Algorithm theoretical for FAPAR and DMP calibration using remote sensing and field data in Moroccan arid areas

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Abstract: - We studied the effectiveness of FAPAR and DMP data at regional scale. In this article, we propose theoretical algorithms for calibration of these data in a larger scale (for all Moroccan rangelands). The study uses Multivariate Polynomial Regression (MPR) via TaylorFit software. The relationship between soil moisture SWI from MetOp-A / ASCAT sensor, fraction of photosynthetically active absorbed radiation absorbed (FAPAR) and dry matter productivity (DMP) from SPOT / VEGETATION and PROBA-V was set at 11 km resolution for ten years. Three types of areas were studied: degraded areas, sparse herbaceous and shrub vegetation. The calibration of phenological indices is made with two hypothesis (areas with low values are divided by 3000 and areas with high values are divided by 100). Multivariate Polynomial Regression (MPR) with TaylorFit expresses clearly errors of current and corrected estimates of FAPAR, DMP and Normalized difference vegetation index (NDVI) data respectively (from Max Err = 116.94 / RMSE = 48.47 to Max Err = 0.04 / RMSE = 0.016) and (hypothesis 2: from Max Err = 30.4 / RMSE = 9.59 to Max Err = 0.30 / RMSE = 0.09). Similarly, in order to compare and verify these results according to field data, a comparison was made over two years. The similarity of FAPAR and DMP data and phytomass measurements is strongly expressed. A significant polynomial correlation is estimated between SWI, dry matter productivity and photosynthetic fraction respectively (Rsq = 0.90) and (Rsq = 0.87). The provision of infor-mation on quality and validation of FAPAR and DMP indices facilitates their use in monitoring drought in these areas.

Key-Words: - Absorbed photosynthetically active radiation fraction (FAPAR), Dry matter productivity (DMP), Normalized difference vegetation index (NDVI), Soil moisture index (SWI), Moroccan rangelands, Multivariate Polynomial Regression, phytomass measurements, Calibration algorithm.

1 Introduction

Over past decade, understanding of interactions between vegetation and climate has generated increasing interest in order to assess impacts of climate change on the carbon cycle [1, 2]. Climate change can be expected to have a significant impact on water and energy cycles, significantly affecting vegetation [3]. For this reason, response of vegetation dynamics, for different types of vegetation cover, to precipitation and temperature anomalies is a subject of current climate research aimed at understanding and predicting how biosphere interacts with carbon, water and energy cycles [4, 5, 6, 7]. Work by [8, 9, 10] has led to a better understanding of vegetation response to climate signals. Studies by [11] have explored correlation structures of vegetation and climate dynamics. Other studies by [12, 13, 14] have investigated vegetation response to extreme climate events. For example, [15] analysed primary productivity reduction caused by drought. Whereas, [16] have shown that there is a strong correlation between water and photosynthetic activity and that use a set of phenology metrics, such as growing season FAPAR, allows a proper analysis impacts of climate change on carbon reservoirs and fluxes.

Soil moisture deficits are one of the most common limitations to primary plant productivity and photosynthesis. Drought monitoring is important for rangeland management and livestock food security [17, 18].

Indices such as NDVI (Normalized difference vegetation index) and FAPAR derived from remote sensing are used in pasture monitoring and forecasting of productivity anomalies [19, 20, 21, 22, 23]. Many authors have demonstrated that relationship between FAPAR and DMP is generally linear for green vegetation, particularly in semi-arid areas [24, 25, 26, 27, 28]. [29, 30, 31] have shown that there is a close relationship between dry matter productivity (DMP) and pasture biomass. Production efficiency models, such as Monteith parametric models have been developed to monitor primary vegetation production [32, 33]. Monteith has suggested that vegetation growth under non-stressed conditions correlates linearly with their radiation utilization efficiency (ERU) multiplied by amount of absorbed photosynthetically active radiation (APAR) [34, 35]. Mahyou used polynomial regression to assess relationships between field data and remotely sensed data in steppes of Eastern Morocco [36].

Specific cues are used to minimize disturbing effects, such as color and brightness of bare soil and to enhance signal from vegetation. While, the methodology for calculating these indices can give more details. Newer static analysis tools such as TaylorFit provide a closer interface to reality of terrain and facilitate results interpretation, minimizing error of false estimation.

In this study, we analyze Multivariate Polynomial Regression Model (MPR), which has proven its usefulness in studies of remote sensing data efficiency used in drought prediction in these steppes [23, 37].

The objective of this study is to highlight the use of this validation model and study of behaviour of FAPAR and DMP phenorological indices and SWI soil moisture in an arid or semi-arid environment. Strong soil moisture-productivity relationship in arid areas may hide more details that could be important for future behavior of carbon cycle.

2 Materials and Methods

2.1 Study area

African rangelands account for 43% of continent's total area, and are divided between shrublands, savannas, steppes and grasslands. Livestock is often raised on bare ground in rainy years [38]. The causes of rangeland degradation are complex in time and space and are often associated with environmental factors in addition to interactions between pastoralism, governance and policies. The extent of these degradations is often debatable, as are their causes and potential solutions for their improvement.

Arid and semi-arid rangelands account for 82 percent of Morocco's dryland area. These are ecosystems with natural or semi-natural vegetation consisting of steppes, shrubs, and grasslands. Their plants are generally used in animal production because their climate and soil are often unfavorable for agriculture. These rangelands are often found in arid and semi-arid zones. 54% of Moroccan national territory where isohyets are less than 600 mm/year [39, 40].

Eastern rangelands (Figure 1), included in second part of this study are dominated by *Macrochloa tenacissima* (47%) and *Artemisia herba-alba* (39%).

In situ assessment of annual phytomass is based on method of [41, 42, 43]. According to this method, data are collected in field at level of selected study areas of 10 x 10 m². Our sampling sites cover a total area of 290 000 ha.

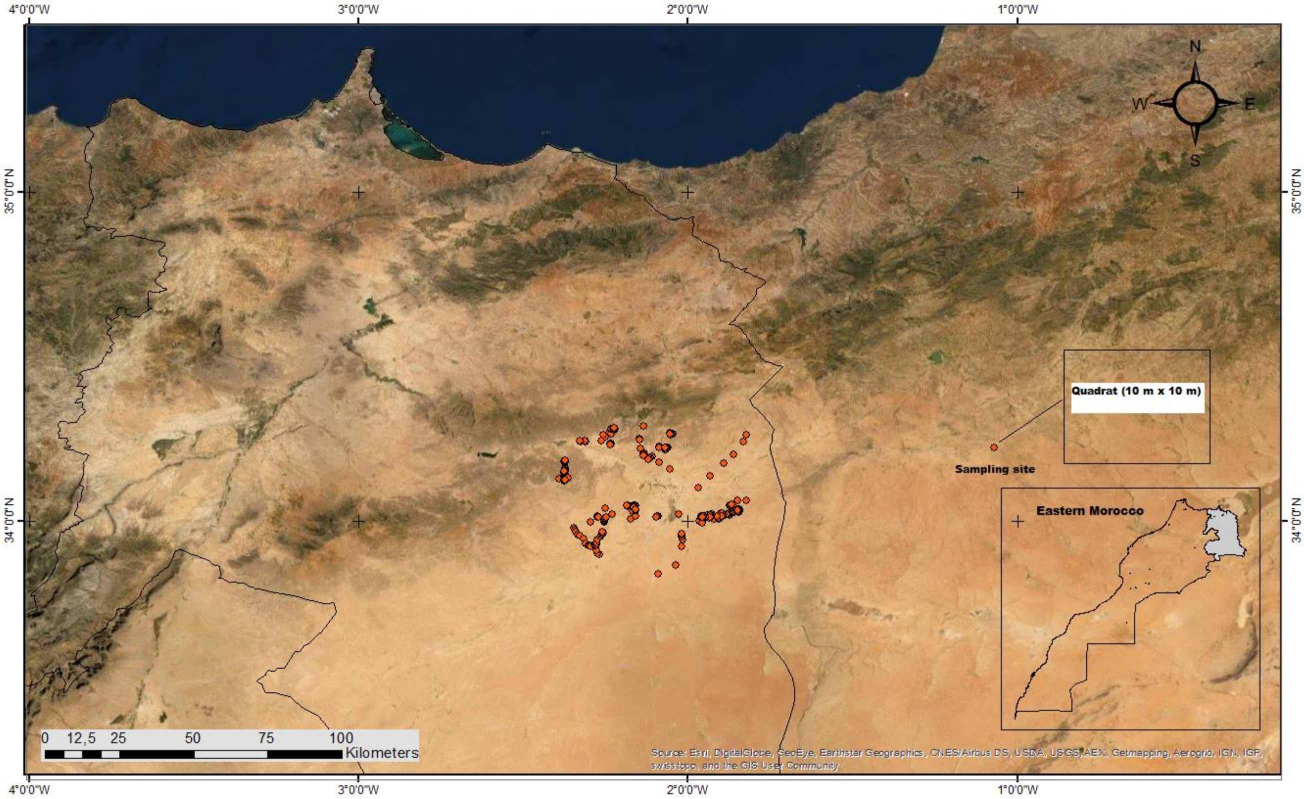


Fig 1. Location of sampling sites in Eastern Moroccan rangelands, illustration of phytomass measurements method of 2014 and 2015.

2.2 Remote sensing data acquisition and preparation

2.2.1 Soil Moisture Index (SWI)

360 decadal time series of SWI images, starting from September 2007 to August 2017 are used. These data are derived from Copernicus Global Land Service Soil Water index (CGLSSWI) version 3 with a spatial resolution of 11 km. 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 [44].

Soil moisture index (SWI) is physically defined as soil moisture content at first meter of soil relative units between wilting level and field capacity. Unit is 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 MetOp-A / ASCAT data [45].

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

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

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

2.2.2 Fraction of absorbed photosynthetically active radiation FAPAR data

A series of CGLSFAPAR data (fraction of photosynthetically active radiation absorbed, from the Copernicus World Terrestrial Service) from 2007 to 2017 version 2, are derived with a resolution of 1 km, and estimated from daily S1 TOC SPOT / VEGETATION and PROBA-V reflectances. FAPAR is relatively linear with respect to reflectance values absorbed by canopy and refers only to green parts of vegetation [46, 47].

2.2.3 Dry Matter Productivity DMP data

DMP dry matter productivity for period 2007-2017 with a resolution of 1 km estimates carbon mass fluxes at local, regional and global scales [48] and has proven useful in plant productivity studies such as grasslands. CGLSDMP (Copernicus Global Terrestrial Service Dry Matter Productivity) data from SPOT / VEGETATION and PROBA-V represents overall growth rate or increase in dry biomass of vegetation and could therefore be used as an indicator of pasture production. DMP product is based on light use efficiency (LUE) approach formulated by Monteith (1972) [34]. The latter reports that vegetation growth is defined as portion of incoming solar radiation used for photosynthesis that is absorbed by plants (APAR, kJAP / m^2 / d), using a number of conversion factors [48] according to the following formula (2):

$$DMP = R.\varepsilon c.fAPAR.\varepsilon LUEc.\varepsilon T.\varepsilon CO2\ \varepsilon AR[.\varepsilon RES] \quad (2).$$

Were LUE: Light use efficiency, εLUE: Optimal use efficiency, εT: Normalized temperature effect, εCO2: Normalized CO2 fertilization effect, εAR: Fraction retained after autotrophic respiration, εRES: Fraction retained after omitted effects (drought, parasites .,.).

2.2.4 Normalized difference vegetation index

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 [49].

2.2.5 Field data

Estimation of annual plants phytomass within a quadrat is based on method of [50] where each annual plant is cut at ground level, dried and then weighed. Drying of a plant is carried out in laboratory in an oven until the weight of plant remains constant at a temperature of 65°C.

In our study, phytomass estimation of our species such as: *Artemisia herba-alba*, *Macrochloa tenacissima*, *Stipa parviflora*, *Noaea mucronata*, *Atractylis serratuloides*, *Peganum harmala* and *Atriplex nummularia*, was based on reference unit method (3): UR [51] which consists in choosing an average plant, whole and representative of a given species in a quadrat**.**

$$PM\ (gr\ MS\ par\ 100\ m^2) = NUR \times PUR\ (gr\ MS\ par\ 100\ m^2) \quad (3).$$

Were PM: Weight of dry matter.
MS: Dry matter.
NUR: Number of references units.
PUR: Weight of reference unit.

2.3 Data pre-processing and statistical analysis

In this work, FAPAR, DMP, NDVI and SWI image series are re-engineered from 1 to 11 km. The index values used are extracted with SPIRITS, software for processing and interpretation of image series derived from remote sensing. Developed for monitoring of vegetation conditions from medium and low resolution satellite images, a large number of tools can be applied. In its common use in crop monitoring, common image series contain daily reflection factors, vegetation indices such as biophysical parameters like FAPAR and DMP [52].

FAPAR and DMP data, both from SPOT VEGETATION and PROBA_V, pose estimation problems and therefore their evaluation and validation will be essential for further analysis.

Thus, many statistical techniques exist in identification of outliers in FAPAR and DMP indices. In our study, a methodology for rapid assessment of estimates quality of these indices was used. NDVI values are used to compare FAPAR and DMP values recovered under two assumptions.

Once estimation errors found in phenological indices are corrected, estimation of productivity of our rangelands is carried out by soil moisture index SWI, for period before April (spring), from a polynomial regression-based algorithm.

Multivariate Polynomial Regression (MPR) modeling approach is very useful in this work. MPR in free online software (TaylorFit) makes MPR models very easy to develop [53]. TaylorFit incorporates polynomial terms with user-defined exponents, including negative expo-nents to test for ratios among variables. MPR can capture data features with comparable accuracy to artificial neural networks but produces representational models that are easier to use and communicate.

TaylorFit uses a step-wise algorithm with cross-validation to ensure model is parsimonious and generalizable. It also facilitates graphical data and model analysis with built-in tools. Recently new tools for sensitivity analysis including the importance ratio are added.

3 Results

3.1 Calibration of FAPAR and DMP data

During the verification and analysis of these data, we were able to differentiate between two categories of phenological indices that are poorly estimated at the level of pastoral areas.

In order to recover coherent values of these two indices, two categories of phenological indices at level of pastoral zones were raised. First with low values are zones of high atlas, eastern, rif, argan zone, pre-Saharan and Saharan. While, second, which has high values of middle atlas, northern atlasic plateaus, and coastal meseta and Mâamora. The low values were divided by 3000 (Hypothesis 1) and the high pixel values were divided by 100 (Hypothesis 2) (Figure 2). Thus, two types of shrub and herbaceous classes of pre-Saharan and Saharan zone are not expressed. This may be due to landscape noise (mountains and plains) and high diversity of vegetation in the study area.

Hypothesis for calibration FAPAR-DMP at areas with low values: We divide raw values / 3000.

Hypothesis for calibration FAPAR-DMP at areas with high values: We divide raw values / 100.

	A	B	C	D	E	F	G	H	I
1	Areas	Rangeland	Year	Month	converted FAPAR	converted DMP(kg/ha)	FAPAR	DMP	NDVI
2	HAC	Shrub	2007_08	September	0,10	0,07	306,9	207,9	0,27
3	HAC	Shrub	2007_08	September	0,11	0,07	319,95	203,85	0,27
4	HAC	Shrub	2007_08	September	0,11	0,07	332,55	204,3	0,27
5	HAC	Shrub	2007_08	October	0,11	0,06	338,4	186,75	0,28
6	HAC	Shrub	2007_08	October	0,12	0,06	355,95	176,4	0,28
7	HAC	Shrub	2007_08	October	0,12	0,06	373,05	165,15	0,28

Hypothesis 1

	A	B	C	D	E	F	G	H	I
1	Areas	Rangeland	Year	Month	converted FAPAR	converted DMP(kg/ha)	FAPAR	DMP	NDVI
2	MA	Shrub	2007_08	September	0,39	0,15	39,303	14,636	0,26
3	MA	Shrub	2007_08	September	0,41	0,15	41,121	14,576	0,26
4	MA	Shrub	2007_08	September	0,44	0,16	43,667	16,273	0,26
5	MA	Shrub	2007_08	October	0,45	0,14	45,061	13,515	0,27
6	MA	Shrub	2007_08	October	0,48	0,12	47,788	12,364	0,27
7	MA	Shrub	2007_08	October	0,53	0,10	52,879	10,394	0,28

Hypothesis 2

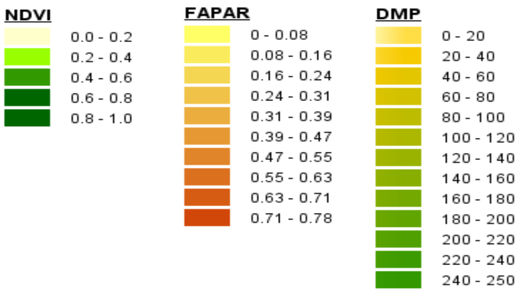


Fig 2. Example of raw and converted data from FAPAR and DMP used in this study.

3.2 Multivariate Polynomial Regression (MPR) in calibration step

Figure 3 and 4 shows that initial and corrected FAPAR and DMP with the first hypothesis (low values / 3000) have a significant correlation with Rsq = 0.98. Mean errors show that corrected data are more consistent than original data (Max Err = 116.94/ RMSE = 48.47) and (Max Err = 0.04/ RMSE = 0.016). On the other hand, figure 5 and 6 shows that initial and corrected FAPAR and DMP with the second hypothesis (high values / 100) have a significant correlation with Rsq = 0.90. Mean errors show that corrected data are more consistent than original data (Max Err = 30.4/ RMSE = 9.59) and (Max Err = 0.30/ RMSE = 0.09).

Original data of all Moroccan rangelands from April 2007 to 2017 show that values of these two indices are outliers and overestimated. These averages do not represent reality of vegetation in the study area.
The results of scaling correction confirm that corrected 11 km resolution data are encouraging for pastoral areas with low recovery rates. The existing 300 m data set may be more accurate.

Unfortunately, these data do not exist in large quantities, whereas our study requires a series of 10 years or less to modeling rangelands phytomass drought.

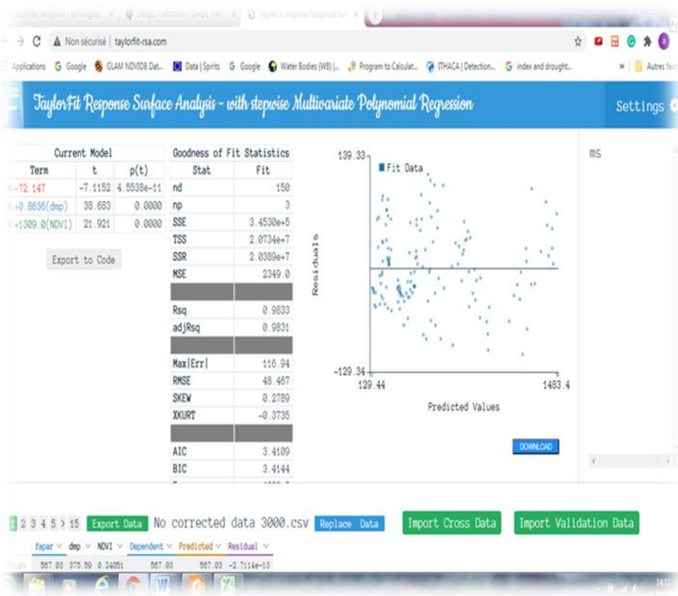


Fig. 3 Multivariate Polynomial Regression (MPR) between actual FAPAR-DMP at areas with low values and NDVI (befor application the hypothesis 1).

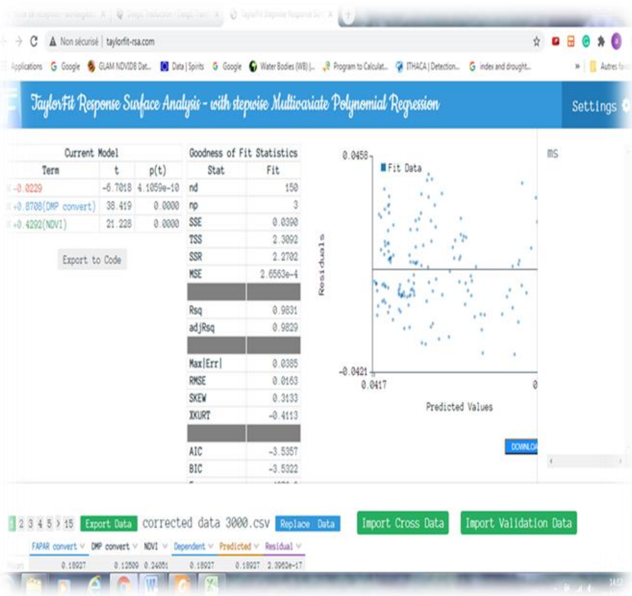
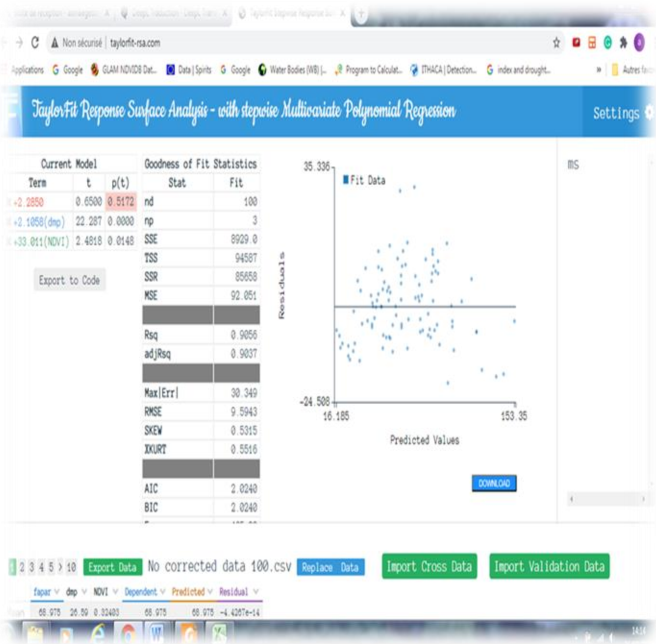


Fig. 4 Multivariate Polynomial Regression (MPR) between corrected FAPAR-DMP at areas with low values and NDVI (after application the hypothesis 1).



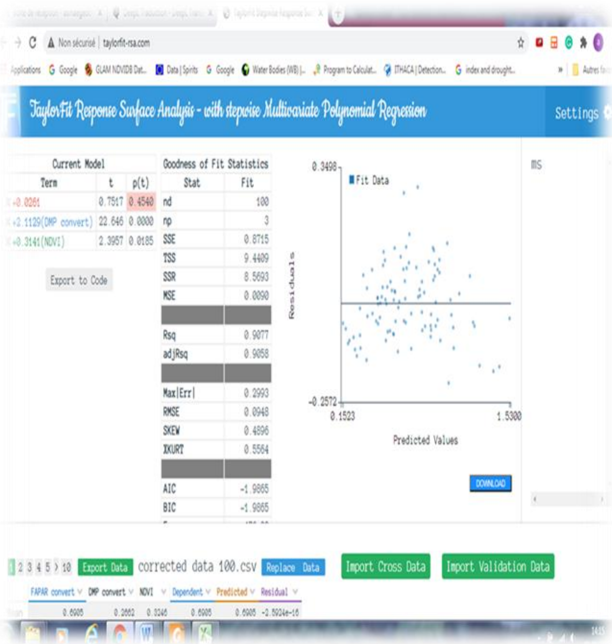


Fig. 5 Multivariate Polynomial Regression (MPR) between actual FAPAR-DMP at areas with high values and NDVI (befor application the hypothesis 2).

Fig. 6 Multivariate Polynomial Regression (MPR) between actual FAPAR-DMP at areas with high values and NDVI (after application the hypothesis 2).

3.3 Multivariate Polynomial Regression (MPR) in modeling step

Relationship between photosynthetic fraction, dry matter production and soil moisture index is made in this study for case of Moroccan rangelands. For this purpose, annual averages of SWI were calculated from November to February and those of phenological indices for period from February to April; according to three types of these rangelands.

Figures 7 and 8 show a good behavior of SWI, FAPAR and DMP indices. A high regression was obtained between SWI and DMP (r^2 = 0.90 / Max Err = 5.97 / RMSE = 2.9). The estimated correlation between SWI and FAPAR soil moisture index is perfect according to three types of courses (r^2 = 0.87 / Max Err = 6.25 / RMSE = 3.25). Based on these results we assume that Multivariate Polynomial Regression Model (MPR) between SWI and FAPAR and DMP tends to estimate production of areas where two indices are very consistent with each other. In particular, estimation with a similar model is even more important because it depends on low soil moisture of rangelands. Similarly, the results that allow us to model pasture production are those based on low SWI.

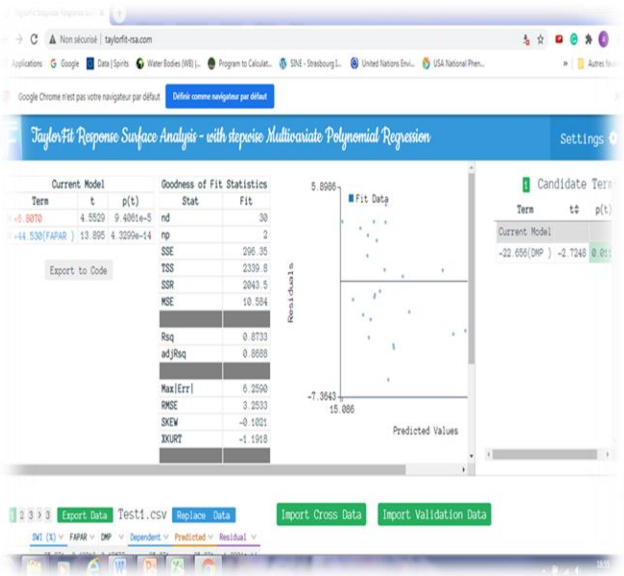


Fig. 7 Multivariate Polynomial Regression (MPR) between SWI (November to February) and FAPAR (February to April) from 2007 to 2017.

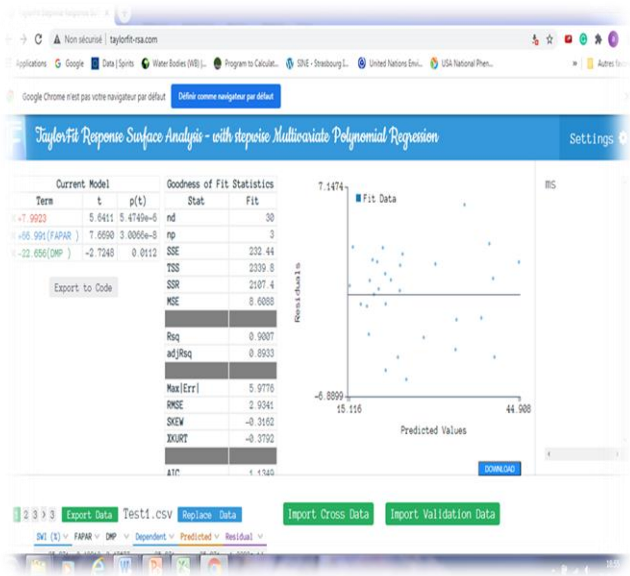


Fig. 8 Multivariate Polynomial Regression (MPR) between SWI (November to February) and DMP (February to April) from 2007 to 2017.

3.4 Comparison between field measurements and data from remote sensing

The estimate of phytomass shows a reduction in production of *Artemisia herba-alba* and an increase in that of *Macrochloa tenacissima*, during year 2015 compared to that of 2014 (Table 1). Also, many species indicative of rangeland degradation are ubiquitous.

In terms of floristic diversity, the dominant perennial species in the study area are represented by: *Macrochloa tenacissima*, *Artemisia herba-alba*, *Peganum harmala*, *Anabasis aphylla* and *Atactylis serratuloides*.

Our floristic sampling during year 2015 allowed us to detect a high field of *Macrochloa tenacissima*, 2496.77 kg/ha, while in field this species is in a moderately degraded state.

Table 1. Result of field phytomass, FAPAR, and DMP data from 2014 and 2015.

Year	Areas	Dry matter productivity	Fraction of absorbed photosynthetically active radiation	Species	Phytomasse (kg /ha)
	Shrubland	**94**	**0,40**	*Artemisia herba alba*	**1871,64**
2014	Sparse vegetation	**18**	**0,11**	*Macrochloa tenacissima*	**361,99**
	Degraded area	**33**	**0,13**	*Peganum harmala*	**0,24**
	Shrubland	**93**	**0,39**	*Artemisia herba alba*	**529,47**
2015	Sparse vegetation	**20**	**0,11**	*Macrochloa tenacissima*	**2496,77**
	Degraded area	**34,67**	**0,14**	*Peganum harmala*	**61,62**
				Atractylis serratuloides	**32,66**
				Noaea mucronata	**42,08**
				Anabasis aphylla	**127,64**

4 Discussion

In order to make effective data derived from remote sensing we have studied possibility of recovering FAPAR photosynthesis and DMP phytomass data on Moroccan rangelands. Once calibrated. these indices will be used to predict phytomass anomalies using SWI soil moisture index.

Soil moisture observations are in principle a more efficient and robust means of quantifying water availability. However. remote sensing approach also has its inherent drawbacks. Soil moisture data obtained by passive remote sensing have significant errors in areas of high vegetation density [54]. Therefore. semi-arid or arid regions have been selected where soil moisture data are more reliable to assess relationships between soil moisture and vegetation. An additional complication is that only soil moisture content of surface layer can be obtained from satellite observations. and not that of all Moroccan rangelands. Thus. for time being. only surface hydrological cycles and their impact on vegetation can be quantified [55].

Recent advances in estimation of biophysical products obtained from Proba-V and SPOT data have made considerable effort to validate them [56, 57, 58]. SPOT-FAPAR product has been extensively validated on a range of vegetation types and climatic regimes. It should be noted that validation refers to both direct and indirect validation. The former refers to comparison of satellite measurements with ground truth, while latter refers to an exercise. The validated products can be used by scientific research community [59, 60, 61, 62]. In our study. Initial values of FAPAR and DMP indices are corrected throughout the study area. Fraction of photosynthetically active radiation absorbed by vegetation and dry matter productivity are important biophysical variables for quantifying water, carbon and nutrient cycling in ecosystems.

5 Conclusion

Ensuring reliability of raw database is an important step especially in studies using remotely sensed data. After this step of verification of two phenological indices: FAPAR and DMP we were able to show that our two phenological indices would be reliable in such a drought forecast. Our data concerning fraction of photosynthetic radiation and productivity of dry matter emanating from two satellites SPOT-VEGETATION and PROBA-V. were evaluated by NDVI method of eMODIS which has shown its validity in many rangeland studies. The provision of pixel quality and validation information greatly facilitated use of these products. With recent research efforts focusing on product consistency. Validation framework can act synergistically to further refine accuracy and precision of these products over long term.

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