

R Data Analysis Project

Weather and Malaria Incidence and Intervention Data for Mozambique

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Background (at least 1 page) (with a literature review and citations)

- malaria affecting a lot of people
- life threatening, # people kills
- Mozambique stats
- preventions include insecticide treated bed-nets, indoor residual spraying
- temporary effect and the protection wears off
- seasonal effect, rainy season, mosquitos breed in standing water
- after rain they breed and increase in number which increases bites/infections
- some time after rain we see rise in cases which is unknown, and something that will be explored in this analysis

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.

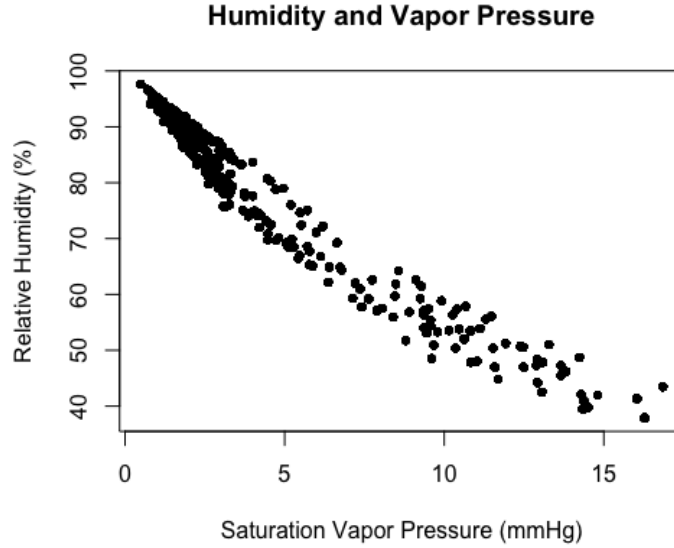
Results (4-5 figures, at least one a map)

Cases increase on average by 0.037 (95% CI: (0.028,0.046), $p < 0.001$) for every one unit increase in ITN protection. As protection ranges from zero to one, this is equivalent to saying there are on average 0.037 more cases for full ITN protection as compared to zero protection. Cases decrease on average by 0.054 (95% CI: (-0.062,-0.047), $p < 0.001$) for every one unit increase in IRS protection. In other words, there are on average 0.054 less cases for full IRS protection as compared to zero protection. For every degree Celsius increase in temperature, malaria cases increase by 0.017 (95% CI: (0.0168,0.0181), $p < 0.001$). For every mm increase in rainfall, malaria cases increase by 0.0010 (95% CI: (0.0009,0.0011), $p < 0.001$). For every one percent increase in relative humidity, malaria cases decrease by 0.0001 (95% CI: (-0.0002,-0.00003), $p = 0.0088$). For every hectoPascal (hPa) increase in surface barometric pressure, malaria cases decrease by 0.0249 (95% CI: (-0.0254,-0.0244), $p < 0.001$).

Table 1: Poisson Regression Results

	Estimate	Lower	Upper	P-Value
Intercept	19.5953	19.0265	20.1642	<0.001
ITN Protection (%)	0.0371	0.0282	0.0459	<0.001
IRS Protection (%)	-0.0543	-0.0618	-0.0468	<0.001
Temperature (°C)	0.0174	0.0168	0.0181	<0.001
Rainfall (mm)	0.001	0.0009	0.0011	<0.001
Relative Humidity (%)	-0.0001	-0.0002	-0.00003	0.0088
Barometric Pressure (hPa)	-0.0249	-0.0254	-0.0244	<0.001

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. The only variable that did not follow previously reported trends was relative humidity, which was associated with a lower number of cases. However, this coefficient was not only extremely small but also much less significant than the others whose p-values were effectively zero, so this relationship

is not concerning.

Figure 2: Malaria cases by province

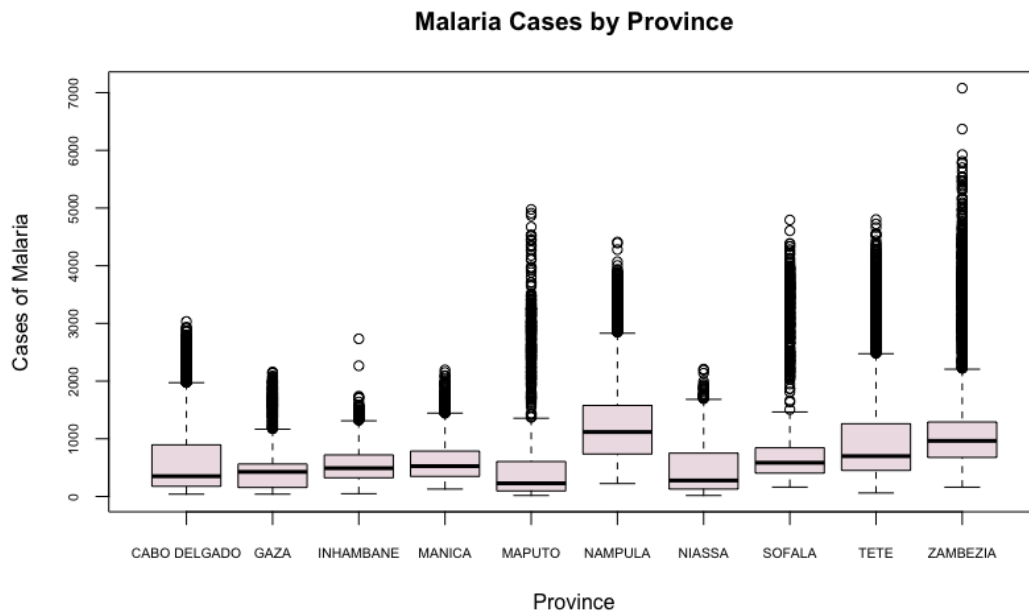


Figure 3: Normalized malaria cases and weather variables lagged by week

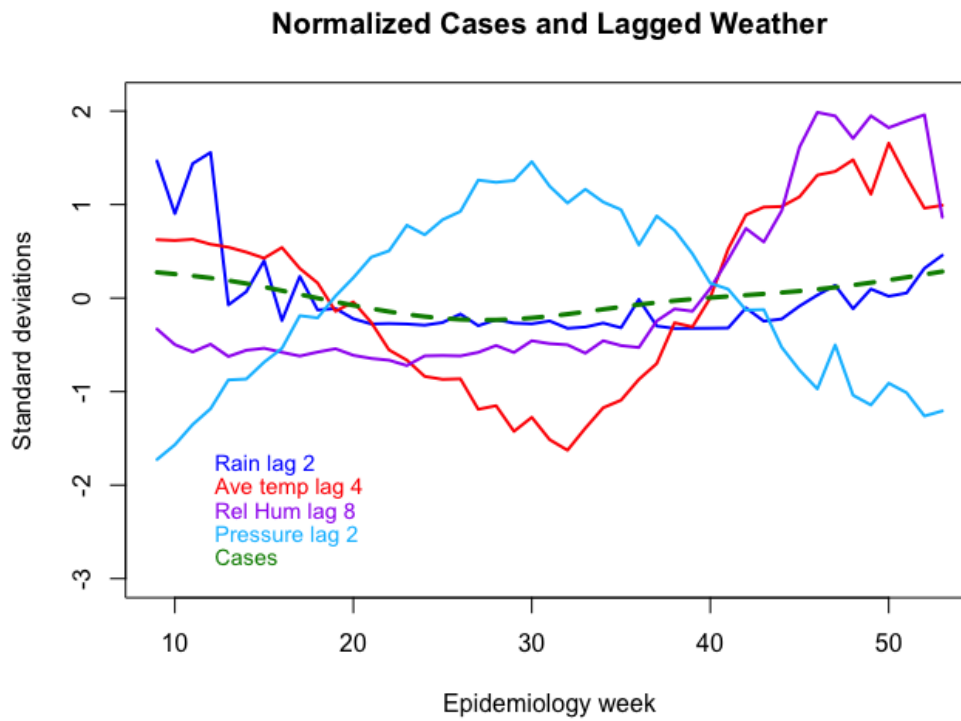
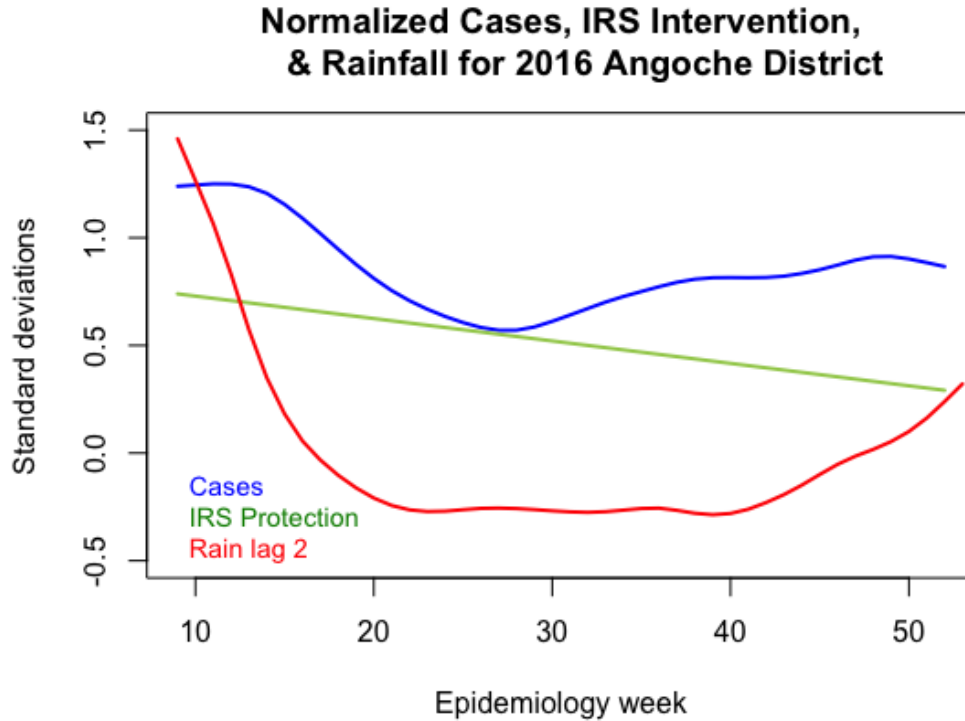


Figure 4: Normalized malaria cases with IRS protection and rainfall for 2016 in the Agnoche District



References

<https://malariajournal.biomedcentral.com/articles/10.1186/1475-2875-12-363>

<http://www.who.int/mediacentre/factsheets/fs310/en/index1.html>

https://www.newvision.co.ug/new_vision/news/1423973/malaria-leading-cause-death-uganda

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<https://malariajournal.biomedcentral.com/articles/10.1186/1475-2875-12-363>

Reproducible Research Information

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