

RESEARCH ARTICLE

Soil carbon sequestration through regenerative agriculture in the U.S. state of Vermont

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Abstract

This study investigates the extent to which land use and management transitions on Vermont's farmland could sequester atmospheric carbon in the soil. We weigh the sequestration potential of several types of regenerative agricultural practices against both business as usual and afforestation scenarios using the Rothamsted Carbon Model. We split the study area into 13 Ecoregions for a finer spatial scale of analysis, with key climate, soil, and land use data specified for each. Empirical soil laboratory data are used to initialize the model to mirror current conditions under each of three agricultural land uses (crops, hay, and pasture) in each Ecoregion. We consult experts as well as the literature to parameterize the anticipated effects of alternative agricultural management practices on soil carbon inputs. In the simulation runs, we find that all non-business-as-usual scenarios sequester carbon over time, with a higher rate of sequestration in the decades immediately after a land use or management change. Among the regenerative agriculture scenarios, conversion to rotational grazing offers the highest soil carbon sequestration potential, at 1,269 kt, or 5.3% above current stocks after ten years. Of all scenarios, afforestation of farmland to non-harvested forest stores the most soil carbon, increasing stocks by 6.5% after ten years, and continuing to sequester at a high rate many decades into the future. We discuss tradeoffs and policy implications, especially in the context of the 2020 Vermont Global Warming Solutions Act, and suggest that payments for ecosystem services for farmers sequestering carbon may have strategic value.

Introduction

As society has increasingly been forced to address anthropogenic climate change, understanding carbon (C) cycles within the terrestrial ecosystem has become critical. The current excess of atmospheric C has resulted from human activities including burning fossil fuels and disruption of soil through land development and tillage [1]. Topsoil globally holds a vast amount of C, at roughly 2.5 trillion metric tonnes, or 3.1 times the quantity of atmospheric C [2]. Soil C

stocks can either increase or decrease depending on land use and management [3]. Globally, about a third of the CO₂ released to the atmosphere results from clearing land for cultivation [4]. Managing land to avoid soil C loss and promote sequestration represents a critical strategy to re-normalize the global C balance [5].

Our study area is the U.S. state of Vermont, and we focus specifically on the 12% of the state's landbase currently in farms [6]. We use a version of the Rothamsted Carbon Model (RothC) [7] to assess the potential for Vermont's farmland soils to sequester C through regenerative agriculture. This scale of analysis lends itself to effective data curation, facilitating both transparency of assumptions and sufficiently-detailed projections. Also, key policy decisions are often implemented at the state level, as in the case of the 2020 Vermont Global Warming Solutions Act [8]. Further, we suggest that the methodology presented is generalizable and can be extended to study soil C sequestration elsewhere.

Soil C and climate change

Most proposed solutions to the climate problem—for example renewable energy—aim to slow or stop greenhouse gas (GhG) emissions, but it is also possible to mitigate GhGs by removing excess C already in the atmosphere. There are two primary sinks for atmospheric C: oceans and land (either through geological or soil sequestration) [1, 3]. For oceanic and geological sequestration, current technologies are uncertain, expensive, and ecologically-risky [9, 10]. In contrast, over the past several decades the potential to sequester large quantities of C into the soil by altering land use and management has been demonstrated conclusively [11, 12].

As a plant grows, it pulls CO₂ out of the atmosphere through photosynthesis. C is returned to the soil as organic matter (SOM) in the form of fungal and bacterial microbes, decaying plant and animal tissue, and chemical products formed through decomposition. These pools of C-rich materials collectively make up the soil's organic C (SOC) stock. Some SOC oxidizes through respiration and is released back to the atmosphere, especially when topsoil is disturbed. In general, the further along its state of decomposition, the more recalcitrant, or resistant to oxidation, a pool of C becomes [1, 3].

The soil's SOC holding capacity is dictated by local environmental and climatological conditions, land use, and physical soil properties [13, 14]. Given consistent land management, SOC will build up in the various pools until it reaches an equilibrium. In general, any change that either limits soil disturbance, adds organic matter, or alters environmental conditions to inhibit oxidation, will result in SOC sequestration over time [1].

Estimates of SOC sequestration potential

Despite growing interest in SOC sequestration as a GhG mitigation strategy, quantifying its potential has become somewhat contentious. For example, the “four per mille” initiative contends that a global SOC increase of 0.4% per year could offset 20–35% of anthropogenic GhG emissions over a 10–20 year timeframe, buying time to build renewable energy capacity [15]. However, projections of total potential SOC sequestration vary widely between 0.41 and 2.45 billion tonnes C/yr, or 4.6% to 27.2% of the current nine billion tonnes of annual global emissions [16].

Reasons for deviations in estimates largely stem from the implicit assumptions necessary to project SOC sequestration at a global scale, across vastly-differing climates, land uses, and societies. For example, some authors are pessimistic about the difficulty and expense of global coordination and monitoring [17], while others are optimistic about the multiple co-benefits associated with SOC sequestration [18]. Enhancing our understanding of the potential for soil to sequester C is of critical importance, both for its near-term potential to offset GhG

emissions, and for its long-term strategic position as a mechanism to reverse atmospheric C buildup.

Regenerative agriculture and carbon

In recent decades, scholars have increasingly recognized the potential for alternative agricultural practices to positively impact the environment, for example through the frameworks of ecosystem services, regenerative agriculture, agroecology, and sustainability theory [19]. Here we focus on regenerative agriculture, which encompasses a suite of goals and corresponding agricultural practices aimed at improving soil health, optimizing resource management, alleviating climate change, and improving water quality and availability [12, 20].

We are specifically interested in the regenerative practices aimed at increasing SOC, although these typically have co-benefits, including water retention, biodiversity, and plant nutrient availability [18]. For cropping systems, such strategies include limited/conservation tillage, cover cropping, crop rotation, and application of manure and compost [5, 11, 14]. For perennial forage systems, scholars focus on the C-building properties of regenerative practices like intensive rotational grazing [21–23].

There is debate in the literature as to the level of carbon sequestration offered by regenerative agriculture, and how it stacks up against other strategies to mitigate GhGs. Some argue that certain practices, notably no-till farming, have been oversold, and that alternative means of curbing emissions are preferential [16, 24]. However, others maintain that regenerative agriculture could offset up to 10% of annual emissions, and therefore advocate for incentives like payments for ecosystem services to encourage farmers to adopt regenerative practices [12, 14].

For this study, we divide regenerative agriculture into two basic categories: (a) adoption of management practices that promote C sequestration while maintaining current agricultural uses, and (b) land use transitions from one form of agriculture to a more regenerative one. Under category (a), for example, a rowcrop farmer may implement cover cropping, manure and compost addition, and/or conservation tillage; while a pasture-based farmer may switch from continuous grazing to intensive rotational grazing. Alternatively, under category (b), a dairy farmer may opt to transition completely away from rowcrops as a livestock feed source and convert their acreage to perennial forage, which offers environmental benefits over cropping systems [22, 23].

Building on these definitions, we formulate three simple regenerative agriculture scenarios. In the first, current agricultural land uses are maintained, but regenerative practices are employed. In the second, all farmland becomes conventionally-managed pasture. In the third, all farmland is converted to intensive rotational grazing. We also include three scenarios to weigh the sequestration associated with the regenerative agriculture scenarios: a business-as-usual scenario and two afforestation scenarios.

Modeling SOC sequestration

A variety of computational models have been developed to project the effects of land use and management change on soil C cycling. The United Nations Food and Agriculture Organization classifies these models according to three levels of complexity [25].

Empirical models and C balance equations (level one) simply extrapolate from observed relationships between changes in a specific environmental or land management variable and resultant changes in SOC stocks. This approach is simplistic, inflexible, and non-complex (i.e. linear), but can provide a first indication of the expected direction and magnitude of SOC change.

Soil process models (level two) simulate SOC dynamics temporally by breaking SOC into a number of conceptual pools or stocks. A set of equations defines how these pools vary in size over time based on C inputs, decomposition rates, and stabilization mechanisms. Examples include YASSO [26], ICBM [27], and RothC [7].

Finally, ecosystem models (level three) incorporate a soil process model with other layers, for example water, nutrient, and/or plant growth submodels, rather than relying on exogenous estimates of C inputs. Examples include EPIC [28] and CENTURY/DayCENT [29]. While these can work well given sufficient calibration, they have extensive, site-specific data requirements, typically rendering them more suitable for studies at the farm or field level.

Since we are interested in evaluating SOC change over time at a regional level, a level-two model offers the best compromise between capturing complex physical processes versus data availability and curation overhead. We elected to use RothC, as it is one of the more widely used of the existing level-two models, both officially by a number of national governments [25], as well as in the academic literature [30–32]. While no model is perfect, RothC has been shown to be among the most predictively-accurate of the existing SOC models: in a comparison between RothC and CENTURY, RothC (using a similar iterative spinup procedure as used here) had the best fit to timeseries SOC data from field experiments [33]. Further, the five C pools modeled in RothC statistically correlate with measured C fractions in topsoil samples [34].

This study builds on and expands the methods used in previous RothC studies in several ways. To parameterize the model, we follow [30] and others, integrating GIS data on land use, climate, and soil with laboratory C measurements. Some RothC studies extrapolate results from a set of example sites to model the full study area (e.g. [31]), but this method relies on somewhat-subjective site selection and can present challenges in extrapolation. Instead, we split the study area into relatively-homogeneous land units using a data-driven approach, somewhat similar to the “UHTU” method of [32]. However, rather than defining custom land units for an individual study, we use the set of Ecoregions already defined by the U.S. EPA [35], facilitating wider applicability of our approach in other contexts and regions.

Goals of this study

This study aims to estimate the comparative magnitude and timeframe of C sequestration stemming from land use and management changes on Vermont farmland. Using RothC, a widely-verified process model of soil C dynamics [7], we evaluate scenarios in which: (a) business-as-usual is continued; (b) current agricultural uses are maintained, but best management practices are employed; (c) all farmland is converted to conventionally-managed pasture; (d) all farmland is converted to intensive rotational grazing; (e) all farmland is afforested with timber harvest; and (f) all farmland is afforested and allowed to mature to old-growth forest. While conversion of all farmland to forest is not realistic, the afforestation scenarios (e & f) serve as boundary objects to compare against the regenerative agriculture scenarios (b, c, & d).

Our aim is to model SOC dynamics in a precise and spatially-explicit way, while maintaining a relatively minimal set of inputs, making RothC a good fit. We combine and expand upon best practices established in previous studies, incorporating several GIS datasets together with expert consultations, and using an iterative spinup procedure based on empirical SOC measurements [30–33]. Our approach is intended to be readily emulated by other researchers using mostly publicly-available data, facilitating accurate comparisons both between different study areas and over time. Our estimates of sequestration potential and the temporal dynamics of SOC buildup are intended to further understanding of SOC sequestration within

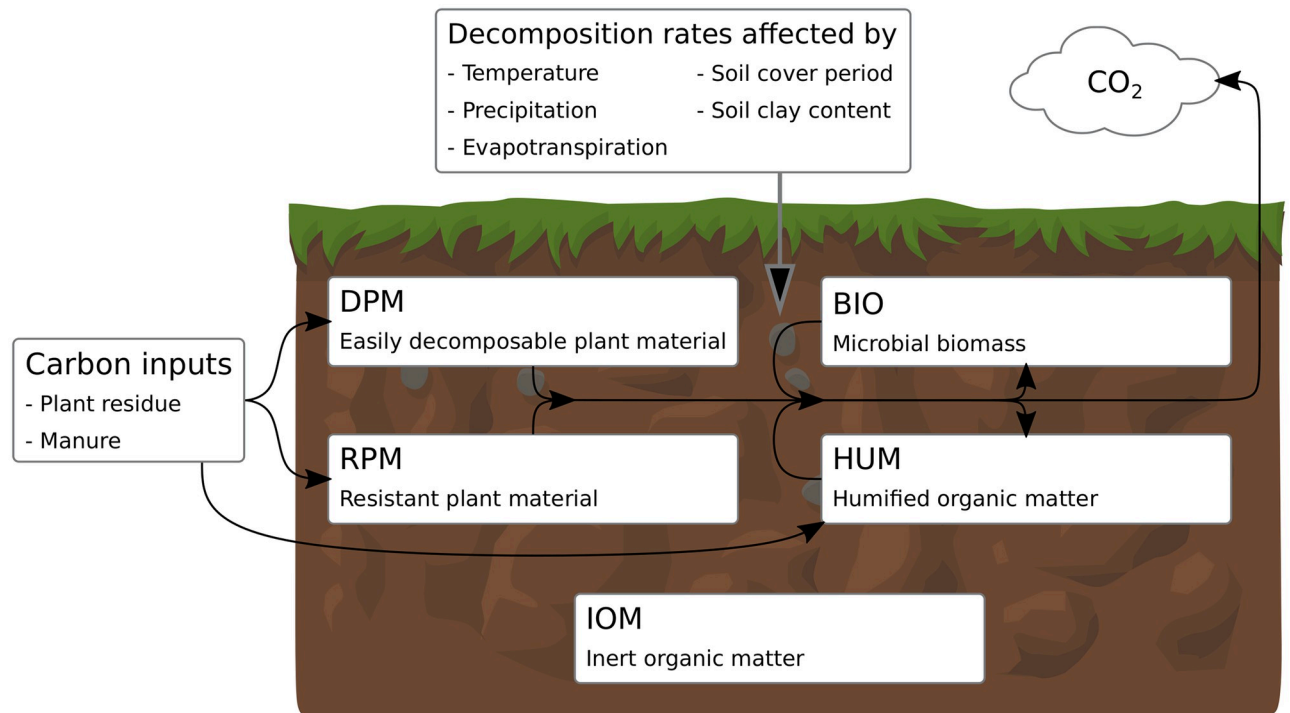


Fig 1. Schematic representation of the RothC model. Depicts the required input data and structure of C pools in the model. Adapted from the RothC manual [7].

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the study area, and to provide guidance on public policy at the regional scale where it is often implemented.

Materials and methods

RothC model

We use a version of RothC [7], ported to the *R* language [36], to model SOC dynamics over time. RothC divides SOC into five pools, analogous to C fractions measured experimentally [34], which decay to specific products at varying rates modulated by input parameters (Fig 1). When properly parameterized, the projections of RothC have been empirically validated for many types of cropland, grassland, and forest ecosystems in non-waterlogged soils across the world [32, 33].

A limitation of RothC is that it only models C in five soil pools, and does not account for non-soil factors affecting C balances, such as C stored in living plant material. Other limitations include an assumption that water inputs infiltrate rather than running off [37], no modeling of direct effects from tillage or short-term priming effects [38], and a relatively simple representation of soil properties based only on clay percent [7]. Additional simplifying assumptions in this study 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; as well as the default topsoil depth of 30cm.

Procedural overview

Fig 2 summarizes the methodology used in this study. Each step is discussed in more detail below. First we unite the raw input datasets using ESRI ArcGIS and import the data into *R*.

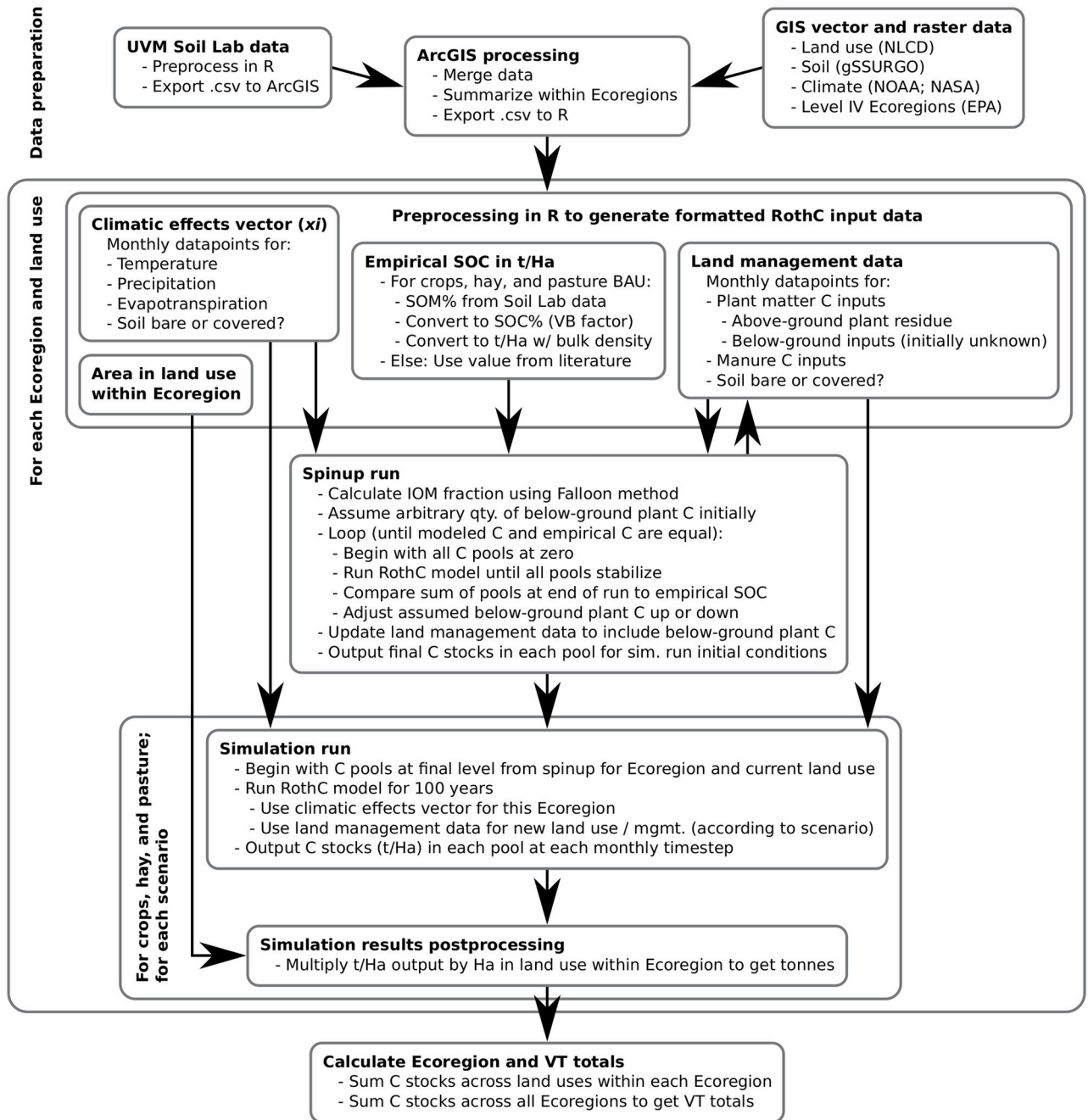


Fig 2. Data processing and model structure flowchart.

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Then we preprocess the input data required to run RothC. For each land use and sub-region, we spin the model up by adjusting assumed below-ground plant C inputs until modeled C stocks match empirical SOC measurements. Using spinup results as initial conditions, we then run simulations for each scenario in each sub-region. Finally, we postprocess the RothC output data for further analysis and interpretation.

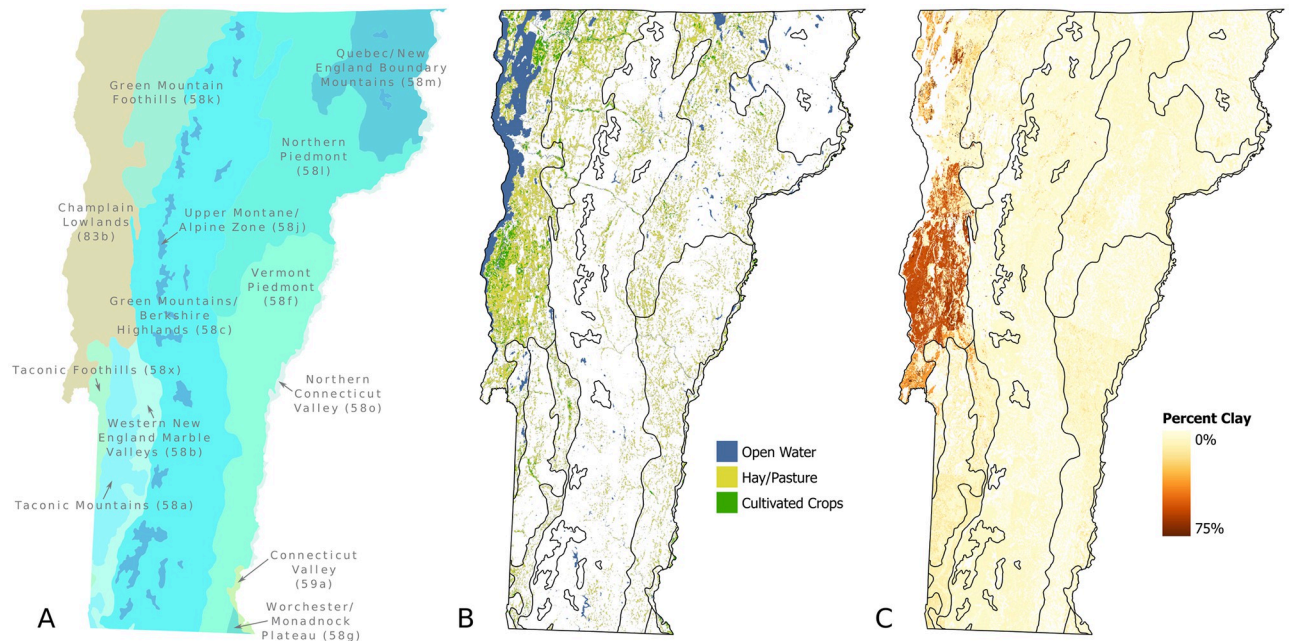


Fig 3. GIS data showing Ecoregions, agricultural land use, and soil clay. (A) Name and code of the 13 EPA Level IV Ecoregions used in the analysis. (B) Location of agricultural parcels (crops and hay/pasture) from the 2016 NLCD, with Ecoregion boundaries. (C) Soil percent clay, from the gSSURGO database, with Ecoregion boundaries.

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Data curation

GIS data. We subdivide our study area (the state of Vermont) into 13 finer units of analysis using a U.S. EPA GIS data product called Level IV Ecoregions (Fig 3, panel A). Ecoregions are defined as being relatively consistent in geology, landforms, soils, vegetation, climate, land use, wildlife, and hydrology [35], making them a good fit for this type of agroecological study. Because they are defined for the entire U.S., using Ecoregions to split the study area makes our methodology more easily extensible to other regions.

For our purposes, an advantage of RothC over other soil C models (e.g. DayCENT, CQUESTR) is that it requires a relatively-minimal set of inputs (see Fig 1). Land uses (crops, hay, and pasture) were drawn from the 2016 National Land Cover Database [39], and soil characteristics (specifically percent clay and bulk density) from the 2020 gSSURGO database [40]. Example data from these sources appear in Fig 3, panels B & C. Precipitation and temperature data were extracted from NOAA GHCN-D weather station reports. We computed monthly averages at each station over the period 1981–2019 [41]. Evapotranspiration for each Ecoregion was calculated from NASA GLDAS remote sensing data [42]. Average monthly climate data points for the entire Vermont study region are shown in Table 1.

For each GIS input dataset, the shapefile or raster was first clipped to the study area, then the required RothC input datapoints were calculated for each of the 13 Ecoregions. The

Table 1. Vermont state average monthly climate data extracted from NOAA GHCN-D and NASA GLDAS.

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Temperature (°C)	-7.7	-5.0	-0.1	6.9	13.0	18.2	20.3	19.9	15.8	8.4	3.8	-3.1
Precipitation (mm)	58.7	52.5	66.9	65.9	87.6	103.0	111.8	96.4	89.9	102.8	78.6	70.3
Evapotranspiration (mm)	16.6	19.5	32.5	56.4	99.8	128.7	143.0	120.3	77.8	39.1	22.1	16.6

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Table 2. Total area and percent in each agricultural land use, per Ecoregion and statewide.

ER code	Ecoregion name	Area (Ha)	Pasture %	Hay %	Crops %	All Ag. %
58a	Taconic Mountains	105,252	3.2	3.4	0.83	7.4
58b	Western New England Marble Valleys	74,834	7.3	7.7	1.7	17
58c	Green Mountains/Berkshire Highlands	758,567	1.7	1.8	0.16	3.7
58f	Vermont Piedmont	316,199	4.2	4.5	0.16	8.9
58g	Worcester/Monadnock Plateau	3,993	1.8	1.9	0.0	3.7
58j	Upper Montane/Alpine Zone	65,685	0.072	0.075	0.0	0.15
58k	Green Mountain Foothills	165,195	8.3	8.7	2.8	20
58l	Northern Piedmont	404,665	6.7	7.1	1.1	15
58m	Quebec/New England Boundary Mountains	178,984	0.64	0.67	0.049	1.4
58o	Northern Connecticut Valley	34,961	6.9	7.2	7.1	21
58x	Taconic Foothills	31,661	6.0	6.3	2.4	15
59a	Connecticut Valley	7,297	5.7	6.0	5.8	18
83b	Champlain Lowlands	342,783	14	14	7.3	35
	All Vermont	2,490,076	5.2	5.4	1.7	12

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gSSURGO database was built by linking relevant sheets on the appropriate keys, then average clay content and bulk density were computed for each Ecoregion. Area sums within each Ecoregion for cropland and hay/pasture were computed from NLCD data (Table 2). Because the NLCD does not differentiate between hay and pasture, we estimate the acreage in each use by splitting the total hay/pasture area using the 2017 USDA Census of Agriculture, which reports 51.3% of forage land in the state being in hay, and the remainder in pasture [6]. Monthly temperature and precipitation values were assigned from the NOAA weather station closest to the centroid of each Ecoregion. Evapotranspiration was averaged from the GLDAS raster values contained within each Ecoregion. Full geoprocessing details appear in [S1 Text](#) and the GIS input dataset in [S1 File](#).

Land management data. RothC also needs data on how farmland is managed under each agricultural use. Specifically, we must codify monthly C inputs from plant residue and added manure, as well as whether the soil is bare or covered with plants each month. We collaborated with USDA Extension Service experts to arrive at estimates for these parameters for the three agricultural land uses in the study.

A simplifying assumption is that the land in each use is managed using one of two styles: historical/business-as-usual (the typical system used by most farmers), or best management (adoption of regenerative practices that build SOC). We consulted our partners and the academic literature to estimate how a typical Vermont farmer under each of these styles manages their land, and how these management practices impact the C returned to the soil from plant residue and manure, as well as whether the soil is typically left bare each month. Land management parameter values used in the model are given in [Table 3](#), and supporting calculations can be found in [S2 Text](#).

For crops, we focus on corn silage, since this is by far the dominant cropping system in the state, representing 84% of all Vermont harvested acreage [6]. For both business-as-usual and best management, we include the stover (plant material left in the field after harvest) as a plant C input, as well as an application of manure in the fall. We make a simplifying assumption that animals are fed exclusively from biomass grown on-farm, meaning that manure additions can appropriately be considered a sequestration measure [43]. In the best management scenario, a cover crop of winter wheat adds additional C from incorporated plant residue each spring, as

Table 3. Monthly RothC land management input values used in the study for each land use and management style.

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Crops												
<i>Historical/business-as-usual (Corn silage; manure in fall; no cover crops)</i>												
Aboveground plant residue C	0	0	0	0	0	0	0	0	0.19	0.19	0	0
Manure C	0	0	0	0	0	0	0	0	0	0	2.6	0
Soil bare or covered? [0, 1]	0	0	0	0	1	1	1	1	1	1	0	0
<i>Best management (Corn silage; manure in fall; winter rye cover crop)</i>												
Aboveground plant residue C	0	0	0	0.35	0.35	0	0	0	0.19	0.19	0	0
Manure C	0	0	0	0	0	0	0	0	0	0	2.6	0
Soil bare or covered? [0, 1]	1	1	1	1	1	1	1	1	1	1	0	1
Hay												
<i>Both management styles same (Three cuts; manure after each cut)</i>												
Aboveground plant residue C	0	0	0	0	0	0	0	0	0	0	0	0
Manure C	0	0	0	0	0	0.87	0	0.87	0	0.87	0	0
Soil bare or covered? [0, 1]	1	1	1	1	1	1	1	1	1	1	1	1
Pasture												
<i>Historical/business-as-usual (Continuous grazing May-Sep; stocking rate = 1.25)</i>												
Aboveground plant residue C	0	0	0	0	0	0	0	0	0	0	0	0
Manure C	0	0	0	0	0.14	0.14	0.14	0.14	0.14	0	0	0
Soil bare or covered? [0, 1]	1	1	1	1	1	1	1	1	1	1	1	1
<i>Best management (Intensive rotational grazing Apr-Oct; stocking rate = 1.5)</i>												
Aboveground plant residue C	0	0	0	0	0	0	0	0	0	0	0	0
Manure C	0	0	0	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0	0
Soil bare or covered? [0, 1]	1	1	1	1	1	1	1	1	1	1	1	1
Forest												
<i>Both management styles same (Mixed New England forest; autumn leaf litter)</i>												
Aboveground plant residue C	0	0	0	0	0	0	0	0.5	0.5	0.5	0.5	0
Manure C	0	0	0	0	0	0	0	0	0	0	0	0
Soil bare or covered? [0, 1]	1	1	1	1	1	1	1	1	1	1	1	1

C inputs are in t/Ha.

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well as extending the period in which the soil is covered. We do not consider no-till farming in this study, as it has been found to primarily change the distribution of SOC between soil strata, rather than increasing SOC stocks [44].

For hay, we assume three cuttings annually, with a manure application after each. On the advice of USDA extension experts, the business-as-usual and best management scenarios are held identical for hay, as there is no widely-used practice that promotes additional sequestration.

For pasture, we take the business-as-usual scenario to be continuous grazing from May to September, and the best-management scenario to be intensive rotational grazing from April to October. Because the stocking rate is typically higher with intensive rotational grazing, and the season longer, somewhat more manure C is returned to the soil. More below-ground plant C is also incorporated due to more vigorous plant growth, with average SOC stocks in U.S. east coast rotationally-grazed pastures being 22% greater than under continuous grazing [22, 23]. The presumed quantity of additional below-ground plant C per month is calculated in the spinup runs, described below.

UVM Soil Lab data. The best method of initializing the model to match real-world conditions requires empirical measurements of SOC with varying land uses and locations [33]. We obtained data from the University of Vermont Soil Lab containing about 20,000 samples collected between 2014 and 2021 at a depth of 15–25 cm. The dataset includes percent SOM, metadata on agricultural land use (crops, hay, or pasture), and location by county. Using these data, we calculate SOC in t/Ha for each land use within each Ecoregion.

Some preprocessing of the Soil Lab data is required. On the advice of the database managers, outliers with SOM values above 3 SDs from the median are excluded. Next we convert percent SOM into percent SOC using a factor of 0.50, a currently-accepted revision of the Van Bemmelen factor, originally estimated at 0.58 [45]. We then multiply percent SOC by bulk density (from the gSSURGO dataset) and convert units to t/Ha. The resultant values, used to spin up the model for each Ecoregion for the three historical/business-as-usual agricultural land uses, are given in Fig 4.

Because the UVM Soil Lab dataset does not include forested land, we instead use SOC estimates from the literature to spin up the model, together with Soil Lab data on SOM content in conservation plantings, which we use as an analogue of forested land where necessary. Based on extensive sampling of New England forests, below-ground C stocks average around 96 t/Ha [46]. This number is used as the default forest C value in all Ecoregions unless the value associated with conservation planting for that region from the UVM Soil Lab data is higher, in which case the conservation planting number is used. Based on measurements from the literature, we approximate the plant-derived C returned to the surface of the soil for forests as 2 t/

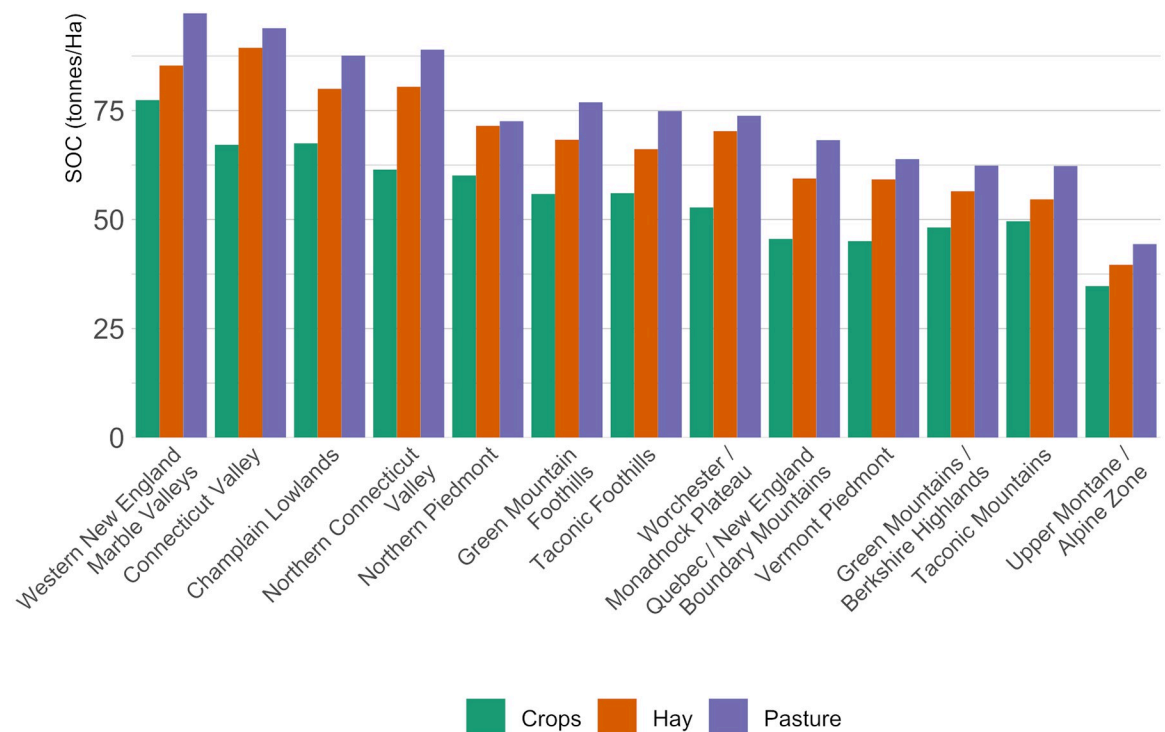


Fig 4. SOC by agricultural land use for each Ecoregion, from the UVM Soil Lab dataset. There is a consistent trend showing cropland having the lowest SOC, hay in the middle, and pasture the most SOC. Weighted averages across the whole state are 63.9 t/Ha C for crops, 71.6 for hay, and 77.6 for pasture. However, these levels vary considerably between Ecoregions, with fertile lowlands typically containing more C, and rocky, mountainous zones less.

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Ha/yr, divided evenly over the months of August to November, when most leaf litter falls [47]. We encode the soil as being covered year-round in forests.

The soil of young New England forests has been shown to hold significantly less C than old-growth forests (averaging 96 vs. 137 t/Ha) [48]. With old-growth forests defined as over 100 years old, in the afforestation to old-growth scenario, we generate a vector to represent the soil's C-holding capacity over time, assuming it increases linearly between the “young” and “old-growth” values over a 100-year timespan.

Spinup runs

Before running scenarios to project potential C sequestration, we must first initialize, or “spin up” the model such that C stocks at t_0 correspond to current empirical conditions. In RothC, given steady land management and climate, C stocks in each pool will asymptotically converge, with the slowest-reacting pool, humus, building over a timeframe of several hundred years. The goal of the spinup procedure is to adjust the assumed below-ground plant C inputs until the total modeled SOC post-spinup matches the empirically-measured SOC for each Ecoregion and land use. The iterative initialization method we employ has been shown to produce the most accurate projections compared to other spinup methods [33, 49, 50].

For agricultural land uses under historical/business-as-usual management, the target SOC values are calculated from the UVM Soil Lab dataset for each Ecoregion. SOC stock targets for forests are based on average values from the literature [46], and for regenerative agricultural practices they are based on the average percent increase in SOC over conventional management observed empirically [22, 23]. While the historical/business-as-usual spinups define the initial conditions for all simulation runs, we still need to execute the spinup procedure for the regenerative agriculture and afforestation scenarios in order to update the land management data with the appropriate quantity of monthly below-ground plant C inputs for these alternative land uses.

The spinup procedure is accomplished by executing repeated runs and adjusting the below-ground plant C inputs, which are difficult or impossible to measure directly [51], until the modeled and empirical values converge. An R optimization process is employed for this purpose, using a fitness function to minimize the difference between empirically-measured C and modeled total C (the sum of all pools). It is assumed that the additional below-ground plant C inputs are split evenly between all months in which the soil is coded “covered”.

While the C target, and therefore the specific spinup result, is unique for each Ecoregion and land use, the characteristic timeframe in which the various C pools reach equilibrium remains similar. To visualize this, Fig 5 plots the C in each pool throughout the spinups, summed across the whole state and including all three agricultural uses. This shows how the decomposable plant material pool quickly reaches equilibrium, biomass and resistant plant material take a decade or two to stabilize, and humified organic matter can take hundreds of years to build. Inert organic matter is static in RothC and is computed as a fraction of total SOC using the Falloon IOM equation (Eq 1) [52].

$$\text{IOM} = 0.049 \cdot \text{SOC}^{1.139} \quad (1)$$

Simulation runs

For the simulations, we run six scenarios, stated in the “Goals of This Study” section, to investigate how land management or land use changes on Vermont farmland could impact SOC stocks over time. In each scenario, C stocks in each pool begin at post-spinup levels corresponding to the historical/business-as-usual version of each agricultural land use within each

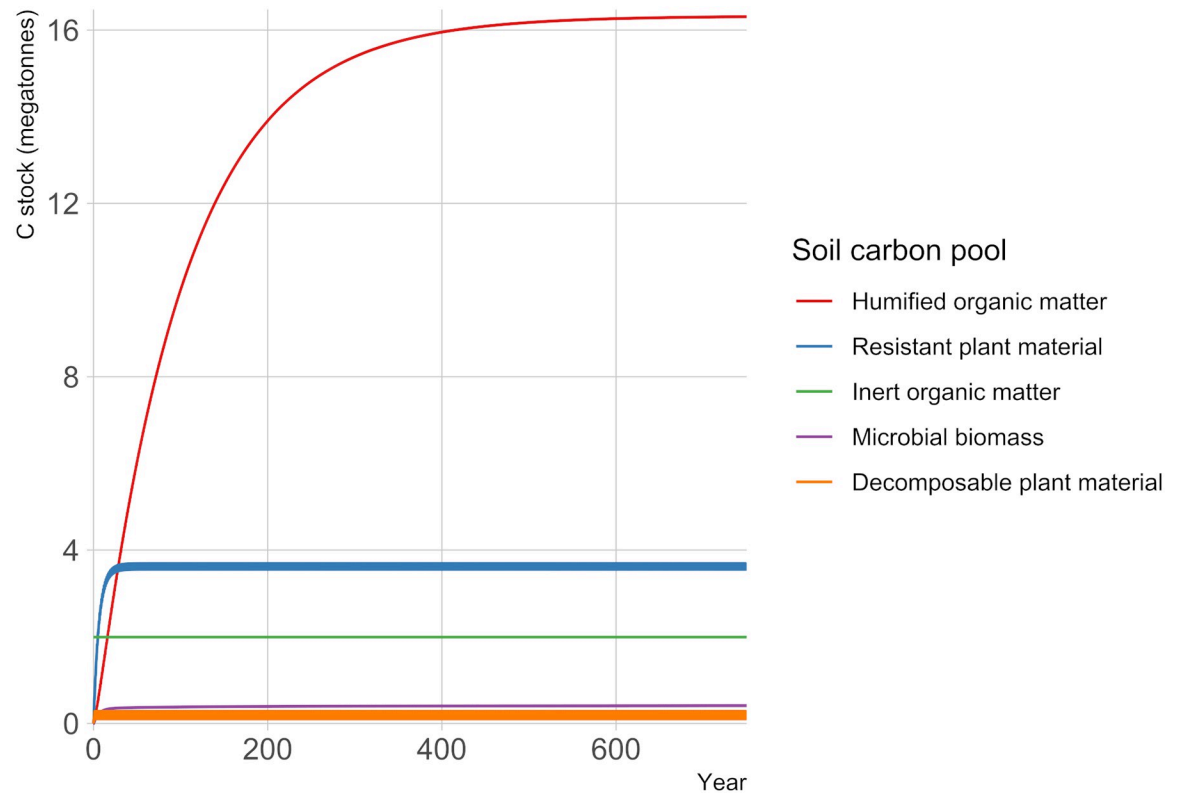


Fig 5. C stocks in each pool summed over all VT farmland during spinup runs. Shows the difference in timeframe required for each pool to stabilize given consistent land use and management. Notably, humified matter takes on the order of several hundred years to build in the soil.

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Ecoregion. Based on the land management data appropriate for the land use or management change associated with each scenario (Table 3, with the addition of below-ground plant-derived C calculated through spinups for each Ecoregion), and assuming static climatic conditions, the simulation is run forward for 100 years. With 13 Ecoregions, three agricultural land uses, and six scenarios, 234 total simulation runs are executed.

Postprocessing simulation data

RothC outputs a monthly timeseries of C stocks in units of t/Ha in each of five C pools. We compute tonnes of C in each pool in each Ecoregion by multiplying the t/Ha values by the total area in each land use in the Ecoregion in Ha. We also sum the C contained in all pools for each land use in each Ecoregion to analyze total sequestration potential. We further extrapolate to the entire study area by summing C stocks across all 13 Ecoregions.

Since the model was spun up to a steady state, in the business-as-usual scenario no sequestration occurs, although annual fluctuations are observed. For the other scenarios, we report total C sequestration (defined as the difference from business-as-usual) over time. We also calculate the annual percent change in C stocks per year, as well as the extent to which sequestration under each scenario would offset Vermont's C emissions, based on two different assumptions of future emission rates.

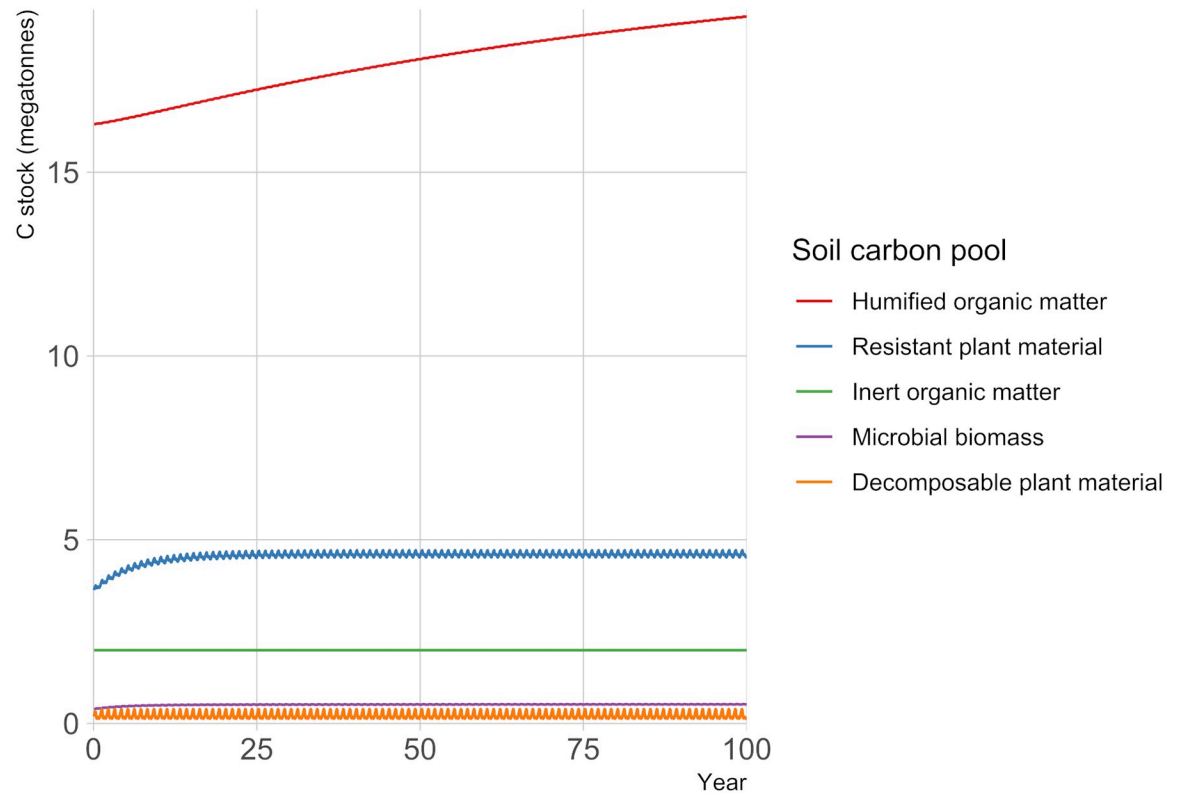


Fig 6. C stocks in each pool summed over all VT farmland under the rotational grazing scenario. Shows the difference in timeframe required for C to be sequestered in each pool. Humified matter is still increasing after 100 years.

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Results

C stock changes by pool

In each scenario (aside from business-as-usual), C in the various pools builds over time as a result of land use and management changes that either increase the quantity of C returned to the soil in the form of plant material and/or manure, or result in the soil being covered throughout more months of the year. For example, Fig 6 shows how C in each pool builds over time for the rotational grazing scenario. For each pool, initially the rate of C sequestration is more rapid, but the ability to sequester additional C reduces as more C is added to the soil, resulting in an asymptotic limit on each pool. The more reactive pools—decomposable plant matter and microbial biomass—build up and reach equilibrium within a few years, whereas the more recalcitrant pools—resistant plant matter and especially humified matter—take decades to build. In fact, humus is still increasing at the end of the 100-year model run, mirroring the timeframe for buildup of humus observed empirically [13]. While within-year fluctuation occurs in all pools, decomposable plant matter is especially sensitive to the seasonality of added plant residue and manure, as well as varying decomposition rates resulting from seasonal temperature and precipitation changes.

Total SOC stock by scenario

Summing all five pools, we plot the C buildup associated with each scenario over time in terms of total SOC at the statewide level (Fig 7). This gives a clear indication of the differences

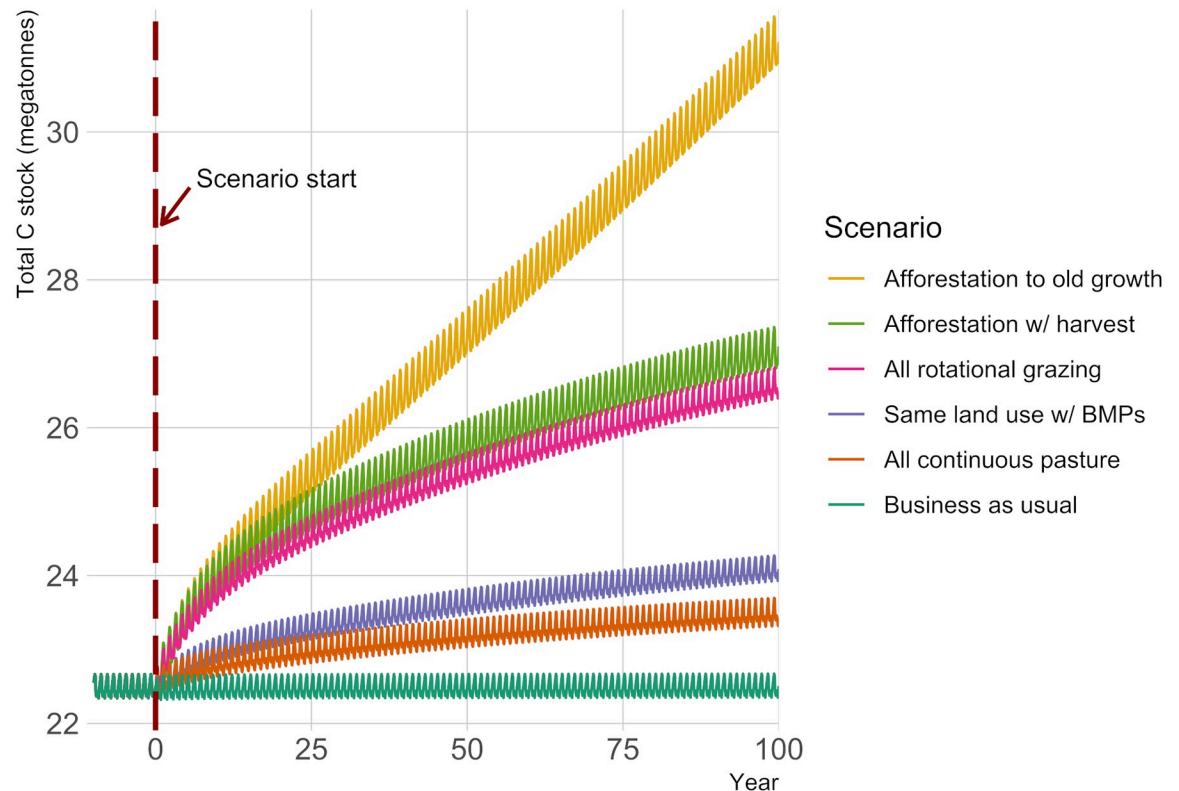


Fig 7. Total SOC stock over time for each scenario summed across all VT farmland. With land use and management changes to Vermont's farmland, SOC stocks increase over baseline. Old-growth afforestation yields the maximum gain in SOC, whereas total conversion to rotational grazing offers the highest sequestration among the regenerative agriculture scenarios.

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between scenarios, as well as the timeframe in which total SOC accrues. We see that, under the business-as-usual scenario, SOC levels fluctuate on an annual basis, but do not change year-on-year. This results from the model being spun up to a steady state using historical climatic conditions and land management practices.

In each of the other scenarios, C accrues in each pool over time, albeit with different rates, annual fluctuations, and maximum potentials. While all three regenerative agriculture scenarios build SOC, model results suggest that maintaining current agricultural land uses (specifically tilled cropland), even with adoption of practices like cover cropping, has a limited sequestration potential when compared with conversion of cropland to well-managed perennial forages. However, the key appears to be a focus on pasture management, specifically intensive rotational grazing, as simply converting cropland to conventionally-managed continuous pasture sequesters less C than if regenerative cropping practices were universally adopted.

An important temporal factor emerging from the simulations relates to the buildup of C associated with old-growth forests. The soils of New England's generally-young forests have been shown to hold around 96 t/Ha C, whereas the soils of the region's few remaining old-growth forests, defined as over 100 years old, can contain 137 t/Ha [46]. Forests managed for timber production, while still having the potential to store a large quantity of C (similar to the rotational grazing scenario), have a lower cap on sequestration than if forests were allowed to grow to maturity. Further, we do not see the same sequestration trajectory, characterized by diminishing returns over time, in the old growth forest scenario as we do in the other

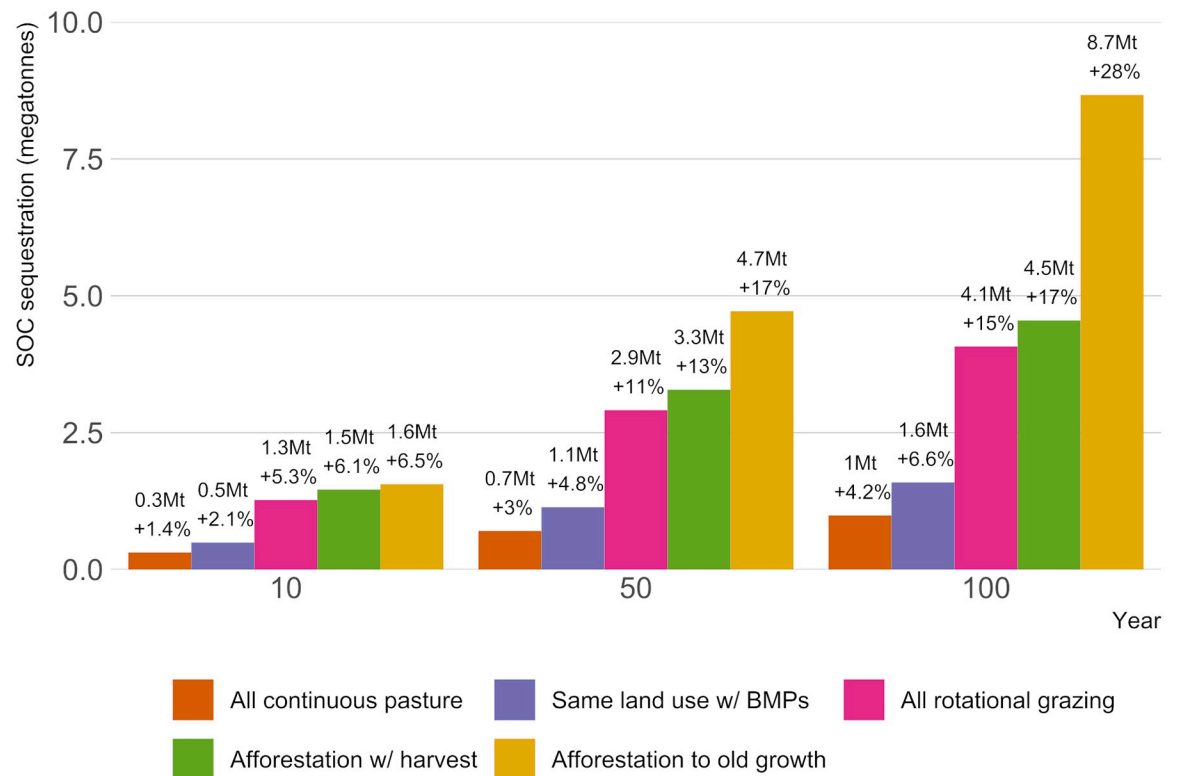


Fig 8. Total SOC sequestration over three time periods for each scenario. Text above each bar shows overall quantity of C sequestered, in megatonnes, and percent increase over baseline.

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scenarios, since, unlike the other scenarios, the C storage capacity of soils in old forests continues to increase throughout the duration of our simulations.

C sequestration by scenario

To further explore the temporal dynamics of C buildup, we plot C sequestration, or the difference in total C stocks between business-as-usual and each alternative scenario, at intervals of 10, 50, and 100 years after the start of the land use or land management transition (Fig 8). While all five non-business-as-usual scenarios sequester C over time, the higher sequestration potential associated with certain types of land use change is especially apparent here. For example, at the 50-year mark, keeping agricultural land in its current use with full adoption of regenerative best management practices would increase the state's total SOC stocks by about 5% over current levels, and a full transition to intensive rotational grazing could increase SOC by 11%. For comparison, transitioning all agricultural land to old-growth forest could increase the state's SOC stocks by 17% over this period. Understanding these dynamics is critical when considering how to weigh tradeoffs between food production, land use, and GhG mitigation.

Potential GhG emissions offset

Currently, the state of Vermont emits about 5.9 megatonnes of CO₂ annually [53]. In 2020, the Vermont Legislature passed the Global Warming Solutions Act (GWSA), which created legally-binding emission reduction targets for the state for the first time [8]. The bill requires the state to reduce emissions to 26% below 2005 levels by 2025, 40% below 1990 levels by 2030,

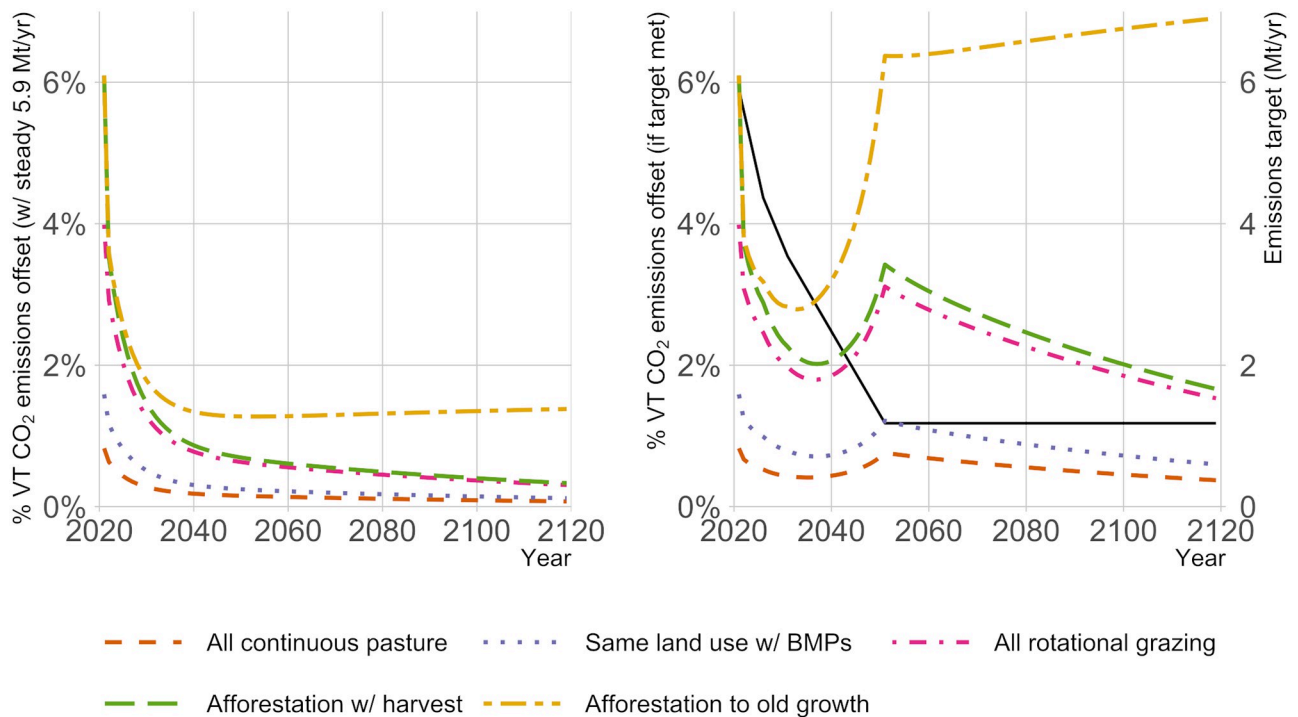


Fig 9. Potential for SOC sequestration in VT farmland soils to offset annual statewide emissions. Left panel shows the percentage of emissions offset under each scenario assuming steady-state emissions of 5.9 Mt CO₂ annually. Right panel shows potential emissions offset assuming Vermont meets the emissions targets of the 2020 GWSA [8] (solid black line).

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and 80% below 1990 levels by 2050. In the legislation, SOC sequestration is one of a suite of emissions-mitigation strategies under consideration.

Using our projections, we can calculate the extent to which each scenario offsets the total GhG emissions of the study area. The left panel of Fig 9 shows the C offset of each scenario assuming ongoing emissions of 5.9 megatonnes annually. We find that the rotational grazing and both afforestation scenarios could offset four to six percent of total statewide emissions over the first few years. However, because SOC sequestration happens more rapidly at first but plateaus over time as the pools of C in the soil reach equilibrium, assuming steady emissions year-on-year, the emissions offset from SOC sequestration in all scenarios diminishes dramatically within just ten years.

The right panel of Fig 9 shows how these offset percentages would differ assuming Vermont meets the emissions targets laid out in the GWSA. The U-shaped curves seen in the years immediately following scenario adoption are the result of emissions dropping according to legislated targets and then stabilizing after 2050. With emissions and sequestration rates both falling over time, SOC sequestration becomes a more efficacious strategy to offset emissions. Assuming emissions targets are met, a regenerative agriculture strategy of full rotational grazing could offset around two to four percent of annual statewide emissions over the next century, whereas full afforestation of farmland could sequester up to seven percent over that timeframe.

Discussion

This study shows that significant, long-term sequestration of atmospheric C is possible through regenerative agriculture in Vermont, and that even more sequestration is possible if

afforestation is considered. Despite only 12% of Vermont's acreage being in agriculture, changes to how this relatively-small fraction of the landbase is used and managed can have sizeable effects on the region's carbon balance, and incentivizing these types of transitions should be considered as part of any policy package aimed at mitigating GhG emissions.

While each scenario we evaluated (best management practices under current agricultural use, transition to continuous pasture, transition to intensive rotational grazing, transition to harvested forest, and transition to old-growth forest) builds SOC over time when compared to business-as-usual, there are significant differences between them. Encouraging farmers to adopt regenerative management practices that maintain existing agricultural land uses would be a positive step, but our results show that large-scale shifts in land use to either well-managed perennial forage or afforestation could be far more potent.

Due to the asymptotically-limited nature of SOC buildup in each pool, all else being equal, the sequestration rate will diminish over several decades [1, 3]. Thus, SOC sequestration may be best characterized as an effective, albeit temporary solution as society transitions to a different type of C economy characterized by reduced fossil fuel use. Fig 9 shows how, if Vermont continues to emit current levels of CO₂, the percent of emissions offset by SOC sequestration from regenerative agriculture or afforestation falls from nearly 6% initially to less than 2% of emissions after just a decade. However, if Vermont meets its legislated emissions targets, SOC sequestration becomes a much longer-term strategy, especially if old-growth afforestation is prioritized.

Compared to the “four per mille” initiative, which suggests that 20–35% of all GhG emissions may be offset by SOC sequestration (if emissions targets are met) [15], the projections obtained here are more modest. To put the differences in SOC sequestration potential in perspective, we reiterate that this analysis focuses only on changes to Vermont's farmland, a small fraction of its total landbase. For regions where a much larger portion of the land is in agriculture, changes in farming practices would likely have a greater effect on the overall C balance of the region. Because the methodology we present here is readily-extensible to other regions, with continued research it should be possible to compare results between regions characterized by different types and intensities of agriculture to gain a better understanding of the potential of farmland C sequestration at a wider scale.

There has been both widespread support for the potential of regenerative agriculture to sequester C [12, 14, 19], as well as more recent pushback from scholars claiming the purported advantages are overstated [16, 24]. One of the challenges lies in defining what is meant by regenerative agriculture, since it is effectively an umbrella term encompassing a wide range of individual practices [20]. Further, opinions have changed somewhat as more data has become available. For example, our understanding of the sequestration potential associated with no-till farming has waned over time, so we do not include it in our scenarios (although it may still confer co-benefits like enhanced soil health and water infiltration) [54]. Practices that directly add C, such as cover cropping and addition of manure and compost, have proven effective at increasing SOC [13], as has conversion of tilled land to perennial pasture [22, 23], which is echoed in our findings. And finally, afforestation has been repeatedly shown to be a strong driver of SOC gains [46]. While afforestation is not a universally-agreed “regenerative agricultural practice,” incorporation of more trees on agricultural land, for example through agroforestry, is a commonly-cited strategy [20].

Regarding land use transitions from cropland to pasture, [24] argue that due to the world's rising demand for crops, any land taken out of crop production will necessitate more land being plied into service elsewhere, likely by clearing forests, and that it is therefore better to maintain intense production on existing acreage, known as a “land-sparing strategy.” It is well understood that tilling land that has built up C over hundreds of years is extremely

undesirable, as this is one of the strongest drivers of climate change globally, accounting for a third of global emissions [4]. As emphasized by our model results, understanding the timeframe required for humus to build in the soil should drive home the tragedy of clearing forest for tillage-based agriculture.

However, we contend that, by focusing on a global scale, [24] miss an important point, namely that these sorts of tradeoffs differ based on local context. In the case of Vermont, the vast majority of crops are not consumed directly by people, but are rather corn and soy for animal feed [6]. Converting land currently in corn silage to pasture-based livestock production, therefore, does not necessitate depriving Vermonters of staple grains or vegetables, but simply shifting the management system of (primarily) dairy farms to a more regenerative and sustainable model. Pasture-based livestock production has also been shown to offer other benefits, including better economic resilience, especially for small and medium farms; a critical consideration for Vermont's dairy sector [55].

Implications for policy

The recently-passed Vermont Global Warming Solutions Act [8] sets out legally-binding state-level emissions targets for the first time. Our findings suggest that, as policymakers discuss SOC sequestration as a potential GhG mitigation strategy, they should consider it alongside other strategies to decrease emissions or increase efficiency, especially with regard to the anticipated timeframe for change associated with each. Further, policymakers will need to weigh the relative benefits of high-sequestration land uses like afforestation against the food security and sustainability benefits associated with locally-produced food and regenerative agriculture. In short, there does not appear to be a magic bullet that both maintains current land uses and sequesters sufficient C to offset emissions in the long term. Despite these complexities, our results show that farmland SOC sequestration has significant potential as part of a wider effort to mitigate climate change in Vermont.

Recently, there have been increasing calls to implement plans that compensate farmers directly for C sequestered, so-called “payments for ecosystem services.” A similar mechanism may also be built into existing and future C cap-and-trade schemes. Pilot programs that are currently operating compensate farmers around \$17–\$22 per tonne of C sequestered [56]. Assuming a rate of \$20/tonne, based on our results, full adoption of regenerative practices, while maintaining existing land uses, could collectively earn Vermont farmers \$9.8 million over ten years. Full conversion of all agricultural land to rotationally-grazed pasture could bring in \$25.4 million over that period; and full afforestation as much as \$31.2 million. As more of these types of programs are implemented, these cash injections into Vermont's rural economies represent another potential upside to farmland C sequestration.

Limitations and future research

This study focuses narrowly on SOC changes resulting from land use and management transitions on Vermont farmland. For a full accounting of the regional C balance, we would also need to consider other factors. RothC only models SOC in the topsoil and does not include C in deeper soil strata, or C stored as above-ground plant biomass, which, for forests, can be 21–48% of total C stocks [46]. The model also does not account for differences in emissions from agricultural management; for example, higher stocking rates lead to greater methane emissions from enteric fermentation, which may offset soil C gains. Further, C dynamics stemming from non-agricultural land uses are not considered in the study. For example, continued aging of currently-forested land represents a C sink. On the other hand, ongoing development that converts forests, farms, or grassland to impervious surfaces like buildings and parking lots

oxidizes C and prevents the growth of plants, representing a C source. A full accounting of projected regional C sources and sinks would require consideration of these and other land use and land management changes beyond farmland topsoil.

Another limitation stems from our spinup procedure. While the method we use is recognized as state of the art [33, 49, 50], it implicitly assumes that, given “business-as-usual,” C stocks may fluctuate throughout each year, but will not rise or fall in the long run. In reality that is almost certainly not true in every situation, but because we don’t have time series data on how SOC has changed in different contexts, it’s a common simplifying assumption.

Further, whereas many Vermont farmers use some type of corn–hay rotation, our model assumes static land uses on each field year-on-year, which may lead to over- or under-estimations of SOC sequestration. Future research will explore the model’s sensitivity to assumptions about the current trajectory of SOC stocks by incorporating historical land management trends. Relatedly, similar to other recent studies [32], we assume steady-state climatic conditions based on long-term average observations. In actuality, it is likely that, with rising temperatures, oxidation rates will increase, putting downward pressure on SOC levels across the board. This is currently a topic we are actively pursuing for a follow-up study. In general, more extensive monitoring of SOC stocks associated with different land uses and physical locations over time would be valuable to enhance the precision of future modeling efforts in Vermont and elsewhere.

A final limitation is that the scenarios we assess simply assume the same type of wholesale change to all farmland simultaneously. In reality, any such transition would take years and would have different levels of adoption in different contexts. The purpose of these scenarios is not to represent a realistic policy prescription or course of action *per se*, but rather to explore SOC sequestration as a lever against atmospheric GhG buildup more generally by illustrating the overall magnitude and temporal characteristics of potential changes. Future research will focus on more realistic scenarios, including exploring tradeoffs between, for example, more-intensive agricultural production on a portion of current farmland, with the remainder returning to forest, versus widespread adoption of less-intensive production methods. Analyzing such tradeoffs will require accounting for differences in both food production quantity and emissions intensity associated with different types of agriculture, which is beyond the scope of this study.

Conclusion

With climate change a pressing global threat, it is imperative to explore all possible mechanisms to mitigate atmospheric greenhouse gas buildup. This data-driven study uses the RothC model to explore the potential for regenerative agriculture in the state of Vermont to sequester SOC over time. We find that changes in agricultural management, especially a shift from row-crops to pasture as a livestock feed source, as well as changes in land use from agriculture to forests, could both play a role in offsetting emissions. The potential offset from SOC sequestration is faster initially and slows as each C pool progressively reaches equilibrium, so this strategy is best conceived as an important, albeit temporary piece of the puzzle as we reduce emissions over the next thirty years or so. However, despite that limitation, encouraging farmers to embrace regenerative practices, including afforestation where feasible, for example through payments for ecosystem services, may be a valuable strategy with multiple co-benefits for soil health, water quality, and rural economies.

Supporting information

S1 Text. GIS processing details.
(PDF)

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

S1 File. GIS input dataset.
(CSV)

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Supervision: Brian Beckage.

Validation: Serge Wiltshire.

Visualization: Serge Wiltshire.

Writing – original draft: Serge Wiltshire.

Writing – review & editing: Serge Wiltshire, Brian Beckage.

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