R Data Analysis Project

Weather and Malaria Incidence and Intervention Data for Mozambique

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Background

Malaria is a leading cause of death globally. The CDC estimates that in 2015 429,000 people died from the disease.[2] The highest malaria death rates occur in Africa, and particularly in young children and pregnant women whose immune systems are weaker. As it is spread through mosquito bites, the amount of transmission can vary depending on several factors. Weather and climate are a large part of that, as warmer climates and wetter regions have a higher incidence level due to being more suited for the mosquitos–or vectors– to breed.[3] In addition, lower altitudes are also more suited for these insects. Because of this, there are natural fluxuations in malaria transmission, with lower numbers after dryer seasons and higher numbers following the rainy seasons following the increase in number of mosquitos. Due to the time it takes for mosquitos to breed, eventually infect someone, and for them to show symptoms and get tested, there is a lagged relationship between when the weather became more hospitable to the vector and malaria cases.

Some of the prevention methods that are used to help prevention transmission include insecticide treated bed nets (ITNs) and indoor residual spraying (IRS).[2] The indoor residual spraying involves spraying the insides of buildings with insecticides.[1] Both of these prevention methods are only temporary in decreasing the number of transmissions. Over time, the bed nets tear and the insecticides wear off, and rates rise again over time.[4]

In this analysis we have explored the amount of protection that these two methods have supplied for Mozambique over the years 2010-2017. During the course of these years, both protection methods were employed across the 142 districts at varying points in time. We modeled then the relationships between malaria cases and the protection that should be supplied to each district after intervention in a decaying manner. In addition, we explored the length of time that there is a lag between weather and incidence. As this exact time frame in unknown for different weather variables, we evaluated several differing lag amounts in order to see how each fit the data.

Data

The data for this analysis include incidence data, malaria intervention data, weather data, and spatial data. The incidence data contains information on the weekly number of cases of malaria reported by districts along with information about each district, and spans from 2010 to 2017. The district information includes square kilometers, province, region, population, and x and y coordinates. Incidence was calculated by dividing cases by the population and multiplying by 1000. The intervention data contains the week and year for each district that the two preventative interventions occurred– insecticide treated bed nets (ITN) and indoor residual spraying (IRS). The weather data originally contained daily information by district on five weather measures– rainfall, temperature, relative humidity, saturation vapor pressure deficit, and surface barometric pressure. All variables in this dataset were averaged by week–except rainfall which was summed–in order to be merge with the other datasets. Lastly the spatial data was geospatial information on the country of Mozambique in order to map the other data spatially. Data was merged based on the district, week, and year.

In order to capture the seasonal effect of weather on malaria trends, the weather information has a lagged relationship with the incidence data. With this lag being unknown, the incidence data was lagged by two, four, and eight weeks to the weather data. This analysis also explored the protection of the interventions over time, in which 100% protection from malaria is assumed at the start week that slowly decays at a linear rate. We assumed 75% protection 6 months after the start for IRS, which translates to a 0.01042 decrease in protection each week, and we assumed 60% protective 96 months after the start for ITN, which translates to a 0.0042 decrease each week. Variables that contained the information for the decay in protection were created for each intervention treatment to be used for analysis where decay ranges from 0 to 1.

Methods

In order to model the relationship between malaria cases and the interventions while controlling for the effects of weather we ran a Poisson regression with glmer. The outcome was cases with an offset for population, including the decay of ITN protection and IRS protecting as covariates while also controlling for rainfall, temperature, relative humidity, and surface barometric pressure. We did not also control for saturation vapor pressure deficit as it was highly correlated with relative humidity which gave a better model fit when used instead (see figure 1). Lastly, a random intercept and slope for district was added in order to account for the correlation of repeated measures and the correlation within districts. To decide which lag to use for each weather variables, we looked at the amount of correlation between the sets of lagged weather variables and malaria cases and chose the ones with the highest correlation.

Results

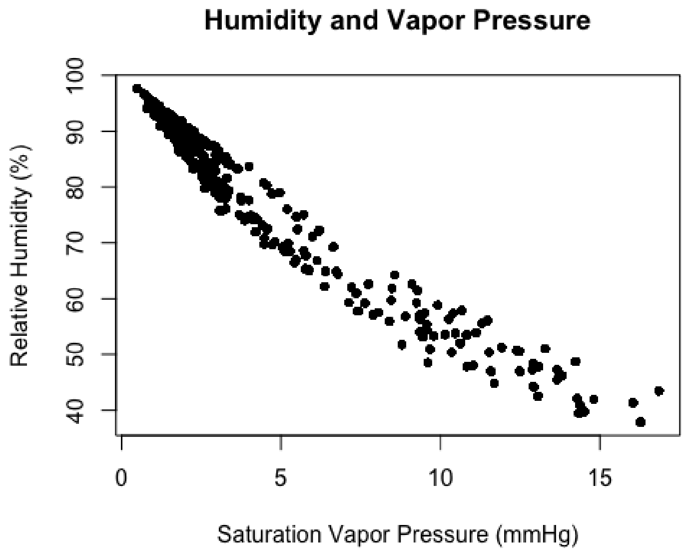
Cases increase on average by 0.0292 (95% CI: (0.0208,0.0376), $p<0.0001$) for every one unit increase in ITN protection. As protection ranges from zero to one, this is equivalent to saying there are on average 0.0292 more cases for full ITN protection as compared to zero protection. Cases decrease on average by 0.0505 (95% CI: (-0.0576,-0.0433), $p<0.0001$) for every one unit increase in IRS protection. In other words, there are on average 0.0576 less cases for full IRS protection as compared to zero protection. For every degree Celsius increase in temperature, malaria cases increase by 0.0174 (95% CI: (0.0168,0.018), $p<0.0001$). For every mm increase in rainfall, malaria cases increase by 0.0009 (95% CI: (0.0008,0.001), $p<0.0001$). For every hectoPascal (hPa) increase in surface barometric pressure, malaria cases decrease by 0.0239 (95% CI: (-0.0243,-0.0234), $p<0.0001$). However there was not a significant relationship with relative humidity, where for every one percent increase in relative humidity ($p=0.4275$). See table 1 for estimate table.

Figure 3 shows the relationships between the normalized lagged weather variables and normalized malaria cases. Figure 4 shows an example of the relationships between cases, the IRS protection and rainfall for one district in a year. A strong dip in cases coincides with both the intervention and a decrease in rainfall. Figure 5 is a map of malaria incidence across the country during one week of 2013. Figure 6 shows the cyclical trends of malaria incidence over several years for one district.

Table 1: Poisson Regression Results

	Estimate	Lower	Upper	P-Value
Intercept	18.7165	18.1945	19.2385	<0.0001
ITN Protection (%)	0.0292	0.0208	0.0376	<0.0001
IRS Protection (%)	-0.0505	-0.0576	-0.0433	<0.0001
Temperature (°C)	0.0174	0.0168	0.018	<0.0001
Rainfall (mm)	0.0009	0.0008	0.001	<0.0001
Relative Humididy (%)	0.0000	0.0000	0.0001	0.4275
Barometric Pressure (hPa)	-0.0239	-0.0243	-0.0234	<0.0001

Figure 1: Correlation between humidity and vapor pressure



Conclusions

The results of our model suggest that there was a counterintuitive relationship between ITN protection and malaria cases. Instead of greater protection lowering rates, we saw that less ITN protection was associated with lower rates of malaria. The results of the IRS protection behaved as we would expect. The higher the IRS protection, the lower the malaria cases. However, while both of these associations were highly significant, they were both incredibly small. For both intervention measures, the difference of cases between full and zero protection was a fraction of a case. So while we are seeing significant results, there do not seem to be clinically significant increases or decreases in malaria cases.

The weather covariates we controlled for mostly behaved as others have reported in the past. Increases in temperature or rainfall were associated with a higher number of cases, as well as increases in pressure being associated with a lower number of cases. In additon, we found that between lags of two, four, and eight weeks, rainfall fit best with the two week lag, temperature fit best with a four week lag, relative humidity fit best with an eight week lag, and pressure fit best with a two week lag.

Figure 2: Malaria cases by province

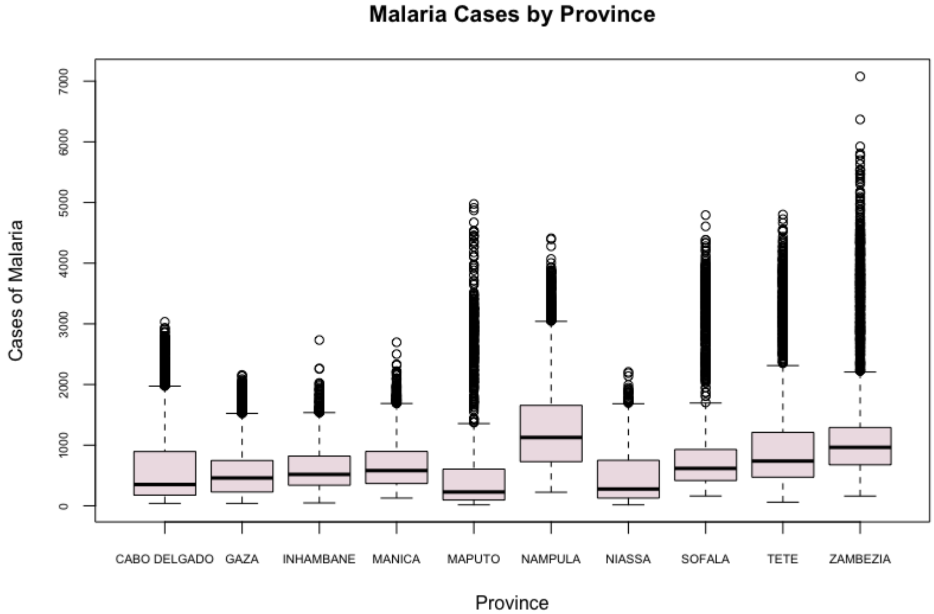


Figure 3: Normalized malaria cases and weather variables lagged by week

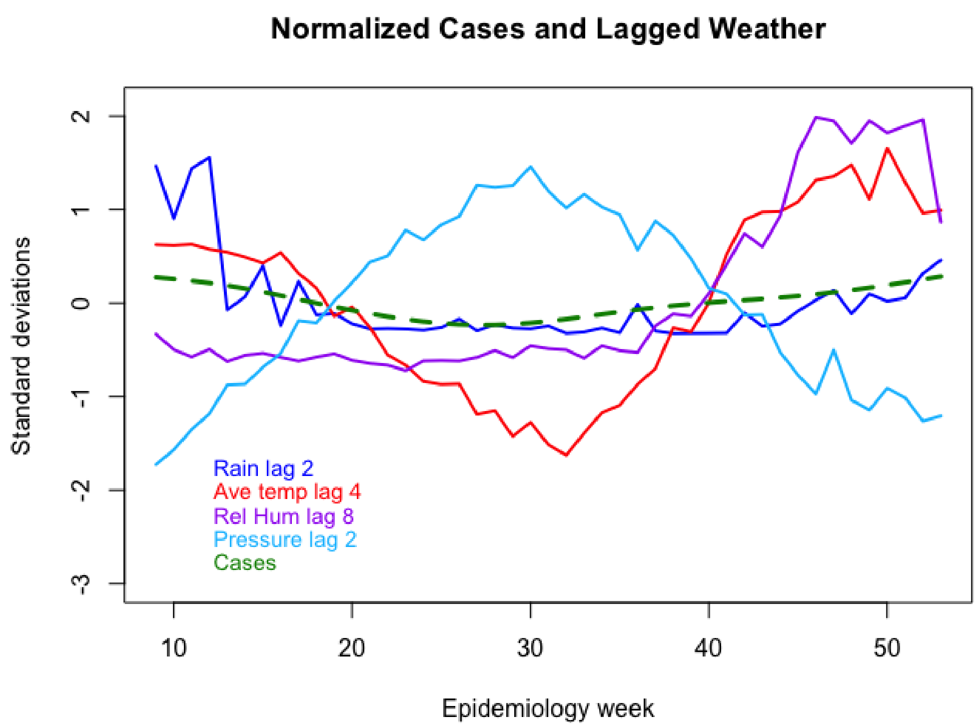


Figure 4: Normalized malaria cases with IRS protection and rainfall for 2016 in the Agnoche District

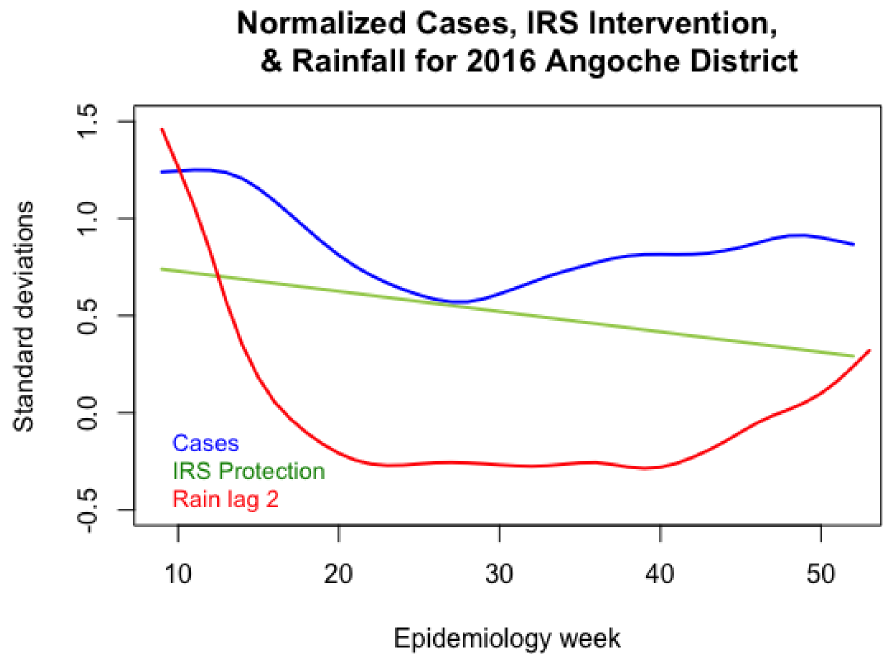


Figure 5: Malaria incidence for 2013 week 20

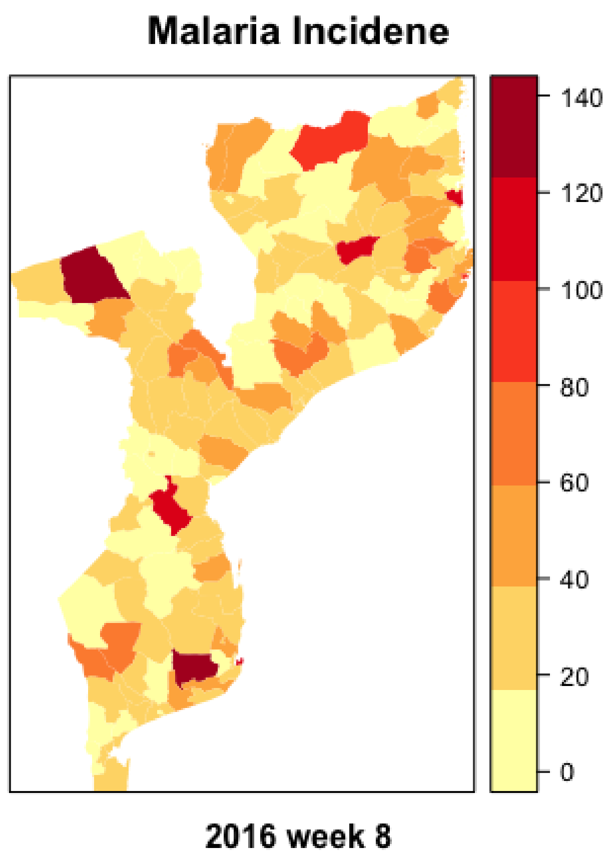
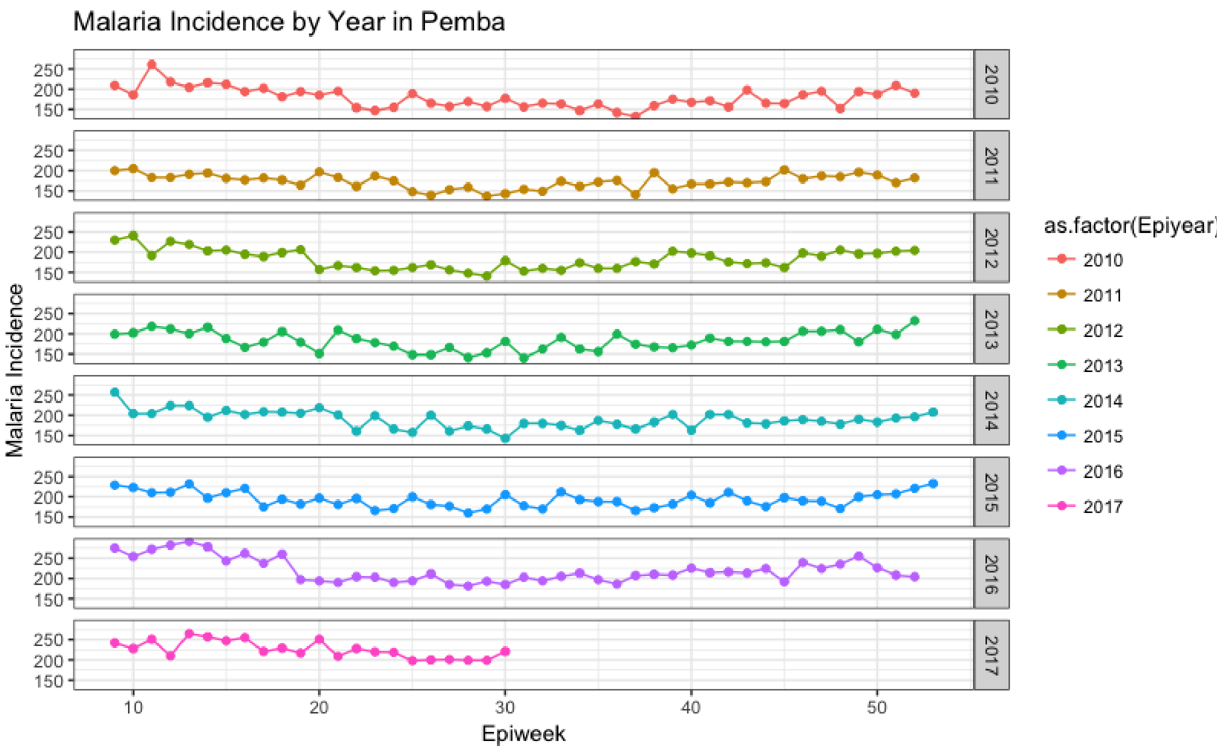


Figure 6: Malaria incidence for all Districts in each year in Pemba



References

1: "Indoor Residual Spraying (IRS)." President's Malaria Initiative, 2017, www.pmi.gov/how-we-work/technical-areas/indoor-residual-spraying.

2: "Malaria." Centers for Disease Control and Prevention, Centers for Disease Control and Prevention, 18 Oct. 2017, www.cdc.gov/malaria/.

3: Paaijmans, Krijn P., et al. "Understanding the Link between Malaria Risk and Climate." Proceedings of the National Academy of Sciences, vol. 106, no. 33, 18 Aug. 2009, www.pnas.org/content/106/33/13844.full.

4: Smithuis, Frank M, et al. "The Effect of Insecticide-Treated Bed Nets on the Incidence and Prevalence of Malaria in Children in an Area of Unstable Seasonal Transmission in Western Myanmar." Malaria Journal, 11 Oct. 2013, malariajournal.biomedcentral.com/articles/10.1186/1475-2875-12-363.

Reproductable Research Information

All work and materials can be found at https://github.com/aforber/RProject.