The Use of Routine Health Facility Data for Malaria Risk Stratification in Mainland Tanzania

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Sumaiyya Gulamraza Esmail Subjali Thawer

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auf Antrag von

First Supervisors: Dr. Emilie Pothin & Prof. Dr. Christian Lengeler
Second Supervisor: PD Dr. Amanda Ross
External Expert: Prof. S. Patrick Kachur

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Prof. Dr. Marcel Mayor
Dekan

"That knowledge which remains only on your tongue is very superficial. The intrinsic value of knowledge is that you act upon it"

~ Ali ibn Abi Talib ~

Nahjul Balagha

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Abbreviations

ACT	Artemisinin-based Combination Therapies
ANC	Antenatal Care
API	Annual Parasite Incidence
BRR	Basic Reproductive Rate
BYM2	Besag-York-Mollié 2
CAR	Conditional Autoregressive
CBS	Case Based Surveillance
CHMT	Council Health Management Team
DEM	Digital Elevation Model
DHIS2	District Health Information Software
EIR	Entomological Inoculation Rate
eLMIS	electronic Logistic Management Information System
EP	Exceedance Probability
EVI	Enhanced Vegetation Index
GMP	Global Malaria Programme
GTS	Global Technical Strategy
HBHI	High Burden for High Impact
HF	Health Facility
HRP	Histidine-Rich Protein
HMIS	Health Management Information System
IHME	Institute of Health Metrics and Evaluation
IDSR	Integrated Disease Surveillance and Response
INLA	Integrated Nested Laplace Approximation
IRS	Indoor Residual Spraying
ITN	Insecticide Treated Nets
LAMP	Loop-mediated Isothermal Amplification
LLIN	Long Lasting Insecticide Nets
LSM	Larval Source Management
M&E	Monitoring & Evaluation
MAE	Mean Absolute Error
MAP	Malaria Atlas Project
MIS	Malaria Indicator Survey

MoH	Ministry of Health
MoHCDGEC	Ministry of Health, Community Development, Gender, Elderly and Children
mRDT	Malaria Rapid Diagnostic Testing
MTR	Mid-Term Review
MVS	Malaria Vector Surveillance
MSDQI	Malaria Service and Data Quality Improvement
NBS	National Bureau of Statistics
NEP	Non-exceedance Probability
NMCP	National Malaria Control Programme
NMP	National Malaria Programme
NMSP	National Malaria Strategic Plan
NTL	Night Time Lights
OPD	Out-Patient Department
*Pf*PR	*Plasmodium falciparum* Prevalence Rate
PMC	Perennial Malaria Chemoprevention
qPCR	quantitative Polymerase Chain Reaction
R2	R-squared
RBM	Roll Back Malaria
RCH	Reproductive and Child Health Clinic
RDT	Malaria Rapid Diagnostic Testing
RMSE	Root Mean Square Error
RR	Reporting Rates
SBCC	Social and Behavioral Change Communication
SMC	Seasonal Malaria Chemoprevention
SMMSP	Supplementary Mid-term Malaria Strategic Plan
SMPS	School Malaria Parasitaemia Survey
SUFI	Scale Up for Impact
TES	Therapeutic Efficacy Studies
TMA	Tanzania Meteorological Agency
TPR	Test Positivity Rate
TSI	Temperature Suitability Index
UDSM	University of Dar es Salaam
WHO	World Health Organization

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Summary

Since 2000, a renewed commitment in malaria control saw an increased investment of funding to support various malaria control interventions across Africa (World Health Organization, 2020a). This resulted in substantial reductions in the disease burden in many parts of Africa (World Health Organization, 2021). However, progress has plateaued in recent years (World Health Organization, 2021) and ten countries in Africa currently account for 66% of the global malaria disease burden (World Health Organization, 2018a). Further donor assistance is unlikely and a new model for improving efficiencies in resource allocations is required to maximize gains.

In line with this, a major pillar of the World Health Organization (WHO) Global Technical Strategy (GTS) 2016-2030 encourages the use of accurate and timely routine data for stratifying sub-national malaria burden to track the changes in malaria epidemiology (World Health Organization, 2015c). The WHO High Burden for High Impact initiative (HBHI) further builds on the principles of the GTS framework and re-emphasizes the use of data to shift away from a "one size fits all" to a more tailored malaria control approach to accelerate progress against malaria (World Health Organization, 2018a). Countries are called upon to use all available health information to stratify the malaria burden in order to deploy effective malaria control tools to areas in greatest need and maximize impact and efficiency (World Health Organization, 2018a). As malaria declines, the heterogeneity in its transmission increases. Many countries have had an unequal distribution of high malaria burden within their national borders, and these high burden areas continue to remain high despite substantial control investment. Identification of high transmission areas would strategically accelerate national disease burden reductions. The purpose of stratifying malaria risk is to unpack this heterogeneity for optimized planning of malaria interventions. This needs to increasingly guide development of national malaria strategic plans (NMSPs) for efficient resource allocation.

Nationally owned routine surveillance systems can provide near real-time and granular data in time and space for stratifying malaria. However, data from these sources have largely remained underutilized due to concerns over completeness and quality (Rowe et al., 2009). As a result, the diversity of Africa's malaria burden has relied on the use of epidemiological modelling of parasite prevalence and opportunistic, and often dated, survey malaria data (Bhatt et al., 2015; Gething et al., 2011b; Noor et al., 2014; Weiss et al., 2019). These models have guided

international priority setting, but at fine scales, can misrepresent trajectories in malaria risk (Kamau et al., 2020b). Current approaches by WHO to estimate malaria burden in 30 countries of Africa involve using modelled prevalence predictions and transforming them into incidence estimates through a modelled non-linear relationship (Alegana et al., 2020; Cameron et al., 2015). However, the ambition is that ultimately all countries provide reliable and accurate routine data to avoid over reliance on modelled estimates.

There is an increasing use of routine data, largely as a result of factors such as the launch of the WHO universal test and treat initiative (World Health Organization, 2012a) that has significantly improved testing rates, the digitization of District Health Information Software (DHIS2) system that has improved health facility (HF) reporting rates (RR) and the emphasis by WHO GTS and HBHI initiatives to use data for decisions all of which are increasing the accountability and usage of these data. Efforts to incorporate routine HF data for risk mapping are emerging although most of these efforts are driven externally due to inadequate analytical capacity within countries. The increasing use of routine data has placed data quality initiatives to become an important operational component of surveillance across countries. Global efforts have introduced surveillance assessment toolkits (World Health Organization, 2022b, 2017a) to ensure a well-functioning surveillance system is in place to capture quality data from the routine information system. This is all expected to further enhance the accountability at level of data collection, aggregation and entry of routine information.

In mainland Tanzania, the diversity in malaria epidemiology within the country's border has historically been described through malaria transmission seasons, urbanization, altitude and community-based parasite prevalence. There is no evidence however, on how these early maps were used to guide malaria control decision making. Recently, a model based geospatial framework using 10 years of community- and school-survey parasite prevalence data was used to highlight the heterogeneous nature of sub-national malaria transmission intensity (Alegana et al., 2021a). Whilst this is useful and provides the country with a baseline for understanding its transmission, these statistical models based on under-powered national household sample health surveys provide only one source of data. Their sustainable updating depends heavily on donor funding to support national household or school based surveys. As such, the need to explore alternative data sources notably from routine Health Management Information System (HMIS) is important. Targeting combinations of interventions based on local epidemiological

criteria, whilst referenced in previous NMSPs, had never been formally established in mainland Tanzania until 2018. In 2017, during a mid-term review (MTR) (National Malaria Control Programme, 2017b), it was recognized that progress towards reducing national parasite prevalence was being made (7% in 2017 (Ministry of Health et al., 2017)), but that further gains would require a strategic redirection of limited resources to achieve a prevalence of less than 1% by 2020. The MTR was followed by a consultative process with a forum of global and national malaria experts. Recommendations from this forum National Malaria Control Program, 2018b), together with those from the WHO GTS 2016-2020 (World Health Organization, 2015c), were used to consider tailoring intervention approaches to the sub-national, local context, based on epidemiological stratification. Such an approach requires a data-driven approach, maximizing survey and routine data to establish epidemiological strata at operational units of programme delivery.

The aim of the work presented in this thesis was to explore and demonstrate the potential of routine HF malaria data to inform malaria risk stratification in mainland Tanzania. The objective was to explore the added value of leveraging information from multiple malaria metrics of the routine surveillance system of Tanzania in combination with survey data to map malaria risk at different spatial resolutions and thereby support the country's ambition towards a more tailored malaria control approach.

This was demonstrated through first conducting key informant interviews with various stakeholders to understand common encountered challenges with using such data for analytical purpose. The objective was to understand the current approaches taken for HF data processing and cleaning. The interviews highlighted some of the existing challenges and the spectrum of methodological approaches currently being used to account for it in order to produce sensible analytical outputs. The key findings of this study recommended the need for developing guidelines addressing gaps in routine data and for handling such data in a systematic manner. This is essential for increasing confidence in the data, increase the usage of routine data for decision making, and generally enhanced harmonization in the approaches taken.

A simple and pragmatic approach that made use of combinations of multiple routine malaria metrics and survey data was then utilized to support NMCP with a macro-stratification risk map at council level for sub-national tailoring of interventions. This was instrumental in

translating the risk map into suitable packages of interventions. The current strategic plan (National Malaria Control Programme, 2021) makes use of this evidence and advocates for tailored interventions through emphasizing burden reduction strategies in moderate-high transmission areas, and elimination strategies in low-very low transmission areas. Importantly, the methodological approach used was well within the capacity of NMCP staff at national level as it did not require data generated through complex survey methods nor utilized complex modelling methods.

The analytics was extended to the granular level of the ward to produce a micro-stratification risk map to further improve resource allocation. As the country is currently implementing the targeted packages of interventions, the goal is to move some of the decision-making processes towards a decentralized malaria control approach where council health management teams (CHMTs) would be empowered to understand the malaria situation in their respective wards and mobilize resources to areas that most need them to further maximize impact. The resulting micro-stratification revealed malaria risk heterogeneity within 80 councils and identified wards that would benefit from community-level focal interventions, such as community-case management, indoor residual spraying and larviciding. Micro-stratification is expected to allow this profound change in health planning processes by promoting a culture of data usage and equip council level with the capacity and tools to understand and appropriately respond to the local situation.

The use of crude aggregated routine data especially at the granular level of the ward for micro-stratification came with some limitations. One of the challenges was the incomplete nature of information in space and time, resulting in lower level administrative units (7% of wards) without empirical data. To overcome sparsity of data, geo-spatial models can leverage available routine information to predict risk in areas without information as well as provide the associated levels of uncertainty. A Bayesian spatio-temporal model was therefore used on test positivity rate (TPR) to leverage routine information and fill existing spatial and temporal gaps. The exceedance/non-exceedance probabilities were used to quantify the uncertainty of the estimated risk within policy relevant thresholds of TPR. Geo-spatial modelling provided a valuable framework for enhancing the use of imperfect routine HF data for malaria micro-stratification at program-relevant administrative units.

As Tanzania moves towards transitioning decisions to lower levels, a strong and robust guidance from national to council levels needs to be continuously provided. Councils that are empowered to make such decisions would require skills for understanding the local heterogeneity and making use of their local data to drive decisions. Whether the operationalization of micro-stratification for micro-planning is feasible and politically acceptable remains to be assessed and will require close monitoring of the processes at all levels. Overall, this work has demonstrated the ability of using local routine data in driving a country-owned stratification process at different spatial resolutions. This can have immediate potential in building a culture of data usage for decision making. Efforts towards strengthening capacity at all levels of the health system remains critical.

1 Introduction

1.1 Malaria epidemiology and control

1.1.1 Epidemiology and burden of malaria

Malaria is an endemic vector-borne disease caused by infection with the protozoan parasite of *Plasmodium* species and transmitted by the female *Anopheles* mosquitoes. The *Plasmodium* genus comprises five species that are responsible for infections in humans. These include *P. falciparum, P. vivax, P. malariae, P. ovale and P. knowlesi*. In sub-Saharan Africa (SSA), *P. falciparum* has had the largest impact and largely responsible for majority of the malaria cases (World Health Organization, 2021).

Malaria is a major public health problem. In 2021, the World Health organization (WHO) estimated 241 million cases of malaria and 627,000 malaria deaths that occurred worldwide across 85 malaria endemic countries (World Health Organization, 2021). Almost 95% of the cases and 96% of malaria deaths were attributed to those coming from the African region (Figure 1.1). Children under 5 years old represent the most vulnerable population group susceptible to infection and account for majority of the deaths.

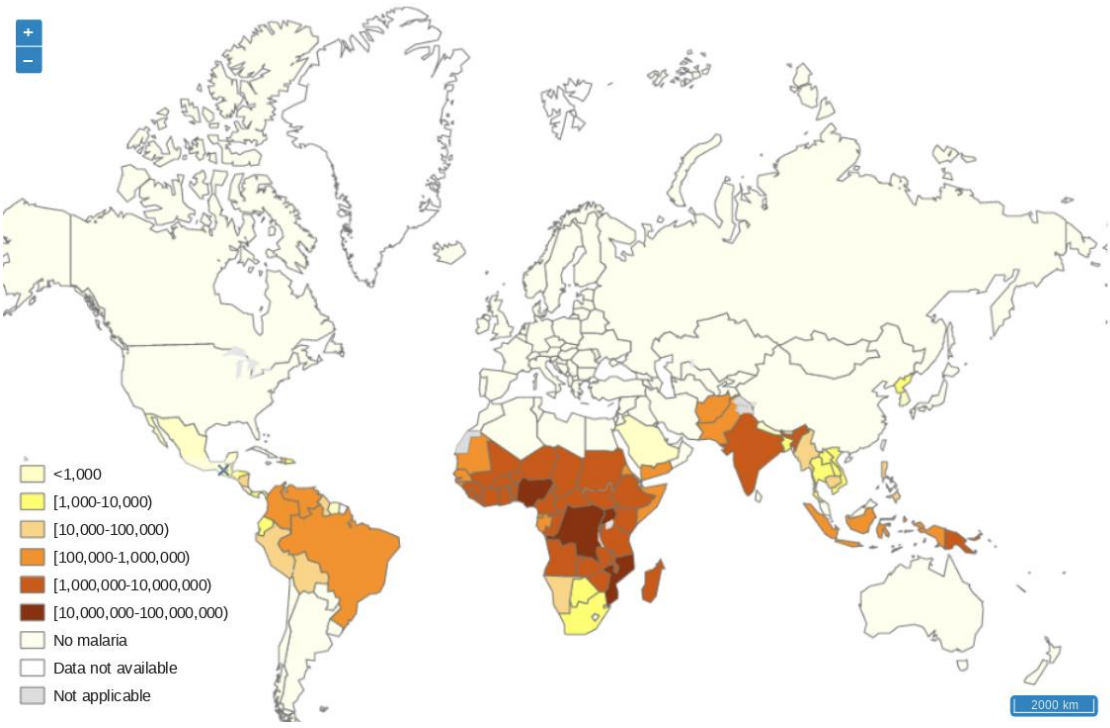


Figure 1.1: Global distribution of malaria cases estimated by the World Health Organization in 2020 (World Health Organization, 2020a)

1.1.2 Malaria transmission

Transmission of malaria is dependent on the interaction between the parasite, vector, human host and environment (Figure 1.2) and understanding this interaction is important for control and prevention measures (Acharya et al., 2017).

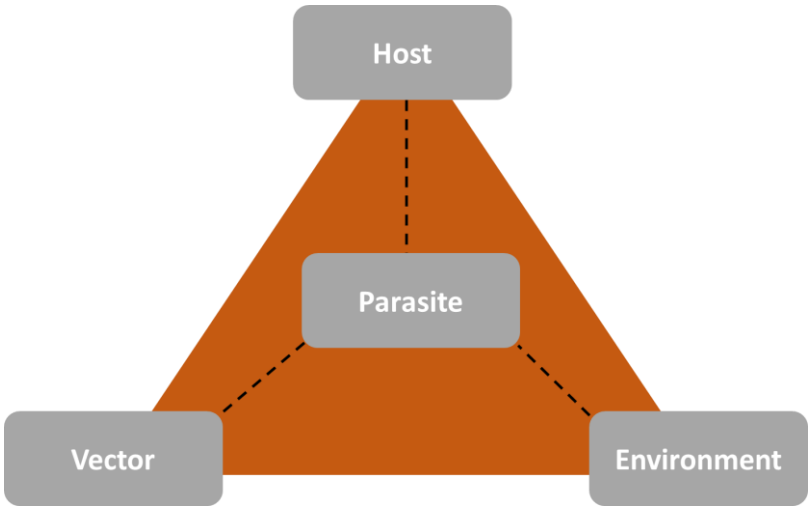


Figure 1.2: Host-Parasite interaction of malaria transmission

The intensity of transmission is influenced by environmental and geographic factors that have long contributed to the spatial and temporal distribution of malaria (Grillet, 2000; Patz et al., 2000). Warm humid conditions such as those in the tropics are more favorable for the parasite developmental life cycle and vector survival and thus drive transmission (Abeku et al., 2003; Gething et al., 2011a; Midekisa et al., 2012). High temperatures allow the complete development of parasites and mosquito larvae and for vector survival (Tanser et al., 2003) whilst rainfall increases the number of breeding sites that favor density of vector populations (Midekisa et al., 2012; Thomson et al., 2017). Sudden changes in weather have been associated with malaria epidemics especially in areas with vulnerable populations who have little or no immunity (Pascual et al., 2008; Snow et al., 1993).

The susceptibility of human populations to malaria infection, exposure and severity also greatly varies (Breman, 2001; Doolan et al., 2009; Heggenhougen et al., 2003). Acquisition of immunity to malaria is dependent on the cumulative exposure to infectious mosquito bites and consequently the age of population (Carneiro et al., 2010; White and Watson, 2018). Acquired immunity determines the age, severity and outcomes of malaria infection (Breman, 2001; Kamau et al., 2022; Paton et al., 2021; Snow et al., 1997).

Other factors also known to contribute to the heterogeneous epidemiology of malaria include socio-economic factors (wealth, education, housing and population distributions) (Carter and Mendis, 2006; Feachem and Sabot, 2008; Greenwood et al., 2008, 2008; Heggenhougen et al., 2003; Protopopoff et al., 2009; Tanner and de Savigny, 2008; Teklehaimanot and Mejia, 2008; Tusting et al., 2016), occupational exposures (Naidoo et al., 2011), political instability (Jaramillo-Ochoa et al., 2019), poor functioning health systems (Sahu et al., 2020), health seeking behaviors (Tanner and Vlassoff, 1998), poor intervention coverage (Steketee and Eisele, 2009) and the rise in insecticide and drug resistance amongst others (Cohen et al., 2022; Heggenhougen et al., 2003; Martens and Hall, 2000; Menard and Dondorp, 2017; Messina et al., 2011; Okumu et al., 2022).

1.1.3 Malaria diagnosis and treatment

For decades, malaria diagnosis was long performed presumptively (D'Acremont et al., 2010; Ochodo et al., 2016). This situation has changed following the launch of the WHO Test, Treat and Track policy in 2011 that has been widely adopted by SSA countries (World Health Organization, 2012a). The initiative advocates for every suspected malaria case to be tested and every confirmed malaria case to be treated with anti-malarial and subsequently be reported through the health management information system (HMIS).

The diagnostic tools currently recommended and used for detecting malaria are quality assured microscopy and antigen-detecting malaria rapid diagnostic tests (mRDT) (World Health Organization et al., 2012a; World Health Organization, 2015a). The use of light microscopy has been the gold standard for over a century and still remains a point-of-care diagnostic in clinical settings (Wu et al., 2015). Microscopy functions by examining Giemsa-stained blood smear (thick and thin) under a microscope to define the parasite density, stage and speciation. The detection threshold for this method is approximately 50-100 parasites/μL in field conditions (Zimmerman and Howes, 2015). However, it's labor-intensive feature and need for well-trained expert limits its applicability in the field (Khairnar et al., 2009).

The introduction of mRDTs allowed for a quicker and easier way of detecting malaria and that was operationally feasible in the field. mRDT functions by detecting the parasite antigen in the blood via the target antigen histidine-rich protein (HRP) 2/3. The detection threshold for mRDTs is 100-200 parasites/μL and can be species- or pan-specific (Hopkins et al., 2008). In

2012, malaria endemic countries saw a wide scale roll-out of inexpensive mRDTs in efforts to strengthen malaria surveillance systems, improve the rational use of Artemisinin-based combination therapies (ACTs) and reduce the risk of antimalarial resistance (World Health Organization, 2011, 2012a, 2015a). Between 2010-2020, 2.2 billion mRDTs had been distributed resulting in an increased rate of diagnostic testing and allowing for improved reporting and quantification of malaria cases (World Health Organization, 2021). Timely testing and treatment of malaria ensures that cases do not further develop into severe disease and death. The ACTs are currently recommended as the first line treatment (World Health Organization, 2015a) to clear blood-stage parasites.

Despite these efforts, challenges remain in adherence to high testing rates and case management across health facilities (HFs) (Plucinski et al., 2018). For instance, variability in testing rate performances across transmission settings (Plucinski et al., 2018) and the administration of anti-malarials without prior testing have been reported across several countries (Burchett et al., 2017; Johansson et al., 2015; World Health Organization, 2021). Data from the recent household surveys conducted across SSA countries showed that the proportion of fevers in children receiving parasitological testing ranged from 13.8% to 66.4% indicating that there still remain gaps in achieving universal testing (World Health Organization, 2021). Several health system issues have been attributed to contribute to this including stock-outs of mRDT (Alegana et al., 2020; Githinji et al., 2013; Hasselback et al., 2014), inadequate training and supervision of health care workers (Zurovac et al., 2018) and access to testing services especially at community level.

Furthermore, there are growing concerns for the effectiveness of the current mRDT with several reports of deletions of the HRP2/3 protein as a result of evolutionary changes to avoid parasite detection across SSA (Jejaw Zeleke et al., 2022; Kong et al., 2021; Prosser et al., 2021; Rogier et al., 2022) thereby increasing the risk of missing infections. In addition, the reported presence of sub-microscopic infections that are undetectable by standard mRDTs is posing a challenge especially in the very low transmission areas where detection of all cases is crucial to prevent any onwards residual transmission (Okell et al., 2012).

The development of other diagnostic tools such as ultrasensitive quantitative polymerase chain reaction (qPCR) (Andrews et al., 2005) improved the detection of malaria parasites to 0.5-5

parasites/μL (Perandin et al., 2004). However, PCR is an expensive diagnostic tool with long processing time and is not practical in low-resource setting (Cordray and Richards-Kortum, 2012; Wu et al., 2015). Another new diagnostic tool is the loop-mediated isothermal amplification (LAMP), a molecular method for detecting malaria with limits of detection of ≤2.0 parasites/μl (Lucchi et al., 2016; Picot et al., 2020). This method is cheaper and easier than PCR and has been reported to have higher sensitivity than the conventional methods (Picot et al., 2020). It is currently recommended for diagnosing imported malaria cases as a first-line method in non-endemic countries (Picot et al., 2020).

1.1.4 Malaria control efforts

In the late 1990's, the launch of the Roll Back Malaria (RBM) initiative (Nabarro and Tayler, 1998) galvanized a renewed interest and financial commitment from many donor organizations that recognized the need of including Africa as part of global efforts for malaria control and elimination (Feachem et al., 2019; Snow and Marsh, 2010). In 2000, heads of state from 44 malaria-endemic country met in Abuja, Nigeria and signed a commitment for halving malaria mortality by 2015 (World Health Organization et al., 2000). The declaration committed countries towards focusing on strengthening health system in order to better deliver malaria care and other preventative tools. The efforts were further complemented by the launch of various organizations such as Bill & Melinda Gates Foundation in 2000, The Global Fund to Fight AIDS, Tuberculosis and Malaria in 2002, and the US President's Malaria Initiative in 2005 that increased investments in the form of technical, operational and financial support in malaria endemic countries. This resulted into development and wide scale deployment of effective malaria control tools such as insecticide treated nets (ITNs), rapid diagnostic kits, and drugs such as ACTs as outlined below (Bhatt et al., 2015; Feachem et al., 2019). The renewed commitment translated into a substantial reduction in the prevalence of malaria infections and disease burden in many parts of Africa (Bhatt et al., 2015; Snow et al., 2017; World Health Organization, 2021).

Vector control interventions have been instrumental for preventing malaria transmission and includes indoor residual spraying (IRS) with insecticides (Oxborough, 2016; Tangena et al., 2020), the use of long lasting insecticide nets (LLINs) (Bhatt et al., 2015; Flaxman et al., 2010; Noor et al., 2009b) and larval source management (LSM) (World Health Organization, 2013). LLINs have been widely distributed in Africa with the proportion of population sleeping under

LLINs in SSA increasing from 2% in 2000 to 43% in 2020 (World Health Organization, 2021). Early studies during the 1980s in the Gambia showed significant protection of insecticide treated nets (ITNs) against clinical disease (Snow et al., 1988) and a 60% reduction in mortality in children under 4 years following use of ITNs (Alonso et al., 1993, 1991). Maintaining high coverage and usage is necessary to achieve malaria elimination. Mass campaigns conducted every 3 years have been useful in ensuring wide scale distribution of LLINs. More continuous channels of distribution have emerged that ensures delivery to the most vulnerable populations such as infants, pregnant women and school children (Theiss-Nyland et al., 2016). Recently, the continuous channels were shown to be more effective at ensuring high population access to nets (Koenker et al., 2022). However, the effectiveness of LLINs is often challenged by the increasing spread of insecticide resistance, quality of nets and low net usage behaviors (Okumu, 2020; Oladipo et al., 2022).

IRS has been effective in preventing indoor biting and involves application of long-acting insecticides on the walls of household structures to kill resting adult *Anopheles* vectors (World Health Organization, 2015b). Unlike LLINs, its effectiveness is not dependent on behavioral factors such as high usage. Its utility and success in reducing malaria transmission was first demonstrated in the 1950's during the global malaria eradication campaign that used Dichlorodiphenyltrichloroethane (DDT). This was later expanded to African countries where many IRS campaigns have been reported to be impactful (Pluess et al., 2010; World Health Organization, 2015b). The rise in insecticide resistance to pyrethroids (Ranson et al., 2011) and the high operational cost of this intervention has challenged the sustainability of IRS. In order to mitigate the rising resistance to pyrethroids, switching to alternative insecticides has been recommended. To date, five main classes of insecticides have been approved by WHO namely carbamates, organochlorines, organophosphates, pyrethroids, and neonicotinoids (World Health Organization, 2015b).

LSM includes strategies aimed at reducing vector replication through preventing the development of mosquito larvae and pupae into adult mosquitoes (Fillinger and Lindsay, 2011; Keiser et al., 2005). Efforts include larviciding, environmental management, modifications to reduce breeding sites and biological control. This intervention is recommended as a supplementary strategy to already ongoing vector control initiatives (World Health Organization, 2013). However, LSM strategies are often accompanied with high operational

costs, high demands for human resources, and the need to reach all productive habitats which often poses a challenge to its effectiveness and sustainability (Fillinger and Lindsay, 2011; Walker and Lynch, 2007). For instance, the short residual effectiveness of larvicides (1-2 weeks *B. thuringiensis israelensis* and 2-3 weeks for *B. sphaericus*) (Shililu et al., 2003) requires frequent applications to breeding habitats that poses a challenge for large scale implementation.

Other preventative efforts developed over the years include chemoprevention therapies that involve administering drugs to the most vulnerable populations in order to suppress any existing infections and onward transmission (World Health Organization, 2022a). The recommended strategies include intermittent preventative therapies for pregnant women (IPTp) (Desai et al., 2018; Henry et al., 2018; World Health Organization, 2012c), perennial malaria chemoprevention (PMC) that was previously referred as IPTi to infants (World Health Organization, 2022a), school children (IPTSc) (Alonso, 2020; Eisele et al., 2020; Galatas et al., 2020; von Seidlein and Greenwood, 2003) and seasonal malaria chemoprevention (SMC) (Cairns et al., 2012; World Health Organization, 2012d, 2022a) for children under 5 years. The rapid effectiveness of these therapies have been widely reported. For instance, IPTp has been shown to reduce the risk of low birth weight, anemia and neonatal mortality (Eisele et al., 2012; Wilson and IPTc Taskforce, 2011), IPTi decreased the occurrence of anemia and hospital admissions with severe malaria (Aponte et al., 2009; Wilson and IPTc Taskforce, 2011) and SMC was shown to be effective in reducing risk of anemia and preventing 75% of clinical and severe malaria cases in children (Meremikwu et al., 2012).

More recently, WHO recommended the adoption of a newly developed vaccine, RTS,S/AS01 for use among children residing in moderate to high transmission areas (Adepoju, 2019; RTS,S Clinical Trials Partnership, 2015). The vaccine, following phase 3 trial in several African countries, demonstrated a protective efficacy of 36% against clinical malaria and 32% against severe malaria in children under 5 years (RTS,S Clinical Trials Partnership, 2015).

1.1.5 Transitioning malaria control strategies

1.1.5.1 Global technical strategy

In 2015, accompanying the efforts made thus far was the launch of a Global Technical Strategy for Malaria 2016–2030 (GTS) by the WHO's Global Malaria Programme to guide malaria

control and elimination. The ambition was "*to reduce malaria incidence and mortality by at least 90%, eliminate malaria from at least 35 countries and prevent malaria re-establishment from malaria free countries by 2030*" (World Health Organization, 2015c). The strategy provides a technical framework to guide countries towards elimination.

The framework of GTS comprises of three pillars and two supporting elements (Figure 1.3). Underlying this framework is the recognition that the rate of progress of countries and areas within countries along the continuum of elimination varies and may require efforts tailored to the transmission context. Pillar 1 aims to provide universal access to malaria prevention, diagnosis and treatment, Pillar 2 considers on how to accelerate and sustain elimination efforts within areas with low transmission and Pillar 3 recognizes the importance of transforming malaria surveillance into a core intervention for promoting evidence-based decisions through the use of accurate and timely routine data (World Health Organization, 2015c). Section 1.2 of this thesis will focus on pillar 3 which forms the basis of this PhD work.

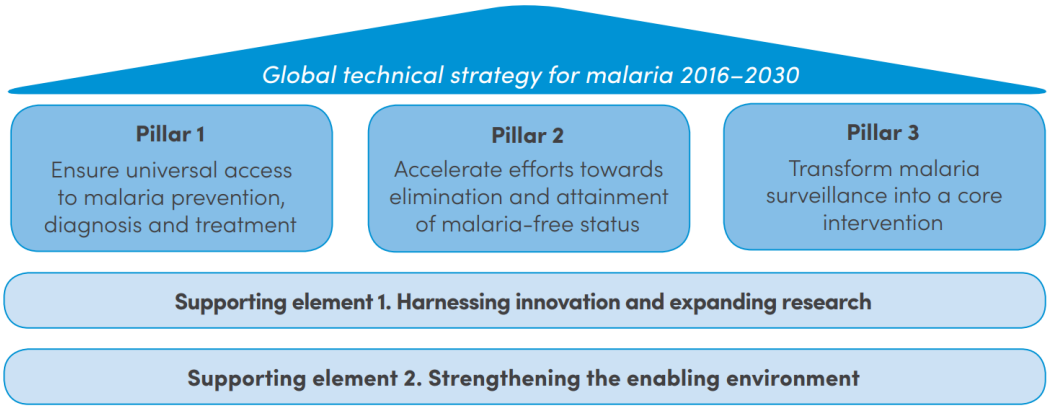


Figure 1.3: Framework of the global technical strategy 2016-2030 (World Health Organization, 2015c)

1.1.5.2 High burden for high impact (HBHI) initiative

In 2018, following the observed stall in the declining progress of malaria trends (World Health Organization, 2021), WHO launched the High Burden for High Impact (HBHI) initiative. Ten countries in Africa currently account for 66% of the global malaria disease burden (World Health Organization, 2018a) (Figure 1.4), despite increases in the deployment of various vector control and disease management strategies. Further increases in international donor assistance are unlikely and hence a new model of improving investment efficiencies is required to

maximize the benefits of interventions in areas likely to achieve the largest disease burden reductions.

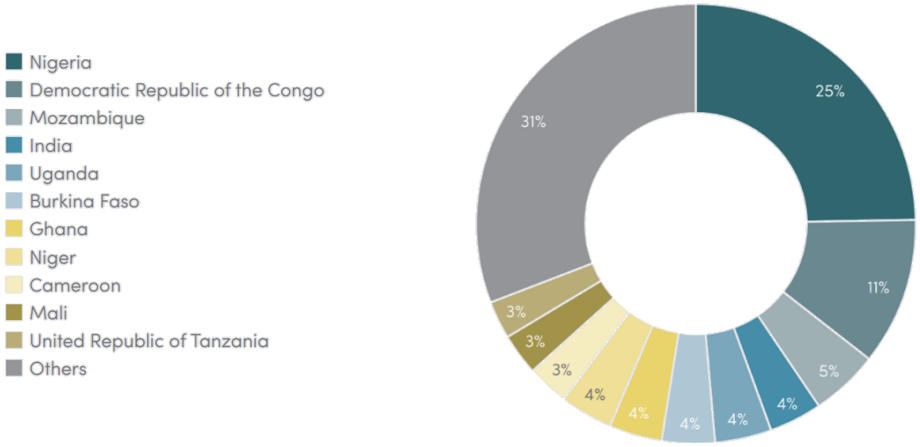


Figure 1.4: The contribution of high burden for high impact (HBHI) initiative countries towards the global burden of malaria (World Health Organization, 2018a)

The HBHI is comprised of four key elements (Figure 1.5): (i) Political will to reduce malaria deaths – This calls for high burden countries to take ownership and dedicate local resources towards reducing mortality; (ii) Strategic information to drive impact – This re-emphasizes the use of data to shift away from a "one size fits all" to a more tailored malaria control approach in order to accelerate progress against malaria (World Health Organization, 2018a). Countries are called upon to make use of available information to stratify the malaria risk in order to deploy effective malaria control tools to areas in greatest need and maximize impact and efficiency (World Health Organization, 2018a). WHO defines malaria risk stratification as "*classification of geographical units according to their current transmission intensity and characteristics of malaria, and, once transmission intensity has been reduced, according to their receptivity to malaria and risk for importation of malaria cases"* (World Health Organization, 2020b); (iii) Better guidance, policies and strategies – This highlights the global commitment towards providing updated guidance to countries based on evidence, country experience and new tools and finally (iv) A coordinated national malaria response – This element emphasizes the importance of a multi-sectoral approach to ensure efficient use of limited resources.

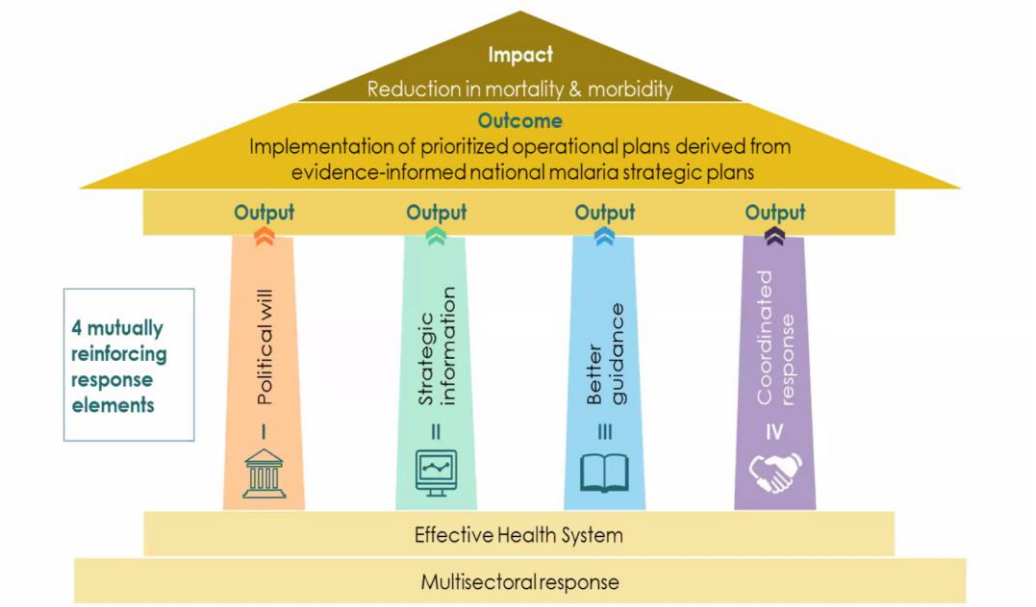


Figure 1.5: The four key elements of the high burden for high impact initiative (Malaria Policy Advisory Committee and World Health Organization, 2020)

The main recommendation is for stratification to be done at subnational level and ideally district or lower levels. For countries moving towards elimination, an even finer-scale mapping at the levels of HF catchment and transmission foci through case based surveillance is required to capture all cases and prevent residual transmission (World Health Organization et al., 2017a).

The concept of a tailored malaria control approach is not new (Noor et al., 2010, 2009a) and although it was only globally introduced by WHO in 2018, there are several countries that have begun formally adopting this approach preceding the HBHI period that is worth highlighting. For instance, since as early as 2007, Kenya, Namibia, Sudan, Mauritania and Mali all demonstrated some evidence of stratified response to malaria control based on malaria risk in their strategic plans (Division of Malaria Control, Republic of Kenya, 2010; National Malaria Control Programme (NMCP), Republic of Namibia, 2010; National Malaria Control Programme (NMCP), Republic of Sudan, 2006; Programme National De Lutte Contre Le Paludisme, Republique Du Mali, 2006; Programme National De Lutte Contre Le Paludisme, republique Islamique De Mauritanie, 2006). Countries located in the Sahel have also conducted some levels of stratified response but this was largely based on seasonality (Cairns et al., 2012). In 2018, mainland Tanzania conducted a comprehensive stratification and sub-national tailored response with support from mathematical modelling to guide re-orientation of its malaria

strategic plan (National Malaria Control Programme, 2018a). All these country experiences served as a benchmark for the formalization and expansion of HBHI. A crucial aspect for countries adopting the HBHI approach is an effective national surveillance system that generates quality routine data to allow programs to inform on their decisions. The next section expands on this important element.

1.2 Malaria surveillance

Malaria surveillance forms the core of the third pillar of the GTS (World Health Organization, 2015c) and emphasizes on strengthening surveillance systems through enhancing the use of local data to inform decision making. Surveillance is defined by WHO as "*a continuous and systematic collection, analysis and interpretation of malaria-related data, and the use of that data in the planning, implementation and evaluation of malaria programmes*" (World Health Organization, 2018b).

In order for countries to sustain the gains made thus far and reach their elimination targets, having a strong surveillance system remains critical. It allows malaria programs to accurately measure the burden, identify the vulnerable areas and population groups most affected by malaria, continuously monitor progress towards set epidemiological targets, design tailored intervention strategies to move towards elimination, allow efficient allocation of resources and finally evaluate the impact of the deployed packages (Lourenço et al., 2019). As such, malaria surveillance should form a central component of strategic plans and be anchored within health information systems. Importantly, capacity to analyze, interpret and use local data should be built at all levels for effective strategic planning and operationalization.

At all levels of the health system and continuum of malaria transmission (Figure 1.6), an effective surveillance system that collects and analyses data should trigger an appropriate response (World Health Organization, 2018b). The type of data generated should provide information on the burden of malaria along with its temporal and spatial distribution. In moderate to high burden areas, surveillance is usually based on passive routine information system providing aggregate numbers of monthly cases as well as information from community surveys to compute indicators such as annual parasite incidence (API), parasite rate and test positivity rates (TPR). Since the case numbers are high, the objective here is to reduce the

malaria burden by ensuring that the whole population has access to suitable interventions. Here, the quality of data and its use can be ensured through maintaining high malaria testing rates, effective management of the detected cases, quality assurance of the diagnostic tools, completeness in the reporting from HFs, continuous surveillance assessment and data quality audits and finally capacity for analyzing the surveillance data for monitoring and response (World Health Organization, 2015c, 2020b, 2018b). In the very low transmission, where there is increased heterogeneity, a more intensive surveillance is needed so that the response is linked to every detected malaria case to help identify the most vulnerable populations at risk and ensure early response to potential outbreaks. Here, a shift from monthly to weekly reporting and eventually to real-time reporting of each case becomes instrumental and a system that allows such notification needs to be established.

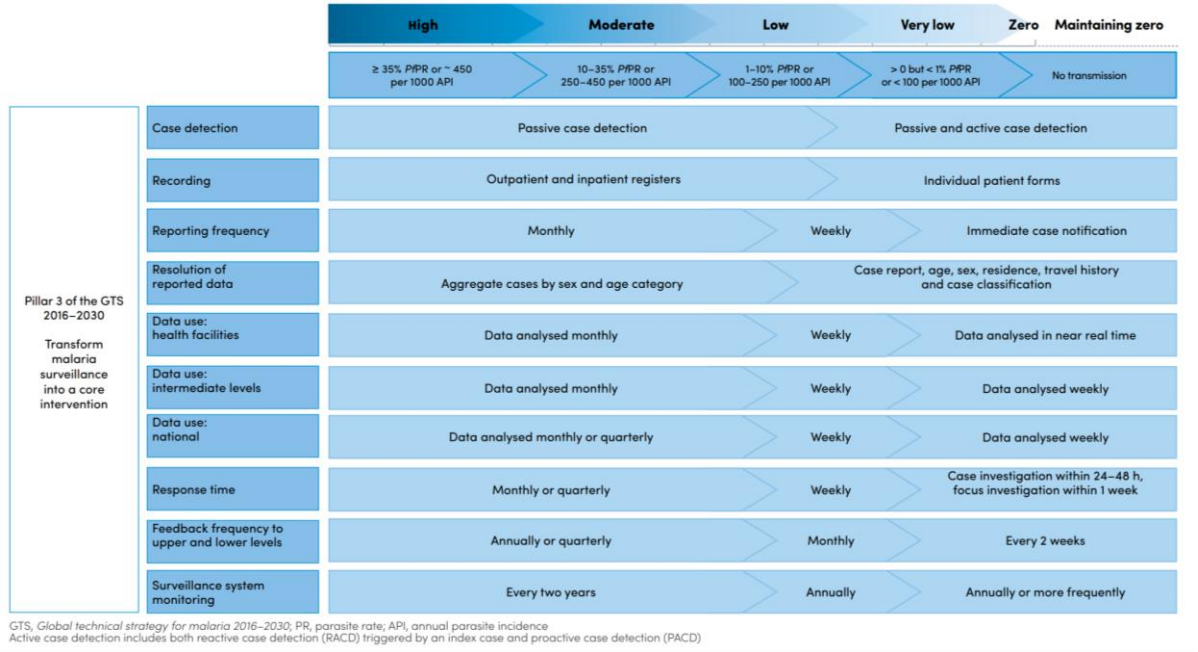


Figure 1.6: World Health Organization Surveillance system processes and requirements along the continuum of malaria transmission (World Health Organization, 2015c).

A malaria surveillance system comprises of various components and include the people, procedures, tools and structure that generate information on malaria cases to allow effective planning, intervention targeting and evaluating the resulting impact (World Health Organization, 2018b). The people include those who are involved with data collection, its use for decisions as well as the patients whose information is being collected. The procedures ensure the accurate recording and reporting of data, information flow, data quality checks, capturing relevant indicators, tracking the geographical distribution of transmission and

population at risk, the effective use of the data for decisions and assessing the level of access to and effectiveness of the interventions. The tools are those that help to capture and visualize the information and include the registers, tally sheets, summary sheets, dashboards and other electronic systems that store the data. And finally the structure is the way the entire system along with human resources are organized (World Health Organization, 2018b).

To ensure a surveillance system is functioning effectively, continuous surveillance assessments becomes imperative to detect any deficiencies that may compromise the ability of a malaria program to utilize it for decision making (World Health Organization, 2022b). This must entail actions such as maintaining up-to-date tools and list of all health care providers, ensuring all information systems are functional, keeping a track of the HF reporting rates (RR) and following up missing or incomplete reports, following up inconsistent reports, maintaining a feedback cycle with HFs and finally ensuring that adequate well-trained staff are available (World Health Organization, 2018b).

1.2.1 Data source platforms for malaria surveillance

Effective malaria surveillance should include multiple aspects to collect and monitor a comprehensive array of information on the parasite, vector and host. Some of these components include epidemiological, entomological, molecular and programmatic surveillance. In this section, the epidemiological data sources used within this project are discussed in greater detail.

1.2.1.1 Periodic surveys

Cross-sectional surveys typically involve collecting data across a population for various indicators of health at one specific time point. Parasite prevalence is collected through cross-sectional surveys, and has been a benchmark measure of malaria endemicity since the early part of the last century (Hay et al., 2008; Metselaar and Van Thiel, 1959). The prevalence of infection in a given community represents a quantity of malaria transmission intensity (Hay et al., 2008) and on a continuous level can be scaled with other mathematical constructs of malaria transmission including the entomological inoculation rate (EIR), basic reproductive rate (BRR) and malaria incidence (Cameron et al., 2015; Gething et al., 2011a; Smith et al., 2005, 2007b).

Historically, parasite prevalence was used to classify malaria transmission and maps of malaria prevalence were used as a means of malaria risk stratification/cartography and still continue to

be extensively used (Alegana et al., 2021a; Hay et al., 2008; Metselaar and Van Thiel, 1959; Omumbo et al., 2013; Snow et al., 2017; Snow and Noor, 2015). However, the classification definitions have changed over time and is discussed in more detail in section 1.2.4. Today, the Demographic and Health Surveys (DHS)/Malaria Indicator Surveys (MIS) are the most widely conducted nationally representative household surveys, occurring in many countries every 2-3 years and powered to provide information at the first administrative level of the region. They usually report a measure of parasite prevalence in children under 5 years old as well as other indicators including information on the access and usage of interventions amongst other indicators.

Some countries also conduct school-based malaria parasitaemia surveys (SMPS) that provide a more rapid and cheaper alternative to household surveys. Such surveys were implemented in several countries during the 1960s (Brooker et al., 2009) to establish national malaria risk profiles, and ever since a series of SMPS have been conducted across African countries such as Tanzania (Chacky et al., 2018), Congo (Swana et al., 2018), Gambia (Okebe et al., 2014), Ghana (Mensah et al., 2021), Malawi (Mathanga et al., 2015), Ethiopia (Ashton et al., 2016) and Kenya (Gitonga et al., 2010). School surveys usually target public primary school children aged between 5 and 16 years and because of their relatively cheaper survey costs compared to DHS/MIS can be powered to provide information at higher spatial administrative areas, for example the second administrative levels of districts (Makenga et al., 2020).

Community based surveys have an advantage of providing a broader picture of the parasite burden in the population in the age group of interest including those that do not access the formal health sector and those asymptomatic to infection. They coincidentally provide information on the coverage and use of control and disease management strategies. However, these surveys are conducted periodically every 2-3 years, do not represent information at higher spatial resolutions, do not capture the seasonality of malaria transmissions, require considerable resources, and may not reflect the current situation in a rapidly changing epidemiological environment. As a result, relying solely on prevalence estimates from surveys is accompanied with spatial and temporal gaps that is unable to capture the local trends. For these reasons, alternative sources of information must be explored to replace costly community-based surveys for sustainable and effective decision making. Routine information from HFs provide near real-time and very granular data in time and space that are inexpensive and easily accessible at

multiple levels of the health system for decision making. Owing to the challenges faced with its quality (Rowe et al., 2009), most risk maps have relied on using interpolated modelled data from community-based surveys to estimate burden of malaria. Efforts to strengthen routine information systems are underway and offer an attractive avenue to provide a richer source of information. This is further discussed in the next section.

1.2.1.2 Routine information systems

One of the core component of a well-functioning health system is its ability to generate quality routine information from HFs. The routine data are primarily reported through HMIS. The HMIS is a routine monthly data collection system operating in every malaria-endemic country in both public and private HFs. It generates a variety of information such as morbidity, mortality, commodities and other indicators on preventative measures. However, information generated from the HMIS have not been extensively used for decisions across Africa owing to weak system structures, poor system performance, poor data quality, no quality assurance practices in place, and the variable diagnostic testing resulting in reporting of more presumptive malaria cases thereby compromising the accuracy of burden estimates (Mbondji et al., 2014; Rowe et al., 2009; World Health Organization, 2011).

As part of efforts to strengthen the HMIS system, many countries have moved towards using a standardized electronic platform, the District Health Information System (DHIS2). DHIS2 is an open source web-based software for reporting, analysis, and dissemination of data for health programs which can be accessed by officials at the district, regional, and national levels through registered credentials. The platform is meant to be used so that each month, HFs provide monthly summary reports to their district representative and the report is then recorded into DHIS2 (Dehnavieh et al., 2019).

Other systems also exist for reporting routine malaria data through different reporting tools and frequency from HFs. This includes the integrated disease surveillance and response (IDSR) system that was adopted by WHO African region in 1998 in efforts to enable timely reporting of selected priority diseases at all levels of the health system to prevent outbreaks and epidemics and enhance effective response (Wolfe et al., 2021). IDSR has two modalities of reporting diseases; immediate notification and routine weekly reporting. Malaria through IDSR is usually reported on a weekly basis. However, in the very low transmission areas, immediate

notification from HFs and household case follow-up through case based surveillance (CBS) is crucial to achieve elimination targets. CBS involves the reporting, classification and investigation of all malaria cases to identify transmission foci caused by locally acquired infection and implement strategies to prevent residual transmission (World Health Organization et al., 2017a). In addition to these general systems, many countries also have other additional information systems in place that are mainly developed and supported by in-country implementing partners. For example, the coconut surveillance system in Zanzibar that captures individual malaria cases from the HFs (Khandekar et al., 2019) and the integrated malaria information storage system (iMISS) system in Mozambique in efforts to strengthen its malaria surveillance system (Malaria Consortium Project Brief, 2019). However, a move towards integrating these systems into existing system platforms is crucial to allow sustainability and country ownership.

1.2.2 Description of available malaria metrics for malaria surveillance

The control interventions against malaria aim to slow transmission at different points of the life cycle of the parasite and along this cycle, there are several points where various metrics can be used to measure the transmission intensity (Carter and Mendis, 2006; Cohen et al., 2017; Hay et al., 2008; Tusting et al., 2014). There are various factors that can affect the suitability of metrics to measure malaria transmission and thereby be integrated into a country's surveillance system. These include; the precision and accuracy of the indicator, associated costs for collection, and the level and frequency available to measure variability across space and time (Cohen et al., 2017; Protopopoff et al., 2009; Tusting et al., 2014). As countries transition in their epidemiological profile from high to moderate to low malaria transmission, the need for good quality granular data to accurately measure the changes in risk of transmission is required to monitor progress, evaluate impact and act according to the situation.

It is important to note that even though epidemiological metrics form the core of most decisions, other malaria related metrics should complement these for more informed decision making. These include entomological (Vector abundance and morphology, biting rates); interventions (access and usage, coverage, efficacy & effectiveness, insecticide resistance), drug and diagnostic efficacy; ecological (climate, environment); behavioral (human and vector); and other contextual factors (socio-economic, urbanization, health system readiness, occupation, conflict/ emergencies, operation-ability and marginalized populations including

refugees) (World Health Organization, 2021). Since the thesis focuses on using epidemiological metrics for stratification, the following sections will mainly focus on this component.

Most malaria metrics often reflect the burden of clinical disease e.g. case incidence or case counts per HF, or they represent in given settings, the transmission intensity (e.g entomological inoculation rate (EIR) or also prevalence of the infection (such as the parasite prevalence). To date, there is no consensus on which metric is ideal to stratify malaria burden and track control efforts. Although several studies have demonstrated the broad relationships between these metrics, they vary and do not hold under all circumstances. summarizes the key characteristics of some of the metrics that shall be explored in the work presented in this PhD thesis.

Parasite prevalence represents the proportion of human population with parasitaemia at a specific point in time (Tusting et al., 2014). It has long been used as the traditional measure for malaria endemicity (Section 1.2.1.1). The rate measures the proportion of individuals out of the sampled population with parasites in their blood as obtained from specific diagnostic methods. The continued reliance on parasite prevalence from household surveys becomes difficult in low transmission areas due to the need for larger sample sizes to tackle the challenges in measuring these metrics at higher frequency and granularity and the associated costs (Yukich et al., 2012). There is therefore a strong need for exploring other metrics to represent the changes in transmission (Cohen et al., 2017; Hay et al., 2008; Yukich et al., 2012) and track malaria control efforts.

Fever test positivity rate (TPR), defined as the proportion of the total number of positive malaria tests among all malaria tests reported by HF laboratories, has been widely used as a surveillance indicator (Bi et al., 2012; Boyce et al., 2016; D'Acremont et al., 2010; Francis et al., 2012; Githinji et al., 2016) for measuring temporal changes in burden of malaria over time (Ceesay et al., 2008) as well as for describing the sub-national heterogeneity in malaria risk (Alegana et al., 2021b; Githinji et al., 2016; Oduro et al., 2016, 2011). It has also been used for assessing the impact of various interventions (Kesteman et al., 2016; Simon P. Kigozi et al., 2020; Tukei et al., 2017). Its practical use as an indicator of malaria morbidity has increased following the launch of WHO test and treat initiative (World Health Organization, 2012a) and is one of the core indicators recommended by WHO (World Health Organization et al., 2012b).

The advantages of TPR are that its inexpensive and rapidly available and provides a clearer denominator since it considers laboratory confirmed cases and suspect fever cases attending and tested at HFs and does not depend on availability of well-defined catchment population (Boyce et al., 2016; Kigozi et al., 2019). It has been shown to be significantly associated with malaria incidence and to be a strong predictor of malaria transmission (Bi et al., 2012; Boyce et al., 2016; Jensen et al., 2009; Kigozi et al., 2019). However, TPR interpretation can be affected by factors such as variability in testing rates, quality and sensitivity of diagnostic tools; treatment seeking behaviors, incidence of non-malarial febrile illness (Boyce et al., 2016; Jensen et al., 2009).

Annual parasite incidence (API) is another metric obtained from routine surveillance and a core indicator recommended for surveillance by WHO. The API is defined as the total number of positive malaria tests performed by mRDT or microscopy at HF laboratories per 1,000 population-at-risk. The use of this indicator to demarcate geographic regions into malaria risk zones (Gwitira et al., 2018) and as an outcome indicator for evaluation of interventions (Bhattarai et al., 2007; Chanda et al., 2012) has been widely documented across several African countries. However, a major limitation of this metric is that it lacks a well-defined denominator since it depends on availability of HF catchment population which is a major challenge across Africa (Macharia et al., 2021). The metric is also highly affected by diagnostic practices, treatment seeking behavior and access to HF (Okiring et al., 2021).

Testing for malaria positivity rate in pregnant women attending antenatal care clinic (ANC) during their first visit represents another rich source of data. Their high attendance rates at ANC makes them an easily accessible surveillance population to track malaria transmission intensity, and provides a simple routine real-time measure of malaria prevalence at higher spatial and temporal resolutions. Prevalence from ANC with high attendance rate has been shown to be associated with community-based malaria prevalence (Brunner et al., 2019; Kitojo et al., 2019; van Eijk et al., 2015) thereby serving as a good measure to reflect to a certain degree, the malaria trends in the community (Gutman et al., 2022; Mayor et al., 2019).

The above mentioned studies, using the various malaria metrics show the potential of routine data through which our understanding of transmission heterogeneity at granular level can be enhanced. The available evidence provides a potential framework for investing in

understanding how these metrics vary across different transmission settings to measure epidemiological changes over time. However, it is important to be cautious of factors such as treatment-seeking rates, poor adherence to testing, quality of diagnostic testing, incomplete RRs and existing inconsistencies in the data all of which can affect the quality of routine data (Rowe et al., 2009).

There are also other epidemiological indicators that can be used for estimating malaria transmission intensity but are difficult to measure in the population. These were not within the scope of this PhD thesis but are briefly outlined below.

The entomological inoculation rate (EIR) represents a good measure for transmission and defined as the expected number of infectious bites per person per period of time. However, its accurate measurement requires direct measurements from the field which can be labor intensive, slow, costly and challenging in areas with low transmission (Hay et al., 2000, 2008; Tusting et al., 2014; Yukich et al., 2012).

The seroconversion rate (SCR) is a function of the antimalarial antibodies present in the blood and reflects the population cumulative exposure to infection. An antibody assay is done to collect the sero-prevalence of parasite specific antigens from the population through cross-sectional surveys (Corran et al., 2007) and a seroconversion rate is subsequently computed using a reversible catalytic model (Pull and Grab, 1974). The SCR was shown to have a strong correlation with EIR (Drakeley and Cook, 2009; Drakeley et al., 2005; Stewart et al., 2009). In very low transmission areas, it can offer high sensitivity due to longevity of antibody responses (Tusting et al., 2014).

Force of infection (FOI) is defined as the number of human malaria infections per person per unit time (Mueller et al., 2012; Tusting et al., 2014) and molecular force of infection (mFOI) is the number of new parasite clones per unit time (Mueller et al., 2012). Both metrics are measured via cohort or repeat cross-sectional studies which can be costly and not suitable for routine collection. However, historically, age-structured prevalence among infants attending welfare clinic have been used.

Basic Reproductive Number (R_o) is the average number of secondary cases arising from a single infectious person in a completely susceptible population (Anderson and May, 1992; Macdonald and Göckel, 1964; Ross, 1911) and reflects how well malaria is transmitted and the efforts required to control it. This metric forms the basis of mathematical models of malaria transmission (Gething et al., 2011a) but is difficult to measure directly.

Malaria mortality rate is defined as the number of deaths due to malaria occurring in a period of time per 100,000 population-at-risk and used for indicating the malaria burden. Reliable sources of this data is usually challenging in SSA since it requires good civil registration and a vital statistic system in place (Rao et al., 2004; Ye et al., 2012). WHO uses estimation methods in many African countries that involves using a verbal autopsy multi-cause model that relies on birth history information collected during household surveys, census data as well various mortality risk factors to estimate deaths for children under 5 years and adjusting per country (World Health Organization, 2021).

Table 1.1: Description of various malaria metrics used for measuring malaria burden and risk

Metric	Description	Level at which data is available	Frequency of collection	Applicability	Cost	Factors to consider (Tusting et al., 2014)	Ability to measure transmission
Parasite prevalence	Proportion of individuals in a community with parasitaemia at a given point in time. It is usually measured through cross-sectional surveys by examining the blood samples from a sample of population	Regional level – DHS/MIS Survey Council level – School malaria parasitaemia surveys	Every 2-3 years	Widely used metric for classifying malaria endemicity as it is easy to measure.	High	Affected by: - Parasite densities in blood - Methods of parasite detection - Age of infection - Development of immunity - Seasonality - Frequency and spatial resolution of surveys	- Varies with endemicity – becomes saturated at higher transmission intensities - Large sample size required at low endemicity - Ceases to be sufficiently sensitive when parasite rates have dropped to a level of between 1% and 3% (Hay et al., 2008) - Age-dependence of prevalence makes it difficult to compare sites with prevalence in different age-groups - Geospatial methods can be employed to provide risk estimates at finer spatial scales and associated measures of uncertainty
Confirmed incidence/ Annual parasite incidence	The rate at which new cases of confirmed malaria occur in a population. It is usually measured as total number of confirmed cases per 1000 population at risk. This can be captured through active case detection and/or passive case detection through diagnostic tests such as mRDT/ microscopy	Health facility level – Passive case detection Community level – Active case detection	Monthly from routine health facility data	Widely used indicator for malaria burden and core indicator recommended by WHO for surveillance (World Health Organization, 2018b)	Low if passively detected High if actively detected	Affected by - Treatment seeking behavior - Definition of the catchment population - Quality of diagnosis - Health worker practices - Reliability depends on the coverage and quality of the reported data by health facility - Development of immunity	- Increases rapidly with transmission intensity. At high transmission levels, incidence does not exceed intermediate transmission levels due to acquired immunity and multiple infections (Ghani et al., 2009) - May not be appropriate for accurately recording a decline in incidence from high to medium endemicity - Incidence from passive detection misses the asymptomatic cases from the community

Metric	Description	Level at which data is available	Frequency of collection	Applicability	Cost	Factors to consider (Tusting et al., 2014)	- Ability to measure transmission
Fever test positivity rate	Proportion of those examined by microscopy or mRDT with parasitaemia	Health facility level	Monthly from routine health facility data	Surrogate to measure the incidence of malaria (Jensen et al., 2009; Joshi et al., 1997), to define the level of malaria endemicity, and to identify malaria high risk areas.	Low	Affected by: - Diagnostic and testing practices (Francis et al., 2012) - Accuracy of diagnostic tests - Access to health care - Reliability depends on the coverage and quality of the reported data by health facility - Incidence of non-malaria fevers	- Estimates affected by changes in incidence of non-malaria fever (Kigozi et al., 2019) - Strong predictor of incidence (Bi et al., 2012; Joshi et al., 1997; Kigozi et al., 2019) - Misses asymptomatic infections
Positivity rate in pregnant women	Proportion of pregnant women examined for malaria and tested positive for parasitaemia	Health facility level	Monthly from routine health facility data	Not yet widely implemented as a surveillance system. Established as a surveillance system in Tanzania.	Additional cost for mRDT diagnostic tests to be considered	Affected by: - ANC attendance - Testing rates at first ANC attendance - Parity - Parasite density in peripheral blood	- Shown to be correlated with community based prevalence estimates but with substantial uncertainty for individual estimates (Brunner et al., 2019; Kitojo et al., 2019) - Can reflect sub-national heterogeneity in community malaria prevalence (Mayor et al., 2019)

1.2.3 Approaches to estimate malaria burden

The precise estimate of malaria burden in SSA remains vague (Snow, 2014). Malaria infection in stable malaria-endemic countries remains a frequent event and not all infected individuals go on to develop symptoms as a result of acquired immunity. Due to the challenges with capturing accurate information from routine data (Rowe et al., 2009), the diversity of Africa's malaria burden has relied on the use of epidemiological modelling of parasite prevalence and opportunistic, and often dated, survey malaria data (Bhatt et al., 2015; Gething et al., 2011b; Noor et al., 2014; Weiss et al., 2019). HF-based data can provide near real-time and very granular data in time and space for surveillance. However, the quality of routine data has often posed a challenge and limited its usefulness in many countries. In particular, lack of timeliness, completeness and accuracy of the data (Chilundo et al., 2004; Githinji et al., 2017; Maina et al., 2017) make it difficult for programs to rely on such data for monitoring and evaluation (M&E), and to track changes in malaria risk with time (Rowe et al., 2009).

Current approaches by WHO in understanding and estimating the malaria burden in Africa involves the use of three methods that are largely dependent on the quality of national surveillance systems (World Health Organization, 2021) (Figure 1.7). The first method entails using malaria incidence estimates from routine data that are adjusted to account for cases that may have been missed from routine reporting systems. The reported cases are adjusted for reporting completeness, likelihood that cases were tested positive and the extent to which health services are utilized (World Health Organization, 2021). This method is done for countries such as Botswana, Eritrea, Ethiopia, The Gambia, Madagascar, Mauritania, Namibia, Rwanda, Senegal and Zimbabwe. The second method estimates the burden directly from the individual cases reported by the routine surveillance system and this approach is largely employed in countries transiting towards malaria elimination and have strong surveillance systems in place (Cibulskis et al., 2011). These countries include Cape Verde, Comoros, São Tomé and Príncipe, South Africa and Eswatini. Whilst the third method involves utilizing modelled prevalence predictions from household surveys that are converted into incidence based on a parasite to incidence relationship established by the Malaria Atlas Project (MAP) (Cameron et al., 2015; Hay et al., 2008). This approach is largely employed in 30 countries where the quality of the routine data did not allow estimating burden from the routine system (Alegana et al., 2020) and accounts for 86% of the cases reported (World Health Organization,

2021). However, the ambition is that ultimately all countries provide reliable and accurate routine data to avoid reliance on modelled estimates (Cibulskis et al., 2011; Mueller et al., 2011).

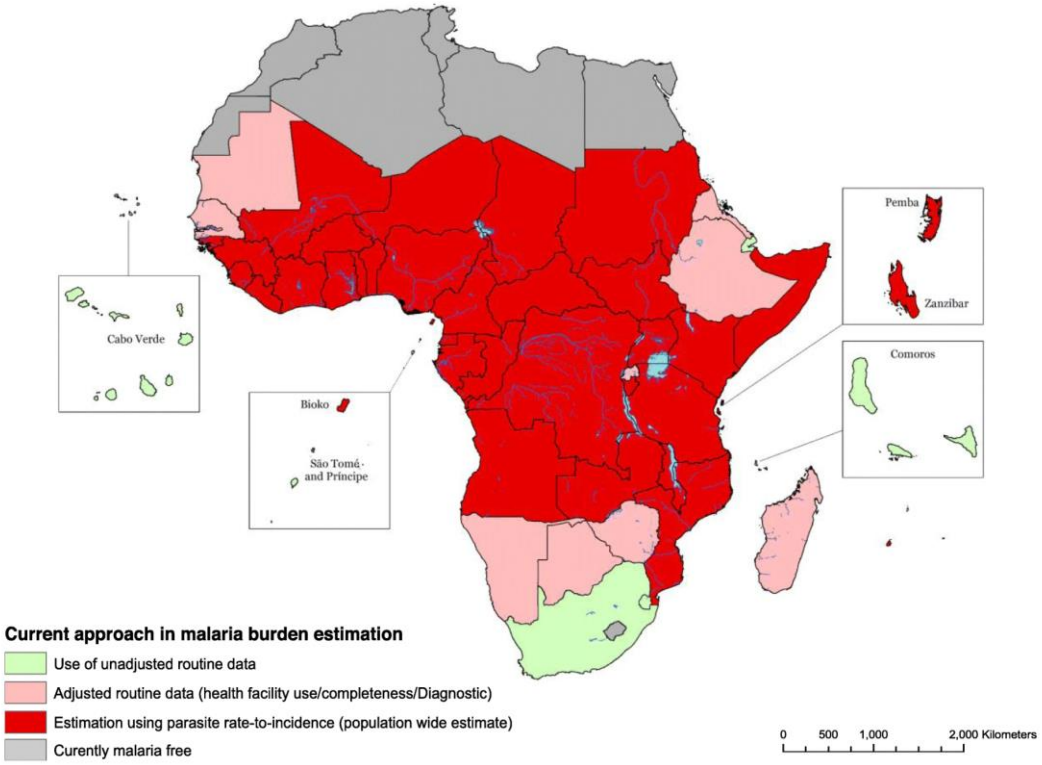


Figure 1.7: Approaches undertaken by World Health Organization to estimate malaria burden in Africa (Alegana et al., 2020)

For routine data to serve as a reliable surveillance system for malaria burden estimation, there are several factors that need to be considered (Alegana et al., 2020). These include (i) an understanding of the treatment seeking behavior, (ii) testing rates, (iii) reporting completeness, (iv) quality of data reported, (v) the inclusion in the DHIS2 of all healthcare providers, and (vi) the catchment population from which these cases arise. An ideal system would capture all this information beginning from all fevers occurring in the community accessing HFs to being tested for malaria and to accurately being recorded and reported in the DHIS2 (Figure 1.8). However, this is rarely the case.

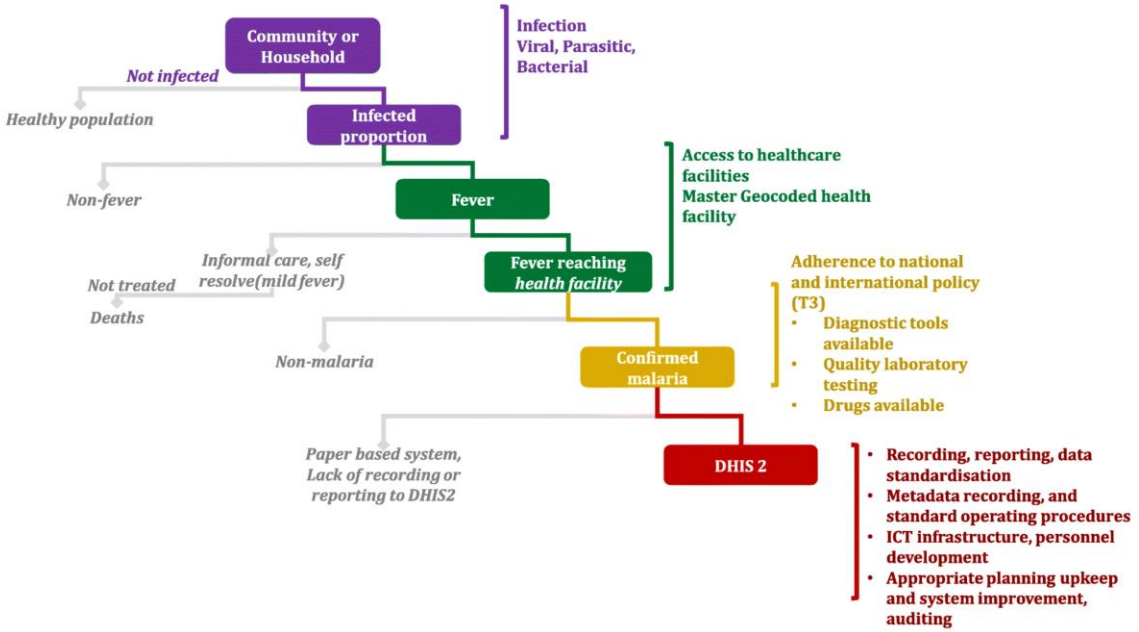


Figure 1.8: Flow of routine health information (Alegana et al., 2020)

Until further investments are made in strengthening the routine surveillance systems of those countries with poor surveillance systems (Figure 1.8), modelling approaches provide a valuable way for producing standardized malaria risk maps for tracking annual progress (Smith et al., 2007a). They are a useful source of data especially at the broader regional levels to understand trends in disease burden. A recent systematic review (Kamau et al., 2020a) that compared the trends of empirical incidences with spatially matched incidence estimates obtained from the parasite to incidence model relationship established by MAP (Cameron et al., 2015) showed that in many locations similar trends in decline of malaria burden were observed. However, this did not hold for areas where progress had either stalled or resurgence of malaria was observed. This demands the need for high quality dense clinical data to not only strengthen modelled predications but also for guiding National Malaria Programmes (NMPs) to plan for strategies within their local context (Cibulskis et al., 2011; Kamau et al., 2020a).

1.2.4 Classification of malaria metrics

The classification of malaria in an epidemiologically meaningful way has long received many discussions. A consensus was initially reached for using prevalence from spleen rate surveys measured in the 2–9 years old age-group to reflect the different endemicity classes and this included holoendemic >75%, hyperendemic 51–75%, mesoendemic 11–50%, and hypoendemic < 10% (World Health Organization, 1951). However, these were later revisited

following suggestions that detection of parasites in the peripheral blood using microscopy has a better specificity (Hay et al., 2008; Metselaar and Van Thiel, 1959). Similar endemicity classes were proposed with this measure but with an additional class holoendemic <1% for children under the age of 1 years. The usefulness and application of these classes still remain vague with the criteria to define these classes changing over time.

During the 1960s, various malariometric criteria were used to define geographical areas that should prepare for a pre-elimination stage, when community-based parasite prevalence (*Pf*PR) was consistently below 2–3% (Smith et al., 2007a). With time, this included indicators based on the prevalence of infections in fevers below 5% (Hay et al., 2008). The current international guidelines for malaria elimination remain unspecific on the precise criteria for accelerating elimination efforts but define low transmission areas where community-based prevalence is between 1–10% and very low as below 1% (World Health Organization, 2018b; World Health Organization et al., 2017a). WHO classifications of higher transmission settings include a moderate group (*Pf*PR 10–35%) and high (*Pf*PR > 35%) (World Health Organization, 2018b). These continue to be arbitrary because the precise relationship between rates of infection, disease outcomes and optimized intervention remain poorly defined (Cibulskis et al., 2011; Nguyen et al., 2020). For instance, the use of ≥30% or ≥40% *Pf*PR has been reported to be used to regard areas as high transmission (Giorgi et al., 2018; Macharia et al., 2018; Noor et al., 2009a, 2012b; Thawer et al., 2020).

There is far less historical evidence of appropriate criteria for the classification of fever infection prevalence and incidence. Suggestions of thresholds for API have been made by WHO to guide countries on the different risk strata (World Health Organization, 2018b). For instance, an API of <5 cases /1000 or TPR <5% have been proposed by WHO to represent an important transition phase for countries moving towards elimination (Boyce et al., 2016; Partnership RBM, 2008; World Health Organization et al., 2012b). However, the recommendations call for countries to guide selection of these cut-offs based on the local context. There is a need for a more robust understanding of the relationship of routine metrics with the traditional measures of prevalence to support cut-off development.

1.2.5 Stratification of geographical units into risk strata

The classification of malaria metrics allows programs to categorize geographical areas into appropriate risk strata. The main purpose of stratifying malaria risk is (i) to guide effective targeting of malaria interventions of control versus elimination. This can contribute to identifying the optimal targeting of intervention mix for malaria strategic plans and ultimately for efficiently allocating resources to maximize impact (World Health Organization, 2020b), (ii) to continuously monitor and track progress of the epidemiological risk and (iii) to evaluate the impact of interventions. Such an analyses of mapping malaria risk should form a core component of malaria program reviews to assess and monitor changes over time and inform on future steps.

1.2.5.1 Historical context of malaria risk mapping

National cartographies of malaria risk were common pre-requisites to guiding malaria control and prevention activities across Africa from the 1950s (Snow and Noor, 2015). These early sub-national risk maps recognized that transmission intensity, seasonality and ecology were unevenly distributed within national borders. The need for malaria risk maps re-emerged during the 1990s thanks to the pan-African initiative Mapping Malaria Risk in Africa (MARA) (LeSueur et al., 1999; MARA, 1999; Snow et al., 1996). In 2005, the MAP was established to assemble and model the spatial patterns of malaria transmission based on parasite prevalence globally (Hay and Snow, 2006).

Owing to the challenges faced with capturing data from routine systems, most risk maps have relied on the use of geospatial models to estimate burden of malaria (Feachem et al., 2019; Gething et al., 2011b; Noor et al., 2014; Weiss et al., 2019). In SSA, various approaches have been used to date to model risk in space and time. With increasing interest and demand for malaria risk mapping, there has been a rise in the development of methodological approaches and its applications (Odhiambo et al., 2020; Odhiambo and Sartorius, 2018). In the absence of empirical routine data, these models have largely interpolated data from community-based surveys and this often comes with varying levels of uncertainty and fail to capture the seasonality of transmission. These maps have been useful in providing baseline information and continue to be widely used for various decision making and planning (Alegana et al., 2020; Feachem et al., 2019; Ghilardi et al., 2020).

Efforts to incorporate nationally owned routine data sources into modelled risk maps are emerging (Nguyen et al., 2020; Omumbo et al., 2013), however, these attempts are often challenged by reduced access to country owned data. Furthermore, such methodologies demand skills to understand the complex statistical methodologies that is often beyond the capacity of most NMPs. Capacitating NMPs to establish a firm surveillance system and to visualize and interpret routine data represents a more sustainable way of promoting data use for decision making (Alegana et al., 2020). Such an avenue offers a simplified way for analyzing real time data that is country led rather than driven externally. Increased usage of maps for local decision making by NMPs was recently shown to correspond with factors such as knowledge and understanding of the source of data and their limitations, trust and perceived ownership of the data together with knowledge and understanding of the processes of map construction (Ghilardi et al., 2020).

1.2.5.2 Country experiences in malaria risk stratification

Following the WHO HBHI initiative, many countries across Africa have attempted to stratify malaria risk for sub-national tailoring of interventions. WHO recently published a technical brief for countries preparing malaria funding requests for global fund to provide guidance on how to approach stratification (World Health Organization, 2020b). Whilst some general guidelines have been provided, the recommendations call for countries to do the stratification based on their local context. A few countries that requested support from WHO to assist with the stratification process for updating their national malaria strategic plans (NMSPs) and global fund applications have performed the analysis based on the conceptual framework presented in Figure 1.9. Meanwhile, other countries have adopted a more country driven approach and performed the analysis based on their local context. To date, no standard guidelines exist and the level and extent of stratification is largely driven by the existence of in-country analytical capacity and availability of good quality local data. Differences in the selection of metrics, level of stratification and selection of suitable thresholds for the metrics are observed across countries. Furthermore, the approaches used for translation of the risk maps into suitable packages of interventions with support from mathematical modelling also varies. Despite the existence of these differences, attempts by countries to adopt the HBHI approach represents an important step towards tackling malaria and onwards to elimination.

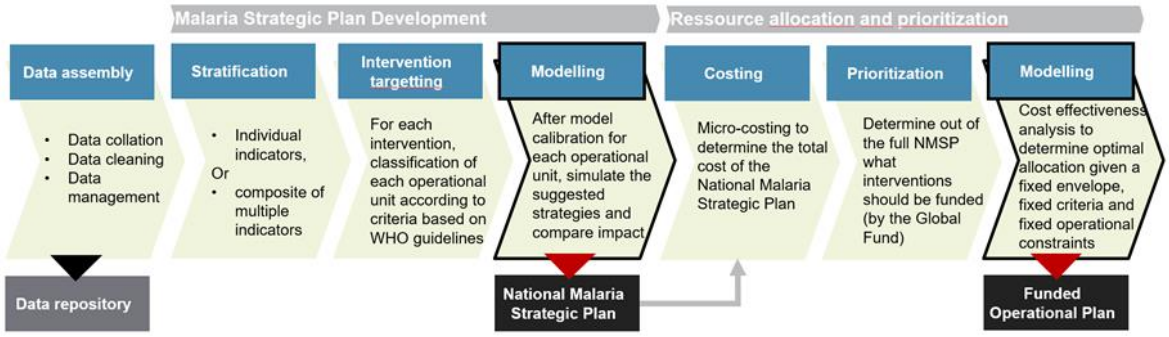


Figure 1.9: World Health Organization framework for malaria stratification (Adopted from slides by Dr. Emilie Pothin)

summarizes published peer-reviewed work describing approaches taken by various countries in Africa pre- and post HBHI to stratify their malaria risk. The aim was to highlight the efforts taken nationally and hence studies that stratified the risk for only a specific area/region/district within a country have not been included. As can be seen, efforts to produce stratification map predates back to the 1990's. Most of these early maps were used to understand the heterogeneity with minimal efforts to translate the maps into operational strategic plans. In the later years, greater efforts can be seen with producing risk maps using both routine and survey data. The most widely used metric to describe the malaria risk was prevalence estimates from surveys used in 48 risk maps across 26 countries followed by incidence used in 34 risk maps across 21 countries. A few countries (3) have also attempted to use combinations of multiple routine metrics and/or prevalence. The use of ANC TPR, malaria mortality, EIR and TPR were also reported in a few studies. The methods used for producing the risk maps largely varied with most countries employing Bayesian spatio-temporal geo-statistical methods to model malaria risk, visualize its patterns and identify spatial clusters. Most of the analytical support for complex statistical methodologies were largely provided by international institutions but involvement of local institutes can also be observed. A few countries have also used simpler approaches entailing scoring systems or regressions to develop their risk map. The distribution of studies by spatial resolution showed that most maps were conducted at the second administrative level of the districts or at the very fine granular pixel levels. Cross-sectional household surveys conducted by DHS/MIS surveys provided a rich source of malaria prevalence estimates for most studies with some also utilizing data from other research surveys conducted in the countries. The countries utilizing routine indicators obtained their data from the HMIS/DHIS2 system. At least 50 risk maps are seen to have been produced during the pre-

HBHI period whilst 37 maps were produced post-HBHI period. In the post-HBHI period, extensive support has been provided to high burden countries by WHO global malaria programme (GMP) to develop epidemiological risk maps that were based on a composite of malaria metrics such as incidence, prevalence and mortality, However, most of the support provided to date is largely unpublished and could therefore not be included in table 1.2.

Table 1.2: National malaria risk stratification maps for countries in Africa available from peer reviewed publications

Country	Epidemiological metrics used	Period of analysis	Data sources	Spatial resolution	Methodological approach	Support from local/ international institute	Reference
Angola	- Prevalence	- 2006-2007	- MIS/DHS Survey	- 1x1km	- Bayesian geo-statistical models	International research institute	(Gosoniu et al., 2010)
Botswana	- Prevalence	- 1961-1962	- National Survey	- 1x1km	- Bayesian geo-statistical models	Local and international research institutes	(Craig et al., 2007)
Burkina Faso	- Prevalence	- 2010	- DHS Survey	- 2.5x2.5km	- Multilevel and Bayesian geo-statistical models	International research institute	(Samadoulougou et al., 2014)
	- Prevalence	- 2010/2011	- DHS Survey	- 1x1km	- Bayesian geo-statistical models	Local and international research institutes	(Diboulo et al., 2016)
	- Malaria in pregnancy incidence rate	- 2015-2017	- HMIS/DHIS2	- Health-district areas - Community level	- Bayesian Spatio-temporal modelling	Local and international research institutes	(Rouamba et al., 2020)
	- Malaria case incidence	- 2013-2020	- HMIS/DHIS2	- Municipality level	- Spatial statistical analysis	Local and international research institutes	(Sangaré et al., 2022)
Burundi	- Malaria case incidence	- 2010	- HMIS/DHIS2	- Health-district level	- GIS based model	Local and international research institutes	(Hassaan et al., 2017)
Cameroon	- Prevalence	- 2000-2015	- DHS Survey	- Regional level - Hot-spot clusters	- Small area spatial statistical analysis	Local and international research institutes	(Tewara et al., 2018)
	- Malaria case incidence	- 2012-2018	- HMIS/DHIS2	- Health district level	- Bayesian Spatio-temporal modelling	Local and international research institutes	(Danwang et al., 2021)
Cabo Verde	- Malaria case incidence	- 1010-2019	- HMIS/DHIS2	- Municipality level	- Multivariable logistic regression	Local and international research institutes	(DePina et al., 2020)

Country	Epidemiological metrics used	Period of analysis	Data sources	Spatial resolution	Methodological approach	Support from local/ international institute	Reference
Comoros	- Malaria case incidence	- 2016	- HMIS/DHIS2	- Village	- Spatial and statistical analysis	Local and international research institutes	(Attoumane et al., 2020)
Cote D'Ivore	- Prevalence	- 1988-2007 -	- School survey	- 1x1km	- Bayesian geo-statistical models -	International research institute	(Raso et al., 2012)
	- Prevalence	- 2011-2012	- School survey	- 1x1km	- Bayesian geo-statistical models	Local and international research institutes	(Houngbedji et al., 2016)
Democratic Republic of Congo	- Prevalence - Under 5 years mortality	- 2007	- DHS Survey	- 1x1km	- Bayesian geo-statistical models	Local and international research institutes	(Taylor et al., 2011)
Eritrea	- Malaria case incidence	- 1996-2003	- HMIS/DHIS2	- District level	- Principal component analysis - Nonhierarchical clustering	Local and international research institutes	(Ceccato et al., 2007)
	- Malaria case incidence	- 2012-2016	- HMIS/DHIS2	- District level	- Nonhierarchical clustering	Local research institute	(Kifle et al., 2019)
Gambia	- Prevalence	- 2012	- School surveys	- District level	- Statistical analysis	Local and international research institutes	(Okebe et al., 2014)
Ghana	- Malaria case incidence	- 1998-2010	- HMIS/DHIS2	- District level	- Spatial statistical analysis	Local and international research institutes	(Appiah et al., 2011)
	- Malaria case incidence	- 2008-2016	- HMIS/DHIS2	- Zonal level	- Univariate time series	Local and international research institutes	(Awine et al., 2018)
	- Prevalence	- 2016	- DHS survey	- 5x5km	- Bayesian geo-statistical models	Local and international research institutes	(Yankson et al., 2019)

Country	Epidemiological metrics used	Period of analysis	Data sources	Spatial resolution	Methodological approach	Support from local/ international institute	Reference
	- Prevalence	- 2017	- DHS survey	- District level	- Hotspot analysis	Local and international research institutes	(Mohammed et al., 2022)
Kenya	- Prevalence	- 1975-2009	- Cross-sectional community-based surveys	- 1x1km	- Bayesian geo-statistical models	Local and international research institutes	(Noor et al., 2009a)
	- Prevalence	- 1980-2015	- MIS/DHS Survey - Other research surveys	- 1x1km	- Bayesian geo-statistical models	Local and international research institutes	(Macharia et al., 2018)
	- Prevalence	- 2010-2020	- MIS/DHS Survey - Other research surveys	- 1x1km	- Bayesian geo-statistical models	Local and international research institutes	(Alegana et al., 2021a)
Madagascar	- Prevalence	- 2011-2016	- MIS/DHS Survey	- 1x1km	- Bayesian geo-statistical models	Local and international research institutes	(Kang et al., 2018)
	- Malaria case incidence	- 2010-2014	- HMIS/DHIS2	- District level	- Cluster analysis	Local and international research institutes	(Ihantamalala et al., 2018)
	- Malaria case proportions	- 2013-2016	- HMIS/DHIS2	- 1x1km	- Spatio-temporal regression model	Local and international research institutes	(Nguyen et al., 2020)
	- Combinations of incidence and prevalence data	- 2013-2016	- HMIS/DHIS2 - MIS/DHS Survey	- 1x1km	- Bayesian geo-statistical models	Local and international research institutes	(Arambepola et al., 2020)
Malawi	- Prevalence	- 1977-2002	- Other cross-sectional surveys	- District level	- Bayesian geo-statistical models	Local and international research institutes	(Kazembe et al., 2006)

Country	Epidemiological metrics used	Period of analysis	Data sources	Spatial resolution	Methodological approach	Support from local/ international institute	Reference
	- Prevalence	- 2000-2010	- MIS/DHS survey - National micro-nutrient surveys - Anemia and parasitemia surveys	- District level	- Bayesian geo-statistical models	Local and international research institutes	(Bennett et al., 2013)
	- Prevalence	- 2000-2017	- MIS/DHS survey - Other cross-sectional surveys	- 1x1km	- Bayesian geo-statistical models	Local and international research institutes	(Chipeta et al., 2019)
	- Malaria case incidence	- 2004-2017	- HMIS/DHIS2	- District level	- Spatio-temporal regression model	Local and international research institutes	(Chirombo et al., 2020)
Mali	- Prevalence	- 2000-2015	- MIS/DHS survey	- Health district level	- Spatial statistical analysis	Local and international research institutes	(Kayentao et al., 2018)
	- Composite of malaria case incidence, malaria mortality, and prevalence	- 2017-2020	- HMIS/DHIS2 - MIS/DHS survey	- Health district level	- Principal component analysis & Univariate and multivariate regression analyses	Local and international research institutes	(Cissoko et al., 2022)
Mauritania	- Malaria case incidence - Prevalence	- 1990-2012	- HMIS - School surveys - Other cross-sectional surveys	- District level	- Statistical retrospective descriptive analysis	Local and international research institutes	(Lekweiry et al., 2015)
Mozambique	- Prevalence	- 2011	- MIS/DHS Survey	- 3x3km	- Bayesian geo-statistical models	International research institutes	(Giardina et al., 2015)
	- Malaria case incidence	- 2010-2017	- HMIS/DHIS2	- District level	- Bayesian geo-statistical models	Local and international research institutes	(Colborn et al., 2018)

Country	Epidemiological metrics used	Period of analysis	Data sources	Spatial resolution	Methodological approach	Support from local/ international institute	Reference
	- Prevalence	- 2018	- MIS/DHS Survey	- Province level	- Bayesian geo-statistical models	International research institute	(Ejigu, 2020)
Namibia	- Malaria case incidence	- 2009	- HMIS/DHIS2	- Constituency level	- Bayesian geo-statistical models	Local and international research institutes	(Alegana et al., 2016)
	- Prevalence	- 1969-1992	- Other research surveys	- 5x5km	- Bayesian geo-statistical models	Local and international research institutes	(Noor et al., 2013a, 2013b)
Niger	- Malaria case incidence	- 2008	- Health facility survey	- Health facility level	- Statistical analysis	Local and international research institutes	(Doudou et al., 2012)
Nigeria	- Prevalence	- 2010	- MIS/DHS survey	- 4x4km	- Bayesian geo-statistical models	Local and international research institutes	(Adigun et al., 2015)
	- Prevalence	- 2007	- Other research surveys	- 1x1km	- Spatial statistical analysis	International research institute	(Onyiri, 2015)
	- Prevalence	- 2015	- MIS/DHS survey	- Regional level - Hot-spots	- Spatial statistical and hot-spot analysis	Local and international research institutes	(Okunlola and Oyeyemi, 2019)
	- Prevalence	- 2015	- MIS/DHS Survey	- 1x1km	- Spatial statistical analysis	International research institute	(Ugwu and Zewotir, 2020)
	- Prevalence	- 2015	- MIS/DHS Survey	- Regional level	- Multilevel regression model	International research institutes	(Oguoma et al., 2021)
	- Prevalence	- 2010-2018	- MIS/DHS Survey	- State level	- Spatial statistical analysis	Local and international research institutes	(Oyibo et al., 2021)
Republic of Djibouti	- Prevalence	- 2008/2009	- MIS/DHS survey	- Hot spots	- Spatial statistical analysis	Local and international research institutes	(Noor et al., 2011)
Rwanda	- Malaria case incidence	- 2012-2018	- HMIS/DHIS2	- Sector level	- Bayesian geo-statistical models	Local and international research institutes	(Semakula et al., 2020)

Country	Epidemiological metrics used	Period of analysis	Data sources	Spatial resolution	Methodological approach	Support from local/ international institute	Reference
	- Prevalence	- 2014-2015	- MIS/DHS Survey	- 1x1km	- Bayesian geo-statistical models	Local and international research institutes	(Nzabakiriraho and Gayawan, 2021)
Senegal	- Prevalence	- 2008-2009	- MIS/DHS Survey	- 4x4km	- Bayesian geo-statistical models	Local and international research institutes	(Giardina et al., 2012)
	- EIR	- 2009-2019	- HMIS	- Regional level	- Spatial statistical analysis	Local research institutes	(Fall et al., 2022)
Somalia	- Prevalence	- 2005, 2007	- MIS/DHS Survey	- Health regional level	- Bayesian geo-statistical models	Local and international research institutes	(Noor et al., 2008)
	- Prevalence	- 2007-2010	- Other cross-sectional surveys	- 1x1km - District level	- Bayesian geo-statistical models	Local and international research institutes	(Noor et al., 2012a)
	- Prevalence	- 2005-2014	- Other cross-sectional surveys	- 1x1km	- Bayesian geo-statistical models	Local and international research institutes	(Giorgi et al., 2018)
Sudan	- Prevalence	- 2000-2010 -	- DHS/MIS - Other cross-sectional surveys	- 5x5km	- Bayesian geo-statistical models	Local and international research institutes	(Noor et al., 2012b)
	- Malaria case incidence	- 2017-2019	- HMIS/DHIS2	- 1x1km	- Bayesian geo-statistical models	Local and international research institutes	(Elagali et al., 2022)
Swaziland	- Prevalence	- 2010	- Cross-sectional survey	- Hot spot clusters	- Statistical analysis - Spatial cluster analysis	Local and international research institutes	(Hsiang et al., 2012)
	- Malaria case incidence	- 2012-2019	- Instant Disease Notification System -	- Cluster level	- Spatial statistical analysis	Local and international research institutes	(Nkya et al., 2021)

Country	Epidemiological metrics used	Period of analysis	Data sources	Spatial resolution	Methodological approach	Support from local/ international institute	Reference
Tanzania	- Prevalence	- 2007-2008	- THMIS survey	- 1x1km	- Bayesian geo-statistical models	Local and international research institutes	(Gosoniu et al., 2012)
	- Prevalence	- 1990-2017	- DHS/MIS survey - Other cross-sectional surveys	- 1x1km	- Bayesian geo-statistical models -	Local and international research institutes	(National Malaria Control Programme, 2021)
	- EIR	- 2010	- MAP	- 10x10km	- Spatial statistical analysis	International research institutes	(Hagenlocher and Castro, 2015)
	- Prevalence	- 2014-2015 -	- School malaria parasitological survey	- Council level	- Spatial statistical analysis	Local and international research institutes	(Chacky et al., 2018)
	- Positivity rate in pregnant women	- 2015-2016	- DHS/MIS survey	- HF Catchment area - Regional level - District Level	- Spatial statistical analysis - Bayesian geo-statistical models	Local and international research institutes	(Brunner et al., 2019; Kitojo et al., 2019)
	- Composite of annual parasite incidence, fever test positivity rate, positivity rate in pregnant women and prevalence in school children	- 2017-2019	- HMIS/DHIS2 - School malaria parasitological survey	- Council level - Ward level	- Simple statistical analysis	Local and international research institutes	(National Malaria Control Programme, 2021; Thawer et al., 2020; Thawer et al, 2022)
	- Prevalence	- 2010-2020	- DHS/MIS survey - Other cross-sectional surveys	- 1x1km	- Bayesian geo-statistical models	Local and international research institutes	(Alegana et al., 2021a)

Country	Epidemiological metrics used	Period of analysis	Data sources	Spatial resolution	Methodological approach	Support from local/ international institute	Reference
Togo	- Prevalence	- 2017	- DHS Survey	- Regional level	- Statistical regression analysis	Local and international research institutes	(Kombate et al., 2022)
Uganda	- Prevalence	- 2000-2003	- Cross-sectional school survey	- 1x1km	- Bayesian geo-statistical models	Local and international research institutes	(Stensgaard et al., 2011)
	- Prevalence	- 2009-2014	- MIS/DHS Survey	- 2x2km	- Bayesian geo-statistical models	Local and international research institutes	(Ssempiira et al., 2017a)
	- Prevalence	- 2014-2015	- MIS/DHS Survey	- 4x4km	- Bayesian geo-statistical models	Local and international research institutes	(Ssempiira et al., 2017b)
	- Malaria case incidence	- 2013-2017	- HMIS/DHIS2	- District level	- Bayesian geo-statistical models	Local and international research institutes	(Ssempiira et al., 2018)
	- Malaria case incidence	- 2015-2019	- HMIS/DHIS2	- Health facility catchment level	- Bayesian geo-statistical models	Local and international research institutes	(Kigozi et al., 2020b)
	- Prevalence	- 2010-2020	- DHS/MIS survey - Other cross-sectional surveys	- 1x1km	- Bayesian geo-statistical models	Local and international research institutes	(Alegana et al., 2021a)
Zambia	- Prevalence	- 2006	- MIS/DHS survey	- 1x1km	- Bayesian geo-statistical models	Local and international research institutes	(Riedel et al., 2010)
	- Malaria in-patients - Malaria mortality	- 2000-2010	- HMIS	- District level	- Spatial statistical and regression analysis	Local and international research institutes	(Masaninga et al., 2013)

Country	Epidemiological metrics used	Period of analysis	Data sources	Spatial resolution	Methodological approach	Support from local/ international institute	Reference
	- Malaria case incidence	- 2009-2011	- HMIS	- District level	- Bayesian geo-statistical models	Local and international research institutes	(Bennett et al., 2014)
	- Prevalence	- 2006-2012	- MIS/DHS survey	- 5x5km	- Bayesian geo-statistical models	Local and international research institutes	(Bennett et al., 2016)
	- Malaria incidence, rate and trends - Malaria mortality	- 2000-2015	- HMIS	- District level	- Spatial statistical analysis and matrix scores - Bayesian geo-statistical models	Local and international research institutes	(Lubinda et al., 2021)
	- Malaria case incidence	- 2009-2015	- HMIS	- HF level	- Bayesian geo-statistical models	Local and international research institutes	(Lubinda et al., 2022)
Zimbabwe	- Malaria case incidence	- 1988-1999	- HMIS	- District level	- Bayesian geo-statistical models	International research institutes	(Mabaso et al., 2005)
	- Malaria case incidence	- 2005-2014	- HMIS	- District level	- Spatial statistical and regression analysis	Local research institutes	(Gwitira et al., 2018)
	- Malaria case incidence	- 2011-2016	- HMIS	- District level	- Spatial statistical and regression analysis	Local research institutes	(Gwitira et al., 2020)
	- Malaria case incidence Malaria mortality	- 2017-2020	- HMIS/DHIS2	- District level	- Retrospective descriptive analysis	Local and international research institutes	(Gavi et al., 2021)
Zanzibar	- EIR	- 2010	- Malaria Atlas Project (MAP)	- 10x10km	- Spatial statistical analysis	International research institutes	(Hagenlocher and Castro, 2015)
	- Malaria cases	- 2015-2020	- Malaria case notification system	- Shehia	- Spatio-temporal hotspot analyses	Local and international research institutes	(Bisanzio et al., 2022)

1.2.6 Opportunities for using routine data for measuring malaria transmission

The availability and quality of routine data is increasingly becoming better as a result of various factors. In response to the WHO's "T3: Test. Treat. Track" initiative (World Health Organization, 2012a), many African countries have increased testing rates at HFs, which are now able to provide data on malaria parasitological diagnosis performed through microscopy or rapid diagnostic tests (RDT) (Bastiaens et al., 2014). Since 2010, over 1 billion mRDTS have been performed globally (World Health Organization, 2021). This, coupled with the digitization of HMIS under the DHIS2 platform that has significantly improved RRs, has greatly strengthened the value of routine data from HFs. The call for countries to use data for strategic decision making by WHO GTS and HBHI initiative is further likely to continue to accelerate improvements in HMIS data completeness and quality. Collectively, these initiatives provide a framework for the increased use of routine surveillance data by NMPs for developing their NMSPs, and reflecting closely the malaria situation in the country.

Several studies have compared measures from routine sources against community prevalence to highlight the representativeness of these indicators (Brunner et al., 2019; Kigozi et al., 2019; Kitojo et al., 2019). Methodological frameworks have been proposed for the use of routine datasets to evaluate the impact of malaria control programs (Ashton et al., 2017; Bennett et al., 2014) and geo-spatial modelling strategies have also attempted to use routine data for creating malaria risk maps (Alegana et al., 2016; Sturrock et al., 2014). All further highlight the potential value of using routine data.

A key step forward would therefore be to understand the different sources of data, how they relate to each other and reflect the different components of the transmission system and importantly, how closely routine data is able to represent the malaria situation in the community (World Health Organization, 2018b). Investing in strengthening the country's existing routine surveillance system would allow for better estimation of malaria burden to guide intervention planning and monitor disease trends. In line with this, WHO with support from partners recently launched the malaria surveillance toolkit to allow countries to assess their surveillance systems to identify key gaps and evaluate data quality and usage (World Health Organization, 2022b).

1.3 Malaria situation analysis in mainland Tanzania

1.3.1 History of malaria risk mapping in mainland Tanzania

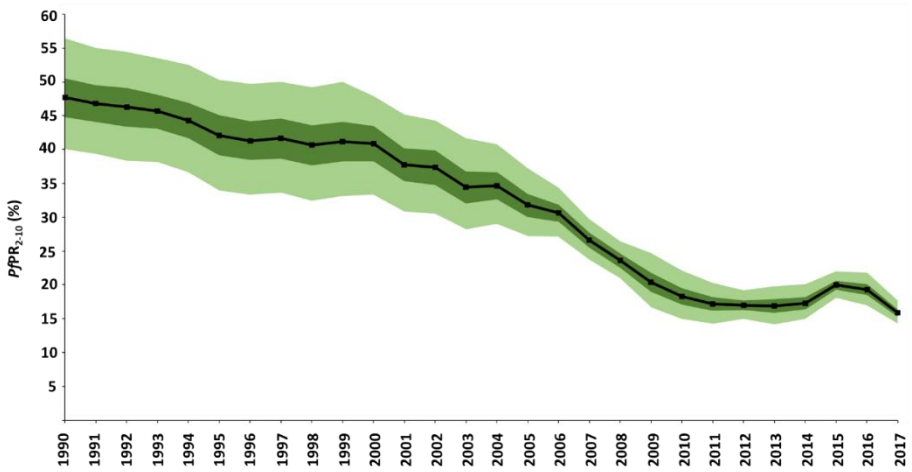
In 1956, the Government of Tanganyika produced the first cartography of malaria risk as part of an Atlas. The transmission was mainly described through the length of seasonality maps informed by expert opinion and climatology (National Malaria Control Programme, 2013). Although the map recognized that the transmission was heterogeneous across the country, no evidence exists that it was used to guide decision making. Later in the 1960's, attempts to review the malaria situation across various regions of the country was initiated by David Clyde and colleagues (Clyde, 1967, 1965, 1962; Clyde and Emanuel, 1965; Clyde and Miluba, 1964; Clyde and Msangi, 1963; Clyde and Mzoo, 1964) and this represented one of the first efforts to collate and understand the malaria epidemiological data in Africa (Clyde, 1967). These data were used by them to describe the malaria risk using the early endemicity classifications that were developed from spleen rates in children and later using parasite rates (Metselaar and Van Thiel, 1959). Four strata as a result were semi-qualitatively described (National Malaria Control Programme, 2013) and included (i) *Highly endemic zones* (*Pf*PR in children> 50%) which included an area covering more than 50% of the country and extended from the coastal and sub-coastal plains, lake zone regions and all the way to the foot of the Eastern Arc Range (ii) *Mesoendemic zones* which included the Rift Valley areas, the dry regions bordering the Central Plateau and the base of Kilimanjaro in the altitude of 850 and 1,250 meter (iii) *Hypo-endemic zones* mostly in the mountainous regions between the altitude of 1,250-1,500 meter and included Pare, Usambara, Arusha, Kilimanjaro and the borders of the Southern Highlands and (iv) *Malaria-free zones* which included the areas in the higher altitude above 1500m such as in Kilimanjaro, and the highlands around the west of Lake Victoria, Njombe region and Iringa Region. These early descriptions of malaria risk provided the baseline of the distribution of malaria endemicity in the country for the next 30 years (National Malaria Control Programme, 2013).

1.3.2 Malaria epidemiology in mainland Tanzania

The transmission of malaria in Tanzania during the 1990 - early 2000's was largely in the meso- and hyper endemic classes with the national average modelled *Pf*$PR_{2\text{-}10yrs}$ being 40%. Following this period, the country saw a marked reduction in the overall parasite prevalence reaching hypo-endemicity levels and this decline in transmission was accompanied with an

increasing trend in the geographical and epidemiological heterogeneity (Figure 1.10). The low transmission areas are consistently found to be in a "corridor" running from North-East to South-West of Tanzania and high transmission areas in North-Western lake zone and in South-Eastern coastal zone. The increasing trends in transmission heterogeneity demands the need to continuously monitor the epidemiological changes at the higher spatial resolutions to track progress and allocate resources more efficiently. Such granular information cannot be acquired solely from sparse community surveys and requires utilizing the country's routine surveillance system, as such, investments towards further strengthening it must be made.

a.



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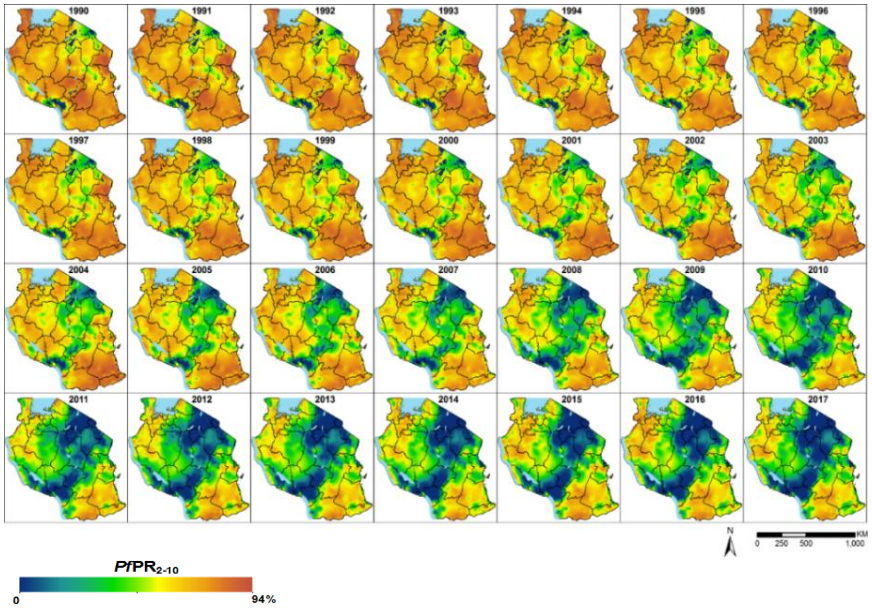


Figure 1.10: (a) The national annual mean (black line), 2.5–97.5% (light green boundaries) interquartile credibility range (ICR) and 25–75% ICR (dark green boundaries) of the posterior *Pf*PR$_{2–10}$ predictions (b) Geographical trends of the posterior *Pf*PR$_{2–10}$ predictions in mainland Tanzania from 1990-2017 (National Malaria Control Programme, 2021)

Recent control efforts in mainland Tanzania have led to the progressive changes in the epidemiological profile of malaria. During the past 15 years, evidence based malaria control interventions have been deployed on a massive scale: Over 100 million ITNs have been distributed since 2004, six million households have been sprayed in targeted regions, 170 million ACT treatments and 100 million mRDT have been supplied to HFs. In addition, the capacity of several thousand health care providers and health management teams has been continuously strengthened. As a result, accessibility, usage and equity of ITNs, mRDTs and ACTs increased over the time. Given the increasing geographic heterogeneity of malaria risk in the country, with some areas nearing local elimination (e.g. Arusha Region), while others remain at very high risk (e.g. Lake Zone), a new approach to planning malaria control that is taking account of this differing risk using local data is now required so as to maximize gains. The next section provides a description of the country's surveillance system that is currently in place to generate some of these local routine information.

1.3.3 Malaria surveillance in mainland Tanzania

The comprehensive malaria surveillance framework of Tanzania (National Malaria Control Programme, 2017a) includes four major pillars: disease, programmatic, transmission and quality services surveillance (Figure 1.11). The disease surveillance component collects data on passive routine reporting done on weekly basis via IDSR system or monthly basis via the HMIS/DHIS2 system. The active case detection collects individual malaria case information in the very low transmission areas via the case based surveillance. The programmatic surveillance gathers information on commodities, preventive services, therapeutic efficacy, insecticide susceptibility and pharmacovigilance. Transmission surveillance brings together parasitological, entomological and climatic information and, finally, the delivery of malaria services in HFs is monitored through quality improvement indicators including the malaria surveillance and data quality improvements and product quality assurance and audits. The framework operates across all levels of the health care delivery system and generates outputs in term of tables, charts and maps. The framework is rigorously linked to response as the outputs inform on the malaria situation, identify any existing issues and respond in an appropriate manner to resolve the issue. For instance, if the information identifies large numbers of presumptive clinical malaria cases being reported, this triggers an assessment of the adherence to testing guidelines at the HF in the form of supportive supervision using the

malaria service and data quality improvement (MSDQI) tool (National Malaria Control Programme, 2017c). This allows identification of the issue and possible ways to rectify by ensuring diagnostic tools and/or trained health workers are available. The following section describes some of the information that is collected and generated from each of the component of the framework whether on a routine or periodic basis.

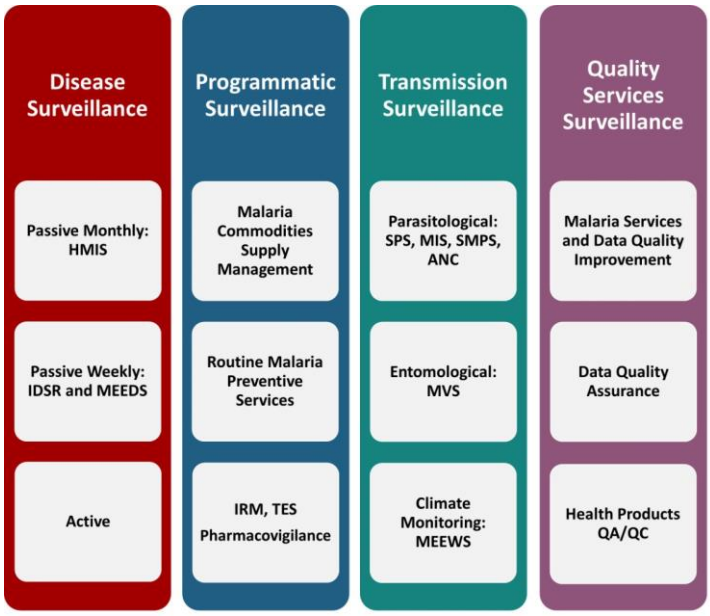


Figure 1.11: The comprehensive malaria surveillance framework of mainland Tanzania (National Malaria Control Programme, 2017a)

1.3.3.1 Periodic sources

NMCP and implementing partners regularly gather periodic malaria information to inform on the malaria situation and track the coverage of the various interventions. This includes:

a) Surveys and surveillance outcomes - e.g. parasitological and entomological data through DHS/MIS surveys conducted every 2-3 years in children under 5 years, biennial school surveys initiated in 2014, and malaria vector surveillance (MVS) in sentinel sites.

b) Programmatic and operational studies - e.g. therapeutic efficacy studies (TES), insecticide resistance monitoring (IRM);

c) Vector control operational performance e.g. IRS, LSM and LLIN distribution;

d) Social and behaviour change communication (SBCC) outputs

e) Malaria service and data quality assessments – MSDQI monitoring provides useful information on the readiness and quality of malaria services and data provided by facilities. This is conducted on a quarterly basis.

1.3.3.2 Routine sources

The basis of the routine data collection in HFs are: HMIS, electronic Integrated Disease Surveillance and Response (eIDSR) and electronic Logistic Management Information System (eLMIS). Other routine information includes climate data from the Tanzania Meteorological Agency (TMA).

Within the HMIS, malaria data on various parameters such as malaria cases, attendances, admissions, testing and deaths are collected on a monthly basis using HMIS collection tools from all HFs. Malaria testing by mRDT among pregnant women attending their first visit at ANC was implemented in Tanzania in mid-2013 and immediately integrated into the routine HMIS (Willilo et al., 2016). Tanzania is amongst the first country in Africa to have implemented routine ANC malaria testing for surveillance. mRDTs are the most common diagnostic tool used. A small proportion of HFs, mainly private, still use microscopy to test for malaria. mRDTS were rolled out in 2009 with country wide scale up in 2013. The HMIS tools also capture malaria service data such as malaria commodities consumption, stock- outs and preventative services provided at reproductive and child health clinic (RCH).

In 2009, the Ministry of Health (MoH), piloted a M&E strengthening initiative to improve the HMIS system, migrating from paper-based system to using an electronic one, DHIS2 system. The DHIS2 was rolled out across the country in 2013 and since its inception, the RRs from the operational HFs have improved dramatically, with current RRs from Out-Patient Department (OPD) over 90%.

Malaria surveillance has also been integrated into the eIDSR platform (Joseph, et al., 2022), which is designed specifically for epidemic diseases, and cases are reported on a weekly basis from all HFs. Other routine data collected include malaria commodities from eLMIS that includes HFs' quarterly requisitions and requests and Epicor 9 that generates stock and commodity movement information. Information from these systems allows for accountability of malaria commodities.

1.3.3.3 NMCP DHIS2 based dashboards for malaria

In order to implement the comprehensive malaria surveillance and response framework, NMCP in 2017 consulted University of Dar es Salaam (UDSM)/DHIS2 team to develop two distinct

and complementary electronic platforms for storage, analysis and use of all available malaria data namely; the NMCP malaria dashboard and, the NMCP composite database (Figure 1.12).

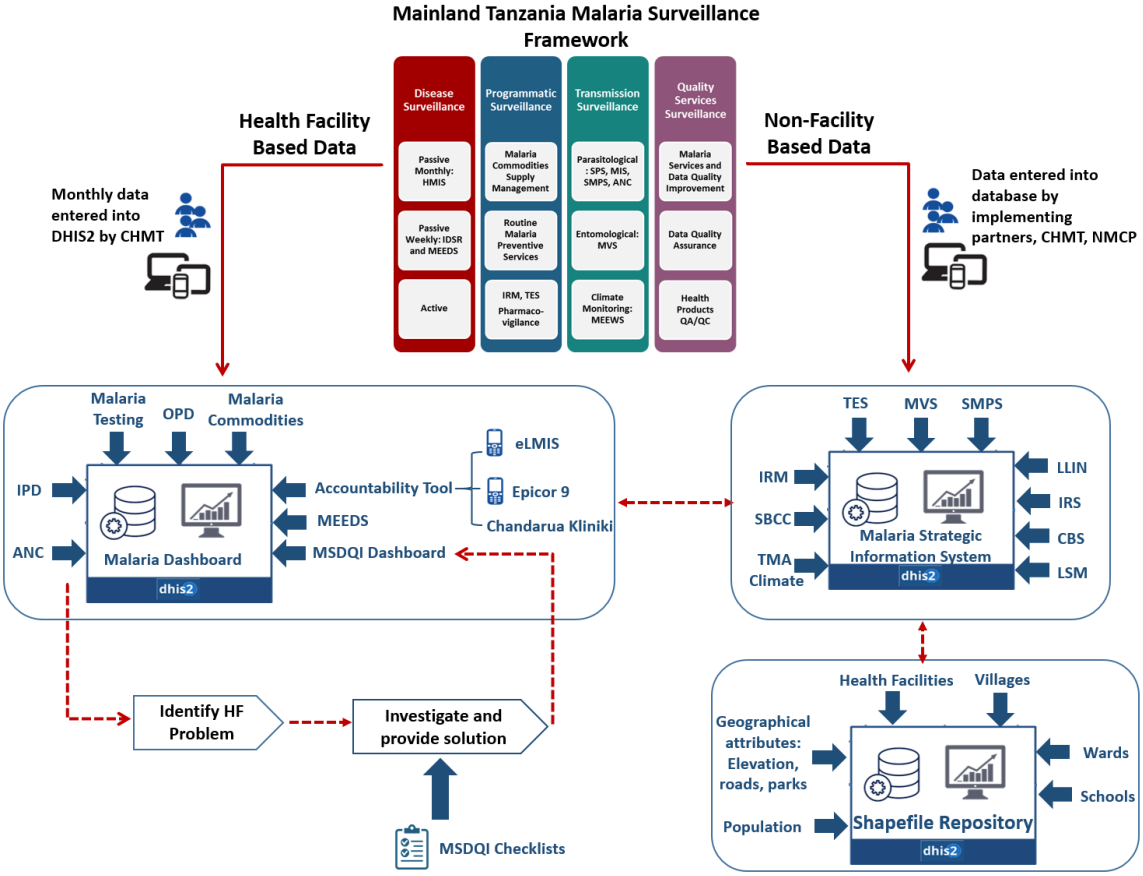


Figure 1.12: The comprehensive structure of the malaria information system of Tanzania (National Malaria Control Programme, 2021)

The **NMCP malaria dashboard** has been developed to facilitate the visualization, interpretation and use of all malaria related information in the HMIS/DHIS2 platform. The dashboard has eight modules and is based on service delivery points at the HFs and data collection tools and includes: a) Uncomplicated malaria diagnosis (OPD), b) malaria testing (Laboratory/testing sites), c) Malaria commodities (pharmaceuticals), d) Severe malaria morbidity (IPD) e) Malaria mortality f) Preventive services (RCH), g) Malaria commodities accountability tools, and h) MSDQI (Figure 1.13). The dashboard is accessible by health teams at regional and council levels via registered login credentials. The training for usage and interpretation of outputs from the malaria dashboard was conducted in 2018 across all the councils of Tanzania (National Malaria Control Programme, 2018). The dashboard allows to

enhance accountability of all malaria related information at multiple administrative levels and monitor the progress of malaria control activities.

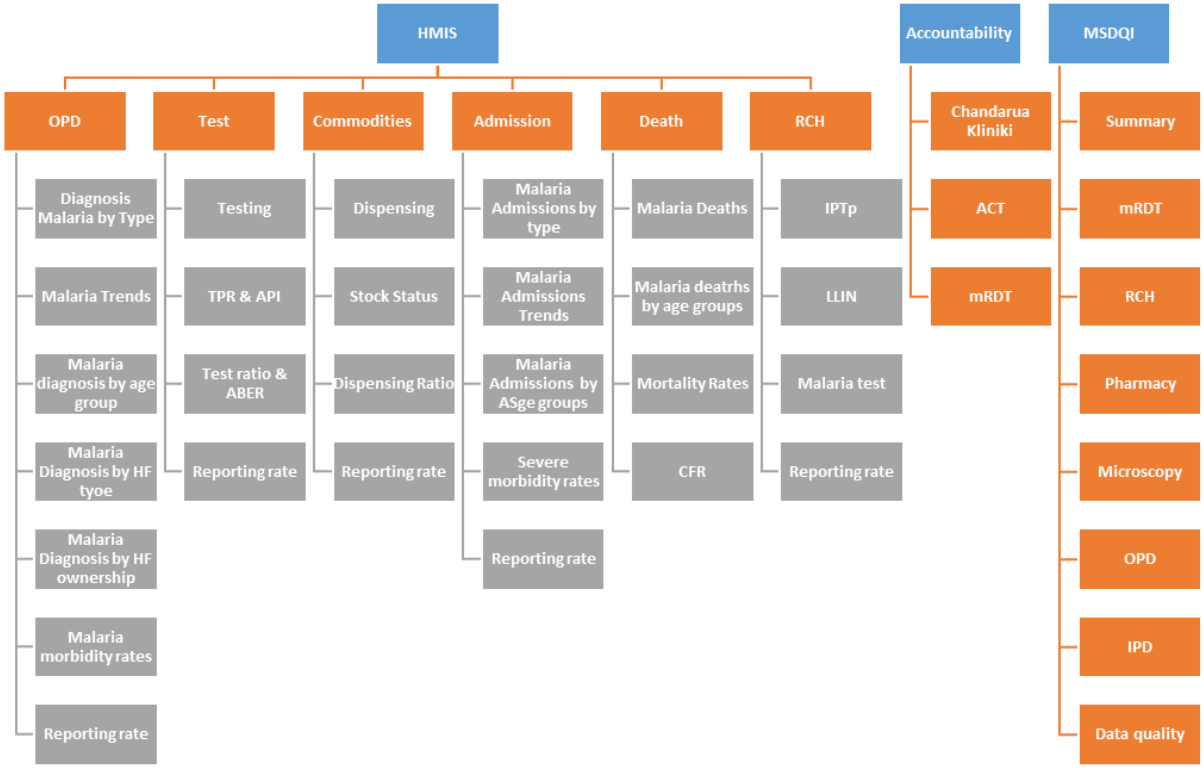


Figure 1.13: Malaria dashboard structure of mainland Tanzania under the DHIS2 platform (National Malaria Control Programme, 2021).

The **NMCP composite database** intends to systematically organize and harmonize malaria information collected outside the routine HMIS system (Figure 1.14). It includes: a) survey and surveillance outcomes - e.g. parasitological and entomological data; b) programmatic and operational studies - e.g. TES and insecticide susceptibility; c) vector control performance indicators, e.g. IRS, LSM and LLIN distribution; d) malaria commodity accountability tool based on eLMIS inputs – e.g. LLIN, pharmaceuticals and diagnostics consumption and services delivery; e) MSDQI monitoring – e.g. services readiness, observation, records review. One of the unique features of the database is the granular level of the data that is not possible under the HMIS/DHIS2. The organization hierarchy will allow analysis for levels up to the village levels with health facilities and schools allocated under these layers. Due to the broader hierarchical layers that this system can accommodate compared to the HMIS DHIS2, data from malaria case based surveillance (mCBS) in councils with very low malaria transmission risk generated at community levels will be collected and visualized under the composite database.

The system is currently under the final stages of development with plans to orient all stakeholders underway.

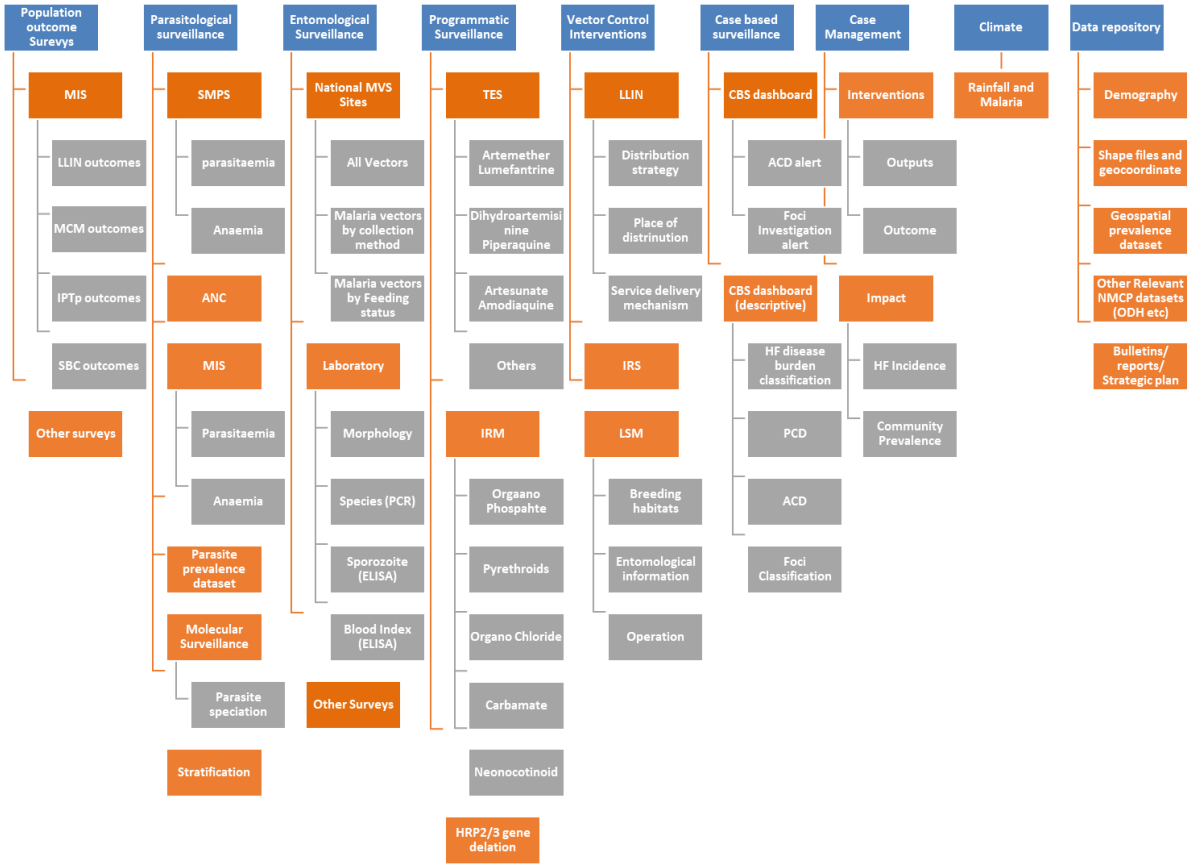


Figure 1.14: The comprehensive structure of the composite database of national malaria control programme (NMCP)

1.3.4 Malaria epidemiology and control strategies in the context of the national malaria strategic plans (NMSPs)

In the 1990's, Tanzania witnessed a pivotal turn in malaria control efforts centred around political commitment. The Government of Tanzania (GoT) launched the NMCP under the Epidemiology and Disease Surveillance Section of the Ministry of Health and Social Welfare (MoHSW). Following the launch, efforts towards raising awareness of malaria included engagement with multiple levels of the health system, development of guidelines for diagnosis, treatment and referral of malaria cases and production of materials for information education and communications (IEC) (National Malaria Control Programme, 2021). Since the launch of the RBM initiative in 1998 to date, mainland Tanzania has developed five, five-year NMSPs in collaboration with stakeholders. These are briefly described below (National Malaria Control Programme, 2021).

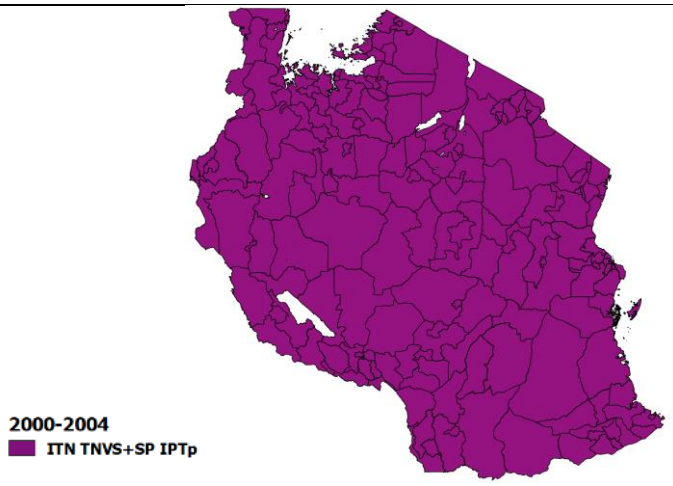
The goal of the 1997–2000 NMSP was to achieve a 50% reduction in case fatality rates, a 30% reduction in malaria incidence in the community and a 30% reduction in severe malaria incidence in children under five years of age by the year 2000 (National Malaria Control Programme, 1997). During this period, the strategy largely focused on promoting case management, detection and prevention of epidemics, malaria prevention in pregnancy, behavioural change, M&E and research. NMCP played a vital role in coordination, technical support and capacity building of some of these activities. Although no risk map was presented, a description of the malaria endemicity across the country based on climatology was provided but this was not used to guide malaria control.

The target of the 2002–2007 NMSP was to reduce mortality and morbidity due to malaria in all 20 regions of the country by 25% by 2007 and by 50% by 2010 through four approaches: (i) improved malaria case management, (ii) vector control through the use of ITNs, (iii) malaria control in pregnancy and (iv) malaria epidemic prevention and control. The core principle of this strategic plan was "scale up for impact" (SUFI) that ensured universal distribution of interventions (National Malaria Control Programme, 2002). This NMSP provided a similar description of the malaria endemicity as the previous strategy but extended this to presenting malaria seasonality maps of MARA project to provide the epidemiological context. During this period, massive international investments and commitments were seen for malaria control. These included commitments made during the Abuja Summit in 2000, the Global Fund to fight AIDS, Tuberculosis and Malaria in 2002, and the U.S. Presidents Malaria Initiative in 2004.

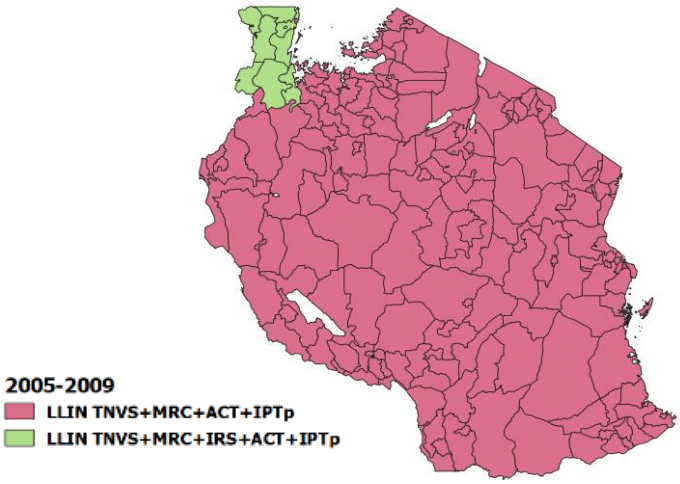
The target of the 2008–2013 NMSP was to reduce the burden of malaria by 80% by the end of 2013. Underlying this strategy was the ambition to align with the RBM Partnership's SUFI. The objective was to attain 80% coverage of interventions by 2013 (National Malaria Control Programme, 2008). The strategy adopted the renewed global interest to move beyond malaria control towards phased malaria elimination. The strategy comprised of two technical strategies (i) malaria diagnosis and treatment; and (ii) integrated malaria vector control with supportive strategies that included monitoring, evaluation and surveillance, community mobilization and capacity building at regional and district levels. During this period, IRS was conducted in high malaria transmission districts, the malaria diagnostics mRDTs were introduced in all public HFs in 2011 which eventually was distributed wide-scale in 2013. In this strategy, descriptions

of malaria endemicity along with modelled risk maps were provided and highlighted three important classifications; unstable seasonal malaria, stable malaria with seasonal variations, and perennial malaria. The risk maps included in this strategy included those from the MARA project of climate suitability and also smoothed, interpolated maps of the proportion of out-patient malaria cases and proportion of deaths due to malaria in children under 5 years. This signified an important step of including information from routine HMIS into risk maps. Figure 1.15 shows the transition in the malaria control strategies across the three strategic plans.

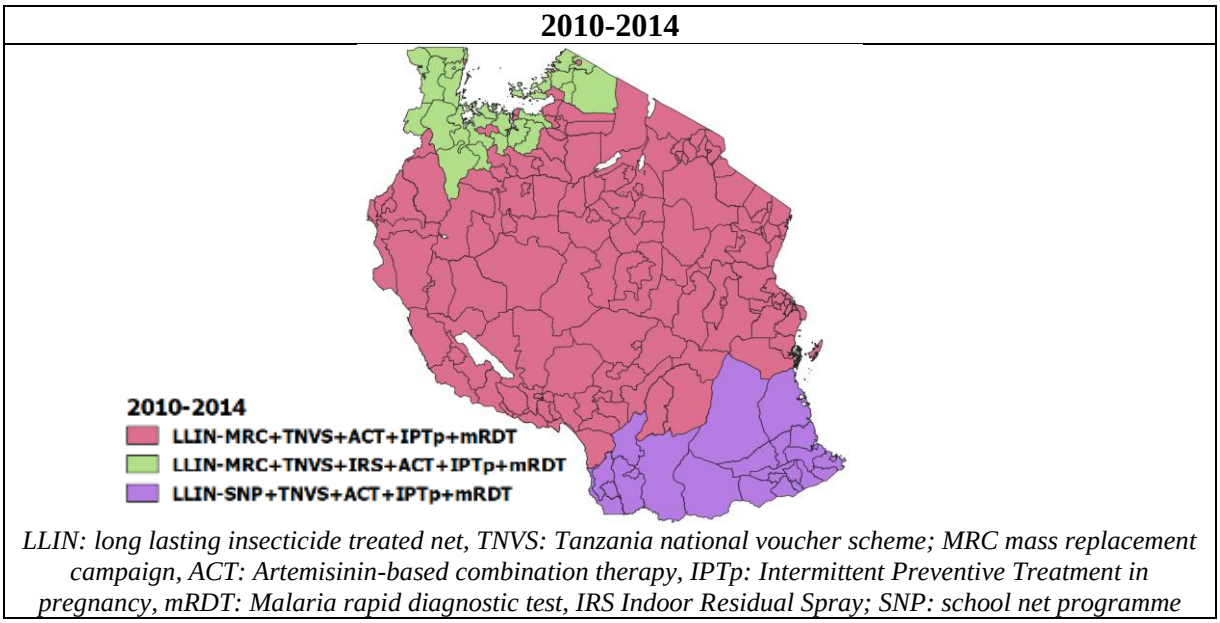
2000-2004



2005-2009



ITN: insecticide treated net; SP: sulfadoxine-pyrimethamine; LLIN: long lasting insecticide treated net; TNVS: Tanzania national voucher scheme; MRC: mass replacement campaign; IRS: Indoor Residual Spray; ACT: Artemisinin-based combination therapy; IPTp: Intermittent Preventive Treatment in pregnancy

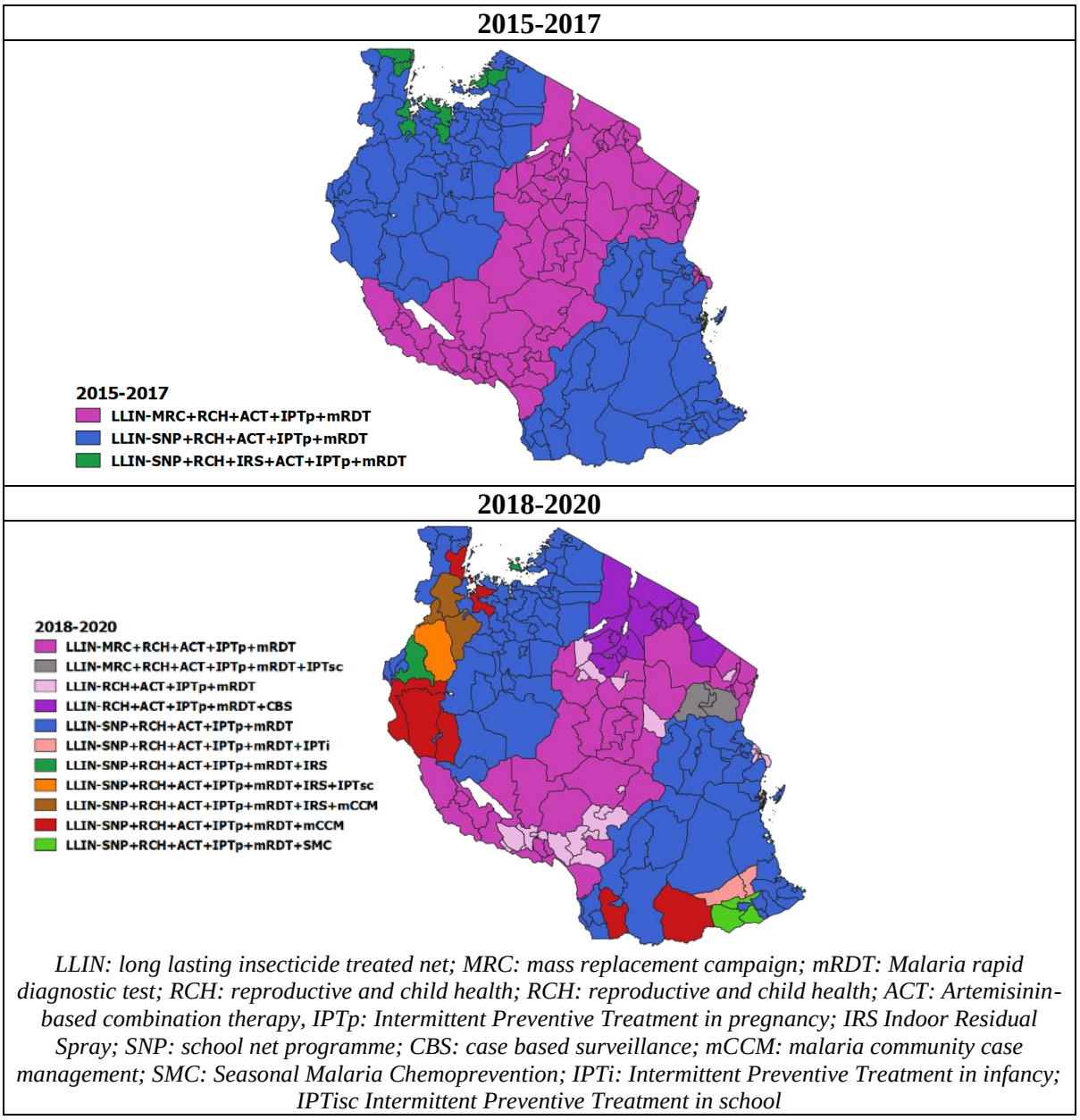


LLIN: long lasting insecticide treated net, TNVS: Tanzania national voucher scheme; MRC mass replacement campaign, ACT: Artemisinin-based combination therapy, IPTp: Intermittent Preventive Treatment in pregnancy, mRDT: Malaria rapid diagnostic test, IRS Indoor Residual Spray; SNP: school net programme

Figure 1.15: Scale up for impact strategy with minimal regional variation (2000 – 2014) (National Malaria Control Programme, 2021)

The target of the 2015–2020 NMSP was to reduce the average malaria prevalence from 10% in 2012 to 5% in 2016 and further to less than 1% in 2020 (National Malaria Control Programme, 2021). At its launch in 2014, the aim was to initially sustain progress and achievements through a universal coverage of existing interventions; and during the second period (2017 to 2020) to consolidate these achievements and explore the feasibility of a malaria pre-elimination phase in defined areas of the country. In 2017, a mid-term review (MTR) was undertaken (National Malaria Control Programme, 2017b). It was recognized that progress towards reducing national parasite prevalence was being made (7% in 2017 (Ministry of Health et al., 2017)), but that further gains would require a strategic redirection of limited resources to achieve a prevalence of less than 1% by 2020. The MTR was followed by a consultative process with a forum of global and national malaria experts. Recommendations from this forum National Malaria Control Program, 2018b), together with those from the WHO GTS 2016-2020 (World Health Organization, 2015c), were used to consider tailoring intervention approaches to the sub-national, local context, based on epidemiological stratification. In line with this, a re-oriented strategy, the Supplementary Mid-term Malaria Strategic Plan (SMMSP) 2018 – 2020 (National Malaria Control Programme, 2018a) was thus developed reflecting this shift in strategic direction (Figure 1.16).

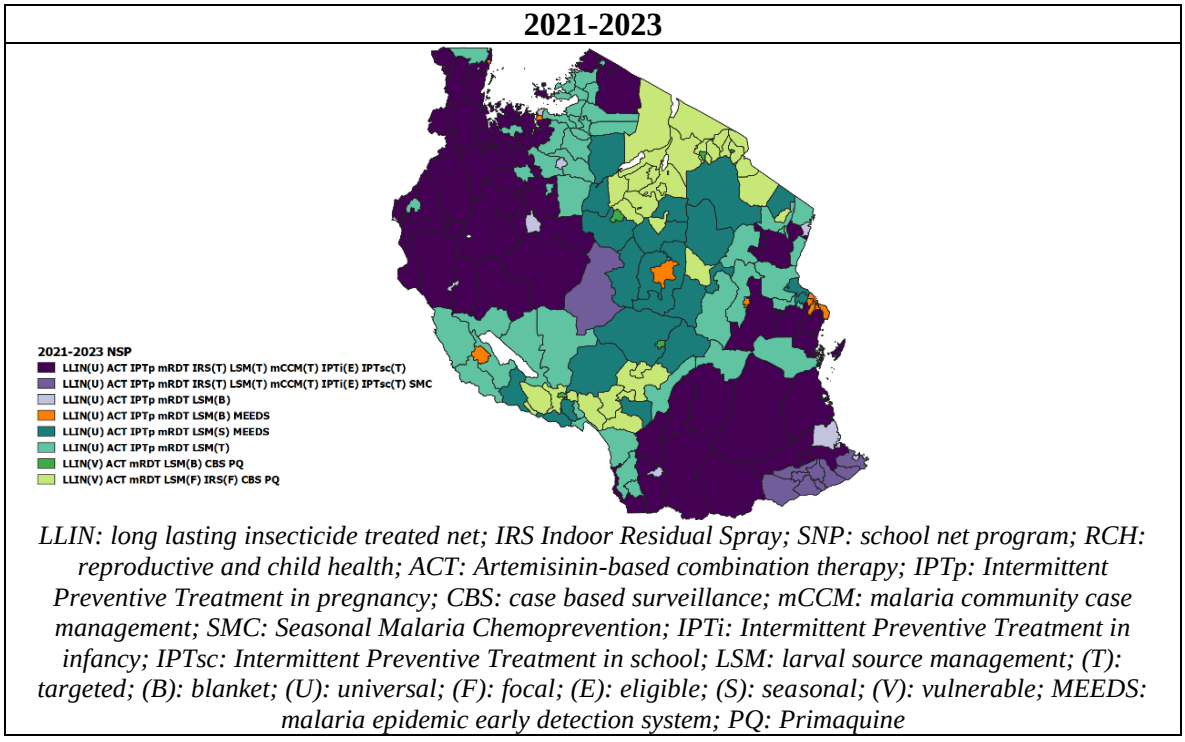
Targeting combinations of interventions based on local epidemiological criteria, whilst referenced in previous NMSPs, had never been formally established in mainland Tanzania until 2018. This requires a data-driven approach, maximizing survey and routine data to establish epidemiological strata at operational units of programme delivery. The strategic phase of 2015-2020 represented an important milestone for mainland Tanzania as it demonstrated the formal use of empirical data from routine and survey sources to extensively describe the malaria risk situation and use it for strategic reorientation.



LLIN: long lasting insecticide treated net; MRC: mass replacement campaign; mRDT: Malaria rapid diagnostic test; RCH: reproductive and child health; RCH: reproductive and child health; ACT: Artemisinin-based combination therapy, IPTp: Intermittent Preventive Treatment in pregnancy; IRS Indoor Residual Spray; SNP: school net programme; CBS: case based surveillance; mCCM: malaria community case management; SMC: Seasonal Malaria Chemoprevention; IPTi: Intermittent Preventive Treatment in infancy; IPTisc Intermittent Preventive Treatment in school

Figure 1.16: The reorientation of malaria strategies from universal to tailored approach according to the epidemiological situation (National Malaria Control Programme, 2021)

The target of the current 2021-2025 NMSP is to reduce the average malaria prevalence in children aged less than 5 years (*Pf*PR$_{6\text{-}59\text{months}}$) from 7% in 2017 to less than 3.5% in 2025 (National Malaria Control Programme, 2021). The strategy fully embraces the operationalization and implementation of targeted malaria control approach at council level, that was conceptualized in the previous strategic plan period (Figure 1.17). The strategic plan has three strategic components (i) integrated malaria vector control; (ii) malaria diagnosis, treatment & preventive therapies, and; (iii) surveillance, monitoring & evaluation that are all supported by overarching supportive strategies: commodities and logistics management; social behavior change & advocacy, and programme management.



LLIN: long lasting insecticide treated net; IRS Indoor Residual Spray; SNP: school net program; RCH: reproductive and child health; ACT: Artemisinin-based combination therapy; IPTp: Intermittent Preventive Treatment in pregnancy; CBS: case based surveillance; mCCM: malaria community case management; SMC: Seasonal Malaria Chemoprevention; IPTi: Intermittent Preventive Treatment in infancy; IPTsc: Intermittent Preventive Treatment in school; LSM: larval source management; (T): targeted; (B): blanket; (U): universal; (F): focal; (E): eligible; (S): seasonal; (V): vulnerable; MEEDS: malaria epidemic early detection system; PQ: Primaquine

Figure 1.17: The tailored interventions currently being implemented in mainland Tanzania (National Malaria Control Programme, 2021)

An important concept that is highlighted in this strategic plan is the country's ambition to shift some of the decision making processes towards a more decentralized malaria control approach. As the country implements a more targeted intervention approach, a move towards a granular micro-stratification at the ward level is being considered to account for the intra-council heterogeneity in malaria transmission. The work presented in Chapter 5 presents some of the work done to support the malaria program in aligning with this vision.

This PhD work focuses on some of the technical support that was provided to the NMCP in the form of developing risk maps using local surveillance data and that was used to support the reorientation and development of its strategic plan. The descriptions provided above in section 1.3.3 on the malaria surveillance systems available in the country provide a basis to understand the platforms in place within the country and sources of information used to support this work. The next section describes in detail some of the specific objectives undertaken to address this.

2 Aims and Objectives

This PhD focuses on all available epidemiological metrics of malaria surveillance from routine health information sources and their potential utility for accurately measuring sub-national malaria risk heterogeneity in time and space. This work represents the first national effort to understand combinations of country-owned epidemiological data from routine sources for conducting malaria stratification to support targeted intervention planning at different spatial resolutions.

Here, efforts towards better understanding of routine malaria data are undertaken to provide insights on the data processing needs, its quality and limitations and to highlight its potential for measuring transmission intensity at different spatial resolutions. Ways to identify suitable cut-offs for each of the routine metrics are also explored. In combination with interventions modelling (done outside the scope of this PhD thesis), the methodological framework developed is expected to guide the country in efficient resource allocations, and in conducting program evaluations. More importantly, the work emphasizes on the importance for continued efforts in strengthening surveillance systems to allow for enhanced usage of routine data to monitor risk and inform policies.

Following the launch of the HBHI initiative that calls for improvements in HMIS systems, the data from routine surveillance sources will become increasingly useful. Utilizing routine data is more pragmatic since it offers a cost-effective way of informing NMPs on their malaria situation and can be rapidly adopted for decision making without the need for sophisticated skills. With improving systems, an enormous opportunity exists to improve efficiencies of malaria funding by targeting specific malaria interventions to the places where these will have greatest impact.

Main Objective:

To develop a methodological approach for the use of routine malaria metrics for measuring transmission intensity and defining sub-national heterogeneity of malaria at different spatial resolutions.

Specific Objectives:

1. To understand the coverage, completeness and quality of malaria metrics from routine sources (mRDT TPR, API and ANC TPR) and explore an optimal approach to using these data for accurately estimating malaria transmission in mainland Tanzania.

2. Macro-stratification (Council level): To develop a robust methodology for malaria stratification at council level using routine indicators. The councils represent the administrative level for operationalization and management of most malaria prevention and control activities, and they serve as resource allocation units for central government support.

3. Micro-stratification (Ward level): To develop a methodology for malaria stratification at ward level using routine indicators and explore robust ways to develop suitable cut-offs for the routine indicators. As countries move towards implementation of targeted packages, a more granular micro-stratification of malaria risk will become increasingly valuable in informing council health managers about the malaria situation in their respective subunits (wards), and thereby support an evidence-based decentralized malaria control planning and implementation.

4. To use geospatial modelling approaches to leverage available routine information to predict risk in areas without information as well as quantify the associated levels of uncertainty. One of the challenges of using HF data at the granular level of the ward is the incomplete nature of information in space and time, resulting in lower level administrative units without empirical data. To overcome sparsity of data, geo-spatial models can be a useful tool for filling these gaps. Specifically, the TPR, a robust index of malaria transmission, was used as an example.

Thesis Outline

The following sections of the thesis begin with first describing the outputs from key informant interviews that were conducted amongst various stakeholders to gain an understanding of the approaches being undertaken to process routine HF data and address the associated data quality

issues for analytical purpose (Chapter 3). This is followed by Chapter 4 that describes the methodology undertaken to support the NMCP with producing council-level macro-stratification risk maps to support a tailored malaria control approach. Chapter 5 extends the analytics further to the ward level to develop micro-stratification risk map to account for the intra-council heterogeneity. Finally, Chapter 6 describes the geo-spatial modelling approach taken to complement the micro-stratification efforts and account for the spatial and temporal gaps and predict the risk for all wards in the country. Each of the chapter corresponds to the sequence of the specific objectives described above.

3 Addressing Data Quality Issues of Routine Health Facility Data

Sumaiyya G. Thawer[1,2*], Branwen Nia Owen[1,2], Monica Golumbeanu[1,2], Christian Lengeler[1,2], Fabrizio Molteni[1,2], Emilie Pothin[1,2,3]

[1] Swiss Tropical and Public Health Institute, Allschwil, Switzerland

[2] University of Basel, Basel, Switzerland

[3] Clinton Health Access Initiative, New York, USA

*Corresponding author:

Sumaiyya G. Thawer, sumaiyya.thawer@swisstph.ch

Perspective piece – Draft version, to be submitted to American journal of tropical medicine and hygiene – Surveillance as a core malaria intervention, supplemental issue

3.1 Abstract

The availability and access to malaria parasitological diagnosis at health facilities (HF), coupled with the adoption of the district health information system (DHIS2), has greatly strengthened the value of routine data. The emphasis in the WHO's Global Technical Strategy 2016-2020 and the High Burden for High Impact initiative for the increased usage of quality routine data to support tailored malaria control approach, is likely to further increase its usage. Data quality checks are precursor to reliable analysis. These quality checks should be seen at two levels: (i) HF level for the purpose of improving data capturing and reporting; (ii) central level for the purpose of analysis to inform policies. While detailed guidelines exist for the former, there are no such guidelines on how to process and systematically handle aggregated routine data biases such as inconsistencies, outliers and missing values. Key informant interviews were thus conducted amongst various stakeholders in 2020 to understand the current approaches taken for HF data processing and cleaning, and assess whether a harmonized approach was needed to address common challenges. The interviews highlighted varying methodological approaches being undertaken depending on the objective of the analysis and recommended the need for developing guidelines addressing gaps in routine data and for handling such data in a systematic manner. This is essential for increasing confidence in the data, increase the usage of routine data for decision making, and generally enhanced harmonization in the approaches taken.

Keywords: Malaria, Routine data, Data Quality

3.2 Background

The use of accurate and timely routine data for tracking the changes in malaria epidemiology, is a major pillar of the WHO's Global Technical Strategy (GTS) 2016-2030; placing surveillance as a core intervention (World Health Organization, 2015c). The WHO's High Burden for High Impact (HBHI) initiative further builds on the principles of the GTS framework and re-emphasizes the use of data to shift away from a "one size fits all" to a more tailored malaria control approach to accelerate progress against malaria (World Health Organization, 2018a). Countries are called upon to use all available health information to stratify the malaria burden in order to deploy effective malaria control tools to areas in greatest need and maximize impact and efficiency (World Health Organization, 2018a).

Nationally owned routine surveillance systems can provide near real-time and granular data in time and space for stratifying malaria risk, tracking progress and supporting effective allocation of targeted interventions. However, data from these sources are underused due to concerns over completeness, quality and its representativeness (Rowe et al., 2009). As a result, the diversity of Africa's malaria burden has relied on the use of geospatial modelling of parasite prevalence and opportunistic, and often dated survey malaria data (Bhatt et al., 2015; Gething et al., 2011b; Noor et al., 2014; Weiss et al., 2019). These models have guided international priority setting, but at fine scales, can misrepresent trajectories in malaria risk (Kamau et al., 2020b). Current approaches by the WHO to estimate malaria burden in 30 countries of Africa involve using modelled prevalence predictions and transforming them into incidence estimates through a modelled non-linear relationship (Alegana et al., 2020; Cameron et al., 2015). However, the ultimate goal is for all countries to provide reliable and accurate routine data to avoid heavy reliance on modelled estimates.

Routine data are increasingly being used. Several factors contribute to this increase: i. the launch of the WHO universal test, treat and track initiative in 2012 (World Health Organization, 2012a) that has significantly improved testing rates, ii. the digitization of the Health management information system (HMIS) under the district health information system (DHIS2) system that has improved RRs, iii. the emphasis that the GTS and HBHI initiatives place on using data for decision-making, and iv. the recent efforts towards implementing continuous data quality audits and surveillance assessments (World Health Organization,

2017b, 2017c, 2022b). Several studies have compared measures from routine sources against community prevalence to highlight the representativeness of these indicators (Brunner et al., 2019; Kamau et al., 2020b; Kigozi et al., 2019; Kitojo et al., 2019). Additionally, methodological frameworks have been proposed for the use of routine datasets to evaluate the impact of malaria control programs (Ashton et al., 2017; Bennett et al., 2014) and geo-spatial modelling strategies have also used routine data for stratifying the malaria risk (Alegana et al., 2016; Odhiambo et al., 2020; Sturrock et al., 2014) and using the resulting malaria risk maps for guiding tailored malaria control approach (Thawer et al., 2020, Runge et al., 2022). All further highlight the potential value of using routine data. Continuing efforts for strengthening surveillance-response systems and capacity to generate quality routine data at national and sub-national levels remains one of the most effective ways for countries to continue their trajectory towards malaria elimination (Tambo et al., 2014).

The increased use of routine data by many programs including malaria and HIV for decision-making calls for high quality and reliable data. Routine data quality checks can be seen to fall into two categories, determined by the objectives of data use. The first are checks conducted at the health facility (HF) level to ensure that data is captured and reported as accurately as possible. Current guidelines by the WHO recommend assessing four core dimensions for understanding the quality of routine data. These include completeness and timeliness of data, internal consistency of reported data (presence of outliers, consistency over time and consistency between data elements), external consistency with other data sources and external comparison with population data (World Health Organization, 2017c). The second category of quality checks are conducted at a more central level. This type of data check is conducted on aggregated routine data for performing analysis to inform decisions. It comprises of approaches for data cleaning in order to handle biases such as outliers and missing values that may be present in routine data in order to produce reliable outputs from the analysis. There are currently minimal guidelines on how to conduct such checks. The WHO guidance on analysis and use of HF data for program managers (World Health Organization, 2018c) provides a useful framework to perform both a desk review and HF survey/ data quality audits to assess and understand the system producing the data and the quality of the data being fed into the HMIS/DHIS2. However, it does not provide sufficient practical guidance on suggestive methods that can be used to handle the existing data quality issues for analytical purpose.

Aiming to understand the current approaches taken to clean routine data, and to assess the need for a harmonized approach to handling commonly encountered problems, key informant interviews were therefore conducted with various stakeholders working on routine data from July-August 2020. Stakeholders included staff from national malaria control programs (NMCPs) and implementing partners providing technical support to malaria-endemic countries. Specifically, we sought to understand which methodologies they used for data cleaning, the level at which the cleaning was undertaken, and how they identified and handled outliers and missing data. The following sections summarize the key findings from the key informant interviews under broad sub-themes.

Data processing and administrative level of data cleaning

Approaches varied and were shaped by the spatial level of the data accessible and the objectives of the analysis. Baseline steps identified included; checking for duplicate monthly reports, checking for inconsistencies in the variables of interest, differentiating zero from missing values, assessing reporting completeness and checking for outliers.

Stakeholders with access to HF level data were able to conduct more comprehensive data cleaning compared to stakeholders with access only to aggregated data available at higher administrative units. Most in-country implementing partners reported having mainly access to monthly routine data aggregated to district levels as provided by malaria programs. However, aggregated data can mask any underlying data quality issues thereby limiting the understanding of the true characteristics of the data.

Inaccurate data

Stakeholders described several types of data inaccuracies. These included inconsistent data, outliers and missing data. Inconsistent data were mainly detected through logical checks in the data such as checking if the total tested for malaria were greater than those attended or those tested positive were greater than total tested. Other errant data such as mismatch between registers and records could not be easily detected from central levels and requires HF data quality audits.

Outliers were most frequently detected through exploratory analysis and visual inspection of the trends at higher aggregated levels of the district to arbitrarily guide detection. Disaggregating the malaria cases by age and inspecting the ratios of all age confirmed malaria cases to that in under 5 years of age to detect skewed ratios was another reported approach. For stakeholders with access to HF level data, more systematic approaches were possible. These included HF by HF trend inspection, modified Z scores, fitting a time series model on monthly data for each HF and detecting values that were outside specific thresholds of the confidence intervals, and using the *Anomalize* package in R (Dancho and Vaughan, 2020) that decomposes data and detects for any anomalies in the remainder component that fall beyond set bands of limits.

The handling of missing data also varied among stakeholders. These included treating outliers as missing values if unable to understand the data, fixing the outliers/ missing values using moving averages, communicating with the NMCP to understand possible reasons for outliers, using time-series regressions to replace outlier points and impute missing values, geo-spatial modelling techniques to impute in space and time and finally in-depth cleaning by revisiting individual HF registers.

Geo-coding of health facilities

An essential element highlighted during the interviews was the need to consider HF representation in the HMIS/DHIS2 system. Ideally, the DHIS2 should represent information from all health-care providers, however this is often not the case in many countries, with a large proportion of HFs missing in the DHIS2. Having updated lists of health providers and their geo-coded information would facilitate understanding of true reporting completeness, and allow for more correct quantification of risks at finer spatial scales.

Age disaggregation in HMIS/DHIS2

An important limitation raised about the HMIS/DHIS2 was the age disaggregation of routine data. Currently, the data is reported by age groups above and below 5 years, limiting the ability to understand malaria morbidity across different age groups. Although the highest burden of malaria occurs in children under 5 years, various studies have reported a shift in burden to children older than 5 years following implementation of malaria control interventions

(Coulibaly et al., 2021; Kigozi et al., 2020a). Concerns over the need for introducing more age bands in the data collection tools in HMIS/DHIS2 were raised.

Indicator definitions and denominator population in DHIS2

Some recurring issues raised when working with indicators under the DHIS2 across several countries was the lack of a data dictionary and changes in the indicator definitions and/or collection making it difficult to compare and monitor metrics over time. Some of these changes may have occurred in response to policy changes to provide improvements, such as, introduction of malaria testing guidelines to reduce presumptive malaria cases, changes in clinical definition of cases and digitization of HMIS under DHIS2 that has gradually improved reporting rates (RRs).

Another issue raised was the lack of denominator populations in the HMIS/DHIS2 from which the cases arise that largely limits the computation of several malaria metrics. For instance, the lack of defined HF catchment population makes it difficult to compute incidence and interpret morbidity trends at HF level. These boundaries need to be informed by HF utilization behaviors, accessibility to HFs, and competition between health providers. However, such data are rarely available at the finer spatial resolutions (Alegana et al., 2020; Macharia et al., 2021). The utility of test positivity rate as a malaria transmission indicator is limited by many countries not capturing information on suspected fever cases, which is the crucial denominator to understand HF testing rates.

Data adjustments for analysis

Depending on the objective of the analysis, various adjustments were applied to the routine data to account for important factors. For crude routine data to provide accurate malaria estimates, all community fever cases should ideally reach HFs and be accurately captured within the DHIS2 (Alegana et al., 2020). However, this is not the case. The use of crude routine data does not account for factors such as treatment seeking rates, incomplete reporting, health utilization behaviors, temporal and spatial missingness in data, the underlying heterogeneous distribution of the population and the differing testing rates between transmission settings, which can potentially under/over-estimate malaria risk. This necessitated adjusting the data to account for some of these factors. Some of the reported adjustments included applying

population weights, adjusting for outpatient attendance to factor for the size of the HF, adjusting for HF RRs and adjusting for treatment seeking rates. The use of geo-spatial modelling also allowed to account for the associated uncertainties in routine data estimates and for any spatial and temporal autocorrelations.

3.3 Recommendations

We found that methodological approaches to cleaning of routine data are varied and depend largely on the objectives of the analysis and level of data aggregation available. The current WHO guidelines provides a useful benchmark for guiding countries on assessing data quality at sub-national levels and triggering appropriate response for improving data capturing and reporting. However, detailed guidelines on how to process existing routine data at centralized levels in a systematic manner for analytical purpose are needed. Addressing commonly encountered challenges when handling routine data from DHIS2 such as poor RRs, varying testing rates, missing values, presence of outliers and suggesting methodologies to deal with them will inform programs on how to better handle routine data for decision-making, increase confidence in the analytical outputs, and enhance harmonization in approaches taken between countries.

These efforts need to be complemented with strengthening analytical capacity at different levels of health systems to build a culture of data usage for decision-making and thereby support a country-owned approach to sustaining malaria control and elimination efforts. Data cleaning and processing should be conducted by or with those close to the data with an understanding of the local contexts.

3.4 Additional Information

3.4.1 Author Contributions

SGT and EP conceptualized the methodological analysis and conducted the interviews. SGT, EP and BO prepared the initial draft manuscript and its finalization. SGT, EP, BO, MG, FM and CL provided critical comments on progressive drafts. All authors reviewed and approved of the final manuscript.

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3.4.3 Competing Interest

The authors declare that they have no competing interests.

3.4.4 Funding

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4 Sub-national Stratification of Malaria Risk in Mainland Tanzania: a Simplified Assembly of Survey and Routine Data

Sumaiyya G. Thawer[1,2]*, Frank Chacky[3,4], Manuela Runge[1,2], Erik Reaves[5], Renata Mandike[3,4], Samwel Lazaro[3,4], Sigsbert Mkude[1], Susan F. Rumisha[6], Claud Kumalija[3], Christian Lengeler[1,2], Ally Mohamed[3,4], Emilie Pothin[1,2,7], Robert W. Snow[8,9¶], Fabrizio Molteni[1,4¶]*

[1]Swiss Tropical and Public Health Institute, Basel, Switzerland

[2] University of Basel, Basel, Switzerland

[3] Ministry of Health, Community Development, Gender, Elderly, and Children, Dodoma, Tanzania

[4] National Malaria Control Programme, Dodoma, Tanzania

[5] Malaria Branch, Division of Parasitic Diseases and Malaria, Centers for Disease Control and Prevention, and US President's Malaria Initiative, Dar es Salaam, United Republic of Tanzania

[6] National Institute for Medical Research, Dar es Salaam, Tanzania

[7]Clinton Health Access Initiative, New York, USA

[8] KEMRI-Welcome Trust Research Programme, Nairobi, Kenya

[9] Centre for Tropical Medicine and Global Health, Nuffield Department of Clinical Medicine, University of Oxford, Oxford, UK

[¶] Joint senior authors

*Corresponding authors:

Fabrizio Molteni, fabrizio.molteni@netcell.org

Sumaiyya G. Thawer, sumaiyya.thawer@swisstph.ch

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4.1 Abstract

Background

Recent malaria control efforts in mainland Tanzania have led to progressive changes in the prevalence of malaria infection in children, from 18.1% (2008) to 7.3% (2017). As the landscape of malaria transmission changes, a sub-national stratification becomes crucial for optimized cost-effective implementation of interventions. This paper describes the processes, data and outputs of the approach used to produce a simplified, pragmatic malaria risk stratification of 184 councils in mainland Tanzania.

Methods

Assemblies of annual parasite incidence and fever test positivity rate for the period 2016-2017 as well as confirmed malaria incidence and malaria positivity in pregnant women for the period 2015-2017 were obtained from routine district health information software. In addition, parasite prevalence in school children (*Pf*PR_{5to16}) were obtained from the two latest biennial council representative school malaria parasitaemia surveys, 2014-15 and 2017. The *Pf*PR_{5to16} served as a guide to set appropriate cut-offs for the other indicators. For each indicator, the maximum value from the past three years was used to allocate councils to one of four risk groups: very low (<1%*Pf*PR_{5to16}), low (1-<5%*Pf*PR_{5to16}), moderate (5-<30%*Pf*PR_{5to16}) and high (≥30%*Pf*PR_{5to16}). Scores were assigned to each risk group per indicator per council and the total score was used to determine the overall risk strata of all councils.

Results

Out of 184 councils, 28 were in the very low stratum (12% of the population), 34 in the low stratum (28% of population), 49 in the moderate stratum (23% of population) and 73 in the high stratum (37% of population). Geographically, most of the councils in the low and very low strata were situated in the central corridor running from the north-east to south-west parts of the country, whilst the areas in the moderate to high strata were situated in the north-west and south-east regions.

Conclusion

A stratification approach based on multiple routine and survey malaria information was developed. This pragmatic approach can be rapidly reproduced without the use of sophisticated statistical methods, hence, lies within the scope of national malaria programmes across Africa.

Keywords: Malaria, epidemiological stratification, routine data, school surveys, Tanzania

4.2 Background

Since 2000, there has been an unprecedented increase in funding to support the coverage of malaria interventions across Africa (World Health Organization, 2019). This renewed commitment translated into a reduction in the prevalence of malaria infection and disease burden in many parts of Africa (Snow et al., 2017; World Health Organization, 2019). However, in recent years, progress has stalled (Snow et al., 2017; World Health Organization, 2019). Ten countries in Africa currently account for 66% of the global malaria disease burden (World Health Organization, 2018a), despite increases in the distribution of effective vector control and disease management strategies. Further increases in international donor assistance are unlikely and a new model of improving investment efficiencies is required to maximize the benefits of interventions in areas likely to achieve the largest disease burden reductions. The World Health Organization (WHO) Global Technical Strategy (GTS) for malaria 2016–2030 revisited an old paradigm of stratifying sub-national malaria burden based on the analysis of past and contemporary malaria data, risk factors and the environment (World Health Organization, 2015c). A major pillar of the GTS 2016-2030 is the use of accurate and timely routine data for tracking the changes in malaria epidemiology.

Since the launch of the WHO "T3" (Test, Treat, Track) initiative in 2012 (World Health Organization, 2012a), many African countries have increased testing rates at health facilities (HFs) and are now able to provide data on malaria parasitological diagnosis performed through microscopy or malaria rapid diagnostic testing (RDT) (Bastiaens et al., 2014). Furthermore, countries have initiated efforts to improve their Health Management Information System (HMIS) system using the open source web-based software known as the District Health Information Software (DHIS2). Adoption of this software in many countries has facilitated the availability and access to routine malaria parasitological diagnosis data generated from HFs which has strengthened the utilization of such data for malaria risk mapping and evaluations of intervention programmes.

Since the 1960s, the epidemiology of malaria in mainland Tanzania has been mainly described through the length of the malaria transmission seasons, urbanization, altitude and community-based parasite prevalence (National Malaria Control Programme, 2014, 2008, 2002). All have highlighted the extreme diversity in the potential, and empirically defined malaria transmission intensity, within the country's borders. A more recent assembly of ten years of community- and school-survey parasite prevalence data was used within a model-based geospatial framework to empirically highlight the heterogeneous nature of sub-national malaria transmission intensity (Chacky et al., 2018; National Malaria Control Programme, 2013; Runge et al., 2020b), and used to describe the country's epidemiological profile in the 2015-2020 National Malaria Strategic Plan (NMSP) (National Malaria Control Programme, 2014). However, these statistical models of opportunistic research data, or under-powered national household sample health surveys, provide only one means to define variations in malaria prevalence. To-date, other data, notably those generated from routine health information systems, have been underutilized and the use of epidemiological evidence to tailor sub-national malaria intervention strategies has been limited. These approaches should be data-driven, using all available routine and survey information and the stratification should be country-led (World Health Organization, 2018a; Ye and Andrada, 2020).

Since the launch of the Roll Back Malaria (RBM) initiative in 1998, the National Malaria Control Programme (NMCP) of mainland Tanzania has developed three, five-year NMSPs (National Malaria Control Programme, 2014, 2008, 2002). The third NMSP covered the period 2015-2020 (National Malaria Control Programme, 2014) and aimed to reduce the national malaria prevalence from 10% in 2012 to 5% in 2017 and further to less than 1% by 2020. The initial ambition of the strategy was to sustain progress and achievements through a universal coverage of existing interventions; and during the second phase (2018 to 2020), to consolidate these achievements and explore the feasibility of a malaria pre-elimination in defined areas of the country (National Malaria Control Programme, 2014).

Although progress was made towards reducing national parasite prevalence from 18% in 2008 (Ministry of Health et al., 2008) to 7% in 2017 (Ministry of Health et al., 2017), a mid-term review (MTR) in 2017 (National Malaria Control Programme, 2017b) recognized that a more strategic allocation of limited resources was needed to ensure continued progress in the future.

The MTR was followed by a consultative meeting with global and national malaria experts (National Malaria Control Programme, 2018a, 2018b). Recommendations from this forum together in concert with the GTS 2016-2020 (World Health Organization, 2015c), reiterated the need to consider tailoring intervention approaches to the sub-national local context, based on epidemiological stratification. To establish epidemiological strata at operational units of programme delivery (councils), a data-driven approach was required, that maximizes the use of survey and routine data. This paper provides an outline of the methods used to assemble infection prevalence and other malaria indicators from routine data to develop a sub-national epidemiological stratification for mainland Tanzania's 184 councils. This paper presents the first documentation of a national effort to combine multiple epidemiological indicators from different data sources to form a composite risk stratification. The process of policy development (Runge et al., 2020a) and the allocation of interventions (National Malaria Control Programme, 2018a) following development of this malaria risk stratification are presented elsewhere.

4.3 Methods

4.3.1 Administrative boundaries and populations at risk

In 2016, mainland Tanzania revised the administrative boundaries to 26 regions and 184 councils (National Bureau of Statistics, 2016a) (See Supplementary Figure S4.1, Supplementary Information). The councils represent the administrative level for operationalization and management of disease prevention and control activities and serve as resource allocation units for central government support. Councils are categorized according to population settings; 137 are rural and 47 are urban councils consisting of three types of urban authorities; city, municipal and town councils (Local Government, 1982; National Bureau of Statistics, 2016a).

The population at risk was obtained from the publicly available 2012 population and housing census in Tanzania conducted by the national bureau of statistics. Information on the population is provided by ward, the most granular level (5th administrative level), and by age and gender (National Bureau of Statistics, 2013). Population data from census conducted in 2002 and 2012 were reconstructed to the 184 councils (National Bureau of Statistics, 2016a)

and projected for the period 2015-2017 using council annual growth rates computed from the average annual continuous growth rate formula.

4.3.2 Data assembly and description of data sources

4.3.2.1 Survey data: school malaria parasitaemia surveys (SMPS)

In mainland Tanzania, nationwide SMPS, targeting public primary school children aged 5-16 years, were conducted in 2014-15 and 2017. During this period, estimates of infection prevalence were available from a total of 711 sampled schools and 115,992 children (See Supplementary Figure S4.2, Supplementary Information). The survey includes malaria rapid diagnostic testing (RDT) and provides information on parasite prevalence representative at the council level (Chacky et al., 2018).

4.3.2.2 Routine data: health facility data from HMIS/DHIS2

In 2009, the Ministry of Health, Community Development, Gender, Elderly and Children (MoHCDGEC) piloted a monitoring and evaluation (M&E) strengthening initiative to improve the HMIS, migrating from paper-based system to using the electronic DHIS2 system. DHIS2 is an open source web-based software platform for reporting, analyzing, and dissemination of data for health programmes which can be accessed by officials at all levels of health care delivery including health facility (HF), council, regional, and national levels through registered credentials. Each month, health facilities provide monthly summary reports with data that are entered into DHIS2. Since its inception in 2013, the reporting rates (RRs) from operational HFs (Supplementary Figure S4.3, Supplementary Information) have improved dramatically with current RRs from Out-Patient Department (OPD) over 90%.

A focal member from the NMCP continuously engages with the M&E technical working group of the MoHCDGC to expand efforts in improving data quality through quality assurance supervisions. Additionally, the NMCP in consultation with the University of Dar es Salaam have developed an electronic platform of all available malaria data within DHIS2: the NMCP interactive malaria dashboard. The dashboard facilitates the visualization, interpretation and use of all malaria related information in the DHIS2 platform and the production of quarterly malaria bulletins for dissemination at regional, council and HF levels.

Based on the recommendations from WHO (World Health Organization, 2018b), as well as consideration of the availability, frequency and robustness of malaria data, the following four routinely collected malaria indicators were selected to conduct the stratification: 1) fever test positivity rate (TPR), 2) annual parasite incidence (API), 3) confirmed malaria incidence and 4) malaria positivity rate in pregnant women.

Fever test positivity rate (TPR)

Monthly laboratory testing reporting tools were introduced in HFs in October 2015 to capture the number of malaria tests performed. The RDTs were introduced in mainland Tanzania in 2009 in several rolled-out phases before country wide scale up was achieved in 2013. Currently, RDTs are the most common diagnostic tool with only a small proportion of HFs, mainly private HFs, that still use microscopy to detect malaria infections. Fever TPR was defined as the proportion of the total number of positive malaria tests among all malaria tests performed in all age groups by *Pf*-Pan RDT and reported by HF laboratories. The denominator was obtained by summing the number of test positive and test negative results across all age groups. For stratification, data for the period 2016 to 2017 were used.

Annual parasite incidence from laboratory (API)

API is one of the core indicators recommended by WHO to be used for malaria risk stratification (World Health Organization et al., 2017). API presents the advantage of being easily available from the routine systems in an inexpensive manner. The API was defined as the total number of all positive malaria tests, among all malaria tests performed across all age groups by *Pf*-Pan RDT or microscopy at HF laboratories per 1,000 projected population per council in 2016 and 2017.

Confirmed malaria incidence from OPD

Ideally, the case incidence per 1,000 population from OPD registers should correspond to the API calculated from the laboratory register. However, since the laboratory reporting tools (Monthly summary reports of the laboratory register) were only introduced in October 2015, overall laboratory RRs of HFs in 2016 was only 49.6%. Therefore, this indicator was also considered in order to account for the low RRs of the monthly laboratory reports in 2016. Confirmed malaria incidence was calculated using data obtained from the OPD registers via

the DHIS2 system. This included all cases diagnosed as malaria using *Pf*-Pan RDT or microscopy. The incidence from OPD was defined as the total number of confirmed malaria cases across all age groups per 1,000 projected council population per year for the period 2015, 2016 and 2017.

Test positivity rate from antenatal care clinics (ANC)

Malaria testing by RDT among pregnant women attending their first visit at ANC clinics was implemented in mainland Tanzania in mid-2013 and integrated into the routine HMIS (Brunner et al., 2019; Kitojo et al., 2019; Willilo et al., 2016). Tanzania is the only country in Africa to have implemented routine ANC malaria testing for surveillance. ANC TPR was defined as the proportion of the total number of positive malaria tests among all malaria tests performed by *Pf*-pan RDT for women attending their first ANC visit. Data used for the stratification process were obtained for the complete years 2015, 2016 and 2017.

4.3.3 Data processing and cleaning

Data from the SMPS required no further processing since the average prevalence per council was used. For all indicators from the HFs, data were downloaded from DHIS2. In this analysis, the completeness for reporting was defined as the number of HF monthly reports received out of the expected number of HF monthly reports. The operational status of the HFs during the observation period was assumed to remain constant. All reports from HFs that were duplicated and HFs with no testing performed in all reporting months were excluded from the analysis. As the DHIS2 database is unable to distinguish zeros from missing values since it marks them as blank, it was assumed that missing values of otherwise complete reports were true zeros. Therefore, when the reporting variable indicated successful form submission, missing values of numerical variables were replaced with zero. The data utilized for stratification covered different years of completeness and coverage as summarized in Table 4.1.

Table 4.1: Indicators used for malaria risk stratification

Source	Indicator	Numerator	Denominator	Period*	Age
SMPS	Parasite prevalence	No. positive *Pf*-pan RDT	No. *Pf*-Pan RDT tests performed in school children	2015, 2017	5–16 years
HMIS/ DHIS2	**Laboratory**				
	Fever Test Positivity Rate	No. positive *Pf*-pan RDT	No. *Pf*-Pan RDT tests performed	2016–2017	All ages
	Annual Parasite Incidence	No. positive *Pf*-pan RDT and microscopy	Per 1,000 population[α]		
	Outpatient Department				
	Confirmed Malaria Incidence	No. positive *Pf*-pan RDT, and microscopy	Per 1,000 population[α]	2015–2017	All ages
	Antenatal Clinic				
	Test Positivity Rate	No. positive *Pf*-pan RDT	No. *Pf*-Pan RDT tests performed in pregnant women at first visit	2015–2017	Reproductive Age

*January 1st to December 31st of the corresponding year; αBased on population estimates from the 2012 census; HMIS=Health Management Information System; DHIS2=District Health Information System 2; RDT=malaria Rapid Diagnostic Test; *Pf=Plasmodium falciparum*; SMPS= School Malaria Parasitaemia Survey

Microsoft Excel was used for cleaning and analysis of the data downloaded from DHIS2 as well as for conducting the stratification. Stratified maps were produced using QGIS software version 3.0.3 (QGIS, 2019).

4.3.4 Stratification

The stratification process included three major processes: 1) indicators were classified according to cut-offs defined; 2) each indicator was categorized into risk groups according to the determined cut-offs and scores assigned to each risk group; 3) the scores were summed per council across indicators, to obtain a combined measure that assigns the councils to the overall risk strata.

4.3.4.1 Classification definition of indicators

During the 1960s, various malariometric criteria were used to define geographical areas that should prepare for a pre-elimination stage, when community-based parasite prevalence (*Pf*PR) was consistently below 2-3% (Hay et al., 2008). With time, this included indicators based on the prevalence of infections in fevers below 5% (World Health Organization, 2014). The current international guidelines for malaria elimination remain unspecific on the precise criteria

for accelerating elimination efforts but define low transmission areas where community-based prevalence is between 1-10% and very low as below 1% (World Health Organization et al., 2017a). WHO classifications of higher transmission settings include a moderate group (*Pf*PR 10-35%) and high (*Pf*PR >35%) (World Health Organization et al., 2017a). These continue to be arbitrary because the precise relationship between rates of infection, disease outcomes and optimized intervention remain poorly defined (Snow and Marsh, 2002; Snow, 2014).

For the stratification in mainland Tanzania, the classification has retained both very low (*Pf*PR_{5-16} <1%) and high (adapted to be a *Pf*PR_{5-16} >30%). Within this range, two additional groups were considered: low (*Pf*PR_{5-16} 1-5%) which provides a pre-very low classification to mitigate against the risks of misclassifying very low areas (Noor et al., 2009a) and moderate prevalence (*Pf*PR_{5-16} 5-30%). There is far less historical evidence of appropriate criteria for the classification of fever infection prevalence and incidence, therefore the prevalence in school children was used to guide the setting of appropriate cut-offs for categorizing these indicators (Table 4.2).

4.3.4.2 Risk categorization and assignment of risk scores per indicator

In a second step, all indicators for each council were categorized and assigned a score from 1-4 corresponding to four groups "very low (1)", "low (2)", "moderate (3)" and "high (4)" according to the cut-offs defined in Table 4.2. A pragmatic, conservative approach was taken that used the maximum of the annual mean values across the reporting years for each indicator per council, to assign councils to one of four strata. The aim was to increase the inclusion of councils that potentially are still at a higher risk to the high stratum, that will receive more control efforts, while avoiding assigning these high-risk councils into strata of reduced control efforts that might lead to rebound effects. For the laboratory indicators; API and RDT TPR, all available data in the observation period 2016-17 were used. Since the overall laboratory RRs of HFs in 2016 was only 49.6%, the assigned scores to these indicators were reduced in weight by an arbitrary factor of 0.5 to account for the low RR.

4.3.4.3 Combination of indicators using scores

To obtain overall malaria risk by council, the sum of the assigned indicator scores was calculated. For each council, the resulting total score ranged from 4 (all indicators indicate

"very low" malaria risk) to 16 (all indicators indicate "high" malaria risk). The scale from 4 to 16 was subdivided into four categories to form the epidemiological strata. Specifically, councils with an overall score ≤6 were allocated to the very low stratum, >6 - ≤10 in the low stratum, >10 - ≤14 in moderate stratum and >14 in the high stratum (Table 4.2). In addition to these 4 epidemiological strata, urban councils were considered as a separate, non-epidemiological stratum with specific operational and intervention needs.

Table 4.2: Cut-offs used to categorize indicators into risk strata and scores assigned per epidemiological strata

Indicator*		Very Low	Low	Moderate	High
School Malaria Parasitaemia Survey					
Parasite prevalence	Prevalence Cut-off	<1	1-<5	5-<30	≥30
	Assigned Score	1	2	3	4
Laboratory					
Fever Test Positivity Rate	Prevalence Cut-off	<5	5-<15	15-<30	≥30
	Assigned Score	0.5	1	1.5	2
Annual Parasite Incidence	Prevalence Cut-off	<15	15-<75	75-<150	≥150
	Assigned Score	0.5	1	1.5	2
Outpatient Department					
Confirmed Malaria Incidence	Prevalence Cut-off	<15	15-<50	50-<150	≥150
	Assigned Score	1	2	3	4
Antenatal Clinic					
Test Positivity Rate	Prevalence Cut-off	<1	1-<3	3-<10	≥10
	Assigned Score	1	2	3	4

*For information on the period of data used for each indicator, See Table 4.1.

4.4 Results

4.4.1 Coverage and completeness

4.4.1.1 Survey data: SMPS

The SMPS was first conducted in 537 schools (49,169 school children) across 166 councils in 2014-2015 (Chacky et al., 2018) and this was increased to cover 629 schools (66,823 school children) in 2017 to accommodate the expansion of administrative boundaries to 184 councils in 2016. During this period, the maximum annual mean prevalence in councils ranged from 0.0% - 76.4% (Table 4.3; See Supplementary Table S4.1, Supplementary Information). Of the

184 councils, 33 (18%) had malaria prevalence <1.0%, whilst 80 (44%) councils had a high malaria prevalence ≥30.0%.

Table 4.3: Descriptive characteristics of the indicators used for malaria risk stratification

Parasite prevalence among school children (SMPS), 2015-17	
No. councils	184
No. schools*	1,166
No. children tested by *Pf*-Pan RDT	115,992
No. children with positive *Pf*-Pan RDT	21,382
Range of the maximum annual mean prevalence in councils (%)	0.0 - 76.4
Median prevalence (%)	20.9
Fever test positivity rate (TPR) from Laboratory, 2016-17	
No. councils	184
No. health facilities*	13,377
No. *Pf*-Pan RDT	22,848,520
No. positive *Pf*-Pan RDT	6,034,067
Range of the maximum annual mean prevalence in councils (%)	0.6 - 71.9
Median prevalence (%)	26.5
Annual parasite incidence (API) from Laboratory, 2016-17	
No. councils	184
No. health facilities*	13,377
No. positive results by *Pf*-Pan RDT and microscopy	8,049,426
Annual population (projected 2017)	50,503,670
Range of the maximum annual mean incidence per 1,000 population in councils	0.0 – 987.2
Median incidence per 1,000 population	88.6
Confirmed malaria incidence from OPD, 2015-17	
No. councils	184
No. health facilities*	21,644
No. confirmed cases by microscopy and *Pf*-Pan RDT in OPD	16,141,172
Annual population (projected 2017)	50,503,670
Range of the maximum of the annual mean incidence per 1,000 population in councils	1.2-603.1
Median incidence per 1,000 population	138.3
Test positivity rate from ANC, 2015-17	
No. councils	184
No. health facilities offering ANC services*	18,513
No. ANC clinics that tested women	18,147
No. pregnant women tested by *Pf*-pan RDT at first ANC visit	4,498,596
No. pregnant women with positive *Pf*-Pan RDT	321,836
Range of the maximum of the annual mean prevalence in councils (%)	0.1-29.2
Median prevalence (%)	8.8

**The number of facilities and schools are presented as the sum of all facilities/schools across the reporting years even if the same facility/school submitted data in the different years.*
SMPS=School Malaria Parasitaemia Survey; RDT=malaria Rapid Diagnostic Test; OPD=Out-patient Department; ANC=Antenatal Care.

4.4.1.2 Routine data: health facility data from HMIS/DHIS2

Table 4.3 summarizes the characteristics and coverage of the maximum annual mean values for the routine positivity rates and incidence indicators used for malaria stratification. In the period 2015-17, a total of 212,311 HF monthly reports were received from 6,437 HFs offering

ANC services resulting in an overall RR of 92% across the councils. During this period, the maximum annual mean malaria prevalence in pregnant women ranged from 0.1% - 29.2% across the 184 councils (Table 4.3; Supplementary Table S4.1, Supplementary Information).

Since the laboratory reporting tools were only introduced in HFs in October 2015, data from laboratory registers in 2016 was received from HFs in 178 councils, and by 2017, HFs in all 184 councils submitted laboratory reports. A total of 107,486 monthly reports were received from 7,188 HFs resulting in an overall RR of 62% during 2016-2017. Of the total malaria tests performed by both microscopy and *Pf*-pan RDT, 8,049,426 were positive for malaria, showing a marked range in the maximum annual mean API from 0.0 – 987.2 per 1,000 population per annum across the councils. During this period, the maximum annual mean fever RDT positivity rates ranged from 0.6% – 71.9% across the councils (Table 4.3; See Supplementary Table S4.1, Supplementary Information). Monthly numbers of confirmed malaria cases in OPD were obtained from 7,588 HFs across 184 councils in the period 2015-17. Of the 273,168 expected monthly HF OPD reports, 237,399 (87%) were received. During this observation period, there were a total of 16,141,172 cases of malaria reported from OPD resulting in the maximum annual mean malaria incidence ranging from 1.2 - 603.1 cases per 1,000 population (Table 4.3, See Supplementary Table S4.1, Supplementary Information).

4.4.2 Classification of indicators

Figure 4.1 shows the spatial distribution by council for the maximum of the average annual values for each of the malaria risk indicators for the period under review. Although variations exist between indicators in terms of the number of councils falling within each risk category, overall a similar pattern of heterogeneity was observed. The councils in the North-West and South-East regions were consistently categorized into the moderate to high-risk groups while the councils in the central corridor running from North-East to South-West were in the low and very low risk groups.

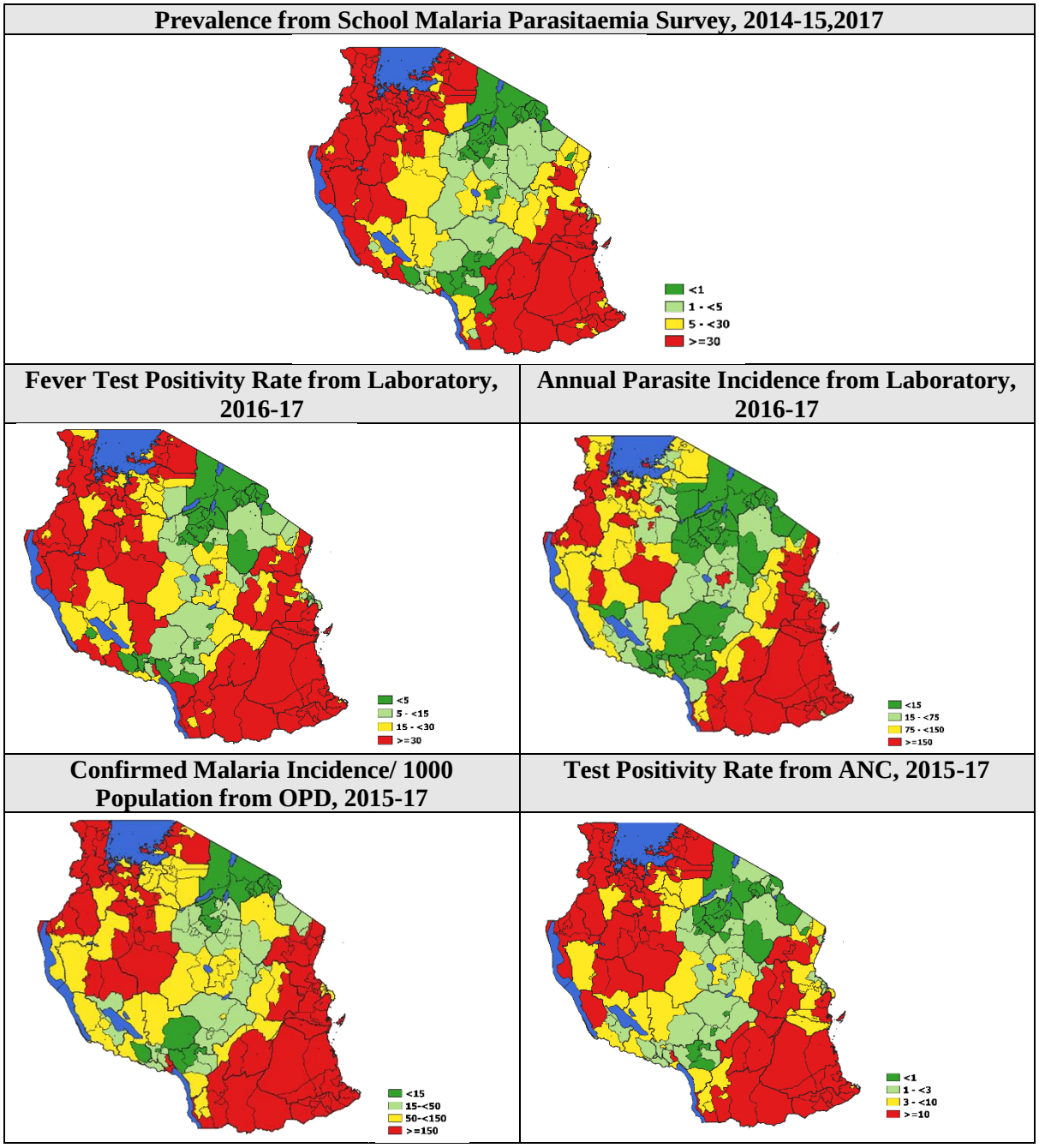
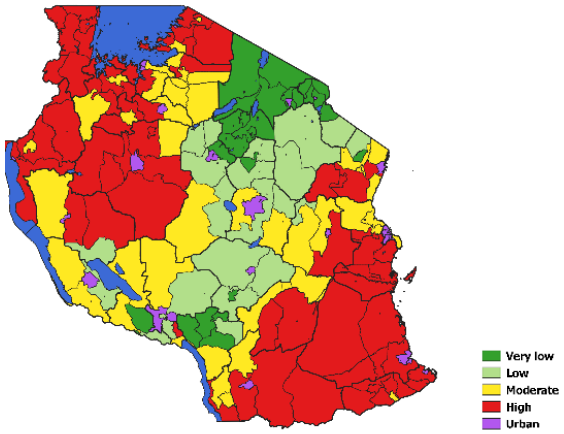


Figure 4.1: Spatial distribution by council of the maximum values of the mean annual malaria risk by type of indicator

4.4.3 Composite malaria risk stratification of councils

The final composite stratification map following the combination of the multiple malaria indicators is shown in Figure 4.2. In the overall malaria stratification map of mainland Tanzania, 12% of the population resided in the 28 councils allocated to the very low strata, 28% of the population were in the 34 councils allocated to the low strata, 23% of the population

resided in the 49 councils allocated in the moderate strata and 37% of the population resided in the 73 councils allocated to the high strata. Although all 25 urban councils were also assigned into one of the four strata, the urban councils were considered as an additional non-epidemiological stratum due to their specific operational and intervention needs (Figure 4.2).



Strata	No. councils	No. urban councils (municipal/city councils)*	Percent population
Very Low	28	2	12%
Low	34	11	28%
Moderate	49	8	23%
High	73	4	37%
Total	**184**	**25**	**100%**

Figure 4.2: Overall distribution of councils by risk strata using the maximum of the mean annual values.

**Urban councils in mainland Tanzania were considered as an additional non epidemiological stratum due to their specific operational and intervention needs.*

4.5 Discussion

This paper presents a novel approach to stratify malaria at sub-national level in mainland Tanzania, using a combination of routine malaria indicators from health facilities and school surveys. The resulting map stratified the burden into four epidemiological risk strata; very low, low, moderate and high plus one non-epidemiological stratum for urban councils. This was used to guide the malaria control programme in revising its malaria strategic plan in an evidence-based manner and in developing targeted intervention packages per strata (National Malaria Control Programme, 2018a).

There are many indicators of malaria risk that can represent sub-national heterogeneity. The precision and bias of each indicator, associated costs for collection and the level and frequency available to measure variability across space and time can affect the suitability of indicators to measure transmission (Tusting et al., 2014). Several studies have attempted to compare measures from routine sources against community prevalence to highlight the representativeness of these indicators (Brunner et al., 2019; Kigozi et al., 2019; Kitojo et al., 2019). However, evidence to suggest which indicator is most suitable to measure transmission is limited and a further understanding of how these vary across different transmission settings would help identify which indicators are most sensitive to council-level transmission strata and how these change over time.

While there are several approaches to malaria risk stratification that have been developed, there is no one specific approach recommended by the WHO. A review that looked at malaria risk maps developed during pre-GTS, across 47 countries (Omumbo et al., 2013) found that most countries rely on either API or infection rates for describing the malaria risks although a range of other indicators have also been used such as qualitative descriptions and climatic suitability. The current methodology presents a pragmatic approach that levers data from routine reporting and national survey data. Not limiting the stratification to only one data source enhances the best use of all available data, and the credibility/robustness of the resulting stratification. Importantly, through a detailed interrogation of routine data, it is possible to make reasoned council indicators to align with other survey data sources for sub-national level stratification, harnessing data from those that seek care at HFs, attend ANC and schools nationwide.

Notably, two of these indicators, the malaria prevalence in pregnant women (from ANC clinics) and among school aged children (from school surveys), not available in many countries, contributed a uniquely rich source of information into the stratification for mainland Tanzania. The high attendance rates of pregnant women at ANC makes them an easily accessible surveillance population to track malaria transmission intensity and provides a simple routine real-time measure of malaria prevalence at higher spatial and temporal resolutions than national household surveys (Mayor et al., 2019). Prevalence from ANC clinics shows a correlation with community-based childhood infection prevalence (Brunner et al., 2019; Kitojo et al., 2019; van Eijk et al., 2015) thereby serving as a good measure to reflect malaria trends in the community.

Community-based malaria parasite prevalence has been a benchmark measure of malaria endemicity since the 1950s (Hay et al., 2008; Metselaar and Van Thiel, 1959) and used in Tanzania as a milestone for controlling progress since 2000s (National Malaria Control Programme, 2002, 2008, 2014). Since survey data obtained from national household surveys are not powered to provide information below regional levels, school-based surveys provide a rapid, cheaper alternative to household sample surveys (Brooker et al., 2009; Nankabirwa et al., 2013) and have been used in several countries during the 1960s (Brooker et al., 2009; Snow and Noor, 2015) to establish national malaria risk profiles. Tanzania's investment into these two surveillance approaches was driven by the need for additional surveillance data as advocated by the GTS. While many countries do not conduct nationwide school surveys nor have a malaria surveillance established in ANC clinics, the basic principle of using other related data layers remains critical to developing a multilayered stratification. Countries might additionally include national household survey data, climatology or abiotic strata such as urban areas (as used in mainland Tanzania).

An important aspect to the methodology undertaken in mainland Tanzania is the simplicity of the design, without requiring complex modelling approaches often beyond the scope of those working within many national malaria programmes across Africa. The approach used was conservative, categorizing councils by their maximal risks over the past 2-3 years. Taking the maximum of multiple years' data is valuable in ensuring that unstable councils prone to rebound of prevalence were not misclassified into the lower strata which improves the validity of the stratification and exposes more councils to aggressive control interventions. Statistical uncertainty is an important concept in risk mapping (Giorgi et al., 2018), but hard to interpret for many control programmes, and such a maximal-conservative use of data is one approach to a public health criterion avoiding "doing harm" (Ye and Andrada, 2020).

The increasing availability of routine information from HFs via DHIS2 offers an attractive scope for analyzing continuous epidemiological trends over time and monitoring service delivery at a frequency and level that is not possible through the national representative household surveys (Bhattacharya et al., 2019). One of the most common criticisms for the use of HMIS data is the extent of the quality of the data reported through DHIS2, thereby leading to unreliable estimates of malaria risk (Rowe et al., 2009). However, as the reporting system in

countries continues to improve, particularly following the launch of the High Burden to High Impact (HBHI) initiative that calls for improvements in HMIS system, the data will become increasingly more reliable. Recent evidence demonstrates the utility of these data, despite their inherent imperfections, for programme evaluations (Ashton et al., 2017, 2019).

There are obvious limitations to the use of routine data that could be improved with the use of new tools and better statistical handling of incomplete data. In the present approach, data from all HFs were used, irrespective of their RRs. Table S4.2 (See Supplementary Table S4.2, Supplementary Information) shows how the proportion of HFs that can be included in the stratification varies depending on which threshold for reporting is applied. The influence on stratification when using only data from HFs with greater than 50% RRs is shown in Figure S4.4 (See Supplementary Figure S4.4, Supplementary Information). Applying a very strict criterion under which only data from HFs with complete reporting are included would mean that a small proportion of HFs could be included in the stratification. However, using a less stringent criterion, for example, including HFs with more than 50% reporting would increase the proportion of HFs that could be included in the stratification and was shown not to affect the overall strata allocation per council. Moreover, the arbitrary approach applied in setting appropriate cut-offs for classifying the routine indicators in to the four risk groups questions the robustness of this approach. Defining accurate risk groups is crucial in ensuring that all councils are designated the correct strata.

Future work might include using all data with appropriate spatial interpolation techniques between missing months and missing reporting facilities (Bennett et al., 2014) or consider the use of sentinel HF data with better RRs. Population distributions within councils are invariably uneven and assuming equivalent access to reporting HFs across a council could be improved with higher resolution population mapping, allowing for a more informed basis for HF-population catchments (Alegana et al., 2012). Furthermore, measures of incidence are influenced by a myriad of factors (Cibulskis et al., 2011). Novel techniques that adjust for treatment seeking behaviors have been developed and applied in malaria incidence estimation (Alegana et al., 2016), however, these require complex models and simpler council-level adjustments are required for who seeks treatment from where (Thwing et al., 2019). Exploring the correlation matrices of the various routine indicators with each other and how they compare

with community based prevalence is important in understanding the nature of the indicators in different transmission settings and defining robust and accurate thresholds for the classification.

Whilst the approach taken here has presumed equivalence between indicators, and a crude weighting applied to others (based on coverage), a more informed basis could be developed to maximize the relationships between indicators. In the absence of any formal guidelines to understand the representativeness, relatedness and appropriate cut-offs for individual strata, this is work planned over the next three years in mainland Tanzania. Meanwhile, the approach taken represents the most simplified means of handling multiple routine and survey composite data.

The stratification approach of mainland Tanzania served as a basis in guiding the malaria control programme in re-defining packages of interventions across the spectrum of malaria risk. No current guidelines exist as to which mix of interventions works best for which strata. In the absence of empirical evidence, using a data-driven approach guided by integration of impact modelling and expert recommendations, the country has developed the most suitable packages based on local context (Runge et al., 2020b). It is proposed to revise data inputs, approaches and strata every three years, as part of mid-term strategic reviews (National Malaria Control Programme, 2017b). With increasing completeness of data, improved methodologies, and a changing impact of revised intervention, the process of stratification becomes dynamic.

Central health planning of malaria control in mainland Tanzania considers the council as the primary unit for resource allocation and policy. As the country moves towards implementing a targeted malaria control approach, a more granular stratification of malaria risk at sub-council level will become increasingly valuable in informing council health managers about their malaria situation. The wards will represent as important planning units especially when transmission intensity declines and stratification at this level will thereby support an evidence-based decentralized malaria control planning and implementation in mainland Tanzania.

4.6 Conclusion

Mainland Tanzania has used a simple and novel methodological approach, combining multiple routine data sources with survey data for local, real-time monitoring of malaria risk at the council level. Whilst the data quality could still be further strengthened, it was sufficient to define and reflect the malaria risk heterogeneity across administrative boundaries. Using knowledge from multiple indicators of transmission increases confidence in stratification and allows for a baseline upon which the current national strategic plan might be judged.

4.7 Declarations

4.7.1 Acknowledgements

The authors would like to thank all the members of the National Malaria Control Programme, of the Ministry of Health, Community Development, Gender, Elderly and Children of mainland Tanzania, President's Office Regional Administration and Local Government offices, WHO country office and development partners: Swiss Agency for Development and Cooperation, U.S. President's Malaria initiative; for their participation and invaluable discussions during the strategic planning workshop held in Bagamoyo in May 2018. The authors also thank Rose Lusinde for providing mapping support. These contributions facilitated the development of the country's malaria risk stratification and subsequent Supplementary Mid-term Malaria Strategic Plan 2018-2020.

4.7.2 Authors' contributions

FM, SGT, FC and MR designed the methodological analysis. SGT compiled the data and performed the analysis. FM, RWS, AM, RM, SM, FC and MR provided input on the interpretation of the analysis. SGT with guidance from RWS and FM prepared the initial draft manuscript and it's finalization. RWS, FM, AM, RM, SM, ER, SR, FC, MR, CL, EP, CK and SL provided critical comments on progressive drafts. All authors reviewed and approved of the final manuscript.

4.7.3 Availability of data and materials

Data from routine HMIS/DHIS2 as well as those from the SMPS are not publicly available and were obtained with request from the National Malaria Control Programme of mainland

Tanzania. Restrictions apply to the availability of these data and permission can be obtained with reasonable request from the Ministry of Health, Community Development, Gender, Elderly and Children of mainland Tanzania.

4.7.4 Competing interest

The authors declare that they have no competing interests.

4.7.5 Ethics approval and consent to participate

This work utilizes secondary aggregated data for analysis for which no ethics approval was required.

4.7.6 Supporting information

Supplementary tables and figures to this work can be found in Supplementary Information.

4.7.7 Funding

Funding for SGT and FM was received from the Swiss Tropical and Public Health Institute - NETCELL Project funded by the Swiss Agency for Development and Cooperation. EP and MR from the Global Fund to Fight Aids, Tuberculosis and Malaria (GFATM) and the Swiss Tropical and Public Health Institute. RWS is supported as a Wellcome Trust Principal Fellow (# 103602 and 212176). RWS also acknowledges support from the UK's Department for International Development under a project entitled *Strengthening the Use of Data for Malaria Decision Making in Africa* (DFID Programme Code # 203155).

4.7.8 Consent for publication

Not applicable.

4.8 Supplementary information

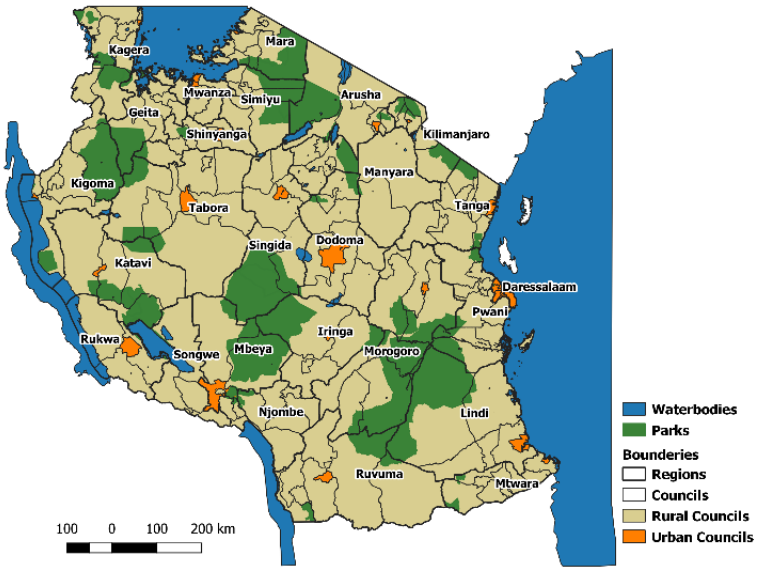


Figure S4.1: Administrative boundaries and distribution of urban and rural councils in mainland Tanzania. *Within the urban councils, town authorities were considered rural due to presence of high numbers of mixed and rural wards within the council thereby resulting in a total of 25 urban councils*

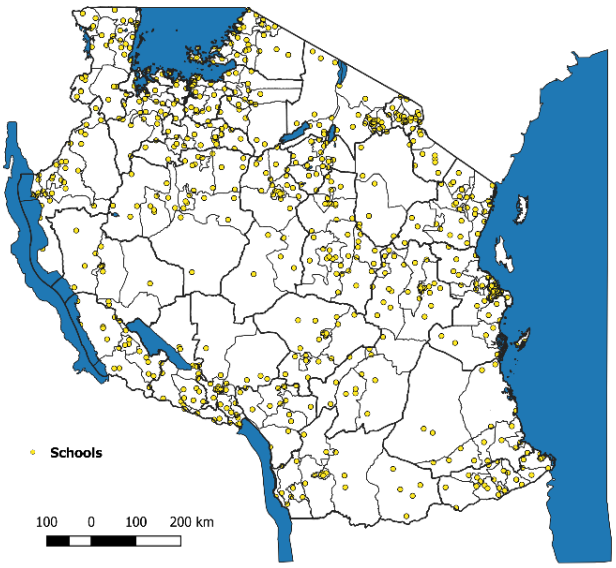


Figure S4.2: Locations of sampled schools for SMPS in 2015 & 2017 (N=711)

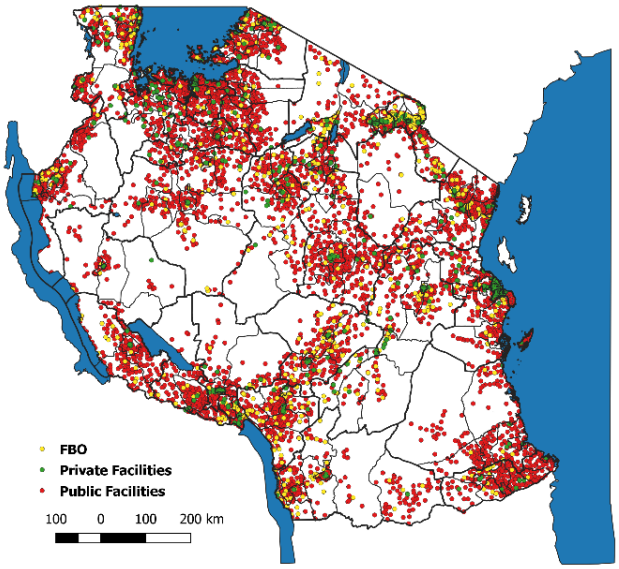


Figure S4.3: Location of operational health facilities by ownership in mainland Tanzania (N=7620) (Source: HFR Portal, www.moh.go.tz/hfrportal/)

Table S4.1: The maximum of the annual mean values per indicator and resulting overall risk strata assigned per council

		SMPS	Routine source: HMIS/DHIS2				Assigned Score						
Region	**Council**	***Pf*PR$_{5to16}$**	**Fever TPR**	**API**	**Malaria Incidence/ 1,000**	**ANC PR**	***Pf*PR$_{5to16}$**	**Fever TPR**	**API**	**Malaria Incidence /1,000**	**ANC PR**	**Total score**	**Stratum**
Arusha	Arusha CC	0.0	1.4	3.3	9.3	0.3	1.0	0.5	0.5	1.0	1.0	4.0	Very Low
Arusha	Arusha DC	0.0	1.2	3.2	5.5	0.5	1.0	0.5	0.5	1.0	1.0	4.0	Very Low
Arusha	Karatu DC	0.0	1.6	2.7	5.5	1.1	1.0	0.5	0.5	1.0	2.0	5.0	Very Low
Arusha	Longido DC	0.6	3.6	0.7	1.2	2.7	1.0	0.5	0.5	1.0	2.0	5.0	Very Low
Arusha	Meru DC	0.2	0.9	2.6	3.6	0.4	1.0	0.5	0.5	1.0	1.0	4.0	Very Low
Arusha	Monduli DC	0.0	1.3	2.5	9.3	1.0	1.0	0.5	0.5	1.0	2.0	5.0	Very Low
Arusha	Ngorongoro DC	0.0	1.6	1.5	5.1	0.6	1.0	0.5	0.5	1.0	1.0	4.0	Very Low
Dar Es Salaam	Ilala MC	4.7	7.7	65.5	96.2	2.8	2.0	1.0	1.0	3.0	2.0	9.0	Low
Dar Es Salaam	Kigamboni MC	5.7	10.6	54.7	86.6	4.0	3.0	1.0	1.0	3.0	3.0	11.0	Moderate
Dar Es Salaam	Kinondoni MC	1.6	5.4	31.0	137.1	1.7	2.0	1.0	1.0	3.0	2.0	9.0	Low
Dar Es Salaam	Temeke MC	2.1	6.6	72.9	109.1	4.3	2.0	1.0	1.0	3.0	3.0	10.0	Low
Dar Es Salaam	Ubungo MC	1.0	4.3	40.9	114.1	2.5	2.0	0.5	1.0	3.0	2.0	8.5	Low
Dodoma	Bahi DC	13.9	9.8	18.1	72.6	3.1	3.0	1.0	1.0	3.0	3.0	11.0	Moderate
Dodoma	Chamwino DC	3.7	15.7	29.6	92.0	1.9	2.0	1.5	1.0	3.0	2.0	9.5	Low
Dodoma	Chemba DC	5.0	16.5	15.3	29.8	1.5	3.0	1.5	1.0	2.0	2.0	9.5	Low
Dodoma	Dodoma MC	0.9	30.4	987.2	80.3	2.0	1.0	2.0	2.0	3.0	2.0	10.0	Low
Dodoma	Kondoa DC	2.2	7.6	5.2	16.1	1.6	2.0	1.0	0.5	2.0	2.0	7.5	Low
Dodoma	Kondoa TC	0.4	1.4	9.1	48.2	0.6	1.0	0.5	0.5	2.0	1.0	5.0	Very Low
Dodoma	Kongwa DC	1.6	10.4	11.7	39.3	1.8	2.0	1.0	0.5	2.0	2.0	7.5	Low
Dodoma	Mpwapwa DC	7.5	16.4	35.5	42.8	3.6	3.0	1.5	1.0	2.0	3.0	10.5	Moderate
Geita	Bukombe DC	47.9	29.3	144.8	143.5	8.7	4.0	1.5	1.5	3.0	3.0	13.0	Moderate
Geita	Chato DC	34.7	31.8	126.3	152.5	21.4	4.0	2.0	1.5	4.0	4.0	15.5	High
Geita	Geita DC	67.1	44.0	153.4	157.3	22.6	4.0	2.0	2.0	4.0	4.0	16.0	High
Geita	Geita TC	47.2	17.7	113.2	114.7	19.0	4.0	1.5	1.5	3.0	4.0	14.0	Moderate
Geita	Mbogwe DC	73.7	34.3	134.3	185.8	21.0	4.0	2.0	1.5	4.0	4.0	15.5	High

		SMPS	Routine source: HMIS/DHIS2				Assigned Score						
Region	**Council**	***Pf*PR$_{5to16}$**	**Fever TPR**	**API**	**Malaria Incidence/ 1,000**	**ANC PR**	***Pf*PR$_{5to16}$**	**Fever TPR**	**API**	**Malaria Incidence /1,000**	**ANC PR**	**Total score**	**Stratum**
Geita	Nyang'hwale DC	74.4	40.8	151.3	189.7	18.2	4.0	2.0	2.0	4.0	4.0	16.0	High
Iringa	Iringa DC	1.1	6.2	10.2	32.3	1.1	2.0	1.0	0.5	2.0	2.0	7.5	Low
Iringa	Iringa MC	0.6	1.7	16.0	51.2	0.7	1.0	0.5	1.0	3.0	1.0	6.5	Low
Iringa	Kilolo DC	2.6	16.1	24.9	49.7	1.6	2.0	1.5	1.0	2.0	2.0	8.5	Low
Iringa	Mafinga TC	0.0	4.5	17.9	27.4	0.8	1.0	0.5	1.0	2.0	1.0	5.5	Very Low
Iringa	Mufindi DC	0.3	13.4	12.4	15.7	1.4	1.0	1.0	0.5	2.0	2.0	6.5	Low
Kagera	Biharamulo DC	39.2	54.9	198.6	197.8	23.7	4.0	2.0	2.0	4.0	4.0	16.0	High
Kagera	Bukoba DC	32.7	31.9	91.0	201.2	22.2	4.0	2.0	1.5	4.0	4.0	15.5	High
Kagera	Bukoba MC	2.5	12.6	60.5	68.5	6.1	2.0	1.0	1.0	3.0	3.0	10.0	Low
Kagera	Karagwe DC	35.7	44.7	147.8	190.8	13.8	4.0	2.0	1.5	4.0	4.0	15.5	High
Kagera	Kyerwa DC	39.1	52.2	280.2	256.8	14.9	4.0	2.0	2.0	4.0	4.0	16.0	High
Kagera	Missenyi DC	68.9	23.3	95.0	264.0	22.2	4.0	1.5	1.5	4.0	4.0	15.0	High
Kagera	Muleba DC	32.5	57.4	265.9	244.5	15.2	4.0	2.0	2.0	4.0	4.0	16.0	High
Kagera	Ngara DC	40.3	49.1	473.2	446.8	18.0	4.0	2.0	2.0	4.0	4.0	16.0	High
Katavi	Mlele DC	32.1	27.5	126.4	193.0	11.7	4.0	1.5	1.5	4.0	4.0	15.0	High
Katavi	Mpanda DC	49.0	38.6	78.3	89.7	9.9	4.0	2.0	1.5	3.0	3.0	13.5	Moderate
Katavi	Mpanda MC	14.3	18.3	88.2	255.3	8.1	3.0	1.5	1.5	4.0	3.0	13.0	Moderate
Katavi	Mpimbwe DC	16.5	21.2	9.3	38.5	3.9	3.0	1.5	0.5	2.0	3.0	10.0	Low
Katavi	Nsimbo DC	69.7	52.1	186.6	209.3	11.8	4.0	2.0	2.0	4.0	4.0	16.0	High
Kigoma	Buhigwe DC	46.7	51.1	169.1	166.8	18.6	4.0	2.0	2.0	4.0	4.0	16.0	High
Kigoma	Kakonko DC	35.2	63.7	461.0	469.9	12.7	4.0	2.0	2.0	4.0	4.0	16.0	High
Kigoma	Kasulu DC	45.6	57.8	173.6	350.1	24.5	4.0	2.0	2.0	4.0	4.0	16.0	High
Kigoma	Kasulu TC	28.1	29.7	103.5	99.1	12.6	3.0	1.5	1.5	3.0	4.0	13.0	Moderate

		SMPS	Routine source: HMIS/DHIS2				Assigned Score						
Region	**Council**	***Pf*PR$_{5to16}$**	**Fever TPR**	**API**	**Malaria Incidence/ 1,000**	**ANC PR**	***Pf*PR$_{5to16}$**	**Fever TPR**	**API**	**Malaria Incidence /1,000**	**ANC PR**	**Total score**	**Stratum**
Kigoma	Kibondo DC	42.9	56.7	389.0	402.5	14.6	4.0	2.0	2.0	4.0	4.0	16.0	High
Kigoma	Kigoma DC	31.1	52.9	290.0	365.9	11.3	4.0	2.0	2.0	4.0	4.0	16.0	High
Kigoma	Kigoma MC	35.4	32.6	171.5	177.2	10.2	4.0	2.0	2.0	4.0	4.0	16.0	High
Kigoma	Uvinza DC	42.3	53.4	123.4	136.4	20.3	4.0	2.0	1.5	3.0	4.0	14.5	High
Kilimanjaro	Hai DC	0.0	0.7	3.2	9.7	0.5	1.0	0.5	0.5	1.0	1.0	4.0	Very Low
Kilimanjaro	Moshi DC	0.3	2.3	3.4	2.8	1.2	1.0	0.5	0.5	1.0	2.0	5.0	Very Low
Kilimanjaro	Moshi MC	0.0	1.2	31.4	63.3	0.5	1.0	0.5	1.0	3.0	1.0	6.5	Low
Kilimanjaro	Mwanga DC	0.8	2.3	6.4	26.2	0.6	1.0	0.5	0.5	2.0	1.0	5.0	Very Low
Kilimanjaro	Rombo DC	0.4	1.6	5.6	2.3	0.6	1.0	0.5	0.5	1.0	1.0	4.0	Very Low
Kilimanjaro	Same DC	2.6	5.2	9.1	17.5	0.7	2.0	1.0	0.5	2.0	1.0	6.5	Low
Kilimanjaro	Siha DC	0.0	1.1	1.6	4.0	1.4	1.0	0.5	0.5	1.0	2.0	5.0	Very Low
Lindi	Kilwa DC	40.6	51.1	378.3	349.9	18.7	4.0	2.0	2.0	4.0	4.0	16.0	High
Lindi	Lindi DC	37.8	56.4	413.5	403.7	22.9	4.0	2.0	2.0	4.0	4.0	16.0	High
Lindi	Lindi MC	7.1	37.6	369.3	365.2	11.4	3.0	2.0	2.0	4.0	4.0	15.0	High
Lindi	Liwale DC	38.3	52.3	437.2	420.1	23.9	4.0	2.0	2.0	4.0	4.0	16.0	High
Lindi	Nachingwea DC	38.0	36.0	213.7	215.6	15.9	4.0	2.0	2.0	4.0	4.0	16.0	High
Lindi	Ruangwa DC	50.7	54.4	348.5	361.6	23.9	4.0	2.0	2.0	4.0	4.0	16.0	High
Manyara	Babati DC	0.2	1.6	4.2	27.3	0.4	1.0	0.5	0.5	2.0	1.0	5.0	Very Low
Manyara	Babati TC	0.9	0.7	21.7	47.8	0.5	1.0	0.5	1.0	2.0	1.0	5.5	Very Low
Manyara	Hanang DC	0.0	1.0	2.2	3.3	0.7	1.0	0.5	0.5	1.0	1.0	4.0	Very Low
Manyara	Kiteto DC	1.3	2.0	0.9	41.3	1.0	2.0	0.5	0.5	2.0	2.0	7.0	Low
Manyara	Mbulu DC	0.0	1.1	0.1	14.9	0.7	1.0	0.5	0.5	1.0	1.0	4.0	Very Low
Manyara	Mbulu TC	0.4	0.6	0.0	17.4	0.1	1.0	0.5	0.5	2.0	1.0	5.0	Very Low
Manyara	Simanjiro DC	1.7	8.7	16.9	50.6	1.7	2.0	1.0	1.0	3.0	2.0	9.0	Low
Mara	Bunda DC	35.1	36.8	99.7	105.8	17.1	4.0	2.0	1.5	3.0	4.0	14.5	High

		SMPS	Routine source: HMIS/DHIS2				Assigned Score						
Region	**Council**	***Pf*PR$_{5to16}$**	**Fever TPR**	**API**	**Malaria Incidence/ 1,000**	**ANC PR**	***Pf*PR$_{5to16}$**	**Fever TPR**	**API**	**Malaria Incidence /1,000**	**ANC PR**	**Total score**	**Stratum**
Mara	Bunda TC	28.9	34.3	64.2	186.2	14.4	3.0	2.0	1.0	4.0	4.0	14.0	Moderate
Mara	Butiama DC	64.9	31.0	72.6	252.2	25.5	4.0	2.0	1.0	4.0	4.0	15.0	High
Mara	Musoma DC	39.1	19.1	45.1	378.7	25.2	4.0	1.5	1.0	4.0	4.0	14.5	High
Mara	Musoma MC	3.8	8.6	110.7	299.0	8.8	2.0	1.0	1.5	4.0	3.0	11.5	Moderate
Mara	Rorya DC	43.3	47.8	77.5	206.4	14.4	4.0	2.0	1.5	4.0	4.0	15.5	High
Mara	Serengeti DC	42.2	46.6	99.3	177.2	12.9	4.0	2.0	1.5	4.0	4.0	15.5	High
Mara	Tarime DC	54.1	34.7	103.2	115.9	12.4	4.0	2.0	1.5	3.0	4.0	14.5	High
Mara	Tarime TC	4.1	16.7	116.2	235.1	12.3	2.0	1.5	1.5	4.0	4.0	13.0	Moderate
Mbeya	Busokelo DC	29.3	31.4	104.1	191.4	11.5	3.0	2.0	1.5	4.0	4.0	14.5	High
Mbeya	Chunya DC	20.9	34.2	119.2	105.3	6.8	3.0	2.0	1.5	3.0	3.0	12.5	Moderate
Mbeya	Kyela DC	32.9	28.8	102.0	234.6	8.6	4.0	1.5	1.5	4.0	3.0	14.0	Moderate
Mbeya	Mbarali DC	1.4	5.3	11.5	9.8	1.2	2.0	1.0	0.5	1.0	2.0	6.5	Low
Mbeya	Mbeya CC	1.2	2.3	12.1	23.8	1.1	2.0	0.5	0.5	2.0	2.0	7.0	Low
Mbeya	Mbeya DC	0.1	7.2	7.5	10.6	3.1	1.0	1.0	0.5	1.0	3.0	6.5	Low
Mbeya	Rungwe DC	10.7	15.0	21.4	46.7	2.6	3.0	1.0	1.0	2.0	2.0	9.0	Low
Morogoro	Gairo DC	1.3	13.0	18.2	26.4	2.6	2.0	1.0	1.0	2.0	2.0	8.0	Low
Morogoro	Ifakara TC	42.1	17.8	99.2	115.2	3.1	4.0	1.5	1.5	3.0	3.0	13.0	Moderate
Morogoro	Kilombero DC	51.9	23.9	133.4	138.7	10.7	4.0	1.5	1.5	3.0	4.0	14.0	Moderate
Morogoro	Kilosa DC	26.9	30.5	88.9	144.0	11.4	3.0	2.0	1.5	3.0	4.0	13.5	Moderate
Morogoro	Malinyi DC	51.0	33.1	102.3	163.2	13.8	4.0	2.0	1.5	4.0	4.0	15.5	High
Morogoro	Morogoro DC	30.4	43.8	157.3	255.8	16.6	4.0	2.0	2.0	4.0	4.0	16.0	High
Morogoro	Morogoro MC	3.2	16.5	82.8	249.2	5.6	2.0	1.5	1.5	4.0	3.0	12.0	Moderate
Morogoro	Mvomero DC	14.2	28.8	76.4	137.9	10.3	3.0	1.5	1.5	3.0	4.0	13.0	Moderate
Morogoro	Ulanga DC	51.0	47.4	227.2	228.4	18.7	4.0	2.0	2.0	4.0	4.0	16.0	High
Mtwara	Masasi DC	38.0	58.7	214.2	244.7	20.2	4.0	2.0	2.0	4.0	4.0	16.0	High

		SMPS	Routine source: HMIS/DHIS2				Assigned Score						
Region	**Council**	***Pf*PR$_{5to16}$**	**Fever TPR**	**API**	**Malaria Incidence/ 1,000**	**ANC PR**	***Pf*PR$_{5to16}$**	**Fever TPR**	**API**	**Malaria Incidence /1,000**	**ANC PR**	**Total score**	**Stratum**
Mtwara	Masasi TC	27.9	40.7	224.0	364.4	15.3	3.0	2.0	2.0	4.0	4.0	15.0	High
Mtwara	Mtwara DC	62.9	63.0	385.6	357.6	20.8	4.0	2.0	2.0	4.0	4.0	16.0	High
Mtwara	Mtwara MC	39.3	25.2	480.2	340.7	9.6	4.0	1.5	2.0	4.0	3.0	14.5	High
Mtwara	Nanyamba TC	46.8	71.9	344.9	354.2	29.2	4.0	2.0	2.0	4.0	4.0	16.0	High
Mtwara	Nanyumbu DC	39.0	63.5	344.9	305.0	28.8	4.0	2.0	2.0	4.0	4.0	16.0	High
Mtwara	Newala DC	48.4	61.9	424.4	369.8	27.4	4.0	2.0	2.0	4.0	4.0	16.0	High
Mtwara	Newala TC	11.6	66.6	74.3	376.6	21.0	3.0	2.0	1.0	4.0	4.0	14.0	Moderate
Mtwara	Tandahimba DC	46.7	48.8	323.7	326.1	24.7	4.0	2.0	2.0	4.0	4.0	16.0	High
Mwanza	Buchosa DC	70.0	42.5	122.5	147.2	21.3	4.0	2.0	1.5	3.0	4.0	14.5	High
Mwanza	Ilemela MC	12.9	18.8	101.5	135.0	9.1	3.0	1.5	1.5	3.0	3.0	12.0	Moderate
Mwanza	Kwimba DC	34.6	26.5	23.6	143.6	8.3	4.0	1.5	1.0	3.0	3.0	12.5	Moderate
Mwanza	Magu DC	54.6	29.2	129.3	133.9	15.1	4.0	1.5	1.5	3.0	4.0	14.0	Moderate
Mwanza	Misungwi DC	53.4	42.9	125.7	140.0	21.1	4.0	2.0	1.5	3.0	4.0	14.5	High
Mwanza	Nyamagana MC	1.7	4.9	8.2	124.3	9.4	2.0	0.5	0.5	3.0	3.0	9.0	Low
Mwanza	Sengerema DC	56.4	29.5	101.6	223.5	20.5	4.0	1.5	1.5	4.0	4.0	15.0	High
Mwanza	Ukerewe DC	56.6	54.5	179.5	183.7	13.6	4.0	2.0	2.0	4.0	4.0	16.0	High
Njombe	Ludewa DC	5.9	33.8	74.2	88.5	4.1	3.0	2.0	1.0	3.0	3.0	12.0	Moderate
Njombe	Makambako TC	0.0	3.4	23.2	14.0	0.7	1.0	0.5	1.0	1.0	1.0	4.5	Very Low
Njombe	Makete DC	0.0	4.1	9.8	10.5	2.0	1.0	0.5	0.5	1.0	2.0	5.0	Very Low
Njombe	Njombe DC	1.7	11.2	14.3	16.1	1.3	2.0	1.0	0.5	2.0	2.0	7.5	Low
Njombe	Njombe TC	0.0	2.4	14.5	17.6	0.7	1.0	0.5	0.5	2.0	1.0	5.0	Very Low
Njombe	Wanging'ombe DC	0.3	6.2	8.8	9.6	1.0	1.0	1.0	0.5	1.0	2.0	5.5	Very Low
Pwani	Bagamoyo DC	73.6	20.2	72.4	184.6	2.0	4.0	1.5	1.0	4.0	2.0	12.5	Moderate
Pwani	Chalinze DC	24.4	45.0	265.6	332.6	9.7	3.0	2.0	2.0	4.0	3.0	14.0	Moderate
Pwani	Kibaha DC	59.5	28.7	331.2	552.0	7.5	4.0	1.5	2.0	4.0	3.0	14.5	High

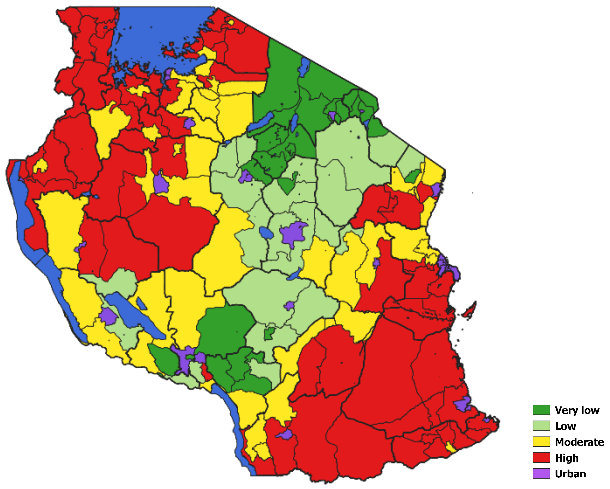
		SMPS	Routine source: HMIS/DHIS2				Assigned Score						
Region	**Council**	***Pf*PR$_{5to16}$**	**Fever TPR**	**API**	**Malaria Incidence/ 1,000**	**ANC PR**	***Pf*PR$_{5to16}$**	**Fever TPR**	**API**	**Malaria Incidence /1,000**	**ANC PR**	**Total score**	**Stratum**
Pwani	Kibaha TC	12.7	5.9	94.2	156.0	3.7	3.0	1.0	1.5	4.0	3.0	12.5	Moderate
Pwani	Kibiti DC	63.3	49.4	272.5	344.6	12.2	4.0	2.0	2.0	4.0	4.0	16.0	High
Pwani	Kisarawe DC	69.0	42.5	318.3	369.3	9.1	4.0	2.0	2.0	4.0	3.0	15.0	High
Pwani	Mafia DC	44.2	32.9	220.6	603.1	13.1	4.0	2.0	2.0	4.0	4.0	16.0	High
Pwani	Mkuranga DC	66.8	50.9	153.2	278.5	11.6	4.0	2.0	2.0	4.0	4.0	16.0	High
Pwani	Rufiji DC	47.3	38.1	365.2	373.1	10.0	4.0	2.0	2.0	4.0	3.0	15.0	High
Rukwa	Kalambo DC	34.1	39.5	138.8	146.9	9.2	4.0	2.0	1.5	3.0	3.0	13.5	Moderate
Rukwa	Nkasi DC	45.3	28.8	76.2	147.7	12.2	4.0	1.5	1.5	3.0	4.0	14.0	Moderate
Rukwa	Sumbawanga DC	11.0	24.7	35.6	44.2	2.7	3.0	1.5	1.0	2.0	2.0	9.5	Low
Rukwa	Sumbawanga MC	1.2	4.7	29.8	72.2	1.1	2.0	0.5	1.0	3.0	2.0	8.5	Low
Ruvuma	Madaba DC	0.0	39.7	336.6	325.5	8.8	1.0	2.0	2.0	4.0	3.0	12.0	Moderate
Ruvuma	Mbinga DC	14.8	35.6	78.8	113.2	6.4	3.0	2.0	1.5	3.0	3.0	12.5	Moderate
Ruvuma	Mbinga TC	1.7	17.7	92.9	110.1	3.9	2.0	1.5	1.5	3.0	3.0	11.0	Moderate
Ruvuma	Namtumbo DC	50.2	57.8	368.1	456.2	20.7	4.0	2.0	2.0	4.0	4.0	16.0	High
Ruvuma	Nyasa DC	30.1	47.7	244.0	228.4	14.2	4.0	2.0	2.0	4.0	4.0	16.0	High
Ruvuma	Songea DC	31.4	52.0	293.3	342.4	10.4	4.0	2.0	2.0	4.0	4.0	16.0	High
Ruvuma	Songea MC	5.9	25.1	155.5	195.5	6.0	3.0	1.5	2.0	4.0	3.0	13.5	Moderate
Ruvuma	Tunduru DC	62.0	59.9	252.4	296.8	25.3	4.0	2.0	2.0	4.0	4.0	16.0	High
Shinyanga	Kahama TC	5.3	17.5	108.9	155.7	8.2	3.0	1.5	1.5	4.0	3.0	13.0	Moderate
Shinyanga	Kishapu DC	30.2	29.4	69.0	131.5	7.1	4.0	1.5	1.0	3.0	3.0	12.5	Moderate
Shinyanga	Msalala DC	52.4	32.0	83.1	125.2	12.3	4.0	2.0	1.5	3.0	4.0	14.5	High
Shinyanga	Shinyanga DC	38.0	42.8	82.8	158.3	12.8	4.0	2.0	1.5	4.0	4.0	15.5	High
Shinyanga	Shinyanga MC	8.1	22.1	157.8	264.5	6.7	3.0	1.5	2.0	4.0	3.0	13.5	Moderate
Shinyanga	Ushetu DC	76.4	42.4	190.4	166.9	22.0	4.0	2.0	2.0	4.0	4.0	16.0	High
Simiyu	Bariadi DC	43.9	31.8	99.3	102.6	13.7	4.0	2.0	1.5	3.0	4.0	14.5	High

		SMPS	Routine source: HMIS/DHIS2				Assigned Score						
Region	**Council**	***Pf*PR$_{5to16}$**	**Fever TPR**	**API**	**Malaria Incidence/ 1,000**	**ANC PR**	***Pf*PR$_{5to16}$**	**Fever TPR**	**API**	**Malaria Incidence /1,000**	**ANC PR**	**Total score**	**Stratum**
Simiyu	Bariadi TC	7.5	22.9	43.6	110.5	8.7	3.0	1.5	1.0	3.0	3.0	11.5	Moderate
Simiyu	Busega DC	27.7	33.2	82.5	94.2	15.0	3.0	2.0	1.5	3.0	4.0	13.5	Moderate
Simiyu	Itilima DC	32.6	17.1	4.0	56.4	10.3	4.0	1.5	0.5	3.0	4.0	13.0	Moderate
Simiyu	Maswa DC	44.4	26.5	51.8	84.6	9.0	4.0	1.5	1.0	3.0	3.0	12.5	Moderate
Simiyu	Meatu DC	9.9	11.1	11.0	85.2	4.7	3.0	1.0	0.5	3.0	3.0	10.5	Moderate
Singida	Ikungi DC	1.1	11.5	14.8	47.4	2.0	2.0	1.0	0.5	2.0	2.0	7.5	Low
Singida	Iramba DC	3.8	10.1	11.3	36.8	1.6	2.0	1.0	0.5	2.0	2.0	7.5	Low
Singida	Itigi DC	2.5	18.4	68.0	116.6	6.6	2.0	1.5	1.0	3.0	3.0	10.5	Moderate
Singida	Manyoni DC	11.8	8.4	23.3	88.6	2.3	3.0	1.0	1.0	3.0	2.0	10.0	Low
Singida	Mkalama DC	3.4	5.7	12.9	30.2	0.6	2.0	1.0	0.5	2.0	1.0	6.5	Low
Singida	Singida DC	0.8	1.9	2.2	19.2	0.5	1.0	0.5	0.5	2.0	1.0	5.0	Very Low
Singida	Singida MC	0.3	2.3	14.4	43.6	0.7	1.0	0.5	0.5	2.0	1.0	5.0	Very Low
Songwe	Ileje DC	3.2	18.2	6.6	47.4	1.5	2.0	1.5	0.5	2.0	2.0	8.0	Low
Songwe	Mbozi DC	0.2	2.7	4.2	9.3	1.6	1.0	0.5	0.5	1.0	2.0	5.0	Very Low
Songwe	Momba DC	32.7	35.5	41.9	77.2	6.9	4.0	2.0	1.0	3.0	3.0	13.0	Moderate
Songwe	Songwe DC	20.9	21.0	28.4	56.3	4.1	3.0	1.5	1.0	3.0	3.0	11.5	Moderate
Songwe	Tunduma TC	1.3	8.3	10.2	14.0	0.4	2.0	1.0	0.5	1.0	1.0	5.5	Very Low
Tabora	Igunga DC	16.0	25.2	32.9	107.6	4.9	3.0	1.5	1.0	3.0	3.0	11.5	Moderate
Tabora	Kaliua DC	39.7	43.6	92.4	100.5	16.4	4.0	2.0	1.5	3.0	4.0	14.5	High
Tabora	Nzega DC	41.2	70.8	17.7	164.3	12.8	4.0	2.0	1.0	4.0	4.0	15.0	High
Tabora	Nzega TC	41.2	24.1	170.8	209.5	9.2	4.0	1.5	2.0	4.0	3.0	14.5	High
Tabora	Sikonge DC	23.2	38.6	233.2	253.5	21.4	3.0	2.0	2.0	4.0	4.0	15.0	High
Tabora	Tabora MC	13.4	26.1	186.3	199.0	10.7	3.0	1.5	2.0	4.0	4.0	14.5	High
Tabora	Urambo DC	37.2	35.0	147.3	177.8	16.0	4.0	2.0	1.5	4.0	4.0	15.5	High
Tabora	Uyui DC	24.4	46.0	82.5	205.1	13.8	3.0	2.0	1.5	4.0	4.0	14.5	High

		SMPS	Routine source: HMIS/DHIS2				Assigned Score						
Region	**Council**	***Pf*PR$_{5to16}$**	**Fever TPR**	**API**	**Malaria Incidence/ 1,000**	**ANC PR**	***Pf*PR$_{5to16}$**	**Fever TPR**	**API**	**Malaria Incidence /1,000**	**ANC PR**	**Total score**	**Stratum**
Tanga	Bumbuli DC	0.5	7.8	22.7	47.2	1.0	1.0	1.0	1.0	2.0	1.0	6.0	Very Low
Tanga	Handeni DC	52.3	54.8	195.9	277.8	15.2	4.0	2.0	2.0	4.0	4.0	16.0	High
Tanga	Handeni TC	49.2	26.7	156.3	179.8	10.2	4.0	1.5	2.0	4.0	4.0	15.5	High
Tanga	Kilindi DC	18.7	39.9	129.5	198.0	10.3	3.0	2.0	1.5	4.0	4.0	14.5	High
Tanga	Korogwe DC	6.8	29.7	107.4	202.0	8.1	3.0	1.5	1.5	4.0	3.0	13.0	Moderate
Tanga	Korogwe TC	1.6	11.1	105.5	200.7	3.7	2.0	1.0	1.5	4.0	3.0	11.5	Moderate
Tanga	Lushoto DC	5.6	6.7	9.6	38.6	3.0	3.0	1.0	0.5	2.0	2.0	8.5	Low
Tanga	Mkinga DC	21.9	32.2	158.1	348.3	6.1	3.0	2.0	2.0	4.0	3.0	14.0	Moderate
Tanga	Muheza DC	22.6	33.6	258.9	411.9	12.7	3.0	2.0	2.0	4.0	4.0	15.0	High
Tanga	Pangani DC	15.2	31.1	256.9	280.0	7.3	3.0	2.0	2.0	4.0	3.0	14.0	Moderate
Tanga	Tanga CC	19.1	7.4	98.8	181.0	1.7	3.0	1.0	1.5	4.0	2.0	11.5	Moderate

Table S4.2: The cumulative proportion of health facilities submitting between 3 – 12 monthly facility reports from OPD, ANC and laboratory in 2015 – 2017 (N = Total number of facilities)

# of monthly reports submitted	Laboratory		OPD			ANC		
	2016 (N=6297)	2017 (N=7078)	2015 (N=7004)	2016 (N=7215)	2017 (N=7425)	2015 (N=5981)	2016 (N=6170)	2017 (N=6362)
3	85.7%	95.8%	98.4%	98.0%	98.7%	99.0%	98.8%	99.3%
6	57.9%	89.9%	95.5%	95.4%	95.9%	97.5%	97.7%	97.7%
9	19.3%	78.9%	87.7%	91.5%	92.4%	95.3%	95.7%	96.0%
12	3.0%	38.9%	59.0%	63.0%	69.3%	76.8%	80.3%	81.7%



Strata	No. councils	No. urban councils (municipal/city councils)	Percent population
Very Low	31	3	36%
Low	32	10	26%
Moderate	50	8	24%
High	71	4	14%
Total	**184**	**25**	**100%**

Figure S4.4: Malaria risk stratification using health facilities with >50% reporting rates

5 The Use of Routine Health Facility Data for Micro-stratification of Malaria Risk in Mainland Tanzania

Sumaiyya G. Thawer[1,2]*, Monica Golumbeanu[1,2], Khalifa Munisi[3,4], Sijenunu Aaron[3,4], Frank Chacky[3,4], Samwel Lazaro[3,4], Ally Mohamed[3,4], Noela Kisoka[1,2], Christian Lengeler[1,2], Fabrizio Molteni[1,2], Amanda Ross[1,2], Robert W. Snow[5,6], Emilie Pothin[1,2,7]

[1] Swiss Tropical and Public Health Institute, Allschwil, Switzerland

[2] University of Basel, Basel, Switzerland

[3] Ministry of Health, Dodoma, Tanzania

[4] National Malaria Control Programme, Dodoma, Tanzania

[5] Population Health Unit, Kenya Medical Research Institute-Wellcome Trust Research Programme, Nairobi, Kenya

[6] Centre for Tropical Medicine and Global Health, Nuffield Department of Clinical Medicine, University of Oxford, Oxford, UK

[7] Clinton Health Access Initiative, New York, USA

*Corresponding author:
Sumaiyya G. Thawer, sumaiyya.thawer@swisstph.ch

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5.1 Abstract

Background

Current efforts to estimate the spatially diverse malaria burden in malaria-endemic countries largely involve the use of epidemiological modelling methods for describing temporal and spatial heterogeneity using sparse interpolated prevalence data from periodic cross-sectional surveys. However, more malaria-endemic countries are beginning to consider local routine data for this purpose. Nevertheless, routine information from health facilities (HFs) remains widely under-utilized despite improved data quality, including increased access to diagnostic testing and the adoption of the electronic District Health Information System (DHIS2). This paper describes the process undertaken in mainland Tanzania using routine data to develop a high-resolution, micro-stratification risk map to guide future malaria control efforts.

Methods

Combinations of various routine malariometric indicators collected from 7,098 HFs were assembled across 3,065 wards of mainland Tanzania for the period 2017-2019. The reported council-level prevalence classification in school children aged 5-16 years (PfPR$_{5-16}$) was used as a benchmark to define four malaria risk groups. These groups were subsequently used to derive cut-offs for the routine indicators by minimizing misclassifications and maximizing overall agreement. The derived-cutoffs were converted into numbered scores and summed across the three indicators to allocate wards into their overall risk stratum.

Results

Of 3,065 wards, 353 were assigned to the very low strata (10.5% of the total ward population), 717 to the low strata (28.6% of the population), 525 to the moderate strata (16.2% of the population), and 1,470 to the high strata (39.8% of the population). The resulting micro-stratification revealed malaria risk heterogeneity within 80 councils and identified wards that would benefit from community-level focal interventions, such as community-case management, indoor residual spraying and larviciding.

Conclusion

The micro-stratification approach employed is simple and pragmatic, with potential to be easily adopted by the malaria programme in Tanzania. It makes use of available routine data that are rich in spatial resolution and that can be readily accessed allowing for a stratification of malaria risk below the council level. Such a framework is optimal for supporting evidence-based,

decentralized malaria control planning, thereby improving the effectiveness and allocation efficiency of malaria control interventions.

Keywords Malaria, Micro-stratification, Routine data, Tanzania

5.2 Introduction

The future of malaria control and elimination depends on characterizing the level of disease risk in time and space, which should be constantly reviewed to guide optimal, tailored malaria control strategies specific to sub-national settings (World Health Organization, 2018a, 2015c). Traditionally, malaria parasite prevalence data among community residents, collected through periodic cross-sectional surveys, has been used to characterize malaria ecologies sub-nationally (Boyd, 1949; Lysenko and Semashko, 1968; Pampana and Russell, 1955; Snow et al., 2017; Snow and Noor, 2015). Over the last 20 years, increasingly complex, model-based, geo-statistical approaches (Diggle et al., 1998; Giorgi et al., 2018) have been applied to assembled community parasite prevalence data to provide interpolated data for high-resolution malaria risk maps (Bhatt et al., 2015; Noor et al., 2014; Odhiambo et al., 2020; Weiss et al., 2019). These approaches have been commonly used at national levels in providing national malaria control programmes (NMCPs) with baseline information on infection risk for various decision-making and planning purposes (Chipeta et al., 2019; Ghilardi et al., 2020; Giorgi et al., 2018; Kang et al., 2018; Macharia et al., 2018; Noor et al., 2009a, 2012b; Raso et al., 2012; Semakula et al., 2020; Ssempiira et al., 2017; Yankson et al., 2019).

However, community parasite prevalence data are collected nationally only periodically every 2-3 years and household sampling strategies lack power for small area estimation. Data are therefore sparse in time and space, and unable to describe the malaria situation continuously and at fine spatial resolutions with precision. A more ubiquitous source of information derives from routine health service data, collected continuously at most populated locations. These data provide a rich source of malariometric indicators in different population age and risk groups. Outside of countries aiming for malaria elimination, where individual case detection is a fundamental requirement, most stable endemic countries have not fully exploited routine data to its full potential. This was largely due to issues with the quality of the data and their completeness (Chilundo et al., 2004; Githinji et al., 2017; Maina et al., 2017). In recent years, these concerns have been tackled across sub-Saharan Africa (SSA) due to various factors such

as the launch of the revitalized WHO policy of test-treat-track (World Health Organization, 2012a) that has increased testing rates, the transition towards the electronic district health information system (DHIS2) that has improved health reporting rates (RRs) (Dehnavieh et al., 2019) and the implementation of continuous data quality assessments (World Health Organization, 2017b). Consequently, routine data are now increasingly recommended and used for national stratification of malaria risk and decision-making (Alegana et al., 2020; Arambepola et al., 2020; Ashton et al., 2017; Awine et al., 2018; Bennett et al., 2014; S.P. Kigozi et al., 2020b; Thawer et al., 2020).

Most national stratifications of malaria risk have considered one or two administrative levels (province, district, council) and are called 'macro-stratification' here. These often correspond to the federal planning of control and resource allocation levels (Alegana et al., 2020). However, marked epidemiological risk heterogeneity has been seen at these levels, and a lower level stratification has been proposed: micro-stratification (Afrane et al., 2013; Alegana et al., 2021b; Oduro et al., 2011). Malaria transmission is spatially heterogeneous in its distribution at every scale, driven by local ecologies, climate and population settlement (Bousema et al., 2012; Carter et al., 2000; Mogeni et al., 2017; Sturrock et al., 2016; Woolhouse et al., 1997). With an increasing empowerment of decentralized health sector governance and recognizing the small area variations in malaria risk, there is a need to improve our abilities to develop more detailed data platforms and risk analyses (World Health Organization, 2018b). Such a more granular stratification of malaria risk will allow for better spatially targeted malaria control responses and hence improve effectiveness and allocation efficiency.

Complex modelling approaches of parasite prevalence are often challenged by limited national capacity and ownership issues (Ghilardi et al., 2020; Lindblade et al., 2019; Omumbo et al., 2013). As NMCPs are gaining more analytic capacity and confidence in using routine DHIS2 data, including the local development of embedded malaria dashboards, quality checks and monthly/quarterly reports, this situation is changing (Byrne and Saebø, 2021; Etamesor et al., 2018; Maïga et al., 2019). Statistical modelling of routine health data, spatially and temporally, in low-income countries is in its nascent stages and largely driven by partners outside of malaria-endemic countries. Data analytics for NMCPs must be transparent and straightforward,

as well as guided by principles of completeness, coverage and inter-operability between various malaria indicators.

This work builds upon previous effort started as a collaborative exercise with the Tanzanian NMCP (Thawer et al., 2020) to improve the use of routine malaria indicators from DHIS2, and propose a novel, pragmatic and data-rich method for implementing malaria risk micro-stratification below council levels.

5.3 Methods

5.3.1 Context

In 2017, during a mid-term review of the national malaria strategic plan (NMSP) (National Malaria Control Programme, 2017b) followed by a malaria expert consultative meeting (National Malaria Control Programme, 2018b), it was recognized that in order to sustain Tanzania's reductions in malaria burden, a more geographic-tailored package of interventions was needed. This led to a country-managed, data-driven approach to develop a macro-stratification malaria risk map at the second level of administrative unit, across 184 councils (Runge et al., 2020a, 2020b; Thawer et al., 2020). Each council was assigned to one of four risk strata: very low, low, moderate, and high. An assembly of survey data from available prevalence surveys, together with routine data was used to define the four risk categories by means of expert-informed empirical ranges of malaria prevalence in school children ($Pf\text{PR}_{5\text{-}16\text{yrs}}$). Routine data included fever test positivity rates (TPR), annual parasite incidence (API) and antenatal attendee test positivity rates (ANC TPR). Based on this novel approach to using multiple data sources revised NMSP was issued in 2018 (National Malaria Control Programme, 2018a). Additional work and consultative processes, as well as intervention mix optimization in each risk strata using stochastic modelling (Runge et al., 2020a, 2020b) led to the development of the NMSP for 2021-2025 (National Malaria Control Programme, 2021). As per NMSP recommendation, the stratification exercise should be renewed every three years, to account for the changing epidemiology of the disease. To extend analytics and support the decentralized health system in Tanzania, the NMSP recommended approaches are repeated for risk stratification at ward levels to account for intra-council heterogeneity.

5.3.2 Administrative boundaries and populations at risk in mainland Tanzania

Mainland Tanzania is organized into multiple administrative levels. The country has 26 administrative regions, divided into 184 councils. Councils serve as the key operational unit for central government resource allocation and planning disease prevention and management activities, with own budgeting abilities. Councils are further divided into wards, which serve as the lower levels of administrative resource units and disease reporting. A total of 3,311 wards have been defined according to the 2012 national census for mainland Tanzania. Out of these, 2,427 are rural, 370 are mixed and 514 are urban (See Supplementary Figure S5.1, Supplementary Information). The number of wards per council range from two to 43 wards depending on the size of the council, and these allow for a much more granular risk definition, especially in areas with marked altitudinal variation. Each ward, depending on its size, includes between one to 18 health facilities (HFs) that serve the surrounding village populations. Unfortunately, the precise HF catchment population remains largely undefined, and aggregated population units for each ward was therefore used for the micro-stratification process. The population for each ward was obtained from the publicly available 2012 population and housing census in Tanzania conducted by the National Bureau of Statistics (National Bureau of Statistics, 2013). Annual growth rates at the council level (computed from the average annual continuous growth rate formula) were applied to the ward population data to project each ward population to the period 2017-2019. This allowed the compute of the denominators for API calculations, and to quantify populations residing in the ward malaria risk classifications.

5.3.3 Routine health facility data processing

Since 2009, the health management and information system (HMIS) of Tanzania has seen an evolution from a paper-based system to the electronic DHIS2 system. DHIS2 is an open source, web-based software platform for reporting, analysis and dissemination of health data. It captures information from both the private (26%) and public (74%) HFs and can be accessed by officials working in the health sector, through registered credentials. The work presented here utilized key malaria data extracted from the HMIS/DHIS2: the total number of falciparum malaria laboratory-confirmed cases, total number of malaria rapid diagnostic tests (RDTs) performed, and total number of confirmed cases and RDT tests performed in pregnant women attending antenatal care (ANC) during their first visits. These data were used to compute three

malaria indicators: API, RDT TPR and ANC TPR (details presented in Table 5.1). Since the majority of reporting HFs (N=7,878 (99%)) providing laboratory services in Tanzania use RDT as the main diagnostic test (88% of total tests performed), and routine microscopy is prone to quality issues (Kahama-Maro et al., 2011) only RDT test results were considered for the micro-stratification analysis.

Table 5.1: Indicators used for malaria risk micro-stratification.

Source	Indicator	Numerator	Denominator	Period*	Age	Level
HMIS/ DHIS2	**Laboratory**					
	Fever Test Positivity Rate (RDT TPR)	No. positive *Pf*-pan RDT	No. *Pf*-Pan RDT tests performed	2017-2019	All ages	Council & Ward
	Annual Parasite Incidence (API)	No. positive *Pf*-pan RDT	Per 1,000 population[α]			
	Antenatal Clinic					
	Test Positivity Rate (ANC TPR)	No. positive *Pf*-pan RDT	No. *Pf*-Pan RDT tests performed in pregnant women at first visit	2017-2019	Reproductive Age	Council & Ward
SMPS	Parasite prevalence	No. positive *Pf*-pan RDT	No. *Pf*-Pan RDT tests performed in school children	2017, 2019	5–16 years	Council

*Periods refer to January 1st to December 31st of the corresponding year. [α]Based on population estimates from the 2012 census. HMIS=Health Management Information System; DHIS2=District Health Information System 2; RDT=malaria Rapid Diagnostic Test; Pf=*Plasmodium falciparum*; SMPS= School Malaria Parasitaemia Survey

5.3.3.1 Data cleaning

Routine malaria data were extracted directly from DHIS2 from a total of 7,988 (94%) reporting HFs for each month for the period January 2017 to December 2019. Duplicate reports and HFs with no testing performed in any of the 36 reporting months were excluded. As the DHIS2 database is unable to distinguish zeros from missing values marking them as blank, it was assumed that missing values of otherwise complete reports were true zeros. A threshold of 50% completeness of reporting across 36 months was used and any HFs with reporting less than this were excluded from the analysis. Furthermore, HFs with more than five consecutive months of missing reports within a year were also excluded from the analysis. Extreme outliers, defined as monthly values that significantly deviated from the HF's overall time series trend across the 36 months, were excluded using the R package *anomalize* (Dancho and Vaughan, 2020) (Supplementary Information: Text S5.1) and visually verified before being subsequently treated as a missing monthly report.

5.3.3.2 Data aggregation

Geographical coordinates of the HFs were obtained from the master HF list of Tanzania (HFR Portal, 2021) and linked to the DHIS2 data using the unique HF identifier code. The ward shape file was then used to allocate the HFs to their respective wards (See Supplementary Figure S5.2, Supplementary Information). Monthly data of the total malaria tests performed and those tested positive from all HFs were aggregated to provide annualized estimates per council and per ward for the reporting period (2017-2019) and subsequently used to compute the three selected routine malaria indicators: 1) RDT TPR; 2) API; and, 3) ANC TPR (definitions of these indicators are presented in Table 1). The monthly data were aggregated for the whole year in order to align with the national strategic plan development and review cycle every three years and provide risk estimates for the period of analysis. The council level estimates were used to derive the cut-offs for categorizing the routine indicators as per the school prevalence classifications (see details of process below) whilst ward level estimates were used for the micro-stratification. A pragmatic, conservative approach was taken to ensure that the maximum ward value from the three years for each indicator was used. Taking the highest of the three annual ward values to reflect the ward estimate for the period of analysis ensured that wards were rather over- than under-allocated into risk strata.

5.3.4 The micro-stratification procedure

The micro-stratification risk scoring was developed in three steps: a) suitable cut-offs were defined to allocate the three routine indicators into four risk categories, based on a pre-classification on the basis of prevalence values in school children; b) the three selected routine indicators assigned to four malaria risk categories were converted into numbered scores; and, c) for each ward, the total score was summed across the three corresponding malaria indicators to obtain an overall score that was used to assign each ward to a risk stratum (very low, low, moderate or high), based on scoring thresholds (see definitions below). The strategic approach undertaken was purposively designed to ensure that the approach was simple and could easily be adapted by the NMCP and health planners at council levels.

5.3.4.1 Definition of indicator cut-offs for malaria risk categorization at the council level

In the micro-stratification process, the classification of prevalence in school children (*Pf*PR_{5-16}) was used as a gold standard in guiding the selection of appropriate cut-offs for converting

the three routine malaria indicators into risk categories. In mainland Tanzania, nationwide school malaria parasitaemia surveys (SMPS) targeting public primary school children have been conducted biennially since 2014 (Chacky et al., 2018). Schools were sampled based on 1) existing public primary schools in each council, and 2) expected malaria endemicity (Chacky et al., 2018; MoHCDGEC, 2021, 2019) to provide credible estimates of infection prevalence in ages 5-16 years for each of the 184 councils. Because of the quality and comprehensiveness of these data, as well as the fact that they were collected concurrently with the routine data, they served as a 'gold' standard for categorizing the routine indicators. Since SMPS results were available at council level, the risk categorization of the three routine indicators was also done first at council level.

The maximum prevalence in school children estimated per council across the past two surveys conducted in 2017 and 2019 was used to define stringent baseline cut-offs for each of the three routine indicators in a systematic process. Firstly, the prevalence in school children was used to define four malaria risk groups: very low (*Pf*PR_{5-16} <1%), low (*Pf*PR_{5-16} 1-<5%), moderate (*Pf*PR_{5-16} 5-<30%), and high (*Pf*PR_{5-16} ≥30%) and each council was categorized into one of these four risk levels. These endemicity cut-offs were guided by WHO classifications along with consultative discussions between NMCP and malaria experts (National Malaria Control Programme, 2018a; Thawer et al., 2020; World Health Organization et al., 2017a).

Secondly, in order to identify the best routine data cut-offs, a misclassification analysis was undertaken against school prevalence categories at the council level. For each routine indicator, the sensitivity, specificity, false positivity rate (FPR), and false negativity rate (FNR) were calculated per risk group for a range of cut-off values to ensure that the most robust cut-off values were selected (Supplementary Table S5.1, Supplementary Information). The selection of robust cut-offs for the routine malaria indicators was guided by a set of criteria, relevant for malaria control: i) maximizing the specificity in the very low and low strata to reduce false positive councils in these strata; ii) maximizing the sensitivity in moderate and high strata in order to reduce the number of false negative councils; and iii) maximizing the overall agreement of the risk groups between school prevalence and routine indicators. These criteria ensured to minimize the misallocation of councils belonging to the higher strata to the lower strata where the largest changes in the intervention packages are seen and was termed as

unacceptable (Supplementary Text S5.2, Supplementary Information). For instance, when selecting the optimal cut-off to define the very low and low risk category for the routine indicators, the criteria was based on trade-offs for minimization of FPR of councils with *Pf*PR_{5-16} >1% and *Pf*PR_{5-16} >5%, respectively, into the lower risk category and maximization of the overall agreement between indicators. Similarly, when selecting the optimal cut-off to define the moderate and high categories for the routine indicators, the criteria were based on trade-offs between minimization of FNR of councils with *Pf*PR_{5-16} >30% to the lower risk category and maximization of the overall agreement between indicators.

Following the selection of suitable cut-offs for all the routine indicators at the council level, the same cut-offs were applied to the routine indicators at the ward level to categorize them into their respective risk groups at that level.

5.3.4.2 Assignment of risk scores at the ward level

In order to combine the risk categories of the three routine indicators into a single stratum value per ward, a combined scoring approach was used for each ward. This entailed assigning numbered scores from 1-4 to each indicator per ward, corresponding to the respective risk categories: ‘very low’ (score 1), ‘low’ (score 2), ‘moderate’ (score 3), and ‘high’ (score 4).

5.3.4.3 Combination of routine indicators

To obtain the overall malaria risk score per ward, the assigned indicator scores were summed across the indicators. The total score ranged from 3 to 12 and was grouped into four risk categories to form the epidemiological strata. Specifically, wards with an overall score ≤3 were allocated to the very low stratum, >3-≤6 to the low stratum, >7-≤9 to moderate stratum, and >9 in the high stratum. Since not all wards had HFs with both ANC and laboratory services, the number of routine indicators per ward differed. As a result, the sub-division of the total score to classify the wards to the overall risk strata differed for those wards with fewer than three routine indicators (Supplementary Table S5.2, Supplementary Information).

5.3.5 Quantification of malaria risk heterogeneity within councils

In order to identify the councils that had the largest variation of malaria risk within their boundaries, the proportion of wards with different ward-level risks was quantified. This

heterogeneity was computed by calculating the number of wards assigned to the moderate and high transmission strata occurring within the councils with *Pf*PR_{5-16} <5% and the number of wards assigned to the very low and low transmission strata occurring within councils with *Pf*PR_{5-16} ≥5%. The corresponding proportion of the total population residing in these wards was also quantified.

R Studio (RStudio, 2020) was used for cleaning and analysis of the data downloaded from DHIS2. All maps were produced using the QGIS software version 3.4.14 (QGIS, 2022).

5.4 Results

5.4.1 Coverage and completeness of routine HMIS/DHIS2 data

Figure 5.1 provides a descriptive summary of the HFs and indicators included in the micro-stratification.

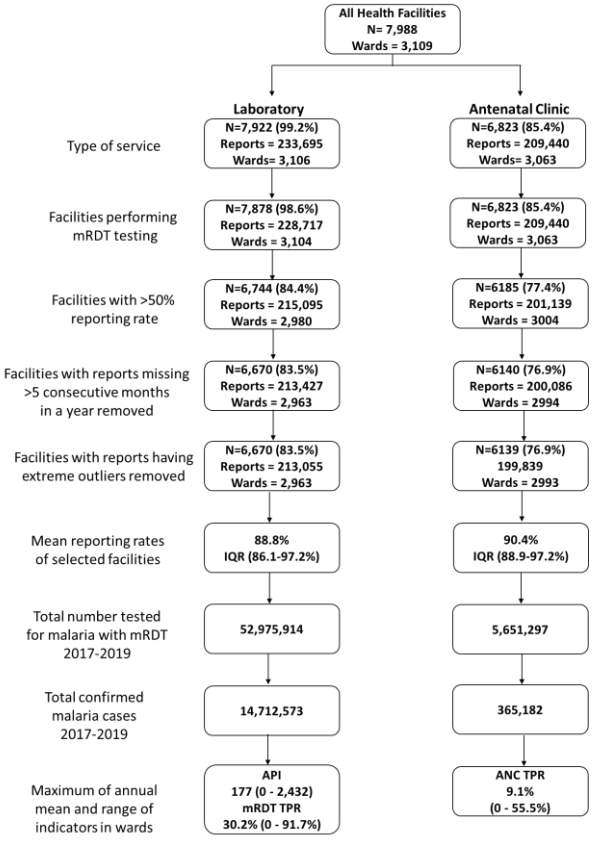


Figure 5.1: Descriptive summary of health facilities for which malaria data were utilized for micro-stratification.
ANC= Antenatal Clinic; IQR= Interquartile Range; API=Annual Parasite Incidence; TPR = Test Positivity Rate.

Of the 7,988 geo-coded HFs, the geo-coordinates for the majority (85%) were obtained from the master HF registry, while for 11% of HFs, the geo-coordinates did not match the indicated ward name in the master HF registry and therefore adjusted accordingly to reflect the indicated ward. A large proportion of these HFs offering malaria services belonged to the public health sector (72%), with 26% belonging to the private sector and 2% whose ownership status was not known at the time of analysis. Dispensary and clinics represented most of all the HFs (85.7%), followed by health centers (10.7%) and hospitals (3.6%) (Supplementary Figure S5.2, Supplementary Information).

Out of the total HFs, 7,878 HFs (98.6%) across 3,104 wards performed RDT diagnostic testing, 6,823 HFs (85%) across 3,063 wards offered antenatal services, whilst no HFs were found across 201 wards (Figure 5.1). When the completeness and consistency of the reports were assessed, the laboratory reports from 1,208 (15.3%) HFs across 141 (4.5%) wards and antenatal reports from 684 HFs (10.0%) across 70 (2.3%) wards were excluded from the analysis (Figure 5.2).

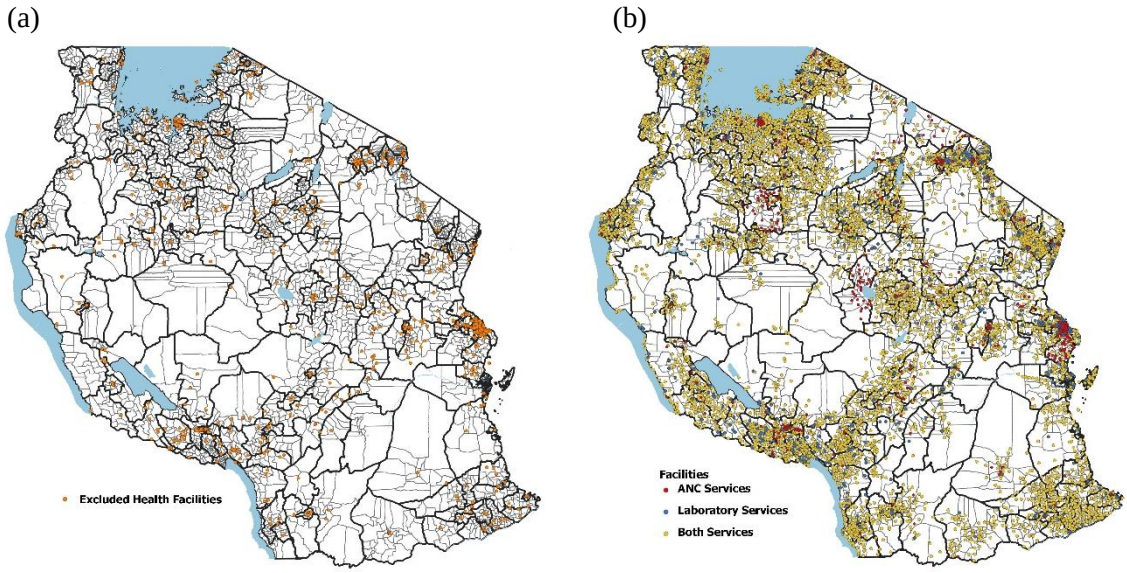


Figure 5.2: (a) Location of health facilities that were excluded (N=890). (b) Location of health facilities by type of service that were utilized for micro-stratification (N=7,098). ANC= Antenatal Clinic.

These HFs had either less than 50% RR, more than five consecutive months of missing reports or reports with extreme outliers. The overall proportion of extreme outliers was low with only 0.2% and 0.1% of total reports from laboratory and ANC registers removed, respectively. The majority of the HFs after exclusion (86% of HFs submitting laboratory reports and 90% of HFs submitting ANC reports) had more than 75% RR across the 36-month period of analysis with

only 14% (across 20 wards) and 10% (across 104 wards) of the HFs with RR between 50-75% for laboratory and ANC reports.

Of the selected HFs used for stratification (n=7,098) (Figure 5.2b), those offering both ANC and laboratory services accounted for 80.5% of all HFs, while 13.5% offering only laboratory services and 6% offering only ANC services. As a result, there were differing numbers of malaria indicators across the wards. Precisely, 2,891 (87.3%) wards had all three routine indicators, 72 (2.2%) wards had only two indicators of RDT TPR and API, while 102 (3.1%) wards had only one indicator of ANC TPR. Excluded HFs with poor RR also accounted for some of the differing numbers of indicators across wards (143 (83%) wards with only one or two indicators and 41 (16%) wards with no HF points).

Data from the laboratory registers of the selected HFs were obtained for a total of 52.9 million malaria tests performed by *Pf*-pan RDT, of which 14.7 million were positive for malaria. Similarly, data from the ANC registers of the selected HFs were obtained for a total of 5.7 million malaria tests performed on pregnant women, of which 365,182 were tested positive for malaria (Figure 5.1). When the distribution of the maximum annual mean values of all the indicators of wards within councils was examined, a heterogeneous distribution across wards was observed (Supplementary Figure S5.6, Supplementary Information). For instance, in councils with *Pf*PR_{5-16} <1%, the API ranged from 0 to 243 per 1,000 populations, RDT TPR ranged from 0 to 76% and ANC TPR ranged from 0 to 10% across wards. The observed heterogeneity within the different councils confirmed the need for further characterizing malaria risk at the ward level.

5.4.2 Risk categorization of councils using routine indicators

For the 2017 and 2019 surveys, estimates of malaria infection prevalence were available from a total of 693 sampled schools and 134,902 children across all 184 councils nationwide (MoHCDGEC, 2021, 2019). During this period, the maximum of the annual mean council prevalence ranged from 0.0-85.0%. Following the allocation of councils to the four malaria risk strata, 38 councils (20.6%) had *Pf*PR_{5-16} <1% (very low risk stratum), 32 councils (17.4%) had *Pf*PR_{5-16} 1-<5% (low risk stratum), 52 councils (28.3%) had *Pf*PR_{5-16} 5-<30% (moderate risk stratum) whilst 62 councils (33.7%) had *Pf*PR_{5-16} ≥30% (high risk stratum).

For each school prevalence risk group, the sensitivity, specificity and overall agreement for the different values of the routine indicator cut-offs are presented in Figure 5.3. A total of two, four and six councils with *Pf*PR_{5-16} >1% were misallocated into the very low strata for the selected cut-offs of RDT TPR, API and ANC TPR, respectively, which translated to an overall agreement of 93% for RDT TPR and API, and of 95% for ANC TPR. Similarly, for the selected low category cut-offs of RDT TPR, API and ANC TPR, a total of two, seven and four councils, respectively, with *Pf*PR_{5-16}>5% were misallocated to the low strata whilst maintaining the overall proportion agreement between indicators at 88% for RDT TPR and ANC TPR and 83% for API. When selecting the optimal cut-off to define the moderate and high categories for the routine indicators, a total of two, seven and four councils with *Pf*PR_{5-16}5-<30% were misallocated into the low or very low strata for the selected cut-offs of RDT TPR, API and ANC TPR, respectively. No councils belonging to the high risk group of *Pf*PR_{5-16}≥30% were misallocated to low and very low risk group by the selected routine indicator cut-offs.

Table 5.2 summarizes the final selected cut-offs derived from the misclassification analysis conducted at the council level, and subsequently applied to categorize each of the routine indicators per ward into the four risk groups.

Table 5.2: Selected routine indicator cut-offs to categorize these indicators into risk groups at ward level.

Prevalence in School Children	**Very Low risk (*Pf*PR_{5-16} <1%)**	**Low risk (*Pf*PR_{5-16} 1-<5%)**	**Moderate risk (*Pf*PR_{5-16} 5-<30%)**	**High risk (*Pf*PR_{5-16} ≥30%)**
Laboratory-based results				
1. Fever Test Positivity Rate	<5	5-<15	15-<30	≥30
2. Annual Parasite Incidence	<10	10-<50	50-<120	≥120
Antenatal Clinic results				
3. Test Positivity Rate	<0.8	0.8-<3	3-<8	≥8

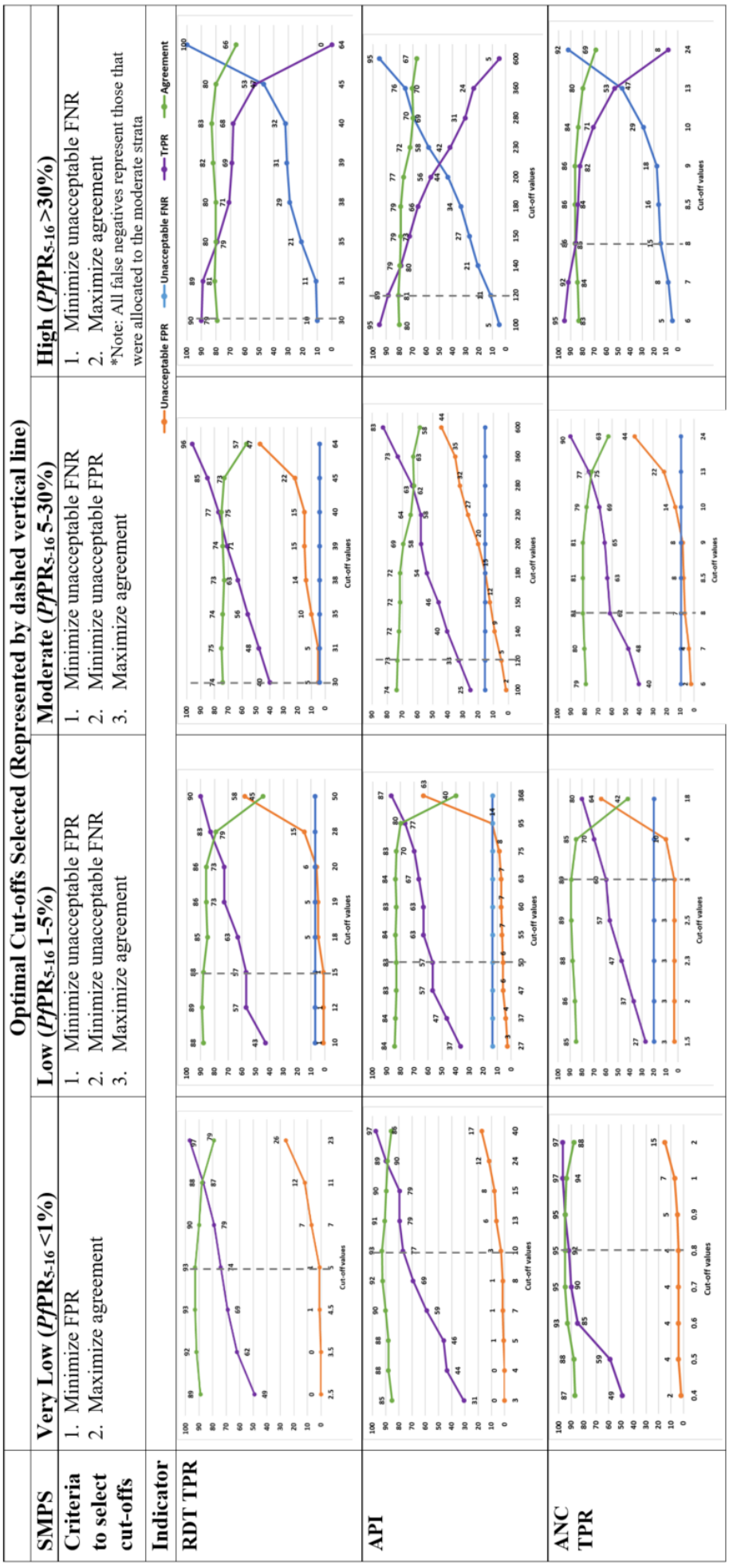
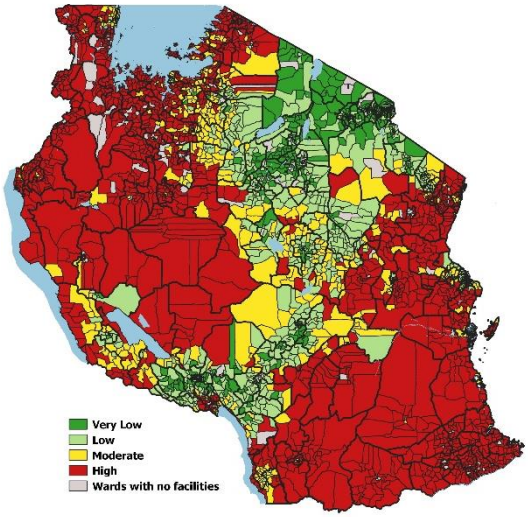


Figure 5.3: Misclassification analysis to select cut-offs for risk categories for the malaria indicators.
FPR = False Positivity Rate; FNR = False Negativity Rate; TrPR = True Positivity Rate; TPR = Test Positivity Rate

The corresponding spatial distribution by ward for each of the malaria risk indicator using the selected cut-offs is summarized in Figure S5.7 (See Supplementary Figure S5.7, Supplementary Information). Although variations exist between indicators in terms of the number of wards falling within each risk category, overall a similar pattern of heterogeneity was observed. The wards in the North-West and South-East of the country were mostly categorized into the moderate to high risk groups, while the wards in the central corridor running from North-East to South-West were mostly in the low and very low risk groups consistently across the three routine indicators.

5.4.3 Micro-stratification of wards and malaria risk heterogeneity

The resulting micro-stratification following the combination of multiple malaria routine indicators is shown in Figure 5.4.



Stratum	# of Wards (% of Population)
Very Low	353 (10.5%)
Low	717 (28.6%)
Moderate	525 (16.1%)
High	1,470 (39.8%)
Total	3,065

Figure 5.4: Micro-stratification of malaria risk in mainland Tanzania for the period 2017-2019

In total, 10.5% of the population resided in the 353 wards allocated to the very low strata, 28.6% resided in the 717 wards allocated to the low strata, 16.1% resided in the 525 wards allocated to the moderate strata, and 39.8% resided in the 1,470 wards allocated to the high strata. The 246 wards with no HFs represented approximately 5% of the total country population and because of the lack of all routine malaria indicators, no stratification could be conducted there.

The micro-stratification process revealed varying levels of heterogeneity within the wards of 80 councils (Figure 5.5; Supplementary Table S5.3, Supplementary Information).

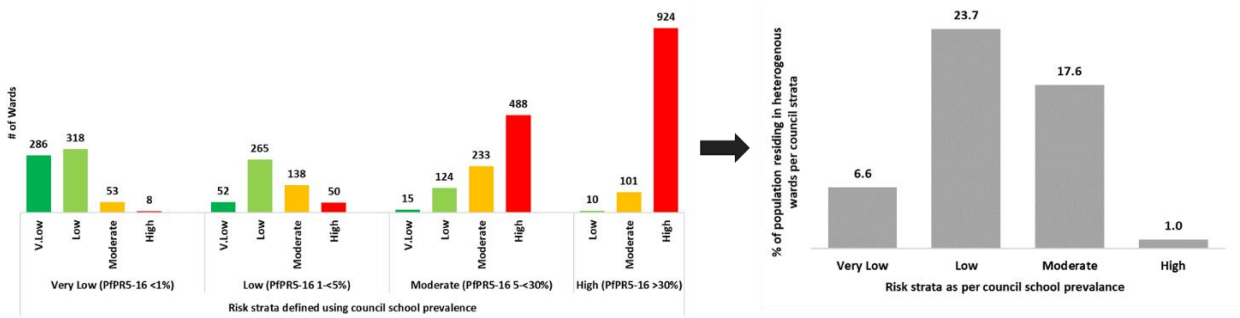


Figure 5.5:Number of heterogeneous wards per council prevalence risk group and corresponding population (%) residing in these wards

Of the councils with very low (*Pf*PR$_{5\text{-}16}$ <1%) and low (*Pf*PR$_{5\text{-}16}$ 1-<5%) prevalence, 12 had 6.6% of the population residing across 61 wards in the moderate-high transmission strata and 30 had 23.7% of the population residing across 188 wards in the moderate-high strata. Similarly, of the councils with moderate (*Pf*PR$_{5\text{-}16}$ 5-<30%) and high (*Pf*PR$_{5\text{-}16}$ >30%) prevalence, 32 had 17.6% of the population residing across the 139 wards in very low-low transmission strata and 6 had 1% of the population residing in the 10 wards with low transmission strata. Overall, councils with low prevalence had the highest proportion of heterogeneous wards (37.2%), followed by councils with moderate prevalence (16.2%), then by councils with very low prevalence (9.2%) and finally the councils with high prevalence (1%).

5.5 Discussion

This paper demonstrates at the level of an entire country the potential of using quality routine malaria indicators in informing on the malaria risk at the more granular levels: the third administrative level (wards). It builds on previous efforts taken by mainland Tanzania in using routine malaria indicators to stratify malaria risk at the second administrative level (councils) (Thawer et al., 2020).

A strong feature of the method presented here is the triangulation of information from multiple malariometric indicators. The selected routine indicators represented a valuable and rich source of data in space and time across different age and immunological groups (children versus all ages and pregnant women). The approach categorized the three selected routine indicators

using school prevalence classifications as a gold standard, since the prevalence rate in children is widely used as a reference metric for defining malaria risk (Alegana et al., 2021a; Weiss et al., 2019). Because of the sampling strategy used in Tanzania for school surveys, it added further confidence to school prevalence serving as an appropriate benchmark for the misclassification analysis. Furthermore, the misclassification analysis was conservative and inclined to allocating wards to higher strata than to the lower strata that would otherwise receive reduced control efforts.

The use of routine indicators was contingent on the availability of data. Using data from HFs with RR >50% ensured the reliability of our estimates. Applying a higher threshold for RR would have meant that only a small proportion of HFs (~20-25%) could be included in the analysis. Hence, the criteria of 50% reporting represented a good compromise between data quality and the number of HF data available for analysis (See Supplementary Figure S5.8, Supplementary Information). Current guidelines by WHO recommends assessing four core dimensions for understanding the quality of routine data. These include: i) completeness and timeliness of data; ii) internal consistency of reported data (presence of outliers, consistency over time and consistency between data elements); iii) external consistency with other data sources; and, iv) external comparison with population data (World Health Organization, 2017b). Due to the limited elements reported within the laboratory registers of Tanzania, the consistency with other data elements was not possible. Generally, the RR for HFs data were high in Tanzania with only a small proportion of reports having extreme outliers, allowing the use of such data in this systematic way for risk assessment. The country has also recently launched the malaria service and data quality improvement tool that involves conducting HF supervision by council health teams on a quarterly basis to assess the malaria related services and data quality performance (National Malaria Control Programme, 2017c).

Although this may not be the case in other countries in SSA and could limit the applicability of this approach elsewhere, it stresses the importance for other countries to work towards strengthening their routine information system and reporting practices. Furthermore, the work presented in this paper made use of the local data available in Tanzania, as such, the approach would need to be tailored in other countries according to available metrics and local context.

The resulting risk map detailed to ward level (Figure 5.4) revealed significant heterogeneity in malaria risk within 80 councils and helped to identify areas where the population could be further prioritized to receive more targeted community-based interventions. For instance, Bumbuli District Council is currently in the very low transmission strata, but the micro-stratification process revealed wards in the moderate and high transmission that could qualify for increased long-lasting insecticidal nets (LLIN) distribution (See Supplementary Figure S5.9, Supplementary Information). Compared to previous approaches of distributing LLINs universally across all wards (Renggli et al., 2013), this new knowledge could finely target LLIN distribution within such wards, allowing a more efficient allocation of resources within a council that was previously assumed to have a uniform risk.

Supporting ministries of health to establish a quantitatively and qualitatively high-performance routine surveillance system, and strengthening the ability of NMCPs to analyse these data for developing stratification risk maps and on from that for decision making, is imperative for more efficient malaria control (Boerma and Mathers, 2015; World Health Organization, 2018a). It is crucial that each malaria-endemic country's capacity is strengthened with regard to reliable data collection, detection of data biases, and its ability for conducting sensible analysis on a routine basis. Increased usage of maps for local decision making by NMCPs promotes knowledge and understanding of the various data sources and their limitations, trust and perceived ownership of the data, and finally increased knowledge and understanding of the processes of map construction (Ghilardi et al., 2020).

The work presented here has some limitations that future work might address. The use of crude estimates of routine data does not account for important factors such as treatment-seeking rates, temporal and spatial missingness in data, the underlying heterogeneous distribution of the population and the differing testing rates between transmission settings, all of which can potentially under/over-estimate positivity rates (Amboko et al., 2020; Maïga et al., 2019). There have been many recent advances in statistical tools that use spatiotemporal modelling and imputation methods to better handle incomplete data and account for important biases present in routine data (Alegana et al., 2020; Bennett et al., 2014; Sturrock et al., 2016). Since these approaches are complex, future work may explore comparing crude routine estimates against more complex statistical data modelling, in order to find an optimum point between accuracy and local ability to handle the data analysis process.

The estimates of the routine indicators used in the present analysis come with uncertainty due to sampling error (See Supplementary Figure S5.10, Supplementary Information). The risk strata assigned to each ward through the approach described in this paper did not account for this uncertainty. Thus the uncertainty in the micro-stratification risk strata was quantified at the ward level. First, the uncertainty of the individual routine indicator estimates, measured using the standard error, were obtained using multilevel regression analysis and then a sampling-based approach was used to estimate the probability of being in each risk strata for each ward (Supplementary Text S5.3, Supplementary Information). The results of the regression and sampling-based analysis (Supplementary Text S5.4, Figure S5.12, Supplementary Information) highlight the importance of considering the variation of indicators when conducting the micro-stratification, and in estimating the certainty of the assigned risk strata. While for the majority of wards (over 60%), considering the variability of indicators did not change the assigned risk stratum, a substantial proportion of wards were more sensitive to the uncertainty in the estimated indicators. These wards had a reasonable probability of being assigned to the risk stratum immediately below that of the initially assigned stratum.

Although the micro-stratification approach adopted by the NMCP in Tanzania was more conservative, ensuring that wards were not misallocated to the lower strata, which would receive fewer vector control interventions, it is important that NMCPs take this uncertainty into account for more efficient planning of interventions. Specifically, the wards with a low assignment probability would require more careful investigation of the possible causes of the greater uncertainty in the estimated indicators. If the uncertainty is partly due to increased transmission heterogeneity, this would suggest that a localized deployment of interventions would be more appropriate compared to a ward-level approach. However, if the uncertainty is due to data collection and reporting, then more efforts need to be channeled towards optimizing the collection procedures.

Obviously, HFs may not always reflect the actual transmission status of the ward since people from surrounding wards may also utilize their services. Furthermore, the estimates may not always represent the universe of all HFs since poor performing HFs and private providers that are not linked to the DHIS2 are not captured without further adaptations. Obtaining accurate estimates of population denominators is currently a major challenge for defining HF catchment areas (Macharia et al., 2021) in view of computing incidence rates, and until this knowledge is

made available, the use of existing operational administrative boundaries as a proxy will continue to serve as the reference guide.

The current micro-stratification only considered the maximum value of the annual estimates for all ages in the past three years from DHIS2. It may be important to overlay the epidemiological risk map with other layers of information that are known to affect transmission such as urbanization, seasonality, monthly trends, disaggregation by age groups, marginalization, intervention coverage, ecological factors as well as socio-economic and population factors.

Furthermore, the availability of a comprehensive list of geo-coded HFs through the master HF list, that is dynamically updated in the HMIS/DHIS2, is a challenge in many parts of SSA (Maina et al., 2019; WHO/USAID, 2018). Ideally, the DHIS2 should represent information from all healthcare providers, however this is often not the case in many countries, with a large proportion of HFs missing in the DHIS2. Availability of an updated list of health providers is crucial to allow understanding of true reporting completeness, and availability of its geo-coded information allows linkage of HFs to its correct administrative boundaries especially at the finer spatial scales for correct quantification of risks. Efforts are needed to encourage countries to geo-reference all HFs and accordingly update their national databases.

Finally, the work presented here did not account for the fact that the relationship between the different indicators that represent different population age groups may not always be linear. An in-depth understanding of how they relate to one another and with more traditional measures of modelled prevalence estimates in the different transmission settings is crucial. Efforts to understand this relationship and incorporate routine data sources into modelled prevalence risk maps are emerging (Yukich et al., 2012).

The WHO High Burden to High Impact (HBHI) strategy recommends countries to conduct stratification analysis at the sub-national levels, preferably at district level or at lower levels in accordance with the local context (World Health Organization, 2020b). Mainland Tanzania has fully adopted a sub-national tailoring of interventions at the council level (National Malaria Control Programme, 2021). It is now recognizing the need for micro-stratification and decentralization of malaria control as indicated in its current strategic plan (National Malaria

Control Programme, 2021). Wards are expected to become the ultimate target for further evidence-based malaria control planning by the Council Health Management Teams (CHMTs), especially for community-based interventions including community case management and focal vector control initiatives such as indoor residual spraying (IRS) and larviciding, down to ward level. Macro-stratification becomes more relevant across councils with homogenous transmission that require universal allocation of interventions across its population. However, for those councils with heterogeneous transmission within its administrative boundaries, these would need concentrated efforts in areas that most need them. The role of CHMTs in highly malaria-endemic countries has been traditionally limited to the operationalization at council level of key preventative malaria interventions such as LLINs, IRS, case management, and intermittent preventative treatment in pregnant women (IPTp), planned at central levels.

Whether the operationalization of micro-stratification and micro-planning is feasible remains to be assessed and will require close monitoring of the processes at all levels to ensure that it is replicated across councils. More importantly, there is a growing need to capacitate CHMTs to assemble, clean, interpret, and understand associated levels of uncertainty in their local data so as to undertake assessments of the local heterogeneity especially of wards that are not transitioning its transmission levels downwards at the same rate as others. For this, the need for granular data is crucial to empower the CHMTs to make use of the local data across health sectors. Micro-stratification is expected to allow this profound change in health planning processes by promoting a culture of data usage and equip council level with the capacity and tools to understand and appropriately respond to the local situation.

5.6 Conclusion

The micro-stratification approach undertaken for mainland Tanzania has moved the agenda from council-level risk mapping to one at ward level reflecting the need for the decentralization of malaria control planning. Continuous efforts to improve routine data remains crucial for ensuring a reliable source of data for local epidemiological monitoring at sub-council level. This can have immediate potential in capacitating CHMTs to take charge of their routine data and respond in an appropriate manner to maximize impact and turn malaria surveillance into a core intervention.

5.7 Declarations.

5.7.1 Ethics approval and consent to participate

This work utilizes secondary aggregated data for analysis for which no ethics approval was required.

5.7.2 Consent for publication

Not applicable.

5.7.3 Availability of data and materials

Data from routine HMIS/DHIS2 are not publicly available and were obtained with request from the National Malaria Control Programme of mainland Tanzania. Restrictions apply to the availability of these data and permission can be obtained with reasonable request from the Ministry of Health of mainland Tanzania.

5.7.4 Competing interest

The authors declare that they have no competing interests.

5.7.5 Funding

Funding for SGT, FM and NK was received from the Swiss Tropical and Public Health Institute – Towards Elimination of Malaria in Tanzania (TEMT) Project funded by the Embassy of Switzerland in Tanzania. EP from the Global Fund to Fight Aids, Tuberculosis and Malaria (GFATM) and the Swiss Tropical and Public Health Institute. RWS is supported as a Wellcome Trust Principal Fellow (# 103602 and 212176). RWS also acknowledges support from the UK's Department for International Development under a project entitled *Strengthening the Use of Data for Malaria Decision Making in Africa* (DFID Programme Code # 203155).

5.7.6 Authors' contributions

SGT, EP, MG, RWS, FM and AR conceptualized the methodological analysis. SGT, FC and KM acquired the data. SGT compiled the data and performed the analysis. EP, RWS, MG, AR, CL, FM, NK, FC, KM, SA, SL and AM provided input on the interpretation of the analysis. SGT with guidance from EP, RWS, MG and AR prepared the initial draft manuscript and its finalization. EP, RWS, MG, AR, CL, FM, NK, FC, KM, SA, SL and AM provided critical comments on progressive drafts. All authors reviewed and approved of the final manuscript.

5.7.7 Acknowledgements

The authors would like to thank all the members of the National Malaria Control Programme, of the Ministry of Health of mainland Tanzania, President's Office al Administration and Local Government offices, WHO country office and development partners for their participation and invaluable discussions to make this work possible.

5.8 Supplementary information

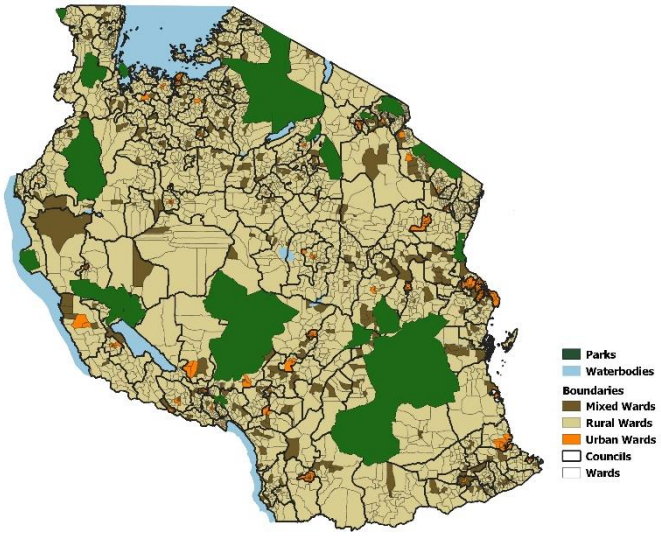


Figure S5.1: Administrative boundaries and distribution of urban, rural and mixed wards in mainland Tanzania.

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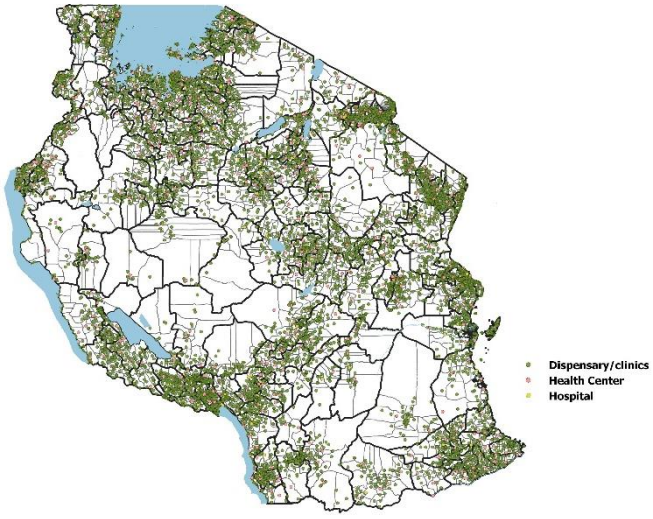

Figure S5.2: Location of health facilities (HFs) by type (n=7,988)

*For 157 (2%) of the total HFs, the ward name in the master HF list did not appear in the existing ward shape file and therefore the geo-coordinate was used to guide the ward location in the shape file. The geo coordinates for another 180 (2%) HFs could not be obtained from the master HF list and thus open source platforms such as Google Earth was used to retrieve the information

Text S5.1 Identification of outliers with the *anomalize* R package:

Extreme outliers in the routine indicator values were defined as the monthly values that significantly deviated from the HF's overall time series trend across the 36 months. The R package anomalize performs the outlier detection on the remainder from a time series analysis after removing the seasonal and trend component (Dancho and Vaughan, 2020). Following decomposition of data through the "Twitter" approach, the inner quartile range of the data series was used to establish the distribution on the remainder. A factor of X9 was used to set the limits above and below the inner quartile range and any remainder beyond the limit was considered an extreme outlier. A visual inspection was done to verify the identified outliers and these were subsequently removed and treated as a missing monthly report.

Table S5.1: Contingency table to compute sensitivity and specificity for each indicator at council level using prevalence categories in school children (*Pf*PR_{5-16}) as the ground truth

		Malaria Indicator	
		Predicted Stratum	**Other Strata**
***Pf*PR$_{5-16}$**	**True Stratum**	True Positive	False Negative
	Other Strata	False Positive	True Negative

Text S5.2 Misclassification analysis

Definitions:

Overall Agreement: proportion of councils that belong to a particular stratum as defined by both the school prevalence and the routine indicator i.e., the proportion of agreement between the indicators.

Sensitivity or True Positivity Rate (TrPR): proportion of councils that belong to a particular stratum as defined by the school prevalence and were correctly classified into that stratum based on the routine malaria indicator.

Specificity or True Negativity Rate (TrNR): proportion of councils that do not belong to a particular stratum as defined by the school prevalence and were correctly not allocated to that stratum based on the routine malaria indicator.

False Positivity Rate (FPR): proportion of councils that do not belong to a particular stratum as defined by the school prevalence but were misclassified to that stratum based on the routine malaria indicator.

False Negativity Rate (FNR): proportion of councils that belong to a particular stratum as defined by the school prevalence but were misclassified and not allocated to that stratum based on routine malaria indicator.

Unacceptable False Positivity Rate (FPR): proportion of councils with *Pf*PR$_{5-16}$ 1-<5%, *Pf*PR$_{5-16}$ 5-30% and *Pf*PR$_{5-16}$ >30% that do not belong to a particular stratum as defined by the school prevalence but were misclassified to a lower stratum based on the routine malaria indicator (Figure S5.3i).

Unacceptable False Negativity Rate (FNR): proportion of councils with *Pf*PR$_{5-16}$ 1-<5%, *Pf*PR$_{5-16}$ 5-30% and *Pf*PR$_{5-16}$ >30% that belong to a particular stratum as defined by the school prevalence but were misclassified to a lower stratum based on the routine malaria indicator (Figure S5.3ii).

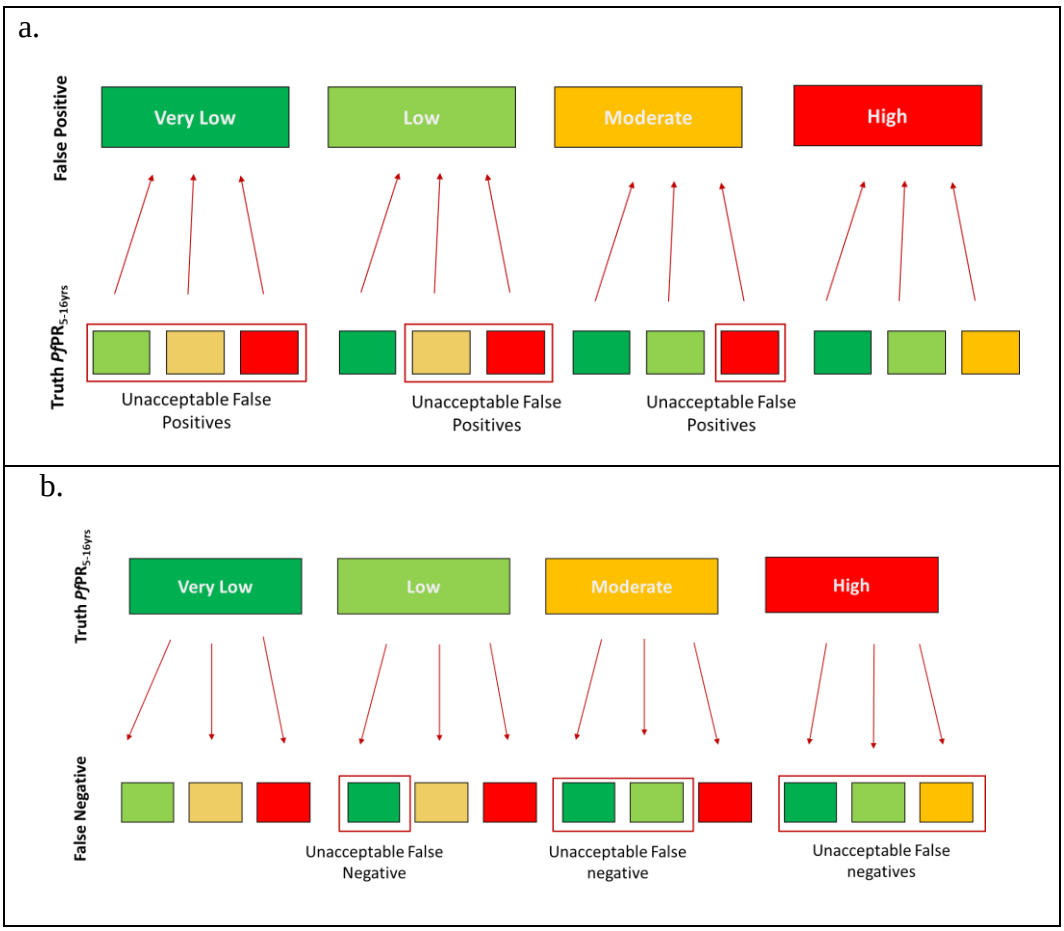

Figure S5.3: (i) Definition of unacceptable false positives per risk stratum, (ii) definition of unacceptable false negatives per risk stratum.

Table S5.2: Total score cut-offs depending on the number of indicators per ward

# of indicators	1	2	3
Very Low	=1	≤2	≤3
Low	=2	3- ≤4	4-≤6
Moderate	=3	5-≤6	7-≤9
High	=4	7-≤8	10-≤12

Text S5.3: Method for incorporating the uncertainty in ward-level routine indicator estimates in order to quantify the uncertainty in the risk stratification.

Estimating the standard errors of the routine indicator estimates:

The risk strata per ward determined from the pragmatic approach did not account for the uncertainty in the routine indicator estimates. Thus, to quantify the uncertainty of the stratification of malaria risk at the ward level, the uncertainty of the individual routine indicator estimates was obtained using multilevel regression models. For each indicator and ward, a generalized linear mixed-effects regression model was defined with a random effect for HF. Precisely, a binomial logistic regression was defined for ANC TPR and mRDT TPR, whilst a Poisson regression was defined for the API. The standard errors of the regression coefficient estimates from the models were used to estimate the variation of the log- or logit- transformed indicators per ward. Subsequently, a sampling-based approach was used to evaluate the uncertainty of the risk strata for the wards.

In absence of information about the total number of HFs per ward and the ratio of the sampled HFs for routine indicators, a conservative assumption was adopted where we consider that the HFs were sampled from an infinite set. In Tanzania, the HF catchment population remains largely undefined. Therefore, to estimate the case incidence per HF, the ratio of HF Outpatient Department (OPD) attendance out of the total ward OPD attendance was used as a proxy to obtain the proportion of population residing within a HF's catchment out of the total ward population. The regression model for the incidence of a HF i of a ward j (Y_{ij}) was defined as follows:

$$Y_{ij} \sim Poisson(\lambda_{ij})$$

$$log\lambda_{ij} = \log(Pop_{ij}) + \beta_j + \epsilon_{ij}$$

$$\beta_j = \gamma_{00} + u_j$$

Where:

λ_{ij} = incidence rate for HF i in ward j

Pop_{ij} = HF catchment population at risk for HF i in ward j

β_j = intercept of the dependent variable in ward j

ϵ_{ij} = residual error for HF i in ward j

u_j = random error component for the deviation of the intercept of a group from the overall intercept

Similarly, for ANC TPR and mRDT TPR of a HF i of a ward j (Y_{ij}), binomial regression models with logit link functions were defined as:

$$Y_{ij} \sim Binomial(P_{ij})$$
$$logit(P_{ij}) = \beta_j + \epsilon_{ij}$$

Where:

P_{ij} = positivity rate for HF i in ward j

β_j = intercept of the dependent variable in ward j

ϵ_{ij} = residual error

The performance of the three regression models was evaluated by inspecting the correlations of the observed values versus the model estimates (Figure S5.4).

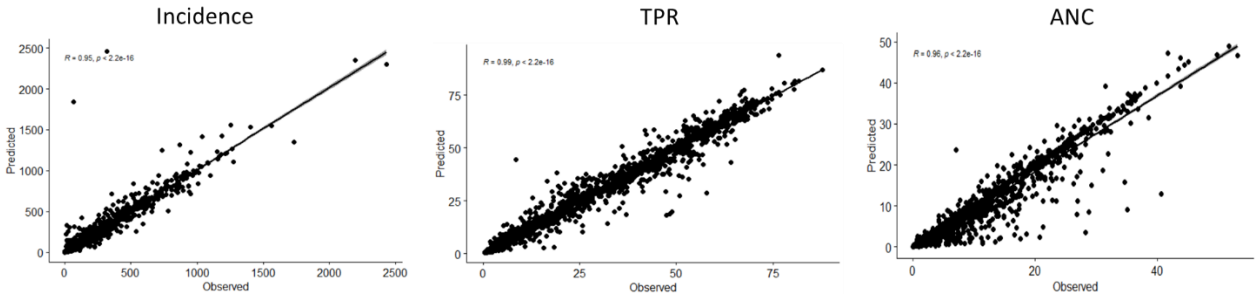

Figure S5.4: Scatter plots of the observed maximum ward indicator values vs the estimates obtained from the regression models.

The standard errors for the regression coefficient estimates from the models were used to define the variability of indicators per ward. The regression analysis could only be performed on wards with collected routine data from more than 1 HF: 1,698 (56.7%) wards with ANC TPR, 1,897 (64%) with mRDT TPR and 1,934 (65.3%) wards with incidence. For the remaining

wards with data from only 1 HF, the average across all the estimated standard errors per indicator was used to represent the uncertainty of the corresponding indicator (Figure S5.5).

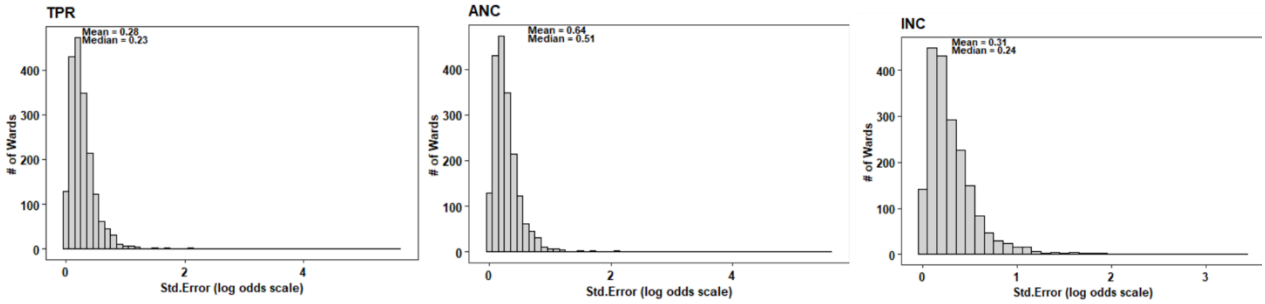

Figure S5.5: Distribution of the estimated standard errors for the wards with collected data from more than one health facility.

Quantification of risk strata uncertainty: the probability of a ward being assigned to a risk stratum:

For each ward, 1000 different sampled sets of indicator values were defined which were then separately used for running the micro-stratification procedure. Each set contained values for the three indicators. For each indicator, these values were sampled from a normal distribution with mean equal to the aggregated maximum indicator value per ward and standard deviation equal to the standard error estimated from the corresponding regression model on the log odds scale. Next, the micro-stratification procedure was separately conducted for each of the 1000 sampled sets of indicator values. Finally, for each ward, the proportion of times the micro-stratification yielded each risk category was computed and used to define the probability of a ward to be assigned to a risk stratum. The risk category with the highest assignment probability was selected to assign a ward to its corresponding risk stratum. The results were summarized through charts and maps and subsequently compared to the risk stratum obtained from the pragmatic approach.

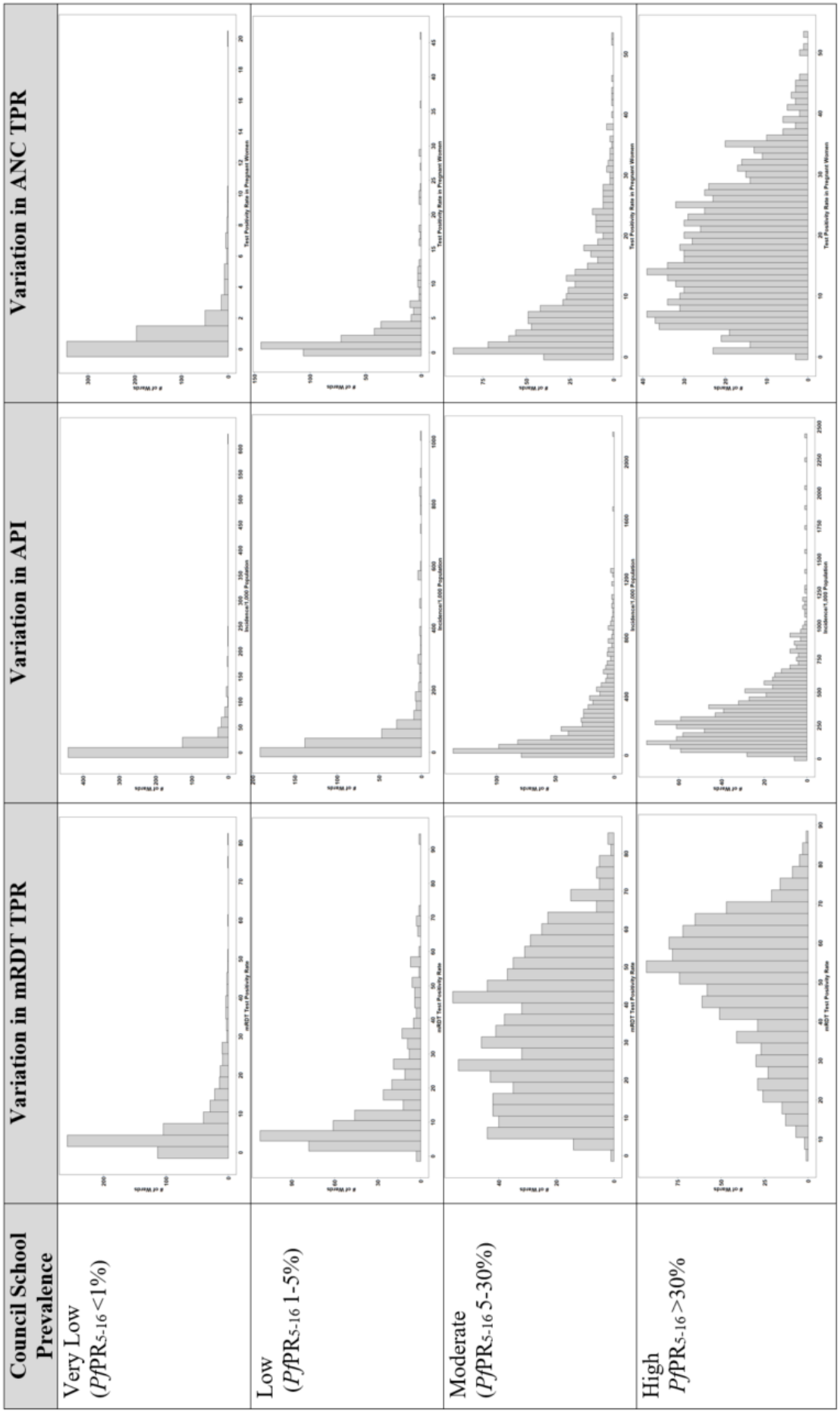

Figure S5.6: Distribution of the routine indicators across wards by council prevalence

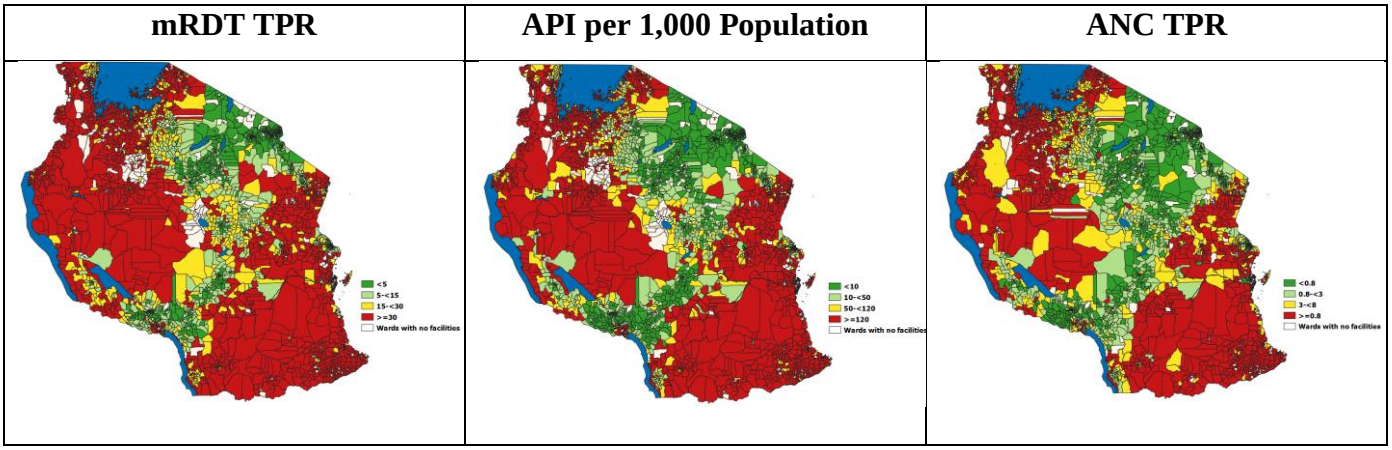

Figure S5.7: Spatial distribution at ward level of the maximum values of the mean annual malaria risk by type of indicator

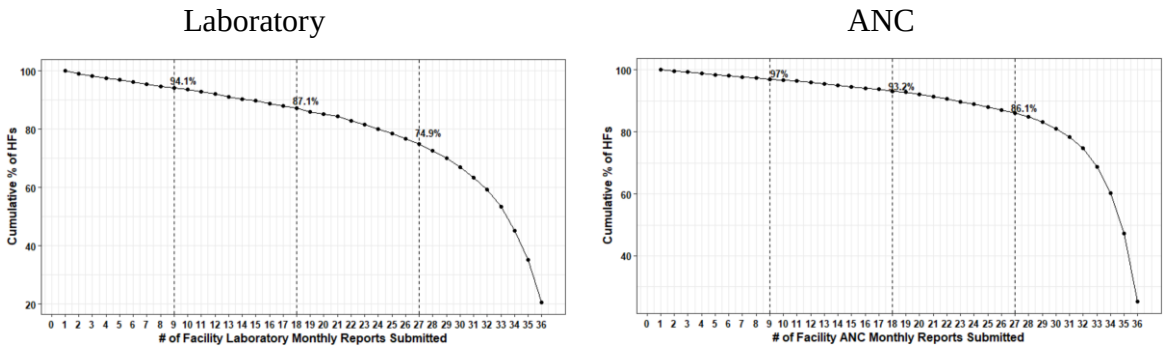

Figure S5.8: Cumulative proportion of facilities submitting 0-36 monthly reports in the period 2017-2019 for laboratory and antenatal clinic (ANC) reports in mainland Tanzania

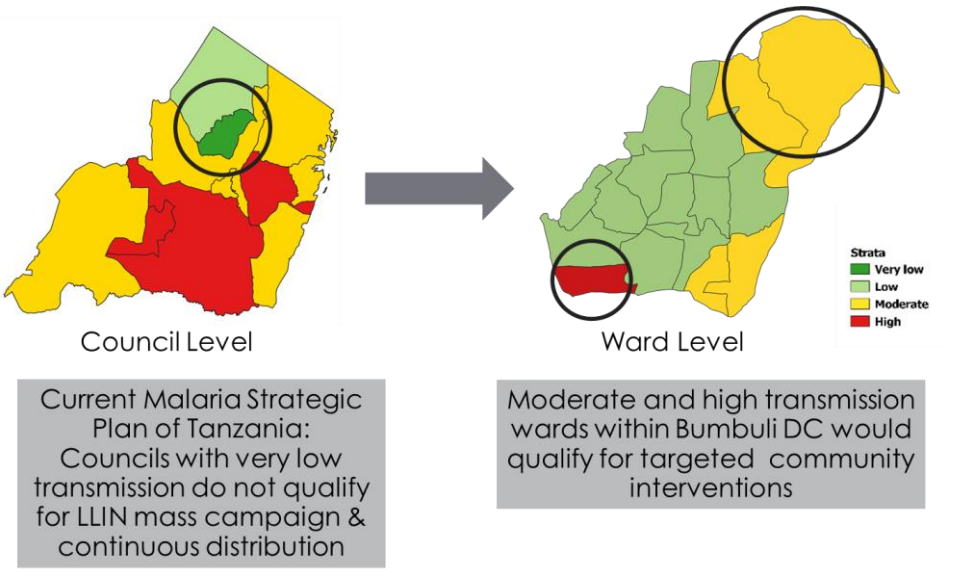

Figure S5.9: Transmission risk across the wards of Bumbuli District Council

Table S5.3 Proportion of heterogeneity per council in mainland Tanzania.

Region	District	% of heterogenous wards	% of population residing in heterogenous wards
Mtwara	Newala Town Council	100.0	100.0
Songwe	Songwe District Council	85.7	79.2
Kagera	Bukoba Municipal Council	81.8	83.6
Songwe	Ileje District Council	77.8	80.8
Simiyu	Meatu District Council	76.0	74.4
Dodoma	Chemba District Council	75.0	78.1
Singida	Itigi District Council	72.7	74.0
Pwani	Kibaha Town Council	70.0	64.2
Ruvuma	Mbinga Town Council	70.0	77.2
Mara	Musoma Municipal Council	66.7	65.4
Dodoma	Bahi District Council	65.0	65.7
Dodoma	Chamwino District Council	62.5	54.0
Dodoma	Mpwapwa District Council	62.1	55.3
Morogoro	Morogoro Municipal Council	57.9	32.1
Simiyu	Itilima District Council	57.9	60.2
Mbeya	Rungwe District Council	52.4	59.9
Njombe	Ludewa District Council	52.2	36.1
Mbeya	Busokelo District Council	50.0	52.0
Mwanza	Nyamagana Municipal Council	50.0	28.2
Simiyu	Bariadi Town Council	50.0	43.7
Morogoro	Gairo District Council	45.5	42.4
Dar Es Salaam	Kigamboni Municipal Council	44.4	26.8
Mwanza	Ilemela Municipal Council	44.4	48.7
Katavi	Mpimbwe District Council	42.9	47.0
Mbeya	Chunya District Council	37.5	32.5
Singida	Ikungi District Council	36.0	37.8
Mbeya	Mbarali District Council	33.3	22.2
Iringa	Kilolo District Council	31.8	33.6
Tanga	Bumbuli District Council	31.3	27.7
Pwani	Bagamoyo District Council	28.6	17.8
Iringa	Iringa District Council	28.0	21.5
Njombe	Njombe District Council	27.3	20.6
Iringa	Mufindi District Council	25.0	20.1
Manyara	Simanjiro District Council	25.0	18.8
Shinyanga	Kishapu District Council	25.0	23.4
Tanga	Tanga City Council	23.8	36.6
Shinyanga	Kahama Town Council	23.5	27.2
Singida	Iramba District Council	23.5	24.4
Dar Es Salaam	Ilala Municipal Council	23.1	9.3
Rukwa	Sumbawanga Municipal Council	23.1	15.8
Morogoro	Ifakara Town Council	22.2	28.7

Region	District	% of heterogenous wards	% of population residing in heterogenous wards
Singida	Manyoni District Council	22.2	18.5
Dar Es Salaam	Kinondoni Municipal Council	20.0	10.8
Tabora	Tabora Municipal Council	20.0	33.1
Dar Es Salaam	Temeke Municipal Council	19.0	15.1
Manyara	Kiteto District Council	16.7	11.1
Mara	Tarime Town Council	16.7	16.3
Njombe	Makambako Town Council	16.7	8.7
Shinyanga	Shinyanga Municipal Council	16.7	18.7
Songwe	Momba District Council	16.7	17.5
Dodoma	Dodoma Municipal Council	16.1	12.0
Dodoma	Kondoa Town Council	14.3	10.2
Katavi	Mpanda Municipal Council	14.3	16.4
Njombe	Makete District Council	14.3	12.1
Mwanza	Kwimba District Council	13.3	11.8
Rukwa	Sumbawanga District Council	13.3	8.7
Simiyu	Maswa District Council	12.0	13.0
Tanga	Lushoto District Council	12.0	9.4
Rukwa	Kalambo District Council	11.8	12.2
Tabora	Igunga District Council	11.5	8.8
Kagera	Bukoba District Council	11.1	12.8
Dodoma	Kongwa District Council	9.1	8.4
Pwani	Kibaha District Council	9.1	15.6
Tabora	Nzega District Council	7.4	7.2
Dar Es Salaam	Ubungo Municipal Council	7.1	4.8
Singida	Mkalama District Council	7.1	5.9
Kilimanjaro	Same District Council	6.7	6.5
Mara	Musoma District Council	6.7	8.5
Ruvuma	Nyasa District Council	6.7	5.5
Ruvuma	Songea Municipal Council	6.7	13.5
Morogoro	Kilosa District Council	6.5	9.3
Morogoro	Mvomero District Council	5.9	2.3
Njombe	Wanging'ombe District Council	5.9	7.1
Rukwa	Nkasi District Council	5.9	5.5
Pwani	Mkuranga District Council	5.6	15.6
Mbeya	Kyela District Council	5.3	3.8
Tanga	Kilindi District Council	5.3	6.4
Kagera	Missenyi District Council	5.0	4.7
Tanga	Korogwe District Council	5.0	9.4
Ruvuma	Mbinga District Council	4.2	4.6
Arusha	Arusha City Council	0.0	0.0
Arusha	Arusha District Council	0.0	0.0
Arusha	Karatu District Council	0.0	0.0

Region	District	% of heterogenous wards	% of population residing in heterogenous wards
Arusha	Longido District Council	0.0	0.0
Arusha	Meru District Council	0.0	0.0
Arusha	Monduli District Council	0.0	0.0
Arusha	Ngorongoro District Council	0.0	0.0
Dodoma	Kondoa District Council	0.0	0.0
Geita	Bukombe District Council	0.0	0.0
Geita	Chato District Council	0.0	0.0
Geita	Geita District Council	0.0	0.0
Geita	Geita Town council	0.0	0.0
Geita	Mbogwe District Council	0.0	0.0
Geita	Nyang'hwale District Council	0.0	0.0
Iringa	Iringa Municipal Council	0.0	0.0
Iringa	Mafinga Town Council	0.0	0.0
Kagera	Biharamulo District Council	0.0	0.0
Kagera	Karagwe District Council	0.0	0.0
Kagera	Kyerwa District Council	0.0	0.0
Kagera	Muleba District Council	0.0	0.0
Kagera	Ngara District Council	0.0	0.0
Katavi	Mlele District Council	0.0	0.0
Katavi	Mpanda District Council	0.0	0.0
Katavi	Nsimbo District Council	0.0	0.0
Kigoma	Buhigwe District Council	0.0	0.0
Kigoma	Kakonko District Council	0.0	0.0
Kigoma	Kasulu District Council	0.0	0.0
Kigoma	Kasulu Town Council	0.0	0.0
Kigoma	Kibondo District Council	0.0	0.0
Kigoma	Kigoma District Council	0.0	0.0
Kigoma	Kigoma Municipal Council	0.0	0.0
Kigoma	Uvinza District Council	0.0	0.0
Kilimanjaro	Hai District Council	0.0	0.0
Kilimanjaro	Moshi District Council	0.0	0.0
Kilimanjaro	Moshi Municipal Council	0.0	0.0
Kilimanjaro	Mwanga District Council	0.0	0.0
Kilimanjaro	Rombo District Council	0.0	0.0
Kilimanjaro	Siha District Council	0.0	0.0
Lindi	Kilwa District Council	0.0	0.0
Lindi	Lindi Municipal Council	0.0	0.0
Lindi	Liwale District Council	0.0	0.0
Lindi	Mtama District Council	0.0	0.0
Lindi	Nachingwea District Council	0.0	0.0
Lindi	Ruangwa District Council	0.0	0.0
Manyara	Babati District Council	0.0	0.0

Region	District	% of heterogenous wards	% of population residing in heterogenous wards
Manyara	Babati Town Council	0.0	0.0
Manyara	Hanang District Council	0.0	0.0
Manyara	Mbulu District Council	0.0	0.0
Manyara	Mbulu Town Council	0.0	0.0
Mara	Bunda District Council	0.0	0.0
Mara	Bunda Town Council	0.0	0.0
Mara	Butiama District Council	0.0	0.0
Mara	Rorya District Council	0.0	0.0
Mara	Serengeti District Council	0.0	0.0
Mara	Tarime District Council	0.0	0.0
Mbeya	Mbeya City Council	0.0	0.0
Mbeya	Mbeya District Council	0.0	0.0
Morogoro	Kilombero District Council	0.0	0.0
Morogoro	Malinyi District Council	0.0	0.0
Morogoro	Morogoro District Council	0.0	0.0
Morogoro	Ulanga District Council	0.0	0.0
Mtwara	Masasi District Council	0.0	0.0
Mtwara	Masasi Town Council	0.0	0.0
Mtwara	Mtwara District Council	0.0	0.0
Mtwara	Mtwara Municipal Council	0.0	0.0
Mtwara	Nanyamba Town Council	0.0	0.0
Mtwara	Nanyumbu District Council	0.0	0.0
Mtwara	Newala District Council	0.0	0.0
Mtwara	Tandahimba District Council	0.0	0.0
Mwanza	Buchosa District Council	0.0	0.0
Mwanza	Magu District Council	0.0	0.0
Mwanza	Misungwi District Council	0.0	0.0
Mwanza	Sengerema District Council	0.0	0.0
Mwanza	Ukerewe District Council	0.0	0.0
Njombe	Njombe Town Council	0.0	0.0
Pwani	Chalinze District Council	0.0	0.0
Pwani	Kibiti District Council	0.0	0.0
Pwani	Kisarawe District Council	0.0	0.0
Pwani	Mafia District Council	0.0	0.0
Pwani	Rufiji District Council	0.0	0.0
Ruvuma	Madaba District Council	0.0	0.0
Ruvuma	Namtumbo District Council	0.0	0.0
Ruvuma	Songea District Council	0.0	0.0
Ruvuma	Tunduru District Council	0.0	0.0
Shinyanga	Msalala District Council	0.0	0.0
Shinyanga	Shinyanga District Council	0.0	0.0
Shinyanga	Ushetu District Council	0.0	0.0

Region	District	% of heterogenous wards	% of population residing in heterogenous wards
Simiyu	Bariadi District Council	0.0	0.0
Simiyu	Busega District Council	0.0	0.0
Singida	Singida District Council	0.0	0.0
Singida	Singida Municipal Council	0.0	0.0
Songwe	Mbozi District Council	0.0	0.0
Songwe	Tunduma Town Council	0.0	0.0
Tabora	Kaliua District Council	0.0	0.0
Tabora	Nzega Town Council	0.0	0.0
Tabora	Sikonge District Council	0.0	0.0
Tabora	Urambo District Council	0.0	0.0
Tabora	Uyui District Council	0.0	0.0
Tanga	Handeni District Council	0.0	0.0
Tanga	Handeni Town Council	0.0	0.0
Tanga	Korogwe Town Council	0.0	0.0
Tanga	Mkinga District Council	0.0	0.0
Tanga	Muheza District Council	0.0	0.0
Tanga	Pangani District Council	0.0	0.0

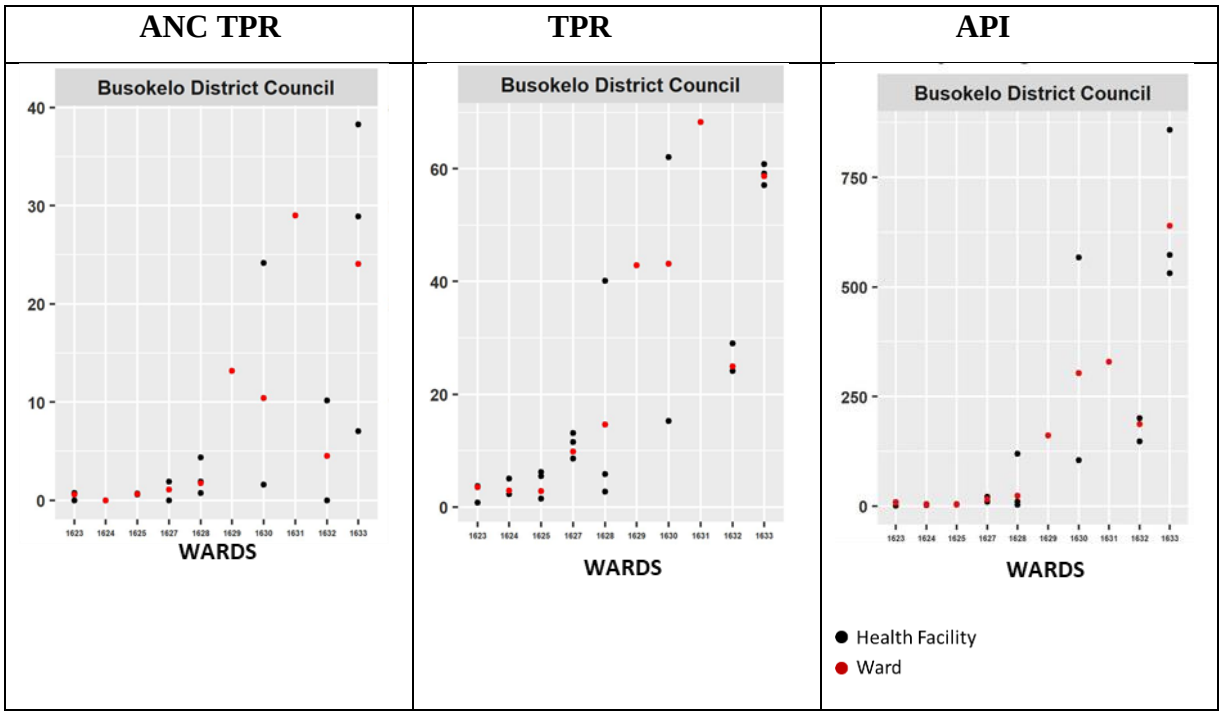

Figure S5.10: Distribution of the routine indicators across health facilities within the wards of Busokelo DC. The dots represent the values of the routine indicators at the health facility (black) and aggregated at the ward level (red).

Text S5.4: The probability of each ward being assigned to a risk stratum

We used a sampling-based approach to estimate the uncertainty in the routine indicators by defining an assignment probability of a ward to a risk stratum. The wards assigned to the very low and high risk strata had on average a higher assignment probability (>90%) than those assigned to the low and moderate strata (average assignment probability below 80% for the low stratum and below 70% for the moderate stratum, Figure S5.11).

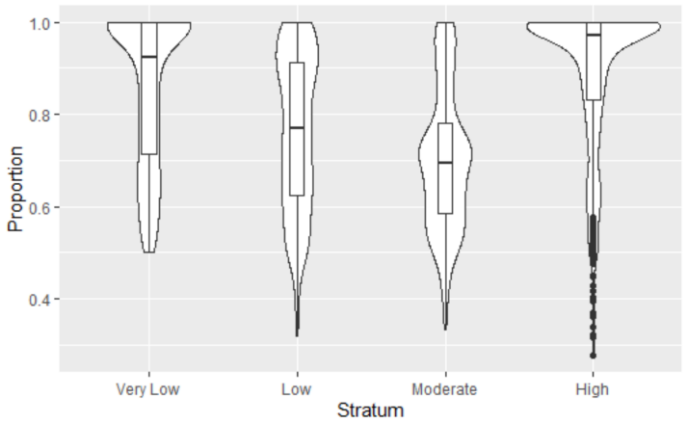

Figure S5.11: Distribution of the assignment probabilities of wards to malaria risk strata

Over 60% of the wards were assigned to the same risk stratum when the indicator variability was considered compared to the initial micro-stratification approach (Figure S5.12-S5.13).

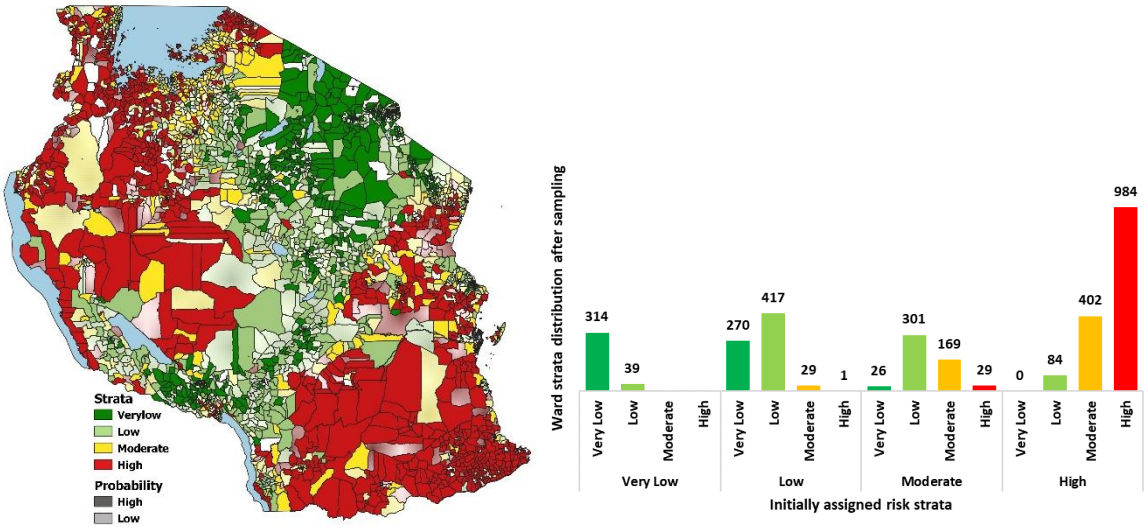

Figure S5.12: Micro-stratification risk map after accounting for indicator variability (the different color shades reflect the assignment probability)

The majority of wards (n=2129, 70%) were assigned to the risk stratum with probabilities larger than 70%, while the remaining 30% of the wards displayed variation in the indicators and had lower assignment probabilities (Figure S5.13). Out of the wards with assignment probability

larger than 70%, 68% were assigned to the same strata as following the initial micro-stratification approach. The remaining 32% were mainly assigned to the immediate lower stratum compared to the initial approach. This was expected, as the initial micro-stratification approach is based on the maximum observed value for the routine indicators and is thus more conservative, avoiding to allocate wards to lower strata. For instance, after sampling and considering the standard errors of indicators, 38% of the wards initially assigned to the low stratum were allocated to the very low stratum, 57% of the wards initially assigned to the moderate strata were assigned to the low stratum and 27% of the wards initially assigned to the high were allocated to the moderate stratum.

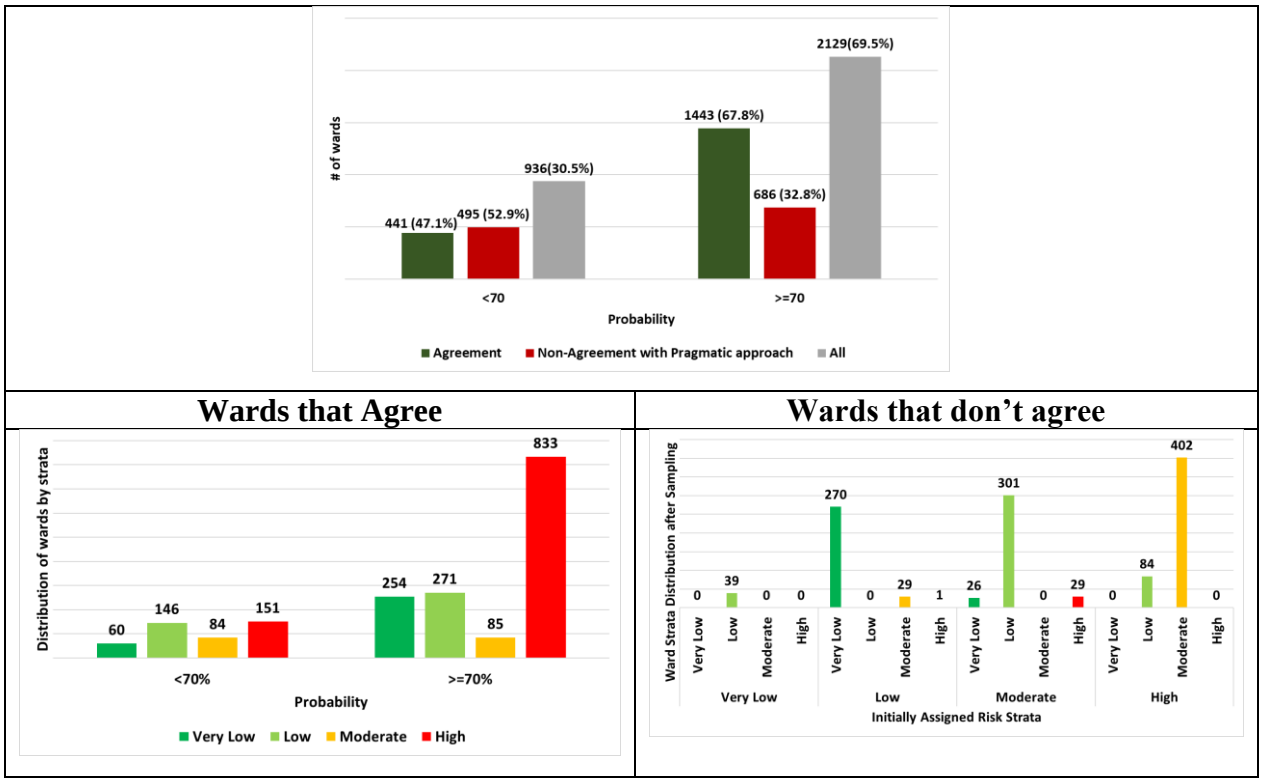

Figure S5.13: Comparison of the initially assigned risk strata vs after sampling disaggregated by probability

6 Spatio-temporal Modelling of Routine Health Facility Data for Malaria Risk Micro-stratification in Mainland Tanzania

Sumaiyya G. Thawer[1,2*], Monica Golumbeanu[1,2], Samwel Lazaro[3,4], Frank Chacky[3,4], Khalifa Munisi[3,4], Sijenunu Aaron[3,4], Fabrizio Molteni[1,2,4], Christian Lengeler[1,2], Emilie Pothin[1,2,5], Robert W. Snow[6,7], Victor A. Alegana[8]

[1] Swiss Tropical and Public Health Institute, Allschwil, Switzerland

[2] University of Basel, Basel, Switzerland

[3] Ministry of Health, Dodoma, Tanzania.

[4] National Malaria Control Programme, Dodoma, Tanzania.

[5] Clinton Health Access Initiative, New York, USA

[6] Population Health Unit, KEMRI-Welcome Trust Research Programme, Nairobi, Kenya.

[7] Centre for Tropical Medicine and Global Health, Nuffield Department of Clinical Medicine, University of Oxford, Oxford, UK.

[8]World Health Organization, Regional Office for Africa, Brazzaville, Republic of Congo

*Corresponding author:
Sumaiyya G. Thawer, sumaiyya.thawer@swisstph.ch

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6.1 Abstract

As malaria transmission declines, the need to monitor the heterogeneity of malaria risk at finer scales becomes critical to guide community-based targeted interventions. Although routine health facility (HF) data can provide epidemiological evidence at high spatial and temporal resolution, its incomplete nature of information can result in lower administrative units without empirical data. To overcome geographic sparsity of data and its representativeness, geo-spatial models can leverage routine information to predict risk in un-represented areas as well as estimate uncertainty of predictions. Here, a Bayesian spatio-temporal model was applied on malaria test positivity rate (TPR) data for the period 2017-2019 to predict risks at the ward level, the lowest decision-making unit in mainland Tanzania. To quantify the associated uncertainty, the probability of malaria TPR exceeding programmatic threshold was estimated. Results showed a marked spatial heterogeneity in malaria TPR across wards. 17.7 million people resided in areas where malaria TPR was high (≥30; 90% certainty) in the North-West and South-East parts of Tanzania. Approximately 11.7 million people lived in areas where malaria TPR was very low (<5%; 90% certainty). HF data can be used to identify different epidemiological strata and guide malaria interventions at micro-planning units in Tanzania. These data, however, are imperfect in many settings in Africa and often require application of geo-spatial modelling techniques for estimation.

Keywords: Bayesian Spatio-temporal, Health Facility, Malaria Test Positivity, Micro-stratification

6.2 Introduction

The importance of targeting interventions through adequate malaria planning and informed decision making has been emphasized by the recently launched World Health Organization (WHO) High Burden High Impact initiative (HBHI) (World Health Organization, 2018a). This initiative encourages national malaria control programs (NMCPs) across Africa to use local, routine and survey data to stratify malaria risk at the national and sub-national levels and accordingly define appropriate targets for their malaria strategic plans (World Health Organization, 2018a). To date, national stratification using available routine data from health information systems has been conducted in several African countries including Burkina Faso (Rouamba et al., 2020), Eritrea (Kifle et al., 2019), Ghana (Awine et al., 2018; Awine and Silal, 2020), Kenya (Alegana et al., 2021b; Gething et al., 2007), Madagascar (Arambepola et al., 2020; Ihantamalala et al., 2018; Nguyen et al., 2020), Malawi (Chirombo et al., 2020), Mali (Cissoko et al., 2022), Namibia (Alegana et al., 2013; Alegana et al., 2016), Rwanda (Semakula et al., 2020), South Africa (Maïga et al., 2019), Swaziland (Sturrock et al., 2014), Tanzania (Runge et al., 2020b; Thawer et al., 2020), Uganda (Kigozi et al., 2020), Zambia (Bennett et al., 2014; Lubinda et al., 2022) and Zimbabwe (Gwitira et al., 2020) with most utilizing incidence as a metric of malaria measure. The sources of data used by NMCPs for national stratification vary between countries and is dependent on the availability, access and quality of information (Alegana et al., 2020; Tusting et al., 2014).

In recent years, the launch of the WHO test and treat policy (World Health Organization, 2012a) along with investments to digitize the health management information system (HMIS) under the electronic district health information software (DHIS2) has resulted in gradual improvements in the quality and completeness of routine data from health facilities (HFs). Routine data offers a source of data that is temporally and spatially much more comprehensive than parasite prevalence from periodic household surveys. They provide real-time and spatially granular information which is essential for effective monitoring and timely planning of interventions.

Most NMCPs in many countries have some form of stratified maps of malaria risk based on aggregating routine data, climatic stratification, or parasite prevalence (Ghilardi et al., 2020; Omumbo et al., 2013). These stratification maps are usually produced at the higher

administrative levels (macro) - or lower administrative levels (micro). Recent malaria guidelines advocate for the use of routine data for monitoring and evaluation at country levels and demonstrate its utility as part of donor requests for monitoring progress (World Health Organization, 2020b). However, at the micro-planning units, limitations of routine HF data including its availability and geographic and temporal representativeness, can limit its utility. These factors contribute to uncertainty in estimates generated from these data and has over the years hindered its direct use for decision making. For example, at the micro-levels, not all areas have HFs resulting in long commuting distance for communities to reach the nearest HF. Thus, the estimation of disease indicators for these communities is not straight forward without application of appropriate spatial modelling techniques. Routine data from communities in areas with HFs may have additional deficiencies such as reporting completeness (Rowe et al., 2009). Conducting disease specific micro-stratification is important for understanding heterogeneity of disease risk. The ability to stratify malaria risk at a finer level will lead to even better spatially targeted responses aligned to the HBHI concept. This becomes increasingly beneficial in areas moving towards lower transmission risk to quantify the levels of heterogeneity and support elimination efforts

For empirical routine data to provide accurate malaria estimates, all community fever cases should ideally reach HFs, be tested and accurately captured within the DHIS2 (Alegana et al., 2020). However, this is often not the case. Routine data do not account for factors such as treatment seeking rates, health utilization behaviors, the underlying heterogeneous distribution of the population and the differing testing rates between transmission settings. All of these, can potentially under/over-estimate malaria risk (Alegana et al., 2020; Maïga et al., 2019). In the absence of complete and perfect empirical data, statistical modelling techniques represents a practical way to close these gaps and obtain best estimates for all settings. Spatio-temporal models have been extensively used for various diseases (Alegana et al., 2020; Elliott and Wartenberg, 2004; Iddrisu et al., 2018; Obaromi et al., 2019) and are based on the principles that data are spatially correlated and observations in adjacent areas will be more similar than observations that are farther away, smoothing risk in space and time according to a neighborhood structure (Odhiambo et al., 2020). The methods allow to efficiently handle incomplete or missing data, account for potential biases (Alegana et al., 2020; Bennett et al., 2014; Sturrock et al., 2016) and are also useful for understanding the associated levels of uncertainty in the data.

Mainland Tanzania has formally adopted macro-stratification as part of its National Malaria Strategic Plan (NMSP) 2021-2025 (National Malaria Control Programme, 2021) aimed at providing tailored combinations of interventions according to council level epidemiological risk (National Malaria Control Programme, 2021; Runge et al., 2020b; Thawer et al., 2020). Multiple metrics have been used to provide a simplified risk-strata per council based on survey data from school children (Chacky et al., 2018) and routine data from DHIS2 (Thawer et al., 2020). To further account for the intra-council heterogeneity and support decentralized planning, the stratification was extended to the ward level to develop a micro-stratification risk map using aggregated routine data as highlighted in previously published work (National Malaria Control Programme, 2021; Thawer et al., 2022). The routine metrics utilized in this micro-stratification approach (Thawer et al., 2022) included annual parasite incidence (API), malaria Rapid Diagnostic Test (mRDT) test positivity rate (TPR), and test positivity rates in pregnant women (ANC TPR). Furthermore, inclusion of data was limited to HFs with a minimum of 50% completeness of reporting. The use of empirical routine data in this micro-stratification approach did not adjust for the existing spatial and temporal gaps nor the related uncertainties, thereby resulting in an incomplete ward-level stratification where5% of all the wards had no HFs and thus no stratification could be conducted here (Thawer et al., 2022).

Here, we used Bayesian conditional auto-regressive (CAR) spatio-temporal modelling techniques to leverage all the available routine data collected over 36 months from all reporting HFs across wards in mainland Tanzania. The aim was to improve previous micro-stratification efforts in mainland Tanzania (Thawer et al., 2022). In this study, we focused on the mRDT TPR, a widely used malaria metric reported by routine health systems (Alegana et al., 2021b; Bi et al., 2012; Boyce et al., 2016; Ceesay et al., 2008; Francis et al., 2012; Githinji et al., 2016; Jensen et al., 2009; Joshi et al., 1997; Kamau et al., 2020b; Kigozi et al., 2019, 2020; Yenew et al., 2021). Malaria TPR has been shown to be significantly associated with malaria incidence and a strong predictor of malaria transmission (Boyce et al., 2016; Jensen et al., 2009; Kigozi et al., 2019). It offers a more consistent and acceptable case definition since it provides a clearer denominator and does not require information on HF catchment population that remains largely undefined (Jensen et al., 2009; Macharia et al., 2021).

6.3 Results

6.3.1 Routine data coverage and description

A total of 7,878 HFs offering laboratory services and performing mRDT testing across the wards of mainland Tanzania were included in the analysis for the reporting period 2017-2019 (Table 6.1). During this period, a total of 228,717 HF monthly reports were received resulting in an overall reporting rate (RR) of 80.7% across 93.7% of wards. Dispensary, laboratories and clinics represented most of all the HFs (85.7%), followed by health centers (10.8%) and hospitals (3.5%) (Supplementary Figure S6.1, Supplementary Information). Of the total malaria tests performed by mRDT (n=56,546,468) in the period of analysis, 15,454,915 (27.3%) were positive for malaria, showing a marked variation in the crude malaria TPR from 0.0 – 82.5% across all wards. The number of HFs per ward widely ranged with higher number of HFs found in urban wards compared to rural wards. A large number of wards consisted of only one (27.9%) or two (29.4%) HFs. Overall, 6.3% of wards had no HFs or non-reporting HFs, corresponding to 4% of the total population.

Table 6.1: The coverage and completeness of malaria Test Positivity Rates (TPR) across wards in mainland Tanzania from 2017-2019.

# of Facilities Performing mRDT Tests	# of Wards	% of Wards			Population Residing (%)	Facility Reporting Rates (%)	mRDT Confirmed Malaria Cases	Total Tested with mRDT	Average Malaria TPR (%) (Min-Max)
		Urban	Mixed	Rural					
0	208	35.1	12.0	52.9	2,094,992 (4%)	-	-	-	-
1	924	12.2	7.7	80.1	10,887,759 (20%)	86.1	2,906,562	9,019,681	32.2 (0.0-82.5)
2	974	7.5	7.8	84.7	13,249,794 (25%)	84.9	4,997,646	14,366,228	34.8 (0.0-79.9)
3	594	11.8	14.0	74.2	9,534,633 (18%)	83.2	3,379,948	10,604,367	31.9 (0.3-81.3)
4	287	15.7	17.8	66.6	5,987,459 (11%)	80.1	2,057,873	7,126,957	28.9 (0.6-71.1)
5	155	28.4	21.9	49.7	3,730,785 (7%)	76.7	1,005,588	4,925,657	20.4 (0.7-63.6)
6	64	31.3	18.8	50.0	1,797,811 (3%)	73.6	433,992	2,280,514	19.0 (0.8-69.9)
7	40	65.0	20.0	15.0	2,094,947 (4%)	70.2	165,987	2,206,765	7.5 (0.7-52.1)
8	27	66.7	18.5	14.8	1,426,109 (3%)	71.1	178,763	1,838,587	9.7 (0.6-43.3)
9	12	66.7	25.0	8.3	614,121 (1%)	64.1	163,956	979,849	16.7 (3.7-51.5)
10+	26	92.3	7.7	0.0	2,301,807 (4%)	65.7	164,600	3,197,863	5.1 (0.7-28.2)
7,878	**3,311**	**15.5**	**11.2**	**73.3**	**53,720,216**	**80.6**	**15,454,915**	**56,546,468**	**27.3 (0.0-82.5)**

6.3.2 Model Selection

Assessment of the coefficients of the predictors selected from the covariates selection procedure (Supplementary Figure S6.3, Supplementary Information) showed that Enhanced Vegetation Index (EVI) (Coefficient: 0.078; Standard Error: 0.002), Night Time Lights (NTL) (-0.043; 0.002) and Temperature Suitability Index (TSI) (0.150; 0.004) were significant predictors of malaria TPR and were therefore included in the analysis.

Comparison of the Deviance Information Criteria (DIC) values between the three model specifications showed that model C had the lowest DIC value (304,069.5) when compared to model A (306,978.1) and model B (307,065.9) (Supplementary Table S6.1). Improving the model complexity improved the model goodness of fit and thereby Model C was selected and implemented. Model validation statistics were computed to validate the model performance and are summarized in Supplementary Table S6.1. The MAE of the selected Model C was computed to be 0.04 suggesting good model precision, the RMSE was 0.06 suggesting low bias and the R2 was 0.91 suggesting a good predictive performance of the model.

Table 6.2 presents the posterior parameters for the selected model. EVI (Posterior mean; confidence interval - 0.236; 0.231 – 0.241) and TSI (0.579; 0.511 – 0.647) were positively associated with malaria TPR indicating that vegetation index and temperatures are favourable for increasing the risk of transmission. As expected, NTL (-0.300; -0.371– -0.229) showed a negative correlation to the malaria risk implying areas in rural settings are more prone to malaria risk. All the model parameters were significant at the 95% credible interval.

Table 6.2: Posterior model parameter estimates

Parameter	Posterior Mean (95% CI) (Log odds scale)
Intercept	-1.594 (-1.692 – -1.495)
EVI	0.236 (0.231 – 0.241)
NTL	-0.300 (-0.371– -0.229)
TSI	0.579 (0.511 – 0.647)

6.3.3 Heterogeneity of predicted TPR at ward level

The heterogeneity in the final modelled malaria TPR risk (Figure 6.1) is evident across the country with higher transmission levels seen in the North-West and South-East parts of the country, whilst lower transmission levels are seen in the central corridor running from the

North-East to South-West parts of the country. At the national level, the predicted mean malaria TPR for the period of analysis was 25.6% (95% credible interval 23.9 – 27.6) with heterogeneity across the wards ranging from as low as 0.2% (0.1-0.4) up to 81.4% (80.9 − 81.9%).

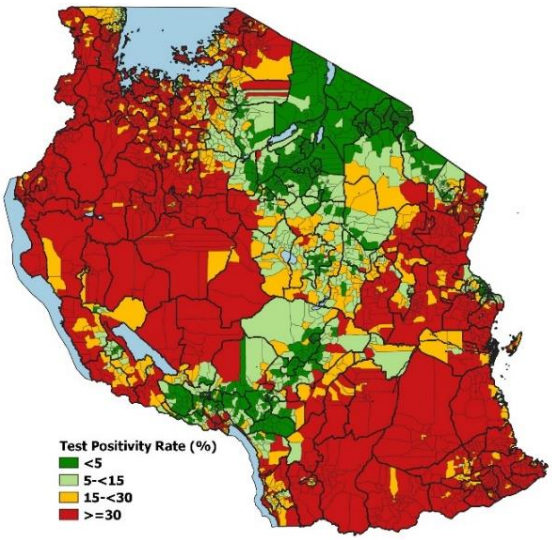


Figure 6.1: Predicted malaria Test Positivity Rates (TPR) in mainland Tanzania

Following classification of the estimated malaria TPR values into risk strata using the NMCP defined thresholds (Supplementary Table S6.2), 1,348 (40.7%) wards were assigned to high transmission risk strata, 583 (17.6%) wards to moderate transmission, 633 (19.1%) wards to low transmission, whilst 747 (22.6%) wards to the very low transmission strata. The average estimated malaria TPR distribution per risk stratum is summarized in Table **6.3**.

Table 6.3: Distribution of wards by transmission strata

Malaria TPR Risk Strata	# of Wards (%)	# of Population Residing (%)	Average Predicted Malaria TPR (Credible Interval %)
Very Low (<5%)	747 (22.6%)	13,795,566 (25.7%)	2.5 (1.9 - 3.3)
Low (5-<15%)	633 (19.1%)	11,967,597 (22.3%)	9.1 (8.0 - 10.7)
Moderate (15-<30%)	583 (17.6%)	8,894,349 (16.6%)	22.2 (20.5 - 24.5)
High (≥30%)	1,348 (40.7%)	19,062,704 (35.5%)	47.5 (44.9 - 50.4)
	3,311 (100%)	**53,720,216 (100%)**	**25.6 (23.9 - 27.6)**

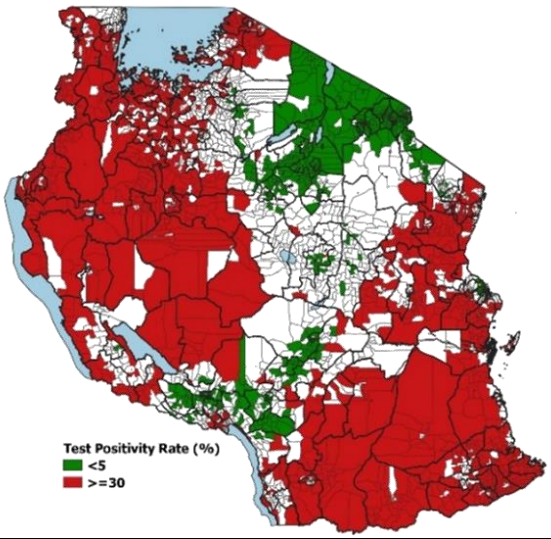
6.3.4 Interpreting uncertainty in malaria TPR at the ward level

The model exceedance and non-exceedance probabilities provided some level of confidence in the assigned risk strata to allow NMCPs and the council health teams to efficiently plan targeted

interventions at the micro levels especially in the extreme high and very low transmission risk areas where the largest transition in intervention packages from control to elimination strategies are observed (National Malaria Control Programme, 2021).

A malaria TPR of ≥30% is the threshold set by the NMCP to denote areas with high transmission and that qualify for the most intensive control interventions. Approximately 17.7 million people (33%) were estimated to reside in 1,227 wards with high transmission risk with a probability of ≥90%. The majority of this population was located predominantly in the North-West and South-East of the country and represent areas that require more concentrated efforts to reduce transmission. Another 11.7 million people (22%) resided in 662 wards in the very low transmission risk of <5% and were found mostly in the North-East councils (Figure 6.2a). These indicate areas in which the possibility for the NMCP to develop elimination strategies that include strengthening surveillance systems should be considered (National Malaria Control Programme, 2021). Approximatively 1.2 million people resided in 104 wards where the assigned risk strata, found to be in the moderate and high strata, had large levels of uncertainty (probability <70%) (Figure 6.2b).

a. Areas of high (≥30%) and very low (<5%) transmission with 90% certainty



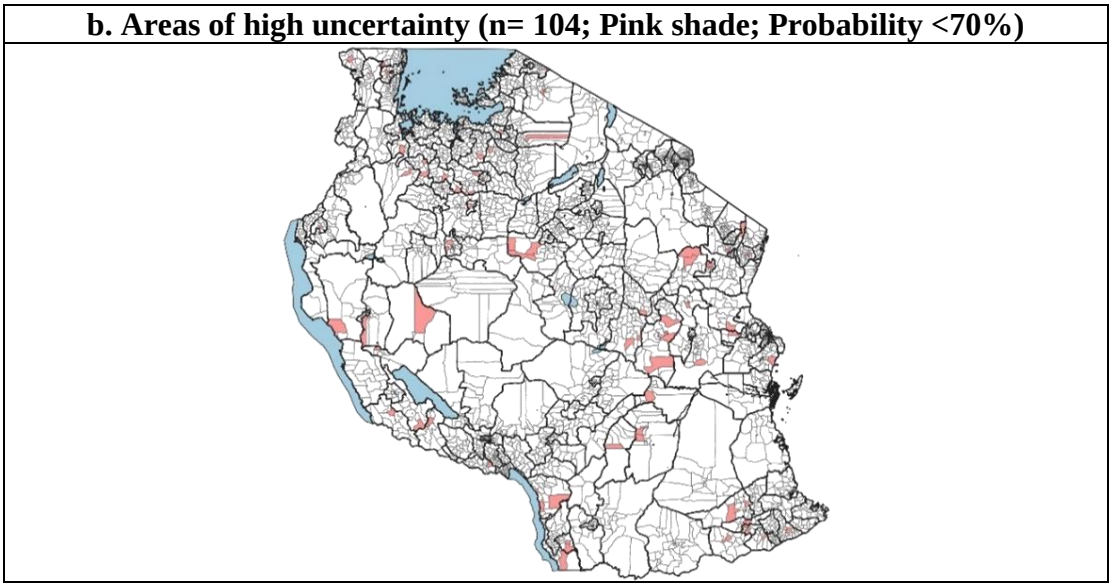


Figure 6.2: Exceedance and non-exceedance probability of predicted malaria Test Positivity Rates (TPR)

Comparison of the risk strata estimated from the model with the empirical estimates of malaria TPR (which did not account for uncertainty) showed 7.4% of the total wards to be misclassified. Amongst these, 68 wards (2.2%) in the low strata were found to be misclassified to the very low risk strata by the empirical malaria TPR. Another 32 wards (1.0%) in the high risk strata were found to be misclassified to the moderate risk strata. These represent areas where the largest impact of misclassification would likely be observed due to the significant differences in the intervention strategies in these strata.

6.4 Discussion

In this work, a Bayesian spatio-temporal modelling framework was used to leverage routine information from HFs and provide robust estimates of malaria risk at ward level. The model allowed to smoothen the risk and fill the spatial and temporal gaps in routine data, handle the associated uncertainty in a robust manner and account for any spatial and temporal dependencies in the data. The analysis highlighted the sub-council level spatial heterogeneities in malaria TPR with higher transmission particularly seen in the North-West and South-East parts of the country. These areas have traditionally been shown to have similar patterns of higher prevalence (Thawer et al., 2020; Chacky et al., 2018; Alegana et al., 2021; Kitojo et al 2019., Brunner et al., 2019). Factors potentially contributing to resilience in changes to the risk could be due to the geographic location, climatic factors and socio-economic factors amongst many.

As countries begin to transition towards lower malaria transmission, the need to monitor the increasing heterogeneities at finer scales and inform appropriate tailored strategies becomes critical. HF data represents an essential source of local information describing the dynamics of the malaria situation with a high level of resolution in time and space. Understanding their structure and representativeness can be useful to replace modelled estimates derived from sparse cross-sectional surveys – the current gold standard. Nevertheless, at the local administrative levels, incomplete HF reporting or non-reporting HFs create varying degrees of spatial and temporal data gaps. Moreover, as observed in this analysis, 57.3% of wards contained only one or two reporting HFs, thereby contributing to a higher level of uncertainty.

The modelling framework used here allowed for a more robust estimation of malaria TPRs by borrowing information from neighboring wards, rather than relying only on limited information from one single ward. In addition to adjusting for the missing information, the approach provides measures of uncertainty that are required to make policy relevant decisions. Previous work done in mainland Tanzania (National Malaria Control Programme, 2021; Thawer et al 2022) used combinations of empirical routine data to develop a micro-stratification risk map, but that approach did not consider the spatial uncertainty for the population at risk. This is important to allow NMCPs to understand the fidelity of estimates, understand progress made towards achieved targets and more confidently transition malaria strategies. The current paper builds on this by providing a more robust estimate of risk. By presenting the risk in terms of exceedance and non-exceedance probabilities, the developed model allows programs to also identify areas with high uncertainty in their assigned risk (Probability <70%). These areas are likely within wards in which there is a natural level of heterogeneity such as major altitudinal changes, natural swamps or man-made agricultural areas. Importantly, these would need to be differentiated from wards with poor HF reporting performances, or those with small numbers of patients tested at a HF resulting in larger uncertainty in actual estimates.

The current approach taken in this paper may be applied to other sub-Saharan African (SSA) countries that are facing challenges with incomplete and missing routine information at the higher spatial scales. In such places, particularly those moving towards lower transmission of risk, the use of real-time routine information becomes important to allow continuous analysis of the existing local heterogeneity. Using statistical models can be valuable to address some of these existing data issues. Nevertheless, continued efforts to strengthen routine surveillance

systems must remain a country priority to help guide local evidence-based planning and implementation.

This study has some limitations. The approach uses routine data that are only representative of the population who seeks care and are laboratory tested. It therefore does not capture the variations in testing rates, infections within the communities that do not reach the facility, or those that are asymptomatic. The unavailability of treatment seeking information at ward level limited the analysis to account for this important factor. Using a combination of metrics from both routine and survey sources could further improve the estimates. Future work may look into leveraging information from both sources to better understand the relationship between the data sources and how well they reflect the different components of the transmission system. Establishing this relationship would also be important to better develop thresholds used for defining risk categories. To date, cut-offs used for defining malaria risk are mainly based on pragmatic, plausible criteria but not linked to likely biological/ epidemiological impacts of specific interventions. There is also a need to consider other layers of malaria-related information to further increase the value of malaria TPR for decision making and provide a more holistic approach to inform malaria policies sub-nationally.

The CAR modelling approach used aggregated estimates per ward and thereby assumed the ward administrative boundaries to represent the catchment population for HFs within wards. This can have several implications. Firstly, it did not account for differing facility utilization behaviors and population movements across neighboring ward borders. Many factors can drive patient choices such as the size of HFs, distance, perceptions and costs (Alegana et al., 2020). Using geo-statistical methods to account for the geo-spatial location of HFs as well as incorporating information on behaviors driving facility usage can better inform the risk estimates. Secondly, the use of aggregated data can mask underlying data quality issues thereby limiting the understanding of the true nature of data (Chilundo et al., 2004; Okello et al., 2019). Finally, the use of aggregated data poses the challenge of the modifiable areal unit problem (MAUP) which is a common geographical statistical problem. This occurs when results are affected by variability introduced through aggregating data or due to changes in the polygon shape used in the analysis (Openshaw, 1984). In this work, data were aggregated to the ward level for providing estimates at a resolution that is programmatically meaningful for micro-stratification

The use of the complex analytical methodologies for dealing with incomplete data demands analytical skills largely beyond the capacity of most NMCPs. Hence, it is important that such methods remain within local research institutions with the required know-how for annual monitoring. Increased usage of maps for local decision making by NMCPs was recently shown to be associated with factors such as knowledge and understanding of the data sources and their limitations, and also trust and perceived ownership of the data (Ghilardi et al., 2020). Therefore, capacitating NMCPs to establish a high-quality surveillance system and to interpret the data after an appropriate analytical process represents a sustainable way of promoting data use for decision making (Alegana et al., 2020).

6.5 Conclusion

This work demonstrated the potential of routine HF data to identify different epidemiological strata and thereby providing the malaria program with an evidence base to guide malaria interventions at micro-planning units in Tanzania. These data, however, are imperfect in many settings in Africa and often require application of geo-spatial modelling techniques for estimation. These techniques allow for filling the existing spatial and temporal data gaps, accounting for statistical uncertainty, and leveraging this rich source of information for optimizing micro-planning of interventions.

6.6 Methods

6.6.1 Geographical scope and context

Mainland Tanzania is organized into multiple administrative levels. The country has 26 administrative s, divided into 184 councils. The councils represent the main administrative level responsible for resource allocation and tailoring interventions as per the national guidelines. Councils are further divided into wards, which serve as the lowest resources allocation and disease reporting unit. A total of 3,311 wards have been defined according to the 2012 national census for mainland Tanzania (Supplementary Figure S6.6, Supplementary Information). There is a range from 2 to 43 wards per council, depending on the size of the council, altitudinal variation and population density.

6.6.2 Routine health facility data processing

Data from 7,878 (93%) reporting HFs across 3,103 (93.7%) wards in mainland Tanzania were used to assemble malaria TPR data (Supplementary Figure S6.1, Supplementary Information). The remaining wards (6.3%) did not have reporting HFs. Aggregated routine data (see data aggregation description below) from the laboratory register representing all ages were obtained from HMIS/DHIS2 for 36 months (2017-2019). DHIS2 is an open source, web-based software platform for reporting, analysis, and dissemination of health data. It captures information from both the private (26%) and public (74%) HFs, and can be accessed by officials working in the health sector through registered credentials. Each month, HFs provide monthly summary reports with data that are entered into DHIS2.

Monthly laboratory testing reporting tools were introduced in HFs in October 2015 to capture: (1) the total number of malaria tests performed by blood slides and mRDT across all age groups, and (2) the number of positive malaria cases. The RRs have gradually improved from 49.6% in 2016 to 87.7% in 2019. mRDTs were introduced in mainland Tanzania in 2009 in several rolled-out phases before country wide scale up was achieved in 2013 (Masanja et al., 2012). Currently, mRDTs are the most widely-used diagnostic method for malaria, with only a small proportion of facilities, mainly private facilities, still using microscopy.

The indicators extracted were used to compute the mRDT TPR, defined as the proportion of the number of malaria laboratory confirmed cases (numerator) amongst the total number of mRDTs performed (denominator).

6.6.2.1 Data cleaning and geocoding

In this analysis, the HMIS data consisted of monthly laboratory reports of all patients tested with mRDT and reported by all public and private HFs with available geo-coordinates. These facilities represented 92.7% (N=7,878) of all HFs offering laboratory testing and those captured in the DHIS2. The remaining 7.3% HFs did not submit any monthly laboratory reports across the entire period of analysis and were therefore excluded. No information was available on whether they simply did not report, or whether they did not test. In Tanzania, only HFs offering laboratory testing services are expected to submit the monthly laboratory reports. However, this information is not clearly demarcated in the current master HF list and therefore understanding the exact proportion of HFs that were missing in the DHIS2 was not possible.

All reports were first checked for duplicate submissions for the same month by the same HF and duplicates were removed. As the DHIS2 database in Tanzania is unable to record zero values, these are marked blank. Hence, to distinguish zero values from missing values, it was assumed that missing values of otherwise complete reports were true zeros. To ensure the correct allocation of HFs to their respective wards, the geographical coordinates of the reporting HFs were obtained from the master registry HF list of Tanzania (HFRPortal, 2021) and linked to the DHIS2 data using the unique HF identifier code. The national ward shapefile was then used to allocate the HFs to their respective wards (Supplementary Figure S6.1, Supplementary Information).

6.6.2.2 Data aggregation and classification

The HMIS monthly data were aggregated for the whole year in order to align with the NMSP development which has cycles of three years, and we therefore provided average risk estimates for the period 2017-19. This resulted in a total of 9,214 space-time data points that were included in the analysis.

The classification of routine metrics into malaria risk categories has been previously defined in the country using prevalence survey data from school children as a gold standard. This classification was guided by a set of criteria ensuring the minimization of misallocation of councils belonging to the higher strata to the lower strata, which would have led to the largest changes in the optimal intervention packages (National Malaria Control Programme, 2021) (Supplementary Table S6.2). We classified the estimated malaria TPR values into risk strata using the national criteria of risk as follows: <5% as very low transmission; 5-<15% as low transmission, 15-<30% as moderate transmission and ≥30% as high transmission (Supplementary Table S6.2).

6.6.3 Environmental and ecological covariates

A set of biologically plausible covariates known to affect malaria risks were considered for the geo-spatial modelling (Odhiambo et al., 2020; Weiss et al., 2015). The data were extracted from open source remote sensing platforms. The covariates included precipitation (CHIRPS, 2022), EVI (NASA, 2022a), TSI (Gething et al., 2011b), NTL (NASA, 2022b) water vapor (NASA, 2021) and the average HF RR within a ward (Supplementary Text S6.1). The covariates were standardized using the observed mean and standard deviation.

A covariate selection procedure was performed in order to select a parsimonious minimal set of covariates (Giorgi et al., 2021; Weiss et al., 2015). The malaria TPR data series were matched to the covariates and a non-spatial generalized linear regression model was applied using the *bestglm* package in R (McLeod and Lai, 2020). This approach selected the best combination of the covariates based on the lowest value of the Bayesian Information Criteria (BIC). TSI, NTL and EVI were among the selected covariates as predictors (Supplementary Text S6.1).

6.6.4 Model specification

A Bayesian Besag-York-Mollié 2 Model (BYM2) (Besag et al., 1991) was used to model the spatial and temporal distribution of malaria TPR at the ward level adjusting for the selected covariates. The model combined the data and prior knowledge to produce posterior probability distributions and predict smoothed malaria TPR estimates thereby filling the missing values for wards with no HF data. The model was used to estimate malaria TPR at the administrative level of the ward and accounted for prediction uncertainty across wards with incomplete data or no reporting facilities (Supplementary Text S6.2).

Let $y(j,k)$ represent total number of positive malaria cases at the ward j, $(j = 1,\ldots,n)$ in year k $(k = 1,\ldots,K)$, and $N(j,k)$ the total people tested for malaria at ward j in year k. The malaria test positivity rate given the selected covariates was modelled using a binomial likelihood:

$$y(j,k)|\eta(j,k) \sim Binomial\big(N(j,k), P(j,k)\big)$$

$$\eta(j,k) = logit\big(P(j,k)\big)$$

Where the link with the chosen environmental and ecological covariates is made through a regression model based on a linear predictor defined as:

$$logit\big(P(j,k)\big) = \beta_0 + X(j,k)'\beta + u_j + v_j + \gamma_k$$

with β_0 the intercept, $X(j,k)$ is a set of selected covariates; β are the corresponding regression parameters; u_j corresponds to the CAR structured spatial random effect that smoothens the data according to a neighbourhood structure. The CAR model was applied to a symmetric spatial neighborhood matrix structure W, developed at the ward level. $W = \{w_{(h,i)}\}$ defines a neighborhood structure across all the wards of the country (Supplementary Figure S6.4, Supplementary Information), where each element w_{hi} connects the wards h and i, i.e., w_{hi} =

1 if wards share a common boundary and w_{hi} = 0 otherwise; v_j corresponds to the unstructured exchangeable component using independent and identically distributed (i.i.d) random effect and γ_k is the temporal random effect specified using i.i.d zero-mean normally distributed random effect.

In order to test the goodness of fit, CAR models with different specifications of the spatio-temporal structures were implemented (Supplementary Table S6.1, Supplementary Information). Model A did not have a spatial random effect component, model B had a spatial random effect component and model C was run with a spatial and temporal random effect structure (Supplementary Table S6.1, Supplementary Information). The model goodness of fit was evaluated using the DIC and the best model was selected and used for subsequent analyses. The model was estimated using Integrated Nested Laplace Approximation (INLA) (Blangiardo et al., 2013; Martins et al., 2013; Rue et al., 2009) (Supplementary Text S6.2, Supplementary Information).

Exceedance probability (EP) and non-exceedance probabilities (NEP) calculated using the fitted spatio-temporal model (Supplementary Text S6.2, Supplementary Information) were used to quantify the likelihood of the malaria TPR estimates to be above the high (≥30%) or below the very low (<5%) malaria risk thresholds. These thresholds represent the pre-defined, policy-relevant thresholds defined by the NMCP in Tanzania. Estimates obtained from the resulting model are only programmatically useful when NMCPs are able to interpret it with its underlying level of uncertainty (Alegana et al., 2021b; Giorgi et al., 2018).

6.6.5 Model validation

To evaluate the predictive performance of the model, a subset of 10% of the dataset was held out randomly. The predictive performance of the model was estimated by computing validation statistics on the hold out data set. The mean absolute error (MAE) was computed as a measure of the absolute differences between the observed and predicted values. The root mean square error (RMSE) was computed to provide a measure of the accuracy of the individual predictions whilst the R-squared (R^2) was computed to provide a measure of the proportion of variation accounted for by the model (Supplementary Text S2, Supplementary Information).

6.6.6 Estimating population at risk by strata

The population for each ward was obtained from the publicly available 2012 population and housing census in Tanzania conducted by the National Bureau of Statistics (National Bureau of Statistics, 2013). Annual growth rates at the council level (National Bureau of Statistics, 2016b) were applied to the ward population data to project each ward population to the period of analysis (2017-2019). These were then used to estimate the total populations residing in each of the identified malaria risk strata.

R Studio (RStudio, 2022) was used for performing analysis of the data downloaded from DHIS2. All maps were produced using the QGIS software version 3.4.14 (Qgis, 2022).

6.7 Additional information.

6.7.1 Acknowledgements

The authors would like to thank all the members of the NMCP of the Ministry of Health of mainland Tanzania, President's Office al Administration and Local Government offices, WHO country office and development partners for their participation and invaluable discussions to make this work possible. The authors also wish to thank Eda Mumo, Noel Joseph and Samuel Muchiri from the KEMRI-Welcome Trust Research Programme for providing technical input and support to make this work possible.

6.7.2 Authors' contributions

SGT, VA and RWS conceptualized the methodological analysis. SGT, FC and KM acquired the data. SGT compiled the data and performed the analysis. VA, RWS, EP and MG provided input on the interpretation of the analysis. SGT with guidance from RWS, VA, EP, CL and MG prepared the initial draft manuscript and its finalization. VA, RWS, EP, MG, CL, FM, FC, KM, SA and SL provided critical comments on progressive drafts. All authors reviewed and approved of the final manuscript.

6.7.3 Ethics approval and consent to participate

This work utilizes secondary aggregated data for analysis for which no ethics approval was required.

6.7.4 Consent for publication

Not applicable.

6.7.5 Availability of data and materials

Data from routine HMIS/DHIS2 are not publicly available and were obtained with request from the National Malaria Control Programme of mainland Tanzania. Restrictions apply to the availability of these data and permission can be obtained with reasonable request from the Ministry of Health of mainland Tanzania.

6.7.6 Competing interest

The authors declare that they have no competing interests.

6.7.7 Funding

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6.8 Supplementary information

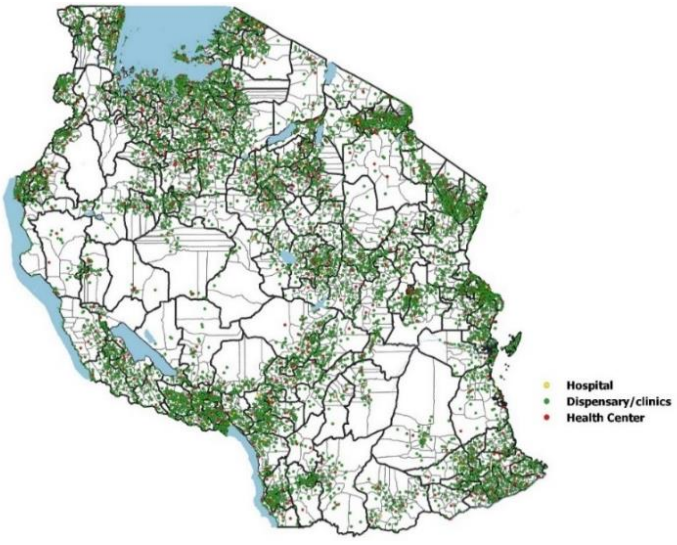

Figure S6.1: Location of health facilities (HFs) by type (n=7,878) *

*For 157 (2%) of the total HFs, the ward name in the master HF list did not appear in the existing ward shape file and therefore the geo-coordinate was used to guide the ward location in the shape file. The geo coordinates for another 180 (2%) HFs could not be obtained from the master HF list and thus open source platforms such as Google Earth was used to retrieve the information. The geo coordinates for 671 (8.5%) HFs did not match the ward name indicated in the master HF list and therefore changed to reflect the correct ward

Text S6.1: Covariate selection

Covariates

The following covariates known to influence malaria transmission were considered for model selection (Figure S6.2) and were extracted per ward polygon in R software.

- *Digital Elevation Model (DEM):* DEM data were obtained from al Centre for Mapping of Resources for Development and available at 30meter resolution (Opendata, 2018). It is a representation of the topographic surface of the Earth.
- *Precipitation*: Precipitation data for 2017-2019 was obtained from the Climate Hazards Group InfraRed Precipitation with Stations (CHIRPS Version 2.0) (CHIRPS, 2022). CHIRPS-2.0 is an open source platform with time series data available at 0.05^{o} x 0.05^{o} spatial resolution and produced by combining quasi-global satellite and observation based precipitation estimates.
- *Enhanced Vegetation Index (EVI):* EVI data for 2017-2019 were obtained from Moderate-resolution Imaging Spectroradiometer (MODIS) sensor imagery (NASA, 2022a). This indicator is a measure of photosynthetic activity and widely used for monitoring vegetation conditions.
- *Temperature Suitability Index (TSI*): TSI is a representation of the optimal development of *P. falciparum* sporozoite and reflects the transmission suitability. It was developed in 2011 at 1 × 1 km spatial resolution (Gething et al., 2011).
- *Average Health Facility Reporting Rates*: The completeness in submission of malaria reports varies across the facilities of mainland Tanzania. To account for the differing rates, the average HF RR was computed per year and per ward.
- *Nighttime lights (NTL)*: This indicator was used to represent the level of urbanization and as a proxy for socioeconomic status (Zhao et al., 2020). The data were derived from DMSP-OLS (2000-2013) and Visible Infrared Imaging Radiometer Suite (VIIRS) (from 2013 - 2020) onboard the Suomi National Polar Partnership (NPP) satellite launched in 2011 with a spatial resolution of approximately 1 km. The data contain the mean of visible band digital number values of cloud-free light detections (NASA, 2021).

- *Humidity:* This indicator is a measure of the amount of water vapor in the atmosphere. Satellite water vapor estimates were obtained from Moderate-resolution Imaging Spectroradiometer (MODIS) (NASA, 2022b) at 5x5km pixel resolution. The amount of water vapor affects the longevity of the malaria vector thereby enabling the full development of the parasites in areas with high humidity and thus transmission.

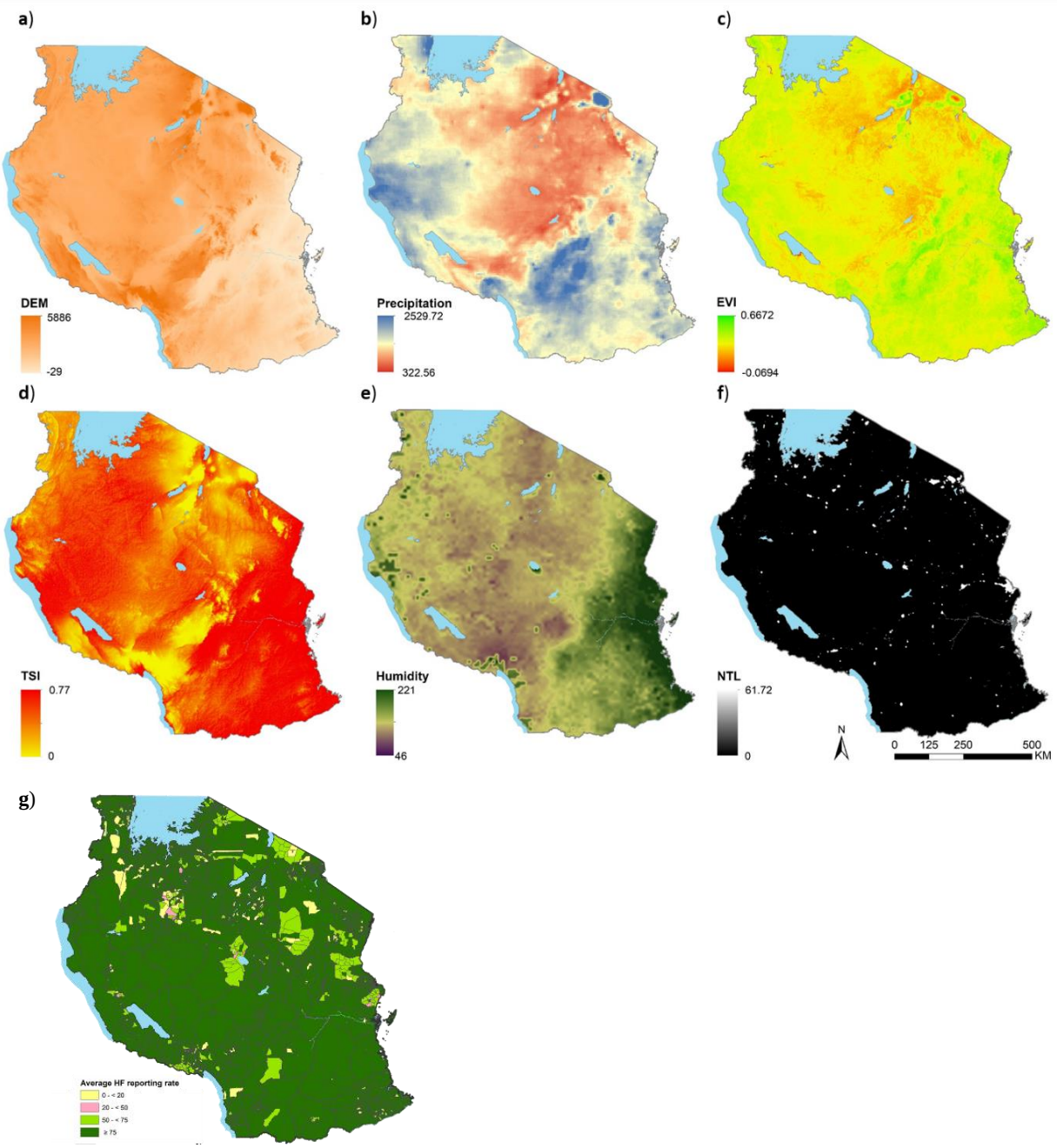

Figure S6.2: Maps of covariates showing: a) Digital Elevation Model (DEM); b) Precipitation; c) Annual mean enhanced vegetation index (EVI); d) Temperature Suitability Index (TSI); e) Humidity; f) Night-time lights (NTL); g) Annual mean health facility reporting rates

Covariate selection process

In order to select the minimum set of covariates for the model, a statistical analysis was performed using the leap algorithm available under the *bestglm* package in R. A cross-validation (CV) approach was implemented based on a ten-fold CV method and the model with the best CV score was selected. The covariates selected from this procedure included DEM, NTL, TSI and EVI. Figure S6.3 shows the decay in CV error based on the subset models. However, since DEM and TSI showed high collinearity, only TSI was retained. The rationale being that temperature is a key determinant of environmental suitability for malaria transmission (Gething et al., 2011) and this index incorporates the mechanism of temperature dependency within the malaria transmission cycle.

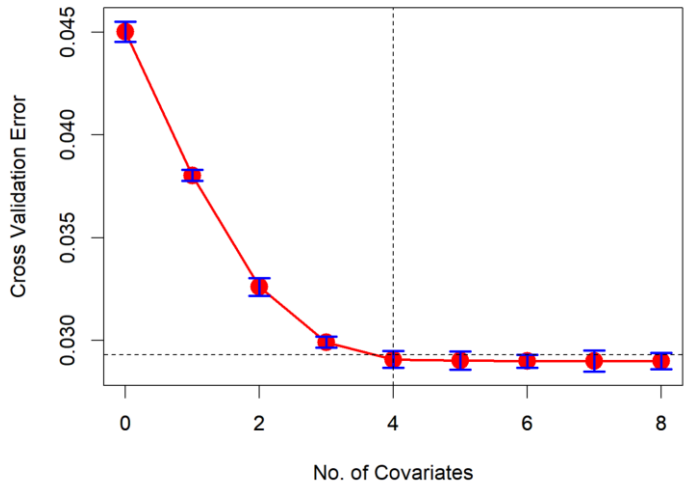

Figure S6.3: Model selection with estimated cross-validation error in red across the number of covariates using 10-fold cross-validation method

Text S2: Model specifications

Model description

The Besag-York-Mollié 2 Model (BYM2) developed takes into account that data may be spatially correlated and observations in neighboring adjacent wards may be more similar than observations in wards that are farther away. It includes a spatial random effect that is assigned a CAR distribution and smoothes the data according to a neighborhood structure, and an unstructured exchangeable component that models uncorrelated noise. The BYM2 model allows to simultaneously capture the heterogeneity and clustering of malaria TPR at ward levels (Iddrisu et al., 2018).

The selected covariates from a preliminary analysis, total mRDT confirmed cases and the total tested for malaria were used to model the spatial and temporal variation of malaria TPR and provide posterior predictions at unsampled locations with associated uncertainty. The selection of other prior information of the parameters followed the standard fixed prior specifications (Illian et al., 2013). R-INLA performs approximate Bayesian inference for the class of latent Gaussian models using analytical approximation and numerical algorithms (Blangiardo et al., 2013).

Exceedance probability (EP) and non-exceedance probabilities (NEP) were used to quantify the uncertainty in the likelihood of estimates of malaria TPR to be above or below the pre-defined policy relevant thresholds respectively. For instance, the probability that the risk of an area is higher than a value c is expressed as $P(pi > c)$. The probability was thus calculated by using the formula $P(pi > c) = 1 - P(pi \leq c)$. Values of the probabilities close to 100% indicate that the $P(pi > c)$ is highly likely to be above the threshold whilst those close to 0% are highly likely to be below the threshold. Values close to 50% indicate high levels of uncertainty. For malaria TPR, a threshold of ≥30% was used to represent the wards with high risk whilst a threshold of <5% was used to represent the wards with very low malaria risk.

Neighborhood matrices

Figure S6.4 shows the adjacency matrices created for mainland Tanzania. Wards sharing a common boundary were considered neighboring wards for borrowing strength in time and space for predicting the malaria TPR estimates.

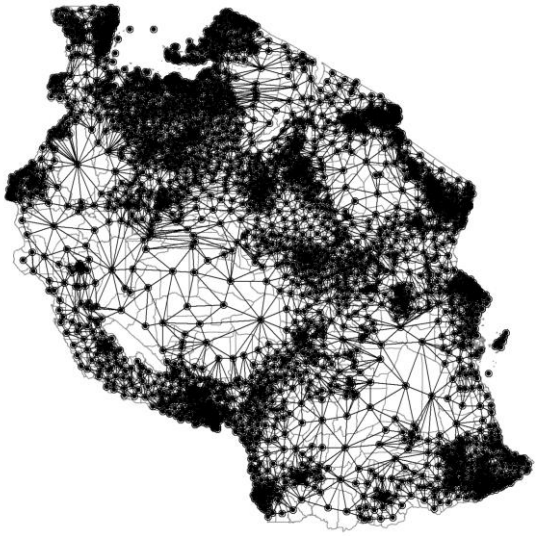

Figure S6.4: Spatial neighborhood matrices for the wards of mainland Tanzania

Model Selection and Validation plots

In order to test the goodness of fit, CAR models with different specifications of the spatio-temporal structures were implemented (Table S6.1). The model performance was validated by computing the MAE, RMSE and R2 on the 10% test hold-out dataset.

Table S6.1: Different specifications of CAR model to test goodness of fit

Model description	Specification	DIC	R2	MAE	RMSE
A. Without spatial random effect	$logit(P(j,k)) = \beta_0 + X(j,k)'\beta + v_j$	306,978.1	0.91	0.04	0.06
B. With spatial random effect	$logit(P(j,k)) = \beta_0 + X(j,k)'\beta + v_j + u_j$	307,065.9	0.91	0.04	0.06
C. With spatial and temporal random effect	$logit(P(j,k)) = \beta_0 + X(j,k)'\beta + v_j + u_j + \gamma_j$	304,069.5	0.91	0.04	0.06

β_0 the intercept; $X(j,k)$ is a set of selected covariates; β are the corresponding regression parameters; u_j corresponds to the CAR structured spatial random effect that smoothens the data according to a neighbourhood structure; v_j corresponds to the unstructured exchangeable component using independent and identically distributed (i.i.d) random effect and γ_k is the temporal random effect specified using i.i.d zero-mean normally distributed random effect.

The semi-variogram of the residuals showed minimum spatial autocorrelation after modelling suggesting that the spatial structure in the data was accounted for (Figure S6.5).

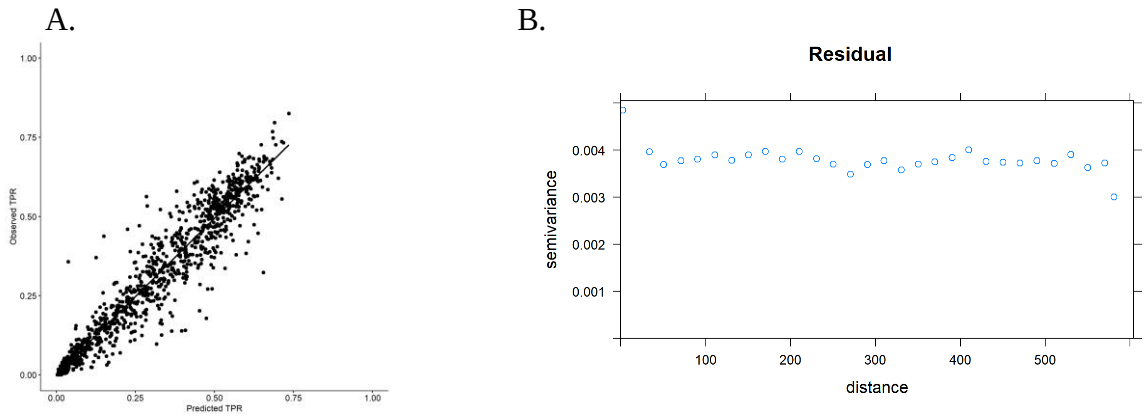

Figure S6.5: A) The scatter plot of observed malaria TPR against predicted modelled malaria TPR for the 10% test dataset. B) Semi-variogram of model residuals with minimum spatial structure

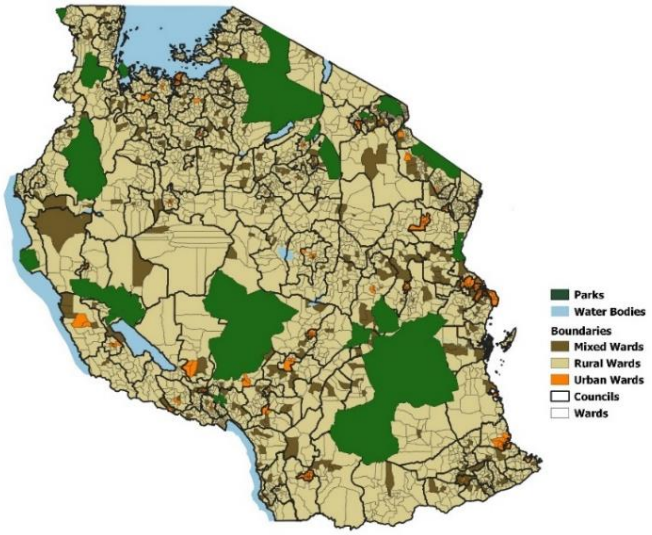

Figure S6.6: Administrative boundaries and distribution of urban (n=2,427), rural (n=514) and mixed wards (n=370) in mainland Tanzania.

Table S6.2: Selected routine indicator cut-offs to categorize into risk groups

Prevalence in School Children (*Pf*PR$_{5-16}$)	**Very Low risk (*Pf*PR$_{5-16}$ <1%)**	**Low risk (*Pf*PR$_{5-16}$ 1-<5%)**	**Moderate risk (*Pf*PR$_{5-16}$ 5-<30%)**	**High risk (*Pf*PR$_{5-16}$ ≥30%)**
1. mRDT Test Positivity Rate (TPR)	<5	5-<15	15-<30	≥30
2. Annual Parasite Incidence (API)	<10	10-<50	50-<120	≥120
3. Test Positivity Rate in Pregnant Women (ANC TPR)	<0.8	0.8-<3	3-<8	≥8

7 Discussion

7.1 Significance of this work

A strong nationally owned routine surveillance system can provide near real-time and granular data in time and space for tracking progress, supporting effective allocation of targeted interventions and surveillance. In this thesis, the potential of using routine data sources to inform malaria risk stratification in mainland Tanzania was explored. The objective was to create a body of work that explored the added value of using routine HF malaria data at different spatial resolutions for supporting malaria planning and understand the caveats surrounding this data. This was demonstrated through first conducting key informant interviews to understand common encountered challenges with using such data for analytical purpose. This was followed by using multiple routine malaria metrics to produce a macro-stratification risk map at council level to support the country towards sub-national tailoring of interventions. The analytics was extended to the granular level of the ward to produce a micro-stratification risk map to further improve resource allocation. Finally, geospatial modelling was used to leverage routine information and fill existing spatial and temporal gaps in routine data. In the following sub-sections, the key outcomes from each of the chapters are highlighted.

7.1.1 Key informant interviews to understand routine data challenges

The key informant interviews conducted with various stakeholders and described in Chapter 3 highlighted existing challenges with using such data and the spectrum of approaches currently being used to address these challenges in order to produce sensible analytical outputs. The objective of these interviews was to understand the current approaches taken for HF data processing and cleaning. The key findings of this study stressed the need for developing guidelines for addressing the existing common challenges with routine data and allowing programs to analyze the data and interpret the outputs in a harmonized, reliable manner.

In Tanzania, assessment of some of the dimensions of data quality indicated improving trends. Whilst varying levels of incomplete reporting, inconsistent reports and outliers have been reported previously (Rumisha et al., 2020), such an analysis was based on data prior to 2017 when the country was still expanding the digitization of the HMIS and introducing data quality audit initiatives (National Malaria Control Programme, 2017c). The digitization of the HMIS system across Tanzania in 2013 has gradually improved the reporting rates (RR) with current rates over 90%. The current assessment in this work showed that the RR for HFs data were

generally high in Tanzania with only a small proportion of reports having extreme outliers, and setting some exclusion criteria allowed to use such data in a systematic way for risk assessment.

The usage of routine data has increased across countries (Alegana et al., 2020) following the emphasis by WHO GTS (World Health Organization, 2015c) and HBHI initiatives (World Health Organization, 2018a) to use data for decisions. This increasing use of routine data has placed data quality initiatives to become an important operational component of surveillance across countries. For instance, Tanzania has recently introduced regular supportive supervision visits and data quality audits as part of the malaria service and data quality improvement initiative (MSDQI) (National Malaria Control Programme, 2017c). Global efforts have also introduced surveillance assessments (World Health Organization, 2022b, 2017a) to ensure a well-functioning surveillance system that is capturing quality data from the routine information system. This is all expected to further enhance the accountability at level of data collection, aggregation and entry of routine information.

7.1.2 Macro-stratification of malaria risk at council level

In Chapter 4, multiple aggregated malaria metrics collected through the routine surveillance system (API, mRDT TPR and ANC TPR) was utilized in combination with survey data to map malaria risk at the council level (Macro-stratification) and thereby support the country's ambition towards a more tailored malaria control approach. This was instrumental in supporting the NMCP with translating the risk map into suitable packages of interventions. The current strategic plan (National Malaria Control Programme, 2021) makes use of this evidence and advocates for tailored interventions through emphasizing burden reduction strategies in moderate-high transmission areas, and elimination strategies in low-very low transmission areas. Importantly, the methodological approach used was well within the capacity of NMCP staff at national level as it did not require data generated through complex survey methods nor utilized complex modelling methods.

7.1.3 Micro-stratification of malaria risk at ward level

As the country is currently implementing targeted packages of interventions, a more granular micro-stratification at the ward level is being considered. The goal is to move some of the decision-making processes towards a decentralized malaria control approach where council health management teams (CHMTs) would be empowered to understand the malaria situation

in their respective wards and mobilize resources to areas that most need them. The micro-stratification risk map in Chapter 5 was therefore developed using multiple aggregated routine malaria metrics at ward level to align with this vision and is reflected in the current strategic plan (National Malaria Control Programme, 2021). These maps are intended to guide operational efforts of these councils to further fine tune targeting of community-based interventions to the wards.

Of the 184 councils, 80 (43.5 %) had varying levels of heterogeneity within their wards. The micro-stratification becomes more relevant in these 80 councils identified to be with heterogeneous transmission within its administrative boundaries, and these would need to concentrate efforts to areas that most need them for more efficient allocation of resources. An important aspect to be considered is that councils that are empowered to make such decisions would require skills for understanding the local heterogeneity and making use of their local data to drive decisions. Here, the capacity of CHMTs will need to be built so that they are able to assemble, clean and interpret their local data. This is discussed in more details in section 7.4 below.

7.1.4 Using geo-spatial modelling to support malaria risk micro-stratification

The use of crude aggregated routine data especially at the granular level of the ward came with some limitations. One of the challenges was the incomplete nature of information in space and time, resulting in lower level administrative units (7% of wards) without empirical data. Moreover, a large proportion of the wards (57%) had only one or two reporting HFs to inform on the risk, thereby contributing to a higher level of uncertainty. To overcome sparsity of data, geo-spatial models can leverage available routine information to predict risk in areas without information as well as provide the associated levels of uncertainty. Various countries have employed a variety of geo-spatial methodological approaches on routine data to support national risk mapping (). A Bayesian spatio-temporal model was therefore used in Chapter 6, using routinely collected TPR to complement the micro-stratification efforts and predict malaria risk at the ward level. The framework allowed for a more robust estimation of TPRs by borrowing information strength from neighboring wards, rather than relying only on limited information from one single ward. The exceedance/non-exceedance probabilities helped to quantify the uncertainty of the estimated risk within policy relevant thresholds of TPR in Tanzania. This allowed to determine the level of confidence in the assigned risk strata and

compute the proportion of population residing in the extreme high and very low transmission risk areas where the largest change in intervention strategies are observed.

In the following sections, the implications of the findings from the Tanzanian stratification work in the context of the potential utility of routine data and its limitations for risk mapping are discussed. This is followed by assessing how the stratification in Tanzania compares with the WHO HBHI methodological framework. The section continues with suggesting efforts that would be needed to enhance country ownership as learnt from the Tanzanian experience. The subsequent section then reviews important issues to be taken into account from a global perspective and finally, important areas to be considered for future work are proposed.

7.2 The use of routine surveillance data

The use of nationally owned routine HF data in Tanzania underscored its potential to inform malaria programs on the heterogeneity of malaria risk that exist within its national boundaries at different spatial scales and in driving a country-owned stratification process. Embedded in this work, is the transition towards a better use of available routine data by the NMCP. Strengthening surveillance-response systems to generate quality routine data at national and sub-national levels remains one of the most effective ways for countries to continue their trajectory towards elimination (Tambo et al., 2014).

For optimal representativeness of malaria burden through HFs, all cases from the community should report to the public HFs (See Figure 1.8, Chapter 1) and these should be reported at the central level through DHIS2 (Alegana et al., 2020). In reality, this is not the case. The use of crude routine data for macro-stratification (Chapter 4) and micro-stratification (Chapter 5) had some limitations since it did not account for factors such as treatment seeking rates, incomplete reporting, health utilization behaviors, temporal and spatial missingness in data, the underlying heterogeneous distribution of the population and the differing testing rates between transmission settings, which can potentially under/over-estimate malaria risk. Whilst at council level, data aggregation may have absorbed some of these biases thereby having minimal effect on overall malaria risk, at the ward level, where limited data is available to inform on the ward risk, it becomes crucial to ensure that only HFs with good quality routine data are used to avoid misclassification of risk (Chapter 5). For this reason, a conservative approach was undertaken in Tanzania, inclined towards allocating wards to higher strata than to the lower strata that

would otherwise receive reduced control efforts. Continued efforts to strengthen routine surveillance systems will provide even better estimates of crude risk. In the absence of complete and perfect empirical data, statistical modelling techniques represents a practical way to close some of these gaps and obtain best estimates at these finer scales (Chapter 6).

Despite the improvements made with routine data collection, in various malaria endemic countries, there still persist data quality issues that can have implications on the data validity of malariometric indicators assembled using such data. For instance, an examination of micro-level practices in Kenya at the level of HF data collection, revealed that the root-causes of most of the challenges with routine data generation are a reflection of wider health system issues (Okello et al., 2019). Various factors attributed to organizational (stock-outs of reporting tools, human capacity and shortage), behavioral (poor data recording practices, poor motivation) and technical factors (Lack of standard operating procedures) were responsible for the poor routine data (Okello et al., 2019; Rumisha et al., 2020). Emphasis on improving the broader systematic issues of a health system is a more sustainable way of improving outcomes of routine data generation. Regular supportive supervision visits conducted by the national level at HFs together with data quality audits that evaluate routine surveillance systems can assist to increase accountability at multiple levels and strengthen the overall quality of routine data.

An essential element that needs to be considered when using routine data is the HF representation in the HMIS/DHIS2 system. For routine surveillance systems to reflect the true burden estimates, it must capture information from the universe of all HFs. In mainland Tanzania, approximately 16% of the HFs did not submit any monthly laboratory reports across the entire period of analysis and were therefore excluded (Chapter 6). No information was available on whether they had poor reporting performances, did not provide testing services or were no longer operational. An in depth exploration is required to further understand the true reporting completeness by comparing the country's comprehensive master facility list (MFL) to the HMIS/DHIS2 system. The availability of geo-coded information for the remaining HFs allowed linkage of HFs to its correct administrative boundaries. This was important especially at the ward level for correct quantification of risks. Effective health planning and decisions for malaria and across health sectors requires an understanding of HF access, identifying marginalized populations, treatment seeking choices, quality of services provided by HFs, all of which depend on the availability of a comprehensive list of HFs and its location (Noor et

al., 2004). Efforts towards encouraging countries to create MFLs linked to the HMIS/DHIS2 system (WHO/USAID, 2018) and create an open-source spatial database that assemble the geo-coded information of 98,745 public HFs from 50 countries are in place (Maina et al., 2019; South et al., 2020; van der Walt and South, 2020a, 2020b). Whilst these efforts have encouraged many countries to build MFLs through HF registries, there still exist gaps in ensuring a universal adoption across all countries in Africa. Furthermore, many inventories are not open access, regularly updated, lack information on the geo-coordinates and are not fully reflected in the DHIS2.

An important limitation that must be acknowledged to the approach taken for stratification in Tanzania is that HFs may not always reflect the actual transmission status of its administrative boundary since people from surrounding wards may also utilize their services. Here, availability of HF catchment boundaries becomes important for computing population denominators and mapping incidence at granular levels. The precise HF catchment population was not available as most of the information on the catchment remains paper-based and yet to be digitized, therefore aggregated ward population currently used by MoH was utilized for the micro-stratification process. These boundaries need to be informed by HF utilization behaviors (distance, cost, culture), accessibility to HFs, and competition between health providers (quality of services) (Alegana et al., 2020). However, such data are rarely available at the finer spatial resolutions and catchment boundaries remain largely undefined (Macharia et al., 2021) making it difficult to understand the incidence per population at such scales. Until this knowledge is made available, the use of spatial modelling techniques and spatial statistical tools to discern these will continue to serve as a proxy (Macharia et al., 2021).

7.3 Malaria risk stratification

7.3.1 Methodological approach

The approach taken in Tanzania made use of a simple and pragmatic method which was instrumental in driving a country-led stratification approach that could easily be adopted by the malaria program for future updates.

The availability of multiple malariometric indicators allowed Tanzania to triangulate information from these local sources that represented information from different age and immunological groups to inform on the malaria risk. Although this may not be the case in other

SSA countries, and the approach would need to be tailored according to local context, it encourages on exploring the use of multiple available local metrics to inform on the malaria risk. Most countries have solely relied on one metric only, either modelled prevalence estimates or malaria incidence to define the risk through the use of complex geo-spatial modelling approaches (, Chapter 1). Complementing the risk maps with other layers of routine malaria information can have great value. However, the use of multiple metrics requires an in-depth understanding of how they relate to one another and with more traditional measures of modelled prevalence estimates in the different transmission settings.

The classification of prevalence in school children (PfPR$_{5-16}$) was used as a gold standard in guiding the selection of appropriate cut-offs for converting the three routine malaria indicators into risk categories. Because of the quality, sampling strategy and comprehensiveness of the school survey data, and the fact that the prevalence rate in children is widely used as a reference metric for defining malaria risk (Alegana et al., 2021a; Weiss et al., 2019), it served as a benchmark for categorizing the routine indicators. The misclassification analysis developed (Chapter 5) was conservative and inclined to allocating councils/wards to higher strata than to the lower strata that would otherwise receive reduced control efforts. The approach undertaken by Tanzania represents one of the first efforts to try and formally select suitable cut-offs for routine metrics compared to the arbitrary approach that is widely undertaken. However, the approach has assumed an independent relationship between the metrics, future work may explore establishing this relationship to provide a more informed basis for defining robust and accurate thresholds (See section 7.6).

7.3.2 Tanzania's malaria stratification approach in the context of the WHO HBHI framework

The stratification work conducted in mainland Tanzania preceded the WHO HBHI initiative in 2018. In 2017, a MTR was undertaken (National Malaria Control Programme, 2017b). It was recognized that progress towards reducing national parasite prevalence was being made (7% in 2017), but that further gains would require a strategic redirection of limited resources to achieve a prevalence of less than 1% by 2020. The MTR was followed by a consultative process with a forum of global and national malaria experts. Recommendations from this forum, together with those from the WHO GTS 2016-2020 (World Health Organization, 2015c), were used to consider tailoring intervention approaches to the local context, based on

epidemiological stratification. The Tanzanian stratification experience set a great example of a country-led application of stratification for sub-national tailoring of interventions. This application aligned well with the later launch of the WHO HBHI vision to promote the use of local data for informing targeted strategies.

The various criteria used with the developed methodological approach for risk stratification were done in close consultation with the malaria program. The work presented in Chapter 4 was instrumental in providing the epidemiological risk strata to support the NMCP for translating the risk map into suitable packages of interventions with support from mathematical modelling (National Malaria Control Programme, 2018a; Runge et al., 2022, 2020a, 2020b). Here, mathematical modelling supported the program with intervention choices by providing the impact of various alternative intervention mixes tailored to the risk strata (Runge et al., 2020a). The intervention mixes that were eventually implemented per council were selected by the program taking into account the financial resources available and operational feasibility. Mathematical dynamic models have been useful to simulate the impact of interventions in geographical areas with different endemicity settings to help programs prioritize resources and select suitable packages that would allow maximizing impact given budget constraints (Gerardin et al., 2017; Hamilton et al., 2017; Owen et al., 2022; Smith et al., 2017; Winskill et al., 2017). Current support provided for the adoption of the HBHI strategy by WHO GMP has placed dynamical modelling as one of the steps in guiding the processes for sub-national tailoring of interventions (World Health Organization, 2020b).

The WHO GMP is currently working with various African countries to provide support on adopting the stratification process (World Health Organization, 2020b). The methodological framework currently utilized by WHO GMP comprises of several key components (Chapter 1.2.5 – Figure 1.9). Countries are first supported with strengthening the generation and use of local data through building comprehensive repositories and dashboards that collates all malaria-related information. This is followed by conducting stratification using multiple metrics. Epidemiological metrics forms the foundation of most decisions and a combination of three malaria metrics are used namely incidence, prevalence and mortality. Countries are recommended to integrate this with other layers of information such as entomological data, climate and seasonality, urbanization, intervention coverage, health system readiness amongst many (World Health Organization, 2020b) to allow for better decision making. Since many

countries did not have prevalence estimates powered at district level nor reliable information on mortality rates, modelled estimates produced by Malaria Atlas Project (MAP) and Institute of Health Metrics and Evaluation (IHME) were utilized. Each of these metrics are then categorized into four to five risk groups using a set of standard cut-offs applied across countries and a scoring system classifies the districts into its overall risk strata (World Health Organization, 2020b). The maps provide a basis for performing situational analysis of the malaria risk and inform on the interventions. For each WHO recommended intervention, the district risk and operational feasibility guides its selection for implementation. Dynamical modelling is then used to assist with estimating the impact of the interventions mixes, assess the intervention coverage needed to reach the set targets, determine the cost-effectiveness of the interventions and guide its prioritization given budget constraints. This allowed the programs to further fine tune the interventions to inform their malaria strategic plans and develop funded operational plans.

Although the WHO recommended HBHI analytical framework is conceptually similar to the approach used in Tanzania, there are several existing differences that need to be highlighted to evaluate how best the efforts can be consolidated. Currently, the choice of epidemiological metrics utilized to stratify the risk differs between the approaches. Whilst the WHO HBHI approach uses a combination of local and global modelled data, Tanzania has solely relied on using local available data. Using local data allows understanding the country specific context and for programs to regularly monitor and update the risk map in line with their strategic plan cycle without having to rely on externally produced modelled risk estimates. This was possible since the biennial schools survey in the country are powered to provide estimates at the council level and generally the data generated from HMIS/DHIS2 have good RRs. The availability of reliable mortality data is currently a challenge in the country and to what extent the inclusion of such a metric would change the stratification risk map needs to be explored. Furthermore, integrating the risk map with other determinants of risk such as entomology, health services access, ecological data to help identify the marginalized vulnerable populations is work planned for future. The current recommendations provided by WHO on the choice of metrics are not intended to be strict allowing flexibility for countries to make their decisions (World Health Organization, 2018b).

Another difference to the approach is the choice of cut-offs derived to categorize the epidemiological metrics. In Tanzania, the cut-offs for the routine metrics was guided by using the classifications of school prevalence as a gold standard through a misclassification analysis (Chapter 5). These cut-offs varied to the standard set of cut-offs used by WHO HBHI across countries. Since the endemicity of malaria varies between countries, developing county-specific thresholds helps to better understand the local context. Future work should attempt to understand risk classifications and how to robustly define them.

To date, there is no consensus on the best approach for stratification and how to translate this for sub-national tailoring of interventions to select the optimal intervention mixes. The WHO HBHI geographically stratified each intervention individually based on a set of criteria. Conversely, Tanzania used the four risk strata presented in chapter 4 as the foundation to develop four packages of interventions whose geographical prioritization within each strata was driven by available resources. To what degree the different approaches impacts the overall selection of intervention mixes is not known. There is a need to integrate more layers of information to define the strata and better link them to sub-national tailoring of interventions to guide the development of evidence-based intervention mixes of prevention vs case management. Current guidelines provided avoid being prescriptive recognizing the country-specific diversity in risk and resources and need for using local information when and where available.

7.4 The need for a more country-led stratification process

A striking feature of the work presented in this thesis is that at all stages, the work has been strongly linked to the management of malaria control activities in the country and its strategic planning by the NMCP and its partners. The work done over the past 3 years together with the NMCP has led to several key outcomes: (i) Enhanced usage of country-owned routine data for decision making (ii) Capacity strengthening within the NMCP to understand the stratification methodology, annually monitor the risk maps and periodically update them aligned with strategic plan development cycle to link to intervention strategies (iii) incorporating the stratification into NMCP's DHIS2 strategic information system dashboard (iv) dissemination of the stratification work by NMCP to council health teams and (v) a country driven and sustainable malaria stratification approach. Achievement of these outcomes were largely

driven by use of nationally owned surveillance data, continuous engagement with NMCP and capacity strengthening efforts. These factors are discussed in more detail below.

Use of nationally owned data: For countries to make rational decisions for malaria control strategies, a good understanding of the distribution of epidemiological risk at national and sub-national levels is required. A study investigating usage of risk maps across 47 malaria endemic countries (Omumbo et al., 2013) revealed that although almost all countries had some form of risk map, the maps developed using nationally owned data through in-country partnerships had higher utility when compared to those available on open source platforms and based on modelled prevalence estimates. Exploration of the usage and perception of malaria risk maps by decision makers in three African countries showed that enhanced usage was driven by understanding of the processes behind developing the maps, perceived ownership and trust in the data used for the risk maps (Ghilardi et al., 2020). The use of locally owned data and its application using a simple and pragmatic approach built a sense of ownership and trust within the NMCPs that drove its adoption for decisions and inclusion in strategic plans for future updates. Aggregated routine data summarized to programmatically relevant units are more likely to be valuable to programs than spatially continuous maps of modelled estimates of risk. It is therefore important that countries continue to strengthen their routine surveillance systems to generate high quality data to garner country ownership of these data.

In Tanzania, use of local data to inform the risk map enhanced the recognition of its value by NMCP resulting in increased efforts to further strengthen it. Some of these efforts included (i) organizing virtual monthly data quality review meetings with CHMTs to review the outputs generated from the malaria dashboard and highlight any pertinent issues for improvement (ii) digitizing the malaria risk maps under the NMCP comprehensive data repository to allow annual monitoring and planning (Figure 7.1) (iii) conducting quarterly HF data quality audits (DQA) as part of the MSDQI supportive supervisions (National Malaria Control Programme, 2017c) that assesses malaria services offered at HFs by assigning performance scores to each HF (Figure 7.2).

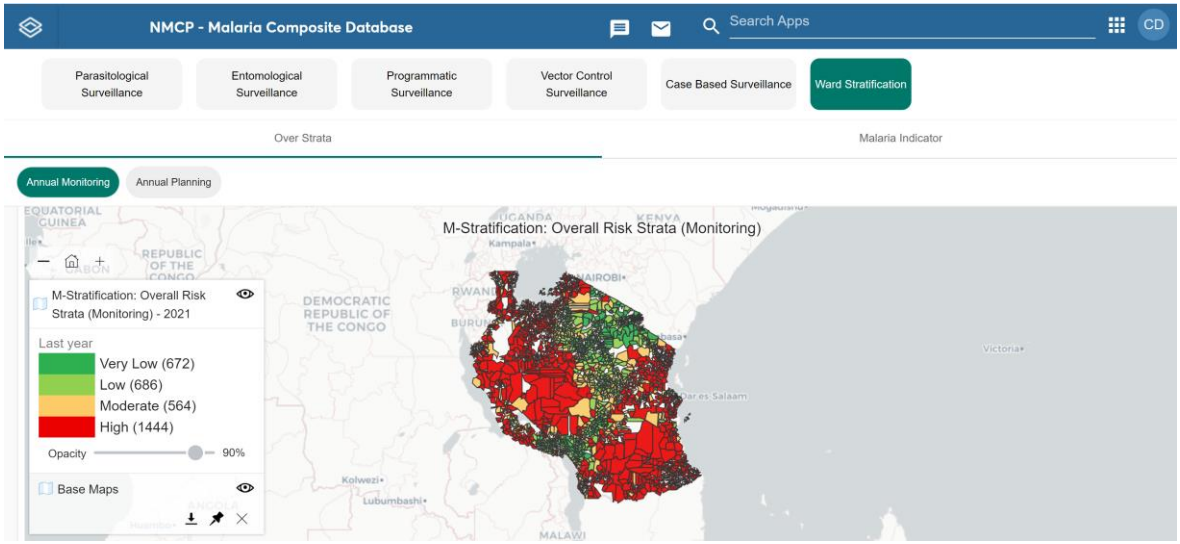

Figure 7.1: Digitization of malaria risk stratification under the NMCP DHIS2 composite database

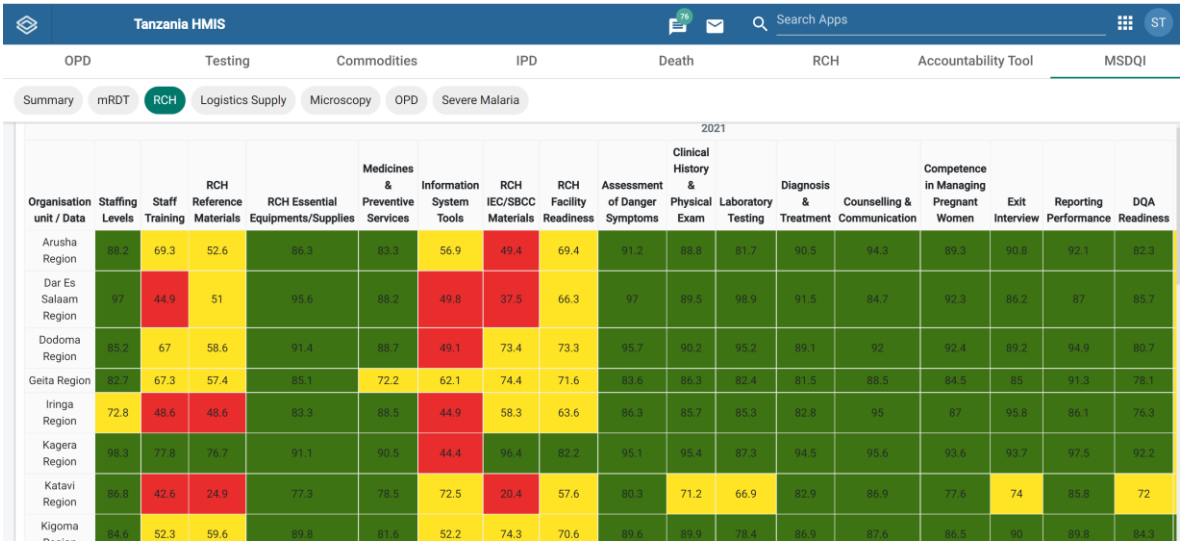

Figure 7.2: Malaria service and data quality improvement (MSDQI) outputs showing health facility performance for various malaria services under the DHIS2 malaria dashboard

Continuous country engagement: A key feature that facilitated the adoption of a country-owned stratification in Tanzania was the strong engagement that existed between NMCP, local implementing partners and other stakeholders. The technical support provided to NMCP entailed a strong day-to-day interaction with SME personnel, meetings and workshops to ensure the methodology was well understood, consensus reached on the selection of suitable metrics and cut-offs, agreement on the spatial scale of analysis and overall risk strata. This was followed by in-depth discussions with mathematical modelers on how best to translate the risk map into suitable packages of interventions. Presence of in-country technical experts allowed

for daily engagement and discussions with the program staff. A list of some of the meetings that were instrumental to the country adoption of stratification are outlined in Table 7.1.

Table 7.1: Key engagements with national malaria control programme and stakeholders in mainland Tanzania that formed the foundation for the stratification of malaria risk and sub-national tailoring of interventions

Meeting/Workshop	Participants	Dates
Malaria Program Review	NMCP, implementing partners, WHO	July 2017
Malaria Expert Meeting	NMCP, implementing partners, WHO, International malaria experts	February 2018
Strategic Planning Workshop	NMCP, implementing partners, WHO, malaria modelers	May/June 2018
Mapping & Writing Workshops – Capacity building	NMCP, implementing partners, KEMRI Wellcome Trust,, malaria modelers	November 2018 January 2019 May 2019
NMCP capacity building workshop on stratification	NMCP, implementing partner	February 2021
Dissemination of stratification concept to al and council health teams	NMCP, implementing partner, RHMT, CHMTs	October 2021
Micro-stratification for micro-planning inception workshops	UDSM/DHIS2, TMA, NMCP, MoH, implementing partner	April 2022
Digitization of stratification in DHIS2	UDSM/DHIS2, NMCP, implementing partner	April-June 2022
Stratification update workshop	NMCP, implementing partner	April 2022

A recent review conducted by the Global Fund showed that the most effective disease strategies occurred when programs were supported by local experts over those based externally, especially, those that involved a broad range of local stakeholders at all levels in the decision making (Sands, 2019). Engagement between the NMCP and local researchers was crucial in supporting the development of country-owned risk maps and evidence informed policies (Ghilardi et al., 2020). Current global efforts for malaria control research are largely driven by external malaria experts affiliated to international organizations that provide technical guidance to African countries (Okumu et al., 2022). A study exploring African collaborations showed that nearly 70% of the research publications involved international collaborators and only 40% of these included authors from the target African country (Hedt-Gauthier et al., 2019). This calls for a need to foster collaborations between the NMCP, in-country institutions and malaria experts to drive major malaria decisions. Addressing these gaps will enable a more localized effective response to malaria.

Capacity strengthening: Although the modelling approaches for risk maps have been useful to provide baseline risk maps for NMCPs, it generates estimates with a level of uncertainty that requires some level of statistical skills to interpret, and these skills are not always present in

NMCPs thereby limiting its application for policy translation. As methodologies in geo-spatial approaches continue to advance, so is the complexity. The computational needs and skill requirements of geo-spatial modelling techniques often limits its application to international experts located outside Africa creating a gap with the NMCP. Hence building knowledge within local research institutions is crucial to ensure such methods remain within the country and modelling efforts do not merely remain an academic exercise. NMCP staff should also be capacitated to understand the analytical process, consequences of incomplete data, training in simple methodological tools and understanding the resulting maps with its associated levels of uncertainty (Ye and Andrada, 2020). An important aspect to the methodology undertaken in mainland Tanzania is the simplicity of its design which could easily be transferred to NMCPs. Holding capacity building workshops (Table 7.1) allowed to transfer the knowledge to SME personnel within NMCP to undertake future analysis. As the country moves towards a decentralized malaria control planning, capacitating CHMTs to assemble, clean and interpret their local data would be crucial to empower them to assess their local heterogeneity. For this, a strong and robust guidance from national to council levels needs to be continuously provided. Supporting NMCPs to establish a strong surveillance-response system and building human resource capacity to generate reliable granular data for improving sub-national malaria burden estimates would be a more practical solution than over relying on modelled estimates. This offers a more simplified way for analyzing real-time data, one that is driven by the country to inform its malaria strategies (Ye and Andrada, 2020).

A recent malaria surveillance system landscaping analysis conducted across SSA showed that some of the most important barriers to malaria control and elimination are deficiencies in human resources, training and analytical capacity, inadequate health information infrastructure, and poor integration of data within NMCPs (Lourenço et al., 2019; Mwenesi et al., 2022). The "Rethinking malaria" initiative is an urgent response to the current malaria crisis and reiterates the need for a country-led malaria eradication by investing in African country leadership, partnerships with multiple stakeholders and concerted efforts towards building health work force at all levels (World Health Organization, 2022c). The capacity should provide broad understanding across disciplines and enable the usage of data for decisions (Okumu et al., 2022). It is therefore essential that countries allocate resources to address these needs and have a coordinated engagement with local research institutions to build the required competencies through targeted training. Existing global guidelines such as WHO Human Resources for

Health Action Framework and WHO-sponsored Checklist for Implementing Rural Pathways to Train, Develop and Support Health Workers in Low and Middle-Income Countries (O'Sullivan et al., 2020) are useful resources to further guide countries on how to close this gap.

7.5 Other challenges to consider

7.5.1 Operational and political feasibility of sub-national tailoring for different administrative levels

To-date, there is no example that has been done to show the influence of finer resolution risk maps on decision making in stable endemic areas. Whether the operationalization of micro-stratification for micro-planning is feasible and politically acceptable remains to be assessed and will require close monitoring of the processes at all levels. As Tanzania moves towards the decentralization of control efforts, there are several important factors that need to be considered.

Firstly, the operational feasibility of implementing interventions at the level of the ward needs to be assessed. This would be more applicable where councils have a heterogeneous distribution of transmission within its wards such as the moderate and low transmission settings identified in Chapter 5. Our findings are consistent with other studies that showed that areas with widespread transmission would benefit more from a uniformly applied intervention strategy where the community effect can be observed. On the other hand, a micro-level community targeting of interventions is more logical and cost-effective in lower transmission settings to accelerate progress (Bousema et al., 2012; Lubinda et al., 2022; Stresman et al., 2019) such as in urban settings (World Health Organization, 2022c). In fact, in the very low transmission areas, working at a much finer spatial resolution to identify hot-spots/foci of transmission to interrupt residual transmission would be critical (Stresman et al., 2019). Most studies conduct their spatial analysis simply based on the spatial resolution of available data which may not necessarily reflect the most suitable programmatically relevant unit (Stresman et al., 2019). It's crucial that the decision undertaken for the level of spatial targeting is linked to transmission dynamics, population movements and programmatic objectives (Stresman et al., 2019).

In Tanzania, traditionally, the role of CHMTs was limited to operationalizing interventions of key malaria control interventions. Implementing a micro-stratification approach would require supporting CHMTs to identify the type of tailored interventions that would be appropriate to implement at these granular levels. Here, a community based approach of delivering the targeted interventions to the most vulnerable populations would be most effective. This will require drawing information from those at the frontline such as the CHMTs who are better placed with the community to provide insights of the local context. Nevertheless, currently there is a lack of clarity on how best programs can develop such locally appropriate approaches and more guidance is needed from the global malaria community. A review by Gosling and colleagues (Gosling et al., 2020) have proposed a reorganization of how malaria services are delivered (Figure 7.3) by enabling district/council health officers to serve as channels between NMCPs and the community in order to accelerate progress. The motivation being that for stratification and sub-national tailoring to be effective, it requires taking into account the broader health system challenges at the periphery that could prevent delivery of these micro strategies (Gosling et al., 2020). Engagement with community leaders would be crucial to understand these challenges since they are better equipped with the knowledge of identifying at-risk populations and could enhance data-driven solutions.

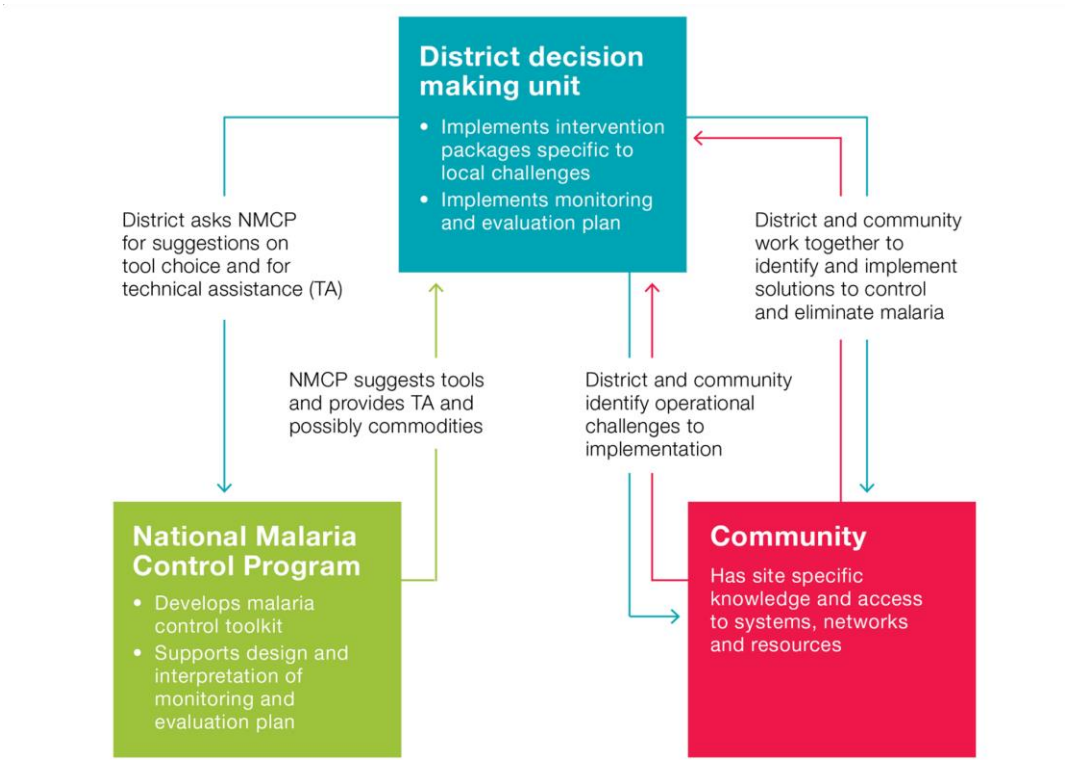

Figure 7.3: A proposed framework for district-level management of malaria control (Gosling et al., 2020)

Second, the political acceptability for the proposed change in the decision-making structure would need to be explored. Implementing such a targeted approach at this granular level can raise concerns by the neighboring communities that are not qualified to receive targeted interventions. Engagement with the local government and community to get their buy-in to support this process would be crucial to avoid any conflicts.

Third, it is important to note that the decentralization of malaria control processes to the council level could potentially come with some risks. Weak leadership by the districts can compromise the quality of malaria control delivery and lead to variable performance between districts. Furthermore, by giving responsibilities to the districts in areas where technical capacity is already weak, could lead to worsening of the situation (Gosling et al., 2020). Hence, accountability, monitoring and assessment of all processes from central to local levels is required.

To move towards a decentralized malaria control process would require countries to consider answering some key questions: What is the most programmatically relevant unit of spatial targeting? How can capacity be sustained at these levels? What kind of structural changes at national and donor levels would be required for transferring decisions to the lower levels? How can community engagement be enhanced to ensure adherence and uptake of interventions? If these are carefully considered, micro-stratification can allow for massive advances in malaria control by placing those at the frontline in the lead and reaching the highly under-served populations (Gosling et al., 2020).

7.5.2 Need for more information beyond epidemiological data

A limitation to the work done in Tanzania is that the stratification has only considered epidemiological metrics thus far. However, it is important that sub-national tailoring is guided by metrics that go beyond epidemiological indicators and include more local information on health system capacity and readiness, availability of human resources, access to health care, entomological data, ecological data, vector and human behavioral information, intervention coverage, location of vulnerable at-risk population and other contextual factors (socio-economic status, occupation, conflicts, location of refugees and internally displaced persons or other humanitarian emergencies) (World Health Organization, 2020b).

Such information is needed at local council/ward level to improve delivery of care especially to the most vulnerable key populations. Such groups include the biologically vulnerable groups (children under 5 years old; pregnant women, HIV infected and immunosuppressed individuals), Occupational/ behaviorally vulnerable groups (Migrant workers, nomads, fisherman, peasants, miners) and socio-economically vulnerable groups (Poor populations, hard to reach population, orphans, prisoners, those residing in the streets, refugees and internally displaced people).

7.6 Future work

There are several areas to the work done here where future work might consider building on. These are discussed below.

i) Quantifying the relationship between prevalence and routine metrics

The stratification done in Tanzania using combinations of malaria metrics has assumed an independent relationship between the different epidemiological indicators that represent different population age groups. However, various studies aiming to understand the relationship between prevalence and routine metrics show that this may not always be linear (Brunner et al., 2019; Kigozi et al., 2019; Kitojo et al., 2019). An in-depth understanding of how they relate to one another and with more traditional measures of modelled prevalence estimates in the different transmission settings is crucial. Future work may look into leveraging information from both sources as a hybrid modelling approach to not only capture the community information but also understand the relationship between both sources of data, and how well they reflect the different components of the transmission system. Establishing this relationship would provide a more informed basis for defining robust and accurate thresholds for risk classification. Classification of metrics allows programs to track progress and allocate appropriate interventions of control versus elimination.

ii) Stratification by age

The risk stratification currently done for Tanzania considered the routine metrics for all age groups without taking into account the attributes of age. Stratification by age is important since children <5 years are at greatest risk for malaria morbidity and mortality. Many malaria control interventions in high transmission settings such as chemo-preventative therapies target children

<5 years, therefore, understanding its distribution would allow for better planning and allocation. Current studies exploring age stratification of malaria shows that the distribution is contingent on the endemicity setting with minimal overall effect on the predicted malaria burden (Kamau et al., 2020b, 2022). An age shift in the burden was shown to occur to older individuals following implementation of malaria control interventions (Kigozi et al., 2020b). For councils/wards in the very low transmission areas, capturing all local cases regardless of age would be crucial to prevent onward transmission. For these reasons, all age groups were included in this work. The current interventions in mainland Tanzania targeting children <5years are solely LLINs distributed during their immunization visits. Other preventative measures such as seasonal malaria chemoprevention (SMC) and intermittent preventative therapy for infants (IPTi) are under operational research in the country. Thus, as Tanzania transitions towards adopting these preventative measures, exploring the impact of crude age bounds available in DHIS2 (under and above 5 years old) would become important.

iii) Comparison between global and local data estimates

Currently, countries supported by the WHO HBHI initiative, are utilizing the modelled prevalence and mortality estimates obtained from global sources such as from MAP and IHME mainly due to the lack of availability of these data within the countries at higher resolutions. However, how well these data represent the local situation at sub-national levels is not known and future work should attempt to explore this. Since Tanzania has a rich source of available local information, efforts to understand how well the global estimates compare with the local situation and the impact on the overall stratification risk maps would represent an important verification process.

7.7 Conclusion

The HMIS is designed to meet the information needs at different levels of the health system (Tilahun et al., 2021). To effectively support evidence based decision making, a coordinated effort to use local data at the multiple levels is crucial (Lemma et al., 2020; Nutley and Reynolds, 2013). The work presented here provided substantial evidence for the potential of various routine malaria metrics to inform on the malaria risk heterogeneity at the different programmatically relevant units. Where routine data presented challenges, the value of geo-spatial modelling approaches in filling the gaps was demonstrated. Continuous efforts to improve routine data remains crucial for ensuring a reliable source of timely data for local

epidemiological monitoring and sub-national tailoring of interventions. However, to make risk stratification an intrinsic part of strategic planning, the critical role of capacity building, country engagement and strengthening nationally-owned surveillance systems needs to be recognized. This can have immediate potential for the NMCPs and CHMTs to take country ownership for making data informed policies. This can help countries maximize impacts on malaria control and turn malaria surveillance into a core intervention.

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