Using Remotely Sensed Data for Social & Economic Decision Making in Zimbabwe

VIRGINIA TECH

Data Science *for the* Public Good

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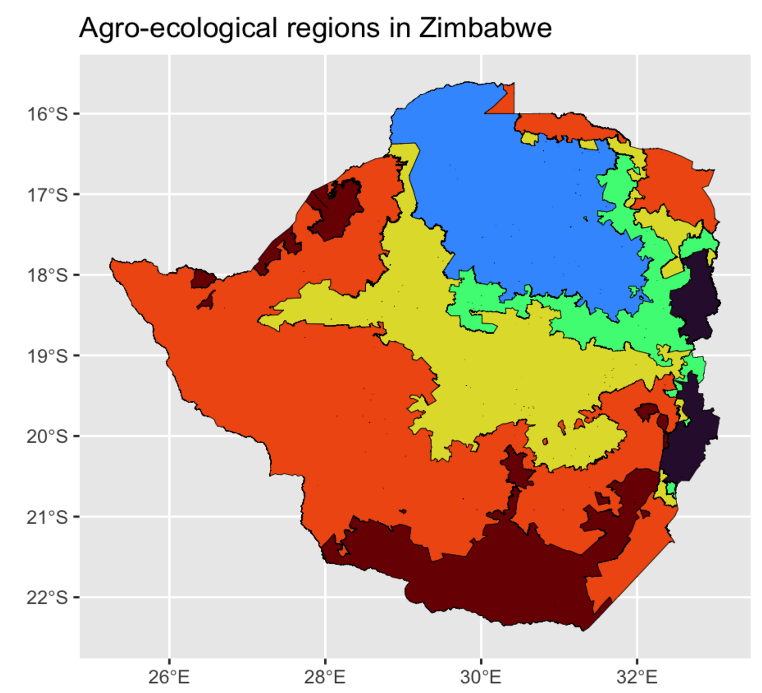
Introduction

- In Zimbabwe, agriculture is a mainstay of the economy and the livelihood for most rural poor.
- Since 2000, the commercial agriculture sector has experienced macroeconomic instability from events like a mismanaged land reform program, diseases, and droughts in 2003 and 2016.
- The remotely sensed climate-related data that are publicly available and suitable for Zimbabwe are Enhanced Vegetation Index (EVI), Precipitation, and Soil Moisture.
- Using these indices, we provide a geospatial analysis of the 2010-11 and 2016-17 maize growing seasons for the five Agro-ecological regions.
- Our analysis is disaggregated to the 60 administrative district-level to study the association between the climate indicators and variables constructed from the 2011 and 2017 national Poverty Income Consumption Expenditure Surveys (PICES).
- The results suggest whether climate data can identify at-risk regions for policy intervention.



Natural Region	Area (000Ha)	% of total area	Annual Rainfall (mm)	Farming Systems
I	613	1.56	>1000	Suitable for dairy farming forestry, tea, coffee, fruit, beef and maize production.
II	7 343	18.68	700-1050	Suitable for intensive farming, based on maize, tobacco, cotton and livestock.
III	6 855	17.43	500-800	Semi-intensive farming region. livestock production, cash and fodder crops.
IV	13 010 036	33.03	450-650	Semi-extensive region. Suitable for farm systems based on livestock and resistant fodder crops. Forestry, wildlife/tourism.
V	10 288 000	26.2	<450	Extensive farming region. Suitable for extensive cattle ranching. Zambezi Valley is infested with tsetse fly. Forestry, wildlife/tourism.

Objectives

- Identify the remotely sensed climate-related data that are publicly available and suitable for Zimbabwe.
- Provide a geospatial analysis of the five Agro-ecological regions in the 2010-11 and 2016-17 growing seasons.
- Examine the association between district-level poverty and climatic conditions.

Data

Remote Sensing Data

Remote sensing is the process of getting information from a distance. Our data are collected by NASA who observes Earth's reflected or emitted energy through sensors on aircrafts or satellites (NASA, 2019).Google Earth Engine then distributes the datasets such as the following:

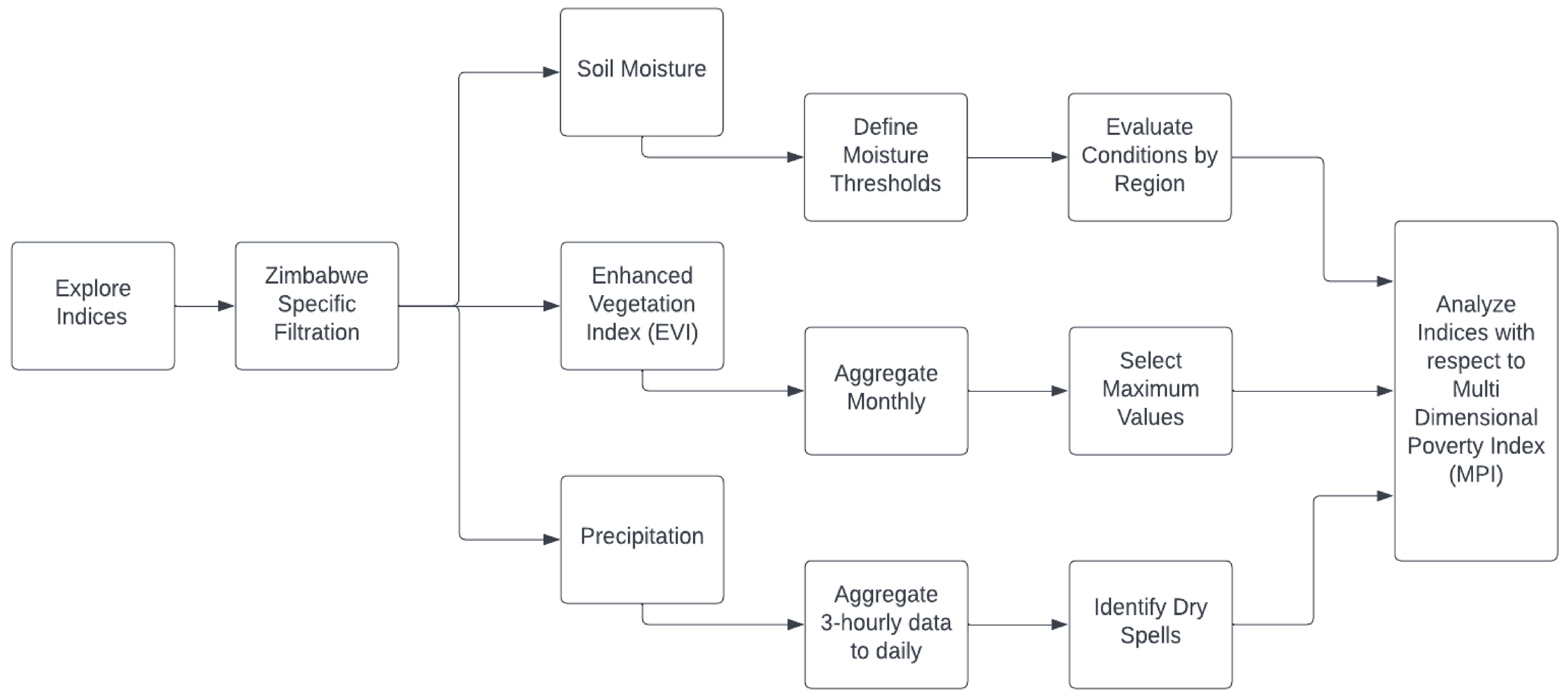
- Enhanced Vegetation Index (EVI) can be used to quantify vegetation greenness and provides a scope to look at vegetation states and processes (NASA, 2019).
- Precipitation has undergone processing through the TMPA Algorithm, and is produced over a 3-hour period, and rendered at a resolution of 27830 meters observed around the global belt (50° North and South).
- Soil Moisture data provides global soil moisture information at a 10 km spatial resolution and includes five indices: Surface and Subsurface soil moisture, Soil moisture profile (percent soil moisture), and surface and subsurface soil moisture anomalies from 2015 to 2022.

PICES Data

The data come from two nationally representative household surveys, called the PICES, conducted by ZIMSTAT: first, from June 2011 to May 2012, and second, from January to December 2017.

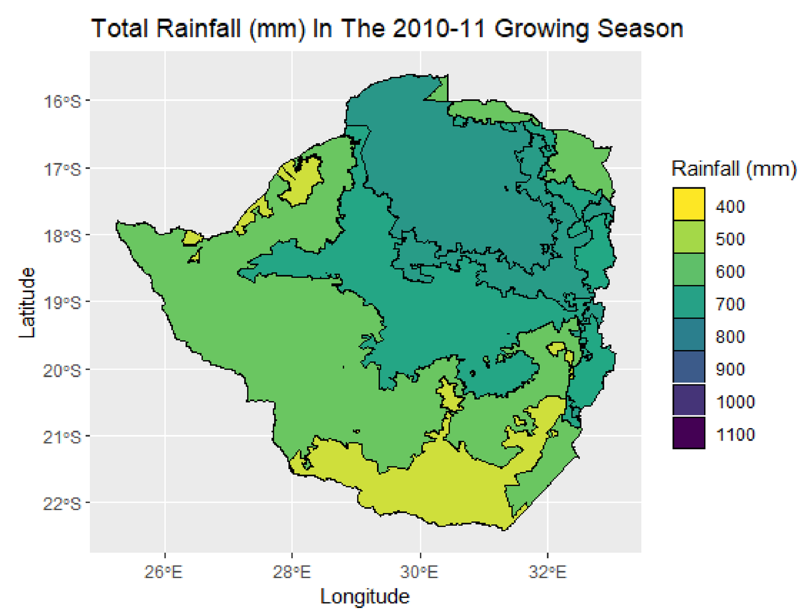
The repeatedly-collected PICES surveys include both household and individual level information. They were conducted in the eight Zimbabwe provinces and the cities Harare and Bulawayo. In 2011–2012 there were 29,748 usable observations (households) while there were 31,193 in 2017

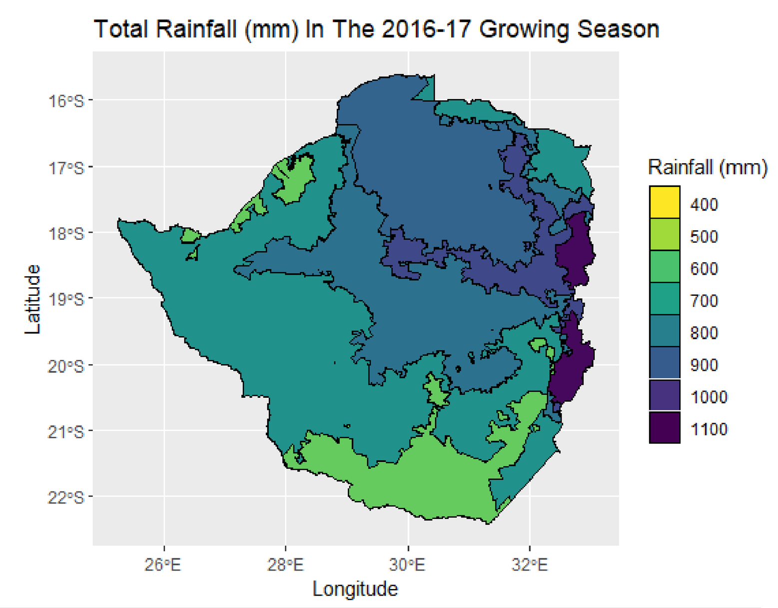
Methodology



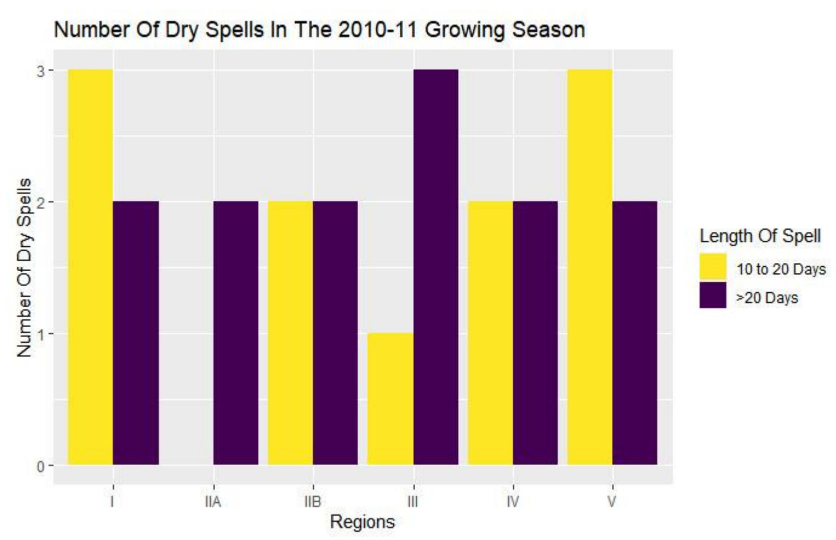
Remote Sensing Results

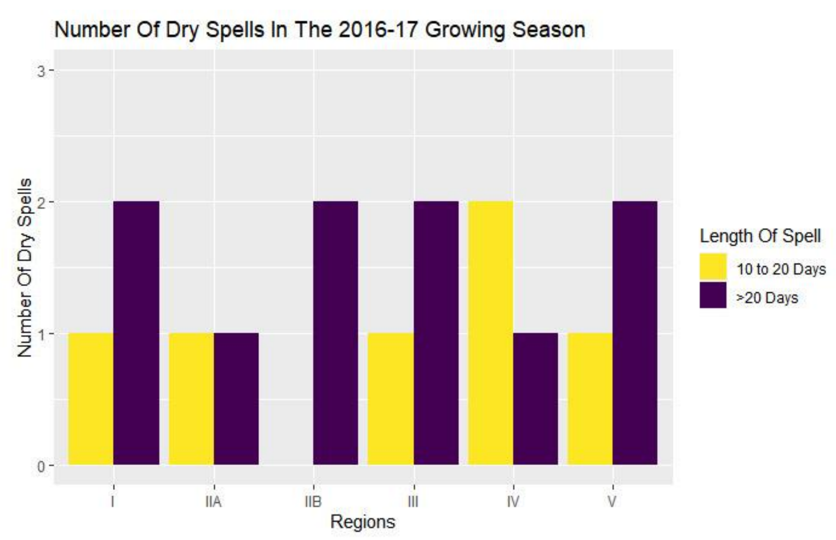
Results from Precipitation Index





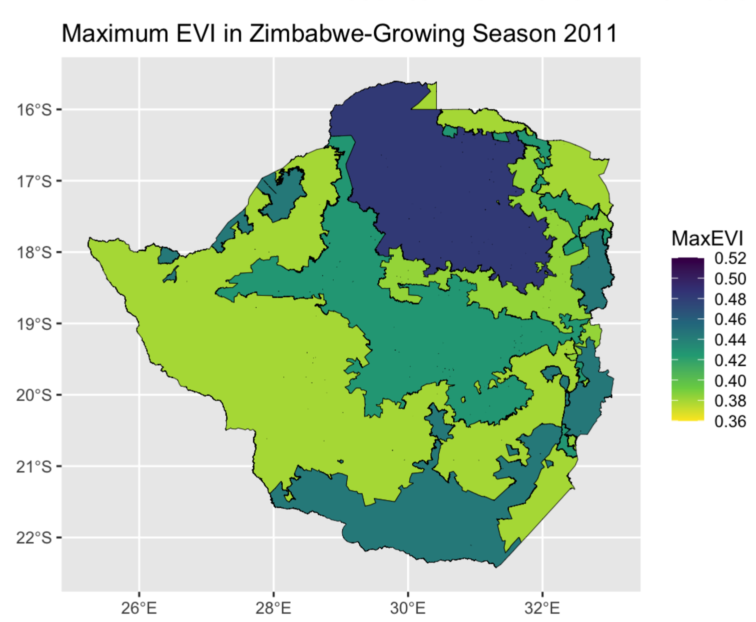
These visualizations show us the total rainfall during the two growing seasons, which when compared indicate that every region received a higher amount of rainfall in 2016-17 than in 2010-11. For maize production, the ideal range of rainfall is 600-700 mm with excess of 1000 mm potentially leading to a decline in maize yields.

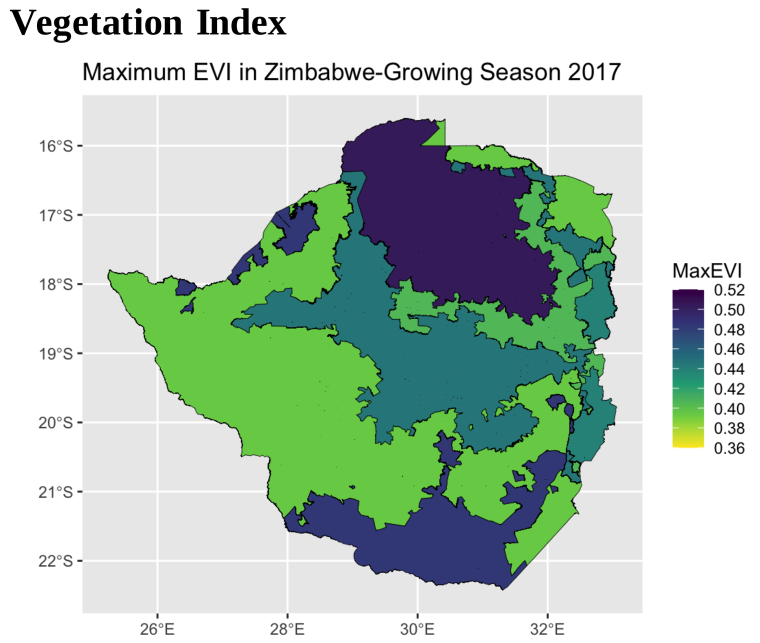




The graph shows the number of dry spells by region; A dry spell is described to be a consecutive series of dry days between 10 to 20 days or 20 days or more. Dry spells play a significant role in agricultural success by indicating plant stress exposure while their length and severity can result in the decreased yields or complete failure of a crop (Nyakudya et al., 2011; Mhizha et al., 2014).

Results from the Enhanced Vegetation Index





The graphs above show the maximum EVI (which corresponds to the density of crops) in Zimbabwe during growing season in 2011 and 2017, respectively. Compared to the growing season in 2011, the deeper color shows that almost every region has a higher maximum EVI during the growing season of 2017. By solely looking at the data, we can also observe that the overall range of maximum EVI during the growing season in 2017 is also higher than in 2011, with the approximate minimum value being 0.4 (higher than 0.38 in 2011) and the approximate maximum value being 0.5 (higher than 0.48 from 2011).

Statistical Results

Correlations Between Poverty & Weather Indices

2011	Poverty Index	No Primary Education	Unenrolled Child	Chronic Illness	Lack of Health Visit	Lack of HH Assets	Lack of Access to Services
Max EVI	0.0689	0.096	-0.00246	0.0687*	-0.0466	0.00554	-0.00391
Total Rainfall (mm)	-0.295**	-0.28**	-0.173	-0.177	-0.195	-0.317**	-0.289**
Dry Spell: >= 10 days	-0.0802	-0.0253	0.0742	-0.0011	-0.0388	0.0126	-0.061
	*** p<0.01, ** p<0.05, * p<0.1						

2017	Poverty Index	No Primary Education	Unenrolled Child	Chronic Illness	Lack of Health Visit	Lack of HH Assets	Lack of Access to Services
Max EVI	0.104	0.221*	0.2	-0.373**	-0.133	0.247*	0.0635
Total Rainfall	-0.152	-0.24*	0.185	-0.245*	0.0771	-0.126	-0.138
Dry Spell: >= 10 days	0.14	0.143	-0.29**	0.28*	-0.0562	0.134	0.155
Avg. Surface Soil Moisture	-0.0347	-0.302*	0.112	-0.143	0.248*	-0.0937	-0.0426
	*** p<0.01, ** p<0.05, * p<0.1						

The graphs above show the correlations between the multidimensional poverty index and the weather indices in district level in 2011 and 2017. In 2011, the correlation coefficient between total rainfall and the poverty index was -0.295. This means that there is an inverse relationship between the two variables, meaning that an increase in rainfall corresponds to a decrease in the poverty index. The coefficient is also statistically significant at the 5 percent level.

Conclusions

- We display the remote sensed data: Enhanced Vegetation Index, Precipitation, and Soil Moisture from the Google Earth Engine and the MPIs in maps and graphs.
- We assess the remote sensed data by agroecological regions in Zimbabwe.
- We use these data at the district level to explore the correlation between remote sensed data and poverty and its other socio-economic components.
- We explore changes between the two most recent waves of PICES surveys (2011 & 2017).

Takeaways

EVI: EVI is highest in Region IIA, which, according to United Nations' Food and Agriculture Organization, is suitable for intensive farming. Region IV has the lowest maximum EVI value, and the FAO describes it as the "semi-extensive" farming region, suitable for resistant fodder crops.

Precipitation: The Northern regions are typically the ones to receive the most rainfall. The Southern region on the other hand receive less rainfall.

Soil Moisture: Regions I through III have dry, and regions IV and V have extremely dry, surface soil moisture levels during planting time. These levels suggest that farmers in all regions are likely to experience stifled germination upon planting; however, farmers in regions IV and V are likely to be more severely impacted.

We observe a negative correlation between total rainfall and the average poverty rate in both years, However, we do not find a significant correlation between other weather indices and the average poverty rate.

Team

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