Performance of similarity analysis in the estimation of forage yields in the Sahelian zone of Niger

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Summary

The study aims to test the performance of similarity analysis in herbaceous fodder biomass estimate in the Nigerian pastoral zone, in a context of insecurity and precipitation spatiotemporal variability. It is carried out on the time series of NDVI decadal images of SPOT VEGETATION for the period from 2001 to 2012 and on fodder biomasses measured in situ during the same period. Similarity analysis compares NDVI seasonal patterns to detect similar years using three criteria: the RMSE (Root Mean squared error), the MAD (Mean absolute Deviation), and R^2. Exploratory statistical analyzes with bootstrap are carried out to better characterize the observations resulting from the simulation. Moreover, the analysis of the parametric and non-parametric correlations is carried out to evaluate the level of link between the simulated data and the real data. The t test and the Wilcoxon test are then carried out in order to compare the means of the actual biomasses with those obtained by the similarity analysis. At the local level, the results indicate that the R^2 is more efficient than the RMSE and the MAD which have almost the same performances. The results of the similarity calculated with R^2 can be used as a proxy to the herbaceous phytomass measured in situ, as there is no significant difference between the simulated mean and the mean measured at the 1% threshold. On the other hand, the results of the similarity calculated with the RMSE and the MAD are not exploitable. Parametric and nonparametric correlations are all significant at the 1% threshold. However, the R^2 are low and vary between 0.32 and 0.45. It therefore seems necessary to continue the research, as numerous studies have revealed very good links between certain indices like the FAPAR, the EVI and the LAI and the aerial phytomasse.

Key words: Forage yield, NDVI, Similarity, Pastoral, Niger**.**

1. Introduction

1.1. Background

The pastoral area of Niger is about 35 million hectares ([1, 2] large. The pastoral monitoring of this region is carried outwith a data collection system that has existed for more than twenty years. The contribution of the State of Niger to this scheme costs about 50 million FCFA per year. This participation does not take human resources into account. This state system remains fragile, due to staff disruptions, to persistent residual insecurity in pastoral areas. Indeed, the Sahelian zone is going through a security crisis[3] preventing technicians and researchers from going the field to make observations. The contribution of satellite observations is very interesting, however,its role is but complementary since it cannotaccount for important parameters such as the floristic composition of rangelands, the dynamics of plant populations, the processes of wind or water erosion, the soil fertility, the intensity and mode of grazing ... Systematic observations and ground measurements must continue, develop and improve, given their role inthe calibration and validation of satellite products.It, therefore, seems imperative to propose a viable and sustainable alternative for monitoring and estimating herbaceous masses combining earth observation data and those of the ground. The similarity method appears to be a good candidate. It is, in principle, a form of reasoning based on Case Based Reasoning or CBR [4-12]. This method is comparable to that of analogues used in meteorology to achieve, among others, forecasting temperatures[13] or precipitation[14-16]. The similarity method has been appliedto SPIRITS software output for the identification of similar years using three criteria of similarity between two series of data. These are theRoot Mean squared error (RMSE), Mean absolute deviation (MAD) and the coefficient of determination R square (R^2) while indicating the tolerable shift in decades. Input datainclude NDVI images of SPOT VEGETATION and MEIA fodder yields to test the performance of similarity measurement criteria such as RMSE, MAD and R^2; finally compare the similarity to the MEIA model and that of the multiple linear regression.The basic assumption of this approach is to consider that two similar years produce equivalent returns. Also, the work is organized around the following points: Presentation of the state of knowledge in terms of similarity; description of equipment and methods; the results and their discussion; the conclusion and the prospects for this study.

1.2. Presentation of the area

The study area corresponds essentially to the pastoral zone of Niger as defined on the maps of the pastoral atlas[17] . It is located between13 ° and 16 ° north latitude and between 2 ° and 12 ° east longitude (Fig.1). The choice of this zone of the Sahel for the validation of the biomass model is mainly linked to the availability of field measurementdata. Like the other Sahelian parts, this zone is characterized by a high spatial and temporal precipitation variability[18, 19]. The climate is of the arid type with a normal rainfall varying between 150 and 300 mm[20]. The duration of the season varies on average from 60 to 120 days for Central and Western Sahel. It is on average 40 days in the northern and eastern Sahel [21].

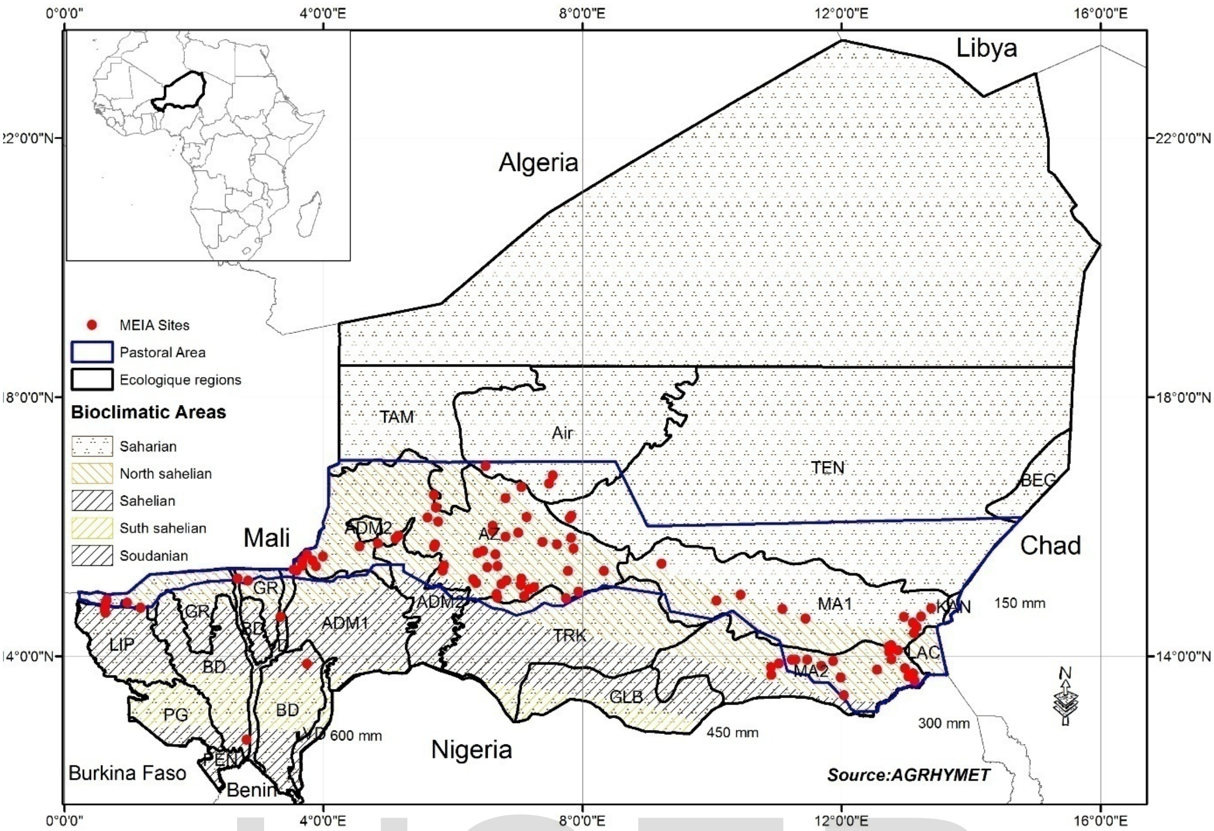

Fig.1: the study area with herbaceous fodder measurement sites

(the northern limit of crops is set by the law of May 1961 which sets the northern limit of crops) ; AderDoutchiMaggia Basin (ADM1); Plateau of AderDoutchiMaggia (ADM2); Steppe of Azaouak (AZ); Plain of the Tarka (TRK); Agricultural Area of Goulbi (GLB); Liptako (LIP); Gourmantchéplateau (PG); Gourma Mali (GM); Basin of the dallols (BD); Air (AIR); Manga desert (MA1); Sahelian Manga (MA2); Ténéré (TEN); Park W Savannah (PW); Valleys of the Dallols (VD).

1.3. Review of literature on similarity

The similarity measure was initially used to demonstrate the degree or the importance of the resemblance or proximity between two objects. Several research studies in statistics are based on data exploration or analysis (data mining) in the fields of thematic application as varied as linguistics, biology, computer science[22]. From the 1900s to the present day, a large number of similarity measures have been published that are applied to several fields. Several studies have contributed to the state of knowledge on measurements and coefficients of similarity. Thus, concerning the studies on the applications to the binary data, 76 similarity measurements[23], and 22 similarity coefficients are noted[24]. Other studies have led to the subdivision of similarity measures into two groups. The measures of similarity that the author describes as group I are those which do not take into account the number of characteristics possessed by none of the two objects compared and those of group II which, on the contrary, take them into account[25]. There is no universal similarity measure for all domains. [26]Subdivided the measures of similarity into global and local measures with the possibility of switching from one scale to another. Despite the large number of similarity indices studied, there is a small number of comparative studies of the performance of these measurements. In cell biology, a comparative study of 20 coefficients was performed to evaluate the performance of different data acquisition conditions in cell formation[27]. The similarity method can be assimilated to the nearest neighbors method or analogous method used in meteorology[15, 28-34]. It is mainly used for the real time rainfall forecast[35, 36]either very

short term [28, 34]or medium term[35]. This method is also used by the African Center of Meteorological Applications for Development (ACMAD) for seasonal forecasts. The main limit of the method by similarity as well as by analogy lies in the historical depth of the archive database. This historical depth, where the number of situations widens the field, but the main limit remains the nature of the criteria of similarity and their functional link with the process, here that of plant production.Agrometeorological data such as ETP (Potential EvapoTranspiration), WRSI (Water Requirement Satisfaction Index), SPI (Standardized Precipitation Index), cumulative rainfall, are cause indicators used to monitor vegetation and estimate biomass.These biomass monitoring and prediction activities are often performed with status indicators such as vegetation indices such as NDVI (Normalized Difference Vegetation Index), LAI (Leaf Area Index), FAPAR (Fraction of Absorbed Photo-synthetically Active Radiation), VCI (Vegetation Condition Index) and sNDVI (Standardized NDVI). For the similarity analysis, between the status indicators and the cause indicators, we preferred the status indicators. That is, NDVI, because its relationships with vegetation productivity have been extensively studied[37-39]. It is observed in research that many similarity measurements have already shown their efficiency with the NDVI. This is the case of the Mahalanobis distance which has been advantageously used to quantify and map biodiversity[40]. The mean square error (mse) and the mean absolute error (mae) are considered as global similarity measurements with spatial alignment.
$mse = \sum_k (a_k - b_k)^2 / ketmae = \sum_k |a_k - b_k| / k$Where ak and bk are respectively the gray level of the kth pixel in the images A and B.
They are only used when images come from the same sensor. The cross-correlationcoefficient, ρ, is also used under the same conditions with $\rho = \frac{\sum_k a_k b_k}{\sqrt{\sum_k a_k^2 \sum_k b_k^2}}$where ak and bk are respectively Gray level of the kieme pixel in images A and B[26].
The mean absolute deviation, MAD is considered as a statistical prediction error measure in the same way as the Root Mean Square Prediction Error, RMSPE [41]. Indeed, it gives the bias on the estimate [42]. Moreover, it allows to compare the predictive performance between two models[43] or to compare simulation results with measurements [44, 45]. It is also a measure of precision of a model[46].The RMSE also called Root Mean Square Deviation (RMSD). The individual difference between a predicted value and an actual value is called the residual value, so the RMSE is only an aggregation of these values constituting the predictive power of the model. It is also used to compare the results obtained from several approaches [47].The coefficient of determination R^2 defines the degree of linkage between two variables by a linear relationship. In this study, these measures can then be used to calculate the similarity between two years, assuming that two similar situations produce similar results. In other words, the hypothesis that two similar years yield equivalent fodder biomasses has been formulated. The coefficient of determination R^2 and the RMSE are also used for model validation[48].

2. Materials and methods

The SPIRITS software was used to analyze the similarity of the seasonal NDVI profiles from SPOT VEGETATION for the period 2001 to 2012, as well as the annual herbaceous fodder biomasses collected by The MEIA (Ministry of Livestock and Animal Industries) over the same period. The method of data collection in situ has been extensively detailed in[49, 50]. The SPIRITS software allows the detection of similar years using the three criteria, RMSE, MAD and R^2. Exploratory statistical analyzes with bootstrap are carried out to characterize the observations resulting from the simulation. Moreover, the analysis of the parametric and non-parametric correlations permit to evaluate the level of link between the simulated data and the actual data. The t test and the Wilcoxon test are then carried out in order to compare the means of the actual yields with those obtained by the similarity analysis. The correlation coefficients of the similarity are finally compared with those of the MEIA model [49] (Fig.2).

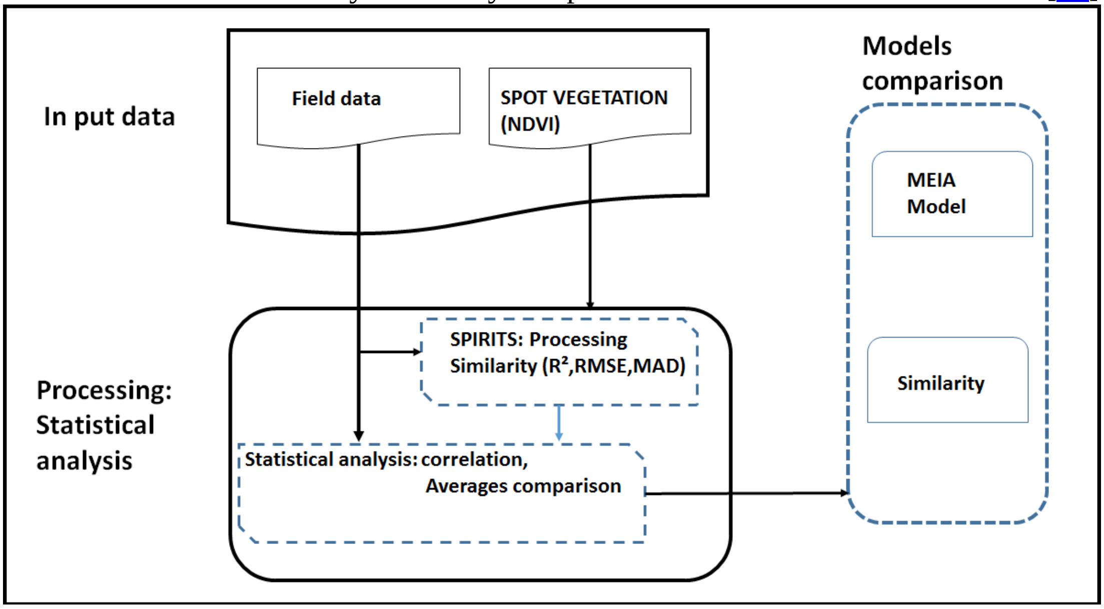

Fig. 2: General outline of the approach

2.1. Generalities about SPIRITS

SPIRITS is a software developed by VITO for the JRC to analyze time series of Earth Observation (EO) data. The latest version, published in February 2015 and downloadable from the JRC website, offers a wide range of features for analyzing time series of low-resolution satellite images such as SPOT-VEGETATION, NOAA-AVHRR, METOP-AVHRR , TERRA-MODIS, ENVISAT-MERIS with an integrated similarity analysis algorithm[51].

2.2. Methods

The methodology is divided into fourparts: 1) Statement of similarity principle 2) Data preparation 3) Processing with SPIRITS software to generate similarity yields; 4) Exploratory statistical analyses, correlation tests and averages comparison.

2.2.1. Principle of the similarity method

The profile of each pixel is realized for the period of active growth of the vegetation, which in the case of the Sahel corresponds to a period of 6 months from May to October (18 decades). Then, a comparison between the profile of the target year and the profiles of the whole time series is carried out by considering either the maximum R^2 or the minimum RMSE or the minimum MAD, with an accepted phenological shift of up to More or less three decades (Fig. 3).

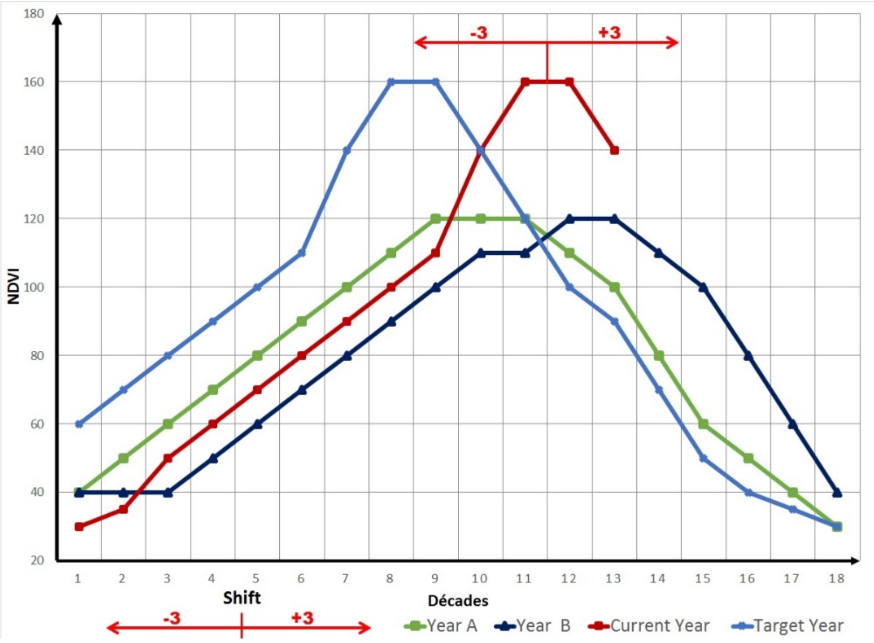

Fig.3: Principle of similarity analysis applied to NDVI decadal series (in numerical code)

2.2.2. Data preparation

The creation of the mask delimiting the 68 sites is a preliminary step in data analysis. The second essential step is to rename the NDVI images according to a nomenclature in order to guarantee their identification by the SPIRITS software and finally to structure the table containing the forage yields measured in the field in a file in text format. To perform the SPIRITS software similarity treatment on only sites in the study area, it is necessary to use the layer of the 68 MEIA sites for in situ survey of the vegetation to produce the mask. The extraction of the pixels actually concerned by the sites passes through the steps consisting in:

- generating 1 km side polygons grid which perfectly superimposes the pixels of the NDVI images of SPOT VEGETATION;
- Superimpose the layer of the sites on that of the grids in order to extract the nine contiguous polygons of 1 km² corresponding to the surface of each site;
- To merge the 9 polygons of 1 km² to make one of 9 km² corresponding to the area of each site;
- Make the spatial join to assign the attributes of each site to the corresponding polygon;
- Give a raster code to each site;
- Transform the polygon layers into raster.

2.2.3. Data processing on SPIRITS

Data processing for similarity can be subdivided into four consecutive steps: project setting; Mapping of similar years; Fodder yield calculation; Extraction of the table containing fodder yields. The processing module establishes a window allowing to document the different input data: the multi-annual images, the information on the temporality that are the periods covered by the data: the period of vegetative growth which runs from May to October; The first months and decade; The last months and decade finally, the shift presenting the slip to be taken into account in the calculation. In this study we took three decades, considering that a delay or a three-decade advance from the mean will have no effect on fodder production at the time lag. The similar year is being sought. This approach theoretically increases the chances of finding a similar year six times; It is also necessary to inform the procedural part which consists in giving the measure of similarity to take (RMSE, MAD or R^2). A minimum threshold of 95% has been set as a condition for any series of pixels to be taken into account in the analysis of the profiles.

2.2.4. Statistical analysis

An exploratory analysis of field observations and those generated by similarity is performed to calculate averages, standard deviation, confidence interval and bootstrap bias. A correlation analysis to calculate the Pearson, Kendall and Spearman coefficients with a bilateral significance test is performed to assess the level of significance of the relationship in the field measurements and the estimates generated by the similarity. The comparison of the mean of the field measurements and the estimates generated by similarity was carried out using parametric and nonparametric tests. These include: the t test by observing its conditions of validity (paired observations, independence of observations, random sampling, normal distribution for differences, and homogeneity of variances) of the Wilcoxon test[52-54].

Averaging Comparison Tests

we applied a parametric test (t test) and a nonparametric test (Wilcoxon test) for the comparison of simulated means and herbaceous mass measurements. The objective of these tests is to see if there is a significant difference between the measurements and the similarity estimates. If there is no significant difference this would mean that we can use the data of similarity as a proxy of the actual data. The two tests are performed mainly for two reasons; the first being related to the fact that the t test is more powerful when the sample follows a normal law and when the number of observations is important[52]on the other hand when the distribution does not follow A normal law or the number of observations is small, it is preferable to favor the nonparametric tests which are in these cases more robust.

T Test

The t test was chosen because the two fodder yields series to be compared which are the real observations and those of the similarity are in sufficient number to apply this test considering the central limit theorem. For each site, there is the variable resulting from the similarity and that resulting from the measurements of the ground. The statistic t in the matched case is calculated according to the following formula: $t = \frac{M_d}{SE_d}$ where Md is the difference between the two averages, the standard error of the difference of the two averages. Before these analyzes, the distributions of the variables were studied through the analysis of symmetries, flattenings and biases[55, 56].

Test de Wilcoxon

According to this method, the observations are classified in pairs[57]. This permits to obtain a count of the signs of the differences in pairs (as in the Signs test) and the ranks of these differences. Y (+) denotes the sum of the ranks of the positive differences; Y (-) denotes the sum of the ranks of the negative differences. The principle is: Y (+) + Y (-) = n (n + 1) / 2 where n is the number of pairs. On average, if both samples come from the same population, Y (+) and Y (-) are both half this value: n (n + 1) / 4 [58, 59].

The correlations

The relationships between the similarity estimates and the field measurements are analyzed with different types of correlation coefficients, Pearson's r, Spearman's ρ and Kendal's τ [54-57]. The Pearson correlation translates the relationship between 2 variables as well as the strength of the link between the variables. The Spearman correlation calculates a coefficient of correlation between the ranks of the values of the two variables, this correlation is used when the distributions of the variables are asymmetric (skewness in English). The interpretation is identical to that of the Pearson correlation. For the Kendall correlation, the Kendall rank correlation coefficient (Kendall τ) is a nonparametric correlation measure. It is used to determine the relationship between two sets of data.

3. Results and Discussion

3.1 Results

The results of the similarity analysis are given here according to the different measurement criteria. They are also declined according to the different spatio-temporal scales, namely the local or national scale, the ecoregions, the bioclimatic zones and finally the years. After the statistical summaries for an overview and a complete characterization of the observations, the results of the parametric and nonparametric correlation tests are presented. At last, the comparison tables of the averages are presented.

3.1.1. Local analysis

Descriptive statistics and correlation of similarity with R^2

Table 1 shows the results of the descriptive statistical analysis carried out on the estimates by similarity with R^2 and the corresponding measures. Bias and confidence intervalsat the 95% threshold achieved with 25,000 sub-samples.

Table 1: Descriptive statistics of similarity using R^2.

				Bootstrap			
						Confidence interval(95 %)	
		Statistics	Standard Error	Bias	Standard Error	lower	Upper
SimulatedBiomass (R^2)	ObsNb	153		0.00	0.00		
	Mean	519.59		-0.19	20.48	478.97	559.37
	SD	253.07		-0.95	9.79	234.55	269.47
	Skewness	-0.06	0.20	0.00	0.12	-0.29	0.18
	Kurtosis	-1. 09	0.39	0.01	0.11	-1.29	-0.81
Actual biomass	ObsNb	153		0.00	0.00		
	Mean	584.05		-0.03	36.50	514.85	657.14
	SD	454.95		-3.14	39.21	380.54	522.16
	Skewness	1.47	0.20	-0.04	0.21	1.09	1.74
	Kurtosis	2.71	0.39	-0.15	0.93	1.29	4.05

Descriptive statistics and correlations of similarity results with RMSE

Table 2 illustrates the results of the descriptive statistical analysis performed on the similarity estimates with the RMSE and the corresponding measures. Bias and confidence intervals at the 95% threshold achieved with 25,000 sub-samples.

Table 2 Descriptive statistics of similarity with RMSE

				Bootstrap			
						Confidence interval (95 %)	
		Statistics	Standard Error.	Bias	Standard Error.	lower	Upper
SimulatedBiomass (RMSE)	Obs Nb	172		0.00	0.00		
	Mean	430.35		-0.51	18.79	393.13	465.46
	SD	249.37		-0.96	10.65	228.85	267.30
	Skewness	0.36	0.19	0.00	0.11	0.15	0.58
	Kurtosis	-0.76	0.37	0.01	0.17	-1.04	-0.36
Actual biomass	Obs Nb	172		0.00	0.00		
	Mean	537.18		-0.04	32.02	475.12	601.12
	SD	415.85		-3.19	38.14	344.35	481.46
	Skewness	1.61	0.19	-0.08	0.29	1.01	1.94
	Kurtosis	3.93	0.37	-0.34	1.33	1.79	5.35

Nb: number; obs: observation; SD: standard deviation

Descriptive statistics and correlations of similarity results with MAD

Table 3 presents the results of the descriptive statistical analysis performed on the similarity estimates with the MAD and the corresponding measurements. Bias and confidence intervals at the 95% threshold performed with 25,000 sub-samples.

Table 3: Descriptive statistics of similarity with MAD

				Bootstrap			
						Confidence interval(95 %)	
		Statistics	Standard Error	Bias	Standard Error	lower	Upper
SimulatedBiomass(MAD)	ObsNb	173		0.00	0.00	173.00	173
	Mean	439.31		0.06	18.65	402.88	477.49
	SD	248.51		-1.13	10.53	225.92	267.81
	Skewness	0.32	0.18	0.00	0.11	0.10	0.54
	Kurtosis	-0.78	0.37	0.01	0.16	-1.06	-0.42
Measuredbiomass	ObsNb	173		0.00	0.00	173.00	173.00
	Mean	541.09		-0.83	30.61	483.52	600.32
	SD	396.31		-3.70	32.54	330.98	459.11
	Skewness	1.35	0.18	-0.07	0.27	0.68	1.76
	Kurtosis	2.76	0.37	-0.31	1.14	-0.09	4.58

Table 4 shows the results of Pearson Kendall and Spearman correlations between observations from similarity and observations measured at a significance level of 1%.

Table 4: Parametric and non-parametric correlations

Similarité	Pearson	Kendall	Spearman
SimulatedBiomass (R^2)	0.327**	0.262**	0.383**
SimulatedBiomass (RMSE)	0.447**	0.379**	0.521*
SimulatedBiomass (MAD)	0.459**	0.381**	0.540*

* Significant at the 10:100 level; ** significant at the 5: 100 level;

Parametric and non-parametric comparison of averages on a national scale

The comparison of the averages at the local scale shows for both tests especially those of t and Wilcoxson that there is no significant difference between the average of the estimates by the similarity by the R^2 and the mean of the measurements. The number of observations is 153 with a relative difference of -11%. On the other hand, the similarities with the RMSE and the MAD give significant differences. These two measures of similarity are practically equivalent in number of observations and in relative difference of averages almost equal to half that of R^2 (Table 5).

Table 5: Comparison of Simulated Means to Global Herbaceous Mass Measurements in T and Wilcoxon Tests by Similarity Measurements

Similarity criterion	actual Mean	Simulated Mean	Absolute Difference	ObsNb	Relative Difference	T Test	Wilcoxon'sTest
RMSE	537.18	430.35	106.83	172	0.20	0.0003***	0.0075*
R^2	584.05	519.60	64.45	153	-0.11	0.0734	0.7723
MAD	541.10	439.30	101.80	173	0.20	0.0003***	0.0035**

* significant at the 1 :100 level ; ** significant at the 5 :1000 level ; *** significant at the 5 : 10000 level ; Nb : number ; obs : observations.

3.1.2. T and Wilcoxon Tests by Year

The comparison of the means by the t test and the Wilcoxon test according to the years shows that: each year there is at least one test which indicates that the difference of the means between the results of the similarity and the actual data is Not significant. Concerning the parametric test, the examination of Table 6 shows that for R^2, three years, namely 2004, 2007, and 2012, gave significant differences; For the RMSE four years in particular 2006, 2007,2008 and 2010 are significant; For the MAD five years namely 2006, 2007, 2008, 2010, and 2012. Concerning the nonparametric test, it emerges from the examination of this same Table that for the R^2, three years namely 2004, 2005 and 2012 gave Significant differences; For the RMSE five years that are 2006, 2007,2008, 2010, 2012 are significant; For the MAD four years namely 2006, 2008, 2010, and 2012 are significant. In conclusion, we find each year at least one measure of similarity gives a difference not significant with the real average either in the t test or Wilcoxon. (Table 6).

Table 6: Parametric and non-parametric tests according to years

Year	Similarity criterion	Actual Mean	Simulated Mean	**obs nb**	Absolute Difference	Relative Difference	T Test	Wilcoxon'sTest
2001	**RMSE**	569.9	461.47	17	108.429	0.19	0.2242	0.2842
	R^2	503.79	582	10	78.206	0.15	0.4714	0.4131
	MAD	569.9	491.35	16	78.5467	0.13	0.3405	0.3778
2002	**RMSE**	340.18	356.21	19	-16.023	-0.04	0.7200	0.5678
	R^2	355.035	464.88	17	-109.85	-0.30	0.1114	0.1415
	MAD	357.365	371.44	17	-14.079	-0.03	0.7591	0.7987
2004	**RMSE**	260.896	312.86	15	-51.971	-0.19	0.1316	0.1514
	R^2	220.827	382.08	11	-161.26	-0.73	0.0137*	0.0210*
	MAD	280.168	344.5	15	-64.332	-0.22	0.0801	0.1046
2005	**RMSE**	520.778	497.16	18	23.6109	0.04	0.7931	0.8650
	R^2	613.271	456	17	157.271	0.25	0.1713	0.2462
	MAD	570.373	507	19	63.3735	0.11	0.5028	0.9854
2006	**RMSE**	700.063	393.71	14	306.349	0.43	0.0429*	0.0353*
	R^2	712.635	576.42	13	136.207	0.19	0.3539	0.8552
	MAD	700.063	391.78	13	308.277	0.44	0.0222*	0.0085*

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2007	**RMSE**	915.376	539	10	376.376	0.41	0.0136*	0.0488*
	R²	968.589	522.75	7	445.839	0.46	0.0017**	0.0156*
	MAD	934.554	557.55	8	376.999	0.40	0.0140*	0.0547
2008	**RMSE**	318.963	401.64	17	-82.684	-0.25	0.0224*	0.0348*
	R²	462.123	551.57	13	-89.448	-0.19	0.3551	0.0906
	MAD	318.963	401.88	17	-82.919	-0.25	0.0235*	0.0267*
2009	**RMSE**	457.015	355.61	13	101.399	0.22	0.3038	0.3054
	R²	443.952	465.25	11	-21.298	-0.04	0.8171	1.0000
	MAD	439.878	409.64	14	30.2352	0.06	0.7077	0.6698
2010	**RMSE**	763.04	502.71	14	260.326	0.34	0.0334*	0.0040***
	R²	867.291	605.06	15	262.229	0.30	0.1095	0.1167
	MAD	635.492	450.78	14	184.706	0.29	0.0178*	0.0085**
2011	**RMSE**	440.475	399.27	22	41.2019	0.09	0.3572	0.3021
	R²	478.425	496.18	15	-17.762	-0.03	0.8025	0.9399
	MAD	448.602	392.52	18	56.0761	0.12	0.2301	0.2253
2012	**RMSE**	1046.71	561.6	10	485.111	0.46	0.0596	0.0488*
	R²	989.65	582.72	10	406.923	0.41	0.0442*	0.0420*
	MAD	1048.95	554.83	11	494.115	0.47	0.0214*	0.0161*

* significant at the 1 :100 level ; ** significant at the 5 :1000 level ; *** significant at the 5 : 10000 level ; Nb : number ; obs : observations.

1.3. Ecoregions analysis

The results of the t and the Wilcoxon tests show that, the level of significance changes according to the ecoregions. Concerning the parametric test, it appears that, for the similarity measure R^2, Aïr and Manga2 gave significant differences; For RMSE, Azaouak and Manga2 showed significant differences; For the MAD, Azaouak and Manga2 showed significant differences. Concerning the nonparametric test, for R^2, Air and Manga2 gave significant differences; For the RMSE only the Manga2 gave a significant difference; For the MAD the differences are significant for Azaouak and Manga2. Finally, for AderDoutchiMagia, Air, Azaouak, Gourma and Manga1, we note that the averages obtained by similarity are not statistically different to the real averages. However, for Manga 2, the difference is significant for all tests and for all similarity measurements (Table 7).

Tableau 7 :Parametric and non-parametric tests according Ecoregions

Ecoregions	Similarity criterion	Actual Mean	Simulated Mean	**obs nb**	Absolute Difference	Relative Difference	T Test	Wilcoxon'sTest
ADM	**RMSE**	422.87	382.71	7	40.16	0.095	0.7232	0.8125
	R²	354.88	422.80	5	67.91	0.19	0.6162	0.6250
	MAD	422.87	404.29	7	18.59	0.04	0.8842	0.8125
AIR	**RMSE**	400.45	408.11	9	-7.66	-0.01	0.8274	0.9102
	R²	460.7	383.62	10	77.08	0.16	0.0379*	0.0488*
	MAD	400.45	408.22	9	-7.77	-0.01	0.8394	0.9102
AZ	**RMSE**	489.60	411.96	93	77.65	0.16	0.0275*	0.1602
	R²	575.51	535.13	76	-40.38	-0.07	0.4543	0.9877
	MAD	489.22	416.42	96	72.81	0.15	0.0146*	0.0446*
GR	**RMSE**	391.65	318.9	10	72.75	0.18	0.5022	0.8457
	R²	287.48	300.67	6	13.18	0.04	0.8287	0.8438
	MAD	391.65	324	10	67.65	0.17	0.5025	0.8457
MG1	**RMSE**	562.55	533.91	34	28.64	0.05	0.6235	0.9667
	R²	547.33	582.58	36	35.25	0.06	0.5354	0.6111
	MAD	563.40	537.11	35	26.29	0.05	0.6610	0.8980
MG2	**RMSE**	717.99	455.85	14	262.13	0.36	0.0224*	0.0107*
	R²	681.05	439.13	15	-241.92	-0.35	0.0087**	0.0181*
	MAD	872.57	512	12	360.57	0.41	0.0090**	0.0068**

* significant at the 1 :100 level ; ** significant at the 5 :1000 level ; Nb : number ; obs : observations.

3.1.4. Bioclimatic zone analysis

Table 8 shows the results obtained with t and Wilcoxon tests in bioclimatic zones. The level of significance of the difference observed between the averages is related to these areas and to the criteria of measurements of similarity. For the parametric test, the examination of this table shows that at the level of R^2, the differences observed in the Sahelian and Saharan zones are significant. On the other hand, in the North-Sahelian zone, they are not; For the RMSE and the MAD, the averages are significantly different in the northern Sahelian and Sahelian zones, whereas they are insignificant for the Saharan zone. As for the nonparametric test, the Table examination shows that for R^2, the averages are significantly different in the Saharan zone; On the other hand they are not for the Sahelian and northern Sahelian zones. For the RMSE and the MAD, there is no significant difference.

Tableau 8: Parametric and non-parametric tests accordingBioclimatic zone

bioclimatic Zone	Similarity criterion	Measured Mean	Simulated Mean	**obs nb**	Absolute Difference	Relative Difference	T Test	Wilcoxon's Test
North-Sahelian	RMSE	553.24	456.60	133	-96.64	-0.17	0.0022**	0.0415*
	R^2	593.91	521.13	116	-72.77	-0.12	0.0621	0.2302
	MAD	563.00	468.14	134	-94.86	-0.17	0.0014***	0.0187*
Sahelian	RMSE	1440.42	326.4	5	-1114	-0.77	0.0081**	0.0625
	R^2	1673.07	548.6	5	-1124.5	-0.67	0.0036***	0.0625
	MAD	1493.22	334.25	4	-1159	-0.77	0.0298*	0.1250
Saharan	RMSE	341.53	342.94	34	1.41	0.00	0.9628	0.9800
	R^2	378.13	509.46	32	131.33	0.34	0.0105*	0.0189*
	MAD	348.38	340.91	35	-7.47	-0.02	0.8060	0.7122

* significant at the 1 :100 level ; ** significant at the 5 :1000 level ; *** significant at the 5 : 10000 level ; Nb : number ; obs : observations.

3.2. Discussion

The descriptive statistical analysis with bootstrap carried out on the similarity data using the R^2 shows that the sample resulting from the similarity is normally distributed and the asymmetry and flattening (skewness, kurtosis) are in the interval [-1.96 ; +1.96] allowing, therefore, a parametric test. The observed biases are weak, which confirms that the results obtained are good and, therefore, applicable. On the other hand, the kurtosis of the measured data deviates from this interval, which recommends the use of a nonparametric test to make a comparison of the averages. Parametric and nonparametric correlations are all significant at the threshold of 0.01 and are lower than those of the MEIA model[49].

The descriptive analysis with bootstrap of the results of the similarity by RMSE shows that the asymmetry and the flattening of the sample are particularly well situated in an interval suggesting to carry out a parametric test, the biases being within acceptable bounds. On the other hand, the kurtosis of the actual data deviates a little too much from zero (3.96), which suggests a nonparametric test even if the law of large numbers allows us to consider the distribution as normal. The correlations of Pearson, Spearman and Kendall are all significant.

As for the descriptive analysis of the similarity results using MAD, the skewness and the kurtosis of the simulationresults are in the interval allowing a parametric test, the biases are acceptable. On the other hand, the kurtosis of the actual data is 2.76, therefore, quite high which suggests a nonparametric test.The correlations of Pearson, Spearman and Kendall are also all significant (Table 4).

The difference between the similarity criteria is confirmed by the variation of kurtosis. The evidenceis given by the difference of the number of observations obtained for R^2, MAD and

RMSE which are respectively 153, 172, 173 which confirms that the MSE and MAE have the same performance in similarity analysis (table5).They are Sensitive to aberrant observations contrary to the correlation coefficient that is less sensitive[26]. These results mean that on a global scale R^2 is more rigorousthan MAD and RMSE. The comparison of the means on the global scale shows that the results of the similarity by the R^2 can be used as proxy of the real data as ted by the relative difference of -11% between averages. On the other hand, the similarities by the RMSE and the MAD give significant differences. The latter are practically equivalent with a relative difference of 19% compared to observationaldata. Moreover, the comparison of the averages by T's test and Wilcoxon's test according to the years shows that there is at least each year a similarity criterion that allows the use of simulated data as proxy to the observed data. In 75% of the cases the R^2 allows the use of its results as proxy to the actual data. For RMSE and MAD, the results can be used in 66% and 59% of cases, respectively. When the results from the three measures of similarity are combined, it is found that every year there is at least one possibility of using the method successfully. However, it is important to note that the performance of R^2 is higher than that of RMSE and MAD. Examination of the results according to the ecoregions shows that the R^2 does not allow the use of similarity as a proxy in Air and Manga2. The same observations are made in parametric testing for RMSE and MAD in Azaouak and Manga2. Regarding the nonparametric test, the results shown by the RMSE do not allow the use of the data in Manga2, the MAD in Azaouak and Manga2. In conclusion, for AderDoutchiMagia, Air, Azaouak, Gourma and Manga1, the results from all these similarity measurements can be used as proxy to real data.However, the method is not conclusive for Manga2. It will then be necessary to look for other measures of similarity or other types of indices for the Manga2. According to the test of t for R^2, similarity cannot be used in the Sahelian and Saharan zones. On the other hand, it is usable in the northern Sahelianzone which is good information, because this zone contains 75% of the sites. The RMSE and the MAD are not usable for the northern Sahelian and Sahelian zones. On the other hand, they are usable in the Saharan zone, which gives a certain complementarity between the measures; The Wilcoxon test shows that for R^2 cannot be used in the Saharan zone but usable in the Sahelian and North Sahelian zones. The same cases are observed for RMSE and MAD. In the light of these first results, this complex approach, with imperfectly independent variables, may lead to difficultiesin the interpretation of the results. The data should be used with some caution because the average number of observations is about 13 for the R^2, 15 for the MAD and the RMSE, which is not a large enough amount of data for such an exercise especially considering the extent of the pastoral area of Niger. It is then necessary to continue the research by exploring other vegetation indices and agro meteorological data and other measures of similarity. For example, FAPAR can be explored, as a study carried out in the Sahel with Senegal data showed Pearson mean r correlations between the soil biomass and the FAPAR cumulative total in the Sahel and the pastoral part which are 0.78 and 0.75, respectively[60]. Also an obvious relationship was found between the NDVI-GPP and NDVI-FAPAR respectively 0.72 and 0.79[61].

4. Conclusion

The study is carried out using NDVI images from SPOT VEGETATION and MEIA forage biomass collected from 68 sites in the pastoral and agro-pastoral areas of Niger. The SPIRITS software is used to perform the similarity calculation between NDVI seasonal profiles from June to October over a 12-year period, using R^2, RMSE and MAD as criteria for measuring similarity. These results allowed to test the performance of the three similarity measuresby comparing the averages of the results obtained from the simulation and the fodder biomass measured in the field. At local level, the results indicate that the R^2 is more efficient than the RMSE and the MAD, which have virtually the same performances. Also, the results of similarity calculated with R² can be used as a proxy to the herbaceous phytomass measured *insitu*, as there is no significant difference between the simulated average and the mean measured at the 1% threshold. On the other hand, the results of the similarity calculated with the RMSE and the MAD are not usable. Parametric and nonparametric correlations are all significant at the 1% threshold. However, R² are low, ranging from 0.32 to 0.45. Therefore, there is a need for further research, as there are many studies that have shown very good links between certain indices such as FAPAR, EVI and LAI and above ground biomass.

5. References

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