Predicting soil carbon loss with warming

Natasja van Gestel[1*], Zheng Shi[2], Kees Jan van Groenigen[3], Craig W. Osenberg[4], Louise C. Andresen[5], Jeffrey S. Dukes[6,7], Mark J. Hovenden[8], Yiqi Luo[9,10], Anders Michelsen[11], Elise Pendall[12], Peter B. Reich[12,13], Edward A. G. Schuur[9,10], and Bruce A. Hungate[9,10]

[1]*Climate Science Center, Texas Tech University, Lubbock, TX 79409, USA.*

[2]*Department of Botany and Microbiology, University of Oklahoma, Norman, OK 73019, USA.*

[3]*Geography, College of Life and Environmental Sciences, University of Exeter, Exeter EX4 4RJ, UK*

[4]*Odum School of Ecology, University of Georgia, Athens, GA 30602, USA.*

[5]*Department of Earth Sciences, University of Gothenburg, Gothenburg, Sweden.*

[6]*Department of Forestry and Natural Resources, Purdue University, West Lafayette, IN 47907, USA.*

[7]*Department of Biological Sciences, Purdue University, West Lafayette, IN 47907, USA.*

[8]*School of Biological Sciences, University of Tasmania, Hobart, Tas. 7001, Australia.*

[9]*Center for Ecosystem Science and Society, Northern Arizona University, Flagstaff, AZ 86011, USA.*

[10]*Department of Biology, Northern Arizona University, Flagstaff, AZ 86011, USA.*

[11]*Department of Biology and Center for Permafrost, University of Copenhagen, Copenhagen, Denmark.*

[12]Hawkesbury Institute for the Environment, Western Sydney University, Penrith, NSW 2751, Australia.
[13]Department of Forest Resources, University of Minnesota, St. Paul, MN 55108, USA.

Crowther et al.[1] reported that the best predictor of surface soil carbon (C; top 10 cm) losses in response to warming is the size of the surface C stock in the soil (*i.e.* C stocks in unwarmed plots), with soils high in soil C also losing more C. This relationship was based on a linear regression of soil C losses and soil C stocks in field warming studies, which was then used to project C losses over time and to generate a map of soil C vulnerability. However, a few extreme data points can strongly influence the slope of a regression line (i.e. high leverage points)[2]. Of the 49 sites in Crowther et al, only five are in the upper half of the C stock range. This paucity of high-soil C data calls into question the robustness of the overall relationship and raises the possibility that this relationship could be substantially altered by new data from sites with relatively high surface C stocks.

We obtained information on soil C losses from published and unpublished data from 94 additional field warming studies worldwide, and thereby tripled the data set used by Crowther and colleagues to a total of 143 studies (Table S1). We performed the same mixed-model regression analyses as used by Crowther et al. to examine spatial patterns of soil carbon responses to warming, by linking these to standing soil C stocks, climate data and soil properties (see Methods for details, Table S2 for study-specific data on soil properties and climate, and Table S3 for Akaike Information Criterion results). We chose the same predictors in our models to compare our results directly to theirs. Our new analysis on the expanded data set shows that warming-induced losses in soil C are not a function of standing C stocks (Fig. 1), challenging the conclusion that future soil C loss can be mapped based on current surface soil C stocks. Consistent with a previous meta-analysis[3], average soil C responses to warming were not statistically different from zero, regardless of whether the full data set was used, or just the data set from Crowther et al. (Extended Data Fig. 1). Even if soil carbon stocks remain unchanged in surface soil, this does not imply that decomposition rates are insensitive to warming. Rather, decomposition rates are likely higher, but so is plant productivity, which may offset C losses from soil. Adding other predictors (e.g. environmental variables and soil properties) added little explanatory power (Table S3) to predicting warming-induced changes in soil carbon stocks, a finding consistent with the results of Crowther and colleagues. Thus, we still lack a clear understanding of the factors that drive spatial variation in the response of soil C to warming.

Our analysis on a much larger data set challenges the finding of Crowther and colleagues that future soil C loss can be projected based on current surface soil C stocks. Projecting changes in soil C stocks with warming thus remains a challenge. Furthermore, we are limited in global predictions of warming effects on soil C because warming experiments are mainly clustered in North America, Europe and China (Fig. 2), with only a handful of experiments in the Southern Hemisphere and in vast areas at high latitudes in the Northern Hemisphere (e.g. Canada and Russia), and no data from the tropics. We suggest that future experimental work focus on regions that are currently underrepresented in our global database. Global experimental data that better capture Earth's diverse terrestrial habitats and an improved integration of data with process-based models[4] might be our best way forward in the next few decades. A collaborative, multi-disciplinary, and international approach is thus required to increase our understanding and quantification of the fate of soil C in a warming world.

References

1. Crowther, T. *et al.* Quantifying global soil C losses in response to warming. *Nature* **504,** 104–108 (2016).
2. Chatterjee, S. & Hadi, A. S. Influential observations, high leverage points, and outliers in linear regression. *Stat. Sci.* **1,** 379–416 (1986).
3. Lu, M. *et al.* Responses of ecosystem carbon cycle to experimental warming: a meta-analysis. *Ecology* **94,** 726–738 (2013).
4. Luo, Y. *et al.* Toward more realistic projections of soil carbon dynamics by Earth system models. *Global Biogeochem. Cycles* **30,** 40–56 (2016).

Supplementary Information is linked to the online version of the paper at www.nature.com/nature.

Author Contributions

N.v.G. extracted data from the literature and constructed the database. L.C.A, J.S.D, M.J.H., A.M, E.P., P.B.R, E.A.G.S., and B.A.H supplied non-published data from specific field warming experiments, N.v.G. wrote the manuscript draft. All authors contributed to interpretation of the findings and final writing of the manuscript.

Author Information

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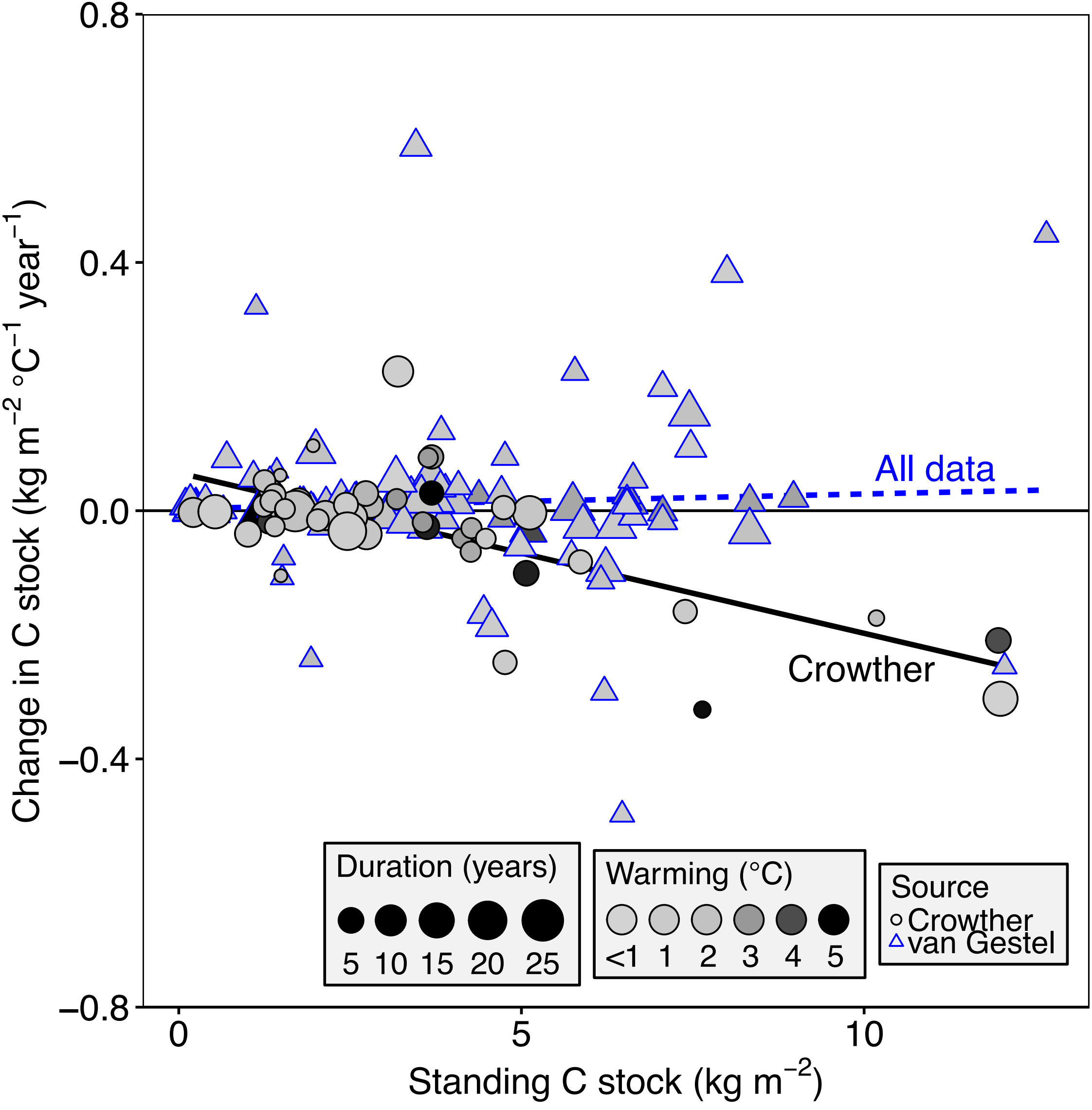
Figure legends

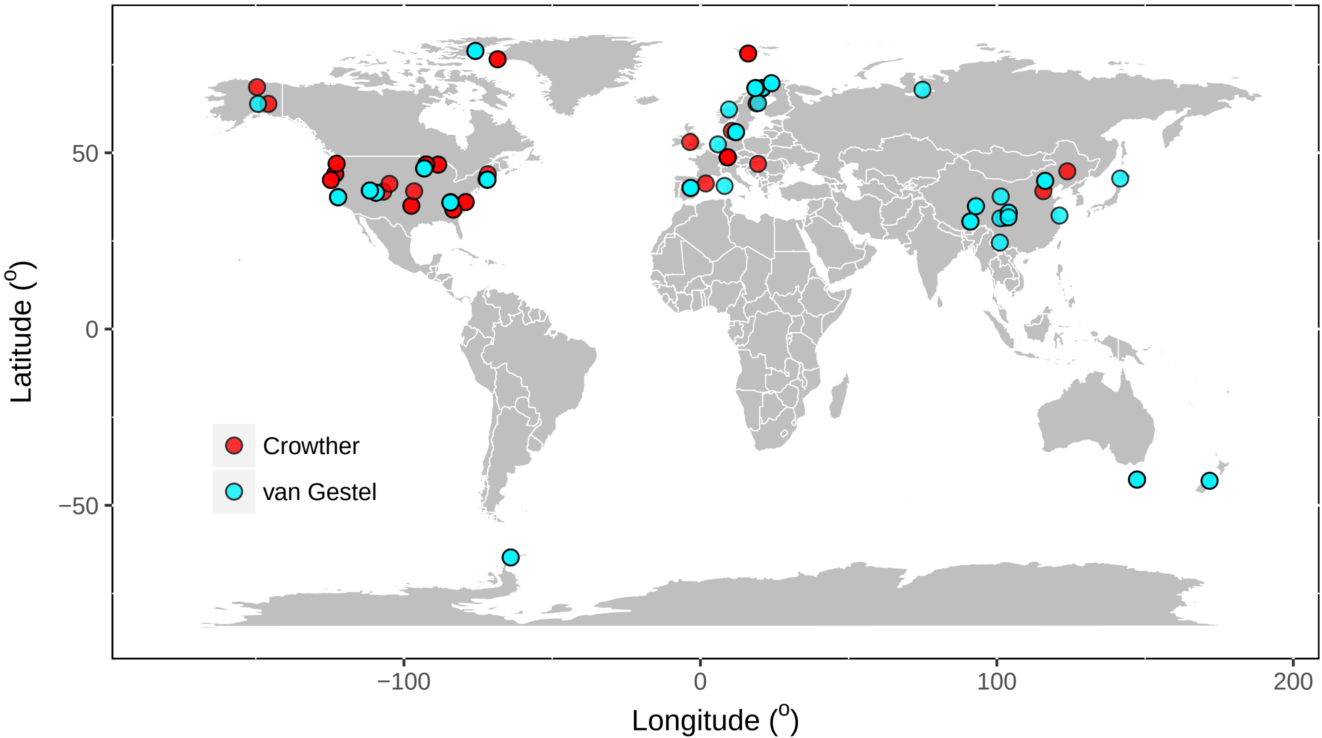
Figure 1. The change in soil C per degree-years warming is not a function of C stock size. The data set includes the data used by Crowther and colleagues[1] (n = 49 studies) and data added by van Gestel et al. (this paper; n = 94 additional studies). The expanded dataset shows no relationship between the warming effect on soil C and the initial C stock size. The r^2 dropped from 0.49 in Crowther et al. (2016) to 0.01 ($P > 0.05$) in the full dataset (n = 143), based on the same regression model using study means, as in their study.

Figure 2. **Location of field warming studies used in our analyses**. The data set includes the data used by Crowther and colleagues[1] (n = 49 studies) and data added by van Gestel et al. (this paper; n = 94 studies). A location may have several separate warming experiments.

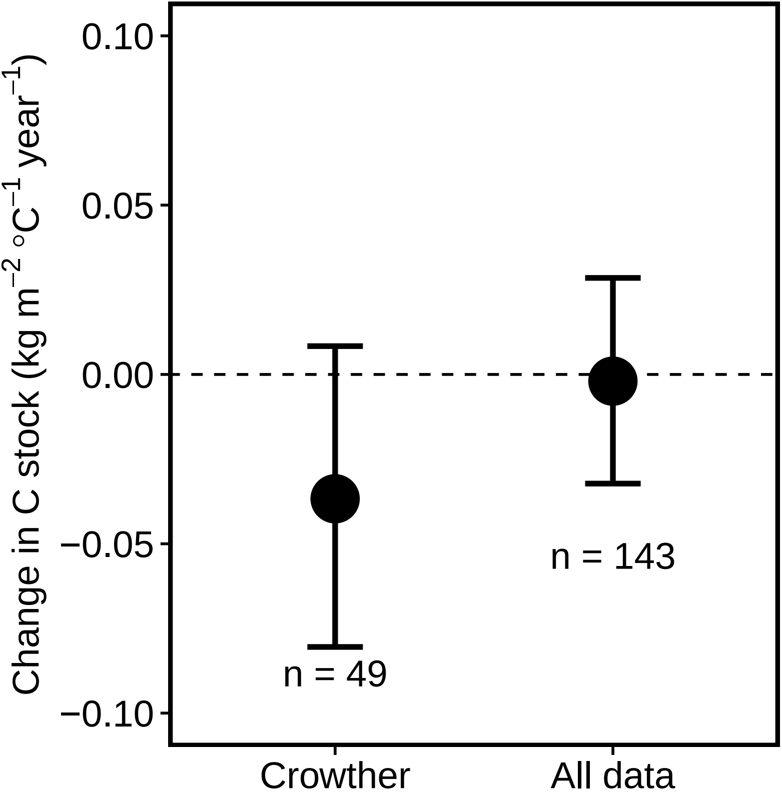
Extended Data Figure 1. Results of a meta-analysis on the change in soil C per degree-years warming. The average response of soil C per degree-years warming is not significantly different from zero (*i.e.* zero is within the 95% confidence interval of the mean) for Crowther et al.'s data set or the full data set. See Supplemental Information for details.



Change in C stock (kg m−2 °C−1 year−1)
0.8
0.4
0.0
−0.4
−0.8
All data
Crowther
Duration (years)
5 10 15 20 25
Warming (°C)
<1 1 2 3 4 5
Source
Crowther
van Gestel
0
5
10
Standing C stock (kg m−2)



Latitude (°)
50
0
−50
−100
0
100
200
Longitude (°)
Crowther
van Gestel



Change in C stock (kg m^{-2} °C^{-1} year^{-1})
0.10
0.05
0.00
−0.05
−0.10
n = 49
n = 143
Crowther
All data

Supplementary Information for

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This supplementary document contains (in this order):

Other Supplementary Information:

databaseS1.csv: Supplementary Data; Main data file to be used with R code.
databaseS2.csv: Supplementary Data regarding bulk density and soil organic matter

Methods

Data compilation and standardization

We compiled data on soil carbon responses to warming from field warming experiments. We used the Web of Science™ (Thomson Reuters, New York, NY) and Google Scholar (Google Inc., Mountain View, CA) to search the literature using the terms: (warming OR "eleva* temperature")+"soil carbon"+field. To be included in our data set, studies had to be conducted in the field (*i.e.* no lab experiments), and means and sample sizes had to be reported. Data were extracted until March 15, 2017 from published figures or tables, or obtained via personal communication. We found 94 additional studies that matched our criteria (Fig. S1, Table S1) and were not included in the data set of Crowther et al. For each site we collected ancillary information, e.g. latitude, longitude, warming method, average temperature increase, and biome (tundra, grassland, shrubland, forest, desert), climate and soil properties. Common methods to elevate temperatures in the field included the use of open-top chambers (OTCs), heating cables and infrared (IR) heaters.

We focused on soil C stocks in the same upper soil layer as Crowther et al. and followed their standardization procedure. For multifactorial studies that crossed temperature with other factors (e.g. N, CO_2), we thus extracted an effect size for each level of the other factor. For example, for a study that combined warming with N addition (T x N), we extracted two effect sizes: one for ambient N and one for elevated N. For sites with multiple single-factor warming experiments (e.g. wet versus dry sites, upland versus lowland), soil C responses, the degree of warming and degree-years were calculated separately, but other environmental data was kept the same.

Soil carbon stocks were converted to kg carbon per m^2. If soil C was reported as percent soil organic matter (SOM), we multiplied SOM by 0.45 (assuming that 45% of SOM is C). To convert soil C data from a volume or weight basis to an area basis we used the bulk density (BD) of the soil for that study. If BD was not reported we estimated BD for the site based on the relationship of BD and SOM across all sites (Fig. S1). We chose this relationship instead of one value across soil types because increasing SOM content reduces BD.

Meta-analyses

We did a meta-analysis on the difference in of soil carbon stocks between warming and control plots per degree-year (i.e. the same units as the y-axis in Fig. 1 in Crowther et al.). This is akin to collapsing the data throughout the carbon stock range onto the y-axis and determining the mean. If soil carbon data were available for multiple time points, we calculated the average soil carbon responses and the average duration of the study for which soil carbon data were available. We did a meta-analysis twice, once for Crowther's et al. data set and again for the combined data set (Crowther's et al. and ours). In this meta-analysis the observations were weighted by duration of the study and replication as follows: $w = (n_c \times n_w)/(n_c + n_w) + (year_c \times year_w)/(year_c + year_w)$[1], with n_c and n_w representing the number of replicates and $year_c$ and $year_w$ representing the average duration over which the soil carbon data was collected for in control and warmed sites, respectively. This weighting scheme assigned higher weights to well-replicated, long-term studies, as results from these studies should be the most reliable. Thus, symbol sizes in the Figure (sizes represent duration of the study) were taken into account. We divided the weights by the number of experiments conducted within a study to prevent multi-factorial studies from dominating the overall average. We chose this weighting scheme in our meta-analysis over the more conventional inverse of the mixed-model variance (i.e. observations with small variance receive heavier weights), because standard deviations were missing for several observations, including in the data set from Crowther and colleagues.

Spatial patterns - linear mixed effects models

We examined spatial patterns of warming effects on soil carbon responses by linking these responses to soil and climate data using the same linear mixed effects model regression analyses as used by Crowther and colleagues (i.e. same random effects and fixed effects). Thus, we included site as a random effect to account for multiple experiments conducted within a study and we used the same predictors. Afterwards, we used the Akaike Information Criterion (AIC) to determine the best model from the proposed set of models. See Supplemental R code for more details on the mixed effects model and Table S3 for the AIC results. The model with the lowest AIC value was the model that included two predictors: soil carbon stock in control plots and the magnitude of warming (Table S3).

Single-factor experiments

The expanded data set includes several multi-factorial studies, both in our data set and the data used by Crowther and colleagues. A mixed-effects model can account for the fact that experiments were conducted at the same site. However, we also analyzed the data by isolating experiments that solely used warming as a climate factor and as such the data were independent. The regression analysis using single-factor experiments confirms our finding that the change in the amount of soil carbon per degree-year warming is not a function of standing soil carbon stocks (Fig. S2).

References (used in Methods)

1. De Graaff, M., Van Groenigen, K.-J., Six, J., Hungate, B. & van Kessel, C. Interactions between plant growth and soil nutrient cycling under elevated CO_2: A meta-analysis. *Glob. Chang. Biol.* **12,** 2077–2091 (2006).

Table S1.

Description of field warming studies in alphabetical order. Information on location, coordinates, warming technique, warming magnitude (ΔT), and ecosystem are given. References used compile the soil carbon data set are provided, except for variables that were obtained through personal communication (PC). Note: Some single-factor warming experiments in a multi-factorial study were already included in Crowther et al.'s data set, and hence are not included in our data set.

Study	Study	Location (lat, long)	Warming method	ΔT (ºC)	Ecosystem	References
Abisko, 1150 m, high T	Abisko, Sweden	68.3N, 20.8E	OTC	4.9	Fell-field	PC
Abisko, 1150 m, high T - N	Abisko, Sweden	68.3N, 20.8E	OTC	4.9	Fell-field	PC
Abisko, 1150 m, low T	Abisko, Sweden	68.3N, 20.8E	OTC	2.4	Fell-field	PC
Abisko, 1150 m, low T - N	Abisko, Sweden	68.3N, 20.8E	OTC	2.4	Fell-field	PC
Abisko, 400 m	Abisko, Sweden	68.4N, 20.8E	OTC	2.3	Tundra	[1,2]
Abisko, 400 m, litter	Abisko, Sweden	68.4N, 20.8E	OTC	2.3	Tundra	[1,2]
Abisko, 450 m, high T	Abisko, Sweden	68.3N, 20.8E	OTC	2.8	Tundra	PC
Abisko, 450 m, high T - N	Abisko, Sweden	68.3N, 20.8E	OTC	3.9	Tundra	PC
Abisko, 450 m, Low T	Abisko, Sweden	68.3N, 20.8E	OTC	3.9	Tundra	PC
Abisko, 450 m low T - N	Abisko, Sweden	68.3N, 20.8E	OTC	2.8	Tundra	PC
Abisko, forest ecotone	Abisko, Sweden	68.4N, 18.8E	OTC	1.3	Forest	[3]
Abisko, Norrbotten, 560m	Abisko, Sweden	68.4N, 18.8E	OTC	1.3	Forest	[3]
Ailaoshan Station	Yunnan Province, China	24.5N, 101W	IR heaters	2.1	Forest	[4]
Alexandra Fiord, ITEX, dry	Canada	78.9N, 75.92W	OTC	2	Tundra	[5]
Alexandra Fiord, ITEX, mesic	Canada	78.9N, 75.92W	OTC	2	Tundra	[5]
Alexandra Fiord, ITEX, wet	Canada	78.9N, 75.92W	OTC	2	Tundra	[5]
Antarctica, Stepping Stones Islands, *Colobanthus*	Antarctica	64.8S, 64W	OTC	2.2	Tundra	[6]
Antarctica, Stepping Stones Islands, *Deschampsia*	Antarctica	64.8S, 64W	OTC	2.2	Tundra	[6]
Aranjuez, high biocrust	Aranjuez, Spain	40.0N, 3.3W	OTC	3	Desert	[7]
Aranjuez, high biocrust - drought	Aranjuez, Spain	40.0N, 3.3W	OTC	3	Desert	[7]
Aranjuez, low biocrust	Aranjuez, Spain	40.0N, 3.3W	OTC	3	Desert	[7]
Aranjuez, low biocrust - drought	Aranjuez, Spain	40.0N, 3.3W	OTC	3	Desert	[7]
BACE, high T	Massachusetts, US	42.4N, 71.9W	IR heaters	3.1	Grassland	PC
BACE, high T - drought	Massachusetts, US	42.4N, 71.9W	IR heaters	2.0	Grassland	PC
BACE, high T - precip	Massachusetts, US	42.4N, 71.9W	IR heaters	3.1	Grassland	PC
BACE, low T	Massachusetts, US	42.4N, 71.9W	IR heaters	0.8	Grassland	PC
BACE, low T - drought	Massachusetts, US	42.4N, 71.9W	IR heaters	2.0	Grassland	PC
BACE, low T – precip	Massachusetts, US	42.4N, 71.9W	IR heaters	0.8	Grassland	PC

BACE, medium T	Massachusetts, US	42.4N, 71.9W	IR heaters	2.3	Grassland	PC
BACE, medium T - drought	Massachusetts, US	42.4N, 71.9W	IR heaters	2.0	Grassland	PC
BACE, medium T - precip	Massachusetts, US	42.4N, 71.9W	IR heaters	2.3	Grassland	PC
Brandbjerg - CO_2	Denmark	55.9N, 12.0E	IR reflective curtains	0.8	Shrubland	PC
Brandbjerg - drought	Denmark	55.9N, 12.0E	IR reflective curtains	0.8	Shrubland	PC
Brandbjerg – drought x CO_2	Denmark	55.9N, 12.0E	IR reflective curtains	0.8	Shrubland	PC
Cass Warming Expt.	New Zealand	43.0S, 175.8W	Heating cables	3	Grassland	[8]
Cass Warming Expt.-N	New Zealand	43.0S, 175.8W	Heating cables	3	Grassland	[8]
Castle Valley	Utah, US	38.4N, 109.5W	IR heaters	2.0	Desert	[9]
Castle Valley – precipitation	Utah, US	38.7N, 109.4W	IR heaters	2.0	Desert	[9]
Cedar Creek	Minnesota, US	45.6N, 93.2W	IR heaters	2.5	Grassland	PC
Cedar Creek – CO_2	Minnesota, US	45.6N, 93.2W	IR heaters	1.5	Grassland	PC
Cedar Creek - drought	Minnesota, US	45.6N, 93.2W	IR heaters	1.5	Grassland	PC
Cedar Creek –drought x CO_2	Minnesota, US	45.6N, 93.2W	IR heaters	1.5	Grassland	PC
Cedar Creek – N	Minnesota, US	45.6N, 93.2W	IR heaters	1.5	Grassland	PC
Cedar Creek – N x CO_2	Minnesota, US	45.6N, 93.2W	IR heaters	1.5	Grassland	PC
Cedar Creek – N x CO_2 x drought	Minnesota, US	45.6N, 93.2W	IR heaters	1.5	Grassland	PC
Cedar Creek – N x drought	Minnesota, US	45.6N, 93.2W	IR heaters	1.5	Grassland	PC
CiPEHR - winter	Alaska, US	63.9N, 149.2W	Snow fences	1.9	Tundra	PC
Damxung, 4313m	China	38.5N, 91.1E	OTC	1.3	Grassland	[10]
Damxung, 4333m	China	38.9N, 91.1E	OTC	1.6	Grassland	[10]
Damxung, 4513m	China	38.5N, 91.1E	OTC	1	Grassland	[10]
Dovrefjell - tundra	Norway	62.3N, 9.62E	OTC	1.3	Tundra	[3]
Duolun County	China	42.0N, 116.3E	IR heaters	1.6	Grassland	[11–14]
Duolun – precipitation	China	42.0N, 116.3E	IR heaters	1.4	Grassland	[11–14]
Duolun - N	China	42.0N, 116.3E	IR heaters	1.8	Grassland	[13]
Flakaliden	Sweden	64.1N, 19.5E	Heating cables	5	Forest	[15]
Great Basin Expt. Range	Utah, US	39.3N, 111.5W	OTC	2	Grassland	[16]
Great Basin Expt. Range - grazing	Utah, US	39.3N, 111.5W	OTC	2	Grassland	[16]
Great Basin Expt. Range – grazing x N	Utah, US	39.3N, 111.5W	OTC	2	Grassland	[16]
Great Basin Expt, Range - N	Utah, US	38.7N, 109.4W	IR heaters	2.0	Grassland	[16]
Haibei, Qinghai-Tibet Plateau	China	37.6N, 101.3E	OTC	1.3	Grassland	[17]
Jasper Ridge - N	Stanford, CA, US	37.4N, 122.2W	IR heaters	0.9	Grassland	PC
Jasper Ridge - N x CO_2	Stanford, CA, US	37.4N, 122.2W	IR heaters	0.9	Grassland	PC
Jasper Ridge - N x CO_2 x precip	Stanford, CA, US	37.4N, 122.2W	IR heaters	0.9	Grassland	PC
Jasper Ridge - N x precipitation	Stanford, CA, US	37.4N, 122.2W	IR heaters	0.9	Grassland	PC
Jasper Ridge - precip	Stanford, CA, US	37.4N, 122.2W	IR heaters	0.9	Grassland	PC
Jasper Ridge - precip x CO_2	Stanford, CA, US	37.4N, 122.2W	IR heaters	0.9	Grassland	PC

Joatka, forest	Norway	69.8N, 24.0E	OTC	0.2	Forest	[3]
Joatka, tundra	Norway	69.8N, 24.0E	OTC	1.2	Tundra	[3]
Latnjajaure Field Station, heath	Sweden	68.4N, 18.5E	OTC	2.0	Tundra	[18,19]
Latnjajaure Field Station, meadow	Sweden	68.4N, 18.5E	OTC	2.0	Tundra	[18,20]
Miyalou Experimental Forest	China	31.6N, 102.6E	OTC	0.6	Forest	[21]
Nagqu	Qinghai-Tibetan Plateau	31.4N, 101.2E	OTC	1.3	Grassland	[17]
Oldebroek	The Netherlands	52.4N, 5.9E	IR reflective curtains	1.3	Shrubland	[22]
ORNL oldfield	Oak Ridge, TN, US	35.9N, 84.3W	OTC	3	Grassland	[23]
ORNL oldfield - CO_2	Oak Ridge, TN, US	35.9N, 84.3W	OTC	3	Grassland	[23]
ORNL oldfield - drought	Oak Ridge, TN, US	35.9N, 84.3W	OTC	3	Grassland	[23]
ORNL oldfield -drought x CO_2	Oak Ridge, TN, US	35.9N, 84.3W	OTC	3	Grassland	[23]
Qingpu	Qingpu district, China	32.2N, 121.1E	IR heaters	1.6	Crop	[24]
Qinghai-Tibet Plateau, 4635m	China	34.8N, 92.9E	IR heaters	2.3	Grassland	[25,26]
Qinghai-Tibet Plateau,	China	34.9N, 92.9E	OTC		Grassland	[27]
Sardinia, Capa Caccia	Italy	40.6N, 8.2E	IR reflective curtains	0.2	Shrubland	[22]
Sichuan, *Abies* forest	Sichuan province, China	31.7N, 103.9E	IR heaters	3.7	Forest	[28]
Sichuan, *Pinus* forest	Sichuan province, China	31.7N, 103.9E	IR heaters	3.7	Forest	[28]
Sichuan, National Nature Reserve, 3000 m	China	33N, 104E	OTC	1.0	Forest	[29]
Sichuan, National Nature Reserve, 3500 m	China	33N, 104E	OTC	0.9	Forest	[29]
TasFACE, C3 grasses	Tasmania	42.7S, 147.3E	IR heaters	1.8	Grassland	PC
TasFACE, C3 - CO_2	Tasmania	42.7S, 147.3E	IR heaters	1.8	Grassland	PC
TasFACE, C4 grasses	Tasmania	42.7S, 147.3E	IR heaters	1.8	Grassland	PC
TasFACE, C4 - CO_2	Tasmania	42.7S, 147.3E	IR heaters	1.8	Grassland	PC
Tazovskiy Peninsula, ITEX	Siberia	67.9N, 74.9E	OTC	0.9	Tundra	[30]
Tomakomai Expt. Forest	Hokkaido, Japan	42.7N. 141.6E	Heating cables	3.5	Forest	[31]

Table S2.

Description of field warming studies in alphabetical order, in terms of average study duration over which soil carbon data were obtained (Years), mean annual temperature (MAT), mean annual precipitation (MAP), soil acidity (pH), percent clay, carbon stocks in warmed and control plots (in kg C m^{-2}) and their standard deviations (sd). Soil data were from the study when available, or else obtained from SoilGrids. Note: Some single-factor warming experiments in a multi-factorial study were already included in Crowther et al.'s data set, and hence are not included in our data set.

Study	Years	MAT (ºC)	MAP (mm)	pH	% clay	Soil C stock control	Soil C stock warmed	sd control	sd warmed
Abisko, 1150 m, high T	5.0	-4.8	500	5.2	13	0.19	0.20	0.06	0.71
Abisko, 1150 m, high T - N	6.0	-4.8	500	5.2	13	0.17	0.16	0.07	0.05
Abisko, 1150 m, low T	5.0	-4.8	500	5.2	13	0.19	0.23	0.06	0.1
Abisko, 1150 m, low T - N	6.0	-4.8	500	5.2	13	0.17	0.26	0.06	0.06
Abisko, 400 m	9.0	-0.7	299	4.2	13	3.36	3.61	NA	NA
Abisko, 400 m, litter	9.0	-0.7	299	4.2	13	3.39	3.77	NA	NA
Abisko, 450 m, high T	10.8	-0.7	299	7.1	13	2.59	2.84	0.61	0.52
Abisko, 450 m, high T - N	8.6	-0.7	299	7.1	13	2.37	2.62	0.48	0.39
Abisko, 450 m, Low T	6.0	-0.7	299	7.1	13	2.57	2.70	0.66	0.91
Abisko, 450 m low T - N	6.0	-0.7	299	7.1	13	2.37	2.55	NA	0.49
Abisko, forest ecotone	2.2	-0.7	304	5.22	13	0.39	0.44	NA	NA
Abisko, Norrbotten, 560m	2.2	-0.7	304	3.86	13	3.83	4.19	NA	NA
Ailaoshan Station	4.0	11.3	1778	4.5	29	3.13	3.27	NA	NA
Alexandra Fiord, ITEX, dry	9.0	-14.6	150	6.6	17	2.00	3.71	1.09	0.55
Alexandra Fiord, ITEX, mesic	9.0	-14.6	150	6.6	17	6.23	4.52	1.69	3.31
Alexandra Fiord, ITEX, wet	9.0	-14.6	150	6.6	17	5.90	5.44	2.20	2.68
Antarctica, Stepping Stones Islands, *Colobanthus*	3.3	-1.7	750	6	1.8	1.09	1.31	0.34	0.58
Antarctica, Stepping Stones Islands, *Deschampsia*	3.3	-1.7	750	6	1.8	0.70	1.05	0.24	0.28
Aranjuez, high biocrust	3.8	15	349	7	22	0.25	0.34	0.10	0.06
Aranjuez, high biocrust - drought	3.8	15	349	7	22	0.24	0.31	0.10	0.10
Aranjuez, low biocrust	3.8	15	349	7	22	0.10	0.19	0.04	0.07
Aranjuez, low biocrust - drought	3.8	15	349	7	22	0.14	0.13	0.05	0.03
BACE, high T	2.9	9.5	1194	5.5	9	6.63	6.71	0.46	0.46
BACE, high T - drought	2.9	9.5	1194	5.5	9	7.06	7.04	0.70	0.39
BACE, high T - precip	2.9	9.5	1194	5.5	9	6.54	6.77	0.49	0.36
BACE, low T	2.9	9.5	1194	5.5	9	6.63	6.61	0.46	0.60
BACE, low T - drought	2.9	9.5	1194	5.5	9	7.06	7.50	0.70	0.32
BACE, low T – precip	2.9	9.5	1194	5.5	9	6.54	6.56	0.43	0.64

BACE, medium T	2.9	9.5	1194	5.5	9	6.63	6.97	0.46	0.52
BACE, medium T - drought	2.9	9.5	1194	5.5	9	7.06	6.95	0.70	0.83
BACE, medium T - precip	2.9	9.5	1194	5.5	9	6.54	6.64	0.43	0.86
Brandbjerg - CO_2	4.4	8	613	4.5	2	4.45	3.90	1.47	1.74
Brandbjerg - drought	4.4	8	613	4.5	2	4.57	3.95	1.79	2.34
Brandbjerg – drought x CO_2	4.4	8	613	4.5	2	4.98	4.79	2.15	1.77
Cass Warming Expt.	2.0	10	1300	5.4	20	4.38	4.53	0.56	0.07
Cass Warming Expt.-N	2.0	10	1300	5.4	20	4.71	4.63	0.23	0.16
Castle Valley	1.5	12.2	236	7.8	13	0.30	0.28	0.13	0.07
Castle Valley – precipitation	1.5	12.2	236	7.8	13	0.30	0.30	0.08	0.07
Cedar Creek	1.0	6.8	799	6	15	1.31	1.31	0.14	0.43
Cedar Creek – CO_2	1.0	6.8	799	6	15	1.51	1.24	0.87	0.21
Cedar Creek - drought	1.0	6.8	799	6	15	1.13	1.95	0.07	1.07
Cedar Creek –drought x CO_2	1.0	6.8	799	6	15	1.93	1.33	0.19	0.35
Cedar Creek – N	1.0	6.8	799	6	15	1.38	1.36	0.43	0.23
Cedar Creek – N x CO_2	1.0	6.8	799	6	15	1.53	1.34	0.27	0.02
Cedar Creek – N x CO_2 x drought	1.0	6.8	799	6	15	2.05	1.98	0.42	1.10
Cedar Creek – N x drought	1.0	6.8	799	6	15	1.43	1.59	0.32	0.43
CiPEHR - winter	2.6	-1	378	4.82	17	5.73	5.55	1.78	2.89
Damxung, 4313m	1.3	1.3	477	6.35	13	5.13	5.13	0.70	0.38
Damxung, 4333m	1.3	1.3	477	6.35	13	6.47	5.87	0.99	0.71
Damxung, 4513m	1.3	1.3	477	6.35	13	12.05	11.62	1.42	1.18
Dovrefjell - tundra	2.2	1.15	473	6.18	6	4.08	4.19	NA	NA
Duolun County	5.3	2.1	382.3	6.84	17	3.28	3.15	0.91	1.08
Duolun – precipitation	5.3	2.1	382.3	6.84	17	2.45	2.47	0.20	0.45
Duolun - N	3.9	2.1	382.3	6.84	17	4.71	4.9	2.60	1.93
Flakaliden	14.4	2	600	4.4	7	1.20	1.10	0.14	0.71
Great Basin Expt. Range	2.1	1.7	902	6.4	20	6.16	5.69	2.89	2.63
Great Basin Expt. Range - grazing	2.1	1.7	902	6.4	20	5.09	5.05	1.60	1.85
Great Basin Expt. Range – grazing x N	2.1	1.7	902	6.4	20	4.76	5.12	1.47	1.68
Great Basin Expt, Range - N	2.1	1.7	902	6.4	20	5.78	6.71	2.85	4.66
Haibei, Qinghai-Tibet Plateau	2.0	-1.7	561	7.3	16	6.21	5.45	1.33	1.70
Jasper Ridge - N	7.6	14	652	6.8	15	1.93	1.88	0.25	0.31
Jasper Ridge - N x CO_2	7.6	14	652	6.8	15	1.96	1.87	0.28	0.30
Jasper Ridge - N x CO_2 x precip	7.6	14	652	6.8	15	1.82	1.88	0.28	0.38
Jasper Ridge - N x precipitation	7.6	14	652	6.8	15	1.83	1.85	0.29	0.29
Jasper Ridge - precip	7.6	14	652	6.8	15	1.78	1.72	0.28	0.29
Jasper Ridge - precip x CO_2	7.6	14	652	6.8	15	1.77	1.83	0.28	0.32
Joatka, forest	2.2	-1.5	354	4.07	7	1.33	1.34	NA	NA
Joatka, tundra	2.2	-1.5	354	4.03	7	1.28	1.23	NA	NA
Latnjajaure Field Station, heath	10.6	-2	848	3.7	8	7.45	10.77	NA	NA

Latnjajaure Field Station, meadow	10.6	-2	848	4.7	8	8.33	7.62	NA	NA
Miyalou Experimental Forest	4.0	8.9	790	6.19	16	3.46	5.63	NA	NA
Nagqu	10.0	-3	450	7.06	16	6.38	6.13	0.85	1.28
Oldebroek	13.0	8.3	1042	3.8	2	3.54	3.83	0.74	0.88
ORNL oldfield	3.5	14.2	1322	5.8	22	3.87	3.76	NA	NA
ORNL oldfield - CO_2	3.5	14.2	1322	5.8	22	3.80	3.86	NA	NA
ORNL oldfield - drought	3.5	14.2	1322	5.8	22	3.89	4.13	NA	NA
ORNL oldfield -drought x CO_2	3.5	14.2	1322	5.8	22	3.82	4.00	NA	NA
Qingpu	3.0	17.7	1044.7	6.1	6.1	2.54	2.46	NA	NA
Qinghai-Tibet Plateau, 4635m	2.0	-3.8	291	8.35	0.03	0.65	0.65	NA	NA
Qinghai-Tibet Plateau,	3.0	-3.8	383	7.7	16	2.15	2.22	NA	NA
Sardinia, Capa Caccia	11.0	16.8	610	7.3	28	3.17	3.28	0.85	0.45
Sichuan, *Abies* forest	3.7	8.9	920	5.55	20	8.33	8.48	0.95	1.44
Sichuan, *Pinus* forest	3.3	8.9	920	5.55	20	8.97	9.16	NA	NA
Sichuan, National Nature Reserve, 3000 m	3.9	2.85	813	5.8	12	7.47	7.75	0.64	0.67
Sichuan, National Nature Reserve, 3500 m	3.9	2.85	813	5.8	12	8.00	9.02	0.99	1.12
TasFACE, C3 grasses	5.9	11.6	560	5.86	21.7	3.03	2.90	NA	NA
TasFACE, C3 - CO_2	5.9	11.6	560	5.86	21.7	3.43	3.48	NA	NA
TasFACE, C4 grasses	5.9	11.6	560	5.86	21.7	3.68	4.31	NA	NA
TasFACE, C4 - CO_2	5.9	11.6	560	5.86	21.7	3.59	3.30	NA	NA
Tazovskiy Peninsula, ITEX	1.3	-8.8	370	5.9	13	12.66	13.91	NA	NA
Tomakomai Expt. Forest	7.0	6.3	1450	5.1	13	5.10	4.17	1.46	0.62

Table S3.
Evaluating predictors of soil carbon responses to warming. Model fits comparing the statistical power gained by explaining soil carbon responses by treatment expressed as degree-Years (additive.treat and interactive), by treatment expressed as degree (additive.dT, interactive.dT), by environmental variables (MAT, MAP, and pH; additive.enviro), and by all variables (additive.all). The additive.dT model has a lower AIC value than any other model. For details on the linear mixed model structure, see supplemental R code.

	Df	AIC	BIC	logLik	deviance	Chisq	Chi df	Pr(>Chisq)
lmer.list$simple	4	-103.1	-91.25	55.55	-111.1	NA	NA	NA
lmer.list$additive.treat	5	-101.4	-86.63	55.72	-111.4	0.3418	1	0.5588
lmer.list$additive.dT	5	-105.3	-90.52	57.67	-115.3	3.89	0	0
lmer.list$interactive	6	-99.6	-81.83	55.8	-111.6	0	1	1
lmer.list$interactive.dT	6	-103.8	-86.06	57.92	-115.8	4.228	0	0
lmer.list$additive.enviro	8	-98.76	-75.06	57.38	-114.8	0	2	1
lmer.list$additive.all	9	-97.69	-71.02	57.84	-115.7	0.9274	1	0.3355

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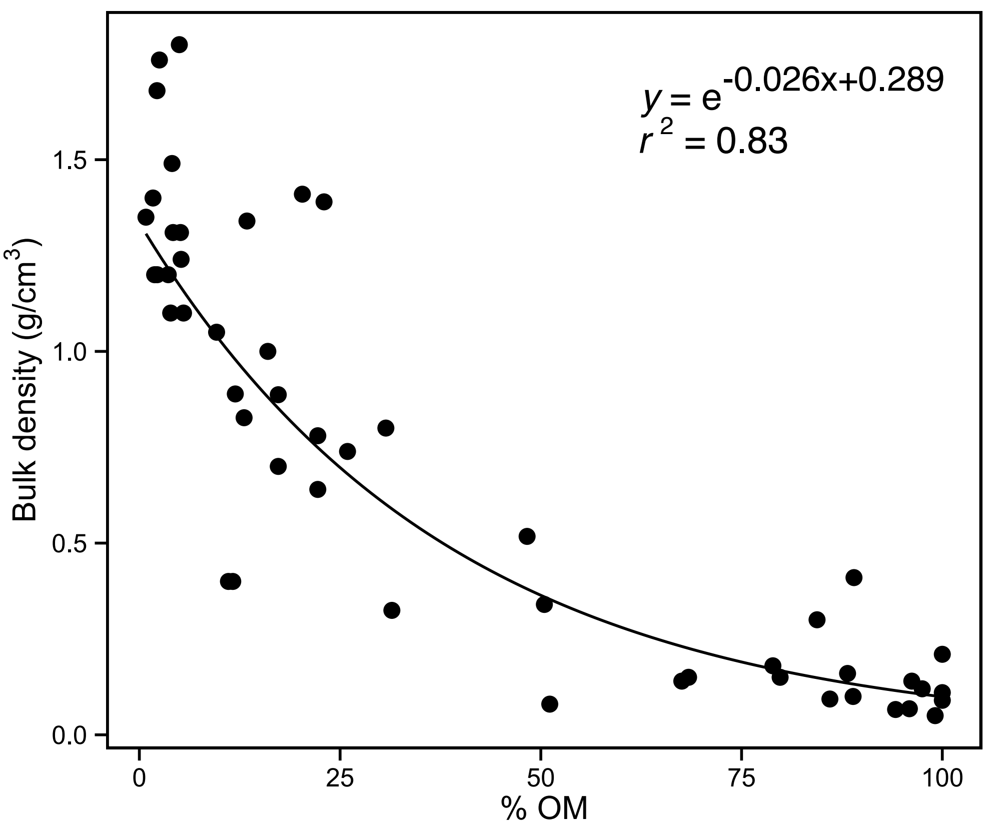
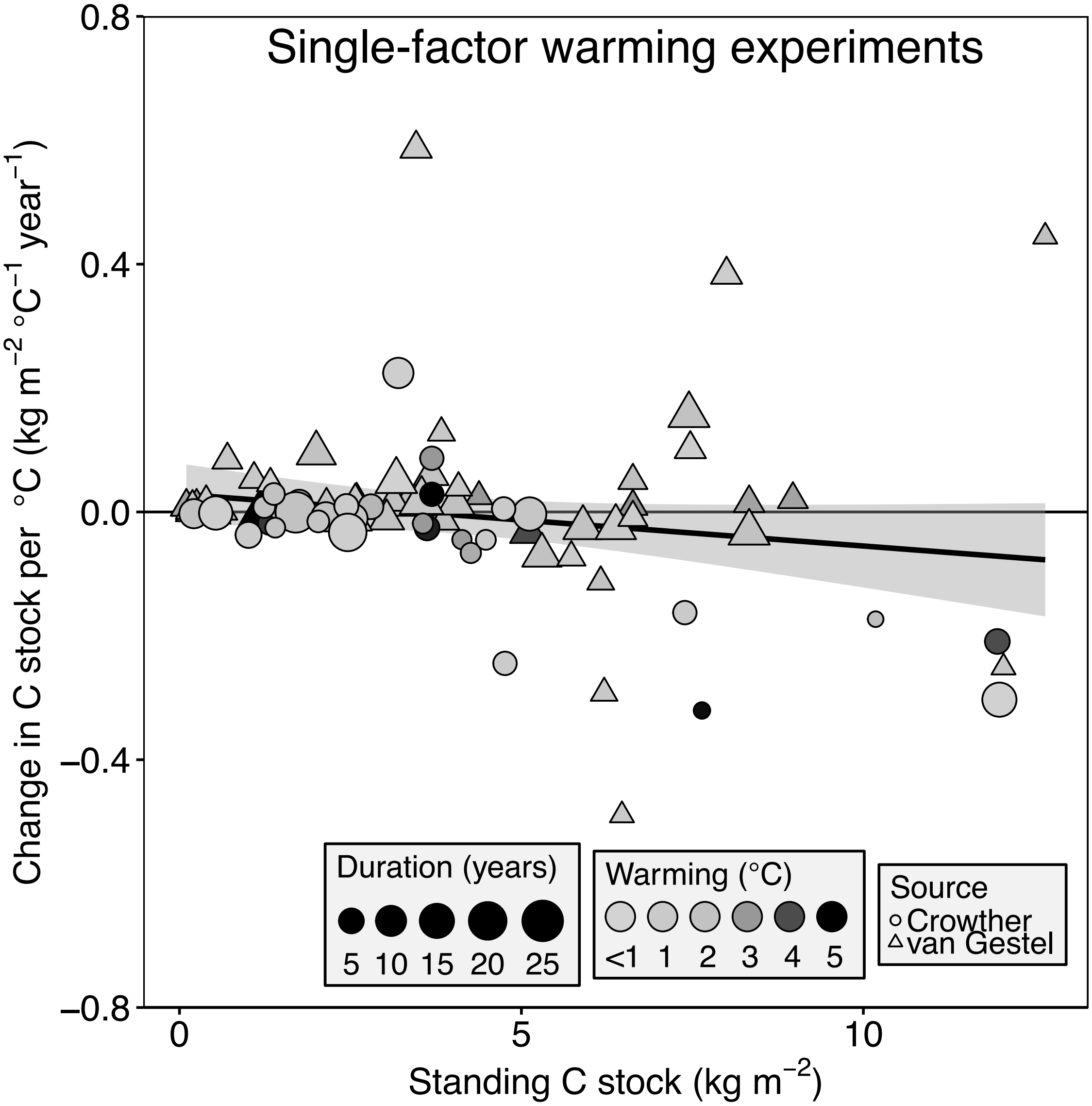


Supplementary Figure S1. **Relationship between bulk density of the soil and the soil organic matter content (% OM)**. This relationship was used to estimate bulk density for a site if site-specific bulk density data was not available. Bulk density data were used to convert soil C data to kg C m^{-2} when necessary.



Supplementary Figure S2.

The change in soil C per degree-years warming in single-factor experiments is not a function of C stock size. We used a subset of the data to increase independence of soil carbon observations. The data set includes single-factor (*i.e.* warming only) experiments from Crowther and colleagues[1] (n = 32 single-factor studies) and data from van Gestel et al. (this paper; n = 52 additional single-factor studies). The combined dataset of single-factor studies (total n = 84) shows no relationship between the warming effect on soil C and the initial C stock size (r^2 =0.02, P > 0.05), and hence, supports our main finding from the full data set.

Supplemental R Code: 'Predicting soil carbon loss with warming'

Natasja van Gestel

September 30, 2017

Read Libraries and set working directory

```
library(plyr)
library(ggplot2)
library(lme4)
library(pander)
library(maps)
library(mapdata)
library(boot)
setwd("~/Documents/Meta-Analysis/Warming_dataAssimilation/Data files")
```

Helper functions

```
meta.fig = function(d, cols = c("average", "lower.ci", "upper.ci", "cat1", "n"
), y.axis = "", ylim=c(-0.1,0.1)) {
  # Set theme
  theme.bw   <- theme_bw() + theme(
    panel.background = element_blank(),
    panel.border = element_rect(colour="black", size=1.5),
    axis.text.x = element_text(size=14),
    axis.text.y = element_text(size=14),
    axis.title = element_text(size = 14),
    plot.title = element_text(hjust = 0.5, size=14), # 0.5 centers the title
    panel.grid = element_blank()
  )
  # Isolate columns of interest (avg, lower.ci, upper.ci)
  d.fig = data.frame(avg=d[,cols[1]], lower.ci=d[,cols[2]], upper.ci=d[,cols[3
]], cat1=d[,cols[4]], n=d[,cols[5]])
  d.fig$cat1 = factor(d.fig$cat1, levels = c("Crowther", "All data"))

  ggplot(d.fig, aes(cat1, avg)) +
      geom_point(size=8) +
      scale_y_continuous(limits=c(ylim[1],  ylim[2])) +
      labs(y=y.axis, x="") +
      geom_errorbar(aes(ymin=avg-(avg-lower.ci), ymax = avg+(upper.ci-avg)), s
ize=1, width=0.2) +
      geom_hline(aes(yintercept=0), linetype=2) +
      geom_text(aes(label=paste0("n = ",n)), size=5, vjust = 7) +
      theme.bw
}

bootstrap = function(x) {
  # Calculate weighted mean (weighted by wt2, which combines study duration an
d # reps)
  # and is downweighted by number of observations within each study
  wm = weighted.mean(x$dC.perDegYr, x$wt2)
```

```
  # Calculate bootstrapped CI of weighted mean using function in package boot
  f <- function(df,i){
    d2 <- df[i,]
    return(weighted.mean(d2$dC.perDegYr,d2$wt2))
  }
  bootNT <- boot(x, f, R=4999)
  boot.results=boot.ci(bootNT, type = c("norm"))
  results = data.frame(sampleMean = wm, lower.ci=boot.results$normal[2], upper
.ci=boot.results$normal[3])
  return(results)
} #end function
```

Data

Read in combined data set (van Gestel and Crowther). The units of carbon stocks in control and warmed plots are kg/m2.

```
d = read.csv("databaseS1.csv")
d$dC <- d$C.warmed - d$C.control
d$degYr = with(d, Years * Tdelta)
d$dC.perDegYr <- d$dC/d$degYr
d$dC.div.Tdelta = d$dC/d$Tdelta
```

Regression model

This section runs the same regressions as Crowther et al. Further details are in Crowther's Supplemental Info, p. 41, "Construct LM" section

Run regression on Crowther et al.'s data set and verify their r2 of 0.49 (n = 49).

```
dCperDegYr.study = lm((C.warmed-C.control)/(Years*Tdelta) ~ C.control, subset(
d, Source=="Crowther"))
summary(dCperDegYr.study)

## 
## Call:
## lm(formula = (C.warmed - C.control)/(Years * Tdelta) ~ C.control, 
##     data = subset(d, Source == "Crowther"))
## 
## Residuals:
##       Min        1Q    Median        3Q       Max 
## -0.183919 -0.027960  0.001134  0.021358  0.246185 
## 
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)    
## (Intercept)  0.060932   0.015986   3.812 0.000401 ***
## C.control   -0.025852   0.003766  -6.864 1.32e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## Residual standard error: 0.06965 on 47 degrees of freedom
## Multiple R-squared:  0.5006, Adjusted R-squared:   0.49 
## F-statistic: 47.11 on 1 and 47 DF,  p-value: 1.315e-08
```

Run regression on entire data set (n = 143)

```
dCperDegYr.study.all = lm((C.warmed-C.control)/(Years*Tdelta) ~ C.control, d)
summary(dCperDegYr.study.all)
```

```
##
## Call:
## lm(formula = (C.warmed - C.control)/(Years * Tdelta) ~ C.control,
##     data = d)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.47032 -0.02449 -0.00612  0.02644  0.58619
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.023030   0.016678   1.381   0.1695
## C.control   -0.006569   0.003716  -1.768   0.0793 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1189 on 141 degrees of freedom
## Multiple R-squared:  0.02168,    Adjusted R-squared:  0.01474
## F-statistic: 3.125 on 1 and 141 DF,  p-value: 0.07928
```

Run regression on experiments that only have warming (i.e. no other interactions) (n = 84) (excludes multifactorial studies)

```
d.T.subset = subset(d, T.only)
dCperDegYr.T.only = lm((C.warmed-C.control)/(Years*Tdelta) ~ C.control, data =
 d.T.subset)
summary(dCperDegYr.T.only)
```

```
##
## Call:
## lm(formula = (C.warmed - C.control)/(Years * Tdelta) ~ C.control,
##     data = d.T.subset)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.46381 -0.03080 -0.01288  0.02096  0.58686
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.029063   0.025009   1.162   0.2486
## C.control   -0.008508   0.004998  -1.702   0.0925 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1381 on 82 degrees of freedom
## Multiple R-squared:  0.03413,    Adjusted R-squared:  0.02235
## F-statistic: 2.897 on 1 and 82 DF,  p-value: 0.09251
```

Model selection

This section is largely unchanged from the corresponding section in Crowther et al., Supplemental Info

```
# Rescale for statistical analyses
data.rescaled = d

# Log-transform some variables
data.rescaled$degYr <- log(data.rescaled$degYr)
data.rescaled$Years <- log(data.rescaled$Years)
data.rescaled$C.control <- log(data.rescaled$C.control)
data.rescaled$C.warmed <- log(data.rescaled$C.warmed)

# Rescale all numeric data
non.numeric.cols = c(1:3,6, 9:11)
data.rescaled[,-non.numeric.cols] <- as.data.frame(apply(data.rescaled[, -non.
numeric.cols], c(2), function(xx){ return((xx-mean(xx, na.rm=TRUE))/sd(xx, na.
rm=TRUE)+1)
}))


# Run LMER (same code as Crowther et al.)
lmer.list <- list(simple = lmer(C.warmed ~ C.control + (1|unique.site), data=d
ata.rescaled),
                  additive.dT = lmer(C.warmed~C.control+Tdelta + (1|unique.sit
e), data=data.rescaled),
                  additive.all = lmer(C.warmed~C.control+map+mat+pH+degYr + pe
rc.clay + (1|unique.site), data=data.rescaled),
                  additive.enviro = lmer(C.warmed~C.control+map+mat+pH + perc.
clay+ (1|unique.site), data=data.rescaled),
                  additive.treat = lmer(C.warmed~C.control+degYr + (1|unique.s
ite), data=data.rescaled),
                  interactive = lmer(C.warmed~C.control*degYr+ (1|unique.site)
, data=data.rescaled),
                  interactive.dT = lmer(C.warmed~C.control*Tdelta+ (1|unique.s
ite), data=data.rescaled))
```

Table S3

This table contains the model selection output (including AIC values)

```
pander(anova(lmer.list$simple, lmer.list$additive.treat, lmer.list$additive.dT
, lmer.list$additive.enviro, lmer.list$additive.all, lmer.list$interactive, lm
er.list$interactive.dT), caption='Model fits comparing the statistical power
gained by explaining carbon responses by treatment expressed as degree-Years (
additive.treat and interactive) or degree (additive.dT, interactive.dT), by en
viromental variables (MAT, MAP, and pH; additive.enviro) and by all variables
(additive.all). The additive.dT model has lowest AIC value than any other mode
l. For details on model structure see supplemental R code.')

## refitting model(s) with ML (instead of REML)
```

Model fits comparing the statistical power gained by explaining carbon responses by treatment expressed as degree-Years (additive.treat and interactive) or degree (additive.dT, interactive.dT), by *enviromental variables (MAT, MAP, and pH; additive.enviro) and by all variables (additive.all). The additive.dT model has lowest AIC value than any other model. For details on model structure see supplemental R code. (continued below)*

	Df	AIC	BIC	logLik	deviance	Chisq
lmer.list$simple	4	-103.1	-91.25	55.55	-111.1	NA
lmer.list$additive.treat	5	-101.4	-86.63	55.72	-111.4	0.3418
lmer.list$additive.dT	5	-105.3	-90.52	57.67	-115.3	3.89
lmer.list$interactive	6	-99.6	-81.83	55.8	-111.6	0
lmer.list$interactive.dT	6	-103.8	-86.06	57.92	-115.8	4.228
lmer.list$additive.enviro	8	-98.76	-75.06	57.38	-114.8	0
lmer.list$additive.all	9	-97.69	-71.02	57.84	-115.7	0.9274

	Chi Df	Pr(>Chisq)
lmer.list$simple	NA	NA
lmer.list$additive.treat	1	0.5588
lmer.list$additive.dT	0	0
lmer.list$interactive	1	1
lmer.list$interactive.dT	0	0
lmer.list$additive.enviro	2	1
lmer.list$additive.all	1	0.3355

Meta-analysis

Generate data used for Extended Data Figure 1.

```
# Add weights (weight by # reps and average duration of the study for which soil C
# data was collected. See De Graaff et al. 2006 (ref 1 in Methods).
d$wt = with(d, (n.rep * n.rep)/(n.rep + n.rep) + (Years * Years)/(Years + Years))

# Downweight weights by the number of observations within a study
d = ddply(d, .(unique.site), transform, wt2 = wt/length(unique.site))

# Arrange data frame, so that Crowther's data is distinct from the 'all data' (Crowther
 + van Gestel)
# This results in 192 rows of data (Crowther's 49 and Crowther + van Gestel of 143)
# Meta-analysis is done on Crowther's only or the entire data set.
d$data.set = "All data"
crowther = d[d$Source=="Crowther",]
crowther$data.set = "Crowther"
d.fig = rbind(d, crowther)

# Bootstrap
meta.results = ddply(d.fig, .(data.set), function(x) bootstrap(x))

# Add number of studies (Figure is done in later section), then reorder data to list "a
ll data" last
meta.results$n = c(143, 49)
```

Figures

Generate Figure 1 in main text. Figure format adopted from Crowther et al.

Figure 1

```
Fig1.main.theme <- theme(
            axis.text.x=element_text(size=14,angle=0,colour="black"),
            axis.text.y=element_text(size=14,angle=0,colour="black"),
            axis.title=element_text(size=14),
            legend.text=element_text(size=12),
            axis.line.x=element_line(color="black"),
            legend.position = "bottom",
            legend.key = element_rect(fill="grey95",size=0,color="grey95"),
            legend.key.size = unit(0.1,"cm"),
            legend.title = element_text(size=12),
            legend.background = element_rect(fill="grey95",color="black"),
            axis.line = element_line(colour = "black"),
            panel.grid.major = element_blank(),
            panel.grid.minor = element_blank(),
            strip.background = element_rect(colour = "black",size = 0.5),
            panel.background = element_rect(colour="black", fill="white"),
            panel.border = element_blank(),
            axis.ticks = element_line(colour="black"),
            legend.box = "horizontal",
            axis.title.y=element_text(vjust=0.1),
            axis.title.x=element_text(vjust=0.1)) +
      theme(legend.justification=c(1,0), legend.position=c(1,0))

# Set color scheme for symbols
ramp <- colorRamp(c('lightgrey', 'grey', 'black'))
use.col.points <- c(rgb( ramp(seq(0, 1, length = 500)), max = 255))

# Reorder to make Crowther's data more visible
d = d[order(d$Source, d$Tdelta, decreasing=T),]

ggplot(d, aes(x=C.control, y = dC.perDegYr)) +
  geom_hline(yintercept=0) +
  geom_smooth(method="lm", aes(group=Source, linetype=Source, color=Source), s
e=F, show.legend = F) +
  geom_point(aes(shape=Source, fill=Tdelta, size=Years, color=Source)) +
  scale_shape_manual(values=c(21,24)) +
  scale_color_manual(values = c("black", "blue")) +
  scale_fill_gradientn(limits=range(c(0,d$Tdelta)), colors = use.col.points, s
pace="Lab" ,labels=c("<1",1,2,3,4,5))+
  scale_y_continuous(limits=c(-0.8,0.8), expand = c(0, 0)) +
  scale_size(range=c(2,7)) +
  xlab(expression("Standing C stock (kg m"^-2*")")) +
  ylab(expression("Change in C stock (kg m"^-2~degree*C^-1~year^-1*")")) +
  Fig1.main.theme +
  guides(size = guide_legend(nrow = 1,label.position = "bottom", label.hjust=0
.5,title.position="top", title=expression("Duration (years)"), legend.box = "v
ertical")) +
  guides(fill = guide_legend(nrow = 1, label.position = "bottom", label.hjust=
0.5,title.position="top", title=expression("Warming ("*degree*C*")"), override
.aes = list(size = 5),legend.box = "vertical"))
```

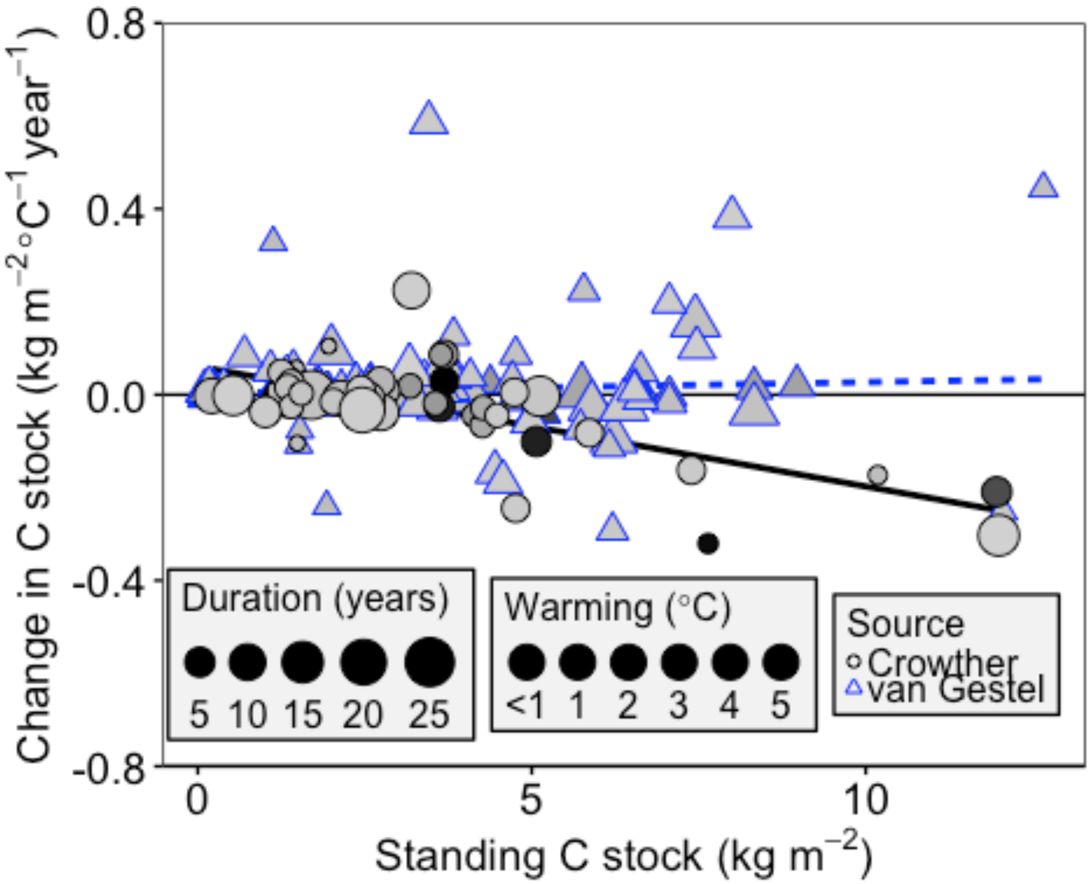
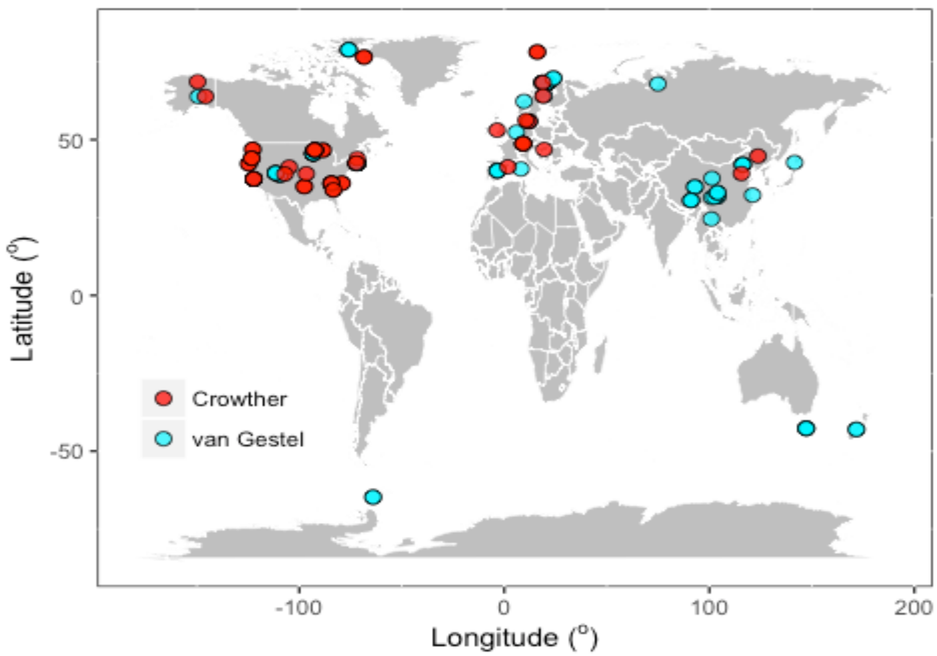


Figure 2 (map)

```
world.map = map_data('world')

ggplot(world.map, aes(x = long, y = lat)) +
    geom_polygon(aes(group=group), fill = "grey75", col = "white", size = .2)
+ # fill areas
    theme(panel.background = element_rect(fill = 'white', colour = 'black')) +
    labs(x = expression(paste("Longitude (" ^o, ")")), y = expression(paste("L
atitude (" ^o, ")"))) +
    geom_point(data=d, aes(fill = Source), size = 2.5, shape = 21, col="black"
, alpha=0.8)+
    scale_fill_manual(values=c("red", "turquoise1")) +
    theme(legend.title = element_blank(), legend.position = c(0.15, 0.3), lege
nd.background = element_blank())
```



Extended Data Figure 1

```
meta.fig(meta.results, cols=c("sampleMean", "lower.ci", "upper.ci", "data.set"
, "n"), y.axis = expression("Change in C stock (kg m"^-2~degree*C^-1~year^-1*"
)"))
```

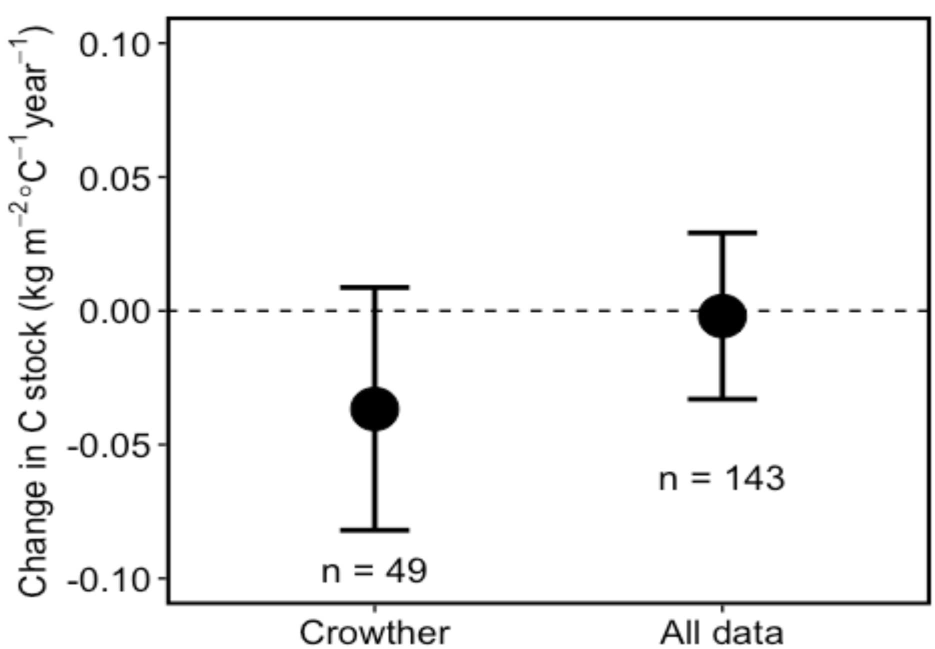


Figure S1 (bulk density) and model

```
bd = read.csv("databaseS2.csv", header = TRUE, sep = ",")

# Run a regression and view the relationship
model = with(bd, lm(log(bulk.density)~percent.om))
a = round(summary(model)[[4]][2], 3)
b = round(summary(model)[[4]][1], 3)
r2 = round(summary(model)[[9]], 3)

x = seq(min(bd$percent.om), max(bd$percent.om))
y = exp(a*x +b)
best.line = data.frame(percent.om=x, bulk.density=y)

ggplot(bd, aes(percent.om, bulk.density)) +
  geom_point(size=3)+
  geom_line(data=best.line) +   # add best-fit line
  labs(x="% OM", y = expression(paste("Bulk density (g/cm" ^3*")"))) +
  theme_bw() +
  theme(panel.grid=element_blank(), panel.border=element_rect(color="black", s
ize=1)) +
  geom_text(x=0.75*max(bd$percent.om), y=0.9*max(bd$bulk.density), label = pas
te("y=exp(", a, "x+", b, ")", "\n r2=", r2, sep=""))
```

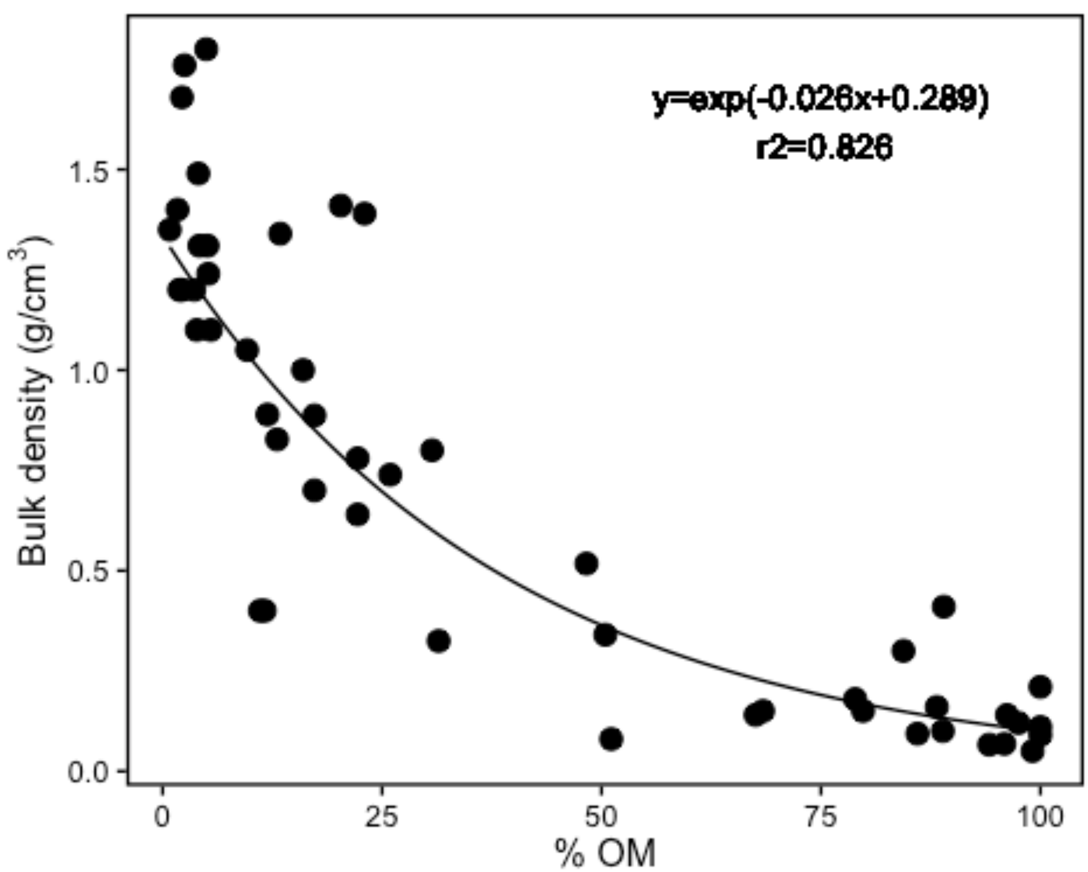


Figure S2 - single factor warming experiments

```
# Reorder data to make Crowther's more visible
d.T.subset = d.T.subset[order(d.T.subset$Source, d.T.subset$Tdelta, decreasing
=T),]

ggplot(d.T.subset, aes(x=C.control, y = dC.perDegYr)) +
    geom_hline(yintercept=0) +
    geom_smooth(method="lm", col="black", show.legend = F) +
    geom_point(aes(shape=Source, fill=Tdelta, size=Years)) +
    scale_shape_manual(values=c(21,24)) +
    scale_fill_gradientn(limits=range(c(0,d$Tdelta)), colors = use.col.points,
 space="Lab" ,labels=c("<1",1,2,3,4,5))+
    scale_y_continuous(limits=c(-0.8,0.8), expand = c(0, 0)) +
    scale_size(range=c(2,7)) +
    xlab(expression("Standing C stock (kg m"^-2*")")) +
    ylab(expression("Change in C stock (kg m"^-2~degree*C^-1~year^-1*")")) +
    Fig1.main.theme +
    guides(size = guide_legend(nrow = 1,label.position = "bottom", label.hjust
=0.5,title.position="top", title=expression("Duration (years)"), legend.box =
"vertical")) +
    guides(fill = guide_legend(nrow = 1, label.position = "bottom", label.hjus
t=0.5,title.position="top", title=expression("Warming ("*degree*C*")"), overri
de.aes = list(size = 5),legend.box = "vertical"))
```