ANALYSIS OF THE DYNAMICS OF VEGETATION IN THE SUDAN-SAHELIAN ZONE : CASE OF THE MOUTOURWA AGRICULTURAL PRODUCTION BASIN (FAR-NORTH CAMEROON)

Abstract

The Moutourwa area in the Far North region of Cameroon is facing a deterioration of its climatic conditions. In this part of the Sudano-Sahelian zone, the soils are fragile and agriculture is not very productive due to various droughts. The statistical analysis study of climatic variability based on satellitic data in the area aims to analyze the dynamics of vegetation. This involves studying the spatio-temporal dynamics of vegetation using vegetation indices. The approach adopted to carry out this study is based on the descriptive statistics of the MODIS NDVI data series from the period 2010 to 2020. The study also analyzes the VCI drought indices in this study area. It appears from these analyzes that the year 2012 has the high average and the year 2015, the lowest average of our study period with 0.51 and 0.274 respectively. The years 2010, 2011, 2013, 2014, 2017, 2018 and 2019 remained around an average of 0.3. The observation of drought indices such as the VCI examines the fluctuation of their values characteristic of the heterogeneity of the vegetation state.

Keywords: **climatic**conditions, drought, NDVI MODIS, VCI, descriptive statistics

Introduction

The Intergovernmental Panel on Climate Change (IPCC) constitutes the global scientific reference in the climate field. In its report published in 2014, it is estimated that human activities have caused global warming of around 1°C above the pre-industrial level (1850-1900). If the trend continues, this warming is expected to reach 1.5°C around 2040 (IPCC, 2018). Even if CC manifests itself differently depending on the region of the world, it will inevitably have repercussions on several spheres of our modern societies. As agriculture is intrinsically linked to climate, it is one of the sectors most vulnerable to the risks and impacts of CC (Smit and Skinner, 2002). By 2050, the world's population is expected to reach nearly 10 billion, requiring an increase in food production of more than 50% (Searchinger*et al*., 2019). This increased demand sometimes forces farmers to adopt agricultural practices that can degrade soil and environmental health. This observation forces humanity to rethink the way it produces and consumes food. The agriculture of tomorrow must therefore be more efficient, while drastically reducing its environmental footprint and providing other ecosystem services such as maintaining or restoring biodiversity (Foley*et al.*, 2011 ; Howden et al., 2007). The expected impacts of CC add to this colossal challenge by significantly disrupting agricultural activities everywhere on the planet.

Many countries are already feeling the effects of climate change, such as erratic and unpredictable rainfall, increased incidence of storms and prolonged droughts.In different regions of the world, the impacts of climate variability manifest themselves in several forms, notably the increase in the intensity or frequency of extreme events. In Cameroon, more particularly the Far North region, the 1970s and 1980s were marked by drought in the Sahel with agro-climatic consequences, water stress characterized by drops in expected agricultural yield indices. Since this period, Far North Cameroon has been faced with a deterioration of its climatic conditions. Lands facing agricultural droughts present impacts affecting not only humans (food crises) and their livestock (shortage of rangelands) but also our environment (sterilization of the soil due to lack of water).

Indeed, the crisis of the late 1980s led to the impoverishment of populations, marked by a significant drop in purchasing power (Mbaïramadji, 2000). This is how the exploitation of fuelwood, formerly intended to satisfy the strict domestic needs of those who harvested it, has today become essentially commercial to meet the strong demand from urban populations (Madi et al., 2003). Likewise, natural formations that we qualify as “bush” as opposed to cultivated areas are subject to pressures whose effects are superimposed: agricultural clearing, fire and overgrazing (Merle and Gautier, 2003). However, nature is compromised, thus promoting the imbalance of the region's ecosystem. The consequences resulting from this imbalance in the ecosystem are the degradation of vegetation cover and a decline in vegetation conditions. It therefore seems important to analyze the interaction between climate dynamics and anthropogenic activities leading to the aforementioned consequences. More specifically, it is a question of: carrying out a study based on descriptive statistics of satellite data series, analyzing the spatio-temporal dynamics and plant cover profiles by developing the resulting maps,analyze the causality of vegetation regression, analyze spatio-temporal dynamics and drought index profilesby developing the resulting maps.

1. MATERIALS AND METHODS

1.1 Materials

1.1.1 Presentation of studied area (Geographical setting)

Moutourwa council (figure 1) is located in the sub division of the same name, Mayo-Kani Division, Far North region. It is limited to the North by the council of Maroua 1 in Diamaré, to the South by Figuil council in Mayo-louti, to the EAST by Kaélé’s council in Mayo-kani and to the West by the council of Ndoukoula in Diamaré.

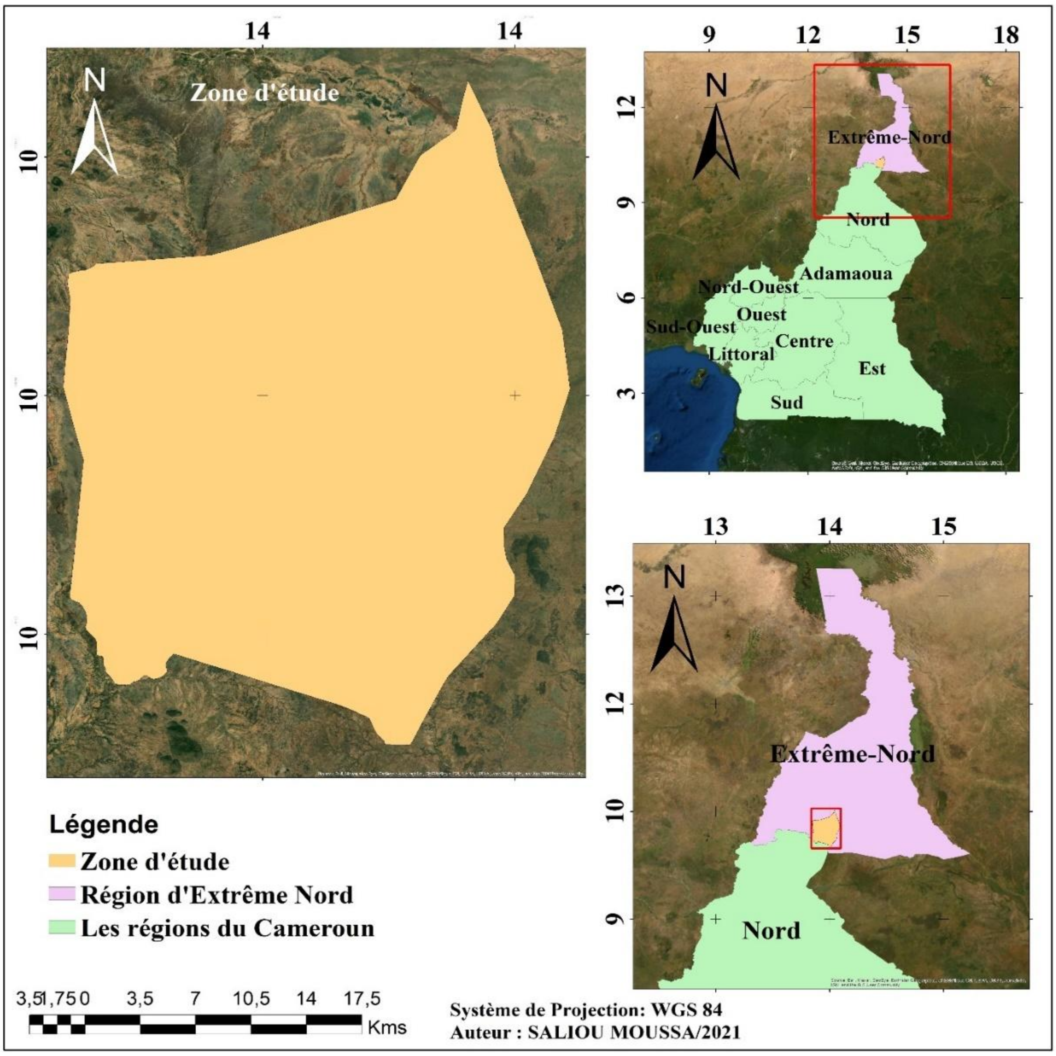


Figure 1 : Moutourwa location map

1.1.2 Vector data

These are the boundary files of Cameroon in Shapefile format (.shp) divided into regions, divisions and councils. These files allowed us to delimit, extract and present our study area: Moutourwa. This data was acquired free of charge from the Diva Gis website (http://www.diva-gis.org/).

1.1.3 Teledetectiondata : normalized Difference Vegetation Index (NDVI)

Terra Moderate Resolution Imaging Spectroradiometer (MODIS) (MOD13Q1) version 6 vegetation index data are generated every 16 days at a spatial resolution of 250 meters (m) as a Level 3 product. NDVI's MOD13Q1 product is called the National Oceanic and Atmospheric Administration-Advanced Very High Resolution Radiometer-derived NDVI continuity index (NOAA-AVHRR). The algorithm chooses the best available pixel value from all acquisitions in the 16-day period. The criteria used are low clouds, low viewing angle and highest NDVI value.The NDVI was downloaded from the Land Processes Distributed Active Archive Center (LPDAAC) (http://lpdaac.usgs.gov/) over the four (04) months of the agricultural campaign in our study area and over a study period of 10 years (2010 to 2020) (table 1).

Table1 : Characteristics of downloaded NDVI MODIS data

Spatial coverage	Tiles used for our study area	Spatial resolution	Time interval	Monthlyscale (agricultural campaign)	Data format
Global	h19v07	250 m	2010 à 2020	June, July, August, September	HDF

For each of the four (04) months, a tile from the MODIS sinusoidal tiling system (h19v07) (figure 2) was downloaded, making it possible to cover the corresponding study areato the NDVI of the month in question.

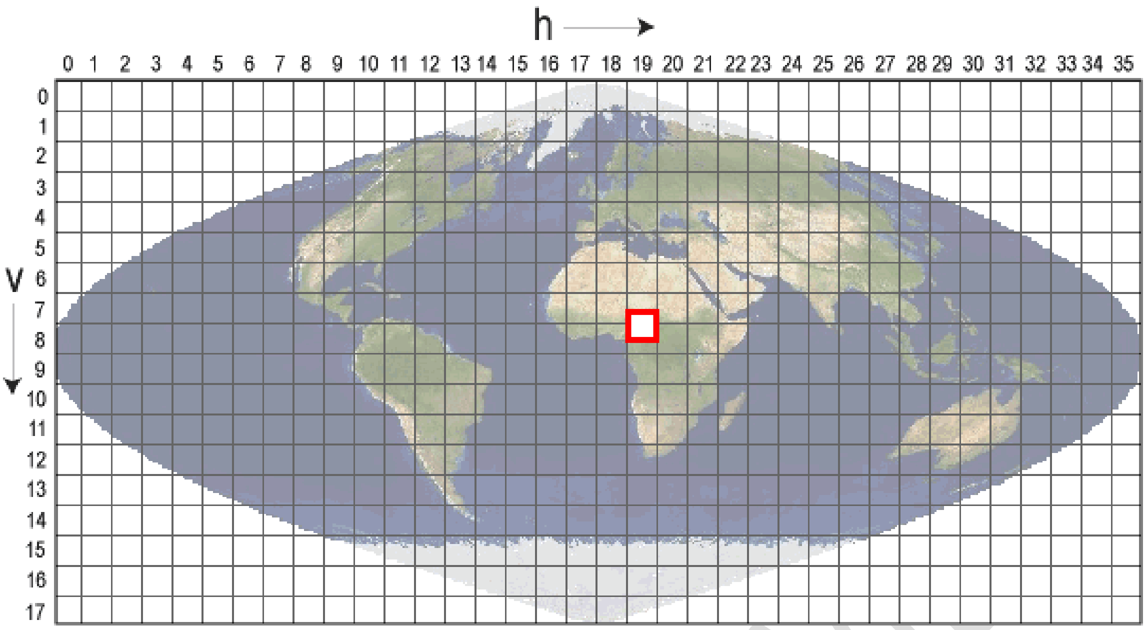


Figure 2 :MODIS sinusoidaltiling system used for NDVI tile download

A large number of software programs were used to achieve the objectives set within the framework of our research project. Theseinclude:

- ENVI Classic 5.1 used for NDVI data preprocessing;
- ArcGis 10.4 used the data processing and layout of the generated index maps;
- Excel 2016 used for processing statistical data and developing curves.

1.2 Methods

1.2.1 Normalized Difference Vegetation Index (NDVI)

Over the past several decades, several types of vegetation index have been developed to aid in the detection of vegetation relative to other cover types such as rock, snow, and soil. Vegetation indices are obtained using a combination of several spectral bands. The values of these indices give the proportion (vegetation cover) of vegetation present in each pixel (Verstraete and Pinty, 1991). Among these many indices, one of the most used is the Normalized Vegetation Index (NDVI). Thanks to the chlorophyll pigment in the leaves, vegetation absorbs strongly in the red (0.6 to 0.7 µm) to carry out photosynthesis and reflects in the near infrared (0.7 to 1.1 µm) because of the anatomical structure leaf cells. This index is obtained from the following formula :

$$NDVI=(PIR-R) / (PIR+R)$$

Where: PIR = Reflectance in the near infrared and R = Reflectance in the Red.

For MODIS, the red channel band is between 0.62 and 0.67 µm and that of the near infrared between 0.841 and 0.876 µm. Daily NDVI acquisitions are generally processed using the "maximum values compositing" algorit+hm to produce decadal images (Holben and Fraser, 2007). NDVI quickly became a valuable vegetation monitoring tool. Indeed, using satellite-measured vegetation indices, important plant resources such as crops, pastures and forests can be monitored at an appropriate spatial scale.

1.2.2 Vegetation Condition Index (VCI)

Characterizing the humidity conditions of vegetation, the VCI (Vegetation Condition Index) is an index which makes it possible to compare the effect of climate on vegetation in non-homogeneous study areas (Kogan, 2002). This index expresses as a percentage the level of growth achieved by vegetation in each zone on a given date compared to the maximum growth recorded in previous years on the same date.

The calculation of the VCI indicator is based on NDVI data at the level of each pixel over the entire period studied. A VCI value around 50% corresponds to an average vegetation growth situation, while values between 50% and 100% indicate optimal or above-normal vegetation conditions. A VCI value of 100% means that the NDVI value for the selected month is equal to the NDVImax, which means that optimal conditions for vegetation exist. Different degrees of severity of vegetative degradation are represented by a VCI value below 50%. A VCI value close to 0% reflects an extremely dry month and an NDVI value that is near its long-term minimum. Low VCI values that persist over several consecutive time intervals indicate the development of drought (Owrangi et al., 2011). The VCI index is calculated by the following formula:

$$VCI=\{(NDVI(i)-NDVI\ min/NDVI\ max-NDVI\ min)\} *100$$

Where NDVI (i) is the NDVI of the period studied, NDVI max: maximum NDVI of the period studied and NDVI min: minimum NDVI of the period studied.

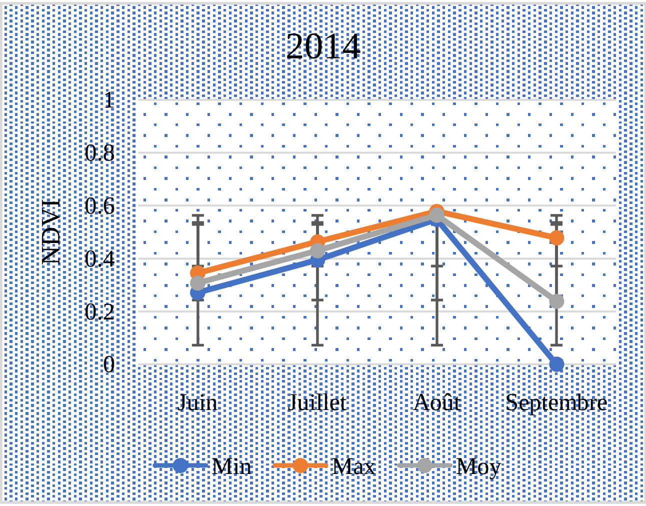
1.2.5 Duration and intensity of the dry season during the study

The climate diagram allows you to examine the state of drought over a specific period. An ombrothermal diagram is a special type of climate diagram representing the monthly variations over a year of **temperatures**and **precipitation**according to standardized gradations: one gradation of the precipitation scale corresponds to two gradations of the temperature scale (P = 2T). It was developed by Gaussen in 1956.This makes it possible to represent the annual course of precipitation and temperatures and to appreciate the relationship between precipitation and temperatures, since drought appears when when the temperature curve passes above the precipitation curve (Charre, 1997).

2. RÉSULTS

2.1Evolution of the inter-seasonal trend of NDVI

The evolution of NDVI profiles provides information on the minima and maxima of NDVI for each season of the study period (figure 3). Thus, we see that the months of September and August represent respectively the months of low productivity and high productivity of vegetation for almost all seasons. These months correspond to the month of harvest or senescence and to the flowering and/or growth phase of the crops. However, certain agricultural seasons (2012, 2016, 2020) do not have similar months relating to minimums. For this category, the minimums correspond to the month of June but the same months relate to the maximums, that is to say the month of August. We cannot therefore accept the hypothesis that these results could be explained by the delay in crop sowing. Likewise, we note that the 2015 agricultural season is special because the month of September represents both low and high productivity of vegetation. This leads to the conclusion that sowing and harvesting were carried out in the same month.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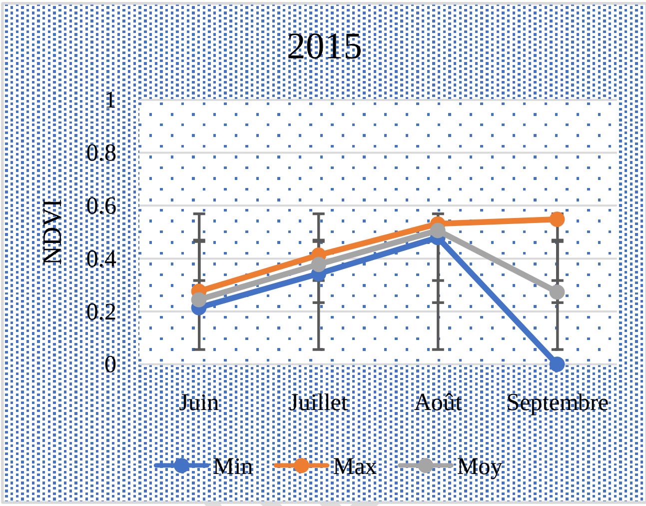
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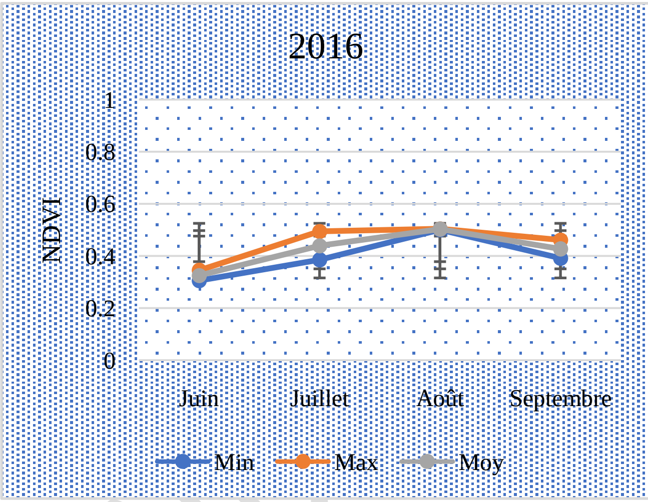
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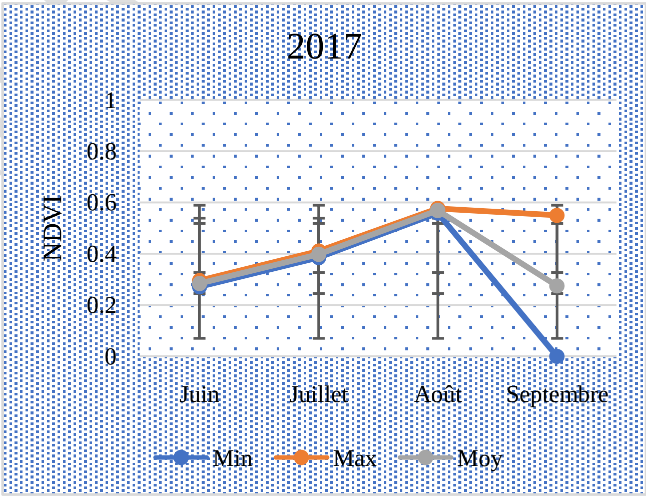
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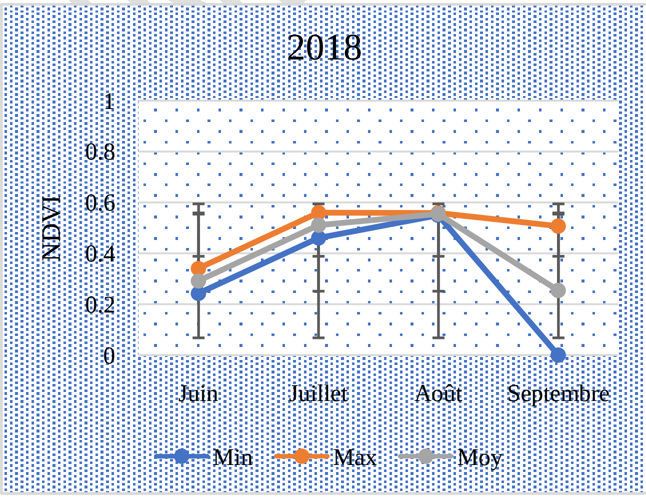
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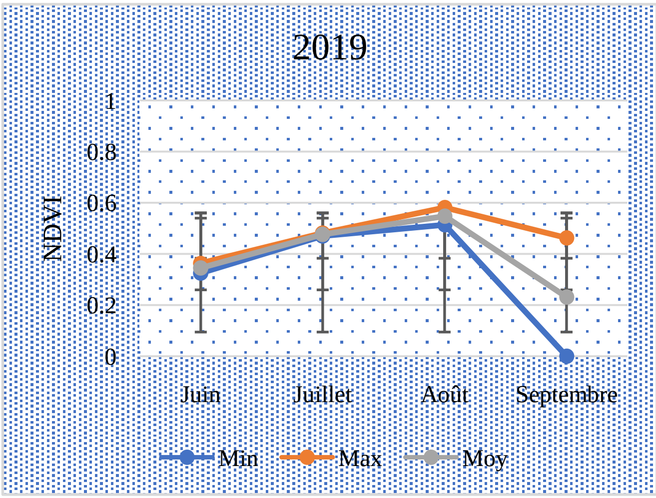
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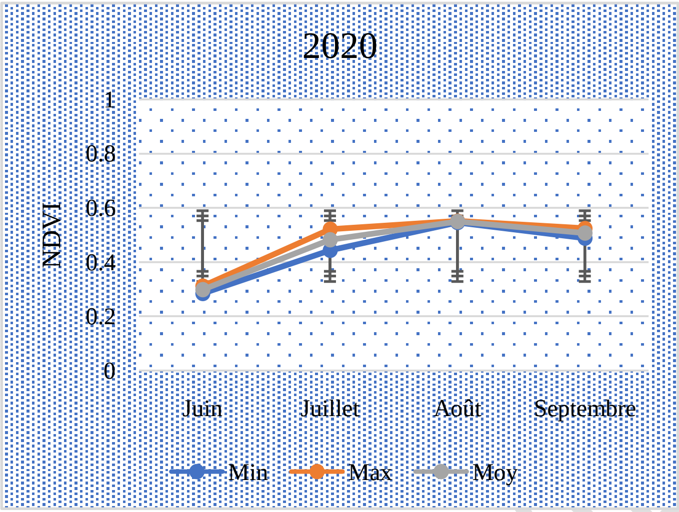

Figure 3 : Inter-seasonal profiles of NDVI

From the above, the evolution curve of the annual averages of NDVI (figure 4) sufficiently shows the year with the highest average. As a result, the year 2012 has the high average and the year 2015, the lowest average of our study period with 0.51 and 0.274 respectively. The years 2010, 2011, 2013, 2014, 2017, 2018 and 2019 remained around an average of 0.3. The year 2020 appears with a slightly higher average (more than 0.4) than the latter.

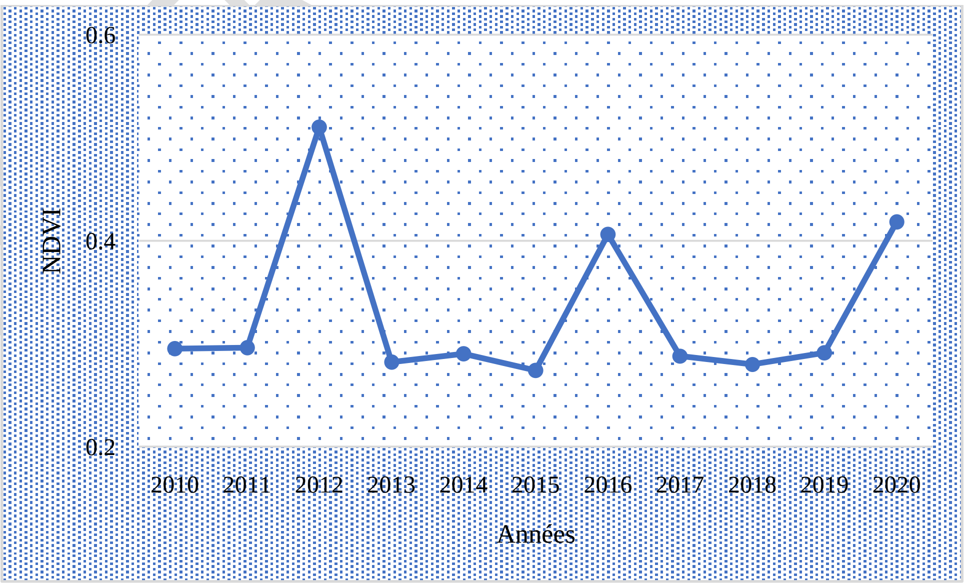

Figure 4 : Inter annual average profiles of NDVI

2.2 Analysisof the spatio-temporal variability of NDVI

The analysis of the variability of NDVI in space and time was carried out for each agricultural season of the study period (2010 to 2020) based on NDVI-MODIS images. The analysis of Figure 5 leads to the following findings: the distribution of plant cover is visibly uniform for all agricultural seasons of the study period, the lower limits (around 0.2) and upper limits (around 0. 7) of NDVI are approximately similar from one season to another. The latter present a slight difference, this is the case for the 2015 agricultural season with the lower limit (0.20605) and the upper limit (0.767762). This implies that the distribution of vegetation cover in the study area is relatively important.

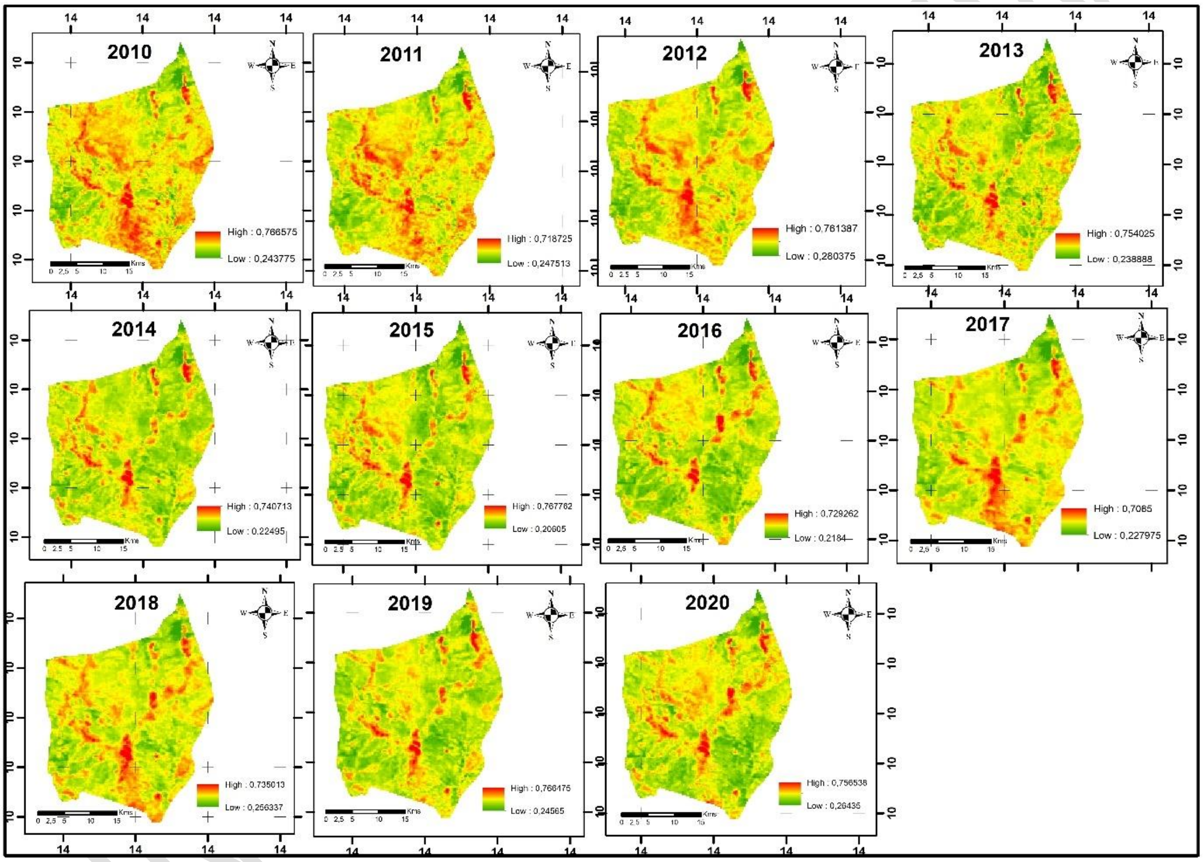

Figure 5 :NDVI's spatio-temporal map from 2010 to 2020

2.3 Inter seasonal variation of the VCI index

The analysis of VCI profiles made it possible to appreciate the drought status of the area throughout the study period. From this assessment, it emerges that all the VCIs are high, that is to say they have values greater than 40. Consequently, these VCIs reflect NDVIs approaching the maximum NDVIs. In other words, the high values of these VCI represent favorable conditions so there is no drought in general during the study period (Figure 6).

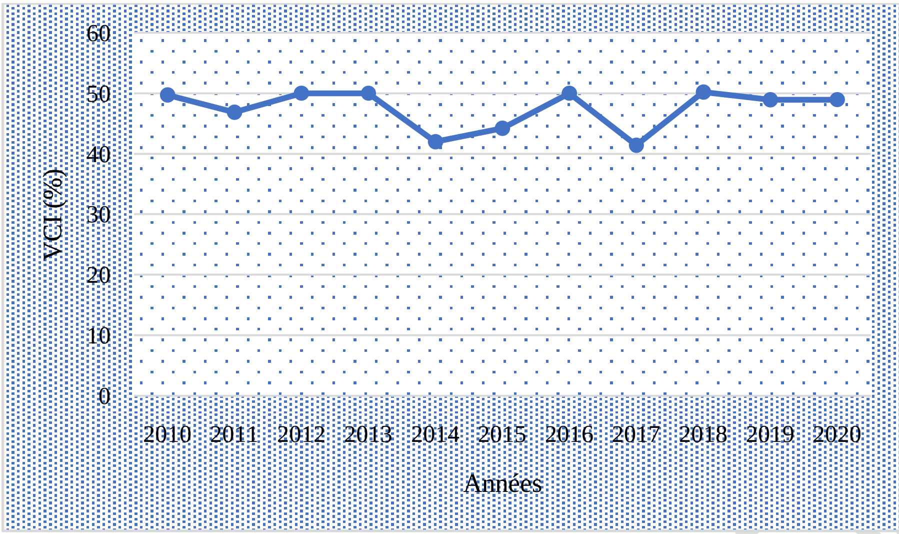

Figure 6 : Inter annual VCI profile curve

Paradoxically, a spatio-temporal assessment evokes the diversity of drought conditions in the study area varying from one period to another. Thus, we record several classes of droughts for a precise monthly data. These classes consist of extreme drought, severe drought, mild drought and the non-occurrence of drought (no drought) depending on the month. An illustrative VCI map from 2020(Figure 7) shows fluctuations indicating that the state of the vegetation is characterized by heterogeneity.

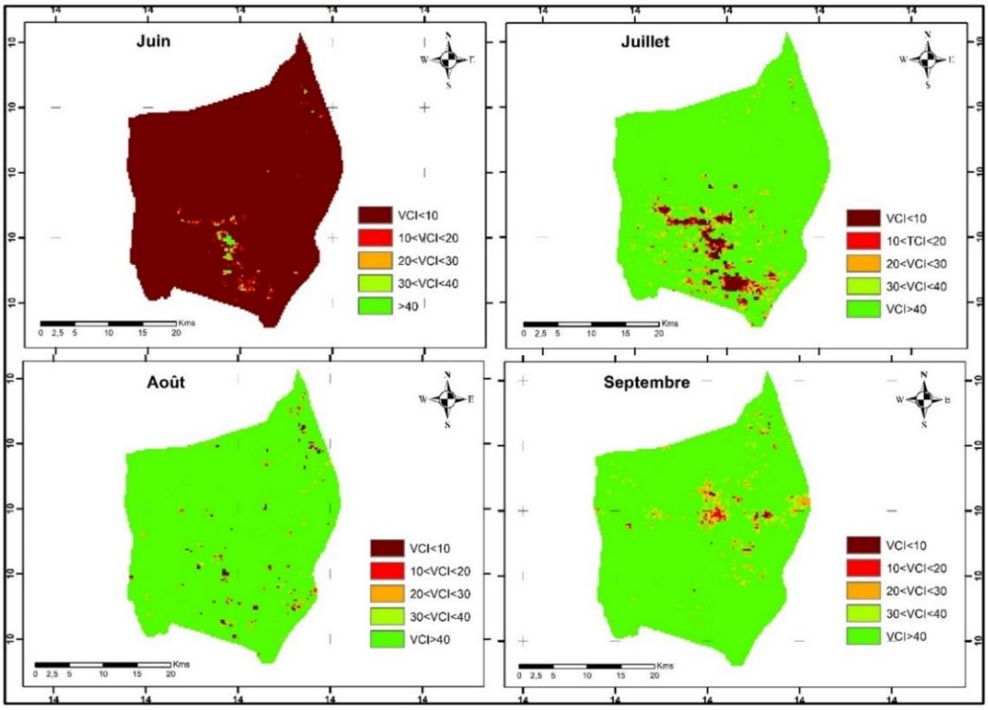

Figure 7 :spatio temporal map of VCI 2020

2.4 Inter seasonal variation of the VHI index

This indicator provides information on the state of health of the vegetation in relation to extreme situations. The inter-seasonal cadence of VHI reflects the appearance of VHI together with the related drought classes. This being said, we recorded VHI greater than 40% for each study season with a peak in 2018 and a minimum in 2017. The VHI presents normal situations in the state of the vegetation: favorable temperature conditions and indices of vegetation close to maximum values.

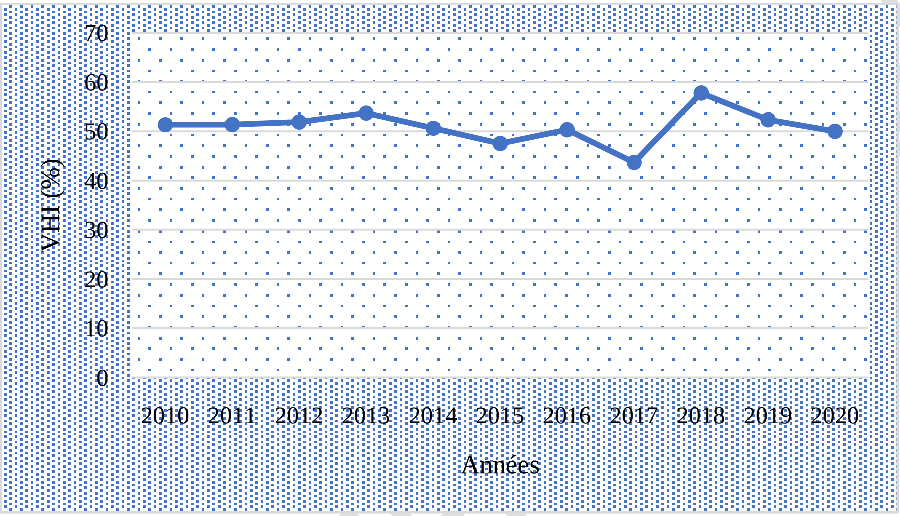

Figure 8 : Inter annual profile curve of VHI

Concerning the inter-monthly analysis of the VHI spatio-temporal map, a map from 2020 is being studied. On this map, all drought classes are represented in June with a high representation of the extreme drought class. Concerning the months of July and August, only the extreme drought class does not appear there, we note the predominance of the “no drought” class. For the September period, two classes (extreme drought and severe drought) are excluded and we see that it is a relatively humid month (figure 9).

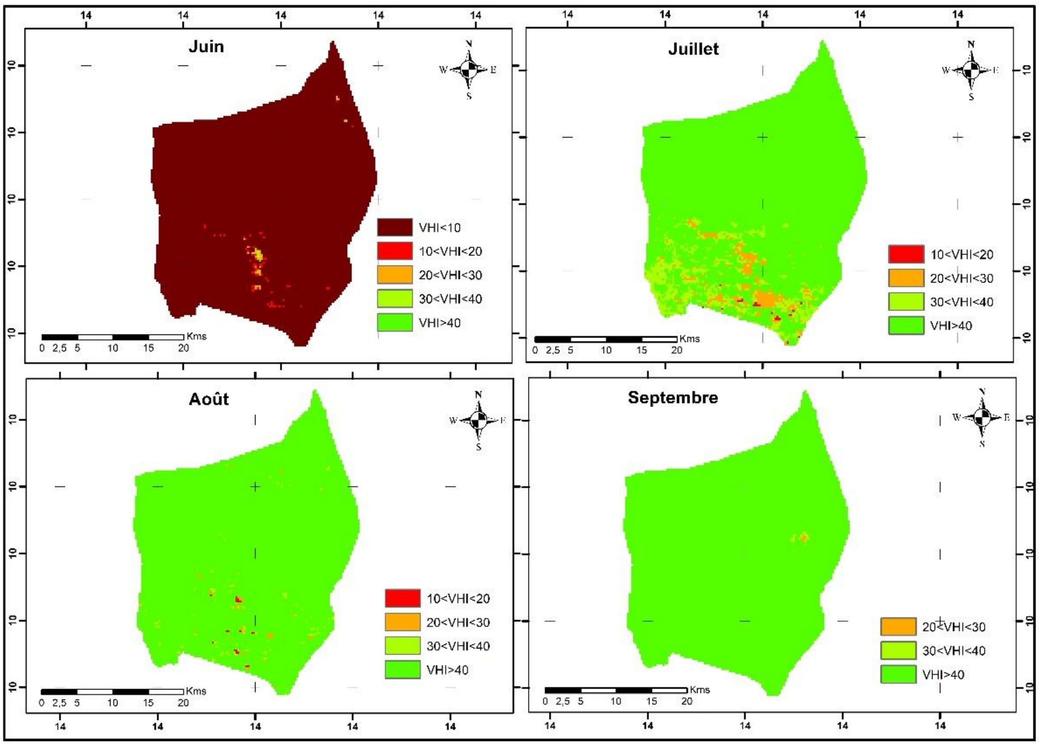

Figure 9 : Spatio temporal map of VHI 2020

3. DISCUSSION

3.1 Evolution of vegetation from 2010 to 2020

In the Moutourwa agricultural production basin, among the four (04) months of significant vegetation production chosen, the month of August is the most important production period during the 10 years of the study. The NDVI characterizes the spatial-temporal evolution of the vegetation in the area. When the rainfall is early, the months of July and August appear as a period of important production (2010, 2013, 2016, and 2018) and when it is late, the months of August and September (2011, 2015 and 2017) are the most important periods for crop production (Figure 3). On average, each rainy season has between four and five dry seasons. Depending on the situation at the beginning, middle or end of the season and also their length, the impact on yields varies (Saha et al., 2017).

3.2 Inter seasonal variation VHI andVCI

The state of health of the vegetation shows that there are no months of drought in the four (04) months studied. This result is verified by the work of Bijaber and Rochdi (2019) and leads to the conclusion that all the study seasons belong to a no drought class (Figure 8) because the index is greater than 35 (Figure 4). However, there are pockets of drought within the months of the season. Several authors who have used the VCI for monitoring droughts have concluded that drought conditions are met when the VCI is less than 35 (Kogan et al., 2004; Layelman, 2015). So, in the present study, during the 10 years (2010 - 2020), the crop production period from June to August does not contain drought conditions.

CONCLUSION

The statistical analysis of climate variability, using indicators calculated from satellite data, makes it possible to highlight the response of the vegetation on the one hand and to compare the state of the vegetation of the period studied on the other. go. Likewise, a descriptive statistical study of satellite data series makes it possible to identify periods during which anomalies in vegetative production are detected following climatic variations. This will allow managers of agricultural environments to make the necessary corrections in order to maintain good vegetative growth. In addition to satellite data, vector data was also used in this research work. The NDVI MODIS was used to calculate the Vegetation Condition Index (VCI) to determine the Vegetation Health Status (VHI). These NDVI data also made it possible to understand the dynamics of agro-climatic parameters. In perspective, the study carried out can be improved by studying the degree of correlation between the classes of calculated indicators and vegetative production during the agricultural campaign, to develop a new index allowing real-time drought monitoring.

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