

1 **Title**

2 Large scale pre-rain vegetation green up across Africa

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4 **Running head**

5 Pre-rain vegetation green up

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25 **Abstract**

26 Information on the response of vegetation to different environmental drivers, including
27 rainfall, forms a critical input to ecosystem models. Currently, such models are run based on
28 parameters that, in some cases, are either assumed or lack supporting evidence (e.g., that
29 vegetation growth across Africa is rainfall-driven). A limited number of studies have reported
30 that the onset of rain across Africa does not fully explain the onset of vegetation growth, for
31 example, drawing on the observation of pre-rain flush effects in some parts of Africa. The
32 spatial extent of this pre-rain green-up effect, however, remains unknown, leaving a large gap
33 in our understanding that may bias ecosystem modelling. This paper provides the most
34 comprehensive spatial assessment to-date of the magnitude and frequency of the different
35 patterns of phenology response to rainfall across Africa, and for different vegetation types.
36 To define the relations between phenology and rainfall, we investigated the spatial variation
37 in the difference, in number of days, between the start of rainy season (SRS) and start of
38 vegetation growing season (SOS); and between the end of rainy season (ERS) and end of
39 vegetation growing season (EOS). We reveal a much more extensive spread of pre-rain
40 green-up over Africa than previously reported, with pre-rain green-up being the norm rather
41 than the exception. We also show the relative sparsity of post-rain green-up, confined largely
42 to the Sudano-Sahel region. While the pre-rain green-up phenomenon is well documented, its
43 large spatial extent was not anticipated. Our results, thus, contrast with the widely held view
44 that rainfall drives the onset and end of the vegetation growing season across Africa. Our
45 findings point to a much more nuanced role of rainfall in Africa's vegetation growth cycle
46 than previously thought, specifically as one of a set of several drivers, with important
47 implications for ecosystem modelling.

48

49 **Introduction**

50 The African continent contains the world's largest area of savanna and around 17% of the
51 world's tropical forests. Savannas alone account for 30% of the primary production from
52 global terrestrial vegetation, underlining the importance of the African vegetation (Grace *et*
53 *al.*, 2006). Indeed, African vegetation contributes 38% of the global climate-carbon cycle
54 feedback (Friedlingstein *et al.*, 2010). In spite of this, African vegetation is relatively under-
55 studied (Adole *et al.*, 2016), and the few existing vegetation models are associated with
56 significant uncertainties (Scheiter & Higgins, 2009; Hemming *et al.*, 2013). Another
57 fundamental concern is the vulnerability of African vegetation to climate change, further
58 worsened by interactions between changes in climatic drivers and anthropogenic land use,
59 which puts at risk both the condition and the amount of overall vegetation cover (IPCC,
60 2014). Apart from their role in global carbon sequestration, the savannas and forests of Africa
61 support a large number of ecosystem services, which are also vulnerable to climatic and
62 anthropogenic changes; for example, the perceived threat to livestock farming and production
63 due to expanding woodlands (Skowno *et al.*, 2016), and reduced crop productivity caused by
64 increasing temperatures and changes in precipitation (Brown & Funk, 2008). These
65 ecosystem services, in addition to their functions, are influenced heavily by the condition of
66 vegetation and its seasonality (Brottem *et al.*, 2014), which could lead to multiple feedbacks
67 into the climate system (Keenan *et al.*, 2014; Buitenwerf *et al.*, 2015; Wu *et al.*, 2016). In the
68 context of anthropogenic, agro-climatic and climate changes, which may affect future
69 ecosystem services, greater understanding of vegetation dynamics across Africa and its
70 drivers is crucial.

71

72 In recent years, the importance of phenology has increased as a result of a wide range of
73 empirical-, modelling- and meta-analysis-based evidence, suggesting that long-term changes

74 in key phenological parameters such as the start of season and end of season are key
75 indicators of biological impact resulting from climate change (Cleland *et al.*, 2007;
76 Richardson *et al.*, 2013). Moreover, the role of several climatic factors has been identified in
77 the seasonal timing and seasonal productivity of vegetation cycles (Ma *et al.*, 2015; Shen *et*
78 *al.*, 2016). Specifically, in arid and semi-arid environments water availability is deemed to be
79 the primary factor controlling vegetation seasonality and growth (Zhang *et al.*, 2005;
80 Chidumayo, 2015). Of particular interest is the close linkage between precipitation and
81 vegetation growth. Studies have suggested that rainfall control of vegetation greening trends
82 (Hickler *et al.*, 2005; Martínez *et al.*, 2011) was associated with the 1980s recovery of
83 vegetation growth from the Sahelian droughts (Olsson *et al.*, 2005). Likewise, parameters
84 estimated from seasonal growth patterns of vegetated land surfaces have been shown to be
85 correlated with derivatives of rainfall data (Zhang *et al.*, 2005; Guan *et al.*, 2014; Verger *et*
86 *al.*, 2016). The start of vegetation growing season (SOS) and start of raining season (SRS)
87 have been shown to be highly correlated by several researchers (Zhang *et al.*, 2005; Guan *et*
88 *al.*, 2014). Despite these general findings, the dynamics of vegetation growth are not identical
89 in areas with similar rainfall regimes, suggesting that rainfall alone does not satisfactorily
90 explain vegetation growth patterns. For example, non-climatic greening was observed in
91 some parts of sub-Saharan Africa (Hoscilo *et al.*, 2014), and no significant relationship was
92 found between SOS and SRS in the northern Sahara desert (Yan *et al.*, 2016).

93

94 “*Pre-rain green-up*” is an interesting phenomenon whereby vegetation growth starts at the
95 end of the dry season, just before the start of the rainy season (Ryan *et al.*, 2017). This
96 phenomenon has been observed as far back as the 1940s in some woody species at the field
97 scale (Miller, 1949). With the emergence of remote sensing of land surface phenology (LSP)
98 (defined as “*the seasonal pattern of variation in vegetated land surfaces observed from*

99 *remote sensing*” (Friedl *et al.*, 2006)), pre-rain green-up has now been observed across larger
100 areas, but mostly in African woodlands (Guan *et al.*, 2014; Ryan *et al.*, 2017; Yan *et al.*,
101 2017). However, the number of studies is limited and does not describe the nature and extent
102 of this relationship at the continental scale. Similarly, only a few studies undertaken at the
103 regional scale have attempted to investigate the lag between the end of rainy season (ERS)
104 and the end of vegetation growing season (EOS) in Africa (Zhang *et al.*, 2005; Yan *et al.*,
105 2017). Therefore, detailed quantification of the magnitude and frequency of this pattern
106 across different vegetation types at the continental scale is currently needed. Consequently,
107 this research seeks to answer the following questions:

- 108 (1) what is the magnitude and spatial distribution of the time lags between vegetation
109 phenophases and rainfall parameters across the different vegetation types in Africa?
- 110 (2) what is the magnitude of the association between vegetation phenological and
111 rainfall parameters across the different vegetation types in Africa?

112

113 Understanding the relationships between LSP and rainfall parameters is critical in developing
114 a robust phenological model and LSP representation in terrestrial ecosystem models.
115 Currently, most global land-atmosphere models have shown varying projections of vegetation
116 response to climate change, associated with large uncertainties in the terrestrial carbon cycle
117 (Shao *et al.*, 2013). These uncertainties are known to arise from inaccurate estimation of
118 seasonal productivity patterns (Restrepo-Coupe *et al.*, 2017), incorrect assumptions in
119 biosphere–atmosphere process models driven by vegetation growth (Whitley *et al.*, 2016),
120 and poor understanding of functional responses of vegetation phenology to climate change
121 (Richardson *et al.*, 2012). Moreover, current climate change models predict uneven rainfall
122 distribution both in terms of timing and amount across the continent; some areas are expected
123 to receive excess rainfall, whereas other regions are expected to receive less (Res *et al.*, 2001;

124 Niang *et al.*, 2014). This in turn, will affect the vegetation phenology and the resulting
125 vegetation-atmosphere feedbacks such as albedo, water, energy and gas fluxes across the
126 region (Wu *et al.*, 2016).

127

128 We used satellite remote sensing and meteorological data to quantify the lag in number of
129 days between SRS and SOS, and ERS and EOS. We further examined the relationships
130 between a range of LSP and rainfall parameters, including the length of growing season
131 (LOS) with length of raining season (LRS), and time of maximum vegetation growth
132 (VItmax) with time of maximum rain (Rtmax), across all of Africa. The productivity-based
133 relationship between Integrated EVI (IntEVI) and cumulative annual rainfall (Rcum) was
134 also explored.

135

136 By investigating the above relationships, we provide the most comprehensive and detailed
137 view of the response of vegetation phenological variables to rainfall across Africa, by
138 vegetation type. This greater insight into the mechanisms underlying African vegetation
139 dynamics provides useful information necessary to support and increase the accuracy of
140 future terrestrial biosphere models (TBMs) and global ecosystem models.

141

142 **Materials and methods**

143 **MODIS data and pre-processing**

144 This study used the Moderate Resolution Imaging Spectroradiometer (MODIS) products
145 (Justice *et al.*, 1998) for LSP estimation and land cover classification. These products were
146 downloaded from NASA's LP DAAC (<https://lpdaac.usgs.gov/>).

147 The MODIS/Terra Surface Reflectance 8-Day L3 Global 500 m data (MOD09A1) from
148 February 2000 to June 2016 were selected for LSP estimation. Apart from the delivery of
149 relatively fine spatial detail, the 500 m spatial resolution was selected because it has the
150 spectral bands required to derive the Enhanced Vegetation Index (EVI). These bands are
151 currently absent in finer spatial resolution MODIS data such as the MOD09Q1 and
152 MOD13Q1. The EVI was developed with the inclusion of the blue reflectance band (B) to
153 correct for atmospheric scattering effects and soil background influences (Huete *et al.*, 2011).

154 It is derived according to the following equation:

155

156
$$EVI = G * \frac{(NIR - Red)}{(L + NIR + C1 * Red - C2 * Blue)}$$

157

158 where the coefficients are L=1 (canopy background adjustment factor); C1= 6 and C2 = 7.5
159 (aerosol correction factors); and G = 2.5 (gain factor) (Huete *et al.*, 2011).

160

161 The EVI was also designed to increase sensitivity in large vegetative biomass regions,
162 consequently overcoming the problems associated with vegetation indices like the normalized
163 difference vegetation index (NDVI) (Huete *et al.*, 2002). Prior to deriving the EVI, residual
164 atmospheric and sensor effects were filtered out and only pixels of the highest quality, which
165 had all possible corrections of MODIS Land Quality Assessment (MODLAND QA), were
166 retained. This was done using the quality assessment procedure as detailed in

167 https://lpdaac.usgs.gov/sites/default/files/public/modis/docs/MODIS_LP_QA_Tutorial-3.pdf

168 ensuring that only high quality pixels were used for this analysis. This involved computing 36
169 different combinations of MODIS land surface reflectance quality parameters from the 32-bit
170 Science Data Set (SDS) Quality Assurance (QA) layer (the 500 m Reflectance Band Quality).
171 All measurements not within these 36 parameters were filtered out, ensuring that only pixels
172 that were atmospherically and adjacently corrected, and of the highest quality on all bands
173 were retained. To produce a time-series of EVI appropriate to analysing the complex growing
174 seasons in Africa, a “cycle” of approximately two years (i.e., 86 “stacked” layers) of EVI
175 data (i.e., the end of July of year 1 to June of year 3) was used. This long cycle was produced
176 to capture yearly estimates of seasonal phenological parameters across Africa, because start
177 of growing season in the northern latitudes commences much earlier in the year than in the
178 southern latitudes.

179

180 To define the vegetation types in Africa, we used the 17-class International Geosphere
181 Biosphere Programme (IGBP) global vegetation classification scheme (Friedl *et al.*, 2002,
182 2010) from the MODIS/Terra Land Cover Type Yearly L3 Global 500 m data (MCD12Q1).
183 We carried out a reclassification, merging similar classes of plant functional types in the
184 IGBP scheme that differ based on extent of canopy cover only, but have similar phenological
185 behaviour. Table 1 shows the 17 classes and the reclassification applied. Croplands and
186 cropland/natural vegetation mosaic were not merged together because cropland/natural
187 vegetation mosaic is a mixture of croplands, forests, shrublands, and grasslands, which may
188 not be sufficiently well defined for use in modelling the pattern of cropland responses to
189 seasonal rainfall. Homogeneous pixels over the 13 years record of the MCD12Q1 were
190 extracted and used to stratify the land cover into their different vegetation types. Five major
191 classes were derived: (1) Croplands, (2) Forest (Deciduous and evergreen forest), (3)

192 Grasslands, (4) Shrublands (Closed and open shrublands), and (5) Woodlands (Woody
193 savannas and savannas) (see Table 1 and Figure 1). However, due to the limited spatial extent
194 of deciduous forest, and persistent clouds in forested areas, further investigation of the forest
195 category was not considered as estimates of LSP may not be reliable.

196

197 **CHIRPS data**

198 This study used the 0.05° gridded rainfall dataset from the Climate Hazards Group InfraRed
199 Precipitation with Station data (CHIRPS). This dataset was generated by combining satellite
200 sensor and station data using smart interpolation techniques, and has been shown to have less
201 bias in examining wet seasons than most other products, especially in data-sparse regions in
202 Africa (Funk *et al.*, 2015). It has also been shown to be more precise in estimating the entire
203 seasonal cycle of rainfall because it is spatially more detailed and corresponds more closely
204 to ground data (Toté *et al.*, 2015). As with the MODIS data, 16 years of daily rainfall data
205 from 2000 to 2016 were downloaded from CHIRPS (<http://chg.geog.ucsb.edu/data/chirps/>).

206

207 **LSP estimation**

208 Several methods have been used to estimate LSP from time-series of vegetation indices
209 (VI)(Atkinson *et al.*, 2012). These methods usually involve a stepwise approach beginning
210 with the removal of “bad” pixels in the time-series, interpolation of the missing values,
211 smoothing of the complete time-series, and estimation of the LSP parameters. In this
212 research, we used the algorithm from Dash *et al.* (2010) and Pastor-Guzman *et al.* (2018) to
213 remove “bad” pixels and interpolate missing values in the EVI time-series. Then the Discrete
214 Fourier Transform (DFT) (Atkinson *et al.*, 2012) was employed to smooth the data
215 temporally.

216

217 The inflection point-based method, which considers points where maximum rate of change
218 occurs in the time-series, was used to estimate the LSP parameters. This method, which has
219 been used extensively, captures explicitly the start and end of growing seasons as there are no
220 pre-defined thresholds (Dash *et al.*, 2010; Qader *et al.*, 2015). A schematic diagram of the
221 methodology is shown in Figure 2. Five LSP parameters (Start of growing season (SOS), End
222 of growing season (EOS), Length of growing season (LOS), time of maximum EVI
223 (VItmax), and Integrated EVI (IntEVI)) were estimated for each cycle (Figure 3). This led to
224 yearly estimates of each LSP parameter for a total of 15 years (2001 – 2015). The derived
225 MODIS Land cover classes were used as a mask to select class-specific LSP parameters.

226

227 **Estimation of rainfall parameters**

228 The start of rainy season (SRS) and end of rainy season (ERS) have been determined in a
229 variety of ways, and there is still no consensus on the most appropriate definition. Examples
230 can be seen in Liebmann *et al.* (2012) and Yan *et al.* (2016) who employed the
231 climatological anomalous accumulation method in determining the start and end of rainy
232 season, and Zhang *et al.* (2005) and Guan *et al.* (2014) who employed the percentage method.
233 In this research, we adopted the definition first proposed by Stern *et al.* (1981), and used by
234 several researchers and meteorological agencies (Sarria-dodd & Jolliffe, 2001; Segele &
235 Lamb, 2005; Mupangwa *et al.*, 2011). This method defines SRS as the first period of two to
236 10 days where specified amounts of rainfall (10, 20, 30 mm) are reached or exceeded
237 followed by no continuous dry period of specified length (7, 8, 10 days). This approach was
238 selected as it is designed to also account for sowing dates in croplands to remove false start
239 dates. To determine the wet and dry periods, a threshold was set to differentiate between wet
240 and dry days. All wet days had at least 0.1 mm rainfall and others below this threshold were
241 classed as dry days (Sarria-dodd & Jolliffe, 2001). Two sets of criteria were adopted to

242 determine the SRS: (1) the first wet day in a 40-day duration after a dry spell where the total
243 rainfall in the first consecutive 10 days is 25 mm or more, which is followed by no
244 consecutive dry period of seven days or more, (2) the first wet day in a 30-day duration after
245 a dry spell where the total rainfall in the first consecutive three days in a row is 15 mm or
246 more, which is followed by no consecutive dry period for 10 days or more. If one of the
247 criteria is not met, then testing resumes considering the other. End of season dates were
248 defined as dates after the start of season where no rain occurs over a period of 20 days or, in a
249 30-day duration, the total number of wet days is less than four (Zhang *et al.*, 2005).

250

251 Due to the complexity of rainy seasons in Africa, especially for regions with a bimodal
252 annual rainfall cycle, results were rigorously cross-checked again for false starts. This
253 involved an iterative procedure to check if start dates occurred around 10% accumulation of
254 the total annual precipitation and end dates occurred after 95% accumulation of total annual
255 precipitation. In addition, spatial agreement was seen in the results when compared with
256 previous studies on seasonal rainfall onset and end date retrievals (Zhang *et al.*, 2005; Brown
257 & de Beurs, 2008; Liebmann *et al.*, 2012; Guan *et al.*, 2014). Other rainfall parameters
258 derived were: the length of rainy season (LRS) which is the number of days between SRS and
259 ERS, time of maximum rainfall (Rtmax) and cumulative annual rainfall (Rcum).

260

261 **Statistical approach**

262 All LSP parameters were aggregated to match the spatial resolution of the rainfall data by
263 assigning the modal value in 10 by 10 0.005⁰ grid cells to a 0.05⁰ grid cell. The mode was
264 used because the mean can be skewed due to the occurrence of outliers, and the median is
265 less representative of the average of a dataset. Pixels showing no clear vegetation seasonality

266 were excluded from the analysis. Pixels with no distinct rainfall seasonality for the entire
267 time-series were also excluded.

268

269 The lag, which is the time difference in number of days between SOS and SRS, and EOS and
270 ERS, was calculated for each land cover type. A -10 and 10 days “no change” category was
271 applied to the start of growing and rainy season lags to account for uncertainties in the SOS
272 and SRS estimates and the MODIS 8-day composites. This range was selected because lags
273 of less than 10 days may sometimes arise due to the difference in the Julian date of the
274 MODIS 8-days composite and the daily rainfall data. Further analysis involved fitting linear
275 regression models to determine the association of spatial shifts with the means of different
276 combinations of LSP and rainfall parameters (Table 2).

277

278 **Results**

279 **Frequency of lags between LSP and rainfall parameters across Africa**

280 The difference between the SRS and SOS can be classified into three categories: SOS
281 arriving (a) before, (b) after, and (c) at the same time as the SRS. Figure 4 presents these
282 differences for cropland, grassland and woodland. Croplands fell mostly in the second
283 category showing SOS arrival after SRS, while grasslands fell into two categories: SOS
284 arriving at the same time as SRS and SOS arriving before SRS. For woodlands, however,
285 SOS arrived much before the SRS.

286

287 Across Africa, SOS generally occurred prior to the SRS except in the Sudano-Sahelian region
288 where SOS occurred after the SRS (Figure 5). The distribution of the pixels seen in Figure 5c
289 is skewed towards positive lag values with more occurring between 15 and 45 days (i.e., SOS
290 before SRS). More than 88% of the studied vegetative area had SOS arriving more than 10
291 days before the SRS, of which 90% was found in woodlands. This phenomenon was
292 distributed across all of Africa, but was ubiquitous in southern Africa, with longer lags
293 concentrated in Angola and Zambia. An estimated 9% of pixels had lags of between -10 and
294 10 days (i.e. SOS and SRS arriving almost at the same time), with over 90% of these
295 occurring in woodlands. As seen in Figure 5, approximately 3% of the studied vegetation,
296 mainly along the Sudano-Sahelian region, had SOS arriving 10 days or more after the SRS
297 (i.e. < -10 days lag), with over 35% of this area belonging to croplands and about 46% to
298 woodlands. Greater areas of cropland with longer lag times were observed in eastern Africa,
299 particularly in Ethiopia, while woodlands were mostly located in western Africa.

300

301 Figure 6 shows the distribution of the lag occurrences within each land cover type. Within
302 cropland, an estimated 10% of pixels had SOS arriving at the same time as the SRS, and over

303 80% had SOS arriving after the SRS. The average lag times for croplands were -18 days in
304 the north and 54 days in the south. In contrast, over 89% of woodlands had SOS arriving
305 before the SRS, with averages of 29 days in the north and 36 days in the south, with longer
306 lag times in the southern woodlands (Figure 5). Grasslands and shrublands had very similar
307 onset lag patterns, with an early SOS before the SRS in over 80% of pixels with average lags
308 of 38 and 34 days, respectively.

309

310 In contrast to the SOS, the EOS generally lagged behind the ERS across all Africa (Figures 4
311 and 7) with a longer lag duration in southern Africa. Interestingly, the Sudano-Sahelian
312 region also exhibited a distinct lag range of between 90 to 120 days with peaks in western
313 and eastern Africa of 120 to 150 days. In addition, the distribution of pixels (Figure 8c),
314 unlike that for SOS, had several peaks within a wide range of values (50 to 120 days). Over
315 90% of pixels had a lag of between 30 to 150 days, with the longest durations occurring in
316 woodlands. While most land cover types had varied lags, the lag for over 70% of grasslands
317 varied between 30 to 60 days.

318

319 In relation to the season lengths (LOS and LRS), areas with SOS arriving after SRS had
320 shorter LOS (Figure 8), when compared to those with SOS arriving before SRS. The average
321 LOS within these pixels varied between 220 ± 30 days to 250 ± 40 days while those with SOS
322 arriving before SRS varied between 270 ± 45 days to 300 ± 30 days. The LRS within both
323 categories of pixels varied greatly, and no observable pattern was detected.

324

325 **Spatial relations between LSP and rainfall parameters**

326 Table 2 shows the complex set of spatial associations between LSP and rainfall parameters
327 (all statistically significant at $p < 0.0000$). While a large association was seen between SOS

328 and SRS ($R^2= 0.92$), IntEVI and Rcum ($R^2= 0.58$), and VItmax and Rtmax ($R^2= 0.52$), other
329 combinations of LSP and rainfall parameters showed very little correlation, especially
330 between EOS and ERS, and LOS and LRS. Interestingly, for grasslands, EOS and ERS, and
331 LOS and LRS produced large R^2 values of 0.76 and 0.87, respectively. The same large
332 association was seen across all LSP and rainfall parameters for grasslands. In contrast, only
333 the timings of onset (i.e., SOS and SRS), maxima (i.e., VItmax and Rtmax) and production
334 (IntEVI and Rcum) produced large R^2 values for woodlands. Although, statistically
335 significant, the correlations between EOS and ERS, LOS and LRS, and LOS and Rcum were
336 very small for woodlands. The same association was observed in shrublands between LOS
337 and Rcum. In contrast, a small association was found between SOS and SRS, and between
338 IntEVI and Rcum, in shrublands when compared to all other land cover types.

339

340 For croplands, similar to most land cover types (excluding grasslands) the correlation
341 between LOS and LRS was small. In addition, only a small association was observed
342 between VItmax and Rtmax for croplands. However, large correlations were observed for
343 SOS and SRS, and LOS and Rcum.

344

345 **Discussion**

346 **Early and late greening response of vegetation to rainfall**

347 Our results suggest that pre-rain vegetation green-up occurs across most of Africa. The
348 results are corroborated by the pre-rain green-up reported previously by a limited set of
349 studies, both ground-based (Childes, 1989; De Bie *et al.*, 1998; Higgins *et al.*, 2011; Seghier
350 & Do, 2012; February & Higgins, 2016) and satellite-based (Guan *et al.*, 2014; Ryan *et al.*,
351 2017; Yan *et al.*, 2017). However, we show that the pre-rain green-up is far more widespread
352 across the entire African continent than previously reported. In addition, we were able to
353 determine quantitatively its occurrence across all the major vegetation types studied,
354 confirming its prevalence mostly in woodlands and grasslands in northern and southern
355 Africa. Our findings show that more pre-rain green-up occurred in woodlands, sometimes as
356 much as 3 months before the onset of rain. This pattern of pre-rain green-up in woodlands
357 was more widespread in the southern part of Africa, consistent with previous work (Ryan *et*
358 *al.*, 2017).

359
360 Several explanations have been proposed for the observed pre-rain green-up. It was suggested
361 that a form of memory mechanism developed from adaptation to previous climatic cues could
362 be responsible for early greening (by about two months) in Miombo woodland in central and
363 southern Africa (Goward & Prince, 1995). Also implicated were daylength and temperature
364 thresholds being responsible for early greening of certain woody plant species in southern
365 Africa (Van Rooyen *et al.*, 1986). Responses of plants to other anticipatory climatic factors
366 besides rainfall have also been reported in the Australian savanna (Prior *et al.*, 2004;
367 Bowman & Prior, 2005). In Senegal, where we also observed pre-rain green-up, it was
368 suggested that air relative humidity occasioned by the Inter-Tropical Convergence Zone
369 (ITCZ) is a major determinant of early leaf flush in this region (Do *et al.*, 2005). Other

370 mechanisms primarily located within plants have been proposed by several researchers. One
371 of these is the rehydration of stem tissues in the dry season caused by reduction in water
372 stress levels following leaf shedding (Reich & Borchert, 1982; Borchert, 1994; Williams *et*
373 *al.*, 1997). During this rehydration process, when the required water potential for plant
374 cellular development is attained, early leafing begins (Reich & Borchert, 1982). The
375 phreatophytic nature of some woody plants (their ability to tap underground water reserves
376 with deep root systems, and utilize the previous season's water and nutrients) and low water
377 consumption have also been suggested to cause early green up (Roupsard *et al.*, 1999; Guan
378 *et al.*, 2014). Similarly, the ability of some woody plants to withdraw and conserve nitrogen
379 and carbon for later use to construct new leaves from these stored reserves has been
380 implicated in early green up (February & Higgins, 2016). These features give savanna trees
381 competitive advantage over their herbaceous neighbours, which can drive temporal niche
382 separation; a possible explanation for pre-rain green-up (Higgins *et al.*, 2011; February &
383 Higgins, 2016; Ryan *et al.*, 2017). Another interesting phenomenon, which may have
384 influenced the pre-rain green-up observed in western Africa, is the reverse phenology of the
385 widely distributed *Faidherbia albida* (Acacia) tree (Roupsard *et al.*, 1999; Seghieri & Do,
386 2012). This species enters leaf out during the dry season and sheds leaves during the rainy
387 season. As described above, its unique facultative phreatophytism and low water
388 consumption are responsible for the reversed phenological pattern. Besides climatic or
389 endogenously plant-controlled causes of early greening, biotic factors such as pressures from
390 herbivory have been hypothesised as reasons for early initiation of leafing in some woody
391 plants (Aide, 1988, 1992). It was suggested that this is an antiherbivore defence mechanism
392 by plants, essentially to escape seasonally from herbivores in order to avoid nutrient losses
393 caused by herbivory (Aide, 1992; Rossatto *et al.*, 2009). However, evidence supporting this
394 strategy in Africa savannas is unavailable (Higgins *et al.*, 2011).

395

396 Contrary to previous work (Guan *et al.*, 2014), our findings showed pre-rain green-up
397 occurring in the vast majority of grasslands across Africa, albeit with a short duration, mostly
398 within 10 to 30 days. This can be attributed to SOS being triggered by the small bouts of
399 rains that occur just before the actual start of the rainy season. This is possible because
400 grasslands have very high sensitivity to water fluctuations (Scholes & Archer, 1997;
401 Whitecross *et al.*, 2017). In addition, the large R^2 values in Table 2 also suggest this tight
402 coupling of grasslands and water availability across the continent. Our results also showed
403 that pre-rain green-up occurred in some of the shrublands which can be explained by their
404 deep root systems (Childes, 1989).

405

406 In contrast to other land cover types, post-rain green-up was largely observed in croplands, all
407 located in the Sudano-Sahelian region (Figures 5 and 6). This region consists mainly of
408 croplands (Figure 1), and is known to have a short rainy season and prolonged dry season
409 (Liebmann *et al.*, 2012; Dunning *et al.*, 2016) (Figure 8). This lengthened dry season usually
410 influences farmers' decision to begin sowing, because despite relying to some extent on
411 climatological history, they generally wait for a major burst of rain and ascertain the status of
412 the soil moisture before commencing sowing (Marteau *et al.*, 2011). The variety of crops
413 being cultivated can also explain the post-rain green-up observed. For example, the different
414 species of millet and sorghum sown are largely dependent on water availability for growth,
415 and these are the main staple crops in the Sudano-Sahelian region, cultivated mostly under
416 rainfed conditions (Guan *et al.*, 2015).

417

418 Woodlands and shrublands found in the Sudano-Sahelian region revealed post-rain green-up.
419 Leafing of dominant woody plants in this region is controlled by rainfall and, as mentioned

420 above, this is caused by the occurrence of marked shorter rainy seasons (Seghieri *et al.*,
421 2009). The woody plants in this region endure long dry seasons of over 8 months. Hence,
422 they depend on the occurrence of the first rains to begin leafing (Seghieri *et al.*, 2009;
423 Seghieri & Do, 2012).

424

425 The early and late greening responses of vegetation also influence the lag between ERS and
426 EOS. For example, longer EOS lags were evident in vegetation with pre-rain green-up
427 phenological patterns. According to several researchers, this early greening before the onset
428 of rains enables plants to obtain early access to, and optimally utilize, nutrients released
429 during the first rains; hence, the longer growing season for such plants (Do *et al.*, 2005).
430 Nevertheless, long EOS lag durations were observed in the Sudano-Sahelian region,
431 especially in croplands with post-rain green-up. As mentioned above, the variety of crops
432 affects the phenological pattern. Crops such as cassava, grown mostly in western Africa, are
433 usually harvested 9 to 18 months after sowing (Ezui *et al.*, 2016), thus, leading to long lags
434 between the ERS and EOS.

435

436 **Relationships between LSP and rainfall parameters**

437 Consistent with previous studies (Zhang *et al.*, 2005; Guan *et al.*, 2014), our analysis revealed
438 large correlations between SOS and SRS across Africa. Notwithstanding this large
439 correlation, vegetation green-up is not driven by rainy season onset as plants green-up early,
440 prior to the rainy season onset. This phenomenon suggests that other factors may have a
441 much greater influence over the onset of the vegetation growing season. However, large
442 correlations were observed for all the major vegetation types in this study, except for
443 shrublands (

444 Table), and this is influenced by the spatial variability in SOS dates across Africa (Adole *et*
445 *al.*, 2018).

446

447 The EOS and ERS had a small association for woodlands and croplands, but large association
448 for shrublands and grasslands. This was expected as the EOS for woodlands extends much
449 later than for ERS. Similarly, because the end of the crop growing season depends largely on
450 sowing date and the variety of crops grown (Brown & de Beurs, 2008), only a small
451 correlation between ERS and crop EOS was expected. The tight coupling of grasslands to
452 water explains the large correlation observed for grasslands, and the large associations
453 between all other grassland LSPs and rain parameters analysed in this study (Table 2).

454

455 The LOS and the total amount of annual rainfall across Africa produced a large association.
456 However, only a small association was observed for woodlands between LOS and the total
457 amount of annual rainfall, and between LOS and LRS. This suggests that the length and total
458 amount of annual rainfall does not significantly influence the length of growing season for
459 woody vegetation. One reason for this could be the ability of woody plants to minimise
460 transpiration over a long period, especially during dry seasons and at the same time maximise
461 photosynthesis (De Bie *et al.*, 1998), thus, leading to a longer LOS than LRS. Nevertheless,
462 the time of maximum greenness produced a large association with time of maximum rainfall,
463 and seasonal integrated EVI produced a large association with total amount of annual rainfall
464 (Table 2). This suggests that rainfall amount affects the seasonal productivity of woodlands.
465 This is in broad agreement with reported increases in productivity in areas with larger
466 amounts of rainfall in some woody species in South Africa (Shackleton, 1999).

467

468 From this research, it is evident that while pre-rain green-up is ubiquitous in Africa, post-rain
469 green-up was limited to the Sudano-Sahelian region. From previous studies (Berg *et al.*,
470 2011; Marteau *et al.*, 2011) and the results of this research, it can be inferred that the post-
471 rain green-up pattern observed in the Sudano-Sahelian region can be explained by the very
472 short, marked rainy season in the region.

473

474 The above observations pose serious challenges for existing terrestrial biosphere models
475 (TBMs) and climate change predictions (Ryan *et al.*, 2017). Currently, TBMs like the
476 dynamic global vegetation models (DVGGM) use only precipitation or soil moisture thresholds
477 in modelling the response of dry deciduous plants to climatic factors (Sitch *et al.*, 2008; Zhao
478 *et al.*, 2013). Some examples of phenological models are the meteorological data-based
479 phenology model (Jolly *et al.*, 2005) and the carbon–nitrogen dynamics (CN) model (Wang
480 *et al.*, 2016). They both depend on seasonal water availability as a cue for vegetation
481 phenology in the tropics. This potentially creates a large bias in estimating phenological
482 events because the parametrisation process in these models does not account for the
483 ubiquitous pre-rain greening phenomenon, which may be triggered by other environmental
484 factors.

485 Another aspect worthy of consideration in these global change models is the feedback role of
486 phenology on climate, mostly through CO₂ uptake (Peñuelas *et al.*, 2009; Wu *et al.*, 2016).

487 As previously mentioned, the African vegetation contributes 38% of the global climate-
488 carbon cycle feedback, mostly coming from its savanna comprised mainly of woodlands
489 (Friedlingstein *et al.*, 2010). In a changing climate of projected increases in temperatures,
490 droughts, soil moisture drying, and decreases in precipitation in Africa, especially southern
491 Africa (Niang *et al.*, 2014), there could be an accompanying shift in precipitation seasonality
492 and intensity. This could result in the delay or absence of the anticipated moisture support for

493 plant growth at the time needed in pre-rain green up woodlands, with likely consequences on
494 net primary productivity. Consequently, this may influence the vegetation-mediated
495 feedbacks on climate systems (a positive feedback on climate change), because of the
496 possible reduction in CO₂ uptake from the African savannas. Similarly, increasing
497 temperatures may influence vegetation-mediated feedbacks on climate change estimates in
498 pre-rain green up plants. Studies have suggested that temperature increases might have
499 caused increased productivity and growth in some southern African woodlands (Bunting *et*
500 *al.*, 2016; Davis *et al.*, 2017), therefore, potentially leading to greater CO₂ uptake.

501

502 In summary, this research presents a comprehensive classification of the different patterns of
503 LSP responses to rainfall in Africa. It confirms the prevalence of pre-rain green-up in Africa,
504 and further demonstrates that this pattern is more widespread across the continent than
505 previously reported. Additionally, we found that both pre-rain and post-rain green-up had a
506 significant influence on EOS lags across different vegetation types. We were also able to
507 quantify the frequencies of these LSP responses (pre-rain and post-rain) across different
508 vegetation types in Africa and provided supporting evidence from previous studies, mostly
509 ground-based. These findings and other advances in phenological studies were possible
510 because of remote sensing methods (Archibald & Scholes, 2007; Studer *et al.*, 2007). As
511 such, the findings are subject to the common limitations associated with these techniques.
512 Examples of limitations are the potential influences from smoothing and LSP estimation
513 techniques, and influences from the type of sensor (Atzberger *et al.*, 2013). Notwithstanding
514 these limitations, the findings and the supporting literature suggest that rainfall is not the only
515 major environmental factor controlling initiation and cessation of vegetation seasonality in
516 Africa. It proposes that although rainfall is important in vegetation growth (as seen in the
517 large correlations between the rainfall and phenological parameters), other environmental

518 factors, and the interplay between these factors, are likely to exert a greater influence on the
519 onset and end of seasonal vegetation growth patterns. Temperature and photoperiodicity have
520 been suggested to be among the most important factors triggering onset of growing season
521 across Africa. The effect of these other factors and the related role of rainfall in seasonal
522 vegetation growth needs to be investigated at the continental scale to advance our
523 understanding of natural ecosystem processes in Africa and their representation in terrestrial
524 biosphere models. This is especially important, considering the need to understand the likely
525 responses of pre-rain green-up under a changing climate, and how these responses might
526 influence global climate change on vegetation-atmosphere feedbacks.

527

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534

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804 **Tables**

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

IGBP number	Initial land cover types	Merged land cover type
1	Evergreen needleleaf forest	Forest
2	Evergreen broadleaf forest	
3	Deciduous needleleaf forest	
4	Deciduous broadleaf forest	
5	Mixed forest	
6	Closed shrublands	Shrublands
7	Open shrublands	
8	Woody savannas	Woodlands
9	Savannas	
10	Grasslands	Grasslands
12	Croplands	Croplands
14	Croplands/natural vegetation mosaic	Croplands/natural vegetation mosaic
11	Permanent wetlands	Non-vegetative cover
13	Urban and built-up land	
15	Permanent snow and ice	
16	Barren or sparsely vegetated	
17	Water	

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810 **Table 2:** Correlation between LSP and rainfall across space. The associations are reported in
 811 R^2 values all at p -value <0.000.

Pheno-rain combinations	Correlation (R^2) (p-value<0.000) by land cover class				
	All	Croplands	Grasslands	Shrublands	Woodlands
SOS and SRS	0.92	0.70	0.95	0.31	0.97
EOS and ERS	0.10	0.23	0.76	0.50	0.07
LOS and LRS	0.27	0.18	0.87	0.28	0.09
LOS and Rcum	0.34	0.79	0.82	0.04	0.09
IntEVI and Rcum	0.58	0.37	0.55	0.12	0.57
VItmax and Rtmax	0.52	0.28	0.75	0.72	0.69

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813

814 **Figure captions**

815 **Figure 1:** Reclassified 2013 MODIS land cover product (MCD12Q1).

816

817 **Figure 2:** Flowchart describing the study methodology in three major steps: (1) data
818 processing, (2) data analysis and (3) statistical analysis.

819

820 **Figure 3:** An illustration of LSP parameters used in this research. Black line illustrates
821 smoothed time-series, (a) Start of season (SOS), (b) End of season (EOS), (c) Length of
822 season (LOS), (d) Time of maximum EVI (VI_{tmax}), and (e) Integrated EVI (IntEVI).

823

824 **Figure 4:** Examples of pixel profiles for a complete cycle of EVI and daily rainfall time-
825 series. EVI time-series is represented by green curved lines while rainfall is represented by
826 black bars. Vertical dashed lines show LSP and rainfall parameters (SOS and EOS in green
827 and SRS and ERS in blue). (a) Croplands in the Sudano-Sahelian region showing SOS
828 arriving after SRS, (b) Grasslands in the Sudano-Sahelian region showing SOS and SRS
829 arriving approximately at the same time, (c) Grasslands in southern Africa showing SOS
830 arriving before SRS, and (d) Woodlands in southern Africa showing SOS arriving well before
831 SRS.

832

833 **Figure 5:** Difference in days between SRS and SOS (i.e., SRS - SOS in days). Positive
834 values indicate SOS arriving before SRS while negative values indicate SOS arriving after
835 SRS. (a) Spatial distribution of SOS and SRS difference in number of days. (b) Proportion of
836 pixels by land cover type in different categories of SOS and SRS lag. (c) Frequency
837 distribution of SRS and SOS difference.

838

839 **Figure 6:** Proportion of pixels in each land cover type in the different categories of SOS and
840 SRS lag.

841

842 **Figure 7:** Differences in days between EOS and ERS (i.e., EOS - ERS in days). Positive
843 values indicate EOS arriving after ERS while negative values indicate EOS arriving before
844 ERS. (a) Spatial distribution of EOS and ERS difference in number of days, (b) Proportion of
845 pixels by land cover type in different categories of EOS and ERS lag, (c) Frequency
846 distribution of EOS and ERS difference.

847

848 **Figure 8:** Spatial pattern of the average of LSP and rainfall parameters between 2001 and
849 2015. (a) SOS and SRS and (b) EOS and ERS (shown in months of the year). (c) LOS and
850 LRS (shown in number of days).

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