Environmental Variables & Mycotoxin Risk in Kongwa, Tanzania

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Figure 1. Children affected by growth stunting in Tanzania

Abstract

- Aflatoxins are likely linked to childhood stunting.
- To prevent continued exposure via food, it is important to understand the environmental factors that increase aflatoxin risk.
- We studied precipitation and soil data as possible risk factors.
- Our analysis found soil pH and precipitation during plant and kernel development to have significant effects on aflatoxin levels.

Introduction

- Aflatoxins are one of the most toxic type of mycotoxins, a family of fungal toxins commonly found in maize and groundnuts (peanuts) in East Africa.[2]
- Aflatoxin levels more than ten times EU allowed concentrations were measured in Kongwa, Tanzania.
- Liver cancer, immunomodulation, reproductive disorders, and growth deficiencies in children linked to chronic aflatoxin exposure[2,3]
- Soil variables, including soil organic carbon, nitrogen content, pH, and soil type are associated with aflatoxin levels.[2] Additional environmental variables include temperature and precipitation.[3]
- Our study is based on 2015 household survey of home grown maize in Kongwa.[5]
- Linked environmental variables from open source satellite and other data sources to each household GPS coordinate

Materials and Methods

- Data for this study is a subset (n=76) of a larger dataset containing households with exclusively homegrown maize
- Flour samples taken from each household and tested for Aflatoxin by ELISA
- Raw Aflatoxin data exhibited excessive non-normal distribution, data was log-transformed

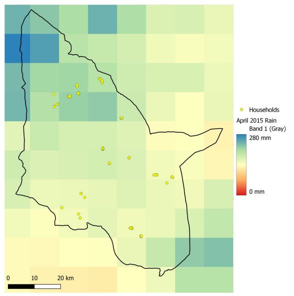

Figure 2. Rainfall in April 2015

- Environmental variables including elevation, precipitation, and soil variables collected based on associations identified in the literature.
- Precipitation data accessed from the NASA Global Precipitation Mission (GPM)
  - Spatial resolution of 10km x 10km, 80 pixels encompassing Kongwa District. The 76 villages were spread across 13 pixels
- Elevation data was obtained from NASA ASTER Global Digital Elevation Model 003.
- Soil variables accessed from SoilGrids250 database
  - Includes organic carbon stock, soil organic carbon, bulk density, nitrogen, cation exchange capacity (CEC), and pH, most collected at three depths: 5-15cm, 15-30cm, and 30-60cm.
  - SoilGrids relies on machine learning methods to extrapolate data from over 150,000 soil profiles.
- All data processed in R
- Final model obtained using Best Subset Regression in R

Results

- Best subset regression first performed with 20 parameters (all variables and all soil depths collected) in R
- Highest explanatory model displayed oppositely-correlated coefficients for same soil variables at different depth increments, despite each variables showing similar values across all depth increments
- Instead opted for a single intermediate depth interval (15-30cm) because values across differing soil depth increments are related[1]
- Best subset regression with 10 possible environmental variables in R used for analysis
- Model with 3 (Model 3) parameters had lowest Akaike Information Criterion (AIC) score (most explanatory power) but relatively low adjusted R-square value
- All coefficients in Model 3 were significant ($p<0.05$).

Table 1. 6 out of 10 best possible linear model outcomes for 10 environmental variables. Model 3 is highlighted for reasons mentioned above.

Model Index	Predictor Variables
1	Rain during kernel drying
2	Rain during plant development, Rain during kernel development
3	Soil pH, Rain during plant development, Rain during kernel development
4	Soil pH, Cation exchange capacity, Rain during plant development, Rain during kernel development
5	Soil pH, Cation exchange capacity, Soil bulk density, Rain during plant development, Rain during kernel development
6	Soil pH, Cation exchange capacity, Soil organic carbon, Elevation, Rain during plant development, Rain during kernel development

Table 3. Summary of linear regression model 3 output in R

	Coefficient Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	24.83218	6.402582	3.878	0.00023
Soil pH	-1.8212	0.888992	-2.049	0.044147
Rain During Plant Development	-0.02724	0.004787	-5.69	2.56E-07
Rain During Kernel Development	0.036216	0.009475	3.822	0.000278
Residual standard error: 1.119 on 72 degrees of freedom Multiple R-squared: 0.3763, Adjusted R-squared: 0.3503 F-statistic: 14.48 on 3 and 72 DF, p-value: 1.781e-07				

Model	Adjusted R^2	R^2	AIC
1	0.252	0.2078	248.4953
2	0.34	0.2893	240.9882
3	0.3763	0.3108	238.6826
4	0.3886	0.3052	239.1774
5	0.4064	0.3132	238.9288
6	0.4104	0.2928	240.4151

Table 2. Output from ols_step_best_subset() with model fit criteria up to 6 parameters

Discussion

- Model 3 revealed the highest explanatory power according to AIC.
- Although Model 3 had a lower adjusted R-square, the model is parsimonious, and all coefficients are significant.
- SoilGrids250 relies on machine learning extrapolation.[1] Although intermediate soil depth intervals were chosen for analysis, behavioral impacts (i.e. farming) on soil may not be accounted for in the machine learning algorithm.
- Uncertainty exists with modeled precipitation data. GPM data differed from another considered data source but seemed more reliable with a wider variety of instruments, better calibration, and less modeling
- Kongwa a relatively small study area compared to areas in prior mycotoxin risk modelling
- Future research will include a larger dataset (around n=2,000) from the same research group[5]

Figure 3. Healthy maize (left) and maize infected by Mycotoxin

References

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