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Categorization of land-cover change processes based on phenological indicators extracted from time series of vegetation index data

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A straightforward method for categorizing temporal patterns of land-cover change is presented. Two successive years of enhanced vegetation index (EVI) data derived from the Moderate Resolution Imagery Spectrometer (MODIS) were analysed. Five phenological indicators were extracted. Based on the inter-annual difference of each of the five indicators, indices of change in phenology were calculated. An unsupervised classification of these five indices of change applied to pixels characterized by a high change magnitude led to the identification of seven categories of land-cover change patterns. Thirty-one per cent of the change pixels could clearly be explained by a difference in only one or two phenological indicators, e.g. a shift in the start of the growing season or an interruption of the growing season due to floods. The remaining change pixels were explained by a combination of more than two indices of change. The output of this analysis is an allocation of change pixels to broad categories of land-cover change as a preliminary step for finer resolution analyses.

1. Introduction

Land-cover changes are the result of land-use changes or natural processes such as climatic variability and natural disturbances. Spatially explicit data on the magnitude and processes of land-cover change are important for studying a range of environmental change issues such as the role of terrestrial ecosystems in the carbon cycle, the frequency and impact of natural disasters, changes in fire regimes, and the impact of land-use change on ecosystem services. Several new satellite sensors provide daily coverage of the entire Earth at a 1-km spatial resolution. A method to detect the overall magnitude of land-cover change based on high temporal frequency data has already been established (Lambin and Strahler 1994). Nevertheless, to address the information requirements of the global environmental change scientific community, detection of the magnitude of land-cover change is not sufficient. There is also a need to identify the nature and causes of detected changes. While such information typically has been available only from field surveys or high-resolution satellite data, we examined methods using time series of remote sensing data to characterize the processes leading to land-cover change.

Vegetation phenology can provide baseline data to monitor land-cover changes associated with events such as fire, drought, land-use conversion, and climate

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fluctuation (Justice et al. 1986, Moody and Johnson 2001). There is a need for methods to separate changes driven mostly by climatic variability, to which an ecosystem is likely to be resilient, from changes driven mostly by land-use change, with a long-term impact on the ecosystem. Ecosystem changes caused by natural disasters such as floods or fires also should be detected as a distinct category. Such analyses would allocate change pixels to broad categories of land-cover change. Furthermore, these analyses would allow the assessment of the influence of climate variability, for example, on food or forage production. Ecosystem vulnerability to fires and the resilience of ecosystems to land-cover change could also be assessed. Finally, these analyses could provide insights into the influence of land-cover change on the carbon cycle, and generate more robust estimates of human-induced land-cover change.

The objective of this study was to develop and test a method to categorize change processes based on patterns detected from temporal series of remotely sensed vegetation index data. The satellite data were provided by the National Aeronautics and Space Administration (NASA) Terra satellite carrying the Moderate Resolution Imagery Spectrometer (MODIS) (launched in December 1999). Southern Africa was selected as the study area. Enhanced vegetation index (EVI) data derived from the 16-day synthesis nadir reflectance adjusted for the bidirectional reflectance distribution function (BRDF)-adjusted reflectance (NBAR) data (MOD43B4) from MODIS were used to monitor photosynthetic activity (Huete et al. 2002, Schaaf et al. 2002, Zhang et al. 2003). Change areas were first identified by applying the multi-temporal change vector technique (Lambin and Strahler 1994, Lambin and Ehrlich 1997) to two years of data. The processes leading to these changes were then defined based on a method that assumes that the change vector magnitude (CVM) for every pixel can be explained by a combination of inter-annual differences in five phenological indicators extracted from EVI temporal profiles.

2. Background

Phenology is generally defined as the timing of recurring biological events and their causes with regard to some meteorological phenomena (Justice et al. 1985, Lloyd 1990). Whereas vegetation maps show a two-dimensional representation of the Earth’s surface, the incorporation of phenological information adds a third (temporal) dimension (Markon 2001) that clearly is useful for dynamic behaviour studies. Stone et al. (1994) have interpreted phenology as an indicator of land-cover change in South America. Also, phenological traits of vegetation, which are closely related to lower atmosphere dynamics (Reed et al. 1994), were important in evaluating changes in climate (Lieth 1998). There is an increasing demand to better understand the relation between climate and plant production patterns (Potter and Brooks 1998). For example, the estimated start, end, and length of the growing season are used widely in food security models, as well as in climatic models (Groten and Ocatre 2002). Several studies mapped land cover or vegetation functional groups on the basis of indicators that identify important attributes of vegetation phenology, such as the start and length of growing season, extracted from smoothed time series of normalized difference vegetation index (NDVI) profiles (Lloyd 1990, Reed et al. 1994, Running et al. 1994). The impact of climate variability on vegetation dynamics has been studied by Roerink et al. (2003) by calculating the total amount of vegetation (mean NDVI) and the seasonal difference (annual NDVI amplitude) by a time series analysis of NDVI satellite images with the Harmonic ANalysis of Time Series (HANTS) algorithm.
Change detection based on time series of wide-field-of-view sensors such as NOAA Advanced Very High Resolution Radiometer (AVHRR), SPOT Vegetation, SeaWIFS, or MODIS has proven to be appropriate for regional studies of largely climate-driven changes in land surface attribute (Lambin and Ehrlich 1997, Kawabata et al. 2001), phenology (Myneni et al. 1997), and net primary production (Behrenfeld et al. 2001). Change detection based on temporal trajectory analysis requires the comparison of temporal development curves, also called time trajectories or time profiles, of remotely sensed indicators, for multiple years. When the time trajectory of one or several remotely sensed indicators for a particular pixel departs from the average (or optimal or previous year time trajectory), a change event is detected.

However, change detection based on data collected throughout the growing season also allows the separation of land-cover change types based on phenological variations in ecosystems (Lambin and Strahler 1994). Patterns of temporal differences in phenology can be used to characterize natural and human-induced land-cover change. For example, conversion from one land-cover type to another, changes in rainfall, and natural disasters will be reflected in changes in phenological attributes such as the start of the growing season or the total vegetation activity. With the availability of still relatively short time series of wide-field-of-view sensors (ten to a couple of years), mostly climate-driven fluctuations in surface conditions of natural ecosystems and impacts of natural disasters (drought, flood, fire) have been detected so far (Behrenfeld et al. 2001, Lupo et al. 2001). Based on a longer time series of 8-km resolution AVHRR data, Tateishi and Ebata (2004) identified up to eleven patterns of change in phenology at a global scale that were related to temperature and precipitation data.

3. Data and study area

3.1 Study area

The study area, located south of 17°S, covers approximately 3,780,000 km² across Angola, Namibia, Botswana, Zimbabwe, Mozambique, and South Africa (figure 1). The area is composed of three primary regions: a central plateau, a nearly continuous escarpment of mountain ranges that ring the plateau on the west, south, and east, and a narrow strip of low-lying land along the coast. Climatic conditions are largely dependent on altitude and proximity to the ocean. The region is characterized by a west–eastward gradient from dry to temperate climate. The arid to semi-arid regions experience a rainy season from October to May. The temperate regions are characterized by summer rainfall from November to February, while the southwestern corner of South Africa has hot, dry summers and rainy winters. Even the wettest variants of this climate are characterized by a marked dry season.

3.2 Remote sensing data

The characteristics of the MODIS instrument on board the Earth Observing System-Terra platform are optimized for global-scale vegetation monitoring. The dataset (MOD43B4) is made of level 2 daily surface reflectance (MOD09 series) at 250- and 500-m resolution, which are aggregated to 1-km spatial resolution. The data are atmospherically corrected (Vermote et al. 2002) and computed from nadir BRDF-adjusted reflectance (NBAR) data (Schaaf et al. 2002). The MODIS algorithm has applied a filter to the data based on quality, cloud, and viewing geometry. The nadir BRDF-adjusted reflectances were computed through a full
model inversion when at least seven cloud-free observations of the surface were available during the 16-day period, or otherwise through a magnitude inversion (Schaaf et al. 2002).

Data covering two successive growing seasons, from 16 October 2000 to 15 October 2002, were analysed. Because some complete scenes were missing, or pixel values were corresponding to no-data, ocean, or noise (based on pixel quality, cloud occurrence, and viewing geometry), a data quality map was produced. This map reflected the number of missing values along the EVI profile running through the two years (i.e. 46 16-day syntheses). To fill in gaps, a least-square quadratic interpolation was performed. Profiles with a maximum number of 16 missing data through the 2-year time series, and with a maximum of four consecutive missing data, were retained. Three per cent of the pixels were considered as not usable. Information on the number of clean syntheses and the number of interpolated values for each pixel was available when interpreting change patterns. No smoothing was applied to the data.

3.3 Land cover and precipitation data

The southern African portion of the eco-climatic map of Africa (White 1983) was used to separate land-cover classes that have identical morphological characteristics but fall in different eco-climatic zones, i.e. for which the growing season occurs at different times of the year. White (1983) delineated 12 vegetation groups within the region of interest. This vegetation map was also used in a stratified sampling scheme described below. Additionally, the African portion of the Global Land Cover 2000
(GLC2000) map (Bartholomé and Belward 2005, Mayaux et al. 2004) was used to
develop the land cover of pixels for which high to very high magnitude of change
was detected. This GLC2000 map of Africa was produced using multi-sensor
satellite observations at a spatial resolution of 1 km for the year 2000.

Monthly rainfall data were extracted from the Global Precipitation Climate
Centre, a German contribution to the World Climate Research Programme
(WCRP) and to the Global Climate Observing System (GCOS) (Rudolf et al.
was assembled from the FAO’s Global Information and Early Warning System
(FAO/GIEWS), the Famine Early Warning System programme (USGS/FEWS),
and Contributions for Natural Disasters (UN/ReliefWeb).

4. Categorization of land-cover change patterns: a methodology

4.1 Vegetation phenology

The categorization of land-cover change processes was based on patterns of inter-
annual variations in the seasonal trajectory of the EVI. The cycle of vegetation
phenology was characterized by three temporal metrics and two greenness metrics
(Lloyd 1990, and adapted from Running et al. 1994) (figure 2): (1) the onset of
greenness (a date); (2) the highest range of photosynthetic activity (dimensionless);
(3) the growing season length (in number of compositing periods); (4) gross primary
production over the year (time-integrated EVI – dimensionless); and (5) the date of
the peak of photosynthetic activity (a date).

Phenological variables such as the onset or length of the growing season can be
defined using hydrological, climatologic, and biological methods (Zhang et al.
2005), depending on the application. Moreover, phenological variables can be
interpreted differently depending on ecological attributes – ecosystems where
vegetation activity is primarily controlled by temperature versus water availability,
evergreen versus deciduous vegetation covers, etc. Therefore, for continental-scale
applications, only theoretical phenological variables can be defined, based on

Figure 2. Theoretical phenological indicators describing a vegetation index profile (adapted
from Running et al. 1994): (1) start of the growing season; (2) maximum EVI range (or EVI
amplitude); (3) growing season length; (4) integrated area below the growing vegetation curve;
(5) date of the maximum EVI value.
globally applicable criteria. Their exact value cannot be validated in the field for all vegetation covers and all possible applications. In this study on land-cover change, the major constraint is to ensure a consistency in the definition of phenological variables across years. Actually, their absolute value is not interpreted per se, as will be made clear below. Rather, their relative value for one year compared to a reference year is interpreted in terms of land-cover change process. It is therefore less important to have a definition of phenological variable that would be in perfect agreement with the hydrological, climatologic, or biological method and that would be validated in the field for all possible vegetation covers present in Africa (a task that would be impossible anyway) than having metrics that can be compared consistently from one year to the other. Below, when we refer to phenological indicators, these should thus be understood as theoretical variables, based on arbitrary thresholds. For example, the date of onset of the growing season and the date of senescence (required to define the growing season length) were defined based on the same threshold, even though, biologically, vegetation greening and yellowing may correspond in some cases to different thresholds in terms of rates of photosynthetic activity.

4.2 Extraction of phenological indicators

The first phenological indicator (IP1) determined was the time of vegetation green-up. In the last fifteen years, a number of different methods have been developed to determine the start of the growing season using time series of NDVI data from AVHRR. These methods have relied on absolute NDVI thresholds (Lloyd 1990, Markon et al. 1995), the largest NDVI increase (Kaduk and Heimann 1996), backward-looking moving averages (Reed et al. 1994), or empirical equations (Moulin et al. 1997). However, such methods are sensitive to VI fluctuations, or do not account for ecosystems characterized by multiple growth cycles. The use of a series of piecewise logistic functions (Zhang et al. 2003) is promising but highly dependent on data quality, and it requires high computing time. Jönsson and Eklundh (2002) fitted Gaussian functions to AVHRR NDVI data before extracting seasonality information to map phenological variables over large areas.

In this study, the VI ratio method (White et al. 1997) was used. The VI is normalized for differences between land covers for each pixel:

\[
\text{EVI}_{\text{ratio}} = \frac{\text{EVI} - \text{EVI}_{\text{min}}}{\text{EVI}_{\text{max}} - \text{EVI}_{\text{min}}}
\]

where \(\text{EVI}_{\text{ratio}}\) is the output ratio for a given pixel, \(\text{EVI}\) is the vegetation index value for that pixel for a given time period, \(\text{EVI}_{\text{max}}\) is the annual maximum EVI for that pixel, and \(\text{EVI}_{\text{min}}\) is the annual minimum EVI for that pixel. \(\text{EVI}_{\text{max}}\) and \(\text{EVI}_{\text{min}}\) are annually redefined. Based on these \(\text{VI}_{\text{ratio}}\) temporal profiles, a threshold of 0.50 was defined to identify the period of greatest increase (onset) and decrease (offset) in \(\text{VI}_{\text{ratio}}\) curves. The method thus searches for the EVI value equal to 50% of its corresponding \(\text{EVI}_{\text{ratio}}\):

\[
\text{EVI}_{\text{onset}} = \frac{1}{2} (\text{EVI}_{\text{max}} - \text{EVI}_{\text{min}}) + \text{EVI}_{\text{min}}
\]

Once the \(\text{EVI}_{\text{onset}}\) threshold values were calculated for the two years, only the lowest absolute EVI value was retained and used to define the date of onset for each of the years. This ensures a consistency across years in the definition of the date of onset,
therefore allowing detection of changes in phenology between years. The start of the growing season (IP1) is a date expressed in units of number of temporal composites, i.e. one unit equals 16 days for this MODIS dataset. A similar approach was used to identify the end of the growing season.

The annual EVI range (IP2) corresponded to the maximum EVI value minus the minimum EVI value. The growing season length (IP3) was the number of compositing periods from the start to the end of the growing season. The fourth phenological indicator (IP4) was the integration of all 23 EVI syntheses forming one year. The fifth phenological indicator (IP5) was the date of the peak EVI.

The inter-annual difference (IND) in each of the phenological indicators was calculated for every pixel as:

\[ \text{IND}_i = \left| \text{IP}_2^i - \text{IP}_1^i \right| \]

where \( \text{IP}_1^i \) and \( \text{IP}_2^i \) represent the values of a phenological indicator for, respectively, year 1 and year 2. As there were five phenological indicators, \( i \) varied from 1 to 5.

### 4.3 Calculation of specialization indices

The change vector magnitude (CVM) was computed using the multi-temporal change vector method (Lambin and Strahler 1994). The CVM is the Euclidean distance between the pixel positions for the current and the previous year in the 23-dimensional space. To avoid including change pixels associated with background noise, high-change pixels were defined based on a change vector magnitude larger than the mean magnitude plus two standard deviations. The specialization indices were only computed for these high-change pixels.

High-change pixels were explained by the relative contribution (in percentage) of the change of each of the five phenological indicators to the overall change detected for that pixel. This was expressed by an ‘index of specialization’ (IS). To control for differences in measurement units, the inter-annual difference in each of the phenological indicators was centred by subtracting the mean \( \overline{\text{IND}}_i \) and standardized (divided by the standard deviation \( S_i \)).

For every change pixel, the corresponding scaled value \( Z_i \) for each of the phenological indicators \( i \) was divided by the range of that scaled dataset and then divided by the sum of the five normalized scaled values to obtain five specialization indices (IS\( _i \)), expressed in percentage:

\[ \text{IS}_i = \frac{\text{nd}_i}{\text{nd}_{\text{sum}}} \times 100 \]  \tag{4}

\[ \text{with nd}_i = \left| \frac{Z_i}{Z_{i,\text{max}} - Z_{i,\text{min}}} \right| \]  \tag{5}

\[ \text{and nd}_{\text{sum}} = \sum_{i=1}^{5} nd_i = 1 \]  \tag{6}

### 4.4 Typology of change patterns

Patterns of land-cover change were categorized based on the relative contribution of each specialization index to the total change in phenology. The approach is illustrated based on five ideal cases (figure 3). A change in the whole season (case 1, figure 3) would involve the five indices of change. A simple shift in the growing season (case 2, figure 3) will lead to high values of IS\( _1 \) and IS\( _5 \) only. A shortening in
the growing season, possibly due to a late season fire or cyclone, to conversion to short-cycle crops, or to rapid deforestation (case 3, figure 3), would be detected by IS$_3$ and IS$_4$. Other indicators would be involved in the case of a late start of the season (case 4, figure 3). A mid-season flood event (case 5, figure 3) would be detected with the same indicators as in case 3, but could be discriminated based on the vegetation curve modality. A binary variable (unimodal or bimodal curve) was then defined by searching secondary starts and ends of growing season based on the same threshold as used above. The algorithm ran first before and after the peak EVI date, and then before and after the first start and end dates encountered. If an EVI curve recovers rapidly – i.e. within the same growing season – after a disturbance caused by a flood for example, a bimodal time profile is detected. A specific change process is detected when a pixel shifts from a unimodal to a bimodal EVI curve (or vice versa) between two years. While the concept illustrated above was based on smooth, continuous curves, it was applied to real data in this study. The relatively short compositing period (16 days) and efficient noise removal in MODIS data pre-processing is such that time series of actual data can be treated as continuous data, even though they are indeed less smooth than idealized curves.

A clustering algorithm was applied to the five specialization index maps and to the categorical variable representing a change in the modality of the EVI curves to identify areas affected by a similar change pattern. The unsupervised iterative self-organizing data analysis (ISODATA) procedure was selected.

Figure 3. Typology of land-cover change patterns based on ideal cases. Case 1: Change in the whole season; Case 2: Shift in the growing season; Case 3: Shortening of the growing season; Case 4: Late growing season; Case 5: Episodic disturbance.
5. Results

Multiple regression analysis showed that 65% of the variance of the CVM (the dependent variable) was explained by the change in the five phenological indicators. Using the partial least squares (PLS) regression technique (Tobias 1997), the adjusted $R^2$ increased to 76%. This was based on a stratified random sample of 1000 pixels in each White vegetation group. These results suggest that inter-annual differences in the five phenological indices capture a large part of the land-cover change patterns detected by the multi-temporal change vectors, but that some residual changes are not well-measured by the phenological metrics. Whether these residual changes correspond to measurement noise, random surface changes, or land-cover change information is difficult to determine and is likely to depend on the application for which the land-cover change analysis is conducted.

For the pixels undergoing land-cover change as detected by the CVM methodology, the unsupervised clustering algorithm identified seven classes corresponding to clearly distinct patterns of change in EVI temporal curves. For each cluster, a large number of EVI profiles were extracted randomly to visualize these patterns of change. Three clusters, representing 4% of the change pixels, identified three classes ($IS_1^+$, $IS_2^+$, and $IS_3^+$) for which change was caused mainly by a change in just one of the phenological indicators. For example, the cluster $IS_1^+$ is associated with pixels for which the index of specialization related to the start of the growing season has a value larger than 60%. A second set of three clusters, representing 27% of the change pixels, identified three classes for which change was mainly caused by changes in two indicators ($IS_1-IS_5$, $IS_2-IS_4$, and $IS_3-IS_4$) – for example, a change in the length of the growing season ($IS_1 > 35\%$) and a change in the date of the maximum EVI value ($IS_5 > 35\%$). The seventh cluster, representing 69% of the change pixels, merges situations characterized by various combinations of changes in the five indices that do not display clear and recurrent temporal patterns of change. The change process for this cluster is difficult to attribute to a single cause in the absence of some good knowledge of the field and of climatic conditions for the two years being compared.

Below, some examples of actual land-cover change patterns associated with changes in one or two phenological indicators are discussed. Each of these examples was allocated to different clusters in the unsupervised classification on the indices of specialization, and was thus discriminated as corresponding to different change processes. Figure 4(a) represents change areas in the driest part of Angola, along the Cubango River. It is dominated by open grassland with sparse shrubs. The mean EVI curve represents a shift in the date of vegetation green-up of about 2.5 months between the two years. The peak EVI value (reflecting the period of maximum vegetation activity) occurred during the same month for the two growing seasons (mid to end of February). The length of the growing season was, on average, 3.4 months for both years. These EVI observations were corroborated by the rainfall distribution over these two years (figure 5(a)). The 2000–2001 rainy season started late but had a peak rainfall in February. That year was associated with more than twice the rainfall amount compared to the following year. The fact that only the $IS_1^+$ index (shift in start of the growing season) had a high value is due to the high resilience of the ecosystem to a late start of rain, helped by abundant rainfall at the heart of the growing season. These abnormal February 2001 precipitations caused some localized flooding and crop damage along the Cubango River (FAO/GIEWS).
The Cape region in South Africa experienced a different pattern of change (figure 4(b)). The land cover of the area affected by change is deciduous shrubland with sparse trees, closed grassland, and open grassland with sparse shrubs. The EVI profile shows that vegetation growth was much greater for the 2001–2002 growing season compared to the previous year. This change was associated with high values of the IS2 and IS4 indices of specialization – i.e. change in the EVI range and in integrated EVI value. The South African Weather Service (SAWS) reported warmer than normal weather over most of the country, followed by cold fronts that brought snow and cold weather during the June–July 2001 period (i.e. at the end of the growing season of the first year) (figure 5(b)).

High change magnitude was also detected close to the city of Gaborone in Botswana (figure 4(c)). Land cover is a woodland mosaic and transition area, with deciduous woodland, deciduous shrubland with sparse trees, grassland, and cropland. The change pattern in the area was characterized by high values in the indices IS1 and IS5. The start of the growing season and the date of maximum EVI value are shifted by 4.2 months on average between the two years. By contrast, the length of the growing season, the EVI range, and the integrated EVI value were identical for the two years. This spectacular shift in the growing seasons is explained by two aspects of rainfall distribution (figure 5(c)): a 2-month delay in the start of the rainy season in 2000, followed by a rainfall deficit – the region recorded less than 65% of the normal rainfall in the 2000–2001 growing season (UN/ReliefWeb).
The major 2001 floods in Central Mozambique, along the Zambezi River, were also clearly discriminated (figure 4(d)). Dominant land covers are closed evergreen lowland forest, closed deciduous forest, and swamp bushland and grassland. The floods were associated mostly with a change in the length of the growing season (IS3), leading to a lower integrated EVI value (IS4). Torrential rains began in the Zambezi valley region in late January 2001 (figure 5(d)). The floods caused a sharp decline in EVI in the course of the growing season, with a partial recovery of EVI values a couple of months later. The flood forced more than 400,000 people to flee their homes for drier ground (UN/ReliefWeb).

6. Discussion

The land-cover change detection and categorization methods used here require time series of remote sensing data with a high temporal frequency and a medium spatial resolution, but also a very low level of noise. These constraints generally are contradictory. The MODIS dataset used in this study is a considerable improvement compared to most previously used datasets. We found remarkable the level of reduction of the noise caused by the atmosphere, and also sensor and viewing geometry. Geometric accuracy was also high given the 1-km resolution of the data, with a geolocation within approximately 50 m (1σ) at nadir according to Wolfe et al. (2002). The 16-day compositing period allowed the capture of subtle changes in vegetation phenology. These improvements in data pre-processing allowed the analysis of land-cover change without having to smooth the time series beforehand.
The change pattern of only 31% of the change pixels could be explained by a change in only one or two phenological indicators. This does not mean that the other 69% of change pixels cannot be categorized but that the change process affecting these pixels leads to more complex patterns of change, and cannot be reduced to one or two simple components of change.

While the computation of three of the phenological indices – EVI range, time-integrated EVI, and date of maximum EVI value – was quite robust, the other two – apparent onset of greenness and growing season length – were dependent on a threshold value and, consequently, were more sensitive to the method used to define this threshold of vegetation activity. Under some climatic conditions, or after a severe drought to which the ecosystem is resilient, EVI profiles can be bimodal over a single year and should be identified as such to avoid extracting spurious values for phenological variables.

Direct validation for this type of study is difficult. One-kilometre resolution pixels were allocated to broad categories of patterns of phenology change that reflected the integrated response from diverse land covers. A comparison with ground measurements could not be conducted directly. A methodology to use fine spatial resolution remote sensing data as an intermediate step between field-based observations and 1-km resolution pixels is needed to validate MODIS-based land-cover change detection and categorization products. However, the lack of high frequency, high spatial resolution data makes validation of inter-annual variability challenging, if not impossible.

Over just two growing seasons, any difference in seasonality in land surface attributes is most likely related to inter-annual climatic variability. Once longer time series of consistent data are available, it will become possible to separate long-term dynamics in land cover from short-term, reversible variations in surface attributes, and to isolate climate-induced changes from anthropogenic changes.

7. Conclusion

The global change scientific community and environmental monitoring programmes require spatially explicit information on the nature, magnitude, and causes of land-cover changes. The information contained in time series of remote sensing data can be analysed to meet part of the information requirement. For locations with high land-cover change magnitudes in southern Africa, it was possible to identify a few typical patterns of change based on five phytophenological indicators extracted from MODIS EVI time profiles. These phenological indicators characterized vegetation dynamics. Seven categories of land-cover change patterns were identified based on the relative contribution of the change in each of the five phenological indicators to the overall change detected for that pixel. With only two years of observation at 1-km spatial resolution, one could only expect to detect and identify change caused mainly by inter-annual climate variability. Areas affected by changes in green-up patterns or natural disasters, to which ecosystems are likely to be resilient, were mapped and categorized.

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