies. Firstly, the particular goal of this dissertation is to examine the relationship between confirmed malaria cases and local environmental risk factors in high malaria endemic areas with spatial analysis. (**Study #1**). Secondly, the objective of this paper is to determine the effect of the presence of livestock on malaria prevalence in malaria-endemic rural areas in Indonesia, in a large endemic setting. (**Study #2**). Thirdly, the last part explored the relationship between the prevalence of malaria and social and demographic factors (**Study #3**). The research data in this dissertation was drawn from four primary sources: routine reporting malaria from health provinces in South Sumatra; the national basic health Research data (Indonesia

(IDN) acronym: Riskesdas); climate data from Meteorology, Climatology, and Geophysics Climatological Agency (IDN acronym: BMKG); and spatial data from Geospatial Information Agency (IDN acronym: BIG) [30,33,34]. In general, these sources provided data for the years 2007 and 2013 [12,13]. The research generated descriptive data for all variables, and the data were analysed using bivariate, and multivariable logistic regression analyses to predict malaria prevalence at a significance level of P value < 0.05. For s**tudy #1**, The malaria cases were distributed over 436 out of 1,613 villages. This study performs both Ordinary least square (OLS) and geographically weighted regression (GWR) analyses to demonstrate connection confirmed malaria cases and potential ecological predictors [33]. The research explored the global pattern and spatial variability relationships among of six potential environmental predictors: were the altitude, aspect, distance from the river, distance from lakes and pond, distance from the forest, and rainfall and confirmed malaria cases in the study area [33]. Local variations in environmental variables potentially predicted confirmed cases of malaria. Therefore, the local spatial epidemiology and the distribution of risks of malaria cases were investigated and associated environmental risks identified using spatial discrimination. This study analysed environmental risk factors for malaria that performs at the global OLS and local GWR modelling at the regional level in South Sumatra.

Further, **study #2** using Riskesdas 2007, the subset included 259,885 study participants who resided in the rural area at 176 regencies of 15 provinces with malaria prevalence higher than the national average. The research used multivariable logistic regressions to investigate the role of several variables in the prevalence or status of malaria. These included "the existence of livestock" and other independent demographic, social and behavioural variables [30]. The participants had been diagnosed positive for malaria by a health professional (i.e., with malaria during the past month). Generally, rapid diagnostic tests (RDTs) and microscopy by health services confirmed the diagnosis. Independent questionnaire data at the individual and household level added further information. This included characteristics of participants (gender, age, education, principal occupation), mosquito bite avoidance behaviour (e.g., sleeping under a mosquito net, using net insecticide, defecating habits), and access to and use of health services (health services access by travelling), environmental sanitation (type of container/media, sewage canal, sewage canal conditions), and, for medium and large livestock, the location of cages. The

binary categories of the independent variables were "yes" and "no" and led to an analysis of a potential relationship with the response variable malaria.

Furthermore, s**tudy #3** used Riskesdas 2013 data[13]. The current study **(# 3**) included 130,585 participants (the population of five provinces in 83 districts endemic to malaria). The third study investigated the relationship between socio-demographic determinants and malaria prevalence using multivariable logistic regression analysis [34].

1.3 Discussion of the results obtained and their relevance with regards to the research question.

Detecting the spatiotemporal distribution and mapping of high-risk areas are useful to strengthen malaria control efforts and ultimately achieve elimination[35].Therefore, understanding the spatial epidemiology of malaria is essential for developing strategies for disease control and elimination[36]. This study provides an exciting opportunity to advance our knowledge of the role of physical environment locally, the presence of livestock in the rural area, and sociodemographic influences on malaria prevalence. Based on the research questions, this study shows that in **study #1** reveals that the most significant correlations with malaria were with the independent variable altitude, distance from forest, and rainfall (global OLS) [33]. However, as noted by the GWR model and in line with recent reviews, the relation between malaria and environmental influences in South Sumatra was found to vary spatially greatly between different regions. The global OLS model reveals that rainfall had a significant positive coefficient, whereas altitude and distance to the forest had substantial negative coefficients. These indicated a meaningful relationship with confirmed malaria cases. Regions with high rainfall, lowland, and areas adjacent to the forest had high malaria cases globally. Whereas there was no meaningful relationship between malaria, and. Environmental factors such as aspect or direction towards the slope, distance from the river, and the distance from lakes and pond globally. On the other hand, in the GWR analysis indicate the determinants of malaria cases at the village level vary geographically. For example, the variable "altitude" and "distance from lakes and ponds" shows a positive correlation and "aspect" presents a negative association with confirmed malaria cases in the North study area (Musi Banyuasin) locally. Also, "Rainfall" and "distance from the river" parameter denotes a positive connection with malaria cases in the eastern part of Musi Rawas and Lahat. Besides, variable "aspects", "distance from lakes and ponds" and "distance from forests" were positively associated with confirmed malaria cases which reported in most study

areas. In line with previous studies, climatic factors that influence the prevalence of malaria include precipitation (rainfall), temperature and humidity[37]. Variations and changes in local weather and meteorological conditions are well known to affect malaria transmission. The effect of climate on the *Anopheles* populations is well established [38]. Rainfall, temperature and humidity are associated with malaria transmission and are important determinants of the dynamics, and the spread of the malaria vector population [38, 39, 40,41, 42.] Altitude significantly influences the type of malaria vectors [25,43]. Moreover, the density of the vector and the frequency of bites on humans [25]. Also, both altitude and direction toward the slopes contribute to the transmission of malaria in the highlands [44]. However, some studies have shown that the drivers of malaria seasonality are not always clear [14]. The understanding concerning the complexity of malaria transmission from climate aspects is still found a significant gap. So, it needs there have been motivated efforts to develop more comprehensive models [15]. At best case, climate variability can provide information for an early warning system for epidemic malaria, and this has been investigated in previous studies [45]. It is crucial that we have a better knowledge of the spatial and temporal patterns of determinants of malaria risk for the prevention and control of the malaria program [46]. Furthermore, GIS presentation of environmental health data could provide an efficient means of translating this knowledge to lay audiences[9]. Further, in **study #2** was in rural malaria endemic areas of 15 highly malaria-endemic provinces in Indonesia and indicated that certain livestock facilitated malaria prevalence and was not suitable as a prophylactic tool. The research found that the participants who raised medium livestock (1.16%, OR = 1.80) had a significantly increased risk of malaria ($P < 0.001$). After adjusting for gender, age, education, job, use of insecticide-treated mosquito nets, and keeping of pets, participants who raised goats, sheep and pigs had an increased likelihood of having malaria (adjusted for other variables; AOR = 2.809; 95% CI 2.207–3.575; $P < 0.001$) [30]. These proceeds lead to the conclusion that the existence of medium-sized livestock (e.g., goats, sheep, and pigs), is a significant risk factor for malaria in the study area. Other principal factors affecting the prevalence of malaria are demographic factors: for gender, age, education, job, use of insecticide-treated mosquito nets, and keeping of pets. The existence of livestock as an essential variable for malaria risk has already been assessed in small to medium scale surveys in both developed and developing countries and has been controversially discussed. One notable finding is the planned control of using livestock to divert the vector bites, called "zooprophylaxis", or

as a switch to draw vectors to insecticide sources, called "insecticide-treated livestock (ITL)." These strategies have been used since malaria was acknowledged to be transmitted by zoophilic vectors [31]. Zooprophylaxis is defined by WHO as “The value of wild or domestic animals, which are not the source hosts of a given condition, to alter the blood-seeking mosquito vectors from the human hosts of that disease"[47]. Active zooprophylaxis consists of strategically placing animals between mosquito breeding sites *and* people's houses. Meanwhile, passive zooprophylaxis is the protective effect of the constant presence of animals within a community [48]. Researcher, Escalar G (1933), Saul A (2003) Kawaguchi (2004), Killeen (2007), et al. in the study stated that since the early 1900s, zooprophylaxis has been recognised as an essential tool to decrease malaria transmission to people in some locations of the world and this approach has been evaluated for another vector-borne disease [48]. Livestock has been considered the most appropriate host for this strategy. The term used to refer to livestock includes cattle and small and large ruminants and other domestic animals, such as buffalo, sheep, goats, donkeys, horses, and pigs [31]. Studies have revealed that ownership of livestock investigated at the household level has a substantial impact on the behaviour of the malaria vector. However, there is no clear risk of malaria exposure to livestock presence [49]. The profusion of *An. gambiae* and *An. arabiensis* in housing is related to the spread of domestic animals and humans[50]. Additionally, livestock is thought to be mostly accountable for generating high mosquito densities. With further analyses, the researchers Bouma and Rowland revealed a strong, positive correlation between the cattle-to-man ratio and malaria incidence [51]. Furthermore, in **study #3** revealed, using multivariable analysis, that independent socio-demographic risk variables were related to malaria prevalence. These were: gender, age, occupation, knowledge about healthcare services, preventative measures against mosquito bites, and housing conditions. Participants who did not know about the available health facilities were 4.2 times more likely to have malaria than those who did know adjusted odds ratio (AOR) = 4.18; 95% CI 1.52 - 11.45; P = 0.005, adjusted by other covariates [34]. Healthcare facilities included in the data were government hospitals, private hospitals, primary healthcare (puskesmas), clinics, midwife practices, integrated health posts (posyandu), village health posts (poskesdes), and village maternity clinics (polindes). The study concluded that health services, as well as their networks, are essential for malaria elimination. To guide the development of effective strategies for malaria elimination needs an understanding of the connections between

malaria and other factors. In Indonesia, little is known about the determinants of malaria prevalence among sociodemographic factors. The potency of the PHC system in achieving those most at risk and reducing the disease burden and that inadequate approach is a significant risk factor particularly for the poor households [52]. Currently, a major component of malaria control strategies to reduce malaria-related mortality and severe morbidity is early diagnosis and prompt treatment at peripheral health services such as village health posts and dispensaries[53]. The study demonstrates that the incidence of hospitalised malaria more than doubled as travel time to the nearest primary care resource built from ten minutes up to two hours. Good access to PHC facilities may reduce the burden of disease by 66%[54]. Recently illustrated from a Tanzanian demographic surveillance site (DSS) section suggests that the most impoverished infants and kids under five years old had higher risks of death than those in the least-poor socio-economic quintiles [23]. Primary education on the prevention of malaria should be built up by the National Malaria Control Programme (NMCP) in all the countries to reduce malaria prevalence, particularly among under-five children[55]. Also, ITN use and the age of the child were found to be significantly related to fever incidence[23]. To focus on the shortcomings in local education about malaria, health personnel worker serving in malaria-endemic regions should be skilled in providing more proper counselling for changing certain deeply ingrained traditional behaviours such as settling time outdoors in the evening, inappropriate use of bed nets and occasional use of insecticides during sleep [56]. This research concludes as follows: **firstly,** regarding the analysis using GWR that the importance of different environmental and geographic parameters for malaria disease was shown at global and village levels in South Sumatra, Indonesia. It has been conclusively shown that the independent variables altitude, distance from forest, and rainfall in global OLS were significantly associated with malaria cases. However, as shown by the GWR model and in line with recent reviews, the relationship between malaria and environmental factors in South Sumatra strongly varied spatially in different regions (**Study #1**). **Secondly,** it has been noted that the presence of only certain livestock is the major risk factor for contracting malaria in rural Indonesia. Raising medium-sized animals in the house was a significant predictor of malaria prevalence (OR = 2.980; 95% CI 2.348–3.782, $P < 0.001$) when compared to keeping such animals outside of the house (OR = 1.713; 95% CI 1.515–1.937, $P < 0.001$). After adjusting for gender, age, access to the community health facility, sewage canal condition, use of mosquito nets and

insecticide-treated bed nets, the participants who raised medium-sized animals inside their homes were 2.8 times more likely to contract malaria than respondents who did not. (**Study #2**). **Thirdly,** this study indicates that there is a relationship between socio-demographic factors and their influence on malaria prevalence. This study reported that the different relationships between malaria and those variables, the socio-demographic factors can affect malaria included characteristics of participants. The analysis of baseline socio-demographic data revealed the following independent risk variables related to malaria prevalence: gender, age, occupation, knowledge of the availability of healthcare services, measures taken to protect from mosquito bites, and housing condition of study participants. Multivariable analysis showed that participants who were unaware of the availability of health facilities were 4.2 times more likely to have malaria than those who were aware of the health facilities. Factors that can be managed and would favour malaria elimination include a range of prevention behaviours at the individual level and using the networks at the community level of primary healthcare centres (**Study #3**). In addition, this research recommends a multi-disciplinary approach to be able to understand transmission. The four components, i.e. human, vector, parasite, and environment, all play an essential role in the system. Therefore, the vector component of the system, the parasite component of the system, those that address environmental and the last two each address the human element. The findings reported here suggest that attention needs to be given to vulnerable populations. Also, improving the accessibility and utilisation of health services to protect the community from malaria effectively. Improving proper environmental sanitation, promoting prevent techniques from mosquito bites, and improving housing conditions. Ensuring appropriate systems, services, and support for reducing malaria prevalence should be a priority for vulnerable groups. Besides, this study recommends having interventions for all components systems that are being scaled up in malaria-endemic areas. The strategies are not enough to focus on in the parasite side, that is treatment, and they address the vector component. So, one of the reasons is that those interventions have prominent implementation protocols that have been designed. The findings of this study have some significant implications for future practice. Taken together, these findings support strong recommendations to campaign for the reduction and elimination of malaria in an endemic area. Finally, providing resources to implement recommendations is essential.

Overview of the manuscripts and publications accepted for release

Malaria is a public health hassle inside the international included in Indonesia. The causes of malaria prevalence are quite complex. Understanding the link among the environmental risk factors, the presence of livestock, and socio-demographic factors will help the decision maker to create a strategy for elimination and eradication of the disease in Indonesia and beyond. Factors which potentially influence malaria prevalence, and which were investigated in the present studies included not only the presence of livestock in a rural area that may affect vector abundance, density, or activity but also physical environmental factors, socio-demographic and behavioural factors. The research also described the direct cause of malaria: plasmodium parasites and vector specificity in Indonesia. The research described spatial epidemiology, climate and the physical environment, livestock issues, and socio-demographics as one determinant of malaria. The general purpose of this doctoral dissertation was to analyse the determinants of malaria in malaria-endemic areas of Indonesia. Relevant analytical methods included univariate, bivariate, and multivariable logistic regression analysis (including Geographically Weighted Regression (GWR)) to explore the relationships between malaria incidence and other epidemiological, local weather, geographic, and socio-demographic data. The overview of the publications accepted for release is below.

Publication #1 summarises the main findings of this PhD dissertation that malaria prevalence was related to different local environments, which varied geographically. This chapter analysed temporal and spatial variations of malaria prevalence and described territories and periods with a higher risk of malaria on a local geographic scale within the endemic malaria country, Indonesia. The research identified local environmental risk factors by comparing GWR and OLS analysis to understand the influence of the local environment on malaria cases. This study hypothesised that the global OLS and local GWR modelling could be performed to analyse the environmental risk factors for malaria case in South Sumatra province, Indonesia, that varied geographically at the regional level. This result of this research expected that would be useful for malaria elimination in a defined geographic area. **Publications #2 - #3**, showed that the presence of livestock and socio-demographic determinants affect malaria prevalence based on the analysis of secondary data from Indonesian regular reporting on malaria and large-scale survey Riskesdas. **Publication #2** used data from the large-scale survey Riskesdas 2007 and hypothesised that there was a relationship between malaria and livestock presence in rural

endemic areas in Indonesia. This part of this paper showed that the presence of livestock was associated with malaria prevalence in eastern Indonesia. Similarly, another study revealed associations between malaria risk and environmental, socio-demographic, and behavioural variables in western Kenya of East Africa [24]. **Publication #2** assessed the significance of the presence of livestock for malaria prevalence in rural areas that had a higher proportion of malaria disease than the national average in Indonesia. **Publication # 3** hypothesised that malaria prevalence (dependent variable) in endemic areas in Indonesia was influenced by the socio-demographic characteristics of the population (independent variable). The research explored socio-demographic variables related to malaria prevalence, characteristics of participants, including gender, age, education, and employment and behaviour (e.g., use of bednets). The large-scale cross-sectional survey of the national basic health research (Riskesdas 2013) provided the socio-demographic data for this study. The design of the overall Riskesdas investigation was mainly to describe the health problems of all the people of Indonesia. It focused on many Indonesian health problems, including malaria and its potential drivers and data specific for this dissertation were derived from this. **Publication #3** analysed the socio-demographic factors noted above and behavioural factors, including accessibility and utilisation of health services and environmental health factors related to malaria prevalence. The socio-demography epidemiological models resulting from the present study are expected to produce comprehensive information both for spatial and non-spatial issues and to provide information for decision-makers to develop effective strategies to reduce and eradicate malaria in Indonesia. The doctoral dissertation may also strengthen national capacities for epidemic preparedness and response in support to the national implementation of the malaria prevention and elimination program in malaria-endemic areas. The success of roadmaps of national malaria elimination programs depends on using a sophisticated One Health approach and local interventions, namely interconnecting biological, social, physical, ecological, vector, local environment topography and weather, and technological processes. The government, academic institutions and some related agencies and the multidisciplinary professional team should support these efforts. At the same time, community awareness must be established to support the country's malaria elimination goals through knowledge sharing, capacity building, operational research, and advocacy.

The manuscripts/publications

This doctoral dissertation is based on the following publications as listed in the following:

Hasyim H, Nursafingi A, Haque U, Montag D, Groneberg DA, Dhimal M, et al.: **Spatial modelling of malaria cases associated with environmental factors in South Sumatra, Indonesia.** *Malar J* 2018, **17:**87., that available in https://malariajournal.biomedcentral.com/articles/10.1186/s12936-018-2230-8

Hasyim H, Dhimal M, Bauer J, Montag D, Groneberg DA, Kuch U, et al.: **Does livestock protect from malaria or facilitate malaria prevalence? A cross-sectional study in endemic rural areas of Indonesia.** *Malar J* 2018, **17:**302., that available in https://malariajournal.biomedcentral.com/articles/10.1186/s12936-018-2447-6

Hasyim H, Dale P, Groneberg DA, Kuch U, Müller R. **Social determinants of malaria in an endemic area of Indonesia**. *Malar J.* 2019;18(1):134. that available in https://malariajournal.biomedcentral.com/articles/10.1186/s12936-019-2760-8

Parts of the doctoral dissertation were also presented at prestigious scientific meetings. An oral presentation was given in the workshop " One Past Health" at Max Planck Institut für Evolutionsbiologie, Plön, Germany from 15-17th February 2017.

Also, a poster was presented at the European Conference on Biodiversity and Health in the Face of Climate Change in Bonn, Germany from 27-29 June 2017.

Presentation of the personal contribution regarding manuscripts/publications

My contribution to the publications in the following:

In the first publication, I was responsible for managing this research, design, and data collection, including malaria case data collected from the Provincial Health Department, Ministry of Health, Indonesia. Further, topography map and climate data (rainfall maps). Primary spatial data is obtained from Indonesia's topographic map known as the Indonesian Topographic Map (RBI), and rainfall maps (annual average) are collected by entering the average annual rainfall data from the BMKG Class I Climatology Station in Palembang, South Sumatra, Indonesia. I analysed data using GWR 4.0 version 4.0.90 and Arc GIS 10.3 used for data processing, analysis, and visualisation. I was responsible for data acquisition, pre-processing, and processing supported by a co-author. I also contribute to the interpretation and display of results and compile papers under supervising my supervisor.

In the second publication, I obtained the Riskesdas sub-dataset as of a large dataset based on a cross-sectional survey of the Indonesia Basic Health Research (Indonesia acronym: Riskesdas), which is organised by National Institute for Health Research and Development with a sample framework conducted by the Central Bureau of Statistics. Besides, the study was conceived and designed by me together with my supervisor. Further, I analysed and interpreted the dataset. Finally, my supervisor and I drafted the manuscript with subsequent contributions and revisions.

In the third publication, I designed and performed the collection and analysis of the Riskesdas sub-dataset and managed the study. I contributed to the interpretation and visualisation of the results using Stata software supervised by my advisor. I also drafted the paper under the supervision and guidance of my supervisor independently.

All authors read and approved all the final manuscripts before publication.

Publication #1 Spatial modelling of malaria cases associated with environmental factors in South Sumatra, Indonesia

Hasyim H, Nursafingi A, Haque U, Montag D, Groneberg DA, Dhimal M, Müller R: Spatial modelling of malaria cases associated with environmental factors in South Sumatra, Indonesia. Malaria Journal 2018, **17:**87.

Hasyim *et al. Malar J (2018) 17:87*
https://doi.org/10.1186/s12936-018-2230-8

Malaria Journal

RESEARCH

Open Access

Spatial modelling of malaria cases associated with environmental factors in South Sumatra, Indonesia

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Abstract

Background: Malaria, a parasitic infection, is a life-threatening disease in South Sumatra Province, Indonesia. This study aimed to investigate the spatial association between malaria occurrence and environmental risk factors.

Methods: The number of confirmed malaria cases was analysed for the year 2013 from the routine reporting of the Provincial Health Office of South Sumatra. The cases were spread over 436 out of 1613 villages. Six potential ecological predictors of malaria cases were analysed in the different regions using ordinary least square (OLS) and geographically weighted regression (GWR). The global pattern and spatial variability of associations between malaria cases and the selected potential ecological predictors was explored.

Results: The importance of different environmental and geographic parameters for malaria was shown at global and village-level in South Sumatra, Indonesia. The independent variables altitude, distance from forest, and rainfall in global OLS were significantly associated with malaria cases. However, as shown by GWR model and in line with recent reviews, the relationship between malaria and environmental factors in South Sumatra strongly varied spatially in different regions.

Conclusions: A more in-depth understanding of local ecological factors influencing malaria disease as shown in present study may not only be useful for developing sustainable regional malaria control programmes, but can also benefit malaria elimination efforts at village level.

Keywords: Geographically weighted regression (GWR), Ordinary least squares (OLS), Akaike information criterion (AIC), Physical environment, Local climate, Sumatra, Rainfall, Elevation, Distance to water

Background

Malaria is a significant public health concern worldwide, including Indonesia [1]. The Indonesian government has set a national goal to be malaria-free by 2030. Currently, 24 out of 576 districts in Indonesia classified as being malaria endemic, and an estimated 45% of Indonesia's total population are living at risk of contracting malaria [2]. In South Sumatra Province, the malaria incidence was 0.46 per 1000 people in 2013. In this province, the proportion of children under 5 years of age who applied mosquito nets was 32.7%, and the percentage of children under five who treated for fever with antimalarial medication was 89.8% in 2013 [2]. Malaria elimination has been a priority in the millennium development goals (MDGs) [3], and since then has continued to be central to the sustainable development goals (SDGs), supporting Indonesia's malaria elimination commitments [4]. It is now essential to generate the knowledge that is necessary to develop lasting policies for the national malaria elimination programme.

Several meteorological and environmental variables are risk factors for malaria [5]. Since specific meteorological,

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environmental factors are at interplay and different factors can affect malaria transmission within a given province [3, 6, 7], it is important to differentiate between factors that influence the vector, the parasite and the host-vector relationship [8]. Atieli et al. have demonstrated that the topographic variables elevation, slope, and aspect are influencing the development of *Anopheles* mosquitoes [9]. In north-eastern Venezuela, there is a significant association of malaria transmission with local spatial variations like population density, lowland location, and proximity to aquatic environments [10]. Elsewhere (e.g., Ethiopia and Senegal) spatial relationships between climatic variability like rainfall and malaria occurrence have been demonstrated [11]. Rainfall indirectly benefits *Anopheles* mosquitoes by increasing relative humidity which prolongs adult longevity [12], and the number of breeding places which in turn favours population growth [13]. Temperature and the extent of water availability for larval breeding are crucial factors in the vector life-cycle, affecting transmission [3]. Vectors and parasites are both highly sensitive to any temperature changes, for example, the parasite proliferation depends on temperatures [14]. Temperatures above 28 °C have been shown to reduce malaria incidence in Africa [15]. In Indonesia, the optimum temperature for malaria mosquitoes ranges between 25 and 27 °C [3]. For the vector-host relationship, factors such as the distance of people's houses from a river, lakes, pond, distance to the regional urban centre [16–18] distance to forest [19, 20] were shown to be significant predictors.

Spatial nonstationary is a condition in which a simple "global" model cannot define the relationship amongst several sets of variables [21]. Thus, global OLS and local GWR modelling was performed to analyse the environmental risk factors for malaria in South Sumatra that vary geographically at the regional level. The locally different ecological factors studied to potentially predict the response variable 'confirmed malaria case' (Y) are altitude (X1), aspect (X2), distance from the river (X3), distance from lakes to pond (X4), distance from the forest (X5), and rainfall (X6).

Methods

Study area

The study area is located between 1°46′ and 4°55′ of southern latitude and between 102°4′ and 104°41′ of eastern longitude and has a total surface area of 46,377.40 km^2 (Fig. 1). It covers eight endemic malaria districts of South Sumatra, Indonesia, namely Lahat, Muara Enim, Musi Banyuasin, Musi Rawas, North Musi Rawas, Ogan Komering Ulu, South Ogan Komering Ulu, and Lubuk Linggau. The topography of the area varies from lowland to mountainous landscapes. The elevation in the study area varies between 0 and 3150 metres above sea level. The climate is tropical and wet [22]. In 2013 in South Sumatra, the lowest rainfall was 31 mm (August) in Lahat district, and the highest rainfall was 613 mm (March) in Palembang City. Monthly average temperatures ranged from 26.6 to 28.3 °C and relative humidity from 81 to 88% in 2013 [23].

Indonesia's South Sumatra Province is home to 7828,700 inhabitants. In 2013, the gross regional domestic product (GRDP) with oil and gas was IDR 231.68 trillion (17.32 billion USD) [22], based on IDR to USD exchange rates at the time of writing. South Sumatra is an ethnically highly diverse province and home to different local languages and diverse cultural and socioeconomic practices [2]. Local people engage in coffee, rubber and palm oil plantation activities or work in the industrial mining area, which shapes not only people's lives but also the environment [24]. Indonesia contributes significantly to deforestation in Southeast Asia. Recent developments of deforestation have led to unsustainable practices which have resulted in a high frequency of deforestation in some regions and are an important factor influencing malaria incidence [25]. Deforestation has been shown to be connected with malaria incidence in the county (Município) of Mâncio Lima, Acre State, Brazil. There, a cross-sectional study shows 48% increase in malaria incidence are associated with cumulative deforestation within respective health districts in 2006 [26].

Study population and data collection

36,372 patients seeked treatment due to suspected malaria fever in 140 primary health centres (PHC) in the study region South Sumatra during January to December 2013. Among them, 3578 were laboratory positive for malaria. The cases spread over 436 out of 1613 villages that were used for unit analysis. The detailed number of malaria cases in different provinces are presented in Fig. 2. The spatial distribution of participants who had confirmed cases of malaria is shown in Fig. 3.

The patients are categorised into "clinical diagnosis", "suspected malaria" and "confirmed malaria cases". Categories "clinical diagnosis" or "suspected malaria" are based on the patient's symptoms and physical findings at examination. A "confirmed malaria case" is a case of malaria diagnosed microscopically (examination of blood specimen/preparation) or rapid diagnosis test (RDT) with positive results for *Plasmodium*. Either RDT or microscopic assessment or both were used to confirm the diagnosis of malaria. The malaria diagnostic data were obtained from the regular health information reporting system of the Provincial Health Office of South Sumatra. The data had been collected during 12 months (January to December 2013) at the village level from patients

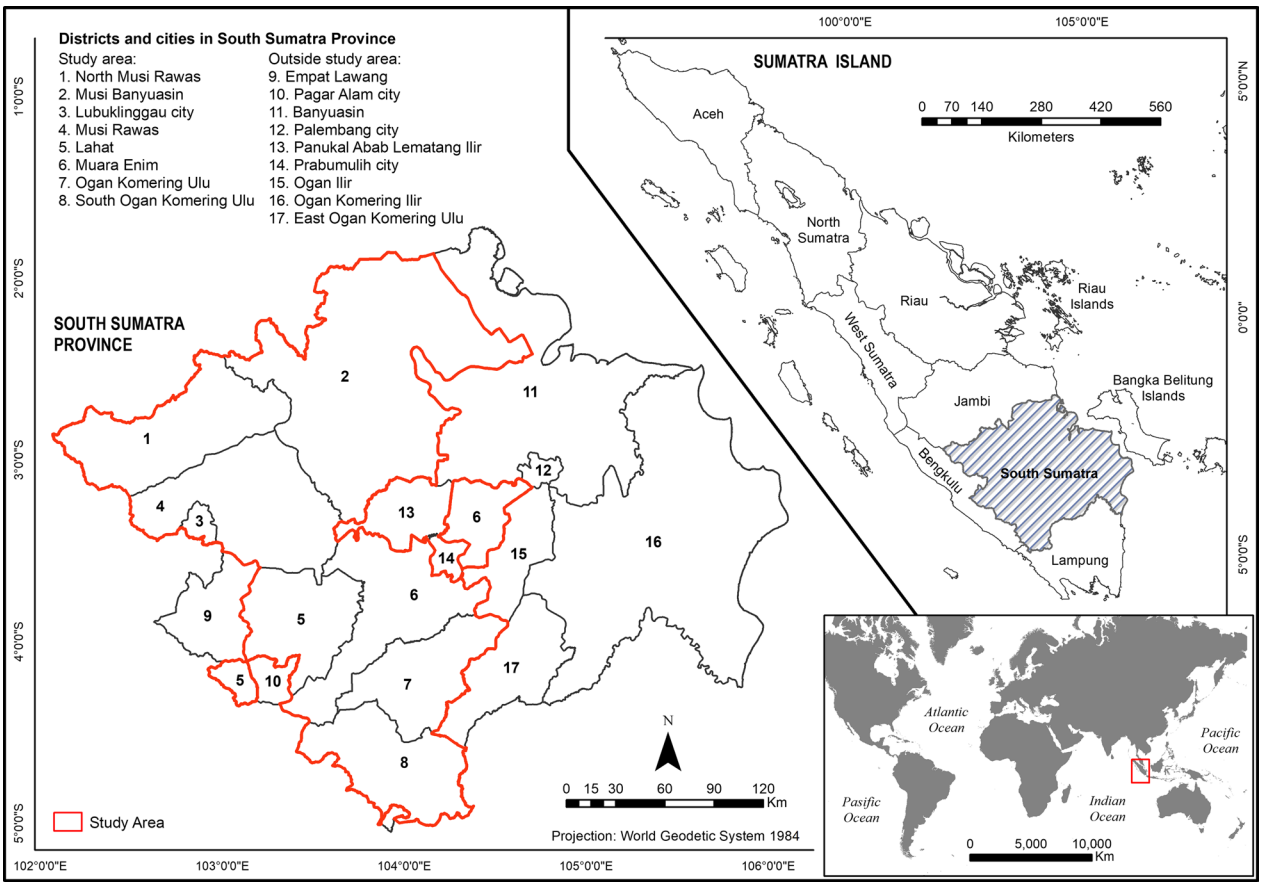


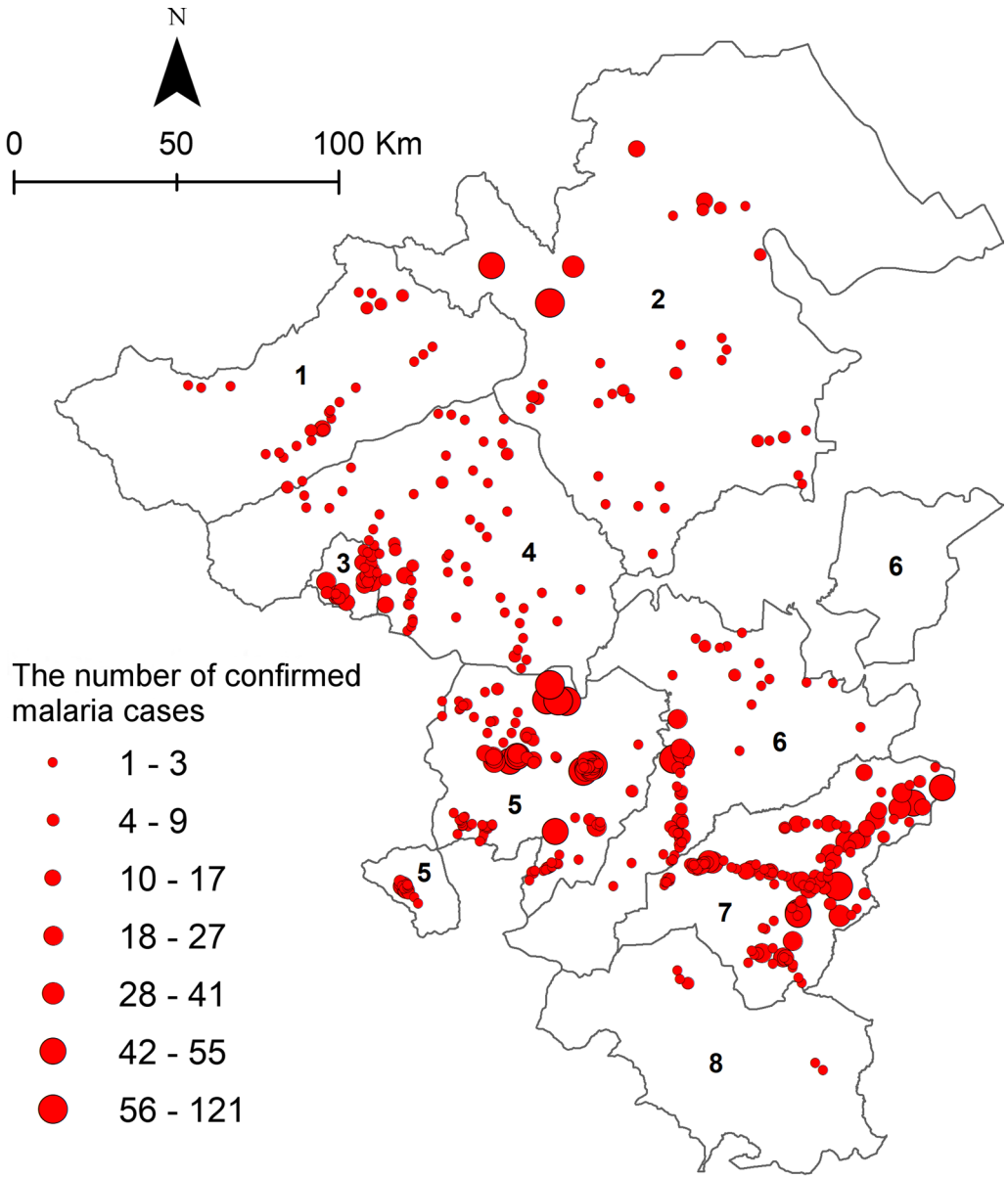
Fig. 1 Map of the study area covering one city and seven districts of South Sumatra Province, Indonesia

seeking treatment in PHC, locally called Pusat Kesehatan Masyarakat ("puskesmas"), and that were reported monthly to the Provincial Health Office via the malaria programmes in the District Health Offices.

Geographic information

The study area map (Fig. 1) uses the World Geodetic System (WGS84) as its reference coordinate system. As shown in Fig. 4, three stages of working with geographic information were distinguished: data acquisition and processing, data analysis and data presentation [27]. GWR 4.0 version 4.0.90 and Arc GIS 10.3 were used for data processing, analysis, and visualization. Malaria case data were collected from the Provincial Health Department, Ministry of Health (see previous paragraph) as well as topographic (toponymy map, hypsographic map, hydrographic maps, land cover map) and climate data (rainfall map). The primary spatial data were obtained from a topographical map of Indonesia (cartographic material) which has a scale of 1:50,000 and consists of several layers of plots grouped. The malaria input data is aggregated village level data with the village centroid used as the spatial unit. This map consisted of a collection of geographic data presented as thematic layers for land cover, hydrographic data and a sheet of hypsography. Indonesian topographic map known as Peta Rupabumi Indonesia (RBI) was updated in 2014. In 2013, topographic data visualisation has been changed into geodatabase cartography to reduce the steps of creating cartography visualisation in topographic mapping activity [28]. These maps were obtained from the Geospatial Information Agency (BIG) of Indonesia. Authorization for the use of the topographical map of Indonesia was provided by the Indonesian Geospatial Information Agency. However, restrictions were put to use the availability of these data and therefore are not publicly available. Data were collected by creating a research protocol which is used under license for the current study. The data that backs the findings of the research are served in the main paper.

The forest cover maps were extracted from the land cover map in 2013 on the scale of 1:250.000. The map was sourced from Ministry of Environment and Forestry, Indonesia. The precipitation map (annual average) was obtained by inserting the data of average yearly rainfall



The primary Anopheles malaria vectors in South Sumatra Provinces:

An. letifer, An. nigerrimus, An. maculatus, An. sinensis, An. barbirostris, An. vagus, and An. sundaicus

Source: Vector and Animal-Borne Disease Control Unit of Research and Development, National Institute of Health Research and Development (NIHRD), Ministry of Health (Indonesia) at Baruraja and some relevant references

Fig. 2 Malaria cases and their geographical locations in the study area

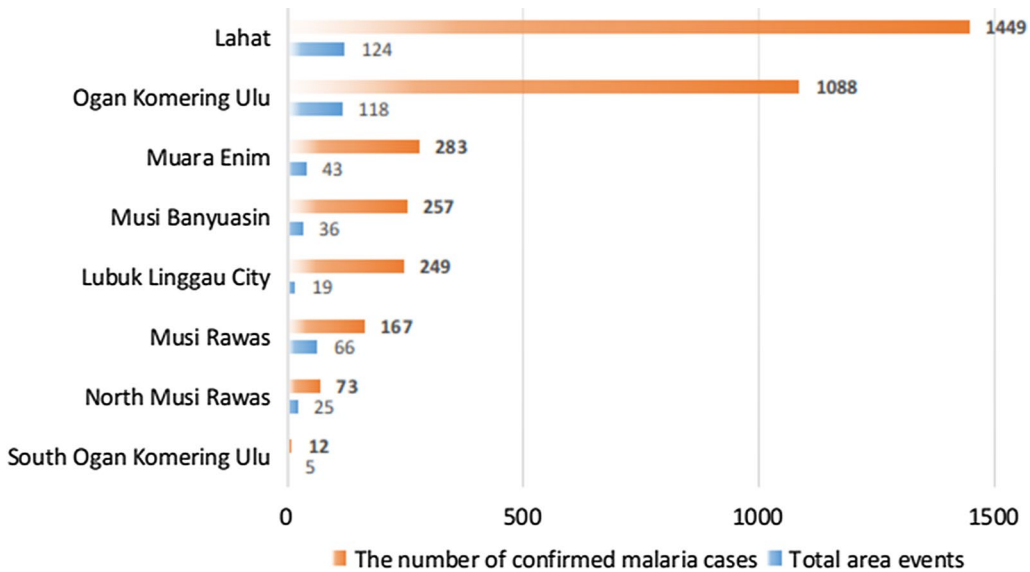


Fig. 3 Malaria cases at village level

from BMKG Climatological Station Class I in Palembang, South Sumatra, Indonesia. The distance between weather observation stations was 50–100 km in flat topography and 10 km in hilly terrain.

Data pre-processing

The malaria distribution map (Fig. 2) was created and six selected explanatory variables plotted (Fig. 5). The altitude map was obtained by interpolation and contouring of the map into a digital elevation model (DEM). Subsequently, the DEM data was converted into a map containing the direction of the slope (aspect). The parameter distance from the river, and distance from lake and pond processed from river, lakes, and ponds maps which were derived from the topographic map whereas distance from the forest processed from forest cover map. These variables were analysed using Euclidean distances. Rainfall parameter was calculated based on annual average rainfall over 5 years, and it was interpolated from several weather observation stations in study area. The rainfall map (isohyets map) was obtained from the scanned maps which are the result of interpolation and classified into several classes. The map needed to be rectified and digitised to get a digital rainfall map.

Data processing and modelling

The response variable "malaria case" and explanatory variables "altitude/aspect", "distance from river", "distance from lake and pond", "distance from forest" and "rainfall" were tested for multicollinearity. Therefore, the values of all explanatory variables were extracted for each case location. An index based on predictive modelling variance, the variance inflation factor (VIF) was used [29]. Multicollinearity could occur when one independent variable was a linear function of another independent variable and previously observed in GWR modelling [30]. The pattern of connection between confirmed malaria cases and environmental factors was expressed by the OLS method. Here, OLS model is called global regression model because the existence of local variation had not taken into account in regression so that the estimate of the regression remained constant. Thus, the regression parameters had the same value for each point within the study area. If spatial heterogeneity occurred in regression parameters, then the information that could not be processed by the global regression model was seen as an error. In such cases, the global regression model was less able to explain the actual data phenomenon [31]. A global regression coefficient value close to zero indicated that the explanatory variables had a small effect on the response variable.

As alternative, the GWR model was used to investigate the relationships between response and explanatory variables since the study area was characterized by spatial heterogeneity [32]. A semiparametric GWR4.09 for Windows (provided by Nakaya et al. [32]) was carried out which is a new release of the windows application software tool for modelling spatially varying relationships among variables by calibrating GWR.

The estimated parameter of the GWR model uses the least squares given the location coordinates as a

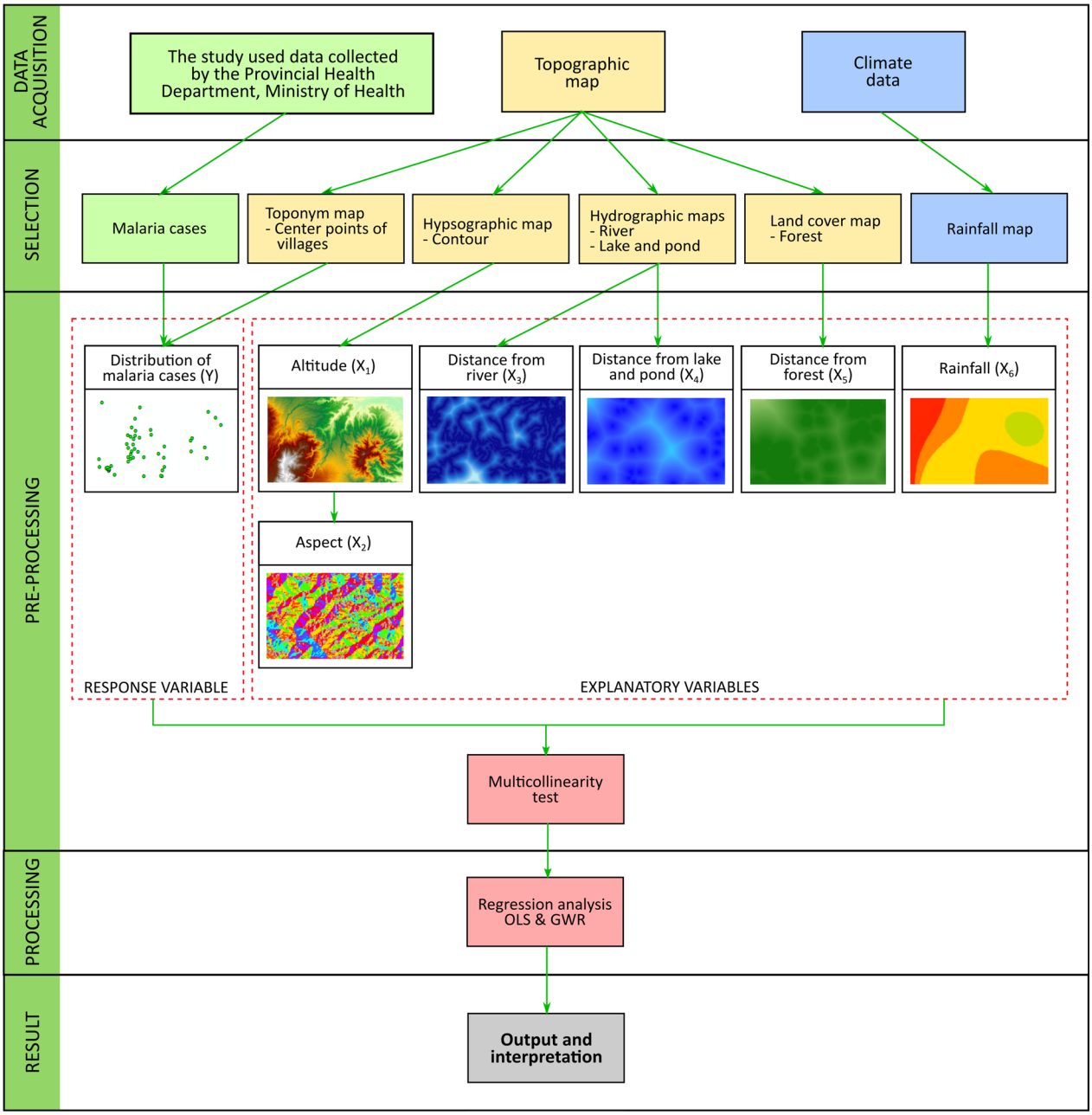


Fig. 4 Flow chart of the research strategy

weighting factor. The influence of the points in this neighbourhood varies according to the distance to the central point [33]. The optimum distance threshold (also known as the bandwidth) or the optimum number of neighbours determined in two ways: by minimising the square of the residuals cross-validation (CV) or by minimising the Akaike Information Criterion (AIC) [34]. At this stage, the type of weighing (kernel type) and optimum bandwidth selection method based were selected on AIC selection criteria. Classic AIC chooses smaller bandwidths in geographically varying coefficients are possible to be under smoothed [32]. In a GWR context, the measurement of utility is the AIC to know whether a global regression model or GWR is most useful [33].

The local GWR model as earlier described is as follows:

$$y_i = \beta_0(u_i, v_i) + \sum_k \beta_k(u_i, v_i)x_{ik} + \varepsilon_i \quad (1)$$

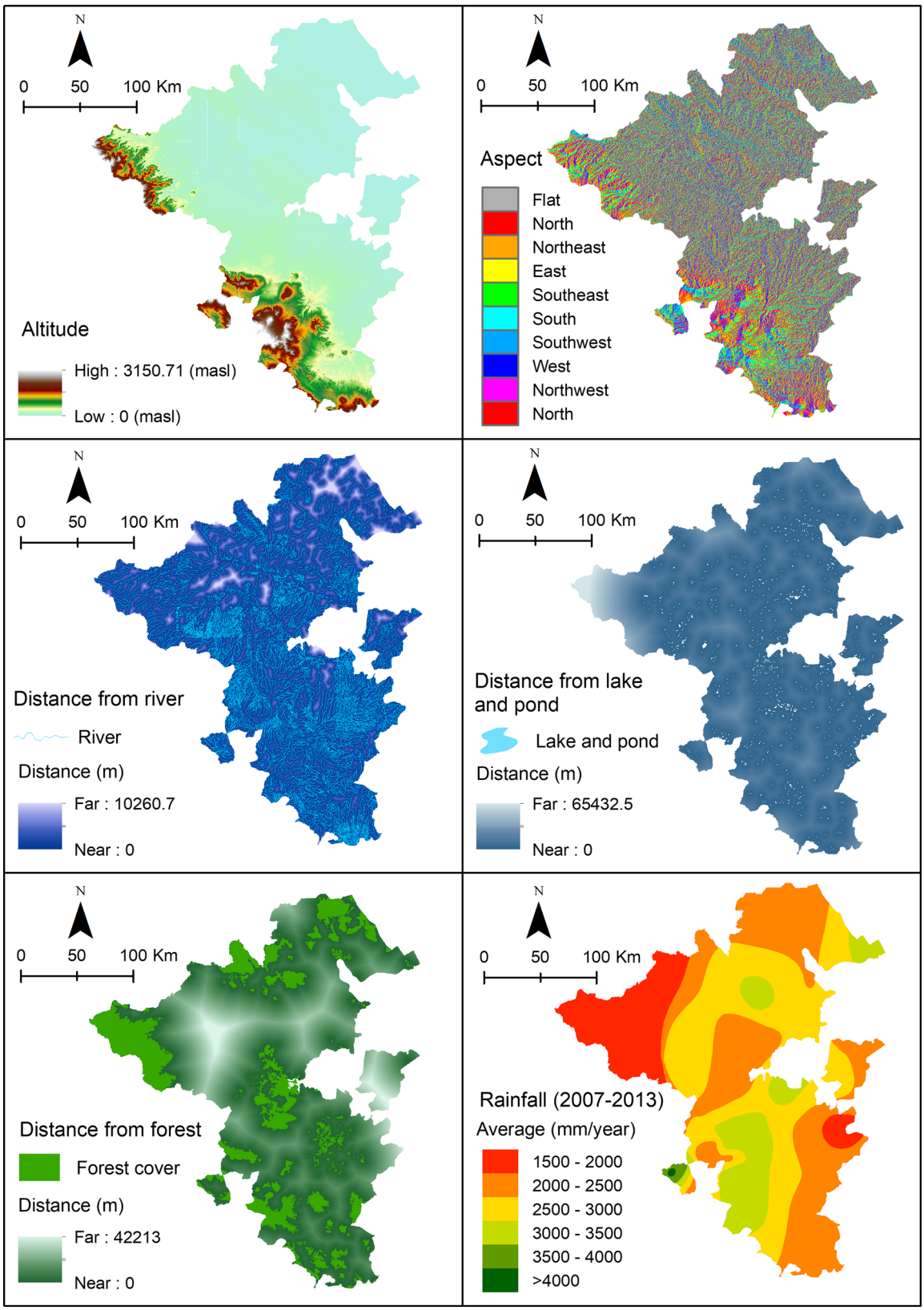


Fig. 5 Each explanatory variable mapped in the study area

Based on the model, y_i, x_{ik}, (u_i, v_i), $\beta_k(u_i, v_i)$, and ε_i were sequentially the response and explanatory variables k to location i, location coordinates to i, realization of the continuous function $\beta_k(u_i, v_i)$ at point i, and Gaussian error to location i. It is noteworthy that the kernel Fixed Gaussian function was used which highlights the optimal bandwidth found by using the Golden section search with the AIC selection criteria. Also, the Gaussian kernel supported the constant weight, and the value became less from the centre of the kernel but never touched zero. The kernel was suitable for fixed kernel because it could prevent the risk of the absence of data in the kernel. The Fixed Gaussian kernel earlier described [33] is as follows:

$$w_{ij} = \exp\left[-\left(d_{ij}/b\right)^2\right] \quad (2)$$

Also, w_{ij} was the weight value observed at the location j to approximate the calculation of the coefficients on area i, d_{ij} was the Euclidean distance between i and j, and b was the size of fixed bandwidth given by the size of metric. The Golden section automatically searched the optimal frequency range value by comparing indicators of the model with the bandwidth size. A positive R^2 indicates a positive correlation. A positive coefficient means X and Y changed in the same direction and if the environmental risk factor increased, then number of confirmed malaria cases increased. Conversely, a negative coefficient means X (explanatory variable) and Y (the response variable) changed in opposite directions. Student's t distribution that had values outside the range of − 1.97 and 1.97 formed a critical region with a 0.05 (95% CI) level of significance, whereas values outside the range of − 2.59 and 2.59 formed critical regions with a 0.01 (99% CI) level of significance. Step-wise computation performed with these data is shown in Fig. 4.

The locally weighed R^2 between the observed and fitted values has been calculated to measure how well the model replicates the local malaria incident values around each observation. A variable is correctly clarified for each location by the model if $R^2 = 1$ with values ranging from 0 to 1.

To compare the performance between global OLS and local GWR, GWR4 software was also used. We performed an ANOVA testing the null hypothesis that the GWR model represents no improvement over a global model. For local GWR, the sufficient number of degrees of freedom was a function of the bandwidth.

Results

Data pre-processing

Multicollinearity does not occur, because the VIF value is less than 10 and the tolerance value is higher than 0.1.

Environmental factors influencing confirmed malaria cases at global level: OLS model

The global OLS model reveals that altitude and distance to the forest (negative coefficients) and rainfall (positive coefficient) significantly influence the number of malaria cases. Confirmed malaria cases are more common in regions with high rainfall, lowland and areas adjacent to forest. On the other hand, environmental factors such as aspect or direction towards the slope, distance from the river, and the distance from lakes to pond do not have any significant association with malaria cases. Based on OLS model each factor has a different predictor of malaria case preferences in GWR model stage.

Environmental factors influencing confirmed malaria cases at local level: GWR model

The results of GWR using Fixed Gaussian are shown in Table 1. The best bandwidth generates 9184 neighbours and a significant spatial relationship with a specific region has been found. The GWR model provides evidence for a locally different influence of environmental factors on malaria cases as shown by varying parameter estimate value (Fig. 6). "Altitude" and "distance from lake and pond" show a positive association and "aspect" a negative association with malaria incidence in the Northern study area (Musi Banyuasin). "Rainfall" and "distance from river" show a positive association with malaria cases in the Eastern part of Musi Rawas and Lahat. The variables "aspect", distance from lake and pond" and "distance from forest" are positively associated with confirmed malaria cases in large parts of the study area. The significance thresholds of explanatory variables according to Student's *t* test in the GWR model are shown in Fig. 7. The local coefficient of determination (local R^2) for confirmed malaria cases at the local level ranges between 0.18 and 1 (Fig. 8).

Table 1 GWR result based on fixed Gaussian (distance) kernel function for geographical weighting

Bandwidth and geographic ranges	Value
Bandwidth size	9184.47
Diagnostic information	
Residual sum of squares	33,549.28
Classic AIC	3482.17
BIC/MDL	4198.30
CV	178.92
R^2	0.69
Adjusted R^2	0.41

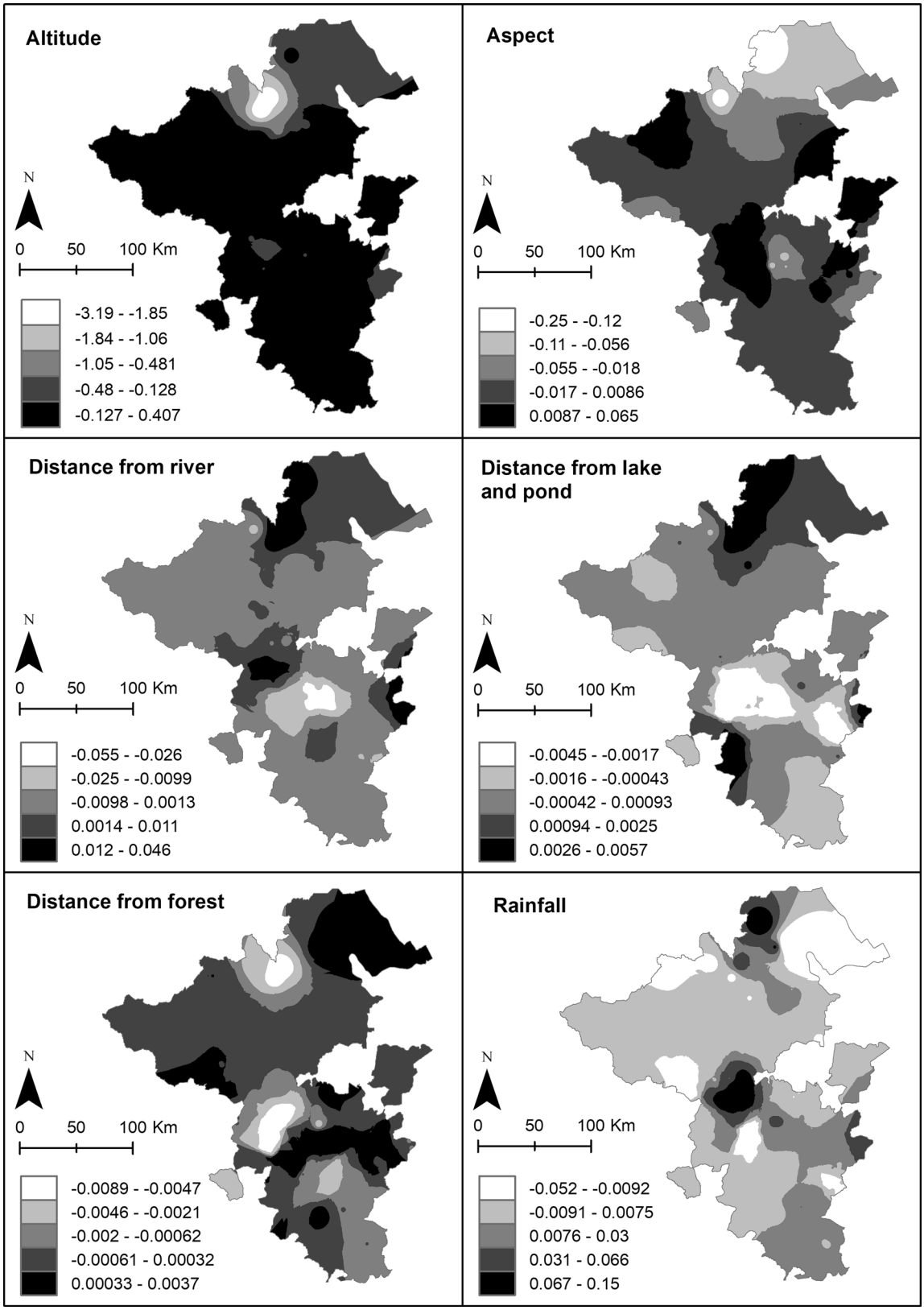


Fig. 6 Predicted value from GWR for parameter estimates of explanatory variables of malaria cases in the study area

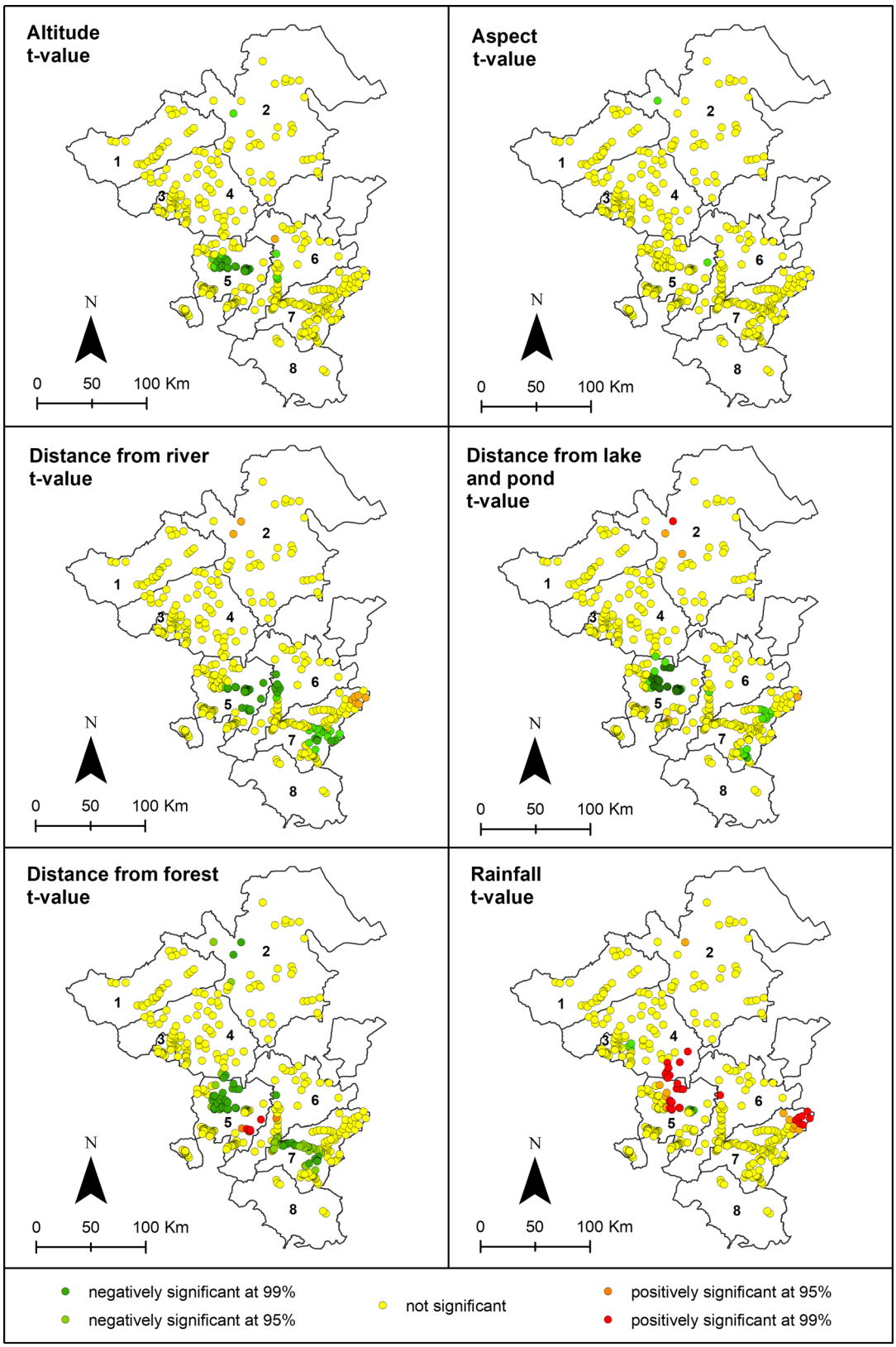


Fig. 7 Student's test significance (95 and 99% confidence interval) for each explanatory variable and village location

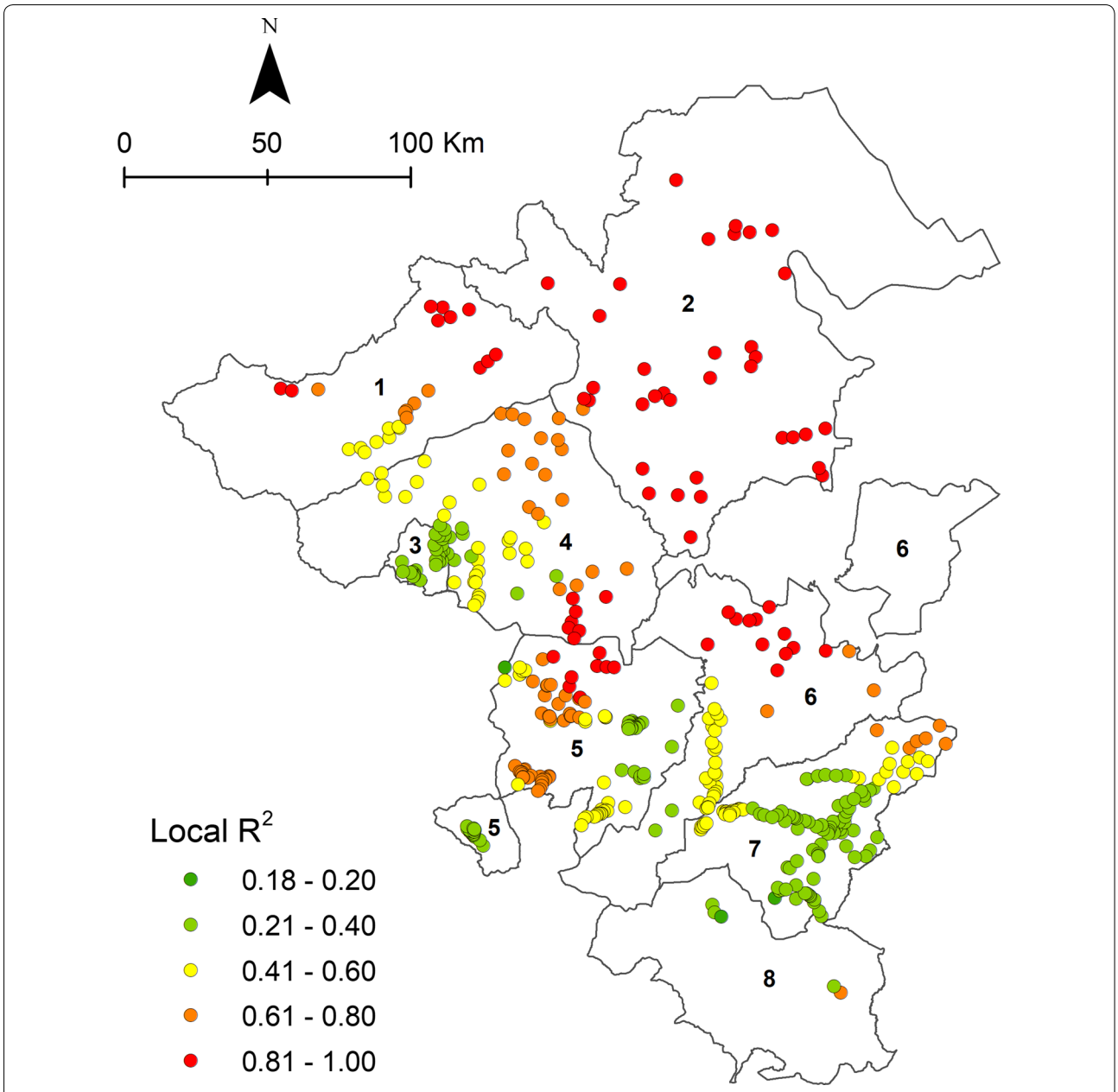


Fig. 8 Goodness-of-fit of GWR model (local coefficient of determination R^2) for malaria cases associated with environmental factors in South Sumatra, Indonesia

Comparison between the two methods OLS and GWR

Like OLS, GWR is a statistical model that provides insights into the relationship between the dependent variable confirmed malaria cases and six independent explanatory variables. GWR is selected as best model based on the residual sum of square, and classic AIC, and the R^2 as stated in Table 2.

The global regression model indicates that the variables have some influence on the study area (Table 3). The

Table 2 Comparison between global OLS and local GWR models

Value	OLS	GWR
Residual sum of square	100,625.26	33,549.28
Classic AIC	3625.82	3482.17
R^2	0.06	0.69
Adjusted R^2	0.05	0.41

global OLS model explains 6.2% variation of malaria incidences by environmental factors ($R^2 = 0.06$). This implies that 93.8% of the malaria incidence is caused by unknown environmental factors related to local variation which are not taken into account in the OLS model [33]. The local GWR explained 68.7% variation in malaria incidences (Y) by environmental factors ($R^2 = 0.69$). The DIFF criterion indicates that the spatial distribution of malaria incidence is associated with the independent variables "altitude", "distance from lakes and pond", "distance from forest", and "rainfall" with local spatial heterogeneity (Table 3). Though the testing of local coefficients for "aspect" and "distance from river" suggests no spatial variability (Table 3).

The GWR model explains the relationship between the response variable "confirmed malaria case" and six explanatory variables significantly better than the global regression model OLS ($F = 2.12$, $P < 0.05$) (Table 4). The best model weights are automatically determined for each location and are mapped in Fig. 7.

Discussion

Climate data are frequently used to predict for the spatial, seasonal and interannual variation for malaria transmission, for example the dynamic malaria model forecasting malaria prevalence with seasonal climate published by Hoshen and Morse [35]. The global OLS model revealed here that altitude, distance to forest, and rainfall significantly influence malaria incidence in South Sumatra. Similarly, land use, humidity, altitude and rainfall have been identified by GWR to determine the regional vulnerability to malaria in Purworejo, Indonesia [36]. However, the GWR model considering spatial heterogeneity explains better the association of malaria case with environmental factors in South Sumatra. Likewise in Venezuela, GWR analysis revealed that ecological interactions that act on different scales play a role in malaria transmission and that modelling enhances the understanding of relevant spatiotemporal variability [10]. The environmental factors shown to be significantly associated with malaria cases vary strongly at the village level. This finding is consistent with those obtained in studies in Ethiopia (Addis Ababa), the Amazon region of Brazil (Rondôia), and Cambodia [11, 37, 38]. A validated OLS can lead to a global policy and a validated relationship with GWR is more appropriate to drive to the local system. A geostatistical model based on analysis of residuals and using climatic, population and topographic variables has also been shown to be an important tool for local malaria prediction in Mali [39]. In the highlands of western Kenya, topographic parameters could be used to identify the risk of malaria and thereby helped to improve malaria monitoring or targeted malaria control activities [9].

The relationship of altitude and malaria cases has been shown in present study as well and may relate to the biology of malaria vectors. Globally, *Anopheline* species diversity and density decline from the lowlands to highlands [40]. Accordingly, poor villagers living in forested lowland areas in Papua, Indonesia, were found to be at higher risk of malaria infection than those in the highlands [41]. In contrast, a positive correlation between altitude and the abundance of *Anopheles* mosquitoes has observed in the highlands of Ethiopia, Colombia and Ecuador, particularly in warmer years [42–44]. This observation may be related to the direction towards the slopes as the distribution and density of mosquito populations may be affected by wind direction [45]. In an Ethiopian study, minimum temperatures were significantly associated with malaria cases in cold areas, while precipitation was associated with transmission in hot areas [46]. In accordance to many studies, malaria case was significantly associated with rainfall in villages of South Sumatra. Rainfall showed correlation with the incidence of clinical malaria cases in Tubu village, Botswana [47]. Variations in monthly rainfall in rural Tanzania were

Table 3 The result of global regression model and geographical variability test of local coefficients for six environmental factors

Variables	Global regression model output				Geographical variability test			
	Estimate	SE	T value	P value	F	DOF for F test		DIFF of criterion
Intercept	7.98	4.63	1.72	0.04	33.20	10.48	261.38	− 347.99
"Altitude (X1)"	− 0.02	0.00	− 4.03	0.00	0.24	12.02	261.38	19.19
"Aspect (X2)"	− 0.01	0.01	− 1.60	0.05	0.55	22.68	261.38	24.91
"Distance from the river (X3)"	0.00	0.00	− 0.84	0.24	1.84	18.15	261.38	− 16.03
"Distance from lakes and pond (X4)"	0.00	0.00	0.39	0.71	0.90	15.04	261.38	7.99
"Distance from forest (X5)"	0.00	0.00	− 3.69	0.00	2.99	14.61	261.38	− 38.12
"Rainfall (X6)"	0.00	0.00	2.38	0.02	13.07	10.17	261.38	− 158.91

largely associated with malaria [48]. Rainfall creates oviposition sites for female mosquitoes, whereas humidity is a key parameter for adult mosquito daily survival [49]. *Anopheline* mosquitoes require stagnant water to complete their larval and pupal development. Thus, rainfall affects the transmission of malaria by providing water to create aquatic habitats. The number of malaria cases was significantly positively connected with higher winter rainfall, but also with a higher average maximum temperature and significantly negatively associated with increasing distance from water bodies in South Africa [50]. Southern Africa Development Community estimates the positive correlation between increasing rainfall and the number of cases in Botswana during 2013 and 2014 [51].

Next to climatic and environmental factors, distance of houses to a forest are interrelated through anthropogenic activities influencing the local and regional climate [52, 53]. These observations can be confirmed for the relationship of malaria case with distance to lake, pond and forest for South Sumatra. A cross-sectional view in Brazil revealed for example that malaria incidence across health districts is positively correlated with the percentage of aggregated deforestation [26]. Indonesia contributes indeed significantly to deforestation in Southeast Asia. *Anopheles* was reported from eight sources at 47 independent sites. The first record of *Anopheles parangensis* from Sumatra was reported by O'Connor and Sopa (1981), but with no details on location [54]. *Anopheles (Cellia) leucosphyrus* is considered to be of epidemiological importance for malaria transmission in forested areas of Sumatra [54]. In current research, the main *Anopheles* vector diversity in each study area was however not investigated.

Present study has identified Lahat as the South Sumatran district in which environmental factors were of greatest relevance for malaria incidence. Lahat District has both lowland and mountain regions and is home to diverse ethnic groups, such as the Gumai who live along the rivers of the highland areas [55].

One of the key activities for malaria elimination should be the establishment of systems and tools to reduce disease burden where local transmission is high. By comparing the local GWR model with the global OLS model (Table 4), it became apparent that GWR yielded new information about the spatial variation of malaria incidence and thereby better explains local phenomena. The variability of malaria cases in our study was due to environmental and geographical local differences [8]. GWR should be used as a diagnostic model discovering spatially varying relationships between confirmed malaria cases and environmental factors. The use of GWR allows the uncovering of significant environmental variation for malaria incidence, which has previously been unobservable in a specific location [56].

Table 4 ANOVA testing the null hypothesis that the GWR model represents no improvement over a global model

Source	SS	DF	MS	F Count	F Table
Global residuals	100,625.26	429.00			
GWR improvement	67,075.98	197.74	339.22		
GWR residuals	33,549.28	231.26	145.07	2.34	2.12

Limitations of research

Due to practical constraints, this study was unable to encompass the entirety of environmental factors, particularly climate parameters, temperature and humidity, for which only limited data were available and hence not-representative data could not be included. Also the factor land use was eliminated. Malaria location information was plotted using a village centre approach which ignored all other locations where actual infections may have occurred (e.g., forests, plantations). The number of positive malaria per village, did not include the specific coordinates of each positive malaria case and thus, each positive case was placed in the centre of the settlement. Therefore, if land use variables would be involved, there will very likely be a strong bias. However, these eliminated or uninvestigated variables may be correlated with existing variables, for example, the temperature connected with altitude and with aspect or direction of the slope. In the same way, land use may be associated with the distance from the river and the distance from lakes and ponds. Thus, although these parameters (temperature, humidity, land use) were excluded from analysis, these environmental factors were represented by our chosen set of variables. In the future, additional explanatory variables should be addressed to provide a comprehensive review of malaria in the study area. It should comprise, for example, the behavior of mosquito vectors and that of community members, the access to and the delivery of health services, and other eco-bio-social factors that affect the incidence of malaria. Despite these limitations, our study sheds light on relevant information, not only in regional but also local realities regarding environmental variation which might interplay with vector-host relationships and sociocultural practice and provide a suitable environment for malaria mosquitoes.

Conclusion

In the present study, the importance of different environmental and geographic parameters for malaria disease was shown at global and village-level in South Sumatra, Indonesia. The independent variables altitude, distance from forest, and rainfall in global OLS were significantly

associated with malaria cases. As shown by GWR model and in line with recent reviews, the relationship between malaria and environmental factors in South Sumatra was found to vary spatially in different regions. A more in-depth understanding of local ecological factors influencing confirmed malaria case cannot only be used for developing sustainable regional malaria control programs but can also benefit malaria elimination efforts at village level.

Authors' contributions
HH was responsible for the management of this study, design and collection of data. Under the supervision of HH, NA performed the data analysis and was responsible for data acquisition, pre-processing, and processing. HH, UH, DM, MD, DAG, UK and RM contributed to the interpretation and visualisation of the results. HH, UH, DM, MD, NA, UK and RM wrote the paper. All authors read and approved the final manuscript.

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Competing interests
The authors declare that they have no competing interests.

Ethics approval and consent to participate
Not applicable.

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Publication #2 Does livestock protect from malaria or facilitate malaria prevalence? A cross-sectional study in endemic rural areas of Indonesia

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Does livestock protect from malaria or facilitate malaria prevalence? A cross-sectional study in endemic rural areas of Indonesia

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Abstract

Background: Ever since it was discovered that zoophilic vectors can transmit malaria, zooprophylaxis has been used to prevent the disease. However, zoopotentiation has also been observed. Thus, the presence of livestock has been widely accepted as an important variable for the prevalence and risk of malaria, but the effectiveness of zooprophylaxis remained subject to debate. This study aims to critically analyse the effects of the presence of livestock on malaria prevalence using a large dataset from Indonesia.

Methods: This study is based on data from the Indonesia Basic Health Research ("Riskesdas") cross-sectional survey of 2007 organized by the National Institute of Health Research and Development of Indonesia's Ministry of Health. The subset of data used in the present study included 259,885 research participants who reside in the rural areas of 176 regencies throughout the 15 provinces of Indonesia where the prevalence of malaria is higher than the national average. The variable "existence of livestock" and other independent demographic, social and behavioural variables were tested as potential determinants for malaria prevalence by multivariate logistic regressions.

Results: Raising medium-sized animals in the house was a significant predictor of malaria prevalence (OR = 2.980; 95% CI 2.348–3.782, $P < 0.001$) when compared to keeping such animals outside of the house (OR = 1.713; 95% CI 1.515–1.937, $P < 0.001$). After adjusting for gender, age, access to community health facility, sewage canal condition, use of mosquito nets and insecticide-treated bed nets, the participants who raised medium-sized animals inside their homes were 2.8 times more likely to contract malaria than respondents who did not (adjusted odds ratio = 2.809; 95% CI 2.207–3.575; $P < 0.001$).

Conclusions: The results of this study highlight the importance of livestock for malaria transmission, suggesting that keeping livestock in the house contributes to malaria risk rather than prophylaxis in Indonesia. Livestock-based interventions should therefore play a significant role in the implementation of malaria control programmes, and focus on households with a high proportion of medium-sized animals in rural areas. The implementation of a "One Health" strategy to eliminate malaria in Indonesia by 2030 is strongly recommended.

Keywords: Malaria, Rural area, Livestock, Zooprophylaxis, Zoopotentation

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Background

Malaria is a life-threatening disease with a widespread and long-term impact on the quality of life and the economy [1, 2]. Infection is caused by the bite of a female *Anopheles* mosquito which is a vector for the *Plasmodium* parasite [3, 4]. In Indonesia, malaria is mostly caused by *Plasmodium vivax* and *Plasmodium falciparum* [5]. Malaria threatens almost half of the world's inhabitants, around 2.3 billion of which live in Asia [4]. In Indonesia, the national average of malaria prevalence was 2.85% in 2007 and 6.0% in 2013 [6, 7]. Livestock contributes significantly to the livelihoods of hundreds of millions around the world. In Indonesia the percentage of people who keep livestock varies geographically and culturally. Regions of Indonesia where a high percentage of families is involved in raising livestock also had the highest prevalences of clinical malaria in the country (East Nusa Tenggara, 12.0%; Papua, 18.4%) [6].

In the context of malaria, animals can play a role in diverting mosquitoes from feeding on humans, thereby preventing transmission of the parasite to humans [8]. Using alternative host species to distract malaria vectors away from people, a concept known as zooprophylaxis, has long been recommended as a potential environmental strategy to reduce malaria transmission [8]. However, increasing opportunities to feed on alternative hosts such as livestock could also increase human exposure to malaria: an increase in the number of animals living close to mosquito breeding sites, resulting in improved availability of blood meals, could alternatively attract more mosquitoes, increase their survival and the risk of disease transmission to humans, a phenomenon known as zoopotentiation [9]. In such a situation, zooprophylaxis may be ineffective because the effect of diverting blood meal seeking mosquitoes to non-human prey may be countered by higher numbers and longer survival of mosquitoes [8]. Nevertheless, the use of animals as bait to attract mosquitoes has been propagated as a promising alternative to insecticide use. For areas where zoophilic vectors transmit malaria, two types of malaria control approaches using livestock have been suggested; zooprophylaxis and insecticide treatment of livestock (ITL) [10]. As understood in this context, zooprophylaxis is supposed to control vector-borne diseases by withdrawing vectors to livestock species within which the pathogen in question cannot spread. By combining the use of insecticide spray with zooprophylaxis, vector populations in some situations may be controlled without mosquitoes developing insecticide resistance [11]. Increased blood feeding on cattle can reduce the likelihood of human infections in the sense of a zooprophylactic effect [12]. A prophylactic effect of livestock on malaria risk has also been observed in Papua New Guinea and Sri Lanka [10]. In Kenya and Zambia, malaria prevalence became significantly reduced in areas where livestock was kept [9]. Donkeys, rabbits and pigs also showed a significant protective effect [13], possibly because vector breeding sites were closer to livestock enclosures than to houses, and especially endophagic and exophilic *Anopheles* species might prefer to feed on the animals [10]. Accordingly, the presence of cattle could be used as a barrier to the spread of malaria [14, 15]. However, research conducted in Pakistan, the Philippines and Ethiopia showed that the presence of cattle can also be a risk factor for the spread of malaria [10]. The practical value of zooprophylaxis and the reasons for observed zooprophylactic success have therefore remained under debate [10]. Part of the controversy about zooprophylaxis versus zoopotentation for malaria prevalence may be accounted for by the variety of analysed livestock species and animal keeping practices, and the associated variable attractiveness for different zoophilic vectors [9, 10]. For example, zooprophylaxis may more likely take place in areas where livestock is kept at a distance from human sleeping quarters at night, and where nets or other protective measures are used, whereas zoopotentiation may be more likely in places where livestock is housed within or near human sleeping quarters at night and where mosquito species prefer human hosts [16].

The present study addresses the relationship between livestock keeping and malaria prevalence in rural endemic areas of Indonesia. The country has been chosen as the geographical centre for this research because:

1. There is high vector diversity as indicated by the presence of 20 *Anopheles* species [17]. The most abundant malaria vector throughout Indonesia is *Anopheles vagus* (46% at 349 sites), whereas *Anopheles bancroftii* was the geographically most constrained one (1%; 7 locations in Papua, 1 in Maluku) [18].
2. 26.14% of Indonesia's population live in malaria epidemic environments. Most of the areas at high risk for malaria are rural and located in eastern Indonesia [6].
3. The practice of keeping livestock is widely distributed throughout the Indonesian population. At the national level, 39.4% of households raise poultry, 11.6% raise medium-sized livestock, i.e., goats, sheep, and pigs, 9.0% raise large-sized animals, i.e., cattle, horses, or buffaloes [6], and 12.5% raise other animals such as dogs, cats or rabbits [6].
4. The Indonesian regions where a high proportion of households is involved in raising livestock also presented the highest prevalence of malaria [6]. Abundant livestock can enhance the survival

and abundance of mosquitoes, and in this situation zooprophylaxis may become ineffective. Similarly, malaria prevalence was higher among families who kept cattle compared to those who did not [19]. While the larvae of some malaria vectors in Indonesia, such as *Anopheles farauti* sensu lato, were found in a wide variety of temporary man-made and animal-made habitats, such as borrow pits, pig-gardens, and pools along rivers and streams [18], other studies have reported the formation of a barrier between anopheline breeding sites and human residential areas through an active deployment of pigs and cows [19]. However, this example of zooprophylaxis has been discussed in a controversial manner.

The hypothesis of the present study is that there is indeed a relationship between the presence of livestock and malaria prevalence in rural endemic areas in Indonesia.

Methods

This study made use of a large dataset based on a cross-sectional survey of the Indonesia Basic Health Research (Indonesia acronym: Riskesdas), in 2007, which is organized by Balitbangkes with a sample framework conducted by the Central Bureau of Statistics (Indonesia acronym: BPS). Riskesdas is a nationwide community-based health research project at the district/city level that is conducted every 5–6 years—a duration that is considered an appropriate interval to assess the development of public health status, risk factors, and the progress of health development efforts.

Study area

The Riskesdas dataset was filtered for participants residing in the rural areas of 15 highly malaria-endemic (above the national average) provinces (Fig. 1). These 15 provinces include West Papua, Papua, East Nusa Tenggara, Central Sulawesi, North Maluku, Bengkulu, Bangka Belitung, Maluku, West Nusa Tenggara, Nanggroe Aceh Darussalam, Central Kalimantan, West Kalimantan, Jambi, Gorontalo and North Sumatera. Moreover, the

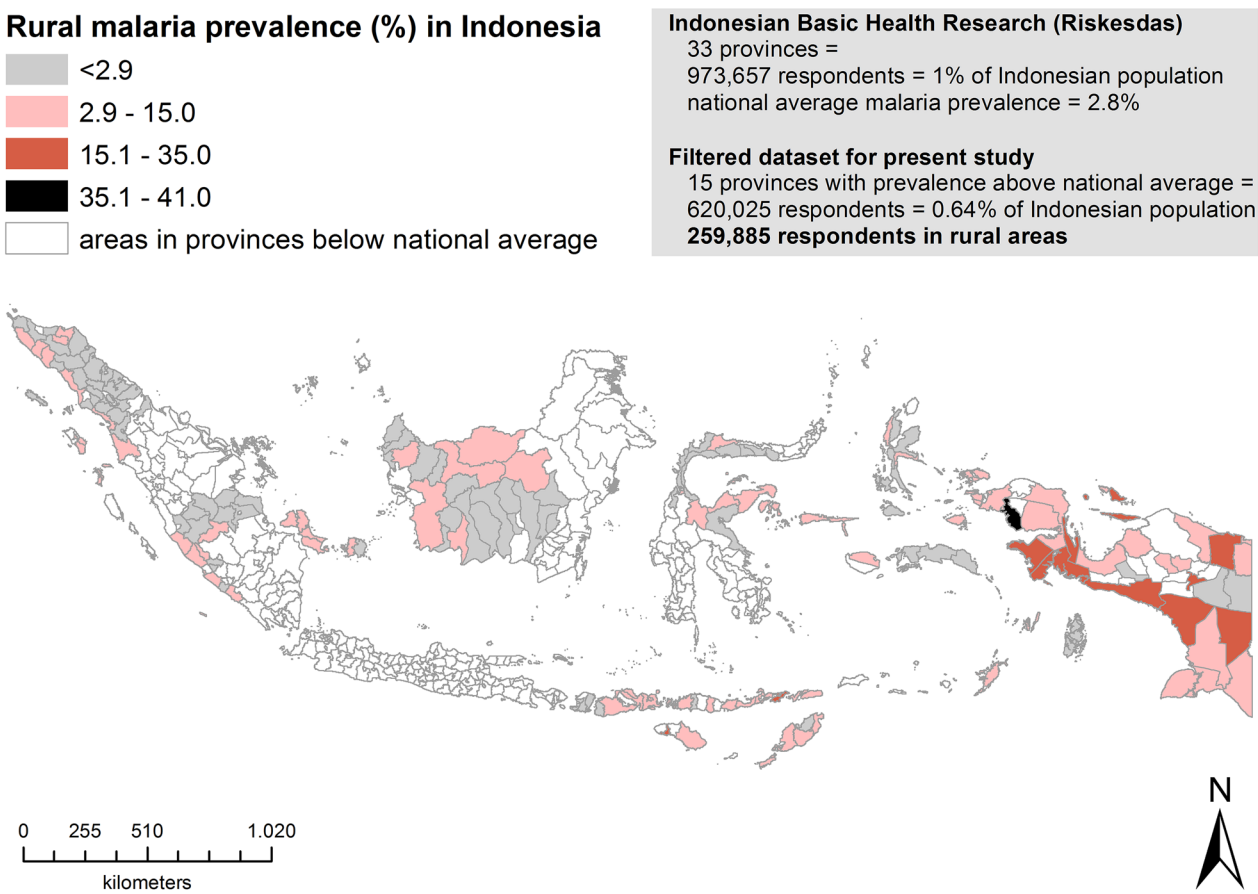

Fig. 1 The proportion of malaria in regencies and cities within rural areas of Indonesian provinces with malaria prevalence above the national average

provinces of Maluku, North Maluku, West Papua, Papua, and East Nusa Tenggara were highly endemic areas.

Research variables

The outcome variable, malaria status, is coded as a binary variable whose value equals one if a participant within the past month was ever diagnosed as being malaria-positive by health professionals [6]. Thus the respondent reported having been diagnosed as malaria-positive by a health professional during the past month. In the questionnaire (code B07): in the last 1 month, has [name] ever been diagnosed to suffer from malaria, which was confirmed by a blood test taken by health professionals. Generally, the diagnosis was confirmed by use of rapid diagnostic tests (RDTs) and microscopy in health services. The interviewer did not check for a malaria infection [6]. Further, an independent data collection was taken from an individual and household questionnaire. All the measurements on each person are made at one point in time [20].

The independent variables, such as characteristics of participants (gender, age, education, principal occupation), behaviour of participants (sleep under a mosquito net, use net insecticide, defecating habits), and accessibility and utilization of health services (participants were able to access health services by travelling), environmental sanitation (type of container/media, sewage canal, sewage canal conditions), and location of cages (medium-sized breeding animals and large-sized breeding animals) were tested for a potential relationship with the response variable malaria using the binary category "yes" and "no". In this study, malaria status include those who have the disease. For a more detailed description of the scope of research variables please refer to Additional file 1.

Study population

Participants of all ages representative of the entire Republic of Indonesia were interviewed with questions related to malaria. Household samples and household members in Riskesdas 2007 are designed to be identical to households and the household member list in the National Socioeconomic Survey (Indonesia acronym: Susenas) 2007 [6]. Regions designated as rural were used as a survey subsample by the location data retrieval used in the Riskesdas survey 2007 [6]. The analyses in the present research are based on a massive dataset with 259,885 out of 973,657 Riskesdas participants who represent a total population size of 30,152,651 Indonesians.

Questionnaires

A set of questionnaires was used as an instrument for data collection. The data collection for Riskesdas was done in two stages: the first stage was begun in August 2007 and continued until January 2008 in 28 provinces; the second stage was in August–September 2008 in five provinces (NTT, Maluku, North Maluku, Papua and West Papua). Riskesdas had mobilized 5619 enumerators, all (502) researchers from the National Institute of Health Research, and 86 lectures from technical health schools, local governments in provincial regions and districts/cities, provincial labs, hospitals, and universities were also involved. The process of editing, entry, and cleaning Riskesdas data was started in early January 2008, while there was also a process for discussing work plans and strategies of analysis. Various questions related to Indonesian health policy were research questions and were finally developed to become variables collected by using several approaches. In Riskesdas 2007, there are around 900 variables spread out in six kinds of questionnaires. The questionnaires covered malaria and included 14 explanatory variables. Regarding raising livestock, data were collected by asking all heads of households whether they were keeping poultry, medium-sized livestock (goats, sheep, and pigs), large-sized livestock (cows, buffaloes, and horses) or pets such as dogs, cats, and rabbits. If livestock was kept, then it was noted whether the livestock was kept inside of the house or outdoors [6].

Statistical analyses

Data were analysed using statistical data processing applications by Stata, taking into account the complex sampling design (using two-stage sampling, for a more detailed description of statistical procedure please refer to Additional file 1). By using a Stata complex sample in processing and analysing Riskesdas data, the validity of analysis result can be optimized. Both univariate and bivariate analyses were carried out using Chi square tests. In the next stage of multivariable analysis, a series of binary logistic regressions were run. Explanatory variables that may have predictive value for the response variable were selected for the multiple regression models (Wald test, $P < 0.25$) [21].

Analysis of multivariable logistic regression was carried out to specify the relationship amongst multiple independent variables with the dependent variable 'malaria prevalence'. The final model includes the following seven explanatory variables: characteristics of participants (gender, age), community health facility, the condition of sewage canal, the behaviour of participants (using mosquito nets, and insecticide-treated mosquito nets), and raising medium-sized breeding animals). In Table 2, the adjusted odds ratio (AOR), as a result of parsimonious logistic models, is shown for independent variables affecting the prevalence of malaria in rural endemic areas of 15 high malaria-endemic provinces of Indonesia.

Results

Malaria prevalence

Prevalence of malaria in Indonesia in 2007, shown in Fig. 1, revealed that malaria prevalence was 3.5% (95% CI 0.033–0.037) in 15 provinces with malaria prevalence higher than the national average (2.85% in 2007) [6]. The study area map uses the World Geodetic System (WGS84) as its reference coordinate system. The mapping of malaria prevalence based on Riskesdas data was performed using the software Aeronautical Reconnaissance Coverage Geographic Information System (ArcGIS 10). The highest malaria prevalence found was 41.0% at South Sorong (marked as a black area in Fig. 1), a regency located in the West Papua province of Indonesia with an area of 3946.94 km^2 and a population of 37,900 (2010 census).

The existence of livestock

Based on the Riskesdas questionnaire, the animals are categorized as livestock, pets and poultry. The term livestock includes large-sized breeding animals (cattle, horses, buffaloes), and medium-sized breeding animals (goats, sheep, pigs). Additionally, poultry, such as chicken and ducks, and pets, such as dogs, cats and rabbits, are included in the term *pets*. With 53.7%, the majority of participants raises chickens, ducks, and birds, followed by pets (dogs, cats, and rabbits; 25.2%), medium-sized breeding animals (goats, sheep, and pigs; 22.2%), and large-sized breeding animals (cows, buffaloes, and horses; 10.2%) (Fig. 2). This research further analysed the raising of both large-sized breeding animals (cattle, horses, buffaloes) and medium-sized breeding animals (goats, sheep, pigs) that are connected with malaria prevalence. This research inevitably reveals that 0.52% (95% CI 0.004–0.007) of participants keep large-sized breeding animals and 1.63% (95% CI 0.014–0.019) of participants keep medium-sized breeding animals inside the house. This study also found that 9.64% (95% CI 0.091–0.102) of the participants keep large-sized breeding animals, and 20.59% (95% CI 0.197–0.215) participants keep medium-sized breeding animals outside of the house. Livestock kept in close proximity to humans can contribute to the higher transmission, as they attract mosquitoes into areas where they will encounter and feed on human hosts opportunistically (zoopotentiation) [22].

Univariate and bivariate analysis

Table 1 summarizes the percentage of participants having or not having been diagnosed positive for malaria for each of the explanatory variables and bivariate analyses (for more details see Additional file 2). In brief, this survey observes the participants who keep large-sized breeding animals inside of the house (0.52%, 95% CI 0.004–0.007), and the participants who keep the animals outside of the house (9.64%, 95% CI 0.091–0.102). It additionally observes, participants who keep medium-sized breeding animals inside of the house (1.63%, 95% CI 0.014–0.019), and the participants who keep the animals outside the house (20.59%, 95% CI 0.197–0.215). Furthermore, Table 2 shows that malaria prevalence is increased in the participants who keep medium-sized breeding animals inside of the house (OR = 2.980; 95% CI 2.348–3.782, $P < 0.001$), and the participants who keep the animals outside of the house (OR = 1.713; 95% CI 1.515–1.937, $P < 0.001$) and who contract malaria more than those who do not have such animals. On the contrary, keeping large-sized breeding animals does not considerably increase malaria prevalence. Besides, males are more likely to have malaria than females (OR = 0.849, 95% CI 0.811–0.888, $P < 0.001$). Participants who are aged

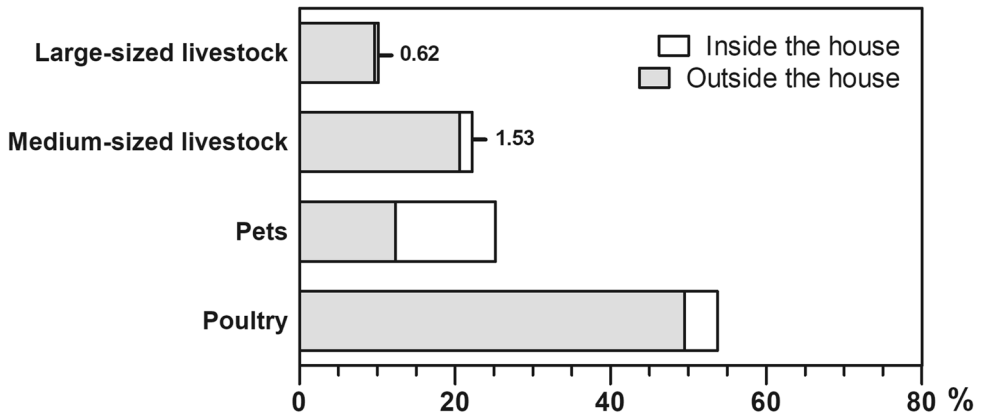

Fig. 2 The proportion of rural population (n = 259,885 household members) raising livestock (%) and the location of cages (inside the house—white bar, outside the house—grey bar) in highly malaria-endemic endemic areas in 15 provinces of Indonesia. The category of poultry includes chicken, ducks and birds. The category of pets includes dogs, cats and rabbits. The category of medium-sized breeding animals includes goats, sheep and pigs. The category of large-sized breeding animals includes cows, buffaloes and horses

Table 1 Description of variables research (%) within the categorical variable: malaria prevalence, characteristics of participants, the accessibility and utilization of health service, environmental sanitation, the behaviour of participants, and the location of cages of livestock

Variable research with n = 259,885	Proportion (%)	95% CI	
		Lower	Upper
The *dependent* variable			
Malaria prevalence			
0. No	96.53	0.963	0.967
1. Yes	3.47	0.033	0.037
The *independent* variables			
Sex			
0. Male	49.29	0.491	0.495
1. Female	50.71	0.505	0.509
Age (years)			
0. Productive age (15–64 years)	60.09	0.598	0.604
1. Not productive age (< 15 and > 64 years)	39.91	0.396	0.402
Education			
0. Completed high school	12.42	0.12	0.128
1. High school not completed	63.98	0.636	0.644
2. < 10 years of age	23.60	0.234	0.238
Main occupation			
0. Other occupation	45.43	0.449	0.46
1. Farmer/fisherman/labourer	30.97	0.304	0.315
2. < 10 years of age	23.60	0.234	0.238
The time to reach the nearest hospital			
0. < 60 min	93.18	0.925	0.938
1. > 60 min	6.82	0.062	0.075
The time to reach the nearest community health facilities			
0. < 60 min	95.24	0.947	0.957
1. > 60 min	4.76	0.043	0.053
The type of container/media used			
0. Closed container	62.57	0.614	0.637
1. Others	37.43	0.363	0.386
The sewage canal			
0. Closed container in the yard	5.52	0.051	0.06
1. Others	94.48	0.94	0.949
The condition of sewage canal			
0. Closed canal	9.92	0.094	0.105
1. Others	90.08	0.895	0.906
Mosquito nets			
0. Yes	43.99	0.428	0.452
1. No	55.22	0.54	0.564
2. No answer	0.79	0.007	0.009
Insecticide-treated bed net			
0. Yes	11.43	0.107	0.122
1. No	29.01	0.279	0.301
2. No answer	59.56	0.584	0.607
The habit of defecate			
0. Yes	44.29	0.433	0.453
1. No	32.11	0.312	0.33
2. < 10 years of age	23.60	0.234	0.238

Table 1 (continued)

Variable research with n = 259,885	Proportion (%)	95% CI	
		Lower	Upper
Raising large-sized breeding animals (cows, buffaloes, horses)			
0. No have	89.84	0.892	0.904
1. Cage inside the house	0.52	0.004	0.007
2. Cage outside the house	9.64	0.091	0.102
Raising medium-sized breeding animals (goats, sheep, pigs)			
0. No have	77.78	0.768	0.788
1. Cage inside the house	1.63	0.014	0.019
2. Cage outside the house	20.59	0.197	0.215

Table 2 The logistic regression analysis associated with the prevalence of malaria in rural highly malaria-endemic endemic areas in 15 provinces of Indonesia, with n = 259,885

Risk factor	*P*-value	Unadjusted OR (95% CI)	*P*-value	Adjusted OR (95% CI)
Sex				
Male versus female	0.000	0.849 (0.811–0.888)	0.000	0.842 (0.804–0.882)
Age (years)				
Productive age (15–64 years) versus not productive age (< 15 and > 64 years)	0.000	0.861 (0.812–0.912)	0.000	0.837 (0.790–0.887)
Community health facility				
< 60 min versus > 60 min	*0.000*	*1.633 (1.251–2.131)*	*0.005*	*1.446 (1.120–1.866)*
The condition of sewage canal				
Close canal versus others	*0.001*	*1.250 (1.095–1.427)*	*0.015*	*1.177 (1.033–1.343)*
Mosquito nets				
Yes versus not	0.000	0.805 (0.727–0.890)	0.157*	0.879 (0.736–1.051)
Yes versus others	*0.002*	*1.911 (1.273–2.868)*	*0.005*	*1.838 (1.208–2.797)*
Insecticide-treated bed net				
Yes versus not	0.000	0.508 (0.439–0.588)	0.000	0.509 (0.440–0.589)
Yes versus others	0.000	0.527 (0.457–0.608)	0.000	0.590 (0.481–0.725)
Raising medium-sized breeding animals				
Not have versus inside	*0.000*	*2.980 (2.348–3.782)*	*0.000*	*2.809 (2.207–3.575)*
Not have versus outside	*0.000*	*1.713 (1.515–1.937)*	*0.000*	*1.643 (1.460–1.849)*

Risk factors with $P < 0.001$ or $P < 0.05$ and OR > 1 are shown in italic face

*$P > 0.05$ a confounding factor

15–64 years (OR = 0.861, 95% CI 0.812–0.912, $P < 0.001$) contract malaria more than those who have not yet reached that age. In addition, most participants who were able to access health services by travelling for more than 60 min (OR = 1.633, 95% CI 1.251–2.131, $P < 0.001$) were more susceptible to contract malaria than participants who were able to access health services by travelling less than 60 min. The majority of participants who use open sewage systems (domestic wastewater or municipal wastewater) at home and those without a sewage system are at higher odds of contracting the disease (OR = 1.250, 95% CI 1.095–1.427, $P = 0.001$) than participants who have closed sewage systems. Participants who were using mosquito nets with OR = 0.805 and insecticide-treated bed nets (ITNs) with OR = 0.508 as protective factors against malaria reveal a decreased malaria prevalence compared to those who do not use such protection. Besides, there was a negative association between the use of insecticide-treated bed nets and the prevalence of malaria (r = − 0.023, $P < 0.001$). This statistic implies for participants who increasingly used ITNs that the prevalence of malaria decreased.

Multivariable logistic regression

The estimated AOR of malaria for participants who kept medium-sized breeding animals (goats, sheep, pigs) inside at home signifies a 2.81 times higher risk of contracting malaria (adjusted for other variables; AOR = 2.809; 95% CI 2.207–3.575; $P < 0.001$) in rural endemic areas of 15 highly malaria-endemic provinces of Indonesia. The other six controlling factors for malaria prevalence relate to sociodemographic factors, socioeconomics and behaviour.

Discussion

In the present study, the presence of medium-sized livestock increased the likelihood of contracting malaria by 2.81. The results of this study therefore suggest that the presence of certain livestock types potentiate malaria risk. Other principal factors affecting the prevalence of malaria were demographic factors such as gender, age, access to health facility, environmental health, and the behaviour of participants concerning protection against malaria by means of mosquito nets and ITNs.

Spatial heterogeneity of malaria prevalence

Spatial variation in malaria prevalence has to be taken into account in Indonesia [23]. The highest malaria prevalence was found in South Sorong, a known malaria endemic province [6]. A gradient of malaria prevalence from rural (58.9%) to urban areas (33.9%) has been known in the Bata district of Equatorial Guinea (EG) [24]. This situation is consistent with the identified high-risk in the rural context that was found in West Papua, Papua [23] and East Nusa Tenggara [6, 25]. A similar variation of spatial malaria distribution was observed in a cross-sectional study in rural areas in Haiti (4–41%), and demographic data indicated some focal disease transmission [26].

Keeping medium-sized animals is a significant determinant for malaria prevalence

This investigation provides evidence for a positive relationship between medium-sized animals that are kept inside the house (AOR = 2.809; 95% CI 2.207–3.575; $P < 0.001$) and the prevalence of malaria in the human population living in rural, highly malaria endemic areas of Indonesia. An explanation for these results could be that the presence of livestock increased the abundance of vectors for *Plasmodium* species. Increasing the availability of host selection for certain livestock could increase human malaria exposure by means of zoopotentiation if the heat and odour cues emitted by animals attract a higher number of vectors to households in or near the area where they are kept [9]. Zoopotentiation could also occur if the physical disturbances created by animals (e.g., puddles, hoof prints, watering sites) increase the potential for larval habitats and thus adult vector density near households. In this study, the participants who had an open sewage canal were at higher odds of contracting malaria than others, highlighting the importance of potential larval habitats near houses. The splitting of people and livestock dwellings on this scale proves to be too large to dodge a zoopotentiation effect [9]. An increasing abundance of goats or sheep has been demonstrated to increase the abundance of *Anopheles* mosquitoes within a radius of 20 m around the household in Kenya [12]. Other evidence for zoopotentation includes positive correlations between donkeys, pigs, and humans, and the abundance of malaria-transmitting mosquitoes [12, 27]. For example, the probability that humans are bitten by the zoophilic *Anopheles stephensi* may increase if one sleeps close to a cow or a goat in the evenings. In contrast, the anthropophily of *Anopheles culicifacies* was only slightly influenced by the presence of livestock. In Kenya, each additional goat or sheep increased the abundance of the local malaria vector [12], and one may assume that there was a higher human biting rate as well. At least participants who kept pigs and sheep in Mozambique had significantly increased odds of malaria infection, although to a lesser extent in the case of sheep [27]. For the zoophilic *An. stephensi*, nightly human biting increased by 38% in the presence of a cow and by 50% in the presence of two goats [19]. An integrative vector control strategy including ITNs and indoor residual spraying (IRS) reduction, combined with ITL, may improve zooprophylactic effectiveness [28].

Keep livestock at a distance

In particular, participants who were raising medium-sized breeding animals inside their home were more likely to have malaria (OR = 2.980; 95% CI 2.348–3.782; $P < 0.001$), and participants who were raising medium-sized breeding animals outside their home were more likely to have malaria (OR = 1.713; 95% CI 1.515–1.937; $P < 0.001$) than those who did not raise the livestock. In contrast to the outcome of the study, livestock may indeed have a prophylactic effect in cases in which only zoophilic vectors are present and livestock is placed in a way to act as a protective barrier for anopheline mosquitoes [10]. Otherwise, zoopotentation often takes place when livestock is kept indoors or near the household and if mosquito vectors are mainly anthropophilic [16]. A parallel approach of insecticide-treated livestock (ITL) and arranging the livestock as far from man as possible is sufficient to reduce malaria [10, 19]. Likewise, in the Macha area in the southern province of Zambia, farm animals revealed a dramatically declining risk of *P. falciparum* infection at the house level, with an increasing

distance between livestock (cattle, goats, dogs, cats) and dwelling structures.

Demographic and social determinants of malaria status

Participants in the age range of 15–64 years, and especially male participants, contracted malaria significantly more than others. Malaria prevalence also differs by gender, with men more likely to be parasitaemic than older women in the Democratic Republic of Congo [29]. Similarly, in a larger scaled survey of households in Ethiopia, the frequency of suspected malaria in men was significantly higher than in women; however, the prevalence of malaria was not significant between genders [30]. In contrast, women in the adult population of an endemic area in Kenya are 50% more likely to become infected with malaria parasites than men [31].

Behavioural determinants of malaria status

Protective behaviour (mosquito nets and ITNs) can reduce the risk of malaria. In rural, highly malaria endemic areas of Indonesia, the risk of contracting malaria significantly decreased if ITNs were used. Similarly, ITNs are the most protruding prevention of malaria in highly endemic areas in Malaysia [32], along with other community-based preventive measures, such as bed nets [33]. Furthermore, ITNs and long-lasting insecticidal nets (LLINs) were combined with indoor residual spraying to accelerate success in malaria control in tropical Africa [34]. Seemingly using of ITNs in 2007 is not more effective for as protection for malaria with ($r = -0.023$, $P < 0.001$), due to the number of ITNs distributed at the time, the number of people protected is low, and lack of good behaviour of the community regarding the use of ITNs in the research area [17, 35]. Furthermore, the malaria program has been using long-lasting insecticidal nets (LLIN), which are more effective than ITNs. LLINs have been used significantly more as an effective alternative to ITNs for over a decade [36].

Limitations of research

A weakness of our study is that the clinical diagnosis of malaria by retrospective interview of last 4 weeks may underestimate malaria positive respondents. We expect that if we would increase the period for clinical diagnosis, more people would report positive malaria diagnosis. The cross-sectional design cannot decide how the chances of getting malaria for participants were before and after exposure to covariate variables. However, the benefits of a large-scale cross-sectional design are the increase in information on preliminary phenomena which subsequently allows for designing studies with particular foci [37]. There are other factors also proven to determine malaria prevalence, such as the bionomics of different *Anopheles* species [38]. Understanding the kind of *Anopheles* species, and the behaviour of *Anopheles* mosquitoes can help conceive how malaria is transmitted and can assist in designing appropriate control strategies. Unfortunately, in the Riskesdas 2007, these factors were not monitored.

Recommendations

In this study, participants who raised medium-sized animals inside their homes had a higher malaria prevalence in 15 provinces throughout the rural malaria endemic areas of Indonesia. Hence, the main recommendation from this study is to keep this livestock outside of the house, and to focus livestock-based interventions on households with a high proportion of medium-sized animals in rural malaria endemic areas of Indonesia. In this context, anthropological studies should be undertaken to understand in the first place why people in different parts of Indonesia are keeping livestock the way they do. Participatory community eco-health approaches might be best suited to work with local people and communities in order to develop a lasting intervention together, since a vertical policy might not be successful [39–41].

Besides, participants aged 15–64 years should be provided with the means for protection from *Anopheles* bites while working in rural malaria endemic areas, including personal protection, behaviour modification and environmental modification. Personal protection includes using insecticides and repellent and the use of long-sleeved clothing and trousers. Environmental modification is aimed at reducing mosquito habitats, covering leaky rooves, among others. There is also a need for improving sanitation by closing sewage canals to reduce the breeding places of *Anopheles* mosquitoes. Seemingly using of ITNs in 2007 is not more effective for as protection for malaria with ($r = -0.023$, $P < 0.001$). This study therefore recommends the distribution of LLINs to all people in rural endemic areas together with community-based interventions to improve the knowledge, attitude and practical use and maintenance of LLINs for malaria prevention.

Conclusions

The presence of medium-sized livestock (goats, sheep, and pigs), is the major risk factor for contracting malaria in rural malaria endemic areas of Indonesia. Sociodemographic and behavioural factors are also important for having a high risk of malaria infection. Thus, livestock-based interventions should be prioritized in Indonesia and focus on households with a high proportion of medium-sized animals in malaria endemic rural areas. 'One Health' community research approaches that encompass the understanding of local perceptions

of malaria, malaria transmission and livestock as well as the use of preventive tools like long-lasting insecticide impregnated bed nets should be strengthened in Indonesia to inform the adequate development of an integrative malaria prevention strategy.

Additional files

Additional file 1. Detailed description of scope of variables and statistical procedure.

Additional file 2. Detailed description of descriptive analysis and bivariate analysis.

Abbreviations

AOR: adjusted odds ratio; API: annual parasite incidence; ArcGIS: Aeronautical Reconnaissance Coverage Geographic Information System; IDHS: Indonesian Demographic and Health Survey; IRS: indoor residual spraying reduction; ITL: insecticide-treated livestock; ITNs: insecticide-treated mosquito nets; IVM: Integrated vector management; LLINs: long-lasting insecticidal net; MHD: man-hour density; MOH: Ministry of Health; NIHRD: National Institute of Health Research and Development; NTT: East Nusa Tenggara; OR: odds ratio; PHCs: Primary health centres; RDTs: rapid diagnostic tests; Riskesdas: Indonesia basic health research (Indonesia acronym: Riset kesehatan Dasar); Ristekdikti: Ministry of Research, Technology and Higher Education (Indonesia acronym: Ristekdikti); Susenas: National Socioeconomic Survey (Indonesia acronym: Susenas); USAID: US Agency for International Development; VBDs: vector-borne diseases; WGS84: World Geodetic System 1984.

Authors' contributions

HH obtained the Riskesdas sub-dataset. The study was conceived and designed by HH, DAG, UK and RM. The data was analysed by HH, MD, JB, UK, DM and RM. RM, DAG, MD, DM and UK drafted the manuscript with subsequent contributions and revisions. All authors read and approved the final manuscript.

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Competing interests

The authors declare that they have no competing interests. RM is currently active as a consultant for the non-profit company PoloGGB, Italy, which aims to develop and assess new genetic vector control tools for malaria vectors in Africa. The present study is however not related to PoloGGB activities.

Availability of data and materials

The raw dataset of Indonesia Basic Health Research 2007 has been generated at the National Institute of Health Research and Development (NIHRD), Ministry of Health (Indonesia). Derived secondary data and analysis/findings of this study are available from the corresponding author (HH) on request.

Consent for publication

Not applicable.

Ethics approval and consent to participate

The ethical clearance for primary data has been obtained from the National Institute for Health Research and Development, Ministry of Health, Republic of Indonesia. The ethical clearance for secondary data used in our paper is not required to be obtained. Since the paper uses secondary data, also the consent to participate is not applicable to the present study.

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Publication #3 Social Determinants of Malaria in an Endemic Area of Indonesia

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Social determinants of malaria in an endemic area of Indonesia

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Abstract

Background: Malaria is an increasing concern in Indonesia. Socio-demographic factors were found to strongly influence malaria prevalence. This research aimed to explore the associations between socio-demographic factors and malaria prevalence in Indonesia.

Methods: The study used a cross-sectional design and analysed relationships among the explanatory variables of malaria prevalence in five endemic provinces using multivariable logistic regression.

Results: The analysis of baseline socio-demographic data revealed the following independent risk variables related to malaria prevalence: gender, age, occupation, knowledge of the availability of healthcare services, measures taken to protect from mosquito bites, and housing condition of study participants. Multivariable analysis showed that participants who were unaware of the availability of health facilities were 4.2 times more likely to have malaria than those who were aware of the health facilities (adjusted odds ratio = 4.18; 95% CI 1.52–11.45; $P = 0.005$).

Conclusions: Factors that can be managed and would favour malaria elimination include a range of prevention behaviours at the individual level and using the networks at the community level of primary healthcare centres. This study suggests that improving the availability of a variety of health facilities in endemic areas, information about their services, and access to these is essential.

Keywords: Multivariable analysis, Malaria prevalence, Social health determinants, Social epidemiology, Community health services

Background

Malaria is a significant public health problem especially in developing countries including Indonesia [1]. Research has shown an enhanced interest in the social aspects of the epidemiology of malaria prevalence [2]. Socio-demographic, environmental, economic, cultural and behavioural factors determine the frequency, severity and outcome of malaria infection [3, 4]. Based on the Indonesian basic health research (*Riskesdas*) the prevalence of malaria in 2013 was 6.0%. The distribution of the disease is focussed on eastern Indonesia [5, 6]. Of 497 districts/municipalities of Indonesia, 54% are endemic areas for malaria. The Ministry of Health (MoH) strategy plan for malaria morbidity targeted an Annual Parasite Incidence (API) of < 1 per 1000 population at risk by 2015 [7]. Nationally, malaria morbidity decreased from 4.1 per 1000 people in 2005 to 0.85 per 1000 by 2015 [7]. Reducing the anopheline vectors has been the subject of many meetings and public health initiatives for decades [8]. It has been proposed to eliminate malaria from Indonesia by 2030, with a variety of agendas particularly for endemic areas [9]. As the burden of malaria is very complicated, its elimination, implemented through an integrated approach, has become an integral part of national development [10]. This study attempts to identify socio-demographic factors that are related to malaria prevalence in Indonesia, such as the characteristics of participants, knowledge of the accessibility and utilization of health services, environmental health factors

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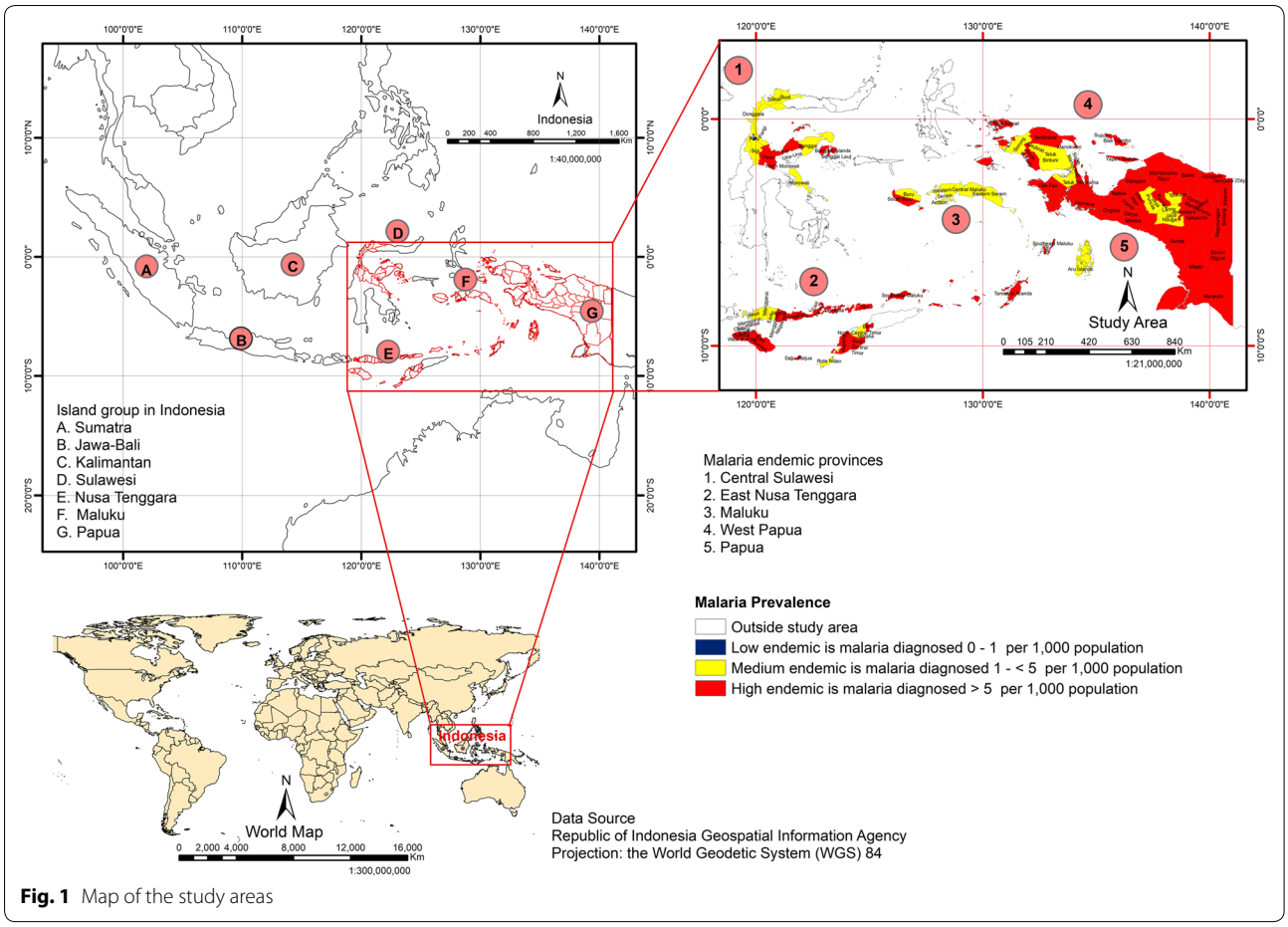

Fig. 1 Map of the study areas

including personal measures to protect from mosquito bites, and the condition of housing structures.

Methods

Study area

The study area covered five out of 33 provinces of Indonesia (83 out of 497 districts and cities in 2013): Central Sulawesi, East Nusa Tenggara, Maluku, Papua, and West Papua Provinces (Fig. 1). These provinces were selected because they had been shown to be highly endemic for malaria both in the 2007 and 2013 basic health research of Indonesia [5, 6]. A "highly malaria endemic" area was defined as having > 5 cases of malaria diagnosed per 1000 population and year which is consistent with the API classification by the MoH of Indonesia. The software ArcGIS 10.3.1 was used for mapping, processing, analysis, and visualization of the data set, and WGS84 was used as the reference coordinate system.

Research design

The design of the Indonesian basic health research, which is called Riskesdas, is a descriptive cross-sectional survey to describe public health problems throughout Indonesia [6]. Figure 2 shows its framework for malaria research. The sample comprised 130,585 participants who represented the population in five highly malaria-endemic provinces.

Research variables

The dependent variable was malaria prevalence and is binary, that is, whether malaria was present or absent. The definition of disease used was diagnosis of the participants (D) with malaria by a physician or professional health worker (Additional file 1: Appendix S1). The data were obtained from a retrospective assessment by health surveyors using a standardised questionnaire. Participants who claimed to have never been diagnosed with malaria were asked whether they had suffered from the specific signs and clinical symptoms of the disease. The term "diagnosed/clinical symptoms" means that the prevalence of illness was based on the diagnosis by a physician or health worker in a health centre or based on the signs and symptoms experienced and reported by participants. The report referred to the disease information

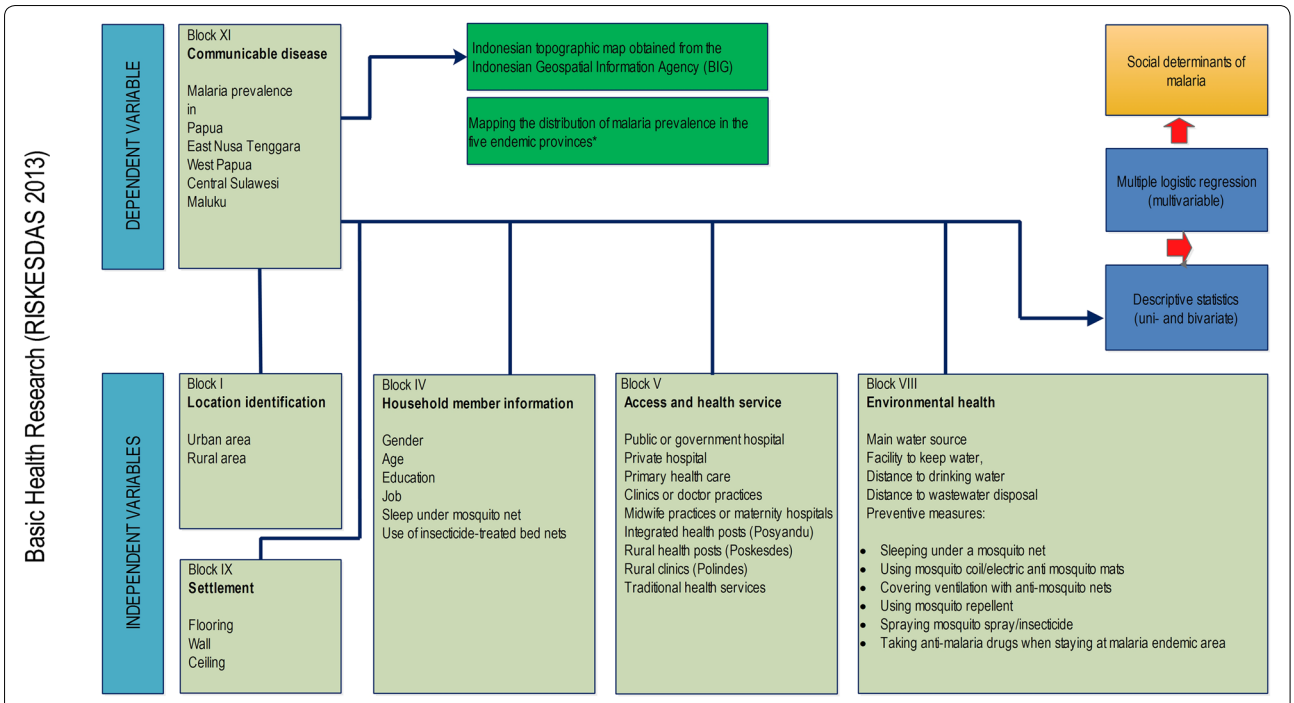

Fig. 2 Framework determinants of malaria among participants in the selected area

collected from interviews using questionnaires and clinically measured interviews [5, 6]. The dependent variable, malaria prevalence, was summarized as a binary variable whose value was one if health experts assessed a participant as having had malaria within the past month [5, 6]. In general, rapid diagnostic tests (RDTs) and microscopy were used to diagnose the disease, but the surveyor did not examine for malaria infection [5, 6].

The explanatory variables consisted of several sociodemographic factors that could affect malaria prevalence including the characteristics of participants, the availability of healthcare services, environmental sanitation including behaviour to prevent mosquito bites, and settlement (Fig. 2, Additional file 1: Appendix S1). These variables were grouped into blocks based on the questionnaire: block I—location identification or household information; block IV—household member information includes sex, age group (year), education and job (occupation), use of bed nets for sleeping and net insecticide; block V—knowledge of available healthcare facilities; block VIII—environmental health including prevention measures against malaria; and block IX—settlement (condition of housing structure). These were the criteria for environmental health in Riskesdas 2013 (joint monitoring programme World Health Organization–the United Nations Children's Fund criteria). Using logistic regression, the independent variables were standardized and modified by considering the survey design [11]. Variables that were transformed into categorical variables were: knowledge of available healthcare facilities, environmental sanitation, prevention measures, and condition of housing structure. All variables were coded as binary dummy variables coded 0 as referent category and coded 1 for a response category of an explanatory variable. Stata was used for data management and analysis [12, Additional file 1: Appendix S1].

Descriptive analysis

The descriptive analysis aimed to identify the characteristics of the independent variables in relation to the dependent variable, malaria prevalence. The variables are summarized in Table 1 and show the baseline sociodemographic characteristics of study participants. The magnitude of risk for having malaria was assessed from the calculated odds ratio (OR) and AOR (bi- and multivariable logistic regression test). If an OR was higher than one, the likelihood of contracting malaria was increased.

Bivariate analysis

The connections between each explanatory variable and the response variable were analysed with bivariate statistics. The Wald test from logistic regression used a *P* cut-off point of 0.25 because statistical significance may not capture importance and the more traditional levels, such as *P* of 0.05, could fail to select variables known to be essential [13]. A cut-off value of 0.25 is supported by

Table 1 Univariate and bivariate analysis of baseline socio–demographic characteristics of participants

Research variables	n = 130,585	95% CI (lb–ub)[a]	OR; 95% CI (lb–ub)[b]	P-value
Malaria				
No	116,073	89.90 (89.15–90.6)		
Yes	14,512	10.10 (9.40–10.85)		
Independent variables				
Location				
Urban	37,389	25.60 (23.07–28.31)		
Rural	93,196	74.40 (71.69–76.93)	0.91 (0.76–1.09)	0.305
Socio–demographic characteristics				
Gender				
Male	64,796	51.08 (50.76–51.40)		
Female	65,789	48.92 (48.60–49.24)	0.90 (0.85–0.94)	0.000
Age of participants in years				
0–4	10,109	8.52 (8.27–8.78)		
5–14	33,378	26.06 (25.60–26.52)	1.32 (1.18–1.49)	0.000
15–24	17,623	15.49 (15.09–15.90)	1.29 (1.14–1.47)	0.000
25–34	19,420	17.09 (16.70–17.47)	1.45 (1.29–1.64)	0.000
35–44	19,604	13.77 (13.47–14.09)	1.58 (1.39–1.80)	0.000
45–54	14,170	8.90 (8.65–9.17)	1.42 (1.24–1.62)	0.000
55–64	8312	4.84 (4.64–5.05)	1.27 (1.09–1.50)	0.003
65–74	3927	2.38 (2.25–2.52)	1.14 (0.96–1.36)	0.147
> 75	4042	2.94 (2.81–3.08)	1.33 (1.12–1.58)	0.001
Education				
Participants considered as higher educated	5935	4.193 (3.853–4.562)		
Participants who had not completed high school education	94,644	72.08 (71.33–72.83)	0.99 (0.83–1.18)	0.878
Participants under 10 years or in preschool	30,006	23.72 (22.93–24.54)	0.84 (0.69–1.03)	0.092
Job (occupation)				
Participants who were not working	77,533	60.12 (59.42–60.82)		
Participants who were working	53,052	39.88 (39.18–40.58)	1.20 (1.12–1.27)	0.000
Use of mosquito nets				
Participants who used mosquito nets at night	61,779	46.19 (44.12–48.27)		
Participants who did not use mosquito nets at night	68,806	53.81 (51.73–55.88)	1.09 (0.97–1.23)	0.153
Use of i insecticide–treated mosquito nets				
Yes	32,150	23.26 (21.73–24.85)		
No	27,510	21.49 (20.03–23.02)	0.90 (0.78–1.04)	0.154
Participants who did not answer and others	70,925	55.26 (53.18–57.31)	1.05 (0.91–1.20)	0.517
Knowledge of households about the healthcare facilities closest to their residence				
Public hospital				
Known	64,817	48.97 (46.47–51.46)		
Not known	65,768	51.03 (48.54–53.53)	0.80 (0.69–0.92)	0.002
Private hospital				
Known	27,836	22.44 (20.32–24.70)		
Not known	102,749	77.56 (75.30–79.68)	0.65 (0.55–0.76)	0.000
Secondary or primary healthcare unit				
Known	116,609	88.92 (87.65–90.08)		
Not known	13,976	11.08 (9.92–12.35)	0.84 (0.70–1.00)	0.051
Clinics or practices of doctors				
Known	32,954	25.7 (23.73–27.77)		
Not known	97,631	74.3 (72.23–76.27)	0.84 (0.73–0.97)	0.019

Table 1 (continued)

Research variables	n = 130,585	95% CI (lb–ub)[a]	OR; 95% CI (lb–ub)[b]	P-value
Midwife practices or maternity hospitals				
Known	18,387	16.59 (14.82–18.52)		
Not known	112,198	83.41 (81.48–85.18)	1.46 (1.24–1.72)	0.000
Integrated health posts (Posyandu)				
Known	56,129	43.23 (41.01–45.47)		
Not known	74,456	56.77 (54.53–58.99)	1.19 (1.06–1.35)	0.004
Village health posts (Poskesdes)				
Known	9932	7.85 (6.63–9.26)		
Not known	120,653	92.15 (90.74–93.37)	1.90 (1.46–2.47)	0.000
Village maternity clinic (Polindes)				
Known	17,312	14.61 (12.95–16.43)		
Not known	113,273	85.39 (83.57–87.05)	1.16 (0.97–1.40)	0.109
Environmental sanitation				
Main water source				
Improved	94,267	72.88 (70.77–74.88)		
Unimproved	36,318	27.12 (25.12–29.23)	1.10 (0.95–1.27)	0.226
Water storage facility				
Improved	127,808	97.56 (96.99–98.03)		
Unimproved	2777	2.44 (1.97–3.01)	1.32 (0.97–1.80)	0.076
Distance from drinking water (time needed to obtain water for drinking)				
Improved	108,053	82.1 (80.44–83.64)		
Unimproved	22,532	17.9 (16.36–19.56)	0.90 (0.77–1.06)	0.218
Wastewater disposal				
Improved	24,099	18.76 (17.35–20.25)		
Unimproved	106,486	81.24 (79.75–82.65)	1.12 (0.98–1.27)	0.089
Slept using a mosquito net				
Yes	63,333	47.44 (45.35–49.54)		
No	67,252	52.56 (50.46–54.65)	1.15 (1.03–1.29)	0.018
Using mosquito coil/electric anti–mosquito mats				
Yes	39,875	31.42 (29.60–33.29)		
No	90,710	68.58 (66.71–70.40)	1.27 (1.13–1.42)	0.000
Covering ventilation holes with anti–mosquito nets				
Yes	8582	6.25 (5.43–7.18)		
No	122,003	93.75 (92.82–94.57)	0.52 (0.43–0.62)	0.000
Using mosquito repellent				
Yes	6562	4.76 (4.18–5.43)		
No	124,023	95.24 (94.57–95.82)	1.06 (0.85–1.31)	0.616
Spraying mosquito spray/insecticide				
Yes	12,004	9.11 (8.10–10.22)		
No	118,581	90.90 (89.78–91.90)	0.66 (0.55–0.79)	0.000
Taking anti–malaria drugs when staying in a malaria endemic area				
Yes	1265	0.92 (0.73–1.16)		
No	129,320	99.08 (98.84–99.27)	0.48 (0.33–0.69)	0.000
Draining the bath water reservoir once a week				
Yes	55,702	41.89 (39.97–43.83)		
No	74,883	58.11 (56.17–60.03)	0.98 (0.87–1.10)	0.698
Settlement or housing condition				
Floors				
Improved	51,788	39.82 (37.95–41.73)		

Table 1 (continued)

Research variables	n = 130,585	95% CI (lb–ub)[a]	OR; 95% CI (lb–ub)[b]	P-value
Unimproved	78,797	60.18 (58.27–62.05)	1.23 (1.08–1.39)	0.001
Walls				
Improved	112,582	85.23 (83.59–86.72)		
Unimproved	18,003	14.77 (13.28–16.41)	1.32 (1.122–1.55)	0.001
Ceiling				
Improved	2192	1.75 (1.45–2.10)		
Unimproved	128,393	98.26 (97.90–98.55)	1.04 (0.72–1.50)	0.835

lb Lower 95% confidence boundary of cell percentage, *ub* Upper 95% confidence boundary of cell percentage

[a] 95% CI of percentage in univariate analysis

[b] 95% CI of percentage in bivariate analysis

literature [14]. Decisions to keep a variable in the "best" model were based on clinical or statistical significance, or on the significance level of a confounder between 0.1 and 0.15 as it might, in combination with other variables, make an important contribution [13]. In the present study, variables could potentially be entered into the multivariable model if the results of the bivariate test had a value of $P < 0.25$.

Multivariable analysis

The multivariable analysis aimed to find the parsimonious logistic regression model. A backward technique was used with stepwise removal of non-significant variables ($P > 0.05$). The regression coefficient was repeatedly re-estimated until no further independent variables were insignificant. However, if $P > 0.05$, the variable was inserted into the multivariable model but only if considered substantially necessary. The variables that had significant results in the descriptive analysis of each variable were selected as candidates for the model for multivariable analysis.

Results

Figure 1 reveals a low prevalence of diagnosed malaria disease at Palu (0.85%) and Donggala (1.56%) districts in Central Sulawesi, and a high malaria prevalence at Intan Jaya (45.96%) and Kepulauan Yapen (38.95%) districts in Papua.

Descriptive analysis

The effect of social determinants on malaria prevalence in five malaria-endemic provinces of Indonesia is summarised in Table 1 and more detailed in Additional file 2: Appendix S2. A large percentage of participants (72.08%) had not completed high school education, and only 4.19% were considered higher educated. Overall the percentage of males (51.08%) was slightly higher than that of females (48.92%). An OR > 1 shows that the probability of the disease is greater for the response category than the referent category of an explanatory variable. The percentage of respondents who reported "do not know the availability of midwife practices, and village health post" was 83.41% and 92.15%, respectively. In the bivariate analysis, participants who were working were 1.2 times more likely to have malaria than those who were not (OR = 1.20; 95% CI 1.12–1.27; $P < 0.001$). The environmental sanitation variable was not statistically significantly associated with malaria prevalence (OR = 1.13; 95% CI 0.99–1.31; $P = 0.081$). Prevention measures against malaria were important: participants who did not take preventive measures were 1.2 times more likely to contract malaria than those who did (OR = 1.18; 95% CI 1.01–1.38; $P = 0.036$). The risk of having malaria was significantly higher for participants who did not know about the availability of healthcare services (OR = 4.22; 95% CI 1.53–11.59; $P = 0.005$). Further, housing conditions were also important: participants who lived in houses made of unimproved materials were 1.3 times more likely to have malaria than those in houses made of improved building materials (OR = 1.30; 95% CI 1.09–1.54; $P = 0.003$) as shown in Table 2.

Logistic multivariable regression

The OR and AOR of factors affecting malaria prevalence are shown in Table 2 and more detailed in Additional file 2: Appendix S2. The participants who were unaware of the availability of or did not utilize health facilities were more likely to have malaria than those who did (AOR = 4.18; 95% CI 1.52–11.45; $P = 0.005$; adjusted by other covariates). The logistic multivariable regression provides an additional dimension to the research results (Table 2). The final model includes the following significant explanatory variables for malaria prevalence: characteristics of participants (gender, age, and job in block IV), knowledge of the availability of health services (in block V), and settlement (condition of housing structure in block IX).

Table 2 Factors associated with malaria prevalence in the endemic area

Research variables	Simple logistic regression analysis		Multiple logistic regression analysis	
	OR (95% CI)[a]	P-value	AOR (95% CI)[b]	P-value
Gender				
Males (Ref.)				
Females	0.90 (0.85–0.94)	0.000	0.91 (0.87–0.96)	0.000
Age of participants in years				
More than 5 years of age (Ref.)				
Children under 5 years of age	0.72 (0.65–0.81)	0.000	0.74 (0.67–0.83)	0.000
Job (occupation)				
Participants who were not working (Ref.)				
Participants who were working	1.20 (1.12–1.27)	0.000	1.13 (1.06–1.20)	0.000
Use of mosquito nets				
Participants who used mosquito nets (Ref.)				
Participants who did not use mosquito nets	1.09 (0.97–1.23)	0.153	–	–
Knowledge about healthcare services				
Healthcare facilities closest to the residence				
Known (Ref.)				
Not known	4.22 (1.53–11.59)	0.005	4.18 (1.52–11.45)	0.005
Environmental health				
Improved (Ref.)				
Unimproved	1.13 (0.99–1.31)	0.081	–	–
Preventive measures				
Using preventive measures (Ref.)				
Not using preventive measures	1.18 (1.01–1.38)	0.036	–	–
Settlement or housing condition				
Improved (Ref.)				
Unimproved	1.30 (1.09–1.54)	0.003	1.30 (1.09–1.54)	0.003

Ref.: The reference category is represented in the contrast matrix as a row of zeros

[a] Crude odds ratio

[b] Adjusted odds ratio

Discussion

Principal findings

Many risk factors increase the likelihood of contracting malaria, particularly the accessibility and utilization of primary healthcare facilities. This study reveals a 4.2-fold increase in the odds of malaria prevalence for participants who do not know about the availability of healthcare facilities compared to those who do know, adjusted by other covariates. The kind of healthcare facilities in this study included government hospitals, private hospitals, primary healthcare (*puskesmas*), clinics, midwife practices, integrated health posts (*posyandu*), village health posts (*poskesdes*), and village maternity clinics (*polindes*). Health services at the primary level in the community as well as their networks are essential for malaria elimination. Healthcare services, particularly for pregnant women, can be delivered during antenatal care (ANC) as pregnant women, infants, and toddlers are especially vulnerable groups for the disease. Malaria is a significant global health issue, especially among pregnant women [15]. Midwives also play a crucial role in health reporting [16]. Although there are physicians and nurses in public and private hospitals, midwives are also needed at the primary level of healthcare and at the community level. Thus, they also need to be equipped with expertise and skills to effectively provide information and promote the prevention of malaria. Particularly at the community level such health promotion and malaria prevention programmes are essential [17]. The findings of this study are consistent with those of one in Uganda where midwives provide malaria-related health promotion and education to pregnant women during every prenatal clinic visit, including direct supervision on how to consume drugs [18]. In sub-Saharan Africa, it has long been recognized that pregnant women are an especially vulnerable group for malaria infection, and that there is a need for active management of the disease in pregnancy as a fundamental part of antenatal care in endemic areas [19].

In Malawi, pregnant women are significant reservoirs of gametocyte transmission which is present in 5% at their first antenatal care visit, and this should not be overlooked in elimination efforts [20].

Explanatory variables

In the present study, the estimated odds of malaria in females was 10% lower than in males. Similarly, in Lundu district, Sarawak, Malaysia, malaria infection was associated in male than a female with seven-fold risk to be malaria-infected [21]. This is consistent with a previous study showing that females performed a protective function in malaria control [22]. In contrast, in Bungoma county, western Kenya, the risk of clinical malaria was related to being female. As well, *Plasmodium falciparum* infection was connected with being male, poorer, and malnourished [23]. Malaria prevalence differs among age groups. In this study, the estimated odds of malaria for the age group from 35 to 44 years were higher than for others. In a similar study in sub-Saharan Africa, a positive microscopic result was significantly associated with being in the age group of 35–44 years compared to 45 years or older [24]. Also, in South Africa malaria is a significant public health problem among adults and more pronounced in the economically active adult male population [25]. Another study in rural Hausa communities in Nigeria showed that malaria was significantly associated with the participant's knowledge, age, and gender [26]. In the present study, the risk of having malaria was 1.2 to 1.13 times higher for those who were working (simple logistic and multiple logistic analysis, respectively) compared to those who were not. Conversely, in a study in Blantyre, Malawi, employment status did not differ between the groups [27].

Several other factors are related to malaria prevalence. These include the lack of prevention measures against malaria, such as bed nets, insecticide treatment and knowledge deficits. In spite of a widespread use of mosquito nets at night and insecticide-treated mosquito nets (ITNs), this is not always significantly associated with reduced malaria prevalence. Nevertheless, the present study indicates that participants in endemic provinces of Indonesia who did not use mosquito nets at night were more likely to have malaria than those who did. Similarly, not using ITNs predicted an increased occurrence of clinical malaria in a study in urban Kano, northwestern Nigeria [28], and an Indian study found that a persistent use of nets resulted in a substantial reduction in malaria cases [29]. Illustrating the variability of the relationship between bed-net use and malaria incidence, a study in southern Ethiopia, where the use of bed-nets was frequent, showed that the prevalence of malaria was also high [30]. Obstacles to the use of ITNs include lack of promotion information and lack of knowledge [31]. A survey in Orissa, India, indicated that appropriate communication strategies should be built up and imparted alongside ITN distribution to promote ITN adoption [31]. A similar finding was reported for south-eastern Nigeria where, despite the community having good knowledge about the use of mosquito nets, few knew about the existence of ITNs [32]. Another investigation in Ghana revealed that participants did not have sufficient knowledge about the behaviour of mosquitoes, which weakened their knowledge of the relationship between malaria control and the use of ITNs [33].

Lack of both information and vector control measures to protect people from malaria have been reported as being related to higher malaria risk [34]. Unquestionably, the dissemination of information and health education for preventive measures against malaria are essential. In a South African study, most participants were confident that indoor residual spraying killed mosquitoes and prevented infection. Their sources of malaria information were from the local health facility, radio, and community meetings [35]. The latter study considered that providing health education on malaria and knowledge about risk factors might change health-related behaviour, and thereupon the spreading of knowledge could decrease malaria infection [30]. The present research in the context of Indonesia concludes that preventive measures against malaria in the environment are important.

Knowledge about the availability of health facilities is also important. This study revealed a 4.2-fold increase of malaria prevalence in participants who did not know about the availability of health facilities compared to participants who did. Increasing distance from the place of residence to the nearest health centre was related to delays in seeking treatment for severe malaria at Jinja Hospital, Uganda [30, 36]. In Cambodia, knowledge about malaria symptoms differed significantly between a village with a health centre and an area that had only village malaria workers. Thus, governments need to enhance community knowledge about malaria symptoms and case management in rural areas [37].

Similarly, in sub-Saharan Africa malaria transmission was determined by knowledge of and access to malaria prevention tools as well as healthcare services [38]. In Mali, knowledge and perceptions related to health condition have an important influence on care-seeking behaviour in the formal health sector [39]. The government of Ghana improved access to healthcare, particularly in a primary healthcare programme, and that was an important contribution towards malaria elimination [40]. In the Asia–Pacific region, the use of traditional medicine and/or traditional healers to treat malaria was related to lack of access to health services (due to geographical or

economic barriers), belief in traditional medicine, and a perception that symptoms of malaria were less severe a disease [41]. In central Cameroon, rural populations tended to visit traditional practitioners more than urban healthcare providers for geographical and financial reasons [42]. Optimizing the role of the "alert village" where the people of the village can easily access health services through village health posts or other health facilities in the area will reduce malaria risk. The alert village is a strategic effort that was created to accelerate the achievement of the millennium development goals to combat malaria [43]. As noted above, the present study concludes that participants who were unaware of available health facilities were more likely to have malaria than those who did know about these.

Even though environmental sanitation was not significantly associated with malaria prevalence in this study, participants who lived in environments with unimproved sanitation more frequently had malaria than those living in environments with improved sanitation. In a Nigerian study, the majority of respondents believed that bushes around the house were significant facilitators of malaria. Some of them stated that the presence of stagnant water was associated with malaria while others mentioned unclean drainage systems [29]. Keeping the outside environment clean can reduce the risk of malaria as shown in a study in rural Nigeria where reductions of malaria prevalence were significantly associated with periodic cleaning of the external environment [44].

With regards to housing condition, the estimated odds ratio of malaria prevalence for participants who lived in houses made of unimproved materials showed that they were 1.3 times more likely to have malaria than those living in houses made of improved building materials. This is consistent with the results of a study in Nigeria where the odds of malaria infection were significantly higher among participants who lived in unimproved houses [45]. A recent review noted that low-quality housing was consistently associated with malaria prevalence, and the authors recommended that this should be further explored along with housing improvements, especially those that reduce mosquito access [46]. A study in the Ananindeua municipality, State of Pará (Brazil), showed an association between poverty and poor living conditions and highlighted that these need to be considered in malaria prevention and control strategies [47]. Another study, conducted in Equatorial Guinea, showed connections between improved building materials over time, housing quality (closed eaves and door/window screens), and reduced malaria incidence [48]. A study in Krogwe, Tanzania, showed that children living in high-quality housing had only a third of the malaria infections compared to those living in poor quality housing [49]. In addition, location is important with households that are very close to the border of forests and swamps being at high risk for malaria [4, 50]. To sum up, unimproved conditions of housing structure were associated with higher malaria prevalence.

Limitations of research

Malaria disease status was retrospectively assessed by a standard Riskesdas questionnaire and not directly based on diagnoses made by healthcare professionals. Thus, the prevalence of malaria could only be estimated from respondents who reported that they had been diagnosed with malaria by professional health workers. There may be other factors which affect malaria prevalence but were not monitored in the Riskesdas survey; these could be the subject of further research. Nevertheless, the present study has the strength of being based on a large sample size, and its analyses were novel and robust and identified relationships that could be useful in the future design of malaria control strategies, at least in the five highly endemic provinces of Indonesia.

Conclusions

This study estimated the socio-demographic factors affecting malaria prevalence in the five highly endemic provinces of Indonesia. These factors included the characteristics of participants, lack of knowledge about the availability of healthcare services, and unimproved housing. Recommendations include increasing community health education regarding the utilization of healthcare facilities, improving community healthcare knowledge, and practices relating to malaria prevention, such as improving the condition of housing structures. These should be considered in upcoming malaria management control strategies.

Additional files

Additional file 1: Appendix S1. Detailed explanation of the scope of variables and analytical method.

Additional file 2: Appendix S2. Detailed description of descriptive analysis.

Abbreviations

ANC: antenatal care; AOR: adjusted odds ratio; API: annual parasite incidence (number of slides positive for parasite × 1000/total population); ArcGIS: aeronautical reconnaissance coverage geographic information system; Balitbangkes: Badan Penelitian dan Pengembangan Kesehatan (National Institute for Health Research and Development); CI: confidence interval; HDI: Health Development Index; ITNs: insecticide-treated mosquito nets; MoH: Ministry of Health; OR: odds ratio/unadjusted odds ratio; Polindes: Pos bersalin desa (village maternity clinic); Poskesdes: Pos kesehatan desa (village health post); Posyandu: Pos pelayanan terpadu (integrated health post); Puskesmas: Pusat

kesehatan masyarakat (primary health care centre); Pv: P-values; RDTs: rapid diagnostic tests; Riskesdas: Riset kesehatan dasar (Basic Health Research).

Authors' contributions
HH designed and performed the collection and analysis of the data and managed the study. PD, RM, DAG and UK contributed to the interpretation and visualization of the results. HH, PD, RM, DAG and UK wrote the paper. All authors read and approved the final manuscript.

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Competing interests
The authors declare that they have no competing interests.

Availability of data and materials
The basic dataset of Riskesdas has been set up at the Balitbangkes of MoH, and the secondary data is available upon request from the corresponding author (HH).

Consent for publication
Not applicable.

Ethics approval and consent to participate
The ethical clearance for the collection and use of the primary data as the data source for this study was given to Riskesdas 2013 with the number LB.02.01/5.2/KE.006/2013. Ethical clearance was obtained from the National Ethical Committee of the Indonesian Ministry of Health (Balitbangkes) in Jakarta (official name: Komisi Nasional Etik Penelitian Kesehatan).

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An Annex

Additional file 1 and 2, an annex of study #2

Additional file 1

A detailed description of the scope of variables and statistical procedure of study #2

Scope of variables

Data management. Data were managed with Stata software as follows: For the dependent variable (malaria), code = 0 indicated healthy participants [no malaria] and code = 1 indicated [have malaria]. Likewise, for the independent variables, a “small” code was given to describe a variable as “good condition” or a “group that is not at risk”. Reference was set to code = 0. Automatically, Stata treated the lowest code in the comparison group as a reference category.

Malaria prevalence. In this study, "having malaria" was defined as participants who have ever been diagnosed with malaria by health workers. Malaria infection was not tested during the interview; this way unrecorded malaria cases cannot be excluded. Malaria was placed into categories, "malaria" or "no malaria" as binary logistics. The data were obtained from the retrospective assessment by health surveyors using a standardised questionnaire.

Characteristics of participants. Gender differences were divided into male and female and were taken from the questionnaire *RKD07. RT block IV no.4.* Age was the lifespan of the participants in years; if age was <1 years "00" was filled in and if the age was ≥97 years "97" was filled in based on the age of the population, according to demographic characteristics. Age categories were created, defined as productive (15-64 years) and not productive (< 15 and > 64 years). Education was defined as the highest level of education attained by participants. Upon completion of high school education, participants were considered as higher educated and coded = 0. However, participants who had not completed high school education were low educated and given a code = 1 and if the respondent <10 years were given the code = 2. These data were taken from questionnaire *RKD RT block IV no.7*. The main occupation of participants was taken from questionnaire *RKD07. RT block IV no.8,* and we divided this variable into three categories. If the main employment of a respondent was not a farmer /fisherman/ labour, then this was given a code = 0. If the main employment was as a farmer /fisherman/ labour, this was given a code = 1, and if the respondent was <10 years, the code = 2 was given.

The accessibility & utilisation of health service. From questionnaire *b6r1b*, time to the hospital was given a code = 0 if the respondent had good access, i.e. if the travel time = < 60 minutes and coded = 1 if travel time was > 60 minutes. The same categories for coding were used for data from questionnaire *b6r2b* to categorise time to the primary health care.

Environmental sanitation. According to questionnaire *d09*, the variable of defecating was given a code = 0 if participants were in the habit of defecating in toilets and a code = 1 if participants did not use toilets or gave no answer. Environmental sanitation, such as the type of container/reservoir used, was given a code = 0 if the container/reservoir was closed or given a code = 1 if not. From questionnaire *b7r9*, the variable of a sewage canal was given a code = 0 if the sewage canal was closed or given a code = 1 if not. In questionnaire *b7r10*, the variable of a chemical sewage canal was given a code = 0 if there was good sanitation (sewerage closed) or given a code = 1 if not.

The behaviour of participants. From questionnaire *b4k10*, the use of mosquito nets was categorised as follows: If participants used mosquito nets at night, these were given a code = 0. If participants did not use mosquito nets, then these were given a code = 1, while if the respondent gave no answer, these were given a code = 2. From questionnaire *b4k11*, the variable of insecticide-treated nets (ITNs) was investigated. Those participants using ITNs were given a code = 0, while if ITNs were not used, these were given a code = 1, and if the participants did not answer or did not sleep using mosquito nets, these were given a code = 2.

The existence of livestock and location of cages. These independent variables were taken from questionnaire *VII.16 at number 16 (1)* and *VII.16 at number 16 (2) b and c* and involved those participants who raised poultry including chicken, ducks and birds, pets including dogs, cats and rabbits and who kept livestock, raising both medium-sized breeding animals (goats, sheep, pigs, etc.) and large-sized breeding animals (cows, buffaloes, horses, etc.). The location of livestock sheds where participants kept breeding animals and were categorised into “cage in the house“, “cage outside the house“, “household without an indoor cage“ and “houses that kept animals outdoors without a cage“, or the respondent did not have cattle. Variables with >2 groups were transformed into dummy variables.

Details of data analysis

Data were analysed using statistical data processing applications by Stata taking into account the complex sampling design [57]. Data about the proportion of participants with malaria prevalence, characteristics of participants, their accessibility and utilisation of health service, environmental sanitation, the behaviour of participants, and the existence of livestock/pets and location of cages were analysed. In bivariate analysis, we use two-way tables for survey data. Survey estimation commands are governed by the svy prefix. The svy option is used with many statistical commands to adjust for the effect of sample design when analysing survey data. The *svy: tabulate* uses *-tabdisp- display tables* command to produce the table. The main difference is that *svy: tabulate* computes a test of independence that is appropriate for complex survey data. The *svyset* manages for survey analysis settings of a dataset to designate variables that contain information about the survey design, such as the sampling units and weights. (Stata Corp LP. 2017). By running a series of bivariate logistic regressions, independent variables that may have predictive value for the dependent variable were selected for the multiple regression model (model 1) (Wald test, $P < 0.25$). Also, the statistically insignificant variable "raising of large-sized breeding animals" was included in the multiple regression model (model 1). To determine the relationship amongst multiple independent variables with the dependent variable malaria prevalence, a final multiple logistic regression analysis (model 2) was computed with the significant explanatory factors from the multiple regression model 1. Confounder variables with a >10% change of odd ratio and $p < 0.05$ were identified: The variables “raising of large-sized breeding animals” and “location of cages”, either indoors or outdoors, possessed co-linearity and hence were omitted from the final regression analysis (model 3). In addition, Pearson's product-moment correlation was run to assess the relationship between ITNs and prevalence of Malaria in 259,885 participants.

Additional file 2

A detailed description of descriptive analysis and bivariate analysis of study #2

Descriptive analysis

Characteristics of participants. The proportion of females (50.7%) was slightly higher than the percentage of males (49.3%), while the proportion of participants who fell in the age range of 15-64 years was the greatest (60.1%). Furthermore, there were more participants, who had a low educated level (57.0%) than higher educated participants. Looking at employment, the proportion of participants whose main work were not a farmer, fisherman or labourer (45.4%) was higher than the other jobs category (31%) or category with participants <10 years [not worked] (23.6%).

The accessibility & utilisation of health service. The general access to health care was found to be good. The accessibility and utilisation of health services (facility: hospital, health centre, sub-health centre, Doctor's practice, nurse practice) were good (93.2%) compared to poor access (6.8%). For primary health care, access was also good (95.2%).

Environmental sanitation. Regarding environmental sanitation, participants who used a type of closed container (62.6%) was much greater than others (37.4%). However, the proportion of participants who had sewage canal from the bathroom/ laundromat/kitchen closed container (5.5%) was smaller than others and those who had a chemical sewage canal with the closed canal (9.9%).

The behaviour of participants. According to the behaviour of the participants, a greater proportion of them did not use mosquito nets (55.2%), and also, the majority of participants did not use insecticide-treated nets (29.0%) given that only 11.4% claimed to use a net insecticide (insecticide-treated nets ITNs). The proportion of participants not using toilets was found to be slightly greater (55.7%) than those who did use toilets (44.3%).

Bivariate analysis

Characteristics of participants. Malaria prevalence differed by gender. Males were more likely to have malaria than females (3.75% males *versus* 3.20% females, $P < 0.001$). Malaria prevalence also differed by age groups. The proportion of participants who in the age range of 15 - 64 years contracted malaria higher than others (3.67%; *versus* 3.17 %, $P < 0.001$).

In addition, participants who had not completed high school education likelihood of contracting malaria than participants were considered as higher educated (3.52% *versus*

3.10%, $P < 0.05$, but odds ratio = 1.00). Participants <10 years [pre-school] had a higher likelihood of contracting malaria than Participants were considered as higher educated (3.51% *versus* 3.10%, $P < 0.05$). The estimated odds of malaria from participants who had not completed high school education were 1.14 times higher than from participants who were considered as higher educated (OR = 1.14, $P < 0.05$).

Participants with a profession as a farmer/fisherman/labour have a higher likelihood of contracting malaria than participants who were not a farmer/fisherman/ labour (3.98% *versus* 3.23%, $P < 0.001$, but odds ratio = 1.00). Estimated odds of malaria for participants <10 years [not worked] was 1.24 times higher than for participants who were not a farmer/fisherman/labour (OR = 1.24, $P < 0.001$), although percentage for malaria is almost similar (3.25% *versus* 3.23%).

The accessibility & utilisation of health service. The proportion of participants, who stated that the accessibility and utilisation of health services at the hospital is good, contracted less malaria than those, who said that the access is not good (3.35% *versus* 5.03%, $P < 0.001$). Similarly, the proportion of participants, who reported that primary health care access is good, contracted less malaria than those, who said that the access was not good (3.37% *versus* 5.39%, $P < 0.001$).

Environmental sanitation. According to environmental sanitation, participants who did not possess of closed containers contracted malaria higher than participants who had others (3.68% *versus* 3.34%, $P = 0.051$). Similarly, participants who had not a closed chemical sewage canal from bathroom/laundromat/kitchen revealed a more likelihood of contracting malaria than others (3.51% *versus* 2.68%, $P < 0.001$). Also, participants who did not possess a closed chemical sewage had a higher likelihood of contracting malaria than others (3.54% *versus* 2.85%, $P < 0.001$).

The behaviour of participants. The difference in malaria prevalence was only minor for participants who did not use mosquito nets with a slightly smaller likelihood of contracting malaria than participants who used mosquito nets at night (3.12% *versus* 3.84%, $P < 0.001$). However, the odds ratio was 1.00 which implies that there is a similar risk of contracting malaria for two groups. Malaria in participants who did not answer was more likely prevalent than in participants who used mosquito nets at night (7.10% *versus* 3.84%, OR = 0.80, $P < 0.001$).

Participants who did not use insecticide-treated nets (ITNs) contracted malaria less likely than those who used mosquito ITNs (3.08% *versus* 5.89%, $P < 0.001$), but the risk for

contracting malaria is equally distributed to two groups (OR = 1). Participants who did not answer contracted less likely malaria than those who used mosquito ITNs (3.19% *versus* 5.89%, OR = 0.51, $P < 0.001$). Indicating the limitation of bivariate analysis for the variable "use of ITNs", there was a negative correlation between use of ITNs with the prevalence of malaria (r = 0.023, $P < 0.001$). This statistic implies the opposite of bivariate statistics: for participants who increasingly used ITNs, the prevalence of malaria decreased. Participants who did not use a toilet revealed not a significant increase in malaria prevalence in comparison to those who used a toilet (3.51% *versus* 3.41%, $P = 0.051$).

The existence of livestock/pets

Participants who kept the pets were more likely to contract malaria than those who did not keep pets (4.61% *versus* 3.08%, OR = 1.152, $P < 0.001$). Similarly, participants who raised poultry contracted more likely malaria than others (3.77% *versus* 3.11%, $P < 0.001$). Likewise, participants who raised medium-sized breeding animals contracted more malaria than those who did not keep medium-sized breeding animals (5.22% *versus* 2.97%, $P < 0.001$). On the contrary, keeping of large-sized breeding animals did not significantly increase malaria prevalence (3.31% *versus* 3.49%, $P = 0.43$).

Location of cages. If untangling between indoor and outdoor caging, participants who kept caged pets outside the house were more likely to contract malaria than those keeping poultry indoors (5.32% *versus* 3.93%, $P < 0.001$). This difference in malaria prevalence was however only minor for participants who raised poultry either (4.19% outdoors *versus* 3.74% indoors, $P < 0.001$). Similarly, the participants who kept medium-sized breeding animals outside the house contracted malaria more than those who kept medium-sized breeding animals indoors (8.35% *versus* 4.98%, $P < 0.001$). The participants who kept large-sized breeding animals outside the house contracted malaria more than those who kept medium-sized breeding animals indoors (4.15% *versus* 3.26%, $P = 0.48$).

Additional file 3

Additional file 3 and 4, an annex of study #3

A detailed explanation of the scope of variables and analytical method.

Scope of variables

Data handling. Data were processed with Stata software as follows: For the dependent variable (malaria), healthy participants (no malaria) were coded 0 and participants who had malaria were coded 1. Likewise, for the independent variables, a “small” code was given to describe a variable as “good condition” or a “group that is not at risk”. Reference was coded as 0. Stata automatically treated the lowest code in the comparison group as a reference category. These data were collected from questionnaire *RKD 2013.*

Malaria prevalence. In this view, "having malaria" was defined as participants who had ever been recognised as having malaria by health workers. Malaria was characterised as "malaria" or "no malaria" as a binary variable. Health surveyors using a standardised questionnaire collected the data by retrospective assessment. Healthcare professionals asked the participants whether they had ever had a diagnosis of a particular disease (D: Diagnosis). The participants who said that they never had any disease diagnosed were further investigated as to whether they used to/presently experienced certain clinical symptoms of such disease (G: Symptoms). The disease of interest was malaria. Prevalence was measured for one year or less. In the present study, the sample size was 130,585 participants who lived in five out of Indonesia's 33 provinces in 2013. Malaria prevalence in 2013 was 6.0 %. The five provinces with the highest malaria prevalence are Central Sulawesi, East Nusa Tenggara, Maluku, Papua, and West Papua Provinces (Figure 4:1).

The characteristics of participants

Gender distinctions were divided into male and female and were taken from questionnaire *b4k4*. The age of the participants was recorded in years; if the age was <1 year "00" was filled in and if the age was ≥97 years "97" was recorded. Age categories were set up and coded as follows: (0) "0 – 4 years"; (1) "5 – 14 years"; (2) "15 – 24 years"; (3) "25 – 34 years"; (4) "35 – 44 years; (5) "45 – 54 years"; (6) "55 – 64 years"; (7) "65 – 74 years"; (8) "more than 75 years ". These data were taken from questionnaire *b4k7*. Education in this paper was defined as the highest level of education attained by participants. Upon completion of high school education, participants were considered as higher educated and

coded = 0. Participants who had not completed high school education were seen as low educated and given a code = 1, and, if the respondent was <10 years, the code = 2. These data were collected from questionnaire *b4k8*. For further analysis, the variable 'age of participants' was coded as binary dummy variables with a code = 0 for participants more than five years of age as referent category and code 1 for less than five years of age. Similarly, for education a code = 0 was given for participants who were considered as higher educated as a referent and a code = 1 was given for others. The primary occupation of participants was taken from questionnaire *b4k9,* and the researcher divided this variable into two groups. If the respondents were not working, they were given a code = 0 and if the respondents were working the code = 1.

The behaviour of the participants. From questionnaire *b4k12,* the use of mosquito nets was categorised as follows: If participants slept under mosquito nets at night, these were given a code = 0. If participants did not use mosquito nets, then these were given a code = 1. From questionnaire *b4k13,* the variable of insecticide-treated nets (ITNs) was examined. Those participants sleeping under ITNs to prevent malaria were given a code = 0, while those who did not use ITNs were given a code = 1, and those who did not answer this question were given a code = 2.

Knowledge of health services. Healthcare service access described in the Riskesdas 2013 refers to the knowledge of households about the healthcare facilities nearest to their residence. In this situation, healthcare workers asked the participants about the accessibility and utilisation of healthcare facilities such as a public hospital or government hospitals; private hospitals; primary healthcare centres (puskesmas/pustu); clinics or doctor practices; midwife practices or maternity hospitals; and integrated health posts (posyandu). The participants were also asked regarding village health posts (poskesdes), village maternity clinics (polindes). From the questionnaire, those participants who knew of the availability of the health facilities were given a code = 0, and those who did not know of the availability of the health facilities were given a code = 1. The questionnaire *b5r2k1* shows the availability of government hospitals and *b5r2k1* indicates the availability of private hospitals. Information on primary healthcare centres was obtained from questionnaire *b5r3k1,* information on clinics/practices from *b5r4k1*, and that on midwife practices or maternity hospitals from *b5r5k*. Data about health facilities such as

integrated health posts, rural health posts, rural clinics, and traditional health services were obtained from questionnaire *b5r6k1*, *b5r7k1*, *b5r8k1*, and *b6cr1*, respectively. For advanced analysis, participants knowing of the availability of health services were further classified using binary dummy variables with a code = 0 for participants who knew about the availability of certain health facilities and 1 for those who did not know about such health facilities.

The kind of health care facilities and health services in Indonesia such as a public hospital or government hospitals; private hospitals; primary health care centres (puskesmas/pustu); clinics or doctor practices; midwife practices or maternity hospitals or maternity hospitals; and integrated health posts (posyandu), village health posts (poskesdes), village maternity, and village clinics (polindes) in generally. [58], [59]

Environmental sanitation. Environmental sanitation included information on the primary source of water, distance to drinking water, and wastewater disposal. According to questionnaire *b8r1a*, participants who had improved drinking water were given the code = 0, and those who did not know the code = 1.

The questionnaire variable *b8r1a* consist of the main clean water supply of household. This variable categorised improved when the participants use water taps, buying water from water taps, drilled well pump, well water sheltered, the water spring protected, and rainwater storage. Contrarily, the variable categorised unimproved for who use well water is not protected, the water spring is not protected, and water from the river, lake, and irrigation.

According to questionnaire *b8r3c*, participants who had an improved primary source of water were given a code = 0, and a code = 1 if it was not improved. The questionnaire variable *b8r3c* consist of drinking water storage. This variable categorised improved when the participants drinking water storage from the dispenser, kettle, thermos, and jerry cans, kind of earthenware jug and bucket, covered pans. In another way; the variable categorised unimproved for who drinking water storage from the bucket, and open pans.

The same categories were coded for participants who responded to drinking water needs in questionnaire *b8r6a*. The questionnaire *b8r6a* is the distance which needed to drinking water needs. This variable categorised improved for participants who get drinking water where the location of the drinking water in the house, the distance to get drinking water needs is less than or equal to 100 meters. Differently, this variable categorised unimproved for participants who get drinking water where the range of drinking water

between 101-1,000 meters and more than 1,000 meters. Wastewater disposal was for those participants who managed domestic wastewater disposal from water taps, kitchens, and bathing areas in questionnaire *b8r10*. Further, for bivariate and multivariable analysis, the environmental sanitation variable was composited into binary dummy variables with a code = 0 for participants whose environmental sanitation was improved and a code = 1 for those with unimproved environmental sanitation. Similar codes were given for the variable of settlement or housing condition of the participants of the study.

Behaviour to prevent mosquito bites. These independent variables were selected from the questionnaire *b8r14*. According to questionnaire *b8r14a,* if participants slept using mosquito nets, they were coded = 0, and if not, = 1. The same categories were coded for participants who used mosquito coils, and electric mosquito repellents in questionnaire *b8r14b*. Similar coding was used for participants who covered ventilation holes with anti-mosquito nets in questionnaire *b8r14c*; participants who used mosquito repellent to avoid mosquito bites in questionnaire *b8r14d*; participants who used spray with mosquito insecticide in questionnaire *b8r14e*; participants seeking anti-malarial drugs for malaria prevention when staying in an endemic malaria area in questionnaire *b8r14f*. Furthermore, behaviours preventing mosquito bites were composited into binary dummy variables with a code = 0 for participants who took prevention measures, and a code = 1 for those who had not.

Housing condition. Questionnaires *b9r4, b9r5,* and *b9r6* regarding “the widest type of tile”, “the widest type of wall”, and “the widest type of ceiling”, respectively, describe conditions of houses inhabited by the participants. Participants who had the kind of housing conditions considered "improved”, were given the code = 0 and the others were given the code = 1.

In this study, the settlement or housing condition is a composite of variables: floors, walls, and ceiling which categorised improved and unimproved. Improved flooring is categorised who those use the kind of the widest floor of housekeeping with ceramics, tiles, marble, and cement floor. Contrarily, unimproved flooring who use the widest floor with cement plastering cracked, boards, bamboo, wicker bamboo, and rattan, and soil. Further, improved wall who those use the kind of the wall of housekeeping with stonewall panels and wood, board, and or plywood. On the contrary, unimproved wall who use the widest wall with bamboo, zinc wall. Also, the variable improved ceiling categorised who use the kind of the widest ceiling of housekeeping with concrete and gypsum. Conversely,

an unimproved wall categorised for participants who use the kind of the widest ceiling of housekeeping: asbestos and GRC board wood and or plywood, woven bamboo or nothing. The criteria environmental health of material houses is based on joint monitoring programme WHO-UNICEF in Riskesdas 2013.

Details of data analysis

Data were analysed using the statistical data processing applications by Stata taking into account the complex sampling design [60]. Data included the proportion of participants with malaria, the characteristics of participants, the behaviour of participants, the accessibility and utilisation of health services, environmental sanitation, mosquito bite prevention measures, and housing conditions. These data were analysed using Stata 14. In univariate analysis we used the command "svy: tabulate" for one-way tabulations for complex survey data. The primary characteristic is that “svy: tabulate” computes a standard of independence that is useful for complex survey data. Parameter confidence intervals and standard errors can optionally be displayed for weighted counts or row, cell, or column proportions. Furthermore, the 95% CI for proportions are set up using a logit transform so that their endpoints always lie between 0 and 1.

Social data analysis commonly uses multivariable regression. In multivariable regression, explanatory variables do not come into the regression simultaneously but step by step according to p-value. The variable which has the largest *p-value* is the first to be removed from the model. The model was retested again to evaluate the effect of the deletion of one variable which had a p-value > 0.05, and it was found to have no confounding effect. As a rule of thumb, if the regression coefficient from the simple regression model changes by more than 10%, then an independent (predictor or explanatory) variable is said to be a confounder. Simple logistic regression analysis refers to the regression application with one dichotomous outcome that is malaria prevalence and one independent variable. At this stage, we show crude odds ratios (OR) with 95% CI. In bivariate analysis, some of the variables with a p-value > 0.05 were still inserted into the multivariable model but only when these variables were considered substantially necessary. Multiple logistic regression analysis applies when there are a single dichotomous outcome and more than one independent variable. It will be referred to as "multivariable analysis”. At this stage, the adjusted odds ratio (AOR) in 95% CI is shown. In the multivariable analysis, we selected only variables with a p-value < 0.05 as presented in table 4:2.

In multiple regression situations, scientists are affected by working out the "strongest" predictors in the analysis. Logistic regression requires a categorical dependent variable. By-passing bivariate logistic regressions, independent variables that may have predictive value for the dependent variable were selected for the multiple regression models (Wald test, $\boldsymbol{P} < 0.25$) [61.]

Additional file 4

A detailed description of the data analysis of study #3

This study uses syntax survey both "svy: tabulate" and "svy: logistic" to show the effect of the social determinants of malaria in an endemic area in 5 *P*rovinces of Indonesia. Descriptions of variables appear in table 4:1 in the text. The univariate and bivariate analysis of baseline socio-demographic characteristics of study participants used a complex design. In this case, it provided basic data and health status indications as well as health contributing factors at household and individual level (characteristics of participants) covering knowledge of health access and utilisation of health services; prevention measures against malaria; environmental health; and settlement.

Descriptive analysis

Characteristics of participants. The percentage of male (51.08%) was slightly higher than the percentage of females (48.92%), while the percentage of participants who fell in the age range of 5-14 years was the highest (26.06%). Furthermore, a significant percentage of participants had not completed high school education (72.08%) and only 4.19% had a higher education is with others at 23.72%. For employment, the percentage of participants not working was 60.12% compared to 39.88 % who do work.

The behaviour of the participants. A higher percentage of participants did not use mosquito nets (53.81%), and the majority of participants did not answer concerning insecticide-treated nets (55.26%) given that only 23.26% claimed to use insecticide treated bed-nets (ITNs).

The accessibility and utilisation of health service. The general knowledge of health access and utilise to healthcare facilities was found to be no good. *P*articipants who thought they did not have knowledge of health access and so did not utilise health services at the public hospital were 51.03%, private hospital (77.56%) and clinics or doctor practices (74.30%), integrated health post (posyandu) (56.77%), village health post (poskesdes) (92.15%), village maternity clinic (polindes) (85.39%) respectively. Also, this study concludes with 95% confidence that the number of people in the population that fall within the category that they did not know the availability or did not utilise midwife practices or maternity hospitals category was 83.41% (95% CI 81.48-85.18). Otherwise, those who have knowledge of access and utilise primary health care (*P*HC) were 88.92% (95% CI 87.65-90.08) which is good compared with other healthcare facilities.

Environmental sanitation.

The scope of water in the Riskesdas 2013 report includes the type of water source for household and drinking purposes. The proportion of households with access to improved water sources in the study areas was 72.88%. Environmental sanitation such as a facility to keep the water (97.56%), and distance to drinking water (82.1%) have overall improved. In the contrary, those who have not improved wastewater disposal comprised 81.24 % (95% CI 79.75 - 82.65)

Behaviour is preventing mosquito bites. *P*articipants asked what they usually do to prevent disease due to mosquito bites. The question regarding a. Using mosquito net; b. Using mosquito coil/electric anti-mosquito mats; c. Covering ventilation with anti-mosquito nets; d. Using mosquito repellent; e. spraying mosquito spray/insecticide, and f. taking anti-malaria drugs when staying at endemic malaria area. In general, participants who have behaviour to self-prevent from mosquito bites still less. It is essential to protect participants from mosquitoes not just to prevent annoying itchy bites, but to stop the spread of diseases that the mosquito can carry. The percentage who did not sleep using mosquito net was 52.56%, and who did not use toxic mosquito was 68.58%. Those who did not use mosquito netting to cover ventilation were 93.75% and who did not use mosquito repellent 95.24%. Those that did not spray mosquito insecticide was 90.9% and did not take anti-malarial drugs was 99.08%.

Housing condition. In common, those who have a material building that was not improved such as flooring (60.18%) and ceiling (98.26%). In contrast, those with improved walls comprised 85.23%.

Bivariate analysis

Characteristics of participants. Malaria prevalence differed by gender and age groups. Estimated odds of malaria prevalence in females is 10% lower than males (OR = 0.90; 95% ; CI = 0.85 - 0.94; $P < 0.001$). It would mean that males have 1.11 times higher odds of malaria prevalence compared to females.

Similarly, the OR estimates of malaria prevalence in children under five years of age are 1.39% less likely to have malaria prevalence than the participants who have more than five years age (OR = 0.72; 95% CI = 0.65 - 0.81; $P < 0.001$). Besides, this study obtains an OR for malaria prevalence of 1.2 times for participants who were working versus those

who were not working. It means that the odds of malaria prevalence are 1.2 times as high (or 20% higher) for those who were working than those who were not working.

The behaviour of the participants. According to the behaviour of the participants, use mosquito nets, and insecticide-treated nets were not significantly related to the prevalence of malaria. However, the *P*articipant did not use mosquito nets at night more likely to have malaria than those who did (OR = 1.09; 95% CI (0.97 - 1.23); *P* = 0.153)

*Knowledge of households about the nearest healthcare facilities to their residence. P*articipants who do not know the availability of or do not utilise healthcare are more likely to have malaria. Estimated odds of malaria prevalence in participants who not know the availability of health facilities and health service is 4.2 times more than participants who know the availability of health facilities (OR = 4.22; 95% CI = 1.53 - 11.59; *P* = 0.005).

Environmental sanitation. In general, participants who do not have improved environmental sanitation more likely to have malaria 1.1 times than those have unimproved environmental sanitation with (OR = 1.13; 95% CI (0.99 - 1.31); *P* = 0.081). In this study, the *P* of the variable was < 0.25. The Wald test from logistic regression used a *P* cut-off point of 0.25 because significance may not capture the importance and the more traditional levels, such as *P* of 0.05 can fail to select variables known to be essential.

Behaviour is preventing mosquito bites. In general, the risk of contracting malaria in participants who had no behaviour to prevent mosquito bites have a higher risk of contracting malaria. Based on the composite variable of this variable, the research reveals that participants who did not take preventive measures from biting mosquitoes were 1.2 times more likely to contract malaria than those who did (OR = 1.18; 95% CI (1.01 - 1.38); *P* = 0.036).

Housing condition. With regards to housing condition, estimated odds of malaria, participants who live in houses composed of unimproved materials were 1.3 times more likely to have malaria than those living in houses composed of improved building materials (OR = 1.30; 95% CI (1.09 -1.54); *P* = 0.003)