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Within-site drivers for soil nutrient variability in plantation forests: A case study from dry sub-humid New Zealand

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ABSTRACT

Precise spatial information on soil properties in plantation forests is needed to improve soil nutrient management and to sustain productivity. Soil nitrogen, phosphorus, potassium, organic matter, carbon and boron are important determinants and indicators of soil fertility and quality. Particularly in forests, these soil properties are highly variable in space and time. In this study, soils were sampled from three plantation forest sites in a dry sub-humid region near Blenheim, New Zealand. Thirty sampling points were selected, and samples were collected from the three sites across a range of slope and aspect strata. Soil samples were analysed for total carbon (totC), total nitrogen (totN), total phosphorus (totP), extractable potassium (exK) and hot-water extractable boron (exB). All examined soil properties varied significantly ($p < 0.05$) within sites. A set of fine-scale (5 m resolution) topographic surfaces, that might explain this variability, were then interpolated or derived in geographic information system software. Topographic surfaces included elevation, aspect, slope, profile and plan curvature, topographic position index (TPI), topographic wetness index (TWI), wind exposition index (WEI), and morphometric protection index (MPI). A generalised linear mixed-effect model was applied to develop predictive models. The study found all soil properties were positively correlated with MPI and negatively correlated with the WEI. This indicated that soil properties were correlated with shelter from surrounding relief and wind. Interestingly, within-site boron levels were correlated with both profile curvature (PrCurv) and topographic wetness index, indicating boron movement through the surface with the movement of soil moisture. The modelling approach in this study has potential for application to sustainable management of plantation forests using spatially-precise estimates of soil fertility.

1. Introduction

Soil is a dynamic resource for growing crops which, in its nature and properties, varies both spatially and temporally (Armson, 1977). The spatial variability of soil properties can occur due to a variety of factors, including pedogenic processes, climate, parent material, topography and biotic and anthropogenic influences (Burrough, 1983; Trangmar et al., 1986). There is copious published literature describing soil variability, including nutrients, on different spatiotemporal scales (Boehm and Anderson, 1997; Burrough, 1983; O'Rourke et al., 2015; Thompson et al., 1997). Despite this, knowledge about local-scale variability of soils is still sparse and requires further investigation. In particular, there is a need to quantify soil variability within sites, the level at which land managers make decisions such as choice of crop species and fertiliser regimes

In some countries, production forestry is moving towards a precision approach that is used in agriculture (Bhakta et al., 2019; Dyck, 2003). Precision forest management requires fine-scale data covering all aspects of forested ecosystems (Salekin et al., 2019). However, one of the main hindrances to precision forestry is acquiring fine-scale soil data, as soil surveys have traditionally overlooked variability within map units (Basayigit and Senol, 2008; Lin et al., 2005). Soil mapping typically partitions the soil in the landscape into discrete entities using map units and field observations that are made using formal knowledge and intuitive judgment (Lin et al., 2005). Consequently, on a soil map, the map unit boundaries are clear lines, but often the quantitative variations within individual map units are described vaguely (Lin et al., 2005). For example, in New Zealand, the Fundamental Soil Layers (FSL) are national-scale soil descriptions in which a coarse polygon-based boundary delineates different soil units, each polygon nominally containing homogeneous soil properties. But the FSL are often erroneous, especially when they are used to describe fine-

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scale quantitative values of different physical and chemical properties (Barringer et al., 2016; Pearse et al., 2015).

An alternative approach to national or regional soil surveying is digital soil mapping (DSM) (Lagacherie and McBratney, 2006; Minasny and McBratney, 2016), which involves:

a. Inputs–field and laboratory observations, including legacy soil observations or soil maps, and new data from statistically-based sampling techniques.
b. Processing–building mathematical or statistical models relating soil observations with their environmental covariates or "scorpan" factors (McBratney et al., 2003).
c. Outputs–spatial soil information systems, which can include outputs in the form of rasters of prediction along with the uncertainty of prediction.

"scorpan" factors are specified by the equation,

$S_a = f\,(s, c, o, r, p, a, n) + e$where S_a is a soil attribute which is a function of soil (s), climate (c), organisms (o), relief (r), parent material (r), age (a) and spatial position (n), and 'e' is spatially correlated residuals (McBratney et al., 2003). "scorpan" includes the five soil-forming factors proposed by Jenny (1994) but allows for additional information from 'soil' (prior knowledge of the soil, such as legacy soil observations) as well as spatial position of the soil in the landscape.

Progress in digital soil mapping (DSM) has been driven by recent developments in remote sensing and geospatial technologies. Importantly, it is now possible to acquire high-resolution land surface and topographic data through digital terrain models (DTM) which show fine-scale topographic relief, a critical "scorpan" variable. The potential for applying DTMs to make spatially-based predictions of soil properties was identified several decades ago by a number of authors (e.g. Gessler et al., 1995; Moore et al., 1993). Digital terrain models have been used to study: 1) large-scale spatial heterogeneity of different soil characteristics in forest areas (Bogunovic et al., 2017; Liu et al., 2011; Wang et al., 2009); 2) spatial variability of important soil chemical characteristics, such as soil pH (Liu et al., 2013), organic carbon (Martín et al., 2016; Patton et al., 2019), apparent electrical conductivity (ECa) (Bogunovic et al., 2017), and nitrogen and phosphorus content (Liu et al., 2013; Wang et al., 2009); and 3) effects of different land-use management practices on various soil properties (Martín-Peinado et al. 2016; Ade et al. 2018). Together, these studies highlight the utility of remote sensing and geo-spatial analysis for digital soil mapping.

In contrast to the large-scale studies reported above, research studies focussing on within-site variability of soil properties for both agricultural and forest soils are infrequent. However, the potential for applying DTMs to make spatially-based predictions of forest soil properties has been identified for some time now (Thwaites and Slater, 2000). Using DTMs, Ryan et al. (2000) empirically tested the effects of topography and environment on soil carbon and phosphorus at both the small-catchment (270 ha) scale and regional scale in south-eastern Australia. Similarly, Murphy et al. (2011) analysed within-catchment variability of forest soil properties in a 40 ha catchment in Alberta, Canada.

An important constraint to studying soil properties in forests is the cost and difficulty of both soil sampling and sample analysis. Typically, forest areas have poor access, mainly due to topography and undergrowth. Therefore, it is time-consuming to carry out intensive field soil sampling. In addition, forests are often located in hill country and steeplands, with a high degree of variation in soil properties across a landscape. Altogether these result in a high cost of sampling, to which is added the cost of processing and analysing soil samples (Dai et al., 2018; Martín-Peinado et al., 2016). Furthermore, conventional soil survey methods are biased towards agricultural sites, and do not account for issues such as sampling sites obstructed by large rocks and woody roots, and localised effects of individual trees on soil properties (O'Connell et al., 2000). There is a need for methods that allow spatial predictions of forest soil properties to be made from relatively few, because expensive and difficult, samples.

Most studies of spatial variability of soil nutrients are based on empirical and geostatistical approaches (Bogunovic et al., 2017; Guan et al., 2017; Martín et al., 2016). Geostatistical approaches such as ordinary and co-kriging have proven useful in previous studies (Guan et al., 2017; Moore et al., 1993; Nourzadeh et al., 2012); however, they rely on large datasets of intensively measured values over the area of interest. The requirement for intensively measured large datasets can be challenging in studies of forest soils due to the aforementioned high costs and sampling difficulties. In addition, geostatistical approaches are limited by their underlying datasets and do not account for any prior knowledge of land management or soil-forming processes that determine soil fertility. For these reasons, geostatistical methods requiring large datasets are not easily applicable to forested landscapes. Nor do approaches such as ordinary and co-kriging explain the underlying processes determining soil variability, specifically at finer spatial scale. Therefore, such approaches have little or no predictive capability for a forested site.

There is a need, especially in forest management, for an alternative, cost-effective model that can explain and predict the relationship between soil fertility and easily-measured site-specific topographic variables at a finer, within-site spatial scale. As such, the main research objectives of this study were to:

i. Determine whether a correlation exists between within-site topographic variables and soil properties, including soil nutrient (nitrogen, phosphorus, potassium, and boron) concentrations and also concentrations of soil carbon and organic matter.
ii. Provide a modelling framework, for predicting levels of soil nutrients and soil carbon and organic matter based on fine-scale topography.

2. Materials and methods

2.1. Experimental sites

The three experimental sites were ex-pasture land situated in a sub-humid climate zone near Blenheim, in the South Island of New Zealand (Fig. 1). Sites A, B, and C have areas of 4.7, 3.7 and 2.2 ha respectively. They are planted with *Eucalyptus globoidea* (Blakely) (Site A) and *Eucalyptus bosistoana* (F. Muell) (Sites B and C) in monocultural stands. Trees were established respectively in 2011, 2009 and 2012. Therefore, at the time of this study they were 6, 8 and 5 years old, with mean heights of 1.54 m, 4.88 m and 2.11 m, correspondingly. At time of planting, the landscape was covered by low-producing pasture, which was controlled with herbicide applied in 1-m diameter spots around each tree immediately after establishment.

The study region is sheltered by high country to the west, south and in some areas to the east, and it is one of the sunniest regions of New Zealand (NIWA, 2017). Warm, dry and settled weather predominates during summer, while winter days often begin with a frost, but are usually mild overall. Typical summer daytime maximum air temperatures range from 20 °C to 26 °C but occasionally rise above 30 °C. Typical winter daytime maximum air temperatures range from 10 °C to 15 °C (NIWA, 2017). Predominant wind directions vary with local topography and proximity to the coast (Chappell, 2016). High temperatures are frequent in Blenheim and may be accompanied by dry Foehn winds from the northwest. Mean annual rainfalls are 550 mm (near Sites A and B) and 650 mm (near Site C) (NIWA, 2017).

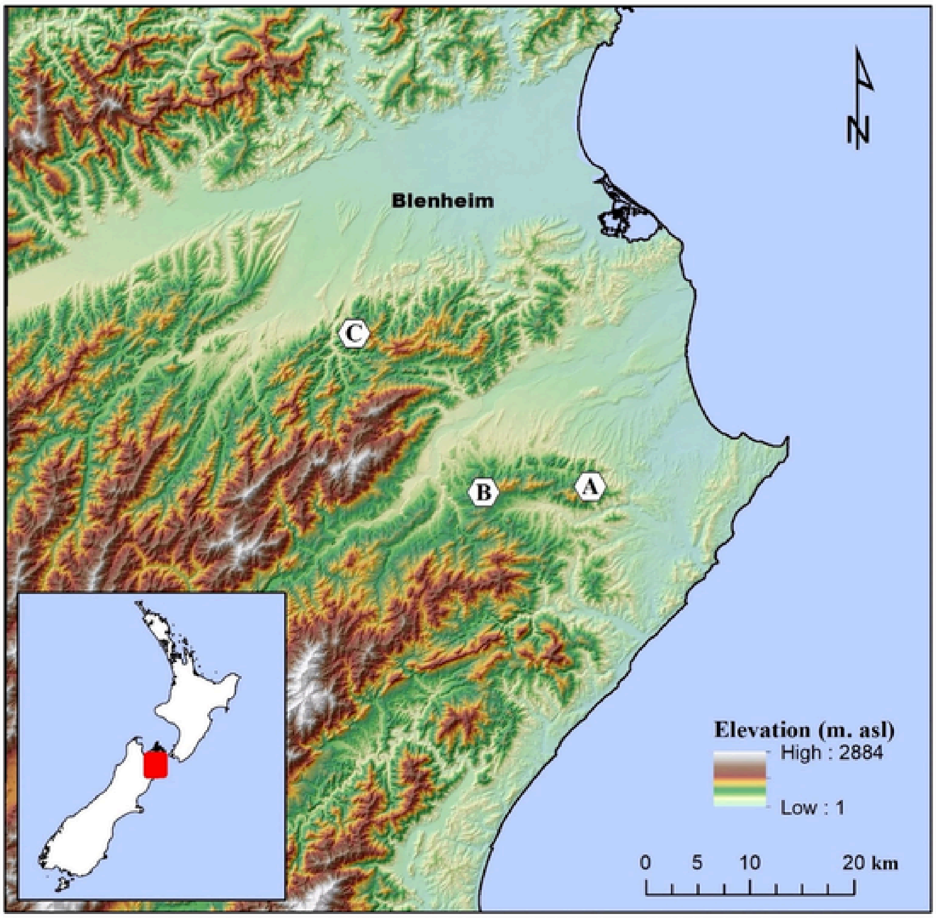

Fig. 1. Study site locations in the South Island of New Zealand.

The soils at these sites are Flaxbourne and Wither Hill soils and are classified as Pallic soils under the New Zealand Soil Classification (Table 1). Pallic soils occur predominantly in the seasonally dry eastern parts of the North and South Islands and the Manawatu region, and cover approximately 12% of New Zealand (Hewitt, 2010). Parent materials are commonly loess derived from schist or greywacke. Pallic soils have pale-coloured, poorly-structured or massive subsoils, due to low contents of iron oxides. Consequently, soils often have slow drainage and limited rooting depth (Manaaki Whenua-Landcare Research, 2020) which can be a limitation for growth of deep-rooting species such as trees.

According to Watt et al. (2021), the trial sites are considered to have low productivity for plantation forest growth, due mainly to soil water deficits in summer and early autumn.

Table 1
Soil classification and representative profile description of three sites according to the New Zealand Soil Classification (NZSB, 1968; Hewitt, 2010).

Sites	*Soil series*	*Class name*	*Representative profile description*
A and B	Flaxbourne Hill soils	Typic Argillic Pallic	15 cm dark-grey friable silt loam over 40 cm olive-brown firm clay loam on pale olive-brown clay loam, very hard when dry, overlying mudstones
C	Wither hill soils	Argillic-sodic Fragic Pallic	12 cm grey-brown firm-friable silt loam over 18 cm brown-yellow–brown massive silt loam, firm, overlying gravels in a silt matrix.

2.2. Topographic data acquisition and processing

Digital terrain models for all sites were produced by carrying a real-time kinetic geo-positioning system (RTK-GPS) on regularly-spaced transect lines across each site. The system collected coordinates and elevations at five-metre intervals along the transects. The elevation points were interpolated into a DTM of 5 m resolution, using an optimised interpolation algorithm in ArcGIS (ESRI, Redlands, CA), as in Salekin et al. (2018).

Next, surfaces for topographic variables were derived from the DTM (Salekin et al., 2019). Each of these topographic variables are different ways of describing the structure and shape of the topographic relief. The topographic variables included elevation, aspect and slope (Travis et al., 1975), profile and plan curvature (Heerdegen and Beran, 1982; Zevenbergen and Thorne, 1987); topographic position index (TPI) (Weiss, 2001); topographic wetness index (TWI) (Beven and Kirkby, 1979; Moore et al., 1991); wind exposition index (WEI) (Gerlitz et al., 2015); and morphometric protection index (MPI) (Yokoyama et al., 2005). All surfaces were interpolated or derived using ArcGIS v.10.4 (ESRI, 2012) or the System for Automated Geoscientific Analysis (SAGA) (Conrad et al., 2015). All the topographic variables for specific points are described in Table 2. In addition, detailed site-by-site descriptive statistics of these variables are provided in Table S3.

Table 2
Description of topographic variables used as independent explanatory variables for modelling. Descriptions are based on Harris and Baird (2018), and the SAGA-GIS Tool Library Documentation (v7.6.2).

Topographic variables	Description
Elevation	Elevation above sea level in meters.
Aspect	Compass direction in degrees.
Slope	Steepness in degrees.
Profile curvature (PrCurv)	Curvature in the vertical (down-slope) plane. For the cell, value < 0 when the surface is convex, >0 when the surface is concave, zero when the surface is linear.
Plan curvature (PlCurv)	Curvature in the horizontal (cross-slope) plane. For the cell, value < 0 when the surface is convex, >0 when the surface is concave, zero when the surface is linear.
Topographic Position Index (TPI)	Value > 0 when the cell is higher than its surroundings, zero when in a flat area or mid-slope and < 0 when lower than its surroundings.
Topographic Wetness Index (TWI)	Greater values correspond to increasing surface wetness Values are relative to rest of study area, can be < 0
Wind Exposition Index (WEI)	Value < 1 indicates wind-shadowed areas, value > 1 indicates areas exposed to wind.
Morphometric Protection Index (MPI)	Analyses the immediate surrounding of each cell up to a given distance and evaluates how the relief protects it. Value > 0 when the cell is protected and < 0 when it is not.

Table 3
Descriptive statistics of topographic attribute variables (n = 30) *.

Topographic variables, units	Min.	Max.	Mean	Std. Dev.
Aspect (°)	0.9	356.9	109.0	130.6
Slope (°)	7.7	30.4	21.5	6.3
Elevation (m. asl)	1.0	269.1	135.2	95.2
PrCurv	−0.09	1.24	0.04	0.23
PlCurv	−1.15	1.65	0.01	0.37
TPI	−13.90	11.98	−2.22	6.52
TWI	−1.98	6.90	1.70	2.46
WEI	0.89	1.18	1.02	0.08
MPI	0.04	0.15	0.12	0.03

*Min: minimum; Max: maximum; SD: standard deviation.

2.3. Soil analysis sampling and data preparation

To cover a wide range of site characteristics, a stratified random sampling design was employed. Each of the three experimental sites was stratified by a combination of aspect and slope. Mainly, classifying by top, middle and toe slope, and then masking with associated dominant aspects, resulting in three main strata for each site. Then, a total of thirty sample collection points (ten points at each site) was randomly assigned to those strata. The stratification and random point generation were undertaken in ArcGIS (ESRI, Redlands, CA). Point locations were exported to a geographic positioning system (GPS) receiver, which was then used to locate the sampling locations at each of the three experimental sites.

At each sampling location, a 1-m pit was dug in July 2017 as part of a wider soil study (pictures of typical profiles are in the supplementary material Figure S1 and S2). To collect the soil samples used in this study, the organic litter layer was carefully removed, and then samples were collected from 0 to 10 cm depth. This depth was chosen to allow comparison of soil analysis results with published New Zealand studies of soil quality (e.g. Sparling et al., 2002). Three independent soil samples of 500gm were taken at each sampling location, placed in a light-proof plastic bag, stored in an insulated container and sent to Hill Laboratories (https://www.hill-laboratories.com) for analysis immediately after collection. The analyses included total carbon (totC, % of soil dry weight), total nitrogen (totN, % of dry weight), total phosphate (totP, mg/kg soil dry weight), extractable potassium (exK, me/100 g soil dry weight), and hot-water extractable boron (exB, mg/kg soil dry weight) (details of analytical procedures are provided in the supplementary material, Table S1).

2.4. Data preparation and description

Topographic variables (Table 3) and soil analysis (Fig. 2, Table 4) were extracted for each sampling point location. Both sets of data were processed and grouped for subsequent analysis into response and explanatory variables. Here, the three soil samples data from each point were averaged and the mean values of soil analyses were used as response variables, and the topographic variables were used as quantitative explanatory variables.

2.5. Data analysis

First, an exploratory statistical analysis was carried out. Minimum (Min), maximum (Max), mean, median, and standard deviation (SD) values were calculated for both dependent and explanatory variables. The Kolmogorov-Smirnov (K-S) test together with skewness and kurtosis values were applied to test the assumption of normal variance of dependent variables (Webster and Oliver, 2007). To assess skewness and kurtosis, Kim (2013) and Mayers (2013) suggested a threshold of $z = \pm 1.96$ be used for samples smaller than 50, in conjunction with visual assessments.

Then an assessment for multicollinearity was performed for all explanatory variables by using the variance inflation factor (VIF) (Fox and Weisberg, 2018). A strong correlation was observed between elevation, slope and aspect, on one hand, and the other potential independent variables on the other hand. Thus, procedures outlined by Cook and Weisberg (2009) were employed to determine whether or not these variables added any statistically significant information. Finally, elevation, slope and aspect did not add any such significant information, and showed strong multicollinearity; therefore, they were excluded from the model-building procedure.

Next, response variables were regressed against independent explanatory variables. The dataset had a hierarchical structure (sampling points were nested within sites) hence spatial autocorrelation was expected. The dataset was unbalanced as it had a non-normal distribution. Therefore, a Generalised Linear Mixed-effects Model (GLMM) (Agresti, 2013; Pinheiro and Chao, 2006) was employed by partitioning unexplained variance and assuming a gamma distribution of errors with an inverse link function. A restricted maximum-likelihood (REML) method was used to estimate the GLMM parameters (Breslow and Clayton, 1993). Also, the Satterthwaite (1946) method was applied to determine approximate denominator degrees-of-freedom for unbalanced data. Study sites were considered as the random effect in the mixed model. The inclusion of explanatory variables in the final models was based on likelihood ratio tests, comparing the null model (i.e. that excluding all predictors) against final models in terms of the Bayesian information criterion (BIC) (Schwarz, 1978). The BIC indicates the statistical magnitude of difference between models, with lower BIC values indicating stronger empirical support for a model (Hoeting et al., 1999). All the explanatory variables, as well as some interactions, were included and tested on a rational basis.

Once the final models had been generated for each of the soil analysis variables, linear regressions with zero intercept were performed be-

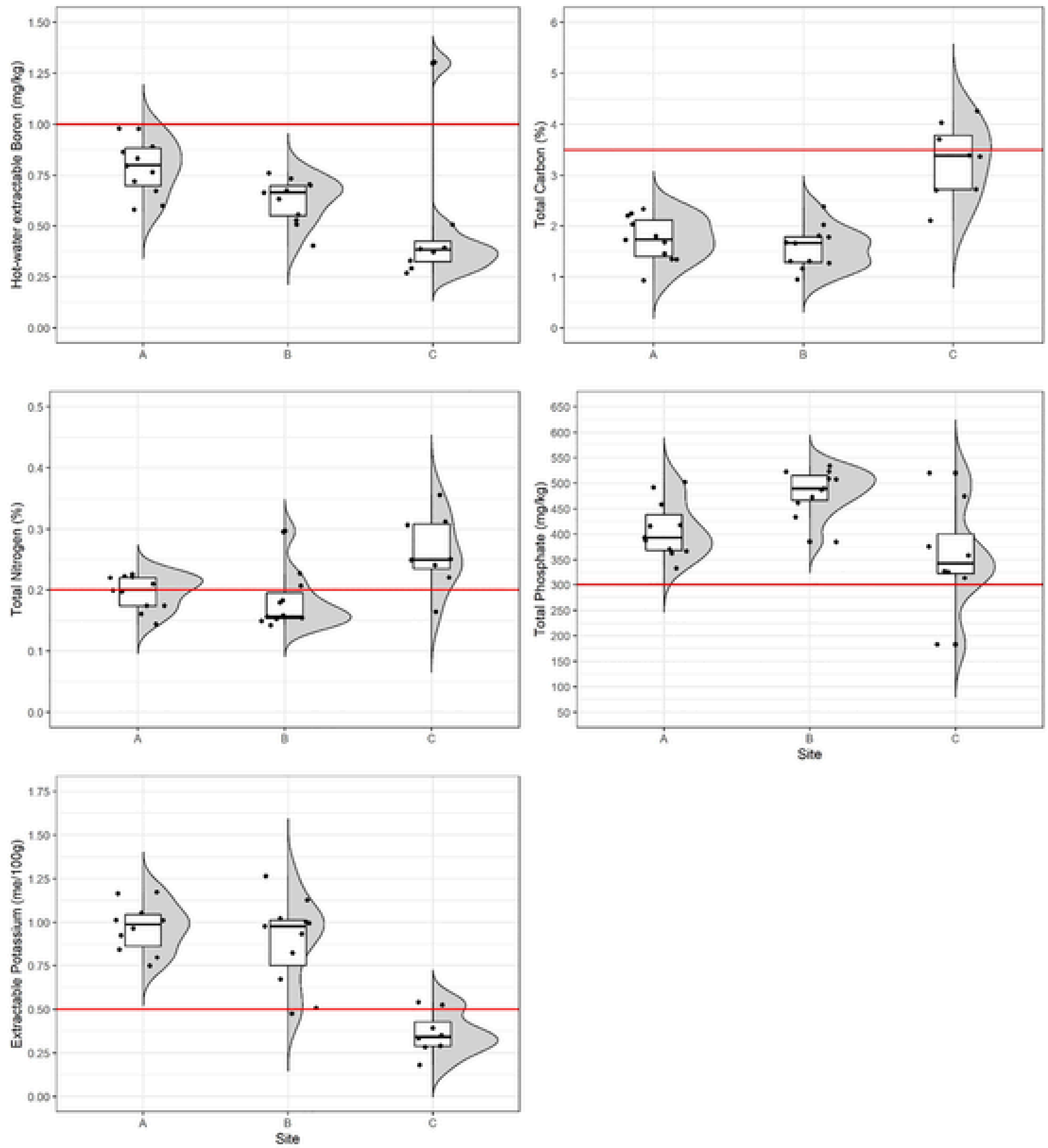

Fig. 2. Measured soil analysis values at three different sites. Box-whisker plots show median of data, half-violin plots show data distribution and red-lines indicate minimum crop requirement thresholds (Kay and Hill, 1998; Salekin et al., Unpublished data; Sparling et al., 2008). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 4
Descriptive statistical analysis for soil analysis variables.*

Nutrients (Unit)	Min.	25%	Median	75%	Max.	Mean	SD
totN (%)	0.14	0.16	0.20	0.22	0.35	0.20	0.05
totP (mg/kg)	183	367.3	425.0	491.3	534	423.3	83.0
exK (me/100 g)	0.18	0.51	0.84	1.01	1.26	0.77	0.32
totC (%)	0.93	1.37	1.80	2.36	4.27	2.09	0.89
exB (mg/kg)	0.27	0.50	0.66	0.76	1.30	0.65	0.23

*Min: minimum; Max: maximum; SD: standard deviation.

tween observed and predicted values and their slope and coefficient of determination (R^2) were used to measure biases of the models (with an unbiased model having a slope of 1). The root mean square error (RMSE), as a measure of goodness-of-fit (Huber, 2004; Stone, 1974), was used as a 'leaving-one-out' or 'jackknife' method of cross-validation (LOOCV) (Arlot and Celisse, 2010).

All statistical analyses were performed in the R statistical environment (R Development Core Team, 2020) by using RStudio as Integrated Development Environment (IDE) (R Studio Team, 2020), "tidyverse" for data wrangling and plotting (Wickham, 2017), and "Metrics" packages for model evaluation (Hamner et al., 2018). GLMMs were obtained by using the "glmer" function from the "lme4" package (Bates et al., 2014).

3. Results

3.1. Descriptive statistics

Descriptive statistics for the topographic attributes are shown in Table 3. Mean aspect was 109.0°, indicating that study sites tended towards easterly aspects (a random distribution of aspects would tend towards a mean of 180°). Sites covered a range of altitudes and slopes, from near sea-level to over 250 m.asl and from gently rolling (7.7°) to steep (30.4°).

Plan and profile curvatures (*PlCurv, PrCurv*) varied from somewhat concave to convex, with means close to zero indicating that both types of profile curvature were represented in the data. Similarly, Topographic Position Index (TPI) covered a range of values, with the mean of close to zero indicating a spread of both elevated and low-lying sites.

TWI ranged from −1.98 to 6.90, suggesting presence of steep ridge sites as well as accumulation areas (basins, gullies). WEI and MPI values suggest that many sites had some protection from exposure to wind, although there were exposed sites with WEI > 1 and MPI close to zero.

The descriptive statistics for all soil analysis variables (totN, totP, totK,totC and exB) over all three sites are shown in Table 4 and Fig. 2. Fig. 2 and standard deviation values in Table 4 suggest a wide range of variability, which was confirmed by the Kolmogorov-Smirnov test ($p \leq 0.05$) (Table S2). High skewness and kurtosis values confirmed the non-normal distribution of the data (Table S2).

3.2. Nitrogen, phosphorus and potassium variability

Different topographic variables used here were found to correlate with soil analysis variables. Total nitrogen (totN) was positively correlated with MPI and TPI but negatively correlated with WEI (Table 5). Total phosphorus (totP) was similarly correlated with MPI and WEI but not with TPI. Extractable potassium (exK) was also negatively correlated with WEI as well as with the PlCurv, which is an indicator of the horizontal alignment of the surface curvature (Table 5).

3.3. Hot water extractable boron and total carbon

As with totN, totP and exK, topographic variables contributed to exB and totC variability models. Total carbon (totC) was positively correlated with MPI (Table 6). On the other hand, exB availability was significantly influenced by an interaction between TWI and PrCurv (Table 6). A topographic location with a higher profile concavity presented a strong correlation between exB and TWI. However, this relationship became weaker with increasing profile convexity (Fig. 3).

3.4. Generalised linear Mixed-effect models (GLMMs)

All the models estimating using the GLMM procedure performed with high precision and low bias. Only models for totN and exB soil analysis values showed a negative bias: −4.751 and −1.060, respectively. This means that all other soil analysis models were slightly overpredicting, whereas the totN and exB models were underpredicting. Besides, RMSE of almost all the soil analysis models indicated minimal errors, except exK, which doubled from fitting (1.239) to validation (3.203) (Table 7). Most of the models predicting soil analysis variables showed a percentage of variance in data (i.e. R^2) that was higher than 50%. However, an R^2 of 0.336 and RMSE value of 431.113 indicated the totP model did not adequately predict soil analysis values. Overall, the effect of topographic variables was important in explaining within-site variation in soil analysis variables (Table 7).

Table 5
Coefficients of generalised linear mixed-effect models for nitrogen, phosphorus and potassium. See Table 2 for abbreviations.

Target Fixed effects	Nitrogen (totN)				Phosphate (totP)				Potassium (exK)			
	Est.	*SE*	*t*	*Sig.*	*Est.*	*SE*	*t*	*Sig.*	*Est.*	*SE*	*t*	*Sig.*
Intercept	4.99215	1.02	4.88	***	0.0024785	0.01	6.16	***	3.043168	0.72	4.25	***
MPI	28.88354	6.60	4.37	***	0.0090198	0.01	3.12	**	–	–	–	–
TPI	0.04681	0.02	2.07	*	–	–	–	–	−0.017045	0.01	−1.78	NS
WEI	−3.28001	1.04	−3.14	**	−0.0010229	0.01	−2.63	**	−0.953393	0.37	−2.55	*
PlCurv	–	–	–	–	–	–	–	–	4.161528	2.09	1.99	*
Random effect												
Site intercept	0.19746	0.028	–	–	$3.831e^{-08}$	$2.470e^{-02}$	–	–	0.1867	0.06	–	–

Note: Est. = Estimate; SE = Standard Error; Sig. = Significance level (*** = $p < 0.001$; ** = $p < 0.01$; * = $p < 0.05$; NS = $p \geq 0.05$).

Table 6
Coefficients of generalised linear mixed-effect models for organic matter, total carbon and hot-water extractable boron. See Table 2 for abbreviations.

Target Fixed effects	Carbon (totC)				Boron (exB)			
	Est.	*SE*	*t*	*Sig.*	*Est.*	*SE*	*t*	*Sig.*
Intercept	0.3892	0.13	2.94	**	2.08983	0.55	3.79	***
MPI	1.3279	0.74	1.79	NS				
TWI	–	–	–	–	−0.03722	0.06	−0.65	NS
PrCurv	–	–	–	–	1.88086	4.66	0.40	NS
TWI × PrCurv	–	–	–	–	2.49192	0.85	2.93	**
Random effect								
Site intercept	0.007319	0.06			0.12966	0.05		

Note: Est. = Estimate; SE = Standard Error; Sig. = Significance level (*** = $p < 0.001$; ** = $p < 0.01$; * = $p < 0.05$; NS = $p \geq 0.05$).

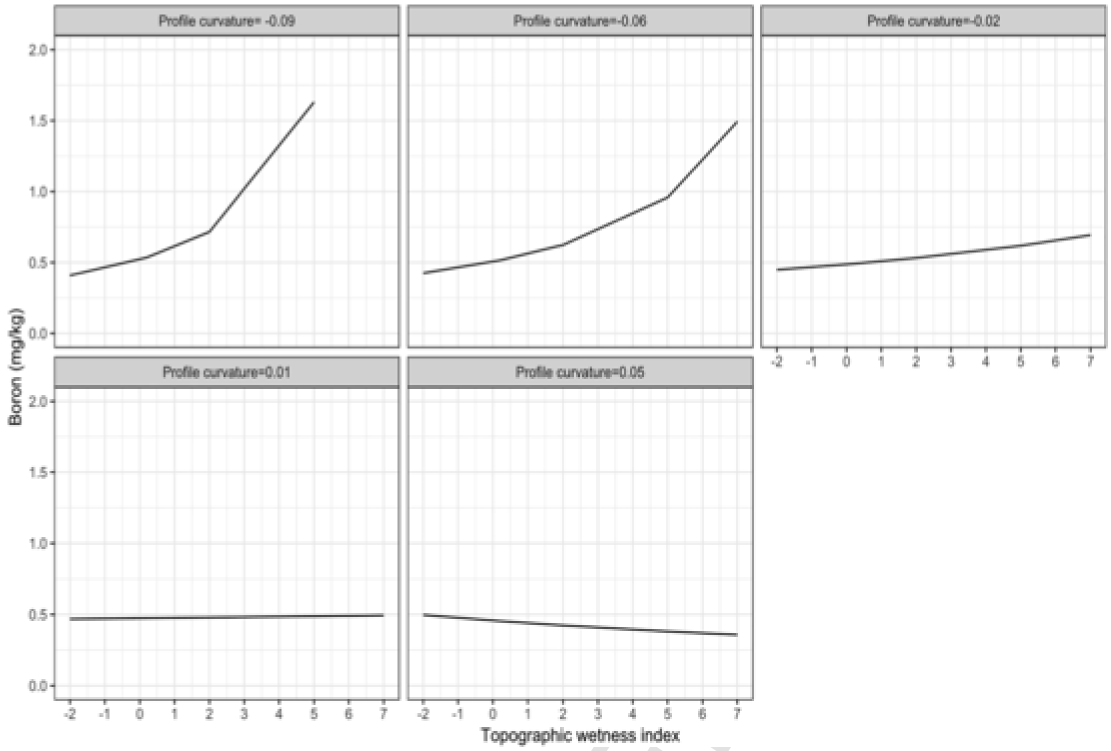

Fig. 3. Effect of interaction of profile curvature with topographic wetness index on within-site boron (exB) availability.

Table 7
Generalised linear mixed-effect model goodness-of-fit and validation statistics.

Soil Analysis Values	Fitting				Validation		
Statistics	Slope (bias)	R^2	RMSE	BIC	Slope (bias)	R^2	RMSE
totN (%)	−4.751	0.520	4.823	−95.587	−4.733	0.452	4.795
totP (mg/kg)	423.319	0.337	431.113	358.143	421.124	0.337	429.057
exK (me/100 g	0.759	0.709	1.239	−0.918	1.732	0.708	3.203
exB (mg/kg)	−1.060	0.594	1.290	−12.015	−1.061	0.596	1.292
totC (%)	1.564	0.615	1.849	60.200	1.591	0.555	1.872

Note: R^2 = coefficient of determination; RMSE = root mean square error; BIC = Bayesian Information Criterion.

4. Discussion

4.1. Within-site topographic factors

The soil analyses values of all the soil nutrients and carbon were influenced by topographic variables, which is consistent with the role of relief as a “scorpan” factor in digital soil mapping. For example, Unger et al. (2010) found that macro-nutrients varied with elevation transects in tropical moist forests in north-eastern Ecuador. Zhang et al. (2016) reported N variation in the central Sichuan Basin, China, and Guan et al. (2017) found high spatial dependency of macro-nutrients in a bamboo forest, in Yong’an City, China.

However, there was still a significant amount of variation in soil analysis values that was not explained by the topographic variables or the random site effects in the model. There are a number of other factors that can contribute to fine-scale variation in soil fertility. For example, Dai et al. (2018) and Murphy et al. (2011) reported that vegetation (forest type), anthropogenic (forest harvesting and slash burning) and hydrological factors played a more important role than topographic variables in the spatial variability of N, P and K availability. All three sites in our study were located in retired pasture lands; hence, within-site nutrient level variability may also be linked with historical pasture growth or soil erosion (Hunter and Smith, 1995).

Most of the soil analysis variables driven by topography relate to topographic shelter and drainage, for example, MPI, TPI, WEI, plan and profile curvature. These variables represent spatial variation in micro-topographical conditions and their associated catenary processes (Milne, 1936; Moore et al., 1993; Patton et al., 2019; Zevenbergen and Thorne, 1987), including erosion, transport and deposition of surficial material as well as mineralisation, leaching, translocation and accumulation of solutes in soil (Hall and Olson, 1991). So, the topographic features in this study were indicative of underlying catenary processes that can affect the measured soil parameters. For example, soil carbon (which is directly correlated with soil organic matter (OM)), had higher values at locations sheltered from the surrounding relief (MPI). Cambardella et al. (1994) reported that surface spatial structure determined soil OM levels in central Iowa soils, and similarly, Patton et al. (2019) described finer-scale soil organic carbon distribution as a function of aspect and hillslope in a semi-arid catchment in Idaho, USA; both results are in line with this study. This may have occurred from the transport and deposition of OM by catenary processes, for example, wind, or surface erosion. It may also reflect a higher rate of primary productivity and therefore OM accumulation in sheltered lower slopes (Burke et al., 1995).

Similarly, soil nitrogen and phosphorus values were greater in locations with low WEI and high MPI, representing sites with lower elevation and higher topographic shelter from wind. Millner and Kemp (2012a); Millner and Kemp (2012b) observed variability in foliar nutrients at local scales for plantations of several different *Eucalyptus* species in New Zealand's hill country and explained these as a result of micro-climatic impacts on soil nutrient mineralisation processes. It is possible that spatial variation in soil nutrient concentrations in our study was driven partly by similar effects of micro-climate on weathering and mineralisation in the soil.

Soil extractable potassium values decreased with higher WEI and increased with higher plan curvature. Plan curvature represents horizontal surface curvature, suggesting that potassium is transported from higher relief and accumulates downslope. Guan et al. (2017) reported similar findings, where a "nugget-to-still" ratio was applied to explain the underlying catenary process of nitrogen, phosphorus and potassium accumulation in Yong'an city, China. Furthermore, profile curvature and topographic wetness index influenced boron availability interactively within the site. Ahmad et al. (2012) and Moraghan and Mascagni (2018) reported several factors influencing boron movement along the soil surface, including moderate to heavy precipitation and mass flow. This may be explained in the context of this study, where boron moves through vertical curvatures (gullies) during wet periods and was deposited as its bioavailability ceased under dry conditions (Barber, 1995; Chang et al., 1983).

4.2. Generalised linear mixed-effect models

The GLMM is a conditional approach for hierarchical datasets where error structure is partitioned based on the parameters, namely fixed and random effects (Lee and Nelder, 2001). As the study's data had a hierarchical structure, the GLMM was applied by assigning fixed (topographic variables) and random (sites) effects at a finer spatial scale. In addition, all the models in this study were validated through the LOOCV procedure, which gives extra confidence and ensures model quality (Minasny et al., 2013). However, LOOCV cannot provide perfectly unbiased estimates (Brus et al., 2011), and the limitation of having only 30 sample points cannot be ignored. A random-effects model with marginally specified regression structure can result from small sample numbers, which is more susceptible to bias and less precision (Heagerty and Kurland, 2001). This may be the case for the totP model's inadequate prediction. Other than totP, the R^2 values of the totN and exK models were in line with those reported by Guan et al. (2017).

4.3. Soil chemical properties and precision silviculture

This study provided useful insights into properties and chemical composition of forest soils at a finer spatial scale. This field-scale information can contribute to soil management within the context of precision silviculture (Rubilar et al., 2018). This is particularly the case for *Eucalyptus* plantations such as those growing on the three sites used in this study. *Eucalyptus* species are widely cultivated as forest plantations in many temperate, subtropical and temperate parts of the world, and nutrient deficiencies have been recorded in almost all regions where commercial *Eucalyptus* plantations have been established. The most frequent deficiencies are in nitrogen, phosphorus and potassium but boron and copper may also limit tree productivity and health (Dell et al., 2001).

In this study, soil analysis results suggested that for many samples, soil nutrients and carbon were at or below the threshold levels defined for productive forest tree growth (Kay and Hill, 1998; Salekin et al., Unpublished data; Sparling et al., 2008). Prediction of where these deficiencies occurred within the study areas would allow targeted applications of fertiliser, woody residue conservation after harvesting, and other soil management techniques in order to remedy these deficiencies. They can also assist with forest management decisions such as matching of tree species to site conditions, or even the decision as to whether the site is suitable for planting in trees.

5. Conclusion

Enhanced understanding of within-site variation in soil properties at a finer spatial scale is useful for diverse and precise field applications. Generally, the variability of soil nutrients is dictated by complex soil-forming processes, shaped in part by relief or topography. The models developed in this study suggested that soil nutrient variability as a function of location in the landscape at a fine spatial scale deserves further investigation. Moreover, causes of variability were shown to range from micro-climatic conditions at the local scale, to the localised effects of differential subsurface water flow caused by relief. The majority of the variability in totN, exK, exB, totC and totP occurred as a result of shelter from surrounding relief and exposure to wind in certain positions.

Despite the small size of the sample data, this study provided clear and rational understanding of variability in soil analysis values, at a fine-scale resolution. However, this study and the presented results are site-specific. Therefore, further investigation by including a wider range of soil types and regional climates needs to be considered to render these results more generalisable.

Finally, all the nutrients and carbon are subject to similar processes of leaching or accumulation and erosion or deposition. Nevertheless, they respond to different sets of topographic variables, which needs further investigation.

Declaration of Competing Interest

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

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Authors contribution

SS with MB and JM conceived the idea and designed the experiment. JM and EGM acquired the funding. SS and MB carried out data collection. SS carried out preliminary investigations, final analysis and writing under the supervision of MB, JM, DFM and EGM. All authors reviewed and edited the final MS.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.catena.2021.105149.

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