

MAPPING REGIONS OF HIGH TEMPORAL VARIABILITY IN AFRICA

René R. Colditz^{ab*}, Christopher Conrad^{ab}, Martin Schmidt^b, Matthias Schramm^b, Michael Schmidt^{ab}, Stefan Dech^{ab}

^a German Aerospace Center (DLR), German Remote Sensing Data Center (DFD), Oberpfaffenhofen, 82234 Wessling, Germany – (rene.colditz, christopher.conrad, michael.schmidt, stefan.dech)@dlr.de

^b University of Würzburg, Department of Geography, Remote Sensing Unit, Am Hubland, 97074 Würzburg, Germany – martin.b.schmidt@stud-mail.uni-wuerzburg.de, matthias.schramm@mail.uni-wuerzburg.de

KEY WORDS: Global Change, Temporal Variability, Land Characterization, Harmonic Analysis, Africa, AVHRR Pathfinder

ABSTRACT:

Long term observation of space-borne remote sensing data provides a means to explore temporal variation on the Earth's surface. This improved understanding of variability is required by numerous global change studies to explain annual and interannual trends and to separate those from individual events. This knowledge also can be included into budgeting and modeling for global change studies. The study employs daily 8km NOAA AVHRR data of the Pathfinder program to study changes in the annual variability of the African continent between 1982 and 2000. The daily data were processed to improved 10-day composites using an iterative approach including metadata and robust statistical techniques. Seasonality analysis using harmonics and its explained variance is combined with cross correlation between years with identical seasonality to account for temporal shifts.

Deserts and the inner-tropical rain forest with none and moderate variability, respectively, are circled by a zone of transition assigned with high variability and changing seasonality. In between there are two gradual units of stability, usually identified as grassland or woodland by continental classifications. This relatively zonal pattern is altered in the eastern tropics and Namibia by varying topography and oceanic influences, respectively. The results can provide a basis for spatial distributed modeling of dynamic hotspots such as the transition zones bordering the savannas and for linking vegetation dynamics with continental climate models.

1. INTRODUCTION

Modeling and monitoring patterns related to global change requires comparative and unbiased long term observations of the Earth's surface suitable for quantitative analysis. Regarding the land surface, vegetation parameters are needed to drive biogeochemical models or to estimate earth-atmosphere interactions (Sellers et al., 1996; DeFries et al., 1995a). In addition, vegetation parameters are also crucial for ¹carbon budgeting, estimating net primary productivity, land cover characterization, and biodiversity modeling (DeFries and Townshend, 1994). All these applications require an analysis of the vegetation dynamics, either within a single year for seasonal analysis or for several years to characterize trends, modifications, or changes.

Because *in situ* measurements of these parameters are inappropriate for global or continental applications, space borne remotely sensed data provide the only means for spatial analysis. Long term observations are frequently employed to estimate landscape change in various ecosystems. The extent and variation of desert environments were studied by Tucker et al. (1994) using 8km AVHRR Pathfinder data. Lambin and Ehrlich (1997) retrieved land cover changes in the sub Saharan Africa with 4km AVHRR GAC data between 1982 and 1991 using the change index approach. A 12-year 4km AVHRR GAC data record has been used by Weiss et al. (2001) to analyze rangelands in semi-desert environments in Saudi Arabia. Long term monitoring of agricultural areas was applied by de Beurs and Henebry (2004a) in Kazakhstan and by Fuller (1998) and Tottrup and Rassmussen (2004) in Senegal. Jakubauskas et al. (2002) used harmonic analysis for crop

identification in the United States. Grasslands and boreal area variability was monitored by Yu et al. (2004) and de Beurs and Henebry (2005). Piwowar and LeDrew (2002) used SMMR data of the northern hemisphere to analyze sea ice cover using autoregressive moving average modeling.

This study employs daily Advanced Very High Resolution Radiometer (AVHRR) data of the Pathfinder program from 1982 to 2000 to indicate regions of high temporal variability for the African continent. The Normalized Difference Vegetation Index (NDVI), widely used for vegetation characterization, was analyzed using statistically robust techniques like harmonic analysis and cross correlation due to known problems with inter-calibration between the sensors (Gutman et al., 1996; Beurs and Henebry, 2004b). Environmental singularities caused additional inherent variation, e.g. the eruption of Mt. Pinatubo in 1991 (Tucker et al., 2001).

2. DATA

The Advanced Very High Resolution Radiometer (AVHRR) of the National Oceanic and Atmospheric Administration (NOAA) provides daily global coverage of the Earth's surface (James and Kalluri, 1994; Maiden and Greco, 1994). No other sensor with high temporal resolution has a longer history with an archive dating back to 1981 and providing a potential for long term variations of the Earth's surface. The Pathfinder AVHRR Land (PAL) program aggregated the data to 8km spatial resolution or one degree and offers three temporal resolutions with daily, 10-day and monthly maximum value composites (James and Kalluri, 1994). This study uses daily 8km Normalized Difference Vegetation Index (NDVI) data, derived from the red and near infrared bands. The NDVI reports

* Corresponding author: René R. Colditz, rene.colditz@dlr.de

vegetation density and greenness. Thus NDVI time series allows monitoring green vegetation dynamics and variation (Justice et al., 1998). For spatial analysis of land cover units, a subset of Africa from the global 8km AVHRR land cover dataset has been used (DeFries et al., 1995b; DeFries et al., 1998; Hansen et al., 2000) (Figure 1).

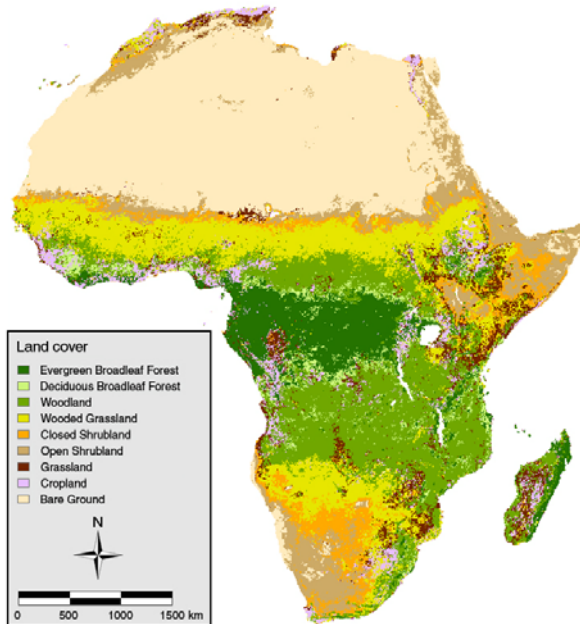


Figure 1: Land cover classification of AVHRR PAL data from 1992-1993 (DeFries et al., 1995b; DeFries et al., 1998; Hansen et al., 2000).

3. METHODS

Daily 8km PAL NDVI data were evaluated employing metadata such as quality (processing history), cloud index, and sun and sensor geometry. A pixel-based iterative approach using several combinations of the metadata was applied to extract uncorrupted NDVI data. During each iteration, data gaps shorter or equal five days were linearly interpolated. A final interpolation closed the remaining data gaps, where no suitable NDVI was found. A statistical outlier analysis using a temporal moving window approach and standard deviation measure corrected for unnatural short-term variations by linearly interpolating those values. A box-car filter was used to reduce more subtle temporal noise. Eventually, the daily data were aggregated to 10-day composites using the maximum value method (Holben, 1986).

The continuous 19 year time series record was split into single years for analysis of seasonality. Accounting for reversed seasonality on the southern hemisphere, the year was defined from July 1st to June 30th for this area. For each year, harmonic analysis was used to evaluate the modality, i.e. seasonality, of each pixel. The harmonic analysis applies a forward and inverse Fourier transformation, where the first periods, called harmonics, reveal the general pattern of the time series and the higher harmonics indicate noise patterns and short-term intra-season variations (Azzali and Menenti, 2000; Jakubauskas et al., 2001; Moody and Johnson, 2001). The explained variance of the first, second, and third harmonic was weighted with empirically derived factors. Harmonics with the highest weighted value indicated the seasonality of the pixel. Pixels with more than three seasons per year were not expected. Pixels

with no seasonality, such as desert areas, were derived assuming a NDVI temporal dynamic range lower than 0.15. The changes in modality indicate regions of high instability in the landscape. The changes in modality were counted and the modality image was classified to derive regions with similar patterns using unsupervised ISODATA clustering with 10 classes, 10 iterations and a convergence threshold of 0.95.

To investigate the temporal variability between years with similar modality, i.e. the temporal shift caused by earlier or later seasons, the annual time series were pair-wise compared using cross correlation. Shifts of ± 8 composites (= 80 days forward and backward) were tested and the highest correlation coefficient and its lag was saved. No-cross correlations were calculated for different modality combinations, because the change in seasonality can likely be caused by land cover change.

4. RESULTS AND DISCUSSION

The following discussion focuses on (1) the analysis of modalities and (2) the analysis of shifts between all pair-wise combinations of years with identical modality.

4.1 Analysis of modality

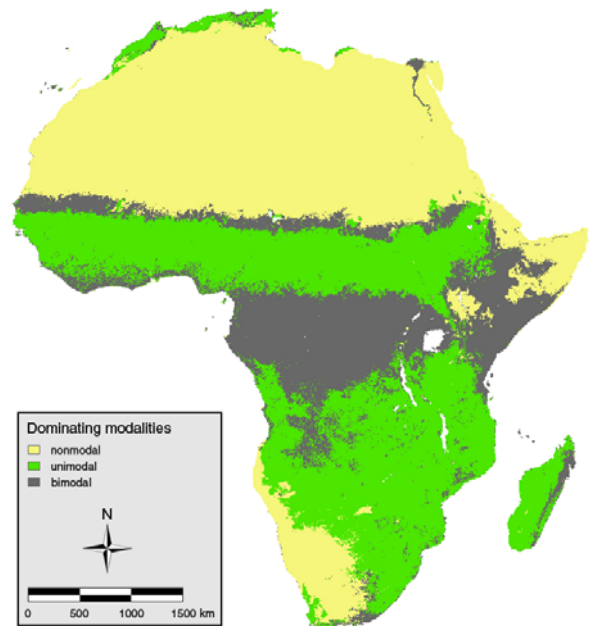


Figure 2: Dominating land cover of AVHRR PAL data. Pixels with more than 2 seasons are insignificant and therefore not displayed.

Figure 2 shows the dominating modality of the 19 year record. The dominating modalities depict non seasonal characteristics in the desert and semi-desert lands. Single season lands dominate the outer tropics, with a distinct belt in the northern hemisphere. Two seasons are depicted in the inner tropics and along the southern Sahara due to high variability in the Sahel zone. The inner tropical bi-seasonal zone extends into eastern Africa and spreads along the Kenyan coast. Also, the transition between the winter and summer rains in South Africa is dominated by two seasons. Rarely pixels are dominated by three seasons, and those pixels do not form a contiguous area.

	non	uni	bi
Evergreen Broadleaf Forest	0	13	87
Deciduous Broadleaf Forest	0	46	54
Woodland	0	79	21
Wooded Grassland	1	85	14
Closed Shrubland	28	38	34
Open Shrubland	78	7	14
Grassland	4	58	37
Cropland	1	65	34
Bare Ground	99	0	1

Table 1: Percentage of dominating modality for each land cover class. non...nonmodal, uni...unimodal, bi...bimodal. Pixels with more than 2 seasons are insignificant and not shown in the table.

Table 1 shows the proportional areas statistics of the dominating seasonality for each land cover class, calculated by combining the land cover map (figure 1) with the dominating modality (figure 2). The statistics prove that evergreen broadleaf forest in the inner tropics is dominated by two seasons, whereas the surrounding savannas are characterized by one season. Open shrublands in Eastern Africa and the Kalahari as well as bare ground in the deserts show no seasonality. Some land cover classes are characterized by two seasonality patterns, e.g. grasslands and croplands, which are distributed throughout Africa. Deciduous broadleaf forest, for example, is located at the edge of one and two seasonal patterns circling the inner tropical rain forests. Potentially the dominated seasonality allows more specific characterization of those land cover classes.

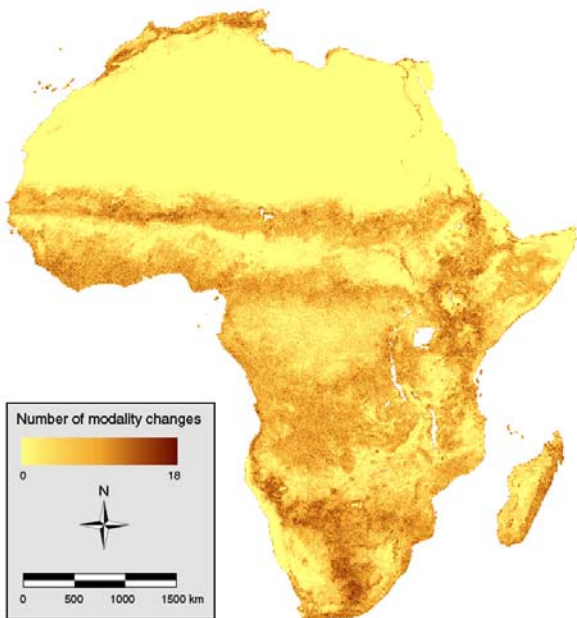
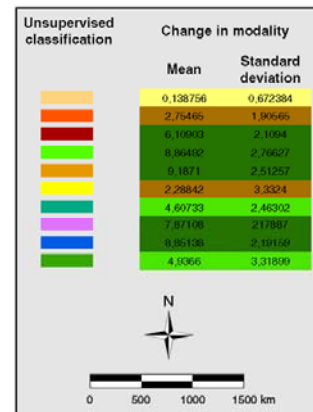
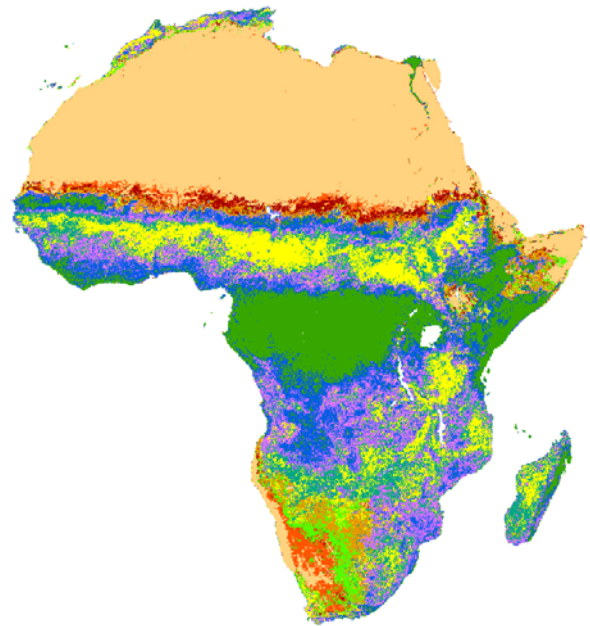


Figure 3: Change of modalities of the AVHRR PAL data.



Figure 4: Classification of 19-year modality image (top) and recode to four units using mean values of modality change image (Figure 3) for each class (bottom).

The change in modalities (see Figure 3) indicates the variation of a land surface in 18 years, where no or few changes show a high stability in annual vegetation dynamics and landscape. Compared to the Saharan desert with no changes, the Mediterranean and Atlas mountains in the north and the Sahel transition zone in the south show higher change in modality. Interestingly, south of the transition zone the Savannas with grassland and woodland seem to have few to no changes. There is a transition zone with many changes around the inner-tropical evergreen rain forest in the low elevation equatorial with high stability. However, this zonal pattern is altered in eastern Africa due to the increasing elevation. Where low-lying portions such as Somalia and coastal Kenya have few changes in modality of the annual vegetation dynamics, the Ethiopian uplands and the Rift-valley area seem to be highly variable. In Southern Africa the variability increases circularly around the inner-tropical portions and decreases again for some wood and grasslands. Also there are very high values circling the Kalahari Desert. Although it has been expected the change in modality will indicate transition zones around semi desert lands which do not receive rainfalls annually, this analysis also indicates areas with wetter conditions. These high changes in modality can be due to their location as transitions to evergreen rainforest, which is variable annually. However, atmospheric conditions with frequent cloud cover can influence the analysis and might not be fully accounted for using the cloud index data during processing.

The multilayer image with modalities for every year was classified with an unsupervised ISODATA classifier to derive regions with similar statistical patterns (Figure 4 top). These patterns were overlain with the changes in modality to calculate mean and standard deviation. The statistics show there are four inherent classes (see also Figure 4 bottom) with no change, ~2.5 changes, ~4.8 changes, and ~8 changes.

4.2 Analysis of shifts

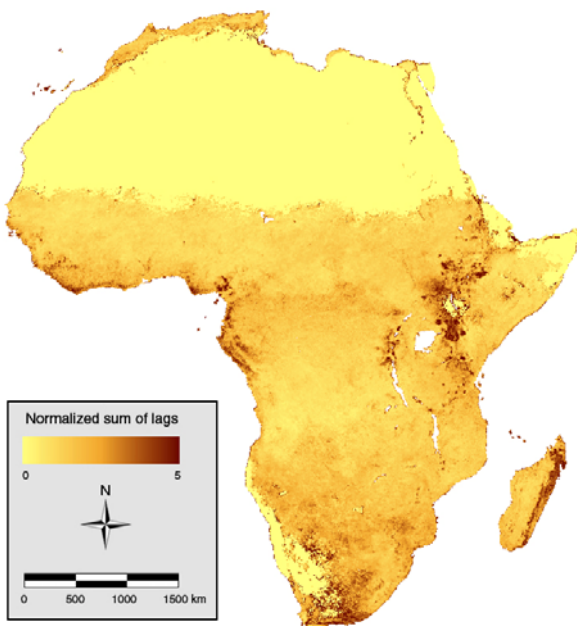


Figure 5: Normalized sum of lags between years of identical seasonality derived from AVHRR PAL data. Lags larger than 5 are infrequent and recoded to 5.

The lag of the highest cross-correlation coefficient of pair-wise comparison between all years with identical modality is analyzed by calculating the absolute sum of all lags divided by the number of comparisons (Figure 5). The sum of lags depicts expected patterns where desert areas of the Sahara and Kalahari show no changes due to non-modal data. The woodlands and grasslands of the southern Congo basin depict less variability than the evergreen rain forest to the north. The higher lags in the rainforest in central and western Africa are also due to varying modalities (see above) and likely due to insufficient atmospheric correction influencing the statistical approaches for temporal analysis.

5. CONCLUSIONS

Despite its coarse resolution, 8km AVHRR Pathfinder data provide a potential for continental land cover analysis, land cover change, and modeling. However, the data have to be properly processed using various sources of metadata, e.g. atmospheric conditions and view and illumination effects. The variability of surface cover types can be studied by comparing surface dynamics of land cover types for several years. The analysis of change in seasonal behavior by studying modalities of surface cover dynamics estimates the variability in land cover variation. While evergreen rainforest and desert areas showed fewer changes, grasslands and woodlands indicate very distinct patterns with less changes in the northern hemisphere and many in the south. Generally there are four distinct groups which can be related to land cover units:

- desert areas (Sahara, Kalahari) with very low changes in modality (less than one)
- stable grass-woodlands of the northern hemisphere with very low changes in modality (average of 2.5 changes), although the changes are higher in the southern hemisphere
- tropical rainforest and savanna in southern Africa (modality change of approximately 4.8)
- shrubland surrounding the desert and savanna in the northern hemisphere with a more dispersed pattern in the southern portion of Africa (approximately 8 changes in modality)

If the general characteristics of the curve are similar, the lag of the highest cross-correlation between two years indicates the period of offset, i.e. whether the season of one year was earlier compared to the other.

Further studies will apply more advanced statistical approaches, e.g. autoregressive modeling, which will be validated and compared to other, similarly processed data. Also the retrieval of modality using thresholds of the explained variance of harmonics will be changed to more fuzzy approaches accounting for unclear patterns in modalities. The results will also be related to global phenomena such as El Nino or droughts.

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