Climate Change & Environmental Health

Examining the influence of climate variability on pathways of diarrheal disease transmission

Motivation

Climate change may influence the transmission and global burden of diarrheal illnesses. Multiple studies have shown that higher temperatures and increased extreme rainfall events are associated with increased prevalence of diarrheal illness.[1] This is significant because current climate projections predict continued temperature increases, more frequent extreme precipitation events and more heat waves.[2] Diarrhea contributes a large share of the global disease burden;[3] even small increases in risk would represent significant impacts. While multiple studies have shown an association between climate variability and diarrheal illness,[1] it is not clear which transmission pathways are influenced and how strongly [**Fig. 1**]. The goal of this project is to contribute evidence on the association between climate variability and household environmental contamination to begin identifying which transmission pathways are significantly influenced.

Research Questions

- How are variations in temperature and precipitation associated with the following in rural areas of Kenya with limited water and sanitation infrastructure:
    - ♦Household stored water quality (*E. coli*)?
    - ♦Child hand contamination (*E. coli*)?
    - ♦Child toy ball contamination (*E. coli*)?
- Does household *E. coli* contamination exhibit seasonal variation?

Methods

1.Extract the following variables for each survey:

Precipitation:

- Total precipitation on day of survey (threshold)
- Total precipitation during week preceding survey (threshold)

Temperature:

- Max temperature on day of survey
- Mean max temperature during week preceding survey

*Note: precipitation variables were grouped into no rain, moderate rain (greater than zero and below 90^{th} percentile), and heavy rain (at or above 90^{th} percentile).

2.Perform linear regression analyses between climate variables and *E. coli* concentration **[Tables 1 & 2].** Perform Poisson regression between climate variables and presence/absence of *E. coli* in the toy ball rinse samples.

Notes:

**E. coli* concentration data was transformed using log10 to meet normality assumptions.

*Presence/absence outcomes were not used for stored water or hands because the prevalence of *E. coli* is very high (above 90%).

*Temperature analyses are bivariate, while precipitation analyses model the impact of no rain and heavy rain together against a reference group of moderate rain.

*Multivariate regression to evaluate combined exposure of temperature and precipitation was not possible due to high collinearity between these variables.

3.Create boxplots of environmental contamination in each month to determine if there is evidence of seasonal variation **[Fig. 2].**

4.Identify significant spatial clustering of contamination using univariate Local Moran's I **[Fig. 3].**

5.Identify significant clustering of contamination in the context of space and time using local outlier analysis (a space-time implementation of Local Moran's I) **[Fig. 4].**

6.Identify significant spatial clustering of regression residuals using univariate Local Moran's I to assess if the model is predicting consistently across the study area **[Fig. 5].**

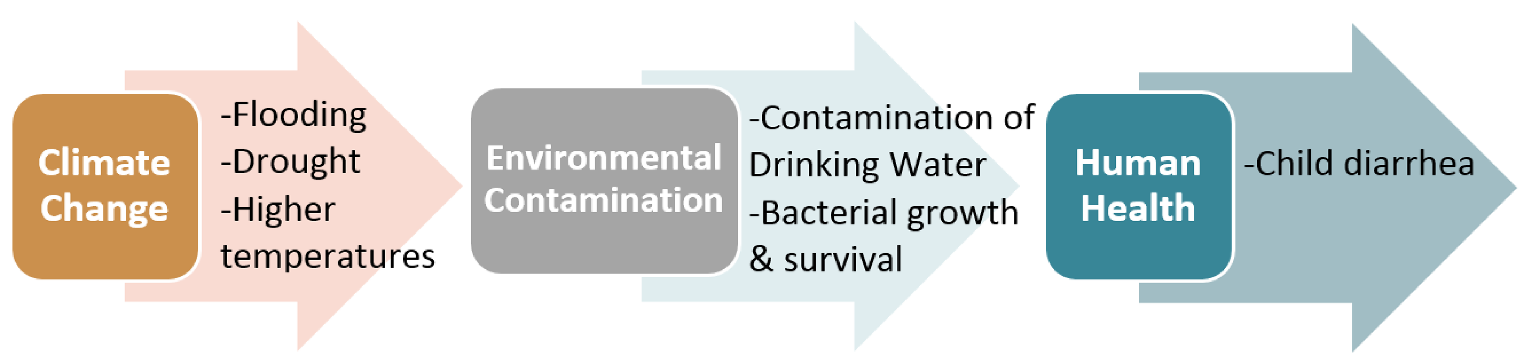

Figure 1: Concept Diagram

Table 1: Surface Water *E. coli* Concentration Bivariate Regression Results

Predictor variable	*Coefficient*	*P-value*	*Direction*
No Precipitation (day of)	0.038	0.595	
Heavy Precipitation (day of)	0.358	0.003	↑
No Precipitation (week before)	0.278	0.007	↑
Heavy Precipitation (week before)	0.256	0.013	↑
Max Temperature (day of)	0.013	0.103	
Mean Max Temperature (week before)	0.020	0.024	↑

Table 2: Hand Rinse *E. coli* Concentration Bivariate Regression Results

Predictor variable	*Coefficient*	*P-value*	*Direction*
No Precipitation (day of)	0.012	0.86	
Heavy Precipitation (day of)	0.201	0.031	↑
No Precipitation (week before)	-0.131	0.11	
Heavy Precipitation (week before)	0.103	0.153	
Max Temperature (day of)	-0.038	<0.001	↓
Mean Max Temperature (week before)	-0.045	<0.001	↓

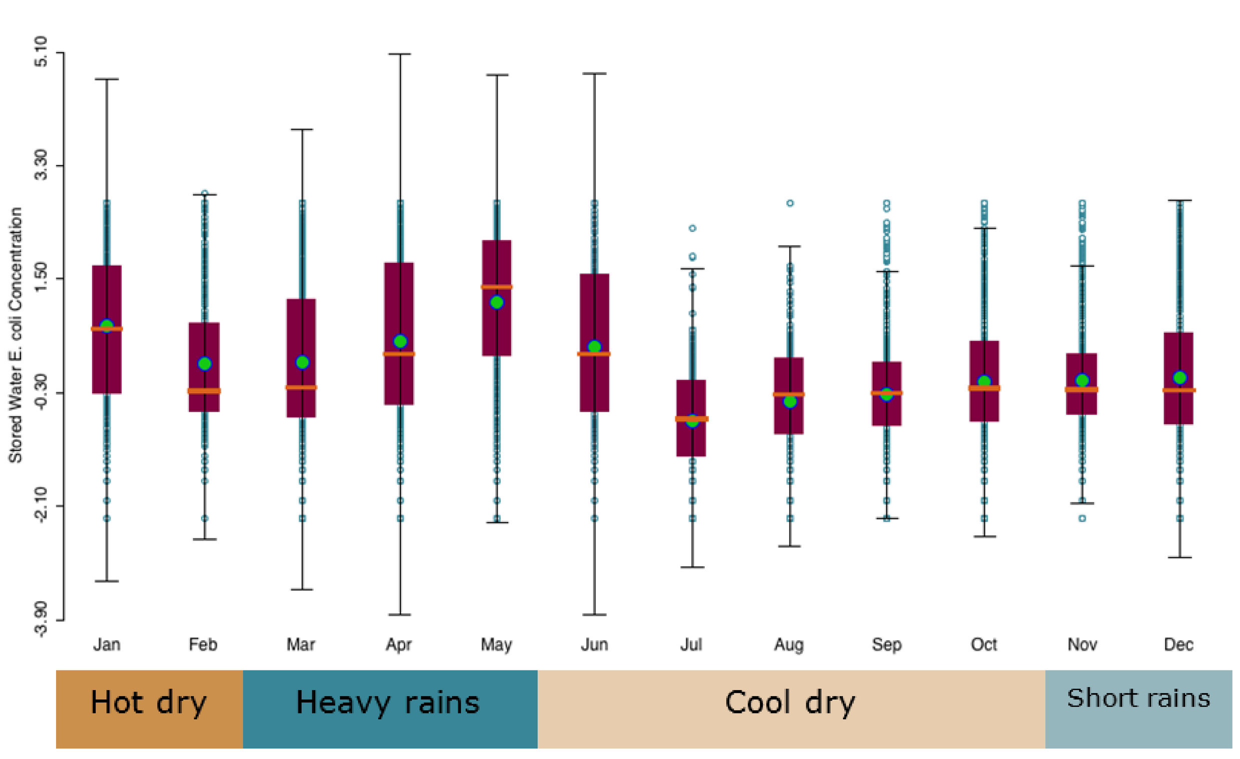

Figure 2: Boxplots of Stored Water *E. coli* Concentration by Month

Results

- Stored water **[Table 1]:** Heavy precipitation (day of, week before), no precipitation (day of), and increased temperature (week before) are associated with increased *E. coli* contamination in stored water.
- Hand rinse **[Table 2]:** Heavy precipitation (day of) is associated with increased E. coli contamination, while increased temperature (day of, week before) is associated with decreased *E. coli* contamination on hands.
- Toy ball rinse: No precipitation (day of) is associated with increased *E. coli* contamination on toys.
- Boxplots **[Fig. 2]** show evidence of a seasonal trend of contamination.
- Local Moran's I **[Fig. 3]** shows clustering of stored water contamination, with high values clustered in the east and low values clustered in the south and northwest. However, this result is limited because it does not reflect temporal variation.
- Local cluster analysis **[Fig. 4]** shows low values clustered in the south and northwest.
- Local Moran's I **[Fig. 4]** shows clustering of residuals, with high values clustered in the east and low values clustered in the south and northwest. This follows the same trend as the clustering of contamination, indicating that this model is over-predicting areas of low contamination and under-predicting high contamination areas.

Conclusions

Temperature and precipitation variability are significantly associated with household environmental contamination, and the association with each pathway (stored water, hands, toys) varies. Overall, these results suggest that climate change will likely lead to increased risk of *E. coli* transmission, but the risk differential may not be uniform across pathways. These results are limited in that they are bivariate and do not account for the combined exposure of temperature and precipitation. The space-time results are limited because the data was not collected evenly through space and time, so spatial variation may be explained by temporal variation in when households were sampled. These results indicate that climate variability may be an important driver of environmental contamination. These results point to the need for further analysis to account for the combined exposure of temperature and precipitation and to quantify the projected increase in diarrheal risk in terms of current climate projections.

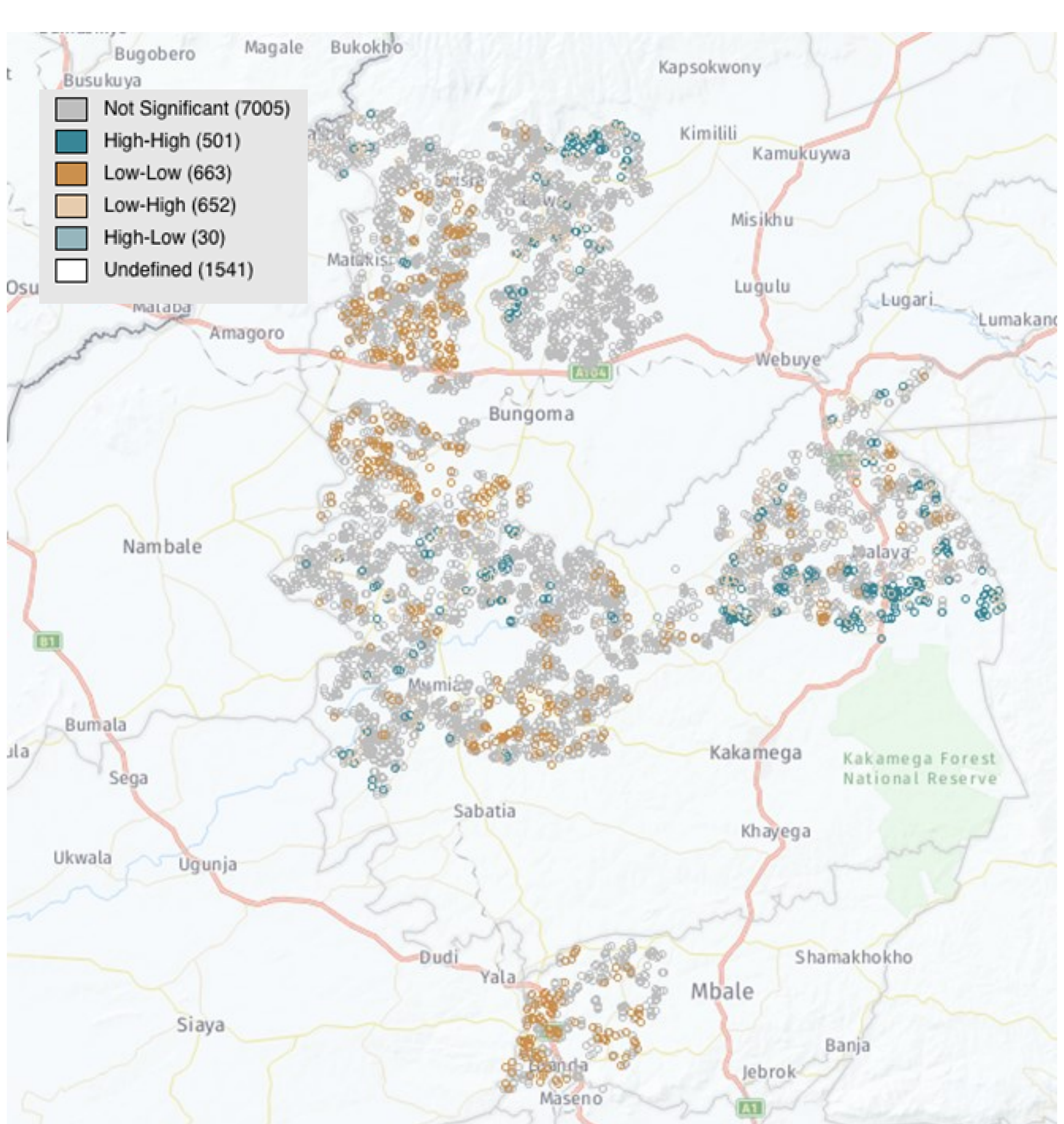

Fig. 3: Stored Water *E. coli* Concentration
Local Cluster Analysis (Space)

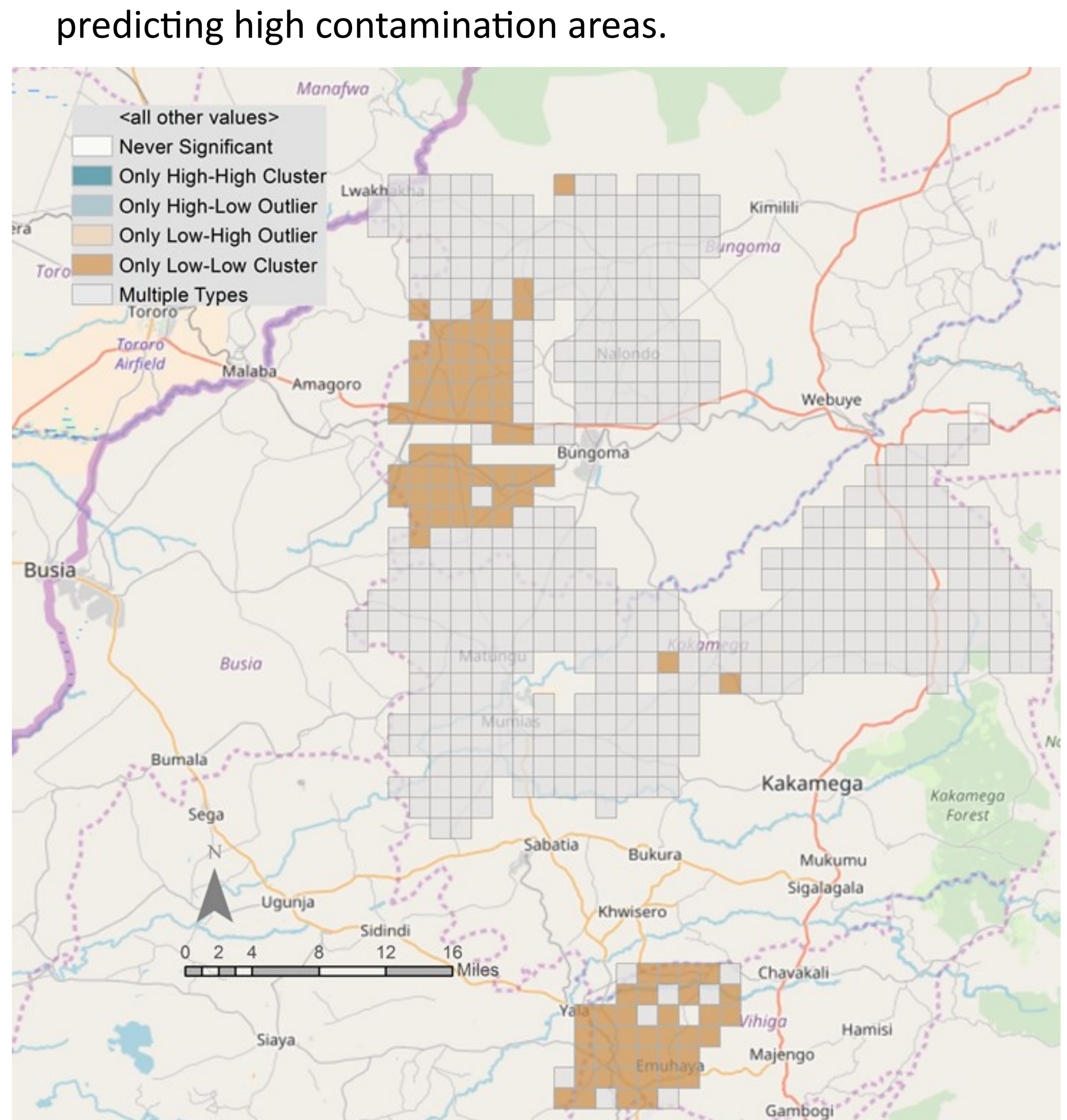

Fig. 4: Stored Water *E. coli* Concentration
Local Cluster Analysis (Space-Time)

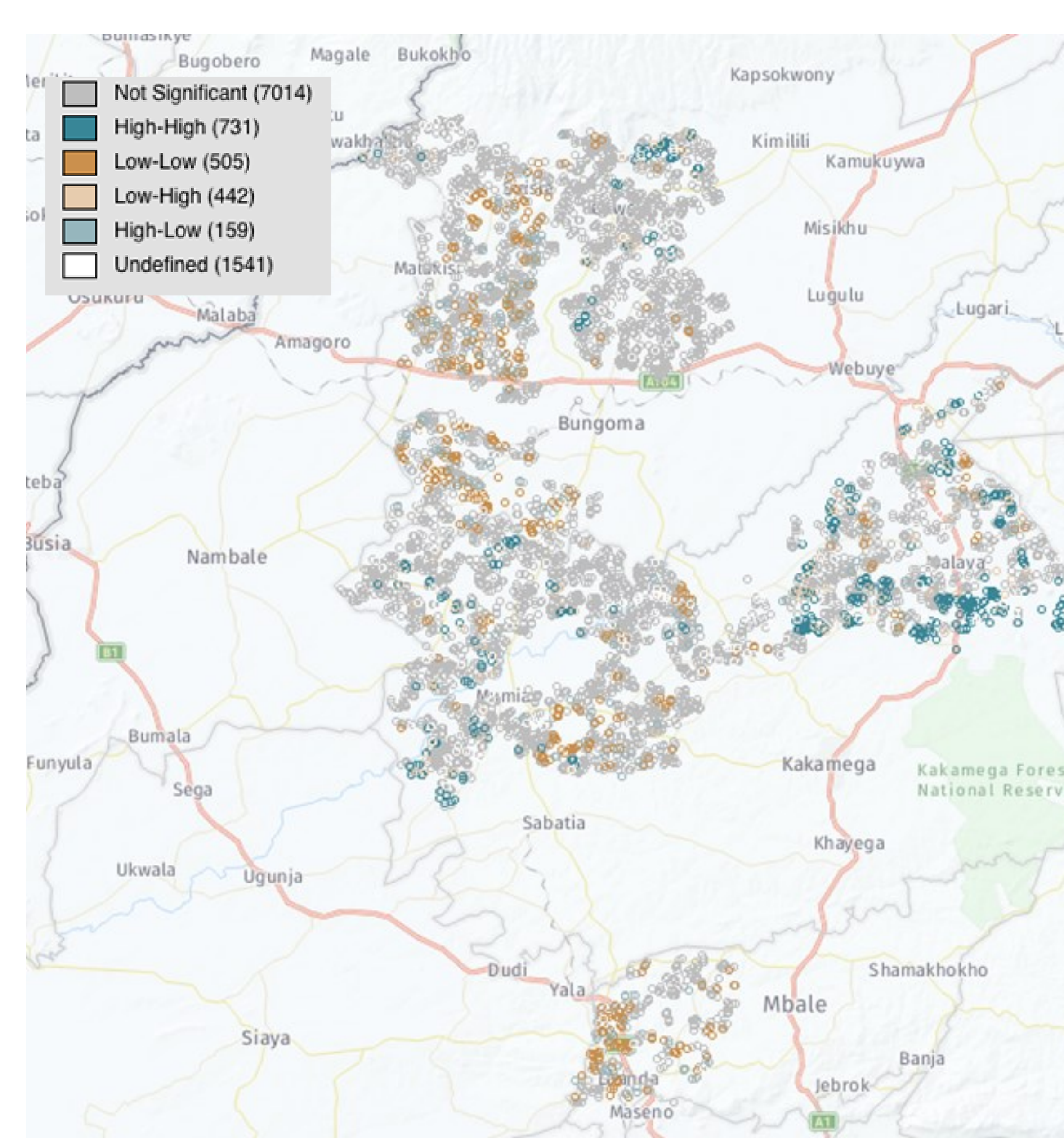

Fig 5: Regression Residuals Local Cluster Analysis (Space)
Outcome: Stored Water *E. coli* Concentration
Predictor: Precipitation Day of

Cartography and Analysis by Julie Powers

GIS 102 May 2018

Coordinate System: WGS 1984 UTM Zone 37N

Projection: Transverse Mercator

Data Sources:

Precipitation: Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS)

Temperature: National Centers for Environmental Prediction (NCEP) Climate Forecast System (CFS)

Environmental Contamination Data: WASH Benefits Project, Kenya

References

1. Levy, K., Woster, A. P., Goldstein, R. S., & Carlton, E. J. (2016). Untangling the impacts of climate change on waterborne diseases: A systematic review of relationships between diarrheal diseases and temperature, rainfall, flooding, and drought. Environmental Science and Technology, 50(10), 4905-4922.
2. IPCC. Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change 2014, 1-33.
3. GBD Diarrhoeal Diseases Collaborators (2017). Estimates of global, regional, and nationalmorbidity, mortality, and aetiologies of diarrhoeal diseases: a systematic analysis for theGlobal Burden of Disease Study 2015. The Lancet Infectious Diseases.