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Article

A quantitative approach to defining soil nutrient regimes within ecosystem classifications for Northwestern Ontario

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Abstract

Soil nutrient regimes (SNRs) are often incorporated in ecosystem classifications. Evaluation of actual nutrient levels associated with these SNRs and the development of complementary soil chemistry regimes (SCRs) could broaden their utility. Using data from 618 forest stands in northwestern Ontario, we developed five-category SCRs using *K*-means clustering and examined relationships among individual nutrients, SCRs, and the SNRs of the Canadian National Vegetation Classification Associations and the Ontario Ecological Land Classification Ecosites. F, A, and B horizon samples were analyzed for organic C (OrgC), total N (TotN), C:N ratio (C:N), cation exchange capacity (CEC), exchangeable bases, base saturation (BaSat), and pH. CEC, pH, and BaSat showed good correspondence across horizons, and together with C:N accounted for much of the variation in chemical properties. There was broad agreement between Association and Ecosite SNRs and B horizon (BHorz) and All horizon (AllHorz) SCRs. C:N decreased while pH and cation metrics increased with increasing SNR and SCR richness. User's accuracies (SNRs vs. SCRs) for the classifications ranged from 31%–39% but increased to 80%–86% for SNR values within ±1 SCR class. Classification trees identified pH class, soil texture, and overstory composition as the principal field-measured factors related to BHorz SCRs.

Key words: ecosystem classification, nutrient regime, soil chemistry, soil properties, Ontario

Introduction

In Canada, forest sites are commonly described at the stand and operational management/mapping level using ecosystem classifications (ECs) and/or ecological land classifications (ELCs) (e.g., Corns 1992; Meades and Roberts 1992; Sims and Uhlig 1992; Ontario Ministry of Natural Resources 2009*a*,*b*; McLaughlan et al. 2010; Saucier et al. 2010; Keys et al. 2011; Mackenzie and Meidinger 2017; Baldwin et al. 2019). Most of these classifications are hierarchical, with the upper levels representing broad climatic, geologic, and/or vegetation zonations and the lower levels addressing finer scale variations in site conditions, landforms, vegetation characteristics, and soil properties (e.g., Crins et al. 2009; Baldwin et al. 2019).

At the finest scales, these classifications usually regard soil moisture and nutrient conditions as the primary environmental gradients influencing forest vegetation. Schematically, these gradients are typically represented by edatopic grids consisting of soil moisture regime (SMR)—soil nutrient regime (SNR) combinations that position individual vegetation or site types along regional gradients of time-averaged soil moisture and nutrient availability (Wilson et al. 2001; MacKenzie and Meidinger 2017). SMRs are based on pedon characteristics such as soil texture, coarse fragment content, soil depth, humus form, and the presence of mottled or gleyed horizons (Brais and Camire 1992; Denholm et al. 2009; DeLong et al. 2011). This represents a semiquantitative approach, given the strong linkages between these attributes and soil hydrologic properties such as hydraulic conductivity and water holding capacity (Assouline and Or 2013). In contrast, SNRs are based on inferred qualitative relationships using a variety of morphological descriptors, including geology, landforms, soil texture, humus form, vegetation typology, and plant indicator species (Klinka et al. 1994; DeLong et al. 2011; Keys et al. 2011). In Ontario, SNRs were often inferred from gradients in the principal axes of vegetation ordinations and linked to the classification typologies (vegetation types) by superimposing the latter on the ordination diagrams (Sims et al. 1997; Chambers et al. 1997; Taylor et al. 2000). In other cases, they were determined using multivariate analyses of morphological pedons and site factors. In either case, they were assigned a posteriori at the classification unit rather than at the individual plot level.

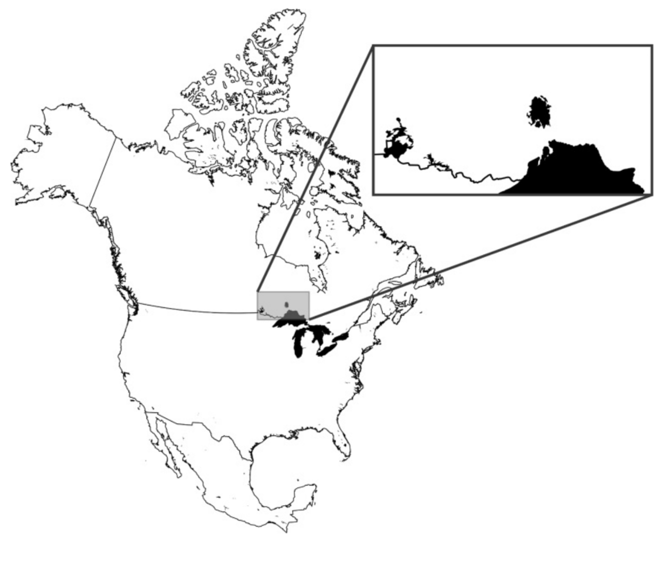
Soil nutrients are key elements governing the structure and function of forest ecosystems. They directly affect plant growth (Binkley and Fisher 2020), stand dynamics and competitive interactions (Coates et al. 2013), carbon cycling (Fernández-Martínez et al. 2014), biodiversity (Fraser et al. 2015), and a wide variety of ecosystem processes and services (Chapin et al. 2011). Incorporating quantitative metrics of nutrient availability in ECs and ELCs should enhance their usefulness for developing sustainable forest management guidelines (Jeglum et al. 2003; Thiffault et al. 2014; Keys et al. 2016; Ontario Ministry of Natural Resources 2022), addressing carbon and nutrient sequestration (Kranabetter 2009; Shaw et al. 2015), investigating potential impacts of climate change (Dieleman et al. 2012; Wieder et al. 2015) and atmospheric deposition (Marty et al. 2017), and examining biodiversity relationships (Aanderud et al. 2018).

To date, most Canadian studies quantifying the soil chemical attributes of SNRs have focused on specific stand types and climatic conditions in British Columbia and Quebec. Emphasis has been placed on (1) providing quantitative estimates of particular growth-limiting nutrients (e.g., mineralizable-N) associated with existing SNRs and (2) examining linkages between SNRs and the productivity (dominant height/site index) of particular tree species (e.g., Bergeron and Bouchard 1983; Kabzems and Klinka 1987*a*, *b*; Courtin et al. 1988; Klinka et al. 1994; Wang and Klinka 1996; Kayahara et al. 1997; Wang 1997; Chen et al. 1998; Splechtna and Klinka 2001; Hamel et al. 2004). Here we extend the first approach by using chemistry metrics measured across multiple horizons and a larger landscape to develop separate soil chemistry regimes (SCRs) using data-intensive statistical approaches. These are then compared with two different empirical SNR classification schemes.

In northern Ontario, two ecological classification systems for forests are now available: the stand level (0.1 – 10 ha) eastern boreal Associations of the Canadian National Vegetation Classification (CNVC) (Chapman et al. 2020) and the operational management/mapping level (10–100 ha) Ecosites of the Ontario Ministry of Natural Resources and Forestry's (OMNRF) Ecological Land Classification (Ontario Ministry of Natural Resources 2009*a*, *b*). The CNVC Associations are based on the vegetation composition and abundance of natural stands >40 years old and pertain to individual stands. The Ecosites are based on stable landscape features (e.g., substrate origin and depth, texture, moisture, and landform) and dominant overstory species (Ontario Ministry of Natural Resources 2009*a*, *b*). Here, we examine the linkages among several soil chemical variables associated with soil fertility (Schoenholtz et al. 2000; Binkley and Fisher 2020) and their relationship with the CNVC Association and Ontario's Ecosite SNRs by:

1) exploring soil nutrient relationships within and across upland forest soil horizons;
2) classifying soil nutrient attributes to develop upland SCRs based on (a) B horizon values (BHorzSCRs) and (b) combined values for the F, A, and B horizons (AllHorzSCRs);
3) investigating how these SCRs and individual chemistry variables vary within and across upland Associations and Ecosites, and their associated SNRs; and
4) determining relationships among the derived B horizon SCRs and site/landform conditions, soil pedon characteristics, and overstory vegetation to provide generalized classification trees for estimating SCRs.

Fig. 1. Location of the study area in northwestern Ontario.



Methods

Study area and data description

The study area encompasses about 90,000 km^2 of boreal and sub-boreal forests in northwestern Ontario, extending from Ignace to the Manitoba border (Fig. 1). The region is underlain by Archean (Precambrian) felsic intrusive rocks of the Superior Province, overlain in some areas by Phanerozoic sedimentary rocks (Thurston 1991). Superimposed on these are distinct landforms resulting from glaciation 10,000–12,000 years B.P. Common surficial deposits include shallow drift, undulating ablation and basal tills, morainal and drumlin features, and large expanses of predominantly thin glacial sediments over rolling to rugged bedrock (Sims and Baldwin 1991; Wester et al. 2018). Glaciofluvial and glaciolacustrine deposits are also common but more localized. The climate varies gradually across the region, with mean annual temperatures between 1.7 °C and 2.7 °C, mean annual precipitation ranging from 615 to 880 mm, and average growing season lengths of 160–190 days (Crins et al. 2009). The upland forests typically include pure and mixed stands of jack pine (*Pinus banksiana* Lamb.), trembling aspen (*Populus tremuloides* Michx.), white birch (*Betula papyrifera* Marsh), balsam fir (*Abies balsamea* (L.) Mill.), white spruce (*Picea glauca* (Moench) Voss), and black spruce (*Picea mariana* (Mill.) BSP). On wetter sites, eastern white cedar (*Thuja occidentalis* L.), balsam poplar (*Populus balsamifera* L.), black ash (*Fraxinus nigra* Marsh.), and tamarack (*Larix laricina* (Du Roi) K. Koch) also occur, whereas eastern white pine (*Pinus strobus* L.) and red pine (*Pinus resinosa* Ait.) are predominantly found across the southern ecotone (Sims et al. 1997; Wester et al. 2018).

During northwestern Ontario EC field campaigns, site, soil pedon, and vegetation data were collected from approximately 2000 100 m^2 plots in forests >40 years old. Plots were

Table 1. Site, soil pedon, and stand predictors used in SNR and SCR analyses.

Variable	Type	Categories (poor to rich)
Bedrock mineralogy[1] (BedMin)	Ordinal ($n = 5$)	(1) Granite, quartzite; (2) granodiorite, gneiss, rhyolite, sandstone; (3) diorite, argillite, conglomerate, breccia; (4) gabbro, schist, slate, mudstone, shale; and (5) basalt, ultramafics, limestone, calcareous sedimentary deposits.
Mode deposition[2,3] (ModDep)	Multinomial ($n = 3$)	(1) Glaciofluvial, (2) till, (3) lacustrine
Stand composition (ConPct, PinePct, DecPct)	Continuous (% basal area)	Coniferous (ConPct), pine only (PinePct), deciduous (DecPct)
Species type (SppType)	Multinomial ($n = 3$) (% basal area)	Conif (>75% coniferous), decid (>75% deciduous), mixed (25%–75% coniferous).
Soil moisture regime[3] (SMR)	Ordinal ($n = 7$)	(1) Dry, (2) moderately fresh, (3) fresh, (4) very fresh, (5) moderately moist, (6) moist, (7) very moist
Drainage class[3] (DrainCl)	Ordinal ($n = 6$)	(1) Very rapid, (2) rapid, (3) well, (4) moderately well, (5) imperfect, (6) poor
Topographic position[3] (TopPos)	Ordinal ($n = 4$)	(1) Crest/upper slope, (2) mid slope, (3) lower and toe slope, (4) depression
CSSC order[4] (CSSOrd)	Multinomial ($n = 4$)	Podzol, brunisol, gleysol, luvisol
Humus form[5] (HumForm)	Ordinal ($n = 4$)	(1) Peatymor, (2) mor, (3) moder, (4) mull
Coarse fragments[3] (CFCont)	Ordinal ($n = 5$)	(1) Absent, (2) few, (3) moderate, (4) abundant, (5) very abundant
Carbonate occurrence[3]	Binary	Yes/no
Forest floor thickness (FFThick)	Continuous (cm)	<40 cm (upland sites only)
A horizon type[4] (AHzType)	Binary ($n = 2$)	Ae, Ah
B horizon type[4] (BHzType)	Multinomial ($n = 4$)	Bf or Bh, Bm, Bg, Bt
B horizon texture (LabTxt)	Continuous (%)	BSand (Sand %), BClay (Clay %)
B horizon texture class[3] (BTxtCl)	Ordinal ($n = 6$)	(1) Coarse-medium sand, (2) fine–very fine sand, (3) silty sand, (4) sandy-silt loam, (5) loam-clay loam, (6) clay
B horizon thickness (BThick)	Continuous (cm)	B horizon thickness
B horizon pHCa class (pHClass)	Ordinal ($n = 6$)	3.5–4.0, 4.1–4.5, 4.6–5.0, 5.1–5.5, 5.6–6.0, and 6.1–7.7

Note: Categorical variables were treated as binary, multinomial, or ordinal variables.
[1]Lloyd et al. 1990; DeLong et al. (2011); Keys et al. (2016); Ontario Geological Survey (2011).
[2]Ontario Geological Survey (2005).
[3]Denholm et al. (2009).
[4]Soil Classification Working Group (1998).
[5]Sims and Baldwin (1996).

selected to be as internally homogenous as possible, based on geomorphology, soil strata, landscape position, and plant community composition. Although sampling was conducted across the full range of site conditions, given the glacial history of the region, the data sets primarily consisted of plots set out on sandy, stony tills. These data were subsequently used to classify CNVC Associations (Chapman et al. 2020) and OMNRF ELC Ecosites (Racey et al. 1996; Ontario Ministry of Natural Resources 2009*a*, *b*) and to interpret SMR and SNR relationships for these typologies. Ecosite SNRs were composed of five classes (very poor, poor, medium, rich, and very rich) based on composite soil and site features (Fig. S1), while Association SNRs were graphically depicted using three broad categories, but with overlap permitted between categories (Chapman et al. 2020). For this initiative, Association authors consulted plot data summaries to assign each Association to one of five SNRs (Table A1).

Site information used in our plot-level analyses included topographic position (TopPos), mode of deposition (ModDep), stand composition, and dominant tree species type (SppType) (Table 1). Soil pedon information included field-estimated coarse fragment content (CFCont); B horizon thickness (BThick); A and B horizon types (HzType); B horizon texture class (BTxtCl); solum depth; forest humus form (HumForm); CSSC soil order (CSSOrd) (Soil Classification Working Group 1998); and derived SMR and drainage class (DrainCl) (Denholm et al. 2009). Vegetation data included overstory stand composition and species type. We also estimated plot-level bedrock mineralogy using spatial data (Ontario Geological Survey 2011) and categorized this using five nutrient richness classes (BedMin) following Lloyd et al. (1990), DeLong et al. (2011), and Keys et al. (2016).

Soil chemistry

Although not used in determining Associations, Ecosites, or their associated SNRs, soil samples were systematically collected for chemical analyses from 618 10 × 10 m EC plots at the same time as pedon descriptions were being compiled. This involved taking bulk samples from each major horizon within a single soil pit, established as close to the centre of the plot as feasible. For any given horizon, material was collected from across the pit face.

Chemical variables subsequently measured or calculated were those commonly associated with forest soil quality, productivity, and health (Schoenholtz et al. 2000; Thiffault et al. 2014). These included organic C (OrgC), total N (TotN), C:N ratio (C:N), pH in both water (pHH_2O), and $CaCl_2$ (pHCa) suspensions, effective cation exchange capacity (CEC), exchangeable bases (ExBase), and base saturation (BaSat), as well as mineral soil texture/particle size (LabTxt). OrgC was determined by loss-on-ignition in a muffle furnace at 500 °C, TotN by the semimicro-Kjeldahl method (Kalra and Maynard 1991), and pHCa in a 1:2 suspension of soil in $CaCl_2$ (0.01 mol/L). We chose pHCa rather than pHH_2O for our analysis because of the former's more robust measurement properties (Miller and Kissel 2010). For mineral soils, LabTxt was determined using the hydrometer method, while ExBase and CEC were assessed using a dilute unbuffered silver thiourea solution (0.01 mol/L Ag^+). Pleysier and Juo (1980) found this method gave good correspondence with CEC and ExBase values obtained using neutral NH_4OAc displacement for ExBase and unbuffered 1 mol/L KCl extraction for exchange acidity (Al + H). They recommended the method for soils dominated by variable-charge colloids and low-activity clays.

We concentrated on upper B horizon relationships because this horizon represents the principal diagnostic horizon and the primary soil nutrient store for most upland boreal forest soils (e.g., Jobbágy and Jackson 2001; Callesen et al. 2007), but we also considered the combined influence of the F, A, and upper B horizons. All nutrients were expressed as concentrations on a dry mass basis. While not representing total nutrient quantities, the use of concentrations avoids the need for accurate estimates of coarse fragment content, soil depth, and fine fraction (<2 mm) bulk density, all of which can be problematic. Soil chemical concentrations have been used previously to quantify soil nutrient regimes (e.g., Klinka et al. 1994; Splechtna and Klinka 2001), and Stevenson et al. (2015), in a New Zealand soil classification study, found little difference in overall principal components analysis (PCA) or cluster analysis results using soil nutrient concentration vs. nutrient content (kg ha^{-1}).

Quantitative analysis

Data preparation and assembly

We first screened the data using box and whisker plots to identify and remove obvious outliers and data input errors from these historic data sets. We then compiled three data sets: a master list comprising all plots with the full suite of chemistry variables for at least one horizon (AllPlots) (695 plots) and the other two containing complete sets of site, soil, and pedon descriptions, as well as chemistry variables for the upper B horizon (BHorz) (618 plots) and for the F, A, and upper B horizons combined (AllHorz) (428 plots). The reduction in AllHorz vs. BHorz plot numbers largely reflected the absence of A horizon samples (and, by inference, the lack of substantive A horizons per se) for about 10% of the plots.

Next, we used a combination of univariate and multivariate statistics to assess individual nutrients and their composite attributes. To improve normality and/or homogeneity of variance, we log-transformed OrgC, TotN, C:N, CEC, and ExBase and arcsine-transformed BaSat. For multivariate analyses, we used a suite of five equally weighted chemical variables for the A and B horizons (TotN, C:N, BaSat, pHCa, and CEC) and three equally weighted variables (TotN, C:N, and pHCa) for the F horizon. ExBase was omitted because of its high correlation with BaSat and CEC, and because ExBase values determined using silver thiourea tend to overestimate those reported using other methods (Pleysier and Juo 1980). OrgC was omitted because of strong collinearity with TotN and because once log-transformed, its influence was circumscribed by TotN and C:N (log(OrgC) = log(C:N) − log(TotN)). For some multivariate analyses (e.g., multiple response permutation procedure (MRPP) and *K*-means clustering), the transformed chemical variables and related environmental descriptors were also converted to standard deviates to account for differences in scale.

Soil nutrient relationships and existing classifications

We used Spearman rank and Pearson product moment correlations to evaluate relationships among individual nutrients, and PCA to identify and depict the variables accounting for the greatest variation in the data sets. PCA constructs linearly related composite variables (components) along orthogonal axes of decreasing covariation (importance). Next, we focused on the 15 Associations and 22 Ecosites for which we had at least nine plots with complete BHorz or AllHorz chemistry data (Tables A1 and A2) by (1) examining relationships among individual soil chemistry variables and overall Association and Ecosite SNR categories using one-way analysis of variance (ANOVA) followed by Tukey's multiple comparison tests; and (2) investigating the multivariate compositional similarity among individual Associations and Ecosites with regard to the suite of BHorz and AllHorz chemistry variables using a MRPP procedure. MRPP is a multivariate technique whereby statistical differences between groups are evaluated by comparing the average Euclidean distance between all pairs of points within each group with a Pearson type III distribution of all possible partitions (McCune and Grace 2002). We accounted for multiple pair-wise hypothesis testing by applying the Benjamini–Hochberg α correction (Waite and Campbell 2006).

Developing and comparing soil nutrient classifications

In a separate analysis, we used *K*-means clustering to develop a new classification of soil nutrient attributes by allocating individual plots to five composite BHorz and AllHorz SCR classes (BHorzSCRs and AllHorzSCRs, respectively). For the AllHorz analysis, we equally weighted the nutrients evaluated for each horizon. *K*-means clustering is well recognized for its ability to form a small number of clusters using the

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local structure within large data sets of continuous variables (Hastie et al. 2009). We used 20 random starts and a maximum of 25 iterations with both data sets. Five clusters represented a near-optimum number as the change in the percentage of variation explained (BHorz variation = 39.6%, AllHorz variation = 59.3%) leveled off with further increases in cluster numbers. To assign each of the five BHorz and AllHorz *K*-means clusters to an SCR class, we ranked the cluster modal and median values for each chemistry variable from lowest to highest "quality" based on increasing TotN, CEC, ExBase, BaSat, and pHCa, and decreasing C:N, and then averaged the individual rankings to assign an overall BHorzSCR and AllHorzSCR.

We depicted the correspondence of the various classifications with confusion matrices and evaluated their correspondence using Cramer's V and Kendall's τB or τC (also known as Kendall's rank correlation coefficient). Cramer's V represents the mean square canonical correlation between nominal variables, and ranges between 0 and 1. Kendall's τB and τC measure the rank correlation between two sets of ordered variables and penalize misclassifications based on their dissimilarity. Values range from 1 (complete agreement), through 0 (random ordering) to −1 (complete inversion). τB applies when the number of rows = number of columns; τC applies when this is not the case (Abdi 2007). When comparing SNRs with SCRs (the reference classification), we also calculated the sample-weighted user's accuracy (the probability that a plot belonging to a particular Ecosite or Association and its assigned SNR correspond to the SCR assigned through *K*-means clustering). Correlation analysis, ANOVA, *K*-means clustering, and confusion matrix evaluations were conducted using NCSS 11 (NCSS Statistical Software 2016) while PCA and MRPP were conducted using PC-ORD 6 (McCune and Mefford 2011).

SCR site/soil/overstory relationships

Most SNR field-based classification schemes use a variety of site, soil pedon, and vegetation descriptors (Table 1 and Fig. S1) to assign an SNR class to a particular plot (Green and Klinka 1994; DeLong et al. 2011; Johnson, J.A., P.W.C. Uhlig, and M.C. Wester (unpublished report)). Pursuing this approach, we first explored relationships between various site and pedon characteristics and BHorzSCRs (e.g., Fig. S1). With continuous and ordered variables, we used multiple regression with variation partitioning (Legendre and Legendre 2012) and Dunn's nonparametric Kruskal–Wallace multiple comparison test. With categorical variables, we used confusion matrices. For pHClass, we divided the pHCa data into six ordered classes (3.5–4.0, 4.1–4.5, 4.6–5.0, 5.1–5.5, 5.6–6.0, and 6.1–7.7).

We then evaluated the ability of these variables to differentiate among SCRs using Classification and Regression Trees (CART) and Random Forests (Hastie et al. 2009). We did so both with and without pHClass and/or LabTxt to assess the importance of these two laboratory-derived variables. These nonparametric, recursive-based machine learning techniques sequentially partition the response variable using any number of predictor variables without relying on particular functional forms or a priori models. They can combine categorical, ordinal, and continuous variables and are well suited to dealing with unbalanced data, missing values, nonlinear relationships, and higher order interactions (De'ath and Fabricus 2000). CART produces readily interpreted, hierarchical, dichotomous keys that are consistent with EC/ELC diagnostic approaches and well suited for field use. We constructed CART classification trees with the R package *rpart* (Therneau et al. 2014) using 10 runs of 10-fold cross-validation with cost-complexity pruning based on the misclassification rate to define the optimum tree size. CART variable importance was calculated as the sum of goodness of split measures for which a given variable represented the primary split, plus the adjusted agreement for all splits in which it was a surrogate. Decision trees were graphically displayed for the four pHClass × LabTxt scenarios using the R package *partykit* (Hothorn and Zeileis 2014).

We compared the relative accuracy of our CART trees with those produced using a Random Forests ensemble tree approach using the *R* package *randomForest* (Liaw and Weiner 2018). CART may have difficulty establishing cut-points for smooth continuous relationships and capturing additive structures (Hastie et al. 2009). Random Forests is designed to reduce the variance of tree-based classifications by building a large collection of decorrelated (bootstrap-produced) trees and then averaging the results. We used $\sqrt{p}$ to grow the trees, where p is the number of independent variables, and aggregated the results from 500 individual trees. Initially, all site, pedon, and overstory variables were considered with subsequent variable removal based on their mean decrease in the Gini coefficient splitting index, while ensuring the out-of-bag classification error rate remained within 2% of the full model.

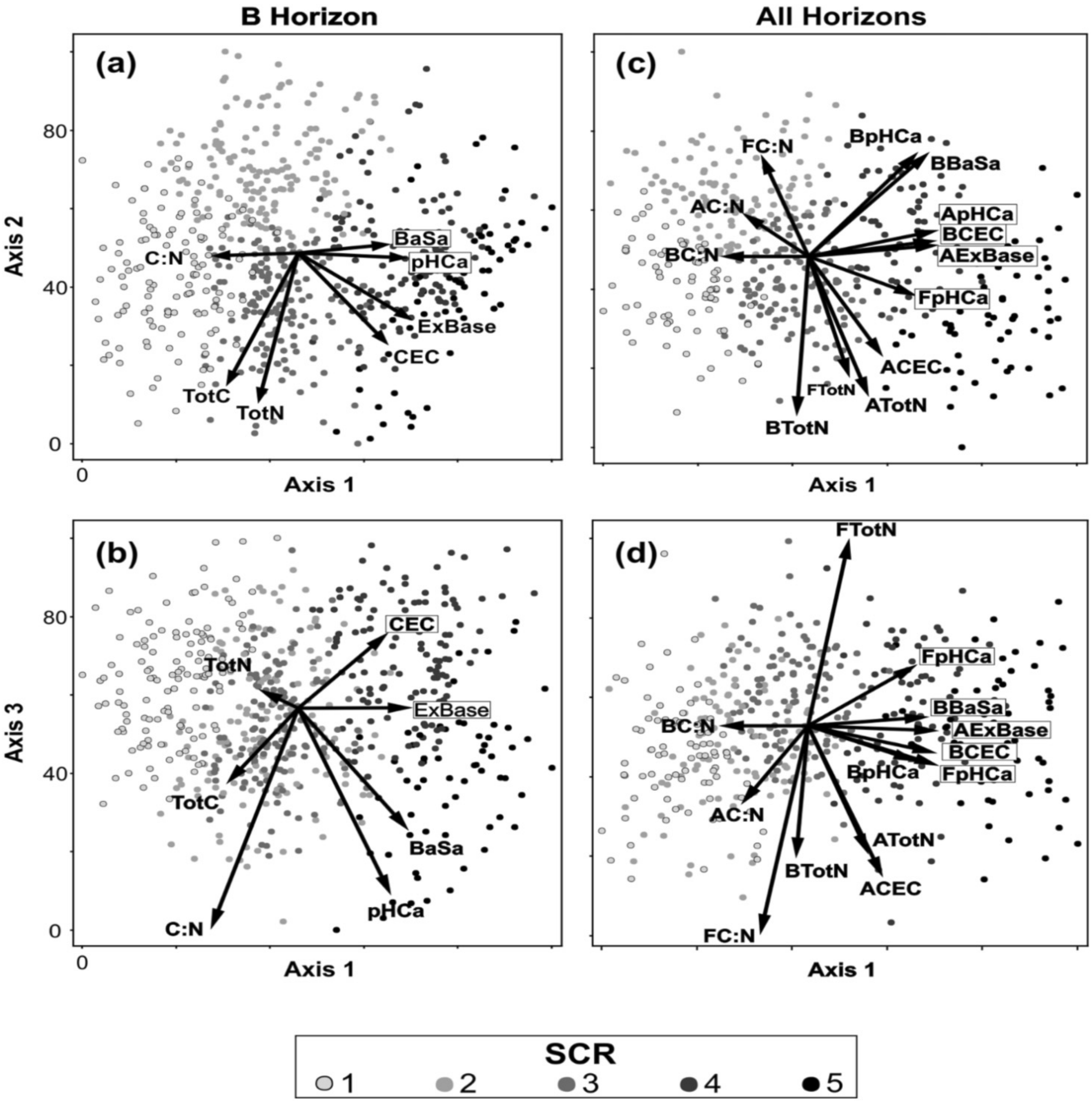
Results

Soil nutrient relationships

The largest number of substantive ($\tau \geq 0.45$) correlations across soil horizons for the various chemical variables occurred with F and A horizon pHCa and with A and B horizon cation metrics (Table S1). Notably, F pHCa was well correlated with the mineral horizons ExBase and BaSat, and moderately so with C:N of all horizons. There were very strong correlations between OrgC and TotN within each mineral soil horizon ($\tau = 0.90$–0.92), but not between horizons, and TotN was not strongly correlated with C:N ($\tau < 0.30$) within either mineral horizon.

With PCA, almost half of the total variation for both the BHorz and AllHorz data sets was accounted for by the first principal component (PC1) (Table S2). PC1 factor loadings for both data sets primarily contrasted pHCa and cation metrics with C:N ratios (Fig. 2). For the BHorz data set, the second and third PCs accounted for 24% and 15% of the variation, and factor loadings were dominated by TotN and C:N, respectively. For the AllHorz data set, the second and third PCs accounted for 14% and 10% of the variation, respectively, and with PC2 TotN factor loadings contrasting with those for B-BaSat and B-pHCa.

Fig. 2. Principal component analyses of the BHorz (*a* and *b*) and AllHorz (*c* and *d*) soil chemistry data. Biplots of chemistry variables (Table 2) are superimposed on the first and second and first and third PCA axes, as are their plot-level SCR assignments. AllHorz variables are preceded by their horizon designation.



Developing and comparing soil nutrient classifications

Both the BHorz and AllHorz *K*-means-derived SCRs showed strong alignment with PC1 (Fig. 2) and broad differentiation of pHCa, various cation metrics, and C:N between classes (Table 2). OrgC and BHorz TotN, while strongly aligned with PC2, did not vary consistently across the SCRs. Comparisons of soil chemistry across Association and Ecosite SNRs also showed a general trend of increasing nutrient levels with increasing SNR richness for all three horizons (Figs. 3 and 4 and Tables S3 and S4). As with the SCR classifications, however, OrgC did not vary consistently across the SNRs for any horizon, nor did TotN in the B horizon.

There was reasonable correspondence between the five-category BHorzSCR and AllHorzSCR classes ($V = 0.61$, $\tau B = 0.72$; Table S5). Differences in class alignment were largely confined to poor vs. medium, and rich vs. very rich classes, giving an overall weighted user's accuracy of 65%. However, when condensed into three-category classifications (poor, medium, and rich), the weighted user's accuracy for predicting AllHorzSCR using BHorzSCR increased from 65% to 85%.

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Table 2. BHorzSCR and AllHorzSCR chemistry by major horizon.

		SCR (number of plots, AllHorz and BHorz)				
Variable	Horizon	Very poor All $n = 102$ B $n = 123$	Poor All $n = 88$ B $n = 152$	Medium All $n = 107$ B $n = 153$	Rich All $n = 87$ B $n = 125$	Very rich All $n = 44$ B $n = 65$
OrgC (%)	F: AllHorz	35.1 ± 7.1^{a}	32.2 ± 7.4^{b}	34.4 ± 6.7^{ab}	33.1 ± 6.5^{ab}	33.0 ± 5.2^{ab}
	A: AllHorz	1.17 ± 0.67^{b}	0.91 ± 0.89^{c}	1.36 ± 0.93^{b}	1.05 ± 0.68^{bc}	3.05 ± 2.40^{a}
	B: AllHorz	1.08 ± 0.62^{a}	0.50 ± 0.33^{c}	1.06 ± 0.67^{ab}	0.44 ± 0.25^{c}	0.90 ± 0.77^{b}
	B: Bhorz	1.36 ± 0.71^{a}	0.41 ± 0.18^{c}	1.24 ± 0.58^{a}	0.41 ± 0.21^{c}	0.74 ± 0.77^{b}
TotN (g/kg)	F: AllHorz	10.2 ± 2.0^{c}	9.8 ± 2.3^{c}	13.9 ± 2.5^{b}	13.7 ± 3.2^{b}	15.7 ± 3.9^{a}
	A: AllHorz	0.59 ± 0.32^{c}	0.50 ± 0.64^{d}	0.85 ± 0.58^{b}	0.79 ± 0.52^{b}	3.14 ± 2.29^{a}
	B: AllHorz	0.59 ± 0.07^{a}	0.27 ± 0.15^{b}	0.64 ± 0.36^{a}	0.37 ± 0.15^{b}	0.71 ± 0.48^{a}
	B: Bhorz	0.75 ± 0.41^{a}	0.23 ± 0.08^{d}	0.73 ± 0.34^{a}	0.38 ± 0.23^{c}	0.54 ± 0.44^{b}
C:N (%)	F: AllHorz	35.4 ± 9.4^{a}	34.0 ± 9.1^{a}	25.1 ± 5.0^{b}	25.1 ± 6.4^{b}	22.1 ± 5.8^{c}
	A: AllHorz	20.2 ± 5.5^{a}	19.1 ± 6.1^{a}	16.0 ± 3.1^{b}	13.9 ± 3.9^{c}	13.7 ± 4.8^{c}
	B: AllHorz	19.0 ± 4.4^{a}	18.0 ± 4.9^{ab}	16.3 ± 3.4^{b}	11.9 ± 3.3^{c}	12.2 ± 3.8^{c}
	B: Bhorz	18.7 ± 4.4^{a}	17.8 ± 5.1^{a}	17.3 ± 3.4^{a}	11.2 ± 2.7^{c}	13.0 ± 4.2^{b}
pHCa	F: AllHorz	3.3 ± 0.4^{e}	3.7 ± 0.5^{d}	4.1 ± 0.5^{c}	4.6 ± 0.7^{b}	5.4 ± 0.5^{a}
	A: AllHorz	3.5 ± 0.3^{d}	3.8 ± 0.4^{c}	3.9 ± 0.4^{c}	4.6 ± 0.3^{b}	5.4 ± 0.6^{a}
	B: AllHorz	4.4 ± 0.3^{c}	4.9 ± 0.3^{b}	4.4 ± 0.3^{c}	5.0 ± 0.6^{b}	5.7 ± 0.8^{a}
	B: Bhorz	4.2 ± 0.3^{d}	4.7 ± 0.4^{c}	4.6 ± 0.3^{c}	4.9 ± 0.4^{b}	6.3 ± 0.5^{a}
CEC meq/1000 g	A: AllHorz	20.4 ± 6.8^{c}	17.1 ± 6.5^{d}	21.4 ± 6.4^{c}	28.0 ± 10.3^{b}	36.3 ± 5.8^{a}
	B: AllHorz	9.8 ± 6.8^{c}	10.8 ± 10.3^{c}	14.7 ± 6.5^{b}	36.2 ± 13.4^{a}	40.6 ± 8.3^{a}
	B: Bhorz	12.3 ± 7.5^{d}	8.2 ± 5.7^{e}	16.9 ± 8.2^{c}	34.2 ± 14.8^{b}	39.9 ± 9.6^{a}
ExBase meq/1000 g	A: AllHorz	5.2 ± 3.8^{e}	9.1 ± 6.3^{d}	12.8 ± 6.3^{c}	26.1 ± 10.6^{b}	35.4 ± 5.7^{a}
	B: AllHorz	4.0 ± 3.0^{d}	9.8 ± 10.3^{c}	10.1 ± 5.5^{b}	35.3 ± 13.8^{a}	39.7 ± 8.1^{a}
	B: Bhorz	3.7 ± 2.4^{e}	5.8 ± 4.4^{d}	13.7 ± 7.7^{c}	33.1 ± 4.9^{b}	39.4 ± 9.3^{a}
% BaSat	A: AllHorz	25.0 ± 14.1^{d}	51.4 ± 23.2^{c}	59.4 ± 20.0^{b}	92.2 ± 9.7^{a}	97.4 ± 3.4^{a}
	B: AllHorz	45.4 ± 22.2^{d}	86.1 ± 12.8^{c}	69.2 ± 19.0^{b}	96.8 ± 5.6^{a}	97.8 ± 3.8^{a}
	B: Bhorz	32.8 ± 14.7^{e}	71.7 ± 19.0^{d}	81.3 ± 13.4^{c}	95.8 ± 6.7^{b}	98.9 ± 2.5^{a}

Note: OrgC, organic carbon; TotN, total nitrogen; C:N, C:N ratio; pHCa, pH measured in $CaCl_2$ suspension; CEC, cation exchange capacity; ExBase, exchangeable bases; and BaSat, base saturation. Shown are mean values and standard deviations for F, A, and B horizons for the AllHorz data set and the Bhorz data set. Sample size (plots, n) per SCR is shown for each data set. For each variable (row), values with the same lower case letter are not significantly different (Tukey–Cramer multiple comparison test, $p < 0.05$).

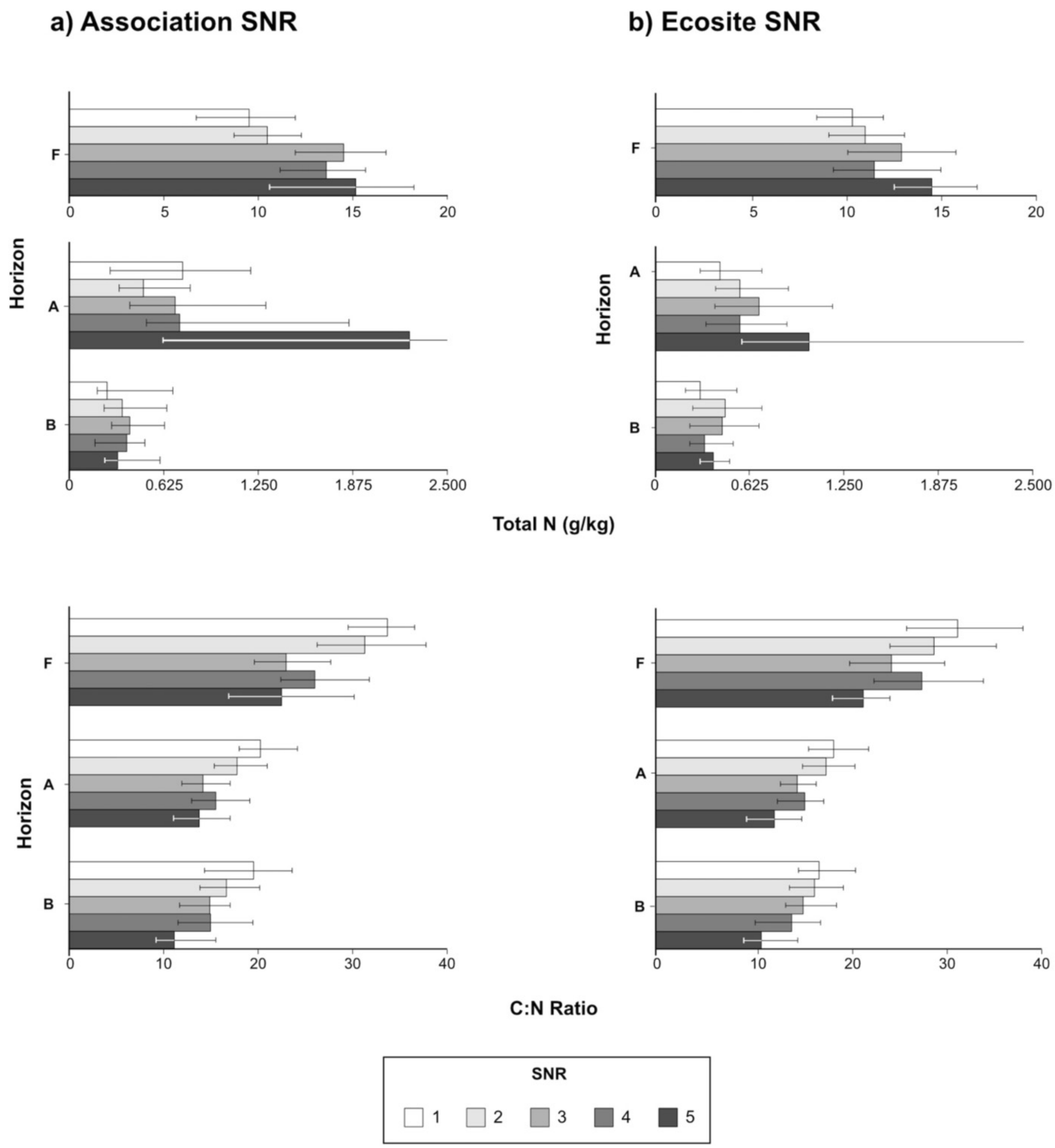
There were often similar general trends (poorer to richer) in plot-level assignment of BHorzSCRs and AllHorzSCRs and of Association and Ecosite SNR categories. The mean user's accuracy relating the SNRs of the various Associations and Ecosites to their assigned BHorz and AllHorz SCRs ranged from 31%–39% among the four SNR–SCR combinations (Tables S6–S9). In 80%–86% of cases, however, Association and Ecosite SNR ratings for a given plot coincided within one category of their BHorz and AllHorz SCRs. BHorz and AllHorz chemistry relationships with individual Associations and Ecosites, and their SNR designations, are discussed further in the Supplementary material.

SCR site/soil/overstory relationships

Among categorical variables (Table S10), ModDep had the strongest association with the BHorzSCR categories ($V = 0.52$, $\tau C = 0.32$), with glaciofluvial and lacustrine deposition types strongly aligned with the poorer and richer SCR categories, respectively. Other variables showing distinct SCR relationships included BHzType ($V = 0.38$, $\tau C = 0.23$), CSSOrd ($V = 0.36$, $\tau C = 0.31$), and AHzType ($V = 0.34$, $\tau C = 0.16$). Bt horizons and Luvisols were strongly associated with rich–very rich SCRs, whereas Bm horizons and Brunisols as well as Podzols were concentrated in the very poor to medium SCRs. Ae horizons were more frequently associated with poor to medium SCRs, whereas Ah horizons were commonly associated with rich to very rich SCRs. TopPos (especially crest/upper vs. toe/depression) and SppType provided some discriminating power despite limited V and τC values, while HumForm (except for mull) did not provide substantive SCR differentiation. Among continuous/ordered variables (Table S11), pHClass ($VP = 0.69$) followed by texture metrics ($VP = 0.42$–0.46) explained the largest proportion of BHorzSCR variation (VP). Richer SCR classes were associated with higher pHs and finer BHorz textures. These were followed by BThick ($VP = 0.20$), DrainCl ($VP = 0.14$), and PinePct ($VP = 0.14$).

The four CART scenarios resulted in resubstitution error rates of 29%–41%, cross-validated error rates of 34%–50%, and 56%–73% of plots correctly classified by BHorzSCR, based on the pruned classifications (Table 3). Use of Random Forests instead of CART had very little effect on error rates (Random Forests out-of-bag error rates vs. CART cross-validated error rates) when LabTxt was included as a variable, but reduced error rates by 3.2%–4.3% when LabTxt was omitted. In almost all cases, the majority of plots assigned by the various CART

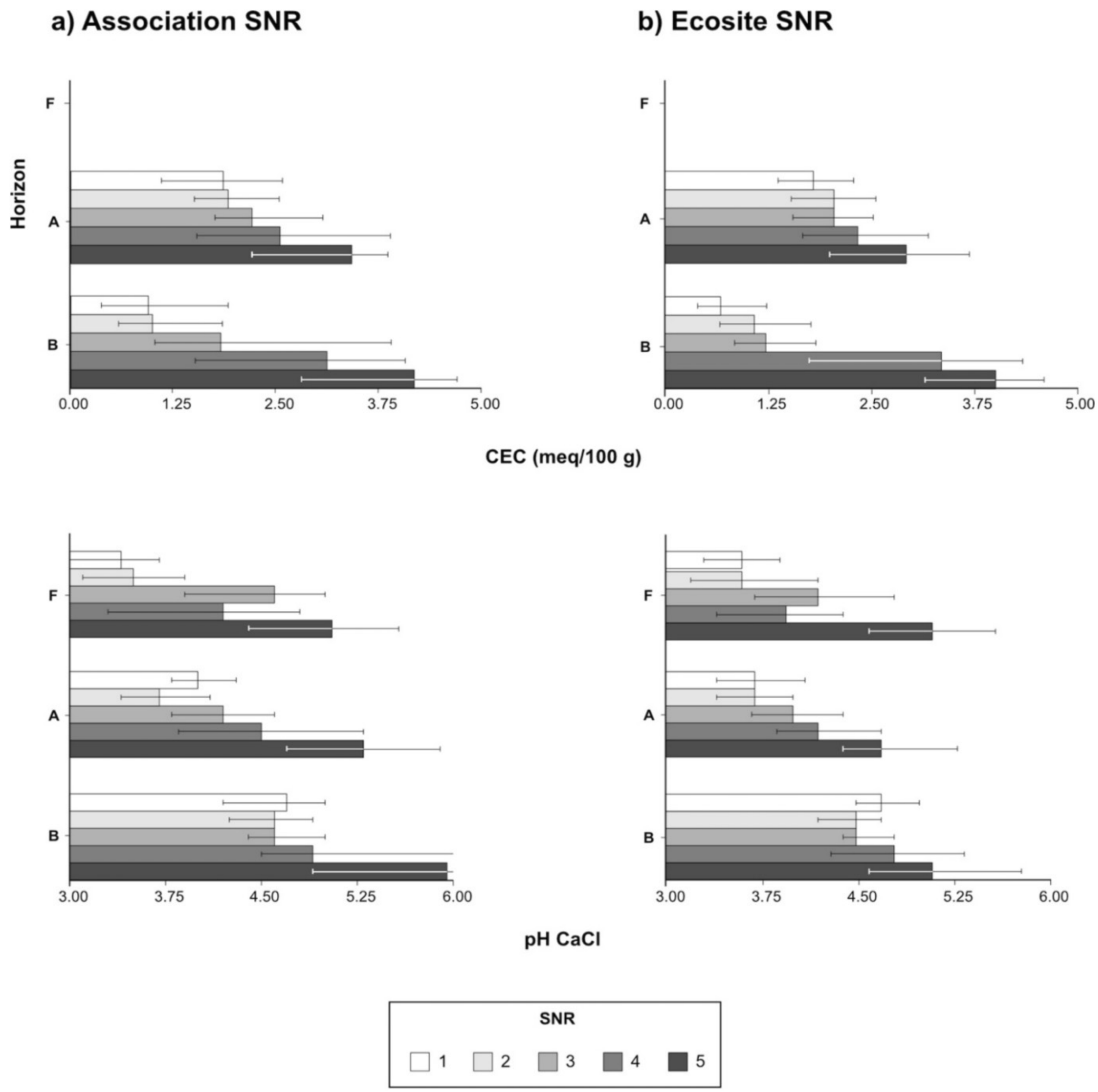
Fig. 3. Median F, A, and B horizon total N (TotN) and C:N ratio (C:N) values for the Association (*a*) and Ecosite (*b*) soil nutrient regimes (SNRs). The SNR codes are as follows: (1) very poor, (2) poor, (3) medium, (4) rich, and (5) very rich. Crossbars represent the 75th percentiles.



scenarios to a given SCR corresponded with their K-means-based BHorzSCR designation (Table 4). The overall user's accuracy, however, varied from 59% to 71%, with the inclusion of pHClass resulting in higher CART user's accuracy for rich and very rich BHorzSCRs. For scenarios 4a (both LabTxt and pHClass) and 4c (no LabTxt) in Table 4, the users' accuracy was lower for the very poor to medium SCRs than the rich to very rich SCRs. For scenario 4b (no pHClass), the differences reflected allocation to only four of the SCRs (no allocation to the very rich class) and, as with scenario 4d, lower accuracy for the very poor and medium SCRs.

Inclusion of both pHClass and LabTxt resulted in the most accurate CARTs, with LabTxt (BClay and BSand) and pHClass driving the major splits in the classification tree (Fig. 5*a*). With the other CART scenarios, the major splits depended on whether pHClass and/or LabTxt were included. With LabTxt included, species composition (ConPct and PinePct) played an important role (Figs. 5*a* and 5*b*), but in its absence, BTxtCl accounted for the initial split, with CFCont and BThick playing important secondary roles (Figs. 5*c* and 5*d*). In both cases, CFCont split plots with vs. without notable CFCont amounts, and with the former loosely associated with poorer

Fig. 4. Median F, A, and B horizon cation exchange capacity (CEC) and pH in $CaCl_2$ (pHCa) values for the Association (*a*) and Ecosite (*b*) soil nutrient regimes (SNRs). The SNR codes are as follows: (1) very poor, (2) poor, (3) medium, (4) rich, and (5) very rich. Crossbars represent the 75th percentiles.



SCRs.When pHClass was included, it accounted for the highest order splits after LabTxt or BTxtCl (Figs. 5*a* and 5*c*), and occurred at multiple stages of the hierarchy. Other factors occurring at lower levels of the various hierarchies included ModDep (LabTxt + pHClass) and TopPos and SppType (no LabTxt or pHClass). With pHClass included, the upper portions of the hierarchies usually separated the richest from the poorer SCRs, with subsequent divisions refining separations among SCRs 1–3. Without pHClass, the hierarchical sequences were more varied, but generally resulted in the richer SCRs still being separated out initially.

As expected, LabTxt (BClay and BSand), pHClass, and BTxtCl received the highest CART variable importance ratings (Table 3). These were followed by ModDep, BHzType, and CSSOrd across all four scenarios, and with CFCont and BThick contributing in the absence of LabTxt. Notably, two soil classification descriptors (BHzType and CSSOrd) had substantive importance ratings but did not appear in the pruned classification trees. In comparison, species composition had low importance rankings across all scenarios except in the absence of both LabTxt and pHClass. With Random Forests, variable importance rankings were similar to those embedded in the CART keys, although BThick played a primary role in the absence of LabTxt, and SMR contributed in the absence of pHClass.

Discussion

Sampling approach

In this study, our goal was to characterize general trends in profile soil chemistry across the broad range of upland Associations and Ecosites in northwestern Ontario. We chose

Table 3. Classification tree (CART) and Random Forests results predicting BHorzSCR from site and pedon variables.

	LabTxt and pHClass variable combination			
Classification accuracy	LabTxt and pHClass	LabTxt, no pHClass	pHClass, no LabTxt	No LabTxt, no pHClass
CART resubstitution error rate (%)	28.9	40.7	32.3	40.7
CART cross-validated error rate (%)	34.7	44.8	41.8	50.0
Random Forests out-of-bag error rate (%)	33.2	43.0	38.6	45.7
CART % classified correctly	72.7	55.8	70.0	61.9
CART variable importance (% contribution, including surrogate splits)/Random Forests importance (mean decrease in the Gini coefficient for specified model variables). N = not identified as important				
BSand	20/110	24/90	n/a	n/a
BClay	18/91	21/81	n/a	n/a
pHClass	16/78	n/a	22/85	n/a
BTxtCl	12/N	15/35	15/80	16/64
ConPct	1/40	3/42	3/53	7/63
PinePct	2/47	3/50	4/62	7/72
CFCont	1/N	1/35	10/56	11/47
BThick	0/65	0/66	8/99	6/105
BHzType	9/N	11/N	8/N	11/N
ModDep	9/N	9/N	13/N	13/39
CSSOrd	8/N	10/N	9/N	10/N
TopPos	3/N	0/N	2/N	4/N
SppType	0/N	2/N	0/N	4/N
SMR	1/N	1/31	4/N	6/43
DrainCl	0/N	0/N	2/N	5/N
AHzType	0/N	0/N	0/N	5/N

Note: Shown are the best-fit error rates and Variable Importance for classification schemes with/without lab texture and pHCa class. Shaded variables contributed directly to the pruned CART diagrams. Definitions of the variables are given in Table 1.

to sample one pedon and multiple horizons from a large number of 10 × 10 m plots rather than taking multiple subsamples at one or two depths from a smaller number of plots. Trade-offs involve defining the population of interest and how best to sample it, given the resources available and the level of accuracy required (Binkley and Fisher 2020, pp. 243–247). Our approach provided reasonable inferences for the entire study area, but likely with somewhat less accuracy than if we had subsampled within plots. Very small sample sizes (numbers of plots) taken over a limited range of Ecosite SNRs (medium–very rich) undoubtedly contributed to the paucity of statistical differences Tamminga et al. (2014) found in Ecosite soil chemistry.

Soil nutrient relationships

The high PC1 factor loadings and strong correlations we found between pH and cation availability are commonly reported for forest soils and likely reflect interactions among acid and base cation availability, cation exchange sites, and soil solution hydrogen ion concentration (Chapin et al. 2011; Mueller et al. 2012). Offsetting these, the sizeable negative PC1 loadings for C:N are consistent with the reduction in forest soil C:N ratios frequently associated with increases in soil pH (Van Sundert et al. 2018). In comparison, while TotN was the leading PC2 variable for both data sets, it did not play an important role in defining the BHorz SCRs. However, both F and A horizon TotN values increased consistently across the AllHorzSCRs (Table 2) and the two SNR classifications (Fig. 3).

The weak mineral soil N vs. C:N correlations and multivariate linkages seem counterintuitive given their common association with gradients in site productivity (Van Cleve et al. 1983), soil quality (Schoenholtz et al. 2000), and some vegetation-based soil nutrient regimes (Chen et al. 1998; Wang 2000; Kranabetter et al. 2007). They are consistent, however, with other soil nutrient studies (Klinka et al. 1994; Cools et al. 2014; Stevenson et al. 2015) and may reflect the strong influence of OrgC composition on such relationships (Booth et al. 2005).

Developing and comparing soil nutrient classifications

Given the importance of soil C and N for ecosystem functioning, the lack of clear differentiation of OrgC and, to

Table 4. Confusion matrices of CART results predicting BHorz SCR (B horizon soil chemistry regime) plot allocations from site and soil pedon variables.

(a) LabTxt and pHClass: $V = 0.720$, $\tau B = 0.700$.

Predicted BHorz SCR	Actual Bhorz SCR: Very poor	Poor	Medium	Rich	Very rich	Predicted plots (n)	User's accuracy (%): Specific	General
Very poor	77	18	20	2	0	117	66	92
Poor	15	90	9	14	0	128	70	
Medium	21	33	111	20	0	185	60	
Rich	0	0	8	75	0	83	90	93
Very rich	0	1	0	1	45	47	96	
Actual plots (n)	113	142	148	112	45	560	Overall accuracy (%)	
							71	92

(b) LabTxt, no pHClass: $V = 0.565$, $\tau B = 0.552$

Predicted Bhorz SCR	Actual Bhorz SCR: Very poor	Poor	Medium	Rich	Very rich	Predicted plots (n)	User's accuracy (%): Specific	General
Very poor	63	26	24	8	4	125	51	89
Poor	14	84	7	13	0	118	71	
Medium	35	32	109	15	11	202	54	
Rich	0	0	8	77	30	115	67	93
Very rich	0	0	0	0	0	0	n/a	
Actual plots (n)	112	142	148	113	45	560	Overall accuracy (%)	
							60	90

(c) pHClass, no LabTxt: $V = 0.682$, $\tau B = 0.657$

Predicted SCR	Actual SCR: Very poor	Poor	Medium	Rich	Very rich	Predicted plots (n)	User's accuracy (%): Specific	General
Very poor	86	34	29	5	0	154	55	91
Poor	9	87	24	17	2	139	63	
Medium	17	20	91	14	1	143	64	
Rich	1	0	4	73	0	78	94	95
Very rich	0	1	0	3	42	46	91	
Actual plots (n)	113	143	148	112	45	560	Overall accuracy (%)	
							68	92

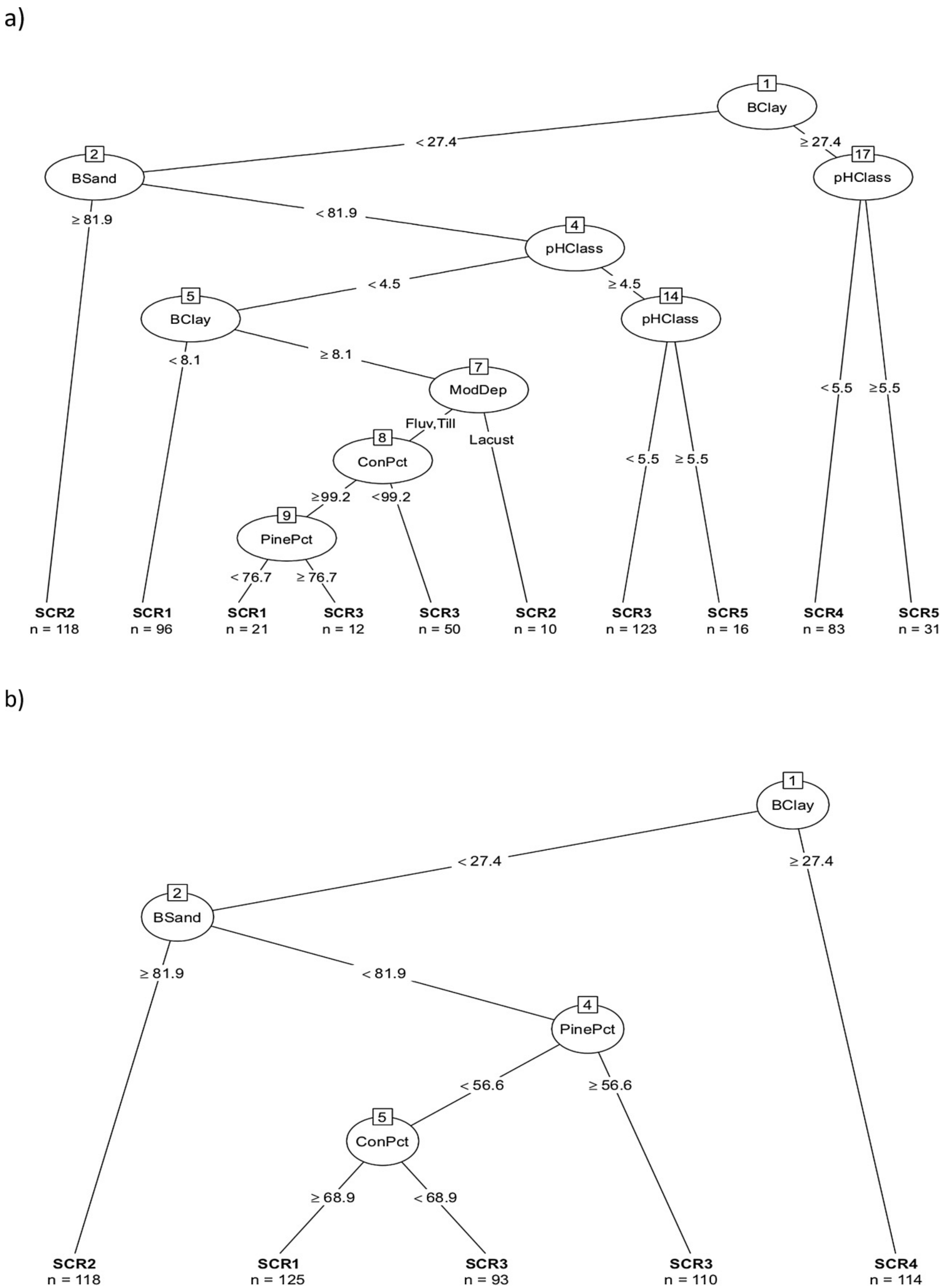
(d) No LabTxt, no pHClass: $V = 0.513$, $\tau B = 0.566$

Predicted SCR	Actual SCR: Very poor	Poor	Medium	Rich	Very rich	Predicted plots (n)	User's accuracy (%): Specific	General
Very poor	66	30	21	6	3	126	53	89
Poor	8	75	12	11	1	107	70	
Medium	38	37	111	21	8	215	51	
Rich	1	0	3	63	16	83	76	96
Very rich	0	0	1	11	17	29	59	
Actual plots (n)	113	142	148	112	45	560	Overall accuracy (%)	
							59	90

Note: Shown are the predicted and actual SCR plot counts and user's accuracy for variable combinations that included or excluded LabTxt (% sand and % clay) and/or pHCa class. Definitions of the variables are given in Table 1.

a lesser extent, TotN among SNR and SCR classes suggests that further refinements or separate SCR classifications for these two variables are warranted. For instance, B horizon *K*-means clustering of log-transformed OrgC and TotN produced a well-defined classification, but with little relationship to the BHorzSCR or Association and Ecosite SNRs ($\tau B < 0.1$) (data not presented). The correspondence of mineral soil OrgC with SNRs is complicated by the influence of soil moisture as well as by its own chemical composition. On drier upland soils, OrgC may serve as an integrative soil quality metric, given its relationship with N and P storage and its provision of cation and anion exchange sites (Van Cleve and Powers 1995). However, on wetter soils, partial anoxic conditions may reduce stand productivity and mineralization rates while

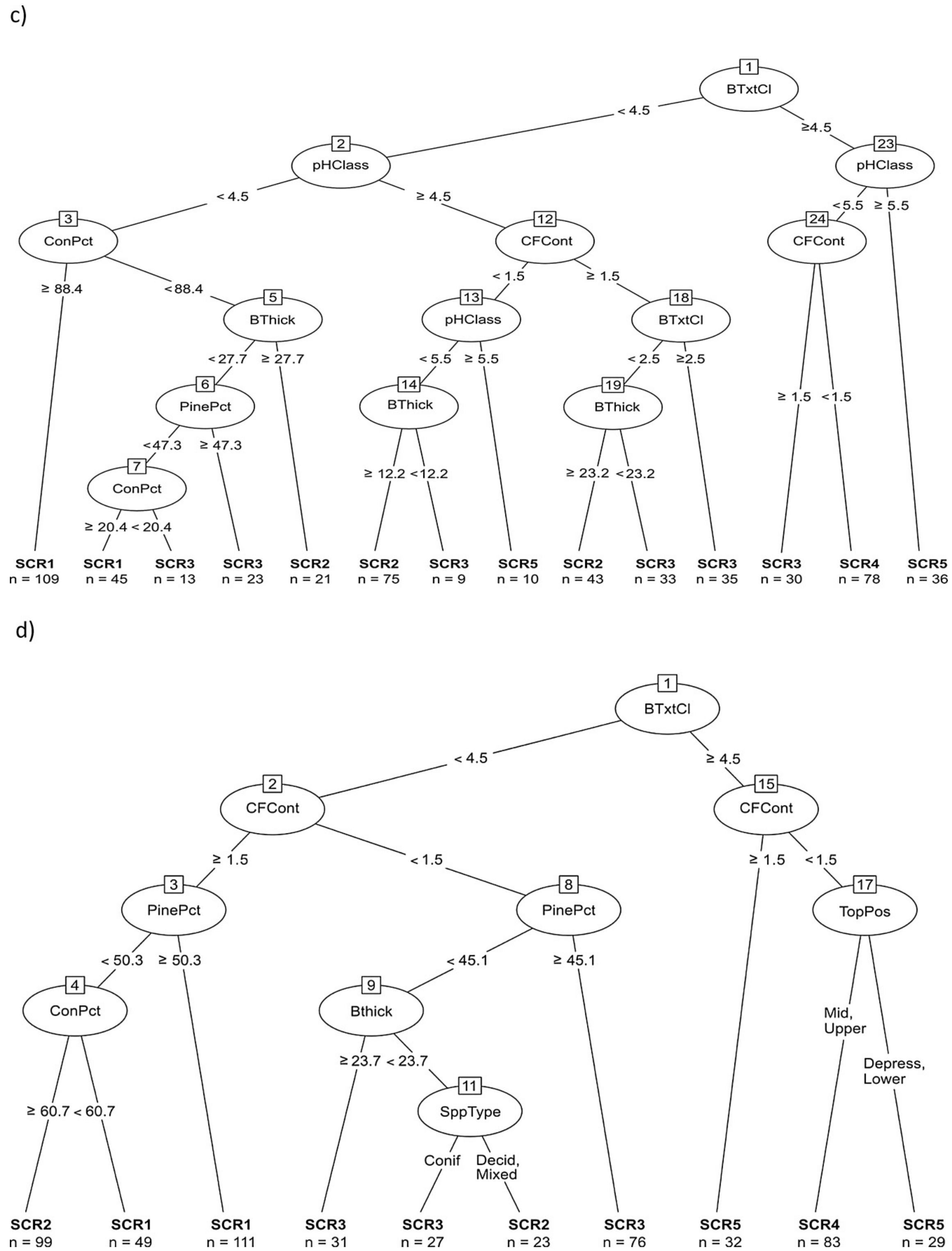
Fig. 5. Classification trees relating BHorz SCRs (soil chemistry regimes) to site, pedon, and stand variables (Table 1): (*a*) with pHClass and LabTxt included; (*b*) with LabTxt but not pHClass included; (*c*) with pHClass but not LabTxt included; and (*d*) with neither pHClass nor LabTxt included as potential explanatory variables.



enhancing OrgC storage. Thus, OrgC relationships with other soil chemistry metrics as well as with site productivity may be parabolic across broad SMR categories (Van Sundert et al. 2018). Nevertheless, good differentiation of C:N across the current SNR and SCR categories suggests these classification schemes capture important components of C and N dynamics, such as litter quality, degree of humification, and rates of nutrient cycling (Zhang et al. 2010).

The large increases in SNR user's accuracy when moving from direct five-class SNR:SCR pairings to SNR matches

Fig. 5. (*concluded*).



within ±1 SCR class suggest that the use of a three-class SCR may be more realistic. This is supported by the statistical differentiation of C:N, pHCa, CEC, and BaSat across three to four rather than all five SCR and SNR categories. Chen et al. (1998) and Wang (1997) also found substantial increases in the SNR user's accuracy when comparing with ±1 SCR class, while numerous authors, including Klinka et al. (1994), Splechtna and Klinka (2001), and Kranabetter et al. (2007), have noted clear differentiation of most individual nutrients across no more than three SCR/SNR classes. This is also consistent with edatopic descriptions of individual Associations and Ecosites, which frequently show them overlapping across adjacent SNRs (Ontario Ministry of Natural Resources 2009*a*, 2009*b*; Chapman et al. 2020).

A few Associations and Ecosites were also assigned a broad range of BHorz and/or AllHorz SCRs. For some boreal types, the effects of wildfire frequency and intensity may directly affect soil chemical properties as well as stand composition (Maynard et al. 2014; Hume et al. 2016). Further, productivity-based SNRs at the poorer end of the spectrum may largely reflect physical limitations resulting from shallow soils, very coarse textures, and/or high stone contents, rather than soil chemical parameters (Schmidt and Carmean 1988). The relationships of particular chemical variables with individual Association and Ecosite SNRs (Figs. S2 and S3) also suggest re-evaluation of SNR designations for some site types.

Notably, the mean BHorzSCR and AllHorzSCR users' accuracy was similar for both the Association and Ecosite SNR classifications. While the Association and Ecosite typologies are based on different criteria (largely vegetation vs. soil/site based), they overlap in their approach to SNR designation. Overstory conditions are directly embedded in the Ecosite definitions, while site and soil conditions related to the various Associations are used to help infer their SNRs. Positive relationships between the Association SNRs and our SCRs are also consistent with studies showing good correlations between soil chemistry and indicator plant species (Wilson et al. 2001; Ewald and Ziche 2017).

SCR site/soil/overstory relationships

SNR field-oriented keys commonly identify humus form followed by soil depth and A horizon type as primary distinguishing attributes (e.g., Klinka et al. 1994; DeLong et al. 2011; Keys et al. 2011). In contrast, initial splits in our CART-based BHorzSCR keys were largely based on soil texture and pH (where available), followed by overstory composition. This likely reflects both the broad array of stand types we considered and the importance of both pH and soil texture as integrative variables that covary with several other chemical measures (Giesler et al. 1998; Vesterdal and Raulund-Rasmussen 1998; Callesen and Raulund-Rasmussen 2004; Callesen et al. 2007, 2019). Finer soil textures provide more numerous cation exchange sites (Hassink 1997) while soil pH has strong biogeochemical linkages with cation exchange capacity and base cation availability, and both metrics often covary with C:N (Meiwes et al. 1986; Hobara et al. 2016; Van Sundert et al. 2018).

Overstory composition repeatedly appeared as an important variable in the various CART and Random Forest BHorzSCR classifications. In this region, deciduous forests occur more frequently on richer sites, whereas conifer-dominated forests occupy a broader spectrum of sites and are often found on drier, nutrient-poor soils (Chapman et al. 2020). These relationships reflect species' autecological characteristics and community assembly along edaphic gradients (Cools et al. 2014; Shaw et al. 2015; Strand et al. 2016), but also involve the effects of individual species (e.g., litter quality and input rates) on soil chemistry at a given site (Vesterdal and Raulund-Rasmussen 1998; Hobbie et al. 2007; Augusto et al. 2015). This suggests that a site's actual chemistry signature may differ to some extent depending on the overstory composition. While not a soil parameter, overstory type increased the prediction accuracy for determining SCRs from site and soil pedon variables. However, when linking SCRs to SNRs, its use as a predictor of those relationships is somewhat tautological, since overstory composition is a defining feature of Association and Ecosite typologies.

Mode of deposition and soil taxonomic groupings have often been used as indicators of soil nutrient status, given their relationship to dominant soil-forming factors (Cools et al. 2014; Shaw et al. 2015; Stevenson et al. 2015; Strand et al. 2016). While BHzType ($V = 0.379$) and CSSOrd ($V = 0.357$) were not included directly in any of the pruned CART or Random Forests models, both contributed substantively to surrogate CART splits across all four models. The use of finer soil taxonomic units (e.g., CSSC Great Groups) may provide greater SCR discriminatory power (Shaw et al. 2015).

It was surprising that humus form showed limited correspondence with the BHorzSCR classification ($\tau C = 0.142$) and was not a contributing variable in the Random Forests or pruned CART models. This may reflect the reduced influence of litter inputs and organic horizon characteristics on soil chemistry at depth (Vesterdal and Raulund-Rasmussen 1998); the limited number of plots with mull or moder humus types included in our study; and the inclusion of overstory species categories that covary with humus form and provide strong linkages with B horizon chemistry (Hobbie et al. 2007; Mueller et al. 2012).

Topographic position, while commonly covarying with nutrient as well as moisture availability (Bridge and Johnson 2000; Moeslund et al. 2013), was not selected by Random Forests and only contributed to the BHorz CART model in the absence of LabTxt and pHClass. Otherwise, related variations in the latter two variables, and hence base cations (Giesler et al. 1998; Hobbie et al. 2007; Van Sundert et al. 2018), provided greater explanatory power. The absence of bedrock mineralogy as a discriminating CART variable, despite its common use as an indicator of soil nutrient status (DeLong et al. 2011; Eimel-Fraga et al. 2014), may reflect the limited variation in regional geology and/or the importance of recent glacial processes (Wester et al. 2018). Soil parent materials can be disconnected from the underlying bedrock, depending on the degree of glacial and postglacial movement and subsequent pedogenic development (Akselsson et al. 2006; Thiffault et al. 2013).

General observations and future work

Given their different origins, there is no a priori reason why SNR and SCR classifications should be directly aligned. SNR classifications are inferred from easily observed site and soil morphological characteristics (e.g., Fig. S1), often with emphasis on stand productivity (Wang 1997; Splechtna and Klinka 2001). As such, they are also intimately linked to and strongly covary with soil moisture regimes (Klinka et al. 1994). It is also possible to have different versions of SCRs depending on the chemical metrics and soil depths of interest. Much of our analysis was based on SCRs derived from *K*-means clustering with equal weighting of TotN, C:N, CEC, BaSat, and pHCa within and between horizons. Different chemistry weighting schemes and various depth functions can be used, depending on purpose (Van Sundert et al. 2018; Ma et al. 2021). In terms of site productivity, the inclusion of soil carbon, nitrogen, and pH metrics (Van Sundert et al. 2019), together with soil texture and "available" P, may provide a good basis.

This study highlights the potential for considering SCRs in combination with inferred SNRs to extend the applications of the eastern boreal CNVC Associations and Ontario's Ecosites. The interacting effects of multiple stressors (e.g., elevated atmospheric deposition, increased disturbance frequency, climate change, and invasive species) emphasize the need to better characterize a variety of chemical factors and inputs (e.g., Ouimet et al. 2013; McLaughlin 2014; Vadeboncoeur et al. 2014). Identifying soil chemical properties associated with these ecological classifications represents a foundational addition, broadening their possible applications (e.g., Timmer and Ray 1988).

Further analyses could address the following: (1) including soil chemistry data sets from adjacent regions to broaden relationships; (2) focusing on Associations and Ecosites that are underrepresented in the current analysis; (3) using plant indicator species to help identify SCRs and individual nutrient relationships; (4) refining predictions of individual nutrients, particularly OrgC and TotN; (5) including additional nutrients such as phosphorous, which also limits productivity in some northern glaciated landscapes (Vadeboncoeur 2010; Ouimet and Moore 2015); (6) exploring and untangling soil chemistry–soil moisture relationships; (7) incorporating depth functions to better account for vertical variations in soil properties and to address nutrient quantities on an area basis (Ma et al. 2021); and (8) using terrain analysis to develop spatial models for mapping SCRs and individual nutrients using linkages with topographic position, landform and vegetation (e.g., Zhao et al. 2013; Blackford et al. 2021).

Conclusions

Soil pH, CEC, and BaSat were well correlated within and across horizons, and together with C:N, they largely distinguished the five *K*-means-derived SCR categories. C:N decreased while pH and cation metrics, but not OrgC or TotN, consistently increased with increasing SCR and SNR richness. The Association and Ecosite SNRs showed broad agreement with the BHorzSCRs and AllHorzSCRs. In most cases, individual nutrients were clearly distinguished across three to four SNR/SCR classes, and the users' accuracies increased markedly for SNR values within ±1 SCR class. Thus, using three-category SCR classifications to distinguish Association and Ecosite soil chemistry may be most appropriate. With CART, pHClass, soil texture, and overstory composition were the principal soil and stand factors discriminating BHorzSCR categories. Notably, the inclusion of pHClass increased prediction accuracy from around 60% to 70%. The continued development of quantitatively derived SCRs should enhance the ability of ecological classifications to capture a wider variety of chemical properties, improve forest growth modelling efforts, and increase the utility of these classifications for addressing various impacts on ecosystem function and health.

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Data availability

Data generated or analyzed during this study are not publicly available due to a one-time confidential data sharing agreement between MNRF and GLFC. Data are, however, available from the corresponding author or his MNRF designate upon reasonable request.

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The authors declare there are no competing interests.

Supplementary material

Supplementary data are available with the article at https://doi.org/10.1139/cjfr-2022-0296.

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Appendices

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Table A1. Description of CNVC Associations (Eastern North American Boreal Forest Macrogroup M495) used in this paper.

Association code (number of plots)	Scientific name	Parent material	Topographic position	Root zone texture	Humus form	Soil moisture regime	Inferred soil nutrient regime
CNVC00207 (69)	*Pinus banksiana (Picea mariana)/Vaccinium angustifolium/Pleurozium schreberi*	Glaciofluvial (53), moraine/till (31)	Crest/upper (44), mid (24), level (21)	Sandy (60), coarse (C.) loamy (28)	Mor (77), moder (20)	Dry (61), mesic (29)	Poor
CNVC00208 (189)	*Picea mariana—P. banksiana/V. angustifolium/P. schreberi*	Moraine/till (40), glaciofluvial (31)	Crest/upper (40), mid (23), level (19)	C. loamy (39), sandy (35)	Mor (69), moder (23)	Mesic (37), dry (32), moist (21)	Poor
CNVC00213 (21)	*Populus tremuloides—Betula papyrifera—P. mariana—P. banksiana/Diervilla lonicera/P. schreberi*	Moraine/till (48), glaciofluvial (29)	Crest/upper (37), mid (35)	C. loamy (45), sandy (32)	Mor (76), moder (18)	Mesic (60), dry (21), moist (16)	Medium
CNVC00215 (9)	*Betula papyrifera—P. tremuloides—P. banksiana/Acer spicatum/Clintonia borealis*	Moraine/till (55), glaciofluvial (25)	Crest/upper (39), mid (32)	Sandy (33), C. loamy (30)	Mor (70), moder (27)	Mesic (61), dry (28)	Rich
CNVC00217 (15)	*Picea mariana—Abies balsamea/Rhododendron groenlandicum/P. schreberi*	Moraine/till (57), glaciofluvial (18)	Mid (39), crest/upper (33)	C. loamy (46), sandy (27)	Mor (85), moder (10)	Mesic (63), moist (20)	Medium
CNVC00231 (41)	*Abies balsamea—B. papyrifera—P. tremuloides/C. borealis*	Moraine/till (57), lacustrine (13), glaciofluvial (12)	Mid (42), crest/upper (26)	C. loamy (37), sandy (21)	Mor (74), moder (19)	Mesic (71), moist (17)	Medium
CNVC00235 (18)	*Abies balsamea—B. papyrifera/A. spicatum*	Moraine/till (69), glaciofluvial (10)	Mid (56), crest/upper (20)	C. loamy (40), sandy (17), silty (12)	Mor (71), moder (24)	Mesic (78), moist (15)	Rich
CNVC00239 (15)	*Betula papyrifera (P. tremuloides)/A. spicatum/C. borealis*	Moraine/till (74), glaciofluvial (10)	Mid (61), crest/upper (21)	C. loamy (47), sandy (18)	Mor (78), moder (18)	Mesic (82), moist (14)	Rich
CNVC00241 (20)	*Populus tremuloides (P. balsamifera)/Alnus incana/Eurybia macrophylla*	Glaciolacustrine (56), moraine/till (13)	Level (48), mid (26)	Clayey (40), fine (F.) loamy (17), C. loamy (14)	Mor (59), moder (24), mull (12)	Moist (59), mesic (33)	Very rich

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Table A1. (*concluded*).

Association code (number of plots)	Scientific name	Parent material	Topographic position	Root zone texture	Humus form	Soil moisture regime	Inferred soil nutrient regime
CNVC00245 (9)	*Pinus banksiana/V. angustifolium/Cladina* spp.	Glaciofluvial (35), bedrock (19), moraine/till (16)	Crest/upper (68), mid (19)	Sandy (43), bedrock (26), C. loamy (26)	Mor (89), moder (7)	Dry (73), very dry (20)	Very poor
CNVC00256 (10)	*Picea glauca—A. balsamea/Streptopus lanceolatus/P. schreberi*	Lacustrine (48), glaciofluvial (24), moraine/till (20)	Crest/upper (39), mid (37)	C. loamy (38), Sandy (19)	Mor (54), moder (44)	Mesic (53), moist (28)	Rich
CNVC00272 (10)	*Populus tremuloides—P. mariana/A. incana*	Lacustrine (35), glaciolacustrine (25), moraine/till (20)	Level (44), crest/upper (21), mid (18)	Clayey (34), F. loamy (18), silty (18)	Mor (59), moder (29)	Moist (47), Mesic (41)	Rich
CNVC00276 (13)	*Picea mariana/R. groenlandicum—V. angustifolium/P. schreberi (Sphagnum* spp.)	Moraine/till (56), organic (17), glaciolacustrine (10)	Mid (35), level (33), lower/toe (16)	Organic (40), C. loamy (22), sandy (16)	Mor (56), peatymor (40)	Moist (44), mesic (30), wet (22)	Poor
CNVC00282 (9)	*Picea mariana/R. groenlandicum—Kalmia angustifolia/Sphagnum* spp.	Organic (45), moraine/till (24), glaciolacustrine (20)	Level (67), mid (13), lower/toe (11)	Organic (47), sandy (5)	Peatymor (82), mor (17)	Wet (65), moist (28)	Very poor
CNVC00295 (9)	*Picea mariana/A. incana/P. schreberi*	Glaciolacustrine (39), moraine/till (26), organic (18)	Level (49), lower/toe (21), mid (21)	Organic (36), clayey (22), F. loamy (7)	Mor (60), peatymor (38)	Moist (39), wet (37), mesic (22)	Rich

Note: Detailed factsheets are available at cnvc-cnvc.ca and cfs.nrcan.gc.ca/publications. The number of plots refers to our BHorz soil chemistry data only, whereas the proportional frequencies of classes for the different variables (e.g., parent material) refer to the most common classes for the Association as a whole.

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Table A2. Description of Ontario Ecological Land Classification Ecosites used in this paper (Ontario Ministry of Natural Resources 2009*a*, *b*).

Ecosite code (number of plots)	Ecosite Name	Overstory species, including dominant % cover	Mode of deposition; depth	Topo-position	Root zone texture	Humus form	SMR	SNR
B033 Tt/Tl (34)	Dry, sandy: red pine—white pine conifer	*Pinus resinosa* +/*Pinus strobus* >20%; often *Betula papyrifera, Pinus banksiana, Picea mariana, Abies balsamea*	Glaciofluvial; deep	Level/lower/mid	Sandy	Fibrimor	Dry	Very poor
B034 Tt/Tl (61)	Dry, sandy; jack pine—black spruce dominated	*Picea mariana* +/*P. banksiana* +/*B. papyrifera* >80%; *B. papyrifera* <20%	Glaciofluvial; deep	Level/lower/mid	Sandy	Fibrimor	Dry	Very poor
B035 Tt/Tl (19)	Dry, sandy; pine—black spruce conifer	*Pinus banksiana* +/*P. mariana* >50% conifer cover; often *P. tremuloides*, *B. papyrifera*, *A. balsamea*	Glaciofluvial; deep	Level/lower/mid	Sandy	Fibrimor	Dry	Very poor
B040 Tt/Tl (17)	Dry, sandy: aspen—birch hardwood	Hardwood: *Populus* spp. +/*Betula* spp., >50% hardwood cover; often *P. banksiana*, *P. mariana*, *A. balsamea*, *Picea glauca*	Morainal, glaciofluvial; deep	Level/lower/mid	Sandy	Fibrimor	Dry	Poor
B048 Tt/Tl (34)	Dry—fresh, coarse; red pine—white pine conifer	*Pinus resinosa* +/*P. strobus* >20%; often *B. papyrifera*, *A. balsamea, P. tremuloides*	Morainal; deep	Crest/upper/mid	Coarse loamy	Fibrimor	Fresh	Poor
B049 Tt/Tl (76)	Dry—fresh, coarse; jack pine—black spruce dominated	Conifer/mixedwood: *P. mariana* +/*P. banksiana* +/*B. papyrifera* >90%; *B. papyrifera* <20%	Morainal; deep	Crest/upper/mid	Coarse loamy	Fibrimor	Fresh	Poor
B050 Tt/Tl (34)	Dry—fresh, coarse; pine—black spruce conifer	*Pinus* +/*P. mariana* >50%; often *P. tremuloides, B. papyrifera, A. balsamea*, *P. glauca*	Morainal; deep	Crest/upper/mid	Coarse loamy	Fibrimor	Fresh	Poor
B052 Tt/T (11)	Dry—fresh, coarse; spruce—fir conifer	*Picea* spp. +/*A. balsamea* >50%; often *P. tremuloides*, *B. papyrifera*, *P. mariana*	Morainal; deep	Crest/upper/mid	Coarse loamy	Fibrimor	Fresh	Medium
B055 Tt/Tl (38)	Dry—fresh, coarse; aspen—birch hardwood	*Populus tremuloides* +/*B. papyrifera* >50%; often *A. balsamea*, *P. glauca*, *P. mariana*	Morainal; deep	Crest/upper/mid	Coarse loamy	Fibrimor	Fresh	Medium
B065 Tt/Tl (38)	Moist, coarse; black spruce—pine conifer	*Picea mariana* +/*P. banksiana* >50% of conifer spp.	Morainal; deep	Many	Coarse loamy	Fibrimor	Moist	Poor

Table A2. (*concluded*).

Ecosite code (number of plots)	Ecosite Name	Overstory species, including dominant % cover	Mode of deposition; depth	Topo-position	Root zone texture	Humus form	SMR	SNR
B070 Tt/Tl (10)	Moist, coarse; aspen—birch hardwood	*Populus tremuloides* +/*B. papyrifera* >50%; often *A. balsamea*, *P. glauca*, *P. mariana*, *P. banksiana*	Morainal; deep	Many	Coarse loamy	Fibrimor	Moist	Medium
B082 Tt/Tl (20)	Fresh, clayey; black spruce—jack pine dominated	*Picea mariana* +/*P. banksiana* >90%; *B. papyrifera* <20%	Glacio-lacustrine; deep	Level/upper/mid	Clayey	Fibrimor	Fresh	Rich
B083 Tt/Tl (23)	Fresh, clayey; black spruce—pine conifer	*Picea mariana* +/*P. banksiana* >50% of conifer cover; often *Populus tremuloides*, *A. balsamea*	Glacio-lacustrine; deep	Level/upper/mid	Clayey	Fibrimor	Fresh	Rich
B085 Tt/Tl (11)	Fresh, clayey; spruce—fir conifer	*Abies balsamea* +/*P. glauca* > 50% of conifer cover; often *P. tremuloides*, *P. mariana*, *B. papyrifera*	Glacio-lacustrine; deep	Level/upper/mid	Clayey	Fibrimor	Fresh	Very rich
B088 Tt/Tl (37)	Fresh, clayey; aspen—birch hardwood	*Populus tremuloides* +/*Betula* spp. >50%; often *A. balsamea*, *P. mariana*, *P. glauca*	Glacio-lacustrine; deep	Level/upper/mid	Clayey	Fibrimor	Fresh	Very rich
B098 Tt/Tl (9)	Fresh, silty-fine loamy; black spruce—jack pine dominated	*Picea mariana* +/*P. banksiana* +/*B. papyrifera* >90%; *B. papyrifera* <20%	Morainal; deep	Level/upper/mid	Silty	Fibrimor	Fresh	Rich
B099 Tt/Tl (16)	Fresh, silty-fine loamy; black spruce—pine conifer	*Picea mariana* +/*P. banksiana* >50%; often *P. tremuloides*, *A. balsamea*, *B. papyrifera*	Glaciofluvial; deep	Level/upper/mid	Silty	Fibrimor	Fresh	Rich
B104 Tt/Tl (10)	Fresh, silty-fine loamy; aspen—birch hardwood	*Populus tremuloides* +/*Betula* spp. >50%; often *A. balsamea*, *P. glauca*, *P. mariana*	Glacio-lacustrine; deep	Level/upper/mid	Silty	Fibrimor	Fresh	Very rich
B130 Tt/Tl (11)	Intolerant hardwood swamp	*Fraxinus nigra* +/*P. tremuloides* +/*Populus balsamifera* >50%; often *A. balsamea*, *B. papyrifera*, *P. mariana*, *P. glauca*	n/a; deep	Level/depression	N/A	N/A	Very moist	Very rich
B222 Tt/Tl (13)	Mineral poor conifer swamp	*Picea mariana*	Glacio-lacustrine; deep	Depression/level	Coarse loamy	Fibrimor	Very moist	Poor
B223 Tt/Tl (11)	Mineral intermediate conifer swamp	*Picea mariana*; often *Larix laricina* +/*Alnus rugosa*	Glacio-lacustrine; deep	Depression/level	Coarse loamy	Fibrimor	Very moist	Medium
B224 Tt/Tl (13)	Mineral-rich conifer swamp	*Thuja occidentalis*; often *P. mariana* +/*A. balsamea* +/*P. glauca* +/*P. tremuloides*	N/A; deep	Depression/level	Coarse loamy	Fibrimor	Very moist	Rich

Note: The +/– designations indicate and/or.