# Combining spectral indices and statistics analysis to proposed a new risk of soil degradation method – application to the Cameroonians shores of lake Chad and its hinterland

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## 1. Context

In the far northern part of Cameroon, the shores of Lake Chad are in the most exposed zone to the risks of soil degradation due to environmental conditions, more severe climatic conditions and modes of uses and exploitation of natural resources (National Action Plan to combat Desertification (PAN/LCD) 2006). It is an area marked by degradation and decline of soil fertility, unsuitable cultivation practices, high extension of barren land, erosion, runoff, and decrease of fallows, overgrazing, and pesticides pollution (Elias Symeonakis and Drake 2010, Seignobos and Iyébi-Mandjek 2000.

*Figure 1: Cattle herd in pasture in far north Cameroon (source: La Tribune Afrique)*

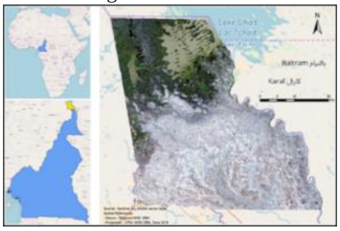

*Figure 4 : Localisation of the study area*

## Background

Several methods help quantifying and mapping soil degradation at different spatial and temporal scales (Terrence and Timothy, 2017). But most of them include several ancillary data as topography map, geology map or land use map, and also need to have field samples of study area (Daniel et al, 2018). Most of these data are not available at the all extend of our study area, that's why we need to developed a new and simple approach to highlighted soils degradation through remote sensing capacity.

## 2. Methodology

Two Sentinel 2 satellite images acquired on April 29, 2017 were used. These images have 13 bands, but only six of them were staked, that is Bands corresponding to blue, green, red, near infrared, Short Wave Infrared1 and 2.

To carry out this study, a total of four vegetation spectral indices and nine soils spectral indices are generated and combined to describe bare soils states, soils properties and vegetation cover.

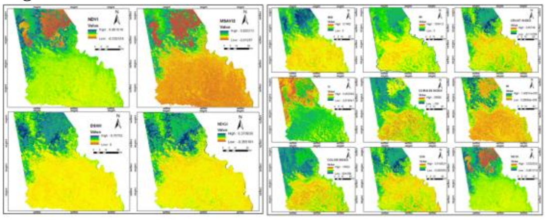

Figure 2: (a) the vegetation indices and (b) the soil indices

Then, all these indices are aggregate as one image (independent variable) and correlated with individual indices (dependent variable) to have correlations and determinations coefficients. Next, principal Component Analysis and factorial analysis are applied to all spectral indices to summarize information, have factorials coordinates and to detect positive and negative correlation. Finally, the model equation is obtained by index weighting with the respective values of the coefficient of determination and factorials coordinates.

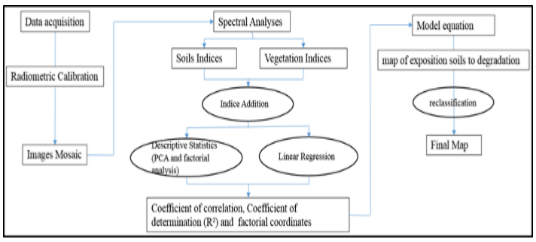


*Figure 3: the flowchart of the methodology*

## References

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## 3. Results

### 3.1 Linear regression

The purpose is to highlight the potential regressions between the synthetic image used here as an explanatory variable, and each of the spectral indices used as variables to explain. It thus appears that NDVI, DSWI, NDGI, TI and the redness index are negatively correlated to the synthetic image. The index most strongly determined by the synthesis image is the brightness index. For vegetation indices, the $R^2$ values are contained between 0,007 and 0,592.

*Table 1: Statistics relations between synthetic image and indices*

| Indices | Correlation Coefficient | Determination Coefficient | P values | |
|---|---|---|---|---|
| | | | Threshold | Test |
| **NDVI** | -0,119 | $R^2$=0,014 | $P < 0{,}0001$ | Important |
| **MSAVI2** | 0,081 | $R^2$=0,007 | $P < 0{,}0001$ | Important |
| **DSWI** | -0,747 | $R^2$=0,558 | $P < 0{,}0001$ | Important |
| **NDGI** | -0,769 | $R^2$=0,592 | $P < 0{,}0001$ | Important |
| **MSI** | 0,743 | $R^2$=0,552 | $P < 0{,}0001$ | Important |
| **BI** | 0,953 | $R^2$=0,909 | $P < 0{,}0001$ | Important |
| **Crust index** | 0,662 | $R^2$=0,438 | $P < 0{,}0001$ | Important |
| **TI** | -0,606 | $R^2$=0,367 | $P < 0{,}0001$ | Important |
| **Cuirass index** | 0,942 | $R^2$=0,887 | $P < 0{,}0001$ | Important |
| **Redness index** | -0,827 | $R^2$=0,684 | $P < 0{,}0001$ | Important |
| **Colour index** | 0,662 | $R^2$=0,438 | $P < 0{,}0001$ | Important |
| **GSI** | 0,685 | $R^2$=0,470 | $P < 0{,}0001$ | Important |
| **NDSI** | 0,119 | $R^2$=0,014 | $P < 0{,}0001$ | Important |

### 3.2 Descriptive statistics

The first two factors of PCA and factorial analysis explain respectively 87.54% and 85.62% of the common variability of the characteristics measured. The first factor contains soil information and the second factor focuses information on vegetation.

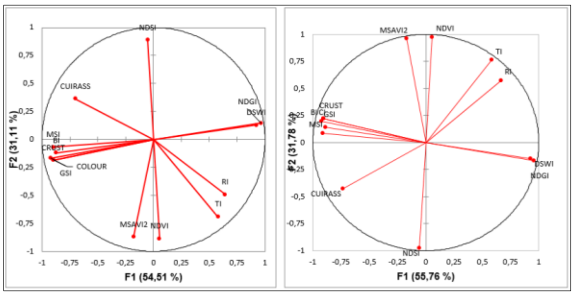


*Figure 5: correlations between variables and factors*

### 3.3 Equation of the model

The index maps are weighting with their coefficient of determination to highlight the individual contribution of each index, and their highest values of factorial coordinates obtained through the factorial analysis and the PCA in order to preserve the best information provided by each of these methods of analysis. This information is combined to compose the following equation:

ndvi*(xmax+Ymax)*$R^2$ + msavi2*(xmax+Ymax)*$R^2$ + dswi*(xmax+Ymax)*$R^2$ + ndgi*(xmax+Ymax)*$R^2$+ msi*(xmax+Ymax)*$R^2$ + bi*(xmax+Ymax)*$R^2$ + crust index*(xmax+Ymax)*$R^2$ + ti*(xmax+Ymax)*$R^2$ + cuirass index*(xmax+Ymax)*$R^2$ + ri*(xmax+Ymax)*$R^2$ + colour index*(xmax+Ymax)*$R^2$ + gsi*(xmax+Ymax)*$R^2$ + ndsi*(xmax+Ymax)*$R^2$ = **RISK OF SOILS DEGRADATION**

### 3.4 Final map

The result of this modelling is a map of risk exposition soils degree to agents and degradation factors. The potential soils exposition state is classified on the map below in five levels of exposition risk from the lower level to the higher.

The "Lower" and "Moderate to low" levels cover occupy respectively 25,214.35 hectares and 130,717.19 hectares. The "Moderate" level of exposition spreads sparsely over an area of 137,404.34 hectares. With 152371.91 hectares, the "High to moderate" level represents the most widespread state of exposition. The "Higher" level occupies 29175.73 hectares.

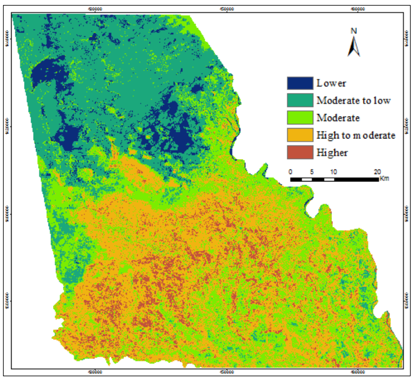


*Figure 6: map of soils exposition risk to degradation*

## 4. Conclusion

The sequential image processing developed in this study allows to model, classify and analyse the soils potentially exposed to the risk of degradation from Sentinel 2 image of April 29, 2017. Thanks to combined techniques of image processing as indices calculation, linear regression, factorial analysis and principal component analysis, the problem of ancillary data and field samples has been skirted and the potential soil degraded highlighted. The results obtained show the spatial distribution of different soil's risk level of degradation throughout the study area, the soil and vegetation influence for each level of risk, and the distribution of these level of risk according to their proximity to the lake.