

# Characterising the response of vegetation cover to water limitation in Africa using geostationary satellites

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## Key Points:

- We detect seasonal decay periods of fractional vegetation cover at Africa from daily geostationary satellite time series at 5 km resolution
- We provide observation-based metrics characterising dynamics of decay periods to improve our understanding in vegetation–water interactions
- The metrics contain valuable information on underlying processes of decay related to water limitation like plant accessible water storage

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**Abstract**

Hydrological interactions between vegetation, soil, and topography are complex, and heterogeneous in semi-arid landscapes. This along with data scarcity poses challenges for large-scale modelling of vegetation-water interactions.

Here, we exploit metrics derived from daily Meteosat data over Africa at ca. 5 km spatial resolution for ecohydrological analysis. Their spatial patterns are based on Fractional Vegetation Cover (FVC) time series and emphasise limiting conditions of the seasonal wet to dry transition: the minimum and maximum FVC of temporal record, the FVC decay rate and the FVC integral over the decay period. We investigate the relevance of these metrics for large scale ecohydrological studies by assessing their co-variation with soil moisture, and with topographic, soil, and vegetation factors.

Consistent with our initial hypothesis, FVC minimum and maximum increase with soil moisture, while the FVC integral and decay rate peak at intermediate soil moisture. We find evidence for the relevance of topographic moisture variations in arid regions, which, counter-intuitively, is detectable in the maximum but not in the minimum FVC. We find no clear evidence for wide-spread occurrence of the “inverse texture effect” on FVC. The FVC integral over the decay period correlates with independent data sets of plant water storage capacity or rooting depth while correlations increase with aridity. In arid regions, the FVC decay rate decreases with canopy height and tree cover fraction as expected for ecosystems with a more conservative water-use strategy. Thus, our observation-based products have large potential for better understanding complex vegetation–water interactions from regional to continental scales.

**Plain Language Summary**

Local-scale processes controlling vegetation dynamics under water limitation are highly uncertain at large scales, despite their importance on global carbon and water cycles. This is particularly pronounced in Africa due to the scarcity of ground measurements despite the importance of African ecosystems due to their contribution to global cycles and their services to population. In order to overcome this problem, we developed a set of metrics based on the fractional vegetation cover observed from the European geostationary satellite. The metrics help diagnose the effects of local-scale ecohydrological processes thanks to their high spatial resolution of ca. 5 km. Initial analyses show consistent continental gradients in the metrics together with strong local variations and corroboration with different datasets from independent sources, in agreement with the literature.

**1 Introduction**

Africa hosts the largest share of undernourished population, and the livelihood of the majority of its population relies on ecosystem services and water availability (Müller et al., 2014). Moreover, African ecosystems contribute strongly to fluctuations of the global carbon cycle (Williams et al., 2007; Weber et al., 2009; Valentini et al., 2014; Palmer et al., 2019). Despite its importance, large uncertainties prevail in understanding the African ecosystems and quantifying spatiotemporal variations of their functioning due to the complexity of continental gradient and scarcity of ground measurements, which has been shown in studies using different data and approaches ranging from in-situ observations (Schmiedel et al., 2021), over remote sensing (Weerasinghe et al., 2020), to ecosystem modelling (C. Martens et al., 2021), as well as systematic literature reviews (Adole et al., 2016).

Savannas cover majority of the African continent (Williams & Albertson, 2004), and water is the limiting factor in such ecosystems, affecting vegetation’s carbon uptake and nitrogen assimilation (Rodríguez-Iturbe et al., 1999). The dominant role of water

65 in African drylands has been shown in various studies (Sankaran et al., 2005, 2008; Mer-  
66 bold et al., 2009; F. Wei et al., 2019). Moreover, evidence suggests that ecosystem func-  
67 tioning – even in the wettest part of the continent, the central African tropical forest –  
68 responds to soil moisture fluctuations (Guan et al., 2013; Gond et al., 2013) along with  
69 co-limitations of other factors such as radiation (Adole et al., 2019). Within the com-  
70 plex rainfall seasonality patterns having unimodal, bimodal or trimodal regimes, less than  
71 5 % of the continent is reported to be non-seasonally humid (Herrmann & Mohr, 2011).

72 Soil moisture is the critical variable that characterises the water limitation of veg-  
73 etation (Porporato et al., 2001), which, in turn, shapes land–atmosphere exchanges of  
74 carbon, water, and energy fluxes (Gentine et al., 2012), phenology (Peñuelas et al., 2004),  
75 and vegetation functional traits (Guan et al., 2015; W. Zhang et al., 2019), along with  
76 their species or biome distribution (Xu et al., 2016). Rainfall is the primary source of  
77 moisture but plant available water in drylands is characterised by non-trivial and com-  
78 plex ecohydrological processes that control the availability of moisture from secondary  
79 sources (D’Odorico et al., 2019). In fact, Wilcox et al. (2017) conceptualised three crit-  
80 ical ecohydrological junctures: (1) infiltration versus overland flow, (2) soil evaporation  
81 versus transpiration, and (3) root water uptake versus drainage, that are all centred around  
82 the hydrological response of the ecosystem.

83 Beyond precipitation intensity, topography, and soil properties, the first juncture  
84 is affected by presence of vegetation patches that interact with overland flow causing the  
85 typical runoff–runon dynamics at hillslope-scale (Ludwig et al., 2005). The second jun-  
86 cture, partitioning of terrestrial evaporation, is critical as an interplay between biologi-  
87 cal activity and productivity, and physical water losses by direct evaporation. Vegeta-  
88 tion transpiration generally dominates terrestrial evaporation (Z. Wei et al., 2017), and  
89 the partitioning is controlled more by vegetation and soil characteristics given the cli-  
90 mate (Nelson et al., 2020), highlighting a pivotal role of vegetation. The third juncture  
91 within the root zone is largely controlled by below-ground vegetation properties, such  
92 as depth and distribution of roots, that control the soil–plant hydraulics continuum. Deep  
93 rooting facilitates access to a larger moisture reservoir, a frequently observed trait in sa-  
94 vanna and woodland ecosystems (Kleidon & Heimann, 1998; Guswa, 2008). In fact, the  
95 diversity and complementarity of ecohydrological plant traits by different species within  
96 ecosystems was shown to determine resilience to drought (Anderegg et al., 2018) and to  
97 maximise plant water use (Scanlon et al., 2005; Caylor et al., 2009).

98 There are further ecohydrological phenomena that should be considered when ex-  
99 ploring vegetation–water interactions, emerging from non-monotonic ecosystem responses  
100 to episodic events, and ephemeral waterbodies occurring across spatial scales. Non-monotonic  
101 effects of soil properties on the interaction between climatological aridity and vegetation  
102 can lead to the frequently observed “inverse texture effect” in arid climates, whereby sandy  
103 soils appear to be associated with less water stress compared to clay soils, due to their  
104 higher infiltration capacity (Noy-Meir, 1973). Additionally, dryland ecosystems locally  
105 return nearly all rainfall back to atmosphere as terrestrial evaporation (Newman et al.,  
106 2006) with very little water draining from the root zone to groundwater (Wilcox et al.,  
107 2017), except extreme rainfall events that episodically recharge aquifers (Taylor et al.,  
108 2013; J. Zhang et al., 2016). Moreover, riparian processes such as river channel losses  
109 from ephemeral rivers can provide critical source of moisture (Tooth, 2000; Mansell &  
110 Hussey, 2005; Jacobson & Jacobson, 2013; Wang et al., 2018). Riparian corridors and  
111 groundwater-fed valleys, therefore, often appear as “green islands” (Eamus et al., 2015),  
112 where access to the shallow groundwater supports vegetation activities. In such ecosys-  
113 tems, the growing season may continue several months after the rain season has ceased  
114 while the trees appear to have access to groundwater via deep roots or recharge their trunks  
115 with water during these times (Guan, Wood, et al., 2014; F. Tian et al., 2018).

116 Previous studies, therefore, provide clear evidence that vegetation functions are con-  
117 trolled by moisture availability in non-humid climate, with moisture availability, itself,

118 emerging from the complex interplay among climate characteristics, vegetation traits,  
 119 hillslope topography, soil properties, and presence of secondary moisture sources, e.g.,  
 120 aquifers. In fact, incorporation of all these ecohydrological factors poses a challenge for  
 121 land-surface modellers (Clark et al., 2015; Fisher & Koven, 2020). One of the main lim-  
 122 itations for models is the specification of rooting depth (Fan et al., 2019). Over recent  
 123 years, several studies have put forward estimations of the rooting depth or effective root-  
 124 ing depth that represents the potential moisture access of the vegetation. A compari-  
 125 son of different estimates, though, reveals a large uncertainty with rooting depth vary-  
 126 ing from a few centimetres to tens of meters for a given location (Wang-Erlandsson et  
 127 al., 2016). This, in part, is caused by the underlying assumptions in the estimation meth-  
 128 ods, whose effect on the prediction cannot be constrained by or validated against obser-  
 129 vations, especially in data scarce regions like Africa. Considering the particular difficul-  
 130 ties associated with below-ground observation of ecosystem and land properties at a large-  
 131 scale, remotely-sensed products of vegetation characteristics, indices, and responses pro-  
 132 vide opportunities to back infer the underlying environmental factors and land surface  
 133 characteristics.

134 Remote sensing vegetation indices has been extensively used to capture phenolog-  
 135 ical states of vegetation, such as detecting onset and length of growing season or peak  
 136 greenness, as well as specific agricultural applications (reviewed in Zeng et al., 2020).  
 137 Moreover, the temporal dynamics of vegetation indices can be exploited to understand  
 138 ecologically relevant concepts such as land cover effects on vegetation dynamics (Yan et  
 139 al., 2017), early green-up of woody vegetation in Africa (Guan, Wood, et al., 2014; Adole  
 140 et al., 2019; Ouédraogo et al., 2020), effects of plant water storage (F. Tian et al., 2018),  
 141 and early diagnosis of climate-induced forest mortality (Liu et al., 2019). The majority  
 142 of vegetation remote sensing studies focusing on Africa are based on image acquisitions  
 143 from polar orbiting satellites like MODIS (Adole et al., 2016), while only a few studies  
 144 are based on vegetation indices derived from the geostationary satellite Meteosat Sec-  
 145 ond Generation (MSG) (e.g.: Guan, Medvigy, et al., 2014; Yan et al., 2017). Geosta-  
 146 tionary satellite based vegetation indices are available in daily temporal resolution, which  
 147 is their biggest advantage compared to polar orbiting satellites where such high resolu-  
 148 tion in time is not possible.

149 In this study, we analyse the daily Fraction of Vegetation Cover (FVC) time se-  
 150 ries from MSG to infer the ecohydrological characteristics of ecosystems over Africa. We  
 151 derive a set of ecohydrological metrics from the vegetation decay period, and evaluate  
 152 their spatial patterns. Our overarching hypothesis is that these metrics, derived from the  
 153 vegetation dynamics over decay periods, contain valuable information on plant water ac-  
 154 cess, presence of secondary moisture sources, and other ecohydrological mechanisms, which  
 155 are modulated by climate, topography, soil properties, groundwater access, as well as veg-  
 156 etation traits and scales. The ecohydrological metrics include (i) robust estimates of the  
 157 minimum and maximum FVC, (ii) FVC integral over the decay period, and (iii) the ex-  
 158 ponential decay rate during dry-down. Using the metrics, we evaluate several hypothe-  
 159 ses that encompass the ecohydrological characteristics of moisture-limited ecosystems  
 160 and the influence of environmental factors and land characteristics therein, such as:

- 161 1. In arid regions, minimum and maximum FVC are larger in sandy soil while this  
 162 covariation is inverted in semi-arid and humid regions. This hypothesis follows the  
 163 “inverse texture effect” (Noy-Meir, 1973) often reported in drylands.
- 164 2. Within similar climatic aridity, secondary moisture sources increase the minimum  
 165 FVC and decrease seasonal FVC range. This hypothesis is derived from the clas-  
 166 sical approach of mapping groundwater-dependent ecosystems – with shallow wa-  
 167 ter table or potentially larger runoff due to topography – as “green islands” of at-  
 168 tenuated seasonality (Eamus et al., 2015).
- 169 3. Time integral of FVC over decay period as a proxy for plant accessible water stor-  
 170 age is larger in semi-arid regions where differences between precipitation and po-

171 tential transpiration are marginally smaller at annual scales than at seasonal scales,  
 172 compared to arid and humid regions. This hypothesis follows the expected opti-  
 173 mal rooting depth of plants considering cost and benefit of developing root struc-  
 174 ture (Guswa, 2010).

175 4. FVC decay rate driven by progressive water limitation becomes lower with increas-  
 176 ing aridity, tree cover and canopy height. This hypothesis assumes FVC mimics  
 177 the decay rate of land evaporation during decay period and follows previously re-  
 178 ported increase in timescale of land evaporation decay with aridity, canopy height,  
 179 and woody vegetation (Teuling et al., 2006; Boese et al., 2019; Martínez-de la Torre  
 180 et al., 2019). Therefore, FVC decay rate would reflect adaptations of ecosystem  
 181 water use strategies.

182 We approach the analysis firstly by looking at the continental scale variations of  
 183 the metrics, together with climatic aridity as the first order driver. This covariation is  
 184 further scrutinised with other environmental factors relevant to the hypotheses given above.  
 185 As aridity metric we chose mean annual root-zone soil moisture from the Global Land  
 186 Evaporation Amsterdam Model (GLEAM).

187 To derive the ecohydrological metrics for the African continent from high-resolution  
 188 remote sensing data (Sec. 2), we developed a robust methodology (Sec. 3) to deal with  
 189 noise, gaps, widely varying dynamics, and data size. The quality diagnostics along with  
 190 the derived metrics and discussion of underlying mechanisms (Sec. 4), and open code  
 191 for derivations, enables future advances in understanding and modelling ecohydrologi-  
 192 cal processes and variability. Furthermore, initial analysis and corroboration with inde-  
 193 pendent data illustrates the potential of applications of the ecohydrological metrics (Sec.  
 194 4).

## 195 2 Data

### 196 2.1 Fraction of Vegetation Cover

197 The FVC, derived from a spectral mixture analysis of the satellite retrievals, is a  
 198 vegetation index summarising the two-dimensional coverage ratio of vegetation per unit  
 199 land area (Trigo et al., 2011). With a range of [0–1], FVC is often used to derive fun-  
 200 damental vegetation indices such as the Leaf Area Index. The FVC product used in this  
 201 study was obtained from the Satellite Application Facility for Land Surface Analysis (LSA-  
 202 SAF) of the European Organisation for the Exploitation of Meteorological Satellites (EU-  
 203 METSAT). The product is based on the retrievals of the Spinning Enhanced Visible and  
 204 Infrared Imager (SEVIRI) sensor on board the MSG satellite (Trigo et al., 2011). As a  
 205 geostationary satellite, the MSG has a circular spatial coverage of Earth centred at 0°  
 206 longitude, and it covers Europe and Africa entirely (see an example of the original FVC  
 207 data for a day in Fig. A1). The SEVIRI is a multispectral optical sensor with 12 spec-  
 208 tral bands, and a temporal resolution of 15 minutes. Under the sub-satellite point (nadir),  
 209 it has 3.1 km spatial resolution in the normal bands, and a high-resolution band with  
 210 1 km spatial resolution. The spatial resolution of the retrieval decreases with distance  
 211 from the nadir, as for all geostationary satellites.

212 The FVC data product is available at daily temporal resolution spanning the time  
 213 period from early 2004 to present. FVC is estimated using parameters of a bidirectional  
 214 reflectance distribution function on the cloud-corrected top of canopy reflectance values  
 215 of three spectral channels namely red, near-infrared, and middle-infrared (LSA-SAF, 2016).  
 216 Thanks to the very high temporal resolution of the SEVIRI sensor, spatial consistency  
 217 of cloud-free data is ensured by the data providers (Trigo et al., 2011), which is also con-  
 218 firmed by studies comparing enhanced vegetation index products of SEVIRI and MODIS  
 219 across the Congo Basin (Yan et al., 2016). Further details of the product, and access to

220 downloading data are available at <https://landsaf.ipma.pt/en/products/vegetation/fvc/>

221 .  
 222 For this study, we selected the spatial domain as the African continent. In order  
 223 to convert the product into equal width grids to facilitate analysis with other products,  
 224 we resampled the original data to spatial resolution of  $0.0417^\circ$  (ca. 5 km) with the near-  
 225 est neighbour method (using `gdalwarp` function in GDAL, GDAL/OGR contributors,  
 226 2020). In terms of temporal domain, we used nearly 16 years of data, from the begin-  
 227 ning of the records in 2004, to the end of 2019.

## 228 **2.2 Ancillary Data**

### 229 **Soil Moisture**

230 We used the third version of GLEAM estimates of root-zone soil moisture (Miralles  
 231 et al., 2011; B. Martens et al., 2017). GLEAM consists a set of modules to estimate dif-  
 232 ferent components of land evaporation simultaneously. Therefore, the model estimates  
 233 multiple products including root-zone soil moisture, (hereafter referred to as soil mois-  
 234 ture). GLEAM data is available at  $0.25^\circ$  space and at daily resolution in time from 2003  
 235 up to date with a small latency. We used mean value of daily estimates from 2004 to 2019  
 236 (parallel to the temporal domain of FVC data used) as a diagnostic for average clima-  
 237 tological aridity in Sec. 4. Additionally, we used daily values to compute temporal cor-  
 238 relation between soil moisture and FVC, after aggregating original FVC data into  $0.25^\circ$   
 239 by simple averaging (see Appendix D for spatial variation of correlation values).

### 240 **Sand Content of Soil**

241 In order to quantify effects of soil texture, we used gridded sand percentage of soil  
 242 data from SoilGrids dataset (Hengl et al., 2017), which is a machine learning based in-  
 243 terpolation of soil profiles at 250 meter resolution. SoilGrids dataset is available glob-  
 244 ally and provides information from different layers, ranging from surface to 2 meters depth.  
 245 Though in this study, for interpretability, we used the average of the top five layers that  
 246 are not deeper than 1 meter for interpretability, and used the data at  $0.0417^\circ$  after ag-  
 247 gregating by simple averaging.

### 248 **Height Above Nearest Drainage**

249 To relate the variation of the metrics to meso-scale heterogeneity and convergence  
 250 of moisture caused by topography, we used the Height Above Nearest Drainage (HAND)  
 251 data from (Yamazaki et al., 2019). Quantifying the vertical distance of a given point to  
 252 the nearest drainage, HAND is closely related to drainage topology and hillslope-scale  
 253 convergence of soil moisture and groundwater (Nobre et al., 2011). The HAND data used  
 254 here is based on the MERIT digital elevation model at a spatial resolution of 3-arc sec-  
 255 ond (ca. 90 m). We used the original high-resolution data after aggregating (simple av-  
 256 erage) to the resolution of the ecohydrological metrics presented in this study ( $0.0417^\circ$ ).

### 257 **Topographic Wetness Index**

258 In order to understand the runoff related effects of topography, we used Topographic  
 259 Wetness Index (TWI), also known as compound topographic index. Being a function of  
 260 both slope and the upstream area that potentially contribute to runoff of a given point,  
 261 TWI is a metric to diagnose topography-induced effects on water cycle at hillslope scales.  
 262 We used TWI data from Amatulli et al. (2020), which is computed by using the MERIT  
 263 digital elevation model at 3-arc seconds, as the in case of HAND. In order to account  
 264 for the high variability of TWI at hillslope scales while aggregating the data into  $0.0417^\circ$ ,  
 265 we first calculated median TWI value of the domain (0.069). Then, we aggregated the  
 266 TWI values by calculating percentage of sub-grid cells having higher TWI values than  
 267 the median value computed in the first step. Eventually, similar to TWI itself, larger val-

268 ues in the normalised TWI means larger potential runoff due to topographic complex-  
 269 ity.

### 270 Accessible Water Storage Capacity and Rooting Depth

271 We used multiple proxies of plant accessible water to understand their effects on  
 272 vegetation dynamics. Effective Rooting Depth (ERD, Yang et al., 2016) is one of those  
 273 products, which is natively at  $0.5^\circ$  spatial resolution. ERD comes from a global parametri-  
 274 sation of a process-based, analytical model of carbon costs and benefits of deeper root-  
 275 ing in plants, proposed by Guswa (2008). In this model, the cost of deeper roots is es-  
 276 timated considering the physical structure of roots like density and length together with  
 277 root respiration, while the benefit is estimated considering water use efficiency, growing  
 278 season length and mean transpiration rate per rooting depth. In order to parametrise  
 279 the model, root and soil properties were obtained from the literature, water use efficiency  
 280 from an ensemble of process based models while climatological information from a long-  
 281 term mean of remote sensing based products.

282 In addition, the Rooting Depth (RD) product from Fan et al. (2017) is also used  
 283 in this study. RD is estimated with inverse modelling of root water uptake profiles in  
 284 three steps, where first soil water profile, as the supply, is estimated using climate, soil  
 285 properties and topography. Thanks to the availability of high-resolution information on  
 286 soil and topography, RD has a much higher spatial resolution ( $0.0083^\circ$ , ca. 1 km) than  
 287 the other products. After estimation of plant water demand using atmospheric condi-  
 288 tions and leaf area index, the supply is allocated as root water uptake using Ohm’s law  
 289 at different soil depths, where amount of infiltration, groundwater recharge, and subse-  
 290 quent uptake were effected (Fan et al., 2017). Note that the model includes multiple forc-  
 291 ing data, with a temporal coverage from 1979 to the time of the study.

292 Apart from the rooting depth products, we also used estimates of plant water stor-  
 293 age capacity. Accessible Water Storage Capacity (AWSC, S. Tian et al., 2019) is de-  
 294 rived at  $0.25^\circ$  by assimilating an ecohydrological model (World-Wide Water, van Dijk  
 295 et al., 2013) with different remote sensing based water observations, namely surface wa-  
 296 ter extent, near-surface soil moisture and variations of terrestrial water storage. World-  
 297 Wide Water is a process based model using atmospheric conditions, containing three soil  
 298 layers to simulate vegetation access to soil moisture, which also accounts for recharge and  
 299 discharge from groundwater. Due to the temporal availability of the forcing data, AWSC  
 300 product is derived using 6 years of data starting from 2010.

301 The forth and last product used to analyse plant accessible water storage capac-  
 302 ity is the Root Zone Storage capacity ( $RZSCR_{U2}$ , Wang-Erlandsson et al., 2016) prod-  
 303 uct derived by contrasting water fluxes observed by remote sensing, precipitation and  
 304 irrigation as influx, and evaporation as outflux. Owing the assumption that plants de-  
 305 velop their roots to optimise their root zone storage capacity, and using a simple approach  
 306 on water fluxes, Wang-Erlandsson et al. (2016) did not use any external information on  
 307 vegetation or soil properties. While different precipitation data are used as forcing data  
 308 with different drought return periods, we used the final product forced by Climate Re-  
 309 search Unit precipitation data (CRU TS3.22, Harris et al., 2014) with the shortest re-  
 310 turn period, 2 year.  $RZSCR_{U2}$ , which is derived using data from 2003 to 2013, is avail-  
 311 able at  $0.5^\circ$  spatial resolution.

312 For a consistent comparison across data at different resolutions, we aggregated all  
 313 data to a common spatial resolution of  $0.5^\circ$  by simple averaging. Note that the spatial  
 314 aggregation may result in loss of the spatial variability prevalent locally and potentially  
 315 captured at a high resolution. Moreover, we only used the grid cells that all products  
 316 have an estimate.

### 317 Canopy Height

Since canopy height is an important indicator of ecosystem functions and is associated mostly with water limitation (Tao et al., 2016), we analysed the effects of canopy height on the decay rate of vegetation cover through their covariation in space. We used the lidar-derived canopy height data from the retrievals of the ICESat satellite at a spatial resolution of 1 km (Simard et al., 2011). We used the data after aggregating (simple average) to  $0.0417^\circ$ .

### Tree Cover

We used tree cover data in order to analyse the sensitivity between the relationship of decay rate of FVC and climatological aridity. We used the tree percent component of the MOD44B Version 6 Vegetation Continuous Fields from MODIS (Dimiceli et al., 2015), which is available globally in 250 meter spatial and annual temporal resolution. We aggregated the product in space to the target resolution of this study by taking the mean of higher resolution grid cells. Finally, we used the median tree cover value over the years covering the temporal domain of FVC data to obtain a time invariant metric, same approach taken for the annual estimates of the metrics derived from FVC (see Sec. 3).

## 3 Methodology

The derivation of the ecohydrological metrics is based exclusively on the daily FVC time series. The method can be divided into four main steps: (i) masking and retrieval of minimum and maximum FVC ( $FVC_{min}$  and  $FVC_{max}$ ), (ii) detection of start and end of the decay periods, (iii) estimation of the decay period FVC integral ( $I_{dp}$ ), and (iv) estimation of the FVC decay rate during dry-down ( $\lambda$ ). Each methodological step is described in detail in the following subsections together with the final products, and their quality diagnostics when needed.

### 3.1 Masking and Retrieval of FVC Extrema

To remove the effect of outliers within a time series, we selected the 2nd and 98th percentiles of the entire records of the FVC data as the minimum ( $FVC_{min}$ ) and the maximum asymptotic values ( $FVC_{max}$ ). To maintain a reliable signal-to-noise ratio before taking further steps, we filtered out any grid cell if  $FVC_{max} < 0.1$  or more than one-third of the time series were missing. Due to the simplicity of the derivation of  $FVC_{min}$  and  $FVC_{max}$  metrics, quality diagnostics were deemed unnecessary, and not derived in this set of metrics.

### 3.2 Detection of Decay Periods

The detection of the decay period was based on a procedure using the first derivative of the smoothed FVC ( $V'$ ) (see Algorithm 1). We smoothed daily time series of the FVC with a 31-day moving average ( $V_{sm}$ ). Then each day in the time series was marked as decay, growth or stable. To do so, we set two thresholds for decay and growth periods as  $th_{decay}$  and  $th_{growth}$ , respectively. After rigorous investigation of time series of individual grid cells, we used the 75th and 70th percentiles of the negative derivative ( $V'$ ) as thresholds  $th_{decay}$  and  $-th_{growth}$  for each grid cell. The magnitude  $th_{decay}$  is, thus, bigger than  $th_{growth}$ , in accordance with the larger gradient in the beginning of the period than the end. Only the magnitude of  $th_{growth}$  was taken as a positive threshold to detect the increase in FVC.

An observation was considered as decay if  $V' < th_{decay}$ , growth if  $V' > th_{growth}$ , and stable if  $th_{decay} \leq V' \leq th_{growth}$ . The resulting time series of classes (decay, growth, or recovery) were then smoothed by retaining the majority of decay and stable against recovery within a 5-day moving window. Complete decay period, which is considered as

365 the initial decay period followed by a stable, non-increasing period, was then identified  
 366 as the period from the beginning of a decay to the end of a stable period. In order to  
 367 ensure robustness of the end of the stable period, especially in hyper-arid regions with  
 368 poor signal-to-noise ratio, we extended the detected decay periods until the next signif-  
 369 icant increase in  $V_{sm}$  ( $> 5\%$  of the corresponding seasonal amplitude of FVC). Note that  
 370 selection of the thresholds and the moving window sizes were based on extensive explo-  
 371 ration and visual inspection of the FVC time series. This was a necessary step to ensure  
 372 the robustness against noise in the data, as well to address the diversity of FVC dynam-  
 373 ics across African ecosystems. To highlight the complexity, some representative time se-  
 374 ries of FVC in selected grid cells across different climatological aridity are included in  
 375 Appendix B, together with soil moisture and precipitation time series.

376 After detection of all decay periods in the time series, we only selected the longest  
 377 one per calendar year. This is necessary for regions where vegetation may potentially  
 378 have two growing (and decaying) seasons within a year. The longest decay period within  
 379 a year is likely to be the most indicative of the largest water limitation, and the under-  
 380 lying ecohydrological mechanisms. When the detected decay period spanned over two  
 381 calendar years, it was assigned as the decay period of the starting year. In total, the de-  
 382 cay period detection algorithm (Algorithm 1) yielded 16,423,339 decay periods in 1,029,847  
 383 grid cells.

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**Algorithm 1** Detection of decay periods from the entire time series

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- 1: Smooth FVC time series with 31 days moving average; to yield  $V_{sm}$
  - 2: Calculate the first derivative of FVC time series from  $V_{sm}$  with daily step size; to yield  $V'$
  - 3: Through the entire time series, set the threshold for decay as  $th_{decay} = \text{percentile}(V', 75)$  where  $V' < 0$
  - 4: Through the entire time series, set the threshold for growth as  $th_{growth} = -1 \times \text{percentile}(V', 70)$  where  $V' < 0$
  - 5: Mark each observation for their corresponding period as:
    - if**  $V' < th_{decay}$  **then** decay
    - else if**  $V' > th_{growth}$  **then** growth
    - else** stable
  - 6: Smooth the classes with a 5-day moving window by majority voting
  - 7: Label consecutive observations marked with decay and followed by stable ones as *decay period*
  - 8: Extend every *decay period* label until  $V_{sm} > \min(V_{sm}) + 0.05 \times (\max(V_{sm}) - \min(V_{sm}))$  is satisfied in the corresponding season
  - 9: For each grid cell, keep only the longest *decay period* per year
- 

384 **3.3 Estimation of the Integral over FVC Decay**

385 We calculated the integral of FVC during decay period ( $I_{dp}$ ) as the total area un-  
 386 der the FVC time series from the start to end of the decay period, with the area under  
 387  $FVC_{min}$  removed. This can be expressed as,

$$I_{dp} = \sum^{decayperiod} (FVC(t) - FVC_{min}) \quad (1)$$

388 Removal of the baseline FVC value ( $FVC_{min}$ ) enhances the signal of seasonal de-  
 389 cay of vegetation with respect to baseline vegetation activity. Note that, upon necessity,  
 390 the full integral (total area under the curve) can be calculated as the sum of  $I_{dp}$  and mul-  
 391 tiplication of decay period duration with minimum FVC ( $D \times FVC_{min}$ ).

392 From the yearly dry season detection, 16 (the number of years) values of  $I_{dp}$  were  
 393 computed for each grid cell. We selected the median of the 16 values as the represen-  
 394 tative inference to be used for spatial analyses. The median was preferred over the mean  
 395 to make the estimation robust against annual variations, for instance, by intermittent  
 396 rain events in the dry season or issues related to FVC derivation. In addition, we also  
 397 calculate and report the normalised robust Standard Error ( $SE$ ) as an indicator of vari-  
 398 ability. The SE is calculated as,

$$SE = \frac{SD_n}{\sqrt{n}} \quad (2)$$

399 where  $SD_n$  is the robust standard error, calculated from the Median Absolute De-  
 400 viation (MAD) across years (with the assumption of a normal distribution, Rousseeuw  
 401 & Croux, 1993), and corrected for the low number of samples ( $n = 16$ ) as:

$$SD_n = MAD \times 1.4826 \times \frac{n}{n-1} \quad (3)$$

402 The robust standard error reflects variability of the metrics among years as well  
 403 as methodological uncertainty, and is therefore suitable for customised filtering in the  
 404 context of spatial analysis.

### 405 3.4 Estimation of FVC Decay Rate

406 Temporal decay of the FVC can be characterised using an exponential function as,

$$FVC(t) = (FVC_{dd} - FVC_{min}) \times e^{-t/\lambda} + FVC_{min} \quad (4)$$

407 where  $FVC_{dd}$  is the initial FVC value in the beginning of a dry-down, and  $\lambda$  is the  
 408  $e$ -folding time (in days). Note that  $\lambda$  is merely an inverse of the exponential decay rate.  
 409 The formulation in Eq. 4 uses  $\lambda$  as it is easier to interpret. In simple terms,  $\lambda$  denotes  
 410 the number of days needed to have a decrease in the seasonal amplitude of FVC ( $FVC_{dd} -$   
 411  $FVC_{min}$ ) to  $1/e$  of its original value during a dry-down event. Note that the selected  
 412 exponential decay function explicitly takes an asymptotic minimum value of the FVC,  
 413 as  $FVC_{min}$ , into account while estimating the decay rate (see Sec. 3.1) since  $FVC_{min}$   
 414 is included in the formulation (Eq. 4).

415 Due to the S-shaped character of temporal vegetation dynamics, functions allow-  
 416 ing different convexity, e.g., logistic functions, have been used to characterise these dy-  
 417 namics (Beck et al., 2006). As exponential decay functions are strictly convex, the con-  
 418 cave part of the decay, which is mostly observed in the beginning of the decay period,  
 419 is not considered for this metric. The latter part of the decay period, with convex cur-  
 420 vature (i.e.: the first derivative is negative while the second is positive), is labelled as ‘dry-  
 421 down’ during the decay period. To define the dry-down period, we first discarded the  
 422 time steps with concave observations (negative first and negative second derivative). Af-  
 423 terwards, we filtered out the convex observations before the inflection point of the FVC,  
 424 that mostly associated with low signal-to-noise ratio at the beginning of the dry-down.  
 425 Once daily observations are marked as convex or concave, we searched for local minimum  
 426 of  $V'$  in the first third of the dry season, and identified the inflection point as the start  
 427 of the dry-down. Note that, in the above process, second derivative of the FVC ( $V''$ ) was  
 428 also smoothed with a 31-day moving window.

429 This procedure effectively removes observations with concave shape in the dry sea-  
 430 son, especially at the beginning of an event. For each event, if more than half of the data  
 431 points showed convexity, we estimated  $\lambda$ , together with  $FVC_{dd}$ , based on an asymptotic

**Algorithm 2** Identification of dry-down periods and modelling of the exponential decay

- 1: Smooth  $V'$  with 31 days moving average; to yield  $V'_{sm}$
- 2: Calculate the second derivative of FVC time series from  $V'_{sm}$  with daily step size; to yield  $V''$
- 3: Smooth  $V''$  with 31 days moving average; to yield  $V''_{sm}$
- 4: Mark each observation with  $V'_{sm} < 0$  as:
  - if**  $V''_{sm} > 0$  **then** convex
  - else** concave
- 5: Ignore convex observations before the inflection point of FVC time series, if there is any
- 6: Ignore concave observations within the decay period and keep the rest as the dry-down period
- 7: Discard any event having more concave observations than convex
- 8: Use Eq. 4 on dry-down period of the decay period to estimate  $\lambda$
- 9: Filter out the estimations with  $NSE < 0.5$  OR  $SE(\lambda) > 0.5 \times \lambda$

432 regression model that minimises least squares error with the Levenberg–Marquardt  
 433 algorithm (Moré, 1978; Elzhov et al., 2016). We used both the Nash–Sutcliffe modelling  
 434 efficiency (NSE; Nash & Sutcliffe, 1970) and the standard error of the model ( $SE_m$ ) to  
 435 assess the estimates of the model fitting. From the multiple  $\lambda$  estimates, only those with  
 436 successful convergence of the Levenberg–Marquardt algorithm with  $NSE > 0.5$  and  $SE_m(\lambda) <$   
 437  $0.5 \times \lambda$  were accepted, the median of which was taken as the representative final  $\lambda$  for  
 438 a grid cell.

439 After defining the final  $\lambda$ , we estimated the variation as done in Sec. 3.3. Unlike  
 440 in Sec. 3.3, the sample size per grid cell ( $n$ ) may change, as  $\lambda$  estimation may not con-  
 441 verge in cases with high noise. We, therefore, also report the number of successful con-  
 442 vergences of the Algorithm 2 as an additional quality diagnostic that can be used for fil-  
 443 tering  $\lambda$  (mapped in Fig. H1).

## 444 4 Results and Discussion

445 In this section, we present and discuss the ecohydrological metrics derived in this  
 446 study. For each metric we show the spatial variation in continental scale by maps along  
 447 with zoomed inset plots (see Appendix E for further information and visual impression  
 448 by corresponding Google Earth cut-outs) to visualise regional variability. Box plots of  
 449 metrics per mean annual root-zone soil moisture show first order variations while heatmaps  
 450 show sensitivity of these first order variations to different parameters addressing the hy-  
 451 potheses given in Sec. 1 (see Sec. 2.2 for the details of the data). Here we present the  
 452 metrics independently, but we summarise their cross-comparison with a density plot in  
 453 Fig. C1.

### 454 4.1 FVC Extremes

455 Spatial distributions of  $FVC_{min}$  and  $FVC_{max}$ , histograms of the distribution over  
 456 the full domain, and six zoomed insets focusing on selected regions are shown in Fig. 2a  
 457 and 2b, respectively (see Fig. F1 for the seasonal dynamics expressed as  $FVC_{max} - FVC_{min}$ ).  
 458 At the continental scale, both  $FVC_{min}$  and  $FVC_{max}$  follow the moisture gradient with  
 459 the highest and the lowest values in humid and arid regions, respectively. Saturation in  
 460 the increase of  $FVC_{max}$  (Fig. 2c) in semi-arid regions suggests that water does not severely  
 461 limit the vegetation cover at the peak of the wet season in regions with intermediate to  
 462 high mean annual soil moisture values (see Fig. E1 for map of mean annual root-zone  
 463 soil moisture as an indicator of climatological aridity together with Google Earth views

of the insets). On the contrary,  $FVC_{min}$  stays low up to intermediate mean annual soil moisture and increases only slightly with it suggesting that water limits FVC severely at the peak of the dry season. Understandably, largest seasonal ranges in FVC are observed in regions with semi-arid climate systems.

In addition to the climate-associated large-scale gradients, the metrics also exhibit a substantial meso-scale heterogeneity. In arid regions,  $FVC_{min}$  is higher in areas closer to perennial water sources, as can be seen near the Senegal and Gambia rivers (Box-A in Fig. 2a).  $FVC_{min}$  is also elevated near large inland deltas and wetlands, i.e. the Okavango Delta (McCarthy, 2006) and the Sudd swamp (Tootchi et al., 2019), Box-D and Box-F in Fig. 2a, respectively, presumably indicating groundwater access by the vegetation in the dry season. Interestingly, the meso-scale spatial patterns differ remarkably between  $FVC_{min}$  and  $FVC_{max}$  with a tendency of  $FVC_{max}$  showing more spatial structure than  $FVC_{min}$ . This is likely because there is too little water input in the dry season to cause big topographic moisture effects for  $FVC_{min}$  except for the perennial secondary water sources. Thus, such meso-scale heterogeneity suggests the importance of secondary water sources in water-limited systems, especially on top of the large climate-driven spatial variations, and highlights the value of  $FVC_{min}$  and  $FVC_{max}$  for ecophysiological studies.

### Inverse Texture Effect

We further tested if an “inverse texture effect” (Noy-Meir, 1973) could be observed from 5 km spatial resolution remote sensing FVC data over continental Africa. In humid regions coarse textured soil is less favourable for vegetation than fine textured soil while in arid regions this pattern is inverted. This inverse texture effect has been documented by several site-scale studies (Sala et al., 1988; Laio et al., 2001; Fernandez-Illescas et al., 2001; Looney et al., 2012). Noy-Meir (1973) suggested this inversion to occur with precipitation values of 300–500 mm/year, although it has also been reported for higher precipitation values (Epstein et al., 1997). The inversion of the texture effect in arid climates is likely due to enhanced infiltration and hydraulic conductivity which reduced soil evaporation losses (Noy-Meir, 1973) and/or due to reduced water stress thanks to lower matrix potentials of sandy soils (Caylor et al., 2005).

We binned soil moisture and sand percentage values to have equal number of observations in each bin of a given variable, and calculated the mean of  $FVC_{min}$  or  $FVC_{max}$  per bin. The resulting heatmaps in Fig. 3 do not show clear patterns of an inverse texture effect where FVC would be expected to increase with sand content. In the driest regions with the lowest mean annual soil moisture level,  $FVC_{min}$  and  $FVC_{max}$  are slightly elevated for low sand content, consistent with the “normal” texture effect. For intermediate aridity levels, no clear and systematic pattern with sand content can be observed. It remains for further studies to clarify to what extent the “inverse texture effect” remains significant, which may be due to spatial resolution and quality of remote sensing data.

### Green Islands

Another phenomenon we investigated are the “green islands” patterns where localised moisture availability supports vegetation activity in otherwise dried down conditions. This approach has been used to detect groundwater dependent ecosystems (Münch & Conrad, 2007; Howard & Merrifield, 2010; Jin et al., 2011; Lv et al., 2013; Barron et al., 2014) or riparian corridors (Everitt & Deloach, 1990; Everitt et al., 1996; Neale, 1997; Akasheh et al., 2008) based on high spatial resolution remote sensing within relatively small regions. Here we analyse if such patterns due to secondary moisture sources are still evident at 5 km resolution and at continental scale by looking at the covariation of  $FVC_{min}$  and  $FVC_{max}$  with HAND and TWI, conditioned on mean aridity (Fig. 3). HAND is a hillslope scale proxy for groundwater accessibility (Fan et al., 2019) while TWI, a

metric considering local slope together with upstream area, is a strong proxy for topographic soil moisture variations (Raduła et al., 2018). Contrary to our expectations, we did not observe a positive effect of these secondary moisture resources in arid regions on  $FVC_{min}$  (Fig. 3a) but instead for  $FVC_{max}$  at high aridity levels (Fig. 3b). This implies that shallow water table support vegetation with additional moisture during the growing period as also shown in Koirala et al. (2017) but that this effect largely disappears in the dry season since most of the secondary moisture resource is also depleted or not available. This suggests that the effect of secondary moisture sources goes much beyond the frequently studied perennial “green islands” phenomenon and is likely more important in the wet rather than the dry season.

## 4.2 Integral of FVC Decay

Integral of FVC time series during decay period,  $I_{dp}$ , is smallest in arid regions, followed by humid regions while the largest  $I_{dp}$  values are observed in semi-arid regions (Fig. 4a). Median values, as well as variations of  $I_{dp}$  within similar climatology is larger when subject to intermediate aridity (Fig. 4c). Uncertainties are larger in some of the hyper-arid regions with low FVC and rare, episodic rainfall (Fig. 4b).

At local scales, variations in  $I_{dp}$  emerge as a combined effect of climate and other ecohydrological factors change over hillslope scales, such as proximity to the nearest drainage or occurrences of shallow water table depth. While a sharp aridity gradient in Sahel is clearly seen at Box-A and Box-B of Fig. 4a, local scale increases in  $I_{dp}$  are also present at riparian zones like Senegal River (Box-A in Fig. 4a). Within similar aridity,  $I_{dp}$  is smaller in seasonally flooding regions like the Sudd swamp (Tootchi et al., 2019), Box-F in Fig. 2a. The highest values of  $I_{dp}$  in the Lower Zambezi, bear strong similarity with the rooting depth product presented in Wang-Erlandsson et al. (2016), and the previously reported seasonal hydrologic buffer (Kuppel et al., 2017) in these regions. This motivates further analysis of  $I_{dp}$  with a plant accessible water storage perspective.

## Plant Accessible Water Storage

Conceptually, plant accessible water storage is related to the vertical distribution of roots, and the water holding capacity of the soil that is determined largely by texture and organic carbon content. The root profile of water-limited ecosystems appears to adapt to the prevailing hydrologic and soil conditions while being constrained by other ecosystem properties and traits (Guswa, 2008; van Wijk, 2011; Fan et al., 2017; Schenk, 2008; Schenk & Jackson, 2002; Laio et al., 2006). Plant accessible water storage controls the propensity and sensitivity of ecosystems to drought stress in dry periods. Various modelling approaches to infer rooting depth or plant water storage capacity have been proposed (explained in detail in Wang-Erlandsson et al., 2016), as it cannot be observed directly but still contains a critical information for global-scale models (Kleidon & Heimann, 1998).

The integral of FVC during dry season should be positively correlated with plant accessible water storage of the soil, as larger water storage would facilitate vegetation activity for longer period during water-limited conditions. The continental-scale patterns of  $I_{dp}$  (Fig. 4a) with the largest values in strongly seasonal semi-arid savanna systems of both hemispheres are qualitatively consistent with the previous observation-based analysis (e.g. Schenk & Jackson, 2002) as well as the optimality-based models (e.g. Kleidon & Heimann, 1998).  $I_{dp}$  declines in hyper-arid regions like the Sahel, Horn of Africa, Southern Africa, as well as the Congo rainforest. A similar pattern would be expected for optimal rooting depth, which increases in regions with small differences between rainfall and potential evaporation in annual scales but large differences in seasonal scales (Laio et al., 2006; van Wijk, 2011). The inset plots in Fig. 4a clearly reveal the landscape scale patterns of  $I_{dp}$ , presumably, due to topography-driven large variations of moisture. This may reflect enhanced and continued moisture supply due to topographic moisture con-

566 vergence or shallow water tables along with possible adaptations of rooting depth to these  
567 local hydrological conditions (Fan et al., 2017).

568 We compared  $I_{dp}$  with 4 products related to plant accessible water storage, namely  
569 two storage capacity products from Wang-Erlandsson et al. (2016) and S. Tian et al. (2019),  
570 and two rooting depth products from Yang et al. (2016) and Fan et al. (2017) at  $0.5^\circ$   
571 across Africa (see Sec. 2.2 for product details). As shown in Fig. 11, there is qualitative  
572 agreement of large values of  $I_{dp}$  with  $AWSC$  and  $RZSCRU2$  in the Miombo woodlands  
573 and, to a lesser extent, also in the northern savannas. All three also agree on low val-  
574 ues in hyper-arid regions like the Sahel, Horn of Africa and in Southern Africa. In or-  
575 der to quantify the extent of agreement among the five estimates, we made a pairwise  
576 comparison of Spearman’s correlation coefficient per climatological aridity via soil mois-  
577 ture (Fig. 6a). While the overall low-to-moderate correlation values among the products  
578 available in the literature demonstrate the scale of the challenge in estimating plant wa-  
579 ter storage capacity or rooting depth, highest correlation was observed between  $I_{dp}$  and  
580  $RZSCRU2$ . Regardless of the product pairs, correlations decrease with increasing humid-  
581 ity, which is presumably related with other limiting factors than water, such as radia-  
582 tion or nutrients.

583 All four independent products utilised meteorological input data for water balance  
584 estimation, and also use remotely-sensed vegetation products in some way. While  $RZSCRU2$   
585 and  $AWSC$  are constrained by hydrological Earth observations, the rooting depth prod-  
586 ucts  $RD$  and  $ERD$  originate largely from different assumptions of optimality and plant  
587 adaptation. Our comparison suggests that estimating plant accessible water storage based  
588 on Earth observation data may be more suitable than the presently-used optimality prin-  
589 ciples over the given resolution and domain of this study, despite the uncertainties of re-  
590 mote sensing data. Using  $I_{dp}$  as an indicator of plant accessible water storage has the  
591 advantage that it is derived from dense time series of a geostationary satellite alone, re-  
592 quiring no additional meteorological inputs or modelling assumptions that introduce their  
593 inherent uncertainties. Furthermore,  $I_{dp}$  features higher spatial resolution than most other  
594 storage capacity data, which provides insights on subsurface moisture variations at meso-  
595 scales.

### 596 4.3 Decay Rate of FVC

597 Similar to  $I_{dp}$ , the  $e$ -folding time ( $\lambda$ ), presented in Fig. 5a, also has a hump-shaped  
598 covariation with climatological aridity at continental scales. We find the lowest  $\lambda$  val-  
599 ues throughout the humid regions and partially in the arid regions, such as edges of the  
600 Sahara desert or the Horn of Africa, while the highest  $\lambda$  values are found in the semi-  
601 arid and arid regions. Though variation of  $\lambda$  (Fig. 5b) suggests that the low values of  
602  $\lambda$  in some hyper-arid regions are associated with higher uncertainty due to low signal-  
603 to-noise ratio.

604 Besides the coherent continental-scale spatial patterns,  $\lambda$  also has strong variations  
605 over meso-scales. Stronger lateral moisture convergence positively affects the  $\lambda$  in the  
606 arid regions, as seen in the Senegal (Box-A, Fig. 5a) and the Niger (partially in Box-B,  
607 Fig. 5a) rivers’ riparian zones in the arid climate. However, lateral moisture convergence  
608 does not always affect  $\lambda$  positively, as seen in the riparian zones of the Upper Zambezi  
609 and the Okavango rivers and their tributaries. Shown in Box-D in Fig. 5a,  $\lambda$  is high around  
610 the Cuando river, the Okavango Delta and the Linyanti swamp, but low in the Barotse  
611 Floodplain (see Cronberg et al. (1995); Zimba et al. (2018) for general information about  
612 the region). Such non-trivial patterns suggest the role of complex interactions between  
613 the vegetation traits and local moisture conditions (Fan et al., 2019), which also affect  
614  $\lambda$ .

### 615 $\lambda$ and Ecosystem Water Use

616  $\lambda$  can corroborate the rate of decrease of plant available water, ecosystem scale wa-  
 617 ter use efficiency, and the propensity to senescence. Ecosystems differ widely in their wa-  
 618 ter use strategies, from being water conservative – typically associated with strong down-  
 619 regulation of stomatal conductance with water deficiency – to aggressive exploitation of  
 620 water resources (Laio et al., 2001). Herbaceous plants are typically aggressive water users  
 621 and cease with the depletion of surface soil moisture. Woody plants risk cavitation and  
 622 death under severe water stress, and such, trees in places with frequent dry periods ben-  
 623 efit from a water saving strategy or senescence for prolonged periods. Konings and Gen-  
 624 tine (2017) inferred ecosystem water-use strategies globally based on diurnal variations  
 625 of vegetation optical depth assuming that those reflect stomatal regulation to maintain  
 626 leaf-water potential. They found an increase in isohydricity, i.e. the degree of stomatal  
 627 regulation and subsequent water savings, with increase in vegetation height, consistent  
 628 with the need of tall trees to prevent hydraulic failure during drought. Teuling et al. (2006)  
 629 characterised decay rate in land evaporation (soil evaporation and transpiration) under  
 630 water limitation using flux tower measurements and found that sites with stronger sea-  
 631 sonality and larger woody coverage have slower decays. This association is confirmed by  
 632 similar studies, for seasonality and canopy height (Boese et al., 2019), and for trees than  
 633 grasses (Martínez-de la Torre et al., 2019). Slower decay of land evaporation of taller/woody  
 634 canopy despite the faster decay of soil moisture with stronger aridity (McColl et al., 2017)  
 635 suggests reduced transpiration or other plant adaptation mechanisms.

636 If the rate of FVC decay was also related to ecosystems’ water use strategy in a  
 637 similar manner, we would expect slower FVC decay (higher  $\lambda$ ) with increasing canopy  
 638 height. In arid and semi-arid regions, we indeed find a tendency of increasing  $\lambda$  with canopy  
 639 height except very tall canopy (Fig. 6b), suggesting that  $\lambda$  incorporates ecosystem wa-  
 640 ter use strategy traits as well as direct or indirect effects of soil moisture therein. How-  
 641 ever, as the climate gets wetter  $\lambda$  tends to decrease with canopy height. A possible ex-  
 642 planation would be the changes in the drought coping strategies in ecosystem scale (Singh  
 643 et al., 2020), or that water consumption, i.e. transpiration, increases with canopy height  
 644 resulting in a faster depletion of moisture storage (Koirala et al., 2017), or increasing ecosys-  
 645 tem water use efficiency with aridity.

646 Sensitivity of the nonlinear relationship between  $\lambda$  and climatological aridity to tree  
 647 cover (see Fig. 6b) shows that  $\lambda$  systematically increases with larger tree cover values  
 648 in arid and semi-arid systems, with peak values observed in semi-arid regions with 26–  
 649 43% of tree cover which overlaps with the reported interval for the transition between  
 650 highly water-stressed forest and savanna (Singh et al., 2020). However this trend is in-  
 651 verted moving towards regions with weaker water-stress, hence denser tree cover, which  
 652 agrees with Singh et al. (2020) as moderately or lowly water-stressed forests do not de-  
 653 velop strong adaptation against water limitation, nor change canopy structure. The agree-  
 654 ment among these two studies having different methodologies shows the value of the observation-  
 655 driven metric  $\lambda$  to gain ecohydrological insights and have a better understand in vegetation-  
 656 water dynamics.

## 657 5 Conclusions

658 Using retrievals of the SEVIRI sensor of the geostationary satellite MSG, we de-  
 659 rived ecohydrological metrics for continental Africa entirely from the temporal dynam-  
 660 ics of the daily Fraction of Vegetation Cover (FVC) time series from 2004 to 2019 at ca.  
 661 5 km (0.0417°) spatial resolution. Our metrics captures both continental scale gradients  
 662 and covariations with climate as well as structured regional variations, e.g. due to to-  
 663 pographic factors. This provides an unprecedented opportunity to improve our under-  
 664 standing of ecohydrological processes across spatial scales over Africa.

665 The minimum asymptotic value of vegetation cover ( $FVC_{min}$ ) can be used to di-  
 666 agnose riparian corridors, seasonal wetlands and floodplains in arid and semi-arid regions

667 with its structured spatial variations over meso-scales. The maximum asymptote of FVC  
 668 ( $FVC_{max}$ ) shows enhanced vegetation growth in arid and semi-arid regions where ecosys-  
 669 tem benefits from shallow groundwater or larger runoff. Therefore,  $FVC_{max}$  may be used  
 670 to diagnose the effect of secondary water resources in semi-arid regions in meso-scales.  
 671 At continental scales,  $FVC_{min}$  did not show a clear pattern neither for “inverse texture  
 672 effect” nor “green islands”, which motivates further studies to understand the extent of  
 673 such local scale processes over large domains, using remote sensing. However, we observed  
 674 positive effect of proximity to groundwater and runoff potential on  $FVC_{max}$  on arid re-  
 675 gions as “green islands”, which suggests  $FVC_{max}$  can reveal importance of secondary  
 676 water resources in growing seasons in arid regions.

677 The integral of FVC time series in decay period ( $I_{dp}$ ) can be used to diagnose the  
 678 buffering capacity of vegetation on moisture limitation and shows broad consistency with  
 679 inferred variations of the plant storage capacity or rooting depth. Since plant accessi-  
 680 ble water storage is an important, also an uncertain, aspect in ecohydrology,  $I_{dp}$  may help  
 681 understand and model ecohydrological processes more accurately. The spatial patterns  
 682 of  $I_{dp}$  may be used to analyse plant water storage capacity in ecohydrological models and  
 683 improve simplistic approaches where this varies only with vegetation type and soil.

684 The last metric presented in this study, the  $e$ -folding time of vegetation cover dur-  
 685 ing dry-down ( $\lambda$ ), reveals the seasonal decay rate of vegetation, which – in the case of  
 686 water-limited regions – emerges from the complex ecohydrological interactions between  
 687 moisture availability and vegetation. Both the continental scale patterns against arid-  
 688 ity and its sensitivity to canopy height and tree cover of  $\lambda$  agrees with the plant adap-  
 689 tation strategies proposed in the literature. This provides a consistent diagnostic power  
 690 on vegetation water interactions over the African continent. Moreover, strong and struc-  
 691 tured variations of  $\lambda$  at meso-scales motivate in-depth analyses of the metric to resolve  
 692 ecohydrological interactions at finer scales, yet over a continental gradient.

693 Overall, given the the large amount of information stored in spatial variations of  
 694 the metrics reflecting different driving mechanisms across spatial scales, the metrics have  
 695 great potential to improve our understanding on vegetation dynamics on: (i) testing hy-  
 696 potheses on understanding relevance of local-scale ecohydrological processes over large  
 697 domains like continental Africa, (ii) better understanding basic ecosystem properties like  
 698 water usage in ecosystem scale and diagnosing their driving factors, and (iii) extracting  
 699 information and reducing uncertainty on concepts like plant water storage capacity. There  
 700 remain multiple opportunities for further synergistic exploitation with retrievals of sur-  
 701 face temperature from geostationary satellites which could provide complementary in-  
 702 dicators on variations of moisture states inferred from an energy balance perspective. The  
 703 suggested algorithms for deriving the metrics and the provision of the code facilitates  
 704 consistent parallel assessments and helps overcome the technical difficulties of dealing  
 705 with large volumes of data and the particularities of vegetation cover retrievals from the  
 706 geostationary satellites.

## 707 **6 Data and Code Availability Statement**

708 All ecohydrological metrics presented in this study are available in standardised  
 709 netCDF data format in <https://doi.org/10.6084/m9.figshare.14987211.v1>, together  
 710 with their quality diagnostics.

711 The R scripts developed for the implementation of the methodology are available  
 712 for research uses. They can be accessed through [https://github.com/caglarkucuk/  
 713 EcohydroMetricsAfrica.git](https://github.com/caglarkucuk/EcohydroMetricsAfrica.git).

714 All the data used in this study are available in the cited literature (see Sec. 2), ex-  
 715 cept the AWSC data from S. Tian et al. (2019) which was obtained from the correspond-  
 716 ing author.

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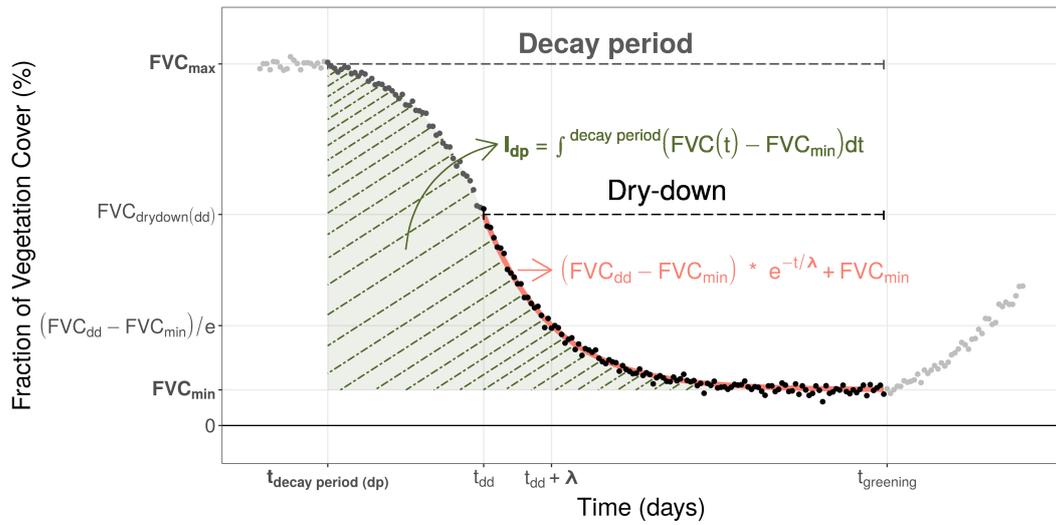


Figure 1: Conceptual plot of the ecohydrological metrics derived from time series using synthetic data. Points represent observations for growing period, early decay period and decay period with dry-down in light grey, grey and black, respectively. Decay and growth periods are defined by presence of decay, i.e., first derivative of the time series, while dry-down period is defined by the convexity of the decay, i.e., using both first and second derivatives (see Sec. 3.4 for details). The shaded area shows the integral of FVC during decay period. The red curve shows the fitted line on the FVC time series during dry-down using the asymptotic exponential decay function. All metrics presented in this study are shown in bold characters.

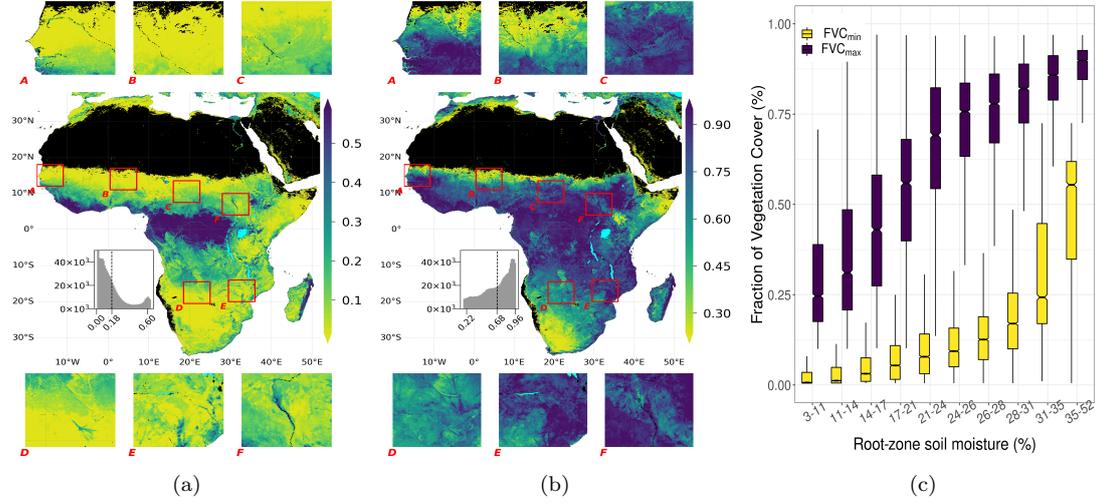


Figure 2: (a) Minimum asymptotic values of FVC,  $FVC_{min}$ , (b) maximum asymptotic values of FVC,  $FVC_{max}$ , (c) box plot showing the variation of  $FVC_{min}$  and  $FVC_{max}$  with mean annual soil moisture. In the maps, histogram of the metrics mapped can be seen inside the main panel, with a dashed line indicating the mean values of the domain, as well as six insets to show local variability (See Appendix E for details of the insets). In all of the following box plots, binning of soil moisture is done automatically to equalise frequency of observations among the bins while median values per each bin are shown in the intermediate line of the boxes, with their 95 % confidence intervals notched. Upper and lower edges of the boxes show the interquartile range (75th and 25th percentiles, respectively) while the error bars show 1.5 times the interquartile range.

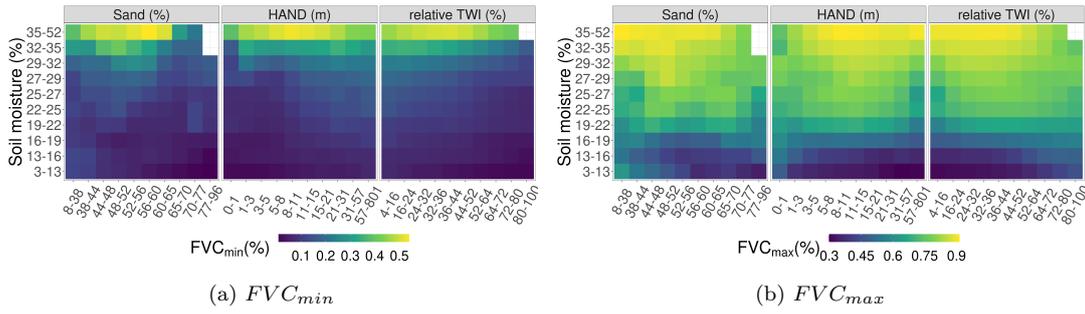


Figure 3: Covariation of asymptote-related metrics and root-zone soil moisture with sand percentage, HAND, and TWI. Note that binning of the continuous variables in x- and y-axes are done automatically to equalise frequency of observations among the bins of a given variable.

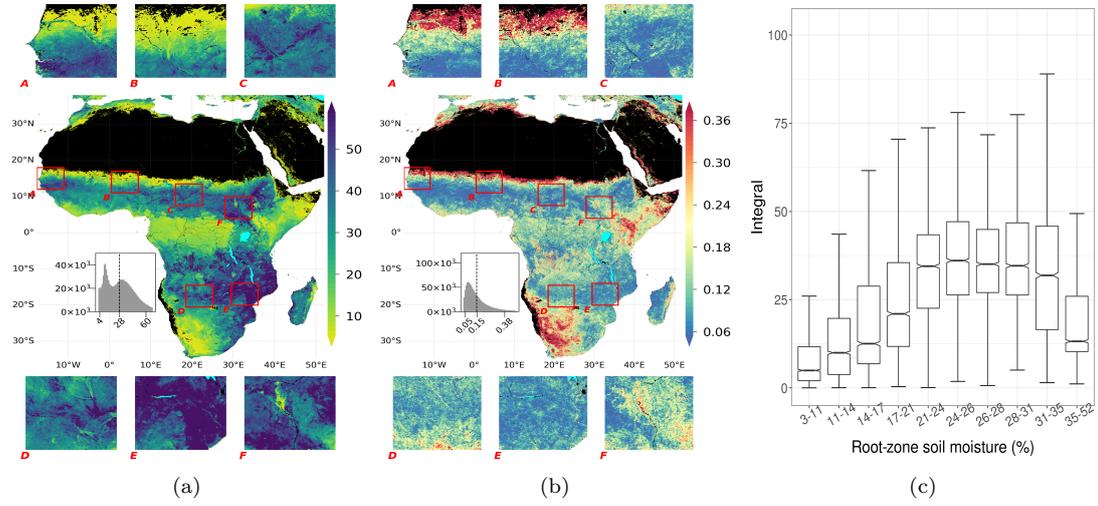


Figure 4: (a) Integral of FVC time series in the decay period,  $I_{dp}$ , (b) variation of  $I_{dp}$ , (c) distribution of  $I_{dp}$  within mean annual soil moisture. See Fig. 2 for plotting details.

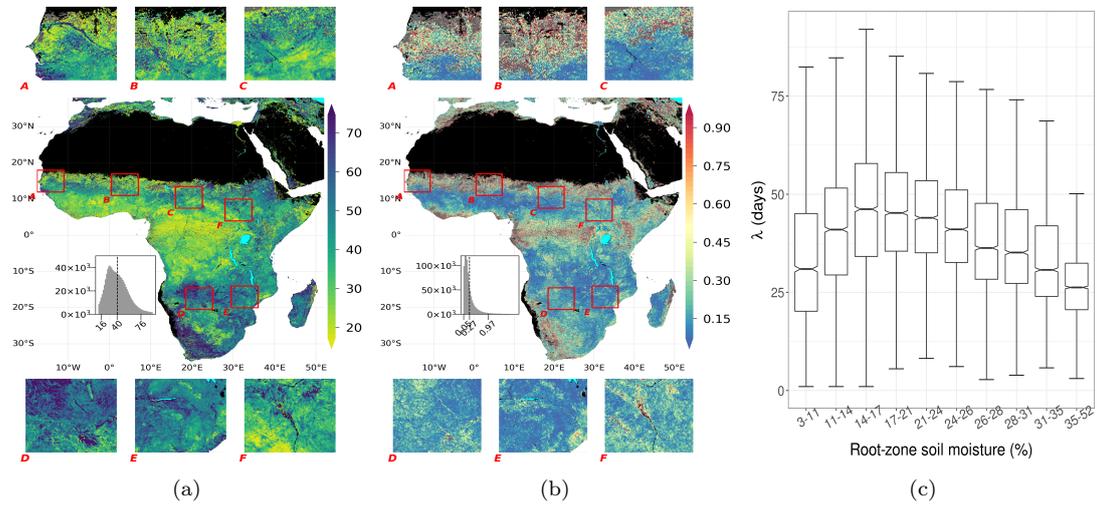


Figure 5: (a) e-folding time of FVC time series during dry-down (in days),  $\lambda$ , (b) variation of  $\lambda$ , (c) distribution of  $\lambda$  within soil moisture. See Fig. 2 for plotting details.

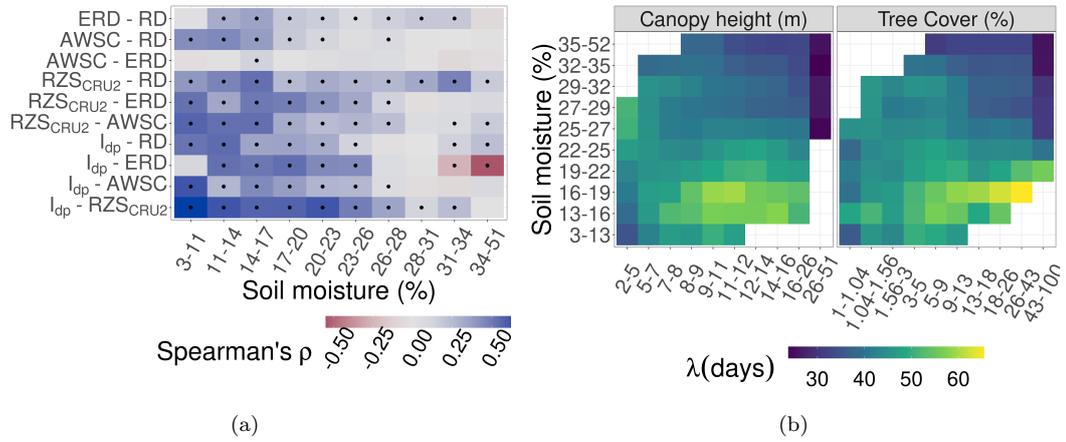


Figure 6: (a) Spearman's correlation coefficients between pairs of products related to plant accessible water content, namely Effective Rooting Depth (ERD) from Yang et al. (2016), Rooting Depth (RD) from Fan et al. (2017), Accessible Water Storage Capacity (AWSC) from S. Tian et al. (2019), Root Zone Storage Capacity ( $RZS_{CRU2}$ ) from Wang-Erlandsson et al. (2016), and integral of FVC during decay period ( $I_{dp}$ ) presented in this study. Black dots indicate significant correlation with  $\rho > 0.05$ . (b) Covariation of  $\lambda$  and root-zone soil moisture with canopy height, and tree cover. Note that binning of soil moisture, canopy height and tree cover are done automatically to equalise frequency of observations among the bins of the given variable.

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## Appendix A An Example Map of the Original FVC Data for a Single Day

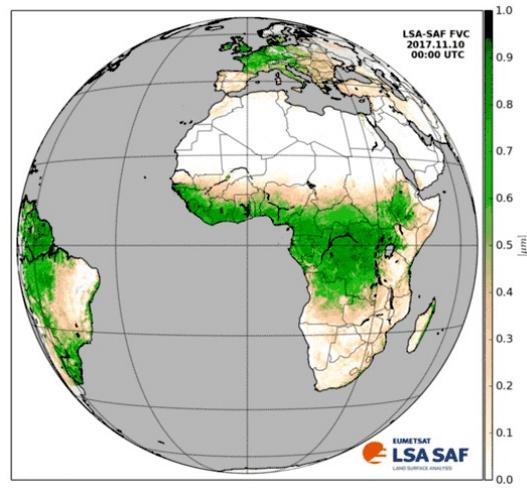


Figure A1: The original FVC data product for a single day, taken from <https://landsaf.ipma.pt/en/products/vegetation/fvc/>

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**Appendix B Time Series of FVC in Example Grid Cells**

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In this subsection; we present 5 years time series of selected grid cells from each bin of mean annual soil moisture values given in the main manuscript to demonstrate the results of the algorithms in grid cell scale.

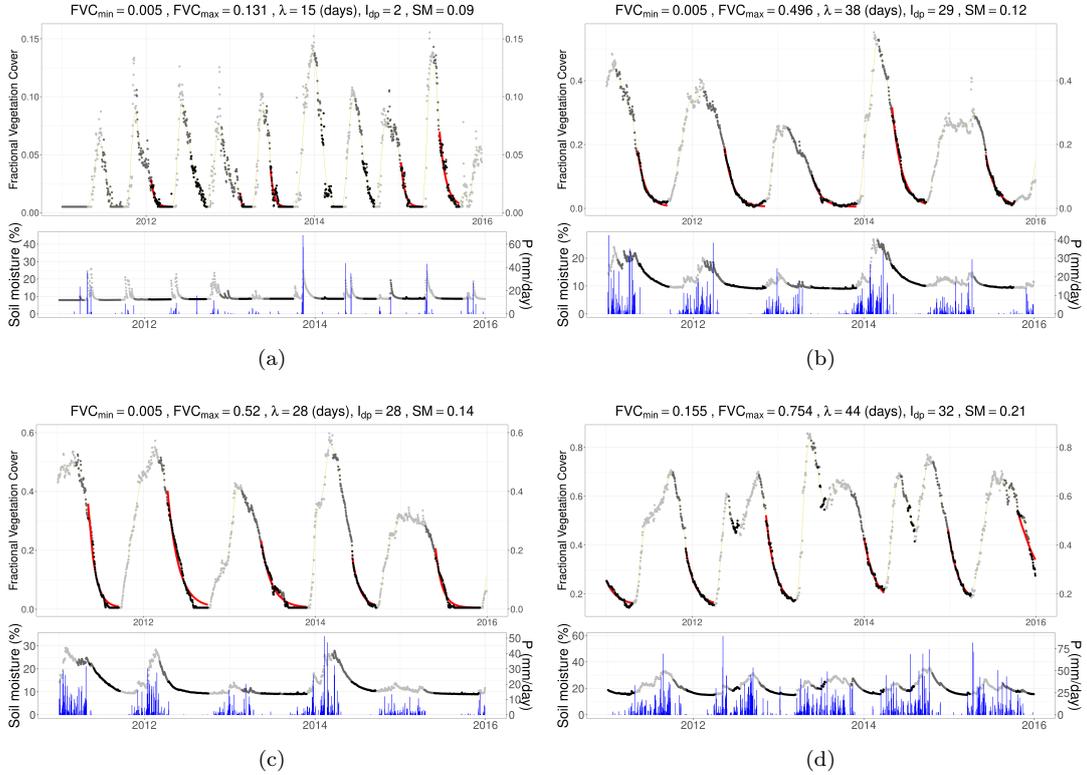


Figure B1: FVC, soil moisture, and precipitation time series of sampled grid cells. Sampling is done to have one grid cell per each bin of soil moisture values given in the plots of the main manuscript. Points for both FVC and soil moisture are coloured according to the state of vegetation activity as growing period is shown in light grey, decay period with dark grey while dry-down during the decay period is shown in black. Fitted curve to estimate  $\lambda$  is shown with red lines while 31-day smoothed FVC values are shown in orange lines at the upper panel, while daily precipitation values are shown with blue bars at the lower panel. Note that daily aggregated precipitation data is obtained from Tropical Rainfall Measuring Mission (TRMM) (2011).

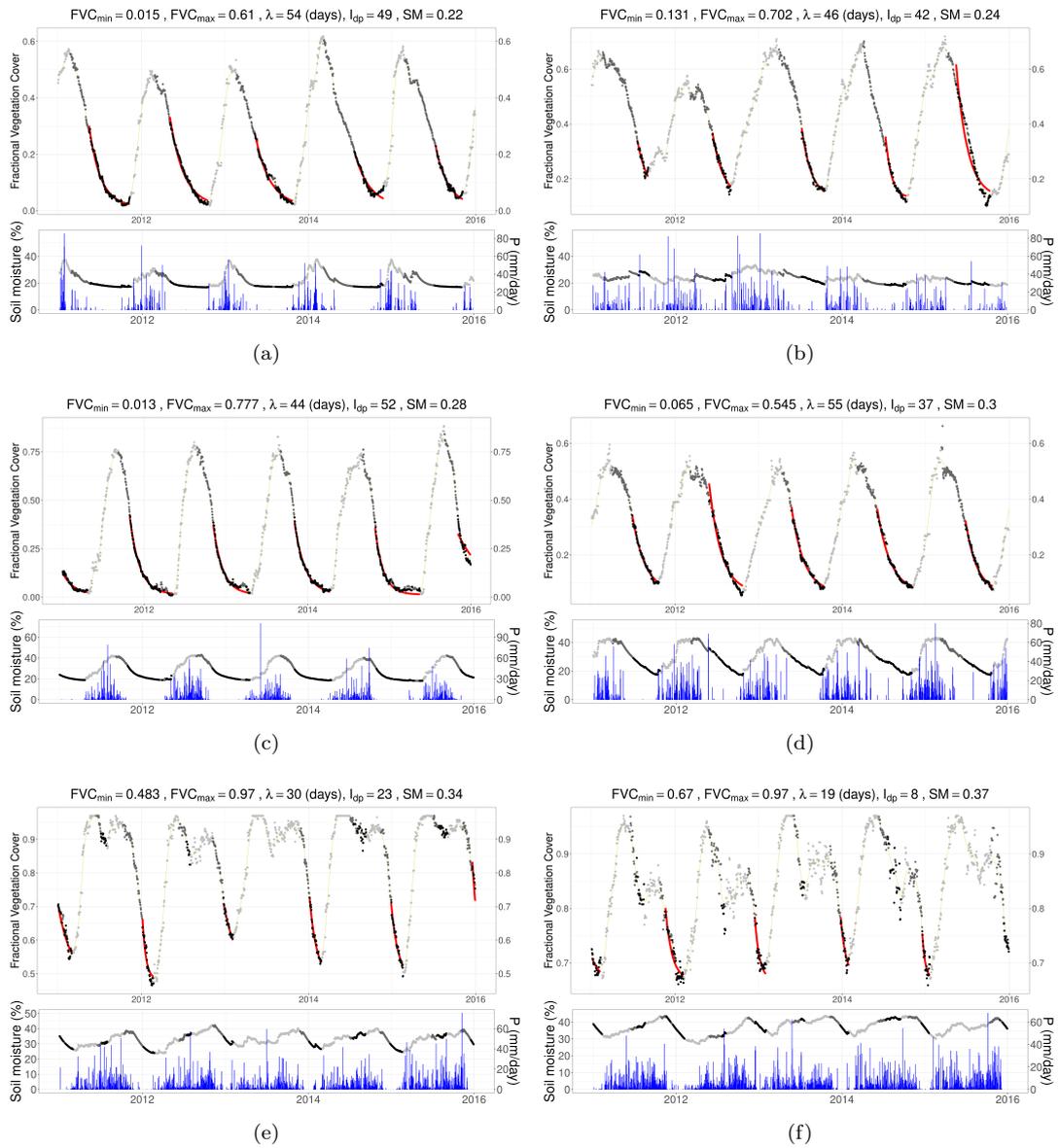


Figure B2: Continuation of Fig. B1 with samples having larger mean annual soil moisture.

## Appendix C Density Plots of the Ecohydrological Metrics

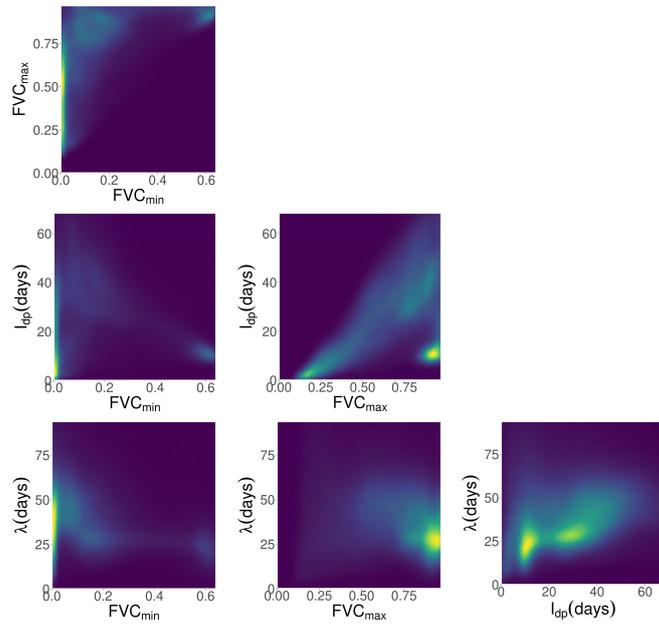


Figure C1: Density plots of the ecohydrological metrics presented in this study.

## Appendix D Temporal Correlation Between FVC and Soil Moisture

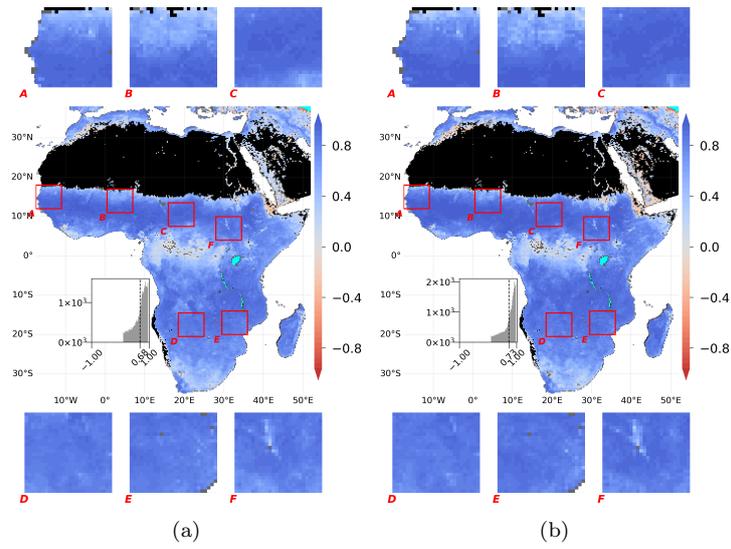


Figure D1: Pixelwise Spearman's correlation of FVC and GLEAM root-zone soil moisture in time for (a) entire time series, (b) time series marked as decay period using FVC.

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## Appendix E Map of Climatological Aridity and Google Earth View of Insets

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Fig. E1 shows the continental map of mean annual root-zone soil moisture (%) from GLEAM and the Google Earth views of the insets. Note that soil moisture values are binned to have equal number of observations in each class. Box-A: the Gambia and large portion of the Senegal rivers; Box-B: a small area of the Niger river mostly showing the transition from the Sahara desert to Sahel; Box-C: more on the transition from Sahel to tropical regions; Box-D: located in one of the most complex regions of Africa in terms of topography and lateral flow of water with lower sections of the Okavango and the Cuando rivers and upper section of the Zambezi river, together with multiple seasonally flooding areas like the Okavango delta, the Barotse Floodplain, and the Linyanti swamp. These seasonal wetlands are vital for the ecosystem and also provides great support against water limitation and heat for not only plants but also animals; Box-E: Lower Zambezi Basin together with the drainage of Lake Malawi to Zambezi. It also covers the Inyanga mountains located between Mozambique and Zimbabwe where a climatic shift happens over the mountain range. Last but not least, Box-F: largely covered by tropical savanna, is divided by the White Nile from South to North, covers the Sudd swamp.

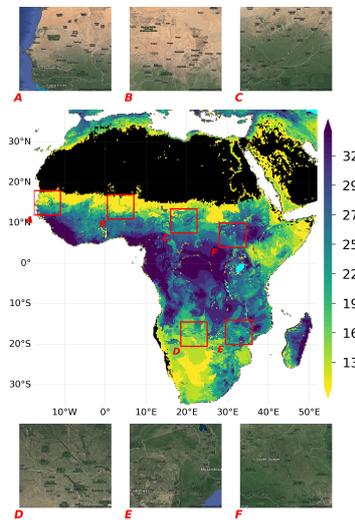


Figure E1: Map of mean annual root-zone soil moisture (%) in the centre and satellite view of the insets. Map and image data of the insets: Google Earth ©2020 TerraMetrics.

**Appendix F Summary of Seasonal Dynamics of FVC,  $FVC_{range}$**

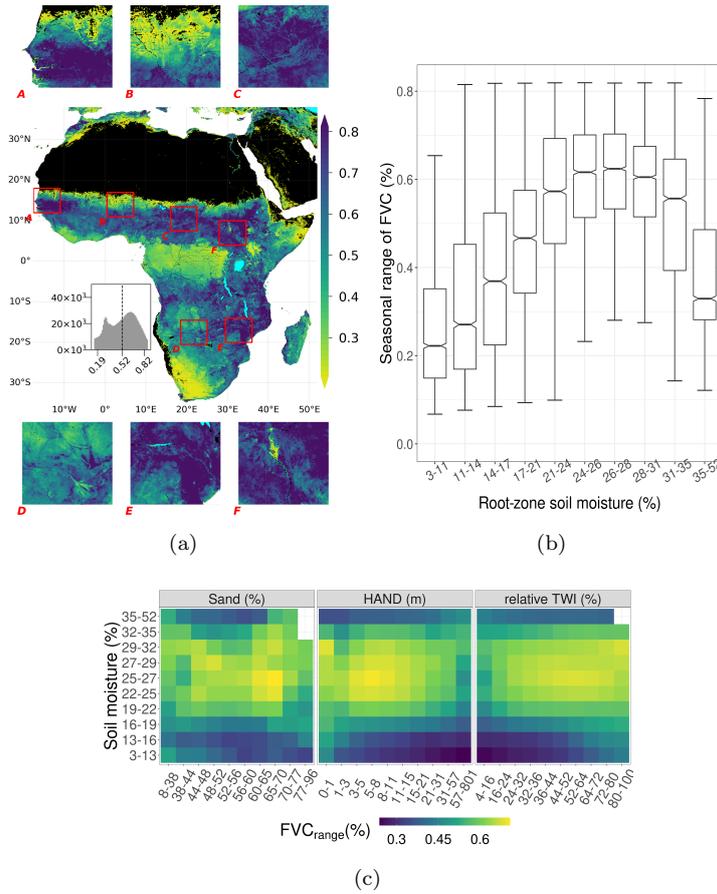


Figure F1: Variations in  $FVC_{range}$  (as  $FVC_{max} - FVC_{min}$ ) (a) in space (b) with climatological aridity (c) similar to Fig. 3a but for  $FVC_{range}$

748 **Appendix G Map of  $I_{dp}$  Normalised by Event Duration**

749 In order to see the effect of event duration to  $I_{dp}$ , we normalised the  $I_{dp}$  values with  
 750 the duration of the specific event  $I_{dp}$  is estimated. Even though spatial patterns remained  
 751 largely the same after normalisation, they became more pronounced in the East Suda-  
 752 nian Savanna and Miombo woodlands in the Southern Africa. Spatial distribution of the  
 753 normalised  $I_{dp}$  is mapped, together with its covariation with soil moisture and the origi-  
 754 nal  $I_{dp}$  is shown in Fig. G1. Note that duration of the event necessary to make the nor-  
 755 malisation is available in the corresponding netCDF file of the metrics (see Sec. 6).

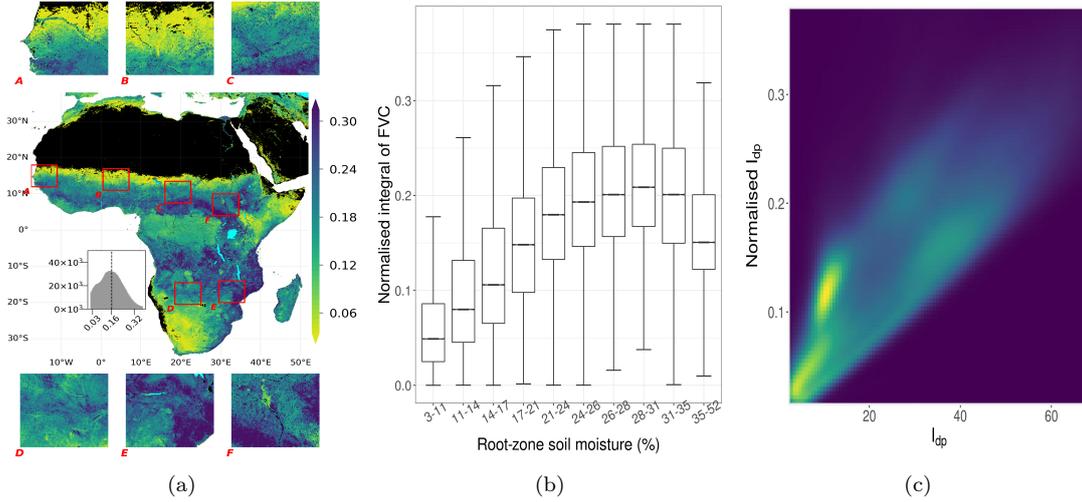


Figure G1: Integral of FVC time series in the decay period normalised by event duration (a) Spatial variation, (b) variation against within mean annual soil moisture (see Fig. 2c for plotting details). (c) density plot against  $I_{dp}$

756 **Appendix H Map of Number of Convergences of Algorithm 2**

757 **Appendix I Maps of Accessible Water Storage Capacity Datasets**

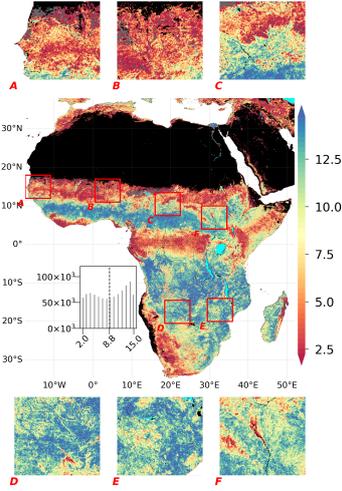


Figure H1: Number of decay periods in which the Algorithm 2 successfully converged.

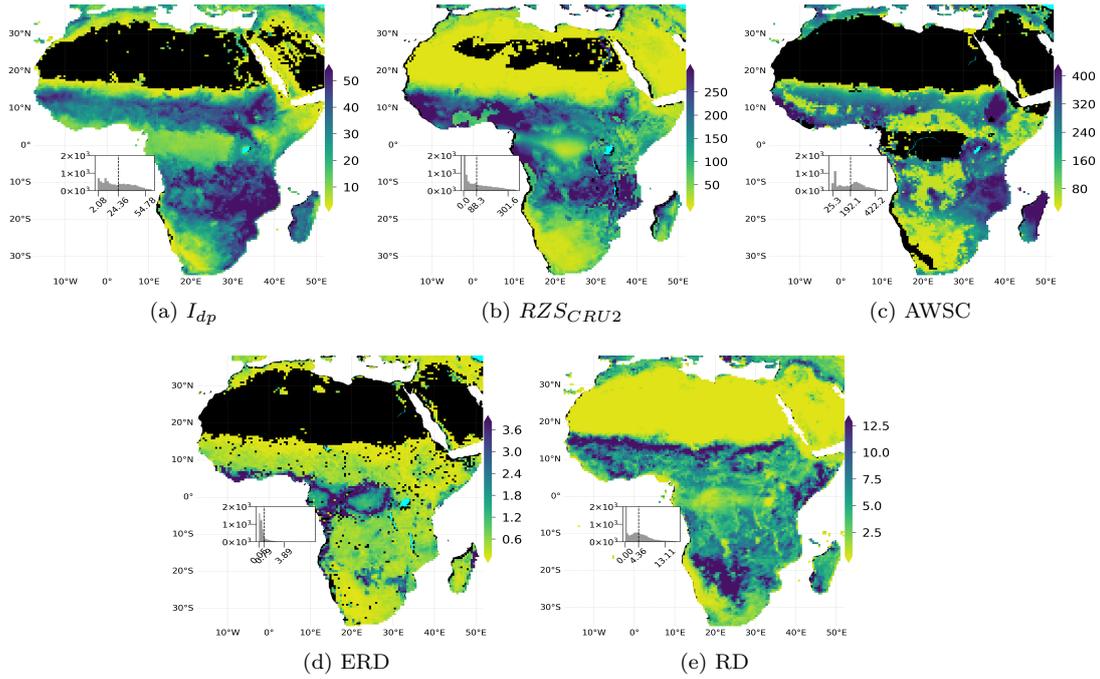


Figure I1: Maps of accessible water storage capacity and rooting depth datasets used in this study. (a) Integral of FVC during decay period,  $I_{dp}$ , (b) Root Zone Storage Capacity ( $RZSCR_{CRU2}$ ) using CRU as precipitation forcing data with 2 years of drought return period from Wang-Erlandsson et al. (2016), (c) Accessible Water Storage Capacity (AWSC) from S. Tian et al. (2019) (d) Effective Rooting Depth (ERD) from Yang et al. (2016), (e) Rooting Depth (RD) from Fan et al. (2017). All products are aggregated to  $0.5^\circ$  and cropped for the study domain.

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