Use of Routine Data in Evaluation: Technical Brief

June 2020

Evaluating the Impact of Malaria Interventions in Zanzibar, 2000–2015: Report Prepared for the U.S. President's Malaria Initiative

This document is part of a series that describes how routine data were used in research and evaluations of health programs and projects. Data for Impact (D4I) has compiled these examples from its own work and the work of others found through a literature review—and consultation with the original authors—to compare ways routine data can be appropriate for evaluations and to shed light on its benefits and shortcomings for evaluation.

A companion guidance document compiling these lessons is available at the D4I website. This suite of materials may be useful for others contemplating using available and routine data in their own work.

This brief outlines an approach used to evaluate malaria programs to transition from malaria control to malaria intervention. The published article can be found here.

Program Description

The U.S. President's Malaria Initiative (PMI) was launched in 2005 with the goal of halving malaria deaths in 15 high-incidence countries through the rapid scale-up of proven interventions. These included the mass distribution of insecticide treated nets (ITNs), indoor residual spraying (IRS), and accurate diagnosis and prompt distribution of artemisinin combination-based therapies (ACT). One country targeted early on by PMI was Tanzania—both its mainland territory and the Zanzibar archipelago. Zanzibar is transitioning from malaria control to malaria elimination. Other countries may seek to replicate this approach and, therefore, an understanding of the contributions of the malaria interventions employed is of interest. However, interventions in Zanzibar were scaled quickly with the aim of universal coverage. This fact complicates evaluation of the effectiveness of the approach due to a lack of adequate "control" data from areas that did not receive interventions. Previous attempts to use health management information systems (HIMS) data to evaluate the effectiveness of universally applied malaria initiatives posed several issues: (1) the evaluations were often restricted to data from a small number of facilities, (2) the data were restricted to short time periods, or (3) the evaluations relied on pre- and post-intervention evaluations without adequate control for potential confounders. Read a published article on the report here: https://www.measureevaluation.org/resources/publications/ja-19-270

Rationale for the use of routine data

The evaluators opted to use routine data housed in the HMIS collected from public health care units (PHCUs) from January 2000–December 2015. Several benefits influenced this choice: (1) records were relatively complete and regularly reported, (2) data were available for the periods before and after interventions, (3) the data were available electronically, (4) additional indicators were available to address potential bias (e.g., use of parasitological testing and all-cause attendance), (5) the data could be combined with census data to estimate the incidence of malaria over time, and (6) the data were believed to capture a high incidence of malaria disease due to high health-seeking behavior at public facilities.

Evaluation questions

The evaluation aimed to answer this key question: What was the impact of each progressively introduced malaria intervention and the combined interventions?

It also sought to shed light on two related questions:

- How did the trend in confirmed malaria incidence change in response to the introduction of interventions, after accounting for climatic variation and seasonality?
- What was the combined impact of these efforts on malaria incidence?

Data description and data management

Data collection

All outpatient and inpatient PHCUs in Zanzibar were eligible for inclusion in the study, and all electronically available monthly reported HMIS data per PHCUs were extracted from January 2000–December 2015. These monthly extracts included the number of people seeking care for any reason at each PHCU, the number of diagnostic tests performed (either rapid diagnostic tests [RDT] or microscopy), and the total number of confirmed malaria cases. There were 158 facilities in Zanzibar that contributed data during this time period.

In addition, population data were compiled from the 2002 and 2012 census. For each year and district, the census data were used to interpolate population estimates (by calculating the average rate of change per district from 2002 to 2012). The data were extrapolated for years beyond 2012 and before 2002. Other covariate data compiled related to climate (which affects mosquito breeding and survival). For the published article, satellite-derived monthly rainfall data were obtained from the United States Geological Survey (USGS) Famine Early Warning System African Data Dissemination Service from 2000–2015. Moderate Resolution Imaging Spectroradiometer (MODIS) satellite data was sourced for the monthly enhanced vegetation index and temperature data from 2000–2015, at 1 km resolution. Satellite-derived climate data were processed to generate district-month means and anomalies. Finally, the evaluators carefully documented the timing, uptake, and scale of the various interventions as they rolled out.

Assessment of usability and quality of data

The usability of the data contributed by the 158 PHCUs was limited in a few instances. In 2000, only 13 of 102 operational PHCUs had access to parasitological confirmatory testing. This rapidly increased in the early 2000s, however two districts—Wete and North B—had no parasitological testing services throughout the pre-intervention period. Without any confirmatory testing and data on the primary outcome, the PHCUs in these two districts were excluded from analysis; there were facilities 18 in Wete and 11 in North B.

Of the 129 PHCUs remaining, 87 were operational at the start of the study period. Of these, 80 (62%) were in operation throughout the study period, 2000–2015. Forty-two more began reporting at some point in this time frame. Monthly reporting for all facilities was high—never falling below 94 percent. For this reason, the data was thought to capture most of the malaria cases in Zanzibar. Cases not included would be among people who sought care in non-public facilities and those who did not seek care at all.

The number of PHCUs operating across Zanzibar increased throughout the evaluation period, potentially increasing access to malaria diagnostic and treatment services. For this reason, the number of attendances for any reason, and the proportion of all patients attending the PHCU who received a malaria test were included in the evaluation.

Data capture in electronic registers

The data were captured over 15 years, with many changes in data processing occurring over this time. In general, however, the data collection method at PHCUs were completed paper forms summarizing the facility indicators (malaria and others) that they were required to report each month. Then, the district health officer entered the data from the forms into the electronic HMIS database. Currently, Zanzibar uses the District Health Information Software, version 2 (DHIS2) to capture HMIS data. Some larger facilities can submit their data directly into DHIS2. The evaluators for this study did not have a password for direct access to DHIS2. Their collaborators in the malaria elimination program were able to "pull" the data from DHIS2 over the time period of interest and format it into an MS Excel file, which was the basis for analysis.

Data availability

The evaluators assessed the completeness of the PHCU monthly reporting data in the HMIS data extracted for each year. The expected number of months of data (calculated as the number of facilities reporting x 12 months per year) was determined and then the actual number of facility-months reported was assessed. The number reported out of the number expected ranged from a high of 100 percent in 2004 and 2008 to a low of 94.9 percent in 2015. For the full study period, 98.3 percent of the months that could have been reported were reported.

It is also of note that the number of facilities that had access to diagnostic testing was quite small in the beginning but, by 2007, all facilities reporting had access to diagnostic confirmatory testing. The completeness of reporting of positive cases among facilities with diagnostic testing was assessed in a similar fashion for overall reporting. In 2000, only 13 facilities (17%) had this capability, but reporting from these was 100 percent. In 2015, 115 (100%) of facilities had this capability with 97 percent reporting of confirmed cases. From 2004 onwards, completeness of reporting of this indicator was high—greater than 95 percent. For years 2001–2003, reporting was greater than 85 percent.

The data for the analysis were, therefore, mostly available. Other data sources, including population data, were not available at the district level by year or by month but could be reasonably estimated from the census surveys in 2002 and 2012, where district-level breakdowns were available.

Intervention data were not available at the district or month level. Coverage was assessed over time by reviewing Demographic and Health Survey (DHS) and Malaria Indicator Survey (MIS) data for surveys conducted in 2004–2005, 2007–2008, 2010, 2011–2012, and 2015–2016. Coverage of various interventions were estimated for Zanzibar main islands of Unguja and Pemba using appropriate sampling weights.

Data accuracy

The evaluation was based solely on cases confirmed through testing, which means there is the potential for bias due to under-reporting of malaria cases in the pre-intervention period in particular, when access to testing was more limited. However, coverage of testing services rapidly increased in 2006, meaning that the reduced access to testing in the early evaluation period would bias the findings towards the null hypothesis: i.e., no effect of interventions on malaria incidence. Furthermore, estimates of the proportion of all-cause outpatient attendees with access to testing were included in the analysis, to try to account for this change.

Another issue that might affect accuracy: facilities came into and out of existence over the 15-year period; 42 of them began reporting during this time and eight stopped reporting. Variations in facility-level data collection procedures and general procedures over time could affect accuracy. However, the proportion of facilities that were reporting data at any given time was quite high, which limits bias due to missing information. Reported access to healthcare remained consistent over the evaluation period, as shown by DHS and MIS survey estimates of the proportion of children under five years of age who presented for treatment of fever.

Also, as will be noted in the next section, many data for the indicator on numbers tested in 2011 were missing.

Missing data

Nearly 62 percent of 2011 data were missing for the numbers tested for malaria in all areas, except for the Central and West districts. While the number of people tested wasn't the primary outcome of the study, it was a covariate tested in the model, and could have resulted in a poorer model fit for 2011.

Data analysis methods used

District-level, monthly incidence of confirmed malaria cases was calculated from the facility HMIS data (numerator), and from the population data estimated per month, per district (denominator). The data were divided into periods: pre-intervention (January 2000–August 2003), ACT-only period (September 2003–December 2005), and ACT plus vector control (January 2006–December 2015). It was evident that crude mean incidence of malaria decreased over time and correlated with these time periods.

However, the main analysis used sought to account for the seasonality and effects of climactic variation on malaria incidence, as well as other potential biases in the data. The study used an interrupted time series approach and assessed the change in trend following the introduction of two key intervention points: ACT only and then ACT plus vector control. The confirmed case count per district was the outcome estimated in the models, using district-level covariates in a random effects, negative binomial model, with district-level population offset. A negative binomial model was used due to over-dispersion (variance exceeded the mean) in the outcome variable.

Several covariates were chosen and included a priori to account for potential biases in the data. First was all-cause outpatient attendance at health facilities to account for potential changes in the population access to health facilities (indeed, the number of health facilities did increase overall). The second was the number of health facilities reporting any data per month, to account for any fluctuations in data reporting. The third was the proportion of outpatients who received a malaria confirmation test, to account for variation in access to malaria testing, which did increase over time.

Other covariates were considered for inclusion in the model. Ten different district-month climate indicators were considered, as was a variable for each, including a one- to two-month lag period as impact of climate may take time to affect malaria incidence. One caveat: if any of the climate indicators were found to be highly collinear with another ($r>0.7$) only one at a time was included in the model. Also considered was the calendar month (1–12) to address seasonality in malaria incidence, island (Pemba or Unguja), individual district dummy variables, the interaction between calendar month and zone, the interaction between calendar month and district, the number of individuals tested for malaria, and malaria test positivity (total confirmed cases divided by the number of people tested). Because each district-month malaria case count is not independent, a one-month lag of the outcome variable was included in the model to account for temporal autocorrelation.

A large number of models were prepared based on biologically plausible combinations of covariates and then short-listed. Models that had large variations in district-level plots of observed and model-predicted cases were removed. Akaike's Information Criterion (AIC), mean square error, and visual inspection of residuals were used to inform model selection of the short-listed models.

The incidence rate ratio (IRR) was used to determine the changes in level and trend for a given time-period, and also the estimated trend for a given time period. The trend overall from 2000–2015, after accounting for interventions and all covariates, was negative (reflecting a reduction in malaria incidence), but this was not statistically significant. The trend for the time period of ACT only (September 2003–December 2005) was negative and statistically significant, as was the trend for the time period of ACT plus vector control. When assessing the estimates of change in trend between each evaluation period, there was evidence for a large reduction in incidence rate in the ACT-only period compared to the pre-intervention period, but a small increase in incidence rate from the ACT-only period to the ACT plus vector control period, reflecting a slowing in the rate of decline of malaria incidence.

Finally, the model developed was used to predict what would have occurred in the absence of the malaria interventions. The model prediction was based on observed climate data and other covariates, except it now assumed that none of the interventions occurred. This was referred to as counterfactual data (i.e., what did not occur). The difference in incidence between the counterfactual data and actual data post-intervention were the basis of an assessment of malaria cases averted.

Limitations in using routine data for evaluation

There were some constraints in using HMIS data over a lengthy (15-year) time period. First, there were changes in the types of information reported. Confirmatory laboratory testing capabilities were not prevalent in 2000 and some districts lacked these capabilities until after 2006, precluding them from analysis. Fluctuations in reporting could bias results (e.g., in 2011 the number of cases sent for confirmatory testing was lower than the number of confirmed lab tests, which is not plausible).

Other information on intervention level of coverage by month and district were not captured in the HMIS. Therefore, a dose response analyses was not possible. Furthermore, with quasi-experimental study designs, it is possible that some of the observed impact could have been attributable to other programs or interventions that took place at the same time as the ACT and vector control interventions and were not separately measured in the model. Finally, some individuals attend private health providers for malaria diagnosis and treatment, and data from private facilities were not consistently available in HMIS data. Consequently, the results could be biased if the proportion of individuals seeking care in the private sector changed over the evaluation period.

What worked well

While there was some potential for bias, and limitations to scope, a large swath of data from PHCUs were available, with a high-level of consistent monthly reporting. Further, the availability of census and climate data allowed for calculations of incidence and for changes in incidence related to climate. Finally, it was possible to generate an estimate of the number of cases averted. While this was not the primary means of determining impact, the ability to quantify and provide a sense of the scale of impact on human life, as opposed to positing only in terms of slopes of trend lines, is highly useful for conveying the importance of these life-saving interventions.

Conclusion

This study was an example of a sophisticated use of routine data, and highlights what can be done when HMIS data is combined with demographic estimates and other data that might improve the predictive ability of a model. In this instance, climate data correlates highly with the incidence of malaria. Further, this robust assessment of impact was possible with only a few indicators gleaned from HMIS data, due to the widespread and consistent reporting over a long period of time, well before and after the introductions of interventions.

One potential drawback of the methods described here is that they are data intensive. It required layers of effort to gather all the demographic and climate data and then manipulate those data to develop usable indicators. Further, the development of the models and their selection requires an advanced understanding of statistical methods. For these reasons, this approach may not be highly practical for all. Nevertheless, it highlights just how much can be done with well-collected routine data.

To learn more, visit www.data4impactproject.org

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