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Connecting competitor, stress-tolerator and ruderal (CSR) theory and Lund Potsdam Jena managed Land 5 (LPJmL 5) to assess the role of environmental conditions, management and functional diversity for grassland ecosystem functions

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S1 Additional figures

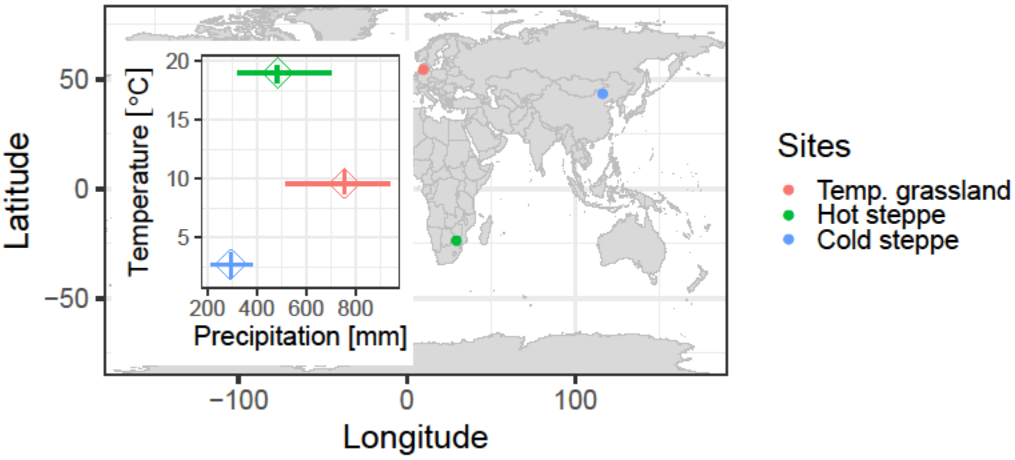

Fig. S1 Location (points) of the three grassland sites and their mean annual temperature and precipitation (squares). Lines show one standard deviation.

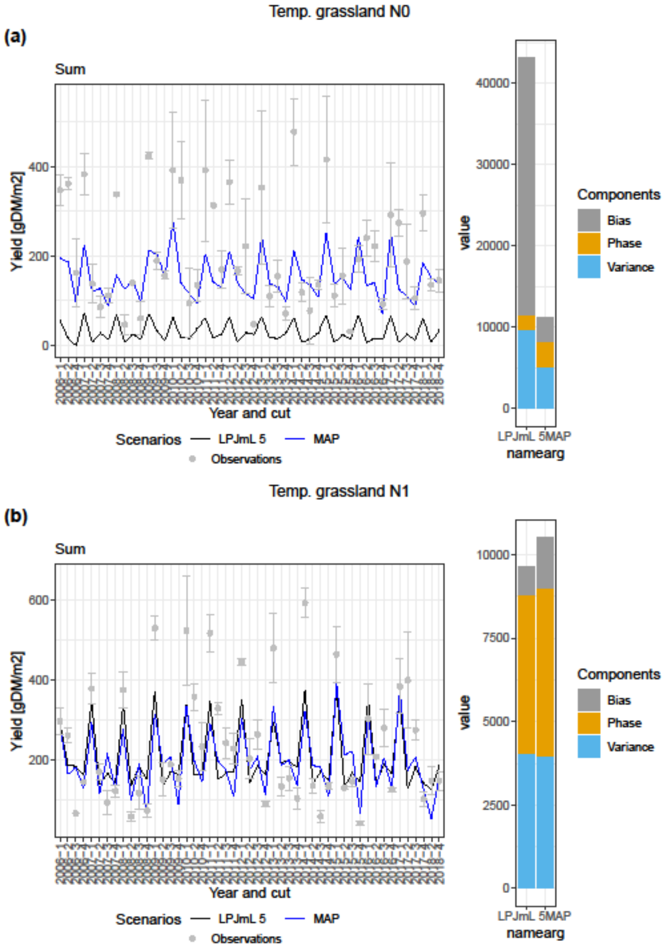

Fig. S2 Dry matter yields in gDMm^{-2} for the unfertilized (a) and fertilised (b) scenario for LPJmL 5.3 (black), the maximum a posteriori (MAP blue) and observations (grey) at the temperate grassland (left). Error bars are one standard deviation. MSE and its components bias (grey), phase (yellow) and variance (blue) for LPJmL 5.3 and the MAP

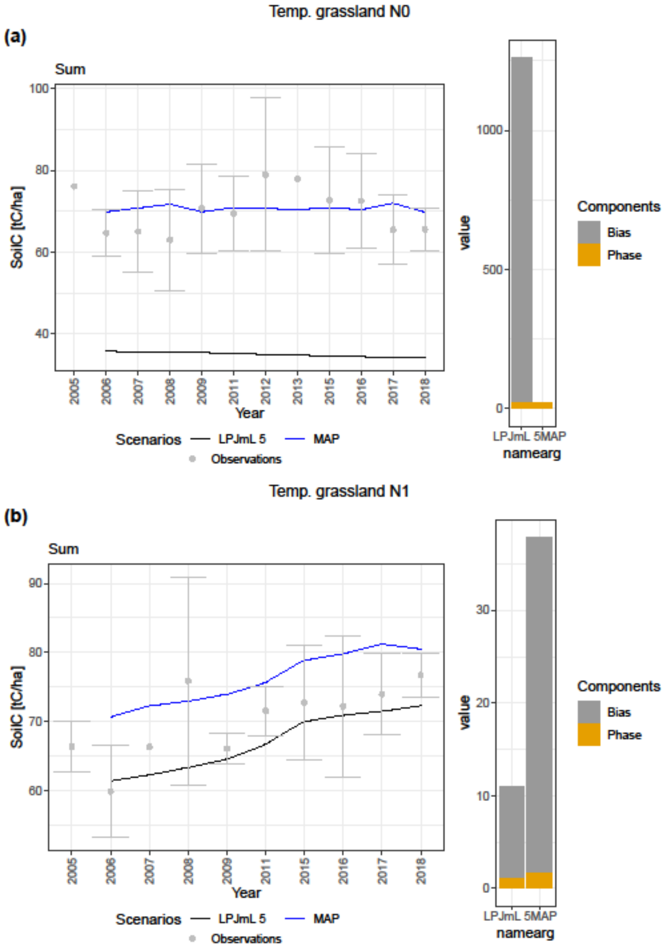

Fig. S3 Soil organic carbon in tCha^{-1} for the unfertilized (a) and fertilised (b) scenario for LPJmL 5.3 (black), the maximum a posteriori (MAP blue) and observations (grey) at the temperate grassland (left). Error bars are one standard deviation. MSE and its components bias (grey), phase (yellow) and variance (blue) for LPJmL 5.3 and the MAP

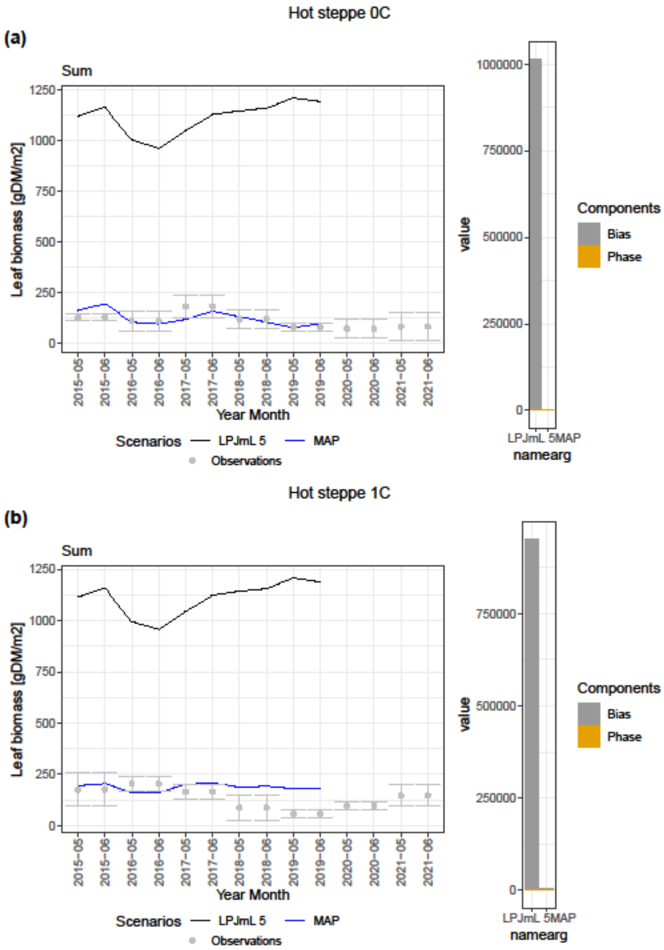

Fig. S4 Leaf biomass in $gDMm^{-2}$ for the ungrazed (a) and grazed (b) scenario for LPJmL 5.3 (black), the maximum a posteriori (MAP blue) and observations (grey) at the hot steppe (left). Error bars are one standard deviation. MSE and its components bias (grey), phase (yellow) and variance (blue) for LPJmL 5.3 and the MAP

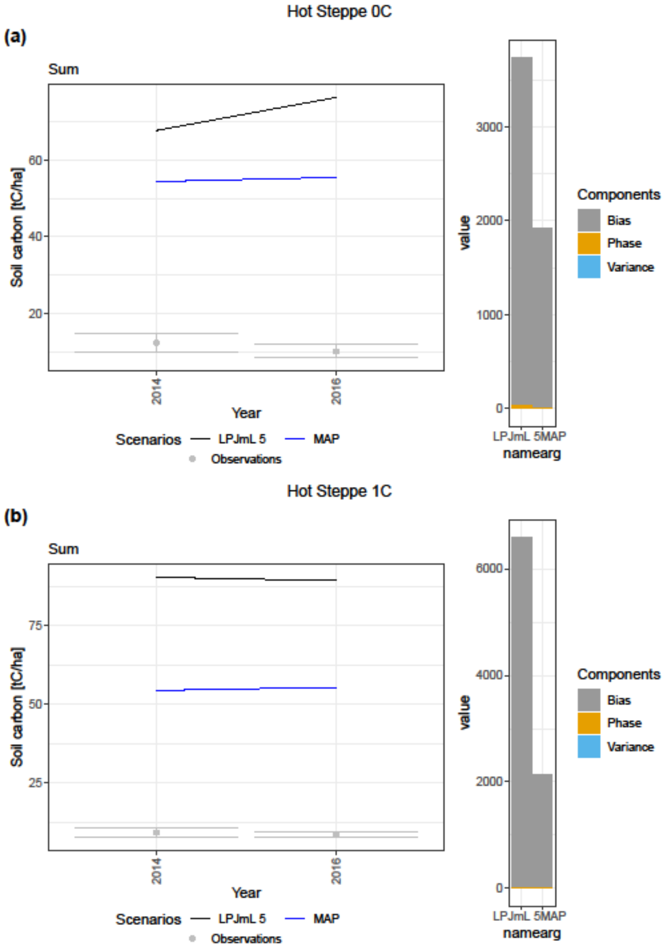

Fig. S5 Soil organic carbon in $tCha^{-1}$ for the ungrazed (a) and grazed (b) scenario for LPJmL 5.3 (black), the maximum a posteriori (MAP blue) and observations (grey) at the hot steppe (left). Error bars are one standard deviation. MSE and its components bias (grey), phase (yellow) and variance (blue) for LPJmL 5.3 and the MAP

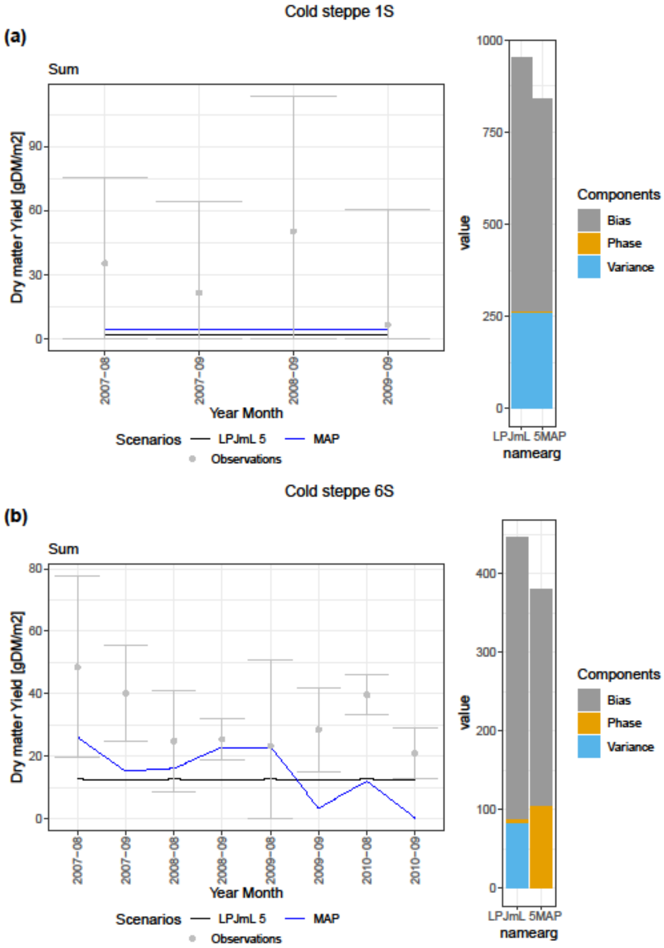

Fig. S6 Grazing offtake in $gDMm^{-2}$ for the extensively (a) and intensively (b) grazed scenario for LPJmL 5.3 (black), the maximum a posteriori (MAP blue) and observations (grey) at the cold steppe (left). Error bars are one standard deviation. MSE and its components bias (grey), phase (yellow) and variance (blue) for LPJmL 5.3 and the MAP

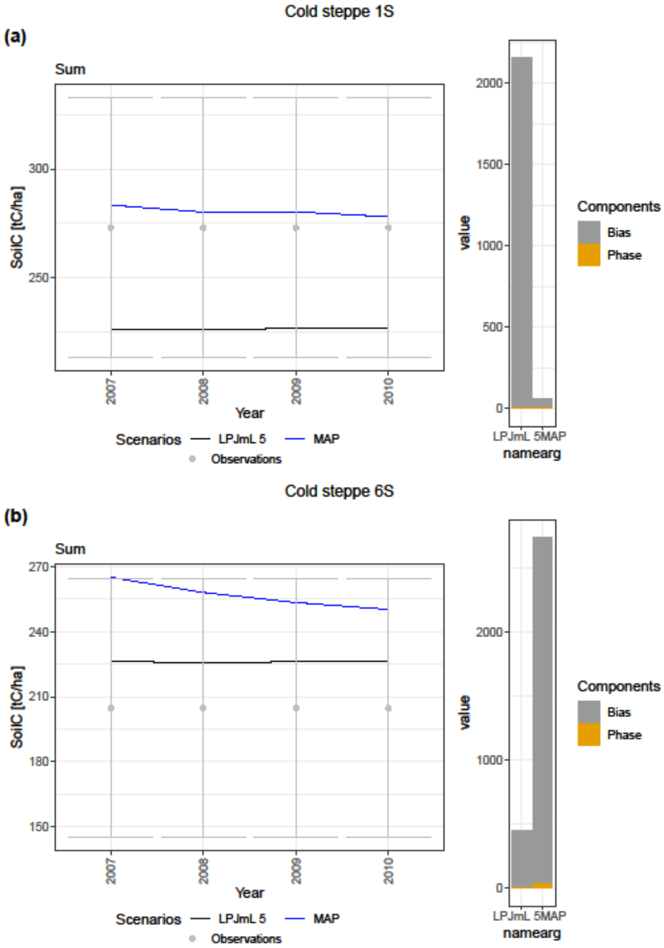

Fig. S7 Soil organic carbon in $tCha^{-1}$ for the extensively (a) and intensively (b) grazed scenario for LPJmL 5.3 (black), the maximum a posteriori (MAP blue) and observations (grey) at the cold steppe (left). Error bars are one standard deviation. MSE and its components bias (grey), phase (yellow) and variance (blue) for LPJmL 5.3 and the MAP

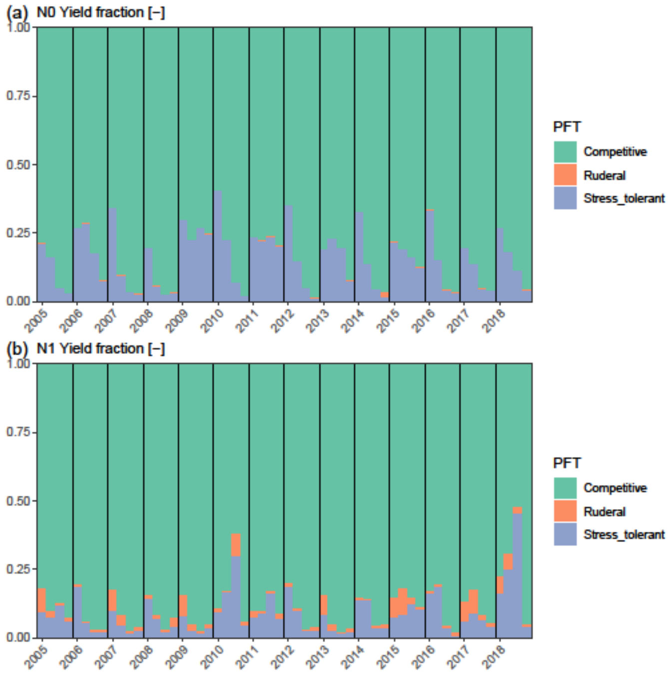

Fig. S8 PFT fractions (colours) of dry matter yield for each cut for the unfertilised (a) and fertilized (b) experiment at the temperate grassland.

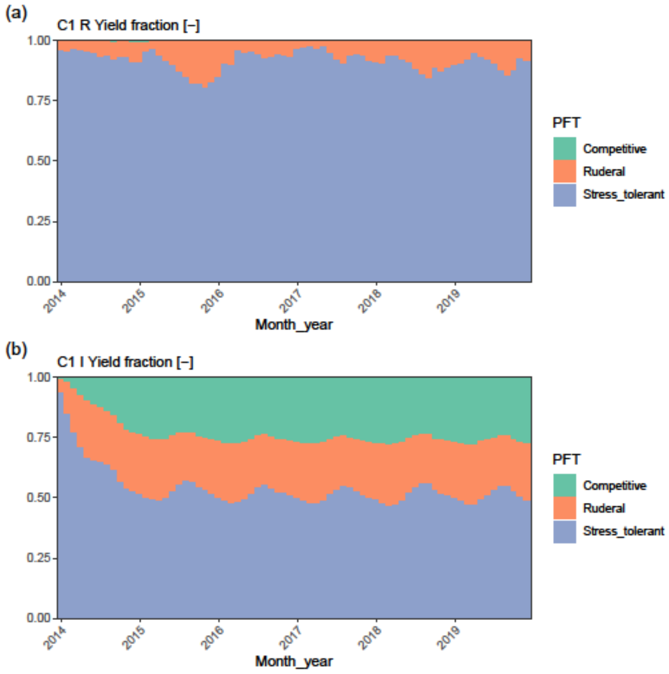

Fig. S9 PFT fractions (colours) of monthly grazing offtake for the rainfed (a) and irrigated (b) experiment at the hot steppe.

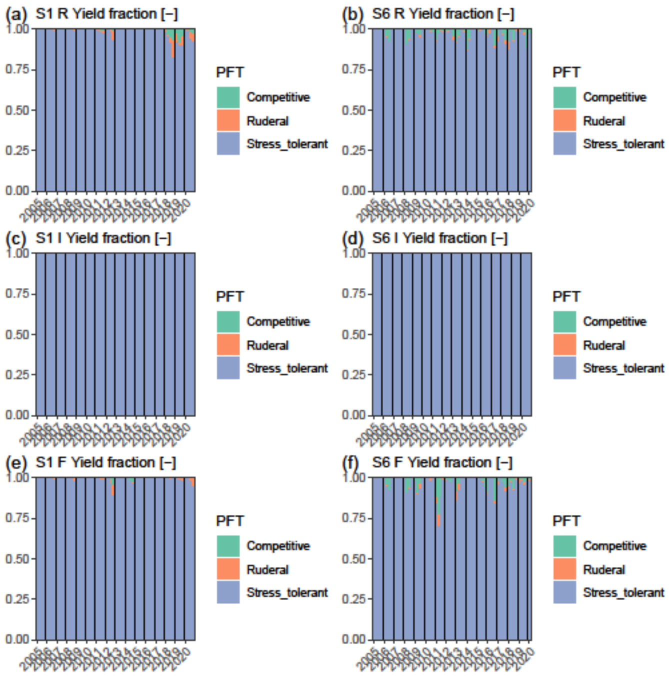

Fig. S10 PFT fractions (colours) of monthly grazing offtake for the extensively (a,c,e) and intensively (b,d,f) grazed experiment for the rainfed (a,b), fertilized (c,d) and irrigated (e,f) scenarios at the cold steppe.

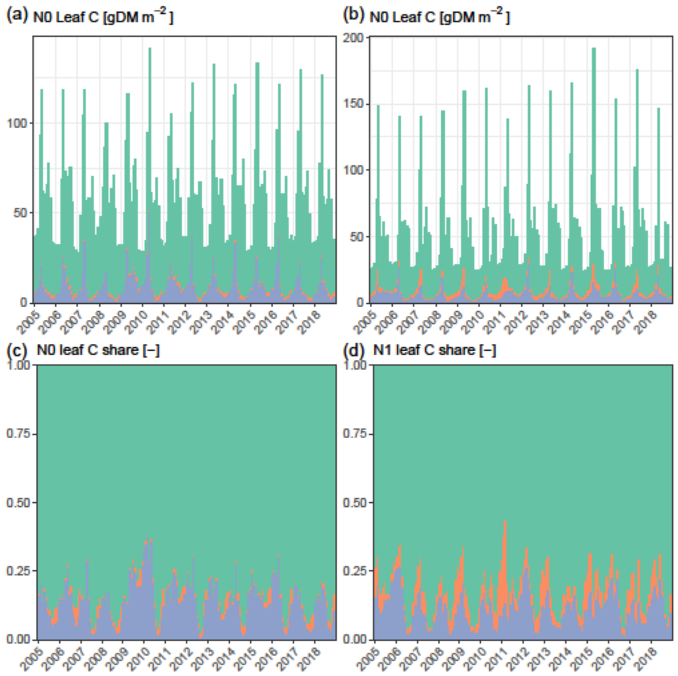

Fig. S11 Total (a,b) and fractional (c,d,) monthly leaf carbon for the unfertilized (a,c) and fertilized (b,d) experiment for each PFT (colours).

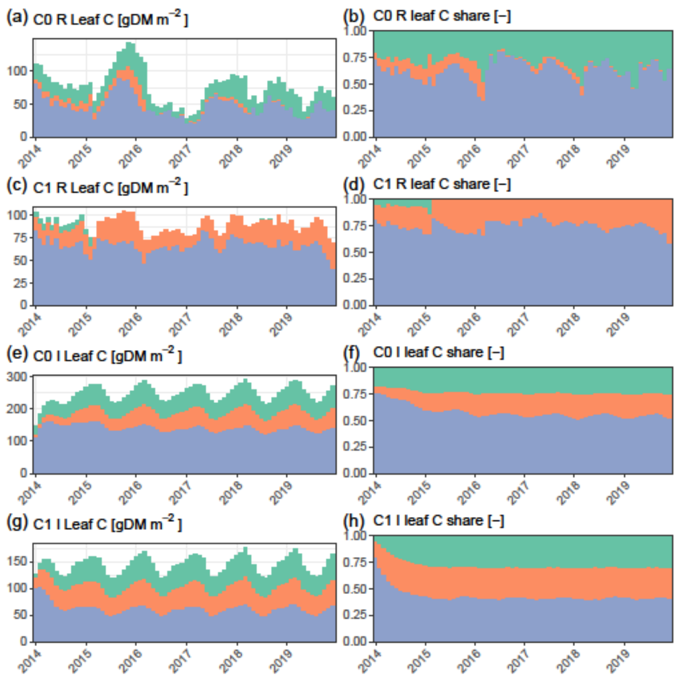

Fig. S12 Total (a,c,e,g) and fractional (b,d,f,h) monthly leaf carbon for the ungrazed (a,b,e,f) and grazed (c,d,g,h) experiment for the rainfed (a-d) and irrigated (e-h) scenarios for each PFT (colours).

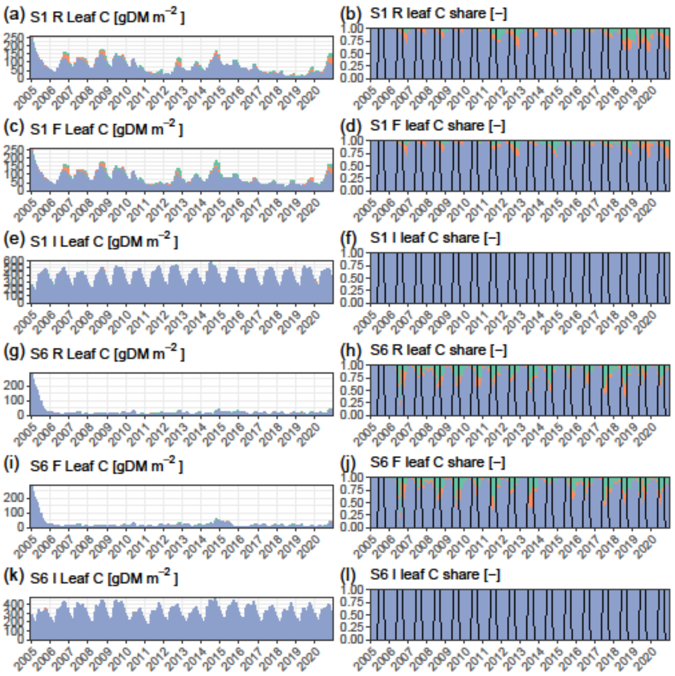

Fig. S13 Total (a,c,e,g,I,k) and fractional (b,d,f,h,j,l) monthly leaf carbon for the extensively (a-f) and intensively (g-l) grazed experiment for the rainfed (a,b,g,h), fertilized (c,d,I,j) and irrigated (e,f,k,l) scenarios for each PFT (colours).

S2 Additional tables

Table S1 Overview of the SLA and leaf longevity data obtained from the TRY database

Name	TRY dataset ID	References
Abisko and Sheffield Database	1	(Cornelissen et al., 2004; Quested et al., 2003)
GLOPNET—Global Plant Trait Network Database	20	(Wright et al., 2004)
Sheffield Database	37	(Cornelissen, 1996; Cornelissen et al., 2004; Diaz et al., 2004)
Leaf Physiology Database	67	(Kattge et al., 2009)
Global A, N, P, SLA Database	94	(Reich et al., 2009)
Tropical Traits from West Java Database	99	(Shiodera et al., 2008)
Functional traits explaining variation in plant life history strategies	285	(Adler et al., 2014)
Plant traits of Arabidopsis thaliana	359	(Blonder et al., 2015)

S3 Model development

S3.1 Phenology dependent allocation

Based on the GSI phenology (Forkel et al., 2014) we calculate the allocation of net primary productivity to leaves and roots (LR) dependent on changes in the temperature and light functions of the phenology (f) as follows:

$$LR = LR_{base} \cdot s_{light} \cdot s_{cold} \tag{S1}$$

With

$$s_i = \begin{cases} 1 + f_i \; if \; \Delta f_i > \epsilon_i \\ 1 \; if - \epsilon_i \leq \Delta f_i \leq \epsilon_i \\ 1 - f_i \; if \; \Delta f_i < -\epsilon_i \end{cases} \quad \text{(S2)}$$

where $i \in (light, cold)$, $\Delta f_i = f_{i,t} - f_{i,t-1}$,$\epsilon_{light} = 0.01$ and $\epsilon_{cold} = 0.001$.

$LR_{base} = LR_{PFT} \cdot 0.5 + (0.5) \cdot \min(w_{scal}, v_{scal})$ where w_{scal} and v_{scal} are the water and nitrogen limitation factors from the photosynthesis (Schaphoff et al., 2018; von Bloh et al., 2018).

S3.2 Manure application

Manure application was implemented as for the annual crops in LPJmL (Herzfeld et al., 2021). Manure is applied with a C:N ratio of 10 and a NH4 fraction of 2/3. Manure is only applied if the mowing management option is used and 24 g/m2 is split across 4 applications of 8, 6, 6 and 4 g/m2 on April 1st, May 31st,July 1st and August 15th. NH4, C and N from manure are added to the first soil layer following *S3-S5*.

$$\Delta NH_4 = manure \cdot fraction_{NH_4} \quad \text{(S3)}$$

$$\Delta C_{soil} = manure \cdot CN_{manure} \quad \text{(S4)}$$

$$\Delta N_{soil} = manure \cdot (1 - fraction_{NH_4}) \quad \text{(S5)}$$

S4 Input data and parameters

S4.1 Climate data and preparation

Data on temperature, precipitation and for the cold steppe also shortwave radiation were available for different time periods (Table S1). For the cold steppe, data did not contain any gaps and we only had to identify and prune leap years. This is required to obtain 365 days per year time-series which are needed to run LPJmL. For pruning we dropped December 31st.

For the temperate grassland and the hot steppe, the data contained gaps that needed to be filled. Additionally, they did not contain a full calendar year at the end and/or the beginning of the time-series for which we had to extrapolate the data. We used two different procedures for the gap filling: A spline fitting (temperature) and a sampler (precipitation).

With the spline fitting we aimed to capture the seasonality trends of the observed temperature (Fig. S14 and S15) but also account for day to day variation. First, we fitted a spline to the temperature data using the smooth.spline function from the stats-package (R Core Team, 2019). Second, to account for day to day variability we scattered the data by a random value we drew from a uniform distribution in the interval x_{min} to x_{max}. For the different sites, we used different percentiles of the difference between the fitted spline and the observed data for the values for x_{min} and x_{max} (Table S1).

For the extrapolation we calculated the average for each day of the year over the time-series for the fitted spline. The values of the respective day of the year were then then used for the extrapolation. This data were also scattered with the same approach as for the gap filling.

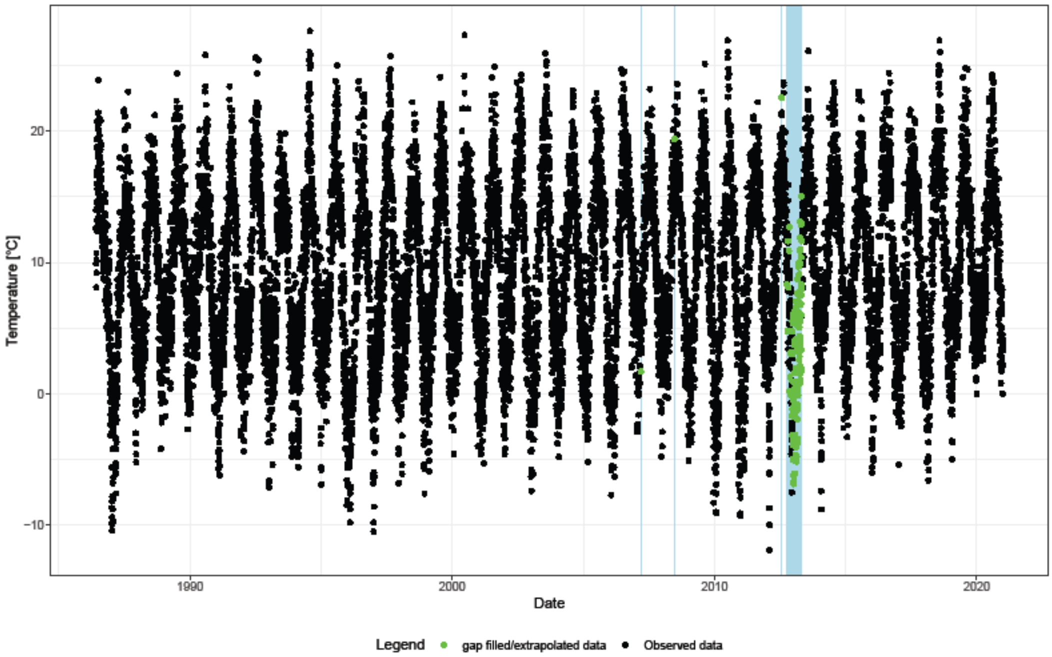

Fig. S14 Daily temperature at the temperate grassland. Colors show observed (black) and gap filled or extrapolated (green) data.

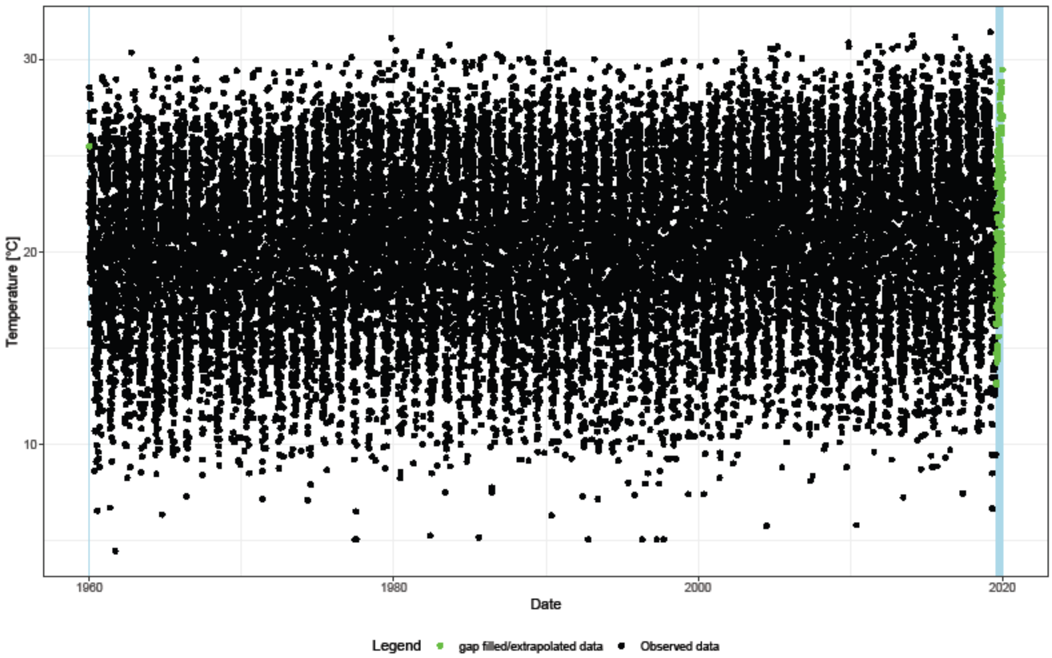

Fig. S15 Daily temperature at the hot steppe. Colors show observed (black) and gap filled or extrapolated (green) data.

For the precipitation (Fig. S16 and S17) we used a sampler for gap filling and extrapolation because the spline fitting did overestimate the number of days with precipitation. We sampled the missing values directly from the observed data at randomly drawn percentiles. This ensures, that the gap-filled data have a similar distribution compared to the original data.

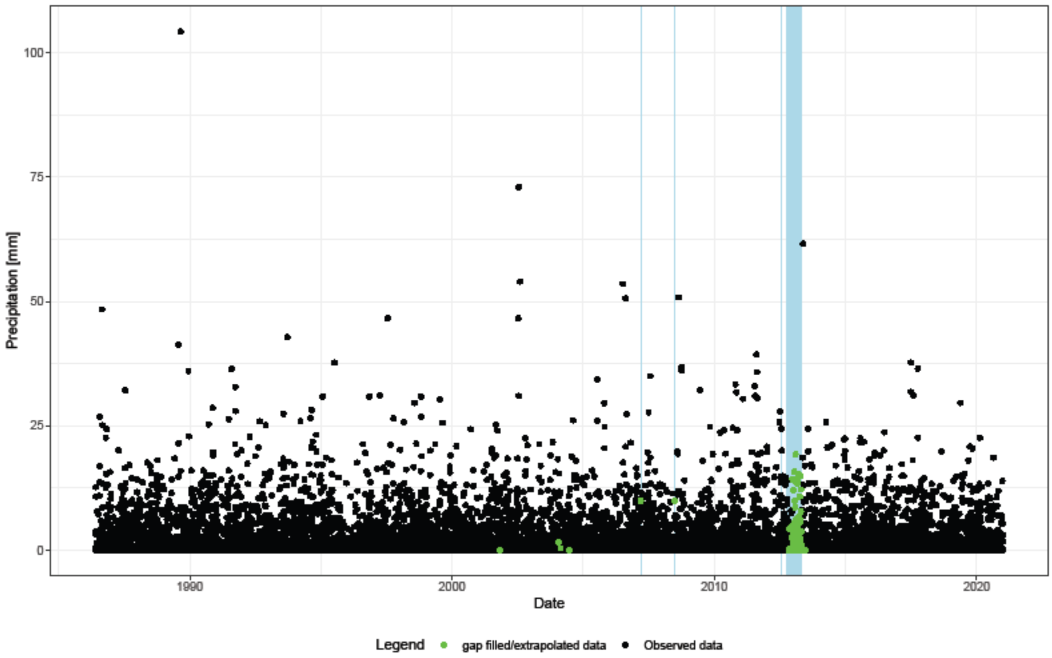

Fig. S16 Daily precipitation at the temperate grassland. Colors show observed (black) and gap filled or extrapolated (green) data.

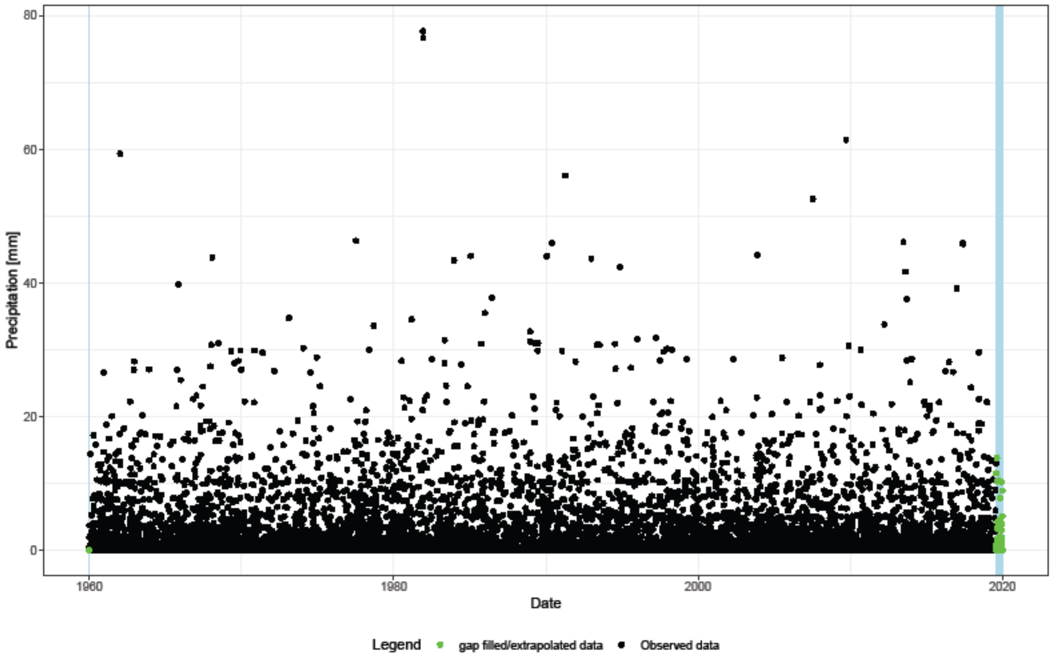

Fig. S17 Daily precipitation at the hot steppe. Colors show observed (black) and gap filled or extrapolated (green) data.

Table S2 Overview of climate products used for the simulations

Site	Variable	Gap-filling	x_{min} to x_{max}	Extrapolation	x_{min} to x_{max}	Source
Temperate grassland	Temperature	Yes	1st-99th percentile	Yes	1st-99th percentile	(DWD, 2021)
Temperate grassland	Precipitation	Yes	-	Yes	-	(DWD, 2021)
Temperate grassland	Radiation	No	-	No	-	-
Temperate grassland	Wind	No	-	No	-	-
Hot steppe	Temperature	No	1st-99th percentile	Yes	5th-95th percentile	(Munjonji et al., 2020)
Hot steppe	Precipitation	No	-	Yes	-	(Munjonji et al., 2020)
Hot steppe	Radiation	No	-	No	-	(Lange and Büchner, 2022)
Hot steppe	Wind	No	-	No	-	(Lange and Büchner, 2022)
Cold steppe	Temperature	No	-	No	-	(Hoffmann et al., 2016; Schönbach et al., 2012)
Cold steppe	Precipitation	No	-	No	-	(Hoffmann et al., 2016; Schönbach et al., 2012)
Cold steppe	Radiation	No	-	No		-
Cold steppe	Wind	No	-	No	-	(Lange and Büchner, 2022)

S4.2 Soil texture

Data on sand, silt and clay content of the soils were used to determine the texture class and hydraulic parameters. Data for each site were available and are listed in Table S3.

Table S3 Sand, silt and clay content of the soils at each site.

Site	Sand [%]	Silt [%]	Clay [%]	Source
Temperate grassland	61	24.2	14.8	(Reinsch et al., 2018a, 2018b)
Hot steppe	80	12	8	(Munjonji et al., 2020)
Cold steppe	62.7	16.8	20.5	(Wiesmeier et al., 2011)

S4.3 Fixed parameters

In addition to the PFT specific parameters we calibrated, we changed several parameters to capture sites specific management and history (Table S4).

Table S4 Adjusted global parameter values

Parameter	Temperate grassland	Hot steppe	Cold steppe
$lsuha_{spinup}$	1.0	$0.\overline{1}$	1.0
$animal_{bw}$	650	450	35
$grazing_{stubble}$	5	5	2
$nfrac_{grassharvest}$	1.0	-	-
$first\_irrig\_year$	-	2014	2005

S5 R packages

We used several R packages for data handling and plotting (Table S5). The ggradar package was not loaded but the ggradar function was adapted to create ggradar_expression.

Table S5 R-packages used for pre/postprocessing and data visulisation

Package (version)	Source
ggplot2(3.3.6), tidyr(1.1.4), dplyr(1.0.7), purr(0.3.4), readr(2.0.2) , stringr(1.4.0), tibble(3.1.8)	(Wickham et al., 2019)
rlang(1.0.4)	(Henry et al., 2022)
ggtern(3.3.5)	(Hamilton and Ferry, 2018)
magrittr(2.0.3)	(Bache and Wickham, 2022)
reshape2(1.4.4)	(Wickham, 2007)
plyr(1.8.6)	(Wickham, 2011)
doParallel(1.0.16)	(Microsoft Corporation and Weston, 2020)
foreach(1.5.1)	(Microsoft and Weston, 2020)
lubridate(1.7.10)	(Grolemund and Wickham, 2011)
tidyselect(1.1.1)	(Henry and Wickham, 2021)
gridExtra(2.3)	(Auguie, 2017)
MASS(7.3-53.1)	(Venables and Ripley, 2002)
Kendall(2.2.1)	(McLeod, 2022)
cowplot(1.1.1)	(Wilke, 2020)
ggradar(0.2)	(Bion, 2022)
LandMark (1.2.0)	(Kowalewski et al., 2018)
PIKTools (1.6)	(Kowalewski and Breier, 2021)

Literature

Adler, P.B., Salguero-Gómez, R., Compagnoni, A., Hsu, J.S., Ray-Mukherjee, J., Mbeau-Ache, C., Franco, M., 2014. Functional traits explain variation in plant life history strategies. Proc. Natl. Acad. Sci. U. S. A. 111, 740–745. https://doi.org/10.1073/pnas.1315179111

Auguie, B., 2017. gridExtra: Miscellaneous functions for “Grid” graphics.

Bache, S.M., Wickham, H., 2022. magrittr: A forward-pipe operator for R.

Bion, R., 2022. ggradar: Create radar charts using ggplot2.

Blonder, B., Vasseur, F., Violle, C., Shipley, B., Enquist, B.J., Vile, D., 2015. Testing models for the leaf economics spectrum with leaf and whole-plant traits in Arabidopsis thaliana. AoB PLANTS 7, plv049. https://doi.org/10.1093/aobpla/plv049

Cornelissen, J.H.C., 1996. An Experimental Comparison of Leaf Decomposition Rates in a Wide Range of Temperate Plant Species and Types. J. Ecol. 84, 573–582. https://doi.org/10.2307/2261479

Cornelissen, J.H.C., Quested, H.M., Gwynn-Jones, D., Van Logtestijn, R.S.P., De Beus, M.A.H., Kondratchuk, A., Callaghan, T.V., Aerts, R., 2004. Leaf Digestibility and Litter Decomposability Are Related in a Wide Range of Subarctic Plant Species and Types. Funct. Ecol. 18, 779–786.

Diaz, S., Hodgson, J.G., Thompson, K., Cabido, M., Cornelissen, J.H.C., Jalili, A., Montserrat-Martí, G., Grime, J.P., Zarrinkamar, F., Asri, Y., Band, S.R., Basconcelo, S., Castro-Díez, P., Funes, G., Hamzehee, B., Khoshnevi, M., Pérez-Harguindeguy, N., Pérez-Rontomé, M.C., Shirvany, F.A., Vendramini, F., Yazdani, S., Abbas-Azimi, R., Bogaard, A., Boustani, S., Charles, M., Dehghan, M., Torres-Espuny, L. de, Falczuk, V., Guerrero-Campo, J., Hynd, A., Jones, G., Kowsary, E., Kazemi-Saeed, F., Maestro-Martínez, M., Romo-Díez, A., Shaw, S., Siavash, B., Villar-Salvador, P., Zak, M.R., 2004. The plant traits that drive ecosystems: Evidence from three continents. J. Veg. Sci. 15, 295–304. https://doi.org/10.1111/j.1654-1103.2004.tb02266.x

DWD, 2021. Wetter und Klima - Deutscher Wetterdienst - Leistungen - Klimadaten Deutschland - Monats- und Tageswerte (Archiv) [WWW Document]. URL https://www.dwd.de/DE/leistungen/klimadatendeutschland/\\klarchivtagmonat.html;jsessionid=A3AB03AA43161688F8D55\\7F88FBF0BF8.live11053?nn=16102 (accessed 6.16.22).

Forkel, M., Carvalhais, N., Schaphoff, S., v. Bloh, W., Migliavacca, M., Thurner, M., Thonicke, K., 2014. Identifying environmental controls on vegetation greenness phenology through model–data integration. Biogeosciences 11, 7025–7050. https://doi.org/10.5194/bg-11-7025-2014

Grolemund, G., Wickham, H., 2011. Dates and times made easy with lubridate. J. Stat. Softw. 40, 1–25.

Hamilton, N.E., Ferry, M., 2018. ggtern: Ternary diagrams using gplot2. J. Stat. Softw. Code Snippets 87, 1–17. https://doi.org/10.18637/jss.v087.c03

Henry, L., Wickham, H., 2021. tidyselect: Select from a set of strings.

Henry, L., Wickham, H., xxhashlite), mikefc (Hash implementation based on M., library), Y.C. (Author of the embedded xxHash, RStudio, 2022. rlang: Functions for Base Types and Core R and “Tidyverse” Features.

Herzfeld, T., Heinke, J., Rolinski, S., Müller, C., 2021. Soil organic carbon dynamics from agricultural management practices under climate change. Earth Syst. Dyn. 12, 1037–1055. https://doi.org/10.5194/esd-12-1037-2021

Hoffmann, C., Giese, M., Dickhoefer, U., Wan, H., Bai, Y., Steffens, M., Liu, C., Butterbach-Bahl, K., Han, X., 2016. Effects of grazing and climate variability on grassland ecosystem functions in Inner Mongolia: Synthesis of a 6-year grazing experiment. J. Arid Environ. 135, 50–63. https://doi.org/10.1016/j.jaridenv.2016.08.003

Kattge, J., Knorr, W., Raddatz, T., Wirth, C., 2009. Quantifying photosynthetic capacity and its relationship to leaf nitrogen content for global-scale terrestrial biosphere models. Glob. Change Biol. 15, 976–991. https://doi.org/10.1111/j.1365-2486.2008.01744.x

Kowalewski, J., Breier, J., 2021. PIKTools: Datasets and functions and data to handle PIK-model data.

Kowalewski, J., Breier, J., Hijmans, R.J., Pebesma, E., Bivand, R., Eterradossi, O., Pasek, J., 2018. LandMark: Benchmarking Functionality for the vegetation model community.

Lange, S., Büchner, M., 2022. Secondary ISIMIP3b bias-adjusted atmospheric climate input data. https://doi.org/10.48364/ISIMIP.581124.1
McLeod, A.I., 2022. Kendall: Kendall rank correlation and mann-kendall trend test.
Microsoft Corporation, Weston, S., 2020. doParallel: Foreach parallel adaptor for the “parallel” package.
Microsoft, Weston, S., 2020. foreach: Provides foreach looping construct.
Munjonji, L., Ayisi, K.K., Mudongo, E.I., Mafeo, T.P., Behn, K., Mokoka, M.V., Linstädter, A., 2020. Disentangling Drought and Grazing Effects on Soil Carbon Stocks and CO2 Fluxes in a Semi-Arid African Savanna. Front. Environ. Sci. 8.
Quested, H.M., Cornelissen, J.H.C., Press, M.C., Callaghan, T.V., Aerts, R., Trosien, F., Riemann, P., Gwynn-Jones, D., Kondratchuk, A., Jonasson, S.E., 2003. Decomposition of Sub-Arctic Plants with Differing Nitrogen Economies: A Functional Role for Hemiparasites. Ecology 84, 3209–3221.
R Core Team, 2019. A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria.
Reich, P.B., Oleksyn, J., Wright, I.J., 2009. Leaf phosphorus influences the photosynthesis–nitrogen relation: a cross-biome analysis of 314 species. Oecologia 160, 207–212. https://doi.org/10.1007/s00442-009-1291-3
Reinsch, T., Loges, R., Kluß, C., Taube, F., 2018a. Effect of grassland ploughing and reseeding on CO2 emissions and soil carbon stocks. Agric. Ecosyst. Environ. 265, 374–383. https://doi.org/10.1016/j.agee.2018.06.020
Reinsch, T., Loges, R., Kluß, C., Taube, F., 2018b. Renovation and conversion of permanent grass-clover swards to pasture or crops: Effects on annual N2O emissions in the year after ploughing. Soil Tillage Res. 175, 119–129. https://doi.org/10.1016/j.still.2017.08.009
Schaphoff, S., Bloh, W. von, Rammig, A., Thonicke, K., Biemans, H., Forkel, M., Gerten, D., Heinke, J., Jägermeyr, J., Knauer, J., Langerwisch, F., Lucht, W., Müller, C., Rolinski, S., Waha, K., 2018. LPJmL4 – a dynamic global vegetation model with managed land – Part 1: Model description. Geosci. Model Dev. 11, 1343–1375. https://doi.org/10.5194/gmd-11-1343-2018
Schönbach, P., Wan, H., Gierus, M., Loges, R., Müller, K., Lin, L., Susenbeth, A., Taube, F., 2012. Effects of grazing and precipitation on herbage production, herbage nutritive value and performance of sheep in continental steppe. Grass Forage Sci. 67, 535–545. https://doi.org/10.1111/j.1365-2494.2012.00874.x
Shiodera, S., Rahajoe, J.S., Kohyama, T., 2008. Variation in longevity and traits of leaves among co-occurring understorey plants in a tropical montane forest. J. Trop. Ecol. 24, 121–133. https://doi.org/10.1017/S0266467407004725
Venables, W.N., Ripley, B.D., 2002. Modern applied statistics with S, 4th ed. Springer, New York.
von Bloh, W., Schaphoff, S., Müller, C., Rolinski, S., Waha, K., Zaehle, S., 2018. Implementing the nitrogen cycle into the dynamic global vegetation, hydrology, and crop growth model LPJmL (version 5.0). Geosci. Model Dev. 11, 2789–2812. https://doi.org/10.5194/gmd-11-2789-2018
Wickham, H., 2011. The split-apply-combine strategy for data analysis. J. Stat. Softw. 40, 1–29.
Wickham, H., 2007. Reshaping data with the reshape package. J. Stat. Softw. 21, 1–20.
Wickham, H., Averick, M., Bryan, J., Chang, W., McGowan, L.D., François, R., Grolemund, G., Hayes, A., Henry, L., Hester, J., Kuhn, M., Pedersen, T.L., Miller, E., Bache, S.M., Müller, K., Ooms, J., Robinson, D., Seidel, D.P., Spinu, V., Takahashi, K., Vaughan, D., Wilke, C., Woo, K., Yutani, H., 2019. Welcome to the Tidyverse. J. Open Source Softw. 4, 1686. https://doi.org/10.21105/joss.01686
Wiesmeier, M., Barthold, F., Blank, B., Kögel-Knabner, I., 2011. Digital mapping of soil organic matter stocks using Random Forest modeling in a semi-arid steppe ecosystem. Plant Soil 340, 7–24. https://doi.org/10.1007/s11104-010-0425-z
Wilke, C.O., 2020. cowplot: Streamlined plot theme and plot annotations for “ggplot2.”

Wright, I.J., Reich, P.B., Westoby, M., Ackerly, D.D., Baruch, Z., Bongers, F., Cavender-Bares, J., Chapin, T., Cornelissen, J.H.C., Diemer, M., Flexas, J., Garnier, E., Groom, P.K., Gulias, J., Hikosaka, K., Lamont, B.B., Lee, T., Lee, W., Lusk, C., Midgley, J.J., Navas, M.-L., Niinemets, U., Oleksyn, J., Osada, N., Poorter, H., Poot, P., Prior, L., Pyankov, V.I., Roumet, C., Thomas, S.C., Tjoelker, M.G., Veneklaas, E.J., Villar, R., 2004. The worldwide leaf economics spectrum. Nature 428, 821–827. https://doi.org/10.1038/nature02403