Long-Term Phenology and Variability of Southern Africa

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Abstract

Satellite-derived phenology allows monitoring of terrestrial vegetation on a global scale and provides an integrative view at the landscape level [7]. Understanding these seasonal phenological patterns is essential to (i) the characterisation and classification of vegetation, (ii) studying the impact of climate change [5], and influence of rainfall variability (iii) monitoring desertification [3] and (iv) detecting changes in land use/land cover.

This study analyzed vegetation phenology across southern Africa in order to investigate which phenometrics (and their inter-annual variability) distinguish biomes based on functional patterns. A second objective was to quantify the inter-annual variability of phenometrics during a 15-year period (1985 to 2000).

1. Introduction

The dynamic phenology of terrestrial ecosystems reflects response of the biosphere to proximal climatic factors (e.g. temperature and rainfall). These climatic drivers, as well as fire, are largely responsible for the geographic distribution of different vegetation zones, e.g. biomes. Satellite-derived phenology furthermore provides the opportunity for defining and mapping vegetation zones (e.g. biomes) based on vegetation function and dynamics.

The objective was to investigate the long-term spatial patterns and inter-annual variability in satellite-derived vegetation phenology in relation to the recently revised biome map of South Africa.

2. Methodology

The 1km² AVHRR data were previously processed and calibrated for sensor degradation. For details see [8]. Daily NDVI data were composited into 10-day maximum value composites. This study was limited to the period 1985-2000 in order to avoid changes in spectral response function of NOAA-16, post 2000. A data gap exists for 1994 due to the failure of NOAA-13.

The long-term, 1km² NDVI data of southern Africa were analyzed using the TIMESAT program developed for the exploration and extraction of seasonality parameters from time-series data [4]. TIMESAT implements three curve fitting procedures based on least squares fit to the upper envelope of vegetation index data, as most noise is negatively biased [4].

Outliers were removed from the time-series. An adaptive Savitsky-Golay filter, which uses local polynomial fitting with small moving windows in two fitting steps proved to be the most successful at producing a smoothed curve while capturing rapid phenological changes. The curve fitting procedure allows the extraction of seasonality parameters (phenometrics) such as start date, end date and length of growing season for each of the growing seasons in the data set.

A user-defined threshold of 10% of the seasonal amplitude (as measured from the left minima of a seasonal curve) is set as the start of growing season (SGS) date. Similarly the end of growing season (EGS) is defined as the date at which the right edge has declined to 10% as measured from the right minima. In order to investigate the sensitivity of the threshold choice, the processing was repeated with a 20% threshold.

Phenometrics for each of the growing seasons were extracted (Fig. 1) with a distinction between “date phenometrics (e.g. start or end of season) and “productivity phenometrics” (e.g. large integral) shown in Table 1.
Long-term means, standard deviations (SD) or coefficients of variation (CV) were calculated across the periods 1985-1993 and 1995-2000 (data gap 1994).

Table 1: Date and productivity phenometrics.

<table>
<thead>
<tr>
<th>Date metric</th>
<th>Productivity metric</th>
</tr>
</thead>
<tbody>
<tr>
<td>a. Start of growing season (SGS)</td>
<td>d. Maximum NDVI value (MAX)</td>
</tr>
<tr>
<td>b. End of growing season (EGS)</td>
<td>e. Small Integral (SI)</td>
</tr>
<tr>
<td>c. Length of growth season</td>
<td>f. Large Integral (LI)</td>
</tr>
<tr>
<td>d. Mid position of growth season</td>
<td>g. Amplitude</td>
</tr>
</tbody>
</table>

Transformed areas such as cultivated land, plantations and built-up areas mapped in National Land Cover 2000 were excluded from further analyses which were only concerned with natural vegetation. A buffer of 1km around the transformed areas was also excluded to avoid adjacency effects.

Analyses were based on the recently revised biome map of South Africa [6]. 400 random points were generated in each of the nine biomes with the exception of forests, where only 200 random points could be placed in the small area. Values (mean, SD, CV) for all the phenometrics in Table 1 were extracted at these 3400 points and used as input in random forest analyses [2].

3. Results and Discussion

South African biomes are distinguished based on vegetation structure and climate characteristics [6] (Fig. 1). Section 3.1 investigates the potential of differentiating biomes based on long-term phenological patterns using decision tree analyses. The inter-annual variability in phenology is discussed in section 3.2.

Fig. 1: Biomes of South Africa after Mucina et al 2006. Transformed shown in white.

3.1 Decision tree analyses of phenometrics per biome

The random forest method produced reliable predictions from the input sample data. Using all the phenometrics the overall prediction had an $R^2$ of 0.75, while $R^2$ values for individual biomes ranged from 0.61 to 0.94 (Fig. 2). Using date-metrics only (Table 1) in random forests reduced the overall explanatory power by 10%.

The importance of different phenometrics in predicting biome class was analysed by calculating the Gini index [2]. This indicated that the mean LI, mean SI, mean MAX and SGS were the most important variables in distinguishing between biomes.
3.2 Mean and Inter-annual variability of phenology of biomes

The inter-annual variability of phenometrics during the 15-year time-series was quantified in terms of date- and productivity related metrics (Table 2).

<table>
<thead>
<tr>
<th>Biome</th>
<th>Start date</th>
<th>Start Date SD (decades)</th>
<th>Middle of Season</th>
<th>Middle of Season SD (decades)</th>
<th>End Date</th>
<th>End Date SD (decades)</th>
<th>Large Integral</th>
<th>Large Integral CV (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grassland</td>
<td>1-10 Oct</td>
<td>2</td>
<td>21-20 Feb</td>
<td>1.8</td>
<td>11-20 Jul</td>
<td>9.4</td>
<td>8.5</td>
<td>12</td>
</tr>
<tr>
<td>Savanna</td>
<td>11-20 Oct</td>
<td>2</td>
<td>11-20 Feb</td>
<td>2.8</td>
<td>1-10 Aug</td>
<td>9.3</td>
<td>6.5</td>
<td>10</td>
</tr>
<tr>
<td>Indian Ocean</td>
<td>1-10 Oct</td>
<td>10</td>
<td>21-20 Feb</td>
<td>9.5</td>
<td>21-31 Jul</td>
<td>9.5</td>
<td>12.5</td>
<td>18</td>
</tr>
<tr>
<td>Coastal Belt</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Forest</td>
<td>11-20 Aug</td>
<td>10</td>
<td>11-20 Jan</td>
<td>1.8</td>
<td>11-20 Jun</td>
<td>8.7</td>
<td>16.5</td>
<td>10</td>
</tr>
<tr>
<td>Albany Thicket</td>
<td>21-30 Sep</td>
<td>10</td>
<td>1-10 Feb</td>
<td>5.2</td>
<td>21-31 Jul</td>
<td>10</td>
<td>7.5</td>
<td>33</td>
</tr>
<tr>
<td>Nama Karoo</td>
<td>11-20 Oct</td>
<td>9.5</td>
<td>1-10 Mar</td>
<td>5</td>
<td>1-10 Aug</td>
<td>9.6</td>
<td>4.6</td>
<td>30</td>
</tr>
<tr>
<td>Succulent Karoo</td>
<td>11-20 May</td>
<td>3.5</td>
<td>21-31 Aug</td>
<td>9.5</td>
<td>21-20 Feb</td>
<td>4.8</td>
<td>5</td>
<td>24</td>
</tr>
<tr>
<td>Fynbos</td>
<td>11-20 May</td>
<td>9.5</td>
<td>1-10 Sep</td>
<td>9.5</td>
<td>1-10 Mar</td>
<td>4.8</td>
<td>6</td>
<td>20</td>
</tr>
<tr>
<td>Desert</td>
<td>11-20 Apr</td>
<td>8</td>
<td>1-10 Sep</td>
<td>9.3</td>
<td>21-31 Mar</td>
<td>5.4</td>
<td>3</td>
<td>36</td>
</tr>
</tbody>
</table>

The 20% threshold provided slightly later dates for SGS and considerable earlier dates for EGS than the 10% threshold. In the Savanna biome, date-related phenometrics calculated with the 10% threshold were either associated with initial green-up from fire-scars in the beginning of the growth season, or the occurrence of fires at the end of the growth season. By using a 20% threshold, fire was eliminated as the dominant driver of date-related phenometrics.

The SD of SGS, EGS and middle of season provided additional support for using a 20% threshold. SD for all date-related phenometrics were considerably lower for the 20% (Table 2b) than for the 10% threshold. By evaluating the spatial distribution of all date-related SD maps, a similar pattern emerged for 20% threshold maps. These patterns are associated with the biome distribution and were stable for standard
deviations of SGS, middle of season and EGS maps.

Fig. 4 maps the mean start of the growing season (SGS) in decades while Fig. 5 maps the standard deviation in start date (SD SGS) expressed in number of days.

The winter rainfall area in the south western part of South Africa can clearly be distinguished by having mean start dates in May. In contrast, the growing season in the summer rainfall region starts in late September and October (Fig. 4).

The Nama Karoo and Desert biomes have the highest variability in SD SGS (Fig. 5). This can be ascribed to highly variable rainfall in these arid regions. In contrast the Grassland, Savanna and Indian Ocean Coastal Belt biomes have the lowest SD for all date-related phenometrics.

An area of exceptional low SD SGS can be seen in the Western Cape close to the Cape Peninsula (Fig. 5). Although this is part of the Fynbos biome, this area is characterised by wheat farming with consistent planting and harvesting dates. This is in contrast with dryland agriculture in the Free State (Grassland biome) with approximately 80 days variability in SGS.

A productivity phenometric (LI) was further analyzed. Fig. 6 shows histograms with mean LI values of the biomes, while LI CV is mapped in Fig. 7. Mean LI was the lowest for the Succulent Karoo, Nama Karoo and Desert biomes, ranging from 0.5-5.0. The Nama Karoo and Desert biomes had LI CV values of 35% and 40% respectively, while the LI CV for Succulent Karoo was much lower at 25% (Fig. 7).
The Forest and Indian Coastal Belt biomes showed the highest mean LI values reaching 15.5 and 12 respectively (Fig. 6) indicating the highest level of seasonal growth of all the biomes. Their LI CV is only 20% and show low inter-annual variability.

Although Albany Thicket showed high productivity with mean LI values at 9, its inter-annual variability is high at 35%, similar to Nama Karoo. Fynbos exhibited lower mean LI values (5) and LI CV (30%) than Albany Thicket.

The Grassland and Savanna biomes had mean LI values of 8 and 6 respectively and their LI CV was low at 15% and 20%.

Fig. 7: Coefficient of variation of Large integral (LI CV).

4. Conclusion

Phenological analysis of satellite data allows improved understanding of the function and dynamics of regional vegetation [1], [5]. This decision tree classification based on mean phenometrics and their inter-annual variability was comparable with biome classification (R² of 0.75) based on vegetation structure and climatic variables [6]. Vegetation zones can thus be defined and mapped based on actual observations of vegetation dynamics. Longer-term satellite data sets can also be used to monitor the changes of the biome characteristics and distribution as a result of future climate change.

SD SGS and CV LI show that five of the nine biomes have inter-annual variability of more than 20%. Inter-annual variability is biome specific and analyses thereof is essential for monitoring long-term changes in phenology.

Analyses of inter-annual variability can thus allow an improved understanding of change monitoring in climate impact studies.

5. References


