A soil nutrient regime index for forest practitioner decisions in Hesse, Germany: spatial explicit modelling of soil chemistry and integration by fuzzy-logic

Felix Heitkamp, Bernd Ahrends, Jan Evers, and Henning Meesenburg

Environmental Control, Northwest German Forest Research Institute, Goettingen, Germany

(felix.heitkamp@nw-fva.de)

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Introduction

- Sustainable forest management demands informed stakeholder decisions
- In Hesse, Germany, geo-ecological conditions are derived from forest site evaluation maps
- Mapping for soil water and nutrient state was done in the field by experts
- Here, we focus on **nutrient mapping**, which was based on ground vegetation, parent material and soil profile morphology (1)
- The site evaluation map of Hesse includes the **nutrient index classes** *rich*, *moderate-good*, *moderate*, *moderate-weak* and *poor*. The sixth class is *carbonatic*

- Soil chemical analyseswere not considered
- A soil nutrient regime index was mapped for ca. 80% (73% released) of Hesse's forests (Figure 3)
- 65% of the site map was classified as *moderate*, whereas *moderate-good* and –*weak* conditions are underrepresented (Table 2) (2)
- Topography and parent material should be main factorsfor nutrient availability, but show inconsistent effects in the current site map

Objectives

- Regionalise forest soil chemical properties which define nutrient availability
- Infer the forest soil nutrient index classes from soil chemistry
- Refine and expand the forest soil nutrient index map

The main goal was to provide an updated forest soil nutrient index map for forestry stakeholders. This map is the base to derive tree species composition and forest management options

Material & Methods

Click for more details: Appendix: Site information

- Federal state Hesse, Germany (21.115 km², 42% forested). Mean annual precipitation: 540-1390 mm; mean annual temperature: 5.2-10.6°C
  - European beech and Norway spruce dominate managed forests (3)
  - Soils often evolved from solifluctive loess with acidic or base poor rocks (4)
  - Cambisols, Stagnosols and Luvisols as predominant Soil Reference Groups (4)
- Soil profile data (n=380, 90 cm depth plus organic layer) with analyses from the National Forest Soil Inventory (NSFI, 2006-2008, 8 x 8 km grid) of Hesse, Lower Saxony and Saxony-Anhalt (Germany) (2)
- Spatial data: Weather data (DWD), Hessian soil map 1:50,000 (4), ATKIS forest cover (5), N-deposition (6)
- Variables for nutrient index inference (7–10): “Intermediately available” K, Ca and Mg stocks (exchangeable cations in mineral soil plus total from organic layer), C/N-ratio (organic layer or Ah), effective cation exchange capacity (CEC_{eff}), base saturation
- Generalised additive models were used for quantification of environmental relationships (11) and parameterised (see Appendix: GAM - Parametrisation) and cross-validated (Figure 1) with the NFSI dataset
- The soil nutrient index was inferred using fuzzy-logic as described by Shi et al. (12) on classified soil chemical variables (7) after introducing variable weighting (see Appendix: Fuzzy logic)

Results

- Modelled soil chemical variables revealed R^2 values between 0.54 and 0.79 after 10-fold cross-validation (Table 1, Figure 1), which was well in the range of other studies (13–16)
- Relationships of nutrient stocks with topography showed that topographic effects on soil properties (stoniness, soil depth, texture…) were included in the soil map (Figure 2)
- Application of fuzzy logic was useful to integrate information of multiple chemical variables to infer a single nutrient index for each soil map polygon (Figure 3), resulting in full coverage of Hesse's forests
- Parent material and especially topography showed much more consistent effects in the modelled soil nutrient index map (Figure 4) as compared to the original map

Soil chemistry

Table 1: Results of 10-fold cross-validation

Response	R^2_{adj}	rRMSD (%)	Mean bias (%)
$_{log}$CEC$_{eff}$ (kmol$_c$ ha^{-1})	0.79	8.2	-0.77
$_{log}$Base saturation (%)	0.54	16.3	-3.46
C/N-ratio	0.61	14.1	0.07
$_{log}$K stocks (kg ha^{-1})	0.70	8.2	-1.54
$_{log}$Ca stocks (kg ha^{-1})	0.68	14.9	-5.3
$_{log}$Mg stocks (kg ha^{-1})	0.70	17.1	-6.0

rRMSD: relative root mean squared deviation

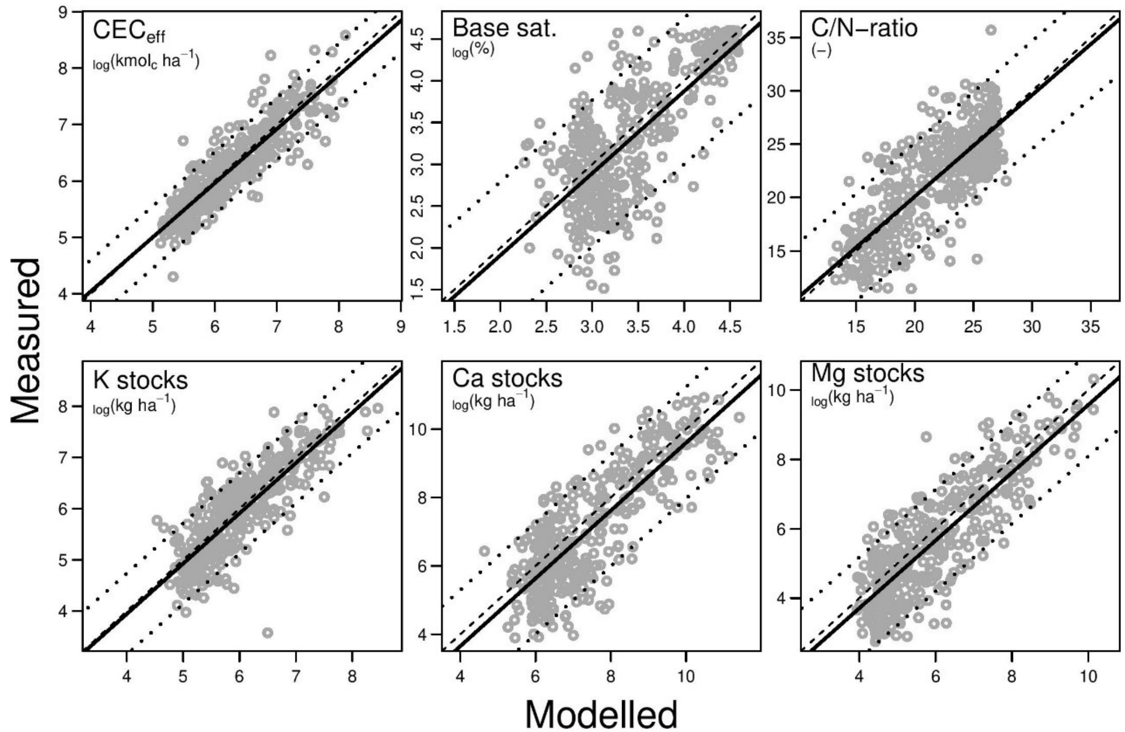


Figure 1: Plots of cross-validated chemical soil variables (n=380).

Solid line: Regression line; Dashed line: 1:1; Dotted line: 95% prediction intervals

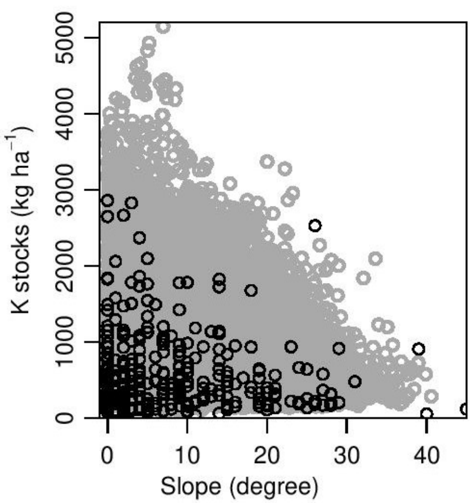


Figure 2: Relation of slope with K stocks. Black: NFSI data (n=380), grey: soil map (n=198763)

Maps of forest soil nutrient index

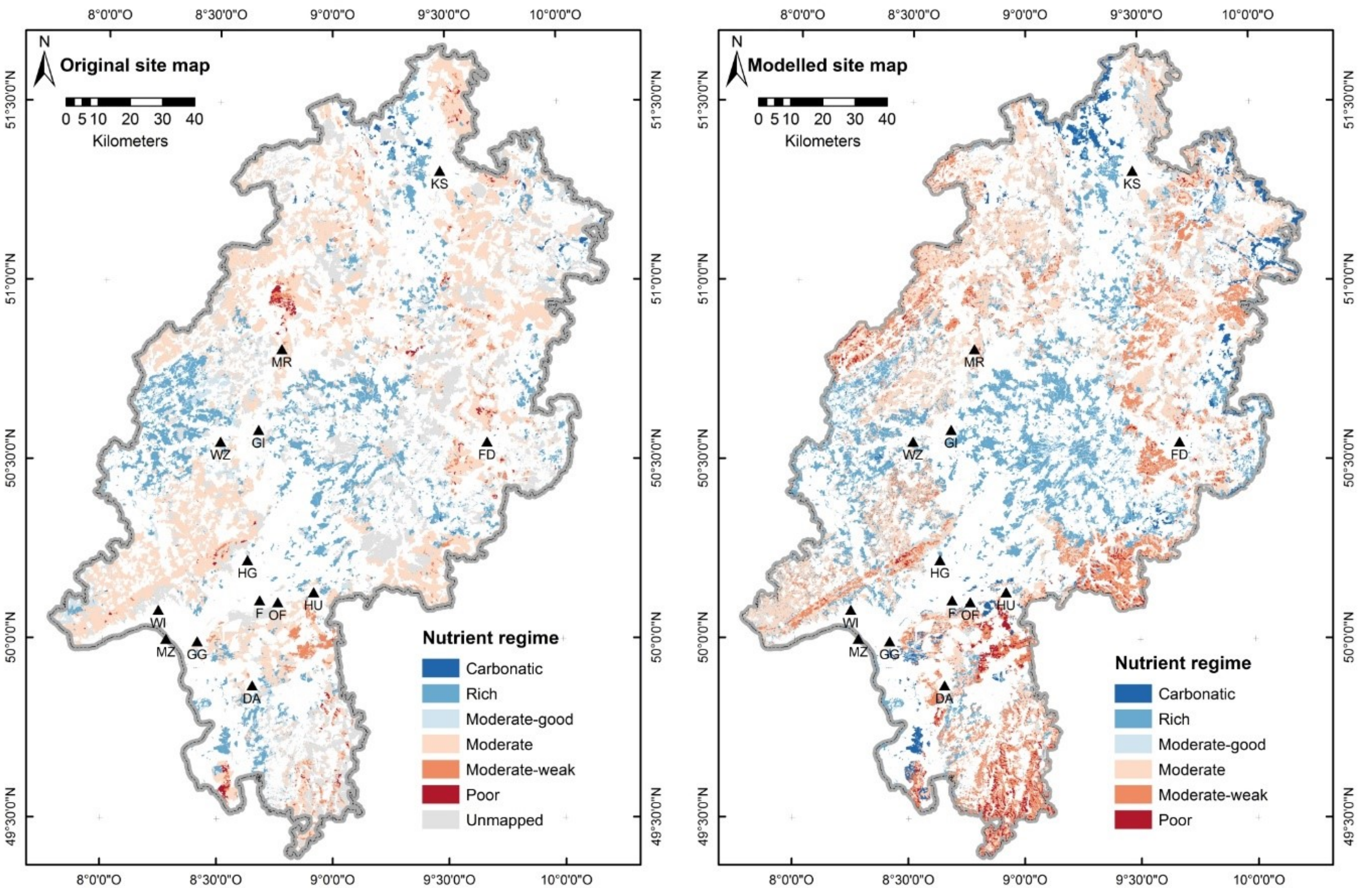


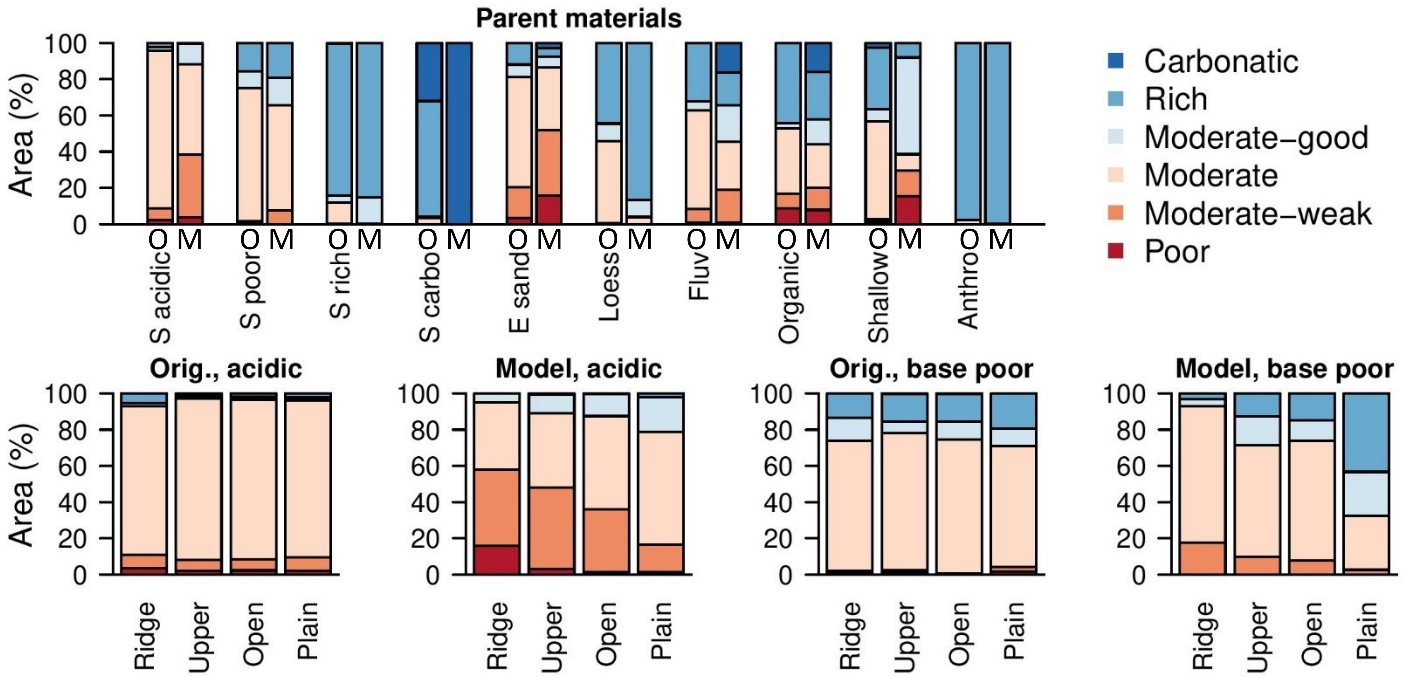
Figure 3: Original and modelled forest soil nutrient index maps of Hesse, Germany

Distribution of the soil nutrient index

Table 2: Soil nutrient index distribution in the orginal map, the NFSI plots with information from the original map, the NFSI plots with manually refined (by using soil chemistry) information*(2)* and in the modelled map (Figure 3)

	Original map (area %)	NFSI Hesse, original map (%.)	NFSI Hesse, refined (%)	Modelled map (area %)
Poor	1.2	4.3	5.0	2.4
Moderate-weak	4.0	2.9	18.7	18.1
Moderate	64.4	66.9	35.3	38.6
Moderate-good	5.3	2.9	11.5	13.0
Rich	24.0	23.0	25.2	23.4
Carbonatic	1.1	-	4.3	4.5
Extent	73% forested area 6324 km²	139 points	139 points	100% forested area, 8690 km²

Parent Material & Topography



O: Original

M: Model

S: Solifluctive loess with acidic/ base poor/ base rich/ carbonatic rocks

E: Eolic

Fluv: Fluviatile

Anthro: Anthropogenic

Upper: Upper slope

Open: Open slope

Figure 4: Distribution of the original and modelled nutrient index across parent material (4) (upper panel) and landforms (17) (lower panels)

Conclusions

- Soil chemical variables were successfully regionalised and provide the spatial explicit base for nutrient index inference
- Inference of the soil nutrient index still demanded expert judgement, but the approach is now inter-subjectively reproducible
- The models are parsimonious with respect to familiar classification and processes, which is important for acceptance among stakeholders
- The updated, modelled map
  - covers Hesse’s complete forest area (as compared to ca. ¾ of the original map)
  - shows finer graduation among “moderate” conditions
  - differentiates clearly by parent material *and* topography

The modelled map provides a sound basis for stakeholder’s management decisions for forests in Hesse, Germany

Appendix: Site information

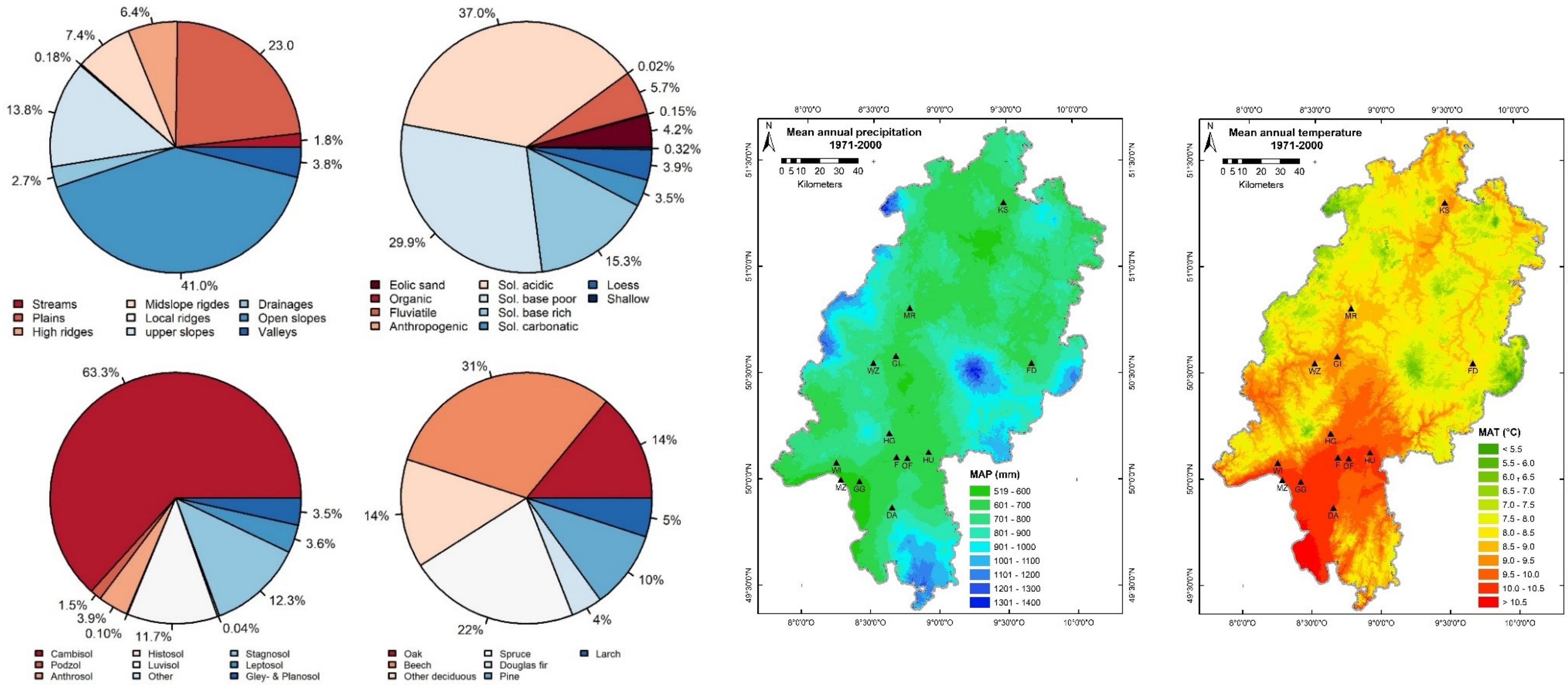


Figure 5: Topography, parent material, reference soil groups, tree species of Hesse’s forests and regionalised mean annual temperature and precipitation (18)

Appendix: GAM - Parametrisation

Table 3: Formulas of the GAMs as implemented in R, adjusted R^2 and deviance explained for the parametrisation set (NFSI, n=380)

Response	Model	R^2_{adj}	Deviance explained (%)
CEC_{eff}	~ te(CEC_{pot}, k=5) + PM + FT + $CaCO_3$	0.70	84
Base saturation	~ te(A, k=3) + te(SSA, k=3) + PM + FT + POD + $CaCO_3$ + SR	0.71	69
C/N-ratio	~ te(N_{dep}, k=5) + PM + SC + SR + FT + POD	0.64	66
K stocks	~ te(A, k=4) + FT + te(SSA, k=5) + $CaCO_3$ + SR + PM	0.68	75
Ca stocks	~ te(SSA, k=5) + te(modBS, k=3) + POD + PM + FT + SC + SR	0.43	73
Mg stocks	~ te(SSA, k=4) + te(CF, k=4) + $CaCO_3$ + SC + PM	0.70	77

CEC_{pot}: potential CEC, derived from texture (19); PM: parent material; FT: forest type (broadleaf, coniferous, mixed); CaCO3: carbonate content class (19); A: aridity index (20); SSA: Specific surface area, derived from texture (21); POD: degree of podzolation (19); SC: soil class; SR: soil region, CF: coarse fragments (> 2 mm); modBS: modelled base saturation

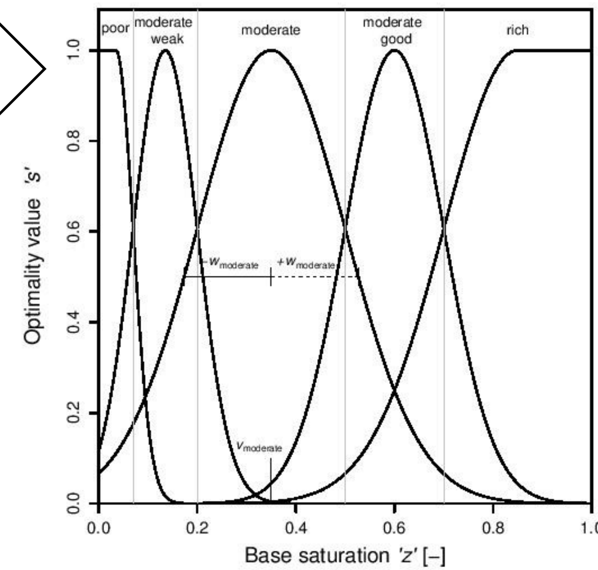
GAM's were set up in R with the package mgcv (22). The C/N-ratio followed a normal distribution (Gaussian family with "identity"-link), base saturation was modelled using a quasibinomial distribution, and all other variables were log-normal distributed (Gamma family with "log"-link). All model residuals were randomly distributed and showed no spatial autocorrelation (Moran's I)

Appendix: Fuzzy logic

Step 1: Rules to define "optimality" for each variable and each class by assigning bell-shaped curves (12). Classification slightly modified after AK Standortskartierung (7)

	Poor	Moderate-weak	Moderate	Moderate-good	Rich
C/N-ratio (-)	> 25	20-25	16-20	12-16	< 12
CEC_{eff} (kmol$_c$ ha^{-1})	< 100	100-250	250-500	500-1000	> 1000
BS (-)	< 0.07	0.07 – 0.2	0.2-0.5	0.5-0.7	> 0.7
K stock (kg ha^{-1})	< 300	300-450	450-600	600-900	> 900
Ca stock (kg ha^{-1})	< 400	400-800	800-2000	2000-4000	> 4000
Mg stock (kg ha^{-1})	< 70	70-140	140-350	350-700	> 700

Example



Step 2: Weighting variables, sum up optimality of weighted variables for each index class

Variable	Poor	Moderate-weak	Moderate	Moderate-good	Rich
Base saturation	30	30	39	44	44
K stocks	35	35	36	35	34
C/N-ratio	35	35	18	8	< 1
CEC_{eff}	< 1	< 1	8	14	21
Ca stocks	< 1	< 1	< 1	< 1	< 1
Mg stocks	< 1	< 1	< 1	< 1	< 1

Step 3: The nutrient index class with the highest sum of weighted optimality values defines the "crisp" class, resulting in the distribution in Figure 3

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