Overview – After briefly analyzing the data streams provided, I was initially curious ***whether farming/herding related conflicts is a function of climate conditions (e.g., temperature, precipitation), a reflection of overall civil unrest in Kenya, or a function of both factors.*** This curiosity drove the rest of my analysis, which was broken into two parts. First, I generated a Kenya-wide analysis to answer this question, and then I dove into a specific county in Kenya, Trans Nzoia (See figure on website), to conduct the same analysis to determine whether similar findings emerged at both a large and a small spatial scope. Below I explain the specific data preparation and time-series analysis that I conducted, and I explain preliminary findings from this exercise. All this information is summarized in a website I created and all R scripts and website formatting can be found at the GitHub page associated with the website.

Data Preparation and Justification – The first task I conducted for this analysis was to spatially match the climate data (i.e., the precipitation and temperature anomaly data) and the conflict data to Kenya and Trans Nzoia. Note that for the quantitative analysis I describe below, I only used the climate anomaly data and the conflict data due to time constraints and my strongest familiarities working with csv files. However, I did briefly examine the land cover and the rainfed area data and used this information to narrow in on Trans Nzoia County for the second analysis (See figure on website here). Next, after briefly analyzing the Kenya and Trans Nzoia conflict data, I noticed that not all the conflict entries were related to farming/herders. So, I then attempted to filter the conflict data that I believed was related to farming and herding based on key words such as farm, herd, cattle, crop, livestock, flock, water, pasture, etc. This gave me a subset of the conflict data that I believe were due to farming/herding for both spatial scale models (see online figure). The final data preparation step I took was to summarize the climate anomaly data across space to generate a mean statistic for each year across all of Kenya and within Trans Nzoia. This data was then fed into the time series quantitative analysis (See figure 1 below).

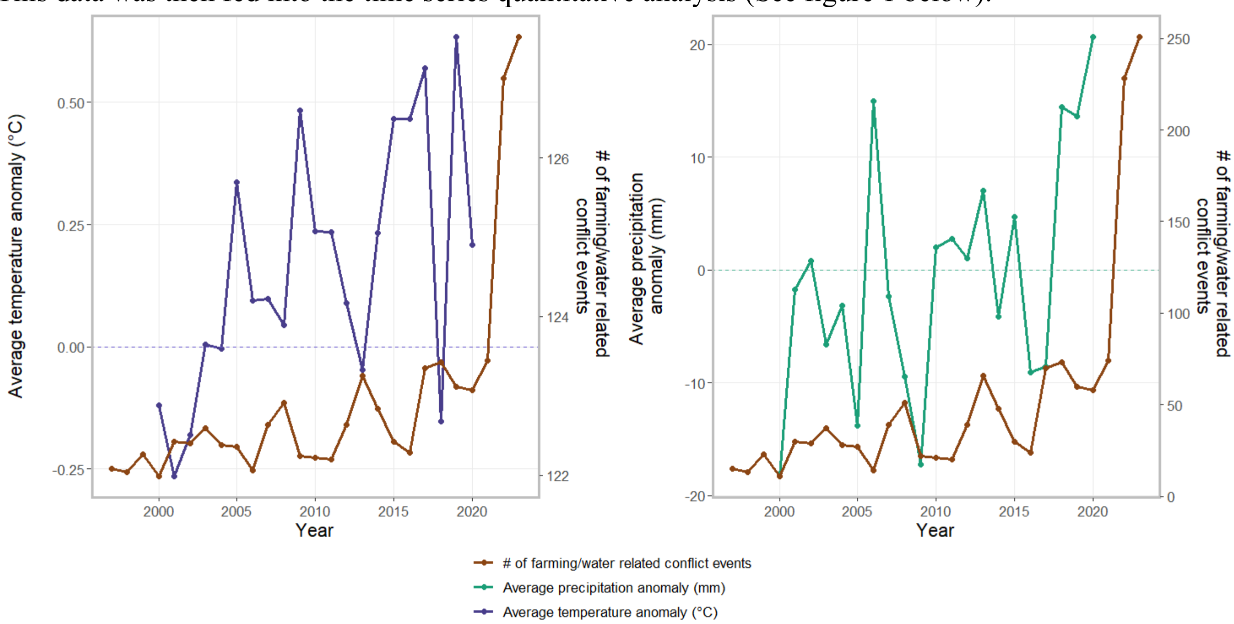

Figure 1. Average temperature (left) and Average precipitation anomaly data (right) against the farming/water related conflict event data used in the Kenya-wide Analysis (see website for Trans Nzoia)

Quantitative Analysis – Given that the climate anomaly and conflict data are time dependent, I conducted a time-series analysis (using an AR1 model) to determine how well the different covariate data sets explain the farming conflict data. The response variable was the farming/conflict data (noted as farming conflict below) and the following data streams were included as predictor variables: total conflicts in Kenya, average precipitation anomaly, average temperature anomaly, and year. A list of the models and their respective AIC scores for both the Kenya-wide and Trans Nzoia analysis are shown below.

Website full link: https://briellekthompson.github.io/KenyaConflictRisks/

Table 1. Descriptions of models run for the time-series analysis with model AIC results for the Kenya and Trans Nzoia analyses. The lowest AIC scores reflect the top model, indicated by **. The top climatic only models are indicated with *

Model	Kenya-Wide Analysis AIC	Trans Nzoia Analysis AIC
Full: farming conflict ~ total conflicts + average precipitation anomaly + average temperature anomaly + year	155	55.0
Unrest only: farming conflict ~ total conflicts	**152****	**51.4****
Climate only: farming conflict ~ average precipitation anomaly + average temperature anomaly	185	71.4
Precipitation only: farming conflict ~ average precipitation anomaly	183	**69.5***
Temperature only: farming conflict ~ average temperature anomaly	183	69.9
Unrest trend: farming conflict ~ total conflicts + year	154	52.5
Climate trend: farming conflict ~ average precipitation anomaly + average temperature anomaly + year	175	72.6
Precipitation trend: farming conflict ~ average precipitation anomaly + year	179	71.1
Temperature trend: farming conflict ~ average temperature anomaly + year	**174***	71.9
Trend only: farming conflict ~ year	177	69.9

Findings – The biggest takeaways were that overall civil unrest is the greatest predictor of farming related conflicts (See **models in Table 1). We further verified this finding by observing how well each model performed in predicting the farming conflict data (Figure 2, see online gif). Nonetheless, we found that if we only considered models that included only climatic data (i.e., removing the total conflicts data), we find that the top climatic model is a temperature trend for the Kenya-wide analysis and the precipitation only model for the Trans Nzoia Analysis (See *models in Table 1). This may indicate that at a finer spatial scale, precipitation drives farming related conflict more than temperature. (See diagnostics)

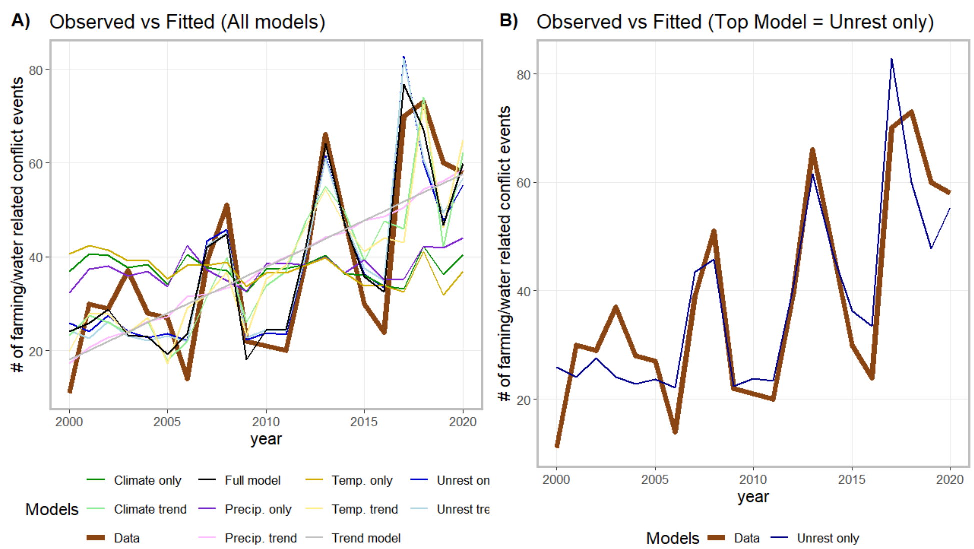

Figure 2. A. Representation of how all the models (shown in color) performed in predicting the farming conflict data (shown in brown). For the Kenya-wide analysis. **B.** Representation of how the top model performed in predicting the data (see website for Trans Nzoia results)

Software used – All analysis was done in R/RStudio and all figures were produced in R, except for the figure explaining the reasoning for selecting Trans Novia for the analysis (see online figure here), which was executed in ArcGIS. I used markdown to create the summary website and git/GitHub for file storage.

Future work – I had additional time I would build a spatial-temporal time series model that performs this similar analysis for more than one county. Further, I would incorporate the land cover and rainfed crop data as additional model covariates. I would also rigorously disentangle farming and herder related conflicts in the large conflict data file and verify that the correct spatial extent is expressed in all data sources. I would wish to obtain other data sources such as fine-scale information on where herding and farming occurs in Kenya and additional covariate data (e.g., irrigation data, agricultural policy change data, agriculture production data, etc.).

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