Ecological Indicators 154 (2023) 110614

Contents lists available at ScienceDirect

Ecological Indicators

journal homepage: www.elsevier.com/locate/ecolind

Evaluation of remotely sensed imagery to monitor temporal changes in soil organic carbon at a long-term grazed pasture trial

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ARTICLE INFO

Keywords:
Soil organic carbon
Long-term monitoring
Temporal changes
Remote sensing
Cover

ABSTRACT

Temporal variation of soil organic carbon (SOC) is driven by land use/management practice, ecosystem conditions and climatic variation. Robust quantification of changes in SOC that is cost-effective and provides a statistical assessment of uncertainty is challenging, particularly in the face of large spatial variability and slow soil SOC changes. Remote-sensing indicators of above-ground vegetation provide some indication of the amount of fresh organic material being supplied to the soil. Although, because of the time taken for this organic material to decay and become incorporated into the soil, there will be a lag between the changes in the indicator of vegetation growth and the resulting changes in SOC. In this work, we investigate how a remotely sensed indicator of vegetation cover can be used with a lag period to predict or indicate changes in SOC for grazed pasture sites at a long-term monitoring study, which has been monitoring soil under different land uses for over forty years. We assessed how well this worked for indicating the SOC changes for different depths in the soil profile. Results suggested that a lagged remotely sensed vegetation cover—the average cover of the two preceding years—provides some indication of SOC changes for the 0–10 cm soil depth, but changes for deeper soil depths were not well predicted. Further, we investigated the potential of using soil data from a point-in-time spatial dataset (e.g. data from a baseline sampling round) to calibrate a relationship between the remotely sensed cover and SOC, which can then be applied to predict or indicate the temporal variation of SOC. Results showed this approach gave large prediction errors, likely because the temporal variation (at a fixed point in space) and spatial variation (for a fixed point in time) of SOC that is predictable by cover differences are not interchangeable.

1. Introduction

Soil organic carbon (SOC) is an important indicator of the soil's many functions, its fertility and structure, and its ability to support healthy plant and animal life (Stockmann et al., 2013). Best management practices have the potential to restore some of the SOC that has been lost since the clearing of native vegetation, to improve agricultural practices and ecosystem services, and to sequester atmospheric CO_2 (Smith et al., 2008; Lal et al., 2018).

Changes in SOC through time are the result of land use/management practice, ecosystem conditions and climatic variation (Stockmann et al., 2013). Robust quantification of change in SOC that is cost-effective and provides a statistical assessment of uncertainty is challenging; this is particularly the case in the presence of large spatial variability and slow SOC gains (Smith et al, 2020; Paustian et al., 2019; Stanley et al., 2023). For these reasons, data from universally available sources—such as freely available remote sensing imagery—that can provide an indication of temporal changes (or spatial differences) at landscape scales can help inform more effective decision making and reduce the costs associated with measurement of SOC (Ladoni et al., 2010; Croft at al., 2012; Paustian et al., 2019).

One place where remotely sensed data (from Earth-observing satellites) could assist in decision making would be the 'where to sample' question. Spatial covariates derived from remote sensing data—and/or from other management information or maps of environmental covariates—can help in the design of sampling strata to estimate spatial means more efficiently (de Gruijter et al., 2006; de Gruijter et al., 2016). Many studies have utilised remote sensing data to better model the

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https://doi.org/10.1016/j.ecolind.2023.110614
Received 11 February 2023; Received in revised form 3 July 2023; Accepted 4 July 2023
Available online 7 July 2023
1470-160X/

spatial and spatio-temporal variation of SOC (Yang et al., 2009; Page et al., 2013; Wilson et al., 2017; Venter et al., 2021). However, relationships between remote-sensing variables and the temporal variation of SOC can be very site-specific (Croft et al., 2012), making it difficult to build broadly applicable *predictive models* of the spatio-temporal variation of SOC. Nonetheless, site-specific *indicators* of temporal changes can still be useful for informing the likelihood of increases or decreases in SOC. This can help to improve understanding of practices that are having a positive impact on SOC changes and assist decision making for policy makers and for landholders. See (Fig. 1).

Major factors that influence SOC stock changes over time in agricultural systems are the impacts of management and climatic changes, through their effects on the input of C from plant litter and roots (and also on the removal through harvested crops and losses due to tillage-induced oxidation; Sokol et al., 2022). Therefore, remote-sensing imagery of above-ground vegetation provides some indication of the amount of fresh organic material being supplied to the soil (Wilson et al., 2017; Kunkel et al., 2022). Although, because of the time taken for this organic material to decay and become incorporated into the soil, there will be a lag between the changes in the indicator of vegetation growth (as measured by remote-sensing data) and the resulting changes in SOC (e.g. Kunkel et al., 2022). For example, Kunkel et al. (2022) found that remotely sensed vegetation index data captured immediately prior to the time of sampling gave a poor correlation with the spatial variation of SOC in grazing land of Eastern Australia. They found that lagged averages of remotely sensed indices correlated better with the *spatial* variation of SOC (in their case, retrospective cumulative average for the normalised difference vegetation index, NDVI, and enhanced vegetation index, EVI). The potential of such lagged remotely sensed vegetation indicators to represent the *temporal* variation of SOC provides the context for the current study. Here we investigate the potential of remote sensing data based on the seasonal fractional cover product (SFC; Joint Remote Sensing Research Program, 2022; https://portal.tern.org.au/seasonal-fractional-cover-australia-coverage-23880/23880) to indicate temporal changes in SOC in improved grazed pastures. This land use represents a significant proportion of the landscape in Queensland, Australia, where this study is focussed, and therefore a better ability to model SOC changes would have widespread applications and benefits.

Valuable understanding of the long-term dynamics of soil and its functions can be gained from long-term monitoring studies (Richter et al., 2007). One such valuable dataset capturing long-term changes in soil is the Brigalow Catchment Study, in Queensland, Australia, where selected sites under different land uses have been sampled since the land was originally cleared in the early 1980s (Cowie et al., 2007; Thornton and Shrestha, 2021). Of particular interest for use in the current work, the study has monitored changes in SOC for long-term grazed pastures sites, offering the opportunity to compare those changes with the temporal variation of the remotely sensed fractional cover data. The repeated sampling of the same fixed points in space means that the resulting dataset can be used to investigate specifically the temporal variation of SOC, without the confounding effects of short-range spatial variation that can be challenging in space-for-time studies (Richter et al., 2007). In this work, we consider the relationship between the remotely sensed fractional cover data and the temporal variation of SOC. We investigate how the cover data can be used with a lag to represent the decay of the plant material and its incorporation into the soil as SOC, and how well this might be expected to predict or indicate changes in SOC for other monitored sites at the study.

This study focused specifically on the ability of remote sensing data for indicating temporal changes in SOC. The aims of this work were:

(i) To use the Brigalow Catchment Study long-term monitoring dataset to compare and assess simple remote sensing indicators of temporal changes in SOC in grazed pastures for different soil depths.
(ii) If any promising indicators of temporal changes in SOC were to be found, then investigate whether their relationship with SOC can be calibrated using data from a point-in-time spatial dataset (e.g., data from a baseline sampling round), which can then be applied to predict the temporal variation of SOC.

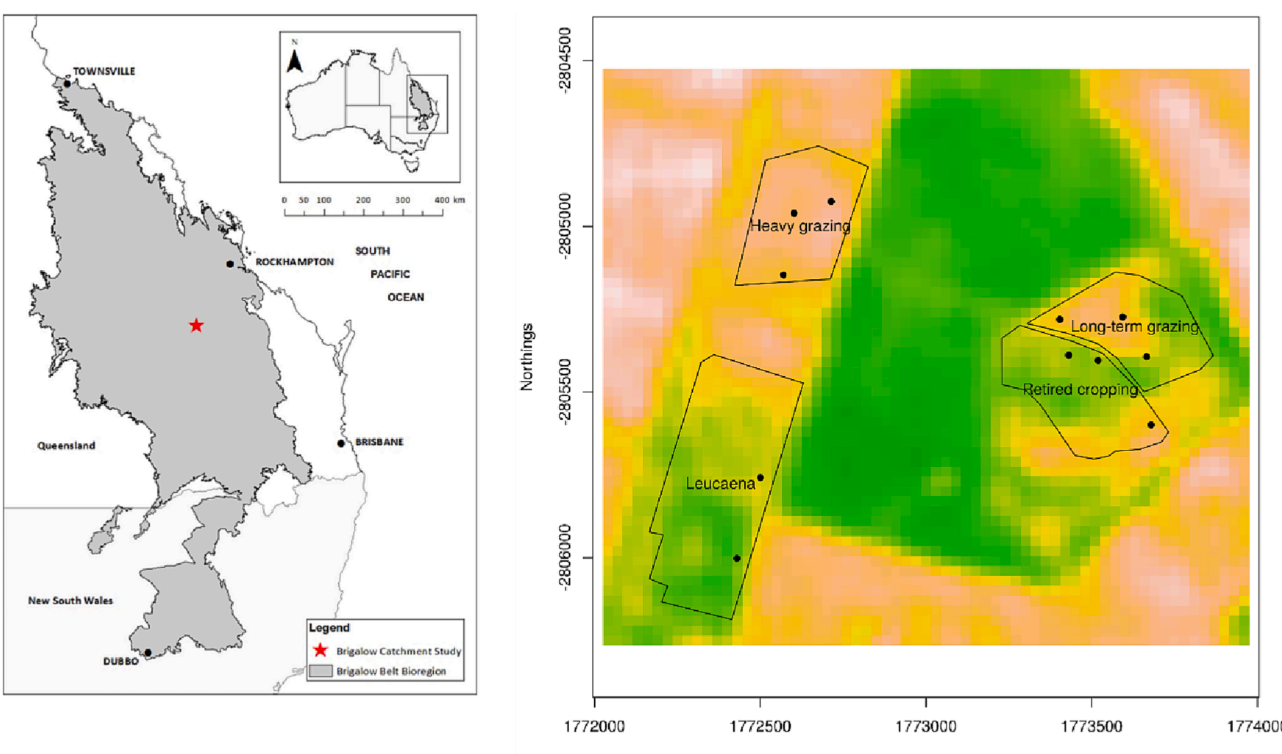

Fig. 1. The location of the Brigalow Catchment Study in Queensland, Australia, and the soil monitoring sites in the four catchments used in this study.

2. Methods

2.1. Soil data: Brigalow catchment study

The Brigalow Catchment Study (BCS) was established to quantify the impact of land development for agriculture on hydrology, productivity and resource condition (http://www.brigalowcatchmentstudy.com/BCSbackground.html; Cowie et al., 2007; Thornton and Shrestha, 2021). It is located near Theodore, Central Queensland (24.81 °S, 149.80 °E), and is representative of the Brigalow Belt Bioregion. It has a semi-arid and subtropical climate, with a mean annual rainfall of 650 mm. The study site in its native condition was dominated by brigalow (*Acacia harpophylla*), either in a monoculture or in association with other species, such as belah (*Casuarina cristata*) and Dawson River blackbutt (*Eucalyptus cambageana*). This association of vegetation is colloquially known as brigalow scrub. The soils are an association of Vertosols, Dermosols, and Sodosols (Australian Soil Classification; Isbell, 2002), and the slope of the land varies across the site between 1.8 and 3.5%.

The study site consists of three catchments (a brigalow native vegetation, a grazed pasture, and a cropping catchment) that have been monitored to determine hydrological relationships for nearly 60 years, and with soil sampling sites within those catchments monitored for over forty years. The native vegetation catchment was retained in virgin condition and represents an uncleared control treatment with which to compare the developed catchments. The grazed pasture catchment was cleared in the early 1980s and planted with buffel grass (*Cenchrus ciliaris*), an improved pasture species, and has been conservatively grazed since then. The cropping catchment was also cleared in the early 1980s and cropped with wheat, barley, sorghum, or chickpeas from 1984 until 2010, when it was planted with butterfly pea as a pasture and conservatively grazed. The study also has two other grazing catchments that have been established more recently, added to the study in 2010: a leucaena improved grass pasture and a heavily grazed improved grass pasture.

We focused on the catchments under grazing management, with the aim of selecting and assessing remote sensing data products to model the temporal variation in SOC. We refer to these as the long-term grazing catchment (LTG), the retired cropping catchment (RC), the Leucaena catchment (L) and the heavily grazed catchment (HG).

Within each of these five catchments, three monitoring sites were established. Soil sampling of the three long-term monitoring sites was undertaken in 1981 (representing a pre-clearing baseline), 1983, 1985, 1987, 1990, 1994, 1997, 2000, 2008, 2014, 2018 and 2022. Soil sampling of the recently established sites was undertaken in 2014, 2018 and 2022 (Leucaena) and in 2018 and 2022 (heavily grazed).

At each monitoring site (a 20-m × 20-m square), five soil samples were taken down to 40 cm and divided into four 10-cm increments, and the five samples bulked for each respective depth. Intact cores were used to calculate bulk densities, and the bulked samples analysed for SOC concentrations using TruMac CN (LECO Corporation, St Joseph, MI, USA). The LECO SOC data for samples up to and including 2014 were measured prior to the current project; as part of this current project, the retained samples from 2018 and the collected samples from 2022 were analysed by LECO. Full sampling and analysis details are given elsewhere (Dalal et al., 2021). For the development and selection of products for indicating temporal changes in SOC, only the data from 1991 (from which point all of the considered remote-sensing products existed) up to and including 2014 were used. Subsequently, for testing the selected products, the data from the recent sampling (the 2018 and 2022 data) were used.

Soil organic carbon stocks were calculated on an equivalent soil mass (ESM) basis, using soil masses of 1101 t/ha, 2287 t/ha and 3682 t/ha to nominally represent the 0–10 cm, 0–20 cm, and 0–30 cm soil depths (as done in previous work, Dalal et al., 2021). The ESM stocks were calculated by summing the stocks of sampled layers until the required ESM value was reached, using the fraction of the final layer needed to reach exactly the ESM. Stocks for the 10–20 cm and 20–30 cm depths were calculated by taking differences in the stocks between the 0–20 cm and 0–10 cm depth stocks, and between the 0–30 cm and 0–20 cm depth stocks. We note here that one outlying SOC stock value was found at one of the three sites in the Leucaena catchment, identified with a particularly low measured topsoil SOC concentration and higher subsoil concentration, and suspected as a mix up of samples. The data from this site were therefore removed, leaving data for just two sites from this catchment instead of three.

2.2. Remote sensing data

2.2.1. Fractional cover

The remote-sensing data we used in this study are derived from the Landsat series of satellites (5,7, and 8), which have been providing imagery at a spatial resolution of 30-m since the mid-1980 s. These satellites have a repeat cycle of 16 days and when two have been operational in tandem (since the launch of Landsat 7 in 1999), they provide imagery of any given site potentially every 8 days (although cloud cover invariably leads to reduced temporal coverage). The long history means that this is a very valuable set of data for examining long-term changes in vegetation, which might be associated with changes in above-ground biomass and changes in the input of organic matter into the soil.

In this work, we considered products based on the Landsat fractional cover to indicate temporal changes in SOC in the modified grazing pastures of the Brigalow Catchment Study. The seasonal fractional cover product (SFC; Joint Remote Sensing Research Program, 2022; https://portal.tern.org.au/seasonal-fractional-cover-australia-coverage-23880/23880; Muir et al., 2011; Flood et al., 2013; Flood, 2013) gives representative values for the proportions of bare, green and non-green cover across a 3-month calendar season. The green and non-green fractions may include a mix of woody and non-woody vegetation. In a preliminary assessment, we considered a range of product combinations (green fraction, total cover fraction), but chose to focus only on the green fraction due to its superior performance. This fraction is an indicator of the fresh aboveground vegetation that will later be incorporated into the soil and decay to become SOC.

2.2.2. Annual mean of the green cover fraction

The annual mean of the green cover fraction was calculated from the four seasonal products for a given year. In some cases, data were missing, for instance due to cloud cover for many of the individual date images, leading to gaps in a seasonal composite image. These gaps were filled on a pixelwise basis using a linear model (before calculation of the annual mean green cover). A linear model was fitted to fill each missing datapoint (each missing pixel in each image) separately, using the data from the five years prior to and including the year of the image with the missing data. The linear models included effects of year and season, and the fitted models were applied to predict and fill the missing data. With gaps filled wherever possible, the data from the four seasons of a year were used to calculate an annual mean green cover for each pixel; any pixels where it was not possible to fill gaps (either due to no data from other seasons in the target year, or due to no data from other years for the target season) were left as missing data. At this stage of analysis, the data from 3x3-pixel windows (i.e. 90-m × 90-m) were averaged before comparison with the soil data at a given monitoring site. We refer to the resulting data as the annual green cover (AGC), shown in Fig. 2 for the sampling sites of the four catchments included in this study.

2.2.3. Multi-year lagged averages of annual green cover

The incorporation of plant biomass into the soil (through roots and litter) leads to changes in SOC as plant material decomposes and becomes incorporated into the soil. The above-ground cover, as viewed from 700 km above the earth's surface, and as a lagged average over a period of years might therefore be a good indicator of SOC. Using lagged

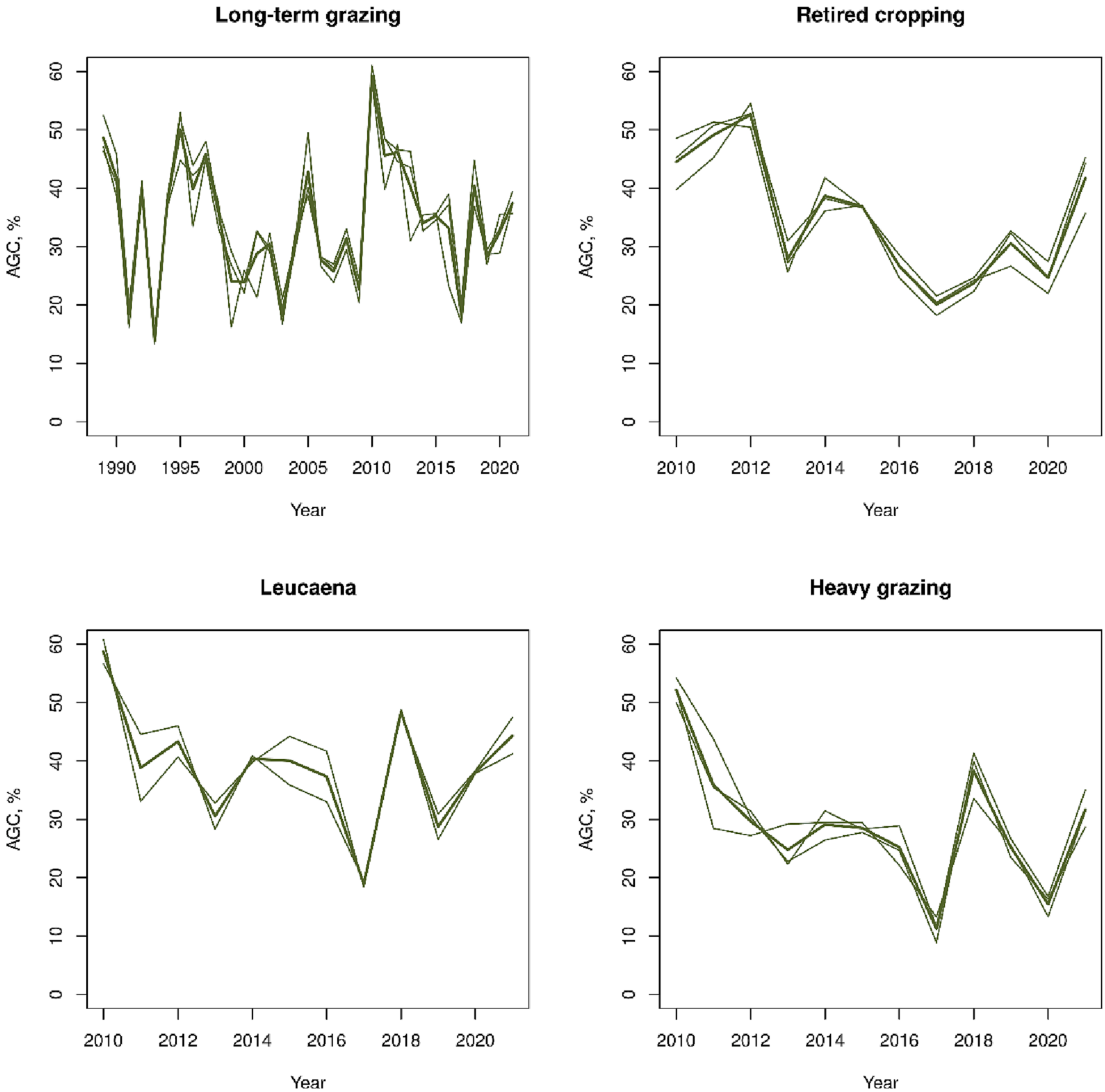

Fig. 2. Annual mean of the fractional green cover data for the four catchments under grazing management. Data for the three soil-sampled sites in each catchment (two for Leucaena) are shown as well as the average of these sites in bold. The long-term grazing catchment is shown from 1989 onwards due to the availability of Landsat imagery, the other catchments since they were established as grazing catchments in 2010. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

cover, rather than cover at the time of interest, helps account for the time that it takes for fresh biomass to decay and become incorporated into the soil where it can be measured as SOC.

We considered different periods for averaging the annual remote-sensing products as an indicator of point-in-time SOC. For a product to be useful to guide sampling strategies, it must be available prior to the time of sampling; therefore, only products using data up to the end of the preceding year were considered. To predict the SOC for a year t, we considered averages of the annual green cover (AGC) data from year t - l_s to year t - l_e, where l_s denotes the number of years lag for the start of the lagged average and l_e the number of years lag for the end of the lagged average. We denote these lagged averages by l_s–l_e, and test products AGC 0–0 (the annual product from the year of interest; just included as a reference), AGC 1–1, AGC 2–1, AGC 3–1, AGC 4–1 and AGC 5–1 (respectively lagged 1-year, 2-year, 3-year, 4-year and 5-year averages of the annual product up to the year before the year of interest).

2.3. Statistics

We compared different remote-sensing products in terms of their correlation with the soil data, using only the data from the sampling of the long-term grazing catchment between 1994 and 2014. The products with the largest positive correlation for the three-site averaged data were selected for further testing.

The data from 2018 and 2022 for the long-term grazing catchment were not used in the initial comparison of products and were retained to provide testing of whether the selected product would predict the unseen data well. Also included as further testing data were the data from the three other grazed catchments (the now-grazed retired long-term cropping catchment, and the two more recently established Leucaena and heavily grazed catchments) at the study. The combined testing data from all four grazed catchments were used to calculate pairwise differences in the SOC between successive sampling rounds, for comparison with the pairwise differences in the selected remote sensing product between those sampling rounds. This tests specifically whether temporal changes in the lagged AGC (over periods of around 4 years) might be used to indicate temporal changes in SOC.

We investigated the potential of using data from a single (perhaps baseline) sampling round to calibrate a simple model—a linear function of the lagged AGC—which could be applied to predict temporal changes in SOC. The 2018 data were chosen as the calibration data for this test since that presented the largest number of sampled sites (11 profiles from 4 grazed catchments). The SOC (ESM, 0–10 cm) data from 2018 were used to fit a linear mixed model (e.g. Lark et al., 2006) with a linear function of the lagged AGC as the fixed effect and with a spatially correlated (zero nugget, exponential covariance function) random effect. We note that although such a model would not usually be fitted with only 11 data in practice—since it would be insufficient data to properly estimate parameters of the spatial covariance function—we apply the approach here to illustrate potential usage. The fitted model was then applied to predict the SOC (ESM, 0–10 cm) of all other sampling dates for all 11 sampled sites, and predictions assessed against the data.

3. Results

3.1. Product selection

The temporal correlations (for the time series of three-site averaged data) between the SOC (on an ESM basis for different nominal soil depths) and the lagged average green cover with lag periods of between 0 and 5 years are shown in Table 1. A lagged average of the preceding two years (2–1) showed the strongest positive correlation (0.89, $p < 0.05$) with the SOC for the 0–10 cm depth. A longer lag (5–1) was the best for the 10–20 cm and 20–30 cm depths, but the correlations were much smaller than for 0–10 cm and not statistically significant. The only other correlation significant at $p < 0.05$ was between the 0–20 cm SOC and AGC 5–1, with that between the 0–10 cm SOC and AGC 1–1 marginally significant at $p < 0.1$.

3.2. Product testing

Based on the data in Table 1, we selected the lagged averaging indicated by bold type in each row of the table for further testing using the data from 2018 and 2022. The time series SOC data for each depth are shown in brown in Fig. 3, with the relevant selected AGC lagged average plotted in blue on the right-hand axes for comparison. To give predictions of the SOC based on the lagged AGC, linear models were

Table 1
Correlations between SOC (on an ESM basis for different nominal soil depths) and the annual green cover with lagged averaging of between 1 and 5 years, using the data between 1994 and 2014 (5 time points). The largest correlation in each row is in bold type.

SOC (ESM), nominal depth	Lag period start and end, years					
	0–0	1–1	2–1	3–1	4–1	5–1
0–10 cm	0.71	0.83	**0.89**	0.72	0.59	0.40
10–20 cm	−0.63	−0.45	−0.35	−0.26	−0.05	**0.36**
20–30 cm	−0.41	−0.64	−0.47	−0.49	−0.40	**0.06**
0–20 cm	0.07	0.45	0.66	0.57	0.67	**0.93**
0–30 cm	−0.31	−0.35	−0.12	−0.18	−0.06	**0.43**

fitted between the lagged AGC and SOC using the 1994–2014 data and applied to predict the SOC; hence the plotted AGC lines can be interpreted on both the left-hand and right-hand axes. The AGC 0–0 data (i.e. AGC from the year of interest) are also plotted in grey for comparison.

Only the product selected for the 0–10 cm soil depth showed good predictions for the 2018 and 2022 data. For this depth, the lagged AGC predicted well the measured SOC with a mean absolute error of 0.06 t ha^{-1} (though for just two data points), with the observed dip in 2018 and the subsequent increase in 2022 forecasted.

Fig. 4 shows the combined testing data from all four grazed catchments, with the pairwise differences in the SOC between successive sampling rounds plotted against the pairwise differences in the selected remote sensing product between those sampling rounds. This shows that of the four cases where the AGC-MEAN 2–1 product increased between successive sampling events, the SOC stock of the 0–10 cm depth increased for only two out of the four cases. For all three cases where AGC-MEAN 2–1 decreased, the 0–10 cm SOC stock also decreased. The slope of the regression line fitted to the two-point differences (for the validation data only) was positive for the 0–10 cm soil depth ($p < 0.1$), although was negative (and with $p > 0.1$) for the 10–20 cm and 20–30 cm depths, indicating the lack of agreement between predicted and observed changes for these lower depths (note that a regression line for the 0–10 cm two-point differences including both validation and calibration data was significant at $p < 0.01$).

These results suggest that while the AGC-MEAN 2–1 product might be providing some information about likely increases and decreases in SOC of the 0–10 cm depth under improved grazing pastures management, there is also a large associated uncertainty, even for sites that are quite similar to those used to select this particular product (i.e. for the sites in the retired cropping, Leucaena and Heavy Grazing catchments of the Brigalow Catchment Study).

3.3. Correlations between soil data for each depth

The correlation between the SOC stocks for the 0–10 cm, 10–20 cm, and 20–30 cm (Table 2) showed that the changes in the 0–10 cm soil depth were not positively related to the changes in the 10–20 cm and 20–30 cm depths, while those for the 10–20 cm and 20–30 cm depths were closely related to each other. This suggests that there might be different processes driving the SOC changes in the top 10 cm to those driving the 10–30 cm changes, which we consider later in the discussion.

Changes for the 0–20 cm SOC were not strongly related to changes for 0–10 ($r = 0.56$), despite that the 0–10 cm soil depth contributes (in most cases) more than half of the SOC to the SOC stocks of the 0–20 cm depth. Furthermore, the SOC stocks for 0–30 were not related to changes for 0–10 cm ($r = -0.06$).

3.4. Potential of using data from a baseline sampling round to calibrate a model (simple linear model of lagged AGC) for temporal changes

The linear mixed model fitted to the 2018 SOC (ESM, 0–10 cm) data, with AGC 2–1 as the fixed effect, represented the linear fixed-effect function, $SOC = 8.05 + 0.34\ AGC\ 2\text{–}1$, with a Wald test of the slope parameter marginally significant ($p < 0.1$). This fitted linear mixed model was then applied to predict the SOC for all other sampling dates for all 11 sampled sites. Fig. 5 shows the resulting predictions (dashed lines) and data (solid lines), with lines coloured by site for the three sites within each catchment (two for Leucaena). As shown by the sometimes large errors between the predicted and observed SOC in these plots, this approach did not work well. The mean absolute error (MAE) of prediction for the data (excluding the 2018 calibration data) from the four catchments was 2.4, 4.1, 3.6 and 2.2 t ha^{-1}, compared with an MAE of 1.4, 0.8, 1.9 and 1.4 t ha^{-1} for the four catchments if the 2018 data were used as predictions for all other sampling times (i.e. no assumed change in SOC). This indicates that the temporal variation and spatial variation of SOC that is predictable by variation in cover—here, the lagged AGC

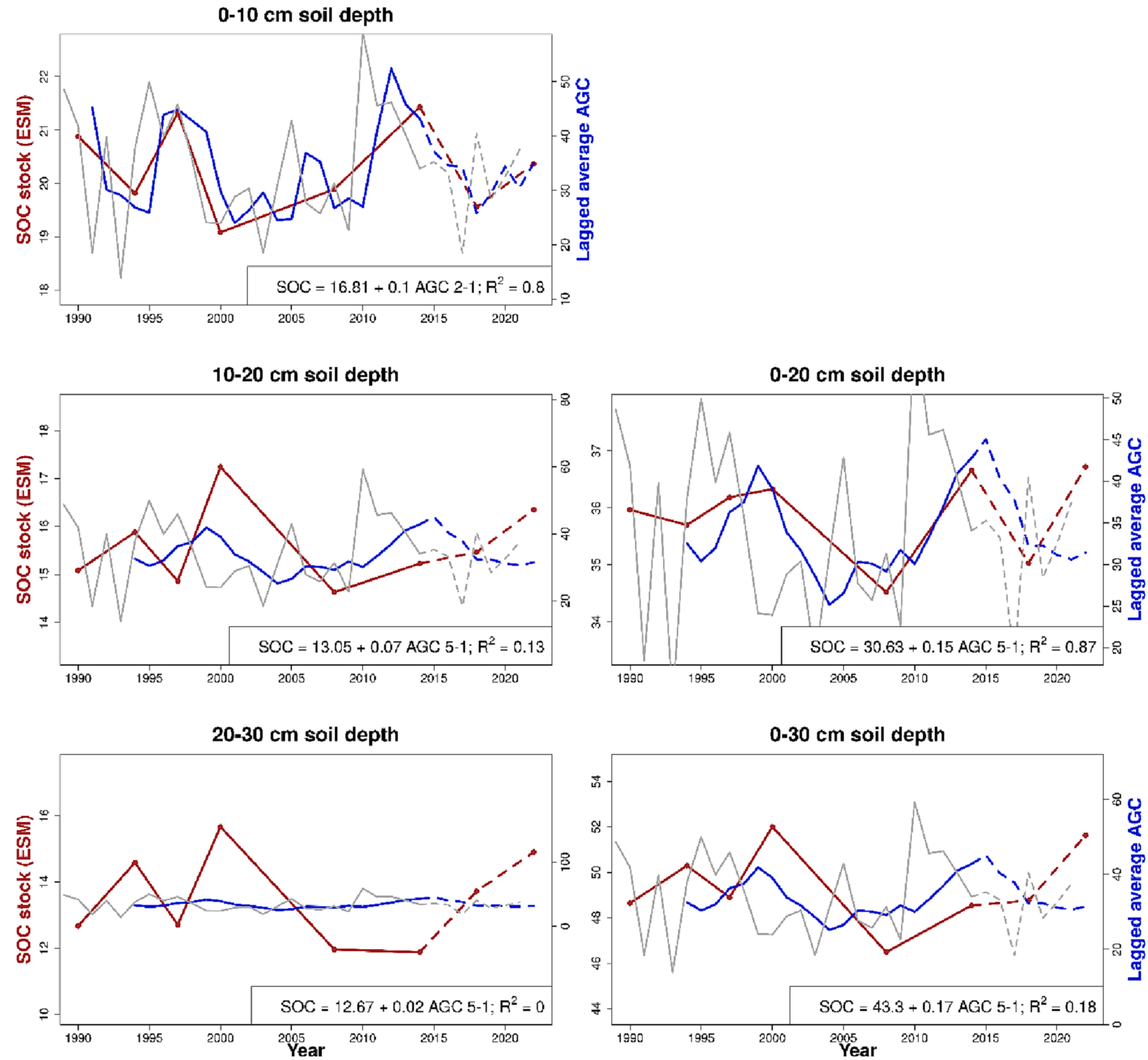

Fig. 3. Soil organic carbon stocks on ESM for the nominal depths 0–10 cm, 10–20 cm, and 20–30 cm (left-hand side), and 0–20 cm and 0–30 cm (right-hand side). The AGC 0–0 reference product is plotted in grey, and the selected lagged AGC product in blue (2–1 for 0–10 cm, and 5–1 for all other depths). The data used to select remote sensing products are shown in the solid lines, and the unseen testing data as the dashed lines. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

(2–1) predicting the SOC (ESM, 0–10 cm)—are not interchangeable.

4. Discussion

4.1. Lagged cover as a predictor of temporal variation in SOC

We used a long-term soil monitoring dataset—the Brigalow Catchment Study—to compare, select and assess remote sensing indicators of temporal changes in SOC stocks for grazed pastures sites. The only indicator with some success was a lagged annual green cover, the average of the green cover fraction (as inferred from the Landsat series of satellites) over the two years preceding a year of interest (referred to here as AGC 2–1). This was selected as an indicator of SOC changes for the 0–10 cm soil depth (on an equivalent soil mass basis), and tested with reasonable success on data not used for selection, indicating correctly the sign of temporal SOC changes (i.e., increases or decreases) for 5 of 7 test cases. This validation demonstrated that increases in AGC 2–1 were associated with a greater likelihood of SOC (0–10 cm, ESM) increase though evidence based on the validation data alone was not highly significant ($p < 0.1$).

Products based on fractional cover were adopted in this work, which Pringle et al. (2014) suggested in a study of SOC stocks might be preferable over time-integrated NDVI as a representation of pasture utilization in western Queensland. A direct comparison between fractional cover products and products based on other vegetation indices such as NDVI was not made here, but could be useful in future.

Many other studies have investigated the potential of remotely sensed indicators of SOC changes. Some consider data from two (or more) periods, and use the remote sensing data to explain spatial variation of SOC. For instance, Yang at al. (2009) used sets of soil data from

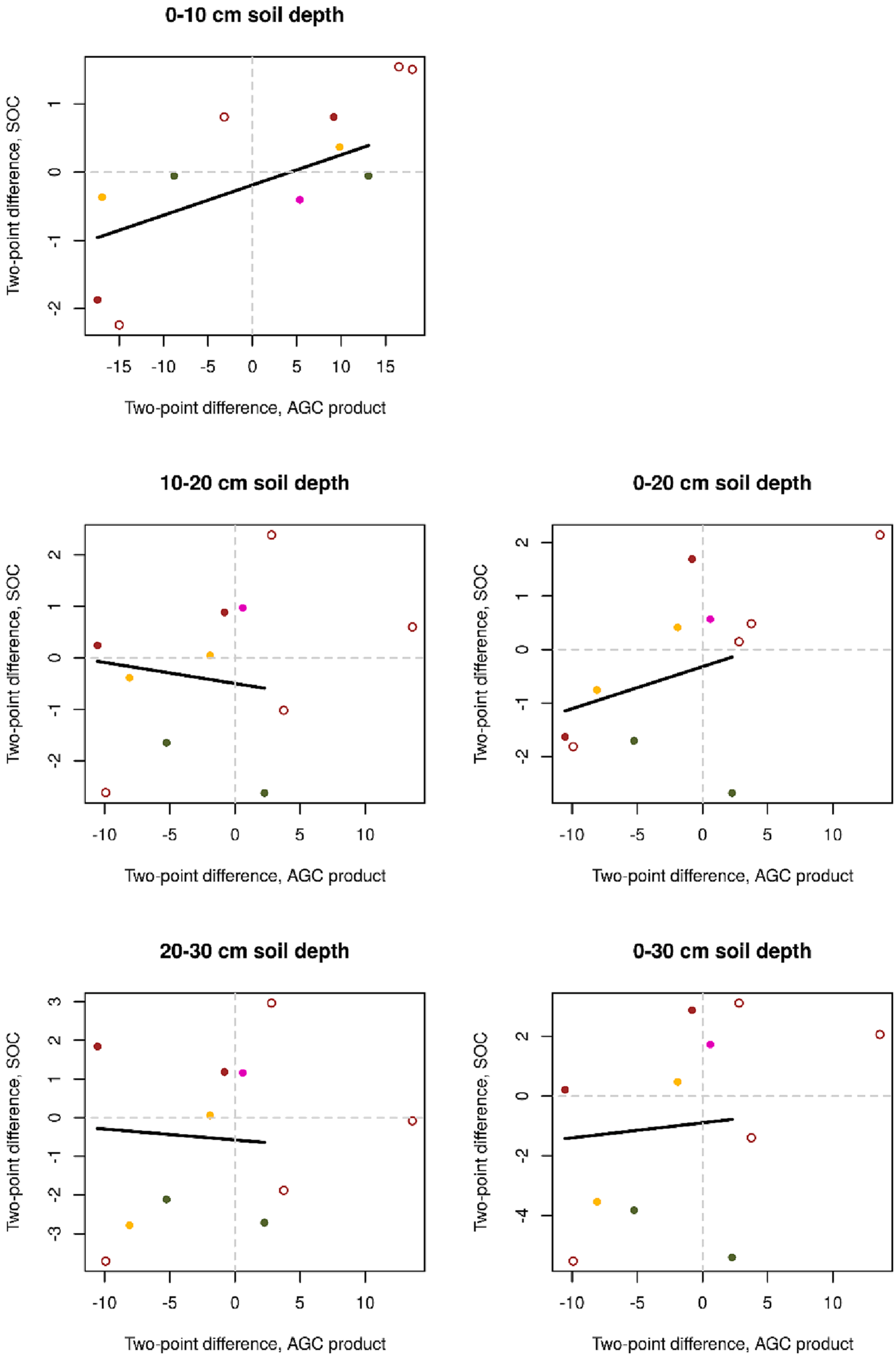

Fig. 4. Two-point differences between successive sampling rounds for the grazing catchment (brown points), the grazing phase of the long-term cropping catchment (golden points), the grazed Leucaena catchment (green points) and the heavily grazed catchment (pink point). The x-axis is the change in the selected AGC product between successive sampling events, and the y-axis is the change in SOC stocks (on an ESM, to represent five nominal depths) between those events. (Only the three-site averaged data are shown.). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

two sampling campaigns across grasslands in the Tibetan Plateau and fitted significant relationships between remotely sensed NDVI and topsoil SOC. Separate relationships were fitted to the data from two periods (1980 s and 2000–2004)—i.e., the relationships represented spatial variation—before the two relationships were applied spatially to map the SOC for the two time periods. This allowed some assessment of broad-scale changes in SOC, found to not show significant changes over the two-decade period.

Other studies consider modelling the spatio-temporal variation of SOC in a single model. For instance, Venter et al. (2021) used a large dataset of SOC stocks in natural vegetation (over South Africa), which contained data collected from across the country over multiple years and spatio-temporal covariates (for a random forest model) aligned to the year of sampling for each soil sample. The lack of repeated measures data (the same locations in space measured on multiple occasions) was highlighted as a limitation to fully validate predictions of SOC changes.

Table 2
Correlations between soil data for different depths (all data from 1981 to 2022 for the long-term grazing 3-site average), with significant correlations in bold type ($p < 0.05$) and marginally significant in italics ($p < 0.1$).

Soil depth	10–20 cm	20–30 cm	0–20 cm	0–30 cm
0–10 cm	**−0.63**	*−0.50*	*0.56*	−0.06
10–20 cm		**0.85**	0.29	**0.76**
20–30 cm			0.29	**0.86**
0–20 cm				**0.74**

Long-term soil monitoring studies offer this benefit, and while not being designed to model large-scale spatial variation, their ability to remove (or reduce) the effects of short-scale spatial variation on estimates of temporal change is valuable.

Kunkel et al. (2022) considered lagged averages of remotely sensed indices as predictors of SOC for grazed pastures (in their case, retrospective cumulative average for the normalised difference vegetation index, NDVI, and enhanced vegetation index, EVI). They found a 24-month average VI correlated best with SOC (in their case to a maximum depth of 21 cm), which is in alignment with our finding of a 2-preceding-year average of the green cover as an indicator of topsoil SOC changes.

4.2. Possible reasons for cover changes predicting SOC changes for the 0–10 cm soil depth but not below 10 cm

The remotely sensed green cover (lagged AGC; 2–1) provided a reasonable indicator of temporal changes in SOC for the 0–10 cm soil depth, but did not provide any indication of SOC changes below 10 cm. We further investigated possible reasons for the lack of predictive ability for SOC changes below 10 cm. A linear mixed model was fitted to the 0–10 cm SOC data (1981–2014) from the three long-term grazing sites, with a site-specific random effect and with year as a fixed effect (as a factor variable to look for evidence of changes or fluctuations, rather than as a numeric variable to look for evidence of a linear trend). The effect of year was significant ($p < 0.001$) indicating that there are temporal differences (fluctuations) in the total SOC for 0–10 cm (note that in agreement with the analysis in Dalal et al., 2021, year as a linear trend was not significant). Similar tests showed marginal evidence for temporal changes in the 10–20 cm total SOC ($p < 0.1$) and no evidence of temporal changes in the 20–30 cm total SOC. It is therefore not surprising that below 10 cm, the remote sensing data were not able to model the temporal variation of SOC. At depth the input and conversion of organic material to SOC occurs differently to the surface, with changes in SOC more likely dominated by microbial conversion of root

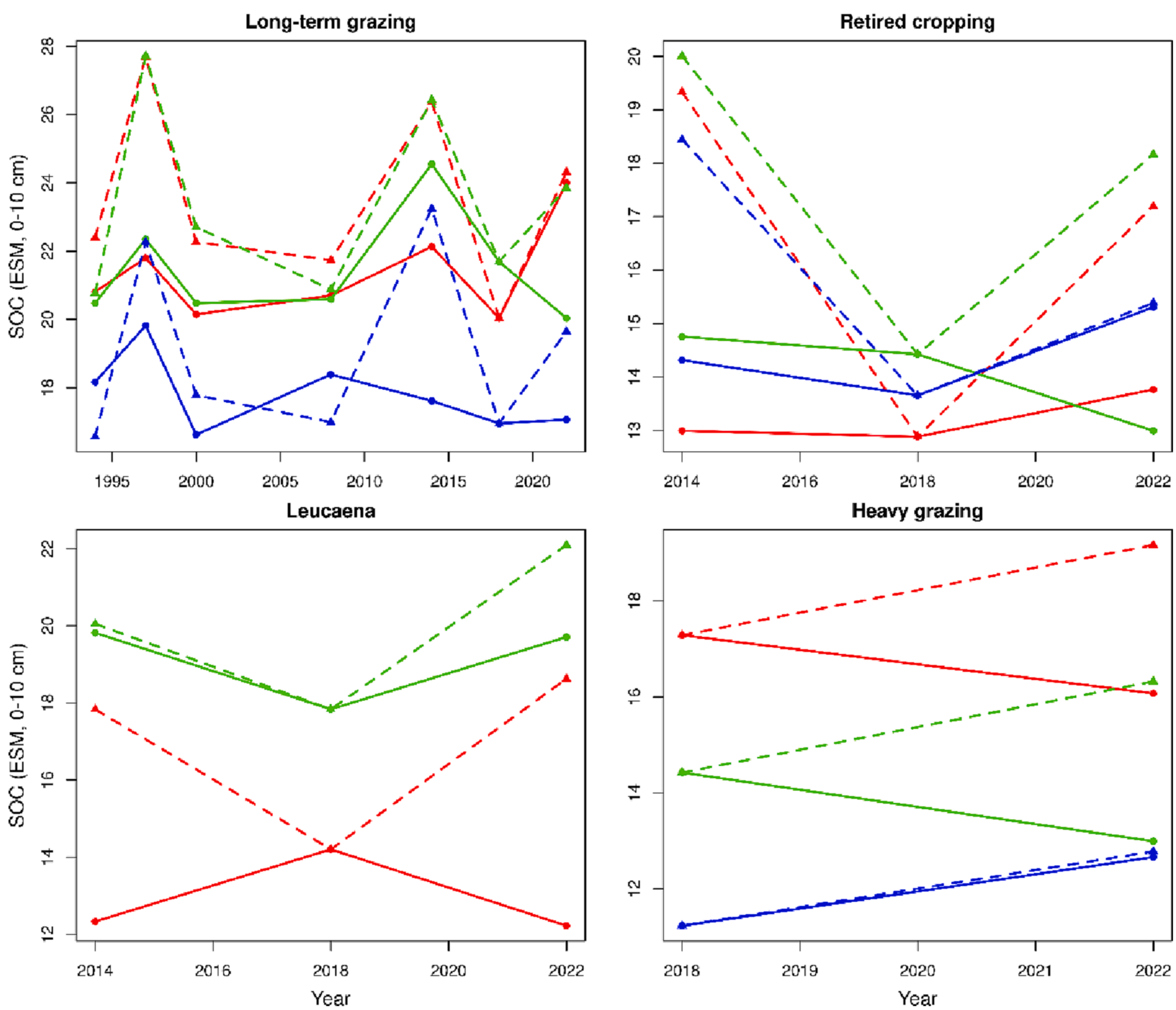

Fig. 5. Predictions of SOC temporal variation based on a linear mixed model for SOC (ESM, 0–10 cm) with lagged AGC (2–1) as the covariate, calibrated using the data from all 11 sampled sites from 2018 only. The colours indicate the site within each catchment; solid lines show the SOC data, and dashed lines show the predictions.

material and dissolved organic C leached from the top layers to SOC, rather than changes in above ground biomass. For example, Jalota et al. (2006) found that buffel grass tops material placed on the surface of the soil decomposed at a faster rate than root material placed at depth, indicating differences in conversion of plant biomass to SOC at depth compared to the surface.

Dalal et al. (2021) analysed the long-term changes in the different fractions of SOC—mineral-associated organic carbon, MAOC; particulate organic carbon, POC; and resistant organic carbon, ROC—of the pasture catchment between 1981 (clearing) and 2014. Their analysis revealed no significant long-term linear trend in any of the fractions for any soil depth, although differences in the relative contribution of each fraction between soil depths, with MAOC the dominant fraction for the topsoil and less so for the deeper soils. We fitted linear mixed models to the 0–10 cm data for the three fractions—in the same way as described above—revealing significant changes (fluctuations) in the MAOC fraction but not the POC or ROC fractions. We also calculated the correlations between the fractions and the total SOC for the 0–10 cm depth ($r = 0.94$ for MAOC, 0.87 for POC, and 0.81 for ROC) suggesting that for this depth, changes (fluctuations) in the total SOC of the topsoil were mostly the results of changes in the MAOC fraction.

4.3. Potential use of lagged AGC for decision support for temporal SOC changes

One application that was considered as a potential use of the lagged AGC product was to be incorporated in decision-support tools for informing temporal changes in SOC. If the product provides a good indication of whether SOC increases are likely, then it might be used when sampling carbon farming projects to help decide on whether SOC increases (since the time of a baseline sampling round) were likely, and therefore whether it would be worthwhile undertaking physical resampling of the project area to estimate these changes (for instance, for gaining carbon credits). However, such schemes are often based on changes for the 0–30 cm soil depth (or deeper), for which the remotely sensed indicators tested in this study did not work well. Further, this approach could increase the ability of users to manipulate sampling times to detect climate-induced changes in SOC and have these credited as management-induced increases. For instance, it might increase the ability of users to baseline a project when the soil carbon was expected to be low (due to recent drought perhaps and the resulting reduced vegetation growth and carbon input into the soil), and subsequently revisit when a wet period had led to improved vegetation growth and greater carbon input into the soil (indicated by an increase in the lagged AGC), irrespective of the management.

However, outside of carbon farming, with further development the approach could still be valuable to help farmers more easily assess the impact their management practices have on surface carbon stocks. This could improve their ability to assess the sustainability of their farming operations given that greater surface SOC stocks are often associated with greater soil stability, increased water infiltration/decreased runoff and generally healthier soils (Stockmann et al., 2013).

Wilson et al. (2017) compared the predictive capacity of short-term (2-year) and long-term (28-year) average EVI for predicting the spatial variation of SOC and found the long-term average to give better predictions. Our study differed in that we focused on the ability of the remote sensing data to predict temporal changes, for which such a long period of averaging might not be so advantageous. The cost-effective detection of temporal changes in SOC at landscape scales, in the presence of large spatial variation, remains a challenge. Stanley et al. (2023) analysed SOC data from rangelands and croplands sites in California and found that the spatial variation was larger in the rangelands than croplands sites, and was generally far larger than the laboratory analytic variation. They also noted that the variation of topsoil SOC might be used to guide decisions around sample size. Given that the topsoil SOC showed the strongest relationship with the lagged AGC in our study, perhaps remotely sensed indices might be useful when making these decisions, in order to make estimation of SOC changes more cost effective.

4.4. Potential use of lagged AGC for spatial stratification

We investigated (Section 3.4) the potential of using spatial data from a single sampling round (perhaps from a baseline sampling round) to calibrate a relationship between the spatio-temporal lagged AGC covariate and SOC, which could then be applied to predict SOC for future sampling rounds (again, the utility of this would be limited by the covariate's ability to predict changes for the 0–30 cm soil depth). Our tests of this approach showed large prediction errors, likely because the temporal (at a fixed point in space) and spatial variation (for a fixed point in time) of SOC that is predictable by cover differences are not interchangeable. Although this test was with only a small spatial dataset (11 sampled sites), the results did not point to it being a generally applicable approach. This suggests that we could not in general expect a model incorporating a spatio-temporal covariate that is calibrated with spatial data from just one sampling round (i.e. one point in time) to give good predictions of the temporal variation of SOC.

However, although the absolute predictions showed large errors, if their spatial variation correlates well with SOC they might still be useful for designing strata for resampling. We therefore investigated another potential application of the work, through using the predictions (and their uncertainties) as inputs to a method for designing spatial strata to optimise design-based estimates of spatial means (de Gruijter et al., 2015; de Gruijter et al., 2016). This analysis is demonstrated in Supplementary Material SM1, though the size of the spatial dataset that the approach is applied with here (data from 11 locations) limits the interpretation of results, and it serves more as an illustration here.

4.5. Limitations

The lack of association between the SOC changes for the 0–10 cm soil depth and those for the 10–20 cm and 20–30 cm depths, combined with the 0–10 cm SOC making up only around 42% of the SOC for the 0–30 cm, meant that the same product (lagged AGC, 2–1) did not work well for predicting changes in the 0–30 cm SOC in this study. The contribution of the 0–10 cm layer to the SOC in the 0–30 cm layer observed in this study (42%) would not seem to be atypical; for instance, data from Dalal & Mayer (1986) from six sites in the same region as our study showed an average of 39% of the 0–30 cm SOC in the top 10 cm. This does not suggest that the product would be useful for predicting SOC changes for carbon accounting schemes that are based on changes for the 0–30 cm soil depth.

The lag between the growth of vegetation (as indicated by remotely sensed cover) and the subsequent changes in SOC will be site-specific and expecting the 2-year lag of the AGC 2–1 selected here to be relevant across all soil types and climates is unrealistic. For example, Jalota et al. (2006) observed differences in the rate of decomposition between different plant materials (wheat, lucerne, buffel, and mulga roots and tops) and found that these were related to lignin concentration. A range of factors, including soil properties, climate and vegetation type, will have an impact on root system carbon inputs and decomposition rates. It is thus possible that different lag periods would be appropriate depending on the vegetation type (and site climatic conditions), increasing the challenge of finding more broadly applicable remote sensing predictors for the temporal variation of SOC. Nonetheless, the fact that a similar lag was found between a remotely sensed vegetation index and SOC changes in Kunkel et al., (2022) for grazing land in eastern Australia provides some support that it might be more generally relevant indicator than the point-in-time cover.

We also investigated whether results were sensitive to using ESM or fixed-depth SOC stocks in the analysis (results not shown). The finding of strong correlations between lagged remote sensing data and SOC for the topsoil, but weaker correlations deeper in the soil profile, was insensitive to this. However, the strongest correlation between lagged AGC and fixed-depth 0–10 cm SOC stock was for a four-year lagged average, highlighting uncertainties around a relevant period of averaging.

Our study chose to focus on the ability of remote sensing data to indicate the temporal dynamics of SOC, using data from a long-term monitoring trial. While the lagged AGC 2–1 provided some indication of changes for topsoil SOC at the grazed pasture sites in the Brigalow Catchment Study, the limited spatial extent means that the wider-scale applicability of the findings remains untested. In further work, it would be useful to investigate whether similar lagged products would be relevant more broadly for indicating temporal changes in SOC, which might give useful information for indicating management practices that are having a positive impact on soil health.

5. Conclusions

Lagged AGC (2–1) (i.e., the average green cover of the two years preceding a year of interest) provided some indication of temporal changes in topsoil SOC (0–10 cm) for the grazing pasture sites of a long-term soil monitoring dataset tested in this study. However, similar lagged cover variables were unable to predict SOC changes for deeper soil (10–20 cm or 20–30 cm), nor for the 0–30 cm soil depth, as would be important for assessing SOC changes for soil carbon accounting. Furthermore, we tested the ability of calibrating a model to predict the temporal changes in SOC based on a point-in-time (spatial) dataset of measured SOC and a spatio-temporal covariate, such as the lagged AGC (as might be available from a baseline sampling round). However, the approach, as tested here (albeit using a limited spatial dataset), gave large errors in predicted SOC. Nonetheless, remotely sensed covariates that are better able to predict SOC changes deeper in the soil would be valuable to help design spatial strata for more efficient sampling, and further work could explore more the potential of such approaches using larger spatial datasets.

CRediT authorship contribution statement

Thomas G. Orton: Methodology, Software, Validation, Formal analysis, Writing – original draft. **Craig M. Thornton:** Resources, Data curation, Investigation, Writing – review & editing. **Kathryn L. Page:** Conceptualization, Writing – review & editing. **Ram C. Dalal:** Conceptualization, Writing – review & editing. **Diane E. Allen:** Conceptualization, Writing – review & editing. **Yash P. Dang:** Conceptualization, Funding acquisition, Supervision, Investigation, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is available on request from the author.

Acknowledgements

This work was funded by Queensland Government's Drought and Climate Adaptation Program. Landsat imagery is provided by the United States Geological Survey, and the support and resources provided by the Queensland Remote Sensing Centre, Department of Environment and Science, is gratefully acknowledged. Thanks are also due to Celso Ferreira Cordova Junior, Rajesh Nomula and Rupinder Daroch for help with soil sampling and sample preparation, to the staff of Queensland Government Chemistry Centre for sample processing and laboratory analyses, and to Fiona Watson for comments on the draft manuscript.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2023.110614.

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