SPATIO-TEMPORAL DYNAMICS OF DROUGHT IMPACTS IN DIFFERENT VEGETATION COVER TYPES USING GOOGLE EARTH ENGINE

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ABSTRACT

Google Earth Engine has provided a platform to access multiple data sources in different scales, which is of interest to time- series analyses in general and for vegetation studies particularly. This paper demonstrated the potential of using this open data source for studying spatio-temporal dynamics of drought impacts. By combining both available simulation and remote sensing observation data, we analyzed how the impact changes due to differences in vegetation cover types and structure. We also discussed the limitation of the platform due to data availability, analysis techniques and accuracy assessment of the work.
Keywords: Google Earth Engine, remote sensing, spatio-temporal, drought, vegetation.

1. INTRODUCTION

Climate change is recognized as one of the major threats for the planet earth in the twenty-first century, which consequences is not the change in average but the overall increase of extreme events (Mishra and Singh 2010). Among this, drought is one of the main subjects that bring a great deal of systematic study, computations of drought frequency, and investigations of impacts of drought on society (Wilhite and Glantz 1985). Characterizing and assessing drought impacts is complicated, as responses can vary in space, time, and among species (Clark et al. 2016). Drought impacts become most apparent when large-scale changes are observed or when water requirements for human or agricultural needs are not met. However, even moderate droughts can have long-lasting impacts on the structure and function of forests and rangelands without these obvious large-scale changes.

Remote sensing is a relatively cost-effective method to monitor the condition of vegetation under water stress across large areas especially for such remote areas with limited data (Jiao et al. 2016). Development in remote sensing approaches attempts to observe direct, secondary, and longer-term effects of drought on vegetation. Still, most works mainly focus on mapping drought impacts connecting with land cover and abandoning the change in temporal and spatial scale in the correlation with the changes of vegetation status. Insufficient information to reflect the complexity of plant- and ecosystem-water interactions limited studying drought impacts from regional scale (using remote sensing data) to plot scale (using field data).

Google Earth Engine (GEE) is a cloud-based platform for planetary-scale geospatial analysis that brings Google's massive computational capabilities to bear on a variety of high-impact societal issues including deforestation, drought, disaster, disease, food security, water management, climate monitoring and environmental protection (Gorelick et al. 2017). With a petabyte archive of Earth observations and related data and an efficient processing software, GEE and the available tools enables users to acquire, process, analyze, and visualize Earth observing data rapidly for any user-specified region across the globe without downloading and processing a large volume of data on the user's desktop (Sazib et al. 2018).

Therefore, the objective of this paper is to demonstrate using Google Earth Engine (GEE) in monitoring drought impacts on vegetation. In this study, we analyzed time series of vegetation conditions in correlation with precipitation accumulated during the dry season of 2016 in Dak Lak Province, Vietnam. We used Normalized Difference Vegetation Index (NDVI) from Landsat 8 dataset to indicate the status of vegetation since its variance over the time represents real responses of vegetation to climate variability (Zeng, Collatz et al. 2013). With a large number of remote sensing datasets in GEE acquired in long-term period, low cost, high frequency and broad observation, we proposed an approach to utilize GEE supporting managers to understand the drought impact on vegetation at a different scale.

2. METHODS

2.1 Study site

The Central Highlands is one of eight agro-ecological regions of Vietnam as well as one of the most sensitive to El Niño effect, which often leads to severe drought during the dry season (Nguyen and Rosbjerg, 2007). With various plateaus surrounded by mountain ranges and inter-annual variations of rainfall mainly influenced by seasonal winds, serious drought has been occurring in the region, reducing the discharges of main rivers by 20-90% (NCHMF, 2016) and has caused varying degrees of damage to agriculture and the livelihoods of people (CCAFS-SEA, 2016).

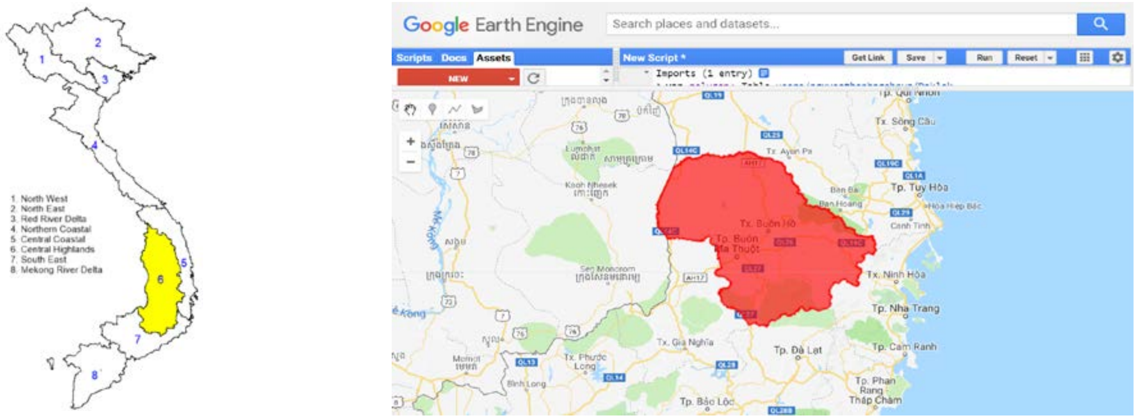


Figure 1. Location of Central Highlands in Vietnam (left- adapted from (CCAFS-SEA, 2016)) and Daklak Province (right- captured at GEE interface)

Among the five provinces of this region, we chose Dak Lak Province as the study site as for its importance in agriculture production and rapid ecosystem changes. This province has the second largest agricultural land area (1.2 million ha). The aggregate area of annual crops is planted mainly with rice, vegetables and other cash crops. The perennial crops are rubber, coffee, black pepper and cashew. As reported by (CCAFS-SEA, 2016), this province has been impacted seriously during drought episodes. The reduction of crop production was estimated for more than 42,400 ha (nearly USD 60 million). Lack of feeds (grasses and forage) and water has also affected the livestock production. However, most of report was on agriculture damage and less information on the status of forestry. Consequently, we focused on analyzing the damage in the vegetation cover, especially the lag impacts in forest ecosystem with a variety of wood and rare animals, mainly in Yok Don National Park, Nam ka Conservation Areas, and Nature Reserves Eakar.

2.2 Collecting data from Google Earth Engine

Normalized Difference Vegetation Index (NDVI) was extracted from Landsat 8 Collection 1 Tier 1 calibrated top-of-atmosphere (TOA) reflectance (Image Collection ID - LANDSAT/LC08/C01/T1_TOA). Calibration coefficients were extracted from the image metadata and the TOA computation followed Chander et al. (2009). The precipitation used to demonstrate the drought episode in this research was the Climate Hazards Group InfraRed Precipitation with Station Data (CHIRPS Pentad) version 2.0 final (Image Collection ID- UCSB-CHG/CHIRPS/PENTAD. This dataset is a 30+ year quasi-global rainfall dataset, incorporating 0.05° resolution satellite imagery with in-situ station data to create gridded rainfall time series for trend analysis and seasonal drought monitoring (Funk, et al 2015).

GEE Code Editor scripts were used to extract Normalized Difference Vegetation Index (NDVI) data from satellite images, one for each of the study areas. The custom scripts combine elements from official Google resources. GEE automatically computed the NDVI and the precipitation of all pixels in the collection to further analyze their trends over time. We used time series chart function to generate time series graphs from the image collections, which included: corresponding image collection and satellite band data, feature collection, and the scale on which the reducer aggregates values over time on a per pixel basis. In this study, the data was scaled at 30m, resampled with the nearest neighbor algorithm.

2.3 Spatio-Temporal analysis

Time series analysis in Earth Engine is complicated due to the difference of pixel size, varying time period and missing data. As a result of these complicating factors, analyzing time series in Earth Engine is unlike traditional methods. Specifically, use joins to define temporal relationships between collection items. Therefore, it is needed to perform preprocessing to reduce those issues by filtering it to the location of interest, masking clouds, and adding the variables in the model.

Many traditional time series methods can be performed in GEE by mapping functions over joined collections. Earth Engine supports a variety of data mining methods using reducers from the simplest linear regression to ordinary least squares regression (OLS), robust Linear Regression or Principal Component Analysis (PCA).

In this study, we used a simple linear model (equation 1) for detrending data and reducing stationarity in the time series (Shumway and Stoffer 2017).

$p_t = \beta_0 + \beta_{1t} + e_t$ - where e_t is a random error (1)

Also, we estimated seasonality of NDVI with a harmonic model (Shumway and Stoffer 2017) (equation 2). To estimate the importance of terms representing seasonality or higher-frequency harmonic behavior (e.g. double-cropping), we used an F-statistic when the model assumptions are satisfied.

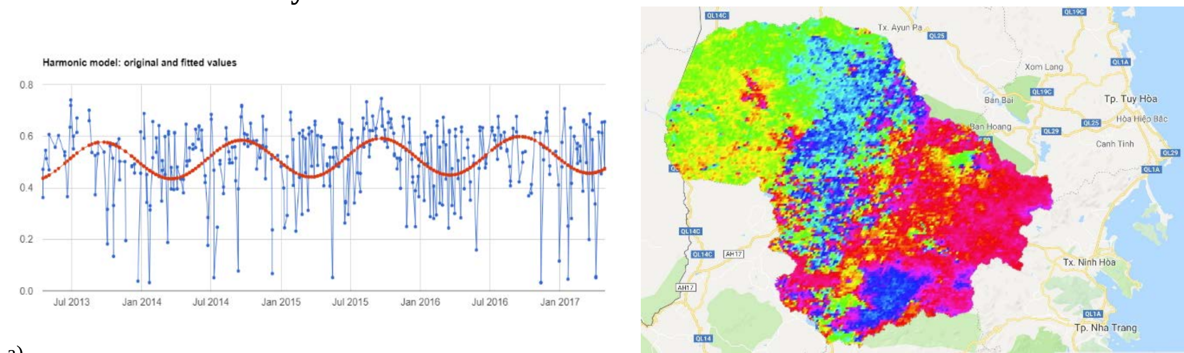
$$p_t = \beta_0 + \beta_{1t} + A\cos(2\pi\omega t - \varphi) + e_t \quad (2)$$

where e_t: random error, A: amplitude, ω: frequency, and φ: phase.

To analyzing the lag effects and dependence of time series data, we analyzed their correspondence between a variable and itself or a covariate during a time scale. The covariance of a time series refers to the dependence (specifically the covariance) of values in the time series at time t with values at time h = t − l, where l is the lag. The correlation is the covariance normalized by the standard deviations of the covariates. Specifically, the cross-covariance and cross-correlation at time t to previous values is useful for defining the lag effects for a variety of other time series analyses. To combine image data with previous values, in GEE, we joined the previous values to the current values by usage of a join to create a lagged collection then use Pearson correlation coefficient to analyze the correlation of NDVI and precipitation.

3. RESULTS AND DISCUSSIONS

3.1 Time series analysis of NDVI



a) b)

Figure 2. Examples of running harmonic analysis in GEE – a) The graph of original and fitted NDVI values- b) Map of phase and amplitude from the model coefficients in HSV (where phase = hue , amplitude = saturation), transformed to RGB

After calculating and preprocessing, we constructed the harmonic time series of NDVI. Although any coefficients in the harmonic can be mapped directly, we also computed and mapped the phase and amplitude of the estimated harmonic model to visualize the decomposed time series as the sum of sinusoids at different frequencies (Shumway and Stoffer, 2017). We can see how the land use and land cover types in the study area were characterized by amplitude and phase values (figure 1-a). High amplitude indicates wide range of seasonal variation. Phase angle indicates the periodicity at which the peak value for the term occurs. Croplands exhibit a strongly unimodal periodic pattern, with a high amplitude values in successive terms. Grasslands have a first-term phase angle close to π, meaning that the peak greenness period is close to midsummer.

Inter-annual variations in the phase values of a term, with the amplitude remaining unchanged, may indicate climatologically – driven variations in the time of onset of greenness or maximum greenness. Changes in the amplitude of a given term, with the phase value remaining constant, may indicate changes in land use/ land cover type or degradation of vegetation condition resulting from drought, flooding or over grazing (Jakubauskas, M. and Legates,D.,2000). We created a map displaying phase and amplitude variation over the study (Figure 2-b). We observed a consistent distribution of phase and amplitude of NDVI time series different by cover types. The agriculture land and grassland showed inter-annual changes in the phase values, whose phenology is driven by principally by seasonal climatic factors. Unexpectedly, only the woody vegetation in South regions of the area tend to have strongly unimodal NDVI curves with the majority of the variance in the data captured by the first harmonic term, while the one locating at the North showed amplitude changes in dry season, indicating signals of drought impacts.

3.2 Lag effect analysis for different cover types

By testing covariance and correlation of NDVI and accumulative precipitation amount in 3 scenarios: 1 month, 2 months and 3 months, we witnessed changes in both spatial distribution and correlation values in different land cover types (figure 3-a,b,c). The correlation seemed to increase in most dense vegetation covers when the lag effects increased. Unsurprisingly, the trend of wetlands and croplands which do not depend on precipitation as the main water source did not change when lag effect changed. Grasslands and shrub-lands even responded strongest in the first month that the drought occurred.

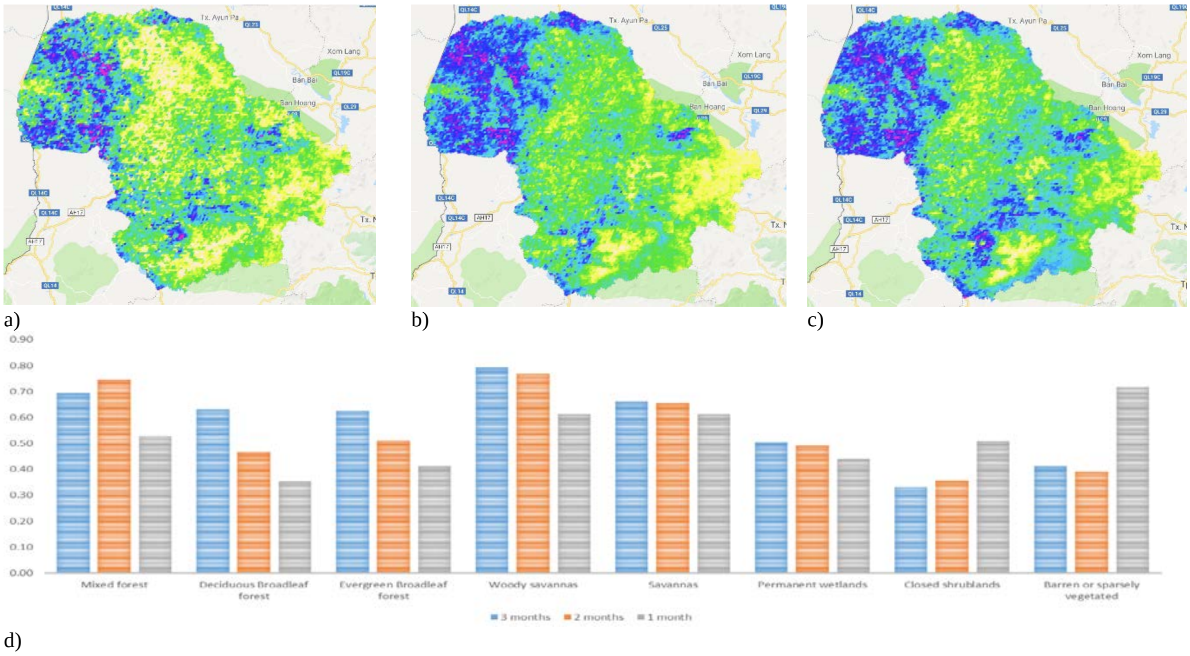


Figure 3. Changes in correlation values due to increasing lag effects in - a) 1 month –b) 2 months – c) 3 months and d) comparisons among different vegetation cover types.

However, vegetation structures also affected strongly to the changes in correlation in vegetation cover (figure 3-d). Broadleaves forests impacted water deficits less in the first two months and then stronger if the drought extended to the third month, while mixed forest began to respond after the second month of drought occur. Other vegetation covers with the mixture in species such as savannas reacted strongly to water deficit since the first lag month.

4. DISCUSSIONS

Undoubtedly, Google Earth Engine Explorer is great for non-data specialists to view datasets, embed outputs in apps, share their own data and code, and export the analysis results. Google Earth Engine supports cloud-based, parallelized geospatial data analysis without any worry about the infrastructure and parallelization decisions or local storage. GEE hosts earth observing images and produced datasets for precipitation, population density, topography, land cover and climate. Users can access GEE through different channels, including a non-programming GUI, the JavaScript API and the Python API. Still, it has limited capabilities for cartography, complex spatial analysis for vector datasets as well as inaccessible parallelization.

To conclude, the study demonstrated a simple but more effective approach to monitoring drought at different scales, which from that to we studied both the advantages and limitations of this platform. However, the massive online public data archive, as well as free cloud-based parallelized geospatial data analysis that GEE provided, are valuable for developing countries like Vietnam. It will support reducing labor-intensive, time-consuming, reproduce difficulties as well as compatibility limitations and enhancing usability and reproducibility of the analyses and results. Specifically, we recommend the establishment of a participant drought assessment tool based on GEE for local users to join in the monitoring and validating process without any request of installation and working with desktop data managing and processing software.

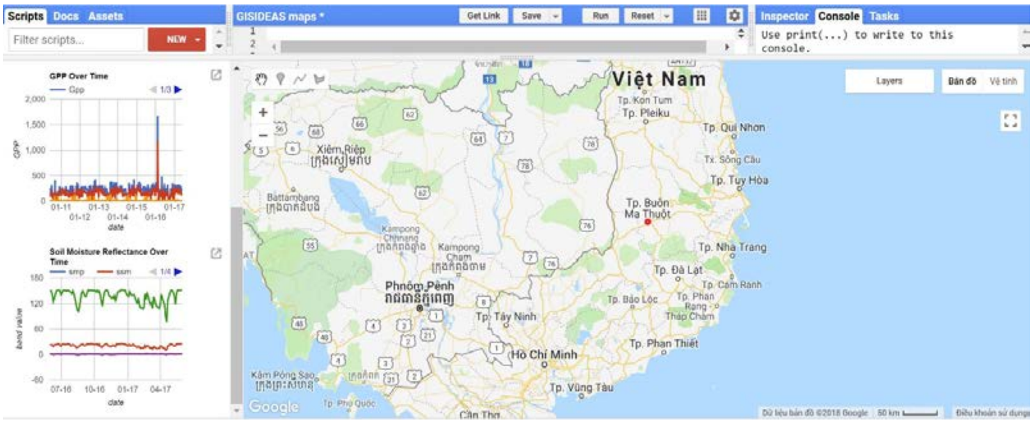


Figure 4. Example of participant drought assessment tool based on GEE

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