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DEVELOPMENT OF FIELD TECHNIQUES TO PREDICT SOIL CARBON, SOIL NITROGEN AND ROOT DENSITY FROM SOIL SPECTRAL REFLECTANCE

A thesis presented in partial fulfillment of the requirements for the degree of

Doctor of Philosophy

in

Soil Science

at Massey University, Palmerston North, New Zealand

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2009

Abstract

The objectives of this research were to develop and evaluate a field method for *in situ* measurement of soil properties using visible near-infrared reflectance spectroscopy (Vis-NIRS). A probe with an independent light source for acquiring soil reflectance spectra from soil cores was developed around an existing portable field spectrometer (ASD FieldSpecPro, Boulder, CO, USA; 350-2500 nm).

Initial experiments tested the ability of the acquired spectra to predict plant root density, an important property in soil carbon dynamics. Reflectance spectra were acquired from soil containing ryegrass roots (*Lolium multiflorum*) grown in Allophanic and Fluvial Recent soils in a glasshouse pot trial. Differences in root density were created by differential nitrogen and phosphorus fertilization. Partial least squares regression (PLSR) was used to calibrate spectral data (pre-processed by smoothing and transforming spectra to the first derivative) against laboratory-measured root density data (wet-sieve technique). The calibration model successfully predicted root densities (r^2 = 0.85, RPD = 2.63, RMSECV = 0.47 mg cm^{-3}) observed in the pots to a moderate level of accuracy. This soil reflectance probe was then tested using a soil coring system to acquire reflectance spectra from two soils under pasture (0-60 mm soil depths) that had contrasting root densities. The PLSR calibration models for predicting root density were more accurate when soil samples from the two soils were separated rather than grouped. A more accurate prediction was found in Allophanic soils (r^2 = 0.83, RPD = 2.44, RMSECV = 1.96 mg g^{-1}) than in Fluvial Recent soils (r^2 = 0.75, RPD = 1.98, RMSECV = 5.11 mg g^{-1}). The Vis-NIRS technique was then modified slightly to work on a soil corer that could be used to measure root contents from deeper soil profiles (15-600 mm depth) in arable land (90-day-old maize crop grown in Fluvial Recent soils). PLSR calibration models were constructed to predict the full range of maize root densities (r^2 = 0.83, RPD = 2.42, RMSECV = 1.21 mg cm^{-3}) and also soil carbon (C) and nitrogen (N) concentrations that had been determined in the laboratory (LECO FP-2000 CNS Analyser; Leco Corp., St Joseph, MI, USA).

Further studies concentrated on improving the Vis-NIRS technique for prediction of total C and N concentrations in differing soil types within different soil orders in the field. The soil coring method used in the maize studies was evaluated in permanent and recent pastoral soils (Pumice, Allophanic and Tephric Recent in the Taupo-Rotorua Volcanic Zone, North Island) with a wide range of soil organic matter contents resulting from different times (1-5 years) since conversion from forest soils. Without any sample preparation, other than the soil surface left after coring, it was possible to predict soil C and N concentrations with moderate success (C prediction $r^2 = 0.75$, RMSEP = 1.23%, RPD = 1.97; N prediction $r^2 = 0.80$, RMSEP = 0.10%, RPD = 2.15) using a technique of acquiring soil reflectance spectra from the *horizontal* cross-section of a soil core (**H** method).

The soil probe was then modified to acquire spectra from the curved *vertical* wall of a soil core (**V** method), allowing the spectrometer's field of view to increase to record the reflectance features of the whole soil sample taken for laboratory analysis. Improved predictions of soil C and N concentrations were achieved with the **V** method of spectral acquisition (C prediction $r^2 = 0.97$, RMSECV = 0.21%, RPD = 5.80; N prediction $r^2 = 0.96$, RMSECV = 0.02%, RPD = 5.17) compared to the **H** method (C prediction $r^2 = 0.95$, RMSECV = 0.27%, RPD = 4.45; N prediction $r^2 = 0.94$, RMSECV = 0.03%, RPD = 4.25).

The **V** method was tested for temporal robustness by assessing its ability to predict soil C and N concentrations of Fluvial Recent soils under permanent pasture in different seasons. When principal component analysis (PCA) was used to ensure that the spectral dimensions (which were responsive to water content) of the data set used for developing the PLSR calibration model embraced those of the "unknown" soil samples, it was possible to predict soil C and N concentrations in "unknown" samples of widely different water contents (in May and November), with a high level of accuracy (C prediction $r^2 = 0.97$, RMSEP = 0.36%, RPD = 3.43; N prediction $r^2 = 0.95$, RMSEP = 0.03%, RPD = 3.44).

This study indicates that Vis-NIRS has considerable potential for rapid *in situ* assessment of soil C, N and root density. The results demonstrate that field root densities in pastoral and arable soil can be predicted independently from total soil C, which will allow researchers to predict C sequestration from root production. The recommended "**V**" technique can be used to assess spatial and temporal variability of soil carbon and nitrogen within soil profiles and across the landscape. It can also be used to assess the rate of C sequestration and organic matter synthesis via root density prediction. It reduces the time, labour and cost of conventional soil analysis and root density measurement.

Acknowledgements

I would like to sincerely thank my chief supervisor, Professor Mike J. Hedley, for his great supervision, brilliant ideas, guidance, advice, effort and patience throughout this study. My sincere thanks go also to my co-supervisors Carolyn B. Hedley and Mike P. Tuohy for their kindness, effort, advice, encouragement and constructive suggestions during my study. My special gratitude goes to my co-supervisor the late Dr. Greg C. Arnold who helped me with the statistical analysis used in this thesis. I am indebted to their invaluable help in the production of journal articles produced from this study.

Many thanks also to Dr. Alec McKay (President of New Zealand Society of Soil Science) who gave me a prestigious award (Summit Quinphos Postgraduate Bursary) in 2007. I really appreciate this. My special thanks to Andreas Hueni who created SpectraProc software for spectral pre-processing. Thanks also to Dr. Dave Scotter for editing the literature review, to Ted Pinkney for manufacturing the prototype soil probe, and to Martin Hawke for his help sample collecting in our Taupo _Rotorua project.

Many thanks to Massey University Staff; Assoc. Prof. P. Loganathan, Dr. Alan Palmer, Dr. Ian Yule, and Dr. Bob Stewart who provided useful consultations; and Prof. Vince Neal, Dr. David Horne, and Assoc. Prof. Marta Camps for their kindness.

Many thanks to the staff of the Fertilizer & Lime Research Centre and Soil & Earth Sciences for their assistance and friendship throughout my study: Moira Hubbard, Bob Toes, James Hanly, Ann West, Ian Furkert, Glenise Wallace, Ross Wallace, Mike Bretherton and Lance Currie.

Many thanks to the New Zealand government who provided me with an NZAID scholarship, and also to the International Student Officers of Massey University: Sue Flynn, Olive Pimentel and Sylvia Hooker, for their support during my study.

My appreciation goes to my friends, postgraduate students: Ieda Sanches, Anja Moebis, Matthew Irwin (NZPA staff), Janice Asing, Peter Bishop, Paramsothy Jeyakumar and Indika Herath, for their friendship.

Last, but not least, my immense gratitude to my parents: the late R. Soerip Padmonobo and Siti Zaenab and my parents-in-law: the late H. Masnin Junaidi and the late Hj. B. Sasih for their support and prayers. To my lovely wife, Agustin Rahmawati, and my lovely children, Muhammad Rahman Haryokusumo and Muhammad Farras Hadikusumo, you all strengthen me, and bring and share happiness.

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List of Abbreviations

ANN	artificial neural networks
ASD	Analytical Spectral Devices
AVIRIS	airborne visible infrared imaging spectrometer
CEC	cation exchange capacity
cf.	compare or consult
DM	dry matter
DT	de-trending
EM	electromagnetic
EMSC	extended multiplicative scatter correction
FIR	far infrared
FSL	fine sandy loam
FT	Fourier transforms
GIS	geographic information system
GPS	geographical positioning system
H method	horizontal method
INS	inelastic neutron scattering
IR	infrared
LAI	leaf area index
LIBS	laser induced breakdown spectroscopy
MeV	multiple of electron volt or one million electron volts
MLR	multiple linear regression
MSC	multiplicative scatter correction
NIR	near infrared
NIRS	near infrared spectroscopy
OM	organic matter
PAR	photosynthetically active radiation
PC	principal component
PCA	principal component analysis
PCR	principal component regression
PLS	partial least squares
PLSR	partial least squares regression

PRESS	predicted residual error sum of square
PVC	polyvinyl chloride
RD	root density
RER	ratio error range
RMSE	root mean square error
RMSECV	root mean square error of cross validation
RMSEP	root mean square error of prediction
RMSEV	root mean square error of validation
RPD	ratio prediction to deviation
RR	ridge regression
SEC	standard error of calibration
SEP	standard error of prediction
SIS	spectral interference subtraction
SL	silt loam
SMLR	stepwise multiple linear regression
SNV	standard normal variate
SNVD	standard normal variate and detrend
SOC	soil organic carbon
SOM	soil organic matter
SWIR	short wave infrared
SW-NIR	short wave near infrared
TIR	thermal infrared
UV	ultra violet
VI	vegetation indices
VIS	visible
Vis	visible
Vis-NIRS	visible near infrared spectroscopy
V method	vertical method
VNIR	visible near infrared
vs	versus
VSS	variable subset selection
WC	water content
yr	year