THE VARIABILITY CLIMATE CHANGE IS RESPONSIBLE FOR IN VEGETATION LOSS IN GHANA

KALONG BONIFACE - UEB3603118
FUGAH SELETEY MITCHELL - UEB3602818
SUPERVISER: MR JUSTICE AMENYO KESSIE

Department of Mathematics and Statistics
University Of Energy and Natural Resource,Sunyani

October 20, 2022

Outline Of Presentation

- Introduction
- Problem Statement
- Objective
- Methodology
- Result and Discussion
- Reference

INTRODUCTION

One would anticipate that the majority of emerging nations, which are still in the early stages of economic development and growth, would have a high forest cover and little deforestation. This, however, has not been the case. Ghana is a lower-middle-income nation that is still working toward middle-income classification. However, it has already begun to see a deforestation rate that is comparable to that of middle-income countries. The rapid population expansion, clearing of field for Galamsey operation,increased domestic need of wood for things like fuel, furniture, construction, and timber exports have all contributed to this trend, Bush fires in the 1980s, climate change, and lax law enforcement have all had an impact.

PROBLEM STATEMENT

The Footprint of vegetation loss is spreading at a very faster rate, causing vegetation loss. This research attempts to segregate the variability climate is responsible for in vegetation loss so as to attribute the residual variability to Galamsey and other related activities such as bush-fires etc.

OBJECTIVE

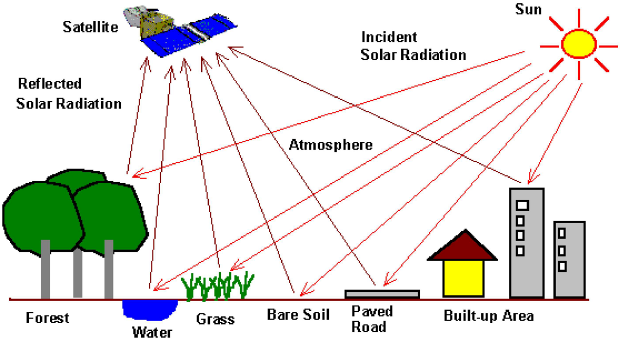
- Perform time series analysis on satellite derived vegetation indices and Climatic Data
- Dissociate or single out the variability climate is responsible for in vegetation loss

Limitation Of The Study

- Missing Data
- Atmospheric factors can distort the visual findings, causing the vegetation's color to shift dramatically from image to image as a result of atmospheric factors (fog, ground moisture, cloud cover)

Data

The Satellite (MOD13) provide consistent,and spatial time series comparisons of global vegetation conditions that can be used to monitor the Earths photosynthetic vegetation activity in support of **change detection**, and biophysical interpretations.For this analysis, we will be using the MOD13Q1 V6 product which contains the Enhanced Vegetation Index (EVI).



Data

$$EVI = G\left[\frac{NIR - Red}{NIR + C_1 Red - C_2 Blue + L}\right] \quad (1)$$

- NIR, Red, and Blue are the surface reflectances that have been fully or partially adjusted
- C1 and C2 are the coefficients of the aerosol resistance term
- L is the canopy background adjustment for correcting the nonlinear, differential
- G is a gain or scaling factor. The MODIS EVI algorithm's chosen coefficients are Where;
  - L=1, C1=6, C2=7.5, and G=2.5.
- $-1 \leq$ EVI ≤ 1

Data Extraction

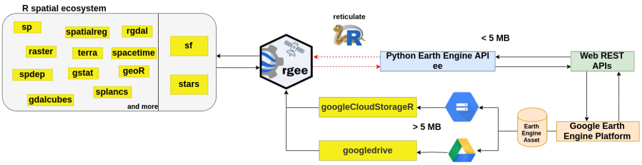


Figure: Data Extraction from Google Earth Engine

- We will summarize the mean EVI values.
- We will apply a smoothing strategy using an ARIMA function to fix the situation where some cells may not have EVI for a particular month.
- Eliminate seasonality before the normalized data is fitted using a linear model.

Data Visualization -(Univariate Analysis)

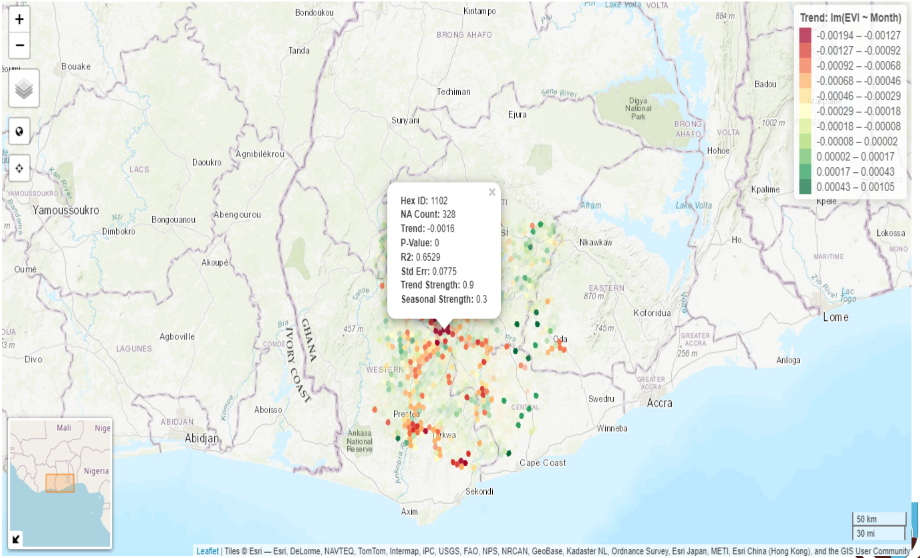


Figure: Vegetation Loss

Methodology -(Multivariate Analysis)

* To help machine learning classifiers works better with time series data .
* Local features or patterns in time series can be found and combined to address challenges involving time-series categorization.
* Then, a method to discover patterns that are helpful for classification is suggested.
* Combine these patterns to create computable categorization rules.

Vector Autoregression (VAR)

It is of the form $y_t = A_1 y_{t-1} + A_2 y_{t-2} + \cdot + A_p y_{t-p} + CD_t + \mu$

where;

- $y_t = (y_{1t}, y_{2t}, ..., y_{kt})'$ is a vector of K observable endogenous variables
- For the purposes of this study, yt = $(EVI_t, Temperature_t, Rain, Precipitation_t, Drought_t, Evaporation_t)'$

where EVI denotes the value of vegetation conditions each month

Structural Analysis (VAR)

- Augmented Dickey Fuller unit root test
- Lag Selection using information Criteria
  - Akaike Information Criterion(AIC)
  - Hannan-Quinn criterion(HQ)
  - Schwarz Criterion(SC)
  - Final Prediction Error criterion(FPE)
- Causality Test (Granger Causality)
- Impulse Response Analysis
- Forecast Error Variance Decomposition (FEVD)

Result (VAR TimeSeries Plot)

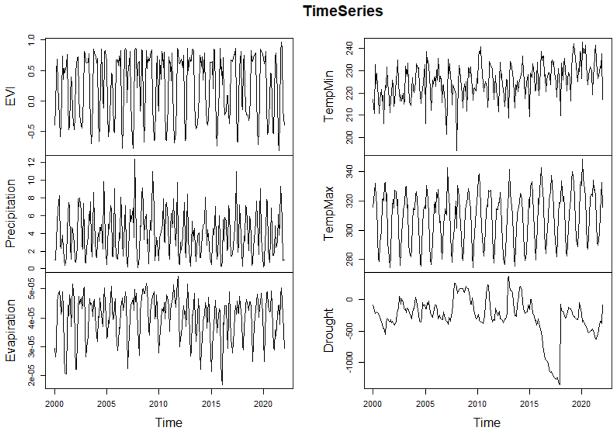


Figure: Time Series Plot

Result -(ADF) unit root test and(Granger Causality)

- H_0: "Process has unit root" vs. H_1: "Process has no unit root".
- Now we made comparison with the critical values under H_0

Since all the test statistic are much lower than all of the critical values we reject H_0 at a significance level $<1\%$. So you can conclude with a very low probability of making an error that your time series has no unit root. So, We reject H_0.

Table: Granger causality tests.

Cause variable	Null hypothesis	F-value	p-value	Decision
Precipitation	does not Granger-cause EVI	2.1563	0.01464	Reject the null hypot
Evaporation	does not Granger-cause EVI	1.5398	0.1112	Fail to Reject the nul
TempMin	does not Granger-cause EVI	3.0049	0.0006276	Reject the null hypot
TempMax	does not Granger-cause EVI	2.7462	0.001685	Reject the null hypot
Drought	does not Granger-cause EVI	0.9235	0.5241	Fail to Reject the nul

Result -(Forecast)

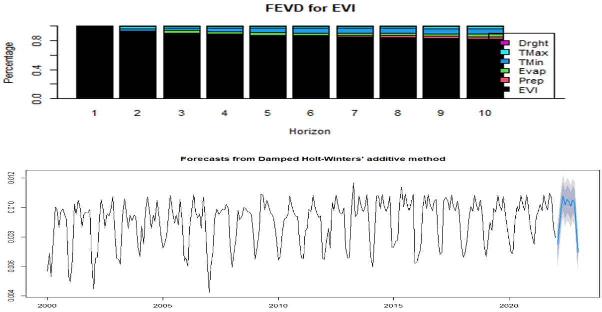


Figure: FEVD and Forecast

Table: EVI forecast for the next 12 month.

Month	Forecast	Lower	Upper	CI
Feb 2022	-0.07548865	-0.65614302	0.5051657	0.5806544
Mar 2022	0.14803164	-0.56646127	0.8625245	0.7144929
Apr 2022	0.69105704	-0.04392727	1.4260414	0.7349843
May 2022	0.72499702	-0.05679272	1.5067868	0.7817897
Jun 2022	0.44066359	-0.41564183	1.2969690	0.8563054
Jul 2022	-0.11537243	-0.98453117	0.7537863	0.8691587
Aug 2022	-0.37165805	-1.24946226	0.5061462	0.8778042
Sep 2022	-0.16672258	-1.05855108	0.7251059	0.8918285
Oct 2022	0.16015717	-0.73872579	1.0590401	0.8988830
Nov 2022	0.37177202	-0.53806829	1.2816123	0.9098403

Accuracy and Discussion

Table: Forecast Accuracy on EVI Training set

ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
-1.384005e-17	2.665621e-01	2.065071e-01	-Inf	Inf	0.00131	0.0123

These findings are consistent with research by L.S Achille et al. They showed that maximum temperature and precipitationăăparticularly in the transition zone, was a better predictor of EVIătrends than minimum Evaporation, although the findings of L.S Achille et al. show that Droughtăis not important.

References

Science of the Total Environment 146644 (781).

Introduction to Multiple Time Series Analysis, Springer-Verlag, Berlin, Germany, 1993

, Distribution of the estimators for autoregressive time series with a unit root, Journal of the American Statistical Association, vol. 74, no. 366, pp. 427431,1979.

THANK YOU!