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Quantifying the environmental controls on African tropical forest dynamics through using a Granger causality framework

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1 Acknowledgement

This thesis was written as a part of my master's degree in bio-science engineering. With this thesis, I tried to contribute to the understanding of the dynamics of the African tropical forests. I was very happy when I got the chance to work on this subject, which brought many of my interests together. The writing of this thesis has been a great learning experience for me. Not only did I learn a lot about tropical forests and climate change, I also gained a lot of experience with geospatial data and programming.

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I'm really glad with how this thesis turned out and what I have learned while writing it. I look forward to the next steps that will be taken in this research area.

Eva Lorrez

Gent, 4/06/2021

2 List of abbreviations

BLUE	Reflectance of blue light
CRU	Climatic Research Unit
GOME-2	Global Ozone Monitoring Experiment-2
GOSIF	Global ‘OCO-2’ SIF data set
GPCC	Global Precipitation Climatology Centre
GPP	Gross Primary Production
ERA5	CERA project information for ECMWF Reanalysis 5th Generation
ESA	European Space Agency
EVI	Enhanced Vegetation index
Mg	Megagram
MODIS	Moderate Resolution Imaging Spectroradiometer
NASA	National Aeronautics and Space Administration
NDVI	Normalized Difference Vegetation index
NIR	Near-Infrared
OCO-2	Orbiting Carbon Observatory-2
Pg	Petagram
RED	Reflectance of red light
SEVIRI	Spinning Enhanced Visible and InfraRed Imager
SIF	Solar Induced Chlorophyll fluorescence
VAR	Vector Autoregression
VI	Vegetation Index
VPD	Vapour Pressure Deficit

3 Abstract English

The African tropical forests are of global importance due to their biodiversity, carbon sink capacity and climate regulation. To be able to predict how the African tropical forests will evolve under the changing climate, it is important to understand the dynamics of the forests and its drivers. So far, the knowledge about these forests is limited. Local political and logistic circumstances make the acquirement of data in these regions challenging. The growing amount of remote sensing observations of African tropical forests gives new opportunities for the monitoring. New emerging techniques and data driven models allow to model these systems without knowledge of underlying mechanisms. The issue of finding the drivers of the vegetation dynamics of the African tropical forests can be seen as a problem of finding causality in time series. Granger causality is an approach that has been proven to be fit for this purpose. Combined with a non-linear predictor it should be able to predict in which regions climate is a driver for vegetation dynamics.

This study aims to test this approach on African tropical forest dynamics. The approach was applied on anomalies of the Enhanced vegetation index (EVI) on a regional scale in Central Africa for the period of 2000 till 2020. The results show that in East Central Africa, vegetation dynamics are to an extent driven by precipitation, temperature and solar radiation. In the rainforest of Central Africa this could not be concluded. The EVI time series in these regions show little variation aside from the seasonal cycle and the long term trend. Some possible reasons were explored: 1) the data used contains a lot of uncertainty and is not capable of describing the vegetation of the African rainforest, or 2) the data characterizes the vegetation dynamics of the African rainforest well and the vegetation anomalies do not show a lot of variation over time. More data needs to be explored to find out whether this Granger causality framework is suitable to find the drivers of the African tropical forest dynamics.

4 Samenvatting Nederlands

De Afrikaanse tropische wouden zijn van globaal belang door hun biodiversiteit, hun capaciteit om koolstof op te slaan en hun klimaat-regulerende invloed. Om te kunnen voorspellen hoe de Afrikaanse tropische wouden zullen evolueren onder het veranderende klimaat, is het belangrijk hun dynamiek te begrijpen. Tot nu toe is de kennis over deze wouden beperkt. Lokale politieke en logistieke omstandigheden maken het verzamelen van data moeilijk. Nieuwe opportuniteiten voor het monitoren van deze bossen doen zich voor door de groeiende hoeveelheid *remote sensing* data. Nieuwe technieken en data gedreven modellen maken het mogelijk om deze systemen te beschrijven zonder kennis van de onderliggende mechanismen. Het vinden van de drijvende factoren van de vegetatiedynamiek van de Afrikaanse tropische wouden, kan herleid worden tot een kwestie van het vinden van causale verbanden tussen tijdsreeksen. *Granger causality* is een methode die hiervoor geschikt is. Gecombineerd met een niet-lineaire predictor kan Granger causality achterhalen in welke regio's klimaat een drijvende factor is van vegetatiedynamiek.

In deze studie wordt deze methode getest op de vegetatiedynamiek van de Afrikaanse tropische bossen. De methode werd toegepast op anomaliën van de *Enhanced vegetation index* (EVI) op een regionale schaal in Centraal-Afrika voor de periode tussen 2000 en 2020. De resultaten tonen aan dat in het oosten van Centraal-Afrika vegetatiedynamiek voor een deel veroorzaakt wordt door neerslag, temperatuur en zonnestraling. In het regenwoud van Centraal-Afrika leiden de resultaten niet tot deze conclusie. De EVI tijdsreeksen in deze regio tonen maar weinig variatie buiten de seizoensgebonden cyclus en de trend op lange termijn. Deze bevinding leidde tot volgende hypothesen: 1) de gebruikte data bevat veel onzekerheid en is niet in staat om de vegetatie van het Afrikaanse regenwoud goed te beschrijven, of 2) de data is wel in staat om de vegetatie goed te beschrijven en de vegetatie anomaliën vertonen weinig variatie doorheen de tijd. Om te weten te komen of dit *Granger causality framework* in staat is om de drijvende factoren van de dynamiek van de Afrikaanse tropische wouden te achterhalen, moet meer data onderzocht worden.

Contents

5 Introduction

5.1 The African rainforest: a unique ecosystem

The African rainforest is the second largest rainforest in the world after the Amazon. It stretches out both north and south of the equator and covers almost 2 million square kilometers in Central Africa. The forest can be divided into four large regions: the central forests of the Congo Basin, the West African rainforest that stretches to the Atlantic Ocean, the forests to the east in the Rift Valley region and the South Congo forests. The forests in the South and West tend to be more fragmented than in Central Africa and form a mosaic with savanna (Figure 1). To the east, the forests tend to be cooler and drier than in the center. The Guineo-Congolian forests of West- and Central-Africa contain 95% of the African rainforest, the Congo-Ogooué Basin (short: Congo Basin) encompasses 89% of the African rainforest, see Figure 2 (Malhi et al., 2013; Adams, 1998; Lewis et al., 2013; Mayaux et al., 2013).

Around the equator, the mean monthly temperature is rather constant around 25 °C and only varies by ±1 °C throughout the year as can be seen in Figure 3. The occurrence of rainforest is mostly constrained by the amount of precipitation. Evergreen forests can only survive when there is around 2000 mm rainfall per year. With increasing latitude, rainfall decreases, the length of the dry season increases and the rainforest gradually turns into other vegetation like dry tropical forest (Guan et al., 2015; Malhi et al., 2013). Precipitation in the Congo Basin seems to be dependent on moisture from the Indian Ocean and from moisture recycling from the land itself (Dyer et al., 2017). The climate in the African rainforest is also driven by large scale phenomena like the Intertropical convergence zone and the Atlantic Multidecadal Oscillation. Over large periods of time these phenomena can cause fluctuations in precipitation and temperature (Gray et al., 2004; Balas et al., 2007).

These phenomena lead to a unique seasonal cycle. The African tropics have two dry and wet periods in a year. June, July, August and December, January, February are the dry periods, with June to August the driest months. The two rain seasons are September, October, November and March, April, May. Most rain falls during September till October

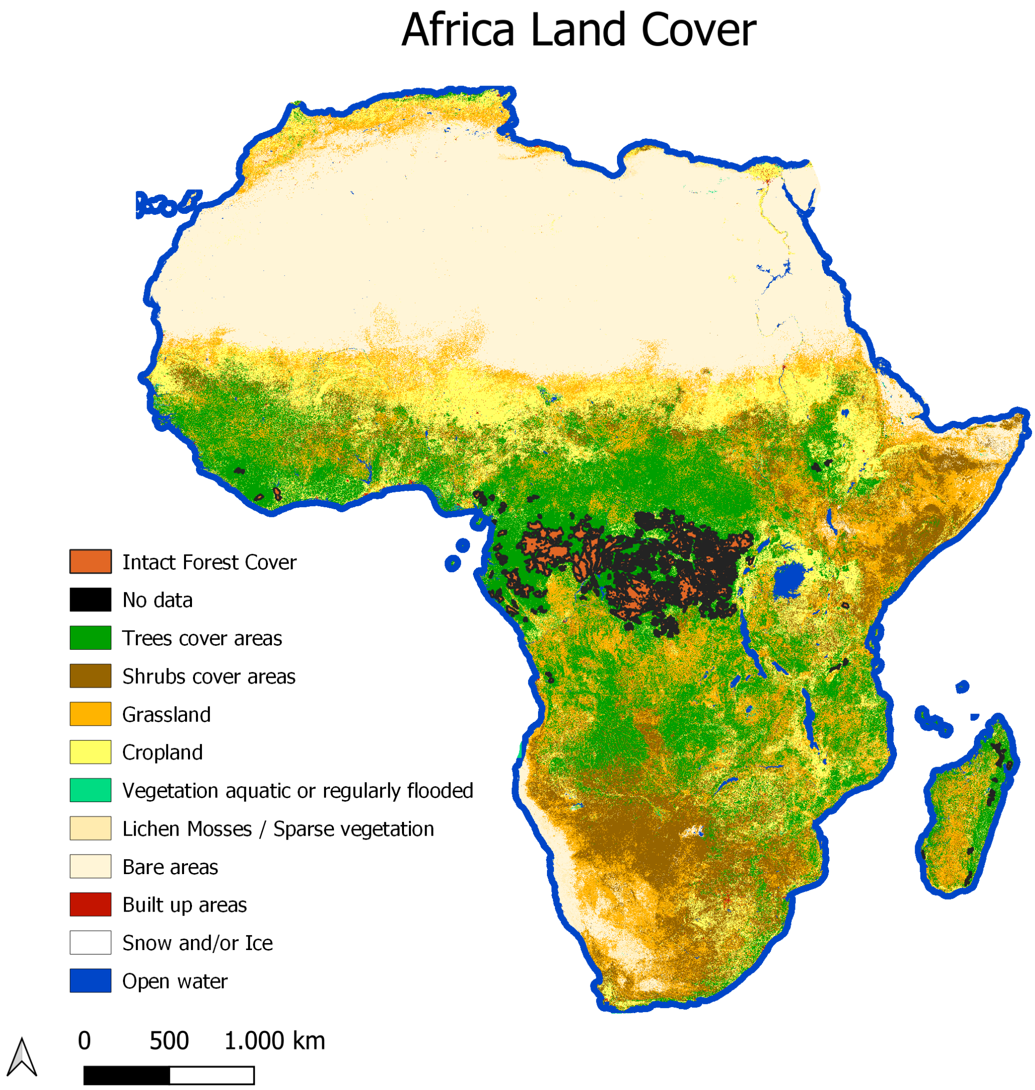


Figure 1: Map of the land cover of Africa combined with a layer of the intact forest cover in Africa (Potapov et al., 2008). ©Contains modified Copernicus data (2015/2016) ©ESA Climate Change Initiative - Land Cover project 2017.

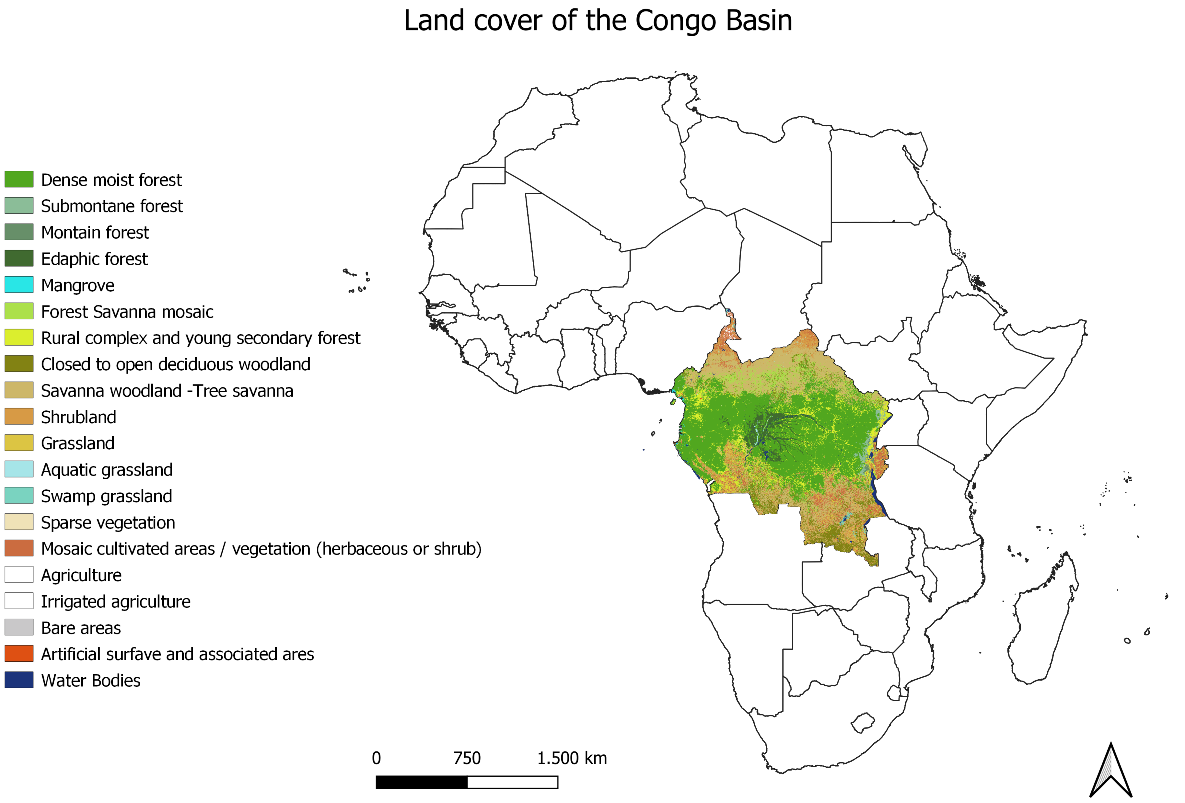


Figure 2: Map of Africa with the ecoregions of the Congo Basin (Verhegghen et al., 2012).

(Nicholson, 2018; Dyer et al., 2017; Washington et al., 2013).

This is in strong contrast to the climate of the Amazon rainforest. The Amazon only has one dry-wet alternation per year, as can be seen in Figure 3. The Amazon also has a higher annual rainfall (2300 mm per year) compared to the Congo Basin (1500 mm per year) (Guan et al., 2015; Y. Jiang et al., 2019). Moreover, in the wettest part of the Amazon rainforest the vegetation growth is limited by light due to cloud cover (Green et al., 2020). Overall, the African rainforest has a drier climate than the Amazon rainforest. Large parts of the Congo Basin rainforest receive a mean annual rainfall lower than the 2000 mm per year needed to sustain evergreen forest and as a result have semi-deciduous vegetation (Y. Jiang et al., 2019).

The African rainforest is home to a very large number of species and therefore vital for global biodiversity. It contains a minimum of 6000 tree species (Slik et al., 2015; Justice et al., 2001). The African rainforest has a mean above-ground biomass of 395.7 $Mg\,ha^{-1}$,

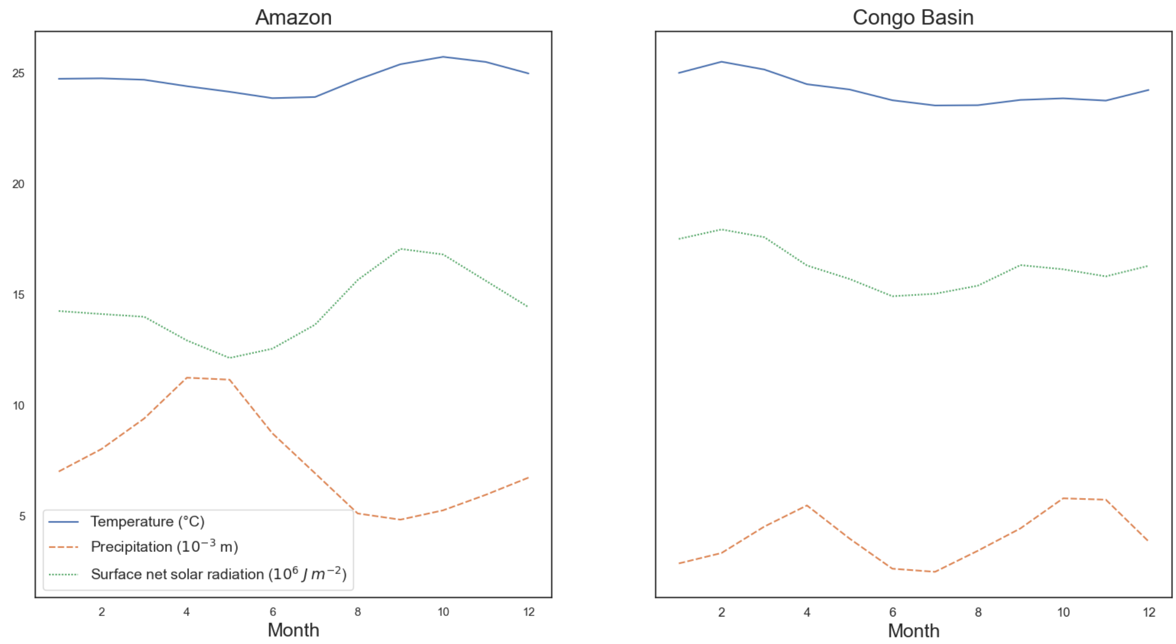


Figure 3: The monthly temperature, precipitation and surface net solar radiation of the Amazon compared to the Congo basin over the span of one year. ERA5 monthly data was used and the average over twenty years was calculated (Muñoz Sabater, 2019).

the Congo Basin reaches 429 $Mg\,ha^{-1}$ (Lewis et al., 2013). When compared with tropical forests in other continents, the African tropical forests have a low stem density and a high above ground biomass (Lewis et al., 2013). For example, the Amazon rainforest has a mean above-ground biomass of 350 $Mg\,ha^{-1}$ (Cummings et al., 2002). The diversity of species in rainforests around the world is positively correlated to the amount of rainfall they receive. Since the African rainforest is drier than other rainforests around the world, the species diversity is lower and the vegetation is semi-deciduous (Adams, 1998).

Just like the climate, the vegetation of the African rainforest shows a unique seasonal pattern. Phenology is the study of these seasonal patterns in nature and their biotic and abiotic causes (Lieth, 1974). The phenology of the African rainforest is complex, leaf shedding and reproduction cycles are species dependent and can vary with the layer of the canopy (Couralet et al., 2013; Schaik et al., 2003). Philippon et al. (2016) show that the greenness of the African rainforest has two peaks throughout the year: in April-May and September-October.

The drivers of these patterns of greenness remain unclear. For example Philippon et al. (2016), Guan et al., 2015 and Gond et al. (2013) show a strong correlation between greenness and rainfall and a smaller influence of light, depending on the season. Philippon et al. (2018) show that the the quality and quantity of light actually has a very big impact on the vegetation, especially in the forests of Western Central-Africa. According to Seddon et al. (2016), the vegetation of the African rainforest responds mainly to cloudiness and temperature. The complexity of the phenology and the difficult conditions for fieldwork in the region result in a rather limited knowledge about the vegetation and its drivers (Malhi et al., 2013; Adole et al., 2016; Washington et al., 2013).

5.2 Forests of local and global importance

Besides the already demonstrated value for biodiversity, the African rainforest shows to be an ecosystem with global importance in many other ways. The African rainforest has a meaningful part in the global carbon cycle being both a sink and a source of carbon (Baccini et al., 2017). It is estimated that the forest is a net sink of 0.5 Pg carbon per year (Lewis et al., 2009). However, the changing climate and human interactions with the forest might flip the switch and turn the forest into a net carbon source due to the impact of higher temperatures and droughts. The long term tropical forest sink might be already declining after a peak in the 1990's. The African tropical forests seem to follow the trend of uptake of carbon in the Amazon, which started to decline earlier (Malhi & Grace, 2000; Lewis, 2006; Hubau et al., 2020).

Another important aspect of the African rainforest is the feedback loop between climate and vegetation. Not only does climate influence vegetation, vegetation also affects climate in multiple ways. The land and the atmosphere exchange both water and energy. In the direction of land to atmosphere this happens under the form of transpiration (moisture from the soil) and evaporation of precipitation. Since a considerable part of the precipitation in the Congo Basin comes from moisture recycling, removal of the vegetation can lead to a decrease in precipitation. In addition, the canopy enhances turbulence and absorbs solar radiation. Therefore, deforestation might cause increasing temperatures and extremes. In this way the rainforest has a cooling effect on the region (Betts, 2004; Dyer et al., 2017).

Not only is the water cycle of the Congo Basin important for the African rainforest, it also has a crucial part in the water cycle of the surrounding regions (Betts, 2004). Spracklen et al. (2012) show that air that passed over the rainforest will cause more rainfall in the neighbouring regions. The change of vegetation in the African rainforest might even have implications on the global water cycle by influencing atmospheric circulations (Betts, 2004).

Complex feedback loops make it difficult to predict the outcome of changing land use and climate. This is partly due to the lagged response of vegetation and atmosphere to climate (Betts et al., 2004). The influence of previous states of different climate variables are visible for different periods. The influence of water lasts longest while temperature and radiation have a more immediate effect (Papagiannopoulou et al., 2017b; Wu et al., 2015).

Lastly, the African rainforest is an essential source of goods and services for local communities. The majority of households in the region depend on the forest for food, fuel, water, medicine and more. For example, in the Democratic Republic of Congo, around 95% of the wood removal from the forests is for the use of woodfuel. The communities living here are therefore very vulnerable to the changing climate and deforestation (Sonwa et al., 2012; MacDicken, 2015; Swingland et al., 2002).

5.3 Increasing pressure on the African rainforest

The African rainforest is subjected to a long term drying trend according to amongst others Zhou et al. (2014), Malhi & Wright (2004), Asefi-Najafabady & Saatchi (2013), Fauset et al. (2012), Justice et al. (2001). Zhou et al. (2014) reported a long term decline in precipitation, canopy water content and greenness. Z. Jiang et al. (2008) state that since the 1980's the length of the dry season of June-August has increased with an average of 8 days per decade. This long term drying influences the rainforest in a different way than short term droughts. The composition of the forest will alter to more drought resistant species (Asefi-Najafabady & Saatchi, 2013; Fauset et al., 2012), eventually maybe to grass and savanna (Willis et al., 2013). This trend will probably continue in the future and will influence the rainforest's biodiversity, carbon cycle and water cycle (Justice et al., 2001). Also global warming will affect the African tropical rainforest through the re-arrangement of zonal circulation (James et al., 2013) and increasing temperatures (Malhi et al., 2013).

It is not just climate that has an influence on the vegetation in the rainforest, humans and their activities play a big part in the state and the future of the forests too. The tropical forests in Africa show signs of long term human presence and disturbance. Currently, human activities like agriculture and logging lead to deforestation in all parts of the tropical forests in Africa (Adams, 1998; Justice et al., 2001; Malhi et al., 2013). According to MacDicken (2015), the Congo Basin lost up to 25 000 square kilometers of forest in the period between 2005 and 2010.

5.4 The African rainforest is important but understudied

The global and local importance of the Congo Basin forest for biodiversity, carbon sequestration, climate and local communities is undeniable. Increasing pressure on the forest will impact biodiversity and communities both locally and globally (Washington et al., 2013; Abernethy et al., 2016). To understand the impact climate change will have on the African rainforest, it's crucial to understand the functioning of the vegetation, its seasonal cycle and its dynamics. Furthermore, knowledge of the interactions between vegetation and climate variables is essential (Adole et al., 2016). To uncover these complex processes and interactions, long-term monitoring is necessary (Malhi & Wright, 2004). However, factors like unstable local politics and logistics make research in the region challenging. Because of these reasons the availability of data is low (Malhi et al., 2013; Adole et al., 2016; Washington et al., 2013). The African rainforest shows many differences with other rainforests in both climate conditions and vegetation, so despite the fact that the Amazon forest has been studied intensively on these subjects, knowledge about the Amazon cannot be extended to the African rainforest. Because of all these reasons, the vegetation dynamics of the African rainforest and their drivers remain mostly unknown.

6 Studying the African tropical forest

Over the past decades, the African tropical forests started being researched. Since then, less than twenty phenology studies have been done in Central Africa. This includes both ground based studies and remote sensing studies (Adole et al., 2016).

6.1 Ground based studies

The phenology of the African rainforest used to be studied mainly through ground-based field work up until the 1990's (Adole et al., 2016). However, due to the conditions in Central African countries, the amount of ground-based phenology studies is low (Malhi et al., 2013). Adole et al. (2016) show that before 2010 only about five ground-based studies were done in this region (e.g. De Mil et al., 2019). The benefit of ground-based studies is that they can give detailed information about the forest. On the downside they have limited spatial and temporal coverage.

6.2 Remote sensing

Since the beginning of 2000, remote sensing has become increasingly important for studying the rainforest and more phenology studies were done. Remote sensing can be used to measure Land surface phenology. This is the seasonal variation in canopy greenness over a vegetated land surface, which can show patterns in vegetation on a large scale (Zhang et al., 2003). Verhegghen et al. (2012), Gond et al. (2013) and Viennois et al. (2013) are examples of studies that mapped the Land surface phenology of the African rainforest through various methods.

Remote sensing allows for a larger spatial coverage, but data is dependent on the temporal and spatial resolution and temporal coverage of the satellite (Adole et al., 2016). A specific issue that arises for remote sensing of rainforest is the constant cloud cover over the forest, which makes it challenging to assemble long term time series. On top of that, the phenological cycle in the rainforest is complex and difficult to detect (Zhang et al., 2014). Another problem is that low availability of ground-based observations leads to limited validation of remote sensing data (Chambers et al., 2007).

A widely used satellite sensor for studying the phenology of the African rainforest is the Moderate-resolution Imaging Spectroradiometer (MODIS). With a spatial resolution of 250 m, 500 m and 1 km its observations are practical for regional studies (Adole et al., 2016). It uses techniques for noise reduction from clouds, atmospheric haze, aerosols and negligible water vapour impacts (Huete et al., 2002).

6.3 Vegetation indices

Vegetation can be studied from space through the use of vegetation indices. These indices have been calculated based on the reflectance spectra of the land surface. Vegetation indices are important proxies for many biochemical and biophysical variables and allow to monitor the green-leaf dynamics (Z. Jiang et al., 2008; Tucker et al., 1985).

6.3.1 Normalized Difference Vegetation Index

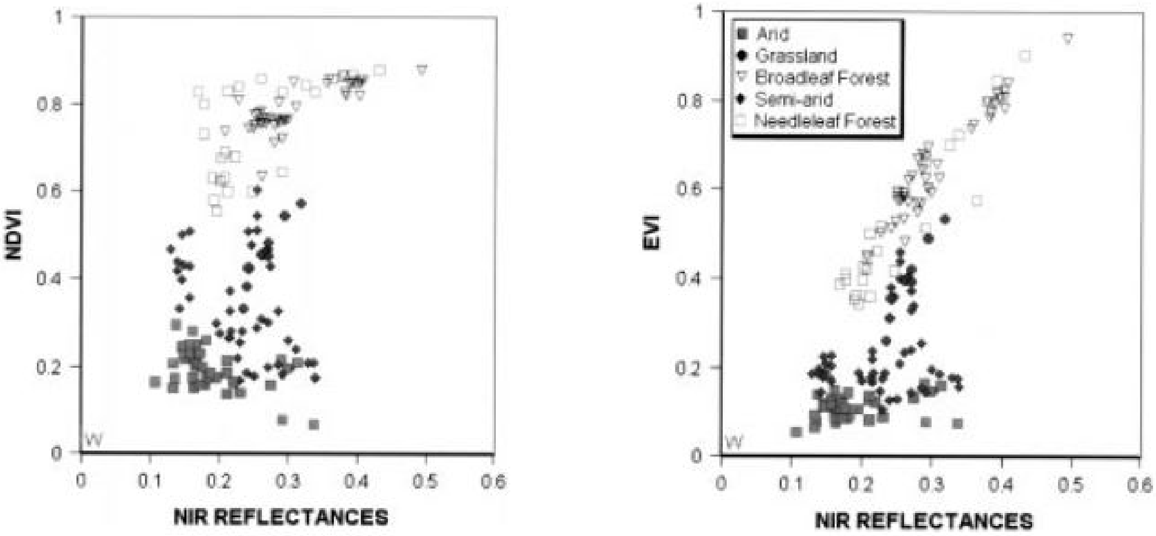
The Normalized Difference Vegetation Index (NDVI) is based on the difference between the reflectance in near-infrared and red wavelengths. In the scattering spectrum of a green leaf, the absorption in the red band is much higher than in the near-red band. High NDVI values indicate dense vegetation, low values indicate bare land or dead vegetation (Myneni et al., 1995; Lillesand et al., 2004).

$$NDVI = \frac{(NIR - RED)}{(NIR + RED)} \tag{1}$$

Most remote sensing studies of Africa used NDVI as a vegetation index (despite the advantages of EVI) because of its long time series availability (Adole et al., 2016).

6.3.2 Enhanced vegetation index

NDVI values can give a misrepresentation of the vegetation in certain condition due to interaction of the atmosphere and soil. The Enhanced vegetation index (EVI) is a modification of the NDVI with a factor to minimize soil background influence and atmospheric scattering (Lillesand et al., 2004). In addition NDVI shows asymptotic behaviour in regions with high biomass where EVI is still sensitive in these regions as



(a) (b)

Figure 4: The response of (a) NDVI and (b) EVI to the NIR reflectance. The different types of vegetation are indicated with different symbols. NDVI shows saturation for increasing NIR reflectance values, which indicate high biomass situations like broadleaf forests. © 1998, IEEE

shown in figure 4b. (Huete et al., 2002; Justice et al., 1998).

$$EVI = G * \frac{(NIR - RED)}{(NIR + C_1 * RED + C_2 * BLUE + L)} \tag{2}$$

With NIR, RED and BLUE the reflectances of respectively the near-infrared, the red and the blue wavelength. G is the grain factor, L is the soil adjustment factor and C_1 and C_2 are the coefficients of the aerosol resistance term (Z. Jiang et al., 2008; Justice et al., 1998).

EVI has been used a lot in studies to characterize the vegetation greenness of the Amazon (e.g. Huete et al., 2006; Saleska et al., 2007; Samanta et al., 2010; Morton et al., 2014) and to a lesser extent the greenness of the African rainforest (e.g. Zhou et al., 2014).

6.3.3 Solar-induced chlorophyll fluorescence

Solar-induced chlorophyll fluorescence (SIF) is a good proxy for photosynthesis and can be used to characterize gross primary production (GPP) (Doughty et al., 2019). SIF also shows to be good at defining droughts in vegetation (Sun et al., 2015). Multiple methods are available for the calculation of SIF, based on the reflectance spectra of the canopy (Miao et al., 2018; Mohammed et al., 2019).

The emergence of SIF products is a promising advancement for vegetation monitoring, since other vegetation indices can only estimate chlorophyll content at a large scale. SIF has already been used to study vegetation dynamics in the Amazon rainforest by, for example, Green et al. (2020). In the African tropics, Robinson et al. (2019) used SIF to characterize drought. SIF has not yet been used to study the vegetation dynamics of the African rainforest.

A problem that arises with the use of SIF is the limited length of remote sensing time series available. The longest available time series spans from 2007 until 2018 and is derived from observations of the Global Ozone Monitoring Experiment-2 (GOME-2). Other sources provide longer data sets of modelled SIF data, for example, the GOSIF data set from Li & Xiao (2019).

6.4 Modelling vegetation dynamics

Vegetation dynamics are the long-term and short-term changes in greenness and productivity of vegetation. They reflect changes in climate, the abiotic environment, biotic interactions, and past disturbances (van der Maarel, 1988). To describe vegetation, these dynamics and their drivers need to be understood. Over the years many different methods have been developed to describe the vegetation dynamics of the African tropical forests.

6.4.1 Process based models

Process based models are a mathematical representation of the functioning of, in this context, ecological systems (Buck-Sorlin, 2013). These models generally need a thorough understanding of the inputs, outputs and mechanisms of a system. For example, De Weirdt et al. (2012), Dury et al. (2018) and Poulter et al. (2009) use process based models to describe and predict vegetation dynamics. However, compared to other processes like photosynthesis, the phenology of rainforests, its drivers and mechanisms are still quite unknown. This leads to a lot of uncertainty and models describing rainforest phenology use many assumptions and are still fairly simple. Because of this, they don't succeed in simulating the phenology of the rainforest (Verbeeck et al., 2011; H. Yan et al., 2017).

Another problem of process based models is revealed by Minaya et al. (2018). They show that these models can become very complex and lead to high computational time.

6.4.2 Data driven models

In their study, Minaya et al. (2018) compared a process-based model with a data driven model and showed that data driven models can characterize vegetation well while needing less computational time. Data driven models learn based only on the input data without making assumptions about the processes. For example, Gond et al. (2013) used an unsupervised classification method to distinguish different vegetation types in the Congo Basin. The pixels of the forest were classified based on their greenness. Philippon et al. (2018) used a clustering algorithm to distinguish different light regimes in the Congo Basin. It is still important to have good knowledge of physical and biological processes to be able to interpret the results.

6.4.3 Statistical methods

Another way to describe vegetation dynamics is through statistical analysis. For example Ndehedehe et al. (2019), Nzabarinda et al. (2021) and Zhou et al. (2014) used statistical metrics to study the relationships between vegetation (NDVI and EVI) and climate variables (precipitation, water availability and temperature) in the African rainforest. These studies all show correlation between precipitation and vegetation greenness in the African rainforest, but correlation does not imply a causal relationship.

6.4.4 Time series analysis and causation

Since large controlled experiments are impossible in climate science, finding causation in time series is challenging (Runge et al., 2019). However, many methods are being developed to deal with this issue. For example Sugihara et al. (2012) developed a nonlinear state space reconstruction method to detect causation in complex ecosystems. A popular method is Granger causality (Granger, 1969). This method does not use correlation but predictability to identify causation. According to McGraw & Barnes (2018), this method is appropriate for modelling vegetation dynamics and their lagged response to climate since it takes into account lagged variables. More details on Granger Causality will be given in the methodology section.

Granger causality can also be used to find relations between variables in non-linear systems (Sugihara et al., 2012; Papagiannopoulou et al., 2017a). Many of the previously discussed studies use linear methods, but since dynamics between climate and vegetation are very complex (e.g. Foley et al., 1998; Green et al., 2017), these interactions can better be described through non-linear models (Zeng et al., 2002; Papagiannopoulou et al., 2017a). Papagiannopoulou et al. (2017a) developed a method that uses a combination of Granger causality and a non-linear algorithm to model vegetation dynamics on a global scale. This method proved to be successful in predicting if climate drives vegetation dynamics in many regions of the world. However, for tropical forests the results were indecisive. This can, according to Papagiannopoulou et al. (2017a), indicate that 1) climate does not cause vegetation dynamics in tropical forests but other factors like human activities do, 2) NDVI shows saturation in high biomass environments and is not a suitable vegetation index in these regions, 3) the data used is not reliable in these regions.

7 Objectives of the study

Many studies have been able to show correlation between climate variables and vegetation dynamics in the African rainforest. On a global scale, models are being developed to find causal relationships in climate time series. The purpose of this study is to bring these two domains together and find out whether the vegetation dynamics of the African tropical forests are caused by the climate variables temperature, precipitation and solar radiation.

The Granger causality framework as developed by Papagiannopoulou et al. (2017a) will be applied on a regional scale, but instead of using NDVI, vegetation will be characterized by both EVI and SIF. This way this study aims to address the unanswered questions in Papagiannopoulou et al. (2017a): 1) whether the use of EVI over NDVI will deal with the high biomass saturation issue and improve the results, 2) if SIF is a good option to characterize vegetation in this approach. To conclude, it will allow to determine 3) if the data in this region is reliable enough for this approach.

8 Methodology

The method used in this thesis was developed by Papagiannopoulou et al. (2017a) and combines a Granger causality framework with a random forest predictor. The framework was used for the prediction of two different vegetation indices: EVI and SIF. For the analysis Python 3 was used (Van Rossum & Drake, 2009).

Two different data sets were constructed for the two vegetation indices. Both data sets consist of a number of features and one label. The features are the time series of the climate variables and their lagged and cumulative values. The label is the time series of the vegetation anomalies.

8.1 Data sets

The climate data sets come from CERA project information for ECMWF Reanalysis 5th Generation (ERA5), see Table 1 (Muñoz Sabater, 2019). These are reanalysis data sets based on remote sensing and in situ data. The temperature product was calculated two meters above the surface. The precipitation data was calculated as the accumulated water that falls on the surface within one month. To characterize solar radiation, the surface net solar radiation was used. This data is calculated as the difference between the amount of solar radiation that reaches the Earth's surface and the amount that is reflected by the Earth's surface, accumulated over a month.

Variable	Product	Spatial resolution	Temporal resolution
Temperature	T2m (ERA5)	0,5°	Monthly
Precipitation	tP (ERA5)	0.5°	Monthly
Radiation	SSR (ERA5)	0.5°	Monthly
Greenness	EVI (MODIS)	1 km	Monthly
Photosynthesis	GOSIF	0.05°	Monthly

Table 1: The different data sets that were used and their spatial and temporal resolution.

The choice for reanalysis data sets was made after closely examining different data sets. For example, in situ temperature and precipitation data from CRU (Harris et al., 2020) and GPCC (Schneider et al., 2020) were considered. The time series turned out to be incomplete due to the decrease of observatory stations in West and Central Africa (Harris et al., 2020).

Soil moisture was not included as a variable because the quality of remote sensing data of soil moisture is low in high biomass situations. Research has shown that the relation between vegetation greenness and soil moisture is insignificant (Ndehedehe et al., 2019).

The first vegetation index that was used is the Enhanced vegetation index (EVI) derived from data of the Moderate Resolution Imaging Spectroradiometer (MODIS). This instrument on NASA's Terra satellite provides long-term time-series of vegetation indices and is used to monitor land, atmosphere and oceans (Justice et al., 1998). The EVI data set has a monthly interval and a spatial resolution of one kilometer (Didan, 2015).

The second vegetation index that was used is the Solar-induced chlorophyll fluorescence (SIF). Since the time-series of remotely sensed SIF products are still short, a modelled SIF product, GOSIF was used. This product has been constructed from OCO-2 data, remote sensing data from MODIS and meteorological reanalysis data using a data-driven approach (Li & Xiao, 2019). The implications of using GOSIF for this study are discussed in section 10.4.

8.2 Preprocessing of the data

The region between 10 and -10 degrees latitude and 0 and 40 degrees longitude was selected as study area, as shown in Figure 5. This area contains parts of Nigeria, Benin, Togo, Cameroon, Chad, Central African Republic, South-Sudan, Ethiopia, Kenia, Uganda, Rwanda, Burundi, Tanzania, Democratic Republic of the Congo, Congo, Angola, Gabon and Equatorial Guinee. The focus is on the Congo Basin, which stretches across Cameroon, Central African Republic, Democratic Republic of the Congo, Republic of the Congo, Equatorial Guinea and Gabon.

After downloading, the data sets were resampled to the spatial resolution of 1°. All data sets already had the desired monthly temporal resolution. The time frame of the study

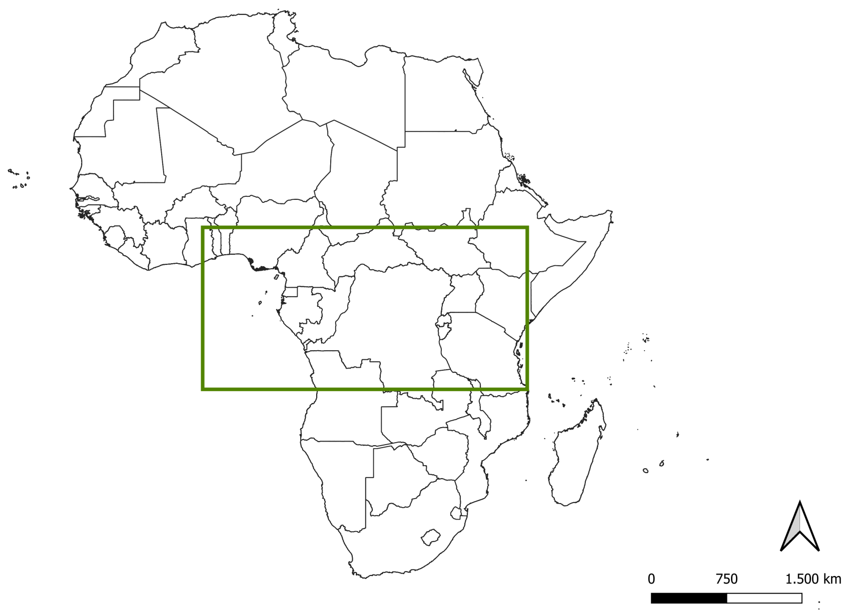


Figure 5: A map of Africa with the study area marked in green.

depends on the availability of data and spans from 2000 until 2020. For the EVI data, a quality control was performed on each pixel based on the quality, usefulness, clouds and aerosols. This information was stored in the "VI quality" layer of the vegetation index product. Pixels with low quality were left out.

For every pixel, the time series of each variable was created over the twenty-one year time frame. Next, for each time step, the anomaly was calculated from the raw data. This is a necessary step to make sure the time series are as stationary as possible, since Granger causality cannot be applied for non-stationary time series. The vegetation index has a clear seasonal cycle, which can very easily predict itself (Papagiannopoulou et al., 2017a). In a first step the long-term trend was removed by subtracting a linear trend from the data. This way, the mean of the time series does not change over time and the time series becomes more stationary. In the second step, the seasonal cycle was subtracted. By assuming that the seasonal cycle stays constant over time and is repeated every year, it can be calculated as the monthly mean over the twenty years. This monthly mean was then subtracted from each corresponding month. The different components of the anomaly decomposition of EVI for one pixel are visualized in Figure 6.

A following step was to add lagged features of the climate variables, since the state of the vegetation at a given point can reflect the climate of the past. Also cumulative features were calculated, because vegetation could reflect the average climate of the last couple of months. The lagged and cumulative variables were added for the previous twelve months, since longer windows did not show improvements according to Papagiannopoulou et al. (2017a).

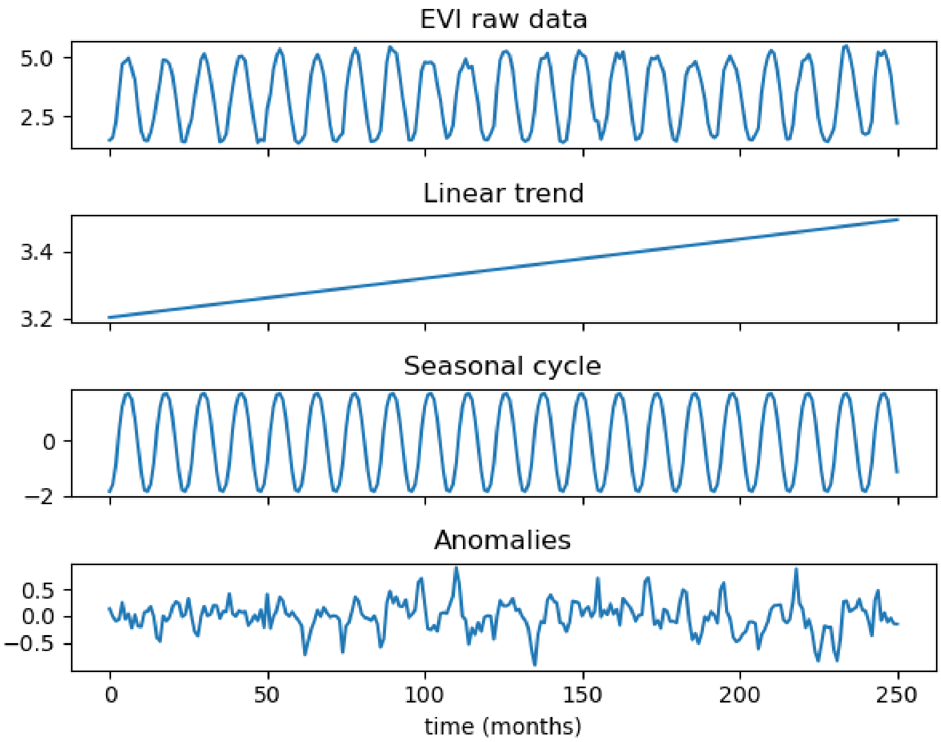


Figure 6: Visualisation of the anomaly decomposition of a time series of EVI. Subtracting the long-term trend and the seasonal cycle from the raw data leads to the anomalies.

8.3 Granger Causality

Granger causality (Granger, 1969) is a form of causality between time series based on predictability. One could say that time series A causes time series B if the auto regression of B improves when information of A is added as predictor. The evaluation of the model happens in a quantitative way since existing statistical tests require stationary time series and linear relationships, which are two demands the data in this thesis do not meet. Instead, the coefficient of determination (R^2) is used. This coefficient shows how much variance of the vegetation index is explained by the prediction. The value increases if the performance of the model increases and reaches a theoretical optimum of one. If the value is negative, the prediction performs worse than the mean of the observations.

This leads to a definition of Granger causality, using R^2: Time series x Granger causes y if $R^2(y, \hat{y})$ increases when $x_{t-1}, x_{t-2}, ..., x_{t-P}$ are included in the prediction of y_t, in contrast to considering $y_{t-1}, y_{t-2}, ..., y_{t-P}$, where P is the lag-time moving window (Papagiannopoulou et al., 2017a).

In practice, this means that two models are compared: a baseline auto-regression model to predict the target time series and a full model, which also includes other time series as predictors. The predictor time series Granger causes the target time series if the performance of the full model is better than that of the baseline model. In this study, the target is the time series of the vegetation anomalies (EVI and SIF) and the predictors are the time series of the climate variables.

8.4 Analysis

Papagiannopoulou et al. (2017a) demonstrated that a non-linear model was more successful at predicting vegetation dynamics in this setting than a linear model. Therefore, a non-linear predictor, random forest from the Scikit-learn library, was used (Pedregosa et al., 2011). A random forest combines the outcomes of a number of decision trees, in this case 100. To avoid over fitting of the model, 5-fold cross validation was applied. In this technique the data set is divided in 5 intervals. Each in turn acts as a test set while the other data is used for training (Papagiannopoulou et al., 2017a).

In the first analysis the non-linear random forest approach was used to find out if climate causes vegetation dynamics. Every pixel was considered a different problem, for which the baseline and full models were trained. For both baseline and full model, the R^2 value was calculated based on 5-fold cross validation. Afterwards, the difference between the R^2 values of the full model and the baseline model was calculated to quantify whether the full model performs better than the baseline model. This analysis was performed for both vegetation indices, EVI and SIF.

In the second analysis the framework was used with a linear vector autoregressive (VAR) method to find out whether the non-linear method did perform better. A ridge regression was used with a regularization term to avoid over-fitting. For more information, see Papagiannopoulou et al. (2017a).

In a last analysis, anomaly time series of vegetation and climate variables were plotted for four pixels in the study area to examine both the spatial and temporal variation between values. The four pixels were selected based on the results of the first analysis. Two pixels, where the model was able to predict the vegetation index, were compared with two pixels where the R^2 value was zero or less.

9 Results

9.1 Enhanced vegetation index

After running the analysis, three outputs were generated for every pixel: the R^2 values of the baseline model, the R^2 values of the full model and the difference between both. These values were plotted as maps for the entire study area and will be discussed in the following sections.

9.1.1 Full model

The results of the full model for EVI are shown in Figure 7. At first sight, the center of the study area, between latitude -5 and 5 and longitude 10 and 30, stands out. In this area, the R^2 values of the pixels are almost all equal to zero. This means that in these pixels, the full model performed poorly and that the full predictor set could not predict the vegetation anomalies. In the east, north and south of the study area the R^2 values of the pixels are higher, with maximum values of around 0.5 in the east. In these pixels, the full model was able to predict the vegetation anomalies.

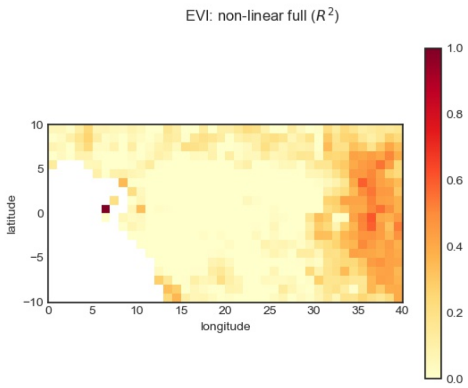
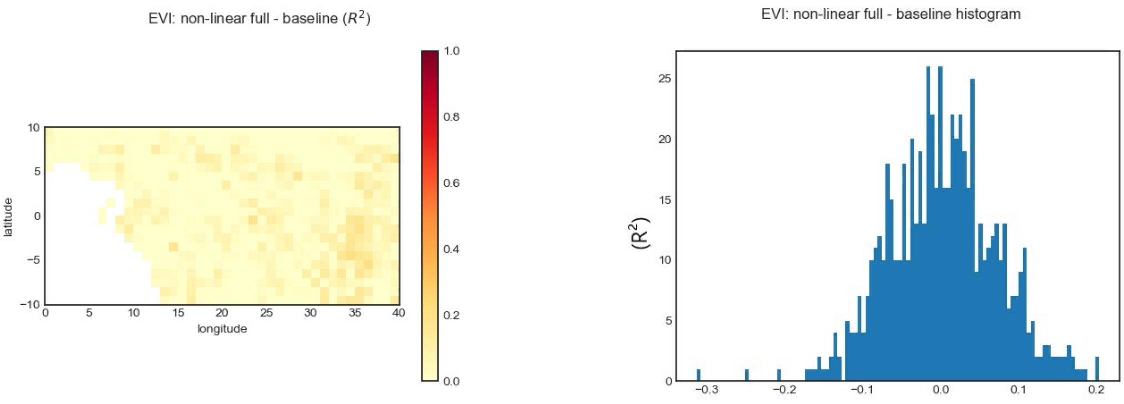


Figure 7: Results of the non-linear full model for EVI. The darker the red, the higher the R^2 value. All values lower than zero are visualized as zero.

9.1.2 Baseline vs full model

To find out if the prediction of EVI anomalies improves by adding climate variables to the predictor set, the full model was compared to the baseline model. Figure **??** shows the results of the difference between the R^2 values of the full model and the baseline model. In the pixels for which the values are higher than zero, the climate anomalies improve the prediction of the EVI anomalies. Therefore, according to the definition of Granger causality, climate partly causes vegetation anomalies in these pixels. In the east of the study area, a group of pixels stands out, where the full model performed slightly better than the baseline model, with a maximum difference of R^2 value of around 0.3. In these pixels climate partly causes changes in vegetation. In most pixels, however, the values of the difference are equal or smaller to zero (Figure **??**. In these pixels the climate anomalies do not add to the prediction and thus, causation of EVI anomalies.

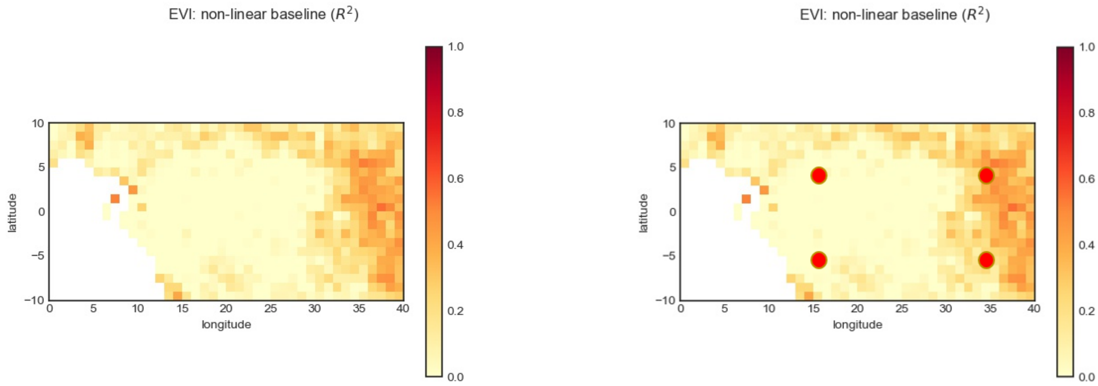


(a) **(b)**

Figure 8: Difference between the full model and the baseline model for EVI with all values smaller than zero visualized as zero (a) and a histogram of the R^2 values (b).

9.1.3 Baseline model

The results of the baseline model can be found in Figure 9a. This figure shows the same pattern as the plot of the results of the full model. In the center of the study area pixels show R^2 values of zero. In the north and south, the pixels have R^2 values around 0.2 and in the east the pixels show the highest values with maximum values of 0.5. Since the baseline model is an auto regressive model and demonstrates how well EVI can predict itself based on previous values, these results should be examined more closely.



(a)

(b)

Figure 9: The results of the non-linear baseline model for EVI (a). Four pixels were selected to compare the time series of EVI (b).

To do this, four pixels were selected in the study area: two in the center where the model performance was low (R^2 values equal to zero) and two in the east where the model performed better (R^2 values around 0.4), see Figure 9b. For these four pixels the anomaly time series of EVI were plotted over the twenty year period. Figure 10a shows that for the pixels with coordinates (5.5, 15.5) and (-5.5, 15.5), for which EVI could not predict itself, the anomaly values mostly stay between the interval $[-0.5, 0.5]$ and show far less variation than for the pixels with coordinates (5.5, 37.5) and (-5.5, 37.5), which anomaly values go up to -2 and 2.

To examine if the anomaly time series of the climate variables follow the same trend, their values were also plotted for the four pixels in Figures 10b to 10d. The difference in variation between the time series of pixels in the east and pixels in the center is not as visible as in the EVI plots.

9.1.4 Non-linear vs linear model

In the second analysis, the non-linear predictor was replaced by a linear model. This analysis was added to examine whether a non-linear method actually is more suitable to describe vegetation dynamics in the African rainforest. Figure 11a shows the difference

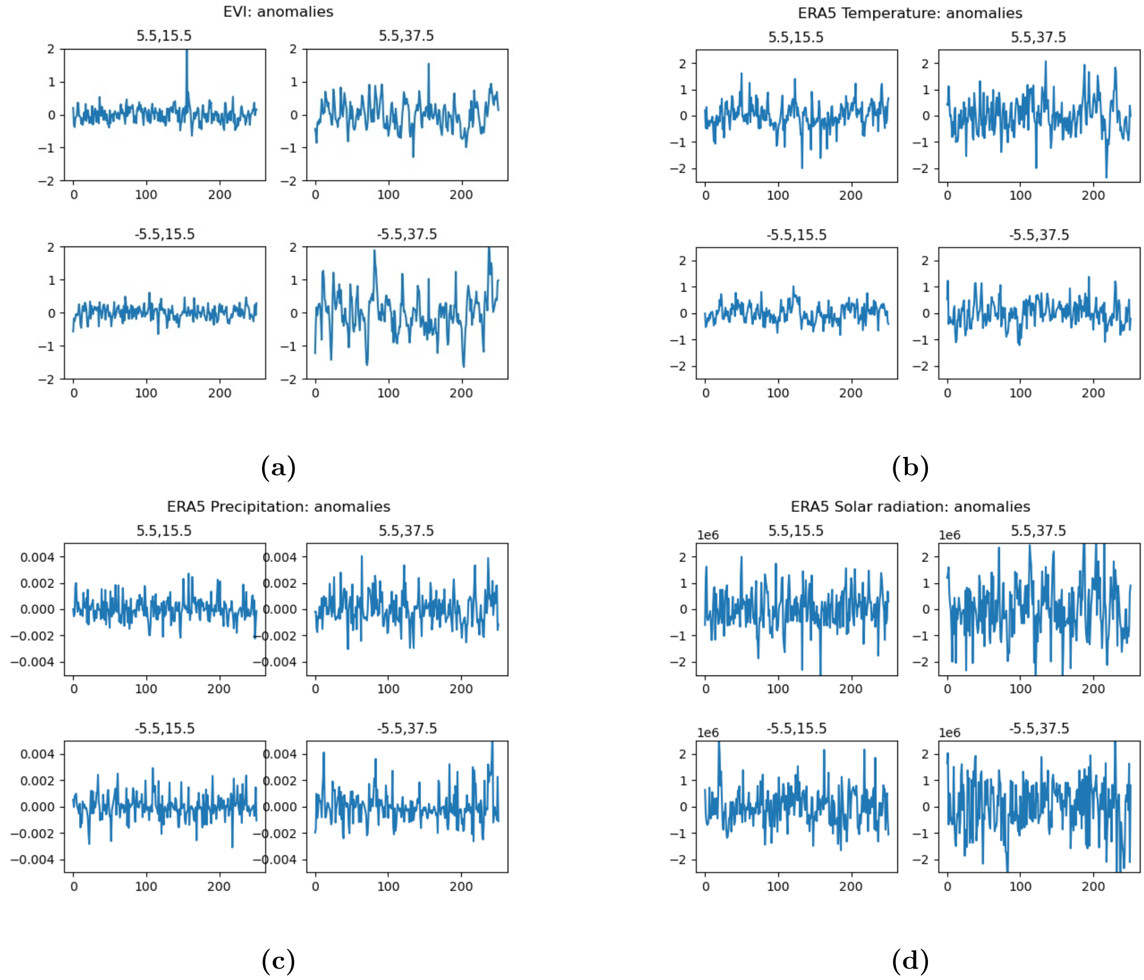
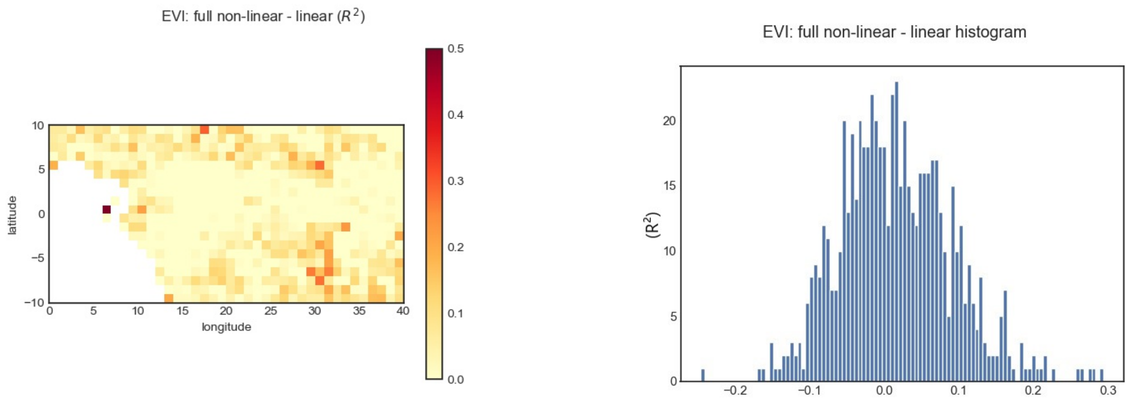


Figure 10: Anomaly time series of (a) EVI, (b) ERA5 temperature, (c) ERA5 precipitation and (d) ERA5 solar radiation over twenty years for the pixels: (5.5, 15.5), (-5.5, 15.5), (5.5, 37.5), (-5.5, 37.5).

between the R^2 values of the non-linear full model and the linear full model and thus, for which pixels the non-linear model performed better than the linear model. In most pixels, the R^2 values are larger than zero (Figure 11b). In the pixels where the difference is zero or smaller, the non-linear method did not show an improvement over the linear method.

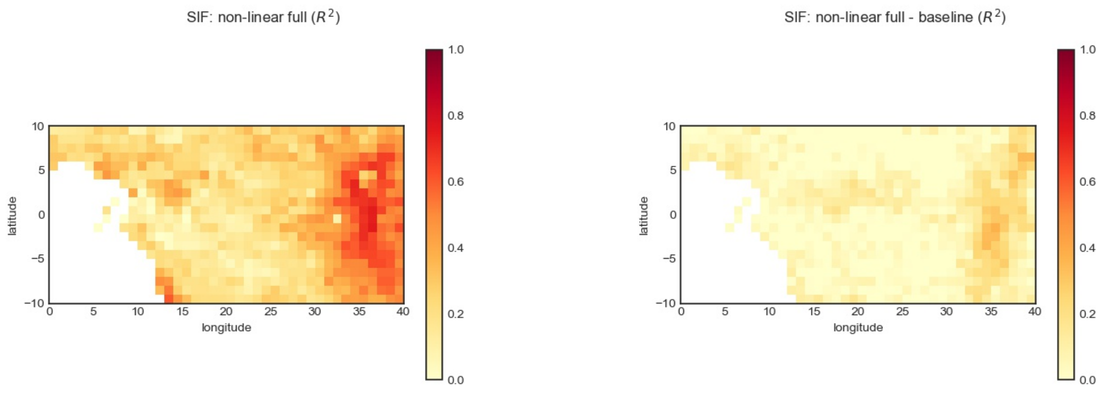


(a) **(b)**

Figure 11: The difference between the non-linear full model and the linear full model for EVI. The values were plotted for each pixel (a), all values lower than zero are visualized as zero. (b) shows a histogram of the values.

9.2 Solar-induced chlorophyll fluorescence

The same analysis was applied to the SIF product. In this section the most important results will be briefly discussed. All other figures can be found in the appendix. The explanation for why the SIF is not analysed as in depth as the EVI will follow in section 10.4.



(a) **(b)**

Figure 12: The results of the non-linear analysis for SIF. (a) shows the results of the non-linear full model, (b) shows the difference between the full model and the baseline model. All values lower than zero are visualized as zero.

The model performs good in most pixels (Figure 12a) with R^2 values between 0.1 and 0.8. The pixels in the east of the study area show the highest R^2 values. To find out whether adding climate variables to the prediction improves the performance, the full model is compared with the baseline model (Figure 12b). Three groups of pixels with values higher than zero stand out: the east of the study area, the coastal region in the west and the north part of the center. For these pixels climate partly causes changes in vegetation.

10 Discussion

10.1 Results versus land cover

The results show that the model was not successful in predicting EVI anomalies, especially not for the center of the study area. In the east of the study area both full and baseline model performed better than in the center. The full model performed slightly better than the baseline model in some pixels, from which can be concluded that in these pixels climate (temperature, precipitation and solar radiation) does cause vegetation anomalies. In the center, interpretation of the results is less straightforward. The full model and the difference between the full model and the baseline model suggest that climate does not cause vegetation anomalies in these pixels. The baseline model, however, shows that the reason for this bad performance might be found in the EVI data itself. The plots of EVI anomaly time series for four different pixels demonstrate that the variation of EVI anomalies is lower in the center of the study area. When the results of the analysis are compared with the land cover map of the region, the land cover type of the regions with different results can be examined, see Figure 13.

The pixels in the east, north and south of the study area are mainly covered with grassland, shrubs and cropland. In the center of the study area the land is covered with forest, or more specifically according to figure 2, with dense moist forest. Fayolle et al. (2014) demonstrate that forests in Central Africa and East Africa are subjected to different climate regimes and have different species composition. In the center, forests are wet and moist, mostly evergreen. To the east, the forests are more dry and trees are mostly deciduous.

It's clear that the type of forest influences the results of the analysis. In the dry forests in East Central Africa, climate partly causes vegetation anomalies. These deciduous forests have more seasonality and, apparently, more anomalies. This variation in vegetation made it possible for the baseline model to predict the EVI anomalies. In the Congo Basin rainforest, time series of EVI anomalies seem to contain too little variation for the model to perform well.

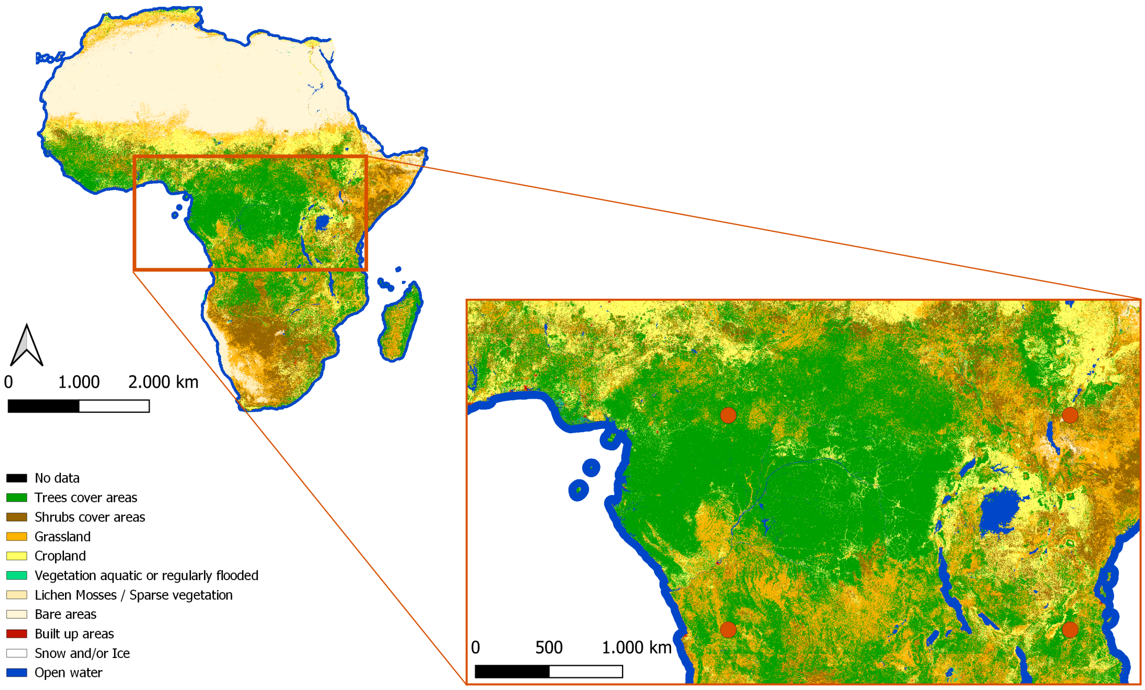


Figure 13: Land cover of the study area. ©Contains modified Copernicus data (2015/2016) ©ESA Climate Change Initiative - Land Cover project 2017.

10.2 Low variation EVI data

The time series of climate anomalies do not seem to show less variation in the rainforest than in the dry forests in East Africa. Therefore, the reason for this low variation of EVI anomalies needs to be sought elsewhere. In this section, some possible explanations are explored.

Some literature points in the direction of the quality of MODIS data. According to D. Yan et al. (2016) and Hmimina et al. (2013), vegetation products of MODIS are not able to capture vegetation dynamics of the African rainforest adequately. D. Yan et al. (2016) compared EVI data of the African rainforest calculated from MODIS images with data calculated from the Spinning Enhanced Visible and InfraRed Imager (SEVIRI) images. The MODIS observations turned out much less likely to capture cloud free images of the Congo Basin than the SEVIRI observations. This resulted in MODIS images not being able to capture the canopy greenness cycles of the rainforest. The difference in performance is due to the types of satellite the two instruments are on. SEVIRI is attached to a geostationary satellite, which allows to make multiple images a day on different times for the same region. MODIS, in contrast, is attached to a polar orbiting satellite, which leads to one image every one or two days. The Terra satellite crosses the equator each day at 10:30 AM local time and around 10 AM local time, the cloud cover is at its maximum above West Central Africa (Dommo et al., 2018). This set of circumstances could lead to a low availability of cloud-free images of the African rainforest provided by MODIS. The MODIS images have been controlled for pixel quality and cloud cover, but persistent cloud cover could lead to high uncertainty of these observations. Also, the methods used for removal of seasonal contamination from atmospheric conditions can influence the analysis. So, to reduce uncertainty, it is crucial to compare with ground based data (Poulter & Cramer, 2009).

That is what Hmimina et al. (2013) did. In this study, in situ NDVI measurements were compared with a 16-day MODIS NDVI product for their ability to describe phenological patterns of rainforests. According to this study, the patterns found in the 16-day MODIS product are more likely due to noise than to phenological changes. This would make MODIS NDVI data not suitable to monitor vegetation dynamics of rainforests. Of course, this does not mean this would also be the case for EVI data.

These studies, in which vegetation products from MODIS were compared with other sources, used data that still contained information about seasonality. This does not necessarily mean that EVI data from these sources would contain more variation in anomaly time series. That leads to the next possible explanation, which is that these low EVI anomaly time series are a good representation of the state of the African rainforest. This would mean that the vegetation of the African rainforest does not change much over time aside from the long term trend and the seasonal cycle.

10.3 Limitations of the Granger causality framework

The anomaly decomposition of the time series for both vegetation and climate variables is a crucial part of this framework. The long-term trend needs to be subtracted from the raw data to make the time series more stationary and the seasonal cycle needs to be removed because it can too easily predict itself (Papagiannopoulou et al., 2017a). However, it seems that not a lot of variation is left in the EVI anomalies for pixels in the African rainforest, which makes the whole approach pointless.

If the quality of the data is the cause of the low variation, it could be interesting to do the approach with other data. If the vegetation of the African rainforest does not show a lot of variation aside from the long term trend and seasonality, this Granger causality approach is not suitable.

The comparison between the linear model and the non-linear model demonstrates that the non-linear model did not perform better in all pixels. Since other studies have shown that climate-vegetation dynamics are are mostly non-linear, we expected to see the non-linear model perform better than the linear model. However, the uncertainty of the data makes it impossible to conclude on the method.

10.4 Limitations of using SIF data

Although the results of the analysis of the SIF data showed promising results, they were not used in this thesis. Time series of SIF from remote sensing are still very short. The GOSIF product that was used here is modelled using a short SIF time series, vegetation data (EVI from MODIS) and climate data with a data driven model. Because of this, the SIF data is not independent and the results cannot be easily interpreted. The climate variables used for the construction of the GOSIF product are the photosynthetically active radiation, the vapor pressure deficit and the air temperature. It would be interesting to apply an approach like the one developed by Papagiannopoulou et al. (2017b) to find out whether precipitation also partly causes SIF.

10.5 Ideas for further research

After considering the results of this research, some new questions arose. The model was not successful in the rainforest, but the reason for this has not been uncovered. In the next section some options are listed for the next steps needed to solve these questions.

First of all, it is important to consider the uncertainty of the used data. For example, Sylla et al. (2013) show that remote sensing observations of precipitation in Africa show uncertainty. Different results were obtained when they compared different sources of data. To reduce this uncertainty, it would therefore be necessary to compare data from different sources.

Secondly, it would be interesting to expand the set of climate variables. Precipitation, temperature and solar radiation have been used frequently in studies up till now, but some recent studies have shown that Vapour Pressure Deficit might be a good predictor for rainforest vegetation dynamics. SIF shows strong sensitivity for Vapour Pressure Deficit (VPD) according to Green et al. (2020). Adding VPD as a variable in their analysis added to the predictive power. Chen et al. (2021) showed that VPD combined with solar radiation was able to describe the phenology of the Amazon forest fairly well, especially in the wettest parts of the forest.

To find the cause of the low variation in vegetation anomalies, more ground based validation of remote sensing data is needed. A next step would be to find out whether different sources of EVI data also result in low anomaly variation. It would be interesting to take a look at data from geostationary satellites and ground based data like for example D. Yan et al. (2016) and Hmimina et al. (2013). EVI data from SEVIRI is not readily available and was therefore not used in this study.

It would also be interesting to repeat this approach in a couple of years with a long time series of independent SIF products if these time series and their anomalies show enough variation for the African rainforest. This way, the use of the Granger causality approach would be justified.

An approach using Artificial Neural Networks like Green et al. (2020) would allow to use raw data without anomaly decomposition. Running multiple models with predictor sets that leave out one variable at a time allows for examining the importance of individual variables.

Besides Granger causality other methods exist to find causality in time-series (Runge et al., 2019). Convergent cross mapping is another method used to find causal relations in time-series (Sugihara et al., 2012). Ye et al. (2015) expanded this approach to distinguish time-delayed causal interactions. This method doesn't need the time series anomalies and has already been used in ecology (Sugihara et al., 2012) and climate science (van Nes et al., 2015) to describe complex non-linear systems, therefore it could possibly be a good option to use in this setup.

11 Conclusion

To conclude we can say that we were partly successful in answering the research question. In the forests of East Central Africa, our framework showed that vegetation dynamics are to a certain extent driven by climate variables, i.e. temperature, precipitation and solar radiation. To find out in what way these climate variables drive changes in vegetation in these regions, further research should be done. For the African rainforest, however, we were not successful in identifying the drivers of the vegetation dynamics. We tried to improve the performance of the framework by using EVI instead of NDVI. In hindsight, it seems that the issue is not the vegetation index itself, but the low variability of anomalies of the vegetation index data in this region.

As for the cause of low variation in EVI anomalies over the African rainforest, two hypotheses were introduced. It could be possible that use of MODIS data leads to uncertainty about the capacity of the EVI data to accurately describe the vegetation of the African rainforest. Alternatively, the data could be a good characterization of the vegetation in the African rainforest, which would mean that the vegetation of the African rainforest does not show much change apart from the seasonal cycle and the long term trend. Whatever the reason of the low variation in EVI anomalies, since using anomalies is crucial for the Granger causality framework, the combination of this approach and data was not successful. A next step would be to examine whether different sources of EVI data capture more variation in EVI anomalies. Validation of remote sensing data with ground based data is crucial for this. If data of other sources show more variation, the Granger causality framework might be an option for further research. Another promising option would be to use independent SIF data when long-term time series become available. If the vegetation anomalies of the African rainforest do not show variation in data from other sources, this Granger causality framework is not suitable to find the drivers of the vegetation dynamics of the African rainforest and other approaches should be explored.

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Appendices

A Results of the analysis for EVI

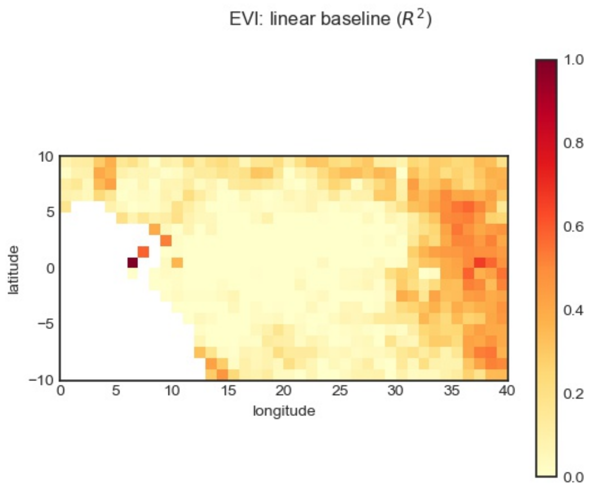

Figure A.1: Results of the linear baseline model for EVI.

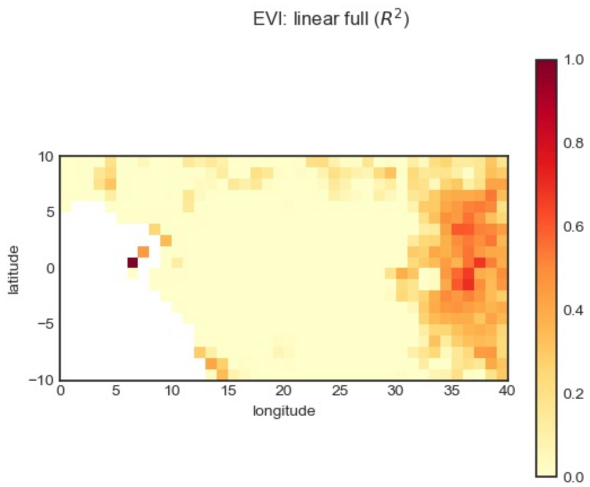

Figure A.2: Results of the linear full model for EVI.

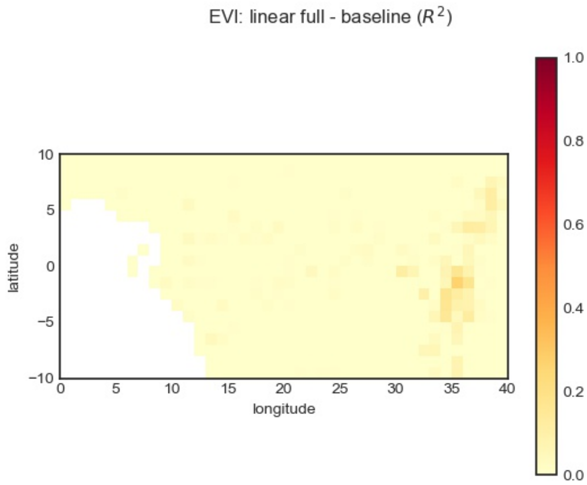

Figure A.3: Results of the difference between the linear full model and the linear baseline model for EVI.

B Results of the analysis for SIF

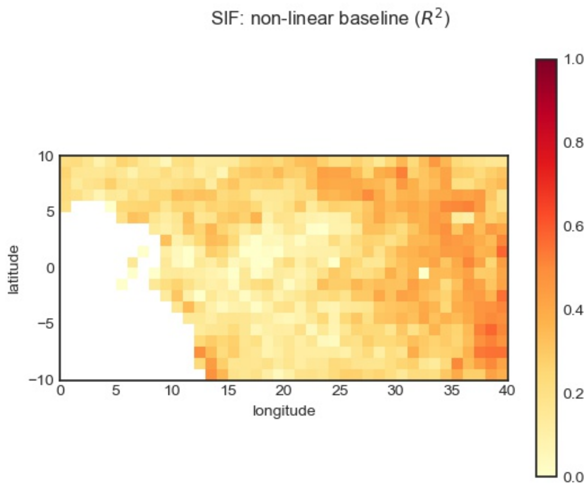

Figure B.1: Results of the non-linear baseline model for SIF.

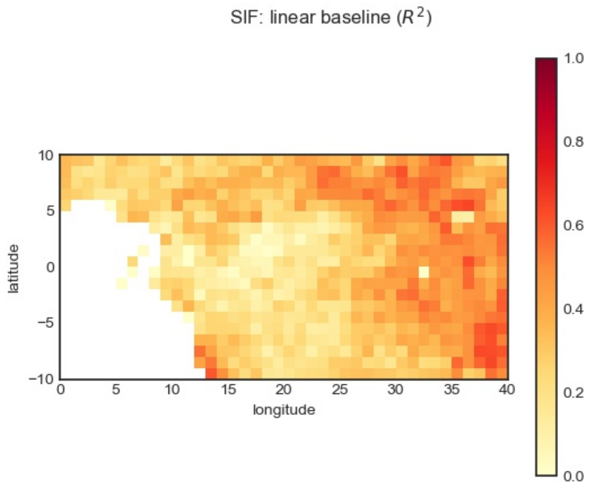

Figure B.2: Results of the linear baseline model for SIF.

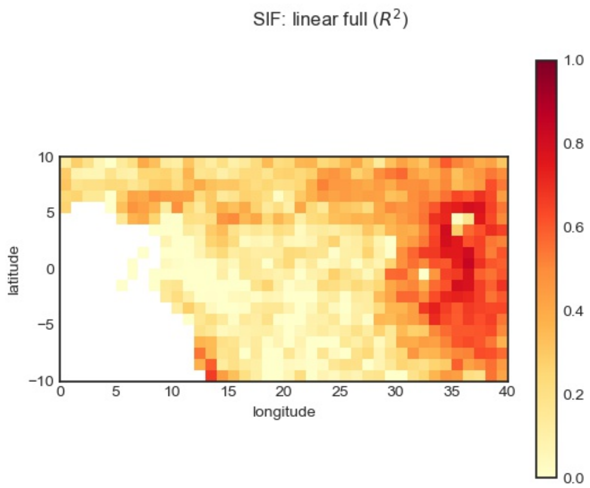

Figure B.3: Results of the linear full model for SIF.

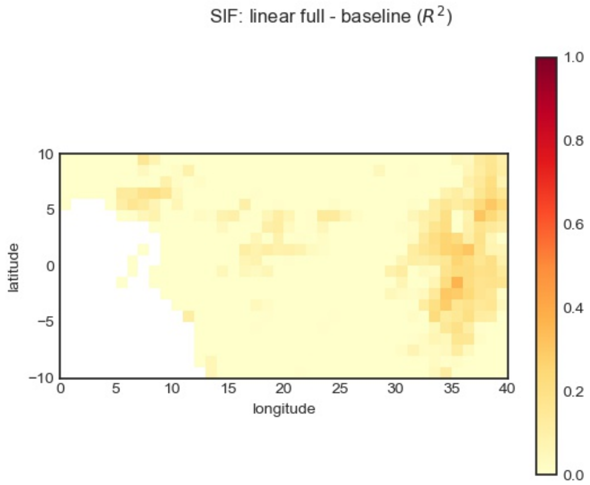

Figure B.4: Results of the difference between the linear full model and the linear baseline model for SIF.

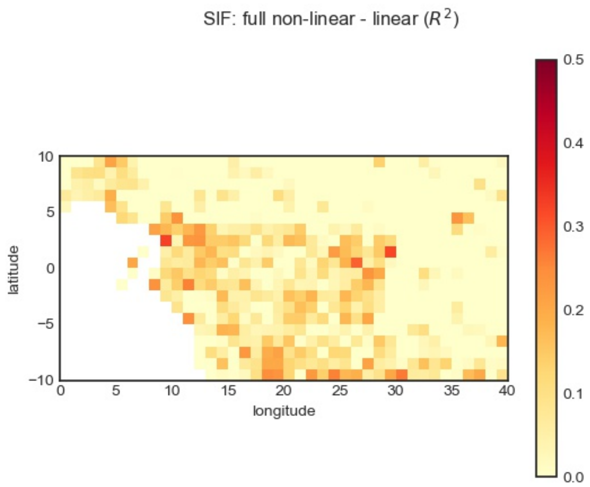

Figure B.5: Results of the difference between the non-linear full model and the linear full model for SIF.