

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

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Abstract

Plant available water is a key driver of ecosystem processes in water-limited systems. The interactions between vegetation, soil moisture, groundwater, and lateral redistribution of moisture in landscapes are complex and very heterogeneous. This complexity, together with the scarcity of relevant observations, creates a major obstacle for large-scale ecohydrological analysis and modelling. Here we exploit recent advancements in remote sensing at high spatial and temporal resolutions to extract relevant information on ecohydrological functioning. Our approach focuses on characterising vegetation dynamics along the seasonal wet to dry season transition, i.e. with progressive water limitation.

We present a set of observation-based metrics to characterise ecohydrological patterns across Africa at 0.0417{degree sign} spatial resolution. These are derived from the daily time series of Fraction of Vegetation Cover (FVC) over the period 2004-2019 from the geostationary satellite Meteosat Second Generation. The metrics include (i) minimum and maximum FVC, (ii) start day, duration, and FVC integral of the dry season, and (iii) the decay rate of FVC during dry-down. The metrics reflect the potential state, temporal extent, and evolution of the limiting factors of FVC, which, in Africa, are predominantly associated with water availability. They provide information on the relevance of secondary moisture sources such as ground water access or ecohydrological buffering due to deep rooting. Analysis of the metrics reveals large-scale gradients with aridity, as well as regional patterns associated with topographic moisture variations. Our observation-based products have large potential for better understanding and modelling the complex vegetation-water interactions from regional to continental scales.

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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

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

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

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

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

Previous studies, therefore, provide clear evidence that vegetation functions are controlled 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° (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° 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°
 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° 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°).

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° ,
 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-

ues in the normalised TWI means larger potential runoff due to topographic complexity.

Accessible Water Storage Capacity and Rooting Depth

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

In addition, the Rooting Depth (RD) product from Fan et al. (2017) is also used in this study. RD is estimated with inverse modelling of root water uptake profiles in three steps, where first soil water profile, as the supply, is estimated using climate, soil properties and topography. Thanks to the availability of high-resolution information on soil and topography, RD has a much higher spatial resolution (0.0083° , ca. 1 km) than the other products. After estimation of plant water demand using atmospheric conditions and leaf area index, the supply is allocated as root water uptake using Ohm's law at different soil depths, where amount of infiltration, groundwater recharge, and subsequent uptake were effected (Fan et al., 2017). Note that the model includes multiple forcing data, with a temporal coverage from 1979 to the time of the study.

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

The forth and last product used to analyse plant accessible water storage capacity is the Root Zone Storage capacity ($RZSCR_{2}$, Wang-Erlandsson et al., 2016) product derived by contrasting water fluxes observed by remote sensing, precipitation and irrigation as influx, and evaporation as outflux. Owing the assumption that plants develop their roots to optimise their root zone storage capacity, and using a simple approach on water fluxes, Wang-Erlandsson et al. (2016) did not use any external information on vegetation or soil properties. While different precipitation data are used as forcing data with different drought return periods, we used the final product forced by Climate Research Unit precipitation data (CRU TS3.22, Harris et al., 2014) with the shortest return period, 2 year. $RZSCR_{2}$, which is derived using data from 2003 to 2013, is available at 0.5° spatial resolution.

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

Canopy Height

318 Since canopy height is an important indicator of ecosystem functions and is asso-
 319 ciated mostly with water limitation (Tao et al., 2016), we analysed the effects of canopy
 320 height on the decay rate of vegetation cover through their covariation in space. We used
 321 the lidar-derived canopy height data from the retrievals of the ICESat satellite at a spa-
 322 tial resolution of 1 km (Simard et al., 2011). We used the data after aggregating (sim-
 323 ple average) to 0.0417° .

324 **Tree Cover**

325 We used tree cover data in order to analyse the sensitivity between the relation-
 326 ship of decay rate of FVC and climatological aridity. We used the tree percent compo-
 327 nent of the MOD44B Version 6 Vegetation Continuous Fields from MODIS (Dimiceli et
 328 al., 2015), which is available globally in 250 meter spatial and annual temporal resolu-
 329 tion. We aggregated the product in space to the target resolution of this study by tak-
 330 ing the mean of higher resolution grid cells. Finally, we used the median tree cover value
 331 over the years covering the temporal domain of FVC data to obtain a time invariant met-
 332 ric, same approach taken for the annual estimates of the metrics derived from FVC (see
 333 Sec. 3).

334 **3 Methodology**

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

342 **3.1 Masking and Retrieval of FVC Extrema**

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

350 **3.2 Detection of Decay Periods**

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

361 An observation was considered as decay if $V' < th_{decay}$, growth if $V' > th_{growth}$,
 362 and stable if $th_{decay} \leq V' \leq th_{growth}$. The resulting time series of classes (decay, growth,
 363 or recovery) were then smoothed by retaining the majority of decay and stable against
 364 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.

Algorithm 1 Detection of decay periods from the entire time series

- 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 λ is the
 408 e -folding time (in days). Note that λ is merely an inverse of the exponential decay rate.
 409 The formulation in Eq. 4 uses λ as it is easier to interpret. In simple terms, λ 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 λ , 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 λ
- 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 λ 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 λ for
 438 a grid cell.

439 After defining the final λ , 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 λ 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 λ (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°
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 (λ), presented in Fig. 5a, also has a hump-shaped
598 covariation with climatological aridity at continental scales. We find the lowest λ 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 λ values are found in the semi-
601 arid and arid regions. Though variation of λ (Fig. 5b) suggests that the low values of
602 λ 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, λ also has strong variations
605 over meso-scales. Stronger lateral moisture convergence positively affects the λ 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 λ 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, λ 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 λ .

615 λ and Ecosystem Water Use

616 λ 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 λ) with increasing canopy
 638 height. In arid and semi-arid regions, we indeed find a tendency of increasing λ with canopy
 639 height except very tall canopy (Fig. 6b), suggesting that λ 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 λ 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 λ and climatological aridity to tree
 647 cover (see Fig. 6b) shows that λ 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 λ 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

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

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

The last metric presented in this study, the e -folding time of vegetation cover during dry-down (λ), reveals the seasonal decay rate of vegetation, which – in the case of water-limited regions – emerges from the complex ecohydrological interactions between moisture availability and vegetation. Both the continental scale patterns against aridity and its sensitivity to canopy height and tree cover of λ agrees with the plant adaptation strategies proposed in the literature. This provides a consistent diagnostic power on vegetation water interactions over the African continent. Moreover, strong and structured variations of λ at meso-scales motivate in-depth analyses of the metric to resolve ecohydrological interactions at finer scales, yet over a continental gradient.

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

6 Data and Code Availability Statement

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

The R scripts developed for the implementation of the methodology are available for research uses. They can be accessed through <https://github.com/caglarkucuk/EcoHydroMetricsAfrica.git>.

All the data used in this study are available in the cited literature (see Sec. 2), except the AWSC data from S. Tian et al. (2019) which was obtained from the corresponding author.

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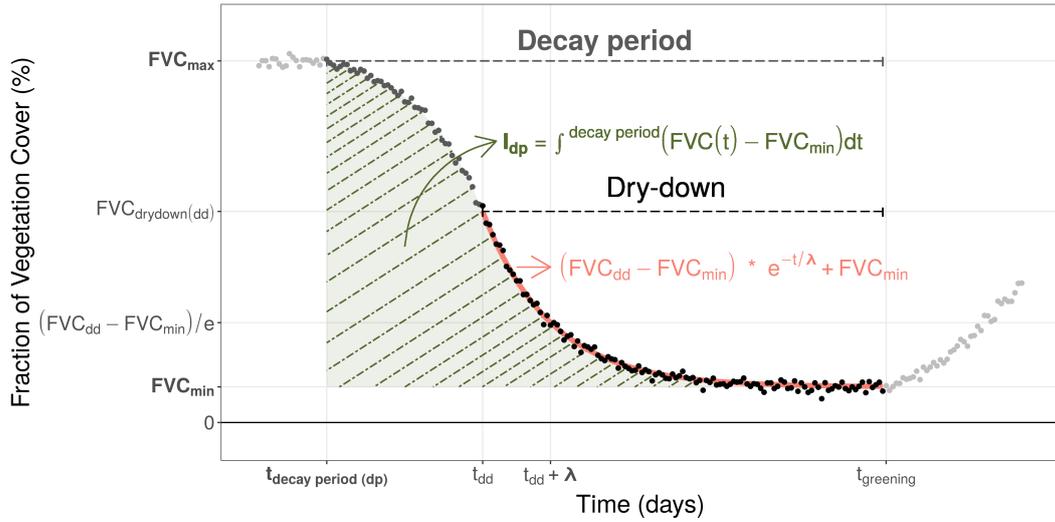


Figure 1: Conceptual plot of the ecohydrological metrics derived from time series using synthetic data. Points represent observations for growing period, early decay period and decay period with dry-down in light grey, grey and black, respectively. Decay and growth periods are defined by presence of 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.

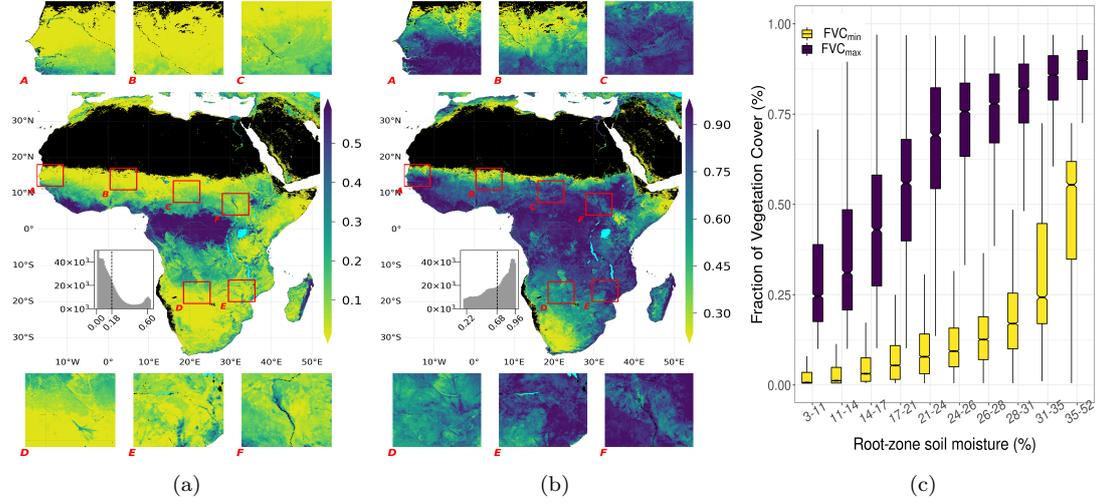


Figure 2: (a) Minimum asymptotic values of FVC, FVC_{min} , (b) maximum asymptotic values of FVC, FVC_{max} , (c) box plot showing the variation of FVC_{min} and FVC_{max} with mean annual soil moisture. In the maps, histogram of the metrics mapped can be seen inside the main panel, with a dashed line 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.

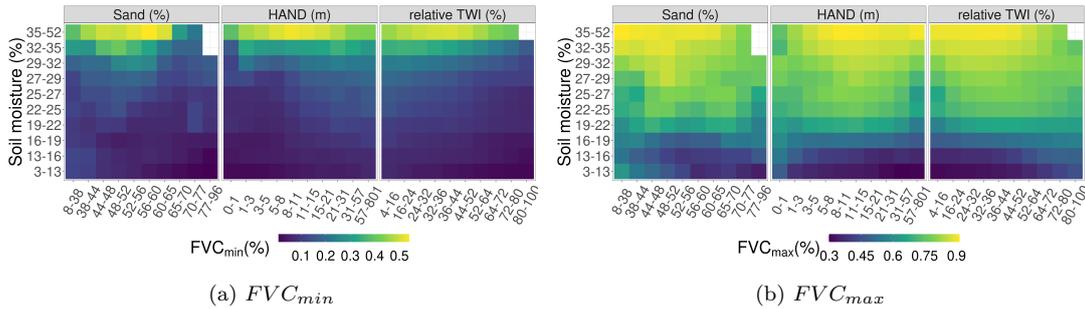


Figure 3: Covariation of asymptote-related metrics and root-zone soil moisture with sand percentage, HAND, and TWI. Note that binning of the continuous variables in x- and y-axes are done automatically to equalise frequency of observations among the bins of a given variable.

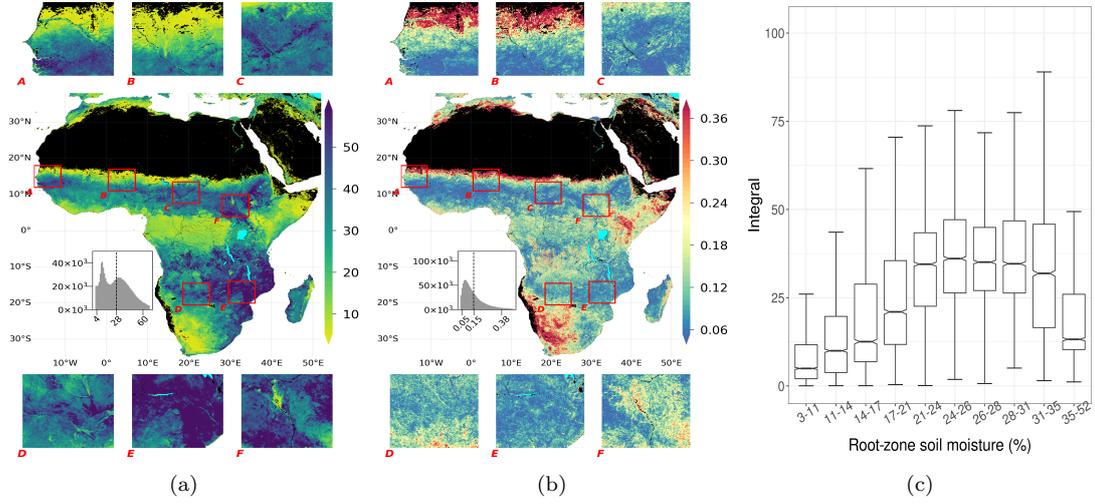


Figure 4: (a) Integral of FVC time series in the decay period, I_{dp} , (b) variation of I_{dp} , (c) distribution of I_{dp} within mean annual soil moisture. See Fig. 2 for plotting details.

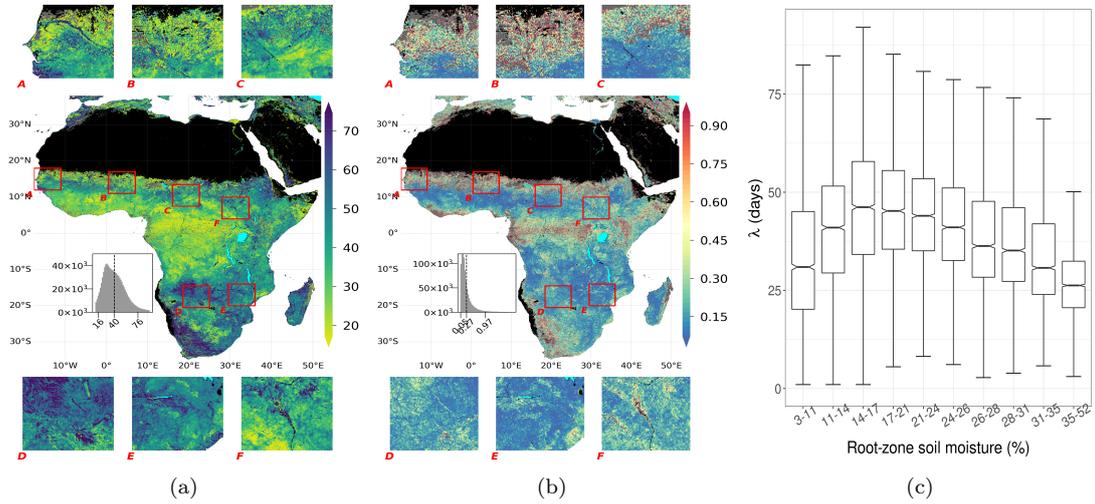


Figure 5: (a) e -folding time of FVC time series during dry-down (in days), λ , (b) variation of λ , (c) distribution of λ within soil moisture. See Fig. 2 for plotting details.

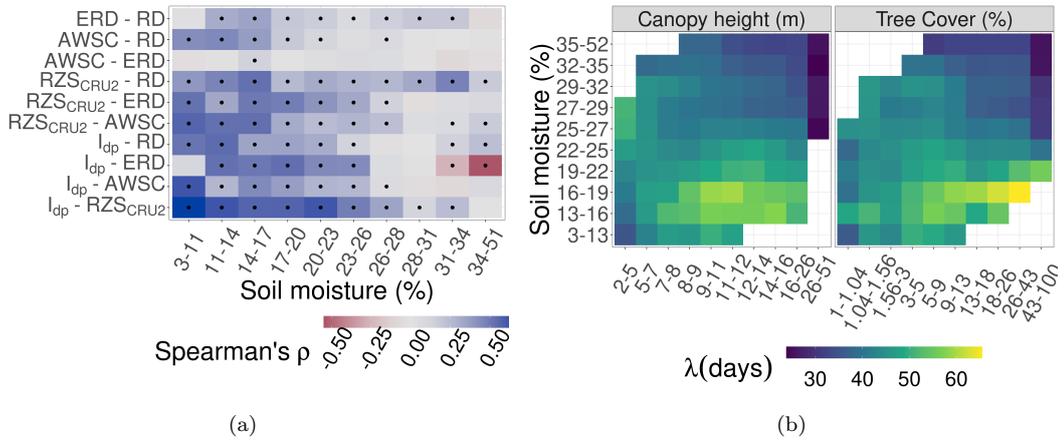


Figure 6: (a) Spearman's correlation coefficients between pairs of products related to plant accessible water content, namely Effective Rooting Depth (ERD) from Yang et al. (2016), Rooting Depth (RD) from Fan et al. (2017), Accessible Water Storage Capacity (AWSC) from S. Tian et al. (2019), Root Zone 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 λ 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.

722
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Appendix A An Example Map of the Original FVC Data for a Single Day

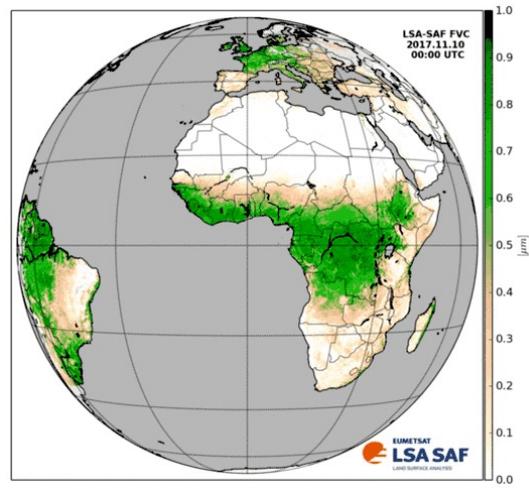


Figure A1: The original FVC data product for a single day, taken from <https://landsaf.ipma.pt/en/products/vegetation/fvc/>

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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.

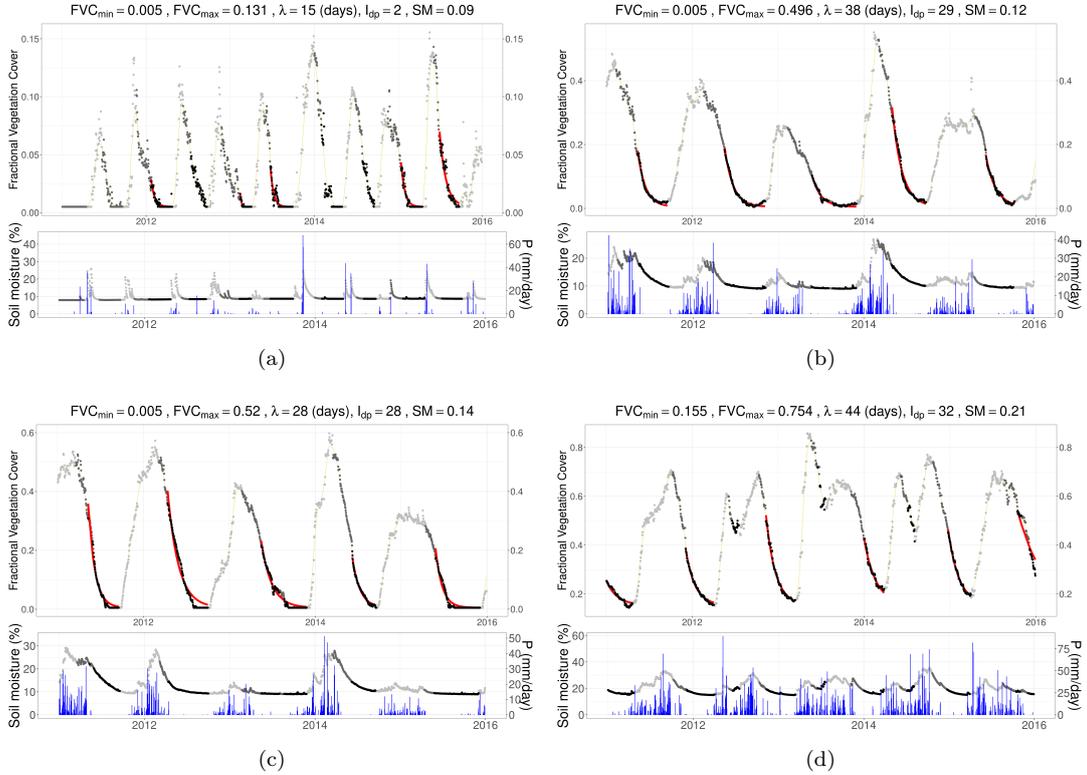


Figure B1: FVC, soil moisture, and precipitation time series of sampled grid cells. Sampling is done to have one grid cell per each bin of soil moisture values given in the plots of the main manuscript. Points for both FVC and soil moisture are coloured according to the state of vegetation activity as 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 λ 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).

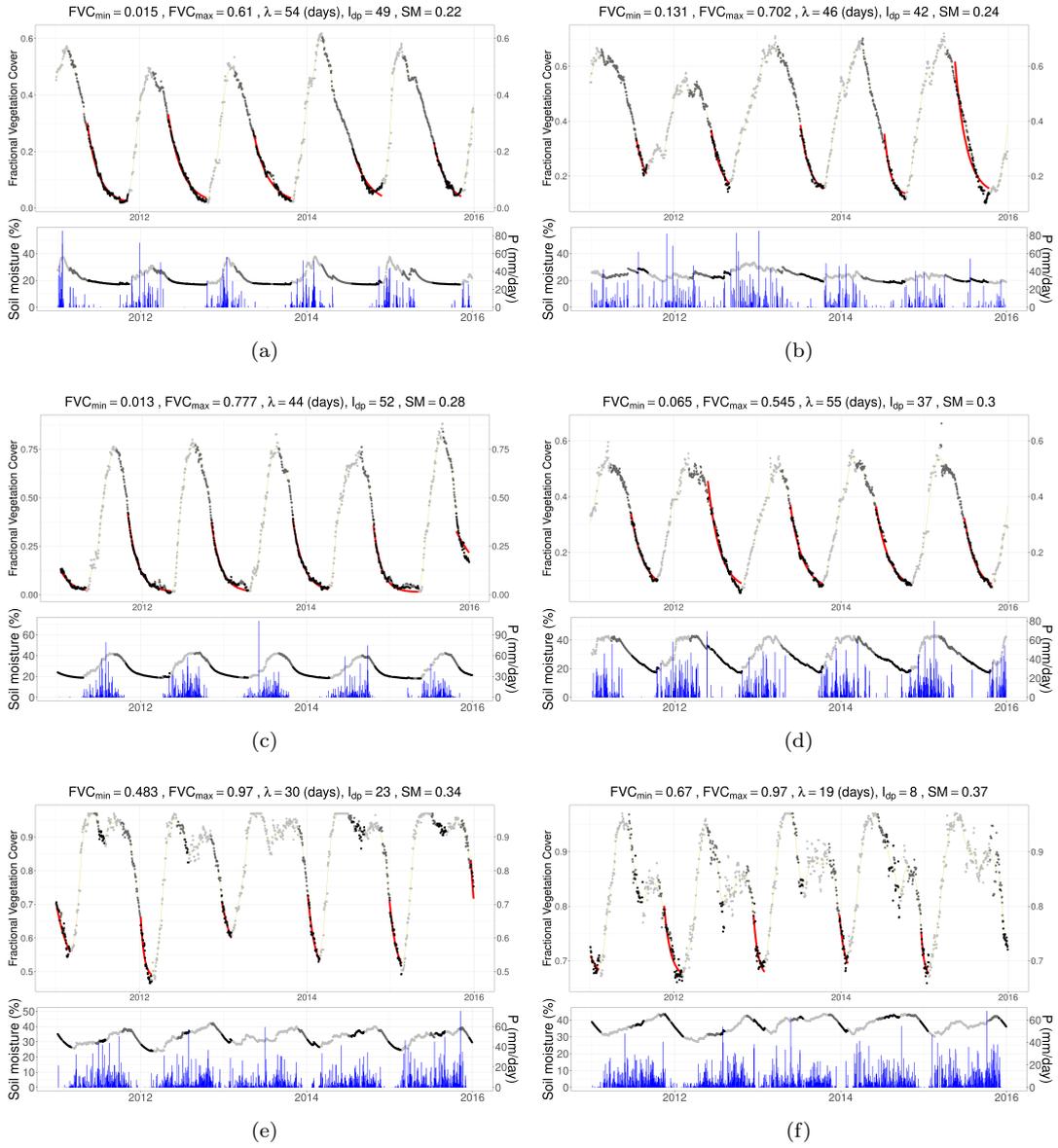


Figure B2: Continuation of Fig. B1 with samples having larger mean annual soil moisture.

Appendix C Density Plots of the Ecohydrological Metrics

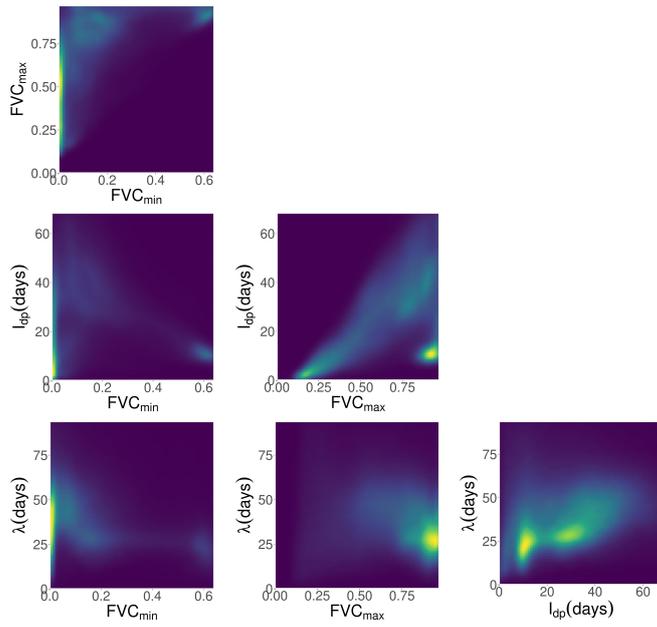


Figure C1: Density plots of the ecohydrological metrics presented in this study.

Appendix D Temporal Correlation Between FVC and Soil Moisture

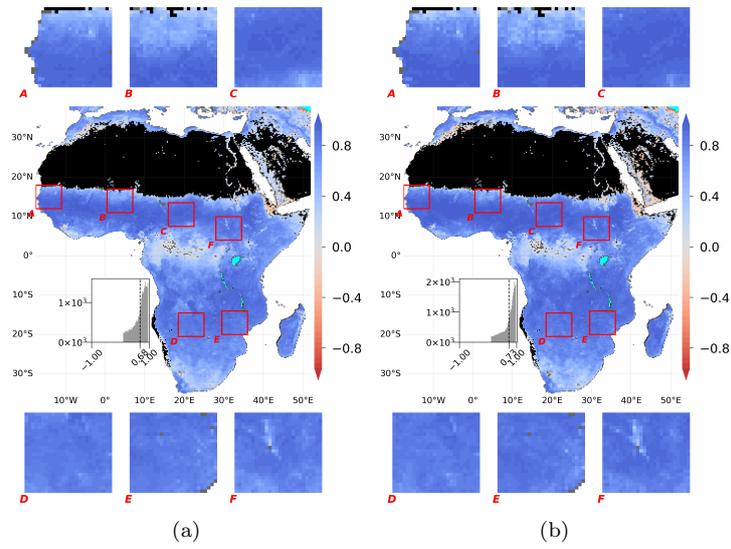


Figure D1: Pixelwise Spearman's correlation of FVC and GLEAM root-zone soil moisture in time for (a) entire time series, (b) time series marked as decay period using FVC.

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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.

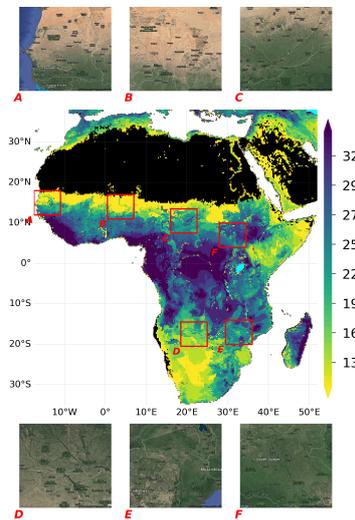


Figure E1: Map of mean annual root-zone soil moisture (%) in the centre and satellite view of the insets. Map and image data of the insets: Google Earth ©2020 TerraMetrics.

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

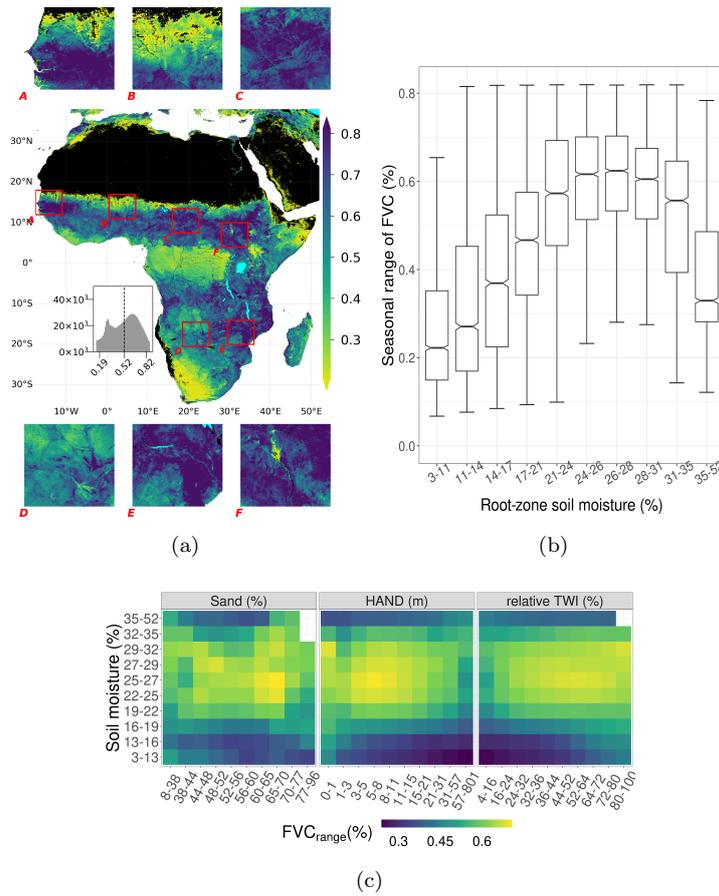


Figure F1: Variations in FVC_{range} (as $FVC_{max} - FVC_{min}$) (a) in space (b) with climatological aridity (c) similar to Fig. 3a but for FVC_{range}

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).

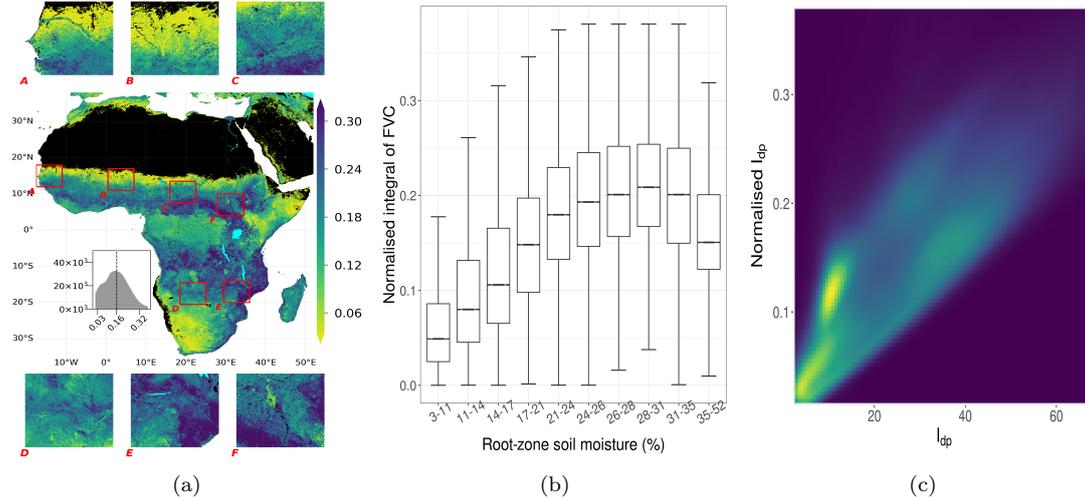


Figure G1: Integral of FVC time series in the decay period normalised by event duration (a) Spatial variation, (b) variation against within mean annual soil moisture (see Fig. 2c for plotting details). (c) density plot against I_{dp}

756 **Appendix H Map of Number of Convergences of Algorithm 2**757 **Appendix I Maps of Accessible Water Storage Capacity Datasets**

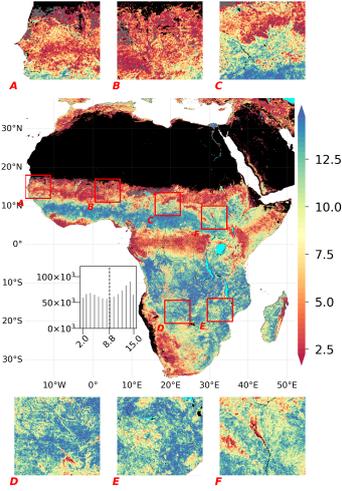


Figure H1: Number of decay periods in which the Algorithm 2 successfully converged.

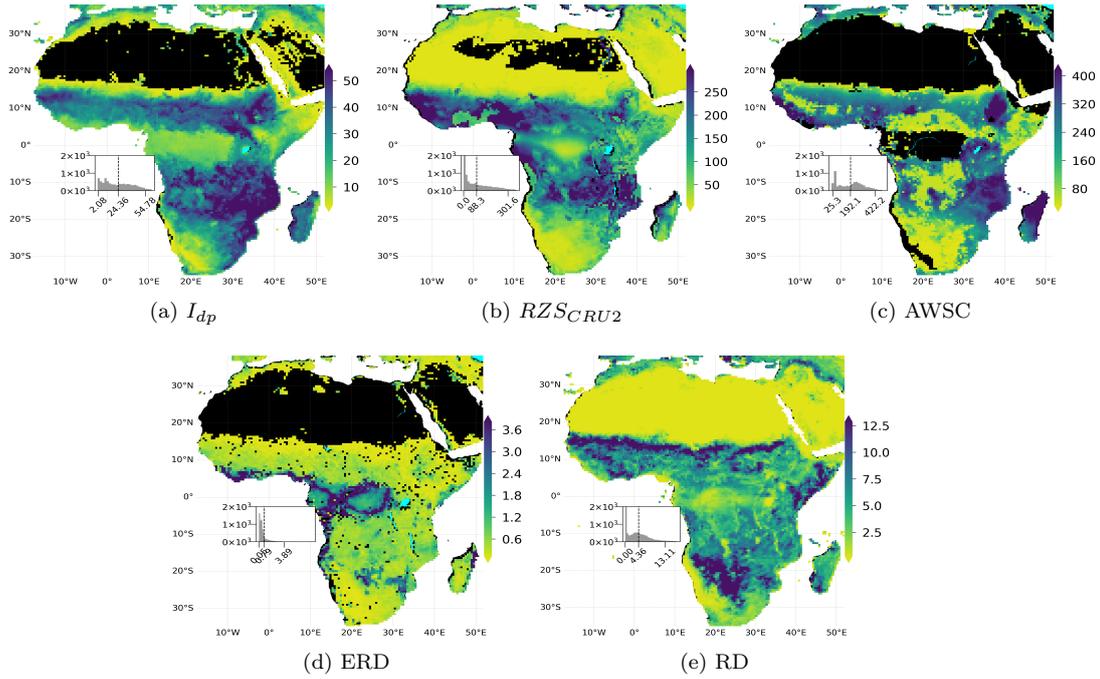


Figure I1: Maps of accessible water storage capacity and rooting depth datasets used in this study. (a) Integral of FVC during decay period, I_{dp} , (b) Root Zone Storage Capacity ($RZSCR_{CRU2}$) using CRU as precipitation forcing data with 2 years of drought return period from Wang-Erlandsson et al. (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° and cropped for the study domain.

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