DEPARTMENT OF PLANNING, INDUSTRY & ENVIRONMENT

Determining baselines, drivers and trends of soil health and stability in New South Wales forests – Regional Forest Agreement regions

NSW Forest Monitoring & Improvement Program

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Cover photo: DPIE soil scientist Mark Young describes a soil in a Hunter Valley forest. Photo: C Murphy/DPIE

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Version 1.1: includes an additional map for Emmerson Aggregate Test in Appendix A

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Contents

Tables

Figures

Executive Summary

On behalf of the NSW Forest Monitoring Steering Committee, the NSW Natural Resources Commission (NRC) engaged the NSW Department of Planning, Industry and Environment (DPIE) and the University of Sydney in collaboration with the University of New England to assess the baselines, drivers and trends for soil stability and health within the NSW Regional Forest Agreement (RFA) regions. This work is part of the wider NSW Government Forest Monitoring and Improvement Program (FMIP).

A framework to evaluate forest soil health and stability

We developed a conceptual framework for the evaluation of soil health and stability which outlines how soil health and function are assessed by comparing the condition of a soil to a reference condition.

We identified potential drivers of change, such as bushfire and land disturbance, and their impacts, such as erosion and loss of soil organic carbon (SOC).

Based on the potential drivers of change and the findings of our literature review, we developed a set of key physical, biological and chemical indicators which would provide measurements of the impacts of such change. Measurement of indicators serves to develop soil functional thresholds and validate existing management practices or inform potential improvements.

Availability of soil data is limited

We conducted a data-gap analysis, which determined that available soil health indicator measurements from the RFA regions are limited and subject to large spatiotemporal variation.

Of the data held in the NSW Soil and Land Information System (SALIS), there are no measurements of soil biological health indicators from the area. In the last decade, less than 50 soil carbon measurements have been collected from across the RFA regions. No bulk density measurements have been collected during this time, which are needed for accurate calculation of belowground carbon stocks. Available measurements of other physical and chemical soil health indicators are similarly limited.

The lack of data limits the certainty of any assessment of trends in overall soil health.

Overall modelled soil health is declining

We developed methods of spatial analysis to evaluate soil health indicators, including digital soil mapping and a novel approach to soil modelling, the data cube, which uses geospatial technology and machine-learning. These approaches allow us to establish key relationships and trends.

We used these methods to evaluate the available data. Despite model performance being limited by the lack of current soil data, the digital soil modelling indicates:

- SOC concentrations have declined slightly between 1990 and 2020, including periods of significant fluctuation likely related to variation in climatic conditions.
- Areas subject to increased ground disturbance from land use activity, in particular forests in which grazing is permitted, have lower concentrations of SOC and higher bulk density (suggesting poorer soil structure and condition) than less disturbed areas.
- Climate change is predicted to contribute to a decline in SOC and a slight rise in pH over most of the region.
- Bushfires have a major influence on SOC with a dramatic loss immediately following the bushfire, followed by a gradual recovery of SOC in the following years.
- The hillslope erosion risk in the RFA regions is highest in summer. A loss of vegetation cover increases the risk of hillslope erosion.

The limited findings indicate potential declines in soil health regardless of land use type, with trends in SOC being of specific concern. Without additional forest soil data, the uncertainties in the baseline and trends of NSW forest soil health will remain.

More data are needed to improve confidence in results

We have designed a conceptual soil monitoring program which would address this urgent need. We propose a program of time-series monitoring that incorporates flexibility such that sampling is focused on areas of concern, and statistical analysis to identify and prioritise indicators with the most significant input values. The program would leverage existing soil data and soil monitoring expertise and would deliver a core dataset from which soil functional thresholds and locations of soil change could be determined.

The data produced by such a program would deliver important insight for strategic direction of resource management and future scenario planning, delivering tangible results to support management of forest soils and maintain or improve the condition of this valuable and threatened resource.

1 Introduction

1.1 Preamble

On behalf of the NSW Forest Monitoring Steering Committee, the NSW Natural Resources Commission (NRC) engaged the NSW Department of Planning, Industry and Environment (DPIE) and the University of Sydney with collaboration from the University of New England to support the NSW Forest Monitoring and Improvement Program (FMIP).

The FMIP seeks to improve forest management decision-making across NSW forests of all tenures (national parks, state forests, crown land and private land) through monitoring, evaluation, research and reporting.

To support this objective, the program has posed state-wide evaluation questions including: *what is the health and stability of soil in forests, and what is their predicted trajectory?*

To answer this question, the program set five tasks:

- Develop metrics for indicators of soil health and stability values
- Propose a conceptual framework for the monitoring of indicator metrics across all tenures
- Propose historic baselines for the indicators of soil health and stability in forests
- Propose additional baselines for the indicators for which there is no current data
- Analyse trends in the indicators of soil health and stability in forests

1.2 Approach and objectives

Our work on this project commenced with a literature review (Milford, 2021) to evaluate the existing research and approaches to the assessment of the health and stability of forest soils. The review determined that reliable data on the health and stability of forest soils are relatively scarce. In forest science, the nature and dynamics of above-ground ecosystems have been examined in some detail, but far less attention has been directed towards soil systems. In soil science, researchers have focused on more intensively-used land, such as agricultural systems, with relatively little research attention directed to forests.

We undertook an evaluation of the available soil data from NSW forests, which confirmed that such data are limited; it is subject to large spatiotemporal variation (refer Section 5) and is not sufficient to enable characterisation of the forest landscapes to which they belong due to variation in terrain, parent material, climate and soil types.

Given these constraints, our approach to assess the baselines, drivers and trends of soil health and stability was as follows:

- Design a conceptual framework for the evaluation of soil health and stability.
- Develop a set of soil indicators (parameters) for measurement and monitoring of soil health and stability.
- Evaluate the existing soil data from NSW forests (including by spatial analysis) in relation to presence, age, geographical coverage, parameters measured, repetition, and accuracy.
- Carry out a data-gap analysis to identify data required to establish baseline values for soil indicators.
- Estimate the current status of soil indicators for which there is sufficient data for analysis.
- Identify potential drivers of change and threats to soil health.

- Determine trends for soil health and stability (including by spatial analysis).
- Propose a soil monitoring program to address data gaps, inform soil and land management and maintain or improve the condition of forest soils.

1.3 Conceptual framework for evaluating soil health and stability

A conceptual framework for the evaluation of soil health and stability is presented in Figure 1 and is described as follows:

- Soils are subject to natural and human disturbances (Section 3.1) which have impacts on the soil (Section 3.2).
- Impacts can be detected by measuring soil health indicators (Section 4).
- The evaluation of the soil health indicator data determines the status of soil indicators.
- This status is compared to that of a reference condition. Differences between the two indicate the health and stability of the soil at that point in time.
- Soil health information is evaluated from across a study area to identify locations of change in soil condition to inform soil and land management practices.
- Ongoing monitoring enables continued evaluation of soil health and stability of the area being monitored to assess the impact of changes to soil and land management.
- Action is taken to maintain or improve soil condition.

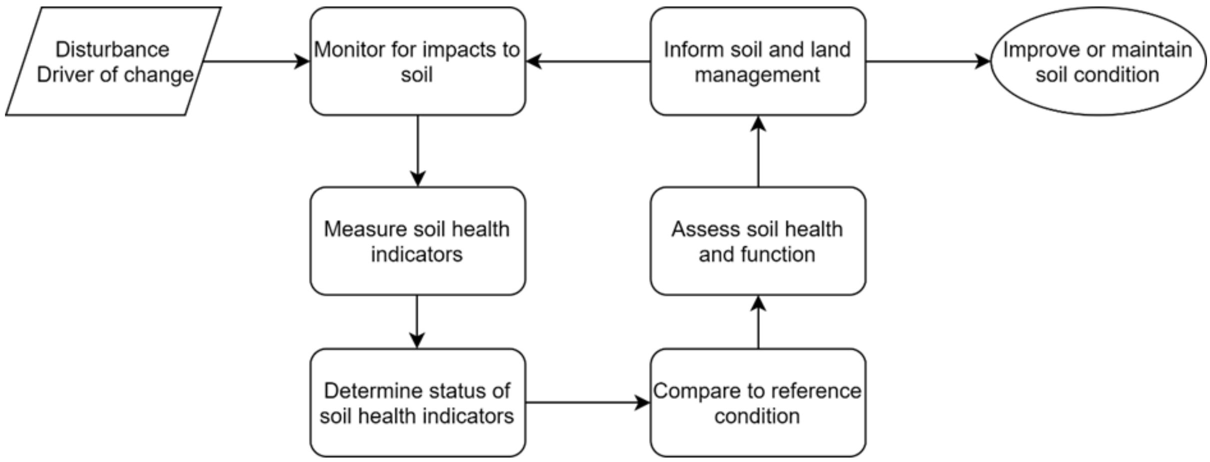


Figure 1 Conceptual framework for evaluating soil health and stability

2 Background

2.1 What is soil health?

The Intergovernmental Technical Panel on Soils of the United Nations' Food and Agriculture Organisation (FAO) defines soil health as:

> *The ability of the soil to sustain the productivity, diversity, and environmental services of terrestrial ecosystems* (ITPS 2020).

A healthy soil typically supplies the essential nutrients, water, oxygen and physical support that plants need to grow and thrive in a particular environment. It is also a dynamic living ecosystem, containing billions of microscopic and larger organisms that carry out a range of vital environmental functions. Its functions are described in Figure 2.

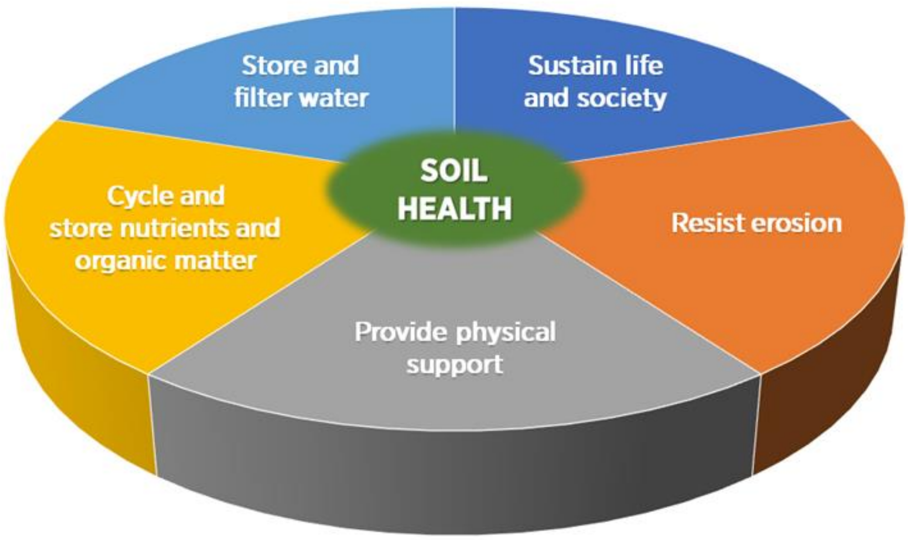


Figure 2 The 5 main functions of healthy soils (modified from Agriculture Victoria 2020)

The health of a soil is defined by its ability to sustain the ecosystem to which it belongs. Forest ecosystems represent a broad grouping of soils, where differences in climate, geological parent material, soil texture (particularly the amount of clay), drainage and slope position result in natural variation in the ability of the soil to hold water, nutrients and carbon.

Some soils are naturally more productive than others, but not necessarily more valuable in terms of the role they play in their natural setting (Burger *et al.* 2010). Therefore, it is necessary to measure the extent to which a managed soil is improved or degraded relative to a state that would naturally occur in that setting (Burger *et al.* 2010).

All soils have been disturbed to some extent by natural and human activity. Thus, for the purpose of this work, we modelled a reference condition (refer Section 6) based on the current status of sites that were likely to have been subject to relatively less human disturbance based on management objectives and exclusions for particular areas.

A similar approach was adopted during the 2008-09 NSW Monitoring Evaluation and Reporting (MER) program (Chapman *et al*. 2011, OEH 2014), where the more a soil indicator has declined relative to a reference condition, the poorer is its health. Key indicators are presented in Section 4.

This report considers the terms ‘soil quality’, ‘soil condition’ and ‘soil health’ to be interchangeable.

2.2 What is soil degradation?

Soil degradation is a loss of soil health. It is the physical, chemical and biological decline in soil quality. It can be the loss of organic matter, decline in soil fertility and structural condition, erosion, adverse changes in salinity, acidity or alkalinity, and the effects of toxic chemicals, pollutants or excessive flooding (DPIE 2019a). Soil degradation can include the following:

- The loss of soil through wind or water erosion at a rate faster than it is formed.
- The removal of soil nutrients exceeding their replacement.
- Deterioration of soil characteristics such that the soil cannot support the ecosystem to which it belongs to its full capacity:
    - Organic matter is depleted.
    - Fertility declines.
    - Soil structure declines (surface sealing or soil compaction occurs).
    - Soil salinity increases.
    - Soil acidity increases.

These impacts and their associated drivers of change are discussed further in Section 3. Metrics used to measure these indicators are discussed in Section 4.

2.3 Why is soil health important?

The prosperity and survival of both the human and natural world is intrinsically and profoundly linked to the health of our soils. The quality and health of our terrestrial, riparian and estuarine environments are highly reliant on the health of our soils.

Humanity depends, and will continue to depend, on soil ecosystems and the services they provide. Some of the services forest soils provide are presented in Table 1

Table 1 Forest soil services

Soil service	Description
Carbon storage	Soils represent a significant component of the terrestrial carbon cycle, globally estimated to contain 3 times more carbon than the atmosphere (Sanderman *et al.* 2017). A considerable portion of global soil carbon is stored in forests (Jandl *et al.* 2007). Protecting soil carbon stocks is necessary to mitigate the effects of climate change (refer Section 2.4). Healthy soils not only contain carbon, but also create the necessary conditions for above-ground carbon sinks (plant biomass) to thrive.
Water quality	Soil health and water quality are intrinsically linked. Healthy soils store water and make it available to vegetation, buffering the environment against the effects of droughts, and filter that water as they release it, recharging groundwater and preventing pollution. Soils which lack healthy functionality may be subject to erosion, releasing sediment and pollutants into waterways. Healthy soils also support the forest vegetation, which intercepts, evaporates, and absorbs precipitation and transpires water back into the atmosphere, as well as surface and subsurface movement of water through infiltration and percolation (Adams *et al.* 2020). Forests play a particularly important role in providing clean, high quality water,

Soil service	Description
	surrounding the drinking water catchments of NSW. The buffering capacity of forest soils ensures a reliable source of quality, fresh water is available for human consumption.
Biodiversity	Below ground, soil organisms such as ants, termites and earthworms have long since been recognised for their role in aerating soils and breaking down leaves and debris, but only in the past few decades have microbiologists begun to reveal an immense diversity of microorganisms and animals that live below ground, ranging from protists, nematodes and tardigrades, to slightly larger animals such as mites, springtails and insect larvae (Pennisi 2020). Each gram of soil is estimated to contain 1×10^9 microorganisms and about 4,000 species (Yarwood *et al.* 2020). Aboveground, soils provide the medium, substrate, biological activity, nutrients and water for native vegetation to grow and thrive. Native wildlife is also reliant on soil health, whether they live above, on or within soils, as they rely on native vegetation for survival.
Pollution biodegradation	Soils filter pollution, contributed to by soil organisms which accumulate pollutants in their bodies, degrade pollutants into smaller, non-toxic molecules, or modify those pollutants into useful metabolic molecules (Turbé *et al.* 2010), preventing harmful contaminants from being released to the air or waterways.
Nutrient cycling	Soils provide nutrients for tree growth, but also provide nutrient cycling and waste decomposition. They are a major reservoir of nutrients for plant uptake and for the decomposition system that mineralises and transforms organic matter, ensuring continued supplies of bioavailable nutrients (Rustad *et al.* 2020).
Economic stability	Soils produce all the timber we use in construction, paper and other industries, adding to its importance as an economic issue. According to the 2018 ABARES State of the Forests Report, the value of production of the forest and wood products industries in 2015-16 was $23.7 billion (ABARES 2018). Healthy soils prevent the high costs associated with land and soil degradation, which an estimate for the year 2011 indicates equates to about AU$1.89 billion per annum (Milford 2021).
Human health	Healthy soils help regulate drought, floods, water-borne diseases and other extreme events, provide landscape stability, prevent the spread of pests and pathogens and provide protection against famine and food insecurity (Lal 2011). Soil health is therefore also a human health issue.

2.4 What does it mean for climate change mitigation?

The NSW Government committed to reaching net-zero emissions by 2050. This commitment refers to an overall balance between greenhouse gases emitted and sequestered and is likely to rely heavily on carbon emission offsets (DPIE 2020).

Historic depletion of soil organic carbon (SOC) resulting from soil and land management offers an opportunity for climate change mitigation, both by restoring carbon sinks and by protecting against further CO_2 emissions. Deforestation and other land-cover changes are thought to be responsible for 53–58% of the difference between current and potential biomass stocks globally (Erb *et al.* 2018). Increasing SOC has been identified as a significant opportunity for natural, sustainable, low-cost climate change mitigation, through a combination of increased sequestration from reforestation as well as avoidable emissions through prevented conversion (Bossio *et al.* 2020).

Despite the importance of SOC stocks in ecosystem function and regulating climate, many uncertainties still exist around the capacity of different soil and land use types to sequester and store carbon and the role of forest soils in climate change abatement.

Forest soils in particular have considerable potential as carbon sinks (Jandl *et al.* 2007), but global estimates of forest soil carbon and potential carbon sequestration are limited by the lack of available data. Characterising soil organic carbon stocks in NSW forests will identify regions for climate change abatement efforts through targeted restoration and conversion prevention.

3 Drivers of change

3.1 Key drivers of change

Soils can take millennia to develop, but their capacity to provide ecosystem services can be compromised in a fraction of that time due to human-induced and natural disturbances (Williams *et al.* 2020).

Forests across different tenures are subject to stresses which are both direct and indirect and which operate across scales of frequency, duration, extent and severity, including:

- Bushfire
- Climate change
- Invasive species and pests
- Forest floor disturbance
- Land use change.

Stresses to soil health are described in Table 2.

Table 2 Stresses to soil health

Stress	Effect on soil
Fire	Fire can have major impacts on nutrient pools. Different nutrients may respond differently to each of these impacts, but certain nutrients including carbon (C), sulfur (S) and nitrogen (N) are particularly susceptible to fire-related losses (Raison 1979; Raison et al. 2009). Post-fire soil erosion can cause sedimentation and long-term impacts on the quality and quantity of water discharging from affected catchments. Fire can also induce soil hydrophobicity, forming water repellent layers in soil (Tulau and McInnes-Clarke 2016). These layers, coupled with loss of vegetation, contribute to accelerated post-fire erosion. Research conducted by Tulau and McInnes-Clark (2016) described how the impacts of hazard reduction burning (or managed fire) vary from those resulting from bushfire (unmanaged fire). Additional research is required on the impacts of hazard reduction burning on soils, as the effects can be more subtle and variable than those resulting from wildfire, where the majority of research has been focused (Tulau and McInnes-Clark 2016). The effects of bushfire are discussed further in Section 6.3.
Climate change	In addition to global temperature increase, elevated greenhouse gas concentrations are predicted to increase the occurrence of precipitation extremes: greater rainfall in already-wet areas and increased drought in already-dry areas. These changes are likely to affect plant productivity, nutrient cycling, and biological populations. Climate change is also expected to increase the severity and frequency of bushfire, floods and pest and pathogen attacks. Changes in climate, coupled with an increase in the frequency and severity of extreme weather events, will have direct and indirect effects on soil formation, productivity and processes, particularly wind and water erosion (refer Table 3). The effects of climate change are discussed further in Section 6.3.
Forest floor disturbance	Disturbance to the forest floor can have cascading effects, manifesting as soil erosion and loss of soil biodiversity, organic matter, soil carbon and associated essential nutrients (Behre 2019).

Stress	Effect on soil
	Forest floor disturbances, such as forestry harvesting operations, stock grazing pressure and the associated removal of vegetation cover, can cause the soil to become compacted and reduce the natural filtering action of the soil (refer Table 3). Damage to the soil structure, in turn, impacts microbial processes and the capacity of the soil to contain carbon and other nutrients. If not managed properly, this can be detrimental to soil and water resources, potentially causing lower soil fertility and increased sediment delivery to streams and rivers. The extent of forest floor disturbance and soil degradation associated with forestry harvesting operations is varied and dependent on factors including tree species selection (quantity and chemical quality of litter, rooting depth) and the thinning regime. Forestry practices which minimise disturbances in the stand structure and soil reduce the risk of unintended carbon loss and associated soil health decline. (Jandl *et al.* 2007) The effects of land disturbance are discussed further in Section 6.
Invasive species	The introduction of invasive species can have profound, and not always predictable, effects on ecosystem processes and soil communities (Ehrenfeld and Scott, 2001). Invasive species, including weeds, insects, pathogens and animals, cause tree stress, decline and mortality, which in turn affects organic matter quantity and quality and microbial activity. They can also alter nutrient mineralization, N-fixation by soil bacteria, mycorrhizal inoculation, decomposition and aeration of soils by earthworms, and aggregation of soils by fungi (Berryman *et al.* 2020), all of which can affect SOC stocks. Invasive species may occur *as* soil fauna (Seidl *et al.* 2018), such as the invasive pathogen *Phytophthora* which causes forest dieback. Not unlike bushfires, invasive species can create soil conditions more susceptible to flash flooding, soil erosion and sediment loading. These impacts are exacerbated by climatic changes, as the range of invasive insects and pathogens is expanding. In recent decades, global trade has removed many dispersal barriers for species and has led to a global redistribution of forest pests (Santini *et al.* 2013).
Land use change	Anthropogenic land conversion, that is, land clearing followed by a new land use, such as grazing or plantation forestry, can lead to complex biophysical and biogeochemical feedbacks. Land use change may alter soil processes such as surface energy balance, hydrologic flow (Croke & Hairsine 2006), and biogeochemical cycling of essential soil nutrients. A loss of surface vegetation cover can result in changes in surface energy balance, increasing the rate of evaporation and the temperature of the soil (Behre 2019). Land use changes which increase vegetation cover, such as those which result from afforestation and management of fast-growing tree species, also impact soil processes and regional rates of carbon sequestration (Jandl *et al.* 2007).

3.2 Potential impacts to soil health

Table 3 describes the impacts that disturbances and stresses can have to soil health and stability.

Table 3 Impacts to soil health

Impacts to soil health	Description
Erosion	Erosion is an insidious form of land degradation which progressively removes topsoil, which is where most of the soil carbon is stored. Continued erosion

Impacts to soil health	Description
	reduces soil quality and the capacity of the soil to hold water and nutrients which support plant life. Water erosion results from rainfall impact and surface water flow. Roads and trails can act as channels during rainfall events and increase the velocity and volume of the water as it flows downhill. Erosion can contribute significantly to the deterioration of waterways, the deterioration of soil fertility, and the release of greenhouse gases into the atmosphere. Wind erosion is the detachment and movement of soil particles by air moving at least 20km per hour. Soils release dust into the air. Airborne dust contributes to carcinogenic outdoor air pollution, where there is a close relationship between exposure to high concentrations of small particulates and increased risk of respiratory infections, heart disease and lung cancer (WHO 2018). Airborne dust in NSW over periods of 2019 has repeatedly broken records for activity and concentration, coinciding with historic lows in groundcover (DPIE 2019b, 2019c).
Decline in soil structure	Soil structure is the architectural arrangement of soil particles and the voids between them. Soil structure defines the physical component of soil condition as it governs water and gas exchange between the atmosphere and the soil. It is sensitive to biological activity, groundcover, management actions and, in some soils, changes in moisture content or salinity. Soil structure is not only important for preventing sediment erosion into water supply systems, but also in preventing landslides. Forests with higher rainfall and steeper terrain have the most to lose in terms of soil retention (McCormick and Showers, 2019). A decline in soil structure can have a marked impact on soil fertility and an increase in greenhouse gas emissions, including carbon dioxide and nitrous oxide. A decline in soil structure can take a considerable amount of time and money to correct (Chapman *et al.* 2011).
Degradation and loss of soil carbon	When soils are disturbed or eroded, the carbon and other greenhouse gases they contain (including methane and nitrous oxide) can be released, causing these soils to act as a source of greenhouse gas. Anthropogenic influences, accelerated by the impacts of climate change, can deplete soil carbon stocks. Carbon held in soils generally cycles more slowly than carbon in other ecosystem pools, subject to natural fluctuation based on inputs, such as leaf litter, dead roots and fungal and bacterial cells and residue, and outputs, such as leaching, erosion and emission by fire (Nave *et al.* 2019). Anthropogenic influences, such as land conversion, soil disturbance and agricultural intensification, accelerated by the impacts of climate change, deplete soil carbon stocks.
Disruption to nutrient cycles	The impact of human disturbance on forest soils and nutrient cycles, including impacts from agriculture, forestry and urbanization, have been increasing in intensity and extent during the last century (Richter 2007). Nutrients needed to drive photosynthesis in plants, such as nitrogen (N), sulfur (S), phosphorus (P), potassium (K) and boron (B), are cycled within forest ecosystems. These nutrients are taken up by plants and returned to the soil in above ground and below ground litter inputs (Prescott 2020; Rustad *et al.* 2020). Disruption to this cycle alters the availability of nutrients for plant growth, and in fact, nutrient supply is often the factor which limits the growth potential of vegetation.

Impacts to soil health	Description
Acidification	In NSW, most forest soils are slightly acidic. However, increasing acidity caused by land-use practices (often referred to as induced soil acidification) can have significant negative impacts on soil condition and plant growth. Acidity can stunt plant growth, disturb nutrient cycles and result in the acidification of waterways.
Salinisation	Soil salinity occurs naturally across much of NSW, with high levels of soluble salts stored in the soil and groundwater as a result of landscape processes occurring over many thousands of years. In some areas, 'induced' salinity results from human activities altering the water balance in the landscape. When this occurs, stored salts are often remobilised and migrate to the ground surface, killing vegetation and altering soil structure (Chapman *et al.* 2011). Soil salinity has been found to impact eucalyptus growth height, stem diameter, crown volume and mean leaf area (Benyon *et al.* 1999). Soil salinity can also cause severe stress to soil organisms, leading to their rapid desiccation (Turbé *et al.* 2010), and can cause profound terrestrial and aquatic ecosystem damage through impacts on water quality both from salt and associated erosion.
Loss of biodiversity and ecosystem resilience	Soils are not only a main repository of terrestrial biodiversity, harbouring one quarter of all species on Earth, but evidence is mounting that soil biodiversity contributes significantly to shaping aboveground biodiversity and the functioning of terrestrial ecosystems. For example, soil organisms have been identified which induce plant defence responses to above ground pests and herbivores (Turbé *et al.* 2010). Soil organisms are also vitally important in the soil carbon cycle, where they decompose dead biomass and release carbon dioxide via respiration. There is also evidence that mutualist fungi, particularly ectomycorrhizal fungi (EMF) are integral to forest tree health (e.g., Sapsford *et al.* 2017) and in some cases mycorrhizal fungal frequencies are linked to canopy condition and dieback (Ishaq *et al.* 2013). These habitats are dynamic, responding to natural and human-generated disturbances, such as compaction, bushfire, invasive species, and climate change (Yarwood *et al.* 2020). Loss in soil biodiversity reduces ecosystem functions and impairs their stability over time (Bardgett & van der Putten 2014). Research on soil response to land use change suggests that soil communities respond and recover much more slowly than initial changes in vegetation and that it can take years, if not decades, before the soil community has become adapted to the changed environmental conditions and establish new equilibria (Turbé *et al.* 2010). While some disturbances to soil communities are inevitable, such as seasonal variation, the accumulation of simultaneous stresses due to anthropogenic disturbances and climate change intensification (e.g., bushfire, drought, the use of pesticides, fertilisers or tillage) can alter the functioning of the ecosystem (Griffiths *et al.* 2000; Turbé *et al.* 2010).

Soils can be safeguarded against disturbances by protecting and improving the physical, biological and chemical components to maintain the resilience and productivity of the system.

4 Indicators of soil health and stability

4.1 Overview

The status of soil indicators is a product of the soil forming factors of climate, parent material, topography, biota and time, as recognised by pioneering soil scientists Dokuchaev (1889) and Jenny (1941) (refer Section 6). Each of these soil-forming factors can be represented by multiple sub factors.

The indicators presented here are those which are likely to detect change over a relatively shorter timescale, such as those influenced by human activity or recent changes in climate (adapted from Amacher *et al.* 2007; Burger *et al.* 2010; Chapman *et al.* 2011).

They were selected based on the findings of the literature review (Milford 2021) and align with the criteria of the *Ecologically Sustainable Forest Management (ESFM) Criteria and Indicators* (NSW EPA 2016) and the Montréal Process (Montréal Process Implementation Group for Australia and National Forest Inventory Steering Committee 2018).

The main functions of a healthy soil (refer Figure 2) fall broadly into three categories of measurement: physical, biological and chemical.

These functions are interdependent and while there is no one indicator of soil quality, the following metrics can be used to quantify the soil's ability to perform these functions and can be monitored over time. When viewed together, these metrics indicate how and to what extent a soil may be becoming degraded (refer Section 2.2).

Future monitoring efforts should incorporate flexibility such that sampling is focused on data collection of indicators with the most significant input values. The feasibility of assessing these indicators holistically in a combined index is discussed further in Section 8.6.

Soil properties that can be used to measure the health of the soil are outlined in Table 4.

Table 4 Indicators of soil health

Measurement type	Soil health indicator
Physical	Topsoil depth
	Bulk density
	Aggregate stability
	Particle size analysis
Biological	Microbial biomass
	Fungal : bacterial ratio
	Mycorrhizal fungal assemblages
Chemical	Total soil organic carbon
	Carbon fractions
	Mineral N (NO_3+NH_3)
	Phosphorus
	pH
	EC

4.2 Physical indicators of soil health

4.2.1 Topsoil depth

Topsoil depth is a surrogate for rooting depth. Change in topsoil depth is indicative of soil loss and decline in soil structure. This is a helpful indicator in areas of anticipated erosion.

4.2.2 Bulk density

Bulk density is an indicator of soil compaction and is the weight of dry soil per unit of volume. Increased bulk density can represent a decrease in water infiltration, available water capacity, soil porosity, plant nutrient availability, and soil microorganism activity, all of which can influence key soil processes and productivity. The indicator is *change* in soil structure because some soils may naturally have poor structure (Chapman *et al.* 2011).

Bulk density is typically expressed in grams/cm^3. Bulk density measurements are also required to calculate carbon stocks (t/ha).

4.2.3 Aggregate stability

Soil aggregate stability is a measure of the ability of the soil to resist disintegration when disruptive forces are applied.

Soil aggregates are groups of soil particles that bind to each other more strongly than to adjacent particles. When unstable aggregates are impacted by rain, soil aggregates may slake or disperse. Dispersed soil particles fill surface pores and a hard physical crust can develop when the soil dries. Infiltration is reduced, which can result in increased runoff and water erosion, and there is a reduction in water availability in the soil for plant growth. A physical crust can also restrict seedling emergence (Kemper & Rosenau 1986).

Soils with high sodicity, or excessive sodium, (i.e. sodic soils) are more prone to slaking, dispersion and the development of crusts and hardset layers.

4.2.4 Particle size analysis

Particle size indicates soil texture. Soils consist of an assemblage of ultimate soil particles (discrete particles) of various shapes and sizes. Particle size analysis groups these particles into separate ranges of sizes and determines the relative proportion by weight of each size range.

4.3 Biological indicators of soil health

4.3.1 Microbial biomass

Soil organisms, including nematodes, collembola, fungi and bacteria, are responsible for a cascade of intricate soil functions such as nutrient cycling, biodegradation of pollutants and soil carbon storage.

Microbial biomass represents the living component of SOC and is considered an estimate of biological activity. It indicates the availability of nutrients in the system and its overall fertility.

4.3.2 Fungal to bacterial ratio

The fungal-to-bacterial ratio is a measure of the proportion of the microbial community that is bacteria, compared to the proportion that is fungi.

Fungal-dominated soils enhance C storage because they have slow C turnover rates and are typically credited with greater growth efficiency (biomass production) compared to bacteria. Declines in fungal ratio are linked to fertiliser and herbicide application.

This measure is therefore a useful tool in determining how quickly nutrient turnover can happen in a soil system and how prone the system is to leaching.

4.3.3 Mycorrhizal fungal assemblages

Mycorrhizal fungi, and in particular arbuscular mycorrhizal fungi (AMF), are emerging as not only indicators, but also key determinants, of soil health (Bardgett & van der Putten 2014). AMF can significantly improve plant nutrient uptake and can determine the performance of plant communities.

Measuring mycorrhizal fungal assemblages provides a sensitive tool to assess soil functionality and may provide an indication of the susceptibility of a system to invasive species. They are also good for tracking understorey growth following disturbance.

4.4 Chemical indicators of soil health

4.4.1 Total soil organic carbon

Soil organic carbon (SOC) is an indicator and key component of soil health. High SOC results in greater water and nutrient retention, creating the necessary conditions for above-ground carbon stores (plant biomass) to thrive. High SOC also improves soil structure which can reduce erosion.

Soil carbon is a commonly proposed (and used) key or 'headline indicator' in soil monitoring programs nationally and internationally (Wilson *et al.* 2010).

From a carbon accounting perspective, SOC monitoring data can be used to assess the net loss or gain of carbon density across various land use/land management scenarios and provides a minimum dataset to underpin soil carbon inventory and potentially, soil carbon trading.

When assessing SOC, surface soil samples are critically important because soil carbon decreases dramatically with depth (Chapman *et al.* 2011).

4.4.2 Carbon fractions

SOC is composed of a mix of particles and materials in different states of, and with different susceptibilities to, decomposition. These various components can be isolated and allocated to biologically significant fractions (Wilson *et al.* 2017).

These carbon fractions are typically described as particulate organic carbon (POC), derived largely from fresh organic inputs, humic organic carbon (HOC), which is typically composed of microbially altered materials associated with mineral particles in soils, and biologically resistant organic carbon (ROC), with a charcoal-like character dominated by poly-aryl carbon groups (Wilson *et al.* 2017).

Carbon fractions have different degrees of stability and turnover rates and can indicate the status of the soil carbon cycle. These fractions, when viewed together, provide an indication of the susceptibility of a soil to carbon loss.

4.4.3 Mineral N

Nitrogen (N) is an important element in terrestrial ecosystems. It is a major limiting nutrient for plant growth and is therefore crucial to ecosystem productivity and soil health. N in soil has been found to be strongly correlated with wood production (Turvey and Smethurst 1994).

Monitoring N (like phosphorus, described below) is important because minor changes can indicate both a loss of fertility in the land being assessed, as well as an influx of the nutrient into sensitive surrounding soil and water systems.

4.4.4 Phosphorus

Phosphorus (P) is another important element in terrestrial ecosystems. It is a major limiting nutrient for plant growth and is therefore crucial to ecosystem productivity and soil health. P in soil has also been found to be strongly correlated with wood production (Turvey and Smethurst 1994).

P accumulation occurs in soils over thousands of years during pedogenesis (Walker and Syers 1976). The natural distribution of soil total P is thought to have undergone spatial changes linked to shifts in climate (Zhu *et al.* 2021) and biome migrations (Siebers *et al.* 2017) over decades and centuries.

Soil P exists in two forms: organic and inorganic, which together make up the measure of total soil P. However, not all soil phosphorus is available for plant uptake. This is expressed as available P.

Phosphorus is often considered in an agricultural context, but above ground plant production in natural ecosystems is also significantly limited by P availability (Hou *et al.* 2020), suggesting that the importance of altered P supply in natural ecosystems has been underestimated. Identifying ultimately limiting nutrients is important because alterations in their supply have the capacity to transform the structure and functioning of ecosystems (Vitousek *et al.* 2010).

An issue affecting many native ecosystems (especially near urban centres and agricultural lands) is raised P levels in soils and waterways – this leads to weeds (and blue green algae in waterways).

For native forest ecosystems, it is the change in P that is crucial, as this can indicate loss of P from the system to which it belongs, into other sensitive environments.

4.4.5 pH

The acidity of forest soil affects a wide range of ecological processes, including the solubility and exchange reactions of inorganic nutrients and toxic metals, the activities of soil animals and microorganisms, and the weathering of soil minerals.

The acidity or alkalinity of soils is measured by soil pH, which is the negative log of the hydrogen ion concentration on a scale of 1 to 14, where 7 is neutral, below 7 is increasingly acidic and above 7 is increasingly alkaline. Soil pH is typically determined and reported for soil monitoring purposes using a 0.01M $CaCl_2$ solution as it is less susceptible to seasonal variation than a pH in water. In NSW, soils have a wide range of pH values, with many being naturally acidic.

Soil pH is determined by the balance between the production and consumption of soil hydrogen ions, which is closely associated with nutrient cycles (e.g., carbon, nitrogen, phosphorus, sulfur and calcium). Changes in soil pH can alter the availability of nutrients, impact biogeochemical processes and have cascading effects on terrestrial ecosystem structure and functions.

Some native forest soils already have very low pHs. Thus, when assessing forests, pH will be assessed as a measure of change, rather than a fixed value.

4.4.6 EC

Electrical conductivity (EC) is used to measure salinity. It is influenced by the concentration and composition of dissolved salts. Salts increase the ability of a solution to conduct an electrical current, so a high EC value indicates a high salinity level.

5 Distribution of available soil data

5.1 Information sources

The primary source for soil information in NSW is the Soil and Land Information System (SALIS). This database is managed by the Soil and Landscape Assessment Team in the Department of Planning, Industry and Environment and forms the basis of our understanding of soil conditions across the state. SALIS contains over 70,000 soil profiles, most of which include laboratory data where samples collected from the profile have been analysed.

The soil data used to estimate baselines and trends in this report (Section 6) were mainly derived from:

- NSW DPIE soil survey information, and
- The NSW Monitoring, Evaluation and Reporting (MER) program.

The majority of soil data for the state comes from these two sources. A small portion of the dataset comes from other NSW and Federal Government and non-government sources.

This NSW information was supplied and modelled by our team to contribute to the Australian Soil Resource Information System (ASRIS), an effort to produce a national soil database (Johnston *et al.* 2003; McKenzie *et al.* 2012).

5.1.1 Soil survey

Most available soil information in NSW has been collected during 1:100,000-scale soil landscape surveys, which began in the 1990s (refer Section 5.3). The objective when collecting these profiles is to provide supporting evidence to classify the soil type(s) of a broad region (soil landscape).

The sampling methodology used by each soil survey varies depending on when, where and by whom the survey was conducted. For example, the depth from which a sample was collected varies from one location to the next, and many locations have only been analysed for a limited set of indicators. As a result, the available data for each profile location range in detail and representativeness.

Around 2,000 of these locations fall within forest areas of the RFA regions, (refer Figure 3): some include laboratory data (refer Table 6) and others are limited to soil descriptions.

Soil survey data provide valuable background information, but lack the following key elements of a monitoring program which enable measurement of soil health and stability through time:

- These profile locations were never revisited and only exist as single point-in-time data. Without repeat sampling of these locations, the data are insufficient to measure soil change through time.
- The profiles are not paired to reference sites (refer Section 2.1), so the data tell very little about the condition of the soil relative to what would be an optimal, functional state for that ecosystem.

These factors serve as limitations to the accuracy and reliability of digital soil mapping efforts based on these data (refer Section 7.2). Spatial analysis does, however, provide a lens through which to visualise the data and an indication of likely trends (refer Section 6).

5.1.2 State-wide monitoring

In Australia, individual states have typically committed limited and episodic resources to soil monitoring, with similarly discontinuous injections of resources from the Federal level; since monitoring requires consistent long-term effort, very little coherent monitoring of soils has been achieved in most jurisdictions (Milford 2021).

The NSW Government's most intensive effort to monitor soils came under the NSW Monitoring, Evaluation and Reporting (MER) program, conducted by the NSW Department of the Environment, Climate Change and Water, now DPIE, in 2008-09 (Bowman 2009; Chapman *et al.* 2011; OEH 2014).

The program, initiated by the NRC, aimed to monitor and evaluate soil condition across NSW. It comprised over 800 sites and where possible, sites were paired on the same soil type across different land uses, including 'reference' sites where the soil was considered to be in a less disturbed state.

Site selection involved the identification of issues from regional natural resource management staff and a stratification process to identify representative combinations of soil, land-use and environmental factors. Each site included a program of soil data collection and laboratory analysis, together with collection of land management information.

The MER program intended to resample monitoring sites on a rolling 5 year program, but no follow-up funding was ever forthcoming. As such, only a small number of these sites (approximately 60) have ever been resampled, and this was undertaken by academic institutions (UNE).

41 MER sites fall within forests of the RFA regions. These data have been incorporated into the models of estimated baseline conditions presented in Section 6, and future forest soil monitoring efforts should incorporate these sites (refer Section 8).

5.2 Spatial distribution

There are approximately 2,100 total profile points with suitable laboratory data from across the RFA regions from SALIS and the MER program. Available data points are shown in Figure 3.

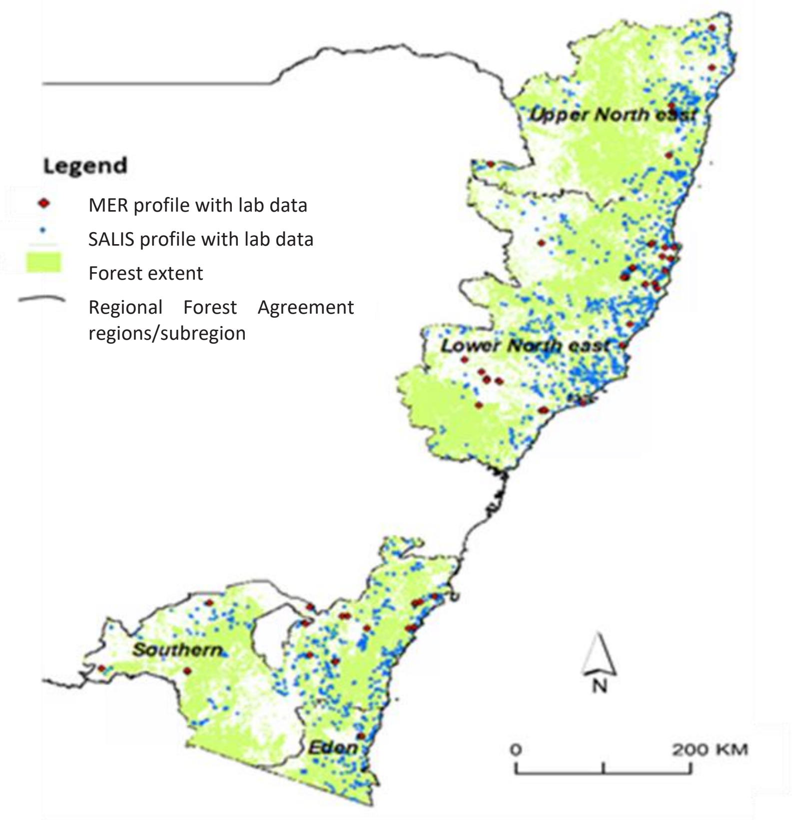


Figure 3 Spatial distribution of soil profiles with laboratory data across RFA regions

Figure 3 shows the lateral distribution of the data. The vertical distribution of the data used in the digital models (Section 6) is also varied, where soil samples were collected from a range of depths.

Table 5 describes the number of soil profiles by tenure and management status. Management status is an approximation based on forest management zones (NSW Government, 2018; State Forests NSW, 1999), discussed further in Section 6.1.2.

Table 5 SALIS and MER data by tenure and management status

Information source	Tenure	Management Status			Total
		Reserved	Forestry operation	Unprotected / Private and leasehold lands	
SALIS	NPWS	673			673
	State Forest[a]	179	393		572
	Private			773	773
	Total				2018
MER	NPWS	9			9
	State Forest[a]	1	8		9
	Private			23	23
	Total				41

[a]based on Forest Management Zones: Reserved: FMZ 1, 2 3a&b; Forest operation: FMZ 4 – 7 including harvest and plantation operations, refer Section 6.1.2 for further detail.

5.3 Temporal distribution

Figure 4 presents the spatial distribution of SOC profile data points across RFA regions for different time slices. As shown, very little monitoring has been undertaken in the last decade.

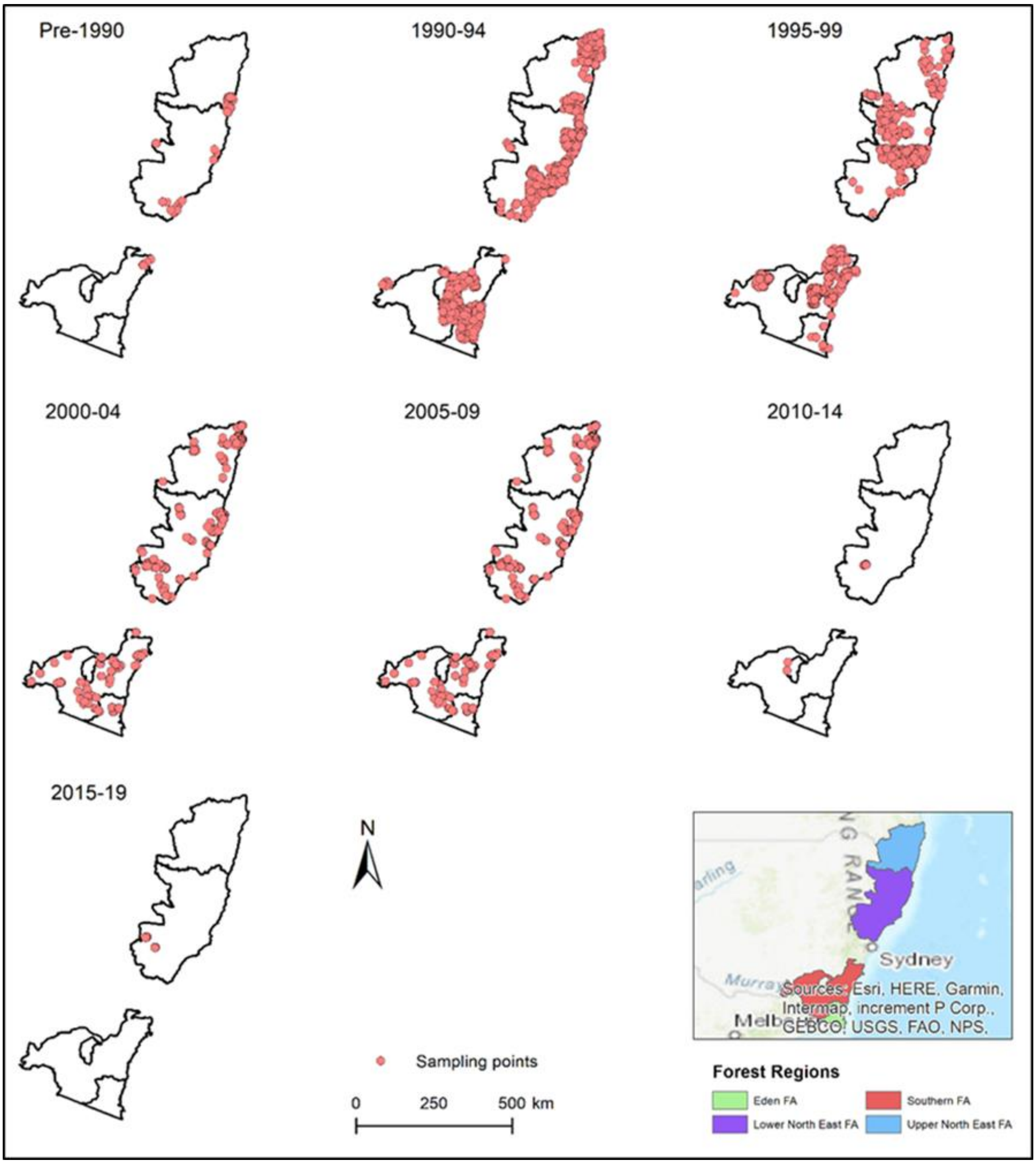


Figure 4 Temporal distribution of surface soil organic carbon measurements across RFA regions

Most soil data were collected in the 1990s, following initiatives such as the 'Decade of Landcare.' Initiated in 1989, this program aimed to increase the adoption of sustainable land management practices by land managers and therefore, like the vast majority of soil information collection in NSW, focused largely on agricultural land. Since this period, funding for soil data collection has declined within state and federal government departments.

Where it has been collected, updated and current soil information from NSW's forested lands, whether in public or private ownership, has generally not been shared. For example, Forestry Corporation of NSW collect soil regolith information within the RFA regions from state forests as part of an inherent soil erosion and water pollution hazard assessment prior to timber harvesting and commencement of roading operations in native forests as a requirement of the Coastal Integrated Forestry Operations Approvals. This information is not submitted to the NSW Soil and Land Information System and is thus not available for this analysis.

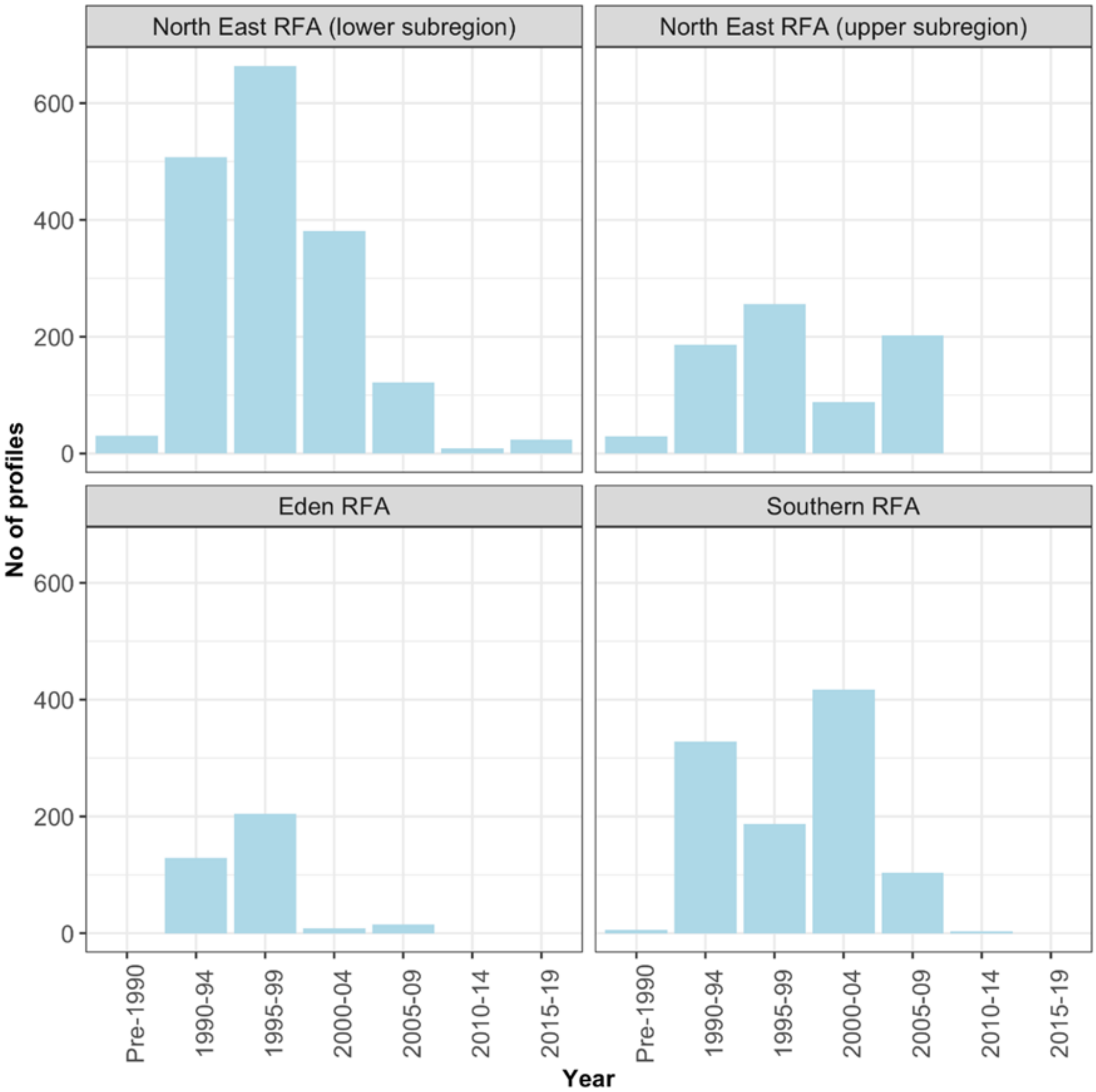


Figure 5 Spatial distribution of surface soil organic carbon measurements across RFA regions

5.4 Critical data gaps

As demonstrated in Table 6, the number of profiles with sufficient data within the RFA regions is limited.

Of the data held in the NSW Soil and Land Information System (SALIS), there are no measurements of soil biological health indicators from the area. In the last decade, less than 50 soil carbon measurements have been collected from across the RFA regions. No bulk density measurements have been collected during this time, which are needed for accurate calculation of belowground carbon stocks. Available measurements of other physical and chemical soil health indicators are similarly limited.

Table 6 Available data for soil health indicators

Measurement type	Soil health indicator	Total sites sampled [a] (approximate)	
		Historical (pre-2010)	Current (2010+)
Physical	Bulk density	41[b]	**0**
	Aggregate stability	1,360	**40**
Biological	Microbial biomass	0	**0**
	Fungal : bacterial ratio	0	**0**
	Mycorrhizal fungal assemblages	0	**0**
Chemical	Total soil organic carbon	1,680	**40**
	Carbon fractions	430	**0**
	Mineral N (NO_3+NH_3)	970	**30**
	Phosphorus	P extractable: 1,360	**40**
	pH	1,900	**100**
	EC	1,900	**100**

Notes:

[a] The exact number of profiles used in the spatial modelling approaches may vary slightly depending on how the data has been sourced for use.

[b] MER NSW forest dataset used to identify change, building on base maps from SLGA

Particle size analysis and topsoil depth are not included in this table. Particle size analysis is only taken once, used in calculation of other soil qualities rather than a stand-alone measure. Topsoil depth is used to compare the same site through time and is not relevant as a stand-alone measure.

6 Estimated historic baselines and trends

6.1 Methods

Baseline values for the key indicators were estimated as follows:

- First, we evaluated the available data using an empirical approach, which simply presents the value of an indicator for each location, regardless of when the sampling occurred. Temporal changes are not accounted for.
- Then, we used digital soil modelling (DSM). DSM enables a comparison of data collected at different times by incorporating variables which represent temperature, precipitation, vegetation cover, soil moisture and other factors. We used this method to produce estimated baseline values of the key indicators for which we have data.
- The results of these methods were supplemented by the outputs of an experimental space-time model. The model holds promise but is limited by soil data sparsity and does not currently estimate any indicators other than soil carbon. The space-time model provides a workflow and prototype for future modelling of forest soil conditions, which will be more applicable after further investment in soil sampling.

Detailed methodologies are included in project update reports: the empirical method and the digital soil modelling and mapping are provided in Appendix A, and the space-time modelling approach in Appendix B.

6.1.1 Empirical data by soil landscape

Soil landscapes are regions which have been determined by soil scientists to share like soil and landscape properties, and therefore have similar properties and management considerations. All soil landscape units have records identifying location of soil data points; type of survey (e.g., MER, soil landscape mapping); and soil field and laboratory data (if available).

These map units come from soil surveys, mostly at 1:100,000 scale, and range in detail and confidence.

Sampled locations occur within the landscape units and vary in terms of their representativeness of the landscape. For example, if samples are collected from an area of the soil landscape that is unusual, such as a slope in an otherwise flat area, these data cannot be considered to represent the whole landscape.

The representativeness of a soil profile is determined based on the following ranked criteria:

- ***Location within forest area****:* soil profiles which fell into the RFA regions forest area were included.
- ***Soil landscape unit****:* soil profiles were sorted based on the soil landscape units in which they were located.
- ***Laboratory data availability***: soil profiles were sorted based on laboratory data availability (some monitoring locations did not have any samples collected and/or analysed).
- ***Representative 'type profile' status:*** 'type profile' designation belongs to soil profiles considered representative of the most common soil type in some portion of the soil landscape. Type profiles are generally assigned to each 'facet' or part of a landscape that has a different soil type (soil property) and generally for each management consideration within the landscape. Since facets are not defined in our published soil landscape linework, identifying the 'type profile' information of the largest facet is an important way to represent soil attributes for an entire map unit. Type profiles for a landscape may fall outside of the forest

area. In some cases, a soil profile in forested land was selected ahead of a designated 'type profile' because of the significant affects that a forested land use has on surface soil properties, particularly organic carbon.

- ***Forest condition representativeness*:** where multiple soil profile locations occur within the forest area within a landscape unit, this measure distinguishes soil profiles characterised by forested land management, prioritising them over soil data from cleared or pasture areas, for example.

Based on the above criteria, a soil profile was selected to represent each soil landscape unit, and the field and laboratory results for each soil property are considered to be representative of the whole landscape unit.

The resulting quality categories for the soil landscape profile data were as follows:

- ***High confidence*:** a profile with laboratory data within the forest area and within the dominant facet of the landscape unit.
- ***Moderate confidenc*e:** a profile with laboratory data within the forest area but not within the dominant facet of the landscape unit.
- ***Low confidence:*** no profiles with laboratory data within the forest area, but representative lab data available for another part of the landscape.
- ***No data*:** no profiles with laboratory data exist within the landscape.

Temporal changes are not accounted for. For example, the empirical approach may present a soil carbon concentration at Location A, sampled in 2000, beside a soil carbon concentration at Location B, sampled in 2018.

6.1.2 Digital soil mapping and modelling

Digital soil mapping provides for statistically verifiable estimates of soil properties using quantitative modelling techniques based on relationships between soil properties and the environment (McBratney *et al*. 2003). The statistical relationships are developed over known soil data points with known environmental conditions and then extrapolated over broad regions using continuous environmental data grids (e.g. climate grids, digital elevation models or gamma radiometric data grids). An early example of digital soil mapping was undertaken over the forests of south-east NSW by Ryan *et al.* (2000), however they used the term "environmental correlation".

The modelling approaches applied in this project were multiple linear regression (MLR) and Random Forest (RF) decision tree methods. The two different approaches do not give identical results but there is typically high consistency between them. They provide valuable data for identifying key drivers of each soil condition indicator.

Modelling of soil properties was carried out using R statistical software (R Core Team 2020). The soil dataset was apportioned 80% as training data and 20% as validation data using a simple random data splitting approach. Detailed methodology is provided in the update reports (Appendix A).

The modelling process relied on additional variables to represent the main soil forming factors of climate, parent material, topography, biota-land management and age of soil (Jenny 1941), together with a bushfire-related variable, as described in Table 7.

Table 7 Variables included in digital soil model

Description of variable	Name	Source
Mean annual rainfall over this 20 year period	Rain_1990_2010	sourced from SILO (Scientific Information for Land Owners) Climate data used for Climate change projections were accessed from the NARCliM program.
Mean annual daily maximum temperatures over this 20 year period.	Tmax_1990_2010	
Mean annual daily minimum temperatures over this 20 year period.	Tmin_1990_2010	
Approximate silica content (%) of the parent material, which relates to its lithology and the resulting soil type (Gray *et al.* 2016).	Silica_index	The statewide grid is based on geological mapping (DPI Geological Survey of NSW, undated) and NSW soil and land mapping from eSPADE (DPIE 2021).
Radiometric potassium, uranium and thorium, an indicator of parent material chemistry.	Radk, Radu and Radth	Geoscience Australia (Minty *et al.* 2009)
The relative proportion of these clays derived from near infra-red (NIR) spectroscopy (Viscarra Rossel 2011).	Kaolinite, Illite and Smectite	TERN data, CSIRO Data Access Portal
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.	W_index	Geoscience Australia
Topographic wetness index, representing potential hydrological conditions (Gallant and Austin 2015).	TWI	CSIRO Data Access Portal
Forest disturbance index (FDI): a new index developed for this project which coarsely reflects forest management. The FDI enables distinction between forest reserve areas, both formal and informal (FDI 1) and forest harvest areas (FDI 2). All remaining woody area was allocated FDI 3, being identified as privately owned or leased forest typically subjected to periodic stock grazing (see Table 8).	FDI	This was derived by combining maps of NPWS estate, Forest Management Zones map (Forestry Corporation of NSW 2020) and NSW land use 2017 maps (DPIE 2020a).
Total vegetation cover (%); includes photo-synthetic (living) and non-photo-synthetic (dead) vegetation cover, being average (mean) cover from year 2000 to date of sampling.	Total_VegCov	CSIRO MODIS fractional vegetation data (Guerschman and Hill 2018)
The number of years since a major bushfire (This does not include hazard reduction burns). For training data: the number of years prior to the date of sampling; for mapping the number of years prior to 2010.	Years_since Bushfire	Rural Fire Service (via NRC data portal)

The analysis of trends in soil condition applied DSM techniques with a ‘space-for-time substitution’ process (refer Appendix A). This process involves use of current spatial patterns to predict past or future trajectories of ecological systems (Pickett 1989; Blois *et al.* 2013). Spatial patterns are used to represent temporal patterns. Limitations of this methodology are further described in Section 7.2.

The Forest Disturbance Index (FDI) was developed for this project to assess broad trends with human disturbance, based on land tenure and management systems (see Table 8). FDI 1 represents lands generally associated with less land use disturbance (e.g. protected zones within State Forests), whereas FDI 3 represents lands generally associated with higher levels of land use disturbance (e.g., private lands subject to periodic grazing). If private forestry lands did not fall within a Forest Management Zone, but were private and leasehold land, they were categorised as FDI 3.

The FDI is a coarse and simple measure of forest management and each FDI category may be subject to a range of disturbance types. For example, within FDI 2, some native forests may only be very lightly logged and disturbed whilst others may be more intensively logged with significant soil disturbance and forest cover reduction. Similarly, some more highly disturbed forest management zones may also include relatively undisturbed riparian exclusion corridors.

This scale of modelling does not distinguish between areas subject to different harvest plans and those in narrow exclusion corridors. Additional data collection through future monitoring efforts would allow for finer scale models which could capture these distinctions.

Table 8 Forest tenures, zones and Forest Disturbance Index

Tenure	Zone	Forest Disturbance Index (FDI)
NPWS estate	All	1
Forest Management Zones[a]	Zone 1 - Special Protection Zone	1
	Zone 2 - Special Management Zone	1
	Zone 3A - Harvesting Exclusions Zone	1
	Zone 3B - Special Prescription Zone	1
	Zone 4 - General Management Zone	2
	Zone 5 - Hardwood Plantations Zone	2
	Zone 6 - Softwood Plantations Zone	2
	Zone 7 - Non Forestry Use Zone	3
	Zone 8 - Areas for further assessment	2[b]
	Zone 90 – Unzoned	3
Private and leasehold lands	All	3

[a] NSW Government (2018); State Forests NSW (1999)

[b] This was incorrectly allocated as FDI 3 in the current study

In the analysis of trends with human disturbance, the model was run with an FDI 1 (relatively undisturbed state) hypothetically applied across the entirety of the RFA regions. Then, the model was rerun with the current (approx. 2010) disturbance status (ie, FDI 1, 2 and 3) to assess the influence of the changed disturbance regime. The difference between the two modelled outputs provide an indication of the change. Further detail and method flowchart are provided in Appendix A, Update 5.

For several soil indicators, no clear trends with forest disturbance index were discernible, but trends were evident for SOC and bulk density (refer Section 6.3). Similar approaches were applied in assessing trends in soil indicators with projected climate change (Gray and Bishop 2018, 2019) and bushfire recovery periods (Gray 2021). Other datasets on forest disturbance, such as forest harvesting history as applied in the Carbon Balance project of the FMIP, could be used as an additional variable to enhance future analysis.

Modelling of changes and trends in hillslope sheet erosion was based on RUSLE, following methods established in Yang (2020). The baseline erosion rates, generated by applying the highest 100th percentile groundcover (year 2001 to 2020), were compared with the current erosion rates and the relative changes calculated.

6.1.3 Space-time framework for digital soil modelling

The results of the empirical and DSM methods were supplemented by the outputs of an experimental prototype model. The model uses a machine learning space-time framework, referred to as the data cube (refer Appendix B).

The data cube is a digital platform built to predict soil health. It uses a data-driven approach, combining machine learning and geospatial technologies. Although the data required are currently limited (refer Section 5), the data cube provides estimates of trends in soil organic carbon through time (refer Section 6.3) and can be incorporated into future work.

The inclusion of the temporal dimension distinguishes this method from the above digital soil mapping approach. Where the DSM compares two outputs (e.g. current state vs. predicted state), the data cube integrates potential predictors that vary in space, time and space, and time (refer Appendix B).

Each measurement of soil organic carbon has a spatial location and date of sampling. From this, values are estimated for a range of covariates such as weather, terrain attributes and remote sensing for the same location and time.

This approach has only been possible in the past decade with free and open access to continental scale datasets for terrain (Grundy *et al.* 2015) and remote sensing platforms (e.g. Landsat, MODIS, Sentinel) providing weekly images across the world (Lewis, Oliver *et al*. 2017).

Table 9 gives an overview of the description of the datasets processed and collated into a data cube for modelling. The data cube consists of SOC measurements, the month and year of profile sampling, as well as the space, and space and time covariates associated with the soil profile locations.

Table 9 Variables included in data cube

Data type	Covariate	Source	Resolution	Note
Response	SOC	SALIS	-	0-30cm depth
Spatial	DEM, slope	Geoscience Australia	90 m	-
	Topographic Wetness Index (TWI), Multi-resolution Valley Bottom Flatness (MrVBF)	ASRIS	90 m	-
	Gama-radiometric data: Potassium; Uranium; Thorium; Radiation dose	SLGA	90 m	-

Data type	Covariate	Source	Resolution	Note
	Silica	-	~100 m	-
	Clay % (0-5)	SLGA	90 m	-
Spatial & temporal	Precipitation	SILO	5 km, monthly	-
	Temperature (min and max)	SILO	5 km, daily	-
	Solar radiation	SILO	5 km, daily	-
	NDVI	LANDSAT	30 m, 16-day	-

All time-varying covariates (NDVI and climate variables) were aggregated to monthly values. Since the effect of these covariates on soil health dynamics depends on current and past conditions, a decay function weighting algorithm was applied to aggregate sixty months (5 years) of the covariate timeseries prior to when the soil profile was sampled. The algorithm attaches more weight to the most recent observations. Feature extraction by this method (instead of taking the mean value over the last 5 years) has been shown to create better predictive models (Wimalathunge and Bishop 2019).

Another key feature of the data cube is the incorporation of the proxy for natural and anthropogenic disturbances of SOC dynamics at the time of soil profile sampling, compared to conditions at discrete times in the past (refer Appendix B). The potential effect of these disturbances is represented in the data cube by incorporating NDVI difference features wherein the NDVI of the previous 1, 2, 3, 6, and 12 months are subtracted from the NDVI of the month of profile sampling.

Sources of variation considered in this approach included differences in depth characteristics of the soil profiles, as well as the use of different analytical methods between laboratories and survey campaigns.

6.2 Estimation of current status

Sophisticated modelling enables an estimation of soil health indicators across the study area, given a range of key parameters. A wider range of data and calibration is required in order to refine the results of these models and broaden their application (refer Section 7.2). These products are to be viewed as a first approximation and will be subject to change when more recent and more representative field data become available for integration.

Details on the current status of soil carbon, bulk density and pH levels are provided in this section, with further detail provided in Appendix A, which also presents data on soil phosphorous and dispersion indicators.

6.2.1 Soil organic carbon

The digital soil modelling indicated that:

- Climatic factors are the main drivers of SOC, that is, the factors controlling the distribution of SOC over the forest areas of the RFA regions.
- SOC increases with decreasing temperature and increasing rainfall.
- SOC is also driven by parent material and soil type.
- Forest disturbance demonstrates a statistically significant negative trend, indicating the higher the level of forest disturbance, the lower the SOC levels.

Estimated SOC concentration maps (in %) for the 0-30 cm across the RFA regions in approximately 2010 are presented in Figure 6. They were produced using the digital soil mapping method, based on over 1,700 soil profiles contained in SALIS (refer Section 6.1.2). Maps are included for mean, plus upper and lower 90% confidence levels.

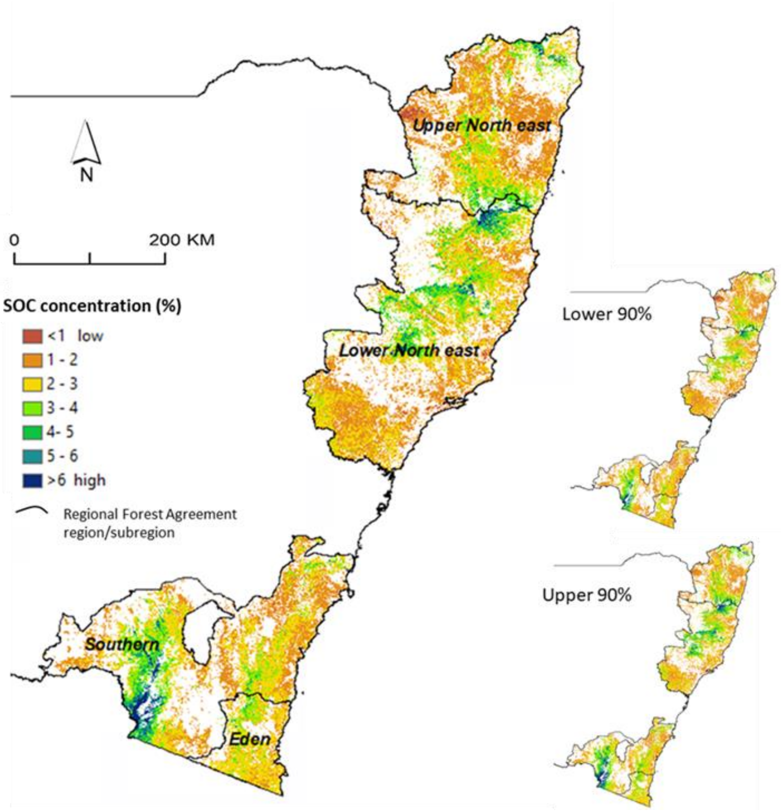


Figure 6 Estimated current surface soil organic carbon concentrations (%) across RFA regions

Soil organic carbon maps were also produced for the 0-10 cm and 10-30 cm layers. Values are typically significantly higher in the 0-10 cm layer, reflecting the usual decline in SOC with depth. Validation results, as provided in Appendix A, Update 4, reveal Lin's concordance of 0.39 for the 0-30 cm depth interval, which indicates only a weak to moderate statistical performance.

Analysis undertaken within the digital soil mapping process (see Appendix A, Update 5) revealed that climatic factors are the main drivers of SOC, ie, the factors controlling the distribution of SOC over the RFA regions. This soil indicator increases with decreasing temperatures and increasing rainfall. These factors control the production of organic matter and the extent of its mineralisation, decomposition and subsequent loss from the soil (Sanderman *et al.* 2010; Wiesmeier *et al.* 2019). SOC levels are typically highest under cool moist conditions and lowest in hot and dry conditions (Gray and Bishop 2019). The influence of projected climate change on SOC is examined further in Section 6.3.3.

The modelling process identified parent material and soil type, as represented by the silica index, as key drivers of SOC. SOC increases with decreasing silica of parent material, indicative of soils of higher clay content and fertility which contribute to higher vegetation growth and stabilisation of soil carbon. Other parent material/soil variables such as radiometric K and Th, and kaolin clay proportion, are also important.

The forest disturbance index (FDI) demonstrates a statistically significant negative trend (refer Appendix A), indicating that the higher the level of forest disturbance, the lower the SOC levels. Highest SOC levels are associated with the least disturbed sites, then decreasing to forests available for harvesting (as per State Forest Management Zones, refer Table 8) and lowest levels associated with privately owned or leased, often grazed forest sites. Similarly, the positive influence of vegetation cover on SOC content is demonstrated.

The variable *Yrs_sinceFire*, representing the length of time since the last major bushfire (not prescribed burn), is revealed to be a strong positive driver of SOC. Levels increase with time since the last major fire event. This relationship is examined more closely in Section 6.3.3.

The modelling identified a positive correlation between topographic slope gradient and SOC in the RFA regions. This suggests the steeper sites have overall higher vegetation densities with less soil disturbance. This is supported by a negative, albeit weak, correlation between the topographic wetness index (TWI) and SOC.

6.2.2 Bulk density

The modelling indicated that within the RFA regions:

- Soil bulk density is most influenced by soil type and parent material.
- Soil bulk density is higher under higher rainfall conditions and may be lower under higher temperatures. The relationship of bulk density with climate warrants further study.
- Forest disturbance demonstrates a statistically significant positive trend, indicating the higher the level of forest disturbance, the higher the bulk density.
- Vegetation cover demonstrates a statistically significant negative trend, indicating the lower the vegetation cover, the higher the bulk density.

Modelled bulk density for the 0-30 cm depth across the RFA regions is presented in Figure 7 (from the Soil Landscape Grid of Australia, approx. 2010).

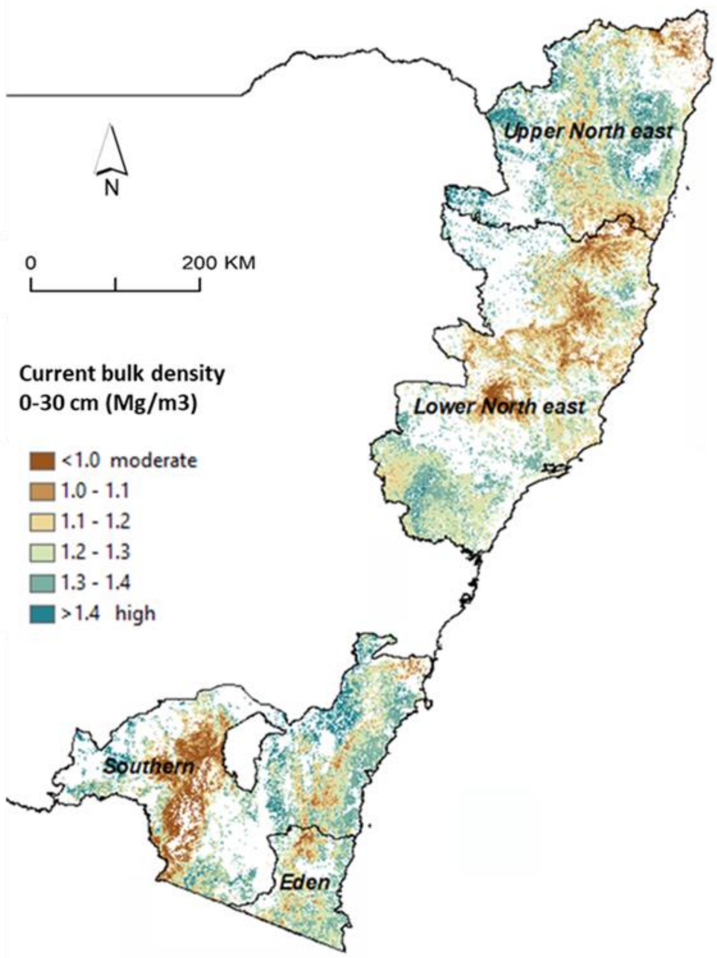


Figure 7 Estimated current surface soil bulk density across RFA regions (mg/m^3) from SLGA

Further analysis undertaken using digital soil mapping techniques in the current project revealed that parent material/soil type indicators such as silica, radiometric K and clay type are dominant drivers of bulk density. The positive correlation with silica reflects the higher bulk density typically associated with sandy soils and the lower bulk density in clay rich well-structured soils.

Rainfall is demonstrated to be another dominant driver. Its positive correlation may reflect the increased leaching of clays from the upper layers of the soil under higher rainfall conditions, thus contributing to more sandy soils with their associated higher bulk density. Temperature is also of moderate influence; the negative correlation possibly indicative of higher clay formation in warm moist conditions, thus driving bulk density lower. The relationship of bulk density with climate in this forest environment warrants further study.

Vegetation cover and forest disturbance index (FDI) are both of moderate influence on bulk density, with negative and positive correlations, respectively. These results reflect the rise in bulk density with lowering vegetation cover and increasing forest disturbance. Vegetation and organic matter serve to improve soil structure, and increased disturbance of soils with the higher FDI leads to soil compaction due to the use of forestry machinery, vehicles and hard-hooved stock: thus both variables contribute to the observed trends. The association of forestry harvesting operations with increased bulk density was reported by Huang *et al*. (1996).

The variable representing years since bushfire did not appear to have any influence on soil bulk density. However, some association might be feasible due to the loss of organic matter after fire, then its gradual recovery.

6.2.3 Acidity

The modelling indicated that within the RFA regions:

- Soil pH is most influenced by soil type and parent material.
- Soil pH is higher (soils are more alkaline) in locations of lower rainfall and higher temperatures.
- Soil pH is lower (soils are more acidic) in locations of higher vegetation cover.

Soil pH_{ca} maps for the 0-30 cm across the RFA regions are presented in Figure 8. The maps represent an estimate of pH_{ca} in approximately 2010. They were produced using the digital soil mapping method (refer Section 6.1.2). Maps are included for mean, plus upper and lower 90% confidence levels.

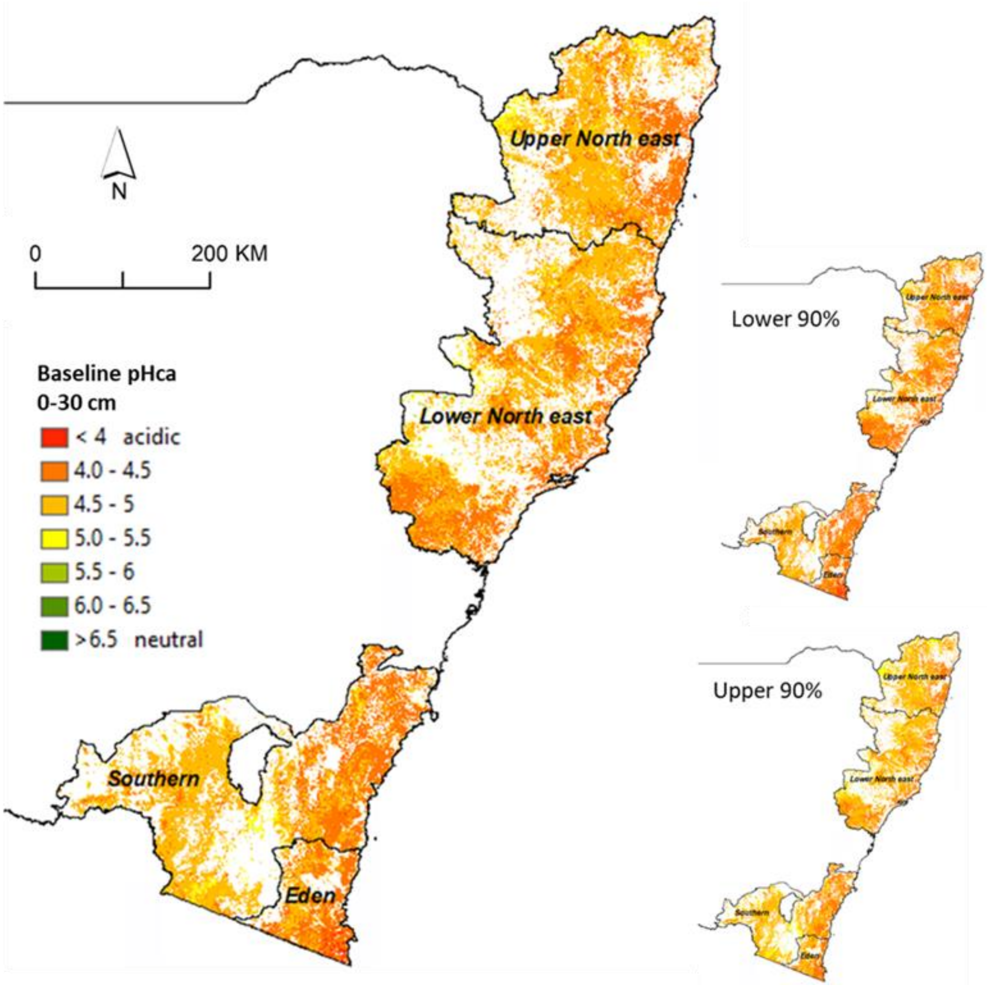


Figure 8 Estimated current surface soil pH across RFA regions (pH units)

Map validation results provided in Appendix A, Update 4, reveal only a weak to moderate statistical performance, with Lin's concordance of 0.35 for the 0-30 cm depth interval.

Parent material and soil type, as represented by the silica index, were revealed as the dominant drivers of soil pH. pH increases, i.e., become more alkaline, with decreasing silica content of parent material, indicative of soils of higher clay content and fertility. Conversely, soils generally become more acidic with more siliceous, sandy soil (Gray *et al.* 2016b). Other parent material/soil variables such as radiometric K and Th, clay proportion and the weathering index were within the top 10 drivers of pH.

Climatic factors are also revealed as key drivers of pH. Soils are shown to become more alkaline with decreasing rainfall and increasing temperatures. This results from the lower levels of leaching that allows basic cations to be retained in the soil and not replaced by hydrogen and aluminium ions

(McKenzie *et al.* 2004; Rubinic *et al.* 2015). The influence of projected climate change on pH is examined further in Section 6.3.3.

The modelling reveals that pH is negatively correlated with vegetation cover over the RFA regions, i.e., the higher the vegetation cover, the more acidic the soil. It is likely that high vegetation cover is associated with release of organic acids. It can be observed that the forest disturbance index (FDI) did not rank in the top ten variables.

The variable representing years since bushfire did not appear to have any influence on the soil pH. However, a rise in pH following forest fires due to the accumulation of basic ash is reported in the literature review of Raison (1979).

6.3 Trends and predictions

Sophisticated modelling enables prediction of changes in soil carbon, bulk density, erosion, and pH levels through time, subject to stresses such as bushfire and climate change, and given a range of key parameters. A wider range of data and calibration is required in order to refine the results of these models and broaden their application (refer Section 7.2). Further detail is provided in Appendix A.

These products are to be viewed as a first approximation and will be subject to change when more recent and more representative field data become available for integration.

6.3.1 Soil carbon loss

6.3.1.1 Findings of data cube model

Figure 9 shows the predicted 0-30 cm SOC maps for the months of June 1990, 2000, 2010 and 2020. While the temporal trend is not generally apparent from these maps, the difference between the SOC for between decades show substantial changes in SOC (Figure 10).

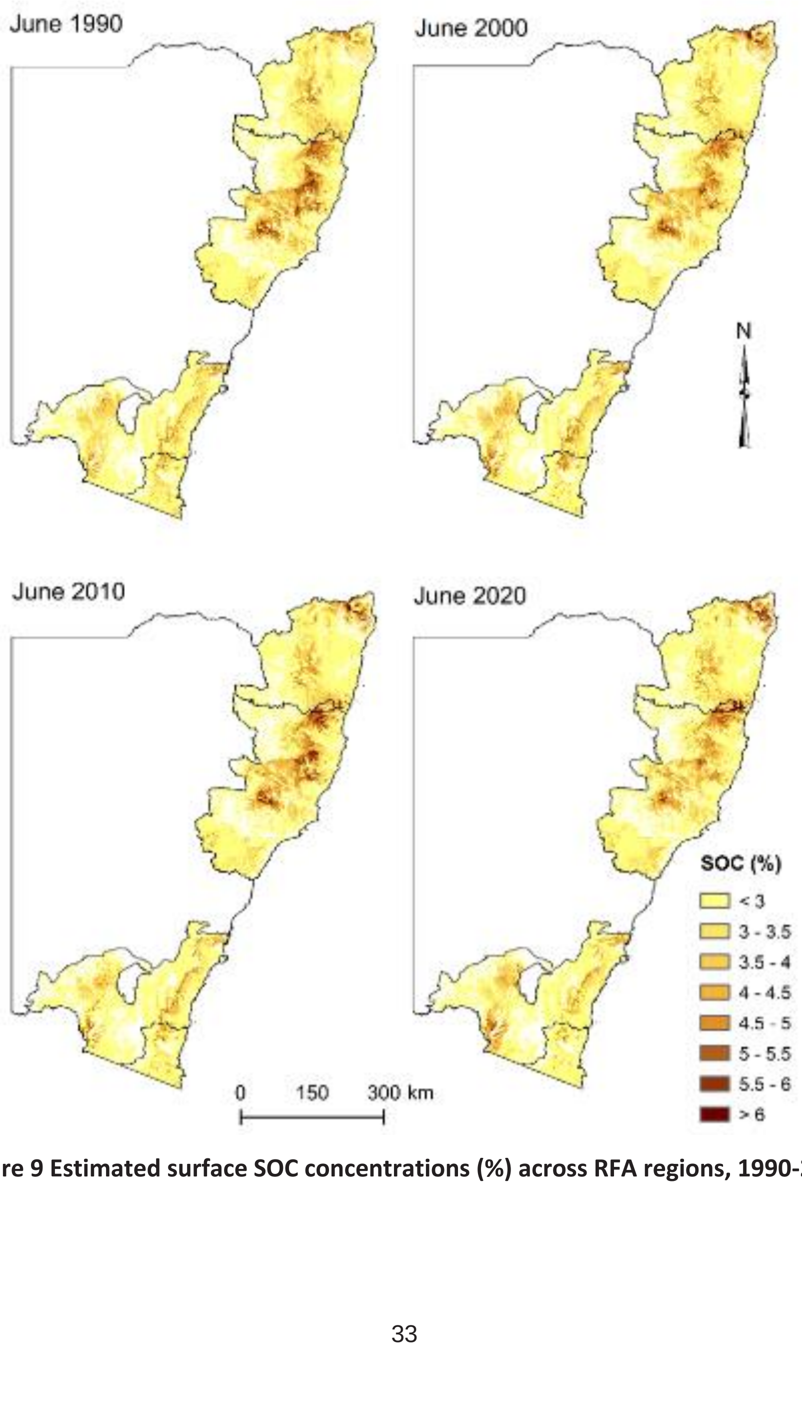


Figure 9 Estimated surface SOC concentrations (%) across RFA regions, 1990-2020

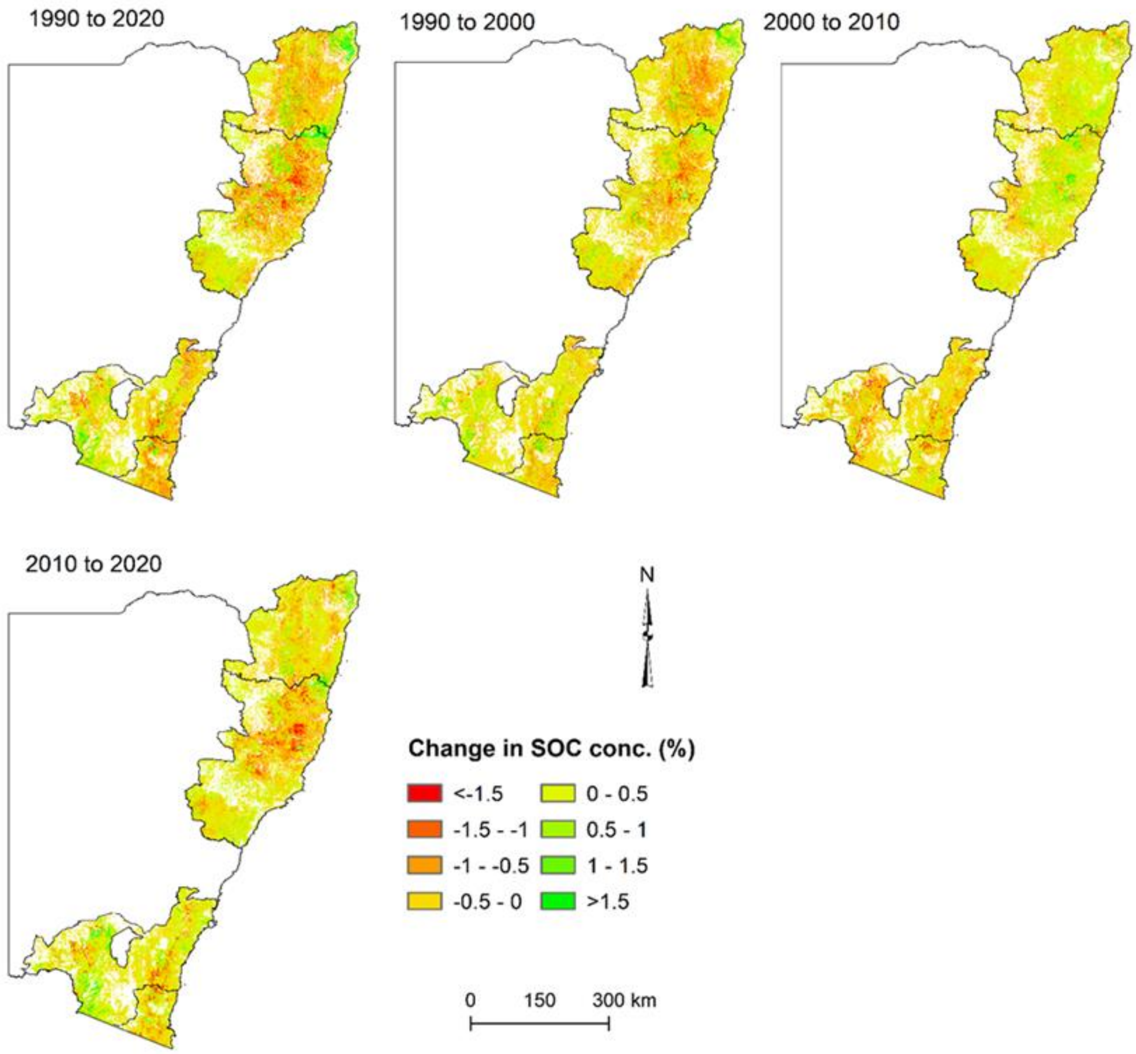


Figure 10 Estimated change in surface SOC concentrations (%) across RFA regions between four time steps, 1990-2020

The statistical significance of the trends is low, as indicated by the lower and upper 90% prediction intervals. Figure 11 presents the 0.05-, 0.5- and 0.95-quantiles of the 0-30 cm SOC for June 2020.

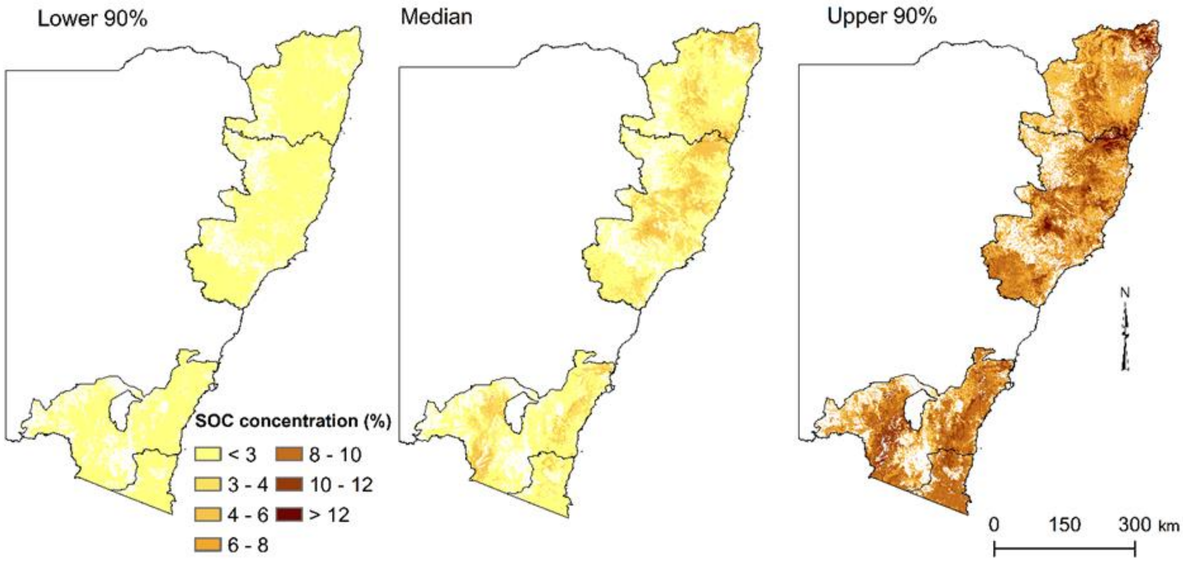


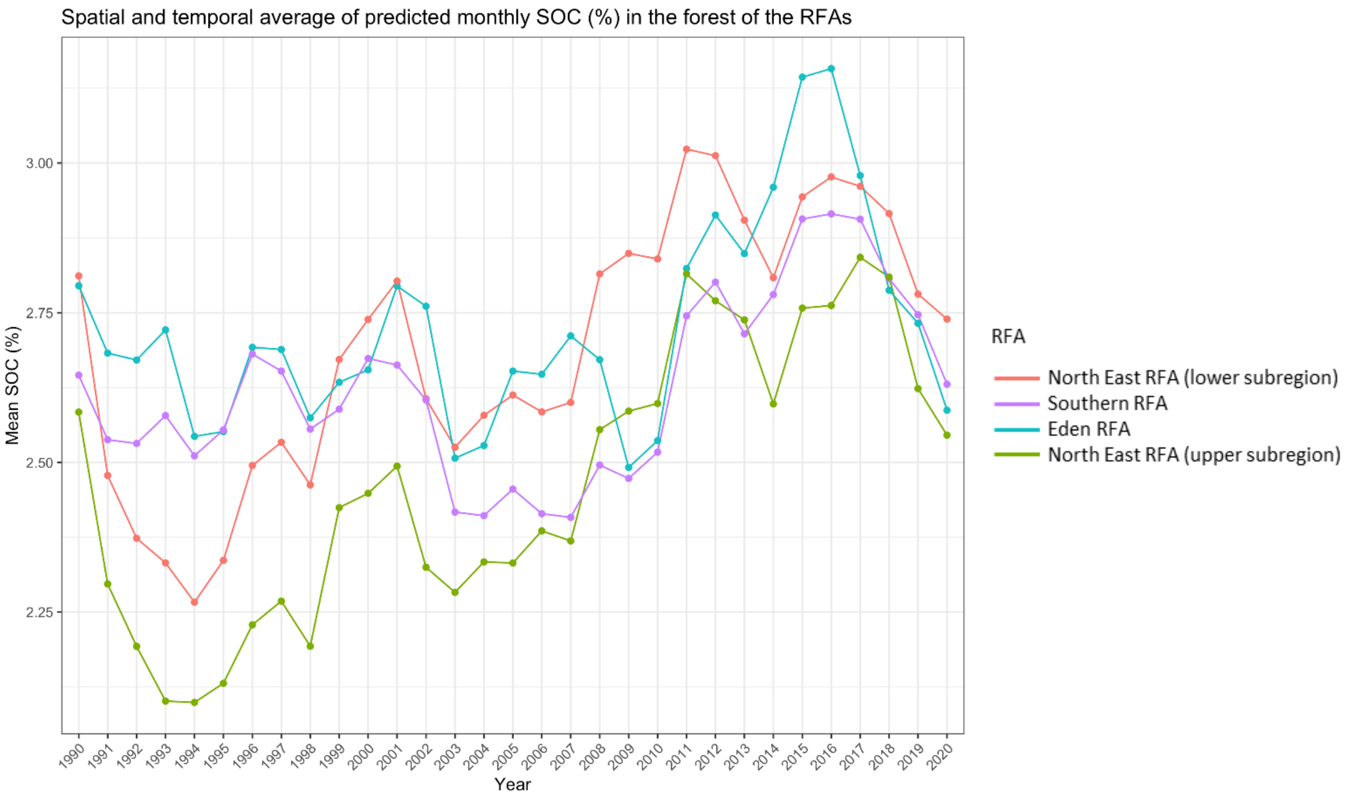
Figure 11 Estimated surface SOC concentrations (%) across RFA regions, 0.05-, 0.5- and 0.95-quantiles for June 2020

We aggregated the SOC time series by RFA regions and by management regime (Figure 12). Management regimes were broadly grouped into reserved (formal and informal), forestry operations (harvesting), and privately owned or leased. The modelling suggests an inverse relationship between the degree of land disturbance and SOC concentrations, with the SOC higher in the reserved (formal and informal) forest and least in the privately owned or leased forest.

This supports the findings of Turner & Lambert (2000) who found an inverse relationship between SOC and land disturbance (native forest compared to plantation forest).

As shown in Figure 12, the data cube model predicts SOC concentrations to have varied through time, with a slight decline between 1990 and 2020 when comparing only these two points in time. For the period prior to 2010, where more observations (soil sample data) are available, little overall change is observed. In the period 2010-2020, the model indicates a possible increasing trend, followed by a sharp decline in recent years. Over-interpretation of these results is cautioned against as the predictions have high uncertainty (refer Appendix B), particularly post-2010, where there are very few observations upon which to train the model (refer Section 5).

We suspect the model is quite responsive to NDVI, and that the trends shown in Figure 12 reflect this. Further sampling in the near future would likely lead to more reliable predictions of SOC for the period 2010-2020, as interpolation is generally better than extrapolation in terms of predictive performance. It will also likely dampen the effect of NDVI on predictions. Overall, the data cube approach has shown what is possible in terms of space and time prediction of soil, but requires more observations to improve its performance, once again highlighting the importance of long-term investment in soil monitoring.



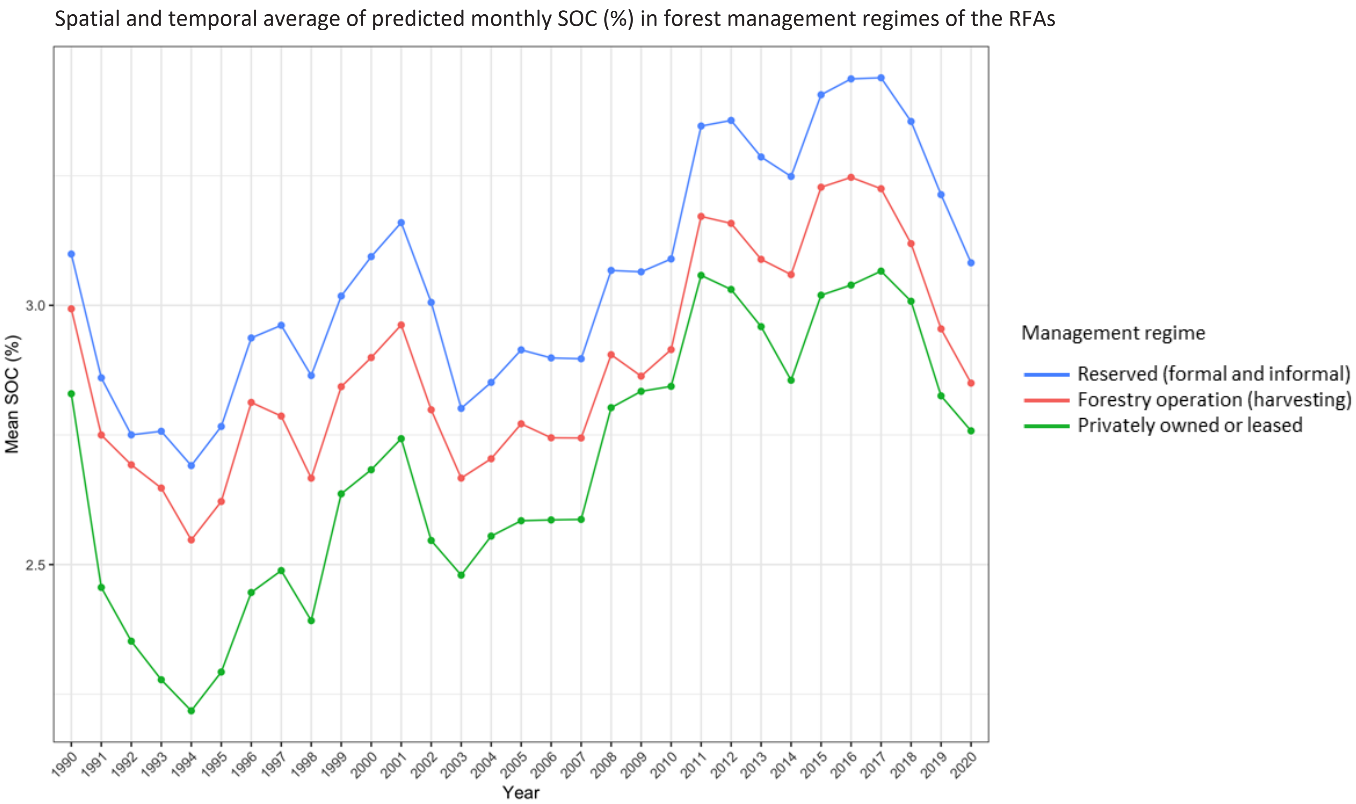


Figure 12 Yearly predicted surface SOC concentrations (%) spatially averaged by RFA region (top) and by management regime (bottom)

6.3.1.2 Modelled impact of increasing land disturbance on SOC

Figure 13 presents the change in SOC content from a hypothetical status of a less disturbed environment (FDI 1, refer Section 6.1.2) to a relatively recent current probable disturbance status (approx. 2010), based on the change in FDI. All other variables were held constant, for example, no change in climate was considered.

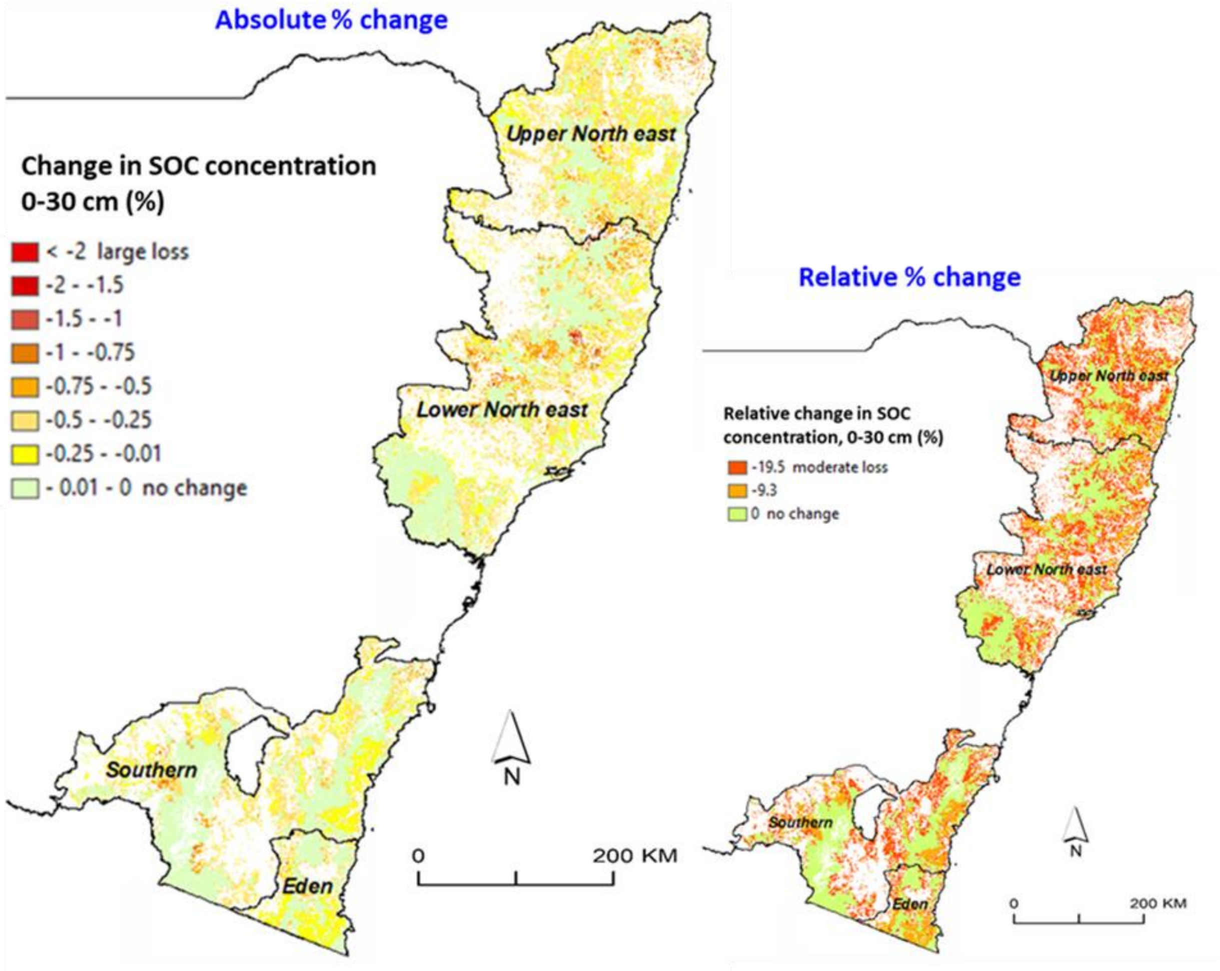


Figure 13 Predicted absolute and relative change (%) in surface SOC concentrations from a hypothetical relatively undisturbed reference condition to current condition

A significant widespread loss of SOC is revealed due to this change in degree of disturbance. SOC decline varies from zero to moderate (>2%) in absolute terms, or over 20% in relative terms. Larger declines are, as expected, associated with the areas of highest disturbance, as revealed by Table 10. No SOC decline occurs over relatively undisturbed lands, then moderate declines (mean -9% in relative terms for 0-30 cm) over partially disturbed lands, and highest declines (mean -20.38% in relative terms) over moderately disturbed, periodically grazed forest lands (as represented by FDI 3). The extent of SOC decline decreases with depth.

Table 10 Mean relative change in SOC with forest disturbance (%)

Forest disturbance index	0-10 cm	10-30 cm	0-30 cm	30-100 cm
1: Relatively undisturbed	0	0	0	0
2: Some disturbance	-10.3	-9.9	-9.3	-5.0
3: Moderate disturbance (periodic grazing)	-21.7	-20.9	-19.5	-10.3

Even greater declines are likely to have been demonstrated if a hypothetical decrease in vegetation cover had been incorporated into the change modelling process (see method description, Section 6.1.2). The modelled loss of soil carbon associated with ground disturbance is consistent with likely lower inputs of organic material to soils and greater decomposition/mineralisation (Jandl *et al.* 2007).

The rate of decline is not uniform, even within each FDI class, but is dependent on the precise combination of environmental factors. Areas with the highest existing SOC levels, such as in wet locations and fertile clay rich soils, lose more SOC than areas with low existing SOC levels, such as in drier locations with low fertility sandy soils. This higher loss applies in both absolute and relative terms, as demonstrated by Gray *et al.* (2016a).

The modelled change in SOC due to human disturbance in each RFA or subregion is presented in Table 11. It reveals the highest overall decline in the Upper North East sub-region (>11% in relative terms, 0-30 cm). Declines are greatest in the surface soils.

Table 11 Mean relative change in SOC from human disturbance by RFA region

RFA Region	0-10 cm	10-30 cm	0-30 cm	30-100 cm
Upper North East subregion	-12.7	-12.3	-11.4	-6.0
Lower North East subregion	-10.3	9.9-	-9.2	-4.9
Southern	-8.8	-8.5	-7.9	-4.2
Eden FA	-7.7	-7.4	-6.9	-3.7

6.3.1.3 Modelled impact of climate change on SOC

The change in SOC stocks arising from projected climate change over NSW has been modelled as part of the NARCliM program (Gray and Bishop 2018, 2019). The study used a far change period, centred around 2070. Results from that study suggest a marked decline in relative terms over the RFA regions to the far change period. These results, isolated to the RFA regions, are presented in Figure 14.

The relative change by RFA region or subregion is presented in Table 12. A mean relative loss of 17% for the 0-30 cm interval is projected over both North east subregions, rising to over 37% relative loss in the Southern region. The results represent the mean of 12 climate model projections under the IPCC intermediate A2 emission scenario applied in the NARCliM program (Evans *et al*. 2014). The magnitude of decline in SOC varied between the different climate models.

The results suggest a continuing loss of SOC and associated soil condition across all systems of land management over the NSW eastern forests. The greatest predicted losses in SOC were identified to occur in areas with currently high SOC stocks. Highland regions, particularly in the southern alps, are predicted to lose the largest quantity of SOC.

The findings suggests that forest managers will have to implement appropriate soil carbon-enhancing strategies even to just maintain current SOC levels. This also has implications for identifying ongoing net carbon emissions from NSW lands, with respect to aiming for Net Zero Emissions (NSW Government 2016; DPIE 2020) and mitigating climate change.

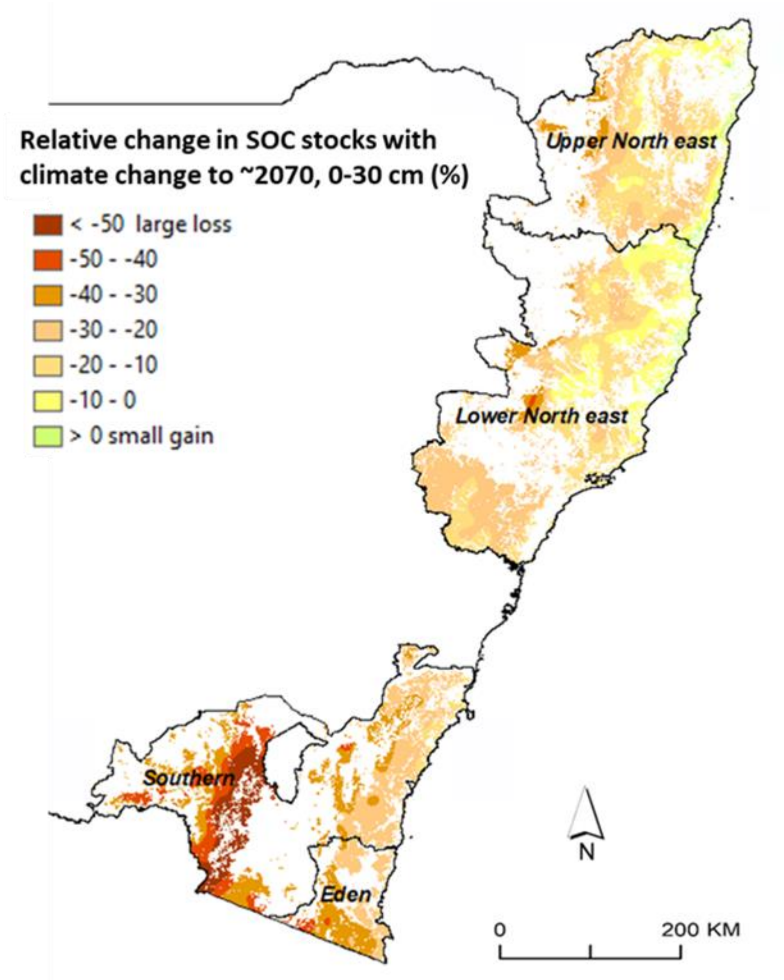


Figure 14 Predicted relative change (%) in surface SOC concentrations with projected climate change to approx. 2070

Table 12 Mean relative change in SOC with climate change to approx. 2070 by RFA region (%)

RFA Region	0-30 cm	30-100 cm
Upper North East subregion	-17.2	-37.6
Lower North East subregion	-17.0	-36.3
Southern	-37.2	-64.0
Eden	-31.1	-55.2

6.3.1.4 Modelled impact of bushfire on SOC

The impact of bushfire was assessed by incorporating a variable into the model which represents the number of years since bushfire (wildfire). There is insufficient soil sampling from burnt areas following the 2019/20 fires to incorporate into the modelling (refer Section 5).

Modelling revealed a strong positive correlation between SOC and the number of years since bushfire. The influence of this variable was strongest when converted to the natural log format (ln) indicating its influence is more pronounced in early rather than later years. This reflects high rates of SOC recovery in early years then progressively lower rates of SOC recovery until a new equilibrium is reached. The modelling suggests a re-equilibrium is reached 75 years after bushfire. The estimated recovery period does not account for additional bushfires during this time.

In the analysis of trends with bushfire, the model was run with the variable representing the number of years since bushfire (wildfire) set to the immediate aftermath of bushfire hypothetically applied across the entire RFA study region (Figure 15). Relative losses of SOC generally range between 40 and 60%, substantially high proportions. The highest rates of loss (in absolute terms) are indicated over locations with high initial SOC levels.

The recovery of SOC after 20 years is presented in Figure 16, suggesting that 62% of carbon originally lost is regained over that time period. This does not account for additional bushfires (wildfires) occurring during that period.

The loss of SOC following bushfire indicated by the modelling is consistent with the findings of other studies. A study of soil conditions 3 years after high intensity fires in Warrumbungles National Park reported relative SOC losses of 35% in sandy soils and 55% in moderately clay-rich soils, followed by a period of recovery (Tulau and McInnes-Clarke 2016). Similar trends have been demonstrated in other Australian and international studies (Bowd *et al.* 2019; Homann *et al.* 2011; Tessler *et al.* 2008; Tulau and McInnes-Clarke 2016), as graphically represented in Figure 17.

Soil data from areas affected by the 2019/20 bushfires represent a critical data gap which future monitoring efforts should seek to address (refer Section 8).

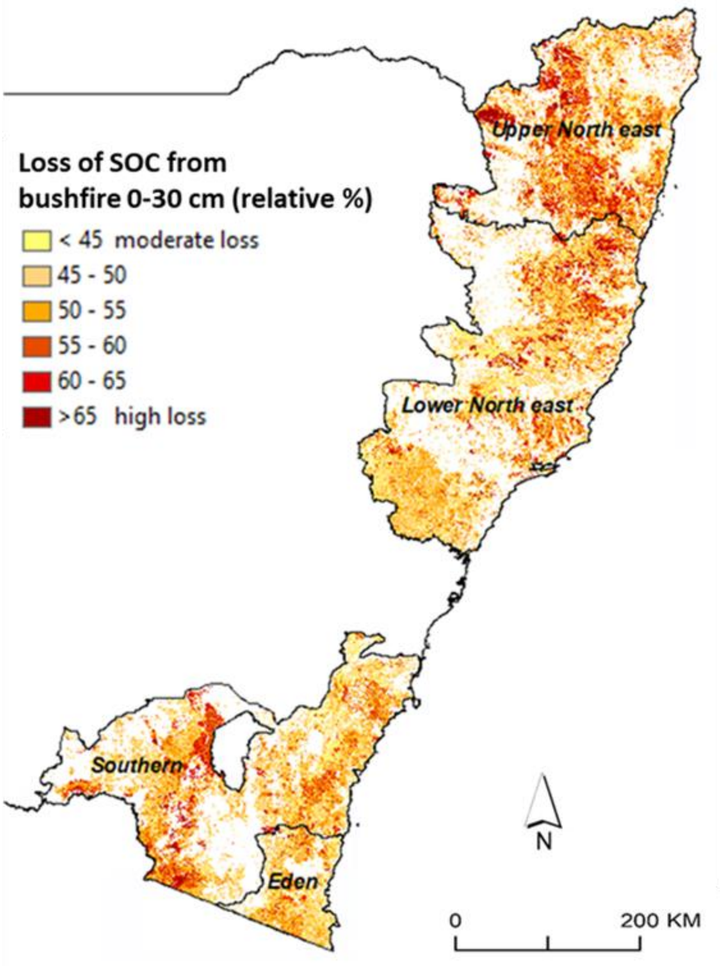


Figure 15 Predicted relative change (%) in surface SOC concentrations immediately following bushfire across RFA regions

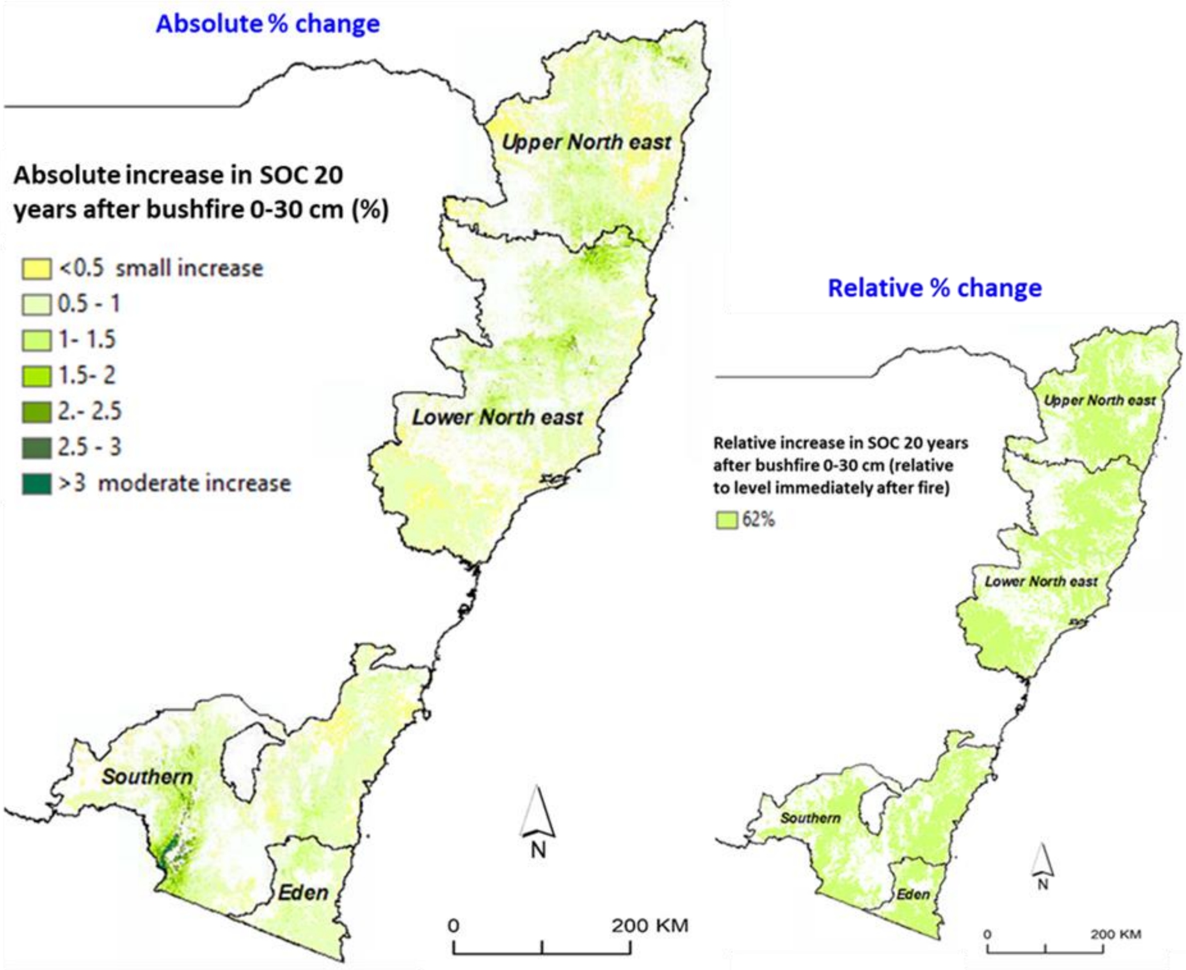


Figure 16 Predicted absolute and relative increase (%) in surface SOC concentrations with 20 years since bushfire across RFA regions

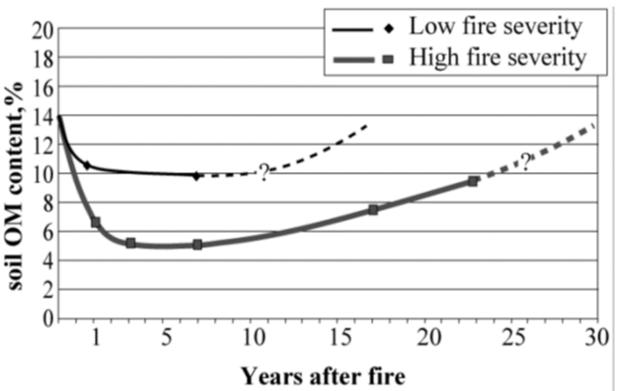


Figure 17 Predicted temporal changes in soil organic matter content following low and high fire severity (after Tessler et al. 2008 in Tulau and McInnes Clarke 2016)

6.3.2 Modelled changes in bulk density

Figure 18 presents the change in bulk density (0-10 cm) from a status of hypothetical relatively undisturbed environment to current probable disturbance status (approx. 2010), based on changes in FDI. All other variables were held constant, that is, no change in climate.

A slight increase in bulk density, particularly over the 0-10 cm interval, is revealed with this hypothetical change in disturbance. The increases range to over 0.2 t/ m^3 or 15% in relative terms Larger increases are, as expected, associated with the areas of higher disturbance, as revealed by Table 13. There is zero change modelled over current minimally disturbed lands, then slight increases (mean 7% in relative terms for 0-10 cm) over partially disturbed lands and highest increases (mean 14% in relative terms for 0-10 cm) over moderately disturbed, often grazed forest lands.

Table 13 Mean relative change in bulk density with forest disturbance (%)

Forest disturbance index	0-10 cm	10-30 cm	0-30 cm
1: Relatively undisturbed	0	0	0
2: Partial disturbance	6.8	6.1	8.1
3: Moderate disturbance (periodic grazing)	14.2	13.6	15.3

These changes reflect the potential impacts of soil compaction from heavy forestry machinery, vehicles and stock, plus potential decreases in vegetation and SOC associated with the change from the relatively undisturbed condition to the current, more disturbed forest environment. Huang *et al*. (1996) similarly report an increase in soil compaction and bulk density with ground disturbance arising from timber harvesting and associated activities.

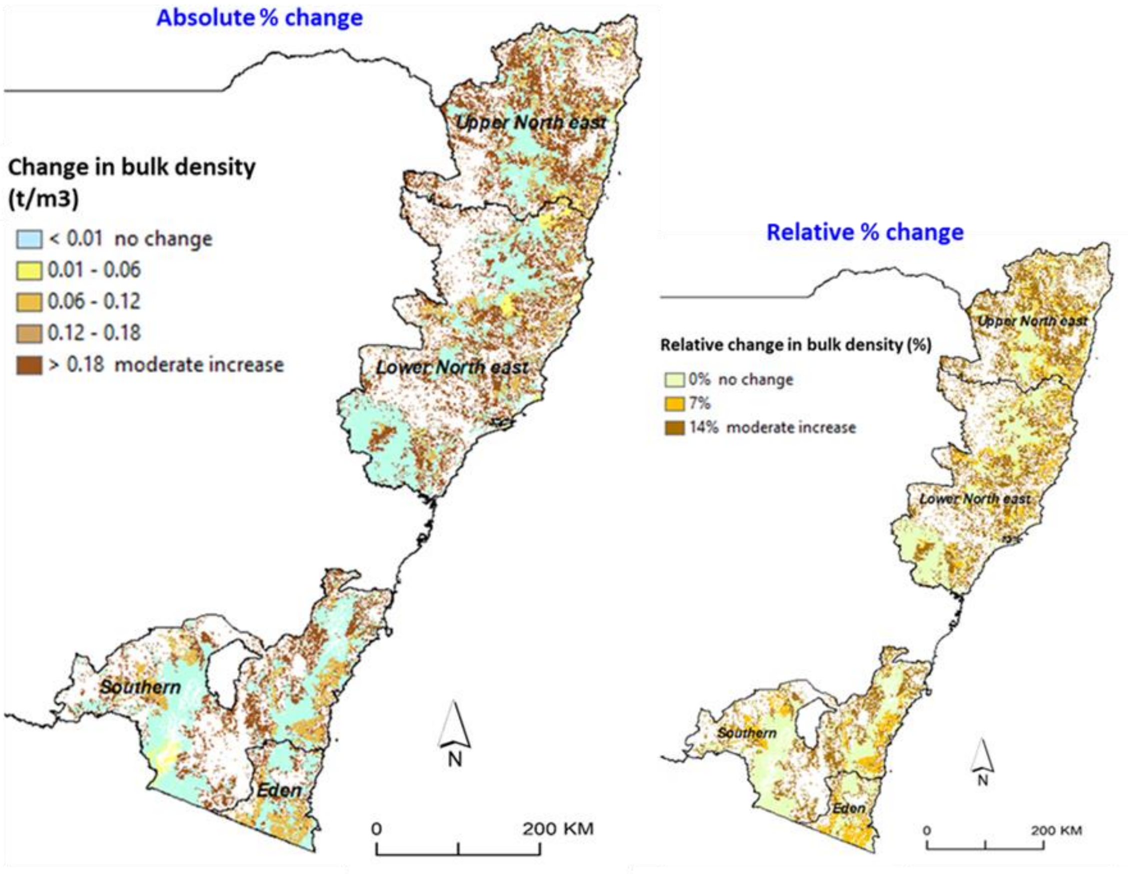


Figure 18 Predicted absolute and relative change (%) in surface soil bulk density from a hypothetical relatively undisturbed reference condition to current condition

The modelled change in bulk density (0-10 cm) for each RFA region is presented in Table 14. It reveals the highest overall increases in the North East subregions.

Table 14 Mean relative change in bulk density from hypothetical relatively undisturbed to current conditions by RFA region (%)

RFA region	0-10 cm	10-30 cm	0-30 cm
Upper North East subregion	8.3	7.6	9.7
Lower North East subregion	6.7	5.9	8.0
Southern	5.0	4.8	5.7
Eden	5.7	5.3	6.5

6.3.3 Modelled changes in acidity

The change in pH arising from projected climate change over NSW has been modelled as part of the NARCliM program (Gray and Bishop 2018, 2019). The study used a far change period, centred around 2070. Results from that study suggest a slight increase to more alkaline soils over the RFA regions to the far change period. These results are presented in Figure 19.

The change by RFA region is presented in Table 15. The most pronounced increases are evident in the Southern region, particularly in the alpine regions, where increases of more than 0.3 pH units are predicted. The results represent the mean of the 12 climate model projections under the IPCC intermediate A2 emission scenario applied in the NARCliM program (Evans *et al*. 2014). The magnitude of change in pH varied between the different climate models.

Over most of the region the changes in pH are relatively minimal in absolute terms. However, any changes in soil pH may affect natural ecosystems, which have established under particular pH ranges. Where significant increases or decreases (e.g. of 0.2 pH units or more) are predicted there is a likelihood that native ecosystems will be adversely affected; this is an issue that may need to be considered and addressed by managers of these ecosystems (Steffen *et al*. 2009; Prober and Wiehl 2012).

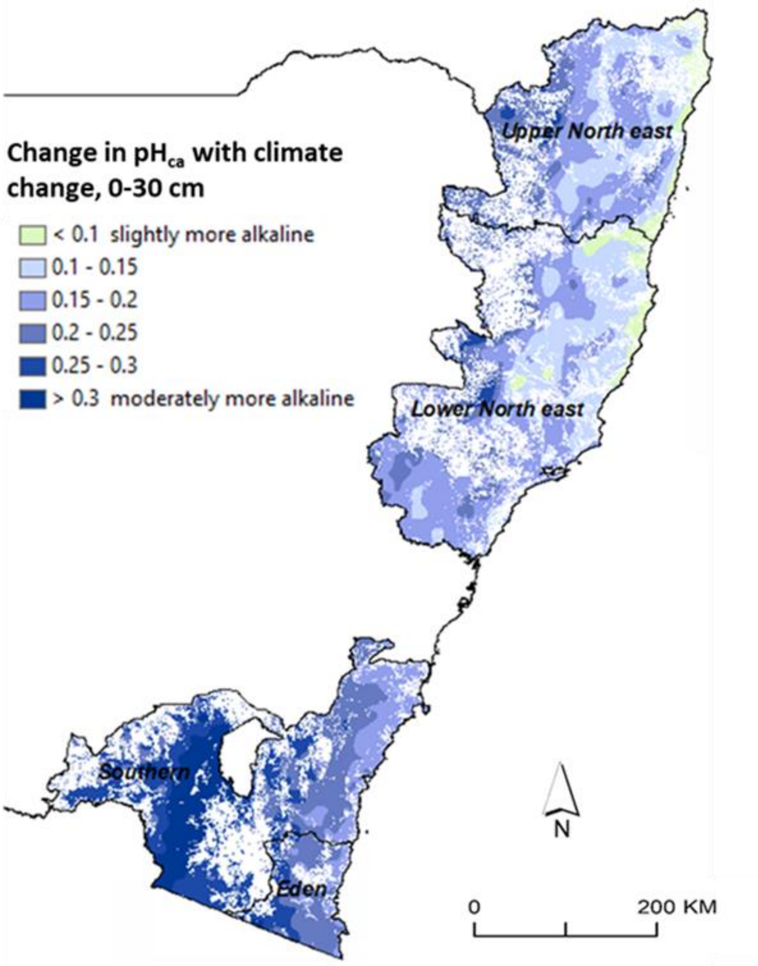


Figure 19 Predicted change in pH_{ca} due to projected climate change to approx. 2070

Table 15 Mean absolute change in pH with climate change to approx. 2070 by RFA region (pH units)

RFA Region	0-30 cm	30-100 cm
Upper North East subregion	0.16	0.13
Lower North East subregion	0.16	0.13
Southern	0.27	0.26
Eden	0.23	0.22

6.3.4 Hillslope erosion

Hillslope erosion, including sheet and rill erosion, is the dominant form of soil loss in NSW (refer Table 3). There are a range of models for estimation of soil loss rates from landscapes. The Revised Universal Soil Loss Equation (RUSLE) is amongst the most widely applied.

The RUSLE has been used to estimate the hillslope erosion rates on monthly and annual basis for the period of 2001 to 2020 and to analyse the state and trends of erosion across NSW (Yang *et al*. 2020). As RUSLE was originally developed for agricultural soils, the cover and management, or C factor, is the major limiting factor for its application in a forest environment. We developed a method (Yang 2014; Yang 2020) on the C factor estimation based on the monthly fractional vegetation cover including photosynthetic vegetation (PV), non-photosynthetic vegetation (NPV) and bare soil (BS). This is the best available method of remotely assessing cover for erosion predictions and is well suited to environments where climate is highly variable and non-green vegetation is a significant component of the overall cover (McKenzie et al. 2017).

This remote sensing based method has advantages to consistently and continuously estimate hillslope erosion over large areas, but is not sufficient to evaluate localised impacts of sediment and runoff delivery as they relate to timber harvesting activities. Future monitoring efforts should assess the interaction of the timber harvesting and forest road and track network with both sediment and runoff delivery.

Figure 20 presents the modelled average hillslope erosion rates (t ha^{-1} yr^{-1}) for the RFA regions across NSW for the period 2001-2020. The modelled hillslope erosion rates vary among the RFA regions, where the North East RFA has the highest hillslope erosion rate (lower subregion, 5.4 t ha^{-1} yr^{-1}, followed by the upper subregion, 4.0 t ha^{-1} yr^{-1}), then the Southern RFA (2.1 t ha^{-1} yr^{-1}) and the Eden RFA (1.7 t ha^{-1} yr^{-1}).

Hillslope erosion has great seasonal and inter-annual variation. Figure 21 shows the predicted annual hillslope erosion (t ha^{-1} yr^{-1}) in the NSW RFA regions for the period 2001-2020. Over this 20-year period, the modelled maximum annual erosion rate was 8.4 t ha^{-1} yr^{-1} in 2013 in the lower North East RFA subregion, which was about 15 times higher than the lowest rate (0.6 t ha^{-1} yr^{-1}) in 2009 in the Eden RFA region. Overall, the hillslope erosion rate in the RFA regions is the highest in summer, especially in February (0.8 t ha^{-1} $month^{-1}$), which is more than 10 times higher than the winter rate (e.g. July < 0.1 t ha^{-1} $month^{-1}$), as shown on Figure 22.

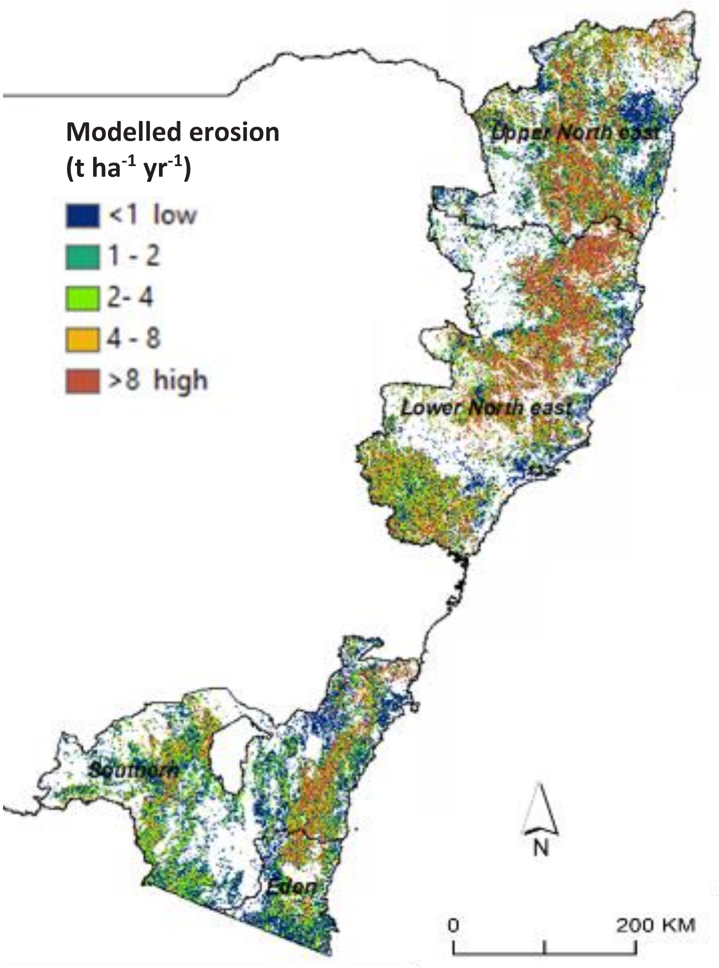


Figure 20 Modelled mean hillslope erosion (t ha^{-1} yr^{-1}) across RFA regions, 2001-2020

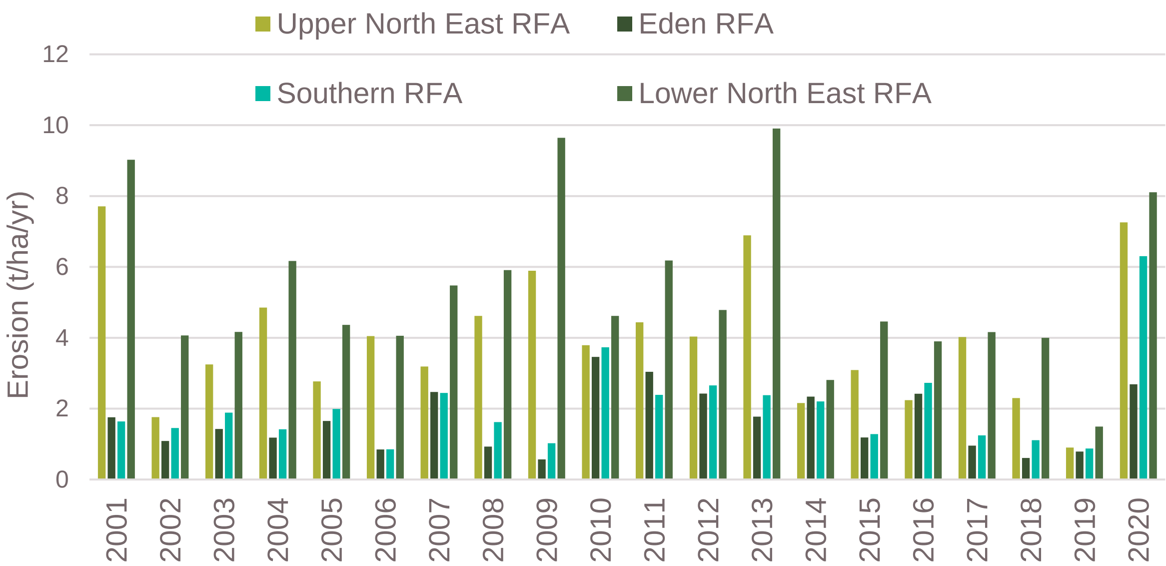


Figure 21 Annual modelled hillslope erosion (t ha^{-1} yr^{-1}) by RFA region, 2001-2020

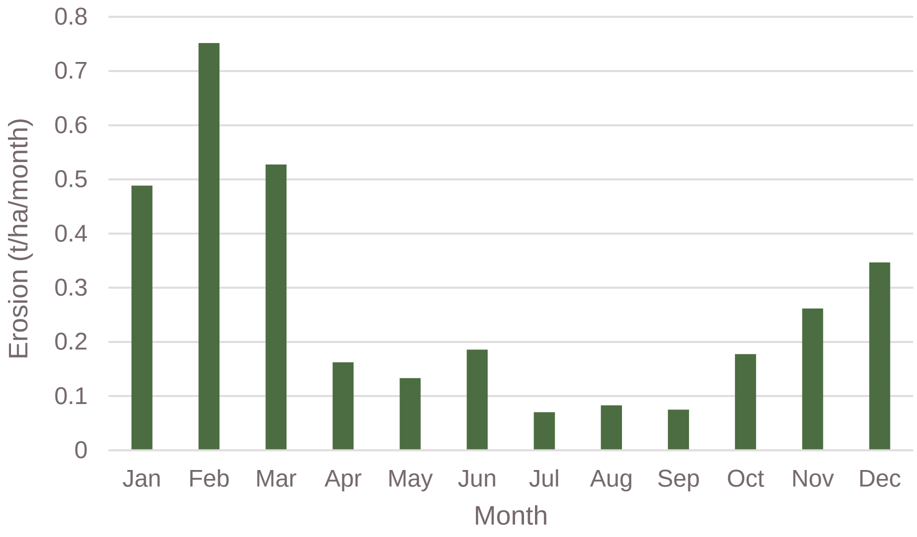


Figure 22 Modelled mean hillslope erosion rate across RFA regions by month, during the period 2001-2020

To evaluate how changes in vegetation impact erosion rates across the RFA regions, we used the estimated erosion rate at the 100th percentile vegetation cover for the period 2001-2020 as the baseline condition and compared it to the estimated erosion rates at the current condition as presented above. The comparison shows that the Southern RFA region has the highest increase in erosion rates (40%), being the most affected by the drop in vegetation cover, while the increase ranges from about 27-29% in North East and Eden RFA regions.

We also modelled the worst scenario assuming the vegetation cover is totally removed. The erosion rate in Lower North East RFA subregion was estimated to be 398 t ha^{-1} yr^{-1}; 313 t ha^{-1} yr^{-1} in the Upper North East RFA subregion; 129 t ha^{-1} yr^{-1} in Southern RFA region; and 119 t ha^{-1} yr^{-1} in Eden RFA region. When we compare these values to the modelled current conditions (Figure 20), we find that erosion rates could increase 60-80 times across NSW RFA regions if the current vegetation cover was totally removed, while other conditions (slopes, slope-length, soil and climate) remain unchanged (Figure 23). This finding emphasises the importance of maintaining adequate vegetation cover to reduce soil loss in the RFA regions, especially on steep lands.

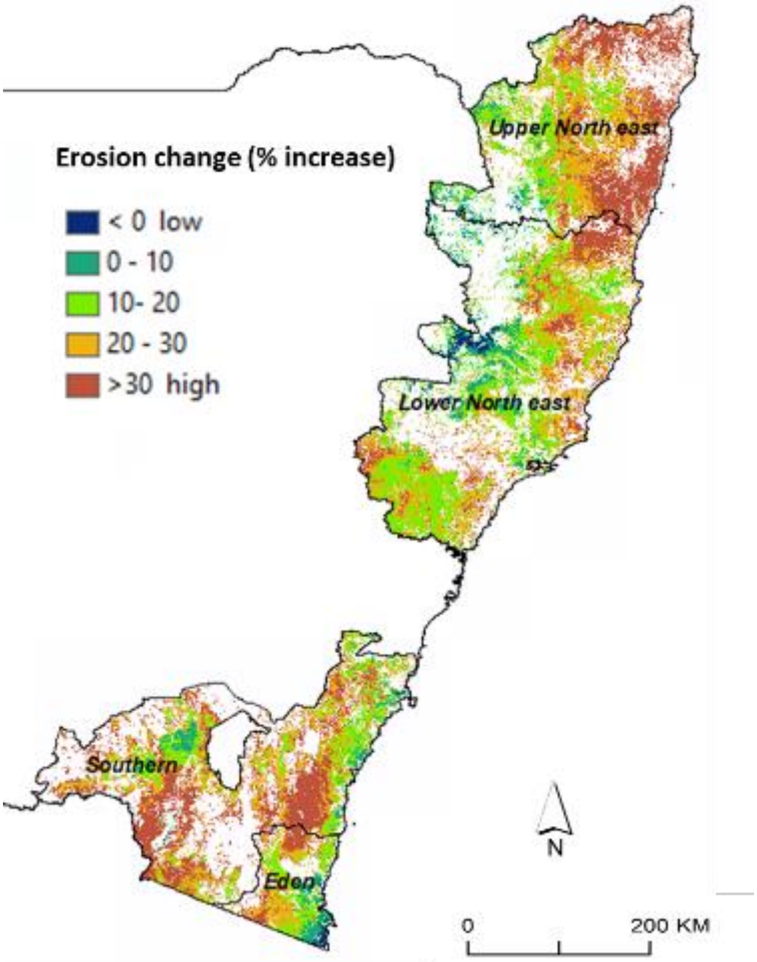


Figure 23 Estimated impact of decrease in vegetation cover from a hypothetical 100th percentile vegetation cover to modelled current vegetation cover on erosion rate (%)

7 Discussion

7.1 Findings

7.1.1 Critical data gaps

Our data-gap analysis determined that the available data of soil health indicators are limited and subject to large spatiotemporal variation.

Critical data gaps exist, as follows:

- The status of biological soil health indicators (microbial biomass, fungal : bacterial ratio, mycorrhizal fungal assemblages) to assess below ground biodiversity and ecosystem resilience.
- The current status of physical soil health indicators (particularly bulk density and aggregate stability) to assess the physical condition of the soil and enable accurate calculation of carbon stocks.
- The current status of chemical soil health indicators within the RFA forest regions, including:
    - Current total SOC and carbon fraction concentrations to map, monitor and forecast soil carbon dynamics.
    - Current phosphorus and nitrogen distributions to evaluate nutrient distribution.
    - Current soil acidity.
    - Current soil salinity.
- The status of soil health indicators following the 2019/20 bushfires.
- Measured change in soil health indicators through time from revisited monitoring sites.
- Measured differences in soil health indicators between paired sites under different types of forest management.

The available data are insufficient to consider all indicators in a combined holistic manner to gain a broad assessment of the condition of NSW forest soils. A meaningful assessment of changes and trends in soil condition requires an ongoing monitoring program (refer Section 8).

Estimates of SOC stocks and distribution remain limited by insufficient data for NSW forests, and indeed for many regions globally (Jackson *et al.* 2017). Forest monitoring provides an opportunity for NSW to lead future national and international efforts in soil carbon accounting.

7.1.2 Summary of driving factors

As discussed in Section 4, the status of soil indicators is the product of multiple factors and sub-factors. The DSM techniques provide a useful approach for identifying key drivers of the component soil condition indicators. The combination of these broad factors is shown to vary for each indicator, as follows:

- Soil organic carbon:
    - SOC is driven mostly by climatic factors, that is, these factors control the distribution of SOC over the RFA regions, where SOC increases with decreasing temperature and increasing rainfall.
    - SOC is also driven by parent material and soil type.

    - Forest disturbance from human activities demonstrates a statistically significant negative trend, indicating the higher the level of forest disturbance, the lower the SOC levels.
    - The number of years since bushfire was also a significant driver of SOC levels.
- Acidity:
    - Soil pH is most influenced by soil type and parent material.
    - Soil pH is higher (soils are more alkaline) in locations of lower rainfall and higher temperatures.
    - Soil pH is lower (soils are more acidic) in locations of higher vegetation cover.
- Bulk density:
    - Bulk density is most influenced by soil type and parent material.
    - Bulk density is higher under higher rainfall conditions and may be lower under higher temperatures.
    - Forest disturbance from human activities demonstrates a statistically significant positive trend, indicating the higher the level of forest disturbance, the higher the bulk density.
    - Vegetation cover demonstrates a statistically significant negative trend, indicating the lower the vegetation cover, the higher the bulk density.

Climate and parent material/soil type were revealed to be strong drivers for all indicators. Topographic factors were not revealed as strong drivers at the broad regional scale, but are likely to be more influential at a local scale. These environmental variables are broadly beyond the control of human influence. The relationship of bulk density with climate warrants further study.

Forest management and the associated vegetation cover factors are important drivers for most soil condition indicators. This finding aligns with previous work evaluating the effects of forest management on soil health (Turner and Lambert 2000).

7.1.3 Summary of trends

Though model performance was low due to limited data, the digital soil mapping and data cube modelling indicate potential declines in SOC across the RFA regions in recent years, regardless of land use.

The modelling revealed the following trends based on different potential soil disturbances:

- Increased forest disturbance (as represented by the FDI) results in decreasing SOC and increasing bulk density, suggesting poorer soil structure and condition. These changes are typical for any human operation that removes carbon-based products and sees a reduction in vegetation cover, such as timber harvesting and stock grazing. The modelling revealed that areas of moderate disturbance (e.g. subject to periodic stock grazing) had greater impact on forest SOC, bulk density and associated soil condition than less disturbed areas.
- Climate change was shown to contribute to a decline in SOC over most of the region. The projected decline in SOC suggests an associated decline in soil condition suggests that forest managers will have to implement appropriate soil carbon-enhancing strategies to maintain current SOC levels. This also has implications for identifying ongoing net carbon emissions from NSW lands, with respect to aiming for Net Zero Emissions (NSW Government 2016; DPIE 2020) and mitigating climate change.
- Climate change was also shown to contribute to a slight rise in pH over most of the region. Any significant change in soil pH, either rise or fall, can be detrimental to natural ecosystems

that are adapted to particular pH ranges. A resulting degree of migration of ecosystems may be an eventual consequence of these changes (Steffen *et al.* 2009).

- Bushfires are demonstrated to have a major influence on SOC, with a dramatic loss predicted immediately following the bushfire, in the order of 50% (relative loss). This is followed by a gradual recovery of SOC in the following years, with over 60% recovery after 20 years and approaching re-equilibrium levels after approximately 75 years. Based on this scenario, SOC may be subject to continuous decline with more frequent fires. Further analysis is required to evaluate this trend. The influences of prescribed and cultural burning on SOC were not assessed in this study, but should be examined in ongoing monitoring programs.

The erosion modelling identified that forests are subject to potential erosion risk, especially in summer. This is likely attributed to steeper terrain; high rainfall quantity and intensity and frequent bushfires in forest lands. Hillslope erosion was identified to be greatly impacted by seasonal and inter-annual variation.

7.2 Limitations

All experimental science and modelling processes are associated with errors due to a range of uncertainties existing in the real world (Refsgaard *et al.* 2007). The ability to spatially capture the main environmental variables that are affecting pedogenesis to a sufficiently fine grain so that they can relate to field measurement is a major challenge facing spatial soil modellers (Ryan *et al.* 2000)

Limitations in the modelling process need to be recognised and the results interpreted with caution. The baseline maps and estimates of change as shown in the maps of Section 6 are suitable at a regional and planning scale but are not applicable at local scale or individual sites. DSM techniques allow us to establish key relationships and trends, which may not be readily apparent when examining single isolated sites.

In addition to the relatively scarce data (refer Section 5), the digital soil mapping and modelling products are subject to various inherent uncertainties, as has been reported by Nelson *et al.* (2011), Bishop *et al.* (2015) and Robinson *et al.* (2015). In the context of soil modelling and simulation, there exist uncertainties related to a lack of information, followed by statistical variability in prediction, which is addressed by estimates of uncertainties and model assessment statistics (Robinson *et al.* 2015).

The validation results of the models upon which the baseline digital soil maps, driving factors and trends were based were not typically strong (refer Appendix A), with Lin's concordance values generally in the range of 0.3 to 0.4, where a value of 1.0 denotes perfect accuracy.

Sources of uncertainty in the spatial modelling of forest soils were identified as follows:

- The general uniformity of environmental conditions in the forested area of eastern NSW, such as the typical moderate to high rainfall, low fertility soils, high vegetation cover and moderate to steep terrain, means there is a lack of contrast in conditions that normally contribute to models of greater strength, such as large variation in soil fertility, terrain, land use and vegetation cover.
- There is incomplete coverage of all required areas of key environmental space, ie, combinations of different environmental conditions, over the forest study area.
- A key variable is the lithology (silica) layer, which typically was one of the most powerful controlling variables. Although lithology for site data is generally reliable, the broader grid used to create the final maps is less reliable as it relies on coarse scale geological mapping.

- The vegetation layer used does not distinguish between different forms of vegetation cover, ie, ground cover or canopy cover, which can contribute to imprecise soil-vegetation relationships.
- The FDI presented and applied in this study is a coarse indicator that does not reflect subtle differences and is insufficient to fully model the impacts of land management, such as those resulting from intensive versus periodic selective harvesting, the date of harvesting operation, or differing intensity of grazing by livestock. The future application of available datasets on forest harvesting history, as applied in the Carbon Balance project of the FMIP, may partially address some limitations of the FDI variable.
- Similarly, the variable representing the number of years since bushfire is of a coarse scale and would not reliably represent variations in intensity of the fire throughout the burnt areas.
- The remote sensing-based method used to estimate hillslope erosion risks enables consistent estimates of hillslope erosion over large areas but is not sufficient to evaluate localised impacts of sediment and runoff delivery as they relate to timber harvesting activities. Future monitoring efforts should assess the interaction of the timber harvesting and forest road and track network with both sediment and runoff delivery.
- Variation in the dates of sampling of profiles within the SALIS dataset means the temporal variation in climatic conditions within a single region will contribute to differing influences on soil properties, even where they were spatially close.
- The analysis of many trends reported here relied on the space-for-time substitution modelling approach. This assumes patterns of variations in space can substitute for patterns of variations in time, which may not always be valid.
- Errors in soil data can also be introduced through field sampling and laboratory inconsistencies. For example, the MIR analysis of soil carbon fractions is subject to significant uncertainty.

Many limitations would be addressed by the proposed monitoring program (refer Section 8). This will allow reliable analysis of trends from both digital modelling and conventional empirical analysis.

8 Conceptual monitoring design

8.1 Overview

Based on the conceptual framework for the evaluation of soil health and stability (refer Section 1.3), we have provided a conceptual outline of monitoring program requirements and presented three program options, each of which would provide a core dataset to determine soil functional thresholds (e.g. appropriate pH ranges for a location) and identify locations of soil change.

8.1.1 Rationale for a Forest Soil Monitoring Program

As discussed in Section 5.4 and highlighted by the digital soil modelling efforts, there is a significant lack of baseline soil health indicator data upon which estimations and predictions can be made. Critical data gaps exist which must be addressed to:

- Generate baseline data for soil health and stability indicators across NSW forests;
- Generate soil carbon data to inform carbon accounting and climate change mitigation efforts;
- Generate values for soil indicators, from which region-specific metrics and thresholds can be derived;
- Determine the relationship between soil health and stability and land management practices to inform future land management decisions; and
- Provide important insight for strategic direction of soil resource management and future scenario planning.

The value of soil data lies in their reliability and currency. Ongoing monitoring is essential to identify trends in forest soil condition and to estimate soil carbon stocks. A monitoring program would separate relatively small temporal change from often-larger spatial variation and would involve periodic return to selected forest soil monitoring sites, with collection of key field and laboratory data.

Soils, particularly topsoils, are a living entity. Previous monitoring programs have not included biological indicators due to historic inadequacies in these types of measurements. Modern soil science relies on biological indicators. The forest monitoring program provides an opportunity to obtain much needed biological and soil biodiversity data.

8.1.2 Linkages with previous work and other monitoring programs

Future monitoring efforts would build upon the work of the NSW state soil monitoring program (MER). We will evaluate the 41 MER monitoring sites which fall within the RFA regions should be evaluated for integration where possible. This will add valuable information to the existing dataset.

Opportunities for linkages with other FMIP initiatives will be explored, with an emphasis on collaboration and data-sharing.

In preparing this conceptual monitoring design, the relevant experiences of DPIE from other current and developing monitoring programs were integrated. There are similarities in approach, particularly with collection methods of soil samples, analysis, data collection and soil variables measured.

8.2 Survey design

It is not feasible to monitor every soil type nor every soil landscape that falls within the RFA regions. Monitoring is therefore to be distributed based on broader ecological regions, which are based on soil-forming factors: geology, topography, climate, soils and vegetation (Mitchell 2002). Such regions, known as Mitchell Landscapes, provide a method of amalgamating several soil landscape map units to guide spatial coverage.

Mitchell Landscapes can be further broadened into meso-ecosystems, which contain between 1 and 7 Mitchell Landscapes, depending on the complexity/variability of important lithologies and terrain.

Figure 24 shows the Mitchell Landscapes and Meso-ecosystems which exist within the RFA regions.

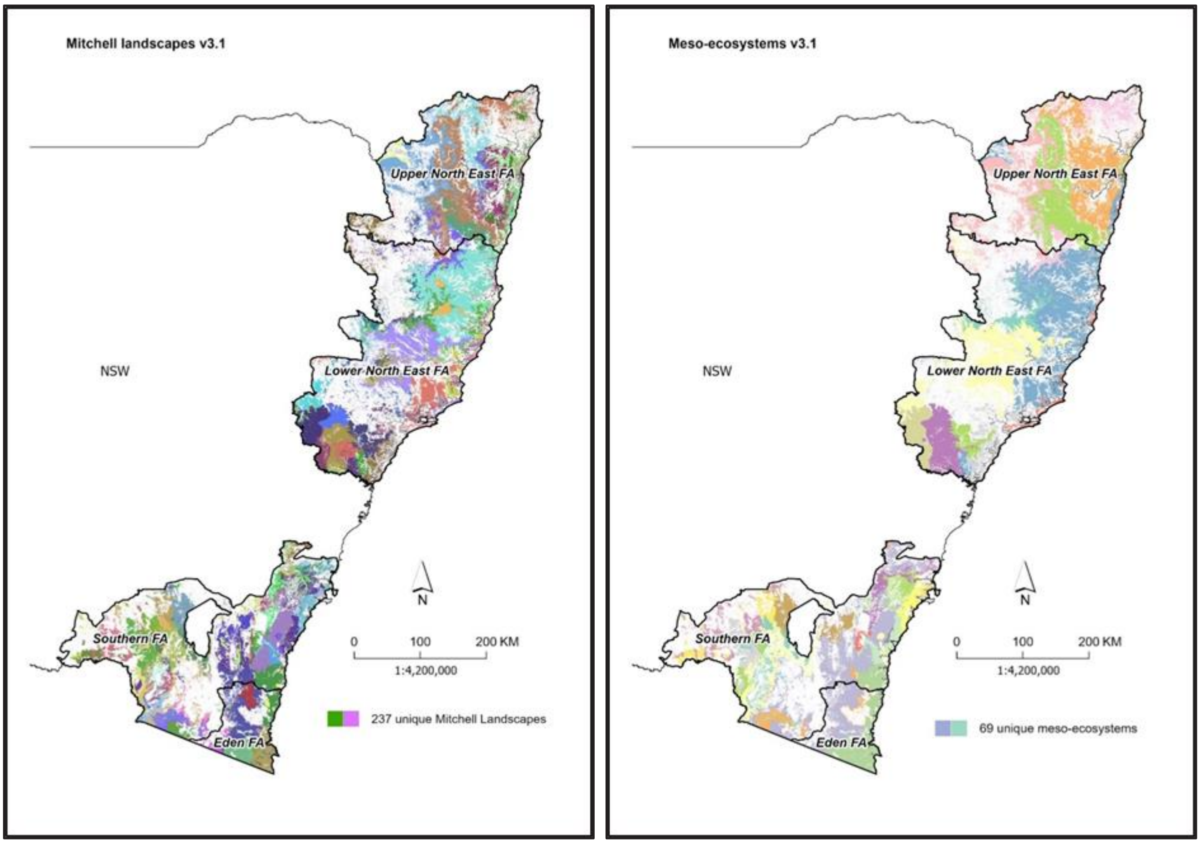


Figure 24 Mitchell landscapes within RFA regions (left); meso-ecosystems (Mitchell landscape groups) within RFA regions (right)

Monitoring sites will be distributed such that data are collected to represent the dominant Mitchell landscape of each meso-ecosystems (refer Section 8.7).

8.3 Monitoring frequency

Monitoring sites are to be established in a staged approach over 5 years and revisiting of sites thereafter on the same rotation. A staged approach offers benefits including (Grealish *et al.* 2011):

- As data becomes available each year the program can be adapted and improved;
- Provides measurements for each year;
- Smooths out the flow of funds required;
- Maintains continuity and visibility of the program

The program requires 5 years to establish, with a recommended 15 years of monitoring (total of 20 years). Based on soil resampling studies that have detected changes with measurements commonly used in forest soils, a resampling interval of 5 years is the maximum recommended (Lawrence *et al.* 2016), particularly for soil organic carbon and its component fractions which have been found to change significantly in as few as 3 years (Wilson *et al.* 2017).

The detailed collection required for the first round of sampling will be reduced in future years, once the soil has been classified and the spatial variation of soil properties across the site is determined.

8.4 Recommended indicators

We will monitor the following suite of indicators at every site:

- Bulk density
- Total soil organic carbon
- Carbon fractions
- pH
- EC
- Particle size analysis (first sampling event only).

Additional indicators will be selected from the following:

- Microbial biomass
- Topsoil depth
- Aggregate stability
- Fungal : bacterial ratio
- Mycorrhizal fungi
- Mineral N (NO_3+NH_3)
- Phosphorus
- DNA extraction (subsamples of extracted metagenomic DNA should be stored permanently for future re-analysis at the Yanco Soil Health and Archive Laboratory)

8.5 Monitoring methodology

8.5.1 Site establishment

Permanent monitoring sites will be established that can be accurately relocated to allow repeat sampling. Repeat measurements will be conducted at the same sites over time to enable analysis of the difference at individual sites and infer trends for selected significant landscapes across NSW forests.

A sample area of 25 × 25 m is suitable to provide an estimate of soil properties at each site (Grealish *et al.* 2011; Wilson *et al.* 2007).

On initial site establishment, a soil profile will be obtained to allow for soil classification and an understanding of below ground conditions.

8.5.2 Site assessment

Site assessment will include: profile description, including soil colour, texture and field tests (first sampling event only); GPS location; and ground cover estimate.

8.5.3 Sample collection

A sampling intensity of 10 surface samples across the site area (25m x 25m) is proposed, which will be combined to form one composite sample for laboratory analysis.

On initial site establishment, soil samples will be collected from 3-4 of the major soil horizons identified in the profile. Following data interpretation of the initial sample results (refer Section 8.6), it is likely that repeat assessments will only need to measure soil surface samples.

8.5.4 Quality assurance

It is essential that all records, observations and samples are taken correctly and consistently following defined program protocols, and that the data are entered into corporate databases for long-term safe keeping. As relatively small changes in soil condition can signify broader environmental trends, it is important that as many sources of error as practicable are eliminated. Sampling error jeopardises the future ability to detect what might be small changes in soil condition.

8.5.5 Soil sample archive

The Yanco laboratory run by DPIE has the capability for long-term archiving of physical, chemical and biological soil samples should further analysis be required.

Soil samples and extracted soil DNA would be stored in an appropriate temperature-controlled archive for future examination.

8.5.6 Data storage and management

It is vitally important that data are stored securely. Soil descriptions from each sample site should be stored securely on the NSW Government's Soil and Land Information System (SALIS) to current data management standards. The information can then be reported to other systems such as the National Soil Information Framework (NSIF).

8.6 Data analysis and interpretation

New soil data should be analysed as per the methods used to estimate baselines and trends. It is recommended that the data cube model be used to incorporate a range of covariates consistent with the spatial location of data collection and the date of sampling.

The model outputs would be used to assess what may be causing an indicator to increase or decrease for a particular location, which can then be used to assess key drivers of soil health and stability across jurisdictions as well as for localised regions.

Each of the proposed indicators will have a different response to environmental and forest management factors and monitoring will reveal differing trends. Each may show desirable or undesirable change, relative to the identified reference state.

The feasibility of combining these indicators into a holistic index for reliable and quantitative assessment of soil health will be explored by DPIE. Previously reported options were presented in the literature review report of Milford (2021) and include the approach adopted during the 2008 MER Program (Chapman et al. 2011; OEH 2014).

Future monitoring efforts should incorporate flexibility, such that sampling may be focused on data collection of indicators with the most significant input values.

DPIE would consider the use of statistical analysis to support a scoring approach to quantify the status of soil health indicators. Statistical methods, such as those proposed by Rinot *et al.* (2018), can identify correlations between indicators and cluster indicators into groups based on function. The use of autocorrelation and principal component analyses allows practitioners to identify the most significant attributes and the relative contribution of each to soil health.

This method can be used to refine sampling strategies by identifying the most significant input values and limiting further monitoring efforts to those parameters, as well as to score sites based on relative performance.

8.7 Options for forest soil monitoring

Considering the meso-ecosystems, Mitchells landscapes, and soil landscapes which make up the forest region, the following monitoring program options are proposed:

Table 16 Options for forest soil monitoring

Program	Description	Strategy	Total
A	The most basic option which meets the minimum requirements to provide baseline soil conditions across NSW forests.	Monitoring the 2 most dominant/highest priority Mitchell Landscapes from each meso-ecosystem. 1 less disturbed control site + 1 test site within each of these 2 landscapes. Nested approach in indicator selection to achieve minimum core values.	Approx. 300 sites
B	The middle option which would determine baseline soil conditions across NSW forests and provide greater precision in determining trends and improved model reliability.	Monitoring the 2 most dominant/highest priority Mitchell Landscapes from each meso-ecosystem. 1 less disturbed control site + 2 test sites within each of these 2 landscapes. Nested approach in indicator selection to achieve minimum core values and provide greater monitoring precision.	Approx. 450 sites
C	The recommended monitoring option which would determine the effect of land management on soil status and comprehensively evaluate areas of changing conditions to further determine how or why.	Monitoring of all Mitchell Landscapes. 1 less disturbed control site + 2 test sites per landscape unit. Representation of different land management practices and/or important local soil variation. Full indicator selection.	Approx. 750 sites

Program option A will use a nested approach in which most sites receive the minimum suite of analysis required to provide a minimum core dataset, while others receive comprehensive analysis of all recommended indicators.

Program option B will use a nested approach in which most sites receive comprehensive analysis of all recommended indicators, while others receive the minimum suite of analysis required.

Program option C will incorporate all recommended indicators for robust and comprehensive analysis and monitoring.

The design incorporates this flexibility for efficient resource allocation and cost-savings. Resources will be allocated such that areas of higher interest receive more comprehensive evaluation, such as locations at higher risk of soil degradation or an area using a specific land management practice of interest.

8.8 Indicative cost estimates

A nested approach is proposed whereby some sites receive comprehensive laboratory analysis and others receive a minimum sample suite. The ratio of each may be scaled based on the program option (refer Section 8.7).

Soil analysis costs per site range from approximately $130 for the minimum sample suite and up to $500 to include all recommended indicators including biological testing. The price depends on the suite of tests chosen.

The initial sampling round incurs an additional $70 for particle size analysis, which is required for initial sampling only. These prices are exclusive of labour costs.

Approximately 1.5 days full time equivalent staff is estimated per site. Assumptions for this calculation include: two-person teams would be required for most locations to align with Work Health and Safety protocols; approximately 8 sites could be sampled per week.

9 Conclusion

This report has been prepared to assess the baselines, drivers and trends of soil health and stability was. This was achieved through the following:

- The design of a conceptual framework for the evaluation of soil health and stability.
- The development of set of soil indicators (parameters) for measurement and monitoring of soil health and stability.
- The evaluation of existing soil data from NSW forests in relation to presence, age, geographical coverage, parameters measured, repetition, and accuracy.
- A data-gap analysis to identify data required to establish baseline values for soil indicators.
- Estimation of the current status of soil indicators for which there are sufficient data for analysis.
- Identification of potential drivers of change and threats to soil health.
- Determination of trends for soil health and stability (including by spatial analysis).
- The design of a soil monitoring program to address data gaps, inform soil and land management and maintain or improve the condition of forest soils.

The assessment of data availability within the RFA regions identified critical data gaps. Of the data held in the NSW SALIS, there are no measurements of soil biological health indicators from the area. In the last decade, less than 50 soil carbon measurements have been collected from across the RFA regions. No bulk density measurements have been collected during this time, which are needed for accurate calculation of belowground carbon stocks. Available measurements of other physical and chemical soil health indicators are similarly limited. Data from the last decade to accurately evaluate the impact of forest management or the effects of recent events, such as the 2019/20 bushfires, are lacking.

We developed methods of spatial analysis to evaluate soil health indicators, including digital soil mapping and a novel approach to soil modelling, the data cube, which uses geospatial technology and machine-learning. These approaches allowed us to establish key relationships and trends.

Based on the available data, we evaluated the status of soil health indicators. Despite model performance being limited by the lack of current soil data, the digital soil modelling indicates:

- SOC concentrations have declined slightly between 1990 and 2020, including periods of significant fluctuation likely related to variation in climatic conditions.
- Areas subject to increased ground disturbance from land use activity, in particular forests in which grazing is permitted, have lower concentrations of SOC and higher bulk density (suggesting poorer soil structure and condition) than less disturbed areas.
- Climate change is predicted to contribute to a decline in SOC over most of the region, suggesting that management intervention may be required to maintain current SOC levels.
- Climate change is predicted to contribute to a slight rise in pH over most of the region.
- Bushfires have a major influence on SOC with a dramatic loss immediately following the bushfire, followed by a gradual recovery of SOC in the following years. Based on our findings, SOC may be subject to continuous decline with more frequent fires. Further analysis is required to evaluate this trend.
- The hillslope erosion risk in the RFA regions is highest in summer. A loss of vegetation cover increases the risk of hillslope erosion.

We have designed a conceptual soil monitoring program which would address this urgent need. We propose a program of time-series monitoring that incorporates flexibility such that sampling is focused on areas of concern, and statistical analysis to identify and prioritise indicators with the most significant input values. The program would leverage existing soil data and soil monitoring expertise and would deliver a core dataset from which soil functional thresholds and locations of soil change could be determined.

The data produced by such a program would deliver important insight for strategic direction of resource management and future scenario planning, delivering tangible results to support management of forest soils and maintain or improve the condition of this valuable and threatened resource.

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Appendix A: Digital soil mapping project supporting reports

NRC Forest Monitoring and Improvement Program

Project 4: Baselines, drivers and trends in soil health and stability

Update 4: Baselines for indicators

NSW DPIE Science and University of Sydney
April 2021

Contents

List of Figures

List of Tables

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The baseline soil condition project is being undertaken by a joint NSW Department of Planning, Industry and Environment (DPIE, Science) and University of Sydney project team. This interim report was primarily prepared by Jonathan Gray, Mark Young, Melissa Moyce, Linda Henderson and Xihua Yang, with coordination by Brian Jenkins and other assistance from Humphrey Milford, Brian Wilson, Tom Bishop and Sabastine Ugbaje.

1 Introduction and overview

The health of soils within forest systems indicates and underpins the overall health, integrity, productivity and ecology of the forest ecosystem and its associated clean water and sustainable timber resources. Key to maintaining the health of forest soils is a knowledge and understanding of their baseline condition. Such baseline data allow us to better understand potential trajectories in soil health under various land management and climate change scenarios, and to understand the implications of these and other disturbances.

This interim report presents products which represent baseline conditions of key indicators of soil health across the RFA regions. Preliminary maps as GIS spatial files and jpeg images are introduced, together with associated data and statistical summaries.

Products from two complementary approaches are presented; (i) an empirical analysis of available DPIE soil data grouped by soil landscape characteristics and (ii) a digital soil modelling and mapping approach. These two approaches present results at differing scales. They are broadly consistent with each other, with minor differences attributed to the differing scales and related time periods applied.

Soil condition is broadly defined here as the extent of decline in key indicators relative to a relatively undisturbed reference state, similar to the approach taken during the 2008-09 NSW Monitoring Evaluation and Reporting (MER) program (Chapman *et al*. 2011, OEH 2014). The more a soil indicator has declined relative to the reference condition, the poorer is its condition. It does not represent an absolute quality for forest productivity. Thus, a soil may be unchanged and in very good condition relative to its reference state, but have poor potential for productive timber growth for commercial harvesting purposes.

The baseline condition maps presented here are intended to represent a baseline condition of several key indicators, from which further decline will be measured, and to provide visual representation of data availability to inform future sampling strategies. The products are based on existing soil data that vary widely in date of collection. Nevertheless, the products are considered to be representative of the period leading up to approximately 2010.

For specific soil profile point data, the original date of sampling is known and these serve as reliable baseline data for these point locations. The suite of MER data points, which was collected according to rigorous sampling protocols (OEH 2009, Chapman *et al*. 2011), forms a particularly valuable baseline dataset for ongoing point-based monitoring.

Key indicators for change in soil condition presented here are:

- total soil organic carbon (SOC) and carbon fractions (%) (particulate organic carbon/humus and resistant organic carbon - charcoal) (% and tonnes/ha)
- pH (1:5 soil to water and $CaCl_2$)
- Phosphorous (mg/kg)
- Bulk density (Mg/m3)
- Aggregate stability (Emerson Aggregate Test)
- Erosion rate (sheet and gully) (tonnes/ha/yr)

Other indicators that are also under consideration are:

- EC (1:5 soil to water)

- Mineral N (NO3 + NH3), (mg/kg)
- Topsoil depth (cm)
- Soil biological community diversity (PLFA/ amplicon and metagenomic sequencing of bacterial (16S) and fungal (ITS) DNA

This report presents details on:

- Methods used for (i) empirical and (ii) modelling approaches.
- A selection of example images, data tables and statistical results for empirical and modelled products representing a broadly current period
- Preliminary discussion on potential application of the products and issues of uncertainty.

2 Methods

This section describes the methods adopted to prepare the baseline maps and data in both the empirical and digital modelling approaches.

2.1 Empirical approach

This approach links existing soil landscape spatial data with NSW SALIS soil profile data. Soil landscape map units are determined by the properties of the soils and the landscapes in which they occur. All soil landscape units have records with location of soil data points, type of survey (eg, MER, soil-landscape mapping) and available soil field and laboratory data.

The approach designates each landscape unit with a representative soil profile, or monitoring location, within the landscape unit. This soil profile was selected based on several ranked criteria to determine the most representative soil data from within a landscape unit, as follows:

- ***Location within forest area**:* soil profiles which fell into the NRC forest study area were compiled.
- ***Soil landscape unit**:* soil profiles were sorted based on the soil landscape units in which they were located.
- ***Laboratory data availability*:** soil profiles are sorted based on laboratory data availability (some monitoring locations may not have had any samples collected and/or analysed).
- ***Representative 'type profile' status:*** 'type profile' designation belongs to soil profiles that are considered representative of the most common soil type of some portion of the soil landscape. Type profiles are generally assigned to all 'facets' or parts of a landscape that have different soil types (soil properties) and generally different management considerations. Since facets are not defined in our published soil landscape linework, identifying the 'type profile' information of the largest facet is an important way to represent soil attributes for an entire map unit. Type profiles for a landscape may fall outside of the forest area. In some cases, a soil profile in forested land was selected ahead of a 'type profile' designated profile because of the significant affects that a forested land use has on surface soil properties, particularly organic carbon.
- ***Forest condition representativeness*:** where multiple soil profile locations occur within the forest area within a landscape unit, this measure distinguishes soil profiles characterised by forested land management, prioritising it over data which may have come from cleared or pasture areas, for example.

Based on the above criteria, a soil profile was selected to represent the soil landscape unit, and the field and laboratory results for each soil property are here considered to be representative of the whole landscape unit. The laboratory data, laboratory method and data source for the indicators are presented in Table 1.

Table 1: **Soil properties: source, laboratory methods and profile numbers for empirical analysis approach**

Soil property	Units	Source and laboratory method[1]	No. of profiles[2]
SOC	%,	from SALIS; mainly Walkley-Black wet oxidation (C6A1) but small proportion of Heanes wet oxidation (6B1) and LECO combustion methods (6B2, 6B2b and 6B3)	1725
pH_{ca}	pH units	from SALIS; pH of 1:5 soil/0.01M calcium chloride extract (4B1). Includes conversions from pH 1:5 soil/water suspension (4A1) using approach of Henderson and Bui (2003)	1976
Emerson Aggregate Test	8 class system	from SALIS; SCS method (513.98)	1453

[1] Methods as listed in OEH (2017) and described in Rayment and Lyons (2011).

[2] Does not include some additional profiles used from outside of forest study area

This product provides a broad indication of likely soil conditions within forest areas, and serves to identify new sites for further sampling in future programs (eg, revisiting of MER sites or collecting additional data from under-sampled soil landscape units and facets) to ensure targeted and informative data collection and effective distribution of resources.

The resulting soil landscape profile data quality categories were as follows:

- ***High confidence**:* a profile with laboratory data within the forest area and is within the dominant facet of the landscape unit.
- ***Moderate confidenc*e:** a profile with laboratory data within the forest area but may not be within the dominant facet of the landscape unit.
- ***Low confidence:*** no profiles with laboratory data within the forest area, but we have representative lab data for another part of the landscape.
- ***No data**:* no profiles with laboratory data exist within the landscape.

Total profile points with suitable laboratory data from SALIS across the NRC study area amounted to almost 2100, with locations as shown on Figure 1.

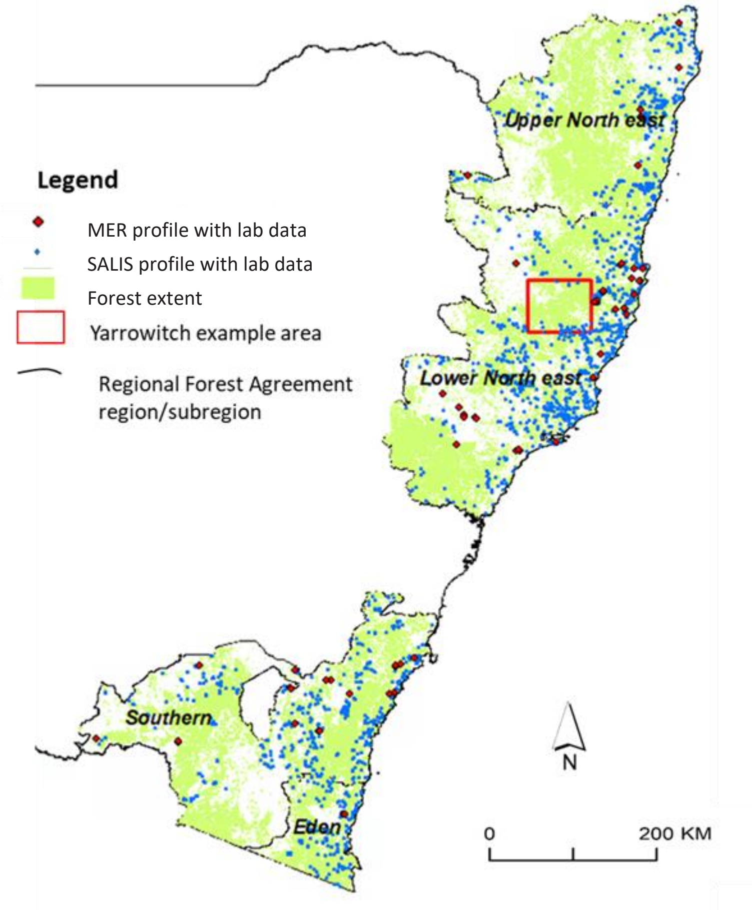

Figure 1: Spatial distribution of soil profiles with laboratory data across RFA regions and Yarrowitch example study area

2.2 Digital soil mapping approach

Digital soil mapping provides for statistically verifiable estimates of soil properties using quantitative modelling techniques based on relationships between soil properties and the environment (McBratney *et al*. 2003). The statistical relationships are developed over known soil data points with known environmental conditions and then extrapolated over broad regions using continuous environmental data grids (e.g. climate grids, digital elevation models or gamma radiometric data grids).

The modelling approaches applied in this project were multiple linear regression and Random Forest decision tree methods. Figure 2 provides an overview of the DSM process adopted to develop the baseline maps.

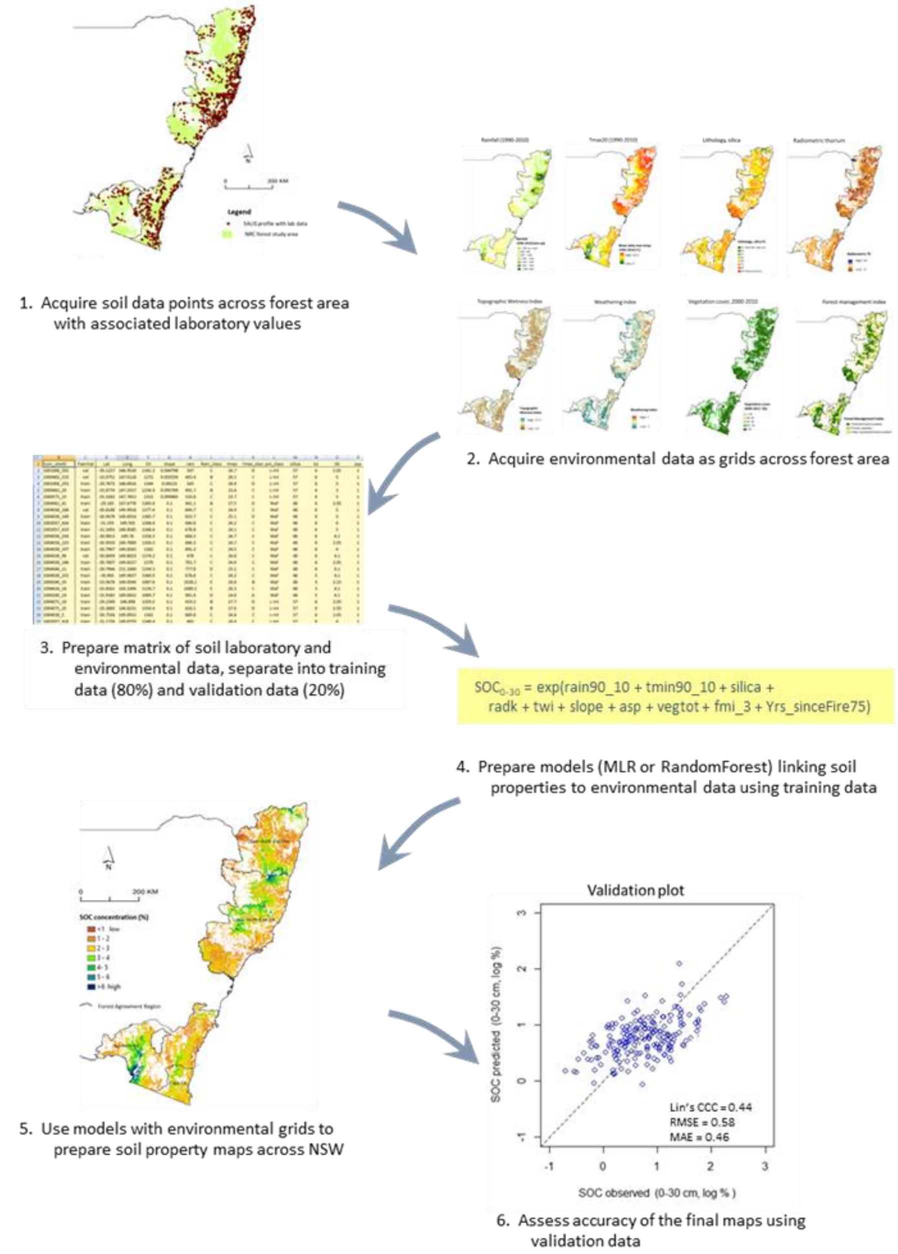

Figure 2: Overview of the digital soil mapping process

2.2.1 Soil data

The required soil data were primarily derived from the NSW Soil and Land Information System (SALIS). The spatial distribution of the data points is shown in Figure 1. Additional sources included the 2008 NSW monitoring, evaluation and reporting (MER) program (DECCW 2009; Chapman *et al*. 2011; OEH 2014). Total P was derived from all eastern State natural resource agencies, as described in Gray *et al*. (2015b). Bulk density data were acquired from the Soil and Landscape Grid of Australia (SLGA) (Grundy *et al*. 2015; Viscarra Rossel *et al*. 2015) in conjunction with data from the MER program

Soil property values reported for the original depth intervals of each soil horizon were converted into standard depth intervals of 0-10, 10-30, 0-30 and 30-100 cm using the equal area splining process of Bishop *et al*. (1999). Table 2 lists the available profile numbers with laboratory data and the data source and laboratory method for each key soil indicator.

Table 2: **Soil properties: source, laboratory methods and profile numbers for digital mapping approach**

Soil property	Units	Source and laboratory method[1]	No. of profiles
SOC	%,	from SALIS; Walkley-Black wet oxidation (C6A1)	1721
SOC fractions	Mg/ha	sourced from Gray *et al*. 2019 based on MER dataset mid-infrared (MIR) spectroscopy,	427[2]
pH_{ca}	pH units	pH of 1:5 soil/0.01M calcium chloride extract (4B1). Includes conversions from pH 1:5 soil/water suspension (4A1) using approach of Henderson and Bui (2003)	2061
P total	mg/kg (ppm)	Maps sourced from OEH (2018); various methods.	1804[3]
Bulk density	Mg/m3	derived from SLGA maps and MER data applying P14A or similar core method (mass of known vol.)	64[4]

[1] Methods as listed in OEH (2017) and described in Rayment and Lyons (2011).
[2] from MER NSW dataset
[3] from SE Australia dataset
[4] MER NSW forest dataset used to identify change, building on base maps from SLGA

2.2.2 Model variables

The variables applied in the modelling process representing the main soil forming factors of climate, parent material, topography, biota-land management and age of soil (Jenny 1941), together with a bushfire related variable, as listed below.

- ***Rain_1990_2010:*** mean annual rainfall over this 20 year period; sourced from SILO (Scientific Information for Land Owners) website (https://www.longpaddock.qld.gov.au/silo/)
- ***Tmax_1990_2010:*** mean annual daily maximum temperatures over this 20 year period; sourced as above
- ***Tmin_1990_2010:*** mean annual daily minimum temperatures over this 20 year period; sourced as above
- ***Silica_index:*** the approximate silica content (%) of the parent material, which relates to its lithology and the resulting soil type (Gray *et al.*, 2016). The statewide grid is based on geological mapping (DPI Geological Survey of NSW, undated) and NSW soil and land mapping from eSPADE (DPIE 2020)
- ***Radk, Radu and Radth:*** radiometric potassium, uranium and thorium, an indicator of parent material chemistry; sourced from Geoscience Australia (Minty *et al.*, 2009).
- ***Kaolin, Illite and Smectite:*** the relative proportion of these clays derived from near infra-red (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 and Austin, 2015); sourced through the CSIRO Data Access Portal.
- ***FDI***: forest disturbance index, a new index developed for this project reflecting the intensity of disturbance associated with the forest management; ranging from 1 for relatively

undisturbed reserves (formal and informal) areas; 2 for forestry harvesting operation areas and 3 for privately owned or leased forest typically subject to periodic stock grazing. Further description is provided in Update 5

- ***Total_VegCov***: total vegetation cover (%); includes photo-synthetic (living) and non-photo-synthetic (dead) vegetation cover, being average (mean) cover from year 2000 to date of sampling, sourced from CSIRO MODIS fractional vegetation data (Guerschman and 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.
- ***Years_sinceFire***: The number of years since a major bushfire. For training data, we used the number of years prior to the date of sampling; sourced from Rural Fire Service (via NRC data portal)

2.2.3 Spatial modelling, mapping and quality assessment

Modelling of soil properties was carried out using R statistical software (R Core Team, 2020). The soil dataset was apportioned 80% as training data and 20% as validation data using a simple random data splitting approach. Modelling applied a combination of multiple linear regression (MLR) and Random Forest decision tree techniques. An overview of the process, as applicable across all of NSW, is presented in Figure 2. Final maps were prepared using 10 bootstrap samples and stacking the resulting outputs (using customised R code). The 10 bootstrap iterations were considered sufficient for the purpose of this study. A natural log transformation was applied to the SOC values to achieve normality. Upper and lower 95% prediction interval maps were derived using results from the 10 iterations.

The models and final maps for each depth interval were validated using the validation datasets as an independent assessment of model quality. Lin's concordance correlation coefficient (LCCC) was used to measure the level of agreement of predicted values with observed values relative to the 1:1 line (Lin 1989). Root mean square error (RMSE), mean absolute error (MAE) and mean error (ME, indicating positive or negative bias) of validation results were also determined. These statistics, together with the confidence interval maps, provide an indication of uncertainty levels that are considered sufficient for the purpose of this study.

2.2.4 Modelling of hillslope erosion

Soil erosion by water includes sheet and rill erosion (also referred to as hillslope erosion) is a major form of land degradation in NSW. Hillslope erosion rates was estimated using the revised universal soil loss equation (RUSLE; Renard et al. 1997) in unit of tonnes per hectare per year (t ha^{-1} yr^{-1}).

As RUSLE was originally developed for agricultural soils, the cover and management, or C factor, is the major limiting factor for its application in a forest environment. We developed a method (Yang 2014; Yang 2020) on the C factor estimation based on the monthly fractional vegetation cover including photosynthetic vegetation (PV), non-photosynthetic vegetation (NPV) and bare soil (BS). This is the best available method of remotely assessing cover for erosion predictions and is well suited to environments where climate is highly variable and non-green vegetation is a significant component of the overall cover (McKenzie et al. 2017).

The rainfall-runoff erosivity (R) factor (MJ mm ha^{-1} hr^{-1} yr^{-1}) in RUSLE was estimated using a daily rainfall erosivity modelling for NSW and long-term rainfall records (Yang and Yu 2015). The soil erodibility (K) factor (t ha h ha^{-1} MJ^{-1} mm^{-1}) was estimated from digital soil mapping products and soil profile data (Yang et al 2017). Slope length and steepness (LS, unitless) factor was calculated, on catchment basis, from hydrologically corrected digital elevation model (SRTM DEM-H) based on comprehensive algorithms considering cumulative overland flow length (Yang 2015). The time series groundcover products (the latest version, V3.1.0) from Moderate Resolution Imaging Spectroradiometer (MODIS) were used to estimate groundcover and the cover and management (C, unitless) factor (Yang 2014). Time-series hillslope erosion was estimated and mapped on monthly and annual bases from 2000 to present. Yang (2020) summarised the state and trends of hillslope erosion in New South Wales (NSW).

The hillslope erosion across the RFA regions are extracted and analysed. We used the highest 100th percentile groundcover to represent the baseline condition and estimated the corresponding hillslope erosion rates across the forestry areas on monthly basis.

3 Results

This section presents a selection of maps and associated data derived from both the empirical and digital mapping approaches. Statistical validation results are presented for the latter approach.

3.1 Empirical approach

A map of soil landscape profile data confidence is provided in Figure 3. There are 2164 soil landscape map units that cover the RFA regions (as determined by the NRC 2008 woody vegetation study area[a]), which has a total area of 87 000 km^2. These map units come from many 1:100,000 surveys and range in detail and confidence. Of these, 788 map units covering 16 750 km^2 or almost 20% of total study area, are identified across these forested areas as class: *No Data*, ie, containing no soil type profile with laboratory information suitable to inform monitoring in forest environments. There are a further 46 map units which have profiles with laboratory data analysis, but are not presented in this report because of laboratory result compatibility issues. For example, the organic carbon map currently represents results from the Walkley-Black wet oxidation test method only. Some recent organic carbon concentration data were derived using the LECO test method, particularly in the alpine region of NSW.

Maps of organic carbon (in %), pH ($CaCl_2$) and Emerson aggregate test for surface soil across the forest area are presented in Figures 4, 5 and 6 respectively. Information is representative of the best soil profile from each map unit within the forested areas.

Not all type profiles with laboratory data have undergone the same analysis as is illustrated in the empirical method maps. Generally, type profiles undergoing laboratory analysis include one of two laboratory test suites:

- ***Comprehensive:*** good range of physical, chemical and cations tests e.g. pH, EC, soil organic carbon, cation analysis, Emersion aggregate test and particle size analysis
- ***Minimal:*** pH, EC and Emerson aggregate Test only

Since not all the key indicators for forest soil monitoring are available for all type profiles, some knowledge gaps also occur in areas with type profiles with minimal test suites.

[a] The NRC 2008 woody vegetation layer is consistent with the time at which the MER program was undertaken and much of our best baseline monitoring data were collected. Future modelling is to incorporate more recent forest cover products.

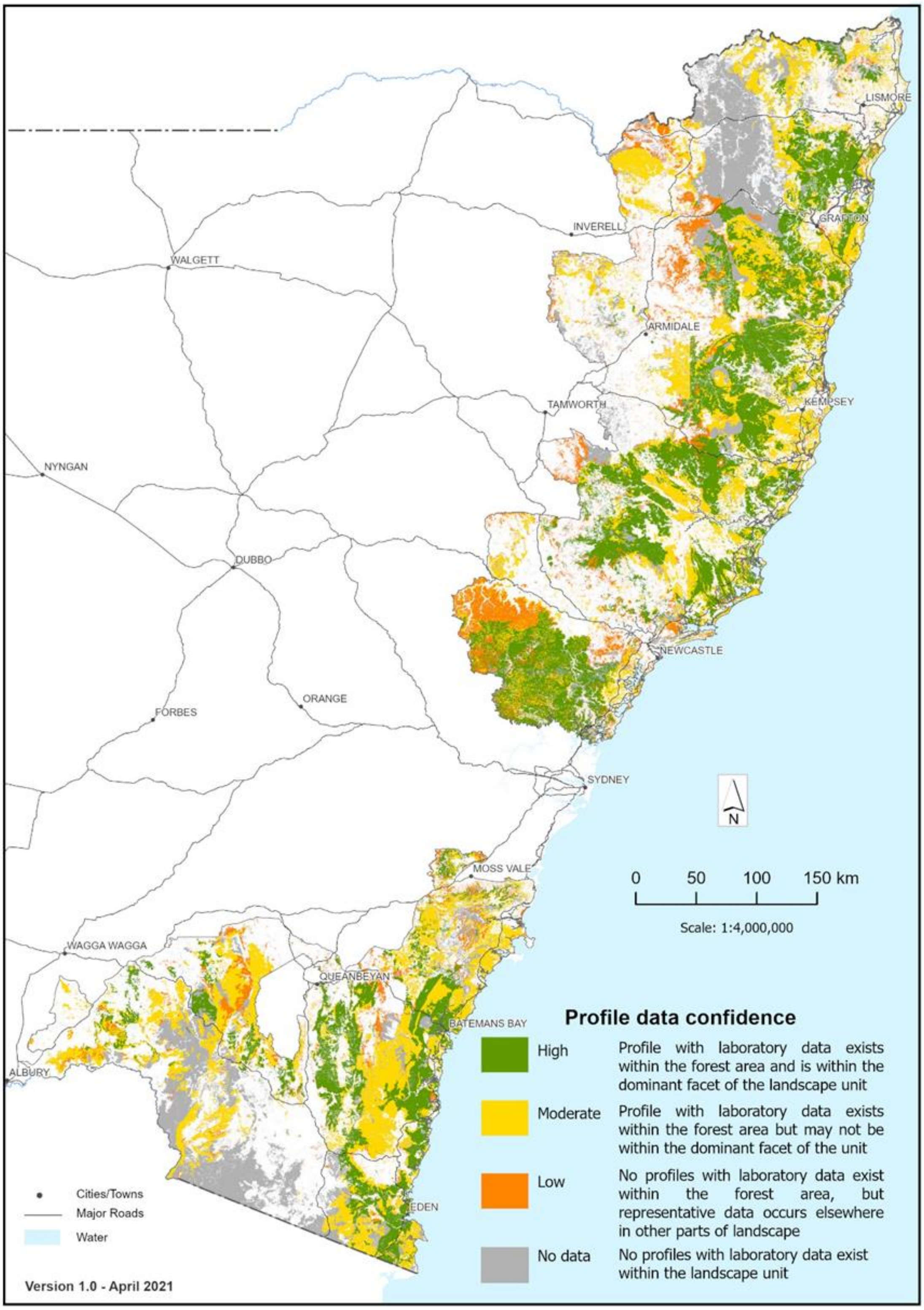

Figure 3: Soil landscape data confidence classes of the RFA regions.

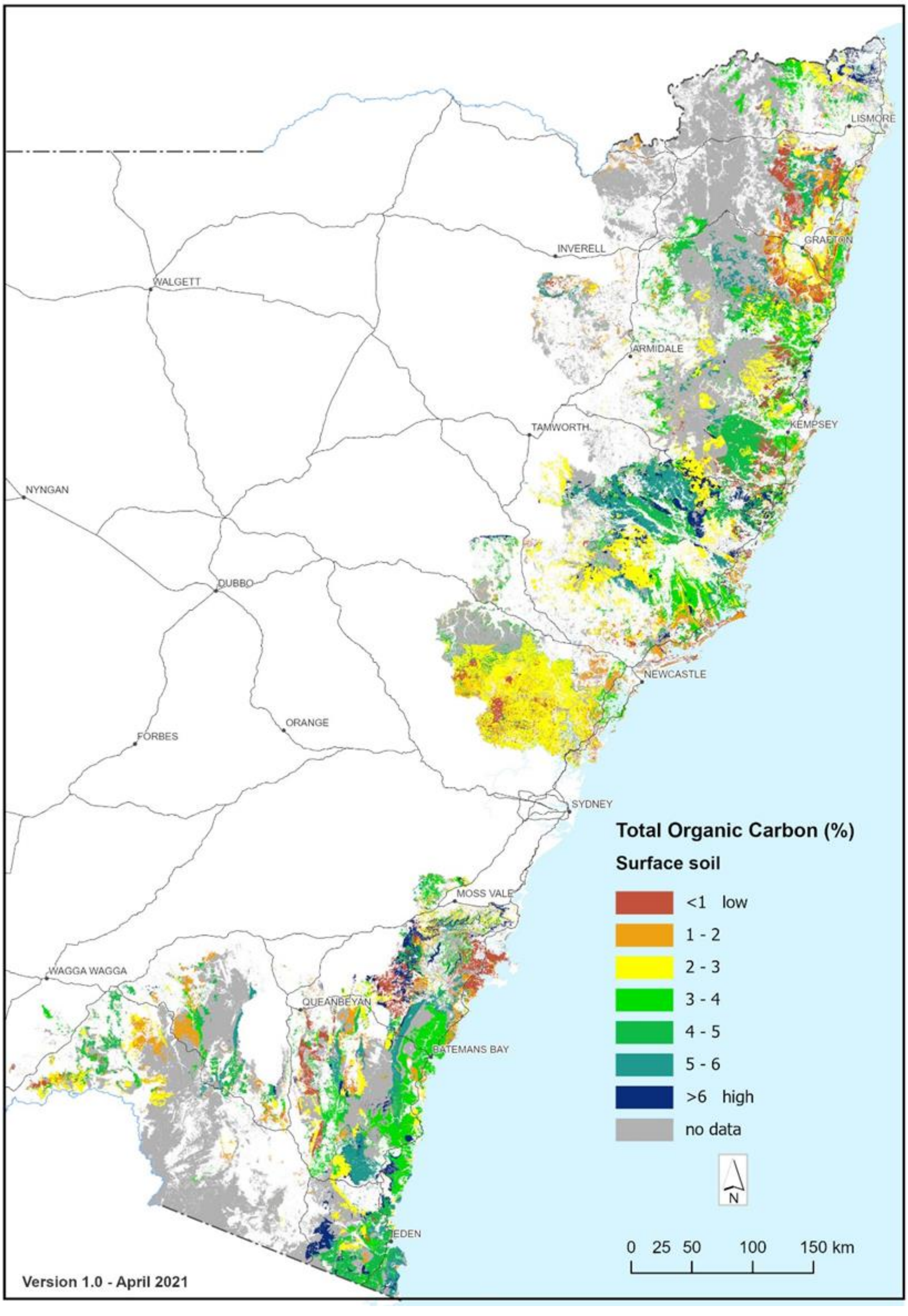

Figure 4: Organic carbon concentrations of surface soil in the RFA regions using representative soil map unit profiles

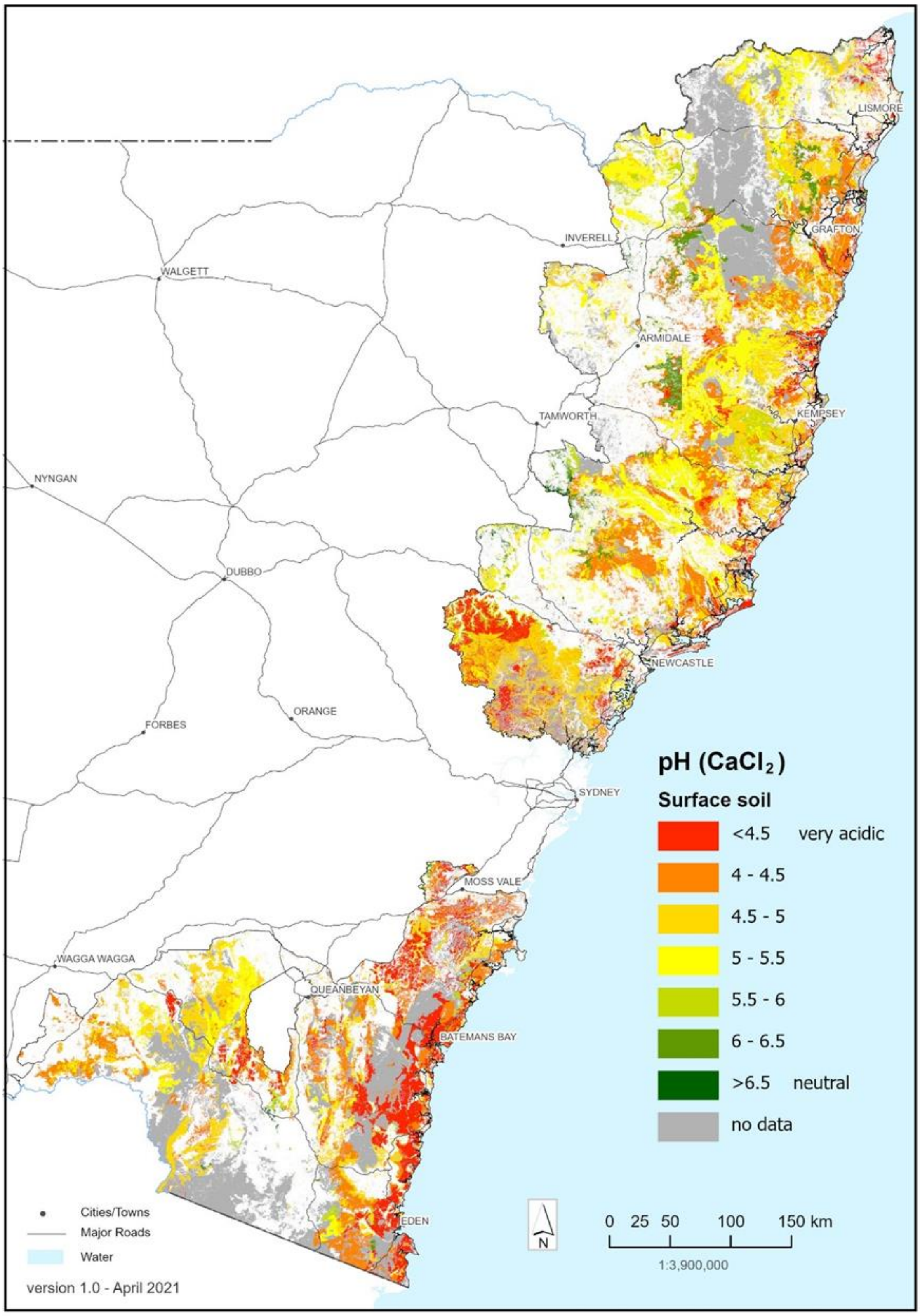

Figure 5: pH levels ($CaCl_2$) of surface soil in the RFA regions using representative soil map unit profiles

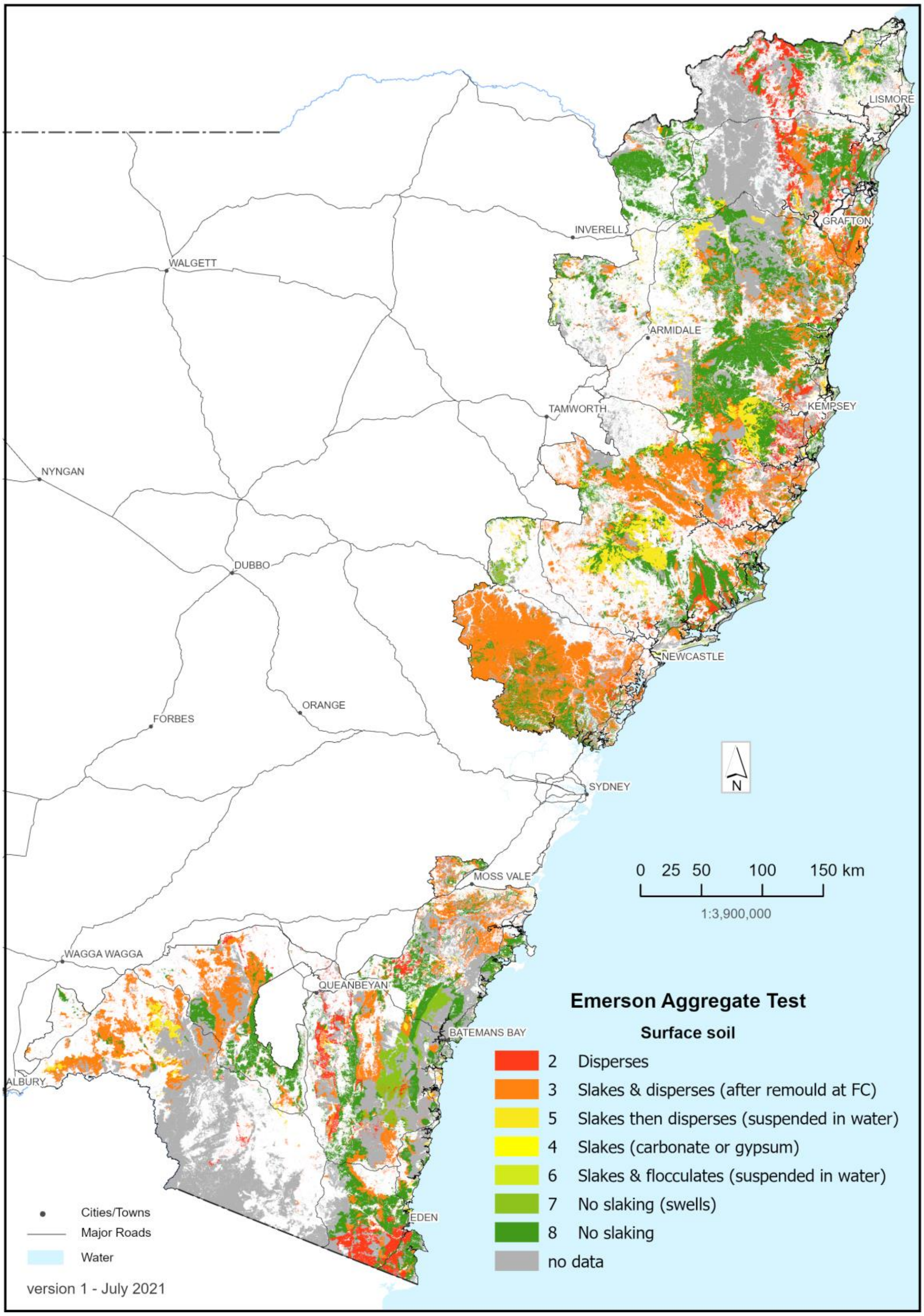

Figure 6: Emerson Aggregate Test of surface soil in the RFA regions using representative soil map unit profiles

3.2 Digital soil mapping approach

3.2.1 Soil organic carbon

SOC concentration maps (in %) for the 0-30 cm across the forest area are presented for current (approx. 2010) baseline in Figure 7. Maps are included for mean, plus upper and lower 90% confidence. Similar layers have been prepared for the 0-10, 10-30 and 30-100 cm depth intervals. An example fine scale map for the current baseline over the Yarrowitch area of mid north coast region is presented in Figure 8.

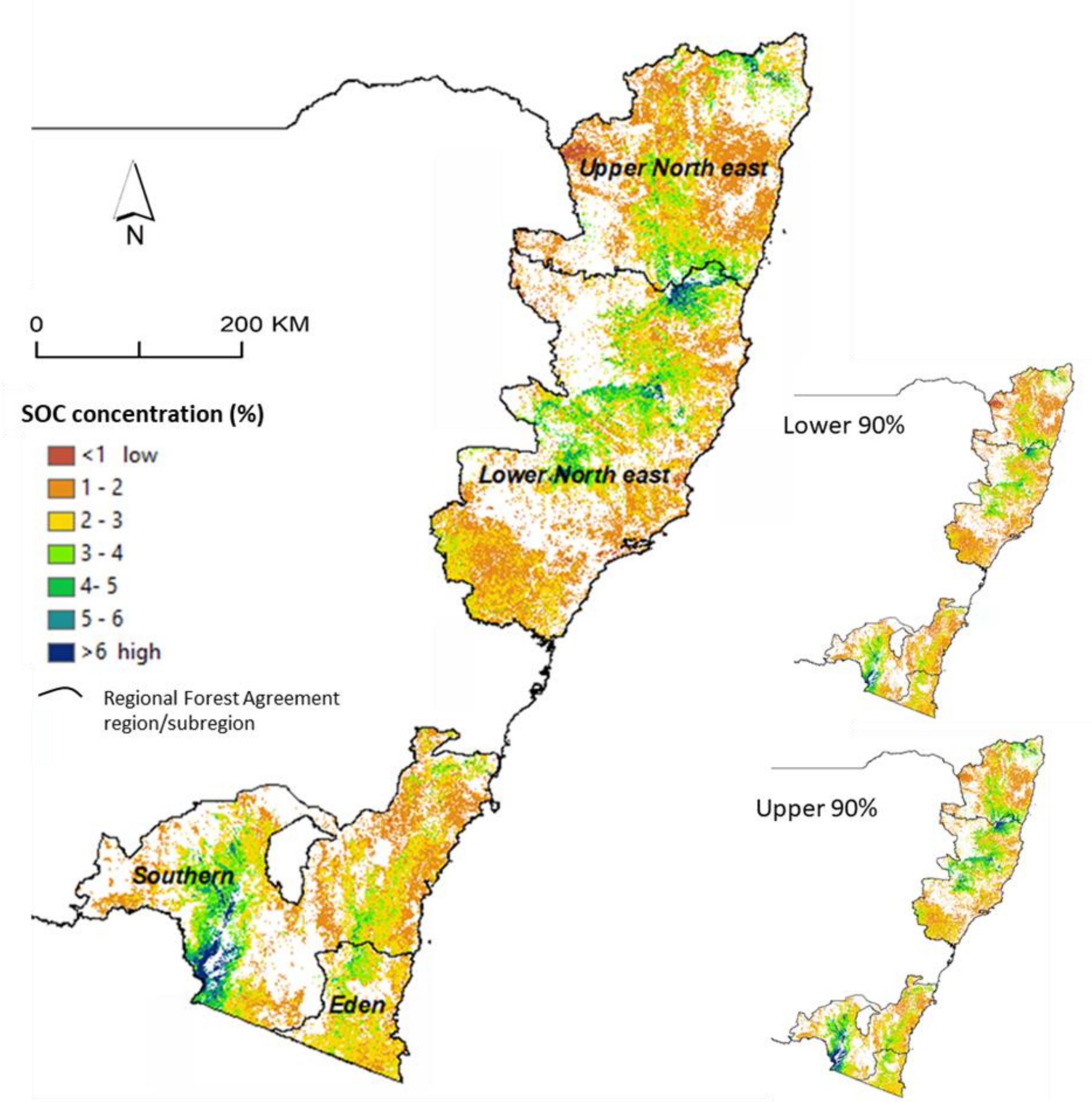

Figure 7: Estimated current surface soil organic carbon concentrations (%) across RFA regions, 0-30 cm

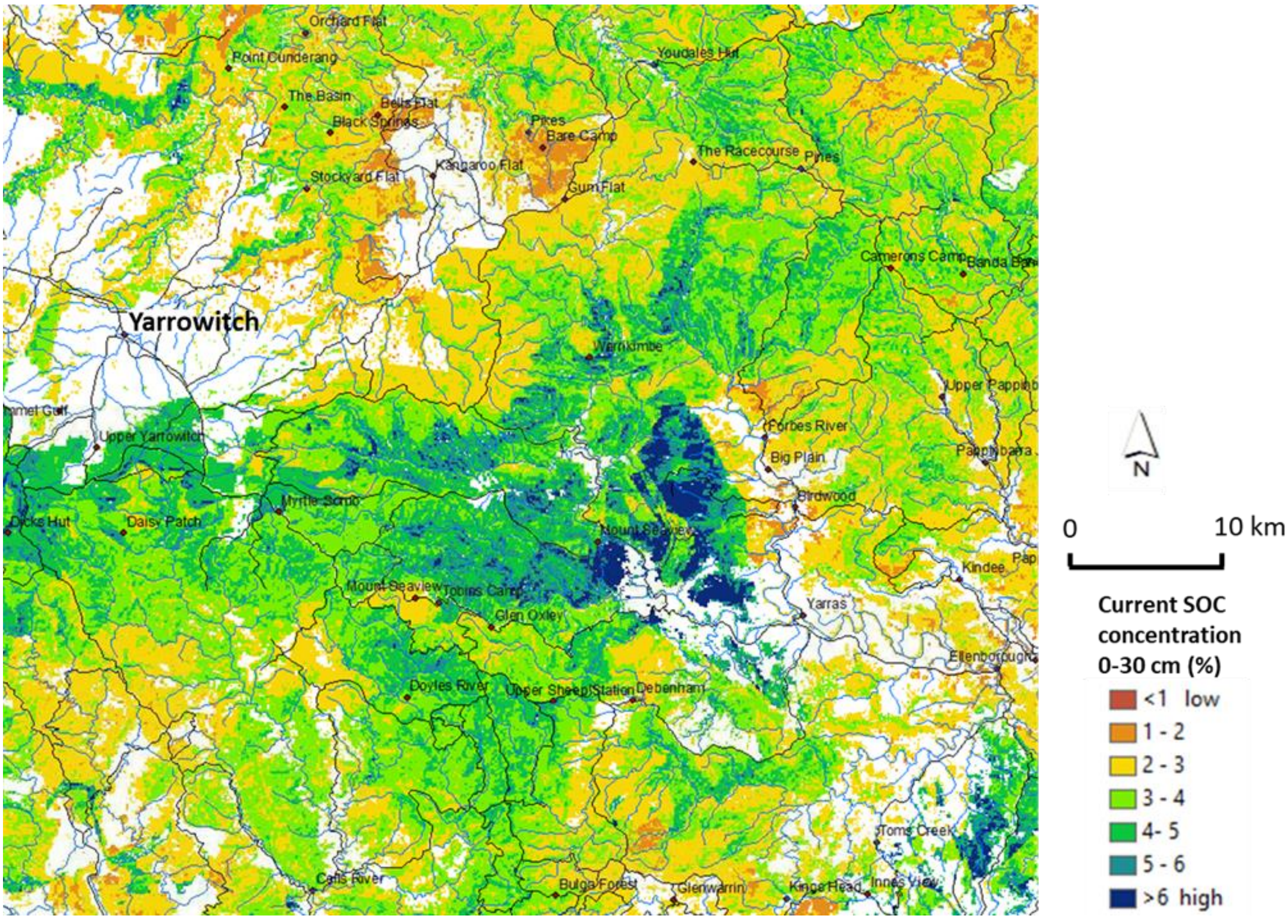

Figure 8: Estimated current surface soil organic carbon concentrations (%), Yarrowitch area, mid north coast NSW region, 0-30 cm

Map validation statistics for all four depth intervals are presented in Table 3, with a visual representation of validation performance for the 0-30 depth interval shown in Figure 9.

Table 3: Validation results for SOC maps

Depth (cm)	Lins CCC	RMSE	MAE	ME
0-10	0.37	0.57	0.46	0.03
10-30	0.35	0.70	0.57	0.01
0-30	0.39	0.57	0.47	0.02
30-100	0.17	0.96	0.78	0.02

CCC: concordance correlation coefficient; RMSE: root mean square error; MAE: mean absolute error; ME: mean error

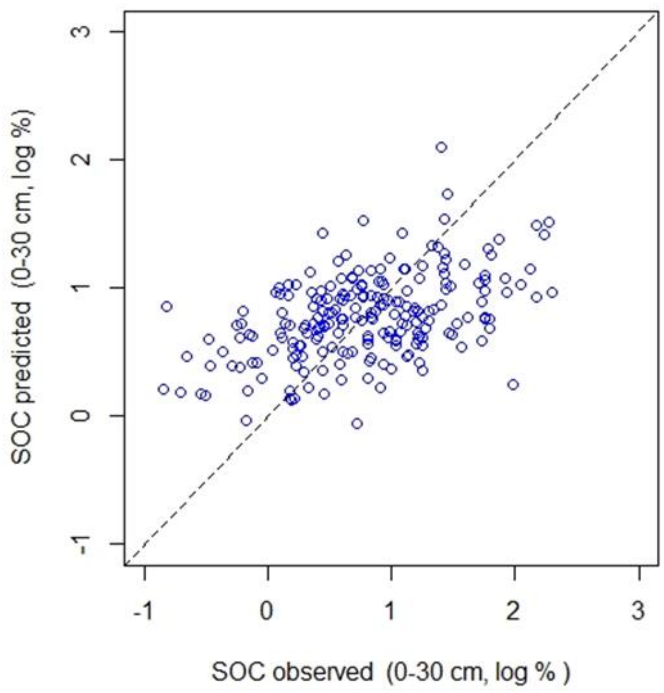

Figure 9: Validation plot of SOC 0-30 cm map

Maps for each of the three soil carbon fractions: particulate organic carbon (POC), humus organic carbon (HOC) and resistant organic carbon (ROC) over the 0-30 cm interval are presented in Figure 10. These were reported fully in Gray *et al* (2019).

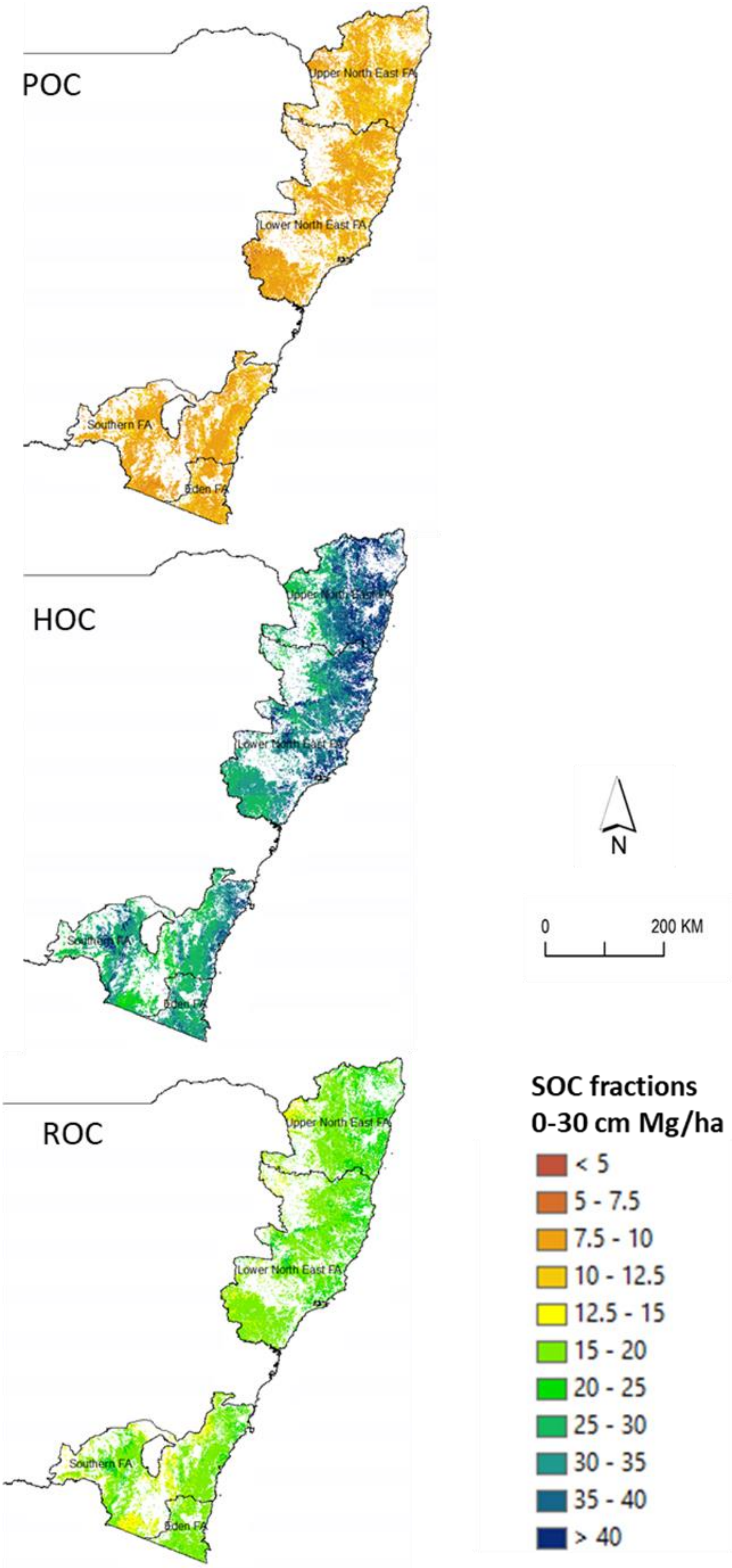

Figure 10: Estimated SOC fractions: POC, HOC and ROC across the RFA regions at 0-30 cm (tonnes/ha), from Gray *et al*. (2019)

3.2.2 pH

Maps of pH_{ca} for the 0-30 cm across the forest study area are presented in Figure 11. Maps are included for mean, plus upper and lower 90% confidence levels and represent current baseline (approx. 2010). Similar layers have been prepared for the 0-10, 10-30 and 30-100 cm depth intervals. An example fine scale map for the current baseline over the Yarrowitch area of mid north coast region is presented in Figure 12.

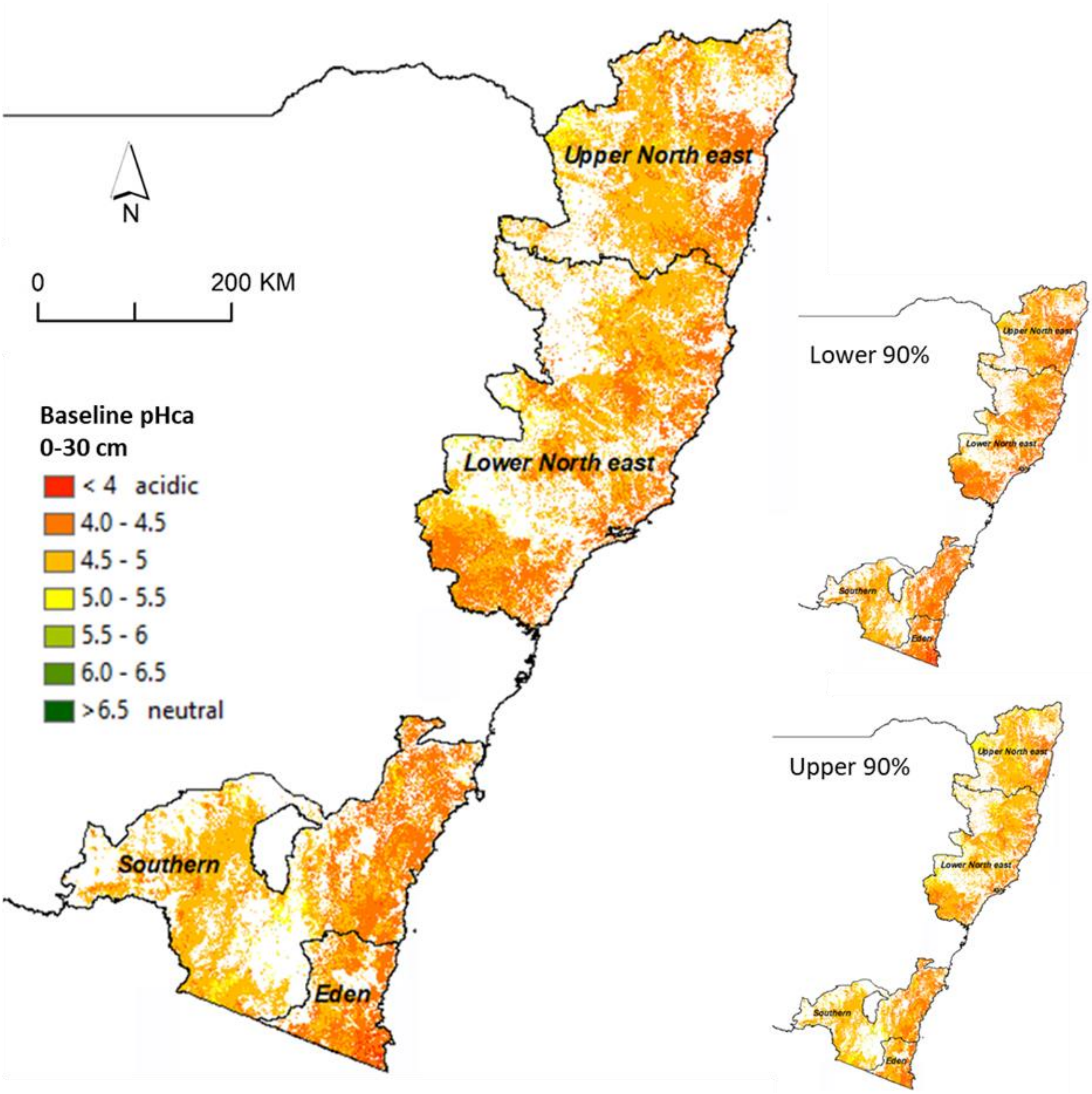

Figure 11: Estimated current surface soil pH across RFA regions, with mean and lower and upper 90% confidence intervals, 0-30 cm (pH units)

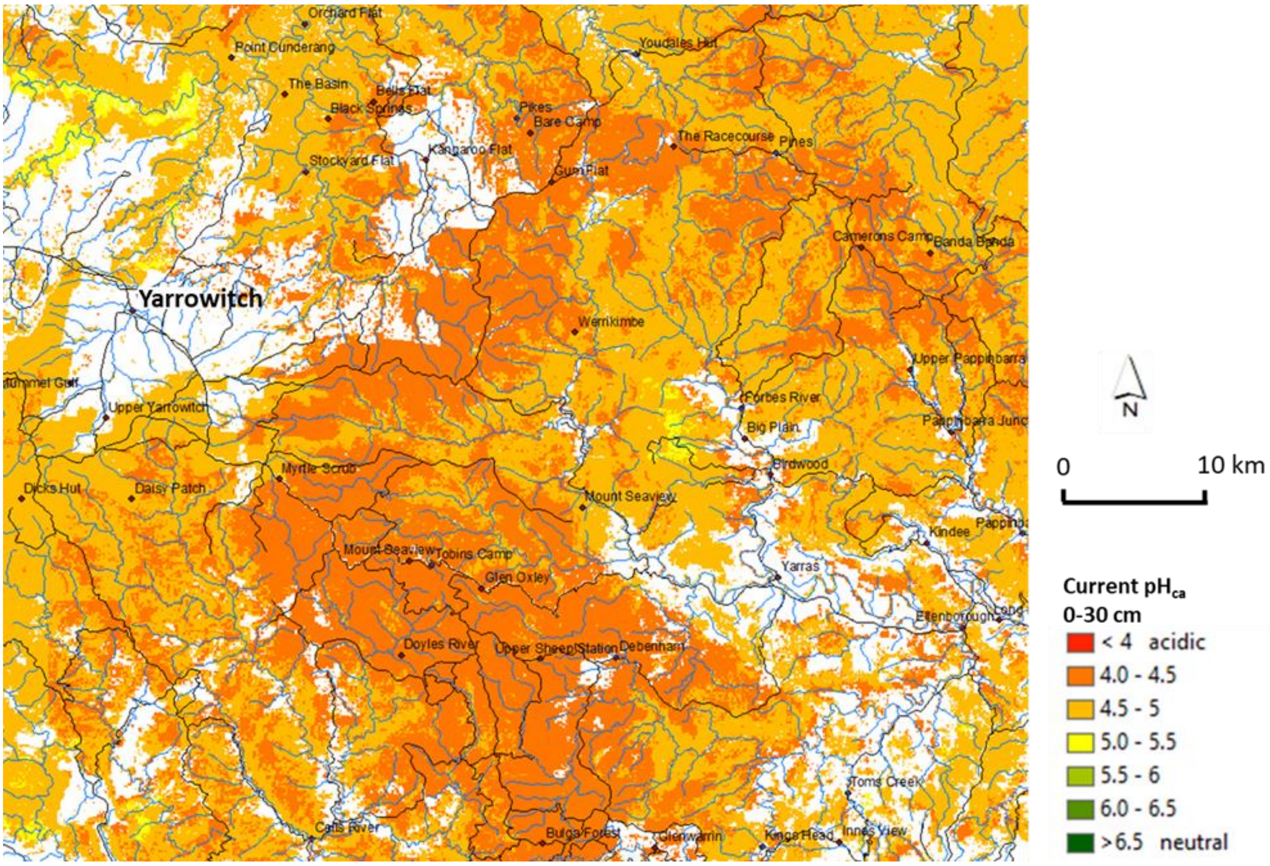

Figure 12: Estimated current surface soil pH across RFA regions, Yarrowitch area, mid north coast NSW region, 0-30 cm

Map validation statistics for all four depth intervals are presented in Table 4, with a visual representation of validation performance for the 0-30 depth interval shown in Figure 13.

Table 4: Validation results for pH maps

Depth (cm)	Lins CCC	RMSE	MAE	ME
0-10	0.37	0.52	0.38	+0.03
10-30	0.39	0.49	0.36	+0.02
0-30	0.35	0.54	0.39	+0.05
30-100	0.31	0.59	0.42	+0.02

CCC: concordance correlation coefficient; RMSE: root mean square error; MAE: mean absolute error; ME: mean error

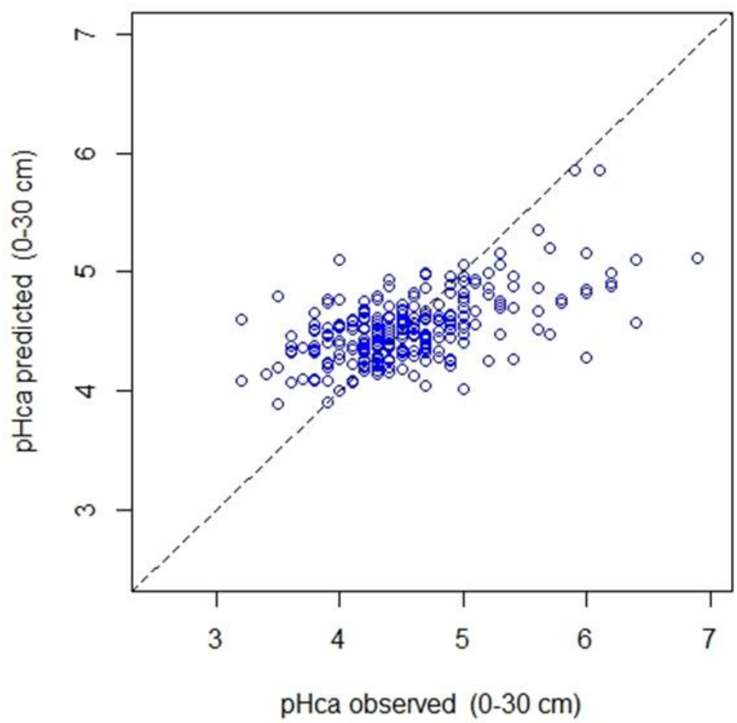

Figure 13: Validation plot of pHca 0-30 cm map

3.2.3 Bulk density

Maps of bulk density for the 0-30 cm across the forest study area are presented in Figure 14. Mean values are shown for the current baseline (from SLGA, approx. 2010) and under the natural undisturbed conditions (modelled in this project, using the SLGA map as a base). Similar layers have been prepared for the 0-10, 10-30 and 30-100 cm depth intervals.

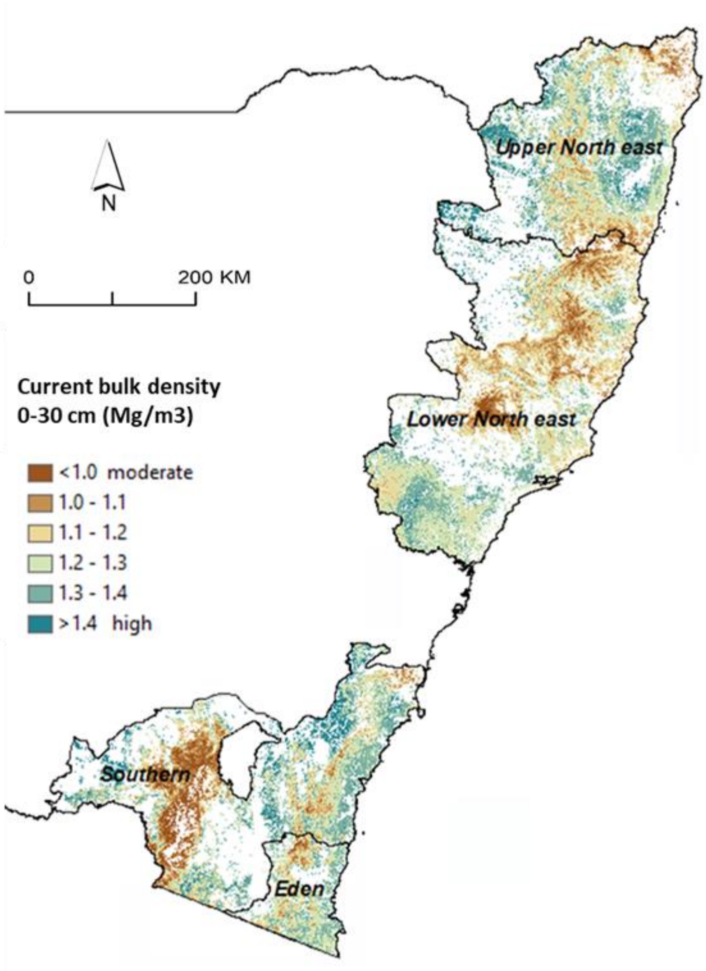

Figure 14: Estimated current surface soil bulk density across RFA regions (mg/m3) from SLGA

3.2.4 Hillslope erosion

Maps representing hillslope erosion rates over the RFA regions, derived from RUSLE modelling, are presented in Figure 15 for baseline (2001-2020) condition and Figure 16 for current baseline. An example fine scale map for the current baseline over the Yarrowitch area of mid north coast region is presented in Figure 17.

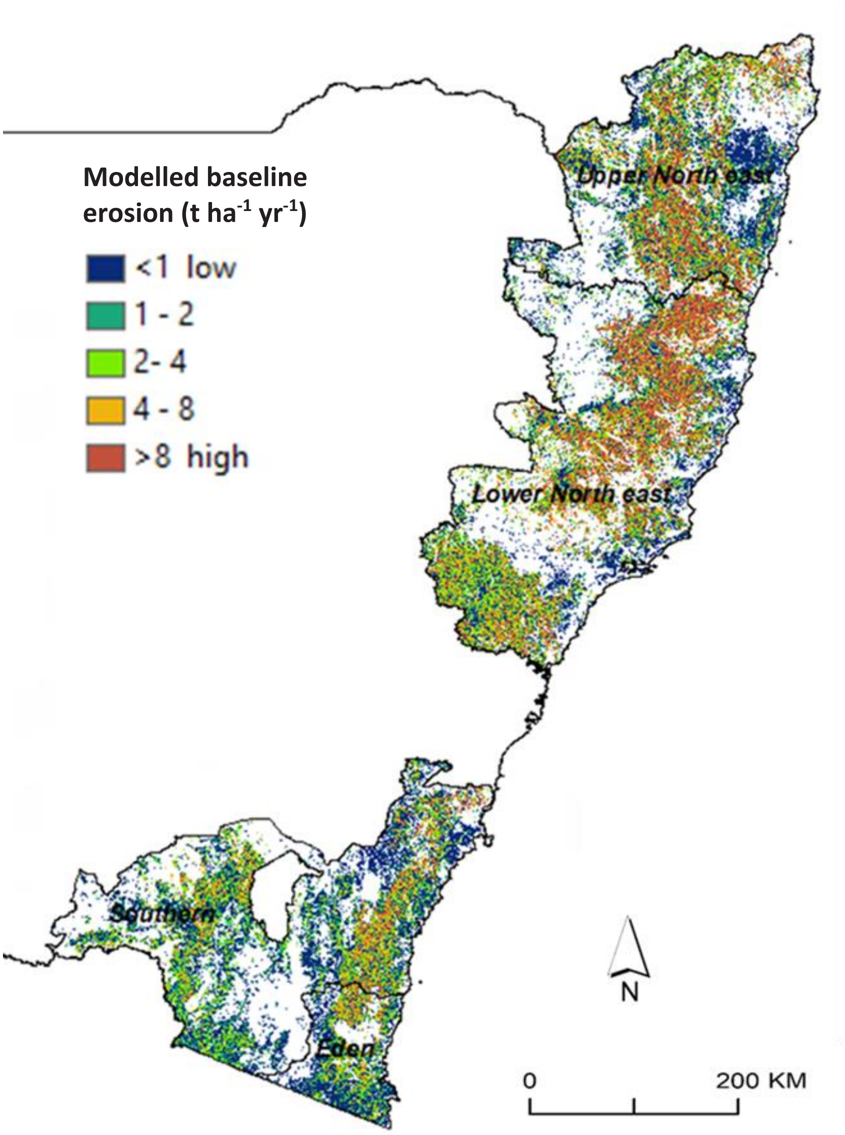

Figure 15: Modelled mean hillslope erosion (t ha-1 yr-1) across RFA regions, 2001-2020, based on RUSLE modelling with 100% percentile ground cover 2001-2020

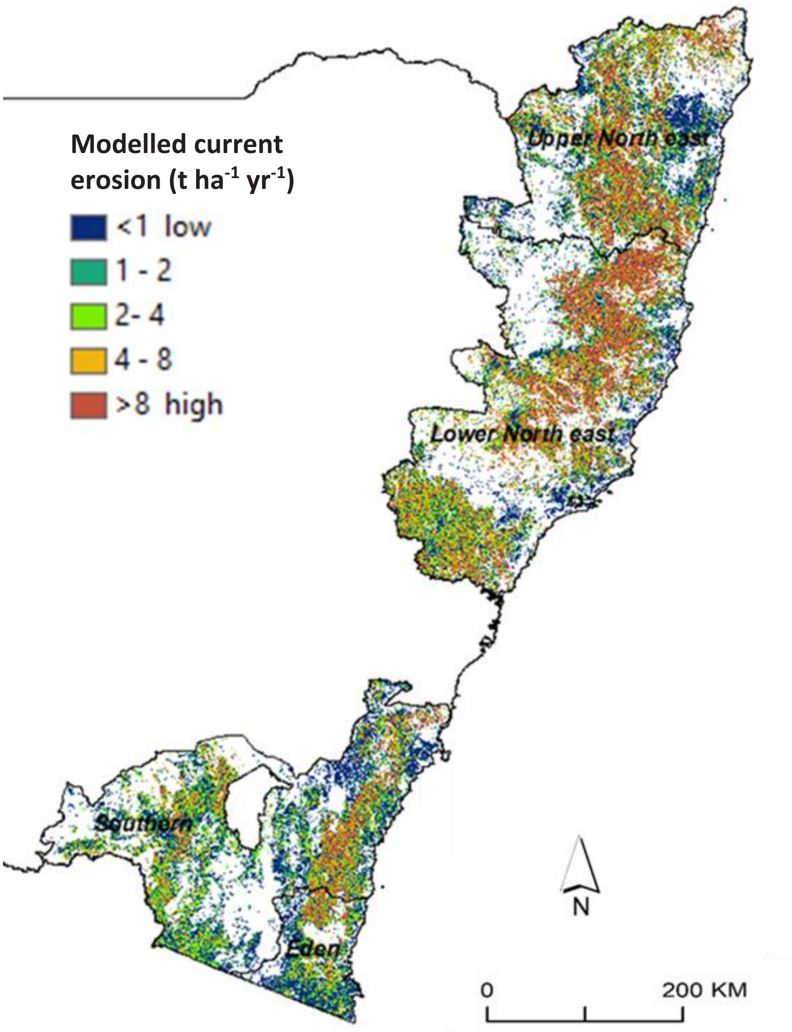

Figure 16: Modelled current hillslope erosion (t ha-1 yr-1) across RFA regions, based on RUSLE modelling, average 2001-2020

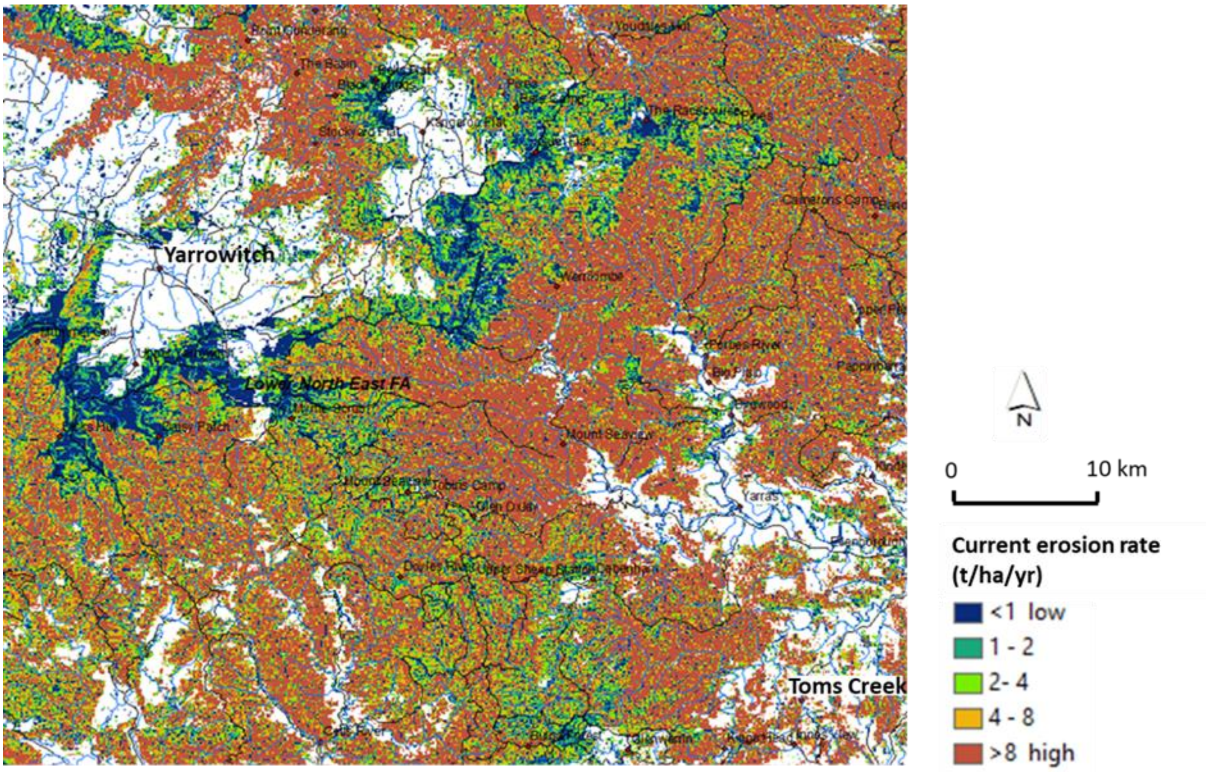

Figure 17: Modelled current hillslope erosion rates, Yarrowitch Region

3.2.5 Total phosphorus

A map of P total for the 0-30 cm across the forest area is presented in Figure 18. Similar layers have been prepared for the 0-10, 10-30 and 30-100 cm depth intervals. These were derived from digital soil mapping over NSW as reported in OEH (2018). An example of a fine scale map over the Yarrowitch area of the mid north coast region is presented in Figure 19.

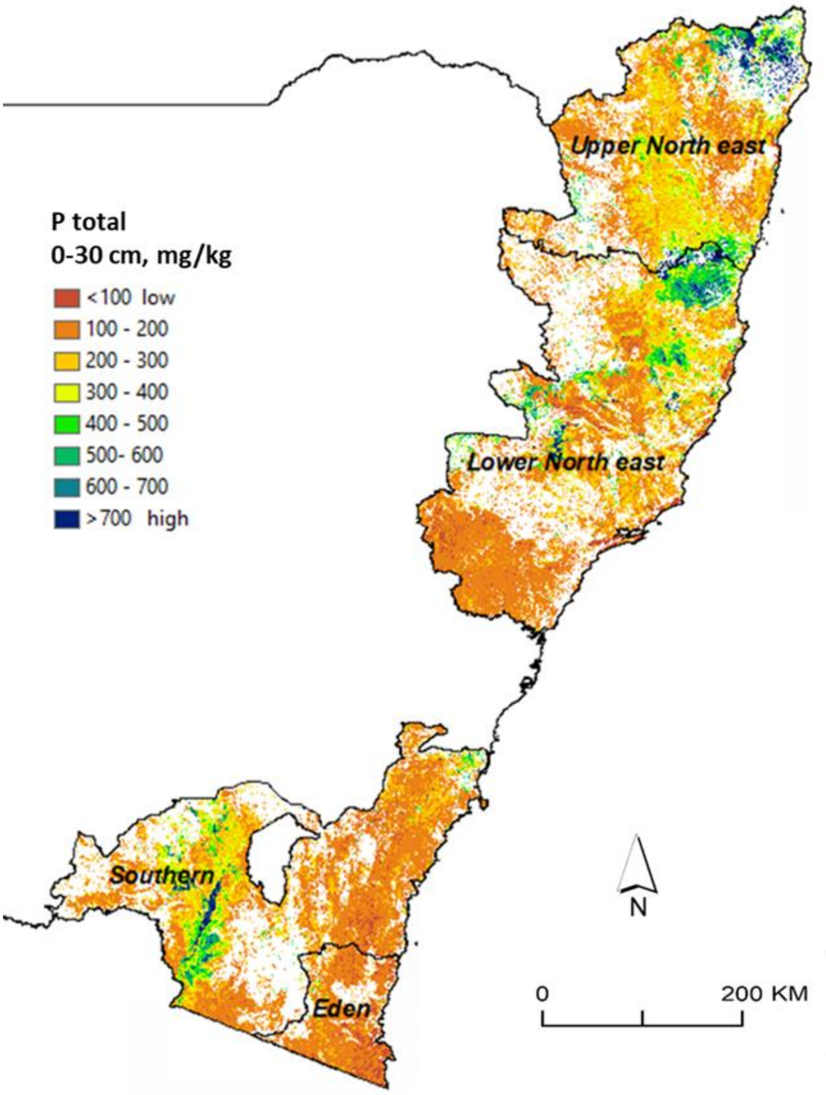

Figure 18: Modelled current P total across RFA regions

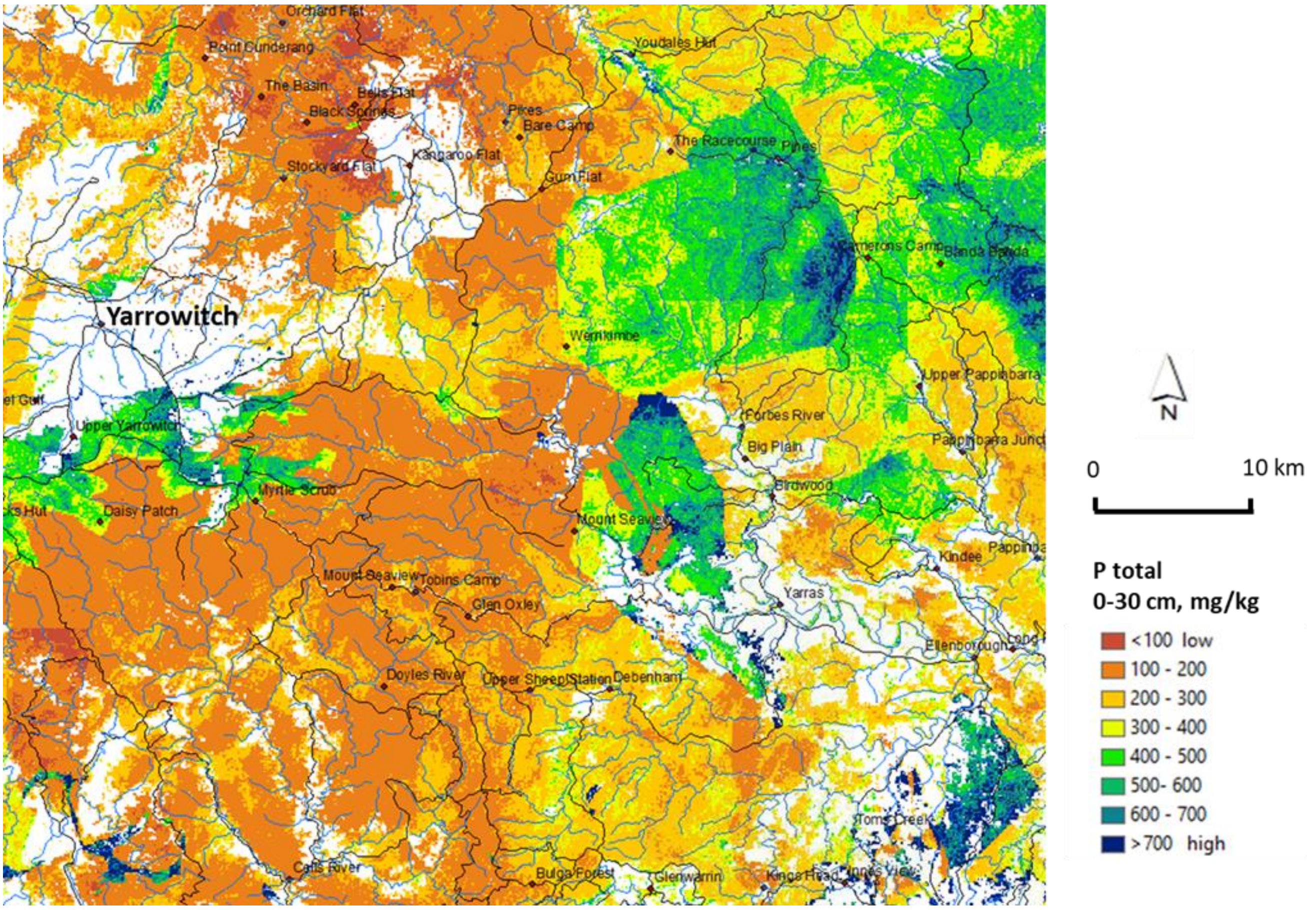

Figure 19: Modelled current P total, Yarrowitch area, mid north coast NSW region, 0-30 cm

4 Discussion

4.1 Overview

Data and spatial products have been prepared to represent baseline soil conditions across the RFA regions of eastern NSW. The products have been developed using a combination of empirical approaches using existing soil landscape data, together with a digital soil mapping approach.

The baseline is broadly considered as the period leading up to approximately 2010. This coincides with the end of a period of extensive soil data collection by the NSW Government around the region, including the suite of data collected for the NSW 2008-09 MER program.

The baseline products include:

- General soil landscape descriptions.
- Point profile data for 2000 profiles in the study area with available key indicator laboratory data.
- Polygonal maps based on soil landscape boundaries, with the key soil condition indicators represented by the most reliable representative soil profile.
- Identification of soil landscape units with inadequate soil profiles to provide for reliable baseline.
- Digital soil maps (rasters) for several of the soil condition indicators at 100 m resolution, including soil properties and sheet erosion rates.

There is general consistency between the outputs of the two approaches.

Data have been provided on a suite of soil condition indicators, including SOC, component carbon fractions, pH, bulk density, sheet erosion, aggregate stability and total P. Other indicators are being explored for additional inclusion, such as EC, N, topsoil depth and soil biological diversity. At this stage it is not possible to reliably assess the condition of all of these indicators, ie, the extent of declines relative to the relatively undisturbed reference state. This means we are not yet in a position to consider all indicators in a combined holistic manner to gain a broad assessment of the condition of NSW forest soils. Although preliminary assessment is possible for some indicators, a meaningful assessment of changes and trends in soil condition requires an ongoing monitoring program.

4.2 Use of products

The baseline products presented here provide information on broadly current conditions of key soil indicators over the RFA regions. They will form the basis of ongoing monitoring programs and trend analysis. An identification of apparent trends based on modelling with existing data will be explored further in the next phase of the project.

The profile points with comprehensive survey descriptions and laboratory data provide a valuable resource for ongoing monitoring programs. Revisiting of these sites with a repeat of laboratory analysis will provide an important record of change in soil properties and condition at these sites. Particularly valuable in this respect are the MER sites which were sampled according to a rigorous and repeatable sampling protocol (DECCW 2009), including 10 sub samples within a 25 m by 25 m grid at each site.

From the products produced to date, it is possible to identify significant gaps in data quantity and quality in the soil landscape units and geomorphic facets across the study area.   Similarly, gaps in soil data over environmental variable space, ie, combinations of the environmental predictors can be identified. This knowledge will be important in guiding future soil condition monitoring programs.

The spatial maps produced by both the empirical and modelling approaches provide a general guide to soil properties and conditions throughout the study area. They may reveal apparent soil limitations and management requirements. However, they cannot be relied on at local scale or individual points. Reliance can only be placed on data from the individual soil profile points, particularly where rigorous sampling and testing protocols were implemented. Where soil conditions at a site vary significantly from that indicated by the maps, these may indicate unusual controlling influences, including excessive land management pressures.

4.3 Issues of uncertainty

As noted above, the spatial maps provided cannot be relied upon at local scale or individual sites. Soils vary in response to wide range of environmental and land management factors and it is not realistically possible to accurately depict these variations in soil distribution, even with extensive field survey or sophisticated modelling techniques.

The empirical derived maps relied on the selection of a single most suitable soil profile to represent the entire soil-landscape unit. Thus, these do not reveal the variations that occur with each unit. Many soil-landscape units did not have suitable representative soil profiles collected within the forested component of that unit. In these cases, the best available profile was taken from a non-forested site in that unit, meaning it is of less reliability for the purpose of this study. The confidence level of each selected type profile is indicative of the reliability of that profile selection and is identified in the data products.

The empirical mapping products are based on catchment scale (1:100,000 scale) soil surveys and data, which identify broad scale soil-landscape units. However, a more detailed local scale product (approximately 1:25,000) would improve effectiveness for forest soil monitoring. Disaggregation of soil mapping into its sub-landscape areas called ‘facets’, would provide greater delineation of different soils types, soil properties and managements requirements that generally occur within the broader soil-landscape units. This will allow information from more than one soil profile in each soil landscape to be used to inform map products.

The digital soil mapping and modelling products are subject to various inherent uncertainties, as has been reported by Nelson *et al*. (2011), Bishop *et al*. (2015) and Robinson *et al*. (2015).

The general uniformity of environmental conditions in the forested area of eastern NSW, such as the typical moderate to high rainfall with low fertility soils and moderate to steep terrain, hinders the modelling and digital mapping process. The region lacks clear differences in many of the control factors that normally lead to strong predictive models, such as large variation in soil fertility, terrain, land use and vegetation cover. Validation results of modelled maps were not strong, with Lin’s concordance correlation coefficients rarely exceeding 0.4 (where a value of 1.0 denotes perfect accuracy).

A common weakness in digital soil mapping is an inadequate coverage of all areas of covariate space. Not all combinations of environmental and forest management conditions were adequately represented in the dataset, resulting in imperfect models.

Weaknesses are apparent in several of the environmental grids used. A key variable is the lithology (silica) layer, which typically was the most powerful controlling variable. Although lithology for site data is generally reliable, the broader grid used to create the final maps is less reliable as it relies on coarse scale geological mapping. The vegetation layer does not distinguish between different forms of vegetation cover, ie, ground cover or canopy cover, which can contribute to imprecise soil-vegetation relationships. The variable representing the number of years since bushfire is of coarse scale and would not reliably represent variations in intensity of the fire throughout the burnt areas. Likewise, the newly created forest management index is an oversimplification of variations in management intensity.

Variation in the dates of sampling of profiles within the SALIS dataset means the temporal variation in climatic conditions within a single region will contribute to differing influences on soil properties, even where they were spatially close. Errors in soil data can also be introduced through field sampling and laboratory inconsistencies. The Walkley-Black method of soil carbon analysis, as used in this dataset, has been stated to under-estimate true values (Skjemstad *et al*. 2000). The MIR analysis of soil carbon fractions is subject to significant uncertainty.

There is uncertainty in the effectiveness of combining the various soil condition indicators into a single meaningful index of soil condition, which has not been attempted at this stage of the project.

5 Conclusion

This preliminary report has presented results on baseline soil conditions over the RFA regions of eastern NSW, representing the period of approximately 2010. A suite of broadly current baseline data and spatial map products are presented. The spatial products will be available as digital images for viewing in GIS mode.

Ongoing analysis in the project will further explore apparent trends in soil condition with forest management, bushfire and climate change. Further analysis of key data gaps will continue. An ongoing monitoring program is required to gain a comprehensive picture of the condition of NSW forest soils.

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NRC Forest Monitoring and Improvement Program

Project 4: Baselines, drivers and trends in soil health and stability

Update 5: Drivers and trends

NSW DPIE Science, May 2021

Contents

List of Figures

List of Tables

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1 Introduction

The need to maintain health and stability of forest soils in order to protect forest ecosystems and associated environmental, cultural and economic values has been recognised by the NSW Natural Resources Commission. Current knowledge on the baseline condition of soils over the eastern NSW forest system was presented in the *Baseline for Indicators* Report (DPIE, submitted to NRC April 2021)

It is important to understand the drivers of soil condition operating in the forest environment, that is, the main environmental and land management factors that influence the status of key soil condition indicators. This is a pre-requisite to understanding and gaining knowledge on their potential trajectories into the future. Forest soil condition may change over time subject to natural and human induced influences. A critical natural influence is climatic change. Human influences include disturbance from land management such forestry harvesting operations and grazing stock access. Influences may be transitional between natural and human induced such as changes in natural fire regimes or faunal populations influenced by human activities.

For broader environmental protection issues, forest soil condition is most usefully defined as the decline in key indicators compared to a relatively undisturbed reference soil. This is similar to the definition adopted in the 2008-09 NSW Monitoring Evaluation and Reporting (MER) program (Chapman *et al*. 2011, OEH 2014). This contrasts with other soil condition definitions that relate to soil productivity for agricultural and commercial forest growth. Knowledge on the extent of change of key indicators such as organic carbon, pH or bulk density (soil structure) from a relatively undisturbed soil, is vital for assessing potential impacts on the health of the entire forest ecosystem.

Ongoing monitoring is important to identify trends in forest soil condition. Monitoring programs involving periodic return to selected forest monitoring sites, with collection of key field and laboratory data, provide valuable data to reliably assess change in forest soil condition and apparent trends. However, at present there are regrettably few such empirical data from forest monitoring sites available to identify drivers and trends. Modelling based on current available data provides an alternative means to identify key drivers of forest soil condition and their trends.

This report presents results of a digital soil modelling (DSM) approach to identify key drivers and apparent trends in forest soil condition. More specifically it:

- Identifies key environmental and land management drivers for a number of soil condition indicators, including SOC, pH, bulk density, phosphorous, sodicity (dispersion percent) and hillslope erosion
- Where data allowed, provide maps and examines trends of change in soil condition indicators due to human disturbance, climate change and bushfire.

2 Methods

2.1 Overview

The project adopted a DSM approach involving both multiple linear regression and random forest techniques to identify key factors influencing each of the main soil condition indicators. The change in several of these indicators due to human disturbance, climate change and bushfire was modelled and mapped by applying a substitution process as outlined more fully in s.2.3. The change in rates of hillslope erosion was modelled and mapped with ArcGIS techniques as outlined in s.2.4. Examples of fine scale map products are presented where possible over a small region around Yarrowitch in the lower north coast of NSW.

2.2 Data and environmental variables

The soil data and environmental variables applied in this phase of the project were outlined in the *Baseline for Indicators* Report (Update 4).

Further details on the key variables used in the soil condition trend analysis are provided below:

- *Rainfall (1990_2010)*: mean annual rainfall over this 20 year period; sourced from SILO (Scientific Information for Land Owners) website (https://www.longpaddock.qld.gov.au/silo/). Climate data used for climate change projections was accessed from the NARCliM program
- *Temperature max (1990_2010)*: mean annual daily maximum temperatures over this 20-year period; this and future climate projections sourced as above
- *Forest disturbance index (FDI):* a new index developed for this project reflecting the intensity of disturbance associated with the forest management; ranging from 1 for relatively undisturbed formal or informal reserves; 2 for forestry harvest operation areas; and 3 for privately owned or leased forest or woodland typically subjected to periodic stock grazing (see Table 1, Figures 1 and 2). This was derived by combining maps of NPWS estate, Forest Management Zones map (Forestry Corporation of NSW 2020) and NSW land use 2017 maps (DPIE 2020a). NPWS estate was all allocated FDI 1. The Forest disturbance index map enables distinction between forest protection areas (FDI 1) and forest harvest operation areas (FDI 2). All remaining woody area was allocated FDI 3, being identified as either "other natural" or "native grazing", and is considered to have the highest level of ongoing disturbance, primarily from uncontrolled stock grazing.
- *Total vegetation cover (%):* includes photo-synthetic (living) and non-photo-synthetic (dead) vegetation cover, being average (mean) cover from year 2000 to date of sampling, sourced from CSIRO MODIS fractional vegetation data (Guerschman and Hill, 2018).
- *Years_since Bushfire*: The number of years since a major bushfire. For training data, it applied the number of years prior to the data of sampling; for mapping it applied the number of years prior to 2010; sourced from Rural Fire Service (via NRC data portal)

Table 1: Forest tenures, zones and Forest Disturbance Index (FDI)

Tenure	Zone	Forest Disturbance Index (FDI)
NPWS estate	All	1
Forest Management Zones[a]	Zone 1 - Special Protection Zone	1
	Zone 2 - Special Management Zone	1
	Zone 3A - Harvesting Exclusions Zone	1
	Zone 3B - Special Prescription Zone	1
	Zone 4 - General Management Zone	2
	Zone 5 - Hardwood Plantations Zone	2
	Zone 6 - Softwood Plantations Zone	2
	Zone 7 - Non Forestry Use Zone	3
	Zone 8 - Areas for further assessment	2[b]
	Zone 90 – Unzoned	3
Private and leasehold lands (often subject to stock grazing)	All	3

[a] NSW Government (2018); Sate Forests NSW (1999)
[b] This was incorrectly allocated as FDI 3 in the current study

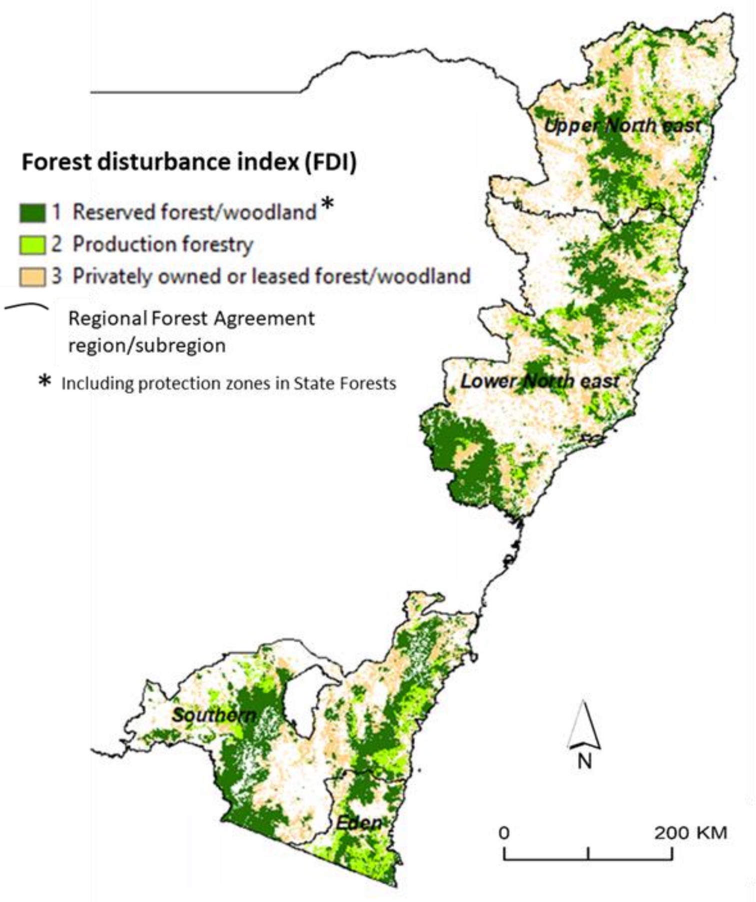

Figure 1: Forest disturbance index over RFA regions

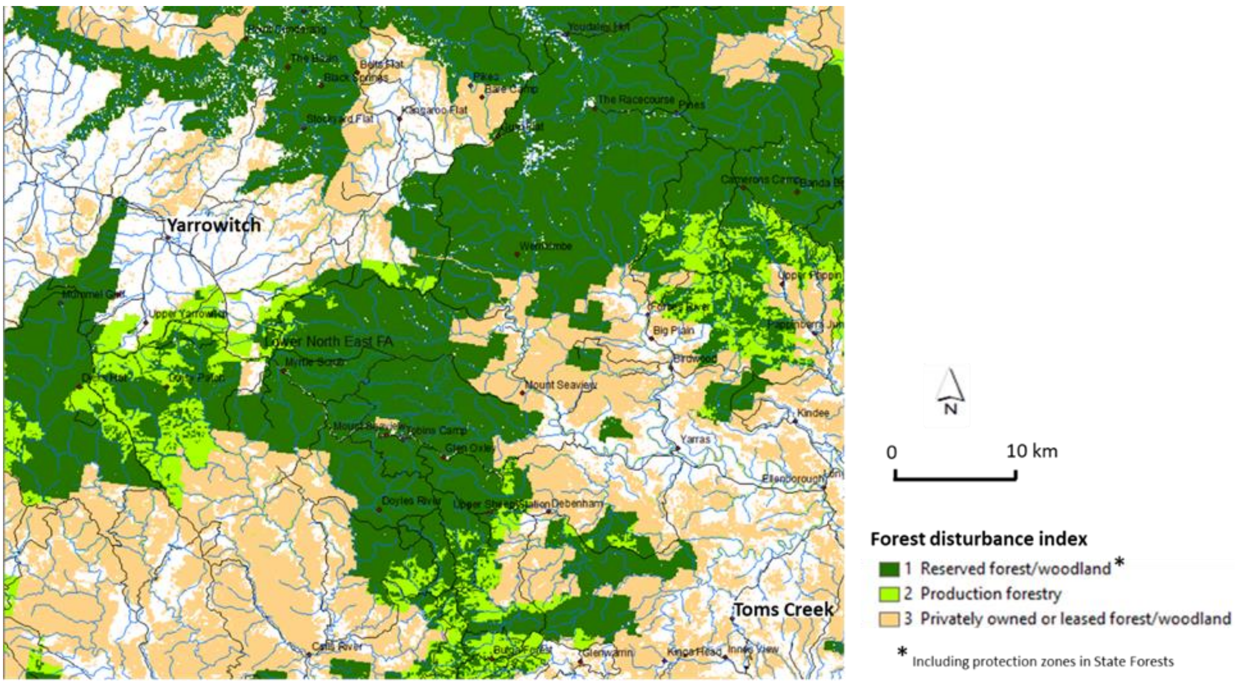

Figure 2: Forest disturbance index over Yarrowitch Region

2.3 Modelling methods

The analysis was undertaken using digital soil mapping (DSM) techniques. An overview of the use of DSM in this project was provided in the *Baseline for Indicators* Report. A combination of multiple linear regression (MLR) and random forest (RF) techniques were applied, to generate spatial products with 100 m resolution. It was performed in R software (R Core Team 2020), with further analysis and map manipulation in ESRI ArcGIS.

By examining 'variable importance plots' generated with RF and standardised regression coefficients with MLR, the relative influence of each variable used in the modelling, and the direction of influence, could be elucidated. The two different approaches do not give identical results but there is typically high consistency between them. They provide valuable data for identifying key drivers of each soil condition indicator.

The analysis of trends in soil condition applied DSM techniques with a 'space-for-time substitution' process. This process involves use of current spatial patterns to predict past or future trajectories of ecological systems (Pickett 1989; Blois *et al.* 2013). Spatial patterns are used to represent temporal patterns. The process, as summarised in Figure 3, involves establishment of a baseline, then a repeat of the modelling under a new regime, typically involving the substitution of a single variable, such as the forest disturbance index (FDI). The difference between the two modelled outputs provide an indication of the change. It can identify whether the change in the subject variable has resulted in an increase or decrease of the soil condition indicator, and the magnitude of such change.

In the analysis of trends with human disturbance, a relatively undisturbed baseline (reference) condition was represented by FDI 1, ie, equivalent to formal or informal reserve status across the entire study area. Then the model was rerun with the current (approx. 2010) disturbance status (ie, FDI 1, 2 and 3) to assess the influence of the changed disturbance regime. For several soil indicators, no clear trends with forest disturbance index were discernible, so the mapping of change with disturbance was not undertaken. Similar concepts and approaches were applied in assessing trends in soil indicators with projected climate change (Gray and Bishop 2018, 2019) and bushfire recovery periods (Gray 2021).

Validation statistics for each baseline map, as presented in *Baseline for Indicators* Report, provide an indication of their performance and reliability of the DSM products. These statistics included R^2, Lin's concordance correlation coefficient and mean absolute error. Combining upper and lower 90% confidence intervals provides further indication of confidence in the change products.

Stratification of key results by forest disturbance index (FDI) was undertaken and presented in data tables. These reveal the different levels of change in the lands of different disturbance intensity, ie, formal or informal reserves, through forests available for harvesting, to privately owned or leased and grazed forests. Further division by Forest Agreement Region was undertaken for some indicators.

Modelling of changes and trends in hillslope sheet erosion was based on RUSLE, following methods established in Yang (2020), as outlined in the *Baseline for Indicators* Report. The baseline erosion rates were generated by applying the highest 100th percentile groundcover over the years 2001 to 2020 together with the other RUSLE variables. Current erosion rates were generated using actual groundcover for each month over the 2001-2020 period. Comparing the current with the baseline levels provided relative change from current to baseline erosion rates.

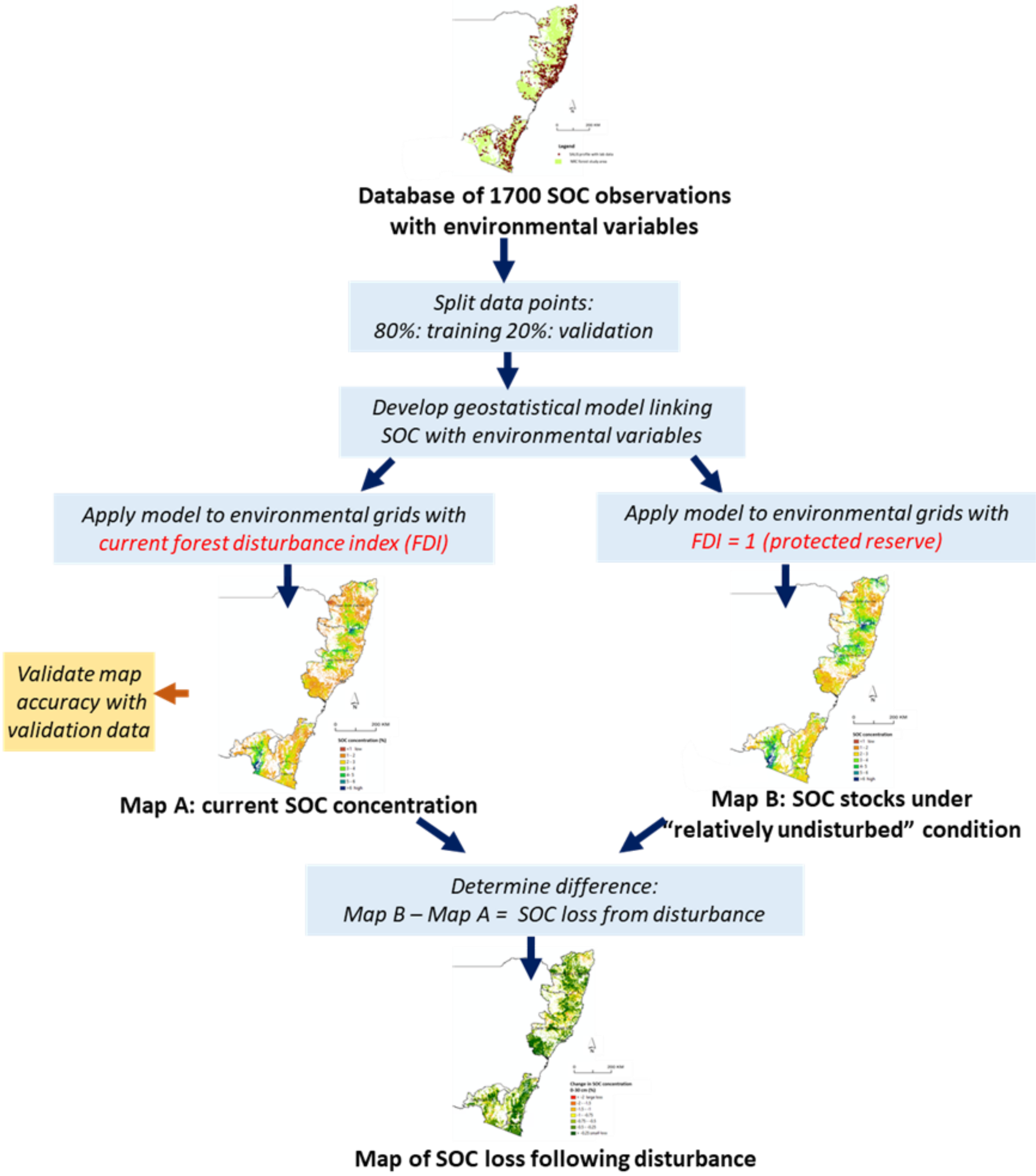

Figure 3: Process for deriving change in soil indicators

3 Results

This section presents modelling results on key driving factors and trends for key soil condition indicators, based on changes in forest management, climate change and bushfire

3.1 Soil organic carbon

3.1.1 Key drivers

The relative influence of the various environmental and land management variables on SOC is presented in the variable importance plot of Figure 4. The associated positive or negative sign reveals the trend of influence. These plots present only the top ten of the 15 variables initially applied. The results are further informed by MLR standardised regression coefficients given in Appendix 1.

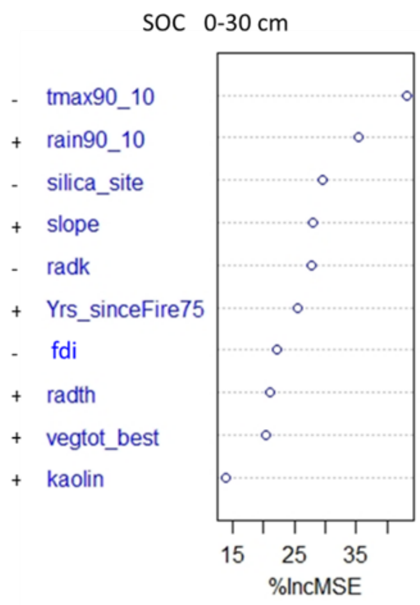

Figure 4: SOC variable importance plot, 0-30 cm

Climatic factors are revealed as the main drivers. SOC increases with decreasing temperatures and increasing rainfall. These factors control the production of organic matter and the extent of its mineralisation, decomposition and subsequent loss from the soil (Sanderman et al 2010; Wiesmeier 2019). SOC levels are typically highest under cool moist conditions and lowest in hot and dry conditions (Gray et al. 2015). The influence of projected climate change on SOC is examined further in s.3.1.3.

Parent material and soil type as represented by the silica index is revealed as a key driver, being ranked just below the climatic indicators. SOC increases with decreasing silica of parent material, indicative of soils of higher clay content and fertility, which contribute to higher vegetation growth and stabilisation of soil carbon. Other parent material/soil variables such as radiometric K and Th, and kaolin clay proportion also feature in the top 10 variables.

The forest disturbance index (FDI) demonstrates a negative trend, indicating that the higher the level of forest disturbance, the lower the SOC levels. Highest SOC levels are associated with formal or informal reserves sites, then decreasing to forests available for harvesting and lowest levels associated with privately owned or leased, often grazed forest sites. This variable is used as a basis for modelling the change with disturbance as presented in the following s.3.1.2. Similarly, the positive influence of vegetation cover on SOC content is demonstrated, however it does not rank as dominantly in this study area as it does when non-forested and agricultural lands are also included in modelling programs.

The variable *Yrs_sinceFire* representing the length of time since the last major bushfire (not prescribed burn) is revealed to be a strong positive driver of SOC. Levels increase with time since the major fire event. This relationship is examined more closely in s.3.1.4

Slope gradient is positively correlated with SOC in the RFA regions. This suggests the steeper sites have overall higher vegetation densities with soil less disturbance. However, the topographic wetness indicator (TWI) did not appear as a significant driver.

3.1.2 Change with increasing disturbance

Figures 5 and 6 present the change in SOC content from a hypothetical status of relatively undisturbed environment to current probable disturbance status (approx. 2010), based on the change in FDI. All other variables were held constant, for example, no change in climate was considered.

A significant widespread loss of SOC is revealed due to this increased degree of disturbance. Declines vary from zero to moderate (>2%) for the 0-30 cm interval. Larger declines are, as expected, associated with the areas of higher disturbance, as revealed by Table 2. No decline occurs over currently reserved lands, then moderate declines (mean -9.3% in relative terms for 0-30 cm depth) over forestry harvest operation lands and highest declines (mean -19.5% in relative terms) over privately owned or leased, often grazed forest lands. The extent of decline decreases with depth.

Table 2: Mean relative change in SOC with forest disturbance (%)

Forest disturbance index	0-10 cm	10-30 cm	0-30 cm	30-100 cm
1: Relatively undisturbed	0	0	0	0
2: Partial disturbance	-10.3	-9.9	-9.3	-5.0
3: Moderate disturbance (periodic grazing)	-21.7	-20.9	-19.5	-10.3

Even greater declines are likely to have been demonstrated if a decrease in vegetation cover had been incorporated into the modelling process. It is evident the increasing ground disturbance is responsible for lower input of organic material to soils and greater decomposition/mineralisation and ultimately loss of soil carbon.

The rate of decline is not uniform, even within each FDI class, but is dependent on the precise combination of environmental factors. Areas with the highest existing SOC levels, such as in wet locations and fertile low clay rich soils lose more SOC than areas with low existing SOC levels such as in drier locations with low fertility sandy soils. This higher loss applies in both absolute and relative terms, as demonstrated by Gray et al. (2016a).

The change in SOC due to human disturbance for each RFA Region is presented in Table 3. It reveals the highest overall decline in the Upper North East subregion (>11% in relative terms, 0-30 cm). Declines are greatest in the surface soils.

Table 3: Mean relative change in SOC with forest disturbance by RFA region (%)

RFA Region	0-10 cm	10-30 cm	0-30 cm	30-100 cm
Upper North East subregion	-12.7	-12.3	-11.4	-6.0
Lower North East subregion	-10.3	9.9-	-9.2	-4.9
Southern	-8.8	-8.5	-7.9	-4.2
Eden	-7.7	-7.4	-6.9	-3.7

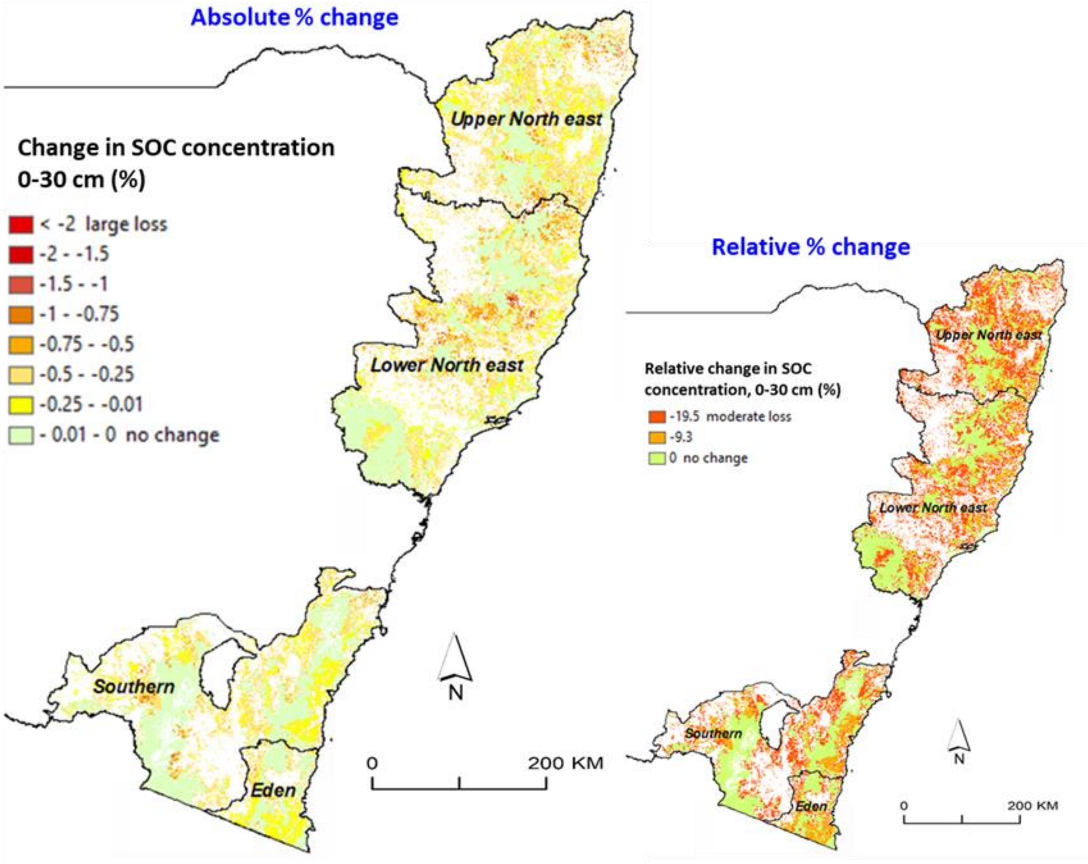

Figure 5: Predicted absolute and relative change (%) in surface SOC concentrations from a hypothetical relatively undisturbed reference condition to current condition across RFA regions

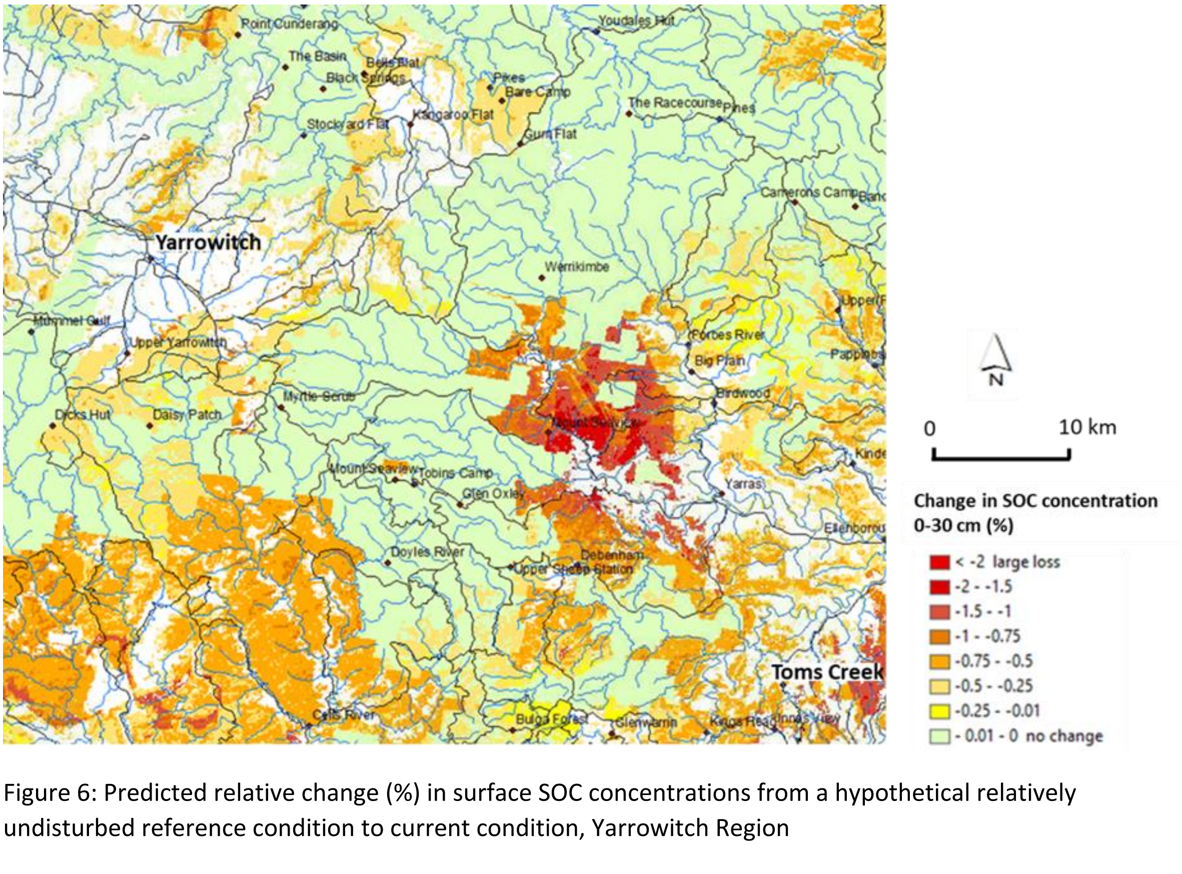

Figure 6: Predicted relative change (%) in surface SOC concentrations from a hypothetical relatively undisturbed reference condition to current condition, Yarrowitch Region

3.1.3 Change from climate change

The change in SOC stocks arising from projected climate change over NSW has been modelled by as part of NARCliM program (Gray and Bishop 2018, 2019). Results from that project suggest a marked decline over the NSW forest area to the far change period, centred around 2070, as shown by Figures 7 and 8. The change by RFA region or subregion is presented in Table 4. A mean relative loss of 17% for the 0-30 cm interval is projected over both North east subregions, rising to over 37% relative loss in the Southern region. The results represent the mean of the 12 climate model projections applied in the NARCliM program. The magnitude of decline in SOC varied between the different climate models.

Their work demonstrated that, again, the greatest losses in SOC occur in areas with currently high SOC stocks. Highland regions, particularly in the southern alps, are predicted to lose the largest quantity of SOC.

The results suggest a continuing loss of SOC and associated soil condition irrespective of land management over the NSW eastern forests. This also has implications for identifying ongoing net carbon emissions from NSW lands, with respect to aiming for Net Zero Emissions (NSW Government 2016; DPIE 2020b) and mitigating climate change.

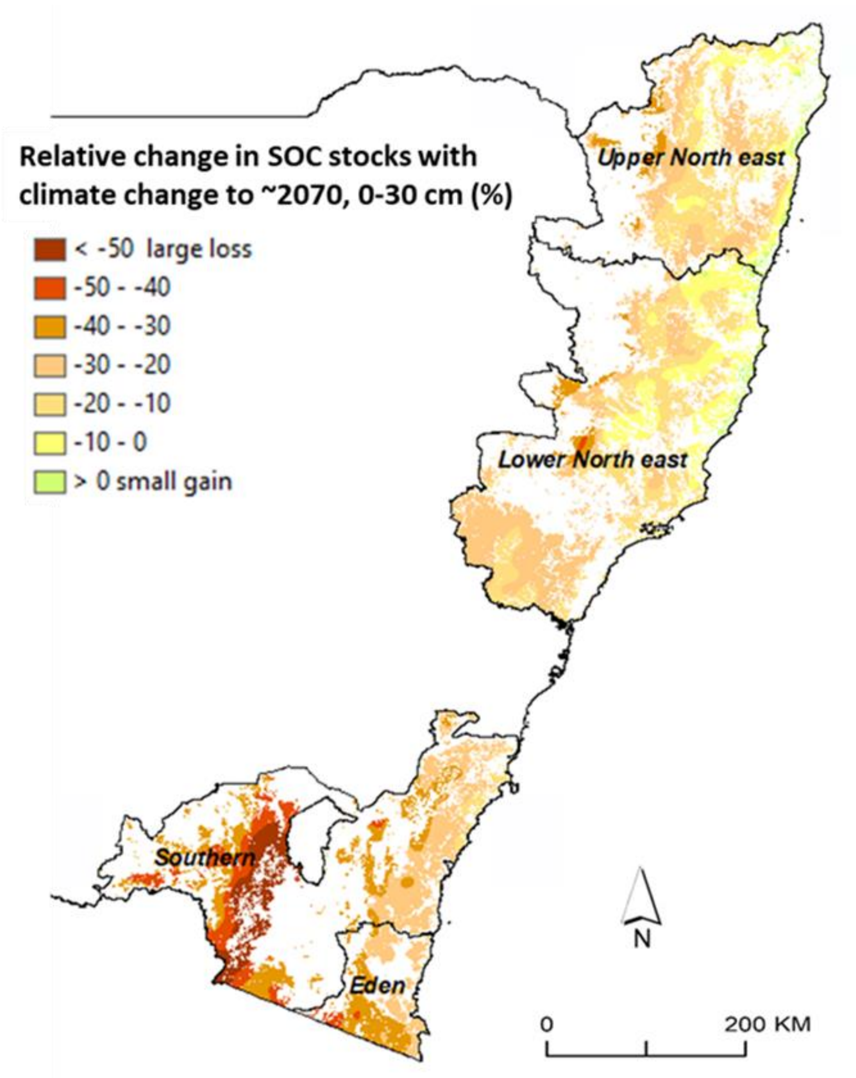

Figure 7: Predicted relative change in SOC stocks due to projected climate change to approx. 2070 (%)

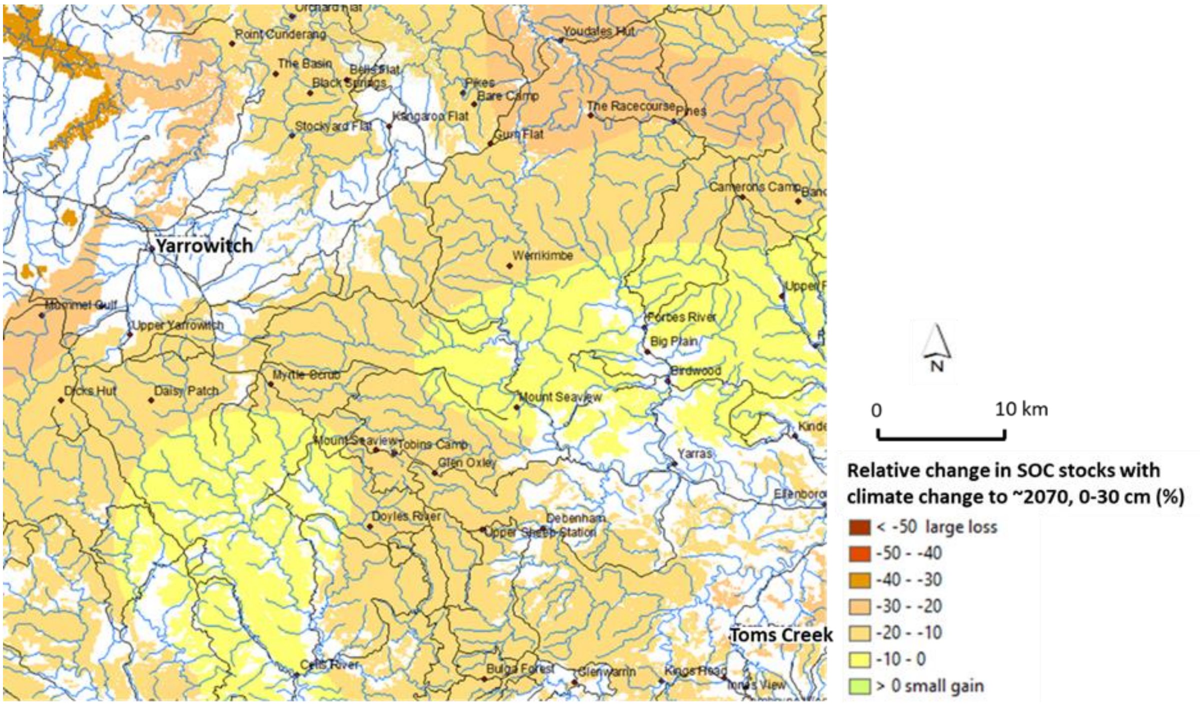

Figure 8: Predicted relative change in SOC stocks due to projected climate change to approx. 2070, Yarrowitch Region (%)

Table 4: Mean relative change in SOC with climate change to approx. 2070 by RFA region (%)

RFA Region	0-30 cm	30-100 cm
Upper North East subregion	-17.2	-37.6
Lower North East subregion	-17.0	-36.3
Southern	-37.2	-64.0
Eden	-31.1	-55.2

3.1.4 Change from bushfire

Modelling revealed a strong positive correlation between SOC and the number of years since bushfire. The influence of this variable was strongest when converted to the natural log format (ln) indicating its influence is more pronounced in the early rather than later years. This reflects high rates of SOC recovery in early years then progressively lower rates of SOC recovery until a new equilibrium is reached. The results suggested a re-equilibrium was approached after 75 years.

Figure 9 presents the modelled immediate loss of SOC (in relative terms) in the aftermath of a hypothetical bushfire across the entire eastern forest region. Losses of SOC generally range between 40 and 60%, substantially high proportions. The recovery of SOC after 20 years is presented in Figure 10 (in absolute terms), which accounts for a large amount of that originally lost.

The highest rates of loss are indicated over locations with high initial SOC levels. These estimates of SOC decline following NSW bushfires derived from this modelling approach are in accord with other studies. Tulau et al. (2016) reported declines in the top 10 cm of approximately 35% SOC (in relative terms) in sandy soils and 55% SOC in moderately clay rich soils three years after high intensity fires in the Warrumbungles National Park of NSW in 2013. Similar trends have been demonstrated in other

Australian and international studies (Bowd et al. 2019; Homann et al. 2011; Tessler et al. 2008; Tulau and McInnes-Clarke 2016), as graphically represented in Figure 11.

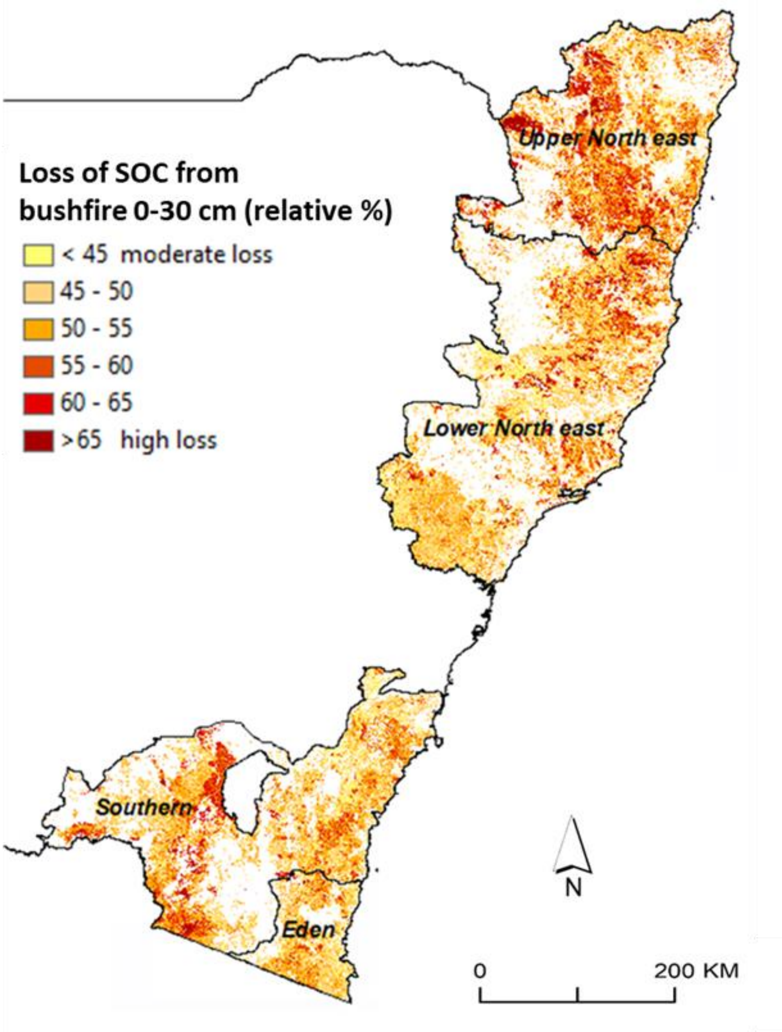

Figure 9: Predicted immediate loss of SOC due to hypothetical bushfire across entire eastern forest area (relative %)

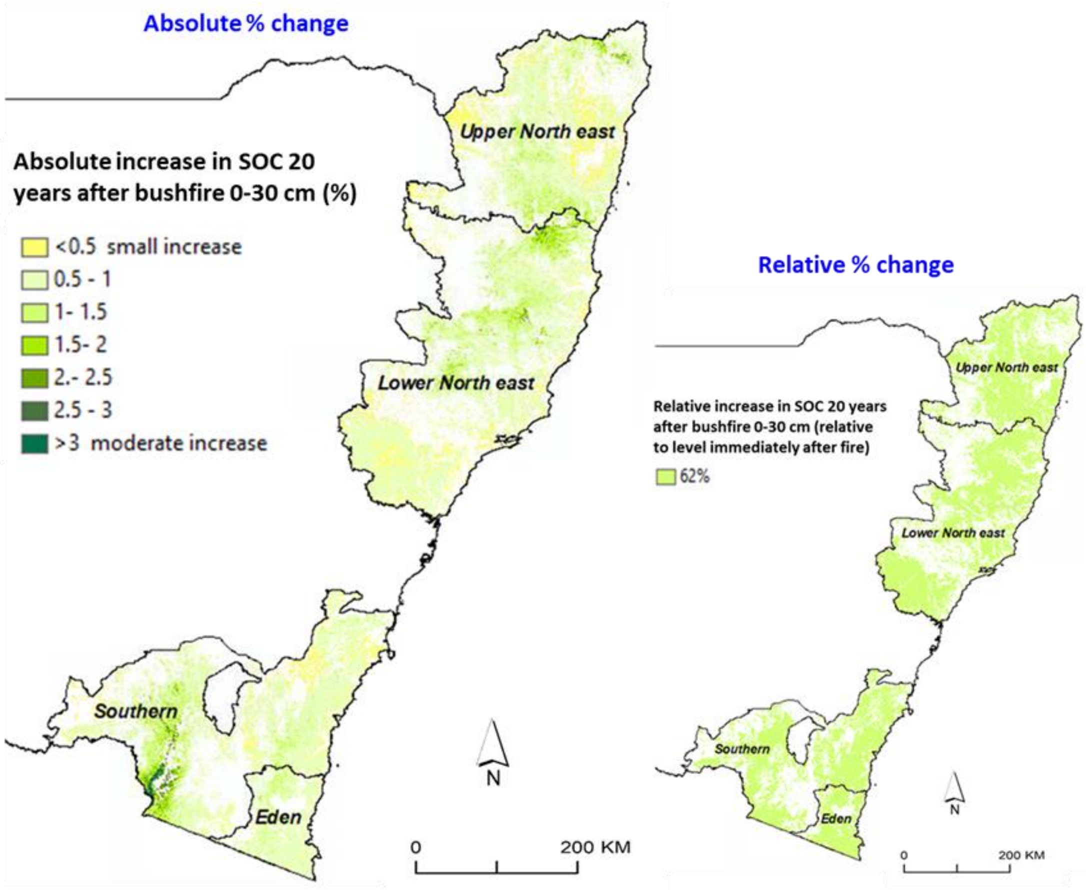

Figure 10: Predicted increase in SOC content 20 years after hypothetical bushfire across entire eastern forest area (main image: absolute %; inset image: relative%)

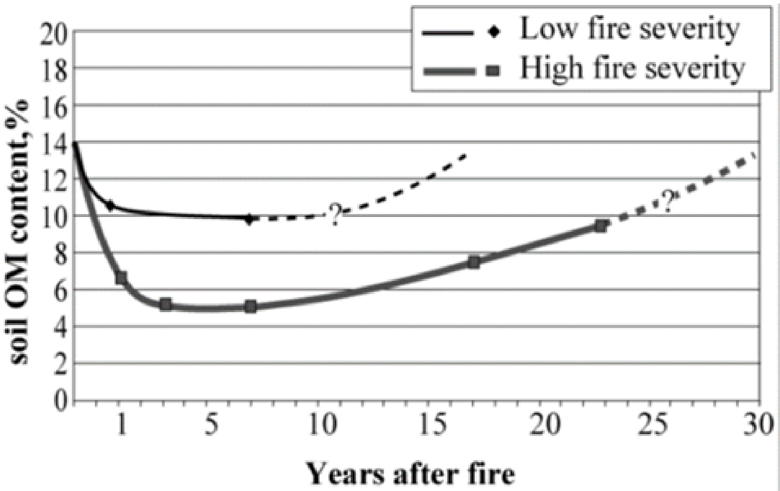

Figure 11. Temporal changes in soil organic matter content following low and high fire severity (after Tessler *et al*. 2008 in Tulau and McInnes Clarke 2016)

3.2 pH

3.2.1 Key drivers

The relative influence of the various environmental and management variables on pH is presented in the variable importance plot of Figure 12, which gives the top ten variables and displaying direction of influence. These results are complemented by the those presented in the table of MLR standardised regression coefficients given in Appendix 1.

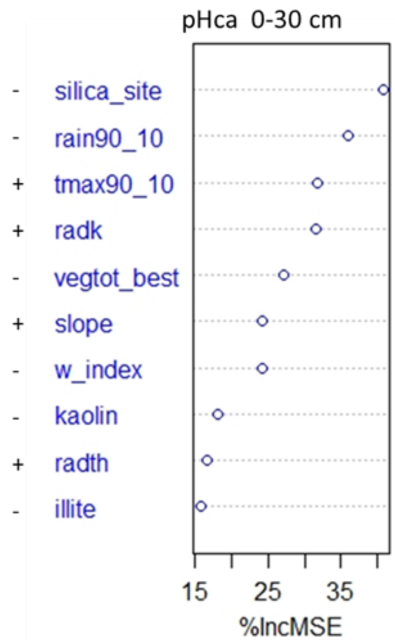

Figure 12: pH variable importance plot, 0-30 cm

Parent material and soil type as represented by the silica index is revealed as the dominant driver over the eastern forest area. pH increases, ie, become more alkaline, with decreasing silica content of parent material, indicative of soils of higher clay content and fertility. Conversely, soils generally become more acidic with more siliceous, sandy soil (Gray et al. 2016b). Other parent material/soil variables such as radiometric K and Th, clay proportion and the weathering index also feature in the top 10 variables.

Climatic factors are also revealed as key drivers of pH. Soils are shown to become more alkaline with decreasing rainfall and increasing temperatures. This results from the lower levels of leaching that allows basic cations to be retained in the soil and not replaced by hydrogen and aluminium ions (McKenzie et al. 2004; Rubinic et al. 2015). The influence of projected climate change on pH is examined further in s.3.1.3.

The modelling reveals that pH is negatively correlated with vegetation cover over the forest study area, ie, the higher the vegetation cover, the more acidic the soil. In mixed use landscapes this same trend is often apparent because the higher fertility more alkaline soils are used for more intensive agricultural purposes, which typically have lesser annual vegetation cover, but this explanation would not apply in this uniformly forested study area. It is likely that high vegetation cover is associated with release of organic acids. It can be observed that the forest disturbance index (FDI) did not rank in the top ten variables. For this reason, the modelling of change between the relatively undisturbed condition to the current conditions produced no meaningful results and those results are not presented.

The results suggest higher pH, more alkaline soils with increasing slope gradients. This is contrary to the normal pedologic behaviour across the broader NSW, where the lower slopes and drainage basins accumulate basic cations which serve to raise pH. The variable representing years since bushfire did not appear to have any influence on the soil pH.

3.2.2 Change from climate change

The change in pH arising from projected climate change over NSW has been modelled as part of the NARCliM program (Gray and Bishop 2018, 2019). Results from that project suggest a slight increase to more alkaline soils over the NSW forest area to the far change period, centred around 2070, as shown by Figures 13 and 14. The change by RFA region is presented in Table 5. The most pronounced increases are evident in the Southern region, particularly in the alpine regions, where increases of more than 0.3 pH units are predicted. The results represent the mean of the 12 climate model projections applied in the NARCliM program. The magnitude of change in pH varied between the different climate models.

Over most of the region the changes in pH are quite small and are not likely to significantly affect silvicultural practices. Any changes in soil pH may affect natural ecosystems, which have normally become established under particular pH ranges. Where significant increases or decreases (e.g. of 0.25 pH units or more) are demonstrated there is a likelihood that native ecosystems will be affected; this is an issue that may need to be considered and addressed by managers of these ecosystems.

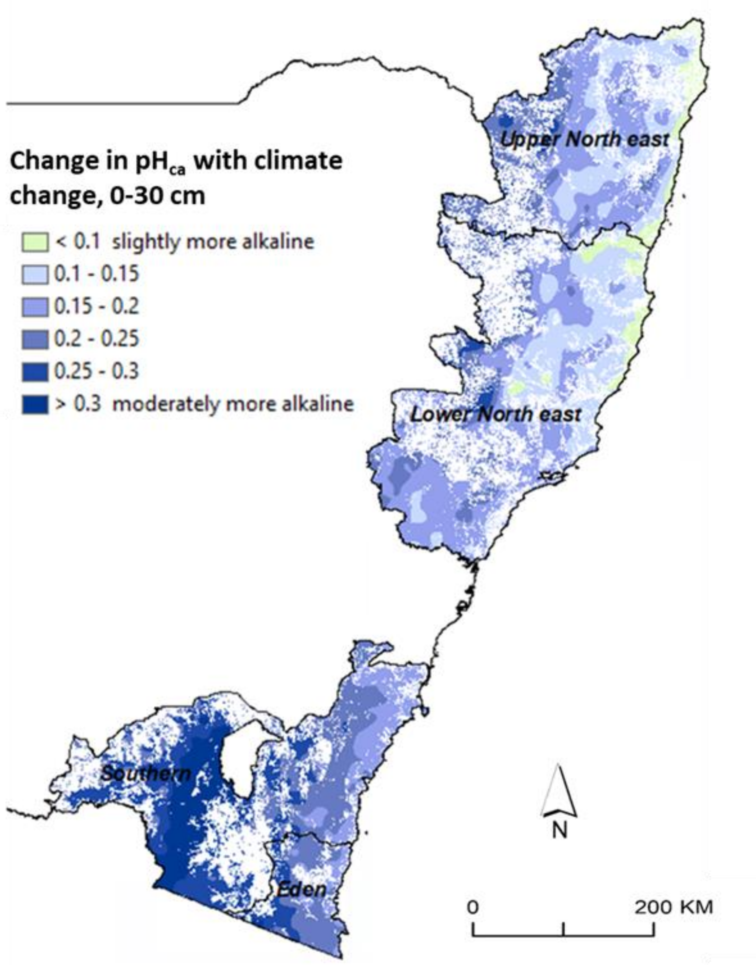

Figure 13: Predicted change in pH$_{ca}$ due to projected climate change to approx. 2070

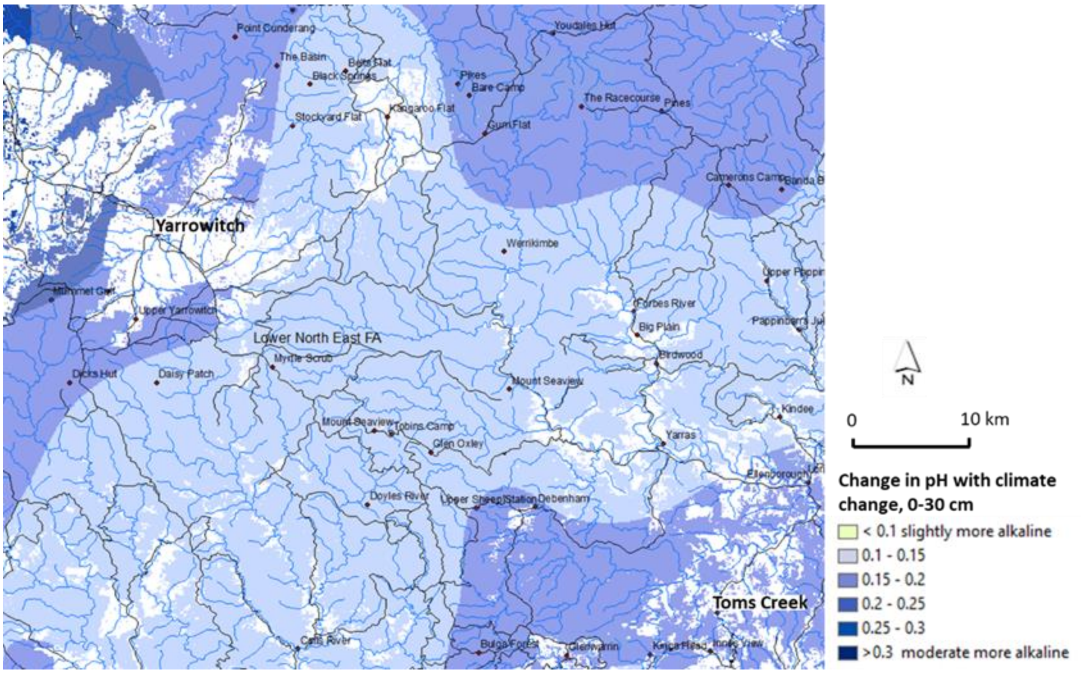

Figure 14: Predicted change in pH_{ca} due to projected climate change to approx. 2070, Yarrowitch Region

Table 5: Mean absolute change in pH with climate change to approx. 2070 by RFA region (pH units)

RFA Region	0-30 cm	30-100 cm
Upper North East subregion	0.16	0.13
Lower North East subregion	0.16	0.13
Southern	0.27	0.26
Eden	0.23	0.22

3.3 Bulk density

3.3.1 Key drivers

The variable importance plot of Figure 15 presents the relative influence of the ten most significant environmental and management variables on bulk density over the 0-10 cm interval. These results are complemented by the MLR standardised regression coefficients given in Appendix 1. The dataset upon which these results were based was not large (n= 52), so the results need to be treated with some caution.

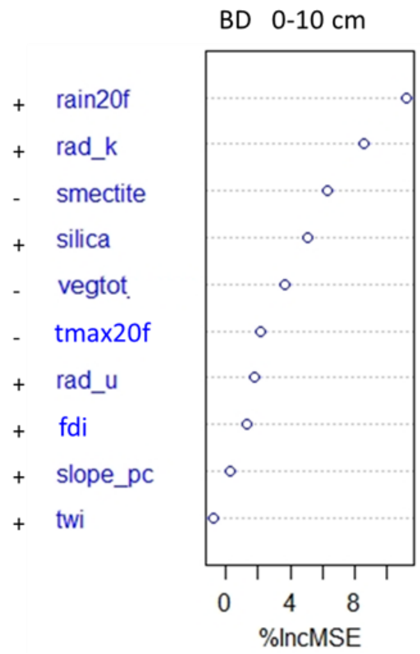

Figure 15: Bulk density variable importance plot, 0-10 cm

The results suggest that parent material/soil type indicators such as silica, radiometric K and clay type are dominant drivers of bulk density. This is particularly borne out by the standardised regression coefficient, which reveals silica index as more than double the next most significant variable. The positive correlation with silica reflects the higher bulk density typically associated with sandy soils and the lower bulk density in clay rich well-structured soils.

Rainfall is demonstrated to be another dominant driver, and in fact is shown as the most influential factor in the above plot. It's positive correlation may reflect the increased leaching of clays out of the soil under higher rainfall conditions, thus contributing to more sandy soils with their associated high bulk density. Temperature is also of moderate influence; the negative correlation possibly indicative of higher weathering and clay formation in warm moist conditions, thus driving bulk density lower.

Vegetation cover and forest disturbance index (FDI) are both of moderate influence of bulk density, with negative and positive correlations respectively. These results reflect the rise in bulk density with lowering vegetation cover and increasing forest disturbance. Vegetation and organic matter serve to improve soil structure, and increased disturbance of soils from the higher FDI leads to soil compaction due to use of machinery and hard hooved stock animals, thus both variables contribute to the observed trends. The FDI is used as a basis for modelling the change with increased disturbance as presented in the following s.3.3.2.

The variable representing years since bushfire did not appear to have any influence on soil bulk density.

3.3.2 Change with disturbance

Figures 16 and 17 presents the change in bulk density (0-10 cm) from hypothetical relatively undisturbed environment to present (approx. 2010), based on changes in FDI. All other variables were held constant, ie, no change in climate.

A slight increase in bulk density, is revealed with this increase in disturbance. The increases range to over 0.2 t/ m^3 or 15% in relative terms. Larger increases are, as expected, associated with the areas of higher disturbance, as revealed by Table 6. There is zero change modelled over current formal or informal reserved lands, then slight increases (mean 7% in relative terms for 0-10 cm) over partially disturbed lands and highest increases (mean 14% in relative terms for 0-10 cm) over moderately disturbed, often grazed forest lands.

Table 6: Mean relative change in bulk density with forest disturbance (%)

Forest disturbance index	0-10 cm	10-30 cm	0-30 cm
1: Relatively undisturbed	0	0	0
2: Partial disturbance	6.8	6.1	8.1
3: Moderate disturbance (periodic grazing)	14.2	13.6	15.3

These changes reflect the potential impacts of soil compaction from heavy machinery and stock, plus potential decrease in vegetation and SOC associated with the change from relatively undisturbed conditions to the current more disturbed forest environment.

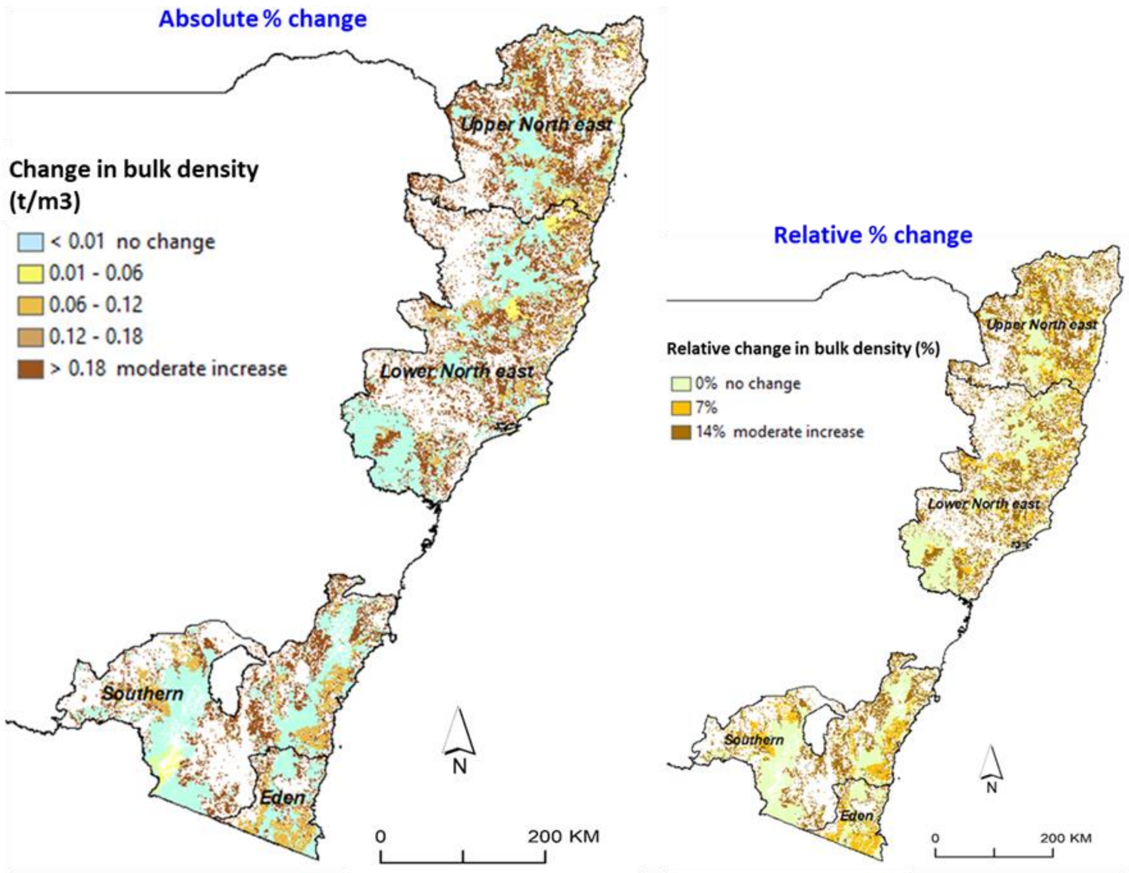

Figure 16: Change in bulk density from hypothetical relatively undisturbed conditions to current condition, 0-10 cm (main image: absolute %; inset image: relative%)

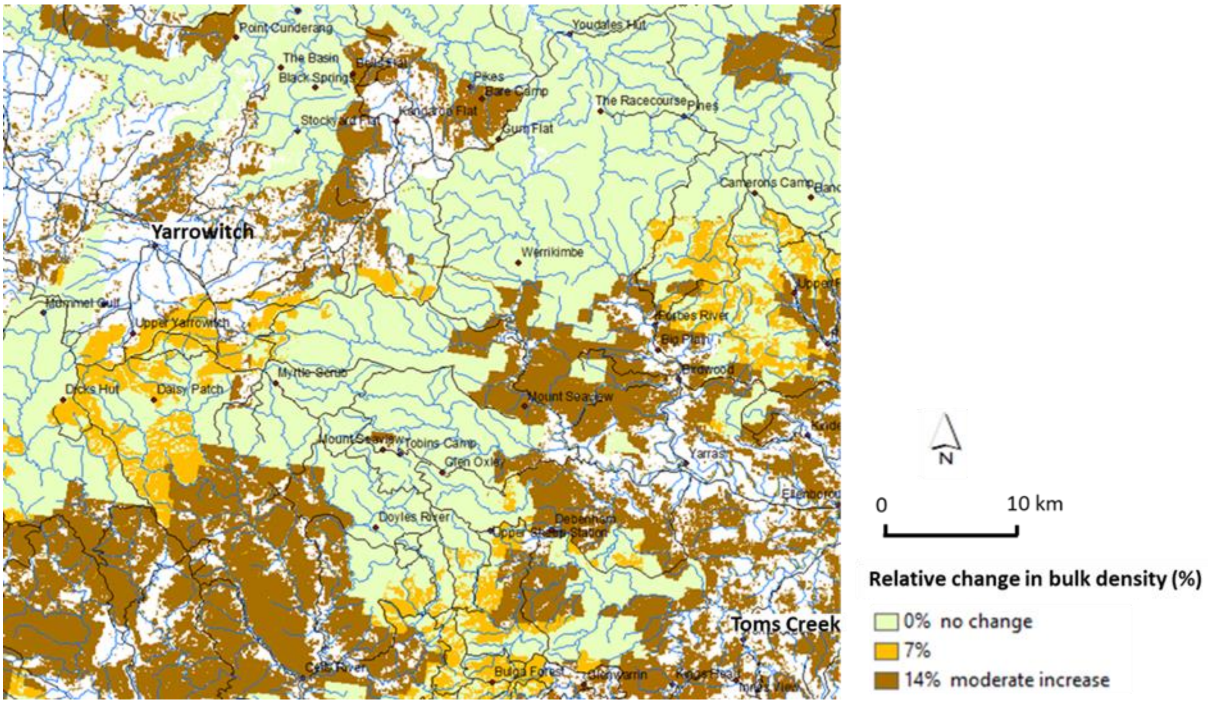

Figure 17: Change in bulk density from hypothetical relatively undisturbed to current condition, Yarrowitch Region, 0-10 cm (t/m^3)

The change in bulk density due to human disturbance for each RFA region is presented in Table 7. It reveals the highest overall increases in the Upper and Lower North East regions. Increases are greatest in the surface soils.

Table 7: Mean relative change in bulk density with forest disturbance by RFA region (%)

RFA Region	0-10 cm	10-30 cm	0-30 cm
Upper North East subregion	8.3	7.6	9.7
Lower North East subregion	6.7	5.9	8.0
Southern	5.0	4.8	5.7
Eden	5.7	5.3	6.5

3.4 Extractable and total phosphorous

3.4.1 Key drivers

The variable importance plot of Figure 18 presents the relative influence of the ten most significant environmental and management variables on extractable P over the 0-30 cm interval. These results are complemented by the MLR standardised regression coefficients given in Appendix 1. The MLR and random forest models developed to explore extractable P were not strong, with maximum Lin's concordance of 0.32 (0-30 cm interval), meaning the results do not have high certainty.

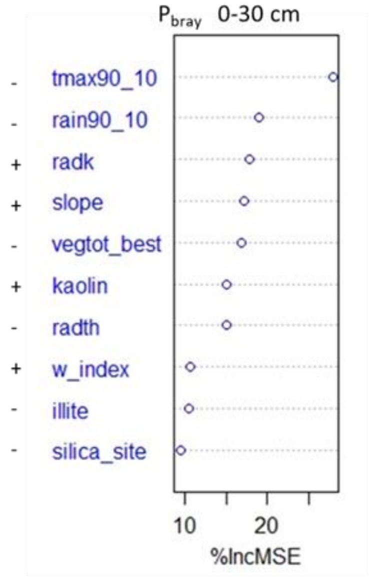

Figure 18: P_{ext} variable importance plot, 0-30 cm

The climatic variables of rainfall and temperature are revealed as the dominant controlling factors of extractable P in the forest environment. Values are shown to increase with decreasing rainfall and decreasing temperatures

The parent material and soil indicators are prominent drivers of P_{ext}, as represented by radiometric K and Th, plus clay composition and silica index. The negative direction of the silica variable reflects the higher values associated with mafic clay rich soils rather than siliceous sandy soils. Higher values are also revealed with more highly weathered soils through the weathering index.

P_{ext}, is shown to increase with more steeply sloping sites and lower vegetation cover sites. Forest management, as represented by FDI and years since bushfire did not have a significant influence on this property.

Previously derived results for total phosphorus (P_{total}), from NSW wide analyses (OEH 2018) indicate a clear dominance of parent material/soil variables, particularly silica index, as a controlling driver. A clear increase with mafic, clay rich soils is again revealed.

3.5 Dispersion percent (sodicity)

3.5.1 Key drivers

The relative influence of the various environmental and management variables on DP (sodicity) is presented in the variable importance plot of Figure 19, which gives the top ten variables and displaying direction of influence. These results are complemented by the those presented in the table of MLR standardised regression coefficients given in Appendix 1. The MLR and random forest models were only weak to moderate strength, with maximum Lin's concordance of 0.30 (0-30 cm interval), meaning the results do not have high certainty.

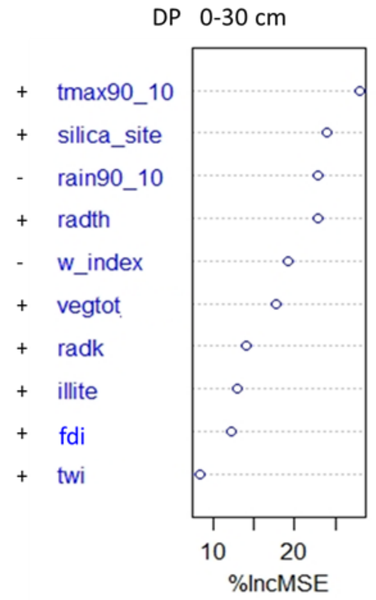

Figure 19: Dispersion percent variable importance plot, 0-30 cm

The climatic variables of maximum temperature and rainfall are revealed as the dominant drivers of DP. Values are shown to increase with increasing temperatures and decreasing rainfall. This reflects the mobile nature of sodium, being easily leached from the soil under moist conditions.

The parent material and soil indicators are prominent drivers of DP, particularly the silica index. The positive direction of the silica variable reflects sodium becoming more dominant relative to other major cations as soils become more siliceous. Additionally, because total cations are low in siliceous soils, even a small addition of sodium through airborne salts derived from the ocean, can result in a relatively large increase in DP.

Vegetation cover and forest management are both revealed as significant drivers of DP. The property is revealed to increase with increasing vegetation cover, but also with increasing forest management disturbance. These somewhat contradictory trends suggest a complex relationship of DP and soil sodicity with forest management.

The weak positive relationship with TWI, suggests higher DP and sodicity on lower parts of the landscape, in accord with accepted pedologic theory. The variable representing years since bushfire did not appear to have any influence on this property.

3.6 Hillslope erosion

Figures 20 and 21 present the relative change (in %) in erosion rate from a modelled baseline condition to modelled current condition. The individual maps representing the two conditions were described and presented in the previously submitted *Baseline for Indicators* Report.

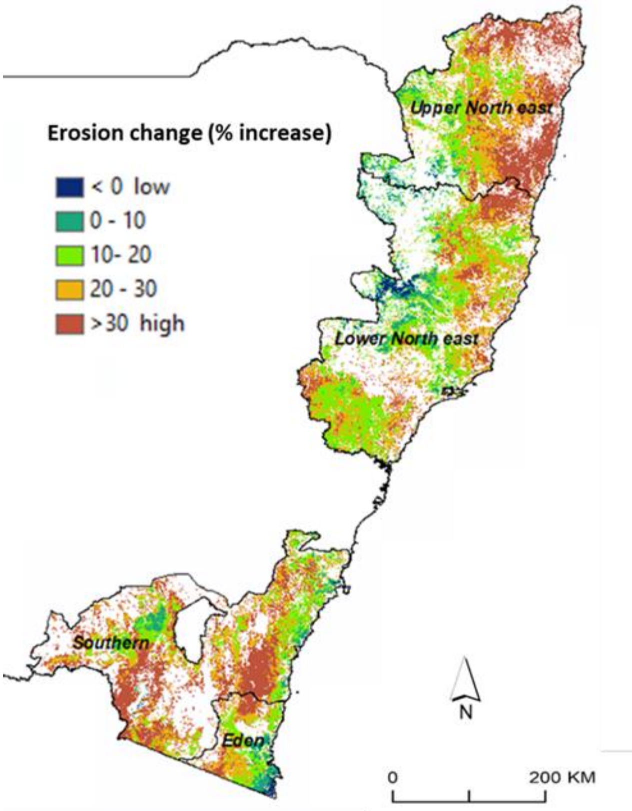

Figure 20: Change in erosion rate between modelled baseline and current condition (%)

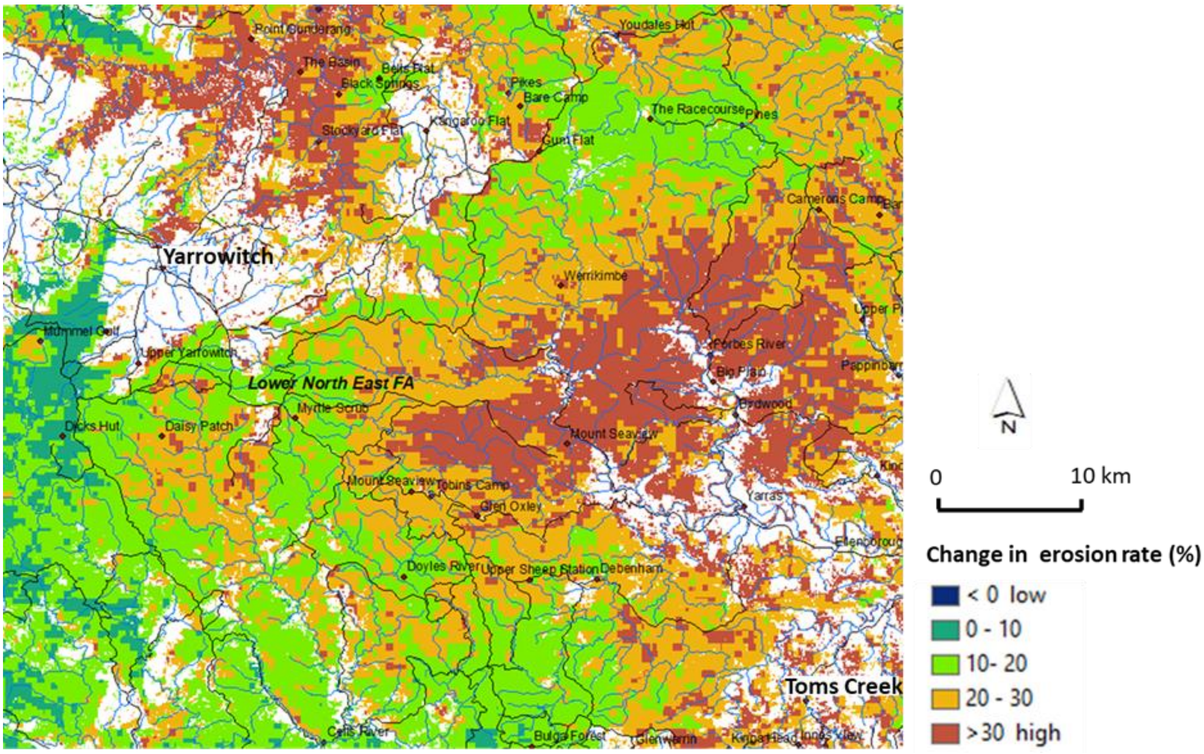

Figure 21: Change in erosion rate between modelled baseline and current condition, Yarrowitch Region (%)

Figure 22 shows the mean annual hillslope erosion rate in the forested lands compared to all NSW from 2001 to 2020. On average, the hillslope erosion rate in the eastern forest area (3.3 t ha^{-1} yr^{-1}) is about three time higher than the state average (1.0 t ha^{-1} yr^{-1}). This can be explained by these three reasons: i) the forested lands are normally in steeper slopes with higher LS values; ii) most of the forested lands are located in eastern coasts where the rainfall amount and intensity are higher compared the state average; 3) there are frequent bushfires in the forested lands which reduced vegetation cover level (thus increased the C factor values).

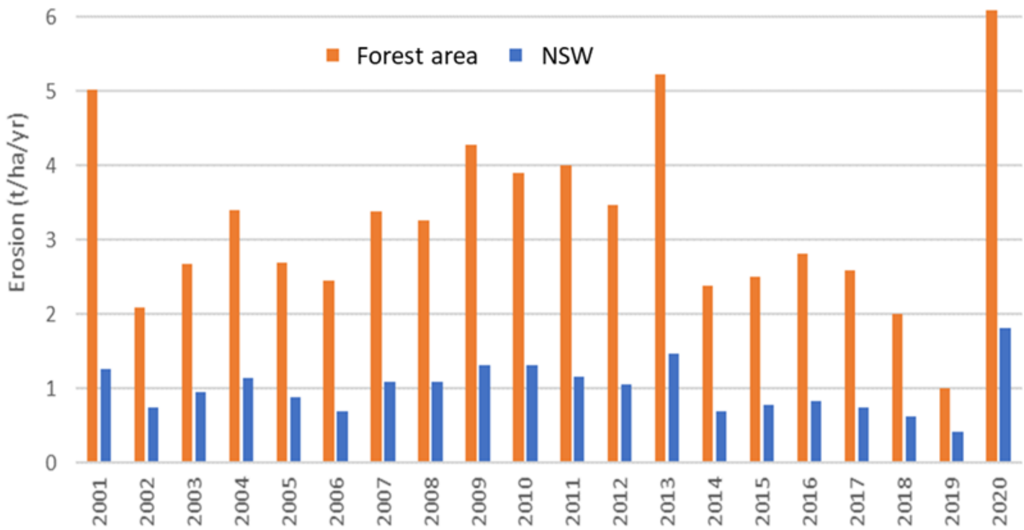

Figure 22: The mean annual hillslope erosion rate in the forested areas compared to all NSW from 2001 to 2020

Figure 23 further compares the annual hillslope erosion rates in the four major Regional Forest Agreement regions (RFAs) across NSW from 2001 to 2020. It shows that Lower North East RFA subregion has the highest hillslope erosion rate (5.4 t ha^{-1} yr^{-1}), followed by Upper North East RFA subregion (4.0 t ha^{-1} yr^{-1}), Southern FA (2.1 t ha^{-1} yr^{-1}) and Eden FA (1.7 t ha^{-1} yr^{-1}). There are also great seasonal and inter-annual variation in hillslope erosion. The maximum erosion rate was almost 10 t ha^{-1} yr^{-1}) in 2013 in Lower North East RFA subregion which was about 17 times higher than the lowest rate (0.6 t ha^{-1} yr^{-1}) in 2009 in Eden RFA. Overall, the hillslope erosion rate in the eastern forest area is the highest in summer, especially in February (0.8 t ha^{-1} $month^{-1}$) which is more than 10 times higher than the winter (e.g. July) rate (<0.1 t ha^{-1} $month^{-1}$) as shown on Figure 24.

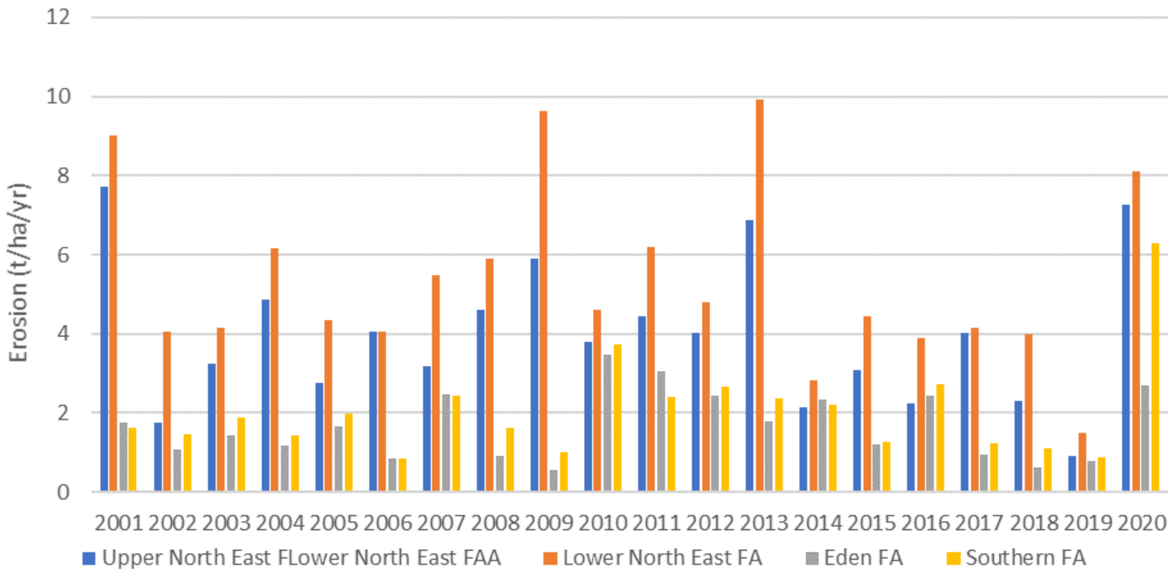

Figure 23: The mean annual hillslope erosion rate in the four major forested areas across NSW from 2001 to 2020.

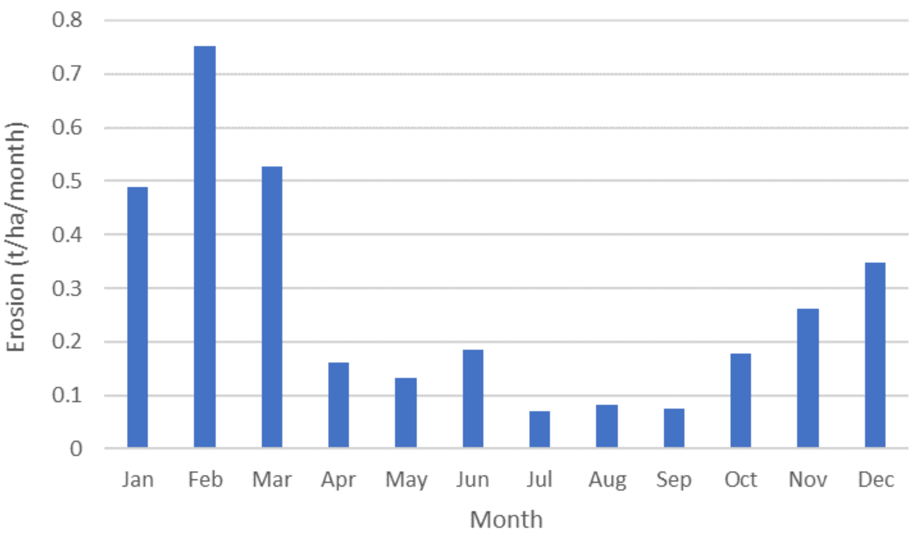

Figure 24: The mean monthly hillslope erosion rate in NSW forested areas during the period 2001-2020.

4 Discussion

Digital soil mapping techniques have been used to provide data and insights into the drivers and trends of change of soil condition over eastern forests of NSW. A lack of existing long-term soil monitoring sites across the region means there is no empirical data to base results on at this stage. As a result, it has been necessary to rely on modelling outputs, based on existing historic soil data held by the NSW Government.

DSM techniques allow us ‘data mine” the existing data to establish key relationships and trends. Such information may not be readily apparent when examining single isolated sites. However, limitations in the modelling process need to be recognised and the results interpreted with caution, as discussed in s.4.3 below. Nevertheless, the results certainly provide a useful overview of key drivers and trends. These can be improved upon with addition of reliable data from appropriately established monitoring program

Data has been provided on six soil condition indicators, being SOC, pH, bulk density, phosphorous, sodicity (dispersion percent) and hillslope erosion. Together these provide a useful assessment of soil condition of forest soils.

4.1 Summary of driving factors

The status of soil indicators and their change are a product of various soil forming factors, climate, parent material, topography, biota and time, as recognised by early pioneering soil scientists Dokuchaev (1989) and Jenny (1941). Each of these soil forming factors can be represented by multiple sub factors. Biota includes all aspects of human influence and land management. The role of bushfire in this scheme is not immediately clear and could be considered as a sixth entirely new class of factor.

The DSM techniques provide a useful approach for identifying key drivers of the component soil condition indicators. The combination of these broad factors is shown to vary for each indicator.

Variable importance plots, as generated through the random forest modelling technique, provide useful visual representation of the relative influence of the different variables in the model. These results were complemented by standardised regression coefficients from multiple linear regression (given in Appendix), which importantly reveal the direction of influence of each variable.

Climate and parent material/soil type were revealed to be strong drivers for all indicators. Topographic factors were not revealed as strong drivers at the broad regional scale, but are likely to be more influential at a local scale. These environmental variables are broadly beyond the control of human influence.

Forest management and the associated vegetation cover factors are demonstrated to be important drivers for most soil condition indicators. They exerted particularly key roles for SOC and bulk density, allowing useful maps of their change with changing land management to be developed.

SOC levels were revealed to decline with increasing disturbance from forestry harvest operations and uncontrolled stock grazing, and the associated reduction in vegetation cover. Bulk density was shown to increase under those conditions, indicative of declining soil structure and soil condition.

The forest disturbance index (FDI) as developed in this project, is a very broad indicator of management. Further insights will be gained when more detailed division of forest management operations are available and assessed, for example, considering the intensity and frequency of logging operations.

The number of years since bushfire was demonstrated to be a key driver of SOC, as further discussed below.

4.2 Summary of trends

This study applied a ‘space for time substitution’ process, where spatial patterns are substituted for temporal patterns (Pickett 1989; Blois *et al.* 2013).It was revealed that increased ground disturbance, as indicated by the FDI, results in decreasing SOC. The change of status from relatively undisturbed reserved lands to forestry harvest lands then to moderate disturbance (uncontrolled grazing by stock) results in progressively lower SOC values. These changes are typically also often associated with decline in vegetation cover, particularly where stock grazing occurs, which also contributing to SOC decline.

The reverse trend was revealed for bulk density, where increasing forest disturbance resulted in a detrimental increase in this indicator, a trend also reported by Huang et al (1996). The disturbance from heavy vehicles and hard hooved stock results in compaction of soils. It is evident that the intensity of disturbance is associated with decline in soil condition. Managers of these forests should endeavour to minimise ground disturbance where possible in order to maintain soil condition.

The influence of climate change on SOC and pH was examined by applying results from the recent NARCliM program (Gray and Bishop 2018, 2019). Trends of strong decline in SOC and slight rise in pH were revealed over the forest study area, however the magnitude of change varied between the 12 different climate models applied in the NARCliM program. The decline in SOC is indicative of a projected decline in soil condition and ecosystem health. Any significant change in soil pH, either rise or fall, can be detrimental to natural ecosystems that are adapted to particular pH ranges. A resulting degree of migration of ecosystems may be a slight consequence that reserve managers need to be aware of. The pH change is unlikely to be a critical issue for forestry production over the times scales considered in this study.

Bushfires are predicted to have a major influence on SOC, with a dramatic loss evident immediately following the bushfire, in the order of 50%, followed by a gradual recovery of content in the following years, approaching re-equilibrium levels after approximately 75 years. The influence of prescribed burning on SOC was not assessed in this study, but it should be examined in ongoing monitoring programs.

4.3 Limitations

The models upon which the driving factors and trends were based were typically not strong, as reported in the *Baseline for Indicators* Report (DPIE, submitted to NRC April 2021), with Lin’s concordance values generally in the range of 0.3 to 0.4. This means all results need to be treated with an element of caution. The estimates of change provided in the maps should not be relied upon at fine scale, but provide a useful first approximation

As mentioned in Baseline report, the overall uniformity of environmental conditions over the region (ie, generally moist climate, infertile soils, steep terrain and high vegetation cover), means there is a lack of contrast in conditions that normally contribute to models of greater strength. There appears to be incomplete coverage of all required areas of key environmental space, ie, combinations of different environmental conditions, over the forest study area. These and other limitations were raised in the Baseline report, together with key references that further discuss potential uncertainties in digital soil modelling applications.

The analysis of many trends reported here relied on the space for time substitution modelling approach. This assumes patterns of variations in space can substitute for patterns of variations in time, which may not always be valid.

At this stage there is insufficient reliable data to fully model the impacts from differing types and levels of forest disturbance. The FDI presented and applied in this study was a very coarse indicator that cannot reflect the subtle differences between various forms of forest management, eg, intensive or periodic selective logging. Similarly, broad assumptions had to made in relation to the bushfire analysis, with local variations in fire intensity from a recorded bushfire event not considered.

These limitations will be partly addressed with the acquisition of more reliable data from carefully selected and meaningful monitoring sites. This will allow more reliable analysis of trends from both digital modelling and conventional empirical analysis approaches.

4.4 Combining indictors to single forest soil condition index

The report has examined drivers and apparent trends in change of a number of separate indicators of forest soil condition. Each indicator has a different response to environmental and forest management factors and have differing trends projecting forward.

Systems are currently being explored by DPIE to combine these indicators into a single soil condition index. Previously reported options as presented in the Literature Review Report (submitted to NRC October 2020) will be considered.

An option being considered is to first normalise the extent of change from the relatively undisturbed soil for each separate indicator, for example by converting to relative change %. Then the average change of the indicators is derived, or perhaps the average of the three most significant changed indicators. From this a system of identifying the overall change in forest soil condition from the separate component indicators is derived. The results of change of the individual component indicators would also be presented in addition to the overall combined single index of forest soil condition.

5 Conclusion

This report has used digital soil mapping techniques to provide data and insights into the drivers and trends of change of soil condition over the RFA regions. The lack of existing long term soil monitoring sites across region means no empirical data was available to base results on at this stage, thus a modelling approach has been necessary.

It was revealed that a change in forest management from relatively undisturbed reserved lands to partial disturbance (forestry harvest operations) then to moderate disturbance (uncontrolled grazing by stock) results in progressively lower SOC values and higher bulk density. Both these indicators point to a decline in forest soil condition under this increased level of disturbance.

Projected climate change into the future is demonstrated to lead to a decline in SOC and rise in pH over the forest area and an overall decline in soil condition. Bushfire is predicted to have a severe impact on SOC and resulting soil condition.

A greater understanding of the driving factors of soil condition and ongoing trends into the future requires further data that can only be obtained with the establishment of a well designed forest soil monitoring program. This should be a priority for the NSW Forest Management Improvement Plan.

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Appendix

Table A1. Standardised regression coefficients from MLR models

Soil forming factor	**Variable**	**Total OC**				**pH**				**Bulk density**		
		0-10[1]	**10-30**	**0-30**	**30-100**	**0-10**	**10-30**	**0-30**	**30-100**	**0-10**	**10-30**	**0-30**
Climate												
	Rainfall	+0.27	+0.32	+0.27	+0.24	-0.15	-0.15	-0.16	-0.18	+0.38	-0.35	-0.01
	Temp_max	- 0.23	- 0.33	- 0.28	-0.12	+0.19	+0.11	+0.13	+0.07	-0.28	+0.13	+0.06
Parent material/soil												
	Silica/lithology	-0.16	-0.21	-0.19	-0.22	-0.27	-0.28	-0.29	-0.19	+0.89	+0.38	+0.60
	Kaolin								-0.09			
	Illite	+0.09	-0.06								+0.18	+0.31
	Smectite					+0.04						
	Rad K	-0.09		-0.08		+0.28	+0.24	+0.26	+0.18		+0.17	
	Rad Th	+0.03			+0.07	-0.11	-0.11	-0.12	-0.15	-0.30		
	Rad U									+0.23		
Relief												
	Aspect index			+0.06	+0.07	0.06	+0.09	+0.09	+0.09		+0.21	+0.15
	Slope	+0.18	+0.17	+0.14	+0.15	+0.10	+0.11	+0.11	+0.08	+0.15		
	Topo wet index	-0.02	-0.05	-0.04		+0.04	+0.04	+0.04	+0.07			
Biota												
	Forest_disturb_index	-0.15	-0.12	-0.14	-0.04					+0.35	+0.04	+0.11
	Veg frac cover	+0.10	+0.06	+0.09	+0.07	-0.12	-0.13	-0.14	-0.15	-0.18	+0.16	+0.09
Age												
	Weathering index					-0.05				+0.42		
Fire												
	Years since fire	+0.14	+0.13	+0.14								

Soil forming factor	**Variable**	**$P_{extractable}$**				**Dispersion Percent (DP)**				**EC**
		0-10	**10-30**	**0-30**	**30-100**	**0-10**	**10-30**	**0-30**	**30-100**	**0-30**
Climate										
	Rainfall	-0.07	-0.06	-0.08	-0.13	-0.13	-0.18	-0.17	-0.14	-0.03
	Temp_max	-0.10	-0.06	-0.09	+0.05	+0.21	+0.19	+0.23	+0.12	-0.01
Parent material/soil										
	Silica/lithology	-0.09	-0.14	-0.09	-0.15		+0.08	+0.05	+0.15	-0.13
	Kaolin		+0.04	+0.05	+0.13		+0.08			+0.08
	Illite					+0.06	+0.06	+0.09	+0.10	-0.09
	Smectite					-0.09	-0.09	-0.09	-0.06	
	Rad K					+0.08	+0.17	+0.13	+0.07	-0.15
	Rad Th	-0.20	-0.27	-0.24	-0.30	+0.06		+0.05		
	Rad U	+0.12	-0.20	+0.15	+0.17					
Relief										
	Aspect index		+0.13							
	Slope	+0.14		+0.15		-0.04	-0.02	-0.06		
	Topo wet index							+0.03		+0.02
Biota										
	Forest_disturb_ index			+0.04		+0.16	+0.15	+0.16	+0.12	
	Veg frac cover	-0.08	-0.14	-0.11	-0.11	+0.14	+0.05	+0.08		-0.18
Age										
	Weathering index	+0.07		+0.07		-0.10		-0.10	-0.05	+0.10
Fire										
	Years since fire					-0.07	-0.08	-0.07	-0.09	

[1] Depth interval (cm)

Appendix B: Data cube project report

Forest Monitoring and Improvement Program
Project 4: Baselines, drivers and trends in soil health and stability
DPIE (Science) and University of Sydney, 6 June 2021

Final report:

1 Introduction

This report presents the final report of trend and drivers of soil health and stability. The report is outline as follows:

- Methods
- Results
- Conclusion

2 Methods

2.1 Preprocessing and collation of data cube

The primary indicator of soil health adopted for this project is soil organic carbon (SOC). We have identified and collated potential space-time predictors of this variable. Figure 1 gives an overview of the description of the datasets processed and collated into a data cube for modelling. The data cube consists of SOC measurements, the month and year of profile sampling, as well as the space, and space and time covariates associated with the soil profile locations.

Table 1: Overview of data collated for modelling

Data type	Covariate	Source	Resolution	Note
Response	Soil organic carbon (SOC)	SALIS	-	0-30 cm
Spatial	DEM, slope	Geoscience Australia	90 m	
	Topographic Wetness Index (TWI), Multi-resolution Valley Bottom Flatness (MrVBF)	ASRIS	90 m	
	Gama-radiometric data • Potassium • Uranium • Thorium • Radiation dose	SLGA	90 m	
	Silica	Gray et al. (2016)	~100 m	
	Clay % (0-5)	SLGA	90 m	
Spatial and temporal	Precipitation	SILO	5 km, monthly	

Data type	Covariate	Source	Resolution	Note
	Temperature (min and max)	SILO	5 km, daily	
	Solar radiation	SILO	5 km, daily	
	NDVI	LANDSAT	30 m, 16-day	

2.1.1 Data cube SOC

The profiles data were obtained from the SALIS database. Figures 1-2 present data of where SOC has been measured in the Regional Forest Area and are based on all the datasets held by DPI-E. Figures 1 present their spatial distribution in RFA regions for different time slices. Figure 2 presents the same data but as number of observations per RFA region with different time slices. In broad terms the number and distribution of soil carbon measurements for each time slice is promising in terms of applying the data cube approach to the pre-2010 period. An obvious issue is the lack of data for 2010 onwards and any predictions for 2010 onwards are assuming pre-2010 vegetation and weather variation represents the 2010+ period where we are extrapolating in time.

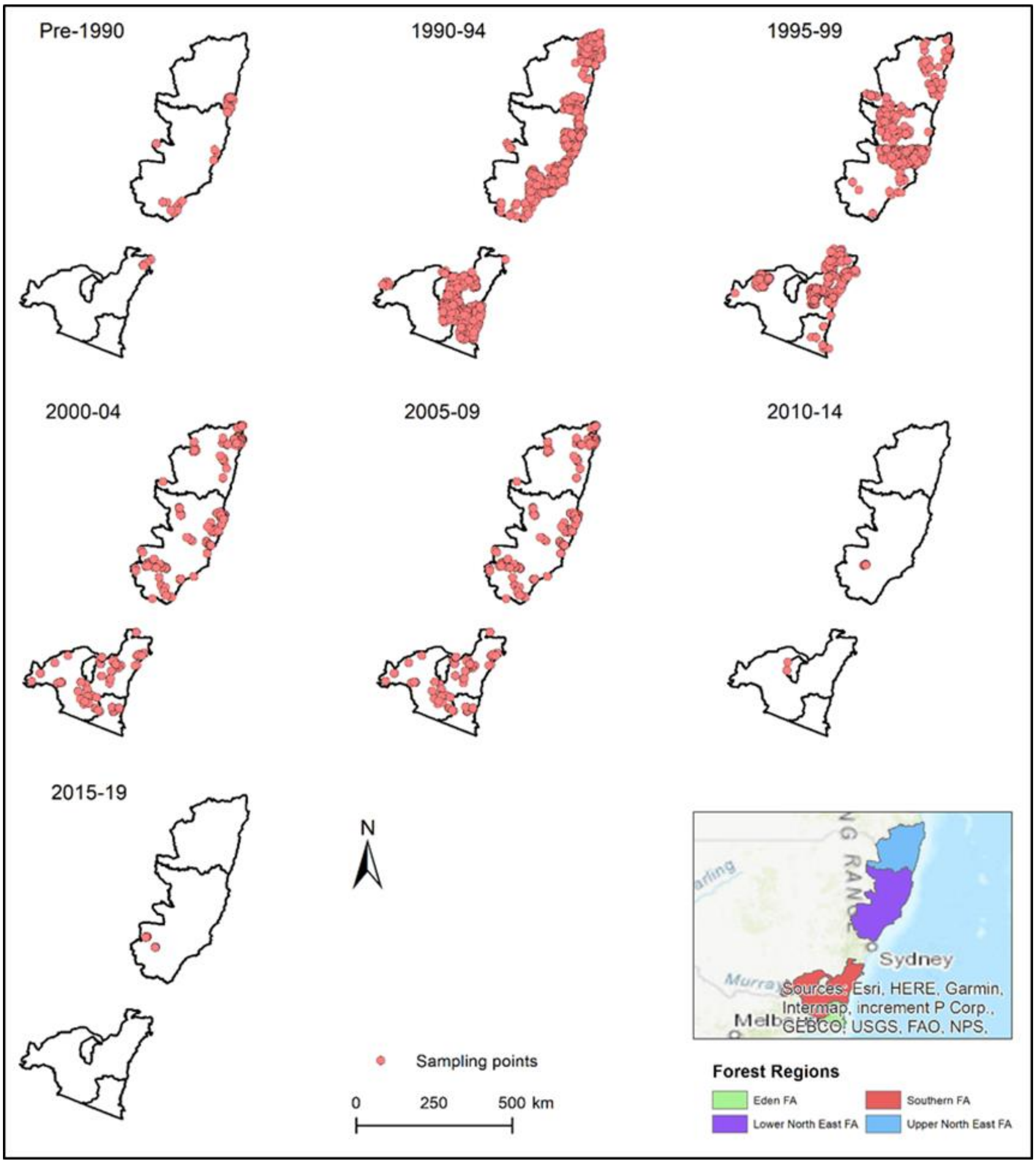


Figure 1. Spatial distribution of surface organic carbon measurements across RFA regions

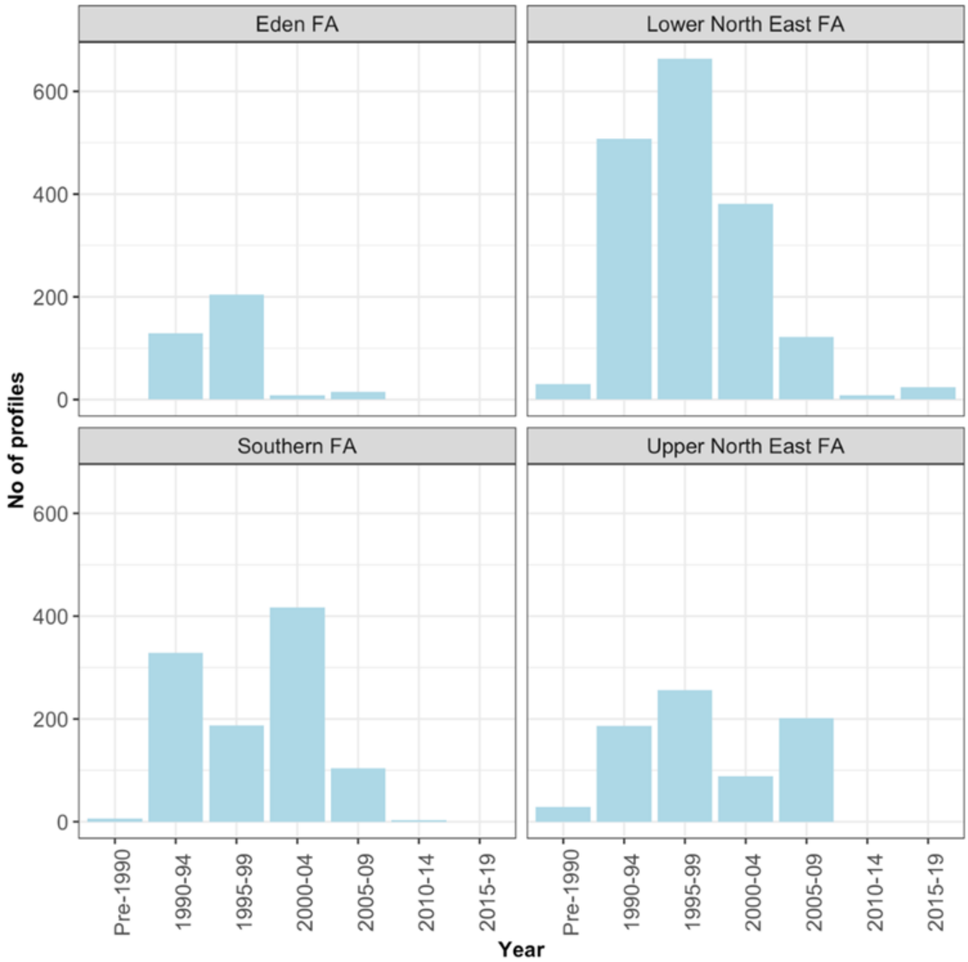


Figure 2. Number of surface organic carbon measurements across RFA regions

In modelling and mapping soil attribute from legacy data such as the one used in this project, certain known sources of variation like differences in depth characteristics of the soil profiles, as well as the use of different analytical methods between laboratories and survey campaigns need to be considered carefully. We dealt with depth variation by harmonising the SOC measurements at different depths to the reference standard depths specifications of the Global Soil Map consortium. We achieved this by applying a mass-preserving spline function (Bishop et al., 1999) and output the means at the standard depths. However, we aggregated the SOC measurements of the first three standard depths (0-5, 5-15 and 15-30 cm) using a depth weighting function and subsequently adopted this for further analysis and reporting. Generally, over half of SOC stored in the top 100 cm of soil is in the top 30 cm (Batjes, 1996) and this layer is impacted the most by human and natural disturbances. We also accounted for variation in SOC measurements arising from the differences in analytical methods by including a field in the data cube indicating what SOC analytical method was used.

Additional SOC data was provided by the University of Sydney. This dataset was collated from a project on bushfire covering the period from 2015 to 2019 (Figure 3). Soil samples were collected at a depth of 0-10 cm from burnt and unburnt sites, totally 78 overall. Because of the limited number of observations in this dataset, it was not added to the data cube but was rather used as an independent test set to evaluate the space-time model. Only points (n = 23)that fall with the forest land cover and were in the RFA were used for this purpose.

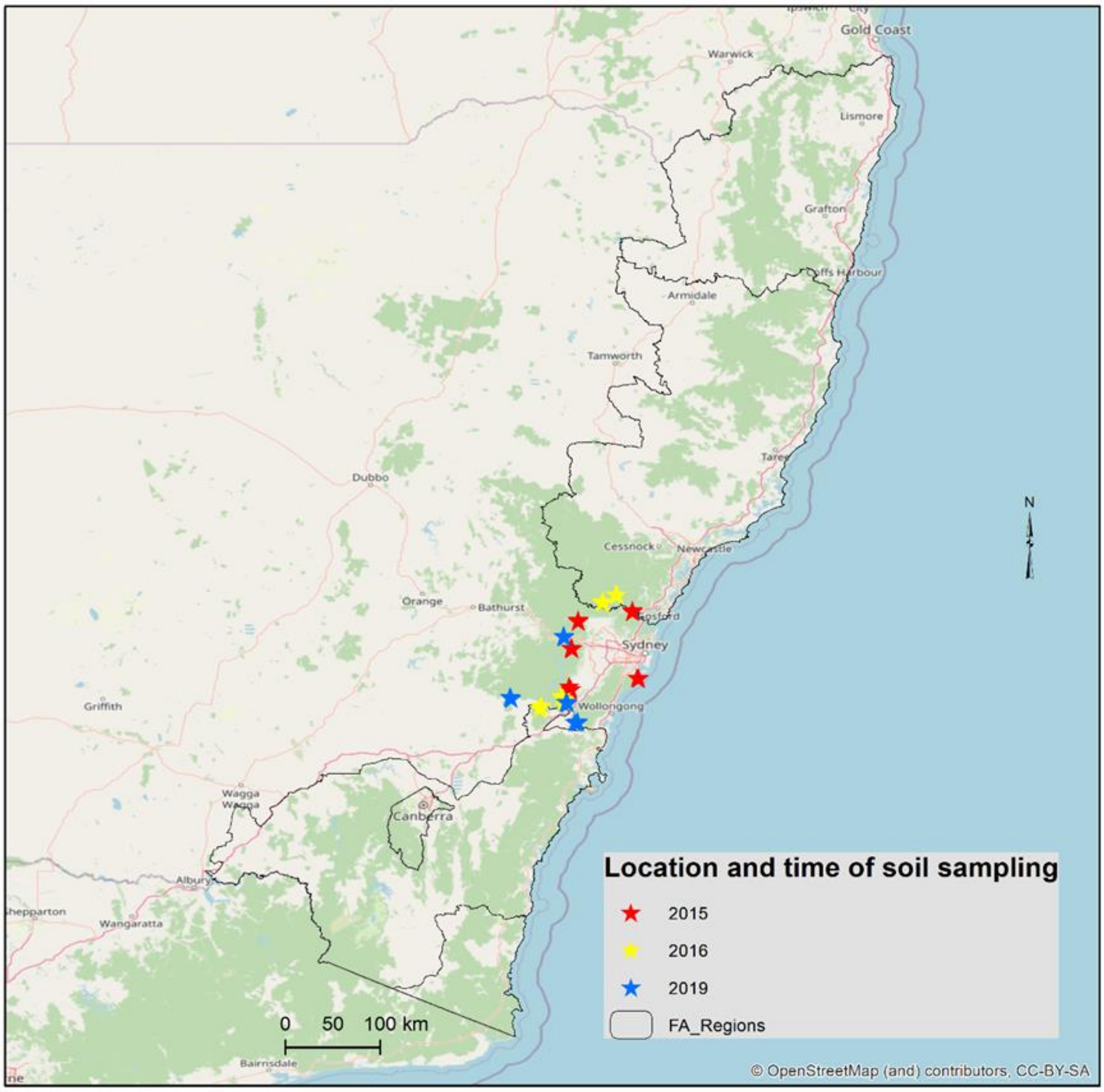


Figure 3. University of Sydney bushfire research soil surveys 2015-2019

2.1.2 Covariates

Potential covariates for SOC prediction consisted of data that vary in space and those that vary in both space and time (Table 1). All time-varying covariates (NDVI and climate variables) were aggregated to monthly values. Since the effect of these covariates on soil health dynamics depends on current and past conditions, we applied a decay function weighting algorithm (Figure 4) to aggregate sixty months (5 years) of the covariate timeseries prior to when the soil profile was sampled. The algorithm attaches more weight to the most recent observations. Feature extraction by this method instead of taking the mean value over the last 5 years has been shown to create better predictive models (Wimalathunge & Bishop, 2019)

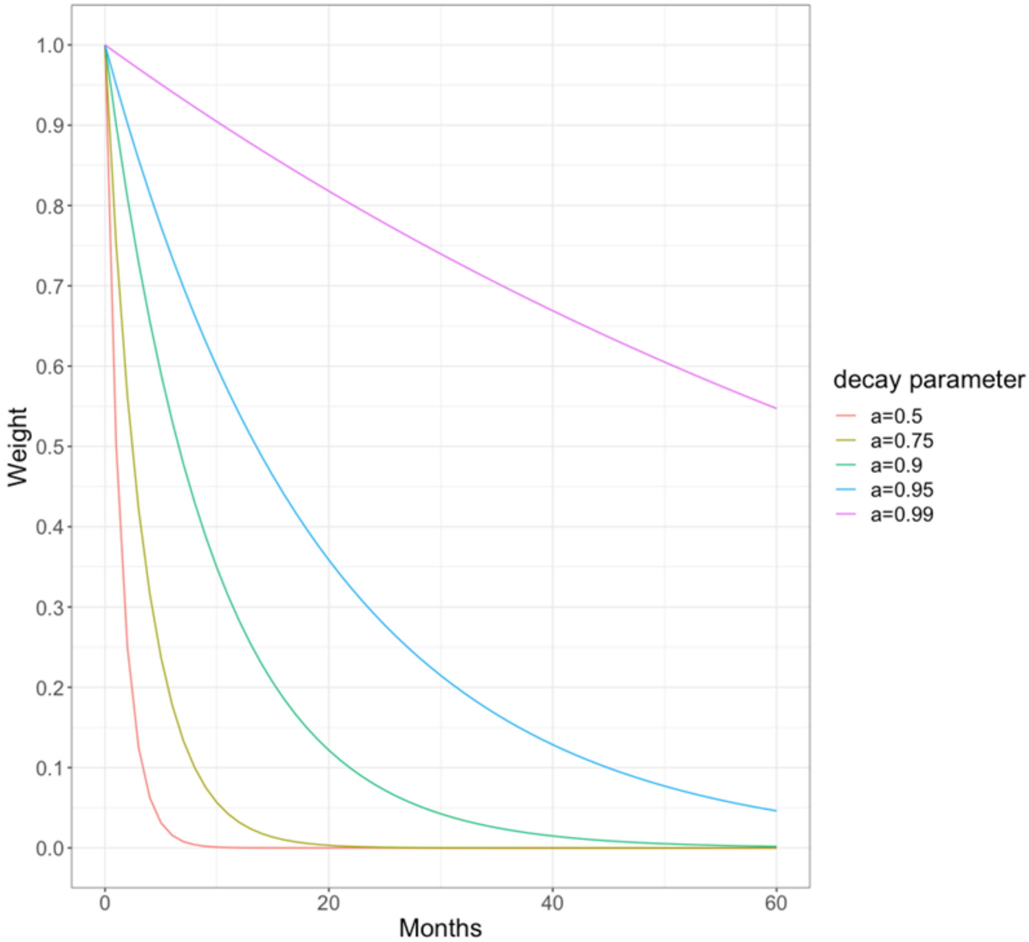


Figure 4: Exponential decay function used to weight the time -varying covariates over prior months to soil profile sampling date.

Another key feature of the data cube is the incorporation of the proxy for natural and anthropogenic disturbances of SOC dynamics at the time of soil profile sampling compared to conditions at discrete times in the past. The potential effect of these disturbances is represented in the data cube by incorporating NDVI difference features wherein the NDVI of the previous 1, 2, 3, 6, and 12 months are subtracted from the NDVI of the month of profile sampling. For example, if there was a fire 2 months ago, we would expect there would be a drop in NDVI between the NDVI today and 3 months ago. This could be useful in situations where we don't have fire or logging spatial data.

While most of the pre-processing and extraction was done in R, a large portion of the NDVI preparation was done in Google Earth Engine (GEE). This is more efficient and circumvents the need of downloading relatively large amount of Landsat scenes, thus freeing up local storage space. The GEE Java scripts used for the NDVI extraction are available and can be to be used to extract NDVI data.

2.2 Modelling and prediction of SOC

2.2.1 Data preparation

Prior to modelling, some initial data preparation steps were carried out. First, data used for modelling was restricted to profiles sampled from the forest landcover class within the RFA. We used the binary landcover forest extent layer of 2008 to extract forest soil profiles. Second, we only retained SOC measurements with values between 0.1 and 15 %, as SOC values below this range are not reliable and values above this range are mostly organic soils which are underrepresented in the region and are difficult to incorporate into models (Gray et al., 2015). In addition some covariates did not completely cover the study area, the main example being the gamma radiometrics survey data. Figure 5 shows the distribution of profiles with complete and incomplete cases.

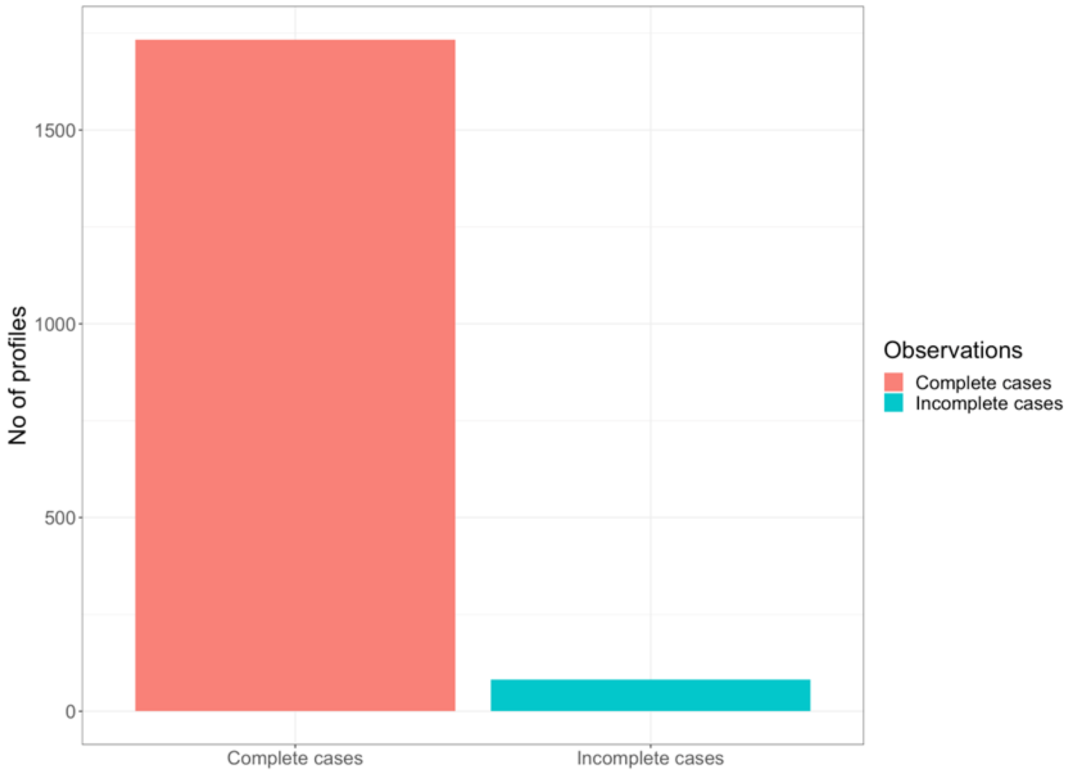


Figure 5: Soil profile distributions with complete and missing covariate observations

2.2.2 Feature selection, modelling and prediction

The data for modelling was partitioned into training and testing sets using a 80:20 stratified random split based on year of sampling. Prior to modelling, a recursive feature elimination algorithm (RFE) (Guyon et al., 2002) was used to select covariates.

Using the selected covariates and the training dataset, a final model was calibrated using quantile regression forest (QRF). Calibration involved the tuning of the number of predictors sampled for splitting at each node (*mtry*) of the RF model using a 10-fold cross-validation approach. The 10-fold cross-validation involves calibrating a model on all but a fold of the training set and validating it on the excluded fold. This is repeated until every fold is used nine times for calibration and once for validation. Out of the three values evaluated for the *mtry* hyperparameter (2, 8 and 15), 5 was determined to be optimal and used to build the final model.

Model performance was evaluated on both the training and test sets. Comparison between observed and predicted SOC was done using the following metrics: root mean square error (RMSE), and the Lin's concordance correlation coefficient (LCCC). LCCC measures the level of agreement between the predicted values with the observed values, relative to the 1:1 line, and the RMSE measures the accuracy of the model.

The estimated model was then used on a stack of regular grid of covariates to predict monthly SOC from January 1990 to December 2021. Since the model was built using QRF, it is possible to make prediction for different quantiles. Therefore, SOC predictions were made for the 0.5-quantile (median) and the 0.05- and 0.95-quantiles as the lower and upper bounds of a 90% prediction interval. The 0.95-quantile SOC prediction can be used as an indicator of the carbon sequestration potential of the soil. The monthly maps of the median SOC were spatially aggregated for the RFAs and the forest disturbance index (FDI, management regimes) to form a temporal timeseries of SOC. For brevity, the monthly values were further averaged to yearly values and then plotted to show the temporal SOC trends. It was not plausible to derive the uncertainty (e.g., 0.05- and 0.95-quantiles) of the spatial aggregates as this requires modelling the spatial autocorrelation of prediction errors (Heuvelink et al., 2020), which is not estimated with QRF. Finally, we created a video animation for 2015 to 2020 monthly SOC maps for the Wauchope area where the NRC forest health project had some experimental plots. This is highlight how the modelling approach could be visualised.

3 Result

3.1 Model selection

Result of the RFE showed the optimal number of covariates to be 15 (Figure 6) out of the 37 originally fed to the algorithm. Adding more covariates did not lead to any significant further decrease in RMSE. While the RFE algorithm retained four soil and terrain space covariates, the remaining were vegetation and climate space-time attributes (Figure 7). In terms of the importance of the selected covariates in the final model, the space-time covariates (i.e., vegetation and climate attributes) ranked higher than the space covariates (i.e., terrain and soil attributes). Generally, NDVI was ranked as the important covariate (ranked between 1 to 6) and clay was ranked the least, with no contribution to the model (Figure 7). Elevation was the highest ranked variable among the soil and terrain covariates (ranked 9). All five exponential decay parameter values were important for NDVI, indicating that substantial temporal smoothing of the variable was used in SOC prediction.

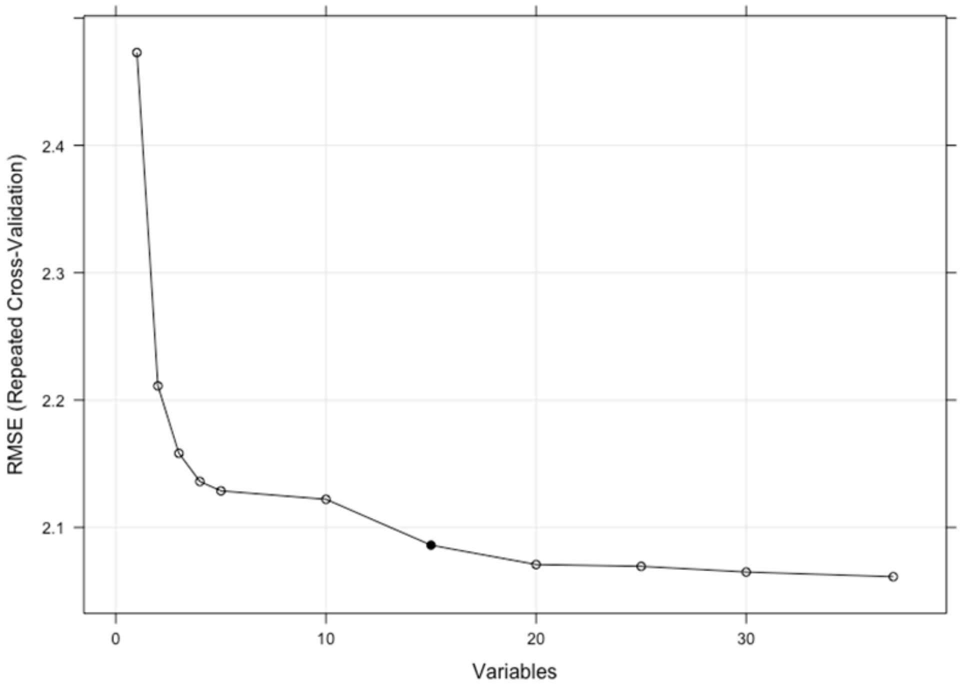


Figure 6: Root mean square error (RMSE) for different subset of covariates included in the random forest model as derived with the RFE.

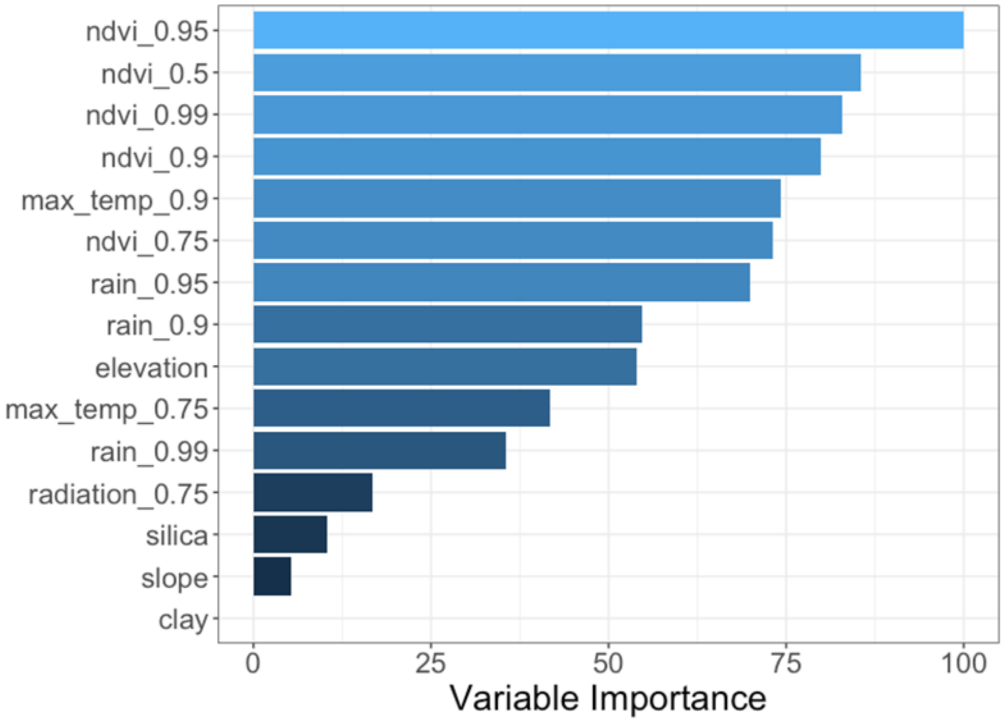


Figure 7: Variable of importance for the 0-30 cm SOC model

3.2 Model evaluation

Evaluation of the prediction model on both the training and test data indicate a reasonable performance, although the model performed better on the training than on the test set (Figure 8). The predicted SOC has less variation than the actual observations. This is not uncommon with empirical prediction methods.

The model, however, performed poorly on the independent dataset obtained from the Uni Sydney (Figure 9). It should be noted that the independent data was quite localised and from an epoch (2015-2019) where there were few soil carbon observations on which to train the model. Thus this gives and indication of the quality of the model when extrapolating to time periods when there is few data (post-2010) as compared to validation set which gives an indication of the model quality when applying it to periods when there are more observations (pre-2010). It should also be noted that the data was collected from 0-10 cm whereas our modelling was performed on 0-30 cm which is another source of error.

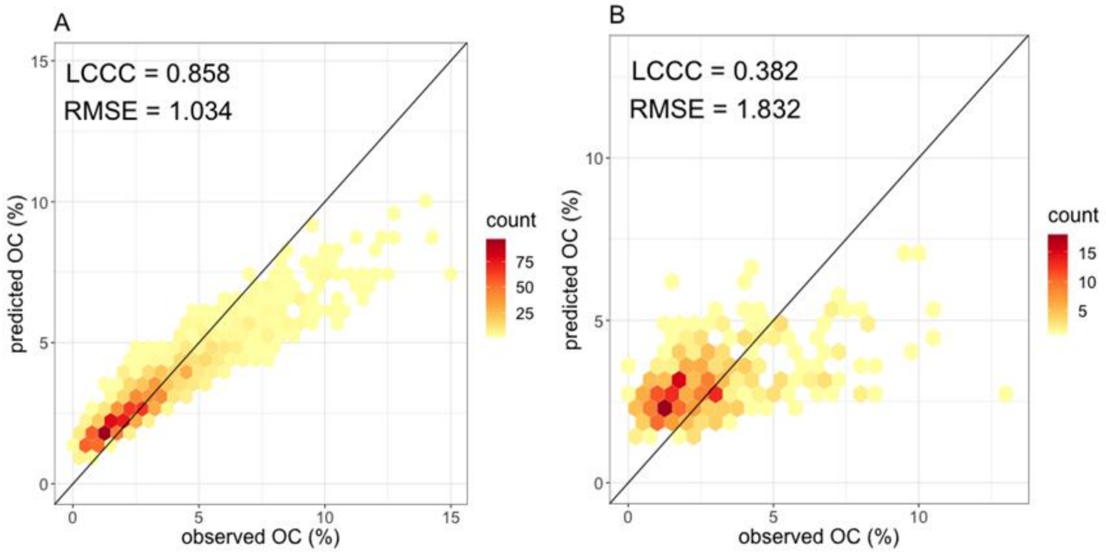


Figure 8: Scatterplot of predicted against observed 0-30 cm soil organic carbon (SOC) based on model evaluated on the (A) training and (B) test data. Diagonal line is the 1:1 line; LCCC, Lin's concordance correlation coefficient; RMSE, root mean square error

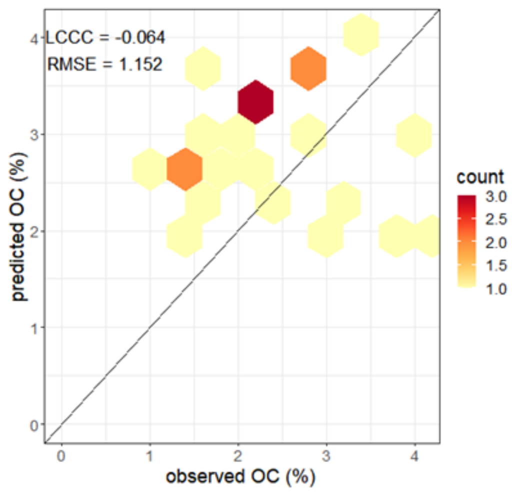


Figure 9: Scatterplot of predicted against observed 0-10 cm soil organic carbon (SOC) based on model evaluated on independent data from the University of Sydney. Diagonal line is the 1:1 line; LCCC, Lin's concordance correlation coefficient; RMSE, root mean square error

3.3 Predicted SOC maps

Figure 10 shows the predicted 0-30 cm SOC maps for the month of June 1990, 2000, 2010 and 2020. While the temporal trend is not generally apparent from the maps, the relative difference between the SOC for 2020 relative to those of 1990, 2000 and 2010 show substantial changes in SOC (Figure 11). Generally, it would appear that there is a substantial decline in SOC in 2020 compared to 1990 levels across large areas of the RFA. An animated GIF of the monthly time series of SOC for a subset within the RFA is shown in Figure 12. However, the trends are far from significant as Figure 13 presents the lower and upper 90% prediction interval for 2020 and it is clear that all previous estimates for each year fall within these bounds. Therefore, while we see a trend of decline we are highly uncertain that it is true and may never know as there has been such sparse measurement of soil carbon in the RFA regions since 2010.

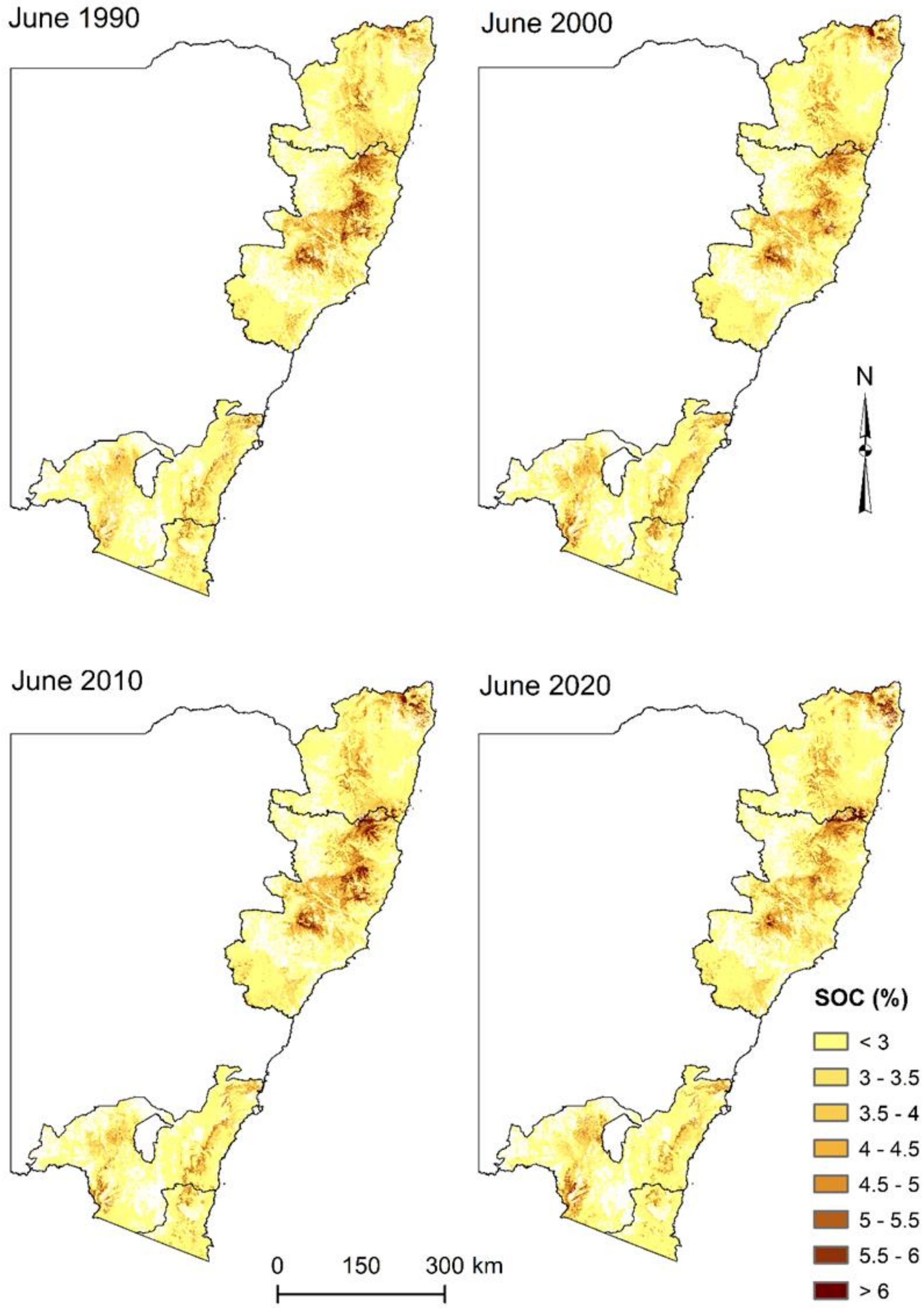


Figure 10: Predicted 0-30 cm SOC in the forest of the RFA

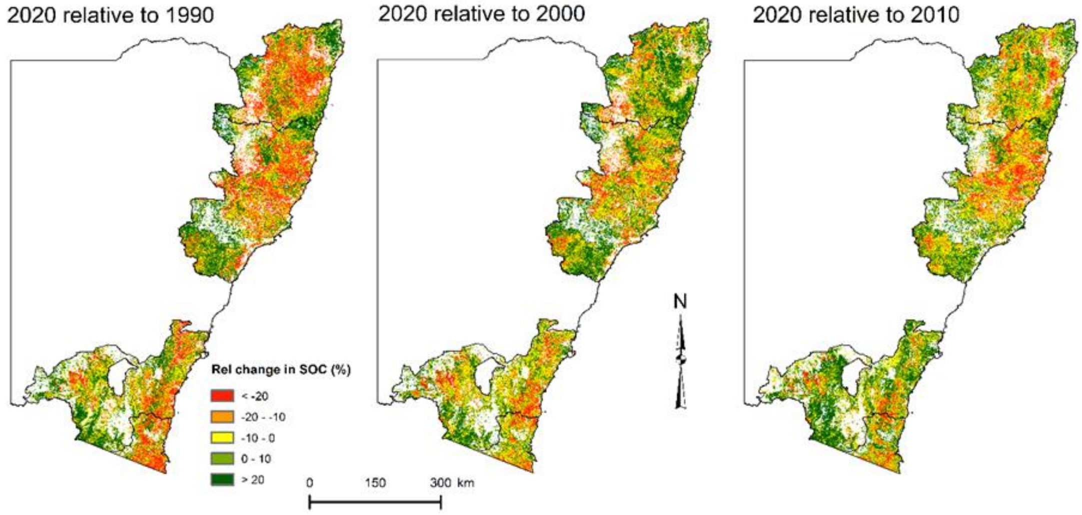


Figure 11: Change in predicted 0-30 cm SOC in 2020 relative to years 1990, 2000 and 2010

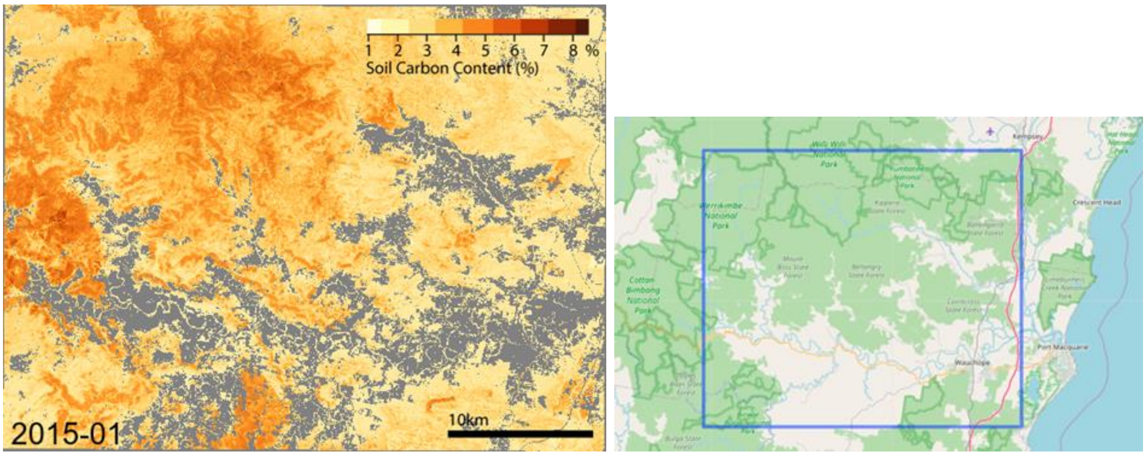


Figure 12: Animation of monthly SOC from 2015 to 2020 (left) in the Wauchope area. The map to the right shows the area on a base map for context.

The difference between the 0.05- and 0.95-quantile maps in Figure 13 indicates a wide 90% prediction interval, which is in agreement with the RMSE in Figure 7.

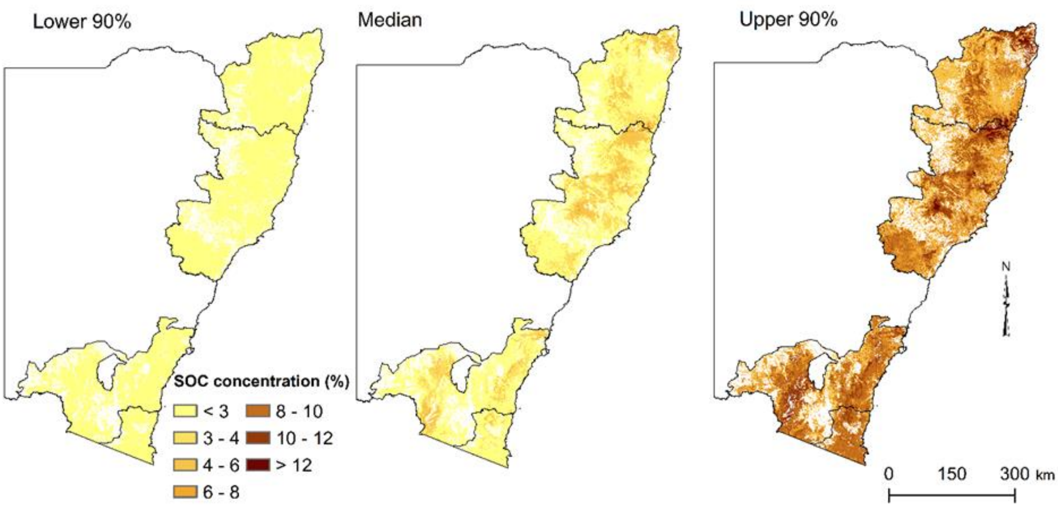


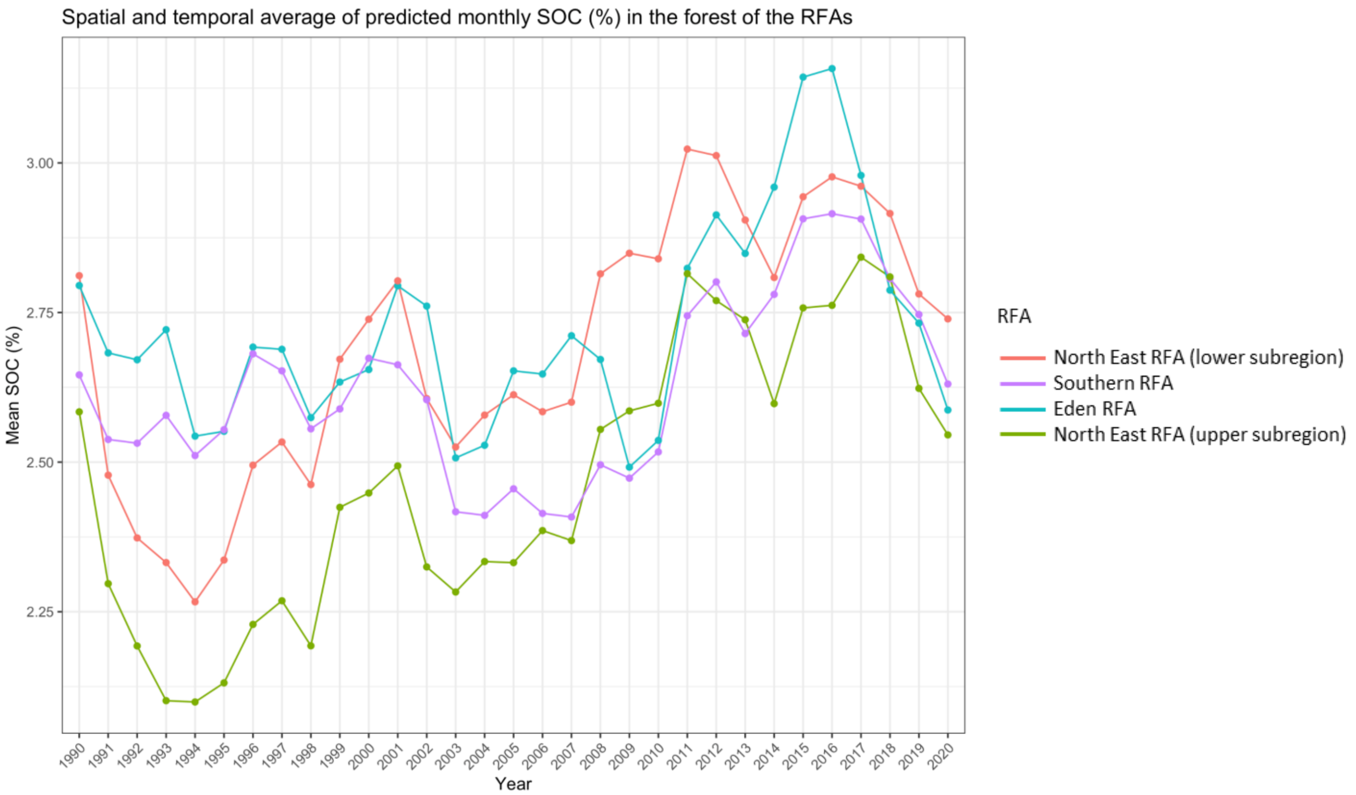
Figure 13: Maps of the 0.05-, 0.5- and 0.95-quantiles of the 0-30 cm SOC for June 2020

3.4 SOC time series

Figures 14 shows the time series of spatially and temporally aggregated monthly SOC in the RFA areas and the management regimes from 1990 to 2020. Although the overall trend in SOC is positive for both the RFAs and the management regimes, segments in the time series show a downward trend. Of particularly note is the downward trend in SOC since 2017.

Interestingly, the predicted SOC under different management regimes show SOC levels are inversely related to the degree of disturbance in the area, with the SOC higher in protected areas and least in unprotected areas.

Once again we are only plotting trends based on our predictions which have some uncertainty and while predictions over regions are generally more precise (Bishop et al., 2015) we would expect these would be non-significant in statistical sense.



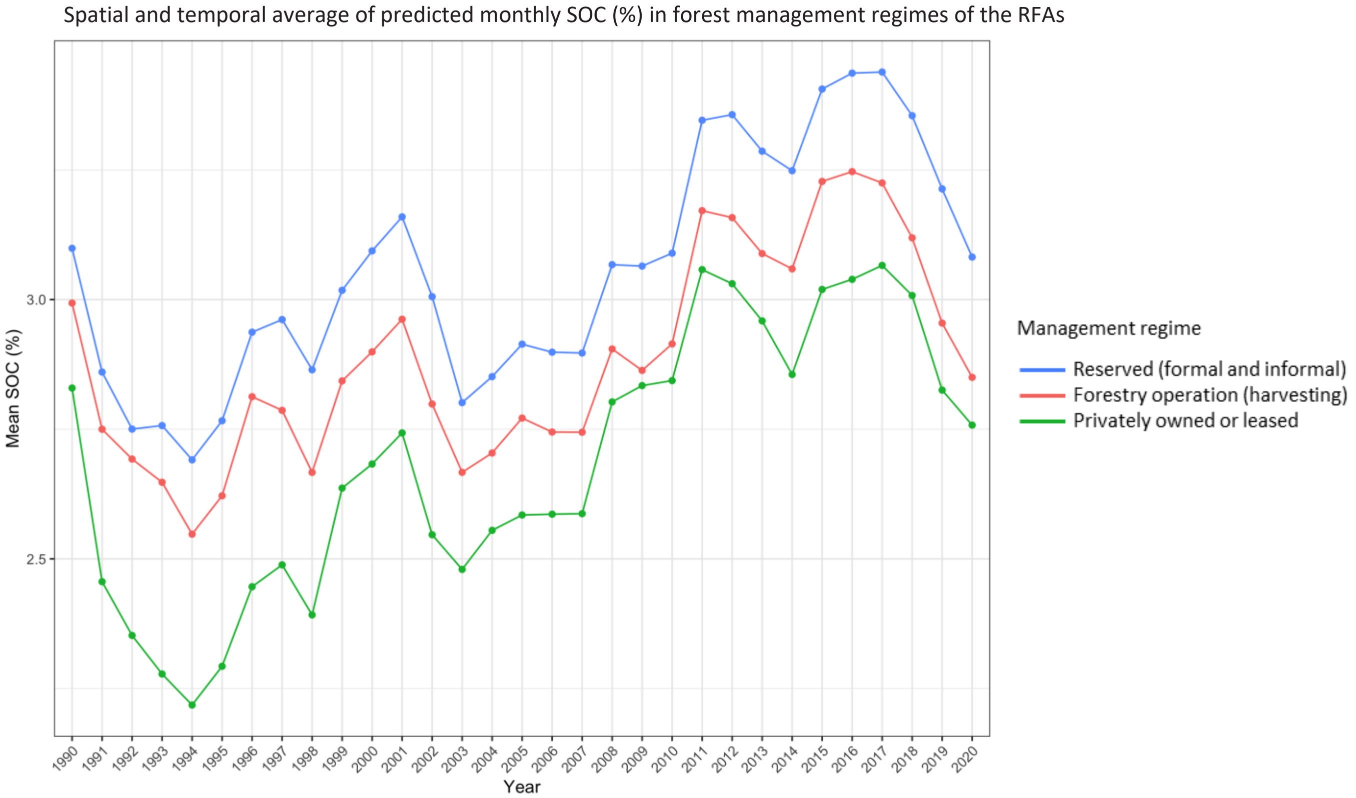


Figure 14: Yearly predicted 0-30 cm SOC (%) spatially averaged for the forests of the RFAs (top) and the management regimes (bottom)

4 Discussion & Conclusions

We have developed a workflow and implemented a prototype model for forest soil SOC in the RFA. The main issue is the data sparsity in the post-2010 period but further investment in sampling in the coming years is likely to improve the model predictions overall and for this period in particular. Recently Meyer & Pebesema (2021) published the concept of area of applicability (AOA) which examines the multivariate attribute space where samples are taken relative to the entire grid of prediction locations. This is to define the AOA for a model in a spatial context, i.e. where the predictions could be useful. Future work could extend this concept to space and time to examine how well we have sampled the multivariate attribute space of the data cube and for each time period produce an area of applicability map.

One further source of improvement is use of prediction methods that account for the spatial and temporal auto-correlation of the observations and offer an interpolation component when predicting. We present some exploratory results on this in the Appendix where we use Gaussian Process Regression (GPR). The method holds promise but due to data sparsity, accounting for the spatial and temporal auto-correlation did not improve the predictions and added unnecessary complexity. This approach has the approach has the advantage of being able to be used to predict at different spatial supports with a plausible uncertainty estimate allowing better testing of trends through time for RFA regions or other spatial units.

Given the major limitation of the work was the lack of soil observations the main recommendation beyond extra sampling effort is to expand the study domain to all of NSW as this will increase the number of observations available. This will help the model learn relationships between covariates and will bring into play superior methods such as GPRs.

5 Scripts

A GitHub repository (https://github.sydney.edu.au/informatics/PIPE-1663-Forest-Soil-Carbon) describes all of the code used to generate the data cube and perform the analysis.

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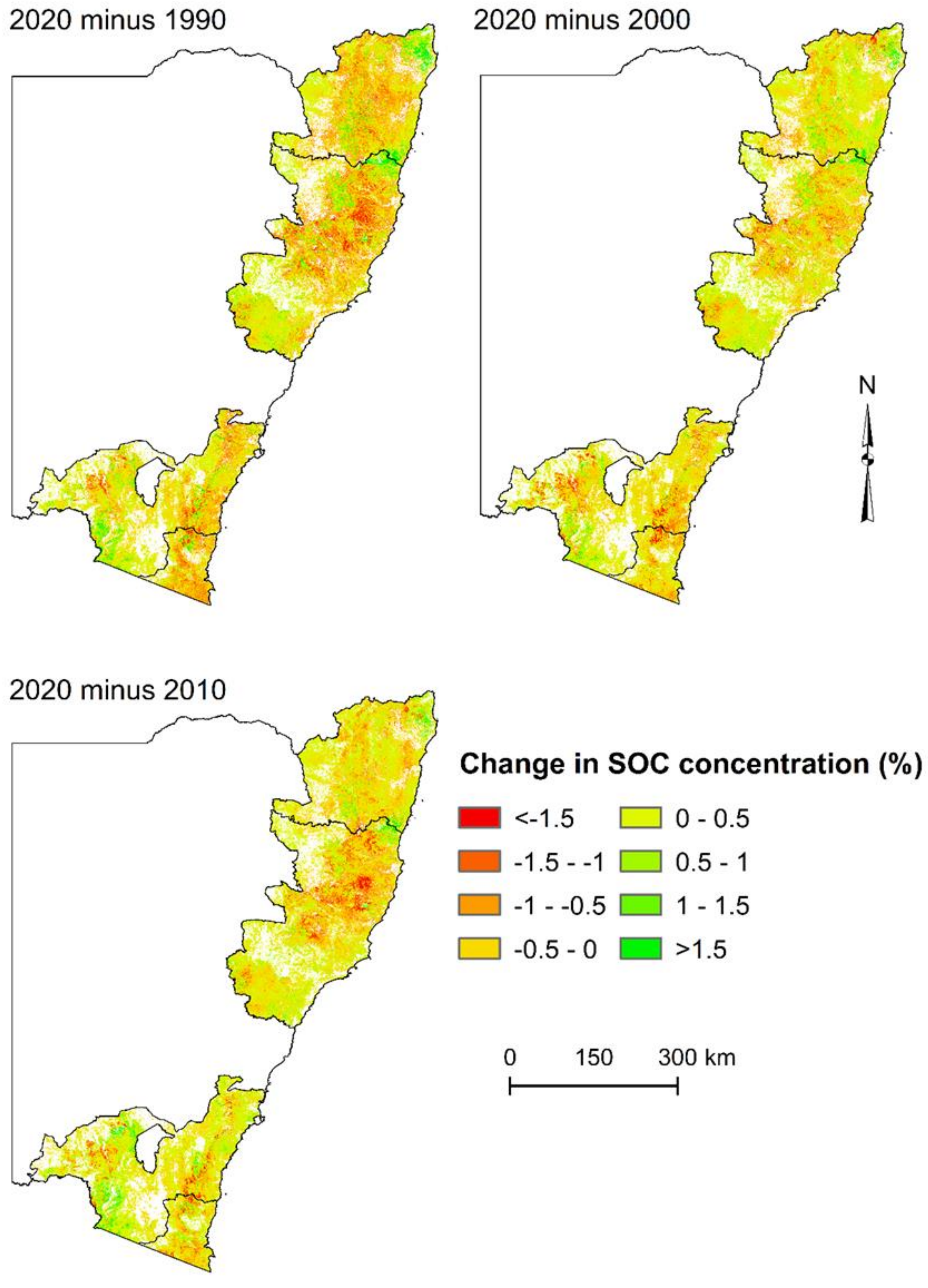
7 Appendices



Appendix 1: Difference maps for predicted 0-30 cm SOC in the forest of the RFA for the year 2020 relative to 1990, 2000 and 2010.

A Probabilistic Machine Learning Framework for Spatial-Temporal Mapping of Soil Carbon

Sebastian Haan, Sydney Informatics Hub

Summary

Here we propose a probabilistic framework that transforms sparse soil measurements and other surface measurements into predictive carbon maps and their uncertainty. The spatial-temporal predictions are performed via Gaussian Processes (GP) with custom kernel to take into account spatial-temporal correlations and complex multi-variate mean function options that depend on additional covariates (e.g. terrain, vegetation, top soil properties).

Some of the main advantages and features of this method are:

- Generation of predictive maps (including uncertainty maps and covariances) at any scale, resolution, or time.
- Consideration of heteroscedatic input uncertainties via modified GP kernel:
  - positional and temporal uncertainties of measurements
  - soil carbon measurement uncertainties
- Input: sparse carbon soil measurements plus surface measurements of multiple covariates (DEM, Temperature, NDVI, Slope etc).
- Output data: Soil Carbon plus their uncertainties as spatial maps at any future time; possible output format options are:
  - Point estimates (as voxels or cells in Cube)
  - Volume integration (averaging prediction and uncertainties over spatial area blocks and time periods) while taking into account predicted point covariances
  - Field (statistical averaging over custom areas as specified in polygon shapefiles)
- Output maps:
  - Prediction maps
  - Uncertainty maps
- Multiple options for covariate-dependent mean function of GP:
  - Bayesian Linear Regression
  - Bayesian Neural Networks
  - XGBoost
  - Random Forest
- Global GP hyperparameter optimisation
- Gaussian Process kernels with sparse spatial-temporal kernels and cholesky decomposition

Other Features:

- Multi-model calculation of Feature Importance (Random Forest, Bayesian Linear Regression, XGBoost, Bayesian Neural Network)
- X-fold cross-validation and Model Prediction plus Uncertainty Evaluation
- Model export and transfer functions for prediction or testing on other areas
- Prediction of spatial covarariance (e.g., for spatial integration)

- Export format options:
  - csv tables
  - geolocation-referenced tiff
  - shapefiles (as polygons for custom areas)
  - images with custom color schemes

Introduction to Gaussian Processes

GPs are a flexible, probabilistic approach using kernel functions with non-parametric priors, and are successfully used in a large range of machine learning problems (see Rasmussen and Williams 2006 for more details). Some of the important advantages of the GP method are that it generates a predictive distribution with a mean and variance for each prediction point and that the GP marginal likelihood function is well defined by the values of their hyper-parameters, which allows it to optimise them exactly. This reasoning about functions under uncertainty and their well-tuned interpolation character allows GPs to work extremely well for sparse data as well as for big data (see (Melkumyan and Ramos 2009) for solving large covariance matrix).

A GP $f(\mathbf{x}) \sim \mathcal{GP}\big(m(\mathbf{x}), k(\mathbf{x}, \mathbf{x}')\big)$ is completely determined by its mean function $m(\mathbf{x}) = \mathrm{E}[f(\mathbf{x})]$ and covariance $k(\mathbf{x}, \mathbf{x}') = \mathrm{E}\big[(f(\mathbf{x}) - m(\mathbf{x}))\big(f(\mathbf{x}') - m(\mathbf{x}')\big)\big]$, essentially placing a multivariate Gaussian distribution over the space of functions that map the input to the output, or informally, to measure the similarity between points as function of, e.g., their distance (the kernel function) and to predict a Gaussian distribution over $f(x^*)$ (i.e., a mean value and variance) at any new sampling location (unseen point) x^* from training data. Here we propose a custom sparse covariance function $\mathbf{K}$ with a spatial-temporal kernel with three correlation lengthscales (x,y,t). Hyperparameters of the GP are optimised using a global optimisation algorithm.

Mean functions

If the mean function is not zero but given by a predictive deterministic function $m_\phi = f(\mathbf{x_c})$, the predicted GP posterior distribution is given by

$$y'|\mathbf{G}, \mathbf{y} \sim \mathcal{N}(m_{\phi'} + \mathbf{K}_{x,x'}^T \mathbf{K}_{x,x}^{-1}\mathbf{y} - \mathbf{m}_{\boldsymbol{\phi}}, \mathbf{K}_{x',x'} + \sigma_S^2 I - \mathbf{K}_{x,x'}^T \mathbf{K}_{x,x}^{-1} \mathbf{K}_{x,x'})$$

The covariates x_c are mostly surface measurements such as DEM, terrain slope, NDVIs, radioactivity, temperature, precipitation, and soil properties (clay, silica).

Bayesian Linear Regression

First, we standardise the data and apply a featurewise power transform scaler via scikit-learn implementation (default option). Power transforms are a family of parametric, monotonic transformations that are applied to make data more like a normal distribution. This is useful for modeling issues related to heteroscedasticity (non-constant variance), or other situations where normality is desired. In detail, the Yeo-Johnson transform (Yeo and Johnson 2000) is applied, which supports both positive or negative data. Note that the Bayesian Regression implementation in MLsoil is not limited only to power transform scaler but includes multiple options of scalers, such as StandardScaler or RobustScaler. After the featurewise scaling of data, a Bayesian ridge regression is performed using the algorithm described in Appendix A of Tipping (2001) where updates of the regularization parameters are done (MacKay 1992). To make the regression more robust, we add an automated feature selection after the initial regression by selecting only features with a ratio of correlation coefficient to standard deviation larger than two. Then a second BayesianRidge regression is made using only the selected features, and the model and coefficients are stored with non-significant coefficients set to zero. Predictions and their uncertainties are then obtained by using the trained model and are scaled back with the powerlaw transform, F.

Probabilistic Neural Network

The probabilistic neural network is implemented by building a custom tensorflow probability model with automatic feature selection for sparsity. This method requires a feature-wise standard scaler.

XGBoost

Here, the XGBoost eXtreme Gradient Boosting implementation of https://github.com/dmlc/xgboost is applied. No data data scaling is required. For more implementation details and hyper parameter settings see xtree.py

Random Forest

The scikit-learn Radom Forest model implementation is applied. No data scaler required. Prediction uncertainties are currently estimates by using the standard deviation and Confidence Intervals of all decision trees. For more implementation details and hyper parameter settings see rf.py

Case study - Soil carbon forest

Data Overview

The proposed probabilistic framework is tested for a region of 140 times 140 km (Latitude: -33.0 to -31.48, Longitude: 151.45 to 152.9) with data that is marked as forest land-cover. The data spans a range of 18 years from 1990 to 2008. To take into account spatial temporal correlations, the data coordinates are projected into Cartesian coordinates for MGA Zone 56 and time-stamps are converted into days starting at 1990. An overview map is shown in Figure 1.

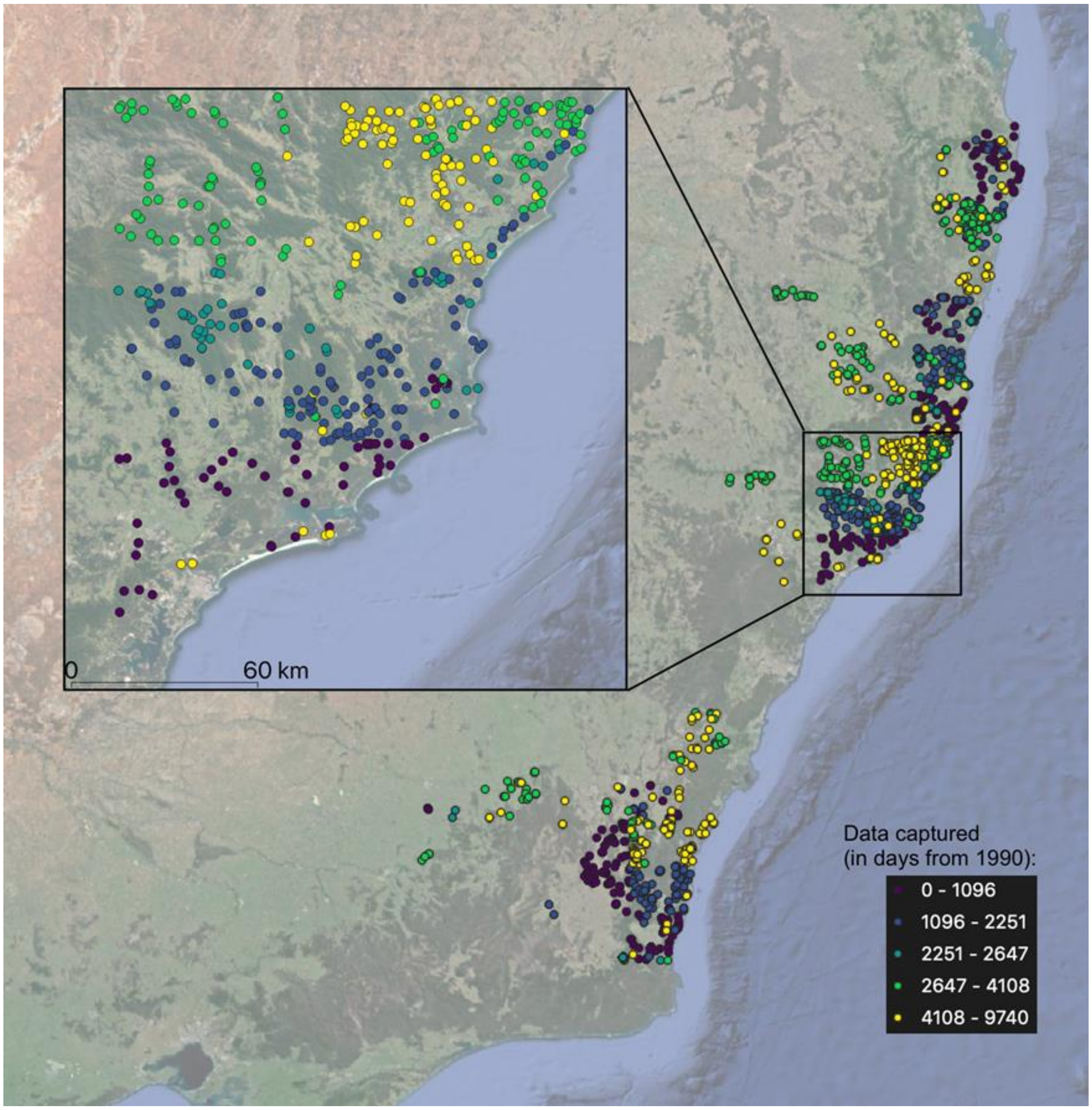


Figure 1. Map of the entire dataset and zoomed the selected region for testing.

Preliminary Results on Subset of Soil Forest

Feature Importance

Feature importance can be determined using multiple models such as Bayesian Linear Regression (see as example Fig 2), Bayesian Neural Networks, XGBoost feature importance scores, or via permutation importance using Random Forests.

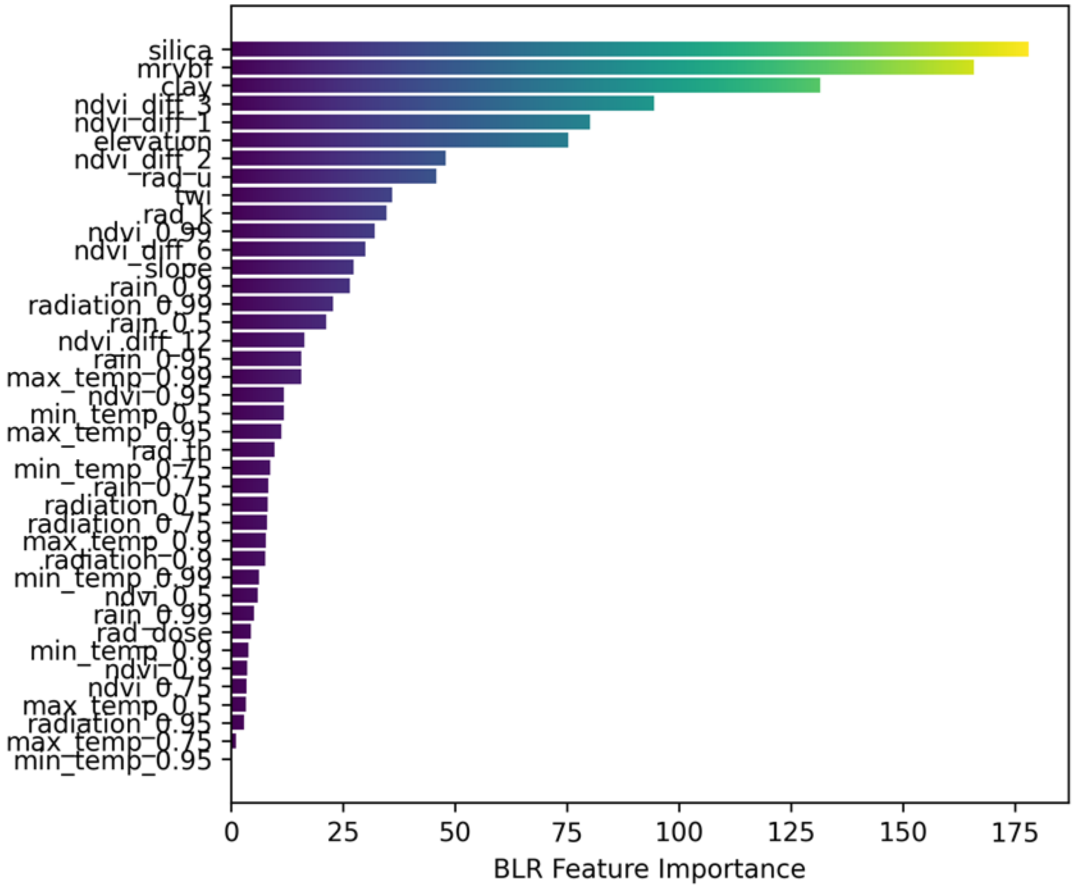


Figure 2. Feature Importance based on statistical significance of correlation coefficients of a Bayesian Linear Regression model.

Cross-Validation

Cross-validation is not only an important test to measure the accuracy of the trained model (e.g., via R2 or RMSE) but also to verify if predicted uncertainties are consistent with errors of the test data. The residual analysis is performed on the validation data with a split in train/validation ratio of 90/10 and 10-fold cross validation. The residual error $RE = Y_{pred} - Y_{ground}$ is defined as the predicted value minus the ground truth for each data point in the validation set. To test whether the predicted uncertainties are consistent with the residual error of the prediction, we can calculate the ratio

$$\theta = \frac{RE^2}{\sigma_{Ypred}^2}$$

The figures below show the best and the worst models in terms of RMSE of a 10 fold cross-validation set using Gaussian Process Model with a Random Forest Mean Function model. For the tested region no significant improvement for the test data is found by adding the Gaussian Process to the mean function. This indicates that there is no significant spatial-temporal correlation for this specific dataset, most likely due to the fact that measurements over time are relatively segregated (see Figure 1).

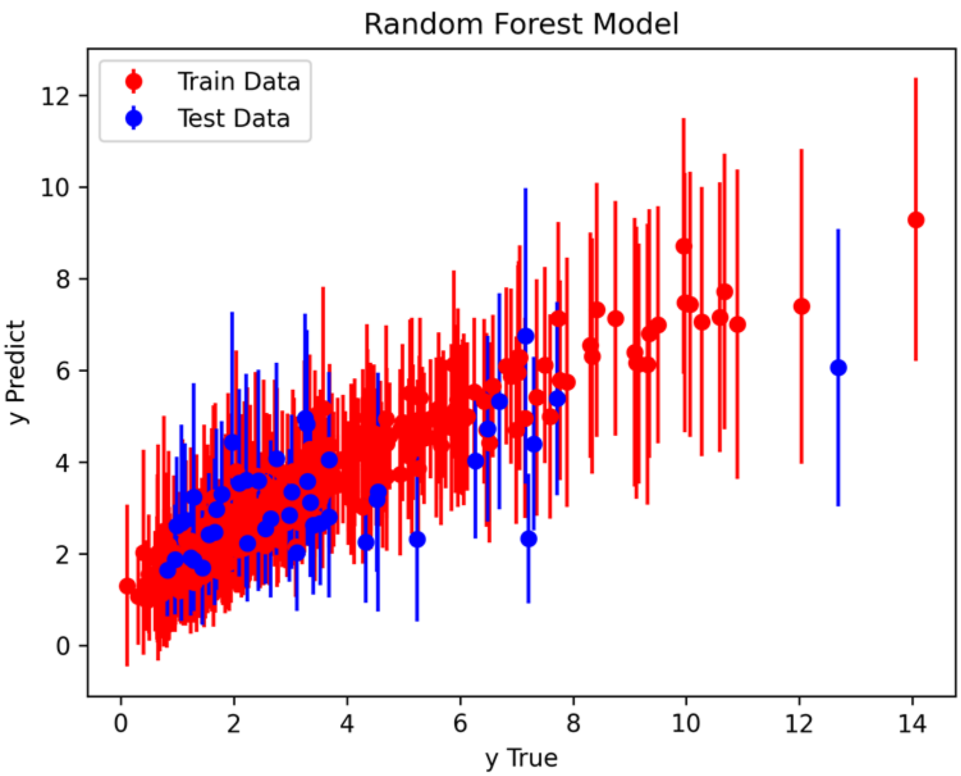


Figure 3. Random Forest best result out of 10 fold-cross-validation.

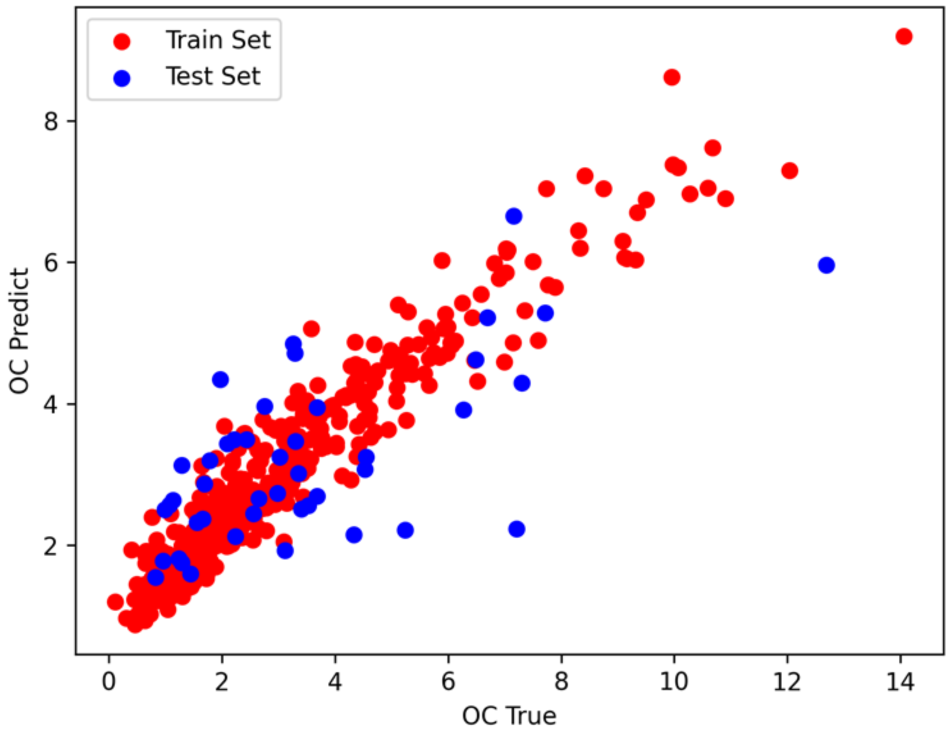


Figure 4. Gaussian Process plus Random Forest best result out of 10 fold-cross-validation.

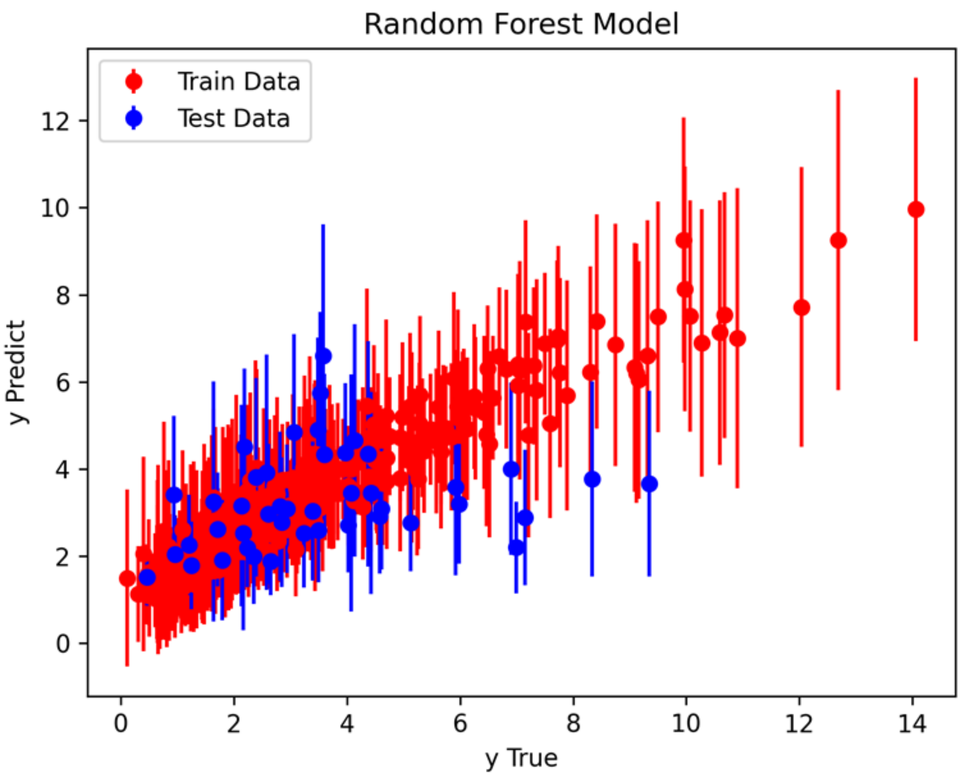


Figure 5. Random Forest worst result out of 10 fold-cross-validation.

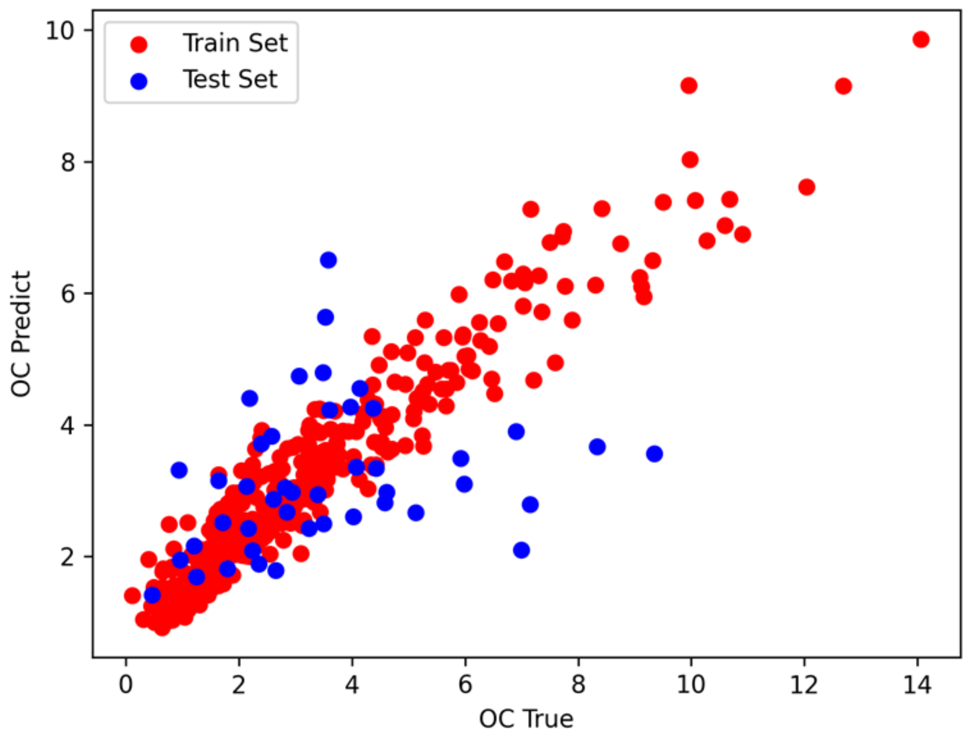


Figure 6. Gaussian Process plus Random Forest worst result out of 10 fold-cross-validation.

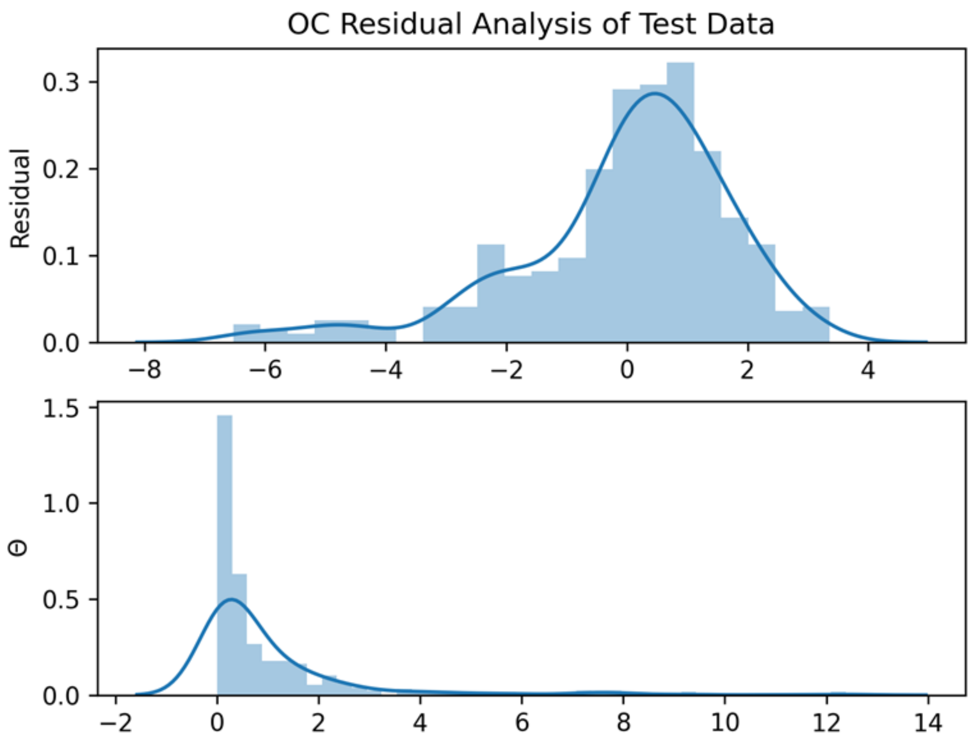


Figure 7. Distribution of the residual error and theta for the aggregated cross-validation test sets.

Prediction Map

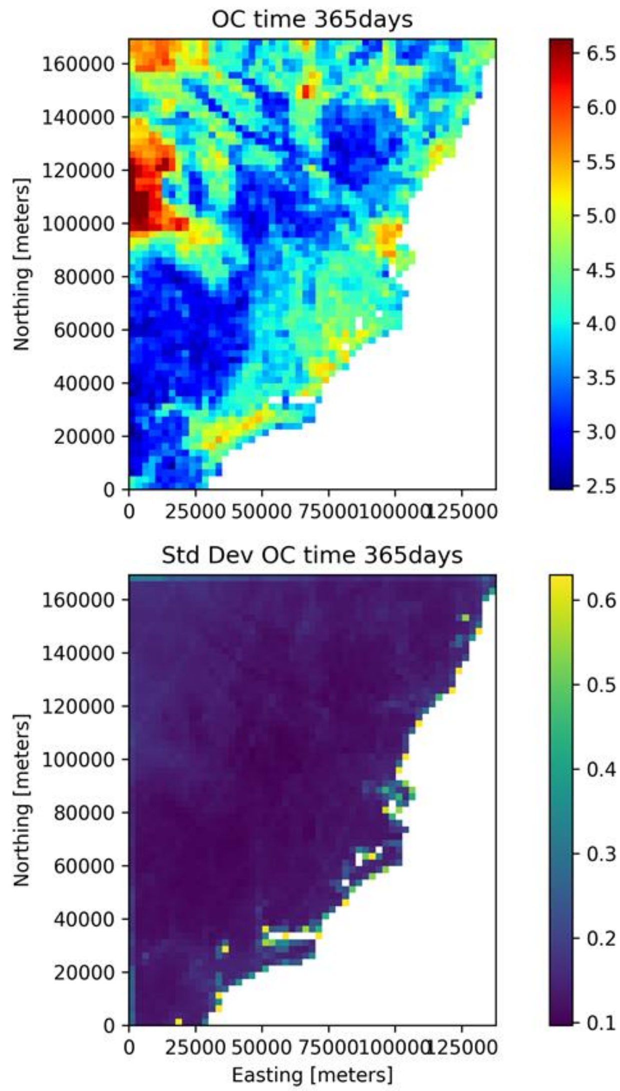


Figure 8. Soil Carbon Prediction and Uncertainty Map for 1991 based on Gaussian Process Model with a Random Forest as mean function.

Acknowledgements

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