MILESTONE 2 – DFR3 – IDT8 – AI4M

MILESTONE NAME: Technical Documentation on AI Model Development, Validation and Calibration

MILESTONE DELIVERABLE: a technical documentation on the processes involved in the development and training of our AI model. This would also involve the presentation of historical malaria data.

DOCUMENTATION ON OUR AI DEVELOPMENTAL AND TRAINING PROCESSES

1. Data Collection and Preprocessing:

Data Acquisition: Our first AI developmental step involves gathering diverse datasets encompassing demographic, environmental, and health factors related to malaria occurrence and prevalence across various population groups. We had successfully carried out this process in our milestone one and we utilized key processes such as accessing existing databases, collaborating with healthcare institutions, and conducting surveys.

As regards the accessing existing databases, we obtained insights from world health organization's african regional office on malaria in cross river state, nigeria, the severe malaria observatory organization on malaria prevalence in nigeria and the national library of medicine on malaria prevalence in Nigeria.

As regards collaborating with healthcare institutions, we collaborated with the General Hospital, Cross River State Ministry of Health, Nigeria where we obtained the annual case registry of malaria incidence for twenty-nine years (1983-2012) from the record unit of the General Hospital, Calabar, Cross River State. We obtained insights on reported malaria cases within our survey area dating as far back as 1983. This retrospective comparative analysis informed certain outcomes on our final data set.

As regards the survey process, we utilized 300 copies of a well-structured questionnaire designed for the study. We distributed these questionnaires to heads of households who bear the healthcare cost of their respective families. We adopted the systematic random sampling technique in the distribution of questionnaires. This sampling method was applied using a table of random numbers. All the houses were listed and numbered based on the population and sample size for the respective communities. The table of random numbers was then used to select each household and in each household (building) only a family was sampled. The numbers randomly selected from the table of random numbers were 0046 and 0057. From the outcome, starting from the first house in each road transect, the third building or household was chosen after which the eighth was sampled in that order. Also, for retrospective comparative analysis, we obtained the annual case registry of malaria incidence for twenty-nine years (1983-2012) from the record unit of the General Hospital, Calabar, Cross River State. Both

descriptive and inferential statistics were used to analyze the collected data. The descriptive statistics used include bar graphs, mean, percentage and tables whereas the inferential statistic mainly comprises the Principal Component Analysis (PCA). PCA was used due to the multidimensional nature of the demographic and socioeconomic data. The analysis was performed to identify significant variables that influence malaria prevalence.

Data reprocessing: Our raw data was made to undergo a reprocessing to clean, format, and standardize it for analysis. This included handling missing values, normalizing numerical features, encoding categorical variables, and addressing outliers. In this case, we utilized for our analysis, the principle component analysis (PCA - Varimax rotated characteristics) to enable us to ascertain the set of demographic and socioeconomic factors responsible for malaria incidence from our survey.

We also utilized the Kaiser rule of extracting only components with eigenvalues >1 to yield four extracted principal components from our data set. The extracted components accounted for 68.2% of total variance in our original data set. PC1 had two sets of socioeconomic variables loaded on it. The variables included type of accommodation (0.816) and monthly income of respondent (0.723). Also, based on the concept of CDV, PC1 epitomized the type of accommodation. PC2 also had two sets of socioeconomic variables; they included the number of children (0.745) and sex of respondents (0.814). This component symbolized the number of children. PC3 contained one set of socioeconomic variables, which is marital status of respondent (0.761). This component signified marital status. PC4 also had one socioeconomic variable that loaded heavily on it; the socioeconomic variable on this component was occupation of respondent (-0.883). PC4 signified occupation. Our results indicated that type of accommodation, number of children, marital status and occupation as the main socioeconomic variables that predispose people to malaria incidence in the study area – this would also be utilized as a predictive point for developing our prediction model.

2. Feature Engineering:

Feature Selection: In this step, we will select relevant features based on domain knowledge, statistical analysis, and machine learning techniques to optimize our model performance while minimizing computational complexity.

Feature Transformation: We will utilize transformations such as scaling, encoding, and dimensionality reduction to enhance the predictive power of our AI4M features and mitigate multicollinearity.

3. Model Selection and Architecture Design:

Algorithm Selection: Based on the nature of our identified problem statement and dataset characteristics, we will select our machine learning algorithms. For our AI4M, we are keen on utilizing choices such as logistic regression, decision trees, random forests, support vector machines, and neural networks.

Architecture Design: For neural network-based approaches, our AI4M architecture will utilize the number of layers, type of activation functions, and optimization algorithms to optimize its performance.

4. Training our AI Model:

Data Splitting: To achieve this, we will divide our dataset into training, validation, and testing sets to evaluate our model's performance effectively and prevent over fitting.

Model Training: Our selected algorithm or neural network architecture will then be trained on the training data using optimization techniques such as gradient descent or stochastic gradient descent to minimize the loss function.

Hyperparameter Tuning: Hyperparameters, including learning rate, regularization parameters, and network architecture parameters, will be fine-tuned using techniques like grid search or random search to optimize our AI model's performance.

5. Model Evaluation and Validation:

Performance Metrics: We will compute various performance metrics such as accuracy, precision, recall, F1-score, and area under our Region Of Focus curve (FOC) on the validation set to assess our model's performance and generalization ability.

Cross-Validation: We will employ cross-validation techniques such as k-fold cross-validation to assess our model's robustness and mitigate bias in performance estimation.

Validation Curves: We are keen on analyzing our learning curves and validation curves to diagnose under fitting or over fitting issues and guide our model's further refinement.

6. Model Deployment and Monitoring:

Deployment: Once our prediction model meets performance criteria, it will be deployed into production environments where it can generate predictions on new, unseen data.

Monitoring: Essentially, we will also ensure continuous monitoring of our model's performance and data quality to detect drifts, biases, or degradation in model accuracy over time. This will involve implementing monitoring systems and feedback loops to retrain the model periodically.

By meticulously following these steps, our AI4M model can effectively predict malaria occurrence and outcomes across diverse demographics, enabling proactive and targeted responses to combat the spread of malaria and improve public health outcomes.

DOCUMENTATION VALIDATION AND CALIBRATION

1. Validation Process:

This process will involve evaluating the performance and generalization ability of our AI model using a separate dataset. Here's how it will be done:

We will first partition our dataset into training, validation, and testing sets, as discussed earlier.

We will train our AI model on the training set using various algorithms and techniques.

The first two processes above would generate certain hyperparameters which will then be fine-tuned using the validation set through techniques like grid search or random search. This will ensure our model's optimal model performance.

We will then analyze the AI4M model's performance using metrics such as accuracy, precision, recall, F1-score, and area under the ROC curve (AUC) on our validation set.

Our end results (predictions, indicators, etc.) will then be analyzed to identify potential areas of improvement and to diagnose issues such as underfitting or overfitting.

2. Calibration Process:

Our calibration process will involve assessing and refining our model's predicted probabilities to ensure they are well-calibrated and reflect the true likelihood of events in relation to it's settings of deployment. We intend to achieve this via the following:

We would utilize reliability diagrams which would be graphical representations that compare the observed frequency of actual outbreaks/prevalence against our model's predicted

probabilities. Deviations from the diagonal line on our reliability graphs will indicate calibration issues.

We are keen on utilizing/applying calibration techniques such as Platt scaling, isotonic regression, or temperature scaling to adjust our model's predicted probabilities and align them with the true probabilities of events (outbreaks/occurrence)

We will then employ cross-validation techniques to assess the effectiveness of our calibration methods and to ensure that they generalize well to unseen data.

To round up this routine, we will evaluate our calibration process using metrics such as calibration error, Brier score, and calibration curves to quantify the discrepancy between predicted probabilities and observed outcomes.

3. Model Refinement and Iteration:

Based on the validation and calibration results, our model may have a need to undergo refinement and iteration to improve its performance and calibration. In the event that this step is required, we are keen on utilizing the following processes:

Further refining of our feature set (predictive output) to capture more relevant information and improve our model's predictive power.

We will also explore alternative algorithms or ensemble techniques to enhance our model's performance and calibration. Implementing ensemble methods such as bagging, boosting, or stacking to combine multiple models and leverage their collective strengths could further enhance our model's performance.

4. Documentation and Reporting:

Throughout our validation and calibration processes, we will ensure that meticulous documentation is maintained to record methodologies, results, and insights gained. A

comprehensive report will be prepared summarizing the findings, including our model's performance metrics, calibration results, and recommendations for further improvement.

HISTORICAL MALARIA DATA

MALARIA CASES

Globally in 2022, there were an estimated 249 million malaria cases in 85 malaria endemic countries and areas (including the territory of French Guiana), an increase of 5 million cases compared with 2021.

The main countries contributing to the increase were Pakistan (+2.1 million), Ethiopia (+1.3 million), Nigeria (+1.3 million), Uganda (+597 000) and Papua New Guinea (+423 000). In 2015, the baseline year of the Global technical strategy for malaria 2016–2030 (GTS), there were an estimated 231 million malaria cases.

Malaria case incidence declined from 81 per 1000 population at risk in 2000 to 57 in 2019. Following a small increase of 3% in 2020, incidence rates have remained stable over the past 3 years. In 2022, malaria case incidence was 58 per 1000 population at risk.

The proportion of cases due to P. vivax decreased from about 8% (20.5 million) in 2000 to 3% (6.9 million) in 2022. Twenty-nine countries accounted for 95% of malaria cases globally. Four countries – Nigeria (27%), the Democratic Republic of the Congo (12%), Uganda (5%) and Mozambique (4%) – accounted for almost half of all cases globally.

The WHO African Region, with an estimated 233 million cases in 2022, accounted for about 94% of cases globally. Between 2000 and 2019, case incidence in the WHO African Region decreased from 370 to 226 per 1000 population at risk, but increased to 232 per 1000 population at risk in 2020, mainly because of disruptions to services during the COVID-19 pandemic. In 2022, case incidence declined to 223 per 1000 population at risk.

Cabo Verde reported zero indigenous cases for 4 consecutive years, ending its malaria epidemic. The WHO South-East Asia Region accounted for about 2% of malaria cases globally. Malaria cases declined by 76%, from 23 million in 2000 to about 5 million in 2022. Malaria case

incidence in this region decreased by 83%, from about 18 cases per 1000 population at risk in 2000 to about three cases per 1000 population at risk in 2022.

In 2022, India accounted for 66% of cases in the region. Almost 46% of all cases in the region were due to P. vivax. Sri Lanka was certified malaria free in 2016 and remains malaria free.

Despite an overall decrease of 11.9% in estimated cases between 2021 and 2022 in the region, increases in cases and incidence were seen in Bangladesh, Indonesia, Myanmar and Thailand.

In the WHO Eastern Mediterranean Region, malaria cases decreased by 38%, from about 7 million cases in 2000 to about 4 million in 2015. Between 2015 and 2022, cases rose by 92% to 8.3 million.

Between 2021 and 2022, the region experienced an increase of 25%, mainly due to a large increase (2.1 million malaria cases) in Pakistan following the catastrophic flooding that affected more than 30 million people.

Over the period 2000–2015, malaria case incidence declined from 20.2 to 9.0 cases per 1000 population at risk, before increasing to 15.2 cases per 1000 population at risk in 2022. Sudan is the leading contributor to malaria in this region, accounting for about 41% of cases. In 2022, the Islamic Republic of Iran reported 1439 cases, which included indigenous cases, despite reporting zero indigenous cases for 4 consecutive years (2018–2021). Saudi Arabia reported zero indigenous cases for the second consecutive year.

In the WHO Western Pacific Region, numbers of malaria cases decreased by 48% in 2021, from 2.6 million cases in 2000 to an estimated 1.4 million cases. An increase of 23% was seen between 2021 and 2022, reaching 1.9 million cases.

Over the same period, malaria case incidence decreased from four to two cases per 1000 population at risk. Papua New Guinea accounted for nearly 90% of all cases in this region in 2022.

China was certified malaria free in 2021. Malaysia had no cases of human malaria for 5 consecutive years, despite experiencing an increase in P. knowlesi malaria cases, with 2500 cases reported in 2022.

In the WHO Region of the Americas, malaria cases declined by 64%, from 1.5 million to 0.6 million. Case incidence declined by 73%, from 13 to 4 cases per 1000 population at risk between 2000 and 2022. The region's progress in recent years has suffered from the major increase in malaria in the Bolivarian Republic of Venezuela, which had about 35 500 cases in 2000, rising to over 483 000 by 2017.

In 2020, however, cases decreased by more than half compared with 2019, to 223 000 cases; they decreased further in 2021 and 2022, to 205 000 and 154 000 cases, respectively. Factors contributing to this reduction were the low levels of population mobility resulting from the

COVID-19 pandemic restrictions, and an increase in malaria diagnosis and treatment commodities.

The Bolivarian Republic of Venezuela, Brazil and Colombia accounted for 73% of all cases in the WHO Region of the Americas. Argentina, Belize, El Salvador and Paraguay were certified malaria free in 2019, 2023, 2021 and 2018, respectively.

MALARIA DEATHS

Globally, malaria deaths declined steadily from 864 000 in 2000 to 586 000 in 2015 and to 576 000 in 2019. In 2020, malaria deaths increased by 10% compared with 2019, to an estimated 631 000. Estimated deaths declined in 2022 to 608 000. The percentage of total malaria deaths in children aged under 5 years decreased from 87% in 2000 to 76% in 2015. Since then, there has been no change.

Globally, the malaria mortality rate (i.e. deaths per 100 000 population at risk) halved from about 29 in 2000 to 15 in 2015. It then continued to decrease but at a slower rate, falling to 14 in 2019. In 2020, the mortality rate increased again, to 15.2, before decreasing slightly to 14.3 in 2022.

About 96% of malaria deaths globally were in 29 countries. Four countries accounted for just over half of all malaria deaths globally in 2022 – Nigeria (31%), the Democratic Republic of the Congo (12%), Niger (6%) and the United Republic of Tanzania (4%).

Malaria deaths in the WHO African Region decreased from 808 000 in 2000 to 548 000 in 2017, before increasing to 604 000 in 2020. Estimated deaths decreased again to 580 000 in 2022.

The malaria mortality rate decreased by 60% between 2000 and 2019, from 143 to 57 deaths per 100 000 population at risk, before rising to 61 in 2020 and decreasing again to 56 in 2022.

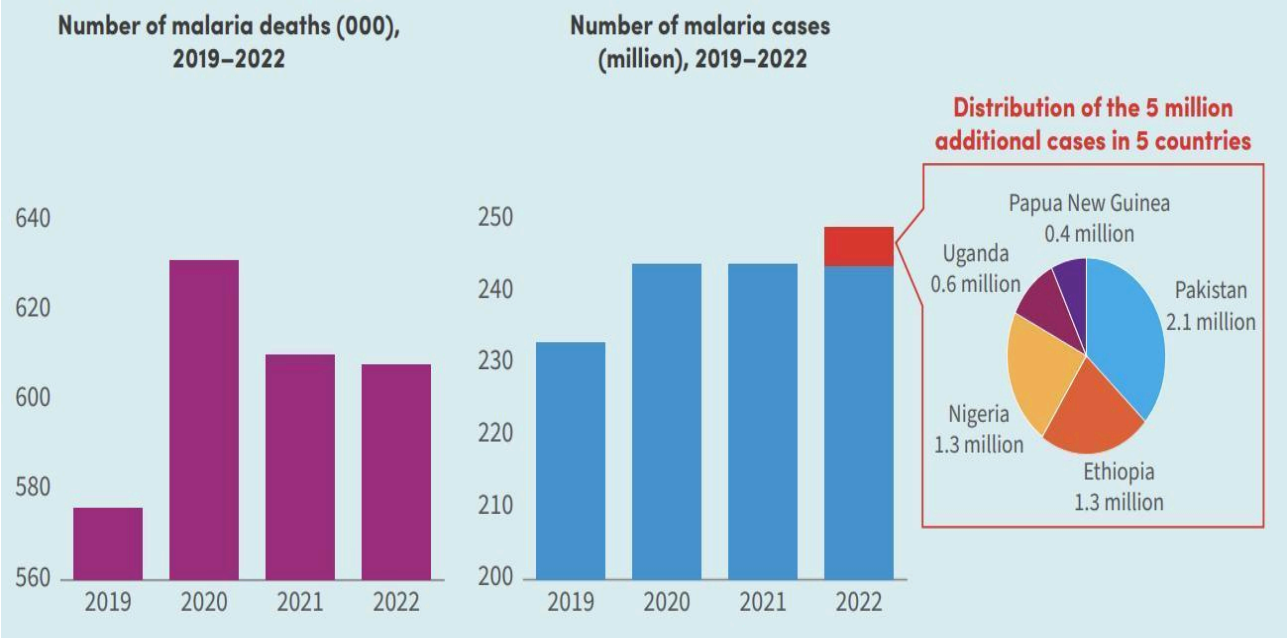
In the WHO South-East Asia Region, malaria deaths decreased by 77%, from about 35 000 in 2000 to 8000 in 2022. India and Indonesia accounted for about 94% of all malaria deaths in the WHO South-East Asia Region.

In the WHO Eastern Mediterranean Region, malaria deaths declined by 45%, from about 13 600 in 2000 to 7500 in 2014, and then more than doubled between 2014 and 2022, to 15 900. Most of the deaths were observed in Sudan, where around 90% of cases are due to P. falciparum, which is associated with a higher case fatality rate than P. vivax.

In the WHO Eastern Mediterranean Region, the malaria mortality rate decreased by 43% between 2000 and 2015, and remained largely unchanged until 2021, before increasing by 14% between 2021 and 2022 to about three deaths per 100 000 population at risk.

In the WHO Western Pacific Region, malaria deaths dropped by 56%, from about 6300 deaths in 2000 to 2600 deaths in 2021. Between 2021 and 2022, there was a 29% increase in deaths to 3600, mainly due to increases in Papua New Guinea.

Between 2000 and 2022, the WHO Region of the Americas experienced a reduction in malaria deaths of 63%, from 850 to 343. The mortality rate decreased by 71%, from 0.7 to 0.2 per 100 000 population at risk.



Source: *WHO database*

Malaria cases and deaths averted

Globally, an estimated 2.1 billion malaria cases and 11.7 million malaria deaths were averted in the period 2000–2022.

Most of the cases and deaths averted were in the WHO African Region (cases 82%, deaths 94%), followed by the WHO South-East Asia Region (cases 10%, deaths 3%). Burden of malaria in pregnancy

In 2022, in 33 moderate and high transmission countries in the WHO African Region, there were an estimated 35.4 million pregnancies, of which 12.7 million (36%) were exposed to malaria infection during pregnancy.

By WHO subregion, prevalence of exposure to malaria during pregnancy in 2022 was highest in west Africa (39.3%) and central Africa (40.1%), and lower in the east and southern Africa sub-region (27.0%).

It is estimated that, without a pregnancy-specific intervention, malaria infection during pregnancy in these 33 countries would have resulted in 914 000 neonates with low birthweight, compared with about 393 000 neonates with low birthweight estimated at the current intermittent preventive treatment during pregnancy (IPTp) coverage levels in the three subregions.

Data on Malaria elimination and prevention of re-establishment

Over time, the elimination of malaria has gained momentum in numerous countries as they approach the milestone of zero indigenous malaria cases and as more countries are certified malaria free.

The number of countries that were malaria endemic in 2000 and that reported fewer than 100 malaria cases increased from six in 2000 to 27 in 2022, a slight decrease from 28 in 2021.

The number of countries with fewer than 10 indigenous cases increased from four in 2000 to 25 in 2021 and 2022.

Between 2000 and 2022, 25 countries that were malaria endemic in 2000 have achieved 3 consecutive years of zero indigenous malaria cases. Twelve of these countries were certified malaria free by WHO.

No countries were certified malaria free in 2022, but three countries – Azerbaijan, Belize and Tajikistan – were granted certification in 2023.

From 2010 to 2022, there was a 72.3% reduction in indigenous malaria cases across the countries and one territory that are part of the malaria eliminating countries for 2025 (E-2025) initiative, with increases observed in 2017–2018 and then again since 2021.

The increase in 2022 was largely due to a surge in cases in the Comoros, which almost doubled its cases from 10 537 in 2021 to 20 675 in 2022. Other countries also experienced substantial increases during this period: Costa Rica more than doubled its caseload, from 189 in 2021 to 409 in 2022.

Panama saw an increase from 4354 in 2021 to 7102 in 2022; Thailand reported a significant increase, from 2426 in 2021 to 6263 in 2022; Honduras more than doubled its cases, from 1542 in 2021 to 3534 in 2022; and Vanuatu had an almost fourfold increase, from 312 in 2021 to 1102 in 2022.

Other countries that reported varying levels of increase in cases for the same period were the Dominican Republic (12.6%), Guatemala (45.7%), Nepal (12.5%), the Republic of Korea (39.4%) and Sao Tome and Principe (46.0%).

There was a resurgence of indigenous cases in the Islamic Republic of Iran in 2022, with 1439 indigenous cases reported in 2022 after 4 consecutive years of zero indigenous cases.

Despite the setbacks, several countries and one territory saw notable reductions in indigenous transmission: Botswana (43.5%), the Democratic People's Republic of Korea (9.3%), Ecuador (38.0%), Eswatini (57.6%), French Guiana (71.6%), Mexico (32.6%) and South Africa (31.3%).

Malaysia reported zero indigenous cases of human Plasmodium species for the fifth consecutive year.

After an outbreak of three cases in Timor-Leste in 2020, the country managed to realign its efforts, achieving 2 consecutive years with zero indigenous cases in 2021 and 2022 (for 36 consecutive months (if 2023 is taken into consideration). Saudi Arabia also achieved 2 consecutive years with zero indigenous cases in 2021 and 2022. Bhutan and Suriname reported zero indigenous cases for the first time.

Over recent years, P. knowlesi has emerged as a notable concern in malaria cases, especially in the WHO South-East Asia Region countries of Indonesia, Malaysia and Thailand.

In 2022, a total of 2768 P. knowlesi cases were reported globally, a decrease of 24.2% compared with 2021 (3651 cases). Indigenous P. knowlesi cases also saw a decrease of 26%, from 3629 cases in 2021 to 2682 cases in 2022.

Malaysia continues to be the predominant source of P. knowlesi cases, followed by Thailand and Indonesia, which contributed 90.5%, 3.1% and 0.1%, respectively, in 2022.

Between 2000 and 2022, the countries of the Greater Mekong subregion (GMS) reported a 55.5% decrease in indigenous malaria cases and an 89.1% decline in indigenous P. falciparum malaria cases. This excludes China, because it is the only country that reported zero indigenous cases and remains malaria free.

In the GMS, indigenous cases increased from 90 082 cases in 2021 to 170 527 in 2022. Similarly, the number of indigenous P. falciparum cases nearly doubled, increasing from 16 490 in 2021 to 30 789 cases in 2022.

Myanmar remains the largest contributor to the region's malaria burden, accounting for 92.4% of indigenous malaria cases and 95% of indigenous P. falciparum malaria cases.

Several E-2025 countries that achieved zero indigenous cases have recently faced challenges related to migrants and border areas. WHO is developing guidance for border malaria, which remains a challenge for malaria elimination and for prevention of re-establishment.

Bhutan, Saudi Arabia and Suriname, having recently attained their first year of reporting zero indigenous cases, are proactively implementing strategies to prevent the reintroduction of indigenous malaria cases.

After 5 years of zero local transmission, the Islamic Republic of Iran is currently facing an outbreak of indigenous malaria cases. Frequent border movement of people contributed to the introduction of cases and to the further re-establishment of local transmission.

Recognizing the policy gaps in the prevention of re-establishment, WHO is in the process of developing guidance for the prevention of re-establishment

Distribution and coverage of malaria diagnosis and treatment

Globally, 3.9 billion rapid diagnostic tests (RDTs) for malaria were sold by manufacturers in 2010–2022, with 82% of these sales being in sub-Saharan African countries. In the same period, NMPs distributed 2.9 billion RDTs – 90% in sub-Saharan Africa.

In 2022, 415.5 million RDTs were sold by manufacturers and 345 million were distributed by NMPs.

Globally, more than 4 billion treatment courses of artemisinin-based combination therapies (ACT) were delivered by manufacturers between 2010 and 2022. About 2.7 billion of these deliveries were to the public sector in malaria endemic countries, and the rest were either public or private sector co-payments (or both), or exclusively through the private retail sector.

National data reported by NMPs in 2010–2022 show that 2.5 billion ACTs were delivered to health service providers to treat people with malaria in the public health sector.

In 2022, some 210 million ACTs were delivered by manufacturers to the public health sector. In the same year, 217 million ACTs were distributed to this sector by NMPs, of which 97% were in sub-Saharan Africa.

Aggregated data from household surveys conducted in sub-Saharan Africa between 2005 and 2022 in 22 countries with at least two surveys (baseline 2005–2011, and most recent 2015–2022) were used to analyse coverage of treatment seeking, diagnosis and use of ACTs in children aged under 5 years.

Comparing the baseline and latest surveys, there was little change in prevalence of fever within the 2 weeks preceding the surveys (median 26% versus 23%) or in treatment seeking for fever (median 65% versus 66%).

Comparisons of the source of treatment between the baseline and more recent surveys show that the proportion who received care from public health facilities increased from a median of 58% to 69%.

The use of community health workers remained low, with a median percentage of 2% in both the baseline and later surveys. The proportion who received care from the private sector decreased from a median of 40% at baseline to 28% in the more recent surveys, indicating an increase in population access to the public health sector and consequently to the associated public surveillance system.

The rate of diagnosis among children aged under 5 years with fever and for whom care was sought increased from a median of 30% at baseline to 54% in the latest household surveys, indicating an improvement in case management, despite evidence of inadequate levels of diagnostic services.

Climate change, malaria and the global response

WHO has declared climate change the single biggest health threat facing humanity.

Climate change threatens to derail progress in global health by affecting livelihoods; increasing the risks of harmful exposures to particulates, pathogens and disease; overburdening health systems; and widening existing inequalities. Thus, climate change is not just a singular threat but a major multiplier of other threats.

Climate change and its interaction with malaria transmission is complex, and empirical evidence to support reliable predictions is sparse.

Climate change is also responsible for more extreme and frequent weather events, such as flooding, which can result in malaria epidemics or severe droughts that suppress transmission for a period but are often followed by epidemics when the rains arrive.

The direction of the effect of climate change on malaria transmission and burden will be non-linear and is likely to vary across different contexts, being dependent on factors such as variations in temperature, rainfall or humidity; the extent of malaria control and elimination; the degree of socioeconomic development; and the management of the environment.

Temperature, rainfall and humidity influence larval development, mosquito survival, parasite development within the mosquito and vector competence. Changes in these aspects will affect vectorial capacity (i.e. the number of new infections that the population of a given vector would induce per case per day at a given place and time), and hence affect the intensity of malaria transmission.

The potential direct effects of climate change on malaria could include expansion of its geographical limit, increases or reductions in transmission intensity within the current limits of transmission, reintroduction of malaria in areas where malaria was eliminated, or imperceptible changes in transmission.

The potential indirect effects of climate change on malaria could include loss of livelihoods and increased economic and food insecurity, displacements and service disruptions, increased difficulty and cost of malaria programmes and variations in access to and quality of health delivery systems.

The empirical evidence of the effect of climate change on malaria transmission is mixed; this is partly because of data limitations, but also because of the many parallel determinants of malaria transmission that occur against a background of a changing climate.

The strongest evidence, perhaps, comes from long time-series data from African highland areas that are on the fringes of endemic transmission; these data suggest that, over recent decades, rising temperatures have led to the expansion of malaria to highland areas.

DATA SOURCE: *World Health Organization Database*