

1 **Major trends in the Land Surface Phenology (LSP) of Africa, controlling**
2 **for land cover change**

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17 **for land cover change**

18 **Abstract**

19 Monitoring land surface phenology (LSP) trends is important in understanding how
20 both climatic and non-climatic factors influence vegetation growth and dynamics.
21 Controlling for land cover changes in these analyses has been undertaken only rarely,
22 especially in poorly studied regions like Africa. Using regression models and
23 controlling for land cover changes, this study estimated LSP trends for Africa from the
24 Enhanced Vegetation Index (EVI) derived from 500 m surface reflectance Moderate
25 Resolution Imaging Spectroradiometer (MODIS) (MOD09A1), for the period of 2001
26 to 2015. Overall End of Season (EOS) showed slightly more pixels with significant
27 trends (12.9% of pixels) than Start of Season (SOS) (11.56% of pixels) and Length of
28 Season (LOS) (5.72% of pixels), leading generally to more “longer season” LOS
29 trends. Importantly, LSP trends that were not affected by land cover changes were
30 distinguished from those that were influenced by land cover changes such as to map
31 LSP changes that have occurred within stable land cover classes and which might,
32 therefore, be reasonably associated with climate changes through time. As expected,
33 greater slope magnitudes were observed more frequently for pixels with land cover
34 changes compared to those without, indicating the importance of controlling for land
35 cover. Consequently, we suggest that future analyses of LSP trends should control for
36 land cover changes such as to isolate LSP trends that are solely climate driven and/or
37 those influenced by other anthropogenic activities or a combination of both.

38

39 **Keywords:** Phenology, Time-series analysis, MODIS, Africa, Vegetation, climate
40 change.

41

42 **1. Introduction**

43 Remote sensing techniques for mapping land surface phenology (LSP), defined “as the
44 seasonal pattern of variation in vegetated land surfaces observed from remote sensing” (M.
45 H. Friedl et al. 2006), provide the capability for long-term observation across large areas,
46 especially those where ground data are lacking (X. Zhang, Tan, and Yu 2014; Julien and
47 Sobrino 2009; X. Zhang, Friedl, and Schaaf 2006; Jeong et al. 2011). Remote sensing has
48 been used to study the response of LSP to climatic and non-climatic factors and has, thus,
49 contributed to increased understanding of climate change impacts on the terrestrial
50 ecosystem. Several authors have used remote sensing to estimate inter-annual trends in LSP
51 (usually related to the timing of specific events). Myneni et al. (1997) was one of the first
52 studies to report a 12 days increase in the length of growing season (LOS) for the Northern
53 Hemisphere during the period 1982–1991 using satellite sensor data. Several other studies
54 have been carried out since then, mostly focusing on LSP trends in the Northern Hemisphere
55 (e. g., Zhou et al., 2001; de Beurs & Henebry, 2005; Delbart et al., 2005; Piao et al., 2007;
56 Julien & Sobrino, 2009; Jeong et al., 2011; Zhu et al., 2012, 2014; Ivits et al., 2012; Zhang et
57 al., 2014; Yang et al., 2015; Liu et al., 2016) with a limited number of studies covering the
58 Southern Hemisphere (Heumann et al. 2007; A Vrieling, De Beurs, and Brown 2008; Anton
59 Vrieling, De Leeuw, and Said 2013; Verbesselt, Hyndman, Newnham, et al. 2010;
60 Verbesselt, Hyndman, Zeileis, et al. 2010; Anton Vrieling, de Beurs, and Brown 2011;
61 Garonna, De Jong, and Schaepman 2016).

62 The above studies estimate LSP trends over a particular inter-annual period and
63 evaluate the possible drivers for such trends, but do not consider land cover changes as a
64 confounding driver that can significantly influence the observable changes in LSP. This lack
65 of research into the influence of land cover changes on LSP trends has been highlighted
66 previously (Reed 2007; Tang et al. 2015; X. Zhang, Tan, and Yu 2014). Additionally, only a

67 limited number of studies have recognised that other non-climatic factors can significantly
68 influence trends in LSP. For example, Krishnaswamy *et al.* (2014) suggested that other
69 factors besides temperature and precipitation were responsible for browning and greening
70 trends in tropical mountain regions; Olsson *et al.* (2005) suggested that changes in vegetation
71 type were responsible for an increase in greening in the Sahel as rainfall only partially
72 explained increasing vegetation cover; and Verbesselt *et al.* (2010a,b), Ivits *et al.* (2012) and
73 Begue *et al.* (2014) identified land management practices as a major factor influencing
74 phenological changes in South Eastern Australia, Europe and Mali, respectively.

75 Because of the potentially confounding influence of land cover changes, it would be
76 preferable to control for these changes, for example, by ensuring that only homogeneous
77 pixels (i.e., those that have a constant land cover throughout the entire time-series) are used to
78 characterise inter-annual trends for comparison with changing climate drivers. This would
79 allow separation of those LSP trends that are solely climate-driven from those that are
80 influenced by non-climatic factors. To the best of our knowledge, Jeganathan *et al.* (2014)
81 may be the only study to have deliberately controlled for land cover changes while analysing
82 inter-annual and seasonal vegetation dynamics.

83 In addition to the above gaps in research methodology, substantial gaps exist with
84 respect to the study of the vegetation phenology of Africa (Adole, Dash, and Atkinson 2016;
85 IPCC 2014). While it has been shown that other factors besides climate are responsible for
86 some variation in phenology and increases in greenness in different regions of the African
87 continent (Herrmann, Anyamba, and Tucker 2005; Martínez *et al.* 2011; Polansky and
88 Boesch 2013), studies investigating this phenomenon across the whole of Africa are limited.

89 This paper represents the first analysis of inter-annual LSP trends in Africa that
90 controls for land cover changes, using MODIS data. The aim was to separate out the LSP
91 trends that are not influenced by (mainly) anthropological disturbances such as deforestation,

92 agricultural land conversion, land management, land degradation, land transformation and
93 urbanization, from trends that may have been influenced by these disturbances.

94

95 **2. Data and methodology**

96 Moderate spatial and temporal resolution satellite sensor data were used for the analysis,
97 specifically the MODIS/Terra Surface Reflectance 8-Day L3 Global 500 m SIN Grid V005
98 data (MOD09A1), and MODIS Land Cover Type Yearly L3 Global 500 m SIN Grid V005
99 data (MCD12Q1). 16 years (18 Feb 2000 – 29 Aug 2015) of MOD09A1 tiles and 13 years
100 (2001 – 2013) of MCD12Q1 tiles covering the entire African continent were downloaded
101 from NASA’s LP DAAC (<https://lpdaac.usgs.gov/>).

102 **2.1. LSP estimation**

103 The Enhanced Vegetation Index (EVI), was selected for use in this research (Huete et al.
104 2002; Reed, Schwartz, and Xiao 2009) and calculated from the MOD09A1 data after residual
105 atmospheric and sensor effects were filtered out in a Quality Assurance (QA) assessment
106 procedure. (see “MODIS Land Products Quality Assurance Tutorial,” 2016 for details of the
107 QA procedure).

108 A time-series cycle of two years EVI stacked data was used to estimate LSP in order to
109 account for non-uniform growing seasons across Africa. The yearly values of Start of Season
110 (SOS), End of Season (EOS) and Length of Season (LOS) in each image pixel for the period
111 of 2001 to 2015 were estimated using the methodology described in (Dash, Jeganathan, and
112 Atkinson 2010). As explained in Dash et al., (2010) the Discrete Fourier Transform (DFT)
113 was applied to smoothen the EVI time-series and to account for the bimodal seasonality and
114 double cropping agricultural systems found in some parts of Africa, the first six harmonics as
115 used. However, only the first season results were considered for this analysis. After

116 smoothing, the LSP parameters used in this study were derived using the inflection point
117 method. This method overcomes the uncertainties of using a pre-defined threshold which
118 may lead to later onset and earlier end of vegetation growing season. An algorithm described
119 in Dash et al., (2010) was used for this study. Beginning from the maximum peak, this
120 algorithm iteratively searches for valley points (change in derivative value). Value points
121 which shows a change in derivative value from positive to negative at the beginning of the
122 growing cycle is the Start of Season (SOS), while a change in derivative value from negative
123 to positive at the decaying end of the phenology cycle is the End of Season (EOS). To ensure
124 the appropriate valley points are identified especially in irregular time-series two major
125 conditions were incorporated into this algorithm: (1) at least four consecutive rising EVI
126 values must be identified before key LSP parameters are defined, and (2) the difference
127 between peak and the valley points must be greater than one fifth of the maximum EVI value.
128 (Schematic diagram of methodology is shown in Figure 1).

129 ***2.2. Land cover change detection and trend analysis***

130 From the MCD12Q1 global land cover data, the 17-class International Geosphere Biosphere
131 Programme (IGBP) global vegetation classification scheme, was selected for analysis (M. A.
132 Friedl et al. 2010; Scean and Estes 2001). This product was chosen because of its relatively
133 fine spatial resolution, high temporal frequency and highest overall accuracy when compared
134 to other land cover data (Bai 2010; Bontemps et al. 2012; Giri et al. 2013). Also, it has been
135 shown to be consistent with other land cover classification outputs (He, Lee, and Warner
136 2017). A reclassification was carried out to group land cover types with similar phenological
137 behaviour into broad categories. Details of this reclassification into broad classes are
138 provided in the
139 Table 1 and Figure 2. Other classes comprising water, permanent wetlands, barren or sparsely

140 vegetated and urban/built-up areas were excluded from the analysis.

141

142 **Table 1:** Reclassification of land cover type into broad categories based on the International
143 Geosphere Biosphere Programme (IGBP) global vegetation classification scheme.

Merged land cover type	Initial land cover types
Evergreen forest	Evergreen needleleaf forest Evergreen broadleaf forest
Deciduous forest	Deciduous needleleaf forest Deciduous broadleaf forest
Shrublands	Closed shrublands Open shrublands
Woody savanna/savanna	Woody savannas Savannas
Grasslands	Grasslands
Croplands	Croplands
Croplands/natural vegetation mosaic	Croplands/natural vegetation mosaic

144

145 To estimate the inter-annual LSP trends, two main categories of pixel were analysed
146 based on the nature of their time-series: (1) only pixels with the same land cover in all years
147 of the time-series of 13 years were used to estimate the temporal trends, and these were
148 separable based on the type of land cover and (2) pixels which changed from one land cover
149 class to another were also analysed, but this time to determine if land cover changes
150 significantly influenced the estimated LSP parameters. The latter category was further
151 characterised into sub-groups based on the number of times the land cover had changed in the
152 entire time-series. Only changes in vegetative land cover were considered. These were
153 classified in the following way: 1) changes between two classes only were labelled as “*one*
154 *change*”, for example, a change from grasslands to croplands; 2) changes between three
155 classes were labelled as “*two changes*”, for example a change from woody savanna to
156 croplands and then to grasslands or back to savanna; 3) and those pixels that changed land
157 cover types more than three times were labelled as “*> two changes*”, (Woody

158 savanna/savanna - cropland/natural vegetation - grasslands - croplands) (See Figure 2 for
159 spatial patterns of land cover types and the different classes of pixels used in this study).

160 The Spearman's non-parametric rank correlation coefficient was used to characterise
161 the magnitude and direction of temporal trends in day of year with significance testing (*F*-
162 test at the 95% confidence level). This test was used because of its robustness in relation to
163 identifying trends in non-Gaussian distributed data (A Vrieling, De Beurs, and Brown 2008;
164 Yue, Pilon, and Cavadias 2002). Simple linear regression was then fitted to estimate the
165 magnitude of the trends in number of days per year.

166

167 **Table 2:** Number and proportion of pixels showing significant positive (Sig. pos.) and significant negative (Sig. neg.) trends (p -value < 0.05) in each land
 168 cover change class. The “no change” class is of greatest interest when analysing trends in LSP because it controls for land cover change (i.e., there was no
 169 land cover change in this group).

Land cover change category	Proportion of pixels in each category	SOS				EOS				LOS			
		Number of pixels		Proportion of pixels		Number of pixels		Proportion of pixels		Number of pixels		Proportion of pixels	
		Sig. pos.	Sig. neg.	Sig. pos.	Sig. neg.	Sig. pos.	Sig. neg.	Sig. pos.	Sig. neg.	Sig. pos.	Sig. neg.	Sig. pos.	Sig. neg.
No change	75%	676823	286722	2.78%	1.18%	687864	387520	2.83%	1.59%	264082	155223	1.09%	0.64%
One change	18%	854507	217825	3.52%	0.90%	838527	352015	3.45%	1.45%	307371	160246	1.26%	0.66%
Two changes	3%	467500	110228	1.92%	0.45%	474940	162754	1.95%	0.67%	241246	89551	0.99%	0.37%
> Two changes	3%	144460	52850	0.59%	0.22%	195508	54218	0.80%	0.22%	144022	28400	0.59%	0.12%
Total	100%	2143290	667625	8.82%	2.75%	2196839	956507	9.04%	3.93%	956721	433420	3.94%	1.78%
Overall sig. (+ & -)		2810915		11.56%		3153346		12.97%		1390141		5.72%	

170

171 3. Results

172 3.1. LSP trend analysis

173 The spatial patterns of SOS for 2001 and 2015 are shown in Figure 3. No clear seasonality
174 was observed in most forested areas in Africa. The LSP trends found to be significant (95%
175 confidence level) were mapped for all LSP parameters, and these mapped trends for SOS are
176 shown in Figure 4. A summary of the significant statistical trends (p -value < 0.05) for all LSP
177 parameters by land cover change group are displayed in Table 2. Overall, less than 13% of
178 pixels in each LSP parameter showed significant trends (see Table 2) and an estimated 70% of
179 these pixels had trends that were significantly positive (i.e., the LSP event date becoming
180 later). For example, of the 12.97% (3,153,346) significant pixels in EOS, 9.04% (i.e., 70% of
181 the total number of significant pixels) were significantly positive.

182 Table 3 also shows the different combinations of LSP trends in this study. An
183 estimated 9% of the entire continent had delayed SOS dates, with 0.75% resulting in “*delayed*
184 *longer season*” (i.e. delayed SOS and increased LOS), 1.36% resulting in “*delayed shorter*
185 *season*” (i.e. delayed SOS and reduced LOS), and 6.62% with no significant LOS trend.
186 Similarly, of the estimated 3% advancing SOS dates, 1.54% led to “*earlier longer season*”
187 (i.e. advanced SOS and increased LOS), 0.05% resulted in “*earlier shorter season*” (i.e.
188 advanced SOS and reduced LOS), and 1.19% resulted in no significant LOS trend (see Table
189 3). These observations suggest that despite significant shifts in SOS and/or EOS dates, there
190 was less change in LOS, indicating that both SOS and EOS are becoming later or earlier in
191 synchrony, as shown in Table 3.

192 There were significant EOS trends which led to apparent changes in LOS. For
193 example 0.38% of earlier EOS led to “*shorter season*” and 1.65% of delayed EOS resulted in
194 “*longer season*”. In general, significant increases in LOS were associated mostly with

195 delayed EOS (2.4%). That is, over 60% of the significant LOS positive trends was influenced
 196 by delayed EOS dates. These were mostly observed in western and eastern Africa. On the
 197 other hand, a shorter LOS was mostly due to a delayed SOS and earlier EOS (see Table 3).
 198 This shorter LOS was seen in similar geographical sub-regions as observed longer LOS.
 199 However, observations were confined to certain regions like northern Nigeria, western
 200 Angola and the savannas of central Africa.

201 **Table 3:** Observed combinations of changes in SOS and EOS (leading to changes in LOS),
 202 showing the percentage of pixels in each combination.

Change in SOS	Change in EOS	Change in LOS	Proportion of area (%)
Earlier	Earlier	Longer season	1.45
Earlier	Earlier	Shorter season	0.05
Earlier	Earlier	-	1.19
Earlier	Delayed	Longer season	0.01
Earlier	-	Longer season	0.08
Earlier	-	Longer season	0.38
Delayed	Delayed	Longer season	0.75
Delayed	Delayed	Shorter season	0.01
Delayed	Delayed	-	6.62
Delayed	Earlier	Shorter season	0.85
Delayed	-	Shorter season	0.50
Delayed	-	Shorter season	1.65

203

204

205 **3.2. LSP trends based on land cover type**

206 The trends in “no change” pixels were identified mainly in woody savanna/savanna and
 207 croplands/natural vegetation mosaic. More specifically, 72% of these significant pixels were
 208 found in woody savanna/savanna, 16% in croplands/natural vegetation mosaic, 7% in
 209 croplands, 4% in grasslands and 1% in shrublands.

210 Corresponding to the general pattern of SOS becoming later (i.e., more significant
 211 positive trends compared to negative trends), woody savanna/savanna had more pixels with

212 trend towards a delayed SOS with a slope of between 2 to 2.4 days year⁻¹ across all Africa
213 (spatial pattern of slope magnitudes and frequency distributions are detailed in Figure 5 and
214 Figure 6). A very small proportion of woody savanna/savanna pixels of about 0.4%,
215 distributed in central and eastern Africa, had a trend towards an earlier SOS with a slope of -3
216 to -4 days year⁻¹. The EOS and LOS trends for woody savanna/savanna were similar to the
217 SOS trends, having more significant positive pixels. However, for woody savanna/savanna
218 the positive LOS trends observed were mostly a result of earlier SOS dates leading to an
219 “*earlier and longer season*”. Croplands/natural vegetation mosaic on the other hand had
220 more “*longer season*” LOS trends. This was due to a delayed EOS only, particularly in West
221 African countries like Mali and Senegal. Although there were delayed SOS trends of
222 approximately 2.3 days year⁻¹, similar rates of change in EOS were observed.

223

224 **3.3. LSP trends based on land cover change**

225 Table 2 shows the number and proportion of land cover change events and their
226 corresponding significant trends. The significant SOS trends in the “*one change*” category
227 with 18% of the total number of pixels had 4.41% of the total significant trend, while the “*no*
228 *change*” category with 75% of the total number of pixels had 3.96% of the total significant
229 trend. In addition, linear regression of a 13 years profile of significant pixels in both the “*one*
230 *change*” and “*two changes*” categories showed significant shifts in LSP parameters. This can
231 be seen in Figure 7, which shows the time-series for three pixels, one in the (a) “*one change*”
232 category, (b) “*two changes*” category, and (c) “*>two changes*” category. In the three cases,
233 the SOS dates shifted from February to June as the land cover changed from woody
234 savanna/savanna to croplands and/or grasslands. The results show that SOS dates were
235 delayed with an average of 9.5 days year⁻¹ in both categories of change. In the same way,

236 EOS dates shifted from December to February with an average increase of 5 days year⁻¹.
237 Inevitably, LOS shortened by an average rate of 4 days year⁻¹ for both categories of change.
238 However, there was no significant difference between the rate of change in the different land
239 cover change categories.

240

241 **4. Discussion**

242 Several studies have suggested that significant changes have occurred in Africa's vegetation
243 in recent decades (Zhou et al. 2014; Eklundh 2003; Herrmann, Anyamba, and Tucker 2005;
244 Martínez et al. 2011). It has also been implied that changes in land cover can equally drive
245 changes in the rate of green-up observed from remote sensing methods (Hoscilo et al. 2015),
246 and the findings of this research support this view. It is, therefore, accepted that changes in
247 land cover can significantly influence observed LSP trends and, consequently, any inferences
248 made about the impact of climate changes on vegetation phenology. Analysis of the set of
249 LSP trends across all of Africa revealed that of the 11.56% (SOS), 12.97% (EOS) and 5.72%
250 (LOS) of pixels that were significantly trending, an estimated 65 – 70% belong to “*changed*”
251 land cover change categories (i.e., pixels that have changed land cover type in the time period
252 2001 to 2013). Although, climatic factors may have contributed to these LSP trends, results
253 show that changes in land cover can also influence LSP trends. This is because phenological
254 response to environmental cues varies based on the type of land cover (Ryan et al. 2017;
255 Guan et al. 2014). Additionally, pixels with a greater slope magnitude were observed more
256 frequently in the “*changed*” pixels category compared to the “*no change*” category (see
257 Figure 7).

258 Previous studies are generally in agreement with our findings (Heumann et al. 2007;
259 Anton Vrieling, De Leeuw, and Said 2013) with respect to the overall pattern of LSP trends
260 and the observation of significant positive LOS being associated mostly with delayed EOS.

261 This was seen irrespective of the datasets and study periods of the different studies, therefore,
262 indicating the influence of other common drivers of LSP. Some interesting differences with
263 previous studies were observed. While Heumann *et al.* (2007) found significant positive
264 trends for LOS across the whole of western Africa, the present results revealed “*delayed*
265 *shorter seasons*” in LOS in northern Nigeria (i.e. significant negative trends in LOS were
266 associated mainly with significant positive trends in SOS). Similarly, the magnitude of the
267 rate of change in days year⁻¹ in this analysis was greater than those from Julien and Sobrino
268 (2009); Vrieling *et al.* (2013) and Zhang *et al.* (2014). These differences could be attributed
269 to the types of dataset and the duration of the study periods used in these studies (X. Zhang,
270 Tan, and Yu 2014; de Beurs and Henebry 2005). While these previous studies used the 8 km
271 AVHRR NDVI datasets with longer duration ranging from 1981 to 2011, none exceeding
272 2011, the present study used the EVI derived from the MODIS/Terra Surface Reflectance 8-
273 Day L3 Global 500 m product. This much finer spatial resolution is expected to reveal greater
274 variation in trends due to the well-known spatial convolution associated with the
275 measurement process. Also, the present study period (2001 to 2015), while not as long as for
276 some previous studies, accounted for more recent seasonal vegetation events across the
277 continent. However, there are some issues associated with these data. The degradation of the
278 blue band (Band 3, 470 nm) in these data has been recorded as having a negative influence on
279 temporal trend analysis previously (Wang *et al.* 2012). In addition, sensor degradation have
280 been shown to influence magnitude of vegetation indices derived from this data, but not
281 seasonality (Y. Zhang *et al.* 2017). Furthermore, the accuracy of the land cover data which is
282 not very high may have influenced the areas of changes observed in the different change
283 categories. Additionally, as a result of the availability of land cover data not exceeding 2013,
284 an assumption that no significant changes in land cover occurred between 2013 and 2015 was
285 made (while noting that Terra MODIS 500 m data are the earliest with the longest time-

286 series; 2000-present). Another assumption in this research was the consistency of the
287 unchanged land cover pixels of cropland/natural vegetation mosaic. **Changes in the**
288 **percentage composition of this land cover type** and inter-annual crop rotation to a different
289 crop type can significantly influence LSP timings. Also, the analysis of LSP trends to
290 determine the magnitude of change based on land cover changes was restricted to the time
291 period 2001 to 2013.

292

293 **5. Conclusion**

294 Trends in phenology are increasingly being used to infer the effects of climate changes on
295 vegetation development and growth patterns. Understanding the drivers of vegetation
296 phenological trends is, therefore, paramount in vegetation-climate studies. However, most
297 studies analyse the relation of phenology with these drivers without due consideration for
298 confounding land cover changes which may also significantly impact LSP. Considering the
299 magnitude of the land cover changes taking place across the African continent, this research
300 controlled for land cover change such as to analyse inter-annual time-series of LSP
301 parameters independent of these effects. For the purposes of comparison, we also analysed
302 LSP trends for pixels for which the land cover changed.

303 When controlling for land cover change, significant trends were observed in all
304 groups of pixels, and an estimated 70% of these trends in both SOS and EOS were
305 significantly positive, that is, mostly delayed SOS and EOS dates. These occurred more in the
306 Sudano-Sahelian and Sudanian regions of Africa. Importantly, the land cover changes
307 significantly affected the LSP trends; larger trends were observed in the “changed” land
308 cover groups. If these land cover changes were not controlled for in the LSP trend analysis,
309 some of the reported trends would have been erroneously significantly larger. Based on these

310 results, we suggest that future analyses of LSP trends should control for land cover changes
311 such as to isolate those LSP trends that are solely climate-driven and/or those influenced by
312 other anthropogenic activities or a combination of both.

313

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