Biogeosciences Discuss., 8, 3953–3998, 2011
www.biogeosciences-discuss.net/8/3953/2011/
doi:10.5194/bgd-8-3953-2011

Biogeosciences Discussions

Analysis of vegetation and land cover dynamics in north-western Morocco during the last decade using MODIS NDVI time series data

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Received: 10 February 2011 – Accepted: 31 March 2011 – Published: 18 April 2011

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Published by Copernicus Publications on behalf of the European Geosciences Union.

Abstract

Vegetation phenology as well as current variability and dynamics of vegetation and land cover including its climatic and human drivers are examined in a region in northwestern Morocco of nearly 22 700 km^2. A gapless time series of Normalized Differenced Vegetation Index (NDVI) composite raster data from 29 September 2000 to 29 September 2009 with a spatial resolution of 250 m and acquired by the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor is utilised. The presented approach allows to compose and analyse yearly land cover maps in a widely unknown region with scarce validated ground truth data by deriving phenological parameters. Results show that high temporal resolution of 16 d is sufficient (a) for determining land cover better than global land cover classifications of Plant Functional Types (PFT) and Global Land Cover 2000 (GLC2000), and (b) for drawing conclusions on vegetation dynamics and its drivers. Areas of stably classified land cover types show climatically driven inter- and intra-annual variability with indicated influence of droughts. The presented approach to determine human-driven influence on vegetation dynamics caused by agriculture results in a more than ten times larger area compared to the stably classified areas. Change detection based on yearly land cover maps shows a gain of high-productive vegetation (cropland) of about 259.3 km^2. However, statistically significant inter-annual trends in vegetation dynamics during the last decade could not be discovered. A sequence of correlations was done to extract the most important period of rainfall for production of green biomass and for the extent of land cover types, respectively. Results show that mean daily precipitation from 1 October to 15 December has high correlation results (max. $r^2 = 0.85$) at intra-annual time scale to NDVI percentiles (50%) of land cover types. Correlation results of mean daily precipitation from 16 September to 15 January and percentage of yearly classified area of each land cover type are medium up to high (max. $r^2 = 0.64$). In all, an offset of nearly 1.5 months is detected between precipitation rates and NDVI in 16 d steps. High-productive vegetation (cropland) is proved to be mainly rain-fed. We conclude that identification, understanding

and knowledge about vegetation phenology, and current variability of vegetation and land cover as well as prediction methods of land cover change can be improved using multi-year MODIS NDVI time series data. This study enhances the comprehension of current land surface dynamics and variability of vegetation and land cover in north-western Morocco offering a fast access especially for estimating the extent of agricultural lands.

1 Introduction

Mapping, quantifying and monitoring of land cover is important to understand the current state of landscape. Since field surveys are also expensive in terms of time, labour and costs and rapidly become outdated (Lucas et al., 2007), the use of satellite-based remote sensor data has been widely applied to get cost-effective land cover data over large geographic regions (Lunetta et al., 2006). Especially if validated ground truth knowledge is scarce as in Morocco, freely available remote sensing data sets are the key to get contiguous spatio-temporal information about land cover and vegetation dynamics (Evrendilek and Gulbeyaz, 2008).

Representing the main part of land cover vivid green vegetation is influenced by several factors like human land use, climate, soil and groundwater conditions, invasion of non-native species, volcanism or tectonics. Regarding human and climatic drivers as the main factors of land cover change, differentiation between human-driven change, climate-driven change, vegetation trends and inter-annual ecosystem variability is still a challenge for land cover research. Identification and prediction of land cover change requires characterising current vegetation dynamics (phenology) and recent inter- and intra-annual variability of land cover in a better way (Bradley and Mustard, 2008).

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1.1 Remote sensing and MODIS time series data

The Normalized Differenced Vegetation Index (NDVI; Sellers, 1985) as an indicator of vivid green vegetation and as descriptor of ecosystem functions has been shown to have great value in assessing ecological responses to environmental changes (Alcaraz-Segura et al., 2009; Pettorelli et al., 2005). NDVI-based approaches are widely used for monitoring vegetation activity by using time series data sets acquired by sensors aboard satellites with short revisit periods, in particular the Advanced Very High Resolution Radiometer (AVHRR; Goward and Prince, 1995; Beck et al., 2006) and the Moderate Resolution Imaging Spectroradiometer (MODIS), respectively. A comparison of NDVI time series data sets acquired by AVHRR and MODIS sensors was done in detail by Brown et al. (2006) and Ji et al. (2008). MODIS as the latest of the sensors is one of the key instruments for NASA's Earth Observing System (EOS) and a major advance over the previous generation of sensors in terms of its spectral (36 bands), spatial (max. 250 m) and temporal (1–2 d for the entire Earth) resolutions (Xiong and Barnes, 2006).

Although moderate spatial resolution of MODIS data is superior to the one of AVHRR data, studies deal already with unmixing strategies and sub-pixel algorithms to get an even higher degree of information (e.g., Roosta and Saradjian, 2007; Benhadj et al., 2011). However, plenty studies use MODIS time series data in combination with ground truth information to map croplands (e.g., Xiao et al., 2005; Chang et al., 2007; Fritz et al., 2008; Wardlow et al., 2008; Shao et al., 2010). General applicability of MODIS NDVI and Enhanced Vegetation Index (EVI) for crop-related land cover classification is shown by Wardlow et al. (2007) proving that MODIS 250 m NDVI data (16 d composites) has a sufficient temporal and spatial resolution for classification of crops in the Great Plains. Characteristic NDVI temporal profiles (endmembers) have been presented for corn, soybean, wheat, alfalfa, paddy rice or fallow ground (Xiao et al., 2005; Wardlow et al., 2007; Chang et al., 2007; Geerken, 2009; Shao et al., 2010).

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Other crop-related studies use MODIS time series data to predict the production of winter wheat (Ren et al., 2008) or to map irrigated areas in India (Thenkabail et al., 2005).

Classification and monitoring studies apart of crop-related themes show that the temporal and spatial resolution of MODIS data have potential for monitoring floating vegetation in lakes (Kiage, 2009), for assessing regions at risk of desertification (Wang et al., 2007) and for discriminating native and invaded grassland species (Huang, 2009).

In terms of entire natural terrestrial ecosystems Evrendilek and Gulbeyaz (2008) showed the potential of MODIS NDVI and EVI time series data sets (16 d composites with 500 m spatial resolution) for estimation and monitoring of seasonal and inter-annual ecosystem dynamics over Turkey. Evrendilek and Gulbeyaz (2008) explored data according to four land cover types (barren lands, grasslands, shrub lands/woody lands and forests), six biogeoclimate zones, four seasons and seven years showing correlations of MODIS EVI- and NDVI time series data with higher mean values and higher standard deviation of NDVI time series data.

1.2 NDVI time series data and vegetation phenology

Reed et al. (1994) used NDVI time series data to describe seasonal dynamics (phenology) of vegetation by deriving multiple phenologic parameters related to vegetation activity. Several studies used these phenologic metrics or dealt with additional indicators to describe vegetation phenology (summary in Bradley and Mustard, 2008; Funk and Budde, 2009).

Using MODIS time series data, a general comparison of satellite measured start of season and actual start of season was done by Wardlow et al. (2006). Soudani et al. (2008) evaluated the time of onset of green-up for temperate deciduous broadleaf forests in France while Archibald and Scholes (2007) examined green-up dates in the African savannah. With regard to rice crops in Italy, Boschetti et al. (2009) produced phenological calendars.

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Even though multiple studies already used remote sensing information for an understanding of the phenology of land surface, it is still in development and is regarded as key to understand land-surface processes (Reed, 2006).

Our study presents a methodology of analysing vegetation and land cover dynamics using MODIS NDVI time series raster data in a widely unknown region in northwestern Morocco of nearly 22 700 km^2. Data on vegetation and land cover dynamics in the study region are extracted to understand and to differentiate between human- and climate-driven changes, as well as ecosystem variability (Fig. 1). In a first step, annual land cover maps have been computed by land cover classification based on a simple hierarchically structured decision tree classifier using phenologic metrics. In a second step, stably classified areas and areas with systematic changes of land cover were extracted to understand current vegetation and land cover dynamics. Extraction of endmembers of stably classified areas allows derivation of phenologic metrics to analyse vegetation trends during the last decade and to discriminate vegetation variability. With focus on areas of high productivity, human-driven impacts caused by agriculture can be proved using a simple approach. In a last step, climate-driven changes were suspected to be mainly caused by presence or absence of precipitation. Thus mean NDVI endmembers of stably classified land cover types were compared to precipitation data of two measurement stations within the study region. A sequence of correlations was done to extract the most important period of rainfall for production of green biomass and for the extent of land cover types, respectively.

2 Materials and methods

2.1 Study region

The study region (Fig. 2) encompasses the cities of Casablanca, Rabat and Salé and covers an area from 32°42′ N to 34°9′ N latitude and from 6°19′ W to 8°27′ W longitude of 22 677.25 km^2 (158.75 km × 200.75 km) ashore. The Atlantic Ocean to north-west and the beginning Middle Atlas to south-east are natural borders. Mean elevation is about 380 m a.s.l., ranging up to 1072 m a.s.l. in the Atlas mountains. Climate near the coast is moderate due to the Canary Current. Mean air temperature of Casablanca is 17.4 °C. Precipitation normally occurs during winter months with a total mean of yearly 423 mm; ranging between 61 and 707 mm (GHCN DATA 1951–2006, Nouasseur station).

2.2 Data set and pre-processing

The gapless NDVI time series dataset of MOD13Q1 product (collection 5) covers nine years (Table 1) and has been acquired from the Warehouse Inventory Search Tool (WIST, 2009). In total 207 NDVI data sets of 16 d composites (Huete et al., 1999) were used. In terms of temporal resolution of composite data see Alexandridis et al. (2008) for the optimum temporal resolution of NDVI time series data for monitoring purposes of natural and cropland vegetation on a nationwide scale.

Although the use of composites already reduces the effect of noise like cloud contamination, shadow, sun angle or aerosol effects (Holben, 1986; Huete et al., 1994), data is still negatively influenced by noise, resulting in generally underestimated NDVI values (Gu, 2006; Hird and McDermid, 2009). Several smoothing techniques like double logistic function-fitting (Beck, 2006; Hird and McDermid, 2009), asymmetric Gaussian function-fitting (Jönsson and Eklundh, 2002; Hird and McDermid, 2009) or Savitzky–Golay filter (Savitzky and Golay, 1964; Chen et al., 2004; Gong, 2006; Doraiswamy, 2007; Hird and McDermid, 2009; Ren et al., 2008) are used to model a nearly noise-free NDVI time series following the main assumption that vegetation follows a continuous sequence drawn by increase, peak and decrease, describing a clear mathematical function. Modelling this mathematical function, smoothing algorithms eliminate depressions of time series data. However, the purpose of these algorithms is not to distinct between depressions caused by clouds or atmospheric disturbance and depressions caused by human induced and/or natural disturbances (Evrendilek and Gulbeyaz, 2008). In order to keep responses to climate or other drivers, it is assumed that

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noise (mostly technical or physical caused) depresses single composites while climate conditions, human impacts or other drivers depress a sequence of composites. Thus, the simple but effective smoothing technique (Eq. 1) introduced by Gu et al. (2006) is applied, which assumes that NDVI is always depressed and never overrated by noise. The algorithm reduces impact of single contaminated data points keeping the upper envelope. Following Gu et al. (2006) the algorithm was applied three times in order to remove single noise contaminations more efficiently.

$$\mathrm{NDVI}_{\mathrm{smooth}} = \mathrm{Max}(\mathrm{NDVI}, 0.25 \times \mathrm{NDVI}_{t-1} + 0.5 \times \mathrm{NDVI}_{t} + 0.25 \times \mathrm{NDVI}_{t+1}) \tag{1}$$

The actual time step is represented by t, the previous by $t-1$ and the following by $t+1$.

Subsequently, data was re-projected into Universal Transverse Mercator (UTM, Zone 29, WGS 84). Incongruous picture elements in the Atlantic Ocean near the coast were eliminated applying a land-water mask, which includes two reservoirs ashore and was derived from Shuttle Radar Topography Mission (SRTM) data.

According to vegetation break during summer months and start of vegetation period at first of October, the NDVI mega-file of 207 composites was divided into nine single data files according to the years of 2001 up to 2009 with 23 composites each. Thus, one data file effectively covers a time period starting at 29 September/30 September and ending at 28 September/29 September due to composite length of 16 d. That way, data set called “2001” encompasses the vegetation period of 2001 starting end of September 2000 and ending end of September 2001.

2.3 Land cover classification

Land cover classifications deliver spatial patterns of land cover types. Within the study region, solely use of NDVI time series data for distinction of land cover types apart of very sparsely vegetated lands and forests is critical since not all grasslands, shrub lands and croplands have a characteristic productivity. Varying altitudes, distance to coast, soils and water availability, as well as multi-crop systems and scarce validated ground truth data hamper a discrimination of these land cover types. Statistical analyses of histograms and scatter plots did not result in any possibility to discriminate different land cover types significantly. Therefore, land cover is discriminated into five defined types as: very sparsely vegetated, sparsely vegetated, forest, high-productive vegetation and low-productive vegetation, where high-productive vegetation and low-productive vegetation discriminate land cover by productivity of green biomass. This approach allows gathering rain fed, irrigated and multi-crop croplands as well as different grasslands and shrub lands in land cover types without discriminating various soils, locations and water supply.

A hierarchically structured binary decision tree classifier is applied since classification methods like maximum likelihood often fail in the Moroccan context due to small parcels of cropland, a high variety of crops and a high heterogeneity of development. Five phenologic metrics are deduced (Fig. 3) for each year from smoothed NDVI time series data to run the decision tree classifier (Fig. 4). In terms of validation, classification accuracy and efficiency of a decision tree classifier rely heavily on the decision tree chosen. Thus, the two most separable types are processed first and the most subtle type pair is discriminated at the bottom of the tree. By so doing, the cumulative error will be minimised (Richards and Yi, 2006).

Following thresholds of NDVI lower than 0.18 (Bradley and Mustard, 2008; Simonneaux, 2007) and lower than 0.2 (Geerken, 2009; Ren et al., 2008), very sparsely vegetated areas were classified by maximum value of NDVI within the vegetation period (MaxV) lower than 0.2.

The perennial land cover type forest with high NDVI values all-the-year is easily to determine in Morocco with freely available Landsat 7 ETM+ scenes. First classification results using training areas showed that it is not possible to delimit land cover type forest by single use of thresholds of NDVI value at the beginning of vegetation period (OnV), NDVI value at the end of vegetation period (EndV) or mean NDVI value of vegetation period (MeanV) because non-forested areas were also classified as land cover type forest. Hence, a combination of the three metrics was applied.

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High-productive vegetation growing on agricultural lands has a higher range (RanV) between MaxV and the minimum of EndV and OnV than wild vegetation according to seed, a dense stand within the vegetation period and a low vegetated surface after crop during the vegetation rest. Benhadj et al. (2008) report NDVI temporal profiles for crop areas in Marrakech (Morocco) showing a RanV greater than 0.4. Other studies report at least a RanV of 0.4 for single crop systems (Chang et al., 2007; Shao et al., 2010).

In distinction to land cover type high-productive vegetation remaining vegetation with less productivity is summarised in land cover type low-productive vegetation. This land cover type may also include croplands with moderate or poor yields having less productivity of green biomass than areas with rich yields.

2.4 Validation

Validation of classification results requires validated in-situ ground truth data, official maps or other validated data. If such data is scarce as in this study, global land cover classification data as Global Land Cover 2000 (GLC, 2000; Mayaux et al., 2003) and MODIS product MOD12 (Strahler et al., 1999) provide information. Out of MOD12 product, land cover maps of Plant Functional Types (PFT) are applied for validation since its allocation of land cover types fits best to previously defined land cover types in this study. Annual classification maps of PFT contain information of 2001 up to 2004 and GLC2000 contains a land cover classification map of 2000.

Initially, GLC2000, PFT and the decision tree classification results are visually validated for the entire study region using additionally freely available Landsat 7 ETM+ data measured within different vegetation periods.

Final validation using ground truth data is done based on an official land use/land cover map of the administrative region of Grand Casablanca (boundary see Fig. 11) for the year 2004 (Agence Urbaine de Casablanca, 2006). To differ the city region into land cover type very sparsely vegetated and land cover type sparsely vegetated, the old medina of Casablanca as very dense city quarter was used as ground truth

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polygon for land cover type very sparsely vegetated and city quarters with less density were used as ground truth polygons for land cover type sparsely vegetated. The official map does not indicate areas with further vegetation specifications apart of forests and croplands. Therefore, additional ground truth polygons have been acquired directly from a SPOT image as e.g. parks in the city of Casablanca, vegetated areas around the runways of airport "Mohammed V" (location see Fig. 6) and the former airport in western Casablanca. Validation using a confusion matrix is done both for the PFT classification of 2004 and decision tree classification result of 2004.

2.5 Characterisation of land cover and land cover dynamics

To describe vegetation and land cover dynamics in the study region from 2001 up to 2009, stably classified areas of land cover types are extracted. Derivation of mean endmembers of stably classified areas provides information about intra-annual and inter-annual dynamics of vegetation. Hence, NDVI percentiles of stably classified areas as well as NDVI percentiles of all classified areas were computed to display inter-annual ecosystem variability. Determination of vegetation trends during the last decade is done by calculating yearly phenologic metrics of endmembers of stably classified areas.

Inter-annual dynamics of land cover (type A as e.g. forest changes to type B as e.g. sparsely vegetated) were identified by comparing all nine annual classification results of 2001 up to 2009. Land cover changes were assumed to be systematic as following:

2001–2002 classified as type A and 2003–2009 classified as type B (2 years + 7 years)
2001–2003 classified as type A and 2004–2009 classified as type B (3 years + 6 years)
2001–2004 classified as type A and 2005–2009 classified as type B (4 years + 5 years)
2001–2005 classified as type A and 2006–2009 classified as type B (5 years + 4 years)
2001–2006 classified as type A and 2007–2009 classified as type B (6 years + 3 years)
2001–2007 classified as type A and 2008–2009 classified as type B (7 years + 2 years)

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Other patterns of classified results are not regarded as systematic changes to insure that fluctuations caused by method or other reasons like inter-annual precipitation variability do not effect monitoring of land cover change.

2.6 Human- and climate-driven impacts

Identification and differentiation of human- and climate-driven impacts by use of NDVI time series data is difficult due to diversity of impacts. Apart of areas with systematic land cover changes, human driven impacts on land cover are detected by following the approach of decision tree classifier which assumes that croplands as productive land surfaces have a higher RanV due to seed and crop. Following this, mean annual RanV from 2001 up to 2009 ($RanV_{mean}$) is computed for each pixel of the study region to assess and indicate human-driven impact apart of land cover classification for the entire time period.

Climate-driven impacts are suspected to be mainly caused by presence or absence of precipitation. Thus, a cross-correlation is done for mean daily precipitation per composite and endmembers of stably classified areas using a lack of zero up to six composites. Further examinations analyse correlations of mean daily precipitation of different time periods and NDVI percentiles (50%) of stably classified areas of each land cover type to identify the time period which has highest correlation values. For that, varying time periods starting at first or sixteenth of each month and longing at least one month or more are applied in order not to overemphasise short term weather events or potential incorrect measurement values. For computation of mean daily precipitation, varying start time (1 July–1 April) and varying end time (+14 d up to end of vegetation period) is applied to cover a possible shift of precipitation-vegetation relation. Extraction of results is done firstly by specifying a common time period with high correlation values at all and secondly by specifying individual time periods with highest correlation values for each land cover type. Analogous, total annual classified area of each land cover type is correlated to mean daily precipitation of different time periods to identify the time period which is most important for the spatial pattern of land cover types.

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For all, available daily precipitation data of two weather measurement stations (Casablanca station at former airport in western Casablanca and Nouasseur station at airport Mohammed V) is utilised, applying only days with valid values at both measurement stations. Measurement values of Casablanca station from 25 August 2001 (199 mm) and of Nouasseur station from 2 April 2002 (270 mm) were set as missing values after checking hourly data and weather situation of a wider area due to heavily distrust.

3 Results

3.1 Classification results and validation

Annual classification results of 2002 to 2009 are presented in Fig. 5. Classification result of 2001 is part of Fig. 6.

Visual comparisons of annual decision tree classification results to Landsat 7 ETM+ data show that analogues to other cities, the city of Casablanca is classified as land cover type very sparsely vegetated in very dense city quarters. Other parts of the town with lower urban density and higher proportions of vegetation are classified as land cover type sparsely vegetated while areas with detached housing in western Casablanca are classified as land cover type low-productive vegetation due to higher NDVI signal caused by raised vegetation coverage. Thus, results of decision tree classifier image cities smaller than they actually are. Contrarily, GLC2000 and PFT overestimate extensions of cities and underestimate extensions of forests and vegetation apart of cropland. Especially GLC2000 misjudges land cover: while urban areas are too big, about 86% of land surface are classified as croplands and other vegetated surfaces are classified with less than 10%. Woody areas in the centre of the study region are too small or not classified as forest at all. A reservoir eastern of Rabat and Salé is not classified as water body while a classified water body in the south-east does not exist. Representatively, Fig. 6 shows a comparison for 2001 with special interest in city region of Casablanca: both, PFT land cover type Urban and built-up and GLC2000 land cover type Cities cover the airport and the cities of Casablanca and Mohammedia as well as vegetated areas in between both cities, vegetated areas around Casablanca (mainly south-east of the town) and parts of Bouskoura forest. Furthermore, PFT classification maps show an urban area south-east of Casablanca which does not exist. In total, PFT classification maps of 2001 up to 2004 reflect land cover better than GLC2000 in the study region.

Although a combination of three phenologic metrics was applied to determine land cover type forest and to minimise classification errors, very few forested areas were classified as land cover type high-productive vegetation and vice versa. We assume the first case occurs in forested areas with less canopy and higher percentage of shrub- and grasslands in understorey. In the second case, classification error in terms of land cover type forest instead of land cover type high-productive vegetation occurs due to classification method which discriminates solely monocrop-systems by RanV without considering irrigated multi-crop-systems. Thus, few croplands exceed all thresholds and are misclassified as land cover type forest.

Validation of land cover classification map of 2004 for the administrative region of Grand Casablanca results in an overall accuracy of 80.24% and a Kappa coefficient of 0.74 (Table 2). The low producer's accuracy of land cover type low-productive vegetation underlines the described problem of a differentiation between cropland and other vegetation if ground truth data is scarce. While outer parts of the airport runways are classified correctly as low-productive vegetation, some inner parts are classified as land cover type high-productive vegetation. This phenomenon may result from a raised supply of water due to surface runoff from runways which facilitates enhanced growth of vegetation. However, the user's accuracy of land cover type low-productive vegetation is about 81.4%. Additional validation of PFT classification of 2004 results in an overall accuracy of 35.47% and a Kappa coefficient of 0.25. This results from overestimated urban surfaces in the study region as previously described but also from determination of training areas for land cover type sparsely vegetated within the city region which is not further subdivided in PFT classification. Accordingly a further validation was done with summarised land cover types very sparsely vegetated and sparsely vegetated and summarised training areas to prove if this is an artefact of the applied method. This way, validation of decision tree classification (PFT classification) resulted in an overall accuracy of 85.47% (62.67%) and a Kappa coefficient of 0.80 (0.48) proving that the determination of land cover types very sparsely vegetated and sparsely vegetated has a certain influence on classification accuracy.

Following higher overall accuracy and better visual validations results, classification maps of applied decision tree classifier in this study are considered to be more appropriate to describe land cover in the study region.

3.2 Characterisation of land cover and land cover dynamics

Comparing classification results, differences are evident: years 2001, 2002 and 2007 have larger areas of land cover type sparsely vegetated and land cover type low-productive vegetation than years 2003, 2006, 2008 and 2009 with higher proportions of areas classified as land cover type high-productive vegetation. In all, stably classified areas (Fig. 7) cover 13.9% ($\sim 3149\,km^2$) of the study region encompassing among other areas the cities of Casablanca, Rabat, Salé and Khouribga as well as almost the entire forested surfaces. Within the nine years, two different land cover types were classified for 64.3% of the study region. Fluctuations occur mainly between land cover type high-productive vegetation and land cover type low-productive vegetation especially in the western, southern and south-eastern part of the study region (compare Fig. 5). This areas have altitudes mostly higher than 280 m a.s.l. or lower than 140 m a.s.l. Further analyses show that 79.6% (95.7%) of areas which are stably classified as land cover type high-productive vegetation are in altitudes of 70 up to 280 m a.s.l. (1–450 m a.s.l.) while fluctuations of productivity and resulting fluctuations of land cover types to low-productive vegetation mainly occur in higher altitudes. Further transitory zones oscillate between land cover types low-productive vegetation and forest at the borders of forested areas, which results mostly from fix classification thresholds in

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combination with inter-annual ecosystem variability. Minor fluctuations occur between land cover types forest and high-productive vegetation due to explained classification limits of the applied approach concerning forests and crop systems.

Screening changes of land cover types, 1.6% (5932 pixels, $\sim 370\,km^2$) of the study region have changed land cover type systematically. Spatial pattern of areas with systematic changes (Fig. 8) show a cluster in the south-western part, one in the eastern part and spots around the cities of Casablanca, Rabat and Salé. Having the advantage of high temporal resolution of NDVI time-series data, it is possible to determine the instant of time at which land cover changed. The cluster in south-west indicates mostly systematic changes from land cover type low-productive vegetation to land cover type high-productive vegetation with highest rates of about $101\,km^2$ in 2003 and $63\,km^2$ in 2004 indicating human-driven impacts. The eastern cluster indicates succession by a shift from land cover type sparsely vegetated to land cover type low-productive vegetation with a maximum rate of nearly $63\,km^2$ in 2003. Analyses of dots at the city borders prove a gain of land cover type sparsely vegetated revealing a loss of land cover type low-productive vegetation and indicating urbanisation as human-driven impact. A matrix with totalised gain and loss of land cover types is presented in Table 3.

Extracted mean endmembers of stably classified areas characterise land cover types intra-annually (Fig. 9) and show highest NDVI values between end of February and beginning of March. Although land cover type low-productive vegetation and land cover type high-productive vegetation are distinguished by thresholds of RanV, endmember of land cover type low-productive vegetation shows higher values in off-season than endmember of land cover type high-productive vegetation. This proves that areas classified as land cover type high-productive vegetation are less vegetated in off-season since higher NDVI values indicate higher proportion of green vegetation. Thus, our approach of collecting croplands in land cover type high-productive vegetation is successful, since agricultural lands have less canopy than grasslands or shrub lands during off-season due to harvest.

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Subsequent results of determination of NDVI percentiles of each year are shown in Fig. 10. Combining it with percentiles of all classified areas of each land cover type within a single year, NDVI percentiles of stably classified areas of each land cover type show similar patterns of inter-annual ecosystem variability during the last decade. Our early hypothesis, the use of total classified areas of each class do not lead to reasonable results, could not be proved. It seems to be possible to estimate inter-annual ecosystem variability in both ways. The shift between both approaches results from classification method: While stably classified areas encompass the core of areas of each land cover type, total classified areas encompass additionally all areas with values of applied phenologic metrics near the thresholds which leads to class fluctuations as already described before.

Analysis of derived phenologic metrics from annual mean endmembers of stably classified areas (Fig. 12) did not result in any significant trend during the last decade. Therefore, derived metrics are not presented.

3.3 Drivers of land cover

Areas with systematic land cover change e.g. from land cover type low-productive vegetation to land cover type high-productive vegetation or from land cover type low-productive vegetation to land cover type sparsely vegetated in areas near cities indicate human-driven impacts. Further on, computing $RanV_{mean}$ of each pixel for the entire time period of 2001 up to 2009 estimates mean human impact referring to agriculture in the study region (Fig. 11). Computation of $RanV_{mean}$ is independent of used classification technique. Results show in terms of forested areas and areas with scarce vegetation (e. g. cities) low values of $RanV_{mean}$ less than 0.3. Thus, areas classified as high-productive vegetation stick out with values of $RanV_{mean}$ greater than 0.4 which was the threshold for delimiting the land cover type high-productive vegetation. In total 52.54% (11 915 km^2) of the study region show $RanV_{mean}$ of at least 0.4. Compared to stably classified areas of land cover type high-productive vegetation (5.11%, 1.158 km^2) it is over ten times more. Hence, $RanV_{mean}$ seems to be an indicator for

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a simple and rapid assessment of human driven impact and extent of croplands, respectively.

Cross-correlation of daily precipitation values measured at both measurement stations results in highest r-square of 0.48 with no shift in time between both stations. Thus, local influence cause approximately 50% of daily precipitation and superior climate events are causal for the other half. Further correlations of mean daily precipitation of different time periods growing in monthly steps show highest values of r-square (0.95) for the time period of October–March including the major part of rainy season. On a yearly base and using mean daily precipitation, correlation of both measurement stations is lower with r-square of 0.85 showing that local seasonal precipitation plays an important role.

Comparisons of mean daily precipitation per composite and endmembers of stably classified areas for each land cover type (Fig. 12) indicate highest results of r-square using an offset of three composites. This means, vegetation reacts with a lack of nearly one and a half month to precipitation changes: raising precipitation causes raising NDVI values and weakening precipitation causes decreasing NDVI values resulting in vegetation rest during summer month due to absence of precipitation. Apart of land cover type very sparsely vegetated with lower r-square values and applying an offset of three composites, correlations of mean daily precipitation per composite and endmembers of stably classified areas for each land cover type range between r-square of 0.2 and r-square of 0.3 for both stations where all correlation values of Nouasseur station are higher than correlation values of Casablanca station. In all, the location of Casablanca station within the city and close to sea seems to reflect more local urban effects and sea effects than Nouasseur station more inland. Thus, data of Nouasseur station is applied for subsequent examinations.

Highest correlation values of mean daily precipitation and NDVI percentile values (50%) of stably classified areas of each land cover type are identified for the common time period from first of October to fifteenth of December. Specifying individual time periods with highest correlation values for each land cover type, solely land cover type

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very sparsely vegetated has higher correlation values at other time periods as from 16 November to 15 December. Correlations are presented in Fig. 13.

In terms of correlations of mean daily precipitation and the yearly extent of classified areas of each land cover type correlations show highest r-square values for the common time period from 16 September to 15 January. Highest correlation values for individual time periods for each land cover class differ from this period except land cover class high-productive vegetation. Concerning land cover type very sparsely vegetated and land cover type sparsely vegetated highest correlation values occur for short time frames before start of actual hydrological year. In this time periods nearly no precipitation occurs and high correlation values are regarded as artefacts. Therefore, the first time period covering at least a part of actual hydrological year is considered to be the individual time period with highest correlation values. Correlations as well as time periods are presented in Fig. 14.

Focussing on precipitation measurements of 2004 a lack of precipitation from mid of December to mid of February occurs in growth period before vegetation maximum is reached. Endmembers of stably classified areas show indentations of NDVI values which are indicated by some arrows in Fig. 12.

4 Discussion

Understanding current vegetation dynamics and variability of land cover in a widely unknown large region with scarce validated ground truth data needs remote sensed spatio-temporal data to provide cost-effective information (Lunetta et al., 2006; Evrendilek and Gulbeyaz, 2008). Applied MODIS time series data have a moderate grain of spatial resolution. Thus, a considerable number of mixed pixels, which represent more than one ground land cover type, are present (Roosta and Saradjian, 2007). Unmixing strategies and sub-pixel algorithms need knowledge about vegetation, land cover and its dynamics. Our study extracts information about vegetation phenology as well as current variability and dynamics of vegetation and land cover proving that

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moderate spatial resolution and high temporal resolution of MODIS time series data are sufficient for this purpose even if ground truth data is scarce as in this case.

Although NDVI is a useful parameter to assess land cover in arid regions (Huang and Siegert, 2006), NDVI values may be partly overrated in areas with scarce vegetation due to signal influence from soil under vegetation (Wang et al., 2008; Edwards et al., 1999). Produced yearly land cover maps, which proved to describe land cover better than global land cover maps, document already raised percentage of areas with sparse vegetation in comparison to global land cover maps especially at higher altitudes in the south-eastern study region (e.g. 2001 in Fig. 6). Following the above statement, percentage may be in fact higher.

Influence of human and climatic drivers on vegetation dynamics can not be proved holistically in a single study. Thus, the approach using $\mathrm{RanV}_{\mathrm{mean}}$ proves human driven impact additionally to extraction of areas with systematically changes of land cover types indicating urbanisation or ploughing up of grassland. Areas of stably classified land cover types show climatically driven inter- and intra-annual variability. Indentations of NDVI values after a lack of precipitation from mid of December to mid of February in 2004 indicate influence of droughts and underline the previous assumption that climatic drivers depress a sequence of composites instead of single values, as formulated for the choice of applied smoothing technique.

Climatic drivers effect large regions causing worse or better biomass production which leads to exceedance or lower deviation of classification thresholds explaining fluctuations between two land cover types. For instance, percentage of areas classified as high-productive vegetation is greater in humid years and lower in arid years. Fluctuations between the two land cover types high-productive vegetation and low-productive vegetation (especially in south-western, southern and south-eastern parts of the study region) can not result from local change in vegetation conditions caused by higher application of fertilisers or implementation of irrigation techniques since they occur in a very widespread manner. Therefore, climate conditions play an important role and agriculture is supposed to be mainly rain-fed in the study region. Nevertheless,

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correlation values of NDVI percentiles (50%) and mean daily precipitation of land cover type high-productive vegetation are lower than r-square values of land cover type low-productive vegetation (Fig. 13d, e). Thus, areas classified as land cover type high-productive vegetation are less dependent on precipitation and we assume higher proportions of irrigated agricultural fields that lead to this result.

In all, correlations of mean daily precipitation and NDVI percentiles (50%) show high and very high r-square values proving, that more precipitation causes higher NDVI values. High and very high correlation results underline that precipitation is the main factor vegetation is dependent on in the study region and that other factors as e.g. temperature are less important.

Analysis of correlation values of mean daily precipitation and percentage of yearly classified area of each land cover type show a positive correlation of land cover types forest and high- productive vegetation as well as a negative correlation for the other land cover types. This means the more precipitation occurs, the less is the percentage of land cover type very sparsely vegetated, land cover type sparsely vegetated and land cover type low-productive vegetation. In other words, areas classified as land cover type sparsely vegetated and land cover type low-productive vegetation increase to some extent by areas fluctuating respectively from land cover type very sparsely vegetated and land cover type sparsely vegetated but in the same time, they decrease to the bigger extent by areas fluctuating respectively to land cover type forest and land cover type high-productive vegetation. In terms of fluctuations from land cover type low-productive vegetation, we have to differ between areas fluctuating to land cover forest which represent above mentioned transitory zones at the borders of forested areas and fluctuations to land cover type high-productive vegetation due to increased productivity. Thus, percentage of areas classified as land cover type high-productive vegetation range from 16% in dry years to 70% in wetter years documenting high fluctuations of land cover types. Overall, correlations of mean daily precipitation and percentage of yearly classified area of each land cover are medium up to high. The best fit period of land cover type forest from 1 February to 15 May seems to result from classification

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method which uses EndV as one threshold. Thus, the period documents the importance of precipitation falling in later periods to exceed the classification threshold. The second highest correlation occurs for this land cover type for the time period from 16 September to 15 May having *r*-square of 0.73 and underlining the importance of precipitation nearly all vegetation period round. Using correlation values of best fit time periods with *r*-square values greater than or equal 0.5, precipitation is the main factor for extends of yearly classified areas of each land cover type. Thus, other factors like human activities and errors resulting from classification, precipitation measurements, remote sensing and statistics are of subordinate importance.

Totally, change detection of land cover for areas with systematically changes has raised value in comparison to commonly change detection techniques, which compare two different points in time since a gapless time series of data in 16-d steps is applied. Thus, misleading due to inter-annual variability (e.g., Fig. 5: 2007 and 2009) is minimised due to applied method of change detection comparing classification results of every single year.

In terms of trends in vegetation dynamics and stably classified areas, a statistically significant trend could not be discovered for the last decade. Kennedy et al. (2009) analysed data up to 2007/2008 proclaiming data records of MODIS vegetation to be currently too short to capture long-term changes. Using nine years of MODIS vegetation time series data up to September 2009, this study maintains Kennedy et al. (2009).

5 Conclusions

The presented approach shows that moderate spatial resolution and high temporal resolution of MODIS time series data are sufficient for drawing conclusions on land cover dynamics and its driving forces in a widely unknown region with sparse validated ground truth knowledge. By deriving phenological parameters from the gapless temporal image time series from 29 September 2000 to 29 September 2009 composition of

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yearly land cover maps is possible. Results of applied decision tree classifier, proved to determine land cover in the study region better than global land cover classifications of PFT and GLC2000. Validation ends in an overall accuracy of 80.24% and a Kappa coefficient of 0.74 for the administrative region of Grand Casablanca. Drawing conclusions on vegetation dynamics and its drivers is possible. This study contributes to a differentiation between human-driven changes, climate-driven changes and inter-annual ecosystem variability.

Areas of stably classified land cover types show climatically driven inter- and intra-annual variability with indicated influence of droughts. The presented approach to determine human-driven influence on vegetation dynamics by $\mathrm{RanV_{mean}}$ results in a more than ten times larger area compared to stably classified areas. It seems to be a good indicator for a simple and rapid assessment of human-driven impacts and extents of annual crop systems, respectively. Regardless, it has to be proved additionally for perennial and multi-crop systems.

Change detection based on yearly land cover maps shows a gain of high-productive vegetation (cropland) of about 259.3 km^2.

Extraction and comparison of NDVI percentiles for stably classified areas and total classified areas of each land cover type show a shift and differences between percentiles keeping a similar pattern. Thus, we suppose, that actual determination of stably classified areas is not as important for first determination of inter-annual vegetation dynamics.

In terms of climate-driven impact vegetation proved to be highly dependent on precipitation and especially croplands are supposed to be mainly rain-fed. Mean daily precipitation from 1 October to 15 December and NDVI percentiles (50%) of land cover types show highest correlations. Analogous, correlations of mean daily precipitation from 16 September to 15 January and percentage of yearly classified area of each land cover type show highest correlation values for a common time period. In all, an offset of nearly 1.5 month is detected between precipitation rates and NDVI values.

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However, precipitation data originated from two measurement stations delivering data of a comparatively small area. Thus, further studies are needed to examine the relation of vegetation and precipitation in the study region in more detail.

In all, vegetation phenology as well as current variability and dynamics of vegetation and land cover including its climatic and human drivers could be extracted for a widely unknown region. However, statistically significant trends in vegetation dynamics could not be discovered. We conclude that identification, understanding and knowledge about vegetation phenology, and current variability of vegetation and land cover as well as prediction methods of land cover change can be improved using multi-year MODIS NDVI time series data. This study enhances the comprehension of current land surface dynamics and variability of vegetation and land cover in north-western Morocco.

Acknowledgement. This study was funded by the Federal Ministry of Education and Research of Germany. We thank Mr. Vincent Simonneaux for his support and his advice in terms of landscape classification in Morocco. We thank Mr. Jens Rogée for preparing NCDC station data and Mr. Marco Otto for revisions and advice.

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Table 1. Overview on used data.

Dataset	Spatial resolution	Corresponding time/time of measurement
Global Land Cover 2000 (GLC 2000) v.3	1000 m	2000
Landsat 7 ETM+	~ 30 m	20 Jan 2001, 8 Feb 2002, 26 Jan 2003, 17 Mar 2004, 10 Mar 2007
MODIS MOD12 (Plant Functional Types, PFT)	1000 m	2001, 2002, 2003, 2004
MODIS MOD13Q1 collection 5	250 m	29 Sep 2000–29 Sep 2009
Occupation du sol Grand Casablanca	–	2004
SPOT 5	2.5 m	16 Mar 2004
SRTM	~ 90 m	2000

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Table 2. Confusion matrix of decision tree classification result of 2004 using ground truth information from the administrative region of Grand Casablanca (gt: ground truth, cl: classified).

Land cover type	Forest (gt)	High-productive vegetation (gt)	Low-productive vegetation (gt)	Sparsely vegetated (gt)	Very sparsely vegetated (gt)
Forest (cl)	88.51%	0%	0%	0%	0%
High-productive vegetation (cl)	7.43%	100%	65.69%	0%	0%
Low-productive vegetation (cl)	4.05%	0%	34.31%	1.24%	0%
Sparsely vegetated (cl)	0%	0%	0%	81.99%	44.44%
Very sparsely vegetated (cl)	0%	0%	0%	16.77%	55.56%
Total (cl)	100%	100%	100%	100%	100%

Table 3. Systematic land cover changes: Gain (+) and loss (–) (pixels/area in km^2/percent of study region).

Land cover type	Forest (+)	High-productive vegetation (+)	Low-productive vegetation (+)	Sparsely vegetated (+)	Very sparsely vegetated (+)
Forest (–)	–	12/0.8/0.00	214/13.4/0.06	–	–
High-productive vegetation (–)	44/2.8/0.01	–	146/9.1/0.04	1/0.1/0.00	–
Low-productive vegetation (–)	243/15.2/0.07	4136/258.5/1.14	–	101/6.3/0.03	–
Sparsely vegetated (–)	–	–	1017/63.6/0.28	–	18/1.1/0.00
Very sparsely vegetated (–)	–	–	–	49/3.1/0.01	–

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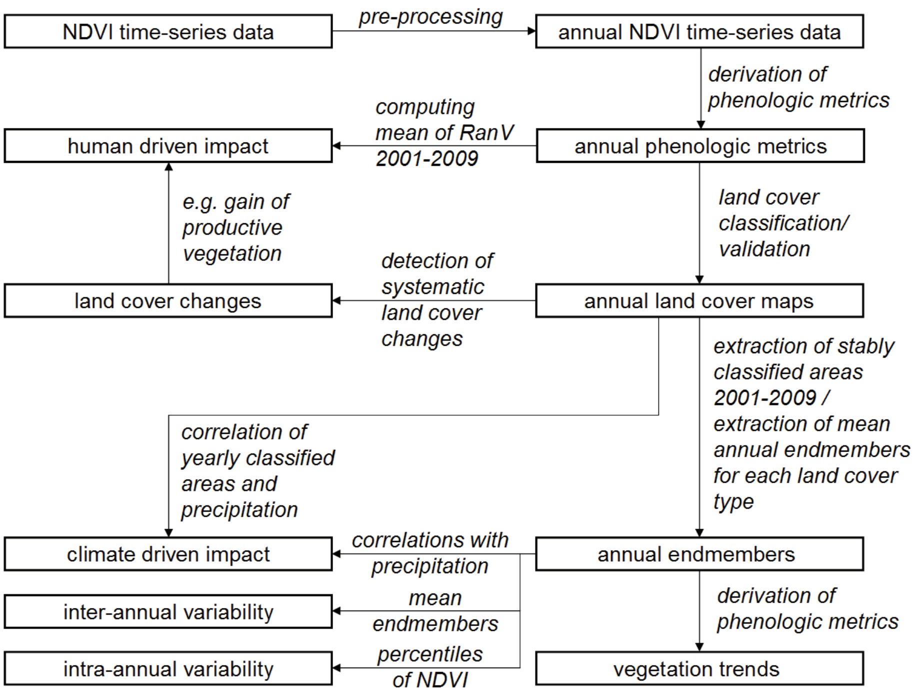

Fig. 1. Workflow.

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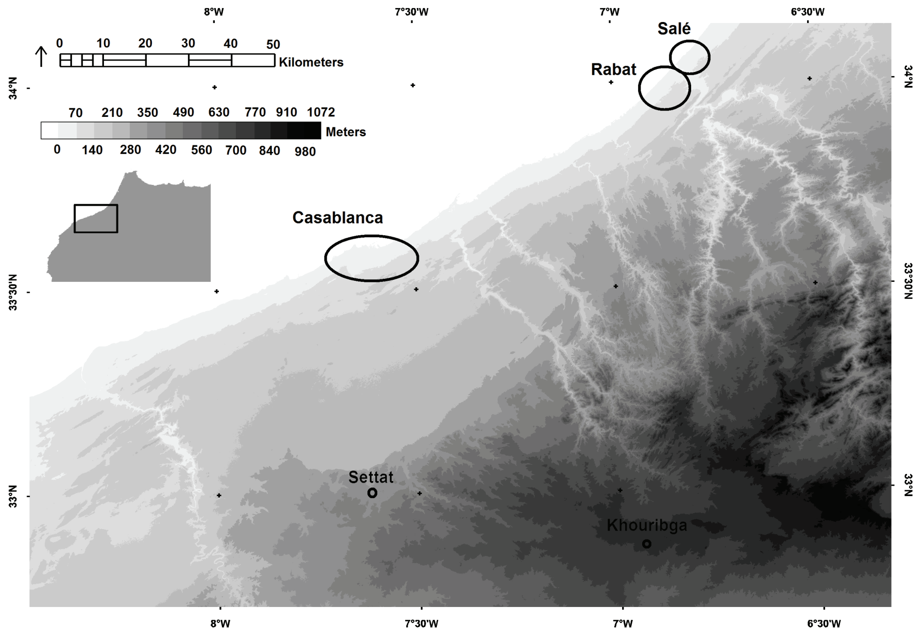

Fig. 2. Elevation of study region.

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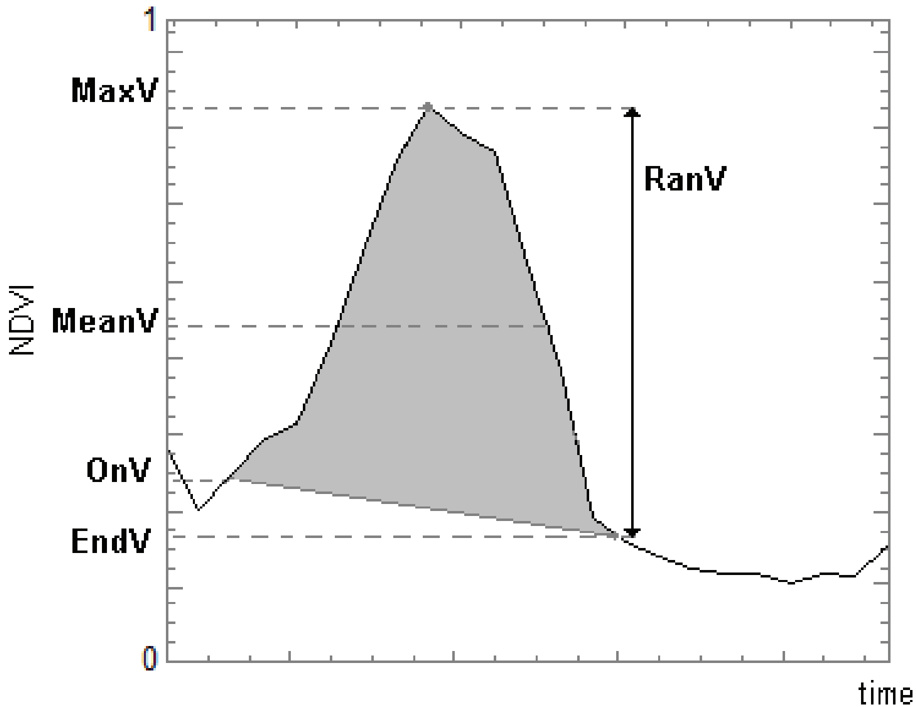

Fig. 3. Derived phenologic metrics according to Reed et al. (1994): MaxV (maximum NDVI value within vegetation period), MeanV (mean NDVI value of vegetation period), OnV (NDVI value at the beginning of vegetation period), EndV (NDVI value at the end of vegetation period), RanV (range between maximum value within vegetation period and minimum of OnV and EndV).

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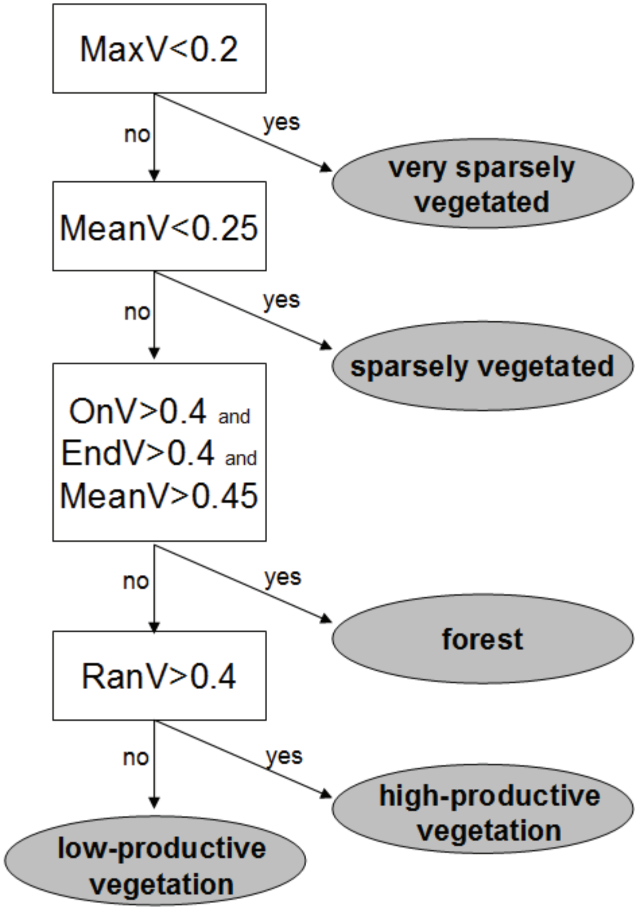

Fig. 4. Hierarchically structured binary decision tree classifier used for annual land cover classifications.

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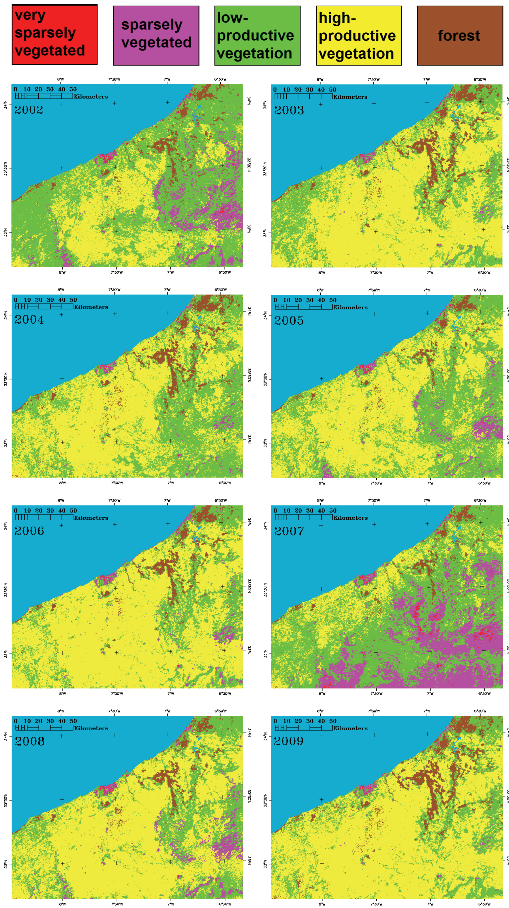

Fig. 5. Annual land cover classification results of 2002 to 2009.

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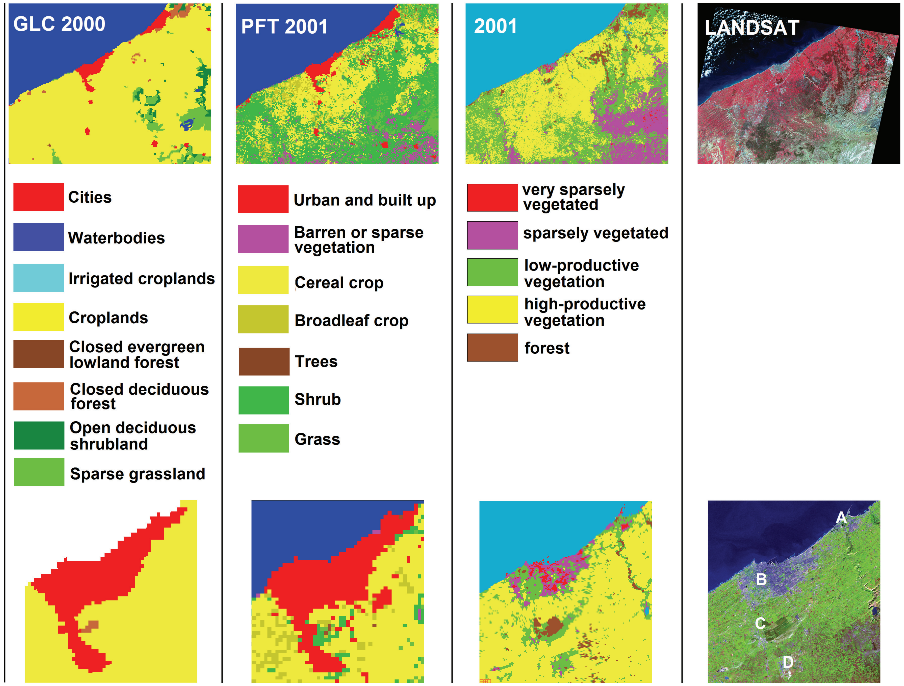

Fig. 6. Comparison of GLC2000, PFT 2001, decision tree classification result of 2001 and Landsat 7 ETM+ (up: bands 4-3-2, down: bands 5-4-1, measured: 20 January 2001). Up: entire study region. Below: zoom to Casablanca region (A – City of Mohammedia, B – City of Casablanca, C – Forest of Bouskoura, D – Airport “Mohammed V”).

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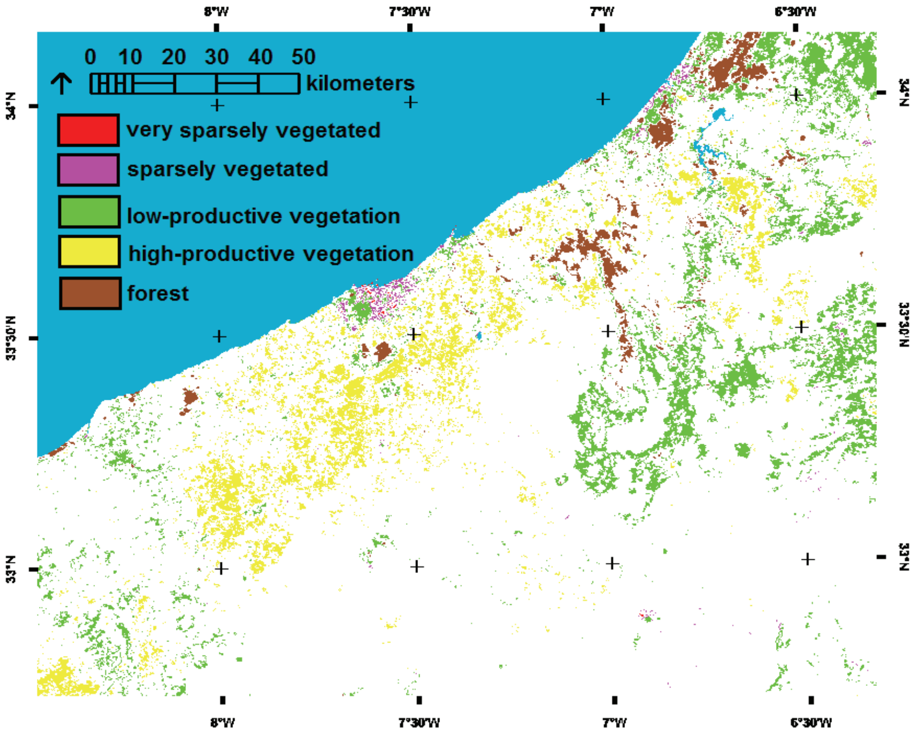

Fig. 7. Stably classified areas 2001–2009.

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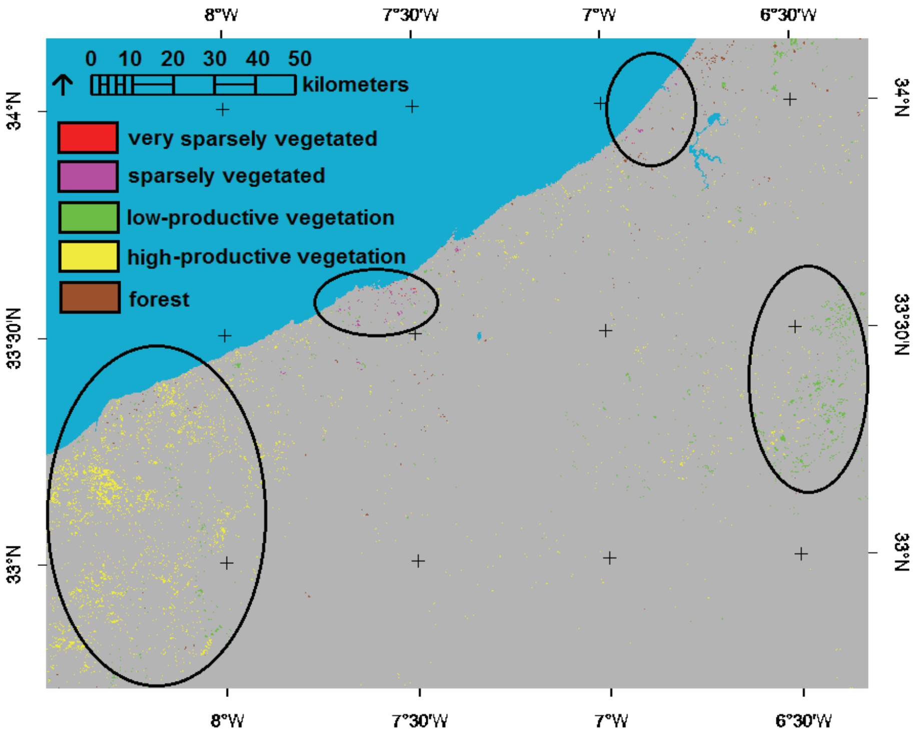

Fig. 8. Spatial distribution of areas with systematic land cover changes. Colours indicate the new land cover type.

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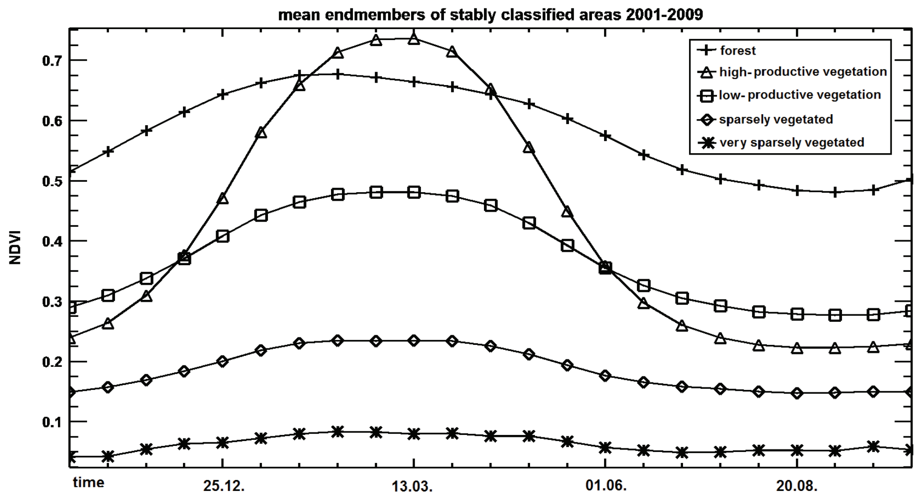

Fig. 9. Mean endmembers of stably classified areas 2001–2009.

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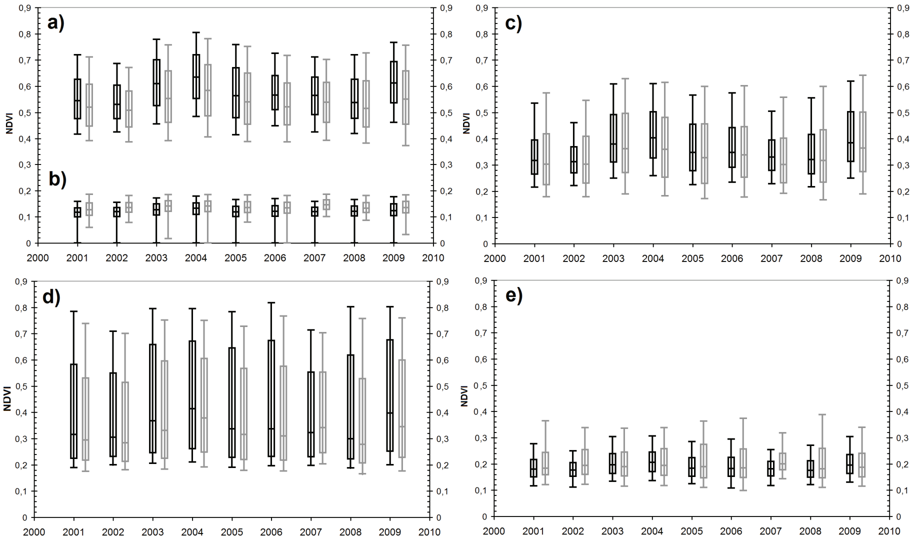

Fig. 10. NDVI percentiles (5%, 25%, 50%, 75%, 95%) for stably classified areas (black) and all classified areas (grey) of land cover types forest **(a)**, very sparsely vegetated **(b)**, low-productive vegetation **(c)**, high-productive vegetation **(d)** and sparsely vegetated **(e)**.

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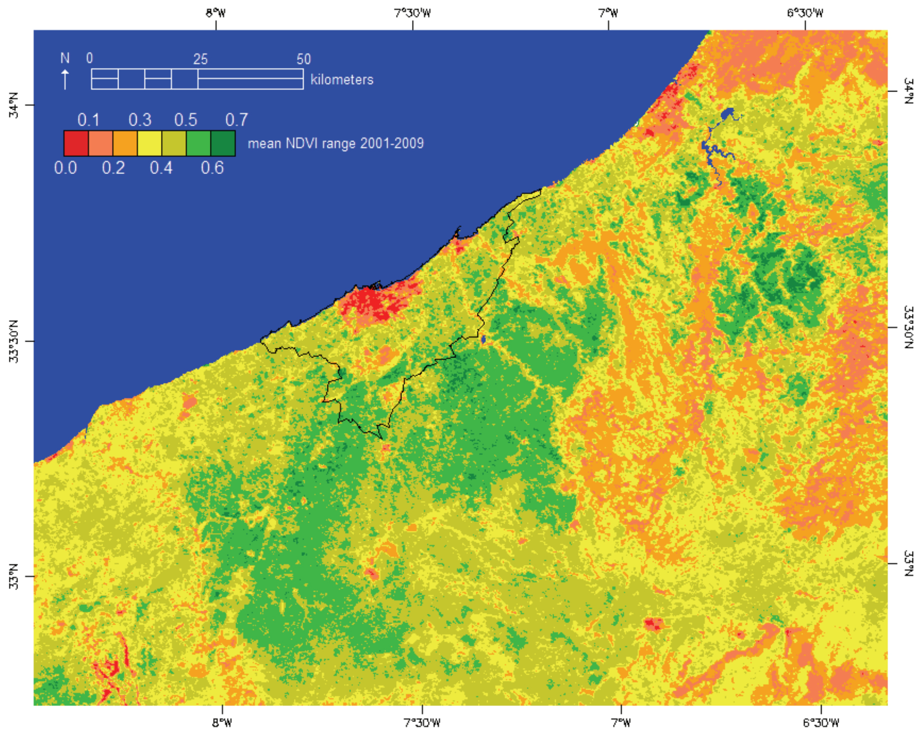

Fig. 11. Mean annual RanV ($RanV_{mean}$) for 2001–2009 with marked borders of the administrative region of Grand Casablanca.

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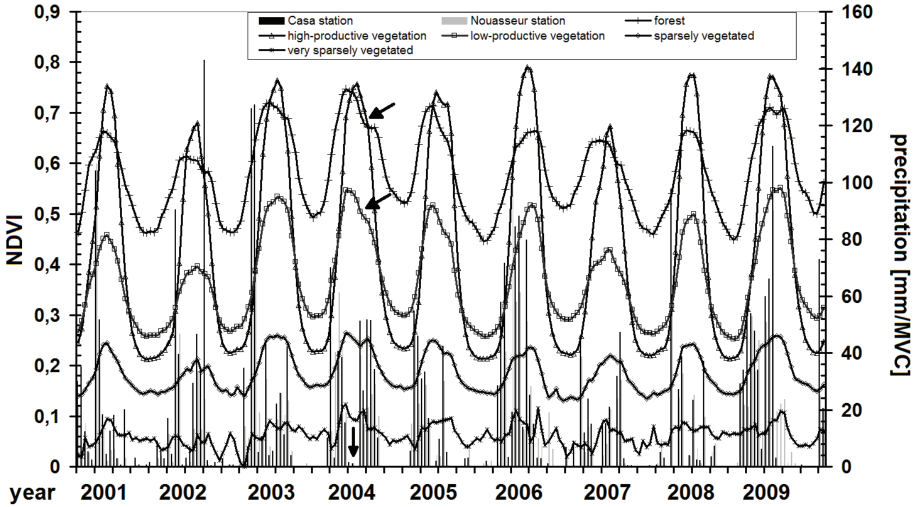

Fig. 12. Endmembers of stably classified areas and accumulated precipitation to composite length. Arrows show indicated influence of droughts due to a lack of precipitation from mid of December to mid of February in 2004.

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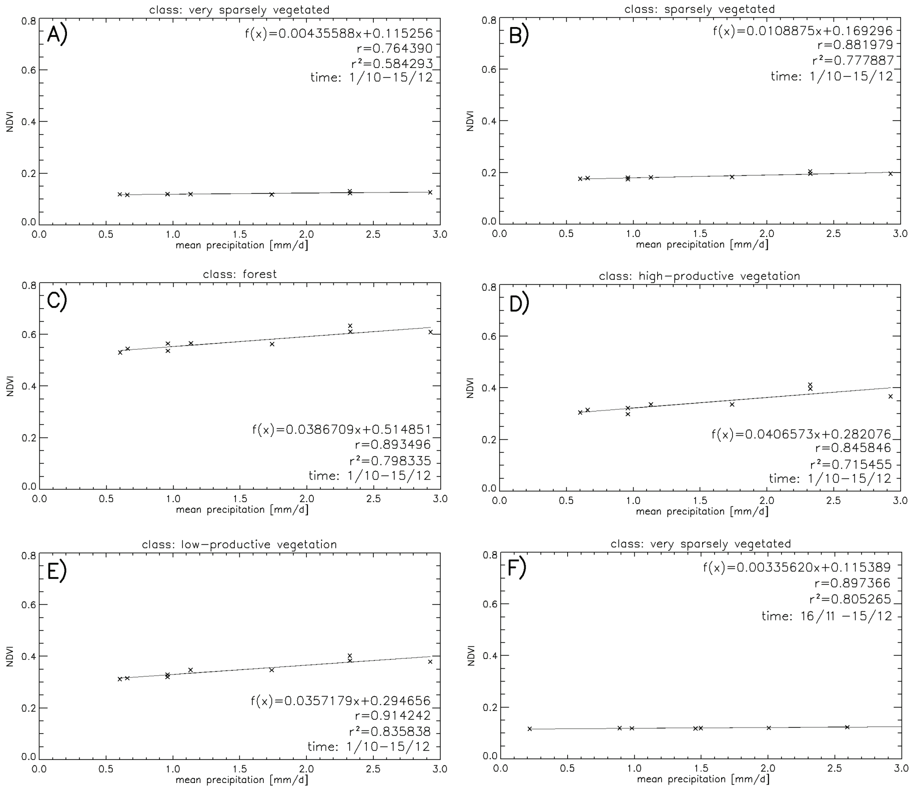

Fig. 13. Correlation of mean daily precipitation and NDVI (percentile 50%) of stably classified areas. Best fit for a common time period **(A–E)** and best individual fit for land cover type very sparsely vegetated **(F)**.

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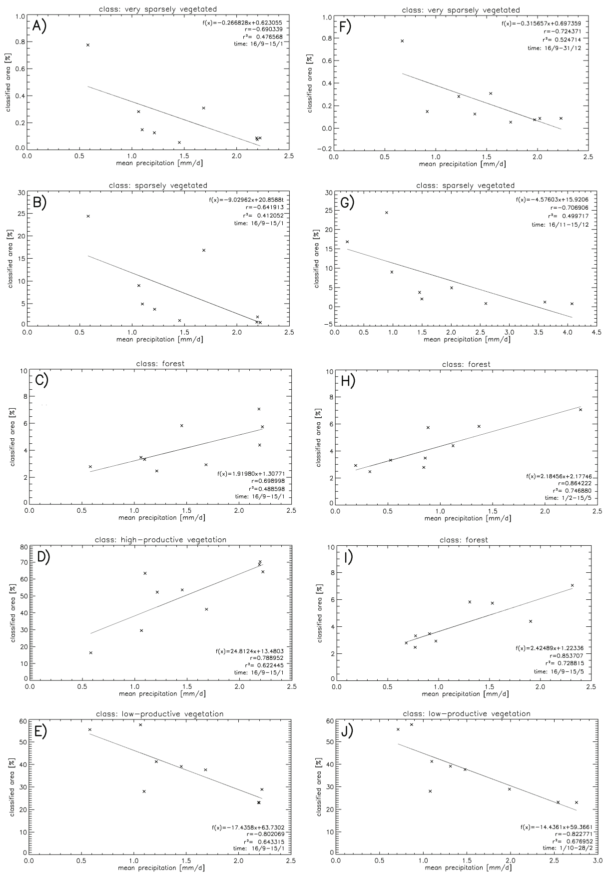

Fig. 14. Correlations of mean daily precipitation and classified area of each land cover type. Best fit for a common time period from 16 September to 15 January **(A–E)** and best individual fit for each land cover type **(F–J)** including second best individual fit for land cover type forest **(I)**.