Efficiency of climate and remote sensing data to drought monitoring in arid areas: Case of Eastern Morocco

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Abstract: - In the current context of climate change and its impact on human and natural resources, remote sensing has some advantages for combating extreme events, especially in pasture arid Morocco. Assessing quality of remote sensing data is an essential step in pastoral areas when droughts that have a significant impact on productivity. In order to provide a method that gives a description of future drought yield situation we have studied two types of regression established between rainfall data measured by station, soil moisture index (SWI), Normalized difference vegetation index (NDVI), Fraction of Absorbed Photosynthetically Active Radiation (FAPAR) and dry matter productivity (DMP) from MetOp-A / ASCAT, eMODIS-TERRA, SPOT VEGETATION and PROBA-V satellites 30 km from 2007 to 2017. The main objective of this study is to test accuracy of these data used for claim not only areas affected by drought, but also areas likely to be affected. The results obtained show that models based on polynomial regression of NDVI, FAPAR, DMP are most consistent and accurate for estimation of herbaceous biomass from rainfall. Using of SWI index must be justified according to averages values. However, drought can be predicted based on results of strong correlations between soil moisture and vegetation index and rainfall anomalies.

Key-Words: - Rainfall, Remote sensing data, Rangeland, Drought.

1 Introduction

Rangelands are arid or semi-arid ecosystems, where rainfall is irregular and evapotranspiration is high. These lands are composed of natural vegetation that depends on rainfall and soil moisture (Le Houérou, 1992 [1], Mahyou et al., 2016 [2], Chen 2014 [3]). Dryland ecosystems cover about 41% of area and more than 2 billion people, 90% of them in developing countries. Recent studies on dynamics of natural vegetation show a reduction of steppes and a change in their floristic composition and a decrease in productivity of rangelands. Overgrazing has an impact on floristic composition and it also causes a decrease in perennial vegetation cover and a development of invasive plant species (Mahyou et al., 2016 [2]). This precarious situation worsens during periods of severe drought where a significant water deficit is observed. Water availability per capita is only two-thirds of minimum level of human well-being. Vulnerability of populations to extreme hydrologic events is high (Douglas et al., 2008 [4], Di Baldassarre et al., 2010 [5]). While, Moroccan agriculture and pastures suffer from severe water resource deficits during prolonged droughts in recent decades (Born et al., 2008 [6], Chbouki et al., 1995 [7], Sowers et al., 2011 [8], Swearingen 1992 [9]). Understanding historical occurrence of drought and its impacts, as well as monitoring current drought conditions, allows the implementation of risk management strategies in pastoral areas. The use of remote sensing data has a number of advantages in determining the impact of drought on vegetation.

The information covers entire territory and repetition of images allows multi-temporal monitoring and estimation of spatio-temporal impact of drought during vegetation growth stage (Kogan, 2002 [10]). The main advantages of remote sensors are ability to monitor large areas and capture spatial variability of Earth's surface, as well as repeatability of data collection that provides opportunity for index analysis. The interest of remote sensing for rangelands lies in fact that several biophysical variables representative of state, development of vegetation are accessible. Numerous indices have been developed to describe vegetation cover while considering atmospheric effects or soil type (Morel, 2014 [11]). Empirical relationships were the first form of model used to estimate returns from remote sensing data. They highlight a link between vegetation spectral signature and an ecophysiological variable of interest. Rainfall derived from satellite images and global circulation models are frequently used for vegetation monitoring in many parts of Africa. The low density of rainfall stations makes calibration and validation of modeled data almost impossible (Rojas et al., 2011 [12], Balaghi et al., 2012 [13]). However, at regional scale rainfall stations are available and allow monitoring of agricultural and pastoral production and therefore ensure food security. Local water balance also depends on evaporation, storage of soil moisture and runoff versus precipitation. Soil moisture index has the advantage of quantitatively describing both wet and dry episodes (Chen, 2014 [3]) and tracking photosynthesis and plant productivity (Xin et al., 2013 [14], Tao et al., 2005 [15]). Many recent studies have attempted to compare and map spatial estimates and measurements of soil moisture in field (Hunt et al., 2009 [16], Zribi et al., 2010 [17], Guerfi et al., 2015 [18], Merlin 2016 [19]).

Drought and vegetation studies generally suggest that there are relationships at global level that hide several regional responses at smaller spatial scales. It is therefore important to note that not only does weather variability play a role, but also general sensitivity or adaptation of vegetation to drought stresses (Chen, 2014 [3]). NDVI and FAPAR were derived from remote sensing and are used in vegetation monitoring and pasture yield prediction (Kogan et al., 2013 [20], Doraiswamy et al., 2003 [21], Prasad et al., 2006 [22], Duveiller et al., 2012 [23]). Many authors have studied the relationship between FAPAR and DMP (Fensholt et al., 2004 [24]; Goward et al., 1992 [25]; Lind et al., 1999 [26]), which has been found to be generally linear for vegetation.

2 Materials and Methods

2.1 Study area

The sites used are located in communes of Ain bni mathar, Tendrara and Bouarfa in eastern Morocco (Figure 1). These rangelands consist of relatively natural vegetation with an area of 30 km are representative of main geomorphological and facies vegetation types of study area. Mean annual precipitation is low and irregular, in order of 148 mm with a minimum of 74 mm and a maximum of 311 mm. Soil level and type are determining factors of soil moisture. Overall rangeland productivity is low, although there are indigenous plants and animal resources, including perennial *Stipa tenacissima* grass forage resources. Population is about 100000 inhabitants, 80% of whom are rural. pastoralism, based mainly on sheep and goats, is main economic activity of region (Mahyou et al., 2018 [27]).

In fact, *Stipa tenacissima* is indifferent to chemical composition of soil. This species can grow on calcareous soils and sands. It thrives well on rocky, shallow, well-drained soils and avoids clays and does not support salty soils and undrained land. Steppe with white sagebrush is found in unsalted depressions and glacis with a medium-to-fine-textured clay-loam soil, with pores clogged on surface, where water is retained for a shorter or longer time, which has effect of increase congestion time. These two species have stages where these two climax species are progressively replaced by species of degradation, such as *Noaea mucronata*, *Atractylis serratuloides*, *Peganum harmala* and *Anabasis aphylla*. Desert Steppes cover fairly large areas in Bouarfa. Among the main steppes encountered, there are steppes of *Fredolia aretioids*, and *Haloxylon scoparium*. It should also be noted that perennial vegetation has the most significant action on soils of highlands without reliefs and rivers. Indeed, when perennial vegetation is degraded or disappeared, there is a constant regression of superficial horizons (MARA, 1992 [28], Mahyou et al., 2010a [29]).

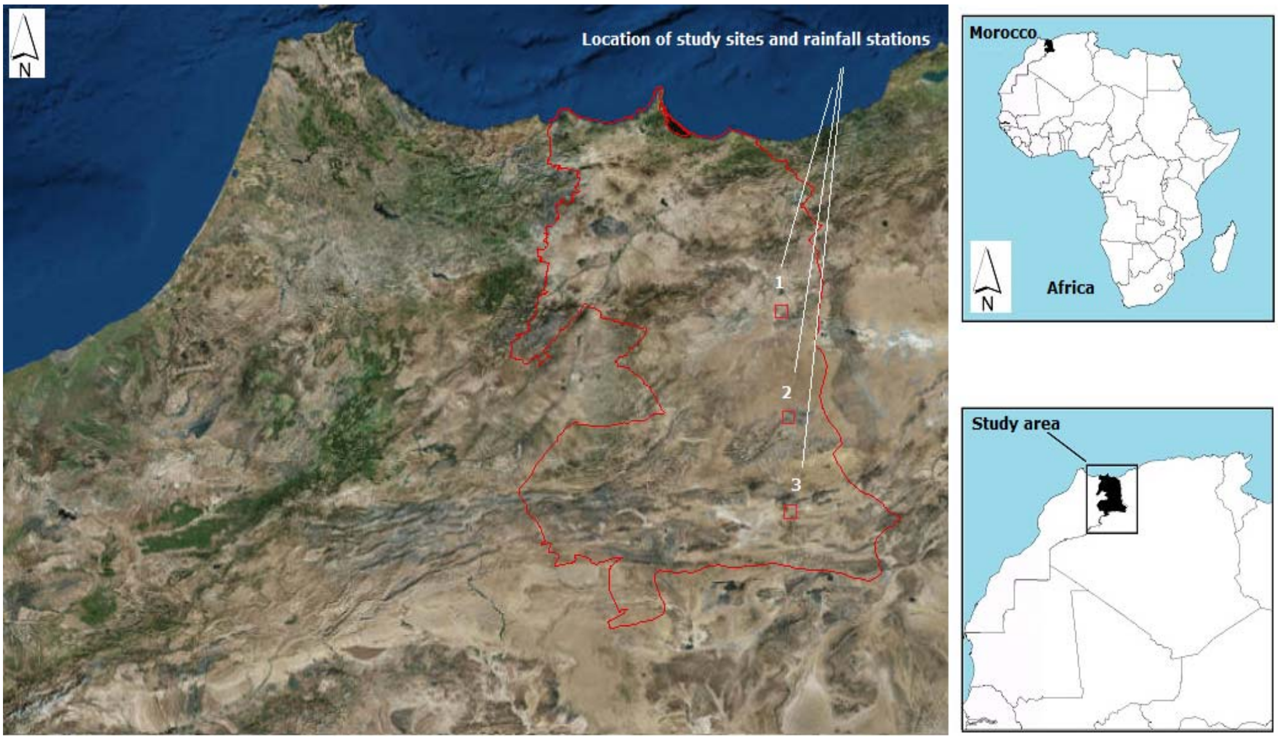


Fig 1. Location map of estimating remote sensing indices and rainfall stations at three rural communes in eastern Morocco (S1: Ain Bni Mathar, S2: Tendrara, S3: Bouarfa).

2.2 Remote sensing data and Rainfall

Rainfall studied here is derived from three stations located in rural communes (Ain Bni Mathar, Tendrara, and Bouarfa). However, four types of indices from 360 images of a WGS-84 projection whose spatial and temporal characteristics are shown in (Table 1) are used in this work. Copernicus Global Land Service (CGLSSWI) soil moisture data for 2007-2017 version 3 are from MetOp-A / ASCAT with spatial resolution of 11 km and geographic coordinates (Long / Lat). The Soil Moisture Index (SWI) is physically defined as the moisture content of the soil at 1 meter from the ground. This index is relatively related to wilt level and field capacity. Its unit is percentage (%) and his physical range value varies from 0 to 100. The vegetation index (NDVI) is calculated from MODIS L1B Terra surface reflectances and corrected using the MODIS algorithms by United States Land Observation and Resources Center (EROS) to produce NDVI emodis. Two series of data of absorbed photosynthetically active radiation and dry matter productivity derived from Copernicus World Terrestrial Service (CGLSFAPAR and CGLSDMP) from 2007 to 2017 version 2 which corresponds to values of reflectance absorbed by canopy and mass flows of carbon are thus used.

Data	Formula	References
CGLSSWI	SWI $(t_n) = \sum^n_i m_s(t_i) e^{tn-ti/T} / \sum^n_i e^{tn-ti/T}$ Pour $t_i \leq t_n$	(Wagner et al., 1999 [30])
	t_n : Observation times of current measurement,	

	t_i : Observation times of previous measurements.	
NDVI-eMODIS	NDVI = (NIR - R)/ (NIR + R) Were NIR is the Near infrared and R is the Red.	(Jenkerson et al., 2010 [31])
CGLSFAPAR	FAPAR = Reflectance absorbed by green part of vegetation.	(Prince, 1991 [32] ; Verger et al. 2015 [33])
CGLSDMP	DMP = R.εc.fAPAR.εLUEc.εT.εCO2 εAR[.εRES] LUE : Efficiency of use of light , εLUE : Optimum use efficiency, εT : Standardized temperature effect, εCO2 : Standardized CO2 fertilization effect, εAR : Fraction preserved after autotrophic respiration, εRES : Fraction preserved after effects omitted (drought, parasites ...).	(Monteith, 1972 [34] ; Swinnen et al., 2017 [35])

Table 1. Characteristics of spatial data "Soil moisture (SWI), vegetation index (NDVI), photosynthetic fraction (FAPAR), dry matter productivity (DMP)" used in this study.

2.3 Spatial and Statistical Analysis

Soil moisture (SWI), vegetation index (NDVI), absorbed active photosynthetic fraction (FAPAR) and dry matter productivity (DMP) data from September 2007 to August 2017 are extract with a raster of 30 km resolution at three sites (Ain bni mathar, Tendrara and Bouarfa) with software for processing and interpreting series of images derived from remote sensing (SPIRITS). This tool includes many image processing features derived from low resolution sensors such as SPOT-VEGETATION, NOAA AVHRR, METOP-AVHRR, TERRA-MODIS, ENVISAT-MERIS and MSG-SEVIRI. It can be used to perform and automate spatial and temporal processing steps over time series and to extract spatially aggregated statistics. Many range of operations facilitated by this program, also indices and their anomalies can be analyzed statistically and mapped quickly (Eerens et al., 2013 [36]).

In this study, we propose a methodology that allows rapid assessment quality of index estimates (SWI, NDVI, FAPAR, DMP) based on ANOVA analysis performed for all variables and rainfall stations in each site. We are also investigating whether SWI soil moisture index averages (November to February), NDVI, FAPAR and DMP (February, March and April) and cumulative precipitation totals can be used (from September to March) according to adjustment functions in order to deduce which one (s) best adapts to estimation of yields and others in these arid and semi-arid ecosystems (Figure 2) . Thus in the case of prediction of the drought we calculate and compare anomalies calculated with the Wilcoxon / Kruskal-Walis test on JMP according to the following formula (1):

Anomaly = (Variable i - (Variable j) Mean) / Std (Variable j) (1)

Variable i: is the value of the variable in time i, Variable j: is the average of the variable in time j, STD: is the standard deviation of the variable in time j.

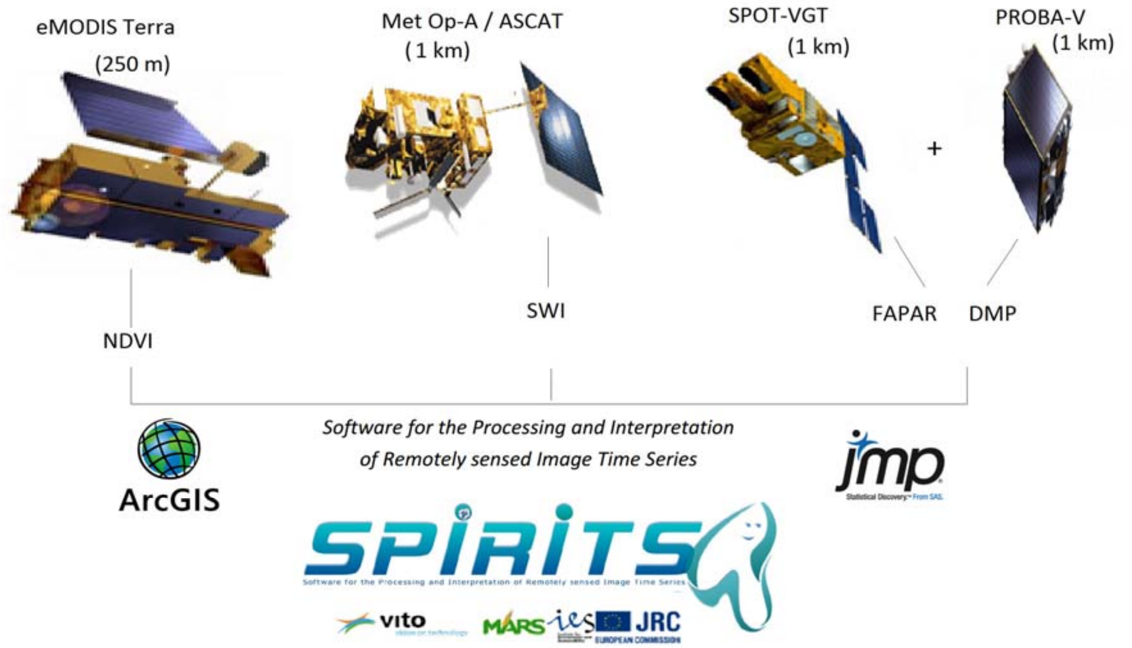


Fig 2. Workflow and remotely sensed data used in this study.

3 Results

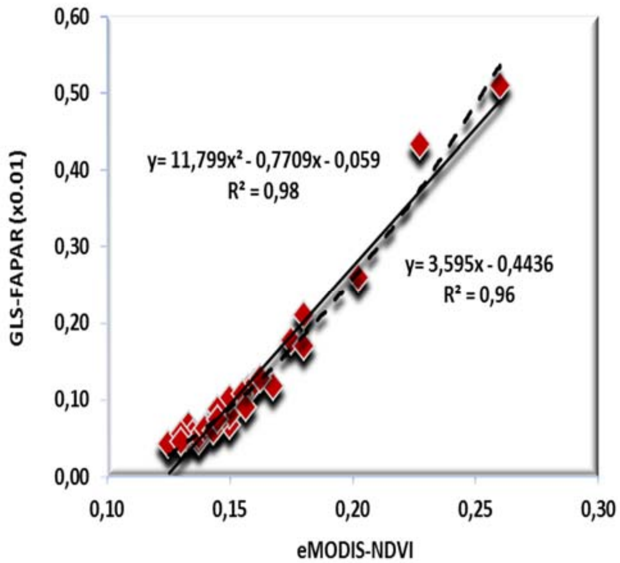
3.1 Validation of FAPAR and DMP data

Since absorbed active photosynthetic radiation fraction (FAPAR) and dry matter productivity (DMP) data from SPOT VEGETATION and PROBA_V pose estimation problems, an assessment and validation step has been essential. For this, averages of these FAPAR and DMP variables studied were re-sampled at 11 km, their digital values were retrieved and correlated with NDVI eMODIS values. To determine vegetation threshold, we used bibliographic studies and NDVI profiles for each site. According to (Minet et al., 2015 [37]) actual value of NDVI giving threshold for vegetation detection is 0.1. Value 110 was chosen for maximum date of end growing season, being minimum values of vegetation and 5 the minimum variation between two decades. The numerical value (DN) is equal to

1.1 / 0.01 = 50. The value 50 corresponds to the minimum value of vegetation and 5 correspond to the minimum variation between two decades 1.1 / 0.1 = 5. In our study, based on the trend of NDVI, values of FAPAR and DMP are recovered by the following formulas (2 and 3):

FAPAR = (DN * 0.01) (2) and DMP = (DN * 0.1) (3)

(Figure 3) shows a strong polynomial correlation between two variables FAPAR and DMP and NDVI with respectively (r^2 = 0.98, r^2 = 0.91) is more accurate than linear regression with (r^2 = 0.96, r^2 = 0.88). FAPAR and DMP averages for February, March and April are correct, but their scale is high relative to NDVI values.



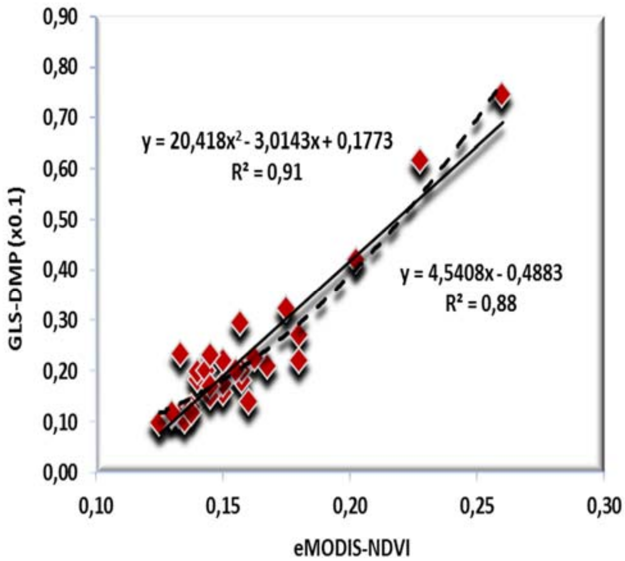


Fig 3. Polynomial (degraded line, R^2 = 0.98 and R^2 = 0.91) and linear (continuous line, R^2 = 0.96 and R^2 = 0.88) correlation between CGLS-FAPAR and CGLS-DMP and eMODIS NDVI data from February to April during the period 2007-2017.

3.2 Variability of averages of vegetation index and rainfall and Soil Moisture Index

Analysis of annual averages comparison gives more detail on variability of vegetation indices, soil moisture and rainfall at the three study sites (Table 2). An average rainfall of 18 mm is highlighted at Ain bni mathar, 17 mm at Tendrara and 12 mm at Bouarfa. The averages of the soil moisture index in Tendrara, Ain Bni Mathar and Bouarfa respectively are 19%; 16% and 14%. Mean trends in vegetation indices are similar to Ain Bni mathar and Bouarfa with 0.14 and 0.15 at Tendrara. According to analysis of averages, FAPAR and productivity at Ain bni mathar is equal to 0.09 kg / ha and 0.18 kg / ha; in Tendrara and Bouarfa values of FAPAR and DMP are 0.08 kg / ha and 0.16 kg / ha.

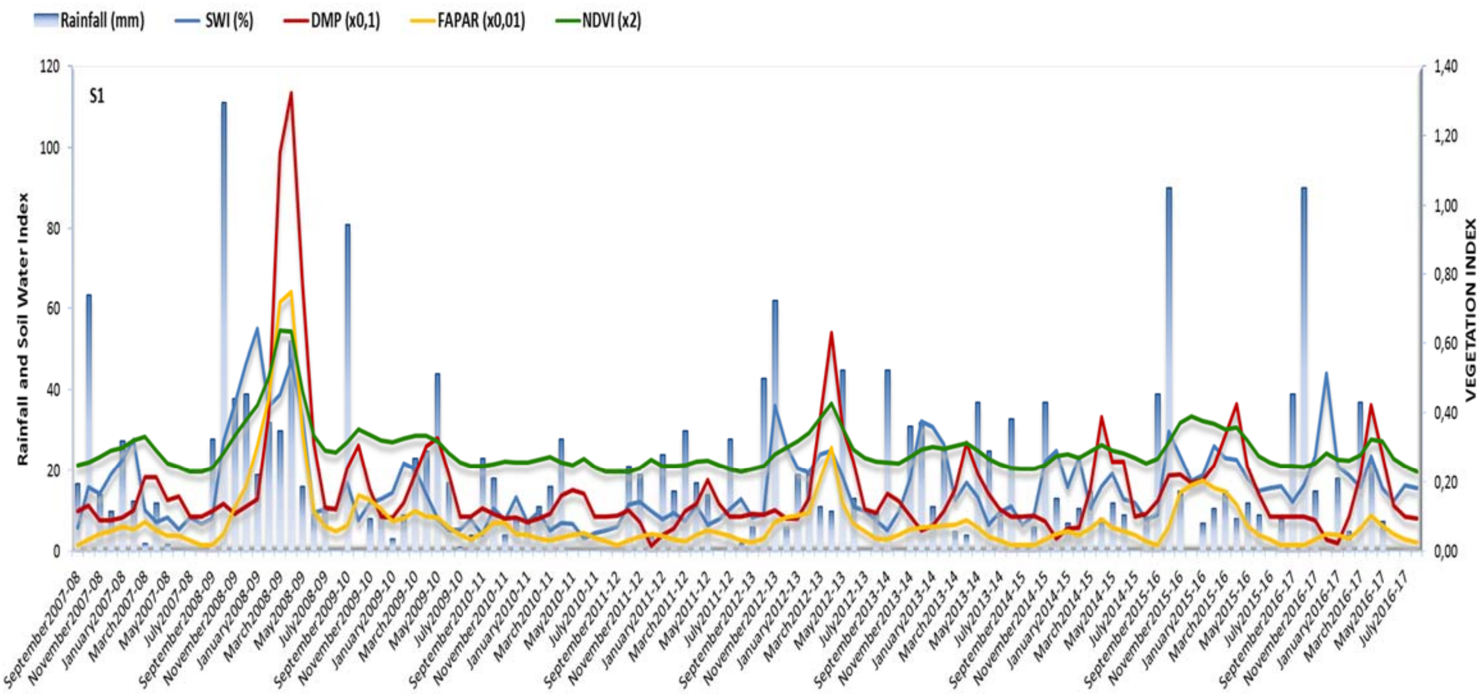
Hydrological monitoring of surfaces relies on models that can predict water flows in space and time (Figure 4). Soil moisture index depends on flow of material, evaporation, infiltration and soil runoff. Estimates of monthly averages from 2007 to 2017 indicate trends of actual rainfall, soil moisture index and vegetation indices of the three rural communes of Ain bni mathar, Tendrara and Bouarfa. The correlation between pixel values of SWI images and rainfall is well established between September and October; between November and December and between March and April.

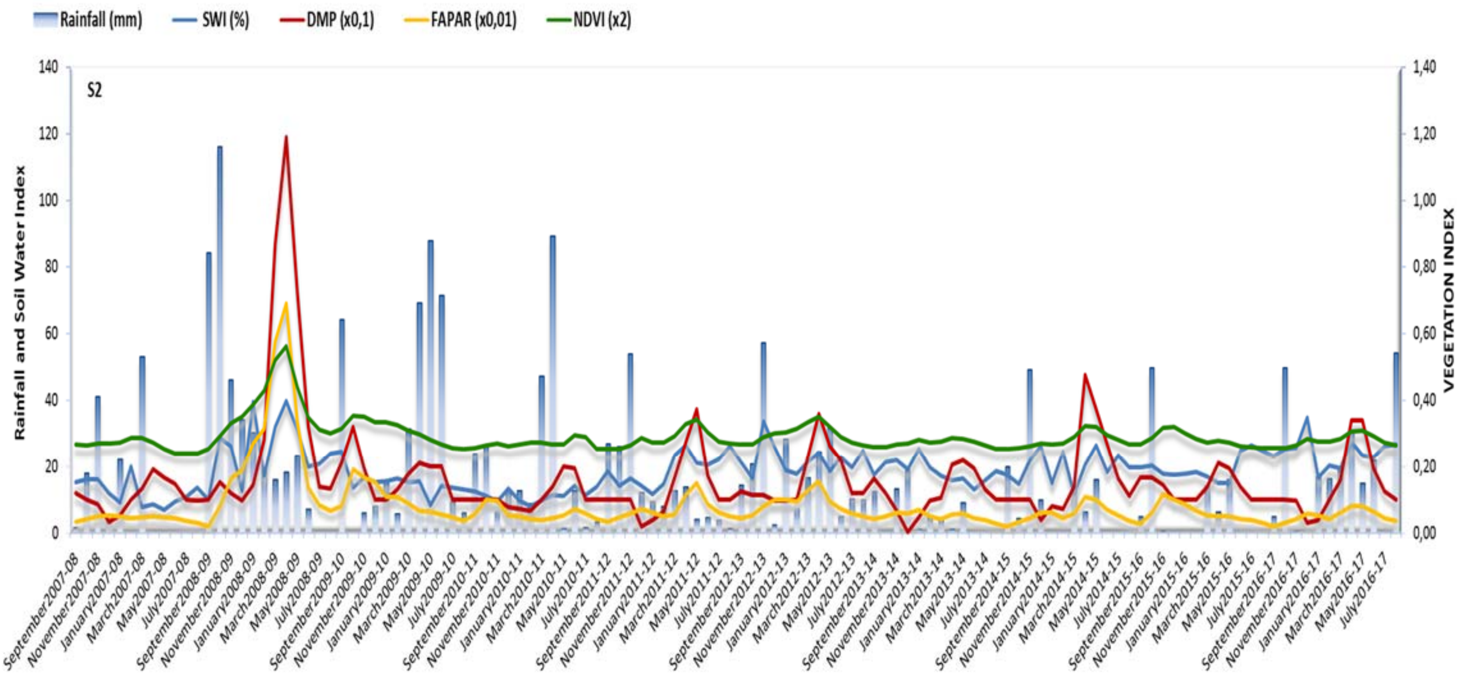
Nevertheless, rainfall values and indices of soil moisture and vegetation varied from year to year. For the three areas studied, index values were relatively high in 2008-09, 2009-10, 2012-13, 2013-14, 2014-15, 2015-2016, 2016-17 and lower in 2007-08 and 2010-11. During drought years NDVI, FAPAR are low. While high DMP in Bouarfa shows that this productivity of dry matter corresponds to vegetations indicative of degradation which resist at extreme conditions.

The results of comparison of rainfall trends and vegetation indices show that station data and satellite images can be used as reliable data but with verification of FAPAR and DMP scales. Since index of soil moisture is dependent on interaction of vegetation. It is noted that this soil moisture decreased in February regenerates rapidly with the growth of vegetation in March and April. The steppe of Ain bni mathar *Stipa tenacissima* is often associated with *Noaea mucronata*, *Peganum harmala*, *Atractylis serratuloids*, *Atractylis humilis*, *Artemisia herba-alba* and *Lygeum spartum*. This stony mixed steppe is mainly located on glacis and slopes where crusts and calcareous slabs with low permeability more or less stability condition of soil moisture index. Nevertheless tendrara at mixed steppes degraded dominated by *Anabasis aphylla*. Desert steppes of *Fredolia aretioids* and *Haloxylon scoparium* in Bouarfa colonize mostly horizontal plateaus and depressions with loamy or silty-clay soils. Due to this diversity of steppe ecosystem, a high variability of soil moisture has been observed.

SITE	Variable	MEAN	MIN	MAX	Std Dev	CV
S1	**SWI**	16.1	3.22	55.2	10.1	62.7
	NDVI	0.14	0.1	0.3	0.05	39.1
	FAPAR	0.09	0.02	0.75	0.11	119.3
	DMP	0.18	0	1.3	0.18	102
	Rainfall	17.8	0	111	19.9	112
S2	**SWI**	18.6	7.17	39.8	6.47	34.8
	NDVI	0.15	0.12	0.28	0.02	16.2
	FAPAR	0.08	0.02	0.69	0.09	109.4
	DMP	0.16	0	1.19	0.15	92.8
	Rainfall	17.2	0	116	22.2	129
S3	**SWI**	13.9	2.86	24.8	4.89	35.1
	NDVI	0.14	0.12	0.24	0.02	15.5
	FAPAR	0.08	0.02	0.4	0.06	73.47
	DMP	0.16	0	0.83	0.12	73.6
	Rainfall	12	0	135	20.7	173

Table 2. Comparison of monthly average rainfall, soil moisture, NDVI, FAPAR and DMP for the three sites (S1: Ain Bni Mathar, S2: Tendrara, S3: Bouarfa) from September 2007 to 2017.


Rainfall (mm)
SWI (%)
DMP (x0,1)
FAPAR (x0,01)
NDVI (x2)
S1
Rainfall and Soil Water Index
VEGETATION INDEX


Rainfall (mm)
SWI (%)
DMP (x0,1)
FAPAR (x0,01)
NDVI (x2)
S2
Rainfall and Soil Water Index
VEGETATION INDEX

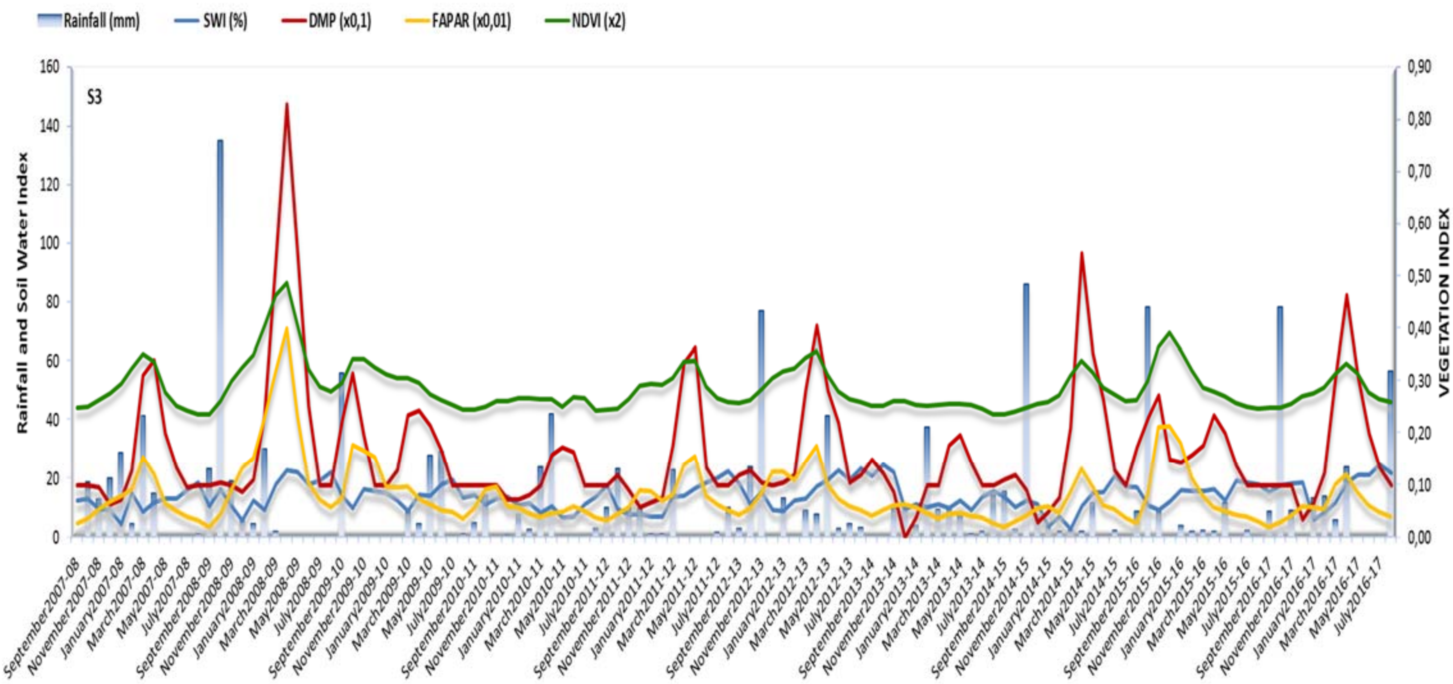


Fig 4. Monthly trends of vegetation indices, rainfall and soil moisture (SWI) at the three sites (S1: Ain Bni Mathar, S2: Tendrara, S3: Bouarfa) between 2007 and 2017.

3.3 Variability of averages anomalies of vegetation index and rainfall and Soil Moisture Index

Soil moisture plays an important role in maintenance of life on earth; its first use is to allow growth of vegetation. It also conditions the establishment of plant stand. Its evaluation is therefore important in hydrology and agronomy, and is a warning parameter for drought. In semi-arid areas, it seems logical that soil moisture anomaly thresholds are equal to rainfall and vegetation index anomalies. Figure 5 shows average of anomalies calculated between 2007 and 2016 in the three pastoral zones of Eastern Morocco. In Ain bni mathar and Tendrara, negative anomalies of rainfall and NDVI, FAPAR, DMP are visible in 2010, 2011, 2013 and 2014. In 2007, 2009 and 2015 rangeland conditions are relatively stable. Precipitation anomalies do not correspond to SWI anomalies in 2013 in Ain bni mathar. In Bouarfa rainfall anomalies and NDVI, FAPAR, DMP are perfectly correlated. While these anomalies are in contrast estimated with respect to anomalies of soil moisture index.

Serious negative NDVI, FAPAR and DMP anomalies were observed between 2009 and 2011, with very poor growth conditions observed for these rangelands in Morocco. Normal growing conditions are observed in 2014-2015. Runway vegetation anomalies in early spring (February to April) mainly reflect soil moisture anomalies for winter period (November to February). During dry years, negative anomalies can be observed for all types of hydrological variables and vegetation. Years of relatively good vegetation are characterized by higher water conditions in winter.

The discrepancies between SWI anomalies are other variables are also present in Bouarfa; we observed negative SWI abnormalities and absence of NDVI, FAPAR, DMP abnormalities and rainfall. The reason for this disagreement can be explained by good temporal distribution of rainfall. In fact, temporal distribution of precipitation can be significant as a total amount to determine vegetation development. Therefore, even if accumulated soil moisture was low, this anomaly eventually led to a normal development of vegetation.

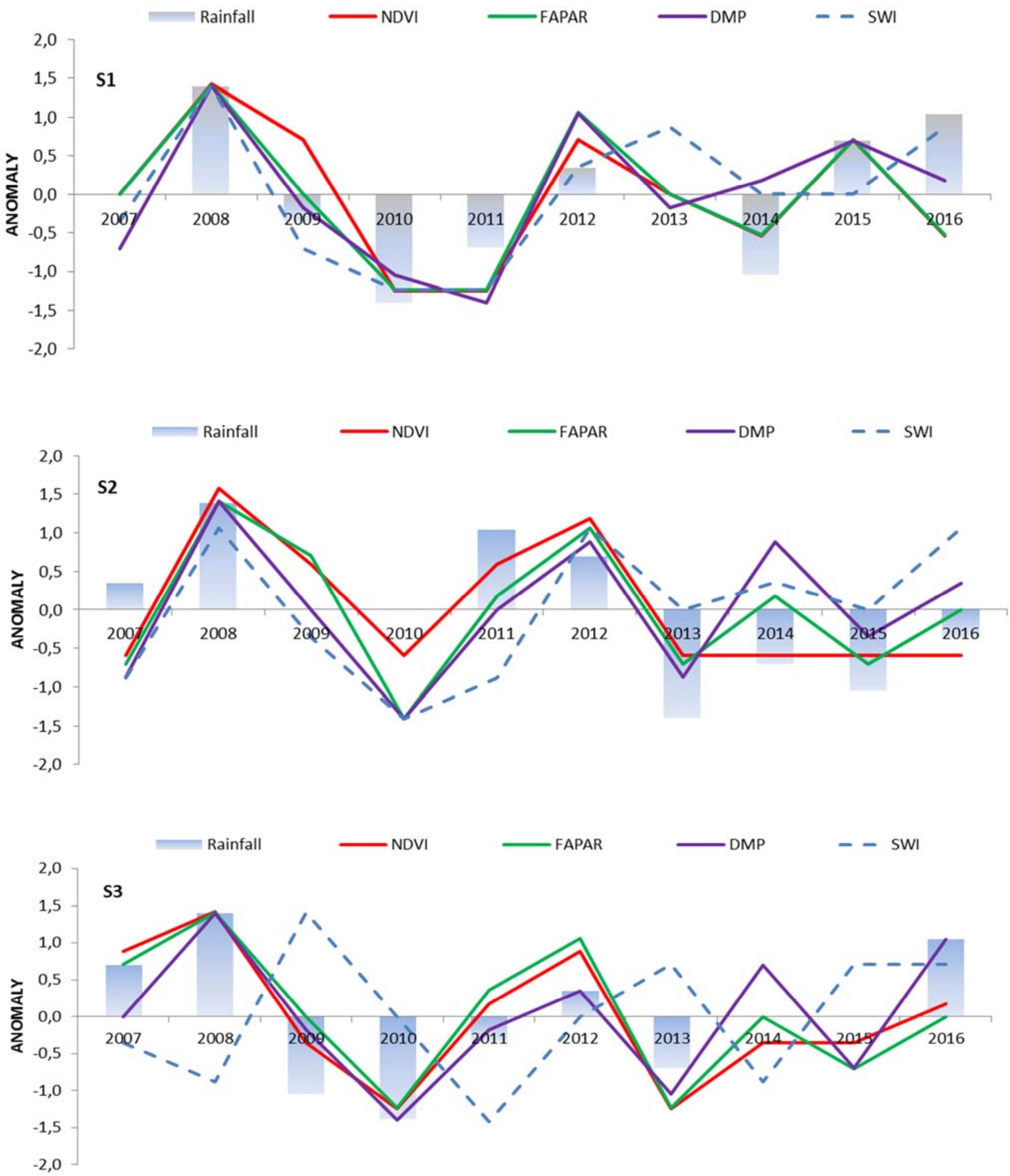


Fig 5. Result of rainfall (September to March), vegetation indices (February to April) and soil moisture (November to February) anomaly at the three sites (S1: Ain Bni Mathar; S2: Tendrara, S3: Bouarfa) between 2007 and 2017.

3.4 Correlation between vegetation indices and soil moisture index

Assuming that soil moisture index is dependent on both soil texture and vegetation typology, this will allow description of conditions in three study areas. The spatial and temporal variability of soil moisture proves that soils studied are diverse and rich in borer, limestone, sand and organic matter.

According to Figure 6, a strong correlation between SWI (November to February) and NDVI, FAPAR and DMP at Ain bni Mathar with (R^2 = 0.66, R^2 = 0.90, R^2 = 0.92) is encouraging to estimate vegetation indices from index of soil moisture is aimed towards that. On the other hand, at two sites (Tendrara and Bouarfa), very weak correlations are observed between SWI and NDVI, FAPAR and DMP respectively with (R^2 = 0.24, R^2 = 0.22, R^2 = 0.28) and (R^2 = 0.24, R^2 = 0.18, R^2 = 0.22). From these results it can be confirmed that SWI index reflects soil typology of areas studied. The SWI index is unable to estimate soil moisture in areas similar to Tendrara and Bouarfa where vegetation is low and soil is sandy in nature.

The aspect on relationship between vegetation and soil moisture from November to February is strongly established in Ain Bni mathar, while the accuracy of the polynomial regression is not established for low values of vegetation indices in Tendrara and low soil moisture in Bouarfa.

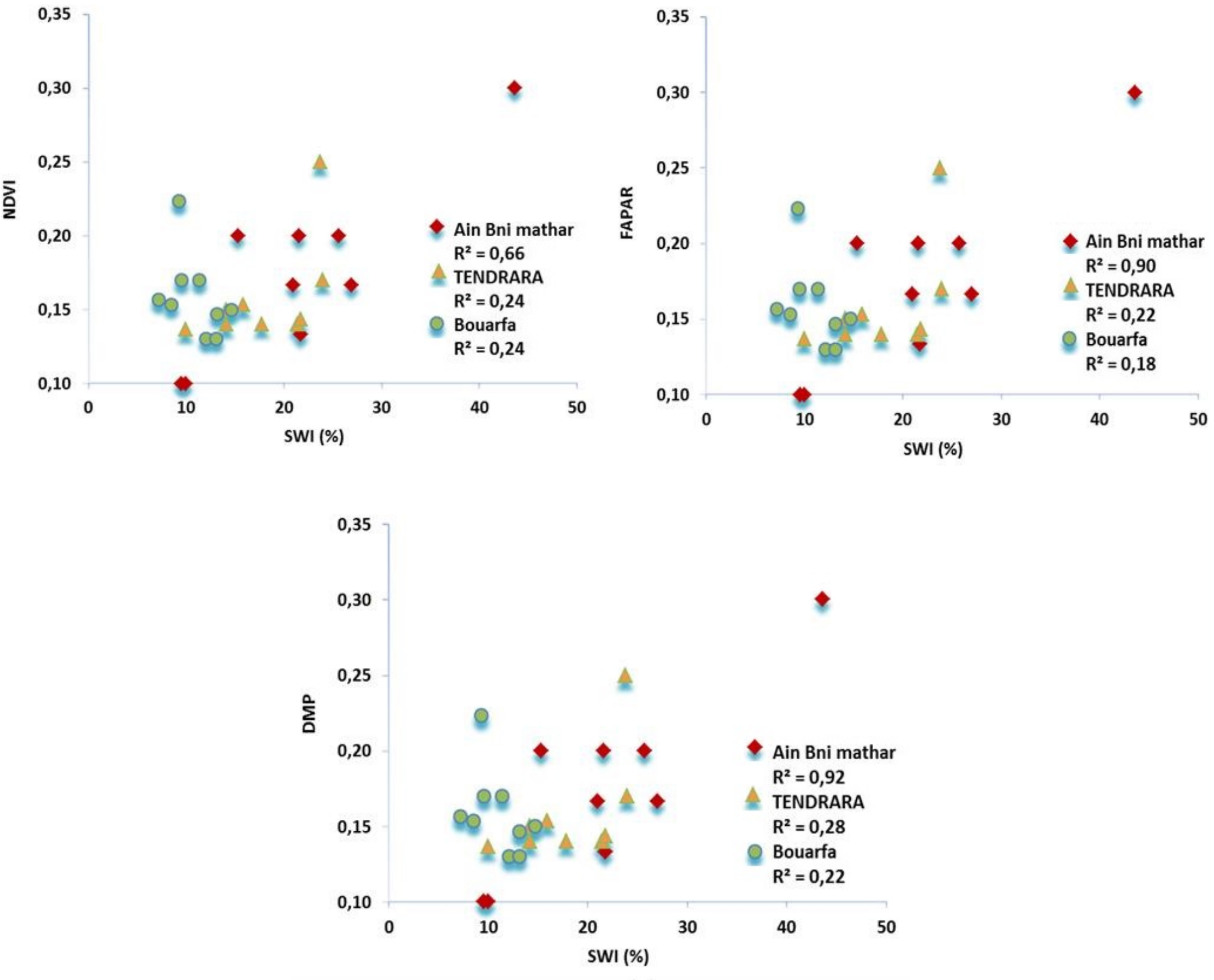
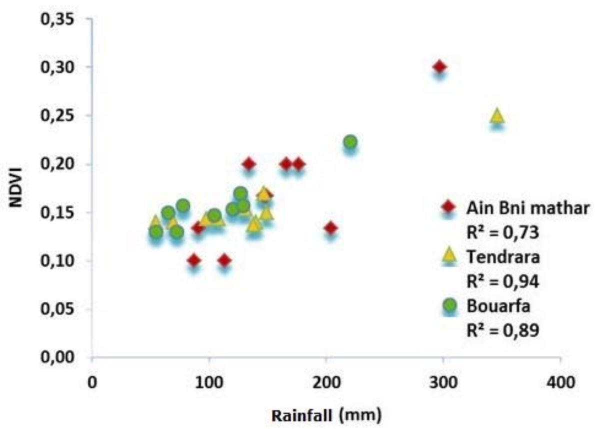
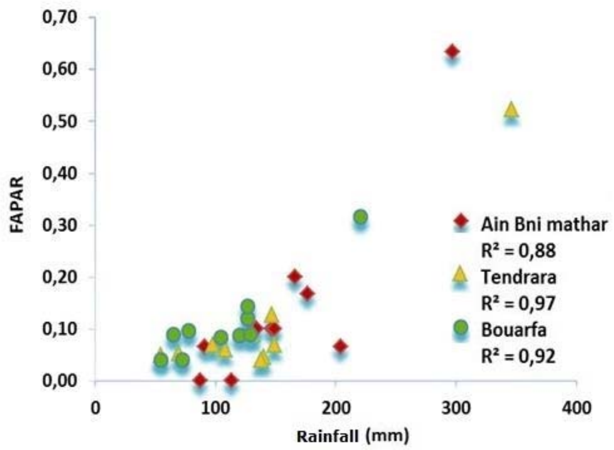


Fig 6. Polynomial regression between NDVI, FAPAR and DMP vegetation indices (February to April) and soil moisture (November to February) at all three sites.

3.5 Correlation between vegetation indices and rainfall

The results of Figure 7 are very promising for an estimation of vegetation index, photosynthetic fraction and dry matter productivity from rainfall stations in the three study areas. Polynomial correlations are perfectly established between NDVI and rainfall with (R^2 = 0.73, R^2 = 0.94, R^2 = 0.89) respectively at Ain Bni mathar, Tendrara and Bouarfa. Correlations between FAPAR and rainfall in these sites are respectively (R^2 = 0.88, R^2 = 0.97, R^2 = 0.92). While relationship between rainfall from September to March and DMP is expressed with (R^2 = 0.90, R^2 = 0.95, R^2 = 0.95). In general rainfall data derived from station are very well correlated with vegetation indices; we can say that means of satellite data are also very well correlated.





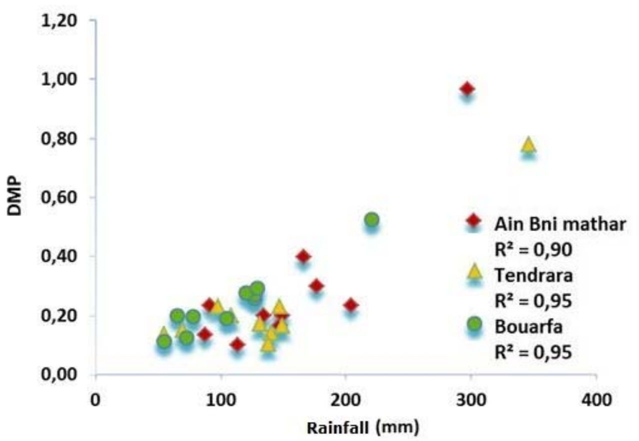


Fig 7. Polynomial correlation between rainfall (September to March) and NDVI, FAPAR and DMP vegetation indices (February to April) at the three sites.

4 Discussion

Before starting any study verification of data put in analysis is an essential step. For drought study in pastoral areas for example and if we chose to analyze between two types of field data and remote sensing space we must compare, criticize and justify different results obtained. Observations of soil moisture are in principle a more efficient and robust means of quantifying availability of water. Soil moisture from passive remote sensing has large errors in areas of high vegetation density (Parinussa et al., 2011 [38]). Therefore, at semi-arid or arid regions, soil moisture index is more reliable for assessing relationships between soil moisture and vegetation (Chen, 2014 [3]). The results clearly confirm that SWI can be used as an indicator of quality of precipitation estimates at regional scale and allow rapid detection of major overestimates and underestimates of precipitation data examined. According to the literature, availability of soil moisture depends on soil structure, vegetation type and climatic conditions.

But most research describes soil moisture index only in terms of soil texture by comparing in situ and satellite-measured data. Velpuri et al., 2016 [39] conducted a direct and qualitative comparison of measured and in situ soil moisture to describe severity of drought in grasslands. For example, NDVI, FAPAR and DMP derived from remote sensing have been used in vegetation monitoring and pasture yield prediction (Kogan et al., 2013 [20], Doraiswamy et al., 2003 [21], Prasad et al., 2006 [22], Duveiller et al., 2012 [23]), Diouf et al., 2014 [40], Diouf et al., 2015 [41], Garba et al., 2012 [42]) showed that there is a close relationship between dry matter productivity (DMP) and pasture biomass. Previous studies have also shown that FAPAR values are slightly higher for hardwood in winter, at higher latitudes and may lead to some overestimation and cloud and snow contamination limits reliability of reflectances used as input into forest. The algorithms (Fang et al., 2013 [43], Claverie et al., 2013 [44], Chen 1996 [45], Chen, 2014 [3]). This proves that remote sensing data also have their inherent drawbacks.

Based on spatial and temporal analysis of remote sensing data, we have retained advantages and disadvantages from perspective of this study on the use of spatial data in arid and semi-arid grazing areas. Soil moisture index SWI is significant and proves that it depends on nature of soil and presence of vegetation; it is sensitive to absence of vegetation in degraded areas. Since there are significant errors in areas of high vegetation density according to (Parinussa et al., 2011 [37]) and reliable in arid and semi-arid zones according to (Chen, 2014 [3]) it saturates in strictly arid zones similar to Tendrara and Bouarfa located in East of Morocco. FAPAR and DMP require a correction of scale compared to NDVI. However the latter is perfectly reliable in drought study in Moroccan rangeland.

5 Conclusions

The evaluation of remote sensing data is usually done in relation to field data. Two other steps seem important which is processing of earth observation data from series of images; and statistical analysis through creation of a regression model between spatial data and those measured in field. Spectral profile model aims to synthesize biological knowledge functioning of pastoral ecosystems and physical parameters of spectral response of plant cover. Nevertheless, this type of model must be tested and probably improve in different conditions and types of vegetation cover.

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