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RESEARCH LETTER

Predictive soil health indicators across a boreal forest to agricultural conversion gradient

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Abstract

A changing climate offers new opportunities to expand agriculture in northern latitudes, and understanding forest-to-agriculture land conversion impacts is critical to ensure soil sustainability. Using the Comprehensive Assessment of Soil Health (CASH) framework, we identified a minimum suite of indicators with little collinearity to reliably predict soil impacts during the conversion of boreal forest to agriculture and a time since conversion gradient (forest, <10 years, >10 and <50 years, and >50 years since conversion). We sampled paired forest and agricultural sites and used multiple linear regression to assess 16 indicators and found four- and six-indicator models predicted the CASH score with varying but reasonable accuracy depending on conversion class. Organic matter, water aggregate stability, and pH were consistent predictors across all classes, as well as one or more micronutrients. The CASH framework appears to be more suitable for agricultural soils and as time since conversion proceeds.

1 | INTRODUCTION

New opportunities to expand agriculture in northern latitudes have created a need to evaluate soil disturbance for short- and long-term agricultural sustainability in new regions. In Canada, changing climate has prompted policies that support land use conversion to expand food production in the boreal and Arctic regions, despite a limited understanding of the impacts of land conversion from forest to agriculture on soil functions and indicators of soil function (Altdorff et al., 2021). Once soil-native vegetation communities are converted to an agricultural system, compaction, erosion, and salinization usually increase, whereas soil organic carbon, biomass, and biological diversity usually decrease due to soil management practices (Ellert & Gregorich, 1996). The most predictive soil function indicators are related to important soil processes such as water cycling, carbon availability, and nutrient dynamics, and they form the basis of soil health assessment approaches.

Although there have been several approaches to assess soil health (Chu et al., 2019; Karlen et al., 2019; Nunes et al., 2021), the Comprehensive Assessment of Soil Health (CASH) framework has been widely accepted as the most consistent and efficient soil health assessment method (Norris et al., 2020). During CASH development, over 40 soil function indicators were assessed and narrowed to the 10 indicators (i.e., soil texture, available water capacity, field penetrometer resistance, wet aggregate stability [WAS], organic matter content, soil proteins, respiration, active carbon, and macro- and micro-nutrient content assessment) that are the

Abbreviations: CASH, Comprehensive Assessment Soil Health; MSI, minimum suite of indicators; WAS, wet aggregate stability.

most sensitive to changes in soil management, represent important soil processes, are consistent and reproducible, easy to sample and interpret, and can be measured at a relatively low cost (Moebius-Clune et al., 2017). Each indicator is weighted based on comparing to other soils, and a cumulative score is developed for a soil ranging from 0 (poor health) to 100 (healthy).

In a previous study using the CASH framework, Benalcazar et al. (2022) assessed the effect of a forest to agricultural land conversion in the northwestern Ontario region. Land conversion to agriculture negatively affected overall soil health scores, with forest sites having higher scores and no difference between agricultural soils converted for <10 years to those >50 years (Benalcazar et al., 2022). The initial breaking and tilling of the forest soil for agriculture appears to be the main disturbance that leads to decreases in overall soil health scores.

During the development of Benalcazar et al. (2022), the authors observed high collinearity in some soil health indicators and performed additional model analyses presented here, which assess the indicators that are most representative and least collinear of the overall CASH soil health score for northwestern Ontario boreal soils. Our objective in this study was to identify a minimum data set that would reliability predict the overall CASH score by land use conversion class and time since conversion from forest to agriculture. We aimed to identify a minimum suite of indicators (MSI) with reduced multicollinearity and fewer inflated model correlations that might have lower cost and effort to measure but are still a suitable suite predictors of overall CASH score across the forest to agriculture and time since agricultural conversion gradients.

2 | MATERIALS AND METHODS

2.1 | Study area, soil sampling, and analysis

Northwestern Ontario is in the Boreal Shield ecozone. This ecozone is characterized by soil orders that include Podzols, Brunisols, Luvisols, and organics that have developed in glacial outwash and till from the superior lobe in the last glaciation (Schut et al., 2011). The climate is dry and warm in summer, cold and wet in winter, mostly covered by snow, with a relatively short growing season (Climate Atlas, 2019; Kishchuk et al., 2016). The Thunder Bay region of northwestern Ontario has a mean annual temperature of 2.3°C, annual precipitation of 726 mm, and a frost-free season of 120.5 days (Climate Atlas, 2019).

Paired forested and adjacent agricultural sites were selected, and agricultural sites were further stratified by time since conversion. Each paired site included a mature mixed wood forest (forest, $n = 18$) and agricultural fields that have been either cultivated for <10 years (<10 years and $n = 12$), between 10 and <50 years (>10 and <50 years, $n = 16$), and >50 years (>50 years and $n = 14$). All agricultural sites were under a conventional management system with tillage, synthetic fertilizer (blend of urea, ammonium sulfate, mono ammonium phosphate, muriate of potash, and zinc sulfate), annual manure applications applied to canola and corn (2800 and 10,300 L ha^{-1}, respectively), and crop rotations of alfalfa, silage corn, grain, barley, canola, and spring wheat (Benalcazar et al., 2022).

We collected 60 composited 0- to 5- and 5- to 15-cm depth soil samples using a split core sampler (AMS Inc.) from July through August 2019. Soils were collected at five plots in each paired forest and agricultural conversion site. Although site areas varied (average 16 ha), plots were located in the four corners and center of the forest area or agricultural field. At each of the five plots, a total of three sub-samples were collected, divided by depth (0–5 and 5–15 cm), and composited. In forest sites, the forest floor O horizon was not sampled, so upper soil layers across the conversion gradient were comparable. Detailed protocols for soil processing are available in the CASH manual (Moebius-Clune et al., 2017). We considered categories of physical, chemical, and biological indicators to investigate the most efficient and least correlated predictors of overall CASH soil health scores. The CASH indicators considered were WAS, surface penetration resistance, subsurface penetration resistance, pH, Phosphorus (P), potassium (K), magnesium (Mg), Iron (Fe), manganese (Mn), zinc (Zn), total nitrogen (N), total carbon (C), organic matter, soil protein, soil respiration, and permanganate oxidizable carbon.

Core Ideas

- We evaluate statistically robust soil health indicators across a gradient of time since boreal forest conversion to agriculture.
- Organic matter, aggregate stability, pH, and micronutrients are the best predictors of Comprehensive Assessment of Soil Health (CASH) score across the gradients.
- The CASH framework is more predictable as time since forest to agricultural conversion proceeds.

2.2 | Statistical analysis

We used multiple linear regression to model the overall CASH cumulative soil health score by assessing the core 16 soil health variables (Moebius et al., 2007). We also use our expert judgment to optimize the most predictable but least collinear variables in each of the physical, chemical, and biological indicator categories across the forest to agriculture and time since conversion gradients. To limit multicollinearity among the physical, biological, and chemical indicators, we used a Pearson's correlation analysis (see Table 1 for all correlations and significance among indicators) where a correlation coefficient >0.7 was considered large enough to warrant variable reduction. We added the variance inflation factor (VIF) and tolerance in multiple regression models to further assess multicollinearity. We reduced variables in the model when the VIF was >4 (Allison, 1999). All analyses were performed using the packages (olsrr) in the R software language (R Core Team, 2021).

3 | RESULTS

With our approach, we were able to reduce the number of soil health variables from 16 to either 4 or 6 (depending on the conversion class) with good predictability for the overall CASH soil health score. Organic matter (OM) is one of the key components of soil health, and the most predictable variable is found across the conversion gradient (Table 2). In addition, WAS and pH were also important soil physical and chemical predictors across the gradient and found to be significant for all four conversion classes. Macro-micronutrients also added to predictability with little multicollinearity. Fe was significant in the three agricultural conversion classes, Zn in forests, and Mn and Mg in the 10–50 years since agricultural conversion class with R^2 ranging from 0.47 for forest soils to 0.82 for soils converted >50 years ago (Table 2).

4 | DISCUSSION

Other studies have shown similar relative predictability of the overall CASH soil health score using subsets of individual indicators, in which biological and physical indicators were the best predictors (Fine et al., 2017; Rekik et al., 2018). These studies, conducted in different climate conditions and latitudes and only in agricultural soils, generally showed that soil organic carbon, penetration resistance, respiration, and WAS were most frequently selected for an MSI. In addition, the Soil Health Institute defined that soil organic carbon concentration, 24-h carbon mineralization, and aggregate stability were the best minimum set of indicators that respond to agricultural management practices, are scalable and affordable, and primarily reflected soil health conditions rather than inherent soil properties; however, soil organic carbon concentrations and 24-h carbon mineralization rates are highly related, leading to inflated correlations (Bagnall et al., 2023). Soil disturbance associated with land conversion in our study drives changes in soil functions and associated physical, chemical, and biological indicators (Benalcazar et al., 2022). We found declines in concentrations of OM, permanganate oxidizable carbon, WAS, soil respiration, autoclave citrate extractable protein, total carbon, and total nitrogen when soils were converted from forest to agriculture and with time since agricultural conversion (Benalcazar et al., 2022). From the list of 16 indicators evaluated in our previous study, four to six were identified as being the MSI that best predict overall CASH soil health score. Soil OM has been identified as a key indicator for evaluating soil functions and affects all physical, chemical, and biological soil processes (Cantone & Schmidt, 2011; Lehmann et al., 2020; Wiesmeier et al., 2019). Soil OM has high correlations with soil protein, soil respiration, and permanganate oxidizable carbon with p-values <0.01 and R^2 ranging from 0.70 to 0.82 (Table 1), which is similar to other studies that showed strong positive correlations with soil OM (Amsili et al., 2021; Congreves et al., 2015; Nunes et al., 2021). As a result, soil OM was selected to represent carbon-related soil health biological processes.

Similarly, WAS is an important soil physical process predictor across all land use classes and represents functions related to the soil's ability to resist soil erosion, and it can be affected by tillage practices, exposing soil organic matter to oxidation, and accelerated microbial decomposition (Helfrich et al., 2006). Soil pH was another indicator that was common across all land use classes and characterizes the soil chemical environment critical for carbon and nutrient cycling processes (Reicosky, 2018). Soil chemical functions related to macro–micronutrients are also important independent predictors, with Fe selected in all three agricultural conversion classes and Zn selected for the forest class. Mn and Mg were also important in the 10–50 years since agricultural conversion class. Concentrations of exchangeable Zn are generally associated with the soil OM in boreal forests (Soon, 1994). Furthermore, Zn is an essential metabolite that is a catalyst for plant cell replication and gene expression (Boardman & McGuire, 1990). Iron is an essential component of the plant's chlorophyll formation and plays a critical role in DNA synthesis, respiration, and photosynthesis. Thus, it activates several enzymes and constitutes the proteins in plants (Jadeja et al., 2021; Rout & Sahoo, 2015). Furthermore, Mn is closely related to Fe due to its interactions with chlorophyll formation and electron transportation and its integral component of oxidation–reduction processes (Marschner, 2011; McHargue, 1922). Like Fe, Mg is also an essential constituent of chlorophyll and is part of the structural component in ribosomes. In addition, Mg serves as an activator of many enzymes involved in carbohydrate metabolism, nucleic acids, and plant defense mechanisms (Marschner, 2011; Senbayram et al., 2015).

Collectively, our models suggest that reliable estimates of the overall CASH framework scores can be predicted from a much smaller MSI, with certainty increasing as soils become more agricultural in nature (i.e., with time since forest to agricultural conversion). Given that CASH was developed for

TABLE 1 Pearson correlation coefficients for Comprehensive Assessment of Soil Health (CASH) indicators. NS is not statistically significant at $\alpha = 0.05$.

Variable	*p*-values	WAS	Sur_PR	Sub_SPR	pH	P	K	Mg	Fe	Mn	Zn	Total N	Total C	OM	Protein	Resp	POXC
1. WAS		–															
2. Sur_PR		NS	–														
3. Sub_SPR		NS	0.89	–													
	p-values		<0.001														
4. pH		−0.31	NS	NS	–												
	p-values	0.01															
5. P		NS	NS	NS	NS	–											
6. K		NS	NS	NS	NS	0.72	–										
	p-values					<0.001											
7. Mg		NS	−0.28	−0.43	38	NS	0.44	–									
	p-values		0.03	<0.001	<0.001		<0.001										
8. Fe		NS	NS	NS	−0.45	−0.26	NS	NS	–								
	p-values				<0.001	0.04											
9. Mn		0.59	−0.26	NS	−0.39	NS	NS	NS	0.33	–							
	p-values	<0.001	0.05		<0.001				0.01								
10. Zn		0.25	0.25	NS	NS	0.61	0.49	NS	NS	NS	–						
	p-values	0.05	0.05			<0.001	<0.001										
11. Total N		0.6	NS	NS	NS	0.31	0.33	0.34	NS	0.55	0.52	–					
	p-values	<0.001				0.02	0.01	<0.001		<0.001	<0.001						
12. Total C		0.58	−0.29	−0.29	NS	0.24	0.27	0.41	NS	0.49	0.48	0.97	–				
	p-values	<0.001	0.02	0.03		0.06	0.04	<0.001		<0.001	<0.001	<0.001					
13. OM		0.58	−0.3	−0.32	NS	NS	0.26	0.5	NS	0.41	0.42	0.9	0.94	–			
	p-values	<0.001	0.02	0.01			0.04	<0.001		<0. 001	<0.001	<0.001	<0.0.01				
14. Protein		0.67	NS	NS	NS	NS	NS	NS	NS	0.64	0.27	0.86	0.88	0.82	–		
	p-values	<0.001								<0.001	0.04	<0.001	<0.001	<0.001			
15. Resp		0.62	NS	NS	NS	NS	0.27	0.38	NS	0.57	0.42	0.78	0.72	0.7	0.69	–	
	p-values	<0.001					0.04	<0.001		<0.001	<0.001	<0.001	<0.001	<0.001	<0.001		
16. POXC		NS	NS	NS	NS	0.37	0.29	0.45	NS	NS	0.49	0.72	0.78	0.82	0.6	0.51	–
	p-values					<0.001	0.03	<0.001			<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	

Abbreviations: OM, organic matter; POXC, permanganate active carbon; Protein, soil protein; Resp, soil respiration; Sub_SPR, surface penetration resistance 15–45 cm; Sur_PR, surface penetration resistance 0–15 cm; Total C, total carbon; Total N, total nitrogen; WAS, wet aggregate stability.

TABLE 2 Variance, tolerance, variance inflation factor, correlation, and significance for each soil health indicator for the four forests to agriculture conversion classes.

Class: forest				**Class: <10 years conversion**			
Variables		**Tolerance**	**VIF**	**Variables**		**Tolerance**	**VIF**
1	WAS	0.57	1.74	1	WAS	0.47	2.09
2	OM	0.59	1.68	2	OM	0.60	1.66
3	pH	0.72	1.38	3	pH	0.31	3.18
4	Zn	0.81	1.22	4	Fe	0.50	2.00
R^2 square = 0.47; p-value = 0.06				R^2 square = 0.66; p-value 0.07			
Class: >10 and <50 years conversion				**Class: >50 years conversion**			
Variables		**Tolerance**	**VIF**	**Variables**		**Tolerance**	**VIF**
1	WAS	0.35	2.80	1	WAS	0.40	2.49
2	OM	0.40	2.47	2	OM	0.32	3.05
3	pH	0.25	3.99	3	pH	0.47	2.10
4	Mg	0.44	2.25	4	Fe	0.38	2.61
5	Mn	0.37	2.65				
6	Fe	0.29	3.39				
R^2 square = 0.72; p-value 0.03				R^2 square = 0.82; p-value 0.002			

Abbreviations: OM, organic matter; VIF, variance inflation factor; WAS, wet aggregate stability.

agricultural soils, it is not surprising forest soil predictability is relatively low compared to longer established agricultural soils (Table 2) and argues for more study to develop better indicators for forest soil health.

5 | CONCLUSION

This study aimed to find a subset of best predictors of the overall CASH soil health score for monitoring the conversion from boreal forest to agriculture in northwestern Ontario. Across the gradient of time since land conversion, four to six soil health indicators were identified to be the most predictive of overall soil health scores. The important soil health variables include organic matter, WAS, pH, and micronutrients. We know from previous studies that the forest conversion to agriculture and length of time in agriculture play an important role in predicting the overall soil health score (Benalcazar et al., 2022).

An important goal of this study was to determine how much less effort and cost could be gained by selecting a smaller yet statistically robust MSI when compared to the CASH assessment. The cost of the standard CASH assessment is about $130 per sample. Using a similar soil analysis laboratory under the supervision of coauthor Kolka, the cost to analyze the physical, biological, and chemical indicators selected here is about $60 per sample, and we estimate a time savings in the lab of about 6 h per sample and a time savings in the field, as penetration resistance is not required. For agricultural soils in northwestern Ontario, the cost/time trade-off appears to be reasonable with good overall soil health prediction for established agricultural soils, but more investigation is needed to develop forest soil health indicators with comparable predictability.

AUTHOR CONTRIBUTIONS

P. Benalcazar: Conceptualization; data curation; formal analysis; investigation; methodology; resources; writing—original draft. **R. Kolka**: Conceptualization; data curation; formal analysis; investigation; methodology; supervision; validation; writing—original draft; writing—review and editing. **A. C. Diochon**: Supervision; writing—review and editing. **R. R. Schindelbeck**: Investigation; methodology; supervision; writing—review and editing. **T. Sahota**: Investigation; writing—review and editing. **B. E. McLaren**: Methodology; supervision; writing—review and editing. **John Stanovick**: Formal analysis; validation; writing—review and editing.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

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