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NEW INVESTIGATION AND CHALLENGE FOR SPATIOTEMPORAL DROUGHT MONITORING USING BOTTOM-UP PRECIPITATION DATASET (SM2RAIN-ASCAT) AND NDVI IN MOROCCAN ARID AND SEMI-ARID RANGELANDS

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Abstract

Zbiri A., Hachmi A., Haesen D., El Alaoui-Faris F.E.: New investigation and challenge for spatiotemporal drought monitoring using bottom-up precipitation dataset (SM2RAIN-ASCAT) and NDVI in Moroccan arid and semi-arid rangelands. Ekológia (Bratislava), Vol. 41, No. 1, p. 90–100, 2022.

Remotely sensed soil moisture products showed sensitivity to vegetation cover density and soil typology at regional dryland level. In these regions, drought monitoring is significantly performed using soil moisture index and rainfall data. Recently, rainfall and soil moisture observations have increasingly become available. This has hampered scientific progress as regards characterization of land surface processes not just in meteorology. The purpose of this study was to investigate the relationship between a newly developed precipitation dataset, SM2RAIN (Advanced SCATterometer (SM2RAIN-ASCAT), and NDVI (eMODIS-TERRA) in monitoring drought events over diverse rangeland regions of Morocco. Results indicated that the highest polynomial correlation coefficient and the lowest root mean square error (RMSE) between SM2RAIN-ASCAT and NDVI were found in a 10-year period from 2007 to 2017 in all rangelands (R = 0.81; RMSE = 0.05). This relationship was strong for degraded rangeland, where there were strong positive correlation coefficients for NDVI and SM2RAIN (R = 0.99). High correlations were found for sparse and moderate correlations for shrub rangeland (R = 0.82 and 0.61, respectively). The anomalies maps showed a very good similarity between SM2RAIN and Normalized Difference Vegetation Index (NDVI) data. The results revealed that the SM2RAIN-ASCAT and NDVI product could accurately predict drought events in arid and semi-arid rangelands.

Key words: new investigation of bottom-up precipitation dataset (SM2RAIN-ASCAT) and NDVI, spatiotemporal drought, monitoring rangelands.

Introduction

Estimating global rainfall from satellite soil moisture data has been a highly innovative idea in hydrological modeling. An inverse approach would be extremely useful in data scar regions. The bottom-up approach is a challenge in hydrological and geophysical studies. However, accurate rainfall estimation is another vital mission.

Based on this concept, some recent studies have shown that satellite soil moisture (SM) data can be effectively employed for correcting satellite and reanalysis rainfall products (Pellarin et al., 2008, 2013; Crow et al., 2009; Chen et al., 2012). It is required to investigate if the assimilation of different observations of SM types improves the simulation of rainfall to control forecast drifts. Nevertheless, this type of model needs to be tested and probably improved under different conditions and types of vegetation cover (Zbiri et al., 2019a).

Firstly, the importance of SM for modeling land atmosphere interactions had increasingly been recognized, prompting much research in the numerical weather prediction (NWP) community in the last decade to improve the representation of SM processes (Jerez et al., 2010; Barthlott et al., 2011). Secondly, the spatial resolution of Advanced SCATterometer (ASCAT), which is in the order of tens of kilometers (25–50 km), is commensurate with the requirements of NWP models, while hydrological models run on much finer spatial grids (Bartalis et al., 2007; Wagner et al., 2010).

ASCAT is an active microwave remote-sensing instrument that was designed for monitoring of winds over the oceans for supporting operational applications. The first user community to take note of the opportunities offered by ASCAT was the NWP community (Zheng, Eltahir, 1998; Isaksen, Stoffelen, 2000; Figa-Saldaña et al., 2002; Liu, 2002; Koster et al., 2004).

Until now, the work of the NWP centers with the ASCAT SM product has concentrated on validation activities, quality assessments, and scientific studies. Thus, more scientific work is still required to characterize the spatio-temporal accuracy of ASCAT SM. Given the central and unifying role of SM in understand-

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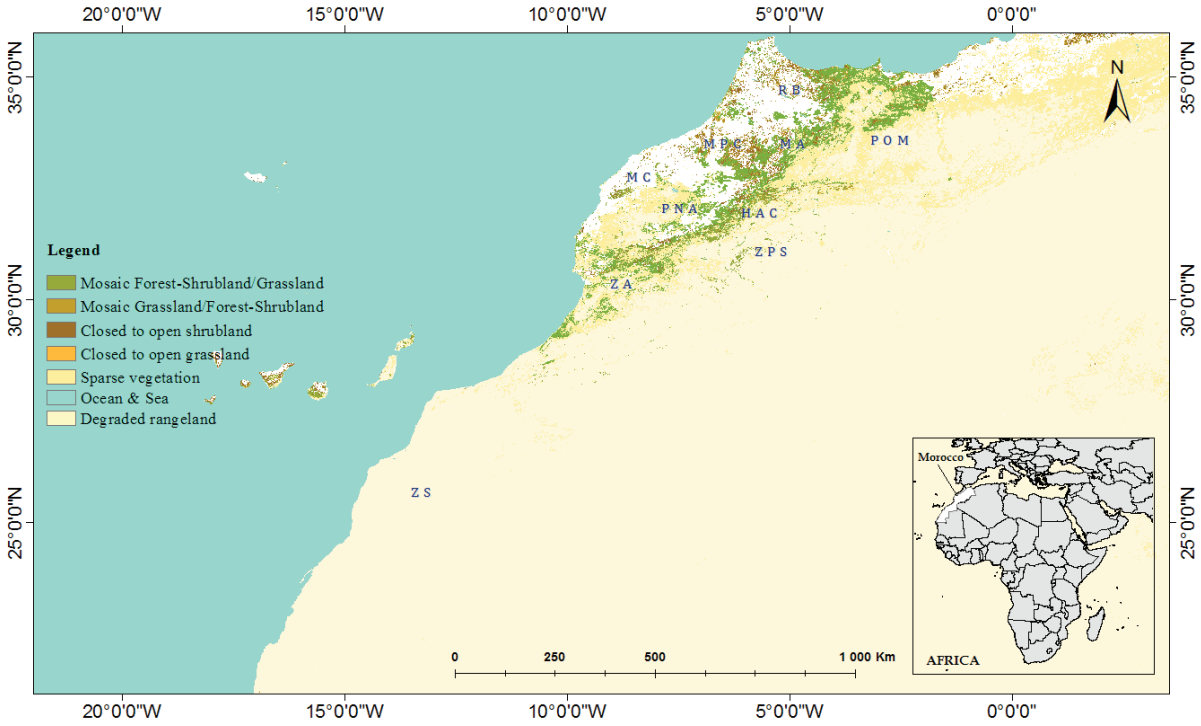


Fig. 1. Map of the study areas in Moroccan rangelands (HA: High Atlas; MA: Middle Atlas; MC: coastal Meseta; MPC: Mâamora; PNA: North Atlas plateaus; POM: Eastern Highlands; RB: Rif; ZA: Argan zone; ZPS: pre-Saharan zone; ZS: Saharan zone).

ing atmospheric, hydrologic, biologic, and geomorphic processes and their interactions (Legates et al., 2011), it has, however, a significant potential in many other applications also.

In recent years, integration of satellite-based SM information on a regional level enables analysis of potential relationships between anomalous soil conditions and increased incidence rates of natural hazards such as flooding and drought events, the latter being directly related to wildfire occurrence (Xiao, Zhuang, 2007). In Moroccan rangelands, Drought Early Warning System has been developed based on the results of strong polynomial correlation between SM and vegetation index (Zbiri et al., 2019a,b). The ASCAT SM product shows that science does not proceed along predetermined pathways. Being an active sensor operated in C-band, ASCAT has often been held to be suboptimal for SM mapping because of its higher sensitivity to surface roughness and vegetation compared to passive L-band sensors (Wagner et al., 1999; Kerr, 2007).

Recent study proposes a new rainfall measurement approach, SM2RAIN, as a way of monitoring rainfall from a satellite perspective. This approach is opposed to the classical perspective that is based on inversion of the atmospheric signals reflected or radiated by atmospheric hydrometeors. SM2RAIN is applied for terrestrial rainfall estimates on a global scale by using SM observations (Brocca et al., 2013).

When accumulated rainfall estimates are needed (daily rainfall), the new approach has the advantage of requiring a much lower number of measurements and, hence, of satellite sensors. However, it has the possibility to estimate only terrestrial rainfall and its dependence on land characteristics (low accuracy for dense vegetation coverage and complex topography) (Brocca et al., 2014, 2016).

In Moroccan rangelands, drought can be predicted based on results of strong correlations between SM and vegetation index and rainfall anomalies (Zbiri et al., 2019a,b).

Rainfall data are essential for drought monitoring (Forootan et al., 2019) and climate studies (Herold et al., 2016; Pendergrass, Knutti, 2018).

Thus, by providing spatial and temporal information, space-based remote sensing data become instrumental in drought detection, assessment, and management (Thenkabail et al., 2004; Wardlow et al., 2012). The local water balance also depends on evaporation, SM storage, and runoff relative to precipitation. The SM index has the advantage of quantitatively describing both dry and wet episodes (Chen, 2014) and tracking photosynthesis and productivity of plants (Xin et al., 2013; Tao et al., 2005). Many studies of drought suggest that there are relationships at a regional level between meteorological variability and sensitivity or adaptation of vegetation to water stress (Chen, 2014). In fact, the pastoral ecosystem with these extreme conditions of drought or cold can resemble an alpine landscape. Snowbed vegetation is one of the plant communities most sensitive to changes because it includes many ecological specialists (Kliment, Valachovič, 2007). The contemporary snowbed communities resemble alpine grassland that existed much more than 50 years ago (Matteodo et al., 2016) and are among the most vulnerable alpine vegetation types. Therefore, this vegetation type offers a good opportunity to study changes taking place in alpine habitats, driven by climate change and grazing cessation (Palaj, Kollár, 2019).

This research explores the role of correlation between SM-2RAIN rainfall and vegetation index to predict drought in arid and semi-arid Moroccan rangelands. The SM index is strongly explained in all rangelands types. In a degraded rangeland, the soil water index (SWI) is saturated. We suppose that SM2RAIN rainfall data give a more efficient and robust model to drought forecast, particularly for these degraded areas.

Material and methods

Study area

This study was carried out in 10 areas of Moroccan dryland (Fig. 1). According to the Global Land Cover classification, three areas, cover, respectively, 36.36 million hectar (ha) of degraded areas, 12.82 million hectar (ha) of sparse vegetation and 3.32 million ha of shrublands. Similar to the Algerian rangelands, the study area is a region geographically located within a steppe ecosystem, whose plant and soil diversity is remarkable, presenting a key indicator for this bioclimatic stage. Land degradation, anthropogenic pressure, and climatic constraints have accentuated the decrease in floristic richness and denuded the soil cover, of which this last wealth persists and resists. The low quantity of organic matter in the soils and other mineral elements under a total limestone level dominate majority of the study stations and along with decrease in rainfall, these form the major causes of disruption of growth and development of plants. Also, inside this type of ecosystem, plants can resist to develop with a minimum of climatic conditions and edaphic cover (Adjabi et al., 2019).

The hydraulic potential of the study area is clearly decreasing. This means that Morocco is today among the countries that are very much concerned about the problem of water stress (Hofste et al., 2019).

The spatial distribution of these water resources is very unequal, with the southern and eastern regions being the most disadvantaged. According to the World Water Resources Institute, Morocco is affected by water stress ranging from 25% to 70% (Hofste et al., 2019).

SM2RAIN

SM2RAIN-ASCAT is a new global scale rainfall product obtained from SM data through the SM2RAIN algorithm (Wagner et al., 2013; Brocca et al., 2014). The primary global daily datasets of SM2RAIN rainfall (mm/day) employed in this study are acquired from ASCAT at a spatial resolution of 12.5 km (Brocca et al., 2019). Ten years' (from 2007 to 2017) cumulative value composite of SM2RAIN images at 250-m spatial resolution were exploited for drought monitoring.

Simple Python and Matlab codes for the extraction of SM-2RAIN-ASCAT rainfall at one or multiple station(s)\location(s) are available at https://zenodo.org/record/3451685.

The SM2RAIN code in Python is available at https://zenodo.org/record/2203560. The SM2RAIN code in Matlab is available at http://hydrology.irpi.cnr.it/download-area/sm2rain-code/. A GeoTIFF version of SM2RAIN-ASCAT dataset is available at https://zenodo.org/record/3520620.

The soil water balance equation for a layer depth Z (L) can be described by the following expression :

$$Zds(t)/dt = p(t) - r(t) - e(t) + g(t) \qquad (1),$$

where $s(t)$ (-) is the relative saturation of the soil or relative SM, t is the time, and $p(t)$, $r(t)$, $e(t)$, and $g(t)$ (L/T) are the precipitation, runoff, evapotranspiration, and drainage rate, respectively.

Whenever it rains, the evaporation rate can be safely assumed as negligible ($e(t) = 0$). Moreover, by assuming that all precipitation infiltrates into the soil, the runoff rate is zero ($r(t) = 0$). For the drainage rate, the following relation may be adopted: $g(t) = as(t)^b$, where a (L/T) and b (-) are two parameters expressing the nonlinearity between drainage rate and soil saturation. The rearrangement of equation (1) with the described assumptions yields:

$$p(t) \approx Zds(t)/dt + as(t)^b \qquad (2).$$

This equation can be used for estimating the precipitation rate from the knowledge of relative SM, $s(t)$, its fluctuations in time, $ds(t)/dt$, and three parameters (Z, a, and b) to be estimated through calibration. Even though the assumptions made for deriving equation (2) might introduce some errors, they allow obtaining a simple (but effective) method for the retrieval of rainfall from SM data (Brocca et al., 2013) that can be easily applied on a global scale.

NDVI-eMODIS

NDVI-eMODIS images with a spatial resolution of 250 m and a projection (WGS 84) were used. This time series of 552 NDVI-eMODIS images dates from September 2007 to August 2017. The vegetation index is calculated from MODIS L1B Terra surface reflectances following to equation (3) (Jenkerson et al., 2010). The sensor provides high temporal resolution images, which are very useful for monitoring significant environmental changes. The Normalized Difference Vegetation Index (NDVI) averages were obtained by the final processing of the eMODIS-based inputs, which consisted of spatial segmentation of the imageries using a mask surrounding Moroccan rangeland and Global Land Cover 2000 (Mayaux et al., 2004).

$$NDVI = (NIR - R)/(NIR + R) \qquad (3),$$

where NIR is near infrared and R is red.

Spatiotemporal and statistical analysis

With Software for the Processing and Interpretation of Remotely sensed Image Time Series (SPIRITS), which is a free software environment for the analysis of time series of remotely sensed images, we can perform spatial and temporal processing of time series. In this experiment, SM2RAIN and NDVI values were obtained by the final processing inputs which consisted of the spatial segmentation of the imageries using a mask surrounding Moroccan rangeland and Global Land Cover 2000.

SPIRITS is a Windows-based software aiming at the analysis of remotely sensed earth observation data. The version currently available (February 2018) was conceived as a graphical user interface (GUI) around a software called Global IMage Processing SoftwarE (GLIMPSE), also developed by the Flemish Institute for Technological Research (VITO). GLIMPSE consists of a set of American National Standards Institute-C programming language ANSI-C executables performing a wide range of dedicated

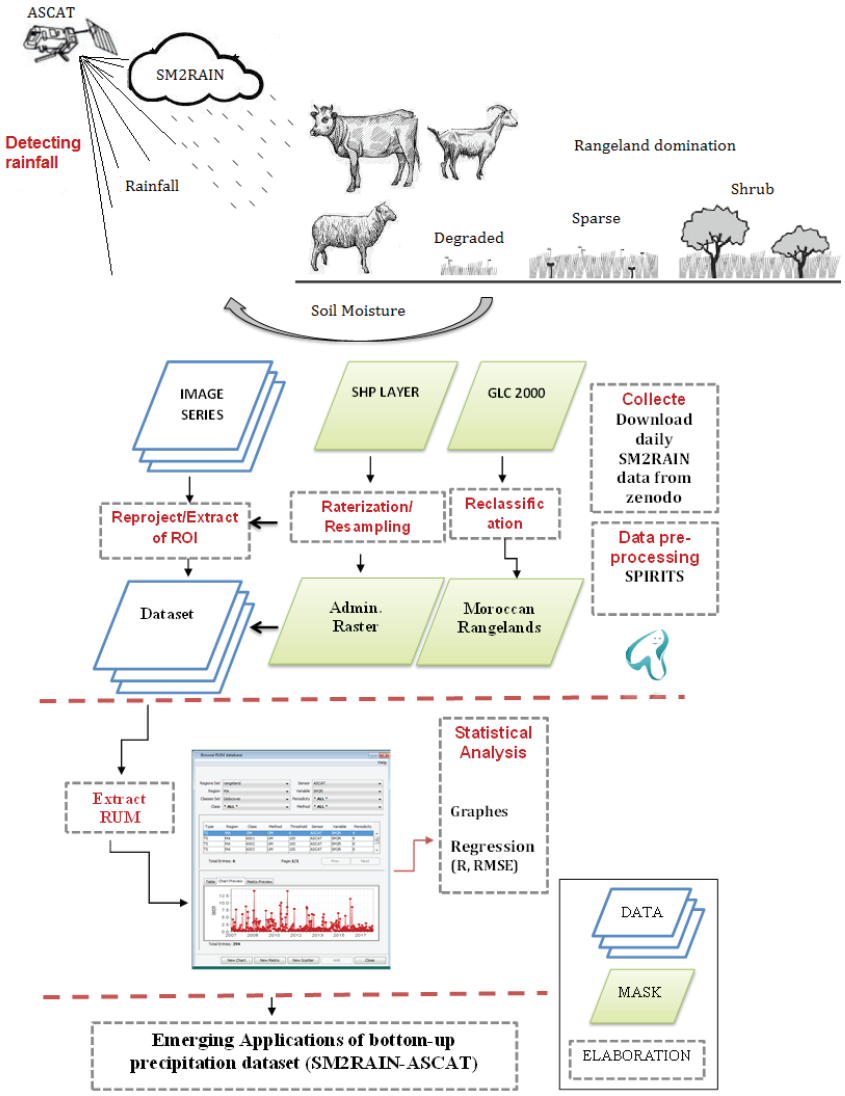


Fig. 2. Processing steps for drought monitoring using bottom-up precipitation dataset (SM2RAIN-ASCAT) and NDVI in Moroccan arid and semi-arid rangelands.

image-processing tasks. GLIMPSE modules can only be accessed via a command line interface, but they can be scripted to set up complex processing chains. SPIRITS provides a convenient GUI, which enables to guide the GLIMPSE modules via an up-to-date interface and run them in the background. However, gradually, a number of new tools were incorporated without relationship with GLIMPSE, for example, the import of imagery in external formats, reproject data, adapt metadata of a satellite image HDR, resampling and generation of maps, and the extraction of regional databases (Eerens, Haesen, 2016).

Statistical analysis was performed by comparing the NDVI averages (from February to April) and cumulates of SM2RAIN rainfall (from November to February) for the 10 rangeland zones in Morocco.

Then, polynomial regression (PR) was tested between this data on three types of dryland classes (shrub, sparse, and degraded areas) and 10 rangeland zones from 2007 to 2017.

The anomalies calculated using two methods of the similarity of each type of data used: absolute difference (AbsDif) to historical average of SM2RAIN and relative difference (RelDif) to historical average of NDVI.

$$ADha(y,p) = X(y,p) - MEAN(p) \quad (4),$$

where X is the SM2RAIN estimate for a given period *p* (from November to February) and MEANp is the mean value of the SM2RAIN during period p, derived from the previously described 10 years of SM2RAIN time series.

$$RDha(y,p) = [X(y,p) - MEAN(p)]/MEAN(p) \quad (5),$$

where X is the NDVI estimate for a given period *p* (from February to April) and MEANp is the mean value of the NDVI dur-

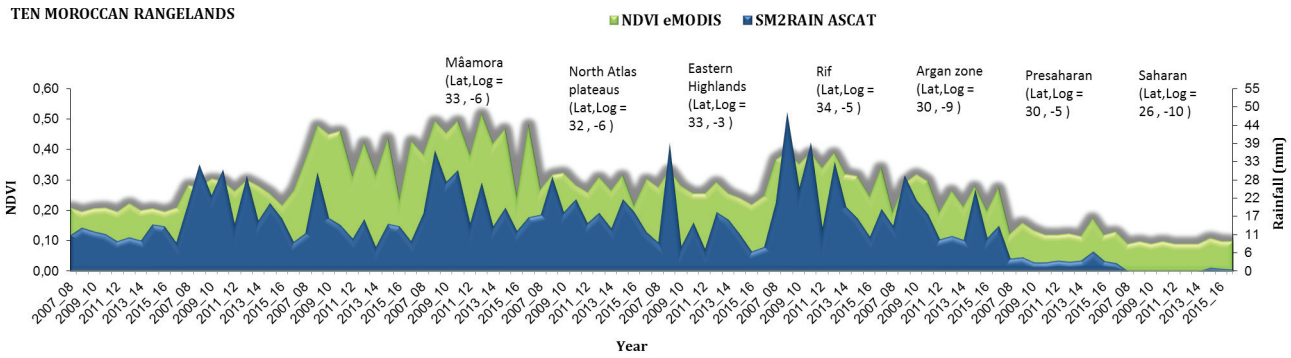


Fig. 3. Monthly trend of SM2RAIN rainfall and NDVI at 10 Moroccan rangelands between 2007 and 2017.

Table 1. NDVI and SM2RAIN statistic for each rangeland category: correlation coefficient *R*, standard deviation Std Dev, and variation coefficient CV value for comparison of years.

	All Moroccan rangelands		Shrub rangeland		Sparse rangeland		Degraded rangeland	
	NDVI	SM2RAIN	NDVI	SM2RAIN	NDVI	SM2RAIN	NDVI	SM2RAIN
Mean	0.30	63.64	0.39	77.5	0.28	62	0.20	47.33
Minimum	0.15	30	0.32	52	0.15	30	0.15	31
Maximum	0.46	112	0.46	112	0.41	102	0.28	70
Std Dev	0.10	22.38	0.05	20.26	0.09	21.76	0.05	15.33
CV	33.58	35.17	12.01	26	31.49	35.09	23.35	32.39
R	0.81	0.82	0.61	0.66	0.82	0.82	0.99	0.99

ing period p, derived from the previously described 10 years of NDVI time series.

The purpose of this study was to verify the effectiveness of polynomial regression (PR) and anomalies to model the relationship between SM2RAIN-ASCAT dataset and NDVI in Moroccan rangelands. We propose a new method of investigation of SM2RAIN rainfall data to forecast drought at the rangeland. The rainfall data can give the information of interest at a regional scale, when SM is saturated (Fig. 2).

Results

Variability of vegetation index and SM2RAIN-ASCAT rainfall data

The temporal evolution of monthly values of NDVI and SM2RAIN, spatially averaged and cumulated over all Moroccan rangelands between 2007 and 2017, is presented in Figs 3 and 4 and Table 1. Time series of monthly NDVI and SM2RAIN from September to August are also shown for three different types of rangeland (shrub, sparse, and degraded rangeland) at 10 zones. The figures show that the two parameters (rainfall conditions and vegetation index status in dryland) studied from 2007 to 2017 are proportional to each other.

According to the estimates, the comparison between NDVI and precipitation shows the periods when these data were poorly estimated, especially in 2011–2012, 2014–2015, and 2016–2017.

A significant difference was observed in the variables' series between the 10 years from November to February. However, for the other months, the difference was nonsignificant between years.

Nevertheless, rainfall data and NDVI values varied between years. For all rangeland categories and areas, SM2RAIN rainfall values were relatively high in 2008–2009, 2010–2011, and 2012–2013.

High SM2RAIN and NDVI estimations were obtained in coastal Meseta and Mâamora. The Saharan areas had the lowest average NDVI values, which differed little between peak and low growth season because of the very low vegetation cover.

Correlation between NDVI and SM2RAIN

These results suggest an increase in vegetation activity during spring, when the conditions for growth are best. In all cases, a highly significant difference was observed in the NDVI series, within the 10 years between February, March, and April. The Moroccan rangelands had higher SM2RAIN values between November and February in all categories. Lower SM2RAIN values were observed starting from June. A significant correlation between rainfall and NDVI was observed from November to February. Figures 5 and 6 show that polynomial correlation is good for sparse and moderate shrub rangeland (R = 0.82 and 0.61, respectively). However, degraded rangeland had strong positive correlation between NDVI and SM2RAIN with coefficient

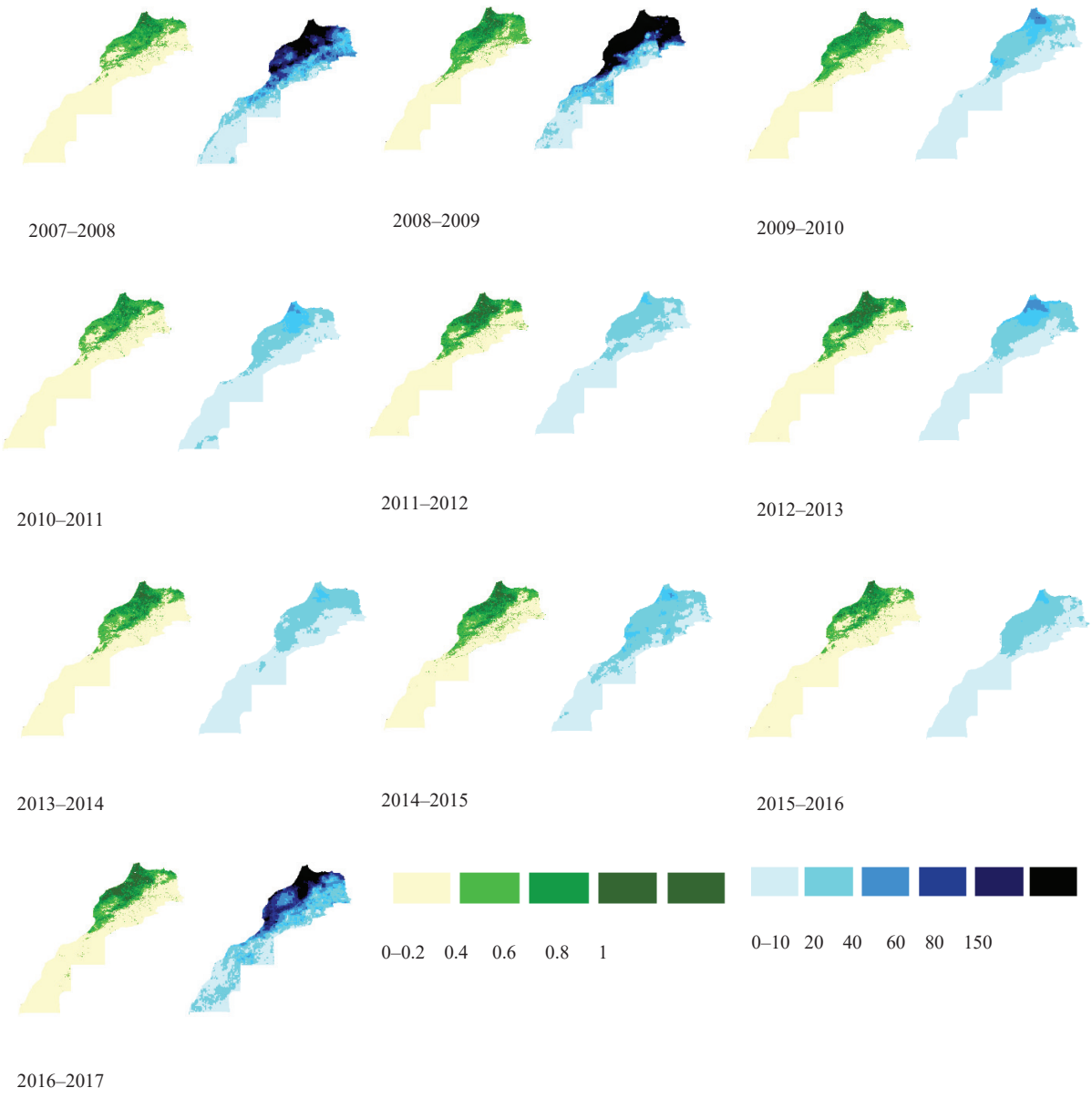


Fig. 4. Spatiotemporal distribution of SM2RAIN-ASCAT rainfall ad NDVI-eMODIS in Morocco between 2007 and 2017.

R = 0.99. For all Moroccan rangelands, the correlation between SM2RAIN data and NDVI was strong (R = 0.81). In Moroccan rangelands, vegetation-growing season is during February, March, and April. We found a good correlation between cumulative rainfall of the period from November to February and NDVI (average of February, March, April). Therefore, we can predict an anomaly of NDVI from February. This allows acting early to manage the drought crisis.

Spatial drought distribution

Spatial anomaly illustrates that the comparative analysis of various indices represents a better interpretation and monitoring of drought for the areas which are majorly affected due to vegetative drought. Figures 7 and 8 show severe SM2RAIN rainfall anomalies for sparse and degraded rangelands, but no NDVI anomalies were detected for the shrub area in 2016–2017. In 2007–2008, 2011–2012, 2013–2014, and 2015–2016, NDVI abnormalities were observed when severe SM2RAIN rainfall anomaly was estimated for High atlas, Eastern Highlands, Argan zone, pre-Saharan, and Saharan areas. Drought related to SM2RAIN rainfall was severe for sparse and degraded vegetation. Similarity of SM2RAIN rainfall and NDVI anomalies is good for all years in these rangelands of Morocco. SM2RAIN is a highly innovative idea in hydrological modeling. This data would be extremely useful in data scar regions of Moroccan arid areas. The spatial and temporal evolution of the new SM2RAIN rainfall is another key parameter such as SM for detecting water stress related to a decrease in NDVI. The anomaly was calculated by the formulae shown in equations 4 and 5. During the period of study,

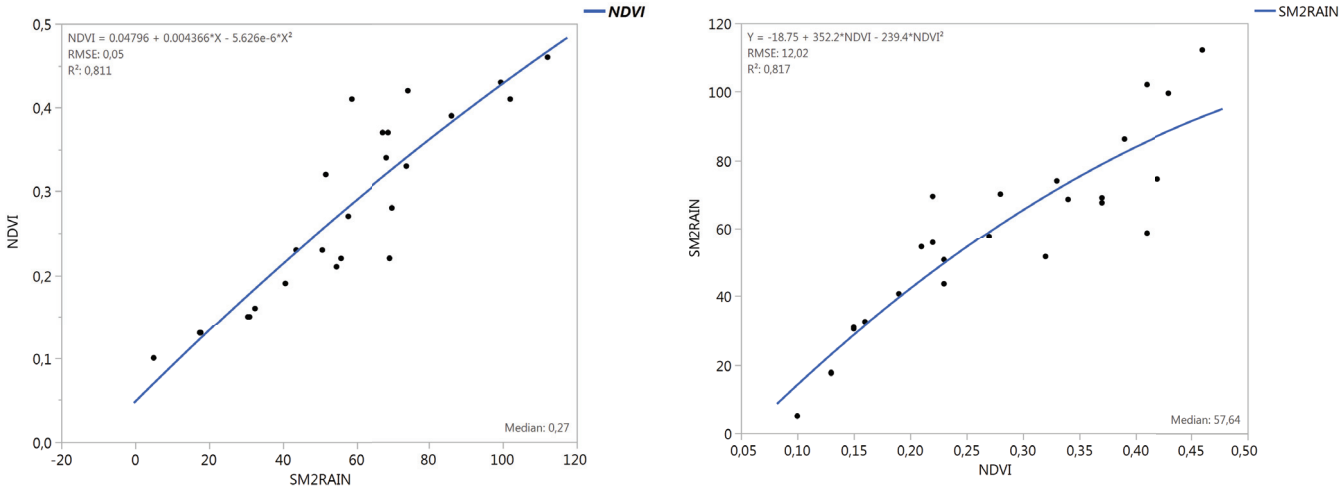


Fig. 5. Predictive modeling with polynomial regression between cumulative SM2RAIN rainfall (from November to February) and average NDVI (from February to April) of all Moroccan rangelands in the period 2007–2017.

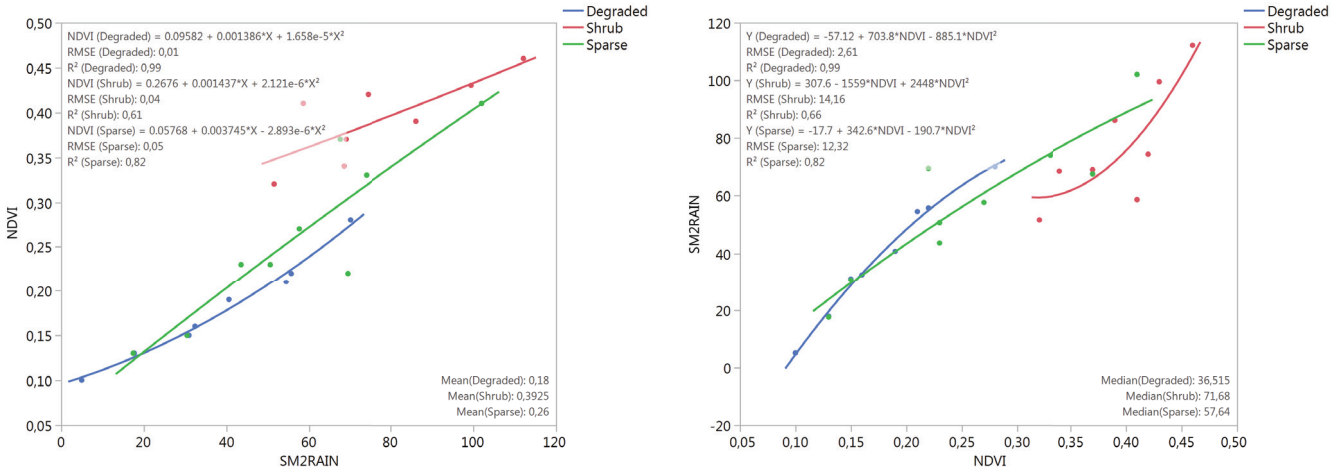


Fig. 6. Predictive modeling with polynomial regression between average NDVI and cumulative SM2RAIN rainfall within a specific framework of layering and shaped functions for three rangeland areas (degraded, shrub, sparse).

spatial distribution of SM2RAIN rainfall anomalies was related to anomalies of vegetation index. However, limitations of SM2RAIN–ASCAT data record consist of the presence of spurious rainfall events due to high-frequency soil moisture fluctuations over the southern areas. Discrepancies between the NDVI and SM2RAIN rainfall anomalies were also present in north and south rangelands. The analysis also shows that this agreement of difference between paired anomalies proves the efficiency of data provided by ASCAT and eMODIS sensors. The results show perfect similarity to the anomalies estimated for each rangeland (shrub, sparse, and degraded areas) during the years from 2007 to 2017. An anomalies time series of precipitation (SM2RAIN) has been calculated to understand the rangelands' water stress condition and correlate it with decrease in vegetation indices. The SM2RAIN–ASCAT rainfall product that can be used as an input for applications such as drought prediction from period between November and February. The anomalies may underestimate the spatial variation of drought affecting the rangelands' vegetation, as illustrated in Figs 7 and 8.

Conclusion

For the majority of the world's land areas, satellite-based precipitation estimates offer the only possible source of near-real-time precipitation accumulation information for operational hydrological applications. However, it is difficult to provide information at more precise levels (Hossain, Anagnostou, 2004).

Rainfall and SM are two important quantities for modeling the interaction between the land surface and the atmosphere (Brocca et al., 2013).

Usually, rainfall observations are used as input data for modeling the decrease in vegetation cover during drought period. SM data have a memory reflecting precipitation amounts and still provide useful information on precipitation accumulation

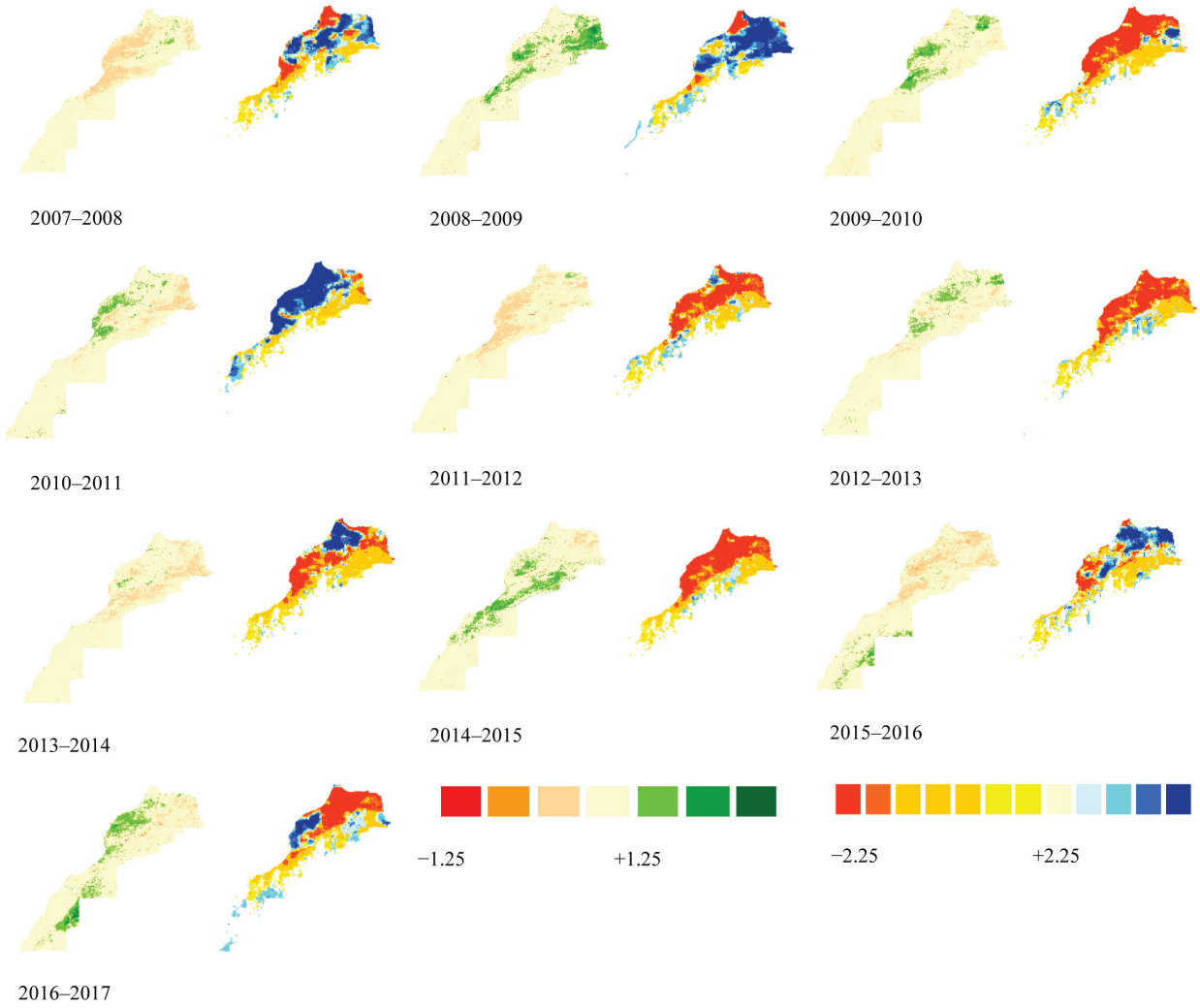


Fig. 7. Maps showing anomalies of SM2RAIN-ASCAT and NDVI in Moroccan rangelands for 10 years from 2007 to 2017.

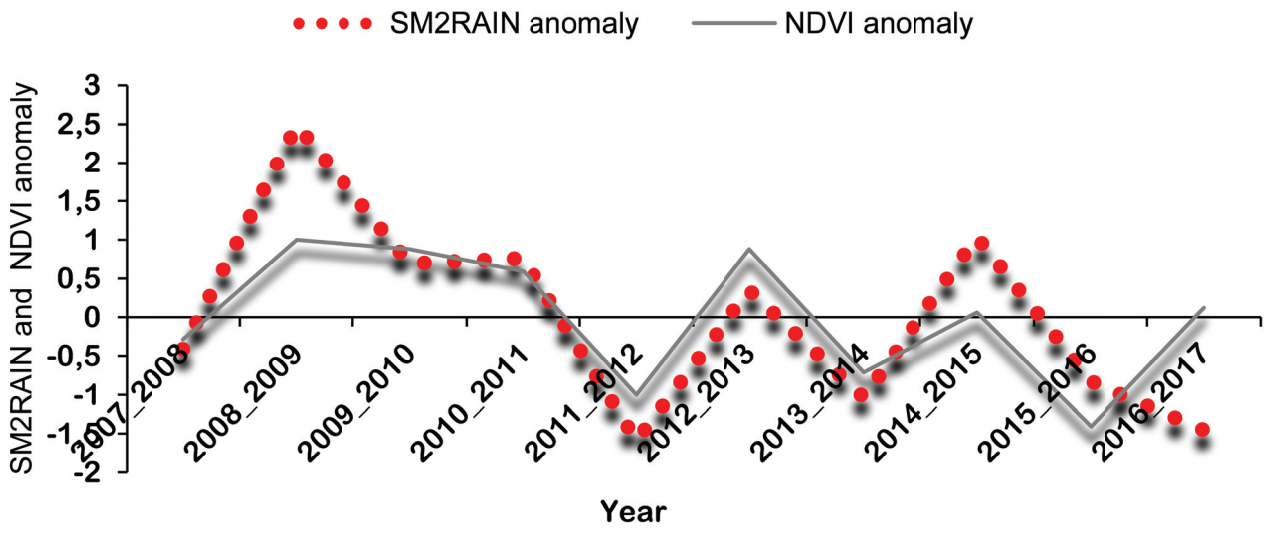


Fig. 8. Graph showing anomalies of SM2RAIN-ASCAT and NDVI in Moroccan rangelands for 10 years from 2007 to 2017.

(Crow, 2003; Pan, Wood, 2006; Crow, Zhan, 2007). Recent studies have shown that surface SM can be utilized in improving rainfall estimation as it reflects recent precipitation. Zhang et al. (2019) highlight that combining SM and historical precipitation information can effectively improve satellite-based precipitation products in near-real time.

However, as Wagner et al. (2013) show, the validation results for ASCAT have overall been quite positive, with ASCAT performing equally well over some regions. Of course, there are also situations where the quality of ASCAT retrievals is problematic over mountainous regions or over some desert areas.

The progress of new work with ASCAT SM is also important in providing more information on product accuracy. For example, SWI data and associated anomalies were applied to drought monitoring and such data are suitable for early warning system in the arid rangelands of Morocco.

After all these years of study, now we have a much better understanding of why the SWI performs so well in degraded dryland. This is because under dry conditions, ASCAT can detect the signal from underground rocks and stones (Wagner et al., 2013; Taylor et al., 2012).

Additionally, in any scientific study, the comparison and validation of different types of data require a clear approach. Datasets that take into account several study domains facilitate understanding of the interactions of the components of an ecosystem. The calibration of SM2RAIN rainfall data uses three parameters (*Z*, *a*, and *b*) for each class by selecting a number of points (equal to 400 for this study) not significantly affected by noise in the SM retrievals (excluding the area covered by forest, desert, and characterized by complex topography) (Brocca et al., 2014).

Overall, the rangeland species seem to be sensitive to drought at the germination and initial growth phases. The germination recovery potential of stressed species can be regarded as a promising candidate in the rehabilitation of Mediterranean disturbed coastal habitats (Dadach et al., 2021). In fact, Faisal et al. (2019) emphasized that the effects of drought depend not only upon the degree and length of water scarcity, but also upon the plant growth phase. Seeds that had failed to germinate under water stress and germinated after being transferred to distilled water are the portion of seeds that form transient soil seed banks germinating naturally in the period of years receiving sufficient amount of rainfall. We assume rainfalls are the predominant environmental cue in triggering seed germination of species. Adequate precipitation adjusts temperatures, mitigates soil salinity, and raises the water potential (Khan, Gulzar, 2003).

Root zone moisture supply is one of the main factors limiting plant growth, particularly in arid and semi-arid zones. Therefore, the moisture content in the soil profile is one of the most important parameters for monitoring and predicting the growth of natural vegetation (Wagner et al., 2013). With respect to the capability of scatterometers for monitoring natural vegetation, Zbiri et al. (2019b) compared SWI time series with NDVI data as derived from images acquired by the Normalized difference vegetation index VEGETATION instrument over Moroccan rangelands. They found that both parameters are closely related and, together, the SWI and NDVI could be used for describing the spatial extent, severity, and persistence of drought episodes over Morocco from 2007 to 2017.

In this study, we tested the new SM2RAIN rainfall measured by SM and NDVI to monitor drought in rangeland. It appears that this method, which takes into account the vegetation types in the rangelands, is more accurate than the one based on area of low cover of vegetation like rangelands. The results of PR show good Pearson correlation values (*R*) and root mean square error (RMSE) between SM2RAIN rainfall and NDVI.

The anomalies show a very good similarity between the new SM2RAIN and NDVI data. The results revealed that the SM-2RAIN-ASCAT product could accurately predict early decrease in production at drought events in arid and semi-arid rangelands before the beginning of the agricultural campaign.

SM2RAIN-ASCAT showed a good performance in detecting drought in Moroccan arid and semi-arid rangelands. Koohi et al. (2021) concluded that the SM2RAIN can be suitable to identify spatiotemporal drought events by depicting well the precipitation pattern in arid regions. The proposed approach has thus still room for improvement and it will become an essential new tool for global-scale rainfall estimation over land surfaces (Brocca et al., 2014). Firstly, considering the initial challenges when starting to use ASCAT SM data in a particular application, the progress made in the various application domains is very promising (Wagner et al., 2013). Secondly, proving that ASCAT can give better information in degraded area.

Importantly, SM2RAIN-ASCAT rainfall demonstrates efficiency to a new investigation over many arid areas and soil typology. Using SM2RAIN rainfall in arid and semi-arid areas as a new way of monitoring yield of vegetation is new challenge. These products can be effectively used for rainfall estimation on a global scale.

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