NDVI time series analysis for desert locust outbreak detection and quantification analysis of its impact on vegetation productivity of Sahel

Evangelos Oikonomopoulos

UNIVERSITY OF TWENTE.

ITC FACULTY OF GEO-INFORMATION SCIENCE AND EARTH OBSERVATION

LUND
UNIVERSITY

NDVI time series analysis for desert locust outbreak detection and quantification analysis of its impact on vegetation productivity of Sahel

_____

Evangelos Oikonomopoulos

Thesis submitted to the department of Physical Geography and Ecosystem Science, Lund University, in partial fulfilment of the requirements for the degree of Master of Science in Geo-information Science and Earth Observation for Environmental Modelling and Management (GEM)

Thesis assessment board:

Per-Ola Olsson
Researcher
&
Torbern Tagesson
Researcher

Exam committee:
Abdulhakim M. Abdi, Researcher
Jonas Ardö, Professor

Disclaimer

This document describes work undertaken as part of a program of study at the University of Lund. All views and opinions expressed herein remain the sole responsibility of the author and do not necessarily represent those of the institute.

Course title:
Geo-Information Science and Earth Observation for Environmental Modelling and Management (Erasmus Mundus: **GEM**)

Level:
Master of Science (MSc)

Course duration:
January 2019 until *June* 2019

Consortium partners:

The GEM master program is a cooperation of departments at 5 different universities:
University of Twente, ITC (The Netherlands)
University of Lund (Sweden)
University of Southampton (UK)
University of Warsaw (Poland)
University of Iceland (Iceland)

Abstract

It has been shown that the semi-arid environment of the Sahelian belt plays an important role in the global carbon uptake as the fluctuation of its primary productivity can be determinant for the global carbon uptake. The insect *Schistocerca gregaria* commonly known as the desert locust is a disturbance factor that can affect the vegetation productivity for consecutive seasons. In this study the detection of the desert locust outbreaks during the 2003-2005 upsurge was attempted through a Time Series Analysis of seasonal NDVI (small integral) coupled with detailed field observations. In cases of severely infested pixels the seasonal greenness could appear to be lower during the suffering season of 2004 compared to the 14-year interannual average of the pixel examined, indicating that the pixel is infested. At the same time Sahel's gross primary productivity (GPP) loss due to the locust outbreak was specified by comparing modeled gross primary productivity estimations between the outbreak and the non-outbreak years. The negative impact on primary productivity was also analyzed for the various stages of locust infestations. The process was based on a z-score statistical analysis while the index of Rain Use Efficiency was introduced in order to optimize the method. The outcome of the study showed that the decrease of seasonal NDVI in the infested pixels during the year of the upsurge is not statistically significant and consequently a relationship between greenness and locust infestations cannot be established for the development of a detection tool. Secondly, a significant negative impact on vegetation productivity due to locust outbreaks cannot be confirmed by analyzing the negative divergence from its interannual average. Furthermore, the claim that NDVI and GPP would indicate exceptionally low productivity performance during the year of the upsurge is disproved by the fact that also in years in which the studied pixels were not infested, those measures demonstrate similarly low behavior. The addition of the RUE index was not proven successful as it was shown that the RUE was highly regulated by the fraction's denominator fluctuation, precipitation. Finally, it has been shown that the negative impact on productivity and seasonal greenness slightly variates between the different stages of infestations. The inadequacy to establish relationship between the field observations and the greenness can be attributed to various factors such as the spatial resolution, the heterogenous nature of vegetation and the field observation selection criteria and treatment.

Table of Content

List of Abbreviations

CHIRPS   Climate Hazards Group InfraRed Precipitation with Station data

DS   Desert Locust

FAO   Food and Agriculture Organization of the United Nations

GPP   Gross Primary Production

IS   Infestation Stages

MODIS   MODerate resolution Imaging Spectroradiometer

NDVI   Normalized Difference Vegetation Index

NDVI_SI   Normalized Difference Vegetation Index Small Integral

RS   Remote Sensing

RUE   Rain Use Efficiency Index

RUE_{GPP} GPP-based RUE

RUE_{NDVI} NDVI-based RUE

TSA   Time Series Analysis

x

List of Tables

List of Figures

1 Introduction

1.1 General

The desert locust has been considered a plague since the times of the agricultural revolution, and it was already mentioned millennia ago in sacred books of civilizations that flourished around the areas of the Middle East, Africa and Southwestern Asia (Latchininsky, 2013). In those early agricultural communities, desert locust plagues could break down the food supply and eliminate their populations, a threat which even today in the 21st century carries on bringing out the risk of famine. Locust invasions have put in risk food security in more than sixty countries, from northern Africa to the Arabian Peninsula covering more than 30 million km^2 (Renier et al., 2015). Apart from the crops, it is also the sparse vegetation that suffered the attacks of folivorous insects affecting its productivity. The sparse vegetation in these semi-arid environments is one of the planet's carbon sinks which serve as important determinants for the inter-annual variability of the global carbon uptake according to recent studies (Poulter et al., 2014), and it is also shown that they contribute up to 60% of the long-term trend in the global terrestrial carbon sink (Ahlström et al., 2015). Thus they play a particularly important role within the dynamics of the global carbon cycle.

At the same time, the fact that extensive outbreaks can overwhelm for long time periods large areas of these ecosystems problematizes the extent of insect disturbances' influential role in carbon dynamics. This stems from the locust's ability to affect negatively the carbon dioxide uptake by destroying the foliage and degrading vegetation's biomass productivity during the growing season when the majority of carbon accumulation takes place (Clark, Skowronski, & Hom, 2010).

Having an overview of the damage is a challenging task and difficult to achieve by using only conventional field observation means. Remote sensing is the only feasible tool for large scale environmental monitoring since it provides spatially explicit observations collected over large areas at various levels of resolution. Regarding the desert locust, different methodological approaches have been used, focusing mainly on the insect's

habitat characteristics and the landscape's structure but not for assessing an upsurge's extent by detecting the damage caused on vegetation (Despland, Rosenberg, & Simpson, 2004; Latchininsky & Sivanpillai, 2010; Pekel et al., 2011; Renier et al., 2015). An infestation detecting tool for the vast area of the Sahelian belt would allow monitoring of this major insect disturbance factor, enlightening how such phenomena spread an evolve (Senf, Seidl, & Hostert, 2017). Furthermore, developing methods for outbreak detection through remotely sensed vegetation characteristics could lead to the quantification of the negative impact which they cause on primary productivity, enabling a deeper understanding of the influences that insect disturbances have on the carbon cycle (P.-O. Olsson, Heliasz, Jin, & Eklundh, 2017).

1.2 Aims of the study

This study firstly aims to investigate the potential of time series analysis on remote sensing imagery for the detection of desert locust outbreaks on the Sahelian belt. Secondly, it aims to specify any significant vegetation productivity loss by using the most contemporary GPP product of the region. Finally, to study the impact's variability on vegetation productivity caused by different stages of locust infestation development.

1.3 Research questions

The research questions were formulated as follows:

I.   Is it possible to define a relationship between field observed locust infestations and remotely sensed vegetation characteristics expressing vegetation productivity?

II. Does the desert locust have a significant impact on Sahel's annual gross primary production?

III. Do infestations at different stages of development affect vegetation productivity in different ways?

2 Background

2.1 Sahel's vegetation productivity

Gross Primary Production (*GPP*) is a measure of vegetation productivity and is defined as the atmospheric CO_2 captured by vegetation at ecosystem scale (Ardo, Tagesson, Jamali, & Khatir, 2018). It is one of the main drivers of ecosystem services, such as climate regulation, carbon sequestration and carbon storage (Torbern Tagesson et al., 2017); therefore, GPP monitoring is crucial for both resource and carbon cycle assessments (Ardo et al., 2018). Monitoring GPP in semi-arid regions is particularly important, as they constitute important sinks for fossil fuel emissions and their inter-annual variation impact the global carbon cycle dynamics (Ahlström et al., 2015; Aredehey, Mezgebu, & Girma, 2018; Le Quere et al., 2018). An improved understanding of how vegetation productivity relates to the effects of climate change is important in order to explain the global carbon uptake fluctuation in response to altering environmental conditions (Hickler et al., 2005; Torbern Tagesson et al., 2017). Consequently, a better understanding of the mechanisms that regulate this variation would enable the construction of improved and more accurate models (Senf et al., 2017).

On a regional scale, the Sahelian ecosystem also provides absolute food dependence for its inhabitants, whose possibility to import resources is generally limited (L. Olsson, 1993). Around 95% of the food produced in the Sahel is for domestic consumption (Abdi, Seaquist, Tenenbaum, Eklundh, & Ardo, 2014), sustaining local communities in many countries, and reaching a population larger than 80 million (Sallaba et al., 2017). Famine events have emerged in periods of low primary productivity caused either by severe drought periods (Ibrahim, 1988) or locust plagues (Waldner, Ebbe, Cressman, & Defourny, 2015).

2.2 Insect outbreaks disturbances

Disturbances are destructive processes that can alter an ecosystem's condition. They are considered integral drivers of ecosystem dynamics accelerating natural regeneration. According to McDowell et al. (2015), "disturbance events occur at a range of spatial and temporal scales and include wind, fire, drought, floods, insects and pathogens, harvest, ice, hail, avalanches, and landslides [...] and can occur instantaneously or over years" (p.115).

Insect outbreaks might particularly occur in different types of biomes, from boreal forests to semi-arid lands, having a traceable impact on the biogeochemical cycles (Edburg et al., 2012) and particularly on the carbon cycle (Kurz, Stinson, & Rampley, 2008). Their quantitative effects on the carbon balance are not, however, well known (Clark et al., 2010; Hicke et al., 2012; Schafer, Clark, Skowronski, & Hamerlynck, 2010), and so their potential presence generate an uncertainty in ecosystems' ability to act as carbon sinks (Hicke et al., 2012; Kurz et al., 2008).

2.3 Desert locust in Sahel

2.3.1 The desert locust

The desert locust (*Schistocerca Gregaria, Forskål*) is considered to be among the insect species with the greatest impact on the primary productivity of vegetation. Its frequent outbreaks could escalate to upsurges or plagues that invade large areas. The desert locust is a short-horned grasshopper of the insect order Orthoptera. It is a defoliator that feeds on the leaves of any kind of vegetation, and considered one of the most dangerous migratory insects in the world due to its ability to cross continents and seas and destroy also the crops (Cressman, 2016; Latchininsky, 2013; Senf et al., 2017; Steedman, 1990). This is the outcome of a complicated lifestyle strategy related to food availability and environmental conditions of its habitat. Its major characteristic is that it exhibits a phase polyphenism in which behavioural, physiological and morphological traits change, due to variations in the local population density (Uvarov, 1966). Specifically, Cressman (2016) mentions that "it has the ability to change its behaviour and physiology, in particular its appearance, in response to environmental conditions, and transform itself from a harmless

solitarious individual to part of a collective mass of insects that form a cohesive swarm" (p.87). This means that where low population density conditions apply, the individuals behave solitariously, tending to avoid each other. In cases where the available food is provided in patches and insects attracted to these localized green areas form dense populations, they start to behave as a unit and after some time they change also their morphology. This phenomenon of behavioural and morphological change is described by the term *gregarization* (Despland et al., 2004). According to Roffey and Popov (1968), "the marked increase in locust numbers on a local scale due to concentration, multiplication, and gregarization, which unless checked, can lead to the formation of hopper bands and swarms is called an outbreak" (p. 448). In cases of contemporaneous outbreaks, able to produce two or more generations of gregarious breeding, the phenomenon escalades to constitute an upsurge (Cressman, 2016).

Apart from the behavioral phases, desert locust as a grasshopper passes through various development phases during its life cycle before it becomes fully mature. After the egg hatching, six larvae or hopper levels follow before fledging, after which the insect is considered as an adult (Symmons & Cressman, 2001). However adults, the insects in this level are not biologically fully mature since it takes some time until they become able to fly and after that some more time in order to be reproductively mature. This entire sequence of maturity levels can last between 75 and 150 days (Symmons & Cressman, 2001)

2.3.2 The 2003-2005 locust upsurge in Sahel

When a gregarization level is reached and insects are concentrated in areas where food becomes limited, mature and able to fly insects migrate looking for more favourable conditions to feed and breed (Ceccato, Cressman, Giannini, & Trzaska, 2007; Cressman, 2016). This happened during the upsurge of 2003-2005 when swarms of insects moved between the winter breeding areas in north-western Africa (Marocco, Algeria, Mauritania) and the summer breeding areas in Sahel (Senegal, Mali, Niger, Sudan). The upsurge started after abnormally heavy rains in remote areas of the Sahel, where locusts fed in patches of rising fresh vegetation quickly congregated to form swarms (Cressman, 2016). In October 2003, outbreaks were confirmed and evolved rapidly to deteriorate the situation by the end of the year and reach an upsurge level (Ceccato et al., 2007). From June to August 2004, swarms arriving in the summer breeding areas invaded the Sahel in massive numbers, coming from northwest Africa and feeding on vegetation growing after the seasonal

rainfalls (Brader et al., 2006). According to numerous infestation reports, more than one breeding cycle occurred, maximizing defoliation damages on vegetation at the heart of the growing season. Infested pastures and croplands affected eight million people and damages diminished harvest from 80%–100% (Brader et al., 2006; Waldner et al., 2015).

2.3.3 Infestation stages

A desert locust infestation can be characterized regarding its defoliating potential in relation to the behavioral and developmental phases of the insects composing it. For example, a populous infestation with mature insects in the gregarious phase is assumed to cause more damage to vegetation compared to infestations where groups of immature insects dominate or insects in the solitarious phase are scattered throughout the area (Symmons & Cressman, 2001). According to this logic, the reported infestations in this study were organized into stages in which the severity of their impact is assumed to have a direct relation to those behavioral and maturity factors. The used data contained information about both factors, the combination of which yielded in many *stages* that could be studied. However, the attention was focused on six combinations that could cause the most severe damage to vegetation. In those six infestation stages, the insects have passed through the fledging point, meaning that they are adults and at the same time they exhibit gregarious behavior being part of populous groups.

2.4 Remote sensing tools

2.4.1 Insect disturbance monitoring and remote sensing

Defoliator insect outbreaks can spread in wide areas and change vegetation phenology by stripping it from its green leaves (McDowell et al., 2015). Those changes can evolve in remote areas far from human supervision, affecting ecosystems' carbon accumulation without being possible to record this effect. In order to study those large-scale processes, data that are spatially explicit while at the same time cover large geographic extents are required. Furthermore, data should deliver a temporal resolution that fits the insect's life-cycle, and allow the assessment of long time series in order to capture natural fluctuations of the insect dynamics (Senf et al., 2017). Remote sensing

fulfils the above-mentioned criteria and can serve as a powerful tool for the study of insect outbreaks across large areas at fine spatial and temporal scale (McDowell et al., 2015). Especially, applying time series analysis (*TSA*) on frequent observations of vegetation traits, allows monitoring, which is temporally accurate, spatially explicit, and can record reliably the consecutive movements of locust swarms across the vast Sahelian area.

After decades of developing remote sensing technologies and methodologies for detection of defoliator insects, the scientific community can now benefit from long series of densely sampled datasets which offer improved detectability (Fraser & Latifovic, 2005) and have the potential for accurate estimates of defoliation severity (Senf et al., 2017). The combination of field observations and TSA could be used to model the relation between insect extensive presence and remotely observed vegetation attributes. In recent years, this approach has been followed by various researchers to provide outbreak mapping or near real-time monitoring tools (P.-O. Olsson et al., 2017; P. O. Olsson, Kantola, Lyytikainen-Saarenmaa, Jonsson, & Eklundh, 2016; Pekel et al., 2011; Renier et al., 2015; Senf et al., 2017). In the study of P. O. Olsson et al. (2016), in particular, a time series methodology based on z-score analysis was attempted for monitoring defoliator insects in boreal forests of Fennoscandia, yielding in dual results related to the characteristics of the landscape.

Analogously, the potential application of time series analysis to detect foliage damage caused by swarms of voracious locusts in Sahel is challenging since the region hosts an inhomogeneous landscape (Karlson & Ostwald, 2016) where the annual greenness fluctuation is regulated by the levels of annual rainfall received which does not follow an exactly recurrent spatiotemporal pattern from year to year. However, the fact that those data are now widely available and provide sufficient temporal depth, makes the approach attractive for investigating the possibility of a monitoring mechanism development.

3 Materials and Methods

3.1 Introduction

The current study attempted to create an empirical model for studying the relationship between field observed locust infestations and remotely sensed vegetation characteristics represented by four series of 14-year long data; 1) the NDVI small integral (a seasonal measure of greenness), 2) the annual GPP 3) the NDVI-based annual rain use efficiency (RUE_{NDVI}) and 4) the GPP-based annual rain use efficiency (RUE_{GPP}). For each of these four MODIS-origin datasets, pixels suffering from extensive locust presence during the growing season of the year 2004 were extracted, and then tested for probable discrepancies from the 14-year norm through a z-score statistical analysis. Furthermore, the NDVI annual profiles of these infested pixels were plotted and visually analyzed in order to reveal any characteristics that could be related to the locust activity. Finally, the magnitude of the locust impact was analyzed for six different stages of locust infestation.

Starting by preprocessing the point data which represent the field observations and the remote sensing data independently, the methodology proceeds to focus on infested areas by extracting the corresponding pixels from the raster datasets based on the field observations. Statistical analysis was then carried out by calculating z-scores for each pixel and then grouping those z-score for each year (mean annual z-score) to create a measure of comparison between the years and draw a conclusion on vegetation's productivity between the infested year and the non-infested ones (Fig. 1).
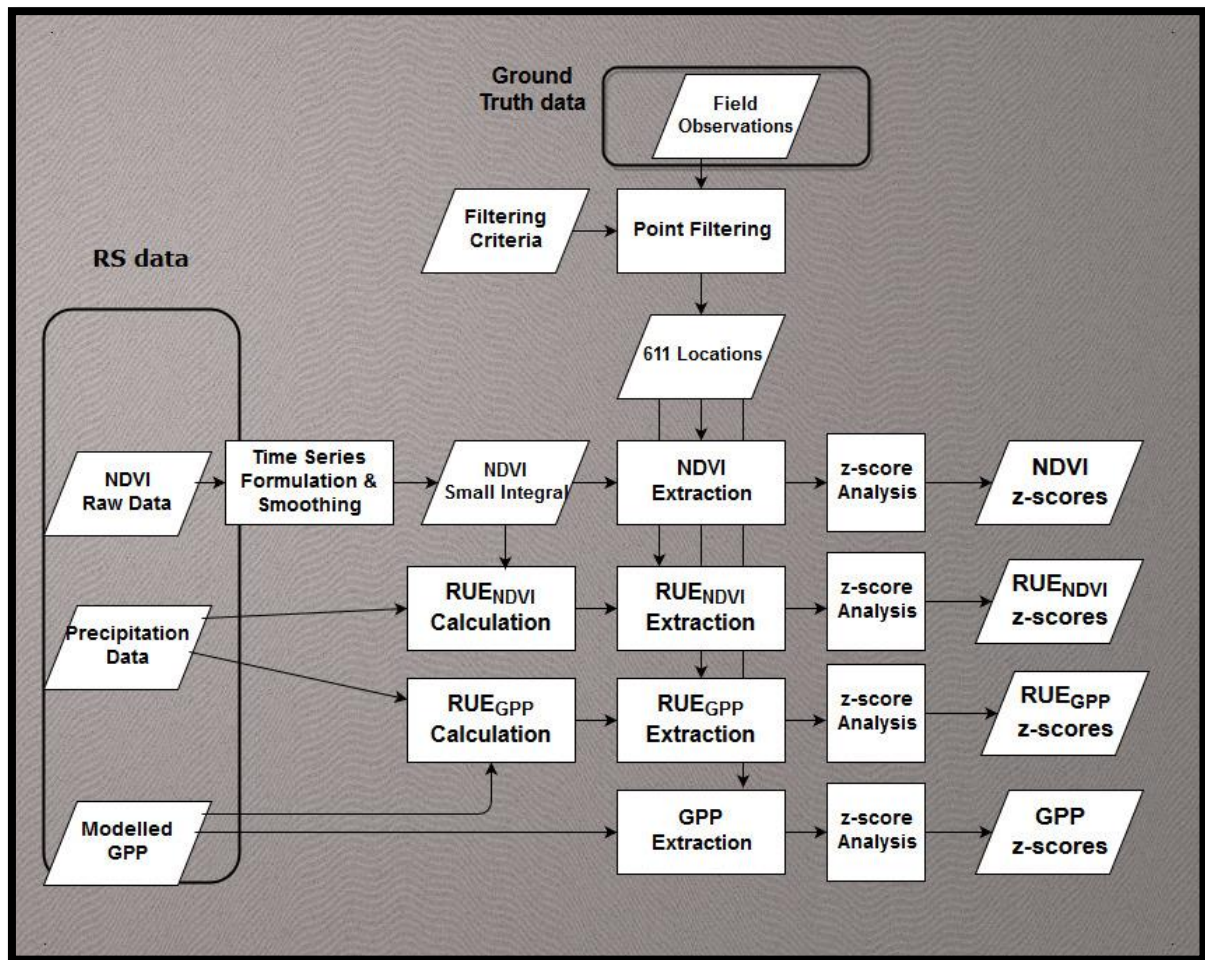
Figure 1: Methodological flow

3.2 Study area

The Sahelian zone forms a belt across Africa, extending from the Atlantic Ocean to the west, to the Red Sea towards the east and bordering the Sahara Desert to the north and the humid savannas of the Sudanian zone to the south (Karlson & Ostwald, 2016). Coincides with the area receiving annual precipitation between 150 and 700 mm increasing southwards (Ardo et al., 2018; Karlson & Ostwald, 2016; Prince et al., 1995) and vegetation productivity follows the precipitation gradient (Herrmann, Anyamba, & Tucker, 2005). Annual grasslands and sparse drought-tolerant woody shrubs are found in the dry areas (Hiernaux et al., 2009), while moving towards higher isohyets more trees and perennial grasses occur. Vegetation phenology follows rainfall seasonality and has one growing season per year which normally lasts from June to October (Abdi et al., 2014).

3.3 Data

3.3.1 Locust field observations

Table 1: Information included into each locust presence field observation report (FAO, 2004)

Field Observation

Observation ID	
Location	
Date	

Infestation

Insect behavior	*(gregarious/solitarious)*
Insect maturity	*(immature/mature)*
Estimated population density	*(bands/groups/swarms)*
Estimated spatial extent	*(in ha)*

Ecology

Vegetation greenness	*(dry/drying/greening/green)*
Vegetation density	*(sparse/dense)*
Soil dryness	*(dry/wet)*

The field data originate from survey operations made by the Food and Agriculture Organization of the United Nations (FAO) for the detection and control of the locust spread and description of its situation and habitat conditions. They were collected across the Sahel following FAO's guidelines (Symmons & Cressman, 2001) under the responsibility of local locust field officers and focus around areas and time periods in which the insects are most likely to be present, according to vegetation conditions, past observations or neighboring important areas, such as highly valuable crops. Those digitized observations

are part of a dataset on locust presence and include, apart from locations and dates, information on the behavior and maturity characteristics of the insects, an estimate of their population density and the areal extent of each infestation, a short description of vegetation's condition (density and greenness), and information about soil's dryness (Table 1). Regarding the studied 2003 – 2005 upsurge, the reported location coordinates are considered reliable since it was the first extensive upsurge event when GPS devices were used for verifying locations.

3.3.2 Remotely sensed data

Remotely sensed vegetation characteristics in this study originate from the MODerate resolution Imaging Spectroradiometer (MODIS) data which were processed to form series of frequent estimates of Normalized Difference Vegetation Index (NDVI) and annual estimates of Gross Primary Productivity (GPP) for the entire Sahelian belt. Regarding the NDVI, Terra/MODIS $250m^2$ spatial resolution, 16-day composites were downloaded (16-day composites; MOD13Q1; collection 6; 250mx250m spatial resolution) for the period between January 2001 and December 2014 (LPDAAC, 2016), while the annual estimates of GPP were retrieved from an earth observation-based modelled GPP product developed based on the light response function, using remotely sensed vegetation indices and incoming photosynthetic active radiation (PAR) as input data (Torbern Tagesson et al., 2017). The output provides spatially explicit GPP estimates across the Sahel at 250x250m spatial resolution. For further information regarding the GPP data, see (Torbern Tagesson et al., 2017). For the calculation of the annual index of rain use efficiency, the necessary rainfall data were provided by the CHIRPS (v2.0) project datasets at a 0.05°x0.05° spatial resolution, based on a conjunction geostationary infrared satellite rainfall estimates and rain gauge observations that are interpolated to produce precipitation grids (Funk et al., 2015). Monthly grids over the 2001-2014 study period were downloaded (http://chg.geog.ucsb.edu/data/chirps/) and then summed on an annual basis to create the annual precipitation estimations.

Mean annual GPP and locust infestations in 2004

Legend

14-year mean annual GPP
High
Low

Africa

Sahelian belt

• Locust infestations

0   225   450   900   1,350   1,800
Kilometers

Figure 2: Mean gross primary production (GPP) in Sahel and locust infestation distribution in 2004

13

Mean annual precipitation and locust infestations in 2004
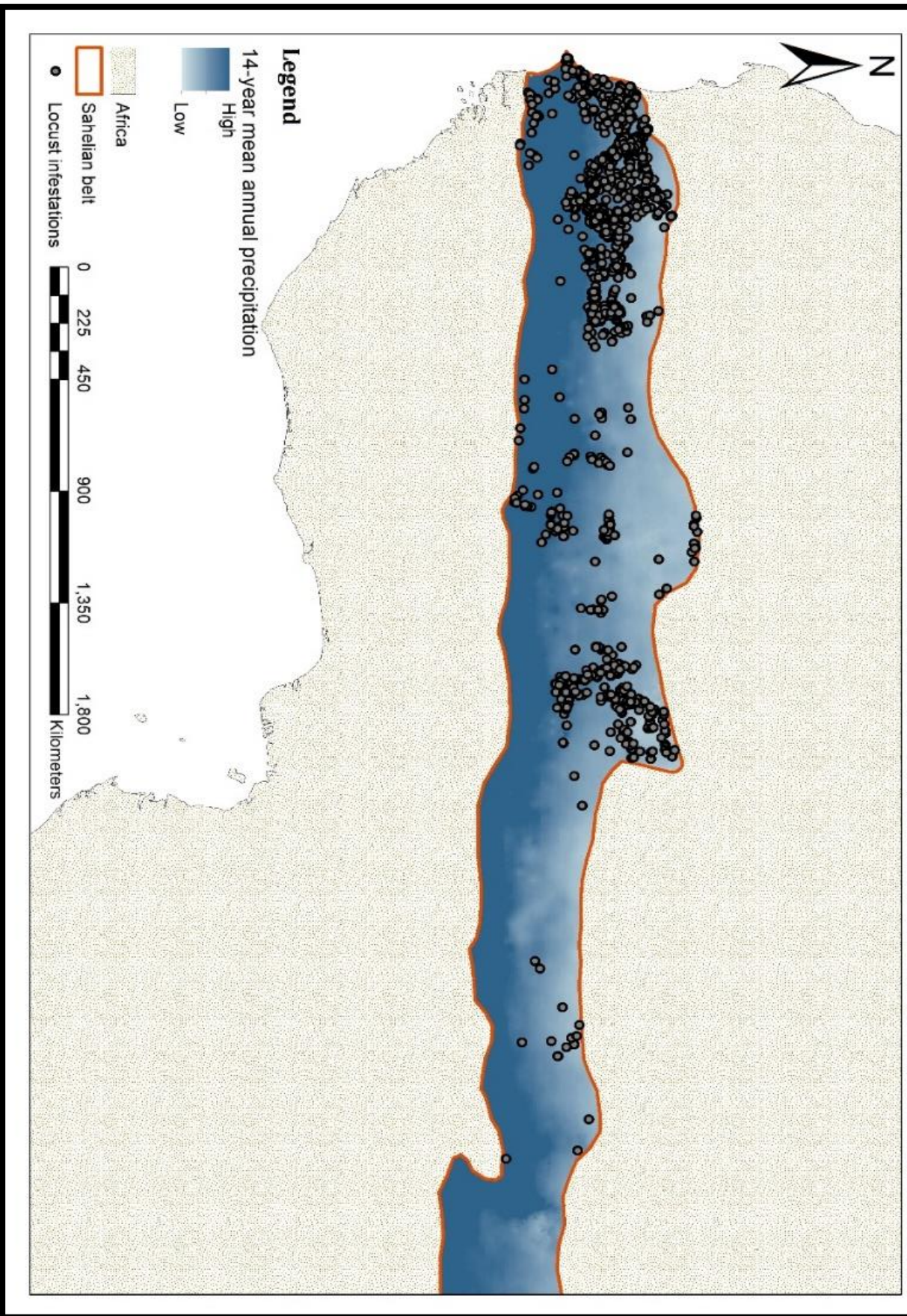
Legend

14-year mean annual precipitation
- High
- Low

Africa

● Sahelian belt
● Locust infestations

0 225 450 900 1,350 1,800
Kilometers

Figure 3: Mean precipitation in Sahel and infestation distribution in 2004

14

3.4 Methodology

3.4.1 Field data processing

Starting from an extensive dataset covering the entire period of the upsurge, the study's methodological approach attempted to make optimal use of the information available, by focusing on infestation cases where characteristics were assumed to allow high detectability margins. From all field observations of locust infestations between 2003 and 2005, only a part was finally used where infestations were considered to have great catastrophic potential. The filtering was carried out according to infestation reported characteristics related to locusts' behavior and maturity, and also the timing they were observed in relation to vegetation's annual development.

Firstly, the insect maturity (non-adults / adults) was considered as an important criterion, in order to exclude less destructive cases. And secondly, the information on their behavioral phase (gregarious/solitarious) was used to focus on the cases where insects are populous and act as coherent groups. The infestation timing regarding vegetation's growth was also considered as an important factor, assuming that plants under defoliating pressure during the growing season would have a less productive year and this difference would be more observable in the NDVI profile attributes and GPP annual estimates. Furthermore, the study was centered around the growing season of 2004, since during this year the upsurge was in full swing and the areas in the Sahel received many large groups of mature insects migrating from the winter breeding areas in northern Africa to the summer breeding areas across the Sahelian belt.

The five criteria according to which the filtering was carried out:
  A. Regarding the insect characteristics and infestation timing
    1) *Locust level of maturity*. In the adult stages, the insects are considered to have the strongest impact on vegetation due to their size and mobility needs. All points referring to non-adults were excluded from the study.
    2) *Behavioural phase.* When locusts exhibit gregarious behavior, they form dense groups of insects that act coherently, with daily patterns of feeding and moving (Cressman, 2016; Symmons & Cressman, 2001). The points referring to groups or swarms of insects were taken into account while those referring to the solitarious phase were excluded from the study.

15

3) ***Infestation timing***. A major part of vegetation's annual development takes place during the start of the growing season which for most parts of the Sahel takes place between June and August (T. Tagesson et al., 2016). In June of 2004, swarms of mature locusts started to arrive in parts of the Sahel looking for favourable conditions to feed and breed (Brader et al., 2006; Food and Agriculture Organization of the United Nations, 2018, May 18). Those groups of mature insects attack the fresh vegetation which grows after the recent rainfalls. Only the observations made during the period between the beginning of June and the end of August of 2004 were included in the study.

B. Regarding methodological optimization

4) ***Areas infested only in 2004.*** To avoid an analysis of pixels that have been infested many times in years other than 2004, which might lead to confusion in the statistical analysis of the time series, the study included pixels where infestations were confirmed only for the year 2004. Consequently, if observations from other years than 2004 were found within a zone of 10km around a 2004 observation, they were excluded from the analysis. In this way, the risk of performing time series analysis in pixels which were infested many times during the 2001-2014 period will be avoided and the results would be thus easier to interpret.

5) ***Pixels completely affected.*** Finally, in order to reassure that each examined pixel depicts an area that is infested in the whole of its surface, the points referring to infestations smaller than an area equivalent to four pixels (25ha) have been excluded from the process.

Finally, among 4918 points representing locust presence, according to field observation reports for the year of 2004, 611 points were finally used to select the corresponding pixels on vegetation characteristics' datasets and extract their annual attributes for the period 2001-2014 (Fig. 6).
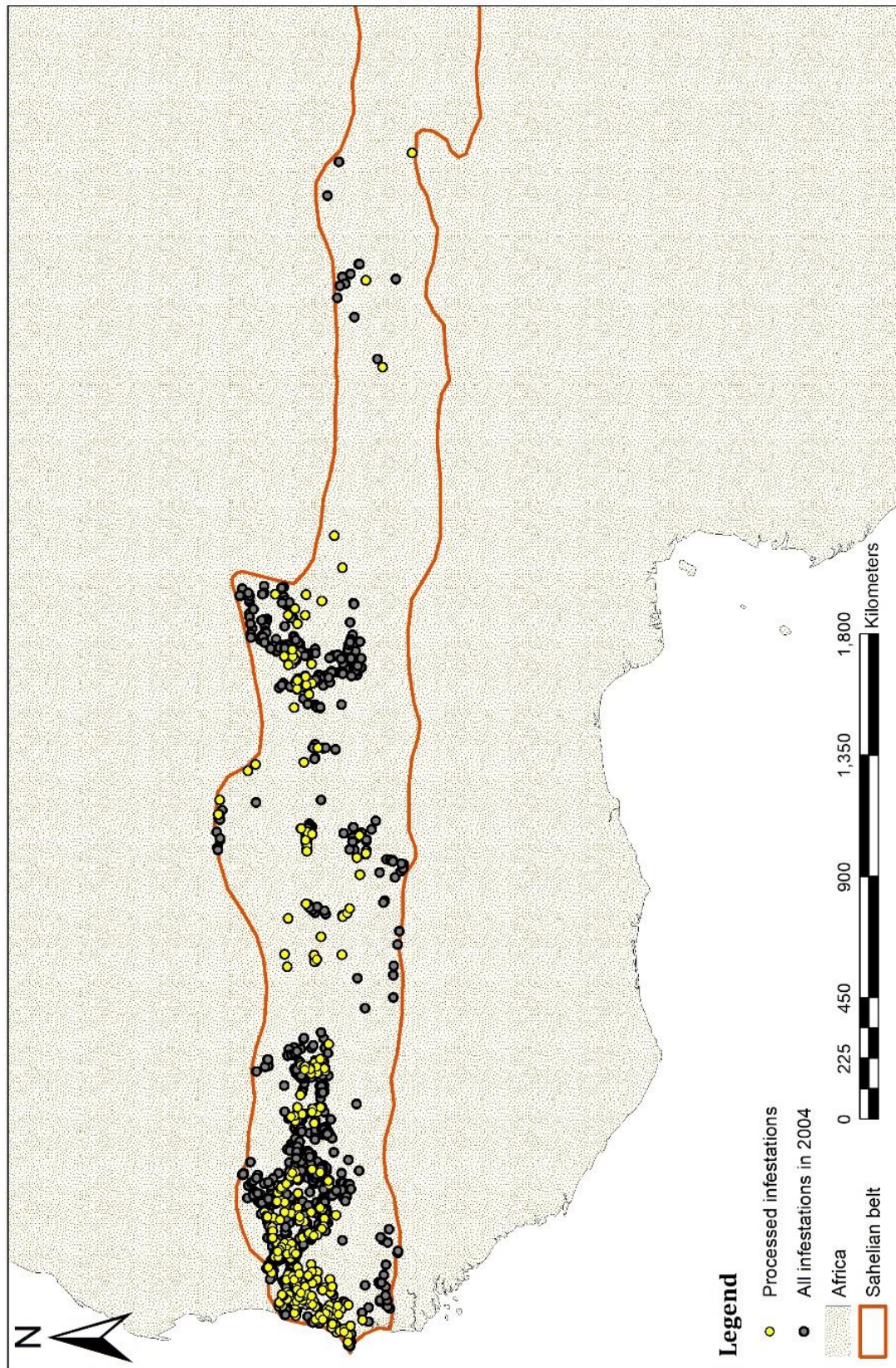
16

Infestation filtering

Figure 4: Locust field observations during 2004 upsurge in total and the 611 selected ones for the study

Legend

- ○ Processed infestations
- ● All infestations in 2004

Africa

Sahelian belt

Kilometers
0 225 450 900 1,350 1,800

3.4.2 Time Series Analysis of NDVI pixel profiles

A Time Series Analysis (*TSA*) is depending on the availability of long and dense sequences of data. The long series of frequently gathered remote sensing data make the TSA a useful tool for monitoring important environmental traits of earth's surface like vegetation. It has been showed that the advantages of TSA for vegetation monitoring rely on the ability to sense subtle fluctuations in growth characteristics (Ali et al., 2013) and the identification of vegetation trends analysing its behaviour over sequences of years. Vegetation greenness is a widely used trait for such analysis, since it can be easily estimated by the means of remote sensing.

The most widely used measure of vegetation greenness is the Normalized Differential Vegetation Index (*NDVI*), a vegetation index calculated based on the spectral response of the photosynthetically active green vegetation, as this is recorded by sensors operating on red (λ = [620nm,700nm]) and near-infrared (λ = [700nm,1100nm]) bands of the electromagnetic spectrum. Since the red band is part of photosynthetically active radiation, it is highly absorbed by the leaves and a small amount of red radiation is recorded by the sensor (Tucker, 1979). On the other hand, in order to avoid overheating, radiation in frequencies of near infrared are highly reflected by the leaves and consequently, high values are recorded in this part of the spectrum.

$$NDVI = \frac{INFRARED - RED}{RED + INFRARED} \qquad (Eq.\ 1)$$

The fraction of the difference of spectral responses to their sum results in a range of values between -1 and 1 (Eq.1). Healthy and dense vegetation are represented by high positive values (>0.5) while moderate positive values [0.2, 0.5] indicate altering patches of vegetation and bare soil. After all, in case of unhealthy vegetation and given an area of specific plant composition, NDVI appears in lower values compared to the unaffected period. Consequently, NDVI's ability to discern healthy and non-healthy vegetation makes it appropriate for defoliator infestations (Fraser & Latifovic, 2005; Senf et al., 2017; Waldner et al., 2015).

Furthermore, it is showed that the NDVI can serve as a productivity indicator in areas covered by sparse vegetation or grasslands, where a linear relationship between vegetation productivity and NDVI seems to exist (Paruelo, Epstein, Lauenroth, & Burke,

1997; Prince, De Colstoun, & Kravitz, 1998). Among the attributes of an NDVI profile representing vegetation's seasonal growth cycle, the small integral is suitable for representing seasonal productivity in Sahel (Fensholt et al., 2013). Small integral refers to the area under the smoothed NDVI seasonal curve excluding the period of the year when vegetation does not appear particularly green (Fig. 5). Consequently, it represents vegetation's main seasonal productivity and is appropriate for its inter-annual comparison of a certain place.

3.4.3 Rain Use Efficiency Index

In semi-arid ecosystems, the relationship between rainfall and vegetation has received a great deal of interest since water availability is considered the most important determinant for vegetation growth in such environments (Fensholt & Rasmussen, 2011; Hickler et al., 2005; Prince et al., 1998; Wessels et al., 2007). Given the light availability and the soil fertility, water is the resource leading to high or low productivity performance as it is the main limiting development factor (Karlson & Ostwald, 2016; Paruelo, Lauenroth, Burke, & Sala, 1999). This is apparent especially in Sahel, where interannual variability in precipitation patterns is observed, in both quantitative and spatial terms (Fensholt & Rasmussen, 2011; Prince et al., 1998). Furthermore, it has been shown that a near-linear relationship between rainfall and vegetation productivity exists in Sahel underlining the importance of water availability as a determinant growth factor there (Fensholt & Rasmussen, 2011; Fensholt et al., 2013; Fensholt, Sandholt, Rasmussen, Stisen, & Diouf, 2006; Lehouerou, Bingham, & Skerbek, 1988; Prince et al., 1998; Rasmussen, 1998). The admission that vegetation development is linearly proportional to the amount of precipitation received is a necessary precondition for the use of the concept of rain use efficiency index.

According to Paruelo et al. (1999), Rain Use Efficiency (*RUE*) is a measure of the response of plant production to variation in precipitation patterns. Technically, RUE is a synthetic normalization index used for masking out the effect of rainfall variation on productivity and is calculated as the ratio between the expression of productivity and precipitation (Prince et al., 1998).

The use of RUE allows normalization of primary productivity for rainfall variability and so enables the study of various factors' impact on vegetation productivity which are not related to water availability, such as insect disturbances or anthropogenic-induced land

degradation (Evans & Geerken, 2004; Fensholt & Rasmussen, 2011). For semi-arid ecosystems, the applicability of RUE is driven by the assumption that the ratio between productivity and rainfall is a conservative value (Lehouerou, 1984; Lehouerou et al., 1988) and the fact that water availability is crucial for photosynthetic performance (Prince et al., 1998). RUE has been a subject of study for diagnosing human-induced land degradation on vegetation in the Sahel under the pressure of climate change (Evans & Geerken, 2004; Fensholt & Rasmussen, 2011; Fensholt et al., 2013; Paruelo et al., 1999; Prince et al., 1998; Wessels et al., 2007). However, it has not been used to detect productivity anomalies caused by insect disturbances.

Since RUE is defined as a measure of productivity divided by the amount of rainfall received (Lehouerou, 1984) and the study makes use of two productivity proxies, correspondingly two versions of RUE were constructed; one based on annual GPP (RUE_{GPP}) and one based on the NDVI seasonal small integral (RUE_{NDVI}) (Eq. 2 and 3). However, Both RUE_{GPP} and RUE_{NDVI} suffer from spatial resolution inconsistency between their constituent elements since GPP and NDVI on the numerators are given in 250×250m pixel size, while precipitation on the denominators is given in coarser, 0.5°×0.5° spatial resolution. Eventually, the two indices have a pixel size of 250m, but they lack precision due to local variations in rainfall.

$$RUE_{GPP} = \frac{GPP}{PRECIPITATION} \qquad (Eq.\ 2)$$

$$RUE_{NDVI} = \frac{NDVI\ small\ integral}{PRECIPITATION} \qquad (Eq.\ 3)$$

3.4.4 Pre-processing of gridded data

Starting from three series of remote sensing data to represent vegetation characteristics (NDVI full-series, GPP annual estimates, and rainfall monthly estimates) and intersecting with 611 selected infestations, statistical analysis was performed for the corresponding to those areas MODIS grid pixels. For the case of NDVI time-series, a pre-processing was necessary in order to smoothen the profiles before the extraction of the seasonal attribute of the small integral. This processing was done in TIMESAT time series

analysis software (Eklundh & Jönsson, 2015; Jonsson & Eklundh, 2002, 2004) under the following parameter choices: NDVI data range = 0.1-1.0, seasonal parameter = 0.5, Number of envelope iterations = 3, adaptation strength = 1, Savitzky–Golay window size = 3, and amplitude season start and end = 0.2 (Jonsson & Eklundh, 2004). Then the small integral was extracted for each growing season yielding in 14 values for each of the 611 infested pixels. Regarding GPP, 14 annual estimates per pixel were retrieved from the source model's output database and finally by combining NDVI and GPP with the downloaded rainfall annual estimates, two rain use efficiency indices were formulated, RUE_{GPP} and RUE_{NDVI} characterizing those pixels for each of the 14 years.

3.4.5 Statistical decision criteria (z-score)

To answer whether discrepancies on vegetation annual characteristics can be observed through statistical testing, a z-score analysis was followed for each of the four 14-year long vegetation characteristics' datasets (NDVI, GPP, RUE_{NDVI}, RUE_{GPP}). Having a measure of vegetation behaviour for fourteen years, this approach allowed the analysis and comparison between those years and particularly 2004 with the rest, "locust free" ones. The z-score or standard score expresses the distance between a given value and the mean of a group of values from which the given value is part. This distance is measured in units of group's standard deviations and it is assumed that the group values follow a standard distribution (Eq.4).

$$Z\_score \ = \ \frac{value \ -mean}{standard \ deviation} \qquad (Eq. \ 4)$$

The approach's advantage relies on taking into account the natural variability of each examined pixel's values allowing comparability between the years. It has been implemented similarly for monitoring disturbances in Fennoscandian boreal forest by P. O. Olsson et al. (2016).

In order to define by statistical measure the point on which locusts' impact on vegetation is traceable according to the z-score logic, a threshold of two standard deviations lower than the interannual average was chosen. This means that in cases where pixels score less than two negative standard deviations (z-score ≤ -2), the discrepancy cannot be explained by the normal variation of the 14 years, indicating an abnormal event causing

low productivity which in the case of the year 2004 is assumed to be the locust defoliating activity. In such case, the differentiation could be considered as significant, and the research question on whether a relationship exists between the infestation and remotely sensed vegetation characteristics examined (NDVI, GPP RUE, RUE) can be answered positively, and for GPP in particular, indicating also that the upsurge caused a significant impact on Sahel's productivity as a response to the second research question. Finally and regarding the third research question, z-score annual values were grouped the six most damaging infestation stages to indicate any differences in severity between them. Those differences would be specified by comparing the negative magnitude of each stage's z-score.

The z-score was calculated for each of the parameters representing vegetation (NDVI small integral, GPP, RUE$_{NDVI}$, RUE$_{GPP}$) for the 611 selected sites with infestations in 2004. In order to compare the year of the upsurge with the rest locust-free years, the mean annual z-score was used after averaging the 611 z-scores, to express each year's the mean deviation from the inter-annual average for the sum of the 611 pixels of interest (Eq.5 and Table 2)

$$M_{z_y} = \frac{Z_{p1_y} + Z_{p2_y} + \cdots + Z_{p611_y}}{611} \qquad (Eq.5)$$

Table 2: Vegetation characteristics expressing productivity and their corresponding statistical measure (mean annual z-score)

Remotely sensed vegetation characteristics	Produced annual z-scores for the 2001-2014 time period
NDVI small integral	$NDVI_{Mz_y}$
Gross Primary Productivity	GPP_{Mz_y}
Rain use efficiency based on the NDVI seasonal small integral	$RUE_{NDVI_{Mz_y}}$
Rain Use Efficiency based on the annual GPP	$RUE_{GPP_{Mz_y}}$

Where:

M_{z_y} is the mean z-score of the year y,

Z_{p1_y} is the z-score of pixel $p1$ in year y,

3.4.6 NDVI seasonal dynamics

Since the available NDVI data allowed the construction of entire time series between 2001 and 2014, by analyzing the seasonal dynamics of NDVI for the affected pixels visually, would give further information on how the infestation is manifested on NDVI that cannot be observed through the z-score analysis of the small integral. By plotting the annual NDVI profiles of affected pixels and comparing the annual shape of 2004 with the rest of the years could reveal profile characteristics which can relate to the locust presence. For example, a short tail of the seasonal NDVI could be a characteristic indication for the locust presence which could not be captured by the z-score analysis of the small integral. Additionally, by focusing on the year of the upsurge and comparing among infested pixels which have been grouped into four levels of affection, fruitful outcomes could be drawn regarding how the locust activity is imprinted on the seasonal NDVI.

In order to do so, the infested pixels were sorted according to their NDVI small integral negative z-score in the year 2004 from lower to higher, so that the severely affected cases appear first. Only the pixels having negative values were taken into account since the cases with positive z-score in 2004 are not in the interest. After this sorting, four groups of ten pixels each were created to represent four cases of infested pixels in four different levels of locust affection. For example, for the group which represents the most severely affected pixel case, ten pixels were randomly selected from the part of the sorted list which contains 5% of the worst cases. That means 5% of the pixels with the most negative z-score values in 2004. Then, the NDVI profiles of those ten pixels were averaged for the 2001-2014 period, to represent the case of the most severe affection. This group was called the 5% group. Similarly, another three groups were formed by pixels which are in the 12,5%, 25% and 50% of the cases with low z-score values (groups of 12,5%, 25%, and 50% respectively).

The visual comparison of the shape of the annual NDVI was carried out firstly between the year 2004 and the rest and then between the four groups during only 2004. The comparison included the length of the growing season and the slope characteristics before and after the maximum seasonal value.

3.4.7 Locust infestation stages

Each field observation report includes an indication of the maturity and behavior of the insects dominating. In order to study any differences in the impact on vegetation caused by different stages of locust infestation development, the six final stages of maturity were selected since these are the cases having the most severe impact on vegetation (Symmons & Cressman, 2001). The 611 selected plots representing infestations were grouped according to the insects' maturity and behavior, and following a severity order, from most to least severe (most sever at the top).

The six maturity stages impact comparison

- ■ *Mature swarms.* Very populous groups of completely mature insects which are copulating or laying eggs.
- ■ *Maturing swarms.* Very populous groups of both immature and mature adult insects.
- ■ *Immature swarms.* Very populous groups of adult insects which have not reached their final stage of development and are not able to fly yet.
- ■ *Mature adult groups.* Groups of completely mature insects which are copulating or laying eggs.
- ■ *Maturing adult groups.* Groups of both immature and mature adult insects.
- ■ *Immature adult groups.* Groups of adult insects which have not reached their final stage of development and are not able to fly yet.

Every group got a z-score for 2004 for both NDVI small integral and annual GPP which served as the measure of comparison between the six groups as the method attempted to reveal the magnitude of the damage they caused.

4 Results

4.1 Impact of the 2004 infestation on the NDVI Small Integral

The assessment of NDVI small integral for severely infested areas in 2004 shows that z-score is lower than the average by 0.65 standard deviations (Z_{NDVI04} = -0.65). This indicates that the annual greenness for pixels infested in 2004 was lower than the time series' average. However, it was still not the lowest since in the year 2002, when no locust outbreaks were reported, NDVI deviation reaches its negative maximum at -1.06 standard deviations from the average, while in years 2011 and 2008 the score is close to the year of the upsurge with -0.47 and -0.39 respectively (Fig. 6).
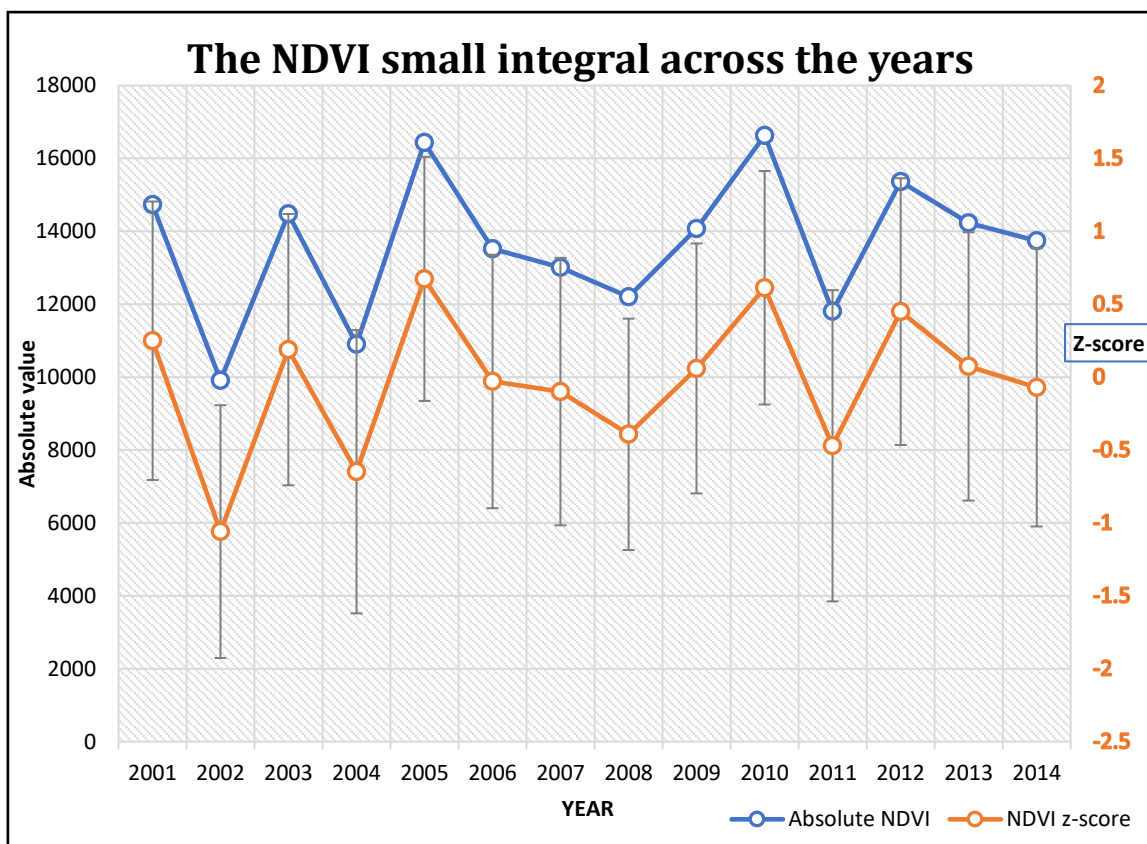
Figure 4: Z-score and absolute value sequence of NDVI small integral for the 611 infested pixels

Furthermore, out of 611 sites examined, in 229 cases (37%) the NDVI small integral was lower than the inter-annual average by more than one standard deviation and only in 14 cases (2%) lower than two standard deviations (Table 3).

Table 3: NDVI small integral, GPP, RUE$_{NDVI}$ and RUE$_{GPP}$ z-scores in 2004

	Average z-score in 2004 (standard deviation)	Percentage of pixels below 1 standard deviation (#absolute number)	Percentage of pixels below 2 standard deviations (#absolute number)
NDVI	-0.65 (±0.83)	37% (#229)	2% (#14)
GPP	-0.44 (±1.13)	24% (#146)	2% (#14)
RUE$_{NDVI}$	0.49 (±0.79)	2% (#12)	0.3% (#2)
RUE$_{GPP}$	0.35 (±0.99)	2% (#11)	0.6% (#4)
Precipitation	-0.72 (±1.13)		

4.2 Impact of the 2004 infestation on the annual GPP

Regarding the magnitude of the locust impact on vegetation productivity, the upsurge year show a decrease over the inter-annual average GPP since it scores -0.44 standard deviations, but again not exceeding the threshold of -2 (Fig. 7). Similarly to the

finding of NDVI, it is ranked third after years 2002 with -0.87 and 2014 -0.75 and only 2% of the pixels score more than two standard deviations lower than the time series' average (Table 3).
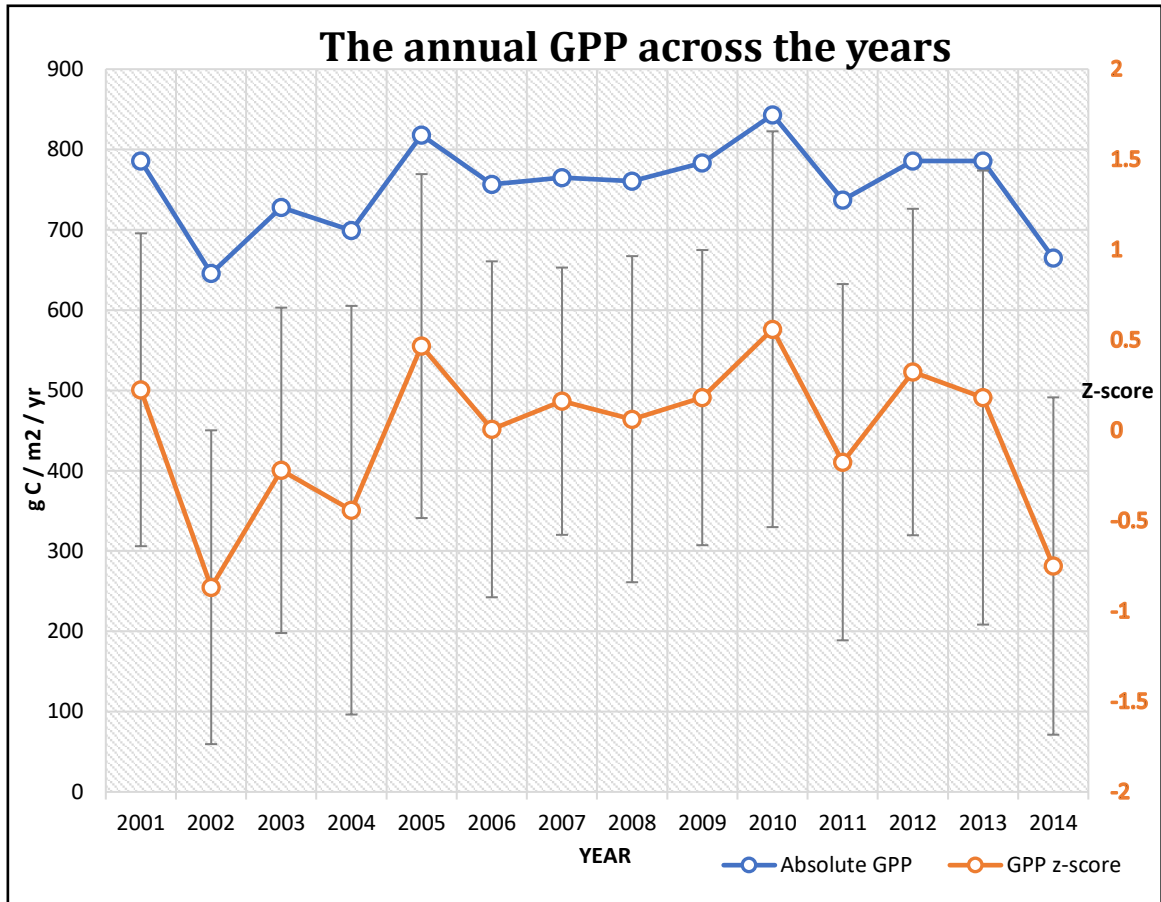

Figure 5: Z-score and absolute GPP sequence for the 611 infested pixels
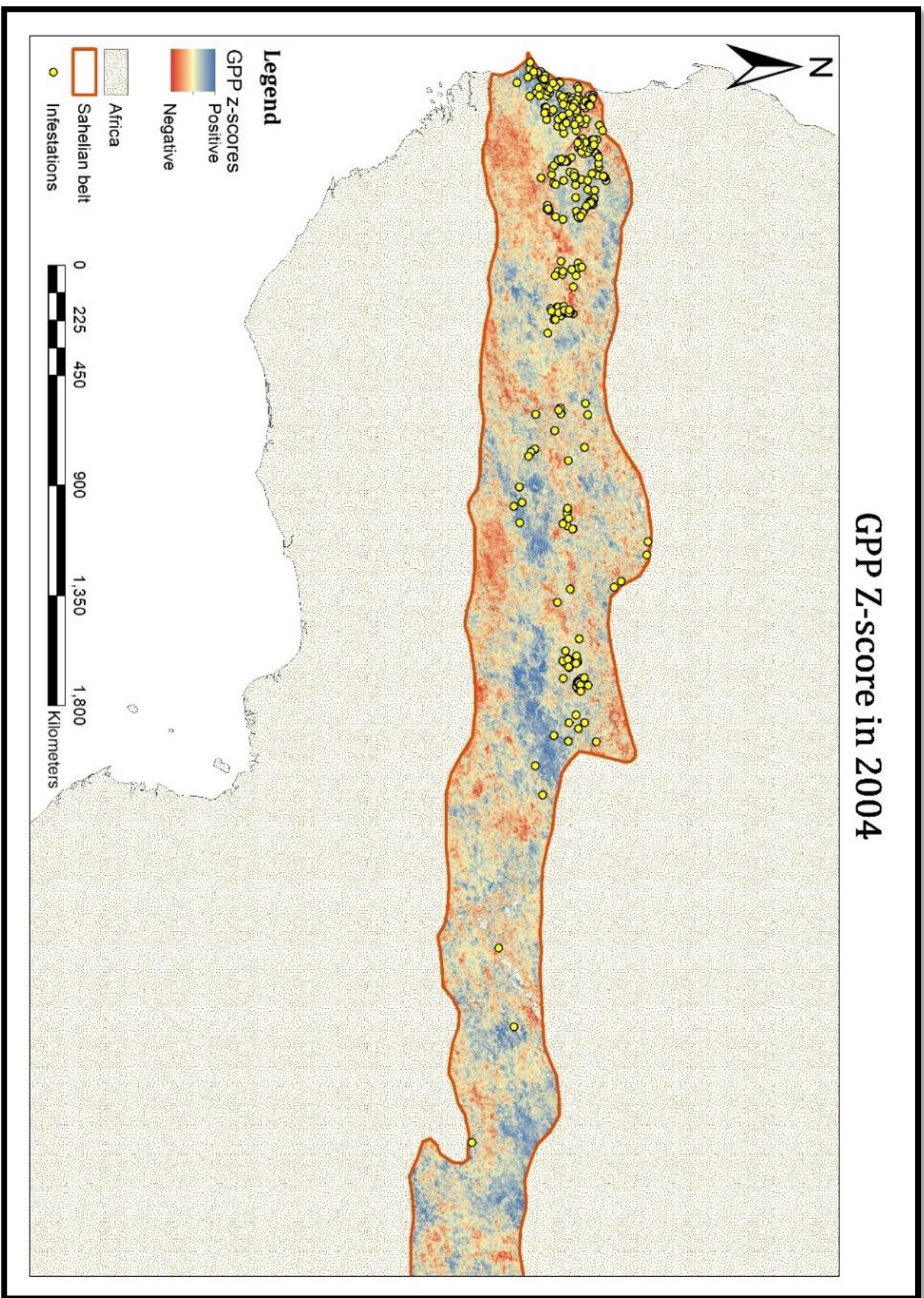
Figure 8: Map of GPP z-scores in 2004 across the Sahel

Figure 6: Map of GPP z-scores in 2004 across the Sahel

4.3 Impact of the 2004 infestation on the Rain Use Efficiency Index

Even though the 611 points were infested, for both RUE_{NDVI} and RUE_{GPP}, the year 2004 appears as a productive year with RUE_{NDVI} and RUE_{GPP} z-scores of 0.49 and 0.38 standard deviations above the average, respectively. This indicates that the infested year had a higher productivity per amount of rainfall than the rest of the time series. According to the precipitation data, it was not a wet nor an exceptionally dry year (Fig.9). In both cases, almost no pixels (0.3 and 0.6%, respectively) score lower than -2 standard deviations from the average (Table 3).
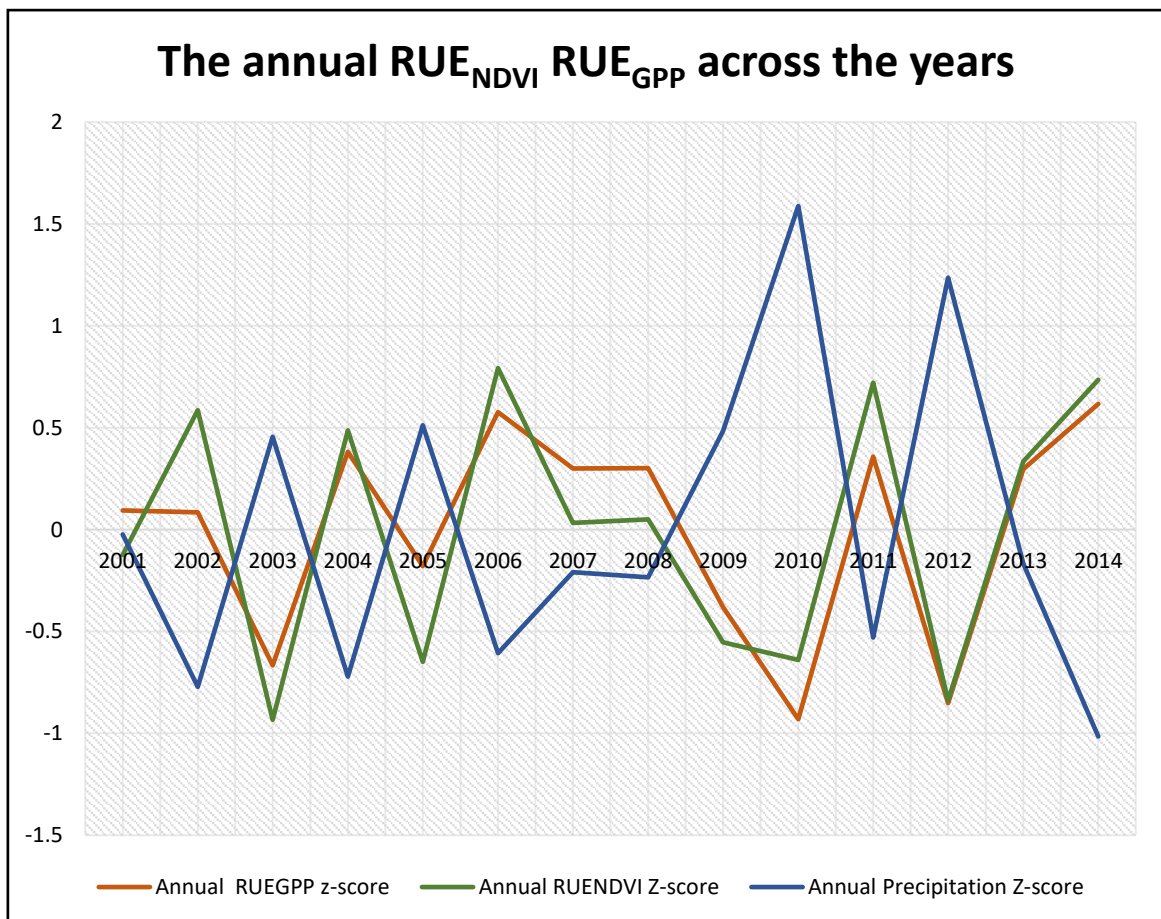
Figure 7: Z-score sequence of annual RUE_{NDVI} and RUE_{GPP} for the 611 infested pixels

4.4 NDVI seasonal dynamics analysis

Plotting the entire NDVI series of the affected pixels reveals that as the level of affection gets more severe, the difference in seasonal greenness between 2004 and the rest of the years gets higher as expected. Regarding the shape of the annual curve and focusing on the growing season, apart from the maximum value, which is among the lowest in 2004, the curve shows a rapid decline of greenness right after the maximum value. This is more apparent in groups 5% and 12.5%, since those pixels are severely affected.
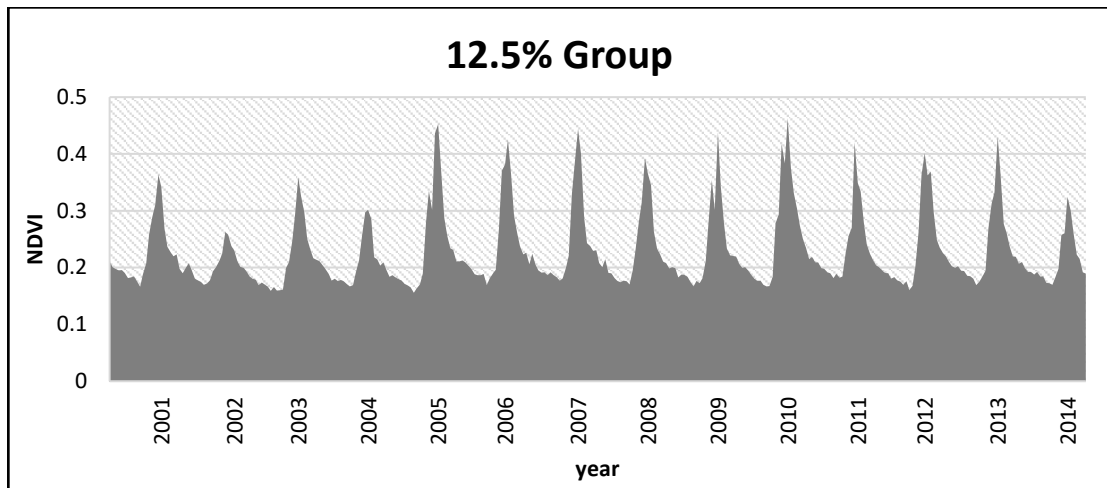
(a)
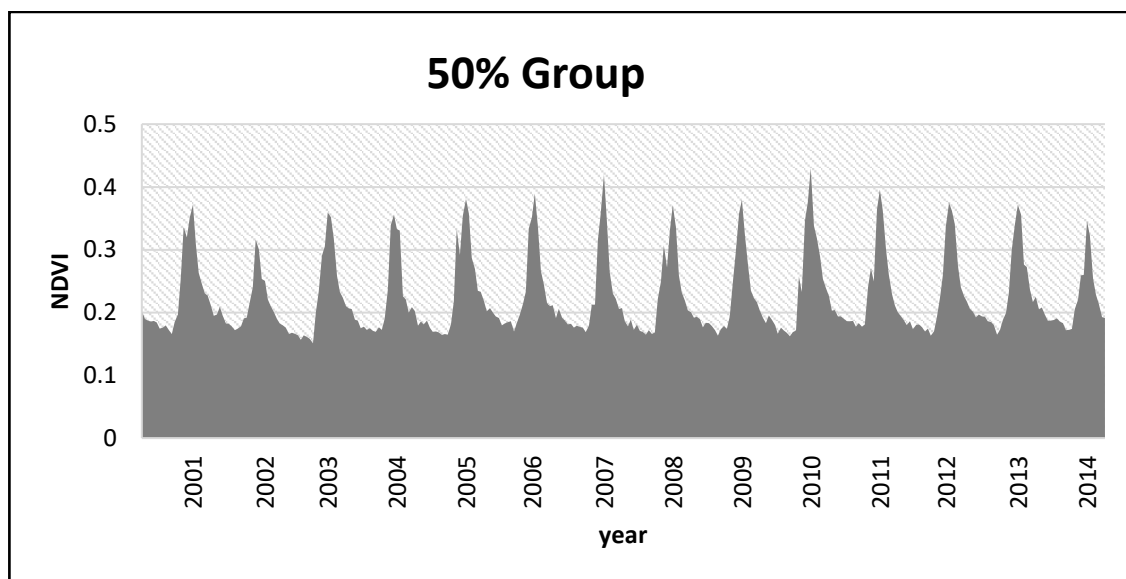
(b)
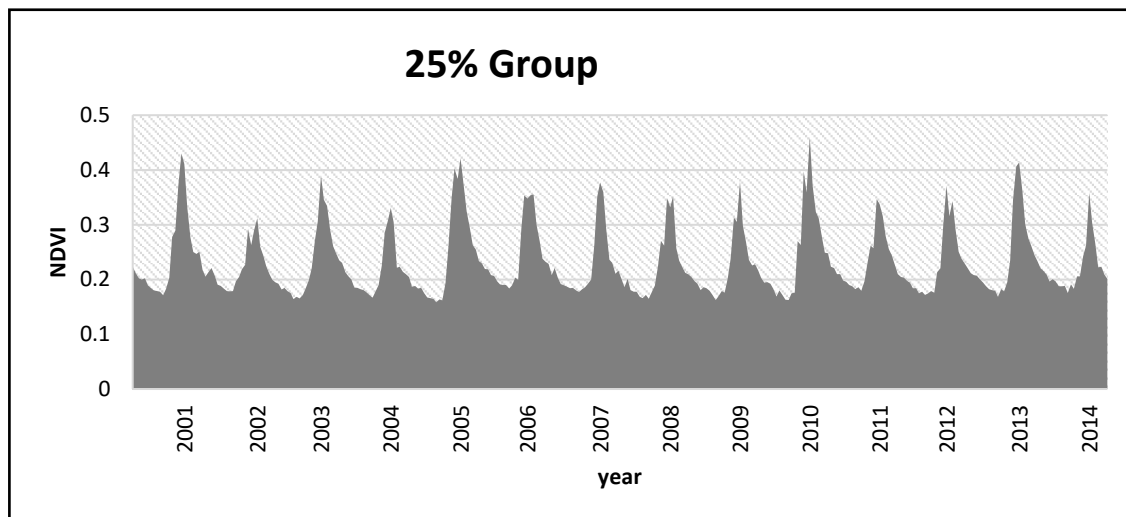
Figure 8: NDVI seasonal dynamics for (a) the 50% group (b) the 25% group
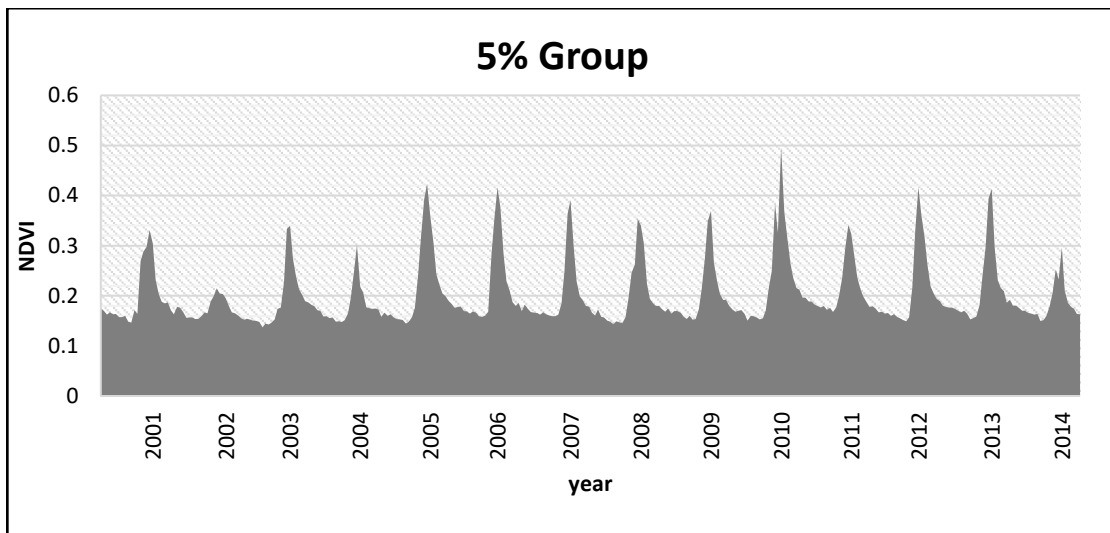
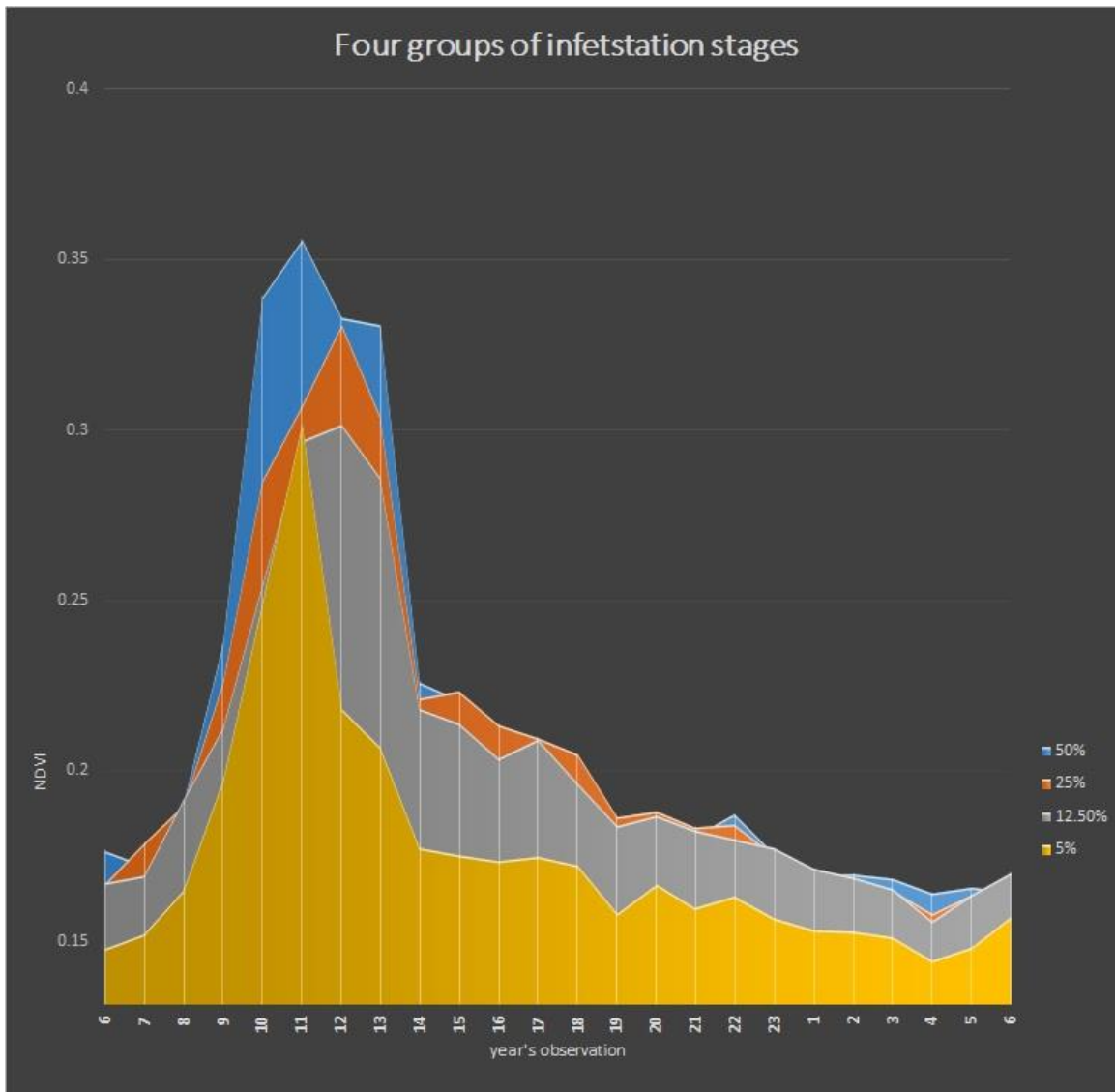*Figure 9: NDVI seasonal dynamics for (a) the 12.5% group (b) the 5% group*

Figure 10: NDVI small integral in 2004 for four stages of infestation (50%, 25%, 12.5% and 5% groups)

By looking at averaged seasonal NDVI for pixels categorized according to different levels of impact severity, the area under the curve appears smaller as the damage gets more extensive, which is expected since the grouping was done based on the small integral. The maximum NDVI value is getting slightly lower as the pixels get more affected and it is always observed in the 11th or the 12th observations of the year. The group of 50% shows maximum value 0.35 on the 11th observation, the 25% group 0.33 at the 12th observation, and both the 12.5% and 5% groups show 0.30 at the 12th an 11th observations respectively.

For all four groups, the annual NDVI increase starts around the 7th observation and it drops significantly at the time of the 14th observation before it gradually reaches the lowest value in the 4th observation of the next season.

However, the 5% group demonstrates a rapid decline right after the maximum value which does not happen with the other groups. This immediate reduction to 0.22 at the 12th and 0.21 at the 13th observations show that the maximum greenness of these pixels lasts much less compared to the less affected pixels which could be attributed to the locust activity. It is also notable that outside the growing season, the group of 5% appears less green compared to the rest of the groups which could indicate a different vegetation cover.

4.5 Locust infestation stages and impact on productivity

Looking at the statistics of the final six stages of locust infestations, out of 611 pixels examined, 73% refer to swarms (mature, maturing and immature swarms) (Table 4). In 42% of the cases, containing both mature and immature insects form very populous groups (swarms) while in nearly one-third of the infestations (28%), those groups contain insects already in the final level of their biological development. In third place (16%), comes the cluster of infestations where the groups of insects are not so populous (adult groups) and both mature and immature insects are found, while groups of purely mature or immature insects hold only 10%.

The impact of swarm infestations appears somewhat more destructive for vegetation productivity since the z-scores of NDVI small integral and the annual GPP are slightly more negative than for the adult groups. This occurs especially looking at the NDVI small integral for the most observed categories ("mature swarms" n = 171, "maturing swarms" n = 258 and for "maturing adult groups" n = 97), where both mature and maturing swarms score in NDVI more than the adult groups (-0.68 and -0.69 as opposed to -0.48 and -0.53, respectively).

Table 4: Percentage of how each infestation stage is represented among the 611 field observations and how each infestation stage deviates from its 14-year interannual average regarding seasonal NDVI small integral and annual GPP

	Percentage of field observations (absolute numbers)	Z-score includes standard deviation of the different groups (#number of cases)	
		NDVI	*GPP*
Mature Swarms	28% (171/611)	-0.68 (#71)	-0.46 (#45)
Maturing Swarms	42% (258/611)	-0.69 (#103)	-0.41 (#61)
Immature Swarms	3% (21/611)	-0.79 (#9)	-0.74 (#9)
Mature Adult Groups	7% (47/611)	-0.49 (#16)	-0.38 (#16)
Maturing Adult Groups	16% (96/611)	-0.53 (#33)	-0.32 (#31)
Immature Adult Groups	3% (18/611)	-0.56 (#5)	-0.42 (#5)

5 Discussion

5.1 The main findings

In this study, the development of a locust outbreak mapping tool was attempted through analysis of satellite-observed vegetation characteristics which are related to productivity and under the guidance of field observations of locust presence. The statistical z-score analysis showed that any decrease of the productivity measures for the infested pixels during the year of the upsurge is not statistically significant and consequently a relationship between remotely sensed vegetation characteristics expressing productivity and locust infestations cannot be established. Looking at the 611 pixels where locust infestations were confirmed by the field data, the NDVI small integral and the annual GPP average z-scores are negative by only 0.65 and 0.44 standard deviations respectively for the year 2004, meaning that the estimated annual greenness and the modelled gross primary productivity were slightly lower than the 2001-2014 inter-annual corresponding averages. In both cases, just 2% of the pixels exceed the significance threshold of two negative standard deviations and only a minority of them, 37% and 24% respectively, has negative divergence which exceeds in magnitude one standard deviation (Table 3).

Furthermore, the fact that the year of the upsurge, 2004, was not the year with the highest negative deviation from the inter-annual average, rose questions on whether factors such as water availability are responsible for this unexpected result. The use of rain use efficiency index was then included to clarify whether similarly low photosynthetic performance between the year of the upsurge and the years when insect outbreak did not occur could be explained by differences in water availability. As water has been considered a determinant development factor for vegetation in Sahel and is suggested that annual primary production follows precipitation spatiotemporal patterns (Fensholt & Rasmussen, 2011; Hickler et al., 2005; Prince et al., 1998; Wessels et al., 2007), the index of rain use efficiency (RUE) was used to explain the reasons behind the reduction during the unproductive years. In the study though, although both RUE_{NDVI} and RUE_{GPP} follow very similar patterns with minor differences, their fluctuation is always the negative of the

corresponding annual rainfall fluctuation (Fig.9). During the years of adequate annual precipitation, RUE indices appear below the average, while this phenomenon inverts immediately when annual precipitation is below the 14-year average and then RUE indices show that vegetation made good use of the amounts of water received. The magnitude of this fluctuation reveals that precipitation highly regulates the behaviour of RUE index and makes it risky to draw safe conclusions about the actual rain efficiency. This phenomenon occurs especially in dry areas of low annual rainfall levels (Lehouerou, 1984; Prince, 1991), which in the current study represent the majority of pixels. Moreover, spatial resolution inconsistency between RUE components adds noise to the index, but in this case might not be the major cause of RUEs weak interpretive ability.

On the other hand, although the analysis on seasonal dynamics of the annual NDVI profiles showed that the shape of the NDVI curve could be an indication of locust activity, this is not enough to establish a relationship between NDVI and locust presence, since the number of pixels which showed this NDVI behavior was very small in comparison to the total number of affected pixels examined. However, it is interesting to notice that the rapid greenness decline in the middle of the growing season right after the seasonal maximum could be attributed to defoliation caused by the insects. Consuming the fresh leaves during this period causes the NDVI estimations to suddenly become lower than normal. This is more apparent looking at the pixels with large seasonal greenness difference between the year 2004 and the interannual average, like those in the 5% group where the greenness drops suddenly from the annual maximum at 0.3 in the 11th observation to around 0.22 in 12th observation which does not happen for the less affected rest of the groups. Additionally, the 5% group shows in general lower NDVI values during the entire 14-year period which might be related to different vegetation cover for the pixels representing this group. In this case, that could mean that areas sparsely covered by vegetation are affected more than those which are covered in higher percentage by green plants.

Regarding the question of whether the desert locust upsurge has an impact on Sahel's annual gross primary production, the results show that a significant impact cannot be confirmed by analyzing the GPP negative divergence from its interannual average. Since the negative z-score for the 611 infested pixels does not reach the magnitude of two standard deviations during the year of the upsurge, any destructive impact on vegetation's productivity cannot be considered as significant. During the growing season of the year of locust upsurge, the modeled GPP for the infested pixels does not variate enough to be

36

attributed to the locust defoliation and so the impact on vegetation productivity of this disturbance factor is not significant.

Finally, the negative impact on productivity and seasonal greenness slightly variates between the different infestation stages. The final and very populous stages of development seem to be more catastrophic since they have slightly more negative z-score values compared to the less populous stages.

5.2 Limitations

The proven weak relation between the remotely sensed vegetation characteristics and the locust outbreak presence could be attributed to reasons related to the data used and the methodologies followed.

The use of moderate spatial resolution images could yield in low discrimination ability in cases of heterogeneous targets, while the phenomenon trying to capture is discernible in finer spatial resolution. In the current case, since vegetation cover alternates between patches of woody plants on a grassy background, in each pixel a variety of spectral responses is recorded. This is confirmed by the study of P. O. Olsson et al. (2016), where the homogenous birch forest of northern Sweden does not suffer from this ambiguity and the z-score analysis produced satisfying results. However, in more fragmented forests of Finland, MODIS spatial resolution was a limitation for the method. Similarly, the patchy landscape structure of the Sahelian environment and the heterogeneity of the samples are considered major challenging factors for remote sensing, based on coarse spatial resolution images, as it was previously ascertained by Senf et al. (2017) and Karlson and Ostwald (2016).

Regarding weaknesses in methodology, the way infested pixels were processed can be a subject of revision. Although an important part of the effort was put into selecting the pixels depicting infested areas, where defoliation would be maximized and this would allow higher detectability, the 611 pixels that were finally selected were all together processed for annual z-score calculation, as they represent a single infestation case. At first, although the Sahelian environment is characterized as semi-arid, it is a very wide area and the pixels studied correspond to different vegetation gradients that are not spectrally identical with each other. More green areas in the south and dryer in the east and north, point out that pixels should have been treated according to their vegetation cover

characteristics. Moreover, as previously mentioned, a sum of different spectral signatures is recorded in the given pixel size which is related to the patchy vegetation pattern. However, since infested pixels were statistically treated as they represent one homogenous spectral condition, this intrinsic diversity does not allow a concrete model of undisturbed vegetation to be determined and then define the abnormal situation by comparison during the z-score analysis.

Looking further into the study's contingent limitations, those could be related to selection criteria of the locust field observation points. Selecting points referring solely to the growing season was driven by the assumption that it was during this period when major damage occurred, since most of the photosynthetic effort takes place then. Swarms and groups of insects are thought to move from one feeding target to another after defoliating completely the existing vegetation. However, the majority of reports for 2004 refer to the late growing season and period after it, which might indicate a different locust behavior than the presumed. In this case, locust might continue hopping across feeding targets until they finally gather in some areas as resources become limited. Unless field data are not representative and mislead, it might explain why the majority of reports refer to this period and why their impact could not be traced during the heart of the growing season.

As already mentioned within a MODIS pixel, a combination of grasses and sclerophyllous woody vegetation is depicted, however, it is the annual grass development which predominantly influences NDVI, since the green grass replaces the spectral signature of bare soil during the growing season while the perennial vegetation contributes less on the observed greenness fluctuation. It can be thus argued that the observed greenness is actually more related to the annual grass. At the same time, because of its fast-growing characteristics, the infested grass could be replaced by fresh one before the local greenness index shows a significant decrease. Considering this defoliation and fast re-growing of the dominant greening factor, the 16-day composite temporal resolution of the series might be insufficiently low to trace fast and small fluctuation of the grass' dynamic phenology.

6 Conclusions

This study indicates that a relationship between remotely sensed vegetation productivity proxies and the presence of desert locust outbreaks at the semi-arid environment of the Sahel is weak. Since infested pixels in 2004 both NDVI small integral and annual GPP appear slightly lower than the inter-annual average and do not exceed the statistical threshold of two standard deviations, the negative divergence observed is not significant. Field confirmed locust presence could not be detected. Neither on seasonal greenness attributes, like the NDVI small integral or the shape of the NDVI seasonal profile nor on annual estimates of primary productivity. The claim that NDVI and GPP would indicate exceptionally low productivity performance during the year of the upsurge is disproved by the fact that also in years in which the studied pixels were not infested, those measures demonstrate similarly low behavior. Furthermore, the use of RUE did not reveal any indication of disturbance by the upsurge, since vegetation was developed adequately in 2004 in relation to the amount of rainfall received this year. Therefore, the presumed pattern of exceptionally low RUE due to locust presence was not confirmed by the analysis. Finally, for six stages of infestation development, more dense groups of insects in swarm formations seem to cause slightly more damage to vegetation foliage than less coherent groups, however, this difference is minor.

References

Abdi, A. M., Seaquist, J., Tenenbaum, D. E., Eklundh, L., & Ardo, J. (2014). The supply and demand of net primary production in the Sahel. *Environmental Research Letters, 9*(9), 11. doi:10.1088/1748-9326/9/9/094003

Ahlström, A., Raupach, M. R., Schurgers, G., Smith, B., Arneth, A., Jung, M., . . . Zeng, N. (2015). The dominant role of semi-arid ecosystems in the trend and variability of the land CO2 sink. *Science, 348*(6237), 895-899. doi:10.1126/science.aaa1668

Ali, A., de Bie, C. A. J. M., Skidmore, A. K., Scarrott, R. G., Hamad, A., Venus, V., & Lymberakis, P. (2013). Mapping land cover gradients through analysis of hyper-temporal NDVI imagery. *International Journal of Applied Earth Observation and Geoinformation, 23*, 301-312. doi:https://doi.org/10.1016/j.jag.2012.10.001

Ardo, J., Tagesson, T., Jamali, S., & Khatir, A. (2018). MODIS EVI-based net primary production in the Sahel 2000-2014. *International Journal of Applied Earth Observation and Geoinformation, 65*, 35-45. doi:10.1016/j.jag.2017.10.002

Aredehey, G., Mezgebu, A., & Girma, A. (2018). Land-use land-cover classification analysis of Giba catchment using hyper temporal MODIS NDVI satellite images. *International Journal of Remote Sensing, 39*(3), 810-821. doi:10.1080/01431161.2017.1392639

Brader, L., Djibo, H., Faye, F. G., Ould Badah, M. A., Ghaout, S., Lazar, P. M., & Nguala, M. (2006). Towards a More Effective Response to Desert Locusts and Their Impacts on Food Security, Livelihood and Poverty. *Food and Agriculture Organization (FAO): Rome, Italy*.

Ceccato, P., Cressman, K., Giannini, A., & Trzaska, S. (2007). The desert locust upsurge in West Africa (2003-2005): Information on the desert locust early warning system and the prospects for seasonal climate forecasting. *International Journal of Pest Management, 53*(1), 7-13. doi:10.1080/09670870600968826

Clark, K. L., Skowronski, N., & Hom, J. (2010). Invasive insects impact forest carbon dynamics. *Global Change Biology, 16*(1), 88-101. doi:10.1111/j.1365-2486.2009.01983.x

Cressman, K. (2016). Desert Locust. In J. F. Shroder & R. Sivanpillai (Eds.), *Biological and Environmental Hazards, Risks, and Disasters* (pp. 87-105). Boston: Academic Press.

Despland, E., Rosenberg, J., & Simpson, S. J. (2004). Landscape structure and locust swarming: a satellite's eye view. *Ecography, 27*(3), 381-391. doi:10.1111/j.0906-7590.2004.03779.x

Edburg, S. L., Hicke, J. A., Brooks, P. D., Pendall, E. G., Ewers, B. E., Norton, U., . . . Meddens, A. J. H. (2012). Cascading impacts of bark beetle-caused tree mortality on coupled biogeophysical and biogeochemical processes. *Frontiers in Ecology and the Environment, 10*(8), 416-424. doi:10.1890/110173

Eklundh, L., & Jönsson, P. (2015) TIMESAT: A software package for time-series processing and assessment of vegetation dynamics. In*: Vol. 22. Remote Sensing and Digital Image Processing* (pp. 141-158).

Evans, J., & Geerken, R. (2004). Discrimination between climate and human-induced dryland degradation. *Journal of Arid Environments, 57*(4), 535-554. doi:10.1016/s0140-1963(03)00121-6

Fensholt, R., & Rasmussen, K. (2011). Analysis of trends in the Sahelian 'rain-use efficiency' using GIMMS NDVI, RFE and GPCP rainfall data. *Remote Sensing of Environment, 115*(2), 438-451. doi:10.1016/j.rse.2010.09.014

Fensholt, R., Rasmussen, K., Kaspersen, P., Huber, S., Horion, S., & Swinnen, E. (2013). Assessing Land Degradation/Recovery in the African Sahel from Long-Term Earth Observation Based Primary Productivity and Precipitation Relationships. *Remote Sensing, 5*(2), 664-686. doi:10.3390/rs5020664

Fensholt, R., Sandholt, I., Rasmussen, M. S., Stisen, S., & Diouf, A. (2006). Evaluation of satellite based primary production modelling in the semi-arid Sahel. *Remote Sensing of Environment, 105*(3), 173-188. doi:10.1016/j.rse.2006.06.011

Food and Agriculture Organization of the United Nations. (2018, May 18). Desert Locust upsurge in 2004–05. Retrieved from http://www.fao.org/ag/locusts/en/archives/1146/web04/index.html

Fraser, R. H., & Latifovic, R. (2005). Mapping insect-induced tree defoliation and mortality using coarse spatial resolution satellite imagery. *International Journal of Remote Sensing, 26*(1), 193-200. doi:10.1080/01431160410001716923

Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., . . . Michaelsen, J. (2015). The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes. *Scientific Data, 2*, 150066. doi:10.1038/sdata.2015.66

Herrmann, S. M., Anyamba, A., & Tucker, C. J. (2005). Recent trends in vegetation dynamics in the African Sahel and their relationship to climate. *Global Environmental Change-Human and Policy Dimensions, 15*(4), 394-404. doi:10.1016/j.gloenvcha.2005.08.004

Hicke, J. A., Allen, C. D., Desai, A. R., Dietze, M. C., Hall, R. J., Hogg, E. H., . . . Vogelmann, J. (2012). Effects of biotic disturbances on forest carbon cycling in the United States and Canada. *Global Change Biology, 18*(1), 7-34. doi:10.1111/j.1365-2486.2011.02543.x

Hickler, T., Eklundh, L., Seaquist, J. W., Smith, B., Ardö, J., Olsson, L., . . . Sjöström, M. (2005). Precipitation controls Sahel greening trend. *Geophysical Research Letters, 32*(21). doi:10.1029/2005GL024370

Hiernaux, P., Mougin, E., Diarra, L., Soumaguel, N., Lavenu, F., Tracol, Y., & Diawara, M. (2009). Sahelian rangeland response to changes in rainfall over two decades in the Gourma region, Mali. *Journal of Hydrology, 375*(1-2), 114-127. doi:10.1016/j.jhydrol.2008.11.005

Ibrahim, F. N. (1988). Causes of the famine among the rural population of the Sahelian zone of the Sudan. *GeoJournal, 17*(1), 133-141. doi:10.1007/BF00209083

Jonsson, P., & Eklundh, L. (2002). Seasonality extraction and noise removal by function fitting to time series of satellite sensor data. *IEEE Transactions of Geoscience and Remote Sensing, 40*(8), 1824 - 1832.

Jonsson, P., & Eklundh, L. (2004). TIMESAT - a program for analyzing time-series of satellite sensor data. *Computers & Geosciences, 30*(8), 833-845. doi:10.1016/j.cageo.2004.05.006

Karlson, M., & Ostwald, M. (2016). Remote sensing of vegetation in the Sudano-Sahelian zone: A literature review from 1975 to 2014. *Journal of Arid Environments, 124*, 257-269. doi:10.1016/j.jaridenv.2015.08.022

Kurz, W. A., Stinson, G., & Rampley, G. (2008). Could increased boreal forest ecosystem productivity offset carbon losses from increased disturbances? *Philosophical Transactions of the Royal Society B-Biological Sciences, 363*(1501), 2261-2269. doi:10.1098/rstb.2007.2198

Latchininsky, A. V. (2013). Locusts and remote sensing: a review. *Journal of Applied Remote Sensing, 7*. doi:10.1117/1.Jrs.7.075099

Latchininsky, A. V., & Sivanpillai, R. (2010). LOCUST HABITAT MONITORING AND RISK ASSESSMENT USING REMOTE SENSING AND GIS TECHNOLOGIES. In A. Ciancio & K. G. Mukerji (Eds.), Integrated Management of Arthropod Pests and Insect Borne Diseases (Vol. 5, pp. 163-188). Retrieved from <Go to ISI>://BIOSIS:PREV201100208306. doi:10.1007/978-90-481-8606-8_7

Le Quere, C., Andrew, R. M., Friedlingstein, P., Sitch, S., Pongratz, J., Manning, A. C., . . . Zhu, D. (2018). Global Carbon Budget 2017. *Earth System Science Data, 10*(1), 405-448. doi:10.5194/essd-10-405-2018

Lehouerou, H. N. (1984). Rain use efficiency - a unifying concept in arid-land ecology. *Journal of Arid Environments, 7*(3), 213-247.

Lehouerou, H. N., Bingham, R. L., & Skerbek, W. (1988). RELATIONSHIP BETWEEN THE VARIABILITY OF PRIMARY PRODUCTION AND THE VARIABILITY OF ANNUAL PRECIPITATION IN WORLD ARID LANDS. *Journal of Arid Environments, 15*(1), 1-18.

LPDAAC. (2016). Vegetation Indices 16-Day L3 Global 0.05DEg CMG, Land Processes Distirbuted Active Archive Center. Retrieved from https://lpdaac.usgs.gov/dataset_discovery/modis/modis_products_table/mod13c1

McDowell, N. G., Coops, N. C., Beck, P. S. A., Chambers, J. Q., Gangodagamage, C., Hicke, J. A., . . . Allen, C. D. (2015). Global satellite monitoring of climate-induced vegetation disturbances. *Trends in Plant Science, 20*(2), 114-123. doi:https://doi.org/10.1016/j.tplants.2014.10.008

Olsson, L. (1993). ON THE CAUSES OF FAMINE DROUGHT, DESERTIFICATION AND MARKET FAILURE IN THE SUDAN. *Ambio, 22*(6), 395-403.

Olsson, P.-O., Heliasz, M., Jin, H., & Eklundh, L. (2017). Mapping the reduction in gross primary productivity in subarctic birch forests due to insect outbreaks. *Biogeosciences, 14*(6), 1703-1719. doi:10.5194/bg-14-1703-2017

Olsson, P. O., Kantola, T., Lyytikainen-Saarenmaa, P., Jonsson, A. M., & Eklundh, L. (2016). Development of a method for monitoring of insect induced forest defoliation - limitation of MODIS data in Fennoscandian forest landscapes. *Silva Fennica, 50*(2), 22. doi:https://doi.org/10.14214/sf.1495

Paruelo, J. M., Epstein, H. E., Lauenroth, W. K., & Burke, I. C. (1997). ANPP estimates from NDVI for the Central Grassland Region of the United States. *Ecology, 78*(3), 953-958. doi:10.1890/0012-9658(1997)078[0953:Aefnft]2.0.Co;2

Paruelo, J. M., Lauenroth, W. K., Burke, I. C., & Sala, O. E. (1999). Grassland precipitation-use efficiency varies across a resource gradient. *Ecosystems, 2*(1), 64-68. doi:10.1007/s100219900058

Pekel, J.-F., Ceccato, P., Vancutsem, C., Cressman, K., Vanbogaert, E., & Defourny, P. (2011). Development and Application of Multi-Temporal Colorimetric Transformation to Monitor Vegetation in the Desert Locust Habitat. *Ieee Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 4*(2), 318-326. doi:10.1109/jstars.2010.2052591

Poulter, B., Frank, D., Ciais, P., Myneni, R. B., Andela, N., Bi, J., . . . van der Werf, G. R. (2014). Contribution of semi-arid ecosystems to interannual variability of the global carbon cycle. *Nature, 509*(7502), 600-+. doi:10.1038/nature13376

Prince, S. D. (1991). SATELLITE REMOTE-SENSING OF PRIMARY PRODUCTION - COMPARISON OF RESULTS FOR SAHELIAN GRASSLANDS 1981-1988. *International Journal of Remote Sensing, 12*(6), 1301-1311. doi:10.1080/01431169108929727

Prince, S. D., De Colstoun, E. B., & Kravitz, L. L. (1998). Evidence from rain-use efficiencies does not indicate extensive Sahelian desertification. *Global Change Biology, 4*(4), 359-374. doi:10.1046/j.1365-2486.1998.00158.x

Prince, S. D., Kerr, Y. H., Goutorbe, J. P., Lebel, T., Tinga, A., Bessemoulin, P., . . . Wallace, J. (1995). GEOGRAPHICAL, BIOLOGICAL AND REMOTE-SENSING ASPECTS OF THE HYDROLOGIC ATMOSPHERIC PILOT EXPERIMENT IN THE SAHEL (HAPEX-SAHEL). *Remote Sensing of Environment, 51*(1), 215-234. doi:10.1016/0034-4257(94)00076-y

Rasmussen, M. S. (1998). Developing simple, operational, consistent NDVI-vegetation models by applying environmental and climatic information: Part I. Assessment of net primary production. *International Journal of Remote Sensing, 19*(1), 97-117. doi:10.1080/014311698216459

Renier, C., Waldner, F., Jacques, D. C., Ebbe, M. A. B., Cressman, K., & Defourny, P. (2015). A Dynamic Vegetation Senescence Indicator for Near-Real-Time Desert Locust Habitat Monitoring with MODIS. *Remote Sensing, 7*(6), 7545-7570. doi:10.3390/rs70607545

Roffey, J., & Popov, G. (1968). ENVIRONMENTAL AND BEHAVIOURAL PROCESSES IN A DESERT LOCUST OUTBREAK. *Nature, 219*(5153), 446-&. doi:10.1038/219446a0

Sallaba, F., Olin, S., Engstrom, K., Abdi, A. M., Boke-Olen, N., Lehsten, V., . . . Seaquist, J. (2017). Future supply and demand of net primary production in the Sahel. *Earth System Dynamics, 8*(4), 1191-1221. doi:10.5194/esd-8-1191-2017

Schafer, K. V. R., Clark, K. L., Skowronski, N., & Hamerlynck, E. P. (2010). Impact of insect defoliation on forest carbon balance as assessed with a canopy assimilation model. *Global Change Biology, 16*(2), 546-560. doi:10.1111/j.1365-2486.2009.02037.x

Senf, C., Seidl, R., & Hostert, P. (2017). Remote sensing of forest insect disturbances: Current state and future directions. *Int J Appl Earth Obs Geoinf, 60*, 49-60. doi:10.1016/j.jag.2017.04.004

Steedman, A. (1990). *Locust handbook*. Chatham, UK: Natural Resources Institute.

Symmons, P. M., & Cressman, K. (2001). Desert Locust Guidelines. In. Rome: Food and Agriculture Organization of the United Nations.

Tagesson, T., Ardö, J., Cappelaere, B., Kergoat, L., Abdi, A., Horion, S., & Fensholt, R. (2017). Modelling spatial and temporal dynamics of gross primary production in the Sahel from earth-observation-based photosynthetic capacity and quantum efficiency. *Biogeosciences, 14*(5), 1333-1348. doi:10.5194/bg-14-1333-2017

Tagesson, T., Fensholt, R., Cappelaere, B., Mougin, E., Horion, S., Kergoat, L., . . . Ardo, J. (2016). Spatiotemporal variability in carbon exchange fluxes across the Sahel. *Agricultural and Forest Meteorology, 226*, 108-118. doi:10.1016/j.agrformet.2016.05.013

Tucker, C. J. (1979). Red and photographic infrared linear combinations for monitoring vegetation. *Remote Sensing of Environment, 8*(2), 127-150. doi:https://doi.org/10.1016/0034-4257(79)90013-0

Uvarov, B. P. (1966). Grasshoppers and Locusts: A Handbook of General Acridology. In (Vol. 1). London, UK: Anti-Locust Research Center at the University Press.

Waldner, F., Ebbe, M. A. B., Cressman, K., & Defourny, P. (2015). Operational Monitoring of the Desert Locust Habitat with Earth Observation: An Assessment. *Isprs International Journal of Geo-Information, 4*(4), 2379-2400. doi:10.3390/ijgi4042379

Wessels, K. J., Prince, S. D., Malherbe, J., Small, J., Frost, P. E., & VanZyl, D. (2007). Can human-induced land degradation be distinguished from the effects of rainfall variability? A case study in South Africa. *Journal of Arid Environments, 68*(2), 271-297. doi:https://doi.org/10.1016/j.jaridenv.2006.05.015

Department of Physical Geography and Ecosystem Science, Lund University

Lund University GEM thesis series are master theses written by students of the international master program on Geo-information Science and Earth Observation for Environmental Modelling and Management (GEM). The program is a cooperation of EU universities in Iceland, the Netherlands, Poland, Sweden and UK, as well a partner university in Australia. In this series only master thesis are included of students that performed their project at Lund University. Other theses of this program are available from the ITC, the Netherlands (www.gem-msc.org or www.itc.nl).

The student thesis reports are available at the Geo-Library, Department of Physical Geography and Ecosystem Science, University of Lund, Sölvegatan 12, S-223 62 Lund, Sweden. Report series started 2013. The complete list and electronic versions are also electronic available at the LUP student papers (https://lup.lub.lu.se/student-papers/search/) and through the Geo-library (www.geobib.lu.se).

1   Soheila Youneszadeh Jalili (2013) The effect of land use on land surface temperature in the Netherlands

2   Oskar Löfgren (2013) Using Worldview-2 satellite imagery to detect indicators of high species diversity in grasslands

3   Yang Zhou (2013) Inter-annual memory effects between Soil Moisture and NDVI in the Sahel

4   Efren Lopez Blanco (2014) Assessing the potential of embedding vegetation dynamics into a fire behaviour model: LPJ-GUESS-FARSITE

5   Anna Movsisyan (2014) Climate change impact on water and temperature conditions of forest soils: A case study related to the Swedish forestry sector

6   Liliana Carolina Castillo Villamor (2015) Technical assessment of GeoSUR and comparison with INSPIRE experience in the context of an environmental vulnerability analysis using GeoSUR data

7   Hossein Maazallahi (2015) Switching to the "Golden Age of Natural Gas" with a Focus on Shale Gas Exploitation: A Possible Bridge to Mitigate Climate Change?

8   Mohan Dev Joshi (2015) Impacts of Climate Change on *Abies spectabilis*: An approach integrating Maxent Model (MAXent) and Dynamic Vegetation Model (LPJ-GUESS)

9   Altaaf Mechiche-Alami (2015) Modelling future wheat yields in Spain with LPJ-GUESS and assessing the impacts of earlier planting dates

10   Koffi Unwana Saturday (2015) Petroleum activities, wetland utilization and livelihood changes in Southern Akwa Ibom State, Nigeria: 2003-2015

11   José Ignacio Díaz González (2016) Multi-objective optimisation algorithms for GIS-based multi-criteria decision analysis: an application for evacuation planning