Volume 5 Issue V, May 2017
ISSN: 2321-9653
International Journal for Research in Applied Science & Engineering Technology (IJRASET)

Improving Fodder Biomass Modeling in The Sahelian Zone of Niger Using the Multiple Linear Regression Method

Issa Garba[1], Bakary Djaby[2], Illa Salifou[4], Ibra Toure[3], Abdallah Samba[1], Yapi Yapo[1], Alio Agoumo[1], Salamatou Soumana[1], Amina Oumarou[1], Bernard Tychon[2]

[1]AGRHYMET Regional Centre / CILSS; [2]University of Liège (ULg); [3]Center for Agricultural Research for Development (CIRAD); [4]University of Niamey (UAM)

Summary: This study was carried out in Niger and aims to propose an improved fodder biomass estimate model using the Multiple Linear Regression (MRM) method. The work was carried out with measurements of herbaceous mass (in situ) made from 2001 to 2012 by the Ministry of Livestock and Animal Industry of Niger (MEIA); rainfalls observed by the Niger Meteorological Office and the meteorological variables from the European Center for Medium-Range Weather Forecasts (ECMWF), processed in AgrometShell (AMS) to derive the agro-meteorological variables; the SPOT VEGETATION NDVI satellite images processed in the "Vegetation Analysis in Space and Time" (VAST) program to derive biophysical variables from the annual NDVI decadal series and finally the estimated rainfall known as RFE from the American institution "Famine Early Warning Systems Network "(FEWSNET) for the calculation of annual rainfall totals. The model was performed by multiple linear regressions with the ascending step-by-step procedure for the selection of variables based on the adjusted R² and the RMSE. Leave One Out Cross Validation (LOOICV) was used to calculate the validation R² and a systematic diagnosis of residues to better characterize the model. Throughout the (national) study area, MRM performed an adjusted R² of 0.68 and a RMSE of 282 kg. Ha^{-1}, the difference between the RMSE of the calibration and that of the validation is 3.72 kg.ha^{-1}. However, it is necessary to continue this research with other indices such as LAI and FAPAR and EVI. Also, it would be interesting to explore ways such as: taking into account the foliage of the trees, adjusting the metrics to the phenology of the herbaceous plants, and those of the woody ones. This work will improve the quality of information used to plan development actions in favor of Niger society in order to protect it against pastoral crises.

Keywords: MRM, MEIA, NDVI, AMS, VAST.

I. INTRODUCTION

A. Background of the study

The Sahel is a broad bio-geographical entity extending from Senegal to Ethiopia[1]. This natural area experiences security challenges that result in enormous human and animal losses in Mali (terrorism and armed rebellion), in Libya (terrorism and tribal war), and in the Lake Chad area (Boko haram in Nigeria, Niger, Chad and Cameroon); climate and demographic challenges with implications on the degradation of natural resources and the food and nutritional security of populations. Pastoral communities are particularly sensitive and affected by these challenges[2]. In recent years several initiatives have been taken in favor of these populations on a continental and regional scale: The MESA program "Monitoring of Environment for Security in Africa" funded by the European Union (EU) contributes to the Implementation of the African Union (AU) strategic framework for pastoralism in Africa. This framework aims to ensure, protect and improve the lives, livelihoods and rights of African pastoralists[3]; the Regional Project for Supporting Pastoralism in the Sahel (PRAPS), financed by the World Bank, which is a concretization of the Nouakchott Declaration of 29 October 2013 ratified by the Heads of State and Government of the six Sahelian countries (Burkina Faso, Niger, Senegal, Mauritania and Chad). This declaration is a commitment to secure pastoralists livelihoods and to increase the gross products of herders 'activities by 30% [4]. The Sahel's rainfall regime is essentially related to the West African monsoon dynamics[5]. This natural area has had to adapt during the Quaternary period to climatic fluctuations between tropical humid and arid climates, and even hyperarid. The distribution of precipitation during the rainy season modulated by their redistribution by surface runoff is a determining factor in the diversity and production of vegetation cover [6]. The increase in climatic variability, the consequences of which are beginning to be felt in the 1970s following the decline in normal rainfall 1941-1960 / 1961-1990 [7]; 1971-2000 / 1981-2010 [8] probably played a role in the observed changes in the current vegetation cover. Depending on the north-south and east-west gradients, high inter-annual variability in fodder production, coupled with large temporal fluctuations in fodder availability in quantity and quality, is observed. It is therefore necessary to establish a method for estimating these fodder productions at the end of the rainy season, with a view to establishing an efficient and effective Pastoral Early Warning System (PEWS) for the nine months of the dry season following. This PEW must be able to provide timely information on the availability of fodder at the spatial scale (local, zonal, national and regional) to the actors of the sector (herders, policy-makers, NGOs, technicians, etc.). The vast and diverse pastoral area of Niger with more than 62 million hectares of pastureland [9] is one of the major forces for the development of the livestock sector. The diversity of vegetation cover enables very different animal species to rub shoulders and thrive on the same territory. Indeed, the country has not only an important asset for socio-economic development, but also an undeniable natural comparative advantage in producing cattle and small ruminants that can be exported to coastal countries and Central Africa. Livestock are mainly cattle, sheep, goats, camels, equines and cows. According to the results of the General Census of Agriculture and Livestock 2005/2007, 31 039 041 head of cattle of all species are estimated, ie 11 238 268 goats (36.2%), 9 192 017 heads of cattle (29.6%), 7,336,088 head of cattle (2,3,6%), 1,477,073 head of asins (4,7%), 1,565,420 head of camelin (5%) and 230,174 d (0.7%) [10]. with a total value of almost 2 000 billion CFA francs, Niger has an important asset for its socio-economic development [9]. Livestock activities contribute fully to food security and the fight against poverty of most households. According to available statistics, livestock production accounts for almost 11.8% of the GDP and 35% of agricultural GDP. It represents an important source of foreign exchange for the State and local authorities, but also contributes significantly to the household budget. The household budgets-consumption survey indicates that the livestock sector contributes more than 15% to the household budget. As for its contribution to meeting food needs, the figure would be 25%[11]. Today, pastoralism is experiencing several constraints, including: - the reduction of the pastoral area due to the extension of the pioneer front of land exploitation (crops, protected areas ...)

This extension of the pioneer front is due to the increase of the population (urbanization and needs of the market of agricultural products and Livestock); - direct obstacles (conflicts and difficulties of crossing borders) and indirect (uncertainties about the existence and conditions of access to the resource), - land tenure (land policies largely affect fodder resources and their management); - access to markets; - health problems, safety, climate change and the recurrence of droughts are added to this list of constraints [12]. There is an urgent need for an appropriate method of estimating fodder resources to contribute to pasture management, decision-making to anticipate and manage pastoral crises; In other words, to have a grazing assessment tool capable of assessing fodder production and their response to factors such as grazing, trampling, etc. The AGRHYMET Regional Centre (ARC), the Ministry of Livestock and Animal Industries (MEIA) of Niger and the Centre de Suivi Ecologique (CSE) of Senegal have carried out estimates of herbaceous mass for 40 years, early warning system to help public authorities making relevant decisions to ensure better food security while ensuring better management of resources. The MEIA and the CSE are based on in situ measured data and the standardized difference vegetation index (NDVI), whose early work dates back to the 1970s [13]. NDVI has been exploited by several authors [14-16] who have demonstrated its performance, but also its limitations in the monitoring and characterization of vegetation on a national scale. In addition, as part of the Early Warning and Agricultural Production Forecast (AP3A) project, the ARC developed the BIOMASAH model for fodder biomass estimate in the Sahel based on the water balance sheet. This model is based on the soil map (texture) and the cumulative satellite rainfall estimated. However, the results from this model have never been validated over a 12-year series. Therefore, it seems imperative to evaluate these models in order to propose a better performance. The relationship between herbaceous biomass measured on the ground and the vegetation indices established by linear regression in the Sahelian region has been extensively treated ([14, 17-32]. However, other studies have shown that the relationship is not always a linear function [33, 34]. According to [35], the exponential and power functions are more efficient than the linear functions. Elsewhere, the multiple linear regression method showed satisfactory performance in estimating agricultural yields [36-38]. In addition, very significant improvements were obtained in Senegal with the multiple linear regression method combining metrics derived from FAPAR and GeoWRSI [39, 40]. The models of the Ministry of Livestock and Animal Industries (MEIA) show disparate R^2 which vary greatly from one year to the next [41]. Moreover, the RMSEs are often very high, which illustrates the instability of this model limited to a single variable. Given the importance of estimating the herbaceous fodder biomass in the Sahel in general and particularly in Niger, a more reliable model is needed to enable users to monitor and estimate fodder resources, have a more reliable method for estimating fodder production to help decision-makers anticipate pastoral crises and meet market needs. The general objective of the study was also to contribute to the improvement of methods for estimating the aerial mass of herbaceous plants. More specifically, it will be necessary to use biophysical and agro-meteorological variables to realize a multiple linear regression model capable of better estimating fodder yield in Niger. The hypothesis of this study is to consider that it is possible to use the metrics derived from the time series of decadal NDVI images of the period of growth of the vegetation using the VAST (Vegetation Analysis in Space and Time) software and associate them with the outputs of AgrometShell agro-meteorological software to derive a set of explanatory variables that will be used in a model for forecasting fodder yields of herbaceous plants.

B. Presentation of the zone

The study area corresponds essentially to the pastoral zone of Niger defined on the maps of the pastoral atlas [42]. It is located between 13 ° and 16 ° north latitude and 2 ° and 12 ° east longitude (Fig.1). The choice of this Sahel zone for the validation of the biomass model is mainly linked to the availability of *in situ* data. Like the other Sahelian parts, this zone is characterized by a high spatial and temporal variability of precipitation[6, 43]. The climate is of the arid type with a normal rainfall varying between 150 and 300 mm [44]. The duration of the season varies on average from 60 to 120 days of rain for the central and western Sahel. It is on average 40 days in the Northern and Eastern Sahel[45].

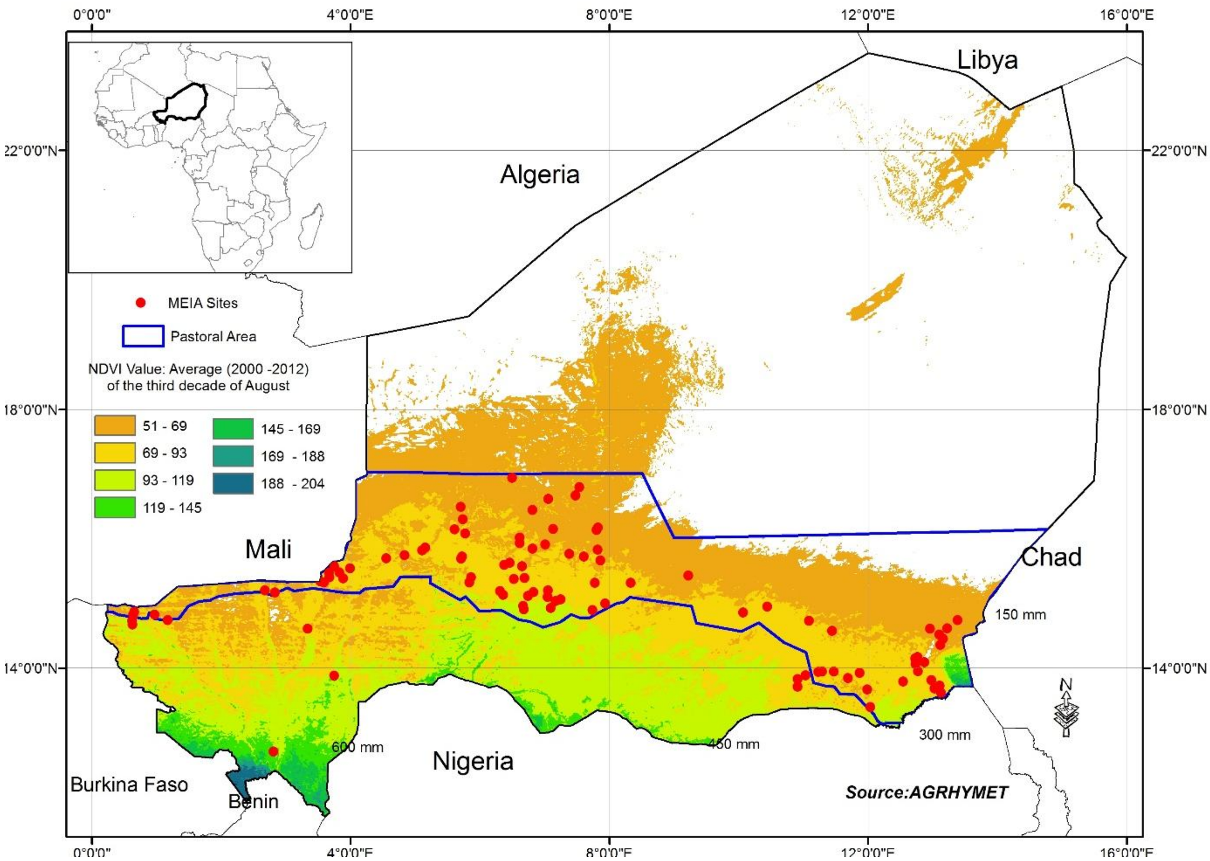


Fig. 1: Geographical location of the study area with geo-localization of herbaceous fodder measurement sites

II. MATERIALS AND METHODS

The model's biophysical data is derived from the NDVI of SPOT-VEGETATION; the agro-meteorological input data are the rainfall measured at all the rainfall stations in the country and those estimated by FEWSNET RFE2 satellite, ETP (potential evapotranspiration) from the European Center for Medium-Range Weather Forecasts (ECMWF). The VAST computer program and the Agrometshell (AMS) software were used to generate the explanatory variables. The explained variable (dependent) is the fodder yield measured on the ground control sites by the MEIA; the statistical analyzes were carried out with the statistical processing software SAS JMP. The stages of statistical processing are subdivided into seven points: (i) the elimination of unnecessary variables; (ii) selection of the most relevant variables; (iii) comprehensive model research (2^k possible models); (iv) selection of the best models (RMSE min and parsimony of parameters); V) cross-validation, vi) residue analysis, and vii) national reference model presentation (Fig 2).

Volume 5 Issue V, May 2017
ISSN: 2321-9653
International Journal for Research in Applied Science & Engineering Technology (IJRASET)

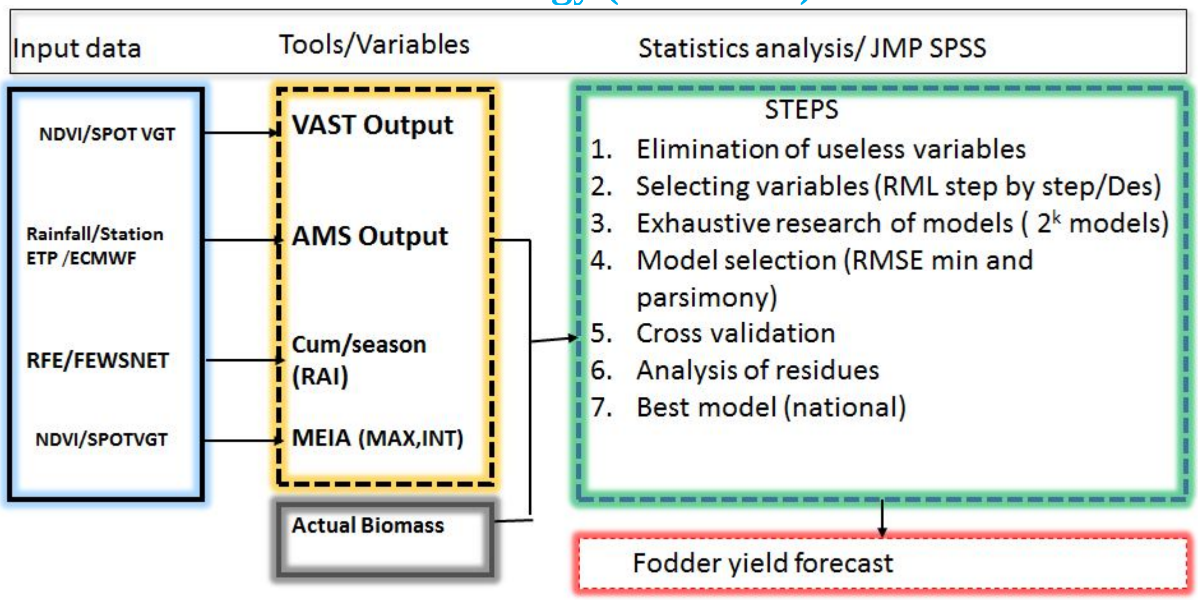


Fig.2: General diagram of the multiple linear regression method leading to fodder yields forecast

A. Material

The material is the set of data, software and programs used to carry out the study. The main data used are:

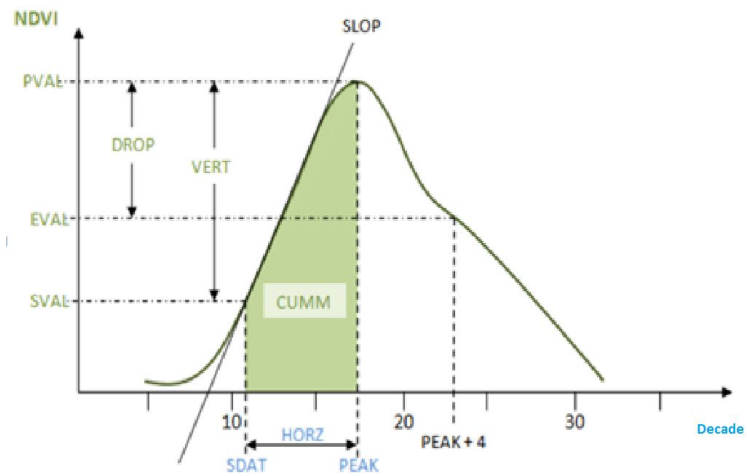
1) The biophysical data (SPOT VEGETATION image series) used to derive some of the exogenous variables (explanatory, independent) of the model using VAST;
2) Meteorological and agronomic data, including rainfall measured at meteorological stations, potential evapotranspiration, vegetation phenology, etc. They are used as input variables for the calculation of AMS software outputs;
3) RFE-FEWSNET annual cumulative rainfall;
4) The maximum and integral NDVI as calculated by the MEIA;
5) Finally, aerial mass measured in situ (MEIA source) is the dependent variable As for software and computer programs, we can mention:
6) Software for processing, analyzing and displaying satellite images (VGTExtract, WINDISP, VAST);
7) Software for calculating agro-meteorological variables (AGROMETSHELL1.157);
8) Statistical analysis software (SAS-JMP and SPSS).
9) Agro-meteorological data
a) *Rainfall*: The rainfall variables come from the AGRHYMET Regional Center (ARC) database. They were structured in a format compatible with the AMS software (calculations of decadal series and the 1971-2000 average per station), and then imported into the software. A total of 199 rainfall stations were entered and used in the AgroMetShell Database (BD AMS) for Niger.
b) *Potential evapotranspiration:* The ECMWF data used cover the period from 1978 to 2012. They permit to calculate the 1978-2000 average and the series from 2001 to 2012 on a decadal time basis. The ECMWF ERA INTERIM data are presented in a grid of points spaced 0.25 degree. To extract the FTEs from the stations containing the measured rainfall, the following steps were followed: i) construction of a regular grid of polygons of 0.25 degree sides. In this grid, each polygon is centered around an ECMWF point; ii) a spatial join to assign the attributes of the ECMWF points to each corresponding grid; iii) using the polygon layer resulting from step (i) to carry out a second spatial join, in order to carry the FTE data on the stations of Niger.
10) *Tools*
a) *VGT Extract:* VGT Extract is free-user-friendly software that can be used in batch mode. It is developed by VITO to decompress, extract a SPOT VEGETATION image from a selected spatial window and save it in an appropriate format (ILWIS, ENVI, RST, GeoTiff, RAW, WINDISP).
b) *VAST:* The VAST acronym for the application means Vegetation Analysis in Space and Time. This computer program was used in our work as a tool to extract the biophysical parameters derived from the annual series of NDVI (1998 to 2012). VAST

Volume 5 Issue V, May 2017
ISSN: 2321-9653
International Journal for Research in Applied Science & Engineering Technology (IJRASET)

was developed in the 1990s by Felix Lee who was at that time technical assistant of FewsNet in Chad, in order to systematically analyze the series of NDV Iimages. The program analyzes the annual series of NDVI images to derive the following phenological parameters (Fig.3):

i) PEAK: the decade at which the NDVI reaches its peak;
ii) SDAT: the decade of the beginning of the growing season;
iii) HORZ = PEAK - SDAT;
iv) SVAL: the value of the NDVI to SDAT;
v) PVAL: the value of the NDVI at PEAK;
vi) GREEN = PVAL - SVAL;
vii) EVAL: the NDVI at PEAK + 4 (about the end of the season);
viii) DROP = PVAL - EVAL;
ix) SLOP: the slope of the line that joins (SDAT, SVAL) to (PEAK, PVAL);
x) CUMM: the sum of the NDVI values from SDAT to PEAK;
xi) SKEW: the ratio between the sum of the 3 NDVI values according to PEAK (from PEAK + 1 to PEAK + 3) and the sum of the 7 values from PEAK - 3 to PEAK + 3.

For practical reasons, the phenological parameters derived from VAST will be repeated in their first three letters.
NDVI images are first recorded according to a particular nomenclature: the name must contain 2 letters followed by 2 digits corresponding to the year, followed by 2 digits for the month and a digit for the decade ending with the extension .Example: DV12021.NEG.



Source: VAST user manual

Fig.3: Metrics diagram calculated using VAST

11) It is a free software developed by the FAO for the Global Information and Early Warning System. It has modules permitting , among others to : display, do analysis of images, vector layers and related databases; to produce graphs representing the evolution of images temporal series (NDVI, rainfall, etc.) relating to an area of interest; superimposing images and administrative unit maps to retrieve statistics; to compute statistics for each pixel of a series of images. It is mainly recognized for the visualization and processing functions of NDVI satellite images, satellite estimated rainfall (RFE) and others such as VAST outputs.
12) *Agrometshell 1.57 (Ams):* A tool developed by FAO in 2007 for crop monitoring and forecasting of agricultural yields. It permits to simulate the water balance sheet and the risks of a production deficit. We used AMS in this work to calculate the agro-meteorological parameters that will constitute the input variables of our fodder yield forecast model ($Kg.MS.ha^{-1}$). AMS contains a database that is easy to update on a regular basis to ensure consistent production of variables. The modules contained in the software, based on the calculation of the water balance sheet, permits to analyze the impact of climatic factors on different crops. In reality, it is a computer program based on the assumption that yields can be explained by the agro-meteorological context of the area under consideration. This tool is used for early warning and food security as it permits to assess climate effects on crops and predicts agricultural yields through statistical modeling. In summary, AMS uses the Crop

Volume 5 Issue V, May 2017
ISSN: 2321-9653

Specific Soil Water Balance (CSSWB) as a water balance model to estimate the impact of climatic conditions on crops [46]. CSSWB calculates the water balance sheet for a decadal time step according to the equation:

Wt = Wt-1 + R - ETc - (r + i) With:

a) Wt, the amount of water stored in the soil at time t
b) Wt-1, the amount of water stored in the soil at the end of the previous period t-1
c) R, the amount of rain accumulated over the period of time t (often a decade)
d) ETc, the potential evapotranspiration of the crop over the period t
e) r, the loss of water due to the flow over period t
f) i, the loss of water due to deep percolation over the period t. The simulation of the water balance in AMS provides several variables, the most important of which are
g) The amount of water required for the complete crop cycle (TWR)
h) End-of-cycle water satisfaction index (Indx, IndxNor, IndxLatest)
i) The initial water content in the soil (SWi)
j) Excess water at different phenological stages of the growth cycle: initial phase, vegetative phase, flowering, maturity and throughout the cycle (given by the sum of the other values): WEXi, WEXv, WEXf, WEXr, WEXt;
k) Water deficit at different phenological stages and total water deficiency at the end of the cycle (WDEFi, WDEFv, WDEFf, WDEFr, WDEFt)
l) Actual evapotranspiration at different phenological stages and its total end-of-cycle value (ETAi, ETAv, ETAf, ETAr, ETAt)
m) Crossing data Cr1a to Cr4a (calculated with actual rainfall data) and Cr1n to Cr4n (Calculated with mean rainfall data over 30 years) indicate the decades to which the rangeland index (RI) crosses the 0.4 * PET line.

These decades can be associated with decades of planting crops. The rangeland index (RI) corresponds to the water satisfaction index developed by FAO calculated over a period of 5 decades with normal evapotranspiration taken at its potential level.

In addition to the data derived from VAST and AgroMetShell, we used the rainfall counts from the beginning of the rainy season (first decade of May to the third decade of October) and estimated by satellite (RAI) derived of RFE2, the maximum (MAX) and integral (INT) of the NDVI used by MEIA to perform simple linear regression.

B. Method

1) *Minimum presence of vegetation:* Knowledge of the value representing the minimum presence of vegetation is necessary for the calculation of the onset date of the vegetative growth season. To determine this minimum vegetation threshold, we used the bibliography and examination of the NDVI profiles of each site. According to the authors, the true value of NDVI representing the minimum threshold of presence of woody and herbaceous vegetation is 0.1 (1). The formula for calculating the numerical value is: NDVI SPOT VEGETATION = (DN * 0.004) - 0.1, this numerical value or Digital Number (DN) equals 0.2 / 0.004 = 50. The NDVI SPOT VEGETATION for the years 2000 to 2012 were used to extract phenological parameters from vegetation at in situ biomass measurement sites. The month of June was chosen as the minimum date for the beginning of the growing season, and that of October as the maximum end date of the growing season, the value DN50 as the minimum value of vegetative presence, 05 as the minimum variation of DN Between two decades. The same operation was performed for the eMODIS images. EMODIS NDVI = (DN * 0,01) -1, if the actual value of the NDVI representing the minimum vegetation presence threshold is 0,1 then the numeric value or numerical value (DN) of this threshold is equal to 1 , 1 / 0.01 = 110. The value 6 is set for the month of June as the minimum onset date of the vegetation season, October (10) as the maximum end of the growing season, DN110 as the minimum value of vegetative presence, 05 as the minimum variation of DN between two decades.
2) *Decades of installation (planting decade).:* To determine the decades in which annual herbaceous vegetation is installed, two possibilities are available in the AMS software: the first one is based on an effective threshold (to be set) for rain, followed by other precipitation for the next two decades; the second is based on a percentage threshold of the total water requirement of the vegetation. The second option was used by setting the threshold at 10%.
3) *Length of vegetation:* There is very little literature on the monitoring of the phenology of natural fodder species. The monitoring of the phenological cycle of certain grasses and legumes shows that the length varies according to the species and the water regime of the environment. The values of this vegetative length vary between 5 and 8 decades depending on the species (2). An average of 7 decades was used as the length of the fodder vegetation length.

Volume 5 Issue V, May 2017
ISSN: 2321-9653

4) *Statistical analysis:* Before any in-depth analysis, it is important to check the sensitivity of our sample by calculating the biases on the parameters of the base sample by performing resampling with remission. If our initial sample follows a normal distribution, then there will be no significant difference between its parameters and those resulting from resampling. The biases thus calculated correspond to the errors on the parameters of the sample. This is the technique called Bootstrap. It was initiated in the late 1970s as another look at the JackkNife method [38, 47-53]. In this study, we created 2000 sub-samples to calculate biases on the mean, variance and standard deviation. Regression is a statistical analysis technique that allows one to decide, to control, and to predict. It permits to formulate a mathematical relationship between the explained variable (endogenous, predicted, and dependent) with one or more explanatory variables (exogenous, preachers, independent). Independent variables in this study were derived from the NDVI image series processed with the VAST program, agro-meteorological data derived from AMS, cumulative rainfall, Max NDVI and Int NDVI. Fodder yields measured *in situ* represent the dependent variable. The specific objectives of our statistical analysis are: to adjust the best model to explain the fodder yield according to the relevant variables derived from AMS and VAST, EFR, MAX and INT of the MEIA; to predict fodder yield values for new values of the explanatory variables. The selection of relevant variables was carried out using the step-by-step descending method.

a) *Step 1: Verify the data:* Data verification was performed by examining the variances of the independent variables in order to make a first choice of those that are the most reliable. This eliminated all explanatory variables with zero variance. This type of variable represents a constant and does not provide useful information in a regression model.

b) *Step 2: Selection of Variables: There* are several types of variable selection procedures such as ascending or descending step-by-step method. The step-by-step procedures initialize with several explanatory variables. The different variables are eliminated or selected according to variance criteria. The top-down method has been favored while reserving the possibility of testing the mixed method. This approach permits to take into account all possible variables without neglecting some. A panel of 34 variables was used. The selection of explanatory variables is an important step in multiple regressions. The step-by-step procedure available on the SAS / JMP software to select the variables was used.

c) *Step 3 and 4: Selection of models;* The selection of models is a well-known problem in statistics, and has been widely developed by several authors[54-58]. Several criteria exist for the selection of the best model: the Root Mean Square Error (RMSE); the Determination coefficient (R^2 which increases with the number of variables); the Adjusted Determination Coefficient (R^2aq which corrects certain defects of R^2 taking into account the number of parameters of the model); Bayesian Information Criterium (BIC); the Akaike Information Criterium (AIC); Akaike Information CriteriumCorrigé (AICC); Coefficient of Mallows (CP if the model is good the Cp is very close to P: p being the number of variables); etc. In general, these criteria do not contradict each other, but they can be better with respect to each other depending on the case and permit to identify the best models. A parsimonious model combines a small number of explanatory variables and gives the highest adjusted R^2. The choice of the best model was based on the highest adjusted R^2, the minimum RMSE and a low number of explanatory variables (no more than 4 variables). The exhaustive search method is very effective for the selection of models especially when we have a limited number of explanatory variables. If we have k explanatory variables, the number of possible models is 2k. The step (selection of the variables) permitted to select a limited number of explanatory variables. The approach adopted with SAS / JMP consists in making the 2k possible combinations and classifying them in descending order according to the adjusted R^2 and according to the number of explanatory variables. This approach permits to select the best model for each number of explanatory variables of the model.

d) *Step 5: Cross-validation;* The Leave-one-out cross validation (LOOCV) technique was used to validate the chosen models in order to identify the best. LOOCV is a technique that is used when the sample size used is small and does not allow for the creation of a separate data group for calibration and sufficient size validation. It permits to choose the optimal model by testing the predictive accuracy and / or generalization error. The procedure consists in subdividing the sample of n observations into k equal subsets, performing the calibration with k-1 subsets and validating with the k^{th} subset, repeating the same operation for all k subsets[59]. The LOOCV is a particular case of the k-fold technique where k = n, it is a very powerful technique permitting to choose the most interesting model[60]. In this study, the LOOCV technique was used to determine the model with the best RMSE (minimized) with a number of variables less than or equal to 4..

e) *Step 6: Residue Analysis:* In the regression approach, a model is considered good only if the residuals obey the normality assumptions that can be examined through the Henri line; the equality of error variances (homoscedasticity) which means that all distributions of Y must have the same standard deviation: the residual variance is then constant on the domain studied;

Volume 5 Issue V, May 2017
ISSN: 2321-9653
International Journal for Research in Applied Science & Engineering Technology (IJRASET)

finally, when there is no multi collinearity [61]. In this work, the residue assumptions were verified with the SAS / JMP software. This is to verify that the residues follow a normal law; in practice, the residuals are represented graphically with respect to the expected response variable to ensure that the graph has no particular structure and finally the Watson-Durbin test is applied which is very suitable for analyzing the autocorrelation especially when there is a constant in regression [58, 62].

f) Step 7: Forecasting: The model chosen at the end of the process can be used to predict new response values using the new explanatory variable values. The mathematical relationship between the explanatory variables (metrics from AMS and VAST) and the explained or dependent variable (herbaceous forage) is used to estimate fodder yield in the form of map products.

III. RESULTS AND DISCUSSION

A. Results

1) *Exploratory analysis of herbaceous mass measurements from 2001 to 2012:* The exploratory analysis of herbaceous mass measurements from 2001 to 2012 on 319 observations shows that the average is about 700 kg MS.ha-1 with a standard deviation of 531 kg MS.ha-1. The results of the 2000-based bootstrap analysis showed that this average ranged from 642 kg to 762 kg in a 95% confidence interval. Biases over the average and standard deviation were 0.96 kg MS.ha^{-1} and -0.85 kg MS.ha^{-1} (Table 1). There is a total of 34 independent variables from the AMS, VAST, FEWSNET RFE seasonal rainfall accumulation and the two variables used by MEIA (INT and MAX).

Table 1: Exploratory analysis of herbaceous mass measurement from 2001 to 2012 using bootstrap (kg MS.ha^{-1})

Terms		Statistic	Standard error	Bootstrap			
				Bias	Standard error	95 % confidence interval	
						below	above
Herba ceous mass	Average	699,11	30,12	0,96	30,20	642,94	762,26
	Variance	282 097,66		-165,40	28 872,303	228 150,66	343 005,93
	Standard Deviation	531,13		-0,85	27,18	477,65	585,67

Unit: kg MS.ha^{-1}

2) *Adjustment of fodder productivity over the entire study area*: it is apparent from the implementation of the variables selection procedure of the descending step-by-step type that the selected variables are the following: MAX, DRO, EVA, HOR, PEA, PVA, SLO (appendix 4.1). The exhaustive search method was applied to these 7 independent variables to establish all possible models. The 27 (128) models are automatically ranked in descending order of the RMSE and according to the number of variables. The results (Table 2) give the top four models. They are listed according to the number of explanatory variables according to the minimum RMSE criteria.

Table2: Four best model according to the number of variables

Models	n°	R² cal	R² aj cal	R² val	RMSE cal. KG MS.ha^{-1}	RMSE val. KG MS.ha^{-1}	Dif RMSE
Y= -603,13+4590,81 max	1	0, 57	0,57	0,57	354,47	353,42	1,05
Y= -1193,01 + 2822,30 max + 15,51 DRO	2	0,62	0,62	0, 61	308.44	310,65	2,21
Y=-388,01+3133,09 max -15,41DRO +17, 62 VER	3	0,66	0,66	0,65	294,16	297,26	3,10
Y= -2190,82+3344,13 MAX -20,46 DRO +20,78 VER+ 74,06 PEA	4	0,69	0,68	0,67	285,22	288,94	3,72

Cal : calculated ; aj : ajusted ; Dif : difference ; val : validation

The best model, according to the criteria of the RMSE is n ° 4. In fact, it gives a relative RMSE of 40%. The four variables selected for this equation are: MAX, DRO, PEA, VER and constant. Examination of the probabilities of the estimated coefficients of this model gives highly significant results at the threshold of 1 per 10 000 (Table 3). The graph of the observed values based on the

International Journal for Research in Applied Science & Engineering Technology (IJRASET)

predicted values for the adjustment is given by Fig.4.

Table 3: Estimate of the coefficient of the four-variable model

Variables	Estimate	Standard Error	T Rapport	Prob.>|t|
Constant	-2190,82	407,51	-5,38	<, 0001*
max	3344,13	513,06	6,52	<, 0001*
DRO	-20,46	2,17	-9,44	<, 0001*
PEA	74,06	16,51	4,49	<, 0001*
VER	20,78	2,80	7,44	<, 0001*

*significant at the 1 for 10000 threshold

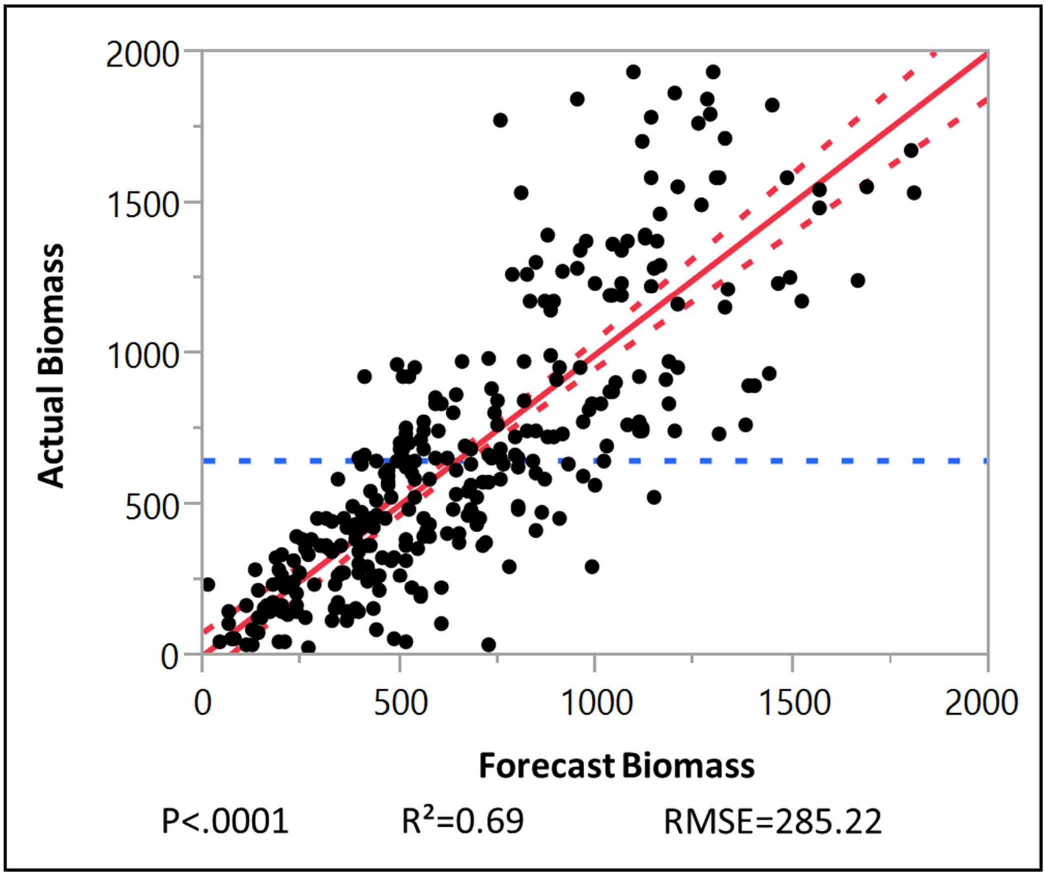


Fig. 4: Observed values as a function of predicted values

3) *Adjustment residue analysis:* The exploratory analysis indicates a standard deviation of 283.33 kg. The results of the bootstrap analysis based on 2,000 sub-samples show that the mean varies from 642 to 762 Kg in a 95% confidence interval. Biases on the average and the standard deviation are respectively 0.89 and - 0.35 small increments (Table 4).

Table 4: bootstrap exploratory analysis of residues

Parameters	Statistics	Bootstrap			
		Bias	Standard Error	95 % Confidence interval	
				Below	Above
Number of observations	319			319	319
Average	0,00	0,89	16,02	-32,49	33,16
Standard Deviation	283,33	-0,35	14,86	255,30	313,02
Variance	80 273,71	24,69	8440,26	65 176,17	97 979,15

Volume 5 Issue V, May 2017
ISSN: 2321-9653
International Journal for Research in Applied Science & Engineering Technology (IJRASET)

Unit: $kg.MS.ha^{-1}$

The diagnosis of the model shows a regular distribution of the residuals along the lines (Fig. 5a), the distribution follows a normal distribution (Fig. 5b) attested by a Durbin-Watson DW index of 1.83 and an autocorrelation percentage of 8.

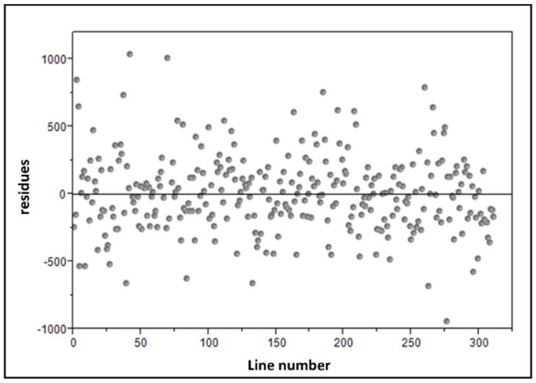


Figure 5 a : Graphic of residue per line

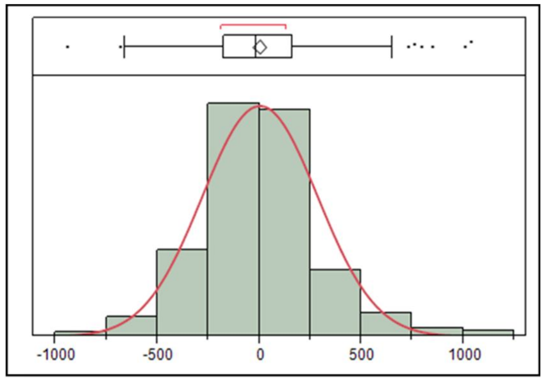


Figure 5 b : Distribution of residues

B. Discussion

Advances in science and technology, especially in statistics, remote sensing and data processing, have resulted in the availability of high-capacity processing machines and the availability of sufficiently long series of satellite images, permitting to carry out fodder yields estimate studies by multiple linear regression with 34 explanatory variables to establish a stable and parsimonious model. Tools such as VAST, TIMESAT, SPIRITS, etc., the availability of long time series of vegetation index images offer the possibility of calculating several metrics characterizing the vegetation profile from germination to senescence. The use of the maximum or the NDVI integral of the vegetative growth season is insufficient to explain the level of forage yield. There are many other metrics characteristic of the seasonal vegetation profile that may contribute to improving the fodder yield estimate model. These metrics of the phenological profile of vegetation growth and development phases may be associated with other agro-meteorological variables such as those derived from AMS. Examination of the annual models obtained by the multiple linear regression shows that the variables can come from VAST, AMS or the MEIA method or from all three at the same time. Statistically, the four-variable national model can be considered good. Indeed, this model is characterized by an adjusted R^2 of 0.68, a validation R^2 of 0.67 and 3.72 kg.ha-1 of RMSE difference (calculated RMSE and RMSE validation). The quality of this model is demonstrated by the diagnosis of residues (regular distribution and normal distribution of residues). The relevant national model variables: MAX (maximum vegetation as calculated by MEIA), DRO (small amplitude), PEA (vegetation Peak decade), VER (large amplitude), are all Metrics derived from NDVI, they are directly related to the cycle of vegetation. It is important to note that in the national one-variable model, the MAX as calculated by MEIA already accounts for 57% of fodder yield, so the three other variables (DRO, VER and PEA) 10%, but reduce the error by 40 kg MS.ha-1. The national model No. 1 variable in Table 2 is available as soon as the vegetation reaches its maximum growth, which means that the first results of the national model can be obtained from the third decade of August or the first decade of the month of September. After four decades, these results can be updated using models 2, 3 and 4 of Table 2. The availability of information on fodder production before the end of the vegetation cycle will enable decision-makers to save time in order to anticipate crises. For the national model with 4 variables (MAX, DRO, PEA, VER), the R^2 is 0.69 (adjusted $R^2 = 0.68$) and the RMSE is equal to 285 ($R^2 = 0.69$ and RMSE = 483 kgMS.ha-1) found in Senegal with a similar model [40]. The comparison of these results shows an advantage of the Niger model compared to that of Senegal because the RMSE found in Senegal is higher than that of Niger by about 200 kg, although in order to make a more objective comparison, the relative RMSEs are needed. However, if this error is related to the total area of the pastoral area of 350,000 km², there is an average annual error of about plus or minus 10,000,000 tones, or about the consumption of about 2 million TLU / 9 months (dry season). Can the planning of a country's interventions be reasonably based on this level of error? If not, it is necessary to continue to explore other avenues for improvement of the current model. These results show an improvement over the simple linear regression model, but they also show that further research is needed. Exploring other indices such as FAPAR, whose strong correlations with real biomass have been shown through recent studies[40, 63]. (Multiple linear regressions permits to model agro-meteorological variables derived from AMS and of biophysical variables derived from VAST. The availability of a series of measurements on the ground and NDVI images permits to test the multiple linear regressions whose performance has been demonstrated. Indeed, this multiple regression method has shown satisfactory performances for the estimating agricultural yields [36-38]. The very interesting results obtained with the metrics derived from AGROMETSHELL and VAST confirm the conclusions of the work[35, 39] which use, on the one hand, the biomass In situ and the phenological parameters derived from the FAPAR series from SPOT VEGETATION; On the other hand, the same metrics associated with other agro-meteorological parameters derived from GeoWRSI. A significant improvement was found in simple linear regression, in both Senegal and Niger.

C. Operational use of results

In the context of a security crisis and climate challenges, the results of this work will contribute to improving the quality of information produced annually on fodder production to assist in decision-making in order to anticipate pastoral crises. An effective and efficient Pastoral Early Warning System (PWS) requires a reliable and timely evaluation of forage production. The reliability of the forecast feed balance depends, among other things, on the quality of the fodder production assessment results and on the reliability of livestock numbers. The explanatory variables of the model are all derived from the NDVI: the maximum value of the NDVI (MAX); the PVAL - EVAL (DRO) value, the decade of the maximum vegetation (PEA), and the amplitude (VER). These are simple variables to be produced with the VAST program, which will facilitate the adoption of the model by the Department. The practical use of the Multiple Linear Regression Model (MRM) is not very different from that of Simple Linear Regression. The fodder mass map can be designed using this equation with 4 explanatory variables, one month after PEAK (decade of the maximum NDVI). The multiple linear regression method applied to agricultural yields having performed interesting results elsewhere can be used for Calculating crop yields of major crops to deduce crop residues that play an important role in feeding livestock. A plug-in extension on Quantum GIS (QGIS) free software can be considered. This extension can help to make the exploitation of the results of this thesis and those of previous studies obtained elsewhere in the agricultural field more operational in order to perform the agricultural yields forecast. The land use / Land cover map (LU / LC) or any other better map is of great use as a mask for calculation. MRM will be applied to estimate fodder yields in pastoral areas. To account for crop residue production, it would be interesting to consider the use of multiple linear regressions which has shown elsewhere its performance in the work [36, 38, 64] in forecasting agricultural yields, with a view to deduce the production of crop residues. The result will be a map containing forage production in pastoral areas and crop residues from cultivated areas.

IV. CONCLUSION

The results showed that the model is stable. Indeed, the difference between the calculated RMSE (282kg $MS.ha^{-1}$) and that of the validation is 3.72 kg, the adjusted R^2 is 0.68 kg with very significant parameters (P <, 0001). Statistically, satisfactory results show a significant improvement in the modeling of fodder biomass production in Niger compared to the simple regression model, whose R^2 is 0.56 with an RMSE of 367 kg DM. ha^{-1} [41]. These results are much more interesting than those of simple linear regression. However, it is necessary to continue the research by exploring the indications such as LAI, EVI and FAPAR and also the calibration of NDVI metrics on phenology, timber accounting and grazing to see if it is possible to improve the forecast.

BIBLIOGRAPHIC REFERENCES

[1] UNESCO, PNUD, and FAO, Écosystèmes pâturés tropicaux. Un rapport sur l'état des connaissances préparé par l'UNESCO, le PNUD et la FAO. Paris, FRANCE: UNESCO, 1981.
[2] DNEP, "Déclaration de N'djamena pour l'Elevage Pastoral: une contribution durable au développement et à la sécurité des espaces saharo-saheliens. colloque régional conférence ministérielle, 7 pages," 2013.
[3] UA, "Union africaine: cadre stratégieque pour le pastoralisme en Afrique: Sécuriser, Protéger et améliorer les vies, les moyens de subsistance et les droits des communautés pastorales, Addis Abeba ,Ethiopie, 56 pages.," 2013.
[4] DNP, "Déclaration de Nouakchott pour le Pastoralisme: Mobilisons ensemble un effort ambitieux pour un pastoralisme sans frotière. conférence des chefs d'Etats et de gouvernements. 4 pages. ," 2013.
[5] AMMA, "La Mousson Ouest Africaine et ses composantes, Livre blanc, 69 pages," 2002.
[6] P. Hiernaux and H. N. Le Houérou, "Les parcours du Sahel," Science et changements planétaires/Sécheresse, vol. 17, pp. 51-71, 2006 2006.
[7] M. Hulme, "Confronting climate change: Risks, implications and responses: Edited by I. M. Mintzer (1992) Cambridge University Press, Cambridge, 352 pp. Hardback £50.00 ISBN 0 521 42091 1; Paperback £19.95, US $34.50 ISBN 0 521 42109 8," Endeavour, vol. 16, 1992/12// 1992.
[8] I. Lona, "Risques climatiques et pratiques culturales du mil et du sorgho au Niger. thèse de doctorat ,Université Abdou Moumouni de Niamey, 248 pages.," 2014.
[9] R. Zakaria, "Revue du secteur de l'élevage au Niger,," FAO et Ministère de l'Elevage et des Indusries Animales (MEIA), Niamey, NIGER 2010.
[10] RGAC, "Recensement générale de l'agriculture et du cheptel, Rapport préparé pour le Gouvernement du Niger par l'Organisation des Nations Unies pour l'alimentation et l'agriculture," Rome2008.
[11] OMD1, "Cadre d'accélération des OMD : Réduire l'extrême pauvreté et la faim Sécurité alimentaire et nutritionnelle au Niger," Niamey NIGER2011.

[12] I. Toure, A. Ickowicz, V. Ancey, P. Gerber, A. Wane, M. Saley, et al., "SIPSA: un système d'information et d'alerte précoce pour accompagner les prises de décision dans le domaine du pastoralisme au Sahel," La politique sectorielle du pastoralisme au Tchad Quelles orientations?, 2011 2011.

[13] J. W. Rouse, R. H. Haas, D. W. Deering, J. A. Schell, and J. C. Harlan, "Monitoring vegetation systems in the Great Plains with ERTS," vol. 1, 1973 1973.

[14] C. O. Justice, J. R. G. Townshend, B. N. Holben, and C. J. Tucker, "Analysis of the phenology of global vegetation using meteorological satellite data," International Journal of Remote Sensing, vol. 6, pp. 1271-1318, 1985 1985.

[15] A. Huete, K. Didan, T. Miura, E. P. Rodriguez, X. Gao, and L. G. Ferreira, "Overview of the radiometric and biophysical performance of the MODIS vegetation indices," Remote Sensing of Environment, vol. 83, pp. 195-213, 2002 2002.

[16] D. B. Lobell and G. P. Asner, "Cropland distributions from temporal unmixing of MODIS data," Remote Sensing of Environment, vol. 93, pp. 412-422, 2004/11/15/ 2004.

[17] M. Bagoudou, D. Issa, W. iruce, and H. John, "Warming Systeme Preliminary:Intergrated livestocck production Project " 1987.

[18] S. M. E. Groten, "NDVI—crop monitoring and early yield assessment of Burkina Faso," TitleREMOTE SENSING, vol. 14, pp. 1495-1515, 1993 1993.

[19] O. Diallo, A. Diouf, N. P. Hanan, A. Ndiaye, and Y. Prevost, "AVHRR monitoring of savanna primary production in Senegal, West Africa: 1987-1988," International Journal of Remote Sensing, vol. 12, pp. 1259-1279, 1991 1991.

[20] P. H. Y. Hiernaux and C. O. Justice, "Suivi du développement végétal au cours de l'été 1984 dans le Sahel Malien," International Journal of Remote Sensing, vol. 7, pp. 1515-1531, 1986/11/01/ 1986.

[21] C. O. Justice and P. H. Y. Hiernaux, "Monitoring the grasslands of the Sahel using NOAA AVHRR data: Niger 1983," International Journal of Remote Sensing, vol. 7, pp. 1475-1497, 1986.

[22] F. Maselli, C. Conese, L. Petkov, and M. A. Gilabert, "Environmental monitoring and crop forecasting in the Sahel through the use of NOAA NDVI data. A case study: Niger 1986–89," International Journal of Remote Sensing, vol. 14, pp. 3471-3487, 1993.

[23] F. Maselli, C. Conese, L. Petkov, and M. A. Gilabert, "Use of NOAA-AVHRR NDVI data for environmental monitoring and crop forecasting in the Sahel. Preliminary results," International Journal of Remote Sensing, vol. 13, pp. 2743-2749, 1992.

[24] F. Maselli, M. Chiesi, A. Barbati, and P. Corona, "Assessment of forest net primary production through the elaboration of multisource ground and remote sensing data," Journal of Environmental Monitoring, vol. 12, pp. 1082-1091, 2010 2010.

[25] F. Maselli, A. D. Gregorio, V. Capecchi, and F. Breda. (2009, 01). Enrichment of land-cover polygons with eco-climatic information derived from MODIS NDVI imagery Journal of Biogeography Volume 36, Issue 4. Journal of Biogeography 36(4), 639-650. Available: http://onlinelibrary.wiley.com/doi/10.1111/j.1365-2699.2008.01981.x/abstract

[26] C. J. Tucker, H. H. Elgin, and J. E. McMurtrey., "Relationship of Red and Photographic Infrared Spectral Radiances to Alfalfa Biomass, Forage Water Content, Percentage Canopy Cover, and Severity of Drought Stress " NASA Technical Memorandum 80272). Greenbelt, MD: Goddard Space Flight Center, 13 pp., 1979.

[27] C. J. Tucker, C. O. Justice, and S. D. Prince, "Monitoring the grasslands of the Sahel 1984-1985," International Journal of Remote Sensing, vol. 7, pp. 1571-1581, 1986.

[28] C. J. Tucker, C. L. Vanpraet, M. J. Sharman, and G. Van Ittersum, "Satellite remote sensing of total herbaceous biomass production in the Senegalese Sahel: 1980–1984," Remote Sensing of Environment, vol. 17, pp. 233-249, 1985 1985.

[29] B. Wylie, J., J. Harrhtgton, B. Maidagi, and I. Denda., "Pasture production in the central and eastern pastoral zones of Niger. Early Warning System Preliminary Report, Integrated Livestock Production Project (Niger/Tufts/USAID). Dec.," 1987.

[30] B. K. Wylie, J. A. Harrington, S. D. Prince, and I. Denda, "Satellite and ground-based pasture production assessment in Niger: 1986-1988," International Journal of Remote Sensing, vol. 12, pp. 1281-1300, 1991/06/01/ 1991.

[31] B. K. Wylie, J. A. H. Jr, R. D. Pieper, and I. Denda, "A satellite-based range assessment system for the Sahel of Africa," Geocarto International, vol. 7, pp. 79-85, 1992/03/01/ 1992.

[32] B. K. Wylie, J. A. H. Jr, S. D. Prince, and I. Denda, "Satellite and ground-based pasture production assessment in Niger: 1986-1988," International Journal of Remote Sensing, vol. 12, pp. 1281-1300, 1991/06/01/ 1991.

[33] A. Bégué, E. Vintrou, D. Ruelland, M. Claden, and D. N., " Can a 25-year trend in Soudano-Sahelian vegetation dynamics be interpreted in terms of land use change? A remote sensing approach. ," GlobalEnvironmental Change, vol. 21, 2011.

[34] H. Santin-Janin, M. Garel, J.-L. Chapuis, and D. Pontier, "Assessing the performance of NDVI as a proxy for plant biomass using non-linear models: a case study on the Kerguelen archipelago,", Polar Biol vol. 32, pp. 861–871, 2009.

[35] Diouf A. A., B. Djaby, M. B. Diop, A. Wele, J.-A. Ndione, and B. Tychon, " Fonction d'ajustement pour l'estimation de la production fourragère herbacée des parcours naturels du Sénégal à partir du NDVI S10 de SPOT-VEGETATION. ," presented at the XXVII Colloque de l'Association Internationale de Climatologie,, Dijon (France). 2014.

[36] R. Balaghi, B. Tychon, H. Eerens, and M. Jlibene, "Empirical regression models using NDVI, rainfall and temperature data for the early prediction of wheat grain yields in Morocco," International Journal of Applied Earth Observation and Geoinformation, vol. 10, pp. 438-452, 2008 2008.

[37] Kouadio L., Newlands N., Davidson A., Zhang Y., and C. A., " Assessing the Performance of MODIS NDVI and EVI for Seasonal Crop Yield Forecasting at the Ecodistrict Scale. ," Remote Sensing, vol. 6, p. 10193, 2014.

[38] L. Kouadio, "Prévisions des rendements du blé d'hiver à échelle régionale par modélisation de la courbe de chute de l'indice foliaire.," Thèse de doctorat: , science et environnement Université de Liège,, Belgique,, 2012.

[39] A. Diouf, M. Brandt, A. Verger, M. Jarroudi, B. Djaby, R. Fensholt, et al., "Fodder Biomass Monitoring in Sahelian Rangelands Using Phenological Metrics from FAPAR Time Series," Remote Sensing, vol. 7, p. 9122, 2015.

[40] A. Diouf, P. Hiernaux, M. Brandt, G. Faye, B. Djaby, M. Diop, et al., "Do Agrometeorological Data Improve Optical Satellite-Based Estimations of the Herbaceous Yield in Sahelian Semi-Arid Ecosystems?," Remote Sensing, vol. 8, p. 668, 2016.

[41] I. Garba, B. Djaby, I. Salifou, A. Boureima, I. Touré, and B. Tychon, "Évaluation des ressources pastorale au sahel Nigérien à l'aide des données NDVI issues de SPOT-VEGETATION et MODIS. ," Photo interprétation European Journal of Applied Remote Sensing, , vol. N°2015/1, pp. 13-26., 2015.

[42] IEMVT, Élevage et potentialités pastorales sahéliennes. Synthèses cartographiques, Niger,. CTA, Wageningen, IEMVT, Maisons-Alfort: IEMVT-CIRAD, CTA, 1987.
[43] M. V. K. Sivakumar, A. Maidoukia, and R. D. Stern, "Agroclimatology of west africa: Niger," ed, 1993.
[44] I. Touré, A. Ickowicz, A. Wane, I. Garba, P. Gerber, I. Atte, et al., Atlas des évolutions des systèmes pastoraux au Sahel: 1970-2012, 2012.
[45] R. Morel, Atlas agroclimatique des pays de la zone du CILSS.: Notice et commentaire. AGRYHMET, Niamey, NIGER: Centre Régional AGRHYMET 1992.
[46] R. G. Allen, H. Hurlbert, L. S. Pereira, M. da Silva, R. D., and M. Smith, "Crop evapotranspiration - guidelines for computing crop water requirements.," Food and Agricultural Organization of the United Nations (FAO) Irrigation and Drain. Paper No. 56, Rome. Pp 300, 1998
[47] B. Efron, "Bootstrap Methods: Another Look at the Jackknife," The Annals of Statistics, vol. 7, pp. 1-26, 1979/01/01/ 1979.
[48] B. Efron, "Nonparametric estimates of standard error: the jackknife, the bootstrap and other methods," Biometrika, vol. 68, pp. 589-599, 1981 1981.
[49] B. Efron, "Estimating the Error Rate of a Prediction Rule: Improvement on Cross-Validation," Journal of the American Statistical Association, vol. 78, pp. 316-331, 1983/06/01/ 1983.
[50] R. Beran, "Better Bootstrap Confidence Intervals: Comment," Journal of the American Statistical Association, vol. 82, pp. 195-196, 1987/03/01/ 1987.
[51] B. Efron, "Missing Data, Imputation, and the Bootstrap," Journal of the American Statistical Association, vol. 89, pp. 463-475, 1994/06/01/ 1994.
[52] B. Efron and R. Tibshirani, "Improvements on Cross-Validation: The .632+ Bootstrap Method," Journal of the American Statistical Association, vol. 92, pp. 548-560, 1997/06/01/ 1997.
[53] B. Efron and R. J. Tibshirani, An introduction to the bootstrap: CRC press, 1994.
[54] P. I. Good and J. W. Hardin, Common errors in statistics (and how to avoid them): John Wiley & Sons, 2012.
[55] K. J. MEIER, J. L. BRUDNEY, and J. BOHTE, Applied Statistics For Public and Nonprofit Administration, 2012.
[56] Richard A. Johnson and G. K. Bhattacharyya, Statistics- Principles and Methods VI Edition ed. United States of America: John Wiley & Sons, Inc., 2010.
[57] Robert Johnson and P. Kuby, Elementary Statistics vol. (11th Ed), 2012.
[58] Ronald M. Weiers, H. J. Heinz, J. B. Gray, and L. H. Peters, "Introduction to Business Statistics," ed: South-Western, Cengage Learning, 2011.
[59] F. Emmert-Streib and M. Dehmer, Information Theory and Statistical Learning, 2009.
[60] P.-A. Cornillon and É. Matzner, Régression: héorie et applications, 2007.
[61] R. A. Johnson and G. K. Bhattacharyya, Statistics- Principles and Methods: John Wiley & Sons, Inc., 2010.
[62] H. B. Badi, Econometrics, , Fifth ed., 2011.
[63] M. Meroni, F. Rembold, M. M. Verstraete, R. Gommes, A. Schucknecht, and G. Beye, "Investigating the relationship between the inter-annual variability of satellite-derived vegetation phenology and a proxy of biomass production in the Sahel," Remote Sensing, vol. 6, pp. 5868-5884, 2014 2014.
[64] L. Kouadio, N. Newlands, A. Davidson, Y. Zhang, and A. Chipanshi, "Assessing the Performance of MODIS NDVI and EVI for Seasonal Crop Yield Forecasting at the Ecodistrict Scale," Remote Sensing, vol. 6, p. 10193, 2014.