



1 **Challenges and opportunities in modelling savanna ecosystems**

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40 **Abstract**

41 The savanna complex is a highly diverse global biome that occurs within the seasonally  
42 dry tropical to sub-tropical equatorial latitudes. Savannas are open-canopy  
43 environments that encompass a broad demographic continuum, often characterised by a  
44 dynamically changing dominance between C<sub>3</sub>-tree and C<sub>4</sub>-grass vegetation, where  
45 frequent environmental disturbances such as fire modulates the balance between  
46 ephemeral and perennial life forms. Climate change is projected to result in significant  
47 changes to the savanna floristic structure, with increases to woody biomass expected  
48 through CO<sub>2</sub> fertilisation in mesic savannas and increased tree mortality expected  
49 through increased rainfall interannual variability in xeric savannas. The complex  
50 interaction between vegetation and climate that occurs in savannas has traditionally  
51 challenged current-generation terrestrial biosphere models (TBMs), which aim to  
52 simulate the interaction between the atmosphere and the land-surface to predict  
53 responses of vegetation to changing in environmental forcing. In this review, we  
54 examine whether TBMs are able to adequately represent savanna dynamics and what  
55 implications potential deficiencies may have for climate change projection scenarios  
56 that rely on these models. We start by highlighting the defining characteristic traits and  
57 behaviours of savanna, how these differ across continents, and how this information is  
58 (or is not) represented in the structural framework of many TBMs. We highlight three  
59 dynamic processes that we believe directly affect the water-use and productivity of the  
60 savanna system, namely: phenology; root-water access; and fire dynamics. Following  
61 this, we discuss how these processes are represented in many current generation TBMs  
62 and whether they are suitable for simulating savanna dynamics. Finally, we give an  
63 overview of how eddy-covariance observations in combination with other data sources,  
64 can be used in model benchmarking and inter-comparison frameworks to diagnose the  
65 performance of TBMs in this environment and formulate roadmaps for future  
66 development. Our investigation reveals that many TBMs systematically misrepresent  
67 phenology, effects of fire and root-water access (if they are considered at all) and that  
68 these should be critical areas for future development. Furthermore, such processes must  
69 not be static (i.e. prescribed behaviour), but be capable of responding to the changing  
70 environmental conditions in order to emulate the dynamic behaviour of savannas.  
71 Without such developments, however, TBMs will have limited predictive capability in  
72 making the critical projections needed to understand how savannas will respond to  
73 future global change.

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75 **1 Introduction**

76 Savanna ecosystems are a diverse and complex biome covering approximately 15 to  
77 20% of the global terrestrial surface (Scholes and Hall, 1996) and provide important in  
78 providing ecosystem services, that maintain biodiversity and support the majority of the  
79 global livestock (van der Werf et al., 2008). Savannas are characterised by a multifaceted  
80 strata of vegetation, where an open C<sub>3</sub>-woody canopy of trees and shrubs overlies a  
81 continuous C<sub>4</sub>-grass layer and occur in regions that experience a seasonal wet-dry  
82 climate, have low topographic relief and infertile soils (Scholes and Archer, 1997).  
83 Savanna vegetation structure (defined by the ratio of woody to herbaceous cover) is  
84 further modulated by disturbance events (predominantly fire) and create demographic  
85 bottlenecks, preventing canopy closure that results in an open, woody system (Scholes  
86 and Archer, 1997). Indeed, fire disturbance is a defining characteristic of savannas,  
87 particularly for mesic regions (mean annual precipitation; MAP > 650 mm), potentially  
88 holding the ecosystem in a 'meta-stable' state, such that if it were excluded this open  
89 C<sub>3</sub>/C<sub>4</sub> system would likely shift to a closed C<sub>3</sub> forest or woodland (Bond et al., 2005;  
90 Sankaran et al., 2005). The role of fire in modulating vegetation structure allows  
91 savannas to occur across a broad demographic continuum, where the density of woody  
92 biomass is coupled to the annual amount of rainfall (Hutley et al., 2011; Lehmann et al.,  
93 2011). These environmental traits and behaviours therefore mark savannas as one of  
94 the most complex terrestrial biomes on the planet, and understanding the vegetation  
95 dynamics and underlying processes of this ecosystem type (especially in response to  
96 future global change) has proven a confronting task for the ecosystem modelling  
97 community (House et al., 2003; Scheiter and Higgins, 2007).

98 Terrestrial biosphere models (TBMs), which aim to predict ecosystem water and carbon  
99 transfer between the land-surface and the atmosphere (among other processes), have  
100 mostly underperformed for savanna ecosystems (Whitley et al., 2015). While the  
101 reasons for this are in some cases model-specific, a general question can be formed  
102 about whether the current generation of TBMs have the predictive capability to  
103 adequately simulate savanna dynamics and their response to future global change.  
104 Additionally, if such limitations do exist, are they a result of an incorrect  
105 parameterisation of physical parameters (e.g. root depth, maximum RuBisCO activity,  
106 sand and clay soil contents, etc.), the misunderstanding or absence of dynamic  
107 biophysical processes (e.g. phenology, root-water uptake, etc.), the challenge of  
108 simulating stochastic events linked to disturbance, or a combination of all three?  
109 Particular attributes that characterise savanna environments, such as frequent fire



110 disturbance, the seasonality of available soil-water, and the annual recurrence of C<sub>4</sub>  
111 grasses (which except for grasslands are absent in other biomes) are not universally  
112 represented in most model frameworks. While some TBMs have been specifically  
113 designed with savanna dynamics in mind (Coughenour, 1992; Haverd et al., 2016;  
114 Scheiter and Higgins, 2009; Simioni et al., 2000), some are closer to modified  
115 agricultural models (Littleboy and Mckean, 1997), with most TBMs attempting to  
116 capture savanna dynamics through calibration to the observed time-series and ad-hoc  
117 substitutions of missing processes (Whitley et al., 2015). Furthermore, little has been  
118 done to investigate why simulating savanna dynamics has fallen outside the scope and  
119 capability of many TBMs, such that these problems can be identified and used in on-  
120 going model development.

121 In this paper we review the current state of modelling for the savanna complex, with  
122 emphasis on how the dynamics and biophysical processes of the savanna ecosystem  
123 may challenge current-generation TBMs. We start with an overview of the global  
124 savanna complex and the many biomes that fall under this definition. Moreover, we  
125 discuss how the distinct characteristics, dynamics and regional differences among global  
126 savanna types may have implications for future global change. We then proceeded to  
127 outline how some of the defining physical processes of savanna are commonly  
128 misrepresented in TBMs and if these hamper the necessary predictive capability to  
129 answer questions on the future of this biome. Finally we conclude with a discussion on  
130 model evaluation and benchmarking for this ecosystem, where we argue that eddy flux  
131 measurements in combination with observations from multiple data sources  
132 (phenocams, remote-sensing products, inventory studies) are needed to give a complete  
133 assessment of whether simulated processes are representative of savanna dynamics.

134

## 135 2. The savanna biome

### 136 2.1 *Characteristics and global extent*

137 Savannas occur in the tropical to sub-tropical equatorial latitudes, occupying a  
138 significant portion of the terrestrial land-surface that experiences a seasonal wet-dry  
139 climate (Fig. 1). Savannas are therefore associated with many ecosystem types and have  
140 a global extent that covers 15.1 million km<sup>2</sup> (almost half) of the African continent  
141 (Menaut, 1983), 2.1 million km<sup>2</sup> of the Cerrado, Campos and Caatinga ecoregions in  
142 South America (Miranda et al., 1997), 1.9 million km<sup>2</sup> of the Australian tropical north



143 (Fox et al., 2001), as well as parts of peninsular India, southeast Asia (Singh et al., 1985),  
144 California and the Iberian peninsula (Ryu et al., 2010a). Despite the large geographical  
145 distribution, the structure of vegetation in these regions has converged towards a  
146 similar formation of mixed C<sub>3</sub> trees and C<sub>4</sub> grasses. However, this similarity can only be  
147 considered from a purely qualitative standpoint, as the floristic structure is the result of  
148 independent but analogous selective pressures imposed by the expansion of C<sub>4</sub> grasses  
149 into these regions 6 to 7 Ma (Osborne and Beerling, 2006). In fact it is difficult to  
150 consider savannas as a singular biome, as in reality they are closer to a set of  
151 independent biomes that may be deflected from equilibrium with their climate due to a  
152 combination of resource limitation (soil-moisture and soil nutrients), growing  
153 conditions (temperature) and frequent disturbances (fire and herbivory) (Lehmann et  
154 al., 2014). Lehmann et al. (2011) quantified the different extents of savanna globally,  
155 showing that for each continent they occupy distinctly different climate spaces. For  
156 example, South American savannas are limited to a high but narrower range of MAP  
157 (~1000 to 2500 mm), while African and Australian savanna occur over lower but wider  
158 range of MAP (~250 to 2000 mm), and are further separated by strong differences in  
159 rainfall interannual variability and soil nutrient contents (Bond, 2008). Furthermore,  
160 Lehmann et al. (2014) shows that different interactions between vegetation, rainfall  
161 seasonality, fire and soil fertility occur on each continent and act as determinants of  
162 above-ground woody biomass for the ecosystem.

163 Differences in the magnitude and interaction of environmental effects have indicated  
164 savanna vegetation dynamics to be region-specific (Bond, 2008; Bowman and Prior,  
165 2005; Lehmann et al., 2014; Lloyd et al., 2008; Scholes and Hall, 1996), such that there  
166 are marked differences in how regional flora (primarily woody species) coordinate their  
167 functional traits to operate within their respective climate space (Cernusak et al., 2011;  
168 Eamus, 1999). For example, major distinctions can be drawn between the savanna flora  
169 of Africa, Australia and South America. Canopies of the African and South American  
170 savanna regions are characterised by shallow rooted, deciduous woody species that  
171 follow a short-term growth strategy that maximises productivity while environmental  
172 conditions are favourable (Archibald and Scholes, 2007; Higgins et al., 2011). In  
173 contrast, the savanna canopies of northern Australia are dominated by deep rooted,  
174 evergreen *Eucalyptus* and *Corymbia* woody species that favour a long-term strategy of  
175 conservative growth that is insured against an unpredictable climate (Bowman and  
176 Prior, 2005; Eamus, 1999). Consequently, the functional traits that support deciduous,  
177 evergreen or annual strategies have a major impact on the water and carbon exchange



178 of the system. For example, Australian mesic savanna tree canopies operate at almost  
179 constant rates of assimilation and transpiration all year round, due to their deep and  
180 extensive root system and ability to make adjustments to canopy leaf area in times of  
181 stress (O'Grady et al., 1999). These differences highlight quite importantly that savanna  
182 ecosystems cannot be simply reduced to a generalised plant functional types (PFT)  
183 applied globally in some LSM and DGVM frameworks. One alternative may be to define  
184 region region-specific PFTs to fully capture the distinctly different dynamics that are  
185 occurring across the ensemble of savanna biomes. A promising alternative approach of  
186 some recent models is to allow savanna composition to emerge from environmental  
187 selection from a mixture of PFTs or trait combinations, reflecting global diversity in  
188 savannah vegetation (e.g. Haverd et al., 2015; Scheiter and Higgins, 2009; Smith et al.,  
189 2001). For the example, the HAVANA model allows traits such tree and grass phenology,  
190 leaf-area, rooting depth and relative cover emerge from the meteorological variations  
191 and their effect on evolving ecosystem state (Haverd et al. 2015). Because traits define  
192 the response of the vegetation to climate, it is important that they are adequately  
193 represented in TBMs.

194

## 195 2.2 *The implications of climate change*

196 Projected global increases in both temperature and the variability of precipitation  
197 patterns as a result of anthropogenic climate change are expected to lead to significant  
198 changes in the structure and diversity of global terrestrial ecosystems (IPCC, 2013;  
199 Rogers and Beringer, 2016). This will make modelling under these transient conditions  
200 difficult, challenging TBMs in how they represent the response of the savanna ecosystem  
201 to structural shifts in vegetation through CO<sub>2</sub> fertilisation, increased rainfall seasonality,  
202 and changing fire dynamics.

203 Savannas may be susceptible to small perturbations in climate and could potentially  
204 shift towards alternate closed-forest or open-grassland states as a result (Scheiter and  
205 Higgins, 2009). The total carbon pool of some savannas can be considered as modest  
206 when compared with other ecosystems (e.g. rainforests). However, in terms of net  
207 primary productivity (NPP), tropical savannas and grasslands occupy the top ranks  
208 among terrestrial biomes, together contributing c. 30% of annual global NPP (Grace et  
209 al., 2006). A shift in the savanna state towards a more closed system, may lead to these  
210 regions becoming a substantially larger carbon sink (Higgins et al., 2010). Observations



211 of increased woody vegetation cover (woody encroachment) in many semi-arid  
212 ecosystems and savannas worldwide over recent decades have been attributed to  
213 positive effects of increased atmospheric CO<sub>2</sub> on plant water-use effects (Donohue et al.,  
214 2009; Fensholt et al., 2012; Liu et al., 2015). Models suggest that such effects are  
215 predicted to continue in the future. CO<sub>2</sub> fertilisation is also expected to favour the more  
216 responsive C<sub>3</sub> vegetation, leading to the competitive exclusion of C<sub>4</sub> grasses via  
217 suppressed grass growth and reduced fire impacts (Bond et al., 2005). Model projections  
218 by Scheiter and Higgins (2009), and Higgins and Scheiter (2012) suggest future range  
219 shifts of African savanna into more arid climates as a consequence of elevated CO<sub>2</sub>, with  
220 concurrent transformation of current savanna habitats to forests under a stationary  
221 rainfall assumption. Recent evidence underscores the significant role of savannas in the  
222 global carbon cycle (Ahlström et al., 2015; Haverd et al., 2016; Poulter et al., 2014).

223 The response of savanna structure and function to changes in precipitation patterns is  
224 highly uncertain (Rogers and Beringer, 2016). Scheiter et al. (2014) investigated the  
225 effect of variable rainfall seasonality, projecting modest to large increases in above-  
226 ground biomass for savannas in northern Australia. The authors showed that woody  
227 biomass in this region increased despite significant changes to precipitation regimes,  
228 being predominantly driven by CO<sub>2</sub> fertilisation and rainfall seasonality determining the  
229 magnitude of the increase (Fig. 2) (Scheiter et al., 2014). However, some studies have  
230 indicated that while increased rainfall seasonality may have a small effect in mesic  
231 savanna systems, it may potentially act as an opposing effect to woody encroachment in  
232 semi-arid savanna systems (Fensham et al., 2009; Hiernaux et al., 2009). For example,  
233 Fensham et al. (2009) have shown significant tree mortality to occur as a result of  
234 drought in a semi-arid savannas in south-west Queensland, suggesting that severe  
235 water-stress may counteract the positive effect of CO<sub>2</sub> fertilisation on ecosystem carbon  
236 balance. Alternatively, forest dieback as a result of increased rainfall seasonality and  
237 more frequent drought occurrence may lead to an expansion of savanna distribution in  
238 some regions. For example, simulations of the Amazon basin have projected a possible  
239 conversion of rainforest to savanna in eastern Amazonia as a result of forest dieback  
240 induced by severe water stress and fire disturbance (Cox et al., 2004; Malhi et al., 2009).

241 Finally, fire can play a critical role in mediating the floristic structure of the savanna  
242 ecosystem, deflecting woody vegetation from its physiognomic potential with climate  
243 (Scholes and Archer, 1997). Increased warming and rainfall seasonality is expected to  
244 alter the interaction between climate, fire and savannas in the future (Beringer et al.,  
245 2014), however we leave discussion of savanna fire dynamics and the ability of TBMs to





246 simulate this process until in the paper. Permanent shifts in the structure and  
247 physiology of the savanna complex as a result of climate change is expected to have a  
248 major impact on the exchange of water, energy and carbon that occurs in this system,  
249 which in turn ultimately affects global biogeochemical cycling and climate (Beringer et  
250 al., 2014; Pitman, 2003).

251

## 252 **2. The capability of models to simulate savanna ecosystems:**

253 The term '*terrestrial biosphere model*' refers to a variety of bottom-up modelling  
254 approaches that simulate coupled dynamics of water, energy, carbon, and in some cases  
255 nutrients in vegetation and soils. TBMs range from stand models, which simulate  
256 specific ecosystems in high detail, up to dynamic global vegetation models (DGVMs),  
257 which can simulate multiple ecosystems at a coarser level. Consequently, TBMs  
258 collectively operate over different temporal and spatial scales and employ processes of  
259 different scope in simulating ecosystem dynamics. However, common to all TBMs is that  
260 they are governed by the same biophysical principles of energy and mass transfer that  
261 determines the dynamics of plant life (Pitman, 2003). Consequently, the predictive  
262 capability of different TBMs at determining the exchange of water, energy and carbon  
263 between the surface and atmosphere should be convergent within a reasonable degree  
264 of error (Abramowitz, 2012). However, model intercomparison and benchmarking  
265 studies have shown that many TBMs are unable to meet reasonable levels of expected  
266 performance as a result of a systematic misrepresentation of certain ecosystem  
267 processes (Abramowitz et al., 2008; Best et al., 2015; Blyth et al., 2011; Mahecha et al.,  
268 2010). The misrepresentations of ecosystem processes is particularly evident in  
269 savannas, for which many TBMs have not been developed for, nor tested on (Baudena et  
270 al., 2015; Whitley et al., 2015). Ecosystem processes critical to savannas, such as the  
271 complex tree-grass phenology (either deciduous-annual, or evergreen-annual), seasonal  
272 competition and access to belowground resources (soil moisture and nutrients) and  
273 stochastic disturbance events (fire), are less prevalent in other ecosystems and are  
274 therefore not well represented (or even missing) in many TBMs (House et al., 2003;  
275 Whitley et al., 2015). Conventional TBMs still lack a lot of this capability and therefore  
276 have limited application for biomes in the seasonally dry tropics, which in turn becomes  
277 a large source of uncertainty in future global studies (Scheiter and Higgins, 2009).  
278 However, we believe that incorporating key processes that drive savanna dynamics into  
279 current-generation TBMs has great potential, considering that even small modifications



280 can lead to large gains in performance (Whitley et al., 2011). Below, we have identified  
281 phenology, root-water uptake and fire disturbance as three critical processes in  
282 savannas that deserve special consideration in modern TBMs.

283

### 284 2.1 Phenology

285 Phenology is an expression for the seasonal dynamics of structural vegetation  
286 properties of an ecosystem, defining its growing season and ultimately its productivity  
287 (Moore et al., 2016a). Here we limit our discussion to the phenology of leaf cover. In  
288 seasonally dry climates phenology is driven by soil-moisture availability and the length  
289 of the growing season for shallow rooting plants is determined by the seasonality of  
290 rainfall (Kanniah et al., 2010; Ma et al., 2013; Scholes and Archer, 1997). Plants respond  
291 differently to water availability, such that phenology is a function of the dominant  
292 species within the ecosystem. Deciduous trees and annual grasses are  
293 photosynthetically active during the wet season only and respectively senesce or  
294 become dormant or senesce at the beginning of the dry season, while evergreen trees  
295 may remain permanently active throughout the year, potentially responding to soil-  
296 moisture depletion by gradually reducing their canopy leaf area (Bowman and Prior,  
297 2005). These dynamics are critically important, as they control the amount and  
298 seasonality of carbon-uptake and water-use. In TBMs, ecosystem phenology is typically  
299 represented in one of two ways. The first is via direct *prescription* of this information as  
300 an additional input to the model, where observations of leaf area index (LAI) (either in-  
301 situ measurements or satellite derived products) are used to express the change in  
302 ecosystem canopy cover over time (Whitley et al., 2011). The second is as a *prognostic*  
303 determination using a growth sub-module, where carbon allocation and leaf metabolic  
304 activity are simulated and dependent upon the time-varying conditions of temperature  
305 and soil-water availability (Scheiter and Higgins, 2009). Prescription of phenology from  
306 observed LAI dynamics requires an accurate determination of the separate tree and  
307 grass components from bulk ecosystem LAI to be feasible for savanna ecosystems  
308 (Whitley et al., 2011). In many cases, this separation is assumed to be static, ignoring the  
309 different seasonal changes in tree and grass cover over time (Scholes and Archer, 1997).  
310 In fact, no models that we are aware of dynamically partitions prescribed LAI Donohue  
311 et al. (2009) offers an *a priori* method that can determine separate tree and grass LAI  
312 signals. This method assumes that the high variability in the bulk signal is attributed to  
313 herbaceous vegetation, such that the remaining, less variable signal is attributed to



314 woody vegetation (Fig. 3). A prescription of separate tree and grass LAI inputs was  
315 found to be necessary for simulating water and carbon exchange for a mesic savanna  
316 site in northern Australia (Whitley et al., 2011), and in determining a reduced error  
317 estimate of the Australian continental water and carbon balance (Haverd et al., 2013) to  
318 which savannas contribute significantly. The major drawback to prescribing LAI as a  
319 model input is that the model's scope is limited to hindcast applications. Because this  
320 information is supplied to the model, the floristic structure and its evolution over time is  
321 fixed, and cannot respond to changing environmental conditions (e.g. shifts in  
322 precipitation patterns) that are likely to have an impact on the tree-grass demography  
323 (Ma et al., 2013). Consequently, a dynamic approach where savanna phenology is  
324 explicitly simulated and dynamically responds to climate and disturbance offers a more  
325 promising path forward.

326 Allocation-growth schemes allow models to express phenology in terms of the evolution  
327 of carbon investment in leaf area over time, limited by the availability of resources for  
328 growth (Haverd et al., 2016). These schemes effectively work by distributing assimilated  
329 carbon (via net primary productivity; NPP) to the root, stem and leaf compartments of  
330 the simulated plant, where allocation to the leaf is dependent on the plant being  
331 metabolically active or dormant (Cramer et al., 2001). In some TBMs, allocation to these  
332 compartments is a fixed ratio (set according to plant functional type) and metabolic leaf  
333 activity is defined through a set of threshold bioclimatic indicators (e.g. photoperiod,  
334 moisture availability and temperature) that determine whether conditions are  
335 favourable for photosynthesis (Jolly et al., 2005). However, more recent advances, use  
336 an alternative approach of dynamically guiding allocation towards the compartment  
337 that most limits a plant's growth (Scheiter and Higgins, 2009) or dynamically optimising  
338 daily allocation, to maximise long-term NPP and control the competitive balance  
339 between trees and grasses (Haverd et al., 2016). The latter approach, based on  
340 optimality theory (Raupach, 2005), is related to the approach followed by Schymanski et  
341 al. (2009), who assumed that vegetation dynamically optimises its properties (root  
342 system and foliage) to maximise its long-term net carbon profit. These approaches,  
343 which assume a more dynamic coupling between allocation and phenology, allow plant  
344 form and community structure to evolve in response to changes in resource availability  
345 (light, water or carbon) over time, with phenology becoming an emergent property of  
346 this process. Dynamic allocation schemes enable a TBM to answer questions regarding  
347 how changing climate or elevated atmospheric CO<sub>2</sub> concentrations may alter structural



348 properties of the ecosystem, and the resultant feedbacks on water, carbon and energy  
349 cycling (Scheiter and Higgins, 2009; Schymanski et al., 2015).

350

### 351 *2.2 Root-water access and uptake*

352 The root zone is critically important in maintaining water and carbon fluxes, as it  
353 defines an ecosystem's accessible belowground resources and vulnerability to  
354 prolonged dry periods (De Kauwe et al., 2015). For seasonally dry climates (common for  
355 savannas), productivity is primarily limited by dry season water-availability (Kanniah et  
356 al., 2010), which is largely determined by the root zone water storage capacity and  
357 hence rooting depth. Co-ordination of the whole soil-root-leaf-atmosphere pathway in  
358 response to the highly seasonal climate is critical to the survival of savanna plants and is  
359 intrinsically linked to their phenology. For example, deciduous and annual savanna  
360 species have shallow root profiles (approx. 0.5 to 2 m) and highly conductive vascular  
361 systems to maximise productivity during the wet season (February and Higgins, 2010).  
362 In contrast, evergreen savanna species invest in highly regulated hydraulic architectures  
363 and deep root systems (> 2 m) that can access deep soil water stores to maintain  
364 continuous productivity throughout the dry season (Bowman and Prior, 2005). It is  
365 therefore critically important that the specific root system and hydraulic architectures  
366 of savanna species be adequately represented in models to simulate water and carbon  
367 fluxes of this system.

368 Soil and plant hydraulic traits such as rooting depth and distribution, stem hydraulic  
369 resistance, and sand and clay contents are typically represented as fixed parameters in  
370 TBMs. Of these traits, the root profile acts as the first-order control on soil-water supply  
371 and therefore determines the capability of a simulated plant to remain active through  
372 rain-free periods (Eamus et al., 1999). The root profile within a soil column is generally  
373 modelled as an exponentially declining of root-surface area with depth, the limit of  
374 which extends to some prescribed level. Although some models are capable of  
375 dynamically determining the size of the root profile as an emergent property of  
376 productivity and climate (e.g. Haverd et al., 2016; Schymanski et al., 2009), more  
377 typically, the maximum rooting depth is fixed at approximately 1.5 to 2.0 m (Whitley et  
378 al., 2015). However, studies have shown that woody plants in semi-arid or seasonally  
379 dry climates (particularly those in Australia) exhibit deep root systems to remain active  
380 during prolonged dry periods (Duursma et al., 2011; Hutley et al., 2000; O'Grady et al.,



381 1999). Numerous modelling studies have shown that a rooting profile of significant  
382 depth (> 2 m) is required to achieve good model-data agreement (Fisher et al., 2007;  
383 Haxeltine and Prentice, 1996; Schymanski et al., 2009; Whitley et al., 2011, 2015). While  
384 characterisation of the rooting depth in savanna modelling exercises may be seen as a  
385 matter of correct parameterisation rather than one of systematic process, its role as a  
386 first-order control on water supply in seasonally water-limited systems gives it  
387 significant weight in the overall determination of carbon uptake. Furthermore, long-  
388 term responses of rooting depth to climate change or elevated atmospheric CO<sub>2</sub>  
389 concentrations may substantially alter structure, resource use and carbon uptake of  
390 savanna ecosystems (Schymanski et al., 2015). Consequently, rooting depths that  
391 sufficiently represent either deciduous or evergreen tree species need to be considered  
392 when modelling savannas.

393 Directly coupled to the characterisation of the root-zone is the systematic process by  
394 which soil-water is extracted by the root system. The process of root-water uptake in  
395 TBMs has been simulated using numerous schemes. One approach assumes that the  
396 amount of extracted water by roots is a function of the root density distribution within  
397 the soil column and is expressed through an additional sink term to the Richard's  
398 equation, which represents the flow of water in an unsaturated soil (Wang et al., 2011).  
399 In such schemes, root-water uptake may be weighted by the distribution of fine-root  
400 biomass in the soil, such that soil-layers with the greatest density of fine-root biomass  
401 largely determine the soil-water status of the plant, its stomatal behaviour, and  
402 therefore its sensitivity to soil drying (Wang et al., 2011). The exponential decay  
403 function conventionally used to describe the root profile in most TBMs (an exception is  
404 Schymanski et al. 2009) can result in simulated stomatal behaviour that is heavily  
405 weighted towards the moisture content of the upper soil profile, making them highly  
406 sensitive to drought (De Kauwe et al., 2015). In reality, the active root distribution of  
407 savannas is not static, nor so limited, but responds dynamically to wherever water is  
408 available. For example, eucalypts occurring in Australian mesic savannas invest in 'dual-  
409 root' systems that are capable of switching their root activity between subsurface and  
410 subsoil respectively to access water continually during both wet and dry seasons (Chen  
411 et al., 2004). Alternative root-water uptake schemes do exist that describe a more  
412 dynamic response to long-term changes in soil conditions. One such scheme by Williams  
413 et al. (2001) considers root activity to change over time and be concentrated towards  
414 parts of the root zone where the plant can sustainably extract the maximal amount of  
415 available water. Consequently, this scheme effectively weights soil-water status over the



416 distribution of fine-root biomass, such that simulated root-water uptake dynamically  
417 responds to the wetting and drying of the soil profile over time (Fig. 4). Another  
418 alternative approach by Schymanski et al. (2008) allows the root zone to dynamically  
419 adjust the vertical distribution of root biomass in the profile to balance canopy water  
420 demand while minimising structural costs of maintaining such a root system . These  
421 alternate schemes offer a more dynamic approach to modelling the hydraulic  
422 architecture of species occurring in savannas and other semi-arid ecosystems, and have  
423 demonstrated high predictive skill in these environments (Schymanski et al., 2008,  
424 2009; Whitley et al., 2011). Therefore, given the distinct seasonality of savanna  
425 ecosystems, dynamic root-water extraction schemes are needed to simulate how the  
426 root zone responds to the evolution of soil-water supply over time.

427

### 428 *2.3 Disturbance*

429 Ecosystem structure and function in seasonally dry tropical systems such as savanna, is  
430 strongly shaped by environmental disturbance, such as persistent herbivory pressures,  
431 frequent low-impact fire events, and infrequent high-impact cyclones (Bond, 2008;  
432 Hutley and Beringer, 2011). Fires have a significant impact on land-surface exchange  
433 and vegetation structure and contribute to greenhouse gas emissions through the  
434 consumption of biomass (Beringer et al., 1995, 2014). Fire has the capacity to alter land-  
435 surface exchange fluxes through the removal of functional leaf area (reduced LAI) and  
436 the blackening of the surface (reduced albedo), temporarily reducing net carbon uptake  
437 (Beringer et al., 2003, 2007) and altering the atmospheric boundary layer to affect  
438 convective cloud formation and precipitation (Görgen et al., 2006; Lynch et al., 2007).  
439 Regarding vegetation structure, fire influences the competitive balance between tree  
440 and grass demographics, suppressing recruitment of woody saplings to adults, thereby  
441 deflecting the system from reaching canopy closure (Beringer et al., 2014; Higgins et al.,  
442 2000). Work by Bond et al. (2005) underlines the potential effect of removing fire from  
443 the savanna system, with substantial increases in woody biomass and major structural  
444 shifts towards closed forests. This is further supported by more empirical studies  
445 involving fire exclusion experiments and showing similar tendencies towards woody  
446 dominance (Bond and Van Wilgen, 1996; Scott et al., 2012). Given that future climate  
447 projections point to predict higher temperatures and less precipitation for sub-tropical  
448 regions (Rogers and Beringer, 2016) the representation of short- and long-term impacts  
449 of fire on savanna structure and function in TBMs may be important in understanding



450 how savanna landscapes may respond to changes in fire frequency and intensity (Bond  
451 et al., 2005).

452 Fire is commonly simulated as a stochastic process, with the probability of occurrence  
453 increasing with the accumulation of litterfall and grass biomass (fuel loads), combined  
454 with dry and windy environmental conditions that promote ignition (generally through  
455 lightning) (Kelley et al., 2014). The simulated amount of biomass consumed after an  
456 ignition event differs among models. Recent advances in simulating savanna fire  
457 processes have led to more complete representations of the complex interaction  
458 between fire and woody vegetation and how this shapes savanna structure. For  
459 example, Scheiter and Higgins (2009) consider a ‘topkill’ probability that suppresses  
460 woody plant succession if fire intensity is of a critical magnitude determined by the  
461 plant’s fire-resisting functional traits (e.g. height, stem diameter, bark thickness). This  
462 scheme allows fire to directly shape the savanna tree population through the dynamics  
463 of woody establishment, resprouting and mortality. Additionally, Kelley et al. (2014)  
464 have similarly considered how fire-resisting functional traits of woody vegetation alter  
465 the fire dynamics of seasonally dry environments. It should be noted that both studies  
466 do not consider anthropogenic ignition events, whereas recent work by Scheiter et al.  
467 (2015) suggests that fire management can be simulated using fixed fire return intervals.

468 Many TBMs simulate fire as an instantaneous event through emissions and removal of  
469 biomass, but may not consider the transient effects that fire has on land-surface after the  
470 event has occurred. It has been demonstrated previously that these post-fire effects on  
471 canopy surface mass and energy exchange can be significant, with fire indirectly  
472 suppressing productivity by *c.* 16% (+0.7 tC ha<sup>-1</sup> yr<sup>-1</sup>) (Fig. 5) (Beringer et al., 2007).  
473 During this period, resprouting rather than climate drives productivity, with respiration  
474 exceeding photosynthesis as a result of the regenerative cost of replacing damaged or  
475 lost stems and leaf area (Cernusak et al., 2006). In fact many modelling analyses of  
476 savannas dynamics have removed the post-fire periods completely from any assessment  
477 of performance, such that evaluation has been limited to periods where the model is  
478 considered to be ‘fit for purpose’ (Whitley et al., 2011, 2015). Fire is an integral part of  
479 savanna dynamics; it is important to include fire events in the analysis of savanna  
480 carbon and water fluxes or model performance. Furthermore, an accurate and robust  
481 representation of fire effects on savanna ecosystems is needed to answer questions  
482 about how savanna dynamics may change under future climate scenarios, as fire  
483 regimes have significant impacts on the carbon balance of these systems (Beringer et al.,  
484 2014).



485 Other disturbance regimes such herbivory pressures and cyclones have limited to no  
486 representation in models. The removal of aboveground biomass through grazing and  
487 browsing, is commonly represented as a set fraction that is removed over time  
488 according to the degree of local agricultural pressures, but has been represented  
489 dynamically in some models (e.g. Pachzelt et al., 2015). Termite pressures have also  
490 been shown to suppress productivity (Hutley and Beringer, 2011), but this loss may be  
491 too small to be considered as a significant consumer of biomass in TBMs. No models that  
492 the authors are aware of simulate the effect of cyclones on vegetation dynamics in  
493 tropical systems despite their impact on long-term ecosystem productivity. Cyclones are  
494 infrequent but high impact disturbance events that occur in any mesic savanna that lies  
495 close to the coastline, and can effectively 'restart' the savanna system through the mass  
496 removal of woody biomass (Hutley et al., 2013). Hutley and Beringer (2011) have shown  
497 that for an Australian mesic savanna, a bimodal distribution of the tree class sizes at the  
498 site indicates two major recruitment events that corresponds with two of the last great  
499 cyclones to occur in the region. Despite the immediate and significant loss of woody  
500 biomass during those events, recovery was possible and pushed this site to a carbon  
501 sink over many decades. Despite the impact that cyclones have on savanna structure it is  
502 somewhat understated in the literature, possibly due to the integrated loss in  
503 productivity over long-periods being small (Hutley et al., 2013). However, we believe  
504 because cyclones modulate savanna structure so strongly, there is a need for such  
505 dynamics to be considered in TBM frameworks, particularly for long-term projections  
506 on productivity. While few models have the capability to simulate the full spectrum of  
507 environmental disturbance effects on savanna ecosystems explicitly, the significant  
508 modulating impact they have on savanna structure and function flags these processes as  
509 a high priority in future model development.

510

### 511 **3. Testing and developing models for application in savannas**

512 Given that there are strong indications that critical savanna processes are likely  
513 misrepresented in current-generation TBMs, there is a clear need for further model  
514 testing and evaluation to be conducted for this ecosystem. Savannas have been the  
515 subject of improved research over the past two decades, resulting in a good and  
516 evolving understanding of their complicated structure, function, and contribution to  
517 global biogeochemical cycling (Higgins and Scheiter, 2012; Lehmann et al., 2014;  
518 Sankaran et al., 2005; Scholes and Archer, 1997). Despite this, our increased





519 understanding of savanna dynamics has not been properly translated into many modern  
520 TBMs, with the effect of major deficiencies in modelling this ecosystem (Whitley et al.,  
521 2015). Consequently, there is still a great necessity for continuous, consistent and  
522 objective studies to test and develop how savanna dynamics are represented and  
523 simulated. Below we highlight how datasets from multiple sources that include eddy  
524 flux towers, satellites, and ground-based *in situ* studies can inform model development  
525 and be used in evaluation and benchmarking studies.

526

### 527 *3.1 Datasets to inform model development*

528 Eddy-covariance (EC) systems that observe the instantaneous response of water, energy  
529 and carbon exchange to variability in climate and the evolution of this response over  
530 time provide crucial information on which to test and develop TBM application in  
531 savanna ecosystems. Quantities measured by EC directly mirror the inputs and outputs  
532 of TBMs, namely turbulent fluxes of water, heat and CO<sub>2</sub> observed in parallel with local  
533 meteorological forcing (e.g. short-wave irradiance; SW, air temperature, rainfall, etc.) at  
534 the same temporal and spatial scale. Consequently, these datasets offer an unparalleled  
535 capability in diagnostic model evaluation (Abramowitz, 2012; Mahecha et al., 2010). The  
536 use of EC datasets to evaluate TBMs and inform further development has been a long  
537 running practice within the ecosystem modelling community, with particular success  
538 being reported for some savanna studies in Australia (Haverd et al., 2013, 2016;  
539 Schymanski et al., 2009; Whitley et al., 2011, 2015). Here we outline two opportunities  
540 of using EC systems to assess model skill for savanna ecosystems are highlighted in  
541 these studies.

542 The first of these addresses the problem of EC datasets representing the integrated sum  
543 of turbulent fluxes for the entire system (i.e. soil, grass, shrubs and trees), and these are  
544 not easily separated. Assessing model performance using bulk measurements does not  
545 consider the separate responses of the functionally different C<sub>3</sub> tree and C<sub>4</sub> grass  
546 components that respond differently to climate (Whitley et al., 2011, 2015). However, a  
547 recent study by Moore et al. (2016b) has shown for a mesic savanna site in Australia  
548 that separate observations of canopy and understorey fluxes can be determined by  
549 using a 'dual tower' EC system that observes turbulent fluxes at reference points above  
550 and beneath the canopy (Fig 6). Datasets such as this provide a valuable resource to  
551 analyse the skill of separate model processes, i.e. simulation of tree and grass leaf gas-



552 exchange, which tests the degree of model equifinality (Bevan and Freer, 2001) at  
553 predicting the bulk ecosystem flux. A further collection of coupled over- and  
554 understory EC datasets is therefore critically needed to verify that simulated tree and  
555 grass dynamics are correctly represented in TBMs.

556 The second opportunity addresses the issue of savanna landscape heterogeneity.  
557 Savannas are not a homogeneous PFT, but rather a continuum of changing tree and  
558 grass demographics that shift biogeographically with rainfall and other factors (Ma et  
559 al., 2013). Ecological gradient studies, such as the Kalahari Transect (Scholes et al.,  
560 2004) and North Australian Tropical Transect (Hutley et al., 2011), have shown  
561 turbulent fluxes along a declining rainfall gradient to be strongly linked to structural  
562 changes in vegetation (Beringer et al., 2011a, 2011b). In essence, the spatial response to  
563 a systematic decline in rainfall represents the possible future temporal response to  
564 changing climate, such that transects can be used to evaluate TBMs by their ability to  
565 emulate the full spectrum of savanna behaviour rather than at just one point. A recent  
566 model intercomparison study by Whitley et al. (2015) used turbulent flux observations  
567 sampled along the NATT to evaluate a set of six TBMs, and documented only poor to  
568 moderate performance being observed. Model evaluations studies that test model  
569 predictive skill across both time and space are therefore crucial to projecting how  
570 savannas dynamically respond to changing climate.

571 While EC systems provide valuable datasets on which to test and develop models, they  
572 are unable to provide a complete evaluation, as they cannot capture long-term temporal  
573 and spatial scale features (e.g. demographic structural shifts in vegetation), nor provide  
574 detail on underlying ecosystem processes (e.g. root-water dynamics and carbon  
575 allocation) (Abramowitz, 2012; Haverd et al., 2013; Keenan et al., 2012)(Abramowitz,  
576 2012; Haverd et al., 2013). Additional sources of data and their collection are therefore  
577 critical to informing how well models are representing the specific dynamics that unique  
578 to savannas. Model inversion studies have shown EC datasets give significant constraint  
579 to predictions of NPP, however extra ancillary data that is informative of other  
580 underlying processes was required to further constrain uncertainty (Haverd et al., 2013;  
581 Keenan et al., 2012). Here, we suggest how each of the three critical savanna processes  
582 highlighted in this paper can potentially be tested in addition to EC datasets. Satellite  
583 derived estimates of remotely sensed near-surface reflectance (Ma et al., 2013; Ryu et  
584 al., 2010b) and digital imagery from 'PhenoCams' (Moore et al., 2016a; Sonnentag et al.,  
585 2012), provide a good resource for testing simulated phenology, particularly the 'green-  
586 up' and 'brown-down' phases. Additionally, Advanced Very High Resolution Radiometer



587 (AVHRR) data can provide ‘burnt area’ maps that quantify the frequency of fire events,  
588 which can inform the probability of occurrence in simulated fire-dynamics. Above- and  
589 belowground carbon inventory studies (Chen et al., 2003; Kgope et al., 2010) provide  
590 highly valuable sources information in how plants allocate their resources for growth,  
591 which can test the efficacy of TBM allocation scheme. Excavation studies that quantify  
592 savanna tree root-systems (Chen et al., 2004) and soil-moisture probes installed to  
593 greater depths (> 2 m) are informative about the evolution of the soil-root zone over  
594 time, and such data may be critical to understanding whether current root-water  
595 extraction schemes in TBMs are capable of simulating the dry season response of  
596 savanna tree species (Whitley et al., 2015). Finally, localised observations of plant traits  
597 such leaf-mass per area, stomatal conductance, tree height, etc. are needed to inform a  
598 better parameterisation of savanna specific PFTs (Cernusak et al., 2011). Given that  
599 there are many interacting effects occurring in savannas, an integration of multiple data  
600 sources is therefore necessary for a more complete evaluation of how well TBMs  
601 perform in this environment.

602

### 603 *3.2 Model evaluation and benchmarking*

604 Multiple dynamic processes drive savanna structure and function, and an understanding  
605 of the causes and reasons for why TBMs systematically misrepresent this ecosystem is  
606 paramount to future development. Consequently, a complete diagnostic evaluation of  
607 model performance in savanna ecosystems requires more than just simple model-model  
608 and model-data comparisons where ‘good performance’ is determined from a score in a  
609 given metric (e.g. a high correlation between observed and predicted values). Instead  
610 evaluation should also consider parsimony, physical representativeness and ‘out-of-  
611 sample’ capability of the model itself (Abramowitz et al., 2008). The Protocol for the  
612 Analysis of Land-Surface models (PALS; <http://www.pals.unsw.edu.au/>) offers such a  
613 formalism, using standardised experiments to benchmark TBMs in terms of how well  
614 they should be expected to perform, based on their complexity and the information used  
615 to drive them (Abramowitz, 2012). In brief, PALS uses a set of empirical benchmarks to  
616 fulfil the role of an arbitrary TBM of increasing complexity by quantifying the amount of  
617 information in the meteorological forcing useful to reproduce water, carbon and energy  
618 exchange. This gives a point of reference to measure at what level of complexity a TBM  
619 is performing, by comparison of the statistical performance between model and  
620 benchmark (Best et al., 2015). For example, we can assess whether a sophisticated,



621 state-of-the-art DGVM can outperform a simple linear regression against shortwave  
622 irradiance (SW) at predicting GPP. If the outcome of this test were negative, then this  
623 may suggest that the model does not capture the sensitivity of GPP to SW accurately,  
624 flagging it as a priority for investigation and development. The important distinction to  
625 make with the benchmarks is that they have no internal state variables such as soil  
626 moisture and temperature, nor any knowledge of vegetation or soil properties; they  
627 represent a purely instantaneous response to the meteorological forcing (Abramowitz et  
628 al., 2008). A direct application of this protocol was presented by Whitley et al. (2015) to  
629 assess the predictive capability of TBMs in savanna ecosystems by comparing model  
630 outputs to 3 simple empirical benchmarks. In this study the authors used 6 calibrated  
631 TBMs to predict ecosystem latent energy and GPP at five savanna sites along the NATT,  
632 and found that in almost all cases the LSMs could perform only as well as a multiple  
633 linear regression against SW, temperature and vapour pressure deficit (Fig 7). While an  
634 additional assessment of other outputs is required, the study highlighted that there are  
635 likely systematic misrepresentations of simulated phenology and root-water access in  
636 some of these models (Whitley et al., 2015). This is the first assessment of its kind for  
637 investigating how well savanna dynamics are captured by modern TBMs, and implies  
638 that without further development TBMs may have limited scope as investigative tools  
639 for future projections of savanna ecosystems.

640

#### 641 **4. Conclusion**

642 There is a large degree of uncertainty as to what impact climate change may have on the  
643 structure and function of savanna ecosystems given their complex interaction with  
644 climate. Projected higher temperatures and rainfall variability, potentially promoting  
645 more frequent fires, could favour  $C_4$  grasses in mesic savanna, while drier conditions are  
646 expected to increase tree mortality in semi-arid savanna. Conversely, increases to  
647 atmospheric  $CO_2$  are expected to favour  $C_3$  trees, reflecting woody encroachment that is  
648 already observed in many savannas globally (Donohue et al., 2009). Climate change  
649 therefore has the potential to alter the carbon balance, which may have major feedbacks  
650 on global climate and biogeochemical cycling. Because TBMs are the only interpreter of  
651 vegetation dynamics available to us that can reconcile the combination of effects  
652 induced by climate change, their predictive capability at representing savanna dynamics  
653 is of significant importance (Scheiter and Higgins, 2009). For TBMs to have the  
654 necessary skill required to simulate savannas under both present and future climate,



655 model development must be concentrated towards more adequate representations of  
656 phenology, root-water uptake, and disturbance dynamics, notably fires. We outline our  
657 recommendations below in these areas:

- 658 (1) Phenology: A dynamic representation of how leaf area responds to seasonally  
659 changing environment conditions, such that it becomes an emergent property of  
660 the coupled dynamics of weather and ecosystem function.
- 661 (2) Root-water uptake: Rooting depth and root distribution profiles that represent the  
662 contrasting strategies of trees and seasonal grasses, including their temporal  
663 dynamics. Additionally, root-water extraction schemes that can dynamically  
664 respond to the wetting and drying of the soil over time, accessing soil-water from  
665 where it is sustainably available rather than where the highest density of root  
666 biomass occurs.
- 667 (3) Disturbances: The role of disturbance (ubiquitous to all savannas) in keeping  
668 savanna systems open needs to be accounted for in models. Models need to  
669 represent the dynamic processes that capture the effect of fire on savanna  
670 composition, particularly in suppressing woody growth. Additionally, recovery  
671 periods whether through fire (re-sprouting) or cyclones (re-establishment)  
672 should also be considered given the dynamic influence these events have on the  
673 long-term carbon balance of savannas.

674 In addition to the recommended areas for TBM development above, we also stress that  
675 any improvements made in the representation of the above processes must be followed  
676 with a more complete evaluation and benchmarking of TBMs that considers multiple  
677 data sources in order to better constrain model uncertainty. We have highlighted that  
678 EC systems provide an unparalleled source of data for testing the predictive capability of  
679 TBMs at simulating water and carbon exchange in savannas. The role of regional flux  
680 communities, such as the OzFlux network (Beringer et al., 2016), will be to advance  
681 applications of EC systems that target savanna characteristics specifically. Indeed, more  
682 studies are needed that measure overstorey and understorey turbulent fluxes (Moore et  
683 al., 2016b), given their ability to quantify the contribution of co-dominant tree and grass  
684 functional types. Additionally, a greater use of ecological transects as tools for model  
685 evaluation are needed to quantify the ability of TBMs to simulate savanna behaviour  
686 over changing floristic structure and climate (Hutley et al., 2011). However, additional  
687 ecological and physiological measurements are also needed to test modelled



688 representations of root-zone water dynamics, carbon allocation and growth, phenology  
689 and the recovery of vegetation after major disturbance events (fire and cyclones);  
690 dynamic processes that cannot be verified by EC datasets alone. Facilities such as the  
691 Australian Super Site Network (Karan et al., 2016) run by the Terrestrial Ecosystem  
692 Research Network (TERN) will be critical to the collection of ecophysiological  
693 information that can inform how savanna dynamics are represented in TBMs.

694 Finally, we outline that future model experiments and inter-comparison studies that  
695 leverage EC and ecophysiological datasets should target each of the three previously  
696 mentioned processes individually. These may include rooting depth and water  
697 extraction experiments that test the sensitivity of TBMs to the dry season transition  
698 period, or fire management studies that investigate how the floristic structure in TBMs  
699 responds to variable fire frequency. Furthermore, such studies must also be conducted  
700 for savanna sites that have well-established datasets to test the processes in question.  
701 For example, we expect that any study that attempts to test or improve the  
702 representation of fire dynamics in TBMs is to be conducted at a site that has a long-  
703 running EC record (given the variable return time of fire events) and a full suite of  
704 concurrent ecophysiological measurements that quantifies the response of vegetation  
705 under post-fire recovery. Improving how savanna ecosystems are represented by TBMs  
706 will likely encompass the consideration of additional processes that have not been  
707 mentioned here. However, we believe that by identifying these processes as the cause  
708 for degraded model performance in this ecosystem, a roadmap for future development  
709 can be constructed that leverages the availability of rich datasets and current state-of-  
710 knowledge.

711

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727



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1085 **Figure Captions:**

1086 **Figure 1:** Global maps of (a) mean annual temperature and (b) mean annual rainfall for  
1087 the period 1901 to 2015, determined from the CRU TS v. 3.23 dataset (Harris et al.,  
1088 2014). The dataset has been clipped to the eco-floristic regions that approximate the  
1089 global extent of savannas using the following plant functional types: tropical moist  
1090 deciduous forest, tropical dry forest, subtropical dry forest and tropical shrubland  
1091 (Ruesch and Gibbs, 2008).

1092 **Figure 2:** Predicted changes to aboveground biomass between 2012 and 2100 for the  
1093 Australian savanna region following three scenarios of projected rainfall seasonality  
1094 according to IPCC SRES A1B (IPCC, 2007). The simulations were conducted using an  
1095 adaptive Dynamic Global Vegetation Model (aDGVM) shows predicted changes to (a)  
1096 present day aboveground biomass, when (b) rainfall seasonality does not change, (c)  
1097 rainfall seasonality increases, and (d) rainfall seasonality decreases. In all cases, the  
1098 aboveground biomass of the Australian savanna region increases, with the magnitude of  
1099 change determined by the degree of seasonality. Reprinted with permission from  
1100 Scheiter et al. (2015).

1101 **Figure 3:** Representation of how changes to (a) tree and grass phenology determines  
1102 changes in (b) savanna gross primary productivity (GPP) for an Australian mesic  
1103 savanna. Time-varying signals of tree and grass LAI (a) are determined from a MODIS  
1104 bulk LAI product using the method of Donohue et al. (2009), and are prescribed as  
1105 inputs to the Soil-Plant-Atmosphere (SPA) model to predict separate tree and grass GPP.  
1106 Data and model outputs are from Whitley et al. (2015) (*this issue*).

1107 **Figure 4:** Simulated differences in total ecosystem latent energy (LE) and the resultant  
1108 evolution of soil moisture content through the soil profile over time for a mesic  
1109 Australian savanna site. Simulations were conducted using two different terrestrial  
1110 biosphere models (TBMs) that use different root-water extraction schemes. The top  
1111 panel (a) shows outputs of savanna water flux using the Community Atmosphere  
1112 Biosphere Land-surface Exchange (CABLE) model, where the density of the fine-root  
1113 biomass weights soil-water extraction. The bottom panel (b) shows outputs of savanna  
1114 water flux from the Soil-Plant-Atmosphere (SPA) model, where soil-water is  
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1117 **Figure 5:** The nonlinear response of net ecosystem productivity (NEP) as the canopy



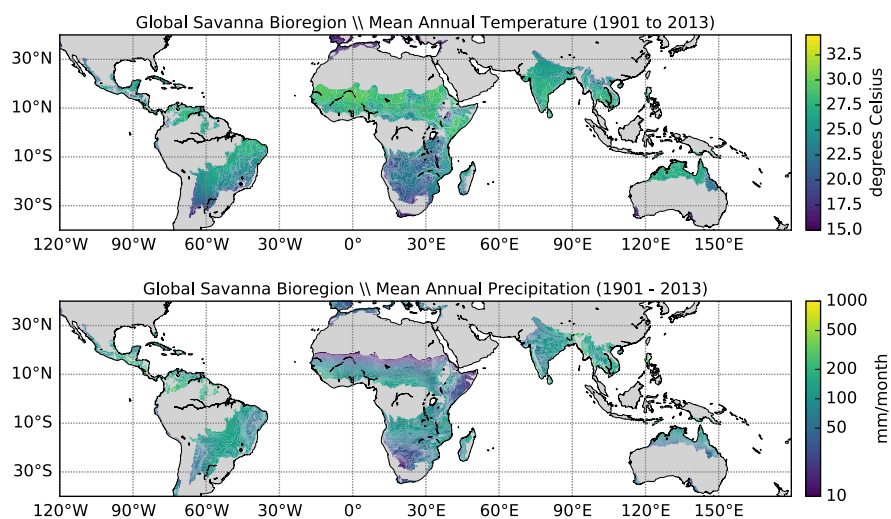
1118 regenerates after a fire event in 2003 at an Australian mesic savanna site. Fire  
1119 disturbance of a sufficient intensity suppresses productivity, pushing the savanna state  
1120 from sink to source over a period of 70 days at this site, as the rate of respiration  
1121 exceeds the rate of assimilation due to resprouting costs. Empirical models created  
1122 using an artificial neural network (NN) describe the 'UnBurnt' and 'Burnt' canopy NEP  
1123 responses over the same period, and their difference estimates the loss of canopy  
1124 productivity as a consequence of fire. Reprinted with permission from Beringer et al.  
1125 (2007).

1126 **Figure 6:** Smoothed (10-day running mean) time-series of understorey (red),  
1127 overstorey (green) and total ecosystem (red) gross primary productivity (GPP) for a  
1128 mesic savanna site in northern Australia. Rainfall is represented as black bars. Negative  
1129 and positive signs represent the savanna state as a carbon source or sink respectively,  
1130 and orange arrows depict the occurrence of fire events. Data products for total  
1131 ecosystem and understorey GPP are inferred from observations of net ecosystem  
1132 exchange using eddy-covariance towers at heights of 23 m and 5 m respectively.  
1133 Overstorey GPP is determined as the difference between the ecosystem and the  
1134 understorey. Reprinted with permission from Moore et al. (2016b) (*this issue*).

1135 **Figure 7:** Rank plot showing the average performance of 6 terrestrial biosphere models  
1136 (TBMs) across the North Australian Tropical Transect (NATT). The closer a model's rank  
1137 is to 1 the better its performance is at predicting latent energy (LE) and gross primary  
1138 productivity (GPP). Empirical benchmarks representing increasing levels of complexity  
1139 (emp1 < emp2 < emp3) are represented as grey lines, and coloured lines denote each  
1140 model. The lines have no scientific value and are used for visual purposes only.  
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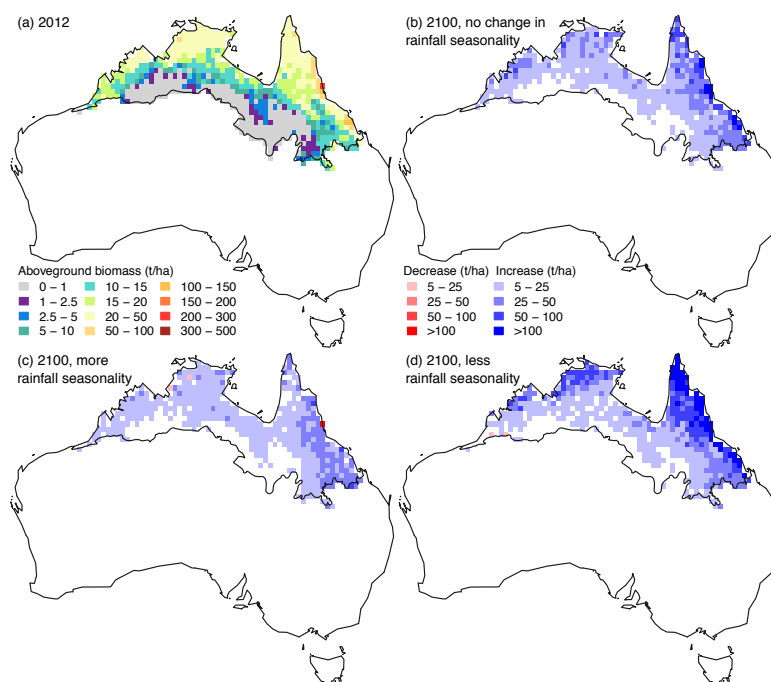
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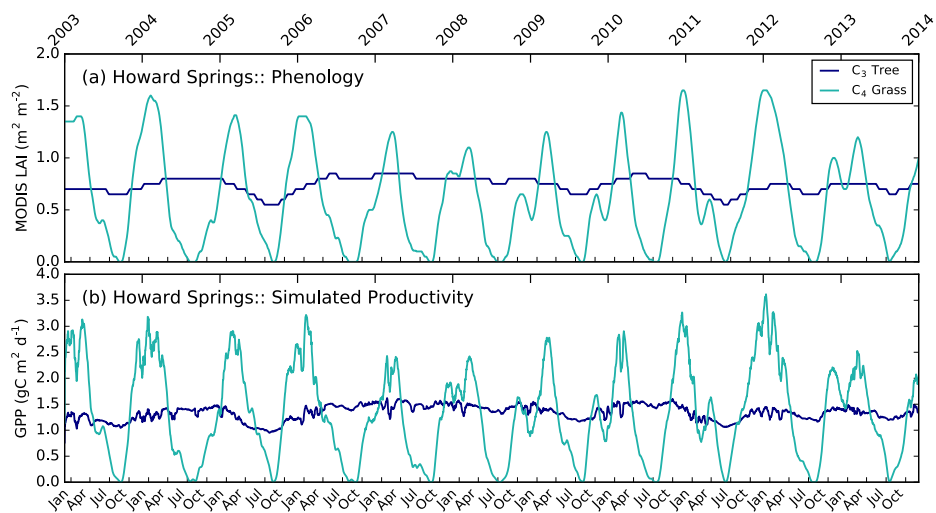
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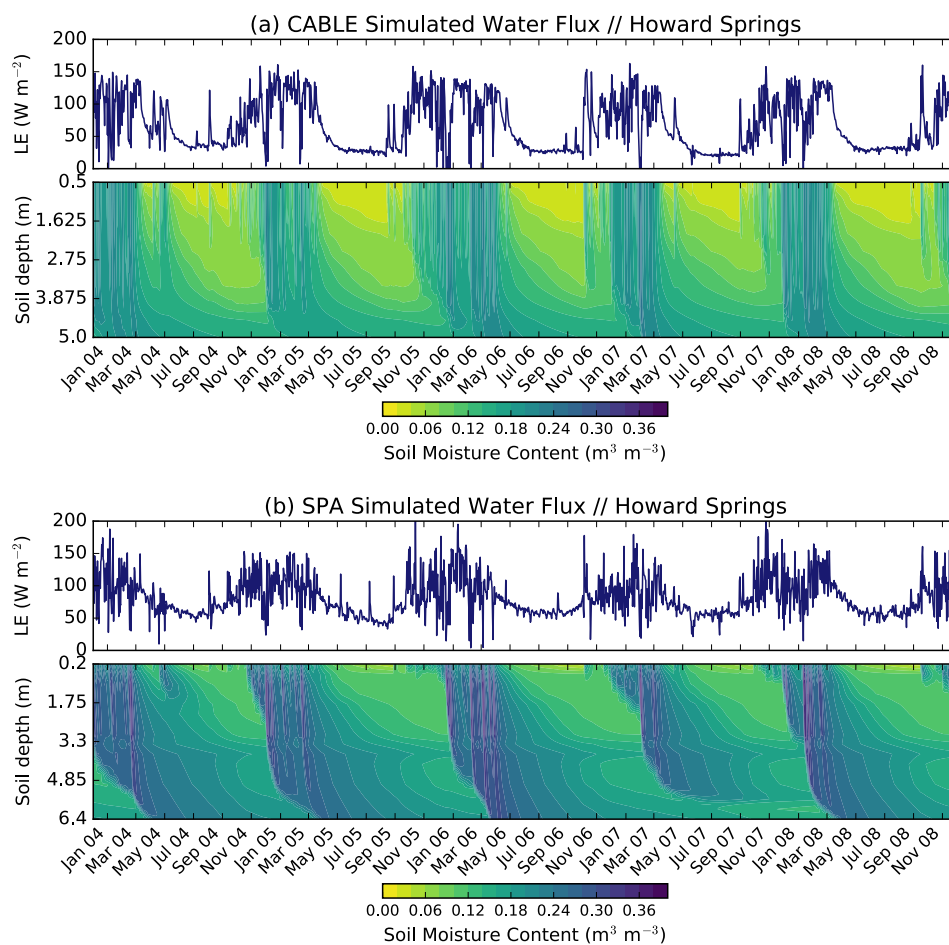


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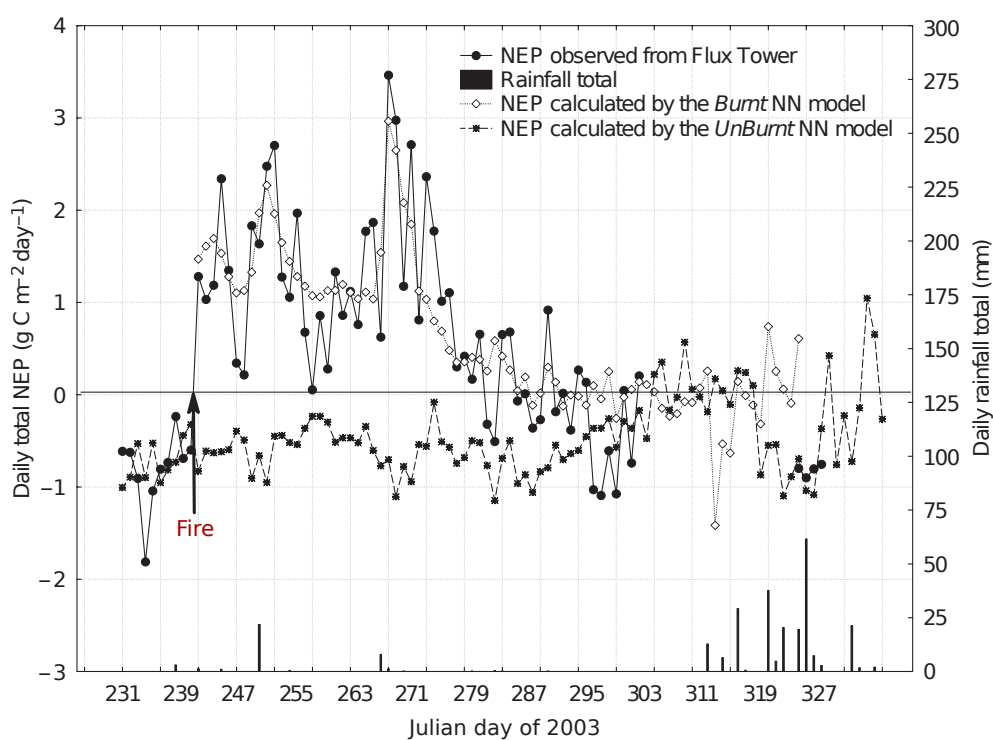
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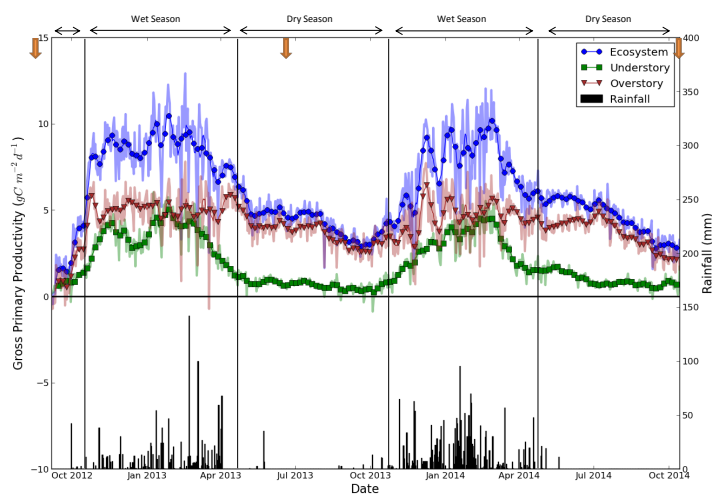
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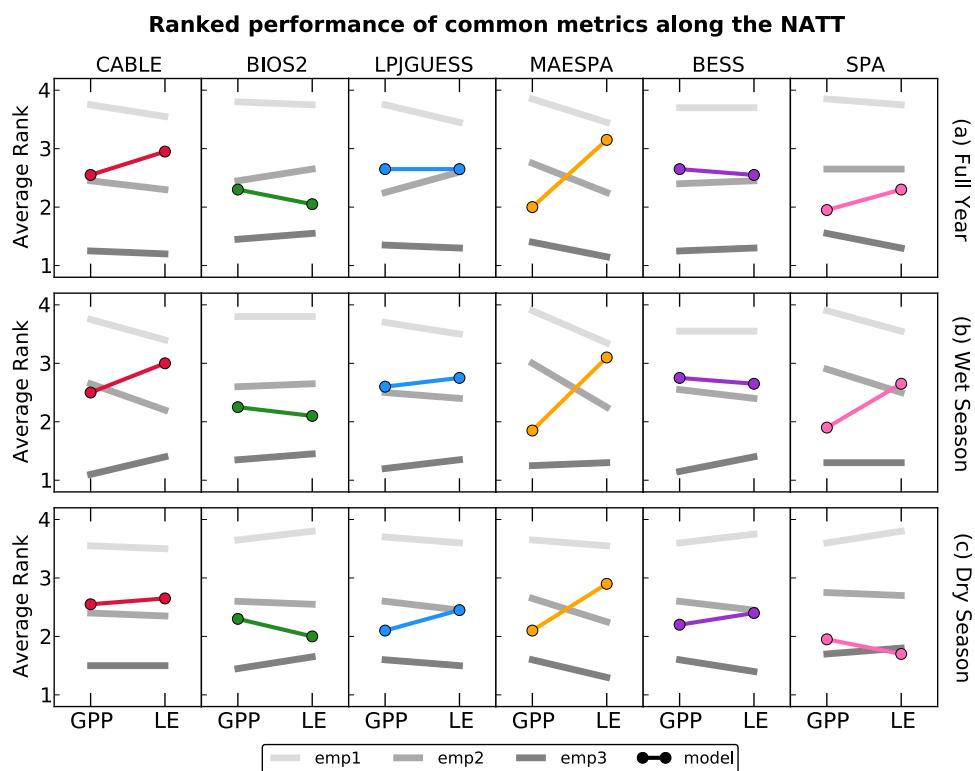
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