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QUANTIFYING GLOBAL SOIL C LOSSES IN RESPONSE TO WARMING

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Generating meaningful greenhouse gas (GHG) emission targets requires an understanding of Earth system dynamics and projections about how they will respond to global change[1–3]. If anthropogenic warming stimulates the loss of carbon from the Earth's surface into the atmosphere, it could drive additional planetary warming. Despite growing evidence that warming enhances soil carbon fluxes to and from the soil[8,12], the net global balance between these responses remains uncertain[1]. Here we present a comprehensive analysis of warming-induced changes in soil carbon stocks by assembling data from 49 field experiments located across North America, Europe and Asia. We find that the effects of warming are contingent upon the size of the initial soil carbon stock, with considerable carbon losses occurring in high-latitude areas. By extrapolating this empirical relationship to the global scale, we provide estimates of global soil carbon sensitivity that may help to constrain Earth System Model projections. Our empirical relationship suggests that global soil carbon stocks in the upper soil horizons will fall by 30 (± 30) to 203 (± 161) Pg C for 1 degree of continuous warming, depending upon the potential acclimatization rate of soil organic matter decomposition. An assumption of annual acclimation yields a conservative estimate that soil C stocks will fall by 55 (± 50) Pg C from the upper soil horizons by 2050, a value that is 12-17% of anthropogenic emissions over this period. Despite the uncertainty in these estimates, the direction of the global soil carbon response is consistent across all acclimatization scenarios. Our analysis provides strong empirical support for the assumption that rising temperatures will stimulate the net loss of soil carbon to the atmosphere, driving a positive land carbon-climate feedback that could accelerate climatic change.

The majority of the Earth's terrestrial C is stored in the soil and changes in the size of this C stock represent a prominent control on atmospheric C concentrations[6–8]. If anthropogenic warming stimulates the loss of even a small proportion of soil C, it could drive substantive additional planetary warming[7,9]. Yet, despite considerable scientific attention in recent decades, there remains no consensus on the direction or magnitude of warming-induced changes in soil C[3,10]. Although there is growing confidence that warming generally enhances fluxes to and from the soil[8,12], the net global balance between these responses remains uncertain and direct estimates of soil C stocks are limited to single-site experiments that generally reveal no detectable effects[1,11–13].

Given the paucity of direct measurements of soil C stock responses to warming, Earth System Models (ESMs) must rely heavily on short-term temperature responses of soil respiration (Q_{10}) to infer long-term changes in global C stocks. Without empirical observations that capture longer-term C dynamics, we are limited in our ability to evaluate model performance, or constrain the uncertainty in model projections[14]. As such, the land C-climate feedback remains one of the largest sources of uncertainty in current ESMs[1–3], restricting our capacity to develop C emissions targets that are compatible with specific climate change scenarios. Direct field measurements of warming-induced changes in soil C stocks are urgently needed to increase confidence in future climate projections[14].

We take advantage of the growing number of climate change experiments around the world to compile the first global database of soil C stock responses to warming. Soil samples were collected from replicate plots in 49 climate change experiments conducted across six biomes, ranging from arctic permafrost to dry Mediterranean forests (Extended data Figure 1). We compared soil C stocks across 'warmed' (treatment) and 'ambient' (control) plots to explore the effects of temperature across sites. The measured differences in soil C stocks represent the net result of long-term changes in soil C inputs (plant production) and outputs (respiration) in response to warming. By linking these soil C responses to climatic and soil characteristics we are able to generate a spatial understanding of the temperature-sensitivity of soil C stocks at a global scale. To standardise collection protocols and account for the considerable variability in soil horizon depths, we focus on C stocks in the top 10 cm of soil. At a global scale, this upper soil horizon contains the greatest proportion of biologically active soil C by depth[6].

The effects of warming on soil C stocks were variable, with positive, negative and neutral impacts observed across sites (Figure 1). However, the direction and magnitude of these warming-induced changes were predictable (Figure 2), being contingent upon the size of standing soil C stocks and the extent and duration of warming. The interaction between ‘control C stocks’ and ‘degree-years’ (the standardised metric to represent the multiplicative product of the extent (°C) and duration (years) of warming) was a strong explanatory variable when predicting warmed C stocks (additive model AIC=383 vs. multiplicative model AIC=381; see SI and Equation 1). Specifically, the impacts of warming were negligible in areas with small initial C stocks, but losses occured beyond a threshold of 20 – 40 kg C m^{-3} and were considerable in soils with ≥ 60 kg C m^{-3} (Figure 1). No other environmental characteristics (mean annual temperature, precipitation, soil texture or pH) significantly ($P > 0.1$) influenced the responses of soil C stocks to warming in our statistical models (additive enviromental with degree-year model AIC=388; see SI).

The dominant role of standing C stocks in governing the magnitude of warming-induced soil C losses is in line with both empirical and theoretical expectations[2,15,16]. The thawing of permafrost soils, where limited C decomposition has led to the accumulation of large C stocks, will undoubtedly contribute to this phenomenon[17,18]. However, our analysis also revealed considerable soil C losses in several non-permafrost regions, suggesting that additional mechanisms may contribute to the vulnerability of large soil C stocks. Presumably, the vulnerability of soils containing large C stocks stems from the high temperature-sensitivity of C decomposition and biogeochemical restrictions on the processes driving soil C inputs. In ecosystems with low initial soil C stocks, minor losses that result from accelerated decomposition under warming may be offset by concurrent increases in plant growth and soil C stabilization[12,19]. In contrast, in areas with larger standing soil C stocks, accelerated decomposition outpaces potential C accumulation from enhanced plant growth, driving considerable C losses into the atmosphere.

By combining our measured soil C responses with spatially-explicit estimates of standing C stocks[17] and soil surface temperature change[20] (using Equation 2), we reveal the global patterns in the vulnerability of soil C stocks (Figure 3). Given that high-latitude regions have the largest standing soil C stocks[17] and the fastest expected rates of warming[15,20], our results suggest that the overwhelming majority of warming-induced soil C losses are likely to occur in Arctic and sub-Arctic regions (Figure 3). These high-latitude C losses drastically outweigh any minor changes expected in mid- and lower latitude regions, providing additional support for the idea of Arctic amplification of climate change feedbacks[15] (Figure 3). These warming-induced soil C losses need to be considered in light of future changes in moisture stress and vegetation growth, which are also likely to respond disproportionately to climate change in high-latitude areas[15]. Notably, the spatial distribution of soil C changes from our extrapolation contradicts projections from the CMIP5 archive of Earth system models[21], which show increases in soil C at high latitudes, presumably due to the increases in plant producitity[22]. The warming-induced losses of soil C that we observe have the potential to offset these vegetation responses, emphasizing the importance of representing soil C vulnerability in the process-based models used in climate change projections.

We extrapolated this relationship over the next 35 years to indicate how global soil C stocks might respond by 2050. The simple extrapolation of our empirical relationship suggests that 1 degree of warming over 35 years would drive the loss of 203 (±161) Pg C from the upper soil horizon (Figure 3). However, this approach implicitly assumes that soil communities never acclimatize to changes in temperature, so are likely to drastically over-estimate total soil C losses. Indeed, as with mechanistic models[23], our assumptions about the rate of soil C acclimatization will strongly influence the magnitude of our predicted C losses (see Figure 3B). For example, a range of recent analyses suggest that soil communities can acclimatize to warming within a year[24–26]. If we assume annual acclimatization to warming in our extrapolation, then approximately 30 (± 30) Pg C would be lost from the surface soil for 1 degree (ºC) of warming. Given that global average soil surface temperatures are projected to increase by ~2 ºC over the next 35 years under a business-as-usual emissions scenario[16], this annual time step extrapolation would suggest that warming could drive the net loss of ~55 (± 50) Pg C from the upper soil horizon. If, as expected, this C entered the atmospheric pool, it would increase the atmospheric burden of CO_2 by approximately 25 ppm over this period.

The global extrapolation of our empirical data is broadly intended to contextualize our measured changes in soil C stocks. We stress that such statistical approaches cannot be used to project soil C losses far into the future because, unlike process-based models, they cannot capture the complex processes that govern long-term C dynamics. For example, extending the observed relationship over several centuries would lead to a global convergence of soil C stocks. Conversely, soil C stocks would increase exponentially in response to environmental cooling. Our linear extrapolation inherits weaknesses from simple single pool models, which can over-predict the magnitude of responses in the long term[2,27]. However, the value of such linear approximations lie in their descriptive strength rather than their predictive capabilities: instead of using short-term flux estimates to project long-term changes in C stocks, our approach allows the scaling of measured C differences over time frames (i.e. decades) represented by the experimental studies. Our results capture the realised temperature-sensitivity of current soil C stocks and can serve as a guideline (or target) for multi-pool process-based models. Specifically, these models can run forward simulations that attempt to reflect the outcomes of the warming experiments that we present. Those models which accurately capture the observed relationships between standing soil C stocks and losses under gradual step increases in global temperature are likely to be the most successful at projecting the land C-climate feedback into the future.

Our analysis reveals a number of outstanding challenges facing empiricists and modelers, which currently limit the certainty of current land C-climate feedback predictions (see Supplemenrary Table 1). These limitations fall into two distinct categories, as more data are necessary to improve (i) our current global estimates of soil C temperature sensitivity, and (ii) modelling efforts to project these soil C responses into the future. First, along with the limited spatial and temporal scale of current warming experiments, perhaps the most critical limitation to our present analysis is the paucity of information about the responses of soil C stocks at depth (below 10 cm). Although the size of C stocks decrease down the soil profile[28], any additional C losses from these deeper soil horizons will undoubtedly enhance the effects we present. Second, incorporating global soil C information into modelling frameworks requires a mechanistic understanding of how warming affects each of the individual components of the ecosystem C cycle. Now that we are beginning to generate a global picture of the temperature-sensitivity of soil C losses (respiration)[8] and total C stocks, our limited understanding of how warming influences global soil C inputs remains a major outstanding source of uncertainty for modelling efforts[1,22]. These efforts also require more information about the interacting effects of other global change factors that may simultaneously influence soil C dynamics. This non-exclusive set of practical challenges calls for concerted, coordinated investment in multi-factor climate change experiments for an extended period of time to generate the data necessary to improve confidence in future climate projections.

In conclusion, our global compilation of experimental data allows us to see past the conflicting results from single-site studies and capture larger patterns in the sensitivity of soil C to warming. The warming-induced changes in soil C stocks reflect the net result of changes in C fluxes into and from the soil, which can augment modelling efforts to project Earth system dynamics into the future. Ultimately, our analysis provides empirical support for the long-held concern that rising temperatures stimulate the loss of soil C into the atmosphere, driving a positive land C-climate feedback that could accelerate planetary warming over the 21st century. Reductions in greenhouse gas emissions are essential if we are to avoid the most damaging impacts of the land C-climate feedback over the rest of this century.

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AUTHOR CONTRIBUTIONS

The study was conceived and designed by TWC and NS. Statistical analysis was performed by KEOTB , MAB, and BLS. Spatial scaling and mapping was performed by WRW and CWR. The manuscript was written by TWC with assistance from CWR, MAB, WRW, KEOTB, SDA and PBR. All other authors reviewed and provided input on the manuscript. Measurements of soil carbon, bulk density and geospatial data from climate change experiments around the world were provided by JCC, MBM, SF, GZ, AJB, BE, SR, AJH, HL, YL, AM, JP, ME, SDF, GK, CP, PHT, LLR, EP, SS, JML, SDA, KKT, BE, LNM, IKS, KSL, YC, FAD, SM, SN, ATC, JMB, SB, JSC, FAD, JG, BRJ, JM, LPM and PBR.

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FIGURE LEGENDS

Figure 1: The effect of warming on soil C losses depends on the initial standing soil C stock. The interaction between warming (degree-years) and standing C stocks is a primary determinant of final warmed soil C stocks (estimated using a mixed effects model; n = 229; see SI). Here, each point represents the difference (mean±SE) between soil C stocks in warmed and ambient plots within an individual experiment. The size of points represents the length of each individual study, and the colour indicates the amount

of warming. The shaded area represents the bootstraped 95% conficence interval (R^2 = 0.49: see supplemental for details).

Figure 2: Validation plots highlighting the predictive strength of the statistical model. Plate A: predicted vs. observed soil C stock values in warmed treatment plots (estimated using statistical Equation 1: $R^2 = 0.95$ – high value is driven by the correlation between C values in control and warmed plots). Black points represent mean values for each study, and the coloured area represents the density of 1000 simulated points randomly selected from within the normal distribution for each study. The 1:1 line is included to highlight perfect correspondence between predicted and observed points and distributions. Plate B: Bootstrapped estimates of model (Equation 2) slope values for different sample sizes. Studies were removed at random, the slope coefficient was calculated and this was repeated 1000 times. Each point represents a bootstrapped estimate of slope for the model that included any given number of studies, and we include the interquartile range and median slope estimates an each number. The average slope value remains unchanged until >38 studies have been removed from the initial analysis (with 49 studies), highlighting that the relationship we present is not disproportionately influenced by the effects of warming in any specific study(s) or site(s).

Figure 3: Spatial and temporal extrapolation of the temperature-vulnerability of soil C stocks. Plate A: Map of soil C vulnerability to warming. This map was generated by extrapolating Equation 2 (i.e. the no-acclimation scenario) using spatially explicit estimates of soil C stocks[17], and soil surface temperature change[20], and reveals the spatial variation in projected surface soil C stock changes (0-15 cm) expected under a 1ºC rise in global average soil surface temperature. Panel B: Total reductions in the global C pool under a 1, and 2ºC global average soil surface warming by 2050, as expected under a full range of different soil acclimatization scenarios (x axis). Shaded areas indicate 95% confidence intervals around the average C losses (dots) for each scenario. The rapid acclimatization scenarios (e.g. 1 week – 1 year) result in lower total soil C losses than the no acclimatization scenario, but all simulations reveal considerable global losses of soil C under warming over the next 35 years. Note that our map predicts some C gains in desert

regions that currently contain almost no soil C. Removing these biochemically questionable responses would marginally enhance the size of the global C losses reported in Pannel B.

METHODS

Data collection and standardisation

Total percentage C and bulk density (BD) data (n=456) were collected from each of the replicated warmed and ambient plots within 49 experimental warming studies located across North America, Europe and Asia. In several of these sites, it was not possible to access these data for deeper soil horizons. Therefore, we standardised collection protocols and account for the considerable variability in soil horizon depths by focusing on the top 10 cm of soil, which contains the majority of the biologically active C. Soil C stocks were then calculated for each plot (percentage C * BD / 100), and expressed as the total mass of C (kg m^{-3} soil) in each plot. Metadata for each study included the mean annual difference in soil surface temperature between warmed and ambient plots and the duration of experimental warming. These were multiplied together to generate the standardised metric ‘degree-years’, (reflecting the extent and duration of warming) to permit the comparison of warming effects across sites. Other collected data included a site-specific geospatial reference (latitude and longitude), which was linked to spatially-explicit estimates of soil characteristics (pH and texture using the SoilGrids database[17]) and climate (using the Bioclim database) following Crowther *et al.*[29]. These climate and soil characteristics were then used to explore the dominant controls on soil C stock sensitivity to warming across our global compilation of experimental studies.

Some of the climate change studies in this analysis containted multiple separate warming experiments. Degree-years and soil C were calculated independently for each study within a site, but all other environmental data were shared. In addition, some sites included multi-factor climate change studies. For these studies, ambient and warmed plots were only compared under equivalent experimental conditions so that all other conditions remained consistent between treatments.

Statistical analysis

We fitted linear mixed models (LMMs) to evaluate the factors that correlate with the measured soil C stocks following warming. Study site was included as a random factor because clustering replicates by location could introduce spatial autocorrelation[30]. The LMMs were fit assuming a Gaussian error distribution in the "lme4" package for the R statistical program[31]. We constructed LMMs that included all of the putative explanatory variables to explain warmed soil C stocks including treatment variables (degrees warmed and degrees warmed across years of study (degree-years)), and environmental characteristics (Standing soil C stocks (control C stocks), Mean Annual Temperature (MAT), Mean Annual Precipitation (MAP), pH (as H^+ ion concentration) and soil texture (with percentage clay as the representative variable)). Given the markedly different ranges in magnitudes of the explanatory variables at a global scale, variables were standardised using a z-transformation prior to use in final models[32], though the response variable (soil C stock) was not standardised. Further, given positive skew in the distributions of degrees, degree-year and control soil C, these variables were also natural-log transformed. Neither of these data transformations significantly altered the statistical outputs, so were retained in final models. The only independent variables that were strongly correlated (pairwise coefficients >0.4) were MAT and MAP, and MAT and percentage clay.

Model selection was performed using maximum likelihood comparison of competing models (see SI), using Akaike information criterion (AIC) and Bayesian information criterion (BIC) approaches providing identical results. Only warming (degrees and degree-years) and standing C stock (control soil C) were the most parsimonious final models, (full model AIC=381 vs. final model AIC=372; Tables S6, S7) and the best-fit model included an interaction between these two variables (addItive model AIC=375 vs. multiplicative model AIC=372; Table S7). All reported *P*-values are quasi-Bayesian, rather than the classical frequentist *P*-values, but retain the same interpretation. We considered coefficients with P<0.05 significant and coefficients with P<0.10 marginally significant. Variance explained by the model was also estimated by calculating R^2 values for the minimally-adequate LMM following Nakagawa and Schielzeth to retain the random effects structure.

The final statistical model was:

$$C_w = a \cdot C_c \cdot \left(\Delta T \Delta t\right) + b \cdot C_c + d \cdot \left(\Delta T \Delta t\right) + \varepsilon \qquad \text{Eqn 1}$$

where *Cw* is the carbon stock in the warmed treatment, Cc the carbon stock in the control plots, *ΔTΔt* the degree-years calculated by multiplying the degrees warmed times the length of the treatment, ε the random effects term controlling for study site (see SI), and *(a, b, d*) represent fitted coefficients for the statistical model.

Statistical model development

To scale the changes in soil C stocks, we re-arranged our statistical equation in order to describe the relationship between standing soil C stocks (control C stocks) and warming (degree-years) over time:

$$\frac{C_w - C_c}{\Delta T \cdot \Delta t} = f \cdot C_c + g \qquad \text{Eqn 2}$$

where *Cw* is the carbon stock in the warmed treatment, Cc the carbon stock in the control plots, *ΔTΔt* the degree-years calculated by multiplying the degrees warmed times the length of the tratement. This new model explained a considerable proportion (R^2=0.606; SI Table 7) of the difference in soil C stocks between studies over treatment. This is futher highlighted in Figure 2.

We used sample-based bootstrapping (as opposed to the study-based bootstrapping in Figure 2b) to evaluate the strength of this simple statistical relationship and to generate a margin of error for global soil C stock projections. Equation 1 was extrapolated with 95%CI bounds by randomly selecting 200 samples from all studies, randomising the control-warmed pairings, and repeating the regression 1000 times. This resulted in normally distributed parameters (see SI Table 4) with the following 95%CI. The intercept-slope pairs were then sampled to create the grey margin of error seen in Figure 1.

The inclusion of a linear effect of 'time' in our analysis implicitly assumes that soils never acclimatize to warming. However, recent studies suggest that soils can acclimatize to warming within an annual time-frame[24–26], so the assumption of no acclimatization is likely to over-estimate total soil C losses. To explore the importance of this acclimatization assumption in determining the magnitude of soil C losses in our extrapolation, we repeated the analysis across a full range of acclimatization scenarios. To simulate different acclimatization rates, we sucessively capped the study years (or experiment duration) at 1 week, 1 month, 6 months, and 1, 5, 7, 8.75, 11.6, 17.5 years, then re-ran the linear regression described above (Eqn 2) with the sample-based bootstrapping. The resulting coefficients are in SI Table 4.

Extrapolation

To estimate changes in global soil C stocks under projected warming scenarios we applied linear changes in soil temperature that result in 1 or 2^{o}C mean warming by 2050 (35 years) that is spatially distributed in a manner consistent with surface soil temperature projections from a single ensemble of the Community Earth System Model (CESM) that was submitted to the CMIP5 archive under RCP8.5 run from 2005 to 2050. We estimated initial soil C stocks in the upper soil horizon (0-15 cm) from the SoilGrids 50-km^2 product[17], that was regridded using bilinear interpolation to the same spatial scale of soil surface temperature projections (roughly 1 degree).

The temporal extrapolations across the 35 years (until 2050) were applied separately for each of the possible acclimatization scenarios described above. First, the single time step approach used the coefficients listed above and illustrated in Figure 1 to generate a 95% confidence interval for projected C losses. On average, roughly 17.5 degree-years and 35 degree-years were seen cumulatively across the globe for the 1 and 2^{o}C warming scenarios, respectively. The exact warming seen by any individual grid was determined by their relative temperature shifts predicted by the CESM run described above. Each subsequent acclimatization scenario was then extrapolated using a given time step for a forward integration where the change in soil C over that time was based on the soil C stock at the beginning and the degree-year change experienced by that site over the duration of at respective time step. For example, the 1-year acclimation scenario used the coefficients from the analysis where or experimental duration was capped at 1 year (see SI, Table 4), and was extrapolated to 2050 using the sum of 35 annual time steps. The predicted soil C losses for a global average warming of 1 and 2 C by 35 years, based on each of the full range of acclimatization scenarios, is presented in Figure 3B. This reveals how our assumption about acclimatization time influences the magnitude of our final expected C losses.

The R code for the full analysis can be found in the Supplementary Material.

References

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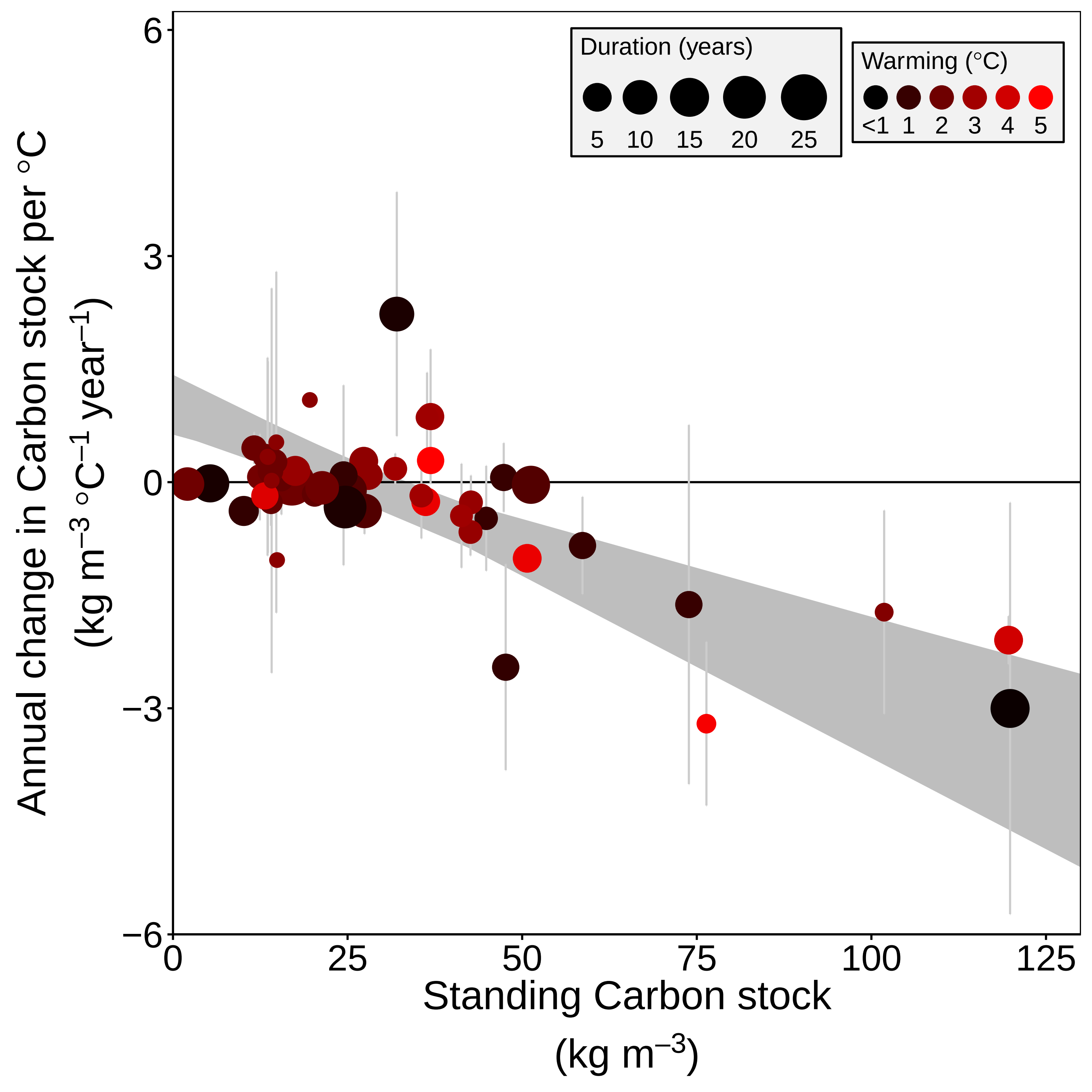
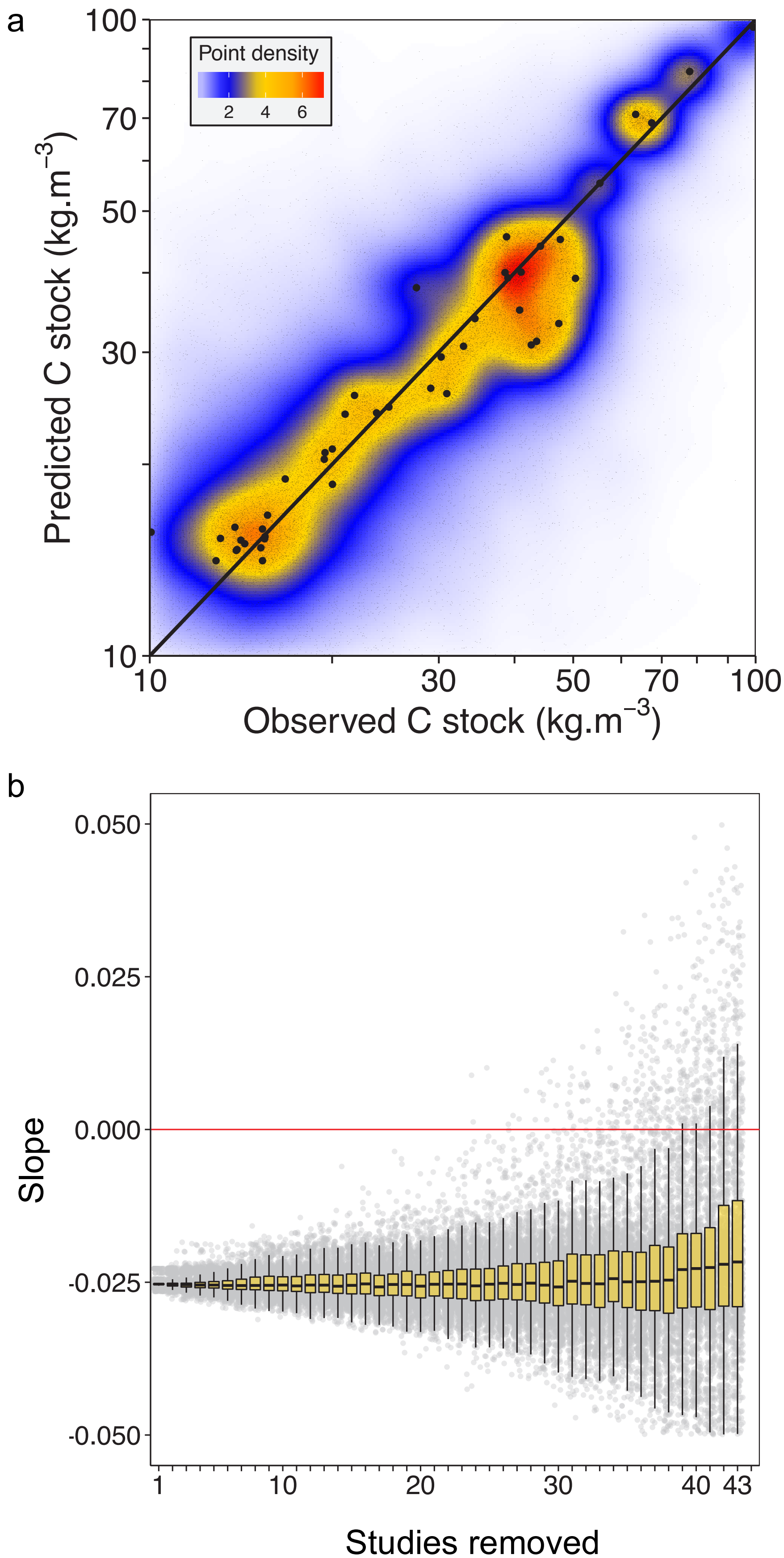
31. Bates, D., Machler, M., Bolker, B. M. & Walker, S. C. Fitting Linear Mixed-Effects Models using lme4. *J. Stat. Softw.* **67,** 1–48 (2014).
32. Gelman, A. Scaling regression inputs by dividing by two standard deviations. *Stat. Med.* **27,** 2865–2873 (2008).

Extended data table 1: List of current limitations in the availability of global data that restrict confidence in our current understanding of the land C-climate feedback. Each of these limitations represents a practical challenge that can be adressed by empiricists to improve the accuracy of benchmarking estimates or to perameterize process-based models that project Earth system dynamics into the future.

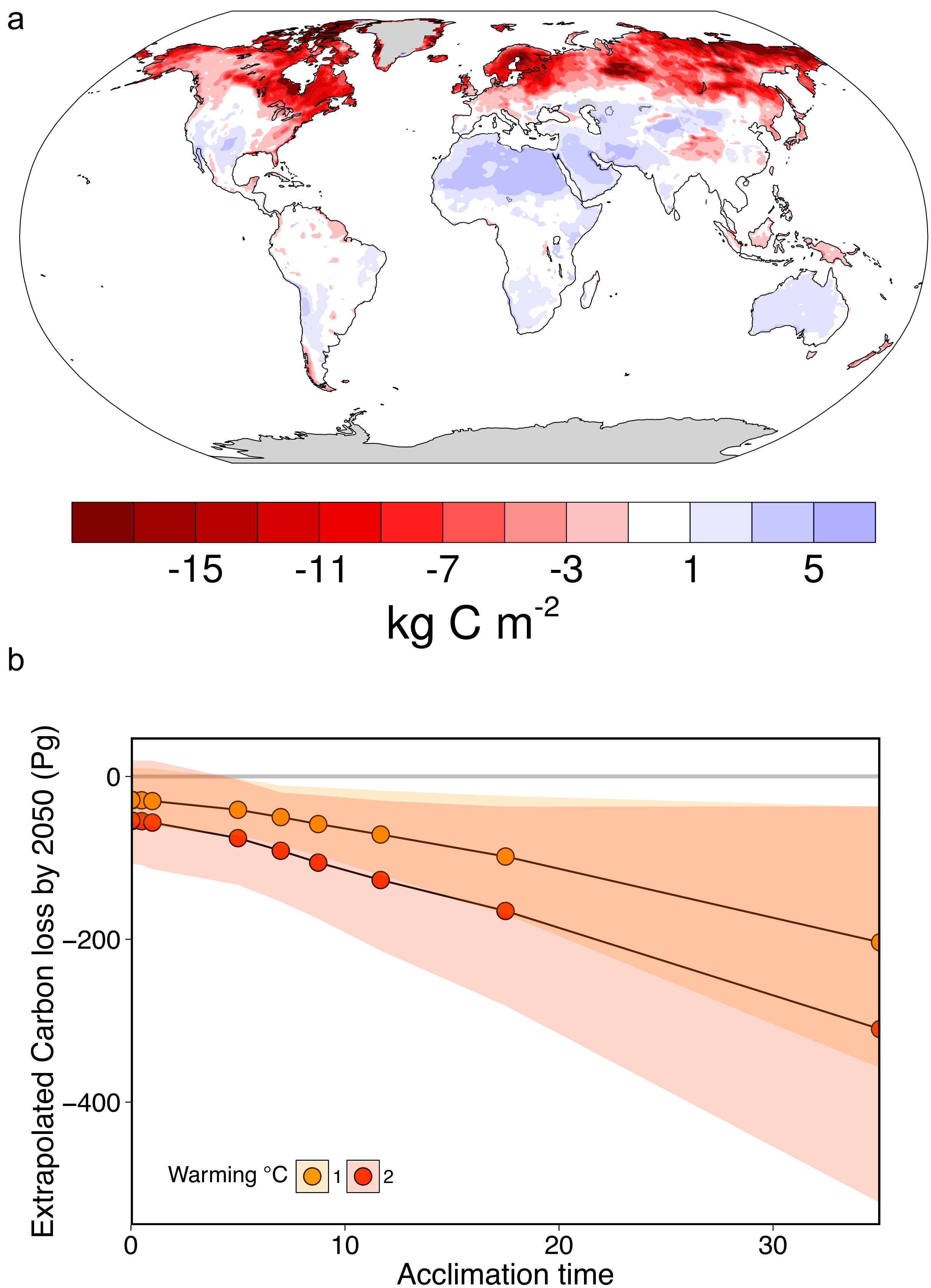
Extended Data Figure 1: Map of study locations. The size of points represents the number of separate warming experiments at that location and colour indicates the biome, as delineated by The Nature Conservancy (http://www.nature.org).

Extended Data Figure 2: Extended extrapolation of our linear model that illustrates some of the limitations of this statistical scaling approach. Figures show soil C projections for initial stocks under (A) 1 degree warming per decade, which converge on the same soil C stocks; or (B) 2 degree cooling per decade, which show exponential increases in soil C stocks. Although both of these responses are unrealistic, we note the time scales (and amount of warming) needed to observe such dynamics are well outside the range of observed manipulations or climate change projections. This highlights that our extrapolation cannot represent a substitute for process-based models, which capture long-term C dynamics. However, under more realistic warming (< 5 degrees C) our extrapolation makes plausible projections over decadal time scale that represent the current temperature sensitivity of soil C stocks.


Duration (years)
5 10 15 20 25
Warming (°C)
<1 1 2 3 4 5
6
3
0
−3
−6
Annual change in Carbon stock per °C
(kg m−3 °C−1 year−1)
0 25 50 75 100 125
Standing Carbon stock
(kg m−3)



a
Point density
2
4
6
Predicted C stock (kg.m−3)
Observed C stock (kg.m−3)
10
30
50
70
100
b
Slope
0.050
0.025
0.000
-0.025
-0.050
1
10
20
30
40
43
Studies removed



a
-15
-11
-7
-3
1
5
kg C m-2
b
Extrapolated Carbon loss by 2050 (Pg)
0
−200
−400
Warming °C
1
2
0
10
20
30
Acclimation time

Supplemental for Crowther et al 2016

K Todd-Brown (ktoddbrown@gmail.com) with M Bradford, W Wieder, B Snoek and T Crowther

July 19, 2016

Contents

List of Tables

LMER model selection

There were several LMER models which were considered as follows:

```
l_ply(names(lmer.list), function(xx){
  cat('------------',xx,'---------------\n')
  print(summary(lmer.list[[xx]]))
  cat('\n')})
```

```
## ------------ simple ---------------
## Linear mixed model fit by REML ['lmerMod']
## Formula: C.warmed ~ C.control + (1 | Study)
##    Data: data.sample.plus.rescaled
##
## REML criterion at convergence: 355.9
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.5629 -0.3810  0.0790  0.5306  3.5029
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  Study    (Intercept) 0.008552 0.09248
##  Residual             0.267455 0.51716
```

```
## Number of obs: 225, groups:  Study, 47
##
## Fixed effects:
##             Estimate Std. Error t value
## (Intercept)  0.16748    0.05222   3.207
## C.control    0.83498    0.03683  22.671
##
## Correlation of Fixed Effects:
##           (Intr)
## C.control -0.696
##
## ------------ addative.dT ---------------
## Linear mixed model fit by REML ['lmerMod']
## Formula: C.warmed ~ C.control + Tdelta + (1 | Study)
##    Data: data.sample.plus.rescaled
##
## REML criterion at convergence: 360.5
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.5572 -0.3849  0.0793  0.5225  3.4958
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  Study    (Intercept) 0.01022  0.1011
##  Residual             0.26726  0.5170
## Number of obs: 225, groups:  Study, 47
##
## Fixed effects:
##              Estimate Std. Error t value
## (Intercept)  0.178727   0.063246   2.826
## C.control    0.833247   0.037661  22.125
## Tdelta      -0.008932   0.038939  -0.229
##
## Correlation of Fixed Effects:
##           (Intr) C.cntr
## C.control -0.490
## Tdelta    -0.550 -0.151
##
## ------------ addative.all ---------------
## Linear mixed model fit by REML ['lmerMod']
## Formula: C.warmed ~ C.control + MAP + MAT + pH + degYr + perClay + (1 |
##     Study)
##    Data: data.sample.plus.rescaled
##
## REML criterion at convergence: 372.7
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.5934 -0.3706  0.0626  0.4693  3.5707
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  Study    (Intercept) 0.01607  0.1268
```

```
##  Residual             0.26328  0.5131
## Number of obs: 225, groups:  Study, 47
##
## Fixed effects:
##             Estimate Std. Error t value
## (Intercept)  0.16429    0.10930   1.503
## C.control    0.81814    0.04336  18.867
## MAP          0.09615    0.08783   1.095
## MAT         -0.11018    0.07926  -1.390
## pH           0.02757    0.06851   0.402
## degYr       -0.04959    0.04116  -1.205
## perClay      0.05873    0.06837   0.859
##
## Correlation of Fixed Effects:
##           (Intr) C.cntr MAP    MAT    pH     degYr
## C.control -0.318
## MAP       -0.450 -0.327
## MAT       -0.004  0.237 -0.666
## pH        -0.638 -0.145  0.710 -0.268
## degYr     -0.313 -0.132  0.064  0.067  0.142
## perClay    0.236  0.256 -0.340 -0.251 -0.589 -0.318
##
## ------------ addative.enviro ---------------
## Linear mixed model fit by REML ['lmerMod']
## Formula: C.warmed ~ C.control + MAP + MAT + pH + perClay + (1 | Study)
##    Data: data.sample.plus.rescaled
##
## REML criterion at convergence: 369.5
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.5907 -0.3791  0.0774  0.4715  3.5187
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  Study    (Intercept) 0.02268  0.1506
##  Residual             0.25938  0.5093
## Number of obs: 225, groups:  Study, 47
##
## Fixed effects:
##             Estimate Std. Error t value
## (Intercept)  0.14078    0.10887   1.293
## C.control    0.79712    0.04424  18.016
## MAP          0.11242    0.09108   1.234
## MAT         -0.11841    0.08329  -1.422
## pH           0.04011    0.07078   0.567
## perClay      0.03427    0.06789   0.505
##
## Correlation of Fixed Effects:
##           (Intr) C.cntr MAP    MAT    pH
## C.control -0.375
## MAP       -0.458 -0.317
## MAT        0.003  0.243 -0.662
## pH        -0.637 -0.124  0.710 -0.271
```

```
## perClay    0.165  0.222 -0.334 -0.260 -0.576
##
## ------------ addative.treat ---------------
## Linear mixed model fit by REML ['lmerMod']
## Formula: C.warmed ~ C.control + degYr + (1 | Study)
##    Data: data.sample.plus.rescaled
##
## REML criterion at convergence: 359.5
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.5558 -0.4998  0.0856  0.5315  3.5699
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  Study    (Intercept) 0.005076 0.07125
##  Residual             0.270188 0.51980
## Number of obs: 225, groups:  Study, 47
##
## Fixed effects:
##             Estimate Std. Error t value
## (Intercept)  0.19959    0.06188   3.225
## C.control    0.84291    0.03613  23.329
## degYr       -0.04100    0.03625  -1.131
##
## Correlation of Fixed Effects:
##           (Intr) C.cntr
## C.control -0.560
## degYr     -0.563 -0.032
##
## ------------ interactive ---------------
## Linear mixed model fit by REML ['lmerMod']
## Formula: C.warmed ~ C.control * degYr + (1 | Study)
##    Data: data.sample.plus.rescaled
##
## REML criterion at convergence: 358.9
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.5838 -0.3893  0.0504  0.5100  3.4128
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  Study    (Intercept) 0.006219 0.07886
##  Residual             0.263818 0.51363
## Number of obs: 225, groups:  Study, 47
##
## Fixed effects:
##                 Estimate Std. Error t value
## (Intercept)      0.13997    0.06706   2.087
## C.control        0.91640    0.04852  18.887
## degYr            0.03077    0.04725   0.651
## C.control:degYr -0.08262    0.03538  -2.335
##
```

```
## Correlation of Fixed Effects:
##             (Intr) C.cntr degYr
## C.control   -0.644
## degYr       -0.648  0.411
## C.cntrl:dgY  0.392 -0.670 -0.643
##
## ------------ interactive.dT ---------------
## Linear mixed model fit by REML ['lmerMod']
## Formula: C.warmed ~ C.control * Tdelta + (1 | Study)
##    Data: data.sample.plus.rescaled
##
## REML criterion at convergence: 363.4
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.5711 -0.3686  0.0840  0.5444  3.5545
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  Study    (Intercept) 0.005715 0.0756
##  Residual             0.269722 0.5193
## Number of obs: 225, groups:  Study, 47
##
## Fixed effects:
##                   Estimate Std. Error t value
## (Intercept)        0.10244    0.07610   1.346
## C.control          0.89176    0.05028  17.737
## Tdelta             0.06505    0.06277   1.036
## C.control:Tdelta -0.05007    0.03434  -1.458
##
## Correlation of Fixed Effects:
##             (Intr) C.cntr Tdelta
## C.control   -0.702
## Tdelta      -0.738  0.483
## C.cntrl:Tdl  0.599 -0.684 -0.803
```

Comparing the BIC scores between the models, the simple regression between the carbon stock in the warmed plots and the mean carbon stock of the control plots has the best score. The model with the addative degree-years or degrees preforms best if we want more then just the basic correlation. There is no notable difference between degree-years and degrees as a determinent for warmed soil carbon stocks.

```r
pander(anova(lmer.list$simple, lmer.list$addative.treat,
             lmer.list$addative.dT, lmer.list$addative.enviro,
             lmer.list$addative.all), caption='Model fits comparing the statistical power
       gained by of treatment (degree-Years, and degree; addative.treat and
       addative.dT respectively) vs enviromental variables (MAT, MAP, and pH;
       addative.enviro) vs all variables include (addative.enviro) to
       explaining warmed soil carbon stocks.')
```

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

Table 1: Model fits comparing the statistical power gained by of treatment (degree-Years, and degree; addative.treat and addative.dT respectively) vs enviromental variables (MAT, MAP, and pH; addative.enviro) vs all variables include (addative.enviro) to explaining warmed soil carbon stocks.

	Df	AIC	BIC	logLik	deviance	Chisq	Chi Df	Pr(>Chisq)
lmer.list$simple	4	354.4	368	-173.2	346.4	NA	NA	NA
lmer.list$addative.treat	5	355	372.1	-172.5	345	1.35	1	0.2453
lmer.list$addative.dT	5	356.3	373.4	-173.2	346.3	0	0	1
lmer.list$addative.enviro	8	360.3	387.6	-172.1	344.3	2.03	3	0.5663
lmer.list$addative.all	9	360.2	390.9	-171.1	342.2	2.097	1	0.1476

The interactive model has both a better AIC and BIC score then even the simple regression. Thus the interative model is the most parsimonious.

```
pander(anova(lmer.list$interactive, lmer.list$interactive.dT, lmer.list$addative.treat,
             lmer.list$simple),
       caption='Model fits comparing the statistical power gained by multiplicative
       vs addative models using the controlled soil carbon stocks and degree-years or degrees
       warmed to explain warmed soil carbon stocks. The interactive degree-years model
       (interactive) signficantly better then the alternative models
       (interactive.dT, addative.treat, and simple) considered.')
```

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

Table 2: Model fits comparing the statistical power gained by multiplicative vs addative models using the controlled soil carbon stocks and degree-years or degrees warmed to explain warmed soil carbon stocks. The interactive degree-years model (interactive) signficantly better then the alternative models (interactive.dT, addative.treat, and simple) considered.

	Df	AIC	BIC	logLik	deviance	Chisq	Chi Df	Pr(>Chisq)
lmer.list$simple	4	354.4	368	-173.2	346.4	NA	NA	NA
lmer.list$addative.treat	5	355	372.1	-172.5	345	1.35	1	0.2453
lmer.list$interactive	6	351.5	372	-169.8	339.5	5.466	1	0.01939
lmer.list$interactive.dT	6	356	376.5	-172	344	0	0	1

Linear regression models

```
pander(merge(subset(modelFits, data=='data.sample', select=-data),
             subset(modelFits, data=='data.study', select=-data),
             by=c('model'), suffixes=c('.sample', '.study'))[,c('model', 'adjR2.sample', 'pvalue.sample
       caption='R2 and p-value of the control soil carbon stock and degree-years or degrees to
       explain warmed soil carbon stocks, the difference between warmed and control soil carbon
       stocks, and the rate of change of soil carbon stocks per degree-year across samples and
       studies.')
```

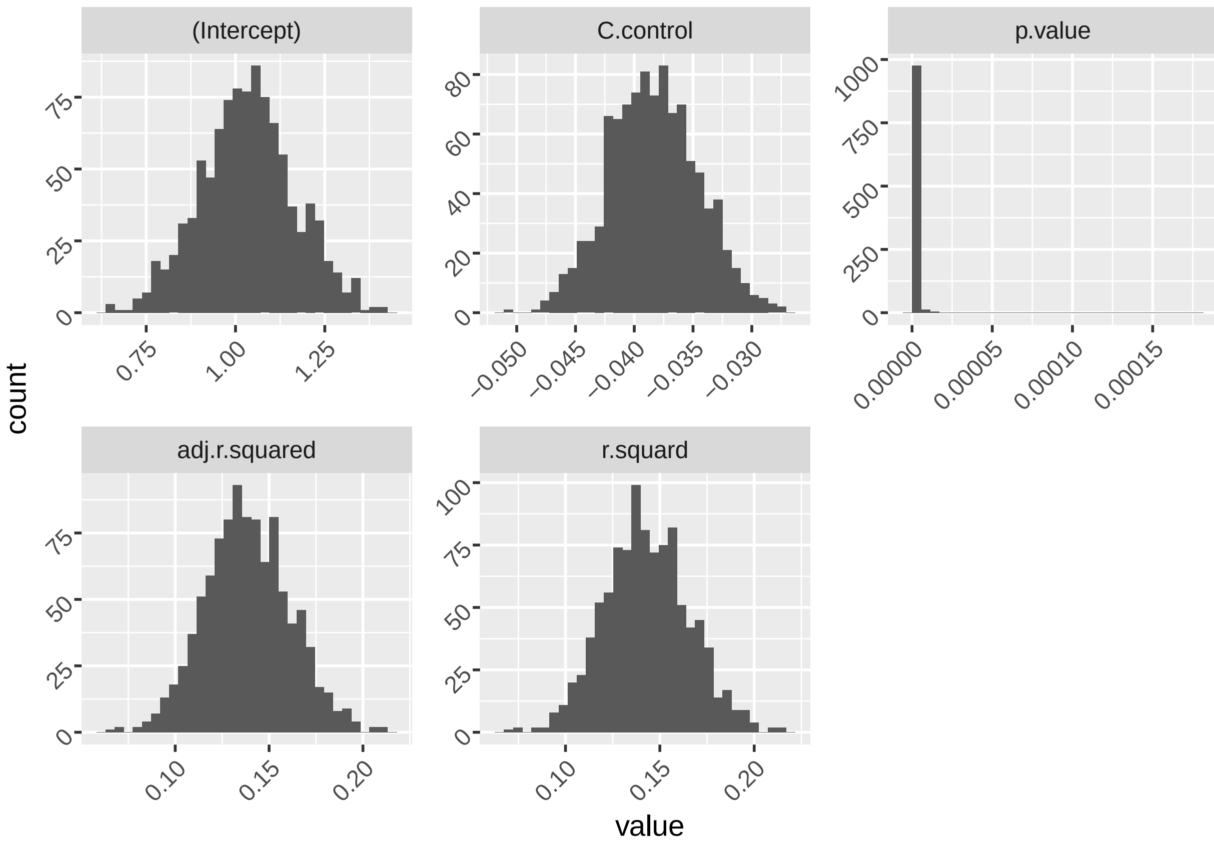
Table 3: R2 and p-value of the control soil carbon stock and degree-years or degrees to explain warmed soil carbon stocks, the difference between warmed and control soil carbon stocks, and the rate of change of soil carbon stocks per degree-year across samples and studies.

model	adjR2.sample	pvalue.sample	adjR2.study	pvalue.study
(C.warmed - C.control)/(Years * Tdelta) ~ C.control	0.139	4.16e-09	0.489	1.4e-08
(C.warmed - C.control)/Tdelta ~ C.control	0.123	3.38e-08	0.304	2.37e-05
C.warmed - C.control ~ C.control * degYr	0.421	6.13e-27	0.606	8.22e-10
C.warmed - C.control ~ C.control * Tdelta	0.374	3.28e-23	0.529	4.32e-08
C.warmed ~ C.control * degYr	0.765	1.61e-70	0.953	1.36e-30
C.warmed ~ C.control * Tdelta	0.746	8.98e-67	0.944	7.51e-29

CI for parameter range

```
ggplot(melt(dCperDegYr.boot)) +
  geom_histogram(aes(x=value)) + facet_wrap(~variable, scales='free') +
  theme(axis.text=element_text(angle = 45, hjust = 1))
```

```
## No id variables; using all as measure variables
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```




```
pander(subset(parRange, type %in% resultsTable$type), caption='95%CI of the coefficents and R2 of the cl
       (warmed-controlled) per degree-year explained by the control soil carbon stock
       [kg-C m^-3], constructed from samples. The type key is as follows: dCperDegYr is the
       change in carbon stock regressed against the degree-year, dCperDeg is the change in
       carbon stock regressed against the degrees warmed, and the time notates a dC per
       degree-year regression where study times were capped at the stated time (ie for yr1 any
       study that ran longer then a year was set to one year and then the change in carbon
       stock agaist degree-year was calculated). ')
```

Table 4: 95%CI of the coefficents and R2 of the change in soil carbon stocks (warmed-controlled) per degree-year explained by the control soil carbon stock [kg-C m^-3], constructed from samples. The type key is as follows: dCperDegYr is the change in carbon stock regressed against the degree-year, dCperDeg is the change in carbon stock regressed against the degrees warmed, and the time notates a dC per degree-year regression where study times were capped at the stated time (ie for yr1 any study that ran longer then a year was set to one year and then the change in carbon stock agaist degree-year was calculated).

	type	intercept	C	p.value	adj.r.squared	r.squard	qrt
1	dCperDegYr	0.8192	-0.04441	3.643e-10	0.1031	0.1076	0.05
2	dCperDegYr	1.034	-0.0384	4.189e-08	0.1379	0.1423	0.5

	type	intercept	C	p.value	adj.r.squared	r.squard	qrt
3	dCperDegYr	1.255	-0.03213	2.344e-06	0.1777	0.1818	0.95
4	dCperDeg	2.774	-0.2133	8.372e-09	0.06361	0.06836	0.05
5	dCperDeg	4.874	-0.1824	4.51e-07	0.1175	0.122	0.5
6	dCperDeg	5.881	-0.1063	0.0001975	0.1518	0.1561	0.95
7	wk1	155.4	-11.08	9.189e-09	0.06995	0.07467	0.05
8	wk1	253.8	-9.541	4.464e-07	0.1176	0.1221	0.5
9	wk1	308.9	-5.75	9.814e-05	0.151	0.1553	0.95
10	mon1	35.1	-2.526	9.691e-09	0.06239	0.06715	0.05
11	mon1	58.24	-2.197	4.341e-07	0.1179	0.1224	0.5
12	mon1	70.01	-1.308	0.0002275	0.1502	0.1546	0.95
13	mon6	5.993	-0.4244	6.101e-09	0.06972	0.07444	0.05
14	mon6	9.759	-0.3667	3.105e-07	0.1206	0.1251	0.5
15	mon6	11.82	-0.2235	0.0001005	0.1544	0.1587	0.95
16	yr1	2.981	-0.2169	4.087e-09	0.06974	0.07446	0.05
17	yr1	4.985	-0.1872	2.859e-07	0.1214	0.1258	0.5
18	yr1	6.033	-0.1146	0.0001002	0.1577	0.162	0.95
22	yr5	0.9947	-0.05858	4.812e-10	0.09862	0.1032	0.05
23	yr5	1.345	-0.05089	2.455e-08	0.1425	0.1468	0.5
24	yr5	1.623	-0.03831	3.894e-06	0.1756	0.1798	0.95
25	yr7	0.9378	-0.05189	2.107e-10	0.1067	0.1113	0.05
26	yr7	1.191	-0.04502	1.102e-08	0.1494	0.1537	0.5
27	yr7	1.429	-0.03665	1.569e-06	0.1824	0.1865	0.95
31	yr8.75	0.8782	-0.04833	1.532e-10	0.1059	0.1104	0.05
32	yr8.75	1.108	-0.04217	1.219e-08	0.1485	0.1529	0.5
33	yr8.75	1.349	-0.03467	1.692e-06	0.1848	0.1889	0.95
37	yr11.6	0.8299	-0.04577	3.323e-10	0.1056	0.1102	0.05

	type	intercept	C	p.value	adj.r.squared	r.squard	qrt
38	yr11.6	1.041	-0.03942	2.646e-08	0.142	0.1464	0.5
39	yr11.6	1.278	-0.03307	1.742e-06	0.1787	0.1828	0.95
43	yr17.5	0.8063	-0.04403	3.715e-10	0.09929	0.1039	0.05
44	yr17.5	1.033	-0.03833	3.842e-08	0.1388	0.1432	0.5
45	yr17.5	1.234	-0.0319	3.473e-06	0.1777	0.1819	0.95
55	yr35	0.8184	-0.04425	5.719e-10	0.1	0.1046	0.05
56	yr35	1.029	-0.0381	4.29e-08	0.1378	0.1422	0.5
57	yr35	1.249	-0.03161	3.368e-06	0.1736	0.1778	0.95

Global Extrapolations

```
temp <- subset(resultsTable, globalWarming %in% c(1,2), c('type', 'globalWarming', 'warmingDistribution
row.names(temp) <- NULL
pander(temp,
       caption='Global soil carbon change across acclimatization assumptions. Type is analygous
       to the key described above. Global warming is the average global warming applied
       linearlly over 35 years. Time step is the size of the time step used in the numerical
       integration. dC is the change in the soil carbon stock for the 5% quantile, 50% quantile,
       and 95% quantile respectively calcuated form the parameter ranges described above.',
       round=c(1,1,1,3,0,0,0))
```

Table 5: Global soil carbon change across acclimatization assumptions. Type is analygous to the key described above. Global warming is the average global warming applied linearlly over 35 years. Time step is the size of the time step used in the numerical integration. dC is the change in the soil carbon stock for the 5% quantile, 50% quantile, and 95% quantile respectively calcuated form the parameter ranges described above.

type	globalWarming	warmingDistribution	timeStep	dC_qrt05	dC_qrt50	dC_qrt95
dCperDeg	1	unif	NA	-131	-62	24
dCperDegYr	1	unif	0.019	0	0	0
dCperDegYr	1	unif	0.083	0	0	0
dCperDegYr	1	unif	0.5	0	0	0
dCperDegYr	1	unif	1	0	0	0
dCperDegYr	1	unif	10	-32	-19	-4

type	globalWarming	warmingDistribution	timeStep	dC_qrt05	dC_qrt50	dC_qrt95
dCperDegYr	1	unif	11.67	-44	-25	-6
dCperDegYr	1	unif	17.5	-99	-57	-13
dCperDegYr	1	unif	20	-129	-74	-17
dCperDegYr	1	unif	25	-201	-116	-27
dCperDegYr	1	unif	30	-290	-167	-39
dCperDegYr	1	unif	35	-394	-227	-53
dCperDegYr	1	unif	4	-5	-3	-1
dCperDegYr	1	unif	5	-8	-5	-1
dCperDegYr	1	unif	7	-16	-9	-2
dCperDegYr	1	unif	8	-21	-12	-3
dCperDegYr	1	unif	8.75	-25	-14	-3
mon1	1	unif	0.083	-58	-29	10
mon6	1	unif	0.5	-59	-30	10
wk1	1	unif	0.019	-59	-29	10
yr1	1	unif	1	-62	-31	10
yr11.6	1	unif	11.67	-125	-74	-19
yr17.5	1	unif	17.5	-177	-104	-27
yr35	1	unif	35	-392	-224	-48
yr5	1	unif	5	-74	-42	-3
yr7	1	unif	7	-87	-51	-12
yr8.75	1	unif	8.75	-100	-60	-14
dCperDeg	1	CESM	NA	-131	-62	24
dCperDegYr	1	CESM	0.019	0	0	0
dCperDegYr	1	CESM	0.083	0	0	0
dCperDegYr	1	CESM	0.5	0	0	0
dCperDegYr	1	CESM	1	0	0	0
dCperDegYr	1	CESM	10	-32	-19	-4
dCperDegYr	1	CESM	11.67	-44	-25	-6
dCperDegYr	1	CESM	17.5	-98	-57	-14
dCperDegYr	1	CESM	20	-127	-74	-18
dCperDegYr	1	CESM	25	-195	-112	-26

type	globalWarming	warmingDistribution	timeStep	dC_qrt05	dC_qrt50	dC_qrt95
dCperDegYr	1	CESM	30	-274	-157	-35
dCperDegYr	1	CESM	35	-360	-206	-43
dCperDegYr	1	CESM	4	-5	-3	-1
dCperDegYr	1	CESM	5	-8	-5	-1
dCperDegYr	1	CESM	7	-16	-9	-2
dCperDegYr	1	CESM	8	-21	-12	-3
dCperDegYr	1	CESM	8.75	-25	-14	-3
mon1	1	CESM	0.083	-57	-29	10
mon6	1	CESM	0.5	-58	-29	10
wk1	1	CESM	0.019	-58	-29	10
yr1	1	CESM	1	-61	-30	10
yr11.6	1	CESM	11.67	-121	-71	-17
yr17.5	1	CESM	17.5	-169	-98	-24
yr35	1	CESM	35	-358	-204	-37
yr5	1	CESM	5	-72	-41	-2
yr7	1	CESM	7	-85	-50	-11
yr8.75	1	CESM	8.75	-97	-58	-13
dCperDeg	2	unif	NA	-263	-125	49
dCperDegYr	2	unif	0.019	0	0	0
dCperDegYr	2	unif	0.083	0	0	0
dCperDegYr	2	unif	0.5	0	0	0
dCperDegYr	2	unif	1	-1	0	0
dCperDegYr	2	unif	10	-64	-37	-9
dCperDegYr	2	unif	11.67	-88	-50	-12
dCperDegYr	2	unif	17.5	-197	-113	-27
dCperDegYr	2	unif	20	-257	-148	-35
dCperDegYr	2	unif	25	-402	-232	-55
dCperDegYr	2	unif	30	-575	-334	-79
dCperDegYr	2	unif	35	-613	-419	-107
dCperDegYr	2	unif	4	-10	-6	-1
dCperDegYr	2	unif	5	-16	-9	-2

type	globalWarming	warmingDistribution	timeStep	dC_qrt05	dC_qrt50	dC_qrt95
dCperDegYr	2	unif	7	-32	-18	-4
dCperDegYr	2	unif	8	-41	-24	-6
dCperDegYr	2	unif	8.75	-49	-28	-7
mon1	2	unif	0.083	-111	-56	20
mon6	2	unif	0.5	-112	-57	19
wk1	2	unif	0.019	-111	-56	20
yr1	2	unif	1	-118	-59	19
yr11.6	2	unif	11.67	-228	-137	-35
yr17.5	2	unif	17.5	-317	-188	-49
yr35	2	unif	35	-612	-416	-95
yr5	2	unif	5	-139	-79	-5
yr7	2	unif	7	-162	-96	-22
yr8.75	2	unif	8.75	-185	-113	-27
dCperDeg	2	CESM	NA	-255	-120	49
dCperDegYr	2	CESM	0.019	0	0	0
dCperDegYr	2	CESM	0.083	0	0	0
dCperDegYr	2	CESM	0.5	0	0	0
dCperDegYr	2	CESM	1	-1	0	0
dCperDegYr	2	CESM	10	-65	-37	-9
dCperDegYr	2	CESM	11.67	-88	-51	-12
dCperDegYr	2	CESM	17.5	-191	-110	-26
dCperDegYr	2	CESM	20	-246	-141	-32
dCperDegYr	2	CESM	25	-366	-210	-43
dCperDegYr	2	CESM	30	-470	-277	-50
dCperDegYr	2	CESM	35	-525	-313	-45
dCperDegYr	2	CESM	4	-10	-6	-1
dCperDegYr	2	CESM	5	-16	-9	-2
dCperDegYr	2	CESM	7	-32	-18	-4
dCperDegYr	2	CESM	8	-41	-24	-6
dCperDegYr	2	CESM	8.75	-50	-29	-7
mon1	2	CESM	0.083	-107	-54	20
mon6	2	CESM	0.5	-109	-55	19

type	globalWarming	warmingDistribution	timeStep	dC_qrt05	dC_qrt50	dC_qrt95
wk1	2	CESM	0.019	-108	-54	20
yr1	2	CESM	1	-114	-57	20
yr11.6	2	CESM	11.67	-214	-127	-30
yr17.5	2	CESM	17.5	-282	-165	-37
yr35	2	CESM	35	-524	-310	-37
yr5	2	CESM	5	-133	-76	-4
yr7	2	CESM	7	-154	-91	-20
yr8.75	2	CESM	8.75	-175	-106	-23

Figures

Change in carbon per degree year with bootstrap

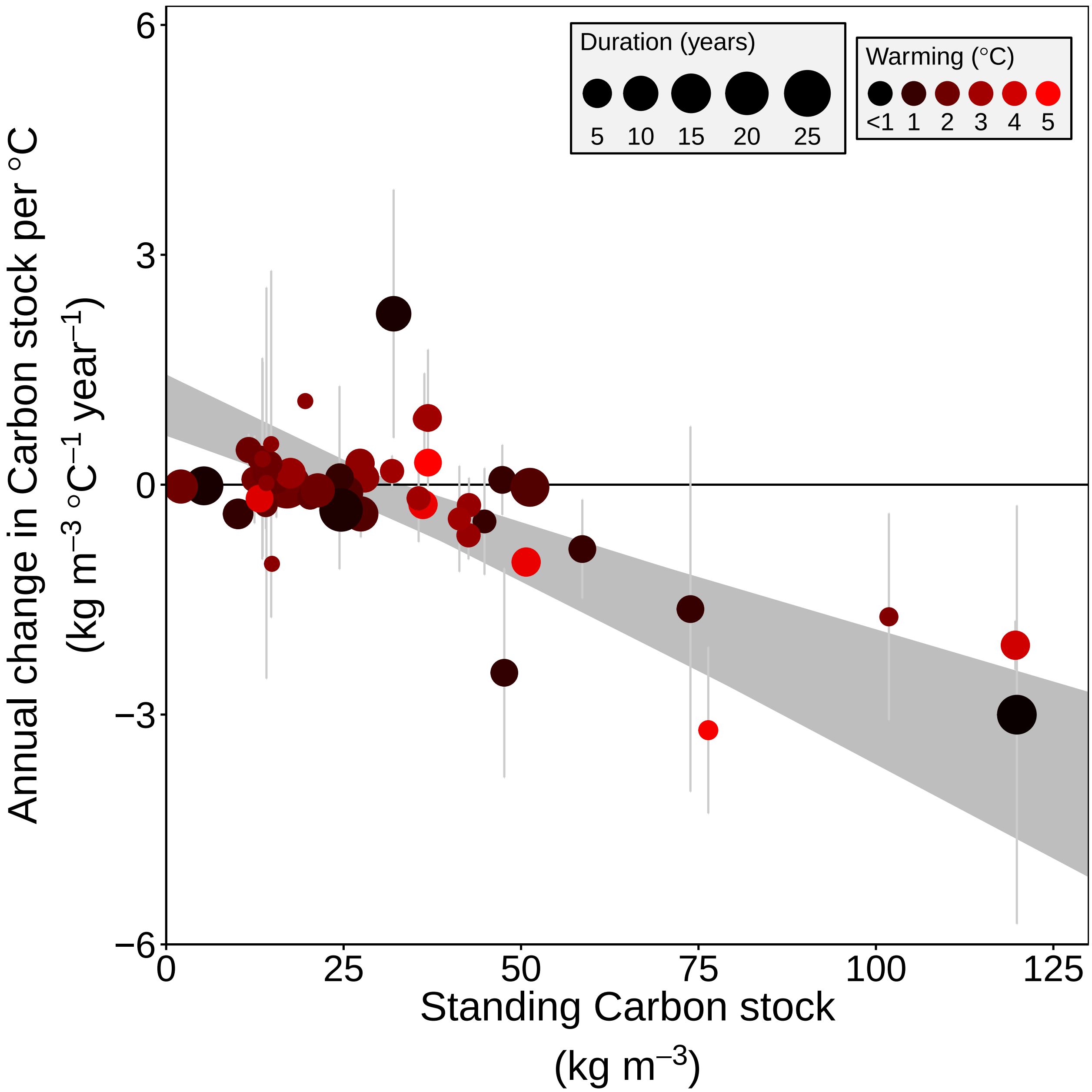
```
Fig1.theme <- theme(axis.text.x=element_text(size=18,angle=0,colour="black"),
                    axis.text.y=element_text(size=18,angle=0,colour="black"),
                    axis.title=element_text(size=20),
                    legend.text=element_text(size=12),
                    axis.line.x=element_line(color="black"),
                    legend.position = "top",
                    legend.key = element_rect(fill="grey95",size=0,color="grey95"),
                    legend.key.size = unit(0.1,"cm"),
                    legend.title = element_text(size=12,face="bold"),
                    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=1.9),
                    axis.title.x=element_text(vjust=-0.4))+
                    theme(legend.justification=c(1,1),
                    legend.position=c(1,1))

  # set color gradient
ramp <- colorRamp(c("black","darkred","red"))
use.col.points <- c(rgb( ramp(seq(0, 1, length = 500)), max = 255))

# generate figure 1
Figure1 <- ggplot(data.study,aes(x=C.control, y=dC.perDegYr)) +
  geom_abline(aes(intercept=parBins$intercept,slope=parBins$slope),
              colour="grey",data=parBins) +
  geom_abline(intercept=0,slope=0,color="black") +
  geom_errorbar(aes(ymax=dC.perDegYr + dC.perDegYr.se,
                    ymin=dC.perDegYr - dC.perDegYr.se),width=0,color="grey80",size=0.5) +
  geom_point(alpha=1, aes(color=Tdelta,size=Years))  +
```

```r
  scale_color_gradientn(limits=range(c(0,data.study$Tdelta)),
                        colours=use.col.points,space="Lab",labels=c("<1",1,2,3,4,5))+
  scale_size(range=c(3,10)) +
  xlab(expression(atop("Standing Carbon stock","(kg m"^-3*")"))) +
  ylab(expression(atop("Annual change in Carbon stock per"*~degree* C,
                       "(kg m"^-3~degree*C^-1~year^-1*")"))) +
  scale_x_continuous(limits=c(0,0.130*1e3), expand = c(0, 0)) +
  scale_y_continuous(limits=c(-6,6.25), expand = c(0, 0)) +
  geom_hline(yintercept=6.25) +
  geom_vline(xintercept=130) +
  guides(color = guide_legend(by.row=T,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"))+
  guides(size = guide_legend(nrow = 1,label.position = "bottom",
                             label.hjust=0.5,title.position="top",
                             title=expression("Duration (years)"),
                             legend.box = "vertical")) +
  Fig1.theme

print(Figure1)
```




```
ggsave(plot = Figure1,
       filename='../figs/Figure01.pdf', width=7.5, height=7.5)
```

Model-data plot for interactive statisitcal model (Figure 2a)

```
print(summary(lm.list$Cw.study))
```

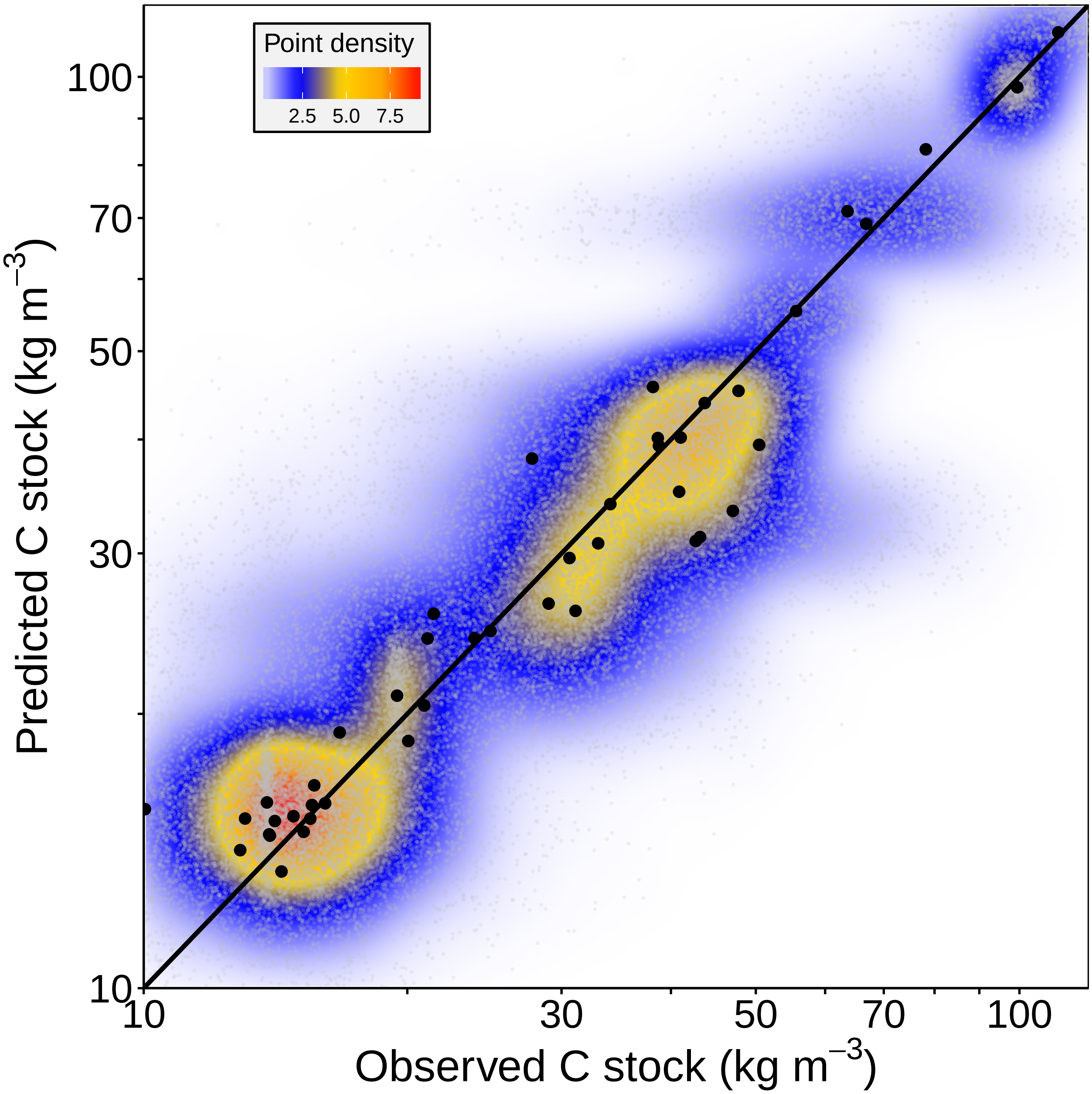
```
##
## Call:
## lm(formula = C.warmed ~ C.control * degYr, data = data.study)
##
```

```
## Residuals:
##      Min       1Q   Median       3Q      Max
## -10.3269  -2.1202  -0.5347   0.8648  14.0377
##
## Coefficients:
##                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)       1.61837    1.56580   1.034    0.307
## C.control         0.96044    0.03789  25.350  < 2e-16 ***
## degYr             0.30065    0.12352   2.434    0.019 *
## C.control:degYr -0.01662    0.00321  -5.176 5.11e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4.924 on 45 degrees of freedom
## Multiple R-squared:  0.9563, Adjusted R-squared:  0.9534
## F-statistic: 328.4 on 3 and 45 DF,  p-value: < 2.2e-16
```

```r
ramp <- colorRamp(c("white","blue","gold","orange","red"))
use.fill <- rgb( ramp(seq(0, 1, length = 255)), max = 255)
fig2aTheme <- theme(axis.text.x=element_text(size=18,angle=0,colour="black"),
                    axis.text.y=element_text(size=18,angle=0,colour="black"),
                    axis.title=element_text(size=20),
                    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 = "vertical",
                    legend.justification=c(0.9,1), legend.position=c(0.3,1),
                    legend.key = element_rect(fill="grey95",size=0,color="grey95"),
                    legend.key.size = unit(0.5,"cm"),
                    legend.title = element_text(size=12,face="bold"),
                    legend.background = element_rect(fill="grey95",color="black"))

figure2a <- ggplot(modelData.df,aes(x=rnd.data,y=rnd.model)) +
  stat_density2d(geom = "raster",aes(fill = ..density..), contour = FALSE,
                 interpolate = TRUE,n=200,show.legend=T) +
  geom_point(size=0.15,alpha=0.2,col="grey") +
  geom_point(data=summaryMD.df,aes(x=data.mean, y=model.mean),
             color="black", size=2) +
  scale_fill_gradientn(colours = use.fill) +
  geom_abline(intercept=0,slope=1,size=1)+
  scale_x_log10(limits=c(10,0.12*1e3), expand = c(0, 0),
                breaks=c(1:10)*10,labels=c(10,"",30,"",50,"",70,"","",100)) +
  scale_y_log10(limits=c(10,0.12*1e3), expand = c(0, 0),
                breaks=c(1:10)*10,labels=c(10,"",30,"",50,"",70,"","",100)) +
  xlab(bquote("Observed C stock (kg "*m^-3*")")) +
  ylab(bquote("Predicted C stock (kg "*m^-3*")")) +
  guides( fill = guide_colourbar(label.position = "bottom",
                                 label.hjust=0.5,title.position="top",
                                 title=expression("Point density"), direction = "horizontal")) +
  fig2aTheme
```

```r
print(figure2a)
```

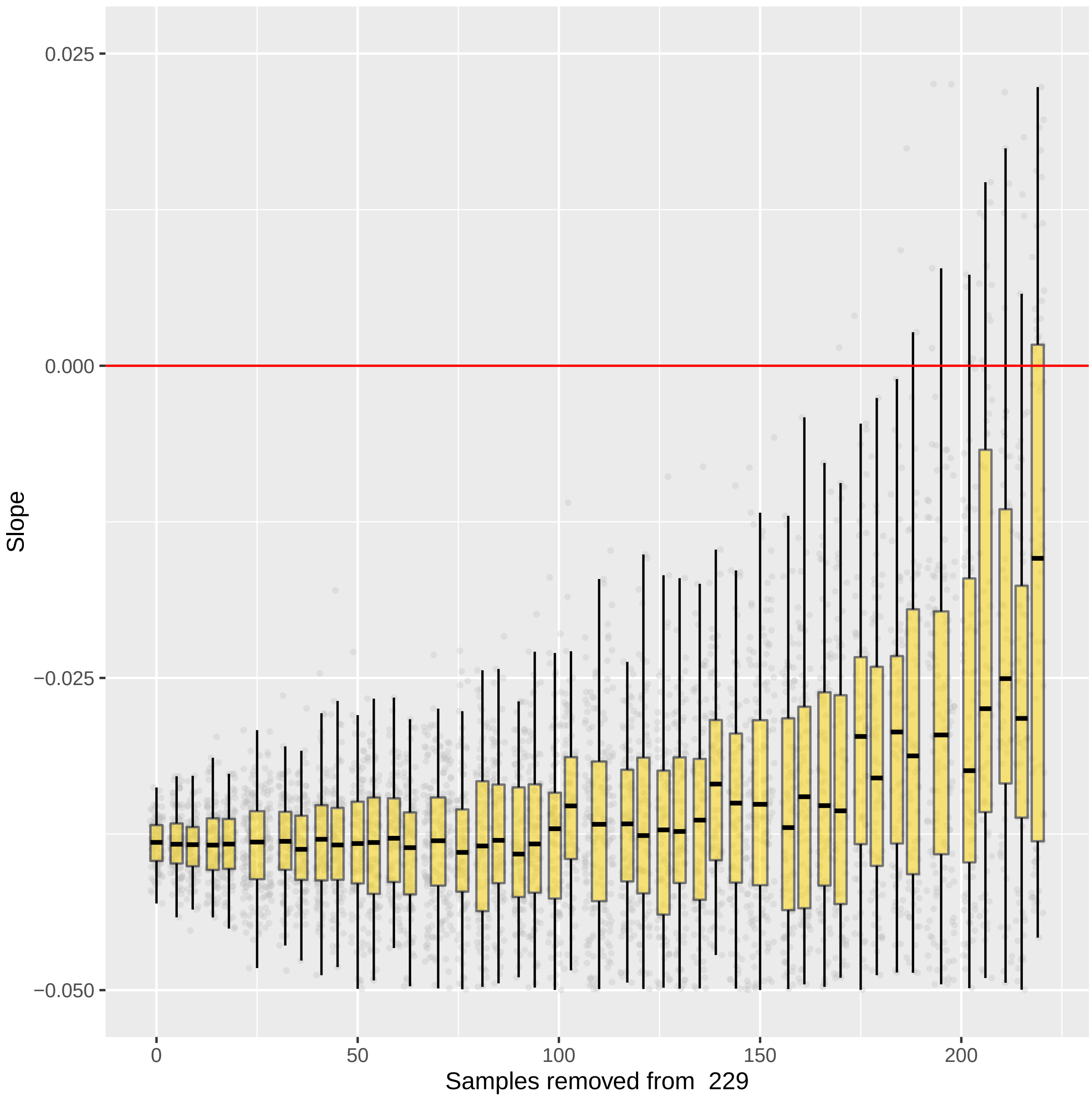



```r
ggsave(plot=figure2a,
       file='../figs/Figure02a.pdf', height=7, width=7)
```

Boot strap slope comparison (Figure 2b)

```r
ggplot(selectSize.sample, aes(x=dim(data.sample)[1]-sampleSize, y=C.control)) +
  geom_jitter(alpha=0.3,color="grey",height=0,size=0.75) +
            scale_y_continuous(limits = c(-0.05, 0.025)) +
            geom_boxplot(aes(group = cut_width(dim(data.sample)[1]-sampleSize, 5)),
```

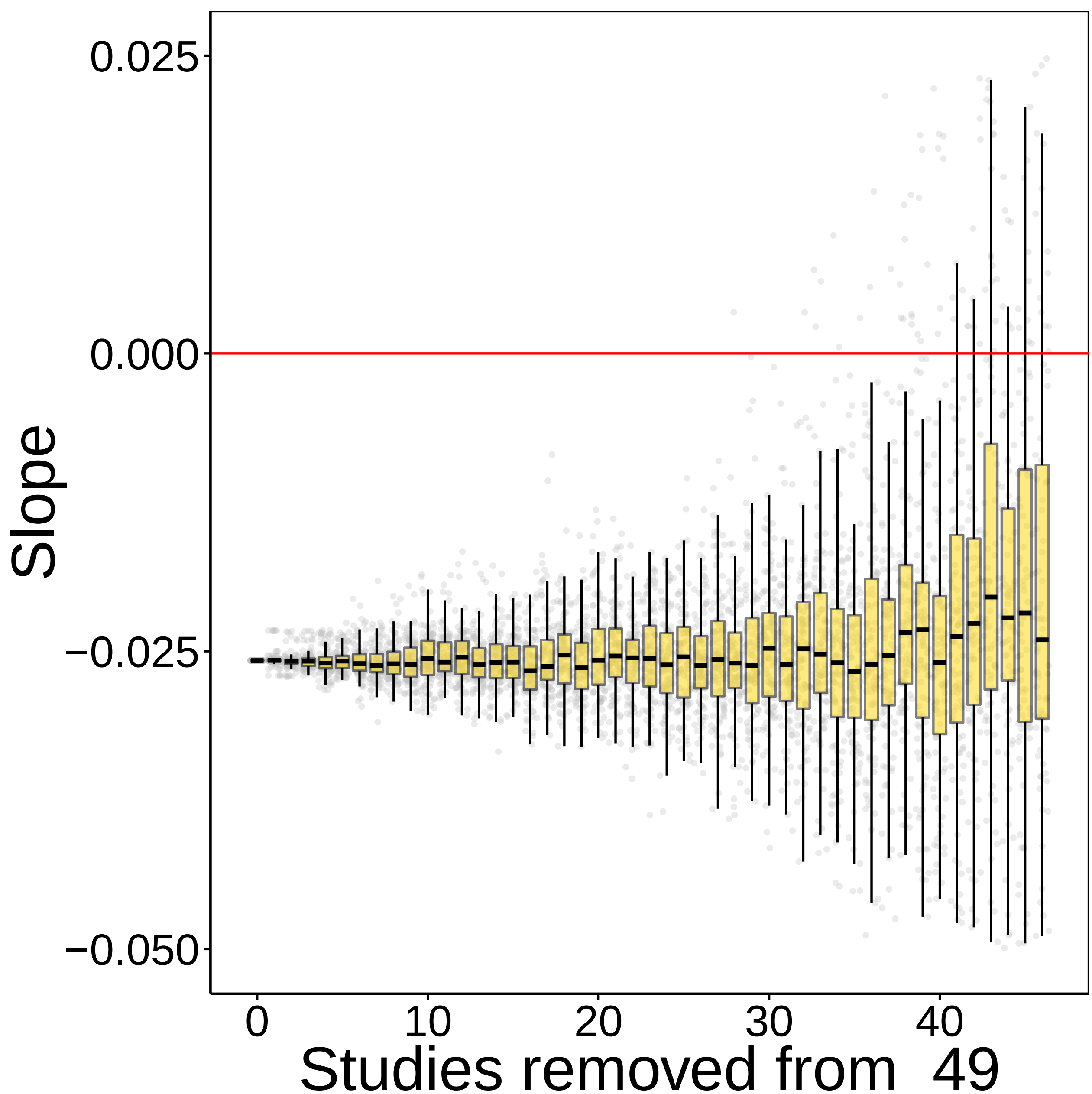
```
                          outlier.size=0, outlier.shape = NA,
                      fill="gold",alpha=0.5,color="black") +
         geom_abline(intercept=0,slope=0,color="red") +
         xlab(paste("Samples removed from ", dim(data.sample)[1])) + ylab("Slope")
```




```
fig2b.pl <- ggplot(selectSize.study, aes(x=dim(data.study)[1]-sampleSize, y=C.control)) +
  geom_jitter(alpha=0.3,color="grey",height=0,size=0.75) +
         scale_y_continuous(limits = c(-0.05, 0.025)) +
         geom_boxplot(aes(group = cut_width(dim(data.study)[1]-sampleSize, 1)),
                          outlier.size=0, outlier.shape = NA,
                      fill="gold",alpha=0.5,color="black") +
         geom_abline(intercept=0,slope=0,color="red") +
         xlab(paste("Studies removed from ", dim(data.study)[1])) + ylab("Slope")
```

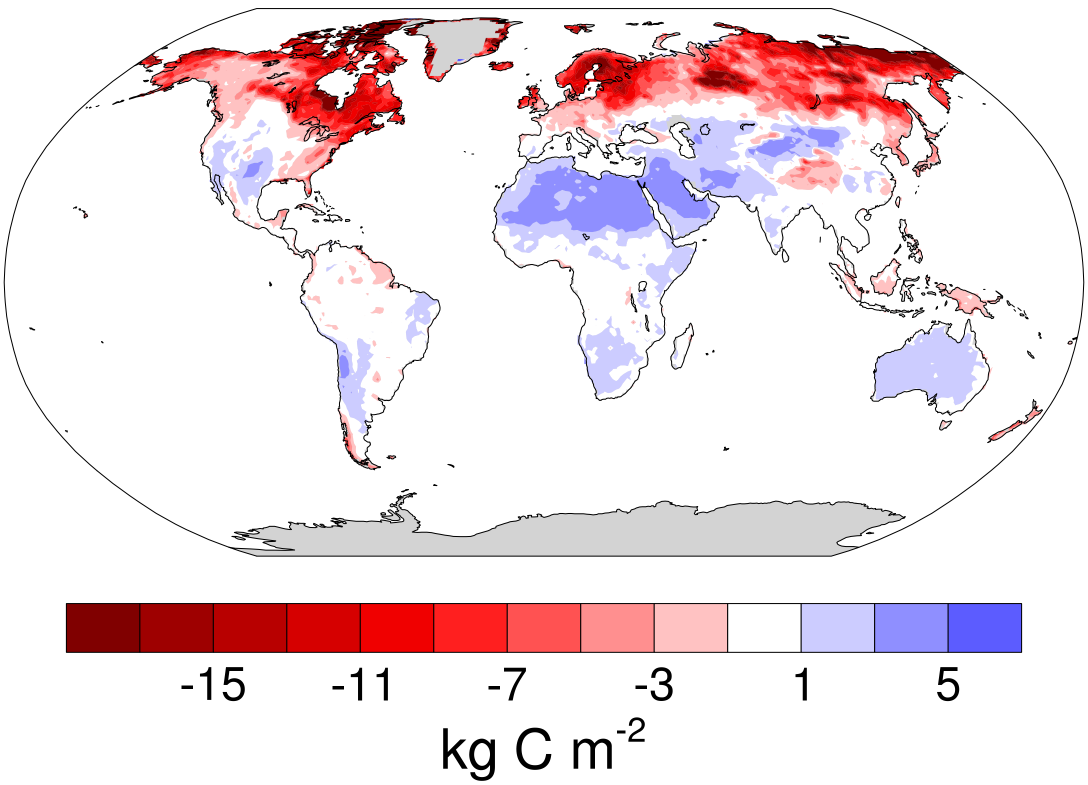
```r
fig2bTheme <- theme(axis.text.x=element_text(size=20,angle=0,colour="black"),
              axis.text.y=element_text(size=20,angle=0,colour="black"),
              axis.title=element_text(size=28),
              axis.line = element_line(colour = "black"),
              panel.grid.major = element_blank(),
              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"))

print(fig2b.pl + fig2bTheme)
```



```r
ggsave('../figs/Figure02b.pdf', fig2b.pl + fig2bTheme, width=7, height=7)
```

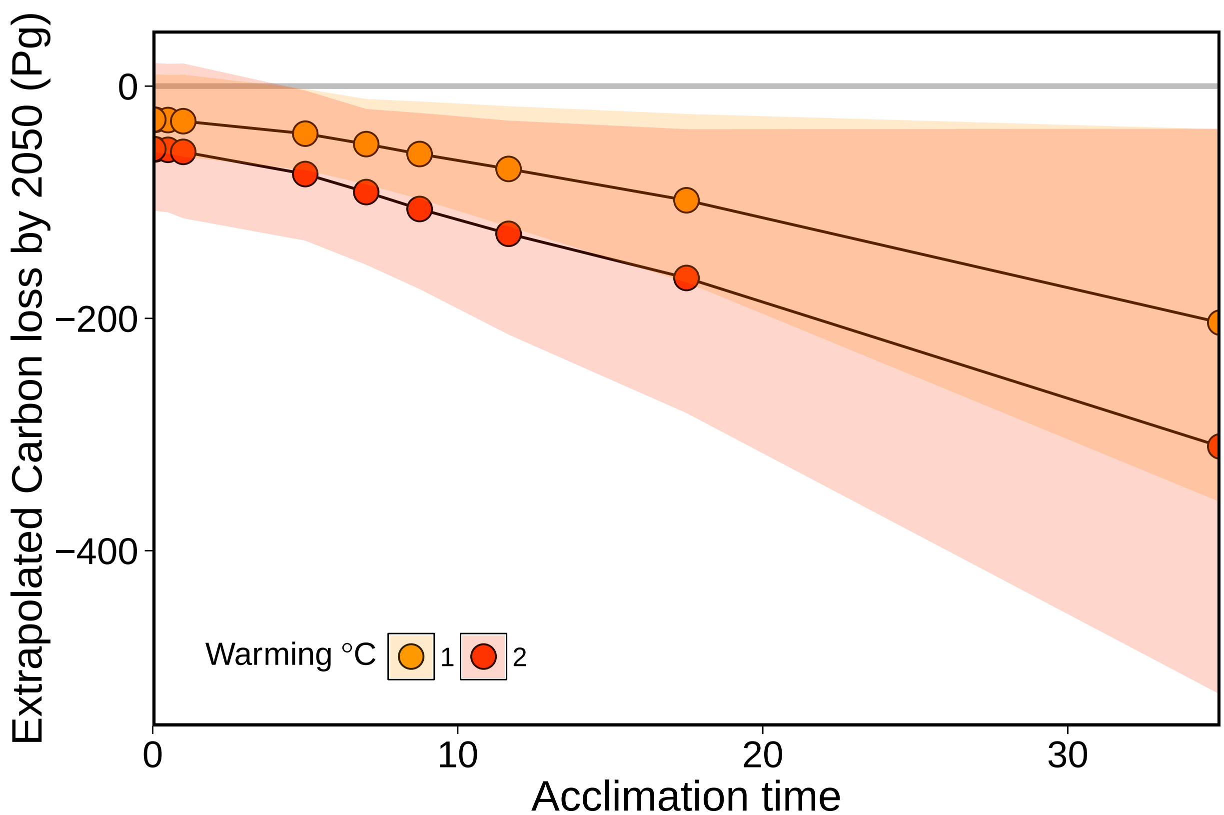
Global carbon vulnerability map (Figure 3a)



See Section “Global carbon loss map code”

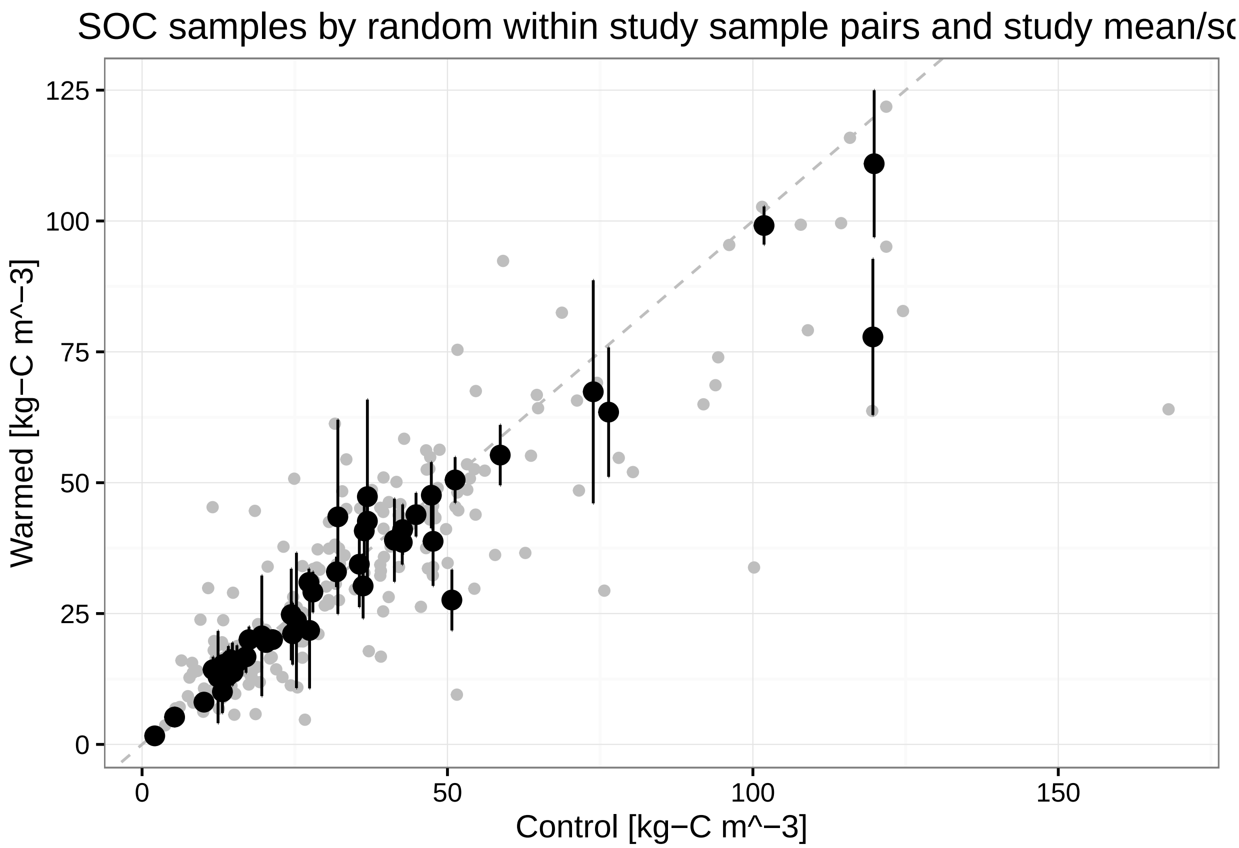
Acclimatization assumptions affects soil carbon losses (Figure 3b)

```
degYrStepIntSimple.pl <- ggplot(subset(resultsTable, !grepl('dCperDeg', type) &
                                         warmingDistribution == 'CESM' &
                                         globalWarming %in% c(1,2))) +
  geom_hline(yintercept=0,col="grey",size=1) +
  geom_line(aes(x=timeStep, y=dC_qrt50, group=warming, fill=globalWarming)) +
  geom_point(aes(x=timeStep, y=dC_qrt50, fill=globalWarming), size=4, shape=21) +
  geom_ribbon(aes(x=timeStep, y=dC_qrt50, ymin=dC_qrt05, ymax=dC_qrt95,
                  fill=globalWarming, guide=NA), alpha=0.2) +
  scale_x_continuous(limits=c(0,35),expand=c(0,0))+
  scale_fill_manual(values=c('#FF9900', '#FF3300'),
                    guide = guide_legend( direction = "horizontal",
                                          title = expression("Warming"*~degree*C))) +
  labs(title='', x='Acclimation time',
       y="Extrapolated Carbon loss by 2050 (Pg)") +
  theme_bw() +
  theme(axis.title=element_text(size=16),
        axis.text=element_text(size=14),
        legend.position=c(0.2,0.1),
        panel.grid.major= element_line(color=NA),
        panel.grid.minor=element_line(color=NA),
        panel.border=element_rect(color="black",fill=NA,size=1),
        axis.ticks=element_line(size=0.25),
        legend.key=element_rect(color="black",fill=NA,size=0.25))
print(degYrStepIntSimple.pl)
```

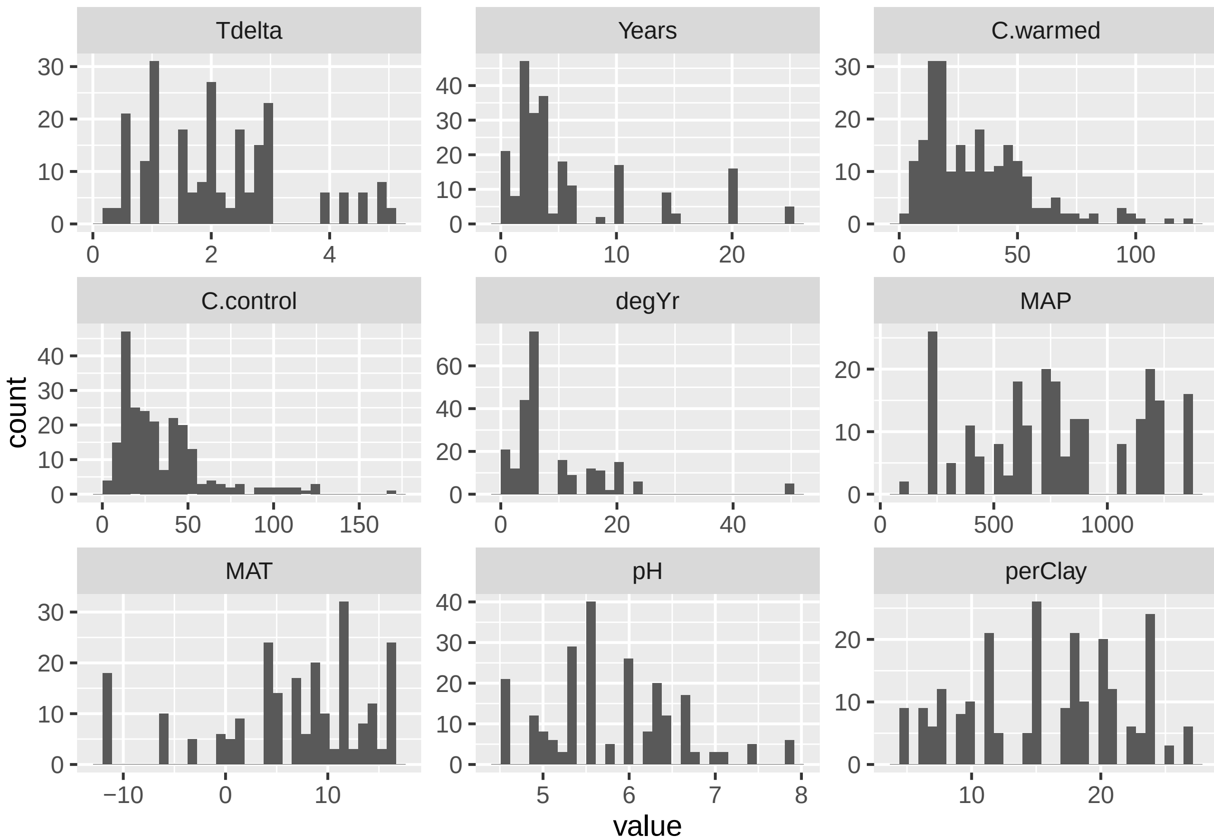


```r
ggsave(degYrStepIntSimple.pl, filename='../figs/Figure03b.pdf',
       height=4.5, width=6.5)
```

Data summary and basic visualizations




```
## No id variables; using all as measure variables
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```




```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

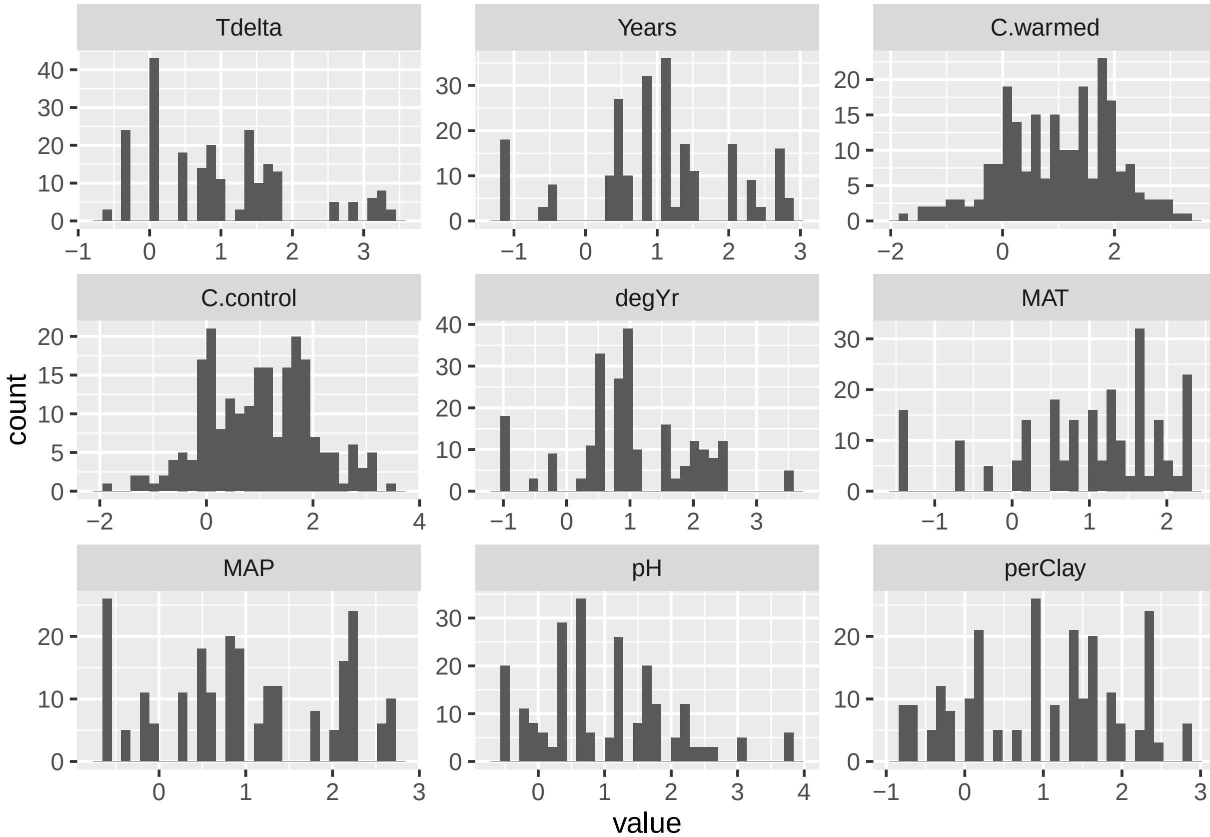


Table 6: Description of study sites including mean annual temperature (MAT), mean annual precipitation (MAP), soil pH, and soil percent clay (perClay). For standardization purposes, all climate data were collected from Bioclim and all soil data were collected from SoilGrids.

Study Description	MAP	MAT	pH	perClay
Delta Junction, AK, USA	298	-3.2	6.6	12
Ford Forest, MI, USA	824	4.4	5.3	8
Ford Forest, MI, USA [precipitation]	824	4.4	5.3	8
FRAGILE Experiment, Svalbard, Norway [grazed]	226	-5.7	6	10
FRAGILE Experiment, Svalbard, Norway	226	-5.7	6	10
INCREASE Clocaenog, Wales, UK	1215	7.1	5.2	11
Gucheng, Hebei, China	543	12.7	7	17
Soil Warming x Nitrogen Addition Study, NH, USA	1142	6.8	4.9	7
Rocky Mountain Biological Laboratory, CO, USA	519	0.5	5.8	14
INCREASE Kiskunsag, Hungary	536	10.9	7.1	18
Krycklan, Sweden	603	8.2	5.5	8
INCREASE Brandbjerg, Demark	609	1	4.6	5
Jasper Ridge, CA, USA	635	13.7	6.2	18
Jasper Ridge, CA, USA [CO2]	635	13.7	6.2	18
Oak Ridge, Tennessee, USA	1347	13.9	5.6	27
Oak Ridge, Tennessee, USA [CO2]	1347	13.9	5.6	27

Study Description	MAP	MAT	pH	perClay
Oklahoma Tall Grass Prairie, OK, USA [clipped grass]	906	16.3	6.7	24
Oklahoma Tall Grass Prairie, OK, USA	906	16.3	6.7	24
Research Station of Songnen Grassland Ecosystem, China	436	5.2	7.9	17
Duke Forest, NC, USA [3 degrees]	1161	14.4	4.9	22
Duke Forest, NC, USA [5 degrees]	1161	14.4	4.9	22
Konza Prarie, KS, USA	872	12	6.4	24
Whitehall, GA, USA [3 degrees]	1230	16.5	4.6	21
Whitehall, GA, USA [5 degrees]	1230	16.5	4.6	21
Dry Heath Env. Control, Sweden	390	-0.1	5.1	6
Prairie Heating and CO2 Enrichment, CO, USA	384	7	7.4	23
INCREASE Garraf, Spain	632	15.5	6.8	25
HOCC-Experiment, Germany	729	8.9	6.3	20
HOCC-Experiment, Germany [precipitation 1]	729	8.9	6.3	20
HOCC-Experiment, Germany [precipitation 2]	729	8.9	6.3	20
HOCC-Experiment, Germany [precipitation 3]	729	8.9	6.3	20
HOCC-Experiment, Germany [precipitation 4]	729	8.9	6.3	20
BioCON, MN, USA [elevated C02, ambient N, negative H20]	761	3.8	5.5	11
BioCON, MN, USA [elevated C02, elevated N, negative H20]	761	3.8	5.5	11
BioCON, MN, USA [elevated C02, elevated N, ambient H20]	761	3.8	5.5	11
BioCON, MN, USA [ambient C02, ambient N, ambient H20]	761	3.8	5.5	11
BioCON, MN, USA [ambient C02, elevated N, negative H20]	761	3.8	5.5	11
BioCON, MN, USA [ambient C02, elevated N, ambient H20]	761	3.8	5.5	11
Heat of Prarie Species 1, OR, USA	1194	11.4	5.3	19
Heat of Prarie Species 1, OR, USA [precipitation]	1194	11.4	5.3	19
Heat of Prarie Species 2, OR, USA [precipitation]	1364	11.4	5.5	15
Heat of Prarie Species 3, WA, USA [precipitation]	1199	10.1	5.3	18
Heat of Prarie Species 2, OR, USA	1364	11.4	5.5	15
Heat of Prarie Species 3, WA, USA	1199	10.1	5.3	18
INCREASE Mols, Denmark	592	7.4	5.3	6
Arctic LTER, AK, USA	237	-11.2	6	15
Hubbard Brook, NH, USA	1082	5.4	5	9
ITEX, Greenland	112	-11.3	NA	NA
ITEX, Greenland [vegetated]	112	-11.3	NA	NA

Table 7: Mean soil carbon [kg-C m^-3] values across control study site with number of samples in each study for the control plots.

Study Description	count.control	C.control	C.sd.control
Delta Junction, AK, USA	5	32.05	NA
Ford Forest, MI, USA	3	36.19	NA
Ford Forest, MI, USA [precipitation]	3	50.72	NA
FRAGILE Experiment, Svalbard, Norway [grazed]	5	58.64	NA
FRAGILE Experiment, Svalbard, Norway	5	73.87	NA
INCREASE Clocaenog, Wales, UK	3	119.9	NA
Gucheng, Hebei, China	3	101.8	NA
Soil Warming x Nitrogen Addition Study, NH, USA	6	119.6	NA
Rocky Mountain Biological Laboratory, CO, USA	5	17.02	NA
INCREASE Kiskunsag, Hungary	3	5.32	NA
Krycklan, Sweden	6	10.13	NA
INCREASE Brandbjerg, Demark	9	44.85	NA
Jasper Ridge, CA, USA	4	14.04	NA
Jasper Ridge, CA, USA [CO2]	4	15.53	NA
Oak Ridge, Tennessee, USA	3	27.96	NA
Oak Ridge, Tennessee, USA [CO2]	3	27.32	NA
Oklahoma Tall Grass Prairie, OK, USA [clipped grass]	6	27.42	NA
Oklahoma Tall Grass Prairie, OK, USA	6	25.27	NA
Research Station of Songnen Grassland Ecosystem, China	6	20.29	NA
Duke Forest, NC, USA [3 degrees]	3	36.89	NA
Duke Forest, NC, USA [5 degrees]	3	36.89	NA
Konza Prarie, KS, USA	12	47.36	NA
Whitehall, GA, USA [3 degrees]	6	12.44	NA
Whitehall, GA, USA [5 degrees]	5	13.16	NA
Dry Heath Env. Control, Sweden	6	51.25	NA
Prairie Heating and CO2 Enrichment, CO, USA	5	17.51	NA
INCREASE Garraf, Spain	3	24.42	NA
HOCC-Experiment, Germany	4	13.84	NA
HOCC-Experiment, Germany [precipitation 1]	4	13.26	NA
HOCC-Experiment, Germany [precipitation 2]	4	11.63	NA
HOCC-Experiment, Germany [precipitation 3]	4	14.55	NA
HOCC-Experiment, Germany [precipitation 4]	4	13.95	NA
BioCON, MN, USA [elevated C02, ambient N, negative H20]	3	13.59	NA
BioCON, MN, USA [elevated C02, elevated N, negative H20]	3	19.6	NA
BioCON, MN, USA [elevated C02, elevated N, ambient H20]	3	14.91	NA

Study Description	count.control	C.control	C.sd.control
BioCON, MN, USA [ambient C02, ambient N, ambient H20]	3	14.13	NA
BioCON, MN, USA [ambient C02, elevated N, negative H20]	3	14.8	NA
BioCON, MN, USA [ambient C02, elevated N, ambient H20]	3	13.54	NA
Heat of Prarie Species 1, OR, USA	5	42.6	NA
Heat of Prarie Species 1, OR, USA [precipitation]	5	42.66	NA
Heat of Prarie Species 2, OR, USA [precipitation]	5	31.82	NA
Heat of Prarie Species 3, WA, USA [precipitation]	5	36.38	NA
Heat of Prarie Species 2, OR, USA	5	35.57	NA
Heat of Prarie Species 3, WA, USA	5	41.31	NA
INCREASE Mols, Denmark	3	47.64	NA
Arctic LTER, AK, USA	16	24.64	NA
Hubbard Brook, NH, USA	8	76.38	NA
ITEX, Greenland	1	2.071	NA
ITEX, Greenland [vegetated]	1	21.36	NA

Table 8: Mean soil carbon [kg-C m^-3] values across warmed study site with number of samples in each study for the warmed plots, their warming treatment [C], and length of treatment [years].

Study Description	Tdelta	Years	count.warmed	C.warmed	C.sd.warmed
Delta Junction, AK, USA	0.5	10.25	5	43.48	18.56
Ford Forest, MI, USA	4.581	5	3	30.27	6.201
Ford Forest, MI, USA [precipitation]	4.581	5	3	27.59	5.819
FRAGILE Experiment, Svalbard, Norway [grazed]	1	4	5	55.28	5.773
FRAGILE Experiment, Svalbard, Norway	1	4	5	67.37	21.31
INCREASE Clocaenog, Wales, UK	0.198	15	3	110.9	14.04
Gucheng, Hebei, China	2.34	0.6667	3	99.14	3.645
Soil Warming x Nitrogen Addition Study, NH, USA	3.989	5	5	77.85	14.91
Rocky Mountain Biological Laboratory, CO, USA	2	25	5	16.74	3.056
INCREASE Kiskunsag, Hungary	0.44	14	3	5.227	1.773
Krycklan, Sweden	0.9	6	6	8.075	1.399
INCREASE Brandbjerg, Demark	1	2	9	43.89	4.177
Jasper Ridge, CA, USA	1.773	2	4	13.09	2.205
Jasper Ridge, CA, USA [CO2]	1.773	2	4	15.65	3.289
Oak Ridge, Tennessee, USA	2.6	5	3	29.1	3.886

Study Description	Tdelta	Years	count.warmed	C.warmed	C.sd.warmed
Oak Ridge, Tennessee, USA [CO2]	2.6	5	3	30.94	2.625
Oklahoma Tall Grass Prairie, OK, USA [clipped grass]	1.479	10	6	21.78	11.09
Oklahoma Tall Grass Prairie, OK, USA	1.479	10	6	23.69	12.93
Research Station of Songnen Grassland Ecosystem, China	1.75	3	6	19.47	0.3409
Duke Forest, NC, USA [3 degrees]	3	4	3	47.34	18.54
Duke Forest, NC, USA [5 degrees]	5	4	3	42.64	3.876
Konza Prarie, KS, USA	1	4	12	47.61	6.327
Whitehall, GA, USA [3 degrees]	2.096	3	6	12.87	8.818
Whitehall, GA, USA [5 degrees]	4.27	4	6	10.05	4.062
Dry Heath Env. Control, Sweden	1.5	14	6	50.53	4.366
Prairie Heating and CO2 Enrichment, CO, USA	2.8	6	5	20.03	2.494
INCREASE Garraf, Spain	0.94	4.5	3	24.81	8.746
HOCC-Experiment, Germany	1.954	3	4	15.47	2.457
HOCC-Experiment, Germany [precipitation 1]	1.954	3	4	15.25	1.427
HOCC-Experiment, Germany [precipitation 2]	1.954	3	4	14.28	2.466
HOCC-Experiment, Germany [precipitation 3]	1.954	3	4	16.14	2.043
HOCC-Experiment, Germany [precipitation 4]	1.954	3	4	14.81	2.861
BioCON, MN, USA [elevated C02, ambient N, negative H20]	2.5	0.42	3	13.94	2.312
BioCON, MN, USA [elevated C02, elevated N, negative H20]	2.5	0.42	3	20.74	11.53
BioCON, MN, USA [elevated C02, elevated N, ambient H20]	2.5	0.42	3	13.82	0.1774
BioCON, MN, USA [ambient C02, ambient N, ambient H20]	2.5	0.42	3	14.15	4.641
BioCON, MN, USA [ambient C02, elevated N, negative H20]	2.5	0.42	3	15.35	4.115
BioCON, MN, USA [ambient C02, elevated N, ambient H20]	2.5	0.42	3	13.9	2.389
Heat of Prarie Species 1, OR, USA	2.75	2.2	5	38.6	4.242
Heat of Prarie Species 1, OR, USA [precipitation]	2.75	2.2	5	41.04	4.821
Heat of Prarie Species 2, OR, USA [precipitation]	2.98	2.16	5	32.97	2.909
Heat of Prarie Species 3, WA, USA [precipitation]	2.94	1.75	5	40.8	6.846
Heat of Prarie Species 2, OR, USA	2.98	2.16	5	34.42	8.201

Study Description	Tdelta	Years	count.warmed	C.warmed	C.sd.warmed
Heat of Prarie Species 3, WA, USA	2.94	1.75	5	39.01	7.942
INCREASE Mols, Denmark	0.9	4	3	38.8	8.516
Arctic LTER, AK, USA	0.53	20	16	21.14	5.913
Hubbard Brook, NH, USA	4.83	0.8333	8	63.48	12.36
ITEX, Greenland	2	9	1	1.635	NA
ITEX, Greenland [vegetated]	2	9	1	20.02	NA

Table 9: Biome of study sites. For standardization purposes, biome allocations were generated using the UNEP biomes map.

Study Description	Biome
Delta Junction, AK, USA	Boreal Forests/Taiga
Ford Forest, MI, USA	Temperate Broadleaf and Mixed Forests
Ford Forest, MI, USA [precipitation]	Temperate Broadleaf and Mixed Forests
FRAGILE Experiment, Svalbard, Norway [grazed]	Tundra
FRAGILE Experiment, Svalbard, Norway	Tundra
INCREASE Clocaenog, Wales, UK	Temperate Broadleaf and Mixed Forests
Gucheng, Hebei, China	Temperate Broadleaf and Mixed Forests
Soil Warming x Nitrogen Addition Study, NH, USA	Temperate Broadleaf and Mixed Forests
Rocky Mountain Biological Laboratory, CO, USA	Temperate Conifer Forests
INCREASE Kiskunsag, Hungary	Temperate Broadleaf and Mixed Forests
Krycklan, Sweden	Temperate Broadleaf and Mixed Forests
INCREASE Brandbjerg, Demark	Boreal Forests/Taiga
Jasper Ridge, CA, USA	Mediterranean Forests, Woodlands and Scrub
Jasper Ridge, CA, USA [CO2]	Mediterranean Forests, Woodlands and Scrub
Oak Ridge, Tennessee, USA	Temperate Broadleaf and Mixed Forests
Oak Ridge, Tennessee, USA [CO2]	Temperate Broadleaf and Mixed Forests
Oklahoma Tall Grass Prairie, OK, USA [clipped grass]	Temperate Grasslands, Savannas and Shrublands
Oklahoma Tall Grass Prairie, OK, USA	Temperate Grasslands, Savannas and Shrublands
Research Station of Songnen Grassland Ecosystem, China	Temperate Grasslands, Savannas and Shrublands
Duke Forest, NC, USA [3 degrees]	Temperate Broadleaf and Mixed Forests
Duke Forest, NC, USA [5 degrees]	Temperate Broadleaf and Mixed Forests
Konza Prarie, KS, USA	Temperate Grasslands, Savannas and Shrublands
Whitehall, GA, USA [3 degrees]	Temperate Broadleaf and Mixed Forests
Whitehall, GA, USA [5 degrees]	Temperate Broadleaf and Mixed Forests
Dry Heath Env. Control, Sweden	Tundra
Prairie Heating and CO2 Enrichment, CO, USA	Temperate Grasslands, Savannas and Shrublands
INCREASE Garraf, Spain	Mediterranean Forests, Woodlands and Scrub

Study Description	Biome
HOCC-Experiment, Germany	Temperate Broadleaf and Mixed Forests
HOCC-Experiment, Germany [precipitation 1]	Temperate Broadleaf and Mixed Forests
HOCC-Experiment, Germany [precipitation 2]	Temperate Broadleaf and Mixed Forests
HOCC-Experiment, Germany [precipitation 3]	Temperate Broadleaf and Mixed Forests
HOCC-Experiment, Germany [precipitation 4]	Temperate Broadleaf and Mixed Forests
BioCON, MN, USA [elevated C02, ambient N, negative H20]	Temperate Broadleaf and Mixed Forests
BioCON, MN, USA [elevated C02, elevated N, negative H20]	Temperate Broadleaf and Mixed Forests
BioCON, MN, USA [elevated C02, elevated N, ambient H20]	Temperate Broadleaf and Mixed Forests
BioCON, MN, USA [ambient C02, ambient N, ambient H20]	Temperate Broadleaf and Mixed Forests
BioCON, MN, USA [ambient C02, elevated N, negative H20]	Temperate Broadleaf and Mixed Forests
BioCON, MN, USA [ambient C02, elevated N, ambient H20]	Temperate Broadleaf and Mixed Forests
Heat of Prarie Species 1, OR, USA	Temperate Broadleaf and Mixed Forests
Heat of Prarie Species 1, OR, USA [precipitation]	Temperate Broadleaf and Mixed Forests
Heat of Prarie Species 2, OR, USA [precipitation]	Temperate Conifer Forests
Heat of Prarie Species 3, WA, USA [precipitation]	Temperate Conifer Forests
Heat of Prarie Species 2, OR, USA	Temperate Conifer Forests
Heat of Prarie Species 3, WA, USA	Temperate Conifer Forests
INCREASE Mols, Denmark	Temperate Broadleaf and Mixed Forests
Arctic LTER, AK, USA	Tundra
Hubbard Brook, NH, USA	Temperate Broadleaf and Mixed Forests
ITEX, Greenland	Tundra
ITEX, Greenland [vegetated]	Tundra

Helper functions

Bootstrap function

```
print(bootStrap.fn)
```

```
## function (data, myFormula, nRuns, sampleSize, lm.weights = NULL,
##     shuffleFn = NULL, numCoef, verbose = FALSE)
## {
##     sampleIndex <- matrix(NA, nrow = nRuns, ncol = sampleSize)
##     lmStats <- matrix(NA, nrow = nRuns, ncol = numCoef + 3)
##     for (ii in 1:nRuns) {
##         if (verbose)
```

```
##             cat(ii, "\n")
##         if (!is.null(shuffleFn))
##             data <- shuffleFn(data)
##         if (verbose)
##             print(head(data))
##         sampleIndex[ii, ] <- sample(1:(dim(data)[1]), size = sampleSize)
##         temp.lm <- lm(myFormula, data[sampleIndex[ii, ], ])
##         fstatArr <- summary(temp.lm)$fstatistic
##         if (verbose)
##             print(summary(temp.lm))
##         lmStats[ii, ] <- c(temp.lm$coefficients, pf(fstatArr[1],
##             fstatArr[2], fstatArr[3], lower.tail = FALSE), adj.r.squared = summary(temp.lm)$adj.r.squ
##             r.squared = summary(temp.lm)$r.squared)
##     }
##     lmStats <- as.data.frame(lmStats)
##     names(lmStats) <- c(names(temp.lm$coefficients), "p.value",
##         "adj.r.squared", "r.squard")
##     if (verbose)
##         cat("\n")
##     if (verbose)
##         print(lmStats)
##     return(lmStats)
## }
```

Read data

```
print(readSamples)
```

```
## function (useMeanBD = TRUE, readControlMeans = FALSE)
## {
##     data <- read.xlsx2("../data/Soil Data Compiled_January 26.xlsx",
##         sheetIndex = 1, colIndex = c(1, 7, 9, 10, 11, 12))
##     names(data) <- c("Study", "Treatment", "Tdelta", "Years",
##         "perC", "bulk_density")
##     data$Tdelta <- round(data$Tdelta, 3)
##     data$perC <- round(data$perC, 3)
##     data$bulk_density <- round(data$bulk_density, 3)
##     if (useMeanBD) {
##         study.bd <- ddply(data[, c("Study", "bulk_density")],
##             .(Study), summarize, bulk_density.sd = sd(bulk_density),
##             bulk_density = mean(bulk_density))
##         data$bulk_density.sd <- NULL
##         data$bulk_density <- NULL
##         data <- merge(study.bd, data)
##     }
##     data$C <- data$perC/100 * data$bulk_density
##     data.sample <- ddply(data, c("Study", "Tdelta", "Years"),
##         function(xx) {
##             warmed <- xx$C[xx$Treatment == "W"]
##             control <- xx$C[xx$Treatment == "C"]
##             if (readControlMeans) {
##                 return(data.frame(C.warmed = warmed, C.control = mean(control)))
```

```
##             }
##             else {
##                 mismatch <- length(warmed) - length(control)
##                 if (mismatch > 0) {
##                   control <- c(control, rep(NA, mismatch))
##                 }
##                 else {
##                   warmed <- c(warmed, rep(NA, abs(mismatch)))
##                 }
##                 return(data.frame(C.warmed = warmed, C.control = sample(control)))
##             }
##         })
##     data.sample$degYr <- data.sample$Years * data.sample$Tdelta
##     return(data.sample)
## }
```

Construct study means and standard deviations

```r
print(readStudyMeans)
```

```
## function (includeBD.sd = FALSE, includeControl.sd = FALSE)
## {
##     data <- read.xlsx2("../data/Soil Data Compiled_January 26.xlsx",
##         sheetIndex = 1, colIndex = c(1, 7, 9, 10, 11, 12))
##     names(data) <- c("Study", "Treatment", "Tdelta", "Years",
##         "perC", "bulk_density")
##     data$Tdelta <- round(as.numeric(data$Tdelta), 3)
##     data$perC <- as.numeric(data$perC)
##     data$bulk_density <- as.numeric(data$bulk_density)
##     data.study <- ddply(data, .(Study, Tdelta, Years, Treatment),
##         summarize, bulk_density.sd = sd(bulk_density), bulk_density = mean(bulk_density),
##         perC.sd = sd(perC), perC = mean(perC), count = length(Treatment))
##     if (includeBD.sd) {
##         data.study$C.sd <- sqrt(data.study$perC/100^2 * data.study$bulk_density.sd^2 +
##             data.study$perC.sd/100^2 * data.study$bulk_density^2)
##     }
##     else {
##         study.bd <- ddply(data[, c("Study", "bulk_density")],
##             .(Study), summarize, bulk_density = mean(bulk_density))
##         data.study$bulk_density.sd <- NULL
##         data.study$bulk_density <- NULL
##         data.study <- merge(study.bd, data.study)
##         data.study$C.sd <- sqrt((data.study$perC.sd/100 * data.study$bulk_density)^2)
##     }
##     data.study$C <- data.study$perC/100 * data.study$bulk_density
##     data.study <- merge(subset(data.study, Treatment == "W",
##         select = -Treatment), subset(data.study, Treatment ==
##         "C", select = -Treatment), by = c("Study", "Years", "Tdelta"),
##         suffixes = c(".warmed", ".control"))
##     if (!includeControl.sd)
##         data.study$C.sd.control <- 0
##     data.study$degYr <- data.study$Years * data.study$Tdelta
```

```
##     data.study$dC <- data.study$C.warmed - data.study$C.control
##     data.study$dC.sd <- sqrt(data.study$C.sd.warmed^2 + data.study$C.sd.control^2)
##     data.study$dC.perDegYr <- data.study$dC/data.study$degYr
##     data.study$dC.perDegYr.sd <- data.study$dC.sd/data.study$degYr
##     if (!includeControl.sd)
##         data.study$C.sd.control <- NA
##     data.study$C.se.control <- data.study$C.sd.control/data.study$count.control
##     data.study$C.se.warmed <- data.study$C.sd.warmed/data.study$count.warmed
##     data.study$dC.perDegYr.se <- data.study$dC.perDegYr.sd/sqrt(rowMeans(data.study[,
##         c("count.warmed", "count.control")]))
##     return(data.study)
## }
```

Convert R data.frame to netCDF file

```r
cat(readLines('../R/Crowther_dSOC_35yr_makeNC.R'), sep = '\n')
```

```
## # Crowther_dSOC_35yr_makeNC.r
## # Will Wieder
## # July 2016
## # converts .csv to .nc file
## # data reordered go give increasing lat &  lon values
##
## library(ncdf)
## library(reshape2)
## library(raster)
## library(rgdal)
##
## #dir <- getwd() #"/Users/wwieder/Desktop/Working_files/Crowther_warming/KTB_results/"
## #setwd(dir)
## file   <- "../R/Crowther_dSOC_35yr_makeNC.R"
## fin    <- "../data/Crowther_dSOC_35yr.csv"
## Data <- read.csv(fin)
## names(Data)
##
## minLAT <- min(Data$lat)
## maxLAT <- max(Data$lat)
## minLON <- min(Data$lon)
## maxLON <- max(Data$lon)
##
## attach(Data)
## names(Data)
##
## #set up depth, lat, lon coordinates
## nLAT   <- length(as.numeric(levels(as.factor(lat))))
## nLON   <- length(as.numeric(levels(as.factor(lon))))
##
## #LAT    <- seq(minLAT,maxLAT,(90 - 89.05759))
## latDATA <- read.csv('../data/LAT.csv') # some rounding errors, read in CSV of LAT from CLM
## LAT <- latDATA$LAT
## LON    <- seq(minLON,maxLON,(360/nLON))
## nOBS   <- length(Data$dC.single)
```

```
## dims   <- c(nLAT, nLON)
##
## #something wrong w/ how lat values ordered in .csv file
## #rewrite lat so values have a regular step (as I thing they should...)
## lat2  <- rep(NA, length(lat))
## start <- 1
## for (i in 1:nLAT) {
##   end         <- start + nLON-1
##   lat2[start:end] <- LAT[i]
##   start       <- end + 1
## }
## #-------------------------------------------------------------
## #   Define Variables
## #-------------------------------------------------------------
##
## VARS  <- c('SOC','landArea','dC.single','dC.multi')
## nVARS <- length(VARS)
##                                  # close VARS loop
## gridSOC <- rasterFromXYZ(data.frame(Data$lon,lat2,Data$SOC), digits=2)
## gridSOC <- t(flip(gridSOC, direction='y') )
##
## gridArea <- rasterFromXYZ(data.frame(Data$lon,lat2,Data$landArea), digits=2)
## gridArea <- t(flip(gridArea, direction='y') )
##
## gridSingle <- rasterFromXYZ(data.frame(Data$lon,lat2,Data$dC.single), digits=2)
## gridSingle <- t(flip(gridSingle, direction='y') )
##
## gridMulti <- rasterFromXYZ(data.frame(Data$lon,lat2,Data$dC.multi), digits=2)
## gridMulti <- t(flip(gridMulti, direction='y') )
##
## #-------------------------------------------------------------
## #---------------write out .nc file----------------------------
## #-------------------------------------------------------------
## # define the netcdf coordinate variables (name, units, type)
## lat      <- dim.def.ncdf("lat","degrees_north", as.double(LAT),  create_dimvar=TRUE)
## lon      <- dim.def.ncdf("lon","degrees_east",  as.double(LON),  create_dimvar=TRUE)
## mv       <- -9999.              # missing value to use
## LATIXY   <- var.def.ncdf("LATIXY", "degrees N", list(lat), mv,
##                         longname="latitude", prec="double")
## LONGXY   <- var.def.ncdf("LONGXY", "degrees E", list(lon), mv,
##                         longname="longitude", prec="double")
## SOC_i    <- var.def.ncdf("SOC_i", units="kg C/m2", list(lon,lat), mv,
##                         longname="Soil C", prec="double")
## area     <- var.def.ncdf("Area", units="m2", list(lon,lat), mv,
##                          longname="grid_area", prec="double")
## dC_Single <- var.def.ncdf("dC_Single", units="kg C/m2", list(lon,lat), mv,
##                           longname="Single Step", prec="double")
## dC_Multi <- var.def.ncdf("dC_Multi", units="kg C/m2", list(lon,lat), mv,
##                           longname="Multi Step", prec="double")
##
## fname <- '../data/Crowther_dSOC_35y.nc'
## ncnew <- create.ncdf( fname, list(LATIXY, LONGXY, SOC_i, area, dC_Single, dC_Multi) )
##
## # Write some values to this variable on disk.
```

```
## put.var.ncdf( ncnew, LATIXY, LAT)
## put.var.ncdf( ncnew, LONGXY, LON)
## put.var.ncdf( ncnew, SOC_i,    as.array(gridSOC))
## put.var.ncdf( ncnew, area,     as.array(gridArea))
## put.var.ncdf( ncnew, dC_Single,as.array(gridSingle))
## put.var.ncdf( ncnew, dC_Multi ,as.array(gridMulti))
##
## att.put.ncdf( ncnew, 0, "created_on",date()       ,prec=NA,verbose=FALSE,definemode=FALSE )
## att.put.ncdf( ncnew, 0, "created_by","Will Wieder",prec=NA,verbose=FALSE,definemode=FALSE )
## att.put.ncdf( ncnew, 0, "created_from",fin        ,prec=NA,verbose=FALSE,definemode=FALSE )
## att.put.ncdf( ncnew, 0, "created_with",file       ,prec=NA,verbose=FALSE,definemode=FALSE )
##
## close.ncdf(ncnew)
##
## print('-------Wrote out .nc files-----------')
## print(ncnew)
```

Main analysis script

```
sessionInfo()
```

```
R version 3.2.2 (2015-08-14)
Platform: x86_64-apple-darwin13.4.0 (64-bit)
Running under: OS X 10.10.5 (Yosemite)

locale:
[1] en_US.UTF-8/en_US.UTF-8/en_US.UTF-8/C/en_US.UTF-8/en_US.UTF-8

attached base packages:
[1] stats     graphics  grDevices utils     datasets  methods   base

other attached packages:
 [1] ncdf4_1.15     xlsx_0.5.7     xlsxjars_0.6.1 rJava_0.9-7
 [5] deSolve_1.12   lme4_1.1-10    Matrix_1.2-3   MASS_7.3-45
 [9] reshape2_1.4.1 pander_0.6.0   plyr_1.8.3     ggplot2_2.0.0

loaded via a namespace (and not attached):
 [1] Rcpp_0.12.2      knitr_1.11       magrittr_1.5     splines_3.2.2
 [5] munsell_0.4.2    colorspace_1.2-6 lattice_0.20-33  minqa_1.2.4
 [9] stringr_1.0.0    tools_3.2.2      grid_3.2.2       gtable_0.1.2
[13] nlme_3.1-122     htmltools_0.2.6  yaml_2.1.13      digest_0.6.8
[17] nloptr_1.0.4     formatR_1.2.1    evaluate_0.8     rmarkdown_0.8.1
[21] labeling_0.3     stringi_1.0-1    scales_0.3.0
```

```
cat(readLines('../R/CrowtherFieldWarmingScript.R'), sep = '\n')
```

```
library(ggplot2) #make pretty plots
library(plyr) #deal with data frames nicely
library(pander) #format tables
panderOptions('table.split.table', Inf) #do not let pander split tables because bad numbering
library(reshape2) #deal with data frames nicely
```

```
library(MASS) #model selection
library(lme4) #random vs fixed effects model
library(deSolve) #solve ode
library(xlsx) #read in excel files

source('../R/bootStrap.fn.R')
source('../R/readSamples.R')
source('../R/readStudyMeans.R')

verbose <- FALSE

##Helper functions
shuffle.sample <- function(data){
  idCol <- setdiff(names(data), c('C.warmed', 'C.control'))
  return(ddply(data, idCol, summarize,
               C.warmed=sample(C.warmed, size=length(Study)),
               C.control=sample(C.control, size=length(Study))))
}

pullPvalue <- function(temp.lm){
  fstatArr <-  summary(temp.lm)$fstatistic
  return(pf(fstatArr[1], fstatArr[2], fstatArr[3], lower.tail = FALSE))
}

##Read in data
studyMeta <- read.xlsx2('../data/Soil Data Compiled_January 26.xlsx',
                        sheetIndex=2, colIndex=c(1, 9,10,11, 13, 16))
names(studyMeta) <- c('Study', 'MAP', 'MAT', 'Biome', 'pH', 'perClay')
studyMeta <- studyMeta[studyMeta$Study != '',]

studyNames <- read.xlsx2('../data/Soil Data Compiled_January 26.xlsx',
                         sheetIndex=7)
names(studyNames) <- c('Study', 'Study Description')
data.sample <- readSamples()
data.study <- readStudyMeans()

if(!identical( setdiff(studyMeta$Study, data.sample$Study),
               setdiff(data.sample$Study, studyMeta$Study)) |
   !identical(setdiff(studyMeta$Study, studyNames$Study),
              setdiff(studyNames$Study, studyMeta$Study))){
  stop('study names do not match')
}

##Convert from g cm^-3 to kg m^-3
data.sample[, c('C.warmed', 'C.control')] <- data.sample[, c('C.warmed', 'C.control')] * 1e3
data.study[, c('bulk_density.warmed', 'C.sd.warmed', 'C.warmed', 'bulk_density.control',
               'C.sd.control',  'C.control', 'dC', 'dC.sd', 'dC.perDegYr', 'dC.perDegYr.sd',
               'C.se.control', 'C.se.warmed', 'dC.perDegYr.se')] <-
  data.study[,
             c('bulk_density.warmed', 'C.sd.warmed', 'C.warmed', 'bulk_density.control',
               'C.sd.control',  'C.control', 'dC', 'dC.sd', 'dC.perDegYr', 'dC.perDegYr.sd',
               'C.se.control', 'C.se.warmed', 'dC.perDegYr.se')] * 1e3
```

```
##Rescale data
#There is clear skew in the histograms of the years, degree-years, and carbon stocks.
#We log-transformed these variables to normalize the distribution for statistical purposes.

data.sample.plus <- merge(data.sample, studyMeta[,c('Study', 'MAT', 'MAP', 'pH', 'perClay')],
                          by='Study', all=TRUE)
data.sample.plus$degYr <- data.sample.plus$Years*data.sample.plus$Tdelta
fullRows <- apply(subset(data.sample.plus, select=-Study), c(1),
                  function(xx){all(is.finite(xx))})

if(verbose) print(sprintf('Throwing out %d samples (rows) because of missing values somewhere.',
                          sum(!fullRows)))

data.sample.plus <- data.sample.plus[fullRows,]
ggplot(melt(subset(data.sample.plus, select=-Study))) +
  geom_histogram(aes(x=value)) + facet_wrap(~variable, scale='free')
cor(subset(data.sample.plus, select=-Study))

data.sample.plus.rescaled <- data.sample.plus

data.sample.plus.rescaled$degYr <- log(data.sample.plus.rescaled$degYr)
data.sample.plus.rescaled$Years <- log(data.sample.plus$Years)
data.sample.plus.rescaled$C.control <- log(data.sample.plus$C.control)
data.sample.plus.rescaled$C.warmed <- log(data.sample.plus$C.warmed)

data.sample.plus.rescaled[,-1] <- as.data.frame(apply(
  data.sample.plus.rescaled[, -1], c(2), function(xx){
    return((xx-mean(xx, na.rm=TRUE))/sd(xx, na.rm=TRUE)+1)
  }))

##Construct LMER
lmer.list <- list(simple = lmer(C.warmed ~ C.control + (1|Study),
                    data=data.sample.plus.rescaled),
             addative.dT = lmer(C.warmed~C.control+Tdelta + (1|Study),
                    data=data.sample.plus.rescaled),
            addative.all = lmer(C.warmed~C.control+MAP+MAT+pH+degYr + perClay + (1|Study),
                    data=data.sample.plus.rescaled),
         addative.enviro = lmer(C.warmed~C.control+MAP+MAT+pH + perClay+ (1|Study),
                    data=data.sample.plus.rescaled),
          addative.treat = lmer(C.warmed~C.control+degYr + (1|Study),
                    data=data.sample.plus.rescaled),
         interactive = lmer(C.warmed~C.control*degYr+ (1|Study),
                                  data=data.sample.plus.rescaled),
         interactive.dT = lmer(C.warmed~C.control*Tdelta+ (1|Study),
                                     data=data.sample.plus.rescaled))

##Construct LM
lm.list <- list(Cw.sample = lm(C.warmed ~ C.control * degYr, data.sample),
                Cw.sample.dT = lm(C.warmed ~ C.control * Tdelta, data.sample),
                dC.sample = lm(C.warmed - C.control ~ C.control * degYr, data.sample),
                dC.dT.sample = lm(C.warmed - C.control ~ C.control * Tdelta, data.sample),
                dCperDegYr.sample = lm((C.warmed-C.control)/(Years*Tdelta) ~ C.control,
                                      data.sample),
                dCperDeg.sample = lm((C.warmed-C.control)/Tdelta ~ C.control,
```

```
                                data.sample),
                Cw.study = lm(C.warmed ~ C.control * degYr, data.study),
                Cw.study.dT = lm(C.warmed ~ C.control * Tdelta, data.study),
                dC.study = lm(C.warmed - C.control ~ C.control * degYr, data.study),
                dC.dT.study = lm(C.warmed - C.control ~ C.control * Tdelta, data.study),
                dCperDegYr.study = lm((C.warmed-C.control)/(Years*Tdelta) ~ C.control,
                                 data.study),
                dCperDeg.study = lm((C.warmed-C.control)/Tdelta ~ C.control,
                               data.study))

modelFits <- ldply(lm.list,
                   function(xx){
                     data.frame(model=as.character(xx$call)[2],
                                data=as.character(xx$call)[3],
                                adjR2 = sprintf('%0.3f', summary(xx)$adj.r.squared),
                                pvalue=sprintf('%0.3g', pullPvalue(xx)))
                   })


##Sample model vs data distributions
interactive.model <- function(pars=summary(lm.list$Cw.study)$coefficients,
                              C.control, C.sd.control, degYr){
  C_degYr.par <- rnorm(1, mean=pars['C.control:degYr', 'Estimate'],
                       sd=pars['C.control:degYr', 'Std. Error'])
  C.par <- rnorm(1, mean=pars['C.control', 'Estimate'], sd=pars['C.control', 'Std. Error'])
  degYr.par <- rnorm(1, mean=pars['degYr', 'Estimate'], sd=pars['degYr', 'Std. Error'])
  inter.par <- rnorm(1, mean=pars['(Intercept)', 'Estimate'],
                     sd=pars['(Intercept)', 'Std. Error'])
  model <- inter.par+ C.par*C.control + degYr.par*degYr + C_degYr.par*C.control*degYr

  return(model)
}

modelData.df <- data.frame()
for(ii in 1:1000){
  modelData.df <- rbind(modelData.df,
                        data.frame(index = 1:length(data.study$C.warmed),
                                   rnd.data=rnorm(n=length(data.study$C.warmed),
                                                  mean=data.study$C.warmed,
                                                  sd=data.study$C.sd.warmed),
                                   rnd.model =
                                     interactive.model(C.control=data.study$C.control,
                                                       C.sd.control=data.study$C.sd.control,
                                                       degYr=data.study$degYr)))
}

summaryMD.df <- ddply(modelData.df, 'index', summarize,
                      data.mean=mean(rnd.data), data.sd=sd(rnd.data),
                      model.mean=mean(rnd.model), model.sd=sd(rnd.model))

##bootstrap slope
selectSize.sample <- adply(floor(seq(10, dim(data.sample)[1], length=50)), c(1),
                           function(xx){
                             ans <- bootStrap.fn(
```

```
                              myFormula=(C.warmed-C.control)/(Years*Tdelta) ~ C.control,
                              data=data.sample, nRuns=100, sampleSize=xx, numCoef=2,
                              shuffleFn=shuffle.sample)
                           ans$sampleSize <- xx
                           return(ans)
                         })


selectSize.study <- adply(3:(dim(data.study)[1]), c(1),
                          function(xx){
                            ans <- bootStrap.fn(
                               myFormula=(C.warmed-C.control)/(Years*Tdelta) ~ C.control,
                               data=data.study, nRuns=100, sampleSize=xx, numCoef=2)
                            ans$sampleSize <- xx
                            return(ans)
                          })

##Pull CI for parameters from subset samples
dCperDeg.boot <- bootStrap.fn(
  myFormula=(C.warmed-C.control)/Tdelta ~ C.control,
  data=data.sample, nRuns=1e3, sampleSize=200, numCoef=2, shuffleFn=shuffle.sample)

dCperDegYr.boot <- bootStrap.fn(
  myFormula=(C.warmed-C.control)/(Years*Tdelta) ~ C.control,
  data=data.sample, nRuns=1e3, sampleSize=200, numCoef=2, shuffleFn=shuffle.sample)


dCperDegYr.mod.boot <- llply(list(wk1=1/52, mon1 = 1/12, mon6 = 6/12, yr1 = 1,
                                  yr4 = 4, yr5 = 5,  yr7 = 7, yr8 = 8,
                                  yr8.75= 8.75, yr10 = 10, yr11.6=35/3,
                                  yr15 = 15,
                                  yr17.5=17.5, yr20 = 20, yr25 = 25, yr30 = 30, yr35 = 35),
                         function(xx){
                           data.sample$Years.mod <- data.sample$Years
                           data.sample$Years.mod[data.sample$Years.mod > xx] <- xx
                           ans <-  bootStrap.fn(
                          myFormula = (C.warmed-C.control)/(Years.mod*Tdelta) ~ C.control,
                             data=data.sample, nRuns=1e3, sampleSize=200,
                             numCoef=2, shuffleFn=shuffle.sample, verbose=FALSE)
                           return(ans)
                         })


parKDE <- kde2d(dCperDegYr.boot$C.control, dCperDegYr.boot$`(Intercept)`, n=100)
parBins <- melt(parKDE$z)
parBins <- subset(parBins, value > max(value)*0.01)
parBins$slope <- parKDE$x[parBins$Var1]
parBins$intercept <- parKDE$y[parBins$Var2]
parBins$alpha <- parBins$value/max(parBins$value)

parRange <- ldply(c(list(dCperDegYr = dCperDegYr.boot,
                       dCperDeg = dCperDeg.boot),
                       dCperDegYr.mod.boot), function(xx){
                       ans <- as.data.frame(apply(xx, c(2),
```

```
                              quantile, c(0.05, 0.5, 0.95)))
                     ans$qrt <- c(0.05, 0.5, 0.95)
                     return(ans)
                     })

names(parRange)[1:3] <- c('type','intercept', 'C')
save(file='../data/parCIforLM.RData', parRange)
```

Extrapolation code

```
cat(readLines('../R/globalExtrapolations.R'), sep='\n')
```

```
###Set up
library(ncdf4)
library(ggplot2)
library(plyr)
verbose <- FALSE
dataDir <- '../data/'
readIn.tsl <- TRUE

#############################
###Read in maps
inputs.ls <- list(soilGrid=list(filename='SoilGrids_0.9x1.25.nc',
                                varName='OCSTHA_M',
                                units='tonnes ha^-1', #convertion factor 1/10 for kg m^-2
                                depthWeight=c(1, 1, 0, 0, 0, 0)),
                  #mid points c(2.5  10.0  22.5  45.0  80.0 150.0) cm
                  #implies 5cm, 10cm, 15cm, 30cm, 60cm, 60cm layer lengths
                  #take top 15cm

                  HWSD=list(filename='surfdata_0.9x1.25_simyr2000_c120906_HWSD_soil.nc',
                            varName='DOM_SOC', #dominatent mapping unit;
                            #alt area weighted AWT_SOC
                            units='kg C m^-2',
                            depthWeight=c(1, 0)), #0-30 cm, 30-70 cm soil layers
                  landfrac=list(filename='sftlf_fx_CESM1-BGC_historical_r0i0p0.nc',
                                varName='sftlf',
                                units='percent'),
                  gridArea=list(filename='areacella_fx_CESM1-BGC_historical_r0i0p0.nc',
                                varName='areacella',
                                units='m2'))

maps.ls <- lapply(inputs.ls, function(args){
  ncin <- nc_open(sprintf('%s%s', dataDir, args$filename))
  if(verbose) print(ncin)
  lon <- ncvar_get(ncin, 'lon') #longitude
  lat <- ncvar_get(ncin, 'lat') #longitude
  ans <- ncvar_get(ncin, args$varName)
  nc_close(ncin)

  if(!is.null(args$depthWeight)){
    ans <- apply(ans, c(1,2), function(xx){sum(args$depthWeight*xx)})
```

```
  }

  dimnames(ans) <- list(lon=lon, lat=lat)
  ans <- as.data.frame.table(ans, stringsAsFactors=FALSE, responseName='value')
  ans <- as.data.frame(lapply(ans, as.numeric))

  return(ans)
})

maps.ls$landArea <- merge(maps.ls$gridArea, maps.ls$landfrac,
                          by=c('lon', 'lat'), suffixes=c('.area', '.perc'))
maps.ls$landArea$value <- maps.ls$landArea$value.area*maps.ls$landArea$value.perc/100

if(readIn.tsl){
  #CESM1-BGC Soil Temperature
  ##Pre-processing in cdo
  ##$cdo yearmean tsl_Lmon_CESM1-BGC_rcp85_r1i1p1_200601-204912.nc
  ##              tsl_yrmean_CESM1-BGC_rcp85_r1i1p1_200601-204912.nc
  ##$cdo sellevidx,1,2,3,4 tsl_yrmean_CESM1-BGC_rcp85_r1i1p1_200601-204912.nc temp.nc
  ##$cdo vertmean temp.nc tsl_yrShortMean_CESM1-BGC_rcp85_r1i1p1_200601-204912.nc

  ncin <- nc_open(sprintf('%stsl_yrShortMean_CESM1-BGC_rcp85_r1i1p1_200601-204912.nc',
                          dataDir))
  if(verbose) print(ncin)
  tsl <- ncvar_get(ncin, 'tsl') #units K
  lon <- ncvar_get(ncin, 'lon') #longitude
  lat <- ncvar_get(ncin, 'lat') #longitude
  time <- ncvar_get(ncin, 'time') #days since 2005-1-1 0:0:0
  nc_close(ncin)

  dimnames(tsl) <- list(lon=lon, lat=lat, yr=(time/365) + 2005)
  tsl <- as.data.frame.table(tsl, stringsAsFactors=FALSE, responseName='value')
  tsl <- as.data.frame(lapply(tsl, as.numeric))

  ##Make the latitudes aggree, off by 1e-6
  tsl$lat <- round(tsl$lat, 2)
  maps.ls <- lapply(maps.ls, function(xx){xx$lat <- round(xx$lat, 2); return(xx)})


  ##Trim tsl to only cover 2015-2049
  tsl <- subset(tsl, yr >= 2015 & yr <=2049)
  tsl.start <- ddply(subset(tsl, yr >= min(yr) & yr < (min(yr)+10)), .(lon, lat),
                     summarize, value=mean(value))
  tsl.end <-  ddply(subset(tsl, yr > max(yr)-10 & yr <= max(yr)), .(lon, lat),
                    summarize, value=mean(value))
  tsl.change <- merge(tsl.start, tsl.end, by=c('lon', 'lat'), suffixes=c('.inital', '.final'))

  if(verbose){
    print(ggplot(tsl.change) + geom_raster(aes(x=lon, y=lat, fill=value.final-value.inital)) +
            labs(title='CESM-BCG temperature change'))
    print(ggplot(tsl.change) + geom_histogram(aes(x=value.final-value.inital)) +
            labs(title='CESM-BCG temperature change'))
  }
}
```

```
if(verbose){
  print(ggplot(maps.ls$soilGrid) + geom_raster(aes(x=lon, y=lat, fill=value/10)) +
          scale_fill_continuous(limits=c(0, 300),low="yellow", high='red') +
          labs( title='Soil Grids'))
  print(ggplot(maps.ls$HWSD) + geom_raster(aes(x=lon, y=lat, fill=value)) +
          scale_fill_continuous(limits=c(0, 100),low="yellow", high='red') + labs(title='HWSD'))

  print(ggplot(maps.ls$landfrac) + geom_raster(aes(x=lon, y=lat, fill=value/100)) +
          scale_fill_continuous(limits=c(0, 1),low="yellow", high='red') +
          labs( title='Land Fraction'))
  print(ggplot(maps.ls$gridArea) + geom_raster(aes(x=lon, y=lat, fill=value)) +
          labs( title='Grid Area'))
  print(ggplot(maps.ls$landArea) + geom_raster(aes(x=lon, y=lat, fill=value)) +
          labs( title='Land Area'))

}

##########################################
##Make one dataframe to work from so that the lat-lon pair up appropreately
##########################################
commonGrid <- merge(maps.ls$landArea,
                    merge(maps.ls$soilGrid, maps.ls$HWSD,
                          by=c('lon', 'lat'), suffixes=c('.SG', '.H')),
                    by=c('lon', 'lat'))
if(readIn.tsl){
  commonGrid <- merge(tsl.change, commonGrid,
                      by=c('lon', 'lat'), suffixes=c('.Dtsl', '.landArea'))
}

commonGrid <- rename(commonGrid, c('value.inital'='inital.temperature',
                                   'value.final'='final.temperature',
                                   'value.area'='cell.area',
                                   'value.perc'='land.percentage',
                                   'value'='land.area',
                                   'value.SG'='SoilGrid.SOC', 'value.H'='HWSD.SOC'))

##Shift the units for soil grid to kg m^-2
commonGrid$SoilGrid.SOC <- commonGrid$SoilGrid.SOC/10

###Remove 0 values
##commonGrid$SoilGrid.SOC[commonGrid$SoilGrid.SOC == 0] <- NA
##commonGrid$HWSD.SOC[commonGrid$HWSD.SOC == 0] <- NA

commonGrid$allFinite <- is.finite(rowSums(subset(commonGrid, select=-HWSD.SOC))) &
  commonGrid$land.area != 0

################################
###Pull temperature normalization from CESM if needed
################################
if(readIn.tsl){
  globalCESM.dT <- with(commonGrid, sum(land.area*
                                          (final.temperature-inital.temperature)*allFinite,
                                        na.rm=TRUE)/sum(land.area*allFinite, na.rm=TRUE))
```

```
}else{
  globalCESM.dT <- NA
}

if(verbose){
  ggplot(commonGrid) + geom_raster(aes(x=lon, y=lat, fill=allFinite)) +
    labs(title='Shared grid cells')
  print(sprintf("Global totals: HWSD = %0.2f Pg,
                SoilGrid = %0.2f Pg, inital T = %0.2f C, dT = %0.2f C",
                with(commonGrid, sum(land.area*(HWSD.SOC)*allFinite, na.rm=TRUE)/1e12),
                with(commonGrid, sum(land.area*(SoilGrid.SOC)*allFinite, na.rm=TRUE)/1e12),
                ifelse(readIn.tsl, with(commonGrid,
                                        sum(land.area*inital.temperature*allFinite, na.rm=TRUE)/
                                          sum(land.area*allFinite, na.rm=TRUE))-273.15, NA),
                globalCESM.dT
  ))
}

##############################
###Run the global extrapolation
###############################
load(sprintf('%sparCIforLM.RData', dataDir))

soilDepth <- 0.15 #in m; for HWSD it's 0.3
##Number of years we run through
runTime <- 35

dC <- function(args, step, Cstock){
  #correct for soil depth but converting stocks from per area to per volume
  #...and then correcting the result from per volume to per area
  return(step*(args$C*Cstock/soilDepth+args$intercept)*soilDepth)
}

##Use the temperature change distribution from CESM from year 2040-2049 and 2015-2024
if(readIn.tsl){
  degWarmedRate.ls <- list(oneDeg=1/runTime, twoDeg=2/runTime,
                           threeDeg=3/runTime, fourDeg=4/runTime,
                     oneDeg_CESM_normed = (commonGrid$final.temperature-
                                             commonGrid$inital.temperature)/
                       globalCESM.dT*1/runTime,
                     twoDeg_CESM_normed = (commonGrid$final.temperature-
                                             commonGrid$inital.temperature)/
                       globalCESM.dT*2/runTime,
                     threeDeg_CESM_normed = (commonGrid$final.temperature-
                                               commonGrid$inital.temperature)/
                       globalCESM.dT*3/runTime,
                     fourDeg_CESM_normed = (commonGrid$final.temperature-
                                              commonGrid$inital.temperature)/
                       globalCESM.dT*4/runTime)
}else{
  degWarmedRate.ls <-list(oneDeg=1/runTime, twoDeg=2/runTime)
}

#Time step for each linear model type
```

```
dtime.ls <- list(wk1=1/52, mon1 = 1/12, mon6 = 6/12, yr1 = 1,
                 yr4 = 4, yr5 = 5,  yr7 = 7, yr8 = 8,
                 yr8.75= 8.75, yr10 = 10, yr11.6=35/3,
                 yr17.5=17.5, yr20 = 20, yr25 = 25, yr30 = 30, yr35 = 35)

resultsFull <- ldply(degWarmedRate.ls, .id='warming', function(degWarmedRate){
  ##Calculate the SOC losses
  SOC.losses <- ddply(parRange, c('type', 'qrt', 'intercept', 'C'),
    function(xx){
      #cat(xx$type)

      C.map <- commonGrid$SoilGrid.SOC

      if(grepl('^dCperDegYr$', xx$type)){
        dC.map <- ldply(dtime.ls, .id=NULL, function(warmedTime){
          degStep <- degWarmedRate/2*warmedTime^2
          return(data.frame(degYr.mean=sum(degStep*commonGrid$land.area, na.rm=TRUE)/
                              sum(is.finite(degStep)*commonGrid$land.area, na.rm=TRUE),
                            timeStep=warmedTime,
                            lon=commonGrid$lon,
                            lat=commonGrid$lat,
                            value.C=C.map,
                            landArea=commonGrid$land.area*commonGrid$allFinite,
                            value.dC=dC(args=xx, step=degStep, Cstock=C.map)))
        })
      }else if(grepl('^dCperDeg$', xx$type)){
        dC.map <- data.frame(degYr.mean=NA,
                             timeStep=NA,
                             lon=commonGrid$lon,
                             lat=commonGrid$lat,
                             value.C=C.map,
                             landArea=commonGrid$land.area*commonGrid$allFinite,
                             value.dC=dC(args=xx, step=degWarmedRate*runTime, Cstock=C.map))
      }else{ ##Cap study
        #print(xx$type)
        #print(!(xx$type %in% names(dtime.ls)) || (runTime/dtime.ls[[xx$type]]) %% 1 != 0)
        if(!(xx$type %in% names(dtime.ls)) ||
              (runTime/dtime.ls[[xx$type]]) %% 1 != 0){
          return(data.frame()) #don't run if you can't cover the entire period
        }
        runningC <- C.map
        degStep <- degWarmedRate/2*dtime.ls[[xx$type]]^2 #cumulative degYr for each time step
        for(ii in seq(0, runTime-1, by=dtime.ls[[xx$type]])){
          runningC <- runningC + dC(args=xx, step=degStep, Cstock=runningC)
        }

        dC.map <- data.frame(degYr.mean=mean(degStep, na.rm=TRUE),
                             timeStep=dtime.ls[[xx$type]],
                             lon=commonGrid$lon,
                             lat=commonGrid$lat,
                             value.C=C.map,
                             landArea=commonGrid$land.area*commonGrid$allFinite,
                             value.dC=runningC-C.map)
      }
```

```
      ##max loss is the inital carbon stock
      dC.map$value.dC[is.finite(dC.map$value.C+dC.map$value.dC) & dC.map$value.dC +
                       dC.map$value.C < 0] <-
        -1*dC.map$value.C[is.finite(dC.map$value.C+dC.map$value.dC) & dC.map$value.dC +
                           dC.map$value.C < 0]

      #dC.map <- merge(dC.map, commonGrid[,c('lon', 'lat', 'land.area', 'allFinite')])
      return(ddply(dC.map, c('timeStep', 'degYr.mean'),
                   summarize, dC=sum(value.dC*landArea, na.rm=TRUE)/1e12))
    }) #end SOC.losses
  }) #end resultsTable

resultsTable <- merge(subset(resultsFull, qrt==0.95,
                             select=c('warming', 'type', 'timeStep', 'degYr.mean', 'dC')),
  merge(subset(resultsFull, qrt==0.05,
               select=c('warming', 'type', 'timeStep','degYr.mean',  'dC')),
              subset(resultsFull, qrt==0.50,
                     select=c('warming', 'type', 'timeStep', 'degYr.mean', 'dC')),
              by=c('warming', 'type', 'degYr.mean', 'timeStep'), suffixes=c('_qrt05', '_qrt50')))
resultsTable <- rename(resultsTable, c('dC'='dC_qrt95'))

resultsTable$dodge.timeStep <- resultsTable$timeStep +
  rnorm(n=length(resultsTable$timeStep), mean=0, sd=0.1)
deg.key <- list("fourDeg"=4,  "oneDeg"=1,   "threeDeg"=3, "twoDeg"=2)
resultsTable$globalWarming <- as.factor(unlist(lapply(strsplit(
  as.character(resultsTable$warming), split="_"), function(xx){deg.key[[xx[[1]]]]})))

resultsTable$warmingDistribution <- unlist(lapply(strsplit(
  as.character(resultsTable$warming), split="_"),
  function(xx){ifelse(length(xx) > 1, 'CESM', 'unif')}))

save(file='../data/globalExtrapolations.RData', resultsTable, resultsFull)

#####################
##Make plots
degYrSingle.pl <- ggplot(subset(resultsTable, grepl('dCperDegYr', type))) +
  geom_point(aes(x=timeStep, y=dC_qrt50)) +
  geom_errorbar(aes(x=timeStep, y=dC_qrt50, ymin=dC_qrt05, ymax=dC_qrt95)) +
  facet_wrap(~warming, nrow=2) +
  labs(title='dC per degree-year across single time steps', x='years', y='Pg C')
ggsave(degYrSingle.pl, filename='../figs/degYrSingleTimeStep.pdf')

degYr.pl <- ggplot(subset(resultsTable, grepl('dCperDegYr', type))) +
  geom_point(aes(x=degYr.mean, y=dC_qrt50, color=grepl('CESM', warming))) +
  geom_ribbon(aes(x=degYr.mean, y=dC_qrt50, ymin=dC_qrt05, ymax=dC_qrt95,
                  fill=grepl('CESM', warming)), alpha=0.3) +
  scale_fill_discrete(guide=guide_legend(title='CESM'))+guides(color=FALSE) +
  labs(title='dC per degree-year across single time steps', x='degree-years', y='Pg C')
ggsave(degYr.pl, filename='../figs/degYr.pdf')

degSingle.pl <- ggplot(subset(resultsTable, 'dCperDeg'== type)) +
  geom_point(aes(x=warming, y=dC_qrt50)) +
  geom_errorbar(aes(x=warming, y=dC_qrt50, ymin=dC_qrt05, ymax=dC_qrt95)) +
```

```
  theme(axis.text.x = element_text(angle = 90, hjust = 1)) + labs(title='dC per degree')
ggsave(degSingle.pl, filename='../figs/degSingleTimeStep.pdf')


degYrStepInt.pl <- ggplot(subset(resultsTable, !grepl('dCperDeg', type))) +
  geom_line(aes(x=timeStep, y=dC_qrt50, group=warming, linetype=warmingDistribution)) +
  geom_ribbon(aes(x=timeStep, y=dC_qrt50, ymin=dC_qrt05, ymax=dC_qrt95, group=warming),
              alpha=0.2) +
  facet_wrap(~globalWarming)
ggsave(degYrStepInt.pl, filename='../figs/degYrMultiTimeStep.pdf')

##See Crowther2016Sup.Rmd for figure code
write.csv(file='../data/degYrMultiTimeStepSimple.csv',
          subset(resultsTable, !grepl('dCperDeg', type) & globalWarming %in% c('1', '2')))

singleStep.pl <- ggplot(subset(resultsTable, grepl('dCperDeg', type) &
                                 globalWarming %in% c(1,2) &
                                 (is.na(timeStep) | timeStep == 35))) +
  geom_point(aes(x=globalWarming, y=dC_qrt50, color=type, shape=warmingDistribution), cex=5) +
  geom_errorbar(aes(x=globalWarming, y=dC_qrt50, color=type, linetype=warmingDistribution,
                    ymin=dC_qrt05, ymax=dC_qrt95)) +
  labs(title='Soil carbon losses at 35 years, one step', x='Average temperature increase',
       y='Global change in soil carbon [Pg C]')
ggsave(singleStep.pl, filename='../figs/singleStep.pdf')
write.csv(file='../data/singleStep.csv',
          subset(resultsTable, grepl('dCperDeg', type) &
                   globalWarming %in% c('1', '2') &
                   (is.na(timeStep) | timeStep == 35), -dodge.timeStep))

########
##Make ncdf file for pretty maps
Cshift <- data.frame(lon=commonGrid$lon, lat=commonGrid$lat,
                     SOC=commonGrid$SoilGrid.SOC,
                     landArea=commonGrid$land.area, #*commonGrid$allFinite,
                     dC.single=dC(args=subset(parRange, type=='dCperDegYr' & qrt==0.5),
                                  step=degWarmedRate.ls$oneDeg_CESM_normed/2*35^2,
                                  Cstock=commonGrid$SoilGrid.SOC))

runningC <- Cshift$SOC
degStep <- degWarmedRate.ls$oneDeg_CESM_normed/2*1^2 #cumulative degYr for each time step
for(ii in seq(0, runTime-1, by=1)){
  runningC <- runningC + dC(args=subset(parRange, type=='yr1' & qrt==0.5),
                            step=degStep, Cstock=runningC)
}
Cshift$dC.multi <- runningC-Cshift$SOC

negFlag <- is.finite(Cshift[, 'dC.single'] + Cshift[, 'SOC']) &
  (Cshift[, 'dC.single'] + Cshift[, 'SOC'] < 0 )
Cshift[negFlag, 'dC.single'] <- -1*Cshift[negFlag, 'SOC']
negFlag <- is.finite(Cshift[, 'dC.multi'] + Cshift[, 'SOC']) &
  (Cshift[, 'dC.multi'] + Cshift[, 'SOC'] < 0 )
Cshift[negFlag, 'dC.multi'] <- -1*Cshift[negFlag, 'SOC']

cat('Single step: ', sum(Cshift$dC.single*Cshift$landArea, na.rm=TRUE)/1e12, '=?=',
```

```
    unlist(subset(resultsTable, grepl('dCperDegYr', type) &
                    globalWarming %in% c(1, 2) &
                    (is.na(timeStep) | timeStep == 35) &
                    warming=='oneDeg_CESM_normed', dC_qrt50)),
    '\nOne yr step: ', sum(Cshift$dC.multi*Cshift$landArea, na.rm=TRUE)/1e12, '=?=',
    unlist(subset(resultsTable, !grepl('dCperDeg', type) & globalWarming %in% c(1, 2) &
                    type=='yr1' & warming=='oneDeg_CESM_normed', dC_qrt50)), '\n')

write.csv(file='Crowther_dSOC_35yr.csv', Cshift)
```

Global carbon loss map code

```
cat(readLines('../ncl/plot_warming_loss.ncl'), sep='\n')
```

```
; July 2016
; Will Wieder
; plots changes in SOC stocks from Kathe's analyses.
; *********************************************************************

load "$NCARG_LIB/ncarg/nclscripts/csm/gsn_code.ncl"
load "$NCARG_LIB/ncarg/nclscripts/csm/gsn_csm.ncl"
load "$NCARG_LIB/ncarg/nclscripts/csm/contributed.ncl"
load "$NCARG_LIB/ncarg/nclscripts/csm/shea_util.ncl"

begin
;----------------------------------------------------------------
;Read in input variables
;---------------------------------------------------------------
 path       = (/"/project/tss/wwieder/soilCN/global_run/warming/"/)
 fin        = path + "Crowther_dSOC_35y.nc"

 data       = addfile(fin, "r")
 SGRD_SOC   = data->SOC_i(:,:)                ; SoilGrids SOC pools, kgC/m2, 0-15 cm
 area       = data->Area
 dC_single  = data->dC_Single
 dC_multi   = data->dC_Multi

 glob_SOCi  = sum(SGRD_SOC  * area) / 1.e12
 glob_dC_s  = sum(dC_single * area) / 1.e12
 glob_dC_m  = sum(dC_multi  * area) / 1.e12

 print(glob_SOCi)
 print(glob_dC_s)
 print(glob_dC_m)

end

;************************************************
; plot SOC losses
; Fig. 3 in manuscript
;************************************************
 fout = path + "Crowther_dSOC_35y_step_wZERO"
```

```
 wks  = gsn_open_wks("ps"  , fout); open a X11 or ps file

 res                        = True
 res@gsnDraw                = False
 res@gsnFrame               = False
 res@cnSmoothingOn          = False
 res@mpProjection           = "Robinson"
 res@mpOutlineOn            = True
 res@lbOrientation          = "Horizontal"
 res@mpPerimOn              = False
 res@mpGridAndLimbOn        = True
 res@mpGridLatSpacingF      = 180
 res@mpGridLonSpacingF      = 180
 res@mpGridLineThicknessF   = 0.
 res@mpGridLineColor        = "transparent"
 res@mpGridMaskMode         = "MaskLand"

  gsn_define_colormap(wks,"BlWhRe")
  res@gsnSpreadColors     = True                   ; use full colormap
  res@gsnSpreadColorEnd   =  68                 ; start with last color
;  res@gsnSpreadColorStart =  2                 ; start with last color
   gsn_reverse_colormap(wks)                       ; reverse colormap


  res@gsnLeftString        = ""
  res@gsnRightString       = ""
  res@cnFillOn             = True
  res@cnLinesOn            = False         ; Turn lines off
  res@cnLineLabelsOn       = False         ; Turn labels off
  res@cnLevelSelectionMode = "ManualLevels"
  res@cnMinLevelValF       = -17  ;  -3.75*5
  res@cnMaxLevelValF       =  5.  ; 0.50*5
  res@cnLevelSpacingF      =  2.  ; 0.5*5
  res@lbLabelStrings       = (/-17.,-15.,-13.,-11.,-9.,-7,-5.,-3.,-1,1.,3.,5./)
;  res@lbLabelStrings       = (/-17.,-13.,-9.,-5.,-1.,1.,5/)
  res@lbLabelFontHeightF   =  0.025                ; make labels larger
  res@lbTitleOn            = True                  ; turn on title
  res@lbTitlePosition      = "Bottom"
  res@lbTitleString        = "kg C m~S~-2~N "
  res@lbTitleFontHeightF   = .030                  ; make title smaller
  res@pmLabelBarOrthogonalPosF = .05               ; move whole thing down

  res@vpXF            = 0.1                 ; make plot bigger
  res@vpYF            = 0.9
  res@vpWidthF        = 0.8
  res@vpHeightF       = 0.8
  plot                = gsn_csm_contour_map(wks,dC_single,res)
  resP                  = True                   ; modify the panel plot
  resP@gsnFrame         = False                  ; don't advance panel plot
  gsn_panel(wks,plot,(/1,1/),resP)               ; now draw as one plot
  frame(wks)


  print("wrote "+fout+".ps")
```

```
delete([/plot, res, resP, wks,fout/])
```