Supporting Information for:

Integrating the evidence for a terrestrial carbon sink caused by increasing atmospheric CO_2

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Notes S1. Standardising CO_2 responses with a β factor

In order to compare across studies that measure different variables at different CO_2 concentrations and at different periods in time, we calculate a standardised CO_2 response metric. This metric is often referred to as the β factor (Friedlingstein et al., 1995; Bacastow and Keeling 1973). Multiple methods have been proposed and here we explore just a few to make an informed choice on the method to calculate β that best suits our purposes and so that the reader can visualise how β relates to different CO_2 response scenarios across a range of realistic CO_2 concentrations. We investigated three methods to calculate β, the normalised response ratio:

$$\beta = (rr_y - 1) / (rr_{CO2} - 1), \qquad \text{(Eq. S1)}$$

log-β (Bacastow and Keeling 1973):

$$\beta_{log} = (rr_y - 1) / \ln(rr_{CO2}), \qquad \text{(Eq. S2)}$$

and log-log-β:

$$\beta_{log\text{-}log} = \ln(rr_y) / \ln(rr_{CO2}), \qquad \text{(Eq. S3)}$$

where $rr_y = y_e/y_a$ and $rr_{CO2} = CO_{2,e}/CO_{2,a}$. y_a and y_e are the value of any response variable at low CO_2 and higher CO_2, and $CO_{2,a}$ and $CO_{2,e}$ are the CO_2 concentrations.

Figure S1 shows the value of the two variations of the β-factors under different CO_2 response scenarios. As is clear from these figures $\beta_{log\text{-}log}$ provides the most consistent characterisation of the CO_2 response. $\beta_{log\text{-}log}$ is independent of the magnitude of the change in CO_2 (Figure S1), and also has a value of 1 when y is proportional to CO_2 (and thus rr_y is directly proportional to rr_{CO2} which is important to identify to evaluate theory, see Section 2.1). We therefore choose $\beta_{log\text{-}log}$ as our standardised CO_2 response metric.

Calculation of uncertainty in $\beta_{log\text{-}log}$ is by error propagation:

$$\sigma_{f(x)} = f(x) \,.\, ((\sigma_{x1}/x_1)^2 + (\sigma_{x2}/x_2)^2 \ldots + (\sigma_{xn}/x_n)^2)^{0.5} \qquad \text{(Eq. S4)}$$

$$\sigma_{\ln(x)} = \sigma_x / x \qquad \text{(Eq. S5)}$$

where f(x) is a function of the vector x that combines the elements of x through multiplication or division, σ_x is a vector of the uncertainty in x, and $\sigma_{\ln(x)}$ is the uncertainty in the scalar ln(x).

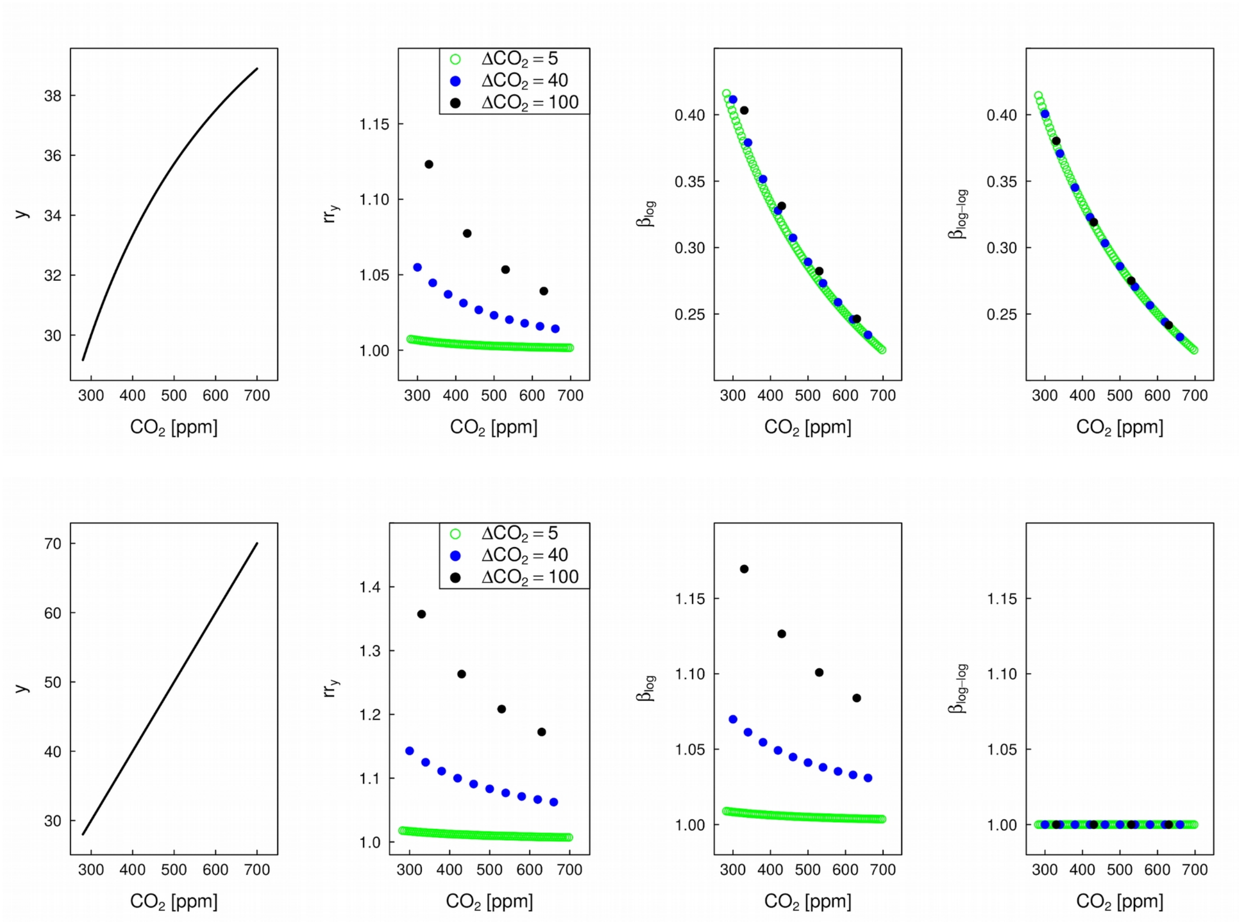

Figure S1. Calculation of response ratio (rr_y, column second from left), β_{log} (Eq. S2, column third from left), and $\beta_{log\text{-}log}$ (Eq. S3, right column) from theoretical CO_2 responses of an arbitrary variable (y, left column) that responds to CO_2 in proportion (lower row) or as a saturating function (upper row). Three different magnitudes of the change in CO_2 are used to calculate the response ratio and βs, 5 pmm (green), 40 ppm (blue), and 100 ppm (black).

Notes S2. Calculation of β from different data types

For time-series that use regression to infer trends we use the y-value of the regression for the first year of data and the last year of data (for y_a and y_e). Where regressions were not given we use means of the first and last five years of the data to calculate x and CO_2. Where response variables were presented per year or per ppm we calculated the full change over the time period by multiplying by the length of, or by the change in CO_2 over, the time period of the data used in the study. Where studies presented only an absolute change, where possible we calculated x_a from a mean value (x_t) recorded at time t by subtracting the cumulative change up until time t. We then calculated x_e from x_a plus the total change.

For iCO2 studies CO_2 concentrations for the beginning and end of the time series were taken from the global annual values used in the most recent TRENDY simulations for the Global Carbon Project (Friedlingstein et al., 2019). For multi-site datasets we use the mean treatment CO_2 values for eCO2 experiments, and the mean start and end year for iCO2 studies (primarily inventory studies). For meta-analysis studies that synthesised results from many different studies but did not report mean CO_2 concentrations, we assume a value of 380 ppm for ambient CO_2 conditions and 550 ppm for elevated CO_2 conditions. To calculate uncertainties in CO_2 we assume a 20 ppm in eCO2 treatments and 5 ppm error in ambient CO_2 treatments or historical iCO2 studies (themes 2-4) to account for spatial variability from the global mean.

We report uncertainties as 95 % confidence intervals, converting from standard error of the mean by a factor of two. Where asymmetric confidence intervals were reported we take the mean of the absolute differences to estimate a single error term. 95 % confidence intervals for β were calculated using error propagation.

Where possible, for small net fluxes (i.e. where both input and output fluxes were of similar magnitude) we calculate β based on the standing stock of carbon. Where mean stocks (y_x) and annual or per ppm changes were reported at source, we calculated the cumulative change (Δy), calculated the initial value (y_a) at $CO_{2,a}$ from the mean stock minus half the change ($y_a = y_x - \Delta y/2$). The value at $CO_{2,e}$ was calculated as: $y_a + \Delta y$.

Notes S3. Modelling leaf and canopy physiology

All modelling was done with the Multi-Assumption Architecture and Testbed (MAAT; Walker et al., 2018). Scripts to generate these data will be posted on Github (https://github.com/walkeranthonyp/MAAT). Leaf-scale photosynthesis was modelled following Farquhar et al. (1980) for C3 plants and Collatz et al., (1992) for C4 plants. Stomatal conductance was modelled following Dewar et al. (2018), which is very closely related to Medlyn et al. (2011). J_{max} was related to V_{cmax} using the relationship commonly employed in many terrestrial biosphere models from Wullscheleger (1993).

Canopy-scale modelling was based on that in SDGVM (see Supporting Information Walker et al., 2017; Woodward and Lomas 2004) a 10-layer, multi-layer approach that includes sun and shade leaves and radiative transfer following Goudriaan (1977). Temperature scaling of V_{cmax} and J_{max} was using the modified Arrhenius (Medlyn et al., 2002). Similar to SDGVM, a daily integral was achieved by assuming sine-wave scaling of photosynthetically active radiation at 20 points throughout the day with the peak scaled to a maximum daily value (2000 μmol m^{-2} s^{-1}). Integration was through trapezoidal integration. A clear sky was assumed and solar zenith angle was assumed zero.

A 1000 member ensemble was run for each scale—instantaneous leaf, instantaneous canopy, and daily canopy. The ensemble copmprised a factorial combination of 100 top-of-canopy V_{cmax} values (mean = 60, sd = 10) and 10 values of the J_{max} to V_{cmax} slope (mean = 1.63, sd = 0.2). For the daily canopy simulations the 1000 member ensemble was run for a factorial combination of three levels of temperature (10, 15, 25 °C) and three levels of relative humidity (50, 70, 90 %).

For each ensemble member of these three scales, β_{dir} was calculated according to Eq. S3 (also Eq. 1 of the main text). Weighted mean β's were calculated by weighting according to the absolute change in a variable with CO_2. Weighted 95 %iles were calculated using the weighted standard deviation multiplied by 2.

Table S1. Weighted β_{dir}'s (and 95 percentiles) from the model ensembles for A_{net}, light-saturated photosynthesis (A_c), light-limited photosynthesis (A_j), iWUE, and g_s.

Scale	ΔCO_2	β_{dir} A_{net}	β_{dir} A_c	β_{dir} A_i	β_{dir} iWUE	β_{dir} g_s
Leaf	historical	0.86 (0.002)	0.86 (0.000)	0.31 (0.003)		-0.28 (0.002)
	future	0.70 (0.175)	0.74 (0.000)	0.23 (0.002)		-0.44 (0.25)
Canopy	historical	0.60 (0.2)	-	-	1.12 (0.01)	-0.56 (0.19)
	future	0.36 (0.2)	-	-	1.06 (0.01)	-0.75 (0.17)
Diurnal canopy	historical	0.60 (0.27)	-	-	1.07 (0.10)	-0.53 (0.17)
	future	0.46 (0.21)	-	-	1.03 (0.07)	-0.62 (0.15)

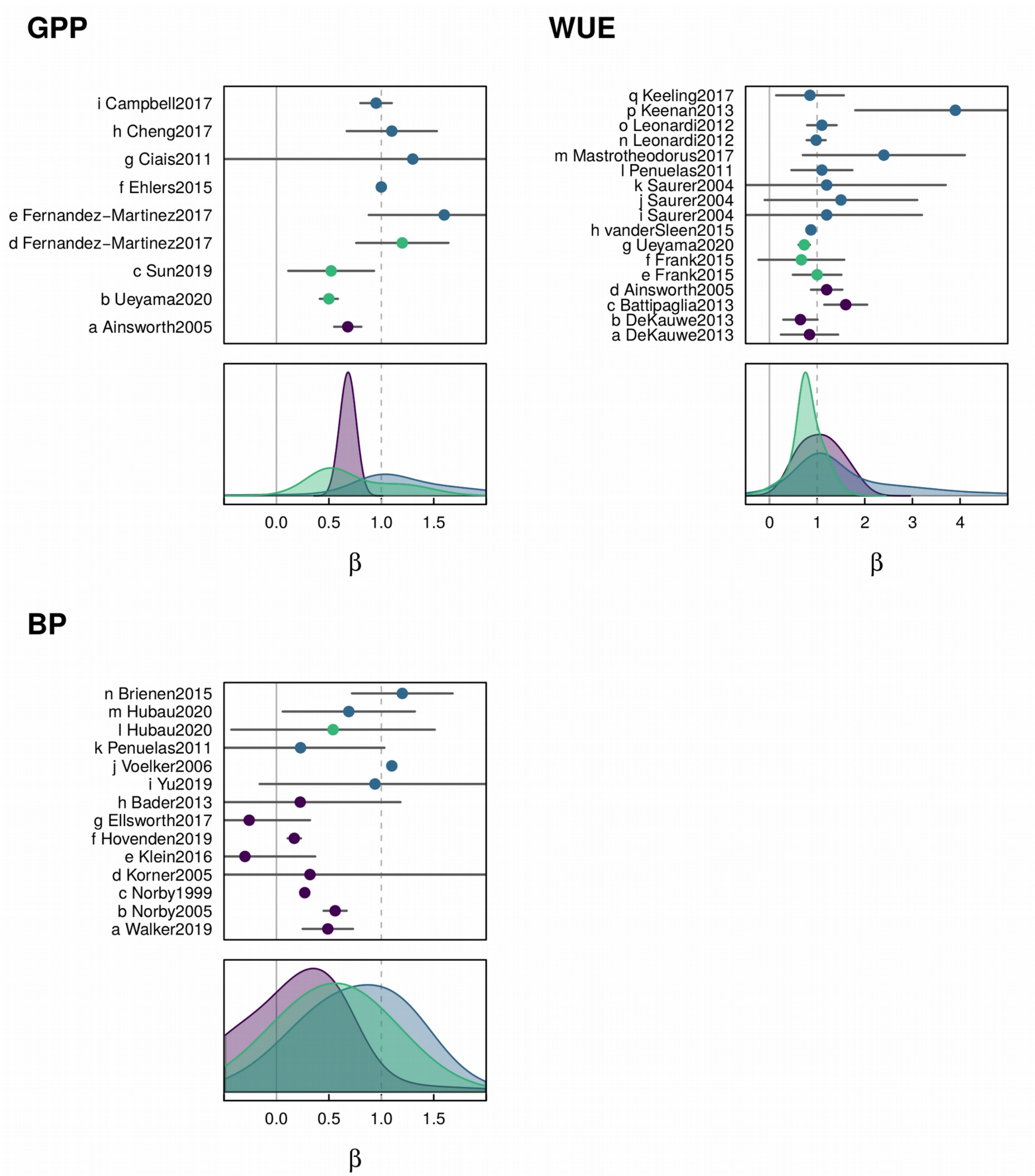

Figure S2. β's with 95 % confidence intervals from Table 2 for GPP, WUE, BP. Data are organised by CO_2 response category—iCO2 (blue), attribution to iCO2 (green), and eCO2 (purple). Also shown are PDFs of merged data for each CO_2 response category. PDFs are generated by drawing 1,000 random samples from the (assumed normal) β distribtions for each study, and then combining all of these samples within each CO_2 response category. Studies with no CI were not included in the PDFs. In presenting variables together we have combined a number of related variables and at different scales, e.g. iWUE, WUE, and inherent WUE at scales from leaf, plant, ecosystem, to global are all presented on the WUE panel (see Table 2 for details).

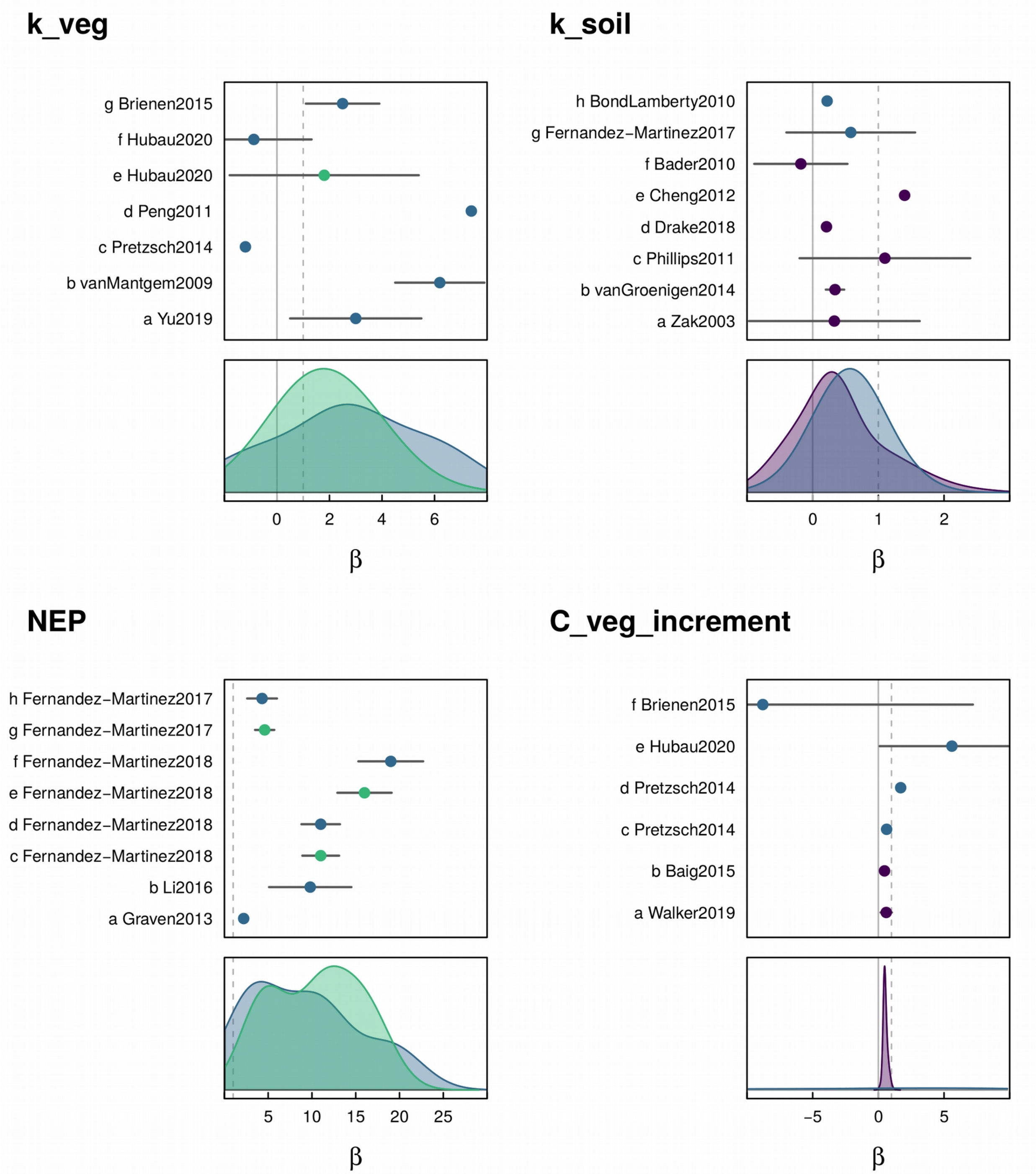

Figure S3. β's with 95 % confidence intervals from Table 2 for k_veg, k_soil, NEP, and C_{veg} increment. Details same as for Fig. S2.

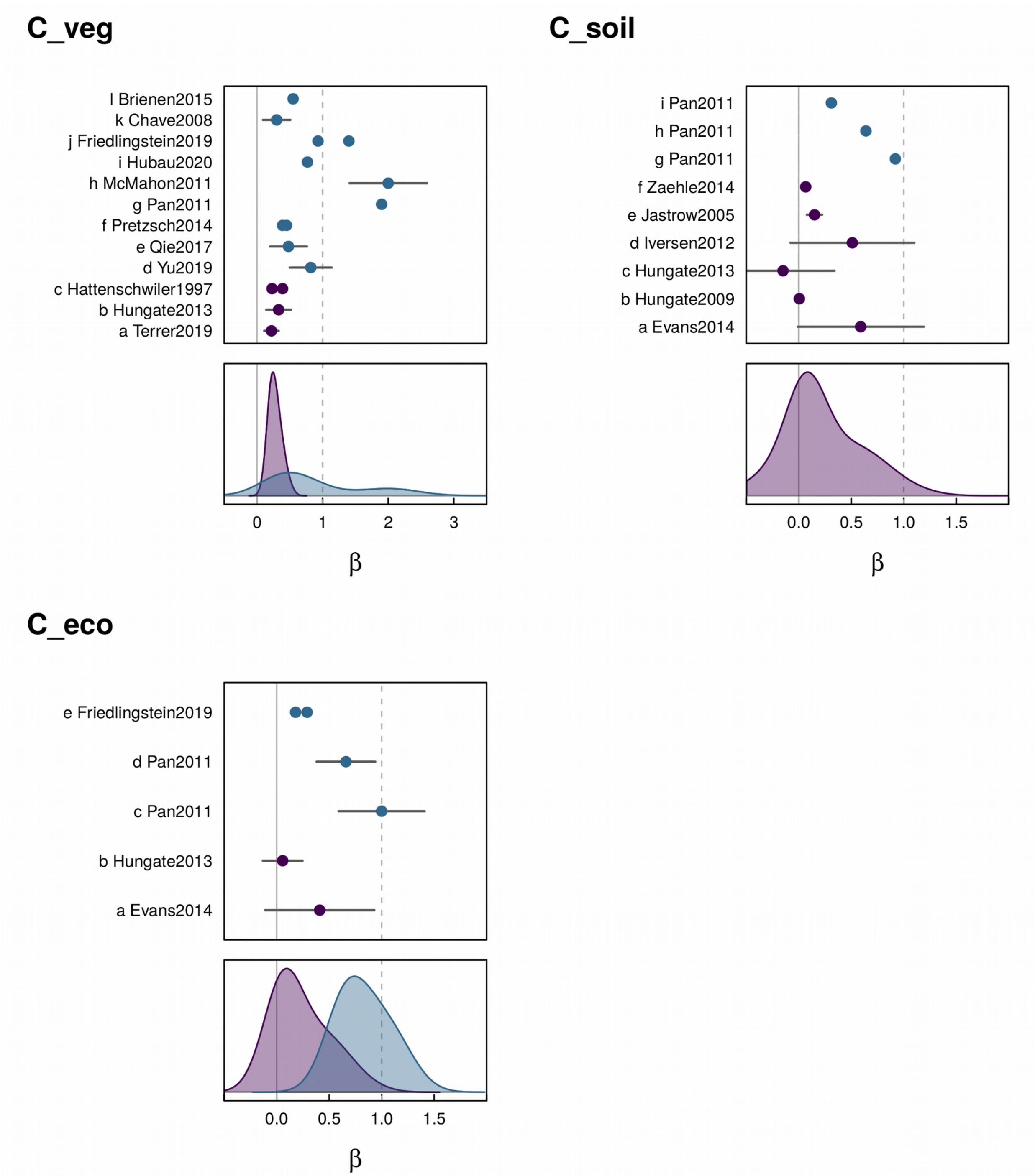

Figure S4. β's with 95 % confidence intervals from Table 2 for C_{veg} , C_{soil}, and C_{eco}. Details same as for Fig. S2.

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