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Analyses of GIMMS NDVI Time Series in Kogi-State, Nigeria

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ABSTRACT

The value of remote sensing data is particularly evident where an areal monitoring is needed to provide information on the earth's surface development. The use of temporal high resolution time series data allows for detecting short-term changes. In Kogi State in Nigeria different vegetation types can be found. As the major population in this region is living in rural communities with crop farming the existing vegetation is slowly being altered. The expansion of agricultural land causes loss of natural vegetation, especially in the regions close to the rivers which are suitable for crop production. With regard to these facts, two questions can be dealt with covering different aspects of the development of vegetation in the Kogi state, the determination and evaluation of the general development of the vegetation in the study area (trend estimation) and analyses on a short-term behavior of vegetation conditions, which can provide information about seasonal effects in vegetation development. For this purpose, the GIMMS-NDVI data set, provided by the NOAA, provides information on the normalized difference vegetation index (NDVI) in a geometric resolution of approx. 8 km. The temporal resolution of 15 days allows the already described analyses. For the presented analysis data for the period 1981-2012 (31 years) were used. The implemented workflow mainly applies methods of time series analysis. The results show that in addition to the classical seasonal development, artefacts of different vegetation periods (several NDVI maxima) can be found in the data. The trend component of the time series shows a consistently positive development in the entire study area considering the full investigation period of 31 years. However, the results also show that this development has not been continuous and a simple linear modeling of the NDVI increase is only possible to a limited extent. For this reason, the trend modeling was extended by procedures for detecting structural breaks in the time series.

Keywords: GIMMS AVHRR, break point analysis, trend analysis, NDVI, time series analysis, Kogi

1. INTRODUCTION AND MOTIVATION

Since long ago, it has been a known fact that plants are an essential resource for all life forms on earth.¹ Humans, animals, as well as the earth's atmosphere benefit from these living, growing organisms in many ways. Supplying food, producing oxygen - these are just two examples to emphasise this statement.¹ The importance of plants is unquestioned and it is thanks to them that the earth can be referred to as "the green planet". But according to the "State of World's Plant Report" from May 2016,² 21 % of the estimated 391,000 global plant species known to science are in danger of extinction. It is widely acknowledged that climate change and human activity are the major forces behind the noticeable change in land-cover in the past decade.² The dominant threat, so the report says, is constituted to be agriculture.² Through cropping, forestry, grazing and urbanisation the land is steadily and irreversibly converted to meet the needs of the growing human population.³ It is for this reason that detailed information about the vegetation cover changes need to be provided. Using "current and accurate information on a global basis regarding the extent and condition of [the land cover, as well as] the world's major food and fibre crops"⁴ different studies have been conducted all around the world. However, many regions, such as Kogi-State in Nigeria (Africa) that highly depend on the agriculture as major economic factor, and thus depend on the

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knowledge of the alteration in the vegetation cover, are still subject of too little research.^{2,5} Aggravated by the fact that there are often no, merely incomplete or outdated data to be found for countries like the one mentioned above, global data is crucial.

With the help of satellite remote sensing, inter-regional information about the vegetation cover can be permanently gathered and distributed in form of multispectral satellite image data. Satellites such as the National Oceanic and Atmospheric Administration (NOAA) satellite series with the Advanced Very High Resolution Radiometer (AVHRR) on board are an important tool to help monitor vegetation dynamics. A measure for the amount of vegetation, its health and vitality is the Normalized Difference Vegetation Index (NDVI).⁵ Calculated using the normalized ratio of differences between the atmospheric radiance in bands of the near-infrared (NIR) and red (R) spectral range (Eq. 1),^{5,6} the NDVI is one of the most famous and "most important [vegetation] indices for detection, identification and evaluation of vegetation".⁷

$$NDVI = \frac{NIR - R}{NIR + R} \quad (1)$$

Established by Rouse et al. (1974)⁸ and Tucker (1979),⁹ the NDVI is based on the general biological principle of photosynthesis⁶ - actively growing vegetation has a high concentration of chlorophyll and thus absorbs light in the red and reflects light in the near-infrared region of the electromagnetic spectrum.^{4,6} If NDVI values exist for the same study area over a long enough period of time, these values can be analysed with methods of the time series analysis to find characteristic structures and regularities in the present time series.¹⁰

The Global Inventory Monitoring and Modelling System (GIMMS), for example, generates NDVI data sets using time series satellite data from NOAA AVHRR, and thus provides over several decade long repeated remote sensing measurements of the same global land areas.⁶ It was shown in several studies like Osunmadewa et al. (2015),⁵ that with the help of these data sets long-term changes in the vegetation cover can be detected.¹¹ The mentioned study was conducted to analyse trends and to detect structural breaks within a given set of GIMMS NDVI data for four selected locations in the chosen study area of Kogi-State. Different linear regression models and a break point analysis were not only performed but the quality of the models was also evaluated establishing a suitable methodology for future research.⁵

As already mentioned, regions such as Kogi-State depend on the knowledge obtained from analysing the vegetation cover changes. Therefore, it is the purpose of this study to continue the work of Osunmadewa et al. (2015)⁵ and to deepen the understanding of the long- and short-term vegetation dynamics in this country. Now, the given NDVI time series of the entire study area are analysed (trend and seasonality) and structural breaks in the data are detected. At the end, suitable maps displaying the different results of the conducted analyses are developed. It is the aim of this study "to find spatial dependences of NDVI in entire Kogi-State and to examine potential discrepancies in the development of Nigerian landscape".⁵ Since Osunmadewa et al. (2015)⁵ found both trends and structural breaks at selected locations, it is obligatory to ask, if trends in the vegetation degradation and structural breaks indicating abrupt vegetation change can be verified area-wide. In sum, the underlying question is and will remain: Can changes in the vegetation cover be seen in the given NDVI data? The results of the time series analyses, that is mostly based on the work of Osunmadewa et al. (2015),⁵ presented in this paper will establish clarity.

The paper is divided into four sections. In the first section, a detailed description on the area of study and the provided data set will be given. The next two sections, are on the analyses of the data. First, we will specify the methodology before we focus on the results by showing and interpreting the developed map representations. The last section contains a discussion of the obtained results.

2. STUDY AREA AND DATA

Since the conducted calculation are solely based on the given data sets, it is the aim of this section to give an overview over the study area and the data, and thus build a basis for the explanations regarding the time series analyses.

2.1 The Study Area Kogi State

Kogi-State, located in the central region of the Federal Republic of Nigeria (Fig. 1), extends from latitude 6.5°N to 8.7°N and longitude 5.3°E to 7.8°E*. With Lokoja as the capital city, the study area consists of 21 different Local Government Areas (LGAs).¹² The state covers an area of approximately 27,747km² and has, according to the 2012 population census, a current population of 3,850,369, respectively.¹³ In 2006 it was estimated "that about 70 % of the population lived in rural areas".¹⁴ Due to the confluence of Nigeria's two largest rivers (River Niger and Benue) at Lokoja, Kogi-State is also called "The Confluence State".¹⁴

Figure 1. Map of Nigeria showing the location of Kogi-State (study area)

The mainly tropical climate of Kogi-State with an annual mean temperature between 23.5°C (minimum) and 33.5°C (maximum) and an annual mean relative humidity commonly over 50 % is characterized by the two main seasons *dry season* and *wet season*. The dry season lasts from November until late February, whereas the Harmattan wind is experienced between December and January. Starting towards the end of March and ending towards the end of October, the total annual rainfall of the wet season varies between 804.5 mm to 1767.1 mm. For an area the size of an entire state, it has to be taken into consideration that the start and end of the wet season differs depending on the part of Kogi-State and that in some very dry years the rainfall may not start until April. This variability in rainfall has a temporally and spatially influence on vegetation.^{5, 12–14}

Kogi-State, mostly a flat land mass, is a semiarid region^{5, 12} with a vegetation cover that can be divided alongside two cardinal directions. While woody-derived savannah and Guinea savannah can be found in the northern part of the state, the southern part consists of rainforests.^{12, 14} Furthermore, gallery forests can be found alongside water courses like the rivers Niger and Benue.⁵ But as the major population of the study area live in rural communities with crop farming as their predominant occupation,¹⁴ the existing vegetation is slowly being altered.⁵ Especially in regions alongside the water courses like the rivers Niger and Benue that are suited for crop production, the natural vegetation is lost.⁵ Changes of the vegetation cover due to the agriculture linked with the variabilities in rainfall and temperature - all these factors have led to the necessity of analysing the vegetation cover.

*Geographical location based on the extend of the first layer of the GIMMS NDVI data set.

2.2 The GIMMS AVHRR 8km NDVI Data Set

The GIMMS NDVI data set used in the present study provides long-term NDVI time series at the regional scale of Kogi-State, Nigeria. As a matter of fact, the mentioned data set is just a subset extracted from a product containing various data sets: the GIMMS AVHRR 8 km NDVI product. The global NDVI product generated by the GIMMS group comprises NDVI data derived from several NOAA AVHRR satellite sensors over the last three decades.⁶ To account for various effects that would otherwise cause systematic distortions in the NDVI time series, several corrections were applied to the GIMMS NDVI product before making it publicly available (see Pinzon et. al (2005),¹⁵ Tucker et. al (2004)⁶ and Tucker et. al (2005)¹⁵ for a more detailed explanation).⁵ The purpose of generating this product is to supply "a satellite record of monthly changes in terrestrial vegetation"⁶ worldwide. Since the start of the first NOAA satellite in 1981, the importance of the AVHRR data in the study of the terrestrial vegetation increased tremendously.¹⁶

The NDVI product, with a spatial resolution of approx. 8 km x 8 km, was constructed as composite images at regular time intervals of 15 days (the temporal resolution).⁶ Due to this, there are two images available per month: one image composing the maximum NDVI values for day 01 to 15 and the second image composing the maximum NDVI values for day 16 to the end of each month.⁶ In total of 24 different images per year are available. Considering that the bimonthly data set spans a time period of 31 years, from July 01, 1981 to January 01, 2012, there are altogether 732 different NDVI-based images contained in the present GIMMS NDVI data set. Note that from now on the images are referred to as bands. Each band holds a total of 342 cells containing relevant, gap-free data⁶ for this study. However, the NDVI values contained in the bands do not range from -1 to 1 as one would have expected based on the definition of the NDVI, but theoretically from -10,000 to 10,000 - the NDVI values were multiplied by 10,000.⁶ NDVI values of -10,000 indicate water and values of 0 indicate bare soil.⁶ By visualising two random bands out of the 732 available bands (Fig. 2) and showing the value distribution of the chosen bands with the help of a histogram (Fig. 3) this can be confirmed. It is also shown that the values are much bigger than -10,000 and a bit smaller than 10,000. Considering all bands, the values range from approx. 580 to 9,750 meaning that the two rivers Niger and Benue that flow through the study area cannot be distinguished on the NDVI values alone. This is on the account of the spatial resolution of the satellite, leading to a certain percentage of information loss in the data. Furthermore, the projection of the GIMMS NDVI data set is the geographical latitude/longitude projection using the World Geodetic System 1984 (WGS 84) datum.

Figure 2. Visualising band 1 and 673 of the GIMMS NDVI data set, the color-coding as shown in the legend has been applied to each band.

Figure 3. Distribution of values in the GIMMS NDVI bands 1 and 673 visualised in Fig. 2, the density curve (in red) shows the continuous probability distribution.

3. METHODOLOGY

The implemented time series analyses are divided into a workflow including four stages. Tab. 1 summarizes the order of the steps for the simultaneously performed analyses and provides a compact overview of the applied methods. Starting point is the determination of the seasonal period. With this classification, the time series is further decomposed into a trend (T), a seasonal (S), and a random (e) component. Using a linear regression, as well as a segmented linear regression - the latter encloses a breakpoint analysis - the trend component is further analysed. In between the different process steps, the quality of the method is assessed using three different stationary tests: The augmented Dickey-Fuller test (ADF), the Phillips-Perron test (PP), and Kwiatkowski-Phillips-Schmidt-Shin test (KPSS).

This chapter describes the methodological part of the study. The general approach of the performed time series analyses will be stated and the listed methods in Tab. 1 will be consecutively introduced in the next few subsections. The purpose of using a particular method and its implementation will be explained. The obtained results of the time series analyses will be presented in Ch. 4 and discussed in Ch. 5.

3.1 General Approach of Time Series Analyses

The order in which a time series analysis is performed depends on the methodology. The results of certain methods are needed in order to apply other methods, thus predetermining the procedure of the time series analysis to some extent. In order to develop a general approach for the time series analyses for this study as presented in Tab. 1, one out of the 342 available cells of the GIMMS NDVI data set was exemplarily analysed. Based on the assumption that the structure of the NDVI time series can be referred to as similar, the time series in cell no. 30 - from now on tagged as time series no. 30 - was selected as a representative of the remaining time series. There are three reasons to choose this kind of approach. First, the computation time while developing the presented approach was shortened. This in turn makes it easier to spot errors in the programming process and to keep track of the obtained results since dealing with a certain amount of data can be confusing. The second and last reason were to get a general idea of the data structure and what results to expect.

Later on, the methods listed in Tab. 1 were transferred to the remaining time series and the results were composited in maps using the same spatial extend as the original data. Note that the results of the time series analysis for time series no. 30 will not be described in detail in this paper, but will rather be used as additional information to give a clearer explanation of the developed maps (see Ch. 4).

Table 1. General workflow of the time series analyses displaying the individual working steps and the methods that were used.

WORKFLOW	METHOD
a) Determining the seasonal period	Periodogram
b) Decomposition and analysis of components	
Seasonal component	Graphical Analysis
Random component	
Checking for remnants of other seasonal periods	Periodogram
Stationary test	ADF-, PP-, KPSS-test
c) Trend analysis	
Linear regression	OLS method
Residual analysis	ADF-, PP-, KPSS-test
Segmented linear regression	Breakpoint analysis
Residual analysis	ADF-, PP-, KPSS-test

3.2 Determining the Seasonal Period

In a time series, both apparent and hidden periodicities can be found.¹⁷ Is the time series periodic, it is mostly unavoidable that values of one period are correlated with values from another period - the values are not independent.¹⁸ The first task of the time series analyses is therefore to search for and, remove these periodicities to facilitate the interpretations drawn from the time series analyses.⁵ Note, that removing the detected periodicities from a time series do not change the remaining features of a time series.¹⁷

A heuristic tool for identifying dominant periods (or frequencies) in the observed series is the periodogram.¹⁷ It is defined as a function of the Fourier frequency λ

$$I(\lambda) = \left[\left(\frac{1}{N} \sum_{t=1}^N (Y_t - \bar{Y}) \cdot \cos(2\pi\lambda t) \right)^2 + \left(\frac{1}{N} \sum_{t=1}^N (Y_t - \bar{Y}) \cdot \sin(2\pi\lambda t) \right)^2 \right] \quad (2)$$

with Y_t a time series, t the time, and N the number of observations. In consequence, the periodogram gives a measure for the intensity with which each possible frequency will appear in the analysed time series.¹⁷ In short, the striking peaks in the periodogram show the existing periodicities in the time series.

Other methods like the autocorrelation function (ACF) and the partial autocorrelation function (PACF) - both methods were not implemented in the present study - can also be used to determine the seasonal period in the time series.⁵

3.3 Decomposition of the Time Series

In Ch. 3.2 it was stated that by removing the detected periodicities from a time series, the remaining features do not change.¹⁷ Since it often occurs that seasonality is to be found in time series, this is a necessary characteristic. Hence, it is generally usual to assume that time series contain the following components:¹⁸

- a trend component T representing a long-term movement,
- a seasonal component S representing a seasonal fluctuation of a relatively steady period, and
- a residual component e representing a residual, irregular, or random effect.¹⁸

A model can be formulated to describe a time series (Y_t) at a specific time t .¹⁰ This can be achieved by either adding the three individual components T, S, and e, or multiplying them, respectively:

$$Y_t = T_t + S_t + e_t \quad (3)$$

$$Y_t = T_t \cdot S_t \cdot e_t \quad (4)$$

The additive model (Eq. 3) is chosen, when the amplitude of seasonality is almost constant over the entire observation time. If, on the other hand, the amplitude increases proportional to the level, the time series is described through the multiplicative model (Eq. 4).^{10,18} Considering that plants are adjusted to the natural environment, regular changes in the environment are in turn reflected in the photosynthetic activity of vegetation. The change with the longest effect on the plants is due to the seasons of the year. Depending on the season the photosynthetic activity increases and decreases, resulting in a typical rhythm that repeats annually. Therefore, a constant vegetation period of one year can be assumed for the present NDVI time series. This assumption is supported by the findings of Osunmadewa et al. (2015).⁵ Since the requirements for the additive models are fulfilled, this model is now the basis for the decomposition of the time series to study the mentioned components individually.¹⁸ With the dominant periodicity detected by using the periodogram, the *decompose* function implemented in R-Statistic can be applied. The function works as follows:

- a) The trend is determined by using the moving average method with a window-size of $n+1$ with n as the frequency of seasonality (Eq. 5). By removing the trend component of the original time series, the seasonal and random components remain.⁵

$$\frac{t_{max} - \frac{n}{2}}{t_{max} + \frac{n}{2}} T_t = \frac{\sum_{i=t-\frac{n}{2}}^{i=t+\frac{n}{2}} Y_i}{n+1} \quad (5)$$

- b) The seasonal component is calculated next. For this purpose, the average is computed for each time unit and over all periods. Afterwards, the average is centered.

$${}_n S_i = \frac{\sum_{j=0}^{m-1} Y_{j \cdot n + i}}{m} \quad (6)$$

Equation 6 can be used to express the seasonal component S_i for a period of one year. The index m stands for number of years.⁵

- c) The random component is the component that is determined last by subtracting the trend and seasonal component from the original time series (Eq. 7).⁵

$$e_t = Y_t - (T_t + S_t) \quad (7)$$

Each component results in a time series that can be analysed separately. Yet, due to the way the components were calculated, the number of values contained in the trend and random component is shorter than the number of values contained in the original time series. The total amount of missing values is equal to the number of observations contained in the length of the seasonality $n(N_n)$. At the beginning and at the end of the components $x = N_n/2$ values are missing.

3.4 Trend Analysis

One of the major objectives in this study is the detection of trends in the present GIMMS NDVI time series "to assess long-term spatio-temporal change in vegetation greenness".⁵ For this purpose, several methods were introduced and applied in the study of Osunmadewa et. al. (2015).⁵ In order to analyse the trend components of the decomposed time series in this study, two of the introduced and implemented methods are used: The ordinary least-squares (OLS) linear regression modelling and the segmented linear regression modelling.

3.4.1 Linear Regression Modelling

First, we assume that the trend component can be modelled by using a straight line - this is the simplest trend-function. To fit a given time series linearly, the least-square method is used.¹⁷ This approach can be expressed through the following OLS model:

$$y = a + b \cdot x \quad (8)$$

with y the dependent variable, x the independent variable, and the coefficients a and b .^{10,19} Since the OLS model "can be used for modeling time series of environmental variables such as vegetation [...]"⁵ the parameters y and x of the model can be replaced by parameters of the problem at hand:⁵

$$NDVI = a + b \cdot t \quad (9)$$

To verbalise this equation: The trend component of the decomposed NDVI time series is a linear function of the time t .⁵ Based on this linear relationship, the linear fit to the given NDVI values represents the temporal trend that is found in the data.^{5,17} The significance of each NDVI value was tested at the significance level $\alpha = 0.05$. The parameter b (slope) indicates in which direction the NDVI develops, depending if it is positive or negative.⁵

3.4.2 Segmented Linear Regression Modelling

There is one problem with the described approach in chapter 3.4.1. Since the linear regression is done over the entire observation time, structural changes that might be present in the time series are ignored - the model does not consider that dependent variable can be influenced by external causes.⁵ A better way to include these changes is by applying the segmented linear regression on the data. As the name already suggest, the observation time is divided into segments with different ranges of time.¹⁹ By fitting a OLS linear regression model to the data contained in each segment (Eq. 10-12) and joining those models together through addition, the segmented linear regression model can be defined as[†]:

$$NDVI_{Segment\ 1} = a_{Segment\ 1} + b_{Segment\ 1} \cdot t, \text{ for } t \leq bp_1 \quad (10)$$

$$NDVI_{Segment\ 2} = a_{Segment\ 2} + b_{Segment\ 2} \cdot t, \text{ for } bp_1 \leq t < bp_2 \quad (11)$$

⋮

$$NDVI_{Segment\ n} = a_{Segment\ n} + b_{Segment\ n} \cdot t, \text{ for } bp_{n-1} \leq t < bp_n \quad (12)$$

$$NDVI = NDVI_{Segment\ 1} + NDVI_{Segment\ 2} + \dots + NDVI_{Segment\ n} \quad (13)$$

The points at which the independent variable is segmented are called breakpoints (bp). Note, that the segmented linear regression model is discontinuous at the breakpoints.¹⁹ That means that the linear regression lines of the different segments are not linked, thus supplying information about the magnitude of the break between the NDVI value before and after the breakpoint.

A tool for detecting breakpoints within a time series is the function *bfast* that is implemented in R-Statistic. This function works in two steps: First, it decomposes the input series into a seasonal, trend, and remainder component and then, it iteratively estimates the time and number of significant changes²⁰ by using the OLS residual-based moving sum (OLS-MOSUM).^{5,21} With *bfast* breakpoints can be detected within the seasonal and trend component.²⁰ Since a trend analysis of the present NDVI time series is solely conducted for the trend component, the seasonal component is set to zero. Furthermore, the slopes and intercepts of the segmented regression lines are estimated.⁵ A special feature of the *bfast*-function is that the character of the regression lines can be defined by certain boundary conditions.⁵ One example for such a boundary condition is the parameter h , representing "the minimal segment size between potentially detected breaks in the trend [component] [...]" given as fraction relative to the sample size [...]"²² Based on the work of Osunmadewa et al.,⁵ the h -parameter is optimally set to 0.15, resulting in a segment size of minimum of 4 years and 2.5 months. One of the reasons to choose $h=0.15$ is that the spread of the confidence interval of the breakpoint is most probably located between the two set values defining the interval - amount to a few months and not to a few years.⁵ However, choosing, for example, a lower value for h will increase the spread of the confidence interval.⁵ For more general information about the *bfast*-function, see Osunmadewa et al. (2015).⁵

[†]Equations adjusted to the present problem, equations based on Ryan (2007).¹⁹

3.5 Stationary Tests

The random component of the decomposed time series, the residuals of the linear regression model, as well as the residuals of the segmented linear regression model need to be statistically assessed by the means of a residual analysis,⁵ to examine the quality of the used method. To do so, the residuals need to be stationary. That means that they have to fulfil the following requirements:

$$m_{residuals} = const. \quad (14)$$

$$\mu = 0 \quad (15)$$

$$v = const. \quad (16)$$

with m the mean value, μ the expectation value, and v the variance.¹⁷ There is a total of three different stationary tests that have been used in the time series analyses to test, if the stated requirements were truly met.

- a) The augmented Dickey-Fuller test (ADF) and the Phillips-Perron test (PP): Both the ADF- and PP-test are unit root tests. They test, if a unit root is present in the time series (null hypothesis). If so, the null hypothesis needs to be accepted and it can be concluded that the time series is not stationary. Note, that the ADF-test has the habit to reject the null hypothesis although the tested time series is non-stationary. The PP-test can be seen as an additional test in order to compensate for this flaw.^{5, 23, 24}
- b) The Kwiatkowski-Phillips-Schmidt-Shin test (KPSS): The KPSS-test is a stationary test. It tests directly, if the present time series is stationary (null hypothesis). If so, the null hypothesis needs to be accepted and it can be concluded that the time series is stationary. A special feature of the KPSS-test is, that level and trend stationary can be tested.^{5, 24, 25}

An overview of the distinct features of each test is summarized in Tab. 2. It is necessary to apply all three tests to the random component of the decomposed time series, since "there is no uniformly powerful test of the unit root hypothesis".²⁴

Table 2. Overview of the ADF-, PP- and KPSS-test.

	ADF / PP	KPSS
H_0 :	Unit root	Stationary
H_A :	Stationary	Non-stationary
Reject H_0 :	Critical value > test value	Critical value < test value
Test for:	Unit root	Stationarity

4. RESULTS

The scientific challenge of this study was the development of suitable map presentations showing the results obtained from 342 simultaneously performed time series analyses for the study area of Kogi-State. Ultimately, a total of 26 different maps were created. The results presented in this paper will focus on 18 out of the 26 developed maps. The maps that are not displayed will be explained throughout the following subsections. The order in which the results will be presented follows the workflow shown in Tab. 1. The results are discussed in Ch. 5.

4.1 Determining the Seasonal Period

The first map developed during this study shows the dominant seasonal period of the present NDVI time series (Fig. 4, right). To have a better understanding of the information displayed in map no. 1, the calculated periodogram of time series no. 30 is analysed first (Fig. 4, left).

Figure 4. Left - The highest peak in the periodogram of the time series no. 30 verifies a seasonal period of one year. Right - Map displaying the seasonal periods for the GIMMS NDVI time series. The results are based on a periodogram calculated for each series.

Two noticeable peaks can be distinguished in the periodogram of time series no. 30. The highest peak is to be found at the frequency 0.042 or respectively $1/24$ with the number 24 as number of observations. Since 24 is the number of observations recorded in one year, the dominant seasonal period is one year - this is the first confirmation of the assumption made in Ch. 3.3. The second peak can be found at the frequency 0.083 or respectively $1/12$. This peak, indicating a seasonal period of half a year, can for now be ignored since it is clearly not the dominant seasonal period of time series no. 30. Is the peak at the frequency 0.083 still present after the seasonal component is removed, it can be said that a second seasonal period can be found in the data.

By calculating a periodogram for each series, determining the maximum peak of the periodogram and composing the obtained results, the first map is generated (see Fig. 4, right). Looking at the map, it is apparent that the assumption made in Ch. 3.3 applies area-wide to all given time series - except for time series no. 123 with a seasonal periodicity of half a year. Assuming that the amount and location of the peaks in each periodogram is the same as for time series no. 30, it can be estimated that the peak of the periodogram at $1/12$ is bigger than the peak at $1/24$. Computing the periodogram for time series no. 123 (not shown), not only asserts this assumption but also shows that the difference between both peaks is minimal. For this reason, the seasonal period for time series no. 123 is set to one year.

To sum it up, the map of the dominant seasonal periods clearly proves that a seasonal period of one year is present within the analysed NDVI time series. The assumption made in Ch. 3.3 was correct.

4.2 Decomposition of the Time Series

Due to the periodogram, the requirement of a known seasonal period is fulfilled for each given NDVI time series. The *decompose* function (see Ch. 3.3) can be used, dividing the time series into a trend, seasonal and random component. Fig. 5 shows exemplarily the result of the decomposition of time series no. 30.

4.2.1 The Trend Component

The trend component is, after visualising the original time series, the first component of the decomposed time series shown in Fig. 5. Although there are numerous sharp declines found within the data of the trend component, in general it can be said that the represented NDVI values are slowly increasing over time. Therefore, it can be concluded that a positive trend is present. It can once again be assumed, that most of the remaining time series will show the same behaviour after decomposing. A throughout analysis of the trend component conducted in the Ch. 4.3 will show, if this assumption is true.

Figure 5. The decomposed time series no. 30 - from top to bottom: The original time series, the trend, the seasonal and the random component.

4.2.2 The Seasonal Component

Looking at the seasonal component of time series no. 30 (Fig. 5), approx. 30 identical seasonal variations can be counted - one seasonal variations spans the time of one year. This is in coherence with the basic knowledge of the time series since the time series contains data from 1981 to 2012 (approx. 30 years) and the dominant seasonal period is one year. Furthermore, two peaks can be found within the annual seasonality. Detecting the inflection points of one of the seasonal variation and determining the dates of the inflection points, it became apparent that the seasonal period is composed of two growing seasons - the first season being roughly in the first half and the second season being roughly in the second half of the year. This is an indicator that the agriculture in Kogi-State uses the double cropping system.

The seasonal variations shown in Fig. 5 can also be seen in the actual data itself. For this reason, all bands from 2009 (Fig. 6) and their value distributions (Fig. 7) are exemplarily visualised. We can see from both plots that the NDVI values rise and fall accordingly to the basic structure of the seasonal period of the decomposed time series no. 30. It can be interpreted in the following way: The first crop is planted at the beginning of the year and ready to be harvested by late spring (in Fig. 6 approx. May/June). At midsummer (around August) the second crop is planted to be harvested from autumn (October) onwards. Therefore, there are two phases the plants or rather the crop goes through: Growing and harvesting. The time in between the planting and harvesting, the plants grow. This, in turn, is shown by a shift in the distribution of the NDVI values to the higher values. However, while harvesting the crop, the distribution of the NDVI values will spread (Fig. 7). This can be explained with the fact that the plants are harvested one after another leading to different NDVI values throughout Kogi-State. Is the growing season over, the distribution of the NDVI will return to values around 4,000 since the crop is completely harvested and the natural vegetation remains.

All in all, it can be estimated that, although it was not verified for every single time series, double-cropping is practiced in the state. It can be further estimated that one growing season contains 12 values. This may be the reason, why, apart from the dominant seasonal period of one year, a second periodicity with the frequency of $1/12$ was found exemplarily in the periodogram of time series no. 30 and was actually detected as the dominant seasonal period in time series no. 123 (see Ch. 4.1). For the latter, this can possibly be explained with a strong harvest in this location.

Verifying the double-cropping in approximately the entire state, another assumption - the amount and location of the peaks is the same for each periodogram - can be asserted to be generally correct.

Figure 6. By showing the GIMMS NDVI data bands of the year 2009 the seasonal change of the vegetation can be visualised.

Figure 7. Distribution of values for the bands shown in Fig. 6

4.2.3 The Random Component

The random component is the last component of the decomposed time series that needs to be analysed and evaluated. Theoretically, it should be completely free from any trend or seasonality since both components were subtracted from the original time series (refer to Ch. 3.3). The necessary condition is that the trend and the seasonal component were computed correctly. The random component is therefore used to assess the quality of the *decompose* function.

To prove that the random part is undoubtedly free from a trend and any seasonal period, the stationary tests ADF, PP and KPSS (for level and trend stationary) introduced in Ch. 3.5 are applied to the random component of the decomposed time series. Taking the information given through Tab. 2 in Ch. 3.5 into consideration, the results are as follows: For the ADF- and PP-test the null hypothesis of a unit root is rejected and for both KPSS-tests the null hypothesis of stationarity is accepted. These decisions are based on the following inequation:

$$\text{critical value} > \text{test value} \quad (17)$$

To summarize, all 4 tests are unmistakably leading to the same conclusion: The random component of the decomposed time series is stationary. That means that no trend or seasonality remains within the random component of any decomposed time series. Generating a map like the one shown in Fig. 4 (right), verifies the latter. The *decompose* function works appropriately.

4.3 Trend Analysis

Based on the results obtained in the previous section, it can be concluded, that the trend component was successfully extracted from the original time series. It is now possible to conduct a trend analyse using the OLS linear regression, as well as the segmented linear regression model according to the explanations in Ch. 3.4 on the trend component of the decomposed time series.

4.3.1 Linear Regression Modelling

The regression lines resulting from the applied OLS linear regression model can each be characterized in greater detail by the following four statistical parameters: slope, residual standard error (RSE), R^2 -value and p-value of the overall F-test. Building upon these parameters, a total of four maps were generated to support evaluating the used model in this sub-section.

From Fig. 8 (left) showing the slope of the regression line, it is apparent that most of the regression lines are strongly increasing over the time with a slope ranging between 10 to 30 and occasionally up to 40. Therefore, it can be concluded that a positive trend is present within the data of most of the time series. This aspect was already assumed in the previous section and can now be verified. On the other hand, regression lines with nearly

Figure 8. The slopes (left) and the RSEs (right) of the linear regression lines for the trend component of the decomposed GIMMS NDVI time series. The results are based on the OLS linear regression model.

no and two regression lines with a slightly negative slope can be found. The locations of the regression lines with these slopes coincide with the location of the river, when the map in Fig. 8 (left) is compared to a map of Kogi-State. It can be argued that the NDVI value is influenced by the water present in these locations, leading to a smaller NDVI-value that is hardly changing over time. Since there are also locations that cannot be related to water bodies, this theory cannot be verified for certain.

The RSE (see Fig. 8, right) is fairly high with values between 150 to 250 indicating that the quality of the linear regression fit is mediocre, although the model fits the given observations for most time series rather adequately. The latter is based on the resulting R^2 -values displayed in Fig. 9 (left). Finally, the overall F-test for regression at the significance level of $\alpha = 0.05$ (results seen in Fig. 9, right) implies, that the regression line resulting from the used OLS model is - except for two cases - significant and can be used to describe the trend of the NDVI signal. This is decided by determining, if the p-value of the overall F-test is smaller than the stated significance level. To assess the reason why two regression lines are not significant, the respective time series need to be analysed in detail (not conducted in this study).

Figure 9. The statistical parameter R^2 (left) and the p-value (right) of the regression lines for the trend component of the decomposed GIMMS NDVI time series. The results are based on the OLS linear regression model.

Nonetheless, the quality of the linear regression model should not be assessed only using the statistical parameters of the regression line, but also by conducting residual analyses. The stationary tests ADF, PP and KPSS (trend and level stationary) are applied on the residuals of the regression line. In Fig. 10 the results of the stationary tests are displayed by counting the number of tests with the results *stationary*. Although some tests in the north-west of Kogi reveal stationary, the result of the three stationary test for the remaining areas is inconclusive. It should not be forgotten that the tests may lead to the wrong conclusion, because, for example, they reject the respective null hypothesis although it should have been accepted. That makes it difficult to decide, if the residuals of the regression line are stationary or non-stationary. However, based on the overall F-test the regression line is significant.

In Ch. 4.2.1, it was recognized that numerous declines are to be found in the trend component of the decomposed time series no. 30. By plotting the regression line resulting from the applied OLS linear regression model (not shown), it becomes apparent that these variations are not considered in the used OLS model. This is in accordance with the findings of the study of Osunmadewa et. al. (2015).⁵ The variations indicate that external factors are influencing the NDVI signal.⁵ In other words, the chosen OLS model does not adjust to these influencing factors. Based on the results obtained from analysing the results of the OLS model, this is most probably the case for every time series. This leads to the question, if a more suitable model can be computed to parametrise the trend of the NDVI signal. For this reason, the segmented linear regression model as a second method is used.

4.3.2 Segmented Linear Regression Modelling

The first step of the second method is to analyse the given trend component for the presence of structural breaks with the help of the *bfast* function (see Ch. 3.4.2). Fig. 11 (left) exemplarily shows the output of this function

Figure 10. The result of the stationary tests for the residuals of the regression lines.

for time series no. 30. With *bfast*, the input time series - the trend component of the decomposed time series - is divided into a new seasonal, trend, and a remainder component. For the segmented linear regression model, only the new trend component is of interest since the information regarding the detected breakpoints are to be found here. As seen in Fig. 11 (right), a total of three to five breakpoints divide the trend component of the decomposed time series into four to six temporal segments. Most frequently four breakpoints are detected within the analysed trend component. This is highly possible due to the chosen *h*-parameters of the *bfast* function limiting the number of possible breakpoints and the number of segments due to the number and length of the segments.⁵ At this point, it can already be said that the segmented linear regression model fits the data within the original trend component better than the OLS linear regression model alone.

Figure 11. Left: From top to bottom - The result of the breakpoint analysis ($h=0.15$) showing the input time series no. 30, as well as the new seasonal, trend, and remainder component. The new trend component contains four breakpoints dividing the component into five segments. Right: The number of breakpoints in the trend component of the GIMMS NDVI time series. The results are based on the iterative break detection using *bfast*.

The first information that characterises the breakpoints is the position of the breakpoint in the time series (see Fig. 12 to 16, left). In the year, in which a breakpoint is detected, the variations of NDVI value was high

Figure 12. The breakpoints detected in the trend component of the decomposed GIMMS NDVI time series (left) and their two-sided confidence interval (right) for the years 1986 to 1989. The results are based on the iterative break detection using *bfast*.

Figure 13. The detected breakpoints (left) and their two-sided confidence interval (right) for the years 1990 to 1993.

Figure 14. The detected breakpoints (left) and their two-sided confidence interval (right) for the years 1994 to 1997.

indicating a change in the vegetation cover. In the trend component of the decomposed time series, breakpoints can be found throughout the years 1986 to 2006. Taking a closer look at Fig. 14 and 15 (left), it can be stated that most breakpoints occurred in 1994 and 2000, respectively. In Fig. 12, 13 and 16 (left) no such statement can be made, since the breakpoints are distributed throughout the years. It is noticeable that there are no breakpoints to be found at the beginning and the end of the time series - the time span of the present time series is 1981 to 2012. This again is a consequence of the chosen parameter $h=0.15$ (see Ch. 3.4.2). As a result, not

Figure 15. The detected breakpoints (left) and their two-sided confidence interval (right) for the years 1998 to 2002.

Figure 16. The detected breakpoints (left) and their two-sided confidence interval (right) for the years 2003 to 2006.

all breakpoints in the analysed time series may have been detected using the *bfast* function. Therefore, it needs to be kept in mind that there is a possibility that breakpoints could still be hidden within the trend component of the decomposed time series.

The second information that characterises the detected breakpoints is its confidence interval on a significance level of $\alpha = 0.05$ (see Fig. 12 to 16, right). For all maps, the minimum width of the interval is 2 values, respectively 1 month. However, the maximum width of the interval ranges between 8 to 47 values, respectively 4 months to approx. 2 years. The width of the confidence interval is not only "an indicator for quality of the breakpoint on appropriate position",⁵ but it "can also be interpreted as a hint for the sharpness of change in the NDVI trend component".⁵ In this case, the confidence interval with a wide of 8 to 47 values are not acceptable and the respective breakpoints need to be removed. Looking at Fig. 15, 16 and also 12 (right), a lot of breakpoints can be dropped. However, only a few inappropriate breakpoints can be found in Fig. 13 and 14 (right). This in turn means that the statement based on Fig. 14 - most breakpoints occurred in this map in the year 1994 - is right. After removing the breakpoints with an unacceptable confidence interval, it is highly possible that other statements regarding the years in which most breakpoints occurred can be made. In this study, the confidence interval of the breakpoint was not taken into consideration. All detected breakvalues were used in the segmented linear regression model. The result of this model can therefore be slightly falsified.

The third and last information that characterises the detected breakpoints, the amount of break, was not computed during this study. The amount of break is a hint for the extent of the change in the NDVI value, since the segmented regression line is not continuous.

After computing the OLS linear regression lines for each segment of the trend component of the decomposed time series, the last step for the trend analysis - the quality assessment of the segmented linear regression model

- can be conducted. Option 1 is to perform the stationary tests ADF, PP and KPSS on the residuals of all regression lines. The outcome (not shown) is for all tests the same: The residuals are stationary; the used method is suitable to parametrise the trend of the NDVI signal.

Option 2 is to compare the RSE of each OLS linear regression model with the respective RSE for the entire segmented linear regression model. The improvement of the RSE for the segmented linear regression model was calculated and visualised in Fig. 17.

Figure 17. The improvement of the linear modelling in percentage terms. The results are based on the RSEs of the segmented linear regression (OLS) lines.

The result is the same for the whole study area. The RSE improved - for some areas just by 5 %, in the middle of the study area up to 55 % and for most areas the RSE improved by approx. 25 to 35 %. This is a clear indicator that the segmented linear regression improved the NDVI trend detection.

5. DISCUSSION AND SUMMARY

There are two main objectives in this study. First, the determination and evaluation of long-term changes in the vegetation cover in Kogi-State through trend estimation. Second, the analyses of the short-term behaviour of the vegetation conditions to provide information about seasonal effects in the vegetation development. To ease the evaluation of the results, maps are generated. By doing so, spatial dependences of NDVI in the study area can easier be discovered and possible variations in the vegetation development of the state can be analysed. In short, this study tries to answer the simple question, if vegetation cover changes can be seen within the given NDVI data for Kogi-State, Nigeria, over the study period of 31 years (1981 to 2012).

Analysing the trends present in the GIMMS NDVI time series using an OLS linear regression model shows that a consistently positive development in the vegetation productivity (greening trend) can be seen in the entire study area over the full study period. Taking a closer look at the locations, where the NDVI trend increases, and where it is rather low, a spatial dependency becomes apparent (see Fig. 8, left). There is a high possibility that locations with a low increase in NDVI trend coincide with the locations of water bodies (for example the rivers Niger and Benue), whereas the locations surrounding the water bodies have a high increase in NDVI trend. The calculated linear trends are - except for two time series - all significant (see Fig. 9, right). But the visualised statistical parameter of the linear regression lines also show that there are noticeable variations between the linear trends indicating a discontinuous development in the vegetation productivity. The statistical analyses of the residuals (see Fig. 10) show that the OLS linear regression model can indeed be used for most of the time series, but the model has limits. A spatial dependency cannot be seen.

The trend analyses need to be extended. The chosen segmented linear regression model considers structural breaks in the time series (breakpoint analysis) and divides the time series into segments. The statistical parameters show that the segmented linear regression is an improvement to the OLS model (see Fig. 17). This, as well as the other stated results, agrees with the findings of the study of Osunmadewa et. al. (2015).⁵ But it must be regarded that the displayed values in Fig. 17 may be slightly falsified, since all detected breakpoints were taken into consideration although the confidence intervals were partly not appropriate. Based on the generated maps in Fig. 12 to 16 (left), it cannot be detected, if "changes in the phenological condition take place at approximately the same time and order".⁵

The second conducted analyses in this study is in regard to the seasonal development in the data. The short-term behaviour of the vegetation condition follows the seasonal period of one year. However, artefacts of other seasonalities are found in the data leading to the typical structure of the seasonal variation (see Fig. 5). This distinct structure is an indicator that the double-cropping system is used in the agriculture of Kogi-State. It clearly shows the big influence of the agriculture on the vegetation in the state, since the crop rotation is overlaying the seasonality of the natural photosynthetic activity of the natural vegetation. In this study, these artefacts have not yet been respected. Osunmadewa et. al. (2015)⁵ already suggested that it is possible to find other seasonalities - except for the seasonality of one year - in the data. The findings of this study confirm this suggestion.

Apart from the studies that have been cited to prove that a change really did happened, the three maps in Fig. 18 displaying the land cover of Kogi-State in 1976, 2005 and 2009 provide another possibility to visualise the change in the vegetation cover. The results are as follows: The land cover map from 1976 shows that, by adding the percentages from the vegetation types being unrelated to agriculture, just 20 % of the whole area is covered with natural vegetation. This map shows clearly that the agriculture strongly dominates the vegetation cover since the mid 1970's. Going on to the land cover maps from 2005 and 2009 it needs to be kept in mind that the time difference between both maps amount to 4 years. Even so, a visual comparison between both ESA maps already shows the vegetation change with the bare eye. The open broadleaved deciduous forest/woodland decreased by 11.4 % and the closed to open shrubland increased by 7.7 %, whereas the mosaic cropland/vegetation increased by 2.3%[‡]. An increase or decrease of a vegetation type by roughly 10 % in an area with a total of 27,747 km² means that nearly 3,000 km² worth of vegetation is lost. On closer examination of the land cover map of 2009, the most noticeable changes occurred in the south of Kogi-State on the east side of the river. As it was already repeatedly mentioned throughout this study, the vegetation near water bodies is exposed to changes due to the expansion and intensification of agriculture as well as the transformation of land for grazing.⁵

Although the exact amount of lost vegetation cannot be estimated with the help of the generated maps it is apparent from the obtained results, that the long- and short-term vegetation cover changes can be detected within the present GIMMS NDVI data set. The generated maps visualising the results of the conducted analyses are a useful tool to estimate areal changes, detect spatial dependences and get an overview about the vegetation dynamic of a whole area at one. Furthermore, adequate information about the vegetation productivity (greening) can easily be gathered for several locations at once. All in all, it can be stated that this study is a successful continuation of the study of Osunmadewa et. al. (2015).⁵

For future research, a seasonality analysis and the cross-correlation of the NDVI time series with a precipitation time series can be recommended.

[‡]Calculations based on the numbers shown in the tables in Fig. 18

Figure 18. Land cover maps of Kogi-State, Nigeria, for the years 1976 (Data received from Babatunde A. Osunmadewa; Institute for Photogrammetry and Remote Sensing, TU Dresden), 2005 and 2009 (Data extracted from ESA GlobCover Portal; Accessed Dec. 14, 2016) with a table displaying the vegetation category of the area in percentage.

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