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RESEARCH ARTICLE

Integrating climate change into projections of soil carbon sequestration from regenerative agriculture

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Abstract

Computational models can project how changes in land use and management will affect soil organic carbon (SOC) stocks over time, but these models usually assume an unchanging climate. We investigate how incorporating climate change projections affects carbon sequestration and SOC stocks. We apply the Rothamsted Carbon model (RothC) to study agricultural land use and management transitions in the U.S. state of Vermont, comparing several regenerative farming strategies, as well as afforestation, against business-as-usual. In 11 relatively-homogeneous Ecoregions within the study area, we run simulations for each land management scenario from 2022–2099, under both projected climate change and the static climate normal from 1991–2021. We use downscaled climate projections from four Global Climate Models, forced by RCP 4.5, that bracket the range of likely climate change. We find that rising temperatures decrease SOC stocks compared to static climate runs by 9.1% to 19.9% across management scenarios, leading to net SOC loss even under many regenerative farming scenarios. Other regenerative practices, notably rotational grazing, could maintain or slightly increase SOC through 2099, and old-growth afforestation could increase statewide stocks by up to 4.5 Mt. Although the potential for farmland management to increase SOC over current levels is diminished when accounting for climate change, it remains important to incentivize regenerative agriculture and afforestation, because this may be the only way to avoid SOC losses by end-of-century.

Introduction

Regenerative agriculture can result in storage, or sequestration, of soil organic carbon (SOC), making it a valuable strategy to mitigate climate change [1]. Computational models can project how agricultural land management is likely to impact SOC stocks, leading to sequestration in some scenarios (e.g. regenerative practices or afforestation) and loss in others (e.g. development or shifts to more tillage-intensive farming practices) [2–4]. However, most SOC models assume a static climate, for example using 30-year historical normals [3–5]. This assumption

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may be reasonable over a short time horizon or for scenario comparison, but is not sufficient for long-term forecasts of SOC stocks. Additionally, climate change and SOC can form a reinforcing feedback loop as increased temperatures drive SOC oxidation, leading to more atmospheric C, and even higher temperatures. Identifying and understanding such feedback loops is critical for establishing effective climate mitigation policy and avoiding tipping points in the climate system [6].

Effect of temperature on SOC

The relationship between climate and SOC is complex, but there is strong evidence that many of the sub-processes underlying decomposition are temperature-dependent, with higher temperatures driving faster decomposition, ultimately leading to SOC loss to the atmosphere [7, 8]. The apparent temperature sensitivity of SOC in a given ecosystem is characterized by multiple context-dependent interactions between soils' chemical and physical properties, water stress, root respiration, aerobic vs. anaerobic decomposition, microbial communities, and other factors [9, 10]. In some cases, a direct correlation between higher temperatures and decreased SOC has not been found in large-scale statistical studies [11]. Overall, while the relationship between temperature and SOC can be obscured due to environmental variability and short timeframes, most scholars agree that temperature-driven SOC oxidation represents a major factor in soil–atmosphere C cycling, and is therefore an important avenue for continued research [9].

SOC modeling

Soil process models are commonly employed to project changes in SOC due to their balance between accuracy and data requirements. These models conceptualize the decomposition process by dividing C-containing materials in the soil with roughly-equal mean residence times into a set of conceptual "pools," and calculating changes in the size of each pool over time [12]. Here we use the Rothamsted Carbon Model (RothC), a widely-used soil process model that has been validated for non-waterlogged soils worldwide [3–5, 12–15].

This paper follows the methodology of previous RothC studies, using primary data to parameterize the model [5], splitting the study area into relatively-homogeneous land units [3], and using an iterative spinup routine to match initial conditions to empirical SOC measurements [16]. We expand on previous studies by using Ecoregions as our units of analysis [4, 17], and incorporating climate projections rather than assuming a continued climate normal in the simulations.

Goals of this study

We previously demonstrated the potential for certain management practices on Vermont farmland to sequester large quantities of SOC, assuming a continuation of recent (1991–2021) climatic conditions [4]. Here we examine the effect of projected climate change on carbon sequestration. We again use the RothC model, but we incorporate a publicly-available dataset of projected climate change [18]. These data were derived from four different Global Climate Models, all forced by RCP 4.5, and downscaled for northern Vermont [18]. We evaluate the same six land management scenarios as [4], which include business-as-usual, several regenerative agriculture scenarios, and two afforestation scenarios. We examine the differences in SOC sequestration resulting from incorporating climate projections compared to historic climate, all else being equal.

Materials and methods

We employ a version of the RothC soil process model [13], ported to the *R* language [19], following the general methodology of our previous study [4]. RothC divides SOC into five pools, which have been shown to mirror empirically-observed SOC fractions [20]. A set of equations define how SOC in each pool decays and stabilizes over time at specific rates, modulated by input paramters including soil properties, precipitation, temperature, whether soil is bare or vegetated, and the timing and quantity of C inputs from manure and plant matter. Relationships between the five SOC pools in RothC, as well as its input parameters, are shown in Fig 1. Full technical details on RothC implementation are available in [13]. The *R* code used in this experiment is in a public Github repository [21].

While RothC is among the best-verified of current SOC models [14], it has several limitations. The model focuses narrowly on soil carbon, whereas there is also C in above-ground plant material. Further, the model assumes water inputs infiltrate rather than running off [22], it does not account for direct effects from tillage or short-term priming effects [23], and its soil properties are based only on clay percent [13]. Additional simplifying assumptions include use of RothC's default pool distributions of 59% DPM, 41% RPM for plants inputs, and 49% DPM, 49% RPM, 2% HUM for manure; and the default topsoil depth of 30cm.

Procedural overview

The majority of the processing and simulation steps are carried over from [4], including all datasets (other than temperature) and land management assumptions used to parameterize the model. Full details of these procedures and can be found in [4].

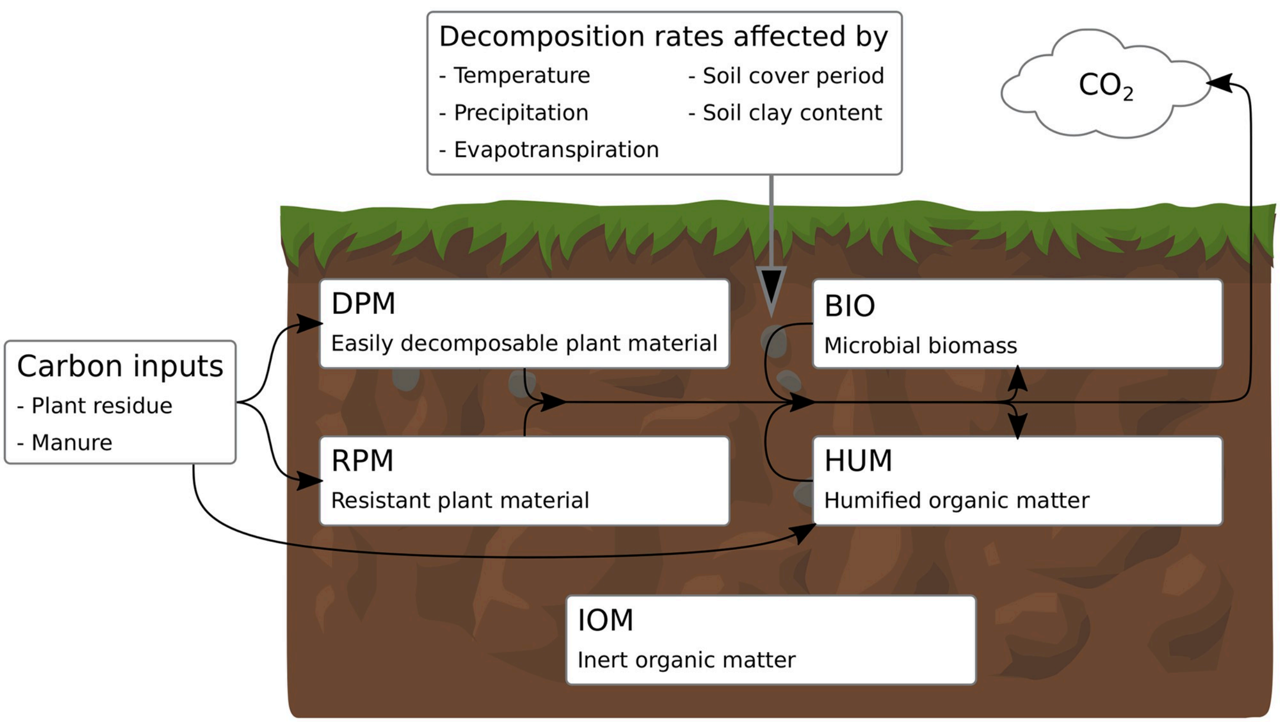

Fig 1. Schematic representation of the RothC model. Depicts the required input data and structure of SOC pools in the model. Adapted from the RothC manual [13]. This figure was previously printed in [4].

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As in [4], we divide the study area into a set of relatively-homogeneous Ecoregions and run the model on each combination of Ecoregion and agricultural use (crops, hay, and pasture) separately, following others [3, 17]. Land use data are derived from the 2016 National Land Cover Database [24] and 2017 USDA Census of Agriculture [25]; soil characteristics from the 2020 gSSURGO database [26]; precipitation from NOAA GHCN-D weather stations [27]; and evapotranspiration from NASA GLDAS remote sensing data [28]. The GIS input data are given in S1 File, and processing details in S1 Text.

Farm management assumptions corresponding to each of the three modeled agricultural uses are generated in consultation with USDA Extension Service experts along with a review of academic literature [25, 29, 30]. Soil cover status and C inputs from plant residue and added manure are set to correspond to the "typical" management practices used by Vermont farmers. For each farmland use, we include both a historical/business-as-usual management scenario and a regenerative farming scenario incorporating practices that build SOC [4]. Land management input data and calculations are given in S2 Text.

Empirical SOM% measurements for each Ecoregion and farmland use are derived from our internal UVM Soil Laboratory dataset, and forest SOM% measurements from the literature [31–33]. These metrics are converted to SOC% using the Van Bemmelen method [34]. Finally, soil bulk density estimates from [26] are used to convert units to t/Ha SOC. These results serve as the targets to spin up the model for each Ecoregion and land use by adjusting the assumed below-ground plant C returned to the soil, following others [14, 35]. The inert organic matter (IOM) fraction is calculated using the Falloon method [36].

The primary difference between [4] and this study is that in the former study temperature normals were derived from NOAA weather station data [27], and monthly values were assumed to be static throughout the simulation. Here we incorporate climate change projections using a dataset with a much finer spatial resolution, and we also calculate 30-year normals from these data [18]. Fig 2 summarizes this study's methodology, highlighting the new procedures that differentiate it from [4].

Climate change data

We utilize temperature projections from a regionally-downscaled climate change dataset [18]. These data are derived using the Climate Multimodal Intercomparison Project's CMIP5 protocol, forced by Representative Concentration Pathway (RCP) 4.5. RCPs codify educated assumptions about how trends in population, energy use, and economics are likely to drive emissions patterns across the globe in the decades to come, with RCP 4.5 being an intermediate scenario. The dataset consists of results from four Global Climate Models (GCMs), which are downscaled using landscape topology, then bias-corrected against historical NOAA observations, resulting in a raster dataset of roughly 0.9km cells across the study area, with daily projections for maximum and minimum temperature in each cell between 1950 and 2099. While all four GCMs project gradually-rising temperatures over time, in general the *ccsm4* GCM yields cooler, drier projections; *miroc-esm* warmer and drier; *noresm1-m* warmer and wetter, and *mri-cgcm3* cooler and wetter. Incorporating multiple alternative GCMs gives a range of scenarios to bound the analysis and account for climate change uncertainty.

Because the RothC model uses a monthly timestep, we first process the temperature data from [18] by computing monthly averages. The data are then converted to geotiff rasters and imported into QGIS software for geoprocessing. The spatial extent of the dataset encompasses much of Vermont, along with parts of New York State, New Hampshire, and Quebec. We calculate averages for the multi-band raster data within the 11 Vermont Ecoregions contained in the data. A limitation of this study, due to the spatial extent of the dataset, is that we do not

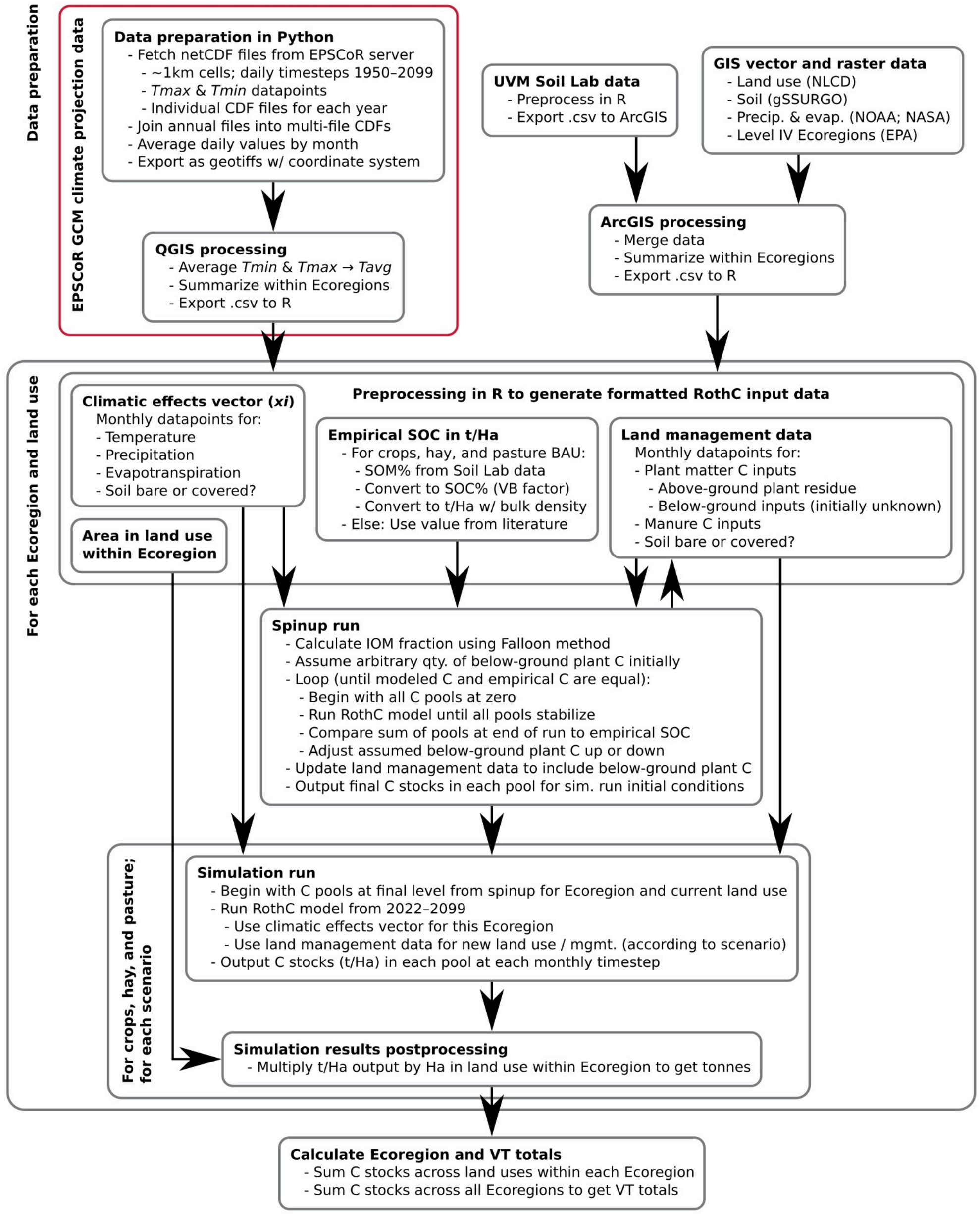

Fig 2. Data processing and model structure flowchart. Red box shows new steps to incorporate climate change projections.

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include two of the 13 Ecoregions within the state. Finally, we calculate mean monthly temperature by averaging minimum and maximum temperatures. These data are exported into *R* where they are integrated into the RothC model [13, 19]. Average temperatures across the study area from the climate dataset appear in Fig 3. The full climate input dataset is given in S2 File.

Spinups and simulation runs

We first initialize (or spin up) the model for each Ecoregion and agricultural use by incrementally adjusting assumed below-ground C inputs such that at the end of the spinup SOC stocks

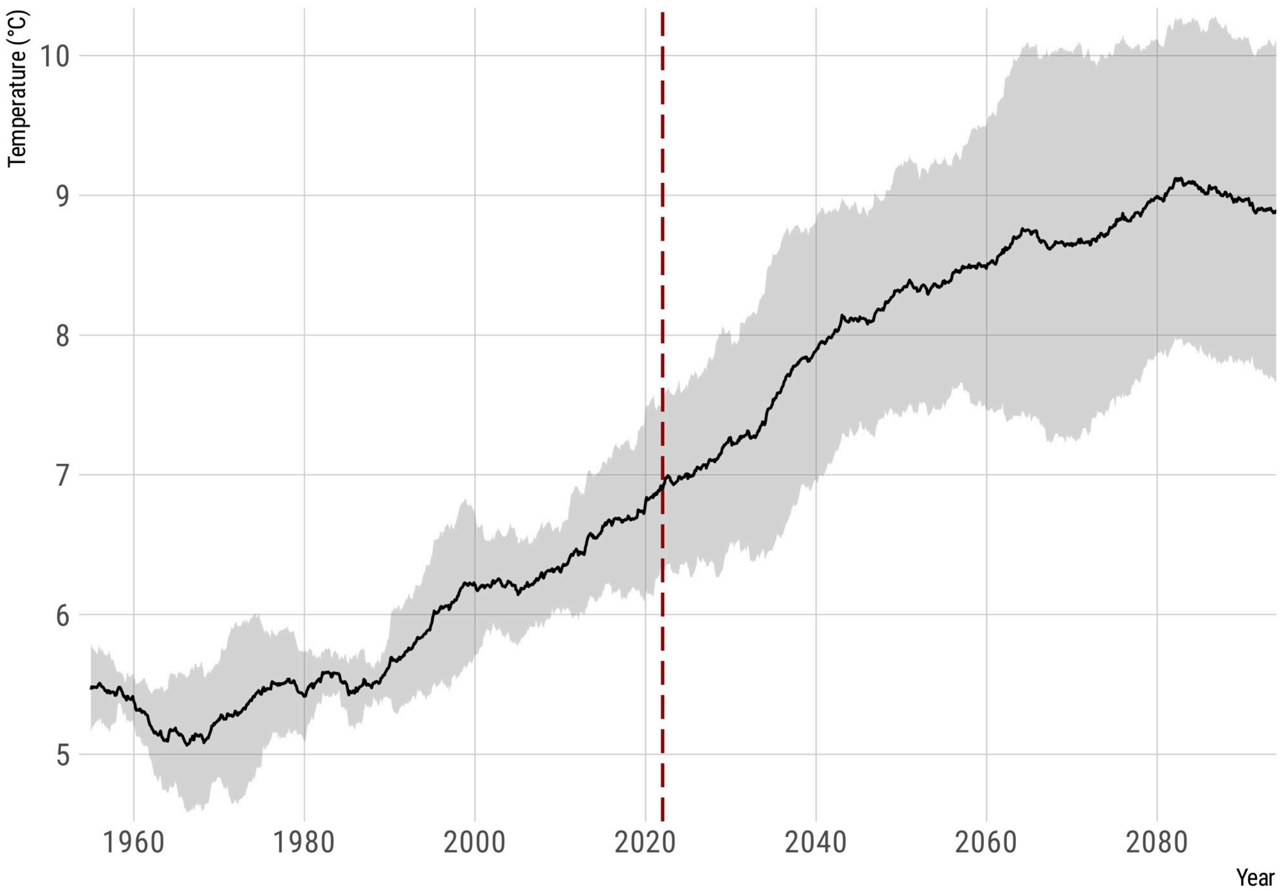

Fig 3. Mean Vermont temperature from GCM projections. Shows average of the four GCMs, using a ten-year rolling mean to better visualize the overall trend. Gray area is the standard deviation between GCMs. Red vertical line indicates the beginning of the simulation (Jan. 2022). After this point, the GCMs' temperature projections show similar trends, but increasingly diverge.

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match empirical observations from the UVM Soil Laboratory, following others [14, 16, 35, 37]. Spinups assume a static climate based on 30-year (1991–2021) monthly temperature normals for each Ecoregion.

We run six scenarios to investigate how land management or land use changes on Vermont farmland will impact SOC stocks over time, following [4]. The scenarios are (a) business-as-usual, (b) best land management practices with current agricultural use, (c) complete shift to pasture-based farming using continuous grazing, (d) complete shift to pasture-based farming using intensive rotational grazing, (e) full afforestation of all agricultural land with timber harvest, and (f) full afforestation of all agricultural land with succession to old-growth forest. For each scenario, we run a climate-change version incorporating temperature projections under RCP 4.5 [18], and a static climate version in which it is assumed that the temperature normal continues throughout the simulation run.

In each scenario, SOC stocks in each pool begin at post-spinup levels corresponding to the historical/business-as-usual version of each agricultural land use within each of the 11 Ecoregions in the study area. Using the land management parameters appropriate for each scenario, the simulation is run forward for 77 years (2022–2099). The model outputs monthly SOC stock projections in t/Ha for each of the five SOC pools over this period.

Simulation output processing

Separate simulation results are obtained for each of the 11 Ecoregions, for each of the three agricultural uses (crops, hay, and pasture), for six scenarios, for each of the four GCMs, and for either a static climate normal or climate change assumption. This yields $11 \times 3 \times 6 \times 4 \times 2 = 1584$ individual simulation runs. From the raw data (in t/Ha per pool per month), we sum across the five SOC pools, and compute total tonnes SOC per Ecoregion by multiplying by the acreage in each agricultural use in that Ecoregion. We then sum these SOC totals for each Ecoregion across the three agricultural uses, and finally sum the results across Ecoregions to arrive at totals for the full study area. This data processing yields SOC measurements (in both t/Ha and total megatonnes [Mt]) for each scenario and GCM, under both the static climate normal and climate change assumptions. Finally, we compute SOC change from the 2022 baseline (around 22.7 Mt total SOC in farmland soils across the study area) to evaluate the extent to which SOC stocks are projected to rise or fall under each scenario.

Results

Incorporation of climate change projections leads to declines of 9.1% to 19.9% in total statewide farmland SOC stocks between 2022 and 2099 across scenarios and GCMs relative to simulation runs utilizing the static climate normal (Fig 4). Under the business-as-usual scenario, climate change causes losses of two to four Mt SOC due to increased soil oxidation, while the static climate runs result in unchanging SOC stocks. With climate change, while regenerative agriculture scenarios retain more SOC than business-as-usual, the downward pressure from increasing temperatures partially or completely offsets the SOC gains found with the same land use scenario under the static climate assumption. Only one management strategy, full afforestation without harvest, results in increased SOC by end-of-century, although gains are substantially reduced from 7.5 Mt with static climate to between two and 4.5 Mt with climate change.

SOC over time

Across scenarios, simulations incorporating the RCP 4.5 climate change projections lead to significant reductions in SOC sequestration as compared to simulations using the 1991–2021 climate normal, but SOC dynamics over time vary by scenario (Fig 5). Under business-as-usual, there is a relatively-constant rate of decline in SOC throughout the simulation, while under other scenarios SOC initially holds steady or increases, and then declines as a result of increased temperatures. Both conversion to conventionally-managed pasture and implementing best management practices within the current agricultural use essentially maintain current SOC stocks for five to ten years, after which they fall precipitously below baseline levels. Transitions to either rotational grazing or harvested forest represent medium-term solutions, building SOC stocks by almost one Mt as of 2040, after which negative pressure from climate change begins to reverse these gains. The only scenario that sequesters SOC over the long term despite climate change pressure is afforestation of farmland with succession to old-growth forest.

SOC by Ecoregion

Both the relative effect of each land management scenario on SOC stocks, as well as the impact of climate change, vary by Ecoregion (Fig 6). We observe greater spatial variability with projected climate change incorporated into the model, resulting from interactions between temperature, soil properties, and the proportion of each agricultural land use associated with each

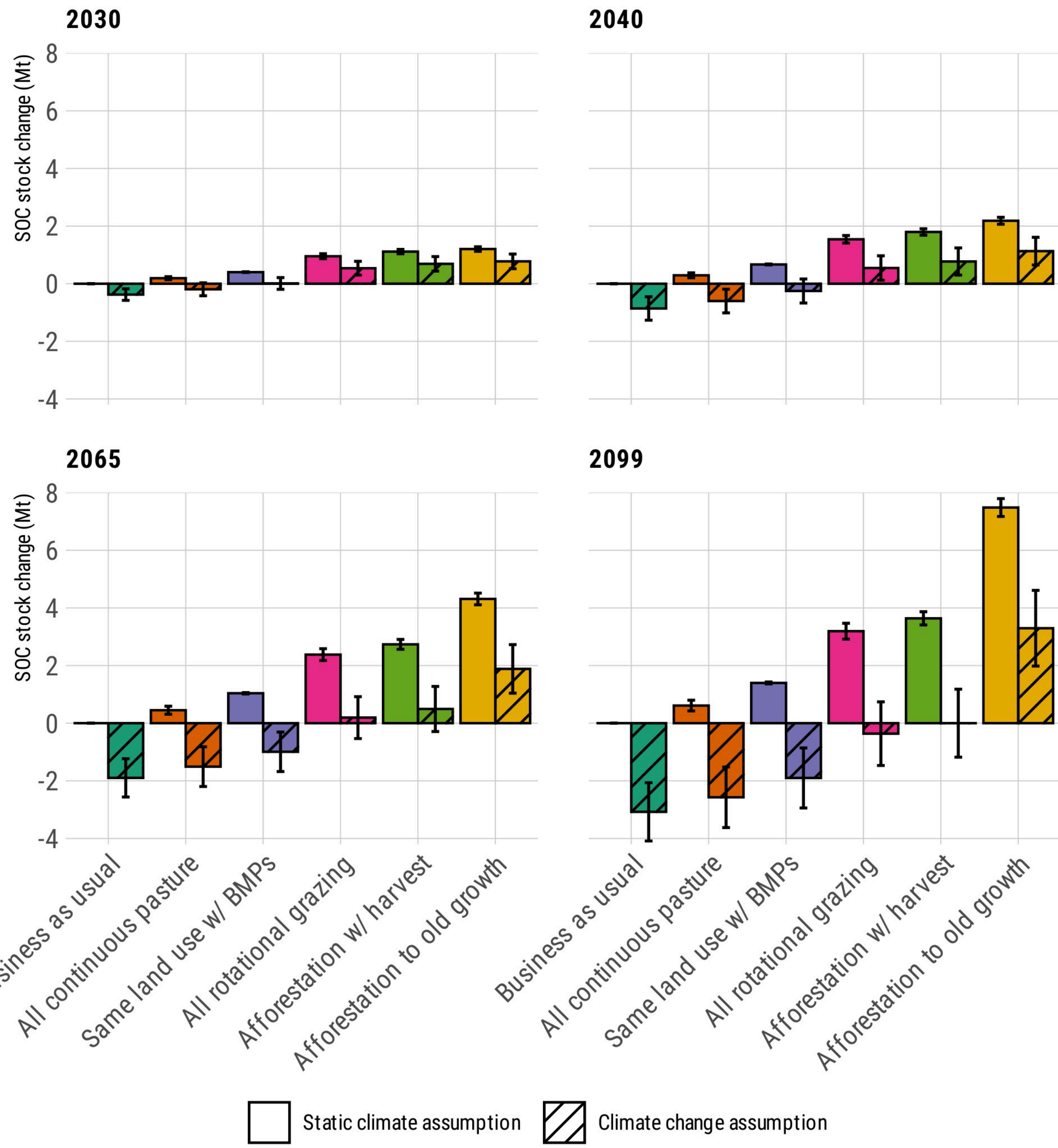

Fig 4. Projected SOC stock change on all Vermont farmland in four future years. Compares a static climate normal assumption against a climate change assumption based on four alternative GCMs. Shows the mean difference in SOC averaged across all four GCMs compared to the 2022 baseline of around 22.7 Mt total SOC in the study area, with standard deviation between GCMs indicated by the error bars.

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Ecoregion. Whereas in the static climate runs business-as-usual results in maintenance of baseline SOC, in the climate change runs most Ecoregions require full conversion of farmland to rotational grazing to maintain current SOC levels after 50 years. With climate change, the afforestation to old growth scenario remains an effective driver of SOC sequestration across all Ecoregions, although there is substantial variation, from 10 t/Ha in the Champlain Lowlands (a prominent agricultural region), to 48 t/Ha in the Vermont Piedmont (near the Connecticut

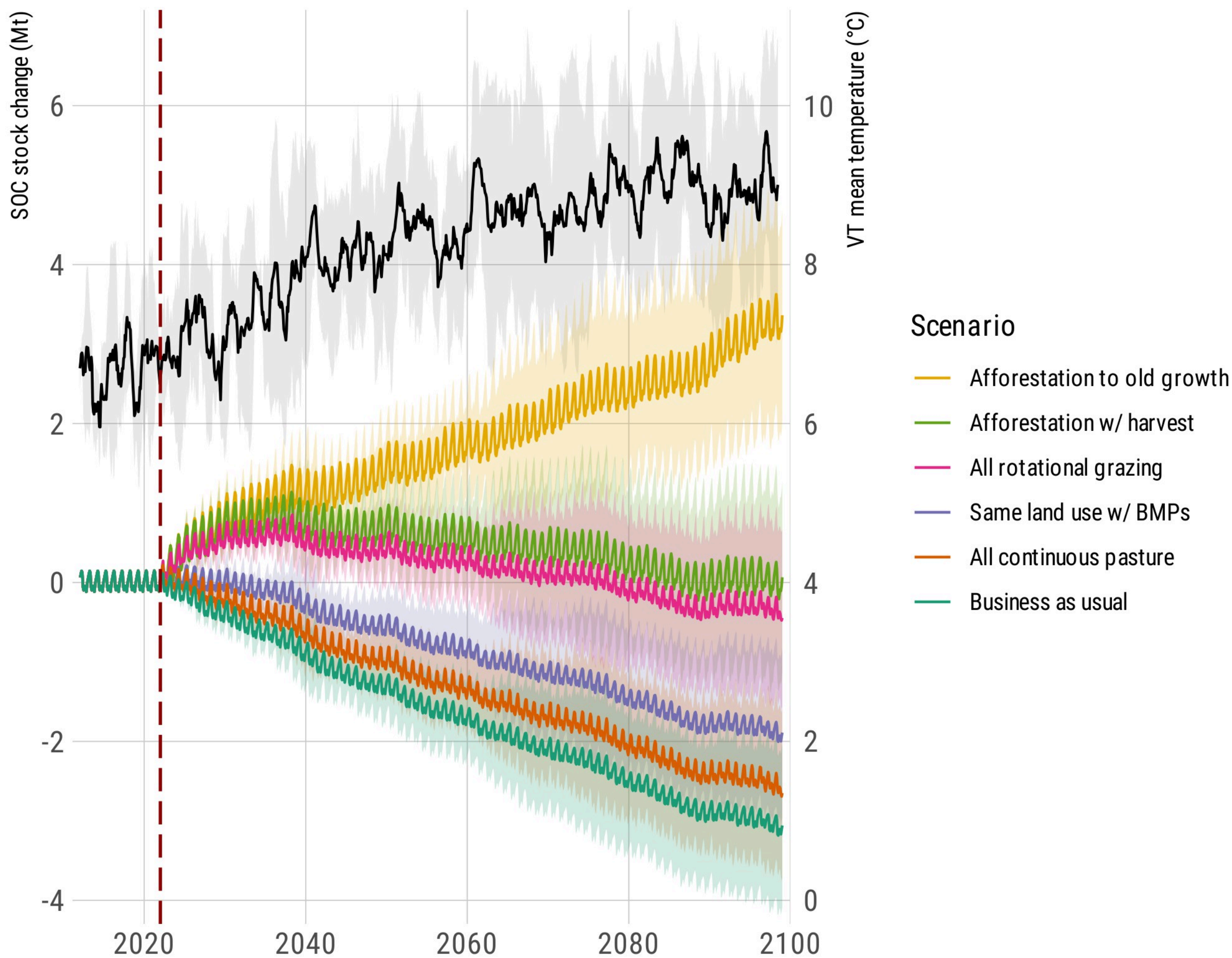

Fig 5. SOC stock change on all Vermont farmland, with projected average temperature. Colored lines show mean SOC stock change from 2022 baseline, and shaded regions indicate standard deviation across the four GCMs. Black line shows projected one-year rolling-mean average temperature for all GCMs (in ˚C, referenced to the right *y* axis), with shaded region indicating standard deviation across GCMs. Dashed red line indicates start of simulation (Jan. 2022).

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River Valley; also heavily agricultural), to 68 t/Ha in the Upper Montane / Alpine Zone. This spatial analysis suggests that an optimal statewide land management strategy should incentivize different types of land use in different Ecoregions.

Discussion

This study shows the importance of climate change when forecasting SOC sequestration in agricultural soils, especially over a timeframe of multiple decades. If we assume a static climate normal in a given simulation run, as has typically been done in other studies [3–5, 12–15], business-as-usual scenarios simply maintain current SOC stocks. In contrast, here we find that accounting for rising temperatures results in a steadily-falling SOC trajectory under identical conditions. SOC is also projected to decline in scenarios which would lead to increased SOC under a static climate assumption: for example, where farmland is converted to continuously-grazed pasture, or where current farmland uses are maintained but best management practices are employed [4]. These regenerative agriculture scenarios increase SOC over business-as-

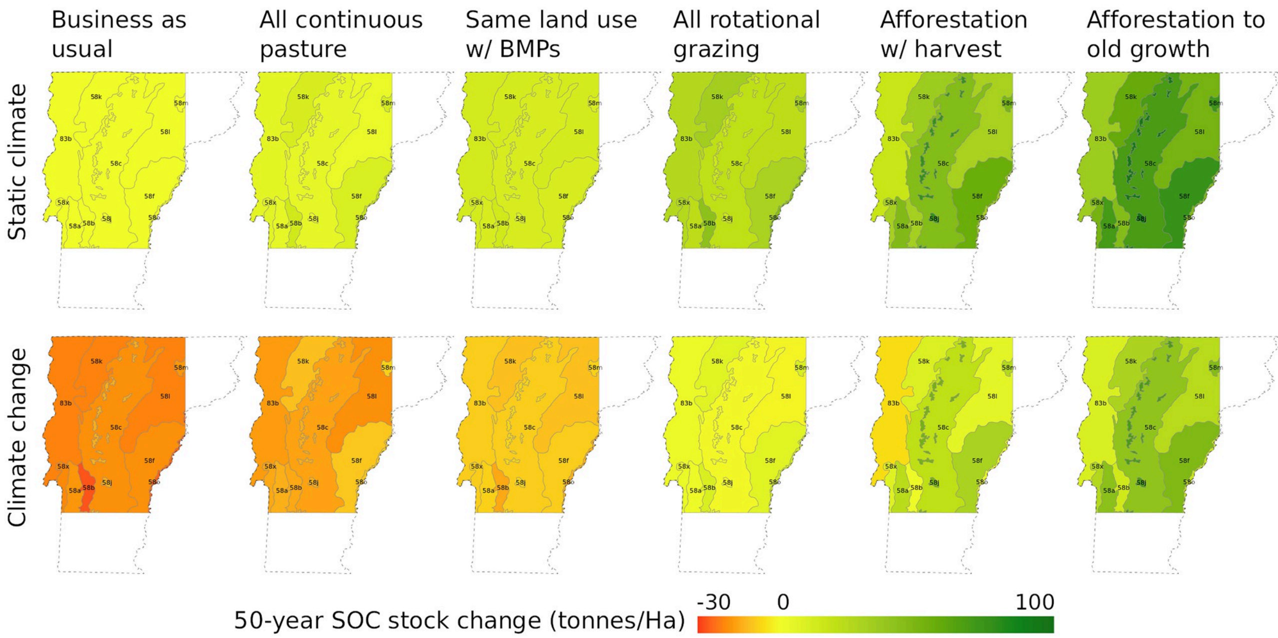

Fig 6. Projected SOC stock change in each Ecoregion, 50 years after land use transition. Color indicates SOC stock change from the 2022 baseline to 2072 (in t/Ha). Top row shows RothC simulation results assuming continued 1991–2021 climate normal, and bottom row shows results with climate change projections under RCP 4.5 averaged across GCMs. Columns correspond to land management scenarios. Shapefile, metadata, and terms of use for Vermont boundaries can be found at [38], and Ecoregions at [39].

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usual under both the static and climate change assumptions, but with climate change accounted for we find that they are not sufficient to offset negative pressure from temperature-driven SOC loss after even a decade.

Our results indicate that both the regenerative agricultural practice of full conversion to rotational grazing as well as afforestation with timber harvest follow relatively-similar SOC stock trajectories. We see a buildup of SOC until around 2040 driven both by increased C returned to the soil and lack of soil disruption by tillage. After 2040, rising temperatures increasingly offset these gains, leading to a slow but steady decrease in SOC in the following decades. This is due to the fact that SOC builds up more quickly at first, after which growth slows as the soil reaches a new equilibrium. Each C pool reaches its asymptotic equilibrium at a different rate, with humified matter taking the longest to stabilize, on the order of several decades [4, 40]. Meanwhile, temperatures are projected to rise gradually, tapering off over tens of decades [18]. In the very long run, we can expect SOC to stabilize at a new equilibrium as temperatures eventually reach an asymptote (likely in the 2100s or beyond), although without significant land use changes this equilibrium SOC level will be far lower than current stocks.

We find that afforestation of farmland with succession to old-growth forest is the only evaluated scenario that provides sufficient C inputs and SOC retention to overcome the downward pressure from rising temperatures over the long term. As forests age, their equilibrium SOC, i.e. the theoretical cap on SOC storage in their soils, tends to increase [31–33]. This dynamic is reflected in our model, with SOC in the simulations gradually ramping up to the levels observed empirically in New England old growth forests. While it is not feasible or even desirable to convert all of Vermont's farmland to forest, our findings strongly suggest that prioritizing old-growth afforestation where possible may be an effective long-term strategy to offset the SOC losses, driven by rising temperatures, on farmland kept in production.

The foregoing results lead to an interesting question: does the fact that climate change will likely decrease SOC stocks across the board mean that encouraging SOC sequestration on Vermont farmlands is simply a losing battle? We contend that this conclusion does not follow from the results obtained. While SOC stocks may fall under some land uses and in some areas as temperatures rise, the relative gain in SOC stocks resulting from regenerative agriculture and afforestation is not significantly altered. In other words, while end-of-century SOC levels may be lower than under a static climate assumption, in the climate change runs the differences between the lowest SOC scenario (business-as-usual) and the regenerative or afforestation scenarios remain similar. In light of this, it could be reasoned that, assuming business-as-usual will result in a downward SOC trajectory, promoting SOC sequestration in whatever ways possible so as not to lose more SOC to the atmosphere than necessary is even more urgent. This is especially relevant when considering the potential reinforcing feedback loop (and associated climate tipping point) driven by rising temperatures, increased SOC oxidation, and even higher temperatures.

Limitations and future research

Two limitations arise from the relationship between temperature and SOC within the RothC model. First, it is assumed that temperature affects decomposition in all pools equally. Future studies could extend the model to simulate the relative effect of temperature differentially for each pool, as suggested by [9].

Second, it has been suggested that increased atmospheric CO_2 concentrations accompanying rising temperatures could, in some cases, increase gross primary productivity of plants, partially-offsetting SOC losses [10]. While predicting these effects remains uncertain, most soil scientists calculate that losses driven by temperature-induced respiration would greatly offset any increase in plant productivity [41]. Nevertheless, a limitation of our study is that RothC does not incorporate climate-driven changes in plant productivity.

A further limitation concerns the spinup procedure we employ. We initialize the model assuming that SOC is in equilibrium at *t*0 (Jan. 2022) in the simulation runs. I.e., we assume that over a time period of at least several decades into the past, land use has not changed and SOC stocks have essentially remained static. However, as a result of climate change that has already occurred, as well as historical land use patterns—for example shifts from forests to pastures to cropland—it is likely that in many locations the year-on-year trajectory of SOC is non-zero at *t*0. This may impact results by putting further downward pressure on SOC stocks under the business-as-usual scenario, since in many locations SOC built up historically by forests may be declining as a result of more-recent agricultural uses, a dynamic we are currently exploring.

Conclusion

Our results indicate that projected climate change will significantly reduce the carbon stored in Vermont's farmland soils without changes in agricultural management. Specifically, transitioning much of Vermont's farmland to either well-managed perennial forage or afforestation will be required to avoid SOC losses by end-of-century. Such changes will likely need to be driven by public policy. Our results emphasize the potential for reinforcing feedbacks between SOC oxidation and the climate system to exacerbate anthropogenic climate change. These findings highlight the importance of incorporating climate change data into SOC models.

Supporting information

S1 File. GIS input dataset.
(CSV)

S2 File. Climate change dataset.
(CSV)

S1 Text. GIS processing details. Table 1. GIS data sources and preprocessing steps.
(PDF)

S2 Text. Plant and manure C input calculations for three agricultural land uses.
(PDF)

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Investigation: Serge Wiltshire.

Methodology: Serge Wiltshire.

Project administration: Serge Wiltshire, Brian Beckage.

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Software: Serge Wiltshire.

Supervision: Brian Beckage.

Validation: Serge Wiltshire.

Visualization: Serge Wiltshire.

Writing – original draft: Serge Wiltshire, Brian Beckage.

Writing – review & editing: Serge Wiltshire.

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