Malaria Consortium's approach to analysis of impact of seasonal malaria chemoprevention

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Report compiled by: Monica Anna de Cola, Data Analyst
Acknowledgements: Christian Rassi, Program Director - SMC
Arantxa Roca-Feltrer, Head of Surveillance, Monitoring & Evaluation
Maddy Marasciulo, US Representative, Global Case Management Specialist
Louise Maranda, Epidemiologist
Benoît Sawadogo, Monitoring and Evaluation Coordinator
Azoukalne Moukenet, Data Analyst
Abraham Ahmadu, Monitoring & Evaluation Specialist
Diego Moroso, Program Director - SMC

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Acronyms and abbreviations

ACCESS-SMC	Achieving Catalytic Expansion of Seasonal Malaria Chemoprevention in the Sahel
CI	Confidence interval
HMIS	Health management information system
LGA	Local government area
MAPS	Malaria Action Program for States
M&E	Monitoring and evaluation
RDT	Rapid diagnostic test
SMC	Seasonal malaria chemoprevention
SPAQ	Sulfadoxine-pyrimethamine and amodiaquine
WHO	World Health Organization

Background

In 2012, the World Health Organization (WHO) issued a policy recommendation for the use of seasonal malaria chemoprevention (SMC) as a preventative intervention for the control of malaria in children under five years. The intervention involves the process of administering the antimalarial drugs sulfadoxine-pyrimethamine and amodiaquine (SPAQ) to children between three and 59 months at four monthly intervals during the peak transmission season. WHO recommends the use of SMC in target areas that are highly seasonal and where the drugs retain sufficient anti-malarial efficacy, which is defined as having 60% of clinical malaria cases that occur within a four-month period (World Health Organization, 2013). To maximise impact, programmes should aim to reach a high coverage in eligible children, sustained across each monthly treatment, on a timely schedule starting at beginning of the peak transmission season. Controlled trials have shown that when SMC is administered to quality standards, it is 75% effective in protecting against uncomplicated and severe malaria cases (World Health Organization (WHO), 2017).

Malaria Consortium has led the rapid roll out of SMC across the Sahel since 2013. Currently, Malaria Consortium implements SMC in Burkina Faso, Chad, and Nigeria. The SMC program includes monitoring and evaluation (M&E) systems to ensure that SMC is implemented to quality standards. Over the lifetime of the program, Malaria Consortium has collected data on delivery, coverage, efficacy, safety, drug resistance, impact and cost through a variety of methods, including routine program data, household surveys, case control studies, and administrative databases.

As part of the Unitaid funded 2015-17 Achieving Catalytic Expansion of Seasonal Malaria Chemoprevention in the Sahel (ACCESS-SMC) program, which was led by Malaria Consortium, Milligan *et altera* from the London School of Hygiene and Tropical Medicine conducted an impact assessment, which explored malaria cases and deaths using reported data from national Health Management Information Systems (HMIS) and sentinel sites (Milligan, 2018). Data abstracted from sentinel sites showed that the estimated average reduction of malaria cases in 2015 and 2016 were 41% and 49% in Burkina Faso; 37% and 25% in Chad; 25% and 25% in Nigeria, respectively. Retrospective case control studies were also conducted in 2016 in each of the countries to assess efficacy. Results from these studies estimated the efficacy of SMC over 28 days post-treatment was 92% in Burkina Faso, 78% in Chad, and 83% in Nigeria.

Malaria Consortium aims to monitor impact on an ongoing basis to assess short- and long-term effects of SMC. Although data from controlled settings shows that SMC is highly efficacious, to-date, robust evidence of impact using routine program or administrative data sources is lacking. Malaria Consortium is committed to refining methods for monitoring impact that is operationally feasible for countries, uses robust methodology, and generates accurate estimates. This report describes Malaria Consortium's general approach to measuring impact, summarises impact analyses methods based on HMIS data used to-date, discusses the limitations of this approach and outlines plans for strengthening our ability to generate evidence of programme impact going forward.

1. Malaria Consortium's approach to impact

Large-scale implementation of SMC programs is expected to have a significant impact on malaria based on the efficacy measured from clinical trials (World Health Organization (WHO), 2017). However, several factors can limit the potential impact of SMC when implemented at scale, including programmatic conditions such as level of coverage achieved, number of cycles administered, quality and timeliness of delivery and administration, as well as other factors affecting the transmission and epidemiology of malaria. In addition, differences in impact estimates between clinical trials and programmes implemented at scale may also be due to issues of measurement, such as access to quality data that is timely, accurate, complete and appropriate for its intended use.

Therefore, to assess impact of SMC, Malaria Consortium collects data and reports on programmatic indicators on quality and coverage through a variety of methods including training and supervision checklists, health worker tally sheets, inventory control cards, end-of-cycle surveys using Lot Quality Assurance Sampling, and more comprehensive end-of-round coverage surveys. By demonstrating the program has reached the expected targets, we can expect a certain level of impact. Impact indicators are then analysed to determine whether the level of protection achieved through routine delivery is comparable to clinical trials, with the understanding of the limitations in controlling for confounding factors. To-date, efforts to validate impact estimates have focused on exploring impact indicators through external data sources, primarily data from national HMIS databases.

2. Assessing feasibility of HMIS data for impact indicators

Using HMIS data collected through the health system is commonly considered the most feasible approach for assessing impact of large-scale public health programs because data is routinely and continuously collected and because it does not require significant additional budgetary and staffing resources. It also reinforces the need to institutionalize interventions, avoiding the establishment of parallel systems, and contributes to strengthening the health system overall.

Although there are many advantages to using HMIS data for monitoring and evaluating programs, it is important to understand the level of quality and appropriateness for its intended use. Therefore, Malaria Consortium sought to assess the strengths and limitations of using HMIS data for SMC impact indicators, with a view to using insights gained to improve and strengthen HMIS in the longer term as well as identify potential complementary and alternative data sources to obtain the most reliable estimates of impact through feasible approaches.

2.1 Methods

Data for impact indicators outlined in **Table 1** were abstracted from the national HMIS over the years of 2013 to 2018 for Burkina Faso and Chad, and 2017 to 2018 for Nigeria and were retrospectively analysed.

Table 1. Definition of variables included in analysis.

Indicator type	Definition	Numerator	Denominator
Malaria cases	Number of malaria cases confirmed by rapid diagnostic test (RDT) or microscopy	Number of malaria cases confirmed by RDT or microscopy	--
Severe malaria Cases	Proportion of severe cases amongst all cases	Number of severe malaria cases	Number of malaria cases confirmed by RDT or microscopy
Malaria mortality	Proportion of reported malaria deaths among all deaths	Number of Malaria Deaths	Number of all-cause deaths
Health facility attendees	Number of children seen at the health facility	Number of malaria cases confirmed by RDT or microscopy	--
Malaria consultation rate	Percentage of malaria cases among health facility attendees	Number of malaria cases confirmed by RDT or microscopy	Number of children seen at the health facility
Test positivity rate	Proportion of malaria cases confirmed by RDT or microscopy amongst suspected cases	RDT Positive + microscopy positive	fever tested by RDT + fever tested by microscopy
Testing rates	Proportion of patients with fever who received a parasitological test amongst all fever cases	Number of fevers tested by RDT or microscopy	Number of fever cases

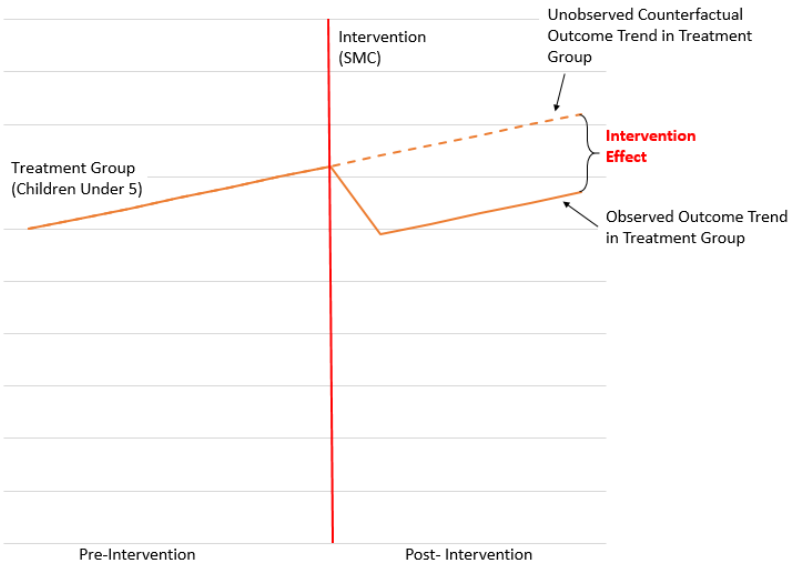
To better understand the quality and appropriateness of the data for use in an impact analysis, an assessment of the completeness and accuracy of data was conducted. Completeness was assessed by calculating the proportion of monthly reports missing amongst all monthly reports required for each indicator. To assess accuracy, various data verification exercises were conducted by comparing spurious data points to the data point in the months before and after the error month, before and after that year, as well as the data point reported in a comparison age group (i.e. a comparison of changes and trends seen in both the under 5 and 5-14 age groups). Further details are provided in **Annex 1. Data quality.**

To assess the effect of SMC, first, descriptive analyses, including summary statistics, were calculated for each indicator, then data were graphically presented by month over the study period stratified by SMC implementation status. Impact indicators were assessed three ways, which are presented in corresponding figures to illustrate the analysis principle:

1. Analysing the change in the target age group before and after SMC was introduced in the same location (**Figure 1**);
2. Analysing the difference in the target age group in areas with SMC implementation with a control group in the target age group in areas without SMC implementation (**Figure 2**);

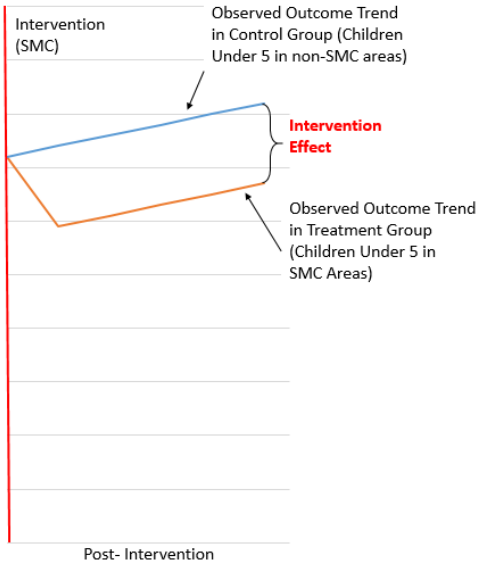
3. Analysing the relative difference between the target age group and another group not in the target age group in the same location before and after the introduction of SMC (**Figure 3**).

Figure 1. Analysing the change in the target group before and after SMC.



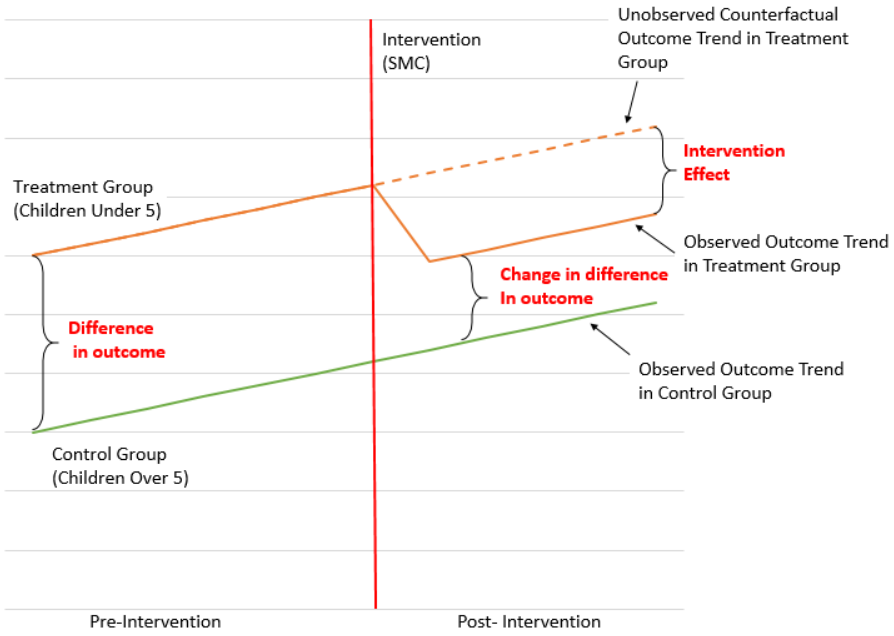
*Not based on actual data

Figure 2. Analysing the difference in the target group in areas with and without SMC.



*Not based on actual data

Figure 3. Analysing the relative difference between the target group and a control group in the same SMC area.



*Not based on actual data

As outlined in **Figure 3**, comparisons between confirmed cases in children under 5 and children 5-14 were made to assess the relative difference between the two groups, similar to a differences-in-differences analysis. The relative difference in malaria cases between the two age groups is expected to remain similar in the absence of SMC even if the number of cases fluctuates throughout the study period as other malaria interventions cover all age groups. If SMC is effective, the ratio of the number of cases in children under 5 to number of cases in children 5-14 is expected to decrease.

To generate estimates of the level of impact of SMC, a Poisson regression model was fitted to the number of cases confirmed by RDT or microscopy reported to health facilities during the SMC distribution months (August, September, October, November) between 2013 and 2018 (or 2017-2018 for Nigeria). Due to inaccuracies and unavailability in denominator data, only absolute cases were analysed for final interpretation of results for this analysis. The model included age group and calendar year as factors, as well as trigonometric terms to adjust for seasonality of malaria transmission. To adjust for the effect of SMC, an indicator variable was set at "1" during the months of implementation for the under 5 group and "0" for months without the intervention or for the over 5 group, where relevant. Confidence intervals were estimated using a robust standard error. To account for variation of effect across facility or district, a random effect model was used.

2.1.1 Data included in the analysis

SMC was introduced in a phased manner by district or local government area (LGA) in each of the countries allowing for the three methods of analysis described previously. Burkina Faso started SMC in 2014 in 7 out of 70 health districts. The districts with SMC gradually expanded each year with 17, 54, 58, and 65 over the span of 2015-2018. The national HMIS in Burkina Faso reports data by district, aggregated for children under 5 years and 5-14 years. For this analysis, data from 2013-2018 were analysed.

In Chad, there are 61 health districts eligible for SMC, however, only 58 send data to the national HMIS for inclusion in this analysis. SMC was also introduced in a phased approach by health districts, starting in 2013. The national HMIS reports data aggregated for children under 5 years and 5-14 years. For this analysis, district-level data from 2013-2018 was included.

Until the end of 2018 in Nigeria, SMC was only implemented in four states; Jigawa, Katsina, Sokoto and Zamfara. For the analysis in Nigeria, only two years (2017-2018) of data were available. For Jigawa and Katsina, LGAs where SMC had not yet been introduced were used as the comparison group. Sokoto and Zamfara implemented SMC in all LGAs so Kebbi State was used as the comparison due to its close proximity and similar climate. The national HMIS reports data at health facility level aggregated for children under 5 and children 5-9 or 10-14 years.

Table 2 outlines the availability of data for the analysis by district or LGA for each country before exclusion for quality. Note that this does not outline the introduction of SMC in each country. For example, some districts in Chad received SMC but did not report data to the HMIS and therefore are not included in the analysis, similarly, only data from 2017to 2018 were available for Nigeria.

Table 2. Number of health districts/LGAs with and without SMC implementation available for analysis by country.

	Burkina Faso		Chad*		Nigeria	
Year	**# of HDs SMC-**	**# of HDs SMC+**	**# of HDs SMC-**	**# of HDs SMC+**	**# of LGAs SMC-**	**# of LGAs SMC+**
2013	70	0	34	4	--	--
2014	63	7	42	0	--	--
2015	53	17	28	17	--	--
2016	16	54	23	31	--	--
2017	8	58	25	33	72	44
2018	5	65	25	34	69	47

*Number of eligible states changes per year due to changing district borders, 2013 started as a pilot and scale up started in 2015

Note: SMC+: districts with SMC implementation; SMC-: districts without SMC implementation

2.2 Findings

Indicators from all three countries were analysed, where data was available. In this report, only select pieces from the analysis are presented to illustrate main findings, limitations of the approach, and how insights from using HMIS data can inform alternative or complementary methods for assessing impact of SMC.

2.2.1 Data quality

HMIS data often suffer from poor quality issues such as incompleteness, inaccuracy, and lack of timely reporting, due to insufficient capacity in the health system, or inadequate system design (Abouzahr, 2005). A review of the quality of HMIS data for each country was conducted, which showed varied results between and within countries, as further detailed in **Annex 1. Data quality**.

2.2.1.1 Completeness

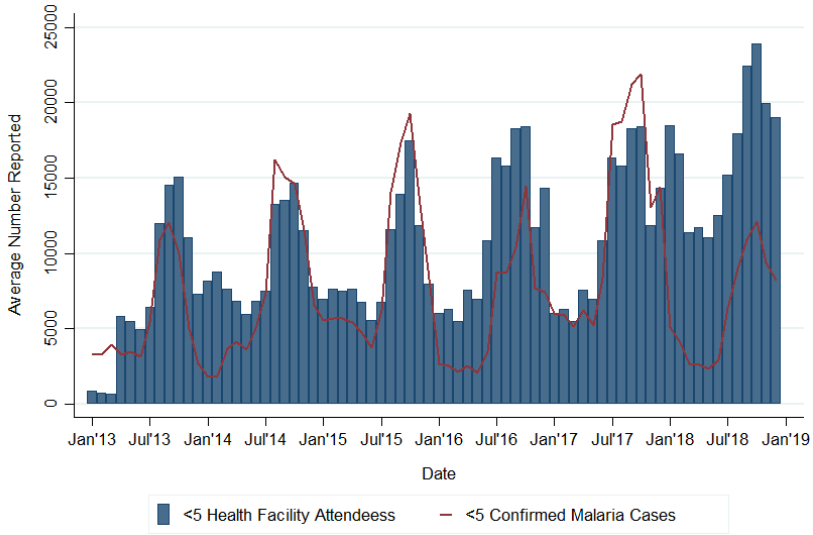
Checks for data completeness were conducted for each country, as defined by the proportion of all monthly reports for each indicator available. Briefly, Burkina Faso showed high completeness of data with less than 1% of missing data points for the relevant indicators. Data coming from Chad and Nigeria showed low completeness ranging from 36-42%. To mitigate potential bias from low completeness, any health facility or district with more than 1 month missing data during the SMC distribution period was excluded.

2.2.1.2 Accuracy

Further checks for data accuracy revealed data entry errors as well as major health data reporting issues. First, common in all countries were obvious data entry errors most likely due to typing errors, entering data into the incorrect field, recording data in the wrong month, etc. The level of data accuracy varied across and within countries.

Additionally, the analysis also revealed major data reporting issues that bring into question the overall accuracy of data that is captured in the national HMIS. For example, in Burkina Faso, approximately 30% of the data points reported more malaria cases in children under 5 than there were children seen that month (**Figure 4**). Similar issues were seen in the other countries. Further follow up regarding data reporting practices and accuracy assessments is needed.

Figure 4. Average number of consultations and confirmed malaria cases reported per month in children under 5, Burkina Faso.



2.2.2 Other factors affecting impact

In addition to factors affecting the quality of HMIS data, there are also external factors that affect the transmission of malaria or introduce confounding into the analysis, which have the potential to mask true epidemiological trends. Although some of these factors can be accounted for in the analysis through various statistical and study design methods, there are some cases in which we cannot control for confounding. It is important to understand the potential factors affecting impact when interpreting results.

2.2.2.1 Accurate denominators

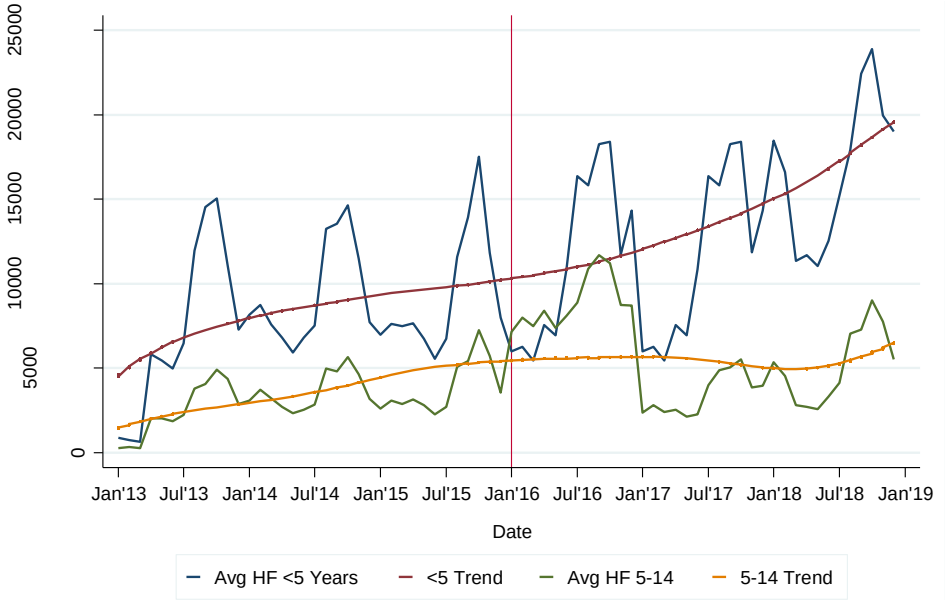
In order to analyse changes in malaria risk, it is essential that both the numerator and denominator are reliable. In all three countries, accurate and up-to-date census data were not available. In the absence of accurate population-based census data, other health-facility based indicators are often used (outlined in **Table 1**). For example, the malaria

consultation rate is calculated as the number of positive RDT tests or the number of positive microscopy tests in children under 5 amongst the number of health facility attendants for children in that age group. For SMC, the number of children under 5 attending the health facility is used as a proxy denominator for the "population at risk." However, as outlined in the data quality section, issues in accuracy of data such as more cases of malaria reported than children seen in that month confound analysis of impact as inaccurate denominators may result in spurious trends.

2.2.2.2 Changes in access to care

Understanding changes in programmes, policy and health facility attendees is essential when using HMIS data as a tool for analysing trends in disease. For example, health facility based data (e.g. total number of consultations) was selected as a proxy to estimate population at risk. This approach relied on the assumption that access to health care remained constant over time. However, in 2016, Burkina Faso eliminated user fees for pregnant women and children under 5. This has resulted in a marked increase in the reported average number of children under 5 attending health facilities. Similar trends are not observed in children aged 5-14 years (**Figure 5**).

Figure 5. Average number of health facility attendees reported per year by age group.



*Red horizontal line indicates introduction of Free Health Care Policy

Similar trends are also noted in the absolute number of confirmed cases reported. In the under 5 age group, reported cases seem to be decreasing starting in 2016, however, a significant spike is noted in 2017. In the 5-14 age group, the number of reported cases remains constant with a slight increase noted after 2013 (**Figure 6, Figure 7**).

Figure 6. Total number of confirmed malaria cases reported per month in children under 5, Burkina Faso.

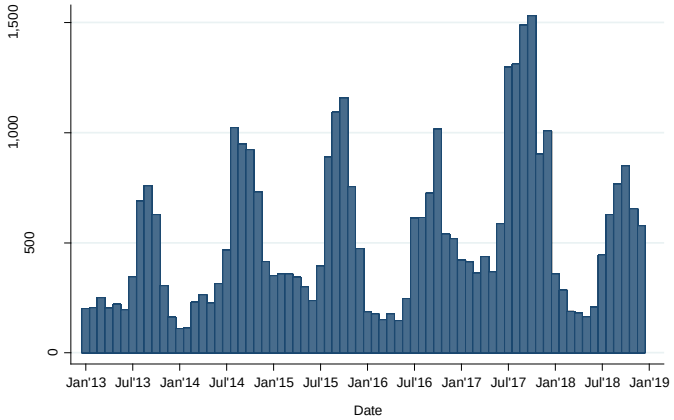
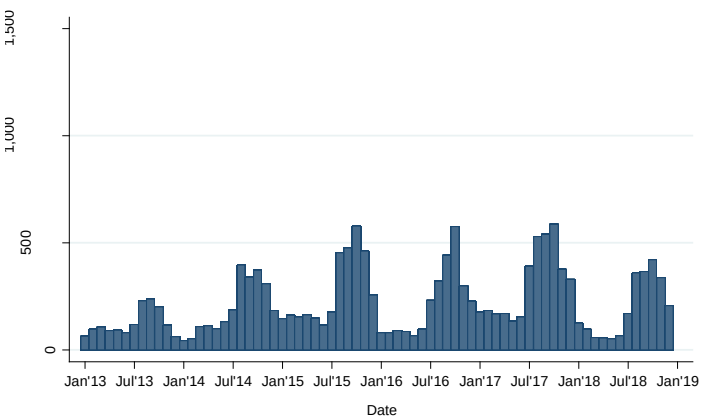


Figure 7. Total number of confirmed malaria cases reported per month in children 5-14 years, Burkina Faso.



Changes in impact indicators trends can also be noted as a result of programs aimed at improving malaria diagnostic, treatment and prevention services as well as those focusing on improved capacity for malaria program management

and information systems. For example, analysis of HMIS data during the ACCESS-SMC impact study highlighted major changes in HMIS reporting in some states in Nigeria resulting in inaccurate epidemiological trends, which were speculated to be due to the introduction of the Malaria Action Program for States (MAPS) project (2011 to 2016) (Milligan, 2018). These programs do increase the completeness and accuracy of health data but also may confound estimates of impact by increasing access to care.

2.2.2.3 Factors affecting epidemiological trends of malaria

In order to generate more accurate estimates of impact of SMC, a range of factors affecting malaria transmission but not captured through HMIS need to be taken into account.

Urban versus rural settings

Malaria incidence is generally lower in urban and peri-urban areas compared to rural areas due to improved housing, fewer mosquito breeding sites, and higher socioeconomic status. Adjusting for the differences in living environments will also require analysis of impact indicators at subnational levels.

Other interventions

Additionally, although malaria is a curable disease with an appropriate and effective treatment, long-term control and prevention measures are required to reduce the burden in an area or country. Therefore, the introduction of new control and prevention measures or interruptions in previous programming, such as bed net use and/or indoor residual spraying, may result in changes in malaria transmission even in areas with SMC implementation.

Seasonality

Finally, SMC is best suited as an intervention in areas where malaria is highly seasonal. For SMC to be effective, programs should begin implementation before the peak transmission season. Analysing data on climate such as rainfall and temperature will provide information on the timeliness of SMC programs and allow for adjustments in impact if needed. For example, it should be noted that the government of Burkina Faso has decided to implement SMC across the entire country even though not all districts meet the WHO-defined eligibility criteria.

2.3 Estimate of impact

As outlined in the methods, a multivariate Poisson regression model was conducted to estimate the level of impact of SMC. Analysis of HMIS data at the national level for each country overall showed no evidence of impact. However, as previously discussed, the quality of data, the limitations of HMIS data reporting, and the inability to adjust for major factors affecting malaria transmission contribute to noise in the analysis and result in inaccurate estimates of effect. Results are presented in **Annex 2. Estimate of impact**.

2.4 Conclusions

Evidence from randomized clinical trials and from implementation of SMC in controlled settings have shown that SMC can have a protective effect of 75% against uncomplicated and severe malaria when implemented to quality standards. Malaria Consortium's approach to evaluating impact of SMC programs is through comparing the expected impact of SMC to impact estimates generated from impact indicators collected by the routine health system (e.g. HMIS data). Differences in these two estimates may be due to a variety of factors including: 1) factors directly affecting the effectiveness of SMC (e.g. coverage, adherence to adequate dosing schedules, timeliness of administration, drug resistance etc.); 2) factors affecting the quality of impact data (e.g. HMIS); 3) other factors influencing the underlying transmission of malaria in the intervention areas.

With regards to quality of impact data, in this analysis, we sought to analyse impact indicators available through the national HMIS from Burkina Faso, Chad, and Nigeria. Overall, the analysis indicated that accurate health data reporting is still a point of improvement for health systems and limitations to the data must be considered when interpreting results from national HMIS. Inaccurate data with no means of verification contribute to noise in the analysis and result in either dampening or amplification of estimated effects. Additionally, the lack of a reliable denominator only allows us to use absolute case numbers with no adjustment for changes in population at risk.

Lastly, other factors could have influenced the true malaria trends in these countries. Information from other sources including data on other interventions such as long lasting insecticidal net (LLIN) use, indoor residual spraying (IRS), transmission intensity, rainfall, and other contextual factors, will allow us to adjust these analyses to account for changes in malaria cases due to other factors.

Based on the results of this analysis Malaria Consortium will continue to work in improving HMIS data collection, adjust methods for analysing HMIS data, as well as triangulate data from other sources to verify impact estimates and analyse factors affecting effectiveness of SMC programs.

3. Next steps

Recognizing the limitations identified through this analysis exercise, we have outlined our next steps for improved methods in measuring impact both in terms of using HMIS data as well as other data sources.

3.1 HMIS data

There are many advantages to using HMIS data for monitoring and evaluating programs. They reduce the need to collect data through additional monitoring systems or surveys, they have larger sample sizes, they have lower cost compared to surveys, cohort or research studies. However, ensuring that the data are accurate and reliable for use in M&E systems remains a challenge.

This analysis has highlighted issues with using HMIS for measuring impact, such as access to health care and data quality reporting. Improving methods for using HMIS data in impact analysis is a priority for Malaria Consortium to support the use of HMIS, prevent parallel reporting systems, and leverage the potential of HMIS. To address the issues outlined regarding HMIS data quality, Malaria Consortium is planning to work with health facility staff at selected sites to increase capacity in quality data reporting and implement continuous data quality monitoring to ensure quality data is captured.

3.2 Monitoring sites

To address immediate concerns of HMIS quality, Malaria Consortium is also in the process of setting up “monitoring sites,” which are health facilities that act in a similar manner as sentinel sites. Facilities will be selected first by requirements of minimum quality standards, such as sufficient staff and sufficient commodities, with a lab available with results linked to patient registers. Then they will be selected by characteristics required for stratification in the analysis, such as other interventions, contextual issues, transmission intensity, urban versus rural, health facility type etc.

3.3 Triangulation of data

As mentioned previously, data from health registers and national HMIS are limited for indicators assessing other factors affecting malaria transmission. Data from the Malaria Consortium SMC programme, including routine programme data, coverage survey data, and other sources, which include data on other interventions, will be overlaid with the national HMIS data and monitoring site data to allow us to conduct more complex analyses such as adjusting for other factors (transmission intensity, urban *versus* rural settings, other interventions, rainfall) and exploring correlations between different factors affecting coverage and impact.
Malaria Consortium is also exploring options for obtaining more accurate denominators, such as conducting enumeration exercises, using digital solutions such as “spatial intelligence tools”[1] and using external data sources such as immunization campaign figures.

3.4 Research

In the absence of quality administrative data through national HMIS, Malaria Consortium is considering conducting systematic research to determine impact. For example, this could involve conducting a cohort or case control study to evaluate the impact of Malaria Consortium led SMC programs in areas of new and longer-term implementation.

[1] Spatial intelligence tools use satellite imagery to identify households, which helps with planning for mass campaigns and determining reliable population estimates. Typically, those tools can then also be used to track delivery of mass campaigns.

Research studies will allow us to generate more accurate estimates of impact by addressing both the issues in quality of administrative data as well as limitations in the type of data captured. Research data can also be overlaid with other data sources to investigate factors affecting coverage and impact.

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Annex 1. Data quality

Completeness

Data completeness is a measure of the degree of missing values in a data set. Missing data can reduce the statistical power of an analysis, create bias in the produced estimates, and reduce the representativeness of the sample, which all may result in invalid conclusions (Kang, 2013).

Data completeness varied between countries. Burkina Faso showed high completeness of data with less than 1% of missing data points for the relevant indicators. Data coming from Chad and Nigeria showed low completeness. In Chad, approximately, 41.3% of data points for the number of confirmed cases of malaria were missing and less than 1% of data points for the number of health facility attendees were missing. For Nigeria, approximately, 36.7% of data points were missing for the number of positive cases of malaria reported and 37.7% of data points were missing for the number of children under 5 attending the health facility.

To mitigate potential bias from completeness we narrowed our analysis to include only the months during the SMC season and excluded any health facility or district with more than 1 month missing data during this period.

Accuracy

Data accuracy refers to whether data reported for the specified indicator is of the correct value, is consistent, and unambiguous. An ambiguous data point is a data point that may not be able to be determined as inaccurate by the analyst. Similar to data completeness, low data accuracy can introduce bias into the analysis resulting in invalid conclusions.

After removing missing data points, further data cleaning was conducted in two steps. First, any obvious data errors were edited by generating summary statistics and identifying major outliers. For example, 12509 versus 125099. Second, any records reported as 15 cases or less per month were removed from the analysis as errors. Both of these methods were verified by comparing the data point in the months before and after the error month, before and after that year, as well as the data point reported in the 5-14 age group. If the surrounding data were reasonably similar, then that data point was considered accurate and kept in the analysis.

In order to analyse trends in malaria beyond absolute cases, it is essential that the numerator and denominator are accurate. A review of data in all countries indicated major health data reporting issues as it was often that more malaria cases were reported than there were children seen that month.

For example, in Burkina Faso, approximately 32.4% (n=3080/9494) of the data points indicated there were more malaria cases reported than patients attending the health facility in that month (**Table 3**). These inconsistencies were similar between the two age groups and between SMC and non-SMC areas.

Table 3. Number of records reporting more malaria cases than health facility attendees in that month for children under 5 and children 5-14 years in Burkina Faso.

	SMC -				SMC +			
	Children under 5 years		Children 5-14 years		Children under 5 years		Children 5-14 years	
Year	# of records (%)	N	# of records (%)	N	# of records (%)	N	# of records (%)	N
2013	248 (34.3%)	723	289 (40.1%)	720	--	--	--	--
2014	237 (35.4%)	670	261 (38.9%)	671	23 (27.4%)	84	34 (40.5%)	84
2015	249 (45.8%)	544	313 (56.7%)	552	85 (41.7%)	204	122 (59.8%)	204
2016	5 (2.6%)	192	16 (8.3%)	192	20 (3.1%)	648	41 (6.4%)	648
2017	81 (56.3%)	144	94 (65.3%)	144	432 (62.2%)	695	530 (76.3%)	695
2018	--	60	--	60	--	780	--	780
Total	820 (35.1%)	2333	973 (41.6%)	2339	560 (23.2%)	2411	727 (30.2%)	2411

These data points were not excluded because this would introduce significant bias into the analysis. First, we were not able to verify whether the number of cases or the number of health facility attendees were incorrect and therefore were unable to determine which variables are the most or least reliable. Additionally, the data points reporting incorrect data with very low confirmed cases and very high health facility attendance would still be

included in the dataset, potentially skewing the rates to appear artificially lower. Due to these inaccuracies, only absolute cases were analysed for final interpretation of results of impact, however, considering the inaccuracies are similar between age groups and SMC status sensitivity analyses of malaria consultation rates are included in the report.

Health facility data are sensitive to changes in reporting practices. For example, when comparing the average number of malaria cases reported in Burkina Faso by SMC status, the seasonal peaks in 2014 and 2015 were much higher in the areas where SMC was implemented (**Figure 8, Figure 9**). Initially, this may give the impression of more malaria cases in SMC areas. However, further analysis revealed that the minimum number of cases reported in areas without SMC was much lower in those years compared to after 2016 and in areas where SMC was introduced (highlighted in **Table 4**).

Figure 8. Average Number of Confirmed Malaria Cases Reported per Month in Children under 5 and 5-14 Years in SMC Areas, Burkina Faso.

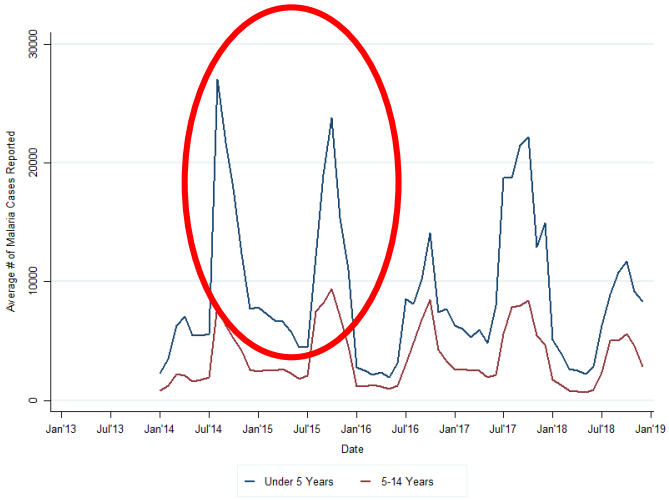

Figure 9. Average Number of Confirmed Malaria Cases Reported per Month in Children under 5 and 5-14 Years in non-SMC Areas, Burkina Faso.

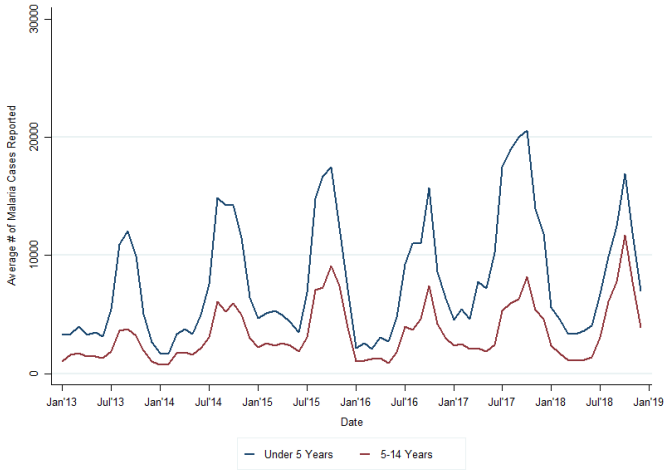

Table 4. Absolute number of malaria cases reported (mean, minimum and maximum) by month for areas with and without SMC, Burkina Faso.

	No SMC					SMC			
Year	**date**	**mean**	**min**	**max**		**date**	**mean**	**min**	**max**
2013	Aug-13	10936.4	261	48092					
	Sep-13	12035.68	1954	41009					
	Oct-13	9954.587	1073	38907					
	Nov-13	5000.934	22	17908					
2014	Aug-14	14864.43	1559	34517		Aug-14	27053.29	10426	48069
	Sep-14	14205.82	733	45426		Sep-14	21653.57	8224	37545
	Oct-14	14225.48	883	43317		Oct-14	17837.86	4624	36638
	Nov-14	11504.91	1499	34287		Nov-14	12314.86	5599	23015
2015	Aug-15	14802.46	1873	29214		Aug-15	12159.94	3298	26097
	Sep-15	16709.52	2871	39165		Sep-15	19030.41	4543	39277
	Oct-15	17490.37	71	44189		Oct-15	23777.65	7522	51759
	Nov-15	12346.48	35	27160		Nov-15	15338.41	4069	33274
2016	Aug-16	11006.25	3622	26289		Aug-16	8107.537	2513	19431
	Sep-16	11003.94	2411	24468		Sep-16	10151.91	2087	49507
	Oct-16	15721.31	2680	42454		Oct-16	14119.8	2923	45521
	Nov-16	8610.938	1913	18428		Nov-16	7418.981	1553	28752
2017	Aug-17	18927.08	7904	42293		Aug-17	18699.95	5682	54258
	Sep-17	20019	4831	44515		Sep-17	21485.93	4906	56639
	Oct-17	20562.08	5188	51881		Oct-17	22146.59	5568	61512
	Nov-17	13988.58	815	38590		Nov-17	12873.58	3874	34124
2018	Aug-18	9868.2	1879	21658		Aug-18	8904.477	2565	25913
	Sep-18	12493.4	1894	24068		Sep-18	10811.18	2331	33162
	Oct-18	16926.8	2331	32089		Oct-18	11740.2	2426	35986
	Nov-18	11913.6	1738	21597		Nov-18	9143.954	2721	26205

Annex 2. Estimate of impact

To generate estimates of the level of impact of SMC, a Poisson regression model was fitted to the number of cases confirmed by RDT or microscopy reported to health facilities during the SMC distribution months (August, September, October, November) between 2013 and 2018 (or 2017-2018 for Nigeria). Due to inaccuracies and unavailability in denominator data, only absolute cases were analysed for final interpretation of results for this analysis. The model included age group and calendar year as factors, as well as trigonometric terms to adjust for seasonality of malaria transmission. To adjust for the effect of SMC, an indicator variable was set at "1" during the months of implementation for the under 5 group and "0" for months without the intervention or for the over 5 group, where relevant. Confidence intervals were estimated using a robust standard error. To account for variation of effect across facility or district, a random effect model was used.

The regression analysis calculates a rate for continuous variables and a rate ratio for categorical variables. However, in this analysis we only included categorical variables, so all estimates should be interpreted as a rate ratio with the comparator variable indicated as 1. First a univariate analysis was conducted to investigate the individual variables impact on malaria. Then significant and a-priory variables were added in a forward stepwise multivariate regression (**Table 5**).

Analysis of HMIS data at the national level for each country overall showed no evidence of impact. However, as previously discussed, the quality of data, the limitations of HMIS data reporting, and the inability to adjust for major factors affecting malaria transmission contribute to noise in the analysis and result in inaccurate estimates of effect.

Table 5. Poisson regression multivariate model for confirmed malaria cases (year + age & SMC +gratuity + district), Burkina Faso 2013-2018.

Variable	Category	Rate ratio (%CI)
Age & SMC	Under 5 SMC-	1
	Under 5 SMC+	1.00 (0.98, 1.03) p=0.85
	Over 5 SMC-	0.90 (0.89, 0.95) p=0.00
	Over 5 SMC+	0.92 (0.89, 0.95) p=0.00
Gratuity	No	1
	Yes	1.00 (0.98, 1.02) p=0.83
Year	2013	1
	2014	1.08 (1.06, 1.10) p=0.00
	2015	1.11 (1.08, 0.13) p=0.00
	2016	1.05 (1.02, 1.08) p=0.00
	2017	1.11 (1.08, 1.14) p=0.00
	2018	1.06 (1.02, 1.09) p=0.00