Monitoring floodplain dynamics in the Sahel region to detect land degradation processes

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ABSTRACT

Most of the major rivers in the Sahel region of West-Africa contain extensive floodplains. These floodplains have a high ecological and economical value. Local communities make use of the floodplain for agriculture, fishing and dry season grazing. The productivity and carrying capacity of the Sahelian floodplains are highly correlated with the extent of the flooding.

Fourier analysis of Moderate Resolution Image Spectrometer (MODIS) time-series data was applied to monitor flooding extent of the Waza-Logone floodplain, located in the north of Cameroon. Fourier transform (FT) enabled the quantification of the temporal distribution of the MIR band and three different indices: the Normalized Difference Vegetation Index (NDVI), the Normalized Difference Water Index (NDWI) and the Enhanced Vegetation Index (EVI). The resulting amplitude, phase and amplitude variance images were used as inputs for an Artificial Neural Network (ANN) to calculate flooding extent for the different years in the time-series. Different combinations of input variables were evaluated by calculating Kappa Index of Agreement (KIA) of the resulting classification maps. The combinations MIR/NDVI and MIR/EVI resulted in the highest KIA values. When the ANN was trained on pixels from different years, a more robust classifier was obtained, which could consistently separate flooded land from dry land for each year.

A rainfall-runoff model will be used to simulate streamflow of the Logone river based on 10-day African Rainfall Estimates (RFE). Once such a model is calibrated for the catchment area, the relationship between streamflow distribution and flooding extent will be analyzed.

Keywords: Floodplains, Sahel, time-series analysis, MODIS, rainfall – runoff model

1 INTRODUCTION

Most of the major rivers in the Sahel region of West-Africa contain extensive floodplains. These floodplains are temporally inundated most years, caused by over bank flooding of the rivers. Flooding starts at the end of the wet season and lasts three to five months, providing the floodplain with nutrients and sediments. The maximum extent of the flooding varies one year to another in response to the amount rainfall in the catchments area. In an average year the total inundated area of the major floodplains in the Sahel is about 67,000 km² [1].

The Sahelian floodplains are of high ecological value. They play an important role in the conservation of biological diversity both on a global and a local scale. The floodplains have an import economical value as well. Local communities, both resident and nomadic, make use of the floodplain for agriculture, fishing and dry season grazing. The vegetation on the floodplains consists mainly of perennial grasses. These grasses have a higher annual biomass production and a longer growing cycle than annual grasses and therefore provide high quality fodder for wildlife and livestock during the dry season. In areas where floodwater is absent for several years, soil condition deteriorates, since soil moisture and nutrients are not replenished anymore, and perennial grasses are replaced by less productive annuals. The availability of perennial grasses, the size of the fish stock and the soil moisture availability for the growing of crops are all correlated with the extent of the flooding. As a consequence the income of the local communities highly depends on the flooding extent as well [1].

Due to their extent and inaccessibility, monitoring the Sahelian floodplains is only feasible by means of remote sensing. In this study, a Moderate Resolution Image Spectrometer (MODIS) 16-day 250m time-series data is used to monitor the yearly flooding extent for the Waza-Logone floodplain, located in the North of Cameroon. Both the MIR band and the Normalized Difference Water Index (NDWI) [2] are sensitive to the presence of water, whether it is free water or water contained in plants, providing information on the inundation pattern. Analysis of the temporal profiles of the Normalized Difference Vegetation Index (NDVI) and the Enhanced Vegetation Index (EVI) [3] enables differentiation between perennial grasses covering the floodplain and annual grasses covering the surrounding dry land, the latter having a shorter growing cycle.

The Fourier Transform (FT) will be used to quantify the intra-annual changes of the different indices and the MIR band. FT decomposes a time-series into a number of periodic signals with different frequencies, characterized by a phase and amplitude value. Similar approaches have been used to classify vegetation types, based on Advanced Very High Resolution Radiometer (AVHRR) NDVI time-series [4] [5] [6]. In this study, phase and amplitude values for those periodic signals explaining most of the time-series variance will be used to differentiate between flooded land, dry land and irrigated rice utilizing an artificial neural network (ANN).

To model the relationship between the amount and distribution of precipitation in the catchments area of the Logone River and the predicted flooding extent, 10-day rainfall estimates (RFE) for Africa [7] will be used. First, a rainfall-runoff model will be established to simulate streamflow in the Logone catchment area. subsequently, the relationship between streamflow and flooding extent will be analyzed.

2 STUDY AREA

The Waza-Logone area is located in the Far North province of Cameroon, i.e. in the semi-arid zone of Africa (figure 1). It stretches from Nigeria across northern Cameroon to Chad, approximately between 10°50'N and 12°30'N, and between 14°0'E and 15°20'E. The average rainfall in the area is 650 mm/ year and the rainy season is from May to September [8]. Rainfall is highly unpredictable, both in space and time, yet all the rain is concentrated in the wet season. Locally, the amount of rainfall may vary greatly, depending on whether or not a storm cell generates precipitation. Flooding starts at the end of the rainy season and lasts for a period of three to five months. Two mechanisms are involved in the seasonal flooding of the floodplain. The first is rain-induced local runoff and the second and most important one is over bank flooding of the Logone River. The volume of floodwater depends mainly on the magnitude of the flood peak, and the duration of the floodwater exceeding the bank full capacity of the Logone River [9].

The floodplain vegetation consists of species-poor perennial grasslands [10]. *Oryza longistaminata* and *Echinochloa pyramidalis* constitute single or two-species stands on the floodplain, but *Vetiveria nigritana* is abundant on the levees of the drainage ditches and on the higher parts of the intact plain. Hardly any perennial grasses can be found in the non-inundated areas, where annual grasses and herbs, and locally thickets of *Acacia seyal* and *Piliostigma reticulatum* occur [11].

More than 100,000 people, both resident and nomadic, use the floodplain area for fishing, dry season grazing and agriculture. Exploitation may vary by site and by season, corresponding to the dynamic character of the floods and the cultural background of the floodplain users. During the dry season particularly, the area plays an essential role in sustaining the rural economy of the region. Fish and wetland sorghum are exported and herds from the wider surroundings in Cameroon, Chad and Nigeria can find fresh pastures and water for their survival in the dry season [1].

Natural floodplains are among the most biologically productive and diverse ecosystems on earth [12]. However, they are also among the most threatened ecosystems. The main causes of floodplain degradation are habitat alteration, flow and flood control, species invasion and pollution [12]. In 1979, a dam was built across the Waza-Logone floodplain, creating Lake Maga, and embankments were constructed along the Logone River, as part of an irrigated rice cultivation program. In combination with a succession of years of below average rainfall, this resulted in a decrease of

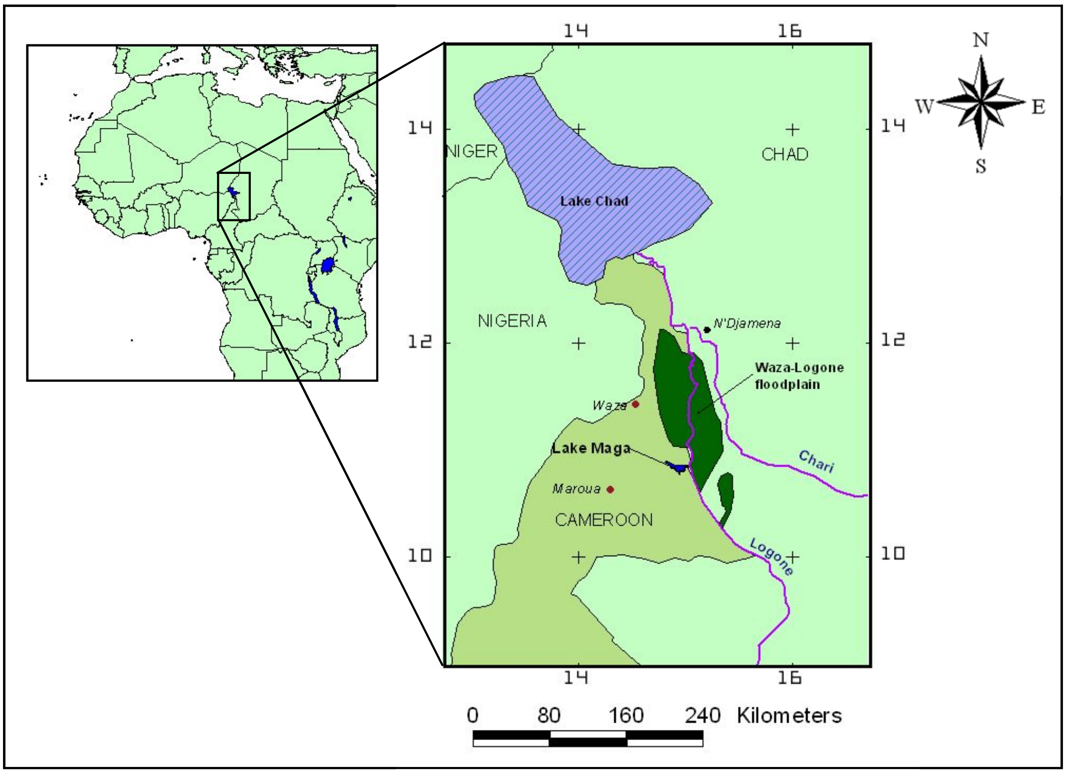

Figure 1. The study area

depth and extent of the flooding. Perennial grasslands were replaced by less productive annual-grass dominated stands, reducing the carrying capacity for wildlife and cattle [13]. From 1988-2003, the World Conservation Union (IUCN), has been working to rehabilitate the degraded Waza Logone floodplain. The general objective of this project was to achieve long-term enhancement of the biodiversity of the Waza Logone area and to provide a sustainable improvement to the quality of life of its population. One of the actions taken to achieve this goal was partial reflooding of the floodplain. This resulted in an increased biodiversity and a partial recovery of the natural resources [1]

3 CALCULATION OF FLOODING EXTENT

3.1. Data

The 16-days composite MODIS Vegetation Indices Product (MOD13Q1) with a spatial resolution of 250 meter was used to calculate flooding extent. It includes two vegetation indices, NDVI and EVI, in addition to composited surface reflectance bands 1-3 and 7 (red, NIR, blue, and MIR). EVI has been developed to optimize the vegetation signal with improved sensitivity in high biomass regions and improved vegetation monitoring through a de-coupling of the canopy background signal and a reduction of atmosphere influences [3]. The two indices are calculated as follows:

$$NDVI = \frac{\rho_{NIR} - \rho_{red}}{\rho_{NIR} + \rho_{red}} \tag{1}$$

$$EVI = 2.5 \cdot \frac{\rho_{NIR} - \rho_{red}}{\rho_{NIR} + 6 \cdot \rho_{red} - 7.5 \cdot \rho_{blue} + 1} \tag{2}$$

Additionally, the Normalized Difference Water Index (NDWI) [2] was calculated, based on the NIR and the MIR band:

$$NDWI = \frac{\rho_{MIR} - \rho_{NIR}}{\rho_{MIR} + \rho_{NIR}} \tag{3}$$

16-day composite MODIS data, covering the Waza-Logone floodplain, was collected for five years, April 2000 – March 2001 to April 2004 – March 2005, with each year containing 23 MODIS images.

3.2. Methodology

The Fourier Transform (FT) was applied to quantify the intra-annual changes for the different time-series (NDVI, EVI, NDWI and the MIR band). FT decomposes a signal into a series of cosine waves (harmonics) and an additive term (the mean). Each harmonic is defined by unique amplitude and phase angle values, where the amplitude is half the height of the harmonic and the phase angle defines the offset between the origin and the peak of the harmonic. The FT is illustrated in figure 2. In figure 2a, the first three harmonics are depicted, resulting from the decomposition of the 2000 – 2001 NDVI time-series for a wetland pixel. In figure 2b, the sum of harmonic 1 to harmonic 3 and the mean is compared with the original signal.

For each year, Fourier analysis was performed on a per-pixel basis, using the Fast Fourier Transform (FFT) algorithm [14]. For ease of computation and interpretation the Fourier analysis was applied on 24 samples instead of 23, by adding an extra image to each time-series. This resulted, for each year and for each variable, in a mean image and a

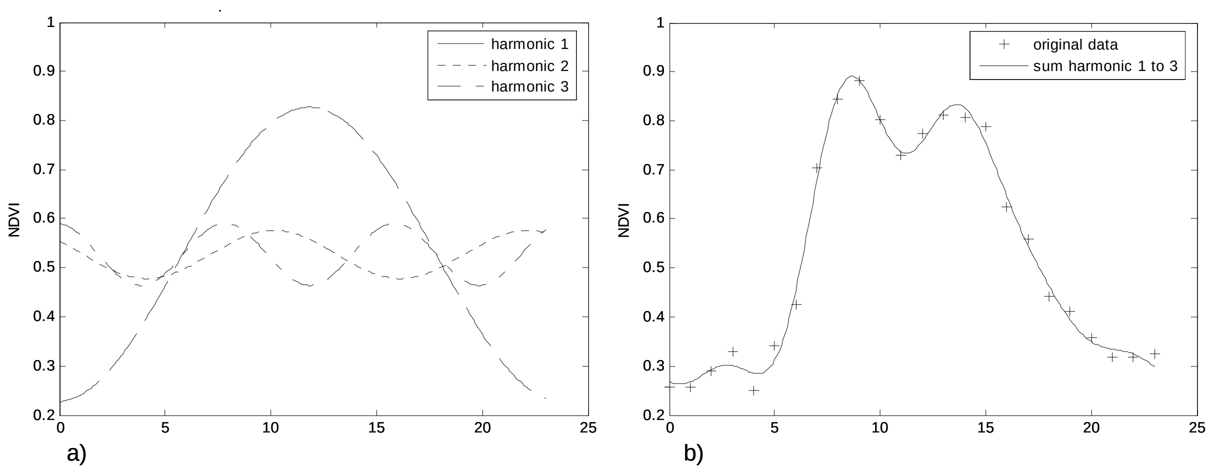

Figure 2. a) Fourier transform of 2001 – 2002 NDVI time-series for wetland pixel; b) Comparison between sum of harmonic 1 to 3 and original NDVI signal

set of amplitude and phase images for the 1st to the 12th harmonic term, corresponding with the frequencies $\frac{1}{24}, \frac{1}{12}, \frac{1}{8}, \ldots, \frac{1}{2}$. Subsequently, the percent variance each harmonic accounts for was calculated, by dividing the variance of each harmonic term with the total variance of all terms using the amplitude values:

$$\text{variance } j^{\text{th}} \text{ harmonic} = \frac{\left(amplitude_j\right)^2}{\sum_{r=1}^{r=N/2}\left(amplitude_r\right)^2} \tag{4}$$

Based on the amplitude, amplitude variance and phase images resulting from the Fourier transform, a supervised land cover/ land use classification of the Waza-Logone area was performed for each year. Four relevant classes were considered: dry land, flooded land, irrigated rice cultivation and open water. An Artificial Neural Network (ANN) was applied to perform the supervised classification. The main advantage of an ANN classifier over a Maximum Likelihood classifier is that it is distribution-free, that is, no underlying model is assumed for the multivariate distribution of the class-specific data in feature space [15]. For a comprehensive discussion of ANNs, the reader is referred to [16]. For this study LNNS, an in-house developed neural network simulator, was used, which can be downloaded from http://dfwm.ugent.be/forman/projecten/bof2002/html/index.htm. Background information about this ANN is described in [17].

For the year 2003, training and test pixels were selected of the different classes (except for the open water class, that was separated by tresholding it in the MIR band) based on field data information, and visual interpretation of the original MODIS time-series. Only data from the 0th (the mean) to the 3rd harmonic were used for training the ANN, since the other harmonics contained mainly noise. First the ANN was trained for the vegetation indices and the MIR band separately. Then, different combinations of variables (MIR/NDVI, MIR/EVI, NDWI/NDVI and NDWI/EVI) were used as input to the ANN, each time combining a 'wetness' indicator with a 'greenness' indicator. Performance of each trained ANN was evaluated calculating the Kappa Index of Agreement (KIA) [18] based on the test pixels. Finally, the ANN with best performance was retained and used to carry out a classification for the other years.

To calculate the flooding extent, pixels classified as flooded land, belonging to a region smaller than a predefined size and located further away than a predefined distance from the Logone River, were eliminated. Inundation of these regions was most probably not caused by over bank flooding of the Logone River. These pixels could represent rain-fed depressions or simply be misclassified. The minimum area treshold was set to 25 pixels (15.6 km²) and the minimum distance threshold was set to 5 km.

3.3. Results and discussion

The KIA for the 2003 classification maps resulting from the ANNs, trained with different combinations of input variables are shown in table 1. When only one variable is used as input to the ANN, the highest KIA value is obtained with amplitude, amplitude variance and phase images of the NDVI time-series (0.950). When a combination of variables is used (MIR/NDVI, MIR/EVI, NDWI/NDVI and NDWI/EVI) as input data, the highest KIA is obtained with the combinations MIR/NDVI and MIR/EVI (0.9853 and 0.9841, respectively). The MIR band outperforms NDWI for all combinations used.

Table 1. The Kappa Index of Agreement (KIA) for the classifications obtained by ANNs with different combinations of inputs

Input	KIA
MIR	0.935
NDVI	0.950
NDWI	0.924
EVI	0.932
MIR/NDVI	0.985
MIR/EVI	0.984
NDWI/NDVI	0.961
NDWI/EVI	0.969

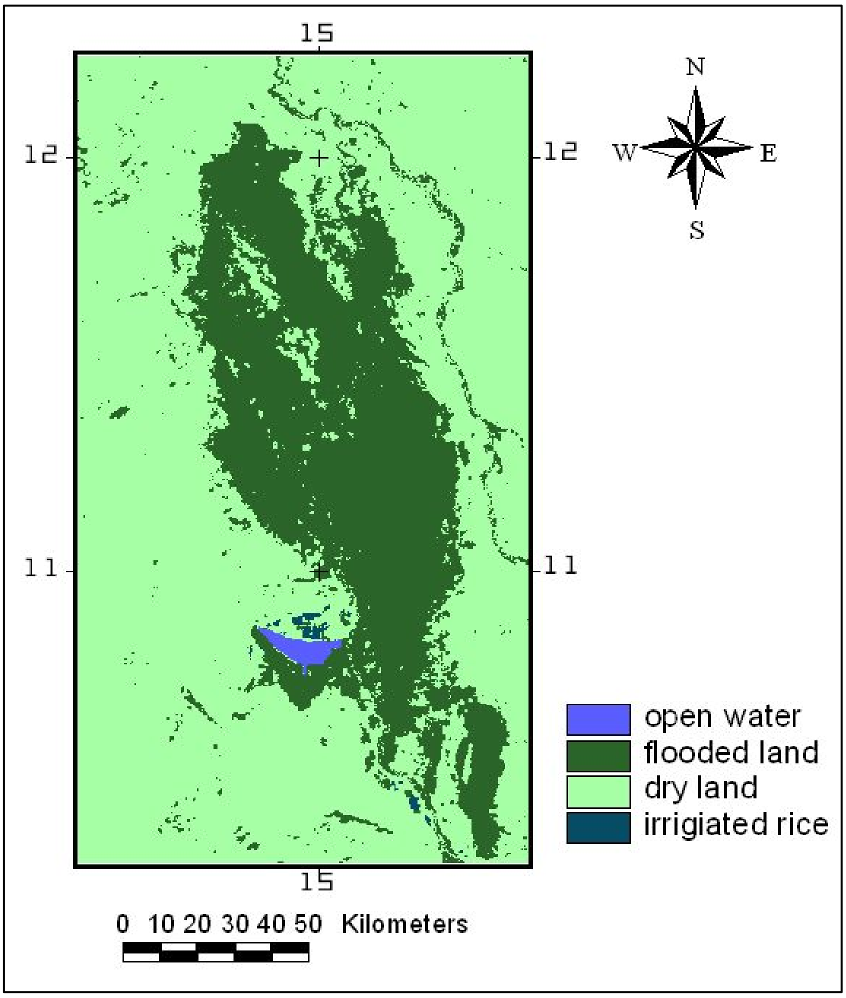

Figure 3. Classification map for 2003 – 2004 based on 0th to 3rd harmonic images of MIR and NDVI time-series

The classification resulting from the ANN trained with the combination MIR/NDVI is shown in figure 3. When this ANN is used to perform a classification for the other years, visual inspection reveals numerous obvious classification errors. Mainly in wet years such as 2001, dry land pixels are misclassified as flooded land. For this reason, extra training and testing pixels were collected for the 2000 – 2001 and 2001 – 2002 time-series based on visual image interpretation. Subsequently, the ANN was trained using the training pixels of the 2000 – 2001, 2001 – 2002 and 2003 – 2004 time-series. In table 2, the KIA of the classifications resulting from ANN trained on the 2003 – 2004 time-seriesand the ANN trained on the different time-series are compared. When training pixels from different years are combined, the KIA increase considerably for the 2000 and 2001 classification maps and only a slight decrease can be observed for the KIA of the 2003 classification map.

When classifications were performed for each time-series, pixels were eliminated according to the minimum distance and minimum area criteria mentioned above. Next, the maximum flooding extent for each year was calculated. As can be concluded from table 3, large inter-annual differences exist. For example, in 2001 an area more than double the size of 2002 was flooded. Figure 4 shows the number of years flooding occurred during the period 2000 – 2004. It can be noticed that the largest inter-annual differences in flooding extent occur on the Cameroonian side of the Logone (to the west of the river).

Table 2. Comparison of ANN performance, when trained on data from a single year, and when trained on data from several years

Year	KIA	
	ANN trained on 2003 data set	ANN trained on 2000, 2001 and 2003 data set
2000 – 2001	0.860	0.950
2001 – 2002	0.760	0.920
2003 – 2004	0.985	0.968

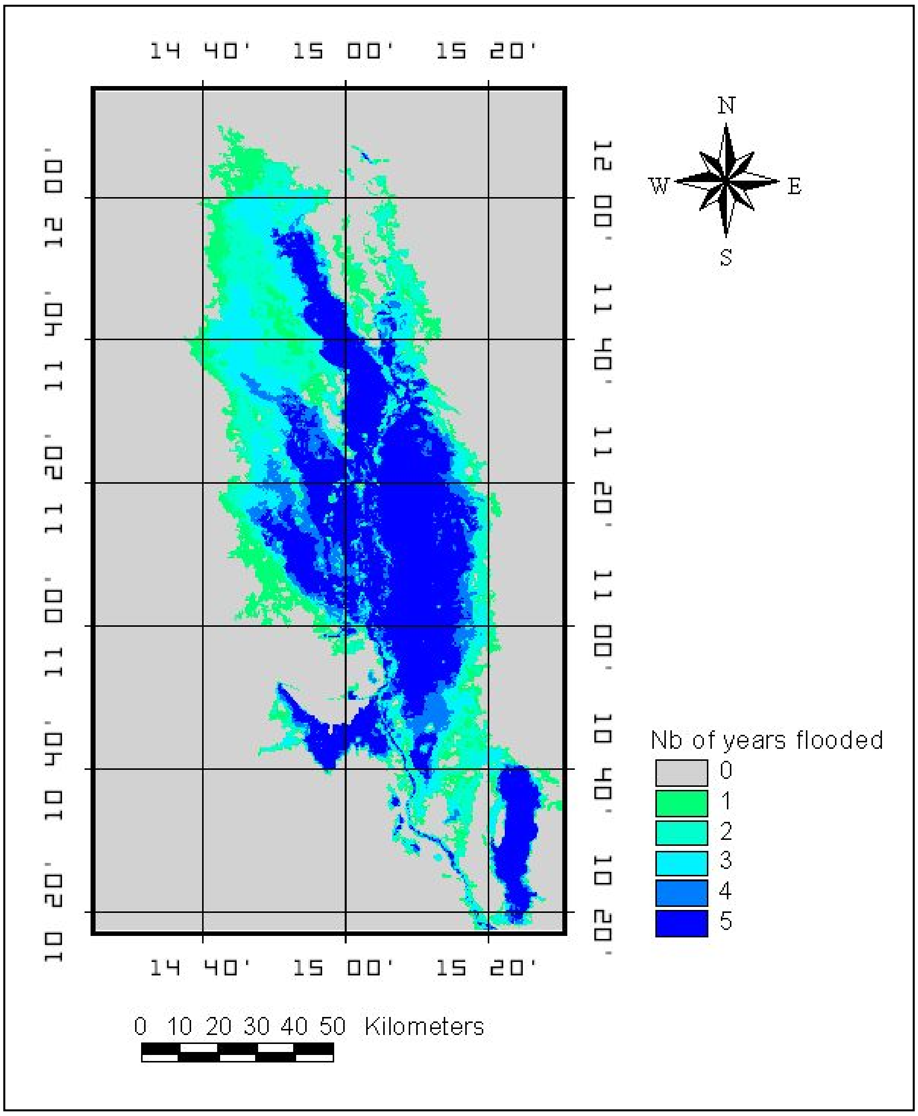

Figure 4. Number of years in which flooding occurred in the Waza-Logone area for the period 2000 – 2004

4 HYDROLOGICAL MODELLING

A hydrological model will be established to simulate streamflow in the Logone catchment area based on 10-day rainfall estimates RFE [7]. Streamflow data from two gauging station, Bongor and Moundou will be used for calibration. When such a model is developed, stream flow can be related to flooding extent. The main problem is the large number of missing streamflow data. For this reason the Pitman model [19] will be used. The advantage of this model is the availability of guidelines for parameter estimation provided by the WR90 study [20] These parameters can then be refined by local calibration. The model is an explicit soil moisture accounting model representing interception, soil moisture and ground water storages, with model functions to represent the inflows and outflows from these. It has been especially developed for semi-arid catchments in the South-African subcontinent, but has also been applied outside the region [21].

Table 3. Extent of the flooding in Waza-Logone region for different years

Year	Area (km²)
2000 – 2001	5982
2001 – 2002	9204
2002 – 2003	4081
2003 – 2004	7918
2004 – 2005	4810

4.1. Input data

Based on the GTOPO30 1 km DEM data set [22], eight sub-basins were delineated within the Logone catchment area. 10-day rainfall estimates RFE for Africa [7] were used to calculate monthly rainfall for each sub-basin. The RFE data is processed by NOAA's Climate Prediction Centre for the United States Agency for International Development (USAID) Famine Early Warning System (FEWS) to assist in the drought and flood monitoring efforts for the African continent. Computation of RFE is based on METEOSAT 7 satellite data, Global Telecommunication System (GTS) rain gauge reports, model analyses of wind and relative humidity, and orography. This data is available for the period 1996 – 2004.

Streamflow records for the period 1996 – 2004 were available for two gauging stations in the catchment area. For Bongor station, situated approximately 100 kilometers upstream from the Waza-Logone floodplain, only three years of streamflow data was available within the period 1996 – 2004. For Moundou station, located 300 kilometers upstream from Bongor, seven years of streamflow data was available within this period.

Information on Potential Evapotranspiration (PET), land cover, soil type and geology was collected for each sub-basin using following data sets:

- Global map of monthly reference evapotranspiration - 10 arc minutes [23]
- 1-km land cover map of Africa [24]
- The digitized soil map of the world [25]
- Map showing geology, oil and gas fields, and geologic provinces of Africa [26]

4.2. Pitman monthly time-step model

The monthly time-step model has two main functions that generate runoff. The first is a symmetrical triangular distribution, defined by two parameters (*ZMIN* and *ZMAX*), representing the catchment absorption rate. If the rainfall in any iteration step Δt is greater than $ZMIN*\Delta t$, then some runoff occurs. The greater the difference between the two parameters, the wider the range of the cumulative distribution and the lower the runoff rate for any rainfall greater than *ZMIN*. The other function is mainly controlled by a maximum moisture storage parameter (*ST*). If the storage level exceeds this value all further rainfall becomes runoff. The moisture storage is depleted by evapotranspiration and drainage using a non-linear soil moisture runoff formulation. This equation is based on a non-linear relationship between current soil moisture storage and runoff from soil moisture. Once the runoff is generated by either of these functions it much reach the catchment outlet as there are no loss functions except those related to artificial abstractions. [27]

4.3. Expected results

The rainfall-runoff model is currently being calibrated. Once the first results are available, the relationship between simulated streamflow at Bongor station (closest to the floodplain) and rainfall in the floodplain area, on one hand, and flooding extent, on the other hand, will be analyzed. Rainfall in the floodplain area influences the soil moisture prior to inundation, while streamflow data of the Logone River determines the duration and the intensity of the over bank flooding.

5 CONCLUSIONS

The flooding extent of the Waza-Logone floodplain, located in the north of Cameroon, was studied using time-series of MODIS 16-day 250m data. Fourier analysis was applied to quantify the temporal distributions of the MIR band and three indices (NDVI, NDWI, and EVI). The resulting amplitude, phase and amplitude variance images for harmonics 0 to 3 were used as inputs for an ANN to differentiate between the different land cover/ land use classes. When the combinations MIR/NDVI and MIR/EVI were used as input to the ANN, the classification map with the highest Kappa Index of Agreement (KIA) was obtained. When the ANN was trained on pixels from different years, a more robust classifier was obtained, which could consistently separate flooded land from dry land for each year. During the period 2000 – 2004 flooded area varied highly from one year to another, reaching a maximum in 2001 – 2002 and a minimum in 2002 – 2003. The extent of the flooding strongly influences the availability of natural resources in the dry season. The considerable interannual differences in flooding extent should therefore be taken into account in view of a sustainable management of these natural resources.

Flooding extent differs from one year to another in response to rainfall in the floodplain area prior to flooding and the streamflow distribution of the Logone river. Streamflow can be simulated using the Pitman model based on African Rainfall Estimates (RFE) data. Subsequently, a model could be constructed that can estimate flooding extent based on the simulated streamflow data. Such a model would enable prediction of possible impacts of a changing climate due to Global Warming, and detection of human-induced anomalies such as hydropower and irrigation projects.

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