CARBON MANAGEMENT
2024, VOL. 15, NO. 1, 2430780
https://doi.org/10.1080/17583004.2024.2430780

Making soil carbon credits work for climate change mitigation

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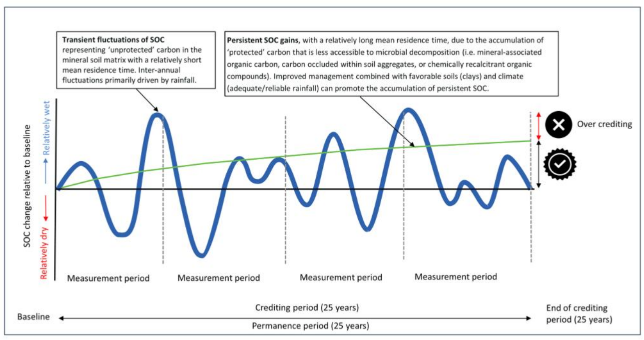
ABSTRACT

In 2023, the Australian Government issued ∼250,000 soil carbon credits following a measurement period characterised by high rainfall (Decile 10). The inferred soil organic carbon (SOC) sequestration rates during this period, ranging from ∼2 to 8 t C $ha^{-1} yr^{-1}$, significantly exceed rates reported in Australian scientific studies (∼0.1 to 1.2 t C $ha^{-1} yr^{-1}$). Our analysis, incorporating SOC and biomass measurements alongside remote sensing of NDVI, reveals that these SOC gains were largely attributable to above-average rainfall rather than project interventions. Moreover, these gains were not sustained when rainfall returned to average levels, raising concerns about the durability of credited sequestration and its additionality beyond natural climatic variability. Our findings demonstrate that current safeguards within the Soil Carbon Method—such as withholding 25% of credits during the first measurement period—are likely insufficient to account for climatic variability. To strengthen the integrity of the carbon crediting system, we recommend extending the minimum measurement period for credit issuance to at least five years. Additionally, governments should establish science-based ‘reasonable bounds’ for expected long-term SOC gains from management practices to sense-check reported outcomes. These measures will ensure that credited SOC sequestration is more closely tied to management-driven outcomes rather than short-term climate-driven fluctuations.

ARTICLE HISTORY
Received 11 April 2024
Accepted 25 October 2024

KEYWORDS
Policy; carbon market; carbon removals; soil carbon; greenhouse gas; climate change mitigation

GRAPHICAL ABSTRACT



A conceptual diagram of “new” carbon entering the soil system over a 25-year crediting period. Transient fluxes of SOC (blue) versus the accumulation of more persistent

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Supplemental data for this article can be accessed online at https://doi.org/10.1080/17583004.2024.2430780.

SOC (green). The risk of over crediting transient fluctuations of SOC is represented by the circle with a cross.

Introduction

In 2023, the Australian Government's Clean Energy Regulator (CER) made a large-scale issuance of ~250,000 carbon credits from six grazing farms, with a market value of ~$5.7 million USD (Q4 2023 Australian Carbon Credit Unit spot price) using the Soil Carbon Method 2021. Re-measurement of soil organic carbon (SOC) stocks, at 2 to 5 years after SOC baseline measurements, were made in 2021 and 2022 when large areas of eastern Australia experienced Decile 10 annual rainfall (the highest 10 per cent of rainfall since 1900) [1]. This issuance has prompted questions about what the change in measured SOC represents – climatic variability or the new and eligible management activity. According to the integrity standards, carbon credits should only be issued for *additional* carbon stored in agricultural soils that is unlikely to have occurred in the absence of the soil carbon project and that the higher level of soil carbon is reasonably expected to be maintained for the permanence period (25 years) [2].

Soils contain the majority of organic carbon stored in terrestrial ecosystems [3] and even a small relative change in SOC can greatly influence future climate [4]. SOC is derived from the decomposition of carbon captured through photosynthesis, meaning that plant productivity set the upper limit to potential carbon inputs to the soil system [5,6]. Plants utilise the carbon assimilated by photosynthesis to build their structural components (both above and below ground) and to fulfil various metabolic requirements. This plant biomass is eventually transferred to the soil through processes like litterfall, rhizodeposition, and decomposition [7]. Around 10-30% of biomass inputs will be stabilised as soil organic matter in the long-term, depending on factors such as soil type and climate [8].

The sequestration of SOC as a strategy for climate change mitigation has been popularised by the aspirational goal established in the 4 per mille initiative [9] launched at the 21st Conference of the Parties (COP21) of the United Nations Framework Convention on Climate Change (UNFCCC). The original premise of 4 per mille was that if global SOC stocks in global soils could be increased by 0.4% per year, the SOC sequestered would offset annual fossil fuel-derived CO_2 emissions. While the feasibility of this proposed rate has been debated extensively [10–13] the 4 per mille goal has inspired national climate solution policies and investments [14] and raised significant awareness on the role of soils in sequestering atmospheric carbon.

Soil organic carbon sequestration is a key priority in the Australian Government's Long-term Emission Reduction Plan for attaining net zero emissions by 2050 [15], while contributing to food security, ecosystem services and achievement of multiple United Nation's Sustainable Development Goals (SDGs) [16]. The Australian Carbon Credit Unit (ACCU) Scheme is a enacted through the Carbon Credits (Carbon Farming Initiative) Act 2011 (CFI Act), with each carbon credit (referred to as an ACCU under the legislation) representing one metric tonne of carbon dioxide equivalent (t CO_2e) of either avoided emissions or C sequestered in the soil or vegetation by a Carbon Farming project over a permanence period of 25 or 100 years. The Carbon Credits (Carbon Farming Initiative – Estimation of Soil Organic Carbon Sequestration using Measurement and Models) Methodology Determination 2021 – hereafter referred to as the Soil Carbon Method 2021 – issues credits based on *measured* changes between SOC baseline stocks and future measured SOC stocks, with mandatory Government discounts for risk of reversal, soil sampling variance, and project emissions, and an additional discount if the 25 year permanence period option is selected (see Table 1 for a summary of the Soil Carbon Method 2021).

The main factors that influence SOC stock changes over time in agricultural systems are the impacts of climatic changes and management practices, through their effects on the inputs of C from plant litter and roots [17]. Rainfall is the primary driver of variability in Australia's carbon cycle, with seasonal, annual and decadal variability interacting to mediate plant composition, productivity, carbon inputs, and carbon losses from microbial activity [18–21]. Generally, increased rainfall enhances primary productivity and the delivery of carbon inputs to the soil organic matter pool through litterfall, root growth, sloughing and exudation [22]. The most apparent trend in plant growth is intra-

Table 1. **Australian soil carbon method 2021 - the carbon credits (carbon farming initiative – estimation of soil organic carbon sequestration using measurement and models) methodology determination 2021.**

Baseline	Credits are issued based on measured changes in soil organic carbon between two points in time, against a static baseline scenario. All subsequent measurements are compared to this initial static baseline.
Measurement intervals	The first measurement occurs 1 to 5 years after baseline sampling, with subsequent measurements required at least every 5 years for the duration of the projects crediting period (25 years).
Net abatement	This represents the increase in SOC stocks, minus any increase in project-related emissions (e.g. increased enteric methane due to higher stocking rates).
Additionality	This criterion ensures that only new management practices are credited, adhering to a "newness" requirement.
Permanence	Projects can choose between 25- or 100-year permanence periods. A 20% reduction in carbon credits is applied for a 25-year permanence period, while a 5% reduction is applied for a 100-year period. Shorter permanence periods carry more uncertainty, so higher discounts help maintain the integrity of carbon credits issued.
Measure/model	Soil core measurements are taken within the Carbon Estimation Area (CEA), which must be divided into at least three strata, with a minimum of three samples per stratum (9 samples per CEA). The model-assisted approach allows for SOC measurements to be spatially modelled or extrapolated over a portion of the project area in an attempt to reduce sampling costs.
SOC measurement	Dry combustion analysis and spectroscopic modelling.
Further discounts	Risk of Reversal Buffer: A 5% reduction in issued credits to account for the risk of carbon stock reversal. SOC Variance Discount: A discount applied for reporting high variability in soil carbon stocks within strata, estimated to be around 5% based on data variability. Temporary Discount: A 25% temporary discount is applied after the first sampling round to manage the risk that the initial rate of SOC increase may not be maintained. These withheld credits will be returned if SOC stocks are sustained. See supplementary information for more detailed information.

annual variation, causing a seasonal saw-tooth pattern [23,24]. Australia also has high year-to-year and decade-to-decade variability in rainfall and pasture growth driven, in part, by the El Niño Southern Oscillation [25,26] and Inter-decadal Pacific Oscillation [27], although the latter may simply reflect clustering of El Niño and La Niña years [28]. Depending on the location, other persistent climate drivers such as the Southern Annular Mode [29] and Indian Ocean Dipole [30,31] also contribute to year-to-year variability in rainfall, which is around 23% more variable than any other country [32].

In 2023, the Australian Government issued approximately 250,000 ACCUs to six soil carbon projects in Queensland (QLD), based on measured increases in SOC over relatively short measurement periods of 2 to 5 years. While management practices likely contributed to *some* of the observed changes, this paper presents evidence suggesting that increased rainfall was the primary driver of SOC gains. Significant uncertainty remains about the persistence of these gains throughout the project's 25-year permanence period, and whether the current safeguard in the Soil Carbon Method – a 25% temporary retention of credits in the first measurement period – is sufficient to account for climatic variability.

This paper aims to offer policy insights by evaluating the risks associated with issuing carbon credits during periods of favourable climatic conditions. To ensure that crediting more accurately reflects genuine management-induced SOC changes rather than short-term climatic variability, we propose two key recommendations for adjusting the current Soil Carbon Method 2021. These include extending the minimum measurement period to at least five years and establishing reasonable bounds for SOC sequestration based on the best available peer-reviewed evidence. Implementing these changes would enhance the integrity of the current policy framework for soil carbon credits.

Materials and methods

Soil carbon projects

In 2023, six soil carbon projects were issued ACCUs: ERF 108333 (94,666 ACCUs), ERF 105067 (85,262 ACCUs), ERF 102074 (66,050 ACCUs), ERF 143770 (3,559 ACCUs), ERF 162497 (2,110 ACCUs), and ERF 158470 (1,362 ACCUs) [33] (Supplement 2). Each of these projects committed to a 25-year permanence period and implemented "improved grazing management" as the strategy intended to increase SOC.

For this study, we selected five of these soil carbon projects (ERF 108333, ERF 105067, ERF 102074, ERF 143770, and ERF 158470) based on criteria ensuring representation from multiple project developers and the availability of valid control sites for paired site comparison to assess the impact of the management changes.

In our analysis, we compared the registered project areas (improved management – Supplement 2) with nearby control sites (no management change, as per the project baseline). Three 20-hectare polygons were randomly selected within each project area for comparison with three systematically selected control polygons (also 20 hectares each) located within 50 km of the carbon project area. The control polygons were chosen to match the project sites in terms of land use (grazing), soil type, clay content, slope, aspect, and to ensure there was no evidence of management change.

The improved management practices under the Soil Carbon Method 2021 included one or a combination of the following: altering stocking rates, adjusting the duration and/or intensity of grazing, improving pastures through seeding, and applying nutrients to address material deficiencies. Management on the control sites followed a business-as-usual approach, with no soil disturbance, pasture renovation, field subdivision, or altered water distribution observed in the ten years prior to the present day, as verified by aerial photography. To reduce the risk of selecting polygons that may have undergone simultaneous management changes with the soil carbon projects, we selected polygons from at least two different properties. Spatial files for the locations of the soil carbon projects were accessed from the CER website [33].

Examining the relative importance of management and rainfall on vegetation

To examine the impact of management change and rainfall on vegetation (with vegetation serving as a proxy for C inputs to the soil) we analysed satellite-derived Normalised Difference Vegetation Index (NDVI) (Landsat-8, 30 m resolution) spanning from 2001 to 2023. NDVI is a widely used numerical indicator that uses the visible and near infrared bands of the electromagnetic spectrum to assess vegetation health and density. It is commonly employed in remote sensing applications to monitor and analyse vegetation dynamics over time and space [34,35].

To estimate the effect of the management intervention (i.e. carbon project implementation) on NDVI, we employed the Difference-in-Differences (DiD) approach using the R package "did" (Figure 1). We compared the difference in NDVI values from polygons within the carbon project area (treatment) against those from polygons outside the project area (control) before and after project intervention. The NDVI values from the treatment and control polygons showed sufficient overlap (with differences not exceeding 5%), allowing us to average across three polygons for each group. The NDVI time series was constructed for the period from 2001 to 2023.

A 12-month moving average filter (left lagging, including data from the past 12 months) was applied to the NDVI dataset set to smooth the data and facilitate trend identification [36]. Additionally,

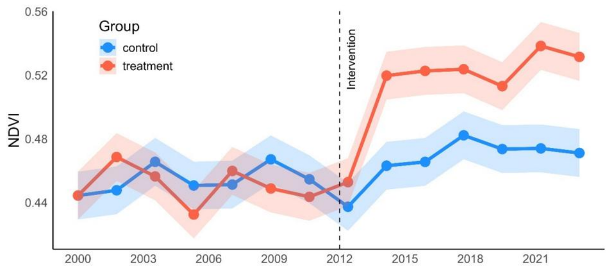

Figure 1. Conceptual representation of difference-in-difference analysis on NDVI time-series for treatment (soil carbon project) and control (outside of carbon project). Project intervention represented by dotted black line. Difference in differences before and after intervention.

we applied the same 12-month moving average filter to the rainfall data to reduce noise from intra-seasonal and local-scale variability. Rainfall data were sourced from the SILO Climate Database [37]. To further aid in identifying trends, a non-parametric smoothed lined was applied to the NDVI data set using the LOESS method (Locally Estimated Scatterplot Smoothing), with a span that responded to 50% of the nearest data points.

The DiD method is useful in studies where random assignment to treatment and control groups is not feasible. A key assumption underlying the DiD approach is the parallel trends assumption, which posits that, in the absence of the intervention, the difference between the treatment and control groups would have remained constant over time. By comparing the changes before and after the intervention, DiD isolates the effect of the intervention from other confounding factors, such as climate that might influence the outcome.

To assess the relative impact of various predictor variable – temperature, rainfall, and treatment – on NDVI, we applied a Random Forest model to the data from each site. The model was applied to data from the first measurement period ranging from 2 to 5 years, depending on the carbon project. We used the Increase in Node Purity metric to gauge the relative importance of each predictor variable. This metric indicates how much each variable contributes to reducing uncertainty or "impurity" in the decision trees within the Random Forest model. The Increase in Node Purity was normalised to sum to 100%, allowing us to express the contribution of each predictor as a percentage.

In-depth analysis at one carbon project site

While five carbon projects are examined for change in NDVI before and after project implementation, we conducted a more in-depth analysis

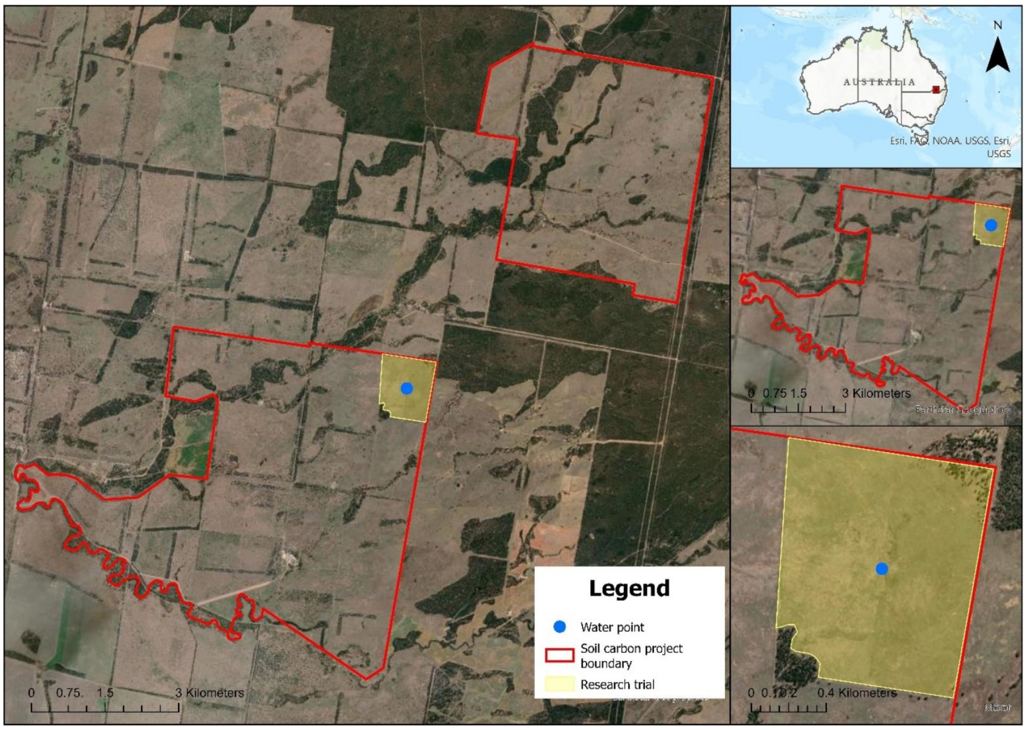

Figure 2. Soil carbon project area boundary (red) for project ERF 102074 and location of the research trial (yellow) within the soil carbon project area. Project boundaries provided by the Clean Energy Regulator [33].

on one soil carbon project (ERF 102074). This property included a research trial funded by Meat & Livestock Australia (P.PSH.2104) within the carbon estimation area of the soil carbon project. Figure 2 illustrates the boundaries of the soil carbon project (∼2800 hectares) and the research project (∼30 hectares). The research trial, established in 2019, aimed to validate a measure-modelling approach to soil carbon accounting using the eddy covariance method [38] and does not capture the full measurement period of the soil carbon project (2016 to 2021). The research trial includes detailed measurements of SOC and biomass stocks from 2019 – 2022. To infer SOC stocks from 2016 to 2019, we used a statistical modelling approach based on measurement of SOC, biomass, rainfall and temperature 2019 – 2023 (see section "Gap filling SOC data for the soil carbon measurement period using modelling").

Soil carbon data from soil carbon project (ID: ERF102074)

Soil cores ($n = 24$) were collected within a 30 hectare field using Balanced Acceptance Sampling (BAS) [39]. Balanced acceptance sampling involves stratification of the project area to lower sampling variance and the cost of estimation when compared to random sampling without stratification. The research area (30 hectares) was divided into three homogenous strata with respect to soil characteristics and vegetation cover. Within each stratum, eight random samples were collected from across the stratum.

Six sampling events occurred at time 0 (December 2019) and at the following intervals: 1 year, 1.5, 2.5, 3, and 3 years 10 months (October 2023) to capture seasonal and annual variability. We returned to the same sampling location for each sampling event (± 7 m with GPS accuracy).

Soil coring was completed to a fixed target depth of 100 cm or the point of refusal in accordance with the Soil Carbon Method 2021. Soil cores were extracted using a hydraulic sampler fitted with PVC-lined push-probe with a typical cutting diameter of 42 mm (range 40.8 to 44 mm). Intact cores were returned to the laboratory and cut to fixed depth intervals (0-10, 10-30, 30-50, 50-70, 70-100 cm) for analysis. Soils were analysed at these 5 depth layers, and results are presented for 0-30, 30-100 cm depth increments according to the Soil Carbon Method 2021.

Whole soil within each depth layer was oven-dried at 40 °C and weighed. Soil moisture was determined from a subsample of ∼50 g, dried at 105 °C (oven dry weight). The remaining whole soil was sieved to <2mm to remove gravel and coarse organic material (roots and litter). After sieving, the air-dried weights of the <2mm (air-dried fine fraction) and >2 mm (gravel) portions were recorded. The bulk density was calculated by dividing the oven-dried weight of the entire sample by the volume of the sample.

Samples were analysed for Total Organic Carbon (TOC) using Dumas high temperature oxidative combustion followed by non-dispersive infrared detection of CO_2 with an elemental analyser (LECO Corporation) - Method 6B2 in [40]. The presence of inorganic C was tested by treating a 1-2 g subsample with 5% v/v of Hydrochloric acid and observing any effervescence. If any inorganic carbon was present, samples were pre-treated using 5-6% sulphurous acid and heated on a hot plate. The process was repeated until the effervescence ceased prior to oxidative combustion according to Method 6B3 [40]. The stock of soil organic carbon in all sub-layers collected and analysed was calculated according to:

$$SOC\ t\ C/ha = OC\ x\ BD\ x\ d\ x\ (1 - g)$$

where:

SOC is the soil organic carbon stock within an individual soil sub-layer (tonnes of soil carbon/ha)

OC is the gravimetric concentration of organic carbon determined for the sub-layer (g organic carbon/100 g oven dry whole soil)

BD is the bulk density of the sub-layer (g oven dry whole soil/cm^3 whole soil)

d is the depth of the sub-layer samples (cm)*g* is gravel proportion (g gravel/100 g over dry whole soil)

The difference in SOC stocks between time intervals was determined on an equivalent soil mass (ESM) basis according to the Soil Carbon Method 2021 (Division 4, Section 13). The ESM is set in the baseline sampling round and acts as a cap to the mass of soil for which carbon stocks are calculated in subsequent sampling rounds.

Pasture biomass data

Repeated aboveground pasture biomass measurements (50 cm x 50 cm) ($n = 24$) were taken before and after grazing at pasture points paired to soil coring sites (using hand-held GPS with an accuracy of ± 5 m). Samples were dried at 60 °C to determine the standing above ground dry matter (DM). A total of 11 sampling events occurred between December 2019 and July 2023.

Gap filling SOC data for the soil carbon measurement period using modelling

To address the absence of measured SOC data for the period from 2016 to 2019, a statistical modelling approach was employed to estimate the missing SOC values. A linear regression model was developed to predict SOC as a function of measured SOC and biomass, as well as NDVI, rainfall, and temperature data from the period 2019 to 2023. This approach enabled us to gap-fill SOC data for the period 2016 to 2019, for which data were unavailable for the research project and undisclosed from the soil carbon project.

Net primary productivity of soil carbon projects

We determined the net primary productivity (NPP) of soil carbon project sites in 2022 (when most carbon projects were re-measured after baseline sampling) using the globally gridded MODIS-NPP [41] extracted for the Australian continent at 500 m pixel resolution. Annual Terra Moderate Resolution Imaging Spectroradiometer (MODIS) GPP and NPP is derived from the sum of all 8-day GPP Net Photosynthesis (PSN) products (MOD17A2H) from the given year. The NPP value is the difference between the GPP and the Maintenance Respiration (MR). The NPP was averaged for 2022 across soil carbon project sites to ascertain a sense-checking value for reported SOC gain by the (soil) Carbon Service Providers. We acknowledge that NPP from remote sensing productions is subject to large uncertainty [42], and therefore validated the NPP value for the ERF 102074 soil carbon project using biomass data (section "Pasture biomass data") (combined with a root/shoot ratio data) and Eddy Covariance flux tower data [38]. Ultimately, deriving the NPP from remote sensing is not intended to be a highly accurate prediction; rather, we suggest it as a value to sense check reported SOC stocks gains.

Data description

SOC and pasture biomass data

This section presents data from the research trial (2019 to 2023) conducted at the same site as the soil carbon project ERF 102074, which was issued 66,050 credits based on re-measurements in 2021 [33]. Although the trial was originally established for other research objectives, the SOC and pasture biomass data collected at this site provide valuable

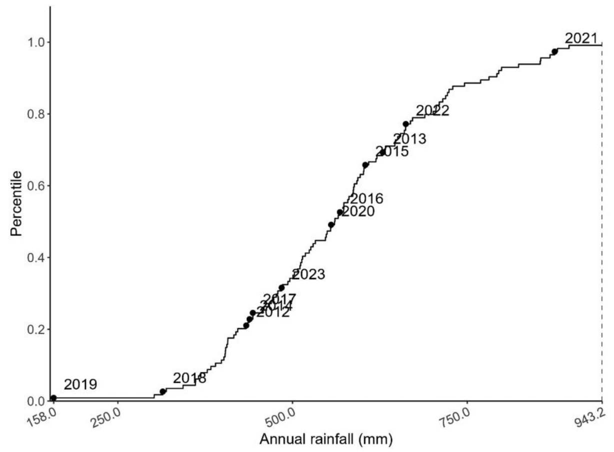

Figure 3. Cumulative probability distribution of annual rainfall (1910-2023) for the research trial site in Southern Queensland, Australia. The years 2011 to 2023 are annotated.

insights into the highly dynamic and the transient nature of SOC over time

In the research trial, the measurement of pasture biomass and SOC stocks commenced during a period of the lowest rainfall on record (2019) (Figure 3). In December 2019, the pasture biomass was <0.2 t dry matter (DM) ha^{-1} and SOC stocks were 74.2 t C ha^{-1} (0-100 cm) (Figure 4 a). In 2021 and 2022, rainfall was 33% higher than the long-term average (1910-2023), increasing pasture biomass to 6.4 t DM ha^{-1} and SOC stocks to 82 t C ha^{-1} (0-100 cm) by May 2022 (Table 2). Over 2.5 years, this equates to SOC gains of 7.7 t C ha^{-1} (0-100 cm) or 3.1 t C ha^{-1} yr^{-1}. These results have been validated by Eddy Covariance flux tower measurements [38]. However, by October 2023, with a return to average annual rainfall, pasture biomass decreased to 3.7 t DM ha^{-1}, while SOC stocks decreased to 75.7 t C ha^{-1} (0-100 cm). This represents a total increase in SOC stocks of 1.4 t C ha^{-1} (2019 to 2023), with an annualised sequestration rate of ~0.4 t C ha^{-1} (0-100 cm). These results indicate that the SOC "peak" observed in 2021 to 2022 was temporary, with ~50% (0-30 cm) to ~80% (0-100 cm) of the SOC gain subsequently "lost" from the soil system as rainfall returned to average conditions.

In 2021, the soil carbon project was re-measured at the SOC "peak" (indicated by the second grey dotted line in Figure 4a), resulting in the issuance of 60,050 credits. However, much of the credited SOC gain has since been lost from the soil, meaning that a substantial portion of these credits no longer represent climate change mitigation. This raises questions about whether the current provisions in the Soil Carbon Method to account for climatic variability are sufficient (see section

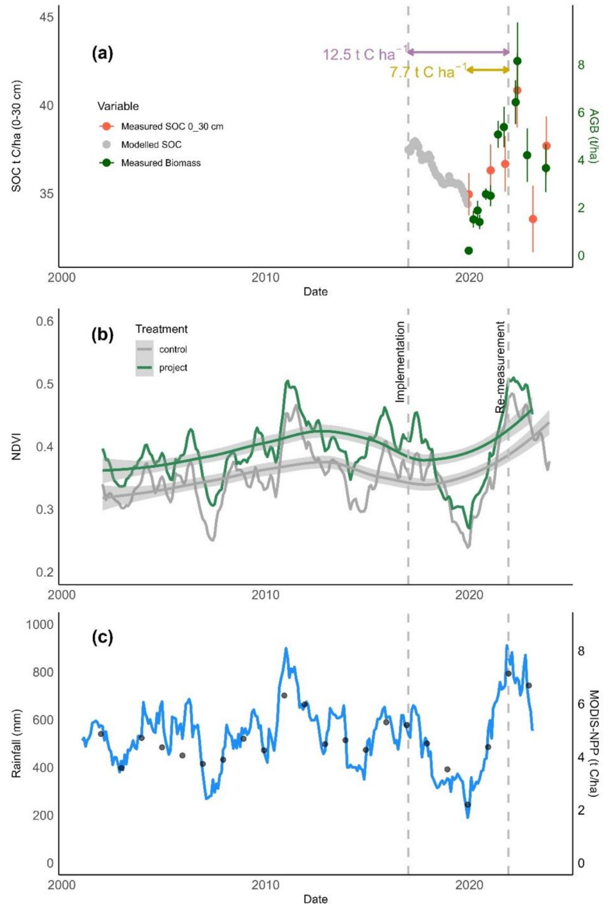

Figure 4. (a) Soil organic carbon (SOC) (t C ha^{-1}) (0-30 cm) and aboveground pasture biomass (t dry matter, DM ha^{-1}) on the grazing research trial site (same site as ERF 102074). Results for 0-100 cm are in Table 2. Purple line shows inferred rates of SOC gain in the carbon project and the yellow line shows SOC gain measured in the research trial, (b) Normalised Difference vegetation Index (NDVI) comparing (i) project site = green (soil carbon project area), (ii) control = grey (area outside the soil carbon project boundary with similar soil type, land use, topography etc.) with LOESS smoothing function applied (see methods), and (c) Rolling 12 month average rainfall (left lagging) (mm) and MODIS-net primary productivity (NPP) (tC/ha) for the carbon project site. The grey dotted lines indicate the first measurement period (2016-2021) for the soil carbon project, the period over which carbon credits were issued.

Table 2. Mean SOC stocks (t C ha^{-1}) (±SE) 0-30 cm and 0-100 cm for six sampling events from December 2019 to October 2023.

Sampling date	Mean SOC (0-30 cm)	SE	Mean SOC (0-100 cm)	SE
December 2019	34.96	1.20	74.27	3.62
January 2021	36.32	1.47	64.49	4.86
October 2021	36.68	1.58	73.39	4.21
May 2022	40.84	2.11	81.98	4.27
February 2023	33.56	1.89	65.54	3.85
October 2023	37.70	1.65	75.67	3.91

"Current safeguards to account for climatic variation are insufficient").

Even when accounting for the impact of rainfall on SOC gains, the inferred rates of SOC gain over the project periods seem unusually high in comparison to SOC measured in the research trial. By examining the CER's Project Register, we can infer the rates of SOC sequestration for this project by calculating the credits issued, factoring in the project's Carbon Estimation Area (CEA), and applying necessary deductions (see Supplement 1 for deductions and Supplement 4b for inferred rates of SOC sequestration). The inferred SOC gain over a five-year period was approximately 12.5 t C ha^{-1}, equating to an annualised SOC gain of ~2.5 t C ha^{-1} yr^{-1}. We can assume that the period from 2016 (when the project was implemented) to 2019 was likely characterised by SOC loss (Figure 4a - see methods for modelling). From the 2019 drought to 2021 (when re-measurement occurred), the research trial measured SOC gains of 7.7 t C ha^{-1}, whereas the soil carbon project measured the accumulation of ~12.5 t C ha^{-1}. This represents an SOC accumulation rate around 60% higher than our observations. This discrepancy could be due to the inherent variability in SOC sampling. However, given the significant difference in reported SOC gains, we also consider the possibility of errors in the application of the method e.g. incomplete removal of root biomass, the difficulty in removing inorganic carbon at depth [43], and the incorrect application of spectroscopic measurement and modelling. It is important to note, however, that since SOC data from Australian Government carbon projects administered by the CER are not publicly available, our inference on this matter remains speculative.

NDVI analysis

The SOC and biomass data from the research trial were integrated with a longer-term record (2001 to 2023) of NDVI to achieve two main objectives: (a) to assess whether the implementation of management practices had a significant impact on NDVI by comparing treatment and control groups before and after soil carbon project implementation using DiD analysis, and (b) to apply a Random Forest model to the NDVI data over the project measurement period (2 to 5 years depending on the project) to evaluate the relative importance of temperature, rainfall, and management practices on NDVI. The NDVI analysis was also extended to the four other soil carbon project sites. This NDVI analysis is based on the assumption that NDVI serves as an indicator of the amount of fresh organic material added to the soil, which can signal potential increase or decreases in SOC stocks [44–46].

NDVI comparisons between the carbon project and control sites are presented in Figure 4b for ERF 102074 and in Figure 5 for the other soil carbon projects (see Supplement 5 for the full NDVI and corresponding rainfall time series for each project). We hypothesized that the implementation of management changes under the soil carbon projects would lead to an increase in NDVI relative to the control sites. For ERF 102074, the project implementation resulted in a marginal but not statistically significant decrease in NDVI compared to the control ($p = 0.07$). A similar pattern was observed in ERF 158470, where the decrease in NDVI relative to the control was statistically significant ($p = 0.01$). In contrast, for ERF 143770 and ERF 108333, there was no significant impact of project implementation on NDVI. ERF 105067 was the only project that showed a positive impact of project implementation on NDVI, although this difference was not statistically significant.

To assess the relative influence of temperature, treatment, and rainfall on NDVI, we applied a Random Forest model to the data at each site. This analysis focused on data from the first measurement period, which ranged from 2 to 5 years depending on the carbon project. To evaluate the relative importance of the predictor variables, we used the Increase in Node Purity metric. This metric reflects how much each variable contributes to reducing uncertainty or "impurity" in the decision trees within the Random Forest model.

To make the contributions comparable, we normalised the Increase in Node Purity so that the total sums to 100%, allowing us to express the importance of each predictor as a percentage. This approach enabled us to quantify and rank the significance of treatment, temperature, and rainfall in predicting NDVI at each site. The Node Purity results are provided for each site in Supplement 6 and summarized across sites in Figure 6 (inset). Our results showed that rainfall, together with temperature, played a dominant role in enhancing the model's predictive power. Specifically, the combined contribution of rainfall and temperature accounted for 83% to 98% of the total Increase in Node Purity, indicating that these variables are crucial in reducing model uncertainty and improving the accuracy of NDVI predictions. Management accounted for 2 to 17% of the total Increase in Node Purity.

While our findings indicate that climate is the dominant factor influencing NDVI variation during the first measurement period, this does not mean that changes in management practices had no

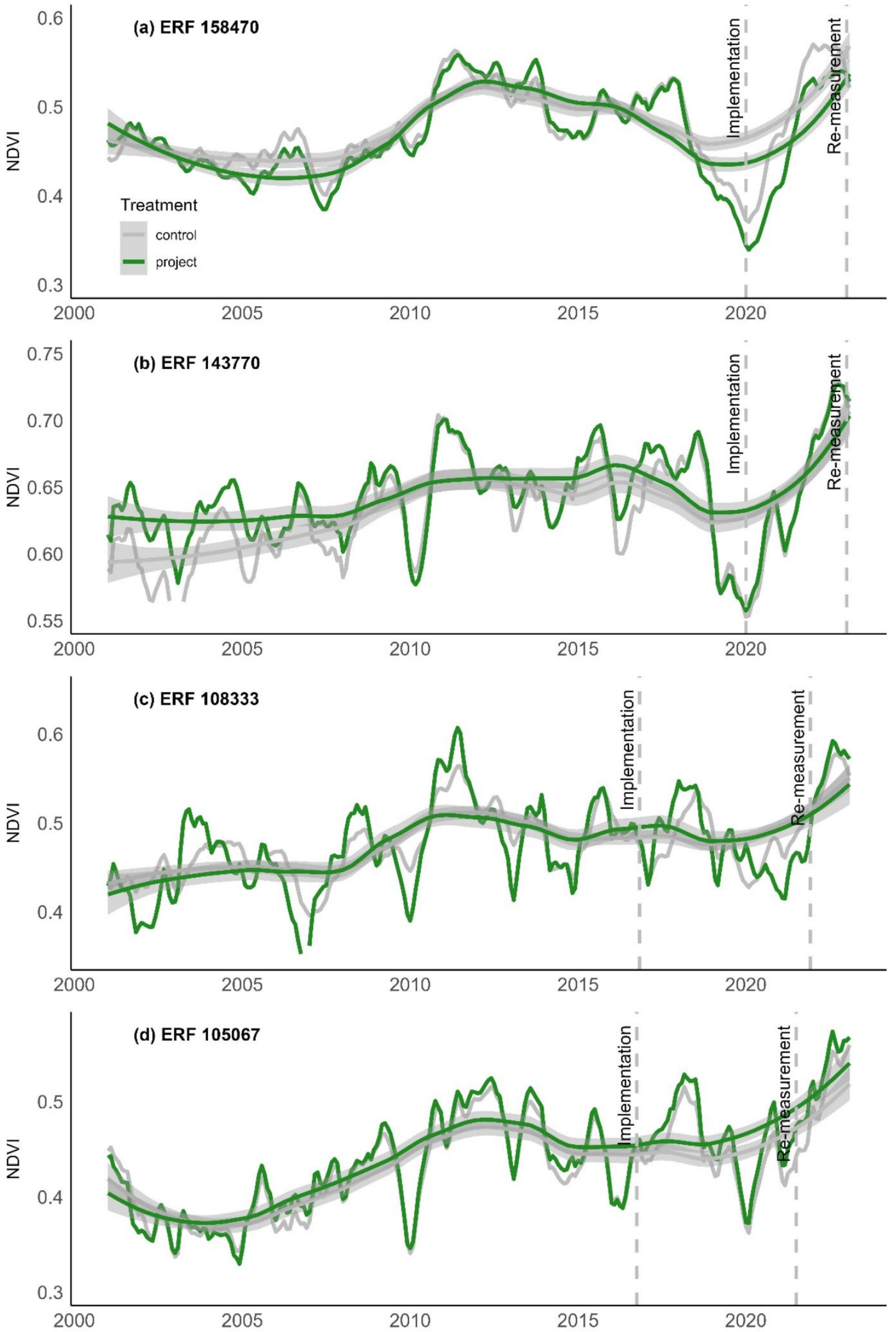

Figure 5. **Normalised Difference vegetation Index (NDVI) comparing for the soil carbon project sites (a to d). Project site = green (soil carbon project area), and control = grey (area outside the soil carbon project boundary with similar soil type, land use, topography etc.) with LOESS smoothing function applied (see methods).**

effect on vegetation. For example, NDVI has limitations in detecting the more subtle variations in vegetation structure and species composition, namely the differences in legume content and perennial versus annual species that may vary between management treatments [5]. Furthermore, NDVI cannot detect belowground biomass (i.e. roots). However, what is critical is that the impact of management on vegetation is much smaller – and more challenging to detect – than the more considerable temporal variation in vegetation driven by climate.

Discussion

In this study, we have presented high-frequency temporal measurements of SOC from a research trial co-located with a soil carbon project, revealing that SOC stocks were transient and primarily influenced by rainfall. We extended this analysis over a longer timeframe and across additional soil carbon project sites (using NDVI as a proxy for C inputs) and found that the implementation of these projects did not significantly increase NDVI relative to control sites. In this section, we will discuss the implications of these findings for the Soil Carbon

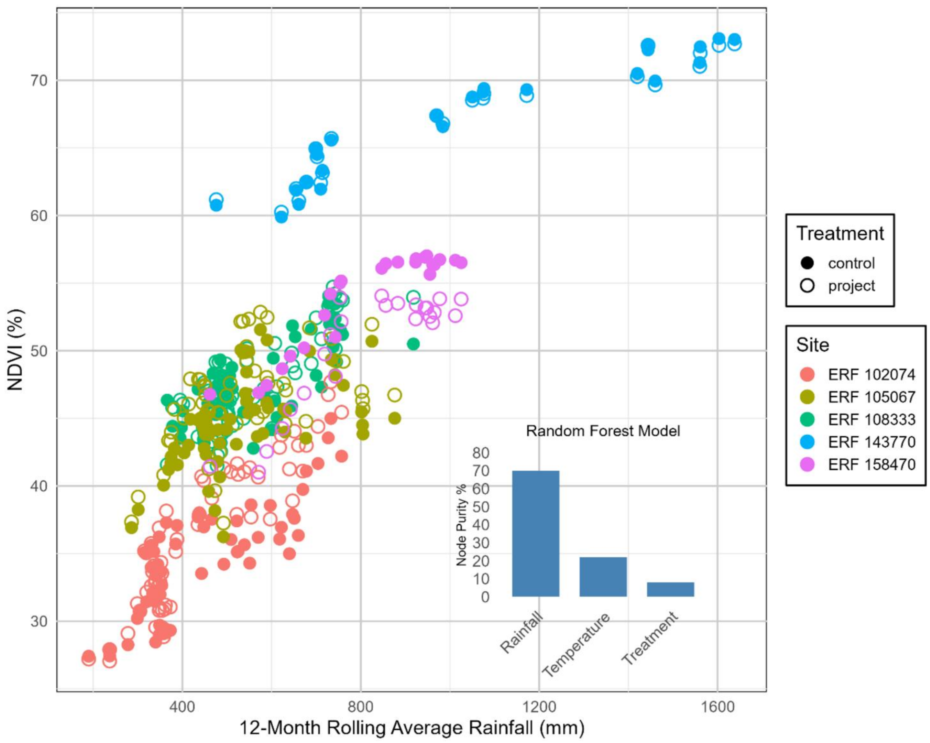

Figure 6. The relationship between NDVI and rainfall as the primary predictor of NDVI in the Random Forest model. The bar graph inset shows the contribution of the predictors (rainfall, temperature, and treatment) to NDVI (average across all sites). Node purity scoring for individual sites is shown in Supplement 6. A higher Node purity score equates to greater importance of predictor variable.

Method, focusing on two key issues: (a) the scientific uncertainty surrounding the long-term persistence of SOC accumulated during favourable climatic conditions, and (b) the apparent inadequacy of the current safeguard within the Soil Carbon Method (a temporary 25% discount in the first reporting period) to account for short-term variability driven by climatic factors. Given these concerns and uncertainty, we propose adjustments to the current Soil Carbon Method to better align crediting with management practice change as opposed to climatic variability.

Scientific uncertainty on long-term SOC dynamics over the remaining project period

Scientific uncertainty on long-term SOC dynamics is due to a lack of high-quality time-series datasets that track paired control and treatment plots in agricultural systems, especially in different contexts [47]. The scarcity of long-term, repeated SOC sampling across different soil types, depths (> 30 cm), climates, and management scenarios results in low confidence, both in Australia and globally, in predicting the climate benefits of SOC sequestration and determining the most effective methods for achieving it [48].

The capacity of soil to retain additional C inputs will largely depend on the ability of the soil to "protect" added organic material [49,50], which in turn depends on clay content and mineralogy, soil structure (micro and macro aggregation), location within the soil profile, chemical nature and composition of organic matter inputs, the occupancy of mineral surfaces by pre-existing carbon compounds, i.e. the degree of SOC saturation [51], and the pedoclimatic conditions and management practices at the particular site [52].

Due to the influence of soil physicochemical properties on the retention of more stable SOC, the ability to retain carbon inputs will likely vary between soil carbon projects, given their different soil properties and pedoclimatic environments. For example, ERF 143770 is located on a coarse-textured soil (∼15% clay content) where SOC accrual and persistence will be more challenging due to the lack of reactive mineral surfaces. In contrast, ERF 102074 with ∼40% clay content will have a greater capacity for stabilising and accumulating mineral-associated SOC due to the higher availability of reactive clay mineral surfaces [53].

Other considerations that generate uncertainty on the long-term ability of soil to build and retain organic carbon include (a) the possibility of SOC saturation whereby soils have a limited storage capacity and that the rate of SOC sequestration decreases as SOC approaches the maximum storage capacity [51], (b) the existence of a priming effect, whereby increased C inputs (i.e. through management change) stimulate soil microbial activity, leading to accelerated decomposition of existing SOC stocks [54,55] particularly at depth [55], (c) building persistent mineral-associated soil organic matter including microbial necromass, which can have a carbon to nitrogen ratio as low as ∼5:1 [56], is reliant on the availability of nitrogen in the form of synthetic or organic fertilisers and legumes that can increase nitrous oxide emissions and negate the benefit of sequestering SOC [57–60] (d) large and unexpected losses – with no obvious moisture or temperature drivers but most likely attributed to a decline in mineral nitrogen availability – have been observed in Australian grazing and cropping systems over the long-term (an increase in SOC for 12 years followed by a reversal back to starting levels after 15 years) [61], (e) as C inputs increase and SOC stocks rise, microbial activity intensifies in response making increases in SOC a temporary phase that reflects a lag between plant inputs and microbial decay until a new SOC-equilibrium is reached [6], and (f) there is strong evidence that SOC stocks will decline under climate change [62–65] particularly in grazing soils in semi-arid and arid regions of Australia [66].

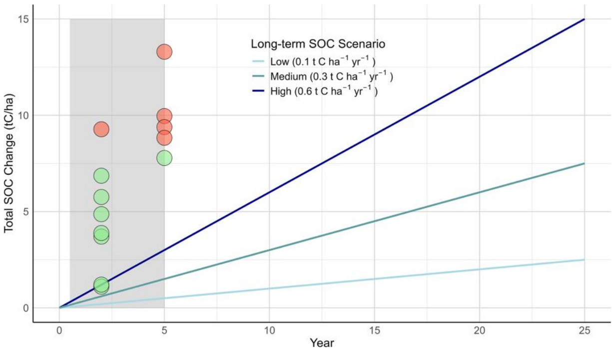

Figure 7. A schematic diagram illustrating the application of a temporary 25% discount on credits during the first measurement period (grey box) for soil carbon projects that have been issued credits (Supplement 4b). The diagram presents realistic long-term scenarios of SOC sequestration categorized into low, medium, and high scenarios. Each point on the diagram represents an individual carbon project that has been issued credits by the Clean Energy Regulator, adjusted by subtracting the temporary 25% discount. The temporary discount is likely to be sufficient only if medium to high rates of SOC sequestration (>0.3 t C ha^{-1} yr^{-1}) are sustained over the entire crediting period (25 years). Projects where over-crediting is likely are indicated in red.

Current safeguards to account for climatic variation are insufficient

The current Soil Carbon Method operates on the assumption that climatic variability – and the resulting SOC "peaks and troughs" – will balance out over a 25-year period, allowing the true effects of management practices to become evident. However, the assumption that climatic variability will balance out over a 25-year period is not supported by empirical evidence (Figure 8).

Rainfall variability in Queensland, Australia (1890 to 2023) is illustrated in Figure 8 revealing multi-decadal patterns of rainfall variability. Hypothetically, if a soil carbon project was implemented in 1930 (scenario 1), the project would have been baselined under lower-than-average rainfall and completed in 1955 under higher-than-average rainfall, likely resulting in a corresponding positive trajectory in SOC (even if no management change was implemented). Similarly, if a carbon project was baselined in 1965 under higher-than-average rainfall conditions (scenario 2) and completed in 2000, there was a downward trajectory in rainfall. Arguably, the ability to maintain or slow the loss of SOC stocks during a downward trajectory in rainfall should warrant the allocation of soil carbon credits. The operation of multi-decadal drivers on rainfall variability highlights the limitations of using a static baseline to assess SOC change over time; however, a detailed discussion of this is beyond the scope of this paper.

The current Soil Carbon Method 2021 includes a safeguard designed to account for short-term fluctuations in SOC due to climatic variability. However, we argue that the 25% temporary retention of credits at the first re-measurement after baseline—a reduction from the 50% retention required in the 2018 Method—may not be sufficient to mitigate the risks associated with climatic fluctuations. Additionally, it is important to acknowledge that if SOC levels peak during subsequent measurement periods, there is no provision for temporary retention of credits.

To assess the sufficiency of the 25% temporary discount of carbon credits, we used peer-reviewed literature to determine reasonable bounds for *long-term* SOC sequestration in Australia's grazing systems. A global synthesis of grassland management impact on SOC stocks showed sequestration rates for grazing of 0.28 t C ha^{-1} yr^{-1}, with the largest increases following conversion from cultivation (0.87 t C ha^{-1} yr^{-1}) and sowing legumes (0.66 t C ha^{-1} yr^{-1}) [68]. In Australian grazing systems, SOC sequestration rates of ∼0.1 to 1.2 t C ha^{-1} yr^{-1} have been reported (mostly to 30 cm) [5, 69–72] although when summarised in a meta-analysis

($n = 19$) there was no overall significant impact of grazing stocking strategies on SOC stocks [73].

Within the reported range of SOC gains, consideration was given to the timeframe over which SOC change occurred and the baseline SOC stocks. For example, in the case of Badgery et al. [70], where SOC gains of 1.2 t ha^{-1} yr^{-1} (0-30 cm) were measured, this occurred over the short-term (~5 years) when cropland (with a low SOC baseline) was converted to pasture, where we expect relatively large SOC gains due to prior SOC depletion [74]. Several international studies demonstrate relatively large long-term SOC gains in grazing systems, e.g. the adoption of the adaptive multi-paddock (AMP) grazing method resulted in SOC gains of 0.6 t C ha^{-1} yr^{-1} (0-100 cm) [75] to 2.3 t C ha^{-1} yr^{-1} (0-100 cm) [76]. However, these studies occurred in climates where annual precipitation far exceeds the average rainfall in the soil carbon project areas examined here. The use of international studies to extrapolate expected SOC sequestration rates in Australia must be applied with caution, as it is likely that sequestering SOC under Australia's typically low soil fertility, high temperatures, and highly variable rainfall patterns is more challenging than in temperate climates [32, 77].

Given existing peer-reviewed data for Australian grazing systems, we suggest that long-term (25 years) SOC sequestration gains of ~0.6 t C ha^{-1} yr^{-1} (0-100 cm) represents a realistic upper bound of what is achievable. In contrast, inferred rates of short-term SOC gain (2 to 5 years) from the soil carbon projects issued credits range from 0.7 to 4.8 t C ha^{-1} yr^{-1} with an average of 3 t C ha^{-1} yr^{-1} (Supplement 4b). When comparing these short-term gains to long-term SOC sequestration scenarios (low, medium, and high), the temporary 25% discount appears sufficient if all projects achieve the high-rate best case scenario (0.6 t C ha^{-1} yr^{-1}). However, if projects only achieve the medium long-term scenario (0.3 t C ha^{-1} yr^{-1}), approximately 40% of projects will be over-credited (Figure 7).

Over crediting in the short term, without a clearly defined legislative mechanism for credit payback if carbon storage is not sustained in the long term, poses a significant risk. Although the legislation states that the Government *may* require credit relinquishment, the specifics of this process are not clearly defined. If the Government does not enforce credit payback in cases of over crediting, the integrity of the ACCU Scheme could be compromised, particularly if these credits are used to offset emissions elsewhere. Conversely, if the Government does implement a payback mechanism, it could be extremely challenging to enforce. Therefore, our recommendation is to proactively avoid this situation by ensuring that credits issued are based on conservative and realistic estimates of long-term carbon sequestration.

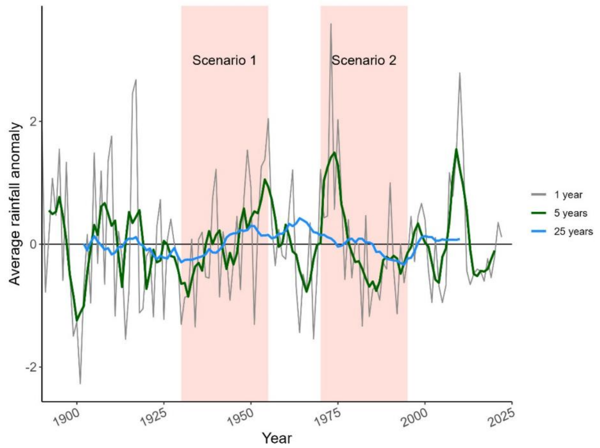

Figure 8. Rainfall temporal variability in pasture growing season (November to March) 1890-2023 represented as standard deviations from the mean rainfall (1890-2023). Rainfall averaged across the main grazing district in Queensland's (~60% of the State's land area carrying over 80% of the State's livestock [67]. 1 year (grey), 5 year (green), and 25 year averages (blue). Boxes represent hypothetical 25 year project crediting periods, with scenario 1 showing a positive trend, and scenario 2 showing a declining trend over 25 years.

Solutions to prevent over crediting in the short-term

We align with the view that soil carbon projects should proceed as the current knowledge base is sufficient to suggest that SOC sequestration is achievable under the right conditions—specifically, with the appropriate combination of soils, climate, and management practices. However, it is crucial to proceed with caution and ensure that credits are tied to management practice changes rather than fluctuations driven by climatic variability.

The most obvious solution to discern the climatic impact on SOC sequestration is pairing the carbon estimation areas within soil carbon project areas with a nearby control site that represents business-as-usual management. This control approach is adopted under the Verra method (VM0042) where control sites must be located within 250 km of project sites in areas with similar climate, soil texture, SOC content, topography, and land use history. However, while conceptually simple, the implementation of a paired measurement site is costly and operationally difficult.

An alternative to a measured control site is to use a national or regional Soil Carbon Monitoring Network to generate longitudinal datasets comprising high-density, within-field sampling data. Such data could be used in SOC biogeochemical models to simulate SOC change attributed to management (i.e. without the climatic signal) and validate the accuracy and robustness of project-level measurements. In Australia, the Terrestrial Ecosystem Network (TERN) [78], in collaboration with the commodity-specific Research and Development Corporations (RDCs) and State and Federal departments, could provide a solid foundation for a sustainable, long-term, and cost-effective monitoring network in agricultural systems.

The design of a robust Soil Carbon Network has been suggested by numerous authors [79–81] and is already being implemented in countries such as New Zealand [82]. In short, intensive research hubs should be established in representative agroecological zones, with high-resolution, continuous measurements of SOC change, demonstrating current and emerging management strategies to optimise SOC, and reduce non-CO_2 greenhouse gases such as N_2O. Micrometeorological flux towers that use the eddy covariance method can provide continuous data on the fluxes of carbon, water, and energy – all critical components of agricultural productivity and profitability. Combining flux tower measurements with management manipulation experiments, satellite remote sensing, direct SOC measurements, and non CO_2 gas monitoring would significantly advance the understanding of SOC and greenhouse gas dynamics and enable the refinement of SOC models to predict the impact of management under different soil types and climatic conditions.

A coordinated Soil Carbon Network using standardised protocols would enable the collection and public dissemination of reference data, promoting more informed decision-making by land managers regarding the potential to implement a registered soil carbon project. Furthermore, such a network would improve the accuracy of Australia's National Greenhouse Gas Inventory and allow progress to be tracked under the National Soil Strategy, the UN Sustainable Development Goals (specifically SDG 15.3), and the FAO's Recarbonisation of Global Agricultural Soils (RECSOIL) program.

The Government should consider establishing "reasonable bounds" for long-term SOC gains resulting from management changes in Australia, as defined by the best available scientific evidence. Any gains above this threshold (e.g. 0.6 t C ha^{-1} yr^{-1} in grazing systems) should be temporarily withheld and only released when sufficient evidence confirms that these rates can be maintained over the long term (e.g. 10 years or two further sampling events). Upper bounds should be defined based on the most relevant scientific evidence for the locality (soil type and climate) and land-use system of the soil carbon project. These bounds can be revised if new evidence emerges that supports higher long-term SOC sequestration rates.

Defining "reasonable bounds" for SOC gains would allow the Government to compare reported SOC gains with those measured in a similar agroecological region and scrutinise what may be excessive claims of SOC sequestration. For example, SOC gains of up to 8.3 t C ha^{-1} yr^{-1} have been reported (Supplement 4a and b), which is unrealistic given that plant productivity – both above and below ground i.e. net primary production (NPP) – sets an upper limit on potential carbon inputs to the soil system [6]. Considering that the average NPP of the carbon project areas was 10.5 t C ha^{-1} yr^{-1} in 2022 (as determined by MODIS-NPP product – see methods), SOC gains of 8 t C ha^{-1} yr^{-1} would imply that ∼80% of fixed carbon was converted to SOC. Similarly, ERF 105067, which experienced pasture dieback and drought during the measurement period [83], has been credited for SOC gains ∼3.5 t C ha^{-1} yr^{-1}, equating to an NPP-to-SOC conversion of ∼50% (annualised SOC gain/average annual NPP). In contrast, scientific studies demonstrate a biomass-to-SOC conversion of around 10 to 30% [8, 84–86] with the research trial presented in this paper showing an NPP-to-SOC conversion of ∼11%. The remaining biomass, not converted to SOC, is either consumed by microbial decomposers and released as CO_2 through respiration (∼two-thirds%) [56,87–90], grazed and metabolised by herbivores (with some carbon returned to the soil *via* excreta), leached from the soil and transported off-site, lost through fire, or left standing as biomass or litter. Therefore, given the high rates of reported SOC gains and NPP-to-SOC conversions, we posit that there may be issues related to the application of the current Soil Carbon Method, such as incomplete removal of root biomass and inorganic carbon at depth, as well as the improper use of spectroscopic techniques. However, without public access to SOC project datasets to scrutinise the data, these concerns remain speculative.

The length of the measurement period, which can currently occur on an annual basis, should be adjusted to at least five years to reduce the impact of inter-annual rainfall variability on SOC gains. This is pertinent to the issuance of credits under ERF 143770 and ERF 158470, which were issued credits over a short time frame (2 years), whereby SOC was baselined during average rainfall conditions and re-measured during "peak" rainfall conditions (Supplement 5). The soil carbon projects that measured over a 5 year period were able to capture inter-annual variation to a greater extent.

Extending the current measurement period to a required 5-year timeframe would also reduce the likelihood of reporting false SOC gains. This issue arises when trying to detect relatively small SOC increases over a short period of time against a background of large SOC stocks that exhibit high spatial and temporal variability [79,81,91,92]. Management practices are expected to increase SOC stocks 0.1 to 1.2 t C ha^{-1} [5,71], whereas background SOC stocks in many soils, just in the top 0-30 cm, can range from 30 to 90 t C ha^{-1}. Therefore, measurement intervals of 5 years or more are generally required to detect statistically significant cumulative SOC stock changes (with a moderate sampling density), given that potential annual SOC stock changes are often less than 1% of the existing stocks [81].

The Government could also consider other measures to increase the conservativeness of short-term crediting, some of which were removed from a previous iteration of the Soil Carbon Method (Measurement of Soil Carbon Sequestration in Agricultural Systems Methodology Determination, 2018). For example, in an earlier version of the method, 50% of the ACCUs generated at the first sampling period were withheld and only returned when a second sampling round demonstrated that the sequestration had been maintained. The Government could also revert to the requirement of regressing at least three sampling events, rather than measuring between two points in time, to "smooth out" SOC peaks and troughs and consider the timing of SOC re-measurement events. For instance, re-sampling events should occur in the same season and if monthly rainfall has been above the long-term average for six consecutive months, re-measurement should be delayed until rainfall returns to levels more representative of the long-term average. Finally, the Government could consider transitioning to a practice-based payment system (where farmers are rewarded for implementing practice change), rather than the current performance output-based system, to simplify implementation and reduce costs [93,94].

Conclusion

We acknowledge the importance of a high-integrity carbon credit scheme, including soil carbon credits, in the transition to lower national greenhouse gas emissions. However, issuing carbon credits for short-term SOC gains – gains that our analysis suggests are largely transient – poses a significant risk to both farmers and the carbon industry, potentially undermining the credibility of the crediting scheme. Until SOC models have been adequately calibrated to account for management change in the Australian grazing context (using data from a coordinated Soil Carbon Network) we propose two key amendments to the current Soil Carbon Method 2021, which should also be considered by other soil carbon crediting schemes. Firstly, the minimum measurement period should be extended to at least five years to reduce the impact of interannual rainfall variability on SOC accumulation and reduce the risk of reporting false SOC gains. Secondly, short-term crediting should be based on reasonable bounds for expected long-term SOC sequestration informed by the best available science, above which credits are temporarily withheld. Ultimately, ensuring the success and integrity of soil carbon credits requires large-scale, collaborative efforts among researchers, Carbon Service Providers, farmers and other stakeholders. The Government should play a key role in overseeing the transparent compilation of data and evidence to ensure that soil carbon credits achieve their intended goal of mitigating climate change.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This manuscript was compiled from data generated in a Meat and Livestock Australia funded project P.PSH.2104.

Data availability statement

The authors confirm that the data supporting the findings of this study are available within the article and its supplementary material.

References

1. Bureau of Meteorology. Recent and historical rainfall maps [Internet]; 2023. [cited 2023 Dec 2]. Available from: http://www.bom.gov.au/climate/maps/rainfall/?variable=rainfall&map=totals&period=daily&region=nat&year=2024&month=02&day=07.
2. ERAC. Emissions Reduction Assurance Committee Information Paper: committee considerations for

interpreting the Emissions Reduction Fund's offsets integrity standards. Version 2.0.; 2021. Available from: extension://efaidnbmnnnibpcajpcglclefindmkaj/https://www.dcceew.gov.au/sites/default/files/documents/erac-information-paper-offsets-integrity-standards.pdf.
3. Scharlemann JPW, Tanner EVJ, Hiederer R, et al. Global soil carbon: understanding and managing the largest terrestrial carbon pool. Carbon Manage. 2014;5(1):81–91. doi:10.4155/cmt.13.77.
4. Jones C, Falloon P. Baveye PC, Laba M, Mysiak J, editors. Sources of uncertainty in global modelling of future soil organic carbon storage. In: Baveye PC, Laba M, Mysiak J, editors. Uncertainties in environmental modelling and consequences for policy making. NATO science for peace and security series C: Environmental security. Dordrecht: Springer. doi:10.1007/978-90-481-2636-1_13
5. Sanderman J, Farquharson R, Baldock J. Soil Carbon Sequestration Potential: a review for Australian agriculture. A Report Prepared for Department of Climate Change and Energy Efficiency; CSIRO Report; 2010.
6. Janzen HH, van Groenigen KJ, Powlson DS, et al. Photosynthetic limits on carbon sequestration in croplands. Geoderma. 2022;416:115810. doi:10.1016/j.geoderma.2022.115810.
7. Cotrufo MF, Soong JL, Horton AJ, et al. Formation of soil organic matter via biochemical and physical pathways of litter mass loss. Nature Geosci. 2015;8(10):776–779. doi:10.1038/ngeo2520.
8. Castellano MJ, Mueller KE, Olk DC, et al. Integrating plant litter quality, soil organic matter stabilization, and the carbon saturation concept. Glob Chang Biol. 2015;21(9):3200–3209. doi:10.1111/gcb.12982.
9. Minasny B, Malone BP, McBratney AB, et al. Soil carbon 4 per mille. Geoderma. 2017;292:59–86. doi:10.1016/j.geoderma.2017.01.002.
10. Baveye PC, Berthelin J, Tessier D, et al. The "4 per 1000" initiative: a credibility issue for the soil science community? Geoderma. 2018;309:118–123. doi:10.1016/j.geoderma.2017.05.005.
11. Chabbi A, Lehmann J, Ciais P, et al. Aligning agriculture and climate policy. Nature Clim Change. 2017;7(5):307–309. doi:10.1038/nclimate3286.
12. Poulton P, Johnston J, Macdonald A, et al. Major limitations to achieving "4 per 1000" increases in soil organic carbon stock in temperate regions: evidence from long-term experiments at Rothamsted Research, United Kingdom. Glob Chang Biol. 2018;24(6):2563–2584. doi:10.1111/gcb.14066.
13. Rumpel C, Amiraslani F, Chenu C, et al. The 4p1000 initiative: opportunities, limitations and challenges for implementing soil organic carbon sequestration as a sustainable development strategy. Ambio. 2020;49(1):350–360. doi:10.1007/s13280-019-01165-2.
14. White RE. The role of soil carbon sequestration as a climate change mitigation strategy: an Australian case study. Soil Syst. 2022;6(2):46–60. doi:10.3390/soilsystems6020046.
15. Henry B, Dalal R, Harrison MT, et al. 2022 Creating frameworks to foster soil carbon sequestration (pp. 767–808).
16. Paustian K, Lehmann J, Ogle S, et al. Climate-smart soils. Nature. 2016;532(7597):49–57. doi:10.1038/nature17174.
17. Stockmann U, Adams MA, Crawford JW, et al. The knowns, known unknowns and unknowns of sequestration of soil organic carbon. Agricult Ecosyst Environ. 2013;164:80–99. doi:10.1016/j.agee.2012.10.001.
18. Gray JM, Bishop TFA, Wilson BR. Factors controlling soil organic carbon stocks with depth in Eastern Australia. Soil Sci Soc Am J. 2015;79(6):1741–1751. doi:10.2136/sssaj2015.06.0224.
19. Hobley E, Wilson B, Wilkie A, et al. Drivers of soil organic carbon storage and vertical distribution in Eastern Australia. Plant Soil. 2015;390(1-2):111–127. doi:10.1007/s11104-015-2380-1.
20. Parton W, Morgan J, Smith D, et al. Impact of precipitation dynamics on net ecosystem productivity. Glob Chang Biol. 2012;18(3):915–927. doi:10.1111/j.1365-2486.2011.02611.x.
21. Rabbi SMF, Tighe M, Delgado-Baquerizo M, et al. Climate and soil properties limit the positive effects of land use reversion on carbon storage in Eastern Australia. Sci Rep. 2015;5(1):17866. doi:10.1038/srep17866.
22. Wiesmeier M, Urbanski L, Hobley E, et al. Soil organic carbon storage as a key function of soils - A review of drivers and indicators at various scales. Geoderma. 2019;333:149–162. doi:10.1016/j.geoderma.2018.07.026.
23. Del Grosso S, Parton W, Stohlgren T, et al. Global potential net primary production predicted from vegetation class, precipitation, and temperature. Ecology. 2008;89(8):2117–2126. doi:10.1890/07-0850.1.
24. Del Grosso SJ, Parton WJ, Derner JD, et al. Simple models to predict grassland ecosystem C exchange and actual evapotranspiration using NDVI and environmental variables. Agric Meteorol. 2018;249:1–10. doi:10.1016/j.agrformet.2017.11.007.
25. McKeon GM, Day KA, Howden SM, et al. Northern Australian savannas: management for pastoral production. Savanna Ecol Manag: Austr Perspect Intercontinental Comparisons. 1990;17(4/5):355–372. doi:10.2307/2845365.
26. Nicholls N. The El Nifio/Southern Oscillation and Australian vegetation. Vegetation. 1991;91(1-2):23–36. doi:10.1007/BF00036045.
27. Power S, Casey T, Folland C, et al. Inter-decadal modulation of the impact of ENSO on Australia. Clim Dyn. 1999;15(5):319–324. doi:10.1007/s003820050284.
28. Power S, Haylock M, Colman R, et al. The predictability of interdecadal changes in ENSO activity and ENSO teleconnections. J Clim. 2006;19:4755–4771.
29. Meneghini B, Simmonds I, Smith IN. Association between Australian rainfall and the Southern Annular Mode. Intl J Climatol. 2007;27(1):109–121. doi:10.1002/joc.1370.
30. Meyers G, McIntosh P, Pigot L, et al. The years of El Niño, La Niña and interactions with the tropical Indian Ocean. In: journal of Climate. 2007;20(13):2872–2880. doi:10.1175/JCLI4152.1.
31. Risbey JS, Pook MJ, McIntosh PC, et al. On the remote drivers of rainfall variability in Australia. Mon Weather

Rev. 2009;137(10):3233–3253. doi:10.1175/2009MWR2861.1.

32. Love G. Impacts of climate variability on regional Australia. In: Nelson GL, editors. Outlook 2005. Conference proceedings, climate session papers. Canberra, ACT, Australia: Australian Bureau and Resource Economics; 2005, p. 10–19.
33. Australian Government. Clean Energy Regulator: emission Reduction Fund Project Register [Internet]; 2023. [cited 2024 Mar 14]. Available from: https://www.cleanenergyregulator.gov.au/ERF/project-and-contracts-registers/project-register.
34. Chen M, Parton WJ, Hartman MD, et al. Assessing precipitation, evapotranspiration, and NDVI as controls of U.S. Great Plains Plant Production. Ecosphere. 2019;10(10):1–17.
35. Edirisinghe A, Hill M, Donald G, et al. Quantitative mapping of pasture biomass using satellite imagery. Int J Remote Sens. 2011;32(10):2699–2724.
36. Li S, XL, JY, LX, GX High-quality vegetation index product generation: a review of NDVI time series reconstruction techniques. Int J Appl Earth Observ Geoinform. 2021;105(5):1–18.
37. SILO. Australian Climate Database, Queensland Department of Environment and Science; 2021.
38. Grace L, Manca F, Mitchell E, et al. iLEAPS-OzFlux Joint Conference; 2023 Ecosystem carbon balance of a subtropical grazing grassland during drought recovery, EC-derived estimates compared to an inventory approach. Auckland, New Zealand.
39. Robertson BL, Brown JA, Mcdonald T, et al. BAS: balanced Acceptance Sampling of Natural Resources. Biometrics. 2013;69(3):776–784. doi:10.1111/biom.12059.
40. Rayment G, Lyons D. Soil Chemical Methods - Australasia. Australasia: CSIRO Publishing; 2010.
41. Running SW, Nemani RR, Heinsch FA, et al. A continuous satellite-derived measure of global terrestrial primary production. BioScience. 2004;54:547–560. doi:10.1641/0006-3568(2004)054[0547:ACSMOG]2.0.CO;2.
42. Minasny B, Arrouays D, Cardinael R, et al. Current NPP cannot predict future soil organic carbon sequestration potential. Comment on "Photosynthetic limits on carbon sequestration in croplands. Geoderma. 2022;424:115975. doi:10.1016/j.geoderma.2022.115975.
43. Bisutti I, Hilke I, Raessler M. Determination of total organic carbon - An overview of current methods. Trends Anal Chem. 2004;23(10-11):716–726. doi:10.1016/j.trac.2004.09.003.
44. Bhunia GS, Kumar Shit P, Pourghasemi HR. Soil organic carbon mapping using remote sensing techniques and multivariate regression model. Geocarto Int. 2019;34(2):215–226. doi:10.1080/10106049.2017.1381179.
45. Kunkel VR, Wells T, Hancock GR. Modelling soil organic carbon using vegetation indices across large catchments in eastern Australia. Sci Total Environ. 2022;817:152690. doi:10.1016/j.scitotenv.2021.152690.
46. Wang H, Wu J, Guang L, et al. Effects of extreme rainfall frequency on soil organic carbon fractions and carbon pool in a wet meadow on the Qinghai-Tibet Plateau. Ecol Indic. 2023;146.
47. Tonitto C, Woodbury PB, McLellan EL. Defining a best practice methodology for modeling the environmental performance of agriculture. Environmental Science and Policy. 2018;87(87):64–73. Vol. doi:10.1016/j.envsci.2018.04.009.
48. Oldfield EE, Lavallee JM, Blesh J, et al. Greenhouse gas mitigation on croplands: clarifying the debate on knowns, unknowns and risks to move forward with effective management interventions. Carbon Manage. 2024;15(1):1–11. doi:10.1080/17583004.2024.2365896.
49. Lehmann J, Kleber M. The contentious nature of soil organic matter. Nature. 2015;528(7580):60–68. doi:10.1038/nature16069.
50. Bai Y, Cotrufo MF. Grassland soil carbon sequestration: current understanding, challenges, and solutions. Science. 2022;377(6606):603–608. doi:10.1126/science.abo2380.
51. Stewart CE, Paustian K, Conant RT, et al. Soil carbon saturation: concept, evidence and evaluation. Biogeochemistry. 2007;86(1):19–31. doi:10.1007/s10533-007-9140-0.
52. Viscarra Rossel RA, Webster R, Zhang M, et al. How much organic carbon could the soil store? The carbon sequestration potential of Australian soil. Glob Chang Biol. 2023;30(1):e17053.
53. Georgiou K, Jackson RB, Vindušková O, et al. Global stocks and capacity of mineral-associated soil organic carbon. Nat Commun. 2022;13(1):3797. doi:10.1038/s41467-022-31540-9.
54. Blagodatskaya E, Kuzyakov Y. Mechanisms of real and apparent priming effects and their dependence on soil microbial biomass and community structure: critical review. Biol Fertil Soils. 2008;45(2):115–131. ():doi:10.1007/s00374-008-0334-y.
55. Schiedung M, Don A, Beare MH, et al. Soil carbon losses due to priming moderated by adaptation and legacy effects. Nat Geosci. 2023;16(10):909–914. doi:10.1038/s41561-023-01275-3.
56. Mitchell E, Scheer C, Rowlings D, et al. Amount and incorporation of plant residue inputs modify residue stabilisation dynamics in soil organic matter fractions. Agric Ecosyst Environ. 2018;256:82–91. ():doi:10.1016/j.agee.2017.12.006.
57. Hungate BA, Dukes JS, Shaw MR, et al. Nitrogen and Climate Change. Science. 2003;302(5650):1512–1513. doi:10.1126/science.1091390.
58. Lugato E, Leip A, Jones A. Mitigation potential of soil carbon management overestimated by neglecting N_2O emissions. Nature Clim Change. 2018;8(3):219–223. doi:10.1038/s41558-018-0087-z.
59. Guenet B, Gabrielle B, Chenu C, et al. Can N_2O emissions offset the benefits from soil organic carbon storage? Glob Chang Biol. 2021;27(2):237–256. ():doi:10.1111/gcb.15342.
60. Grace P, De Rosa D, Shcherbak I, et al. Revised emission factors for estimating direct nitrous oxide emissions from nitrogen inputs in Australia's agricultural production systems: a meta-analysis. Soil Res. 2023;62(1). doi:10.1071/SR23070.

61. Badgery WB, Mwendwa JM, Anwar MR, et al. Unexpected increases in soil carbon eventually fell in low rainfall farming systems. J Environ Manage. 2020; 261:110192. doi:10.1016/j.jenvman.2020.110192.
62. Chen J, Elsgaard L, van Groenigen KJ, et al. Soil carbon loss with warming: new evidence from carbon-degrading enzymes. Glob Chang Biol. 2020;26(4): 1944–1952. doi:10.1111/gcb.14986.
63. Crowther TW, Todd-Brown KEO, Rowe CW, et al. Quantifying global soil carbon losses in response to warming. Nature. 2016;540(7631):104–108. doi:10.1038/nature20150.
64. Grace PR, Post WM, Hennessy K. The potential impact of climate change on Australia's soil organic carbon resources. Carbon Balance Manag. 2006;1(1):14. doi: 10.1186/1750-0680-1-14.
65. Luo Z, Eady S, Sharma B, et al. Mapping future soil carbon change and its uncertainty in croplands using simple surrogates of a complex farming system model. Geoderma. 2019;337:311–321. doi:10.1016/j.geoderma.2018.09.041.
66. Viscarra Rossel RA, Zhang M, Behrens T, et al. A warming climate will make Australian soil a net emitter of atmospheric CO2. Npj Clim Atmos Sci. 2024; 7(1). doi:10.1038/s41612-024-00619-z.
67. Clean Energy Regulator. Understanding your soil carbon project. Emissions Reduction Fund simple method guide for soil carbon projects registered under the Carbon Credits (Carbon Farming Initiative - Estimation of Soil Organic Carbon Sequestration using Measurement and Models) Methodology Determination 2021 [Internet]; 2023 [cited 2024 Mar 19]. Available from: https://www.cleanenergyregulator.gov.au/DocumentAssets/Documents/Understanding%20your%20soil%20carbon%20project%20-%20Simple%20method%20guide.pdf.
68. Conant RT, Cerri CEP, Osborne BB, et al. Grassland management impacts on soil carbon stocks: a new synthesis. Ecol Appl. 2017;27(2):662–668. doi:10.1002/eap.1473.
69. Badgery WB, Simmons AT, Murphy BW, et al. The influence of land use and management on soil carbon levels for crop-pasture systems in Central New South Wales, Australia. Agric Ecosyst Environ. 2014; 196:147–157. doi:10.1016/j.agee.2014.06.026.
70. Badgery W, Murphy B, Cowie A, et al. Soil carbon market-based instrument pilot – the sequestration of soil organic carbon for the purpose of obtaining carbon credits. Soil Res. 2021;59(1):12–23. doi:10.1071/SR19331.
71. Gray JM, Wang B, Waters CM, et al. Digital mapping of soil carbon sequestration potential with enhanced vegetation cover over New South Wales, Australia. Soil Use Manag. 2022;38(1):229–247. doi:10.1111/sum.12766.
72. Debney A, Lobry de Bruyn L. The effect of grazing management and legumes on soil organic carbon stocks in pastoral systems relevant to the Australian Carbon Credit Unit Scheme: a critical review. Soil Res. 2024;62(2). doi:10.1071/SR23118.
73. McDonald SE, Badgery W, Clarendon S, et al. Grazing management for soil carbon in Australia: a review. J Environ Manage. 2023;347:119146. doi:10.1016/j.jenvman.2023.119146.
74. Muleke A, Harrison MT, Eisner R, et al. Clarifying confusions over carbon conclusions: antecedent soil carbon drives gains realised following intervention. Global Environmental Change Advances. 2023;1: 100001. doi:10.1016/j.gecadv.2023.100001.
75. Mosier S, Apfelbaum S, Byck P, et al. Adaptive multi-paddock grazing increases soil carbon and nitrogen stocks and stabilization through mineral association in southeastern U.S. grazing lands. J Environ Manage. 2021;288:112409. doi:10.1016/j.jenvman.2021.112409.
76. Rowntree JE, Stanley PL, Maciel ICF, et al. Ecosystem impacts and productive capacity of a multi-species pastured livestock system. Front Sustain Food Syst. 2020;4:544984. doi:10.3389/fsufs.2020.544984.
77. Meyer RS, Cullen BR, Whetton PH, et al. Potential impacts of climate change on soil organic carbon and productivity in pastures of south eastern Australia. Agric Syst. 2018;167:34–46. doi:10.1016/j.agsy.2018.08.010.
78. Karan M, Liddell M, Prober SM, et al. The Australian SuperSite Network: a continental, long-term terrestrial ecosystem observatory. Sci Total Environ. 2016; 568:1263–1274. Oct 15 doi:10.1016/j.scitotenv.2016.05.170.
79. Smith P, Soussana J-F, Angers D, et al. How to measure, report and verify soil carbon change to realize the potential of soil carbon sequestration for atmospheric greenhouse gas removal. Glob Chang Biol. 2020;26(1):219–241. doi:10.1111/gcb.14815.
80. Novick K, Metzger S, Anderegg W, et al. Informing nature-based climate solutions for the United States with the best-available science. Glob Chang Biol. 2022;28(12):3778–3794. doi:10.1111/gcb.16156.
81. Paustian K, Collier S, Baldock J, et al. Quantifying carbon for agricultural soil management: from the current status toward a global soil information system. Carbon Manage. 2019;10(6):567–587. Vol. 10, doi:10.1080/17583004.2019.1633231.
82. Whitehead D, McNeill SJE, Mudge PL. Regional and national changes in soil carbon stocks with land-use change from 1990 to 2016 for New Zealand. Reg Environ Change. 2021;21(4):121–129. doi:10.1007/s10113-021-01837-4.
83. Carbon Link. First at-scale soil carbon projects show overwhelming benefit for grazing industries. Media Release. 2023. Available from: https://carbonlink.com.au/wp-content/uploads/CarbonLink-ACCUs-Flow-Media-Release-June-2023-1.pdf.
84. Mitchell E, Scheer C, Rowlings DW, et al. The influence of above-ground residue input and incorporation on GHG fluxes and stable SOM formation in a sandy soil. Soil Biol Biochem. 2016;101:104–113. doi: 10.1016/j.soilbio.2016.07.008.
85. Parton W, Silver WL, Burke IC, et al. Global scale similarities in nitrogen release patterns during long-term decomposition. Science. 2007;315(5810):361–364. doi: 10.1126/science.1134853.
86. Villarino SH, Pinto P, Jackson RB, et al. Plant rhizodeposition: a key factor for soil organic matter

formation in stable fractions. Sci Adv. 2021;7(16): 3176. doi:10.1126/sciadv.abd3176.
87. Mitchell E. The fate of above-ground carbon inputs as stable SOM and GHGs [dissertation]. Queensland University of Technology e-prints; 2020.
88. Mitchell E, Scheer C, Rowlings D, et al. Important constraints on soil organic carbon formation efficiency in subtropical and tropical grasslands. Glob Chang Biol. 2021;27(20):5383–5391. doi:10.1111/gcb.15807.
89. Mitchell E, Scheer C, Rowlings D, et al. Trade-off between 'new' SOC stabilisation from above-ground inputs and priming of native C as determined by soil type and residue placement. Biogeochemistry. 2020; 149(2):221–236. doi:10.1007/s10533-020-00675-6.
90. Powlson DS, Neal AL. Influence of organic matter on soil properties: by how much can organic carbon be increased in arable soils and can changes be measured?. In Proceedings of the International Fertiliser Society (Vol. 862, pp. 1-32). International Fertiliser Society (IFS); 2021.
91. Stanley P, Spertus J, Chiartas J, et al. Valid inferences about soil carbon in heterogeneous landscapes. Geoderma. 2023;430:116323. doi:10.1016/j.geoderma.2022.116323.
92. Slessarev EW, Mayer A, Kelly C, et al. Initial soil organic carbon stocks govern changes in soil carbon: reality or artifact? Glob Chang Biol. 2023;29(5):1239–1247. doi:10.1111/gcb.16491.
93. Batjes NH, Ceschia E, Heuvelink GBM, et al. Towards a modular, multi-ecosystem monitoring, reporting and verification (MRV) framework for soil organic carbon stock change assessment. Carbon Manag. 2024;15(1): 2410812.
94. World Bank. Soil Organic Carbon MRV Sourcebook Agricultural Landscapes. Washington, DC: World Bank; 2021.