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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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Tese apresentada ao Programa de Pós-Graduação em Botânica, Universidade de Brasília, como parte dos requisitos para obtenção do título de Doutora em Botânica.

Orientador: Dr. Fabian Borghetti

Brasília, DF

2023

ADALGISA MARIA CHAIB FERREIRA

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

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Aos meus filhos,

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 CO_2 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 [CO_2], 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 [CO_2], 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

Chaib Ferreira, Adalgisa Maria (2022), “Climate_dryspells”, Mendeley Data, V1, doi: 10.17632/mvd6mntz5p.1

Chaib Ferreira, Adalgisa Maria (2022), “Dryspells_initialdata”, Mendeley Data, V1, doi: 10.17632/459sdxmwm4.1

Chaib Ferreira, Adalgisa Maria (2022), “Dryspells_final_mesurements”, Mendeley Data, V1, doi: 10.17632/ywmn9cb8g3.1

Capítulo II

Chaib Ferreira, Adalgisa Maria (2022), “Climate_cenarios”, Mendeley Data, v1http://dx.doi.org/10.17632/286cjk5k55.1DOI (is reserved but not active)

SUMÁRIO

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 CO_2 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 CO_2 atmosférico acima de 800ppm (Meinshausen et al., 2019). A maior disponibilidade atmosférica carbono deve aumentar a frequência com que a Rubisco se liga ao CO_2 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 em ambientes com maior [CO_2] atmosférica pode levar a um maior acúmulo de biomassa, principalmente em espécies C3 (Ainsworth and Long, 2005; Hoffmann et al., 2000; Rosa et al., 2019; Souza et al., 2016).

No Cerrado, em particular, além do aumento da [CO_2] deve haver um aumento de cerca de 2,5°C na temperatura média (ver seção 5.2). Estima-se que o aumento da temperatura deve levar a um maior déficit de pressão de vapor (VPD). Esse aumento do VPD deve intensificar a evapotranspiração e acelerar a perda de água do solo, levando a estações secas mais intensas, com valores de humidade relativa do ar mais baixos durante essa estação (Hoffmann et al., 2012). Em relação à precipitação é esperada redução de dias com precipitação durante a estação chuvosa, com maior frequência e duração dos períodos sem chuva durante a estação chuvosa, ou seja, aumento de veranicos (Pascale et al., 2016). Veranicos prolongados podem causar estresse hídrico e afetar o recrutamento de plântulas (Hoffmann, 1996), principalmente em um cenário que a maior demanda por transpiração irá exigir maior disponibilidade de água no solo (Kumarathunge et al, 2020).

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

Devido ao curto período associado a mudanças climáticas consideravelmente sensíveis, é possível que o genótipo de plântulas expostas às condições climáticas de 2100 seja muito próximo ao genótipo das plântulas encontradas no cenário climático atual. Isso permite que experimentos testando os efeitos do cenário climático futuro em plântulas obtidas de sementes dispersas no cenário atual possam obter resultados úteis para compreender as respostas dessas espécies em 2100.

A maioria dos experimentos feitos até o momento para compreender as respostas de plântulas às condições ambientais projetadas para o fim do século se concentram em um ou dois parâmetros ambientais, como temperatura ou disponibilidade hídrica, não obtendo resultados para interações mais complexas, as quais são mais prováveis de serem vivenciadas pelas plantas (Parmesan and Hanley, 2015). Quando essas condições ambientais atuam simultaneamente podem ter consequências diferentes no metabolismo da plântula de quando ocorrem isoladamente, como amplificar possíveis prejuízos ou benefícios (Correia et al., 2018; Prasch and Sonnewald, 2015). Assim, alguns trabalhos indicam vantagens em uma maior [CO_2] para espécies arbóreas (Bellasio et al., 2018), pois confere a essas um aumento na taxa fotossintética e maior acúmulo de biomassa, permitindo uma maior capacidade de rebrotar em caso de perda da parte aérea Ainsworth and Long, 2005; Hoffmann et al., 2000; Rosa et al., 2019; Souza et al., 2016), enquanto outros estudos indicam que a alta concentração de CO_2 atmosférico não promove aumento da biomassa quando associado a altas temperaturas (Duan et al., 2015).

Enquanto a maior oferta de carbono atmosférico associado a temperaturas mais altas no cenário futuro pode favorecer o ganho de biomassa e acelerar o crescimento de plântulas durante a fase de estabelecimento (Mndela et al, 2022; Ncisana et al, 2022; Wang and Wang, 2021), a variação da precipitação associada a temperaturas mais elevadas pode levar a um estresse hídrico e anular o efeito fertilizante do alto CO_2 atmosférico (Westerband et al, 2019). Espécies arbóreas de ambiente savânico tendem a investir mais em profundidade de raiz do que espécies florestais (Hoffmann et al, 2004; Paganeli et al, 2020), o que permite alcançar fontes mais estáveis de água durante o ano. Porém, a maior demanda por evapotranspiração ocasionada por temperaturas mais altas e oferta irregular de água, devido às alterações previstas para a precipitação no cenário futuro, podem prejudicar o desenvolvimento inicial dessas plântulas durante a estação chuvosa (Kumarathunge et al, 2020).

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

Embora as espécies arbóreas de savanas tenham sido selecionadas para habitarem um ambiente com sazonalidade da precipitação e longos períodos sem chuva durante a estação seca, não sabemos como as plântulas irão ser afetadas pelas maiores temperaturas e pela variação da disponibilidade hídrica durante a fase de estabelecimento esperadas para o cenário de 2100. Nesse contexto podemos perguntar qual será o impacto dos cenários climáticos previstos pelo IPCC para 2100 no recrutamento de plântulas de espécies arbóreas no Cerrado, considerando maior temperatura, redução do número de dias com precipitação durante a estação chuvosa, e maior [CO_2] atmosférico. Será que serão favorecidas pelo aumento de [CO_2] atmosférico, e conseguirão fazer uso mais eficiente da água? Ou será que os prejuízos causados pelas altas temperaturas e déficit hídrico no solo serão mais determinantes em seu desenvolvimento que o possível benefício causado pela maior [CO_2]?

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

Já as temperaturas elevadas associadas à alta [CO_2] do cenário futuro permitirão maior acúmulo de biomassa durante a fase de crescimento inicial de espécies arbóreas de savana do Cerrado, permitindo crescimento mais acelerado quando comparadas às plântulas observadas no cenário climático atual.

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2. OBJETIVO

2.1. OBJETIVO GERAL

Compreender o desempenho de plântulas de espécies arbóreas de cerrado *sensu stricto* diante de diferentes cenários climáticos a partir da simulação do clima atual e daquele projetado pelo IPCC para o período entre 2080 e 2100 (SSP 3-7.0), em câmaras climáticas programadas para variação nos níveis de CO_2, temperatura e na frequência de irrigação.

2.2. OBJETIVOS ESPECÍFICOS

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

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

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

3. ORGANIZAÇÃO DA TESE E PLANO DE PUBLICAÇÃO

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

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

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

4. CAPÍTULO I

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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Early development of two savanna tree species under simulated dry spells

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[1]

Highlights

- Dry spells of up to 15 d did not affect the growth of *Qualea grandiflora* seedlings.
- Dry spells of 15 d caused reduction of *Tabebuia aurea* seedlings root biomass.
- *Tabebuia aurea* seedlings invested more biomass in shoot growth and root elongation when submitted to dry spells.
- The investment in total leaf biomass and net assimilation rate can explain why both species differed in their dry spell treatments response.

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[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.

ABSTRACT

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

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

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

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

The extent of root growth achieved by young plants of savanna tree species during the rainy season may determine their survival during the dry season (García-Núñez et al., 2019; Kanegae et al., 2000). Although this strategy can be decisive for their survival during the dry season, it can be compromised by the occurrence of dry spells during the rainy season. For example, soil water potential was lowered to ca. -1.3 MPa (at 5 cm soil depth) during a dry spell of 9 days, which reduced the emergence and survival rate of *Bowdichia virgilioides* seedlings compared with seedlings that were not exposed to dry spell (Braz et al., 2000). Similarly, there was a 0.67- and 2.6-fold increase, respectively, in the recruitment rates of *Roupala montana* and *Miconia albicans* seedlings under irrigation when compared with unirrigated seedlings exposed to dry spells of at least 9 days during the rainy season (Hoffmann, 1996).

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

4.2. MATERIALS AND METHODS

4.2.1. Species studied and seed collection

Qualea grandiflora and *Tabebuia aurea* are widely distributed in savanna physiognomies of the Cerrado (Ratter et al., 2003). Both species are deciduous, anemochorous, and typical of *cerrado sensu stricto* physiognomy (Capuzzo et al., 2012; Ratter et al., 2003), generally occurring on red latosol. The seeds of these species have no dormancy (da Ponte et al., 2020; Santos et al., 2019). Seeds were collected between September and October 2017 in savanna areas located in the municipality of Pirenópolis, Goiás state (15° 84′ S, 48° 97′ W; 800 m a.s.l.), at the Brasília National Park (15° 38′ S, 48° 01′ W; 1.100 m a.s.l.), and the Fazenda Água Limpa (15° 95′ S, 47° 92′ W; 1.200 m a.s.l.), in the Federal District. Seeds were collected from 10 healthy trees at least 50 meters apart from each other and taken to the *Laboratório de Termobiologia* of the University of Brasília (Darcy Ribeiro Campus). Seeds were processed and stored at for further analysis.

4.2.2. Climate data

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

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

4.2.3. Equipment and assembly and disassembly of the experiment

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

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

After 60 days, 10 seedlings of *T aurea* and 8 seedlings of *Q*. *grandiflora* were chosen at random for initial measurements (Table S2). These initial measurements were important for the calculations of plant growth variables (Table S3). The remaining seedlings were randomly distributed in groups of 10 (*T. aurea*) or 8 (*Q. grandiflora*) seedlings per treatment. To be subjected to the dry spell treatments, the 60-day-old seedlings were transferred from the plastic bags to plastic tubes (100 cm high and 10 cm in diameter), closed at the base with a perforated lid to allow the draining of excess water. The tubes were filled with the same substrate as the bags and evenly distributed in the phytotron to standardize the effects of the chamber environment on seedling growth. The dry spells were simulated by controlling the frequency of irrigation and the volume of water provided per each tube per treatment; daily irrigation (no dry spell), irrigation every 8 days, and irrigation every 15 days. The volume of water provided at each irrigation event was calculated in order that, at the end of the experiment, each seedling in each treatment received the same amount of water (Table S4). The simulated dry spell experiment lasted for 130 days, roughly representing the remaining of the rainy season (January–April).

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

4.2.4. Data collection

At the beginning (60 days old seedlings) and the end (190 days old seedlings) of the experiment, the following growth parameters of *T. aurea* and *Q. grandiflora* seedlings were measured for each treatment (no dry spell, 8-day dry spell, 15-day dry spell): seedling height (H), taproot length (RL) and number of leaves (Lnum) per individual. Thereafter, the root (primary and secondary roots were separated and only taproot was considered) and the shoot (including stems and leaves separately) parts of the seedlings were separately oven-dried at 70 °C for 48 h. When present, the cotyledons were also dried but were not included in the shoot mass. After drying, the following variables were determined: total seedling dry mass (TM), root dry mass (RM), shoot dry mass (SM), leaf dry mass (LM), root mass fraction (RMF), shoot mass fraction (SMF), leaf mass fraction (LMF), and root:shoot ratio (R:S ratio). Relative growth rate (RGR) was calculated based on total dry mass. Taproot elongation rate (RER) and specific taproot length (STRL) (see Tomlinson et al., 2012) were calculated based on taproot mass and taproot length (Table S3). The leaf area necessary to calculate the specific leaf area (SLA) was obtained by analysing the images of previously scanned well developed fresh leaves (three per seedling) from 10 seedlings per treatment for *T. aurea* and 8 seedlings per treatment for *Q. 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 length (RL = 20.62 cm) (Table S2). *Tabebuia aurea* seedlings had a SM around 50% lower than RM, and a root:shoot (R:S) ratio of 1.82. Also, similar to *Q. grandiflora*, the shoot height of *T. aurea* corresponded to roughly 25% of the taproot length (RL = 9.46 cm) (Table S2). The RL of *Q. grandiflora* seedlings was more than twice that of *T. aurea*; however, Lnum and SLA were similar between the two species. The STRL of *Q. grandiflora* was close to 20 times higher than that of *T. aurea* (Table S2).

4.3.2. Biomass variables after dry spell treatments

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

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

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

4.3.3. Growth variables after dry spell treatments

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

In contrast, for *T. aurea* seedlings, RGR significantly decreased (Kruskal–Wallis P = 0.021 and Nemenyi P = 0.016) with increasing duration of dry spells, decreasing from 0.026 g g^{-1} d^{-1} in seedlings irrigated daily to 0.023 g g^{-1} d^{-1} in seedlings irrigated every 15 days (Fig. 2B). Similarly, NAR of *T. aurea* seedlings decreased according to the dry spell treatment, ranging from 0.0016 g cm^{-2} d^{-1} in seedlings irrigated daily to 0.0006 g cm^{-2} d^{-1} in seedlings irrigated every 15 days (Fig. 2D). STRL significantly increased (Kruskal–Wallis P = 0.01, Nemenyi P = 0.007) with increasing duration of the dry spells, ranging from 9.24 cm g^{-1} in seedlings irrigated daily to 22.12 cm g^{-1} in seedlings irrigated every 15 days (Fig. 1D). There were no significant differences in H, RL (Kruskal–Wallis test P = 0.1), RER (Kruskal–Wallis P = 0.1), Lnum (Kruskal–Wallis P = 0.11), and SLA (Kruskal–Wallis P = 0.712) among the treatments (Table S5, Fig. 2C). Height ranged from 6–9 cm, RL from 98–102 cm, and RER from 0.68–0.71 cm d^{-1}.

4.3.4. Trait correlations

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

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

4.4. DISCUSSION

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

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

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

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

4.4.2. Tabebuia aurea: comparison between treatments

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

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

On the other hand, the significant increase in the STRL of *T. aurea* seedlings exposed to dry spells of 15 days in comparison to those irrigated daily suggests that, irrespective of the reduction in biomass allocation to the roots, seedlings of *T. aurea* maintained a RER under moderate dry spells. These results indicate that the decrease in RM did not translate into a decrease in RL. It is important to highlight that RGR was inversely correlated with STRL (Fig. S1 and S2), suggesting that the decrease in RGR did not affect seedling investment in taproot elongation. Similar results have been observed among seedlings of other Cerrado tree species (Saboya and Borghetti, 2012; Zhou et al., 2020), indicating that these species might prioritise access to water at greater depths in detrimental of root mass storage.

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

4.4.3. Species comparison

The major filters controlling tree seedling recruitment in savannas are drought and fire (Moreira & Klink, 2000; Gignoux et al., 2009). In mesic savannas, root adaptations, such as rapid taproot growth, may be more related to water availability than to RGR ratio or R:S (Tomlinson et al., 2012, 2014). The STRL values recorded in *Q. grandiflora* seedlings (ranging from 70 $m.g^{-1}$ to 97 $m.g^{-1}$) in comparison to those measured in *T. aurea* seedlings (ranging from 9 $m.g^{-1}$ to 22 $m.g^{-1}$), suggest that *Q. grandiflora* invests more in root elongation than in root biomass during the initial growth stage, what might represent an important growth strategy for seedlings to reach deeper soil horizons (Tomlinson et al., 2012). Toward the end of the wet season the upper layers of the soils dry first (Kanegae et al, 2000), what makes the investment in deeper roots a major strategy to cope with drought stress (Padilla and Pugnaire, 2007; Tomlinson et al., 2012; Boonman et al., 2020; Saboya and Borghetti, 2012). A previous study on Mediterranean tree species conducted in a semi-natural condition field site reported that water availability was more important in seedling survival than was biomass allocation to the roots (Padilla and Pugnaire, 2007), indicating that a higher STRL can contribute to avoid drought stress. On the other hand, the RER of both species were similar irrespective of the dry spell treatments (Table S2).

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

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

4.5. CONCLUSION

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

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Declaration of Competing Interest

The authors declare no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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4.7. FIGURES

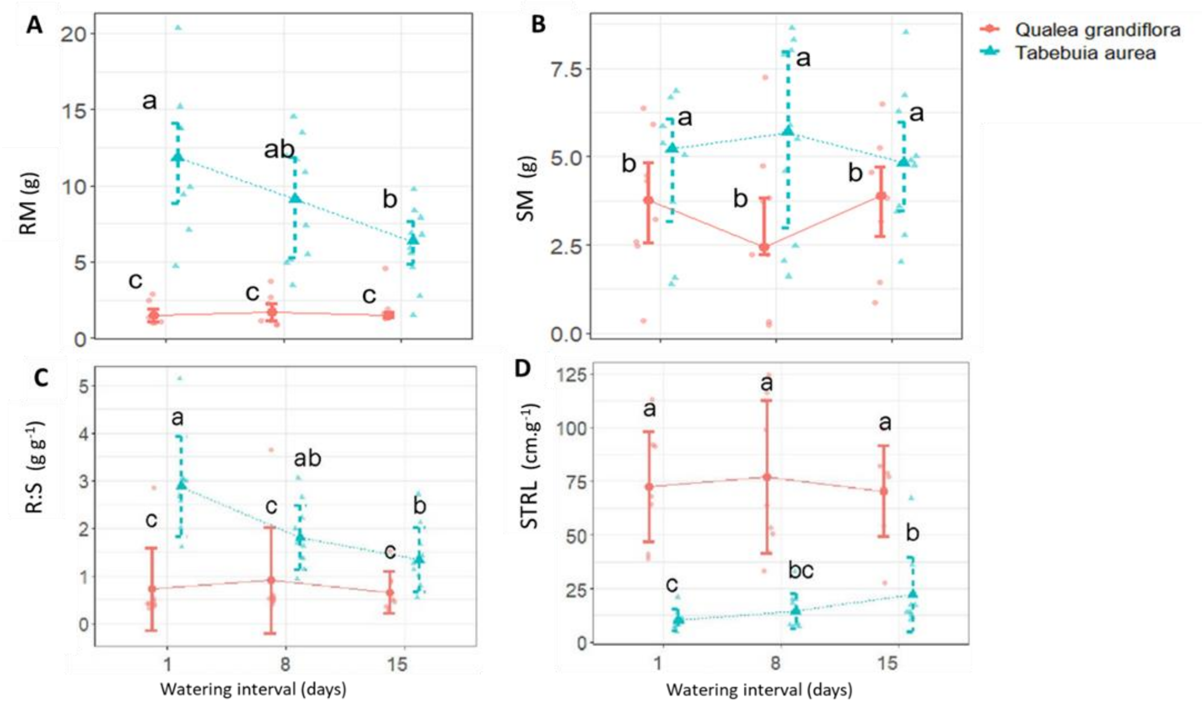

Fig. 1.1 Root dry mass (RM), shoot dry mass (SM), root: shoot ratio (R:S), and specific taproot length (STRL) of *Qualea grandiflora* (red) and *Tabebuia aurea* (blue) seedlings exposed to different irrigation treatments (dry spells): daily irrigation, irrigation every 8 d, irrigation every 15 d. Seedlings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

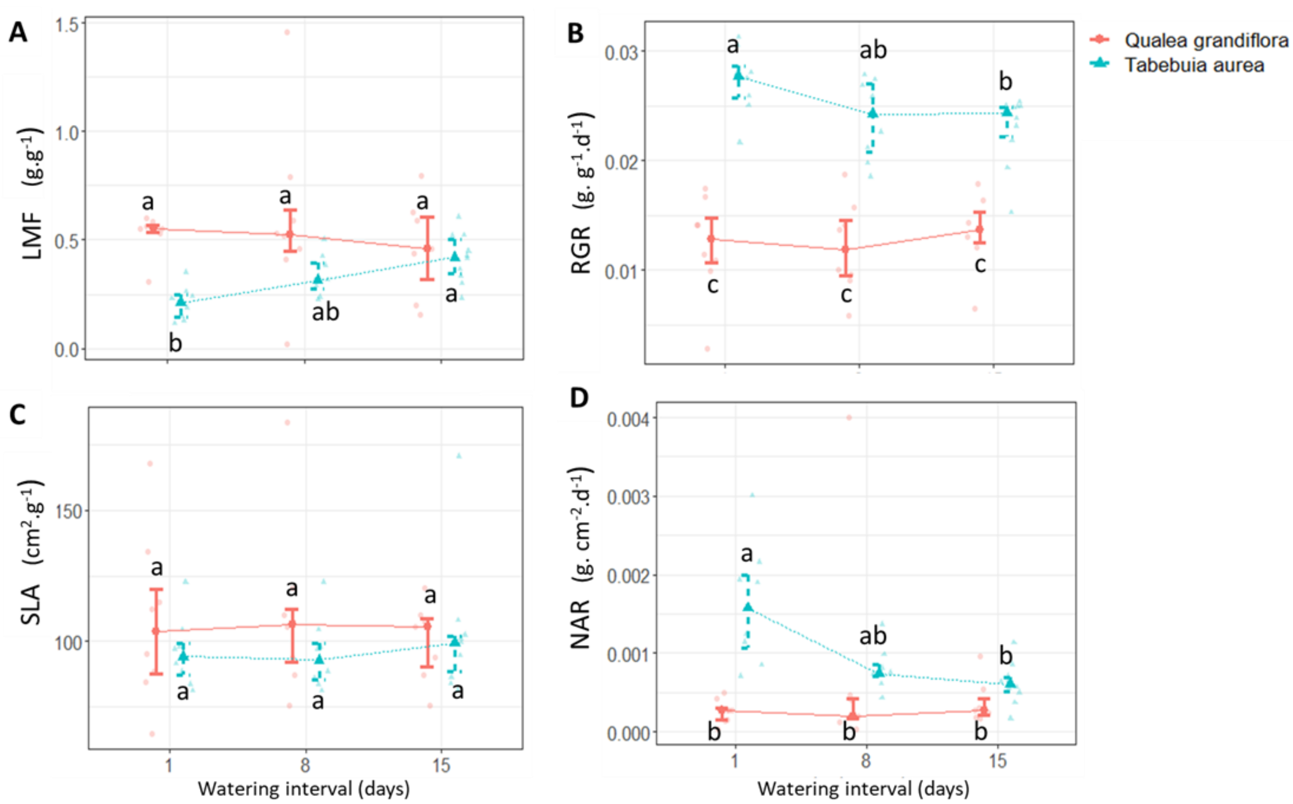

Fig. 1.2. Leaf mass fraction (LMF), relative growth rate (RGR), specific leaf area (SLA), and net assimilation rate (NAR) of *Qualea grandiflora* (red) and *Tabebuia aurea* (blue) seedling exposed to different irrigation schedules (dry spell treatments): daily irrigation, irrigation every 8 d, irrigation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

4.8. SUPPLEMENTARY MATERIALS

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

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/dm^3) 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).

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

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

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

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

	Test		**TM**	**RM**	**SM**	**RMF**	**SMF**	**R:S**	**RGR**	**Lnum**	**H**	**RL**	**RER**	**STRL**	**SLA**
Q. grandiflora	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		-	-	-	-	-	-	-	-	-	-	-	-	-
T. aurea	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	-

Note: the treatments include daily irrigation × irrigation at every 8 d (1×8); daily irrigation × irrigation every 15 d (1×15); irrigation every 8 d × 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 biomass fraction (RMF), shoot biomass fraction (SMF), biomass partition (R:S ratio), 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-type growth chamber at the Thermobiology Laboratory of the University of Brasília, Brasília, Brazil. Statistical significance was set at: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

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

		Initial measurements (Days after germination)	**Final measurements (Watering interval)**		
		60	**1 day**	**8 days**	**15 days**
Qualea grandiflora	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
	SM (g)	0.26 ± 0.018	3.797 ± 0.641	3.778 ± 0.638	3.693 ± 0.618
	RMF ($g.\ g^{-1}$)	0.3 ± 0.015	0.288 ± 0.011	0.336 ± 0.014	0.362 ± 0.050
	SMF ($g.\ g^{-1}$)	0.7 ± 0.015	0.711 ± 0.011	0.663 ± 0.022	0.637 ± 0.050
	R:S ($g.\ g^{-1}$)	0.43 ± 0.031	0.408 ± 0.022	0.509 ± 0.024	0.651 ± 0.160
	Lnum	5.1 ± 0.324	20.50 ± 1.679	20.428 ± 1.469	16.714 ± 1.537
	H (cm)	6.09 ± 0.401	27.087 ± 2.286	27.8 ± 1.970	23.6 ± 2.215
	RL (cm)	20.62 ± 0.723	106.775 ± 2.833	115.671 ± 4.427	114.987 ± 4.648
	RER ($cm.d^{-1}$)	0.34 ± 0.012	0.661 ± 0.022	0.730 ± 0.034	0.725 ± 0.035
	STRL ($cm.g^{-1}$)	198.84 ± 15.772	97.401 ± 28.968	74.034 ± 13.387	70.314 ± 8.069
	RGR ($g.g^{-1}.d^{-1}$)	-	0.012 ± 0.001	0.013 ± 0.001	0.012 ± 0.001
	SLA ($cm^2.g^{-1}$)	137.66 ± 5.243	112.448 ± 10.938	111.343 ± 12.165	99.975 ± 5.393
	LMF ($g.\ g^{-1}$)	-	0.529 ± 0.032	0.599 ± 0.145	0.467 ± 0.081
	NAR ($g.cm^{-2}.d^{-1}$)	-	0.0002 ± 0.0005	0.0007 ± 0.0004	0.0003 ± 0.0001
	LM (g)	-	2.874 ± 0.599	2.621 ± 0.604	2.885 ± 0.597
Tabebuia aurea	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
	SM (g)	0.54 ± 0.036	5.331 ± 0.910	5.485 ± 0.913	4.799 ± 4.387
	RMF ($g.\ g^{-1}$)	0.63 ± 0.025	0.726^{a} ± 0.024	0.625^{ab} ± 0.026	0.543^{b} ± 0.032
	SMF ($g.\ g^{-1}$)	0.37 ± 0.025	0.273^{b} ± 0.024	0.374^{ab} ± 0.026	0.456^{a} ± 0.032
	R:S ($g.\ g^{-1}$)	1.82 ± 0.189	2.961^{a} ± 0.394	1.804^{ab} ± 0.204	1.342^{b} ± 0.205
	Lnum	5.8 ± 0.359	10.40 ± 0.858	10.40 ± 0.866	8.60 ± 0.724
	H (cm)	2.35 ± 0.222	6.540 ± 0.768	6.714 ± 0.757	8.484 ± 0.985
	RL (cm)	9.46 ± 0.549	101.790 ± 1.572	101.940 ± 1.572	98.31 ± 0.689
	RER ($cm.d^{-1}$)	0.16 ± 0.009	0.710 ± 0.012	0.707 ± 0.012	0.683 ± 0.005
	STRL ($cm.g^{-1}$)	9.7 ± 0.928	9.243^{b} ± 1.608	14.498^{ab} ± 2.651	22.124^{a} ± 5.811
	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

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

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	$g.g^{-1}$	RM/TM	Pérez-Harguindeguy et al., 2013
SMF	$g.g^{-1}$	SM/TM	Pérez-Harguindeguy et al., 2013
LMF	$g.g^{-1}$	LM/TM	Shipley, 2002
R:S	$g.g^{-1}$	RM/SM	Pérez-Harguindeguy et al., 2013
RGR	$g.g^{-1}.d^{-1}$	$(lnTMf - \underline{lnTMi})/d$	Tomlinson et al., 2012
RER	$cm.d^{-1}$	$(RLf - \underline{RLi})/d$	Tomlinson et al., 2012
STRL	$cm.g^{-1}$	RL/RM	Tomlinson et al., 2012
SLA	$cm^2.g^{-1}$	$[(LA_1/LM_1) + (LA_2/LM_2) + (LA_3/LM_3)] /3$	Pérez-Harguindeguy et al., 2013
NAR	$g.\ cm^{-2}.d^{-1}$	RGR/ (LMF * SLA)	Shipley, B., 2002 (adapted)

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).

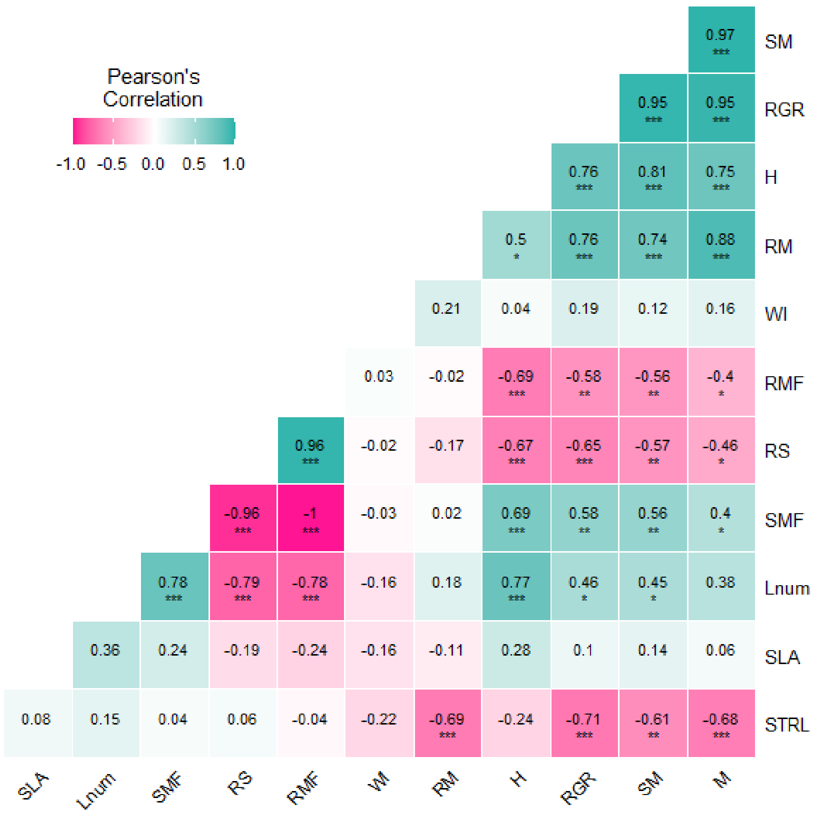

Figure S1.1. Pearson's correlation coefficients among the growth parameters of *Qualea grandiflora* (Table S3) subjected to different irrigation treatments (WI) (Table S2). The parameters include root dry mass (RM), shoot dry mass (SM), root biomass fraction (RMF), shoot biomass fraction (SMF), biomass 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: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

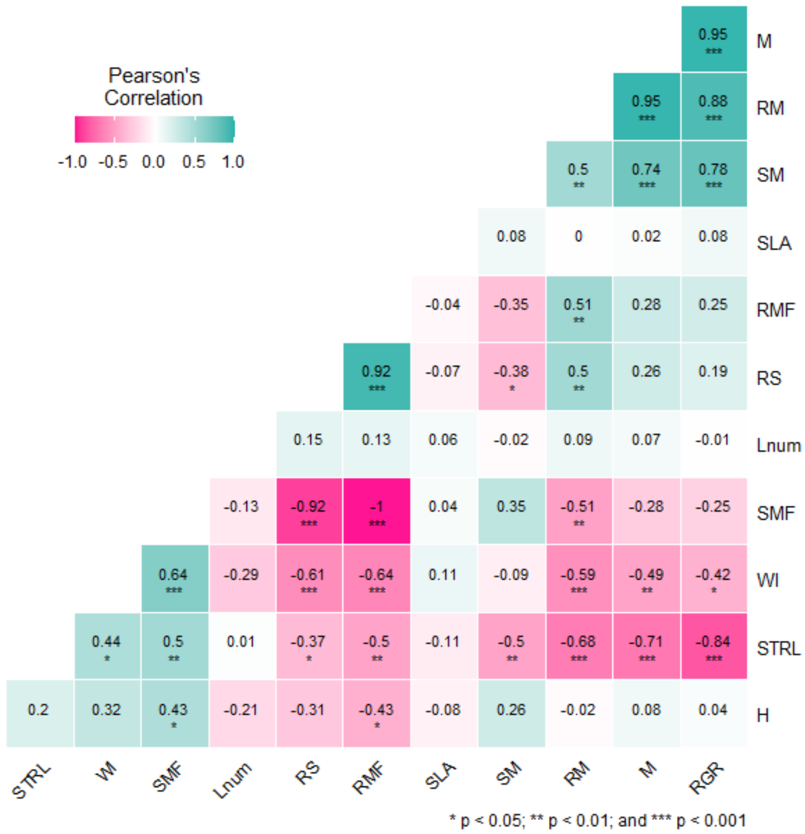

Figure S1.2. Pearson's correlation coefficients among the growth parameters of *Tabebuia aurea* exposed to different irrigation treatments (WI) (Table S2). The parameters include root dry mass (RM), shoot dry mass (SM), root biomass fraction (RMF), shoot biomass fraction (SMF), biomass partition (R:S), 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 chamber in the Thermobiology Laboratory of the University of Brasília, Brazil. Statistical significance was set at * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

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

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

5. CAPÍTULO II

Efeito da elevação da temperatura e do CO_2 atmosférico previstos para 2100 no desenvolvimento inicial de espécies arbóreas de savana

RESUMO

A savana brasileira (Cerrado) é considerada um hotspot de biodiversidade. No entanto, as áreas nativas do Cerrado têm sido ameaçadas pelo desenvolvimento agrícola. Além disso, as mudanças climáticas podem aumentar a pressão de seleção de espécies e, juntos, ambos os processos podem levar a uma grave perda de biodiversidade e de serviços ambientais. Portanto, é importante entender como as espécies vão responder às mudanças climáticas. Nosso objetivo foi investigar como as plântulas de espécies arbóreas respondem a um cenário climático futuro simulado em câmaras de crescimento (fitotrons). Selecionamos quatro espécies arbóreas amplamente distribuídas no Cerrado: *Qualea grandiflora* (Vochysiaceae), *Hymenaea stignocarpa* (Fabaceae), *Tabebuia aurea* (Bignoniaceae) e *Kielmeyera coriacea* (Clusiaceae). Dispusemos suas sementes para germinar em câmaras a 28°C e, a seguir, criamos as mudas em vasos preenchidos com Latossolo Vermelho e areia (proporção de 3x1) a 28°C sob irrigação por 30 dias sob irrigação. Em seguida, transferimos as mudas para tubos plásticos de 1 m de altura e 0,1 m de diâmetro para os experimentos de crescimento. Após 30 dias, 30 indivíduos de cada espécie foram retirados para as medidas iniciais, e outros 30 indivíduos foram transferidos para cada fitotron, totalizando 90 plantas por espécie. Um dos fitotrons foi configurado com o cenário climático atual, com base nos dados climáticos dos últimos 50 anos do Cerrado, onde as temperaturas máxima e mínima foi de 28 °C e 18 °C e a concentração de CO_2 ([CO_2]) foi de 420 ppm. O outro fitotron foi definido com a prospecção IPCC SSP 3-7,0 para a região do Cerrado para 2100 (base de dados: WorldClim), onde as temperaturas máximas e mínimas atingiram 2,5 °C acima do cenário climático atual, e [CO_2] foi de 860 ppm. A umidade foi de 85% para ambos os fitotrons. As plantas foram cultivadas por 120 dias, sendo irrigadas a cada dois dias com 120 ml de água corrente. Após esse período, procedeu-se à contagem de folhas dos indivíduos e, em seguida, todas as plantas foram desenraizadas e levadas para secar a 70 °C. Após a secagem, a biomassa das plantas foi medida por partes: total, raiz, parte aérea e folhas. Observamos um aumento significativo de biomassa no cenário futuro para todas as espécies, provavelmente relacionado à fertilização com CO_2. No entanto, *K. coriacea* e *H. stignocarpa* investiram na raiz e na parte aérea a mesma proporção de biomassa no cenário climático futuro e no cenário climático atual. *Q. grandiflora* e *T. aurea* investiram mais de 2 vezes em biomassa aérea do que radicular das plantas quando estavam sob cenário climático futuro. O aumento da massa aérea para *H. stignocarpa*, *Q. grandiflora* e *T. aurea* pode estar refletindo o número de folhas que foi maior nos indivíduos no cenário futuro em comparação aos incubados no cenário climático atual. Em conclusão, quando a água não é escassa na fase de recrutamento, há ganho de carbono em resposta ao cenário climático futuro simulado, mas sua distribuição pode variar entre as espécies.

ABSTRACT

Effect of predicted rise in temperature and atmospheric CO_2 by 2100 on early development of savanna tree species

The Brazilian savanna (Cerrado) is considered a biodiversity hotspot. However, Cerrado´s native areas have been threatened by agricultural development. In addition, climate change may increase species selection pressure and, together, both processes may lead to a serious loss of biodiversity and environmental services. Therefore, it is important to understand how species are going to respond to climate change. We aimed to investigate how tree seedlings respond to a future climate scenario simulated in growth chambers (phytotrons). We selected four widely distributed tree species from the Cerrado savanna: *Qualea grandiflora* (Vochysiaceae), *Hymenaea stignocarpa* (Fabaceae), *Tabebuia aurea* (Bignoniaceae) and *Kielmeyera coriacea* (Clusiaceae). We disposed their seeds to germinate in chambers at 28°C, and then raised the seedlings in pots filled with Red Latosol and sand (proportion of 3x1) under irrigation at 28 °C for 30 days. After that, we transferred the seedlings to plastic tubes of 1 m high and of 0.1 m in diameter for the growth experiments. When the first pair of leaves appeared, 30 individuals of each species were taken for initial measures, and other 33 individuals were transferred to each phytotron, summing up a total of 96 plants per species. One of the phytotrons was set with the current climate scenario, based on the last 50 years climate data from the Cerrado where max and min temperatures was 28 °C and 18 °C, and CO_2 concentration ([CO_2]) was 420 ppm. The other phytotron was set with the IPCC SSP 3-7,0 prospection for the Cerrado region for 2100 (WorldClim), where max and min temperatures reached 2.5 °C higher than at current climate scenario, and [CO_2] was 860 ppm. Humidity was 85 % for both phytotrons. Plants were grown for 120 days, being irrigated every two days with 120 ml of tap water. After this period, we proceeded with leaf counting of the individuals and then all plants were uprooted and taken to dry at 70 °C. After drying, plants biomass was measured by parts: total, root, shoot, and leaves. We observed a significant increase of biomass in the future scenario for all species, probably related to CO_2 fertilization. However, *K. coriacea* was the only one that invested more carbon on roots than shoot, with 57 % more root biomass under future climate scenario. *H. stignocarpa* invested the same proportion on root and shoot under future climate scenario as under current climate scenario. *Q. grandiflora* and *T. aurea* invested more than 2 times in shoot than root biomass of plants when they were under future climate scenario. The increase in shoot mass for *H. stignocarpa*, *Q. grandiflora* and *T. aurea* can be reflecting the leaf number that was bigger in individuals under the future scenario in comparison to those incubated in current climate scenario. In conclusion, when water is not scarce at the recruitment stage, there is carbon gain in response to the simulated future climate scenario, but its distribution can vary among species.

5.1. INTRODUÇÃO

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

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

Por sua vez, a velocidade em que as mudanças têm ocorrido faz com que o genótipo de plântulas submetidas ao cenário climático futuro seja muito semelhante ao das plântulas encontradas no cenário climático atual (Hoffmann & Sgró, 2011). A fase de crescimento inicial é o estágio mais vulnerável na vida da planta, fazendo da capacidade de plântulas em suportar as condições climáticas futuras um gargalo na sobrevivência do indivíduo e na manutenção da espécie em uma determinada área (Leck et al, 2008). Assim, a permanência de espécies arbóreas de savanas nesses ambientes irá depender, em grande parte, de sua plasticidade e capacidade de aclimatação às novas condições ambientais (Larson et al, 2020; Lewandrowski et al., 2021; Nicotra et al, 2010).

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

Embora a elevação da temperatura possa levar à queda da eficiência fotossintética devido à menor afinidade da Rubisco com o dióxido de carbono e ao aumento da respiração mitocondrial (Lambers & Oliveira, 2019), projeta-se que a concentração de CO_2 atmosférico seja o dobro da observada atualmente em 2100 (Meinshausen et al., 2019), o que pode favorecer a assimilação de carbono e evitar o aumento da fotorrespiração (Dusenge et al., 2019). Estudos testando o efeito de concentrações elevadas de CO_2 no crescimento inicial de espécies arbóreas de savanas mostram um maior ganho de biomassa nessas condições (Hoffmann, 2000; Kgope et al., 2010; Buitenwerf et al, 2012), o que favorece o estabelecimento de novos indivíduos.

Devido ao efeito oposto que temperaturas elevadas e a alta concentração de CO_2 atmosférico podem ocasionar na fisiologia das plantas, estudos que avaliem o efeito conjunto desses dois fatores são extremamente importantes. Apgaua e colaboradores (2019) observaram efeito sinérgico entre a [CO_2] e a temperatura elevados em plântulas de espécie de Eucalyptus nativa de savana em ambiente natural, que promoveu o aumento no crescimento e na aquisição de biomassa quando a água não foi um fator limitante. Isso indica que a interação entre a temperatura e o CO_2 elevados pode favorecer o recrutamento de espécies arbóreas de savanas. No entanto, dependendo da capacidade de aclimatação foliar, a temperatura elevada pode reduzir a aquisição de carbono por plântulas expostas a altos níveis de CO_2 atmosférico, mesmo sem haver restrição hídrica (Murphy& Way, 2021).

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

A facilidade de obtenção de CO_2 devido a sua maior disponibilidade no cenário futuro pode ocasionar menor investimento em área e biomassa foliar, permitindo que o carbono direcionado para a fração aérea seja utilizado no crescimento em altura (Qi et al, 2019), podendo favorecer a sobrevivência no caso de passagem de fogo (Rodriguez-Cubillo et al, 2021) ou o melhor desenvolvimento no caso de sombreamento pelo componente herbáceo (Gignoux et al, 2016).

Além da maior aquisição de CO_2, o aumento da temperatura pode acelerar o metabolismo, aumentando a taxa de crescimento e o desenvolvimento das plântulas (Ncisana et al, 2022). Portanto espera-se que no cenário futuro as plântulas apresentem maior acúmulo de biomassa em comparação ao cenário atual e desenvolvimento de plântulas mais acelerado.

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

5.2. MATERIAIS E MÉTODOS

5.2.1. ÁREA DE ESTUDO

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

As sementes de *Kielmeyera coriacea*, *Tabebuia aurea* e *Qualea grandiflora* foram coletadas de 10 indivíduos adultos, sadios, com distância de no mínimo 1km entre eles. Entre agosto e novembro de 2019 no Parque Nacional de Brasília (15° 38' 28" S 48° 1' 15" O – ICMBio) em cerrado *sensu stricto*, e levadas para armazenamento em sacos de papel em câmara fria (18°C) no Laboratório de Termobiologia (UnB, Brasília – Brasil). As sementes de *Hymenaea stigonocarpa* foram gentilmente oferecidas pela Rede de Sementes do Cerrado, que nos cedeu quantidade suficiente de sementes saudáveis, coletadas em 2020 na região da Chapada dos Veadeiros, no Estado de Goiás (14° 10' S 47° 30' O) em cerrado *sensu stricto* que também foram e levadas para armazenamento em sacos de papel em câmara fria (18°C) no Laboratório de Termobiologia (UnB, Brasília – Brasil).

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

Após a emissão do primeiro par de folhas de cada espécie (cerca 20 dias para *Hymenaea stigonocarpa* e 30 dias para as demais espécies), as plantas foram agrupadas em três grupos buscando a melhor homogeneidade possível, levando em conta a altura, tamanho das folhas e diâmetro da base do caule. Para cada espécie, dois grupos foram compostos por 35 indivíduos (a serem levados às duas câmaras fitotrôn, ver seções 2.2.1 e 2.2.2), e o terceiro grupo composto por 30 indivíduos para medidas iniciais das mudas antes do início do experimento nos fitotrôns (Apêndice II – Dados Iniciais). O uso de um número maior de indivíduos levados aos fototrôns teve o objetivo de garantir um número mínimo de 30 indivíduos por espécie e por tratamento para as análises estatísticas (seção 2.5). Todos os indivíduos usados nos experimentos nos fitotrôns foram transferidos em um mesmo dia.

5.2.2. CALIBRAGEM DOS FITOTRONS

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

Os dados de precipitação diária e temperatura ao longo do dia dos últimos 60 anos (de 1960 a 2020), obtidos de estações meteorológicas distribuídas por todo o território do Cerrado, relativos aos meses de novembro a abril (INPE, 2020), foram utilizados para estabelecer o volume e frequência de irrigação e a umidade relativa do ar utilizados nos dois cenários, e a rampa de temperatura programada para o fitotron com o cenário atual. Também foi programada uma rampa de luminosidade ao longo do dia, sendo igual para os dois fitotrons, com fotoperíodo de 13h de luminosidade, conforme a duração do dia durante o verão na maior parte da região do Cerrado. A irrigação foi realizada a cada dois dias, por método de gotejamento automatizado. Considerando que 1 mm de água precipitado corresponde a 1000 ml/m^2 de água e utilizando a área superficial do tubo em que cada planta foi cultivada para calcular o volume de água a ser ofertado a cada indivíduo.

A precipitação média obtida a partir desses dados foi de 230mm/mês. Esse valor foi utilizado para calcular a irrigação ofertada para cada muda conforme descrito anteriormente. A temperaturas máxima (diurna) e mínima (noturna) encontradas foram de 30°C e 20°C, respectivamente, e a umidade relativa do ar variou em média entre 65% e 80% (tabela S2.2). A concentração de CO_2 atmosférico no cenário atual foi de 420ppm (Magalhães et al., 2019), e a densidade de fluxo de fótons acima das plantas em um plano horizontal variou entre 210 μmol/m^2/s e 700 μmol/m^2/s (tabela S2.2).

Para definir os parâmetros do cenário futuro utilizamos o cenário SSP3-7.0 proposto pelo IPCC (2020). O cenário SSP3-7.0 utiliza modelos que consideram uma forte mudança de uso da terra e altas emissões de aerossóis, o que o levou a ser considerado um importante experimento no projeto CMIP6 (Neill et al., 2016). Apesar de não ser o cenário com a maior previsão de concentração de CO_2 em 2100, o cenário SSP3-7.0 pode ser o que deve trazer piores consequências econômicas e sociais para a região da América Latina, inclusive com os maiores índices de perda de produto interno bruto (PIB) (Chen et al., 2020).

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

Os dados de precipitação e temperatura máxima e mínima utilizados no cenário futuro foram provenientes do modelo MIROC6-ES2L, pertencentes ao banco de dados da fase 6 do Projeto de Intercomparação de Modelo Acoplado (CMIP6), com *downscale* calibrado segundo o patamar climático WorldClim 2.1 e obtido na resolução 2,5 minutos (Fick et al, 2017). Foram considerados os dados das projeções para o período entre 2081 e 2100, obtidos na plataforma WorldClim (Worldclim, 2020) em formato *geotiff.* e posteriormente visualizados no programa Qgis (versão 3.14). Um *shapefile* do Cerrado (Assis et al, 2019), foi sobreposto ao mapa contendo os dados climáticos de precipitação e temperatura máxima e mínima, dentro do qual foram distribuídos aleatoriamente 100 pontos afastados entre si (Figura S2.1). Foi feita uma média com os valores atribuídos a cada ponto disposto no território do Cerrado, relativos aos meses entre dezembro e março, para cada variável climática. As médias de temperatura obtidas foram 2.5°C acima do encontrado para o cenário atual, assim estabelecidas a temperatura mínima 22.5°C e a máxima 32.5°C para o cenário futuro simulado em nosso experimento (tabela S2.2).

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

A concentração de CO_2 atmosférico utilizado no cenário futuro foi de 862.8 ppm, projetada para o ano de 2100 no Hemisfério Sul no cenário SSP 3-7.0, de acordo com o modelo MIROC6-ES2L (Meinshausen et al., 2019).

5.2.3. COLETA DE DADOS

Após 120 dias de crescimento nos cenários climáticos simulados, as plantas foram removidas dos tubos para medidas de crescimento. As plantas foram cuidadosamente retiradas dos tubos com auxílio de uma mangueira com água corrente para desprendimento da terra das raízes, evitando perda de raízes laterais que pudesse interferir no valor de biomassa radicular final.

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

5.2.4. ANÁLISES ESTATÍSTICAS

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

A comparação entre os dois cenários foi feita em cada atributo medido para cada espécie separadamente, utilizando-se modelos lineares generalizados com o pacote glm2 (Donoghoe, 2018), com o comando glm2() (α=0.05). As variáveis preditoras foram espécies (*Kielmeyera coriacea*, *Tabebuia aurea*, *Qualea grandiflora* e *Hymenaea stigonocarpa*) e cenário (atual e futuro). As variáveis resposta foram altura, diâmetro basal, número de folhas comprimento da raiz principal, massa seca total, massa seca radicular, massa seca aérea, fração de biomassa radicular, fração de biomassa aérea e taxa de crescimento relativo. Para determinar a família de distribuição para os dados analisados em cada modelo utilizamos os pacote fitdistplus (Delignette-muller et al., 2013), com o comando gofstat(), e os testes “adtest”, “cvmtest” e “kstest”. As distribuições Gamma ou gaussiana foram as adequadas dos atributos medidos na análise de regressão para comparação entre os cenários. (Todas as análises podem ser encontradas no Apêndice IV)

5.3. RESULTADOS

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

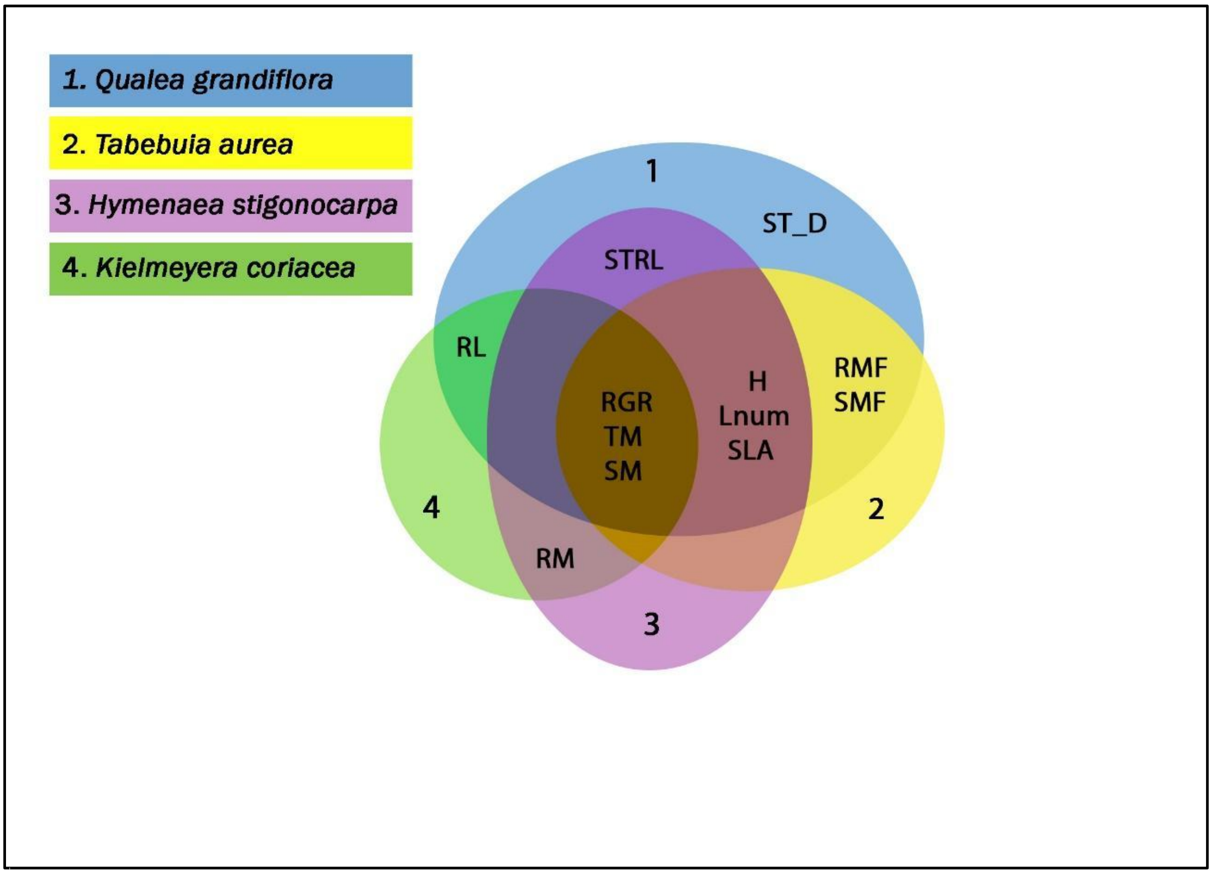

Figura 5.3.1. Diagrama de Venn onde cada conjunto representa uma espécie, e os elementos contidos em cada conjunto são os parâmetros que apresentaram diferença significativa entre os cenários ($p < 0.05$). Sendo esses parâmetros: diâmetro da base do caule (ST_D), comprimento específico da raiz principal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

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

Q. grandiflora foi a espécie que obteve o maior ganho em H quando submetida ao cenário futuro ($t= - 8.621$, $p<0.001$), apresentando um incremento de cerca de 55% (Fig 2), enquanto que *T. aurea* apresentou incremento em H de aproximadamente 35% ($t= - 4.969$, $p<0.001$) (Fig 3) e *H. stigonocarpa* de 30% ($t= - 4.547$, $p<0.001$) (Fig 4). Assim como H, o Ln apenas não apresentou aumento significativo no cenário futuro para *K. coriacea* (Fig 5), enquanto que *Q. grandiflora* foi a espécie que apresentou a maior variação em Ln, com um aumento de cerca de 130% (t= - 5.514, p<0.001), para *H. stigonocarpa* esse aumento foi de 85% (t= -6.765, p<0.001) e para *T. aurea* de 65% (t= - 8.354, p<0.001).

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

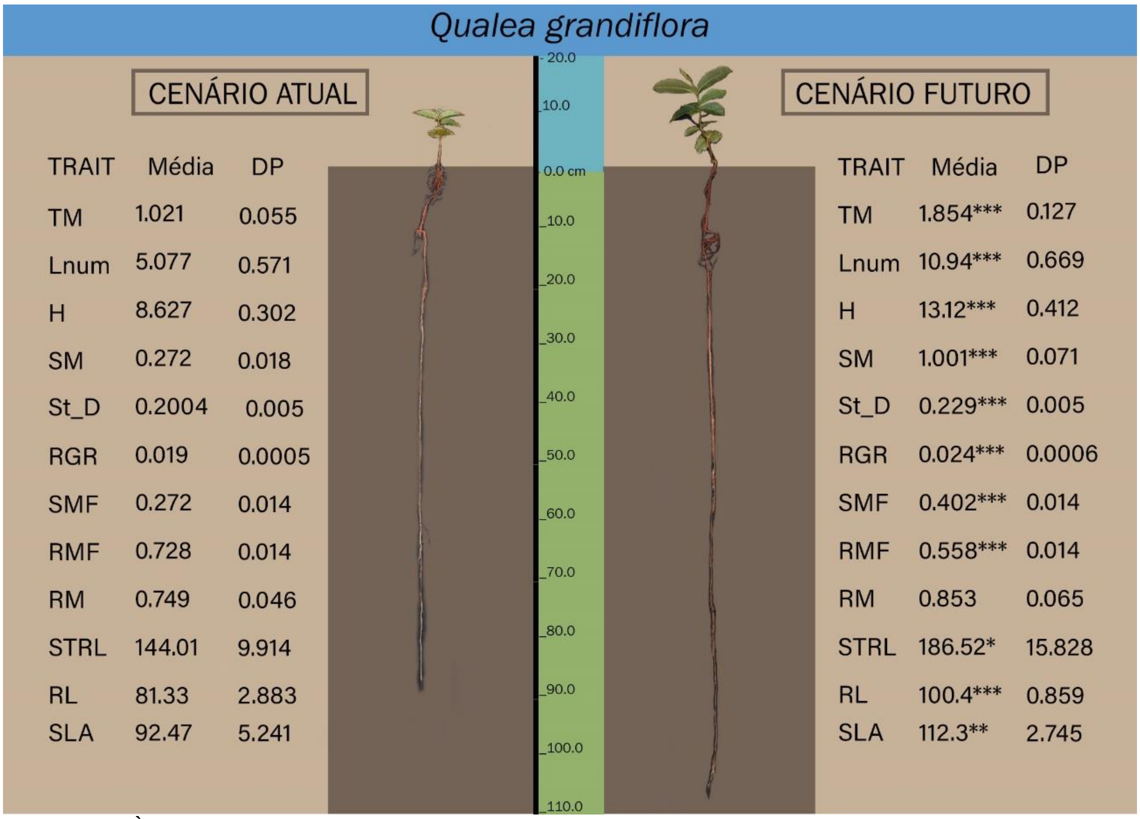

Figura 5.3.2. À esquerda: plântula de *Qualea grandiflora* (n=30) crescida durante 120 dias em fitotron com o cenário atual. À direita: plântula de *Qualea grandiflora* (n=30) crescida durante 120 dias em fitotron com o cenário futuro projetado para 2100 na região central do Brasil. Para cada cenário,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

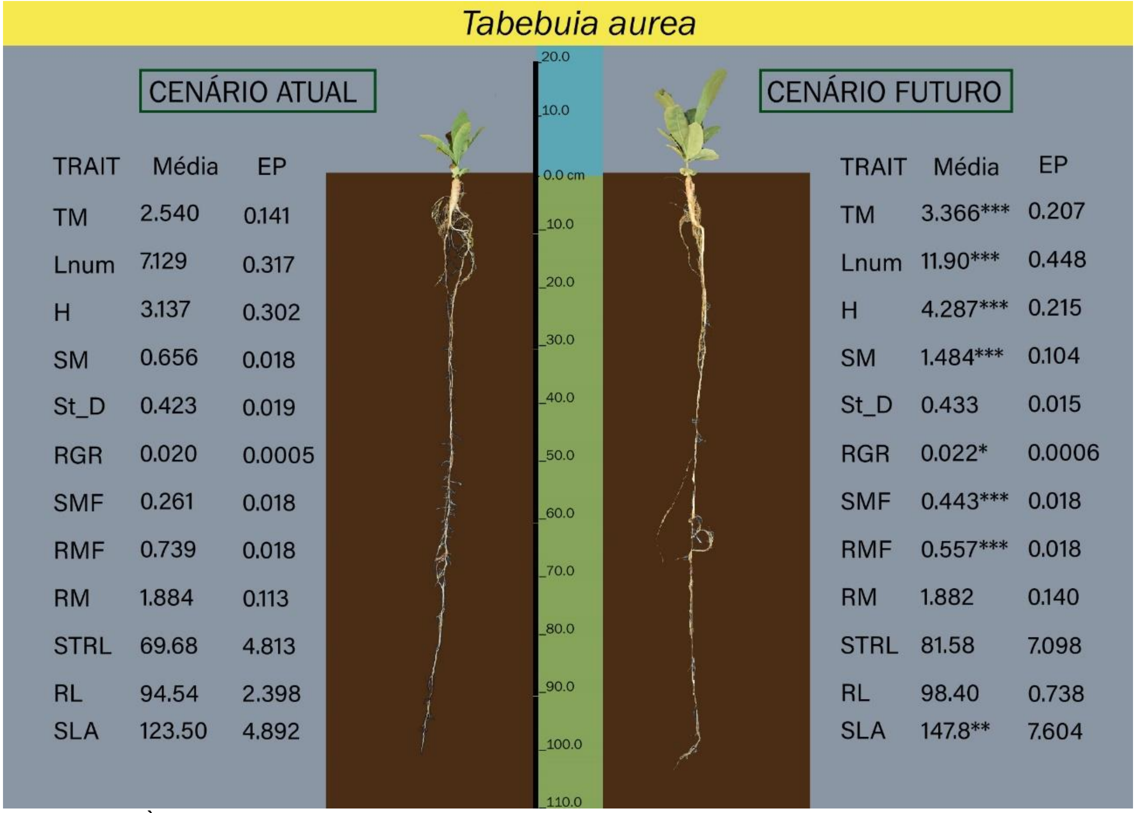

Figura 5.3.3. À esquerda: plântula de *Tabebuia aurea* (n=30) crescida durante 120 dias em fitotron com o cenário atual. À direita: plântula de *Tabebuia aurea* (n=30) crescida durante 120 dias em fitotron com o cenário futuro projetado para 2100 na região central do Brasil. Para cada cenário, estão apresentados na figura os valores correspondentes de média e erro padrão dos parâmetros (seção 5.2.3): TM(g), Lnum, H (cm), SM (g), St_D (cm), RGR (g g^{-1}d^{-1}), SMF, RMF, RM (g), STRL (cm g^{-1}), RL (cm), SLA (cm^{2}g^{-1}).

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

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

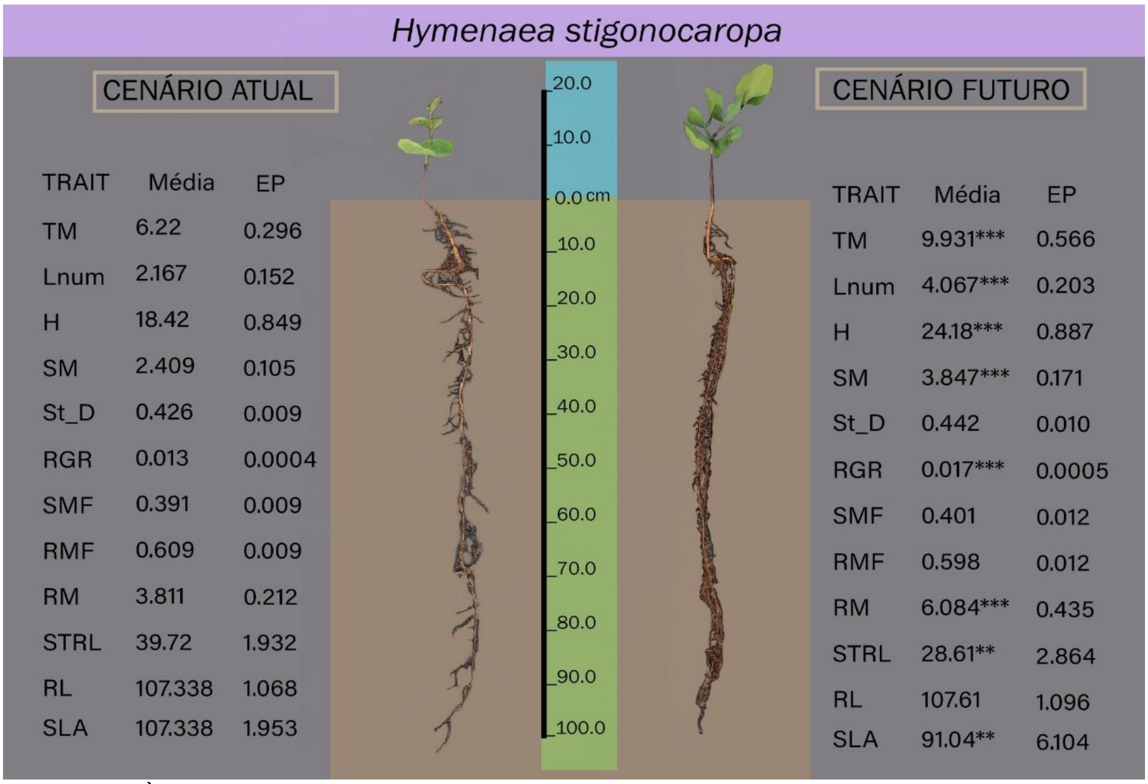

Figura 5.3.4: À esquerda: plântula de *Hymenaea stignocarpa* (n=30) crescida durante 120 dias em fitotron com o cenário atual. À direita: plântula de *Hymenaea stignocarpa* (n=30) crescida durante 120 dias em fitotron com o cenário futuro projetado para 2100 na região central do Brasil. Para cada cenário,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

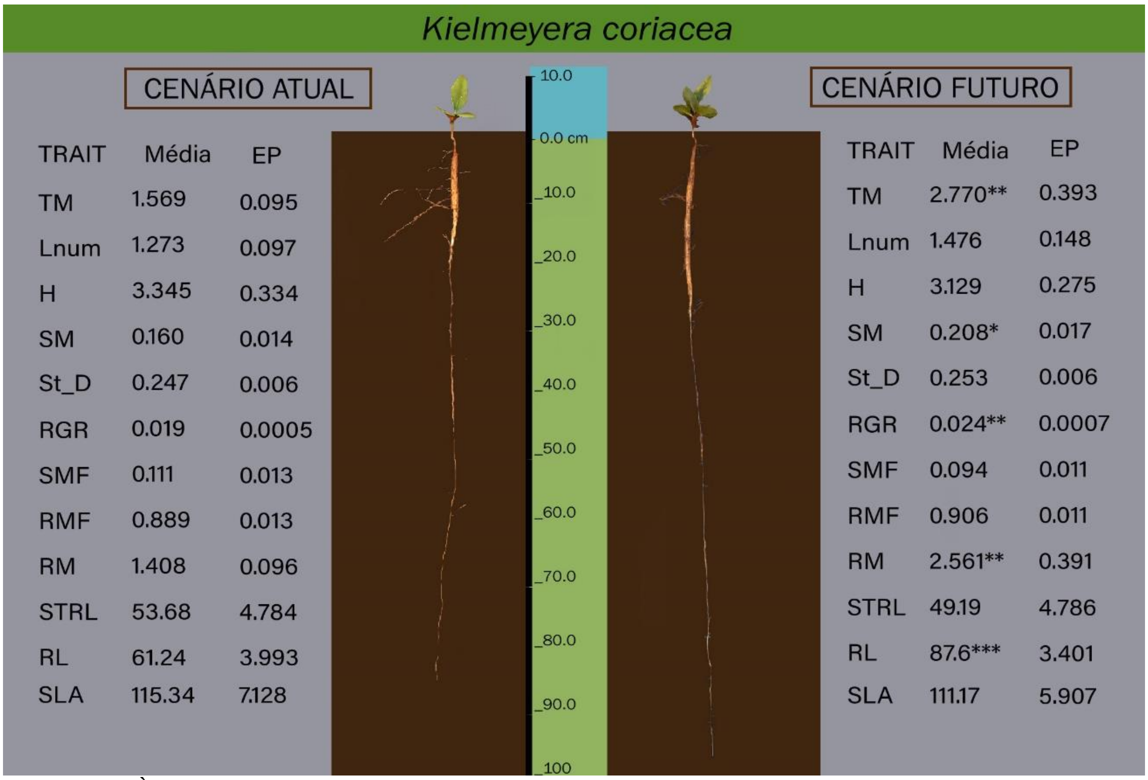

Figura 5.3.5: À esquerda: plântula de *Kielmeyera coriacea* (n=30) crescida durante 120 dias em fitotron com o cenário atual. À direita: plântula de *Kielmeyera coriacea* (n=30) crescida durante 120 dias em fitotron com o cenário futuro projetado para 2100 na região central do Brasil. Para cada cenário,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

DISCUSSÃO

O cenário futuro utilizado em nosso experimento provocou o aumento de biomassa das plântulas de todas as espécies estudadas. A maior assimilação de carbono observada em plântulas submetidas ao cenário futuro deve-se à maior eficiência da Rubisco, aumentando a assimilação de CO_2 e reduzindo as taxas de fotorrespiração (Drake et al, 1997).

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

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

H. stigonocarpa se comportou de modo conservativo no cenário futuro em relação ao SLA, apresentando redução desse parâmetro (Figura 2.4) e produzindo folhas mais espessas, o que permite uma maior economia de recursos uma vez que a maior concentração de CO_2 atmosférico permite a mesma captação desse recurso a partir de uma área foliar menor (Wang et al, 2020). Por outro lado, *Q. grandiflora* e *T. aurea* tiveram aumento do SLA, apresentando maior área foliar para um mesmo valor de massa seca investida. O maior investimento em biomassa foliar no cenário futuro observado para de *Q. grandiflora* e *T. aurea* pode indicar uma priorização em alocar recursos para obter um crescimento mais acelerado, caracterizando um comportamento aquisitivo (Grime& Pierce, 2012; Fagundes et al, 2022; Weigelt et al., 2021). Além disso, para que a planta possa aumentar assimilação de carbono por um período maior em um ambiente com alta concentração de CO_2 atmosférico, é preciso um aumento da relação dreno-fonte (Amsterdam, 1991), o que pode ter contribuído para que essas espécies apresentassem um maior investimento na fração aérea do que na fração radicular no cenário futuro, reforçando a ideia de que *Q. grandiflora* e *T. aurea* apresentaram comportamento aquisitivo (Figuras 2.2 e 2.3).

Em relação à produção foliar, três das quatro espécies estudadas (*Q. grandiflora*, *T. aurea* e *H. stigonocarpa*) apresentaram maior número de folhas (Figuras 2.2, 2.3 e 2.4). Mesmo apresentando um maior número de folhas e maior biomassa foliar no cenário futuro, *H. stigonocarpa* manteve a partição de biomassa apresentada no cenário atual e foi a única espécie que apresentou aumento de biomassa de raiz secundária no cenário futuro (Figura S2.2). A maior oferta de CO_2 no cenário futuro pode fazer com que a disponibilidade de nutrientes do solo limite o crescimento e a taxa fotossintética (Wieder et al, 2015). Como a composição do solo nos dois cenários climáticos era semelhante, a alta [CO_2] do cenário futuro pode ter levado à maior produção de raízes secundárias em *H. stigonocarpa* para obtenção de nutrientes e manutenção do ganho mais acelerado de biomassa nesse cenário (Iversen, 2010). Embora *H. stigonocarpa* tenha apresentado no geral um crescimento mais acelerado no cenário futuro devido à maior aquisição de biomassa, a redução do SLA e a manutenção do padrão de alocação de biomassa podem indicar que a espécie apresenta um comportamento conservativo, em que a prioridade é alocar recursos para garantir a sobrevivência do indivíduo frente a possíveis distúrbios (Grime& Pierce, 2012; Fagundes et al, 2022; Weigelt et al., 2021).

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

Embora tanto *K. coriacea* quanto *T. aurea* apresentem órgão de reserva subterrâneo, as duas espécies aparentam adotar diferentes estratégias de sobrevivência. Enquanto *K. coriacea* manteve a proporção entre biomassa radicular e aérea nos dois cenários estudados, *T. aurea* apresentou aumento de massa seca aérea no cenário futuro e a massa seca radicular manteve um valor semelhante nos dois cenários, resultando em um maior investimento em biomassa aérea em relação à biomassa radicular de *T. aurea* no cenário futuro em comparação ao cenário atual. Considerando esse aspecto, podemos considerar que *K. coriacea* teve um comportamento mais conservativo em relação à distribuição da biomassa, pois em ambiente de savana é muito comum a perda da parte aérea e a necessidade do uso de reservas subterrâneas para rebrotar (Bond, 2008). O xilopódio é um órgão de reserva que teve origem em diversos momentos evolutivos, podendo ser encontrado em espécies com origens filogenéticas muito distintas (Simon & Pennington, 2012). O xilopódio pode ser fonte de diversos recursos como água, nutrientes e carboidratos em momentos de escassez, sendo possível que diferentes filtros ambientais tenham favorecido o desenvolvimento desse órgão em diferentes espécies (Simon & Pennington, 2012). É possível que estudos filogenéticos associados aos resultados obtidos em nosso experimento, possam ajudar a responder quais pressões evolutivas levaram à divergência das respostas apresentadas por essas espécies no presente trabalho.

A aquisição de biomassa durante o estágio inicial de desenvolvimento de uma planta pode estar associada à massa da semente (Baraloto et al, 2005; Saatkamp et al, 2019). A variação na biomassa total observada entre o cenário futuro e o atual de *K. coriacea*, *Q. grandiflora* e *T. aurea* foi semelhante (cerca de 0,8g) (Figuras 2.2, 2.3 e 2.5), enquanto que ao mesmo tempo *H. stigonocarpa* apresentou um incremento de biomassa total de 3,7g no cenário futuro (Figura 2.4). *K. coriacea*, *Q. grandiflora* e *T. aurea* são dispersas por anemocoria, possuem sementes mais leves e cotilédones fotossintetizantes, enquanto que *H. stigonocarpa* é dispersa por zoocoria e possui sementes maiores e mais pesadas, apresentando cotilédones de reserva. Esse resultado reforça estudos que defendem que a variação do incremento de biomassa e a taxa de crescimento relativo são mais pronunciados em plantas com sementes maiores quando submetidas a maiores temperaturas e [CO_2] (Jones & Reekie, 2007; Khurana& Singh, 2004).

Q. grandiflora foi a única que passou a alocar mais da metade da biomassa total para fração aérea no cenário futuro (Figura 2.2). Mesmo sendo uma espécie com grande plasticidade fenotípica (Buzatti et al., 2019) e a que apresenta a maior frequência e distribuição no Cerrado (Ratter et al., 2003), sua distribuição é restrita ao Cerrado (da Ponte et al, 2020). Sendo o padrão de distribuição de biomassa um atributo relacionado ao tipo de ambiente em que a espécie se encontra (Qi et al, 2019), esse resultado torna-se surpreendente. Por outro lado, a inversão no padrão de alocação de biomassa foi observada em outros experimentos com elevação de temperatura e [CO_2] (Avila et al, 2020; Forbes et al, 2020; Apgaua et al, 2019). No caso de espécies de *Eucalyptus* em savanas, a modificação do padrão de alocação de biomassa só foi observada quando o CO_2 elevado foi aplicado juntamente com temperaturas mais altas, caso contrário apenas se observou o aumento da biomassa em função da maior oferta de carbono atmosférico (Apgaua et al, 2019).

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

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

5.4. CONCLUSÃO

Nosso trabalho evidencia que o cenário futuro esperado para 2100 favoreceu o desenvolvimento inicial de espécies arbóreas de savana neotropical. Devido ao incremento significativo de biomassa observado no cenário futuro em todas as espécies estudadas, com maior proporção na fração aérea em metade dessas espécies, nossos resultados trazem fortes indícios de que a elevação da [CO_2] atmosférico pode ser um fator importante do processo de adensamento arbóreo que vem ocorrendo mundialmente em savanas, com maior velocidade em savanas da América do Sul podendo levar a grande perda de biodiversidade (Rosan et al., 2019; Abreu et al., 2017). A elevação da [CO_2] e da temperatura no cenário futuro provocou ao mesmo tempo o incremento de atributos que contribuem para o aumento do sombreamento em savanas (H, Ln, SM) e o alcance de profundidades maiores no perfil do solo (RL). O efeito das mudanças climáticas a nível de indivíduo pode ter grandes consequências na composição da vegetação e deve ser considerado em ações de preservação ambiental para a melhor preservação da biodiversidade em savanas.

5.5. REFERÊNCIAS

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5.6. MATERIAL SUPLEMENTAR

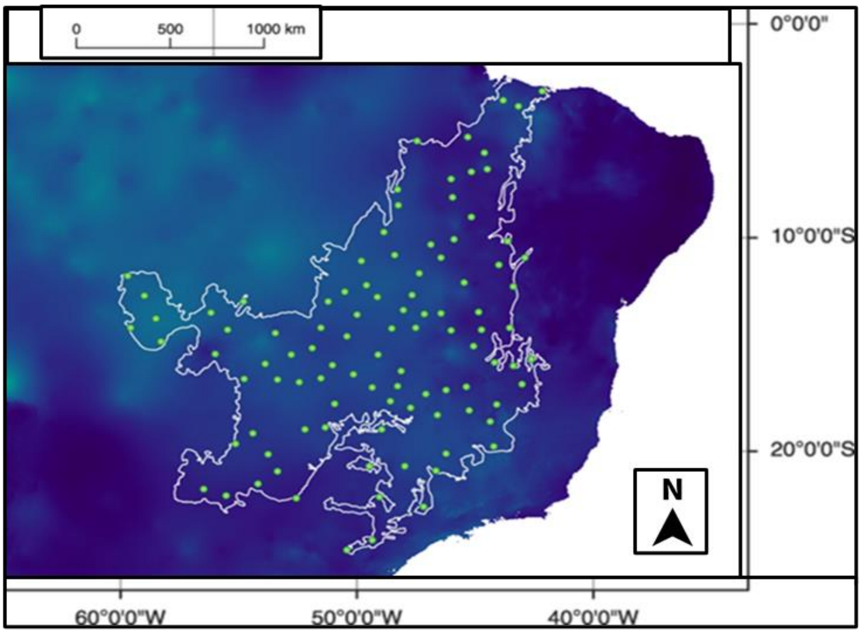

Figura S2.1: Distribuição de 100 pontos aleatórios no território do bioma Cerrado para obtenção dos dados de temperatura máxima, temperatura mínima, e precipitação previstos para os meses de dezembro a abril de 2100 de acordo com o SSP 3-7.0, segundo o modelo MIROC6-ES2L (MIROC6) do IPCC.

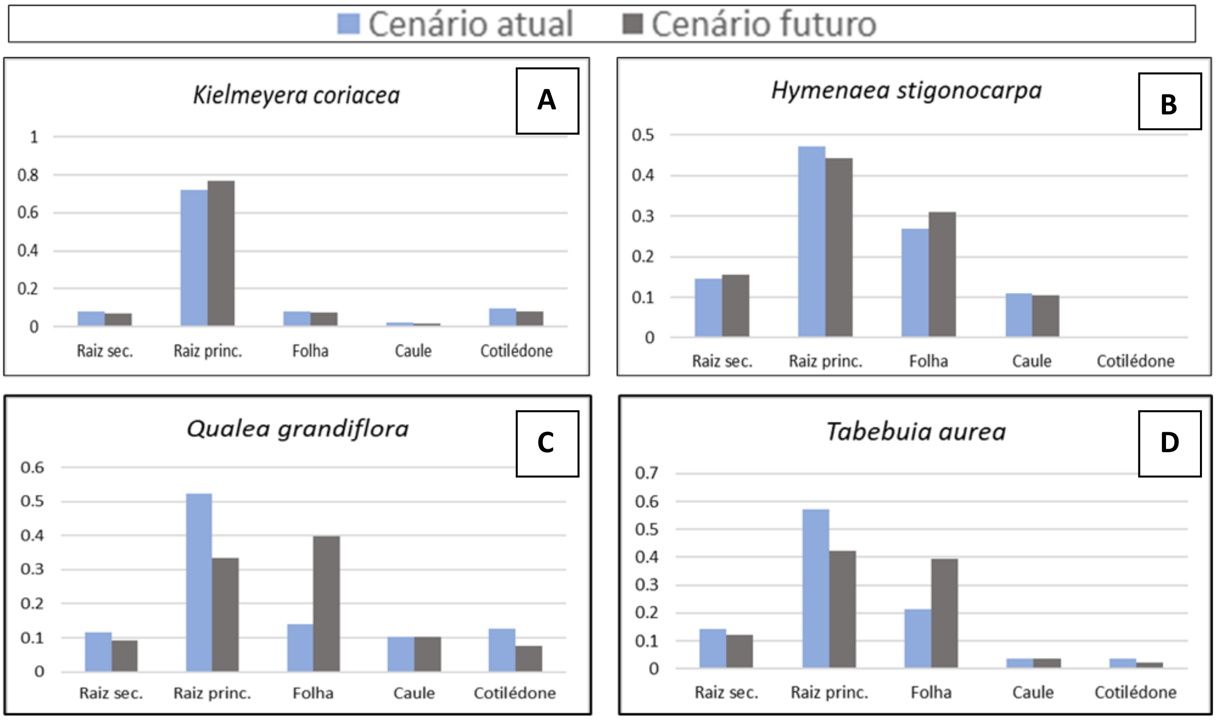

Figura S2.2. Distribuição da biomassa de plântulas de *K. coriacea* (A), *H. stigonocarpa* (B), *Q. grandiflora* (C), *T. aurea* (D) após 120 sob o cenário atual (azul – barras à esquerda) ou sob o cenário futuro (cinza – barras à direita) simulados em fitotron no Laboratório de Termobiologia (Universidade 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).

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

Parâmetro	unidade	solo + areia	solo original
COMPLEXO SORTIVO			
pH em H2O,	na	5.6	5.7
FÓSFORO - P, extraído com Mehlich	mg/dm3 = ppm	1.8	1.3
CÁLCIO - Ca	cmolc/dm3 = mE/100mL	0.4	0.3
MAGNÉSIO - Mg	cmolcdm3 = mE/100mL	0.1	0.1
POTÁSSIO - K	cmolcdm3 = mE/100mL	0.01	0.04
SÓDIO - Na	cmolcdm3 = mE/100mL	0.07	0.07
ALUMÍNIO - Al	cmolcdm3 = mE/100mL	0.8	0.7
ACIDEZ (H + Al)	cmolcdm3 = mE/100mL	3.2	3
SOMA DAS BASES	cmolcdm3 = mE/100mL	0.6	0.5
CAPACIDADE DE TROCA DE CÁTIONS - CTC ou T, a pH 7	cmolc/dm3	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/dm3 = ppm	0.03	0.04
COBRE DISPONÍVEL - Cu	mg/dm3 = ppm	0.4	0.3
FERRO DISPONÍVEL - Fe	mg/dm3 = ppm	111	73.6
MANGANÊS DISPONÍVEL - Mn	mg/dm3 = ppm	14.9	4.6
ZINCO DISPONÍVEL - Zn	mg/dm3 = ppm	1	0.7
ENXOFRE DISPONÍVEL - S	mg/dm3 = ppm	2.9	7.1
COMPOSIÇÃO GRANULOMÉTRICA			
Argila	g/Kg	550	500
Areia	g/Kg	375	300
Silte	g/Kg	75	200

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

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.

Horário (h)	**temperatura (°C)**		**Umidade relativa (%)**	**Luz (μmol / m^2 / 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	-

Nota: Na última coluna, cada "X" refere-se a um conjunto de lâmpadas acesas nos fitotrons. Ao todo são três conjuntos de lâmpadas em cada fitotrôn. A incidência luminosa ao nível da parte superior dos tubos onde se encontravam as plantas era de 210 µmol / m^2 / s quando haviam um conjunto de lâmpadas acesas ("X"), de 420 µmol / m^2 / s quando haviam dois conjuntos de lâmpadas acesas ("XX"), e de 700 µmol / m^2 / s quando haviam três conjuntos de lâmpadas acesas ("XXX").

6. CONCLUSÃO GERAL

No geral pudemos observar que quando submetidas a temperatura e concentração de CO_2 elevadas, plântulas de espécies arbóreas de savana apresentam a intensidade de alocação de biomassa para a fração radicular ou aérea dependerá do grau de tolerância ao estresse ambiental encontrado pela plântula. Nossos resultados indicam que a alocação de biomassa e o desenvolvimento da parte aérea, assim como o investimento em comprimento da raiz principal, foi mais importante do que o acúmulo de biomassa nas raízes.

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

7. APÊNDICES

7.1. APÊNDICE I: DADOS DO CAPÍTULO 1

7.1.1. Dados inciais

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

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

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

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

7.2. APÊNDICE II: DADOS DO CAPÍTULO 2

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

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

1973

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

1974

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

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

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

1980

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

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

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

```
##   18/11/2022
##  gráficos de correlação de Qg e Ta

library(readxl)
f_Planilha_S3_dbrutos_final_artigo_veranicos_ <- read_excel("C:/Users/dalch/Desktop/Doutorado - geral/artigo Veranicos 2021/Editado Elsevier/conferindo revisão da Elsevier/f_Planilha_S3_dbrutos_final(artigo_veranicos).xlsx",
                                                col_types = c("text", "numeric", "numeric",
                                                              "numeric", "numeric", "numeric",
                                                              "numeric", "numeric", "numeric",
                                                              "numeric", "numeric", "numeric",
                                                              "numeric", "numeric", "numeric",
                                                              "numeric"))
View(f_Planilha_S3_dbrutos_final_artigo_veranicos_)

attach(f_Planilha_S3_dbrutos_final_artigo_veranicos_)

################
## Fazendo nova análise para incluir parâmetros sugeridos pelo revisor no
#### segundo pedido de revisão da Flora
library(readxl)

f_Planilha_S3_dbrutos_final_LMF_ <- read_excel("C:/Users/dalch/Desktop/f_Planilha_S3_dbrutos_final(LMF).xlsx",
                                        col_types = c("text","numeric","skip", "numeric",
```

```
                                               "numeric", "numeric", "numeric",
                                               "numeric", "numeric", "numeric",
                                               "numeric", "numeric", "numeric",
                                               "numeric", "numeric", "numeric",
                                               "numeric", "skip", "skip", "skip",
                                               "skip", "skip", "skip", "numeric",
                                               "numeric", "numeric", "numeric"))
View(f_Planilha_S3_dbrutos_final_LMF_)

attach(f_Planilha_S3_dbrutos_final_LMF_)

library(tidyverse)
library(flexplot)
library(ggplot2)
library(dplyr)
library(car)
library(fitdistrplus)

Qd1 <- f_Planilha_S3_dbrutos_final_LMF_ %>% na.omit()
attach(Qd1)

esp <- c(Qd1$species)
esp
tratamento <- c(Qd1$tratamento)
tratamento
H <- c(Qd1$H)
Lnum <- c(Qd1$Lnum)
```

```
RM      <- c(Qd1$RM)
SM      <- c(Qd1$SM)
TM      <- c(Qd1$TM)
RMF     <- c(Qd1$RMF)
SMF     <- c(Qd1$SMF)
STRL    <- c(Qd1$STRL)
RER     <- c(Qd1$RER)
RGR     <- c(Qd1$RGR)
RL    <- c(Qd1$RL)
SLA    <- c(Qd1$SLA)
RS <- c(Qd1$RS)
LMF <- c(Qd1$LMF)
LMt <- c(Qd1$LMt)
NAR <- c(Qd1$NAR)
LAm <- c(Qd1$LAm)


#################### correlação sem separar os tratamentos:
library(metan)
library(corrplot)
library(RColorBrewer)



###Qualea:

data_Qg.ver <- f_Planilha_S3_dbrutos_final_LMF_[
```

```
  f_Planilha_S3_dbrutos_final_LMF_$species == "Qualea grandiflora",
  ]
data_Qg.ver_no_na<- data_Qg.ver %>% na.omit()
data_Qg.ver_no_na

## médias e erro
################## tratamentos separados:
Qd1$tratamento <- as.factor(Qd1$tratamento)
tratamento <-as.factor(Qd1$tratamento)
tratamento

### para Qg

data_Qg.ver1 <- data_Qg.ver_no_na[data_Qg.ver_no_na$tratamento == "1",-(2) ]
data_Qg.ver1

data_Qg.ver8 <- data_Qg.ver_no_na[data_Qg.ver_no_na$tratamento == "8",-(2) ]
data_Qg.ver8

data_Qg.ver15 <- data_Qg.ver_no_na[data_Qg.ver_no_na$tratamento == "15",-(2) ]
data_Qg.ver15

QgH_1 <- c(data_Qg.ver1$H)
QgLnum_1 <- c(data_Qg.ver1$Lnum)
QgRM_1  <- c(data_Qg.ver1$RM)
QgSM_1  <- c(data_Qg.ver1$SM)
QgTM_1  <- c(data_Qg.ver1$TM)
```

```
QgRMF_1 <- c(data_Qg.ver1$RMF)
QgSMF_1 <- c(data_Qg.ver1$SMF)
QgSTRL_1<- c(data_Qg.ver1$STRL)
QgRER_1 <- c(data_Qg.ver1$RER)
QgRGR_1 <- c(data_Qg.ver1$RGR)
QgRL_1  <- c(data_Qg.ver1$RL)
QgSLA_1 <- c(data_Qg.ver1$SLA)
QgRS_1 <- c(data_Qg.ver1$RS)
QgLMF_1 <- c(data_Qg.ver1$LMF)
QgLMt_1 <- c(data_Qg.ver1$LMt)
QgNAR_1 <- c(data_Qg.ver1$NAR)
QgLAm_1 <- c(data_Qg.ver1$LAm)



m_QgH_1<- mean(QgH_1)
m_QgH_1
se_QgH_1 <- sd(QgH_1) / sqrt(8)
se_QgH_1

m_QgLnum_1<- mean(QgLnum_1)
m_QgLnum_1
se_QgLnum_1 <- sd(QgLnum_1) / sqrt(8)
se_QgLnum_1

m_QgRM_1<- mean(QgRM_1)
m_QgRM_1
```

```
se_QgRM_1 <- sd(QgRM_1) / sqrt(8)
se_QgRM_1

m_QgSM_1<- mean(QgSM_1)
m_QgSM_1
se_QgSM_1 <- sd(QgSM_1) / sqrt(8)
se_QgSM_1

m_QgTM_1<- mean(QgTM_1)
m_QgTM_1
se_QgTM_1 <- sd(QgTM_1) / sqrt(8)
se_QgTM_1

m_QgRMF_1<- mean(QgRMF_1)
m_QgRMF_1
se_QgRMF_1 <- sd(QgRMF_1) / sqrt(8)
se_QgRMF_1

m_QgSMF_1<- mean(QgSMF_1)
m_QgSMF_1
se_QgSMF_1 <- sd(QgSMF_1) / sqrt(8)
se_QgSMF_1


m_QgRS_1<- mean(QgRS_1)
m_QgRS_1
se_QgRS_1 <- sd(QgRS_1) / sqrt(8)
```

```
se_QgRS_1

m_QgSTRL_1<- mean(QgSTRL_1)
m_QgSTRL_1
se_QgSTRL_1 <- sd(QgSTRL_1) / sqrt(8)
se_QgSTRL_1

m_QgRGR_1<- mean(QgRGR_1)
m_QgRGR_1
se_QgRGR_1 <- sd(QgRGR_1) / sqrt(8)
se_QgRGR_1

m_QgRER_1<- mean(QgRER_1)
m_QgRER_1
se_QgRER_1 <- sd(QgRER_1) / sqrt(8)
se_QgRER_1

m_QgSLA_1<- mean(QgSLA_1)
m_QgSLA_1
se_QgSLA_1 <- sd(QgSLA_1) / sqrt(8)
se_QgSLA_1

m_QgRL_1<- mean(QgRL_1)
m_QgRL_1
se_QgRL_1 <- sd(QgRL_1) / sqrt(8)
se_QgRL_1
```

```
m_QgLMF_1<- mean(QgLMF_1)
m_QgLMF_1
se_QgLMF_1 <- sd(QgLMF_1) / sqrt(8)
se_QgLMF_1

m_QgLMt_1<- mean(QgLMt_1)
m_QgLMt_1
se_QgLMt_1 <- sd(QgLMt_1) / sqrt(8)
se_QgLMt_1

m_QgNAR_1<- mean(QgNAR_1)
m_QgNAR_1
se_QgNAR_1 <- sd(QgNAR_1) / sqrt(8)
se_QgNAR_1

m_QgLAm_1<- mean(QgLAm_1)
m_QgLAm_1
se_QgLAm_1 <- sd(QgLAm_1) / sqrt(8)
se_QgLAm_1

###
QgH_8 <- c(data_Qg.ver8$H)
QgLnum_8 <- c(data_Qg.ver8$Lnum)
QgRM_8  <- c(data_Qg.ver8$RM)
QgSM_8  <- c(data_Qg.ver8$SM)
QgTM_8  <- c(data_Qg.ver8$TM)
```

```
QgRMF_8 <- c(data_Qg.ver8$RMF)
QgSMF_8 <- c(data_Qg.ver8$SMF)
QgSTRL_8<- c(data_Qg.ver8$STRL)
QgRER_8 <- c(data_Qg.ver8$RER)
QgRGR_8 <- c(data_Qg.ver8$RGR)
QgRL_8  <- c(data_Qg.ver8$RL)
QgSLA_8 <- c(data_Qg.ver8$SLA)
QgRS_8 <- c(data_Qg.ver8$RS)

m_QgH_8<- mean(QgH_8)
m_QgH_8
se_QgH_8 <- sd(QgH_8) / sqrt(8)
se_QgH_8

m_QgLnum_8<- mean(QgLnum_8)
m_QgLnum_8
se_QgLnum_8 <- sd(QgLnum_8) / sqrt(8)
se_QgLnum_8

m_QgRM_8<- mean(QgRM_8)
m_QgRM_8
se_QgRM_8 <- sd(QgRM_8) / sqrt(8)
se_QgRM_8

m_QgSM_8<- mean(QgSM_8)
m_QgSM_8
se_QgSM_8 <- sd(QgSM_8) / sqrt(8)
```

```
se_QgSM_8

m_QgTM_8<- mean(QgTM_8)
m_QgTM_8
se_QgTM_8 <- sd(QgTM_8) / sqrt(8)
se_QgTM_8

m_QgRMF_8<- mean(QgRMF_8)
m_QgRMF_8
se_QgRMF_8 <- sd(QgRMF_8) / sqrt(8)
se_QgRMF_8

m_QgSMF_8<- mean(QgSMF_8)
m_QgSMF_8
se_QgSMF_8 <- sd(QgSMF_8) / sqrt(8)
se_QgSMF_8


m_QgRS_8<- mean(QgRS_8)
m_QgRS_8
se_QgRS_8 <- sd(QgRS_8) / sqrt(8)
se_QgRS_8

m_QgSTRL_8<- mean(QgSTRL_8)
m_QgSTRL_8
se_QgSTRL_8 <- sd(QgSTRL_8) / sqrt(8)
se_QgSTRL_8
```

```
m_QgRGR_8<- mean(QgRGR_8)
m_QgRGR_8
se_QgRGR_8 <- sd(QgRGR_8) / sqrt(8)
se_QgRGR_8

m_QgRER_8<- mean(QgRER_8)
m_QgRER_8
se_QgRER_8 <- sd(QgRER_8) / sqrt(8)
se_QgRER_8

m_QgSLA_8<- mean(QgSLA_8)
m_QgSLA_8
se_QgSLA_8 <- sd(QgSLA_8) / sqrt(8)
se_QgSLA_8

m_QgRL_8<- mean(QgRL_8)
m_QgRL_8
se_QgRL_8 <- sd(QgRL_8) / sqrt(8)
se_QgRL_8


m_QgLMF_8<- mean(QgLMF_8)
m_QgLMF_8
se_QgLMF_8 <- sd(QgLMF_8) / sqrt(8)
se_QgLMF_8
```

```
m_QgLMt_8<- mean(QgLMt_8)
m_QgLMt_8
se_QgLMt_8 <- sd(QgLMt_8) / sqrt(8)
se_QgLMt_8

m_QgNAR_8<- mean(QgNAR_8)
m_QgNAR_8
se_QgNAR_8 <- sd(QgNAR_8) / sqrt(8)
se_QgNAR_8

m_QgLAm_8<- mean(QgLAm_8)
m_QgLAm_8
se_QgLAm_8 <- sd(QgLAm_8) / sqrt(8)
se_QgLAm_8

###
QgH_15 <- c(data_Qg.ver15$H)
QgLnum_15 <- c(data_Qg.ver15$Lnum)
QgRM_15  <- c(data_Qg.ver15$RM)
QgSM_15  <- c(data_Qg.ver15$SM)
QgTM_15  <- c(data_Qg.ver15$TM)
QgRMF_15 <- c(data_Qg.ver15$RMF)
QgSMF_15 <- c(data_Qg.ver15$SMF)
QgSTRL_15<- c(data_Qg.ver15$STRL)
QgRER_15 <- c(data_Qg.ver15$RER)
QgRGR_15 <- c(data_Qg.ver15$RGR)
QgRL_15  <- c(data_Qg.ver15$RL)
```

```
QgSLA_15 <- c(data_Qg.ver15$SLA)
QgRS_15 <- c(data_Qg.ver15$RS)

m_QgH_15<- mean(QgH_15)
m_QgH_15
se_QgH_15 <- sd(QgH_15) / sqrt(8)
se_QgH_15

m_QgLnum_15<- mean(QgLnum_15)
m_QgLnum_15
se_QgLnum_15 <- sd(QgLnum_15) / sqrt(8)
se_QgLnum_15

m_QgRM_15<- mean(QgRM_15)
m_QgRM_15
se_QgRM_15 <- sd(QgRM_15) / sqrt(8)
se_QgRM_15

m_QgSM_15<- mean(QgSM_15)
m_QgSM_15
se_QgSM_15 <- sd(QgSM_15) / sqrt(8)
se_QgSM_15

m_QgTM_15<- mean(QgTM_15)
m_QgTM_15
se_QgTM_15 <- sd(QgTM_15) / sqrt(8)
se_QgTM_15
```

```
m_QgRMF_15<- mean(QgRMF_15)
m_QgRMF_15
se_QgRMF_15 <- sd(QgRMF_15) / sqrt(8)
se_QgRMF_15

m_QgSMF_15<- mean(QgSMF_15)
m_QgSMF_15
se_QgSMF_15 <- sd(QgSMF_15) / sqrt(8)
se_QgSMF_15

m_QgRS_15<- mean(QgRS_15)
m_QgRS_15
se_QgRS_15 <- sd(QgRS_15) / sqrt(8)
se_QgRS_15

m_QgSTRL_15<- mean(QgSTRL_15)
m_QgSTRL_15
se_QgSTRL_15 <- sd(QgSTRL_15) / sqrt(8)
se_QgSTRL_15

m_QgRGR_15<- mean(QgRGR_15)
m_QgRGR_15
se_QgRGR_15 <- sd(QgRGR_15) / sqrt(8)
se_QgRGR_15

m_QgRER_15<- mean(QgRER_15)
```

```
m_QgRER_15
se_QgRER_15 <- sd(QgRER_15) / sqrt(8)
se_QgRER_15

m_QgSLA_15<- mean(QgSLA_15)
m_QgSLA_15
se_QgSLA_15 <- sd(QgSLA_15) / sqrt(8)
se_QgSLA_15

m_QgRL_15<- mean(QgRL_15)
m_QgRL_15
se_QgRL_15 <- sd(QgRL_15) / sqrt(8)
se_QgRL_15

##### Tabebuia
data_Ta.ver <- f_Planilha_S3_dbrutos_final_LMF_[
  f_Planilha_S3_dbrutos_final_LMF_$species == "Tabebuia aurea",-(2) ]
data_Ta.ver_no_na<- data_Ta.ver %>% na.omit()
data_Ta.ver_no_na

data_Ta.ver1 <- data_Ta.ver_no_na[data_Ta.ver_no_na$tratamento == "1",-(2) ]
data_Ta.ver1

data_Ta.ver8 <- data_Ta.ver_no_na[data_Ta.ver_no_na$tratamento == "8",-(2) ]
data_Ta.ver8

data_Ta.ver15 <- data_Ta.ver_no_na[data_Ta.ver_no_na$tratamento == "15",-(2) ]
```

```
data_Ta.ver15

TaH_1 <- c(data_Ta.ver1$H)
TaLnum_1 <- c(data_Ta.ver1$Lnum)
TaRM_1  <- c(data_Ta.ver1$RM)
TaSM_1  <- c(data_Ta.ver1$SM)
TaTM_1  <- c(data_Ta.ver1$TM)
TaRMF_1 <- c(data_Ta.ver1$RMF)
TaSMF_1 <- c(data_Ta.ver1$SMF)
TaSTRL_1<- c(data_Ta.ver1$STRL)
TaRER_1 <- c(data_Ta.ver1$RER)
TaRGR_1 <- c(data_Ta.ver1$RGR)
TaRL_1  <- c(data_Ta.ver1$RL)
TaSLA_1 <- c(data_Ta.ver1$SLA)
TaRS_1 <- c(data_Ta.ver1$RS)

m_TaH_1<- mean(TaH_1)
m_TaH_1
se_TaH_1 <- sd(TaH_1) / sqrt(10)
se_TaH_1

m_TaLnum_1<- mean(TaLnum_1)
m_TaLnum_1
se_TaLnum_1 <- sd(TaLnum_1) / sqrt(10)
se_TaLnum_1

m_TaRM_1<- mean(TaRM_1)
```

```
m_TaRM_1
se_TaRM_1 <- sd(TaRM_1) / sqrt(10)
se_TaRM_1

m_TaSM_1<- mean(TaSM_1)
m_TaSM_1
se_TaSM_1 <- sd(TaSM_1) / sqrt(10)
se_TaSM_1

m_TaTM_1<- mean(TaTM_1)
m_TaTM_1
se_TaTM_1 <- sd(TaTM_1) / sqrt(10)
se_TaTM_1

m_TaRMF_1<- mean(TaRMF_1)
m_TaRMF_1
se_TaRMF_1 <- sd(TaRMF_1) / sqrt(10)
se_TaRMF_1

m_TaSMF_1<- mean(TaSMF_1)
m_TaSMF_1
se_TaSMF_1 <- sd(TaSMF_1) / sqrt(10)
se_TaSMF_1

m_TaRS_1<- mean(TaRS_1)
m_TaRS_1
se_TaRS_1 <- sd(TaRS_1) / sqrt(10)
```

```
se_TaRS_1

m_TaSTRL_1<- mean(TaSTRL_1)
m_TaSTRL_1
se_TaSTRL_1 <- sd(TaSTRL_1) / sqrt(10)
se_TaSTRL_1

m_TaRGR_1<- mean(TaRGR_1)
m_TaRGR_1
se_TaRGR_1 <- sd(TaRGR_1) / sqrt(10)
se_TaRGR_1

m_TaRER_1<- mean(TaRER_1)
m_TaRER_1
se_TaRER_1 <- sd(TaRER_1) / sqrt(10)
se_TaRER_1

m_TaSLA_1<- mean(TaSLA_1)
m_TaSLA_1
se_TaSLA_1 <- sd(TaSLA_1) / sqrt(10)
se_TaSLA_1

m_TaRL_1<- mean(TaRL_1)
m_TaRL_1
se_TaRL_1 <- sd(TaRL_1) / sqrt(10)
se_TaRL_1
```

```
###

TaH_8 <- c(data_Ta.ver8$H)
TaLnum_8 <- c(data_Ta.ver8$Lnum)
TaRM_8  <- c(data_Ta.ver8$RM)
TaSM_8  <- c(data_Ta.ver8$SM)
TaTM_8  <- c(data_Ta.ver8$TM)
TaRMF_8 <- c(data_Ta.ver8$RMF)
TaSMF_8 <- c(data_Ta.ver8$SMF)
TaSTRL_8<- c(data_Ta.ver8$STRL)
TaRER_8 <- c(data_Ta.ver8$RER)
TaRGR_8 <- c(data_Ta.ver8$RGR)
TaRL_8  <- c(data_Ta.ver8$RL)
TaSLA_8 <- c(data_Ta.ver8$SLA)
TaRS_8 <- c(data_Ta.ver8$RS)

m_TaH_8<- mean(TaH_8)
m_TaH_8
se_TaH_8 <- sd(TaH_8) / sqrt(10)
se_TaH_8

m_TaLnum_8<- mean(TaLnum_8)
m_TaLnum_8
se_TaLnum_8 <- sd(TaLnum_8) / sqrt(10)
se_TaLnum_8

m_TaRM_8<- mean(TaRM_8)
```

```
m_TaRM_8
se_TaRM_8 <- sd(TaRM_8) / sqrt(10)
se_TaRM_8

m_TaSM_8<- mean(TaSM_8)
m_TaSM_8
se_TaSM_8 <- sd(TaSM_8) / sqrt(10)
se_TaSM_8

m_TaTM_8<- mean(TaTM_8)
m_TaTM_8
se_TaTM_8 <- sd(TaTM_8) / sqrt(10)
se_TaTM_8

m_TaRMF_8<- mean(TaRMF_8)
m_TaRMF_8
se_TaRMF_8 <- sd(TaRMF_8) / sqrt(10)
se_TaRMF_8

m_TaSMF_8<- mean(TaSMF_8)
m_TaSMF_8
se_TaSMF_8 <- sd(TaSMF_8) / sqrt(10)
se_TaSMF_8


m_TaRS_8<- mean(TaRS_8)
m_TaRS_8
```

```
se_TaRS_8 <- sd(TaRS_8) / sqrt(10)
se_TaRS_8

m_TaSTRL_8<- mean(TaSTRL_8)
m_TaSTRL_8
se_TaSTRL_8 <- sd(TaSTRL_8) / sqrt(10)
se_TaSTRL_8

m_TaRGR_8<- mean(TaRGR_8)
m_TaRGR_8
se_TaRGR_8 <- sd(TaRGR_8) / sqrt(10)
se_TaRGR_8

m_TaRER_8<- mean(TaRER_8)
m_TaRER_8
se_TaRER_8 <- sd(TaRER_8) / sqrt(10)
se_TaRER_8

m_TaSLA_8<- mean(TaSLA_8)
m_TaSLA_8
se_TaSLA_8 <- sd(TaSLA_8) / sqrt(10)
se_TaSLA_8

m_TaRL_8<- mean(TaRL_8)
m_TaRL_8
se_TaRL_8 <- sd(TaRL_8) / sqrt(10)
se_TaRL_8
```

```
##
TaH_15 <- c(data_Ta.ver15$H)
TaLnum_15 <- c(data_Ta.ver15$Lnum)
TaRM_15  <- c(data_Ta.ver15$RM)
TaSM_15  <- c(data_Ta.ver15$SM)
TaTM_15  <- c(data_Ta.ver15$TM)
TaRMF_15 <- c(data_Ta.ver15$RMF)
TaSMF_15 <- c(data_Ta.ver15$SMF)
TaSTRL_15<- c(data_Ta.ver15$STRL)
TaRER_15 <- c(data_Ta.ver15$RER)
TaRGR_15 <- c(data_Ta.ver15$RGR)
TaRL_15  <- c(data_Ta.ver15$RL)
TaSLA_15 <- c(data_Ta.ver15$SLA)
TaRS_15 <- c(data_Ta.ver15$RS)

m_TaH_15<- mean(TaH_15)
m_TaH_15
se_TaH_15 <- sd(TaH_15) / sqrt(10)
se_TaH_15

m_TaLnum_15<- mean(TaLnum_15)
m_TaLnum_15
se_TaLnum_15 <- sd(TaLnum_15) / sqrt(10)
se_TaLnum_15

m_TaRM_15<- mean(TaRM_15)
```

```
m_TaRM_15
se_TaRM_15 <- sd(TaRM_15) / sqrt(10)
se_TaRM_15

m_TaSM_15<- mean(TaSM_15)
m_TaSM_15
se_TaSM_15 <- sd(TaSM_15) / sqrt(10)
se_TaSM_15

m_TaTM_15<- mean(TaTM_15)
m_TaTM_15
se_TaTM_15 <- sd(TaTM_15) / sqrt(10)
se_TaTM_15

m_TaRMF_15<- mean(TaRMF_15)
m_TaRMF_15
se_TaRMF_15 <- sd(TaRMF_15) / sqrt(10)
se_TaRMF_15

m_TaSMF_15<- mean(TaSMF_15)
m_TaSMF_15
se_TaSMF_15 <- sd(TaSMF_15) / sqrt(10)
se_TaSMF_15

m_TaRS_15<- mean(TaRS_15)
m_TaRS_15
se_TaRS_15 <- sd(TaRS_15) / sqrt(10)
```

```
se_TaRS_15

m_TaSTRL_15<- mean(TaSTRL_15)
m_TaSTRL_15
se_TaSTRL_15 <- sd(TaSTRL_15) / sqrt(10)
se_TaSTRL_15

m_TaRGR_15<- mean(TaRGR_15)
m_TaRGR_15
se_TaRGR_15 <- sd(TaRGR_15) / sqrt(10)
se_TaRGR_15

m_TaRER_15<- mean(TaRER_15)
m_TaRER_15
se_TaRER_15 <- sd(TaRER_15) / sqrt(10)
se_TaRER_15

m_TaSLA_15<- mean(TaSLA_15)
m_TaSLA_15
se_TaSLA_15 <- sd(TaSLA_15) / sqrt(10)
se_TaSLA_15

m_TaRL_15<- mean(TaRL_15)
m_TaRL_15
se_TaRL_15 <- sd(TaRL_15) / sqrt(10)
se_TaRL_15

###### correlação
Qgcorr<-corr_coef(data_Qg.ver_no_na)

plot(Qgcorr, col.low = "#FF8493",  col.high ="#20B2AA") #esse foi o escolhido!

corr_plot(data_Qg.ver_no_na)
```

```
###Tabebuia
data_Ta.ver <- f_Planilha_S3_dbrutos_final_artigo_veranicos_[
  f_Planilha_S3_dbrutos_final_artigo_veranicos_$species == "Tabebuia aurea",
  -(2) ]
data_Ta.ver_no_na<- data_Ta.ver %>% na.omit()
data_Ta.ver_no_na

Tacorr<-corr_coef(data_Ta.ver_no_na)

plot(Tacorr, col.low = "#FF1493",  col.high ="#20B2AA") #esse foi o escolhido!

corr_plot(data_Qg.ver_no_na)

#####################
## análises estatísticas para Tabebuia.
##
###### como diferem?
library(PMCMR)

##################### como eu fiz antes para comparar as sp separadamente:
#T_RM<-(dados.v[1:33,]$RM)
#T_trat.v<-(dados.v[1:33,]$tratamento)
#str(T_trat.v)
#T_trat<-as.factor(T_trat.v)
#T_trat
#posthoc.kruskal.nemenyi.test(T_RM, T_trat, method = "Tukey")
#############################################################
### como estou fazendo agora:
data_Ta.ver <- f_Planilha_S3_dbrutos_final_LMF_[
  f_Planilha_S3_dbrutos_final_LMF_$species == "Tabebuia aurea",]
data_Ta.ver_no_na<- data_Ta.ver %>% na.omit()
data_Ta.ver_no_na

TaH <- c(data_Ta.ver_no_na$H)
```

```
TaLnum <- c(data_Ta.ver_no_na$Lnum)
TaRM  <- c(data_Ta.ver_no_na$RM)
TaSM  <- c(data_Ta.ver_no_na$SM)
TaTM <- c(data_Ta.ver_no_na$TM)
TaRMF <- c(data_Ta.ver_no_na$RMF)
TaSMF <- c(data_Ta.ver_no_na$SMF)
TaSTRL<- c(data_Ta.ver_no_na$STRL)
TaRER <- c(data_Ta.ver_no_na$RER)
TaRGR <- c(data_Ta.ver_no_na$RGR)
TaRL  <- c(data_Ta.ver_no_na$RL)
TaSLA <- c(data_Ta.ver_no_na$SLA)
TaRS <- c(data_Ta.ver_no_na$RS)
TaLMF <- c(data_Ta.ver_no_na$LMF)
TaLMt <- c(data_Ta.ver_no_na$LMt)
TaNAR <- c(data_Ta.ver_no_na$NAR)
TaLAm <- c(data_Ta.ver_no_na$LAm)

T_trat.v <- as.factor(data_Ta.ver_no_na$tratamento)
T_trat.v

kruskal.test(TaRM ~ T_trat.v)
kruskal.test(TaSM ~ T_trat.v)
kruskal.test(TaRMF ~ T_trat.v)
kruskal.test(TaSMF ~ T_trat.v)
kruskal.test(TaH ~ T_trat.v)
kruskal.test(TaLnum ~ T_trat.v)
kruskal.test(TaRGR ~ T_trat.v)
kruskal.test(TaRER ~ T_trat.v)
kruskal.test(TaSTRL~ T_trat.v)
kruskal.test(TaRS ~ T_trat.v)
kruskal.test(TaSLA ~ T_trat.v)
kruskal.test(TaLMF ~ T_trat.v)
kruskal.test(TaLMt ~ T_trat.v)
kruskal.test(TaNAR ~ T_trat.v)
```

```
kruskal.test(TaLAm ~ T_trat.v)


posthoc.kruskal.nemenyi.test(TaRM, T_trat.v, method = "Tukey")
posthoc.kruskal.nemenyi.test(TaSM, T_trat.v, method = "Tukey")
posthoc.kruskal.nemenyi.test(TaRMF, T_trat.v, method = "Tukey")
posthoc.kruskal.nemenyi.test(TaSMF, T_trat.v, method = "Tukey")
posthoc.kruskal.nemenyi.test(Taalt, T_trat.v, method = "Tukey")
posthoc.kruskal.nemenyi.test(TaLnum, T_trat.v, method = "Tukey")
posthoc.kruskal.nemenyi.test(TaRGR, T_trat.v, method = "Tukey")
posthoc.kruskal.nemenyi.test(TaRER, T_trat.v, method = "Tukey")
posthoc.kruskal.nemenyi.test(TaSTRL, T_trat.v, method = "Tukey")
posthoc.kruskal.nemenyi.test(TaRS, T_trat.v, method = "Tukey")
posthoc.kruskal.nemenyi.test(TaSLA, T_trat.v, method = "Tukey")
posthoc.kruskal.nemenyi.test(TaLMF, T_trat.v, method = "Tukey")
posthoc.kruskal.nemenyi.test(TaLMt, T_trat.v, method = "Tukey")
posthoc.kruskal.nemenyi.test(TaNAR, T_trat.v, method = "Tukey")
posthoc.kruskal.nemenyi.test(TaLAm, T_trat.v, method = "Tukey")

#####################
## análises estatísticas para Qualea.
data_Qg.ver <- f_Planilha_S3_dbrutos_final_LMF_[
  f_Planilha_S3_dbrutos_final_LMF_$species == "Qualea grandiflora",
]
data_Qg.ver_no_na<- data_Qg.ver %>% na.omit()
data_Qg.ver_no_na


Q_trat.v <- as.factor(data_Qg.ver_no_na$tratamento)
Q_trat.v

QgH <- c(data_Qg.ver_no_na$H)
QgLnum <- c(data_Qg.ver_no_na$Lnum)
QgRM  <- c(data_Qg.ver_no_na$RM)
```

```
QgSM  <- c(data_Qg.ver_no_na$SM)
QgTM  <- c(data_Qg.ver_no_na$TM)
QgRMF <- c(data_Qg.ver_no_na$RMF)
QgSMF <- c(data_Qg.ver_no_na$SMF)
QgSTRL<- c(data_Qg.ver_no_na$STRL)
QgRER <- c(data_Qg.ver_no_na$RER)
QgRGR <- c(data_Qg.ver_no_na$RGR)
QgRL  <- c(data_Qg.ver_no_na$RL)
QgSLA <- c(data_Qg.ver_no_na$SLA)
QgRS <- c(data_Qg.ver_no_na$RS)
QgLMF <- c(data_Qg.ver_no_na$LMF)
QgLMt <- c(data_Qg.ver_no_na$LMt)
QgNAR <- c(data_Qg.ver_no_na$NAR)
QgLAm <- c(data_Qg.ver_no_na$LAm)

kruskal.test(QgRM ~ Q_trat.v)
kruskal.test(QgSM ~ Q_trat.v)
kruskal.test(QgRMF ~ Q_trat.v)
kruskal.test(QgSMF ~ T_trat.v)
kruskal.test(QgH ~ Q_trat.v)
kruskal.test(QgLnum ~ Q_trat.v)
kruskal.test(QgRGR ~ Q_trat.v)
kruskal.test(QgRER ~ Q_trat.v)
kruskal.test(QgSTRL~ Q_trat.v)
kruskal.test(QgRS ~ Q_trat.v)
kruskal.test(QgSLA ~ Q_trat.v)
kruskal.test(QgLMF ~ Q_trat.v)
kruskal.test(QgLMt ~ Q_trat.v)
kruskal.test(QgNAR ~ Q_trat.v)
kruskal.test(QgLAm ~ Q_trat.v)
```

```
data_Qg.ver <- f_Planilha_S3_dbrutos_final_LMF_[
  f_Planilha_S3_dbrutos_final_LMF_$species == "Qualea grandiflora",
]
data_Qg.ver_no_na<- data_Qg.ver %>% na.omit()
data_Qg.ver_no_na

#################
# comparar as sp
LMF.v<- glm(LMF*esp_num~tratamento)
LMF.v

library(cowplot)

a<- flexplot(RGR ~ tratamento | species, data = Qd1, se = F, alpha = .3)+
  scale_x_discrete(limits = c("1", "8","15"))
plot_grid(a)

b<- flexplot(LMF ~ tratamento | species, data = Qd1, se = F, alpha = .3)+
  scale_x_discrete(limits = c("1", "8","15"))


c<- flexplot(NAR ~ tratamento | species, data = Qd1, se = F, alpha = .3)+
  scale_x_discrete(limits = c("1", "8","15"))

d<- flexplot(SLA ~ tratamento | species, data = Qd1, se = F, alpha = .3)+
  scale_x_discrete(limits = c("1", "8","15"))

cowplot::plot_grid(a,b,c,d)

########### um gráfico mais bonito

x= flexplot(LMF ~ tratamento + species,
            data = Qd1, se = F, alpha = .3) +
  scale_x_discrete(limits = c("1", "8","15"))
```

```
z= flexplot(RGR ~ tratamento + species,
            data = Qd1, se = F, alpha = .3) +
  scale_x_discrete(limits = c("1", "8","15"))

y = flexplot(SLA ~ tratamento + species,
             data = Qd1, se = F, alpha = .3) +
  scale_x_discrete(limits = c("1", "8","15"))

w = flexplot(NAR ~ tratamento + species,
             data = Qd1, se = F, alpha = .3) +
  scale_x_discrete(limits = c("1", "8","15"))
 cowplot::plot_grid(x, z, y, w, nrow = 2)
```

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

```
 library(readxl)
Dados_cen_final_nov2022_ <- read_excel("C:/Users/dalch/Desktop/TESE (final)/tese_PARTES/5. cap 2/6. dados/Dados_cen(final_nov2022).xlsx",
                               col_types = c("text", "text", "numeric",
                                             "numeric", "numeric", "numeric",
                                             "numeric", "numeric", "numeric",
                                             "skip", "numeric", "numeric", "numeric",
                                             "numeric", "numeric", "numeric",
                                             "numeric", "numeric", "numeric",
                                             "numeric", "numeric", "numeric"))
View(Dados_cen_final_nov2022_)


attach(Dados_cen_final_nov2022_)
dados1<-c(Dados_cen_final_nov2022_)
dados<-na.omit(dados1)
head(dados)
str(dados)

dados.df<-data.frame(dados)
str(dados.df)

library(tidyverse)
library(flexplot)
library(ggplot2)
library(dplyr)
library(car)
library(fitdistrplus)
dados.df<-data.frame(Dados_cen_final_nov2022_)


####### O Leo da Ana me ajudou pq estava dando NAs no cen
```

```
#ele me passou esse código:
dados_no_na <- Dados_cen_final_nov2022_ %>% na.omit()
str(dados_no_na)


esp <- c(dados_no_na$sp)
esp
cen <- c(dados_no_na$cen)
cen
d_base <- c(dados_no_na$ST_D)
H <- c(dados_no_na$H)
Lnum <- c(dados_no_na$Lnum)
RM      <- c(dados_no_na$RM)
SM      <- c(dados_no_na$SM)
Mt      <- c(dados_no_na$TM)
RMF     <- c(dados_no_na$RMF)
SMF     <- c(dados_no_na$SMF)
LMF     <- c(dados_no_na$LMF)
STRL    <- c(dados_no_na$STRL)
RER     <- c(dados_no_na$RER)
RGR     <- c(dados_no_na$RGR)
RL    <- c(dados_no_na$RL)
ScRM    <- c(dados_no_na$ScRM)
TpRM    <- c(dados_no_na$TpRM)
StM    <- c(dados_no_na$StM)
SLA    <- c(dados_no_na$SLA)

################ separando por espécie para fazer as análises

data_Kc <- dados_no_na[dados_no_na$sp == "Kc", ]
data_Kc

data_Ta <- dados_no_na[dados_no_na$sp == "Ta", ]
data_Ta
```

```
data_Qg <- dados_no_na[dados_no_na$sp == "Qg", ]
data_Qg

data_Hs <- dados_no_na[dados_no_na$sp == "Hs", ]
data_Hs

###############
#
###################### dados de Qg para cada cenário!!! ##############################

Qg_F <- data_Qg[data_Qg$cen=="F", ]
Qg_A <- data_Qg[data_Qg$cen=="A", ]

summary(Qg_A)
summary(Qg_F)

###################### dados de Ta para cada cenário!!! ##############################

Ta_F <- data_Ta[data_Ta$cen=="F", ]
Ta_A <- data_Ta[data_Ta$cen=="A", ]

summary(Ta_A)
summary(Ta_F)

###################### dados de Kc para cada cenário!!! ##############################

Kc_F <- data_Kc[data_Kc$cen=="F", ]
Kc_A <- data_Kc[data_Kc$cen=="A", ]

summary(Kc_A)
summary(Kc_F)
```

```
###################### dados de Hs para cada cenário!!! #############################

Hs_F <- data_Hs[data_Hs$cen=="F", ]
Hs_A <- data_Hs[data_Hs$cen=="A", ]

summary(Hs_A)
summary(Hs_F)

######
#######################
############################## massa total Mt #######################################
#dados_cenarios_ago2022_
#flexplot e GLM de todas as sp
#
###
## flexplot
Mt_all= flexplot(TM ~ cen + sp,
         data = dados_no_na, se = F, alpha = .3) + scale_x_discrete(limits=c("A","F")) +  ## para arrumar ordem dos dados no eixo x
  theme(axis.text.x = element_text(angle=0, hjust=1, vjust=.2))

Mt_all

### boxplot para todas
ggplot(dados_no_na, aes(x=esp, y=MT, fill=cen)) +
  geom_boxplot()


#############boxplot para Qg


ggplot(data_Qg, aes(x=sp, y=TM, fill=cen)) +
  geom_boxplot()
```

```
###### GLM para Qg

hist(TM)
Mt_Qg<- c(data_Qg$TM)

hist(Mt_Qg)

fnorm<-fitdist(data_Qg$TM, distr = "norm")
fgamma<-fitdist(data_Qg$TM, distr = "gamma")
plot(fnorm)
plot(fgamma)
par(mfrow=c(1,1))
famm_Mt_Qg<-gofstat(list(fnorm,fgamma),fitnames = c("norm","gamma"))
denscomp(list(fnorm,fgamma),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_Mt_Qg$chisqpvalue
famm_Mt_Qg$chisqtable

## Anderson-Darling test
famm_Mt_Qg$adtest
## Cramer von Mises test
famm_Mt_Qg$cvmtest
##Kolmogorov - Smirnov test
famm_Mt_Qg$kstest


Mt_m1_Qg<-glm(data_Qg$TM~cen,family = Gamma(),data = data_Qg)
Mt_m1_Qg
summary(Mt_m1_Qg)


#################### para Ta ######
####
```

```
### boxplot para Ta

ggplot(data_Ta, aes(x=esp., y=TM, fill=cen)) +
  geom_boxplot()

### GLM para Ta

Mt_Ta<- c(data_Ta$TM)

hist(Mt_Ta)

fnorm2<-fitdist(data_Ta$TM, distr = "norm")
fgamma2<-fitdist(data_Ta$TM, distr = "gamma")
plot(fnorm2)
plot(fgamma2)
par(mfrow=c(1,1))
famm_Mt_Ta<-gofstat(list(fnorm2,fgamma2),fitnames = c("norm","gamma"))
denscomp(list(fnorm2,fgamma2),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_Mt_Ta$chisqpvalue
famm_Mt_Ta$chisqtable

## Anderson-Darling test
famm_Mt_Ta$adtest
## Cramer von Mises test
famm_Mt_Ta$cvmtest
##Kolmogorov - Smirnov test
famm_Mt_Ta$kstest


Mt_m1_Ta<-glm(data_Ta$TM~cen,family = Gamma(),data = data_Ta)
Mt_m1_Ta
summary(Mt_m1_Ta)
```

```
#####
################### para Kc  #######
### boxplot para Kc

ggplot(data_Kc, aes(x=esp, y=TM, fill=cen)) +
  geom_boxplot()

###### GLM

Mt_Kc<- c(data_Kc$TM)

hist(Mt_Kc)

fnorm3<-fitdist(data_Kc$TM, distr = "norm")
fgamma3<-fitdist(data_Kc$TM, distr = "gamma")
plot(fnorm3)
plot(fgamma3)
par(mfrow=c(1,1))
famm_Mt_Kc<-gofstat(list(fnorm3,fgamma3),fitnames = c("norm","gamma"))
denscomp(list(fnorm3,fgamma3),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_Mt_Kc$chisqpvalue
famm_Mt_Kc$chisqtable

## Anderson-Darling test
famm_Mt_Kc$adtest
## Cramer von Mises test
famm_Mt_Kc$cvmtest
##Kolmogorov - Smirnov test
famm_Mt_Kc$kstest
```

```
Mt_m1_Kc<-glm(data_Kc$TM~cen,family = Gamma(),data = data_Kc)
Mt_m1_Kc
summary(Mt_m1_Kc)

#####
#################### para Hs
### boxplot para Hs

ggplot(data_Hs, aes(x=esp, y=Mt, fill=cen)) +
  geom_boxplot()

###### GLM para Hs

Mt_Hs<- c(data_Hs$TM)

hist(Mt_Hs)

fnorm4<-fitdist(data_Hs$TM, distr = "norm")
fgamma4<-fitdist(data_Hs$TM, distr = "gamma")
plot(fnorm4)
plot(fgamma4)
par(mfrow=c(1,1))
famm_Mt_Hs<-gofstat(list(fnorm4,fgamma4),fitnames = c("norm","gamma"))
denscomp(list(fnorm4,fgamma4),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_Mt_Hs$chisqpvalue
famm_Mt_Hs$chisqtable

## Anderson-Darling test
famm_Mt_Hs$adtest
## Cramer von Mises test
famm_Mt_Hs$cvmtest
```

```
##Kolmogorov - Smirnov test
famm_Mt_Hs$kstest


Mt_m1_Hs<-glm(data_Hs$TM~cen,family = Gamma(),data = data_Hs)
Mt_m1_Hs
summary(Mt_m1_Hs)


############################## ScRM #############################################
#dados_cenarios_ago2022_
#flexplot e GLM de todas as sp
#
###
## flexplot
ScRM_all= flexplot(ScRM ~ cen + sp,
        data = dados_no_na, se = F, alpha = .3) + scale_x_discrete(limits=c("A","F")) +  ## para arrumar ordem dos dados no eixo x
  theme(axis.text.x = element_text(angle=0, hjust=1, vjust=.2))

ScRM_all

### boxplot para todas
ggplot(dados_no_na, aes(x=esp, y=ScRM, fill=cen)) +
  geom_boxplot()


#############boxplot para Qg


ggplot(data_Qg, aes(x=sp, y=ScRM, fill=cen)) +
  geom_boxplot()

###### GLM para Qg
```

```
hist(ScRM)
ScRM_Qg<- c(data_Qg$ScRM)

hist(ScRM_Qg)

fnorm<-fitdist(data_Qg$ScRM, distr = "norm")
fgamma<-fitdist(data_Qg$ScRM, distr = "gamma")
plot(fnorm)
plot(fgamma)
par(mfrow=c(1,1))
famm_ScRM_Qg<-gofstat(list(fnorm,fgamma),fitnames = c("norm","gamma"))
denscomp(list(fnorm,fgamma),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_ScRM_Qg$chisqpvalue
famm_ScRM_Qg$chisqtable

## Anderson-Darling test
famm_ScRM_Qg$adtest
## Cramer von Mises test
famm_ScRM_Qg$cvmtest
##Kolmogorov - Smirnov test
famm_ScRM_Qg$kstest


ScRM_m1_Qg<-glm(data_Qg$ScRM~cen,family = Gamma(),data = data_Qg)
ScRM_m1_Qg
summary(ScRM_m1_Qg)


#################### para Ta ######
####
### boxplot para Ta
```

```
ggplot(data_Ta, aes(x=sp, y=ScRM, fill=cen)) +
  geom_boxplot()

### GLM para Ta

ScRM_Ta<- c(data_Ta$ScRM)

hist(ScRM_Ta)

fnorm2<-fitdist(data_Ta$ScRM, distr = "norm")
fgamma2<-fitdist(data_Ta$ScRM, distr = "gamma")
plot(fnorm2)
plot(fgamma2)
par(mfrow=c(1,1))
famm_ScRM_Ta<-gofstat(list(fnorm2,fgamma2),fitnames = c("norm","gamma"))
denscomp(list(fnorm2,fgamma2),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_ScRM_Ta$chisqpvalue
famm_ScRM_Ta$chisqtable

## Anderson-Darling test
famm_ScRM_Ta$adtest
## Cramer von Mises test
famm_ScRM_Ta$cvmtest
##Kolmogorov - Smirnov test
famm_ScRM_Ta$kstest


ScRM_m1_Ta<-glm(data_Ta$ScRM~cen,family = Gamma(),data = data_Ta)
ScRM_m1_Ta
summary(ScRM_m1_Ta)
```

```
#####
################### para Kc  #######
### boxplot para Kc

ggplot(data_Kc, aes(x=sp, y=ScRM, fill=cen)) +
  geom_boxplot()

###### GLM

ScRM_Kc<- c(data_Kc$ScRM)

hist(ScRM_Kc)

fnorm3<-fitdist(data_Kc$ScRM, distr = "norm")
fgamma3<-fitdist(data_Kc$ScRM, distr = "gamma")
plot(fnorm3)
plot(fgamma3)
par(mfrow=c(1,1))
famm_ScRM_Kc<-gofstat(list(fnorm3,fgamma3),fitnames = c("norm","gamma"))
denscomp(list(fnorm3,fgamma3),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_ScRM_Kc$chisqpvalue
famm_ScRM_Kc$chisqtable

## Anderson-Darling test
famm_ScRM_Kc$adtest
## Cramer von Mises test
famm_ScRM_Kc$cvmtest
##Kolmogorov - Smirnov test
famm_ScRM_Kc$kstest
```

```
ScRM_m1_Kc<-glm(data_Kc$ScRM~cen,family = Gamma(),data = data_Kc)
ScRM_m1_Kc
summary(ScRM_m1_Kc)

#####
#################### para Hs
### boxplot para Hs

ggplot(data_Hs, aes(x=sp, y=ScRM, fill=cen)) +
  geom_boxplot()

###### GLM para Hs

ScRM_Hs<- c(data_Hs$ScRM)

hist(ScRM_Hs)

fnorm4<-fitdist(data_Hs$ScRM, distr = "norm")
fgamma4<-fitdist(data_Hs$ScRM, distr = "gamma")
plot(fnorm4)
plot(fgamma4)
par(mfrow=c(1,1))
famm_ScRM_Hs<-gofstat(list(fnorm4,fgamma4),fitnames = c("norm","gamma"))
denscomp(list(fnorm4,fgamma4),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_ScRM_Hs$chisqpvalue
famm_ScRM_Hs$chisqtable

## Anderson-Darling test
famm_ScRM_Hs$adtest
## Cramer von Mises test
famm_ScRM_Hs$cvmtest
##Kolmogorov - Smirnov test
```

```
famm_ScRM_Hs$kstest


ScRM_m1_Hs<-glm(data_Hs$ScRM~cen,family = Gamma(),data = data_Hs)
ScRM_m1_Hs
summary(ScRM_m1_Hs)


############################## TpRM ##############################################
#dados_cenarios_ago2022_
#flexplot e GLM de todas as sp
#
###
## flexplot
TpRM_all= flexplot(TpRM ~ cen + sp,
                   data = dados_no_na, se = F, alpha = .3) + scale_x_discrete(limits=c("A","F")) +  ## para arrumar ordem dos dados no eixo x
  theme(axis.text.x = element_text(angle=0, hjust=1, vjust=.2))

TpRM_all

### boxplot para todas
ggplot(dados_no_na, aes(x=esp, y=TpRM, fill=cen)) +
  geom_boxplot()


#############boxplot para Qg


ggplot(data_Qg, aes(x=esp, y=TpRM, fill=cen)) +
  geom_boxplot()

###### GLM para Qg

```

```
hist(TpRM)
TpRM_Qg<- c(data_Qg$TpRM)

hist(TpRM_Qg)

fnorm<-fitdist(data_Qg$TpRM, distr = "norm")
fgamma<-fitdist(data_Qg$TpRM, distr = "gamma")
plot(fnorm)
plot(fgamma)
par(mfrow=c(1,1))
famm_TpRM_Qg<-gofstat(list(fnorm,fgamma),fitnames = c("norm","gamma"))
denscomp(list(fnorm,fgamma),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_TpRM_Qg$chisqpvalue
famm_TpRM_Qg$chisqtable

## Anderson-Darling test
famm_TpRM_Qg$adtest
## Cramer von Mises test
famm_TpRM_Qg$cvmtest
##Kolmogorov - Smirnov test
famm_TpRM_Qg$kstest


TpRM_m1_Qg<-glm(data_Qg$TpRM~cen,family = Gamma(),data = data_Qg)
TpRM_m1_Qg
summary(TpRM_m1_Qg)


#################### para Ta ######
####
### boxplot para Ta

```

```
ggplot(data_Ta, aes(x=esp., y=TpRM, fill=cen)) +
  geom_boxplot()

### GLM para Ta

TpRM_Ta<- c(data_Ta$TpRM)

hist(TpRM_Ta)

fnorm2<-fitdist(data_Ta$TpRM, distr = "norm")
fgamma2<-fitdist(data_Ta$TpRM, distr = "gamma")
plot(fnorm2)
plot(fgamma2)
par(mfrow=c(1,1))
famm_TpRM_Ta<-gofstat(list(fnorm2,fgamma2),fitnames = c("norm","gamma"))
denscomp(list(fnorm2,fgamma2),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_TpRM_Ta$chisqpvalue
famm_TpRM_Ta$chisqtable

## Anderson-Darling test
famm_TpRM_Ta$adtest
## Cramer von Mises test
famm_TpRM_Ta$cvmtest
##Kolmogorov - Smirnov test
famm_TpRM_Ta$kstest


TpRM_m1_Ta<-glm(data_Ta$TpRM~cen,family = Gamma(),data = data_Ta)
TpRM_m1_Ta
summary(TpRM_m1_Ta)
```

```
#####
################### para Kc  #######
### boxplot para Kc

ggplot(data_Kc, aes(x=esp, y=TpRM, fill=cen)) +
  geom_boxplot()

###### GLM

TpRM_Kc<- c(data_Kc$TpRM)

hist(TpRM_Kc)

fnorm3<-fitdist(data_Kc$TpRM, distr = "norm")
fgamma3<-fitdist(data_Kc$TpRM, distr = "gamma")
plot(fnorm3)
plot(fgamma3)
par(mfrow=c(1,1))
famm_TpRM_Kc<-gofstat(list(fnorm3,fgamma3),fitnames = c("norm","gamma"))
denscomp(list(fnorm3,fgamma3),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_TpRM_Kc$chisqpvalue
famm_TpRM_Kc$chisqtable

## Anderson-Darling test
famm_TpRM_Kc$adtest
## Cramer von Mises test
famm_TpRM_Kc$cvmtest
##Kolmogorov - Smirnov test
famm_TpRM_Kc$kstest


TpRM_m1_Kc<-glm(data_Kc$TpRM~cen,family = Gamma(),data = data_Kc)
```

```
TpRM_m1_Kc
summary(TpRM_m1_Kc)

#####
#################### para Hs
### boxplot para Hs

ggplot(data_Hs, aes(x=esp, y=TpRM, fill=cen)) +
  geom_boxplot()

###### GLM para Hs

TpRM_Hs<- c(data_Hs$TpRM)

hist(TpRM_Hs)

fnorm4<-fitdist(data_Hs$TpRM, distr = "norm")
fgamma4<-fitdist(data_Hs$TpRM, distr = "gamma")
plot(fnorm4)
plot(fgamma4)
par(mfrow=c(1,1))
famm_TpRM_Hs<-gofstat(list(fnorm4,fgamma4),fitnames = c("norm","gamma"))
denscomp(list(fnorm4,fgamma4),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_TpRM_Hs$chisqpvalue
famm_TpRM_Hs$chisqtable

## Anderson-Darling test
famm_TpRM_Hs$adtest
## Cramer von Mises test
famm_TpRM_Hs$cvmtest
##Kolmogorov - Smirnov test
famm_TpRM_Hs$kstest
```

```
TpRM_m1_Hs<-glm(data_Hs$TpRM~cen,family = Gamma(),data = data_Hs)
TpRM_m1_Hs
summary(TpRM_m1_Hs)


############################## StM ##############################################
#dados_cenarios_ago2022_
#flexplot e GLM de todas as sp
#
###
## flexplot
StM_all= flexplot(StM ~ cen + sp,
          data = dados_no_na, se = F, alpha = .3) + scale_x_discrete(limits=c("A","F")) +  ## para arrumar ordem dos dados no eixo x
  theme(axis.text.x = element_text(angle=0, hjust=1, vjust=.2))

StM_all

### boxplot para todas
ggplot(dados_no_na, aes(x=esp, y=StM, fill=cen)) +
  geom_boxplot()


#############boxplot para Qg


ggplot(data_Qg, aes(x=esp, y=StM, fill=cen)) +
  geom_boxplot()

###### GLM para Qg

hist(StM)
StM_Qg<- c(data_Qg$StM)
```

```
hist(StM_Qg)

fnorm<-fitdist(data_Qg$StM, distr = "norm")
fgamma<-fitdist(data_Qg$StM, distr = "gamma")
plot(fnorm)
plot(fgamma)
par(mfrow=c(1,1))
famm_StM_Qg<-gofstat(list(fnorm,fgamma),fitnames = c("norm","gamma"))
denscomp(list(fnorm,fgamma),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_StM_Qg$chisqpvalue
famm_StM_Qg$chisqtable

## Anderson-Darling test
famm_StM_Qg$adtest
## Cramer von Mises test
famm_StM_Qg$cvmtest
##Kolmogorov - Smirnov test
famm_StM_Qg$kstest


StM_m1_Qg<-glm(data_Qg$StM~cen,family = Gamma(),data = data_Qg)
StM_m1_Qg
summary(StM_m1_Qg)


################### para Ta ######
####
### boxplot para Ta

ggplot(data_Ta, aes(x=esp., y=StM, fill=cen)) +
  geom_boxplot()
```

```
### GLM para Ta

StM_Ta<- c(data_Ta$StM)

hist(StM_Ta)

fnorm2<-fitdist(data_Ta$StM, distr = "norm")
fgamma2<-fitdist(data_Ta$StM, distr = "gamma")
plot(fnorm2)
plot(fgamma2)
par(mfrow=c(1,1))
famm_StM_Ta<-gofstat(list(fnorm2,fgamma2),fitnames = c("norm","gamma"))
denscomp(list(fnorm2,fgamma2),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_StM_Ta$chisqpvalue
famm_StM_Ta$chisqtable

## Anderson-Darling test
famm_StM_Ta$adtest
## Cramer von Mises test
famm_StM_Ta$cvmtest
##Kolmogorov - Smirnov test
famm_StM_Ta$kstest


StM_m1_Ta<-glm(data_Ta$StM~cen,family = Gamma(),data = data_Ta)
StM_m1_Ta
summary(StM_m1_Ta)


#####
#################### para Kc  #######
```

```
### boxplot para Kc

ggplot(data_Kc, aes(x=esp, y=StM, fill=cen)) +
  geom_boxplot()

###### GLM

StM_Kc<- c(data_Kc$StM)

hist(StM_Kc)

fnorm3<-fitdist(data_Kc$StM, distr = "norm")
fgamma3<-fitdist(data_Kc$StM, distr = "gamma")
plot(fnorm3)
plot(fgamma3)
par(mfrow=c(1,1))
famm_StM_Kc<-gofstat(list(fnorm3,fgamma3),fitnames = c("norm","gamma"))
denscomp(list(fnorm3,fgamma3),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_StM_Kc$chisqpvalue
famm_StM_Kc$chisqtable

## Anderson-Darling test
famm_StM_Kc$adtest
## Cramer von Mises test
famm_StM_Kc$cvmtest
##Kolmogorov - Smirnov test
famm_StM_Kc$kstest


StM_m1_Kc<-glm(data_Kc$StM~cen,family = Gamma(),data = data_Kc)
StM_m1_Kc
summary(StM_m1_Kc)
```

```
#####
################### para Hs
### boxplot para Hs

ggplot(data_Hs, aes(x=esp, y=StM, fill=cen)) +
  geom_boxplot()

###### GLM para Hs

StM_Hs<- c(data_Hs$StM)

hist(StM_Hs)

fnorm4<-fitdist(data_Hs$StM, distr = "norm")
fgamma4<-fitdist(data_Hs$StM, distr = "gamma")
plot(fnorm4)
plot(fgamma4)
par(mfrow=c(1,1))
famm_StM_Hs<-gofstat(list(fnorm4,fgamma4),fitnames = c("norm","gamma"))
denscomp(list(fnorm4,fgamma4),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_StM_Hs$chisqpvalue
famm_StM_Hs$chisqtable

## Anderson-Darling test
famm_StM_Hs$adtest
## Cramer von Mises test
famm_StM_Hs$cvmtest
##Kolmogorov - Smirnov test
famm_StM_Hs$kstest
```

```
StM_m1_Hs<-glm(data_Hs$StM~cen,family = Gamma(),data = data_Hs)
StM_m1_Hs
summary(StM_m1_Hs)


###############################  TLM   ##############################################
#dados_cenarios_ago2022_
#flexplot e GLM de todas as sp
#
###
## flexplot
TLM_all= flexplot(TLM ~ cen + sp,
         data = dados_no_na, se = F, alpha = .3) + scale_x_discrete(limits=c("A","F")) +  ## para arrumar ordem dos dados no eixo x
  theme(axis.text.x = element_text(angle=0, hjust=1, vjust=.2))

TLM_all

### boxplot para todas
ggplot(dados_no_na, aes(x=esp, y=TLM, fill=cen)) +
  geom_boxplot()


#############boxplot para Qg


ggplot(data_Qg, aes(x=esp, y=TLM, fill=cen)) +
  geom_boxplot()

###### GLM para Qg

hist(TLM)
TLM_Qg<- c(data_Qg$TLM)

hist(TLM_Qg)
```

```
fnorm<-fitdist(data_Qg$TLM, distr = "norm")
fgamma<-fitdist(data_Qg$TLM, distr = "gamma")
plot(fnorm)
plot(fgamma)
par(mfrow=c(1,1))
famm_TLM_Qg<-gofstat(list(fnorm,fgamma),fitnames = c("norm","gamma"))
denscomp(list(fnorm,fgamma),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_TLM_Qg$chisqpvalue
famm_TLM_Qg$chisqtable

## Anderson-Darling test
famm_TLM_Qg$adtest
## Cramer von Mises test
famm_TLM_Qg$cvmtest
##Kolmogorov - Smirnov test
famm_TLM_Qg$kstest


TLM_m1_Qg<-glm(data_Qg$TLM~cen,family = Gamma(),data = data_Qg)
TLM_m1_Qg
summary(TLM_m1_Qg)


################### para Ta ######
####
### boxplot para Ta

ggplot(data_Ta, aes(x=esp., y=TLM, fill=cen)) +
  geom_boxplot()

### GLM para Ta
```

```
TLM_Ta<- c(data_Ta$TLM)

hist(TLM_Ta)

fnorm2<-fitdist(data_Ta$TLM, distr = "norm")
fgamma2<-fitdist(data_Ta$TLM, distr = "gamma")
plot(fnorm2)
plot(fgamma2)
par(mfrow=c(1,1))
famm_TLM_Ta<-gofstat(list(fnorm2,fgamma2),fitnames = c("norm","gamma"))
denscomp(list(fnorm2,fgamma2),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_TLM_Ta$chisqpvalue
famm_TLM_Ta$chisqtable

## Anderson-Darling test
famm_TLM_Ta$adtest
## Cramer von Mises test
famm_TLM_Ta$cvmtest
##Kolmogorov - Smirnov test
famm_TLM_Ta$kstest


TLM_m1_Ta<-glm(data_Ta$TLM~cen,family = Gamma(),data = data_Ta)
TLM_m1_Ta
summary(TLM_m1_Ta)


#####
#################### para Kc  #######
### boxplot para Kc

```

```
ggplot(data_Kc, aes(x=esp, y=TLM, fill=cen)) +
  geom_boxplot()

###### GLM

TLM_Kc<- c(data_Kc$TLM)

hist(TLM_Kc)

fnorm3<-fitdist(data_Kc$TLM, distr = "norm")
fgamma3<-fitdist(data_Kc$TLM, distr = "gamma")
plot(fnorm3)
plot(fgamma3)
par(mfrow=c(1,1))
famm_TLM_Kc<-gofstat(list(fnorm3,fgamma3),fitnames = c("norm","gamma"))
denscomp(list(fnorm3,fgamma3),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_TLM_Kc$chisqpvalue
famm_TLM_Kc$chisqtable

## Anderson-Darling test
famm_TLM_Kc$adtest
## Cramer von Mises test
famm_TLM_Kc$cvmtest
##Kolmogorov - Smirnov test
famm_TLM_Kc$kstest


TLM_m1_Kc<-glm(data_Kc$TLM~cen,family = Gamma(),data = data_Kc)
TLM_m1_Kc
summary(TLM_m1_Kc)

#####
```

```
################### para Hs
### boxplot para Hs

ggplot(data_Hs, aes(x=esp, y=TLM, fill=cen)) +
  geom_boxplot()

###### GLM para Hs

TLM_Hs<- c(data_Hs$TLM)

hist(TLM_Hs)

fnorm4<-fitdist(data_Hs$TLM, distr = "norm")
fgamma4<-fitdist(data_Hs$TLM, distr = "gamma")
plot(fnorm4)
plot(fgamma4)
par(mfrow=c(1,1))
famm_TLM_Hs<-gofstat(list(fnorm4,fgamma4),fitnames = c("norm","gamma"))
denscomp(list(fnorm4,fgamma4),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_TLM_Hs$chisqpvalue
famm_TLM_Hs$chisqtable

## Anderson-Darling test
famm_TLM_Hs$adtest
## Cramer von Mises test
famm_TLM_Hs$cvmtest
##Kolmogorov - Smirnov test
famm_TLM_Hs$kstest


TLM_m1_Hs<-glm(data_Hs$TLM~cen,family = Gamma(),data = data_Hs)
TLM_m1_Hs
```

```
summary(TLM_m1_Hs)


############################## SLA #############################################
#dados_cenarios_ago2022_
#flexplot e GLM de todas as sp
#
###
## flexplot
SLA_all= flexplot(SLA ~ cen + sp,
         data = dados_no_na, se = F, alpha = .3) + scale_x_discrete(limits=c("A","F")) + ## para arrumar ordem dos dados no eixo x
  theme(axis.text.x = element_text(angle=0, hjust=1, vjust=.2))

SLA_all

### boxplot para todas
ggplot(dados_no_na, aes(x=esp, y=SLA, fill=cen)) +
  geom_boxplot()


#############boxplot para Qg


ggplot(data_Qg, aes(x=esp, y=SLA, fill=cen)) +
  geom_boxplot()

###### GLM para Qg

hist(SLA)
SLA_Qg<- c(data_Qg$SLA)

hist(SLA_Qg)

fnorm<-fitdist(data_Qg$SLA, distr = "norm")
```

```
fgamma<-fitdist(data_Qg$SLA, distr = "gamma")
plot(fnorm)
plot(fgamma)
par(mfrow=c(1,1))
famm_SLA_Qg<-gofstat(list(fnorm,fgamma),fitnames = c("norm","gamma"))
denscomp(list(fnorm,fgamma),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_SLA_Qg$chisqpvalue
famm_SLA_Qg$chisqtable

## Anderson-Darling test
famm_SLA_Qg$adtest
## Cramer von Mises test
famm_SLA_Qg$cvmtest
##Kolmogorov - Smirnov test
famm_SLA_Qg$kstest


SLA_m1_Qg<-glm(data_Qg$SLA~cen,family = Gamma(),data = data_Qg)
SLA_m1_Qg
summary(SLA_m1_Qg)


################### para Ta ######
####
### boxplot para Ta

ggplot(data_Ta, aes(x=esp., y=SLA, fill=cen)) +
  geom_boxplot()

### GLM para Ta

SLA_Ta<- c(data_Ta$SLA)
```

```
hist(SLA_Ta)

fnorm2<-fitdist(data_Ta$SLA, distr = "norm")
fgamma2<-fitdist(data_Ta$SLA, distr = "gamma")
plot(fnorm2)
plot(fgamma2)
par(mfrow=c(1,1))
famm_SLA_Ta<-gofstat(list(fnorm2,fgamma2),fitnames = c("norm","gamma"))
denscomp(list(fnorm2,fgamma2),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_SLA_Ta$chisqpvalue
famm_SLA_Ta$chisqtable

## Anderson-Darling test
famm_SLA_Ta$adtest
## Cramer von Mises test
famm_SLA_Ta$cvmtest
##Kolmogorov - Smirnov test
famm_SLA_Ta$kstest


SLA_m1_Ta<-glm(data_Ta$SLA~cen,family = Gamma(),data = data_Ta)
SLA_m1_Ta
summary(SLA_m1_Ta)


#####
################### para Kc  #######
### boxplot para Kc

ggplot(data_Kc, aes(x=esp, y=SLA, fill=cen)) +
  geom_boxplot()
```

```
###### GLM

SLA_Kc<- c(data_Kc$SLA)

hist(SLA_Kc)

fnorm3<-fitdist(data_Kc$SLA, distr = "norm")
fgamma3<-fitdist(data_Kc$SLA, distr = "gamma")
plot(fnorm3)
plot(fgamma3)
par(mfrow=c(1,1))
famm_SLA_Kc<-gofstat(list(fnorm3,fgamma3),fitnames = c("norm","gamma"))
denscomp(list(fnorm3,fgamma3),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_SLA_Kc$chisqpvalue
famm_SLA_Kc$chisqtable

## Anderson-Darling test
famm_SLA_Kc$adtest
## Cramer von Mises test
famm_SLA_Kc$cvmtest
##Kolmogorov - Smirnov test
famm_SLA_Kc$kstest


SLA_m1_Kc<-glm(data_Kc$SLA~cen,family = Gamma(),data = data_Kc)
SLA_m1_Kc
summary(SLA_m1_Kc)

#####
#################### para Hs
### boxplot para Hs
```

```
ggplot(data_Hs, aes(x=sp, y=SLA, fill=cen)) +
  geom_boxplot()

###### GLM para Hs

SLA_Hs<- c(data_Hs$SLA)

hist(SLA_Hs)

fnorm4<-fitdist(data_Hs$SLA, distr = "norm")
fgamma4<-fitdist(data_Hs$SLA, distr = "gamma")
plot(fnorm4)
plot(fgamma4)
par(mfrow=c(1,1))
famm_SLA_Hs<-gofstat(list(fnorm4,fgamma4),fitnames = c("norm","gamma"))
denscomp(list(fnorm4,fgamma4),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_SLA_Hs$chisqpvalue
famm_SLA_Hs$chisqtable
## Anderson-Darling test
famm_SLA_Hs$adtest
## Cramer von Mises test
famm_SLA_Hs$cvmtest
##Kolmogorov - Smirnov test
famm_SLA_Hs$kstest

SLA_m1_Hs<-glm(data_Hs$SLA~cen,family = Gamma(),data = data_Hs)
SLA_m1_Hs
summary(SLA_m1_Hs)

########################################   altura H    ########################
#
```

```
#flexplot e GLM de todas as sp
## flexplot
H_all= flexplot(H ~ cen + esp.,
                data = dados_no_na, se = F, alpha = .3) + scale_x_discrete(limits=c("A","F")) +   ## para arrumar ordem dos dados no eixo x
  theme(axis.text.x = element_text(angle=0, hjust=1, vjust=.2))

H_all

#############boxplot para Qg

ggplot(data_Qg, aes(x=esp., y=H, fill=cen)) +
  geom_boxplot()
###### GLM para Qg
hist(H)
H_Qg<- c(data_Qg$H)

hist(H_Qg)
fnorm<-fitdist(data_Qg$H, distr = "norm")
fgamma<-fitdist(data_Qg$H, distr = "gamma")
plot(fnorm)
plot(fgamma)
par(mfrow=c(1,1))
famm_H_Qg<-gofstat(list(fnorm,fgamma),fitnames = c("norm","gamma"))
denscomp(list(fnorm,fgamma),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_H_Qg$chisqpvalue
famm_H_Qg$chisqtable

## Anderson-Darling test
famm_H_Qg$adtest
## Cramer von Mises test
famm_H_Qg$cvmtest
##Kolmogorov - Smirnov test
```

```
famm_H_Qg$kstest
famm_H_Qg$adtest

H_m1_Qg<-glm(data_Qg$H~cen,family = Gamma(),data = data_Qg)
H_m1_Qg
summary(H_m1_Qg)


################### para Ta ######
### boxplot para Ta
ggplot(data_Ta, aes(x=esp., y=H, fill=cen)) +
  geom_boxplot()
### GLM para Ta

H_Ta<- c(data_Ta$H)

hist(H_Ta)

fnorm2<-fitdist(data_Ta$H, distr = "norm")
fgamma2<-fitdist(data_Ta$H, distr = "gamma")
plot(fnorm2)
plot(fgamma2)
par(mfrow=c(1,1))
famm_H_Ta<-gofstat(list(fnorm2,fgamma2),fitnames = c("norm","gamma"))
denscomp(list(fnorm2,fgamma2),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_H_Ta$chisqpvalue
famm_H_Ta$chisqtable
## Anderson-Darling test
famm_H_Ta$adtest
## Cramer von Mises test
famm_H_Ta$cvmtest
##Kolmogorov - Smirnov test
```

```
famm_H_Ta$kstest
H_m1_Ta<-glm(data_Ta$H~cen,family = Gamma(),data = data_Ta)
H_m1_Ta
summary(H_m1_Ta)

H_m2_Ta<-glm(data_Ta$H~cen,family = gaussian(),data = data_Ta)
H_m2_Ta
summary(H_m2_Ta)

#####
################### para Kc  #######
### boxplot para Kc

ggplot(data_Kc, aes(x=esp., y=H, fill=cen)) +
  geom_boxplot()

###### GLM

H_Kc<- c(data_Kc$H)

hist(H_Kc)

fnorm2<-fitdist(data_Kc$H, distr = "norm")
fgamma2<-fitdist(data_Kc$H, distr = "gamma")
plot(fnorm2)
plot(fgamma2)
par(mfrow=c(1,1))
famm_H_Kc<-gofstat(list(fnorm2,fgamma2),fitnames = c("norm","gamma"))
denscomp(list(fnorm2,fgamma2),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_H_Kc$chisqpvalue
famm_H_Kc$chisqtable
```

```
## Anderson-Darling test
famm_H_Kc$adtest
## Cramer von Mises test
famm_H_Kc$cvmtest
##Kolmogorov - Smirnov test
famm_H_Kc$kstest


H_m1_Kc<-glm(data_Kc$H~cen,family = Gamma(),data = data_Kc)
H_m1_Kc
summary(H_m1_Kc)

#####
#################### para Hs
### boxplot para Hs

ggplot(data_Hs, aes(x=esp., y=H, fill=cen)) +
  geom_boxplot()

###### GLM para Hs

H_Hs<- c(data_Hs$H)

hist(H_Hs)

fnorm4<-fitdist(data_Hs$H, distr = "norm")
fgamma4<-fitdist(data_Hs$H, distr = "gamma")
plot(fnorm4)
plot(fgamma4)
par(mfrow=c(1,1))
famm_H_Hs<-gofstat(list(fnorm4,fgamma4),fitnames = c("norm","gamma"))
denscomp(list(fnorm4,fgamma4),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
```

```
famm_H_Hs$chisqpvalue
famm_H_Hs$chisqtable

## Anderson-Darling test
famm_H_Hs$adtest
## Cramer von Mises test
famm_H_Hs$cvmtest
##Kolmogorov - Smirnov test
famm_H_Hs$kstest


H_m1_Hs<-glm(data_Hs$H~cen,family = Gamma(),data = data_Hs)
H_m1_Hs
summary(H_m1_Hs)

#############################    d_base   ##########
#
#flexplot e GLM de todas as sp
#
###
## flexplot
d_base_all= flexplot(d_base ~ cen + esp.,
                     data = dados_no_na, se = F, alpha = .3) + scale_x_discrete(limits=c("A","F")) +  ## para arrumar ordem dos dados no eixo x
  theme(axis.text.x = element_text(angle=0, hjust=1, vjust=.2))

d_base_all

#############boxplot para Qg

ggplot(data_Qg, aes(x=esp., y=d_base, fill=cen)) +
  geom_boxplot()

###### GLM para Qg

```

```
hist(d_base)
d_base_Qg<- c(data_Qg$d_base)

hist(d_base_Qg)

fnorm<-fitdist(data_Qg$d_base, distr = "norm")
fgamma<-fitdist(data_Qg$d_base, distr = "gamma")
plot(fnorm)
plot(fgamma)
par(mfrow=c(1,1))
famm_d_base_Qg<-gofstat(list(fnorm,fgamma),fitnames = c("norm","gamma"))
denscomp(list(fnorm,fgamma),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_d_base_Qg$chisqpvalue
famm_d_base_Qg$chisqtable

## Anderson-Darling test
famm_d_base_Qg$adtest
## Cramer von Mises test
famm_d_base_Qg$cvmtest
##Kolmogorov - Smirnov test
famm_d_base_Qg$kstest
famm_d_base_Qg$adtest


d_base_m1_Qg<-glm(data_Qg$d_base~cen,family = Gamma(),data = data_Qg)
d_base_m1_Qg
summary(d_base_m1_Qg)


#################### para Ta ######
####
### boxplot para Ta
```

```
ggplot(data_Ta, aes(x=esp., y=d_base, fill=cen)) +
  geom_boxplot()

### GLM para Ta

d_base_Ta<- c(data_Ta$d_base)

hist(d_base_Ta)

fnorm2<-fitdist(data_Ta$d_base, distr = "norm")
fgamma2<-fitdist(data_Ta$d_base, distr = "gamma")
plot(fnorm2)
plot(fgamma2)
par(mfrow=c(1,1))
famm_d_base_Ta<-gofstat(list(fnorm2,fgamma2),fitnames = c("norm","gamma"))
denscomp(list(fnorm2,fgamma2),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_d_base_Ta$chisqpvalue
famm_H_Ta$chisqtable

## Anderson-Darling test
famm_d_base_Ta$adtest
## Cramer von Mises test
famm_d_base_Ta$cvmtest
##Kolmogorov - Smirnov test
famm_d_base_Ta$kstest


d_base_m1_Ta<-glm(data_Ta$d_base~cen,family = Gamma(),data = data_Ta)
d_base_m1_Ta
summary(d_base_m1_Ta)
```

```
d_base_m2_Ta<-glm(data_Ta$d_base~cen,family = gaussian(),data = data_Ta)
d_base_m2_Ta
summary(d_base_m2_Ta)

#####
################### para Kc  #######
### boxplot para Kc

ggplot(data_Kc, aes(x=esp., y=d_base, fill=cen)) +
  geom_boxplot()

###### GLM

d_base_Kc<- c(data_Kc$d_base)

hist(d_base_Kc)

fnorm3<-fitdist(data_Kc$d_base, distr = "norm")
fgamma3<-fitdist(data_Kc$d_base, distr = "gamma")
plot(fnorm3)
plot(fgamma3)
par(mfrow=c(1,1))
famm_d_base_Kc<-gofstat(list(fnorm3,fgamma3),fitnames = c("norm","gamma"))
denscomp(list(fnorm3,fgamma3),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_d_base_Kc$chisqpvalue
famm_d_base_Kc$chisqtable

## Anderson-Darling test
famm_d_base_Kc$adtest
## Cramer von Mises test
famm_d_base_Kc$cvmtest
##Kolmogorov - Smirnov test
```

```
famm_d_base_Kc$kstest


d_base_m1_Kc<-glm(data_Kc$d_base~cen,family = Gamma(),data = data_Kc)
d_base_m1_Kc
summary(d_base_m1_Kc)

#####
#################### para Hs
### boxplot para Hs

ggplot(data_Hs, aes(x=esp., y=d_base, fill=cen)) +
  geom_boxplot()

###### GLM para Hs

d_base_Hs<- c(data_Hs$d_base)

hist(d_base_Hs)

fnorm4<-fitdist(data_Hs$d_base, distr = "norm")
fgamma4<-fitdist(data_Hs$d_base, distr = "gamma")
plot(fnorm4)
plot(fgamma4)
par(mfrow=c(1,1))
famm_d_base_Hs<-gofstat(list(fnorm4,fgamma4),fitnames = c("norm","gamma"))
denscomp(list(fnorm4,fgamma4),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_d_base_Hs$chisqpvalue
famm_d_base_Hs$chisqtable

## Anderson-Darling test
famm_d_base_Hs$adtest
```

```
## Cramer von Mises test
famm_d_base_Hs$cvmtest
##Kolmogorov - Smirnov test
famm_d_base_Hs$kstest


d_base_m1_Hs<-glm(data_Hs$d_base~cen,family = Gamma(),data = data_Hs)
d_base_m1_Hs
summary(d_base_m1_Hs)

##############################  RGR   ##########
#
#flexplot e GLM de todas as sp
#
###
## flexplot
RER_all= flexplot(RGR ~ cen + esp,
          data = dados_no_na, se = F, alpha = .3) + scale_x_discrete(limits=c("A","F")) +  ## para arrumar ordem dos dados no eixo x
  theme(axis.text.x = element_text(angle=0, hjust=1, vjust=.2))

RGR_all

#############boxplot para Qg

ggplot(data_Qg, aes(x=esp, y=RGR, fill=cen)) +
  geom_boxplot()

###### GLM para Qg

hist(RGR)

RGR_Qg<- c(data_Qg$RGR)

hist(RGR_Qg)
```

```
fnorm<-fitdist(data_Qg$RGR, distr = "norm")
fgamma<-fitdist(data_Qg$RGR, distr = "gamma")
plot(fnorm)
plot(fgamma)
par(mfrow=c(1,1))
famm_RGR_Qg<-gofstat(list(fnorm,fgamma),fitnames = c("norm","gamma"))
denscomp(list(fnorm,fgamma),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_RGR_Qg$chisqpvalue
famm_RGR_Qg$chisqtable

## Anderson-Darling test
famm_RGR_Qg$adtest
## Cramer von Mises test
famm_RGR_Qg$cvmtest
##Kolmogorov - Smirnov test
famm_RGR_Qg$kstest
famm_RGR_Qg$adtest


RGR_m1_Qg<-glm(data_Qg$RGR~cen,family = Gamma(),data = data_Qg)
RGR_m1_Qg
summary(RGR_m1_Qg)


#################### para Ta ######
####
### boxplot para Ta

ggplot(data_Ta, aes(x=esp, y=RGR, fill=cen)) +
  geom_boxplot()

```

```
### GLM para Ta

RGR_Ta<- c(data_Ta$RGR)

hist(RGR_Ta)

fnorm2<-fitdist(data_Ta$RGR, distr = "norm")
fgamma2<-fitdist(data_Ta$RGR, distr = "gamma")
plot(fnorm2)
plot(fgamma2)
par(mfrow=c(1,1))
famm_RGR_Ta<-gofstat(list(fnorm2,fgamma2),fitnames = c("norm","gamma"))
denscomp(list(fnorm2,fgamma2),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_RGR_Ta$chisqpvalue
famm_H_Ta$chisqtable

## Anderson-Darling test
famm_RGR_Ta$adtest
## Cramer von Mises test
famm_RGR_Ta$cvmtest
##Kolmogorov - Smirnov test
famm_RGR_Ta$kstest


RGR_m1_Ta<-glm(data_Ta$RGR~cen,family = Gamma(),data = data_Ta)
RGR_m1_Ta
summary(RGR_m1_Ta)

RGR_m2_Ta<-glm(data_Ta$RGR~cen,family = gaussian(),data = data_Ta)
RGR_m2_Ta
summary(RGR_m2_Ta)
```

```
#####
################### para Kc  #######
### boxplot para Kc

ggplot(data_Kc, aes(x=esp, y=RGR, fill=cen)) +
  geom_boxplot()

###### GLM

RGR_Kc<- c(data_Kc$RGR)

hist(RGR_Kc)

fnorm3<-fitdist(data_Kc$RGR, distr = "norm")
fgamma3<-fitdist(data_Kc$RGR, distr = "gamma")
plot(fnorm3)
plot(fgamma3)
par(mfrow=c(1,1))
famm_RGR_Kc<-gofstat(list(fnorm3,fgamma3),fitnames = c("norm","gamma"))
denscomp(list(fnorm3,fgamma3),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_RGR_Kc$chisqpvalue
famm_RGR_Kc$chisqtable

## Anderson-Darling test
famm_RGR_Kc$adtest
## Cramer von Mises test
famm_RGR_Kc$cvmtest
##Kolmogorov - Smirnov test
famm_RGR_Kc$kstest


RGR_m1_Kc<-glm(data_Kc$RGR~cen,family = Gamma(),data = data_Kc)
```

```
RGR_m1_Kc
summary(RGR_m1_Kc)

#####
################### para Hs   ######
### boxplot para Hs

ggplot(data_Hs, aes(x=esp, y=RGR, fill=cen)) +
  geom_boxplot()

###### GLM para Hs

RGR_Hs<- c(data_Hs$RGR)

hist(RGR_Hs)

fnorm4<-fitdist(data_Hs$RGR, distr = "norm")
fgamma4<-fitdist(data_Hs$RGR, distr = "gamma")
plot(fnorm4)
plot(fgamma4)
par(mfrow=c(1,1))
famm_RGR_Hs<-gofstat(list(fnorm4,fgamma4),fitnames = c("norm","gamma"))
denscomp(list(fnorm4,fgamma4),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_RGR_Hs$chisqpvalue
famm_RGR_Hs$chisqtable

## Anderson-Darling test
famm_RGR_Hs$adtest
## Cramer von Mises test
famm_RGR_Hs$cvmtest
##Kolmogorov - Smirnov test
famm_RGR_Hs$kstest
```

```
RGR_m1_Hs<-glm(data_Hs$RGR~cen,family = Gamma(),data = data_Hs)
RGR_m1_Hs
summary(RGR_m1_Hs)

##############################    RER   ##########
#
#flexplot e GLM de todas as sp
#
###
## flexplot
RER_all= flexplot(RER ~ cen + esp,
                  data = dados_no_na, se = F, alpha = .3) + scale_x_discrete(limits=c("A","F")) +  ## para arrumar ordem dos dados no eixo x
  theme(axis.text.x = element_text(angle=0, hjust=1, vjust=.2))

RER_all

#############boxplot para Qg

ggplot(data_Qg, aes(x=esp, y=RER, fill=cen)) +
  geom_boxplot()

###### GLM para Qg

hist(RER)

RER_Qg<- c(data_Qg$RER)

hist(RER_Qg)

fnorm<-fitdist(data_Qg$RER, distr = "norm")
fgamma<-fitdist(data_Qg$RER, distr = "gamma")
plot(fnorm)
```

```
plot(fgamma)
par(mfrow=c(1,1))
famm_RER_Qg<-gofstat(list(fnorm,fgamma),fitnames = c("norm","gamma"))
denscomp(list(fnorm,fgamma),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_RER_Qg$chisqpvalue
famm_RER_Qg$chisqtable

## Anderson-Darling test
famm_RER_Qg$adtest
## Cramer von Mises test
famm_RER_Qg$cvmtest
##Kolmogorov - Smirnov test
famm_RER_Qg$kstest
famm_RER_Qg$adtest


RER_m1_Qg<-glm(data_Qg$RER~cen,family = Gamma(),data = data_Qg)
RER_m1_Qg
summary(RER_m1_Qg)


################### para Ta ######
####
### boxplot para Ta

ggplot(data_Ta, aes(x=esp, y=RER, fill=cen)) +
  geom_boxplot()

### GLM para Ta

RER_Ta<- c(data_Ta$RER)

```

```
hist(RER_Ta)

fnorm2<-fitdist(data_Ta$RER, distr = "norm")
fgamma2<-fitdist(data_Ta$RER, distr = "gamma")
plot(fnorm2)
plot(fgamma2)
par(mfrow=c(1,1))
famm_RER_Ta<-gofstat(list(fnorm2,fgamma2),fitnames = c("norm","gamma"))
denscomp(list(fnorm2,fgamma2),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_RER_Ta$chisqpvalue
famm_RER_Ta$chisqtable

## Anderson-Darling test
famm_RER_Ta$adtest
## Cramer von Mises test
famm_RER_Ta$cvmtest
##Kolmogorov - Smirnov test
famm_RER_Ta$kstest


RER_m1_Ta<-glm(data_Ta$RER~cen,family = Gamma(),data = data_Ta)
RER_m1_Ta
summary(RER_m1_Ta)

RER_m2_Ta<-glm(data_Ta$RER~cen,family = gaussian(),data = data_Ta)
RER_m2_Ta
summary(RER_m2_Ta)

#####
#################### para Kc  #######
### boxplot para Kc

```

```
ggplot(data_Kc, aes(x=esp, y=RER, fill=cen)) +
  geom_boxplot()

###### GLM

RER_Kc<- c(data_Kc$RER)

hist(RER_Kc)

fnorm3<-fitdist(data_Kc$RER, distr = "norm")
fgamma3<-fitdist(data_Kc$RER, distr = "gamma")
plot(fnorm3)
plot(fgamma3)
par(mfrow=c(1,1))
famm_RER_Kc<-gofstat(list(fnorm3,fgamma3),fitnames = c("norm","gamma"))
denscomp(list(fnorm3,fgamma3),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_RER_Kc$chisqpvalue
famm_RER_Kc$chisqtable
## Anderson-Darling test
famm_RER_Kc$adtest
## Cramer von Mises test
famm_RER_Kc$cvmtest
##Kolmogorov - Smirnov test
famm_RER_Kc$kstest

RER_m1_Kc<-glm(data_Kc$RER~cen,family = Gamma(),data = data_Kc)
RER_m1_Kc
summary(RER_m1_Kc)
#####
#################### para Hs   ######
### boxplot para Hs
```

```
ggplot(data_Hs, aes(x=esp, y=RER, fill=cen)) +
  geom_boxplot()
###### GLM para Hs

RER_Hs<- c(data_Hs$RER)

hist(RER_Hs)
fnorm4<-fitdist(data_Hs$RER, distr = "norm")
fgamma4<-fitdist(data_Hs$RER, distr = "gamma")
plot(fnorm4)
plot(fgamma4)
par(mfrow=c(1,1))
famm_RER_Hs<-gofstat(list(fnorm4,fgamma4),fitnames = c("norm","gamma"))
denscomp(list(fnorm4,fgamma4),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_RER_Hs$chisqpvalue
famm_RER_Hs$chisqtable
## Anderson-Darling test
famm_RER_Hs$adtest
## Cramer von Mises test
famm_RER_Hs$cvmtest
##Kolmogorov - Smirnov test
famm_RER_Hs$kstest

RER_m1_Hs<-glm(data_Hs$RER~cen,family = Gamma(),data = data_Hs)
RER_m1_Hs
summary(RER_m1_Hs)

##############################    SLA   ##########
#
#flexplot e GLM de todas as sp
## flexplot
SLA_all= flexplot(SLA ~ cen + esp,
```

```
              data = dados_no_na, se = F, alpha = .3) + scale_x_discrete(limits=c("A","F")) +  ## para arrumar ordem dos dados no eixo x
  theme(axis.text.x = element_text(angle=0, hjust=1, vjust=.2))
SLA_all
#############boxplot para Qg

ggplot(data_Qg, aes(x=esp, y=SLA, fill=cen)) +
  geom_boxplot()
###### GLM para Qg
hist(SLA)
SLA_Qg<- c(data_Qg$SLA)

hist(SLA_Qg)
fnorm<-fitdist(data_Qg$SLA, distr = "norm")
fgamma<-fitdist(data_Qg$SLA, distr = "gamma")
plot(fnorm)
plot(fgamma)
par(mfrow=c(1,1))
famm_SLA_Qg<-gofstat(list(fnorm,fgamma),fitnames = c("norm","gamma"))
denscomp(list(fnorm,fgamma),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_SLA_Qg$chisqpvalue
famm_SLA_Qg$chisqtable
## Anderson-Darling test
famm_SLA_Qg$adtest
## Cramer von Mises test
famm_SLA_Qg$cvmtest
##Kolmogorov - Smirnov test
famm_SLA_Qg$kstest
famm_SLA_Qg$adtest

SLA_m1_Qg<-glm(data_Qg$SLA~cen,family = Gamma(),data = data_Qg)
SLA_m1_Qg
summary(SLA_m1_Qg)
```

```
################### para Ta ######
####
### boxplot para Ta
ggplot(data_Ta, aes(x=esp, y=SLA, fill=cen)) +
  geom_boxplot()

### GLM para Ta
SLA_Ta<- c(data_Ta$SLA)
hist(SLA_Ta)
fnorm2<-fitdist(data_Ta$SLA, distr = "norm")
fgamma2<-fitdist(data_Ta$SLA, distr = "gamma")
plot(fnorm2)
plot(fgamma2)
par(mfrow=c(1,1))
famm_SLA_Ta<-gofstat(list(fnorm2,fgamma2),fitnames = c("norm","gamma"))
denscomp(list(fnorm2,fgamma2),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_SLA_Ta$chisqpvalue
famm_SLA_Ta$chisqtable
## Anderson-Darling test
famm_SLA_Ta$adtest
## Cramer von Mises test
famm_SLA_Ta$cvmtest
##Kolmogorov - Smirnov test
famm_SLA_Ta$kstest

SLA_m1_Ta<-glm(data_Ta$SLA~cen,family = Gamma(),data = data_Ta)
SLA_m1_Ta
summary(SLA_m1_Ta)
SLA_m2_Ta<-glm(data_Ta$SLA~cen,family = gaussian(),data = data_Ta)
SLA_m2_Ta
summary(SLA_m2_Ta)
```

```
#####
################### para Kc  #######
### boxplot para Kc

ggplot(data_Kc, aes(x=esp, y=SLA, fill=cen)) +
  geom_boxplot()
###### GLM

SLA_Kc<- c(data_Kc$SLA)
hist(SLA_Kc)
fnorm3<-fitdist(data_Kc$SLA, distr = "norm")
fgamma3<-fitdist(data_Kc$SLA, distr = "gamma")
plot(fnorm3)
plot(fgamma3)
par(mfrow=c(1,1))
famm_SLA_Kc<-gofstat(list(fnorm3,fgamma3),fitnames = c("norm","gamma"))
denscomp(list(fnorm3,fgamma3),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_SLA_Kc$chisqpvalue
famm_SLA_Kc$chisqtable
## Anderson-Darling test
famm_SLA_Kc$adtest
## Cramer von Mises test
famm_SLA_Kc$cvmtest
##Kolmogorov - Smirnov test
famm_SLA_Kc$kstest

SLA_m1_Kc<-glm(data_Kc$SLA~cen,family = Gamma(),data = data_Kc)
SLA_m1_Kc
summary(SLA_m1_Kc)

################### para Hs   ######
### boxplot para Hs
```

```
ggplot(data_Hs, aes(x=esp, y=SLA, fill=cen)) +
  geom_boxplot()

###### GLM para Hs

SLA_Hs<- c(data_Hs$SLA)
hist(SLA_Hs)
fnorm4<-fitdist(data_Hs$SLA, distr = "norm")
fgamma4<-fitdist(data_Hs$SLA, distr = "gamma")
plot(fnorm4)
plot(fgamma4)
par(mfrow=c(1,1))
famm_SLA_Hs<-gofstat(list(fnorm4,fgamma4),fitnames = c("norm","gamma"))
denscomp(list(fnorm4,fgamma4),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_SLA_Hs$chisqpvalue
famm_SLA_Hs$chisqtable

## Anderson-Darling test
famm_SLA_Hs$adtest
## Cramer von Mises test
famm_SLA_Hs$cvmtest
##Kolmogorov - Smirnov test
famm_SLA_Hs$kstest

SLA_m1_Hs<-glm(data_Hs$SLA~cen,family = Gamma(),data = data_Hs)
SLA_m1_Hs
summary(SLA_m1_Hs)

##############################    Lnum   #########################
##flexplot e GLM de todas as sp

```

```
## flexplot
nL_all= flexplot(nL ~ cen + esp,
                 data = dados_no_na, se = F, alpha = .3) + scale_x_discrete(limits=c("A","F")) +  ## para arrumar ordem dos dados no eixo x
  theme(axis.text.x = element_text(angle=0, hjust=1, vjust=.2))

nL_all
#############boxplot para Qg

ggplot(data_Qg, aes(x=esp, y=nL, fill=cen)) +
  geom_boxplot()

###### GLM para Qg

hist(nL)
nL_Qg<- c(data_Qg$nL)

hist(nL_Qg)

fnorm<-fitdist(data_Qg$nL, distr = "norm")
fgamma<-fitdist(data_Qg$nL, distr = "gamma")
plot(fnorm)
plot(fgamma)
par(mfrow=c(1,1))
famm_nL_Qg<-gofstat(list(fnorm,fgamma),fitnames = c("norm","gamma"))
denscomp(list(fnorm,fgamma),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_nL_Qg$chisqpvalue
famm_nL_Qg$chisqtable

## Anderson-Darling test
famm_nL_Qg$adtest
## Cramer von Mises test
famm_nL_Qg$cvmtest
```

```
##Kolmogorov - Smirnov test
famm_nL_Qg$kstest


nL_m1_Qg<-glm(data_Qg$nL~cen,family = Gamma(),data = data_Qg)
nL_m1_Qg
summary(nL_m1_Qg)

################### para Ta ######
### boxplot para Ta

ggplot(data_Ta, aes(x=esp, y=nL, fill=cen)) +
  geom_boxplot()

### GLM para Ta
nL_Ta<- c(data_Ta$nL)

hist(nL_Ta)
fnorm2<-fitdist(data_Ta$nL, distr = "norm")
fgamma2<-fitdist(data_Ta$nL, distr = "gamma")
plot(fnorm2)
plot(fgamma2)
par(mfrow=c(1,1))
famm_nL_Ta<-gofstat(list(fnorm2,fgamma2),fitnames = c("norm","gamma"))
denscomp(list(fnorm2,fgamma2),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_nL_Ta$chisqpvalue
famm_nL_Ta$chisqtable
## Anderson-Darling test
famm_nL_Ta$adtest
## Cramer von Mises test
famm_nL_Ta$cvmtest
##Kolmogorov - Smirnov test
```

```
famm_nL_Ta$kstest

nL_m1_Ta<-glm(data_Ta$nL~cen,family = Gamma(),data = data_Ta)
nL_m1_Ta
summary(nL_m1_Ta)

nL_m2_Ta<-glm(data_Ta$nL~cen,family = gaussian(),data = data_Ta)
nL_m2_Ta
summary(nL_m2_Ta)
#################### para Kc  #######
### boxplot para Kc
ggplot(data_Kc, aes(x=esp, y=nL, fill=cen)) +
  geom_boxplot()

###### GLM
nL_Kc<- c(data_Kc$nL)
hist(nL_Kc)

fnorm3<-fitdist(data_Kc$nL, distr = "norm")
fgamma3<-fitdist(data_Kc$nL, distr = "gamma")
plot(fnorm3)
plot(fgamma3)
par(mfrow=c(1,1))
famm_nL_Kc<-gofstat(list(fnorm2,fgamma2),fitnames = c("norm","gamma"))
denscomp(list(fnorm2,fgamma2),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_nL_Kc$chisqpvalue
famm_nL_Kc$chisqtable
## Anderson-Darling test
famm_nL_Kc$adtest
## Cramer von Mises test
famm_nL_Kc$cvmtest
##Kolmogorov - Smirnov test
```

```
famm_nL_Kc$kstest

nL_m1_Kc<-glm(data_Kc$nL~cen,family = Gamma(),data = data_Kc)
nL_m1_Kc
summary(nL_m1_Kc)

#################### para Hs   ######
### boxplot para Hs
ggplot(data_Hs, aes(x=esp, y=nL, fill=cen)) +
  geom_boxplot()

###### GLM para Hs

nL_Hs<- c(data_Hs$nL)

hist(nL_Hs)
fnorm4<-fitdist(data_Hs$nL, distr = "norm")
fgamma4<-fitdist(data_Hs$nL, distr = "gamma")
plot(fnorm4)
plot(fgamma4)
par(mfrow=c(1,1))
famm_nL_Hs<-gofstat(list(fnorm4,fgamma4),fitnames = c("norm","gamma"))
denscomp(list(fnorm4,fgamma4),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_nL_Hs$chisqpvalue
famm_nL_Hs$chisqtable
## Anderson-Darling test
famm_nL_Hs$adtest
## Cramer von Mises test
famm_nL_Hs$cvmtest
##Kolmogorov - Smirnov test
famm_nL_Hs$kstest
```

```
nL_m1_Hs<-glm(data_Hs$nL~cen,family = Gamma(),data = data_Hs)
nL_m1_Hs
summary(nL_m1_Hs)

############################## STRL ##########################
#flexplot e GLM de todas as sp
## flexplot
STRL_all= flexplot(STRL ~ cen + esp,
                   data = dados_no_na, se = F, alpha = .3) + scale_x_discrete(limits=c("A","F")) +  ## para arrumar ordem dos dados no eixo x
  theme(axis.text.x = element_text(angle=0, hjust=1, vjust=.2))

STRL_all
#############boxplot para Qg
ggplot(data_Qg, aes(x=esp, y=STRL, fill=cen)) +
  geom_boxplot()

###### GLM para Qg
hist(STRL)
STRL_Qg<- c(data_Qg$STRL)
hist(STRL_Qg)
fnorm<-fitdist(data_Qg$STRL, distr = "norm")
fgamma<-fitdist(data_Qg$STRL, distr = "gamma")
plot(fnorm)
plot(fgamma)
par(mfrow=c(1,1))
famm_STRL_Qg<-gofstat(list(fnorm,fgamma),fitnames = c("norm","gamma"))
denscomp(list(fnorm,fgamma),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_STRL_Qg$chisqpvalue
famm_STRL_Qg$chisqtable
## Anderson-Darling test
famm_STRL_Qg$adtest
## Cramer von Mises test
```

```
famm_STRL_Qg$cvmtest
##Kolmogorov - Smirnov test
famm_STRL_Qg$kstest

STRL_m1_Qg<-glm(data_Qg$STRL~cen,family = Gamma(),data = data_Qg)
STRL_m1_Qg
summary(STRL_m1_Qg)

################### para Ta ######
### boxplot para Ta

ggplot(data_Ta, aes(x=esp, y=STRL, fill=cen)) +
  geom_boxplot()

### GLM para Ta

STRL_Ta<- c(data_Ta$STRL)

hist(STRL_Ta)
fnorm2<-fitdist(data_Ta$STRL, distr = "norm")
fgamma2<-fitdist(data_Ta$STRL, distr = "gamma")
plot(fnorm2)
plot(fgamma2)
par(mfrow=c(1,1))
famm_STRL_Ta<-gofstat(list(fnorm2,fgamma2),fitnames = c("norm","gamma"))
denscomp(list(fnorm2,fgamma2),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_STRL_Ta$chisqpvalue
famm_STRL_Ta$chisqtable
## Anderson-Darling test
famm_STRL_Ta$adtest
## Cramer von Mises test
famm_STRL_Ta$cvmtest
```

```
##Kolmogorov - Smirnov test
famm_STRL_Ta$kstest

STRL_m1_Ta<-glm(data_Ta$STRL~cen,family = Gamma(),data = data_Ta)
STRL_m1_Ta
summary(STRL_m1_Ta)

STRL_m2_Ta<-glm(data_Ta$STRL~cen,family = gaussian(),data = data_Ta)
STRL_m2_Ta
summary(STRL_m2_Ta)
#################### para Kc  #######
### boxplot para Kc

ggplot(data_Kc, aes(x=esp, y=STRL, fill=cen)) +
  geom_boxplot()

###### GLM
STRL_Kc<- c(data_Kc$STRL)
hist(STRL_Kc)

fnorm3<-fitdist(data_Kc$STRL, distr = "norm")
fgamma3<-fitdist(data_Kc$STRL, distr = "gamma")
plot(fnorm3)
plot(fgamma3)
par(mfrow=c(1,1))
famm_STRL_Kc<-gofstat(list(fnorm3,fgamma3),fitnames = c("norm","gamma"))
denscomp(list(fnorm3,fgamma3),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_STRL_Kc$chisqpvalue
famm_STRL_Kc$chisqtable
## Anderson-Darling test
famm_STRL_Kc$adtest
## Cramer von Mises test
```

```
famm_STRL_Kc$cvmtest
##Kolmogorov - Smirnov test
famm_STRL_Kc$kstest


STRL_m1_Kc<-glm(data_Kc$STRL~cen,family = Gamma(),data = data_Kc)
STRL_m1_Kc
summary(STRL_m1_Kc)

################### para Hs   ######
### boxplot para Hs

ggplot(data_Hs, aes(x=esp, y=STRL, fill=cen)) +
  geom_boxplot()

###### GLM para Hs
STRL_Hs<- c(data_Hs$STRL)
hist(STRL_Hs)

fnorm4<-fitdist(data_Hs$STRL, distr = "norm")
fgamma4<-fitdist(data_Hs$STRL, distr = "gamma")
plot(fnorm4)
plot(fgamma4)
par(mfrow=c(1,1))
famm_STRL_Hs<-gofstat(list(fnorm4,fgamma4),fitnames = c("norm","gamma"))
denscomp(list(fnorm4,fgamma4),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_STRL_Hs$chisqpvalue
famm_STRL_Hs$chisqtable
## Anderson-Darling test
famm_STRL_Hs$adtest
## Cramer von Mises test
famm_STRL_Hs$cvmtest
```

```
##Kolmogorov - Smirnov test
famm_STRL_Hs$kstest


STRL_m1_Hs<-glm(data_Hs$STRL~cen,family = Gamma(),data = data_Hs)
STRL_m1_Hs
summary(STRL_m1_Hs)

#############################    RMF  #########################
#
#flexplot e GLM de todas as sp
## flexplot
RMF_all= flexplot(RMF ~ cen + esp,
                  data = dados_no_na, se = F, alpha = .3) + scale_x_discrete(limits=c("A","F")) +  ## para arrumar ordem dos dados no eixo x
  theme(axis.text.x = element_text(angle=0, hjust=1, vjust=.2))

RMF_all

#############boxplot para Qg
ggplot(data_Qg, aes(x=esp, y=RMF, fill=cen)) +
  geom_boxplot()

###### GLM para Qg

hist(RMF)
RMF_Qg<- c(data_Qg$RMF)
hist(RMF_Qg)

fnorm<-fitdist(data_Qg$RMF, distr = "norm")
fgamma<-fitdist(data_Qg$RMF, distr = "gamma")
plot(fnorm)
plot(fgamma)
par(mfrow=c(1,1))
famm_RMF_Qg<-gofstat(list(fnorm,fgamma),fitnames = c("norm","gamma"))
```

```
denscomp(list(fnorm,fgamma),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_RMF_Qg$chisqpvalue
famm_RMF_Qg$chisqtable
## Anderson-Darling test
famm_RMF_Qg$adtest
## Cramer von Mises test
famm_RMF_Qg$cvmtest
##Kolmogorov - Smirnov test
famm_RMF_Qg$kstest

RMF_m1_Qg<-glm(data_Qg$RMF~cen,family = Gamma(),data = data_Qg)
RMF_m1_Qg
summary(RMF_m1_Qg)

#################### para Ta ######
### boxplot para Ta

ggplot(data_Ta, aes(x=esp, y=RMF, fill=cen)) +
  geom_boxplot()

### GLM para Ta
RMF_Ta<- c(data_Ta$RMF)

hist(RMF_Ta)
fnorm2<-fitdist(data_Ta$RMF, distr = "norm")
fgamma2<-fitdist(data_Ta$RMF, distr = "gamma")
plot(fnorm2)
plot(fgamma2)
par(mfrow=c(1,1))
famm_RMF_Ta<-gofstat(list(fnorm2,fgamma2),fitnames = c("norm","gamma"))
denscomp(list(fnorm2,fgamma2),legendtext = c("norm","gamma"))
#results of the tests
```

```
## chi square test (with corresponding table...)
famm_RMF_Ta$chisqpvalue
famm_RMF_Ta$chisqtable
## Anderson-Darling test
famm_RMF_Ta$adtest
## Cramer von Mises test
famm_RMF_Ta$cvmtest
##Kolmogorov - Smirnov test
famm_RMF_Ta$kstest

RMF_m1_Ta<-glm(data_Ta$RMF~cen,family = Gamma(),data = data_Ta)
RMF_m1_Ta
summary(RMF_m1_Ta)

RMF_m2_Ta<-glm(data_Ta$RMF~cen,family = gaussian(),data = data_Ta)
RMF_m2_Ta
summary(RMF_m2_Ta)

#################### para Kc  #######
### boxplot para Kc
ggplot(data_Kc, aes(x=esp, y=RMF, fill=cen)) +
  geom_boxplot()

###### GLM
RMF_Kc<- c(data_Kc$RMF)

hist(RMF_Kc)
fnorm3<-fitdist(data_Kc$RMF, distr = "norm")
fgamma3<-fitdist(data_Kc$RMF, distr = "gamma")
plot(fnorm3)
plot(fgamma3)
par(mfrow=c(1,1))
famm_RMF_Kc<-gofstat(list(fnorm3,fgamma3),fitnames = c("norm","gamma"))
denscomp(list(fnorm3,fgamma3),legendtext = c("norm","gamma"))
```

```
#results of the tests
## chi square test (with corresponding table...)
famm_RMF_Kc$chisqpvalue
famm_RMF_Kc$chisqtable

## Anderson-Darling test
famm_RMF_Kc$adtest
## Cramer von Mises test
famm_RMF_Kc$cvmtest
##Kolmogorov - Smirnov test
famm_RMF_Kc$kstest


RMF_m1_Kc<-glm(data_Kc$RMF~cen,family = Gamma(),data = data_Kc)
RMF_m1_Kc
summary(RMF_m1_Kc)

#################### para Hs   ######
### boxplot para Hs
ggplot(data_Hs, aes(x=esp, y=RMF, fill=cen)) +
  geom_boxplot()
##### GLM para Hs

RMF_Hs<- c(data_Hs$RMF)

hist(RMF_Hs)
fnorm4<-fitdist(data_Hs$RMF, distr = "norm")
fgamma4<-fitdist(data_Hs$RMF, distr = "gamma")
plot(fnorm4)
plot(fgamma4)
par(mfrow=c(1,1))
famm_RMF_Hs<-gofstat(list(fnorm4,fgamma4),fitnames = c("norm","gamma"))
denscomp(list(fnorm4,fgamma4),legendtext = c("norm","gamma"))
#results of the tests
```

```
## chi square test (with corresponding table...)
famm_RMF_Hs$chisqpvalue
famm_RMF_Hs$chisqtable
## Anderson-Darling test
famm_RMF_Hs$adtest
## Cramer von Mises test
famm_RMF_Hs$cvmtest
##Kolmogorov - Smirnov test
famm_RMF_Hs$kstest

RMF_m1_Hs<-glm(data_Hs$RMF~cen,family = Gamma(),data = data_Hs)
RMF_m1_Hs
summary(RMF_m1_Hs)

##############################   SMF  #########################
#flexplot e GLM de todas as sp
###
## flexplot
SMF_all= flexplot(SMF ~ cen + esp,
                  data = dados_no_na, se = F, alpha = .3) + scale_x_discrete(limits=c("A","F")) +  ## para arrumar ordem dos dados no eixo x
  theme(axis.text.x = element_text(angle=0, hjust=1, vjust=.2))
SMF_all

#############boxplot para Qg
ggplot(data_Qg, aes(x=esp, y=SMF, fill=cen)) +
  geom_boxplot()
###### GLM para Qg

hist(SMF)
SMF_Qg<- c(data_Qg$SMF)
hist(SMF_Qg)

fnorm<-fitdist(data_Qg$SMF, distr = "norm")
fgamma<-fitdist(data_Qg$SMF, distr = "gamma")
```

```
plot(fnorm)
plot(fgamma)
par(mfrow=c(1,1))
famm_SMF_Qg<-gofstat(list(fnorm,fgamma),fitnames = c("norm","gamma"))
denscomp(list(fnorm,fgamma),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_SMF_Qg$chisqpvalue
famm_SMF_Qg$chisqtable
## Anderson-Darling test
famm_SMF_Qg$adtest
## Cramer von Mises test
famm_SMF_Qg$cvmtest
##Kolmogorov - Smirnov test
famm_SMF_Qg$kstest

SMF_m1_Qg<-glm(data_Qg$SMF~cen,family = Gamma(),data = data_Qg)
SMF_m1_Qg
summary(SMF_m1_Qg)

#################### para Ta ######
### boxplot para Ta

ggplot(data_Ta, aes(x=esp, y=SMF, fill=cen)) +
  geom_boxplot()

### GLM para Ta
SMF_Ta<- c(data_Ta$SMF)

hist(SMF_Ta)
fnorm2<-fitdist(data_Ta$SMF, distr = "norm")
fgamma2<-fitdist(data_Ta$SMF, distr = "gamma")
plot(fnorm2)
plot(fgamma2)
```

```
par(mfrow=c(1,1))
famm_SMF_Ta<-gofstat(list(fnorm2,fgamma2),fitnames = c("norm","gamma"))
denscomp(list(fnorm2,fgamma2),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_SMF_Ta$chisqpvalue
famm_SMF_Ta$chisqtable
## Anderson-Darling test
famm_SMF_Ta$adtest
## Cramer von Mises test
famm_SMF_Ta$cvmtest
##Kolmogorov - Smirnov test
famm_SMF_Ta$kstest


SMF_m1_Ta<-glm(data_Ta$SMF~cen,family = Gamma(),data = data_Ta)
SMF_m1_Ta
summary(SMF_m1_Ta)
SMF_m2_Ta<-glm(data_Ta$SMF~cen,family = gaussian(),data = data_Ta)
SMF_m2_Ta
summary(SMF_m2_Ta)

#####
################### para Kc  #######
### boxplot para Kc
ggplot(data_Kc, aes(x=esp, y=SMF, fill=cen)) +
  geom_boxplot()

###### GLM

SMF_Kc<- c(data_Kc$SMF)
hist(SMF_Kc)

fnorm3<-fitdist(data_Kc$SMF, distr = "norm")
```

```
fgamma3<-fitdist(data_Kc$SMF, distr = "gamma")
plot(fnorm3)
plot(fgamma3)
par(mfrow=c(1,1))
famm_SMF_Kc<-gofstat(list(fnorm3,fgamma3),fitnames = c("norm","gamma"))
denscomp(list(fnorm3,fgamma3),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_SMF_Kc$chisqpvalue
famm_SMF_Kc$chisqtable
## Anderson-Darling test
famm_SMF_Kc$adtest
## Cramer von Mises test
famm_SMF_Kc$cvmtest
##Kolmogorov - Smirnov test
famm_SMF_Kc$kstest

SMF_m1_Kc<-glm(data_Kc$SMF~cen,family = Gamma(),data = data_Kc)
SMF_m1_Kc
summary(SMF_m1_Kc)
#################### para Hs   ######
### boxplot para Hs
ggplot(data_Hs, aes(x=esp, y=SMF, fill=cen)) +
  geom_boxplot()

###### GLM para Hs
SMF_Hs<- c(data_Hs$SMF)
hist(SMF_Hs)

fnorm4<-fitdist(data_Hs$SMF, distr = "norm")
fgamma4<-fitdist(data_Hs$SMF, distr = "gamma")
plot(fnorm4)
plot(fgamma4)
par(mfrow=c(1,1))
```

```
famm_SMF_Hs<-gofstat(list(fnorm4,fgamma4),fitnames = c("norm","gamma"))
denscomp(list(fnorm4,fgamma4),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_SMF_Hs$chisqpvalue
famm_SMF_Hs$chisqtable

## Anderson-Darling test
famm_SMF_Hs$adtest
## Cramer von Mises test
famm_SMF_Hs$cvmtest
##Kolmogorov - Smirnov test
famm_SMF_Hs$kstest


SMF_m1_Hs<-glm(data_Hs$SMF~cen,family = Gamma(),data = data_Hs)
SMF_m1_Hs
summary(SMF_m1_Hs)
##############################   St_dens  #########################
#
#flexplot e GLM de todas as sp

###
## flexplot
St_dens_all= flexplot(St_dens ~ cen + esp,
                      data = dados_no_na, se = F, alpha = .3) + scale_x_discrete(limits=c("A","F")) +  ## para arrumar ordem dos dados no eixo x
  theme(axis.text.x = element_text(angle=0, hjust=1, vjust=.2))
St_dens_all

#############boxplot para Qg
ggplot(data_Qg, aes(x=esp, y=St_dens, fill=cen)) +
  geom_boxplot()

###### GLM para Qg
```

```
hist(St_dens)

St_dens_Qg<- c(data_Qg$St_dens)
hist(St_dens_Qg)

fnorm<-fitdist(data_Qg$St_dens, distr = "norm")
fgamma<-fitdist(data_Qg$St_dens, distr = "gamma")
plot(fnorm)
plot(fgamma)
par(mfrow=c(1,1))
famm_St_dens_Qg<-gofstat(list(fnorm,fgamma),fitnames = c("norm","gamma"))
denscomp(list(fnorm,fgamma),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_St_dens_Qg$chisqpvalue
famm_St_dens_Qg$chisqtable
## Anderson-Darling test
famm_St_dens_Qg$adtest
## Cramer von Mises test
famm_St_dens_Qg$cvmtest
##Kolmogorov - Smirnov test
famm_St_dens_Qg$kstest



St_dens_m1_Qg<-glm(data_Qg$St_dens~cen,family = Gamma(),data = data_Qg)
St_dens_m1_Qg
summary(St_dens_m1_Qg)

#################### para Ta ######
### boxplot para Ta
ggplot(data_Ta, aes(x=esp, y=St_dens, fill=cen)) +
  geom_boxplot()
```

```
### GLM para Ta
St_dens_Ta<- c(data_Ta$St_dens)

hist(St_dens_Ta)

fnorm2<-fitdist(data_Ta$St_dens, distr = "norm")
fgamma2<-fitdist(data_Ta$St_dens, distr = "gamma")
plot(fnorm2)
plot(fgamma2)
par(mfrow=c(1,1))
famm_St_dens_Ta<-gofstat(list(fnorm2,fgamma2),fitnames = c("norm","gamma"))
denscomp(list(fnorm2,fgamma2),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_St_dens_Ta$chisqpvalue
famm_St_dens_Ta$chisqtable
## Anderson-Darling test
famm_St_dens_Ta$adtest
## Cramer von Mises test
famm_St_dens_Ta$cvmtest
##Kolmogorov - Smirnov test
famm_St_dens_Ta$kstest

St_dens_m1_Ta<-glm(data_Ta$St_dens~cen,family = Gamma(),data = data_Ta)
St_dens_m1_Ta
summary(St_dens_m1_Ta)

St_dens_m2_Ta<-glm(data_Ta$St_dens~cen,family = gaussian(),data = data_Ta)
St_dens_m2_Ta
summary(St_dens_m2_Ta)

################### para Kc  #######
### boxplot para Kc
```

```
ggplot(data_Kc, aes(x=esp, y=St_dens, fill=cen)) +
  geom_boxplot()

###### GLM
St_dens_Kc<- c(data_Kc$St_dens)

hist(St_dens_Kc)

fnorm3<-fitdist(data_Kc$St_dens, distr = "norm")
fgamma3<-fitdist(data_Kc$St_dens, distr = "gamma")
plot(fnorm3)
plot(fgamma3)
par(mfrow=c(1,1))
famm_St_dens_Kc<-gofstat(list(fnorm3,fgamma3),fitnames = c("norm","gamma"))
denscomp(list(fnorm3,fgamma3),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_St_dens_Kc$chisqpvalue
famm_St_dens_Kc$chisqtable
## Anderson-Darling test
famm_St_dens_Kc$adtest
## Cramer von Mises test
famm_St_dens_Kc$cvmtest
##Kolmogorov - Smirnov test
famm_St_dens_Kc$kstest

St_dens_m1_Kc<-glm(data_Kc$St_dens~cen,family = Gamma(),data = data_Kc)
St_dens_m1_Kc
summary(St_dens_m1_Kc)

#####
#################### para Hs   ######
### boxplot para Hs
```

```
ggplot(data_Hs, aes(x=esp, y=St_dens, fill=cen)) +
  geom_boxplot()

###### GLM para Hs

St_dens_Hs<- c(data_Hs$St_dens)

hist(St_dens_Hs)
fnorm4<-fitdist(data_Hs$St_dens, distr = "norm")
fgamma4<-fitdist(data_Hs$St_dens, distr = "gamma")
plot(fnorm4)
plot(fgamma4)
par(mfrow=c(1,1))
famm_St_dens_Hs<-gofstat(list(fnorm4,fgamma4),fitnames = c("norm","gamma"))
denscomp(list(fnorm4,fgamma4),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_St_dens_Hs$chisqpvalue
famm_St_dens_Hs$chisqtable
## Anderson-Darling test
famm_St_dens_Hs$adtest
## Cramer von Mises test
famm_St_dens_Hs$cvmtest
##Kolmogorov - Smirnov test
famm_St_dens_Hs$kstest

St_dens_m1_Hs<-glm(data_Hs$St_dens~cen,family = Gamma(),data = data_Hs)
St_dens_m1_Hs
summary(St_dens_m1_Hs)

##############################   SM  ##########################
#
#flexplot e GLM de todas as sp
```

```
## flexplot
SM_all= flexplot(SM ~ cen + esp,
         data = dados_no_na, se = F, alpha = .3) + scale_x_discrete(limits=c("A","F")) +  ## para arrumar ordem dos dados no eixo x
  theme(axis.text.x = element_text(angle=0, hjust=1, vjust=.2))
SM_all
#############boxplot para Qg

ggplot(data_Qg, aes(x=esp, y=SM, fill=cen)) +
  geom_boxplot()

###### GLM para Qg

hist(SM)
SM_Qg<- c(data_Qg$SM)

hist(SM_Qg)
fnorm<-fitdist(data_Qg$SM, distr = "norm")
fgamma<-fitdist(data_Qg$SM, distr = "gamma")
plot(fnorm)
plot(fgamma)
par(mfrow=c(1,1))
famm_SM_Qg<-gofstat(list(fnorm,fgamma),fitnames = c("norm","gamma"))
denscomp(list(fnorm,fgamma),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_SM_Qg$chisqpvalue
famm_SM_Qg$chisqtable
## Anderson-Darling test
famm_SM_Qg$adtest
## Cramer von Mises test
famm_SM_Qg$cvmtest
##Kolmogorov - Smirnov test
famm_SM_Qg$kstest
```

```
SM_m1_Qg<-glm(data_Qg$SM~cen,family = Gamma(),data = data_Qg)
SM_m1_Qg
summary(SM_m1_Qg)

################### para Ta ######
### boxplot para Ta

ggplot(data_Ta, aes(x=esp, y=SM, fill=cen)) +
  geom_boxplot()

### GLM para Ta
SM_Ta<- c(data_Ta$SM)
hist(SM_Ta)

fnorm2<-fitdist(data_Ta$SM, distr = "norm")
fgamma2<-fitdist(data_Ta$SM, distr = "gamma")
plot(fnorm2)
plot(fgamma2)
par(mfrow=c(1,1))
famm_SM_Ta<-gofstat(list(fnorm2,fgamma2),fitnames = c("norm","gamma"))
denscomp(list(fnorm2,fgamma2),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_SM_Ta$chisqpvalue
famm_SM_Ta$chisqtable

## Anderson-Darling test
famm_SM_Ta$adtest
## Cramer von Mises test
famm_SM_Ta$cvmtest
##Kolmogorov - Smirnov test
famm_SM_Ta$kstest
```

```
SM_m1_Ta<-glm(data_Ta$SM~cen,family = Gamma(),data = data_Ta)
SM_m1_Ta
summary(SM_m1_Ta)
SM_m2_Ta<-glm(data_Ta$SM~cen,family = gaussian(),data = data_Ta)
SM_m2_Ta
summary(SM_m2_Ta)

#################### para Kc  #######
### boxplot para Kc
ggplot(data_Kc, aes(x=esp, y=SM, fill=cen)) +
  geom_boxplot()

###### GLM
SM_Kc<- c(data_Kc$SM)

hist(SM_Kc)
fnorm3<-fitdist(data_Kc$SM, distr = "norm")
fgamma3<-fitdist(data_Kc$SM, distr = "gamma")
plot(fnorm3)
plot(fgamma3)
par(mfrow=c(1,1))
famm_SM_Kc<-gofstat(list(fnorm3,fgamma3),fitnames = c("norm","gamma"))
denscomp(list(fnorm3,fgamma3),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_SM_Kc$chisqpvalue
famm_SM_Kc$chisqtable
## Anderson-Darling test
famm_SM_Kc$adtest
## Cramer von Mises test
famm_SM_Kc$cvmtest
##Kolmogorov - Smirnov test
famm_SM_Kc$kstest
```

```
SM_m1_Kc<-glm(data_Kc$SM~cen,family = Gamma(),data = data_Kc)
SM_m1_Kc
summary(SM_m1_Kc)

################### para Hs   ######
### boxplot para Hs

ggplot(data_Hs, aes(x=esp, y=SM, fill=cen)) +
  geom_boxplot()

###### GLM para Hs

SM_Hs<- c(data_Hs$SM)

hist(SM_Hs)
fnorm4<-fitdist(data_Hs$SM, distr = "norm")
fgamma4<-fitdist(data_Hs$SM, distr = "gamma")
plot(fnorm4)
plot(fgamma4)
par(mfrow=c(1,1))
famm_SM_Hs<-gofstat(list(fnorm4,fgamma4),fitnames = c("norm","gamma"))
denscomp(list(fnorm4,fgamma4),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_SM_Hs$chisqpvalue
famm_SM_Hs$chisqtable
## Anderson-Darling test
famm_SM_Hs$adtest
## Cramer von Mises test
famm_SM_Hs$cvmtest
##Kolmogorov - Smirnov test
famm_SM_Hs$kstest
```

```
SM_m1_Hs<-glm(data_Hs$SM~cen,family = Gamma(),data = data_Hs)
SM_m1_Hs
summary(SM_m1_Hs)

##############################   SM  #########################
#flexplot e GLM de todas as sp
## flexplot
RM_all= flexplot(RM ~ cen + esp,
                 data = dados_no_na, se = F, alpha = .3) + scale_x_discrete(limits=c("A","F")) +  ## para arrumar ordem dos dados no eixo x
  theme(axis.text.x = element_text(angle=0, hjust=1, vjust=.2))

RM_all

#############boxplot para Qg

ggplot(data_Qg, aes(x=esp, y=RM, fill=cen)) +
  geom_boxplot()
###### GLM para Qg
hist(RM)

RM_Qg<- c(data_Qg$RM)
hist(RM_Qg)
fnorm<-fitdist(data_Qg$RM, distr = "norm")
fgamma<-fitdist(data_Qg$RM, distr = "gamma")
plot(fnorm)
plot(fgamma)
par(mfrow=c(1,1))
famm_RM_Qg<-gofstat(list(fnorm,fgamma),fitnames = c("norm","gamma"))
denscomp(list(fnorm,fgamma),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_RM_Qg$chisqpvalue
famm_RM_Qg$chisqtable
## Anderson-Darling test
```

```
famm_RM_Qg$adtest
## Cramer von Mises test
famm_RM_Qg$cvmtest
##Kolmogorov - Smirnov test
famm_RM_Qg$kstest



RM_m1_Qg<-glm(data_Qg$RM~cen,family = Gamma(),data = data_Qg)
RM_m1_Qg
summary(RM_m1_Qg)

#################### para Ta ######
####
### boxplot para Ta
ggplot(data_Ta, aes(x=esp, y=RM, fill=cen)) +
  geom_boxplot()

### GLM para Ta

RM_Ta<- c(data_Ta$RM)
hist(RM_Ta)
fnorm2<-fitdist(data_Ta$RM, distr = "norm")
fgamma2<-fitdist(data_Ta$RM, distr = "gamma")
plot(fnorm2)
plot(fgamma2)
par(mfrow=c(1,1))
famm_RM_Ta<-gofstat(list(fnorm2,fgamma2),fitnames = c("norm","gamma"))
denscomp(list(fnorm2,fgamma2),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_RM_Ta$chisqpvalue
famm_RM_Ta$chisqtable
## Anderson-Darling test
```

```
famm_RM_Ta$adtest
## Cramer von Mises test
famm_RM_Ta$cvmtest
##Kolmogorov - Smirnov test
famm_RM_Ta$kstest

RM_m1_Ta<-glm(data_Ta$RM~cen,family = Gamma(),data = data_Ta)
RM_m1_Ta
summary(RM_m1_Ta)
RM_m2_Ta<-glm(data_Ta$RM~cen,family = gaussian(),data = data_Ta)
RM_m2_Ta
summary(RM_m2_Ta)

#####
#################### para Kc  #######
### boxplot para Kc
ggplot(data_Kc, aes(x=esp, y=RM, fill=cen)) +
  geom_boxplot()

###### GLM

RM_Kc<- c(data_Kc$RM)
hist(RM_Kc)
fnorm3<-fitdist(data_Kc$RM, distr = "norm")
fgamma3<-fitdist(data_Kc$RM, distr = "gamma")
plot(fnorm3)
plot(fgamma3)
par(mfrow=c(1,1))
famm_RM_Kc<-gofstat(list(fnorm3,fgamma3),fitnames = c("norm","gamma"))
denscomp(list(fnorm3,fgamma3),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_RM_Kc$chisqpvalue
famm_RM_Kc$chisqtable
```

```
## Anderson-Darling test
famm_RM_Kc$adtest
## Cramer von Mises test
famm_RM_Kc$cvmtest
##Kolmogorov - Smirnov test
famm_RM_Kc$kstest


RM_m1_Kc<-glm(data_Kc$RM~cen,family = Gamma(),data = data_Kc)
RM_m1_Kc
summary(RM_m1_Kc)

#################### para Hs   ######
### boxplot para Hs
ggplot(data_Hs, aes(x=esp, y=RM, fill=cen)) +
  geom_boxplot()
###### GLM para Hs
RM_Hs<- c(data_Hs$RM)
hist(RM_Hs)
fnorm4<-fitdist(data_Hs$RM, distr = "norm")
fgamma4<-fitdist(data_Hs$RM, distr = "gamma")
plot(fnorm4)
plot(fgamma4)
par(mfrow=c(1,1))
famm_RM_Hs<-gofstat(list(fnorm4,fgamma4),fitnames = c("norm","gamma"))
denscomp(list(fnorm4,fgamma4),legendtext = c("norm","gamma"))
#results of the tests
## chi square test (with corresponding table...)
famm_RM_Hs$chisqpvalue
famm_RM_Hs$chisqtable
## Anderson-Darling test
famm_RM_Hs$adtest
## Cramer von Mises test
famm_RM_Hs$cvmtest
```

```
##Kolmogorov - Smirnov test
famm_RM_Hs$kstest

RM_m1_Hs<-glm(data_Hs$RM~cen,family = Gamma(),data = data_Hs)
RM_m1_Hs
summary(RM_m1_Hs)
```

###

7.4.1. ANÁLISES ESTATÍSTICAS DO CAPÍTULO II

```
############ Qg ################################################

summary(Qg_A)
     sp                cen                 ST_D               H               Lnum       
 Length:26          Length:26          Min.   :0.1460   Min.   : 6.400   Min.   : 1.000  
 Class :character   Class :character   1st Qu.:0.1822   1st Qu.: 7.300   1st Qu.: 3.000  
 Mode  :character   Mode  :character   Median :0.2057   Median : 8.550   Median : 5.000  
                                       Mean   :0.2004   Mean   : 8.627   Mean   : 5.077  
                                       3rd Qu.:0.2157   3rd Qu.: 9.650   3rd Qu.: 6.750  
                                       Max.   :0.2410   Max.   :13.000   Max.   :12.000  
       RL              TpRM             ScRM              StM               TLM         
 Min.   : 51.00   Min.   :0.2456   Min.   :0.0300   Min.   :0.05990   Min.   :0.04990  
 1st Qu.: 71.50   1st Qu.:0.4619   1st Qu.:0.0924   1st Qu.:0.09978   1st Qu.:0.09058  
 Median : 81.80   Median :0.5934   Median :0.1154   Median :0.10950   Median :0.16160  
 Mean   : 81.33   Mean   :0.6196   Mean   :0.1300   Mean   :0.11058   Mean   :0.16123  
 3rd Qu.: 89.65   3rd Qu.:0.7599   3rd Qu.:0.1518   3rd Qu.:0.12235   3rd Qu.:0.18682  
 Max.   :104.20   Max.   :0.9876   Max.   :0.4552   Max.   :0.16220   Max.   :0.38670  
       RM               SM               TM               RS              LMF         
 Min.   :0.3300   Min.   :0.1271   Min.   :0.4571   Min.   :1.443   Min.   :0.04726  
 1st Qu.:0.5656   1st Qu.:0.2111   1st Qu.:0.8351   1st Qu.:2.152   1st Qu.:0.12586  
 Median :0.7361   Median :0.2544   Median :1.0468   Median :2.828   Median :0.15265  
 Mean   :0.7496   Mean   :0.2718   Mean   :1.0214   Mean   :2.961   Mean   :0.15866  
 3rd Qu.:0.8883   3rd Qu.:0.3200   3rd Qu.:1.1590   3rd Qu.:3.034   3rd Qu.:0.20934  
 Max.   :1.2451   Max.   :0.4638   Max.   :1.6724   Max.   :5.562   Max.   :0.33082  
      RMF              SMF              SLA              RGR               STRL       
 Min.   :0.5907   Min.   :0.1524   Min.   : 33.71   Min.   :0.01371   Min.   : 85.57  
 1st Qu.:0.6820   1st Qu.:0.2479   1st Qu.: 81.88   1st Qu.:0.01717   1st Qu.:110.55  
 Median :0.7387   Median :0.2613   Median : 99.06   Median :0.01877   Median :123.87  
 Mean   :0.7280   Mean   :0.2720   Mean   : 92.47   Mean   :0.01885   Mean   :144.01  
 3rd Qu.:0.7521   3rd Qu.:0.3180   3rd Qu.:106.45   3rd Qu.:0.01995   3rd Qu.:173.16  
 Max.   :0.8476   Max.   :0.4093   Max.   :134.86   Max.   :0.02586   Max.   :287.05  
      RER        
 Min.   :0.2808  
```

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

```
      RER
 Min.   :0.5356
 1st Qu.:0.6676
 Median :0.7189
 Mean   :0.7057
 3rd Qu.:0.7551
 Max.   :0.8137

std.error(Qg_A$H)
[1] 0.301614
> std.error(Qg_F$H)
[1] 0.4117004
>
> std.error(Qg_A$ST_D)
[1] 0.004658353
> std.error(Qg_F$ST_D)
[1] 0.005512798
>
> std.error(Qg_A$RL)
[1] 2.882626
> std.error(Qg_F$RL)
[1] 0.8586068
>
> std.error(Qg_A$Lnum)
[1] 0.5708915
> std.error(Qg_F$Lnum)
[1] 0.6698872
>
> std.error(Qg_A$TM)
[1] 0.05521322
> std.error(Qg_F$TM)
[1] 0.1272773
>
> std.error(Qg_A$RM)
```

```
[1] 0.0465318
> std.error(Qg_F$RM)
[1] 0.06512664
>
> std.error(Qg_A$SM)
[1] 0.01762037
> std.error(Qg_F$SM)
[1] 0.07081724
>
> std.error(Qg_A$RMF)
[1] 0.01420205
> std.error(Qg_F$RMF)
[1] 0.0141594
>
> std.error(Qg_A$SMF)
[1] 0.01420205
> std.error(Qg_F$SMF)
[1] 0.0141594
>
> std.error(Qg_A$RGR)
[1] 0.0005130239
> std.error(Qg_F$RGR)
[1] 0.0006035291
>
> std.error(Qg_A$SLA)
[1] 5.241104
> std.error(Qg_F$SLA)
[1] 2.745227
>
> std.error(Qg_A$STRL)
[1] 9.914294
> std.error(Qg_F$STRL)
[1] 15.82884
```

```
##########################

##summary(Mt_m1_Qg)
Call:
glm(formula = data_Qg$TM ~ cen, family = Gamma(), data = data_Qg)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-0.74991  -0.25362  -0.03065   0.13787   0.65972

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.97903    0.06668  14.683  < 2e-16 ***
cenF        -0.43976    0.07422  -5.925 1.91e-07 ***

##summary(ScRM_m1_Qg)

Call:
glm(formula = data_Qg$ScRM ~ cen, family = Gamma(), data = data_Qg)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.1807  -0.5375  -0.1771   0.1676   2.1301

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)    7.693      1.149   6.698 1.01e-08 ***
cenF          -2.367      1.348  -1.756   0.0845 .

##summary(TpRM_m1_Qg)

Call:
glm(formula = data_Qg$TpRM ~ cen, family = Gamma(), data = data_Qg)
```

```
Deviance Residuals:
     Min        1Q    Median        3Q       Max
-0.90232  -0.36760  -0.06129   0.22342   0.96737

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   1.6139     0.1286  12.545   <2e-16 ***
cenF         -0.1116     0.1669  -0.669    0.506

##summary(StM_m1_Qg)

Call:
glm(formula = data_Qg$StM ~ cen, family = Gamma(), data = data_Qg)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-0.75079  -0.15619  -0.02901   0.12038   0.65851

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   9.0435     0.5320  17.000  < 2e-16 ***
cenF         -4.0301     0.5929  -6.797 6.92e-09 ***

##summary(SLA_m1_Qg)

Call:
glm(formula = data_Qg$SLA ~ cen, family = Gamma(), data = data_Qg)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-0.86447  -0.07781   0.01418   0.12851   0.40268

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
```

```
(Intercept)  0.0108144  0.0004632  23.347  < 2e-16 ***
cenF        -0.0019110  0.0005737  -3.331  0.00152 **

##summary(H_m1_Qg)

Call:
glm(formula = data_Qg$H ~ cen, family = Gamma(), data = data_Qg)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-0.50040  -0.14558  -0.00312   0.11251   0.44198

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.115916   0.004078  28.422  < 2e-16 ***
cenF        -0.039686   0.004722  -8.404 1.47e-11 ***

## summary(ST_D_m1_Qg)

Call:
glm(formula = data_Qg$ST_D ~ cen, family = Gamma(), data = data_Qg)

Deviance Residuals:
      Min         1Q     Median         3Q        Max
-0.301028  -0.080318   0.001454   0.082100   0.220583

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   4.9890     0.1271  39.246  < 2e-16 ***
cenF         -0.6253     0.1609  -3.886 0.000268 ***

## summary(RGR_m1_Qg)

Call:
```

```
glm(formula = data_Qg$RGR ~ cen, family = Gamma(), data = data_Qg)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-0.30248  -0.10315  -0.01426   0.06795   0.33377

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   53.052      1.487  35.688  < 2e-16 ***
cenF         -10.942      1.818  -6.017 1.35e-07 ***

## summary(Lnum_m1_Qg)

Call:
glm(formula = data_Qg$Lnum ~ cen, family = Gamma(), data = data_Qg)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-1.28193  -0.35650   0.00553   0.17184   1.00343

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.19697    0.01786  11.031 9.12e-16 ***
cenF        -0.10556    0.01931  -5.466 1.06e-06 ***

##summary(STRL_m1_Qg)

Call:
glm(formula = data_Qg$STRL ~ cen, family = Gamma(), data = data_Qg)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.9450  -0.3572  -0.1258   0.2723   1.0104
```

```
Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.0069441  0.0005897  11.776   <2e-16 ***
cenF        -0.0015828  0.0007148  -2.214   0.0308 *



##summary(RMF_m1_Qg)

Call:
glm(formula = data_Qg$RMF ~ cen, family = Gamma(), data = data_Qg)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-0.29366  -0.09690   0.00116   0.05704   0.51485

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  1.37364    0.03984   34.48   <2e-16 ***
cenF         0.79921    0.06868   11.64   <2e-16 ***

##summary(SM_m1_Qg)

Call:
glm(formula = data_Qg$SM ~ cen, family = Gamma(), data = data_Qg)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-1.15517  -0.28838  -0.06816   0.20630   0.65814

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   3.6791     0.2706  13.596  < 2e-16 ***
cenF         -2.6800     0.2784  -9.628 1.48e-13 ***
```

```
##summary(RM_m1_Qg)

Call:
glm(formula = data_Qg$RM ~ cen, family = Gamma(), data = data_Qg)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-0.77340  -0.35935  -0.02685   0.21959   0.77829

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   1.3340     0.1019  13.086   <2e-16 ***
cenF         -0.1623     0.1293  -1.255    0.215

## summary(RL_m1_Qg)

Call:
glm(formula = data_Qg$RL ~ cen, family = Gamma(), data = data_Qg)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-0.43305  -0.02786   0.00081   0.03386   0.25846

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.0122955  0.0003019  40.721  < 2e-16 ***
cenF        -0.0023371  0.0003719  -6.285  4.9e-08 ***


################################################ Ta
##################################################

summary(Ta_A)
      sp            cen              ST_D            H            Lnum
```

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

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

```
 3rd Qu.:0.6797
 Max.   :0.7448

###
> std.error(Ta_A$H)
[1] 0.1150076
> std.error(Ta_F$H)
[1] 0.2146761
>
> std.error(Ta_A$ST_D)
[1] 0.01897175
> std.error(Ta_F$ST_D)
[1] 0.01545983
>
> std.error(Ta_A$RL)
[1] 2.398475
> std.error(Ta_F$RL)
[1] 0.7385989
>
> std.error(Ta_A$Lnum)
[1] 0.3170494
> std.error(Ta_F$Lnum)
[1] 0.4481123
>
> std.error(Ta_A$TM)
[1] 0.141469
> std.error(Ta_F$TM)
[1] 0.2074348
>
> std.error(Ta_A$RM)
[1] 0.113367
> std.error(Ta_F$RM)
[1] 0.1398907
>
```

```
> std.error(Qg_A$SM)
[1] 0.01762037
> std.error(Ta_F$SM)
[1] 0.1042436
>
> std.error(Ta_A$RMF)
[1] 0.01781508
> std.error(Ta_F$RMF)
[1] 0.01825998
>
> std.error(Ta_A$SMF)
[1] 0.01781508
> std.error(Ta_F$SMF)
[1] 0.01825998
>
> std.error(Ta_A$RGR)
[1] 0.0005543409
> std.error(Ta_F$RGR)
[1] 0.0005995452
>
> std.error(Ta_A$SLA)
[1] 4.892494
> std.error(Ta_F$SLA)
[1] 7.603923
>
> std.error(Ta_A$STRL)
[1] 4.813579
> std.error(Ta_F$STRL)
[1] 7.097902


#####################
##summary(Mt_m1_Ta)
```

```
Call:
glm(formula = data_Ta$TM ~ cen, family = Gamma(), data = data_Ta)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-0.98860  -0.20279  -0.02146   0.22410   0.64462

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.39366    0.02290  17.191  < 2e-16 ***
cenF        -0.09656    0.02886  -3.346  0.00143 **

##summary(ScRM_m1_Ta)

Call:
glm(formula = data_Ta$ScRM ~ cen, family = Gamma(), data = data_Ta)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-1.57636  -0.42375  -0.05134   0.24601   1.13221

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   2.6022     0.2391  10.881 9.88e-16 ***
cenF         -0.3064     0.3212  -0.954    0.344

##summary(TpRM_m1_Ta)

Call:
glm(formula = data_Ta$TpRM ~ cen, family = Gamma(), data = data_Ta)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-1.11915  -0.29088  -0.09637   0.20250   0.70217
```

```
Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.66679    0.04478   14.89   <2e-16 ***
cenF         0.02474    0.06507    0.38    0.705

##summary(StM_m1_Ta)

Call:
glm(formula = data_Ta$StM ~ cen, family = Gamma(), data = data_Ta)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.0871  -0.5068  -0.2556  -0.0705   3.2873

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)    9.293      2.213   4.200 9.14e-05 ***
cenF          -1.626      2.888  -0.563    0.575

##summary(SLA_m1_Ta)

Call:
glm(formula = data_Ta$SLA ~ cen, family = Gamma(), data = data_Ta)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-0.49915  -0.19649  -0.03150   0.07719   0.73918

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.0080971  0.0003672  22.048  < 2e-16 ***
cenF        -0.0013312  0.0004818  -2.763  0.00763 **
```

```
## summary(H_m1_Ta)

Call:
glm(formula = data_Ta$H ~ cen, family = Gamma(), data = data_Ta)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-0.49482  -0.19612  -0.01177   0.11161   0.44730

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.31880    0.01381  23.084  < 2e-16 ***
cenF        -0.08552    0.01721  -4.969 6.11e-06 ***

## summary(ST_D_m2_Ta)

Call:
glm(formula = data_Ta$ST_D ~ cen, family = gaussian(), data = data_Ta)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-0.14506  -0.06456  -0.01950   0.03500   0.27493

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.42256    0.01723  24.532   <2e-16 ***
cenF         0.01044    0.02456   0.425    0.672

##summary(RGR_m1_Ta)

Call:
glm(formula = data_Ta$RGR ~ cen, family = Gamma(), data = data_Ta)

Deviance Residuals:
```

```
     Min        1Q    Median        3Q       Max  
-0.55040  -0.09898   0.02418   0.11032   0.21258  

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)   49.158      1.315  37.387   <2e-16 ***
cenF          -4.708      1.786  -2.636   0.0107 *  

##summary(Lnum_m1_Ta)

Call:
glm(formula = data_Ta$Lnum ~ cen, family = Gamma(), data = data_Ta)

Deviance Residuals: 
     Min        1Q    Median        3Q       Max  
-0.52719  -0.16760   0.00838   0.11752   0.57013  

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept)  0.140271   0.005750  24.396  < 2e-16 ***
cenF        -0.056238   0.006732  -8.354 1.38e-11 ***

## summary(RMF_m2_Ta)

Call:
glm(formula = data_Ta$RMF ~ cen, family = gaussian(), data = data_Ta)

Deviance Residuals: 
      Min         1Q     Median         3Q        Max  
-0.215909  -0.060700  -0.005448   0.044092   0.210712  

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)  0.73892    0.01789  41.308  < 2e-16 ***
```

```
cenF        -0.18176    0.02551  -7.126 1.66e-09 ***

## summary(SM_m2_Ta)

Call:
glm(formula = data_Ta$SM ~ cen, family = gaussian(), data = data_Ta)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-1.05967  -0.31883   0.04337   0.22567   1.05583

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.65623    0.08351   7.858 9.52e-11 ***
cenF         0.82795    0.11909   6.953 3.26e-09 ***

##ummary(RM_m1_Ta)

Call:
glm(formula = data_Ta$RM ~ cen, family = Gamma(), data = data_Ta)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-1.19401  -0.30114  -0.04404   0.19814   0.70858

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.5307810  0.0354876  14.957   <2e-16 ***
cenF        0.0006665  0.0506359   0.013     0.99

##summary(RL_m1_Ta)

Call:
glm(formula = data_Ta$RL ~ cen, family = Gamma(), data = data_Ta)
```

```
Deviance Residuals:
     Min        1Q    Median        3Q       Max
-0.98840  -0.01426   0.00698   0.02789   0.20253

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.0105777  0.0001990  53.143   <2e-16 ***
cenF        -0.0004147  0.0002782  -1.491    0.141

##summary(STRL_m2_Ta)

Call:
glm(formula = data_Ta$STRL ~ cen, family = gaussian(), data = data_Ta)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-45.917  -20.790   -4.635   10.871  138.157

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   69.685      5.979  11.655   <2e-16 ***
cenF          11.891      8.525   1.395    0.168

######################################## Hs
###############################################

summary(Hs_A)
      sp                cen                 ST_D              H              Lnum
 Length:30          Length:30          Min.   :0.3440   Min.   :10.40   Min.   :1.000
 Class :character   Class :character   1st Qu.:0.3924   1st Qu.:16.00   1st Qu.:2.000
 Mode  :character   Mode  :character   Median :0.4243   Median :17.60   Median :2.000
                                       Mean   :0.4268   Mean   :18.42   Mean   :2.167
                                       3rd Qu.:0.4631   3rd Qu.:20.95   3rd Qu.:3.000
                                       Max.   :0.5390   Max.   :31.00   Max.   :4.000
```

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

```
                                   3rd Qu.:0.4780   3rd Qu.:26.80   3rd Qu.:5.000
                                   Max.   :0.5600   Max.   :39.20   Max.   :6.000
       RL            TpRM           ScRM            StM             TLM
 Min.   : 98.0   Min.   :1.053   Min.   :0.2308   Min.   :0.4802   Min.   :1.712
 1st Qu.:103.8   1st Qu.:3.408   1st Qu.:1.0377   1st Qu.:0.6584   1st Qu.:2.404
 Median :107.5   Median :4.479   Median :1.3816   Median :0.8807   Median :2.992
 Mean   :107.8   Mean   :4.473   Mean   :1.6110   Mean   :0.8826   Mean   :2.964
 3rd Qu.:111.8   3rd Qu.:5.500   3rd Qu.:2.0025   3rd Qu.:1.0144   3rd Qu.:3.303
 Max.   :120.0   Max.   :8.774   Max.   :6.7021   Max.   :1.4414   Max.   :4.857
       RM               SM              TM               RS              LMF
 Min.   : 1.675   Min.   :2.261   Min.   : 3.992   Min.   :0.7231   Min.   :0.2097
 1st Qu.: 4.769   1st Qu.:3.246   1st Qu.: 7.856   1st Qu.:1.3589   1st Qu.:0.2735
 Median : 5.502   Median :3.854   Median : 9.806   Median :1.5317   Median :0.3078
 Mean   : 6.084   Mean   :3.847   Mean   : 9.931   Mean   :1.5574   Mean   :0.3089
 3rd Qu.: 7.454   3rd Qu.:4.387   3rd Qu.:11.846   3rd Qu.:1.8481   3rd Qu.:0.3345
 Max.   :12.271   Max.   :6.212   Max.   :17.657   Max.   :2.5605   Max.   :0.4601
      RMF              SMF              SLA              RGR              STRL
 Min.   :0.4197   Min.   :0.2809   Min.   : 47.59   Min.   :0.00935   Min.   :12.65
 1st Qu.:0.5761   1st Qu.:0.3511   1st Qu.: 80.31   1st Qu.:0.01585   1st Qu.:19.56
 Median :0.6050   Median :0.3950   Median : 86.68   Median :0.01814   Median :24.25
 Mean   :0.5988   Mean   :0.4012   Mean   : 91.04   Mean   :0.01729   Mean   :28.61
 3rd Qu.:0.6489   3rd Qu.:0.4239   3rd Qu.: 92.13   3rd Qu.:0.01952   3rd Qu.:30.84
 Max.   :0.7191   Max.   :0.5803   Max.   :257.04   Max.   :0.02271   Max.   :93.98
      RER
 Min.   :0.6610
 1st Qu.:0.7022
 Median :0.7528
 Mean   :0.7541
 3rd Qu.:0.8044
 Max.   :0.9028

std.error(Hs_A$H)
[1] 0.8497383
> std.error(Hs_F$H)
```

```
[1] 0.8870252
>
> std.error(Hs_A$ST_D)
[1] 0.009277045
> std.error(Hs_F$ST_D)
[1] 0.01010964
>
> std.error(Hs_A$RL)
[1] 1.068566
> std.error(Hs_F$RL)
[1] 1.09648
>
> std.error(Hs_A$Lnum)
[1] 0.15225
> std.error(Hs_F$Lnum)
[1] 0.203042
>
> std.error(Hs_A$TM)
[1] 0.2968778
> std.error(Hs_F$TM)
[1] 0.5660409
>
> std.error(Hs_A$RM)
[1] 0.2123691
> std.error(Hs_F$RM)
[1] 0.4348676
>
> std.error(Hs_A$SM)
[1] 0.1053035
> std.error(Hs_F$SM)
[1] 0.1711766
>
> std.error(Hs_A$RMF)
[1] 0.008866564
```

```
> std.error(Hs_F$RMF)
[1] 0.01234643
>
> std.error(Hs_A$SMF)
[1] 0.008866564
> std.error(Hs_F$SMF)
[1] 0.01234643
>
> std.error(Hs_A$RGR)
[1] 0.0004199812
> std.error(Hs_F$RGR)
[1] 0.0005701719
>
> std.error(Hs_A$SLA)
[1] 1.953027
> std.error(Hs_F$SLA)
[1] 6.104325
>
> std.error(Hs_A$STRL)
[1] 1.9324
> std.error(Hs_F$STRL)
[1] 2.863996
################################
##summary(Mt_m1_Hs)

Call:
glm(formula = data_Hs$TM ~ cen, family = Gamma(), data = data_Hs)

Deviance Residuals:
    Min        1Q    Median       3Q       Max
-0.79160  -0.18266  -0.04913   0.18464   0.63639

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
```

```
(Intercept)  0.160772   0.008452  19.023  < 2e-16 ***
cenF        -0.060075   0.009972  -6.024 1.24e-07 ***

##summary(ScRM_m1_Hs)

Call:
glm(formula = data_Hs$ScRM ~ cen, family = Gamma(), data = data_Hs)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.4740  -0.4228  -0.1367   0.2677   1.8626

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   1.1103     0.1264   8.785 3.01e-12 ***
cenF         -0.4896     0.1448  -3.381   0.0013 **

##summary(TpRM_m1_Hs)

Call:
glm(formula = data_Hs$TpRM ~ cen, family = Gamma(), data = data_Hs)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-1.16747  -0.27067  -0.04291   0.18711   0.75876

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.34359    0.02071  16.593  < 2e-16 ***
cenF        -0.12001    0.02471  -4.858 9.38e-06 ***

##summary(StM_m1_Hs)

Call:
```

```
glm(formula = data_Hs$StM ~ cen, family = Gamma(), data = data_Hs)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-0.55269  -0.22235  -0.00981   0.17824   0.53413

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  1.51440    0.07617  19.882  < 2e-16 ***
cenF        -0.38136    0.09513  -4.009 0.000177 ***

##summary(SLA_m1_Hs)

Call:
glm(formula = data_Hs$SLA ~ cen, family = Gamma(), data = data_Hs)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-0.58558  -0.12623  -0.02651   0.07028   1.25333

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.0136244  0.0006950  19.605  < 2e-16 ***
cenF        -0.0026404  0.0008927  -2.958  0.00448 **

##summary(H_m1_Hs)

Call:
glm(formula = data_Hs$H ~ cen, family = Gamma(), data = data_Hs)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-0.52199  -0.13766  -0.02419   0.12391   0.56992
```

```
Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.054289   0.002263  23.995  < 2e-16 ***
cenF        -0.012932   0.002844  -4.547 2.82e-05 ***

##summary(ST_D_m1_Hs)

Call:
glm(formula = data_Hs$ST_D ~ cen, family = Gamma(), data = data_Hs)

Deviance Residuals:
      Min         1Q     Median         3Q        Max
-0.268673  -0.088835   0.009772   0.083037   0.245155

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  2.34302    0.05225  44.845   <2e-16 ***
cenF        -0.08305    0.07259  -1.144    0.257

## summary(RGR_m1_Hs)

Call:
glm(formula = data_Hs$RGR ~ cen, family = Gamma(), data = data_Hs)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-0.55757  -0.11011  -0.00885   0.12079   0.28581

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   75.618      2.448  30.886  < 2e-16 ***
cenF         -17.767      3.083  -5.764 3.33e-07 ***

## summary(Lnum_m1_Hs)
```

```
Call:
glm(formula = data_Hs$Lnum ~ cen, family = Gamma(), data = data_Hs)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-0.68517  -0.28954  -0.07899   0.21398   0.68271

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.46154    0.02813  16.406  < 2e-16 ***
cenF        -0.21564    0.03188  -6.765 7.27e-09 ***

##summary(STRL_m1_Hs)

Call:
glm(formula = data_Hs$STRL ~ cen, family = Gamma(), data = data_Hs)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-0.71866  -0.28525  -0.07539   0.14266   1.48016

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.025175   0.001981  12.707   <2e-16 ***
cenF        0.009775   0.003390   2.884   0.0055 **

## summary(RMF_m1_Hs)

Call:
glm(formula = data_Hs$RMF ~ cen, family = Gamma(), data = data_Hs)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
```

```
-0.33558  -0.04270   0.00320   0.06718   0.18896

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  1.64377    0.02935  56.007   <2e-16 ***
cenF         0.02633    0.04184   0.629    0.532

##summary(SM_m1_Hs)

Call:
glm(formula = data_Hs$SM ~ cen, family = Gamma(), data = data_Hs)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-0.51842  -0.13717  -0.02556   0.13006   0.52072

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.41513    0.01831  22.672  < 2e-16 ***
cenF        -0.15519    0.02160  -7.184 1.44e-09 ***

##summary(RM_m1_Hs)

Call:
glm(formula = data_Hs$RM ~ cen, family = Gamma(), data = data_Hs)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-1.06301  -0.23774  -0.08251   0.16381   0.79424

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.26239    0.01682   15.60  < 2e-16 ***
cenF        -0.09802    0.01984   -4.94 6.99e-06 ***
```

```
##summary(RL_m1_Hs)

Call:
glm(formula = data_Hs$RL ~ cen, family = Gamma(), data = data_Hs)

Deviance Residuals:
      Min         1Q     Median         3Q        Max
-0.097706  -0.038686  -0.003731   0.044516   0.108748

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  9.315e-03  9.372e-05  99.391   <2e-16 ***
cenF        -4.261e-05  1.322e-04  -0.322    0.748

################################################ Kc
###########################################


summary(Kc_A)
      sp                cen                ST_D              H              Lnum
 Length:22          Length:22          Min.   :0.2065   Min.   :1.800   Min.   :1.000
 Class :character   Class :character   1st Qu.:0.2263   1st Qu.:2.525   1st Qu.:1.000
 Mode  :character   Mode  :character   Median :0.2445   Median :3.000   Median :1.000
                                       Mean   :0.2474   Mean   :3.345   Mean   :1.273
                                       3rd Qu.:0.2649   3rd Qu.:3.400   3rd Qu.:1.750
                                       Max.   :0.3030   Max.   :7.300   Max.   :2.000
       RL             TpRM             ScRM              StM               TLM
 Min.   :25.30   Min.   :0.6195   Min.   :0.05650   Min.   :0.01690   Min.   :0.0474
 1st Qu.:48.50   1st Qu.:0.8563   1st Qu.:0.09975   1st Qu.:0.02533   1st Qu.:0.0865
 Median :63.15   Median :1.2578   Median :0.12445   Median :0.02625   Median :0.1138
 Mean   :61.24   Mean   :1.2516   Mean   :0.15697   Mean   :0.03403   Mean   :0.1264
 3rd Qu.:71.38   3rd Qu.:1.5051   3rd Qu.:0.21377   3rd Qu.:0.03742   3rd Qu.:0.1396
 Max.   :97.60   Max.   :2.1173   Max.   :0.35800   Max.   :0.08500   Max.   :0.3483
       RM              SM              TM              RS              LMF
```

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

```
 Max.   :103.0   Max.   :7.822   Max.   :0.3830   Max.   :0.10880   Max.   :0.3274
       RM              SM              TM              RS              LMF
 Min.   :0.9862   Min.   :0.0950   Min.   :1.188   Min.   : 3.374   Min.   :0.01034
 1st Qu.:1.6330   1st Qu.:0.1576   1st Qu.:1.789   1st Qu.: 7.862   1st Qu.:0.05514
 Median :1.9857   Median :0.1996   Median :2.206   Median :10.809   Median :0.06889
 Mean   :2.5613   Mean   :0.2087   Mean   :2.770   Mean   :14.529   Mean   :0.07782
 3rd Qu.:2.5626   3rd Qu.:0.2440   3rd Qu.:2.779   3rd Qu.:13.400   3rd Qu.:0.09991
 Max.   :8.0758   Max.   :0.3952   Max.   :8.471   Max.   :65.761   Max.   :0.20386
      RMF              SMF              SLA              RGR              STRL
 Min.   :0.7714   Min.   :0.01498   Min.   : 63.59   Min.   :0.01864   Min.   : 8.17
 1st Qu.:0.8872   1st Qu.:0.06944   1st Qu.: 94.16   1st Qu.:0.02131   1st Qu.:37.26
 Median :0.9153   Median :0.08468   Median :115.03   Median :0.02298   Median :48.07
 Mean   :0.9058   Mean   :0.09422   Mean   :111.17   Mean   :0.02390   Mean   :49.19
 3rd Qu.:0.9306   3rd Qu.:0.11284   3rd Qu.:131.85   3rd Qu.:0.02570   3rd Qu.:66.55
 Max.   :0.9850   Max.   :0.22864   Max.   :158.61   Max.   :0.03231   Max.   :90.15
      RER
 Min.   :0.2926
 1st Qu.:0.6050
 Median :0.6625
 Mean   :0.6343
 3rd Qu.:0.7378
 Max.   :0.7685


std.error(Kc_A$H)
[1] 0.3343746
> std.error(Kc_F$H)
[1] 0.2750015
>
> std.error(Kc_A$ST_D)
[1] 0.005887214
> std.error(Kc_F$ST_D)
[1] 0.005916295
>
```

```
> std.error(Kc_A$RL)
[1] 3.993005
> std.error(Kc_F$RL)
[1] 3.400739
>
> std.error(Kc_A$Lnum)
[1] 0.09718591
> std.error(Kc_F$Lnum)
[1] 0.1483087
>
> std.error(Kc_A$TM)
[1] 0.09507547
> std.error(Kc_F$TM)
[1] 0.3935572
>
> std.error(Kc_A$RM)
[1] 0.09603925
> std.error(Kc_F$RM)
[1] 0.3909287
>
> std.error(Kc_A$SM)
[1] 0.01425702
> std.error(Kc_F$SM)
[1] 0.01715668
>
> std.error(Kc_A$RMF)
[1] 0.01300992
> std.error(Kc_F$RMF)
[1] 0.01072463
>
> std.error(Kc_A$SMF)
[1] 0.01300992
> std.error(Kc_F$SMF)
[1] 0.01072463
```

```
>
> std.error(Kc_A$RGR)
[1] 0.0005230258
> std.error(Kc_F$RGR)
[1] 0.0007581438
>
> std.error(Kc_A$SLA)
[1] 7.127763
> std.error(Kc_F$SLA)
[1] 5.90682
>
> std.error(Kc_A$STRL)
[1] 4.783939
> std.error(Kc_F$STRL)
[1] 4.786222
>
#################
##summary(Mt_m1_Kc)

Call:
glm(formula = data_Kc$TM ~ cen, family = Gamma(), data = data_Kc)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-0.74230  -0.37128  -0.06882   0.12814   1.37137

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.63737    0.06770   9.415 8.35e-12 ***
cenF        -0.27635    0.07825  -3.532  0.00104 **

##summary(ScRM_m1_Kc)

Call:
```

```
glm(formula = data_Kc$ScRM ~ cen, family = Gamma(), data = data_Kc)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.1128  -0.4458  -0.1908   0.3492   0.9552

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   6.3705     0.7426   8.578 1.08e-10 ***
cenF         -0.5962     1.0130  -0.589    0.559

## summary(TpRM_m1_Kc)

Call:
glm(formula = data_Kc$TpRM ~ cen, family = Gamma(), data = data_Kc)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-0.83664  -0.46263  -0.08065   0.11694   1.47570

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.79899    0.09736   8.207 3.45e-10 ***
cenF        -0.38026    0.11048  -3.442  0.00134 **

## summary(StM_m1_Kc)

Call:
glm(formula = data_Kc$StM ~ cen, family = Gamma(), data = data_Kc)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-0.62691  -0.28520  -0.12546   0.07628   1.20722
```

```
Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   29.388      3.152   9.323  1.1e-11 ***
cenF          -4.253      4.190  -1.015    0.316

## summary(SLA_m1_Kc)

Call:
glm(formula = data_Kc$SLA ~ cen, family = Gamma(), data = data_Kc)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-1.17616  -0.14342   0.03802   0.15381   0.44026

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.0086698  0.0004958   17.49   <2e-16 ***
cenF        0.0003258  0.0007233    0.45    0.655

##summary(H_m1_Kc)

Call:
glm(formula = data_Kc$H ~ cen, family = Gamma(), data = data_Kc)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-0.56189  -0.22907  -0.10705   0.01622   1.02268

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.29891    0.02790  10.712 1.87e-13 ***
cenF         0.02072    0.04137   0.501    0.619

##summary(ST_D_m1_Kc)
```

```
Call:
glm(formula = data_Kc$ST_D ~ cen, family = Gamma(), data = data_Kc)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-0.22394  -0.08471  -0.01244   0.07736   0.22305

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  4.04263    0.09424  42.896   <2e-16 ***
cenF        -0.10008    0.13316  -0.752    0.457

##summary(RGR_m1_Kc)

Call:
glm(formula = data_Kc$RGR ~ cen, family = Gamma(), data = data_Kc)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-0.25856  -0.11678  -0.00378   0.07618   0.31711

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   50.474      1.450  34.809  < 2e-16 ***
cenF          -8.641      1.902  -4.545 4.79e-05 ***

##summary(Lnum_m1_Kc)

Call:
glm(formula = data_Kc$Lnum ~ cen, family = poisson(), data = data_Kc)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
```

```
-0.4165  -0.4165  -0.2513   0.4088   1.0988

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)   0.2412     0.1890   1.276    0.202
cenF          0.1483     0.2607   0.569    0.569

## summary(STRL_m1_Kc)

Call:
glm(formula = data_Kc$STRL ~ cen, family = Gamma(), data = data_Kc)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-1.38666  -0.26285  -0.02745   0.22560   0.77734

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.018627   0.001715  10.863 1.22e-13 ***
cenF        0.001700   0.002571   0.661    0.512

## summary(RMF_m1_Kc)

Call:
glm(formula = data_Kc$RMF ~ cen, family = Gamma(), data = data_Kc)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-0.25230  -0.02305   0.01378   0.03868   0.08506

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  1.12446    0.01487   75.62   <2e-16 ***
cenF        -0.02044    0.02108   -0.97    0.338
```

```
## summary(SM_m1_Kc)

Call:
glm(formula = data_Kc$SM ~ cen, family = Gamma(), data = data_Kc)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-0.72227  -0.30224  -0.06573   0.13965   0.95281

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   6.2339     0.5287  11.790 9.44e-15 ***
cenF         -1.4412     0.6728  -2.142   0.0382 *

##summary(RM_m1_Kc)

Call:
glm(formula = data_Kc$RM ~ cen, family = Gamma(), data = data_Kc)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-0.82397  -0.41620  -0.06683   0.15417   1.41747

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.70995    0.08165   8.695 7.53e-11 ***
cenF        -0.31953    0.09370  -3.410  0.00147 **

##summary(RL_m1_Kc)

Call:
glm(formula = data_Kc$RL ~ cen, family = Gamma(), data = data_Kc)
```

```
Deviance Residuals:
     Min        1Q    Median        3Q       Max
-0.77083  -0.12946   0.03652   0.12903   0.50535

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.0163302  0.0008763  18.636  < 2e-16 ***
cenF        -0.0049153  0.0010775  -4.562 4.53e-05 ***
```