**Hydrology and
Earth System
Sciences
Discussions**

Technical Note: Comparing and ranking soil-moisture indices performance over Europe, through remote-sensing of vegetation

E. Peled[1]**, E. Dutra**[2]**, P. Viterbo**[2,3]**, and A. Angert**[1]

[1]The Institute of Earth Sciences, The Hebrew Univ. of Jerusalem, Jerusalem 91904, Israel
[2]IDL, CGUL, Univ. of Lisbon, Lisbon, Portugal
[3]Institute of Meteorology, Lisbon, Portugal

Correspondence to: A. Angert (angert@huji.ac.il)

HESSD

6, 6247–6264, 2009

**Comparing and
ranking soil-moisture
indices performance
over Europe**

E. Peled et al.

Title Page	
Abstract	Introduction
Conclusions	References
Tables	Figures
◁	▷
◀	▶
Back	Close
Full Screen / Esc	
Printer-friendly Version	
Interactive Discussion	

E. Peled et al.

Abstract

Climate change induces long-term changes in soil-moisture. These changes can have important effects on the terrestrial biosphere, which can feedback into the climate system. In the past years there have been many attempts to produce and improve global soil-moisture datasets, however, comparing and validating these various datasets is not an easy task. Here, interannual variations in indices of soil moisture are compared to interannual changes in vegetation, as captured by NDVI. By comparing the correlations of the different indices with NDVI we evaluated which soil moisture index provides the most reliable soil moisture representation. We showed that NDVI can be used as an external validation dataset to soil moisture indices, in areas that are classified as warm temperate climate with hot or warm dry summers. Using the best performing index, NSM (Normalizes Soil Moisture), and the ICA (Independent Component Analysis) technique, we analyzed the response of vegetation to temperature and soil-moisture stresses over Europe.

1 Introduction

Having reliable information on the spatial and temporal variability of soil moisture is a key to many practical and scientific problems. Reliable soil-moisture data crucially improves long-term weather forecasts (Seneviratne et al., 2006; Ferranti and Viterbo, 2006), and helps to prepare better for drought. In addition, long-term changes in soil-moisture, induced by climate-change (Sheffield and Wood, 2007), can have important effects on the terrestrial biosphere, which feedback into the climate system through the carbon cycle (Angert et al., 2005; Fung et al., 2005).

Given these needs, there have been many attempts to produce and improve global soil-moisture datasets (Dai et al., 2004; Dutra et al., 2008; McKee et al., 1993; Palmer, 1965; Wells et al., 2004). Allegedly, some of these datasets have advantages over others. However, comparing and validating these various datasets is not an easy task.

E. Peled et al.

Ground-based soil moisture measurements are accurate, but hard to compare to the large scale datasets because of their point-based nature, their limited coverage, and the well-known high spatial variability of soils. Remote sensing methods on the other hand, provide extensive spatial and temporal coverage of soil moisture, but these
5 methods can only sense the top few centimeters of soil, and become less sensitive to soil moisture in vegetated regions as the vegetation water content increases (Wang et al., 2007). Another approach focuses on assessing soil moisture, not by modeling, but by remote sensing of vegetation.

This approach uses a well-known index for assessing vegetation spatial and tempo-
10 ral variability: the Normalized Difference Vegetation Index (NDVI). This index is based on the differential absorption of red and near infrared (NIR) light by leaves, and is linearly correlated with the fraction of photosynthetic active radiation absorbed by plants (Tucker and Sellers, 1986). The basic idea of this approach is that temporal variations in soil moisture cause changes in vegetation, which can be captured by NDVI.
15 However, the correlations between soil-moisture estimated by this approach to field measurements are low (Tadesse et al., 2005; Wang et al., 2007), probably because soil-moisture is not the only factor controlling vegetation and factors like temperature and management can also come into play. Using NDWI (Normalized Difference Water Index) instead of NDVI did not produce improved correlations (Gu et al., 2008).
20 Due to the limitations of the various methods for validating soil-moisture indices discussed above, we suggest here a somewhat different approach for using the NDVI signal. In the current study, interannual variations in indices for soil moisture are compared to interannual changes in vegetation, as captured by NDVI. The NDVI signal is affected by changes in vegetation leaf area and chlorophyll content, induced not only
25 by soils-moisture but also by other natural and anthropogenic factors such as temperature, and management. However, in areas and seasons in which soil-moisture is the main limiting factor, a better soil-moisture estimate will result in a better correlation with NDVI. Thus, comparing the correlation of the different indices with NDVI will enable to evaluate which soil moisture index provides the most reliable soil moisture

representation. This is of course true only if all indices are derived independently of NDVI (for example, no optical reflectance data were used to create them). One should emphasize that the correlation for a single pixel may be randomly high. However, by integrating large areas, and by focusing on long time series of interannual variability,
5 we mostly eliminate this problem. In addition to ranking the soil moisture indices based on correlation with NDVI, we have explored the spatial distribution of this correlation, and its relationship with other variables.

2 Data and methods

2.1 Soil moisture

10 In the current research we have used five indices for soil- moisture:

The Palmer Drought Severity Index (PDSI): This index is a standardized measure of surface soil-moisture conditions which integrates moisture inputs (precipitation), and outputs (drainage and evapotranspiration). Here, we have used the global PDSI calculated by Dai et al. (2004) at a resolution of 2.5° by 2.5°, based on observed monthly
15 surface air temperature and precipitation.

Despite its popularity, PDSI has several limitations; these include an inherent time scale, and the uncertainty of the index to the amount of water available for plant use in different soil types. A common critique of the PDSI is that the behavior of the index at various locations is inconsistent, making spatial comparisons of PDSI values difficult
20 (Heim, 2002; Lloyd-Hughes and Saunders, 2002; Sims et al., 2002).

The Self-Calibrating PDSI (SC-PDSI): This index was suggested to be a more appropriate index for geographical comparison of climates of diverse regions (Wells et al., 2004). SC-PDSI improves the performance of the PDSI by automating the calculations of the empirical constants used in the PDSI algorithm. This was achieved by
25 determining, for each location, the climatic characteristic weighting factor (K) using the historical climatic data from only that location. In a similar way, the duration factors are

calculated separately for wet and dry spells, thus influencing the sensitivity of the index for changes in the moisture regime (Van Der Schrier et al., 2006). Due to the computed modifications, the SC-PDSI is claimed to behave in a consistent, predictable manner as well as to represent the climates of diverse locations in a more realistic way (Wells et al., 2004). We have used a 0.5° grid, monthly temporal resolution dataset (Van Der Schrier et al., 2006).

The Standardized Precipitation Index (SPI), proposed by McKee et al. (1993) is an alternative to PDSI, and was designed to quantify the precipitation deficit for multiple time scales. SPI represents a statistical z-score or the number of standard deviations (following a gamma probability distribution transformed to a normal distribution) for the deviation of precipitation, accumulated over a given period, from the mean. One advantage of SPI is that it can be tailored to specific needs. For example, SPI is routinely calculated for 1-, 3-, and 6- months (Heim, 2002; McKee et al., 1993). An obvious disadvantage it that SPI accounts only for moisture inputs, but not outputs. In the current study we have calculated SPI3 (i.e., with 3 months aggregation period) from precipitation datasets from two sources:

The Global Precipitation Climatology Project (GPCP), which merges data from over 6000 rain gauge stations and from satellite observations into a 2.5° global grid, monthly rainfall dataset (Xie et al., 2003).

The European Centre for Medium-Range Weather Forecasts (ECMWF) Re-Analysis project (ERA-40), which produces a long time-series of consistent meteorological analyses based on simulations with the best-fit between modeled results and observations (Uppala et al., 2005). We have used the 1° spatial resolution and averaged over the daily precipitation accumulation data to monthly temporal resolution.

The Normalized total depth Soil Moisture (NSM) is a model-based drought index proposed recently (Dutra et al., 2008). This index represents the standardize anomalies in soil moisture. Soil moisture is calculated by the TESSEL land surface model (Viterbo and Beljaars, 1995; Van den Hurk et al., 2000) forced by the ERA-40 precipitation, downwelling radiation and near surface meteorology. The model uses four soil

Comparing and ranking soil-moisture indices performance over Europe

E. Peled et al.

layers that vary in depth (0–7, 7–28, 28–100 and 100–289 cm). The NSM is based on the integrated soil moisture over these four layers. So far the NSM dataset is available for Europe. The model output was averaged into monthly time scale, and interpolated to 1° spatial resolution.

2.2 NDVI data

In this study, we have used the Global Inventory Modeling and Mapping Studies (GIMMS) version-g NDVI dataset on 1° by 1°, and 8 km spatial resolutions and monthly temporal resolution from 1982 to 2002 (Pinzon et al., 2005;Tucker et al., 2005).

2.3 Land-cover data

The Vegetation Continuous Fields (VCF) collection contains estimates of the proportional coverage of woody vegetation, herbaceous vegetation, and bare ground in each grid-cell (500 m resolution). The product is derived from all seven bands of the MODerate-resolution Imaging Spectroradiometer (MODIS) sensor onboard NASA's Terra satellite (Hansen et al., 2003a, b).

2.4 Statistical analyses

All soil-moisture indices datasets were re-gridded to 1° by 1° by linear interpolation or by averaging, to enable comparison with the NDVI dataset.

For NDVI (1° resolution) and for each soil moisture index, the average summer (June, July, August – JJA) and spring (March, April, May – MAM) soil moisture was calculated for every grid cell in Europe for the period 1982–2002 (45×66 grid cells). The interannual variability was captured by calculating the JJA and MAM normalized anomalies.

The linear correlation coefficient (r) between the time series of NDVI anomalies and the soil moisture anomalies in each of the indices was calculated for every grid cell in Europe. In addition, we have calculated the linear correlation coefficient (r) between

the time series of area-mean NDVI anomalies and the area-mean soil moisture anomalies, for specific areas (see results and discussion). We have also applied to the NDVI data set the Independent Component Analysis (ICA), which is an advanced method for separating a multivariate signal into additive subcomponents (Hyvrinen and Oja, 2000).
By this analysis we have tried to separate the response of NDVI to temperature and soil-water stress.

One area, Iberia, was chosen for a more detailed case study, in which we examined the correlation between NSM and NDVI at higher resolution of 16 km (re-gridded from the 8 km dataset), and the relations between the strength of this correlation and land-cover.

3   Results and discussion

The strength of the correlation between summer NDVI and each soil-moisture index is shown in Fig. 1. The correlation maps show few broad areas, where positive correlations are evident in all indices. Others, mostly northern areas, show negative correlation, which is probably related to the correlation between summer temperature and precipitation, and the strong control of temperature on vegetation in these areas. Some areas show positive correlation only with part of the indices. For example, the SPI3-EMCWF and SPI3-GPCP maps show strong correlation in parts of Eastern Europe. However, for all indices, significant positive correlations were found in the rectangle areas covering Iberia (9.5° W–0.5° W, 36.5° N–43.5° N), and parts of North Africa (6.5° W–11.5° E, 35.5° N–37.5° N) and Western Turkey (26.5° E–31.5° E, 36.5° N–41.5° N). In these areas, the mean correlation coefficient (r) exceeded 0.4 in the two best performing indices, NSM and SC-PDSI , and the mean p-value was <0.01 (P is <0.01 for r>0.51 and p<0.05 for r>0.37). For these three areas, we have also calculated the correlation between the time-series of NDVI (averaged over each area), and soil-moisture indices (also averaged over each area). This averaging brought all datasets to the same (very coarse) resolution, and thus removed bias caused by the

Comparing and ranking soil-moisture indices performance over Europe

E. Peled et al.

Full Screen / Esc

Printer-friendly Version

Interactive Discussion

Comparing and ranking soil-moisture indices performance over Europe

E. Peled et al.

Printer-friendly Version

Interactive Discussion

different original resolutions.

The correlations of the area-mean time series indicate (Table 1) that the NSM index outperformed in two areas, Iberia and Western Turkey, while SC-PDSI gave the highest correlations in one – Northern Africa. Hence, we conclude that these two indices represent the actual soil-moisture better than the PDSI, SPI3-EMCWF and SPI3-GPCP indices. Surprisingly, SPI3-GPCP performed worse than SPI3-EMCWF, although the former is based on observed precipitation, and the later on modeled one. As we have expected, the correlations between soil moisture and NDVI in spring (MAM) are not significant at Iberia and Western Turkey ($r < 0.04$ for NSM), and much weaker than in summer at Northern Africa ($r = 0.25$ for NSM versus $r = 0.76$ in summer).

The positive correlation found in Iberia and parts of North Africa and Western Turkey, is expected to relate to high sensitivity to soil-moisture. Indeed, these areas are relatively dry, and according to the TESSEL simulation the mean JJA soil moisture is less than 83% of that of the mean value for Europe. The mean JJA temperature (EM-CWF) is above 21°C, versus less than 13.5°C for Europe on average. According to the Koppen-Geiger classification (Kottek et al., 2006) these areas are almost entirely under climate classified as warm temperate climate (CS) with hot (CSa) or warm (Csb) dry summers. In agreement, the NDVI in these areas is reduced in summer, while the mean for Europe shows seasonal maximum at that time (Fig. 2). We have also found no significant correlation (at $P < 0.05$) between inter-annual variation in JJA temperature and NDVI at these regions, which strengthen the conclusion that soil-moisture is the leading source of variability. In addition, the plant functional type (PFT) distribution in these areas is different than those of the rest of Europe. According to the Vegetation Continuous Fields dataset (Hansen et al., 2003b) the percentage of area not cover by trees is 85% in Iberia, 95% in Northern-Africa, and 84% in Western-Turkey, while only 78% in entire Europe.

We have performed a more detailed case study for Iberia, using a 16km spatial resolution NDVI dataset (Table 2). The correlations coefficient in this resolution was found to be much lower than that obtain when correlating the time series of each broad geo-

graphical area (Table 1). The significant correlations in areas classified as "bare soil" indicate that at least some of these areas are sometime vegetated. The correlation with NSM was found to increase with lower tree cover. Hence, it seems that the response of grasses to soil-moisture stress is higher. Grasses, in contrast to trees, have no access to deep soil water, and as a result, we have expected that areas with low tree cover will have better correlation with the normalized soil-water of the first three model layers (down to 100 cm depth) that are used to derive NSM, than with NSM itself. Indeed, the correlation (r) of NDVI at 16 km resolution with the normalized soil-water in the surface layers (which we named NSMS – Normalized Soil Moisture at the Surface) at grid-cells where the tree cover is less than 10%, is 0.39 on average, versus 0.33 for the same grid-cells when we use all layers (NSM). In contrast, in grid-cells where the tree-cover was high (>50%) the correlation of NDVI with the fourth layer (0.64 m to 1.945 m) was higher ($r=0.19$) than the correlation with NSM ($r=0.13$), although still not significant. It is possible that in areas with high tree-cover the Photochemical Reflectance Index (PRI) will be better suited for tracing soil-moisture stress than NDVI (Goerner et al., 2009). A follow-up study should also investigate if there is a different response for evergreen and deciduous trees.

Based on the above results, we have calculated also the correlation of NDVI in 1° degree resolution with NSMS. The results, summarized in Table 1, show that NSMS is better correlated with vegetation than NSM, in the three geographical areas with relatively high correlations. Moreover, NSMS had higher correlations than any other soil moisture index; making it the most reliable one based on the criterion we have defined. The higher correlation of tree-covered surface with the fourth layer indicates that NSM also has good reliability, when the interest is estimating the soil moisture anomalies also at deeper levels. The highly parameterized formulation of PDSI, or the simple approach of the SPI was shown to be less reliable than the more physically based water balance of the NSM.

We have utilized the NSM to asses the relative importance of temperature and soil moisture on NDVI in summer and spring. We divided Europe into three regions, based

on summer mean temperature ("Hot">19°C, "Cold"<16°C, 16°C<"Warm"<19°C), and performed an ICA analysis on the JJA NDVI interannual anomalies in each region. The leading ICAs were then correlated with the area-mean JJA temperature, with NSM (representing soil-moisture), and with the original NDVI signal (to asses the percentage of variability captured by each IC). This process was then repeated for MAM. The results, summarized in Table 3, indicate that in summer the leading ICs for the hot and warm regions are correlated only with soil-moisture, and there is no evidence for temperature effect on NDVI. In contrast, the hot and warm regions do show dependence of NDVI on temperature in spring, and only a weak soil-moisture effect. The cold region shows only temperature effect both in summer and spring. These results indicate that in areas with mean summer temperature above 16°C, it is possible to separate the contribution of temperature and precipitation on NDVI (and maybe also productivity) by focusing on different seasons.

4 Conclusions

The correlations between interannual variations in NDVI and the soil-moisture indices are highest in areas with hot and dry summers, as expected. Higher correlation is associated with grassland rather than with forests. The NSMS index was found to have the highest correlation with NDVI, having the best representation of the interannual variations in the surface soil-moisture stress. NSM carries additional information on deeper soil-moisture. These results have obvious implications for further soil-moisture based studies.

Full Screen / Esc

Printer-friendly Version

Interactive Discussion

References

Angert, A., Biraud, S., Bonfils, C., Henning, C. C., Buermann, W., Pinzon, J., Tucker, C. J., and Fung, I.: Drier summers cancel out the CO2 uptake enhancement induced by warmer springs, PNAS, 102, 10823–10827, 2005.

5 Dai, A. G., Trenberth, K. E., and Qian, T. T.: A global dataset of Palmer Drought Severity Index for 1870-2002: Relationship with soil moisture and effects of surface warming, J. Hydrometeorol., 5, 1117–1130, 2004.

Dutra, E., Viterbo, P., and Miranda, P. M. A.: ERA-40 reanalysis hydrological applications in the characterization of regional drought, Geophys. Res. Lett., 35, L19402,

10 doi:10.1029/2008GL035381, 2008.

Ferranti, L. and Viterbo, P.: The European summer of 2003: Sensitivity to soil water initial conditions, J. Climate, 19, 3659–3680, 2006.

Fung, I. Y., Doney, S. C., Lindsay, K., and John, J.: Evolution of carbon sinks in a changing climate, PNAS, 102, 11201–11206, 2005.

15 Goerner, A., Reichstein, M., and Rambal, S.: Tracking seasonal drought effects on ecosystem light use efficiency with satellite-based PRI in a Mediterranean forest, Remote Sens. Environ., 113, 1101–1111, 2009.

Gu, Y. X., Hunt, E., Wardlow, B., Basara, J. B., Brown, J. F., and Verdin, J. P.: Evaluation of MODIS NDVI and NDWI for vegetation drought monitoring using Oklahoma Mesonet soil

20 moisture data, Geophys. Res. Lett., 35, L22401, doi:10.1029/2008GL035772, 2008.

Hansen, M. C., DeFries, R. S., Townshend, J. R. G., Carroll, M., Dimiceli, C., and Sohlberg, R. A.: Development of 500 meter vegetation continuous field maps using MODIS data, IGARSS 2003: IEEE International Geoscience and Remote Sensing Symposium, Proceedings, 264–266, 2003b.

25 Heim, R. R.: A review of twentieth-century drought indices used in the United States, B. Am. Meteorol. Soc., 83, 1149–1165, 2002.

Hyvrinen, A. and Oja, E.: Independent component analysis: algorithms and applications, Neural Netw., 13, 411–430, doi:10.1016/S0893-6080(00)00026-5, 2000.

Kottek, M., Grieser, J., Beck, C., Rudolf, B., and Rubel, F.: World map of the Koppen-Geiger cli-

30 mate classification updated, Meteorol. Z., 15, 259–263, doi:10.1127/0941-2948/2006/0130, 2006.

Lloyd-Hughes, B. and Saunders, M. A.: A drought climatology for Europe, Int. J. Climatol., 22,

Comparing and ranking soil-moisture indices performance over Europe

E. Peled et al.

◄◄	►►
◄	►
Back	Close

Full Screen / Esc

1571–1592, doi:10.1002/Joc.846, 2002.

McKee, T. B., Doesken, N. J., and Kleist, J.: The relationship of drought frequency and duration to time scales, 8th AMS Conference on Applied Meteorology, Anaheim CA, 179–184, 1993.

Palmer, W. C.: Meteorological drought, U.S Weather Bureau, Washington D.C, 58, 1965.

Pinzon, J., Brown, M. E., and Tucker, C. J.: Satellite time series correction of orbital drift artifacts using empirical mode decomposition, in: Hilbert-Huang Transform: Introduction and Applications, edited by: Huang, N., 167–186, 2005.

Seneviratne, S. I., Luthi, D., Litschi, M., and Schar, C.: Land-atmosphere coupling and climate change in Europe, Nature, 443, 205–209, 2006.

Sheffield, J. and Wood, E. F.: Projected changes in drought occurrence under future global warming from multi-model, multi-scenario, IPCC AR4 simulations, Clim. Dynam., 31, 79–105, 2007.

Sims, A. P., Niyogi, D. D. S., and Raman, S.: Adopting drought indices for estimating soil moisture: A North Carolina case study, Geophys. Res. Lett., 29(8), 1183, doi:10.1029/2001GL013343, 2002.

Tadesse, T., Brown, J. F., and Hayes, M. J.: A new approach for predicting drought-related vegetation stress: Integrating satellite, climate, and biophysical data over the US central plains, ISPRS J. Photogramm., 59, 244–253, doi:10.1016/j.isprsjprs.2005.02.003, 2005.

Tucker, C., Pinzon, J., Brown, M., Slayback, D., Pak, E., Mahoney, R., Vermote, E., and El Saleous, N.: An extended AVHRR 8km NDVI dataset compatible with MODIS and SPOT vegetation NDVI data, Int. J. Remote Sens., 26, 4485–4498, 2005.

Tucker, C. J. and Sellers, P. J.: Satellite remote-sensing of primary production, Int. J. Remote Sens., 7, 1395–1416, 1986.

Uppala, S. M., Kallberg, P. W., Simmons, A. J., Andrae, U., Bechtold, V. D., Fiorino, M., Gibson, J. K., Haseler, J., Hernandez, A., Kelly, G. A., Li, X., Onogi, K., Saarinen, S., Sokka, N., Allan, R. P., Andersson, E., Arpe, K., Balmaseda, M. A., Beljaars, A. C. M., Van De Berg, L., Bidlot, J., Bormann, N., Caires, S., Chevallier, F., Dethof, A., Dragosavac, M., Fisher, M., Fuentes, M., Hagemann, S., Holm, E., Hoskins, B. J., Isaksen, L., Janssen, P. A. E. M., Jenne, R., McNally, A. P., Mahfouf, J. F., Morcrette, J. J., Rayner, N. A., Saunders, R. W., Simon, P., Sterl, A., Trenberth, K. E., Untch, A., Vasiljevic, D., Viterbo, P., and Woollen, J.: The ERA-40 re-analysis, Q. J. Roy. Meteor. Soc., 131, 2961–3012, doi:10.1256/Qj.04.176, 2005.

Van den Hurk, B. J. J. M., Viterbo, P., Beljaars, A. C. M., and Betts, A. K.: Offline validation of the ERA40 surface scheme, edited by: Memo, E. T., Eur. Cent. for Medium-Range Weather

Comparing and ranking soil-moisture indices performance over Europe

E. Peled et al.

Full Screen / Esc

Forecasts, Reading, UK, 42 pp., 2000.

Van Der Schrier, G., Briffa, K. R., Jones, P. D., and Osborn, T. J.: Summer moisture variability across Europe, J. Climate, 19, 2818–2834, 2006.

Viterbo, P. and Beljaars, A. C. M.: An improved land-surface parameterization scheme in the EMCWF model and its validation, J. Climate, 8, 2716–2748, 1995.

Wang, X. W., Xie, H. J., Guan, H. D., and Zhou, X. B.: Different responses of MODIS-derived NDVI to root-zone soil moisture in semi-arid and humid regions, J. Hydrol., 340, 12–24, doi:10.1016/j.jhydrol.2007.03.022, 2007.

Wells, N., Goddard, S., and Hayes, M. J.: A self-calibrating Palmer Drought Severity Index, J. Climate, 17, 2335–2351, 2004.

Xie, P. P., Janowiak, J. E., Arkin, P. A., Adler, R., Gruber, A., Ferraro, R., Huffman, G. J., and Curtis, S.: GPCP Pentad precipitation analyses: An experimental dataset based on gauge observations and satellite estimates, J. Climate, 16, 2197–2214, 2003.

Comparing and ranking soil-moisture indices performance over Europe

E. Peled et al.

Title Page

Abstract | Introduction

Conclusions | References

Tables | Figures

◄ | ►

◄ | ►

Back | Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion

Table 1. Correlation coefficients (r) between the (area-mean) interannual variability in summer (JJA) NDVI and soil-moisture estimated by various indices.

	SPI3-GPCP	SPI3-EMCWF	PDSI	SC-PDSI	NSM	NSMS
Iberia	0.33	0.71	0.70	0.73	0.78	0.80
N. Africa	0.33	0.68	0.67	0.78	0.76	0.84
W. Turkey	0.31	0.65	0.45	0.56	0.78	0.79

Table 2. The mean coefficient of correlation (r) between interannual variability in summer NDVI of 16 km by 16 km grid-cells in Iberia, and NSM, stratified by fractional land cover.

Bare Cover	r	Tree Cover	r	Grass Cover	r
0–5%	0.22	0–5%	0.35	0–40%	0.15
5–10%	0.30	5–15%	0.30	40–60%	0.26
10–20%	0.32	15–30%	0.28	60–70%	0.31
20–30%	0.37	30–40%	0.21	70–80%	0.30
30–40%	0.44	40–60%	0.18	80–90%	0.30
40–100%	0.44	60–100%	0.14	90–100%	0.25

Table 3. ICA analysis results for summer (JJA) and spring (MAM) NDVI for three regions of Europe, separated by the mean summer temperature. Displayed is the percentage of NDVI variance explained by the two leading IC's, and the coefficient of determination (r^2) between each IC and the regions anomalies of temperature and soil moisture (NSM). Empty fields indicated that no second IC was found.

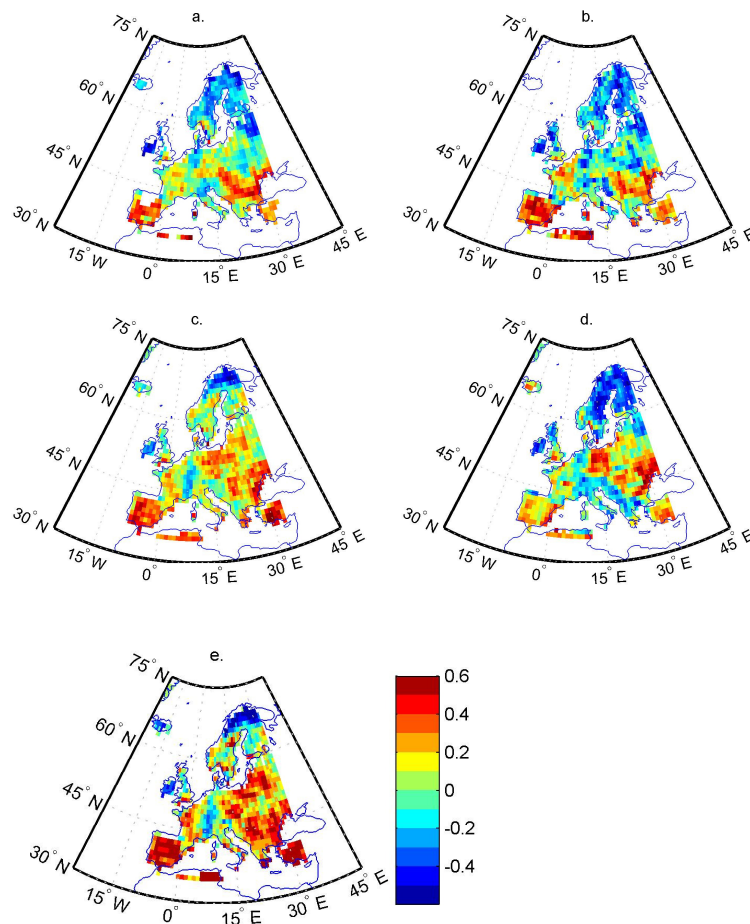|	JJA			MAM		
	Hot	Warm	Cold	Hot	Warm	Cold
IC1 – % Expl.	63	61	47	50	24	59
IC2 – % Expl.	32	20	41	11		21
IC1-Temp.	0.10	0.09	0.32	0.52	0.29	0.34
IC2-Temp.	0.00	0.08	0.31	0.17		0.00
IC1-Moist	0.36	0.29	0.06	0.12	0.05	0.02
IC2-Moist	0.02	0.06	0.10	0.27		0.01

Fig. 1. Coefficients (r) of correlation between interannual anomalies in Europe JJA NDVI and soil moisture indices: PDSI **(a)**, SC-PDSI **(b)**, SPI3-EMCWF **(c)**, SPI3-GPCP **(d)** and NSM **(e)**.
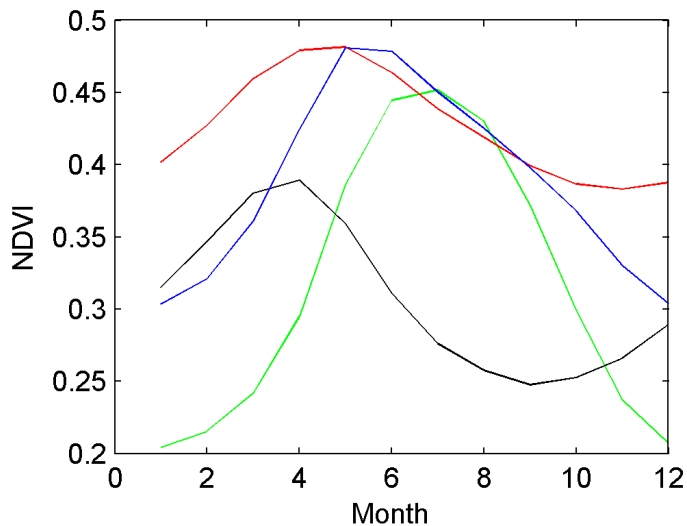
Fig. 2. Mean seasonal changes in NDVI over Europe (green), Iberia (red), Northern Africa (black) and Western Turkey (blue).