Technical Report

Stratification of Malaria Incidence in Papua New Guinea (2011-2019): Contribution Towards a Catchment-based Control Policy

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Abbreviations

ACT	Artemisinin-based combination therapy
BCC	Behaviour Change Communication
EBK	Empirical Bayesian Kriging
eNHIS	electronic National Health Information System
GFATM	Global Fund to Fight AIDS, Tuberculosis and Malaria
HF	Health Facility
LLIN	Long-lasting insecticidal net
MIS	Malaria Indicator Survey
mRDT	Malaria Rapid Diagnostic Test
NDoH	National Department of Health
NHIS	National Health Information System
NMCP	National Malaria Control Programme
P. falciparum	*Plasmodium falciparum*
P. vivax	*Plasmodium vivax*
PNG	Papua New Guinea
PNGIMR	Papua New Guinea Institute of Medical Research
RAM	Rotarians Against Malaria
SMS	School Malaria Survey
Swiss TPH	Swiss Tropical and Public Health Institute

Executive Summary

1. Altitude influences conducive conditions for malaria transmission in PNG. For every rise of 200m in altitude in PNG, average air temperature roughly drops by one degree Celsius. In principle, areas at altitudes above 800-1600 meters exhibit critical temperature conditions around 21-23°C that still allow parasite development over the lifespan of the mosquito.
2. Catchment areas and populations of 808 health facilities (HFs) across PNG were delineated and linked to annual malaria cases (2011- 2019).
3. Both clinical and mRDT-confirmed cases show a decrease with altitude; no malaria cases were reported in HFs above 2600 meters.
4. Malaria annual incidence (2011- 2019) was, on average, 184.8 per 1000 population in catchment areas up to 800m, 120.2 at 800m to 1600m, and 44.7 at 1600 to 2600m altitude. In areas above the two altitudinal thresholds 800m and 1600m, air temperature drops below 23°C and 19°C, respectively.
5. Malaria incidence is high (> 200 cases per 1000) in 26% of the catchment areas, mainly in West Sepik, Milne Bay, West New Britain and New Ireland. In contrast, 46.4% of the catchment areas, mainly in the Highlands, Bougainville and Central, have a low incidence (<100 per 1000).
6. While incidence had declined during the period (2014-2016) mainly in Momase and Southern regions, malaria has resurged in the last three years (2017-2019). The coastal areas in Milne Bay, Morobe, West Sepik, and New Ireland are among the provinces with catchment areas demonstrating high inter-annual variability, and likely vulnerable to epidemics related to breakdown of malaria interventions.
7. In 156 HFs, the monthly number of malaria cases among children (i.e. under 15 years) was less than one over the period 2011-2019. These HFs are located mainly in the Highlands, Bougainville and NCD.
8. Stratification maps show very low-to-low strata in the Highlands and the Southern region (NCD, Central and Western provinces) and Bougainville. In contrast, patches of high-risk strata are modelled in Momase, Islands and Milne Bay province. Besides, moderate stratum predominates throughout the mainland provinces, especially Morobe, Western and Northern provinces.

9. While 35.5% of PNG population (~3.4 million in 2020) live in areas that are at high or moderate risk of malaria in PNG, 40.4% (~ 3.8 million) of the people reside in very low risk areas.
10. In four provinces, relatively large proportions of their populations (> 50%) reside in high-risk areas: East New Britain, West Sepik, New Ireland and Milne Bay.
11. There is a need to support the PNG national malaria control programme in the allocation of malaria interventions at a sub-national level, ideally down to catchment areas, if operationally feasible, by using disease-modelling tools and building country capacity for evidence-based programmatic decision making.

Contents

1 Introduction

Malaria remains a leading cause of morbidity and mortality in Papua New Guinea (PNG), with an annual estimate of 1.5 million cases that represents 81% of the disease burden in the West Pacific Region (1). A plethora of microcosms isolated by rugged terrain and poor infrastructure makes malaria a highly localized problem in PNG (2). With a predominance of *Plasmodium falciparum* followed by *P. vivax*, local strains rapidly adapt to changes of endemicity that result in differential responses to antimalarial and disease control (3-7). Furthermore, eleven species of mosquitoes - belonging to *the Anopheles punctulatus* group - complement one another's niche in malaria transmission (8-11). Therefore, the risk of malaria is highly heterogeneous, between and within the regions of PNG, which is operationally challenging for control.

Since 2004, the Global Fund to Fight AIDS, Tuberculosis and Malaria (GFATM) has supported PNG to scale up malaria control (12, 13). Key interventions including long-lasting insecticidal mosquito nets (LLINs), malaria Rapid Diagnostic Tests (mRDTs), Artemisinin-based Combination Therapy (ACT) and campaigns of Behaviour Change Communication (BCC) were delivered at village and health facility levels (13-16). Also, mobilization of resources has involved capacity building and strengthening the management of malaria control program (14, 17-20). Although these intensified efforts had resulted in a remarkable decline in malaria prevalence from 11% in 2008/09 to < 1% by 2013/14 (21). A resurgence in prevalence to 9.5% was seen during the last Malaria Indicator Survey (MIS) in 2016/17 (22, 23). Likewise, annual incidence has increased 20-40% across the four regions of PNG occurred between 2016 and 2017 (Malaria Reports, personal communication, 2018).

Due to a reduction in the funding available for malaria control in PNG in recent years, LLINs are no longer distributed at altitudes > 2000 m, while only children < 5 years are targeted in areas at 1600-1900m (RAM, personal communication, 2019). This policy shift has mainly concerned the population living in the Highlands region. Although malaria is not a significant health problem in the Highlands, decision-making should consider local settings where the environment is receptive and seasonal or epidemic malaria transmission may occur. Indeed, local outbreaks could be devastating for unprotected people who lack immunity to the disease. Therefore, stratification of the risk of malaria at a micro-spatial scale could help to efficiently r allocate limited resources for maximum impact.

Previous epidemiological studies considered coastal lowlands holo-endemic for malaria, while highlands region contained epidemic-prone and non-malarious areas (2, 4). Early work in 1973 divided the country into five-risk strata in the country: holo, hyper, hypo, hypo-to-meso, and mesoendemic (24). At that time, hyper-endemicity prevailed in coastal areas while mountainous areas were mainly hypo-endemic. Later, a micro-stratification exercise in the Highlands and Momase regions (2001-2005) reported a difference in composition of strata between the regions and within their provinces (2, 25-29). However, it is unclear how the scale-up of malaria control interventions has affected these strata.

Surveillance data collected in catchment areas of health facilities could be useful in a stratification of malaria risk. In PNG healthcare is delivered via a decentralized system that involves five levels: central, provincial, district, sub-district, and village. The primary delivery unit of public health services to local communities is the health facility. These health facilities constitute the base of the National Health Information System (NHIS). In particular, confirmed and clinical malaria cases that present at health facilities are regularly reported to the NHIS using paper registry books at health facilities and monthly paper summaries, which are digitized, at a provincial level (19). This dataset is more comprehensive covering the whole country instead of small study sites. While under-sampling of specific groups - such as children under five years- is common in field studies, malaria registry contains a good representation of these vulnerable cohorts. Although asymptomatic cases are unlikely to seek treatment (especially in holoendemic areas), malaria screening and medication are free of charge that encourages sick people to visit nearby public health units.

In this report, we investigated risk factors of malaria in PNG at the level of health facility catchment areas and mapped the incidence for the whole country. Available topographic, climatic, epidemiological and operational data could be useful to stratify malaria in PNG, to assist decision-makers to mobilize limited resources for malaria control in this country.

2 Methodology

2.1 Study area

PNG is the largest country in the Southwest Pacific with an estimated population of eight million and an area of 462,840 km^2. The country is composed of the eastern part of New Guinea and surrounding archipelagos of offshore islands. PNG can be divided into four geographical regions (Highlands, Islands, Momase and Southern region) which contain 22 province-level division, including 20 provinces, the Autonomous Region of Bougainville, and the National

Capital District (NCD), see Appendix A. While the Highlands region is composed of seven provinces, 13 coastal provinces, Bougainville and NCD lie in the other three regions of PNG. The climate of coastal provinces is characterized by modest fluctuation in annual temperature and torrential rainfall amounts that can reach 4000 mm (except parts of Southern region, which are relatively dry). As in the Highlands region, there are two seasons (i.e., rainy and relatively dry season) in the coastal areas.

2.2 Datasets

2.2.1 Location of health facilities

An updated list of health facilities (HFs) in PNG 2019 was acquired from the National Department of Health (NDoH). The list contains 808 HFs, excluding aid posts, with their codes and type. Geographical locations of HFs were obtained from three sources: 1) a PNGIMR geocoded dataset from a health facility survey conducted in 2014; 2) a UNDP excel sheet with latitude and longitude of HFs available online on the website Humanitarian Data Exchange 2018; 3) Shapefiles extracted from maps generated by RAM for data collected during LLINs distribution campaigns. Hence, a master sheet was compiled, corrected for duplications and codes of NDoH. Google Earth was further used to check and confirm locations of HFs.

2.2.2 Population distribution

Geocoded data of census units (wards/villages) in PNG were obtained for the 2011 National Population and Housing Census, published by the National Statistical Office (NSO) of PNG. This dataset contains 27,000 census units but with over 10% of duplicates in their geolocations.

In addition, we obtained from HDX a high-resolution population density map developed by Facebook in partnership with Columbia University. In generation of this dataset, Convolutional Neural Networks were used to combine high-resolution satellite images with the best available census data (for further details on methodology, see https://dataforgood.fb.com). In particular, the Facebook dataset for PNG contains the geo-coordinates of 691,933 residential building/places and associated estimates of overall population 2015. Instead of using the dataset's population, NSO census units 2011 we spatially joined with the Facebook raster dataset. NSO adjusted growth rates for each province, based on the 2011 census,) were used to project the population for each residential place in the years 2012-2020.

2.2.3 Malaria cases reported by NHIS

Annual NHIS malaria reports between 2011 and 2019 were obtained from NDOH. These excel sheets contain annual numbers of confirmed malaria cases by health facility and according to the diagnosis technique used (mRDT/microscopy), age groups (children under five, children 5-14 years, and adults), sex (males and females), and *Plasmodium* species. Besides, numbers of reports received per year, numbers of clinical cases (inpatients and number of outpatients prescribed ACT) are provided in these sheets. According to NHIS, HFs are responsible for aggregation of the daily malaria registry data reported at their premise and dependent aid posts within the catchment. Paper-based forms are submitted to the Provincial Health Office. There, the latter is responsible for entering the summarized reports in the NHIS electronic forms. Further, crosschecks including cleaning and re-entry are done at the national level to ensure the quality of provided data (19).

2.2.4 Elevation raster of PNG

Tiles of elevation raster for PNG were retrieved from the Global 3D Digital Elevation Model TanDEM-X (for further details see https://www.dlr.de). Elevation dataset -- which developed by the German Aerospace Center (DLR) -- has a high resolution of 90x90 meters with a height accuracy of one meter. Previously, two radar satellites (TanDEM-X and TerraSAR-X) were used to capture images of the earth surface for four years (2011-2015) but from different view angles. Further, DLR had processed and resampled the original TanDEM-X images (of 12m resolution) to create the current version of TanDEM-X. Hence, raster tiles were collated and clipped for the geographical extent of PNG before the merged raster was corrected for the elevation of water bodies and bordering lines using ArcGIS Desktop 10.5.

2.2.5 Friction surface of PNG

A raster of global friction surface was obtained from the website of the Malaria Atlas Project (MAP) to estimate the travel time between human settlements and health facilities (30). Initially, MAP raster -- at a resolution of 1x1 km-- was constructed by merging Open Street Map (OSM) with a distance-to-roads database obtained from the Google in November 2016 and March 2016. The pixel values represent speeds of movement, i.e. minutes required to travel one meter, for which the fastest mode of transport between the two datasets was given a precedence. A country level raster was extracted for PNG using the clipping tool of ArcGIS.

2.2.6 Climatic data of PNG

WorldClim is a set of global gridded data that contains layers of average monthly climatic variables for the period 1970-2000. Average monthly datasets for air temperature, vapour pressure and rainfall for PNG were retrieved from WorldClim Version 2.3 (31). This source includes gridded raster maps with spatial resolution of one km^2. In ArcGIS, climatic maps were clipped to the country extent and corrected for water bodies and bordering lines in PNG.

2.3 Analytical methods

2.3.1 Zonal statistics of altitude, population and temperature.

For this task, we added an external tool: "Zonal Statistics as Table 2" to the Spatial Analysis toolset to prevent overlapping of polygons when calculating the areal altitude of catchments. Averages of the altitude of census units were calculated in buffers of six km radius using the zonal statistics tool of ArcGIS. The cut-off of the buffer was based on travel time chosen in delineation of catchment area (see section 3.3). Increments of 200m were used to show percentages of people and households living in specific altitude.

Elevation raster of PNG was resampled to a resolution of one km2 to ensure correspondence in the resolution of WorldClim temperature and TanDEM-X elevation. The zonal statistics tool was used to associate average altitude with grids of annual temperature (1 km2). The raster of altitude and mean annual temperature was converted to points feature and grid centres.

2.3.2 Accessibility map of health facilities

The raster of friction surface of PNG was updated for Open Street Map (OSM) data 2020, to account for new roads and extensions reported after the release of MAP dataset 2015. Hence, OSM road vectors of PNG were downloaded, rasterized into $1km^2$ grid cells and merged with the MAP friction raster using ArcGIS. Averages of travel time to cross grid cells of different road types were used to generate lookup table and update pixel values corresponding to OSM roads in the friction map.

To generate accessibility map of HFs, Cost Distance tool of ArcGIS was used to identify nearest health facilities to human settlements and calculate their travel time. The tool uses a least-cost-path algorithm to cumulate the cost of crossing grid cells (/minute) between the source (i.e. human settlements) and destination cells (i.e. health facilities), according to the following equation:

$$d_i(HF_j) = \min_i \sum_{i=1}^{n} c_{i-1} + \beta \frac{\alpha_1 + \alpha_2}{2} \quad , \quad \begin{cases} \beta = 1, & \angle = 180° \\ \beta = 1.414214, & \angle = 90° \end{cases}$$

Where: $d_i(j)$ = least cost of travel from a human settlement i to HF j, c= minimum cost of travel taken over all neighbours of i, α=travel cost to cross between centres of cell 1 and cell neighbour 2, β= a constant dependent on the link angle between the two cells (perpendicular or diagonal).

Hence, different routes are tested before a path with a shortest travel time is determined. The ArcGIS tool produces two separate raster maps: 1) travel cost to nearest HF, and 2) allocation index of nearest health facility for each grid cell. The two pixel values corresponding to human settlements were extracted and a table containing travel time and index of nearest health facility was created.

2.3.3 Delineation of catchment areas

The map of travel cost to nearest HF was used in delineation of catchment areas. We assumed that treatment seekers would only visit nearest HF reachable within specific threshold of travel time. Accessibility threshold of two-hours was used to delineate the catchment areas of HFs The selection of the two hours was based on previous surveys of HFs in PNG which show varied but high travel time across the regions ranging between 43-88 minutes (32). In addition, meetings with health providers at HFs -- during the malaria indicator survey 2019/20 -- suggested a health seeker could travel a maximum of two hours to reach a near health facility.

2.3.3.1 Calculation of population size in catchment areas

A bottom-up approach was used to calculate the total population living in the catchment areas, provinces, and country. Hence, the total of population in the human settlements - projected from census 2011 - was summed up in each of the administrative levels.

Further, we assumed that HFs within access distance of one-hour are shared by the same pool of treatment seekers. Hence, catchment populations were summed up before evenly divided between the sharing HFs. In addition, we calculated the total numbers of people living in each stratum and province by spatially joining the human settlements with a vector feature converted from the raster map.

2.4 *Malaria incidence*

Monthly clinical and confirmed cases reported by HFs were used to calculate malaria incidence. Only HFs with more at least 12 monthly reports during the ten years (2011-2019) were included in the analyses.

The average annual incidence per 1000 in a catchment of a health facility was calculated for years (2011-2019) using the number of reported cases in a specific year divided by the projected population of the catchment and by the frequency of received reports in that year, according to the following equation:

$$I_{xy} = \frac{\sum_{m=1}^{q} N_{xm}}{\mathrm{P}_{xy} \times \mathrm{q}_{xy}} \times 12 \times 1000$$

Where: I_{xy}= average annual incidence rate of HF "x" in year "y", N_{xm}= total of reported cases at HF x in month m, P_{xy}= projected population in a catchment of HF x in the year y, q = total of reported months in year y and health facility x.

District-specific growth rates --provided by NSO --were used to project the population of a catchment in a specific year using the following growth formula:

$$P_{xy} = P_{x0}\, e^{r_n t}$$

Where: P_y = the projected population of catchment x at year y, P_{x0} = the population at catchment area x in the census year 2011, r_n = growth rate specific to n district where the catchment area x lie (/year), t= difference between the projected and census year (y-2011).

Further, populations of specific age groups and sex were estimated assuming that their proportions in the census year 2011 remain constant.

The spatial joining tool of ArcGIS was used to link the locations of HFs with the NHIS excel sheets of cases and with the projected population living in the catchments. To classify the risk of malaria, four categories of average annual incidence per 1000 population were generated: high (> 10 cases), medium (1-10), low (≤ 1 case), and zero incidences.

Figures on average incidence rates at HFs during the period 2011-2019 against altitude of catchment areas were generated using boxplot package in R. While a solid box used to span the interquartile range (i.e., Q1 to Q3), the segment line inside each boxplot indicated the median value over the nine years, and the solid lines (whiskers) were extended to include roughly 99% of values. The upper whisker is at the minimum of Error bars = ±1.5* Interquartile range (IQR).

2.4.1 Catchment areas with few malaria cases among children

To identify catchment areas with limited malaria cases among children (2011-2019), we purposefully selected HFs with the following criteria: i) average monthly number of confirmed cases is less than one case per reported month; ii) more than 100 children were tested using microscopy and/or RDTs; iii) proportion of positive children 0-14yrs among all positive cases is less than 30%.

Population size in these catchment areas and average annual incidence rates among the general population were calculated and grouped by altitude. The total number of LLINs issued in these catchment areas during distribution campaigns (2011-2019) was summed up.

2.4.2 Modelling of malaria risk strata

We employed empirical Bayesian kriging (EBK) of ArcGIS to interpolate malaria risk between catchment areas across PNG. EBK is a geostatistical technique that uses an iterative process of subsetting and simulations to model best estimates in non-sampled locations. EBK employs a restricted maximum likelihood (RML) methodology to optimize the model parameter. A general assumption in kriging is that there is an overall spatial arrangement of the measured points beside the distance (i.e. spatial dependence between proximal features more than distal ones). Hence, unmeasured locations can be interpolated using weighted measured values, according to the following equations:

$$\hat{Z}_{(s_0)} = \sum_{i=1}^{N} \lambda_i \, \acute{Z}_{(s_i)} | Z, \theta_i$$

$$\lambda_i = \frac{f(Z|\theta_i)}{\sum_{i=1}^{N} f(Z|\theta_i)}$$

Where: $\acute{Z}(s_i)$ =simulated value at location i, Z= measured values, λ_i= weight for measured value at location i, θ_i= empirical prior distribution of model parameters, s_0= the prediction location, N=number of observed locations.

Unlike other kriging methods, EBK allows a more accurate estimation of standard error based on a set of semivariograms instead of a single one:

$$\sigma^2_{z(s_0)}|Z = \sum_{i=1}^{N} \lambda_i \left(\sigma^2_{z(s_0)}|Z, \theta_i + \left(Z_{s_0}|Z, \theta_i - \hat{Z}_{(s_0)}\right)^2 \right)$$

Where: $\sigma^2_{z(s_0)}$= variance of prediction Z at location s_0. For more details on algorithms of EBK see (33).

Two risk maps were generated using EBK tool in the Geostatistical Analyst of ArcMap. The input points features were the average annual incidence of malaria (2011-2019) using: (1) suspected cases (i.e., clinical cases + confirmed cases), and (2) confirmed cases among the children group (i.e., mRDTs and microscopy positive cases among children under 15 years age). With an overlap factor 1.4, semivariograms for subsets of 100 catchment areas were simulated and parameters were automatically adjusted. Cell size in raster maps was set to one km^2. A mask of PNG country boundaries was used as a geographical extent to clip the risk maps.

Four strata of average annual incidence per 1000 – adjusted to interpolated surface -- were depicted in the risk maps: very low, low, moderate, and high. We applied PNG-specific cut-offs based on the frequency distribution of incidence values as the cut-offs proposed in the World Health Organization's Framework for malaria elimination did not result in sufficient disaggregation across PNG (34).

2.4.2.1 Cross-validation of the models

Cross-validation is a process where the entire dataset is employed to verify the model performance by removing data points one at a time-step and evaluate the predicted value based on other neighbouring data points in the searching window. In ArcGIS, The Geostatistical Analyst tool automatically generates five statistics of cross-validation for EBK models: mean error (ME), root-mean-square error (RMSE), average standard error (ASE), mean standardized error (MSE), and root-mean-square standardized error (RMSSE) (35). For more details on equations of these statistics, see Appendix B.

A good fit EBK model will have the following criteria: 1) an ME nearly zero; 2) small and similar values of RMSE and ASE; and 3) a RMSSE error close to one (35). Hence, we experimented for optimal models by tuning up EBK parameters to obtain reasonable statistics of cross-validation, independently for incidence rates among general population and children.

3 Results

3.1 Landscape and altitude

A centrally running ridge of mountains and intervening valleys from the northeast to southwest, characterizes the mainland of PNG. While altitude in the Highlands region exceeds 4,500m above sea level, the altitude drops to sea level in coastal areas (mainly in Momase and Southern regions), see Figure 1.

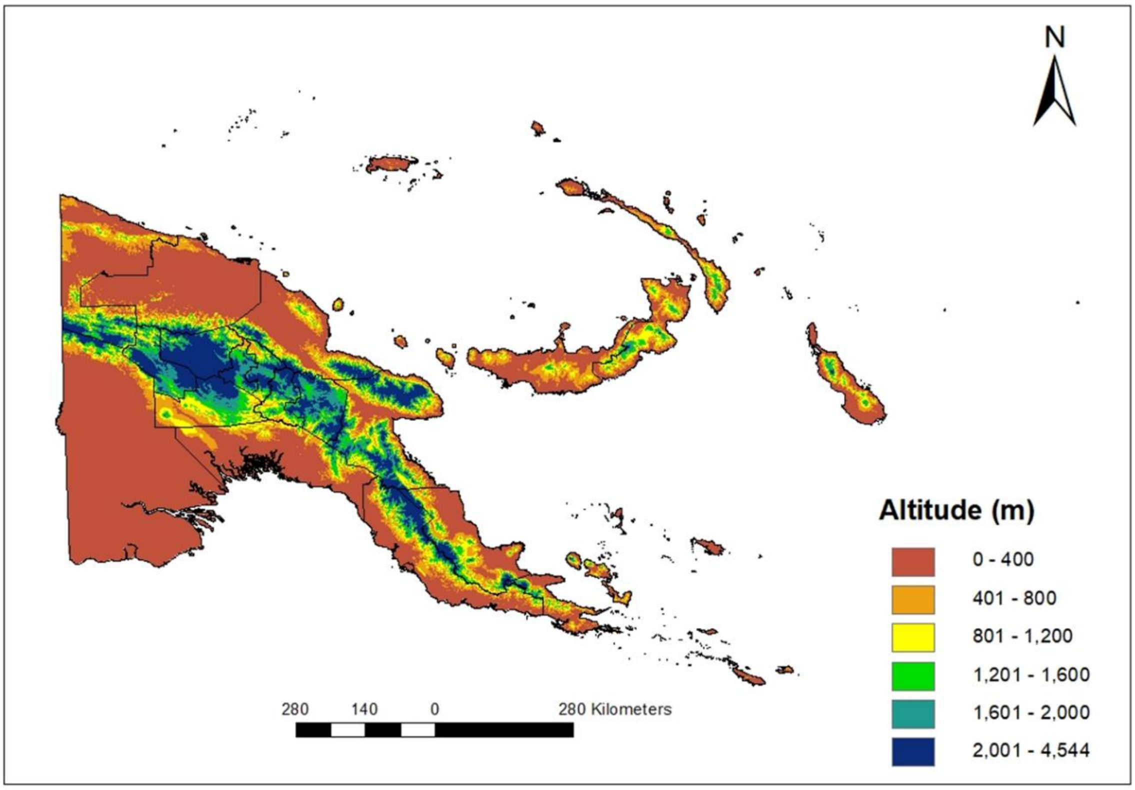

Figure 1. Elevation map of Papua New Guinea. The map shows altitude at a 90m resolution with a height accuracy of one meter. PNG has a central mountain range ranging northeast to southwest along the main island of the country. Data source: Global 3D elevation model TanDEM-X.

3.2 Climatic suitability for malaria

Across PNG, mean annual temperature (1970-2000) has ranged from 0.5 to 27.8°C, while mean annual precipitation has ranged from 1202mm to 7322mm. In the mainland, the large difference in temperature between coastal and inland is mainly attributed to altitude, i.e. the central mountain range. Figure 2 shows a linear relationship between altitude and temperature in PNG (R^2=0.97, RMSE=61). Approximately, for every rise of 200m of altitude in PNG, air temperature roughly drops one degree Celsius. The strong association of temperature and altitude could allow stratification of malaria in PNG. One of the critical stages in malaria transmission is the time needed for development of *Plasmodium* in the mosquito, i.e., the extrinsic incubation period (EIP), which mainly depends on air temperature. The red box in Figure 2 captures a range of 21-23°C, and associated altitudes 800-1600m. In general, areas above 1600m have an average annual temperature below 20°C. While the average life expectancy of malaria vectors is 20-30 days, EIP at 20°C for *P. falciparum* and *P. vivax* is 20 days and 30 days, respectively (Reference). Hence, local transmission of malaria is hypothetically challenging to occur in areas above this altitude because EIP could exceed the lifetime of adult mosquitoes. Annual averages and seasonal change in temperature and precipitation are shown in Appendix C.

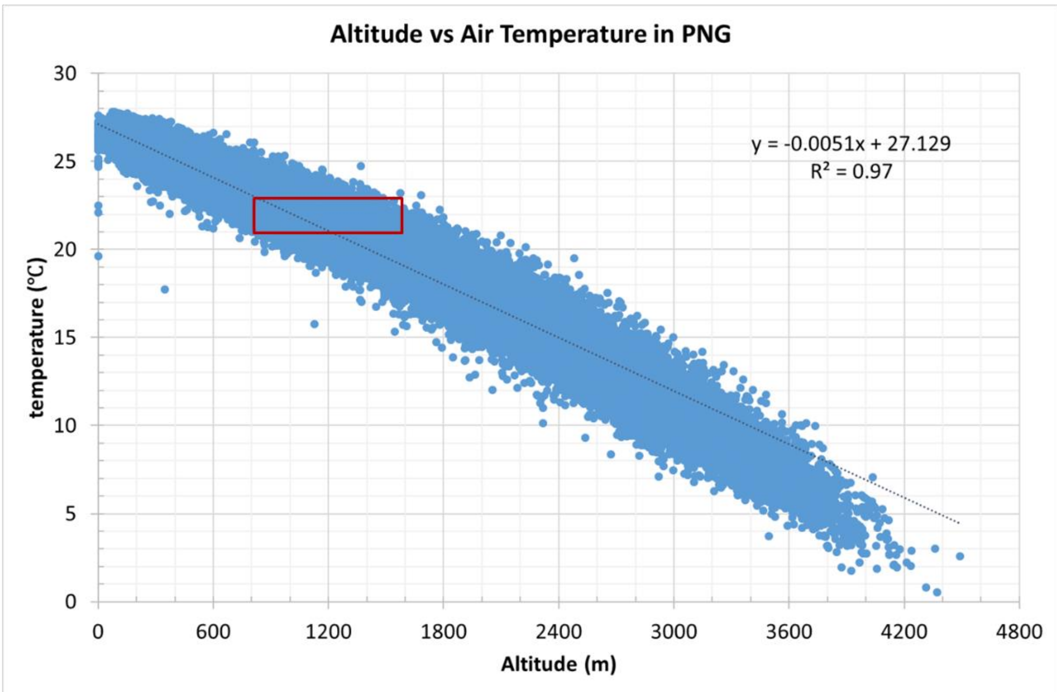

Figure 2. The relationship between altitude and air temperature in PNG. The dots represent WorldClim average annual temperature (1970-2000) in grids of one km^2.

3.3 Distribution of health facilities

The distribution of 808 HFs in PNG is shown in Figure 3. The mapped HFs are 31 hospitals (including 10 district hospitals), 196 health centres, 455 sub-health centres, 89 urban clinics, and 37 community health posts.

Apparently, the majority of HFs (33.8%) clusters in the Highlands Region because of the high population density. However, Morobe and Manus provinces have the largest and smallest numbers of working HFs, 53 and 13, respectively. Most of offshore small islands of PNG are serviced by aid posts, which usually supervised by nearest health centres or sub-health centres. Due to unknown functionality status, we excluded 2672 aid posts from this analysis.

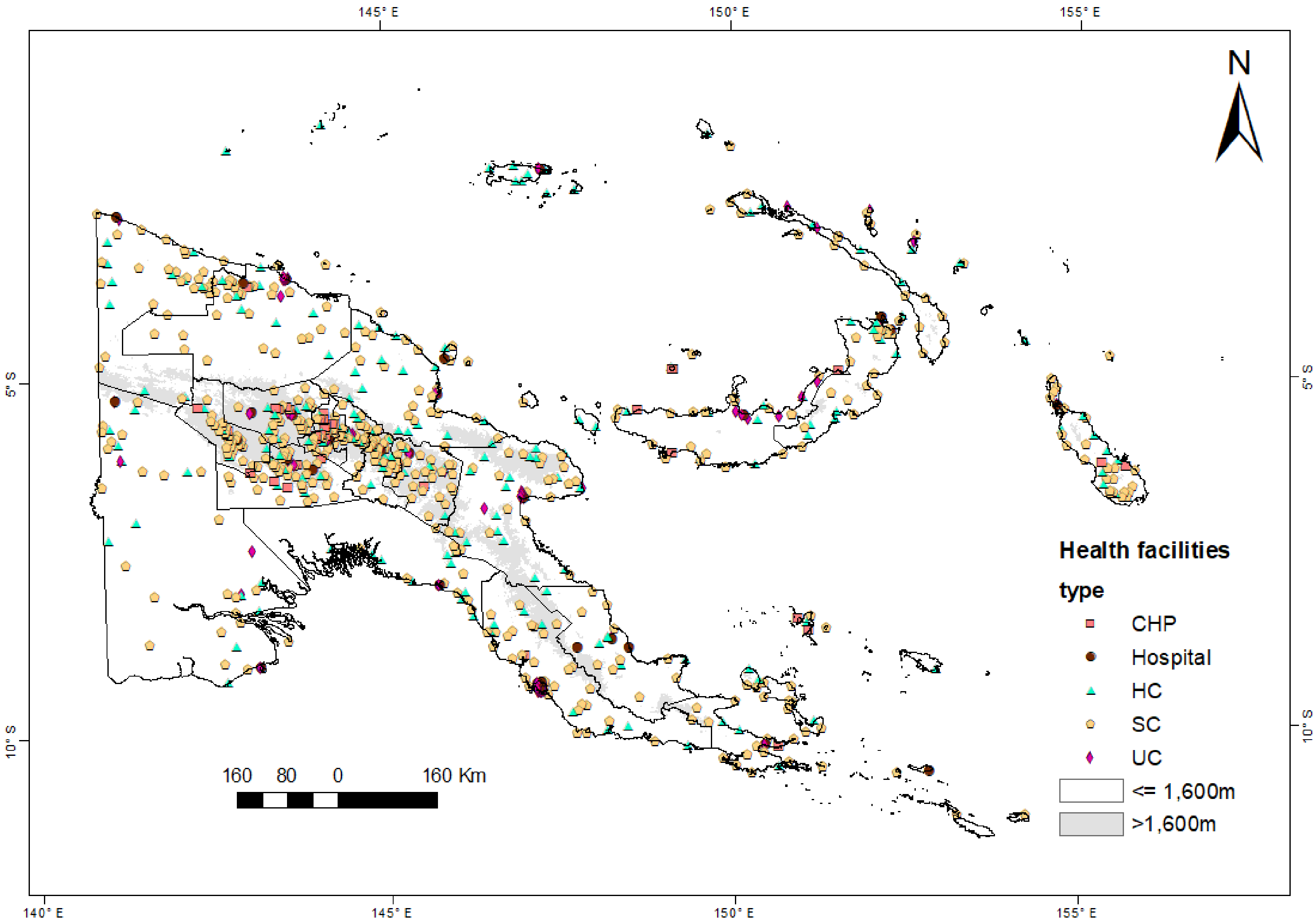

Figure 3. Distribution of health facilities in Papua New Guinea. Locations of 808 health facilities: HC= Health Centre; SC= Health Sub Centre; CHP= Community Health Post; UC= Urban Clinic.

3.4 *Population distribution and altitude*

The distribution of the population and corresponding number of households by altitude are shown in Figure 4. Approximately half of the population lives in coastal areas (below 800m) and one third in highland areas (1600-2000m). In particular, coastal areas below 200m are home to 3.5 million people using the 2019 projection (i.e. out of 9.6 million in the country).

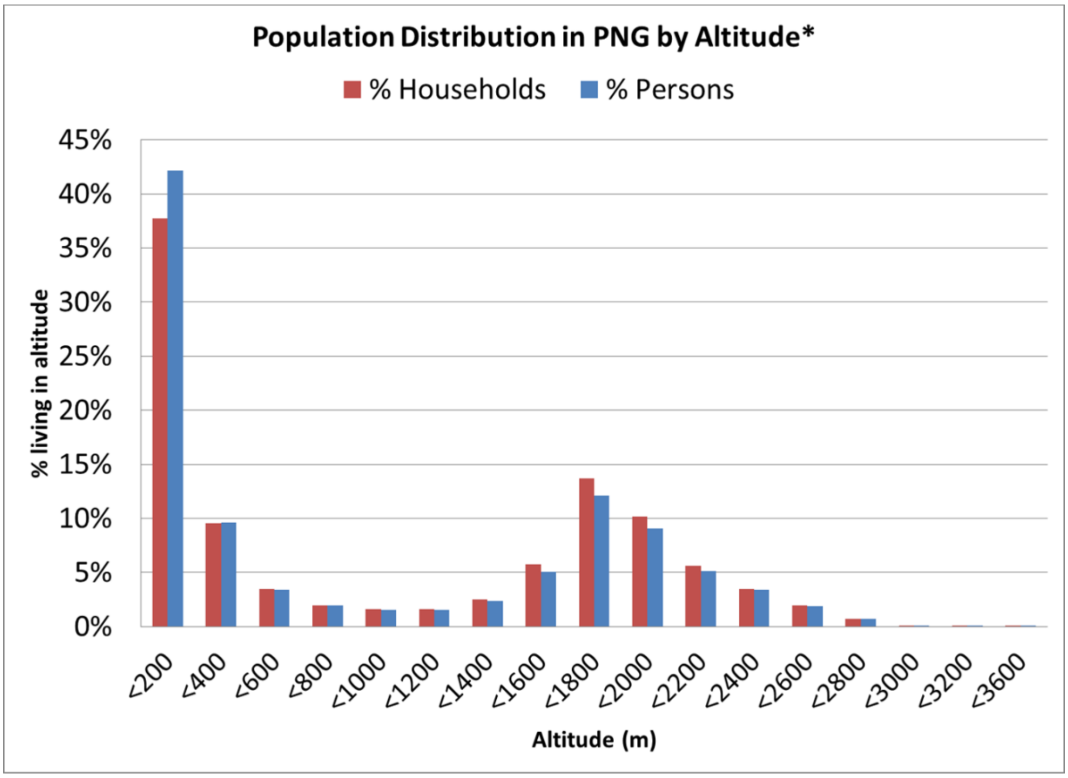

Figure 4. Population distribution in PNG 2011. Percentages of population and households in PNG by altitude. *Average altitude of census units in a radius of one km. Data source: 2011 National Population and Housing Census, NSO-PNG.

3.5 *Access of population to nearest HF*

Figure 5 shows a map of travel time of population from their residential places to nearest HFs. Apparently, road networks in coastal areas (mainly Momase and Islands) and Highlands reduce travel time needed by population to reach closest HFs to less than two hours. High proportions (>85%) of population in NCD, East New Britain, New Ireland, Bougainville and Hela have easy access (i.e., travel time less than one hour) to HFs. In contrast, significant proportions of population (>30%) have a difficult access to HFs (i.e. exceeding two hours) in Gulf, Western, Madang, East Sepik and West Sepik provinces, see Appendix D.

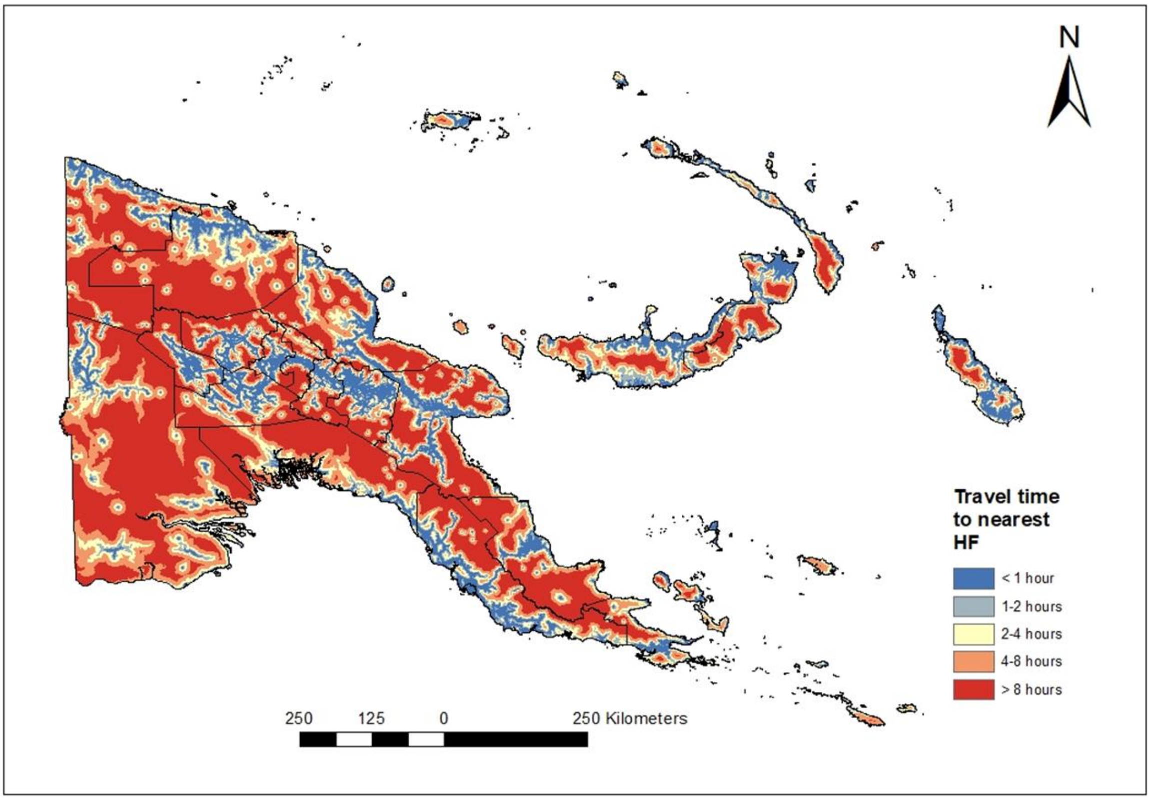

Figure 5. **Travel time (hours) of population from their residential places to nearest health facilities**. Travel time from grid cells (30x30 m^2) to nearest HF using fastest mode of transportation.

3.6 Catchment areas of HFs

Catchment areas of 808 HFs were delineated using the Facebook map of residential places. Table 1 summarizes characteristics of the catchment areas by province. On average, the catchment population is 12,045 ranging from 812 to 149,605 and the altitude is 850m ranging from four to 3033. While a treatment seeker needs an average of 32 minutes (ranged 10 to 117) to reach the closest HF, the distance from their houses averages 3170m (ranged 100 to 7608).

Table 1. Characteristics of catchment areas of HFs: averages of population, altitude, travel time and travel distance. Minimum and Maximum values are in parentheses

Province	No. HFs	Population	Altitude (m)	Travel time (minutes)	Travel distance (m)
Bougainville	38	7253 (1345, 19782)	204 (10, 987)	28 (18, 69)	3520 (1206, 5192)
East New Britain	32	10809 (1252, 30113)	274 (14, 1078)	31 (13, 68)	3681 (2018, 5181)
Manus	13	6048 (967, 24580)	80 (18, 286)	44 (12, 82)	2915 (492, 5063)
New Ireland	32	9186 (812, 45426)	109 (12, 321)	31 (17, 63)	3341 (100, 4828)
West New Britain	38	9015 (1291, 25029)	128 (6, 339)	36 (12, 79)	3077 (889, 5043)
Central	41	7789 (1118, 26411)	497 (33, 2036)	27 (12, 91)	3063 (134, 5019)
Gulf	21	7598 (1422, 22159)	379 (16, 1658)	44 (11, 94)	3321 (1613, 5512)
Milne Bay	44	7268 (1299, 20185)	185 (20, 1378)	46 (13, 80)	3351 (100, 5683)
National Capital District	27	18335 (3680, 100617)	85 (7, 193)	1 (10, 5)	899 (100, 2945)
Northern	20	9840 (1441, 27860)	368 (54, 1273)	41 (16, 74)	3777 (2274, 5308)
Western	42	5824 (846, 40697)	213 (16, 1832)	34 (12, 72)	2533 (247, 4906)
Chimbu	36	17337 (1038, 50373)	1947 (894, 2810)	31 (14, 117)	3040 (1229, 5232)
Eastern Highlands	37	19573 (1378, 43677)	1830 (1371, 2334)	35 (11, 86)	3818 (761, 6086)
Enga	42	15608 (1390, 68922)	2363 (1420, 2845)	36 (16, 77)	3011 (1254, 4655)
Hela	36	19302 (1166, 62816)	1839 (704, 2793)	20 (13, 58)	3004 (845, 7312)
Jiwaka	28	15026 (2074, 48221)	1566 (102, 2290)	29 (18, 54)	2901 (1561, 4081)
Southern Highlands	48	16220 (1595, 68162)	1668 (572, 2376)	28 (14, 80)	3353 (65, 7608)
Western Highlands	46	10690 (1295, 43506)	1977 (721, 3032)	30 (11, 88)	2594 (798, 4369)
East Sepik	49	11026 (1168, 25260)	199 (4, 455)	35 (11, 92)	3368 (100, 5397)
Madang	48	11533 (1144, 35698)	398 (56, 2519)	36 (11, 82)	3713 (908, 7300)
Morobe	53	16138 (1128, 149606)	818 (80, 2046)	36 (11, 77)	3430 (845, 5010)
West Sepik	37	9076 (1046, 61056)	475 (100, 1896)	36 (17, 93)	3453 (459, 6416)

3.7 *Summary of malaria reports (2011-2019)*

Table 2 summarizes the malaria indicators reported by HFs obtained through NHIS during the period 2011-2019. Overall, 66,621 monthly reports were obtained; however, not all HFs had been regularly reporting, ranging between 705 HFs in 2013 versus 783 HFs in 2019.

The reports showed similar numbers of mRDT positive results and ACT prescriptions (outpatients and inpatients), 2,533,985 and 2546967, respectively. Nonetheless, small numbers of microscopy positive results were reported (598,684) because of low coverage rates across PNG with microscopy service.

Apparently, coverage of HFs by mRDT-tests and ACT administrations have increased in PNG since the GFATM-supported rollout in 2011/2012 particularly scaled up during the last two years 2018-2019. Similarly, positivity rate using mRDTs has been steadily rising from 31% in 2011 to 50% in 2019.

Table 2. Summary of malaria reports at health facilities, PNG (2011-2019)

Year	*Health facilities*	*reports received*	*Positive microscopy slides (%)**	*Positive mRDTs (%)**	*ACT outpatients*	*ACT inpatients*
2011	727	7,947	75,513 (36%)	10,161 (31%)	11,717	2,657
2012	725	7,618	67,985 (39%)	86,395 (34%)	66,777	4,773
2013	705	6,693	59,290 (44%)	173,489 (37%)	157,036	10,603
2014	733	7,252	65,370 (50%)	202,277 (37%)	195,819	10,491
2015	733	7,263	74,633 (53%)	229,561 (41%)	282,515	6,817
2016	735	7,223	82,481 (52%)	323,440 (43%)	444,221	46,817
2017	729	7,161	70,477 (49%)	408,010 (46%)	460,821	49,288
2018	750	7,499	62,973 (47%)	488,722 (48%)	371,300	6,903
2019	783	7,965	39,962 (51%)	611,930 (50%)	413,356	5,056
Overall	**783**	**66,621**	**598,684 (46%)**	**2,533,985 (44%)**	**2,403,562**	**143,405**

* Positivity rates.

3.8 Malaria incidence and altitude

Overall, the annual incidence (2011-2019) at catchment areas of HFs has averaged 137.4 [95% CI 128.8, 146], cases per 1000. The incidence rates show a significant decrease from 184.8 [95% CI 173.9, 195.8] in areas below/at 800m, 120.2 [95% CI 97.8, 142.7] in 800-1600m, to 44.7 [95% CI 36.9, 52.5] in catchments above 1600m, (adjusted R^2=0.26, $p<0.001$), see Figure 6. In areas above the two altitudinal thresholds 800m and 1600m, air temperature drops below 23°C and 19°C, respectively.

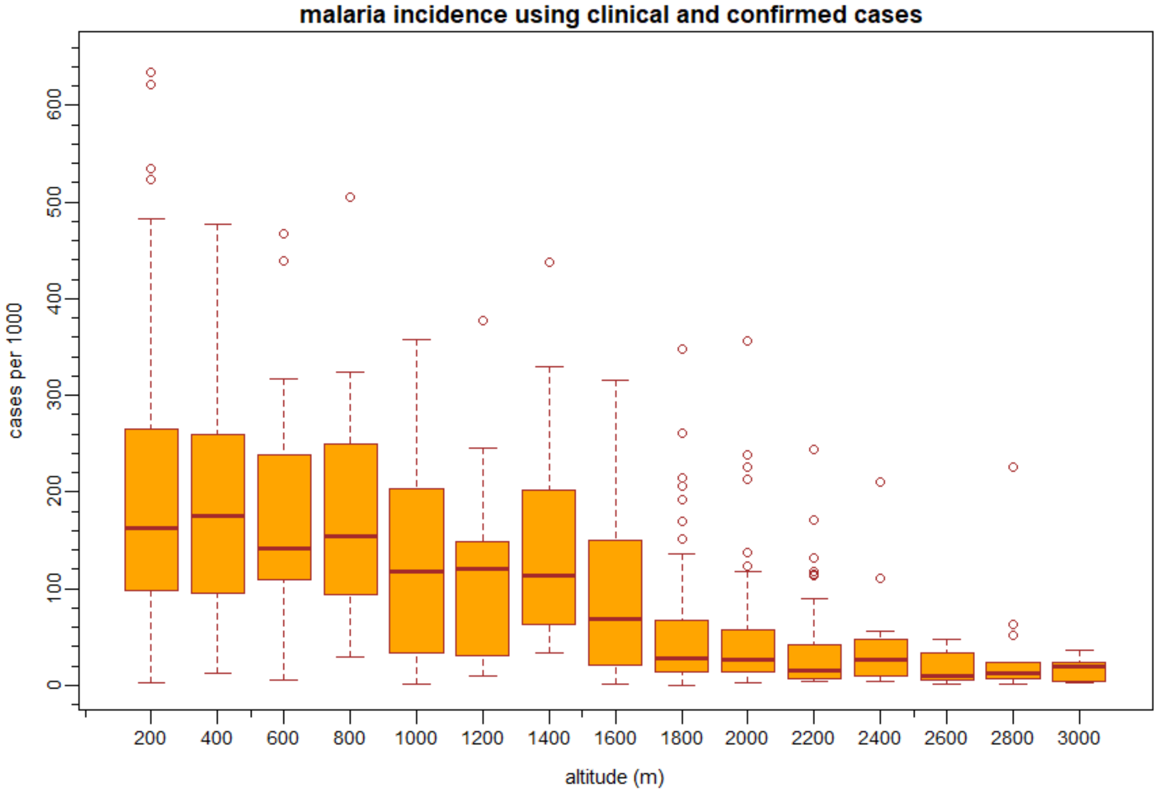

Figure 6. **Average annual incidence of malaria (per 1000) at catchment areas of health facilities, PNG (2011 -2019).** The average altitude (meters) and estimated population within two hours travel distance are used.

Figure 7 contains four subplots (a-d) of malaria incidence by altitude, using positive mRDTs, positive slides of microscopy, prescriptions of ACT among outpatients and inpatients. The decrease of incidence with altitude is clearer using mRDTs or ACT outpatients compared to microscopy and ACT inpatients.

In particular, using mRDTs confirmed cases (Figure 7a), the average annual incidence below/at 800m was 78.1 per 1000 [95%CI 71.6, 84.5], while the rate significantly dropped to 15.3 [95%CI 8.6, 22] at 800-1600m and 3.8 [95%CI 2.8, 4.8] in catchment areas above 1600m altitude. The 1600m altitude differentiates between HFs of high and low incidence using ACT outpatients, see Figure 7c. In contrast, a decrease in catchment areas above 800m and 1600m was uncertain using positive microscopy cases (Figure 7b) or ACT inpatients (Figure 7d).

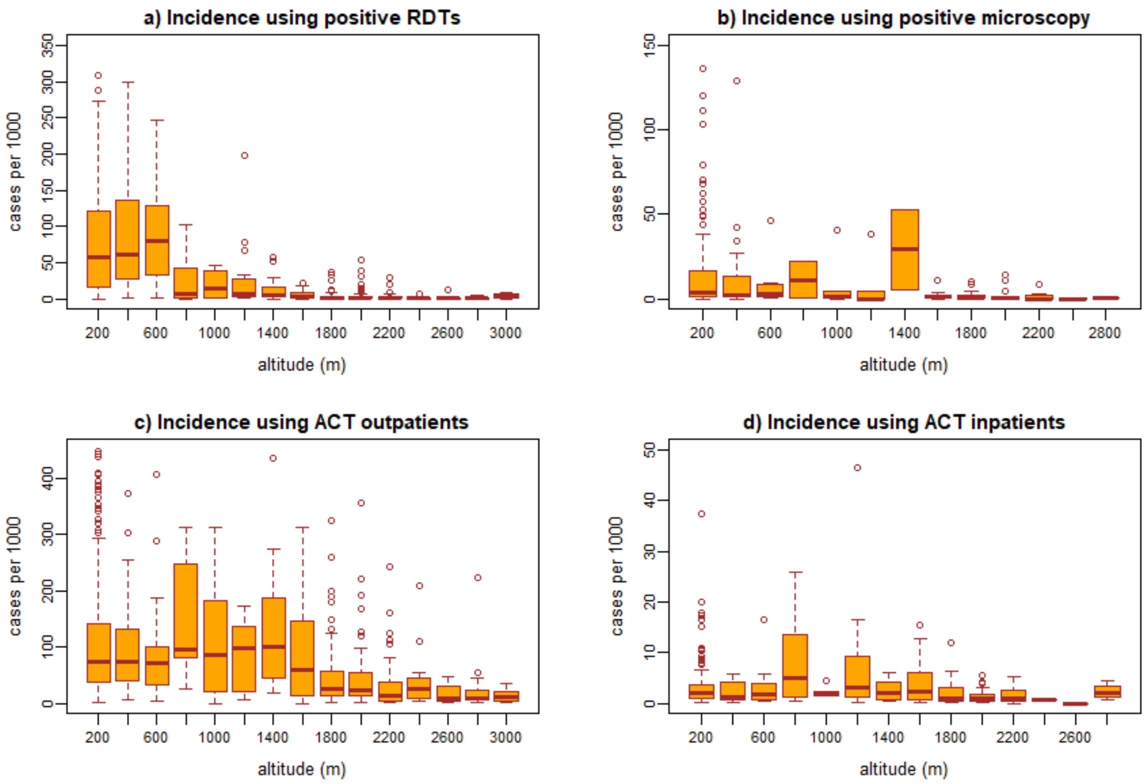

Figure 7. Average annual incidence of malaria in catchment areas of health facilities by altitude according to method, PNG (2011-2019). Annual incidence among the populations of catchment areas using: a) positive mRDTs, b) positive microscopy slides, c) outpatients received ACTs, and d) inpatients received ACT.

Figure 8 confirms previous findings on incidence and altitude among children, which are less mobile and could reflect local transmission of malaria in their catchment areas. Hence, annual incidence among children under five have significantly declined at areas above the 800m and 1600m: from 159.4 [95% CI 143.2, 175.7] to 24.4 [95% CI 9.5, 39.3] and to 3.2 [95% CI 2.1, 4.3], cases per 1000, respectively (Figure 8a). Similarly, in the age group 5-14 years, the rates decreased from 106.2 [95% CI 96.8, 115.6] to 16.5 [95% CI 8.5, 24.5] and to 2.95 [95% CI 1.98, 3.9], respectively (Figure 8c). The patterns of decrease in incidence with altitude are shown in positive cases using RDTs but not microscopy (Figures 8a and 8c versus Figures 8b and 8d).

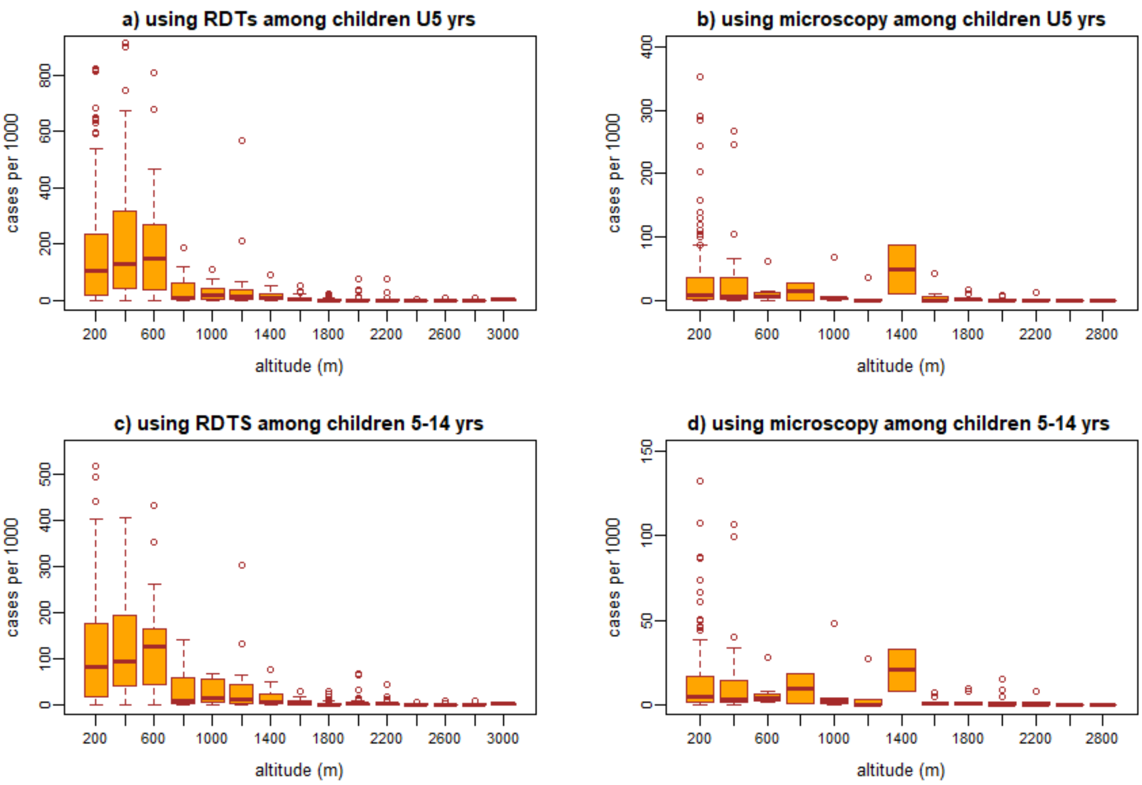

Figure 8. Average annual incidence of malaria in catchment areas of health facilities among children, PNG (2011-2019). Incidence rates per 1000, using: a) children under five years old (U5) using mRDTs, b) children under five years old (U5) using microscopy, c) children under (5-14) years old using mRDTs, and d) children (5-14) years old using microscopy.

3.9 Inter-annual variability of incidence (2011-2019)

Figure 9 shows average annual incidence (2011-2019) in 806 HFs across PNG. Malaria incidence is very high-to-high (> 200 cases per 1000) in 26% of the HFs, mainly in West Sepik, Milne Bay, West New Britain and New Ireland. In contrast, 46.4% of the catchment areas, mainly in the Highlands, Bougainville and Central provinces, have a low-to-very low incidence (<100 per 1000). The estimated population living in catchment areas having a high-to-moderate incidence (=>100 per 1000) is 40.7% of the whole population in PNG, i.e. 4 million people in 2019.

Maps of annual incidence for the years 2011-2019 show a change of malaria risk across PNG over the years, see Figure 10. While incidence rates had declined between (2014-2016) mainly in Momase and Southern regions, malaria has resurged in these two regions in the last three years (2017-2019). The coastal areas in Milne Bay, Morobe, West Sepik, and New Ireland are among the provinces with catchment areas demonstrating high inter-annual variability, i.e. likely vulnerable to epidemics related to breakdown of malaria interventions. On the contrary, the situation of high and low incidence has largely remained unchanged in the Islands (except Bougainville) and Highlands regions, respectively.

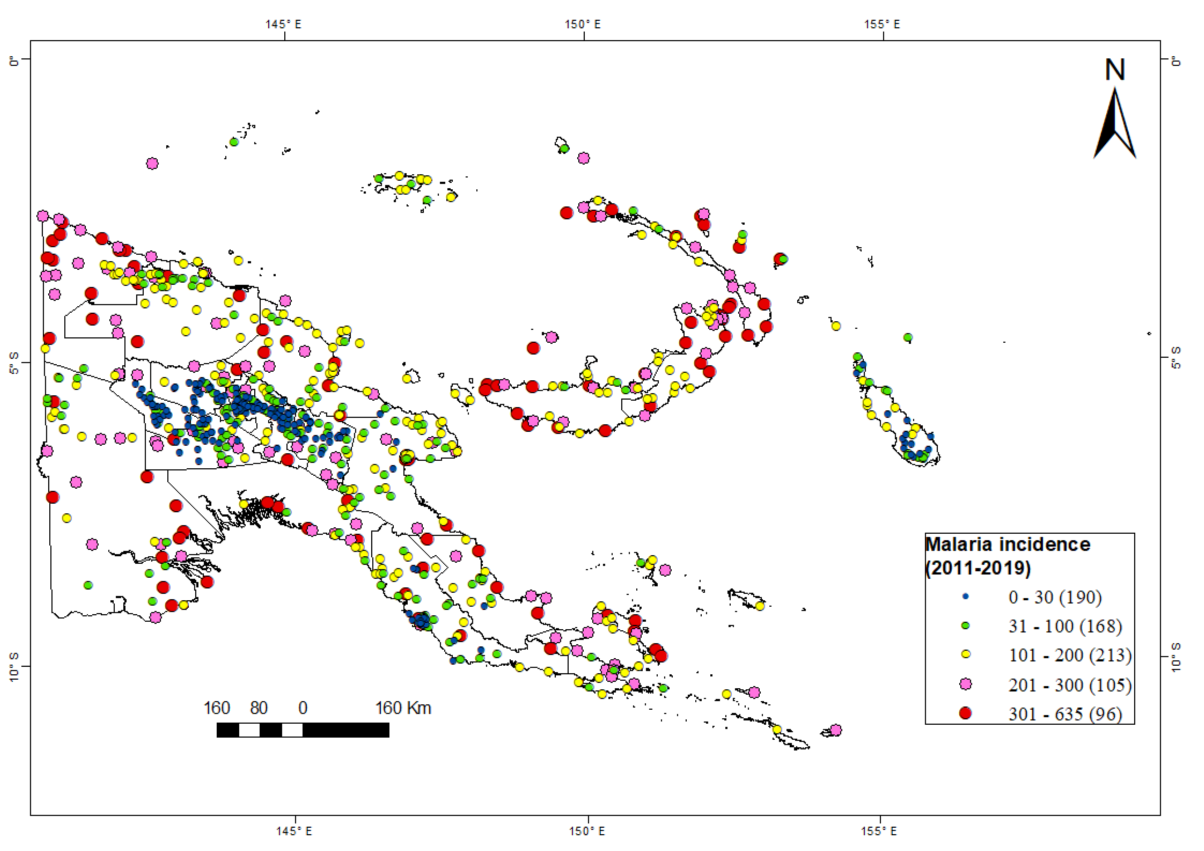

Figure 9. Average annual incidence of malaria per 1000 in catchment areas of 806 health facilities, PNG (2011-2019). Annual incidence is calculated using clinical (outpatients and inpatients) and confirmed (positive mRDTs and microscopy slides) cases, among the population in the catchment area of health facility.

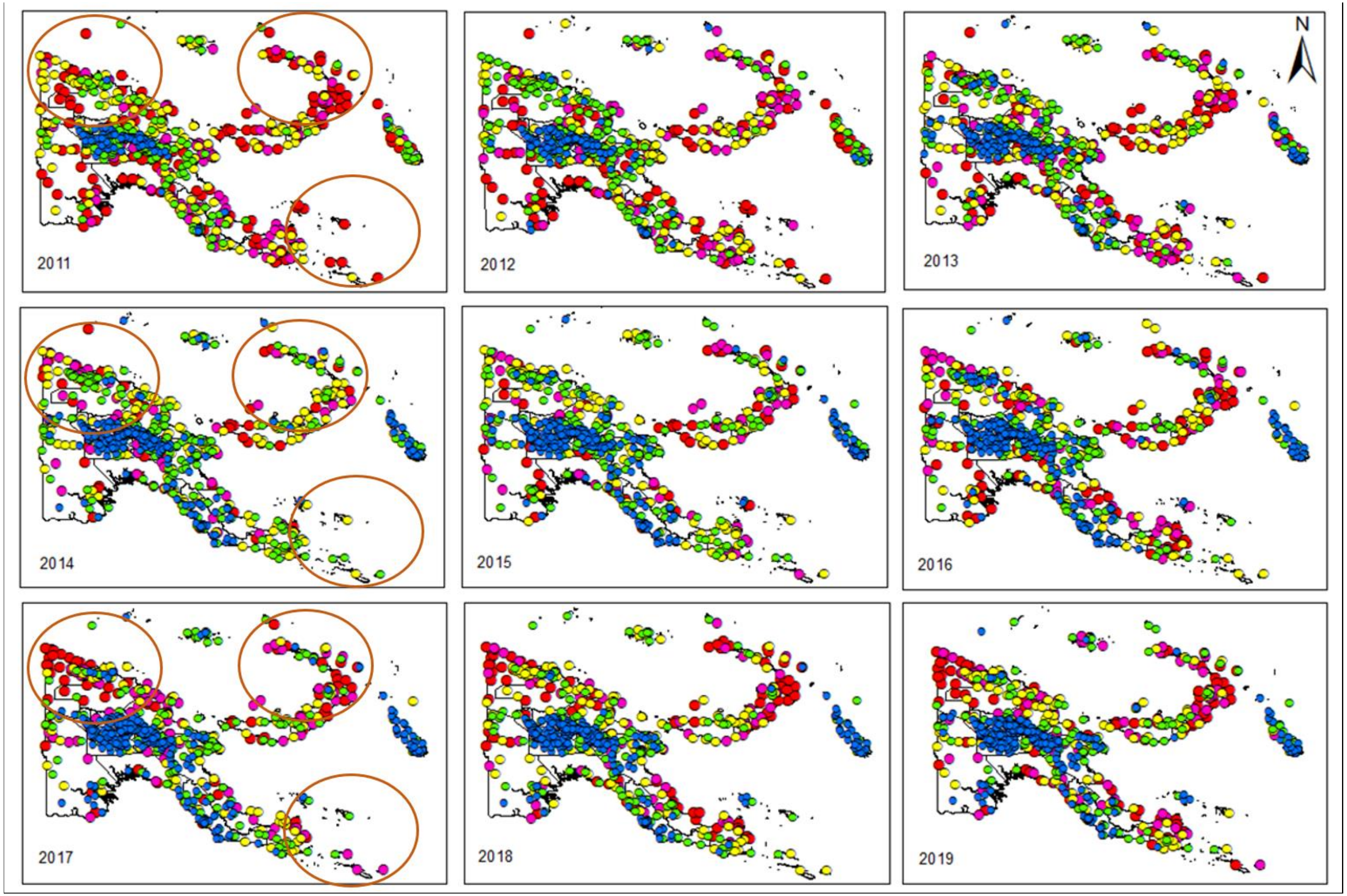

Figure 10. Yearly maps of malaria annual incidence in catchment areas of health facilities, PNG (2011-2019). Five categories of incidence per 1000: > 300 (red), 300-200 (pink), 200-100 (yellow), 100-30 (green), and <30 (blue). Incidence was calculated using confirmed (microscopy+ mRDTs) and clinical (inpatient+ outpatients) cases, among the catchment's population of the year.

3.10 HFs with few malaria cases among children

Overall, 26% of the PNG population (i.e. 2.3 million) live in areas where few children cases reported in their HFs. In 156 HFs, monthly malaria cases among the children population (i.e. under 15 years) was less than one case in each over the period (2011-2019). The HFs with few cases are mainly in the Highlands, Bougainville and NCD, see Figure 11. The positivity rate had averaged 9% among the children, but increased in the Highlands (>1600m) compared to coastal areas, see Table 3.

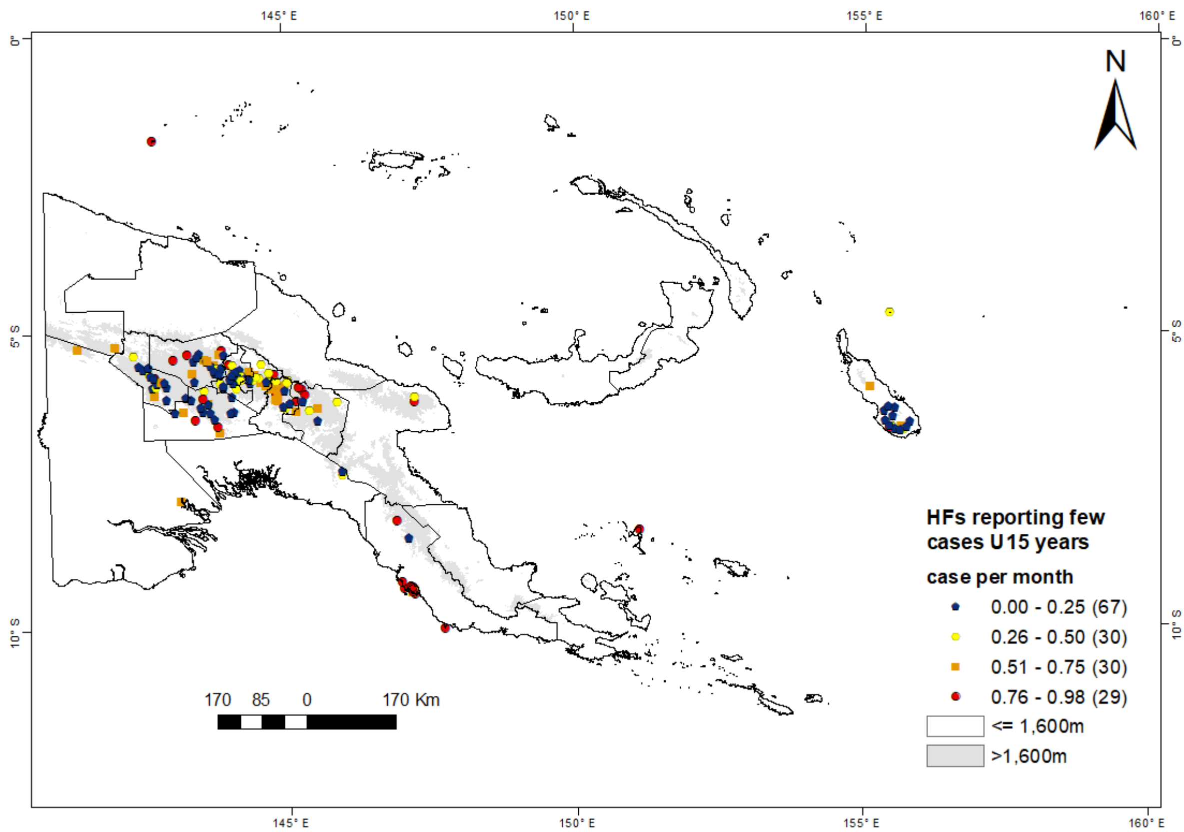

Figure 11. Health facilities (HFs) reporting few malaria cases among children <15 years in PNG (2011-2019). The average number of malaria cases in children reported per month per HF is less than one.

Table 3. Health facilities with few reported malaria cases among children under 15 years (om average, less than one case per monthly report) by altitude, PNG (2011-2019).

Altitude (m)	No. HFs	Children cases[1]	Positivity rate[2]	Total Population	Total LLINs issued[3]
≤ 400	28	959 (32.9%)	5.8% [1.6, 14.6]	261,563	105,248
400- 800	3	79 (22.8%)	5.1% [1.1, 8.2]	21,233	4,999
800- 1200	4	147 (37.1%)	6.6% [3.1, 12.8]	41,793	7,486
1200- 1600	10	173 (28.7%)	11.8% [0, 28.6]	112,782	40,076
1600- 2000	66	1,141 (20.7%)	8.6% [0, 31.2]	1,076,492	464,496
2000- 2400	22	531 (19.4%)	10.2% [0.3, 30.6]	376,782	170,702
2400- 2800	20	281 (14.5%)	13% [0, 42.1]	385,575	147,478
> 2800	3	55 (18.7%)	11% [4.9, 19.9]	193,69	12,186
All	**156**	**3,366 (22.9%)**	**9% [0, 42.1]**	**2,295,589**	**952,671**

[1] Total confirmed cases of children under 15 years, proportion relative to confirmed cases among general population are in parenthesis. [2] Average positivity rates among tested children, minimum-maximum rates are in brackets. [3] Total LLINs distributed between 2011-2019 in the catchments areas.

3.11 Strata of malaria incidence using EBK models

3.11.1 Cross-validation of EBK models

Parameters of EBK models are summarized in Table 4. Diagnostics of cross-validation in ArcGIS show that chosen parameters resulted in good fitting models using incidence both for general population and for children, Figures 12a and 12b, respectively.

RMSSE when using incidence of general population and children indicates reasonable variability in the predictions, 1.03 and 1.02, respectively. The values of RMSE vs. ASE are small and similar, 89.43 vs. 91.03 and 72.5 vs. 66.7, general population and children, respectively. However, the mean prediction error were close but below zero, -5.5 and -1.4, general population and children, respectively.

3.11.2 Strata of malaria risk

Figure 13 and Figure 14 show risk strata of malaria using average annual incidence for the period 2011-2019 among the general population and children under 15 years, respectively. Interpolations of incidence rates at catchment areas of HFs have resulted in similar spatial patterns regardless of which indicator was used (i.e. clinical and confirmed cases used for general population versus confirmed cases only for children). However, prominent areas with high malaria risk mainly in Momase and Southern provinces were modelled using incidence among children rather than in the general population. The risk of malaria is very low or low in the Highlands and the Southern region (NCD, Central and Western provinces) and Bougainville. Besides, moderate risk strata predominate throughout the mainland provinces, especially Morobe, Western and Northern provinces.

Table 4. Parameters of stratification models using empirical Bayesian kriging tool in Geostatistical Analyst, ArcGIS

Input dataset	Incidence among general population	Incidence among children under 15 years
Subset Size	30	100
Overlap Factor	1.4	1
Number of Simulations	100	100
Transformation	Empirical	Empirical
Semivarigoram Type	K-Bessel	Exponential
Neighbourhood type	Standard Circular	Standard Circular
Maximum neighbours	7	10
Minimum neighbours	2	3
Sector type	-	4 Sectors with 45° offset
Angle	-	0
Radius (ha)	1.59	1.98

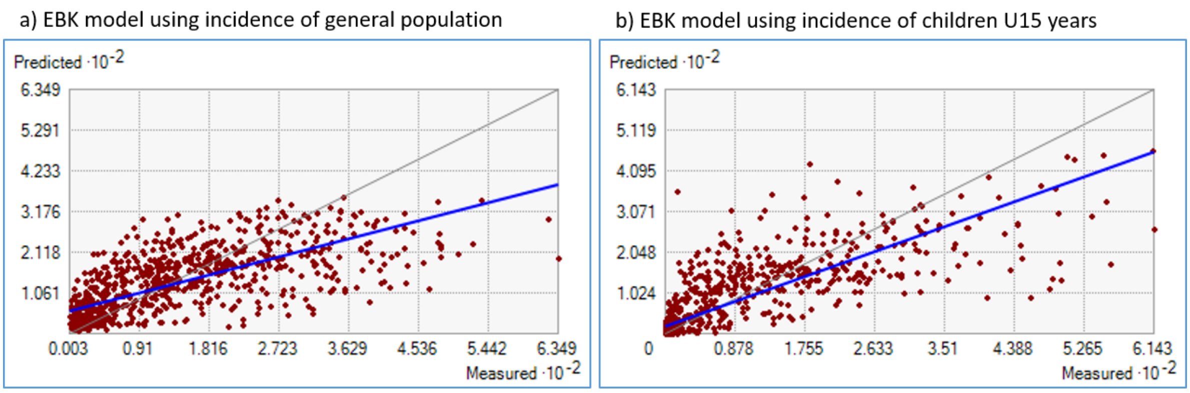

Figure 12. Cross-validation of empirical Bayesian kriging (EBK) models. Predicted versus measured values at catchment areas: (a) using incidence of general population, (b) using incidence of children under 15 years.

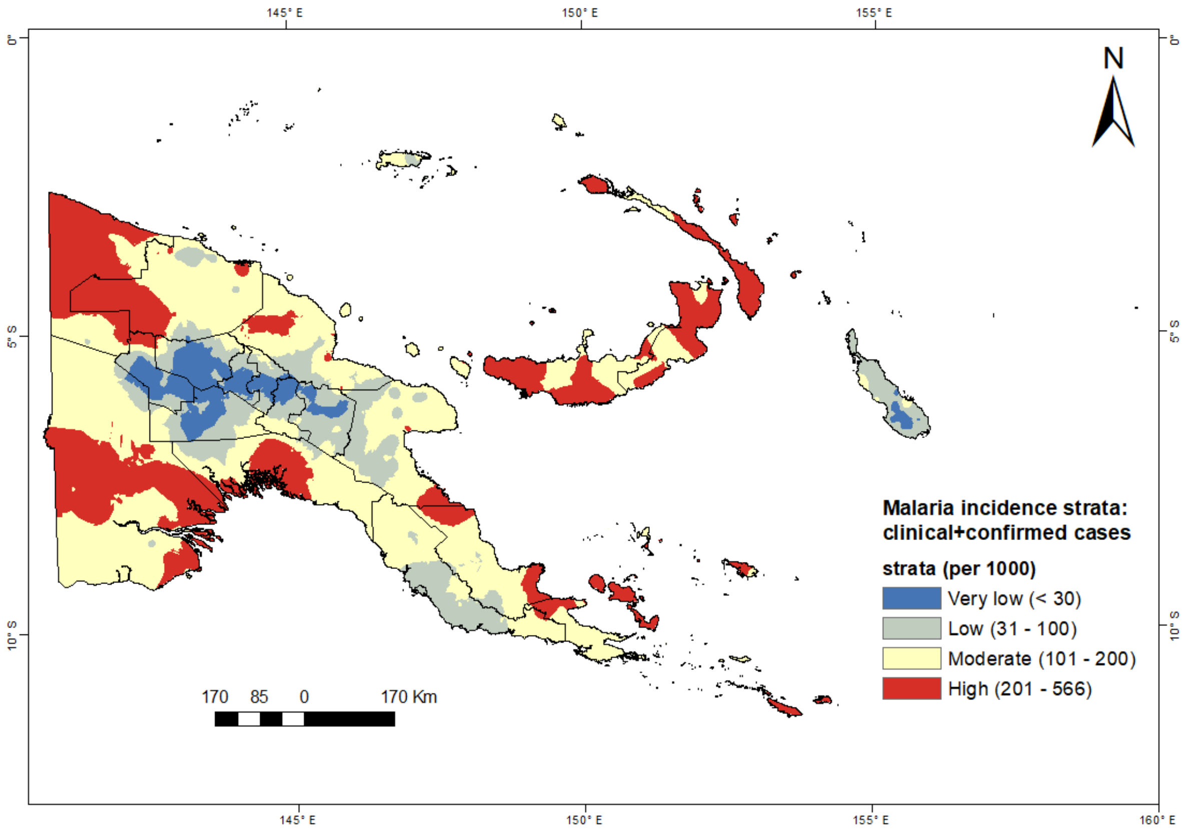

Figure 13. Malaria risk strata using average annual incidence of clinical and confirmed cases among general population, PNG, 2011-2019. Four strata interpolated using empirical Bayesian kriging at catchments of HFs: very low (<30), low (30-100), moderate (100-200), and high (>200 cases per 1000).

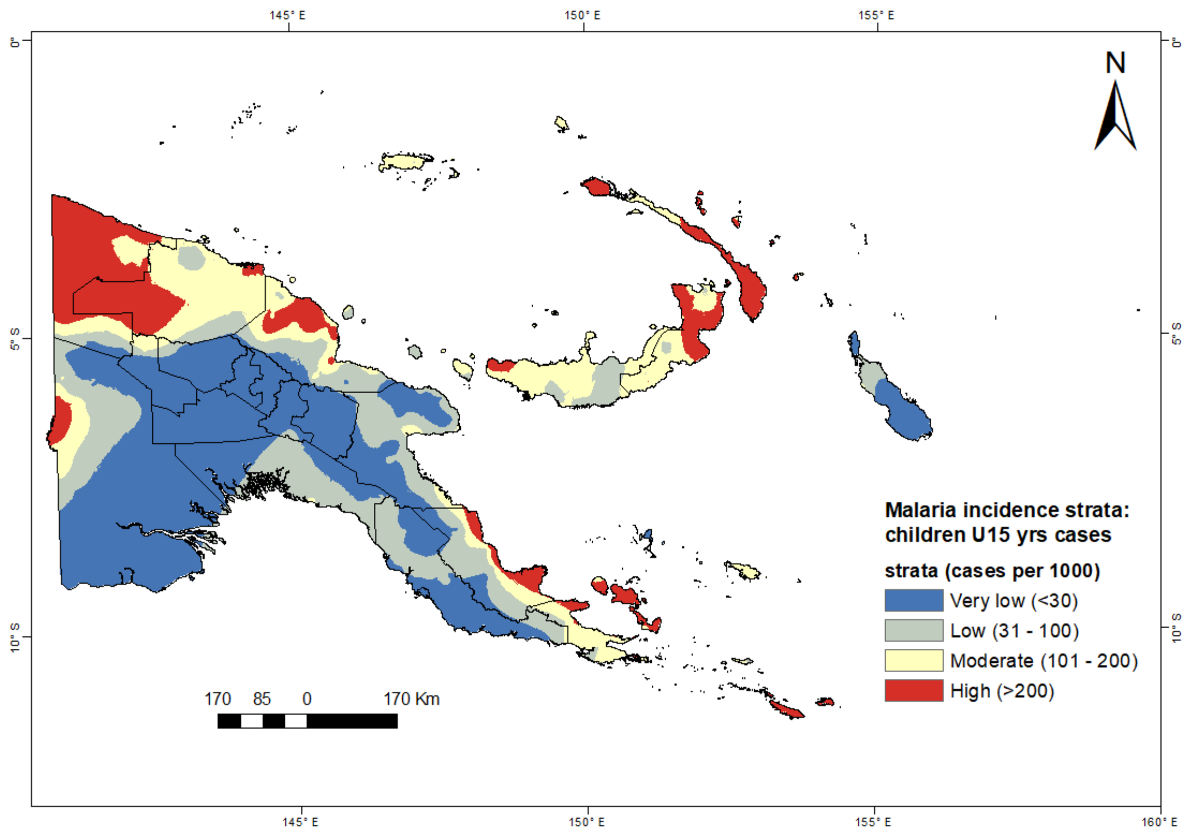

Figure 14. Malaria risk strata using average annual incidence of confirmed cases among children (<15 years), PNG, 2011-2019. Four strata interpolated using empirical Bayesian kriging at catchments of HFs: very low (≤30), low (30-100), moderate (100-200), and high (>200 cases per 1000).

3.12 Population living at risk strata by province

Table 5 summarizes population living at each risk strata by province as of 2020. Accordingly, 35.5% of PNG population (~3.4 million) live in areas that are at high or moderate risk of malaria. In four provinces, relatively large proportions of the population (> 50%) reside in high-risk areas: East New Britain, West Sepik, New Ireland and Milne Bay. In contrast, very low risk strata, which are 40% of the country population (~ 3.8 million), cluster in the provinces of the Highlands region and Bougainville.

Table 5. Population distribution of PNG by province according to malaria incidence strata, 2020

Province	HFs[a]	Population 2020 [b]	% population living at risk strata [c]			
			Very low	Low	Moderate	High
Bougainville	35	298,761	31.8%	51.3%	16.9%	0.0%
East New Britain	32	308,184	0.0%	0.0%	24.9%	75.1%
Manus	13	51,937	0.0%	20.2%	78.5%	1.3%
New Ireland	32	210,275	0.0%	0.6%	40.2%	59.2%
West New Britain	36	301,947	0.0%	0.0%	64.2%	35.8%
Central	41	289,315	0.0%	68.5%	31.4%	0.1%
Gulf	21	124,487	0.0%	5.3%	77.2%	17.5%
Milne Bay	43	323,448	0.0%	0.0%	49.0%	51.0%
National Capital District	25	369,365	0.0%	100.0%	0.0%	0.0%
Northern	19	220,664	0.0%	45.4%	38.9%	15.7%
Western	42	192,349	0.1%	2.2%	63.4%	34.3%
Chimbu	35	658,476	82.6%	16.1%	1.3%	0.0%
Eastern Highlands	37	755,272	68.5%	28.0%	3.2%	0.2%
Enga	37	736,446	84.3%	14.9%	0.3%	0.4%
Hela	32	735,038	94.8%	3.7%	0.0%	1.5%
Jiwaka	28	683,719	71.7%	24.4%	3.9%	0.0%
Southern Highlands	41	736,825	62.8%	36.9%	0.3%	0.0%
Western Highlands	41	486,508	90.5%	9.5%	0.0%	0.0%
East Sepik	45	511,302	0.0%	19.3%	40.0%	40.7%
Madang	48	620,662	0.5%	19.5%	55.1%	24.9%
Morobe	53	722,663	0.8%	43.0%	32.6%	23.5%
West Sepik	36	263,498	0.0%	6.2%	22.0%	71.8%
PNG (all provinces)	**772**	**9,601,141**	**40.4%**	**24.3%**	**19.8%**	**15.5%**

(a) Number of health facilities functioning and reporting on malaria to NHIS, NDOH.

(b) Projected population in 2020 by province based on a district-specific growth rate, NSO, PNG.

(c) Breaks of risk strata based on interpolated surface of incidence per 1000: very low (<30), low (30-100), moderate (100-200), and high (>200).

4 Discussion

The main contributions of this stratification work are three-fold. First, we used passively collected health information system data to map incidence and stratify risk of malaria in PNG at a microscale of catchment areas of HFs. Second, we determined altitudinal thresholds that influence malaria risk and examined the effects on different population groups. Third, we delineated the catchment areas of HFs and estimated the population at risk by strata using geostatistical modelling methods.

The negative relationship between malaria and altitude was historically documented in PNG (25, 27, 28, 36-38). In this work, we quantified the relationship between altitude and malaria incidence in PNG at a high resolution where malaria transmission happens, i.e. catchment areas of health facilities. A key finding is that there are two altitudinal thresholds where malaria declines significantly in PNG. Hence, the annual incidence at altitudes ≤800m was 184.8 per 1000 population, while the rates decreased to 120.2 at 800-1600m and 44.7 at 1600-2600m, i.e. where the average temperature drops below 23 and 19 °C, respectively.

The influence of altitude on malaria mechanistically occurs through the negative relationship between altitude and temperature. Temperature regulates the extrinsic incubation period (EIP) of *Plasmodium* in the mosquito, the longevity of adult mosquitoes, and the development time of their aquatic stages. A recent study showed parallel increases in annual temperature (0.33 °C per year) and malaria incidence (3.15 per 1000) in the Highlands (1996-2007) (39). A warmer climate could increase the risk of malaria epidemics especially in nonimmune populations in the Highlands. Therefore, there is a need for further studies that address the potential impact of climate change on malaria in PNG and a robust surveillance-response system to detect and respond to local foci.

The findings on malaria incidence strata presented here correspond with the results of previous five MIS conducted in 2008/09, 2010/11, 2013/14, 2016/17 and 2019/20 (13, 22, 23). Stratification maps in this work confirm negligible or low-risk strata along the central mountain range in the Highlands, Bougainville and NCD. In contrast, patches of high risk are mainly modelled in Momase and Islands provinces. Also, moderate strata predominate throughout the coastal provinces on the mainland of PNG. In the MIS 2016/17, the lowest prevalence was in the Highlands (1.2%) while Momase region (10.6%) observed the highest prevalence(22). Provinces with highest prevalence included Madang (16%), Milne Bay (10.8%), East Sepik

(8.8%), New Ireland (8.7%) and West Sepik (7.9%) (7). In 2017, West Sepik, East Sepik, Madang, New Ireland and Milne Bay had reported the highest incidence, exceeding 200 cases per 1000.

We also identified 156 HFs that report few monthly malaria cases (on average less than one) among children, mainly in the Highlands and Bougainville. In these catchment areas, almost one million LLINs were distributed between 2010-2019. However, the use of bed nets by people in the Highlands during the MIS 2016/17 was <50% (22).

Although we have successfully stratified malaria risk in PNG using routine incidence data applied at a microscale level of catchment areas, a limitation of this work is the lack of other complementary historical data. A more comprehensive stratification work should include malaria register at village level, and data collected in entomological and prevalence surveys. The cumulative prevalence data of MIS (2009/10, 2012/13, 2014/15, 2016/17 and 2019/20) could be a good indication of where there are infections, particularly in areas with high movement of people. A further limitation inherent in the use of heath information system data are potential data quality issues in the routine reports.

Instead of a one-size-fits-all malaria control policy in PNG, we suggest tailoring and targeting of control interventions (e.g., LLINs, ACTs, and mRDTs) at sub-national level. Catchment areas with high and moderate risk should be given priority in the allocation of interventions that reduce morbidity and transmission. Implications of this rational policy will include increasing the replacement rate and effectiveness of LLINs at transmission hotspots and preventing the shortage of ACTs where treatment is essential to alleviate malaria burden. In low risk areas, there is a need for an effective surveillance-response system to prevent the risk of severe epidemics. Such a systems may complement (or, in some cases, replace) blanket coverage with other interventions if local transmission is unlikely. For example, sentinel sites could be established or reporting of local cases by HFs could be strengthened in low-risk catchment areas. Since 2014, an electronic national health information system (eNHIS) has been rolled out in PNG. Hence, a near real-time reporting system to digitize and disseminate HF-based information on treatment seeker including malaria was established (40). The cost of strengthening eNHIS or maintenance of sentinel sites is much cheaper than provision of malaria commodities in areas with rare cases reported. However, the case reporting needs to be linked to immediate response action implemented by local authorities that are adequately resourced for this task.

We found that catchments in the coastal provinces - mainly in West Sepik, Milne Bay, and New Ireland provinces - exhibit high inter-annual variability. Reasons of these fluctuations in these holo-endemic areas are likely the effect of the interventions and subsequent effect of reduced coverage/effectiveness (41). This is coupled with the effect of varying degrees of availability of mRDTs. A recent work has reported poor quality of LLINs distributed in PNG after 2013 based on bio-efficacy assay against the local malaria vector (42). In addition, inter-annual variability of climatic factors such as temperature and rainfall (e.g., El Nino effect) may contribute to this observation. Hence, shortage of malaria commodities (i.e., ACT and mRDTs) at coastal catchments could result in severe epidemics and needs a better mobilization of resources.

A limitation of the current work is the lack of analysis of seasonal patterns of malaria incidence and on modelling the risk strata. Previous studies showed a limited seasonality in most of Momase lowlands (4, 11, 43), while a pronounced seasonal cycle was documented in the Islands and Southern regions including NCD (24, 44). Besides, severe malaria epidemics were reported in the Highlands between April and July at altitudes 1300-1600 m, i.e., during the switch from the rainy to dry seasons (2, 29, 37, 45, 46). However, the predominance of *P. falciparum* seen in epidemics at Highlands probably relates to seasonal migrations for agriculture purposes during the rainy season towards the beginning of the dry season. Hence, seasonality of rainfall and related socioeconomic factors needs to be explored in a further work.

Another risk factor that we did not investigate here is the effect of population mobility on malaria risk. In PNG, there is a continuous movement between the Highlands and coastal provinces for trade (e.g. betel nuts and vegetables) and other reasons. Also, Highlanders frequent to intermountain valleys for subsistence farming. In addition, there are thousands of migrant workers in mines companies (e.g., NewCrest Mining in Lihir and Ok Tedi in Western province) and developmental projects (e.g., PNG LNG), who transit through malarious areas (47, 48). Hence, the inclusion of the socioeconomic factors that govern population movements between different risk areas is necessary to improve the stratification work. In addition, spatial weights of socioeconomic ties of inhabitants in catchment areas with other ones should be considered in malaria stratification.

Entomological risk factors were not included in this report. Previous studies showed a difference in distribution and vectorial capacity between malaria mosquitoes in PNG that have implications for malaria transmission and vector control. Among the five significant vectors of malaria in PNG, three species are widespread through the country but with no influence of altitude or coastal distance: *An. koliensis, An. punctulatus and An. hinesorum*. In contrast, *An. farauti (s.s.)* tends to exist in coastal areas and *An. farauti* 4 is limited to the northern part of PNG. Temporal and spatial heterogeneities in abundance were also reported between the malaria mosquitoes in PNG, even between nearby villages (10, 11, 49). While some common nocturnal activity patterns, e.g. related to village entry and host seeking predominantly before midnight has been described recently (49), previous studies also found differences in biting time between different vectors. While species of *An. farauti (s.l.)* prefer early biting, *An. koliensis* and *An. punctulatus* usually feed late (9). However, there also seems to be behavioural plasticity and change in species composition and biting behaviour linked to the rollout of vector control interventions, which may compromise intervention effectiveness (50, 51). Hence, updated maps on vectors distribution including information on their biting behaviour and vectorial capacity are essential to generate interventional strata map.

Although the obtained malaria reports give a total of cases according to the type of infection, we could not analyse incidence by *Plasmodium* species. First, the decline of incidence (or malaria cases) using microscopy with altitude increase was inconsistent especially in mid-altitude catchment areas between 1000m and 1400m. In fact, only a minority of health facilities provide malaria microscopy services and report malaria numbers based on microscopy diagnosis in PNG, particularly following the rollout of mRDTs. Secondly, the quality of microscopy results especially differentiation between *Plasmodium* species is questionable at the periphery. However, parasite composition in catchment areas is essential and should be considered in future work. Previous studies showed a change in species composition in PNG following the "unaccomplished" control and eradication efforts in the 1970s (24, 52). Hence, *P. falciparum* has prevailed over the country (4, 7, 43), while *P. vivax* remained dominant only in low-risk areas at the Highlands (37). The MIS in 2016/17 revealed that *P. falciparum* predominated in coastal areas (61.2%) followed by *P. vivax* (31.6%) and *P. malariae* (1.8%). However, no case of *P. ovale* was detected in the Highlands or coastal provinces. In addition, 5.9% of malaria cases were mixed infections of *P. falciparum* and *P. vivax*. Further, the MIS 2016/17 revealed high variability in *Plasmodium* composition between the provinces (22).

Recently, a school malaria survey (SMS) was carried out in the Highlands to investigate local transmission of malaria (53). The SMS was combined with a reactive case detection (RCD) at the households in the seven provinces of the region. Using malaria RDTs, the SMS found only 13 positive cases among 5,575 tested students and seven cases among 1,048 tested household members. The very low prevalence of infection suggests little local transmission in the Highlands but a risk of importation from other areas. We have divided the SMS surveyed areas into four strata: 1) very low with more epidemic risk at altitudes <1200m, 2) very low with less epidemic risk at 1200-1600m, 3) very low dominated by importation at 1600m-2000m, and 4) extremely low risk with only importation at altitudes above 2000m, which provides complementary evidence to this stratification report.

Cross-validation of the stratification model showed a satisfactory performance in prediction verified by five error-related statistics. Empirical Bayesian kriging has the advantage of being more accurate for small datasets compared to other geostatistical modelling tools. In contrast, large datasets increase the computing time needed to produce raster maps of EBK. We tried other geostatistical methods - such as Inverse Distance weighting, simple kriging and cokriging - but we found EBK is more suitable to model incidence data with minimal prediction error. Nevertheless, there is a need to investigate the role of altitude and other predictors using Bayesian regression kriging methods (54).

An integral part of malaria stratification modelling is answering questions about what and where different malaria interventions should be implemented to maximize the effectiveness of interventions and minimize the costs. Ideally, disease modelling tools especially mechanistic methods are available and have been successfully used to improve decision making by national malaria programs (55-60). In Tanzania, malaria risk was stratified at a sub-national level using complementary datasets on incidence (from the health system) and prevalence (from surveys) and on different population groups. Cut-offs and scores of malaria indicators assigned to risk groups and to the country administrative councils revealed that 12% of the population are living in a very low stratum compared to 23% and 37% percent in moderate and high strata (55). A challenge for this type of stratification is the decision on which cut-offs to use for the categorization of risk strata. While there is some guidance from WHO (34), the strata may have to be adapted for each country, as done in this report, to ensure sufficient disaggregation in a given context. Further, a mathematical model was developed using OpenMalaria platform to evaluate the impact of allocation of interventions in Tanzania. Simulations of the model has anticipated a failure to achieve the target of 1% prevalence by 2020 unless the control efforts are intensified with supplementary interventions (56).

In PNG, a blend of geostatistical tools and mathematical modelling tools could be useful to assist in decision-making on malaria control by computationally examining the impact of different scenarios of allocation of interventions at operational units in PNG.

Conclusions and recommendations: Altitude is among the risk factors to stratify malaria in PNG. Stratification maps show clustering of very low to low-risk strata in provinces of Highlands, NCD and Bougainville. In contrast, modelled patches of high and moderate risk are mainly in provinces of Momase, Islands and Southern regions. We estimated a population of 3.4 million lives in areas that are at high or moderate risk of malaria (i.e. in catchment areas with >100 cases per 1'000 population per year). However, the risk of malaria is highly variable in low-lying catchment areas and needs further research to identify other factors.

There is a need to support the PNG national malaria control programme in the tailoring and targeting of malaria control interventions at sub-national scale using disease modelling tools and building the country capacity for implementing a data-driven control approach.

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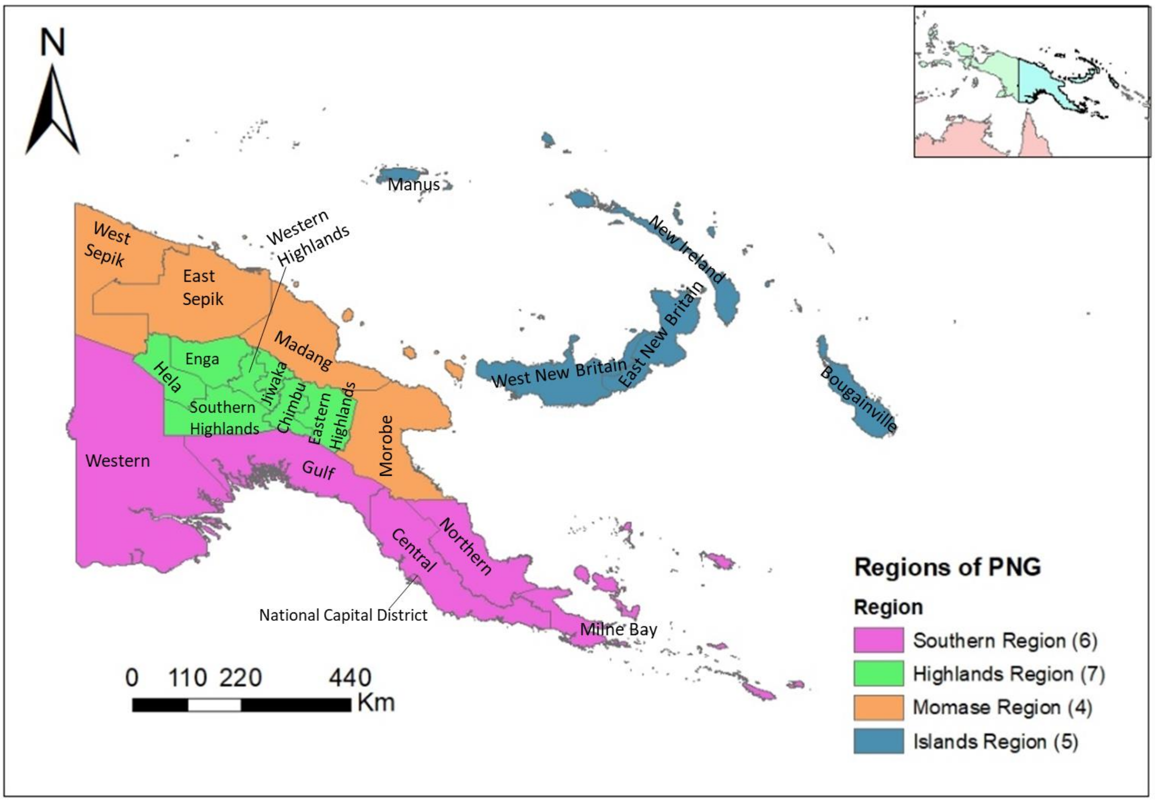
Appendix A. Administrative regions and provinces of PNG



Appendix B. Statistics of cross-validation of EBK models

From documentation on Cross-validation of empirical Bayesian Kriging models, Geostatistical Analyst, ArcGIS 10.6 (accessed 06/27/2021)

- Mean Error—the averaged difference between the measured and the predicted values.

$$\frac{\sum_{i=1}^{n}\left(\hat{Z}(\mathbf{s}_i) - z(\mathbf{s}_i)\right)}{n}$$

- Root Mean Square Error—indicates how closely your model predicts the measured values. The smaller this error, the better.

$$\sqrt{\frac{\sum_{i=1}^{n}\left(\hat{Z}(\mathbf{s}_i) - z(\mathbf{s}_i)\right)^2}{n}}$$

- Average Standard Error—The average of the prediction standard errors.

$$\sqrt{\frac{\sum_{i=1}^{n}\hat{\sigma}^2(\mathbf{s}_i)}{n}}$$

- Mean Standardized Error—The average of the standardized errors. This value should be close to 0.

$$\frac{\sum_{i=1}^{n}\left(\hat{Z}(\mathbf{s}_i) - z(\mathbf{s}_i)\right)/\hat{\sigma}(\mathbf{s}_i)}{n}$$

- Root Mean Square Standardized Error—This should be close to 1 if the prediction standard errors are valid. If the root-mean-squared standardized error is greater than 1, you are underestimating the variability in your predictions. If the root-mean-square-standardized error is less than 1, you are overestimating the variability in your predictions.

$$\sqrt{\frac{\sum_{i=1}^{n}\left[\left(\hat{Z}(\mathbf{s}_i) - z(\mathbf{s}_i)\right)/\hat{\sigma}(\mathbf{s}_i)\right]^2}{n}}$$

Appendix C. Temperature and precipitation in PNG

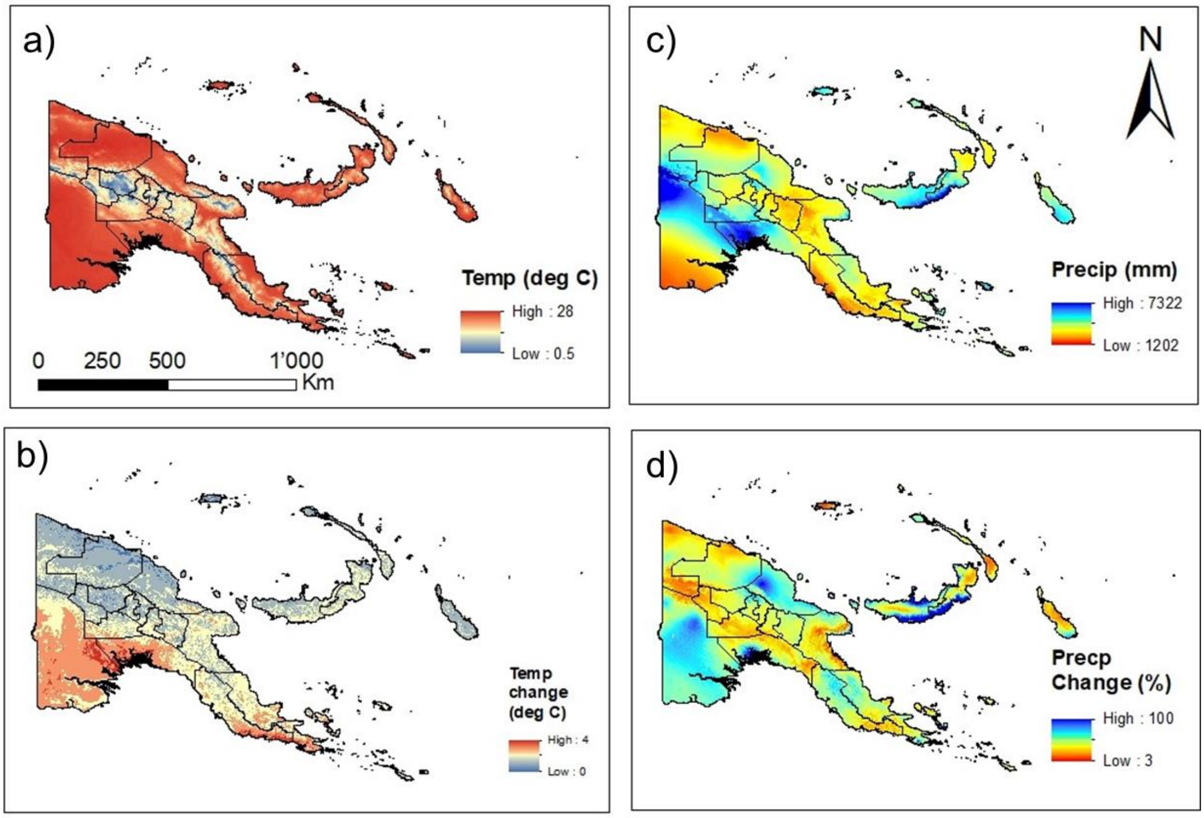


Figure B1. Annual means and seasonal changes of temperature and precipitation in PNG (1970-2000): a) annual average of temperature (°C), b) seasonal change of temperature (warmest-coldest month), c) annual average of precipitation (mm), d) seasonal change of precipitation (wettest-driest month).

Appendix D. Population distribution by travel time to HFs

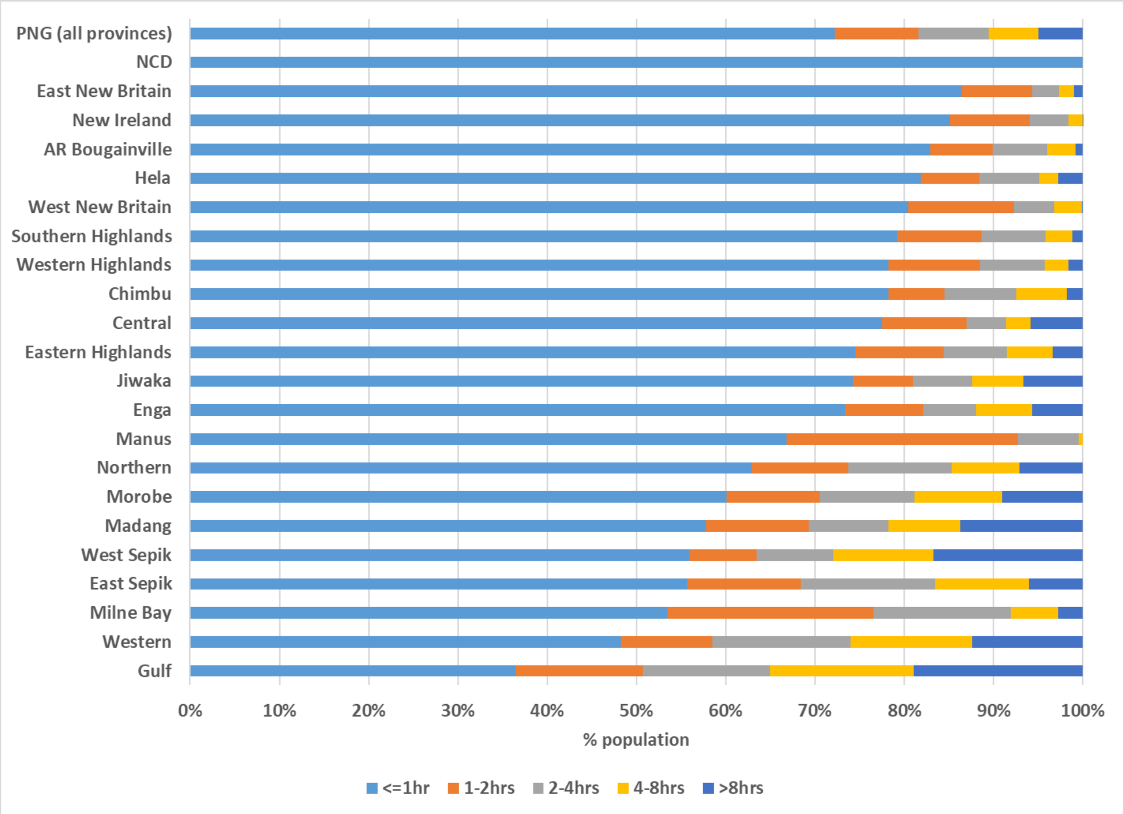


Figure C1. Population distribution according to travel time (hours) to the nearest health facilitiy, by province.