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Change in Soil Organic Carbon Stocks under 12 Climate Change Projections over New South Wales, Australia

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Digital soil mapping (DSM) techniques combined with space-for-time substitution (SFTS) processes were used to map and examine soil organic carbon (SOC) changes caused by projected climate change over New South Wales, Australia until ~2070. Twelve projections were derived from four global climate models downscaled with three regional climate models. A marked variation in the direction and magnitude of SOC change was demonstrated with the different projections. Mean state-wide predictions (0–30 cm depth) ranged between 2.9 Mg ha⁻¹ gain and 8.7 Mg ha⁻¹ SOC loss. Greater consistency among climate change projections is required before we can confidently predict SOC changes. By using averaged results from the 12 projections, broad trends were revealed for the change in SOC over two intervals (0–30 and 30–100 cm). A mean loss rate of 2.0 Mg ha⁻¹ for the upper interval was demonstrated and a total loss of 737 Tg of CO₂ equivalent for the entire depth to 100 cm but the 95% confidence interval was wide. Although changes are primarily controlled by the balance between changing temperatures and rainfall, the extent of change also depends on the environmental regime, with differing changes demonstrated over 36 current climate–parent material–land use combinations (e.g., projected mean SOC decline is <1 Mg ha⁻¹ for dry–highly siliceous–cropping but >15 Mg ha⁻¹ for wet–mafic–native vegetation).

This DSM–SFTS technique offers a viable alternative to dynamic simulation techniques for predicting and identifying patterns in the change of soil properties caused by climate change.

Abbreviations: CCCMA, Canadian Centre for Climate Modeling and Analysis 31 model; CSIRO, Commonwealth Scientific and Industrial Research Organization; DEM, digital elevation model; DSM, digital soil mapping; IPCC, Intergovernmental Panel on Climate Change; MIROC, Model for Interdisciplinary Research on Climate 32 model; NARClim, NSW and Australian Capital Territory Regional Climate Modeling; NSW, New South Wales; Rain, mean annual rainfall; SOC, soil organic carbon; SFTS, space-for-time substitution; Tmax, mean annual daily maximum temperature.

Core Ideas

• Potential changes in soil organic C to 2070 mapped (100-m grid) and examined.
• The direction and magnitude of change varied between the 12 climate projections.
• Differing changes revealed for 36 current climate–parent material–land use regimes.
• Digital soil mapping–space-for-time substitution is useful for climate change study.

Climate change will impact on many aspects of the global environment and civilization generally, with changes in our soil resources being one important yet not widely understood consequence. Changes in key soil properties such as SOC content will influence agricultural productivity and our ability to feed and support the growing world population. Native ecosystems will be impacted, with modifications to species distribution and abundance at local, regional, and national scales. Changes in the potential of soils to sequester C or release it to the atmosphere are crucial for climate change modeling and mitigation strategies (Lal et al., 2007; Baldock et al., 2012).

Although there has been widespread work on the relationship of climate to soils, dating back to the pioneering work of Dokuchaev in 1899 (Dokuchaev, 1967 transliteration) and Jenny (1941) up to more recent studies such as Fantappiè et al. (2011), relatively few studies have developed spatial predictions of the changes...
in soil properties under formal climate change projections, especially at fine regional scales. Studies that have been reported are primarily focused on changes to SOC, reflecting its importance to climate change modeling and mitigation strategies and also agricultural productivity and the ecosystem health more broadly.

The majority of these studies have applied dynamic simulation modeling approaches such as the C dynamics simulation models of RothC (Coleman and Jenkinson, 1999) and SOCRATES (Grace et al., 2006). Global simulation studies on SOC change have been undertaken by several workers and different conclusions are drawn depending on the global climate model, regional climate model, Intergovernmental Panel on Climate Change (IPCC) emission scenario (Nakicenovic and Swart, 2000), and C dynamics model selected. Overall global increases in SOC by 2100 have been reported by Lucht et al. (2006), Yurova et al. (2010), and Gotschalk et al. (2012), with the magnitude of increase depending on the global climate model and emission scenario. In contrast, however, Jones et al. (2005) reported a decrease in global SOC by the end of the century, as did Smith (2012) and Ito (2005) for at least some global climate model and emission scenarios. All studies demonstrate large variations in both the direction and the extent of SOC change over different regions of the globe, even with the same climate model. Lal (2004) and Gotschalk et al. (2012) reported higher latitude regions underwriting overall losses and tropical regions undergoing overall gains.

At the country or regional level, SOC change under climate change has been spatially simulated in a number of recent studies, ranging from 250 m to over 50 km resolution, including in North America (Smith et al., 2009; Follett et al., 2012; Dib et al., 2014; Zhong and Xu, 2014; Byrd et al., 2015; Orem et al., 2015), in Asia (Hashimoto et al., 2012; Zhao et al., 2013, 2015), and in Europe and the Mediterranean region (Smith et al., 2005, 2006; Álvaro-Fuentes and Paustian, 2011; Álvaro-Fuentes et al., 2012).

In contrast to dynamic simulation modeling, there appears to be very little previous use of digital soil mapping (DSM) approaches for predicting SOC and other soil property changes under climate change. Digital soil mapping approaches use data mining and statistical techniques to predict soil properties using a range of environmental covariates (McBratney et al., 2003). The use of DSM approaches for this purpose was proposed by Minasny et al. (2013), who described it as the “static–empirical” modeling approach, being an alternative to the “dynamic–mechanistic simulation” approach. They demonstrated its application with a 500-km² study predicting SOC change in southern New South Wales (NSW), Australia, with 250-m grid spacing. Yigini and Panagos (2016) recently adopted a similar approach in their modeling of SOC stock change (1 km resolution) in Europe to 2050 under climate and land use change.

These DSM approaches could be described as space-for-time substitution, a process used to infer future trajectories of natural systems from contemporary spatial patterns. It assumes that the drivers of the spatial patterns also drive temporal changes (Pickett, 1989, Blois et al., 2013). For example, the change in a soil property over time caused by new given climate conditions can be demonstrated by examining soils from different sites with that given climate but otherwise similar soil-forming conditions. Changes in climate over space substitute for changes over time. It has been widely used in biodiversity modeling and increasingly for climate change-driven biodiversity studies, although there is debate about its effectiveness (Blois et al., 2013). However, to date, it has rarely been reported in pedological studies, although Barraclough et al. (2015) recently used it to test whether climate change had had an impact on soil C contents in England and Wales.

In this study, we used DSM techniques combined with SFTS to examine the potential change in SOC from projected climate change over the entire state of NSW in the coming decades. Change in SOC is considered a priority for Australian soil monitoring programs (McKenzie and Dixon, 2006). Twelve climate change projections were applied, derived from four global climate models, each downscaled with three regional climate models that were sourced from the NSW and Australian Capital Territory Regional Climate Modeling (NARChM) project (Evans et al., 2014; Office of Environment and Heritage, 2014). The primary aims of our study were to:

- Demonstrate the viability of using a DSM–SFTS technique to spatially quantify changes in soil properties caused by the influence of future climate change, with reference to SOC;
- Assess the consistency of predictions of SOC change among different global and regional climate models; and
- Assess whether the SOC changes vary systematically according to environmental conditions, based on current climate–parent material (soil type)–land use regimes.

**MATERIALS AND METHODS**

In overview, the process commenced with the compilation of the required SOC datasets and environmental grids representing soil-forming factors over eastern Australia and NSW, which included current climate data. Statistical models were then developed over eastern Australia, these effectively representing SOC content under the baseline climate. The broader eastern Australian province was used for model development, as it encompassed broader climate ranges that may be encountered under the projected climate change and because data points were scarce in western NSW (see Fig. 1). Twelve projected climate grids over three time periods (1990–2009, 2020–2039, and 2060–2079) were then substituted for the baseline climate data in these models to prepare predictive digital maps of the soil properties over NSW under these future climate conditions. By comparing the predicted future soil property maps with current maps, the extent of change in SOC was derived for each 100-m pixel. Further analysis of the change was undertaken with a breakdown according to current climate–parent material–land use subclasses.
Soil Profile Dataset

Soil profile datasets over eastern Australia were acquired from the five state government soil resource agencies, based on their 2011 data holdings, plus the Federal Government’s Commonwealth Scientific and Industrial Research Organization (CSIRO) data from 2001. These included data collected back to the 1960s and earlier. This combined dataset predates the recently compiled National Soil Site Collation (Searle, 2014). Only those profiles with SOC laboratory data plus parent material descriptors that could be reliably classified were used. The final dataset contained profile numbers as follows: Queensland, 1504; NSW, 1788; Victoria, 224; Tasmania, 350; South Australia, 585; and CSIRO (eastern states), 760. This amounted to a total of 5211 profiles (Fig. 1). The dataset was compiled using Microsoft Access (version 2013, Microsoft Corp., Redmond, WA) with further organizing and sorting using Microsoft Excel (version 2013, Microsoft Corp.). Values reported for each soil horizon over the entire original dataset were converted into five standard depth intervals: 0 to 5, 5 to 15, 15 to 30, 30 to 60, and 60 to 100 cm using the equal area splining process of Bishop et al. (1999) and Malone et al. (2009). These intervals conform to those adopted in the Soil and Landscape Grid of Australia (Terrestrial Ecosystem Research Network, 2014; Grundy et al., 2015) and GlobalSoilMap.net (Sanchez et al., 2009; Arrouays et al. 2014) down to the 100-cm level. Models developed from this large eastern Australian dataset were used to generate the digital maps for NSW alone.

Soil Organic C Data

The great majority of the laboratory analyses of SOC from the above dataset were undertaken via the Walkley–Black wet oxidation method; however ~5% used LECO (Saint Joseph, MI) and other combustion methods, as described by Rayment and Lyons (2010). The variation in different laboratory methods caused by the different dates and jurisdictions of the analyses resulted in a degree of inconsistency in the test results and potential error in the predictive models. The Walkley–Black method has been reported to underestimate total SOC levels (Skjemstad, 2000) but no correction was applied, as there is much uncertainty regarding the most appropriate correction factor (Conyers et al., 2011; Bui et al., 2009). The final analysis excluded samples with less than 0.1% SOC, as these were considered unreliable, and those with greater than 18% SOC, as these are always defined as organic materials in the Australian Soil Classification (Iseb, 2002). Such soils are not common in the region and are difficult to model and the extreme SOC values can distort modeling relationships. Organic C mass (Mg ha⁻¹) was derived in addition to concentration (%), using the bulk density grids produced through DSM techniques from the Soil and Landscape Grid of Australia (Terrestrial Ecosystem Research Network, 2014).

The Covariates

Covariates were selected to represent the key soil forming factors of climate, parent material, relief, biota, and age as outlined below.

Climate

For the current climate used in the preparation of initial Cubist models, we used the following variables: Mean annual rainfall (mm yr⁻¹, Rain) and mean annual daily maximum temperature (°C, T_max). These were derived from 2.5-km Australia-wide climate grids from the Australian Bureau of Meteorology (http://www.bom.gov.au/climate/averages/climatology/gridded-data-info/gridded-climate-data.shtml, accessed 3 Aug. 2016) with interpolation of cell values down to a 100-m grid, using the ArcGIS Interpolation Spline tool (ESRI Inc., Redlands, CA). The values represent the mean values obtained over the 1961 to 1990 period, which coincides with the period when a large proportion of the soil profiles were collected, meaning these climate grids are appropriate for this soil modeling exercise.

For the projected climate used in the preparation of output grids under climate change: 12 climate models derived from the NARCLiM program (Evans et al., 2014; Office of Environment and Heritage, 2014) were used for Rain and T_max grids across NSW averaged over each of the three periods: 1990 to 2009 (representing “current” conditions), 2020 to 2039 (near future), and 2060–2079 (moderately far future). These NARCLiM
Table 1. Parent material classes and typically associated soils†

<table>
<thead>
<tr>
<th>Parent material class</th>
<th>Common examples</th>
<th>Typical Australian Soil Classification soils‡</th>
<th>Typical WRB soils§</th>
<th>Typical Soil Taxonomy soils¶</th>
</tr>
</thead>
<tbody>
<tr>
<td>Siliceous- upper (&lt;75% silica)</td>
<td>Quartz sands (alluvial or aeolian), pure quartzite, chert, quartz sandstone and silstone</td>
<td>Quartzose Rudosols and Tenosols, Podzols</td>
<td>Arenosols, Podzols</td>
<td>Spodosols (Quartzipsamments), Inceptisols, (Psamments)</td>
</tr>
<tr>
<td>Siliceous- lower (65–75% silica)</td>
<td>Granite, rhyolite, andesimellite, granite, rhyolite, andesimellite, granodiorite, dacite, greywacke, feldspathic or lithic sandstone</td>
<td>Kandosols, base poor (low fertility) Chromosols, Kurosolos &amp; Sodosols</td>
<td>Acrisols, Alisols, Cambisols, Ferralsols, Retisols, Umbri soils Durisols, Lixisols, Planosols, Solornetz</td>
<td>Alisol, Aridisols and Oxisols, (Ildults)</td>
</tr>
<tr>
<td>Intermediate (52–65% silica)</td>
<td>Trachyte, syenite, monzonite, diorite, andesite, mudstone, argillaceous sediments (shale, etc.), alluvial gray and brown clays</td>
<td>Dermosols, Ferrosols, gray and brown Vertosols; base rich (fertile) Chromosols, Kurosools and Sodosols</td>
<td>Chernozems, Kastanozems, Luvisols</td>
<td>Mollisols (Udolls, Ustolls, Kandudults, Mollic paleudult)</td>
</tr>
<tr>
<td>Mafic (&lt;52% silica)</td>
<td>Gabbro, dolerite, basalt, alluvial black cracking clay</td>
<td>Black Vertosols, Ferrosols</td>
<td>Nitosols, Phaeozems, Vertisols</td>
<td>Vertisols</td>
</tr>
</tbody>
</table>

† First approximations for common soil types only; most soil types will extend into the adjoining parent material classes.
‡ Based on Isbell et al. (1997); Gray and Murphy (1999), and Gray et al. (2014).
§ World Reference Base for Soil Resources (WRB); based on International Union of Soil Sciences Working Group WRB (2014) and Gray et al. (2011).
¶ Based on Soil Survey Staff (2010) and Gray et al. (2011).

Other Covariates

Covariates relating to other soil forming factors are listed below. For the purposes of this work, these were assumed to be constant over the modeling period.

- Parent material: (i) Silica index (lithology class) – an index representing the composition of the parent material estimated using documented average chemical composition (Gray et al., 2014, 2015a). For example, granite is moderately siliceous with approximately 73% silica, whereas basalt is mafic material with only approximately 48% silica. Parent materials with higher silica content typically give rise to soils with more quartzose sandier textures with lower chemical fertility. For model development, parent material descriptors recorded at each site were used to derive silica indices; for the final digital soil maps, the 1:250 000 scale polygonal geology map from NSW Geological Survey (Maitland, NSW, Australia) were used. For post-modeling interpretation purposes, these were grouped into four classes as shown in Table 1, which also presents typically associated soil types. (ii) Radiometrics – gamma radiometric K, U, and Th, derived from airborne surveys from Geoscience Australia (Canberra, ACT, Australia).
- Relief: (i) Topo-slope index – an index that combines topographic position and slope gradient, representing the degree to which a site is subject to depletion (1) or accumulation (6) of water, soil particles and chemical materials. Data were derived from field data and a 100-m digital elevation model (DEM) (Gray et al., 2015a). (ii) Topographic wetness index – a widely used index that represents potential hydrological conditions based on slope and catchment area, as derived
from DEMs (Terrestrial Ecosystem Research Network, 2014; Gallant and Austin, 2015). (iii) Slope – slope gradient in percent as derived from a 100-m DEM. (iv) Aspect index – an index to represent the amount of solar radiation received by sites, ranging from 1 for flat areas and gentle north or northwest facing slopes to 10 for steep south and southeast slopes (in the southern hemisphere, Gray et al., 2015a), derived from a 100-m DEM.

- Age: (i) Weathering index – an index to represent the degree of weathering of parent materials, based on radiometric data (Wilford, 2012). A 90-m grid was accessed from Geoscience Australia.

- Biota: (i) Land disturbance index – an index that reflects the intensity of disturbance associated with the land use, where 1 denotes natural ecosystems and 6 denotes intensive cropping, based on 1:25 000 scale land use mapping (Office of Environment and Heritage, 2007; Gray et al., 2015a). (ii) Ground cover – total vegetation cover (photosynthetic and nonphotosynthetic) derived from CSIRO 2011 MODIS fractional vegetation data (Guerschman et al., 2009). These variables are held constant into the future.

### Developing Models and Statistical Analysis

Analysis was performed using R statistical software (R Core Team, 2013). The soil dataset was apportioned 80% as training data and 20% as validation data (following stratification by state) with modeling carried out by Cubist linear piecewise decision tree models (Quinlan, 1992) using the Cubist package of Kuhn et al. (2014). Natural log transformations were applied to the SOC values to address the observed skewness in the response.

The models for each depth interval were validated using the validation datasets. Lin's concordance correlation coefficient was used to measure the level of agreement of predicted values with observed values, relative to the 1:1 line (Lin, 1989). The $R^2$, RMSE, standardized RMSE (RMSE divided by mean estimate), and mean error were also determined.

The Cubist models were applied to the NSW covariate grids with the projected NARClim climate layers to prepare maps over NSW for SOC for each of the three time periods in this SFTS process (Pickett, 1989; Blois et al., 2013).

Log values were back-transformed into natural scales. The maps were replicated using the 12 NARClim climate model grids; thus there were maps for five depths, three time periods and 12 climate model grids, giving 180 maps in total. The five depth intervals were then amalgamated into two broad-depth intervals: upper soil (0–30 cm) and lower soil (30–100 cm), using a depth weighted averaging process. Absolute changes over the two change periods (1990–2009 to 2060–2079) for each climate model were calculated for each pixel.

The state-wide changes in SOC for both depth intervals and change periods for each of the 12 climate models were presented in column plots. These also show the mean change and 95% confidence interval of change (based on 1.96 times the standard error from the 12 model predictions). Uncertainty analysis of the final map layers was not undertaken, partly because no validation points representing future conditions are available, but further research will endeavor to incorporate cross-validation techniques such as those demonstrated by Malone et al. (2014) and Kidd et al. (2015).

### Partition into Environmental Subclasses

In addition to presenting mean results of change over the entire state, the results from the 12 models were also partitioned according to their current climate–parent material–land use subclasses to observe the degree of response in different environmental regimes. The 36 subclasses were based on the grouping of three covariates as follows:

- Current climate: Three broad classes based on the ratio of $\text{Rain to } T_{max}$: dry, $<25$; moist, 25–50; wet, $>50$.
- Parent material: four classes as shown in Table 1, which also presents the typically associated soil types.
- Land use classes: three broad classes: native vegetation, grazing, and cropping.

Plots were prepared showing the mean and 95% confidence interval (being $1.96 \times \text{SE}$) for each subclass based on the 12 climate change projections, derived from the geographic information system results.

### RESULTS

Validation results for the initial Cubist models developed using the baseline (1961–1990) climate data are presented in Table 2. The models are shown to be meaningful, with Lin's concordance values being up to 0.73 in the surface layers but decreasing in strength in lower intervals, as mirrored by the rise in the standardized RMSE values.

Results from the five depth intervals were combined into just two depth intervals: upper soil (0–30 cm) and lower soil (30–100 cm). Primary attention was given to the results for the second change period (1990–2009 to 2060–2079). More detailed results and full digital maps (100-m resolution) from this study are available for public download through the Adapt NSW website (Office of Environment and Heritage, 2014). The change is reported on a state-wide basis and then by physical zones including climate–parent material (soil type)–land use regime.

### Table 2. Validation statistics of soil organic C Cubist models †.

<table>
<thead>
<tr>
<th>Depth interval, cm</th>
<th>N</th>
<th>Lin's CCC</th>
<th>RMSE, log %</th>
<th>Std RMSE</th>
<th>ME, log %</th>
</tr>
</thead>
<tbody>
<tr>
<td>0–5</td>
<td>1029</td>
<td>0.73</td>
<td>0.55</td>
<td>0.66</td>
<td>0.018</td>
</tr>
<tr>
<td>5–15</td>
<td>1007</td>
<td>0.73</td>
<td>0.53</td>
<td>0.73</td>
<td>0.015</td>
</tr>
<tr>
<td>15–30</td>
<td>792</td>
<td>0.62</td>
<td>0.62</td>
<td>1.20</td>
<td>0.020</td>
</tr>
<tr>
<td>30–60</td>
<td>588</td>
<td>0.52</td>
<td>0.65</td>
<td>2.20</td>
<td>0.086</td>
</tr>
<tr>
<td>60–100</td>
<td>426</td>
<td>0.37</td>
<td>0.66</td>
<td>3.80</td>
<td>0.073</td>
</tr>
</tbody>
</table>

† CCC, concordance correlation coefficient; Std RMSE, standardized RMSE (RMSE divided by mean of estimate); ME, mean error (prediction – observed)
State-wide Change

The absolute change in SOC stocks across NSW for both depth intervals and change periods predicted from each of the 12 climate models and their mean is presented in Fig. 2. The predicted changes vary substantially with the different climate models and their differing projections. The 95% confidence interval encompasses zero change in all four columns of Fig. 2, albeit generally only narrowly. The MIROC and CCCMA models, the wetter models, almost all suggest an increase in SOC stocks over both depth intervals and change periods, with up to over 2.9 Mg ha\(^{-1}\) increase being predicted by the MIROC3 model for the upper depth interval in the second change period. By contrast, the CSIRO models, the driest models, suggest notable decreases of up to 8.7 Mg ha\(^{-1}\) for CSIRO1 for the same depth and change period. The ECHAM models all reveal a slight decrease in SOC stocks.

Nevertheless, using averaged results from the 12 climate models, broad trends in change are revealed. The results suggest an overall decline in SOC stocks across NSW, with the extent of change becoming less pronounced at lower intervals and more pronounced over the second change period. From the mean of the 12 models, in the upper depth interval (0–30 cm), there was an average 1.5 Mg ha\(^{-1}\) decrease to the 2030 period and 2.0 Mg ha\(^{-1}\) to the 2070 period. There was only a slight mean decline in the lower depth intervals (30–100 cm), with only a 0.7 and 0.4 Mg ha\(^{-1}\) decline to the 2030 and 2070 periods, respectively. Close examination of these results reveals that the overall rate of SOC decline per year was lower for the second change period than for the first change period, which is attributable to the increasingly higher rainfall projected in the later years, which at least partly compensates for the steadily rising temperatures.

Based on the average of all 12 climate models and if we recognize the substantial uncertainties, most of the eastern and central-eastern regions of the state are projected to undergo a decrease in SOC stocks, with the most notable decline occurring over the alpine Snowy Mountain region of the far southeast, whereas the central-western and western regions undergo a slight increase in stocks, as shown for the upper 0 to 30 cm interval by Fig. 3. There are several exceptions to these trends, such as moderate increases in stocks in the central coastal regions around Sydney.
The results can be used to gain an estimate of total change of SOC and equivalent CO₂ over NSW caused by climate change, as presented in Table 3. Given that the area of NSW is 80.36 million ha, the total SOC loss from the top 100 cm, based on the average rates of SOC loss from the 12 models, is estimated at 193 Tg CO₂ equivalent for the far change period. The 95% confidence interval for CO₂ equivalent change ranges from a gain of 321 Tg to a loss of 1735 Tg. For comparison purposes, the mean estimate of change (loss to atmosphere) is equivalent to approximately five times the total greenhouse gas emissions over NSW (estimated at 142 Tg in 2013, including other greenhouse gases and agricultural emissions; Office of Environment and Heritage, 2015), but with the 95% confidence interval ranging from over 2 yr equivalent additions to the soil to over 12 yr equivalent losses to the atmosphere.

In addition to uncertainty arising from the different climate models, there is uncertainty from the digital modeling and mapping process used to derive the change estimates. The RMSE of the initial models for the original five depth intervals is relatively high, ranging up to 0.66 (% log scale) in the deepest layer (Table 2). Additional uncertainty parameters associated with the final map generation were not quantified but are also likely to be significant. The predicted state-wide changes in SOC all appear to be within the envelope of uncertainty. Further treatment of the sources of uncertainty is given later in the Discussion.

**Change by Environmental Regime**

The projected SOC changes are primarily dependent on the balance between the changing temperatures and rainfall over any region, generally decreasing with rising temperatures and declining rainfall (Jenny, 1980; Badgery et al., 2013; Viscarra Rossel et al., 2014; Gray et al., 2015b). However, the extent of the SOC change also varies depending on the environmental and land use regime, which add complexity to the above trends. A breakdown of the SOC change for the upper (0–30 cm) depth intervals over the second change period by the current climate–parent material–land use subclasses is presented in Fig. 4. Each column presents the mean plus the upper and lower 95% confidence intervals derived from the 12 climate models for each subclass. Only where the column does not intersect the zero change line can we be confident (at the 95% level) of a change based on the 12 climate models (but not considering the additional sources of uncertainty).

The plots reveal that the extent of SOC stock change varies with different current climate–parent material–land use regimes. For example, a mean loss of less than 1.0 Mg ha⁻¹ is projected for the dry–highly siliceous–cropland regime, whereas a loss of 15.3 Mg ha⁻¹ is projected for the moist–mafic–native vegetation regime. Although there are several anomalies, a trend of increasing loss of SOC stock with increasingly moist current conditions, less siliceous (more mafic), and less intensive land use is apparent.

**DISCUSSION**

**Variation of Predictions between Models**

The final predictions and spatial arrangement of SOC changes across NSW vary greatly with the different climate models and their differing projections, which hinders our ability to draw clear conclusions. There are some climate models that predict an increase in SOC magnitude but others that predict a decrease. For example, at the state-wide level in the second change period and 0 to 30 cm depth, the predicted change in SOC stocks varied from a 2.9 Mg ha⁻¹ increase to an 8.7 Mg ha⁻¹ decrease, depending on the model applied. Such variation applies at the state-wide level down to smaller regions and individual environmental regimes.

A wide range in future SOC stock projections derived by using different global climate models and emission scenarios has been widely demonstrated (Ito, 2005; Lucht et al., 2006; Yurova et al., 2010; Gottschalk et al., 2012). The uncertainty in SOC introduced by different climate models is reported to be greater than the uncertainty introduced by CO₂ emission pathway scenarios (Smith et al., 2006; Falloon et al., 2007; Gottschalk et al., 2012).

The variation in SOC projections among the different climate models over NSW in this study appears to be mainly attributable to the wide variations in projected regional rainfall change, as against the more uniformly increasing regional temperatures, a situation also reported by Falloon et al. (2007) in their global study.

Additionally, the application of other IPCC emission scenarios apart from the intermediate A2 scenario selected in this study would introduce further variations in the climate projections and associated soil property predictions. As the scientific community refines global climate change projections, we may become more certain of them and thus obtain more reliable projections of soil property change into the future.

<table>
<thead>
<tr>
<th>Mean and confidence interval</th>
<th>Depth Change in SOC stock per ha</th>
<th>Total change</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>cm</td>
<td>Mg ha⁻¹</td>
</tr>
<tr>
<td>Upper 95%</td>
<td>0–30</td>
<td>0.116</td>
</tr>
<tr>
<td></td>
<td>30–100</td>
<td>0.974</td>
</tr>
<tr>
<td></td>
<td>0–100</td>
<td>0.88</td>
</tr>
<tr>
<td>Lower 95%</td>
<td>0–30</td>
<td>-4.186</td>
</tr>
<tr>
<td></td>
<td>30–100</td>
<td>-1.707</td>
</tr>
<tr>
<td></td>
<td>0–100</td>
<td>-0.474</td>
</tr>
<tr>
<td>Mean</td>
<td>0–30</td>
<td>-2.035</td>
</tr>
<tr>
<td></td>
<td>30–100</td>
<td>-0.367</td>
</tr>
<tr>
<td></td>
<td>0–100</td>
<td>-1.93</td>
</tr>
</tbody>
</table>

† Area of NSW: 80.36 million ha
Broad Trends in Predicted SOC Change

Despite the differences demonstrated by each of the 12 climate models and despite the considerable modeling uncertainties, some broad trends are apparent. From the average of the models over NSW as a whole, an overall slight to moderate decline of SOC stocks was revealed. Declines are most pronounced in the east of the state, particularly in the highlands of the far southeast. By approximately 2070, a mean estimate of 737 Tg of CO$_2$ equivalent are projected to be lost from NSW soils to the atmosphere; however, the 95% confidence interval of the estimates are broad. When compared with the approximate total greenhouse gas emissions from NSW (142 Tg in 2013), the change does not appear dramatic.

The results from this study reflect well established soil property–climate trends. Drier conditions result in lower SOC levels (Jenny, 1980; Lal, 2004; Badgery et al., 2013; Viscarra Rossel et al., 2014; Gray et al., 2015b; Hobley et al., 2015). The direction and magnitude of change at any location will be defined by the integrated effects across all processes involved in emission and consumption or storage of C (Baldock et al., 2012; Gottschalk et al., 2012).

Additionally, this study has demonstrated that the extent of change is also influenced by the precise environmental regime, as represented by the current climate–parent material (soil type)–land use combination. A broad trend of increasing loss of SOC stock with increasingly moist current conditions, less siliceous (more mafic), and less intensive land use is apparent, despite some anomalies, a trend we also observed following large-scale vegetation clearance over NSW (Gray et al., 2016). These trends suggest that the extent of absolute change in SOC with the projected climate change is broadly dependent on the initial SOC levels in the soil. Soils with inherently high SOC levels will lose more SOC than those with inherently low SOC levels, at least in absolute terms. We recently demonstrated the inherently higher SOC storage levels of soils under moist, mafic parent material (with associated higher fertility soils) and high vegetation cover regimes across eastern Australia (Gray et al., 2015b).

The overall slight to moderate decline of SOC stocks in NSW, particularly in the east of the state, suggested by our study accords with the declining SOC levels over the small area of southern NSW reported by Minasny et al. (2013), who appeared to use climate projections from the Australian government based on up to 40 global climate models (Climate Change in Australia, 2015). The generally hotter and drier conditions in the future for Australia as reported by Baldock et al. (2012) using these CSIRO climate projections would suggest lower SOC levels but those authors themselves state that the direction and magnitude of SOC change is still under debate because of the modeling uncertainties.

Our results are broadly consistent with those presented in a global map (0.5° resolution) by Gottschalk et al. (2012) using 10 climate model–emission scenario combinations to 2100. There is, however, little consistency with the global maps presented at the same coarse scale and time frame by Ito (2005), who showed broad increases based on seven climate models and the A2 emission scenario, and Lucht et al. (2006), who showed varying trends with two global climate models.

The trends of change in SOC vary substantially in different parts of NSW, depending on the precise combination of key environmental factors, particularly current climate, parent material (reflecting soil type), and land use. The predictions vary from a notable rise in some regions of the state to a notable decline in other regions over the two change periods. The extent and direction of change tends to follow observable trends with respect to these environmental factors, with greater declines being associated with soils with wetter, more mafic, and less disturbed land use regimes.

Application of the SOC Change Maps

Complete digital maps at 100-m pixel resolution and further details on our results for the SOC change are available for public download through the Adapt NSW website (Office of Environment and Heritage, 2014). The predicted changes have implications for the future condition of NSW soils and climate change mitigation strategies. Soil condition and agricultural
productivity generally improve with increased organic C content because of the enhanced physical, chemical, and biological properties (Jenny 1980; Charman and Roper, 2007; Lal et al., 2007; Baldock et al., 2012; Murphy, 2015). The opposite effect applies with declines in SOC content. Farmers may need to consider measures to counter potential declines, such as implementing management practices that better retain soil moisture (Stokes and Howden, 2010). Changes in soil condition caused by climate change may also impact native ecosystems (Steffen et al., 2009).

The maps deserve consideration during any climate change mitigation programs that are based on increased soil C sequestration (Lal et al., 2007; Wilson et al., 2011; Baldock et al., 2012; Smith, 2012). Those regions of NSW, where the soil C storage has been shown to have a declining trend, such as in the east and south, will require even greater C-enhancing actions to produce the desired soil C increases. On the other hand, those regions of the state with a projected slight increase in SOC, such as in the west and central west, will gain assistance toward their C sequestration programs.

Modeling Uncertainties

There are numerous sources of uncertainty associated with the application of the DSM–SFTS technique in this study in addition to the uncertainty arising from the different climate models, which need to be recognized when assessing results and drawing final conclusions. Uncertainties arise from the initial establishment of the Cubist statistical models based on the training soil point dataset, as reflected in the relatively high RMSE values (Table 2). Further uncertainties are associated with creation of the actual digital map layers based on these models with available covariate grids. Final map uncertainties were not quantified in this study. These uncertainties reflect inherent weaknesses in our modeling process that are common to many DSM projects, such as inherently poor relationships between the soil properties and the selected environmental covariates, a lack of representativeness of particular environments in the training dataset, errors and inconsistencies in the laboratory data, weaknesses in the covariate grid layers including downscaling of coarse climate and other grids to 100 m, reliance on other modeled data such as the bulk density layer, and others (McBratney et al., 2003; Nelson et al., 2011; Bishop et al., 2015; Robinson et al., 2015).

Through the use of the SFTS process, there is an assumption that the statistical relationships with the climate developed under current conditions will hold true into the future with a changing climate but there is uncertainty in this. Some minor potential anomalies were evident in components of the Cubist decision tree models. Occasional rules of the decision trees, representing particular covariate combinations at particular depths, had climate trends in the terminal regression models that did not accord with well-established soil property–climate relationships and thus gave questionable results when applied under future climate regimes. For example, the second of nine rules for SOC at the 5 to 15 cm interval, indicated a very slight increase in SOC with increasing temperatures rather than the expected opposite trend, a trend that carries through into the future maps for that covariate space. This may represent a weakness in the application of the SFTS process with the Cubist DSM approach. Some covariates included in the study, such as ground cover, may also have a certain climatic signal but these were kept constant throughout the future modeling periods and thus may distort the final results. The extent and consequences of such interactions should be explored prior to final covariate selection in future studies.

No account was taken of other related impacts associated with climate change such as changes to land use and management, vegetation patterns, erosion hazard, fire regimes, and seasonal climatic patterns, which may all impact on soil conditions. Smith et al. (2006) claim changes in land use and vegetation structure will outweigh the effects of climate change in influencing future SOC levels in European forests. The modeling could be improved with better assumptions and details on these conditions in the future time periods.

Feedback processes related to soil–atmosphere C dynamics were not included in the applied climate models. These include the exchange of C between the soil and atmosphere and possible increased vegetation growth and organic inputs arising from increased atmospheric CO2 levels (Ito, 2005; Jones et al., 2005; Friedlingstein et al., 2006; Smith et al., 2008; Ostle et al., 2009; Gottschalk et al., 2012). Belowground processes in the C cycle–climate system are reported to be much less understood than the aboveground processes (Heimann and Reichstein, 2008, Zhong and Xu, 2014).

The modeling did not consider the period of time required by soils to re-equilibrate with the changing climatic conditions, an issue recognized by Baldock et al. (2012). A period of 20 yr for soil C to approach equilibrium has been used by the IPCC but equilibrium is reported to be reached in 100 yr in temperate regions and even longer in boreal regions (IPCC, 1997; Smith, 2008). Periods of 20 to 50 yr for SOC re-equilibration to altered land use were demonstrated by Guo and Gifford (2002) and Skjemstad et al. (2004). Nevertheless, the clear response of SOC and other key soil properties to the current prevailing climate has been remarked on by several workers (Jenny, 1980; Bui et al., 2006).

Future research in this field will need to quantify the levels of uncertainty from all sources of potential error, particularly if predicted values are to be applied in C trading schemes (Baldock et al., 2012). The more dynamic simulation approaches, as adopted in most previous soil–climate change studies, may be more successful in addressing many of these uncertainties than the DSM–SFTS approach applied here. Nevertheless, the DSM–SFTS approach has been shown to present useful first approximations of the likely changes in SOC under different climate change scenarios.

CONCLUSION

This study has demonstrated that application of the DSM–SFTS approaches can be useful for the fine-scale spatial prediction of SOC change under the influence of climate change,
although several sources of uncertainty are identified. The approach is a feasible alternative to the more widely adopted dynamic simulation approaches.

It was demonstrated that the choice of climate change projection has a great bearing on the final predictions, with the direction and magnitude of the predicted SOC changes across NSW varying markedly among the 12 global and regional climate models applied. It is evident that greater consistency among climate change projections is required before we can confidently predict SOC and soil behavior generally under climate change.

Despite the uncertainties, the averaged results from the different climate models provide a useful first approximation of the likely changes in SOC as a result of climate change across NSW over the coming decades. The results add to our knowledge of SOC behavior under climate change. It was demonstrated that although the SOC changes are primarily controlled by the balance between changing temperatures and rainfall, the extent of change is also dependent on the precise environmental regime, as represented by the current climate–parent material (soil type)–land use combination.

Results such as those presented here for NSW may assist land managers to prepare more fully for potential changes in soil condition due to ongoing climate change. They may provide valuable inputs into other environmental modeling programs and have implications for climate mitigation strategies based on soil C sequestration. Further refinement of global and regional climate change projections will help to improve the quality and reliability of soil property change maps such as these.

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