Chapter 4

Harnessing Earth Observation and Satellite Information for Monitoring Desertification, Drought and Agricultural Activities in Developing Countries

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Additional information is available at the end of the chapter

http://dx.doi.org/10.5772/55499

1. Introduction

With the drastic advances in technology over the past decades, the availability, as well as the quantity, of large data sets for research in almost every scientific field has increased dramatically. More specifically, the availability of earth observation-based imagery data and satellite information for research purposes and practical applications has grown with many organizations such as the European Organisation for the Exploitation of Meteorological Satellites (EUMETSAT), the National Aeronautics Space Administration (NASA), the National Oceanic and Atmospheric administration (NOAA), the Flemish Institute for Technological Research (VITO), etc. for example, through GEONETCast, which is part of the core Global Earth Observation System of Systems (GEOSS), the users do not need to repeatedly build ground receiving stations for different satellites [1]. However, despite a wealth of remotely sensed data provided by GEONETCast, investments in science technology and innovations is often a low priority for decision and policy makers in most developing countries in Africa, Asia and global emerging economies like India and Brazil. Yet, most of these countries face serious environmental risks and development challenges which require reliable and timely access to accurate Earth Observation (EO) data and derived environmental information for their sustainable development. In particular, there is a clear need for research on the integration and utility of remote sensing data and products into the risk assessment cycle, scenario development and impact forecasting, in view of global (climate) change [2].

Climate alterations, although global in nature, may have different impacts in different regions of the world. Reports of Intergovernmental Panel on Climate Change (IPCC) showed that the global average surface temperature has increased over the 20th century by about 0.6ºC [3]. Global Circulation Models have projected that this rise in temperature may increase to a range of 1.5 – 5.8ºC by the end of the century. Results of crop growth modeling under climate change scenarios suggest that agriculture, and thus human well-being, will be negatively affected by climate change, especially in developing countries [4]. The vulnerability to drought and land degradation has increased in the past decades and this is especially true due to increased population pressure and limited livelihood options in drought-prone areas [5]. Significant gaps in observing systems exist, especially in developing countries, and timely access to both surface-based and space observations is still a challenge in many locations.

Global-scale population growth and economic development will have a large impact on water supply and demand, and it is necessary to understand the interactions between climate change and variability, hydrology and human systems, in order to have a view on future water vulnerabilities [6]. Since developing countries will become more susceptible to climate variability and drought, it is essential to develop climate (impact) monitoring services. A climate service involves broad partnerships of producer and user organizations, climate scientists, climate service providers, economists and social scientists. It provides an opportunity to interlink global, national and regional information systems; to provide essential information to policy makers, decision takers and to the public in general at regional and local scales, and a provide for a distributed decision-relevant research and development capability [7]. The climate service for the developing countries might focus on collaborative problem solving. Also capacity building and the improvement of infrastructure, related to the acquisition of advanced remote sensing technologies and the installation of satellite receiving stations by, is needed.

The gist of this chapter is therefore to strengthen the capacities of the regional scientific community to provide stakeholders from drought to agricultural activities with satellite information that is directly useful to improve decision-making in the context of the developing countries. The chapter is based on four case studies from Africa, South America, India and Europe to demonstrate the utility of satellite imagery data obtained from free or low cost platforms in providing information to address the above environmental issues, which are critical particularly in developing countries. Based on the expertise, experience and interest of a regional network of scientists from Uganda, Brazil, India, and Europe, the chapter focuses on harnessing satellite remote sensing resources and products for drought monitoring of areas subject to or in risk of land degradation processes, agricultural productivity and drought assessment. The following paragraphs include a series of example cases where time series of satellite imagery is used to monitor the impact of climate (change):

i. Degradation monitoring over South America

ii. Relation of NDVI with the moisture Index over the regions of different climatic types

iii. Sugarcane yield estimation and modelling based on NDVI data over Southeastern Brazil and

iv. Production and yield estimates of five major crops over Uganda

http://dx.doi.org/10.5772/55499

The importance of each of the above aspects in the context of assessing, monitoring and managing the natural hazards such as desertification, drought and risk management are discussed in detail in the individual sections.

All case studies make use of time series of Normalized Difference Vegetation index (NDVI), an index of vegetation activity that can be derived from broad band measurements in the visible and infrared channels onboard satellite instruments and which is directly related to the photosynthetic capacity of plants [8]., Satellite sensors such as NOAA Advanced Very High Resolution Radiometer (AVHRR), Moderate Imaging Spectroradiometer (MODIS), Système Pour l'Observation de la Terre (SPOT) Vegetation etc. provide NDVI data on different intervals (8-day, 10-day, monthly and seasonal). NDVI value varies minus one (-1) to plus one (+1), whereby low NDVI values (< 0.2) reflect sparse vegetation, and higher NDVI values (> 0.4) reflect high vegetation densities. Several studies looked into the interannual variability and trends of NDVI in relation to meteorological parameters such as rainfall, temperature etc [9-11].The long time series of NOAA AVHRR has been widely used to relate the synoptic meteorology/climatology to understand the vegetation dynamics, vegetation response to climate and climate vegetation feedback mechanism [5, 12-14]. The studies of [9, 15-17] concluded that AVHRR NDVI is a valuable tool to monitor and asses large scale agricultural droughts. Other studies use NDVI time series derived from MODIS [18-20] or SPOT-Vegetation [21, 22].

In this work, the authors made use of NDVI imagery datasets derived from different satellites to relate the respective crop and climatic parameters to understand the sensitivity of NDVI with these parameters and further to use them for vegetation monitoring over large areas which contributes to risk management.

2. Time series analysis for desertification monitoring

In the last decades, remote sensing technologies started to contribute enormously in documenting changes in land cover and monitoring desertification, drought and agricultural activities on regional and global spatial scales. Although desertification is highlighted as one of the most important global environmental issues, both desertification and greening processes have been reported on global scale [23-26]. These processes are related in many ways with other environmental issues, such as climate change and the carbon cycle, loss of biodiversity and sustainability of agriculture [27]. Also in South America environmental change is an important concern. In the last decades, South American ecosystems underwent important functional modifications due to climate alterations and direct human interventions on land use and land cover [28]. In South America, the main forest conversion process in the humid tropics in the period 1990-1997 was the clear-cutting of closed, open, or fragmented forest to make room for agriculture at a rate of approximately 1.7 million ha per year [29]. Apart from deforestation, also forest degradation occurs, a process leading to a temporary or permanent deterioration in the density or structure of vegetation cover or its species composition. Land degradation in arid, semi-arid and dry sub-humid areas is called desertification, and is the result of various factors, including climatic variations and human activities [30].

To determine desertification conditions, this case study focuses on vegetation dynamics in South America over a long time period based on a time series of low spatial resolution, high temporal resolution NDVI derived from SPOT-Vegetation, and to recognize to which extent this variability can be attributed to variability in rainfall, since rainfall is one of the most determinant factors of vegetation growth. In general, and especially in semi-arid regions, strong correlations between precipitation and the NDVI can be found. Therefore, the NDVI can be used as an indicator for vegetation status and vegetation response to precipitation variability. This study expands the analysis, as was performed on the Andes region [31] to South American continental level. In the first phase, trends of vegetation and precipitation indices are analyzed. In a next step, through correlation of NDVI and precipitation dynamics, these areas where the evolution of vegetation is not related to climate only and human induced impacts play an imperative role can be identified.

The time series of SPOT-Vegetation 10-daily composite NDVI data (April 1998 – March 2012) at 1 km resolution (http://www.vgt.vito.be/) was smoothed [32] and consequently synthesized to monthly images using the maximum value composite technique. Also 10-daily rainfall estimates at 0.25° resolution, available from the European Centre for Medium-Range Weather Forecasts (ECMWF) through MeteoConsult and the Monitoring Agricultural ResourceS (MARS) unit, were combined to retrieve monthly composites. The spatial resolution of the NDVI time series was degraded in order to fit the rainfall estimates using a weighted average approach. Many authors remove seasonality by integrating the data into annual values (e.g. [25, 28, 33]). In this study, in order to remove seasonal vegetation changes and thus facilitate the interpretation through the historical record, deviations from the 'average' situation were calculated for the NDVI time series using the Standardized Difference Vegetation Index (SDVI) [34] and for the precipitation time series using the Standardized Precipitation Index (SPI) [35]. In a next step, for each pixel a correlation analysis is performed on the monthly NDVI and SPI datasets, in order to identify the temporal scale at which the environment is most sensitive to precipitation anomalies (the so-called 'best lag').

The results of the correlation analysis between NDVI and SPI are shown in Figure 1. Positively correlated (blue) areas suggest precipitation-vegetation coupling. In general, high positive correlation with best lags between 3 – 6 months are found in the semi-arid regions of South America, while weak (or even negative) correlation at all time scales was found in both the hot and humid zones and the deserts and high mountainous areas. These positive relationships between vegetation greenness and rainfall in drylands, where biomass production is determined by the amount of rainfall, and the opposite in humid and cold regions, where rainfall is not the limiting factor for vegetation growth, and deserts, where there is no rainfall at all, is consistent with findings of other authors, such as [33, 36].

In order to identify if a pixel is greening or degrading, and after identifying the best lag for each pixel, linear least squares trend analyses were performed on the SDVI time series and the SPI time series, taking into account the accumulated rainfall over the respective best lag. Only trends with Pearson correlation coefficients significantly different from zero (at significance level $p < 0.05$) are considered significant trends. Figure 2 shows the slope of the significant linear trends of vegetation greenness and precipitation anomalies, SDVI and SPI respectively.

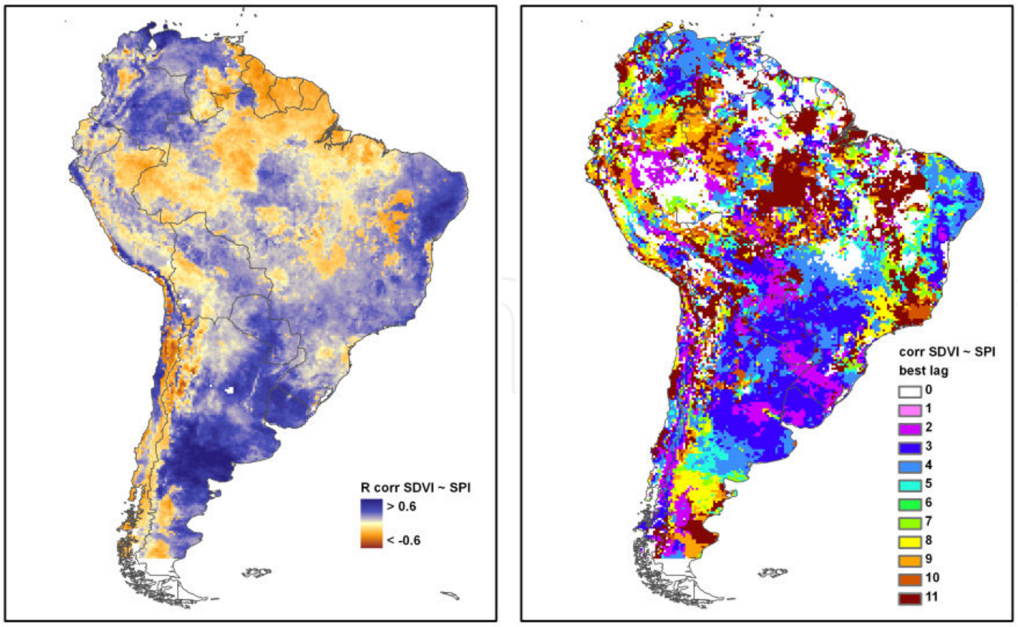

Figure 1. Correlation analysis between NDVI and SPI. Best lag expressed in months.

SDVI show slight but significant (P<0.05) positive trends in large areas in the northern part of South America, but significant negative trends in Argentina and the Peruvian coast. The results are comparable, but far more pronounced than results from annual series trend analysis, such as from [25, 28]. Also the SPI shows positive trends in the north-west of South America and the centre of Brazil. Negative precipitation trends are found in Argentina, the Peruvian coast and north-east of Brazil.

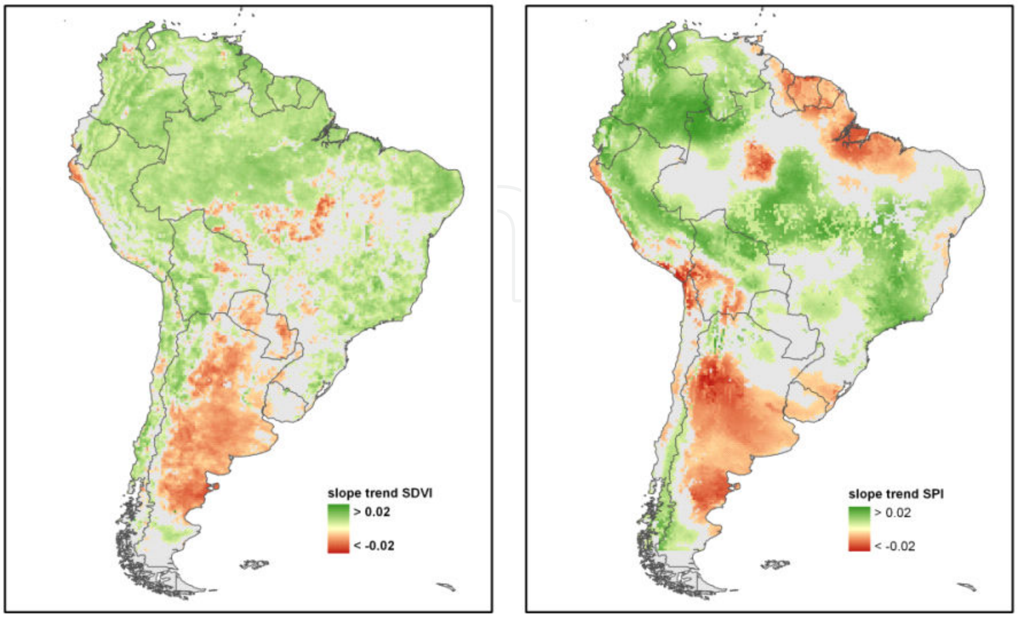

Figure 2. Slope of the trend analysis of SDVI (left) and SPI (right). Non significant trends are masked in grey.

Following the trend analyses, a decision tree approach is adopted in order to interpret the results. Five queries are stipulated: (1) Does the time series of SDVI show a significant trend? (2) Are significant trends in SDVI coupled to significant correlations between NDVI and SPI? (3) Are significant trends in SDVI linked to significant trends in SPI? (4) Does the SDVI show a positive trend? (5) Do trends in SDVI correspond to trends in SPI?

The first question is meant to identify the focus area, i.e. pixels where the de-seasoned vegetation index (i.e. SDVI) shows a significant linear trend over time. The second and third queries are used to identify areas that differ in their relationship between vegetation and precipitation trends, respectively, while queries 4 and 5 are meant to distinguish positive and negative trends that are linked to trends in precipitation. On the other hand, it is possible to identify regions where positive or negative trends in vegetation are not linked to changes in precipitation and other climate variables or human impact play an imperative role. In step 4, pixels are divided in greening or degrading pixels. In the last step, both the trends in SDVI and SPI are evaluated.

The results of the decision tree analysis are shown in Figure 3. Green classes show a significant positive trend in SDVI coupled to an increase in SPI. Red classes show a coupling between a decrease in SDVI and SPI. The yellow and orange classes are classes where SDVI and SPI show an opposite trend. Argentina is clearly suffering from vegetation degradation linked to a decline in precipitation, which confirms the findings of [35]. The opposite is going on in Colombia and some parts of Brazil, where a process of greening seems to be linked to an increase in precipitation. Nevertheless, Brazil shows a patchy result, with some areas showing an increase in SDVI, although the precipitation decreases (yellow areas in Figure 3), and other areas showing a decline in vegetation, although precipitation increases (orange area in Figure 3), probably related to deforestation or forest degradation.

The resulting map can be used to estimate the coupling between vegetation (SDVI) and precipitation (SPI), shown in Figure 4. Three estimations are made: (A) a large estimation where significant trends in SDVI are coupled with trends in precipitation when SPI shows the same trend (significant or not); (B) an average estimation where significant trends in SDVI are linked to trends in precipitation when SPI shows a significant trend; and (C) a conservative estimation where significant trends in SDVI are linked to trends in precipitation when the SPI shows a significant trend and the correlation between NDVI and SPI is significant.

In estimation A, also weak trends in SPI are taken into account. These non-significant trends in precipitation are most probably not by itself responsible for significant trends in SDVI. Together with other variables like temperature change or human impact, these weak changes in precipitation might however give an extra impulse to greening or degradation processes. It is also possible that an increase in precipitation does not result in higher vegetation cover because the area is covered with climax vegetation or, the other way round, a decrease in precipitation does not result in further degradation because the area is already covered with minimal vegetation growth. Estimations A and B show little difference. The difference between estimation B and C is based on the significance of the correlation between NDVI and SPI, and shows larger differences, mainly in the greening pixels. In many pixels that show a positive

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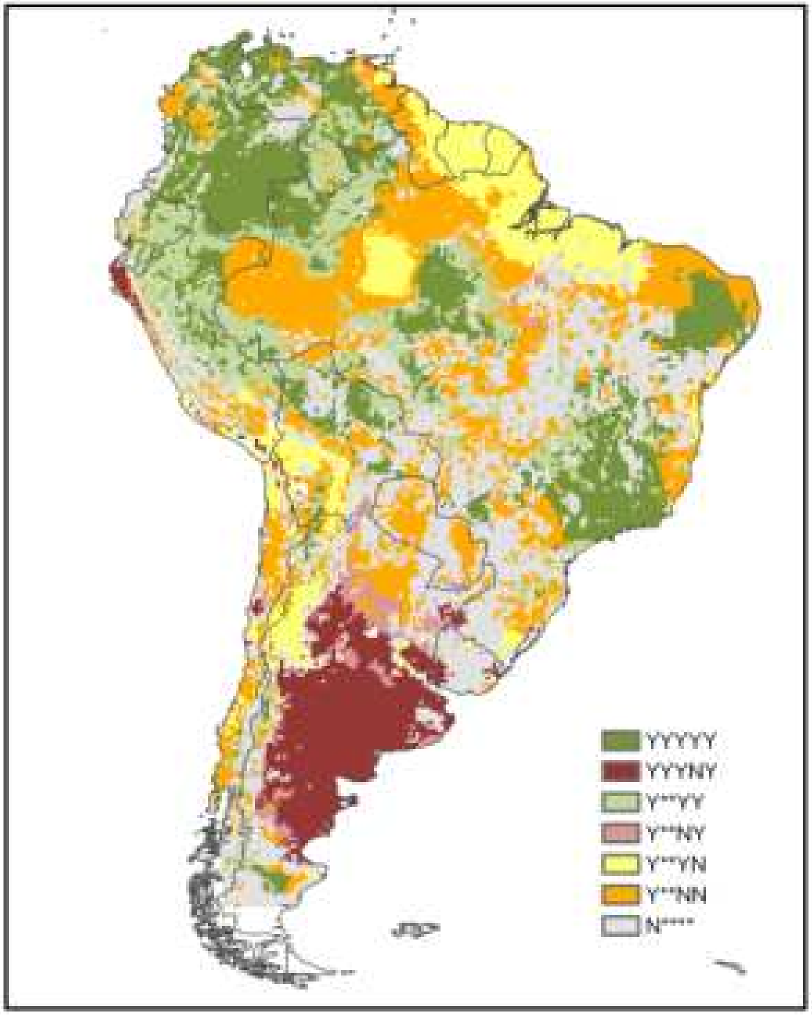

Figure 3. Result of the decision tree approach. Pixels are classified according to the 5 queries described in the text (where Y and N refer to a 'yes' or 'no' answer to the query, and * to either Y or N): green areas show an increase in SDVI, coupled to a significant positive trend in SPI (dark green) or not (light green); red areas show a decrease in SDVI, coupled to a significant negative trend in SPI (dark red) or not (light red); yellow areas show a positive trend in SDVI, but a negative trend in SPI; orange areas show a negative trend in SDVI, but a positive trend in SPI. Pixels without a significant trend in SDVI are masked in grey.

trend in SDVI, vegetation greenness is not significantly correlated to SPI. It is therefore not certain that in these areas the increase in SDVI is coupled to an increase in precipitation.

From the conservative estimation, we can conclude that in 8% of South America, vegetation degradation is coupled to a significant decrease in the amount of precipitation in the last 14 years. Our results corroborate with the findings of [37]. In contrast, in 18% of the subcontinent, vegetation greenness has significantly increased over the last 14 years, coupled to an increase in precipitation. For 46% of the study area, significant degradation or greening processes could not be linked to changes in precipitation over time, indicating human impact or the influence of other climatic factors, such as temperature. Finally, and without taking into account the link with trends in precipitation, 40% of the subcontinent is showing an increase in photosynthetic activity over time, while desertification is taking place in 32% of the area.

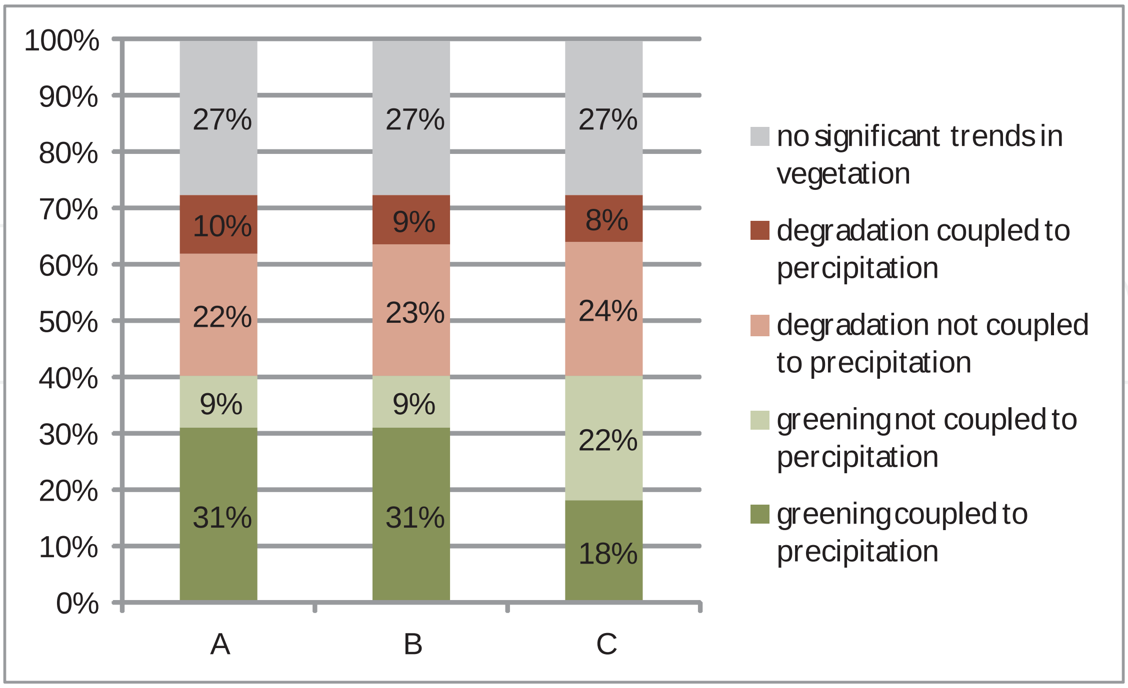

Figure 4. Large (A), average (B) and conservative (C) estimation of the linkage of greening and degradation to changes in precipitation over time. In case of estimation B and C, the yellow areas in Figure 3 are included in the light green fraction, while the orange areas in Figure 3 are included in the light red fraction.

3. Time series analysis for drought monitoring

Drought is a recurrent feature of the Indian climate and usually begins at any season and can prolong for many years. The study of drought characteristics is to ascertain the spatial and temporal distribution of droughts, synoptic meteorological conditions associated. The definition of drought mainly depends on the precipitation deficiency. Studies on droughts in India have been reported by many scientists based on the rainfall anomalies over a particular region [38-40]. According to India Meteorological Department (IMD) guidelines, drought is defined as the consequent rainfall deficiency (below 19% of normal) for a period of 2 consecutive weeks. However, this criterion varies from country to country, based on the meteorological/climatological conditions such as percentage of moisture present, land topography etc.

Drought is of different types including meteorological droughts, agricultural droughts, hydrological drought and socioeconomic droughts. These are based on the variations of rainfall, crop water, surface water and economic conditions respectively. These droughts show variation with respect to the climatology which prevails of that region. The climatology of a region is a replica of the severity of drought. The climatology can be derived from the Thornthwaite Climate System by taking the inputs of rainfall and water need. The model gives the amount of moisture (annual/seasonal) from which the classification of climate can be studied.

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In view of the above, the present study focuses in obtaining the climates in different parts of Karnataka state which is located at the western half of the Deccan Palateau of India. The Moisture Index values which are the basis for delineating climatic type were compared with the AVHRR NDVI to understand the drought climatology in different test regions of Karnataka, India (Figure 5).

Figure 5. Study area of the present investigation

The rainfall (P) and potential evapotranspiration (PE) data for the period 1982 to 2000 was downloaded from [41]. This data is based on the global rainfall and temperature (PE can be calculated from temperature) data sets of Climate Research Unit, University of East Anglia, United Kingdom. This was averaged for all the districts of Karnataka state till the year 2000 and uploaded website.

Taking the inputs of P and PE, we run awater balance model and derived the monthly Aridity Index (I_A) and Humidity Index (I_H). Moisture Index (I_M) which is the basis to tell the climatology of a region can be obtained by subtracting I_A from $I_{H.}$. Table 1 below shows the infered climate types based on I_M as per Thoronthwaite Climate Approach [42, 43].

Moisture Index(IM)	Climatic Type	Notation
100 & above	Perhumid	A
80 to 100	Humid	B4
60 to 80	Humid	B3
40 to 60	Humid	B2
20 to 40	Humid	B1
0 to 20	Moist Subhumid	C2
-20 to 0	Dry Subhumid	C1
-40 to -20	Semiarid	D
-60 to -40	Arid	E

Table 1. Classification of climatic types based on Thoronthwaite Approach

The selected districts for the study are Chikkamagaluru, Belgaum, Chamrajnagar and Gulbarga of which climates are Humid, Dry subhumid, Semiarid and Arid. A comparative study was made with the seasonal values of IM and NDVI using time series and correlation analysis.

Table 2 shows the climatology of the four selected test sites during the period of 1982 to 2000. The overall climate of the test regions for the study period represented the humid, dry subhumid, semi arid and arid for Chikkamagaluru, Belgaum, Chamrajanagar and Gulbarga districts respectively.

Year	Climate Type			
	Chikkamagaluru	Belgaum	Chamarajanagar	Gulbarga
1982	C1	C1	D	E
1983	B1	C2	D	E
1984	C2	D	D	E
1985	C1	D	D	E
1986	C2	D	D	E
1987	C1	D	D	E
1988	B2	C1	D	E
1989	C2	D	D	E
1990	C1	D	D	E
1991	B1	C1	D	E
1992	B2	C2	D	E
1993	B1	B1	C1	E
1994	B2	C2	D	E
1995	C2	C1	D	E
1996	B1	D	D	E
1997	B1	C1	C1	E
1998	B2	C2	C2	E
1999	B1	B1	C1	E
2000	B1	C2	D	E

Table 2. Climatic types of test regions from 1982 to 2000

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3.1. Chikkamagaluru (Humid region)

The climatic types of Chikkamagaluru were dominated by humid type which is followed by the dry sub humid type. Chikmagalore (Humid region) recorded a maximum I_M of 450 during the year 1994 (Figure 6). The variation of I_M shows that it has increased from June to August in all years and recorded a comparative less value in the month of September. In a similar way, the NDVI progressed from June to September in all years with a maximum value of 0.55 for September, 1992. It is conspicuous that the variability in NDVI is more than I_M and the trends of I_M and NDVI were increasing. The correlation coefficient of these two indices is +0.08 which is very poor. The studies of [38, 39] also suggested that understanding the relation of NDVI with rainfall and its by-products is a very difficult task in humid regions. Since the plenty of moisture is already available in the soil, the vegetation can utilize the moisture for its growth and in such case it may not directly/immediately dependant on rainfall derived indices in humid regions.

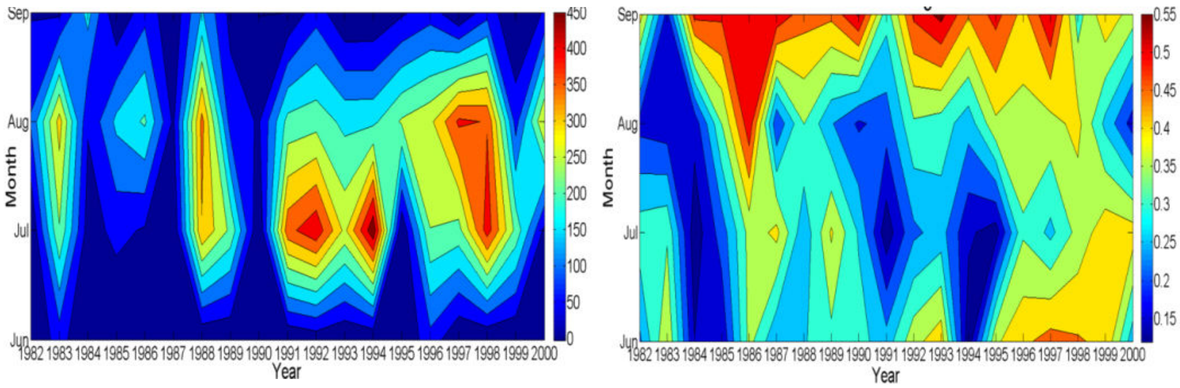

Figure 6. Variation of IM and NDVI – Chikkamagaluru

3.2. Belgaum (Dry subhumid)

The climate of Belgaum varied from semi arid to 1st humid type during the study period. 10 years of the study period show the subhumid climates followed by semi arid in 7 years. The variation of I_M with NDVI over Belgaum unraveled the low variability of I_M associated with high variations of NDVI (Figure 7). The maximum NDVI is 0.55 that is during September of 1984 and 1992 linked with the very low values of I_M. The I_M values were around zero during all the years of study period in June and July months countered by the low values of NDVI. There is no sea – saw relation found between I_M and NDVI over this region. The correlation in this case was also found to be very poor and insignificant.

3.3. Chamrajnagar (Semiarid)

From Table 2, it is noticed that Chamrajanagar shows the arid climate category in 15 years of the study period. The years such as 1993, 1997, 1998 and 1999 displayed subhumid climates. The climatic types of this region are the good representative of climatic features over the study

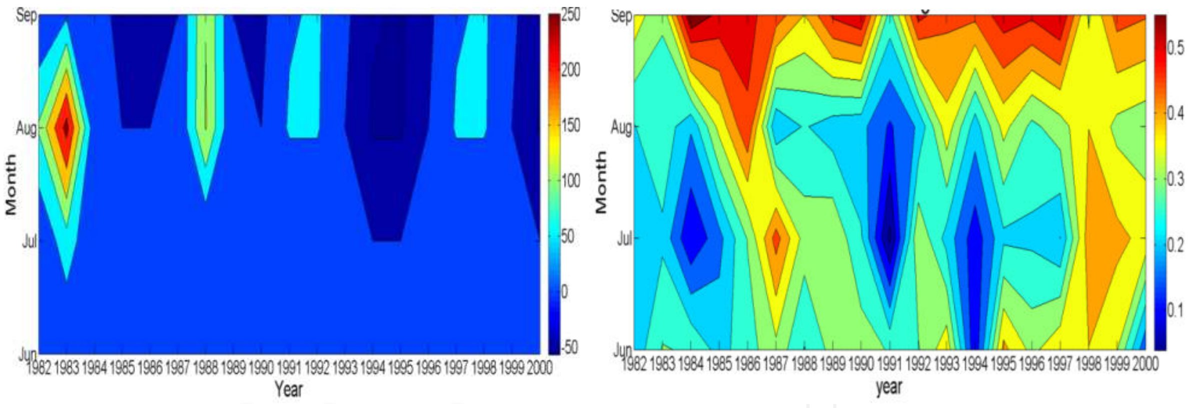

Figure 7. Variation of I_M and NDVI – Belgaum

period. In the case of semi arid region of Chamrajnagar, the variability of I_M and NDVI is better as compared with the humid and dry subhumid regions (Figure 8). The overall I_M is varied from -10% in the year 1984 to a maximum of 44% during the year 1998 for the south west monsoon season. Accordingly NDVI, also varied from 0.26 to a high value of 0.42 in the year 1996. The values of NDVI are less in this region than previously mentioned areas but the trends of I_M are NDVI were positive with slopes of 0.824 and 0.002 for I_M and NDVI respectively along with the standard deviations of 11.5 and 0.05. The correlation of these two data sets is 0.42 at 0.05 level of significance which infers the good agreement of I_M and NDVI. From this analysis, it can be noticed that the deficiency of moisture which is represented by I_M in this study was well reflected by low NDVI values and adequate moisture conditions are supported by the moderate vegetation conditions.

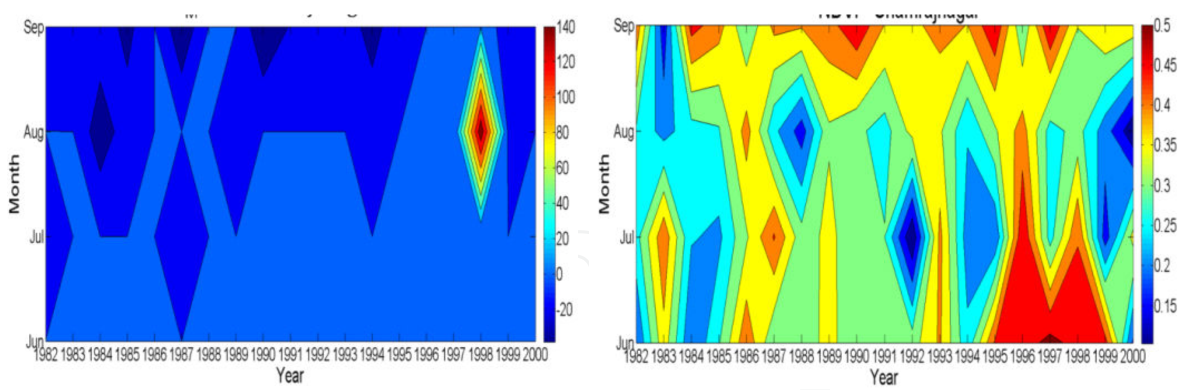

Figure 8. Variation of I_M and NDVI – Chamrajanagar

3.4. Gulbarga (Arid)

All the years of study period are dominated by the arid category for this region. The comparison of I_M and NDVI yielded good results in the arid region of selected test sites (Figure 9). The interannual variability was found to be very high both in I_M and NDVI where as I_M varied from -77% during August of 1982 to zero value during September month in the years 1983 and 1992

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with the corresponding NDVI values of 0.055 and 0.127 respectively. The time series plot for I_M and NDVI for the total south west monsoon season display the one to one linear agreement where the trends of both were highly increasing than other test regions (Figure 8). The slopes of the trends were 1.68 and 0.007 respectively. The standard deviations of 14 and 0.05 infer that the interannual variability of I_M is more than NDVI from which it can be noticed that the vegetation over a region may not respond immediately to the rainfall/available moisture despite there is a dependence of vegetation on rainfall/available moisture. The time series plot of I_M and NDVI (Figure 10) shows that the maximum of amount of moisture of-12% have seen in the year of 1998 with the NDVI value of maximum NDVI of 0.269 that is recorded during the entire study period. The correlation in this case is +0.64 which is at 0.01 level of significance which shows the strong agreement between I_M and NDVI.

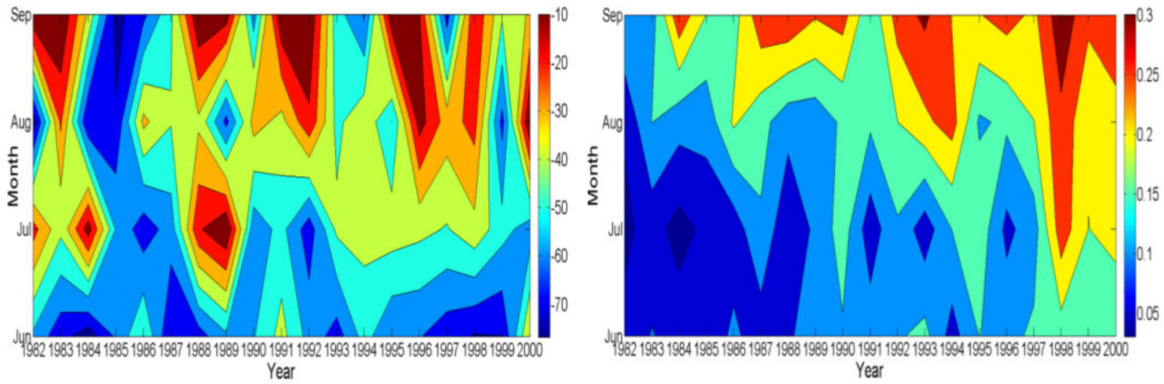

Figure 9. Variation of I_M and NDVI – Gulbarga

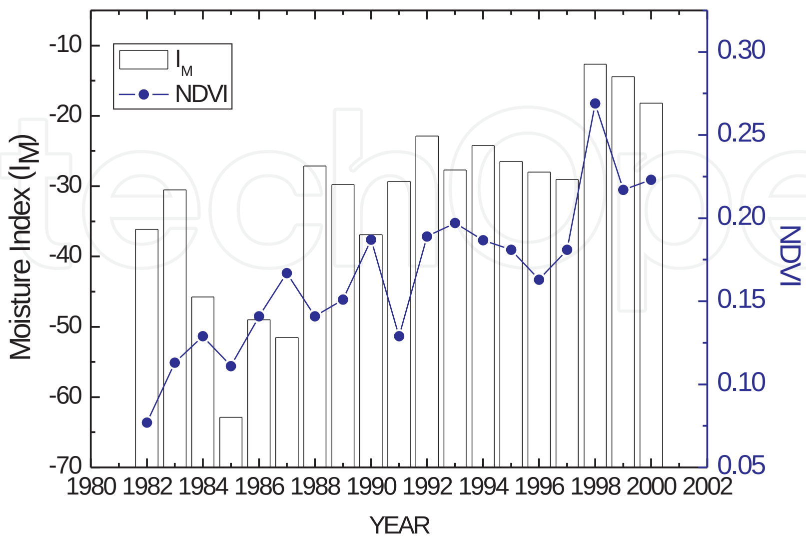

Figure 10. Time series of I_M and NDVI for southwest monsoon

The study commenced with the retrieval of I_M values from the water balance model on monthly basis over different selected test regions those represent the various climatic types such as humid, dry sub humid, semi arid and arid. The knowledge of different climatic types enables us to understand the climatology of the test regions during the study period. Since these climates were derived from the I_M values, they replicate the status of the moisture content available which is very essential input to decide the crops fate. The comparison study of I_M with the satellite derived NDVI shown very interesting features of sensitivity of NDVI with I_M over different climatic types. The study inferred the poor correlation such that no linear and significant relation of I_M with NDVI over humid and dry subhumid regions. The reason for this could be the plenty of available moisture over these regions and even temporary perturbations of land surface conditions may not affect the crops/agriculture. The relation grown up to strong when the comparison closes from semi arid to arid regions. Especially, Gulbarga, arid region displayed very strong relation of I_M with NDVI which unraveled the poor/good vegetative conditions associated with low/high values of I_M. The correlation of +0.65 is a good supporting factor to say that the relation is substantial. The overall analysis of the present study suggested that the relation of I_M with NDVI is very strong and it is of immense use for the studies of drought monitoring in the arid areas as compared with the other climatic types.

4. Quantification of sugarcane crop productivity: A study case in Southeastern Brazil

Agriculture represents an important segment of the economy of Brazil. Over the past 30 years, Brazilian agricultural growth and development has been guided by policies and technologies based on research for development. Remote sensed imagery plays an important role in agricultural crop production over large area, quantitatively and non-destructively, because agricultural crops are often difficult to access, and the cost of ground estimating productivity can be high. The recent development of GEONETCast–EUMETCast data has allowed us to obtain frequent and accurate measurements of a number of basic agrometeorological parameters (e.g. evapotranspiration, surface albedo, surface temperature, solar radiation, rainfall etc.). The GEONETCast–EUMETCast real-time and on-line data dissemination systems represent global network of satellite-based data dissemination systems designed to distribute space-based, air-borne and in situ data, metadata and products to diverse communities.

To determine agriculture productivity, this case study aimed to develop a GEONETCast-EUMETCast product-based method of estimating the productivity of sugarcane using an agrometeorological spectral model. The study was carried out in the Municipalities of Barretos and Morro Agudo, located in the state of São Paulo, Southeastern Brazil (Figure 11). The analysis was performed for 2009/2010 and 2010/2011 year's crop.

The values of sugarcane parameters used such as Respiration Factor (RF) (0.5 for temp. ≥ 20°C and 0.6 for temp <20°C); Agricultural Productivity Factor (APF) (2.9), Yield Response Factor (Ky) and Crop Co-efficient (Kc) were taken from [44-46]. The EUMETCast service is installed at Laboratory of Analysis and Processing of Satellite Images (LAPIS) at Federal University of

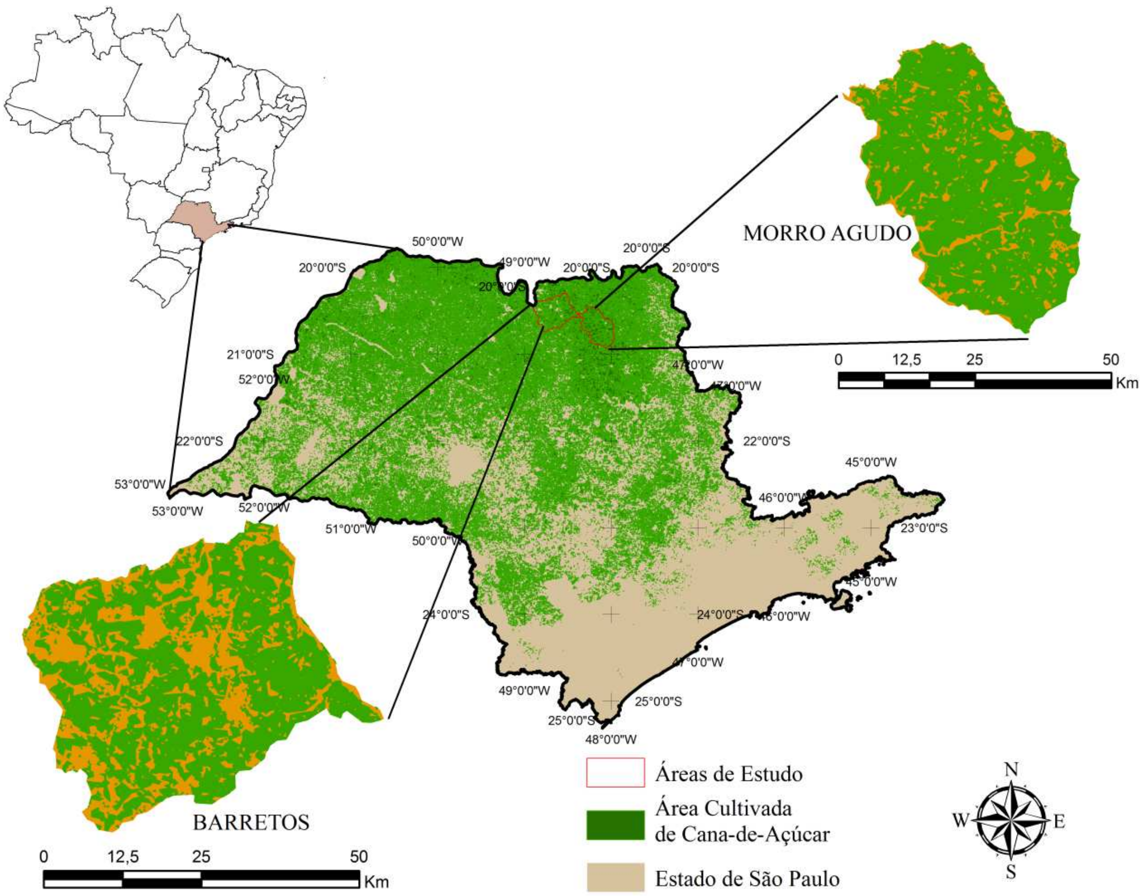

Figure 11. Spatial variability of crop yields (2010/2011) of Barretos and Morro Agudo in Sao Paulo, Brazil.

Alagoas (UFAL). The remote sensing data of NDVI S10, Production of Dry Matter (DMP) are available at the website http://www.lapismet.com and SPOT Vegetation indices of VITO were collected form http://free.vgt.vito.be/.

This application proposes to test a remote sensing approach to quantify estimates of sugarcane productivity over the Coruripe municipality with the Integrated Land and Water Information System, (ILWIS, 3.7.1) GIS software. ILWIS was used to compute sugarcane crop estimates for each pixel in NDVI DMP and ETp images by applying radiative, aerodynamic and energy balance physics in 7 computational steps. These images are currently provided over both daily and 10 day composites at about a 3km and 1km spatial resolution, by EUMETSAT and VITO respectively.

Step 1: Input NDVI and DMP databases using algorithm adapted from GEONETCast Toolbox

To implement a methodology for the ingestion of both the NDVI and DMP databases (raster) into ILWIS, specific routines of GEONETCast–toobox are adapted to import the datsets. For the ingestion procedure, based on a GIS approach using open source components, it requires additional work on corrections using overlays (Status map and LOG–file) to mask all appropriate areas of sugarcane crops over the Coruripe municipality.

Step 2: Computation of Fractional Vegetation Cover (FVC) from NDVI

For each pixel, the NDVI is converted to Fractional Vegetation Cover (FVC) by means of the the formula of [47]. The FVC is the one biophysical parameter that determines the contribution partitioning between bare soil and vegetation for surface evapotranspiration, photosynthesis, albedo, and other fluxes crucial to land–atmosphere interactions.

FVC= 1.1101*NDVI – 0.0857.

Step 3: Computation of Leaf Area Index (LAI) from FVC

For each pixel, the FVC is converted to Leaf Area Index (LAI) by means of the formula of [48]. The LAI, defined, as the total one-sided leaf area per unit ground area, is one of the most important parameters characterizing a canopy. Because LAI most directly quantifies the plant canopy structure, it is highly related to a variety of canopy processes, such as evapotranspiration, interception, photosynthesis and respiration.

LAI= –2Ln (1 – FVC).

Step 4: Computation of growth factor from LAI

[49] developed a simple approach for deriving growth rate equation from LAI. Experimental evidence indicated that the growth rate of several agricultural crop species increases linearly with increasing amounts of LAI, when soil water nutrients are not limiting [46]. The following equation is used:

$CGF = 0.515 - e^{[-0.667 - (0.515 * LAI)]}$

where *CGF* = Corrected Growth Factor. Experimental evidence indicated that the growth rate of several agricultural crop species increases linearly with increasing amounts of LAI, when soil water nutrients are not limiting.

Step 5: Computation of maximum yield potential (Yp)

The final equation that was used to derive maximum yield potential (Yp) includes evaporative fraction corrected growth factor (CGF), respiration factor (BF), agricultural productivity factor (APF) and production of dry matter (DMP) product.

$Y_p = CGF * BF * APF * DMP$

where Yp is the maximum yield potential (kg ha^{-1}).

Step 6: Retrieval of evapotranspiration (ET_p) via Land Surface Analysis –Satellite Application Facility (LSA SAF) ET_p product

The crop coefficient is defined as the ratio of crop evapotranspiration, ET_r, to reference evapotranspiration, ET_p. K_c is crop specific and ranges from zero to over unity, depending on the crop growth stage. Crop evapotranspiration at any time during the growing season is the product of reference evapotranspiration and the crop coefficient.

$ET_r = ET_p * K_c$

Crop coefficients was developed for nearly all crops by measuring crop water use with lysimeters and dividing the crop water use by reference evapotranspiration for each day during the growing season of 2009/2010 [50].

The recent development of LSA–SAF products has allowed us to obtain frequent and accurate measurements of a number of basic agrometeorological parameters (e.g. surface albedo, surface temperature, evapotranspiration). The satellite estimated agrometeorological parameters have several advantages compared to conventional measurements of agrometeorological data in ground meteorological network.

Step 7: Estimation of sugarcane productivity

The sugarcane yield estimation model over the growing season, on a biweekly basis, is accomplished by using an agrometeorological model integrated to ILWIS according to [46]:

$$Y_e = Y_p[1 - ky(1 - ET_r/ET_p)]$$

where Y_e is the estimated yield (kg ha^{-1}), Y_p the maximum yield (kg ha^{-1}), k_y the yield response factor; ET_r the actual evapotranspiration (mm) and ET_p the maximum evapotranspiration (mm). Maximum yield (Y_p) is established by the genetic characteristics of the crop and by the degree of crop adaptation to the environment.

The resulting map of the estimated yield (Y_e) is clipped to mask the Coruripe municipality boundaries in the State of Alagoas, Brazil. To establish correct coordinates, Map calculation within the ILWIS is used to implement this procedure. Flow diagram of methodology of quantifying sugarcane productivity via satellite products is shown in Figure 12.

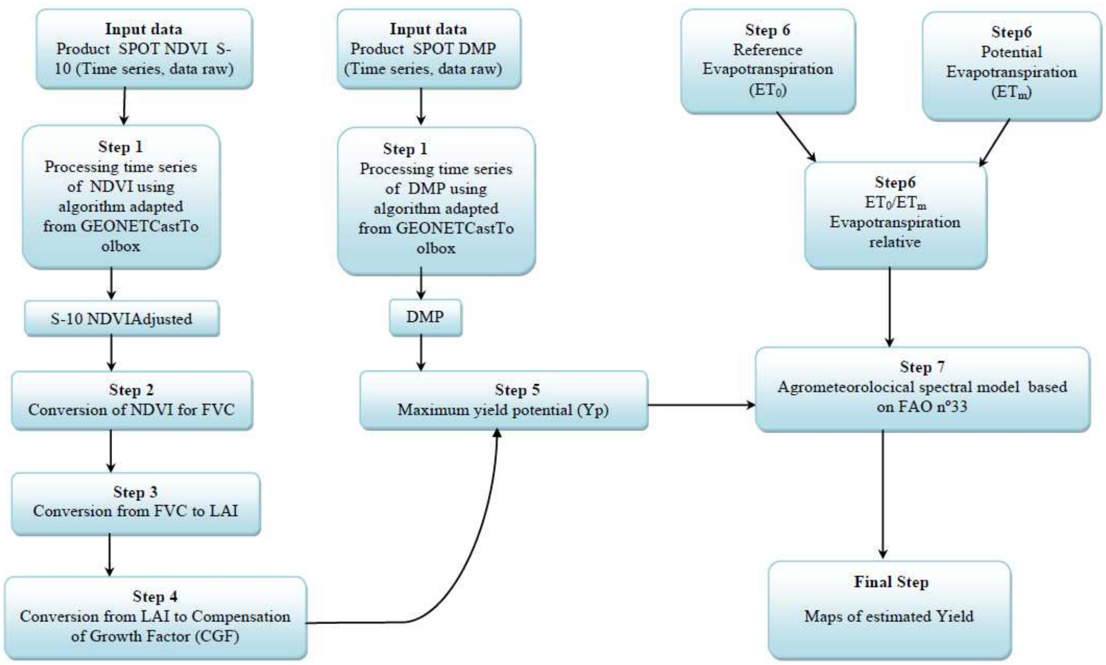

Figure 12. Flow diagram of methodology of quantifying sugarcane productivity via satellite products.

Figure 12 shows the spatial variations in sugarcane production over the Barretos and Morro Agudo municipalities for 2009/2010 and 2010/2011. The figure clearly indicates high spatial patterns in yield variability. This could be due to the mixing of significant fraction of observed pixels for the "arable pixel" and "non-arable pixel" within the municipalities. The quantified results give sugarcane yield mean range of 50 to 135 Ton ha^{-1}.The results obtained here represents a first step towards an operational use of ILWIS tools in Brazil using NDVI S-10, DMP SPOT and ETo for operational estimating of sugarcane productivity. Overall, the model was able to identify (Figure 12) and quantify (Table 3) the spatial variability of agricultural production over the municipalities analysed. Therefore, the methodology is useful for developing estimates of operational support for the sugarcane productivity [51].

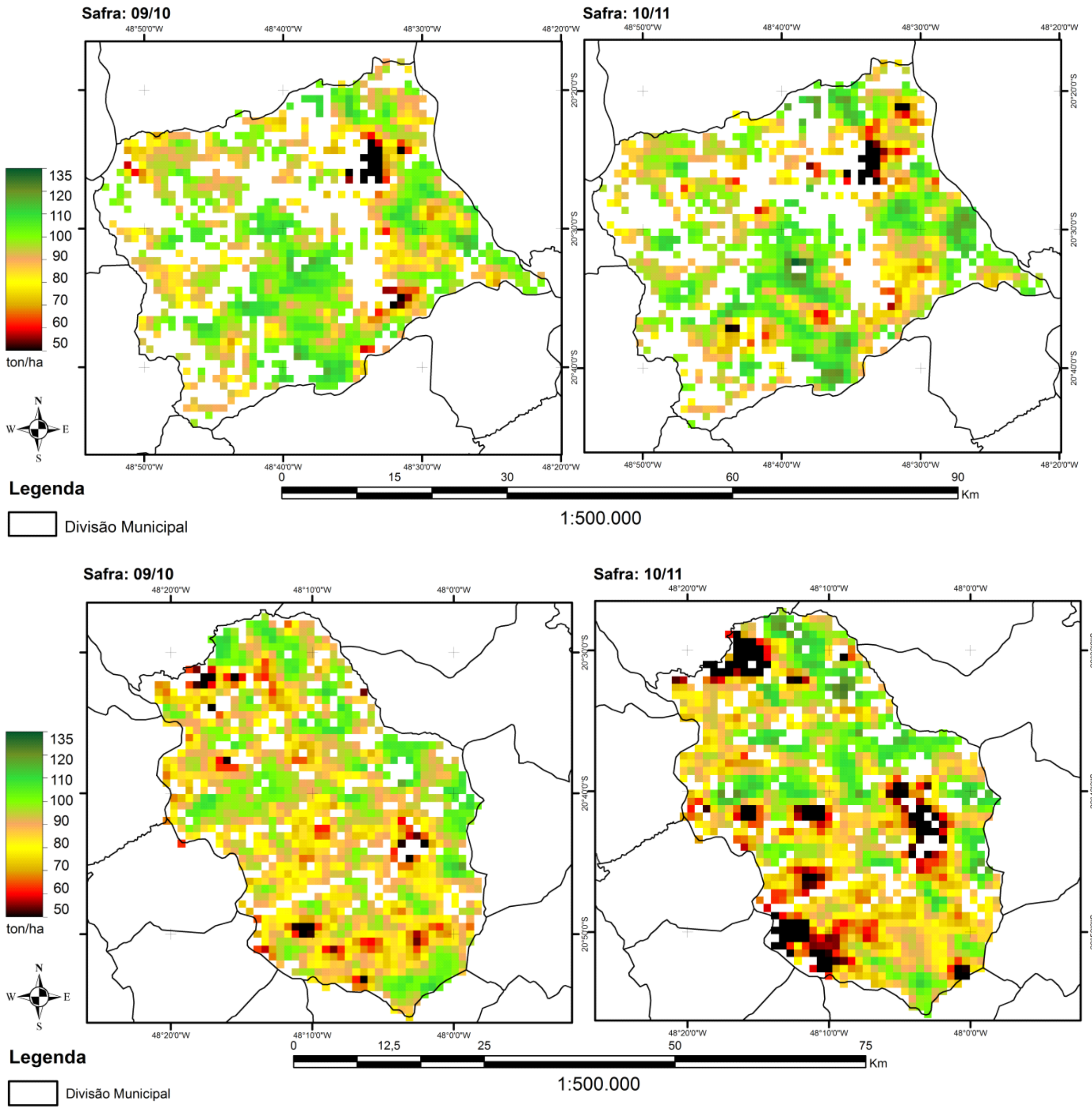

Figure 13. Spatial variability of crop yields over the Barretos and Morro Agudo municipalities for 2009/2010 and 2010/2011.

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Mean Productivity (t/ha)		
Barretos	Crop	
	2009/2010	2010/2011
Agrometeorological model	93,15	93,31
CONAB	96,21	93,29
Mean Productivity (t/ha)		
Morro Agudo	Crop	
	2009/2010	2010/2011
Agrometeorological model	87,96	84,10
CONAB	93,60	87,25

Table 3. Comparison between the productivity of sugarcane using an agrometeorological spectral model and harvested crop yield from National Food Supply Company (CONAB).

5. Time series analysis for agriculture monitoring: Uganda

The economy of Uganda and its development goals are heavily premised on agriculture. Over 79% of the households are engaged in agriculture while 73% are directly or indirectly employed in the agricultural sector. Uganda's agriculture is however almost entirely rain-fed and very susceptible to climate risks. Studies indicate that Uganda's agricultural sector will be adversely affected by climate variability and projected climatic changes making real time monitoring of crop growth and crop productivity very important for better adaptation to climate variability and climate change. Quantitative analyzes reveal that the agricultural sector in Uganda needs to grow at an annual rate of 7% to effectively contribute to national development. Currently, the rate of agricultural growth in Uganda is below the population growth. With the threats of climate change and variability, Uganda needs to among other things harness geo-information technologies (remote sensing and geographical information systems) to improve agricultural productivity.

Remotely sensed images are powerful tools in monitoring crop productivity and yields. In most developed countries and emerging developing countries like Brazil and India, remote sensing has been greatly harnessed to plan for agriculture production, monitor crop growth and estimate yields. This is paramount in the sense that timely interventions can be taken and obviates possibilities of famine and food insecurity. Although there have been strides taken to improve the utility of remote sensing in the agriculture some developing countries, a lot remains to be done to make it more efficient, relevant and more productive. An investigation of the causative factors of the low utility and uptake of remote sensing in the agricultural sector in Uganda implicates a number of factors ranging from low capacities to expensive images. Recent developments have however extended numerous opportunities in utilizing remote sensing in the agricultural sector.

The onset of utilization of remotely sensed techniques in Uganda was in the early 1990s spearheaded by the National Biomass Project and focused largely on land use and land cover mapping. The activities of the National Biomass Project were later taken on by the National Forestry Authority (NFA) but the domains and scope remained largely the same with more focus on land use, land cover and related aspects being given priority. Apart from the NFA, academic institutions of higher learning and to some extent some research institutions like the National Agriculture Research Laboratory Kawanda (NARL) and the National Environment Management Authority (NEMA) have some remote sensing application either for teaching or research. In general, the remote sensing applications in Uganda in the agricultural field are scattered and more project based. This is partly due to the fact that there is lack of a government agency with a clear mandate to spearhead and propel the utility of remote sensing application in the country. Nevertheless, some efforts through the government cooperation with UN agencies such as the FAO regularly provide some information analyzed at the regional level for early warning in the agricultural sector. Some of the historical constraints to efficiently harnessing remote sensing in natural resource management in Uganda are generally those also experienced in other developing countries in Africa including the high costs of imagery data, processing software, coarse resolution of images, inadequate physical and human capacities and weak institutions. To-date, most of the issues to do with data costs and software have been significantly resolved with many freely available images, open source versatile software or special low for developing countries on commercial software. The contemporary challenge now is more of institutional/agency capacities, human capacities and policy environment for enhancing the utilization of remote sensing in the country.

A range of great opportunities, hitherto unavailable exist now for effectively using remote sensing in agriculture and natural resource management, notably through; (a) datasets disseminated through the Geonetcast Platform (b) freely available and downloadable datasets (c) open source softwares and low cost commercial softwares. Details of the Geonetcast is fully described in various sources (e.g. [48-50]). In brief, its a low cost facility which enables dissemination of near real time satellite imagery data. It is part of the emerging Global Earth Observation system of Systems (GEOSS), led by the Group on Earth Observation (GEO), for environmental analysis [54]. The Geonetcast does not require internet connectivity which is always a major constrain in developing countries and the data is disseminated at a very high temporal resolution through a ground recieving station, making monitoring easy. The facility streams diverse datasets which can broadly be used in environmental monitoring covering agriculture, water, soils, fire forestry etc. The data can be processed using the ILWIS software, where a specific toolbox has been developed.

In this case study, we demonstrate the utility of relatively low spatial but high temporal resolution satellite images from earth observation systems in monitoring and assessment of agricultural productivity in Uganda. There are two main inputs i.e. production data and remotely sensed data. Production data was obtained online from the FAOSTAT [55]. We extracted the annual yield, production and harvested area of the top five crops produced in Uganda according to FAOSTAT; (1) plantain/banana (2) cassava (3) sweet potatoes (4) sugarcane and (5) maize for 10 years spanning from 2001 to 2010. Bananas/plantain (*Musa spp*) are largely grown in central, western and eastern (highland areas) parts of Uganda. As perennial crops, banana are year round crops. Cassava (*Manihot esculenta*) is an important food security crop in Uganda with the largest production coming from eastern and northern Uganda. Cassava accounts for approximately 13% of the daily caloric intake in Uganda. Cassava is commonly planted in the first season which is around February-march in most parts of the country and its also a perennial crop. Sweet potatoes (*Ipomoea batatas*) are also a food security crop in Uganda grown largely in the mid to high altitude regions of the country

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(1000-3000 meters above sea level). They are annual crops grown twice a year with the first season between February and June, while the second season stretches from September to November. They thrive well in the deep volcanic soils of Southwesten Uganda and Eastern Uganda. Sugarcane (*Saccharum officinarum*) in Uganda is largely grown on large plantations mainly in the near east and western Uganda. There are also a couple of out growers who are supported by sugar companies. It is mainly an income generating perennial crop. Maize (*Zea mays L.*) is grown in almost every part of the country and is a major staple food crop. It is an annual crop grown twice a year (March to June and September to November) in areas of the country where biophysical conditions are supportive. To ease the analysis, the production and yields for the five crops were compounded into one annual value.

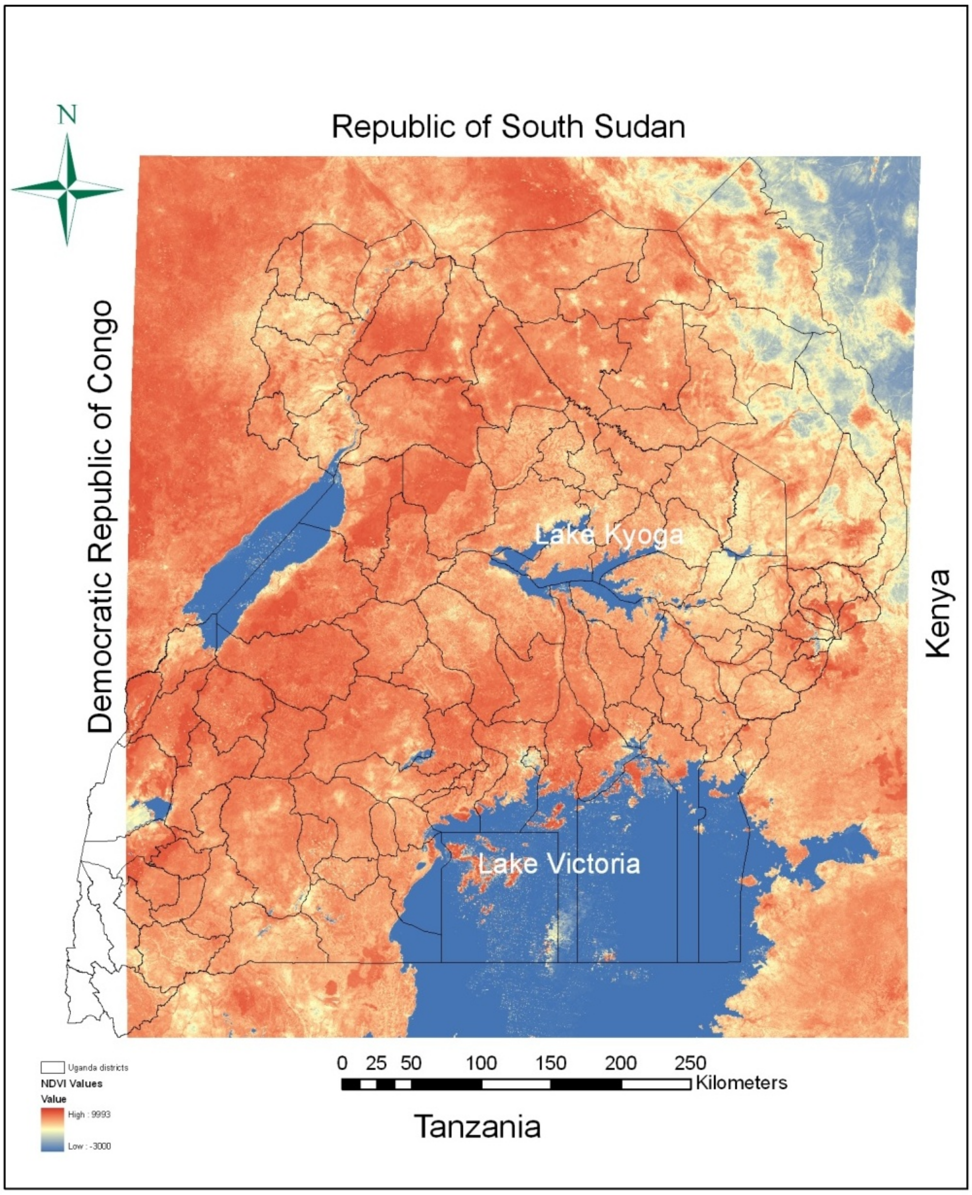
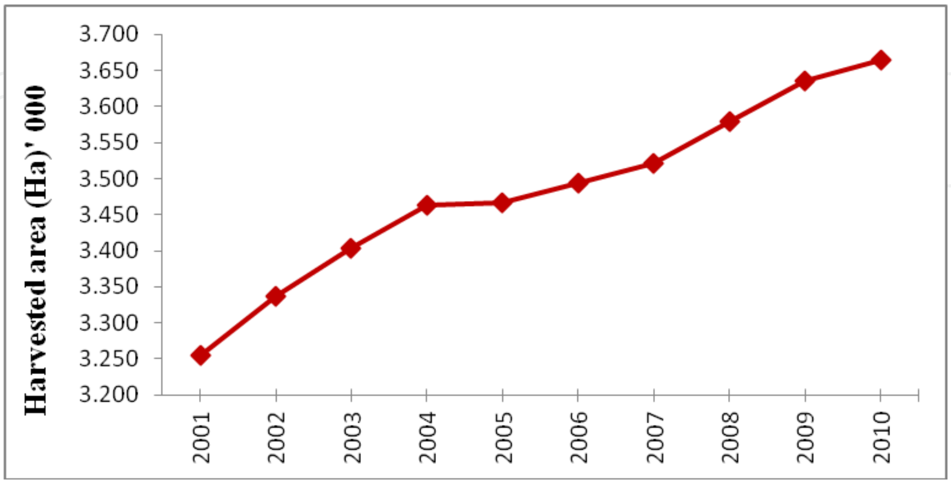


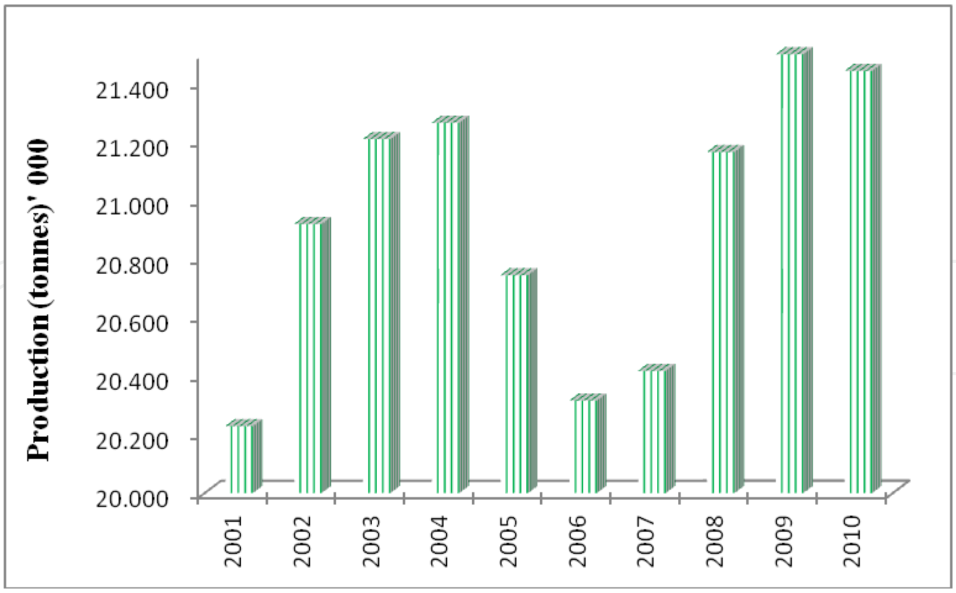
Figure 14. Scope of study

The results on harvested area, production and yields are shown in Figures 15, 16 and 17 respectively.



Data obtained from FAOSTAT

Figure 15. Harvested area of five crops between 2001 and 2010.



Data obtained from FAOSTAT

Figure 16. Production (compunded) trends of five selected crops between 2001 and 2010 compounded

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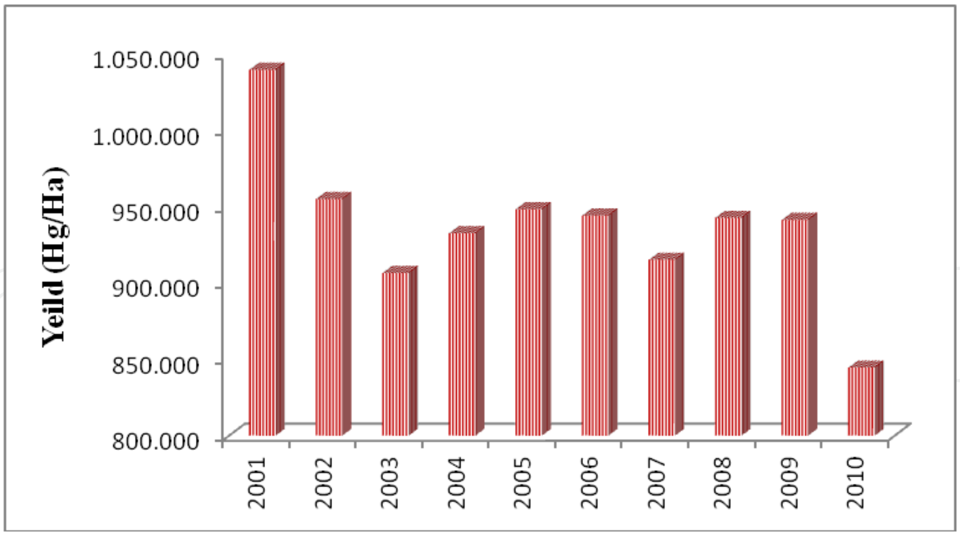

Data obtained from FAOSTAT

Figure 17. Yields (compounded) of five major crops between 2001 and 2010

The results based on the three factors i.e. area harvested, production and yields do not depict a definitive trend. In terms of harvested area, there is an increasing trend, implying that more areas are being converted for cultivation of the specified crops (Figure 15). Production between 2001 and 2010 has modestly increased. Yields per hectare are however more variable and actually show and generally declining trend. Bearing in mind that production is increasing, it becomes explicit that the increments in production are related to extensification rather than intensification. In most cases, extensification entails conversion of ecologically sensitive and fragile areas such as wetlands or reclamation of forest area which has its environmental implications. Subjected to a statistical analysis, the results revealed a strong and positive correlation between the yields and production area (r^2=0.52, $p<0.05$).

Remote sensing analysis was on the MODIS NDVI data, which has a spatial and temporal resolution of 250 m and 16 days respectively. For each year 23 images are available in a decal arrangement. For the 10 year period, we downloaded a total of 230 images in HDI format and processed them in ERDAS Imagine where file format conversions were undertaken and later ILWIS for arithmetic analysis. Individual images (23 decades) for each year were stacked to generate a single profile for each year. Relevant statistics such as the mean, standard deviation, coefficient of variation were late extracted. The spatial distributions of average NDVI for selected years are shown in Figure 18, while Figure 19 gives the temporal average NDVI dynamics for the 10 years. Mean average NDVI value is 0.56. In spatial terms, the southern part of the country registers higher NDVI values than the northern part. This is not surprising in light of the coverage in terms of natural cover and the crops grown which significantly entail banana and a range of annual crops grown in two seasons. The North Eastern part is particularly poorest in terms of annual average NDVI values. Understandably it is a semi arid region and generally more tailored to livestock enterprises than cropping enterprises. Annual NDVI values for the whole country were subjected to a correlation analysis with production and yield data, resulting into poor and insignificant correlations (r^2=0.19 to 0.2.1). The low coefficient are partly explained by the fact that some crops like sugarcane are eother irrigated or are grown in areas almost permanently under water (wetlands). However when the data was collapsed into the growing seasons and the water bodies excluded from the analysis, better and significant correlations were obtained (r^2 0.46 to 0.61, $P<0.05$) demonstrating the efficacy of using NDVI for crop monitoring and yield prediction. In light of the expected variability and changes in climate, coupled with the availability of data in real time, the NDVI analysis represents a great potential in sustainable adaptation where from both a policy perspective and direct intervention. This has positive implications in timely provisioning of information to farmers, adaptation to climate change and variability as well as enabling science based policy options for appropriate interventions. Specific prediction coefficients for different crops and regionalized to the climatic conditions can be helpful to local governments where timely interventions can obviate social instability related to crop failures. On the other hand, predictions of higher yields can also enable relevant agencies to solicit for markets for the produce, improving the welfare and livelihood of the farmers, who in the context of Uganda are largely small holder farmers. All these can only be realized if there is a good policy framework that ties all the relevant pieces in the chain i.e. science, production, markets and institutions.

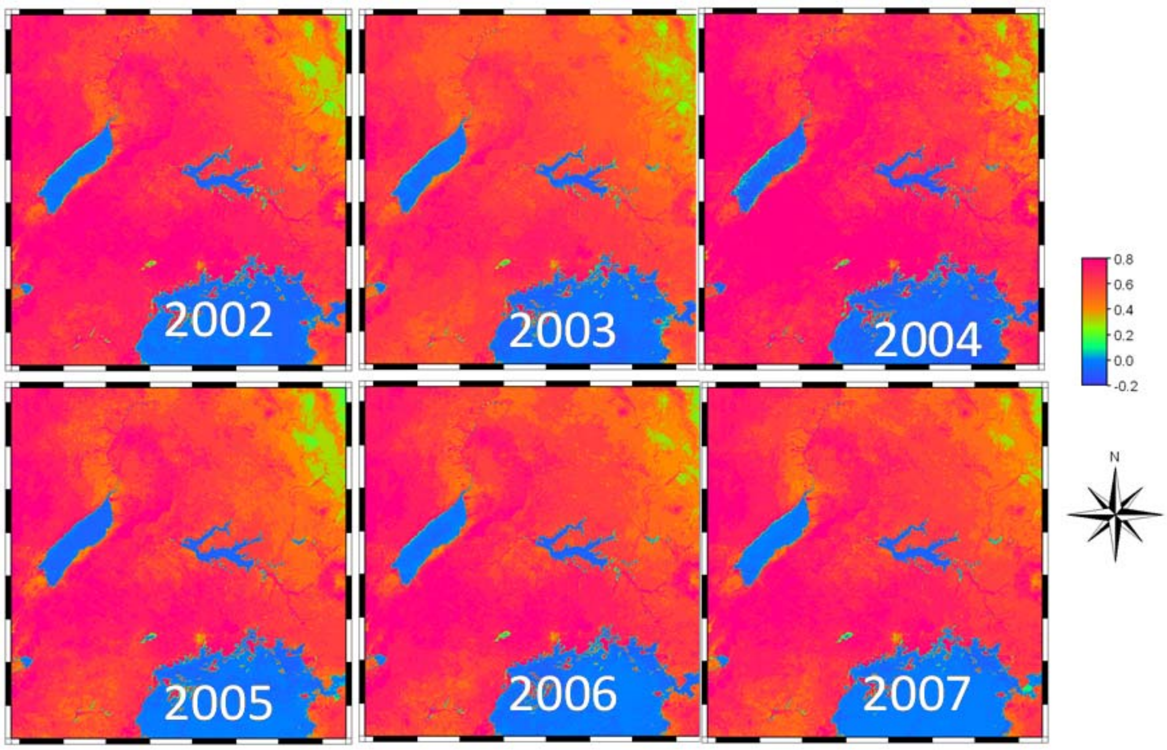

Figure 18. Average annual NDVI for selected years

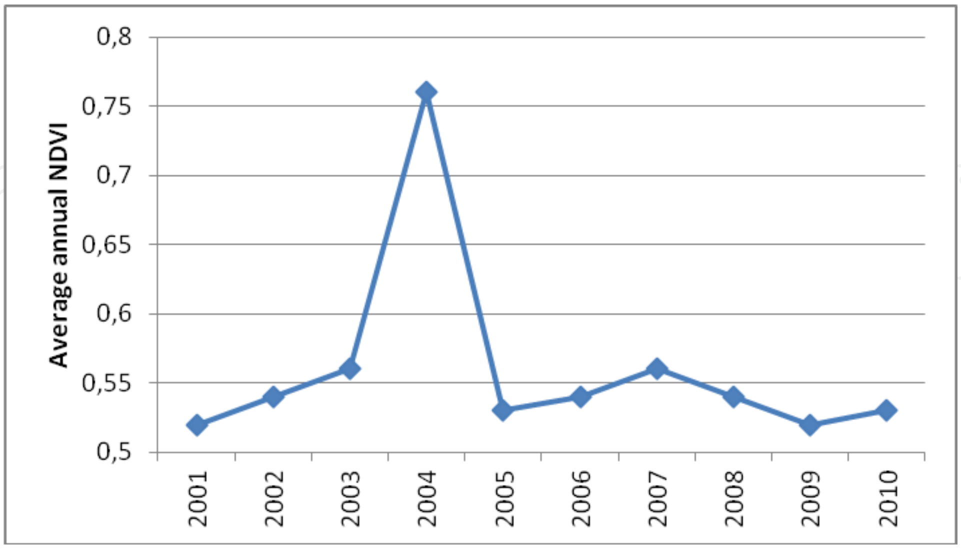

Figure 19. Variation of annual NDVI values between 2001 and 2010

6. Outlook and conclusions

We have provided four multi-disciplinary case studies on the power of using remote sensing technologies, and more specifically time series analysis of low resolution satellite derived indicators, for monitoring and analysing land cover changes, desertification, drought and agricultural activities on different spatio-temporal scales. Generating this information at finer temporal resolutions is crucial for reducing risks to disaster, preparedness and formulation of strategies for better adaptation to climate change particularly the increasing dramatic hydro-meteorological events in developing and emerging countries.

This chapter provides a variety of methodologies of processing chains over satellite data, allowing the monitoring of areas subject to or in risk of desertification and land degradation processes. This chapter provides new insights related on the use of remote sensing data for climate (change) impact monitoring, which will contribute to the advance of warning systems and adaptation measures in developing and emerging countries. The focus of future activities should however focus on institutional support and capacity building for impact assessments for Africa, South America and India. The importance of training and joint cooperation with local providers and users cannot be overestimated.

One of the most robust, multi-purpose and yet simple remote sensing index is the NDVI. NDVI imagery data is widely available for immediate use at almost no cost. This has been given emphasis in this chapter through demonstration of its utility in various environmental and production domains. The section 2 of the chapter mainly emphasizes the relation between trends of vegetation greenness and rainfall over a long term period, taking into account the time lag between rainfall and vegetation response. As a result, areas of greening or degradation can be identified, and the process can be linked or not to changes in precipitation.

The section 3 of the chapter tells the mode of relation between NDVI and moisture index over different climatic regions. The relation was found to be poor over humid and dry subhumid regions where as it is improving in semi arid and arid regions. The relation of above cannot be taken as granted in the humid regions though it is implicitly understood that NDVI maintains positive relation with IM. The study infers that the NDVI and IM relations cannot be used to characterize the drought over humid regions but can be taken as an indicator in arid and semi arid regions. This is particularly relevant for adaptation purposes in semi arid regions which cover big chunks in Africa, India and some parts of Southern America.

Section 4 of the chapter mainly focuses on the estimation of sugar cane yields in Southeastern Brazil by using spatial tools which have been integrated in ILWIS 3.7.1, open source software. This study underpins that the NDVI data along with the other meteorological data is of immense use for the estimation of crop yields. This gives a business orientation on the utility of spatial tools, but also has a livelihood implication where small scale farmers or out growers are involved in sugarcane production. Interestingly, sugarcane is a major crop in all the case study countries in this chapter.

The last section of the chapter also gives more emphasis on yield estimates of five major crops in Uganda. The results of the study showed that the production between 2001 and 2010 has modestly increased with the variability in yields. Also, this analysis showed that the extensification of crops is dominated by intensification and it is implied that the increments in production are related to extensification.

In a nutshell, the chapter demonstrates how remotely sensed data available in the public domain freely or at very low cost can be harnessed to address critical challenges in developing countries pertaining to environment, agricultural productivity, drought, desertification and ultimately climate change adaptation. The chapter shows that relating the satellite derived vegetation indices with existing models and parameters can be useful proxies to understand the various phenomena of the crops. However, despite the availability of the technology, full benefits from available remotely sensed imagery resources for developing countries can only be realized when enabling policies are formulated and implemented and concerted capacity development is undertaken to establish a critical human resource base. This will enable the policy makers to go for the risk managing practices such as agricultural crop reinsurance schemes, drought defining criteria etc.

In light of the resource constraints in developing countries, cooperation and collaboration is important to develop a nucleus of future demand and contributing to new scientific insights related to projected changes in drought drawing information from satellite data, which will contribute to the improvement of warning systems and adaptation measures in developing and emerging countries.

http://dx.doi.org/10.5772/55499

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