Carbon cycle feedbacks represent large uncertainties in climate change projections, and the response of soil carbon to climate change contributes the greatest uncertainty to this. Future changes in soil carbon depend on changes in litter and root inputs from plants and especially on reductions in the turnover time of soil carbon ($\tau_s$) with warming. An approximation to the latter term for the top one metre of soil ($\Delta C_{s,\tau}$) can be diagnosed from projections made with the CMIP6 and CMIP5 Earth System Models (ESMs), and is found to span a large range even at 2 °C of global warming ($-196 \pm 117$ PgC). Here, we present a constraint on $\Delta C_{s,\tau}$ which makes use of current heterotrophic respiration and the spatial variability of $\tau_s$ inferred from observations. This spatial emergent constraint allows us to halve the uncertainty in $\Delta C_{s,\tau}$ at 2 °C to $-232 \pm 52$ PgC.
Climate–carbon cycle feedbacks\textsuperscript{1} must be understood and quantified if the Paris Agreement Targets are to be met\textsuperscript{6}. Changes in soil carbon represent a particularly large uncertainty\textsuperscript{3,12}, with the potential to significantly reduce the carbon budget for climate stabilisation at 2 °C global warming.\textsuperscript{8} Previous studies have investigated the response of soil carbon to climate change based on both observational studies\textsuperscript{9} and Earth System Models (ESMs)\textsuperscript{10}. ESMs are coupled models which simulate both climate and carbon cycle processes. Projects such as the Coupled Model Inter-comparison Project (CMIP)\textsuperscript{11,12} have allowed for consistent comparison of the response of soil carbon under climate change from existing state-of-the-art ESMs. However, the uncertainty due to the soil carbon feedback did not reduce significantly between the CMIP3 and CMIP5 model generations\textsuperscript{6}, or with the latest CMIP6 models (see Fig. 1 and Supplementary Fig. 1), such that the projected change in global soil carbon still varies significantly amongst models\textsuperscript{13}.

This study uses an alternative method to obtain a constraint on the ESM projections of soil carbon change. In previous studies, emergent constraints based on temporal trends and variations have been used successfully to reduce uncertainty in climate change projections\textsuperscript{14}. Our approach follows the method used in Chadburn et al.\textsuperscript{15}, where a spatial temperature sensitivity is used to constrain the future response to climate change—which we term as a spatial emergent constraint. Our study combines the Chadburn et al.\textsuperscript{15} method with the soil carbon turnover analysis of Koven et al.\textsuperscript{16} to get a constraint on the sensitivity of soil carbon turnover to global warming.

Soil carbon ($C_s$) is increased by the flux of organic carbon into the soil from plant litter and roots, and decreased by the breakdown of that organic matter by soil microbes which releases CO\textsubscript{2} to the atmosphere as the heterotrophic respiration flux ($R_h$). If the vegetation carbon is at steady-state, litter-fall will equal the Net Primary Production of plants (NPP). If the soil carbon is also at steady-state—and in the absence of significant fire fluxes and other non-respiratory carbon losses—the litter-fall, NPP, and $R_h$ will be approximately equal to one another. Even over the historical period, when atmospheric CO\textsubscript{2} has been increasing and there has been a net land carbon sink, this approximation holds well (see Supplementary Fig. 4).

In order to separate the effects of changes in NPP from the effects of climate change on $R_h$, we define an effective turnover time\textsuperscript{17} for soil carbon as $\tau_s = C_s/R_h$. The turnover time of soil carbon is known to be especially dependent on temperature\textsuperscript{3}. A common assumption is that $\tau_s$ decreases by about 7% per °C of warming (equivalent to assuming that $q_{10} = 2$)\textsuperscript{18}. However, this sensitivity differs between models, and also between models and observations.

We can write a long-term change in soil carbon ($\Delta C_s$) as the sum of a term arising from changes in litter-fall ($\Delta C_{s,l}$), and a term arising from changes in the turnover time of soil carbon ($\Delta C_{s,h}$):

$$\Delta C_s = \Delta C_{s,l}(t) + \Delta C_{s,h}(t) = \tau_{s,0} \Delta R_h(t) + R_h \Delta \tau_s(t)$$

Model projections of the first term ($\Delta C_{s,l}$) differ primarily because of differences in the extent of CO\textsubscript{2}-fertilisation of NPP, and associated nutrient limitations. The second term ($\Delta C_{s,h}$) differs across models because of differences in the predicted future warming, and because of differences in the sensitivity of soil carbon decomposition to temperature (which includes an influence from faster equilibration of fast-turnover compared to slow-turnover carbon pools under changing inputs\textsuperscript{19}). This study provides an observational constraint on the latter uncertainty. As the vast majority of the CMIP6 and CMIP5 models do not yet represent vertically resolved deep soil carbon in permafrost or peatlands, we focus our constraint on carbon change in the top 1 metre of soil. To ensure a fair like-for-like comparison we also exclude the two CMIP6 models that do represent vertically-resolved soil carbon (CESM2 and NorESM2), although this has a negligible effect on our overall result. Our study therefore applies to soil carbon loss in the top 1 metre of soil only. Below we show that it is possible to significantly reduce the uncertainty in this key feedback to climate change using current-day spatial data to constrain the sensitivity to future warming.

**Results and discussion**

**Proof of concept.** For each ESM, we begin by calculating the effective $\tau_s$ using time-averaged (1995–2005) values of $C_s$ and $R_h$ at each grid-point, and applying our definition of $\tau_s = C_s/R_h$. We do likewise for observational datasets of soil carbon in the top 1 metre\textsuperscript{19,20} and time-averaged (2001–2010) heterotrophic respiration\textsuperscript{21}, as shown in Fig. 2. Figure 2c shows the map of inferred values of $\tau_s$, from these observations, with a notable increase from approximately 7 years in the warm tropics to over 100 years in the cooler high northern latitudes.

Similar maps can be diagnosed for each of year of data, for each ESM, and for each future scenario, giving time and space varying values of $\tau_s$ for each model run. This allows us to estimate $\Delta C_{s,h}$ via the last term on the right of Eq. (1). For each ESM, the $R_h$ value is taken as the mean over the decade 1995–2005, to overlap with the time period of the observations and to maintain consistency across CMIP generations. Individual grid-point $\tau_s$ values are calculated for each year before calculating area-weighted global totals of $\Delta C_{s,h}$. The uncertainty of $\Delta C_{s,h}$ stems from the uncertainty in soil carbon turnover ($\tau_s$), and the uncertainty due to differing climate sensitivities of the models. In this study, we aim to quantify and constrain the uncertainty in $\tau_s$. To isolate the latter uncertainty, we consider $\Delta C_{s,c}$ for differing levels of global mean warming in each model. The resulting dependence of global total $\Delta C_{s,c}$ on global warming is shown in Fig. 1a, for each of the ESMs considered in both CMIP6 and CMIP5 (seven CMIP6 ESMs and nine CMIP5 ESMs), and for three Shared Socioeconomic Pathways (SSP): SSP126, SSP245 and SSP585 (CMIP5)\textsuperscript{22}, or the equivalent Representative Concentration Pathways (RCP): RCP2.6, RCP4.5 and RCP8.5 (CMIP5)\textsuperscript{23}. In all cases $\Delta C_{s,c}$ is negative, which is consistent with the soil carbon turnover time decreasing with warming. The more surprising thing to note is the huge range in the projections, with a spread at 2 °C global mean warming of approximately 400 PgC, regardless of future SSP/RCP scenario. Figure 1b plots the fractional change in soil carbon $\Delta C_{s,c}/C_{s,0}$, showing that there is a large range of effective $q_{10}$ sensitivities between the model projections.

Unfortunately, we do not have time-varying observational datasets of $C_s$ and $R_h$ that might allow us to directly constrain this projection uncertainty. Instead we explore whether the observed spatial variability in $\tau_s$ (as shown in Fig. 2c) provides some observational constraint on the sensitivity of $\tau_s$ to temperature. In doing so, we are motivated by Chadburn et al.\textsuperscript{15} who used the correlation between the observed geographical distributions of permafrost and air temperature to constrain projections of future permafrost area under global warming. Similarly, we use ESMs to test whether the spatial variation in $\tau_s$ reveals the sensitivity of soil carbon turnover to temperature. The spatial patterns of $\tau_s$ in CMIP5 simulations and observations were previously shown in Koven et al.\textsuperscript{16}, and here we test whether such relationships can be used to estimate the response of soil carbon to future climate change, using a combination of CMIP6 and CMIP5 models.

Figure 3a is a scatter plot of log $\tau_s$ against temperature, using the $\tau_s$ values shown in Fig. 2c and mean temperatures from the...
Fig. 1 Uncertainty in future changes in soil carbon due to reduction in turnover time. $\Delta C_s$ vs. $\Delta T$ plot diagnosed from sixteen Earth System Models (seven CMIP6 ESMs and nine CMIP5 ESMs), for three different future scenarios: SSP126, SSP245, SSP585, or RCP2.6, RCP4.5, RCP8.5, respectively. a The change in soil carbon due to the change in soil carbon turnover time against change in global mean temperatures; b The fractional change in soil carbon due to the change in soil carbon turnover time against change in global mean temperatures, and compared to different effective $q_{10}$ sensitivities.

Fig. 2 Spatial variability of soil carbon turnover time inferred from observations. Maps of a observed soil carbon ($C_s$) to a depth of 1 m (kg C m$^{-2}$)$^{19,20}$, b observed heterotrophic respiration ($R_h$) (kg C m$^{-2}$ yr$^{-1}$)$^2$; and c inferred soil carbon turnover time ($\log \tau_s$) (yr).
WFDEI dataset over the period 2001–2010. The thick black-dotted line is a quadratic fit through these points. Also shown for comparison are equivalent quadratic fits for each model (coloured lines), using the model log(τ) and mean near-surface air temperature (T) values for each grid-point, over an overlapping period with the observations (1995–2005). There is a spread in the individual data points due to variation in soil moisture, soil type, and other soil parameters. The model specific spread in the data can be seen for the CMIP6 and CMIP5 models in Supplementary Figs. 2 and 3, respectively. Although models do not account for every possible factor contributing to this spread, the spread of points in the models is generally similar to the observations. However, differences between the best-fit functions relating τ to T are evident between the models, and between the models and the observations.

This suggests that we may be able to constrain ΔCₛₜₐₜ using the observed τₛ vs. T fit from the observations, but only if we can show that such functions can be used to predict ΔCₛₜₐₜ under climate change. In order to test that premise, we attempt to reconstruct the time-varying ΔCₛₜₐₜ projection for each model using the time-invariant τₛ vs. T fit across spatial points (Fig. 3a), and the time-invariant R₀,₀ field. The change in soil carbon turnover time (Δτₛ(t)) for a given model run is estimated at each point based-on the τₛ vs. T curve, and the time-varying projection of T at that point. A local estimate of the subsequent change in soil carbon can then be made based-on the farthest right-hand term of Eq. (1) (R₀,₀ Δτₛ), which can be integrated up to provide an estimated change in global soil carbon in the top 1 metre (ΔCₛₜₐₜ).

Figure 3b shows the result of this test for all models and all respective SSP/RCP scenarios. The axes of this plot show equivalent variables which represent the global ΔCₛₜₐₜ between the mean value for 2090–2100 and the mean value for 1995–2005. The y-axis represents the actual values for each model as shown in Fig. 1, and the x-axis represents our estimate derived from spatial variability (as in Fig. 3a). As hoped, actual vs. estimated values cluster tightly around a one-to-one line with an r² correlation coefficient value of 0.90. Although some hot-climate regions will inevitably experience temperatures beyond those covered by current-day spatial variability, these tend to be regions with low soil carbon, so this does not have a major impact on the success of our method.

**Spatial emergent constraint.** This gives us confidence to use the τₛ vs. T fit and R₀,₀ from observations to constrain future projections of ΔCₛₜₐₜ. To remove the uncertainty in future ΔCₛₜₐₜ due to the climate sensitivity of the models, we investigate a common amount of global mean warming in each model. Figure 4a is similar to Fig. 3b but instead for the more policy-relevant case of 2 °C of global warming. As before, the y-axis represents the modelled ΔCₛₜₐₜ, and the x-axis is our estimate derived from spatial variability. Once again, the actual and estimated values of ΔCₛₜₐₜ cluster around the one-to-one line (with r² = 0.87). The model range arises partly from differences in the initial field of heterotrophic respiration (R₀,₀), and partly from differences in Δτₛ (compare first row to penultimate row of Table 1).

The vertical green line in Fig. 4a represents the mean estimate when the τₛ vs. T relationship and the R₀,₀ field from the model are replaced with the equivalents from the observations. The spread shown by the shaded area represents the relatively small impact on ΔCₛₜₐₜ of differences in modelled spatial climate change patterns at 2 °C of global warming. In order to estimate the remaining uncertainty in ΔCₛₜₐₜ, we treat this spread as equivalent to an observational uncertainty in an emergent constraint approach. We apply a standard statistical approach to estimate the probability density function of the y-axis variable (model ΔCₛₜₐₜ),...
accounting for both this observational spread and the quality of the emergent relationship. To test the robustness to the choice of observations we have repeated the analysis with different datasets that represent heterotrophic respiration, which produces strongly-overlapping emergent constraints, and completing the analysis with both CMIP6 and CMIP5 models shows that the result is also robust to the choice of model ensemble (see Table 1).

Figure 4b shows the resulting emergent constraint (blue line), and compares to the unweighted histogram of model values (grey blocks), and a Gaussian fit to that prior distribution (black line). The spatial emergent constraint reduces the uncertainty in ΔC_s at 2 °C of global warming from −196 ± 117 PgC to −232 ± 52 PgC (where these are mean values plus and minus one standard deviation for the top 1 metre). This same method can be applied to (where these are mean values plus and minus one standard deviation). This is similar to the method used in Koven et al.16.

Methods

Obtaining spatial relationships. In this section we explain how the quadratic relationships representing the spatial log t_s-temperature sensitivity shown in Fig. 3a (and Supplementary Figs. 2, 3 and 6) were derived, for both the Earth System Models (ESMs) in CMIP6 and CMIP5, and using the observational data. This is similar to the method used in Koven et al.16.

Table 2 CMIP6 models.

| Model       | Institute                                                                 |
|-------------|---------------------------------------------------------------------------|
| ACCESS-ESM1-5 | Australian Community Climate and Earth Systems Simulator, Australia       |
| BCC-CSM2-MR | The Beijing Climate Center, China                                          |
| CanESM5     | Canadian Centre for Climate Modelling and Analysis, Canada                 |
| CNRM-ESM2-1 | CNRM/CERFACS, French Centre National de la Recherche Scientifique, France |
| IPSL-CM6A-LR| Institut Pierre-Simon Laplace, France                                     |
| MIROC-ES2L  | Atmosphere and Ocean Research Institute and Japan Agency for Marine-Earth Science and Technology, Japan |
| UKESM1-O-LL | NERC and Met Office Hadley Centre, UK                                     |

Table 3 CMIP5 models.

| Model       | Institute                                                                 |
|-------------|---------------------------------------------------------------------------|
| BNU-ESM     | College of Global Change and Earth System Science, China                  |
| CanESM2     | Canadian Centre for Climate Modelling and Analysis, Canada                 |
| CESM1-CAM5  | National Science Foundation, Department of Energy, NCAR, USA              |
| GFDL-ESM2G  | NOAA Geophysical Fluid Dynamics Laboratory, USA                            |
| GISS-ES-R   | NASA Goddard Institute for Space Studies, USA                             |
| HadGEM2-ES  | Met Office Hadley Centre, UK                                              |
| IPSL-CM5A-LR| Institut Pierre-Simon Laplace, France                                     |
| MIROC-ESM   | Atmosphere and Ocean Research Institute and Japan Agency for Marine-Earth Science and Technology, Japan |
| NorESM-M    | Norwegian Climate Centre, Norway                                          |

Obtaining spatial relationships for CMIP6 models. The CMIP6 models used in this study are shown in the Table 2, and the CMIP5 models used in this study are shown in Table 3. To obtain model specific spatial log t_s-temperature relationships, the following method was used. A reference time period was considered (1995–2005), this was taken as the end of the CMIP5 historical simulation to be consistent across CMIP generations and to best match the observational data time frame considered. Then, monthly model output data was time averaged over this period, for the output variables ‘soil carbon content’ C_s in kg m^{-2}, ‘heterotrophic respiration carbon flux’ R_h in kg m^{-2} s^{-1}, and ‘air temperature’ in K. The variables C_s and R_h were used to obtain values for soil carbon turnover time t_s in years, using the equation t_s = C_s/(R_h × 86400 × 365). The model temperature variable units were converted from K to °C.

For each model, values of log t_s were plotted against the corresponding spatial temperature data to obtain the spatial log t_s-temperature plot. Then, quadratic fits (using the python package numpy polyfit) are calculated for each model, which represent the spatial log t_s relationship and sensitivity to temperature. These model specific relationships are shown by the coloured lines in Fig. 3a in the main manuscript, and in Supplementary Fig. 2 for CMIP6 and in Supplementary Fig. 3 for CMIP5.

Obtaining spatial relationships for observations. Following Koven et al.16, we estimated observational soil carbon data (to a depth of 1 m) by combining the Harmonized World Soils Database (HWSD)19 and Northern Circumpolar Soil Carbon Database (NCSCD)20 soil carbon datasets, where NCSCD was used where overlap occurs. To calculate soil carbon turnover time, t_s, using the following equation: t_s = C_s/R_h, we require a global observational dataset for heterotrophic respiration. In the main manuscript, CARDAMOM (2001–2010) heterotrophic respiration (R_h) is used21. We completed a sensitivity study on the choice of observational heterotrophic respiration dataset, see below. The WFDEI dataset is
used for our observational air temperatures (2001–2010)\textsuperscript{24}. Then, these datasets can be used to obtain the observational log $\tau_s$-temperature relationship, using the same quadratic fitting as with the models. This represents the ‘real-world’ spatial temperature sensitivity of log $\tau_s$, and is shown by the thick-dotted-black line in Fig. 3a of the main manuscript. A comparison of the derived observational relationships can be seen in Supplementary Fig. 6.

### Observational sensitivity study

We completed a sensitivity study to investigate our constraint dependence on the choice of observational heterotrophic respiration dataset (CARDAMOM (2001–2010))\textsuperscript{25}. The other observational datasets considered are as follows: NDFP-08 ‘Interannual Variability in Global Soil Respiration on a 0.5 Degree Grid Cell Basis’ dataset (1980–1994)\textsuperscript{26}, Global spatiotemporal distribution of soil respiration modelled using a global database\textsuperscript{30}, and MÖDIS net primary productivity (NPP) (2000–2014)\textsuperscript{31}. Supplementary Fig. 4 shows scatter plots showing one-to-one comparisons of these observational datasets against one another, and Supplementary Fig. 5 shows the corresponding comparisons of the equivalent log $\tau_s$ values calculated from each dataset.

The CARDAMOM $R_0$ dataset is used in the main manuscript for the following two main reasons: firstly, we calculate $\tau_s$ using heterotrophic respiration which allows for consistency between models and observations, and secondly, the dataset does not use a prescribed $q_{0s}$ sensitivity\textsuperscript{21}. Instead, the CARDAMOM $R_0$ dataset was derived by explicitly assimilating observations into a process-based diagnostic land-surface model. To test the robustness of our results, we also repeated our analysis with MÖDIS NPP and Raich 2002, for both CMIP6s and CMIP5 together, and as such comparisons. Supplementary Fig. 6 shows the observational log $\tau_s$-temperature relationships, derived using each of these observational datasets. The results are presented in Table 1 which shows the constrained values of $\Delta C_s$, at 2°C global mean warming.

We decided not to complete the paper analysis using the Hashimoto dataset since not only is it inconsistent with the three other datasets considered, it also shows an arbitrary maximum resolution level (Supplementary Fig. 4), which likely results from the assumed temperature-dependence of soil respiration in this dataset which takes a quadratic form\textsuperscript{32}. The quadratic form is justified based on a site-level study in which it is used to fit temporal dynamics. However, the parameters for the quadratic function that are fitted in the Hashimoto study are very different from those in the site-level study, which therefore suggests that the same relationship does not apply to the global distribution of mean annual soil respiration.

#### Equation for the soil carbon turnover time component of soil carbon change

The equation used in this study for the component of the change in soil carbon ($\Delta C_s$) due to the change in soil carbon turnover time ($\Delta \tau_s$) was derived in the following way. Starting with the equation for soil carbon (based on the definition of $t_\tau$):

$$C_s = R_0 \cdot t_s$$

As discussed in the main manuscript, we can write this change in soil carbon ($\Delta C_s$) as the sum of a term arising from changes in litter-fall ($\Delta C_{s,L}$), and a term arising from changes in the turnover time of soil carbon ($\Delta C_{s,h}$):

$$\Delta C_s = \Delta (R_0 \cdot t_s) \approx \Delta C_{s,L}(t) + \Delta C_{s,h}(t) = t_s \cdot \Delta R_0(t) + R_0 \cdot \Delta t_s(t)$$

Hence, the equation for the component of soil carbon change due to the change in $t_s$ is:

$$\Delta C_{s,t} = R_0 \cdot \Delta t_s$$

In this study we use $R_0$ from the reference period (‘present day’), which we call $R_{0,0}$, to allow us to investigate the response of $\Delta C_{s,t}$ as a result of the response of $t_s$ to climate change.

#### Modeled future temperature

The proof of principle figure (Fig. 3b) considers $\Delta C_{s,t}$ between the end of the 21st century (2090–2100), for each future SSP scenario (SSP126, SSP245, SSP585)\textsuperscript{23} or equivalent future RCP scenario (RCP26, RCP4.5 and RCP8.5)\textsuperscript{23}, and our reference period from the historical simulation (1995–2005), for each CMIP6 DSM and CMIP5 DSM, respectively.

To consider specific $\Delta T$ of global warming (Fig. 4), the future spatial temperature profiles at specific mean warming levels, for example: 1°C, 2°C and 3°C global mean warming, were calculated as follows. The temperature change is calculated from our reference period (1995–2005), and then a 5-year rolling mean of global mean warming is taken to remove some of the interannual variability. Once the year that the given temperature increase has been reached is obtained, a time average including $\pm 5$ years is taken, and the spatial temperature distribution of that model averaged over the deduced time period is used for the calculations of future $\tau_s$.

#### Anomaly correction for future temperature projections

To remove uncertainty due to errors in the models’ historical simulation, a spatial future temperature anomaly was projected using each model and each respective future SSP/RCP scenario separately. To calculate this, the temperature at the reference time frame (1995–2005), which overlaps the WFDIE observational temperature data time frame (2001–2010), is subtracted from the future temperature profile for each model (as calculated above), to calculate the temperature change. Then, this temperature anomaly is added onto the observational temperature dataset to give a model-derived future ‘observational’ temperature for each model.

#### Proof of concept for our method

Our methodology relies on the idea that the spatial temperature sensitivity can be used to project and constrain the temporal sensitivity of $\tau_s$ to temperature, and subsequently global warming. To test the robustness of this method, $\Delta C_{s,h}$ calculated using model $\Delta t_s$ and temperature sensitivity relationships.

The change in soil carbon turnover time ($\Delta \tau_s$) was either calculated using model output data to obtain model-derived $\Delta \tau_s$, as follows:

$$\Delta \tau_s = t_s^i - t_s^0$$

Or calculated using the derived quadratic log $\log \tau_s$-temperature relationships to obtain relationship-derived $\Delta \tau_s$, which is based on the following equation:

$$\Delta \tau_s = \exp(p(T^i)) - \exp(p(T^0))$$

where, $T$ is near surface air temperature, and $T^i$ represents a future temperature, and $T^0$ represents historical (present day) temperature from our reference period (1995–2005). The exponentials (exp) are taken to turn log $\tau_s$ values to $\tau_s$ values. $p(T)$ represents the quadratic log $\tau_s$-temperature relationship as a function of temperature to obtain our estimated $\tau_s$.

These $\Delta \tau_s$ values are then put back into the Eq. (4) (with model-specific $R_{0,0}$ to obtain the corresponding $\Delta C_{s,h}$ values. The proof of principle figure (Fig. 3b) investigates the robustness of our method, where projections of model and relationship-derived values of $\Delta C_{s,h}$ are compared, and an $r^2$ value of 0.90 is obtained. The correlation of the data was also tested when investigating different levels of global mean warming to obtain the constrained values (Fig. 4). The $r^2$ values for were as follows: 1°C is 0.84, 2°C is 0.87 and 3°C is 0.87.

#### Calculating constrained values

To obtain the constrained values of $\Delta C_{s,h}$, the model-derived future ‘observational’ temperature for each model is used together with the observational derived log $\log \tau_s$-temperature relationship, to project values for future $\tau_s$. Then this together with relationship-derived $\tau_s$ deduced using the observational temperature dataset, can be used to calculate $\Delta \tau_s$. Finally global $\Delta C_{s,h}$ can be obtained by multiplying $\Delta \tau_s$ by the observational dataset for $R_{0,0}$ (using Eq. (4)), and then calculating a weighted-global total. As each model-derived future ‘observational’ temperature is considered separately, we obtain a range of projected observational-constrained $\Delta C_{s,h}$ values.

We have now obtained a set of $x$ and $y$ values, corresponding to the relationship-derived and modelled values of $\Delta C_{s,h}$, respectively, for each ESM. Where we have an $x$ and $y$ value for each model, representing the modelled $\Delta C_{s,h}$ (y values), and the model specific relationship-derived $\Delta C_{s,h}$ (x values). We also have an $x_{0s}$ value representing the mean observational-constrained $\Delta C_{s,h}$ value, and a corresponding standard deviation due to the uncertainty in the modelled spatial profiles of future temperatures. We follow the method used in Cox et al. 2018, which can be seen in the ‘Least-squares linear regression’ section and the ‘Calculation of the PDF for ECS’ section of the methods from this study\textsuperscript{32}. Using this method, we obtain an emergent relationship between our $x$ and $y$ data points, which we can use together with our $x_{0s}$ and corresponding standard deviation to produce a constraint on our $y$-axis. This is shown in Fig. 4a. From this we obtain a constrained probability density function on $\Delta C_{s,h}$, with a corresponding uncertainty bounds which we consider at the 68% confidence limits ($\pm 1$ standard deviation). Figure 4b shows the probability density functions representing the distribution of the range of projections, before and after the constraint. This method allows us to calculate a constrained probability density function on $\Delta C_{s,h}$ at each year of global mean warming, using the data seen in Fig. 4a for 2°C warming, and our corresponding constrained values for 1°C and 3°C warming. Figure 4c shows the resultant constrained mean value of $\Delta C_{s,h}$, obtained for each year of global mean warming, and the corresponding uncertainty bounds at the 68% confidence limits ($\pm 1$ standard deviation).

#### Calculating effective $q_{0s}$ for change in soil carbon

Simple models of soil carbon turnover are often based on just a $q_{0s}$ function, which means that $t_s$ depends on temperature as follows:

$$t_s = t_{s,0} \exp \left(-0.1 \log q_{0s}(\Delta T)\right)$$

We compared the results for $\Delta C_{s,h}$ that would be derived from a simple $q_{0s}$ function with our emergent constraint results for $\Delta C_{s,h}$, to estimate an effective $q_{0s}$ sensitivity of heterotrophic respiration.

To do this, we can obtain an equation for $\Delta \tau_s$ derived from Eq. (8). This is done by considering the following, where $t_{s,0}$ is an initial $t_s$, we can substitute in $t_s$ in temperature sensitivity form to obtain an equation for $\Delta \tau_s$ in temperature sensitivity form:

$$\Delta \tau_s = \tau_s^i - \tau_s^0$$


\[ \Delta r_s = r_s \exp ((-0.1 \log q_{10}) \Delta T) - r_s \]

Then, we can substitute this \( \Delta r_s \), into Eq. (4) and simplify to obtain an equation relating \( \Delta C_{st} \) and \( \Delta T \):

\[ \Delta C_{st} = R_{st} r_s \exp ((-0.1 \log q_{10}) \Delta T) - 1 \]

(11)

This equation was used to calculate different \( \Delta C_{st} - \Delta T \) sensitivity curves based on different values on \( q_{10} \), for example \( q_{10} = 2 \), with different amounts of global mean warming to represent \( \Delta T \) and initial observational soil carbon stocks \( C_{so} \). These curves can be seen on Figs. 1b and 4c. Note that there is no direct relationship between the effective \( q_{10} \) for soil carbon change shown in Figs. 1b and 4c, and the spatial \( \tau_s - T \) relationships in Fig. 3a. Our \( q_{10} \) value is an effective \( q_{10} \) value that indicates the sensitivity of global soil carbon (in the top 1 metre) to global mean temperature.

Data availability
The datasets analysed during this study are available online: CMIP5 model output [https://esgf-node.llnl.gov/search/cmip5/], CMIP6 model output [https://esgf-node.llnl.gov/search/cmip6/], The WPDEI Meteorological Forcing Data [https://eda.ucar.edu/ datasets/d3142r2/], CARDAMOM Heterotrophic Respiration [https://dashdata.is.ed.ac.uk/handle/10283/875], MODIS Net Primary Production [https://lpdaac.usgs.gov/available in the following online repository [https://github.com/rebeccamayvarney/soiltau_ec]].

Code availability
The Python code used to complete the analysis and produce the figures in this study is available in the following online repository [https://github.com/rebeccamayvarney/soiltau_ec].

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Author contributions
R.M.V., S.E.C, and P.M.C designed the study and drafted the manuscript, and R.M.V. did the analysis and produced the figures. P.F. provided insightful guidance on the best way to derive and represent soil carbon turnover. C.D.K provided the initial code and gave advice on the differing representation of soil carbon in the CMIP6 model ensemble. E.I.B provided observational datasets for: heterotrophic respiration, soil respiration, net primary production and temperature. G.H. provided observational soil carbon data. All co-authors provided guidance on the study at various times and suggested edits to the draft manuscript.

Competing interests
The authors declare no competing interests.

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Additional information
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Correspondence and requests for materials should be addressed to R.M.V.

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