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

Quantifying The Status of Galamsey With Time Series Analysis

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Outline Of Presentation

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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.

Introduction Con't

The purpose of this paper is to establish an understanding in time series analysis on remotely sensed data. Which will introduced us to the fundamentals of time series modeling, including decomposition, autocorrelation and modeling historical changes in Galamsey Operation in Ghana, the Cause,Dangers and it's Environmental impact

Introduction Con't

Galamsey also known as "gather them and sell",*Owusu-Nimo2018* is the term given by local Ghanaian for illegal small-scale gold mining in Ghana . The major cause of Galamsey is unemployment among the youth in Ghana *Gracia2018*. Young university graduates rarely find work and when they do it hardly sustains them. The result is that these youth go the extra mile to earn a living for themselves and their family.

PROBLEM STATEMENT

The Footprint of Galamsey is Spreading at a very faster rate, causing vegetation loss.Other factors accounting to vegetation loss may largely include climate change,urban and exurban development, bush fires. But not much works or research has been done to tell the extent to which Galamsey causes 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.

Research Questions

To address the challenge of the vegetation variability in this work, the following several statements were formed:

- Are there any changes in vegetation cause by Galamsey and Climate change in Ghana?
- Is there any relationship between vegetation and land surface temperature in Ghana?

OBJECTIVE

The purpose is to establish an understanding in time series analysis on remotely sensed data. We will be introduced to the fundamentals of time series modeling, including decomposition, auto-correlation and modeling historical changes.

- Perform time series analysis on satellite derived vegetation indices
- Estimate the extent to which Galamsey causes vegetation loss in Ghana.
- Dissociate or single out the variability climate is responsible for in vegetation loss

Significance Of The Study

In this study, we want to examine the effects of climatic change on Ghana's vegetation during these thirty years.

- This study allows us to explore climatic differences and climate-related drivers.
- It offers a chance to research how climatic variability affects the ecosystem and human health.
- This study explores historical and projected vegetation and climate data, by sector, impacts, key vulnerabilities and what adaptation measures can be taken.
- It also explores the overview for a general context of how climate change is affecting Ghana.

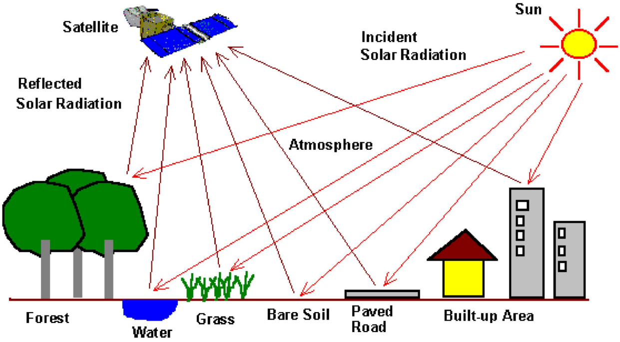
Limitation Of The Study

The goal of time series modeling is to employ the simplest model feasible to account for as much data as possible while still developing an explanatory model of the data that does not over-fit the issue set.

- Missing Data
- It is almost certain that data from distant sensing will not provide the same level of precision.
- 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 Earth's 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

$$EVI = G\frac{NIR - Red}{NIR + C1Red - C2Blue + L}$$

Figure:

NIR, Red, and Blue are the surface reflectances that have been fully or partially adjusted for Rayleigh scattering and ozone absorption due to the atmosphere; C1 and C2 are the coefficients of the aerosol resistance term (which uses the blue band to correct for aerosol influences in the red band); L is the canopy background adjustment for correcting the nonlinear, differential NIR and red radiant transfer through a canopy; and G is a gain or scaling factor. The MODIS EVI algorithm's chosen coefficients are L=1, C1=6, C2=7.5, and G=2.5.

Data

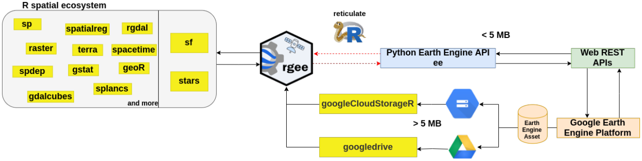


Figure: Data Extraction from Google Earth Engine

Instead of analyzing the imagery directly, 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. Once NA values have been eliminated, the time series will be divided to eliminate seasonality before the normalized data is fitted using a linear model. We will go to classify our data on the map and map it after we have extracted the linear trend.

Methodology

we will first collect data from Google Earth Engine in order to choose EVI values and Climate Change data.

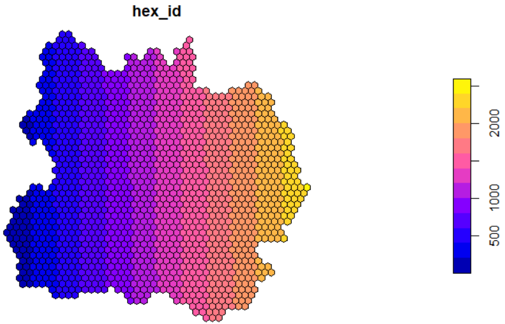


Figure: Creating Hex cell(Polygons) on the Study Area

Methodology Cont'

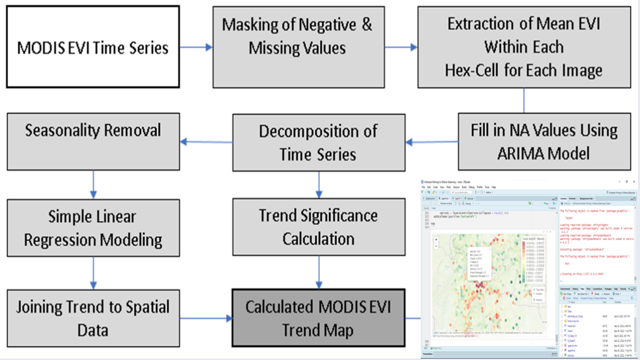


Figure: Flow Chart to Galamsey Detection

Methodology Cont'

* 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

explanation

- Augmented Dickey Fuller unit root test
- Lag Selection using information Criteria (AIC,HQ,SC,FPE)
- Causality Test (Granger Causality)
- Impose Analysis
- Decomposition of Variance (FEVD)

Measures of forecast accuracy

Definitions	Observation y_t	Forecast $\hat{y}_t$	Forecast error $e_t = y_t - \hat{y}_t$

Accuracy measure	Calculation
Mean Absolute Error	$MAE = average(\lvert e_t \rvert)$
Mean Squared Error	$MSE = average(e_t^2)$
Mean Absolute Percentage Error	$MAPE = 100 \times average(\lvert \frac{e_t}{y_t} \rvert)$
Mean Absolute Scaled Error	$MASE = MAE/Q$

* Where Q is a scaling constant.

Result

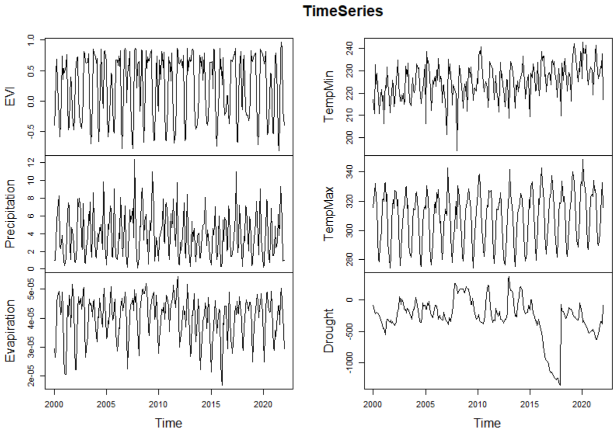


Figure:

Result Causality

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

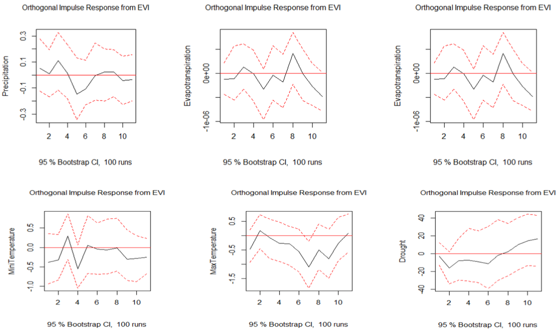


Figure:

Result

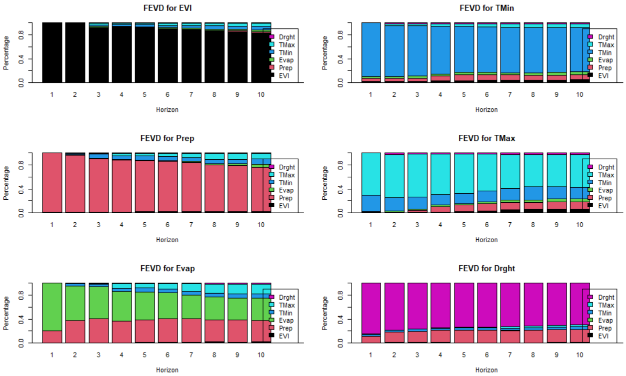


Figure:

Discussion

The Granger and immediate causality tests reveal that only three climate factors have an impact on malaria. The impulse response analyses show that the ninth, third, and tenth months, respectively, had the strongest favorable effects of maximum temperature, relative humidity, and rainfall on malaria. With less than 20% of the variability in the trend of EVI being explained by historical innovations in Climate Change, the decomposition of predicted variance shows varied degrees of EVI dependence on climatic variables. Policymakers can utilize the study's findings to assist them develop policies by understanding how climatic variability affects the incidence of EVI in the Study Area.

References

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