

## Drought monitoring using soil water index and normalized difference vegetation index time series in Moroccan rangelands

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*Abstract:* - Drought phenomenon is one kind of a disaster that can significantly affect the density of vegetation in any area, especially dry regions. In rangelands of Morocco, it is essential to understand sensitivity of vegetation to soil moisture stress on different classes of land cover and corresponding temporal response to improve prediction of drought and yield anomaly. This study tries to express drought effect on vegetation cover in Moroccan pastoral areas. At first, annual average of soil water index (SWI) derived from MetOp-A /ASCAT data (11 km spatial resolution) and Normalized Difference Vegetation Index (NDVI) derived from Moderate Resolution Spectro-Radiometer eMODIS-TERRA (250 m spatial resolution) was calculated from 2007 to 2017. Afterward, rangelands were classified into three groups including no vegetation (degraded areas), poor vegetation (sparse), and dense vegetation (shrub). Results showed a high correlation between SWI and NDVI of all rangelands. This relationship is strong for shrub rangeland, there were strong positive correlation coefficients for NDVI and SWI ( $R^2 = 0.96$ ). Moderate correlations were explain for degraded and sparse rangeland ( $R^2 = 0.54$  and  $0.52$ ) respectively. Drought monitoring using disaggregating SWI anomaly time series in these rangelands in Morocco offers possibility of operational use of soil moisture data at high resolution. The results of anomalies shows a range high than 90 %, this explains that our method is important for characterizing dryness related to soil moisture stress for all Moroccan rangelands. Remote sensing is important to rangeland drought monitor, from the security of water resources to the mitigation of water hazards in the context of climate change. This dryland ecosystem should be managed in a way that enables them to provide ecosystem services that meet human demands for social development. Prediction drought should provide sufficient motivation to reach a consensus on unified water and vegetation management throughout the region.

*Key-Words:* - Drought, Normalized Difference Vegetation Index (NDVI), Soil moisture Index (SWI), Different types of Moroccan rangelands, remote sensing

## 1 Introduction

Drought is one of the costliest natural disasters that can lead to a reduction in water supply, deteriorate water quality and finally forage disappointment (Riebsame et al., 1991[1]). Drought is especially a concern for rangeland management. In the rangeland, drought effects on vegetation lead to significant consequences concerning livelihood and socio-economic development. In fact, water deficiency during droughts has led to a reduction in forage and livestock production (Dutta et al., 2015 [2], Knutson and Fuchs, 2016 [3], Derner and Angustine, 2016 [4]). In rangelands of northern Africa in particular, drought is the most important natural phenomenon linked to climate change, which continuously affects large areas of rangeland and therefore has serious repercussions forage production, population life expectancy and the economic performance.

A monitoring system that is able to deliver timely warnings of droughts can contribute toward the making of appropriate and timely decisions in response to drought in rangeland areas. Rainfall is one of the most important parameters that provide information on water availability and potential occurrence of drought (Velpuri et al., 2016 [5]). Generally, drought monitoring has been based on weather station observations, which we do not have continuous spatial coverage needed to characterize and monitor detailed spatial pattern of drought conditions.

However, several recent studies have indicated the occurrence of the opposite pattern, namely "dry becomes wet, wet becomes dry" (Greve et al., 2014 [6]). The average precipitation in the arid regions has increased in both measured data and climate models over the past 30 years (Donat et al., 2016 [7]). The temperature change and alternation of precipitation may have both positive and negative impacts on the fragile ecosystem of arid and semi-arid regions (Yang et al., 2019 [8]).

In recent decades, several studies have used remote sensing data to monitor a variety of dynamic land surface processes (Anderson et al., 2007[9], Reed et al., 1994 [10], Yang et al., 1998 [11], Peters et al., 2002 [12]). Satellite remote sensing provides a synoptic view of earth and a spatial context for measuring the impacts of drought. The spatially and temporally continuous coverage offered by satellite data enhances the value of these drought monitoring products. Currently, the normalized difference vegetation index (NDVI) data play an important role in ecosystem monitoring (Kogan, 1995 [13], Gu et al., 2007 [14], Brown et al., 2008 [15]). NDVI which is the normalized reflectance difference

between the near infrared and visible red bands (Rouse et al., 1974 [16], Tucker, 1979 [17]) is used extensively in monitoring of vegetation drought. Using NDVI in drought monitoring and assessment has been described several times during the last (Kogan, 1991 [18], Kogan, 1995 [13], Yang et al., 1998 [11], McVicar and Bierwirth, 2001 [19], Heim, 2002 [20], Ji and Peters, 2003 [21], Ntale and Gan, 2003 [22], Wan et al., 2004 [23], Dai et al., 2004 [24]). Farrar et al. (1994) [25] are examined variability of NDVI over semiarid for different soil types. Richard and Pocard, (1998) [26] are demonstrated sensitivity of NDVI to seasonal and interannual rainfall variations in southern Africa.

Similarly, soil moisture is widely recognized as essential for drought risk assessments as well as vegetative stress predictions (Robinson et al., 2008 [27], Dobriyal et al., 2012 [28]). Soil moisture is depleted; gradients in soil water potential gradually degrade, negatively affecting vegetation. Soil moisture droughts can be defined as a lack of soil moisture causing vegetation disappointment (Cammalleri et al., 2016 [29]). Soil moisture can be measured locally at the desired temporal resolution and depth using in situ techniques. However, in situ soil moisture observations are lacking over large spatial scales (Ochsner et al., 2013 [30]). Exploiting remote sensing for soil moisture monitoring has attracted great interest. In fact, a number of techniques to derive spatiotemporal estimates of soil moisture from satellite retrievals are now available. However, there are currently various reliable and feasible methods available to measure soil moisture content from point scale to global scale. The development of highly accurate measurement techniques, efficient data loggers and data transmission systems allow continuous monitoring. As an alternative, remote sensing data can be employed to obtain continuous and large-scale measurements of soil moisture (Njoku and Entekhabi, 1996 [31], Fernández-Prieto et al., 2012 [32], Kornelsen and Coulibaly, 2013 [33], Xu et al., 2014 [34]).

The Copernicus Global Land Service (CGLS) provides a series of bio-geophysical products on state and evolution of Earth's surface on a global scale. Soil Moisture Index (SWI) is estimated in a timely manner and supplemented by long-term time series. In regional analyses for East Africa, soil moisture index anomalies for the year 2017 were in good agreement with vegetation health index and rainfall data provided by (FAO, 1987 [35]) illustrating SWI product's ability to reflect large-scale hydrological patterns and their impact on vegetation health. In particular, SWI seems to be

very sensitive to hydrological droughts. Finally, strong dynamics of soil moisture on a large scale is evident in SWI dataset, giving us confidence in the quality of the product (Bauer-Marschallinger et al., 2018 [36]). Analysis of SWI and NDVI showed a subsequent increase in soil moisture and vegetation moisture content. On contrary, NDVI was stable or decreased in some cases due to low vegetation cover and moist soil background (Hunt et al., 2009 [37]).

In Morocco, density and quality of climatic observations are better than in most other parts of northern Africa, but still relatively rare compared to Europe (Born et al., 2008 [38]). The analysis of climate and climate variability always starts with acquisition of observational information in a region of interest. Also, soil moisture can be measured by various methods in the field or by spatial remote sensing unfortunately in Morocco; networks that can provide us with information on the state of flawless soil moisture are non-existent. However, in the study of rangeland drought, hydrological indices should also be used with vegetation indices to provide a clear picture of rangeland drought.

The objective of this study is to propose a simple and accurate method for drought assessment using remote sensing time series in particular for the case of rangeland in arid region of North Africa. It is based on two satellite products having different spatial resolutions, namely eMODIS NDVI and Copernicus Global Land Service Soil Water index.

## 2 Materials and Methods

### 2.1 Study area

The study area is Moroccan rangelands representing a total area about 53 million hectares (Figure 1). These rangelands are ecosystems with natural or semi-natural vegetation contributing to the

livelihood of thousands of low-income rural people (Mahyou et al., 2010 [39]). They are found in regions where isohyets are less than 600 mm/year (Le Houérou, 2006 [40]).

According to Global Land Cover classification we considered three types of rangelands. For simplicity, the “rangelands” in this study represents a combination of degraded rangeland sparse vegetation, and shrub rangeland covering respectively (68 %, 25 %, and 7 %) of the total rangelands areas. Based on the ecosystem characterized by heterogeneous vegetation. Shrub rangelands are dominated by *Rosmarinus officinalis*, *Pistacia lentiscus*, *Acacia raddiana*... ect. Sparse rangelands are dominated by *Artemisia herba-alba*, *Stipa tenacissima*, *Lygeum spartum* and degraded rangelands by *Noaea mucronata*, *Atractylis serratuloides*, *Anabasis aphylla*, *Peganum harmala*. We also find *Asphodelus microcarpus* and *Urginea maritima* (Le Houérou, 2006 [40], MARA, 1992 [41], Mayaux et al., 2004 [42]). Soils are generally poor in organic matter and largely dominated by lithosols. Some rangelands are located on a sandy or loamy-clay substrate (Etienne, 1996 [43]). The most part of Moroccan rangelands has a collective status, and are the main source of feed for livestock, which covered a third of the total food needs. The livestock sector covers about 1 100 000 rural households (Narjisse, 2006 [44]). Rangelands of Morocco are suffering from human-induced degradation, mainly due to overgrazing and cultivation combined to drought. As a result, erosion caused by wind and/or water, soil degradation and the long-term loss of vegetation cover (UNCCD, 1994 [45], Berkat et al., 2004 [46], Aïdoud et al., 2006 [47]).

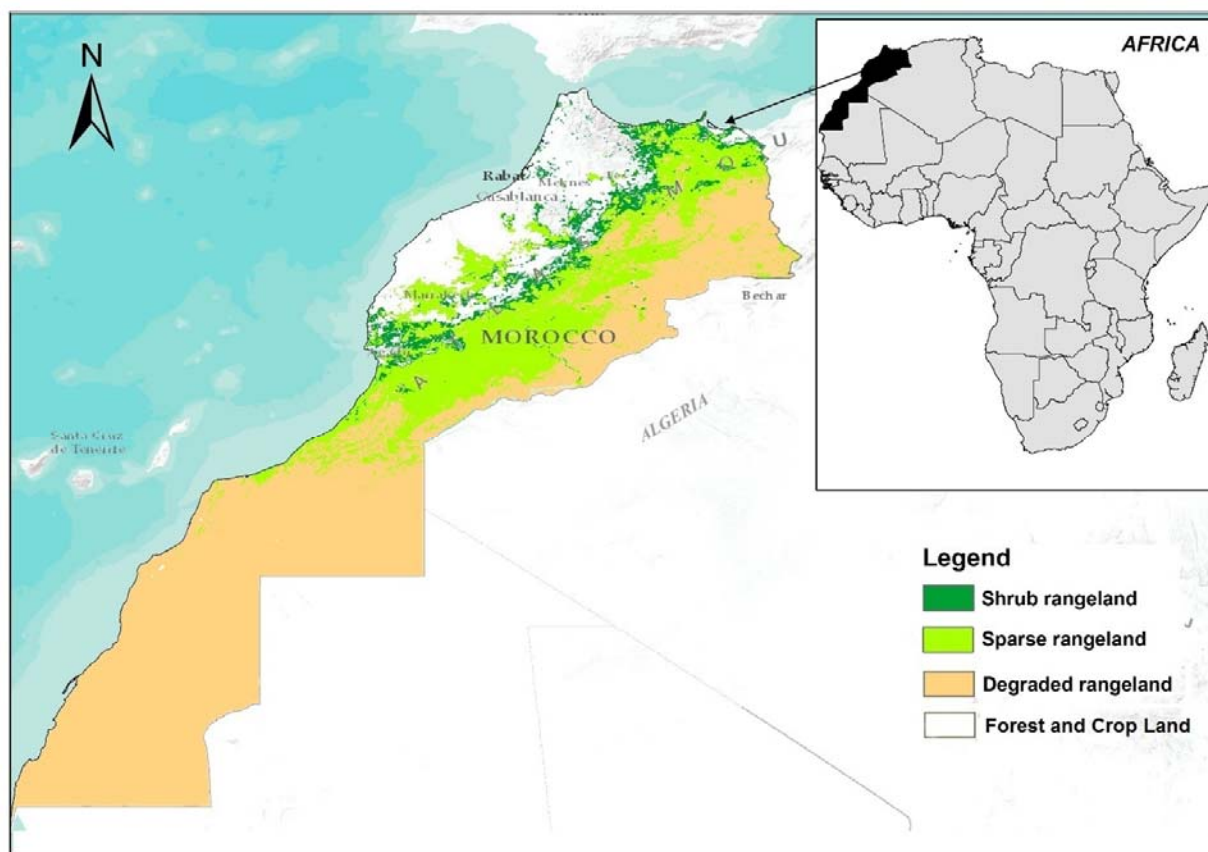


Fig 1. Location of the study area in Moroccan rangelands, illustration of three groups including no vegetation (degraded areas), poor vegetation (sparse), and dense vegetation (shrub) (Mayaux et al., 2004 [42]).

## 2.2 Remote sensing data acquisition and preparation

### 2.2.1 Soil Moisture Index (SWI)

The time series of 360 decadal SWI images, starting from September 2007 to August 2017 are used. These data are derived from the Copernicus Global Land Service Soil Water index (CGLSSWI) version 3 with a spatial resolution of 11 km. The pixel values of these experimental sites are extracted with a land cover mask Global Land Cover 2000 (GLC 2000) according to three classes of shrub, sparse and degraded areas (Mayaux et al., 2004 [42]).

The soil moisture index (SWI) is physically defined as soil moisture content at the first meter of soil relative units between the wilting level and the field capacity. The unit is the percentage (%) and physical range of parameter values from 0 to 100.

The SWI algorithm, initially developed at the Technical University of Vienna and later improved by other research groups, uses an infiltration model that describes relationship between surface soil moisture and soil moisture over time. The algorithm

is based on a two-layer water balance model to estimate soil moisture ( $m_s$ ) profile extracted from the MetOp-A / ASCAT data (Wagner et al., 1999 [48]).

In this model, water content of reservoir layer is described in terms of index, which is only controlled by previous soil moisture conditions in surface layer, so that the influence of the measurements decreases with increasing time as shown in Equation (1):

$$SWI(t_n) = \frac{\sum n_i m_s(t_i) e^{(t_n - t_i)/T}}{\sum n_i e^{(t_n - t_i)/T}} \quad (1)$$

Where  $t_n$  is the observation time of the current measurement and  $t_i$  are the observations times of the previous measurements.

### 2.2.2 eMODIS NDVI data

Ten-year's average-value composite NDVI images at 250 m spatial resolution were exploited to drought monitoring. Images used in this study belonged to the eMODIS collection developed by

the United States Geological Survey's (USGS) and Earth Resources Observation and Science Center (EROS). The data acquired by the MODIS on board NASA's Moderate-Resolution Imaging Spectroradiometer Terra and Aqua satellites (Jenkerson et al. 2010 [49]).

The sensor provides high temporal resolution images, which are very useful for monitoring significant environmental changes (2). The NDVI averages were obtained by the final processing of the eMODIS-based inputs which consisted of the spatial segmentation of the imageries using a mask surrounding Moroccan rangeland and Global Land Cover 2000 (Mayaux et al., 2004 [42]).

$$\text{NDVI} = (\text{NIR}-\text{R})/(\text{NIR}+\text{R}) \quad (2).$$

Where NIR is the Near infrared and R is the Red.

### 2.3 Anomaly indices

Anomaly indices for the NDVI and SWI which provides a quantitative illustration of vegetation and soil moisture stress and the influence of drought on the vegetation. These indices are based on statistics derived from the NDVI and SWI time series and were referred to as the vegetation and moisture anomaly indices written as shown in Equation (3) and (4):

$$\text{NDVI anomaly} = (\text{NDVI}_i - (\text{NDVI}_i)_{\text{mean}} / \text{std}(\text{NDVI}_i)) \quad (3).$$

And

$$\text{SWI anomaly} = (\text{SWI}_j - (\text{SWI}_j)_{\text{mean}} / \text{std}(\text{SWI}_j)) \quad (4).$$

Where  $\text{NDVI}_i$  is the NDVI estimate for a given period  $i$  (from February to April),  $(\text{NDVI}_i)_{\text{mean}}$  is the mean value of the NDVI during period  $i$ , derived from the previously described 10 years of NDVI time series and  $\text{std}(\text{NDVI}_i)$  corresponds to the standard deviation of the NDVI values estimated for period  $i$  over the same 10-year period.

Where  $\text{SWI}_j$  is the SWI estimate for a given period  $j$  (from November to February),  $(\text{SWI}_j)_{\text{mean}}$  is the mean value of the SWI during period  $j$ , derived from the previously described 10 years of SWI time series; and  $\text{std}(\text{SWI}_j)$  corresponds to the standard deviation of the SWI values estimated for period  $j$  over the same 10-year period.

The parameters these are for calculating this anomaly are required (First year, Last year) and it is important to include the year of the output IMG date in the calculation.

The processing of Soil water index and eMODIS vegetation index data was done by Software for the Processing and Interpretation of Remotely Sensed

Image Time Series (SPIRITS). This software is based in java, aiming at the analysis of remotely sensed earth observation data. Although it includes a wide range of general purpose functionalities, the focus lies on the processing of time series of images. It can be used to perform and to automatize many spatial and temporal processing steps on time series. Statistics can be plotted in seasonal graphs to be shared with analysts and decision makers (Eerens et al., 2013 [50]).

### 2.4 Statistical Analysis

The global analysis of SWI and NDVI data were performing by one-way analysis of variance and comparison of means using the Least Significant Difference (LSD) method ( $p < 0.05$ ). Minimum, maximum, mean and coefficient of variation values were derived for the complete data set for SWI and NDVI. The monthly SWI and NDVI were compared by using Variance Analysis method (ANOVA).

Polynomial regression models, linking SWI and NDVI were developed. The average SWI from November to February of shrub rangeland, sparse vegetation and degraded rangeland are correlated to average of NDVI from February to April. NDVI and SWI are established for all Moroccan rangelands and for each rangelands categories (shrub, sparse and degraded rangelands).

### 2.5 Spatial Analysis

The primary datasets of SWI employed in this study are acquired from MetOp-A / ASCAT at a spatial resolution of 11 km. Using statistical regression between NDVI and SWI we estimate SWI1 with 250 m as shown in Equation (5):

$$\text{SWI1} = a * (\text{NDVI})^2 - b * (\text{NDVI}) + c \quad (5).$$

Keeping us the residual image and we adding back original image values. DisPATCH stands for Disaggregation based on Physical and Theoretical Scale Change (Merlin et al., 2012 [51]). It is also described as theoretical because the change of scale relies on mathematical tools with ArcGIS raster calculator.

According to the studies of Carlson et al. (1986) [52], (1994) [53], (1995) [54] there is a relationship among soil moisture, NDVI, and LST, which can be expressed through a regression formula. It is possible to change of soil moisture scale from 11 km to 250 m based on this relationship (Bindhu, 2014 [55], He et al., 2015 [56]).

## 3 Results

### 3.1 Tendency of NDVI and SWI

The temporal evolution of monthly values of NDVI and SWI, spatially averaged over all Moroccan rangelands between 2007 and 2017 is presented in Figure 2. Time series of monthly NDVI and SWI from September to August are also shown for three different types of rangeland (shrub, sparse and degraded rangeland). It may be noted that information about the rangeland type was obtained from the Global Land Cover 2000 database (Mayaux et al., 2004 [42]).

Nevertheless, NDVI and SWI values have varied between years. For all rangelands categories, NDVI values was relatively high in 2008-09, 2009-10, 2010-11, 2012-13, and low in 2007-08, 2013-14 and 2015-16, and coincided with peaks and troughs in growing season NDVI. For shrub rangeland, low SWI values appeared in 2007-08, 2011-12, 2013-14, 2014-15 and 2015-16, and peak values appeared in 2008-09, 2009-10, 2010-11, 2012-13 and 2016-17. For sparse rangelands, all low SWI values appeared in 2007-08, 2010-11, 2014-15, 2015-16, and peak values appeared in 2008-09, 2009-10, 2011-12, 2012-13 and 2016-17. For the degraded rangeland, high SWI values occurred in 2008-09, 2009-10, 2011-12, 2012-13 and 2016-17 and low values occurred in 2007-08, 2013-14, 2014-15 and 2015-16.

In different time series there was a significant difference between the rangeland categories. The degraded areas had the lowest average NDVI values, which differed little between peak and low growth season because of the very low vegetation cover. These results suggest that the occurrence of

November to February in all categories. The lower SWI values are observed during June in all categories of rangelands. A significant difference was observed in the SWI series, between the 10 years for November to February (Table 1).

However, for the other months the difference is non-significant between years. The correlations

contrasting temporal trends in the overall area depends on the nature of the land cover, with well-vegetated areas undergoing an increase in vegetation activity and degraded areas suffering a process of further degradation.

However, the time variability of the NDVI may also be explained by the evolution of climatic conditions, as discussed below. The shrub rangeland had higher NDVI values with an average equal to 0.32 (CV = 19 %). The degraded rangelands had the lowest average NDVI values (mean = 0.17 and CV = 10 %), which differed little between months and years caused by a low vegetation cover. The sparse rangelands had an average NDVI of 0.20 (CV = 26 %). The important average NDVI values occurred between February to April in all categories. The NDVI values showed positive temporal trends for all categories, particularly for shrub and sparse rangeland where the trends were almost significant. The lower NDVI values are observed during August for different categories of rangelands.

These results suggest an increase in vegetation activity during spring, when the conditions for growth are best. In all cases, a very high significant difference can be observed in the NDVI series, between the 10 years for the months of February, March and April (Table 1). However, for the other months the difference is non-significant. The shrub rangeland had higher SWI values with an average of 24 % (CV = 50 %). The degraded rangelands had the lowest average SWI values (mean = 15 % (CV = 23 %)) and the sparse rangelands had an average SWI corresponding to 18 % (CV = 24 %). The shrub rangeland had higher SWI values, and the important average SWI values occurred between were moderate for degraded and sparse rangeland ( $R^2 = 0.54$  and  $0.52$ ) respectively. However, for shrub rangeland, there were strong positive correlation coefficients for NDVI and SWI ( $R^2 = 0.96$ ).

	<b>All</b>		<b>Shrub rangeland</b>		<b>Sparse rangeland</b>		<b>Degraded rangeland</b>	
	NDVI	SWI	NDVI	SWI	NDVI	SWI	NDVI	SWI
<b>Mean</b>	0.23	19	0.32	24	0.2	18	0.17	15
<b>Minimum</b>	0.16	10	0.22	9	0.13	10	0.14	9
<b>Maximum</b>	0.32	36	0.44	56	0.34	31	0.22	25
<b>Std Dev</b>	0.04	6	0.06	12	0.05	4	0.02	3
<b>CV</b>	19	33	19	50	26	24	10	23

<b>R2</b>	0.92	0.91	0.96	0.75	0.52	0.53	0.54	0.59
<b>p-value</b>	<,0001*	<,0001*	<,0001*	0.0078*	0.0765	0.0705	0.0660	0.0432*

Table 1. NDVI and SWI statistic for each rangeland category; R2 and p-value for year's comparison.

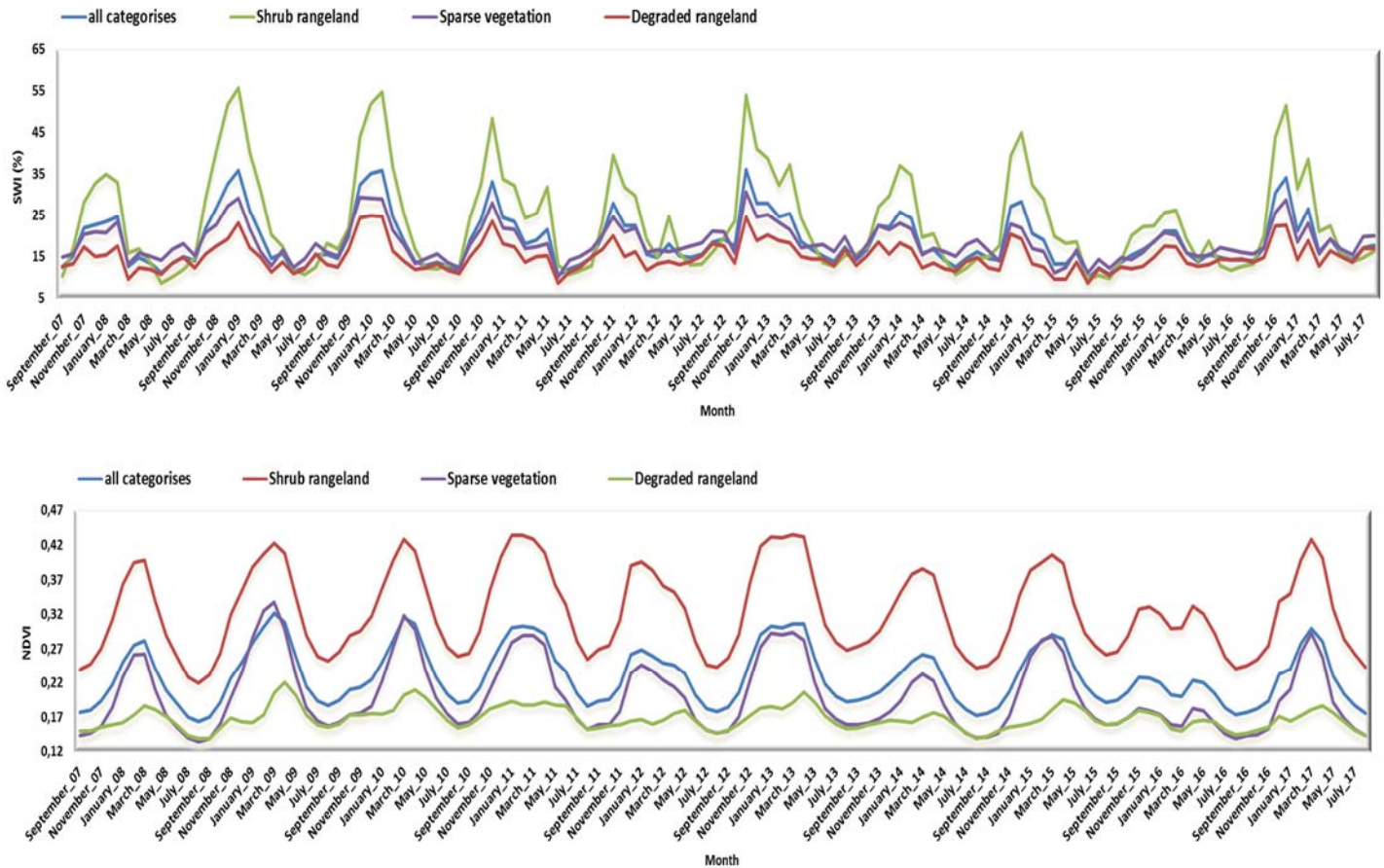


Fig 2. Monthly time-series between 2007 and 2017 of SWI and NDVI averaged over all Moroccan rangelands; and for three types (degraded areas), (sparse), and (shrub) of Moroccan rangeland.

### 3.2 Anomaly detection

Figure 3 shows SWI and NDVI anomalies calculated for ten years from 2007 to 2017 in pastoral areas of Morocco. The negative anomalies of SWI and NDVI are visible during 2007-08, 2011-12 and 2013-14. These negative anomalies actually represent a complete failure of the all seasons. However, the number of failures observed for 2014-15 exceeds all previously observed records. Severe negative anomalies of NDVI were observed during 2015-16, with very poor growth conditions observed for all rangelands of Morocco. Normal vegetation conditions are observed during 2014-15.

The anomalies of rangeland vegetation during early spring (February to April) mainly reflect the anomalies of soil moisture for the winter period (November to February). During dry years, negatives anomalies can be observed for both types

of values NDVI and SWI. The years characterized by fairly good vegetation are characterized by higher water conditions during the winter. With the exception of the year 2014-15, where the bad water conditions are observed during the period with normal vegetation.

Discrepancies between the NDVI and SWI anomalies are also present during 2014-15; we observed negatives anomalies of SWI and absence of NDVI anomalies. The reason for this disagreement can be explained by the good temporal distribution of rainfall. In fact, the temporal distribution of rainfall can be important as the total amount to determine the development of vegetation. Therefore, even if the accumulated soil moisture was low, this delay anomaly eventually led to a normal development of vegetation.

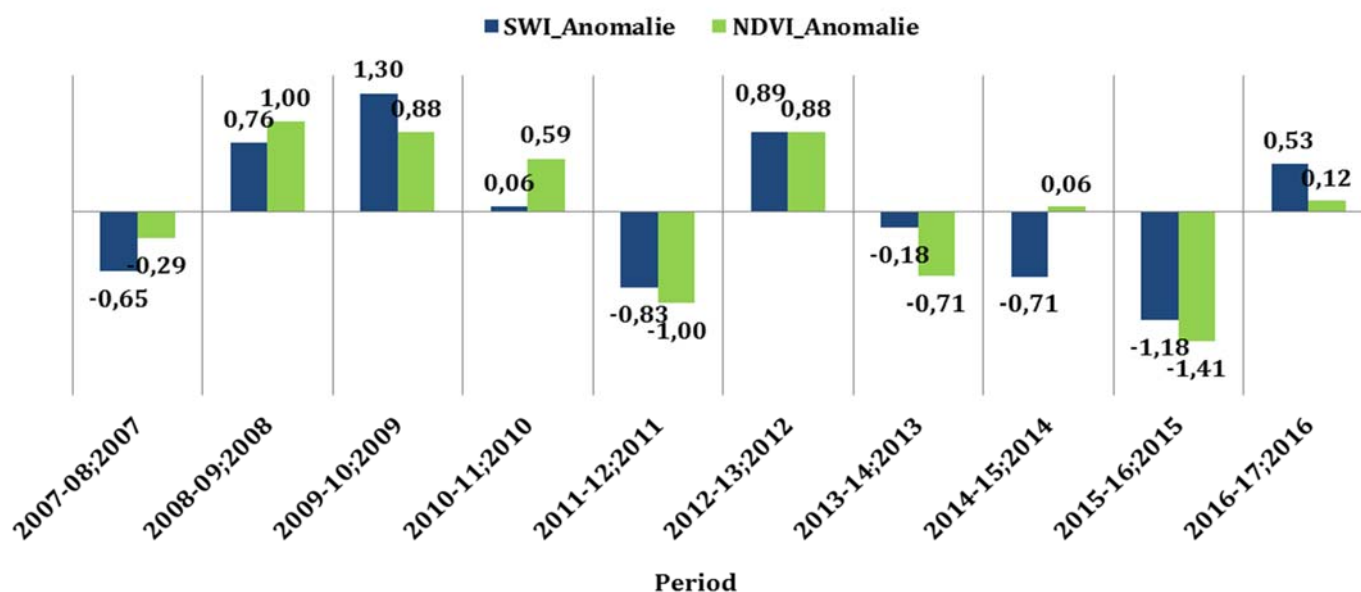


Fig 3. NDVI and SWI anomalies of all Moroccan rangelands from 2007 to 2017.

### 3.3 Relationship between NDVI and SWI

It can be seen from the above analysis that SWI can affect NDVI, and the effect of SWI seems more significant than the effect of rainfall. The effects of SWI and NDVI varied for different rangeland types; therefore, we conducted correlation analyses for all Moroccan rangeland and separate correlation analyses for each rangeland type to compare the differences between them.

In the first, the correlation is explain between realy SWI at 11 km and NDVI at 250 m. Figures 4, 5 shows that the polynomials correlations coefficients for NDVI and SWI were all much higher. For all, average NDVI (from February to April) correlated strongly with average SWI (from November to February) ( $R^2 = 0.93$ ;  $R^2 = 0.92$ ). Liners correlations were estimated between actual and predicted NDVI and SWI ( $R^2 = 0.92$ ;  $R^2 = 0.93$ ).

The vegetation indices are known to correlate with moisture index values (Carlson et al., (1986) [52], (1994) [53], (1995) [54], Kramer and Boyer, 1995 [57], Rodriguez-Iturbe, 2000 [58]) and this trend can be clearly observed during the rainy seasons. In dry years, there is an exceptionally large decrease in the humidity index, associated with stabilization or even a decrease in the NDVI. The tendency of soil moisture and vegetation index of the three types of rangeland is very similar.

The regression models generally fitted the observed NDVI values well, although for all rangeland areas in November to February. A better fit was obtained in November to February for well vegetated areas (shrub, and sparse rangeland) than for less vegetated regions (degraded rangeland), as shown by the lower  $R^2$  values. However, there were differences between land cover classes. The effect of the soil moisture was positive in all cases, with high moisture yielding elevated NDVI values. This reflects the importance of moisture at the winter, at the start of the growing period. The high correlation between SWI and NDVI shows that the model based on the soil moisture index is excellent compared to rainfall in Morocco pastoral areas.

This result demonstrates the feasibility of using a polynomial regression to estimate the NDVI, which can be particularly useful for making rapid diagnostics in drought periods, using just two types of satellite data, without the need for physical models. Preliminary regional estimations of the expected vegetation growth could thus be proposed, without the need to analyze satellite images. With such an approach, it is also possible to make preliminary estimations of vegetation growth as a function of different scenarios (Zribi et al., 2011 [59]). We also supposed that disaggregate SWI data to 250 m can increase correlation factor.



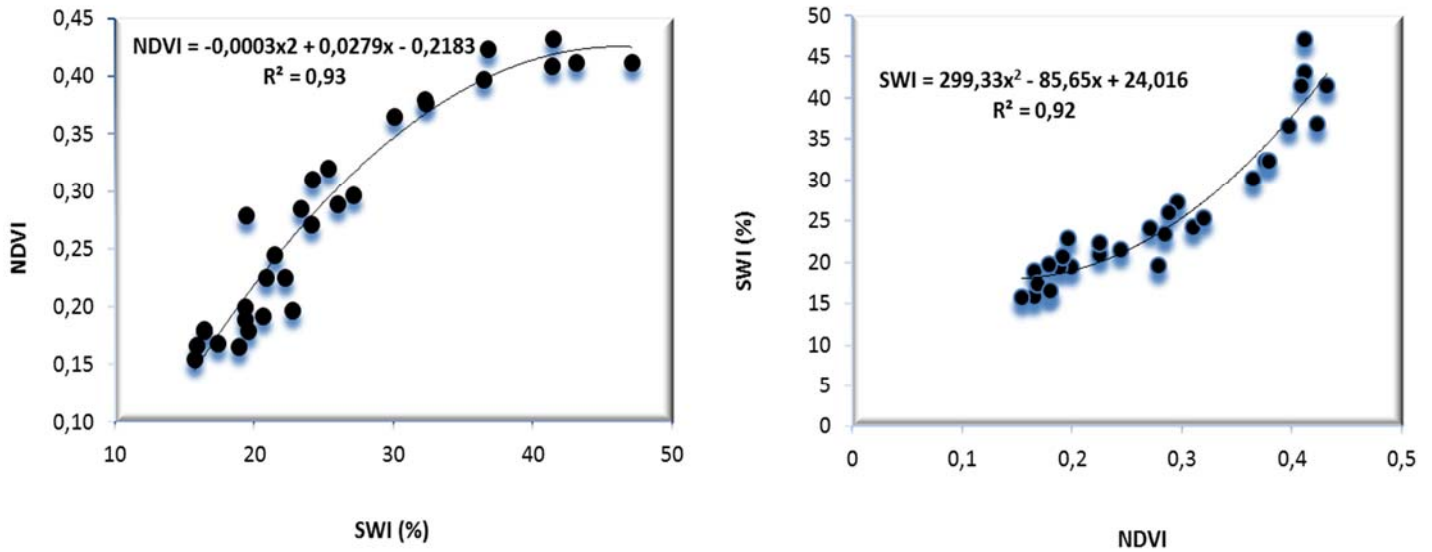


Fig 4. Correlation between SWI and NDVI of all Moroccan rangelands.

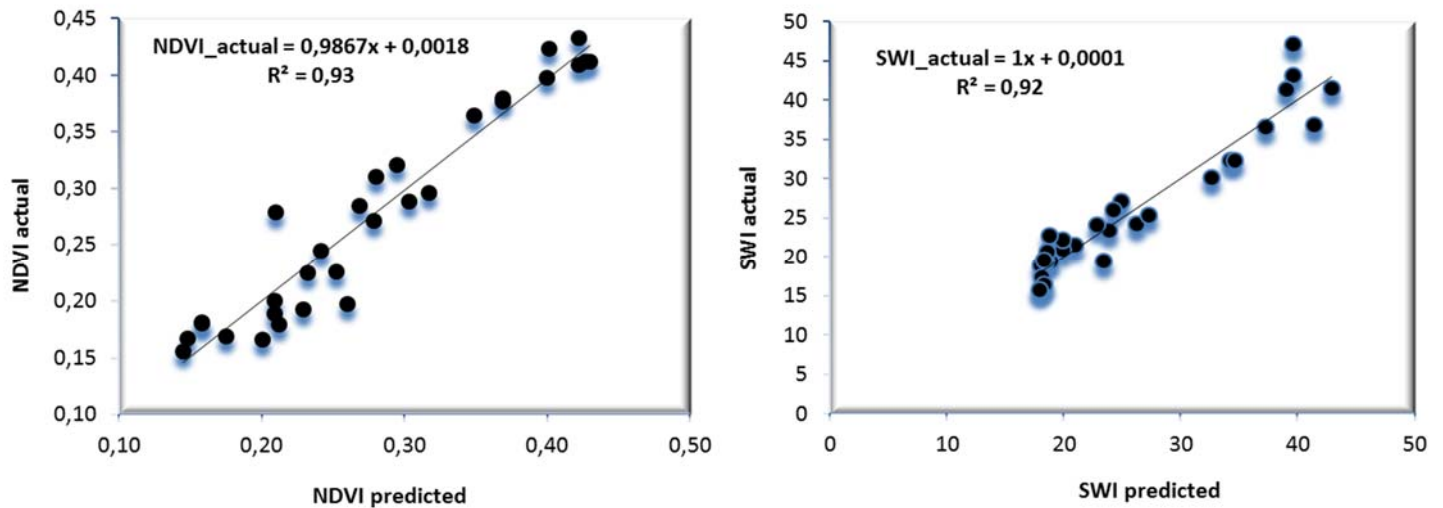


Fig 5. Correlation between really and predicted SWI and NDVI of all Moroccan rangelands.

### 3.4 Spatial drought distribution

Figure 6 shows moderate SWI anomalies for shrub, sparse and degraded rangelands but no NDVI anomalies was observed for degraded area in 2007-08. In 2011-12, severe NDVI abnormalities were observed for all types of vegetations when moderate SWI anomaly is estimated for sparse area. During 2013-14, no SWI anomalies were observed for

shrub and sparse but NDVI anomalies it was severe. During 2014-15, drought related to SWI was severe for sparse and degraded vegetation and an absence of NDVI abnormalities. 4 years show us a difference in anomalies distribution. For the rest of years, similarity of SWI and NDVI anomalies is good in these rangelands of Morocco.

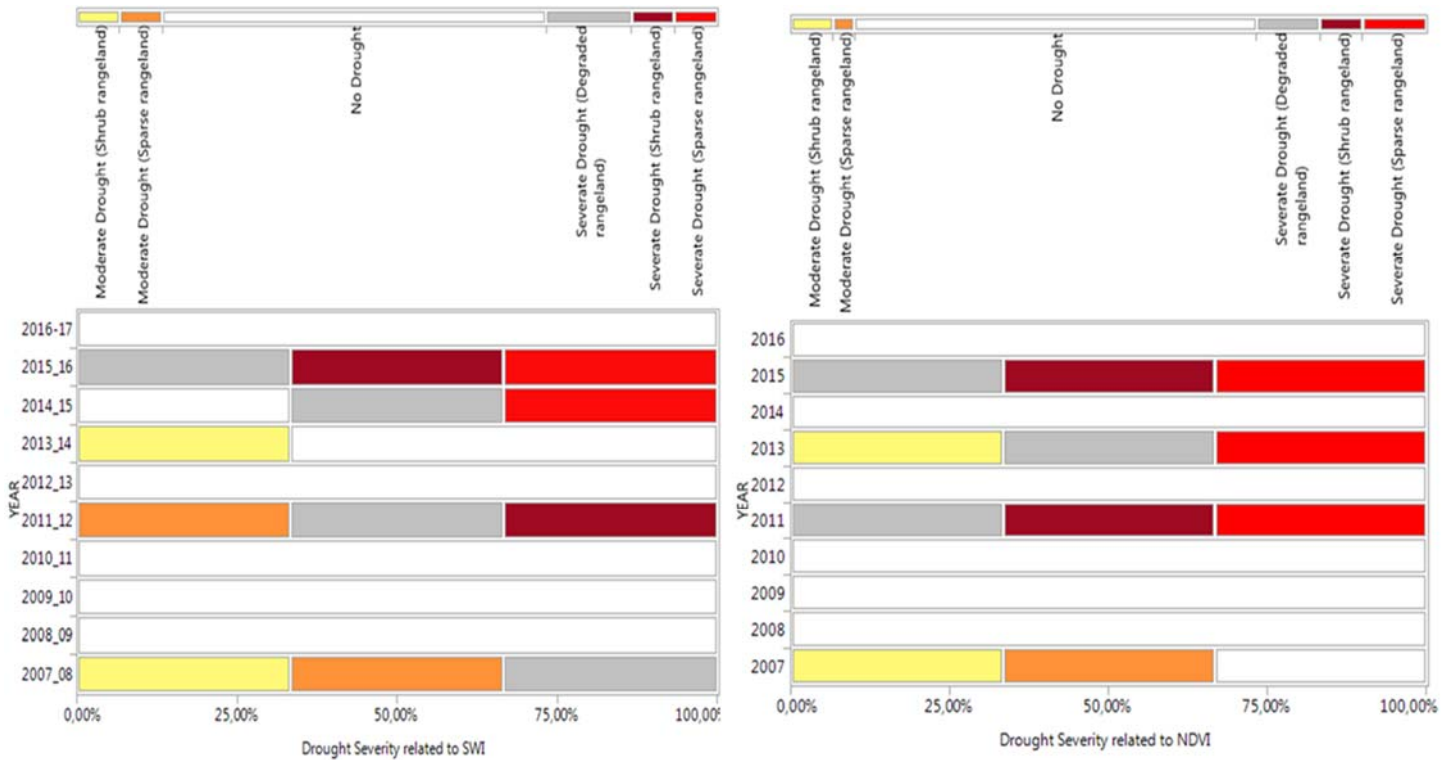
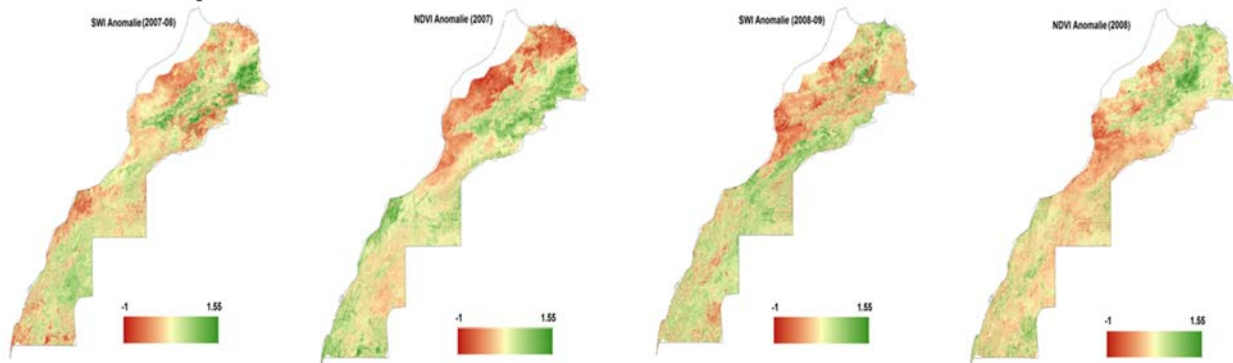


Fig 6. Drought matrix for three types of Moroccan rangelands.

The spatial and temporal evolution of soil moisture is a key parameter for detecting water stress related to a decrease in NDVI. The anomaly was calculated by its formula as shown in Equation (3 and 4). Physical range of NDVI anomaly and SWI anomaly values is from  $-1$  to  $1.55$ . Figure 7 shows that during the period of study the spatial distribution of soil moisture index anomalies is related to anomalies of vegetation index. However, a little difference for the southern zones where soil moisture show high humidity in these desert areas devoid of vegetation. Discrepancies between the NDVI and SWI anomalies are also present in north and south rangelands. Analysis of SWI and NDVI anomalies shows a subsequent increase in soil moisture and vegetation moisture content. On

contrary, NDVI was stable or decreased in some cases due to low vegetation cover in deserted rangeland and moist soil background (Hunt et al., 2009 [37]).

The SWI anomaly images disaggregated to 250 m with polynomial regression as shown in Equation (5) are perfectly correlated with the state of NDVI emodis canopy during the years 2007 to 2016. The anomalies of disaggregate SWI and NDVI dataset show the high homogeneities of pixels values. The results show perfect similarity to anomalies estimated for each rangeland (shrub, sparse and degraded areas).



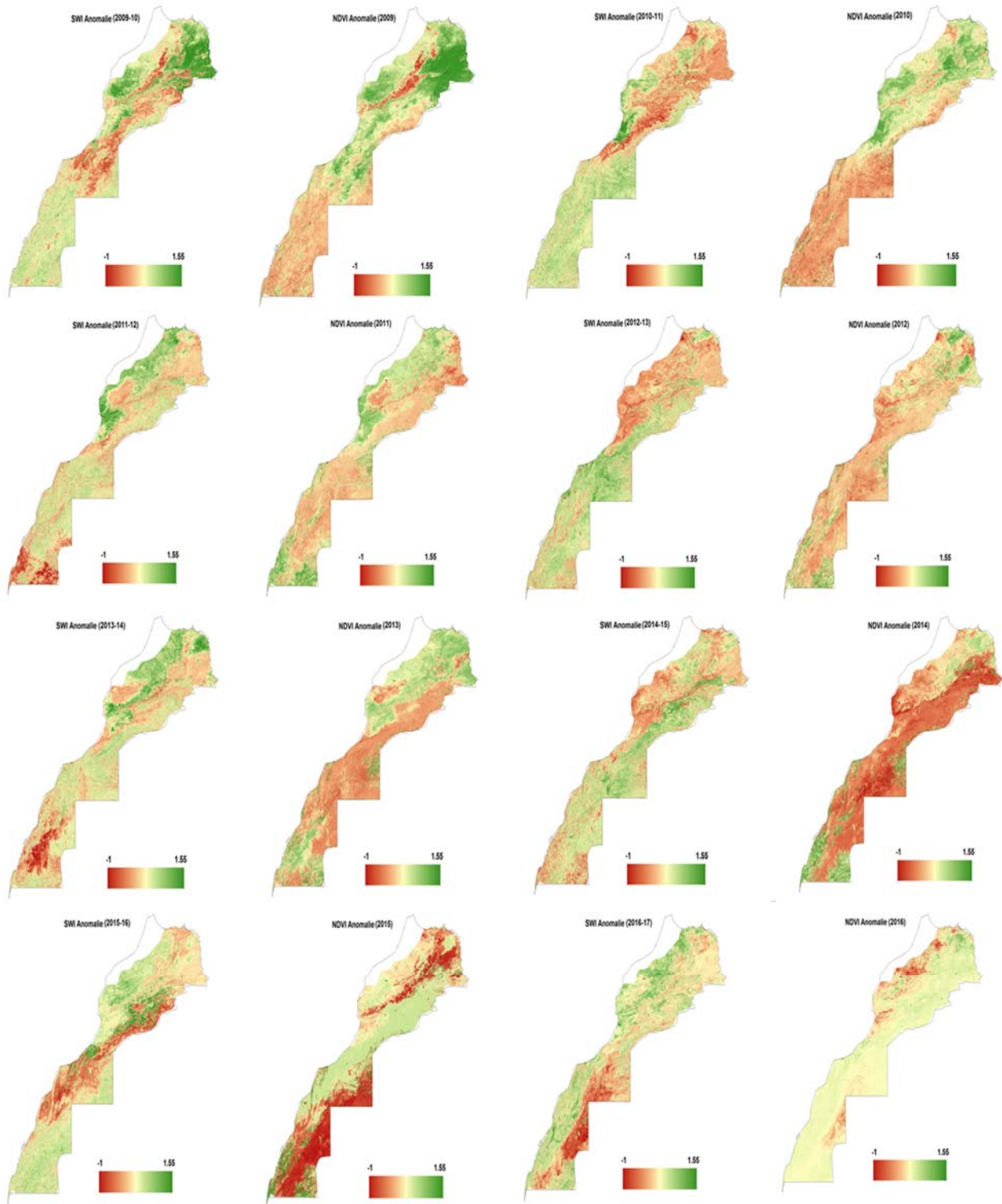


Fig 7. SWI and NDVI anomalies of all Moroccan rangelands between 2007 and 2017.

#### 4 Discussion

Many studies have focused on the detection and mapping of soil moisture (Hunt et al., 2009 [37], Zribi et al., 2010 [59], Guerfi et al., 2015 [60], Merlin, 2016 [61]). Others have tried to demonstrate

soil water index as an indicator of appropriate agricultural drought (Boyer, 1982 [62], Panu and Sharma, 2002 [63], Narasimhan et Srinivasan, 2005 [64], Ceppi et al., 2013 [65], Fernández et al., 2015 [66], West et al., 2018 [67]). According to the literature, the availability of soil moisture is a

function of soil structure, vegetation type and climatic conditions. Based on this classification we propose magnitudes of soil moisture stress thresholds compared to the different types of Moroccan rangelands. But most of research describes soil moisture index according only to soil texture by comparing data in situ and measured by satellite. For example, Velpuri et al. (2016) [5] carried out a direct and qualitative comparison of measured and in situ soil moisture to describe the severity of drought for grassland. So far no study has demonstrated the link between soil moisture and NDVI of different types of rangeland vegetation. This index of the hydrological state of the soil is not yet fully recognized and therefore used scientifically. Due to its linking-processes condition, soil moisture is placed squarely in the center of the spectrum of drought classifications and drought indicators (Ochsner et al., 2013 [30]). However, as Torres et al. (2013) [68] mentioned, most of the drought assessment methods are based on long-term atmospheric data, such as rainfall and temperature, but they typically do not consider site-specific soil properties. This is the case of most of the agricultural drought indices proposed so far. The Crop Moisture Index, CMI is based on a subset of the calculations required for the Palmer Drought Severity Index (PDSI) (Palmer, 1965 [69], 1968 [70]), which is primarily a meteorological drought index. The CMI originated as a way to calculate the water balance using historic records of precipitation and temperature.

The Climatic Moisture Index, while it was first used for forestry applications (Hogg, 1994 [71], 1997 [72]). According to Albergel et al. (2008) [73] the relationship between SWI and NDVI must be analyzed at local scale. Vegetation types particularly dependent of water existing in soil profile, heterogeneity of soil texture. It could be used for making appropriate and timely decisions in response to drought. This approach could be implemented operationally, to improve early warning systems, and would be complementary to other forecast methodologies based on climate analysis (Funk and Brown, 2006 [74]).

Several studies in the past have focused on disaggregating the coarse resolution soil moisture data based on the fine resolution visible and the NIR data. Most of these studies use the correlation between NDVI and SWI or Land Surface Temperature (LST). In general, these methods do a statistical regression between NDVI or its derivatives (aggregated to the resolution of LST), and the actual LST, and use the developed regressive relationship to disaggregate the coarse

resolution LST into a resolution LST (Agam et al., 2007 [75], Kustas et al., 2003 [76], Yang et al., 2010 [77]).

The residuals which are generated at coarse resolution are added back to the simulated temperatures based on the assumption that across the set of fine resolution pixels which constitute the original coarser pixel, the residual remain constant and is equal to the value generated at the coarser level. But adding back constant residuals fails to account for the spatial variability that occurs at the finer level and this in turn results in creating a “boxy artifact” in the disaggregated temperature under situations when the residual associated with a given pixel is exceptionally different from the neighboring pixels (Agam et al., 2007 [75]). Hence, a method that would disaggregate the residuals to a finer scale would be desirable in the context of heterogeneous terrain (Bindhu, 2014 [55]). Disaggregation algorithm today called DisPATCh is based on Physical and Theoretical Scale Change. It is also described as theoretical because the change of scale relies on mathematical tools (Merlin et al., 2005 [78], 2008 [80], 2012 [51], 2013 [81]).

In our study, the primary datasets of SWI employed are acquired from MetOp-A / ASCAT at a spatial resolution of 11 km. We are also using statistical regression between NDVI and SWI we estimate SWI1 with 250 m as shown in Equation (5). Keeping us the residual image and we adding back original image values. DisPATCh stands for Disaggregation based on Physical and Theoretical Scale Change. It is also described as theoretical because the change of scale relies on mathematical tools with ArcGIS raster calculator.

The monthly soil moisture index reflects the reality of the soil moisture status directly related to the vegetation growth process in the rangelands. Information on the beginning of the growing season allows the estimation of phenological types, as well as the water requirements of vegetation. Hence it is imperative to know the amount of soil moisture due to the appearance of precipitation that initiates the plant growth process (Chandrasekar et al., 2011 [82]).

From the SWI index studied, it can be seen that the soils of the rangelands in Morocco have a high retention capacity, and allow natural vegetation to develop even in the event of insufficient rainfall, which explains the increase in the NDVI and its resistance even during the dry season. For example, Chen et al. (2005) [83] studied the prediction of water flow in arid areas of China. Many spatio-temporal studies have been published using geographical information system (GIS) and remote

sensing (RS) to monitoring relationship between change of grassland areas and groundwater (Chen et al., 2006 [84], 2009 [85], 2012 [86]).

Ecological and environmental problems are the main concerns of the governments of Africa countries. The ecosystem is fragile in the arid and semi-arid regions. Climate change and human disturbance could easily cause significant ecosystem changes or even ecological disasters (Levintanus, 1992 [87], Erdinger et al., 2011 [88]). Studies of natural resources and environmental problems are important for ecosystem protection and socio-economic development. Rangeland drought monitoring and natural resource exploitation should be managed in a sustainable way that will benefit future generations. Given that water is the key factor affecting grazing in Morocco, water use efficiency and productivity should be emphasized in the future (Hojyaz et al., 2013 [89], Devkota et al., 2015 [90]).

## 5 Conclusion

The objective of this study is to propose an analysis of the relationship between soil moisture and vegetation development, using satellite databases only, for the evaluation of moisture and vegetation conditions. The spatial and temporal study of these variables allows the characterization of magnitudes of soil moisture stress thresholds compared to the different types of Moroccan rangelands. The relationship between SWI and NDVI is strong for shrub rangeland, there were high positive correlation coefficients for NDVI and SWI ( $R^2 = 0.96$ ). The correlations were moderate for degraded and sparse rangeland ( $R^2 = 0.54$  and  $0.52$ ) respectively. This also proves that the Moroccan steppe ecosystem dominated by the heterogeneity of these species. The degraded parts take a lot of space with the success scenarios of drought. Drought monitoring using SWI and NDVI anomalies time series in these rangelands in Morocco offers the possibility of operational use of soil moisture data at 250 m. The results shows a range high than 90 %, this explains that our method is important for characterizing dryness related to soil moisture stress for all Moroccan rangelands. The next step is to forecast the vegetation index from the SWI soil moisture index. Future work will include an analysis of this approach at more local scales using soil moisture and other climatic and phenological data.

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Software, A.Z., D.H.; Supervision, A.Z., H.M. and F.A.F.

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