

Soil and vegetation feedbacks on climate change in high mountain ranges of the Tibetan Plateau: using near and mid-infrared spectroscopy (FT-NMIRS) in soil properties, phosphorus (P) as example

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Introduction

The Tibetan Plateau is the third-largest glaciated area of the world and is one of the most sensitive regions due to climate warming, such as fast-melting permafrost, dust blow and overgrazing in recent decades. . Climate warming and land-use change can reduce soil organic carbon (SOC) stocks as well as soil nitrogen (N) and phosphorus (P) contents and soil quality. Many species showed their distributions by climate-driven shifts towards higher elevation. In Tibetan Plateau, however, the elevational variations of the alpine grassland are rare and it is largely unknown how the grass line will respond to global warming and whether soils play a major role. With this research, the hypothesis would be tested that soil quality, given by SOC, N and P stocks and content, is a driving factor for the position and structure of the grass line and that soil quality is one of the major controls of biodiversity and biomass production in high-mountain grassland ecosystems. A Fourier transformation near and mid-infrared spectroscopy (FT-NMIRS) should be used to measure soil P fractions rapid and for large numbers of soil samples, and analyze environmental factors, including temperature, precipitation, soil development, soil fertility, and the ability of plants to adapt to the environmental impact of climate using FT-NMIRS. We explored first near-infrared spectroscopy (NIRS) in soils from grassland on the Tibetan Plateau, northwestern China and extracted P fractions of 196 samples from Haibei Alpine Meadow Ecosystem Research Station, Chinese Academy of Sciences, at four depths increments (0-10 cm 10-20 cm 20-40 cm and 40-70 cm) with different pre-nutrient additions of N and P (Table 1). The fractionation data were correlated with the corresponding NIRS soil spectra and showed significant differences for depth increments and fertilizer amendments. The r^2 of NIRS calibrations to predict P in traditional Hedley fractions (Table 2) ranged between 0.12 and 0.90.

Material & Methods

• Soil samples

Table 1. Nutrient addition to grassland soils experiment by CAS (N: nitrogen, P: phosphorous)

Treatments	Fertilizer	Amount (ha ⁻¹ yr ⁻¹)
P	Triple Superphosphate (TSP)	50 kg
NP	Carbamide CO(NH ₂) ₂ +TSP	50 kg P +100 kg N
N25	Carbamide CO(NH ₂) ₂ ²	25 kg
N50	Carbamide CO(NH ₂) ₂ ²	50 kg
N100	Carbamide CO(NH ₂) ₂ ²	100 kg
Control	-	-

• Hedley Fractionation

Table 2. The Hedley fractionation steps according to published theory and assignment of Hedley P fractions to soil P pools			
Fractions and Pools	Extraction Procedure ^{a,b}		Properties and bonding Forms of Pi and Po in the Fractions ^c
Labile P	Resin -P	Anion-exchange resin in bag, 0.5 M HCl, 16h	mostly Pi, marginal Po; biologically most available P form; adsorbed on surface of crystalline compounds
	NaHCO ₃ -P	0.5 M NaHCO ₃ , pH 8.5, 16h	highly labile P; Pi likely to be plant-available, associated with Fe and Al oxides; Po easily mineralized
Moderate P	NaOH -P	0.1 M NaOH, 16h	moderately labile P; Pi associated with Fe and Al oxides; Po involved in slow transformation processes
Stable P	HCl _{conc} -P	HCl _{conc} 85 °C, 20 min	very stable Pi; covers P in primary minerals; Po in very stable pools, eventually also derived from particulate organic matter
	Residual -P	0.5 M H ₂ SO ₄	highly resistant and occluded P forms

a Niederberger et al., 2015

b Alt et al., 2011

c Pätzold et al., 2013

• NIRS models

All soil samples were scanned with an integrating sphere measured by diffuse reflectance using a Fourier transform near-infrared reflectance spectrometer (Tensor 37, Bruker Optic GmbH, Ettlingen, Germany). The sample is inserted into the sample cup with the bottom of the glass and placed on the scanner and measured as it rotates. Each spectrum consists of 64 independent scans. Five replicate measurements were made for each sample over the entire spectrum from 11500 to 3800 nm.

We used cross-validation and external-validation to determine the accuracy of the NIRS models . For cross validation, one samples is removed from the data set and validated against the remaining subset. This process is repeated until every sample was used once for validation. For external validation the data set was divided into two parts randomly to ensure independency of the two subsets. One subset was used as calibration data set to develop the model. The best model is defined by the lowest cross-validation root-mean-square error (RMSECV) value with higher ratio of (standard error of prediction to the standard deviation (RPD) value (Table 3).

Results

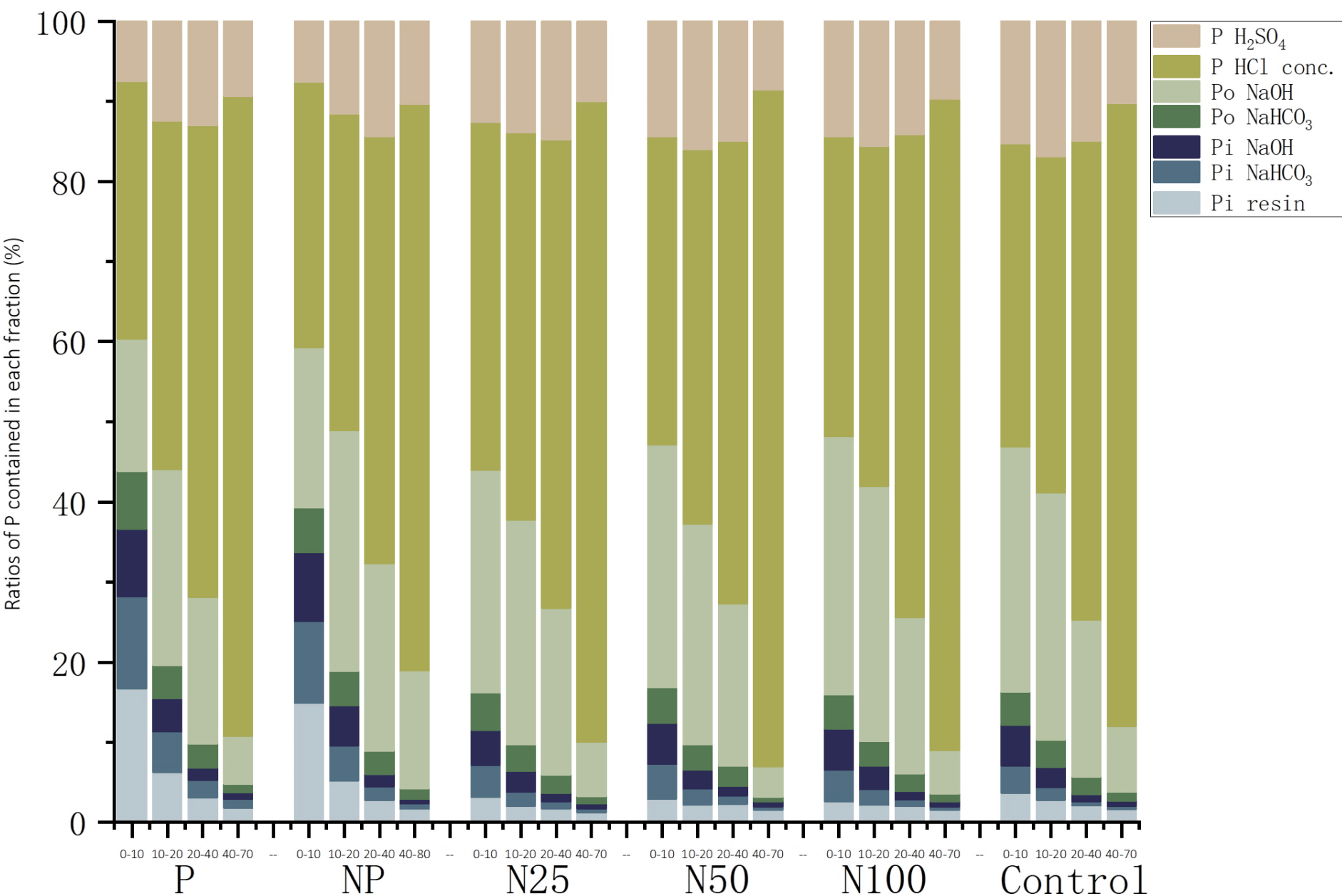


Figure 1. Mean proportions of Hedley P fractions for different nutrient amendment

- The total P values of all Hedley fractions covered a wide range from 0 to 503 µg g⁻¹ soil. For each depth increment and amen dment, the labile P fractions (Resin –P and NaHCO₃ -P) and moderately labile (NaOH -P) showed comparably lower values. Labile P and moderate P showed the same proportion of about 3-4% of total P and Stable P covered about 65 % (Figure 1).

- For the NIRS models, both RPD and r^2 values are higher for cross validation than for external validation for all seven Hedley fr actions (Table 3) and the applicability of the NIRS models based on the RPD values according to published results are given. For the majority of the fractions, the moderate P pool and stable P pool, the NIRS model could predict well.

Conclusion & Outlook

- The fractionation data were correlated with the corresponding NIRS soil spectra and showed significant differences for depth increments and fertilizer amendments as well as the NIRS model prediction quality, which was higher for organic than for in-organic P fractions.

- The results indicate that using NIRS to predict the P fractions can be a promising approach compared with traditional Hedley fractionation for soils in alpine grasslands on the Tibetan Plateau.

- However, for some P fractions, especially the labile P pool, the calibration results were not precise enough to be used due to the limited number of samples.

- The NIRS model, as well as the MIRS model based on larger soil sampling number will be built to predict relevant soil physi- cal and chemical properties.

References

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