Received: 31 May 2021 | Revised: 27 September 2021 | Accepted: 29 September 2021

DOI: 10.1111/sum.12766

Soil Use and Management | WILEY

RESEARCH PAPER

Digital mapping of soil carbon sequestration potential with enhanced vegetation cover over New South Wales, Australia

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Abstract

Digital soil maps of soil organic carbon (SOC) sequestration potential resulting from a hypothetical 10% relative increase in long-term vegetation cover are presented at 100-m resolution across the state of New South Wales (NSW) in southeast Australia. This land management outcome is considered realistically achievable for many land managers, using strategies such as revegetation, grazing management or crop residue management. A mean state-wide potential increase of 5.4 Mg ha^{-1} over the 0- to 30-cm depth interval was derived. Assuming a 20-year period of re-equilibration, this equates to an average SOC increase of 0.27 Mg ha^{-1} year^{-1}. Sequestration potential is systematically influenced by a combination of climate, soil parent material and current vegetation cover, for example only 1.6 Mg ha^{-1} SOC under dry conditions in sandy, infertile soil material with sparse vegetation cover, compared with 15.9 Mg ha^{-1} under wet conditions in clay-rich, fertile soil material with moderate–high vegetation cover. The outputs could be used to identify locations of highest sequestration potential and thereby help prioritize areas and inform decisions on sequestration programmes. Future application of the method at field scale with high levels of accuracy, together with strategic sampling, may provide statistically reliable estimates of carbon sequestration, for application in carbon trading schemes such as Australia's Emissions Reduction Fund. The modelling involved a conceptually transparent 'space-for-time substitution' process. Multiple linear regression (MLR) and random forest (RF) modelling techniques were applied, but only MLR gave consistently meaningful results. The apparent failing of RF in this application warrants further examination.

KEYWORDS

climate change mitigation, digital soil mapping, soil carbon sequestration, space-for-time substitution, vegetation cover

1 | INTRODUCTION

If we have any hope of keeping climate change within safe boundaries, global emissions need to fall to zero within the next three decadesThis was the key message from the Intergovernmental Panel on Climate Change report on limiting global warming to 1.5°C (IPCC, 2018), according to the World Economic Forum (2019). The sequestration of carbon in soils through land management changes represents a major avenue for achieving net zero emissions by mid-century, a target that has already been adopted by at least 17 countries worldwide (World Economic Forum, 2019). The importance of enhancing global soil organic carbon (SOC) stocks was recognized at the 2015 United Nations Paris Climate Change Conference, and the associated launch at the Conference sidelines of the '4 per mille Soils for Food Security and Climate' programme, with its aspirational goal of 0.4% increase in global SOC stocks per year. Such an increase in the top 1 m of global agricultural soils is considered sufficient to offset 20%–35% of global anthropogenic greenhouse gas emissions (Minasny et al., 2017). The estimated global technical potential for soil carbon sequestration ranges widely up to 4.6 Pg C year^{-1} (Lal et al., 2018; Smith et al., 2020a). Benefits to soil health, agricultural productivity and other ecosystem services from the enhancement of SOC have also been recognized (Cowie et al., 2018; Lal et al., 2007; Meyer et al., 2015; Murphy, 2015).

Agricultural lands (cropland and grazing land) offer a substantial opportunity for SOC sequestration, given that these areas have typically undergone large declines in SOC relative to their naturally vegetated state, with a median loss of 28% in the top 30 cm found in a recent global meta-study (Sanderman et al., 2017). Numerous studies have investigated SOC sequestration rates resulting from modified land use and management practices; meta-studies suggest typical rates of 0.2–0.6 Mg ha^{-1} year^{-1} following improved land management practices, with rates varying widely between practices, soil types and environments (Luo et al., 2010; Minasny et al., 2017; Page et al., 2020; Sanderman et al., 2010; Smith et al., 2020a).

There is growing interest in creating incentives for enhancing soil carbon, including through emissions trading. Several schemes operate around the globe to facilitate trading in credits from soil carbon (Gledhill et al., 2011; Government of Alberta, 2021; Stabinsky, 2012) including the Australian Emissions Reduction Fund (ERF) through the *Carbon Credits (Carbon Farming Initiative) Act 2011* (CER, 2021). The Australian scheme has two methodologies, one based on default values, and another based on directly measured changes in SOC stock. The default approach has generated no interest to date as the highly conservative estimates of sequestration create insufficient incentive for market participation, while uptake of the measured method has been slow because of the high cost of participation with the required field sampling and laboratory analyses (Badgery et al., 2020; Waters et al., 2020).

The effectiveness of emissions trading schemes and other policies to promote soil carbon enhancement has been questioned because of a range of issues including the inconsistent relationship between management practices and SOC change and the high spatial and temporal variability in SOC stock, leading to large uncertainties in sequestration estimates (Gledhill et al., 2011; Powlson et al., 2011; 2016; Amundsen & Biardeau, 2018; Lam et al., 2013; Schlesinger et al., 2019; Simmons et al., 2021). Costly field sampling and laboratory analyses required for monitoring and verification in measurement-based carbon trading schemes mean participation may not be economically viable (Badgery et al., 2020; Sanderman et al., 2010; Smith et al., 2020b; White et al., 2021). Better data on SOC sequestration potential and the relationship of land management to SOC stock change are needed to inform initiatives supporting SOC management and to increase the participation in soil carbon trading.

Soil carbon sequestration is widely excluded from vegetation-based emissions abatement projects under carbon trading schemes, because of high the costs and uncertainties, as is the case in Australia under its ERF programme (Waters et al., 2020). Thus, those programmes are omitting a substantial emissions abatement component. The need for integration of vegetation-based and soil-based sequestration programmes is apparent.

The SOC sequestration potential has been estimated for different land use categories (Lal et al., 2018) and for many countries (Minasny et al., 2017). In Australia, regional-scale estimates of SOC sequestration potential have been developed using a 'potential capability index' (Baldock et al., 2009) and conservative estimates for potential SOC increase under various land management practices have been produced by the Australian Government (Department of Environment & Energy, 2019). However, few studies have attempted to present SOC sequestration potential at a finer spatial resolution, which is needed by landholders to inform decisions on participation in carbon markets. This information would also support strategic prioritization of SOC sequestration incentives by governments. When fine-scale mapping with acceptable accuracy is combined with advanced sampling design (De Gruitjer et al., 2016), it may provide a basis for statistically reliable SOC sequestration estimates for specific changes in land management (Minasny et al., 2017).

Extensive research has been carried out on the environmental and land management drivers for SOC stock

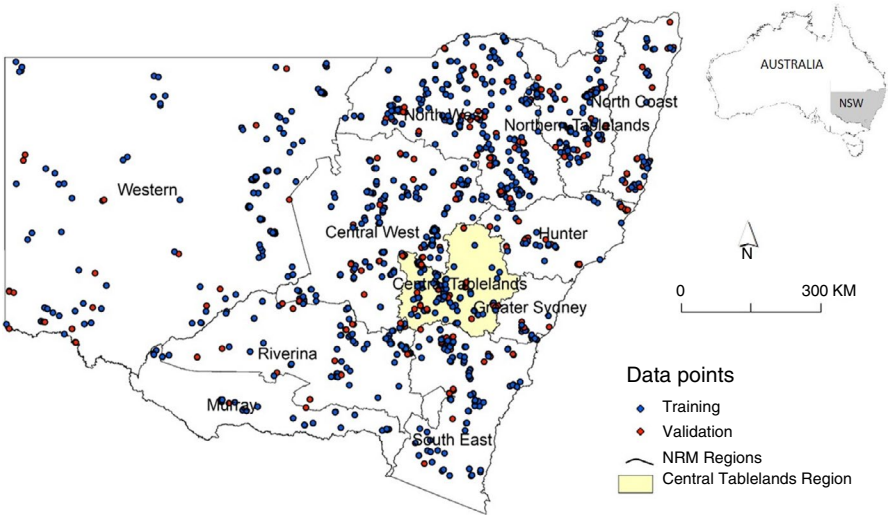

FIGURE 1 Data points including training and validation, and 11 natural resource management regions across New South Wales

in Australia and globally (e.g. Angst et al., 2018; Badgery et al., 2013; Gray et al., 2015; Knowles & Singh, 2003; Luo et al., 2010; Rabbi et al., 2015; Viscarra Rossel et al., 2014; Wiesmeier et al., 2019; Xiong et al., 2014). Another suite of studies has examined rates of SOC change under different land use and land management conditions, as reported in several meta-studies (Guo & Gifford, 2002; Lal et al., 2018; Luo et al., 2010; Minasny et al., 2017; Page et al., 2020; Sanderman et al., 2010; Stockmann et al., 2013). Few studies explicitly consider the precise environmental and land management factors controlling the rates of SOC change, particularly in a holistic and quantitative manner (Baldock et al., 2009).

This study demonstrates a digital soil mapping process for spatial identification of potential SOC sequestration under an easily measured land management change, being a hypothetical long-term 10% relative increase in vegetation cover, across NSW, Australia. Such a change in vegetation cover could be achieved through a range of strategies including revegetation, grazing management, crop and associated residue management, and the use of fertilizer and other amendments to correct soil constraints. The maximum potential SOC sequestration, assuming maximum vegetation cover (equivalent to nature reserve status), is also demonstrated. Specifically, the study aims to:

- develop fine-scale (100 m) resolution digital soil maps of potential SOC sequestration under enhanced vegetation cover over NSW and subregions;
- identify locations of highest sequestration potential that can help to prioritize areas for sequestration programmes; and
- identify key trends in SOC sequestration potential under different environmental and land management conditions.

2 | METHODS

2.1 | Overview

The study applied a digital soil mapping 'space-for-time substitution' approach, with a bootstrapping model framework. It involved development of a statistical model of current SOC stocks (to 30-cm depth) under current land use and vegetation cover conditions over NSW, then applying the model to estimate SOC stock under a hypothetical relative 10% increase in vegetation cover (e.g. increasing from 70% to 77%). This increase is considered feasible while maintaining agricultural land use, and thus is more relevant to policymakers than potential SOC stock increases under maximum vegetation with no anthropogenic disturbance. The difference in SOC stocks between those two modelled scenarios was indicative of the realistic magnitude of feasible sequestration achievable in the long term. Vegetation cover included live plants, standing dead vegetation and surface litter.

2.2 | Study area

The state of NSW, in eastern Australia, covers an area of 810,000 km^2, slightly larger than France or Texas (Figure 1). Climate varies from warm temperate in the north and east, to hot arid in the far west and subalpine in the highlands of the south–east. Mean annual rainfall varies from less than 200 mm to over 2,000 mm, while mean annual maximum daily temperatures range from approximately 12–30°C. The physiography is marked by a mountain range, the Great Dividing Range, that runs down the east coast generally 100–300 km inland; it is low by world standards, only reaching a maximum of 2,200 m in the south. West from this range, the undulating terrain gives way to typically flat inland plains.

Surface geology is characterized by siliceous and intermediate igneous and sedimentary rocks in the higher relief eastern regions with alluvial sands, silts and clays occupying most of the flatter western regions. Mafic volcanics of Tertiary age occur as frequent remnants in the east. Soils vary from very high to very low-fertility types, depending on climatic, parent material and topographic conditions (DPIE, 2020a). This variation in environmental conditions gives rise to a wide range of land uses, including nature reserves, native and plantation forestry, grazing on native and introduced pastures, horticulture, dryland and irrigated cropping and urban development.

A localized case study was carried out over the Central Tablelands Local Land Services Region, a NSW natural resource management (NRM) region. It is located in the central region of NSW and occupies an area of 30,300 km^2 (Figure 1). It is a heterogeneous region, displaying climatic, physiographic, soil and land use characteristics representative of much of NSW.

2.3 | The SOC data set

An initial data set of 2,153 points was prepared, each with SOC stock (in Mg ha^{-1}) for the 0- to 30-cm depth interval. The data set comprised data sourced from:

- NSW Monitoring, Evaluation and Reporting (MER) programme of the NSW Government during 2008–2009 (OEH, 2014), covering major land uses of agriculture, forestry and conservation;
- National Soil Carbon Research Program (SCaRP) 2009–2012, https://csiropedia.csiro.au/soil-carbon-research-program/) (Sanderman et al., 2011), covering agricultural land uses; and
- Recent NSW Department of Primary Industries projects, including Waters et al. (2015; 2016); Orgill et al. (2017) and Badgery et al. (2020) covering agricultural land uses.

Samples were collected in soil cores at four depth increments down to 30 cm and sieved to <2 mm to remove gravel. SOC concentration analysis was by LECO combustion furnace (Rayment & Lyons, 2011; Method 6B2b and 6B3). Bulk density (BD, g cm^{-3}) was determined on core subsamples dried at 105°C following methods described by McKenzie et al. (2002) and Dane and Topp (2002). SOC stocks were calculated from concentration and bulk density for each depth increment, then summed to obtain stocks at 0–30 cm.

Sites with SOC greater than 200 Mg ha^{-1}, indicative of organic soils, were excluded, as these tend to distort meaningful modelling trends and only occupy a tiny fraction of total area. The data set was randomly divided into 80% training data (1724 points) and 20% validation data (429 points).

2.4 | Model variables

A selection of 15 environmental variables were applied, representing the main soil-forming factors of climate, parent material, topography, biota–land cover and age of soil, as listed below.

- *Rain_20*: mean annual rainfall over the 20 years prior to date of sampling; sourced from SILO (Scientific Information for Land Owners) website (https://www.longpaddock.qld.gov.au/silo/).
- *Tmin_20*: mean annual daily minimum temperatures over the 20 years prior to date of sampling; sourced as above.
- *Silica_index*: approximate silica content (%) of the soil parent material, an indicator of the composition and fertility of the resulting soil; for example, parent materials with high silica content typically give rise to quartz-rich sandy soils with low cations and chemical fertility (Gray et al., 2016).
- *Rad_k*, *Rad_u and Rad_th*: radiometric potassium, uranium and thorium, indicators of parent material chemistry; sourced from Geoscience Australia (Minty et al., 2009).
- *Kaolinite*, *Illite and Smectite*: the relative proportions of these clays derived from near-infrared (NIR) spectroscopy (Viscarra Rossel, 2011); sourced through the CSIRO Data Access Portal (https://data.csiro.au/dap/search?q=TERN+Soil).
- *TWI*: topographic wetness index, representing potential hydrological conditions (Gallant & Austin, 2015); sourced through the CSIRO Data Access Portal.
- *Slope*: slope gradient in per cent as derived from a 100-m DEM.
- *Asp*: aspect index; to represent the amount of solar radiation received by sites, ranging from 1 (high-radiation sites) to 10 (low-radiation sites) (Gray et al., 2015).
- *LDI*: land disturbance index; reflecting the intensity of disturbance associated with the land use, ranging from 1 for undisturbed conservation areas to 6 for highly disturbed cropping land (Gray, Bishop, & Yang, 2015); land use sourced from 1:25,000-scale land-use mapping (DPIE, 2020b).
- *Total_VegCov*: total vegetation cover (%); includes photosynthetic (living) vegetation (PV) and non-photosynthetic (dead) vegetation (NPV) cover, being average (mean) cover from year 2000 to date of sampling;

sourced from CSIRO MODIS fractional vegetation data (Guerschman & Hill, 2018).

- *W_index*: weathering index; representing the degree of weathering of parent materials, regolith and soil, based on gamma radiometric data (Wilford, 2012), an indicator of the age of the soil and landscape; sourced from Geoscience Australia.

The final selection of 10 variables was generally restricted to the statistically strongest ones, based on p values less than 0.05 from the MLR models; however, *Tmin_20* was retained despite being weaker than this, as it performed strongly in random forest models (Supplementary Information 1, Table S1.1). The independence of each variable was also tested with the variance inflation factor (VIF), an index for collinearity detection in regression analyses, which revealed all values less than 10, indicative of acceptable independence (Supplementary Information 1, Table S1.2).

2.5 | The modelling approach

The approach, summarized in Figure 2, could be described as digital soil mapping with 'space-for-time substitution', in which contemporary spatial patterns are used to infer past or future trajectories of ecological systems (Blois et al., 2013; Pickett, 1989). In this case, a model relating SOC to changes in vegetation cover through space is used to estimate SOC response to changes in the extent of vegetation cover through time. The spatial patterns substitute for temporal patterns. After trialling both multiple linear regression (MLR) and random forest (RF) statistical modelling methods using R statistical software (R Core Team, 2020), it was evident that only the former method gave reliable and meaningful results. Consistent widespread anomalies were evident using the RF method in this substitution modelling approach, as discussed further in Discussion (s.4.5) and demonstrated in Supplementary Information 2.

An exploratory MLR model was developed from the training data using the 10 most influential variables, achieving a coefficient of determination (R^2) of 0.56 (full details provided in Supplementary Information 1). This model was applied against raster layers (of 100-m resolution) representing each variable over the whole state. To provide more robust modelling, a bootstrap procedure was repeated 100 times with MLR models using the same 10 variables and training data set. This applied a sampling with the replacement method, to obtain 100 random subsamples of the training data. A standard seed was set at the beginning of each model run, using the 'set seed' function, to ensure repeatability between different runs. At the end, the predicted values from 100 models were returned and used to derive an average (mean) layer of current SOC stocks, the 5% and 95% prediction limits and the associated 90% prediction interval (PI). Validation of the mean SOC map was undertaken using the originally set aside 20% validation data set, deriving the coefficient of determination R^2, Lin's concordance correlation coefficient (CCC, giving level of agreement relative to the 1:1 line), root mean square error (RMSE) and mean absolute error (MAE).

Next, maps of potential SOC stocks were prepared under the soil–carbon-enhancing land management, that is with an extra 10% (relative) vegetation cover. This involved increasing the *Total_VegCov* layer by 10% (i.e. *Total_VegCov* x 1.1), with vegetation cover not exceeding 100%. Again, maps for mean SOC stocks plus 90% PI limits and range were prepared. No validation was possible for these maps representing this hypothetical change in land management. The difference between the mean SOC stocks under the two sets of conditions, that is current and enhanced vegetation cover, gave the potential sequestration for each 100-m pixel.

The 90% PI limits and range for the current and enhanced vegetation cover scenarios were prepared as direct outputs in R from the bootstrapping process with 100 iterations. For SOC change (sequestration), the PI range map was derived by combining the above-prepared PI upper and lower limits (UL and LL), as shown in Equation 1:

$$\text{SOC change PI range} = (\text{Enhanced SOC}_{\text{UL}} - \text{Current SOC}_{\text{LL}}) - (\text{Enhanced SOC}_{\text{LL}} - \text{Current SOC}_{\text{UL}}). \quad (1)$$

Total potential sequestration of SOC (expressed as both carbon and carbon dioxide equivalent, in Tg, million tonnes) across the state was derived by multiplying the average rate per hectare by the total area.

For the state-wide results, no areas were masked out because of current land use status or serious soil constraints. In many conservation reserves, particularly in the western drier regions of NSW, increasing vegetation cover can be achieved through, for example, better management of feral animals that currently contribute to lower ground cover. Similarly, for many urban areas the required increase in vegetation cover is at least theoretically possible with government and community support. The areas of entirely sealed surfaces associated with cities and infrastructure, together with rock outcrop, were not considered significant at the scale of this study.

Further analyses of the final sequestration layer involved stratifying output by different approaches: (i) by the eleven NRM regions of NSW, (ii) by broad land use and (iii) by 36 environmental classes, being climate—soil

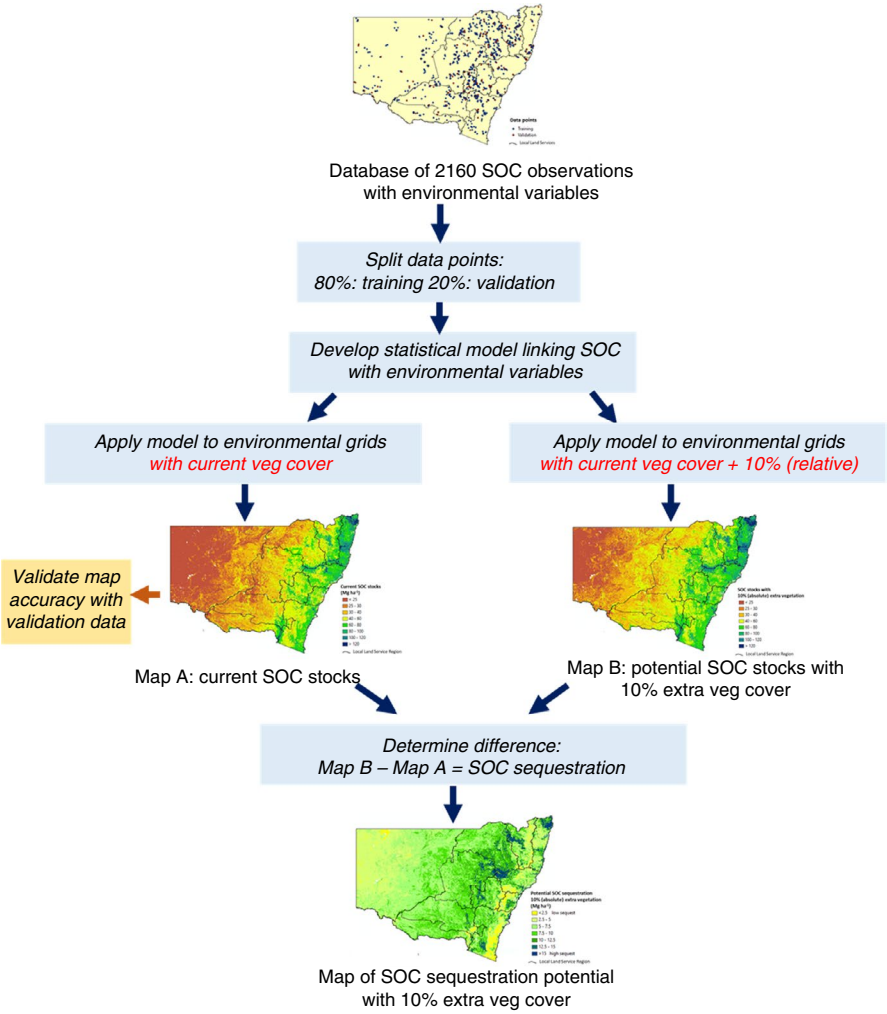

FIGURE 2 Method flow chart

parent material—vegetation cover classes, to gain more insights into the spatial patterns of soil carbon sequestration. The environmental classes were used only for this final approach (iii), to create meaningful zones across the state, and were as follows:

- Climate: classified into three annual rainfall/minimum temperature classes: (i) dry: <27; (ii) moist: 27–65; and (iii) wet: >65 (mm rain/°C);
- Soil parent material: classified into 4 classes (i) mafic (e.g. basalt, <=52% silica); (ii) intermediate (e.g. diorite, 52%–65% silica); (iii) siliceous lower (e.g. granodiorite, 65%–75%); and (iv) siliceous upper (e.g. quartz sandstone, >75% silica);
- Vegetation cover: classified into three vegetation cover classes: (i) low: <=65% mean cover; (ii) moderate: 65%–80% mean cover; and (iii) moderate–high: 80%–90% mean cover. For this additional environmental class analysis only, high vegetation cover (90%–100%) was not included, as the full 10% increase is not achievable, thus allowing a clearer identification of trends, as revealed in the resulting bar plot.

For comparison purposes, analysis using the same overall procedure was also undertaken to estimate maximum SOC sequestration potential under conditions of realistic maximum vegetation cover. The realistic maximum vegetation cover was derived by interpolation across the state from existing nature reserves. This vegetation cover ranges from approximately 40% in the dry far western nature reserves to almost 100% in the moist far eastern nature reserves. Further details on the method to derive maximum sequestration potential and the outputs are presented in Supplementary Information 3.

3 | RESULTS

3.1 | State-wide results

The map of current SOC stocks had moderate statistical performance, with a Lin's CCC using the independent validation data set of over 0.7, as presented with other validation results in Figure 3.

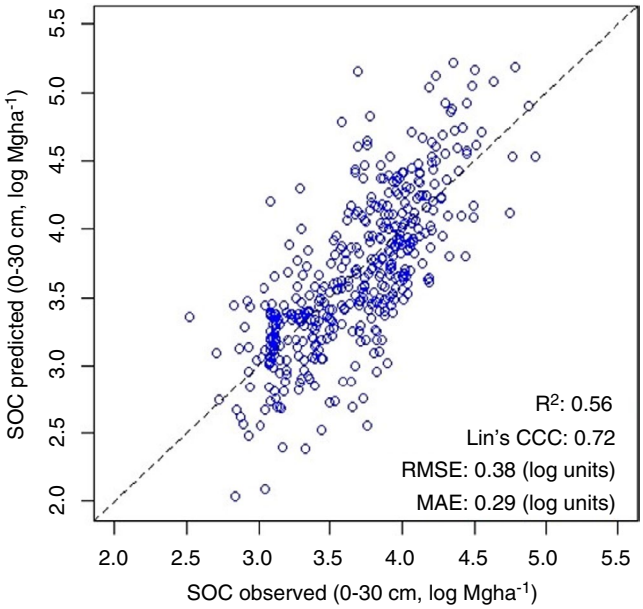

FIGURE 3 Validation plot for current SOC stocks (predicted v observed) (log Mg ha^{-1}). (R^2, coefficient of determination; CCC, concordance correlation coefficient; RMSE, root mean square error; MAE, mean average error)

The state-wide maps of SOC stocks based on MLR with 100 bootstrap runs under current conditions and with a 10% relative increase in vegetation cover are presented in Figure 4a and b, respectively. The state-wide map of sequestration potential with the increased vegetation cover is presented in Figure 4c. The associated 90% PI range maps are also included in these figures. Similar maps for maximum potential SOC sequestration under maximum vegetation cover are presented in the Supplementary Information (Figure S3.2).

The change in SOC stocks, or potential sequestration under the 10% (relative) increased vegetation cover, varied from 0 to >20 Mg ha^{-1}, with a mean state-wide change of 5.4 Mg ha^{-1}. The means from the lower and upper 90% prediction limits were 0.02 and 10.9 Mg ha^{-1}, respectively. Areas that currently already approached 100% vegetation cover, such as the forested areas of eastern NSW, showed little sequestration potential, as they could not achieve the full 10% increase, having over 90% cover initially.

Broad state-wide trends in sequestration potential with respect to the 36 environmental classes as outlined in Methods are revealed in Figure 5. Potential sequestration under a 10% relative increase in vegetation cover tended to be highest in wetter climate, low silica (clay-rich) soil parent materials and moderate–high initial vegetation cover (80%–90%). For example, it was estimated only 1.6 Mg ha^{-1} would be sequestered under conditions of dry climate, siliceous soil material and initial low vegetation cover, compared with 15.9 Mg ha^{-1} under wet climate, low silica (clay-rich) soil material and initial moderate–high vegetation cover. Figure 5 provides a broad indication of the extent of SOC sequestration that could be expected under different environmental conditions across the state.

No substantial difference in sequestration rates was observed between the broad land uses of cropping, grazing and native vegetation at the state scale, with all land uses being subject to the same 10% increase in vegetation cover. Average sequestration rates for each land use were all close to the combined (all use) average. This suggests that the extent of SOC sequestration arising from the enhanced vegetation cover is primarily controlled by climate, soil material composition and initial vegetation cover, with the specific land use being of lesser significance.

In terms of relative percentage increase in SOC stocks (i.e. percentage change with the enhanced vegetation cover relative to the initial SOC stocks), the potential increase varied from 2.0% to 22.9%. For sites with less than 90% vegetation cover, where the full benefit of the 10% enhanced vegetation cover was experienced, the relative increase in SOC stock was typically over 20%.

The mean total state-wide sequestration with 10% increase in vegetation cover was over 410 Tg SOC, or over 1500 Tg carbon dioxide equivalent (CO_2e) (Table 1). If the SOC was assumed to be sequestered over a 20-year period, this would equate to an annual sequestration rate of 75 Tg year^{-1} CO_2e. A comparison of these estimates with total NSW annual emissions reported from all sources is made in Discussion.

The modelled maximum sequestration potential over NSW under a hypothetical maximum vegetation cover, equivalent to in nature reserves, was demonstrated to be almost double that from the 10% vegetation cover increase, as presented in Table S1. The mean maximum hypothetical sequestration rate was modelled at 11.9 Mg ha^{-1}, with total state-wide sequestration of 910 Tg SOC.

3.2 | Results by natural resource management region

The sequestration potential across each NRM region of NSW is provided in Table 1, which presents mean plus the 90% PI range. The total sequestration potential of each region was a product of the mean potential sequestration rate per hectare and its area (in hectares). Thus, although the western NRM region had the lowest mean potential sequestration rate, its enormous area led it to having the highest mean total sequestration potential at 580 Tg CO_2e. A similar table presenting results for maximum potential SOC sequestration under realistic maximum vegetation cover, equivalent to nature reserves, is presented in Supplementary Information 3 (Table S3.1).

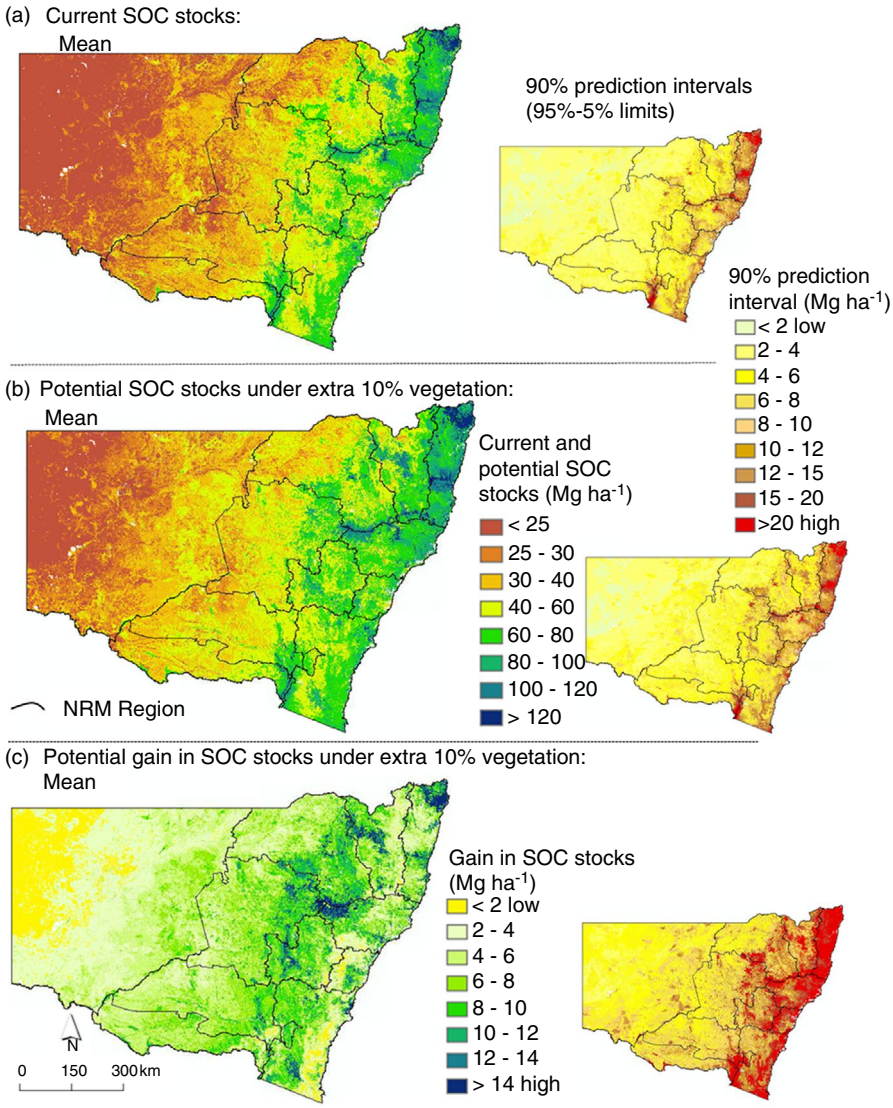

FIGURE 4 Current and potential change in SOC stocks under 10% (relative) extra vegetation cover, with mean and 90% prediction intervals (0–30 cm, Mg ha^{-1}). a. Current SOC stocks; b. potential SOC stocks; and c. potential change in SOC stocks (sequestration). For a and b, 90% PI is 95%-5% limits; for c, 90% PI is derived from Eq. 1

3.3 | Regional case study

To facilitate regional application of the study outputs, it is useful to examine the sequestration results together with key supporting variable grids at a regional scale, here presented for the Central Tablelands NRM Region (Figure 6). The supporting environmental variable maps contribute to a better understanding of the regional variation in results.

The sequestration potential arising from 10% relative increase in vegetation cover throughout the region (Figure 6f) represents the difference between the modelled current SOC stocks (Figure 6d) and the stocks modelled with the increased vegetation cover (Figure 6e). The areas of highest sequestration potential occur in the central west of the region, where values exceed 15 Mg ha^{-1}. These areas are currently used for cropping and grazing (Figure 6a) and are associated with parent materials that give rise to highly fertile clay-rich soils (Figure 6b).

Areas of low sequestration potential occur in the far eastern section of the region, where values are typically less than 3 Mg ha^{-1}. These areas are characterized by undisturbed or partially disturbed native vegetation in nature reserves and timber production forests (Figure 6a), with existing very high vegetation cover (Figure 6c), on highly siliceous parent materials that give rise to low-fertility sandy soils (Figure 6b). As many of these areas have vegetation cover approaching 100%, they could not achieve the full 10% increase in cover. Compounding this is the low-fertility sandy soils, which have low potential to sequester SOC.

The spatial patterns of sequestration potential revealed for this region reflect the interplay of environmental factors as discussed above and presented in Figure 5. The influence of climatic controls is less evident at this local scale, but nevertheless localized differences in climate would still be playing a role. Mean values are typically lower in drier NRM regions such as the western region

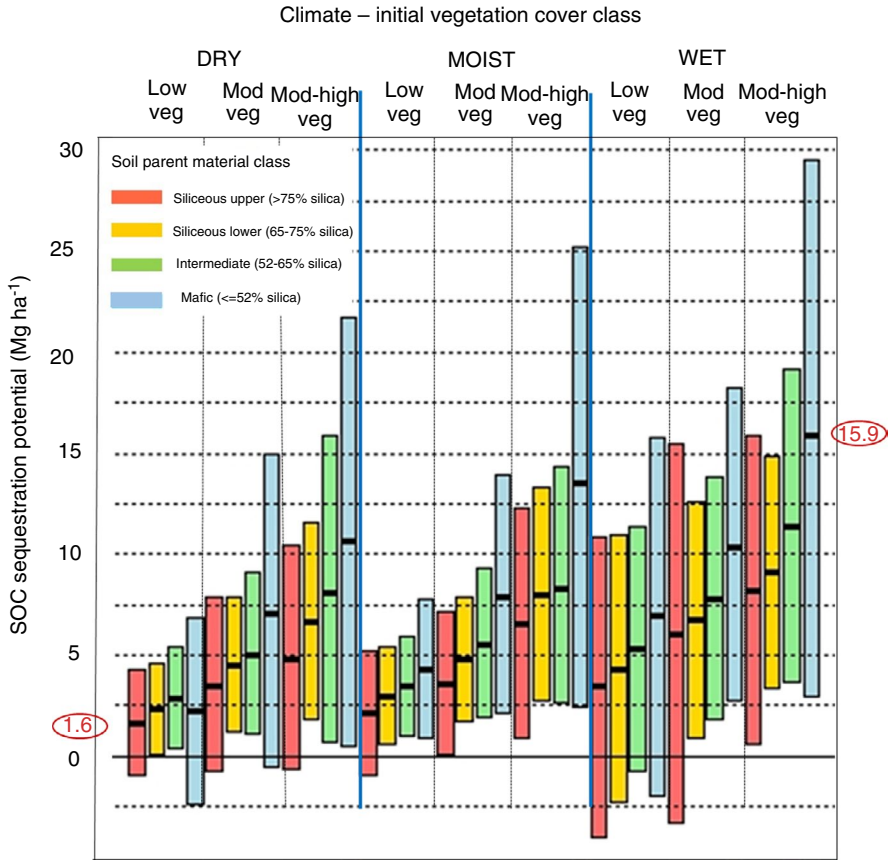

FIGURE 5 SOC sequestration potential (with 10% relative increase in long-term vegetation cover) by climate–soil parent material–initial vegetation cover class over NSW; mean and 90% prediction interval range (0–30 cm depth, Mg ha^{-1}). Refer to Methods for definition of classes. Note that mod-high veg refers to 80%–90% vegetation cover, with areas of 90%–100% cover being excluded for this plot only.

TABLE 1 Potential SOC sequestration for each of 11 NRM regions with long-term 10% relative vegetation cover increase

NRM Region[1]	Area (km^2)	Mean (Mg ha^{-1})	Potential sequestration, *n* (Tg)	CO_2 *e* (Tg) Mean (and 5%–95% *prediction limits*)
Central Tablelands	30,265	7.7	23.4	86 (*7* to *165*)
Central West	87,375	6.9	60.0	220 (*69* to *377*)
Greater Sydney	11,453	5.5	6.4	24 (*−19* to *66*)
Hunter	30,905	7.2	22.3	82 (*−40* to *205*)
Murray	41,372	6.0	24.8	91 (*9* to *175*)
North Coast	29,553	8.0	23.6	87 (*−88* to *261*)
North West	76,807	7.0	53.6	197 (*51* to *347*)
Northern Tablelands	36,819	6.8	25.0	92 (*−16* to *199*)
Riverina	65,656	5.9	39.0	143 (*38* to *252*)
South East	54,422	6.4	35.0	128 (*−49* to *306*)
Western	296,818	3.3	98.4	361 (*45* to *685*)
All NSW	761,444	5.4	411.5	1509 (*7* to *3038*)

[1]Refer to Figure 1.

and higher in wetter NRM regions such as the North Coast region.

Similar trends, but with higher magnitude values, are demonstrated over this region for the maximum potential SOC sequestration under realistic maximum vegetation cover, equivalent to nature reserves, as presented in Supplementary Information 3 (Figure S3.3).

4 | DISCUSSION

4.1 | Overview of results

We have demonstrated a method for the spatial derivation of SOC sequestration potential under a consistent land management change across a large geographic

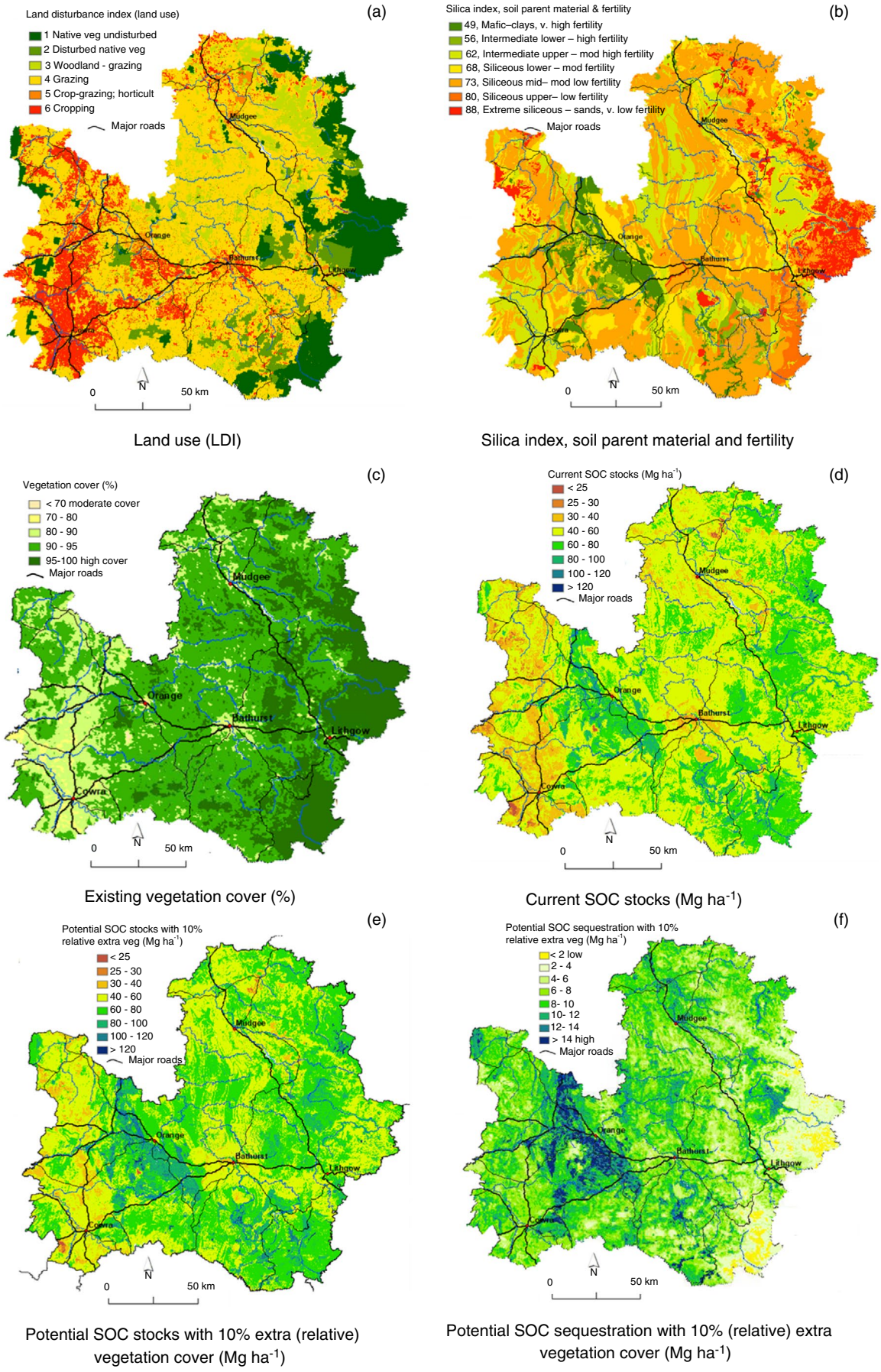

FIGURE 6 Key maps for potential SOC sequestration with 10% (relative) increase in vegetation cover for the Central Tablelands NRM Region

region. It involved a hypothetical 10% (relative) increase in long-term vegetation cover (based on remotely sensed derived fractional vegetation cover). Adopting management practices to achieve this increase in cover is considered achievable for many landholders across the state, but it is recognized it may be more difficult in dry western regions where vegetation levels less than 50% are widespread (Leys et al., 2020). Changes in vegetation cover could be achieved through a variety of practices including natural regeneration, tree planting, effective grazing management, feral pest control, perennial pasture establishment, crop residue management and overcoming soil constraints to plant growth (e.g. liming to ameliorate acidic soil). It should not require additional water through irrigation to achieve the increase. At locations where the existing vegetation cover approached 100%, such as in the eastern native forests, the full benefit of a 10% increase would not be experienced.

The benefit of an outcome-based approach (i.e. potential SOC sequestration under a 10% increase in long-term cover) is that the potential can be compared across a range of land uses, for which different practices are relevant. Land managers can decide the most economically viable and practical way to achieve that increase without having a prescribed practice. This approach also enables agility in land management under a variable and changing climate.

The period over which the soil carbon change occurs would be considered as the period of re-equilibration of SOC stocks resulting from the altered vegetation cover regime. Although it may require several decades to fully equilibrate, much of the increase is likely over one to two decades. Highest rates are likely in the earlier years (Badgery et al., 2020).

The modelled results indicated substantial SOC sequestration potential across NSW with a 10% relative increase in long-term vegetation cover, notwithstanding the wide prediction interval. The mean total sequestration of over 1,500 Tg CO_2e is almost 12 times the reported total annual emissions for NSW of approximately 130 Tg CO_2e/year for the years 2016–2018 (DISER, 2020). By assuming a 20-year period for this sequestration, some 75 Tg year^{-1} CO_2e or approximately 58% of reported total annual NSW emissions are potentially abated. It represents approximately four times the reported annual emissions from agriculture alone of 19 Tg CO_2e year^{-1} over the 2016–2018 period (DISER, 2020).

The results from the alternative approach that assumed maximum vegetation cover (equivalent to nature reserve status) (Supplementary Information 3) provided estimates of realistic maximum potential sequestration levels, similar to the concept of 'carbon saturation' level (Sanderman et al., 2010; Six et al., 2002). As would be expected, this approach produced significantly higher values for potential SOC sequestration compared with only a 10% increase in vegetation cover. For example, state-wide sequestration potential is estimated at almost 3340 Tg, CO_2e (Table S3.1). However, converting agricultural land to vegetation cover under nature reserve status across broad landscapes is not a feasible nor desirable goal, so this approach has not been emphasized in this study.

4.2 | Use of the maps

The maps and associated products derived from this study can serve as a useful guide in the selection of priority areas for carbon sequestration programmes. The spatial layers, including individual maps for NRM regions, will be made available on an NSW Government data portal (https://www.seed.nsw.gov.au/) or upon request to the authors. The products allow landholders to assess the broad potential of their properties to sequester SOC and thus inform decisions on whether to participate in carbon trading schemes. The delineation of areas of low to high sequestration potential may assist NRM bodies and government agencies to identify priority areas for attention and funding support.

The participation in carbon trading schemes can require extensive sampling and laboratory analysis for monitoring, reporting and verification purposes. These costs can reduce the viability of soil carbon projects, especially when considered together with other associated administrative costs. In Australia, from inception in 2013 to June 2019, only one project has generated carbon credits under the Australian Commonwealth Government's Emissions Reduction Fund (ERF) scheme using the soil carbon 'measurement' method (CER, 2019). It is widely recognized that some form of robust soil carbon modelling, combined with targeted site measurements and remote sensing, will be necessary to achieve economic viability and widespread participation in carbon trading schemes (Cowie et al., 2012; De Gruitjer et al., 2016; Minasny et al., 2017; Sanderman et al., 2010). The 'space-for-time substitution' modelling approach demonstrated in this study, but applied at a finer scale with higher accuracy, may serve to support such a low-cost soil carbon estimation method, that is, using modelling combined with targeted soil sampling.

In Australia, many emissions abatement projects under ERF carbon trading scheme are based on increased vegetation cover, but carbon sequestration in soil is rarely considered as an additional component (Waters et al., 2020). Products such as presented here, identifying areas of high SOC sequestration potential, may encourage the inclusion of the SOC sequestration component into such vegetation

focused programmes, thus increasing the overall viability of such programmes.

The results provide useful estimates of potential total SOC sequestration to inform climate change policy and mitigation strategies at the national, state or regional level. They help to quantify the extent to which SOC sequestration may contribute to meeting emissions targets such as the NSW Government's target of net zero by 2050 (DPIE, 2020c; NSW Government, 2016), and similar targets of many other jurisdictions worldwide (World Economic Forum, 2019).

4.3 | Comparison with other studies

There appear to be few examples of spatial mapping at regional or country level of sequestration potential at the fine resolution used in this study. A coarse scale map of 'potential capability index', which identified areas of low, medium and high sequestration potential across Australia, was presented by Baldock et al. (2009). This was based on subindices for potential carbon gain, loss and current stocks, considering factors of climate, soil clay content, land use and loss of SOC since clearing. That product provides useful estimates of relative sequestration potential across broad regions of Australia, suitable for broad-scale strategy development, but cannot be applied locally. Our current study matches well with the broad trends revealed by that product over NSW.

Unlike a number of previous studies, our study does not directly derive potential annual rates of SOC sequestration, but rather the total sequestration potentially achieved following an additional 10% vegetation cover, when a new equilibrium is reached over an unspecified period of time. Nevertheless, if an assumption is made that the re-equilibration of SOC levels occurs over a given period, then approximate annual rates of sequestration can be estimated. Applying a 20-year period for re-equilibration, the state-wide average sequestration rate was estimated as 0.27 Mg ha^{-1} year^{-1}.

This rate is only approximately half the rate of 0.6 Mg ha^{-1} year^{-1} reported by Minasny et al. (2017) as required by all soils globally to achieve the goal of '4 per mille Soils for Food Security and Climate' as launched at the sidelines of the United Nations Climate Change Conference in Paris, 2015. This initiative aims to achieve 0.4% annual increase in SOC to 1.0-m depth in global soils (Lal et al., 2018; Minasny et al., 2017).

The converted estimates from our study are broadly in accord with reported sequestration rates following improved land management from international, Australian and NSW studies, a selection of which are presented in Table 2. These studies suggest average SOC sequestration rates of 0.2–0.5 Mg ha^{-1} year^{-1} following conservation farming and improved land management practices, but towards the lower levels in drier rangelands.

In comparison, the current default values for SOC sequestration rates under three land management practices provided on a broad polygonal basis by the Australian Government for application in carbon trading under its ERF (Department of Environment & Energy, 2019) suggest low rates over most of the country. For example, for conversion of crop to pasture, only a small proportion of the cropland area achieves the highest rate of 0.23 Mg ha^{-1} year^{-1}; and similarly for sustainable intensification, only a small proportion achieves rates above 0.16 Mg ha^{-1} year^{-1}. These rates are lower than those derived from our current research and most other past Australian and NSW studies, and appear intentionally conservative to avoid the risk of over-allocation of carbon credits.

A meta-analysis of 74 studies by Guo and Gifford (2002) assessed relative SOC changes associated with land management changes. Increases in SOC stocks over decadal periods were 19% for crop to pasture, 18% for crop to plantation and 53% for crop to secondary forest transitions. These values are broadly in agreement with the results from our study of typically >20% relative increase with 10% increase in vegetation cover.

4.4 | Factors influencing SOC sequestration potential

The results of this study build on existing knowledge of the factors controlling SOC sequestration under carbon-enhancing land management. It is evident that levels of SOC accumulation in soils are controlled by a combination of factors, chiefly climate, parent material-soil type and current vegetation cover management, with other factors such as topographic position and age of the soil/landscape also contributing.

Sequestration rates tend to increase with increasing moisture (based on rainfall and temperatures), increasing soil fertility and increasing initial vegetation cover (up to the 90% cover threshold). These general trends are shown in Figure 5. It is evident that these key contributing factors cannot be considered in isolation when attempting to understand and estimate potential sequestration rates. The trends revealed by Figure 5 are similar to those presented for the distribution of total SOC stocks by Gray, Bishop, and Yang (2015), Gray et al. (2019). Initial vegetation cover is revealed to be more important than broad land use class, for which sequestration rates did not vary substantially at the state-wide scale. The examination of sequestration rate trends with changes in vegetation cover needs to consider that sites with greater than 90% cover

TABLE 2 SOC sequestration rates with improved land management from a selection of international, Australian and NSW studies

Location	Management practice	Depth (m)	SOC seq rate (Mg ha^{-1} year^{-1})	Study
Global				
	Best management practice in managed agricultural land (most 5–30 years)	most <0.3	0.2–0.5	Minasny et al. (2017)
	Cropping conservation farming (most <30 years)	most <0.5	0.2–0.5	Page et al. (2020)
	Improved crop management (20 years)	0.3	0.56–1.15	Zomer et al. (2017)
Australia				
	Improved land management (10–40 years)	most <0.3	0.1–0.4	Minasny et al. (2017)
	Improved crop management (most <40 years)	most <0.5	0.2–0.3	Sanderman et al. (2010)
NSW				
Central West	Conversion crop to pasture (5 years)	0.3	1.2	Badgery et al. (2020)
Liverpool Plains	Perennial pastures (lucerne) (8 years)	0.2	0.33	Young et al. (2009)
Southern NSW	Management of grazing pressure (8 years)	0.3	1.04	Orgill et al. (2017); Waters et al. (2016)
Southern NSW	Including pasture phases in crop rotations (18 years)	0.2	0.23	Helyar et al. (1997)
	As above (10 years)	0.3	0.02–0.26	Chan et al. (2011)
NSW wheatbelt	Incorporation of wheat stubble (20 years)	0.3	up to 0.2	Liu et al. (2014)
Southeastern NSW	Nutrient and grazing management (20 years)	0.6	0.60	Coonan et al. (2019)

cannot increase by the full 10%; thus, their sequestration potential is limited.

The role of these multiple factors working in combination in controlling potential SOC sequestration has been recognized by others. It is embodied in the concept of carbon zones of Murphy et al. (2010), Murphy et al. (2012) and in the potential capability index of Baldock et al. (2009). Lal et al. (2018) provide global estimates of SOC sequestration rates and total potential storage under different land uses and subcategories. While they do not stratify their estimates by other soil-forming factors, they recognize that 'the rate of SOC sequestration ranges depending on soil, climate and cropping system'.

Several studies have referred to the important role of soil clay content as a key controlling factor (Baldock et al., 2009; Stockmann et al., 2013). Our study highlights the importance of clay mineralogy in addition to percentage clay content. Soils with clays of high specific surface area such as smectite have greater SOC storage potential than those with clays of lower specific surface area such as illite or kaolinite (Wiesmeier et al., 2019). The silica index applied in this study provides a useful indicator of the overall mineralogical composition of the soil, including its component clays (Gray et al., 2016).

Some studies have somewhat simplistically implied that the potential for SOC sequestration is greatest in soils with current low SOC stocks. While this may be true in relation to areas within the same combination of soil and environmental conditions, it should not be considered a universal guiding principle. Where current carbon stocks are low because of dry climate or low inherent soil fertility, such areas have low potential for further significant increase without substantial human intervention, such as irrigation or application of nutrients. However, where SOC stocks are low in areas within an environmental regime that is normally associated with large SOC stocks, then such areas would indeed have high potential for SOC sequestration. Sanderman et al. (2010) similarly recognized that the highest potential for sequestration is where SOC levels are low in soils with high carbon saturation levels. These are the areas that should be targeted for successful carbon sequestration programmes and participation in carbon trading schemes.

4.5 | Effectiveness of our methods

The underlying 'space-for-time substitution' strategy and MLR modelling process adopted in this study (Figure 2) are conceptually straight forward, allowing the process and results to be understood and evaluated by a large range of potential users. This substitution

approach has been applied effectively with respect to SOC change in several recent studies (Adhikari et al., 2019; Gray & Bishop, 2019; Olaya-Abril et al., 2017; Yigini & Panagos, 2016). The approach has a high degree of transparency, unlike many process-based models such as RothC (Coleman & Jenkinson, 1999) or FullCAM used to produce Australia's national greenhouse inventory (Richards & Evans, 2004).

The validation statistics for the current SOC stocks suggest at least moderate statistical performance with, for example, Lin's CCC being over 0.7. In addition to these statistics, the upper 95% and lower 5% prediction limits and prediction interval maps provide further indication of the reliability of the maps and associated products. Reliable validation of the potential sequestration estimates presented in this study would require a series of controlled field trials and widespread carbon auditing at farm scale.

Digital soil mapping methods such as applied in this study are associated with a number of limitations that contribute to uncertainty in final products, including weaknesses in sampling design, insufficient representation of all covariate space, errors in base environmental grids, laboratory errors and collinearity between model variables (Bishop et al., 2015; Nelson et al., 2011; Robinson et al., 2015). Alternative validation techniques to those adopted in our study may be desirable. It has been demonstrated that randomly splitting available data into separate training and validation data sets typically overestimates prediction accuracy, because of spatial autocorrelation between the training and validation sites (Meyer et al., 2019; Ploton et al., 2020).

Our method employed a number of assumptions that may not truly reflect reality. We assumed a uniform and linear response from a 10% relative increase in vegetation cover (PV and NPV as revealed by MODIS satellite imagery), so it did not distinguish between different types of vegetation cover such as woody tree canopy cover, pasture grass, crop cover or non-living vegetation litter. In reality, the contribution to SOC stocks from these different vegetation types would differ, as would the time required for SOC re-equilibration to occur; issues that should ideally be incorporated into future refinements of the modelling approach. Other alternatives to average MODIS vegetation cover, such the dry season vegetation cover, could also offer opportunity for improved modelling results.

It is to be expected that significant differences will frequently occur between measured SOC stocks at specific sites and the stocks identified in current SOC digital maps, generated as the first step of this process. No soil map over an extensive region, either of conventional or of digital form, will perfectly reflect the local site conditions. However, we suggest that our modelled maps showing the sequestration potential (i.e. change between the current and potential future stocks) should generally be more reliable than our current stocks maps considered alone. Therefore, although our estimates for absolute current and future stocks may regularly differ significantly from laboratory analyses of samples collected over specific sites, we believe our estimates of potential change (sequestration) should still be meaningful and scientifically defensible.

Mapped results over specific areas could be evaluated against key covariate spatial layers (available upon request to authors) to improve their usability and confidence. For example, a local knowledge of errors in the underlying variable maps, such as an incorrect representation of soil parent material, may allow the final sequestration potential to be revised at local scale.

It is noteworthy that the random forest (RF) modelling technique for the analysis did not appear to be reliable or suitable for use in this 'space-for-time substitution' modelling process, as demonstrated in Supplementary Information 2. The RF models were effective for the current SOC stock maps, giving superior validation statistics to the MLR technique, similarly reported by Wang et al. (2018) for NSW rangelands and others elsewhere (Veronesi & Schillaci, 2019). However, following the substitution of current vegetation cover with the enhanced vegetation cover layer (current plus 10%) the resulting RF products appeared highly spurious, with vast areas (approximately 30% of NSW) revealing a decline in SOC, and almost all the remainder revealing only minor increase (< 6 Mg ha^{-1}). This widespread apparent negative correlation of SOC stock with vegetation cover is contrary to basic principles of soil science and most studies on key SOC drivers. In comparison, the MLR models revealed a clear state-wide positive response to the enhanced conditions with consistent increases ranging from zero to over 20 Mg ha^{-1}.

It appears the non-linear nature of RF modelling is not suitable for modelling the impact of a linear change in a single variable as adopted in this study. With application of decision tree models, changing a single variable means individual pixels may fall in a different branch of the tree, with significantly different end values. The problem may be an example of covariate shift, which occurs when training and test data sets have differing distributions (Quiñonero-Candela et al., 2009). Similar problems were encountered during conceptually similar 'space-for-time substitution' approaches adopted during the modelling of changes in soil with climate change (Gray & Bishop, 2016, 2019 and Wang et al., in press). This apparent weakness in decision tree approaches warrants further examination.

5 | CONCLUSION

Digital maps of potential SOC sequestration following a hypothetical 10% relative increase in vegetation cover across NSW have been developed, this being a land management change realistically achievable by many land managers. The maps provide useful estimates of sequestration potential per unit area at 100-m resolution and allow for estimates of total CO_2e sequestration over the state or smaller subregions. By assuming a period of re-equilibration such as 20 years, annual sequestration rates can be inferred. Supplementary results were also presented for maximum sequestration potential under maximum vegetation cover status. The products, including individual maps at NRM region level, will be made available on an NSW Government data portal (https://www.seed.nsw.gov.au/) or upon request to the authors.

The fine-scale maps and associated products derived from this study can serve as a useful guide for governments in selection of priority areas for carbon sequestration programmes. They may allow landholders to broadly assess the potential of their properties and districts to sequester SOC and thus inform decisions on whether to participate in carbon trading schemes. Future application of the method at finer scale with higher accuracy, in combination with an efficient verification and auditing sampling design, could form the basis of statistically reliable estimates of SOC gains under altered land management. Such a combination of geospatial modelling with limited field measurement may represent a feasible avenue for economically viable participation in carbon trading schemes in Australia and beyond.

It has been demonstrated that SOC sequestration potential is controlled by a combination of factors acting together, chiefly climate, soil type and vegetation cover. Quantitative estimates of sequestration potential for 36 combinations of these factors have been graphically presented, with clear trends being evident. The importance of understanding the local soil and site conditions in estimating potential SOC sequestration is evident.

The 'space-for-time substitution' modelling approach in a digital soil mapping framework adopted for this study is relatively straightforward and transparent, which may facilitate greater acceptance by potential users of the resulting products. The apparent superior effectiveness of the linear MLR models over the non-linear random forest (decision tree) models that appeared to fail is important to note for future possible applications of the 'space-for-time substitution' modelling process.

The results may provide useful estimates of potential soil carbon sequestration that is needed to inform emissions reduction policies such as net zero targets being established by many jurisdictions. They can help us to better understand the valuable role that improved land management can play in reducing net greenhouse gas emissions and thereby mitigating climate change.

ACKNOWLEDGEMENTS

Support for this research project was provided by our respective organizations, the NSW Department of Planning, Industry and Environment (Science, Economics and Insights Division) and the NSW Department of Primary Industries. Further support was provided through the *Primary Industries Productivity and Abatement Program*, an initiative under the NSW *Government's Net Zero Plan*, *Stage One*: *2020-2030*.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available in the NSW Government environmental data portal at https://www.seed.nsw.gov.au/

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SUPPORTING INFORMATION

Additional supporting information may be found in the online version of the article at the publisher's website.

How to cite this article: Gray, J. M., Wang, B., Waters, C. M., Orgill, S. E., Cowie, A. L., & Ng, E. L. (2021). Digital mapping of soil carbon sequestration potential with enhanced vegetation cover over New South Wales, Australia. *Soil Use and Management*, 00, 1–19. https://doi.org/10.1111/sum.12766

Digital mapping of soil carbon sequestration potential with enhanced vegetation cover over New South Wales, Australia

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Soil Use and Management, Oct 2021

SUPPLEMENTARY INFORMATION

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Supplementary Information 2: Comparison of potential sequestration maps from random forest and multiple linear regression models

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Supplementary Information 1: Multiple linear regression model details

Initial exploratory MLR model

log(SOC) ~ 4.146+0.000355**Rain*_20+0.00495**Tmin_20*-0.0212**Silica_index*-1.305**Illite*-0.885**Smectite*
-0.0163**Rad_th*-0.0182**TWI*-0.0584**LDI* +0.0207**Total_VegCov* +0.0428**W_index*

Table S1.1: MLR model parameters with training data (n = 1724)

Variable	Estimate	Std. Error	t value	Pr(>|t|)	
Intercept	4.15E+00	2.42E-01	17.114	< 2e-16	***
Rain_20	3.55E-04	6.28E-05	5.651	1.86E-08	***
Tmin_20	4.95E-03	5.84E-03	0.848	0.39676	
Silica_index	-2.12E-02	1.62E-03	-13.088	< 2e-16	***
Illite	-1.31E+00	5.26E-01	-2.481	0.01319	*
Smectite	-8.85E-01	1.69E-01	-5.234	1.86E-07	***
Rad_th	-1.63E-02	2.87E-03	-5.68	1.58E-08	***
TWI	-1.82E-02	6.02E-03	-3.027	0.00251	**
LDI	-5.84E-02	9.57E-03	-6.096	1.34E-09	***
Total_VegCov	2.07E-02	1.21E-03	17.177	< 2e-16	***
W_index	4.28E-02	1.09E-02	3.919	9.24E-05	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.3719 on 1713 degrees of freedom

Multiple R-squared: 0.5597, Adjusted R-squared: 0.5572

F-statistic: 217.8 on 10 and 1713 DF, p-value: < 2.2e-16

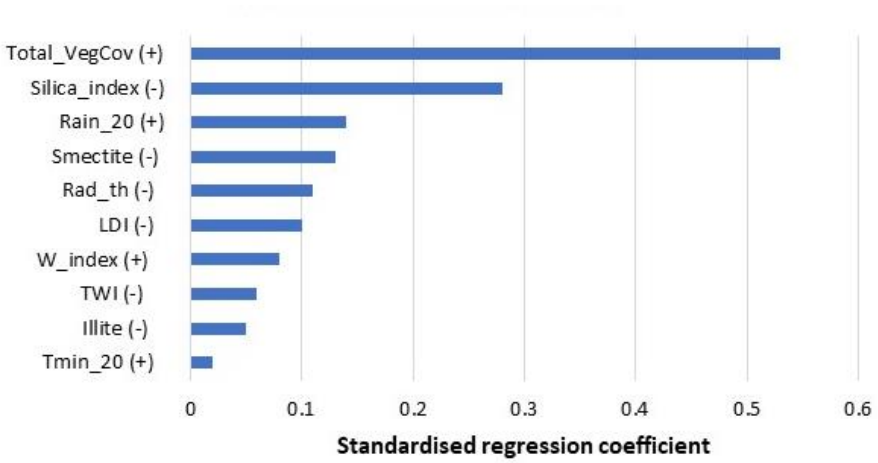


Figure S1.1: Variable importance plot from MLR standardised regression coefficients

Validation with test dataset (n = 429)

Lin's CCC: 0.72

RMSE: 0.38 (log units)

Mean error: 0.009 (log units)

Mean abs error: 0.29 (log units)

Median abs error: 0.24 (log units)

Table S1.2: Variance inflation factor (VIF) for assessment of collinearity of MLR variables

Variable	VIF
Rain_20	2.58
Tmin_20	2.35
Silica_index	1.75
Illite	1.31
Smectite	2.28
Rad_th	1.41
TWI	1.56
LDI	1.13
Total_VegCov	3.68
W_index	1.44

Supplementary Information 2: Comparison of potential sequestration maps from random forest and multiple linear regression models

Consistent anomalies are evident when random forest models are applied in the 'space-for-time substitution' modelling process. From Figure S2.1(a) using RF modelling, large areas are shown to have negative sequestration with additional 10% relative increase of vegetation cover, which it the opposite to normal expected trends. Few areas display sequestration > 6 Mg ha-^{1}.

This compares with Figure S2.1b using MLR modelling, where the map displays regular results with no apparent anomalies. All areas show positive sequestration with additional vegetation cover as expected, including many areas that show significant sequestration (>12 t ha-^{1}). The results are all explainable by key climate, soil and land management factors.

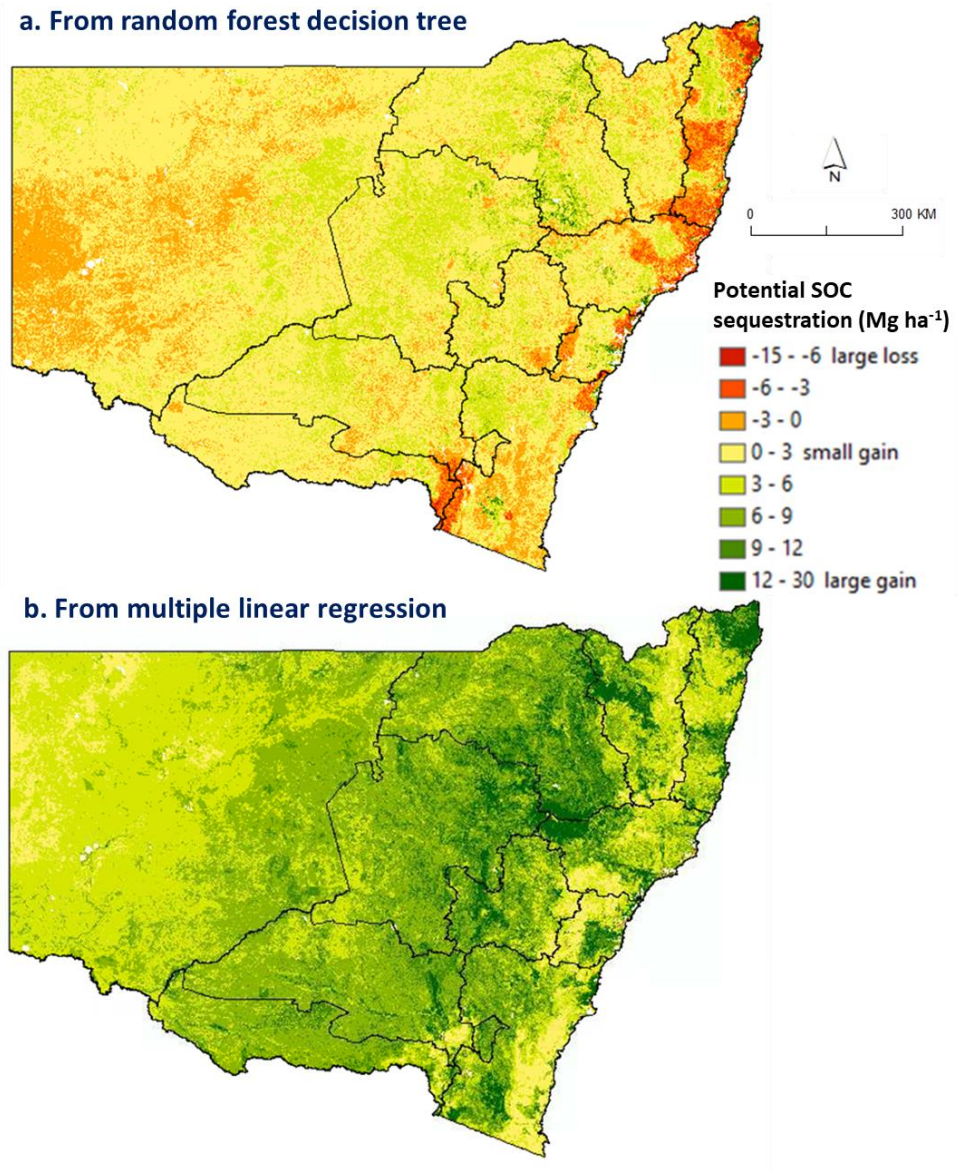


Figure S2.1. Comparison of potential sequestration maps from (a) random forest and (b) multiple linear regression models

Supplementary Information 3: Maximum sequestration potential

The realistic maximum SOC sequestration potential was modelled by applying the same 'space-for-time substitution' procedure as presented in the Methods section but applying conditions of realistic maximum vegetation cover. The vegetation cover was taken to be that of hypothetical native vegetation reserve status, as presented in Figure S3.1 and produced as follows. The original MODIS total vegetation cover raster layer (*Total_VegCov*) was masked to the areas of nature reserves across NSW, then converted to point shapefile with 5 km spacing, with significant outliers then manually removed. This file was then interpolated across the entire State, using the interpolation IDW tool in ArcGIS, then converted back into raster grid with 100m resolution.

Note that even higher vegetation cover layers, and thus sequestration potential, could be achieved with additional human intervention, such as irrigation and fertiliser addition For this set of maximum sequestration models, all pixels were allocated a land disturbance index (LDI) of 1, indicating nature reserve status; for example, crop land (LDI 6) being remodelled at LDI 1. Results across all NSW and for the Central Tablelands region are presented in Figure S3.2

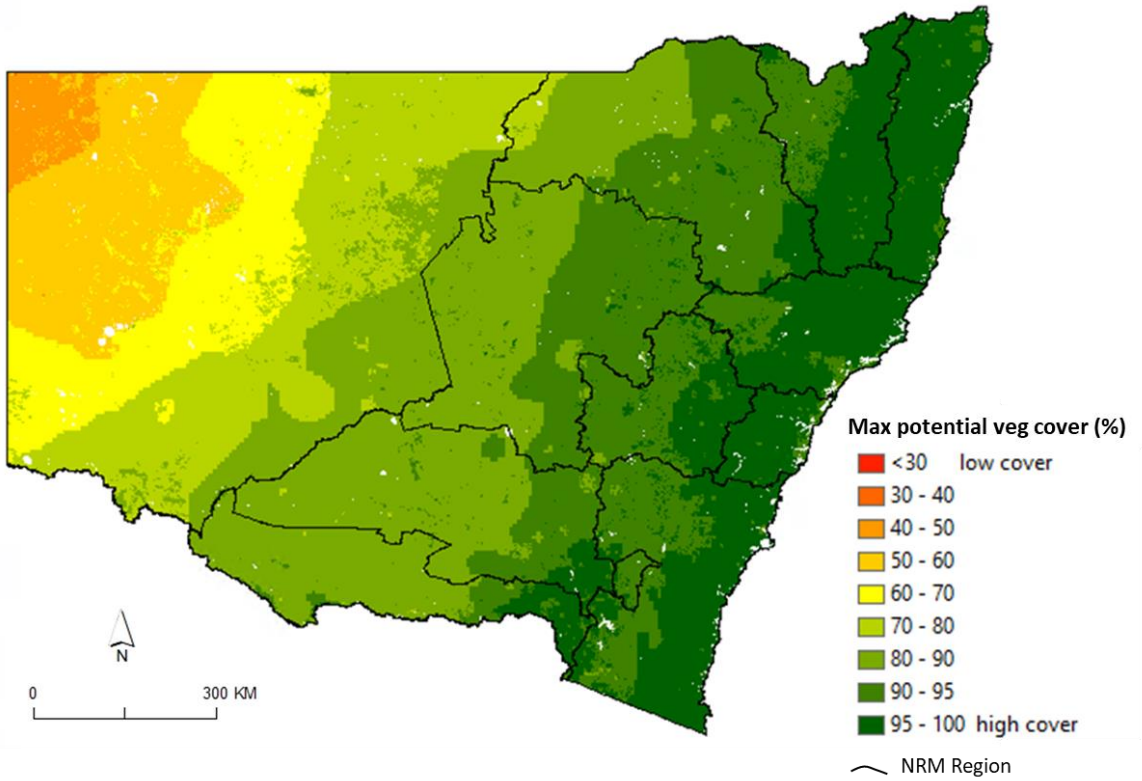


Figure S3.1: Maximum potential vegetation cover, based on interpolation from existing nature reserves

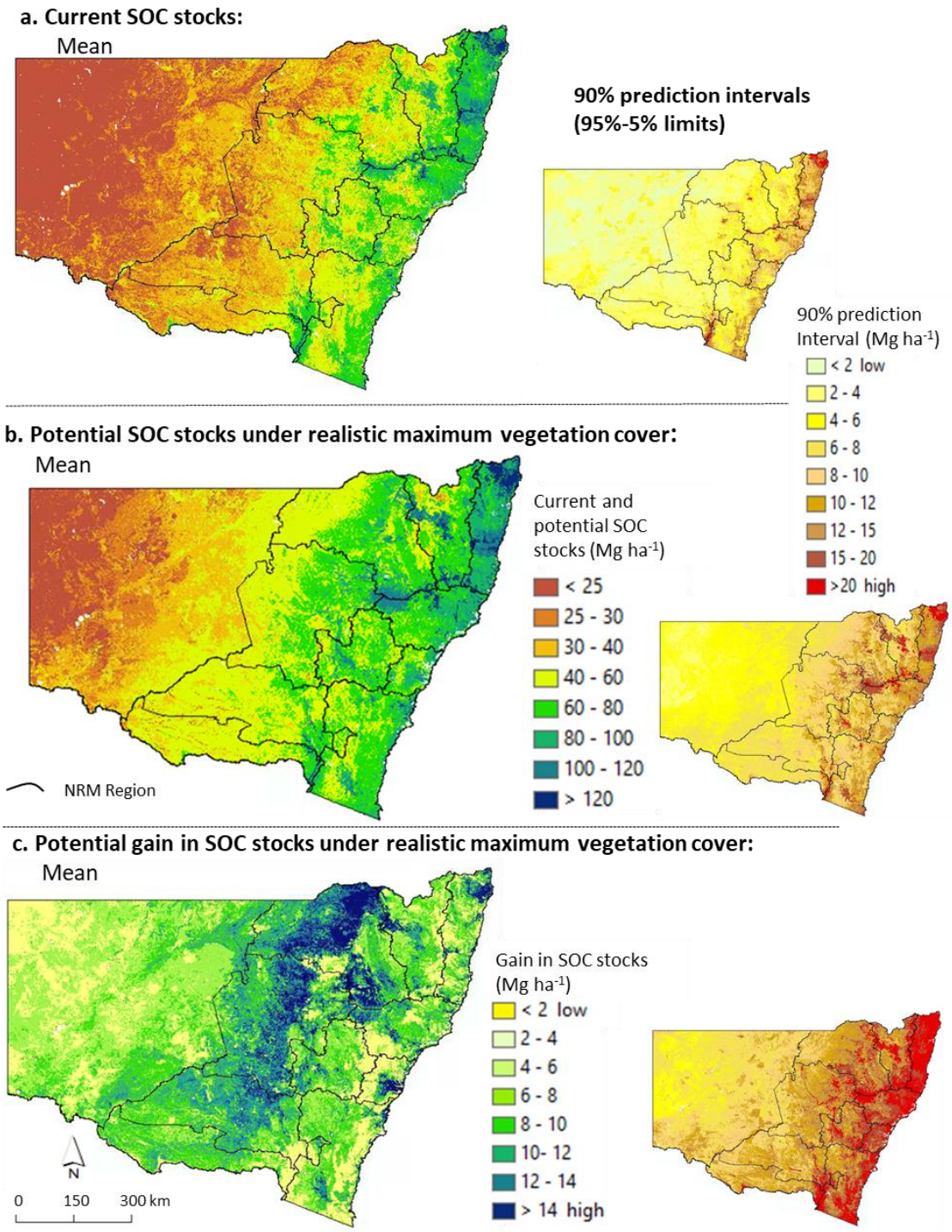
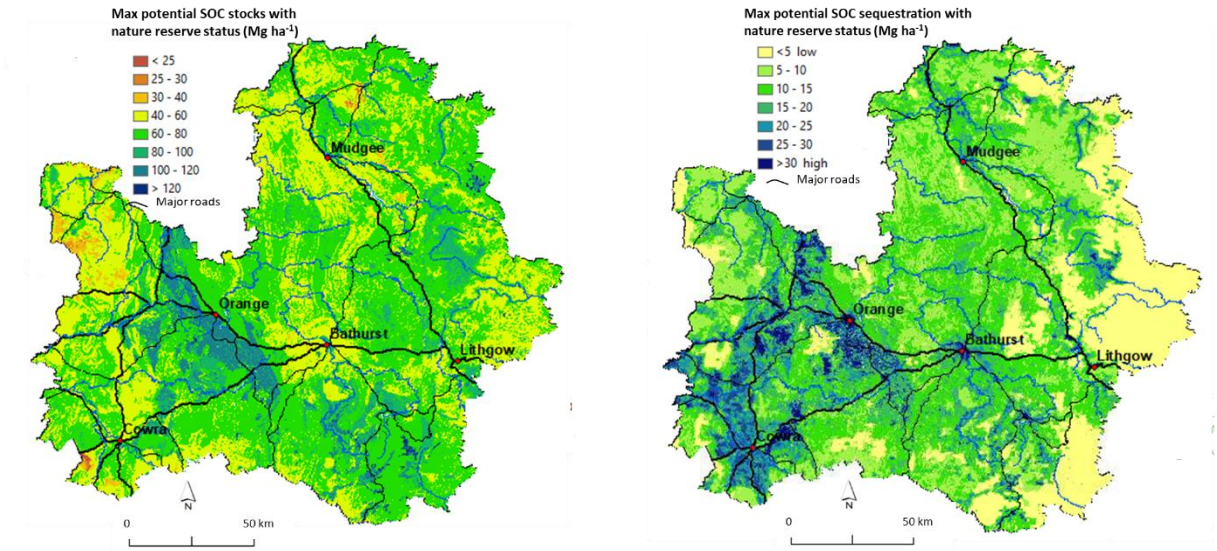


Figure S3.2. Maximum potential change in SOC stocks under realistic maximum vegetation cover, with mean and 90% prediction intervals (0-30 cm, Mg ha^{-1}). (a) Current SOC stocks; (b) Maximum potential SOC stocks; (c) Maximum potential change in SOC stocks (sequestration). For a and b, 90% PI is 95%-5% limits, for c, 90% PI is derived from Eq. 1 (main article)

Table S3.1: Potential maximum SOC sequestration for each of 11 NRM regions under nature reserve status

NRM Region[1]	Area (km^2)	Mean ($Mg\ ha^{-1}$)	Potential sequest'n (Tg)	CO_2e (Tg) Mean (and 5%-*95% prediction limits*)
Central Tablelands	30,265	10.6	32.0	117 (*18-202*)
Central West	87,375	18.6	162.8	597 (*385-797*)
Greater Sydney	11,453	11.0	12.6	46 (*-2-85*)
Hunter	30,905	11.6	35.8	131.3 (*-3-252*)
Murray	41,372	11.0	45.3	166 (*63-255*)
North Coast	29,553	11.7	34.6	127 (*-47-296*)
North West	76,807	21.8	167.2	613 (*401-803*)
Northern Tablelands	36,819	11.2	41.1	151 (*22-273*)
Riverina	65,656	15.4	101.4	372 (*224-509*)
South East	54,422	8.8	48.1	176 (*-41-343*)
Western	296,818	7.7	229.3	841 (*380-1238*)
All_NSW	761,444	11.9	910.2	3338 (*1403-5051*)

[1] refer to Figure 1 (main article)



a. Max potential SOC stocks with realistic maximum vegetation cover ($Mg\ ha^{-1}$)

b. Maximum potential SOC sequestration with realistic maximum vegetation cover ($Mg\ ha^{-1}$)

Figure S3.3. Maximum potential stocks (a) and gain in SOC stocks (b) under realistic maximum vegetation cover.