Malaria Prevention: Are high-risk households in Kenya receiving treatments?

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Malaria is considered a significant threat to public health and a socio-economic burden in countries where the disease is either endemic or epidemic.1 The government of Kenya developed the “National MALARIA Strategy 2009-2017” in response to this threat.2 This strategy outlined 6 objectives the first of which is “to have at least 80% of people living in malaria risk areas using appropriate malaria preventive interventions.” The two primary non-pharmaceutical interventions identified in the plan are Indoor Residual Spraying (IRS) and Long Lasting Insecticidal Nets (ILLNs). The strategy outlined for achieving the intervention objective included the initial mass distribution of ILLNs areas where malaria is either endemic (western lowlands) or epidemic-prone (western highlands) followed by routine distribution of ILLNs to pregnant women and children under 1 year of age and a subsidized sale of ILLNs. The strategy also outlined the use of widespread IRS in followed by focalized treatment in epidemic-prone areas.

The World Health Organization (WHO) recommends prioritizing the administration of interventions to pregnant women and children followed by progressively achieving intervention coverage of all community members. The preferential administration of interventions to pregnant women and young children reflects the disproportionate health cost borne by this group. However, previous research has identified the benefit of additionally targeting interventions at those with the highest risk of infections.3 Moreover, remotely-sensed topographic data has been previously validated as a tool for assessing risk of malaria infection.4,5 Our primary objective was to use topographic data, combined with household surveys of intervention use, to determine if existing protocols of intervention administration simultaneously targeted households with high health risk and high infection risk. Since intervention administration differed between the epidemic-prone and endemic regions we also sought to compare the distribution of interventions between these two regions.

To gather information on intervention use we obtained individual survey data of 17,823 members of 3,984 households at two sites in Kenya. These two sites represent the western highland (hereafter “epidemic-prone”, N=3380) and lowland (hereafter “endemic”, N=604) populations. Both sites have had partial treatment with both LLINs and IRS. At the time of the survey the epidemic-prone site had more prevalent LLIN usage whereas the endemic site had more prevalent IRS. Each occupant of the 3,984 households was interviewed about LLIN usage and household IRS. Additional information for each participant was also collected such as age, sex, and relation to the head of the household. Since both interventions under investigation are administered at the household level we summarized the information from the individual surveys into household attributes. For each unique house we calculated the number of individuals under 1, the number of individuals over 1 and under 5, and the number of individuals over 65. We also determined if each house had received a LLIN or IRS. Since responses among household members were not consistent we assigned a treatment to the house if any member of the house responded affirmatively. We assigned an age-based health risk score (age-based risk hereafter) to each household with the following formula:

Risk Score=(2×Children≤1)+(1<Children≤5)+(Adults>65)

We assigned twice the weight to children under 1 since they have the highest risk of the categories.6,7

To determine infection risk, we utilized 90 meter resolution elevation data from the National Aeronautics and Space Administration (NASA) Shuttle Radar Topography Mission (SRTM).8 The epidemic-prone site was sufficiently covered by tile number 43-12 but we utilized two adjacent tiles (43-13 and 44-13) in order to eliminate possible edge effects for eastern households at the endemic site. We assigned each household a risk for exposure to mosquitoes (infection risk hereafter) by deriving a continuous risk surface over the study area. We used a Topographical Wetness Index (TWI) derived from the DEM data to determine areas likely to provide breeding habitat for mosquitoes. The TWI combines the total basin area (the area from which water will flow to a particular point) with the slope at that point to determine the amount of water likely to accumulate and provide breeding habitat for mosquitoes. We used the statistical programming language R with the packages “SDMTools” and “raster” to calculate TWI using a multi-directional flow model.9,10,11,12 We restricted our TWI measurements to identify areas with low water out-flow by including a measure of local aspect variance. We assumed the infection risk of a household was inversely related to the distance to one or more of these high-wetness areas. Therefore, we applied a Gaussian filter with σ=10 to create a weighted average of mosquito risk for each cell in the study area. We then assigned each house the risk score of the cell in which it was located.

To determine if current administration protocols targeted households with both high infection risk and high health risk we standardized each risk measure and added them to create a combined risk score (measured in standard deviations from the sample population). We used a logistic model to evaluate whether households with high risk were more likely to receive an intervention. We also modelled each risk separately to determine if existing protocols of intervention administration were adequately addressing either risk. If we found evidence of a non-linear relationship in any model we categorized the risk score into quartiles and re-fit with a means model.

The odds of receiving either an LLIN or IRS are higher for households with higher combined risk, but only at the epidemic-prone site (table 1). For each 1 standard deviation increase in combined-risk at the epidemic-prone site the probability of receiving an LLIN increases 27% (Odds Ratio (OR): 1.27, 95% CI: 1.18, 1.35) and the probability of IRS increases 15% (OR: 1.15, 95% CI: 1.03, 1.29). At the endemic site, we found no preferential administration of either treatment to high combined-risk households. We found some evidence, from the fitting of a restricted cubic spline, of a non-linear relationship between the log-odds of net use and combined risk at the endemic site. However, modelling the mean risk for each risk quantile did not change our results.

The probability of ILLN use at the epidemic-prone site was more strongly associated with age-based risk, whereas the probability of IRS at the epidemic-prone site was more strongly associated with infection risk. However, we did not find the same pattern at the endemic site where we found households with high infection risk were actually significantly less likely to receive IRS (OR: 0.35, 95% CI: 0.14, 0.83).

The two sites had very different rates of use for both LLINs and IRS. The endemic site had recently received 3 consecutive years of IRS (as prescribed by the National MALARIA Strategy) resulting in 97.4% of all households reporting IRS. However, only 7.6% of households in the endemic site reported LLIN use. Conversely, 34.6% of households in the epidemic-prone site reported LLIN use but only 7.6% of households reported IRS. The widespread use of IRS in the endemic site makes it difficult to determine whether high risk households preferentially received the intervention but we found no evidence that spraying was targeted at high risk households. This result is in contrast to the epidemic-prone site where we found evidence of preferential administration of both LLINs and IRS (despite the relatively low occurrence of IRS).

Our measure of infection risk may be more suitable to the epidemic-prone site which has more pronounced topographical features. Previous research on the use of TWI for prediction of malaria has been performed at sites similar to our epidemic-prone site but not our endemic site.4 Moreover, TWI algorithms are known to be sensitive to the general terrain to which they are applied.12 However, since our method only relies on identifying the relative risk of infection among households within a community we believe the potential problems are minimal. For large scale applications of TWI comparing households in different topographical regions care should be taken to account for terrain differences.

We found significant evidence of targeted interventions at the epidemic-prone site but not at the endemic site. This likely reflects the differential administration of interventions at these two sites. A mass distribution campaign took place at the endemic site 1 year prior to our survey. Despite this, roughly half of the un-sprayed households had higher than average risk with half of these in the upper-most quartile of risk. The incorporation of a targeted administration could have potentially left only very low-risk households untreated. Given the additional benefit achieved by targeting interventions to households with the highest risk, and the widespread availability of elevation data provided by the USGS, we believe the incorporation of TWI for identifying households with high infection risk can improve current protocols of intervention administration.

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Table 1. Odds of receiving a treatment as a function of combined risk. Odds ratios represent the effect of an increase of 1 standard deviation in the combined risk measure.

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