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Efeitos das alterações climáticas previstas para 2100 no desenvolvimento inicial de espécies arbóreas de Cerrado

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Orientador: Dr. Fabian Borghetti

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**EFEITOS DAS ALTERAÇÕES CLIMÁTICAS PREVISTAS PARA 2100 NO
DESENVOLVIMENTO INICIAL DE ESPÉCIES ARBÓREAS DE CERRADO**

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Morena Chaib Ferreira e Jorge Chaib Ferreira,
por quem eu quero ser sempre melhor a cada dia.*

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1 Feminismo e política, Flávia Biroli & Luis Felipe Miguel, editora Boitempo. ISBN:9788575593967

As forças da Natureza

*Quando o sol,
se derramar em toda a sua essência,
desafiando o poder da ciência, pra combater o mal.*

*E o mar,
com suas águas bravias,
levar consigo o pó dos nossos dias,
vai ser um bom sinal.*

*Os palácios vão desabar sob a força de um temporal,
e os e os cantos vão sufocar o barulho infernal.*

*Os homens vão se revelar dessa farsa descomunal,
Vai voltar tudo ao seu lugar, afinal.*

Vai resplandecer, uma chuva de prata, do céu vai descer. (- lalaia)

O esplendor da mata vai renascer, e o ar de novo, vai ser natural.

Vai florir, cada grande cidade, o mato vai cobrir. (- ô ô)

das ruínas um novo povo vai surgir, e vai cantar afinal.

As pragas e as ervas daninhas,

As armas e os homens de mal, vão desaparecer nas cinzas de um carnaval.

Foto: Adalgisa Chaib

João Nogueira



RESUMO

As mudanças climáticas aceleradas pela ação humana têm causado extinções e reduzido a biodiversidade em todo o mundo. Ambientes que apresentam alta frequência de distúrbios, como as savanas, pode estar particularmente ameaçados. O bioma Cerrado, um hotspot de biodiversidade, é composto principalmente por formações savânicas e vem sofrendo grande pressão devido às perdas de habitats e mudanças climáticas. Para compreender os impactos das mudanças climáticas na vegetação do Cerrado, fizemos dois experimentos com espécies arbóreas amplamente distribuídas nesse bioma. No primeiro experimento utilizamos as espécies *Qualea grandiflora* e *Tabebuia aurea* para testar o efeito de diferentes durações de veranicos (dias consecutivos sem chuva durante a estação chuvosa) no seu desenvolvimento, utilizando tratamentos de irrigação com intervalos de 1d, 8d e 15d. Os tratamentos de irrigação não causaram mortalidade de plântulas de ambas as espécies. O desenvolvimento inicial de *Q. grandiflora* não apresentou alterações entre os diferentes tratamentos de irrigação. O tratamento com 15d entre irrigações causou menor acúmulo de biomassa radicular de *T. aurea* provavelmente devido ao estresse hídrico. No entanto, o crescimento da raiz principal de *T. aurea* não sofreu alteração entre os tratamentos de irrigação. A profundidade da raiz principal pode ser uma estratégia importante para a sobrevivência de plântulas de espécies arbóreas em savanas, pois permite que alcancem frações do solo onde a água fica disponível por mais tempo ao longo do ano. No segundo experimento utilizamos *Kielmeyera coriacea*, *Qualea grandiflora*, *Tabebuia aurea* e *Hymenaea stigonocarpa* para observar parâmetros de crescimento das plântulas dessas espécies em dois diferentes cenários: atual, baseado em dados históricos; e futuro, baseado nas projeções do IPCC para 2100 segundo o SSP3-7.0, que para a região do Cerrado significa uma temperatura 2,5°C acima da temperatura atual em média e concentração atmosférica de CO₂ de 860ppm. Todas as espécies apresentaram aumento da taxa de crescimento relativo e da biomassa total quando submetidas ao cenário futuro. A distribuição de biomassa encontrada no cenário atual de *K. coriacea* e *H. stigonocarpa* se manteve quando submetidas ao cenário futuro, enquanto que *Q. grandiflora* e *T. aurea* apresentaram maior investimento em biomassa aérea do que radicular devido à elevação da temperatura e da concentração de gás carbônico. *K. coriacea* foi a espécie que apresentou menor alteração dos parâmetros observados no cenário futuro e *Q. grandiflora* foi a espécie que apresentou maior alteração do crescimento inicial. Embora as respostas ao cenário futuro tenham variado de acordo com a espécie, todas as espécies apresentaram maior acúmulo de biomassa e maior taxa de crescimento relativo no cenário futuro.

Palavras-chave: Mudanças climáticas, plântula, fitotron, biomassa, plasticidade, estresse, elevada [CO₂], temperatura elevada, *Kielmeyera coriacea*, *Qualea grandiflora*, *Tabebuia aurea*, *Hymenaea stigonocarpa*.

ABSTRACT

Human-accelerated climate change has caused extinctions and reduced biodiversity around the world. Environments with a high frequency of disturbances, such as savannas, may be particularly threatened. The Cerrado biome, a biodiversity hotspot, is mainly composed of savanna formations and has been under great pressure due to habitat loss and climate change. To understand the impacts of climate change on Cerrado vegetation, we carried out two experiments with tree species widely distributed in this biome. In the first experiment we used the species *Qualea grandiflora* and *Tabebuia aurea* to test the effect of different durations of dry spells on their development, using irrigation treatments with intervals of 1d, 8d and 15d. Simulated dry spells did not cause seedling mortality of both species. The initial development of *Q. grandiflora* showed no changes between the different irrigation treatments. Treatment with 15d between irrigations caused less accumulation of *T. aurea* root biomass, probably due to water stress. However, *T. aurea* taproot growth did not change between irrigation treatments. The taproot depth may be an important strategy for the survival of seedlings of tree species in savannas. In the second experiment, we used *Kielmeyera coriacea*, *Qualea grandiflora*, *Tabebuia aurea* and *Hymenaea stigonocarpa* to observe seedling growth parameters of these species in two different scenarios: current, based on historical data; and future, based on IPCC projections for 2100 according to SSP3-7.0. All species showed an increase in the relative growth rate and in the total biomass when submitted to the future scenario. The biomass distribution found in the current scenario of *K. coriacea* and *H. stigonocarpa* was maintained when submitted to the future scenario, while *Q. grandiflora* and *T. aurea* showed greater investment in shoot than root biomass due to the increase in temperature and concentration. of carbon dioxide. *K. coriacea* was the species that presented the smallest change of the parameters observed in the future scenario and *Q. grandiflora* was the species that presented the greatest alteration of the initial growth. Although responses to the future scenario varied in relation to the species, all species presented higher biomass and relative growth rate under the future scenario.

Keywords: Climate change, seedling, phytotron, biomass, plasticity, stress, high [CO₂], high temperature, *Kielmeyera coriacea*, *Qualea grandiflora*, *Tabebuia aurea*, *Hymenaea stigonocarpa*.

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1. TM: Biomassa total (total dry mass)
2. RM: biomassa radicular (root dry mass)
3. SM: biomassa aérea (shoot dry mass)
4. RMF: fração de biomassa radicular (root mass fraction)
5. SMF: fração de biomassa aérea (shoot mass fraction)
6. RGR: taxa de crescimento relativo (relative growth rate)
7. STRL: comprimento específico da raiz principal (specific taproot length)
8. H: altura da plântula (seedling height)
9. RL: comprimento da raiz principal (taproot length)
10. SLA: área específica foliar (specific leaf area)
11. RER: taxa de alongamento da raiz principal (taproot elongation rate)
12. R:S: partição de biomassa entre raiz e parte aérea (biomass partition root and shoot rate)
13. ST_D: diâmetro da base do caule (stem base diameter)
14. Lnum: número de folhas da plântula (leaf number)

DADOS BRUTOS

Capítulo I

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Capítulo II

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Data, v1<http://dx.doi.org/10.17632/286cjk5k55.1>DOI (is reserved but not active)

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1. INTRODUÇÃO GERAL

O clima tem sido apontado como o principal agente na determinação da distribuição da vegetação ao redor do mundo (Boonman et al., 2022; García-Valdés et al., 2018; Madani et al., 2018; Vicente-Serrano et al, 2020; Hansson et al, 2023). As mudanças climáticas aceleradas pela ação humana trazem uma preocupação latente em relação à biodiversidade (Cordeiro et al., 2021; Velazco et al., 2019). Estudos mostram que o risco de extinção tem se agravado cada vez mais (Pörtner et al., 2022). As alterações de temperatura e precipitação já têm causado efeitos negativos em plantações e levado diversas espécies de plantas nativas a extinções localizadas (Cahill et al., 2013). Muitos estudos que buscam projetar a distribuição futura de espécies nativas, no intuito de localizar áreas críticas para preservação, baseiam-se na teoria de nichos climáticos, assumindo que esses os fenótipos apresentados no cenário atual irão se manter em um cenário futuro (Román-Palacios and Wiens, 2020), deixando de lado importantes informações a nível do indivíduo relacionadas à plasticidade fenotípica que podem afetar o a mortalidade ou a sobrevivência de indivíduos e, portanto, o recrutamento (Ibáñez et al., 2007; Vanderwel et al., 2013). Apesar da importância da plasticidade fenotípica na relação entre as condições ambientais e a capacidade de permanência de uma espécie em um determinado local (Aubin et al., 2016; Nicotra et al., 2010), pouco se sabe sobre o comportamento de espécies nativas do Cerrado sujeitas às condições climáticas esperadas para 2100.

Estima-se que a concentração de CO₂ atmosférico tenha aumentado drasticamente desde o início da era industrial, saindo de cerca de 280 ppm na época pré-industrial para os atuais 400 ppm (Physical and Basis, 2013; Jin et al, 2023). Projeções para 2100 estimam concentrações de CO₂ atmosférico acima de 800ppm (Meinshausen et al., 2019). A maior disponibilidade atmosférica carbono deve aumentar a frequência com que a Rubisco se liga ao CO₂ em relação às ligações com O₂, aumentando a eficiência fotossintética e reduzindo a taxa de fotorrespiração (Mndela et al, 2022, Wang and Wang, 2021). Essa maior eficiência da Rubisco

26 em ambientes com maior [CO₂] atmosférica pode levar a um maior acúmulo de biomassa,
27 principalmente em espécies C3 (Ainsworth and Long, 2005; Hoffmann et al., 2000; Rosa et al.,
28 2019; Souza et al., 2016).

29 No Cerrado, em particular, além do aumento da [CO₂] deve haver um aumento de cerca
30 de 2,5°C na temperatura média (ver seção 5.2). Estima-se que o aumento da temperatura deve
31 levar a um maior déficit de pressão de vapor (VPD). Esse aumento do VPD deve intensificar a
32 evapotranspiração e acelerar a perda de água do solo, levando a estações secas mais intensas,
33 com valores de umidade relativa do ar mais baixos durante essa estação (Hoffmann et al.,
34 2012). Em relação à precipitação é esperada redução de dias com precipitação durante a estação
35 chuvosa, com maior frequência e duração dos períodos sem chuva durante a estação chuvosa,
36 ou seja, aumento de veranicos (Pascale et al., 2016). Veranicos prolongados podem causar
37 estresse hídrico e afetar o recrutamento de plântulas (Hoffmann, 1996), principalmente em um
38 cenário que a maior demanda por transpiração irá exigir maior disponibilidade de água no solo
39 (Kumarathunge et al, 2020).

40 A fase de plântula é a mais vulnerável na vida da planta (Leck et al, 2008), pois essa já
41 não recebe as proteções de que usufrui a semente, e tampouco desenvolveu estruturas de defesa
42 ou biomassa suficientes para defender-se de predadores, patógenos ou rebrotar em caso de perda
43 da parte aérea (Macedo et al, 2022). A forma com que as plântulas respondem às mudanças
44 climáticas interfere diretamente no recrutamento de plântulas e sua sobrevivência,
45 representando um gargalo importante na dinâmica de populações vegetais, e por isso é
46 fundamental compreender essas respostas para melhor projetar alterações da distribuição de
47 espécies em resposta às mudanças climáticas (Canham and Murphy, 2016).

48 Devido ao curto período associado a mudanças climáticas consideravelmente sensíveis,
49 é possível que o genótipo de plântulas expostas às condições climáticas de 2100 seja muito
50 próximo ao genótipo das plântulas encontradas no cenário climático atual. Isso permite que

51 experimentos testando os efeitos do cenário climático futuro em plântulas obtidas de sementes
52 dispersas no cenário atual possam obter resultados úteis para compreender as respostas dessas
53 espécies em 2100.

54 A maioria dos experimentos feitos até o momento para compreender as respostas de
55 plântulas às condições ambientais projetadas para o fim do século se concentram em um ou dois
56 parâmetros ambientais, como temperatura ou disponibilidade hídrica, não obtendo resultados
57 para interações mais complexas, as quais são mais prováveis de serem vivenciadas pelas plantas
58 (Parmesan and Hanley, 2015). Quando essas condições ambientais atuam simultaneamente
59 podem ter consequências diferentes no metabolismo da plântula de quando ocorrem
60 isoladamente, como amplificar possíveis prejuízos ou benefícios (Correia et al., 2018; Prasch
61 and Sonnewald, 2015). Assim, alguns trabalhos indicam vantagens em uma maior [CO₂] para
62 espécies arbóreas (Bellasio et al., 2018), pois confere a essas um aumento na taxa fotossintética
63 e maior acúmulo de biomassa, permitindo uma maior capacidade de rebrotar em caso de perda
64 da parte aérea Ainsworth and Long, 2005; Hoffmann et al., 2000; Rosa et al., 2019; Souza et
65 al., 2016), enquanto outros estudos indicam que a alta concentração de CO₂ atmosférico não
66 promove aumento da biomassa quando associado a altas temperaturas (Duan et al., 2015).

67 Enquanto a maior oferta de carbono atmosférico associado a temperaturas mais altas no
68 cenário futuro pode favorecer o ganho de biomassa e acelerar o crescimento de plântulas
69 durante a fase de estabelecimento (Mndela et al, 2022; Ncisana et al, 2022; Wang and Wang,
70 2021), a variação da precipitação associada a temperaturas mais elevadas pode levar a um
71 estresse hídrico e anular o efeito fertilizante do alto CO₂ atmosférico (Westerband et al, 2019).
72 Espécies arbóreas de ambiente savânico tendem a investir mais em profundidade de raiz do que
73 espécies florestais (Hoffmann et al, 2004; Paganeli et al, 2020), o que permite alcançar fontes
74 mais estáveis de água durante o ano. Porém, a maior demanda por evapotranspiração
75 ocasionada por temperaturas mais altas e oferta irregular de água, devido às alterações previstas

76 para a precipitação no cenário futuro, podem prejudicar o desenvolvimento inicial dessas
77 plântulas durante a estação chuvosa (Kumarathunge et al, 2020).

78 O Cerrado, segundo maior bioma brasileiro, representa um dos 25 *hotspots* de
79 biodiversidade global, com alto grau de endemismo, onde aproximadamente 45% das espécies
80 vegetais são endêmicas (Myers et al., 2000). Chegou a ocupar cerca de 25% da área do Brasil
81 e abriga nascentes das três das maiores bacias hidrográficas da América do Sul: Araguaia-
82 Tocantins, Prata e São Francisco (Fonseca & Silva Júnior, 2004). O Cerrado é coberto
83 predominantemente por formações savânicas, que ocupam aproximadamente 70% da área do
84 bioma (Coutinho, 2006; França et al., 2020; MapBiomas, 2023). Apesar da sua importância
85 devido à biodiversidade e recursos hídricos que abriga, o Cerrado é hoje a principal fronteira
86 agrícola brasileira, e mais de 50% de sua vegetação original já foi desmatada em função da
87 agricultura e ocupação urbana (Lahsen et al., 2016), necessitando de estudos que possibilitem
88 conhecer o comportamento de espécies nativas para alcançar melhores resultados de
89 preservação desse ecossistema.

90 Embora as espécies arbóreas de savanas tenham sido selecionadas para habitarem um
91 ambiente com sazonalidade da precipitação e longos períodos sem chuva durante a estação seca,
92 não sabemos como as plântulas irão ser afetadas pelas maiores temperaturas e pela variação da
93 disponibilidade hídrica durante a fase de estabelecimento esperadas para o cenário de 2100.
94 Nesse contexto podemos perguntar qual será o impacto dos cenários climáticos previstos pelo
95 IPCC para 2100 no recrutamento de plântulas de espécies arbóreas no Cerrado, considerando
96 maior temperatura, redução do número de dias com precipitação durante a estação chuvosa, e
97 maior [CO₂] atmosférico. Será que serão favorecidas pelo aumento de [CO₂] atmosférico, e
98 conseguirão fazer uso mais eficiente da água? Ou será que os prejuízos causados pelas altas
99 temperaturas e déficit hídrico no solo serão mais determinantes em seu desenvolvimento que o
100 possível benefício causado pela maior [CO₂]?

101 Espera-se que veranicos prolongados associados a altas temperaturas prejudiquem o
102 desenvolvimento inicial de espécies arbóreas de cerrado *sensu stricto*, provocando estresse
103 hídrico devido à maior demanda por água nessas condições em comparação ao desenvolvimento
104 observado no cenário climático atual.

105 Já as temperaturas elevadas associadas à alta [CO₂] do cenário futuro permitirão maior
106 acúmulo de biomassa durante a fase de crescimento inicial de espécies arbóreas de savana do
107 Cerrado, permitindo crescimento mais acelerado quando comparadas às plântulas observadas
108 no cenário climático atual.

109

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274 2. OBJETIVO

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276 2.1. OBJETIVO GERAL

277 Compreender o desempenho de plântulas de espécies arbóreas de cerrado *sensu stricto*
278 diante de diferentes cenários climáticos a partir da simulação do clima atual e daquele projetado
279 pelo IPCC para o período entre 2080 e 2100 (SSP 3-7.0), em câmaras climáticas programadas
280 para variação nos níveis de CO₂, temperatura e na frequência de irrigação.

281

282 2.2. OBJETIVOS ESPECÍFICOS

283 • Avaliar o efeito de diferentes intervalos de irrigação no desenvolvimento inicial
284 de espécies de Cerrado *sensu stricto* no intuito de simular diferentes intensidades de veranicos
285 para compreender seu possível impacto durante o período de recrutamento de plântulas de
286 espécies arbóreas.

287 • Avaliar o desenvolvimento inicial por meio de traços funcionais relacionados à
288 aquisição de biomassa de plântulas de espécies arbóreas de Cerrado *sensu stricto* quando
289 submetidas a um cenário climático previsto para 2100.

290 • Comparar o padrão de crescimento e a correlação entre os traços funcionais
291 observados em plântulas de espécies arbóreas de Cerrado *sensu stricto* quando submetidas ao
292 cenário climático atual e a um cenário com aumento de temperatura e veranicos recorrentes
293 com duração de 8 ou 15 dias.

294

295 3. ORGANIZAÇÃO DA TESE E PLANO DE PUBLICAÇÃO

296 Para desenvolver a pesquisa da tese foram realizados dois experimentos, os quais
297 separam a tese em dois capítulos: Capítulo I – Desenvolvimento inicial de espécies arbóreas
298 sob veranicos simulados, e Capítulo II – Experimento de cenários climáticos.

299 O Capítulo I desta tese é composto por um trabalho submetido para a revista científica
300 Flora (Elsevier) no dia 13 de agosto de 2022 e aceito em fevereiro de 2023.

301 O Capítulo II da tese apresenta uma proposta de artigo a ser submetido para a revista
302 Global Change Biology ainda em 2023. Nesse artigo discutimos a contribuição do cenário
303 climático previsto para 2100 para a região do Cerrado no fenômeno de adensamento arbóreo
304 em savanas utilizando o resultado de um experimento que mediu diferentes atributos funcionais
305 no desenvolvimento inicial de 4 espécies arbóreas submetidas a esse cenário climático simulado
306 em câmara de fitotron.

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4. CAPÍTULO I

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Early development of two savanna tree species
under simulated dry spells

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Early development of two savanna tree species under simulated dry spells

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324 **Early development of two savanna tree species under simulated dry spells**

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337 ¹

338 **Highlights**

339 ● Dry spells of up to 15 d did not affect the growth of *Qualea grandiflora* seedlings.

340 ● Dry spells of 15 d caused reduction of *Tabebuia aurea* seedlings root biomass.

341 ● *Tabebuia aurea* seedlings invested more biomass in shoot growth and root elongation when

342 submitted to dry spells.

343 ● The investment in total leaf biomass and net assimilation rate can explain why both

344 species differed in their dry spell treatments response.

¹ Abbreviations: TM, total dry mass; RM, root dry mass; SM, shoot dry mass; RMF, root biomass fraction; SMF, shoot biomass fraction; RGR, relative growth rate; STRL, specific taproot length; H, plant height; RL, taproot length; SLA, specific leaf area; RER, taproot elongation rate; R:S, biomass partition root and shoot rate.

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350 **ABSTRACT**

351 The seedling stage represents a bottleneck in plants' life cycle, particularly in savanna
352 environments, where the rainy season is the major window of opportunity for seedling
353 development and recruitment of new individuals. However, an increase in the duration and
354 frequency of dry spells (days without rain during the rainy season) is expected due to climate
355 change, which may affect species recruitment and establishment. The aim of this study was to
356 examine the effect of simulated dry spells on the growth performance and biomass of *Qualea*
357 *grandiflora* and *Tabebuia aurea* seedlings. Seedlings (60 days-old) were exposed to three
358 irrigation treatments (daily irrigation, irrigation every 8 days, and irrigation every 15 days) for
359 130 days. We found no mortality in any of the irrigation treatments for both species. Although
360 the growth parameters of *Q. grandiflora* were not significantly affected by the dry spells, the
361 species invested more in shoot growth than in root growth. In contrast, there was a significant
362 decrease in the root dry mass, root:shoot ratio, root biomass fraction, and relative growth rate
363 of *T. aurea* seedlings exposed to dry spells of 15 days; but there was a significant increase in
364 the specific taproot length and shoot biomass fraction. Overall, the plants showed species-
365 specific responses to the dry spell treatments, and dry spells of up to 15 days did not cause
366 seedling mortality. Further, *T. aurea* seedlings invested more resources in taproot growth in
367 response to dry spells. The development of deep-reaching taproots could be an effective
368 physiological adaptation strategy for the survival and establishment of young plants and the
369 resilience of native tree populations under future adverse climate scenarios.

370 **Keywords:** Savanna; Dry spell; Biomass Partition; Seedling; Drought Stress

371

4.1. INTRODUCTION

In seasonal environments, such as savannas, plant growth and recruitment of new individuals are usually limited to the rainy season, which is conducive for the initial development of plant species (Escobar et al., 2018; Higgins et al., 2000; Oliveira et al., 2005). Approximately 70% of the Cerrado biome is occupied by savanna-like vegetation (Ribeiro and Walter, 2008), constituting the largest area of savanna in South America (Sano et al., 2019; Werneck et al., 2012) and a biodiversity hotspot (Myers et al., 2000). However, the diversity and environmental services of the Cerrado biome are at considerable risk of degradation caused by agricultural expansion (Coelho et al., 2020; Franoso et al., 2020; Sano et al., 2019). In addition to the dry condition of the savanna, wildfires are among the main factors responsible for tree seedling mortality (Borghetti et al., 2019; Pellizzaro et al., 2017). Although it could take more than 3 years for wildfire to reoccur in the same location (Pereira Junior et al., 2014), the dry season might reach seedlings with no more than 6 months after germination (Escobar et al., 2018). Therefore, to successfully establish, it is crucial for plants to develop adaptive features to tolerate drought-associated fire and water deficit during the dry season (Gignoux et al., 2009).

In the Cerrado, tree seeds tend to germinate at the beginning of the rainy season (Escobar et al., 2018), subsequently using this wet period for their initial development and establishment. However, periods of dry spell (days without rain during the rainy season) can interfere with plant growth, which can compromise the development of new individuals (de Mattos et al., 2002). Dry spells represent a determinant factor promoting seedling mortality (Higgins et al., 2000; Kanegae et al 2000; Hoffmann, 1996). As dry seasons might cause the mortality of seedlings and young tree individuals (Pellizzaro et al., 2017), dry-spell-induced drought stress could impact the survival and recruitment rates of young trees under natural conditions (Gignoux et al., 2009). Particularly, dry spells have considerable impacts on seedlings with

397 poorly developed root systems incapable of sufficient water uptake (Goldstein et al., 2008). The
398 longer the dry spells, the greater the water deficit and their effects on seedling development
399 (Blanco-Martínez et al., 2022). Extended periods of drought during the rainy season were
400 observed to be associated with lower total biomass, higher root biomass, and height reduction
401 in young tree individuals (Westerband et al., 2019).

402 Previous studies have reported high survival rates, but low photosynthesis rate and
403 vegetative growth in native *Dipteryx alata* tree seedlings exposed to varying degrees of drought
404 stress (Matos et al., 2018). Drought stress tolerance may vary depending on the species and
405 duration of the water deficit period (Westerband et al., 2019). Regardless of the species, drought
406 stress has been shown to stimulate root growth in the seedlings of Mediterranean tree species
407 (Padilla, et al., 2007). Species with storage cotyledons produced longer roots (≈ 40 cm) after 3
408 months when compared with species with photosynthetic cotyledons (≈ 20 cm) (Saboya and
409 Borghetti, 2012). Additionally, Saboya and Borghetti (2012) reported that root length was at
410 least four times the shoot length for three Cerrado tree species after 80 days of growth,
411 indicating a higher biomass investment in root than in shoot system among these seedlings.
412 Seedlings of savanna species tend to invest considerably more in root than in shoot growth than
413 seedlings of forest species (Hoffmann et al., 2004; Poorter and Garnier, 2007; Tomlinson et al.,
414 2014).

415 The extent of root growth achieved by young plants of savanna tree species during the
416 rainy season may determine their survival during the dry season (García-Núñez et al., 2019;
417 Kanegae et al., 2000). Although this strategy can be decisive for their survival during the dry
418 season, it can be compromised by the occurrence of dry spells during the rainy season. For
419 example, soil water potential was lowered to ca. -1.3 MPa (at 5 cm soil depth) during a dry spell
420 of 9 days, which reduced the emergence and survival rate of *Bowdichia virgilioides* seedlings
421 compared with seedlings that were not exposed to dry spell (Braz et al., 2000). Similarly, there

422 was a 0.67- and 2.6-fold increase, respectively, in the recruitment rates of *Roupala montana*
423 and *Miconia albicans* seedlings under irrigation when compared with unirrigated seedlings
424 exposed to dry spells of at least 9 days during the rainy season (Hoffmann, 1996).

425 In the Cerrado region, dry spells of 5 to 15 days are common during the rainy season
426 (da Silva et al., 2008). Moreover, climate change models indicate that there may be an increase
427 in the duration and frequency of dry spells in this region (Magalhães et al., 2019). Therefore,
428 investment in root development during the rainy season might be important for the recruitment
429 of Cerrado species. In this study, we examined the effects of simulated dry spells of 8 and 15
430 days on the initial development of two Cerrado species widely distributed in the savanna
431 vegetation: *Tabebuia aurea* (Silva Manso) Benth. & Hook. f. ex. S. Moore (Bignoniaceae) and
432 *Qualea grandiflora* Mart. (Vochysiaceae). We expected that seedlings exposed to dry spells of
433 eight days present higher root biomass and reduction of shoot growth, and seedlings exposed
434 to dry spells of 15 days present reduction of total biomass but higher taproot elongation. It is
435 anticipated that our findings can improve the understanding of climate change impacts on the
436 recruitment of native species.

437 4.2. MATERIALS AND METHODS

438 4.2.1. Species studied and seed collection

439 *Qualea grandiflora* and *Tabebuia aurea* are widely distributed in savanna
440 physiognomies of the Cerrado (Ratter et al., 2003). Both species are deciduous, anemochorous,
441 and typical of *cerrado sensu stricto* physiognomy (Capuzzo et al., 2012; Ratter et al., 2003),
442 generally occurring on red latosol. The seeds of these species have no dormancy (da Ponte et
443 al., 2020; Santos et al., 2019). Seeds were collected between September and October 2017 in
444 savanna areas located in the municipality of Pirenópolis, Goiás state (15° 84' S, 48° 97' W; 800
445 m a.s.l.), at the Brasília National Park (15° 38' S, 48° 01' W; 1.100 m a.s.l.), and the Fazenda
446 Água Limpa (15° 95' S, 47° 92' W; 1.200 m a.s.l.), in the Federal District. Seeds were collected

447 from 10 healthy trees at least 50 meters apart from each other and taken to the *Laboratório de*
448 *Termobiologia* of the University of Brasília (Darcy Ribeiro Campus). Seeds were processed
449 and stored at for further analysis.

450 4.2.2. *Climate data*

451 The Cerrado central region has an Aw climate according to the Köppen-Geiger
452 classification (Cardoso et al., 2014). The average temperature and rainfall in the region between
453 October and March are around 24.7 °C and 1,284 mm, respectively (Cardoso et al., 2014). The
454 irrigation volume used in this study was based on the average precipitation values recorded
455 from January to April between 1960 and 2016 (Table S1), which was obtained from an
456 automatic climatological station of the National Institute of Meteorology (INMET, 2017). The
457 relative humidity values were also obtained from the climate data (see section 2.3).

458 Due to the proximity of seedlings to the soil and the direct effects of soil temperature on
459 root development (Kaspar and Bland, 1998; Onwuka, 2018), we defined the minimum and
460 maximum temperature in the growth chamber based on the soil temperature estimates (section
461 2.3). To obtain these values, we used the minimum and maximum historical atmospheric
462 temperature average obtained between 1960 and 2016 (INMET, 2017 – spreadsheet S1) and
463 calculated the soil temperature by correlating these two variables (Ooi et al., 2009).

464 4.2.3. *Equipment and assembly and disassembly of the experiment*

465 The experiment was performed in a climatic chamber (Phytotron type, Eletrolab,
466 Brazil), which allowed the regulation of temperature, air moisture, photosynthetic photon flux
467 density (PPFD), gas concentration, and photoperiod. The chamber was equipped with a
468 manually operated drip irrigation system. The experimental conditions of the chamber were
469 based on historical climatic data (section 4.2.2) and defined as follows: carbon dioxide
470 concentration of 400 $\mu\text{l l}^{-1}$, photoperiod of 12 h, alternating fixed day/night temperature 38/28
471 °C (12 h/12 h), relative humidity of 70%, and PPFD of 700 $\mu\text{mol m}^{-2} \text{s}^{-1}$ (da Silva et al., 2008).

472 The experiment was started in May 2018. The seeds were germinated in Petri dishes containing
473 filter paper and distilled water in a germination chamber (Eletrolab, Brazil) under a 12 h
474 photoperiod at 28 °C. After the radicle protrusion, the seedlings were transferred to plastic bags
475 (20 cm height and diameter of 10 cm) filled with dystrophic red latosol (obtained from a soil
476 deep of 30 cm), which was collected from a preserved area at the *Fazenda Água Limpa*. The
477 soil was mixed with sand (3:1 ratio) to keep soil aeration during the experiment. Soil samples
478 (with and without sand) were sent for physical and chemical analyses (Table S1). The initial
479 establishment of the seedlings was conducted in these plastic bags, which were watered every
480 two days for 60 days to assure a high rate of survival. As in the Cerrado anemochoric species
481 disperse seeds at the beginning of the rainy season (October–November) (Escobar, 2018), the
482 simulated dry spell treatments started at a period corresponding to January, when the occurrence
483 of dry spells is usually higher (Assad, 1994).

484 After 60 days, 10 seedlings of *T aurea* and 8 seedlings of *Q. grandiflora* were chosen at
485 random for initial measurements (Table S2). These initial measurements were important for the
486 calculations of plant growth variables (Table S3). The remaining seedlings were randomly
487 distributed in groups of 10 (*T. aurea*) or 8 (*Q. grandiflora*) seedlings per treatment. To be
488 subjected to the dry spell treatments, the 60-day-old seedlings were transferred from the plastic
489 bags to plastic tubes (100 cm high and 10 cm in diameter), closed at the base with a perforated
490 lid to allow the draining of excess water. The tubes were filled with the same substrate as the
491 bags and evenly distributed in the phytotron to standardize the effects of the chamber
492 environment on seedling growth. The dry spells were simulated by controlling the frequency of
493 irrigation and the volume of water provided per each tube per treatment; daily irrigation (no dry
494 spell), irrigation every 8 days, and irrigation every 15 days. The volume of water provided at
495 each irrigation event was calculated in order that, at the end of the experiment, each seedling in
496 each treatment received the same amount of water (Table S4). The simulated dry spell

497 experiment lasted for 130 days, roughly representing the remaining of the rainy season
498 (January–April).

499 After 130 days, the seedlings were carefully removed from the tubes using a gentle
500 stream of running water over a fine mesh to remove the soil and other debris from the root
501 system. Measurements of the growth variables (section 4.2.4) were taken from these seedlings
502 the same day they were removed from the phytotron (Fig. S3).

503 4.2.4. Data collection

504 At the beginning (60 days old seedlings) and the end (190 days old seedlings) of the
505 experiment, the following growth parameters of *T. aurea* and *Q. grandiflora* seedlings were
506 measured for each treatment (no dry spell, 8-day dry spell, 15-day dry spell): seedling height
507 (H), taproot length (RL) and number of leaves (Lnum) per individual. Thereafter, the root
508 (primary and secondary roots were separated and only taproot was considered) and the shoot
509 (including stems and leaves separately) parts of the seedlings were separately oven-dried at 70
510 °C for 48 h. When present, the cotyledons were also dried but were not included in the shoot
511 mass. After drying, the following variables were determined: total seedling dry mass (TM), root
512 dry mass (RM), shoot dry mass (SM), leaf dry mass (LM), root mass fraction (RMF), shoot
513 mass fraction (SMF), leaf mass fraction (LMF), and root:shoot ratio (R:S ratio). Relative growth
514 rate (RGR) was calculated based on total dry mass. Taproot elongation rate (RER) and specific
515 taproot length (STRL) (see Tomlinson et al., 2012) were calculated based on taproot mass and
516 taproot length (Table S3). The leaf area necessary to calculate the specific leaf area (SLA) was
517 obtained by analysing the images of previously scanned well developed fresh leaves (three per
518 seedling) from 10 seedlings per treatment for *T. aurea* and 8 seedlings per treatment for *Q.*
519 *grandiflora* seedling/treatment combination using ImageJ software.

4.2.5. Statistical analysis

The dry spell treatments were considered as predictor variables, while the variables measured at the end of the experiment and the indices (section 2.4) were considered as dependent variables. Results were considered statistically significant at $P < 0.05$. All analyses were conducted in the R program (RStudio Team, 2020), using the *PMCMR* package (Pohlert, 2016). Kruskal-Wallis non-parametric test was used to analyse the data due to the low number of individuals in the samples (Kruskal and Wallis, 1952; Morgan, 2017). Then, pairwise post-hoc test for multiple comparisons of mean rank sums for unreplicated blocked data was performed (Nemenyi-Test) to identify stochastic dominance between irrigation treatments when we found significant differences in the Kruskal-Wallis' test (Pohlert, 2016). Graphs showing the biomass dispersion of observations, interquartile ranges, and medians were generated using the *Flexplot* package (Fife, 2019) in the R program. Pearson's correlation analysis was performed to determine the relationships between the traits using the *Multi Environment Trials Analysis* package (Olivoto, 2019) and the `corr_coef()` command. The raw data used in the initial analysis can be found in worksheet S2 and the raw data from the final analysis in worksheet S3 of the supplementary material.

4.3. RESULTS

No mortality was observed during the experimental period. The P values of the data analysed (section 2.5), including biomass and growth variables (section 2.4) of *Q. grandiflora* and *T. aurea* seedlings are shown in Table S5.

4.3.1. Initial growth variables before dry spell treatments

Sixty days-old *Qualea grandiflora* seedlings showed a shoot dry mass (SM = 0.26 g) at least twice as large as the root dry mass (RM = 0.11 g), corresponding to *ca.* 70% of the total mass (TM = 0.38 g), while the average shoot height (H) was near to 30% of the average taproot

545 length (RL = 20.62 cm) (Table S2). *Tabebuia aurea* seedlings had a SM around 50% lower
546 than RM, and a root:shoot (R:S) ratio of 1.82. Also, similar to *Q. grandiflora*, the shoot height
547 of *T. aurea* corresponded to roughly 25% of the taproot length (RL = 9.46 cm) (Table S2). The
548 RL of *Q. grandiflora* seedlings was more than twice that of *T. aurea*; however, Lnum and SLA
549 were similar between the two species. The STRL of *Q. grandiflora* was close to 20 times higher
550 than that of *T. aurea* (Table S2).

551 4.3.2. Biomass variables after dry spell treatments

552 After 130 days of simulated dry spells, we observed that these treatments did not
553 significantly affect the TM (Kruskal–Wallis $P = 0.1785$), RM (Kruskal–Wallis $P = 0.810$), and
554 SM (Kruskal–Wallis $P = 0.954$) of *Q. grandiflora* seedlings. Specifically, TM ranged from 5.4–
555 5.7 g, RM from 1.6–2.0 g, and SM from 3.7–3.8 (Table S2; Fig. 1A, B). Notably, *Q. grandiflora*
556 showed lower investment in root mass than in shoot mass, with SM constituting 60–70% of TM
557 in all treatments (Table S2). SMF and RMF (Kruskal–Wallis $P = 0.193$) and R:S ratio (Fig. 1C;
558 Kruskal–Wallis $p = 0.193$) were also not significantly affected by the dry spell treatments in
559 comparison to the control (no dry spell). Specifically, R:S ranged from 0.40 in the control group
560 to 0.65 in plants under the 15-d dry spell treatment (Fig. 1C). Most of SMF was composed by
561 LMF, where LM of *Q. grandiflora* seedlings ranged from 60% of TM (under 8 days dry spell)
562 to 47% of TM (under 15 days dry spell), while in *T. aurea* seedlings LMF had a significant
563 statistical increase according to the dry spell duration, ranging from 20% of TM when no dry
564 spell was applied to 42% of TM when submitted to 15 days of dry spell.

565 There was a significant decrease in the TM (Kruskal–Wallis $P = 0.021$) and RM
566 (Kruskal–Wallis $P = 0.007$) of *T. aurea* seedlings with increasing dry spells; the RM decreased
567 by ca. 55% in seedlings irrigated every 15 days compared to control seedlings (Fig. 1A, Fig.
568 S4). However, there was no significant difference (Kruskal–Wallis $P = 0.689$) in the SM of *T.*
569 *aurea* among the treatments (Fig. 1B). Additionally, there was a significant decrease (Kruskal–

570 Wallis $P = 0.036$, Nemenyi test $P = 0.028$) in the RMF of *T. aurea* seedlings with increasing
571 dry spell duration, accounting for 73% of TM in seedlings irrigated daily to 54% of the TM in
572 seedlings exposed to dry spells of 15 days. In contrast, there was a significant increase
573 (Kruskal–Wallis $P = 0.036$) in the SMF of *T. aurea* seedlings with increasing dry spell duration,
574 accounting for 27% in seedlings irrigated daily to 46% of the TM in seedlings exposed to dry
575 spells of 15 days. Additionally, there was a significant decrease (Nemenyi test $P = 0.028$) in the
576 R:S ratio, from 2.96 under daily irrigation to 1.34 under irrigation every 15 days (Fig. 1C).

577 4.3.3. Growth variables after dry spell treatments

578 For *Q. grandiflora* seedlings, simulated dry spells did not significantly affect the growth
579 parameters RGR (Kruskal–Wallis $P = 0.999$), shoot height Kruskal–Wallis $P = 0.735$) and root
580 length (Kruskal–Wallis $P = 0.379$) (Table S2, S5; Fig. 2B). In accordance, no significant
581 statistical difference was observed among treatments for SLA (Kruskal–Wallis $P = 0.861$),
582 LMF (Kruskal–Wallis $P = 0.862$) and NAR (Kruskal–Wallis $P = 0.644$) for *Q. grandiflora*
583 seedlings (Table S2, S5; Fig. 2).

584 In contrast, for *T. aurea* seedlings, RGR significantly decreased (Kruskal–Wallis $P =$
585 0.021 and Nemenyi $P = 0.016$) with increasing duration of dry spells, decreasing from 0.026 g
586 $\text{g}^{-1} \text{ d}^{-1}$ in seedlings irrigated daily to $0.023 \text{ g g}^{-1} \text{ d}^{-1}$ in seedlings irrigated every 15 days (Fig.
587 2B). Similarly, NAR of *T. aurea* seedlings decreased according to the dry spell treatment,
588 ranging from $0.0016 \text{ g cm}^{-2} \text{ d}^{-1}$ in seedlings irrigated daily to $0.0006 \text{ g cm}^{-2} \text{ d}^{-1}$ in seedlings
589 irrigated every 15 days (Fig. 2D). STRL significantly increased (Kruskal–Wallis $P = 0.01$,
590 Nemenyi $P = 0.007$) with increasing duration of the dry spells, ranging from 9.24 cm g^{-1} in
591 seedlings irrigated daily to 22.12 cm g^{-1} in seedlings irrigated every 15 days (Fig. 1D). There
592 were no significant differences in H, RL (Kruskal–Wallis test $P = 0.1$), RER (Kruskal–Wallis
593 $P = 0.1$), Lnum (Kruskal–Wallis $P = 0.11$), and SLA (Kruskal–Wallis $P = 0.712$) among the

594 treatments (Table S5, Fig. 2C). Height ranged from 6–9 cm, RL from 98–102 cm, and RER
595 from 0.68–0.71 cm d⁻¹.

596 4.3.4. Trait correlations

597 RGR of *Q. grandiflora* was positively correlated with RM ($r = 0.81$) and H ($r = 0.62$),
598 and negatively correlated with STRL ($r = -0.83$). In contrast, SLA was not significantly
599 correlated with any of the parameters (Fig. S1). Details of Pearson's correlation analysis for *Q.*
600 *grandiflora* are shown in Figure S1.

601 RGR of *T. aurea* was negatively correlated with STRL ($r = -0.85$), but not significantly
602 with RMF ($r = 0.28$). SLA of *T. aurea* was not significantly correlated with any variable. The
603 results of Pearson's correlation analysis for *T. aurea* are shown in Figure S2.

604

605 4.4. DISCUSSION

606 In the present study, we observed different responses in the seedling growth of two
607 savanna tree species to simulated dry spells. While the growth variables of *Q. grandiflora*
608 seedlings were similar among the different dry spell treatments, the growth variables of *T. aurea*
609 seedlings were affected by the dry spell duration; notably they reduced TM when subjected to
610 longer dry spells (Table S2). These results indicate that the dry spell treatments used in our
611 experiment did not substantially result in drought stress among seedlings of *Q. grandiflora*, but
612 apparently promoted a drought stress in seedlings of *T. aurea*. Taken together, these results
613 suggest that seedling responses to dry spells may be related to species-specific growth strategies
614 these tree species might present at their initial growth stage.

4.4.1. *Qualea grandiflora*: comparison between treatments

Dry spell treatments did not affect the biomass of *Qualea grandiflora* seedlings. There was no significant difference between TM, RM or SM of *Qualea grandiflora* seedlings subjected to different treatments. As drought stress usually leads to a reduction in biomass acquisition (Mundim and Pringle, 2018; Aziz et al., 2017), these results suggest that the dry spell treatments did not cause drought stress on *Qualea grandiflora* seedlings.

Previous studies have reported higher biomass investment in RM, compared with SM, in *Q. grandiflora*, with R:S ratio ranging from 2.5 to 3.5 among seedlings 125 to 150 days-old (Felippe and Dale, 1990; Moreira and Klink, 2000). In contrast, we observed a higher investment in SM among *Q. grandiflora* seedlings, with R:S ranging from 0.41 (under daily irrigation) to 0.65 (under dry spell of 15 days) in 190 days-old seedlings (Table S2). These results might be related to the phenotypic plasticity of *Q. grandiflora* (Buzatti et al., 2019). Norden et al. (2009) reported that the initial growth stage of *Qualea sp* is considerably affected by light conditions, and low light conditions can suppress shoot growth instead of stimulating etiolation. *Qualea grandiflora* is among the most widely distributed tree species in the Cerrado biome (Eiten, 1972; Ratter et al., 2003). The species can be found in several physiognomies, including closed-canopy (such as *cerradão*), to open-canopy as savannas (*cerrado sensu stricto*) and open savannas (*campo sujo* and *campo limpo*) (da Ponte et al., 2020; Eiten, 1972; Ratter et al., 2003).

SLA, H, and Lnum of *Q. grandiflora* were not significantly affected by increasing dry spells. After 130 days of dry spell treatments, the RL of *Q. grandiflora* seedlings varied between 106 and 115 cm (Table S2), which was significantly longer than the roots of 150 days-old *Q. grandiflora* seedlings (~57cm) reported by Moreira and Klink (2000).

The RGR values recorded for 190 days-old *Q. grandiflora* seedlings (0.012–0.013) grown in the phytotrons are consistent with values reported in literature (0.015) for seedlings

640 125 to 150 days-old grown under field conditions (Felippe and Dale, 1990; Moreira and Klink,
641 2000). This result suggests that seedlings of *Q. grandiflora* were able to keep a growth rate
642 similar to what they might present if grown under field conditions. Because higher leaf area per
643 unit of leaf biomass can allow seedlings to increase carbon assimilation (Gibert et al., 2016),
644 seedlings usually present a positive correlation between SLA and RGR. However, we did not
645 find a significant correlation between these parameters for *Q. grandiflora* seedlings. Previous
646 studies reporting SLA values for *Q. grandiflora* were mainly focused on adult plants (Franco
647 et al., 2005) and correlation between SLA and RGR can vary depending on the species' life
648 stage (Gibert et al., 2016), and light or nutrient availability (Shipley, 2002; Osone et al., 2008).
649 According to these studies, positive correlation between SLA and RGR are found in
650 experiments where light availability is low (Shipley, 2002) or experiments conducted with very
651 small seedlings (Wright et al., 2019).

652 Previous studies have reported a seedling height (H) ranging from 5.3 to 8 cm for one-
653 year-old individuals of *Q. grandiflora* grown under field conditions (Franco, 2002; Pellizzaro
654 et al., 2017). In the present study the average seedling height was around 7 cm for 60 days-old
655 seedlings, and between 22 and 25 cm for 190 days-old seedlings depending on the dry spell
656 treatment. However, we should consider that seedlings growing under field conditions face
657 different conditions in comparison to those growing under controlled experimental conditions.
658 Unfortunately, we have not found any information regarding the number of leaves in seedlings
659 of the species selected for the present study.

660 Root growth was not influenced by the dry spell treatments for *Q. grandiflora* seedlings,
661 which maintained RER and STRL similar between the different treatments (Table S2). These
662 results suggest that during the experimental period in the phytotron water shortage did not
663 impair the growth of *Q. grandiflora* seedlings.

4.4.2. *Tabebuia aurea*: comparison between treatments

664 Previous studies reported that when subjected to an irrigation interruption of 10 days,
665 150 days-old *T. aurea* seedlings showed a decrease in their rates of photosynthesis and
666 transpiration, which returned to their previous values four days after the irrigation was set again
667 (Oliveira et al., 2011). Our results revealed a progressive decrease in the TM of *T. aurea*
668 seedlings with increasing duration of the dry spells (Table S2), which might be related to an
669 effect of drought stress on their rates of transpiration and photosynthesis (Westerband et al.,
670 2019; Eziz et al., 2017). Aboveground growth parameters are usually affected when water is a
671 limiting resource (Eziz et al., 2017). Despite the RM reduction among *T. aurea* seedlings, SLA,
672 Lnum and H were not influenced by the dry spell treatments (Table S2). Previous studies
673 showed that Cerrado tree seedlings present a strong stomatal control (Bucci et al., 2008;
674 Goldstein et al., 2008; Quesada et al., 2008), which might be sufficient to avoid the effects of a
675 drought stress, although it might result in a lower carbon acquisition and reduced dry mass
676 incorporation (McDowell et al., 2008). Our study revealed that, although the total dry mass was
677 reduced by the dry spells, *T. aurea* seedlings kept key parameters for photosynthesis as SLA
678 and number of leaves virtually unchanged, irrespective of the treatments.

680 The significant decrease of the TM of *T. aurea* seedlings associated with the
681 maintenance of the SM indicate that biomass allocation to the roots was reduced by the dry
682 spell treatments, thus resulting in an increase in SMF and decrease in RMF. This outcome is
683 somewhat inconsistent with previous studies, since savanna species are expected to invest more
684 resources in root biomass when exposed to drought stress (Matos et al., 2018).

685 On the other hand, the significant increase in the STRL of *T. aurea* seedlings exposed
686 to dry spells of 15 days in comparison to those irrigated daily suggests that, irrespective of the
687 reduction in biomass allocation to the roots, seedlings of *T. aurea* maintained a RER under
688 moderate dry spells. These results indicate that the decrease in RM did not translate into a

689 decrease in RL. It is important to highlight that RGR was inversely correlated with STRL (Fig.
690 S1 and S2), suggesting that the decrease in RGR did not affect seedling investment in taproot
691 elongation. Similar results have been observed among seedlings of other Cerrado tree species
692 (Saboya and Borghetti, 2012; Zhou et al., 2020), indicating that these species might prioritise
693 access to water at greater depths in detriment of root mass storage.

694 Notably, there were no major differences in growth rates and biomass allocation patterns
695 between *T. aurea* seedlings irrigated daily and those exposed to dry spells of 8 days, suggesting
696 that relatively short dry spells might not compromise the growth and development of this
697 species under field conditions. However, we found that dry spells of 15 days negatively affected
698 the initial growth of *T. aurea* seedlings in comparison to those irrigated daily, indicating that
699 longer periods under water shortage might impact their recruitment rates under field conditions.
700 Considering that the total volume of water supplied in each treatment was the same, our results
701 corroborate that the frequency and intensity of drought stress represents a stronger and more
702 direct factor controlling seedling survival and growth than the total water available for a certain
703 period (Tomlinson et al., 2012).

704 4.4.3. Species comparison

705 The major filters controlling tree seedling recruitment in savannas are drought and fire
706 (Moreira & Klink, 2000; Gignoux et al., 2009). In mesic savannas, root adaptations, such as
707 rapid taproot growth, may be more related to water availability than to RGR ratio or R:S
708 (Tomlinson et al., 2012, 2014). The STRL values recorded in *Q. grandiflora* seedlings (ranging
709 from 70 m.g⁻¹ to 97 m.g⁻¹) in comparison to those measured in *T. aurea* seedlings (ranging from
710 9 m.g⁻¹ to 22 m.g⁻¹), suggest that *Q. grandiflora* invests more in root elongation than in root
711 biomass during the initial growth stage, what might represent an important growth strategy for
712 seedlings to reach deeper soil horizons (Tomlinson et al., 2012). Toward the end of the wet
713 season the upper layers of the soils dry first (Kanegae et al, 2000), what makes the investment

714 in deeper roots a major strategy to cope with drought stress (Padilla and Pugnaire, 2007;
715 Tomlinson et al., 2012; Boonman et al., 2020; Saboya and Borghetti, 2012). A previous study
716 on Mediterranean tree species conducted in a semi-natural condition field site reported that
717 water availability was more important in seedling survival than was biomass allocation to the
718 roots (Padilla and Pugnaire, 2007), indicating that a higher STRL can contribute to avoid
719 drought stress. On the other hand, the RER of both species were similar irrespective of the dry
720 spell treatments (Table S2).

721 While SLA of *Q. grandiflora* and *T. aurea* seedlings were very similar irrespective of
722 the treatments, RGR of *T. aurea* seedlings was twice that of *Q. grandiflora* (Table S2). The
723 duration of dry spells did not affect *Q. grandiflora* RGR, NAR, SLA nor LMF, indicating that
724 gas exchange was similar for seedlings of *Q. grandiflora* in all treatments (Fig 2). On the other
725 hand, even though SLA of *T. aurea* seedlings was not affected by the treatments, its LMF
726 increased with the dry spell duration, what suggests that the RGR decrease of *T. aurea*
727 seedlings under longer dry spells is related to a decrease of NAR (Fig. 2). These results indicate
728 that, for a given value of SLA, *T. aurea* seedlings presented higher NAR in comparison to *Q.*
729 *grandiflora* seedlings (Shipley, 2002).

730 Drought-tolerance and avoidance mechanisms seem to be linked to the conservative–
731 acquisitive gradient, where water storage is positively correlated with acquisitive strategies
732 (Fagundes et al., 2022). The presence of water storage traits, as root storage organs (da Silva
733 and Rossatto, 2019) might allow acquisitive species to occupy regions subjected to dry spells
734 (Fagundes et al., 2022). In our study, to maintain a high carbon acquisition level, a higher
735 stomatal conductance and gas exchange might be necessary to provide *T. aurea* physiological
736 conditions for biomass incorporation, revealing an acquisitive strategy for this species (Grime
737 and Pierce, 2012). As mentioned before, stomata closure response to drought stress might
738 explain why dry spells of 15 days affected TM of *T. aurea* seedlings in comparison to seedlings

739 irrigated daily. The understanding of the physiological strategies adopted by *Q. grandiflora*
740 seedlings to cope with water shortage, however, demands further studies.

741 4.5. CONCLUSION

742 Our findings showed that the growth rates and biomass variables of *Q. grandiflora* were
743 not significantly affected by dry spells for up to 15 days. In contrast, there was a significant
744 decrease in total biomass of *T. aurea* seedlings when exposed to dry spells of 15 days, although
745 the root length and aboveground variables were not affected by water shortage, suggesting
746 that root elongation might be a priority of biomass allocation when experiencing drought stress.
747 Seedlings producing deeper roots might reach soil layers with a more stable water availability,
748 a major strategy to cope with drought stress. Future studies under field conditions will unravel
749 the importance of root length investment for the recruitment of new individuals under harsh
750 savanna landscapes.

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761 **Declaration of Competing Interest**

762 The authors declare no known competing financial interests or personal relationships
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764 4.6. REFERENCES

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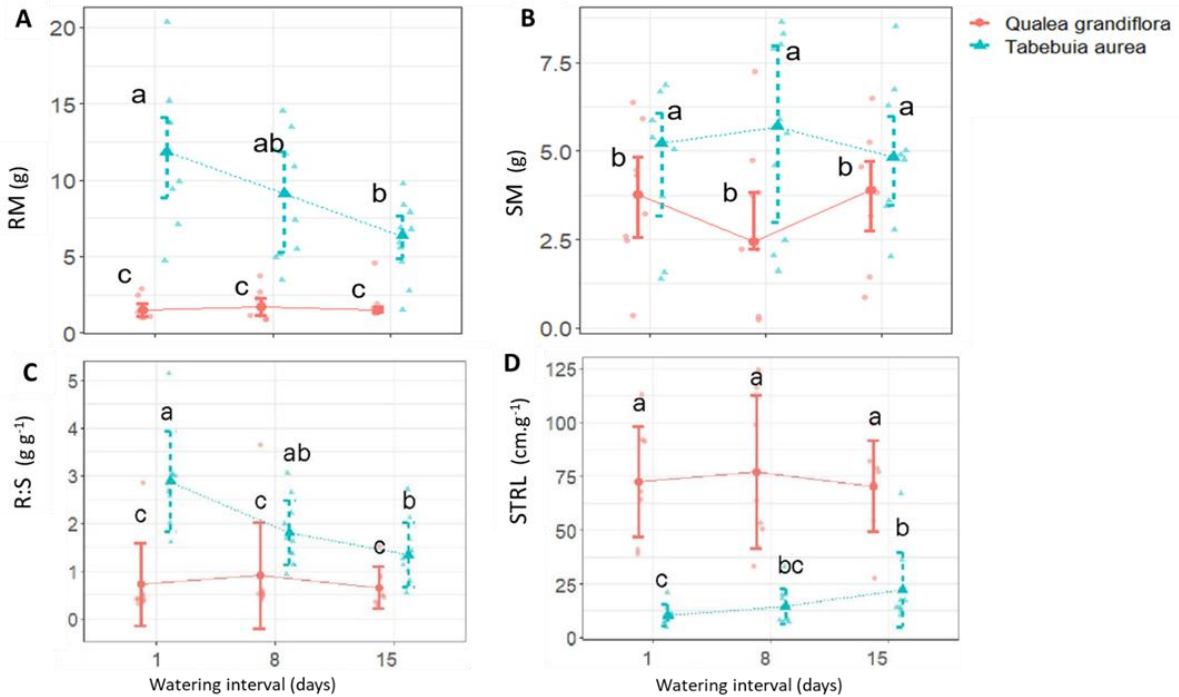
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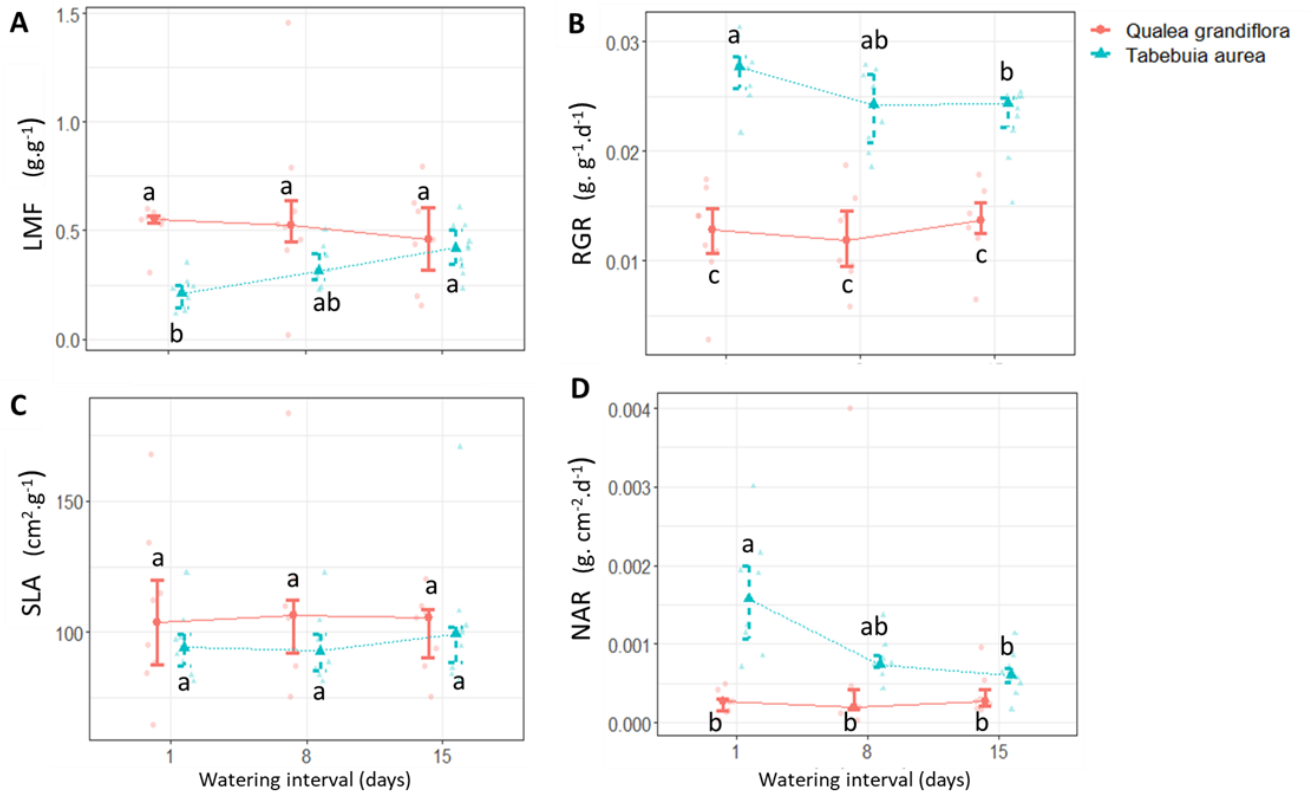
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4.7. FIGURES



997 **Fig. 1.1** Root dry mass (RM), shoot dry mass (SM), root: shoot ratio (R:S), and specific taproot length (STRL) of
998 *Qualea grandiflora* (red) and *Tabebuia aurea* (blue) seedlings exposed to different irrigation treatments (dry
999 spells): daily irrigation, irrigation every 8 d, irrigation every 15 d. Seedlings (60-d old) grown under daily irrigation
1000 in red latosol and sand (3:1) were subjected to irrigation treatments for 130 d in tubes (100 cm high and 10 cm
1001 diameter) filled with the same substrate in a phytotron chamber under 13 h photoperiod, alternating temperatures
1002 of 38/28 °C (12 h/12 h), relative humidity of 70%, and photosynthetic photon flux density of 700 $\mu\text{mol m}^{-2} \text{s}^{-1}$.
1003 Different letters indicate significant differences among treatments based on Tukey or Nemenyi tests (Tables S3
1004 and S4). The bars indicate the interquartile range, and the horizontally connected central points indicate the
1005 medians. Eight *Q. grandiflora* and 10 *T. aurea* seedlings were used for each treatment. The experiment was
1006 conducted between July and October 2018 at the University of Brasília Thermobiology Laboratory, Brasília,
1007 Brazil.

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1010 **Fig. 1.2.** Leaf mass fraction (LMF), relative growth rate (RGR), specific leaf area (SLA), and net assimilation rate
 1011 (NAR) of *Qualea grandiflora* (red) and *Tabebuia aurea* (blue) seedling exposed to different irrigation schedules
 1012 (dry spell treatments): daily irrigation, irrigation every 8 d, irrigation every 15 d. For experimental details refer to
 1013 Fig. 1. Different letters indicate significant differences based on Tukey or Nemenyi tests (Tables S3 and S4). The
 1014 bars indicate the interquartile range, and the horizontally connected central points indicate the medians. Eight *Q.*
 1015 *grandiflora* and 10 *T. aurea* seedling were used for each treatment.

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1017 4.8. SUPPLEMENTARY MATERIALS

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1019 **Early development of two savanna tree species under simulated dry spells**

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Table S1.1. Chemical and physical characteristics of experimental soils (Dystrophic Red Latosol) with and without the addition of washed medium sand in the proportion 3: 1 (soil: sand).

Parameters	Unities	Unchanged soil	Soil with sand
Macro nutrients			
<i>pH in water</i> -		5.1	5.1
<i>pH in CaCl2</i> -		4.3	4.4
<i>M.O.</i>	dag/Kg	4.0	3.5
<i>C Org</i>	%	2.3	2.0
<i>P</i>	mg/dm ³	< 0.3	0.7
<i>K</i>	mg/dm ³	32.8	47.,5
<i>S</i>	mg/dm ³	5.3	7.4
<i>Ca</i>		0.4	0.7
<i>Mg</i>	cmol c/dm ³	0.2	0.3
<i>Al</i>	cmol c/dm ³	0.5	0.3
<i>H+Al</i>	cmol c/dm ³	5.6	5.9
<i>CTC</i>	cmol c/dm ³	6.3	7.0
<i>V</i>	%	11	16
<i>M</i>	%	42	21
<i>Ca/Mg</i> -		2.0	2.3
<i>Ca/K</i> -		4.8	5.8
<i>Mg/K</i> -		2.4	2.5
<i>K</i>	%	1	2
<i>Ca</i>	%	6	10
<i>Mg</i>	%	3	4
<i>Na</i>	%	0	0
<i>H+Al</i>	%	90	84
<i>B</i>	mg/dm ³	0.2	0.1
<i>Zn</i>	mg/dm ³	0.3	0.5
<i>Fe</i>	mg/dm ³	118.8	164.9
<i>Mn</i>	mg/dm ³	2.5	10.6
<i>Cu</i>	mg/dm ³	0.5	0.3
<i>Silt</i>	%	28.2	18.5
<i>Clay</i>	%	68.0	52.0
<i>Sand</i>	%	3.8	29.5
<i>Classification</i> -		Heavy clay	Clay
<i>Type of soil¹</i> -		Type 3	Type 3

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Note: tThe experiment was preformed between July and October 2018 in a phytotron-type growth chamber in the Laboratório de Termobiologia of the University of Brasília, Brazil. The soil was collected at Fazenda Água Limpa (15° 95' S, 47° 92' W;, 1.200 m asl.H), from 30-cm soil depth. The pH in water (1:2.5 soil/water) was checked with a pH meter, and the organic matter was determined with colorimetric techniques using potassium dichromate, and C Org was expressed in percentage of Carbon g per sample g (Fontana and Campos, 2017). Cation exchange capacity – CEC (cmolc/dm³) was calculated by S+H+Al (H+Al extracted by 198 calcium acetate, 0.5 mol/L at pH 7.0). Base saturation (V) and Al saturation (m) are expressed in percentage of CEC. Nutrient analysis followed Mehlich (1953) with modifications; The element P was estimated by molybdate – ascorbic acid reaction followed by spectrometry (Teixeira et al., 2017); The elements K, Ca, Mg, Zn, Fe, Mn, Na and Cu were estimated by a modified Mehlich methodology followed by atomic spectrometry (Teixeira et al., 2017). K, Ca, Mg, Na and H+Al are presented as change complex saturation percentage. Total Sulphur (S) measurements followed the mono-calcium-phosphate methodology (Sinclair, 1973), and Boron (B) was extracted using hot water. Soil texture was determined by dispersion of fine air-dried soil with NaOH, high rotation agitation, sedimentation, and determination of clay by densimetry in the supernatant, coarse sand and fine sand separated by sieving and silt calculated by difference (dos Santos et al., 2018). All analyses were conducted by Campo Análises Ltda (Paracatu-MG, Brazil).

1041 **Table S1.2.** Irrigation frequency and volume applied to *Qualea grandiflora* and *Tabebuia*
 1042 *aurea* seedlings during the experimental period (July and October 2018).

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WI	Irrigation frequency	Total number of irrigations	Each irrigation volume (ml)	Each irrigation time	Total volume in 130 days (ml)
1	Daily	130	58	2'20''	7.540
8	At each 8 days	16	471	18'40''	7.540
15	At each 15 days	8	942	35'	7.540

1044 Note: the experiments were performed in a phytotron-type growth chamber in the Thermobiology Laboratory of the
 1045 University of Brasília, Brazil.

1046 **Table S1.3.** *P*-values of the effects of the treatments and interactions between the treatments on the growth
 1047 and biomass parameters based on Kruskal-Wallis (KW) and Nemenyi-Test (NM) of *Qualea*
 1048 *grandiflora* and *Tabebuia aurea* seedlings.

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	Test	TM	RM	SM	RMF	SMF	R:S	RGR	Lnum	H	RL	RER	STRL	SLA
<i>Q. grandiflora</i>	KW	0.999	0.810	0.954	0.193	0.193	0.193	0.999	0.151	0.735	0.379	0.379	0.974	0.861
	NM	-	-	-	-	-	-	-	-	-	-	-	-	-
<i>T. aurea</i>	KW	0.021*	0.007**	0.689	0.036*	0.036*	0.036*	0.021*	0.110	0.252	0.100	0.100	0.010*	0.712
	NM 1x8	0.466	0.230	-	0.248	0.248	0.248	0.466	-	-	-	-	0.371	-
	NM 1x15	0.016*	0.005**	-	0.028*	0.028*	0.028*	0.016*	-	-	-	-	0.007**	-
	NM 8x15	0.252	0.296	-	0.604	0.604	0.604	0.252	-	-	-	-	0.218	-

1050 the treatments include daily irrigation × irrigation at every 8 d (1×8); daily irrigation × irrigation every 15 d (1×15); irrigation every 8 d ×
 1051 irrigation every 15 d (8×15). The parameters compared were (Table S3): total dry biomass (TM), root dry mass (RM), shoot dry mass (SM), root
 1052 mass fraction (RMF), shoot biomass fraction (SMF), biomass partition (R:S ratio), number of leaves (Lnum), seedling height (H), taproot length
 1053 (RL), specific taproot length (STRL), relative growth rate (RGR), root elongation rate (RER), and specific leaf area (SLA). The experiment was
 1054 performed between July and October 2018 in a phytotron-type growth chamber at the Thermobiology Laboratory of the University of Brasília,
 1055 Brasília, Brazil. Statistical significance was set at: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

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1057 **Table S1.4.** The growth and biomass parameters of *Qualea grandiflora* and *Tabebuia aurea* seedlings
 1058 before (60-d-old, initial measurements) and after (190-d-old, final measurements) different irrigation
 1059 treatments.

	Initial measurements (Days after germination)		Final measurements (Watering interval)		
	60	1 day	8 days	15 days	
TM (g)	0.38 ± 0.021	5.365 ± 0.924	5.747 ± 1.006	5.587 ± 0.863	
RM (g)	0.11 ± 0.006	1.567 ± 0.289	1.968 ± 0.362	1.894 ± 0.416	
Q SM (g)	0.26 ± 0.018	3.797 ± 0.641	3.778 ± 0.638	3.693 ± 0.618	
u RMF (g. g ⁻¹)	0.3 ± 0.015	0.288 ± 0.011	0.336 ± 0.014	0.362 ± 0.050	
a SMF (g. g ⁻¹)	0.7 ± 0.015	0.711 ± 0.011	0.663 ± 0.022	0.637 ± 0.050	
e R:S (g. g ⁻¹)	0.43 ± 0.031	0.408 ± 0.022	0.509 ± 0.024	0.651 ± 0.160	
g Lnum	5.1 ± 0.324	20.50 ± 1.679	20.428 ± 1.469	16.714 ± 1.537	
r H (cm)	6.09 ± 0.401	27.087 ± 2.286	27.8 ± 1.970	23.6 ± 2.215	
a RL (cm)	20.62 ± 0.723	106.775 ± 2.833	115.671 ± 4.427	114.987 ± 4.648	
n RER (cm.d ⁻¹)	0.34 ± 0.012	0.661 ± 0.022	0.730 ± 0.034	0.725 ± 0.035	
d STRL (cm.g ⁻¹)	198.84 ± 15.772	97.401 ± 28.968	74.034 ± 13.387	70.314 ± 8.069	
i RGR (g.g ⁻¹ .d ⁻¹)	-	0.012 ± 0.001	0.013 ± 0.001	0.012 ± 0.001	
f SLA (cm ² .g ⁻¹)	137.66 ± 5.243	112.448 ± 10.938	111.343 ± 12.165	99.975 ± 5.393	
l LMF (g. g ⁻¹)	-	0.529 ± 0.032	0.599 ± 0.145	0.467 ± 0.081	
o NAR (g.cm ² .d ⁻¹)	-	0.0002 ± 0.0005	0.0007 ± 0.0004	0.0003 ± 0.0001	
r LM (g)	-	2.874 ± 0.599	2.621 ± 0.604	2.885 ± 0.597	
TM (g)	1.52 ± 0.126	19.224 ^a ± 2.718	14.770 ^{ab} ± 2.012	10.796 ^b ± 1.183	
RM (g)	0.97 ± 0.103	13.893 ^a ± 2.096	8.891 ^{ab} ± 1.181	5.996 ^b ± 0.835	
T SM (g)	0.54 ± 0.036	5.331 ± 0.910	5.485 ± 0.913	4.799 ± 4.387	
a RMF (g. g ⁻¹)	0.63 ± 0.025	0.726 ^a ± 0.024	0.625 ^{ab} ± 0.026	0.543 ^b ± 0.032	
e SMF (g. g ⁻¹)	0.37 ± 0.025	0.273 ^b ± 0.024	0.374 ^{ab} ± 0.026	0.456 ^a ± 0.032	
b R:S (g. g ⁻¹)	1.82 ± 0.189	2.961 ^a ± 0.394	1.804 ^{ab} ± 0.204	1.342 ^b ± 0.205	
u Lnum	5.8 ± 0.359	10.40 ± 0.858	10.40 ± 0.866	8.60 ± 0.724	
a H (cm)	2.35 ± 0.222	6.540 ± 0.768	6.714 ± 0.757	8.484 ± 0.985	
a RL (cm)	9.46 ± 0.549	101.790 ± 1.572	101.940 ± 1.572	98.31 ± 0.689	
r RER (cm.d ⁻¹)	0.16 ± 0.009	0.710 ± 0.012	0.707 ± 0.012	0.683 ± 0.005	
e STRL (cm.g ⁻¹)	9.7 ± 0.928	9.243 ^b ± 1.608	14.498 ^{ab} ± 2.651	22.124 ^a ± 5.811	
a RGR (g. g ⁻¹ .d ⁻¹)	-	0.026 ^a ± 0.001	0.025 ^{ab} ± 0.001	0.023 ^b ± 0.001	
SLA (cm ² .g ⁻¹)	145.45 ± 6.773	94.134 ± 4.052	94.713 ± 4.159	99.540 ± 10.993	
LMF (g. g ⁻¹)	-	0.206 ± 0.022	0.345 ± 0.027	0.417 ± 0.036	
NAR (g.cm ² .d ⁻¹)	-	0.0016 ± 0.0002	0.0008 ± 0.00008	0.0006 ± 0.00008	
LM (g)	-	3.905 ± 0.575	5.079 ± 0.827	4.379 ± 0.584	

1060 Note: the seedlings (60 d after germination) were subjected to different irrigation treatments: daily irrigation, irrigation every 8
 1061 d, and irrigation every 15 d. The parameters measured include total dry mass (TM) root dry mass (RM), shoot dry mass (SM),
 1062 root biomass fraction (RMF), shoot biomass fraction (SMF), biomass partition (R:S ratio), number of leaves (Lnum), seedling
 1063 height (H), taproot length (RL), root elongation rate (RER), specific taproot length (STRL), relative growth rate (RGR), and
 1064 specific leaf area (SLA). The means are presented as means ± standard deviation (SD). The experiment was performed between
 1065 July and October 2018 in a phytotron-type growth chamber in the Thermobiology Laboratory of the University of Brasília, Brazil.
 1066 Different letters across rows indicate significant statistical differences at $p < 0.05$.

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Table S1.5. Methodology and references used to calculate traits of the seedlings studied during the experiment of simulated dry spells performed in a phytotron-type growth chamber in the Laboratório de Termobiologia of the University of Brasília, Brazil.

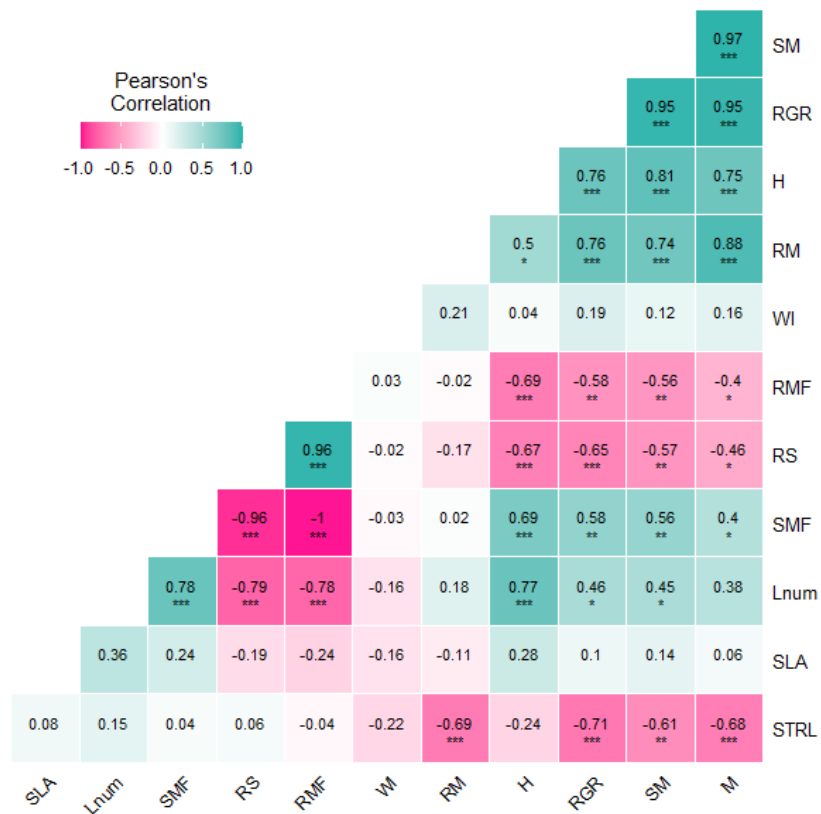
Trait	Unit	Formula	Reference
TM	G	Plant total dry mass	Pérez-Harguindeguy et al., 2013
RM	G	Taproot dry mass	Pérez-Harguindeguy et al., 2013
SM	G	All leaves and stem dry mass	Pérez-Harguindeguy et al., 2013
LM	G	All leaves dry mass	Pérez-Harguindeguy et al., 2013
RMF	$g \cdot g^{-1}$	RM/TM	Pérez-Harguindeguy et al., 2013
SMF	$g \cdot g^{-1}$	SM/TM	Pérez-Harguindeguy et al., 2013
LMF	$g \cdot g^{-1}$	LM/TM	Shipley, 2002
R:S	$g \cdot g^{-1}$	RM/SM	Pérez-Harguindeguy et al., 2013
RGR	$g \cdot g^{-1} \cdot d^{-1}$	$(\ln TM_f - \ln TM_i)/d$	Tomlinson et al., 2012
RER	$cm \cdot d^{-1}$	$(RL_f - RL_i)/d$	Tomlinson et al., 2012
STRL	$cm \cdot g^{-1}$	RL/RM	Tomlinson et al., 2012
SLA	$cm^2 \cdot g^{-1}$	$[(LA_1/LM_1) + (LA_2/LM_2) + (LA_3/LM_3)] / 3$	Pérez-Harguindeguy et al., 2013
NAR	$g \cdot cm^{-2} \cdot d^{-1}$	$RGR / (LMF * SLA)$	Shipley, B., 2002 (adapted)

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Note: the experiments were performed in a phytotron-type growth chamber in the Laboratório de Termobiologia of the University of Brasília, Brazil. Traits calculated: total dry mass (TM), root dry mass (RM), shoot dry mass (SM), leaf dry mass (LM), root biomass fraction (RMF), shoot biomass fraction (SMF), leaf biomass fraction (LMF), biomass partitioning (R:S ratio), relative growth rate (RGR), root elongation rate (RER), specific taproot length (STRL) and specific leaf area (SLA), and net assimilation rate (NAR).

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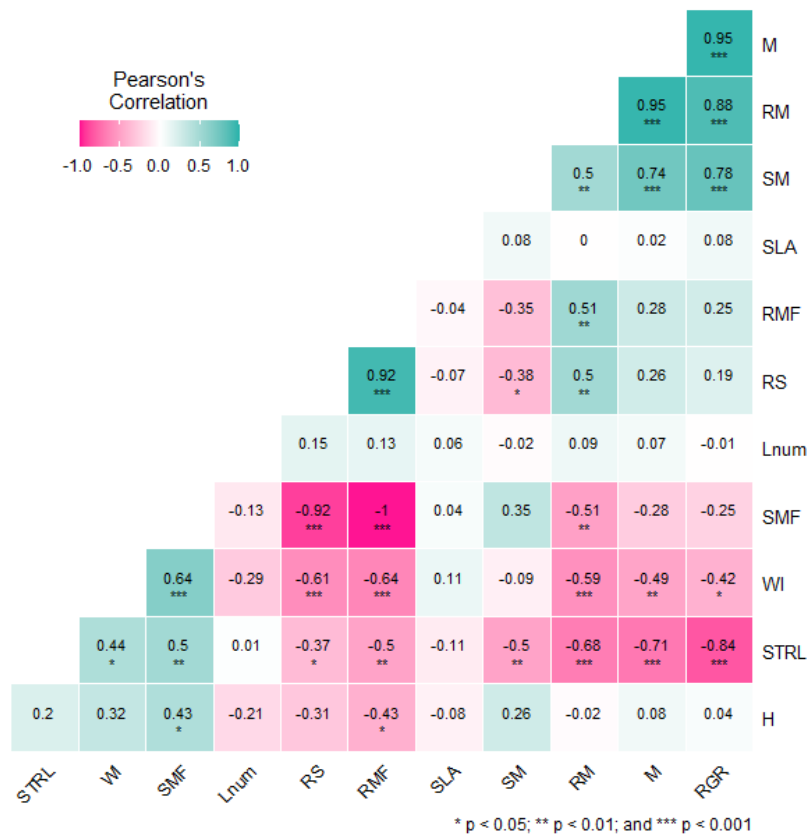


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Figure S1.1. Pearson's correlation coefficients among the growth parameters of *Qualea grandiflora* (Table S3) subjected to different irrigation treatments (WI) (Table S2). The parameters include root dry mass (RM), shoot dry mass (SM), root biomass fraction (RMF), shoot biomass fraction (SMF), biomass partition (R:S), number of leaves (Lnum), seedling height (H), taproot length (RL), specific taproot length (STRL), relative growth rate (RGR), root elongation rate (RER), and specific leaf area (SLA). The experiment was performed between July and October 2018 in a phytotron growth chamber in the Thermobiology Laboratory of the University of Brasília Brazil. Statistical significance was set at: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

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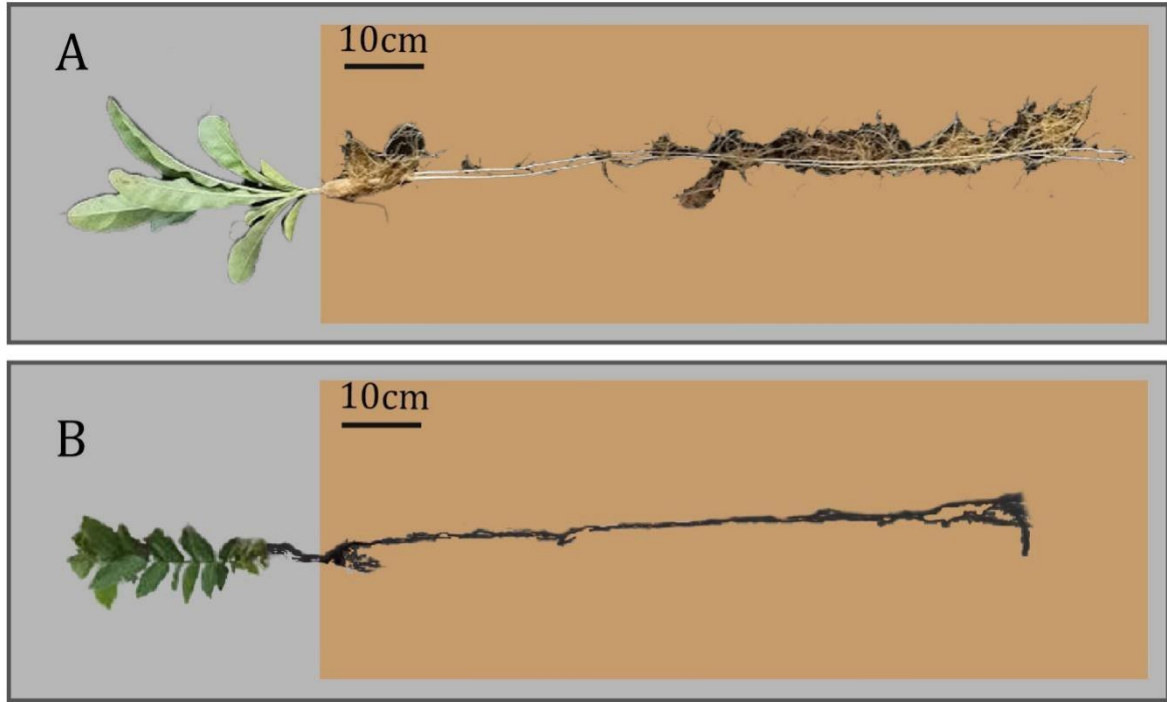
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1097 **Figure S1.2.** Pearson's correlation coefficients among the growth parameters of *Tabebuia aurea* exposed to different irrigation
 1098 treatments (WI) (Table S2). The parameters include root dry mass (RM), shoot dry mass (SM), root biomass fraction (RMF),
 1099 shoot biomass fraction (SMF), biomass partition (R:S), number of leaves (Lnum), seedling height (H), taproot length (RL),
 1100 specific taproot length (STRL), relative growth rate (RGR), root elongation rate (RER), and specific leaf area (SLA). The
 1101 experiment was performed between July and October 2018 in a phytotron chamber in the Thermobiology Laboratory of the
 1102 University of Brasília, Brazil. Statistical significance was set at * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

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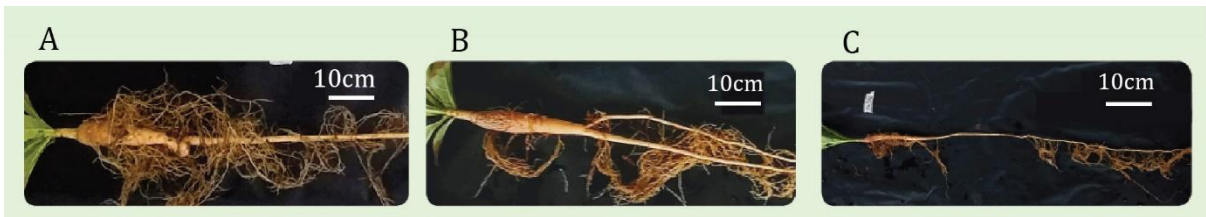
1107 **Figure S1.3.** Sample of each species at the end of the experiment of dry spells in the phytotron. The experiment was
1108 performed between July and October 2018 in a phytotron chamber in the Laboratório de Termobiologia of the University
1109 of Brasília, Brazil. A) Plant of *Tabebuia aurea* after receiving water every day during 130 d in the phytotron. B) Plant of
1110 *Qualea grandiflora* after receiving water every day during 130 d in the phytotron.

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1116 **Figure S1.4.** Figures presents a close view of the root storage organ of a sample of *Tabebuia aurea* after receiving the
1117 different dry spell treatment at the phytotron during 130 days: A) seedlings irrigated every day, B) seedlings irrigated each
1118 8 days and C) seedlings irrigated each 15 days. The experiment was performed between July and October 2018 in a
1119 phytotron chamber in the Laboratório de Termobiologia of the University of Brasília, Brazil.

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5. CAPÍTULO II

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Efeito da elevação da temperatura e do

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CO₂ atmosférico previstos para 2100 no

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desenvolvimento inicial de espécies

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1137 **RESUMO**

1138 A savana brasileira (Cerrado) é considerada um hotspot de biodiversidade. No entanto, as áreas nativas
1139 do Cerrado têm sido ameaçadas pelo desenvolvimento agrícola. Além disso, as mudanças climáticas
1140 podem aumentar a pressão de seleção de espécies e, juntos, ambos os processos podem levar a uma
1141 grave perda de biodiversidade e de serviços ambientais. Portanto, é importante entender como as
1142 espécies vão responder às mudanças climáticas. Nosso objetivo foi investigar como as plântulas de
1143 espécies arbóreas respondem a um cenário climático futuro simulado em câmaras de crescimento
1144 (fitotrons). Selecionamos quatro espécies arbóreas amplamente distribuídas no Cerrado: *Qualea*
1145 *grandiflora* (Vochysiaceae), *Hymenaea stignocarpa* (Fabaceae), *Tabebuia aurea* (Bignoniaceae) e
1146 *Kielmeyera coriacea* (Clusiaceae). Dispusemos suas sementes para germinar em câmaras a 28°C e, a
1147 seguir, criamos as mudas em vasos preenchidos com Latossolo Vermelho e areia (proporção de 3x1) a
1148 28°C sob irrigação por 30 dias sob irrigação. Em seguida, transferimos as mudas para tubos plásticos de
1149 1 m de altura e 0,1 m de diâmetro para os experimentos de crescimento. Após 30 dias, 30 indivíduos de
1150 cada espécie foram retirados para as medidas iniciais, e outros 30 indivíduos foram transferidos para
1151 cada fitotron, totalizando 90 plantas por espécie. Um dos fitotrons foi configurado com o cenário
1152 climático atual, com base nos dados climáticos dos últimos 50 anos do Cerrado, onde as temperaturas
1153 máxima e mínima foi de 28 °C e 18 °C e a concentração de CO₂ ([CO₂]) foi de 420 ppm. O outro fitotron
1154 foi definido com a prospecção IPCC SSP 3-7,0 para a região do Cerrado para 2100 (base de dados:
1155 WorldClim), onde as temperaturas máximas e mínimas atingiram 2,5 °C acima do cenário climático
1156 atual, e [CO₂] foi de 860 ppm. A umidade foi de 85% para ambos os fitotrons. As plantas foram
1157 cultivadas por 120 dias, sendo irrigadas a cada dois dias com 120 ml de água corrente. Após esse período,
1158 procedeu-se à contagem de folhas dos indivíduos e, em seguida, todas as plantas foram desenraizadas e
1159 levadas para secar a 70 °C. Após a secagem, a biomassa das plantas foi medida por partes: total, raiz,
1160 parte aérea e folhas. Observamos um aumento significativo de biomassa no cenário futuro para todas as
1161 espécies, provavelmente relacionado à fertilização com CO₂. No entanto, *K. coriacea* e *H. stignocarpa*
1162 investiram na raiz e na parte aérea a mesma proporção de biomassa no cenário climático futuro e no
1163 cenário climático atual. *Q. grandiflora* e *T. aurea* investiram mais de 2 vezes em biomassa aérea do que
1164 radicular das plantas quando estavam sob cenário climático futuro. O aumento da massa aérea para *H.*
1165 *stignocarpa*, *Q. grandiflora* e *T. aurea* pode estar refletindo o número de folhas que foi maior nos
1166 indivíduos no cenário futuro em comparação aos incubados no cenário climático atual. Em conclusão,
1167 quando a água não é escassa na fase de recrutamento, há ganho de carbono em resposta ao cenário
1168 climático futuro simulado, mas sua distribuição pode variar entre as espécies.

1169 **ABSTRACT**

1170 **Effect of predicted rise in temperature and atmospheric CO₂ by 2100 on early development of**
1171 **savanna tree species**

1172 The Brazilian savanna (Cerrado) is considered a biodiversity hotspot. However, Cerrado's native areas
1173 have been threatened by agricultural development. In addition, climate change may increase species
1174 selection pressure and, together, both processes may lead to a serious loss of biodiversity and
1175 environmental services. Therefore, it is important to understand how species are going to respond to
1176 climate change. We aimed to investigate how tree seedlings respond to a future climate scenario
1177 simulated in growth chambers (phytotrons). We selected four widely distributed tree species from the
1178 Cerrado savanna: *Qualea grandiflora* (Vochysiaceae), *Hymenaea stignocarpa* (Fabaceae), *Tabebuia*
1179 *aurea* (Bignoniaceae) and *Kielmeyera coriacea* (Clusiaceae). We disposed their seeds to germinate in
1180 chambers at 28°C, and then raised the seedlings in pots filled with Red Latosol and sand (proportion of
1181 3x1) under irrigation at 28 °C for 30 days. After that, we transferred the seedlings to plastic tubes of 1
1182 m high and of 0.1 m in diameter for the growth experiments. When the first pair of leaves appeared, 30
1183 individuals of each species were taken for initial measures, and other 33 individuals were transferred to
1184 each phytotron, summing up a total of 96 plants per species. One of the phytotrons was set with the
1185 current climate scenario, based on the last 50 years climate data from the Cerrado where max and min
1186 temperatures was 28 °C and 18 °C, and CO₂ concentration ([CO₂]) was 420 ppm. The other phytotron
1187 was set with the IPCC SSP 3-7,0 prospection for the Cerrado region for 2100 (WorldClim), where max
1188 and min temperatures reached 2.5 °C higher than at current climate scenario, and [CO₂] was 860 ppm.
1189 Humidity was 85 % for both phytotrons. Plants were grown for 120 days, being irrigated every two days
1190 with 120 ml of tap water. After this period, we proceeded with leaf counting of the individuals and then
1191 all plants were uprooted and taken to dry at 70 °C. After drying, plants biomass was measured by parts:
1192 total, root, shoot, and leaves. We observed a significant increase of biomass in the future scenario for
1193 all species, probably related to CO₂ fertilization. However, *K. coriacea* was the only one that invested
1194 more carbon on roots than shoot, with 57 % more root biomass under future climate scenario. *H.*
1195 *stignocarpa* invested the same proportion on root and shoot under future climate scenario as under
1196 current climate scenario. *Q. grandiflora* and *T. aurea* invested more than 2 times in shoot than root
1197 biomass of plants when they were under future climate scenario. The increase in shoot mass for *H.*
1198 *stignocarpa*, *Q. grandiflora* and *T. aurea* can be reflecting the leaf number that was bigger in individuals
1199 under the future scenario in comparison to those incubated in current climate scenario. In conclusion,
1200 when water is not scarce at the recruitment stage, there is carbon gain in response to the simulated future
1201 climate scenario, but its distribution can vary among species.

1202 5.1. INTRODUÇÃO

1203 As savanas representam aproximadamente um terço da vegetação terrestre, no entanto
1204 ainda falta muito conhecimento a respeito do funcionamento de seus mecanismos ecológicos e,
1205 conseqüentemente, falta informação que oriente sobre meios de conservação e restauração
1206 ambiental (Buisson et al, 2021, 2022). O relatório divulgado pelo Painel Intergovernamental de
1207 Mudanças Climáticas (IPCC) em 2022 afirma que os *hotspots* mais ameaçados pelas mudanças
1208 climáticas na América do Sul são as savanas (Pörtner et al., 2022). Entre essas, está a savana
1209 brasileira conhecida como “Cerrado”, sendo a savana mais biodiversa do mundo, da qual apenas
1210 20% do território permanece bem preservado (Strassburg et al., 2017). Tendo em vista a pressão
1211 sofrida pelo Cerrado tanto pela perda de habitat (Diniz-filho et al, 2020), quanto pelas mudanças
1212 climáticas, estudos que tratem da capacidade de estabelecimento de indivíduos sob o cenário
1213 climático futuro previsto para essa região são de grande importância para a preservação da
1214 biodiversidade.

1215 As mudanças climáticas aceleradas pela ação humana vêm ocorrendo em uma
1216 velocidade que dificulta que ocorra adaptação das espécies, e diversas populações de
1217 determinadas espécies têm migrado para regiões onde o clima passou a ser favorável para seu
1218 desenvolvimento (Mathys et al, 2018; Zu et al, 2021). Porém, uma série de fatores como
1219 topografia, competição, fertilidade sob condições climáticas futuras, alcance em distância e
1220 velocidade de dispersão e distúrbios como o fogo podem dificultar a migração, reduzindo a
1221 velocidade de expansão geográfica da espécie e impossibilitando que alcancem locais
1222 apropriados para seu estabelecimento a tempo (Hampe, 2011; Liang et al, 2018; Beloiu et al,
1223 2022; Boisvert- Marsh et al, 2022).

1224 Por sua vez, a velocidade em que as mudanças têm ocorrido faz com que o genótipo de
1225 plântulas submetidas ao cenário climático futuro seja muito semelhante ao das plântulas

1226 encontradas no cenário climático atual (Hoffmann & Sgró, 2011). A fase de crescimento inicial
1227 é o estágio mais vulnerável na vida da planta, fazendo da capacidade de plântulas em suportar
1228 as condições climáticas futuras um gargalo na sobrevivência do indivíduo e na manutenção da
1229 espécie em uma determinada área (Leck et al, 2008). Assim, a permanência de espécies arbóreas
1230 de savanas nesses ambientes irá depender, em grande parte, de sua plasticidade e capacidade de
1231 aclimação às novas condições ambientais (Larson et al, 2020; Lewandrowski et al., 2021;
1232 Nicotra et al, 2010).

1233 Em savanas, a sobrevivência de plântulas de espécies arbóreas depende, entre outras
1234 coisas, do bom aproveitamento da janela de oportunidade representada pela estação chuvosa
1235 (Escobar et al, 2018). A elevação da temperatura projetada para 2100 pode reduzir essa janela
1236 de oportunidade ao acelerar a redução do potencial hídrico do solo após o início da estação seca
1237 devido ao aumento do déficit de pressão de vapor de água (VPD) e conseqüente redução a
1238 umidade relativa do ar (Hofmann et al., 2021), o que pode prejudicar o estabelecimento de
1239 novos indivíduos. Além disso, temperaturas mais elevadas podem aumentar a demanda por
1240 transpiração, exigindo maior alongamento radicular para permitir o alcance de frações do solo
1241 onde a água continua disponível por mais tempo após o fim das chuvas (Villalobos-Vega et al.,
1242 2014; Padilla and Pugnaire, 2007; Tomlinson et al., 2012; Boonman et al., 2020; Saboya &
1243 Borghetti, 2012). Por outro lado, as temperaturas mais elevadas esperadas para o cenário
1244 climático futuro podem favorecer o recrutamento de indivíduos ao aumentar a taxa de
1245 crescimento radicular (Stevens et al, 2014).

1246 Embora a elevação da temperatura possa levar à queda da eficiência fotossintética
1247 devido à menor afinidade da Rubisco com o dióxido de carbono e ao aumento da respiração
1248 mitocondrial (Lambers & Oliveira, 2019), projeta-se que a concentração de CO₂ atmosférico
1249 seja o dobro da observada atualmente em 2100 (Meinshausen et al., 2019), o que pode favorecer
1250 a assimilação de carbono e evitar o aumento da fotorrespiração (Dusenge et al., 2019). Estudos

1251 testando o efeito de concentrações elevadas de CO₂ no crescimento inicial de espécies arbóreas
1252 de savanas mostram um maior ganho de biomassa nessas condições (Hoffmann, 2000; Kgope
1253 et al., 2010; Buitenwerf et al, 2012), o que favorece o estabelecimento de novos indivíduos.

1254 Devido ao efeito oposto que temperaturas elevadas e a alta concentração de CO₂
1255 atmosférico podem ocasionar na fisiologia das plantas, estudos que avaliem o efeito conjunto
1256 desses dois fatores são extremamente importantes. Apgaua e colaboradores (2019) observaram
1257 efeito sinérgico entre a [CO₂] e a temperatura elevados em plântulas de espécie de Eucalyptus
1258 nativa de savana em ambiente natural, que promoveu o aumento no crescimento e na aquisição
1259 de biomassa quando a água não foi um fator limitante. Isso indica que a interação entre a
1260 temperatura e o CO₂ elevados pode favorecer o recrutamento de espécies arbóreas de savanas.
1261 No entanto, dependendo da capacidade de aclimatação foliar, a temperatura elevada pode
1262 reduzir a aquisição de carbono por plântulas expostas a altos níveis de CO₂ atmosférico, mesmo
1263 sem haver restrição hídrica (Murphy & Way, 2021).

1264 Espécies arbóreas de savana tendem a alocar uma maior fração de biomassa para a
1265 fração radicular (raízes e órgão de reserva abaixo do solo), o que confere a elas maior proteção
1266 no caso de ocorrência de fogo e maior resistência ao déficit hídrico do solo causado pela
1267 sazonalidade da precipitação (Bucci et al, 2008; Oliveira & Klink, 2005; Kanegae et al, 2000).

1268 A facilidade de obtenção de CO₂ devido a sua maior disponibilidade no cenário futuro
1269 pode ocasionar menor investimento em área e biomassa foliar, permitindo que o carbono
1270 direcionado para a fração aérea seja utilizado no crescimento em altura (Qi et al, 2019), podendo
1271 favorecer a sobrevivência no caso de passagem de fogo (Rodriguez-Cubillo et al, 2021) ou o
1272 melhor desenvolvimento no caso de sombreamento pelo componente herbáceo (Gignoux et al,
1273 2016).

1274 Além da maior aquisição de CO₂, o aumento da temperatura pode acelerar o
1275 metabolismo, aumentando a taxa de crescimento e o desenvolvimento das plântulas (Ncisana
1276 et al, 2022). Portanto espera-se que no cenário futuro as plântulas apresentem maior acúmulo
1277 de biomassa em comparação ao cenário atual e desenvolvimento de plântulas mais acelerado.

1278 Para compreender como o cenário climático esperado para 2100 irá afetar o
1279 desenvolvimento inicial de espécies arbóreas de uma savana neotropical, simulamos os meses
1280 da estação chuvosa do cenário climático atual e do cenário futuro previsto para 2100 (Pörtner
1281 et al., 2022) em câmaras fitotrôn contendo plantas de 4 espécies amplamente distribuídas no
1282 Cerrado e comparamos os dados de biomassa e crescimento inicial obtidos nos dois cenários
1283 climáticos.

1284 5.2. MATERIAIS E MÉTODOS

1285 5.2.1. ÁREA DE ESTUDO

1286 O Cerrado, segundo maior bioma brasileiro, é considerado um *hotspot* de biodiversidade
1287 global (Myers et al., 2000), com alto grau de endemismo (Forzza et al, 2012), e está localizado
1288 no centro do território brasileiro, conectando os outros biomas. As savanas são a vegetação
1289 dominante, cobrindo cerca de 70% da região (da Silva & Bates, 2002). A região é formada por
1290 platôs que variam entre 500 e 1.700 m de altitude (Ribeiro & Walter, 2008). O solo do Cerrado
1291 é predominantemente composto por Latossolo Vermelho, um solo profundo, altamente
1292 intemperizado, apresentando em geral baixa fertilidade e alta acidez e saturação de alumínio
1293 (Abreu et al, 2017). A precipitação anual média é de 2.300 mm. O Cerrado abriga a maior área
1294 do Aquífero Guarani, além das principais nascentes das três maiores bacias hidrográficas do
1295 Brasil (Oliveira et al, 2017).

1296 As sementes de *Kielmeyera coriacea*, *Tabebuia aurea* e *Qualea grandiflora* foram
1297 coletadas de 10 indivíduos adultos, sadios, com distância de no mínimo 1km entre eles. Entre

1298 agosto e novembro de 2019 no Parque Nacional de Brasília (15° 38' 28" S 48° 1' 15" O –
1299 ICMBio) em cerrado *sensu stricto*, e levadas para armazenamento em sacos de papel em câmara
1300 fria (18°C) no Laboratório de Termobiologia (UnB, Brasília – Brasil). As sementes de
1301 *Hymenaea stigonocarpa* foram gentilmente oferecidas pela Rede de Sementes do Cerrado, que
1302 nos cedeu quantidade suficiente de sementes saudáveis, coletadas em 2020 na região da
1303 Chapada dos Veadeiros, no Estado de Goiás (14° 10' S 47° 30' O) em cerrado *sensu stricto* que
1304 também foram e levadas para armazenamento em sacos de papel em câmara fria (18°C) no
1305 Laboratório de Termobiologia (UnB, Brasília – Brasil).

1306 A partir de 15 de setembro de 2020 lotes de 250 sementes de cada espécie foram
1307 colocados para germinar sobre papel filtro embebido com água destilada, em placas de Petri
1308 com 10 sementes, sendo ao todo 25 placas de Petri por espécie, em câmara a temperatura
1309 constante de 28°C e fotoperíodo de 12h. Quando observada a curvatura da radícula emitida por
1310 cada semente, essa era transferida para saco plástico com 25cm de altura e 10cm de diâmetro,
1311 uma semente germinante por saco, preenchido com solo nativo de área de cerrado *sensu stricto*
1312 (Latosolo vermelho distrófico), retirado da “Fazenda água Limpa” (UnB – Distrito Federal,
1313 Brasil) no ano de 2019, misturado com areia lavada na proporção de 3:1 (solo:areia). Para
1314 produção das mudas, as plântulas permaneceram em área externa coberta do laboratório de
1315 Termobiologia (UnB, Brasília), com temperatura ambiente, entre 18°C e 35°C. Foi feita
1316 irrigação a cada dois dias, ou diária quando necessário, de modo que a água não fosse limitante
1317 para o desenvolvimento das plântulas.

1318 Após a emissão do primeiro par de folhas de cada espécie (cerca 20 dias para *Hymenaea*
1319 *stigonocarpa* e 30 dias para as demais espécies), as plantas foram agrupadas em três grupos
1320 buscando a melhor homogeneidade possível, levando em conta a altura, tamanho das folhas e
1321 diâmetro da base do caule. Para cada espécie, dois grupos foram compostos por 35 indivíduos
1322 (a serem levados às duas câmaras fitotrôn, ver seções 2.2.1 e 2.2.2), e o terceiro grupo composto

1323 por 30 indivíduos para medidas iniciais das mudas antes do início do experimento nos fitotrôns
1324 (Apêndice II – Dados Iniciais). O uso de um número maior de indivíduos levados aos fototrôns
1325 teve o objetivo de garantir um número mínimo de 30 indivíduos por espécie e por tratamento
1326 para as análises estatísticas (seção 2.5). Todos os indivíduos usados nos experimentos nos
1327 fitotrôns foram transferidos em um mesmo dia.

1328 5.2.2. CALIBRAGEM DOS FITOTRONS

1329 Foram utilizadas duas câmaras climáticas *walk-in* (fitotrôns), modelo EL011, com
1330 dimensões internas (cm) de 227 (largura) x 216 (profundidade) x 246 (altura), produzidos e
1331 montados pela empresa Eletrolab. Para ambos os cenários climáticos (atual e futuro) foi feita
1332 uma média dos parâmetros climáticos (precipitação, temperatura e umidade relativa do ar)
1333 obtidos em estações meteorológicas (cenário atual) e projetados (cenário futuro) para os meses
1334 de dezembro a março para ambos os cenários (seções 1.2.1 e 1.2.2).

1335 Os dados de precipitação diária e temperatura ao longo do dia dos últimos 60 anos (de
1336 1960 a 2020), obtidos de estações meteorológicas distribuídas por todo o território do Cerrado,
1337 relativos aos meses de novembro a abril (INPE, 2020), foram utilizados para estabelecer o
1338 volume e frequência de irrigação e a umidade relativa do ar utilizados nos dois cenários, e a
1339 rampa de temperatura programada para o fitotron com o cenário atual. Também foi programada
1340 uma rampa de luminosidade ao longo do dia, sendo igual para os dois fitotrons, com fotoperíodo
1341 de 13h de luminosidade, conforme a duração do dia durante o verão na maior parte da região
1342 do Cerrado. A irrigação foi realizada a cada dois dias, por método de gotejamento automatizado.
1343 Considerando que 1 mm de água precipitado corresponde a 1000 ml/m² de água e utilizando a
1344 área superficial do tubo em que cada planta foi cultivada para calcular o volume de água a ser
1345 ofertado a cada indivíduo.

1346 A precipitação média obtida a partir desses dados foi de 230mm/mês. Esse valor foi
1347 utilizado para calcular a irrigação ofertada para cada muda conforme descrito anteriormente. A
1348 temperaturas máxima (diurna) e mínima (noturna) encontradas foram de 30°C e 20°C,
1349 respectivamente, e a umidade relativa do ar variou em média entre 65% e 80% (tabela S2.2). A
1350 concentração de CO₂ atmosférico no cenário atual foi de 420ppm (Magalhães et al., 2019), e a
1351 densidade de fluxo de fótons acima das plantas em um plano horizontal variou entre 210
1352 $\mu\text{mol}/\text{m}^2/\text{s}$ e 700 $\mu\text{mol}/\text{m}^2/\text{s}$ (tabela S2.2).

1353 Para definir os parâmetros do cenário futuro utilizamos o cenário SSP3-7.0 proposto
1354 pelo IPCC (2020). O cenário SSP3-7.0 utiliza modelos que consideram uma forte mudança de
1355 uso da terra e altas emissões de aerossóis, o que o levou a ser considerado um importante
1356 experimento no projeto CMIP6 (Neill et al., 2016). Apesar de não ser o cenário com a maior
1357 previsão de concentração de CO₂ em 2100, o cenário SSP3-7.0 pode ser o que deve trazer piores
1358 consequências econômicas e sociais para a região da América Latina, inclusive com os maiores
1359 índices de perda de produto interno bruto (PIB) (Chen et al., 2020).

1360 Em estudos realizados com os modelos apresentados para o CMIP5, os modelos que
1361 apresentaram melhores resultados para os biomas brasileiros, inclusive o Cerrado, foram o
1362 MIROC5 e o HadGEM2-ES (Almagro et al., 2020). Em nosso trabalho utilizamos o modelo
1363 MIROC-ES2L (Hajima et al., 2020), que além de ser baseado no modelo MIROC5.2, traz um
1364 componente que considera a interação carbono-nitrogênio para contabilizar o controle de
1365 nutrientes do solo no crescimento de plantas e no sumidouro terrestre de carbono (Hajima et
1366 al., 2020).

1367 Os dados de precipitação e temperatura máxima e mínima utilizados no cenário futuro
1368 foram provenientes do modelo MIROC6-ES2L, pertencentes ao banco de dados da fase 6 do
1369 Projeto de Intercomparação de Modelo Acoplado (CMIP6), com *downscale* calibrado segundo
1370 o patamar climático WorldClim 2.1 e obtido na resolução 2,5 minutos (Fick et al, 2017). Foram

1371 considerados os dados das projeções para o período entre 2081 e 2100, obtidos na plataforma
1372 WorldClim (Worldclim, 2020) em formato *geotiff*. e posteriormente visualizados no programa
1373 Qgis (versão 3.14). Um *shapefile* do Cerrado (Assis et al, 2019), foi sobreposto ao mapa
1374 contendo os dados climáticos de precipitação e temperatura máxima e mínima, dentro do qual
1375 foram distribuídos aleatoriamente 100 pontos afastados entre si (Figura S2.1). Foi feita uma
1376 média com os valores atribuídos a cada ponto disposto no território do Cerrado, relativos aos
1377 meses entre dezembro e março, para cada variável climática. As médias de temperatura obtidas
1378 foram 2.5°C acima do encontrado para o cenário atual, assim estabelecidas a temperatura
1379 mínima 22.5°C e a máxima 32.5°C para o cenário futuro simulado em nosso experimento
1380 (tabela S2.2).

1381 A variação na precipitação da estação chuvosa como um todo encontrada na comparação
1382 entre os dois cenários a serem simulados foi cerca de 7% menor no cenário futuro que no atual.
1383 Com base em resultados anteriores (Capítulo I desta tese), concluímos que essa variação seria
1384 muito pequena para uma aplicação experimental devido à capacidade de retenção de água do
1385 substrato utilizado além de ser semelhante ao erro experimental imposto pelo equipamento de
1386 irrigação. Portanto, para reduzir o número de variáveis experimentais decidimos aplicar a
1387 mesma quantidade de água nos dois cenários simulados. Foi mantida uma irrigação de 120ml
1388 de água por plântula a cada dois dias para ambos os cenários.

1389 A concentração de CO₂ atmosférico utilizado no cenário futuro foi de 862.8 ppm,
1390 projetada para o ano de 2100 no Hemisfério Sul no cenário SSP 3-7.0, de acordo com o modelo
1391 MIROC6-ES2L (Meinshausen et al., 2019).

1392 5.2.3. COLETA DE DADOS

1393 Após 120 dias de crescimento nos cenários climáticos simulados, as plantas foram
1394 removidas dos tubos para medidas de crescimento. As plantas foram cuidadosamente retiradas

1395 dos tubos com auxílio de uma mangueira com água corrente para desprendimento da terra das
1396 raízes, evitando perda de raízes laterais que pudesse interferir no valor de biomassa radicular
1397 final.

1398 Assim que toda a terra era removida, as plantas permaneceram com as raízes imersas
1399 em água até serem separadas em partes da seguinte maneira: raiz principal, raiz secundária,
1400 caule, cotilédones – quando presentes – e folhas. As seguintes medidas foram tomadas: Altura
1401 das plantas (H), comprimento da raiz principal (RL), diâmetro da base (St_D), e número de
1402 folhas (Lnum) área foliar e massa seca correspondente de três folhas de cada indivíduo (quando
1403 possível) para cálculos do SLA. Cada parte da plântula foi identificada quanto ao indivíduo,
1404 espécie e cenário a que foi submetida e colocadas para secar em estufa a 70°C para estimativa
1405 de massa seca. As seguintes medidas foram obtidas: biomassa total (TM), biomassa da raiz -
1406 raiz principal e secundárias - (RM), biomassa aérea (SM). Com estas medidas foi possível
1407 calcular a fração de biomassa radicular (RMF), a fração de biomassa aérea (SMF), a área
1408 específica foliar (SLA), e a taxa de crescimento relativo baseado na biomassa (RGR), com base
1409 na variação da biomassa durante o período do experimento (conforme tabela S1.5 do capítulo I
1410 desta tese).

1411 5.2.4. ANÁLISES ESTATÍSTICAS

1412 Todas as análises foram realizadas no programa R na plataforma RStudio (RStudio
1413 Team (2020), 2020). A análise exploratória dos dados, assim como os gráficos apresentados
1414 nesse trabalho foram feitas com o pacote flexplot() (Fife, 2019) ou ggplot2 (Wickham, 2009).

1415 A comparação entre os dois cenários foi feita em cada atributo medido para cada espécie
1416 separadamente, utilizando-se modelos lineares generalizados com o pacote glm2 (Donoghoe,
1417 2018), com o comando glm2() ($\alpha=0.05$). As variáveis preditoras foram espécies (*Kielmeyera*
1418 *coriacea*, *Tabebuia aurea*, *Qualea grandiflora* e *Hymenaea stigonocarpa*) e cenário (atual e

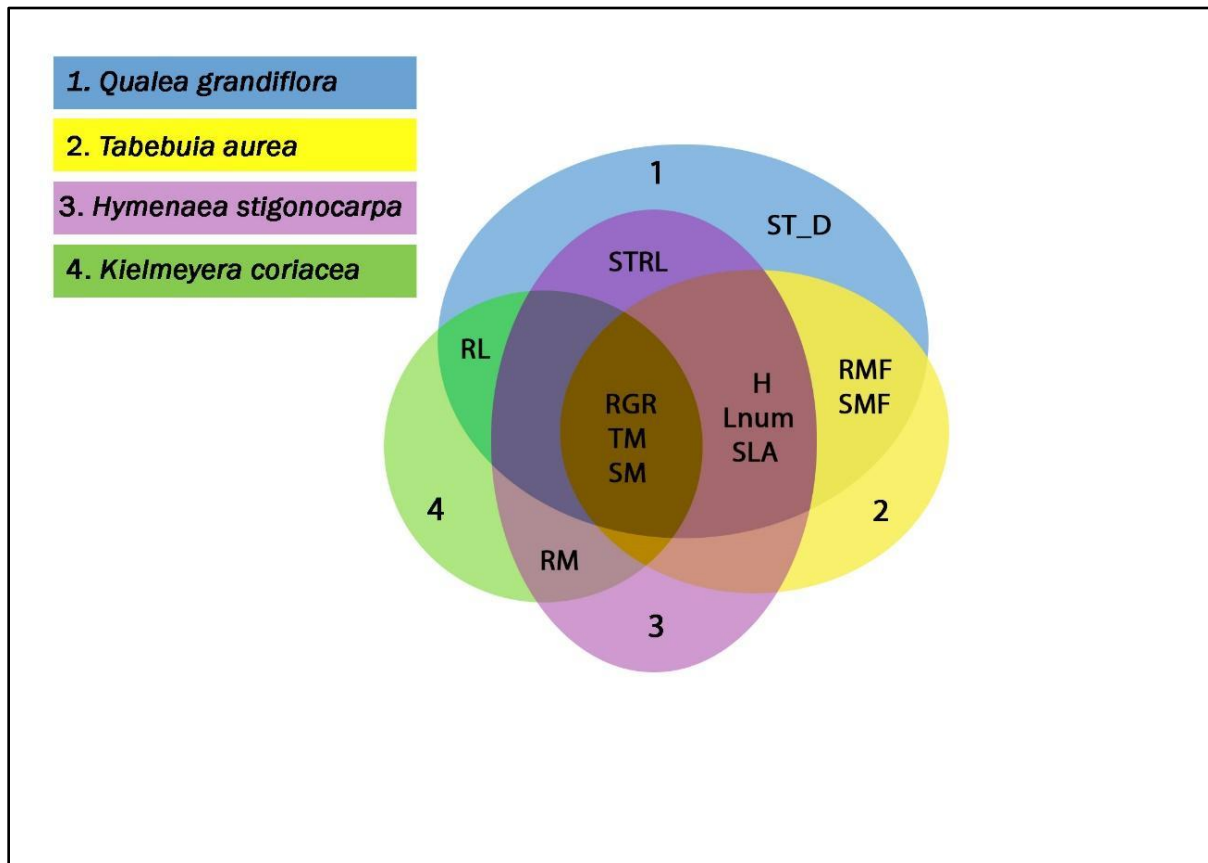
1419 futuro). As variáveis resposta foram altura, diâmetro basal, número de folhas comprimento da
1420 raiz principal, massa seca total, massa seca radicular, massa seca aérea, fração de biomassa
1421 radicular, fração de biomassa aérea e taxa de crescimento relativo. Para determinar a família de
1422 distribuição para os dados analisados em cada modelo utilizamos os pacote fitdistplus
1423 (Delignette-muller et al., 2013), com o comando gofstat(), e os testes “adtest”, “cvmtest” e
1424 “kstest”. As distribuições Gamma ou gaussiana foram as adequadas dos atributos medidos na
1425 análise de regressão para comparação entre os cenários. (Todas as análises podem ser
1426 encontradas no Apêndice IV)

1427 5.3. RESULTADOS

1428 Todas as espécies apresentaram aumento significativo ($p < 0.05$) de TM, SM e RGR no
1429 cenário futuro em comparação às plantas crescidas sob o cenário atual (Fig 1).

1430

1431



1432 **Figura 5.3.1.** Diagrama de Venn onde cada conjunto representa uma espécie, e os elementos contidos em cada conjunto são
 1433 os parâmetros que apresentaram diferença significativa entre os cenários ($p < 0.05$). Sendo esses parâmetros: diâmetro da base
 1434 do caule (ST_D), comprimento específico da raiz principal (STRL), comprimento da raiz principal (RL), taxa de crescimento
 1435 relativo (RGR), massa seca total (TM), massa seca aérea (SM), altura (H), número de folhas (Lnum), área específica foliar
 1436 (SLA), fração de biomassa radicular (RMF), fração de biomassa aérea (SMF) e massa seca radicular (RM).

1437

1438 A espécie que apresentou diferença significativa de maior número de parâmetros foi *Q.*
 1439 *grandiflora*, tendo apresentado aumento nos valores observados no cenário futuro em 11 dos
 1440 13 parâmetros. *K. coriacea* apresentou o menor número de parâmetros com diferença entre os
 1441 cenários, com alteração de 5 dos 13 parâmetros avaliados. Tanto *H. stigonocarpa* quanto *T.*
 1442 *aurea* apresentaram diferença significativa entre os cenários em 8 dos 13 parâmetros (Fig 1).

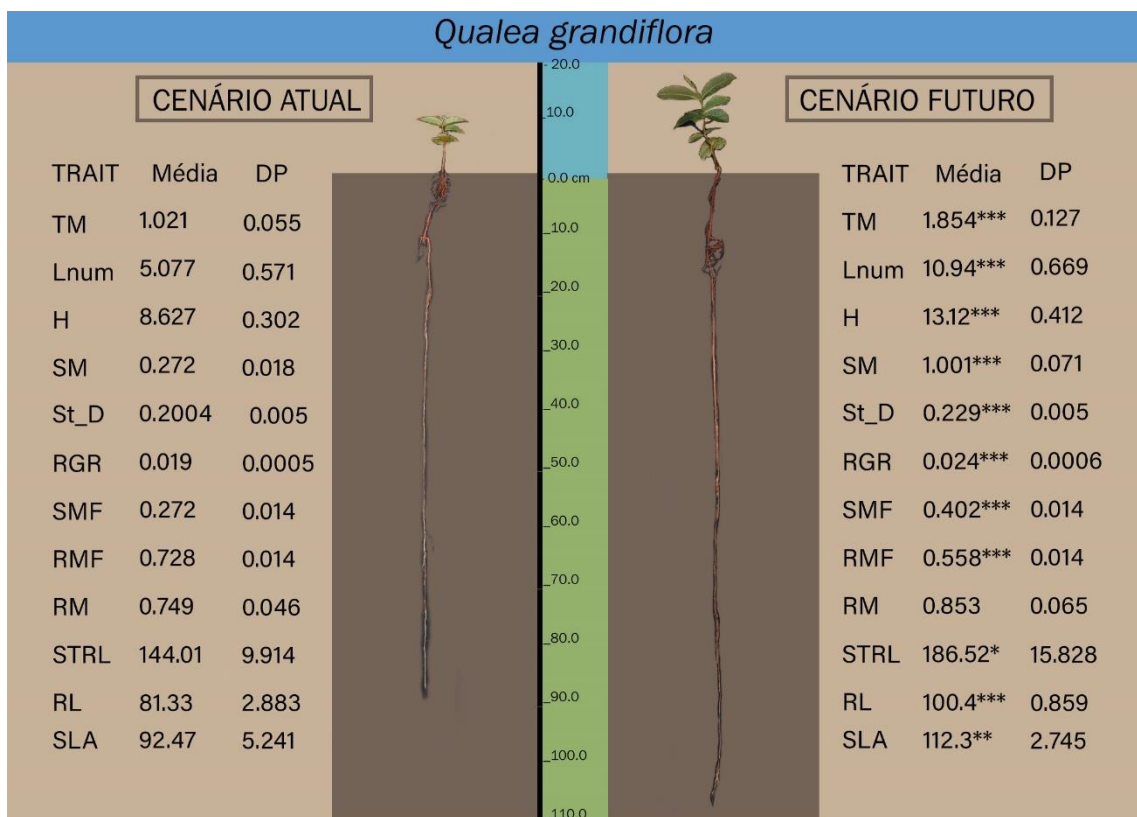
1443 *Q. grandiflora* foi a espécie que obteve o maior ganho em H quando submetida ao
 1444 cenário futuro ($t = - 8.621$, $p < 0.001$), apresentando um incremento de cerca de 55% (Fig 2),
 1445 enquanto que *T. aurea* apresentou incremento em H de aproximadamente 35% ($t = - 4.969$,
 1446 $p < 0.001$) (Fig 3) e *H. stigonocarpa* de 30% ($t = - 4.547$, $p < 0.001$) (Fig 4). Assim como H, o Ln
 1447 apenas não apresentou aumento significativo no cenário futuro para *K. coriacea* (Fig 5),

1448 enquanto que *Q. grandiflora* foi a espécie que apresentou a maior variação em Ln, com um
 1449 aumento de cerca de 130% ($t = -5.514$, $p < 0.001$), para *H. stigonocarpa* esse aumento foi de
 1450 85% ($t = -6.765$, $p < 0.001$) e para *T. aurea* de 65% ($t = -8.354$, $p < 0.001$).

1451 O St_D não foi um parâmetro muito influenciado pelo cenário futuro, tendo apresentado
 1452 incremento significativo ($t = -3.864$, $p < 0.001$) apenas para *Q. grandiflora* (Fig 1 e 2).

1453

1454

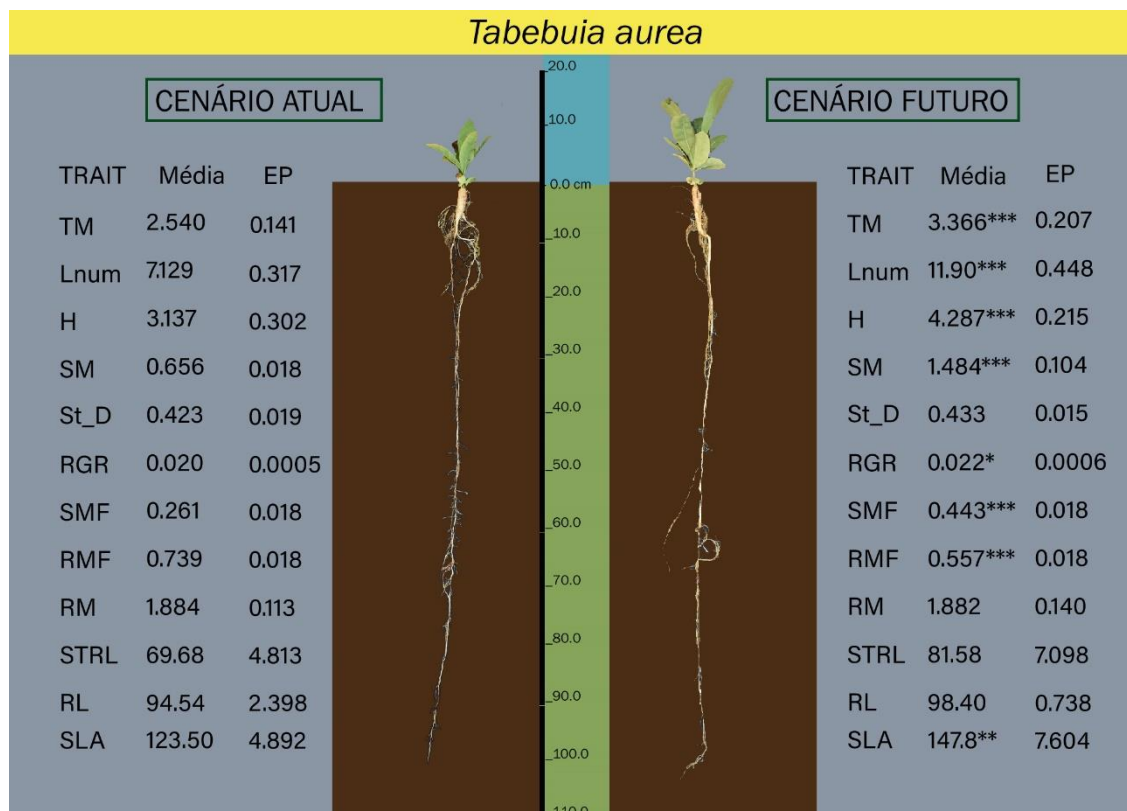


1455 **Figura 5.3.2.** À esquerda: plântula de *Qualea grandiflora* (n=30) crescida durante 120 dias em fitotron com o cenário
 1456 atual. À direita: plântula de *Qualea grandiflora* (n=30) crescida durante 120 dias em fitotron com o cenário futuro
 1457 projetado para 2100 na região central do Brasil. Para cada cenário, estão apresentados na figura os valores
 1458 correspondentes de média e erro padrão dos parâmetros (seção 5.2.3): TM(g), Lnum, H (cm), SM (g), St_D (cm), RGR
 1459 ($g\ g^{-1}d^{-1}$), SMF, RMF, RM (g), STRL ($cm\ g^{-1}$), RL (cm), SLA (cm^2g^{-1}).

1460

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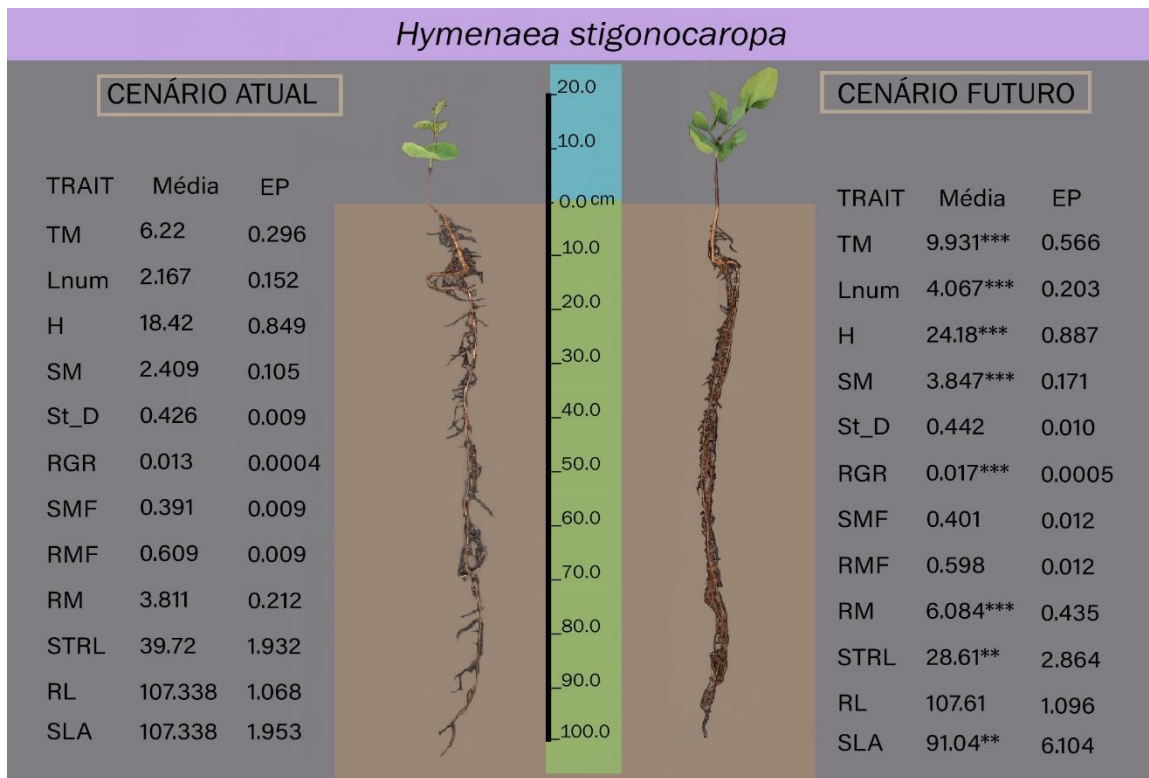


1463 **Figura 5.3.3.** À esquerda: plântula de *Tabebuia aurea* (n=30) crescida durante 120 dias em fitotron com o cenário
 1464 atual. À direita: plântula de *Tabebuia aurea* (n=30) crescida durante 120 dias em fitotron com o cenário futuro projetado
 1465 para 2100 na região central do Brasil. Para cada cenário, estão apresentados na figura os valores correspondentes de
 1466 média e erro padrão dos parâmetros (seção 5.2.3): TM(g), Lnum, H (cm), SM (g), St_D (cm), RGR (g g⁻¹d⁻¹), SMF,
 1467 RMF, RM (g), STRL (cm g⁻¹), RL (cm), SLA (cm²g⁻¹).

1468 O RL teve aumento significativo ($t = -4.184$, $p < 0.001$) para *K. coriacea*, com incremento
 1469 de aproximadamente 40% (figura 4), e para *Q. grandiflora* ($t = -6.018$, $p < 0.001$), com
 1470 incremento de aproximadamente 25% (figura 2).

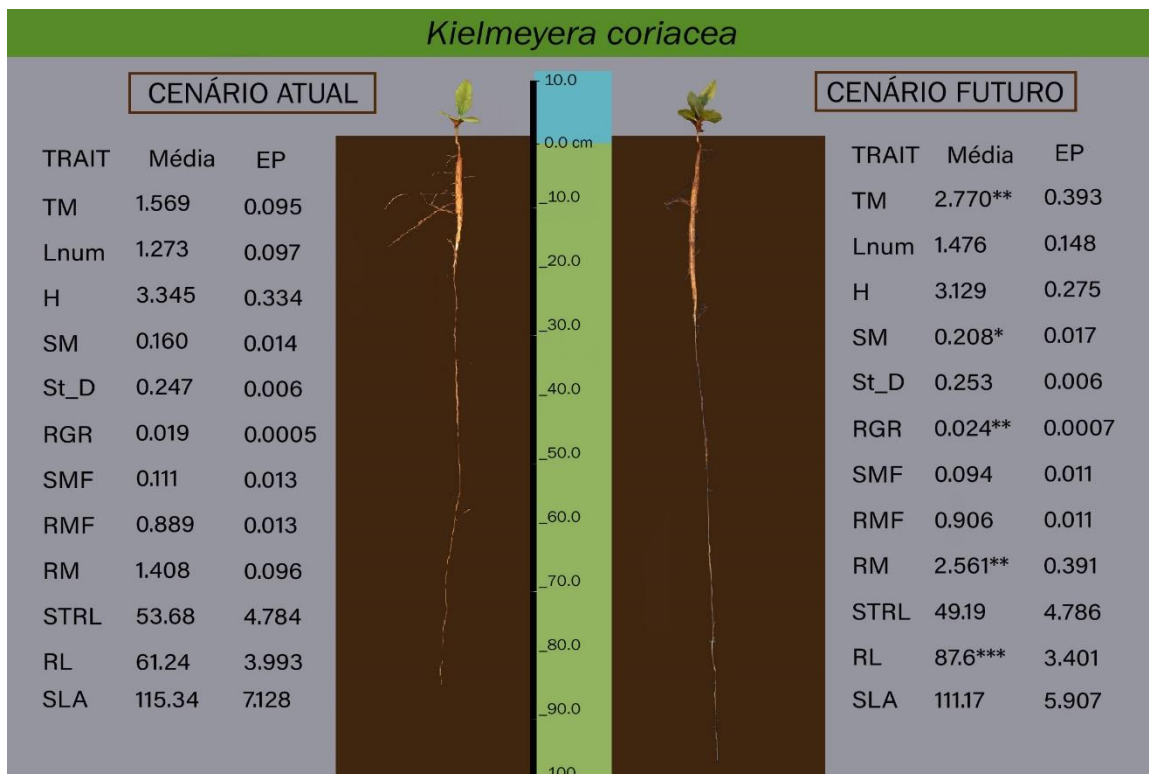
1471 Quando comparadas às plantas submetidas ao cenário atual, houve em média um
 1472 aumento de cerca de 75% de *Q. grandiflora* (figura 2), 30% de *T. aurea* (figura 3), 60% de *H.*
 1473 *stigonocarpa* (figura 4) e 50% da TM de *K. coriacea* (figura 5). Houve aumento significativo
 1474 da biomassa radicular (RM) apenas para *K. coriacea* ($t = -2.837$, $p = 0.007$), sendo em média
 1475 de 55% maior em comparação ao cenário atual, e para *H. stigonocarpa* ($t = -4.94$, $p < 0.001$),
 1476 que teve aproximadamente 60% mais RM no cenário futuro. O maior incremento em SM foi de
 1477 *Q. grandiflora* (175%), seguido de *T. aurea* (109%), *H. stigonocarpa* (65%) e por último *K.*
 1478 *coriacea* (12%).

1479



1480 **Figura 5.3.4:** À esquerda: plântula de *Hymenaea stigonocarpa* (n=30) crescida durante 120 dias em fitotron com o
 1481 cenário atual. À direita: plântula de *Hymenaea stigonocarpa* (n=30) crescida durante 120 dias em fitotron com o cenário
 1482 futuro projetado para 2100 na região central do Brasil. Para cada cenário, estão apresentados na figura os valores
 1483 correspondentes de média e erro padrão dos parâmetros (seção 5.2.3): TM(g), Lnum, H (cm), SM (g), St_D (cm), RGR
 1484 ($g\ g^{-1}d^{-1}$), SMF, RMF, RM (g), STRL ($cm\ g^{-1}$), RL (cm), SLA (cm^2g^{-1}).

1485



1486 **Figura 5.3.5:** À esquerda: plântula de *Kielmeyera coriacea* (n=30) crescida durante 120 dias em fitotron com o cenário
 1487 atual. À direita: plântula de *Kielmeyera coriacea* (n=30) crescida durante 120 dias em fitotron com o cenário futuro
 1488 projetado para 2100 na região central do Brasil. Para cada cenário, estão apresentados na figura os valores
 1489 correspondentes de média e erro padrão dos parâmetros (seção 5.2.3): TM(g), Lnum, H (cm), SM (g), St_D (cm), RGR
 1490 ($g\ g^{-1}d^{-1}$), SMF, RMF, RM (g), STRL ($cm\ g^{-1}$), RL (cm), SLA (cm^2g^{-1}).

1491

1492 DISCUSSÃO

1493 O cenário futuro utilizado em nosso experimento provocou o aumento de biomassa das
1494 plântulas de todas as espécies estudadas. A maior assimilação de carbono observada em
1495 plântulas submetidas ao cenário futuro deve-se à maior eficiência da Rubisco, aumentando a
1496 assimilação de CO₂ e reduzindo as taxas de fotorrespiração (Drake et al, 1997).

1497 A forma com que uma planta aloca a biomassa está relacionada com a disponibilidade
1498 de recursos no ambiente em que se encontra (Qi et al., 2019). A diferença de disponibilidade
1499 de carbono atmosférico e temperatura entre os cenários testados em nosso trabalho resultou em
1500 diferenças quanto à partição de biomassa, resultando em dois grupos sob a influência do cenário
1501 futuro: 1) manutenção do padrão de alocação de biomassa (*H. stigonocarpa* e *K. coriacea*)
1502 (Figuras 2.3 e 2.4); 2) aumento de alocação de biomassa na fração aérea e alocação de biomassa
1503 radicular semelhante à do cenário atual (*Q. grandiflora* e *T. aurea*) (Figuras 2.1 e 2.2). Essa
1504 diferença pode indicar que as espécies apresentam diferenças na capacidade de captação ou
1505 aproveitamento dos recursos ambientais disponíveis, sugerindo diferentes formas de
1506 aclimatação ao cenário futuro.

1507 *Q. grandiflora* apresentou maior comprimento da raiz principal sem ter aumentado a
1508 biomassa radicular no cenário futuro, resultando em menor investimento de biomassa por
1509 comprimento radicular, o que é considerado uma estratégia para permitir o acesso à água
1510 (Tomlinson et al, 2012). Diante da intensificação da estação seca esperada para o cenário futuro
1511 (Hoffman et al., 2021; Weigelt et al., 2021) o desenvolvimento mais acelerado da raiz principal
1512 para alcançar maiores profundidades do solo no cenário futuro apresentado por *K. coriacea* e
1513 *Q. grandiflora* é uma resposta apresentada no cenário futuro que pode contribuir para o
1514 recrutamento de espécies arbóreas de savana.

1515 *H. stigonocarpa* se comportou de modo conservativo no cenário futuro em relação ao
1516 SLA, apresentando redução desse parâmetro (Figura 2.4) e produzindo folhas mais espessas, o

1517 que permite uma maior economia de recursos uma vez que a maior concentração de CO₂
1518 atmosférico permite a mesma captação desse recurso a partir de uma área foliar menor (Wang
1519 et al, 2020). Por outro lado, *Q. grandiflora* e *T. aurea* tiveram aumento do SLA, apresentando
1520 maior área foliar para um mesmo valor de massa seca investida. O maior investimento em
1521 biomassa foliar no cenário futuro observado para de *Q. grandiflora* e *T. aurea* pode indicar uma
1522 priorização em alocar recursos para obter um crescimento mais acelerado, caracterizando um
1523 comportamento aquisitivo (Grime& Pierce, 2012; Fagundes et al, 2022; Weigelt et al., 2021).
1524 Além disso, para que a planta possa aumentar assimilação de carbono por um período maior
1525 em um ambiente com alta concentração de CO₂ atmosférico, é preciso um aumento da relação
1526 dreno-fonte (Amsterdam, 1991), o que pode ter contribuído para que essas espécies
1527 apresentassem um maior investimento na fração aérea do que na fração radicular no cenário
1528 futuro, reforçando a ideia de que *Q. grandiflora* e *T. aurea* apresentaram comportamento
1529 aquisitivo (Figuras 2.2 e 2.3).

1530 Em relação à produção foliar, três das quatro espécies estudadas (*Q. grandiflora*, *T.*
1531 *aurea* e *H. stigonocarpa*) apresentaram maior número de folhas (Figuras 2.2, 2.3 e 2.4). Mesmo
1532 apresentando um maior número de folhas e maior biomassa foliar no cenário futuro, *H.*
1533 *stigonocarpa* manteve a partição de biomassa apresentada no cenário atual e foi a única espécie
1534 que apresentou aumento de biomassa de raiz secundária no cenário futuro (Figura S2.2). A
1535 maior oferta de CO₂ no cenário futuro pode fazer com que a disponibilidade de nutrientes do
1536 solo limite o crescimento e a taxa fotossintética (Wieder et al, 2015). Como a composição do
1537 solo nos dois cenários climáticos era semelhante, a alta [CO₂] do cenário futuro pode ter levado
1538 à maior produção de raízes secundárias em *H. stigonocarpa* para obtenção de nutrientes e
1539 manutenção do ganho mais acelerado de biomassa nesse cenário (Iversen, 2010). Embora *H.*
1540 *stigonocarpa* tenha apresentado no geral um crescimento mais acelerado no cenário futuro
1541 devido à maior aquisição de biomassa, a redução do SLA e a manutenção do padrão de alocação

1542 de biomassa podem indicar que a espécie apresenta um comportamento conservativo, em que a
1543 prioridade é alocar recursos para garantir a sobrevivência do indivíduo frente a possíveis
1544 distúrbios (Grime & Pierce, 2012; Fagundes et al, 2022; Weigelt et al., 2021).

1545 Assim como *H. stigonocarpa*, *K. coriacea* também manteve a partição de biomassa do
1546 cenário futuro semelhante à observada no cenário atual, além de não apresentar alteração do
1547 SLA e nem do número de folhas quando submetida ao cenário futuro (Figura 2.5). O maior
1548 investimento no comprimento da raiz principal acompanhado de maior investimento em
1549 biomassa da raiz principal, aparentando maior investimento no órgão de reserva radicular
1550 (Figura 5), contribuem para compreender o comportamento de *K. coriacea* como conservativo
1551 (Grime & Pierce, 2012; Fagundes et al, 2022; Weigelt et al., 2021). Entre as espécies utilizadas,
1552 *K. coriacea* foi a menos plástica, o que indica uma baixa influência das alterações ambientais
1553 testadas na expressão gênica dessa espécie.

1554 Embora tanto *K. coriacea* quanto *T. aurea* apresentem órgão de reserva subterrâneo, as
1555 duas espécies aparentam adotar diferentes estratégias de sobrevivência. Enquanto *K. coriacea*
1556 manteve a proporção entre biomassa radicular e aérea nos dois cenários estudados, *T. aurea*
1557 apresentou aumento de massa seca aérea no cenário futuro e a massa seca radicular manteve
1558 um valor semelhante nos dois cenários, resultando em um maior investimento em biomassa
1559 aérea em relação à biomassa radicular de *T. aurea* no cenário futuro em comparação ao cenário
1560 atual. Considerando esse aspecto, podemos considerar que *K. coriacea* teve um comportamento
1561 mais conservativo em relação à distribuição da biomassa, pois em ambiente de savana é muito
1562 comum a perda da parte aérea e a necessidade do uso de reservas subterrâneas para rebrotar
1563 (Bond, 2008). O xilopódio é um órgão de reserva que teve origem em diversos momentos
1564 evolutivos, podendo ser encontrado em espécies com origens filogenéticas muito distintas
1565 (Simon & Pennington, 2012). O xilopódio pode ser fonte de diversos recursos como água,
1566 nutrientes e carboidratos em momentos de escassez, sendo possível que diferentes filtros

1567 ambientais tenham favorecido o desenvolvimento desse órgão em diferentes espécies (Simon
1568 & Pennington, 2012). É possível que estudos filogenéticos associados aos resultados obtidos
1569 em nosso experimento, possam ajudar a responder quais pressões evolutivas levaram à
1570 divergência das respostas apresentadas por essas espécies no presente trabalho.

1571 A aquisição de biomassa durante o estágio inicial de desenvolvimento de uma planta
1572 pode estar associada à massa da semente (Baraloto et al, 2005; Saatkamp et al, 2019). A
1573 variação na biomassa total observada entre o cenário futuro e o atual de *K. coriacea*, *Q.*
1574 *grandiflora* e *T. aurea* foi semelhante (cerca de 0,8g) (Figuras 2.2, 2.3 e 2.5), enquanto que ao
1575 mesmo tempo *H. stigonocarpa* apresentou um incremento de biomassa total de 3,7g no cenário
1576 futuro (Figura 2.4). *K. coriacea*, *Q. grandiflora* e *T. aurea* são dispersas por anemocoria,
1577 possuem sementes mais leves e cotilédones fotossintetizantes, enquanto que *H. stigonocarpa* é
1578 dispersa por zoocoria e possui sementes maiores e mais pesadas, apresentando cotilédones de
1579 reserva. Esse resultado reforça estudos que defendem que a variação do incremento de biomassa
1580 e a taxa de crescimento relativo são mais pronunciados em plantas com sementes maiores
1581 quando submetidas a maiores temperaturas e [CO₂] (Jones & Reekie, 2007; Khurana& Singh,
1582 2004).

1583 *Q. grandiflora* foi a única que passou a alocar mais da metade da biomassa total para
1584 fração aérea no cenário futuro (Figura 2.2). Mesmo sendo uma espécie com grande plasticidade
1585 fenotípica (Buzatti et al., 2019) e a que apresenta a maior frequência e distribuição no Cerrado
1586 (Ratter et al., 2003), sua distribuição é restrita ao Cerrado (da Ponte et al, 2020). Sendo o padrão
1587 de distribuição de biomassa um atributo relacionado ao tipo de ambiente em que a espécie se
1588 encontra (Qi et al, 2019), esse resultado torna-se surpreendente. Por outro lado, a inversão no
1589 padrão de alocação de biomassa foi observada em outros experimentos com elevação de
1590 temperatura e [CO₂] (Avila et al, 2020; Forbes et al, 2020; Apgaua et al, 2019). No caso de
1591 espécies de *Eucalyptus* em savanas, a modificação do padrão de alocação de biomassa só foi

1592 observada quando o CO₂ elevado foi aplicado juntamente com temperaturas mais altas, caso
1593 contrário apenas se observou o aumento da biomassa em função da maior oferta de carbono
1594 atmosférico (Apgaua et al, 2019).

1595 A longo prazo, a limitação de recursos pode levar a uma estagnação ou até mesmo a
1596 queda do aumento da taxa de crescimento no cenário futuro (Maschler et al, 2022). Porém o
1597 incremento de biomassa na fase de plântula em espécies arbóreas de savana favorece a
1598 sobrevivência de plântulas diante de distúrbios ambientais que normalmente controlam essas
1599 populações, como o fogo e a sazonalidade da precipitação (Cardoso et al., 2016; Freschet et al.,
1600 2021, Gignoux et al., 2009, Moreira & Klink, 2000), podendo gerar um grande impacto no
1601 ecossistema (Kgope et al., 2010).

1602 Em conjunto nossos resultados indicam que o cenário climático esperado para 2100 no
1603 Cerrado favorece o desenvolvimento inicial de espécies arbóreas frente aos principais fatores
1604 que controlam as populações dessas espécies (Cardoso et al., 2016; Freschet et al., 2021,
1605 Gignoux et al., 2009, Moreira & Klink, 2000). Além de facilitar o aumento do número de
1606 indivíduos de espécies arbóreas, esse cenário futuro também estimula o crescimento aéreo e a
1607 produção foliar, o que poderá intensificar o sombreamento em áreas de savana e prejudicar o
1608 estabelecimento de espécies do estrato herbáceo típicas de savana que demandam alta
1609 luminosidade (Raymundo et al, 2022). Por outro lado, a sazonalidade da precipitação e a
1610 intensificação do estresse hídrico durante a estação seca no cenário futuro (Hofmann et al.,
1611 2021) poderão limitar a ocupação dessas áreas por espécies sensíveis ao estresse hídrico
1612 (Villalobos-Veja et al., 2014). Em geral, a resistência à seca e ao sombreamento estão
1613 associadas a diferentes conjuntos de atributos funcionais, fazendo com que essas estratégias
1614 ocorram de modo independente entre si (Markesteyn & Poorter, 2009).

1615 5.4. CONCLUSÃO

1616 Nosso trabalho evidencia que o cenário futuro esperado para 2100 favoreceu o
1617 desenvolvimento inicial de espécies arbóreas de savana neotropical. Devido ao incremento
1618 significativo de biomassa observado no cenário futuro em todas as espécies estudadas, com
1619 maior proporção na fração aérea em metade dessas espécies, nossos resultados trazem fortes
1620 indícios de que a elevação da [CO₂] atmosférico pode ser um fator importante do processo de
1621 adensamento arbóreo que vem ocorrendo mundialmente em savanas, com maior velocidade em
1622 savanas da América do Sul podendo levar a grande perda de biodiversidade (Rosan et al., 2019;
1623 Abreu et al., 2017). A elevação da [CO₂] e da temperatura no cenário futuro provocou ao mesmo
1624 tempo o incremento de atributos que contribuem para o aumento do sombreamento em savanas
1625 (H, Ln, SM) e o alcance de profundidades maiores no perfil do solo (RL). O efeito das mudanças
1626 climáticas a nível de indivíduo pode ter grandes consequências na composição da vegetação e
1627 deve ser considerado em ações de preservação ambiental para a melhor preservação da
1628 biodiversidade em savanas.

1629 5.5. REFERÊNCIAS

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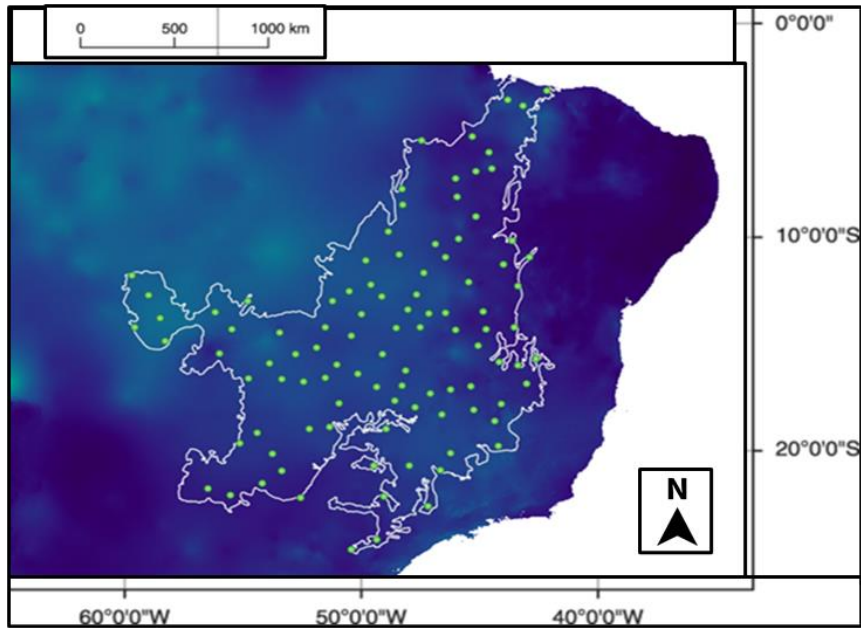
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5.6. MATERIAL SUPLEMENTAR

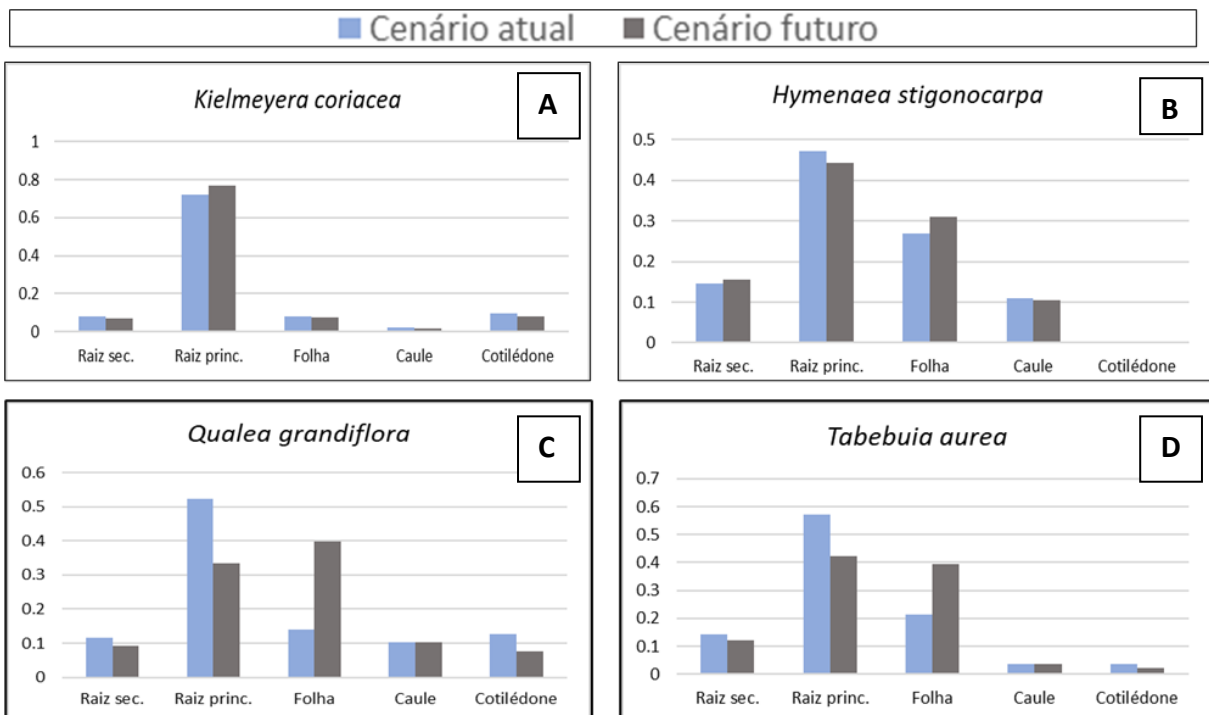


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Figura S2.1: Distribuição de 100 pontos aleatórios no território do bioma Cerrado para obtenção dos dados de temperatura máxima, temperatura mínima, e precipitação previstos para os meses de dezembro a abril de 2100 de acordo com o SSP 3-7.0, segundo o modelo MIROC6-ES2L (MIROC6) do IPCC.

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Figura S2.2. Distribuição da biomassa de plântulas de *K. coriacea* (A), *H. stigonocarpa* (B), *Q. grandiflora* (C), *T. aurea* (D) após 120 dias sob o cenário atual (azul – barras à esquerda) ou sob o cenário futuro (cinza – barras à direita) simulados em fitotron no Laboratório de Termobiologia (Universidade de Brasília), entre setembro de 2020 e abril de 2021. As barras representam os valores em g das frações de biomassa de raiz secundária (Raiz sec.), frações de biomassa de raiz secundária, frações de biomassa de raiz principal (Raiz princ.), frações de biomassa foliar (Folha), frações de biomassa caulinar (Caule), e frações de biomassa do cotilédone (Cotilédone).

1908

1909 **Tabela S2.1.** Análise de solo extraído da Fazenda Água Limpa (UnB, Brasília - DF) misturado com areia
 1910 na proporção de 3:1, e sem ter sido misturado.

1911

Parâmetro	unidade	solo + areia	solo original
COMPLEXO SORTIVO			
pH em H ₂ O,	na	5.6	5.7
FÓSFORO - P, extraído com Mehlich	mg/dm ³ = ppm	1.8	1.3
CÁLCIO - Ca	cmolc/dm ³ = mE/100mL	0.4	0.3
MAGNÉSIO - Mg	cmolcdm ³ = mE/100mL	0.1	0.1
POTÁSSIO - K	cmolcdm ³ = mE/100mL	0.01	0.04
SÓDIO - Na	cmolcdm ³ = mE/100mL	0.07	0.07
ALUMÍNIO - Al	cmolcdm ³ = mE/100mL	0.8	0.7
ACIDEZ (H + Al)	cmolcdm ³ = mE/100mL	3.2	3
SOMA DAS BASES	cmolcdm ³ = mE/100mL	0.6	0.5
CAPACIDADE DE TROCA DE CÁTIONS - CTC ou T, a pH 7	cmolc/dm ³	3.8	3.5
SATURAÇÃO por BASES - V, em	%	15	15
SATURAÇÃO por ALUMÍNIO - m	%	58	58
SATURAÇÃO com SÓDIO - ISNa	%	12	14
CARBONO ORGÂNICO - C	g/kg	11.5	16.1
MATÉRIA ORGÂNICA - MO	g/kg	19.8	27.7
MICRONUTRIENTES			
BORO DISPONÍVEL - B, em	mg/dm ³ = ppm	0.03	0.04
COBRE DISPONÍVEL - Cu	mg/dm ³ = ppm	0.4	0.3
FERRO DISPONÍVEL - Fe	mg/dm ³ = ppm	111	73.6
MANGANÊS DISPONÍVEL - Mn	mg/dm ³ = ppm	14.9	4.6
ZINCO DISPONÍVEL - Zn	mg/dm ³ = ppm	1	0.7
ENXOFRE DISPONÍVEL - S	mg/dm ³ = ppm	2.9	7.1
COMPOSIÇÃO GRANULOMÉTRICA			
Argila	g/Kg	550	500
Areia	g/Kg	375	300
Silte	g/Kg	75	200

1912 Nota: O solo com areia foi utilizado como substrato para as plântulas no experimento de cenários climáticos realizado em
 1913 fitotron no laboratório de Termobiologia (Universidade de Brasília).
 1914
 1915
 1916
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1920

Tabela S2.2 Temperatura (°C) e umidade relativa do ar (%) programadas nos dois fitotrons conforme o cenário climático simulado em cada um: cenário atual ou cenário futuro.

1923

Horário (h)	temperatura (°C)		Umidade relativa (%)	Luz ($\mu\text{mol} / \text{m}^2 / \text{s}$)
	Cenário atual	Cenário futuro		Cenário atual e futuro
0:00	24	26.5	80	-
1:00	24	26.5	80	-
2:00	24	26.5	80	-
3:00	24	26.5	80	-
4:00	22	24.5	85	-
5:00	22	24.5	85	-
6:00	22	24.5	85	-
7:00	22	24.5	85	210
8:00	20	22.5	85	210
9:00	20	22.5	85	210
10:00	23	25.5	85	420
11:00	23	25.5	85	700
12:00	25	27.5	85	700
13:00	27	29.5	80	700
14:00	27	29.5	70	700
15:00	30	32.5	65	420
16:00	30	32.5	65	420
17:00	30	32.5	65	210
18:00	27	29.5	70	210
19:00	27	29.5	70	210
20:00	27	29.5	70	-
21:00	27	29.5	70	-
22:00	25.5	28	80	-
23:00	25.5	28	80	-

1924: Na última coluna, cada “X” refere-se a um conjunto de lâmpadas acesas nos fitotrons. Ao todo são três conjuntos de lâmpadas em cada
1925 ão. A incidência luminosa ao nível da parte superior dos tubos onde se encontravam as plantas era de 210 $\mu\text{mol} / \text{m}^2 / \text{s}$ quando haviam
1926 um conjunto de lâmpadas acesas (“X”), de 420 $\mu\text{mol} / \text{m}^2 / \text{s}$ quando haviam dois conjuntos de lâmpadas acesas (“XX”), e de 700 $\mu\text{mol} / \text{m}^2$
1927 quando haviam três conjuntos de lâmpadas acesas (“XXX”).

1928

6. CONCLUSÃO GERAL

1929

1930 No geral pudemos observar que quando submetidas a temperatura e concentração de
1931 CO₂ elevadas, plântulas de espécies arbóreas de savana apresentam a intensidade de alocação
1932 de biomassa para a fração radicular ou aérea dependerá do grau de tolerância ao estresse
1933 ambiental encontrado pela plântula. Nossos resultados indicam que a alocação de biomassa e o
1934 desenvolvimento da parte aérea, assim como o investimento em comprimento da raiz principal,
1935 foi mais importante do que o acúmulo de biomassa nas raízes.

1936 O aumento de copa (Ln), altura (H) e biomassa aérea (SM) encontrados em nosso
1937 trabalho estão de acordo com resultados obtidos em simulações que indicam o risco de
1938 adensamento arbóreo em savanas (Kumar et al 2021). Porém é importante enfatizar que os
1939 diferentes níveis e tipos de plasticidade no processo de aclimatação ao cenário futuro irão variar
1940 conforme a espécie e podem influenciar o cenário futuro de diferentes formas. Portanto, para
1941 uma projeção mais localizada dos impactos do cenário climático futuro, é importante levar em
1942 consideração a composição florística e conhecer melhor as respostas das espécies nativas a esse
1943 cenário esperado.

1944 7. APÊNDICES

1945 7.1. APÊNDICE I: DADOS DO CAPÍTULO 1

1946 7.1.1. *Dados iniciais*

1947

species	days old	plant	H	Lnum	RL	SM	RM	M	RM:SM	SLA	STRL	RER	SMF	RMF
T. aurea	60	1	2.50	6.00	7.41	0.55	0.52	1.07	0.96	146.97	14.14	0.12	0.51	0.49
T. aurea	60	2	3.10	6.00	7.92	0.43	0.48	0.91	1.11	160.72	16.60	0.13	0.47	0.53
T. aurea	60	3	1.80	6.00	12.19	0.66	1.43	2.09	2.17	128.22	8.51	0.20	0.32	0.68
T. aurea	60	4	2.00	6.00	9.65	0.51	0.92	1.43	1.82	92.86	10.49	0.16	0.35	0.65
T. aurea	60	5	3.70	4.00	9.73	0.33	0.98	1.30	2.99	157.33	9.97	0.16	0.25	0.75
T. aurea	60	6	2.40	6.00	7.40	0.59	0.97	1.55	1.65	162.19	7.66	0.12	0.38	0.62
T. aurea	60	7	2.30	8.00	10.39	0.59	1.09	1.68	1.86	156.72	9.51	0.17	0.35	0.65
T. aurea	60	8	1.90	6.00	12.15	0.73	1.42	2.15	1.94	155.46	8.56	0.20	0.34	0.66
T. aurea	60	9	2.60	6.00	9.04	0.56	0.79	1.35	1.41	156.44	11.40	0.15	0.41	0.59
T. aurea	60	10	1.20	4.00	8.73	0.50	1.17	1.67	2.36	137.64	7.46	0.15	0.30	0.70
Q. grandiflora	60	1	4.50	6.00	18.60	0.24	0.14	0.38	0.59	123.24	132.86	0.31	0.63	0.37
Q. grandiflora	60	2	7.50	5.00	20.90	0.36	0.11	0.47	0.32	126.78	183.33	0.35	0.76	0.24
Q. grandiflora	60	3	5.40	6.00	22.70	0.21	0.08	0.30	0.39	160.71	273.49	0.38	0.72	0.28
Q. grandiflora	60	4	4.30	4.00	17.40	0.20	0.09	0.29	0.47	137.65	187.10	0.29	0.68	0.32
Q. grandiflora	60	5	6.00	6.00	21.60	0.24	0.12	0.36	0.50	129.45	180.00	0.36	0.67	0.33
Q. grandiflora	60	6	6.50	4.00	19.30	0.28	0.12	0.41	0.44	126.31	155.65	0.32	0.70	0.30
Q. grandiflora	60	7	6.90	6.00	20.80	0.29	0.11	0.41	0.38	130.87	185.71	0.35	0.72	0.28
Q. grandiflora	60	8	6.50	6.00	23.40	0.28	0.10	0.37	0.36	158.79	238.78	0.39	0.74	0.26

1948

1949

7.1.2. DADOS FINAIS

species	plant	trat.	H	Lnum	SM	RM	TM	RS	SLA	RGR	STRL	RER
T. aurea	1	1	8	12	1.5760	4.7060	6.2820	2.9860	97.5379	0.0195	20.8245	0.6811
T. aurea	2	1	6	12	6.6708	20.3697	27.0405	3.0536	79.4110	0.0300	4.9043	0.6957
T. aurea	3	1	8	12	11.4690	17.7025	29.1715	1.5435	83.7613	0.0305	5.6715	0.6995
T. aurea	4	1	10	10	5.3660	26.9736	32.3396	5.0268	97.7589	0.0313	3.7333	0.7018
T. aurea	5	1	4	11	5.0525	15.1921	20.2446	3.0068	97.0856	0.0279	6.5165	0.6888
T. aurea	6	1	4	15	3.7029	9.9138	13.6167	2.6773	91.5137	0.0250	9.9962	0.6895
T. aurea	7	1	6	9	1.3790	7.0922	8.4712	5.1430	88.6142	0.0216	13.7757	0.6788
T. aurea	8	1	4	8	5.8622	9.4323	15.2945	1.6090	104.5853	0.0259	11.2910	0.7465
T. aurea	9	1	6	5	6.8594	13.7736	20.6330	2.0080	81.1130	0.0280	8.2694	0.8034
T. aurea	10	1	11	10	5.3732	13.7776	19.1508	2.5641	122.6428	0.0275	7.4541	0.7172
T. aurea	1	8	8	12	8.6421	11.9284	20.5705	1.3803	97.5379	0.0280	8.2157	0.6811
T. aurea	2	8	6	12	8.2880	13.4895	21.7775	1.6276	79.4110	0.0284	7.4058	0.6957
T. aurea	3	8	8	12	7.8693	7.3713	15.2406	0.9367	83.7613	0.0259	13.6204	0.6995
T. aurea	4	8	10	10	8.0018	10.8669	18.8687	1.3581	97.7589	0.0274	9.2667	0.7018
T. aurea	5	8	4	11	2.4651	5.4694	7.9345	2.2187	97.0856	0.0212	18.1007	0.6888
T. aurea	6	8	4	15	1.6113	4.9278	6.5391	3.0583	88.6142	0.0198	20.1104	0.6895
T. aurea	7	8	6	9	5.8801	11.7007	17.5808	1.9899	104.5853	0.0269	8.3499	0.6788
T. aurea	8	8	6	5	2.0411	3.4604	5.5015	1.6954	81.1130	0.0185	32.9153	0.8034
T. aurea	9	8	8	8	5.4877	14.5319	20.0196	2.6481	86.2611	0.0278	7.1223	0.7234
T. aurea	10	8	11	10	4.5725	5.1655	9.7380	1.1297	122.6428	0.0226	19.8819	0.7172
T. aurea	1	15	10	8	8.5048	4.6324	13.1372	0.5447	81.4089	0.0248	21.2633	0.6849
T. aurea	2	15	5	12	3.4269	2.7351	6.1620	0.7981	99.1982	0.0193	35.9402	0.6834
T. aurea	3	15	8	6	6.2866	7.9057	14.1923	1.2575	108.0730	0.0253	12.6238	0.6949
T. aurea	4	15	9	5	5.0098	8.3465	13.3563	1.6660	86.3370	0.0249	11.5977	0.6718
T. aurea	5	15	12	8	6.7344	6.8747	13.6091	1.0208	100.8356	0.0250	13.9933	0.6672
T. aurea	6	15	3	8	2.7798	5.8996	8.6794	2.1223	102.4169	0.0218	17.2046	0.7080
T. aurea	7	15	8	10	4.8974	5.5567	10.4541	1.1346	83.9266	0.0231	17.2404	0.6641
T. aurea	8	15	9	8	3.5905	9.7611	13.3516	2.7186	94.6073	0.0249	10.3779	0.7065
T. aurea	9	15	10	10	4.7530	6.7817	11.5347	1.4268	99.4796	0.0239	14.2147	0.6688
T. aurea	10	15	12	11	2.0119	1.4748	3.4867	0.7330	170.4490	0.0152	66.7887	0.6849

1950

species	plant	trat.	RMF	SMF	RL	LA 1	LA2	LA3	LM1	LM2	LM 3	LMt	LMF	NAR
T. aurea	1	1	0.749	0.251	98.00	93.17	91.45	105.25	1.014	0.887	na	1.105	0.176	0.0011
T. aurea	2	1	0.753	0.247	99.90	105.32	61.9	92.99	1.257	0.825	na	5.888	0.218	0.0017
T. aurea	3	1	0.607	0.393	100.40	76.2	71.83	93.93	0.873	0.930	1.082	5.491	0.188	0.0019
T. aurea	4	1	0.834	0.166	100.70	107.02	86.04	78.65	0.998	0.897	0.873	4.785	0.148	0.0022
T. aurea	5	1	0.750	0.250	99.00	33.31	20.91	26.8	0.502	0.179	0.248	4.662	0.230	0.0012
T. aurea	6	1	0.728	0.272	99.10	14.42	10.09	19.47	0.160	0.131	0.181	3.255	0.239	0.0011
T. aurea	7	1	0.837	0.163	97.70	70.04	76.74	44.87	0.783	0.795	0.562	1.088	0.128	0.0019
T. aurea	8	1	0.617	0.383	106.50	23.79	28.67	30.5	0.246	0.267	0.278	5.358	0.350	0.0007
T. aurea	9	1	0.668	0.332	113.90	30.52	35.88	22.82	0.441	0.300	0.418	2.370	0.115	0.0030
T. aurea	10	1	0.719	0.281	102.70	57.02	51.09	57.87	0.530	0.335	0.537	5.042	0.263	0.0009
T. aurea	1	8	0.580	0.420	98.00	93.17	91.45	105.25	1.014	0.887	na	8.142	0.396	0.0007
T. aurea	2	8	0.619	0.381	99.90	105.32	61.9	92.99	1.257	0.825	na	7.797	0.358	0.0010
T. aurea	3	8	0.484	0.516	100.40	76.2	71.83	93.93	0.873	0.930	1.082	7.680	0.504	0.0006
T. aurea	4	8	0.576	0.424	100.70	107.02	86.04	78.65	0.998	0.897	0.873	7.247	0.384	0.0007
T. aurea	5	8	0.689	0.311	99.00	33.31	20.91	26.8	0.502	0.179	0.248	2.297	0.290	0.0008
T. aurea	6	8	0.754	0.246	99.10	70.04	76.74	44.87	0.783	0.795	0.562	1.477	0.226	0.0010
T. aurea	7	8	0.666	0.334	97.70	23.79	28.67	30.5	0.246	0.267	0.278	5.572	0.317	0.0008
T. aurea	8	8	0.629	0.371	113.90	30.52	35.88	22.82	0.441	0.300	0.418	1.717	0.312	0.0007
T. aurea	9	8	0.726	0.274	103.50	82.93	69.04	83.47	0.929	0.810	0.991	4.732	0.236	0.0014
T. aurea	10	8	0.530	0.470	102.70	57.02	51.09	57.87	0.530	0.335	0.537	4.132	0.424	0.0004
T. aurea	1	15	0.353	0.647	98.50	91.01	92.27	83.43	1.068	1.061	1.158	7.957	0.606	0.0005
T. aurea	2	15	0.444	0.556	98.30	71.96	102.88	103.46	0.808	0.969	1.011	3.211	0.521	0.0004
T. aurea	3	15	0.557	0.443	99.80	80.08	116.68	123.08	0.745	1.059	1.156	5.851	0.412	0.0006
T. aurea	4	15	0.625	0.375	96.80	60.13	80.76	85.12	0.814	0.914	0.879	4.486	0.336	0.0009
T. aurea	5	15	0.505	0.495	96.20	56.38	54.09	55.97	0.524	0.587	0.545	6.097	0.448	0.0006
T. aurea	6	15	0.680	0.320	101.50	56.77	40.74	23.26	0.514	0.368	0.270	2.606	0.300	0.0007
T. aurea	7	15	0.532	0.468	95.80	69.32	49.64	45.56	0.791	0.589	0.571	4.466	0.427	0.0006
T. aurea	8	15	0.731	0.269	101.30	40.8	40.97	45.87	0.446	0.431	0.471	3.101	0.232	0.0011
T. aurea	9	15	0.588	0.412	96.40	42.11	54.61	66.85	0.475	0.517	0.642	4.211	0.365	0.0007
T. aurea	10	15	0.423	0.577	98.50	38.11	41.85	33.25	0.219	0.238	0.206	1.808	0.519	0.0002

1951

1952

species	plant	trat.	H	Lnum	SM	RM	TM	RS	SLA	RGR	STRL	RER
Q. grandiflora	1	1	36	24	5.910	2.486	8.396	0.421	112.454	0.017	41.194	0.628
Q. grandiflora	2	1	29	20	4.464	1.611	6.074	0.361	88.520	0.014	64.064	0.634
Q. grandiflora	3	1	27	22	3.222	1.056	4.278	0.328	134.043	0.011	91.098	0.581
Q. grandiflora	4	1	27	28	1.020	0.372	1.392	0.364	167.681	0.003	291.095	0.673
Q. grandiflora	5	1	13	12	2.608	1.368	3.975	0.524	84.650	0.011	71.658	0.594
Q. grandiflora	6	1	31	18	6.369	2.914	9.283	0.457	64.790	0.017	39.128	0.717
Q. grandiflora	7	1	28	18	4.309	1.715	6.024	0.398	95.432	0.014	67.988	0.737
Q. grandiflora	8	1	26	22	2.479	1.023	3.502	0.413	115.181	0.010	112.990	0.730
Q. grandiflora	1	8	23	22	2.225	0.890	3.115	0.400	120.159	0.009	116.245	0.636
Q. grandiflora	2	8	22	14	2.229	1.152	3.381	0.517	107.448	0.010	98.776	0.716
Q. grandiflora	3	8	34	22	7.251	3.742	10.993	0.516	75.496	0.019	33.115	0.794
Q. grandiflora	4	8	24	22	2.447	1.114	3.560	0.455	105.742	0.010	124.259	0.905
Q. grandiflora	5	8	25	15	3.732	2.290	6.022	0.614	183.326	0.014	50.736	0.734
Q. grandiflora	6	8	35	24	4.750	2.683	7.433	0.565	93.988	0.016	41.782	0.703
Q. grandiflora	7	8	32	24	3.819	1.911	4.730	0.500	87.089	0.014	53.326	0.624
Q. grandiflora	8	8	15	5	0.331	1.727	2.057	0.785	109.908	0.006	63.767	0.687
Q. grandiflora	1	15	28	20	3.961	1.288	5.249	0.325	120.159	0.013	99.573	0.827
Q. grandiflora	2	15	33	18	6.477	1.599	8.076	0.247	107.448	0.016	71.433	0.719
Q. grandiflora	3	15	29	19	5.241	4.608	9.849	0.879	75.496	0.018	27.907	0.830
Q. grandiflora	4	15	14	8	0.887	1.358	2.245	1.532	105.742	0.007	78.916	0.665
Q. grandiflora	5	15	9	na	1.445	1.328	2.773	0.918	183.326	0.008	77.062	0.627
Q. grandiflora	6	15	27	14	4.547	1.628	6.174	0.358	93.988	0.014	82.089	0.868
Q. grandiflora	7	15	28	20	3.175	1.434	4.609	0.452	87.089	0.012	71.429	0.628
Q. grandiflora	8	15	21	18	3.819	1.911	5.730	0.500	109.908	0.014	54.111	0.636

1953

1954

species	plant	trat.	RMF	SMF	RL	LA 1	LA2	LA3	LM1	LM2	LM 3	LMt	LMF	NAR
Q. grandiflora	1	1	0.296	0.704	102.40	42.94	31.48	26.36	0.380	0.299	0.222	4.614	0.550	0.0003
Q. grandiflora	2	1	0.265	0.735	103.20	26.72	16.69	20.74	0.303	0.187	0.235	3.548	0.584	0.0003
Q. grandiflora	3	1	0.247	0.753	96.20	30.1	19.44	17.33	0.215	0.150	0.131	2.579	0.603	0.0001
Q. grandiflora	4	1	0.267	0.733	108.20	4.93	5.2	6.81	0.033	0.030	0.038	0.740	0.532	0.0000
Q. grandiflora	5	1	0.344	0.656	98.00	16.55	10.7	15.77	0.183	0.155	0.167	1.231	0.310	0.0004
Q. grandiflora	6	1	0.314	0.686	114.00	38.17	35.81	22.08	0.605	0.559	0.329	4.998	0.538	0.0005
Q. grandiflora	7	1	0.285	0.715	116.60	39.47	39.72	25.98	0.414	0.419	0.270	3.307	0.549	0.0003
Q. grandiflora	8	1	0.292	0.708	115.60	21.69	16.77	12.69	0.192	0.139	0.114	1.978	0.565	0.0002
Q. grandiflora	1	8	0.286	0.714	103.40	22.54	23.24	18.27	0.191	0.192	0.150	1.8335	0.589	0.0001
Q. grandiflora	2	8	0.341	0.659	113.80	27.17	21.24	28.86	0.271	0.181	0.275	1.555	0.460	0.0002
Q. grandiflora	3	8	0.340	0.660	123.90	45.88	26.27	42.79	0.616	0.333	0.585	5.822	0.530	0.0005
Q. grandiflora	4	8	0.313	0.687	138.40	18.56	14.84	10.04	0.176	0.136	0.098	1.856	0.521	0.0002
Q. grandiflora	5	8	0.380	0.620	116.20	3.46	3.92	3.07	0.040	0.027	0.010	0.116	0.019	0.0040
Q. grandiflora	6	8	0.361	0.639	112.10	31.55	24.45	23.48	0.339	0.267	0.241	3.057	0.411	0.0004
Q. grandiflora	7	8	0.404	0.807	101.90	27.51	17.19	17.29	0.320	0.195	0.198	3.732	0.789	0.0002
Q. grandiflora	8	8	0.839	0.161	110.10	26.53	25.04	21.43	0.237	0.229	0.198	2.995	1.456	0.0000
Q. grandiflora	1	15	0.245	0.755	128.20	22.54	23.24	18.27	0.191	0.192	0.150	3.093	0.589	0.0002
Q. grandiflora	2	15	0.198	0.802	114.20	27.17	21.24	28.86	0.271	0.181	0.275	5.063	0.627	0.0002
Q. grandiflora	3	15	0.468	0.532	128.60	45.88	26.27	42.79	0.616	0.333	0.585	4.333	0.440	0.0005
Q. grandiflora	4	15	0.605	0.395	107.20	18.56	14.84	10.04	0.176	0.136	0.098	0.450	0.201	0.0003
Q. grandiflora	5	15	0.479	0.521	102.30	3.46	3.92	3.07	0.040	0.027	0.010	0.204	0.074	0.0006
Q. grandiflora	6	15	0.264	0.736	133.60	31.55	24.45	23.48	0.339	0.267	0.241	0.975	0.158	0.0010
Q. grandiflora	7	15	0.311	0.689	102.40	27.51	17.19	17.29	0.320	0.195	0.198	3.666	0.796	0.0002
Q. grandiflora	8	15	0.334	0.666	103.40	26.53	25.04	21.43	0.237	0.229	0.198	2.622	0.458	0.0003

1955

1956

1957

7.2. APÊNDICE II: DADOS DO CAPÍTULO 2

1958

7.2.1. DADOS FINAIS

sp	cen	ST_D	H	Lnum	RL	TpRM	ScRM	StM	CotM	TLM	RM	SM	TM
Kc	A	0.216	3.1	1	66.2	0.6195	0.0587	0.0253	0.1086	0.0828	0.6782	0.1081	0.7863
Kc	A	0.2655	3	2	25.3	1.2105	0.2871	0.0453	0.1941	0.1909	1.4976	0.2362	1.7338
Kc	A	0.249	2.4	1	58	1.4083	0.3156	0.0255	0.1655	0.0976	1.7239	0.1231	1.847
Kc	A	0.261	2.7	1	84.5	1.2993	0.1298	0.0254	0.1645	0.1247	1.4291	0.1501	1.5792
Kc	A	0.303	3.5	2	86	1.8625	0.259	0.0446	0.17	0.1303	2.1215	0.1749	2.2964
Kc	A	0.276	3.4	1	97.6	1.8478	0.1532	0.0388	0.1571	0.1414	2.001	0.1802	2.1812
Kc	A	0.2145	2.6	1	71.3	1.415	0.2248	0.021	0.1567	0.0739	1.6398	0.0949	1.7347
Kc	A	0.2285	6.5	1	36	0.7834	0.095	0.0257	0.1677	0.134	0.8784	0.1597	1.0381
Kc	A	0.263	2.8	2	48	1.2917	0.358	0.0333	0.1682	0.196	1.6497	0.2293	1.879
Kc	A	0.2255	3.5	1	55	1.3991	0.1292	0.0254	0.1834	0.1068	1.5283	0.1322	1.6605
Kc	A	0.2615	2.7	2	62.8	1.5352	0.099	0.077	0.0322	0.1122	1.6342	0.1892	1.8234
Kc	A	0.232	3.4	1	80.2	1.224	0.1197	0.0311	0.1617	0.0722	1.3437	0.1033	1.447
Kc	A	0.2095	7.2	1	31	1.6098	0.0565	0.049	0.1848	0.1154	1.6663	0.1644	1.8307
Kc	A	0.2065	7.3	1	50	2.1173	0.1152	0.019	0.2218	0.1047	2.2325	0.1237	2.3562
Kc	A	0.285	2	1	68.7	1.6067	0.1807	0.0219	0.207	0.0807	1.7874	0.1026	1.89
Kc	A	0.2325	2.3	1	31.7	1.1238	0.1154	0.0229	0.1562	0.1834	1.2392	0.2063	1.4455
Kc	A	0.233	3	2	67.5	1.1725	0.144	0.03	0.1574	0.146	1.3165	0.176	1.4925
Kc	A	0.2335	2.5	1	60.5	0.7468	0.07	0.0254	0.2077	0.1	0.8168	0.1254	0.9422
Kc	A	0.208	3.5	2	91	1.1241	0.0318	0.0364	0.1368	0.1319	1.1559	0.1683	1.3242
Kc	A	0.293	3	2	47.7	0.9862	0.102	0.0268	0.1287	0.1199	1.0882	0.1467	1.2349
Kc	A	0.2255	2	1	78	1.1481	0.26	0.033	0.15	0.0773	1.4081	0.1103	1.5184
Kc	A	na	na	na	na	na	na	na	na	na	na	na	na
Kc	A	0.217	3	1	25.9	1.2357	0.0609	0.0386	0.164	0.0851	1.2966	0.1237	1.4203
Kc	A	0.262	2.7	2	66	2.1488	0.2752	0.0463	0.1891	0.1912	2.424	0.2375	2.6615
Kc	A	0.252	2.2	1	71.4	0.7549	0.0827	0.0232	0.1754	0.0474	0.8376	0.0706	0.9082
Kc	A	0.2685	1.8	1	38	0.683	0.1053	0.0169	0.2051	0.3483	0.7883	0.3652	1.1535
Kc	A	0.24	3	1	63.5	0.813	0.1079	0.085	0.0235	0.178	0.9209	0.263	1.1839
Kc	A	0.2295	3.12	1	68.7	1.0208	0.0603	0.025	0.1096	0.0902	1.0811	0.1152	1.1963

1959

1960

sp	cen	ST_D	H	Lnum	RL	TpRM	ScRM	StM	CotM	TLM	RM	SM	TM
Ta	A	0.358	3.4	8	98.2	1.722	0.5052	0.0849	0.1025	0.8527	2.2272	0.9376	3.1648
Ta	A	0.4395	3	6	94.5	1.3598	0.298	0.0755	0.0818	0.7906	1.6578	0.8661	2.5239
Ta	A	0.334	2.4	8	97.4	1.3247	0.3884	0.0526	0.0561	0.5653	1.7131	0.6179	2.331
Ta	A	0.6105	4.5	10	102	1.5455	0.4758	0.1473	0.0912	1.1899	2.0213	1.3372	3.3585
Ta	A	0.345	2.5	10	95.2	1.2006	0.3099	0.0684	0	0.8971	1.5105	0.9655	2.476
Ta	A	0.348	2.7	8	98.3	0.5417	0.1589	0.0513	0.0595	0.3405	0.7006	0.3918	1.0924
Ta	A	0.4205	3.1	8	93.2	1.5444	0.5328	0.0974	0.0845	0.7163	2.0772	0.8137	2.8909
Ta	A	0.441	3.7	4	96	1.3237	0.1778	0.1002	0.1075	0.4608	1.5015	0.561	2.0625
Ta	A	0.4625	3.3	6	98	2.0043	0.4881	0.0824	0.0897	0.6172	2.4924	0.6996	3.192
Ta	A	0.4395	3.5	6	94	1.832	0.4123	0.0819	0.0788	0.5967	2.2443	0.6786	2.9229
Ta	A	0.4405	4.5	12	96	1.304	0.2257	0.0913	0.0865	0.705	1.5297	0.7963	2.326
Ta	A	0.46	3.3	6	95.9	1.7676	0.4449	0.1023	0.1133	0.6629	2.2125	0.7652	2.9777
Ta	A	0.3965	3.2	6	95.2	1.817	0.633	0.0786	0.0777	0.1167	2.45	0.1953	2.6453
Ta	A	0.4335	3.2	8	93.4	2.0255	0.484	0.92	0.0817	0.6905	2.5095	1.6105	4.12
Ta	A	0.3745	3.4	10	95.1	1.0534	0.242	0.0642	0.0736	0.8126	1.2954	0.8768	2.1722
Ta	A	0.3155	2.2	4	96	0.9534	0.2641	0.0286	0.0935	0.3088	1.2175	0.3374	1.5549
Ta	A	0.358	2.5	6	98	1.2239	0.8333	0.0556	0.09	0.7102	2.0572	0.7658	2.823
Ta	A	0.3895	2.3	8	97	1.7527	0.2726	0.0652	0.0841	0.5895	2.0253	0.6547	2.68
Ta	A	0.4335	3	6	97	1.749	0.5219	0.1029	0.094	0.779	2.2709	0.8819	3.1528
Ta	A	0.3275	2.8	6	29	0.38	0.046	0.0428	0.0702	0.3102	0.426	0.353	0.779
Ta	A	0.2775	1.9	6	77.2	1.3184	0.1548	0.0449	0.0737	0.398	1.4732	0.4429	1.9161
Ta	A	0.54	2.8	7	95.3	1.5178	0.3988	0.0928	0.0733	0.1099	1.9166	0.2027	2.1193
Ta	A	0.485	3.3	6	97.8	1.8914	0.6753	0.0931	0.0483	0.1827	2.5667	0.2758	2.8425
Ta	A	0.3175	2.9	8	97.2	0.8644	0.2676	0.0476	0.1189	0.4443	1.132	0.4919	1.6239
Ta	A	0.6975	3.9	8	95.7	2.2558	0.4672	0.1155	0.1099	0.874	2.723	0.9895	3.7125
Ta	A	0.555	3.2	6	96.9	2.1702	0.358	0.1157	0.0862	0.6757	2.5282	0.7914	3.3196
Ta	A	0.315	3	6	95.2	1.2822	0.228	0.0582	0.0636	0.3469	1.5102	0.4051	1.9153
Ta	A	0.686	4.2	6	115	2.6826	0.7795	0.1605	0.1017	0.1727	3.4621	0.3332	3.7953
Ta	A	0.3115	2.5	6	96	1.3322	0.1533	0.0527	0.0856	0.3771	1.4855	0.4298	1.9153
Ta	A	0.442	4.02	8	107	1.6555	0.4629	0.1019	0.099	0.6401	2.1184	0.742	2.8604
Ta	A	0.345	3.02	8	98	1.0959	0.2528	0.0597	0	0.0731	1.3487	0.1328	1.4815

1961

1962

1963

sp	cen	ST_D	H	Lnum	RL	TpRM	ScRM	StM	CotM	TLM	RM	SM	TM
Qg	A	0.2095	10.2	7	88.6	0.4316	0.2078	0.1231	0.1255	0.1871	0.6394	0.3102	0.9496
Qg	A	0.241	8.6	6	104	0.7899	0.4552	0.1333	0.1455	0.294	1.2451	0.4273	1.6724
Qg	A	0.2175	7	na	na	0.6833	0.0596	0.1356	0.1453	0.0285	0.7429	0.1641	0.907
Qg	A	0.18	7.3	6	77.3	0.6433	0.171	0.1035	1.064	0.1853	0.8143	0.2888	1.1031
Qg	A	0.207	6.4	3	100.2	0.5429	0.1956	0.1128	0.1037	0.1306	0.7385	0.2434	0.9819
Qg	A	0.222	8.5	2	74.5	0.488	0.1226	0.1065	0.125	0.1022	0.6106	0.2087	0.8193
Qg	A	0.1695	8	0	46	0.3363	0.0975	0.089	0.151	na	0.4338	0.089	0.5228
Qg	A	0.146	7.3	4	70.5	0.2456	0.0844	0.0599	0.1132	0.0672	0.33	0.1271	0.4571
Qg	A	0.189	10.2	7	68.3	0.359	0.03	0.1015	0.0821	0.1331	0.389	0.2346	0.6236
Qg	A	0.197	10	8	104.2	0.9876	0.1297	0.1074	0.1293	0.3349	1.1173	0.4423	1.5596
Qg	A	0.215	8.5	3	97.5	0.4409	0.061	0.119	0.0991	0.0559	0.5019	0.1749	0.6768
Qg	A	0.206	8.7	6	85	0.5434	0.1573	0.108	0.1308	0.1391	0.7007	0.2471	0.9478
Qg	A	0.1965	13	8	60.5	0.6625	0.0713	0.1175	0.1351	0.278	0.7338	0.3955	1.1293
Qg	A	0.233	9.5	11	84	0.3677	0.1018	0.1201	0.1215	0.1637	0.4695	0.2838	0.7533
Qg	A	0.1835	8	6	54.5	0.172	0.1547	0.0888	0.1154	0.1413	0.3267	0.2301	0.5568
Qg	A	0.207	9	8	57	0.5026	0.048	0.0992	0.129	0.186	0.5506	0.2852	0.8358
Qg	A	0.1715	7.5	6	65.5	0.3775	0.1157	0.0928	0.0542	0.2489	0.4932	0.3417	0.8349
Qg	A	0.216	10.5	3	78	0.7241	0.093	0.1622	0.1267	0.0867	0.8171	0.2489	1.066
Qg	A	0.1725	9.7	12	51	0.5204	0.1847	0.0771	0.127	0.3867	0.7051	0.4638	1.1689
Qg	A	0.2	7.9	6	85.4	0.7663	0.1019	0.106	0.1008	0.2173	0.8682	0.3233	1.1915
Qg	A	0.237	8.5	1	97.5	0.7245	0.1355	0.1277	0.1282	0.0499	0.86	0.1776	1.0376
Qg	A	0.162	6.5	4	78	0.4532	0.068	0.0654	0.09	0.1064	0.5212	0.1718	0.693
Qg	A	0.2135	7	1	82.6	0.7406	0.1544	0.111	0.1114	0.0499	0.895	0.1609	1.0559
Qg	A	0.1745	9	1	90	0.8163	0.0922	0.113	0.1202	0.0532	0.9085	0.1662	1.0747
Qg	A	0.2055	9.3	2	85	0.9752	0.1151	0.1529	0.121	0.0655	1.0903	0.2184	1.3087
Qg	A	0.1895	7.3	6	81	0.9466	0.1439	0.08	0.129	0.1737	1.0905	0.2537	1.3442
Qg	A	0.2165	10	4	103	0.8561	0.1249	0.1551	0.1	0.1717	0.981	0.3268	1.3078
Qg	A	0.225	7.3	3	81	0.6943	0.1063	0.1244	0.1768	0.1655	0.8006	0.2899	1.0905
Qg	A	0.179	6.6	4	65	0.5101	0.1083	0.0956	0.0933	0.1595	0.6184	0.2551	0.8735
Qg	A	na	na	na	na	0.6796	0.1836	0.0888	0.104	0.1903	0.8632	0.2791	1.1423
Qg	A	na	na	na	na	0.4916	0.1232	0.097	0.139	0.1643	0.6148	0.2613	0.8761

1964

1965

sp	cen	ST_D	H	Lnum	RL	TpRM	ScRM	StM	CotM	TLM	RM	SM	TM
Hs	A	0.448	17.5	2	97.2	2.1475	0.642	0.827	na	1.9052	2.7895	2.7322	5.5217
Hs	A	0.373	21.4	3	109	2.5902	0.8633	0.54	na	1.6082	3.4535	2.1482	5.6017
Hs	A	0.418	16	2	108	1.7708	0.2945	0.6392	na	1.198	2.0653	1.8372	3.9025
Hs	A	0.4445	24.4	3	103.8	2.9777	0.9388	0.892	na	1.7339	3.9165	2.6259	6.5424
Hs	A	0.3885	14.8	1	111.5	3.6405	0.2971	0.635	na	2.038	3.9376	2.673	6.6106
Hs	A	0.4885	18.4	2	110	4.3108	1.1599	0.8952	na	2.2348	5.4707	3.13	8.6007
Hs	A	0.3905	18.9	3	112.2	2.7923	0.3861	0.51	na	1.6412	3.1784	2.1512	5.3296
Hs	A	0.426	17.3	2	115.6	2.2125	1.3468	0.5485	na	2.04	3.5593	2.5885	6.1478
Hs	A	0.456	24	3	105	2.7374	0.6548	0.7716	na	1.4887	3.3922	2.2603	5.6525
Hs	A	0.5325	10.4	1	108	3.7977	1.4987	0.735	na	1.7368	5.2964	2.4718	7.7682
Hs	A	0.442	19.7	2	97.8	3.0653	0.5556	0.6387	na	1.676	3.6209	2.3147	5.9356
Hs	A	0.3505	15	2	113.6	3.0873	0.369	0.4626	na	1.2414	3.4563	1.704	5.1603
Hs	A	0.413	20.1	2	100.2	2.974	0.4482	0.6737	na	1.677	3.4222	2.3507	5.7729
Hs	A	0.4875	11	1	113.2	4.099	2.0108	0.6642	na	1.6808	6.1098	2.345	8.4548
Hs	A	0.398	17	4	114.4	2.0182	0.6821	0.4109	na	0.955	2.7003	1.3659	4.0662
Hs	A	0.4225	12	1	106.9	2.0564	0.962	0.5587	na	1.6231	3.0184	2.1818	5.2002
Hs	A	0.344	20.8	2	117	2.5832	1.1753	0.564	na	1.5807	3.7585	2.1447	5.9032
Hs	A	0.3485	12.4	2	100.5	2.0978	0.5928	0.4253	na	1.0217	2.6906	1.447	4.1376
Hs	A	0.3645	13.5	2	106	1.7666	0.3572	0.4553	na	1.0484	2.1238	1.5037	3.6275
Hs	A	0.3595	17.4	1	105.4	2.3161	0.5354	0.4407	na	1.3779	2.8515	1.8186	4.6701
Hs	A	0.4265	24	1	107	3.1481	1.0417	0.9646	na	1.7825	4.1898	2.7471	6.9369
Hs	A	0.413	26.5	3	107	3.4642	2.2806	0.898	na	2.3828	5.7448	3.2808	9.0256
Hs	A	0.4655	31	4	115.5	3.027	1.118	0.9047	na	2.3922	4.145	3.2969	7.4419
Hs	A	0.4165	17.7	2	101.8	2.1612	0.6234	0.5775	na	1.5545	2.7846	2.132	4.9166
Hs	A	0.539	21	3	112.2	4.6202	1.3144	1.0106	na	2.4412	5.9346	3.4518	9.3864
Hs	A	0.408	19.2	2	102.8	2.5752	1.1034	0.5598	na	1.7805	3.6786	2.3403	6.0189
Hs	A	0.4685	25.6	3	104.5	2.8391	1.5163	0.8563	na	2.5127	4.3554	3.369	7.7244
Hs	A	0.4095	16	2	105.5	2.5959	1.2004	0.458	na	1.6335	3.7963	2.0915	5.8878
Hs	A	0.4705	23.2	3	116	4.6836	1.7103	0.7192	na	2.4763	6.3939	3.1955	9.5894
Hs	A	0.4355	16.5	2	98.5	2.0608	0.6626	0.5551	na	1.965	2.7234	2.5201	5.2435
Hs	A	0.469	16.4	2	101.4	4.5613	0.9586	0.9164	na	2.4119	5.5199	3.3283	8.8482

1966

sp	cen	ST_D	H	Lnum	RL	TpRM	ScRM	StM	CotM	TLM	RM	SM	TM
Kc	F	0.254	3.5	1	80.3	1.0834	0.2198	0.0351	0.1451	0.1836	1.3032	0.2187	1.5219
Kc	F	0.2555	3.8	1	89.8	1.3493	0.0777	0.0208	0.1768	0.1607	1.427	0.1815	1.6085
Kc	F	0.278	3	3	81.5	0.904	0.0822	0.0245	0.0871	0.1772	0.9862	0.2017	1.1879
Kc	F	0.2145	2.5	1	94.8	1.25	0.383	0.0366	0.093	0.163	1.633	0.1996	1.8326
Kc	F	0.243	2.9	2	76	1.5881	0.0649	0.0306	0.2372	0.2134	1.653	0.244	1.897
Kc	F	0.2795	3.5	2	89.9	2.413	0.2339	0.0471	0.147	0.2116	2.6469	0.2587	2.9056
Kc	F	0.244	2.03	2	83.7	1.748	0.1336	0.0293	0.1258	0.295	1.8816	0.3243	2.2059
Kc	F	0.238	2.2	1	97	2.018	0.0995	0.027	0.143	0.08	2.1175	0.107	2.2245
Kc	F	0.226	4.2	1	96.4	1.2785	na	na	na	na	1.2785	na	1.2785
Kc	F	0.2495	2.5	1	100	1.7477	0.078	0.035	0.13	0.1226	1.8257	0.1576	1.9833
Kc	F	0.255	2.7	1	94.3	2.115	0.0799	0.0226	0.199	0.1988	2.1949	0.2214	2.4163
Kc	F	0.2425	2.7	1	100	5.1904	0.1422	0.0435	0.1356	0.0896	5.3326	0.1331	5.4657
Kc	F	0.2815	2.4	2	77.5	1.3686	0.3051	0.044	0.1558	0.2101	1.6737	0.2541	1.9278
Kc	F	0.225	7.5	2	99.6	2.258	0.3046	0.0745	0.2992	0.2398	2.5626	0.3143	2.8769
Kc	F	0.2465	2.5	2	96.5	2.143	0.2219	0.0408	0.1659	0.178	2.3649	0.2188	2.5837
Kc	F	0.2425	2.4	1	73	0.9734	0.1429	0.0254	0.1517	0.0724	1.1163	0.0978	1.2141
Kc	F	0.231	2.4	1	88	1.765	0.22071	0.03318	0.1916	0.1869	1.98571	0.22008	2.20579
Kc	F	0.2345	2.8	1	0.53	1.2625	0.0537	0.0276	0.1797	na	1.3162	0.0276	1.3438
Kc	F	0.2505	3	2	98.5	1.1945	0.0443	0.0398	0.1844	0.3274	1.2388	0.3672	1.606
Kc	F	0.276	2	1	98	2.2007	0.1263	0.0201	0.2528	0.1641	2.327	0.1842	2.5112
Kc	F	0.2415	3	1	73	1.3216	na	0.0296	0.2348	na	1.3216	0.0296	1.3512
Kc	F	0.2695	3.2	1	60.9	1.2306	0.1182	0.0387	0.2305	0.1866	1.3488	0.2253	1.5741
Kc	F	0.269	3.4	1	86	0.8236	0.1255	0.0358	0.2725	na	0.9491	0.0358	0.9849
Kc	F	0.1965	2.5	2	85.4	1.6184	0.1838	0.0361	0.1325	na	1.8022	0.0361	1.8383
Kc	F	0.3145	5.7	3	103	7.8218	0.254	0.1088	0.1531	0.2864	8.0758	0.3952	8.471
Kc	F	0.2815	2.8	4	71.8	1.9852	0.117	0.0354	0.2097	0.2379	2.1022	0.2733	2.3755
Kc	F	0.2655	2.5	1	98.7	1.453	0.1896	0.0423	0.1295	0.1038	1.6426	0.1461	1.7887
Kc	F	0.201	3	1	50	6.1202	0.1271	0.0294	0.1511	0.0656	6.2473	0.095	6.3423
Kc	F	0.22	2.7	1	99.2	1.4124	0.1335	0.0293	0.1556	0.0973	1.5459	0.1266	1.6725
Kc	F	0.1985	2.03	2	99.1	1.2019	0.1954	0.0262	0.1735	na	1.3973	0.0262	1.4235
Kc	F	0.269	3	1	55.2	2.2802	0.2565	0.039	0.1756	0.1503	2.5367	0.1893	2.726
Kc	F	0.276	2.7	1	85.6	2.4429	0.1736	0.0305	0.2354	0.1318	2.6165	0.1623	2.7788

1967

1968

sp	cen	ST_D	H	Lnum	RL	TpRM	ScRM	StM	CotM	TLM	RM	SM	TM
Ta	F	0.648	2.5	10	97	2.025	0.6816	0.1199	0.0825	1.6686	2.7066	1.7885	4.4951
Ta	F	0.484	3.2	8	94.4	2.6435	0.633	0.1177	0.0749	0.9383	3.2765	1.056	4.3325
Ta	F	0.4	4	12	96.5	2.1264	0.4055	0.1227	na	1.5842	2.5319	1.7069	4.2388
Ta	F	0.3915	5.4	16	96.8	0.9568	0.4136	0.1061	na	0.3184	1.3704	0.4245	1.7949
Ta	F	0.6365	6.4	10	93.8	1.93	0.4159	0.1703	na	1.956	2.3459	2.1263	4.4722
Ta	F	0.3725	4.2	11	97.2	1.8245	0.455	0.95	na	1.1953	2.2795	2.1453	4.4248
Ta	F	0.445	5	12	97	0.7609	0.2522	0.0765	0.0873	1.097	1.0131	1.1735	2.1866
Ta	F	0.521	4.4	10	104	1.151	0.3638	0.1112	0.0574	1.4252	1.5148	1.5364	3.0512
Ta	F	0.384	3	11	102	1.759	0.9387	0.0942	na	2.4458	2.6977	2.54	5.2377
Ta	F	0.3865	3.5	12	98.4	1.711	0.2851	0.075	0.0466	1.223	1.9961	1.298	3.2941
Ta	F	0.4685	5	12	96.4	2.4129	0.5651	0.1677	0.0998	2.0479	2.978	2.2156	5.1936
Ta	F	0.38	3.4	12	94.1	1.5187	0.2813	0.0722	0.087	0.9902	1.8	1.0624	2.8624
Ta	F	0.45	6.4	12	96	1.5684	0.6003	0.1411	0.0808	1.694	2.1687	1.8351	4.0038
Ta	F	0.4135	3.6	8	97	2.4171	0.4926	0.0874	0.0918	0.7922	2.9097	0.8796	3.7893
Ta	F	0.3455	4.4	12	95	1.3975	0.5974	0.0766	0.0779	1.4611	1.9949	1.5377	3.5326
Ta	F	0.4795	4	12	101	1.1671	0.3071	0.1312	na	1.3982	1.4742	1.5294	3.0036
Ta	F	0.3925	4.5	14	96.4	1.0652	0.2565	0.0885	0.0362	1.0179	1.3217	1.1064	2.4281
Ta	F	0.415	5	18	98.3	1.0753	0.5517	0.1091	0.0661	1.874	1.627	1.9831	3.6101
Ta	F	0.435	3.3	14	96.7	2.7118	0.7257	0.1096	0.0733	1.7125	3.4375	1.8221	5.2596
Ta	F	0.624	4.3	12	98	2.4168	1.13	0.1779	0.0417	2.3	3.5468	2.4779	6.0247
Ta	F	0.3665	6.5	10	102	0.4642	0.1337	0.0953	0.0813	0.3533	0.5979	0.4486	1.0465
Ta	F	0.5005	5.1	18	106.8	0.7654	0.4926	0.1467	na	1.882	1.258	2.0287	3.2867
Ta	F	0.3375	6.2	13	94.5	1.0023	0.5046	0.1025	0.0761	1.2506	1.5069	1.3531	2.86
Ta	F	0.322	4.5	10	100	1.0817	0.1543	0.0827	0.0736	0.9472	1.236	1.0299	2.2659
Ta	F	0.468	4.7	14	97	0.9738	0.3657	0.1109	0.0784	1.4312	1.3395	1.5421	2.8816
Ta	F	0.4055	3.5	10	98.5	0.7504	0.1944	0.0495	0.0709	0.8858	0.9448	0.9353	1.8801
Ta	F	0.4115	2.6	10	96.5	1.025	0.5106	0.0908	0.0692	1.5798	1.5356	1.6706	3.2062
Ta	F	0.388	2.5	10	113	1.0889	0.089	0.0568	0.0805	0.6857	1.1779	0.7425	1.9204
Ta	F	0.324	4.2	12	97	1.2607	0.2705	0.0674	0.042	1.13	1.5312	1.1974	2.7286
Ta	F	0.42	5.5	14	96.5	0.9983	0.2889	0.1125	0.0849	2.3723	1.2872	2.4848	3.772
Ta	F	0.4425	2.8	10	100.5	1.7455	0.2761	0.061	0.0294	1.0021	2.0216	1.0631	3.0847

1969

sp	cen	ST_D	H	Lnum	RL	TpRM	ScRM	StM	CotM	TLM	RM	SM	TM
Qg	F	0.223	11.6	11	101	0.8118	0.36	0.1853	0.1312	0.6511	1.1718	0.8364	2.0082
Qg	F	0.2835	15.3	8	99.6	1.1088	0.527	0.2802	0.1573	1.0385	1.6358	1.3187	2.9545
Qg	F	0.178	14.4	6	103.1	0.4208	0.2038	0.185	0.1689	0.6859	0.6246	0.8709	1.4955
Qg	F	0.191	12.2	6	102.1	0.2304	0.121	0.118	0.0967	0.318	0.3514	0.436	0.7874
Qg	F	0.2075	13.8	7	101	0.77	0.0938	0.2076	0.1224	0.7165	0.8638	0.9241	1.7879
Qg	F	0.2295	10.4	8	106.5	1.07	0.18	0.1567	0.1511	0.6255	1.25	0.7822	2.0322
Qg	F	0.2235	7.6	20	104	0.2973	0.24	0.15	0.1385	0.5792	0.5373	0.7292	1.2665
Qg	F	0.194	11.3	5	100	0.349	0.094	0.1172	0.1275	0.3566	0.443	0.4738	0.9168
Qg	F	0.2685	14.7	9	103.4	1.017	0.219	0.2425	0.127	1.341	1.236	1.5835	2.8195
Qg	F	0.248	15.4	10	102.5	0.9965	0.2706	0.2245	0.1682	1.587	1.2671	1.8115	3.0786
Qg	F	0.2155	11.3	6	101	0.6149	0.1438	0.1838	0.1529	0.5658	0.7587	0.7496	1.5083
Qg	F	0.1725	10.4	11	99.8	0.3914	0.0865	0.088	0.198	0.4707	0.4779	0.5587	1.0366
Qg	F	0.2115	11.2	12	100.5	0.3907	0.0705	0.0846	0.1241	0.3966	0.4612	0.4812	0.9424
Qg	F	0.177	11.5	14	100.3	0.2775	0.0863	0.11	0.0672	0.3698	0.3638	0.4798	0.8436
Qg	F	0.216	14.2	10	100.3	0.5363	0.189	0.1613	0.1413	0.7979	0.7253	0.9592	1.6845
Qg	F	0.249	11.8	12	103.2	0.3559	0.124	0.1804	0.1495	0.7272	0.4799	0.9076	1.3875
Qg	F	0.2355	10	19	99	0.39	0.1399	0.2143	0.1776	0.8237	0.5299	1.038	1.5679
Qg	F	0.2315	12.5	12	103.2	0.8187	0.2818	0.2039	0.13	0.8173	1.1005	1.0212	2.1217
Qg	F	0.2205	19.8	10	82.6	0.8281	0.1096	0.2851	0.1442	1.0965	0.9377	1.3816	2.3193
Qg	F	0.276	17.4	11	93.2	1.532	0.168	0.3282	0.093	1.3321	1.7	1.6603	3.3603
Qg	F	0.17	11.7	6	99.8	0.6257	0.05606	0.0882	0.1081	0.152	0.68176	0.2402	0.92196
Qg	F	0.2265	11.5	13	93	0.3565	0.1427	0.1562	0.1188	0.522	0.4992	0.6782	1.1774
Qg	F	0.218	11.3	20	111.2	0.6779	0.0744	0.1866	0.11	1.0566	0.7523	1.2432	1.9955
Qg	F	0.2815	15.5	9	101	1.149	0.2377	0.3611	0.1528	1.2839	1.3867	1.645	3.0317
Qg	F	0.2285	14.7	14	100.6	0.446	0.166	0.2236	0.1015	0.8822	0.612	1.1058	1.7178
Qg	F	0.2515	14.6	9	100.3	0.747	0.112	0.2555	0.1322	0.985	0.859	1.2405	2.0995
Qg	F	0.268	14	8	99.6	0.657	0.1737	0.24	0.104	0.7274	0.8307	0.9674	1.7981
Qg	F	0.2535	12.3	16	100	0.454	0.1	0.19	0.1012	0.715	0.554	0.905	1.459
Qg	F	0.2375	13.5	12	100.5	0.533	0.0899	0.179	0.1629	0.55	0.6229	0.729	1.3519
Qg	F	0.2735	15.4	12	107.2	0.852	0.2235	0.2977	0.19	1.339	1.0755	1.6367	2.7122
Qg	F	0.2555	14.2	12	103.3	0.579	0.91	0.3043	0.1277	1.239	1.489	1.5433	3.0323
Qg	F	0.236	14	11	100	0.7799	0.0958	0.2028	0.1021	0.958	0.8757	1.1608	2.0365
Qg	F	0.211	13.4	12	91	0.903	0.1051	0.1908	0.1408	0.742	1.0081	0.9328	1.9409

1970

sp	cen	ST_D	H	Lnum	RL	TpRM	ScRM	StM	CotM	TLM	RM	SM	TM
Hs	F	0.3665	16.9	2	120	4.1813	0.5971	0.6155	na	2.0741	4.7784	2.6896	7.468
Hs	F	0.484	27.3	3	114	6.7801	2.0496	1.1739	na	3.4415	8.8297	4.6154	13.4451
Hs	F	0.409	16.3	6	114.5	2.9467	0.5666	0.5018	na	1.785	3.5133	2.2868	5.8001
Hs	F	0.5025	28.6	6	105.2	4.904	1.5676	1.1313	na	4.1475	6.4716	5.2788	11.7504
Hs	F	0.48	22.6	5	110	4.2549	1.4194	0.8997	na	3.188	5.6743	4.0877	9.762
Hs	F	0.4695	39.2	5	113	3.7989	1.382	1.3548	na	4.8573	5.1809	6.2121	11.393
Hs	F	0.4855	29.5	3	110.5	5.6415	1.248	1.4414	na	2.9082	6.8895	4.3496	11.2391
Hs	F	0.556	26.9	5	113.5	4.276	1.1004	1.193	na	3.2807	5.3764	4.4737	9.8501
Hs	F	0.4355	30.5	5	118.7	5.1571	1.0319	0.9642	na	3.4579	6.189	4.4221	10.6111
Hs	F	0.4525	25.8	5	108	6.0944	2.2947	0.9151	na	3.6155	8.3891	4.5306	12.9197
Hs	F	0.392	21.9	2	110.2	3.3116	1.811	0.7553	na	2.7512	5.1226	3.5065	8.6291
Hs	F	0.334	23.9	4	98	4.1001	1.2766	0.6405	na	3.0318	5.3767	3.6723	9.049
Hs	F	0.456	26.5	3	103.8	2.528	0.6627	1.0057	na	2.1743	3.1907	3.18	6.3707
Hs	F	0.379	19	4	104	3.1304	1.5707	0.6422	na	2.8422	4.7011	3.4844	8.1855
Hs	F	0.431	23.5	4	105	4.7167	2.6528	0.707	na	3.1755	7.3695	3.8825	11.252
Hs	F	0.454	24.5	3	100.1	3.9309	1.5727	0.7881	na	2.816	5.5036	3.6041	9.1077
Hs	F	0.472	28.6	6	108.9	5.569	6.7021	1.0173	na	4.3682	12.2711	5.3855	17.6566
Hs	F	0.3925	23.7	4	100.4	3.4778	1.055	0.8292	na	2.3845	4.5328	3.2137	7.7465
Hs	F	0.341	24	4	99	1.0534	0.6219	0.4802	na	1.8366	1.6753	2.3168	3.9921
Hs	F	0.5835	29.7	5	100.7	4.9299	2.6485	1.3712	na	4.4183	7.5784	5.7895	13.3679
Hs	F	0.47	22.4	4	105	5.9964	2.3868	0.8897	na	3.4668	8.3832	4.3565	12.7397
Hs	F	0.481	19	3	107	5.8999	1.1586	0.8735	na	2.734	7.0585	3.6075	10.666
Hs	F	0.4855	21.5	5	118.4	4.8162	2.8852	0.8808	na	3.3107	7.7014	4.1915	11.8929
Hs	F	0.3685	24.8	4	110	2.1966	0.2308	0.5485	na	1.7122	2.4274	2.2607	4.6881
Hs	F	0.459	25.2	5	103.5	4.7725	0.7281	0.8744	na	2.9516	5.5006	3.826	9.3266
Hs	F	0.4005	17.5	4	105.6	3.3847	1.3812	0.6302	na	2.1954	4.7659	2.8256	7.5915
Hs	F	0.458	21	4	104	1.9144	1.1507	0.5866	na	2.2076	3.0651	2.7942	5.8593
Hs	F	0.4335	31.5	5	101	5.295	2.1873	1.1713	na	3.2244	7.4823	4.3957	11.878
Hs	F	0.56	20.9	3	101	6.5977	1.8611	0.9807	na	3.2753	8.4588	4.256	12.7148
Hs	F	0.4585	20.7	3	111	8.7739	2.3946	1.1048	na	3.257	11.1685	4.3618	15.5303
Hs	F	0.4075	21.7	3	112	4.6825	0.7818	0.8806	na	2.4636	5.4643	3.3442	8.8085

1971

sp	cen	RS	LMF	RMF	SMF	SLA	RGR	STRL	RER
Kc	A	6.273821	0.105303	0.862521	0.137479	100.6905	0.015121	106.8604	0.47381
Kc	A	6.34039	0.110105	0.863767	0.136233	134.671	0.021985	20.90045	0.10767
Kc	A	14.00406	0.052842	0.933351	0.066649	129.232	0.022545	41.18441	0.39705
Kc	A	9.520986	0.078964	0.904952	0.095048	101.3977	0.021158	65.03502	0.631563
Kc	A	12.12979	0.056741	0.923837	0.076163	127.8661	0.021947	46.1745	0.578307
Kc	A	11.10433	0.064827	0.917385	0.082615	128.6639	0.021369	52.81957	0.665092
Kc	A	17.27924	0.042601	0.945293	0.054707	121.5347	0.020536	50.38869	0.480716
Kc	A	5.500313	0.129082	0.846161	0.153839	94.31013	0.017293	45.95354	0.200585
Kc	A	7.194505	0.104311	0.877967	0.122033	119.7839	0.021196	37.16033	0.288154
Kc	A	11.56051	0.064318	0.920385	0.079615	130.531	0.019071	39.31099	0.327083
Kc	A	8.637421	0.061533	0.896238	0.103762	116.8013	0.019958	40.90672	0.391076
Kc	A	13.00774	0.049896	0.928611	0.071389	171.2205	0.020206	65.52288	0.588304
Kc	A	10.13564	0.063036	0.910198	0.089802	113.5167	0.022269	19.25705	0.156725
Kc	A	18.0477	0.044436	0.9475	0.0525	114.0714	0.024483	23.61498	0.323392
Kc	A	17.42105	0.042698	0.945714	0.054286	173.8335	0.022353	42.75845	0.483188
Kc	A	6.006786	0.126877	0.857281	0.142719	na	0.020743	28.20787	0.167267
Kc	A	7.480114	0.097822	0.882077	0.117923	68.9914	0.019293	57.5693	0.449311
Kc	A	6.513557	0.106135	0.866907	0.133093	147.5373	0.016736	81.01232	0.422917
Kc	A	6.868093	0.099607	0.872904	0.127096	na	0.019775	80.95365	0.695238
Kc	A	7.41786	0.097093	0.881205	0.118795	123.0503	0.018652	48.36747	0.30058
Kc	A	12.76609	0.050909	0.927358	0.072642	123.0377	0.019435	67.93833	0.536088
Kc	A	10.48181	0.059917	0.912906	0.087094	na	0.020584	20.95978	0.115015
Kc	A	na	na	na	na	na	na	na	na
Kc	A	10.20632	0.071839	0.910765	0.089235	na	0.026242	30.71482	0.476276
Kc	A	11.86402	0.052191	0.922264	0.077736	115.7853	0.016408	94.58206	0.520238
Kc	A	2.158543	0.301951	0.683398	0.316602	26.80633	0.017164	55.6369	0.20551
Kc	A	3.501521	0.150351	0.777853	0.222147	54.2048	0.016689	78.10578	0.399735
Kc	A	9.384549	0.075399	0.903703	0.096297	na	0.018868	67.30016	0.496131

1972

sp	cen	RS	LMF	RMF	SMF	SLA	RGR	STRL	RER
Ta	A	2.375427	0.269433	0.703741	0.296259	117.736	0.023613	57.02671	0.696
Ta	A	1.914098	0.313245	0.656841	0.343159	123.0525	0.021728	69.49551	0.665167
Ta	A	2.772455	0.242514	0.734921	0.265079	125.1528	0.021065	73.52608	0.689333
Ta	A	1.511591	0.354295	0.601846	0.398154	127.9725	0.024108	65.99806	0.727667
Ta	A	1.564474	0.362318	0.610057	0.389943	119.6413	0.02139	79.29369	0.665455
Ta	A	1.788157	0.311699	0.64134	0.35866	171.9796	0.014627	181.4658	0.691074
Ta	A	2.552784	0.247778	0.718531	0.281469	142.7933	0.02267	60.34706	0.648926
Ta	A	2.676471	0.223418	0.728	0.272	114.2705	0.01988	72.52399	0.672066
Ta	A	3.562607	0.193358	0.780827	0.219173	145.5671	0.023296	48.89488	0.682951
Ta	A	3.30725	0.204147	0.767833	0.232167	122.2087	0.022575	51.31004	0.650164
Ta	A	1.92101	0.303095	0.657653	0.342347	154.0694	0.020702	73.61963	0.666557
Ta	A	2.891401	0.222621	0.743023	0.256977	125.3793	0.022727	54.25436	0.665738
Ta	A	12.5448	0.044116	0.926171	0.073829	87.7404	0.021406	52.39406	0.649355
Ta	A	1.558212	0.167597	0.609102	0.390898	112.1417	0.024979	46.11207	0.634839
Ta	A	1.477418	0.374091	0.596354	0.403646	104.9396	0.019817	90.2791	0.648548
Ta	A	3.608477	0.198598	0.783009	0.216991	133.2804	0.016585	100.6923	0.635313
Ta	A	2.686341	0.251576	0.728728	0.271272	124.9353	0.021245	80.0719	0.650938
Ta	A	3.093478	0.219963	0.755709	0.244291	158.3191	0.020839	55.34318	0.643125
Ta	A	2.575009	0.247082	0.72028	0.27972	116.1471	0.022108	55.46026	0.643125
Ta	A	1.206799	0.398203	0.546855	0.453145	198.6555	0.011099	76.31579	0.111008
Ta	A	3.326259	0.207714	0.768853	0.231147	104.7609	0.018076	58.55583	0.484651
Ta	A	9.455353	0.051857	0.904355	0.095645	89.599	0.018857	62.78825	0.624961
Ta	A	9.306381	0.064274	0.902973	0.097027	84.14083	0.021133	51.70773	0.644341
Ta	A	2.301281	0.273601	0.697087	0.302913	117.0699	0.016537	112.4479	0.629924
Ta	A	2.751895	0.235421	0.733468	0.266532	106.3883	0.022849	42.42397	0.618473
Ta	A	3.194592	0.203549	0.761598	0.238402	105.0224	0.021995	44.65026	0.627634
Ta	A	3.727968	0.18112	0.788493	0.211507	125.4715	0.017797	74.24739	0.614656
Ta	A	10.39046	0.045504	0.912207	0.087793	71.65653	0.022843	42.86886	0.76
Ta	A	3.456259	0.196888	0.775597	0.224403	144.6911	0.017662	72.06125	0.616061
Ta	A	2.854987	0.22378	0.740596	0.259404	160.797	0.020701	64.63304	0.699394
Ta	A	10.15587	0.049342	0.910361	0.089639	92.94007	0.015716	89.42422	0.631212

sp	cen	RS	LMF	RMF	SMF	SLA	RGR	STRL	RER
Qg	A	2.061251	0.19703	0.673336	0.326664	102.6022	0.014952	205.2827	0.664404
Qg	A	2.913878	0.175795	0.744499	0.255501	106.7113	0.025859	131.6622	0.805688
Qg	A	4.527118	0.031422	0.819074	0.180926	41.6356	0.020246	147.8121	0.778165
Qg	A	2.819598	0.167981	0.738192	0.261808	112.9091	0.022041	120.1617	0.560734
Qg	A	3.0341	0.133007	0.752113	0.247887	129.5997	0.020974	184.5644	0.770826
Qg	A	2.925731	0.124741	0.74527	0.25473	78.24149	0.018965	152.6639	0.525405
Qg	A	4.874157	na	0.829763	0.170237	na	0.014917	136.7826	0.268649
Qg	A	2.596381	0.147014	0.721943	0.278057	95.50796	0.013708	287.0521	0.489369
Qg	A	1.658142	0.213438	0.623797	0.376203	134.8619	0.016506	190.2507	0.46955
Qg	A	2.526113	0.214735	0.716402	0.283598	105.5254	0.023494	105.5083	0.752308
Qg	A	2.86964	0.082595	0.741578	0.258422	88.451	0.016359	221.1386	0.695043
Qg	A	2.835694	0.146761	0.739291	0.260709	104.4157	0.019237	156.4225	0.588205
Qg	A	1.855373	0.24617	0.649783	0.350217	104.1025	0.020735	91.32075	0.378803
Qg	A	1.654334	0.217311	0.623258	0.376742	105.3211	0.017274	228.4471	0.579658
Qg	A	1.419817	0.253772	0.586746	0.413254	na	0.014691	316.8605	0.327521
Qg	A	1.930575	0.222541	0.65877	0.34123	92.37421	0.018163	113.4103	0.348889
Qg	A	1.443371	0.29812	0.590729	0.409271	89.82511	0.017129	173.5099	0.397742
Qg	A	3.282845	0.081332	0.76651	0.23349	62.53685	0.019099	107.7199	0.498548
Qg	A	1.520267	0.330824	0.603217	0.396783	93.67374	0.019842	98.00154	0.280806
Qg	A	2.685431	0.182375	0.728661	0.271339	122.6861	0.019679	111.4446	0.549365
Qg	A	4.842342	0.048092	0.828836	0.171164	34.87749	0.018582	134.5756	0.645397
Qg	A	3.03376	0.153535	0.752092	0.247908	105.6739	0.015378	172.1094	0.490635
Qg	A	5.562461	0.047258	0.847618	0.152382	33.70908	0.018285	111.5312	0.514884
Qg	A	5.466306	0.049502	0.845352	0.154648	39.84375	0.018422	110.2536	0.572248
Qg	A	4.992216	0.05005	0.833117	0.166883	79.69272	0.019949	87.16161	0.533488
Qg	A	4.298384	0.129222	0.811263	0.188737	112.7913	0.020156	85.56941	0.502481
Qg	A	3.001836	0.131289	0.750115	0.249885	65.12625	0.019944	120.313	0.673023
Qg	A	2.761642	0.151765	0.734159	0.265841	94.72681	0.018535	116.6643	0.502481
Qg	A	2.424147	0.182599	0.707956	0.292044	108.4245	0.016815	127.426	0.37845
Qg	A	3.092798	0.166594	0.755668	0.244332	126.0417	0.018749	na	na
Qg	A	2.352851	0.187536	0.701746	0.298254	110.89	0.016709	na	na

sp	cen	RS	LMF	RMF	SMF	SLA	RGR	STRL	RER
Hs	A	1.020972	0.345039	0.505189	0.494811	68.25115	0.013027	45.26193	0.528261
Hs	A	1.607625	0.287091	0.616509	0.383491	77.04706	0.013163	42.08169	0.613768
Hs	A	1.124156	0.306983	0.529225	0.470775	74.49436	0.009662	60.98938	0.782243
Hs	A	1.491489	0.265025	0.598634	0.401366	89.33158	0.014491	34.85912	0.742991
Hs	A	1.473101	0.096058	0.595649	0.404351	59.51683	0.014587	30.62766	0.814953
Hs	A	1.747827	0.259839	0.636076	0.363924	70.4369	0.017047	25.51731	0.800935
Hs	A	1.477501	0.307941	0.596367	0.403633	79.82124	0.012574	40.18193	0.813889
Hs	A	1.375043	0.331826	0.578955	0.421045	102.5627	0.013909	52.24859	0.84537
Hs	A	1.500774	0.26337	0.600124	0.399876	84.9757	0.013124	38.35757	0.747222
Hs	A	2.14273	0.223578	0.681805	0.318195	65.71434	0.015516	28.43827	0.754054
Hs	A	1.564306	0.282364	0.610031	0.389969	64.6013	0.013091	31.90552	0.662162
Hs	A	2.028345	0.240567	0.669787	0.330213	75.59827	0.01183	36.79591	0.804505
Hs	A	1.455822	0.290495	0.592804	0.407196	60.55349	0.012841	33.692	0.683784
Hs	A	2.605458	0.198798	0.722643	0.277357	78.74662	0.016133	27.61649	0.79375
Hs	A	1.976938	0.234863	0.664084	0.335916	86.05516	0.009597	56.68417	0.804464
Hs	A	1.383445	0.312123	0.580439	0.419561	53.21801	0.011794	51.98405	0.7375
Hs	A	1.75246	0.26777	0.636689	0.363311	77.11022	0.012926	45.29266	0.827679
Hs	A	1.859433	0.246931	0.65028	0.34972	81.20258	0.009753	47.90733	0.680357
Hs	A	1.412383	0.289014	0.585472	0.414528	67.03006	0.008502	60.00226	0.723009
Hs	A	1.567964	0.295047	0.610586	0.389414	77.06642	0.010738	45.50753	0.717699
Hs	A	1.525172	0.256959	0.603987	0.396013	59.63783	0.014239	33.98876	0.731858
Hs	A	1.751036	0.264005	0.636501	0.363499	na	0.016569	30.88736	0.731858
Hs	A	1.257242	0.32145	0.556981	0.443019	80.36892	0.014861	38.15659	0.80708
Hs	A	1.306098	0.316174	0.566367	0.433633	62.3732	0.011095	47.10346	0.679825
Hs	A	1.719277	0.260078	0.632255	0.367745	75.0233	0.016767	24.28466	0.771053
Hs	A	1.57185	0.295818	0.611175	0.388825	66.04637	0.012869	39.91923	0.688596
Hs	A	1.292787	0.325294	0.56385	0.43615	79.78439	0.015058	36.80744	0.703509
Hs	A	1.815109	0.277438	0.644774	0.355226	77.59405	0.012676	40.64101	0.712281
Hs	A	2.000908	0.258233	0.666767	0.333233	62.15922	0.016955	24.76727	0.804386
Hs	A	1.080671	0.37475	0.519386	0.480614	81.84916	0.011659	47.79697	0.650877
Hs	A	1.658474	0.026107	0.623844	0.376156	63.75699	0.016249	22.2305	0.676316

1975

sp	cen	RS	LMF	RMF	SMF	SLA	RGR	STRL	RER
Kc	F	5.958848	0.120639	0.856298	0.143702	na	0.020831	74.11852	0.594395
Kc	F	7.862259	0.099907	0.887162	0.112838	77.41228	0.021134	66.55303	0.672515
Kc	F	4.88944	0.149171	0.830205	0.169795	143.666	0.018639	90.15487	0.605015
Kc	F	8.181363	0.088945	0.891084	0.108916	63.59391	0.019842	75.84	0.638021
Kc	F	6.77459	0.112493	0.871376	0.128624	69.71689	0.022984	47.85593	0.56131
Kc	F	10.23154	0.072825	0.910965	0.089035	137.9832	0.023814	37.25653	0.609259
Kc	F	5.802035	0.133732	0.852985	0.147015	na	0.022522	47.8833	0.583196
Kc	F	19.78972	0.035963	0.951899	0.048101	117.5353	0.021524	48.06739	0.660367
Kc	F	na	na	na	na	na	na	75.40086	0.660847
Kc	F	11.58439	0.061816	0.920536	0.079464	133.9299	0.020784	57.21806	0.689418
Kc	F	9.913731	0.082275	0.908372	0.091628	na	0.022002	44.58629	0.634115
Kc	F	40.06461	0.016393	0.975648	0.024352	131.8506	0.028829	19.26634	0.689418
Kc	F	6.586777	0.108984	0.868192	0.131808	120.096	0.022924	56.62721	0.569617
Kc	F	8.153357	0.083354	0.89075	0.10925	115.026	0.026234	44.10983	0.75848
Kc	F	10.8085	0.068893	0.915315	0.084685	107.3573	0.025515	45.03033	0.737758
Kc	F	11.41411	0.059633	0.919447	0.080553	na	0.019171	74.99486	0.539339
Kc	F	9.022674	0.084732	0.900226	0.099774	94.15549	0.024116	49.85836	0.662537
Kc	F	47.68841	na	0.979461	0.020539	na	0.018231	0.419802	-0.09846
Kc	F	3.373638	0.203861	0.771357	0.228643	70.97869	0.021307	82.46128	0.755457
Kc	F	12.63301	0.065347	0.926649	0.073351	106.095	0.025489	44.53129	0.757738
Kc	F	44.64865	na	0.978094	0.021906	na	0.018187	55.23608	0.467708
Kc	F	5.986684	0.118544	0.856871	0.143129	94.91481	0.020762	49.48805	0.415362
Kc	F	26.51117	na	0.963651	0.036349	na	0.016351	104.4196	0.569271
Kc	F	49.92244	na	0.980362	0.019638	na	0.020199	52.76817	0.564583
Kc	F	20.43472	0.033809	0.953347	0.046653	158.6122	0.032307	13.16832	0.713228
Kc	F	7.691914	0.100147	0.884951	0.115049	na	0.025218	36.16764	0.528529
Kc	F	11.24298	0.058031	0.918321	0.081679	106.396	0.02246	67.92842	0.763988
Kc	F	65.76105	0.010343	0.985021	0.014979	139.965	0.03001	8.169668	0.292593
Kc	F	12.2109	0.058176	0.924305	0.075695	85.44596	0.02186	70.23506	0.768452
Kc	F	53.33206	na	0.981595	0.018405	na	0.018627	82.45278	0.671615
Kc	F	13.40042	0.055136	0.930558	0.069442	131.2293	0.025762	24.2084	0.369006
Kc	F	16.12138	0.047431	0.941593	0.058407	128.5116	0.025704	35.04032	0.630145

1976

1977

1978

1979

sp	cen	RS	LMF	RMF	SMF	SLA	RGR	STRL	RER
Ta	F	1.513335	0.371204	0.602122	0.397878	110.6415	0.026538	47.90123	0.686
Ta	F	3.102746	0.216572	0.756261	0.243739	102.1411	0.026231	35.71023	0.664333
Ta	F	1.483332	0.373738	0.597315	0.402685	114.832	0.026048	45.38187	0.681833
Ta	F	3.228269	0.177391	0.763497	0.236503	127.6735	0.018887	101.1706	0.684333
Ta	F	1.103278	0.437369	0.524552	0.475448	114.5992	0.026061	48.60104	0.648525
Ta	F	1.062555	0.270137	0.515165	0.484835	120.2692	0.025973	53.27487	0.676393
Ta	F	0.863315	0.501692	0.463322	0.536678	147.6577	0.020196	127.4806	0.674754
Ta	F	0.985941	0.467095	0.49646	0.50354	143.1914	0.022927	90.35621	0.732131
Ta	F	1.062087	0.466961	0.515054	0.484946	117.0578	0.027356	57.98749	0.715738
Ta	F	1.537827	0.37127	0.605962	0.394038	131.6494	0.023363	57.51023	0.68065
Ta	F	1.344105	0.394312	0.573398	0.426602	na	0.027065	39.95193	0.66439
Ta	F	1.694277	0.345933	0.628843	0.371157	152.7708	0.022221	61.96089	0.645691
Ta	F	1.181788	0.423098	0.54166	0.45834	210.4633	0.024748	61.20888	0.655806
Ta	F	3.307981	0.209062	0.767873	0.232127	134.3618	0.024304	40.13074	0.663871
Ta	F	1.297327	0.413605	0.564712	0.435288	120.628	0.023738	67.97853	0.647742
Ta	F	0.963907	0.465508	0.490811	0.509189	110.2152	0.021729	86.53929	0.674375
Ta	F	1.194595	0.419217	0.544335	0.455665	117.077	0.020067	90.49944	0.638438
Ta	F	0.820433	0.519099	0.45068	0.54932	143.4559	0.023166	91.41635	0.653281
Ta	F	1.886559	0.325595	0.653567	0.346433	153.316	0.026106	35.65897	0.640781
Ta	F	1.431373	0.381762	0.58871	0.41129	143.7122	0.026956	40.54949	0.645891
Ta	F	1.332813	0.337602	0.571333	0.428667	188.0818	0.013387	219.7329	0.676899
Ta	F	0.620102	0.572611	0.382755	0.617245	166.0412	0.022259	139.5349	0.714109
Ta	F	1.113665	0.437273	0.526888	0.473112	116.5242	0.021181	94.28315	0.61876
Ta	F	1.200117	0.418024	0.545479	0.454521	155.8408	0.01908	92.44707	0.651298
Ta	F	0.868621	0.496669	0.464846	0.535154	217.1358	0.020915	99.60978	0.628397
Ta	F	1.010157	0.471145	0.502526	0.497474	285.4691	0.017655	131.2633	0.639847
Ta	F	0.919191	0.492733	0.478947	0.521053	104.4918	0.02173	94.14634	0.62458
Ta	F	1.586397	0.357061	0.613362	0.386638	154.3713	0.017682	103.7745	0.744848
Ta	F	1.278771	0.414132	0.561167	0.438833	168.6199	0.020343	76.94138	0.623636
Ta	F	0.51803	0.628924	0.341251	0.658749	137.9828	0.022796	96.66433	0.619848
Ta	F	1.901609	0.324861	0.655364	0.344636	223.6837	0.021273	57.57663	0.650152

sp	cen	RS	LMF	RMF	SMF	SLA	RGR	STRL	RER
Qg	F	1.401004	0.324221	0.583508	0.416492	132.632	0.027538	124.4149	0.778135
Qg	F	1.240464	0.351498	0.553664	0.446336	95.5183	0.03108	89.82684	0.765291
Qg	F	0.717189	0.458643	0.417653	0.582347	120.5652	0.024833	245.0095	0.797401
Qg	F	0.805963	0.403861	0.446279	0.553721	85.77824	0.018948	443.1424	0.788226
Qg	F	0.934747	0.400749	0.483137	0.516863	122.7987	0.026472	131.1688	0.778135
Qg	F	1.598057	0.307795	0.615097	0.384903	114.6577	0.027149	99.53271	0.813664
Qg	F	0.736835	0.457323	0.42424	0.57576	157.1311	0.022889	349.815	0.791141
Qg	F	0.934994	0.388962	0.483202	0.516798	114.4343	0.019978	286.533	0.755105
Qg	F	0.780549	0.475616	0.438376	0.561624	83.50319	0.030099	101.6716	0.785736
Qg	F	0.699476	0.515494	0.411583	0.588417	97.18098	0.029559	102.86	0.744109
Qg	F	1.01214	0.375124	0.503017	0.496983	115.0947	0.023408	164.2544	0.731178
Qg	F	0.855379	0.454081	0.461026	0.538974	111.3187	0.020175	254.9821	0.720833
Qg	F	0.958437	0.42084	0.489389	0.510611	126.6165	0.019354	257.2306	0.726868
Qg	F	0.758233	0.438359	0.431247	0.568753	129.6658	0.018399	361.4414	0.725144
Qg	F	0.756151	0.473672	0.430573	0.569427	105.3193	0.024153	187.0222	0.718946
Qg	F	0.528757	0.524108	0.345874	0.654126	114.3107	0.022495	289.9691	0.743732
Qg	F	0.510501	0.525352	0.337968	0.662032	129.7065	0.022211	253.8462	0.667876
Qg	F	1.077654	0.38521	0.518688	0.481312	111.6877	0.02465	126.0535	0.701747
Qg	F	0.678706	0.472772	0.404303	0.595697	113.9174	0.025368	99.74641	0.535618
Qg	F	1.023911	0.396423	0.505907	0.494093	93.92329	0.028358	60.83551	0.621102
Qg	F	2.838301	0.164866	0.739468	0.260532	104.2642	0.017928	159.5014	0.674328
Qg	F	0.736066	0.44335	0.423985	0.576015	108.4332	0.019901	260.8696	0.619489
Qg	F	0.605132	0.529491	0.376998	0.623002	117.6045	0.023772	164.036	0.754101
Qg	F	0.842979	0.423492	0.4574	0.5426	98.97953	0.027091	87.90252	0.673148
Qg	F	0.553445	0.513564	0.35627	0.64373	113.4422	0.022583	225.5605	0.669974
Qg	F	0.692463	0.469159	0.409145	0.590855	103.6142	0.024175	134.2704	0.667593
Qg	F	0.858693	0.404538	0.461988	0.538012	113.9589	0.022412	151.5982	0.646641
Qg	F	0.612155	0.490062	0.379712	0.620288	110.6983	0.020792	220.2643	0.649742
Qg	F	0.854458	0.406835	0.460759	0.539241	105.565	0.020201	188.5553	0.653618
Qg	F	0.657115	0.493695	0.396542	0.603458	103.9911	0.025401	125.8216	0.700128
Qg	F	0.964816	0.408601	0.491046	0.508954	92.11797	0.026259	178.4111	0.670128
Qg	F	0.754394	0.470415	0.430002	0.569998	111.0618	0.023197	128.2216	0.644744
Qg	F	1.080725	0.382297	0.519398	0.480602	146.9613	0.022827	100.7752	0.575513

1981

1982

1983

1984

sp	cen	RS	LMF	RMF	SMF	SLA	RGR	STRL	RER
Hs	F	1.776621	0.277732	0.63985	0.36015	64.33503	0.015876	28.69921	0.902767
Hs	F	1.913095	0.255967	0.656723	0.343277	83.41847	0.021423	16.81391	0.846164
Hs	F	1.536339	0.307753	0.605731	0.394269	99.17484	0.013365	38.85703	0.842928
Hs	F	1.22596	0.352967	0.550756	0.449244	47.5871	0.019963	21.45188	0.756013
Hs	F	1.38814	0.326572	0.581264	0.418736	79.53097	0.018231	25.85255	0.800872
Hs	F	0.834001	0.426341	0.454744	0.545256	92.76503	0.019675	29.74545	0.82891
Hs	F	1.583939	0.258757	0.612994	0.387006	89.67273	0.019548	19.58699	0.805545
Hs	F	1.201779	0.333063	0.545822	0.454178	82.58905	0.018315	26.5435	0.833583
Hs	F	1.399561	0.325876	0.583257	0.416743	82.09384	0.01901	23.01681	0.882181
Hs	F	1.851653	0.279844	0.649326	0.350674	89.27722	0.020099	17.72119	0.753994
Hs	F	1.460887	0.318828	0.593642	0.406358	86.29901	0.016462	33.27697	0.773814
Hs	F	1.464123	0.335043	0.594176	0.405824	104.6303	0.01689	23.90186	0.663904
Hs	F	1.003365	0.341297	0.50084	0.49916	98.23083	0.013729	41.06013	0.716156
Hs	F	1.349185	0.347224	0.57432	0.42568	91.03035	0.015844	33.22259	0.711548
Hs	F	1.898133	0.282216	0.65495	0.34505	84.11452	0.018685	22.26133	0.720476
Hs	F	1.527039	0.309189	0.60428	0.39572	92.27408	0.016797	25.46491	0.676726
Hs	F	2.278544	0.247398	0.694987	0.305013	79.71878	0.022708	19.55468	0.755298
Hs	F	1.410461	0.307816	0.585142	0.414858	88.68161	0.015352	28.86883	0.679405
Hs	F	0.723109	0.460059	0.419654	0.580346	74.56216	0.00935	93.98139	0.661003
Hs	F	1.30899	0.330516	0.56691	0.43309	na	0.020045	20.42638	0.676047
Hs	F	1.924297	0.272126	0.658037	0.341963	85.86313	0.019619	17.51051	0.7141
Hs	F	1.956618	0.256329	0.661776	0.338224	76.09796	0.018046	18.1359	0.731799
Hs	F	1.837385	0.278376	0.647563	0.352437	104.4581	0.01901	24.5837	0.832684
Hs	F	1.073738	0.365223	0.517779	0.482221	87.06954	0.010677	50.07739	0.751696
Hs	F	1.437689	0.316471	0.589775	0.410225	73.96983	0.016711	21.68675	0.694678
Hs	F	1.686686	0.289192	0.627794	0.372206	85.60776	0.014905	31.19922	0.713099
Hs	F	1.096951	0.376769	0.523117	0.476883	73.26831	0.012633	54.32511	0.699064
Hs	F	1.702186	0.27146	0.629929	0.370071	91.7072	0.018832	19.0746	0.672749
Hs	F	1.9875	0.257597	0.665272	0.334728	257.0403	0.019429	15.30837	0.672749
Hs	F	2.560525	0.209719	0.719143	0.280857	88.61613	0.021184	12.65116	0.760468
Hs	F	1.633963	0.279684	0.620344	0.379656	97.56193	0.01621	23.91885	0.76924

1985

1986

1987

1988

1989

1990 7.3. APÊNDICE III: SCRIPT DE ANÁLISES ESTATÍSTICAS NO
1991 R DO CAPÍTULO 1

1992 ## 18/11/2022

1993 ## gráficos de correlação de Qg e Ta

1994

1995 library(readxl)

1996 f_Planilha_S3_dbrutos_final_artigo_veranicos_ <- read_excel("C:/Users/dalch/Desktop/Doutorado -
1997 geral/artigo Veranicos 2021/Editado Elsevier/conferindo revisão da
1998 Elsevier/f_Planilha_S3_dbrutos_final(artigo_veranicos).xlsx",

1999 col_types = c("text", "numeric", "numeric",

2000 "numeric", "numeric", "numeric",

2001 "numeric", "numeric", "numeric",

2002 "numeric", "numeric", "numeric",

2003 "numeric", "numeric", "numeric",

2004 "numeric"))

2005 View(f_Planilha_S3_dbrutos_final_artigo_veranicos_)

2006

2007 attach(f_Planilha_S3_dbrutos_final_artigo_veranicos_)

2008

2009 #####

2010 ## Fazendo nova análise para incluir parâmetros sugeridos pelo revisor no

2011 ##### segundo pedido de revisão da Flora

2012 library(readxl)

2013

2014 f_Planilha_S3_dbrutos_final_LMF_ <-

2015 read_excel("C:/Users/dalch/Desktop/f_Planilha_S3_dbrutos_final(LMF).xlsx",

2016 col_types = c("text", "numeric", "skip", "numeric",

```
2017 "numeric", "numeric", "numeric",
2018 "numeric", "numeric", "numeric",
2019 "numeric", "numeric", "numeric",
2020 "numeric", "numeric", "numeric",
2021 "numeric", "skip", "skip", "skip",
2022 "skip", "skip", "skip", "numeric",
2023 "numeric", "numeric", "numeric"))
2024 View(f_Planilha_S3_dbrutos_final_LMF_)
2025
2026 attach(f_Planilha_S3_dbrutos_final_LMF_)
2027
2028 library(tidyverse)
2029 library(flexplot)
2030 library(ggplot2)
2031 library(dplyr)
2032 library(car)
2033 library(fitdistrplus)
2034
2035 Qd1 <- f_Planilha_S3_dbrutos_final_LMF_ %>% na.omit()
2036 attach(Qd1)
2037
2038 esp <- c(Qd1$species)
2039 esp
2040 tratamento <- c(Qd1$tratamento)
2041 tratamento
2042 H <- c(Qd1$H)
2043 Lnum <- c(Qd1$Lnum)
```

```
2044 RM <- c(Qd1$RM)
2045 SM <- c(Qd1$SM)
2046 TM <- c(Qd1$TM)
2047 RMF <- c(Qd1$RMF)
2048 SMF <- c(Qd1$SMF)
2049 STRL <- c(Qd1$STRL)
2050 RER <- c(Qd1$RER)
2051 RGR <- c(Qd1$RGR)
2052 RL <- c(Qd1$RL)
2053 SLA <- c(Qd1$SLA)
2054 RS <- c(Qd1$RS)
2055 LMF <- c(Qd1$LMF)
2056 LMt <- c(Qd1$LMt)
2057 NAR <- c(Qd1$NAR)
2058 LAm <- c(Qd1$LAm)
2059
2060
2061 ##### correlação sem separar os tratamentos:
2062 library(metan)
2063 library(corrplot)
2064 library(RColorBrewer)
2065
2066
2067
2068 ###Qualea:
2069
2070 data_Qg.ver <- f_Planilha_S3_dbrutos_final_LMF_[]
```

```

2071   f_Planilha_S3_dbrutos_final_LMF_$species == "Qualea grandiflora",
2072   ]
2073   data_Qg.ver_no_na<- data_Qg.ver %>% na.omit()
2074   data_Qg.ver_no_na
2075
2076   ## médias e erro
2077   ##### tratamentos separados:
2078   Qd1$tratamento <- as.factor(Qd1$tratamento)
2079   tratamento <-as.factor(Qd1$tratamento)
2080   tratamento
2081
2082   ### para Qg
2083
2084   data_Qg.ver1 <- data_Qg.ver_no_na[data_Qg.ver_no_na$tratamento == "1",-2] ]
2085   data_Qg.ver1
2086
2087   data_Qg.ver8 <- data_Qg.ver_no_na[data_Qg.ver_no_na$tratamento == "8",-2] ]
2088   data_Qg.ver8
2089
2090   data_Qg.ver15 <- data_Qg.ver_no_na[data_Qg.ver_no_na$tratamento == "15",-2] ]
2091   data_Qg.ver15
2092
2093   QgH_1 <- c(data_Qg.ver1$H)
2094   QgLnum_1 <- c(data_Qg.ver1$Lnum)
2095   QgRM_1 <- c(data_Qg.ver1$RM)
2096   QgSM_1 <- c(data_Qg.ver1$SM)
2097   QgTM_1 <- c(data_Qg.ver1$TM)

```

```

2098  QgRMF_1 <- c(data_Qg.ver1$RMF)
2099  QgSMF_1 <- c(data_Qg.ver1$SMF)
2100  QgSTRL_1<- c(data_Qg.ver1$STRL)
2101  QgRER_1 <- c(data_Qg.ver1$RER)
2102  QgRGR_1 <- c(data_Qg.ver1$RGR)
2103  QgRL_1 <- c(data_Qg.ver1$RL)
2104  QgSLA_1 <- c(data_Qg.ver1$SLA)
2105  QgRS_1 <- c(data_Qg.ver1$RS)
2106  QgLmf_1 <- c(data_Qg.ver1$LMF)
2107  QgLmt_1 <- c(data_Qg.ver1$LMt)
2108  QgNAR_1 <- c(data_Qg.ver1$NAR)
2109  QgLAm_1 <- c(data_Qg.ver1$LAm)
2110
2111
2112
2113  m_QgH_1<- mean(QgH_1)
2114  m_QgH_1
2115  se_QgH_1 <- sd(QgH_1) / sqrt(8)
2116  se_QgH_1
2117
2118  m_QgLnum_1<- mean(QgLnum_1)
2119  m_QgLnum_1
2120  se_QgLnum_1 <- sd(QgLnum_1) / sqrt(8)
2121  se_QgLnum_1
2122
2123  m_QgRM_1<- mean(QgRM_1)
2124  m_QgRM_1

```

2125 `se_QgRM_1 <- sd(QgRM_1) / sqrt(8)`
2126 `se_QgRM_1`
2127
2128 `m_QgSM_1<- mean(QgSM_1)`
2129 `m_QgSM_1`
2130 `se_QgSM_1 <- sd(QgSM_1) / sqrt(8)`
2131 `se_QgSM_1`
2132
2133 `m_QgTM_1<- mean(QgTM_1)`
2134 `m_QgTM_1`
2135 `se_QgTM_1 <- sd(QgTM_1) / sqrt(8)`
2136 `se_QgTM_1`
2137
2138 `m_QgRMF_1<- mean(QgRMF_1)`
2139 `m_QgRMF_1`
2140 `se_QgRMF_1 <- sd(QgRMF_1) / sqrt(8)`
2141 `se_QgRMF_1`
2142
2143 `m_QgSMF_1<- mean(QgSMF_1)`
2144 `m_QgSMF_1`
2145 `se_QgSMF_1 <- sd(QgSMF_1) / sqrt(8)`
2146 `se_QgSMF_1`
2147
2148
2149 `m_QgRS_1<- mean(QgRS_1)`
2150 `m_QgRS_1`
2151 `se_QgRS_1 <- sd(QgRS_1) / sqrt(8)`

```
2152 se_QgRS_1
2153
2154 m_QgSTRL_1<- mean(QgSTRL_1)
2155 m_QgSTRL_1
2156 se_QgSTRL_1 <- sd(QgSTRL_1) / sqrt(8)
2157 se_QgSTRL_1
2158
2159 m_QgRGR_1<- mean(QgRGR_1)
2160 m_QgRGR_1
2161 se_QgRGR_1 <- sd(QgRGR_1) / sqrt(8)
2162 se_QgRGR_1
2163
2164 m_QgRER_1<- mean(QgRER_1)
2165 m_QgRER_1
2166 se_QgRER_1 <- sd(QgRER_1) / sqrt(8)
2167 se_QgRER_1
2168
2169 m_QgSLA_1<- mean(QgSLA_1)
2170 m_QgSLA_1
2171 se_QgSLA_1 <- sd(QgSLA_1) / sqrt(8)
2172 se_QgSLA_1
2173
2174 m_QgRL_1<- mean(QgRL_1)
2175 m_QgRL_1
2176 se_QgRL_1 <- sd(QgRL_1) / sqrt(8)
2177 se_QgRL_1
2178
```



```
2179
2180 m_QgLMF_1<- mean(QgLMF_1)
2181 m_QgLMF_1
2182 se_QgLMF_1 <- sd(QgLMF_1) / sqrt(8)
2183 se_QgLMF_1
2184
2185 m_QgLMt_1<- mean(QgLMt_1)
2186 m_QgLMt_1
2187 se_QgLMt_1 <- sd(QgLMt_1) / sqrt(8)
2188 se_QgLMt_1
2189
2190 m_QgNAR_1<- mean(QgNAR_1)
2191 m_QgNAR_1
2192 se_QgNAR_1 <- sd(QgNAR_1) / sqrt(8)
2193 se_QgNAR_1
2194
2195 m_QgLAm_1<- mean(QgLAm_1)
2196 m_QgLAm_1
2197 se_QgLAm_1 <- sd(QgLAm_1) / sqrt(8)
2198 se_QgLAm_1
2199
2200 ###
2201 QgH_8 <- c(data_Qg.ver8$H)
2202 QgLnum_8 <- c(data_Qg.ver8$Lnum)
2203 QgRM_8 <- c(data_Qg.ver8$RM)
2204 QgSM_8 <- c(data_Qg.ver8$SM)
2205 QgTM_8 <- c(data_Qg.ver8$TM)
```

```

2206  QgRMF_8 <- c(data_Qg.ver8$RMF)
2207  QgSMF_8 <- c(data_Qg.ver8$SMF)
2208  QgSTRL_8<- c(data_Qg.ver8$STRL)
2209  QgRER_8 <- c(data_Qg.ver8$RER)
2210  QgRGR_8 <- c(data_Qg.ver8$RGR)
2211  QgRL_8  <- c(data_Qg.ver8$RL)
2212  QgSLA_8 <- c(data_Qg.ver8$SLA)
2213  QgRS_8  <- c(data_Qg.ver8$RS)
2214
2215  m_QgH_8<- mean(QgH_8)
2216  m_QgH_8
2217  se_QgH_8 <- sd(QgH_8) / sqrt(8)
2218  se_QgH_8
2219
2220  m_QgLnum_8<- mean(QgLnum_8)
2221  m_QgLnum_8
2222  se_QgLnum_8 <- sd(QgLnum_8) / sqrt(8)
2223  se_QgLnum_8
2224
2225  m_QgRM_8<- mean(QgRM_8)
2226  m_QgRM_8
2227  se_QgRM_8 <- sd(QgRM_8) / sqrt(8)
2228  se_QgRM_8
2229
2230  m_QgSM_8<- mean(QgSM_8)
2231  m_QgSM_8
2232  se_QgSM_8 <- sd(QgSM_8) / sqrt(8)

```

```
2233 se_QgSM_8
2234
2235 m_QgTM_8<- mean(QgTM_8)
2236 m_QgTM_8
2237 se_QgTM_8 <- sd(QgTM_8) / sqrt(8)
2238 se_QgTM_8
2239
2240 m_QgRMF_8<- mean(QgRMF_8)
2241 m_QgRMF_8
2242 se_QgRMF_8 <- sd(QgRMF_8) / sqrt(8)
2243 se_QgRMF_8
2244
2245 m_QgSMF_8<- mean(QgSMF_8)
2246 m_QgSMF_8
2247 se_QgSMF_8 <- sd(QgSMF_8) / sqrt(8)
2248 se_QgSMF_8
2249
2250
2251 m_QgRS_8<- mean(QgRS_8)
2252 m_QgRS_8
2253 se_QgRS_8 <- sd(QgRS_8) / sqrt(8)
2254 se_QgRS_8
2255
2256 m_QgSTRL_8<- mean(QgSTRL_8)
2257 m_QgSTRL_8
2258 se_QgSTRL_8 <- sd(QgSTRL_8) / sqrt(8)
2259 se_QgSTRL_8
```

```
2260
2261  m_QgRGR_8<- mean(QgRGR_8)
2262  m_QgRGR_8
2263  se_QgRGR_8 <- sd(QgRGR_8) / sqrt(8)
2264  se_QgRGR_8
2265
2266  m_QgRER_8<- mean(QgRER_8)
2267  m_QgRER_8
2268  se_QgRER_8 <- sd(QgRER_8) / sqrt(8)
2269  se_QgRER_8
2270
2271  m_QgSLA_8<- mean(QgSLA_8)
2272  m_QgSLA_8
2273  se_QgSLA_8 <- sd(QgSLA_8) / sqrt(8)
2274  se_QgSLA_8
2275
2276  m_QgRL_8<- mean(QgRL_8)
2277  m_QgRL_8
2278  se_QgRL_8 <- sd(QgRL_8) / sqrt(8)
2279  se_QgRL_8
2280
2281
2282  m_QgLMF_8<- mean(QgLMF_8)
2283  m_QgLMF_8
2284  se_QgLMF_8 <- sd(QgLMF_8) / sqrt(8)
2285  se_QgLMF_8
2286
```

```

2287  m_QgLMt_8<- mean(QgLMt_8)
2288  m_QgLMt_8
2289  se_QgLMt_8 <- sd(QgLMt_8) / sqrt(8)
2290  se_QgLMt_8
2291
2292  m_QgNAR_8<- mean(QgNAR_8)
2293  m_QgNAR_8
2294  se_QgNAR_8 <- sd(QgNAR_8) / sqrt(8)
2295  se_QgNAR_8
2296
2297  m_QgLAm_8<- mean(QgLAm_8)
2298  m_QgLAm_8
2299  se_QgLAm_8 <- sd(QgLAm_8) / sqrt(8)
2300  se_QgLAm_8
2301
2302  ###
2303  QgH_15 <- c(data_Qg.ver15$H)
2304  QgLnum_15 <- c(data_Qg.ver15$Lnum)
2305  QgRM_15 <- c(data_Qg.ver15$RM)
2306  QgSM_15 <- c(data_Qg.ver15$SM)
2307  QgTM_15 <- c(data_Qg.ver15$TM)
2308  QgRMF_15 <- c(data_Qg.ver15$RMF)
2309  QgSMF_15 <- c(data_Qg.ver15$SMF)
2310  QgSTRL_15<- c(data_Qg.ver15$STRL)
2311  QgRER_15 <- c(data_Qg.ver15$RER)
2312  QgRGR_15 <- c(data_Qg.ver15$RGR)
2313  QgRL_15 <- c(data_Qg.ver15$RL)

```

```
2314 QgSLA_15 <- c(data_Qg.ver15$SLA)
2315 QgRS_15 <- c(data_Qg.ver15$RS)
2316
2317 m_QgH_15<- mean(QgH_15)
2318 m_QgH_15
2319 se_QgH_15 <- sd(QgH_15) / sqrt(8)
2320 se_QgH_15
2321
2322 m_QgLnum_15<- mean(QgLnum_15)
2323 m_QgLnum_15
2324 se_QgLnum_15 <- sd(QgLnum_15) / sqrt(8)
2325 se_QgLnum_15
2326
2327 m_QgRM_15<- mean(QgRM_15)
2328 m_QgRM_15
2329 se_QgRM_15 <- sd(QgRM_15) / sqrt(8)
2330 se_QgRM_15
2331
2332 m_QgSM_15<- mean(QgSM_15)
2333 m_QgSM_15
2334 se_QgSM_15 <- sd(QgSM_15) / sqrt(8)
2335 se_QgSM_15
2336
2337 m_QgTM_15<- mean(QgTM_15)
2338 m_QgTM_15
2339 se_QgTM_15 <- sd(QgTM_15) / sqrt(8)
2340 se_QgTM_15
```

```
2341
2342 m_QgRMF_15<- mean(QgRMF_15)
2343 m_QgRMF_15
2344 se_QgRMF_15 <- sd(QgRMF_15) / sqrt(8)
2345 se_QgRMF_15
2346
2347 m_QgSMF_15<- mean(QgSMF_15)
2348 m_QgSMF_15
2349 se_QgSMF_15 <- sd(QgSMF_15) / sqrt(8)
2350 se_QgSMF_15
2351
2352 m_QgRS_15<- mean(QgRS_15)
2353 m_QgRS_15
2354 se_QgRS_15 <- sd(QgRS_15) / sqrt(8)
2355 se_QgRS_15
2356
2357 m_QgSTRL_15<- mean(QgSTRL_15)
2358 m_QgSTRL_15
2359 se_QgSTRL_15 <- sd(QgSTRL_15) / sqrt(8)
2360 se_QgSTRL_15
2361
2362 m_QgRGR_15<- mean(QgRGR_15)
2363 m_QgRGR_15
2364 se_QgRGR_15 <- sd(QgRGR_15) / sqrt(8)
2365 se_QgRGR_15
2366
2367 m_QgRER_15<- mean(QgRER_15)
```

```

2368 m_QgRER_15
2369 se_QgRER_15 <- sd(QgRER_15) / sqrt(8)
2370 se_QgRER_15
2371
2372 m_QgSLA_15<- mean(QgSLA_15)
2373 m_QgSLA_15
2374 se_QgSLA_15 <- sd(QgSLA_15) / sqrt(8)
2375 se_QgSLA_15
2376
2377 m_QgRL_15<- mean(QgRL_15)
2378 m_QgRL_15
2379 se_QgRL_15 <- sd(QgRL_15) / sqrt(8)
2380 se_QgRL_15
2381
2382 ##### Tabebuia
2383 data_Ta.ver <- f_Planilha_S3_dbrutos_final_LMF_[
2384   f_Planilha_S3_dbrutos_final_LMF_$species == "Tabebuia aurea",- (2) ]
2385 data_Ta.ver_no_na<- data_Ta.ver %>% na.omit()
2386 data_Ta.ver_no_na
2387
2388 data_Ta.ver1 <- data_Ta.ver_no_na[data_Ta.ver_no_na$tratamento == "1",- (2) ]
2389 data_Ta.ver1
2390
2391 data_Ta.ver8 <- data_Ta.ver_no_na[data_Ta.ver_no_na$tratamento == "8",- (2) ]
2392 data_Ta.ver8
2393
2394 data_Ta.ver15 <- data_Ta.ver_no_na[data_Ta.ver_no_na$tratamento == "15",- (2) ]

```



```
2395 data_Ta.ver15
2396
2397 TaH_1 <- c(data_Ta.ver1$H)
2398 TaLnum_1 <- c(data_Ta.ver1$Lnum)
2399 TaRM_1 <- c(data_Ta.ver1$RM)
2400 TaSM_1 <- c(data_Ta.ver1$SM)
2401 TaTM_1 <- c(data_Ta.ver1$TM)
2402 TaRMF_1 <- c(data_Ta.ver1$RMF)
2403 TaSMF_1 <- c(data_Ta.ver1$SMF)
2404 TaSTRL_1<- c(data_Ta.ver1$STRL)
2405 TaRER_1 <- c(data_Ta.ver1$RER)
2406 TaRGR_1 <- c(data_Ta.ver1$RGR)
2407 TaRL_1 <- c(data_Ta.ver1$RL)
2408 TaSLA_1 <- c(data_Ta.ver1$SLA)
2409 TaRS_1 <- c(data_Ta.ver1$RS)
2410
2411 m_TaH_1<- mean(TaH_1)
2412 m_TaH_1
2413 se_TaH_1 <- sd(TaH_1) / sqrt(10)
2414 se_TaH_1
2415
2416 m_TaLnum_1<- mean(TaLnum_1)
2417 m_TaLnum_1
2418 se_TaLnum_1 <- sd(TaLnum_1) / sqrt(10)
2419 se_TaLnum_1
2420
2421 m_TaRM_1<- mean(TaRM_1)
```

```
2422 m_TaRM_1
2423 se_TaRM_1 <- sd(TaRM_1) / sqrt(10)
2424 se_TaRM_1
2425
2426 m_TaSM_1<- mean(TaSM_1)
2427 m_TaSM_1
2428 se_TaSM_1 <- sd(TaSM_1) / sqrt(10)
2429 se_TaSM_1
2430
2431 m_TaTM_1<- mean(TaTM_1)
2432 m_TaTM_1
2433 se_TaTM_1 <- sd(TaTM_1) / sqrt(10)
2434 se_TaTM_1
2435
2436 m_TaRMF_1<- mean(TaRMF_1)
2437 m_TaRMF_1
2438 se_TaRMF_1 <- sd(TaRMF_1) / sqrt(10)
2439 se_TaRMF_1
2440
2441 m_TaSMF_1<- mean(TaSMF_1)
2442 m_TaSMF_1
2443 se_TaSMF_1 <- sd(TaSMF_1) / sqrt(10)
2444 se_TaSMF_1
2445
2446 m_TaRS_1<- mean(TaRS_1)
2447 m_TaRS_1
2448 se_TaRS_1 <- sd(TaRS_1) / sqrt(10)
```

```
2449 se_TaRS_1
2450
2451 m_TaSTRL_1<- mean(TaSTRL_1)
2452 m_TaSTRL_1
2453 se_TaSTRL_1 <- sd(TaSTRL_1) / sqrt(10)
2454 se_TaSTRL_1
2455
2456 m_TaRGR_1<- mean(TaRGR_1)
2457 m_TaRGR_1
2458 se_TaRGR_1 <- sd(TaRGR_1) / sqrt(10)
2459 se_TaRGR_1
2460
2461 m_TaRER_1<- mean(TaRER_1)
2462 m_TaRER_1
2463 se_TaRER_1 <- sd(TaRER_1) / sqrt(10)
2464 se_TaRER_1
2465
2466 m_TaSLA_1<- mean(TaSLA_1)
2467 m_TaSLA_1
2468 se_TaSLA_1 <- sd(TaSLA_1) / sqrt(10)
2469 se_TaSLA_1
2470
2471 m_TaRL_1<- mean(TaRL_1)
2472 m_TaRL_1
2473 se_TaRL_1 <- sd(TaRL_1) / sqrt(10)
2474 se_TaRL_1
2475
```

```

2476   ###
2477
2478   TaH_8 <- c(data_Ta.ver8$H)
2479   TaLnum_8 <- c(data_Ta.ver8$Lnum)
2480   TaRM_8 <- c(data_Ta.ver8$RM)
2481   TaSM_8 <- c(data_Ta.ver8$SM)
2482   TaTM_8 <- c(data_Ta.ver8$TM)
2483   TaRMF_8 <- c(data_Ta.ver8$RMF)
2484   TaSMF_8 <- c(data_Ta.ver8$SMF)
2485   TaSTRL_8 <- c(data_Ta.ver8$STRL)
2486   TaRER_8 <- c(data_Ta.ver8$RER)
2487   TaRGR_8 <- c(data_Ta.ver8$RGR)
2488   TaRL_8 <- c(data_Ta.ver8$RL)
2489   TaSLA_8 <- c(data_Ta.ver8$SLA)
2490   TaRS_8 <- c(data_Ta.ver8$RS)
2491
2492   m_TaH_8 <- mean(TaH_8)
2493   m_TaH_8
2494   se_TaH_8 <- sd(TaH_8) / sqrt(10)
2495   se_TaH_8
2496
2497   m_TaLnum_8 <- mean(TaLnum_8)
2498   m_TaLnum_8
2499   se_TaLnum_8 <- sd(TaLnum_8) / sqrt(10)
2500   se_TaLnum_8
2501
2502   m_TaRM_8 <- mean(TaRM_8)

```

```
2503 m_TaRM_8
2504 se_TaRM_8 <- sd(TaRM_8) / sqrt(10)
2505 se_TaRM_8
2506
2507 m_TaSM_8<- mean(TaSM_8)
2508 m_TaSM_8
2509 se_TaSM_8 <- sd(TaSM_8) / sqrt(10)
2510 se_TaSM_8
2511
2512 m_TaTM_8<- mean(TaTM_8)
2513 m_TaTM_8
2514 se_TaTM_8 <- sd(TaTM_8) / sqrt(10)
2515 se_TaTM_8
2516
2517 m_TaRMF_8<- mean(TaRMF_8)
2518 m_TaRMF_8
2519 se_TaRMF_8 <- sd(TaRMF_8) / sqrt(10)
2520 se_TaRMF_8
2521
2522 m_TaSMF_8<- mean(TaSMF_8)
2523 m_TaSMF_8
2524 se_TaSMF_8 <- sd(TaSMF_8) / sqrt(10)
2525 se_TaSMF_8
2526
2527
2528 m_TaRS_8<- mean(TaRS_8)
2529 m_TaRS_8
```

```
2530 se_TaRS_8 <- sd(TaRS_8) / sqrt(10)
2531 se_TaRS_8
2532
2533 m_TaSTRL_8 <- mean(TaSTRL_8)
2534 m_TaSTRL_8
2535 se_TaSTRL_8 <- sd(TaSTRL_8) / sqrt(10)
2536 se_TaSTRL_8
2537
2538 m_TaRGR_8 <- mean(TaRGR_8)
2539 m_TaRGR_8
2540 se_TaRGR_8 <- sd(TaRGR_8) / sqrt(10)
2541 se_TaRGR_8
2542
2543 m_TaRER_8 <- mean(TaRER_8)
2544 m_TaRER_8
2545 se_TaRER_8 <- sd(TaRER_8) / sqrt(10)
2546 se_TaRER_8
2547
2548 m_TaSLA_8 <- mean(TaSLA_8)
2549 m_TaSLA_8
2550 se_TaSLA_8 <- sd(TaSLA_8) / sqrt(10)
2551 se_TaSLA_8
2552
2553 m_TaRL_8 <- mean(TaRL_8)
2554 m_TaRL_8
2555 se_TaRL_8 <- sd(TaRL_8) / sqrt(10)
2556 se_TaRL_8
```

```
2557
2558 ##
2559 TaH_15 <- c(data_Ta.ver15$H)
2560 TaLnum_15 <- c(data_Ta.ver15$Lnum)
2561 TaRM_15 <- c(data_Ta.ver15$RM)
2562 TaSM_15 <- c(data_Ta.ver15$SM)
2563 TaTM_15 <- c(data_Ta.ver15$TM)
2564 TaRMF_15 <- c(data_Ta.ver15$RMF)
2565 TaSMF_15 <- c(data_Ta.ver15$SMF)
2566 TaSTRL_15<- c(data_Ta.ver15$STRL)
2567 TaRER_15 <- c(data_Ta.ver15$RER)
2568 TaRGR_15 <- c(data_Ta.ver15$RGR)
2569 TaRL_15 <- c(data_Ta.ver15$RL)
2570 TaSLA_15 <- c(data_Ta.ver15$SLA)
2571 TaRS_15 <- c(data_Ta.ver15$RS)
2572
2573 m_TaH_15<- mean(TaH_15)
2574 m_TaH_15
2575 se_TaH_15 <- sd(TaH_15) / sqrt(10)
2576 se_TaH_15
2577
2578 m_TaLnum_15<- mean(TaLnum_15)
2579 m_TaLnum_15
2580 se_TaLnum_15 <- sd(TaLnum_15) / sqrt(10)
2581 se_TaLnum_15
2582
2583 m_TaRM_15<- mean(TaRM_15)
```

```
2584 m_TaRM_15
2585 se_TaRM_15 <- sd(TaRM_15) / sqrt(10)
2586 se_TaRM_15
2587
2588 m_TaSM_15<- mean(TaSM_15)
2589 m_TaSM_15
2590 se_TaSM_15 <- sd(TaSM_15) / sqrt(10)
2591 se_TaSM_15
2592
2593 m_TaTM_15<- mean(TaTM_15)
2594 m_TaTM_15
2595 se_TaTM_15 <- sd(TaTM_15) / sqrt(10)
2596 se_TaTM_15
2597
2598 m_TaRMF_15<- mean(TaRMF_15)
2599 m_TaRMF_15
2600 se_TaRMF_15 <- sd(TaRMF_15) / sqrt(10)
2601 se_TaRMF_15
2602
2603 m_TaSMF_15<- mean(TaSMF_15)
2604 m_TaSMF_15
2605 se_TaSMF_15 <- sd(TaSMF_15) / sqrt(10)
2606 se_TaSMF_15
2607
2608 m_TaRS_15<- mean(TaRS_15)
2609 m_TaRS_15
2610 se_TaRS_15 <- sd(TaRS_15) / sqrt(10)
```



```

2611 se_TaRS_15
2612
2613 m_TaSTRL_15<- mean(TaSTRL_15)
2614 m_TaSTRL_15
2615 se_TaSTRL_15 <- sd(TaSTRL_15) / sqrt(10)
2616 se_TaSTRL_15
2617
2618 m_TaRGR_15<- mean(TaRGR_15)
2619 m_TaRGR_15
2620 se_TaRGR_15 <- sd(TaRGR_15) / sqrt(10)
2621 se_TaRGR_15
2622
2623 m_TaRER_15<- mean(TaRER_15)
2624 m_TaRER_15
2625 se_TaRER_15 <- sd(TaRER_15) / sqrt(10)
2626 se_TaRER_15
2627
2628 m_TaSLA_15<- mean(TaSLA_15)
2629 m_TaSLA_15
2630 se_TaSLA_15 <- sd(TaSLA_15) / sqrt(10)
2631 se_TaSLA_15
2632
2633 m_TaRL_15<- mean(TaRL_15)
2634 m_TaRL_15
2635 se_TaRL_15 <- sd(TaRL_15) / sqrt(10)
2636 se_TaRL_15
2637
2638 ##### correlaçã
2639 Qgcorr<-corr_coef(data_Qg.ver_no_na)
2640
2641 plot(Qgcorr, col.low = "#FF8493", col.high = "#20B2AA") #esse foi o escolhido!
2642
2643 corr_plot(data_Qg.ver_no_na)
2644

```

```

2645   ###Tabebuia
2646   data_Ta.ver <- f_Planilha_S3_dbrutos_final_artigo_veranicos_[
2647     f_Planilha_S3_dbrutos_final_artigo_veranicos_$species == "Tabebuia aurea",
2648     -(2) ]
2649   data_Ta.ver_no_na<- data_Ta.ver %>% na.omit()
2650   data_Ta.ver_no_na
2651
2652   Tacorr<-corr_coef(data_Ta.ver_no_na)
2653
2654   plot(Tacorr, col.low = "#FF1493", col.high = "#20B2AA") #esse foi o escolhido!
2655
2656   corr_plot(data_Qg.ver_no_na)
2657
2658   #####
2659   ## análises estatísticas para Tabebuia.
2660   ##
2661   ##### como diferem?
2662   library(PMCMR)
2663
2664   ##### como eu fiz antes para comparar as sp separadamente:
2665   #T_RM<-(dados.v[1:33,]$RM)
2666   #T_trat.v<-(dados.v[1:33,]$tratamento)
2667   #str(T_trat.v)
2668   #T_trat<-as.factor(T_trat.v)
2669   #T_trat
2670   #posthoc.kruskal.nemenyi.test(T_RM, T_trat, method = "Tukey")
2671   #####
2672   ### como estou fazendo agora:
2673   data_Ta.ver <- f_Planilha_S3_dbrutos_final_LMF_[
2674     f_Planilha_S3_dbrutos_final_LMF_$species == "Tabebuia aurea",]
2675   data_Ta.ver_no_na<- data_Ta.ver %>% na.omit()
2676   data_Ta.ver_no_na
2677
2678   TaH <- c(data_Ta.ver_no_na$H)

```

```

2679 TaLnum <- c(data_Ta.ver_no_na$Lnum)
2680 TaRM <- c(data_Ta.ver_no_na$RM)
2681 TaSM <- c(data_Ta.ver_no_na$SM)
2682 TaTM <- c(data_Ta.ver_no_na$TM)
2683 TaRMF <- c(data_Ta.ver_no_na$RMF)
2684 TaSMF <- c(data_Ta.ver_no_na$SMF)
2685 TaSTRL<- c(data_Ta.ver_no_na$STRL)
2686 TaRER <- c(data_Ta.ver_no_na$RER)
2687 TaRGR <- c(data_Ta.ver_no_na$RGR)
2688 TaRL <- c(data_Ta.ver_no_na$RL)
2689 TaSLA <- c(data_Ta.ver_no_na$SLA)
2690 TaRS <- c(data_Ta.ver_no_na$RS)
2691 TaLMF <- c(data_Ta.ver_no_na$LMF)
2692 TaLMt <- c(data_Ta.ver_no_na$LMt)
2693 TaNAR <- c(data_Ta.ver_no_na$NAR)
2694 TaLAm <- c(data_Ta.ver_no_na$LAm)
2695
2696 T_trat.v <- as.factor(data_Ta.ver_no_na$tratamento)
2697 T_trat.v
2698
2699 kruskal.test(TaRM ~ T_trat.v)
2700 kruskal.test(TaSM ~ T_trat.v)
2701 kruskal.test(TaRMF ~ T_trat.v)
2702 kruskal.test(TaSMF ~ T_trat.v)
2703 kruskal.test(TaH ~ T_trat.v)
2704 kruskal.test(TaLnum ~ T_trat.v)
2705 kruskal.test(TaRGR ~ T_trat.v)
2706 kruskal.test(TaRER ~ T_trat.v)
2707 kruskal.test(TaSTRL~ T_trat.v)
2708 kruskal.test(TaRS ~ T_trat.v)
2709 kruskal.test(TaSLA ~ T_trat.v)
2710 kruskal.test(TaLMF ~ T_trat.v)
2711 kruskal.test(TaLMt ~ T_trat.v)
2712 kruskal.test(TaNAR ~ T_trat.v)

```

```

2713 kruskal.test(TaLAm ~ T_trat.v)
2714
2715
2716 posthoc.kruskal.nemenyi.test(TaRM, T_trat.v, method = "Tukey")
2717 posthoc.kruskal.nemenyi.test(TaSM, T_trat.v, method = "Tukey")
2718 posthoc.kruskal.nemenyi.test(TaRMF, T_trat.v, method = "Tukey")
2719 posthoc.kruskal.nemenyi.test(TaSMF, T_trat.v, method = "Tukey")
2720 posthoc.kruskal.nemenyi.test(Taalt, T_trat.v, method = "Tukey")
2721 posthoc.kruskal.nemenyi.test(TaLnum, T_trat.v, method = "Tukey")
2722 posthoc.kruskal.nemenyi.test(TaRGR, T_trat.v, method = "Tukey")
2723 posthoc.kruskal.nemenyi.test(TaRER, T_trat.v, method = "Tukey")
2724 posthoc.kruskal.nemenyi.test(TaSTRL, T_trat.v, method = "Tukey")
2725 posthoc.kruskal.nemenyi.test(TaRS, T_trat.v, method = "Tukey")
2726 posthoc.kruskal.nemenyi.test(TaSLA, T_trat.v, method = "Tukey")
2727 posthoc.kruskal.nemenyi.test(TaLMF, T_trat.v, method = "Tukey")
2728 posthoc.kruskal.nemenyi.test(TaLMt, T_trat.v, method = "Tukey")
2729 posthoc.kruskal.nemenyi.test(TaNAR, T_trat.v, method = "Tukey")
2730 posthoc.kruskal.nemenyi.test(TaLAm, T_trat.v, method = "Tukey")
2731
2732 #####
2733 ## análises estatísticas para Qualea.
2734 data_Qg.ver <- f_Planilha_S3_dbrutos_final_LMF_[
2735   f_Planilha_S3_dbrutos_final_LMF_$species == "Qualea grandiflora",
2736 ]
2737 data_Qg.ver_no_na<- data_Qg.ver %>% na.omit()
2738 data_Qg.ver_no_na
2739
2740
2741 Q_trat.v <- as.factor(data_Qg.ver_no_na$tratamento)
2742 Q_trat.v
2743
2744 QgH <- c(data_Qg.ver_no_na$H)
2745 QgLnum <- c(data_Qg.ver_no_na$Lnum)
2746 QgRM <- c(data_Qg.ver_no_na$RM)

```

```
2747 QgSM <- c(data_Qg.ver_no_na$SM)
2748 QgTM <- c(data_Qg.ver_no_na$TM)
2749 QgRMF <- c(data_Qg.ver_no_na$RMF)
2750 QgSMF <- c(data_Qg.ver_no_na$SMF)
2751 QgSTRL<- c(data_Qg.ver_no_na$STRL)
2752 QgRER <- c(data_Qg.ver_no_na$RER)
2753 QgRGR <- c(data_Qg.ver_no_na$RGR)
2754 QgRL <- c(data_Qg.ver_no_na$RL)
2755 QgSLA <- c(data_Qg.ver_no_na$SLA)
2756 QgRS <- c(data_Qg.ver_no_na$RS)
2757 QgLMF <- c(data_Qg.ver_no_na$LMF)
2758 QgLMt <- c(data_Qg.ver_no_na$LMt)
2759 QgNAR <- c(data_Qg.ver_no_na$NAR)
2760 QgLAm <- c(data_Qg.ver_no_na$LAm)
2761
2762 kruskal.test(QgRM ~ Q_trat.v)
2763 kruskal.test(QgSM ~ Q_trat.v)
2764 kruskal.test(QgRMF ~ Q_trat.v)
2765 kruskal.test(QgSMF ~ T_trat.v)
2766 kruskal.test(QgH ~ Q_trat.v)
2767 kruskal.test(QgLnum ~ Q_trat.v)
2768 kruskal.test(QgRGR ~ Q_trat.v)
2769 kruskal.test(QgRER ~ Q_trat.v)
2770 kruskal.test(QgSTRL~ Q_trat.v)
2771 kruskal.test(QgRS ~ Q_trat.v)
2772 kruskal.test(QgSLA ~ Q_trat.v)
2773 kruskal.test(QgLMF ~ Q_trat.v)
2774 kruskal.test(QgLMt ~ Q_trat.v)
2775 kruskal.test(QgNAR ~ Q_trat.v)
2776 kruskal.test(QgLAm ~ Q_trat.v)
2777
2778
2779
2780
```

```

2781 data_Qg.ver <- f_Planilha_S3_dbrutos_final_LMF_[
2782   f_Planilha_S3_dbrutos_final_LMF_$species == "Qualea grandiflora",
2783 ]
2784 data_Qg.ver_no_na<- data_Qg.ver %>% na.omit()
2785 data_Qg.ver_no_na
2786
2787 #####
2788 # comparar as sp
2789 LMF.v<- glm(LMF*esp_num~tratamento)
2790 LMF.v
2791
2792 library(cowplot)
2793
2794 a<- flexplot(RGR ~ tratamento | species, data = Qd1, se = F, alpha = .3)+
2795   scale_x_discrete(limits = c("1", "8","15"))
2796 plot_grid(a)
2797
2798 b<- flexplot(LMF ~ tratamento | species, data = Qd1, se = F, alpha = .3)+
2799   scale_x_discrete(limits = c("1", "8","15"))
2800
2801
2802 c<- flexplot(NAR ~ tratamento | species, data = Qd1, se = F, alpha = .3)+
2803   scale_x_discrete(limits = c("1", "8","15"))
2804
2805 d<- flexplot(SLA ~ tratamento | species, data = Qd1, se = F, alpha = .3)+
2806   scale_x_discrete(limits = c("1", "8","15"))
2807
2808 cowplot::plot_grid(a,b,c,d)
2809
2810 ##### um gráfico mais bonito
2811
2812 x= flexplot(LMF ~ tratamento + species,
2813           data = Qd1, se = F, alpha = .3) +
2814   scale_x_discrete(limits = c("1", "8","15"))

```

```
2815
2816 z= flexplot(RGR ~ tratamiento + species,
2817             data = Qd1, se = F, alpha = .3) +
2818             scale_x_discrete(limits = c("1", "8","15"))
2819
2820 y = flexplot(SLA ~ tratamiento + species,
2821             data = Qd1, se = F, alpha = .3) +
2822             scale_x_discrete(limits = c("1", "8","15"))
2823
2824 w = flexplot(NAR ~ tratamiento + species,
2825             data = Qd1, se = F, alpha = .3) +
2826             scale_x_discrete(limits = c("1", "8","15"))
2827 cowplot::plot_grid(x, z, y, w, nrow = 2)
2828
2829
2830
```

2831 7.4. APÊNDICE IV: SCRIPT DE ANÁLISES ESTATÍSTICAS NO
2832 R DO CAPÍTULO 2

```
2833 library(readxl)
2834 Dados_cen_final_nov2022_ <- read_excel("C:/Users/dalch/Desktop/TESE (final)/tese_PARTES/5. cap
2835 2/6. dados/Dados_cen(final_nov2022).xlsx",
2836                           col_types = c("text", "text", "numeric",
2837                                        "numeric", "numeric", "numeric",
2838                                        "numeric", "numeric", "numeric",
2839                                        "skip", "numeric", "numeric", "numeric",
2840                                        "numeric", "numeric", "numeric",
2841                                        "numeric", "numeric", "numeric",
2842                                        "numeric", "numeric", "numeric"))
2843 View(Dados_cen_final_nov2022_)
2844
2845
2846 attach(Dados_cen_final_nov2022_)
2847 dados1<-c(Dados_cen_final_nov2022_)
2848 dados<-na.omit(dados1)
2849 head(dados)
2850 str(dados)
2851
2852 dados.df<-data.frame(dados)
2853 str(dados.df)
2854
2855 library(tidyverse)
2856 library(flexplot)
2857 library(ggplot2)
2858 library(dplyr)
2859 library(car)
2860 library(fitdistrplus)
2861 dados.df<-data.frame(Dados_cen_final_nov2022_)
2862
2863
2864 ##### O Leo da Ana me ajudou pq estava dando NAs no cen
```



```

2865 #ele me passou esse código:
2866 dados_no_na <- Dados_cen_final_nov2022_ %>% na.omit()
2867 str(dados_no_na)
2868
2869
2870 esp <- c(dados_no_na$sp)
2871 esp
2872 cen <- c(dados_no_na$cen)
2873 cen
2874 d_base <- c(dados_no_na$ST_D)
2875 H <- c(dados_no_na$H)
2876 Lnum <- c(dados_no_na$Lnum)
2877 RM <- c(dados_no_na$RM)
2878 SM <- c(dados_no_na$SM)
2879 Mt <- c(dados_no_na$TM)
2880 RMF <- c(dados_no_na$RMF)
2881 SMF <- c(dados_no_na$SMF)
2882 LMF <- c(dados_no_na$LMF)
2883 STRL <- c(dados_no_na$STRL)
2884 RER <- c(dados_no_na$RER)
2885 RGR <- c(dados_no_na$RGR)
2886 RL <- c(dados_no_na$RL)
2887 ScRM <- c(dados_no_na$ScRM)
2888 TpRM <- c(dados_no_na$TpRM)
2889 StM <- c(dados_no_na$StM)
2890 SLA <- c(dados_no_na$SLA)
2891
2892 ##### separando por espécie para fazer as análises
2893
2894 data_Kc <- dados_no_na[dados_no_na$sp == "Kc", ]
2895 data_Kc
2896
2897 data-Ta <- dados_no_na[dados_no_na$sp == "Ta", ]
2898 data-Ta

```

```

2899
2900 data_Qg <- dados_no_na[dados_no_na$sp == "Qg", ]
2901 data_Qg
2902
2903 data_Hs <- dados_no_na[dados_no_na$sp == "Hs", ]
2904 data_Hs
2905
2906 #####
2907 #
2908 ##### dados de Qg para cada cenário!!! #####
2909
2910 Qg_F <- data_Qg[data_Qg$scen=="F", ]
2911 Qg_A <- data_Qg[data_Qg$scen=="A", ]
2912
2913 summary(Qg_A)
2914 summary(Qg_F)
2915
2916 ##### dados de Ta para cada cenário!!! #####
2917
2918 Ta_F <- data_Ta[data_Ta$scen=="F", ]
2919 Ta_A <- data_Ta[data_Ta$scen=="A", ]
2920
2921 summary(Ta_A)
2922 summary(Ta_F)
2923
2924 ##### dados de Kc para cada cenário!!! #####
2925
2926 Kc_F <- data_Kc[data_Kc$scen=="F", ]
2927 Kc_A <- data_Kc[data_Kc$scen=="A", ]
2928
2929 summary(Kc_A)
2930 summary(Kc_F)
2931
2932

```

```

2933 ##### dados de Hs para cada cenário!!! #####
2934
2935 Hs_F <- data_Hs[data_Hs$scen=="F", ]
2936 Hs_A <- data_Hs[data_Hs$scen=="A", ]
2937
2938 summary(Hs_A)
2939 summary(Hs_F)
2940
2941 #####
2942 #####
2943 #####                massa        total        Mt
2944 #####
2945 #dados_cenarios_ago2022_
2946 #flexplot e GLM de todas as sp
2947 #
2948 ###
2949 ## flexplot
2950 Mt_all= flexplot(TM ~ cen + sp,
2951                 data = dados_no_na, se = F, alpha = .3) + scale_x_discrete(limits=c("A","F")) + ## para
2952 arrumar ordem dos dados no eixo x
2953 theme(axis.text.x = element_text(angle=0, hjust=1, vjust=.2))
2954
2955 Mt_all
2956
2957 ### boxplot para todas
2958 ggplot(dados_no_na, aes(x=esp, y=MT, fill=cen)) +
2959   geom_boxplot()
2960
2961
2962 #####boxplot para Qg
2963
2964
2965 ggplot(data_Qg, aes(x=sp, y=TM, fill=cen)) +
2966   geom_boxplot()
2967

```

```

2968 ##### GLM para Qg
2969
2970 hist(TM)
2971 Mt_Qg<- c(data_Qg$TM)
2972
2973 hist(Mt_Qg)
2974
2975 fnorm<-fitdist(data_Qg$TM, distr = "norm")
2976 fgamma<-fitdist(data_Qg$TM, distr = "gamma")
2977 plot(fnorm)
2978 plot(fgamma)
2979 par(mfrow=c(1,1))
2980 famm_Mt_Qg<-gofstat(list(fnorm,fgamma),fitnames = c("norm","gamma"))
2981 denscomp(list(fnorm,fgamma),legendtext = c("norm","gamma"))
2982 #results of the tests
2983 ## chi square test (with corresponding table...)
2984 famm_Mt_Qg$chisqpvalue
2985 famm_Mt_Qg$chisqtable
2986
2987 ## Anderson-Darling test
2988 famm_Mt_Qg$adtest
2989 ## Cramer von Mises test
2990 famm_Mt_Qg$cvmtest
2991 ##Kolmogorov - Smirnov test
2992 famm_Mt_Qg$kstest
2993
2994
2995 Mt_m1_Qg<-glm(data_Qg$TM~cen,family = Gamma(),data = data_Qg)
2996 Mt_m1_Qg
2997 summary(Mt_m1_Qg)
2998
2999
3000 ##### para Ta #####
3001 #####

```

```

3002   ### boxplot para Ta
3003
3004   ggplot(data_Ta, aes(x=esp., y=TM, fill=cen)) +
3005     geom_boxplot()
3006
3007   ### GLM para Ta
3008
3009   Mt_Ta<- c(data_Ta$TM)
3010
3011   hist(Mt_Ta)
3012
3013   fnorm2<-fitdist(data_Ta$TM, distr = "norm")
3014   fgamma2<-fitdist(data_Ta$TM, distr = "gamma")
3015   plot(fnorm2)
3016   plot(fgamma2)
3017   par(mfrow=c(1,1))
3018   famm_Mt_Ta<-gofstat(list(fnorm2,fgamma2),fitnames = c("norm","gamma"))
3019   denscomp(list(fnorm2,fgamma2),legendtext = c("norm","gamma"))
3020   #results of the tests
3021   ## chi square test (with corresponding table...)
3022   famm_Mt_Ta$chisqpvalue
3023   famm_Mt_Ta$chisqtable
3024
3025   ## Anderson-Darling test
3026   famm_Mt_Ta$adtest
3027   ## Cramer von Mises test
3028   famm_Mt_Ta$cvmtest
3029   ##Kolmogorov - Smirnov test
3030   famm_Mt_Ta$kstest
3031
3032
3033   Mt_m1_Ta<-glm(data_Ta$TM~cen,family = Gamma(),data = data_Ta)
3034   Mt_m1_Ta
3035   summary(Mt_m1_Ta)

```

```

3036
3037
3038 #####
3039 ##### para Kc #####
3040 ### boxplot para Kc
3041
3042 ggplot(data_Kc, aes(x=esp, y=TM, fill=cen)) +
3043   geom_boxplot()
3044
3045 ##### GLM
3046
3047 Mt_Kc<- c(data_Kc$TM)
3048
3049 hist(Mt_Kc)
3050
3051 fnorm3<-fitdist(data_Kc$TM, distr = "norm")
3052 fgamma3<-fitdist(data_Kc$TM, distr = "gamma")
3053 plot(fnorm3)
3054 plot(fgamma3)
3055 par(mfrow=c(1,1))
3056 famm_Mt_Kc<-gofstat(list(fnorm3,fgamma3),fitnames = c("norm","gamma"))
3057 denscomp(list(fnorm3,fgamma3),legendtext = c("norm","gamma"))
3058 #results of the tests
3059 ## chi square test (with corresponding table...)
3060 famm_Mt_Kc$chisqpvalue
3061 famm_Mt_Kc$chisqtable
3062
3063 ## Anderson-Darling test
3064 famm_Mt_Kc$adtest
3065 ## Cramer von Mises test
3066 famm_Mt_Kc$cvmtest
3067 ##Kolmogorov - Smirnov test
3068 famm_Mt_Kc$kstest
3069

```

```

3070
3071 Mt_m1_Kc<-glm(data_Kc$TM~cen,family = Gamma(),data = data_Kc)
3072 Mt_m1_Kc
3073 summary(Mt_m1_Kc)
3074
3075 #####
3076 ##### para Hs
3077 ### boxplot para Hs
3078
3079 ggplot(data_Hs, aes(x=esp, y=Mt, fill=cen)) +
3080   geom_boxplot()
3081
3082 ##### GLM para Hs
3083
3084 Mt_Hs<- c(data_Hs$TM)
3085
3086 hist(Mt_Hs)
3087
3088 fnorm4<-fitdist(data_Hs$TM, distr = "norm")
3089 fgamma4<-fitdist(data_Hs$TM, distr = "gamma")
3090 plot(fnorm4)
3091 plot(fgamma4)
3092 par(mfrow=c(1,1))
3093 famm_Mt_Hs<-gofstat(list(fnorm4,fgamma4),fitnames = c("norm","gamma"))
3094 denscomp(list(fnorm4,fgamma4),legendtext = c("norm","gamma"))
3095 #results of the tests
3096 ## chi square test (with corresponding table...)
3097 famm_Mt_Hs$chisqpvalue
3098 famm_Mt_Hs$chisqtable
3099
3100 ## Anderson-Darling test
3101 famm_Mt_Hs$adtest
3102 ## Cramer von Mises test
3103 famm_Mt_Hs$cvmtest

```

```

3104  ##Kolmogorov - Smirnov test
3105  famm_Mt_Hs$kstest
3106
3107
3108  Mt_m1_Hs<-glm(data_Hs$TM~cen,family = Gamma(),data = data_Hs)
3109  Mt_m1_Hs
3110  summary(Mt_m1_Hs)
3111
3112
3113  #####
3114  #####
3115  #dados_cenarios_ago2022_
3116  #flexplot e GLM de todas as sp
3117  #
3118  ###
3119  ## flexplot
3120  ScRM_all= flexplot(ScRM ~ cen + sp,
3121                    data = dados_no_na, se = F, alpha = .3) + scale_x_discrete(limits=c("A","F")) + ## para
3122  arrumar ordem dos dados no eixo x
3123  theme(axis.text.x = element_text(angle=0, hjust=1, vjust=.2))
3124
3125  ScRM_all
3126
3127  ### boxplot para todas
3128  ggplot(dados_no_na, aes(x=esp, y=ScRM, fill=cen)) +
3129  geom_boxplot()
3130
3131
3132  #####boxplot para Qg
3133
3134
3135  ggplot(data_Qg, aes(x=sp, y=ScRM, fill=cen)) +
3136  geom_boxplot()
3137
3138  ##### GLM para Qg

```

ScRM


```

3139
3140 hist(ScRM)
3141 ScRM_Qg<- c(data_Qg$ScRM)
3142
3143 hist(ScRM_Qg)
3144
3145 fnorm<-fitdist(data_Qg$ScRM, distr = "norm")
3146 fgamma<-fitdist(data_Qg$ScRM, distr = "gamma")
3147 plot(fnorm)
3148 plot(fgamma)
3149 par(mfrow=c(1,1))
3150 famm_ScRM_Qg<-gofstat(list(fnorm,fgamma),fitnames = c("norm","gamma"))
3151 denscomp(list(fnorm,fgamma),legendtext = c("norm","gamma"))
3152 #results of the tests
3153 ## chi square test (with corresponding table...)
3154 famm_ScRM_Qg$chisqpvalue
3155 famm_ScRM_Qg$chisqtable
3156
3157 ## Anderson-Darling test
3158 famm_ScRM_Qg$adtest
3159 ## Cramer von Mises test
3160 famm_ScRM_Qg$cvmtest
3161 ##Kolmogorov - Smirnov test
3162 famm_ScRM_Qg$kstest
3163
3164
3165 ScRM_m1_Qg<-glm(data_Qg$ScRM~cen,family = Gamma(),data = data_Qg)
3166 ScRM_m1_Qg
3167 summary(ScRM_m1_Qg)
3168
3169
3170 ##### para Ta #####
3171 #####
3172 ### boxplot para Ta

```

```

3173
3174 ggplot(data_Ta, aes(x=sp, y=ScRM, fill=cen)) +
3175   geom_boxplot()
3176
3177 ### GLM para Ta
3178
3179 ScRM_Ta<- c(data_Ta$ScRM)
3180
3181 hist(ScRM_Ta)
3182
3183 fnorm2<-fitdist(data_Ta$ScRM, distr = "norm")
3184 fgamma2<-fitdist(data_Ta$ScRM, distr = "gamma")
3185 plot(fnorm2)
3186 plot(fgamma2)
3187 par(mfrow=c(1,1))
3188 famm_ScRM_Ta<-gofstat(list(fnorm2,fgamma2),fitnames = c("norm","gamma"))
3189 denscomp(list(fnorm2,fgamma2),legendtext = c("norm","gamma"))
3190 #results of the tests
3191 ## chi square test (with corresponding table...)
3192 famm_ScRM_Ta$chisqpvalue
3193 famm_ScRM_Ta$chisqtable
3194
3195 ## Anderson-Darling test
3196 famm_ScRM_Ta$adtest
3197 ## Cramer von Mises test
3198 famm_ScRM_Ta$cvmtest
3199 ##Kolmogorov - Smirnov test
3200 famm_ScRM_Ta$kstest
3201
3202
3203 ScRM_m1_Ta<-glm(data_Ta$ScRM~cen,family = Gamma(),data = data_Ta)
3204 ScRM_m1_Ta
3205 summary(ScRM_m1_Ta)
3206

```

```

3207
3208 #####
3209 ##### para Kc #####
3210 ### boxplot para Kc
3211
3212 ggplot(data_Kc, aes(x=sp, y=ScRM, fill=cen)) +
3213   geom_boxplot()
3214
3215 ##### GLM
3216
3217 ScRM_Kc<- c(data_Kc$ScRM)
3218
3219 hist(ScRM_Kc)
3220
3221 fnorm3<-fitdist(data_Kc$ScRM, distr = "norm")
3222 fgamma3<-fitdist(data_Kc$ScRM, distr = "gamma")
3223 plot(fnorm3)
3224 plot(fgamma3)
3225 par(mfrow=c(1,1))
3226 famm_ScRM_Kc<-gofstat(list(fnorm3,fgamma3),fitnames = c("norm","gamma"))
3227 denscomp(list(fnorm3,fgamma3),legendtext = c("norm","gamma"))
3228 #results of the tests
3229 ## chi square test (with corresponding table...)
3230 famm_ScRM_Kc$chisqpvalue
3231 famm_ScRM_Kc$chisqtable
3232
3233 ## Anderson-Darling test
3234 famm_ScRM_Kc$adtest
3235 ## Cramer von Mises test
3236 famm_ScRM_Kc$cvmtest
3237 ##Kolmogorov - Smirnov test
3238 famm_ScRM_Kc$kstest
3239
3240

```

```

3241 ScRM_m1_Kc<-glm(data_Kc$ScRM~cen,family = Gamma(),data = data_Kc)
3242 ScRM_m1_Kc
3243 summary(ScRM_m1_Kc)
3244
3245 #####
3246 ##### para Hs
3247 ### boxplot para Hs
3248
3249 ggplot(data_Hs, aes(x=sp, y=ScRM, fill=cen)) +
3250   geom_boxplot()
3251
3252 ##### GLM para Hs
3253
3254 ScRM_Hs<- c(data_Hs$ScRM)
3255
3256 hist(ScRM_Hs)
3257
3258 fnorm4<-fitdist(data_Hs$ScRM, distr = "norm")
3259 fgamma4<-fitdist(data_Hs$ScRM, distr = "gamma")
3260 plot(fnorm4)
3261 plot(fgamma4)
3262 par(mfrow=c(1,1))
3263 famm_ScRM_Hs<-gofstat(list(fnorm4,fgamma4),fitnames = c("norm","gamma"))
3264 denscomp(list(fnorm4,fgamma4),legendtext = c("norm","gamma"))
3265 #results of the tests
3266 ## chi square test (with corresponding table...)
3267 famm_ScRM_Hs$chisqpvalue
3268 famm_ScRM_Hs$chisqtable
3269
3270 ## Anderson-Darling test
3271 famm_ScRM_Hs$adtest
3272 ## Cramer von Mises test
3273 famm_ScRM_Hs$cvmtest
3274 ##Kolmogorov - Smirnov test

```

```

3275 famm_ScRM_Hs$kstest
3276
3277
3278 ScRM_m1_Hs<-glm(data_Hs$ScRM~cen,family = Gamma(),data = data_Hs)
3279 ScRM_m1_Hs
3280 summary(ScRM_m1_Hs)
3281
3282
3283 #####
3284 #####
3285 #dados_cenarios_ago2022_
3286 #flexplot e GLM de todas as sp
3287 #
3288 ###
3289 ## flexplot
3290 TpRM_all= flexplot(TpRM ~ cen + sp,
3291                   data = dados_no_na, se = F, alpha = .3) + scale_x_discrete(limits=c("A","F")) + ## para
3292 arrumar ordem dos dados no eixo x
3293 theme(axis.text.x = element_text(angle=0, hjust=1, vjust=.2))
3294
3295 TpRM_all
3296
3297 ### boxplot para todas
3298 ggplot(dados_no_na, aes(x=esp, y=TpRM, fill=cen)) +
3299 geom_boxplot()
3300
3301
3302 #####boxplot para Qg
3303
3304
3305 ggplot(data_Qg, aes(x=esp, y=TpRM, fill=cen)) +
3306 geom_boxplot()
3307
3308 ##### GLM para Qg
3309

```

TpRM

```

3310 hist(TpRM)
3311 TpRM_Qg<- c(data_Qg$TpRM)
3312
3313 hist(TpRM_Qg)
3314
3315 fnorm<-fitdist(data_Qg$TpRM, distr = "norm")
3316 fgamma<-fitdist(data_Qg$TpRM, distr = "gamma")
3317 plot(fnorm)
3318 plot(fgamma)
3319 par(mfrow=c(1,1))
3320 famm_TpRM_Qg<-gofstat(list(fnorm,fgamma),fitnames = c("norm","gamma"))
3321 denscomp(list(fnorm,fgamma),legendtext = c("norm","gamma"))
3322 #results of the tests
3323 ## chi square test (with corresponding table...)
3324 famm_TpRM_Qg$chisqpvalue
3325 famm_TpRM_Qg$chisqtable
3326
3327 ## Anderson-Darling test
3328 famm_TpRM_Qg$adtest
3329 ## Cramer von Mises test
3330 famm_TpRM_Qg$cvmtest
3331 ##Kolmogorov - Smirnov test
3332 famm_TpRM_Qg$kstest
3333
3334
3335 TpRM_m1_Qg<-glm(data_Qg$TpRM~cen,family = Gamma(),data = data_Qg)
3336 TpRM_m1_Qg
3337 summary(TpRM_m1_Qg)
3338
3339
3340 ##### para Ta #####
3341 #####
3342 ### boxplot para Ta
3343

```

```

3344 ggplot(data_Ta, aes(x=esp., y=TpRM, fill=cen)) +
3345   geom_boxplot()
3346
3347   ### GLM para Ta
3348
3349   TpRM_Ta<- c(data_Ta$TpRM)
3350
3351   hist(TpRM_Ta)
3352
3353   fnorm2<-fitdist(data_Ta$TpRM, distr = "norm")
3354   fgamma2<-fitdist(data_Ta$TpRM, distr = "gamma")
3355   plot(fnorm2)
3356   plot(fgamma2)
3357   par(mfrow=c(1,1))
3358   famm_TpRM_Ta<-gofstat(list(fnorm2,fgamma2),fitnames = c("norm","gamma"))
3359   denscomp(list(fnorm2,fgamma2),legendtext = c("norm","gamma"))
3360   #results of the tests
3361   ## chi square test (with corresponding table...)
3362   famm_TpRM_Ta$chisqpvalue
3363   famm_TpRM_Ta$chisqtable
3364
3365   ## Anderson-Darling test
3366   famm_TpRM_Ta$adtest
3367   ## Cramer von Mises test
3368   famm_TpRM_Ta$cvmtest
3369   ##Kolmogorov - Smirnov test
3370   famm_TpRM_Ta$kstest
3371
3372
3373   TpRM_m1_Ta<-glm(data_Ta$TpRM~cen,family = Gamma(),data = data_Ta)
3374   TpRM_m1_Ta
3375   summary(TpRM_m1_Ta)
3376
3377

```

```

3378 #####
3379 ##### para Kc #####
3380 ### boxplot para Kc
3381
3382 ggplot(data_Kc, aes(x=esp, y=TpRM, fill=cen)) +
3383   geom_boxplot()
3384
3385 ##### GLM
3386
3387 TpRM_Kc<- c(data_Kc$TpRM)
3388
3389 hist(TpRM_Kc)
3390
3391 fnorm3<-fitdist(data_Kc$TpRM, distr = "norm")
3392 fgamma3<-fitdist(data_Kc$TpRM, distr = "gamma")
3393 plot(fnorm3)
3394 plot(fgamma3)
3395 par(mfrow=c(1,1))
3396 famm_TpRM_Kc<-gofstat(list(fnorm3,fgamma3),fitnames = c("norm","gamma"))
3397 denscomp(list(fnorm3,fgamma3),legendtext = c("norm","gamma"))
3398 #results of the tests
3399 ## chi square test (with corresponding table...)
3400 famm_TpRM_Kc$chisqpvalue
3401 famm_TpRM_Kc$chisqtable
3402
3403 ## Anderson-Darling test
3404 famm_TpRM_Kc$adtest
3405 ## Cramer von Mises test
3406 famm_TpRM_Kc$cvmtest
3407 ##Kolmogorov - Smirnov test
3408 famm_TpRM_Kc$kstest
3409
3410
3411 TpRM_m1_Kc<-glm(data_Kc$TpRM~cen,family = Gamma(),data = data_Kc)

```



```

3412 TpRM_m1_Kc
3413 summary(TpRM_m1_Kc)
3414
3415 #####
3416 ##### para Hs
3417 ### boxplot para Hs
3418
3419 ggplot(data_Hs, aes(x=esp, y=TpRM, fill=cen)) +
3420   geom_boxplot()
3421
3422 ##### GLM para Hs
3423
3424 TpRM_Hs<- c(data_Hs$TpRM)
3425
3426 hist(TpRM_Hs)
3427
3428 fnorm4<-fitdist(data_Hs$TpRM, distr = "norm")
3429 fgamma4<-fitdist(data_Hs$TpRM, distr = "gamma")
3430 plot(fnorm4)
3431 plot(fgamma4)
3432 par(mfrow=c(1,1))
3433 famm_TpRM_Hs<-gofstat(list(fnorm4,fgamma4),fitnames = c("norm","gamma"))
3434 denscomp(list(fnorm4,fgamma4),legendtext = c("norm","gamma"))
3435 #results of the tests
3436 ## chi square test (with corresponding table...)
3437 famm_TpRM_Hs$chisqpvalue
3438 famm_TpRM_Hs$chisqtable
3439
3440 ## Anderson-Darling test
3441 famm_TpRM_Hs$adtest
3442 ## Cramer von Mises test
3443 famm_TpRM_Hs$cvmtest
3444 ##Kolmogorov - Smirnov test
3445 famm_TpRM_Hs$kstest

```

```

3446
3447
3448 TpRM_m1_Hs<-glm(data_Hs$TpRM~cen,family = Gamma(),data = data_Hs)
3449 TpRM_m1_Hs
3450 summary(TpRM_m1_Hs)
3451
3452
3453 ##### StM #####
3454 #dados_cenarios_ago2022_
3455 #flexplot e GLM de todas as sp
3456 #
3457 ###
3458 ## flexplot
3459 StM_all= flexplot(StM ~ cen + sp,
3460                   data = dados_no_na, se = F, alpha = .3) + scale_x_discrete(limits=c("A","F")) + ## para
3461 arrumar ordem dos dados no eixo x
3462   theme(axis.text.x = element_text(angle=0, hjust=1, vjust=.2))
3463
3464 StM_all
3465
3466 ### boxplot para todas
3467 ggplot(dados_no_na, aes(x=esp, y=StM, fill=cen)) +
3468   geom_boxplot()
3469
3470
3471 #####boxplot para Qg
3472
3473
3474 ggplot(data_Qg, aes(x=esp, y=StM, fill=cen)) +
3475   geom_boxplot()
3476
3477 ##### GLM para Qg
3478
3479 hist(StM)
3480 StM_Qg<- c(data_Qg$StM)

```

```

3481
3482 hist(StM_Qg)
3483
3484 fnorm<-fitdist(data_Qg$StM, distr = "norm")
3485 fgamma<-fitdist(data_Qg$StM, distr = "gamma")
3486 plot(fnorm)
3487 plot(fgamma)
3488 par(mfrow=c(1,1))
3489 famm_StM_Qg<-gofstat(list(fnorm,fgamma),fitnames = c("norm","gamma"))
3490 denscomp(list(fnorm,fgamma),legendtext = c("norm","gamma"))
3491 #results of the tests
3492 ## chi square test (with corresponding table...)
3493 famm_StM_Qg$chisqpvalue
3494 famm_StM_Qg$chisqtable
3495
3496 ## Anderson-Darling test
3497 famm_StM_Qg$adtest
3498 ## Cramer von Mises test
3499 famm_StM_Qg$scvmtest
3500 ##Kolmogorov - Smirnov test
3501 famm_StM_Qg$kstest
3502
3503
3504 StM_m1_Qg<-glm(data_Qg$StM~cen,family = Gamma(),data = data_Qg)
3505 StM_m1_Qg
3506 summary(StM_m1_Qg)
3507
3508
3509 ##### para Ta #####
3510 #####
3511 ### boxplot para Ta
3512
3513 ggplot(data_Ta, aes(x=esp., y=StM, fill=cen)) +
3514 geom_boxplot()

```

```

3515
3516   ### GLM para Ta
3517
3518   StM_Ta<- c(data_Ta$StM)
3519
3520   hist(StM_Ta)
3521
3522   fnorm2<-fitdist(data_Ta$StM, distr = "norm")
3523   fgamma2<-fitdist(data_Ta$StM, distr = "gamma")
3524   plot(fnorm2)
3525   plot(fgamma2)
3526   par(mfrow=c(1,1))
3527   famm_StM_Ta<-gofstat(list(fnorm2,fgamma2),fitnames = c("norm","gamma"))
3528   denscomp(list(fnorm2,fgamma2),legendtext = c("norm","gamma"))
3529   #results of the tests
3530   ## chi square test (with corresponding table...)
3531   famm_StM_Ta$chisqpvalue
3532   famm_StM_Ta$chisqtable
3533
3534   ## Anderson-Darling test
3535   famm_StM_Ta$adtest
3536   ## Cramer von Mises test
3537   famm_StM_Ta$cvmtest
3538   ##Kolmogorov - Smirnov test
3539   famm_StM_Ta$kstest
3540
3541
3542   StM_m1_Ta<-glm(data_Ta$StM~cen,family = Gamma(),data = data_Ta)
3543   StM_m1_Ta
3544   summary(StM_m1_Ta)
3545
3546
3547   #####
3548   ##### para Kc #####

```

```

3549   ### boxplot para Kc
3550
3551   ggplot(data_Kc, aes(x=esp, y=StM, fill=cen)) +
3552     geom_boxplot()
3553
3554   ##### GLM
3555
3556   StM_Kc<- c(data_Kc$StM)
3557
3558   hist(StM_Kc)
3559
3560   fnorm3<-fitdist(data_Kc$StM, distr = "norm")
3561   fgamma3<-fitdist(data_Kc$StM, distr = "gamma")
3562   plot(fnorm3)
3563   plot(fgamma3)
3564   par(mfrow=c(1,1))
3565   famm_StM_Kc<-gofstat(list(fnorm3,fgamma3),fitnames = c("norm","gamma"))
3566   denscomp(list(fnorm3,fgamma3),legendtext = c("norm","gamma"))
3567   #results of the tests
3568   ## chi square test (with corresponding table...)
3569   famm_StM_Kc$chisqpvalue
3570   famm_StM_Kc$chisqtable
3571
3572   ## Anderson-Darling test
3573   famm_StM_Kc$adtest
3574   ## Cramer von Mises test
3575   famm_StM_Kc$cvmtest
3576   ##Kolmogorov - Smirnov test
3577   famm_StM_Kc$kstest
3578
3579
3580   StM_m1_Kc<-glm(data_Kc$StM~cen,family = Gamma(),data = data_Kc)
3581   StM_m1_Kc
3582   summary(StM_m1_Kc)

```

```

3583
3584 #####
3585 ##### para Hs
3586 ### boxplot para Hs
3587
3588 ggplot(data_Hs, aes(x=esp, y=StM, fill=cen)) +
3589   geom_boxplot()
3590
3591 ##### GLM para Hs
3592
3593 StM_Hs<- c(data_Hs$StM)
3594
3595 hist(StM_Hs)
3596
3597 fnorm4<-fitdist(data_Hs$StM, distr = "norm")
3598 fgamma4<-fitdist(data_Hs$StM, distr = "gamma")
3599 plot(fnorm4)
3600 plot(fgamma4)
3601 par(mfrow=c(1,1))
3602 famm_StM_Hs<-gofstat(list(fnorm4,fgamma4),fitnames = c("norm","gamma"))
3603 denscomp(list(fnorm4,fgamma4),legendtext = c("norm","gamma"))
3604 #results of the tests
3605 ## chi square test (with corresponding table...)
3606 famm_StM_Hs$chisqpvalue
3607 famm_StM_Hs$chisqtable
3608
3609 ## Anderson-Darling test
3610 famm_StM_Hs$adtest
3611 ## Cramer von Mises test
3612 famm_StM_Hs$cvmtest
3613 ##Kolmogorov - Smirnov test
3614 famm_StM_Hs$kstest
3615
3616

```

```

3617 StM_m1_Hs<-glm(data_Hs$StM~cen,family = Gamma(),data = data_Hs)
3618 StM_m1_Hs
3619 summary(StM_m1_Hs)
3620
3621
3622 ##### TLM #####
3623 #dados_cenarios_ago2022_
3624 #flexplot e GLM de todas as sp
3625 #
3626 ###
3627 ## flexplot
3628 TLM_all= flexplot(TLM ~ cen + sp,
3629                   data = dados_no_na, se = F, alpha = .3) + scale_x_discrete(limits=c("A","F")) + ## para
3630 arrumar ordem dos dados no eixo x
3631   theme(axis.text.x = element_text(angle=0, hjust=1, vjust=.2))
3632
3633 TLM_all
3634
3635 ### boxplot para todas
3636 ggplot(dados_no_na, aes(x=esp, y=TLM, fill=cen)) +
3637   geom_boxplot()
3638
3639
3640 #####boxplot para Qg
3641
3642
3643 ggplot(data_Qg, aes(x=esp, y=TLM, fill=cen)) +
3644   geom_boxplot()
3645
3646 ##### GLM para Qg
3647
3648 hist(TLM)
3649 TLM_Qg<- c(data_Qg$TLM)
3650
3651 hist(TLM_Qg)

```

```

3652
3653  fnorm<-fitdist(data_Qg$TLM, distr = "norm")
3654  fgamma<-fitdist(data_Qg$TLM, distr = "gamma")
3655  plot(fnorm)
3656  plot(fgamma)
3657  par(mfrow=c(1,1))
3658  famm_TLM_Qg<-gofstat(list(fnorm,fgamma),fitnames = c("norm","gamma"))
3659  denscomp(list(fnorm,fgamma),legendtext = c("norm","gamma"))
3660  #results of the tests
3661  ## chi square test (with corresponding table...)
3662  famm_TLM_Qg$chisqpvalue
3663  famm_TLM_Qg$chisqtable
3664
3665  ## Anderson-Darling test
3666  famm_TLM_Qg$sadtest
3667  ## Cramer von Mises test
3668  famm_TLM_Qg$scvmtest
3669  ##Kolmogorov - Smirnov test
3670  famm_TLM_Qg$kstest
3671
3672
3673  TLM_m1_Qg<-glm(data_Qg$TLM~cen,family = Gamma(),data = data_Qg)
3674  TLM_m1_Qg
3675  summary(TLM_m1_Qg)
3676
3677
3678  ##### para Ta #####
3679  #####
3680  ### boxplot para Ta
3681
3682  ggplot(data_Ta, aes(x=esp., y=TLM, fill=cen)) +
3683    geom_boxplot()
3684
3685  ### GLM para Ta

```



```

3686
3687 TLM_Ta<- c(data_Ta$TLM)
3688
3689 hist(TLM_Ta)
3690
3691 fnorm2<-fitdist(data_Ta$TLM, distr = "norm")
3692 fgamma2<-fitdist(data_Ta$TLM, distr = "gamma")
3693 plot(fnorm2)
3694 plot(fgamma2)
3695 par(mfrow=c(1,1))
3696 famm_TLM_Ta<-gofstat(list(fnorm2,fgamma2),fitnames = c("norm","gamma"))
3697 denscomp(list(fnorm2,fgamma2),legendtext = c("norm","gamma"))
3698 #results of the tests
3699 ## chi square test (with corresponding table...)
3700 famm_TLM_Ta$chisqpvalue
3701 famm_TLM_Ta$chisqtable
3702
3703 ## Anderson-Darling test
3704 famm_TLM_Ta$adtest
3705 ## Cramer von Mises test
3706 famm_TLM_Ta$cvmttest
3707 ##Kolmogorov - Smirnov test
3708 famm_TLM_Ta$skstest
3709
3710
3711 TLM_m1_Ta<-glm(data_Ta$TLM~cen,family = Gamma(),data = data_Ta)
3712 TLM_m1_Ta
3713 summary(TLM_m1_Ta)
3714
3715
3716 #####
3717 ##### para Kc #####
3718 ### boxplot para Kc
3719

```

```

3720 ggplot(data_Kc, aes(x=esp, y=TLM, fill=cen)) +
3721   geom_boxplot()
3722
3723 ##### GLM
3724
3725 TLM_Kc<- c(data_Kc$TLM)
3726
3727 hist(TLM_Kc)
3728
3729 fnorm3<-fitdist(data_Kc$TLM, distr = "norm")
3730 fgamma3<-fitdist(data_Kc$TLM, distr = "gamma")
3731 plot(fnorm3)
3732 plot(fgamma3)
3733 par(mfrow=c(1,1))
3734 famm_TLM_Kc<-gofstat(list(fnorm3,fgamma3),fitnames = c("norm","gamma"))
3735 denscomp(list(fnorm3,fgamma3),legendtext = c("norm","gamma"))
3736 #results of the tests
3737 ## chi square test (with corresponding table...)
3738 famm_TLM_Kc$chisqpvalue
3739 famm_TLM_Kc$chisqtable
3740
3741 ## Anderson-Darling test
3742 famm_TLM_Kc$adtest
3743 ## Cramer von Mises test
3744 famm_TLM_Kc$cvmtest
3745 ##Kolmogorov - Smirnov test
3746 famm_TLM_Kc$kstest
3747
3748
3749 TLM_m1_Kc<-glm(data_Kc$TLM~cen,family = Gamma(),data = data_Kc)
3750 TLM_m1_Kc
3751 summary(TLM_m1_Kc)
3752
3753 #####

```

```

3754 ##### para Hs
3755 ### boxplot para Hs
3756
3757 ggplot(data_Hs, aes(x=esp, y=TLM, fill=cen)) +
3758   geom_boxplot()
3759
3760 ##### GLM para Hs
3761
3762 TLM_Hs<- c(data_Hs$TLM)
3763
3764 hist(TLM_Hs)
3765
3766 fnorm4<-fitdist(data_Hs$TLM, distr = "norm")
3767 fgamma4<-fitdist(data_Hs$TLM, distr = "gamma")
3768 plot(fnorm4)
3769 plot(fgamma4)
3770 par(mfrow=c(1,1))
3771 famm_TLM_Hs<-gofstat(list(fnorm4,fgamma4),fitnames = c("norm","gamma"))
3772 denscomp(list(fnorm4,fgamma4),legendtext = c("norm","gamma"))
3773 #results of the tests
3774 ## chi square test (with corresponding table...)
3775 famm_TLM_Hs$chisqpvalue
3776 famm_TLM_Hs$chisqtable
3777
3778 ## Anderson-Darling test
3779 famm_TLM_Hs$adtest
3780 ## Cramer von Mises test
3781 famm_TLM_Hs$cvmttest
3782 ##Kolmogorov - Smirnov test
3783 famm_TLM_Hs$ksstest
3784
3785
3786 TLM_m1_Hs<-glm(data_Hs$TLM~cen,family = Gamma(),data = data_Hs)
3787 TLM_m1_Hs

```

```

3788 summary(TLM_m1_Hs)
3789
3790
3791 ##### SLA #####
3792 #dados_cenarios_ago2022_
3793 #flexplot e GLM de todas as sp
3794 #
3795 ###
3796 ## flexplot
3797 SLA_all= flexplot(SLA ~ cen + sp,
3798                   data = dados_no_na, se = F, alpha = .3) + scale_x_discrete(limits=c("A","F")) + ## para
3799 arrumar ordem dos dados no eixo x
3800 theme(axis.text.x = element_text(angle=0, hjust=1, vjust=.2))
3801
3802 SLA_all
3803
3804 ### boxplot para todas
3805 ggplot(dados_no_na, aes(x=esp, y=SLA, fill=cen)) +
3806 geom_boxplot()
3807
3808
3809 #####boxplot para Qg
3810
3811
3812 ggplot(data_Qg, aes(x=esp, y=SLA, fill=cen)) +
3813 geom_boxplot()
3814
3815 ##### GLM para Qg
3816
3817 hist(SLA)
3818 SLA_Qg<- c(data_Qg$SLA)
3819
3820 hist(SLA_Qg)
3821
3822 fnorm<-fitdist(data_Qg$SLA, distr = "norm")

```

```

3823 fgamma<-fitdist(data_Qg$SLA, distr = "gamma")
3824 plot(fnorm)
3825 plot(fgamma)
3826 par(mfrow=c(1,1))
3827 famm_SLA_Qg<-gofstat(list(fnorm,fgamma),fitnames = c("norm","gamma"))
3828 denscomp(list(fnorm,fgamma),legendtext = c("norm","gamma"))
3829 #results of the tests
3830 ## chi square test (with corresponding table...)
3831 famm_SLA_Qg$chisqpvalue
3832 famm_SLA_Qg$chisqtable
3833
3834 ## Anderson-Darling test
3835 famm_SLA_Qg$adtest
3836 ## Cramer von Mises test
3837 famm_SLA_Qg$scvmtest
3838 ##Kolmogorov - Smirnov test
3839 famm_SLA_Qg$skstest
3840
3841
3842 SLA_m1_Qg<-glm(data_Qg$SLA~cen,family = Gamma(),data = data_Qg)
3843 SLA_m1_Qg
3844 summary(SLA_m1_Qg)
3845
3846
3847 ##### para Ta #####
3848 #####
3849 ### boxplot para Ta
3850
3851 ggplot(data_Ta, aes(x=esp., y=SLA, fill=cen)) +
3852   geom_boxplot()
3853
3854 ### GLM para Ta
3855
3856 SLA_Ta<- c(data_Ta$SLA)

```

```

3857
3858 hist(SLA_Ta)
3859
3860 fnorm2<-fitdist(data_Ta$SLA, distr = "norm")
3861 fgamma2<-fitdist(data_Ta$SLA, distr = "gamma")
3862 plot(fnorm2)
3863 plot(fgamma2)
3864 par(mfrow=c(1,1))
3865 famm_SLA_Ta<-gofstat(list(fnorm2,fgamma2),fitnames = c("norm","gamma"))
3866 denscomp(list(fnorm2,fgamma2),legendtext = c("norm","gamma"))
3867 #results of the tests
3868 ## chi square test (with corresponding table...)
3869 famm_SLA_Ta$chisqpvalue
3870 famm_SLA_Ta$chisqtable
3871
3872 ## Anderson-Darling test
3873 famm_SLA_Ta$adtest
3874 ## Cramer von Mises test
3875 famm_SLA_Ta$cvmtest
3876 ##Kolmogorov - Smirnov test
3877 famm_SLA_Ta$kstest
3878
3879
3880 SLA_m1_Ta<-glm(data_Ta$SLA~cen,family = Gamma(),data = data_Ta)
3881 SLA_m1_Ta
3882 summary(SLA_m1_Ta)
3883
3884
3885 #####
3886 ##### para Kc #####
3887 ### boxplot para Kc
3888
3889 ggplot(data_Kc, aes(x=esp, y=SLA, fill=cen)) +
3890 geom_boxplot()

```

```

3891
3892 ##### GLM
3893
3894 SLA_Kc<- c(data_Kc$SLA)
3895
3896 hist(SLA_Kc)
3897
3898 fnorm3<-fitdist(data_Kc$SLA, distr = "norm")
3899 fgamma3<-fitdist(data_Kc$SLA, distr = "gamma")
3900 plot(fnorm3)
3901 plot(fgamma3)
3902 par(mfrow=c(1,1))
3903 famm_SLA_Kc<-gofstat(list(fnorm3,fgamma3),fitnames = c("norm","gamma"))
3904 denscomp(list(fnorm3,fgamma3),legendtext = c("norm","gamma"))
3905 #results of the tests
3906 ## chi square test (with corresponding table...)
3907 famm_SLA_Kc$chisqpvalue
3908 famm_SLA_Kc$chisqtable
3909
3910 ## Anderson-Darling test
3911 famm_SLA_Kc$adtest
3912 ## Cramer von Mises test
3913 famm_SLA_Kc$cvmtest
3914 ##Kolmogorov - Smirnov test
3915 famm_SLA_Kc$kstest
3916
3917
3918 SLA_m1_Kc<-glm(data_Kc$SLA~cen,family = Gamma(),data = data_Kc)
3919 SLA_m1_Kc
3920 summary(SLA_m1_Kc)
3921
3922 #####
3923 ##### para Hs
3924 ### boxplot para Hs

```

```

3925
3926 ggplot(data_Hs, aes(x=sp, y=SLA, fill=cen)) +
3927   geom_boxplot()
3928
3929 ##### GLM para Hs
3930
3931 SLA_Hs<- c(data_Hs$SLA)
3932
3933 hist(SLA_Hs)
3934
3935 fnorm4<-fitdist(data_Hs$SLA, distr = "norm")
3936 fgamma4<-fitdist(data_Hs$SLA, distr = "gamma")
3937 plot(fnorm4)
3938 plot(fgamma4)
3939 par(mfrow=c(1,1))
3940 famm_SLA_Hs<-gofstat(list(fnorm4,fgamma4),fitnames = c("norm","gamma"))
3941 denscomp(list(fnorm4,fgamma4),legendtext = c("norm","gamma"))
3942 #results of the tests
3943 ## chi square test (with corresponding table...)
3944 famm_SLA_Hs$chisqpvalue
3945 famm_SLA_Hs$chisqtable
3946 ## Anderson-Darling test
3947 famm_SLA_Hs$adtest
3948 ## Cramer von Mises test
3949 famm_SLA_Hs$cvmtest
3950 ##Kolmogorov - Smirnov test
3951 famm_SLA_Hs$kstest
3952
3953 SLA_m1_Hs<-glm(data_Hs$SLA~cen,family = Gamma(),data = data_Hs)
3954 SLA_m1_Hs
3955 summary(SLA_m1_Hs)
3956
3957 ##### altura H #####
3958 #

```



```

3959 #flexplot e GLM de todas as sp
3960 ## flexplot
3961 H_all= flexplot(H ~ cen + esp.,
3962               data = dados_no_na, se = F, alpha = .3) + scale_x_discrete(limits=c("A","F")) + ## para
3963 arrumar ordem dos dados no eixo x
3964   theme(axis.text.x = element_text(angle=0, hjust=1, vjust=.2))
3965
3966 H_all
3967
3968 #####boxplot para Qg
3969
3970 ggplot(data_Qg, aes(x=esp., y=H, fill=cen)) +
3971   geom_boxplot()
3972 ##### GLM para Qg
3973 hist(H)
3974 H_Qg<- c(data_Qg$H)
3975
3976 hist(H_Qg)
3977 fnorm<-fitdist(data_Qg$H, distr = "norm")
3978 fgamma<-fitdist(data_Qg$H, distr = "gamma")
3979 plot(fnorm)
3980 plot(fgamma)
3981 par(mfrow=c(1,1))
3982 famm_H_Qg<-gofstat(list(fnorm,fgamma),fitnames = c("norm","gamma"))
3983 denscomp(list(fnorm,fgamma),legendtext = c("norm","gamma"))
3984 #results of the tests
3985 ## chi square test (with corresponding table...)
3986 famm_H_Qg$chisqpvalue
3987 famm_H_Qg$chisqtable
3988
3989 ## Anderson-Darling test
3990 famm_H_Qg$adtest
3991 ## Cramer von Mises test
3992 famm_H_Qg$cvmtest
3993 ##Kolmogorov - Smirnov test

```

```

3994 famm_H_Qg$kstest
3995 famm_H_Qg$adtest
3996
3997 H_m1_Qg<-glm(data_Qg$H~cen,family = Gamma(),data = data_Qg)
3998 H_m1_Qg
3999 summary(H_m1_Qg)
4000
4001
4002 ##### para Ta #####
4003 ### boxplot para Ta
4004 ggplot(data_Ta, aes(x=esp., y=H, fill=cen)) +
4005   geom_boxplot()
4006 ### GLM para Ta
4007
4008 H_Ta<- c(data_Ta$H)
4009
4010 hist(H_Ta)
4011
4012 fnorm2<-fitdist(data_Ta$H, distr = "norm")
4013 fgamma2<-fitdist(data_Ta$H, distr = "gamma")
4014 plot(fnorm2)
4015 plot(fgamma2)
4016 par(mfrow=c(1,1))
4017 famm_H_Ta<-gofstat(list(fnorm2,fgamma2),fitnames = c("norm","gamma"))
4018 denscomp(list(fnorm2,fgamma2),legendtext = c("norm","gamma"))
4019 #results of the tests
4020 ## chi square test (with corresponding table...)
4021 famm_H_Ta$chisqpvalue
4022 famm_H_Ta$chisqtable
4023 ## Anderson-Darling test
4024 famm_H_Ta$adtest
4025 ## Cramer von Mises test
4026 famm_H_Ta$svmtest
4027 ##Kolmogorov - Smirnov test

```

```

4028 famm_H_Ta$kstest
4029 H_m1_Ta<-glm(data_Ta$H~cen,family = Gamma(),data = data_Ta)
4030 H_m1_Ta
4031 summary(H_m1_Ta)
4032
4033 H_m2_Ta<-glm(data_Ta$H~cen,family = gaussian(),data = data_Ta)
4034 H_m2_Ta
4035 summary(H_m2_Ta)
4036
4037 #####
4038 ##### para Kc #####
4039 ### boxplot para Kc
4040
4041 ggplot(data_Kc, aes(x=esp., y=H, fill=cen)) +
4042   geom_boxplot()
4043
4044 ##### GLM
4045
4046 H_Kc<- c(data_Kc$H)
4047
4048 hist(H_Kc)
4049
4050 fnorm2<-fitdist(data_Kc$H, distr = "norm")
4051 fgamma2<-fitdist(data_Kc$H, distr = "gamma")
4052 plot(fnorm2)
4053 plot(fgamma2)
4054 par(mfrow=c(1,1))
4055 famm_H_Kc<-gofstat(list(fnorm2,fgamma2),fitnames = c("norm","gamma"))
4056 denscomp(list(fnorm2,fgamma2),legendtext = c("norm","gamma"))
4057 #results of the tests
4058 ## chi square test (with corresponding table...)
4059 famm_H_Kc$chisqpvalue
4060 famm_H_Kc$chisqtable
4061

```

```

4062  ## Anderson-Darling test
4063  famm_H_Kc$adtest
4064  ## Cramer von Mises test
4065  famm_H_Kc$cvmtest
4066  ##Kolmogorov - Smirnov test
4067  famm_H_Kc$kstest
4068
4069
4070  H_m1_Kc<-glm(data_Kc$H~cen,family = Gamma(),data = data_Kc)
4071  H_m1_Kc
4072  summary(H_m1_Kc)
4073
4074  #####
4075  ##### para Hs
4076  ### boxplot para Hs
4077
4078  ggplot(data_Hs, aes(x=esp., y=H, fill=cen)) +
4079    geom_boxplot()
4080
4081  ##### GLM para Hs
4082
4083  H_Hs<- c(data_Hs$H)
4084
4085  hist(H_Hs)
4086
4087  fnorm4<-fitdist(data_Hs$H, distr = "norm")
4088  fgamma4<-fitdist(data_Hs$H, distr = "gamma")
4089  plot(fnorm4)
4090  plot(fgamma4)
4091  par(mfrow=c(1,1))
4092  famm_H_Hs<-gofstat(list(fnorm4,fgamma4),fitnames = c("norm","gamma"))
4093  denscomp(list(fnorm4,fgamma4),legendtext = c("norm","gamma"))
4094  #results of the tests
4095  ## chi square test (with corresponding table...)

```

```

4096 famm_H_Hs$chisqpvalue
4097 famm_H_Hs$chisqtable
4098
4099 ## Anderson-Darling test
4100 famm_H_Hs$adtest
4101 ## Cramer von Mises test
4102 famm_H_Hs$cvmtest
4103 ##Kolmogorov - Smirnov test
4104 famm_H_Hs$kstest
4105
4106
4107 H_m1_Hs<-glm(data_Hs$H~cen,family = Gamma(),data = data_Hs)
4108 H_m1_Hs
4109 summary(H_m1_Hs)
4110
4111 ##### d_base #####
4112 #
4113 #flexplot e GLM de todas as sp
4114 #
4115 ###
4116 ## flexplot
4117 d_base_all= flexplot(d_base ~ cen + esp.,
4118                       data = dados_no_na, se = F, alpha = .3) + scale_x_discrete(limits=c("A","F")) + ## para
4119 arrumar ordem dos dados no eixo x
4120 theme(axis.text.x = element_text(angle=0, hjust=1, vjust=.2))
4121
4122 d_base_all
4123
4124 #####boxplot para Qg
4125
4126 ggplot(data_Qg, aes(x=esp., y=d_base, fill=cen)) +
4127   geom_boxplot()
4128
4129 ##### GLM para Qg
4130

```

```

4131 hist(d_base)
4132 d_base_Qg<- c(data_Qg$d_base)
4133
4134 hist(d_base_Qg)
4135
4136 fnorm<-fitdist(data_Qg$d_base, distr = "norm")
4137 fgamma<-fitdist(data_Qg$d_base, distr = "gamma")
4138 plot(fnorm)
4139 plot(fgamma)
4140 par(mfrow=c(1,1))
4141 famm_d_base_Qg<-gofstat(list(fnorm,fgamma),fitnames = c("norm","gamma"))
4142 denscomp(list(fnorm,fgamma),legendtext = c("norm","gamma"))
4143 #results of the tests
4144 ## chi square test (with corresponding table...)
4145 famm_d_base_Qg$chisqpvalue
4146 famm_d_base_Qg$chisqtable
4147
4148 ## Anderson-Darling test
4149 famm_d_base_Qg$adtest
4150 ## Cramer von Mises test
4151 famm_d_base_Qg$cvmtest
4152 ##Kolmogorov - Smirnov test
4153 famm_d_base_Qg$kstest
4154 famm_d_base_Qg$adtest
4155
4156
4157 d_base_m1_Qg<-glm(data_Qg$d_base~cen,family = Gamma(),data = data_Qg)
4158 d_base_m1_Qg
4159 summary(d_base_m1_Qg)
4160
4161
4162 ##### para Ta #####
4163 #####
4164 ### boxplot para Ta

```

```

4165
4166  ggplot(data_Ta, aes(x=esp., y=d_base, fill=cen)) +
4167    geom_boxplot()
4168
4169  ### GLM para Ta
4170
4171  d_base_Ta<- c(data_Ta$d_base)
4172
4173  hist(d_base_Ta)
4174
4175  fnorm2<-fitdist(data_Ta$d_base, distr = "norm")
4176  fgamma2<-fitdist(data_Ta$d_base, distr = "gamma")
4177  plot(fnorm2)
4178  plot(fgamma2)
4179  par(mfrow=c(1,1))
4180  famm_d_base_Ta<-gofstat(list(fnorm2,fgamma2),fitnames = c("norm","gamma"))
4181  denscomp(list(fnorm2,fgamma2),legendtext = c("norm","gamma"))
4182  #results of the tests
4183  ## chi square test (with corresponding table...)
4184  famm_d_base_Ta$chisqpvalue
4185  famm_H_Ta$chisqtable
4186
4187  ## Anderson-Darling test
4188  famm_d_base_Ta$adtest
4189  ## Cramer von Mises test
4190  famm_d_base_Ta$cvmtest
4191  ##Kolmogorov - Smirnov test
4192  famm_d_base_Ta$kstest
4193
4194
4195  d_base_m1_Ta<-glm(data_Ta$d_base~cen,family = Gamma(),data = data_Ta)
4196  d_base_m1_Ta
4197  summary(d_base_m1_Ta)
4198

```

```

4199 d_base_m2_Ta<-glm(data_Ta$d_base~cen,family = gaussian(),data = data_Ta)
4200 d_base_m2_Ta
4201 summary(d_base_m2_Ta)
4202
4203 #####
4204 ##### para Kc #####
4205 ### boxplot para Kc
4206
4207 ggplot(data_Kc, aes(x=esp., y=d_base, fill=cen)) +
4208   geom_boxplot()
4209
4210 ##### GLM
4211
4212 d_base_Kc<- c(data_Kc$d_base)
4213
4214 hist(d_base_Kc)
4215
4216 fnorm3<-fitdist(data_Kc$d_base, distr = "norm")
4217 fgamma3<-fitdist(data_Kc$d_base, distr = "gamma")
4218 plot(fnorm3)
4219 plot(fgamma3)
4220 par(mfrow=c(1,1))
4221 famm_d_base_Kc<-gofstat(list(fnorm3,fgamma3),fitnames = c("norm","gamma"))
4222 denscomp(list(fnorm3,fgamma3),legendtext = c("norm","gamma"))
4223 #results of the tests
4224 ## chi square test (with corresponding table...)
4225 famm_d_base_Kc$chisqpvalue
4226 famm_d_base_Kc$chisqtable
4227
4228 ## Anderson-Darling test
4229 famm_d_base_Kc$adtest
4230 ## Cramer von Mises test
4231 famm_d_base_Kc$cvmtest
4232 ##Kolmogorov - Smirnov test

```



```

4233 famm_d_base_Kc$kstest
4234
4235
4236 d_base_m1_Kc<-glm(data_Kc$d_base~cen,family = Gamma(),data = data_Kc)
4237 d_base_m1_Kc
4238 summary(d_base_m1_Kc)
4239
4240 #####
4241 ##### para Hs
4242 ### boxplot para Hs
4243
4244 ggplot(data_Hs, aes(x=esp., y=d_base, fill=cen)) +
4245   geom_boxplot()
4246
4247 ##### GLM para Hs
4248
4249 d_base_Hs<- c(data_Hs$d_base)
4250
4251 hist(d_base_Hs)
4252
4253 fnorm4<-fitdist(data_Hs$d_base, distr = "norm")
4254 fgamma4<-fitdist(data_Hs$d_base, distr = "gamma")
4255 plot(fnorm4)
4256 plot(fgamma4)
4257 par(mfrow=c(1,1))
4258 famm_d_base_Hs<-gofstat(list(fnorm4,fgamma4),fitnames = c("norm","gamma"))
4259 denscomp(list(fnorm4,fgamma4),legendtext = c("norm","gamma"))
4260 #results of the tests
4261 ## chi square test (with corresponding table...)
4262 famm_d_base_Hs$chisqpvalue
4263 famm_d_base_Hs$chisqtable
4264
4265 ## Anderson-Darling test
4266 famm_d_base_Hs$adtest

```

```

4267  ## Cramer von Mises test
4268  famm_d_base_Hs$cvmtest
4269  ##Kolmogorov - Smirnov test
4270  famm_d_base_Hs$skstest
4271
4272
4273  d_base_m1_Hs<-glm(data_Hs$d_base~cen,family = Gamma(),data = data_Hs)
4274  d_base_m1_Hs
4275  summary(d_base_m1_Hs)
4276
4277  ##### RGR #####
4278  #
4279  #flexplot e GLM de todas as sp
4280  #
4281  ###
4282  ## flexplot
4283  RER_all= flexplot(RGR ~ cen + esp,
4284                    data = dados_no_na, se = F, alpha = .3) + scale_x_discrete(limits=c("A","F")) + ## para
4285  arrumar ordem dos dados no eixo x
4286  theme(axis.text.x = element_text(angle=0, hjust=1, vjust=.2))
4287
4288  RGR_all
4289
4290  #####boxplot para Qg
4291
4292  ggplot(data_Qg, aes(x=esp, y=RGR, fill=cen)) +
4293  geom_boxplot()
4294
4295  ##### GLM para Qg
4296
4297  hist(RGR)
4298
4299  RGR_Qg<- c(data_Qg$RGR)
4300
4301  hist(RGR_Qg)

```

```

4302
4303 fnorm<-fitdist(data_Qg$RGR, distr = "norm")
4304 fgamma<-fitdist(data_Qg$RGR, distr = "gamma")
4305 plot(fnorm)
4306 plot(fgamma)
4307 par(mfrow=c(1,1))
4308 famm_RGR_Qg<-gofstat(list(fnorm,fgamma),fitnames = c("norm","gamma"))
4309 denscomp(list(fnorm,fgamma),legendtext = c("norm","gamma"))
4310 #results of the tests
4311 ## chi square test (with corresponding table...)
4312 famm_RGR_Qg$chisqpvalue
4313 famm_RGR_Qg$chisqtable
4314
4315 ## Anderson-Darling test
4316 famm_RGR_Qg$adtest
4317 ## Cramer von Mises test
4318 famm_RGR_Qg$scvmtest
4319 ##Kolmogorov - Smirnov test
4320 famm_RGR_Qg$kstest
4321 famm_RGR_Qg$adtest
4322
4323
4324 RGR_m1_Qg<-glm(data_Qg$RGR~cen,family = Gamma(),data = data_Qg)
4325 RGR_m1_Qg
4326 summary(RGR_m1_Qg)
4327
4328
4329 ##### para Ta #####
4330 #####
4331 ### boxplot para Ta
4332
4333 ggplot(data_Ta, aes(x=esp, y=RGR, fill=cen)) +
4334 geom_boxplot()
4335

```

```

4336   ### GLM para Ta
4337
4338   RGR_Ta<- c(data_Ta$RGR)
4339
4340   hist(RGR_Ta)
4341
4342   fnorm2<-fitdist(data_Ta$RGR, distr = "norm")
4343   fgamma2<-fitdist(data_Ta$RGR, distr = "gamma")
4344   plot(fnorm2)
4345   plot(fgamma2)
4346   par(mfrow=c(1,1))
4347   famm_RGR_Ta<-gofstat(list(fnorm2,fgamma2),fitnames = c("norm","gamma"))
4348   denscomp(list(fnorm2,fgamma2),legendtext = c("norm","gamma"))
4349   #results of the tests
4350   ## chi square test (with corresponding table...)
4351   famm_RGR_Ta$chisqpvalue
4352   famm_H_Ta$chisqtable
4353
4354   ## Anderson-Darling test
4355   famm_RGR_Ta$adtest
4356   ## Cramer von Mises test
4357   famm_RGR_Ta$scvmtest
4358   ##Kolmogorov - Smirnov test
4359   famm_RGR_Ta$kstest
4360
4361
4362   RGR_m1_Ta<-glm(data_Ta$RGR~cen,family = Gamma(),data = data_Ta)
4363   RGR_m1_Ta
4364   summary(RGR_m1_Ta)
4365
4366   RGR_m2_Ta<-glm(data_Ta$RGR~cen,family = gaussian(),data = data_Ta)
4367   RGR_m2_Ta
4368   summary(RGR_m2_Ta)
4369

```

```

4370 #####
4371 ##### para Kc #####
4372 ### boxplot para Kc
4373
4374 ggplot(data_Kc, aes(x=esp, y=RGR, fill=cen)) +
4375   geom_boxplot()
4376
4377 ##### GLM
4378
4379 RGR_Kc<- c(data_Kc$RGR)
4380
4381 hist(RGR_Kc)
4382
4383 fnorm3<-fitdist(data_Kc$RGR, distr = "norm")
4384 fgamma3<-fitdist(data_Kc$RGR, distr = "gamma")
4385 plot(fnorm3)
4386 plot(fgamma3)
4387 par(mfrow=c(1,1))
4388 famm_RGR_Kc<-gofstat(list(fnorm3,fgamma3),fitnames = c("norm","gamma"))
4389 denscomp(list(fnorm3,fgamma3),legendtext = c("norm","gamma"))
4390 #results of the tests
4391 ## chi square test (with corresponding table...)
4392 famm_RGR_Kc$chisqpvalue
4393 famm_RGR_Kc$chisqtable
4394
4395 ## Anderson-Darling test
4396 famm_RGR_Kc$adtest
4397 ## Cramer von Mises test
4398 famm_RGR_Kc$cvmtest
4399 ##Kolmogorov - Smirnov test
4400 famm_RGR_Kc$kstest
4401
4402
4403 RGR_m1_Kc<-glm(data_Kc$RGR~cen,family = Gamma(),data = data_Kc)

```

```

4404 RGR_m1_Kc
4405 summary(RGR_m1_Kc)
4406
4407 #####
4408 ##### para Hs #####
4409 ### boxplot para Hs
4410
4411 ggplot(data_Hs, aes(x=esp, y=RGR, fill=cen)) +
4412   geom_boxplot()
4413
4414 ##### GLM para Hs
4415
4416 RGR_Hs<- c(data_Hs$RGR)
4417
4418 hist(RGR_Hs)
4419
4420 fnorm4<-fitdist(data_Hs$RGR, distr = "norm")
4421 fgamma4<-fitdist(data_Hs$RGR, distr = "gamma")
4422 plot(fnorm4)
4423 plot(fgamma4)
4424 par(mfrow=c(1,1))
4425 famm_RGR_Hs<-gofstat(list(fnorm4,fgamma4),fitnames = c("norm","gamma"))
4426 denscomp(list(fnorm4,fgamma4),legendtext = c("norm","gamma"))
4427 #results of the tests
4428 ## chi square test (with corresponding table...)
4429 famm_RGR_Hs$chisqpvalue
4430 famm_RGR_Hs$chisqtable
4431
4432 ## Anderson-Darling test
4433 famm_RGR_Hs$adtest
4434 ## Cramer von Mises test
4435 famm_RGR_Hs$scvmtest
4436 ##Kolmogorov - Smirnov test
4437 famm_RGR_Hs$skstest

```

```

4438
4439
4440 RGR_m1_Hs<-glm(data_Hs$RGR~cen,family = Gamma(),data = data_Hs)
4441 RGR_m1_Hs
4442 summary(RGR_m1_Hs)
4443
4444 ##### RER #####
4445 #
4446 #flexplot e GLM de todas as sp
4447 #
4448 ###
4449 ## flexplot
4450 RER_all= flexplot(RER ~ cen + esp,
4451                 data = dados_no_na, se = F, alpha = .3) + scale_x_discrete(limits=c("A","F")) + ## para
4452 arrumar ordem dos dados no eixo x
4453 theme(axis.text.x = element_text(angle=0, hjust=1, vjust=.2))
4454
4455 RER_all
4456
4457 #####boxplot para Qg
4458
4459 ggplot(data_Qg, aes(x=esp, y=RER, fill=cen)) +
4460 geom_boxplot()
4461
4462 ##### GLM para Qg
4463
4464 hist(RER)
4465
4466 RER_Qg<- c(data_Qg$RER)
4467
4468 hist(RER_Qg)
4469
4470 fnorm<-fitdist(data_Qg$RER, distr = "norm")
4471 fgamma<-fitdist(data_Qg$RER, distr = "gamma")
4472 plot(fnorm)

```

```

4473 plot(fgamma)
4474 par(mfrow=c(1,1))
4475 famm_RER_Qg<-gofstat(list(fnorm,fgamma),fitnames = c("norm","gamma"))
4476 denscomp(list(fnorm,fgamma),legendtext = c("norm","gamma"))
4477 #results of the tests
4478 ## chi square test (with corresponding table...)
4479 famm_RER_Qg$chisqpvalue
4480 famm_RER_Qg$chisqtable
4481
4482 ## Anderson-Darling test
4483 famm_RER_Qg$adtest
4484 ## Cramer von Mises test
4485 famm_RER_Qg$scvmtest
4486 ##Kolmogorov - Smirnov test
4487 famm_RER_Qg$skstest
4488 famm_RER_Qg$adtest
4489
4490
4491 RER_m1_Qg<-glm(data_Qg$RER~cen,family = Gamma(),data = data_Qg)
4492 RER_m1_Qg
4493 summary(RER_m1_Qg)
4494
4495
4496 ##### para Ta #####
4497 #####
4498 ### boxplot para Ta
4499
4500 ggplot(data_Ta, aes(x=esp, y=RER, fill=cen)) +
4501   geom_boxplot()
4502
4503 ### GLM para Ta
4504
4505 RER_Ta<- c(data_Ta$RER)
4506

```



```

4507 hist(RER_Ta)
4508
4509 fnorm2<-fitdist(data_Ta$RER, distr = "norm")
4510 fgamma2<-fitdist(data_Ta$RER, distr = "gamma")
4511 plot(fnorm2)
4512 plot(fgamma2)
4513 par(mfrow=c(1,1))
4514 famm_RER_Ta<-gofstat(list(fnorm2,fgamma2),fitnames = c("norm","gamma"))
4515 denscomp(list(fnorm2,fgamma2),legendtext = c("norm","gamma"))
4516 #results of the tests
4517 ## chi square test (with corresponding table...)
4518 famm_RER_Ta$chisqpvalue
4519 famm_RER_Ta$chisqtable
4520
4521 ## Anderson-Darling test
4522 famm_RER_Ta$adtest
4523 ## Cramer von Mises test
4524 famm_RER_Ta$cvmtest
4525 ##Kolmogorov - Smirnov test
4526 famm_RER_Ta$kstest
4527
4528
4529 RER_m1_Ta<-glm(data_Ta$RER~cen,family = Gamma(),data = data_Ta)
4530 RER_m1_Ta
4531 summary(RER_m1_Ta)
4532
4533 RER_m2_Ta<-glm(data_Ta$RER~cen,family = gaussian(),data = data_Ta)
4534 RER_m2_Ta
4535 summary(RER_m2_Ta)
4536
4537 #####
4538 ##### para Kc #####
4539 ### boxplot para Kc
4540

```

```

4541 ggplot(data_Kc, aes(x=esp, y=RER, fill=cen)) +
4542   geom_boxplot()
4543
4544 ##### GLM
4545
4546 RER_Kc<- c(data_Kc$RER)
4547
4548 hist(RER_Kc)
4549
4550 fnorm3<-fitdist(data_Kc$RER, distr = "norm")
4551 fgamma3<-fitdist(data_Kc$RER, distr = "gamma")
4552 plot(fnorm3)
4553 plot(fgamma3)
4554 par(mfrow=c(1,1))
4555 famm_RER_Kc<-gofstat(list(fnorm3,fgamma3),fitnames = c("norm","gamma"))
4556 denscomp(list(fnorm3,fgamma3),legendtext = c("norm","gamma"))
4557 #results of the tests
4558 ## chi square test (with corresponding table...)
4559 famm_RER_Kc$chisqpvalue
4560 famm_RER_Kc$chisqtable
4561 ## Anderson-Darling test
4562 famm_RER_Kc$adtest
4563 ## Cramer von Mises test
4564 famm_RER_Kc$cvmtest
4565 ##Kolmogorov - Smirnov test
4566 famm_RER_Kc$kstest
4567
4568 RER_m1_Kc<-glm(data_Kc$RER~cen,family = Gamma(),data = data_Kc)
4569 RER_m1_Kc
4570 summary(RER_m1_Kc)
4571 #####
4572 ##### para Hs #####
4573 ### boxplot para Hs
4574

```

```

4575 ggplot(data_Hs, aes(x=esp, y=RER, fill=cen)) +
4576   geom_boxplot()
4577 ##### GLM para Hs
4578
4579 RER_Hs<- c(data_Hs$RER)
4580
4581 hist(RER_Hs)
4582 fnorm4<-fitdist(data_Hs$RER, distr = "norm")
4583 fgamma4<-fitdist(data_Hs$RER, distr = "gamma")
4584 plot(fnorm4)
4585 plot(fgamma4)
4586 par(mfrow=c(1,1))
4587 famm_RER_Hs<-gofstat(list(fnorm4,fgamma4),fitnames = c("norm","gamma"))
4588 denscomp(list(fnorm4,fgamma4),legendtext = c("norm","gamma"))
4589 #results of the tests
4590 ## chi square test (with corresponding table...)
4591 famm_RER_Hs$chisqpvalue
4592 famm_RER_Hs$chisqtable
4593 ## Anderson-Darling test
4594 famm_RER_Hs$adtest
4595 ## Cramer von Mises test
4596 famm_RER_Hs$cvmtest
4597 ##Kolmogorov - Smirnov test
4598 famm_RER_Hs$kstest
4599
4600 RER_m1_Hs<-glm(data_Hs$RER~cen,family = Gamma(),data = data_Hs)
4601 RER_m1_Hs
4602 summary(RER_m1_Hs)
4603
4604 ##### SLA #####
4605 #
4606 #flexplot e GLM de todas as sp
4607 ## flexplot
4608 SLA_all= flexplot(SLA ~ cen + esp,

```

```

4609         data = dados_no_na, se = F, alpha = .3) + scale_x_discrete(limits=c("A","F")) + ## para
4610 arrumar ordem dos dados no eixo x
4611     theme(axis.text.x = element_text(angle=0, hjust=1, vjust=.2))
4612     SLA_all
4613     #####boxplot para Qg
4614
4615     ggplot(data_Qg, aes(x=esp, y=SLA, fill=cen)) +
4616     geom_boxplot()
4617     ##### GLM para Qg
4618     hist(SLA)
4619     SLA_Qg<- c(data_Qg$SLA)
4620
4621     hist(SLA_Qg)
4622     fnorm<-fitdist(data_Qg$SLA, distr = "norm")
4623     fgamma<-fitdist(data_Qg$SLA, distr = "gamma")
4624     plot(fnorm)
4625     plot(fgamma)
4626     par(mfrow=c(1,1))
4627     famm_SLA_Qg<-gofstat(list(fnorm,fgamma),fitnames = c("norm","gamma"))
4628     denscomp(list(fnorm,fgamma),legendtext = c("norm","gamma"))
4629     #results of the tests
4630     ## chi square test (with corresponding table...)
4631     famm_SLA_Qg$chisqpvalue
4632     famm_SLA_Qg$chisqtable
4633     ## Anderson-Darling test
4634     famm_SLA_Qg$adtest
4635     ## Cramer von Mises test
4636     famm_SLA_Qg$scvmtest
4637     ##Kolmogorov - Smirnov test
4638     famm_SLA_Qg$skstest
4639     famm_SLA_Qg$adtest
4640
4641     SLA_m1_Qg<-glm(data_Qg$SLA~cen,family = Gamma(),data = data_Qg)
4642     SLA_m1_Qg
4643     summary(SLA_m1_Qg)

```

```

4644
4645 ##### para Ta #####
4646 #####
4647 ### boxplot para Ta
4648 ggplot(data_Ta, aes(x=esp, y=SLA, fill=cen)) +
4649   geom_boxplot()
4650
4651 ### GLM para Ta
4652 SLA_Ta<- c(data_Ta$SLA)
4653 hist(SLA_Ta)
4654 fnorm2<-fitdist(data_Ta$SLA, distr = "norm")
4655 fgamma2<-fitdist(data_Ta$SLA, distr = "gamma")
4656 plot(fnorm2)
4657 plot(fgamma2)
4658 par(mfrow=c(1,1))
4659 famm_SLA_Ta<-gofstat(list(fnorm2,fgamma2),fitnames = c("norm","gamma"))
4660 denscomp(list(fnorm2,fgamma2),legendtext = c("norm","gamma"))
4661 #results of the tests
4662 ## chi square test (with corresponding table...)
4663 famm_SLA_Ta$chisqpvalue
4664 famm_SLA_Ta$chisqtable
4665 ## Anderson-Darling test
4666 famm_SLA_Ta$adtest
4667 ## Cramer von Mises test
4668 famm_SLA_Ta$cvmtest
4669 ##Kolmogorov - Smirnov test
4670 famm_SLA_Ta$kstest
4671
4672 SLA_m1_Ta<-glm(data_Ta$SLA~cen,family = Gamma(),data = data_Ta)
4673 SLA_m1_Ta
4674 summary(SLA_m1_Ta)
4675 SLA_m2_Ta<-glm(data_Ta$SLA~cen,family = gaussian(),data = data_Ta)
4676 SLA_m2_Ta
4677 summary(SLA_m2_Ta)

```

```

4678 #####
4679 ##### para Kc #####
4680 ### boxplot para Kc
4681
4682 ggplot(data_Kc, aes(x=esp, y=SLA, fill=cen)) +
4683   geom_boxplot()
4684 ##### GLM
4685
4686 SLA_Kc<- c(data_Kc$SLA)
4687 hist(SLA_Kc)
4688 fnorm3<-fitdist(data_Kc$SLA, distr = "norm")
4689 fgamma3<-fitdist(data_Kc$SLA, distr = "gamma")
4690 plot(fnorm3)
4691 plot(fgamma3)
4692 par(mfrow=c(1,1))
4693 famm_SLA_Kc<-gofstat(list(fnorm3,fgamma3),fitnames = c("norm","gamma"))
4694 denscomp(list(fnorm3,fgamma3),legendtext = c("norm","gamma"))
4695 #results of the tests
4696 ## chi square test (with corresponding table...)
4697 famm_SLA_Kc$chisqpvalue
4698 famm_SLA_Kc$chisqtable
4699 ## Anderson-Darling test
4700 famm_SLA_Kc$adtest
4701 ## Cramer von Mises test
4702 famm_SLA_Kc$cvmtest
4703 ##Kolmogorov - Smirnov test
4704 famm_SLA_Kc$kstest
4705
4706 SLA_m1_Kc<-glm(data_Kc$SLA~cen,family = Gamma(),data = data_Kc)
4707 SLA_m1_Kc
4708 summary(SLA_m1_Kc)
4709
4710 ##### para Hs #####
4711 ### boxplot para Hs

```

```

4712
4713 ggplot(data_Hs, aes(x=esp, y=SLA, fill=cen)) +
4714   geom_boxplot()
4715
4716 ##### GLM para Hs
4717
4718 SLA_Hs<- c(data_Hs$SLA)
4719 hist(SLA_Hs)
4720 fnorm4<-fitdist(data_Hs$SLA, distr = "norm")
4721 fgamma4<-fitdist(data_Hs$SLA, distr = "gamma")
4722 plot(fnorm4)
4723 plot(fgamma4)
4724 par(mfrow=c(1,1))
4725 famm_SLA_Hs<-gofstat(list(fnorm4,fgamma4),fitnames = c("norm","gamma"))
4726 denscomp(list(fnorm4,fgamma4),legendtext = c("norm","gamma"))
4727 #results of the tests
4728 ## chi square test (with corresponding table...)
4729 famm_SLA_Hs$chisqpvalue
4730 famm_SLA_Hs$chisqtable
4731
4732 ## Anderson-Darling test
4733 famm_SLA_Hs$adtest
4734 ## Cramer von Mises test
4735 famm_SLA_Hs$cvmtest
4736 ##Kolmogorov - Smirnov test
4737 famm_SLA_Hs$kstest
4738
4739 SLA_m1_Hs<-glm(data_Hs$SLA~cen,family = Gamma(),data = data_Hs)
4740 SLA_m1_Hs
4741 summary(SLA_m1_Hs)
4742
4743 ##### Lnum #####
4744 ##flexplot e GLM de todas as sp
4745

```

```

4746  ## flexplot
4747  nL_all= flexplot(nL ~ cen + esp,
4748                data = dados_no_na, se = F, alpha = .3) + scale_x_discrete(limits=c("A","F")) + ## para
4749  arrumar ordem dos dados no eixo x
4750  theme(axis.text.x = element_text(angle=0, hjust=1, vjust=.2))
4751
4752  nL_all
4753  #####boxplot para Qg
4754
4755  ggplot(data_Qg, aes(x=esp, y=nL, fill=cen)) +
4756  geom_boxplot()
4757
4758  ##### GLM para Qg
4759
4760  hist(nL)
4761  nL_Qg<- c(data_Qg$nL)
4762
4763  hist(nL_Qg)
4764
4765  fnorm<-fitdist(data_Qg$nL, distr = "norm")
4766  fgamma<-fitdist(data_Qg$nL, distr = "gamma")
4767  plot(fnorm)
4768  plot(fgamma)
4769  par(mfrow=c(1,1))
4770  famm_nL_Qg<-gofstat(list(fnorm,fgamma),fitnames = c("norm","gamma"))
4771  denscomp(list(fnorm,fgamma),legendtext = c("norm","gamma"))
4772  #results of the tests
4773  ## chi square test (with corresponding table...)
4774  famm_nL_Qg$chisqpvalue
4775  famm_nL_Qg$chisqtable
4776
4777  ## Anderson-Darling test
4778  famm_nL_Qg$adtest
4779  ## Cramer von Mises test
4780  famm_nL_Qg$cvmtest

```



```

4781  ##Kolmogorov - Smirnov test
4782  famm_nL_Qg$kstest
4783
4784
4785  nL_m1_Qg<-glm(data_Qg$nL~cen,family = Gamma(),data = data_Qg)
4786  nL_m1_Qg
4787  summary(nL_m1_Qg)
4788
4789  ##### para Ta #####
4790  ### boxplot para Ta
4791
4792  ggplot(data_Ta, aes(x=esp, y=nL, fill=cen)) +
4793    geom_boxplot()
4794
4795  ### GLM para Ta
4796  nL_Ta<- c(data_Ta$nL)
4797
4798  hist(nL_Ta)
4799  fnorm2<-fitdist(data_Ta$nL, distr = "norm")
4800  fgamma2<-fitdist(data_Ta$nL, distr = "gamma")
4801  plot(fnorm2)
4802  plot(fgamma2)
4803  par(mfrow=c(1,1))
4804  famm_nL_Ta<-gofstat(list(fnorm2,fgamma2),fitnames = c("norm","gamma"))
4805  denscomp(list(fnorm2,fgamma2),legendtext = c("norm","gamma"))
4806  #results of the tests
4807  ## chi square test (with corresponding table...)
4808  famm_nL_Ta$chisqpvalue
4809  famm_nL_Ta$chisqtable
4810  ## Anderson-Darling test
4811  famm_nL_Ta$adtest
4812  ## Cramer von Mises test
4813  famm_nL_Ta$cvmtest
4814  ##Kolmogorov - Smirnov test

```

```

4815 famm_nL_Ta$skstest
4816
4817 nL_m1_Ta<-glm(data_Ta$nL~cen,family = Gamma(),data = data_Ta)
4818 nL_m1_Ta
4819 summary(nL_m1_Ta)
4820
4821 nL_m2_Ta<-glm(data_Ta$nL~cen,family = gaussian(),data = data_Ta)
4822 nL_m2_Ta
4823 summary(nL_m2_Ta)
4824 ##### para Kc #####
4825 ### boxplot para Kc
4826 ggplot(data_Kc, aes(x=esp, y=nL, fill=cen)) +
4827   geom_boxplot()
4828
4829 ##### GLM
4830 nL_Kc<- c(data_Kc$nL)
4831 hist(nL_Kc)
4832
4833 fnorm3<-fitdist(data_Kc$nL, distr = "norm")
4834 fgamma3<-fitdist(data_Kc$nL, distr = "gamma")
4835 plot(fnorm3)
4836 plot(fgamma3)
4837 par(mfrow=c(1,1))
4838 famm_nL_Kc<-gofstat(list(fnorm2,fgamma2),fitnames = c("norm","gamma"))
4839 denscomp(list(fnorm2,fgamma2),legendtext = c("norm","gamma"))
4840 #results of the tests
4841 ## chi square test (with corresponding table...)
4842 famm_nL_Kc$chisqpvalue
4843 famm_nL_Kc$chisqtable
4844 ## Anderson-Darling test
4845 famm_nL_Kc$adtest
4846 ## Cramer von Mises test
4847 famm_nL_Kc$cvmtest
4848 ##Kolmogorov - Smirnov test

```

```

4849 famm_nL_Kc$skstest
4850
4851 nL_m1_Kc<-glm(data_Kc$nL~cen,family = Gamma(),data = data_Kc)
4852 nL_m1_Kc
4853 summary(nL_m1_Kc)
4854
4855 ##### para Hs #####
4856 ### boxplot para Hs
4857 ggplot(data_Hs, aes(x=esp, y=nL, fill=cen)) +
4858   geom_boxplot()
4859
4860 ##### GLM para Hs
4861
4862 nL_Hs<- c(data_Hs$nL)
4863
4864 hist(nL_Hs)
4865 fnorm4<-fitdist(data_Hs$nL, distr = "norm")
4866 fgamma4<-fitdist(data_Hs$nL, distr = "gamma")
4867 plot(fnorm4)
4868 plot(fgamma4)
4869 par(mfrow=c(1,1))
4870 famm_nL_Hs<-gofstat(list(fnorm4,fgamma4),fitnames = c("norm","gamma"))
4871 denscomp(list(fnorm4,fgamma4),legendtext = c("norm","gamma"))
4872 #results of the tests
4873 ## chi square test (with corresponding table...)
4874 famm_nL_Hs$chisqpvalue
4875 famm_nL_Hs$chisqtable
4876 ## Anderson-Darling test
4877 famm_nL_Hs$adtest
4878 ## Cramer von Mises test
4879 famm_nL_Hs$scvmtest
4880 ##Kolmogorov - Smirnov test
4881 famm_nL_Hs$skstest
4882

```

```

4883 nL_m1_Hs<-glm(data_Hs$nL~cen,family = Gamma(),data = data_Hs)
4884 nL_m1_Hs
4885 summary(nL_m1_Hs)
4886
4887 ##### STRL #####
4888 #flexplot e GLM de todas as sp
4889 ## flexplot
4890 STRL_all= flexplot(STRL ~ cen + esp,
4891                   data = dados_no_na, se = F, alpha = .3) + scale_x_discrete(limits=c("A","F")) + ## para
4892 arrumar ordem dos dados no eixo x
4893   theme(axis.text.x = element_text(angle=0, hjust=1, vjust=.2))
4894
4895 STRL_all
4896 #####boxplot para Qg
4897 ggplot(data_Qg, aes(x=esp, y=STRL, fill=cen)) +
4898   geom_boxplot()
4899
4900 ##### GLM para Qg
4901 hist(STRL)
4902 STRL_Qg<- c(data_Qg$STRL)
4903 hist(STRL_Qg)
4904 fnorm<-fitdist(data_Qg$STRL, distr = "norm")
4905 fgamma<-fitdist(data_Qg$STRL, distr = "gamma")
4906 plot(fnorm)
4907 plot(fgamma)
4908 par(mfrow=c(1,1))
4909 famm_STRL_Qg<-gofstat(list(fnorm,fgamma),fitnames = c("norm","gamma"))
4910 denscomp(list(fnorm,fgamma),legendtext = c("norm","gamma"))
4911 #results of the tests
4912 ## chi square test (with corresponding table...)
4913 famm_STRL_Qg$chisqpvalue
4914 famm_STRL_Qg$chisqtable
4915 ## Anderson-Darling test
4916 famm_STRL_Qg$adtest
4917 ## Cramer von Mises test

```

```

4918 famm_STRL_Qg$cvmtest
4919 ##Kolmogorov - Smirnov test
4920 famm_STRL_Qg$kstest
4921
4922 STRL_m1_Qg<-glm(data_Qg$STRL~cen,family = Gamma(),data = data_Qg)
4923 STRL_m1_Qg
4924 summary(STRL_m1_Qg)
4925
4926 ##### para Ta #####
4927 ### boxplot para Ta
4928
4929 ggplot(data_Ta, aes(x=esp, y=STRL, fill=cen)) +
4930   geom_boxplot()
4931
4932 ### GLM para Ta
4933
4934 STRL_Ta<- c(data_Ta$STRL)
4935
4936 hist(STRL_Ta)
4937 fnorm2<-fitdist(data_Ta$STRL, distr = "norm")
4938 fgamma2<-fitdist(data_Ta$STRL, distr = "gamma")
4939 plot(fnorm2)
4940 plot(fgamma2)
4941 par(mfrow=c(1,1))
4942 famm_STRL_Ta<-gofstat(list(fnorm2,fgamma2),fitnames = c("norm","gamma"))
4943 denscomp(list(fnorm2,fgamma2),legendtext = c("norm","gamma"))
4944 #results of the tests
4945 ## chi square test (with corresponding table...)
4946 famm_STRL_Ta$chisqpvalue
4947 famm_STRL_Ta$chisqtable
4948 ## Anderson-Darling test
4949 famm_STRL_Ta$adtest
4950 ## Cramer von Mises test
4951 famm_STRL_Ta$cvmtest

```

```

4952  ##Kolmogorov - Smirnov test
4953  famm_STRL_Ta$kstest
4954
4955  STRL_m1_Ta<-glm(data_Ta$STRL~cen,family = Gamma(),data = data_Ta)
4956  STRL_m1_Ta
4957  summary(STRL_m1_Ta)
4958
4959  STRL_m2_Ta<-glm(data_Ta$STRL~cen,family = gaussian(),data = data_Ta)
4960  STRL_m2_Ta
4961  summary(STRL_m2_Ta)
4962  ##### para Kc #####
4963  ### boxplot para Kc
4964
4965  ggplot(data_Kc, aes(x=esp, y=STRL, fill=cen)) +
4966    geom_boxplot()
4967
4968  ##### GLM
4969  STRL_Kc<- c(data_Kc$STRL)
4970  hist(STRL_Kc)
4971
4972  fnorm3<-fitdist(data_Kc$STRL, distr = "norm")
4973  fgamma3<-fitdist(data_Kc$STRL, distr = "gamma")
4974  plot(fnorm3)
4975  plot(fgamma3)
4976  par(mfrow=c(1,1))
4977  famm_STRL_Kc<-gofstat(list(fnorm3,fgamma3),fitnames = c("norm","gamma"))
4978  denscomp(list(fnorm3,fgamma3),legendtext = c("norm","gamma"))
4979  #results of the tests
4980  ## chi square test (with corresponding table...)
4981  famm_STRL_Kc$chisqpvalue
4982  famm_STRL_Kc$chisqtable
4983  ## Anderson-Darling test
4984  famm_STRL_Kc$adtest
4985  ## Cramer von Mises test

```

```

4986 famm_STRL_Kc$scvmtest
4987 ###Kolmogorov - Smirnov test
4988 famm_STRL_Kc$kstest
4989
4990
4991 STRL_m1_Kc<-glm(data_Kc$STRL~cen,family = Gamma(),data = data_Kc)
4992 STRL_m1_Kc
4993 summary(STRL_m1_Kc)
4994
4995 ##### para Hs #####
4996 ### boxplot para Hs
4997
4998 ggplot(data_Hs, aes(x=esp, y=STRL, fill=cen)) +
4999   geom_boxplot()
5000
5001 ##### GLM para Hs
5002 STRL_Hs<- c(data_Hs$STRL)
5003 hist(STRL_Hs)
5004
5005 fnorm4<-fitdist(data_Hs$STRL, distr = "norm")
5006 fgamma4<-fitdist(data_Hs$STRL, distr = "gamma")
5007 plot(fnorm4)
5008 plot(fgamma4)
5009 par(mfrow=c(1,1))
5010 famm_STRL_Hs<-gofstat(list(fnorm4,fgamma4),fitnames = c("norm","gamma"))
5011 denscomp(list(fnorm4,fgamma4),legendtext = c("norm","gamma"))
5012 #results of the tests
5013 ## chi square test (with corresponding table...)
5014 famm_STRL_Hs$chisqpvalue
5015 famm_STRL_Hs$chisqtable
5016 ## Anderson-Darling test
5017 famm_STRL_Hs$adtest
5018 ## Cramer von Mises test
5019 famm_STRL_Hs$scvmtest

```

```

5020  ##Kolmogorov - Smirnov test
5021  famm_STRL_Hs$kstest
5022
5023
5024  STRL_m1_Hs<-glm(data_Hs$STRL~cen,family = Gamma(),data = data_Hs)
5025  STRL_m1_Hs
5026  summary(STRL_m1_Hs)
5027
5028  ##### RMF #####
5029  #
5030  #flexplot e GLM de todas as sp
5031  ## flexplot
5032  RMF_all= flexplot(RMF ~ cen + esp,
5033                    data = dados_no_na, se = F, alpha = .3) + scale_x_discrete(limits=c("A","F")) + ## para
5034  arrumar ordem dos dados no eixo x
5035  theme(axis.text.x = element_text(angle=0, hjust=1, vjust=.2))
5036
5037  RMF_all
5038
5039  #####boxplot para Qg
5040  ggplot(data_Qg, aes(x=esp, y=RMF, fill=cen)) +
5041  geom_boxplot()
5042
5043  ##### GLM para Qg
5044
5045  hist(RMF)
5046  RMF_Qg<- c(data_Qg$RMF)
5047  hist(RMF_Qg)
5048
5049  fnorm<-fitdist(data_Qg$RMF, distr = "norm")
5050  fgamma<-fitdist(data_Qg$RMF, distr = "gamma")
5051  plot(fnorm)
5052  plot(fgamma)
5053  par(mfrow=c(1,1))
5054  famm_RMF_Qg<-gofstat(list(fnorm,fgamma),fitnames = c("norm","gamma"))

```



```

5055 denscomp(list(fnorm,fgamma),legendtext = c("norm","gamma"))
5056 #results of the tests
5057 ## chi square test (with corresponding table...)
5058 famm_RMF_Qg$chisqpvalue
5059 famm_RMF_Qg$chisqtable
5060 ## Anderson-Darling test
5061 famm_RMF_Qg$adtest
5062 ## Cramer von Mises test
5063 famm_RMF_Qg$cvmtest
5064 ##Kolmogorov - Smirnov test
5065 famm_RMF_Qg$kstest
5066
5067 RMF_m1_Qg<-glm(data_Qg$RMF~cen,family = Gamma(),data = data_Qg)
5068 RMF_m1_Qg
5069 summary(RMF_m1_Qg)
5070
5071 ##### para Ta #####
5072 ### boxplot para Ta
5073
5074 ggplot(data_Ta, aes(x=esp, y=RMF, fill=cen)) +
5075   geom_boxplot()
5076
5077 ### GLM para Ta
5078 RMF_Ta<- c(data_Ta$RMF)
5079
5080 hist(RMF_Ta)
5081 fnorm2<-fitdist(data_Ta$RMF, distr = "norm")
5082 fgamma2<-fitdist(data_Ta$RMF, distr = "gamma")
5083 plot(fnorm2)
5084 plot(fgamma2)
5085 par(mfrow=c(1,1))
5086 famm_RMF_Ta<-gofstat(list(fnorm2,fgamma2),fitnames = c("norm","gamma"))
5087 denscomp(list(fnorm2,fgamma2),legendtext = c("norm","gamma"))
5088 #results of the tests

```

```

5089  ## chi square test (with corresponding table...)
5090  famm_RMF_Ta$chisqpvalue
5091  famm_RMF_Ta$chisqtable
5092  ## Anderson-Darling test
5093  famm_RMF_Ta$adtest
5094  ## Cramer von Mises test
5095  famm_RMF_Ta$cvmttest
5096  ##Kolmogorov - Smirnov test
5097  famm_RMF_Ta$kstest
5098
5099  RMF_m1_Ta<-glm(data_Ta$RMF~cen,family = Gamma(),data = data_Ta)
5100  RMF_m1_Ta
5101  summary(RMF_m1_Ta)
5102
5103  RMF_m2_Ta<-glm(data_Ta$RMF~cen,family = gaussian(),data = data_Ta)
5104  RMF_m2_Ta
5105  summary(RMF_m2_Ta)
5106
5107  ##### para Kc #####
5108  ### boxplot para Kc
5109  ggplot(data_Kc, aes(x=esp, y=RMF, fill=cen)) +
5110    geom_boxplot()
5111
5112  ##### GLM
5113  RMF_Kc<- c(data_Kc$RMF)
5114
5115  hist(RMF_Kc)
5116  fnorm3<-fitdist(data_Kc$RMF, distr = "norm")
5117  fgamma3<-fitdist(data_Kc$RMF, distr = "gamma")
5118  plot(fnorm3)
5119  plot(fgamma3)
5120  par(mfrow=c(1,1))
5121  famm_RMF_Kc<-gofstat(list(fnorm3,fgamma3),fitnames = c("norm","gamma"))
5122  denscomp(list(fnorm3,fgamma3),legendtext = c("norm","gamma"))

```

```

5123 #results of the tests
5124 ## chi square test (with corresponding table...)
5125 famm_RMF_Kc$chisqpvalue
5126 famm_RMF_Kc$chisqtable
5127
5128 ## Anderson-Darling test
5129 famm_RMF_Kc$adtest
5130 ## Cramer von Mises test
5131 famm_RMF_Kc$cvmtest
5132 ##Kolmogorov - Smirnov test
5133 famm_RMF_Kc$skstest
5134
5135
5136 RMF_m1_Kc<-glm(data_Kc$RMF~cen,family = Gamma(),data = data_Kc)
5137 RMF_m1_Kc
5138 summary(RMF_m1_Kc)
5139
5140 ##### para Hs #####
5141 ### boxplot para Hs
5142 ggplot(data_Hs, aes(x=esp, y=RMF, fill=cen)) +
5143   geom_boxplot()
5144 ##### GLM para Hs
5145
5146 RMF_Hs<- c(data_Hs$RMF)
5147
5148 hist(RMF_Hs)
5149 fnorm4<-fitdist(data_Hs$RMF, distr = "norm")
5150 fgamma4<-fitdist(data_Hs$RMF, distr = "gamma")
5151 plot(fnorm4)
5152 plot(fgamma4)
5153 par(mfrow=c(1,1))
5154 famm_RMF_Hs<-gofstat(list(fnorm4,fgamma4),fitnames = c("norm","gamma"))
5155 denscomp(list(fnorm4,fgamma4),legendtext = c("norm","gamma"))
5156 #results of the tests

```

```

5157  ## chi square test (with corresponding table...)
5158  famm_RMF_Hs$chisqpvalue
5159  famm_RMF_Hs$chisqtable
5160  ## Anderson-Darling test
5161  famm_RMF_Hs$adtest
5162  ## Cramer von Mises test
5163  famm_RMF_Hs$cvmttest
5164  ##Kolmogorov - Smirnov test
5165  famm_RMF_Hs$kstest
5166
5167  RMF_m1_Hs<-glm(data_Hs$RMF~cen,family = Gamma(),data = data_Hs)
5168  RMF_m1_Hs
5169  summary(RMF_m1_Hs)
5170
5171  ##### SMF #####
5172  #flexplot e GLM de todas as sp
5173  ###
5174  ## flexplot
5175  SMF_all= flexplot(SMF ~ cen + esp,
5176                    data = dados_no_na, se = F, alpha = .3) + scale_x_discrete(limits=c("A","F")) + ## para
5177  arrumar ordem dos dados no eixo x
5178  theme(axis.text.x = element_text(angle=0, hjust=1, vjust=.2))
5179  SMF_all
5180
5181  #####boxplot para Qg
5182  ggplot(data_Qg, aes(x=esp, y=SMF, fill=cen)) +
5183  geom_boxplot()
5184  ##### GLM para Qg
5185
5186  hist(SMF)
5187  SMF_Qg<- c(data_Qg$SMF)
5188  hist(SMF_Qg)
5189
5190  fnorm<-fitdist(data_Qg$SMF, distr = "norm")
5191  fgamma<-fitdist(data_Qg$SMF, distr = "gamma")

```

```

5192 plot(fnorm)
5193 plot(fgamma)
5194 par(mfrow=c(1,1))
5195 famm_SMF_Qg<-gofstat(list(fnorm,fgamma),fitnames = c("norm","gamma"))
5196 denscomp(list(fnorm,fgamma),legendtext = c("norm","gamma"))
5197 #results of the tests
5198 ## chi square test (with corresponding table...)
5199 famm_SMF_Qg$chisqpvalue
5200 famm_SMF_Qg$chisqtable
5201 ## Anderson-Darling test
5202 famm_SMF_Qg$adtest
5203 ## Cramer von Mises test
5204 famm_SMF_Qg$scvmtest
5205 ##Kolmogorov - Smirnov test
5206 famm_SMF_Qg$kstest
5207
5208 SMF_m1_Qg<-glm(data_Qg$SMF~cen,family = Gamma(),data = data_Qg)
5209 SMF_m1_Qg
5210 summary(SMF_m1_Qg)
5211
5212 ##### para Ta #####
5213 ### boxplot para Ta
5214
5215 ggplot(data_Ta, aes(x=esp, y=SMF, fill=cen)) +
5216   geom_boxplot()
5217
5218 ### GLM para Ta
5219 SMF_Ta<- c(data_Ta$SMF)
5220
5221 hist(SMF_Ta)
5222 fnorm2<-fitdist(data_Ta$SMF, distr = "norm")
5223 fgamma2<-fitdist(data_Ta$SMF, distr = "gamma")
5224 plot(fnorm2)
5225 plot(fgamma2)

```

```

5226 par(mfrow=c(1,1))
5227 famm_SMF_Ta<-gofstat(list(fnorm2,fgamma2),fitnames = c("norm","gamma"))
5228 denscomp(list(fnorm2,fgamma2),legendtext = c("norm","gamma"))
5229 #results of the tests
5230 ## chi square test (with corresponding table...)
5231 famm_SMF_Ta$chisqpvalue
5232 famm_SMF_Ta$chisqtable
5233 ## Anderson-Darling test
5234 famm_SMF_Ta$adtest
5235 ## Cramer von Mises test
5236 famm_SMF_Ta$cvmtest
5237 ##Kolmogorov - Smirnov test
5238 famm_SMF_Ta$kstest
5239
5240
5241 SMF_m1_Ta<-glm(data_Ta$SMF~cen,family = Gamma(),data = data_Ta)
5242 SMF_m1_Ta
5243 summary(SMF_m1_Ta)
5244 SMF_m2_Ta<-glm(data_Ta$SMF~cen,family = gaussian(),data = data_Ta)
5245 SMF_m2_Ta
5246 summary(SMF_m2_Ta)
5247
5248 #####
5249 ##### para Kc #####
5250 ### boxplot para Kc
5251 ggplot(data_Kc, aes(x=esp, y=SMF, fill=cen)) +
5252   geom_boxplot()
5253
5254 ##### GLM
5255
5256 SMF_Kc<- c(data_Kc$SMF)
5257 hist(SMF_Kc)
5258
5259 fnorm3<-fitdist(data_Kc$SMF, distr = "norm")

```

```

5260  fgamma3<-fitdist(data_Kc$SMF, distr = "gamma")
5261  plot(fnorm3)
5262  plot(fgamma3)
5263  par(mfrow=c(1,1))
5264  famm_SMF_Kc<-gofstat(list(fnorm3,fgamma3),fitnames = c("norm","gamma"))
5265  denscomp(list(fnorm3,fgamma3),legendtext = c("norm","gamma"))
5266  #results of the tests
5267  ## chi square test (with corresponding table...)
5268  famm_SMF_Kc$chisqpvalue
5269  famm_SMF_Kc$chisqtable
5270  ## Anderson-Darling test
5271  famm_SMF_Kc$adtest
5272  ## Cramer von Mises test
5273  famm_SMF_Kc$cvmttest
5274  ##Kolmogorov - Smirnov test
5275  famm_SMF_Kc$kstest
5276
5277  SMF_m1_Kc<-glm(data_Kc$SMF~cen,family = Gamma(),data = data_Kc)
5278  SMF_m1_Kc
5279  summary(SMF_m1_Kc)
5280  ##### para Hs #####
5281  ### boxplot para Hs
5282  ggplot(data_Hs, aes(x=esp, y=SMF, fill=cen)) +
5283    geom_boxplot()
5284
5285  ##### GLM para Hs
5286  SMF_Hs<- c(data_Hs$SMF)
5287  hist(SMF_Hs)
5288
5289  fnorm4<-fitdist(data_Hs$SMF, distr = "norm")
5290  fgamma4<-fitdist(data_Hs$SMF, distr = "gamma")
5291  plot(fnorm4)
5292  plot(fgamma4)
5293  par(mfrow=c(1,1))

```

```

5294 famm_SMF_Hs<-gofstat(list(fnorm4,fgamma4),fitnames = c("norm","gamma"))
5295 denscomp(list(fnorm4,fgamma4),legendtext = c("norm","gamma"))
5296 #results of the tests
5297 ## chi square test (with corresponding table...)
5298 famm_SMF_Hs$chisqpvalue
5299 famm_SMF_Hs$chisqtable
5300
5301 ## Anderson-Darling test
5302 famm_SMF_Hs$adtest
5303 ## Cramer von Mises test
5304 famm_SMF_Hs$scvmtest
5305 ##Kolmogorov - Smirnov test
5306 famm_SMF_Hs$skstest
5307
5308
5309 SMF_m1_Hs<-glm(data_Hs$SMF~cen,family = Gamma(),data = data_Hs)
5310 SMF_m1_Hs
5311 summary(SMF_m1_Hs)
5312 ##### St_dens #####
5313 #
5314 #flexplot e GLM de todas as sp
5315
5316 ###
5317 ## flexplot
5318 St_dens_all= flexplot(St_dens ~ cen + esp,
5319                       data = dados_no_na, se = F, alpha = .3) + scale_x_discrete(limits=c("A","F")) + ## para
5320 arrumar ordem dos dados no eixo x
5321   theme(axis.text.x = element_text(angle=0, hjust=1, vjust=.2))
5322 St_dens_all
5323
5324 #####boxplot para Qg
5325 ggplot(data_Qg, aes(x=esp, y=St_dens, fill=cen)) +
5326   geom_boxplot()
5327
5328 ##### GLM para Qg

```



```

5329
5330 hist(St_dens)
5331
5332 St_dens_Qg<- c(data_Qg$St_dens)
5333 hist(St_dens_Qg)
5334
5335 fnorm<-fitdist(data_Qg$St_dens, distr = "norm")
5336 fgamma<-fitdist(data_Qg$St_dens, distr = "gamma")
5337 plot(fnorm)
5338 plot(fgamma)
5339 par(mfrow=c(1,1))
5340 famm_St_dens_Qg<-gofstat(list(fnorm,fgamma),fitnames = c("norm","gamma"))
5341 denscomp(list(fnorm,fgamma),legendtext = c("norm","gamma"))
5342 #results of the tests
5343 ## chi square test (with corresponding table...)
5344 famm_St_dens_Qg$chisqpvalue
5345 famm_St_dens_Qg$chisqtable
5346 ## Anderson-Darling test
5347 famm_St_dens_Qg$adtest
5348 ## Cramer von Mises test
5349 famm_St_dens_Qg$cvmtest
5350 ##Kolmogorov - Smirnov test
5351 famm_St_dens_Qg$kstest
5352
5353
5354
5355 St_dens_m1_Qg<-glm(data_Qg$St_dens~cen,family = Gamma(),data = data_Qg)
5356 St_dens_m1_Qg
5357 summary(St_dens_m1_Qg)
5358
5359 ##### para Ta #####
5360 ### boxplot para Ta
5361 ggplot(data_Ta, aes(x=esp, y=St_dens, fill=cen)) +
5362 geom_boxplot()

```

```

5363
5364   ### GLM para Ta
5365   St_dens_Ta<- c(data_Ta$St_dens)
5366
5367   hist(St_dens_Ta)
5368
5369   fnorm2<-fitdist(data_Ta$St_dens, distr = "norm")
5370   fgamma2<-fitdist(data_Ta$St_dens, distr = "gamma")
5371   plot(fnorm2)
5372   plot(fgamma2)
5373   par(mfrow=c(1,1))
5374   famm_St_dens_Ta<-gofstat(list(fnorm2,fgamma2),fitnames = c("norm","gamma"))
5375   denscomp(list(fnorm2,fgamma2),legendtext = c("norm","gamma"))
5376   #results of the tests
5377   ## chi square test (with corresponding table...)
5378   famm_St_dens_Ta$chisqpvalue
5379   famm_St_dens_Ta$chisqtable
5380   ## Anderson-Darling test
5381   famm_St_dens_Ta$adtest
5382   ## Cramer von Mises test
5383   famm_St_dens_Ta$scvmtest
5384   ##Kolmogorov - Smirnov test
5385   famm_St_dens_Ta$skstest
5386
5387   St_dens_m1_Ta<-glm(data_Ta$St_dens~cen,family = Gamma(),data = data_Ta)
5388   St_dens_m1_Ta
5389   summary(St_dens_m1_Ta)
5390
5391   St_dens_m2_Ta<-glm(data_Ta$St_dens~cen,family = gaussian(),data = data_Ta)
5392   St_dens_m2_Ta
5393   summary(St_dens_m2_Ta)
5394
5395   ##### para Kc #####
5396   ### boxplot para Kc

```

```

5397
5398  ggplot(data_Kc, aes(x=esp, y=St_dens, fill=cen)) +
5399    geom_boxplot()
5400
5401  ##### GLM
5402  St_dens_Kc<- c(data_Kc$St_dens)
5403
5404  hist(St_dens_Kc)
5405
5406  fnorm3<-fitdist(data_Kc$St_dens, distr = "norm")
5407  fgamma3<-fitdist(data_Kc$St_dens, distr = "gamma")
5408  plot(fnorm3)
5409  plot(fgamma3)
5410  par(mfrow=c(1,1))
5411  famm_St_dens_Kc<-gofstat(list(fnorm3,fgamma3),fitnames = c("norm","gamma"))
5412  denscomp(list(fnorm3,fgamma3),legendtext = c("norm","gamma"))
5413  #results of the tests
5414  ## chi square test (with corresponding table...)
5415  famm_St_dens_Kc$chisqpvalue
5416  famm_St_dens_Kc$chisqtable
5417  ## Anderson-Darling test
5418  famm_St_dens_Kc$adtest
5419  ## Cramer von Mises test
5420  famm_St_dens_Kc$cvmtest
5421  ##Kolmogorov - Smirnov test
5422  famm_St_dens_Kc$skstest
5423
5424  St_dens_m1_Kc<-glm(data_Kc$St_dens~cen,family = Gamma(),data = data_Kc)
5425  St_dens_m1_Kc
5426  summary(St_dens_m1_Kc)
5427
5428  #####
5429  ##### para Hs #####
5430  ### boxplot para Hs

```

```

5431
5432  ggplot(data_Hs, aes(x=esp, y=St_dens, fill=cen)) +
5433    geom_boxplot()
5434
5435  ##### GLM para Hs
5436
5437  St_dens_Hs<- c(data_Hs$St_dens)
5438
5439  hist(St_dens_Hs)
5440  fnorm4<-fitdist(data_Hs$St_dens, distr = "norm")
5441  fgamma4<-fitdist(data_Hs$St_dens, distr = "gamma")
5442  plot(fnorm4)
5443  plot(fgamma4)
5444  par(mfrow=c(1,1))
5445  famm_St_dens_Hs<-gofstat(list(fnorm4,fgamma4),fitnames = c("norm","gamma"))
5446  denscomp(list(fnorm4,fgamma4),legendtext = c("norm","gamma"))
5447  #results of the tests
5448  ## chi square test (with corresponding table...)
5449  famm_St_dens_Hs$chisqpvalue
5450  famm_St_dens_Hs$chisqtable
5451  ## Anderson-Darling test
5452  famm_St_dens_Hs$adtest
5453  ## Cramer von Mises test
5454  famm_St_dens_Hs$cvmtest
5455  ##Kolmogorov - Smirnov test
5456  famm_St_dens_Hs$kstest
5457
5458  St_dens_m1_Hs<-glm(data_Hs$St_dens~cen,family = Gamma(),data = data_Hs)
5459  St_dens_m1_Hs
5460  summary(St_dens_m1_Hs)
5461
5462  ##### SM #####
5463  #
5464  #flexplot e GLM de todas as sp

```

```

5465  ## flexplot
5466  SM_all= flexplot(SM ~ cen + esp,
5467                  data = dados_no_na, se = F, alpha = .3) + scale_x_discrete(limits=c("A","F")) + ## para
5468  arrumar ordem dos dados no eixo x
5469  theme(axis.text.x = element_text(angle=0, hjust=1, vjust=.2))
5470  SM_all
5471  #####boxplot para Qg
5472
5473  ggplot(data_Qg, aes(x=esp, y=SM, fill=cen)) +
5474  geom_boxplot()
5475
5476  ##### GLM para Qg
5477
5478  hist(SM)
5479  SM_Qg<- c(data_Qg$SM)
5480
5481  hist(SM_Qg)
5482  fnorm<-fitdist(data_Qg$SM, distr = "norm")
5483  fgamma<-fitdist(data_Qg$SM, distr = "gamma")
5484  plot(fnorm)
5485  plot(fgamma)
5486  par(mfrow=c(1,1))
5487  famm_SM_Qg<-gofstat(list(fnorm,fgamma),fitnames = c("norm","gamma"))
5488  denscomp(list(fnorm,fgamma),legendtext = c("norm","gamma"))
5489  #results of the tests
5490  ## chi square test (with corresponding table...)
5491  famm_SM_Qg$chisqpvalue
5492  famm_SM_Qg$chisqtable
5493  ## Anderson-Darling test
5494  famm_SM_Qg$adtest
5495  ## Cramer von Mises test
5496  famm_SM_Qg$scvmtest
5497  ##Kolmogorov - Smirnov test
5498  famm_SM_Qg$kstest
5499

```

```

5500 SM_m1_Qg<-glm(data_Qg$SM~cen,family = Gamma(),data = data_Qg)
5501 SM_m1_Qg
5502 summary(SM_m1_Qg)
5503
5504 ##### para Ta #####
5505 ### boxplot para Ta
5506
5507 ggplot(data_Ta, aes(x=esp, y=SM, fill=cen)) +
5508   geom_boxplot()
5509
5510 ### GLM para Ta
5511 SM_Ta<- c(data_Ta$SM)
5512 hist(SM_Ta)
5513
5514 fnorm2<-fitdist(data_Ta$SM, distr = "norm")
5515 fgamma2<-fitdist(data_Ta$SM, distr = "gamma")
5516 plot(fnorm2)
5517 plot(fgamma2)
5518 par(mfrow=c(1,1))
5519 famm_SM_Ta<-gofstat(list(fnorm2,fgamma2),fitnames = c("norm","gamma"))
5520 denscomp(list(fnorm2,fgamma2),legendtext = c("norm","gamma"))
5521 #results of the tests
5522 ## chi square test (with corresponding table...)
5523 famm_SM_Ta$chisqpvalue
5524 famm_SM_Ta$chisqtable
5525
5526 ## Anderson-Darling test
5527 famm_SM_Ta$adtest
5528 ## Cramer von Mises test
5529 famm_SM_Ta$scvmtest
5530 ##Kolmogorov - Smirnov test
5531 famm_SM_Ta$kstest
5532
5533

```

```

5534 SM_m1_Ta<-glm(data_Ta$SM~cen,family = Gamma(),data = data_Ta)
5535 SM_m1_Ta
5536 summary(SM_m1_Ta)
5537 SM_m2_Ta<-glm(data_Ta$SM~cen,family = gaussian(),data = data_Ta)
5538 SM_m2_Ta
5539 summary(SM_m2_Ta)
5540
5541 ##### para Kc #####
5542 ### boxplot para Kc
5543 ggplot(data_Kc, aes(x=esp, y=SM, fill=cen)) +
5544   geom_boxplot()
5545
5546 ##### GLM
5547 SM_Kc<- c(data_Kc$SM)
5548
5549 hist(SM_Kc)
5550 fnorm3<-fitdist(data_Kc$SM, distr = "norm")
5551 fgamma3<-fitdist(data_Kc$SM, distr = "gamma")
5552 plot(fnorm3)
5553 plot(fgamma3)
5554 par(mfrow=c(1,1))
5555 famm_SM_Kc<-gofstat(list(fnorm3,fgamma3),fitnames = c("norm","gamma"))
5556 denscomp(list(fnorm3,fgamma3),legendtext = c("norm","gamma"))
5557 #results of the tests
5558 ## chi square test (with corresponding table...)
5559 famm_SM_Kc$chisqpvalue
5560 famm_SM_Kc$chisqtable
5561 ## Anderson-Darling test
5562 famm_SM_Kc$adtest
5563 ## Cramer von Mises test
5564 famm_SM_Kc$cvmtest
5565 ##Kolmogorov - Smirnov test
5566 famm_SM_Kc$kstest
5567

```

```

5568 SM_m1_Kc<-glm(data_Kc$SM~cen,family = Gamma(),data = data_Kc)
5569 SM_m1_Kc
5570 summary(SM_m1_Kc)
5571
5572 ##### para Hs #####
5573 ### boxplot para Hs
5574
5575 ggplot(data_Hs, aes(x=esp, y=SM, fill=cen)) +
5576   geom_boxplot()
5577
5578 ##### GLM para Hs
5579
5580 SM_Hs<- c(data_Hs$SM)
5581
5582 hist(SM_Hs)
5583 fnorm4<-fitdist(data_Hs$SM, distr = "norm")
5584 fgamma4<-fitdist(data_Hs$SM, distr = "gamma")
5585 plot(fnorm4)
5586 plot(fgamma4)
5587 par(mfrow=c(1,1))
5588 famm_SM_Hs<-gofstat(list(fnorm4,fgamma4),fitnames = c("norm","gamma"))
5589 denscomp(list(fnorm4,fgamma4),legendtext = c("norm","gamma"))
5590 #results of the tests
5591 ## chi square test (with corresponding table...)
5592 famm_SM_Hs$chisqpvalue
5593 famm_SM_Hs$chisqtable
5594 ## Anderson-Darling test
5595 famm_SM_Hs$adtest
5596 ## Cramer von Mises test
5597 famm_SM_Hs$cvmtest
5598 ##Kolmogorov - Smirnov test
5599 famm_SM_Hs$kstest
5600
5601

```



```

5602 SM_m1_Hs<-glm(data_Hs$SM~cen,family = Gamma(),data = data_Hs)
5603 SM_m1_Hs
5604 summary(SM_m1_Hs)
5605
5606 ##### SM #####
5607 #flexplot e GLM de todas as sp
5608 ## flexplot
5609 RM_all= flexplot(RM ~ cen + esp,
5610                 data = dados_no_na, se = F, alpha = .3) + scale_x_discrete(limits=c("A","F")) + ## para
5611 arrumar ordem dos dados no eixo x
5612 theme(axis.text.x = element_text(angle=0, hjust=1, vjust=.2))
5613
5614 RM_all
5615
5616 #####boxplot para Qg
5617
5618 ggplot(data_Qg, aes(x=esp, y=RM, fill=cen)) +
5619   geom_boxplot()
5620 ##### GLM para Qg
5621 hist(RM)
5622
5623 RM_Qg<- c(data_Qg$RM)
5624 hist(RM_Qg)
5625 fnorm<-fitdist(data_Qg$RM, distr = "norm")
5626 fgamma<-fitdist(data_Qg$RM, distr = "gamma")
5627 plot(fnorm)
5628 plot(fgamma)
5629 par(mfrow=c(1,1))
5630 famm_RM_Qg<-gofstat(list(fnorm,fgamma),fitnames = c("norm","gamma"))
5631 denscomp(list(fnorm,fgamma),legendtext = c("norm","gamma"))
5632 #results of the tests
5633 ## chi square test (with corresponding table...)
5634 famm_RM_Qg$chisqpvalue
5635 famm_RM_Qg$chisqtable
5636 ## Anderson-Darling test

```

```

5637 famm_RM_Qg$adtest
5638 ## Cramer von Mises test
5639 famm_RM_Qg$cvmtest
5640 ##Kolmogorov - Smirnov test
5641 famm_RM_Qg$kstest
5642
5643
5644
5645 RM_m1_Qg<-glm(data_Qg$RM~cen,family = Gamma(),data = data_Qg)
5646 RM_m1_Qg
5647 summary(RM_m1_Qg)
5648
5649 ##### para Ta #####
5650 #####
5651 ### boxplot para Ta
5652 ggplot(data_Ta, aes(x=esp, y=RM, fill=cen)) +
5653   geom_boxplot()
5654
5655 ### GLM para Ta
5656
5657 RM_Ta<- c(data_Ta$RM)
5658 hist(RM_Ta)
5659 fnorm2<-fitdist(data_Ta$RM, distr = "norm")
5660 fgamma2<-fitdist(data_Ta$RM, distr = "gamma")
5661 plot(fnorm2)
5662 plot(fgamma2)
5663 par(mfrow=c(1,1))
5664 famm_RM_Ta<-gofstat(list(fnorm2,fgamma2),fitnames = c("norm","gamma"))
5665 denscomp(list(fnorm2,fgamma2),legendtext = c("norm","gamma"))
5666 #results of the tests
5667 ## chi square test (with corresponding table...)
5668 famm_RM_Ta$chisqpvalue
5669 famm_RM_Ta$chisqtable
5670 ## Anderson-Darling test

```

```

5671 famm_RM_Ta$adtest
5672 ## Cramer von Mises test
5673 famm_RM_Ta$cvmtest
5674 ##Kolmogorov - Smirnov test
5675 famm_RM_Ta$kstest
5676
5677 RM_m1_Ta<-glm(data_Ta$RM~cen,family = Gamma(),data = data_Ta)
5678 RM_m1_Ta
5679 summary(RM_m1_Ta)
5680 RM_m2_Ta<-glm(data_Ta$RM~cen,family = gaussian(),data = data_Ta)
5681 RM_m2_Ta
5682 summary(RM_m2_Ta)
5683
5684 #####
5685 ##### para Kc #####
5686 ### boxplot para Kc
5687 ggplot(data_Kc, aes(x=esp, y=RM, fill=cen)) +
5688   geom_boxplot()
5689
5690 ##### GLM
5691
5692 RM_Kc<- c(data_Kc$RM)
5693 hist(RM_Kc)
5694 fnorm3<-fitdist(data_Kc$RM, distr = "norm")
5695 fgamma3<-fitdist(data_Kc$RM, distr = "gamma")
5696 plot(fnorm3)
5697 plot(fgamma3)
5698 par(mfrow=c(1,1))
5699 famm_RM_Kc<-gofstat(list(fnorm3,fgamma3),fitnames = c("norm","gamma"))
5700 denscomp(list(fnorm3,fgamma3),legendtext = c("norm","gamma"))
5701 #results of the tests
5702 ## chi square test (with corresponding table...)
5703 famm_RM_Kc$chisqpvalue
5704 famm_RM_Kc$chisqtable

```

```

5705  ## Anderson-Darling test
5706  famm_RM_Kc$adtest
5707  ## Cramer von Mises test
5708  famm_RM_Kc$cvmtest
5709  ##Kolmogorov - Smirnov test
5710  famm_RM_Kc$kstest
5711
5712
5713  RM_m1_Kc<-glm(data_Kc$RM~cen,family = Gamma(),data = data_Kc)
5714  RM_m1_Kc
5715  summary(RM_m1_Kc)
5716
5717  ##### para Hs #####
5718  ### boxplot para Hs
5719  ggplot(data_Hs, aes(x=esp, y=RM, fill=cen)) +
5720    geom_boxplot()
5721  ##### GLM para Hs
5722  RM_Hs<- c(data_Hs$RM)
5723  hist(RM_Hs)
5724  fnorm4<-fitdist(data_Hs$RM, distr = "norm")
5725  fgamma4<-fitdist(data_Hs$RM, distr = "gamma")
5726  plot(fnorm4)
5727  plot(fgamma4)
5728  par(mfrow=c(1,1))
5729  famm_RM_Hs<-gofstat(list(fnorm4,fgamma4),fitnames = c("norm","gamma"))
5730  denscomp(list(fnorm4,fgamma4),legendtext = c("norm","gamma"))
5731  #results of the tests
5732  ## chi square test (with corresponding table...)
5733  famm_RM_Hs$chisqpvalue
5734  famm_RM_Hs$chisqtable
5735  ## Anderson-Darling test
5736  famm_RM_Hs$adtest
5737  ## Cramer von Mises test
5738  famm_RM_Hs$cvmtest

```

```
5739  ##Kolmogorov - Smirnov test
5740  famm_RM_Hs$kstest
5741
5742  RM_m1_Hs<-glm(data_Hs$RM~cen,family = Gamma(),data = data_Hs)
5743  RM_m1_Hs
5744  summary(RM_m1_Hs)
5745
5746
```

```

5747 #####
5748           7.4.1.  ANÁLISES ESTATÍSTICAS DO CAPÍTULO II
5749 ##### Qg #####
5750
5751 summary(Qg_A)
5752   sp      cen      ST_D      H      Lnum
5753 Length:26   Length:26   Min. :0.1460 Min. : 6.400 Min. : 1.000
5754 Class :character Class :character 1st Qu.:0.1822 1st Qu.: 7.300 1st Qu.: 3.000
5755 Mode :character Mode :character Median :0.2057 Median : 8.550 Median : 5.000
5756           Mean :0.2004 Mean : 8.627 Mean : 5.077
5757           3rd Qu.:0.2157 3rd Qu.: 9.650 3rd Qu.: 6.750
5758           Max. :0.2410 Max. :13.000 Max. :12.000
5759   RL      TpRM      ScRM      StM      TLM
5760 Min. : 51.00 Min. :0.2456 Min. :0.0300 Min. :0.05990 Min. :0.04990
5761 1st Qu.: 71.50 1st Qu.:0.4619 1st Qu.:0.0924 1st Qu.:0.09978 1st Qu.:0.09058
5762 Median : 81.80 Median :0.5934 Median :0.1154 Median :0.10950 Median :0.16160
5763 Mean : 81.33 Mean :0.6196 Mean :0.1300 Mean :0.11058 Mean :0.16123
5764 3rd Qu.: 89.65 3rd Qu.:0.7599 3rd Qu.:0.1518 3rd Qu.:0.12235 3rd Qu.:0.18682
5765 Max. :104.20 Max. :0.9876 Max. :0.4552 Max. :0.16220 Max. :0.38670
5766   RM      SM      TM      RS      LMF
5767 Min. :0.3300 Min. :0.1271 Min. :0.4571 Min. :1.443 Min. :0.04726
5768 1st Qu.:0.5656 1st Qu.:0.2111 1st Qu.:0.8351 1st Qu.:2.152 1st Qu.:0.12586
5769 Median :0.7361 Median :0.2544 Median :1.0468 Median :2.828 Median :0.15265
5770 Mean :0.7496 Mean :0.2718 Mean :1.0214 Mean :2.961 Mean :0.15866
5771 3rd Qu.:0.8883 3rd Qu.:0.3200 3rd Qu.:1.1590 3rd Qu.:3.034 3rd Qu.:0.20934
5772 Max. :1.2451 Max. :0.4638 Max. :1.6724 Max. :5.562 Max. :0.33082
5773   RMF      SMF      SLA      RGR      STRL
5774 Min. :0.5907 Min. :0.1524 Min. : 33.71 Min. :0.01371 Min. : 85.57
5775 1st Qu.:0.6820 1st Qu.:0.2479 1st Qu.: 81.88 1st Qu.:0.01717 1st Qu.:110.55
5776 Median :0.7387 Median :0.2613 Median : 99.06 Median :0.01877 Median :123.87
5777 Mean :0.7280 Mean :0.2720 Mean : 92.47 Mean :0.01885 Mean :144.01
5778 3rd Qu.:0.7521 3rd Qu.:0.3180 3rd Qu.:106.45 3rd Qu.:0.01995 3rd Qu.:173.16
5779 Max. :0.8476 Max. :0.4093 Max. :134.86 Max. :0.02586 Max. :287.05
5780   RER
5781 Min. :0.2808

```

```

5782 1st Qu.:0.4897
5783 Median :0.5294
5784 Mean :0.5449
5785 3rd Qu.:0.6311
5786 Max. :0.8057
5787 > summary(Qg_F)
5788 sp cen ST_D H Lnum
5789 Length:33 Length:33 Min. :0.1700 Min. :7.60 Min. :5.00
5790 Class :character Class :character 1st Qu.:0.2115 1st Qu.:11.50 1st Qu.:8.00
5791 Mode :character Mode :character Median :0.2285 Median :13.40 Median :11.00
5792 Mean :0.2292 Mean :13.12 Mean :10.94
5793 3rd Qu.:0.2515 3rd Qu.:14.60 3rd Qu.:12.00
5794 Max. :0.2835 Max. :19.80 Max. :20.00
5795 RL TpRM ScRM StM TLM
5796 Min. :82.6 Min. :0.2304 Min. :0.05606 Min. :0.0846 Min. :0.1520
5797 1st Qu.:99.8 1st Qu.:0.3914 1st Qu.:0.09580 1st Qu.:0.1567 1st Qu.:0.5658
5798 Median :100.5 Median :0.6257 Median :0.14270 Median :0.1900 Median :0.7274
5799 Mean :100.4 Mean :0.6657 Mean :0.18774 Mean :0.1995 Mean :0.8015
5800 3rd Qu.:103.1 3rd Qu.:0.8281 3rd Qu.:0.21900 3rd Qu.:0.2400 3rd Qu.:1.0385
5801 Max. :111.2 Max. :1.5320 Max. :0.91000 Max. :0.3611 Max. :1.5870
5802 RM SM TM RS LMF
5803 Min. :0.3514 Min. :0.2402 Min. :0.7874 Min. :0.5105 Min. :0.1649
5804 1st Qu.:0.5373 1st Qu.:0.7292 1st Qu.:1.3519 1st Qu.:0.6995 1st Qu.:0.3964
5805 Median :0.7587 Median :0.9328 Median :1.7879 Median :0.8060 Median :0.4384
5806 Mean :0.8534 Mean :1.0010 Mean :1.8544 Mean :0.9109 Mean :0.4288
5807 3rd Qu.:1.1005 3rd Qu.:1.2432 3rd Qu.:2.1217 3rd Qu.:0.9648 3rd Qu.:0.4737
5808 Max. :1.7000 Max. :1.8115 Max. :3.3603 Max. :2.8383 Max. :0.5295
5809 RMF SMF SLA RGR STRL
5810 Min. :0.3380 Min. :0.2605 Min. :83.5 Min. :0.01793 Min. :60.84
5811 1st Qu.:0.4116 1st Qu.:0.5090 1st Qu.:104.0 1st Qu.:0.02079 1st Qu.:124.41
5812 Median :0.4463 Median :0.5537 Median :111.7 Median :0.02341 Median :164.04
5813 Mean :0.4602 Mean :0.5398 Mean :112.3 Mean :0.02375 Mean :186.52
5814 3rd Qu.:0.4910 3rd Qu.:0.5884 3rd Qu.:117.6 3rd Qu.:0.02626 3rd Qu.:253.85
5815 Max. :0.7395 Max. :0.6620 Max. :157.1 Max. :0.03108 Max. :443.14

```

```
5816     RER
5817   Min.  :0.5356
5818   1st Qu.:0.6676
5819   Median :0.7189
5820   Mean   :0.7057
5821   3rd Qu.:0.7551
5822   Max.   :0.8137
5823
5824   std.error(Qg_A$H)
5825   [1] 0.301614
5826   > std.error(Qg_F$H)
5827   [1] 0.4117004
5828   >
5829   > std.error(Qg_A$ST_D)
5830   [1] 0.004658353
5831   > std.error(Qg_F$ST_D)
5832   [1] 0.005512798
5833   >
5834   > std.error(Qg_A$RL)
5835   [1] 2.882626
5836   > std.error(Qg_F$RL)
5837   [1] 0.8586068
5838   >
5839   > std.error(Qg_A$Lnum)
5840   [1] 0.5708915
5841   > std.error(Qg_F$Lnum)
5842   [1] 0.6698872
5843   >
5844   > std.error(Qg_A$TM)
5845   [1] 0.05521322
5846   > std.error(Qg_F$TM)
5847   [1] 0.1272773
5848   >
5849   > std.error(Qg_A$RM)
```



```
5850 [1] 0.0465318
5851 > std.error(Qg_F$RM)
5852 [1] 0.06512664
5853 >
5854 > std.error(Qg_A$SM)
5855 [1] 0.01762037
5856 > std.error(Qg_F$SM)
5857 [1] 0.07081724
5858 >
5859 > std.error(Qg_A$RMF)
5860 [1] 0.01420205
5861 > std.error(Qg_F$RMF)
5862 [1] 0.0141594
5863 >
5864 > std.error(Qg_A$SMF)
5865 [1] 0.01420205
5866 > std.error(Qg_F$SMF)
5867 [1] 0.0141594
5868 >
5869 > std.error(Qg_A$RGR)
5870 [1] 0.0005130239
5871 > std.error(Qg_F$RGR)
5872 [1] 0.0006035291
5873 >
5874 > std.error(Qg_A$SLA)
5875 [1] 5.241104
5876 > std.error(Qg_F$SLA)
5877 [1] 2.745227
5878 >
5879 > std.error(Qg_A$STRL)
5880 [1] 9.914294
5881 > std.error(Qg_F$STRL)
5882 [1] 15.82884
5883
```

```

5884 #####
5885
5886 ##summary(Mt_m1_Qg)
5887 Call:
5888 glm(formula = data_Qg$TM ~ cen, family = Gamma(), data = data_Qg)
5889
5890 Deviance Residuals:
5891     Min       1Q   Median       3Q      Max
5892 -0.74991 -0.25362 -0.03065  0.13787  0.65972
5893
5894 Coefficients:
5895             Estimate Std. Error t value Pr(>|t|)
5896 (Intercept)  0.97903   0.06668  14.683 < 2e-16 ***
5897 cenF        -0.43976   0.07422  -5.925 1.91e-07 ***
5898
5899 ##summary(ScRM_m1_Qg)
5900
5901 Call:
5902 glm(formula = data_Qg$ScRM ~ cen, family = Gamma(), data = data_Qg)
5903
5904 Deviance Residuals:
5905     Min       1Q   Median       3Q      Max
5906 -1.1807 -0.5375 -0.1771  0.1676  2.1301
5907
5908 Coefficients:
5909             Estimate Std. Error t value Pr(>|t|)
5910 (Intercept)   7.693     1.149   6.698 1.01e-08 ***
5911 cenF         -2.367     1.348  -1.756  0.0845 .
5912
5913 ##summary(TpRM_m1_Qg)
5914
5915 Call:
5916 glm(formula = data_Qg$TpRM ~ cen, family = Gamma(), data = data_Qg)
5917

```

```

5918 Deviance Residuals:
5919   Min     1Q   Median     3Q      Max
5920 -0.90232 -0.36760 -0.06129  0.22342  0.96737
5921
5922 Coefficients:
5923             Estimate Std. Error t value Pr(>|t|)
5924 (Intercept)  1.6139     0.1286  12.545 <2e-16 ***
5925 cenF        -0.1116     0.1669  -0.669  0.506
5926
5927 ##summary(StM_m1_Qg)
5928
5929 Call:
5930 glm(formula = data_Qg$StM ~ cen, family = Gamma(), data = data_Qg)
5931
5932 Deviance Residuals:
5933   Min     1Q   Median     3Q      Max
5934 -0.75079 -0.15619 -0.02901  0.12038  0.65851
5935
5936 Coefficients:
5937             Estimate Std. Error t value Pr(>|t|)
5938 (Intercept)  9.0435     0.5320  17.000 < 2e-16 ***
5939 cenF        -4.0301     0.5929  -6.797 6.92e-09 ***
5940
5941 ##summary(SLA_m1_Qg)
5942
5943 Call:
5944 glm(formula = data_Qg$SLA ~ cen, family = Gamma(), data = data_Qg)
5945
5946 Deviance Residuals:
5947   Min     1Q   Median     3Q      Max
5948 -0.86447 -0.07781  0.01418  0.12851  0.40268
5949
5950 Coefficients:
5951             Estimate Std. Error t value Pr(>|t|)

```

```

5952 (Intercept) 0.0108144 0.0004632 23.347 < 2e-16 ***
5953 cenF      -0.0019110 0.0005737 -3.331 0.00152 **
5954
5955 ##summary(H_m1_Qg)
5956
5957 Call:
5958 glm(formula = data_Qg$H ~ cen, family = Gamma(), data = data_Qg)
5959
5960 Deviance Residuals:
5961      Min       1Q   Median       3Q      Max
5962 -0.50040 -0.14558 -0.00312  0.11251  0.44198
5963
5964 Coefficients:
5965             Estimate Std. Error t value Pr(>|t|)
5966 (Intercept) 0.115916  0.004078  28.422 < 2e-16 ***
5967 cenF      -0.039686  0.004722  -8.404 1.47e-11 ***
5968
5969 ## summary(ST_D_m1_Qg)
5970
5971 Call:
5972 glm(formula = data_Qg$ST_D ~ cen, family = Gamma(), data = data_Qg)
5973
5974 Deviance Residuals:
5975      Min       1Q   Median       3Q      Max
5976 -0.301028 -0.080318  0.001454  0.082100  0.220583
5977
5978 Coefficients:
5979             Estimate Std. Error t value Pr(>|t|)
5980 (Intercept)  4.9890    0.1271  39.246 < 2e-16 ***
5981 cenF      -0.6253    0.1609  -3.886 0.000268 ***
5982
5983 ## summary(RGR_m1_Qg)
5984
5985 Call:

```

```

5986 glm(formula = data_Qg$RGR ~ cen, family = Gamma(), data = data_Qg)
5987
5988 Deviance Residuals:
5989     Min       1Q   Median       3Q      Max
5990 -0.30248 -0.10315 -0.01426  0.06795  0.33377
5991
5992 Coefficients:
5993             Estimate Std. Error t value Pr(>|t|)
5994 (Intercept)  53.052     1.487  35.688 < 2e-16 ***
5995 cenF        -10.942     1.818  -6.017 1.35e-07 ***
5996
5997 ## summary(Lnum_m1_Qg)
5998
5999 Call:
6000 glm(formula = data_Qg$Lnum ~ cen, family = Gamma(), data = data_Qg)
6001
6002 Deviance Residuals:
6003     Min       1Q   Median       3Q      Max
6004 -1.28193 -0.35650  0.00553  0.17184  1.00343
6005
6006 Coefficients:
6007             Estimate Std. Error t value Pr(>|t|)
6008 (Intercept)  0.19697     0.01786  11.031 9.12e-16 ***
6009 cenF        -0.10556     0.01931  -5.466 1.06e-06 ***
6010
6011 ##summary(STRL_m1_Qg)
6012
6013 Call:
6014 glm(formula = data_Qg$STRL ~ cen, family = Gamma(), data = data_Qg)
6015
6016 Deviance Residuals:
6017     Min       1Q   Median       3Q      Max
6018 -0.9450 -0.3572 -0.1258  0.2723  1.0104
6019

```

```

6020 Coefficients:
6021     Estimate Std. Error t value Pr(>|t|)
6022 (Intercept) 0.0069441 0.0005897 11.776 <2e-16 ***
6023 cenF      -0.0015828 0.0007148 -2.214 0.0308 *
6024
6025
6026
6027 ##summary(RMF_m1_Qg)
6028
6029 Call:
6030 glm(formula = data_Qg$RMF ~ cen, family = Gamma(), data = data_Qg)
6031
6032 Deviance Residuals:
6033     Min       1Q   Median       3Q      Max
6034 -0.29366 -0.09690  0.00116  0.05704  0.51485
6035
6036 Coefficients:
6037     Estimate Std. Error t value Pr(>|t|)
6038 (Intercept) 1.37364   0.03984  34.48 <2e-16 ***
6039 cenF        0.79921   0.06868  11.64 <2e-16 ***
6040
6041 ##summary(SM_m1_Qg)
6042
6043 Call:
6044 glm(formula = data_Qg$SM ~ cen, family = Gamma(), data = data_Qg)
6045
6046 Deviance Residuals:
6047     Min       1Q   Median       3Q      Max
6048 -1.15517 -0.28838 -0.06816  0.20630  0.65814
6049
6050 Coefficients:
6051     Estimate Std. Error t value Pr(>|t|)
6052 (Intercept) 3.6791    0.2706  13.596 < 2e-16 ***
6053 cenF       -2.6800    0.2784  -9.628 1.48e-13 ***

```

```

6054
6055 ##summary(RM_m1_Qg)
6056
6057 Call:
6058 glm(formula = data_Qg$RM ~ cen, family = Gamma(), data = data_Qg)
6059
6060 Deviance Residuals:
6061     Min       1Q   Median       3Q      Max
6062 -0.77340 -0.35935 -0.02685  0.21959  0.77829
6063
6064 Coefficients:
6065             Estimate Std. Error t value Pr(>|t|)
6066 (Intercept)  1.3340     0.1019  13.086 <2e-16 ***
6067 cenF        -0.1623     0.1293  -1.255  0.215
6068
6069 ## summary(RL_m1_Qg)
6070
6071 Call:
6072 glm(formula = data_Qg$RL ~ cen, family = Gamma(), data = data_Qg)
6073
6074 Deviance Residuals:
6075     Min       1Q   Median       3Q      Max
6076 -0.43305 -0.02786  0.00081  0.03386  0.25846
6077
6078 Coefficients:
6079             Estimate Std. Error t value Pr(>|t|)
6080 (Intercept)  0.0122955 0.0003019  40.721 < 2e-16 ***
6081 cenF        -0.0023371 0.0003719  -6.285 4.9e-08 ***
6082
6083
6084 #####
6085 #####
6086
6087 summary(Ta_A)
6088     sp      cen      ST_D      H      Lnum

```

Ta

6089 Length:31 Length:31 Min. :0.2775 Min. :1.900 Min. :4.000
 6090 Class :character Class :character 1st Qu.:0.3450 1st Qu.:2.750 1st Qu.:6.000
 6091 Mode :character Mode :character Median :0.4205 Median :3.100 Median :6.000
 6092 Mean :0.4226 Mean :3.137 Mean :7.129
 6093 3rd Qu.:0.4510 3rd Qu.:3.400 3rd Qu.:8.000
 6094 Max. :0.6975 Max. :4.500 Max. :12.000
 6095 RL TpRM ScRM StM TLM
 6096 Min. :29.00 Min. :0.380 Min. :0.0460 Min. :0.0286 Min. :0.0731
 6097 1st Qu.:95.20 1st Qu.:1.253 1st Qu.:0.2474 1st Qu.:0.0569 1st Qu.:0.3437
 6098 Median :96.00 Median :1.518 Median :0.3884 Median :0.0819 Median :0.5967
 6099 Mean :94.54 Mean :1.500 Mean :0.3843 Mean :0.1076 Mean :0.5486
 6100 3rd Qu.:97.90 3rd Qu.:1.792 3rd Qu.:0.4860 3rd Qu.:0.1011 3rd Qu.:0.7133
 6101 Max. :115.00 Max. :2.683 Max. :0.8333 Max. :0.9200 Max. :1.1899
 6102 RM SM TM RS LMF
 6103 Min. :0.426 Min. :0.1328 Min. :0.779 Min. :1.207 Min. :0.04412
 6104 1st Qu.:1.494 1st Qu.:0.3985 1st Qu.:1.989 1st Qu.:2.111 1st Qu.:0.19512
 6105 Median :2.021 Median :0.6786 Median :2.645 Median :2.772 Median :0.22342
 6106 Mean :1.884 Mean :0.6562 Mean :2.540 Mean :3.823 Mean :0.22201
 6107 3rd Qu.:2.258 3rd Qu.:0.8399 3rd Qu.:3.065 3rd Qu.:3.509 3rd Qu.:0.27152
 6108 Max. :3.462 Max. :1.6105 Max. :4.120 Max. :12.545 Max. :0.39820
 6109 RMF SMF SLA RGR STRL
 6110 Min. :0.5469 Min. :0.07383 Min. :71.66 Min. :0.01110 Min. :42.42
 6111 1st Qu.:0.6774 1st Qu.:0.22179 1st Qu.:105.71 1st Qu.:0.01847 1st Qu.:53.32
 6112 Median :0.7349 Median :0.26508 Median :122.21 Median :0.02113 Median :64.63
 6113 Mean :0.7389 Mean :0.26108 Mean :123.50 Mean :0.02034 Mean :69.68
 6114 3rd Qu.:0.7782 3rd Qu.:0.32263 3rd Qu.:138.04 3rd Qu.:0.02262 3rd Qu.:75.28
 6115 Max. :0.9262 Max. :0.45315 Max. :198.66 Max. :0.02498 Max. :181.47
 6116 RER
 6117 Min. :0.1110
 6118 1st Qu.:0.6306
 6119 Median :0.6489
 6120 Mean :0.6351
 6121 3rd Qu.:0.6693
 6122 Max. :0.7600


```

6123 > summary(Ta_F)
6124     sp          cen          ST_D          H          Lnum
6125 Length:30     Length:30     Min. :0.3220 Min. :2.500 Min. : 8.00
6126 Class :character Class :character 1st Qu.:0.3846 1st Qu.:3.425 1st Qu.:10.00
6127 Mode :character Mode :character Median :0.4125 Median :4.250 Median :12.00
6128           Mean :0.4330 Mean :4.287 Mean :11.90
6129           3rd Qu.:0.4635 3rd Qu.:5.000 3rd Qu.:12.75
6130           Max. :0.6480 Max. :6.500 Max. :18.00
6131     RL          TpRM          ScRM          StM          TLM
6132 Min. : 93.80 Min. :0.4642 Min. :0.0890 Min. :0.04950 Min. :0.3184
6133 1st Qu.: 96.50 1st Qu.:1.0080 1st Qu.:0.2774 1st Qu.:0.07812 1st Qu.:0.9932
6134 Median : 97.00 Median :1.2139 Median :0.4096 Median :0.10430 Median :1.3244
6135 Mean : 98.40 Mean :1.4461 Mean :0.4356 Mean :0.13044 Mean :1.3537
6136 3rd Qu.: 99.62 3rd Qu.:1.8081 3rd Qu.:0.5414 3rd Qu.:0.11935 3rd Qu.:1.6877
6137 Max. :113.00 Max. :2.7118 Max. :1.1300 Max. :0.95000 Max. :2.4458
6138     RM          SM          TM          RS          LMF
6139 Min. :0.5979 Min. :0.4245 Min. :1.046 Min. :0.518 Min. :0.1774
6140 1st Qu.:1.3261 1st Qu.:1.0626 1st Qu.:2.761 1st Qu.:0.992 1st Qu.:0.3487
6141 Median :1.5813 Median :1.5329 Median :3.246 Median :1.197 Median :0.4161
6142 Mean :1.8817 Mean :1.4842 Mean :3.366 Mean :1.402 Mean :0.4036
6143 3rd Qu.:2.3293 3rd Qu.:1.8318 3rd Qu.:4.180 3rd Qu.:1.532 3rd Qu.:0.4671
6144 Max. :3.5468 Max. :2.5400 Max. :6.025 Max. :3.308 Max. :0.6289
6145     RMF          SMF          SLA          RGR          STRL
6146 Min. :0.3413 Min. :0.2321 Min. :102.1 Min. :0.01339 Min. : 35.66
6147 1st Qu.:0.4980 1st Qu.:0.3950 1st Qu.:117.1 1st Qu.:0.02049 1st Qu.: 54.33
6148 Median :0.5449 Median :0.4551 Median :140.6 Median :0.02253 Median : 81.74
6149 Mean :0.5572 Mean :0.4428 Mean :147.8 Mean :0.02250 Mean : 81.58
6150 3rd Qu.:0.6050 3rd Qu.:0.5020 3rd Qu.:155.5 3rd Qu.:0.02567 3rd Qu.: 96.07
6151 Max. :0.7679 Max. :0.6587 Max. :285.5 Max. :0.02736 Max. :219.73
6152     RER
6153 Min. :0.6188
6154 1st Qu.:0.6420
6155 Median :0.6545
6156 Mean :0.6634

```

```
6157 3rd Qu.:0.6797
6158 Max. :0.7448
6159
6160 ###
6161 > std.error(Ta_A$H)
6162 [1] 0.1150076
6163 > std.error(Ta_F$H)
6164 [1] 0.2146761
6165 >
6166 > std.error(Ta_A$ST_D)
6167 [1] 0.01897175
6168 > std.error(Ta_F$ST_D)
6169 [1] 0.01545983
6170 >
6171 > std.error(Ta_A$RL)
6172 [1] 2.398475
6173 > std.error(Ta_F$RL)
6174 [1] 0.7385989
6175 >
6176 > std.error(Ta_A$Lnum)
6177 [1] 0.3170494
6178 > std.error(Ta_F$Lnum)
6179 [1] 0.4481123
6180 >
6181 > std.error(Ta_A$TM)
6182 [1] 0.141469
6183 > std.error(Ta_F$TM)
6184 [1] 0.2074348
6185 >
6186 > std.error(Ta_A$RM)
6187 [1] 0.113367
6188 > std.error(Ta_F$RM)
6189 [1] 0.1398907
6190 >
```

```
6191 > std.error(Qg_A$SM)
6192 [1] 0.01762037
6193 > std.error(Ta_F$SM)
6194 [1] 0.1042436
6195 >
6196 > std.error(Ta_A$RMF)
6197 [1] 0.01781508
6198 > std.error(Ta_F$RMF)
6199 [1] 0.01825998
6200 >
6201 > std.error(Ta_A$SMF)
6202 [1] 0.01781508
6203 > std.error(Ta_F$SMF)
6204 [1] 0.01825998
6205 >
6206 > std.error(Ta_A$RGR)
6207 [1] 0.0005543409
6208 > std.error(Ta_F$RGR)
6209 [1] 0.0005995452
6210 >
6211 > std.error(Ta_A$SLA)
6212 [1] 4.892494
6213 > std.error(Ta_F$SLA)
6214 [1] 7.603923
6215 >
6216 > std.error(Ta_A$STRL)
6217 [1] 4.813579
6218 > std.error(Ta_F$STRL)
6219 [1] 7.097902
6220
6221
6222 #####
6223 ##summary(Mt_m1_Ta)
6224
```

```

6225 Call:
6226 glm(formula = data_Ta$TM ~ cen, family = Gamma(), data = data_Ta)
6227
6228 Deviance Residuals:
6229     Min       1Q   Median       3Q      Max
6230 -0.98860 -0.20279 -0.02146  0.22410  0.64462
6231
6232 Coefficients:
6233             Estimate Std. Error t value Pr(>|t|)
6234 (Intercept)  0.39366   0.02290  17.191 < 2e-16 ***
6235 cenF        -0.09656   0.02886  -3.346  0.00143 **
6236
6237 ##summary(ScRM_m1_Ta)
6238
6239 Call:
6240 glm(formula = data_Ta$ScRM ~ cen, family = Gamma(), data = data_Ta)
6241
6242 Deviance Residuals:
6243     Min       1Q   Median       3Q      Max
6244 -1.57636 -0.42375 -0.05134  0.24601  1.13221
6245
6246 Coefficients:
6247             Estimate Std. Error t value Pr(>|t|)
6248 (Intercept)  2.6022   0.2391  10.881 9.88e-16 ***
6249 cenF        -0.3064   0.3212  -0.954  0.344
6250
6251 ##summary(TpRM_m1_Ta)
6252
6253 Call:
6254 glm(formula = data_Ta$TpRM ~ cen, family = Gamma(), data = data_Ta)
6255
6256 Deviance Residuals:
6257     Min       1Q   Median       3Q      Max
6258 -1.11915 -0.29088 -0.09637  0.20250  0.70217

```

```

6259
6260 Coefficients:
6261     Estimate Std. Error t value Pr(>|t|)
6262 (Intercept) 0.66679  0.04478  14.89 <2e-16 ***
6263 cenF      0.02474  0.06507   0.38  0.705
6264
6265 ##summary(StM_m1_Ta)
6266
6267 Call:
6268 glm(formula = data_Ta$StM ~ cen, family = Gamma(), data = data_Ta)
6269
6270 Deviance Residuals:
6271    Min     1Q   Median     3Q    Max
6272 -1.0871 -0.5068 -0.2556 -0.0705  3.2873
6273
6274 Coefficients:
6275     Estimate Std. Error t value Pr(>|t|)
6276 (Intercept)  9.293     2.213  4.200 9.14e-05 ***
6277 cenF       -1.626     2.888 -0.563  0.575
6278
6279 ##summary(SLA_m1_Ta)
6280
6281 Call:
6282 glm(formula = data_Ta$SLA ~ cen, family = Gamma(), data = data_Ta)
6283
6284 Deviance Residuals:
6285    Min     1Q   Median     3Q    Max
6286 -0.49915 -0.19649 -0.03150  0.07719  0.73918
6287
6288 Coefficients:
6289     Estimate Std. Error t value Pr(>|t|)
6290 (Intercept) 0.0080971 0.0003672 22.048 < 2e-16 ***
6291 cenF      -0.0013312 0.0004818 -2.763 0.00763 **
6292

```

```

6293  ## summary(H_m1_Ta)
6294
6295  Call:
6296  glm(formula = data_Ta$H ~ cen, family = Gamma(), data = data_Ta)
6297
6298  Deviance Residuals:
6299      Min       1Q   Median       3Q      Max
6300  -0.49482 -0.19612 -0.01177  0.11161  0.44730
6301
6302  Coefficients:
6303      Estimate Std. Error t value Pr(>|t|)
6304  (Intercept)  0.31880   0.01381  23.084 <2e-16 ***
6305  cenF        -0.08552   0.01721  -4.969 6.11e-06 ***
6306
6307  ## summary(ST_D_m2_Ta)
6308
6309  Call:
6310  glm(formula = data_Ta$ST_D ~ cen, family = gaussian(), data = data_Ta)
6311
6312  Deviance Residuals:
6313      Min       1Q   Median       3Q      Max
6314  -0.14506 -0.06456 -0.01950  0.03500  0.27493
6315
6316  Coefficients:
6317      Estimate Std. Error t value Pr(>|t|)
6318  (Intercept)  0.42256   0.01723  24.532 <2e-16 ***
6319  cenF         0.01044   0.02456  0.425  0.672
6320
6321  ##summary(RGR_m1_Ta)
6322
6323  Call:
6324  glm(formula = data_Ta$RGR ~ cen, family = Gamma(), data = data_Ta)
6325
6326  Deviance Residuals:

```

```

6327      Min    1Q  Median    3Q    Max
6328 -0.55040 -0.09898 0.02418 0.11032 0.21258
6329
6330 Coefficients:
6331      Estimate Std. Error t value Pr(>|t|)
6332 (Intercept) 49.158    1.315 37.387 <2e-16 ***
6333 cenF      -4.708    1.786 -2.636 0.0107 *
6334
6335 ##summary(Lnum_m1_Ta)
6336
6337 Call:
6338 glm(formula = data_Ta$Lnum ~ cen, family = Gamma(), data = data_Ta)
6339
6340 Deviance Residuals:
6341      Min    1Q  Median    3Q    Max
6342 -0.52719 -0.16760 0.00838 0.11752 0.57013
6343
6344 Coefficients:
6345      Estimate Std. Error t value Pr(>|t|)
6346 (Intercept) 0.140271  0.005750 24.396 < 2e-16 ***
6347 cenF      -0.056238  0.006732 -8.354 1.38e-11 ***
6348
6349 ## summary(RMF_m2_Ta)
6350
6351 Call:
6352 glm(formula = data_Ta$RMF ~ cen, family = gaussian(), data = data_Ta)
6353
6354 Deviance Residuals:
6355      Min    1Q  Median    3Q    Max
6356 -0.215909 -0.060700 -0.005448 0.044092 0.210712
6357
6358 Coefficients:
6359      Estimate Std. Error t value Pr(>|t|)
6360 (Intercept) 0.73892  0.01789 41.308 < 2e-16 ***

```

```

6361  cenF    -0.18176  0.02551 -7.126 1.66e-09 ***
6362
6363  ## summary(SM_m2_Ta)
6364
6365  Call:
6366  glm(formula = data_Ta$SM ~ cen, family = gaussian(), data = data_Ta)
6367
6368  Deviance Residuals:
6369      Min       1Q   Median       3Q      Max
6370  -1.05967 -0.31883  0.04337  0.22567  1.05583
6371
6372  Coefficients:
6373      Estimate Std. Error t value Pr(>|t|)
6374  (Intercept) 0.65623   0.08351   7.858 9.52e-11 ***
6375  cenF         0.82795   0.11909   6.953 3.26e-09 ***
6376
6377  ##summary(RM_m1_Ta)
6378
6379  Call:
6380  glm(formula = data_Ta$RM ~ cen, family = Gamma(), data = data_Ta)
6381
6382  Deviance Residuals:
6383      Min       1Q   Median       3Q      Max
6384  -1.19401 -0.30114 -0.04404  0.19814  0.70858
6385
6386  Coefficients:
6387      Estimate Std. Error t value Pr(>|t|)
6388  (Intercept) 0.5307810  0.0354876  14.957 <2e-16 ***
6389  cenF         0.0006665  0.0506359   0.013  0.99
6390
6391  ##summary(RL_m1_Ta)
6392
6393  Call:
6394  glm(formula = data_Ta$RL ~ cen, family = Gamma(), data = data_Ta)

```



```

6395
6396 Deviance Residuals:
6397   Min    1Q  Median    3Q    Max
6398 -0.98840 -0.01426  0.00698  0.02789  0.20253
6399
6400 Coefficients:
6401             Estimate Std. Error t value Pr(>|t|)
6402 (Intercept) 0.0105777  0.0001990  53.143 <2e-16 ***
6403 cenF      -0.0004147  0.0002782  -1.491  0.141
6404
6405 ##summary(STRL_m2_Ta)
6406
6407 Call:
6408 glm(formula = data_Ta$STRL ~ cen, family = gaussian(), data = data_Ta)
6409
6410 Deviance Residuals:
6411   Min    1Q  Median    3Q    Max
6412 -45.917 -20.790 -4.635  10.871 138.157
6413
6414 Coefficients:
6415             Estimate Std. Error t value Pr(>|t|)
6416 (Intercept) 69.685    5.979  11.655 <2e-16 ***
6417 cenF        11.891    8.525   1.395  0.168
6418
6419 #####
6420 #####
6421
6422 summary(Hs_A)
6423   sp      cen      ST_D      H      Lnum
6424 Length:30   Length:30   Min. :0.3440 Min. :10.40 Min. :1.000
6425 Class :character Class :character 1st Qu.:0.3924 1st Qu.:16.00 1st Qu.:2.000
6426 Mode :character Mode :character Median:0.4243 Median :17.60 Median :2.000
6427             Mean :0.4268 Mean :18.42 Mean :2.167
6428             3rd Qu.:0.4631 3rd Qu.:20.95 3rd Qu.:3.000
6429             Max. :0.5390 Max. :31.00 Max. :4.000

```

```

6430      RL      TpRM      ScRM      StM      TLM
6431  Min. : 97.2  Min. :1.767  Min. :0.2945  Min. :0.4109  Min. :0.955
6432  1st Qu.:103.0  1st Qu.:2.174  1st Qu.:0.5649  1st Qu.:0.5421  1st Qu.:1.561
6433  Median :107.0  Median :2.765  Median :0.9011  Median :0.6369  Median :1.679
6434  Mean :107.3  Mean :2.910  Mean :0.9006  Mean :0.6603  Mean :1.749
6435  3rd Qu.:112.2  3rd Qu.:3.133  3rd Qu.:1.1715  3rd Qu.:0.8132  3rd Qu.:2.020
6436  Max. :117.0  Max. :4.684  Max. :2.0108  Max. :1.0106  Max. :2.513
6437      RM      SM      TM      RS      LMF
6438  Min. :2.065  Min. :1.366  Min. :3.627  Min. :1.021  Min. :0.02611
6439  1st Qu.:2.893  1st Qu.:2.135  1st Qu.:5.211  1st Qu.:1.391  1st Qu.:0.25728
6440  Median :3.590  Median :2.343  Median :5.896  Median :1.545  Median :0.27990
6441  Mean :3.811  Mean :2.409  Mean :6.220  Mean :1.593  Mean :0.26857
6442  3rd Qu.:4.179  3rd Qu.:2.717  3rd Qu.:7.316  3rd Qu.:1.751  3rd Qu.:0.30770
6443  Max. :6.394  Max. :3.452  Max. :9.589  Max. :2.605  Max. :0.37475
6444      RMF      SMF      SLA      RGR      STRL
6445  Min. :0.5052  Min. :0.2774  Min. : 53.22  Min. :0.008502  Min. :22.23
6446  1st Qu.:0.5817  1st Qu.:0.3635  1st Qu.: 64.88  1st Qu.:0.011803  1st Qu.:32.35
6447  Median :0.6070  Median :0.3930  Median : 75.31  Median :0.013059  Median :39.14
6448  Mean :0.6084  Mean :0.3916  Mean : 73.40  Mean :0.013224  Mean :39.72
6449  3rd Qu.:0.6365  3rd Qu.:0.4183  3rd Qu.: 79.81  3rd Qu.:0.014793  3rd Qu.:46.70
6450  Max. :0.7226  Max. :0.4948  Max. :102.56  Max. :0.017047  Max. :60.99
6451      RER
6452  Min. :0.5283
6453  1st Qu.:0.6850
6454  Median :0.7402
6455  Mean :0.7368
6456  3rd Qu.:0.8035
6457  Max. :0.8454
6458  > summary(Hs_F)
6459      sp      cen      ST_D      H      Lnum
6460  Length:30  Length:30  Min. :0.3340  Min. :16.30  Min. :2.000
6461  Class :character  Class :character  1st Qu.:0.4022  1st Qu.:21.12  1st Qu.:3.000
6462  Mode :character  Mode :character  Median :0.4550  Median :23.80  Median :4.000
6463  Mean :0.4425  Mean :24.18  Mean :4.067

```

```

6464          3rd Qu.:0.4780 3rd Qu.:26.80 3rd Qu.:5.000
6465          Max. :0.5600 Max. :39.20 Max. :6.000
6466      RL      TpRM      ScRM      StM      TLM
6467      Min. :98.0 Min. :1.053 Min. :0.2308 Min. :0.4802 Min. :1.712
6468      1st Qu.:103.8 1st Qu.:3.408 1st Qu.:1.0377 1st Qu.:0.6584 1st Qu.:2.404
6469      Median :107.5 Median :4.479 Median :1.3816 Median :0.8807 Median :2.992
6470      Mean :107.8 Mean :4.473 Mean :1.6110 Mean :0.8826 Mean :2.964
6471      3rd Qu.:111.8 3rd Qu.:5.500 3rd Qu.:2.0025 3rd Qu.:1.0144 3rd Qu.:3.303
6472      Max. :120.0 Max. :8.774 Max. :6.7021 Max. :1.4414 Max. :4.857
6473      RM      SM      TM      RS      LMF
6474      Min. :1.675 Min. :2.261 Min. :3.992 Min. :0.7231 Min. :0.2097
6475      1st Qu.:4.769 1st Qu.:3.246 1st Qu.:7.856 1st Qu.:1.3589 1st Qu.:0.2735
6476      Median :5.502 Median :3.854 Median :9.806 Median :1.5317 Median :0.3078
6477      Mean :6.084 Mean :3.847 Mean :9.931 Mean :1.5574 Mean :0.3089
6478      3rd Qu.:7.454 3rd Qu.:4.387 3rd Qu.:11.846 3rd Qu.:1.8481 3rd Qu.:0.3345
6479      Max. :12.271 Max. :6.212 Max. :17.657 Max. :2.5605 Max. :0.4601
6480      RMF      SMF      SLA      RGR      STRL
6481      Min. :0.4197 Min. :0.2809 Min. :47.59 Min. :0.00935 Min. :12.65
6482      1st Qu.:0.5761 1st Qu.:0.3511 1st Qu.:80.31 1st Qu.:0.01585 1st Qu.:19.56
6483      Median :0.6050 Median :0.3950 Median :86.68 Median :0.01814 Median :24.25
6484      Mean :0.5988 Mean :0.4012 Mean :91.04 Mean :0.01729 Mean :28.61
6485      3rd Qu.:0.6489 3rd Qu.:0.4239 3rd Qu.:92.13 3rd Qu.:0.01952 3rd Qu.:30.84
6486      Max. :0.7191 Max. :0.5803 Max. :257.04 Max. :0.02271 Max. :93.98
6487      RER
6488      Min. :0.6610
6489      1st Qu.:0.7022
6490      Median :0.7528
6491      Mean :0.7541
6492      3rd Qu.:0.8044
6493      Max. :0.9028
6494
6495      std.error(Hs_A$H)
6496      [1] 0.8497383
6497      > std.error(Hs_F$H)

```

```
6498 [1] 0.8870252
6499 >
6500 > std.error(Hs_A$ST_D)
6501 [1] 0.009277045
6502 > std.error(Hs_F$ST_D)
6503 [1] 0.01010964
6504 >
6505 > std.error(Hs_A$RL)
6506 [1] 1.068566
6507 > std.error(Hs_F$RL)
6508 [1] 1.09648
6509 >
6510 > std.error(Hs_A$Lnum)
6511 [1] 0.15225
6512 > std.error(Hs_F$Lnum)
6513 [1] 0.203042
6514 >
6515 > std.error(Hs_A$TM)
6516 [1] 0.2968778
6517 > std.error(Hs_F$TM)
6518 [1] 0.5660409
6519 >
6520 > std.error(Hs_A$RM)
6521 [1] 0.2123691
6522 > std.error(Hs_F$RM)
6523 [1] 0.4348676
6524 >
6525 > std.error(Hs_A$SM)
6526 [1] 0.1053035
6527 > std.error(Hs_F$SM)
6528 [1] 0.1711766
6529 >
6530 > std.error(Hs_A$RMF)
6531 [1] 0.008866564
```

```

6532 > std.error(Hs_F$RMF)
6533 [1] 0.01234643
6534 >
6535 > std.error(Hs_A$SMF)
6536 [1] 0.008866564
6537 > std.error(Hs_F$SMF)
6538 [1] 0.01234643
6539 >
6540 > std.error(Hs_A$RGR)
6541 [1] 0.0004199812
6542 > std.error(Hs_F$RGR)
6543 [1] 0.0005701719
6544 >
6545 > std.error(Hs_A$SLA)
6546 [1] 1.953027
6547 > std.error(Hs_F$SLA)
6548 [1] 6.104325
6549 >
6550 > std.error(Hs_A$STRL)
6551 [1] 1.9324
6552 > std.error(Hs_F$STRL)
6553 [1] 2.863996
6554 #####
6555 ##summary(Mt_m1_Hs)
6556
6557 Call:
6558 glm(formula = data_Hs$TM ~ cen, family = Gamma(), data = data_Hs)
6559
6560 Deviance Residuals:
6561     Min       1Q   Median       3Q      Max
6562 -0.79160 -0.18266 -0.04913  0.18464  0.63639
6563
6564 Coefficients:
6565             Estimate Std. Error t value Pr(>|t|)

```

```

6566 (Intercept) 0.160772 0.008452 19.023 < 2e-16 ***
6567 cenF      -0.060075 0.009972 -6.024 1.24e-07 ***
6568
6569 ##summary(ScRM_m1_Hs)
6570
6571 Call:
6572 glm(formula = data_Hs$ScRM ~ cen, family = Gamma(), data = data_Hs)
6573
6574 Deviance Residuals:
6575     Min       1Q   Median       3Q      Max
6576 -1.4740 -0.4228 -0.1367  0.2677  1.8626
6577
6578 Coefficients:
6579             Estimate Std. Error t value Pr(>|t|)
6580 (Intercept)  1.1103    0.1264   8.785 3.01e-12 ***
6581 cenF        -0.4896    0.1448  -3.381 0.0013 **
6582
6583 ##summary(TpRM_m1_Hs)
6584
6585 Call:
6586 glm(formula = data_Hs$TpRM ~ cen, family = Gamma(), data = data_Hs)
6587
6588 Deviance Residuals:
6589     Min       1Q   Median       3Q      Max
6590 -1.16747 -0.27067 -0.04291  0.18711  0.75876
6591
6592 Coefficients:
6593             Estimate Std. Error t value Pr(>|t|)
6594 (Intercept)  0.34359    0.02071  16.593 < 2e-16 ***
6595 cenF        -0.12001    0.02471  -4.858 9.38e-06 ***
6596
6597 ##summary(StM_m1_Hs)
6598
6599 Call:

```

```

6600 glm(formula = data_Hs$StM ~ cen, family = Gamma(), data = data_Hs)
6601
6602 Deviance Residuals:
6603     Min       1Q   Median       3Q      Max
6604 -0.55269 -0.22235 -0.00981  0.17824  0.53413
6605
6606 Coefficients:
6607             Estimate Std. Error t value Pr(>|t|)
6608 (Intercept)  1.51440    0.07617  19.882 < 2e-16 ***
6609 cenF        -0.38136    0.09513  -4.009 0.000177 ***
6610
6611 ##summary(SLA_m1_Hs)
6612
6613 Call:
6614 glm(formula = data_Hs$SLA ~ cen, family = Gamma(), data = data_Hs)
6615
6616 Deviance Residuals:
6617     Min       1Q   Median       3Q      Max
6618 -0.58558 -0.12623 -0.02651  0.07028  1.25333
6619
6620 Coefficients:
6621             Estimate Std. Error t value Pr(>|t|)
6622 (Intercept)  0.0136244  0.0006950  19.605 < 2e-16 ***
6623 cenF        -0.0026404  0.0008927  -2.958  0.00448 **
6624
6625 ##summary(H_m1_Hs)
6626
6627 Call:
6628 glm(formula = data_Hs$H ~ cen, family = Gamma(), data = data_Hs)
6629
6630 Deviance Residuals:
6631     Min       1Q   Median       3Q      Max
6632 -0.52199 -0.13766 -0.02419  0.12391  0.56992
6633

```

```

6634 Coefficients:
6635     Estimate Std. Error t value Pr(>|t|)
6636 (Intercept) 0.054289  0.002263  23.995 < 2e-16 ***
6637 cenF      -0.012932  0.002844  -4.547 2.82e-05 ***
6638
6639 ##summary(ST_D_m1_Hs)
6640
6641 Call:
6642 glm(formula = data_Hs$ST_D ~ cen, family = Gamma(), data = data_Hs)
6643
6644 Deviance Residuals:
6645     Min       1Q   Median       3Q      Max
6646 -0.268673 -0.088835  0.009772  0.083037  0.245155
6647
6648 Coefficients:
6649     Estimate Std. Error t value Pr(>|t|)
6650 (Intercept) 2.34302  0.05225  44.845 <2e-16 ***
6651 cenF      -0.08305  0.07259  -1.144  0.257
6652
6653 ## summary(RGR_m1_Hs)
6654
6655 Call:
6656 glm(formula = data_Hs$RGR ~ cen, family = Gamma(), data = data_Hs)
6657
6658 Deviance Residuals:
6659     Min       1Q   Median       3Q      Max
6660 -0.55757 -0.11011 -0.00885  0.12079  0.28581
6661
6662 Coefficients:
6663     Estimate Std. Error t value Pr(>|t|)
6664 (Intercept) 75.618  2.448  30.886 < 2e-16 ***
6665 cenF      -17.767  3.083  -5.764 3.33e-07 ***
6666
6667 ## summary(Lnum_m1_Hs)

```



```

6668
6669 Call:
6670 glm(formula = data_Hs$Lnum ~ cen, family = Gamma(), data = data_Hs)
6671
6672 Deviance Residuals:
6673     Min       1Q   Median       3Q      Max
6674 -0.68517 -0.28954 -0.07899  0.21398  0.68271
6675
6676 Coefficients:
6677             Estimate Std. Error t value Pr(>|t|)
6678 (Intercept)  0.46154   0.02813  16.406 < 2e-16 ***
6679 cenF        -0.21564   0.03188  -6.765 7.27e-09 ***
6680
6681 ##summary(STRL_m1_Hs)
6682
6683 Call:
6684 glm(formula = data_Hs$STRL ~ cen, family = Gamma(), data = data_Hs)
6685
6686 Deviance Residuals:
6687     Min       1Q   Median       3Q      Max
6688 -0.71866 -0.28525 -0.07539  0.14266  1.48016
6689
6690 Coefficients:
6691             Estimate Std. Error t value Pr(>|t|)
6692 (Intercept)  0.025175  0.001981  12.707 < 2e-16 ***
6693 cenF         0.009775  0.003390   2.884 0.0055 **
6694
6695 ## summary(RMF_m1_Hs)
6696
6697 Call:
6698 glm(formula = data_Hs$RMF ~ cen, family = Gamma(), data = data_Hs)
6699
6700 Deviance Residuals:
6701     Min       1Q   Median       3Q      Max

```

```

6702 -0.33558 -0.04270 0.00320 0.06718 0.18896
6703
6704 Coefficients:
6705     Estimate Std. Error t value Pr(>|t|)
6706 (Intercept) 1.64377  0.02935 56.007 <2e-16 ***
6707 cenF      0.02633  0.04184  0.629  0.532
6708
6709 ##summary(SM_m1_Hs)
6710
6711 Call:
6712 glm(formula = data_Hs$SM ~ cen, family = Gamma(), data = data_Hs)
6713
6714 Deviance Residuals:
6715     Min       1Q   Median       3Q      Max
6716 -0.51842 -0.13717 -0.02556  0.13006  0.52072
6717
6718 Coefficients:
6719     Estimate Std. Error t value Pr(>|t|)
6720 (Intercept) 0.41513  0.01831 22.672 < 2e-16 ***
6721 cenF      -0.15519  0.02160 -7.184 1.44e-09 ***
6722
6723 ##summary(RM_m1_Hs)
6724
6725 Call:
6726 glm(formula = data_Hs$RM ~ cen, family = Gamma(), data = data_Hs)
6727
6728 Deviance Residuals:
6729     Min       1Q   Median       3Q      Max
6730 -1.06301 -0.23774 -0.08251  0.16381  0.79424
6731
6732 Coefficients:
6733     Estimate Std. Error t value Pr(>|t|)
6734 (Intercept) 0.26239  0.01682 15.60 < 2e-16 ***
6735 cenF      -0.09802  0.01984 -4.94 6.99e-06 ***

```

```

6736
6737  ##summary(RL_m1_Hs)
6738
6739  Call:
6740  glm(formula = data_Hs$RL ~ cen, family = Gamma(), data = data_Hs)
6741
6742  Deviance Residuals:
6743      Min       1Q   Median       3Q      Max
6744 -0.097706 -0.038686 -0.003731  0.044516  0.108748
6745
6746  Coefficients:
6747      Estimate Std. Error t value Pr(>|t|)
6748 (Intercept) 9.315e-03 9.372e-05 99.391 <2e-16 ***
6749 cenF      -4.261e-05 1.322e-04 -0.322  0.748
6750
6751 #####
6752 #####
6753
6754
6755  summary(Kc_A)
6756      sp      cen      ST_D      H      Lnum
6757 Length:22 Length:22 Min. :0.2065 Min. :1.800 Min. :1.000
6758 Class :character Class :character 1st Qu.:0.2263 1st Qu.:2.525 1st Qu.:1.000
6759 Mode :character Mode :character Median :0.2445 Median :3.000 Median :1.000
6760      Mean :0.2474 Mean :3.345 Mean :1.273
6761      3rd Qu.:0.2649 3rd Qu.:3.400 3rd Qu.:1.750
6762      Max. :0.3030 Max. :7.300 Max. :2.000
6763      RL      TpRM      ScRM      StM      TLM
6764 Min. :25.30 Min. :0.6195 Min. :0.05650 Min. :0.01690 Min. :0.0474
6765 1st Qu.:48.50 1st Qu.:0.8563 1st Qu.:0.09975 1st Qu.:0.02533 1st Qu.:0.0865
6766 Median :63.15 Median :1.2578 Median :0.12445 Median :0.02625 Median :0.1138
6767 Mean :61.24 Mean :1.2516 Mean :0.15697 Mean :0.03403 Mean :0.1264
6768 3rd Qu.:71.38 3rd Qu.:1.5051 3rd Qu.:0.21377 3rd Qu.:0.03742 3rd Qu.:0.1396
6769 Max. :97.60 Max. :2.1173 Max. :0.35800 Max. :0.08500 Max. :0.3483
6770      RM      SM      TM      RS      LMF

```

```

6771  Min. :0.6782 Min. :0.0706 Min. :0.7863 Min. :2.159 Min. :0.04260
6772  1st Qu.:0.9627 1st Qu.:0.1135 1st Qu.:1.1966 1st Qu.: 6.684 1st Qu.:0.05235
6773  Median :1.4633 Median :0.1484 Median :1.6199 Median : 9.828 Median :0.06457
6774  Mean :1.4085 Mean :0.1604 Mean :1.5690 Mean : 9.994 Mean :0.08760
6775  3rd Qu.:1.6622 3rd Qu.:0.1792 3rd Qu.:1.8429 3rd Qu.:12.607 3rd Qu.:0.10506
6776  Max. :2.2325 Max. :0.3652 Max. :2.3562 Max. :18.048 Max. :0.30195
6777  RMF      SMF      SLA      RGR      STRL
6778  Min. :0.6834 Min. :0.05250 Min. :26.81 Min. :0.01512 Min. :19.26
6779  1st Qu.:0.8697 1st Qu.:0.07352 1st Qu.:104.43 1st Qu.:0.01763 1st Qu.: 40.98
6780  Median :0.9076 Median :0.09242 Median :120.66 Median :0.02008 Median : 49.38
6781  Mean :0.8893 Mean :0.11068 Mean :115.34 Mean :0.01981 Mean : 53.68
6782  3rd Qu.:0.9265 3rd Qu.:0.13033 3rd Qu.:129.09 3rd Qu.:0.02180 3rd Qu.: 65.40
6783  Max. :0.9475 Max. :0.31660 Max. :173.83 Max. :0.02448 Max. :106.86
6784  RER
6785  Min. :0.1077
6786  1st Qu.:0.3063
6787  Median :0.4113
6788  Mean :0.4058
6789  3rd Qu.:0.5110
6790  Max. :0.6651
6791  > summary(Kc_F)
6792  sp      cen      ST_D      H      Lnum
6793  Length:21  Length:21  Min. :0.2010 Min. :2.000 Min. :1.000
6794  Class :character Class :character 1st Qu.:0.2380 1st Qu.:2.500 1st Qu.:1.000
6795  Mode :character Mode :character Median :0.2505 Median :2.700 Median :1.000
6796  Mean :0.2536 Mean :3.129 Mean :1.476
6797  3rd Qu.:0.2760 3rd Qu.:3.000 3rd Qu.:2.000
6798  Max. :0.3145 Max. :7.500 Max. :3.000
6799  RL      TpRM      ScRM      StM      TLM
6800  Min. : 50.0 Min. :0.904 Min. :0.0443 Min. :0.02010 Min. :0.0656
6801  1st Qu.: 81.5 1st Qu.:1.369 1st Qu.:0.0995 1st Qu.:0.02940 1st Qu.:0.1226
6802  Median : 94.8 Median :1.765 Median :0.1422 Median :0.03660 Median :0.1641
6803  Mean : 87.6 Mean :2.388 Mean :0.1732 Mean :0.03978 Mean :0.1689
6804  3rd Qu.: 98.7 3rd Qu.:2.280 3rd Qu.:0.2339 3rd Qu.:0.04230 3rd Qu.:0.2101

```

```

6805 Max. :103.0 Max. :7.822 Max. :0.3830 Max. :0.10880 Max. :0.3274
6806 RM SM TM RS LMF
6807 Min. :0.9862 Min. :0.0950 Min. :1.188 Min. :3.374 Min. :0.01034
6808 1st Qu.:1.6330 1st Qu.:0.1576 1st Qu.:1.789 1st Qu.:7.862 1st Qu.:0.05514
6809 Median :1.9857 Median :0.1996 Median :2.206 Median :10.809 Median :0.06889
6810 Mean :2.5613 Mean :0.2087 Mean :2.770 Mean :14.529 Mean :0.07782
6811 3rd Qu.:2.5626 3rd Qu.:0.2440 3rd Qu.:2.779 3rd Qu.:13.400 3rd Qu.:0.09991
6812 Max. :8.0758 Max. :0.3952 Max. :8.471 Max. :65.761 Max. :0.20386
6813 RMF SMF SLA RGR STRL
6814 Min. :0.7714 Min. :0.01498 Min. :63.59 Min. :0.01864 Min. :8.17
6815 1st Qu.:0.8872 1st Qu.:0.06944 1st Qu.:94.16 1st Qu.:0.02131 1st Qu.:37.26
6816 Median :0.9153 Median :0.08468 Median :115.03 Median :0.02298 Median :48.07
6817 Mean :0.9058 Mean :0.09422 Mean :111.17 Mean :0.02390 Mean :49.19
6818 3rd Qu.:0.9306 3rd Qu.:0.11284 3rd Qu.:131.85 3rd Qu.:0.02570 3rd Qu.:66.55
6819 Max. :0.9850 Max. :0.22864 Max. :158.61 Max. :0.03231 Max. :90.15
6820 RER
6821 Min. :0.2926
6822 1st Qu.:0.6050
6823 Median :0.6625
6824 Mean :0.6343
6825 3rd Qu.:0.7378
6826 Max. :0.7685
6827
6828
6829 std.error(Kc_A$H)
6830 [1] 0.3343746
6831 > std.error(Kc_F$H)
6832 [1] 0.2750015
6833 >
6834 > std.error(Kc_A$ST_D)
6835 [1] 0.005887214
6836 > std.error(Kc_F$ST_D)
6837 [1] 0.005916295
6838 >

```

```
6839 > std.error(Kc_A$RL)
6840 [1] 3.993005
6841 > std.error(Kc_F$RL)
6842 [1] 3.400739
6843 >
6844 > std.error(Kc_A$Lnum)
6845 [1] 0.09718591
6846 > std.error(Kc_F$Lnum)
6847 [1] 0.1483087
6848 >
6849 > std.error(Kc_A$TM)
6850 [1] 0.09507547
6851 > std.error(Kc_F$TM)
6852 [1] 0.3935572
6853 >
6854 > std.error(Kc_A$RM)
6855 [1] 0.09603925
6856 > std.error(Kc_F$RM)
6857 [1] 0.3909287
6858 >
6859 > std.error(Kc_A$SM)
6860 [1] 0.01425702
6861 > std.error(Kc_F$SM)
6862 [1] 0.01715668
6863 >
6864 > std.error(Kc_A$RMF)
6865 [1] 0.01300992
6866 > std.error(Kc_F$RMF)
6867 [1] 0.01072463
6868 >
6869 > std.error(Kc_A$SMF)
6870 [1] 0.01300992
6871 > std.error(Kc_F$SMF)
6872 [1] 0.01072463
```

```

6873 >
6874 > std.error(Kc_A$RGR)
6875 [1] 0.0005230258
6876 > std.error(Kc_F$RGR)
6877 [1] 0.0007581438
6878 >
6879 > std.error(Kc_A$SLA)
6880 [1] 7.127763
6881 > std.error(Kc_F$SLA)
6882 [1] 5.90682
6883 >
6884 > std.error(Kc_A$STRL)
6885 [1] 4.783939
6886 > std.error(Kc_F$STRL)
6887 [1] 4.786222
6888 >
6889 #####
6890 ##summary(Mt_m1_Kc)
6891
6892 Call:
6893 glm(formula = data_Kc$TM ~ cen, family = Gamma(), data = data_Kc)
6894
6895 Deviance Residuals:
6896     Min       1Q   Median       3Q      Max
6897 -0.74230 -0.37128 -0.06882  0.12814  1.37137
6898
6899 Coefficients:
6900             Estimate Std. Error t value Pr(>|t|)
6901 (Intercept)  0.63737   0.06770   9.415 8.35e-12 ***
6902 cenF        -0.27635   0.07825  -3.532 0.00104 **
6903
6904 ##summary(ScRM_m1_Kc)
6905
6906 Call:

```

```

6907 glm(formula = data_Kc$ScRM ~ cen, family = Gamma(), data = data_Kc)
6908
6909 Deviance Residuals:
6910   Min     1Q   Median     3Q      Max
6911 -1.1128 -0.4458 -0.1908  0.3492  0.9552
6912
6913 Coefficients:
6914             Estimate Std. Error t value Pr(>|t|)
6915 (Intercept)  6.3705     0.7426   8.578 1.08e-10 ***
6916 cenF        -0.5962     1.0130  -0.589  0.559
6917
6918 ## summary(TpRM_m1_Kc)
6919
6920 Call:
6921 glm(formula = data_Kc$TpRM ~ cen, family = Gamma(), data = data_Kc)
6922
6923 Deviance Residuals:
6924   Min     1Q   Median     3Q      Max
6925 -0.83664 -0.46263 -0.08065  0.11694  1.47570
6926
6927 Coefficients:
6928             Estimate Std. Error t value Pr(>|t|)
6929 (Intercept)  0.79899     0.09736   8.207 3.45e-10 ***
6930 cenF        -0.38026     0.11048  -3.442 0.00134 **
6931
6932 ## summary(StM_m1_Kc)
6933
6934 Call:
6935 glm(formula = data_Kc$StM ~ cen, family = Gamma(), data = data_Kc)
6936
6937 Deviance Residuals:
6938   Min     1Q   Median     3Q      Max
6939 -0.62691 -0.28520 -0.12546  0.07628  1.20722
6940

```



```

6941 Coefficients:
6942           Estimate Std. Error t value Pr(>|t|)
6943 (Intercept) 29.388    3.152  9.323 1.1e-11 ***
6944 cenF      -4.253    4.190 -1.015  0.316
6945
6946 ## summary(SLA_m1_Kc)
6947
6948 Call:
6949 glm(formula = data_Kc$SLA ~ cen, family = Gamma(), data = data_Kc)
6950
6951 Deviance Residuals:
6952      Min       1Q   Median       3Q      Max
6953 -1.17616 -0.14342  0.03802  0.15381  0.44026
6954
6955 Coefficients:
6956           Estimate Std. Error t value Pr(>|t|)
6957 (Intercept) 0.0086698  0.0004958  17.49 <2e-16 ***
6958 cenF      0.0003258  0.0007233   0.45  0.655
6959
6960 ##summary(H_m1_Kc)
6961
6962 Call:
6963 glm(formula = data_Kc$H ~ cen, family = Gamma(), data = data_Kc)
6964
6965 Deviance Residuals:
6966      Min       1Q   Median       3Q      Max
6967 -0.56189 -0.22907 -0.10705  0.01622  1.02268
6968
6969 Coefficients:
6970           Estimate Std. Error t value Pr(>|t|)
6971 (Intercept) 0.29891   0.02790  10.712 1.87e-13 ***
6972 cenF      0.02072   0.04137   0.501  0.619
6973
6974 ##summary(ST_D_m1_Kc)

```

```

6975
6976 Call:
6977 glm(formula = data_Kc$ST_D ~ cen, family = Gamma(), data = data_Kc)
6978
6979 Deviance Residuals:
6980   Min     1Q   Median     3Q      Max
6981 -0.22394 -0.08471 -0.01244  0.07736  0.22305
6982
6983 Coefficients:
6984             Estimate Std. Error t value Pr(>|t|)
6985 (Intercept)  4.04263   0.09424  42.896 <2e-16 ***
6986 cenF        -0.10008   0.13316  -0.752  0.457
6987
6988 ##summary(RGR_m1_Kc)
6989
6990 Call:
6991 glm(formula = data_Kc$RGR ~ cen, family = Gamma(), data = data_Kc)
6992
6993 Deviance Residuals:
6994   Min     1Q   Median     3Q      Max
6995 -0.25856 -0.11678 -0.00378  0.07618  0.31711
6996
6997 Coefficients:
6998             Estimate Std. Error t value Pr(>|t|)
6999 (Intercept)  50.474     1.450  34.809 < 2e-16 ***
7000 cenF         -8.641     1.902  -4.545 4.79e-05 ***
7001
7002 ##summary(Lnum_m1_Kc)
7003
7004 Call:
7005 glm(formula = data_Kc$Lnum ~ cen, family = poisson(), data = data_Kc)
7006
7007 Deviance Residuals:
7008   Min     1Q   Median     3Q      Max

```

```

7009 -0.4165 -0.4165 -0.2513 0.4088 1.0988
7010
7011 Coefficients:
7012      Estimate Std. Error z value Pr(>|z|)
7013 (Intercept) 0.2412    0.1890  1.276  0.202
7014 cenF      0.1483    0.2607  0.569  0.569
7015
7016 ## summary(STRL_m1_Kc)
7017
7018 Call:
7019 glm(formula = data_Kc$STRL ~ cen, family = Gamma(), data = data_Kc)
7020
7021 Deviance Residuals:
7022      Min       1Q   Median       3Q      Max
7023 -1.38666 -0.26285 -0.02745  0.22560  0.77734
7024
7025 Coefficients:
7026      Estimate Std. Error t value Pr(>|t|)
7027 (Intercept) 0.018627  0.001715 10.863 1.22e-13 ***
7028 cenF      0.001700  0.002571  0.661  0.512
7029
7030 ## summary(RMF_m1_Kc)
7031
7032 Call:
7033 glm(formula = data_Kc$RMF ~ cen, family = Gamma(), data = data_Kc)
7034
7035 Deviance Residuals:
7036      Min       1Q   Median       3Q      Max
7037 -0.25230 -0.02305  0.01378  0.03868  0.08506
7038
7039 Coefficients:
7040      Estimate Std. Error t value Pr(>|t|)
7041 (Intercept) 1.12446  0.01487 75.62 <2e-16 ***
7042 cenF      -0.02044  0.02108 -0.97  0.338

```

```

7043
7044 ## summary(SM_m1_Kc)
7045
7046 Call:
7047 glm(formula = data_Kc$SM ~ cen, family = Gamma(), data = data_Kc)
7048
7049 Deviance Residuals:
7050     Min       1Q   Median       3Q      Max
7051 -0.72227 -0.30224 -0.06573  0.13965  0.95281
7052
7053 Coefficients:
7054             Estimate Std. Error t value Pr(>|t|)
7055 (Intercept)  6.2339     0.5287  11.790 9.44e-15 ***
7056 cenF        -1.4412     0.6728  -2.142  0.0382 *
7057
7058 ##summary(RM_m1_Kc)
7059
7060 Call:
7061 glm(formula = data_Kc$RM ~ cen, family = Gamma(), data = data_Kc)
7062
7063 Deviance Residuals:
7064     Min       1Q   Median       3Q      Max
7065 -0.82397 -0.41620 -0.06683  0.15417  1.41747
7066
7067 Coefficients:
7068             Estimate Std. Error t value Pr(>|t|)
7069 (Intercept)  0.70995     0.08165   8.695 7.53e-11 ***
7070 cenF        -0.31953     0.09370  -3.410  0.00147 **
7071
7072 ##summary(RL_m1_Kc)
7073
7074 Call:
7075 glm(formula = data_Kc$RL ~ cen, family = Gamma(), data = data_Kc)
7076

```

```

7077 Deviance Residuals:
7078   Min     1Q   Median     3Q      Max
7079 -0.77083 -0.12946  0.03652  0.12903  0.50535
7080
7081 Coefficients:
7082             Estimate Std. Error t value Pr(>|t|)
7083 (Intercept)  0.0163302  0.0008763  18.636 < 2e-16 ***
7084 cenF        -0.0049153  0.0010775  -4.562 4.53e-05 ***

```