Arid Land Research and Management, 26:271–284, 2012

ISSN: 1532-4982 print/1532-4990 online
DOI: 10.1080/15324982.2012.694398

Evaluation of Aridity Indices Using SPOT Normalized Difference Vegetation Index Values Calculated Over Different Time Frames on Iberian Rain-Fed Arable Land

Attila Bussay[1], Tibor Tóth[2], Valentinas Juškevičius[1], and Lorenzo Seguini[1]

[1]European Commission, Joint Research Center, Institute for Environment and Sustainability, Ispra, Italy
[2]Institute for Soil Sciences and Agricultural Chemistry, Centre for Agricultural Research, Hungarian Academy of Sciences, Budapest, Hungary

The objective of this study was to find the best-performing aridity index and time-frame in the Iberian Peninsula characterizing the effect of dryness on agricultural production. To achieve this goal time-series of 5 aridity indices for 1998 October–2009 December time-period were calculated on a 25 × 25 km grid, and the closest relationship with plant biomass was determined. Plant biomass was represented by the SPOT-VEGETATION Normalized Difference Vegetation Index (NDVI) satellite data masked out for rain-fed arable land for the period between 1998 and 2009, and also by official yield statistics of Spain and Portugal between 1999 and 2009. Aridity indices calculated for time frames matching the entire vegetative period resulted in the highest correlation coefficients with NDVI and with the crop yield. There was a difference between the two time frames covering twelve months. In contrast with the calendar year, using the hydrological year (1 October–30 September) ensured a very strong correlation between NDVI data and most aridity indices, with UNEP and Water Deficit aridity indices outperforming the others. Among the shorter time frames of April-October, January–October, and October–June, the latter provided very strong correlation between vegetation, UNEP and Water Deficit indices surpassing Budyko, De Martonne, and Thornthwaite aridity indices.

Keywords aridity index, Iberian Peninsula, Normalized Difference Vegetation Index, time frame

Received 3 February 2012; accepted 22 March 2012.

This work was partially supported by the Hungarian National Science Foundation (OTKA), Grant No. NN79835.

Address correspondence to Attila Bussay, European Commission, Joint Research Center, Institute for Environment and Sustainability, Institute for Environment and Sustainability, Via E. Fermi 2749, 1-21027 Ispra (VA), Italy. E-mail: attila.bussay@jrc.eceuropa.eu

Biomass and yield display high variability in space and time in semi-arid, rain-fed regions from one growing season to the other. This is due to varying rainfall, which is the main limiting factor for crop growth (Wang et al., 2003). Crop biomass accumulation also depends strongly on physical and chemical properties of the soil, its water holding capacity, thermal and irradiation conditions, as well as agro-techniques applied on the land concerned, such as irrigation and fertilization (Schultz and Halpert, 1993; Kawabata et al., 2001; Vicente-Serrano et al., 2006).

Aridity indices have been used for regional characterization of water scarcity. In the Mediterranean region many authors (e.g., Piervitali et al., 1997; Turkes, 1999; Piervitali and Colacino, 2003; Costantini et al. 2009) have previously applied aridity indices for climatological and meteorological studies.

In order to find the optimal aridity index and time frames it would be important to know which are the most appropriate to express the relationship between aridity and agricultural production describing the year-to-year variation of yields.

Our basic hypothesis is that the biomass accumulation is in proportion to the aridity from year to year. The relationship between biomass and aridity provides the possibility to evaluate the aridity indices objectively from an agronomical point of view. The main purpose of this research work was to find the best performing aridity index and to determine the time frame which provides the closest relationship (and accordingly the highest correlation coefficient) with remotely sensed NDVI values. To discover this relationship, the biomass dynamics were considered during the vegetative period of the dominant rain-fed crops. The Iberian Peninsula was selected as the area of the present study because of its proper climate, agriculture, and adequate data coverage.

Materials and Methods

Meteorological Data

Daily minimum and maximum temperatures, precipitation, mean vapour pressure, global radiation, mean wind speed and potential evapotranspiration were used as input variables in order to focus on aridity. Meteorological data were obtained from the Monitoring Agricultural Resources UNIT of the EC Joint Research Centre in Ispra, Italy (JRC/MARS) for this study (Micale and Genovese, 2004). The original database contains daily weather data which are collected from the Global Telecommunication System of the World Meteorological Organization, from national and local meteorological stations as well as from independent observation networks (Micale and Genovese, 2004). In particular, 141 Spanish and 26 Portuguese weather stations supplied most of the data, as these undertook continuous observations. Additionally, 121 Spanish and 10 Portuguese meteorological stations provided intermittent observations. The received data were automatically quality checked by specific software "AMDAC" and interpolated on a 25×25 km regular grid using the routine data procedure of the JRC/MARS database (Micale and Genovese, 2004). Interpolation consisted of two steps: first was the determination of the most representative meteorological stations for each grid cell and second was the calculation of the simple average of weather parameters with altitude correction between the stations and centre point of grid-cell. Taking into consideration the high density of meteorological stations, as well as the short time-window (11 years) the meteorological data were considered to be homogeneous. The potential evapotranspiration

(PET) was calculated by the Penman-Monteith equation (Allen et al., 1998) following the regular algorithm (Micale and Genovese, 2004) that is currently used for the JRC/MARS database.

Because of extreme precipitation (e.g., 410 mm between November 2000 and February 2001 instead of 191 mm as in a typical year), the extremely wet hydrological year of 2001 was not included in the calculations. Unusual rainfall excess and temporal distribution of precipitation caused extraordinary problems in agriculture and had an adverse effect on the biomass accumulation and yields. The aridity indices are not capable of delineating wet years perfectly; consequently, this year was left out of the study. Data from this year would not support the study of our hypothesis and could cause distortion in the estimated regression equation.

NDVI Data

The NDVI dataset was taken from the Regional Unmixed Means (RUM) database. The RUM database is based on an aggregation scheme of weighted average (Eerens et al., 2004) determined for each CORINE Land Cover (CLC) class (Nunes de Lima, 2005) within an area of interest as administrative boundaries (Genovese et al., 2001) or grid of 25 $\times$ 25 km. The SPOT VEGETATION Normalized Difference Vegetation Index (NDVI) data-set for each 10-day period (10 days composite values) for the years of 1999 to 2009 time period were prepared by JRC/MARS's Agri4Cast Action. The raw satellite images were processed using typical procedure: mosaicking methods, condensing into 10 days composites, and finally calculating the weighted NDVI values.

The raw satellite images were collected by the ground segment of SPOT-VGT at daily basis. Geometric (Henry and Meygret, 2000) and radiometric calibration (Sylvander et al., 2000) took place before the NDVI computation. The 10-day composite was produced according to the Maximum Value Composite (MVC) methodology (Holben, 1986). Pixels recognized as cloudy, snowed or with missing data are flagged accordingly. For each considered grid of 25 $\times$ 25 km all pixels inside are used for calculating the average NDVI value of the cell according to the following formula:

$$\overline{NDVI_{r,c,t}} = \sum_{i=1}^{n_{r,i}} W_{r,c,t,i} * NDVI_i$$

with weighting factor:

$$W_{r,c,t,i} = \frac{a_{c,t,i} * f_{c,i}}{\sum\limits_{\mathrm{i}=1}^{n_{r,i}} a_{c,t,i} * f_{c,i}},$$

where $\overline{NDVI}_{r,c,t}$: is the value of NDVI for the region r, for given class c, threshold t representing the minimum surface of class c in a pixel considered valid for the computation (Eerens et al., 2004); $n_{r,i}$ is the number of pixels in the region r with not flagged observations; $f_{c,\ i}$ is the surface fraction of the class c in the pixel i; $a_{c,t,i}$ is a coefficient that assumes value of 1 if $f_{c,i}$ is above the t threshold: otherwise has value of 0; $NDVI_i$ is the value of the i pixel.

The selection of SPOT-VGT NDVI images can be properly justified with the usage of the same sensors for the whole considered period and with the homogeneity of the satellite data, but unfortunately this satellite has only been active since 1998 (Balaghi et al., 2008). Hence, the NDVI values at 25×25 km grid resolution were used. Data were derived only for rain-fed arable land (Code 211 according to CLC land cover classification). The dataset does not contain cells comprising less than 14% of rain-fed arable land. In total 682 grid cells of the Iberian Peninsula, an area with a varying degree of climatic aridity (Vicente-Serrano et al., 2006), were analyzed.

First, during processing the NDVI data, grid cells with higher than 10% of irrigated land cover (as indicated by CLC database) were eliminated. There were 486 cells remaining out of the total 682 where irrigated land comprises less than 10% area of the given grid cell. From the dataset of 10-days composite values monthly average NDVI values were calculated resulting in a table with 4,860 rows in total. This table has columns for each 12 months and rows containing the cell's ID number and the year's number. Further NDVI Average and Maximum values of the time frames were calculated. Maximum value was defined as the highest monthly average vegetation index value of the time frame.

Five time frames, calendar year (1 January–31 December); hydrological year (1 October–30 September); 1 October–30 June; 1 January–31 October; and 1 April–31 October were selected to match the typical data collection/reporting periods and the vegetative periods of representative crops grown in rain-fed arable lands.

Aridity Indices

As the aridity index is commonly determined for monthly or longer periods, the daily precipitation and potential evapotranspiration data of the JRC/MARS database were summed up to monthly data. From the meteorological data, five generally accepted and frequently used aridity indices, (based on several climatic parameters) were calculated for five primarily defined time frames. During this study, the longest available homogeneous time series of SPOT-VGT NDVI values and meteorological data were available for 11 years at European scale, although ideally for a study of climatic aridity index, a longer period is applied.

The UNEP or UNESCO Index (UNEP, 1992) is the ratio of annual precipitation and potential evapotranspiration. An area is considered to be semi-arid or arid if this index is less than 0.5 or 0.2, respectively. This index was used in recent studies throughout the Mediterranean by Le Houerou (2004), as well as Gao and Giorgi (2008). For country-scale evaluations, it was applied by Costantini et al. (2009) for Italy, and Paltineanu et al. (2007) for Romania, as well as for desertification studies by Scordo et al. (2009). The problem with this index is that PET "can only be inferred, but not actually measured" (Minoru, 2009). In spite of this, it is used in agro-meteorological practice as one of the main input variables for soil moisture and crop models.

The Budyko Index (Oliver, 2005) is the ratio of the mean annual net radiation and the product of the mean annual precipitation and the latent heat of water. An area is considered to be semi-arid or arid if this index is higher than 2.3 or 3.4, respectively. This index is dimensionless.

The De Martonne Index (De Martonne, 1909) is the ratio of the mean annual precipitation and the mean annual temperature value, plus 10°C. Mueller et al.

(2007) suggested the application of De Martonne Index values less than 30 mm/°C to delineate areas where the irrigation is beneficial. According to Paltineanu et al. (2007) the threshold value for this index is 15-20 mm/°C for semi-arid regions.

The Thornthwaite Index (Thornthwaite, 1948) is Water Deficit divided by the sum of potential evapotranspiration calculated for the Deficient Months. Water Deficit is defined as the sum of monthly differences between precipitation and potential evapotranspiration for Deficient Months. These latter are those months during which precipitation is less than potential evapotranspiration.

The Water Deficit Index is the numerical difference between the sum of precipitation and the potential evapotranspiration.

Agro-Statistical Data

The countries' statistical data were used during the evaluation procedure of aridity indices. The Spanish and Portuguese statistical yield series on cereals was obtained from the webpage of Eurostat (Eurostat, 2011). Cereals were defined according to the European statistics and involved the data of wheat, durum wheat, barley, rye, oats, and so forth, but excluding rice (which is cultivated under irrigated conditions) as well as green maize. The temporal trend of yield time-series of cereals is not significant since the value of the Pearson Correlation is just 0.199, and consequently the agro-technological effect can be regarded as constant. In agro-meteorological practice it is usually assumed that the yield variability is determined only by weather elements; the effects of other agro-technical and economic factors are less important, and in this case these may be considered negligible (Genovese and Bettio, 2004; Balaghi et al., 2008). The high inter-annual fluctuation of grain yield supports this observation and underlines the main (primary) importance of different thermal and water supply conditions between different years (Martyniak et al., 2007).

Results and Discussion

Relationship Between NDVI and Statistical Yield

NDVI data could be specially important and profitable in the semi-arid Mediterranean region where the inter-annual variability of crop parameters, such as biomass accumulation, leaf area index, yield, crop-growth, and phenological development, are high. NDVI images are extensively used to monitor the vegetation and to achieve yield assessment or yield forecast (e.g., Kogan, 2001; Genovese et al., 2001; Balaghi et al., 2008).

As a first step, it is important to examine the relationship between statistical yields and NDVI values. The main question is whether the NDVI data are appropriate to characterise the yield formation in this case with higher temporal and spatial resolution than with statistical yield data? The correlation coefficients of the Table 1 present normal (excluding 2001) time-series. It is obvious that incorporation of the extreme year 2001 decreases the correlation coefficients significantly; nevertheless, the trend of the relationship remains unchanged.

A very strong correlation exists between the vegetation index of normal time-series and the reported yield of cereals (Table 1). Albeit all values are significant at the 1% level, but the calendar year is less relevant. The maximum correlation coefficients slightly exceeding 0.91 were detected using the hydrological year and

Table 1. Pair-wise correlation coefficients between yearly average NDVI values and aridity indices as well as cereal yield calculated with different time frames for the years 1999–2009, excluding 2001

Time frames	Correlation coefficients calculated with NDVI values					
NDVI of time frames	UNEP/UNESCO	Budyko	De Martonne	Thornthwaite	Water Deficit	Statistical Yield (Cereals)
Calendar year	0.448	–0.386	0.359	0.587	0.543	0.796**
Hydrological year	0.948**	–0.880**	0.891**	0.269	0.947**	0.914**
April-October	0.507	–0.465	0.460	0.758*	0.608*	0.894**
January-October	0.632	–0.605	0.567	0.621	0.700*	0.899**
October-June	0.976**	–0.922**	0.935**	0.464	0.979**	0.913**

Note: "**" and "*" indicate correlation coefficients significant at 0.01 or 0.05 level, respectively.

October-June time frames. These values certify the use of the NDVI values as proxies of the cereal yield in this area. Our main aim was to investigate aridity indices, but the strong correlation confirms the possibility to work out NDVI-based yield forecasting regression methods for the Iberian Peninsula (Genovese et al., 2001) by applying appropriate crop mask and using additional auxiliary thermal and moisture variables (Balaghi et al., 2008).

Additionally, the strong correlation through all vegetative periods ensures the continuous temporal monitoring of crops and suggests the possibility of elaborating an NDVI-based aridity index (Cannizzaro et al., 2002) which could be capable of providing information for the Mediterranean region with higher spatial resolution than the conventional aridity indices.

Temporal Analysis of NDVI Curves and Related Cropping Patterns

NDVI curves were analysed for the Iberian Peninsula in order to understand how NDVI reflects the climatic conditions and crop patterns. The differences in distinct regional crop patterns and phenology can be identified by the help of local vegetation index curves (Suzuki et al., 2001; Klisch et al., 2006). Three distant regions of the Iberian Peninsula were defined as "geographical extremes." Northwest geographical extreme refers to W 4° 24′ 47.39″ – W 6° 08′ 14.25″, N 41° 16′ 45.44″ – N 42° 55′ 05.55″, Northeast to W 0° 00′ 06.05″ – E 3° 23′ 55.18″, N 40° 43′ 28.17″ – N 42° 08′ 28.21″ and Southwest to W 7° 13′ 19.99′ – W 8° 47′ 38.55″, N 36° 52′ 10.34″ – N 38° 33′ 31.85″. Each value of regional extreme curve was calculated as the mean of 21 analysed pixels. These curves thus indicate differences in vegetation indices for the extreme locations of the Iberian Peninsula (Figure 1). It is evident that the minimum values of the curves were reached in September or October when the water supply and the life activity of plants are minimal. The peak values were observed from March to May. The curve of the south-western extreme indicates mostly cereals. The abrupt autumn increase of the curve is caused by the winter

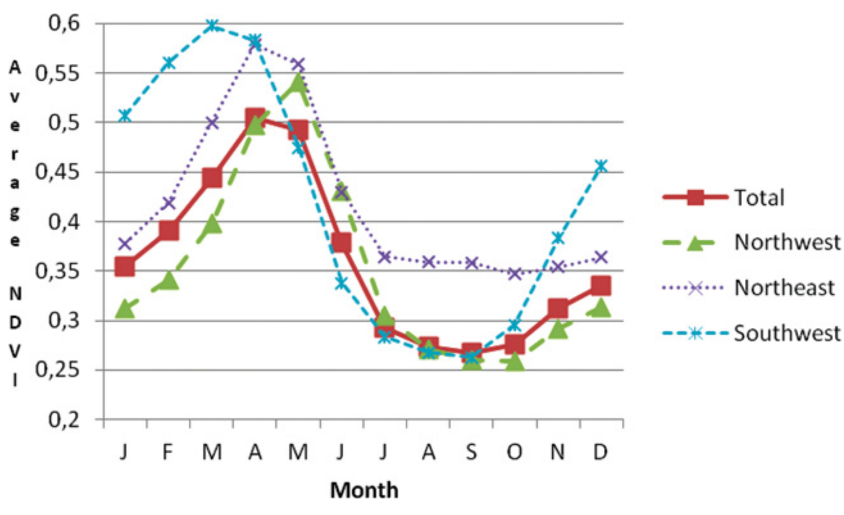

Figure 1. Average SPOT NDVI values on rain-fed Iberian croplands showing geographical extremes of the peninsula. Each regional curve is the mean of 21 analyzed pixels. (Figure available in color online.)

cereals and the sudden increase between January and March shows growth of spring cereals. The highest peak values of NDVI curve indicate favourable agrometeorological conditions and massive biomass accumulation from February to April. In the north-eastern extreme there are summer crops, such as maize and sunflower, showing a higher, nearly constant plateau at the peak of the NDVI curve. In the north-western extreme cereals dominate, but the curve lags behind that of the south-west because of the delayed phenological development of cultivated crops (due to the different thermal conditions).

Vegetation Index Values in the Different Time Frames

Taking into consideration the temporal course of NDVI curves, the crop patterns of the Iberian Peninsula and the climatological practice, five time frames were defined. The calendar year shows vegetation index values of the over-wintering and the newly seeded autumn crops of the following vegetative period, but neglects the autumn season and refill period of the previous year.

The hydrological year integrates the vegetation index of the winter cereals and summer crops, as well better modelling the yearly hydrological and agronomical/ phenological cycle. According to Table 2, the NDVI and aridity index values, calculated for both the calendar and hydrological years did not much differ, probably due to the equal length of the considered time frame. These two indices differ just in the temporal shift, which is the main reason for the similarity in simple statistical characteristics.

The April–October time frame reflects the biomass of summer crops, such as sunflower and maize. Since this time frame coincides with the driest months, the aridity indices, including minimums of the April–October time frame, show extreme values. The average vegetation index of the April–October time frame is less than the yearly average vegetation index (Table 2).

The January–October time frame reflects the biomass development of spring cereals, winter cereals and summer crops. Since this time frame includes rainy winter months, the aridity indices of the January–October time frame do not reflect very dry conditions. The average vegetation index of the January–October time frame is larger than the yearly average vegetation index (Table 2).

The October–June time frame reflects the biomass change of both winter and spring cereals. The aridity indices of the October–June time frame reflect the wettest conditions, particularly the maxima, since the time frame covers the rainy months. The average vegetation index of the October–June time frame is the largest among the average vegetation indices of all time frames (Table 2).

For each time frame, each aridity index showed significant correlations pair-wise at the 0.01 level, except for two cases of the Thornthwaite versus Budyko and Thornthwaite versus De Martonne correlation coefficients calculated for the calendar years, which were significant only at the 0.05 level (values are not shown). In spite of this similarity, the indices were very different to reveal the effect of aridity on crop production.

Correlation between Aridity and Vegetation Index Values

In the case of the hydrological year, high correlation coefficients were calculated between the vegetation index and the UNEP, Water Deficit, Budyko and De

Table 2. Mean, minimum, and maximum values of average NDVI values and aridity indices calculated with different time frames for the years 1999–2009, excluding 2001

Time frames	Average [minimum]-[maximum] values of aridity indices					
NDVI of time frames Mean [Min]–[Max]	UNEP/UNESCO Mean [Min]–[Max]	Budyko Mean[Min]–[Max]	De Martonne Mean [Min]–[Max]	Thornthwaite Mean [Min]–[Max]	Water Deficit Mean [Min]–[Max]	Statistical Yield (Cereals) Mean [Min]–[Max]
Calendar year 0.361 [0.332]–[0.384]	0.398 [0.264]–[0.472]	2.12 [1.77]–[2.91]	19.2 [13.8]–[22.0]	−0.74 [−0.86]–[−0.63]	−710 [−929]–[−579]	31.2 [20.7]–[38.5]
Hydrological year 0.361 [0.326]–[0.393]	0.377 [0.234]–[0.462]	2.27 [1.78]–[3.27]	18.1 [12.3]–[21.9]	−0.74 [−0.82]–[−0.62]	−735 [−971]–[−601]	NA
April-October 0.356 [0.322]–[0.378]	0.266 [0.165]–[0.384]	4.01 [2.87]–[6.04]	8.8 [5.5]–[12.0]	−0.78 [−0.89]–[−0.68]	−704 [−842]–[−542]	NA
January-October 0.368 [0.331]–[0.397]	0.325 [0.206]–[0.420]	2.79 [2.23]–[3.95]	14.0 [9.7]–[17.0]	−0.74 [−0.86]–[−0.66]	−751 [−946]–[−600]	NA
October-June 0.389 [0.348]–[0.428]	0.551 [0.343]–[0.719]	2.66 [2.01]–[3.85]	17.6 [11.7]–[22.3]	−0.62 [−0.73]–[−0.43]	−316 [−497]–[−189]	NA

Note: Yield is expressed in 100 kg/ha. NA = not applicable, the yield reported for the Calendar year was used.

Martonne indices, as well as the reported cereal yield (Table 1). For this time frame the Water Deficit and UNEP aridity indices provided the strongest correlation (Figure 2). In this region these two indices are the most suitable for following the effect of aridity on rain-fed crops. It is clear that the relationship is not completely linear between vegetation index and aridity indices (as also reported by Vicente-Serrano et al., 2006) and that the magnitude of aridity of particular years is different with different indices. The Budyko and De Martonne indices showed similar, but slightly less strength of correlation with the vegetation indices, and their choice as indicators might be decided on the availability of data used for their calculations. Despite their reliability, this is partially the reason why these indices are spread in agro-meteorological and hydrological practice (e.g., Paltineanu et al., 2007; Costantini et al., 2009). The Thornthwaite index resulted in the lowest, r = 0,269 correlation coefficient (r = 0.292 including year 2001) for the time frame of hydrological year, which can be deducted from its calculation method.

No significant correlation was calculated for the calendar year time frame between NDVI and aridity indices. This underlines the lack of physical background

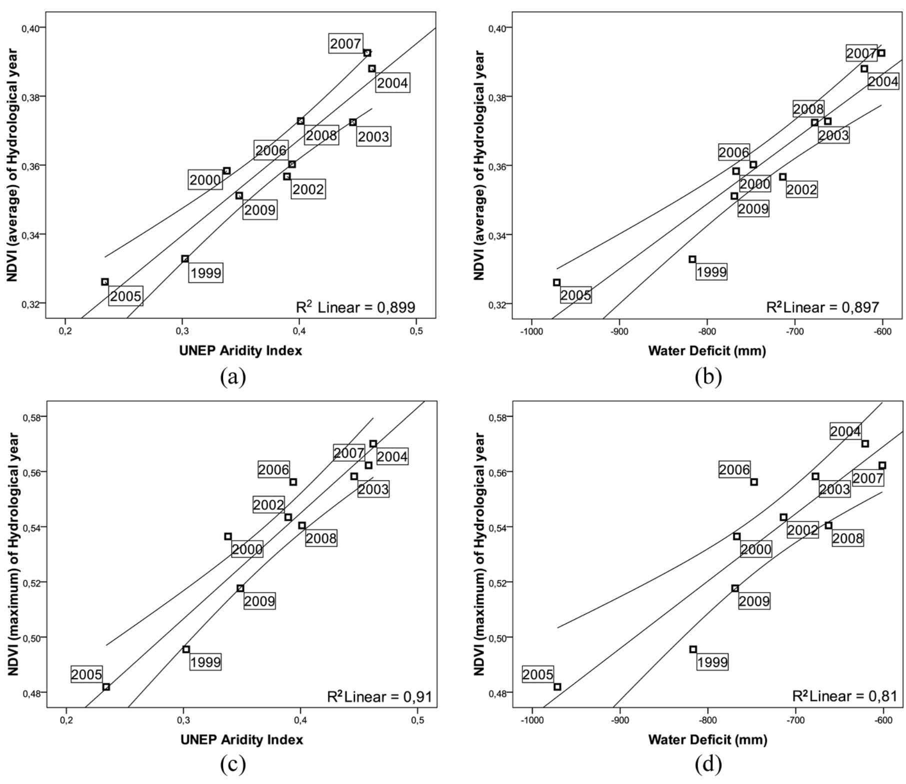

Figure 2. Scatterplots of yearly average NDVI values and the aridity indices calculated for the Hydrological year with UNEP (a) and Water Deficit aridity indices (b), yearly maximum NDVI values and the aridity indices calculated for the Hydrological year with UNEP (c), and Water Deficit aridity indices (d), indicating the particular years between 1999 and 2009, excluding 2001. The fitted linear regression line with 95% confidence intervals and determination coefficient (Rsq) are shown.

of this time frame, and questions its usefulness for describing the crop season in the Iberian Peninsula.

The shorter January–October and April–October time frames provided some weak and some moderately strong relationships for most aridity indices (Table 1). The Water Deficit index was significant at the 5% level for both time frames, reaching 0.700 and 0.608 correlation coefficients, respectively. These correlation coefficients were slightly altered to 0.655 and 0.620, respectively, performing the calculations over the entire 1998–2009 period. The Thornthwaite index, which provided low correlation coefficient values for other longer time frames, somewhat surprisingly reached 0.758 ($r = 0.744$ including year 2001), being significant at the 5% level for the April–October time frame. A similar linear relationship was demonstrated between NDVI and the Thornthwaite index by Piao et al. (2005) for arid and semi-arid regions of China. The better summer half year performance of the Thornthwaite index originates from the definition of this index, because it is calculated only for the Deficient Months. The Thornthwaite index is appropriate for the characterization of the summer half year, when it generally out-performs the other four aridity indices. This index is frequently used for climatological studies (e.g., Cannizzaro et al., 2002), but seems to have drawbacks for agronomical purposes in certain cases, for example, when the crop growing season involves the winter months.

For the October–June time frame, a very strong correlation was found between the vegetation index values and most aridity index values, with the only exception being the Thornthwaite index. This time-period covers the vegetative season of winter and spring cereals, confirming the assumption that the best tailored time frame results in the strongest relationship.

When, instead of using average NDVI, the maximum NDVI values of the particular time frames were used, results were very similar to the UNEP aridity index (Figure 2a and c), but the Water Deficit index showed a less tight relationship (Figure 2b and d). Nevertheless, there was significant correlation at the 0.01 level.

Conclusions

A strong correlation was detected between the masked and spatially weighted NDVI values of rain-fed areas and cereal yield of the Iberian Peninsula. This relationship validates the potential of applying NDVI-based yield forecasting methods for the Iberian Peninsula and similar semi-arid regions.

Statistical relationships were ascertained between climate variability depicted by aridity indices and variation in growth and yield of rain-fed arable lands characterised by NDVI. The two best performing aridity indices, that is, the UNEP and Water Deficit indices, are calculated from the same data, viz. the precipitation and the potential evapotranspiration. The Budyko, De Martonne, and Thornthwaite indices, which use simpler mathematical formulae and reduced input data requirements, are less suitable for this purpose. These indices are however, very useful for regions where the humidity or global radiation data availability is limited, similar to the De Martonne aridity index in Turkey (Deniz et al., 2011).

Aridity indices calculated for time frames matching the entire vegetative period (i.e., the hydrological year and October-June time frames) resulted in stronger correlation with NDVI and also with crop yields. If the omitted months are not considered, it is not suggested to use the less than 12 months' time frame for long term studies. Such interpretation with incomplete data series can be misleading.

As there is no great difference between the vegetation indices of calendar and hydrological years (Table 2), these values are interchangeable for climatological purposes over longer periods. Nonetheless, the hydrological year proved to be more reliable for agronomical and agro-meteorological studies due to its physical and hydrological base. For assessing the effect of the meteorological conditions on the biomass/yield of arable areas, in particular years the October–June time frame is also suitable.

The average NDVI values as well as the maximum monthly NDVI of the time frame values resulted in similar correlation coefficients with aridity indices. A more stable relationship is assumed with average vegetation indices since these values cover all months of the given time frame.

Our results are directly applicable when the biomass of rain-fed arable land is contrasted with aridity indices. Based on the results, it is straightforward to choose the optimal time frame and aridity index for quantifying the effect of aridity on the yields/biomass of crops.

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