INFRARED SPECTROSCOPY FOR RAPID AND ACCURATE MEASUREMENT OF SOIL PROPERTIES

Budiman Minasny

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GLOBAL SOIL PARTNERSHIP

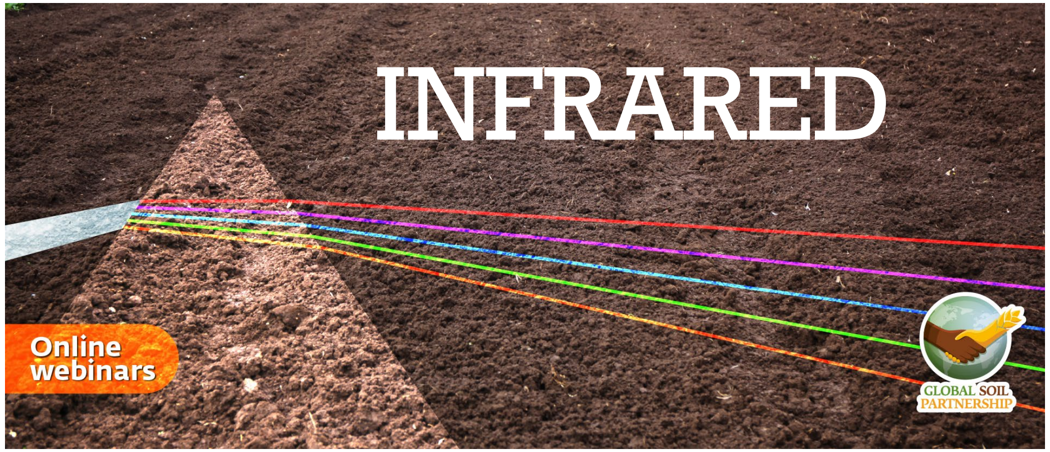
FAO GLOSOLAN Webinar 16 September 2021

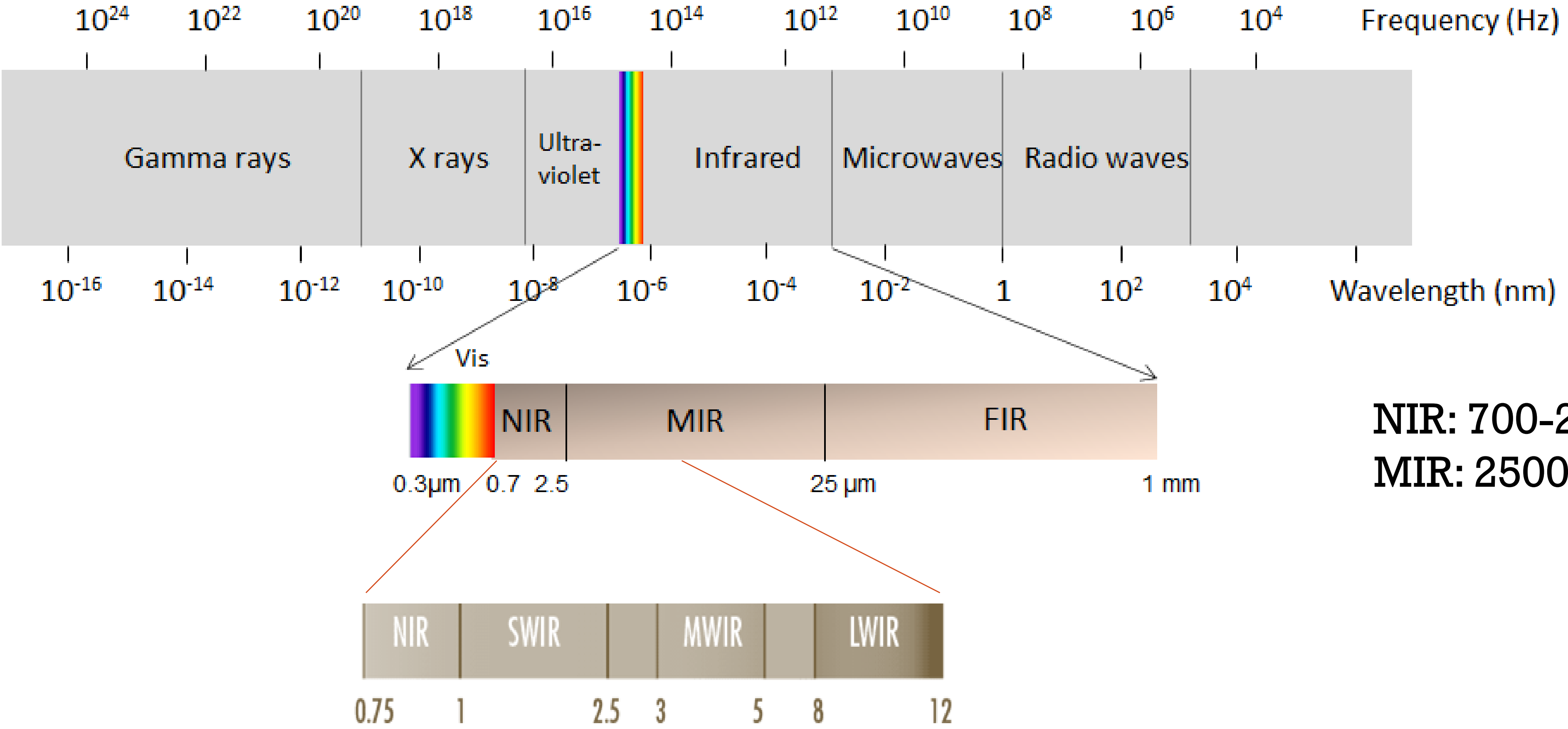
Sydney Institute of Agriculture

THE UNIVERSITY OF SYDNEY

ACKNOWLEDGEMENT OF THE COUNTRY

I would also like to acknowledge the Gadigal People of the Eora Nation on who's land I am standing today. As the traditional custodians of Australia, they have a long and rich history of caring for the country.





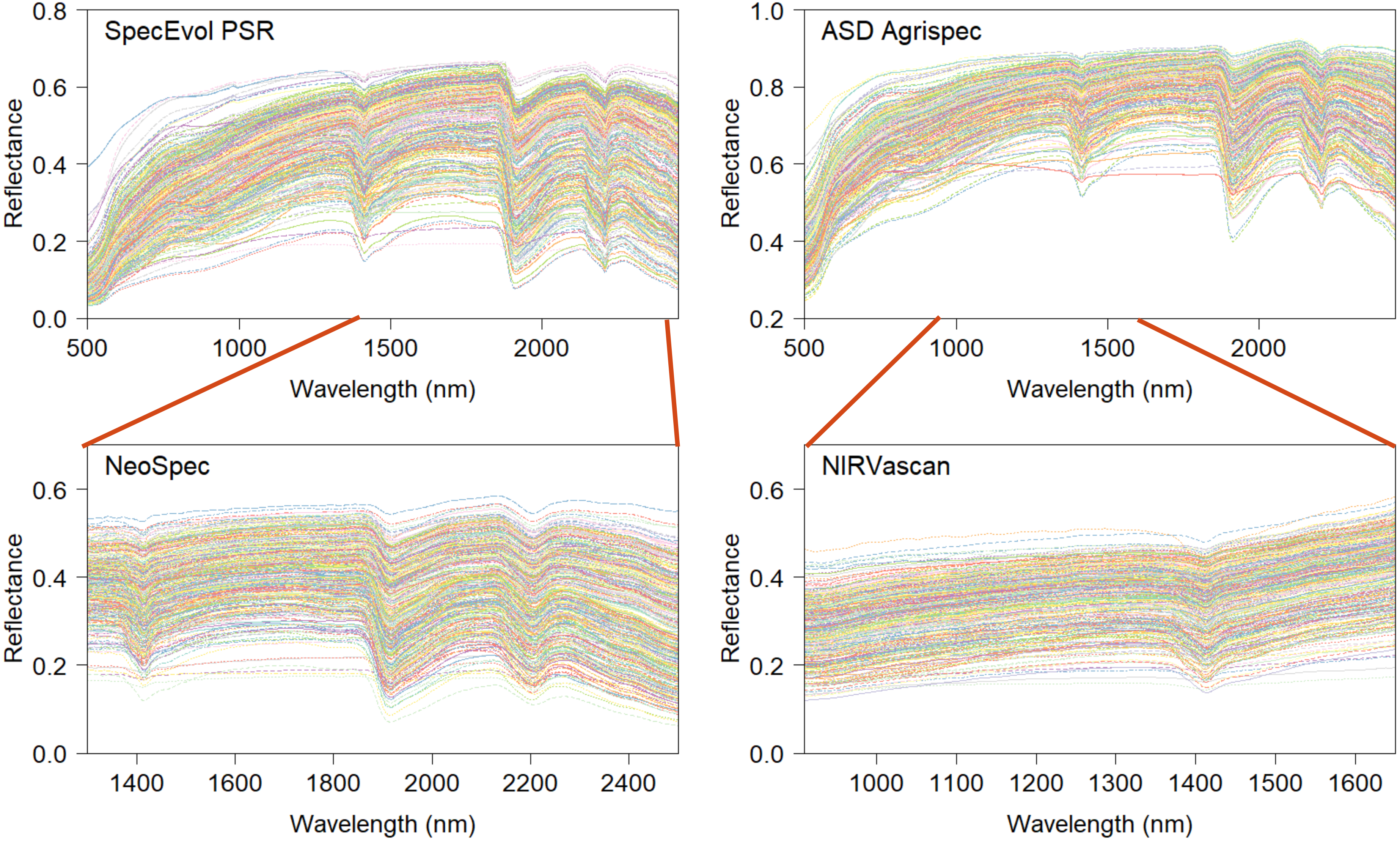
NIR: 700-2500 nm
MIR: 2500-25000 nm

CONTENTS

- (Vis) NIR Applications
- NIR in the field
- Some words about calibration and accuracy
- MIR for accurate lab measurements

NIR APPLICATIONS IN SOIL SCIENCE

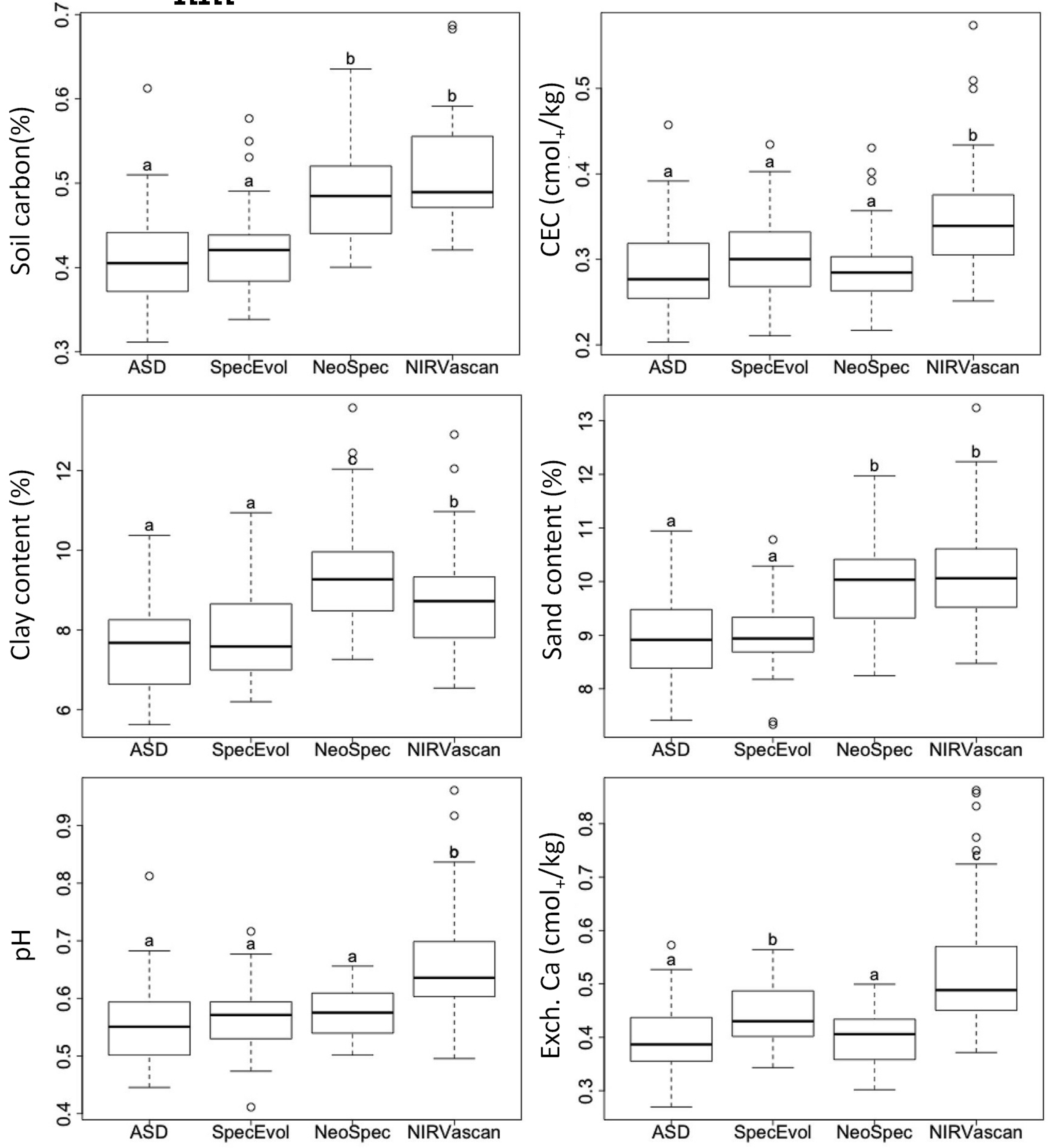
Potential of Low Cost Infrared Spectrometer



Evaluating low-cost portable near infrared sensors for rapid analysis of soils from South Eastern Australia
Y Tang, E Jones, B Minasny - Geoderma Regional, 2020

400-2450 nm | 1300-2450 | 900-1650 | 400-2450 | 1300-2450 | 900-1650

RMSE
(Root Mean Squared Error)



Evaluating low-cost portable near infrared sensors for rapid analysis of soils from South Eastern Australia
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Geoderma Regional 22 (2020) e00319

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Developing a soil spectral library using a low-cost NIR spectrometer for precision fertilization in Indonesia

Wartini Ng [a,*], Husnain [c], Linca Anggria [b], Adha Fatmah Siregar [b], Wiwik Hartatik [b], Yiyi Sulaeman [c], Edward Jones [a], Budiman Minasny [a]

BBSDLP

Balai Besar Litbang Sumber Daya Lahan Pertanian

Badan Litbang Pertanian

Kementerian Pertanian

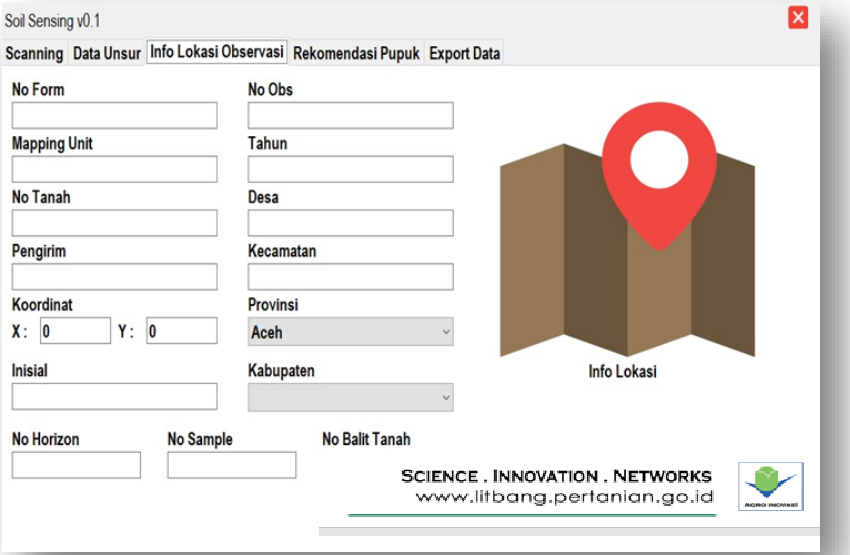
Smart Soil Sensor Kit Ver 1.0

Table 4
Predictive performance of the NeoSpectra NIR spectrometer using the Cubist model.

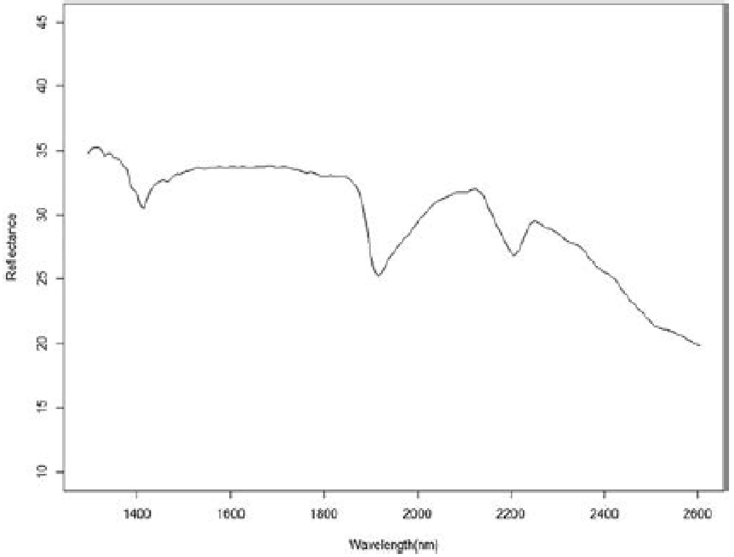
Properties	Calibration			Validation		
	R^2	RMSE	bias	R^2	RMSE	bias
Sand (%)	0.62	12.59	−1.1	0.45	15.2	−0.28
Silt (%)	0.38	11.49	−0.46	0.22	13.14	−0.26
Clay (%)	0.67	11.63	−0.15	0.52	14.22	0.57
pH_{H_2O}	0.71	0.61	−0.02	0.6	0.72	0
pH_{KCl}	0.68	0.58	−0.04	0.54	0.69	−0.01
$C_{Organic}$ (%)*	0.73	0.23	−0.01	0.57	0.29	0
Total N (%)*	0.69	0.04	0	0.52	0.05	0
C/N	0.3	2.69	−0.33	0.12	3.15	−0.01
Potential P (mg 100 g^{-1})*	0.62	0.63	0.04	0.47	0.74	0.01
Potential K (mg 100 g^{-1})*	0.56	0.74	−0.06	0.44	0.84	0.01
Available P Olsen (mg kg^{-1})*	0.33	0.78	−0.04	0.09	0.94	0.02
Available P Bray (mg kg^{-1})*	0.42	0.74	−0.08	0.3	0.82	0.01
Available K Morgan (mg kg^{-1})*	0.24	0.81	−0.05	0.08	0.9	−0.03
P retention (%)	0.89	10.55	0.28	0.75	16.14	−0.66
Exchangeable Ca (cmol(+) kg^{-1})	0.81	6.75	−0.7	0.71	8.32	0.17
Exchangeable Mg (cmol(+) kg^{-1})	0.72	3.08	−0.38	0.59	3.66	0.1
Exchangeable K (cmol(+) kg^{-1})	0.29	0.34	−0.08	0.19	0.35	0.01
Exchangeable Na (cmol(+) kg^{-1})	0.45	1.8	−0.23	0.24	2.16	0
Sum of bases (cmol(+) kg^{-1})	0.83	7.85	−0.5	0.72	9.99	0.2
CEC (cmol(+) kg^{-1})	0.66	5.79	−0.4	0.54	6.77	0.14
Base saturation (%)	0.74	15.64	0.95	0.57	20.38	0.85

R^2 – coefficient of determination, RMSE – root mean squared error.
* Subjected to log-transformation.

Smart Soil Sensor Kit Ver 1.1



Collected spectra

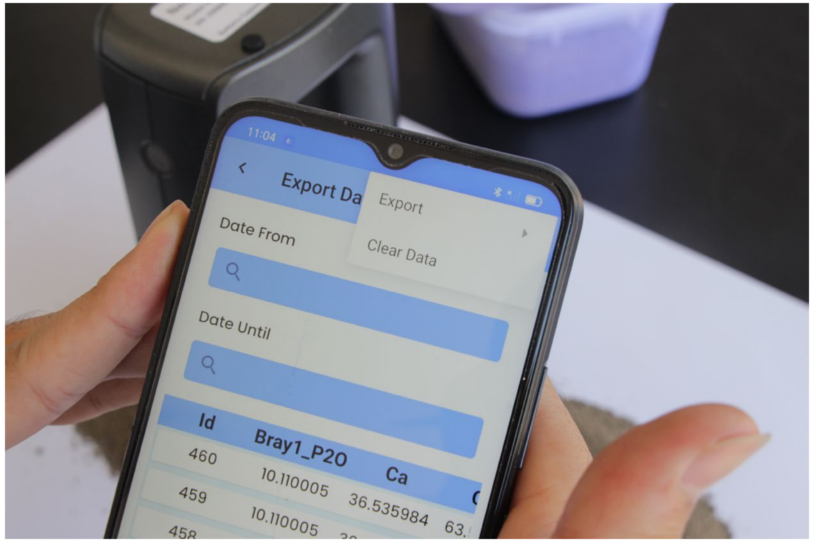


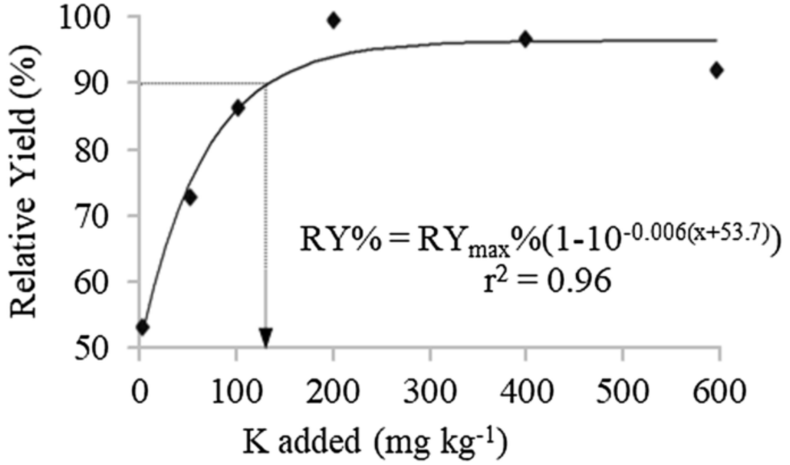
Chemometric predictions	
Sand (%)	78.1
Silt (%)	2.6
Clay (%)	19.3
pH_{H_2O}	5.91
Organic carbon (%)	0.46
Total N (%)	0.1
P retention (%)	18.92
CEC (cmol(+) kg^{-1})	9.21
Potential P (mg 100 g^{-1})	Low
Potential K (mg 100 g^{-1})	Low
Available P Bray (mg kg^{-1})	Low
Available K Morgan (mg kg^{-1})	Low
Exchangeable K (cmol(+) kg^{-1})	Low

BBSDLP
Balai Besar Litbang Sumber Daya Lahan Pertanian
Badan Litbang Pertanian
Kementerian Pertanian

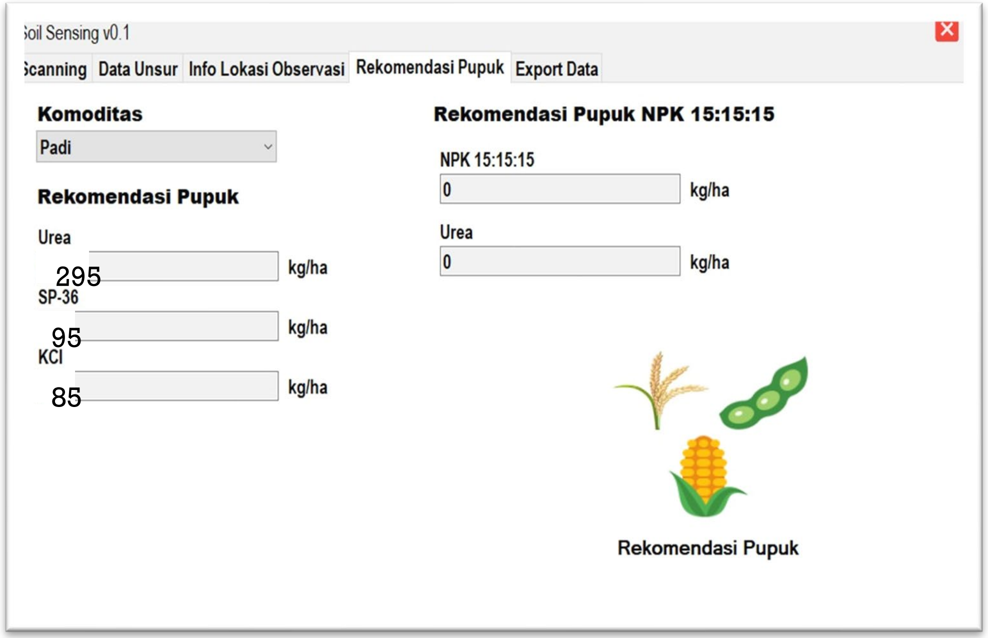
Smart Soil Sensing Kit Ver 1.1

- S3K Ver 1.1 launched in 2021.
- This new version is built with android system-based program.

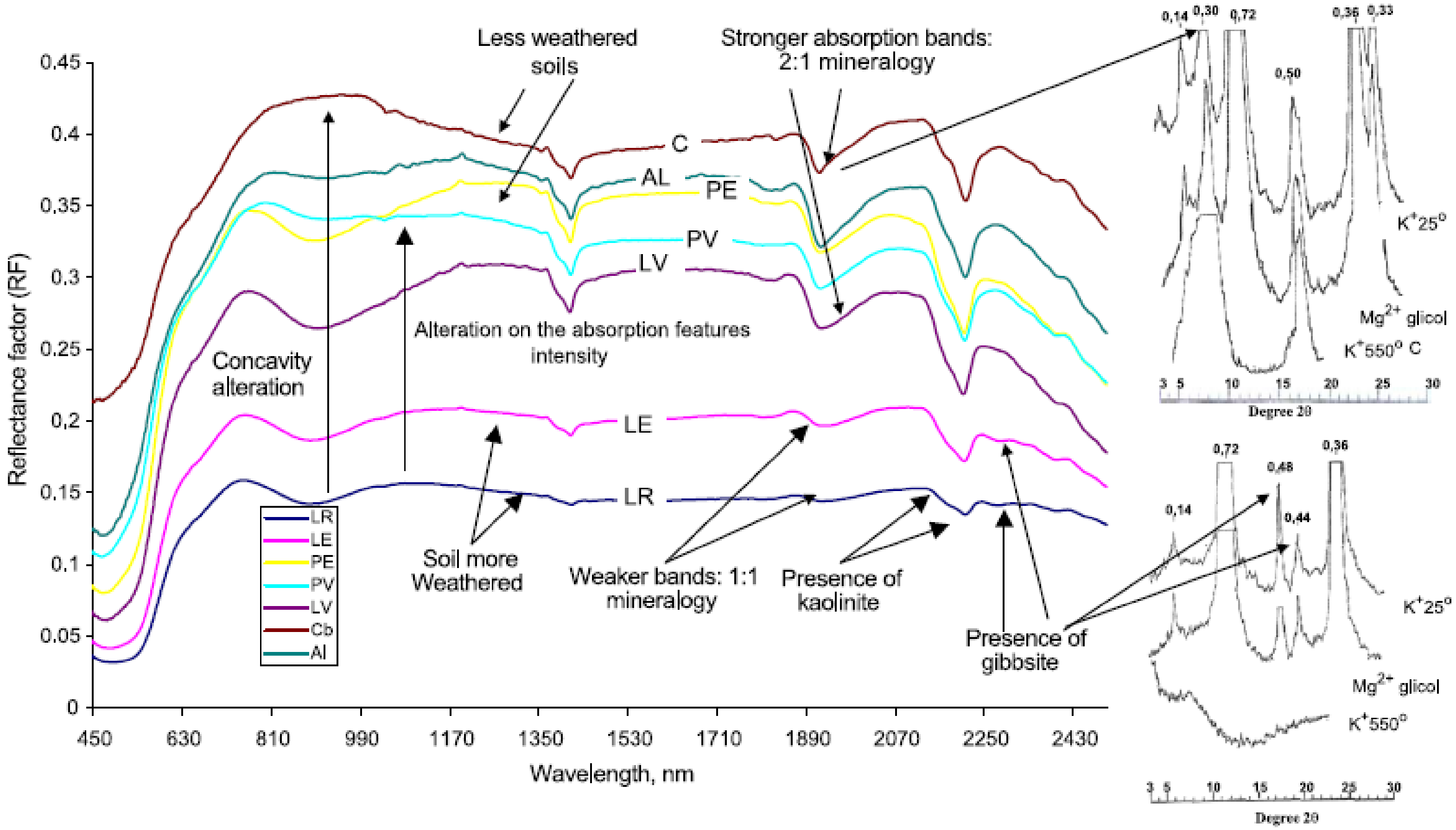




From Spectra to
Fertilizer Recommendation

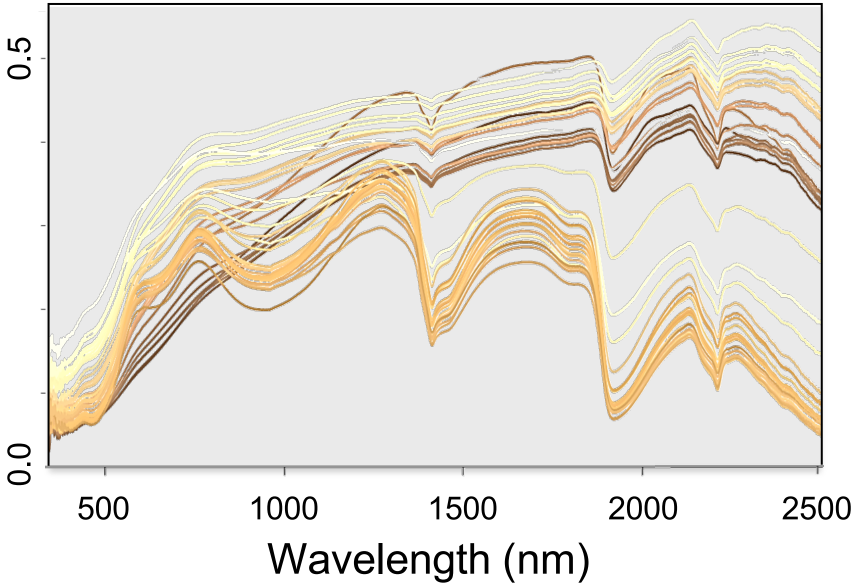


NEAR INFRARED FOR FIELD SOIL INFERENCE

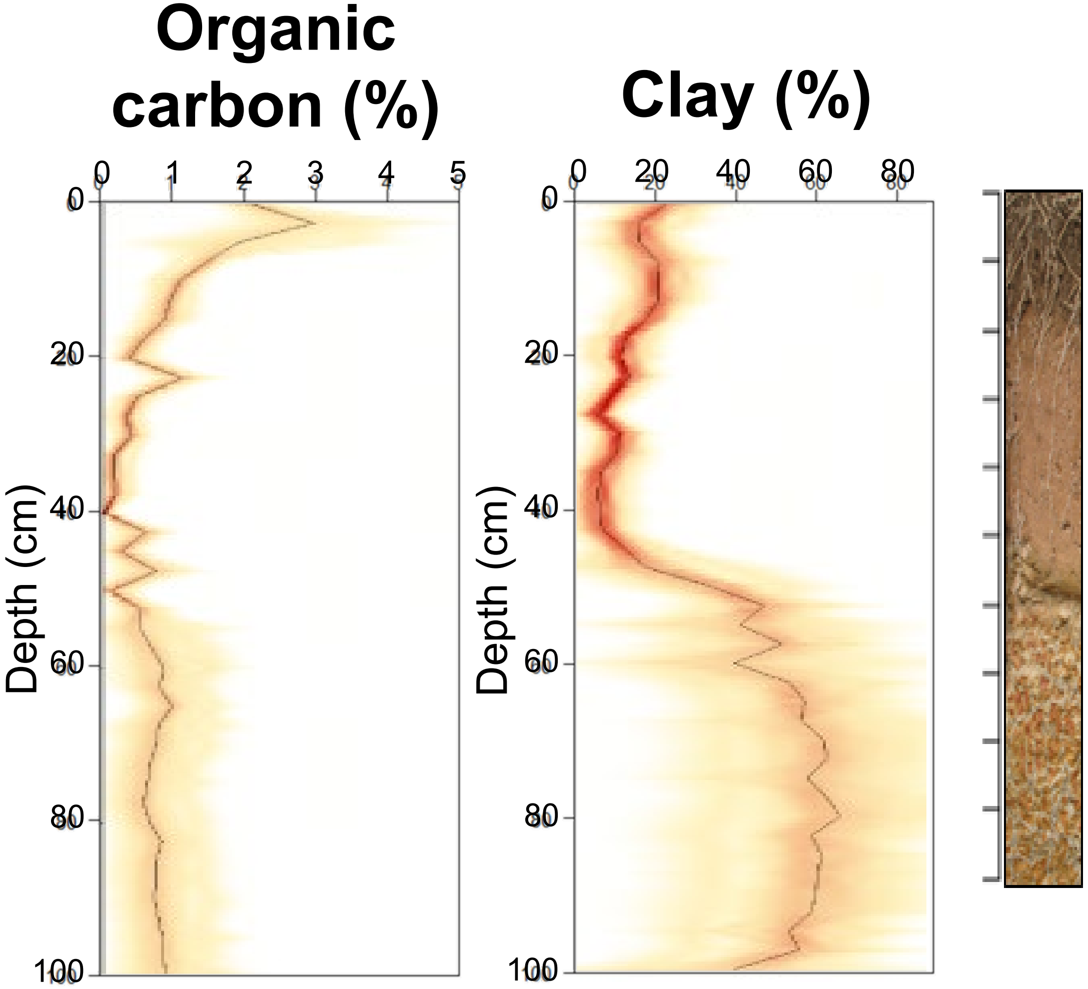


(Dematte er al. 2004)

SCANNING IN-SITU USING VISNIR SPECTROMETER

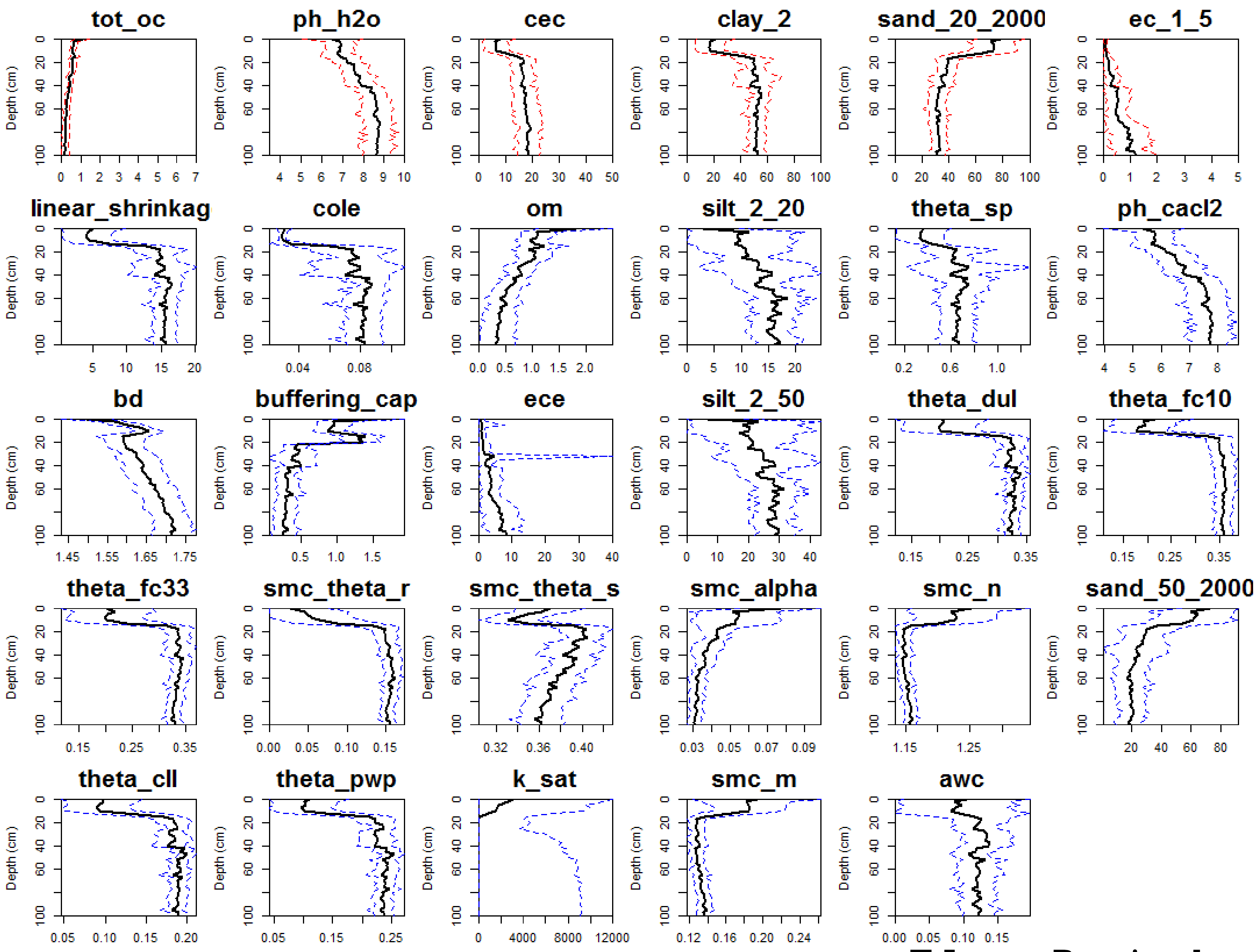


Predict properties directly from VisNIR



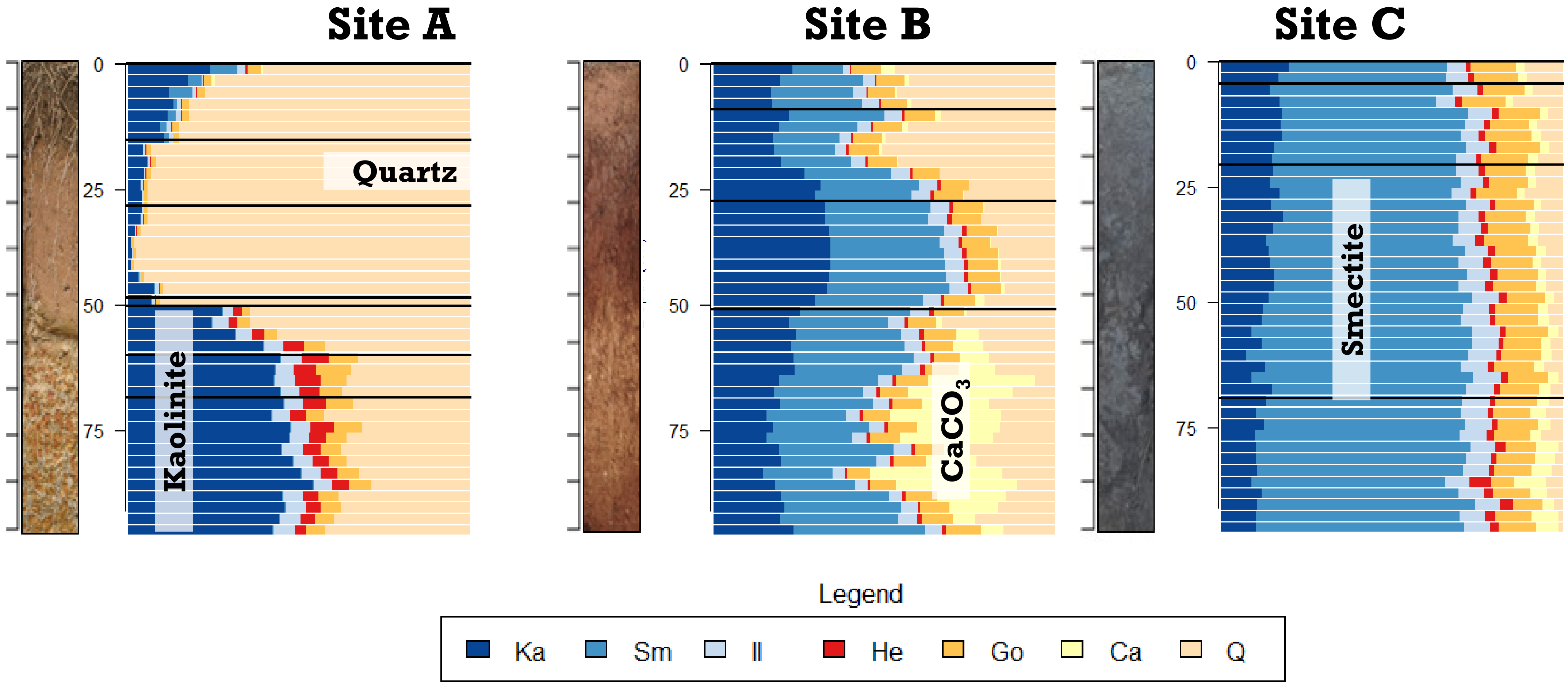
E.Jones. Proximal sensing in soil profiles

SOIL SPECTRAL INFERENCE SYSTEM

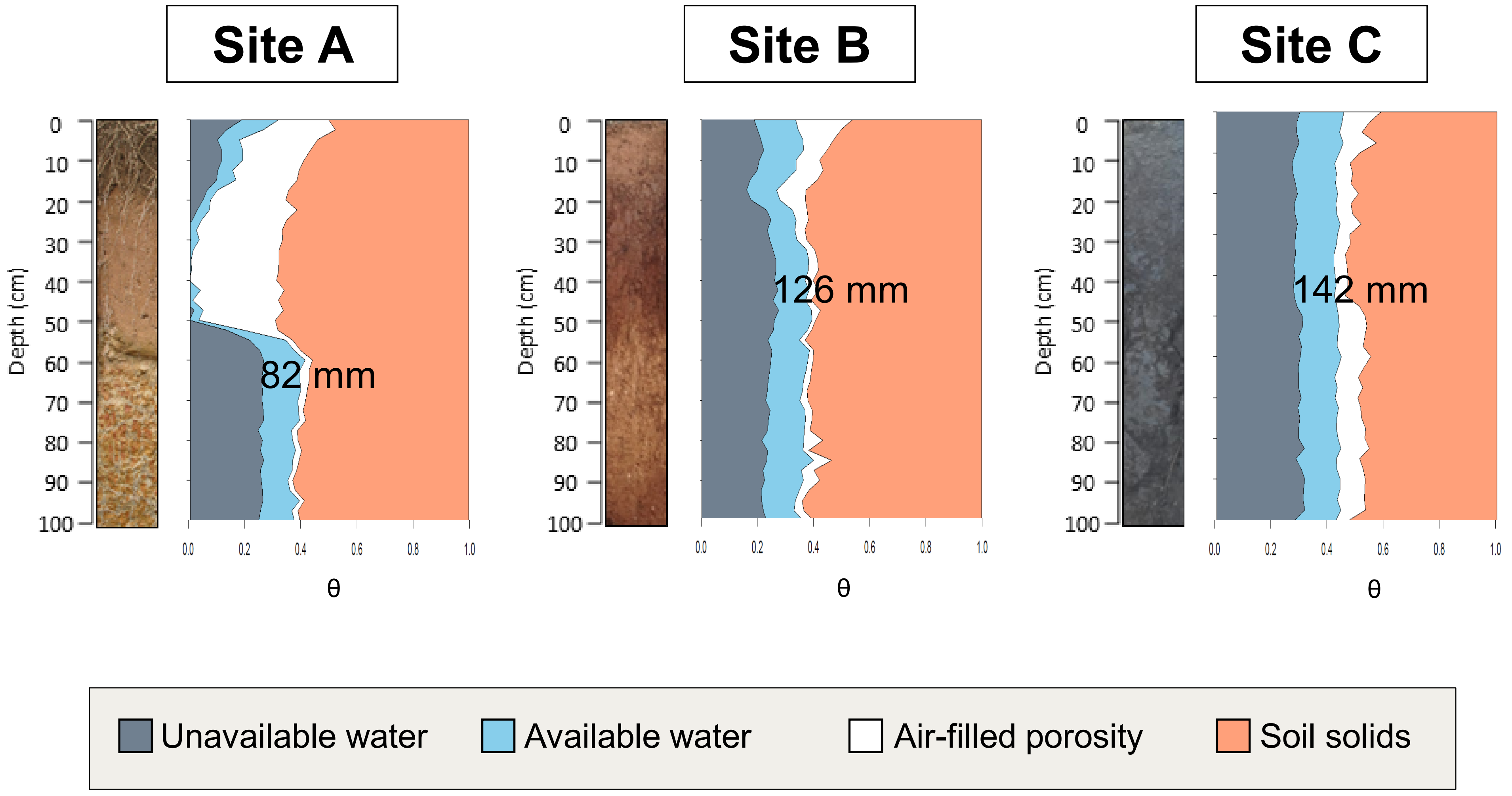


E.Jones. Proximal sensing in soil profiles

MINERAL COMPOSITION



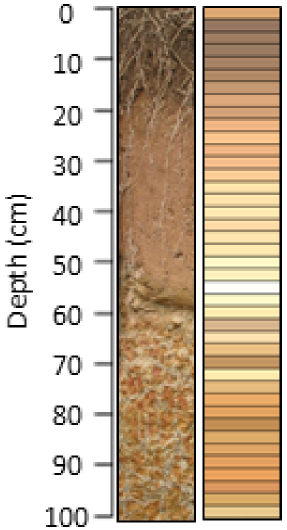
SPEC-SINFERS PREDICTED VOLUMETRIC RELATIONS.



E.Jones. Proximal sensing in soil profiles

SUMMARY – CROPPING POTENTIAL

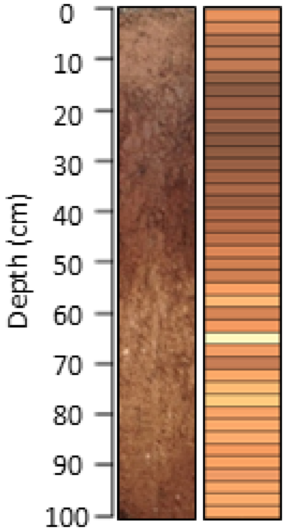
Site A



Sandy
Infertile
Low AWC

Heavy clay
Non-expansive
Infertile
No $CaCO_3$

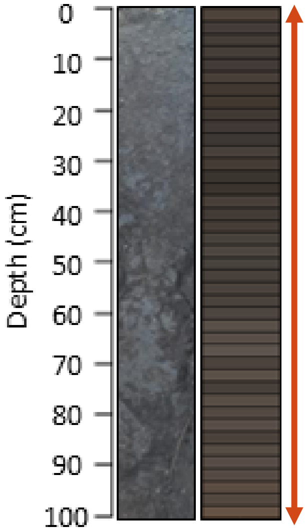
Site B



Mod. AWC
Mod. clay
Fertile

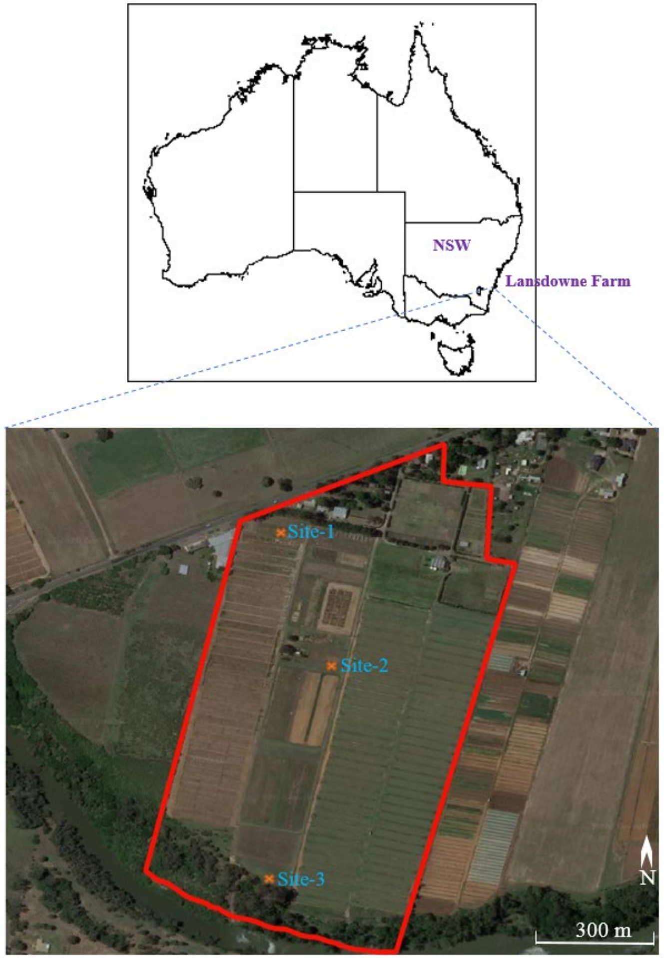
High $CaCO_3$

Site C

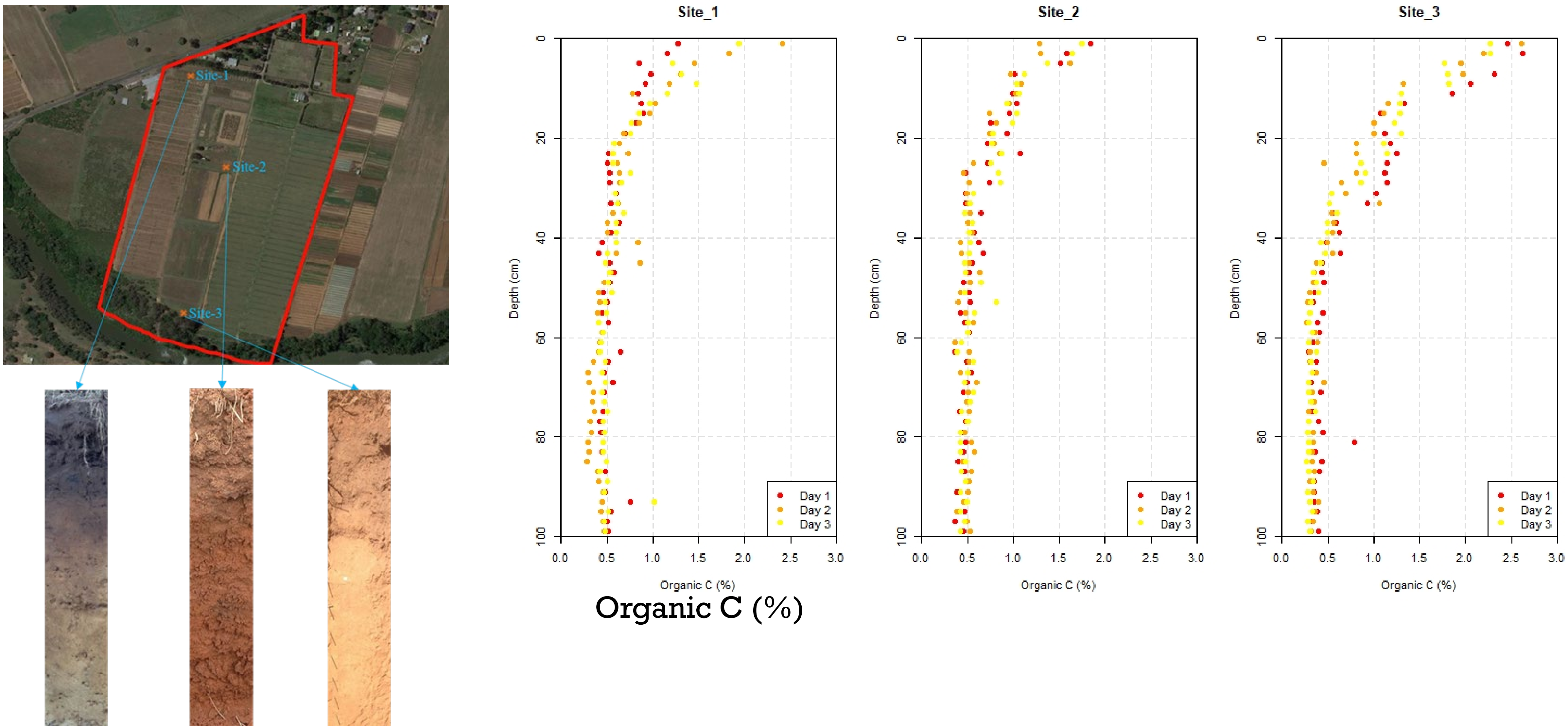


Clayey
Fertile
Mod. $CaCO_3$
High AWC

NIR PENETROMETER



Murad et al. (The University of Sydney)
A VisNIR Penetrometer System For Predicting Soil Carbon Under Australian Conditions

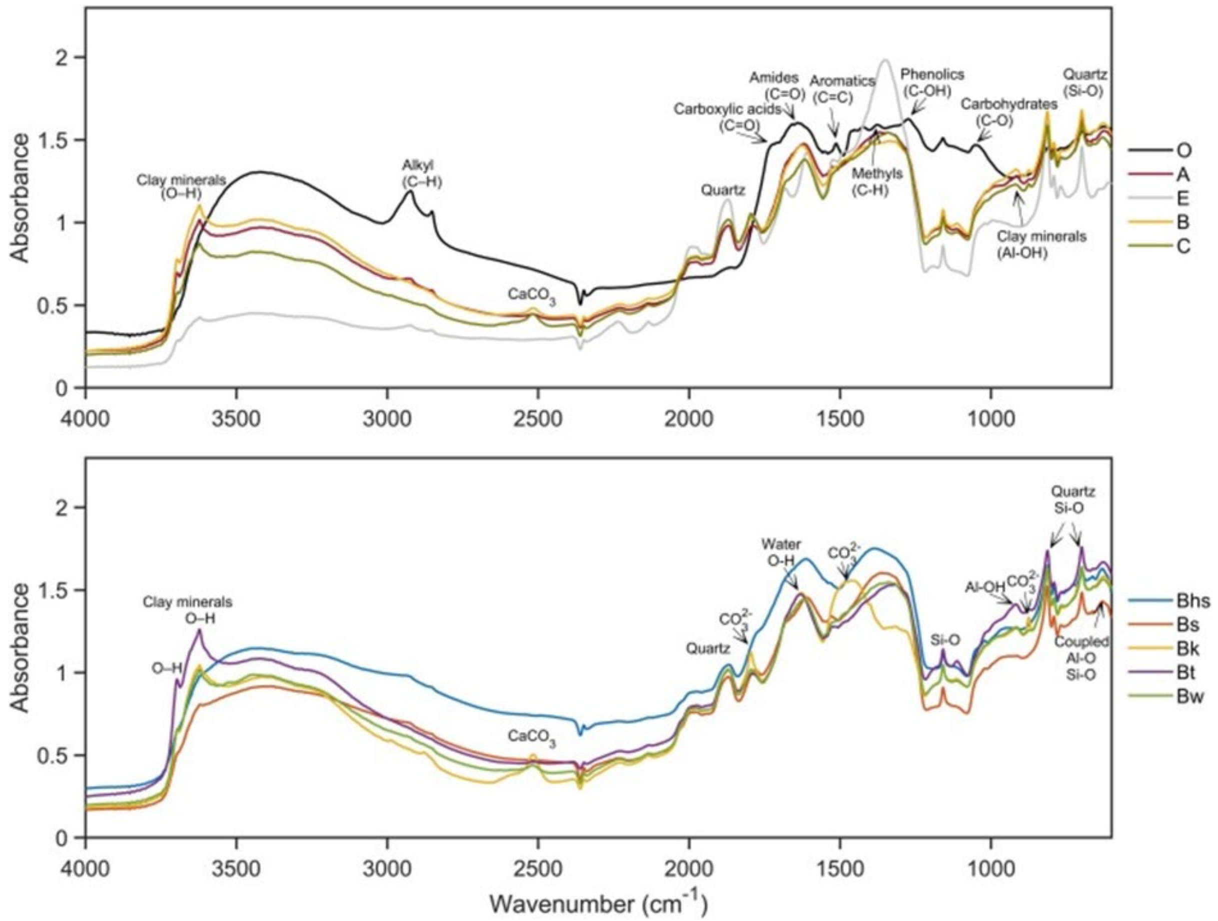


Organic C (%)

Murad et al. (The University of Sydney)
A VisNIR Penetrometer System For Soil Carbon AUDIT Under Australian Conditions

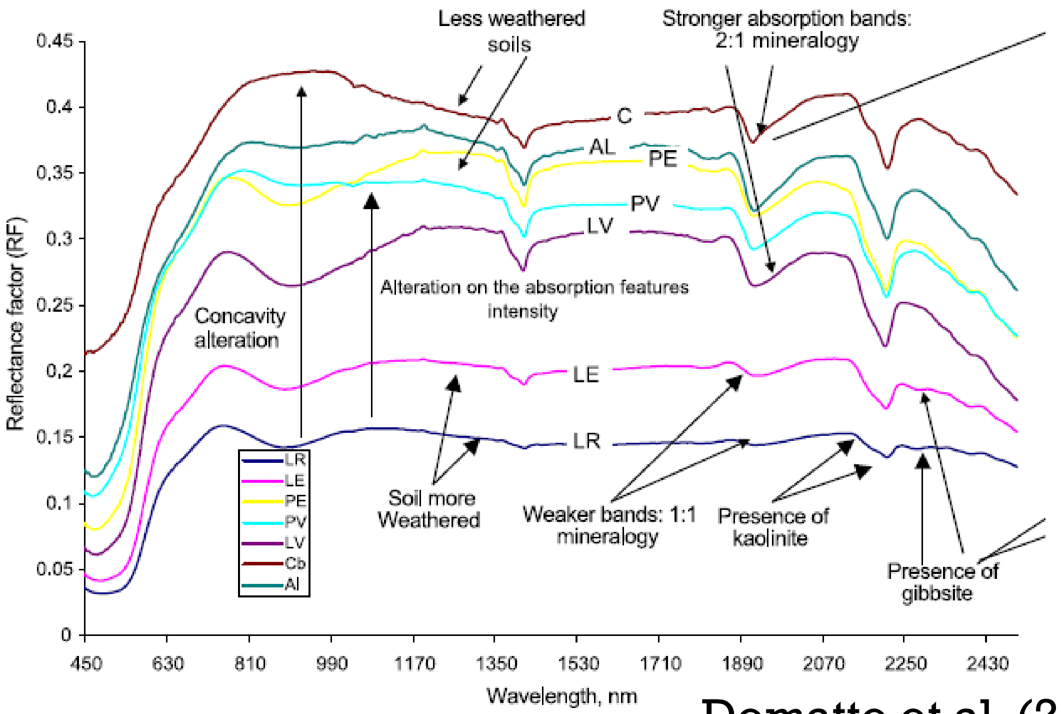
MIR FOR LAB SOIL ANALYSIS

MIR SPECTROSCOPY FOR LAB ANALYSIS



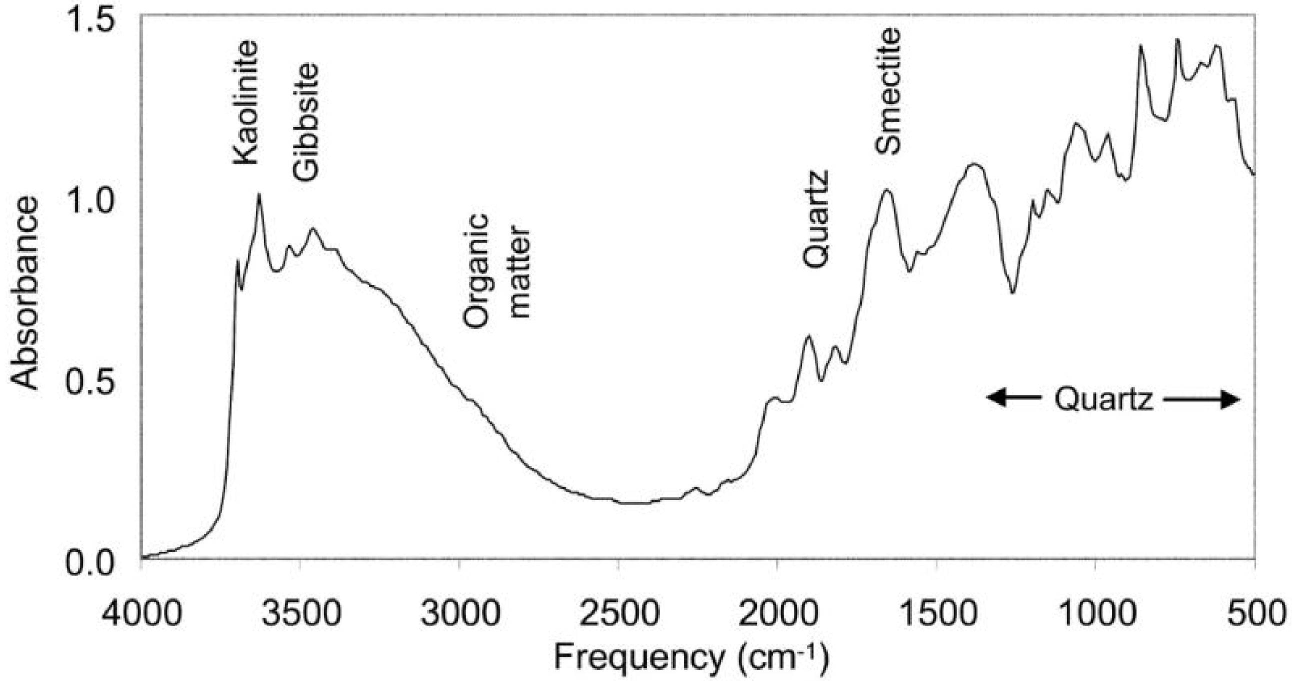
(Zhang et al. 2019)

NIR



Dematte et al. (2004)

MIR



Janik et al. (2017)

Robust field use, spectra not affected too much by field conditions

Overtone, broad & diffuse peaks

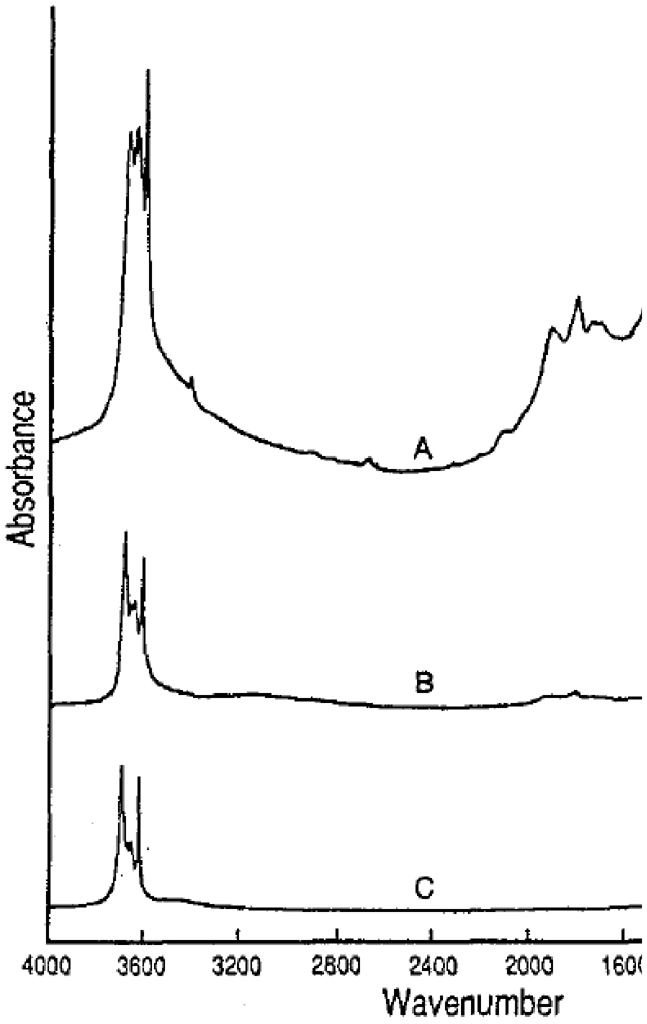
Suitable for field analysis

Not robust for field use, spectra affected too much by the environment & surface roughness

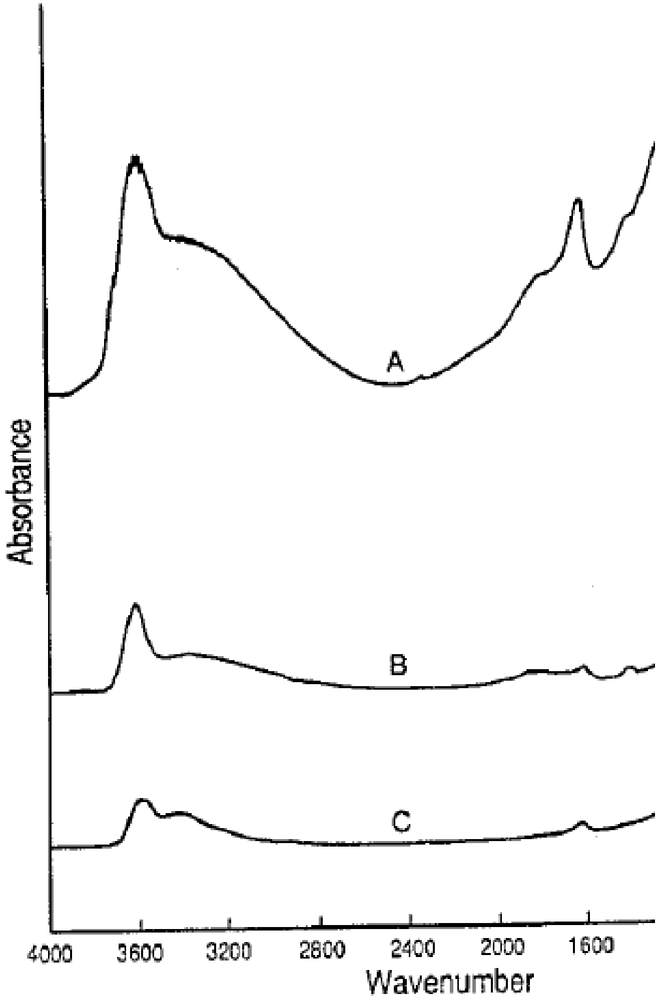
Fundamental molecular vibrations, well-defined peaks

Suitable for lab analysis

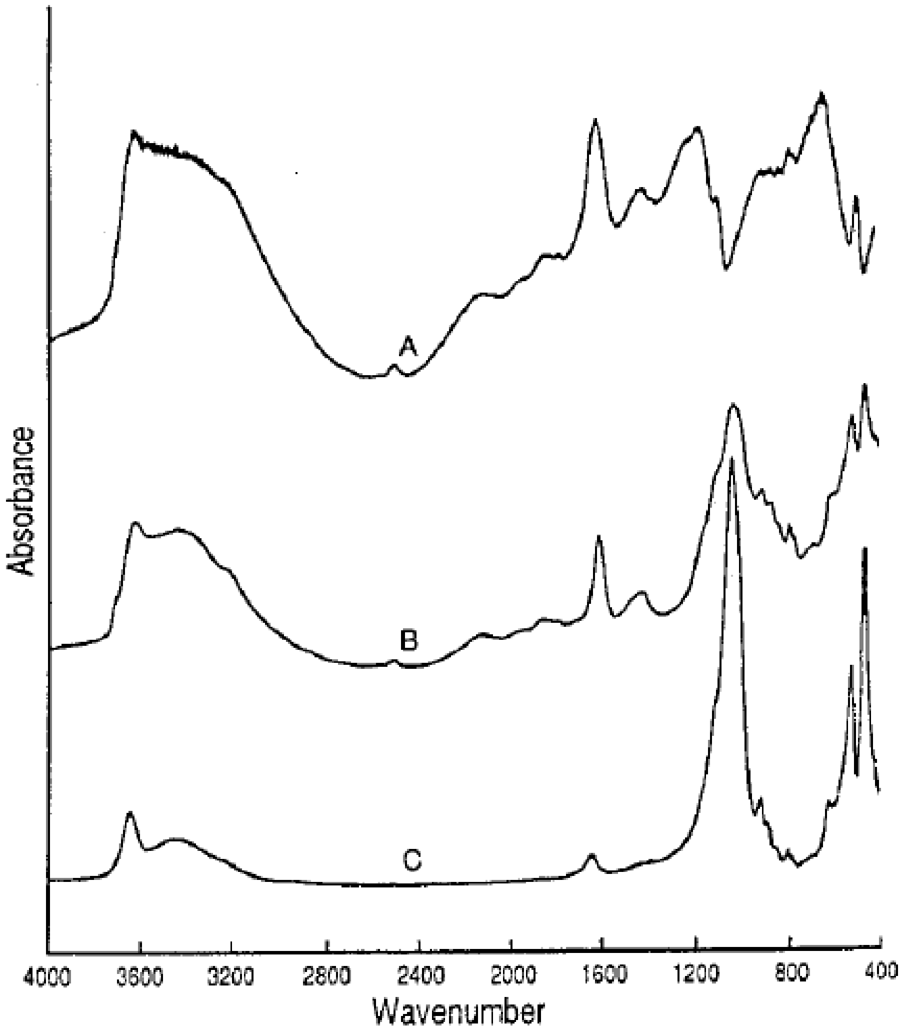
kaolinite



illite



montmorillonite



Nguyen et al. (1991)

MIR SPECTROSCOPY FOR LAB ANALYSIS

- After 23 years

Australian Journal of Experimental Agriculture, 1998, **38**, 681–96 681

Can mid infrared diffuse reflectance analysis replace soil extractions?

L. J. Janik[AB], *R. H. Merry and J. O. Skjemstad*[A]

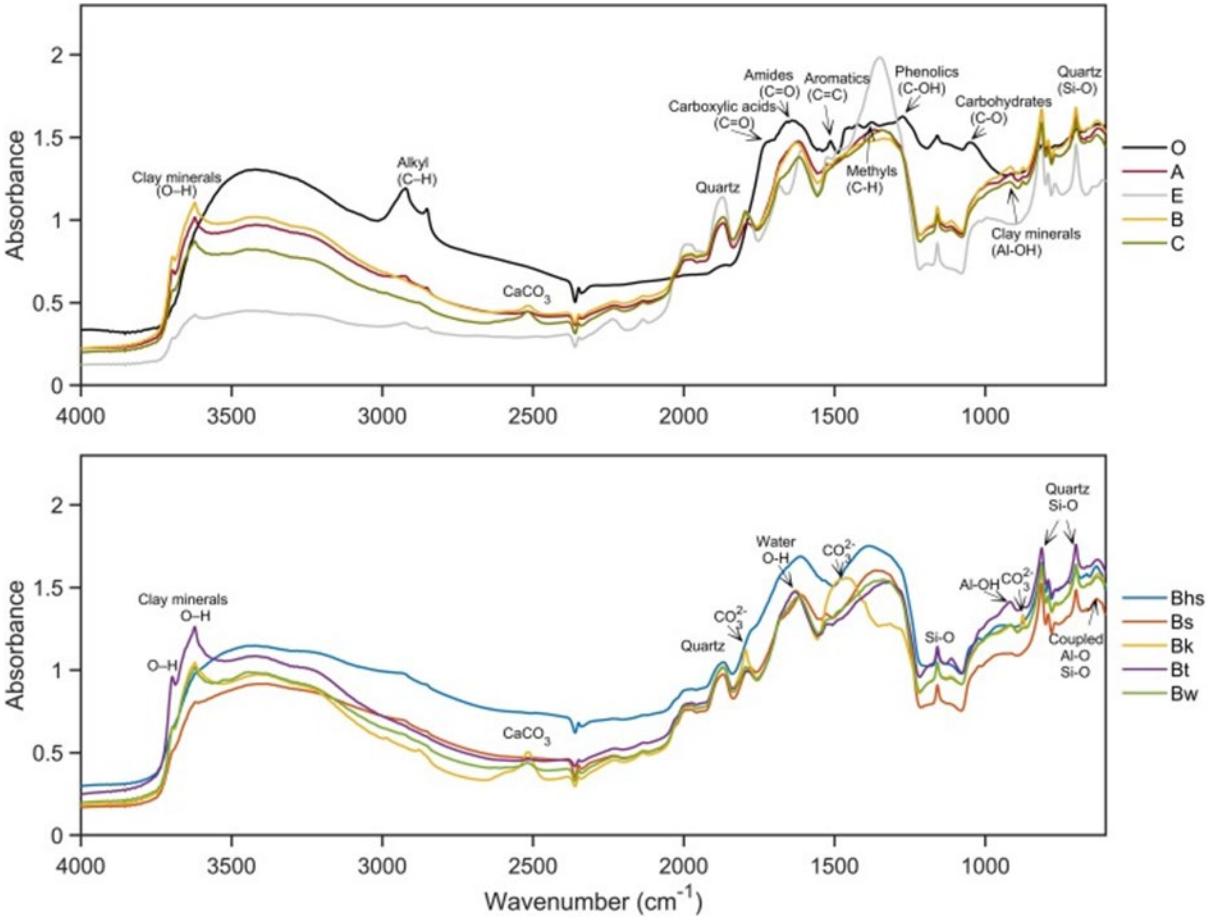
[A] CSIRO, Land and Water, PMB No. 2, Glen Osmond, SA 5064, Australia.
[B] Corresponding author; e-mail: les.janik@adl.clw.csiro.au

Summary. Recent developments in infrared spectroscopy and computer software, together with decreasing spectrometer costs, have resulted in an increase in the potential for soil analysis. Infrared spectroscopy in both the near and mid infrared ranges allows rapid acquisition of soil information at quantitative and qualitative, or indicator, levels for use in agriculture and environmental monitoring. In this paper, we describe how mid infrared diffuse reflectance analysis can provide results comparable in accuracy with many traditional extractive and digestion laboratory methods in soil studies, with the possibility of either replacing or enhancing them. Examples are given for estimation of lime requirement, organic carbon, exchangeable cations, air-dry moisture, clay content and biological indicators. Infrared methodology appears to have advantages in facilitating some soil analyses that are otherwise very time-consuming or expensive, or where spatially dense data is required.

CALIBRATION & ACCURACY

CALIBRATION

Spectra



Calibration Functions

f()

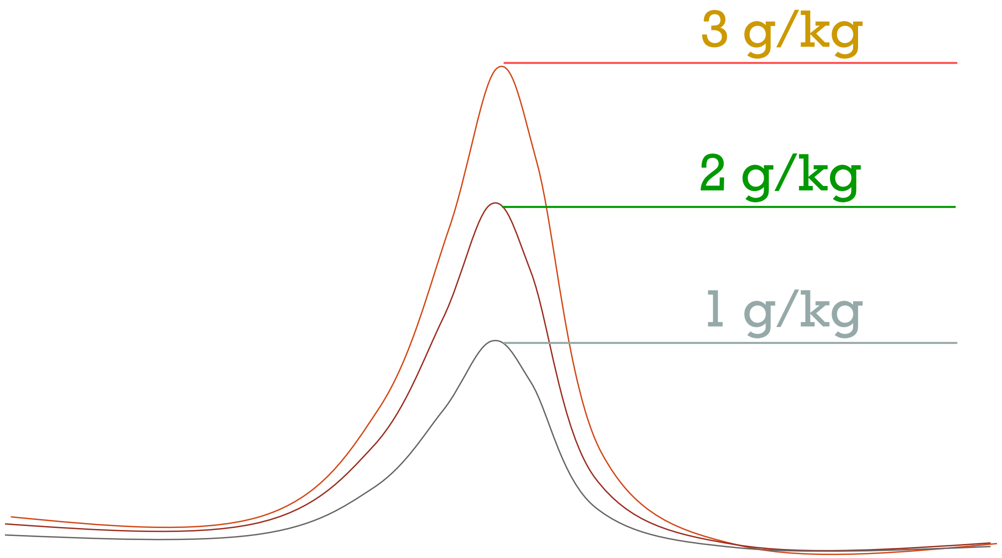
Soil properties

Soil texture
pH
OC
$CaCO_3$
CEC
K, Ca, Mg
N,P
…

CALIBRATION

Relating spectra to soil properties

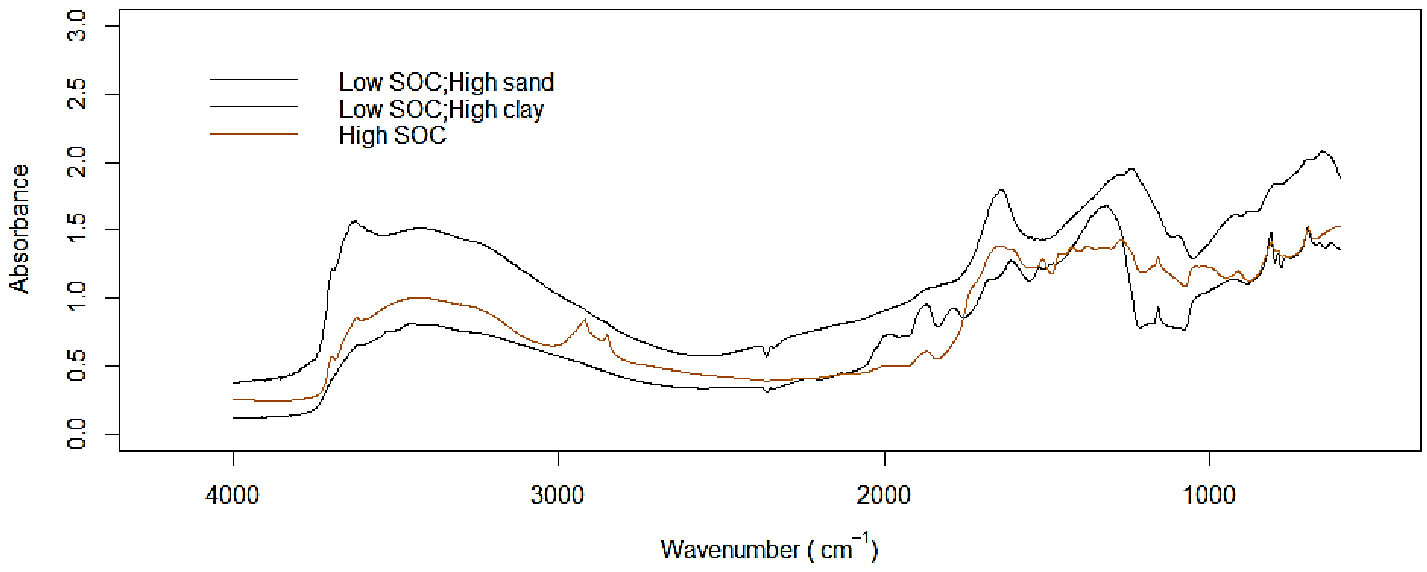
If the Beer Lambert's law was observed :



Univariate Calibration

$\mathbf{a} = a_0 + k\mathbf{C} + e$

CALIBRATION METHODS



Since the Beer Lambert's law is not observed,

The shape of the spectra
Is more meaningful
than
Reflectance at particular wavelengths

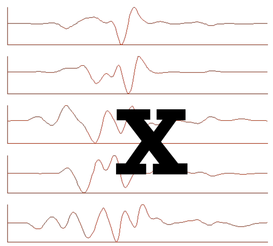
Multivariate Calibration

(using the whole spectra)

CALIBRATION

Linear models

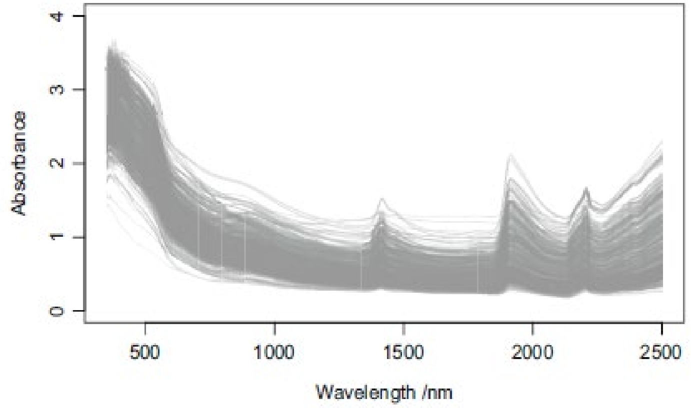
Response[s] e.g. Soil OC		Spectra [predictors]		Regression coefficients		Residuals



$$\begin{pmatrix} \mathbf{y} \end{pmatrix} = \begin{pmatrix} \mathbf{X} \end{pmatrix} \times \begin{pmatrix} \mathbf{b} \end{pmatrix} + \begin{pmatrix} \mathbf{r} \end{pmatrix}$$

MULTIVARIATE CALIBRATION

- Problems :
  - The spectra are highly correlated
  - There can be more variables than number of samples (large *p*, small *n*)



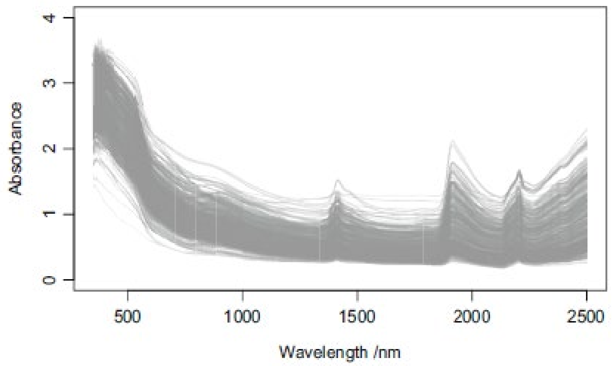
- Some solutions:
  - Reducing the dimension of **X** via calculation of latent variables
  - Variables selection

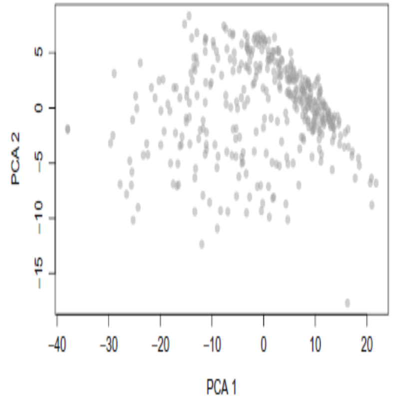
- Methods:
  - Linear multivariate methods, e.g. PLS
  - Machine learning methods

PCA

Principal component analysis

$$\mathbf{P} \times \mathbf{X} = \mathbf{T} + \mathbf{R}$$





transformation matrix

Spectra

scores (new descriptors)

Residuals

PARTIAL LEAST SQUARES (PLS)

- PLS regression decomposes both **X** and **Y** as a product of a common set of orthogonal factors and a set of specific loadings (Wold, 1960)
- Then set up a regression model between the scores and **Y**.

ACURACY ASSESSMENT

Statistics

- Root-mean square error (accuracy)

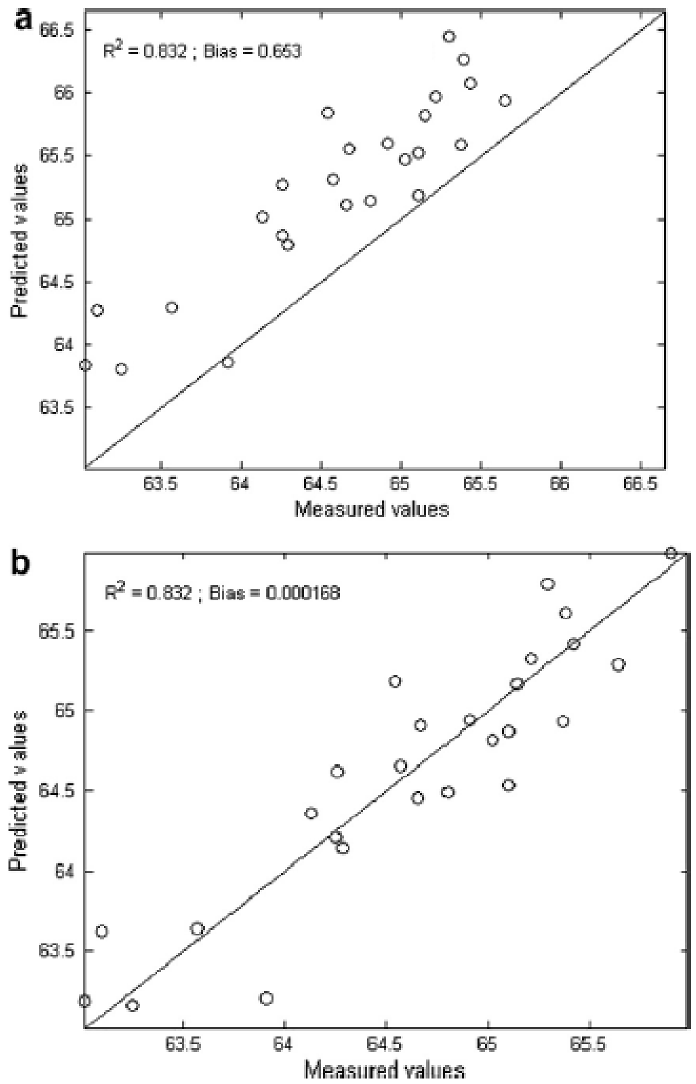
In the NIR literature it is called SEP (standard error of prediction)

$$MSE = \sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

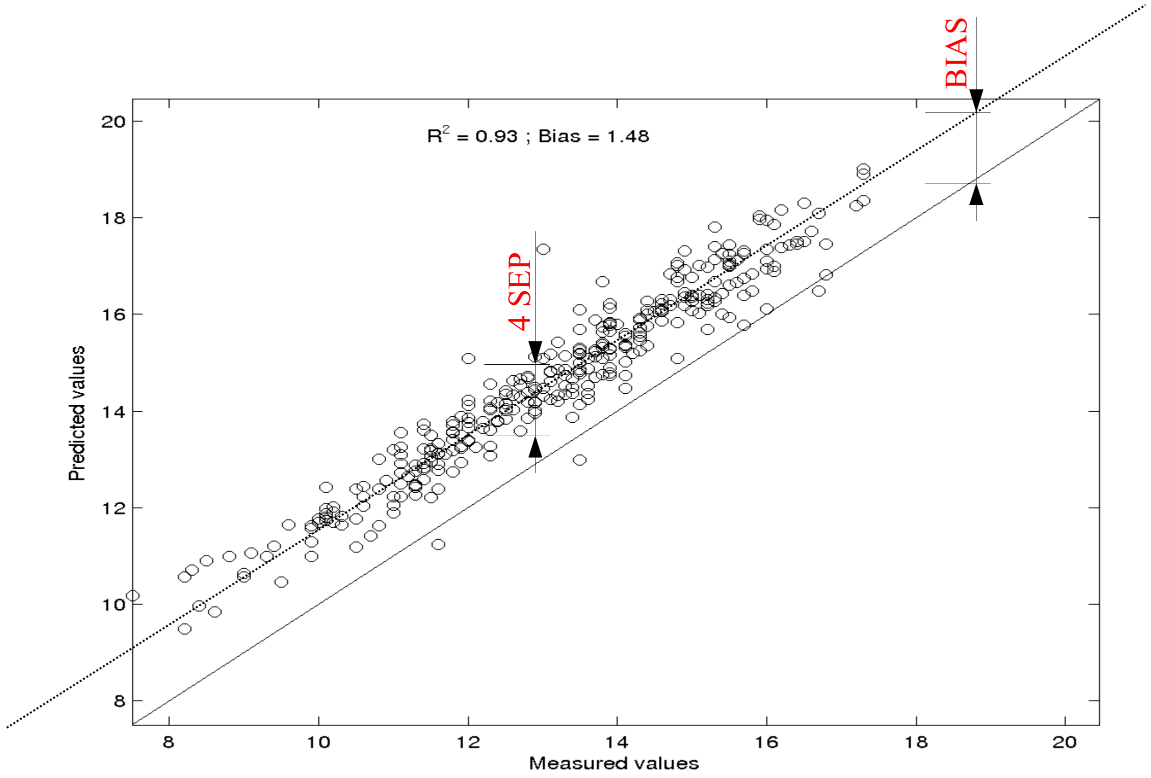
$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

- Mean error (bias)

$$ME = \sum_{i=1}^{n}(y_i - \hat{y}_i)$$



STANDARD ERROR OF PREDICTION



Std Err of Prediction (SEP)=RMSE

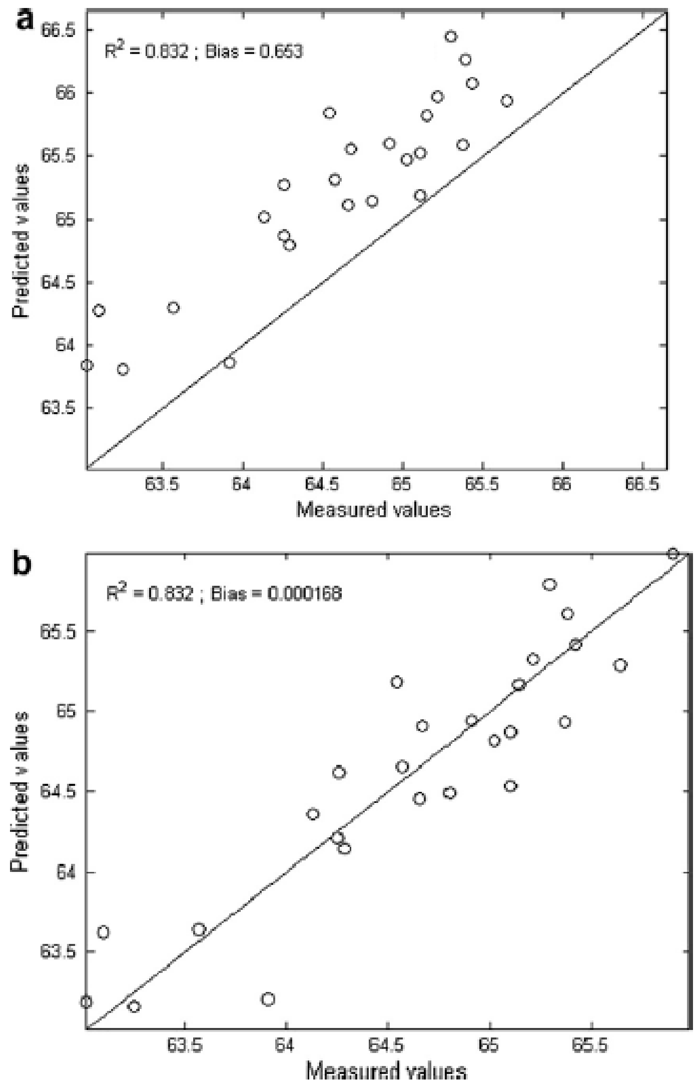
95% of the errors are in [BIAS-2*SEP ; BIAS+2*STD]

COEFFICIENT OF DETERMINATION, R^2

$$R^2 = 1 - \frac{SS_{residual}}{SS_{total}}$$

$$SS_{total} = \sum_i (y_i - \bar{y})^2$$

$$SS_{residual} = \sum_i (y_i - \hat{y}_i)^2$$

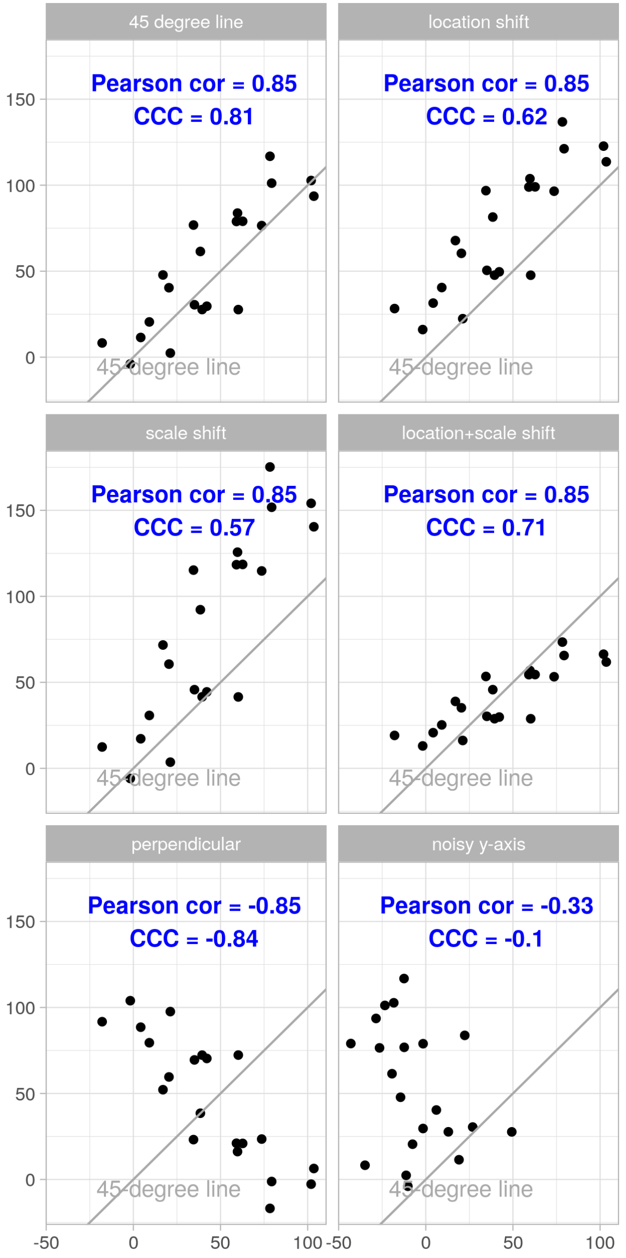


PREDICTION QUALITY

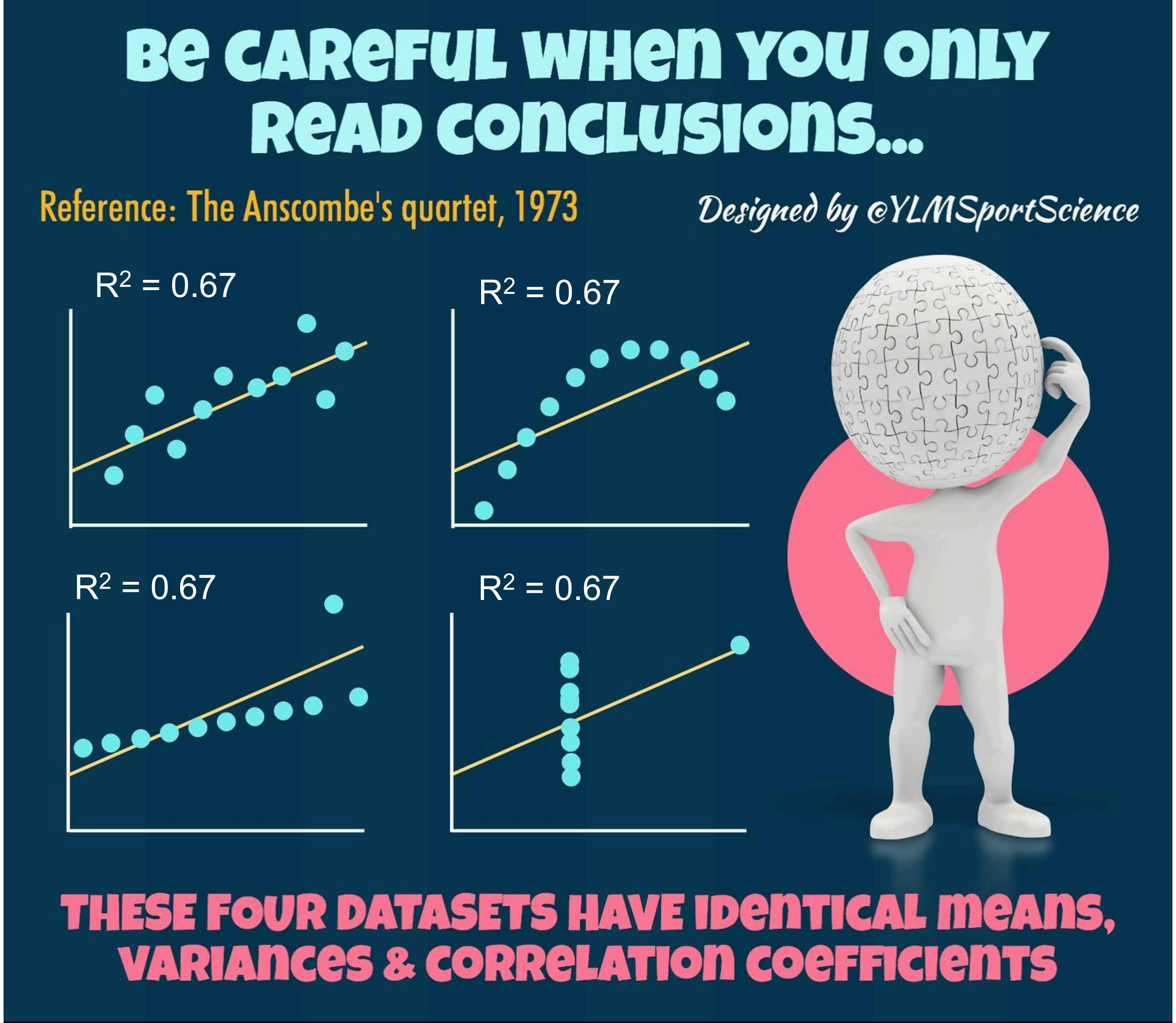
Lin's Concordance correlation coefficient

- Lin (1989)
- Evaluates agreement between pairs of observations by measuring variation from the 45° line

$$\rho_c = \frac{2\,\sigma_{12}}{\sigma_1^2 + \sigma_2^2 + (\mu_1 - \mu_2)^2}$$



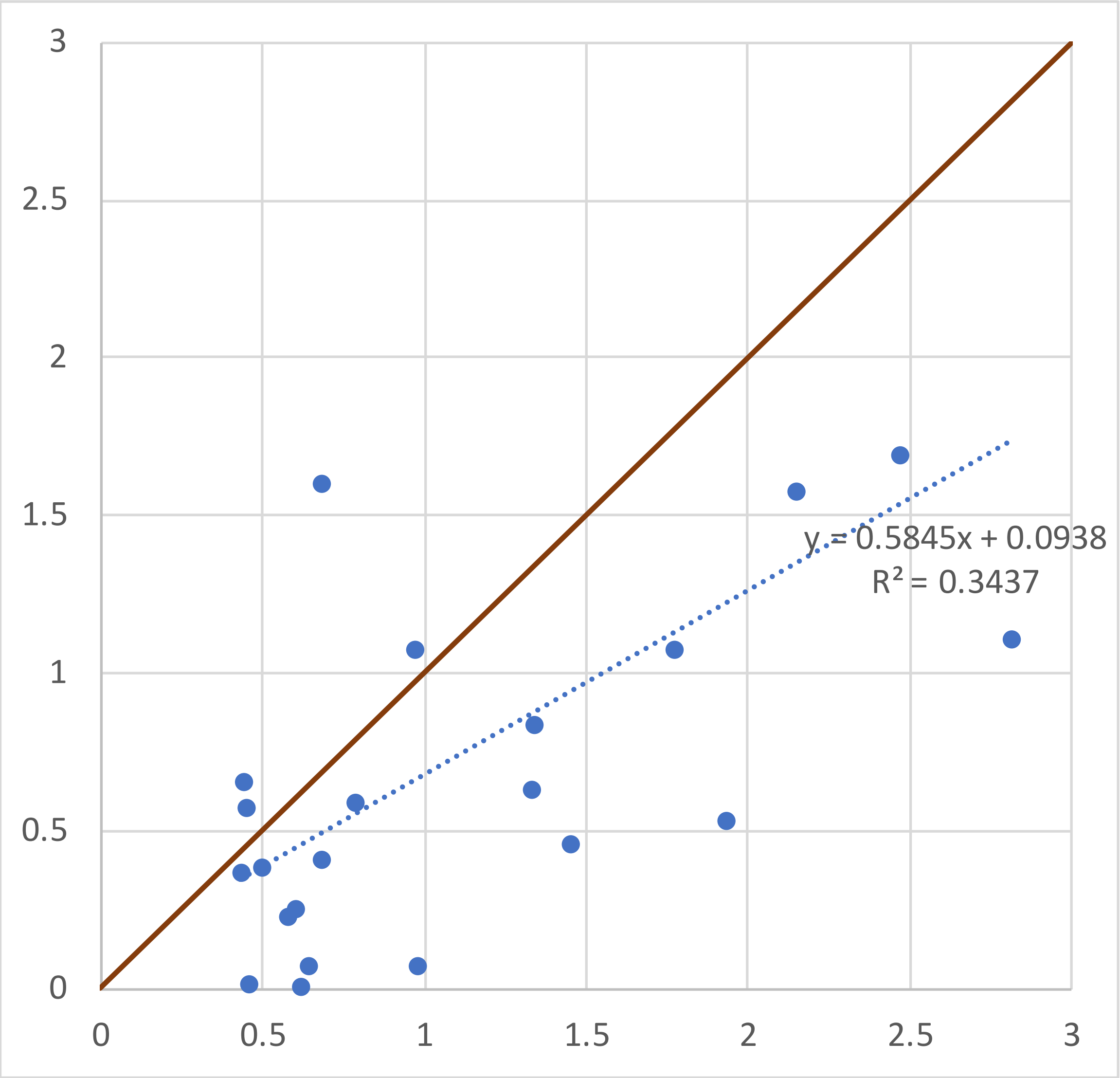
https://www.alexejgossmann.com/ccc/



Property	Value
Mean of x	9
Sample variance of x	11
Mean of y	7.50
Sample variance of y	4.125
Correlation between x and y	0.816
Linear regression line	y = 3.0 + 0.5x
Coefficient of determination R^2	0.667
Lin's concordance correlation coefficient between x and y	0.633

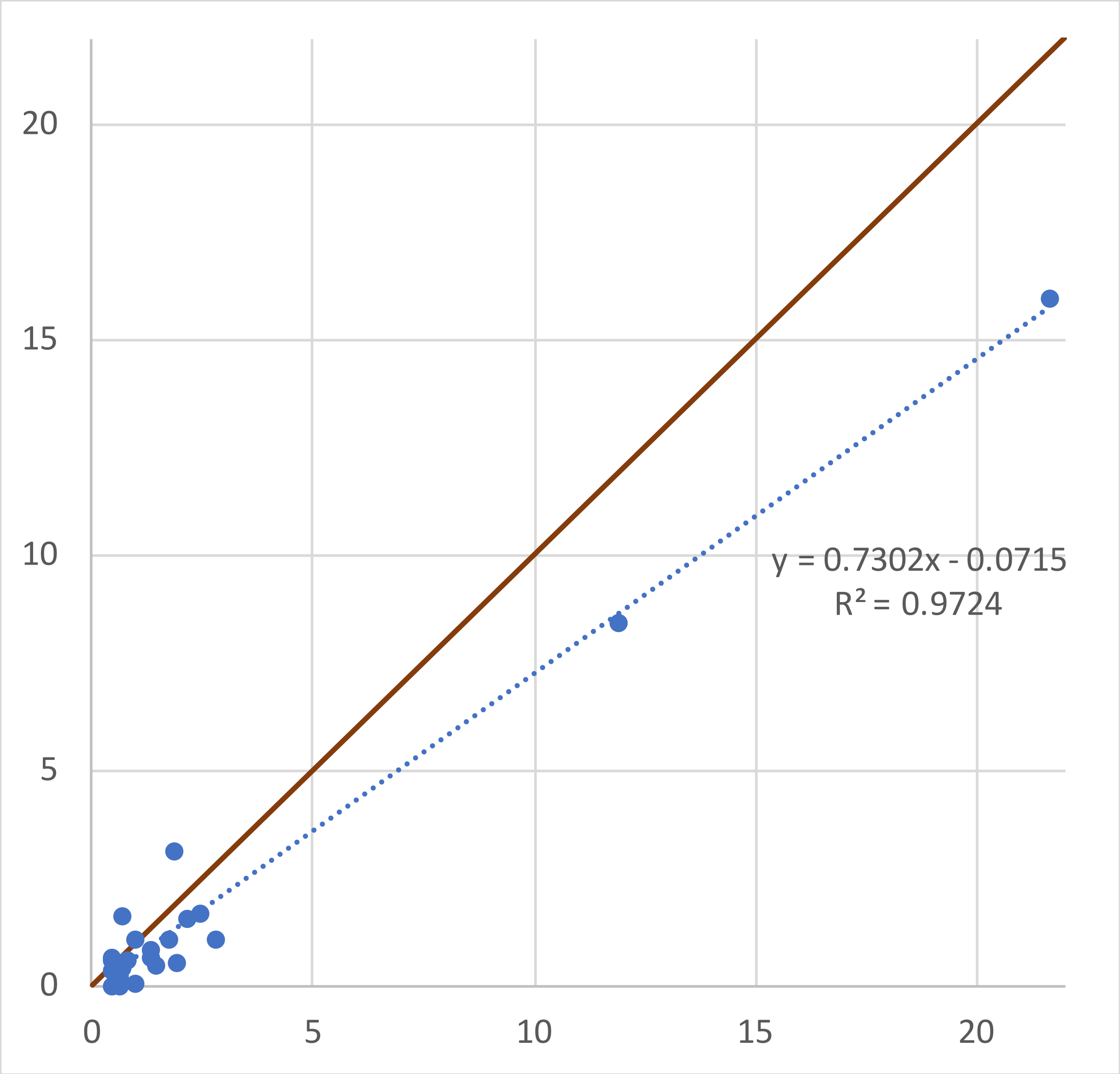
https://en.wikipedia.org/wiki/Anscombe%27s_quartet

HOW TO LIE WITH R^2



Std. dev = 0.72
RMSE = 0.74
RPD = 0.97
CCC = 0.41
N=23

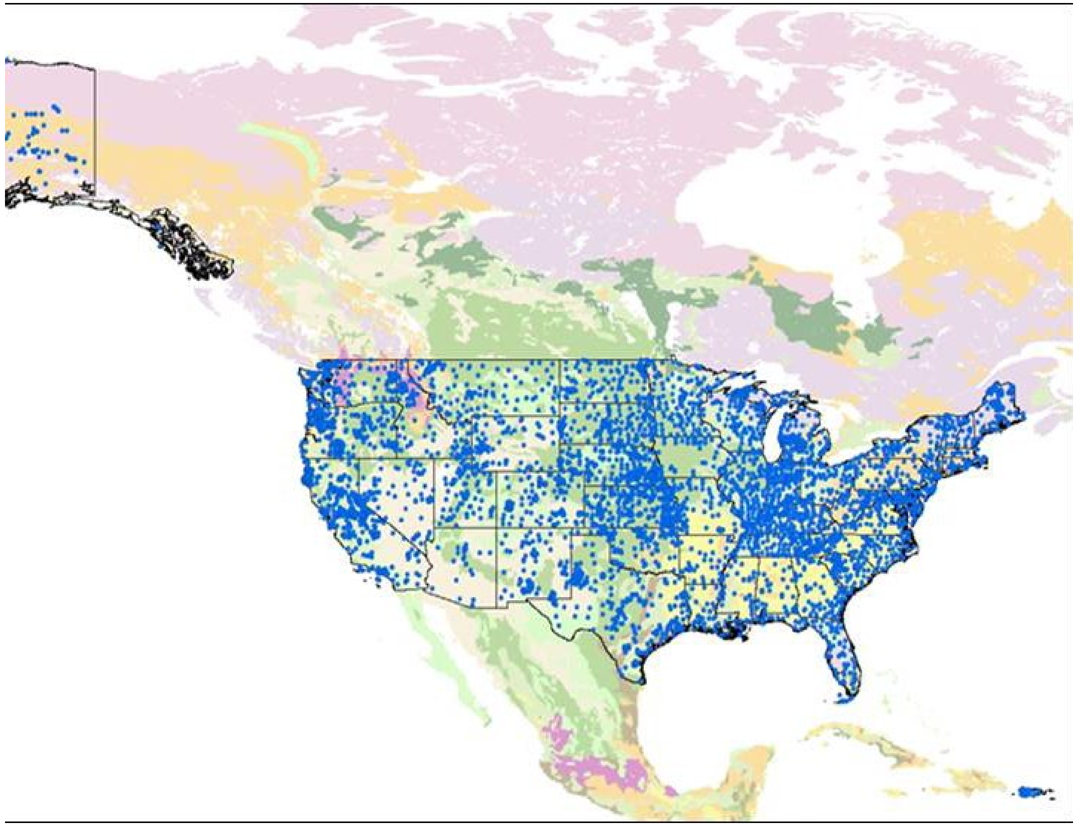
HOW TO LIE WITH RPD & R^2



Std. dev = 4.55
RMSE = 1.60
RPD = 2.83
CCC = 0.89
N=25

MIR FOR ACCURATE SOIL MEASUREMENTS

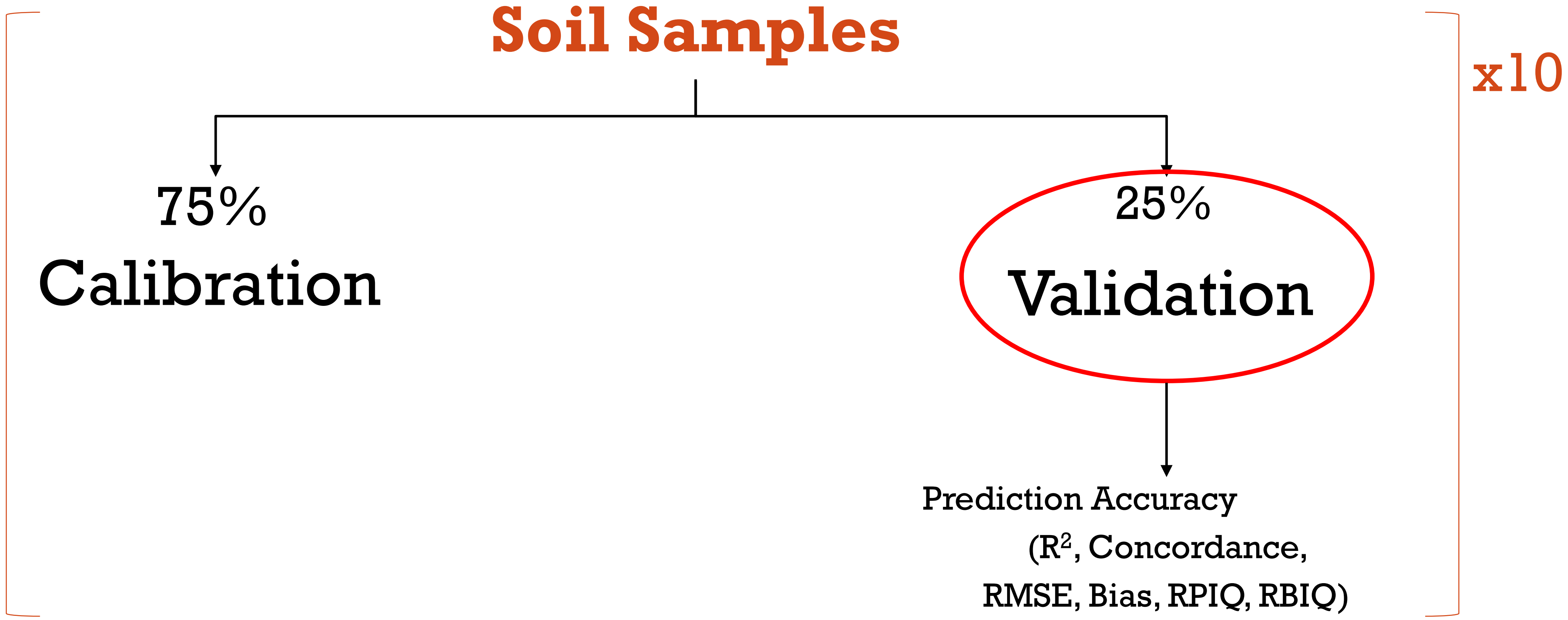
USDA-KSSL DATABASE



- Kellogg Soil Survey Laboratory (KSSL) database.
- Contained measurements of>17,000 pedons from the USA with well-documented and precise standard operating procedures.
- MIR & Soil analysis

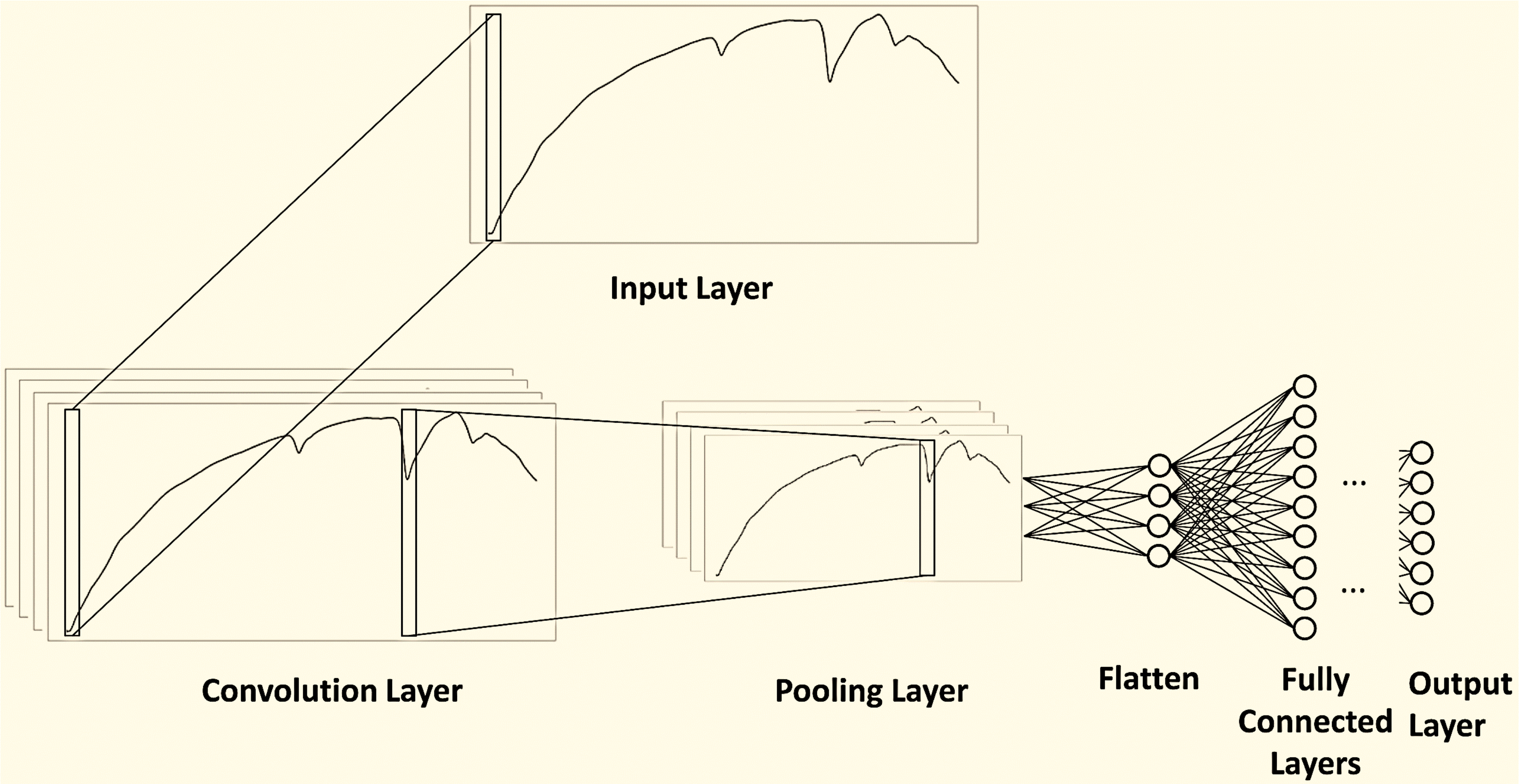
MODEL CALIBRATION

- Memory Based Learning (Local) PLS Regression Method



Ng, W., Minasny, B., Montazerolghaem, M., Padarian, J., Ferguson, R., Bailey, S. and McBratney, A.B., 2019. Convolutional neural network for simultaneous prediction of several soil properties using visible/near-infrared, mid-infrared, and their combined spectra. *Geoderma*, *352*, pp.251-267.

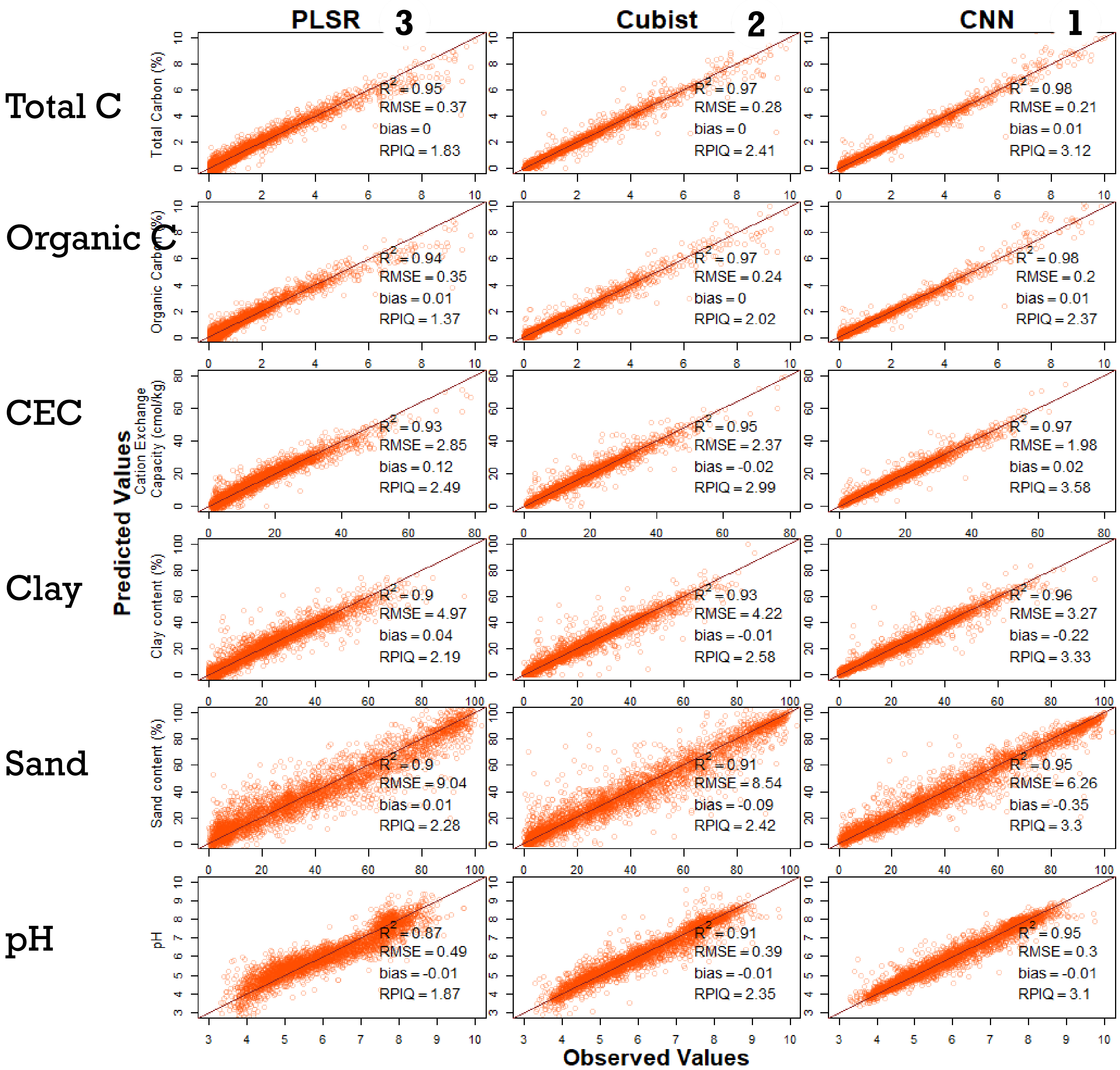
DEEP LEARNING: CNN



CNN on MIR

On Average:
37% more accurate than PLSR

22% more accurate than Cubist



Ng, W., Minasny, B., Montazerolghaem, M., Padarian, J., Ferguson, R., Bailey, S. and McBratney, A.B., 2019. Convolutional neural network for simultaneous prediction of several soil properties using visible/near-infrared, mid-infrared, and their combined spectra. *Geoderma*, *352*, pp.251-267.

WHAT OTHER SOIL PROPERTIES THAT CAN BE WELL PREDICTED?

- ~ 200 soil physical, chemical & biological properties
- WE ONLY MODEL MINERAL SOILS!

ACCURACY ASSESSMENT

Accuracy	R^2	Concordance	RPIQ	St. Bias
A	0.901 (0.82-0.99)	0.946	2.353 (0.82-1.85)	0.001
B	0.847 (0.76-0.86)	0.915	1.263 (0.54-1.71)	0.001
C	0.665 (0.58-0.74)	0.800	0.821 (0.20-1.34)	0.007
D	0.486 (0.10-0.60)	0.659	0.490 (0.02-1.10)	0.029

Multiple criteria:

R^2 = variance explained
Concordance: agreement at 1:1 line
RPIQ = Interquartile range/RMSE

St. Bias = Bias/Interquartile range

SOIL CHEMICAL PROPERTIES

Proposition

- Properties related to soil mineral components and surface chemistry can be well predicted (infrared-responsive chromophores)
- Properties related to soil solution (extraction) chemistry cannot be well predicted
- Elements in high concentration and related to soil minerals can be well predicted

Geoderma 153 (2009) 155–162

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Geoderma

journal homepage: www.elsevier.com/locate/geoderma

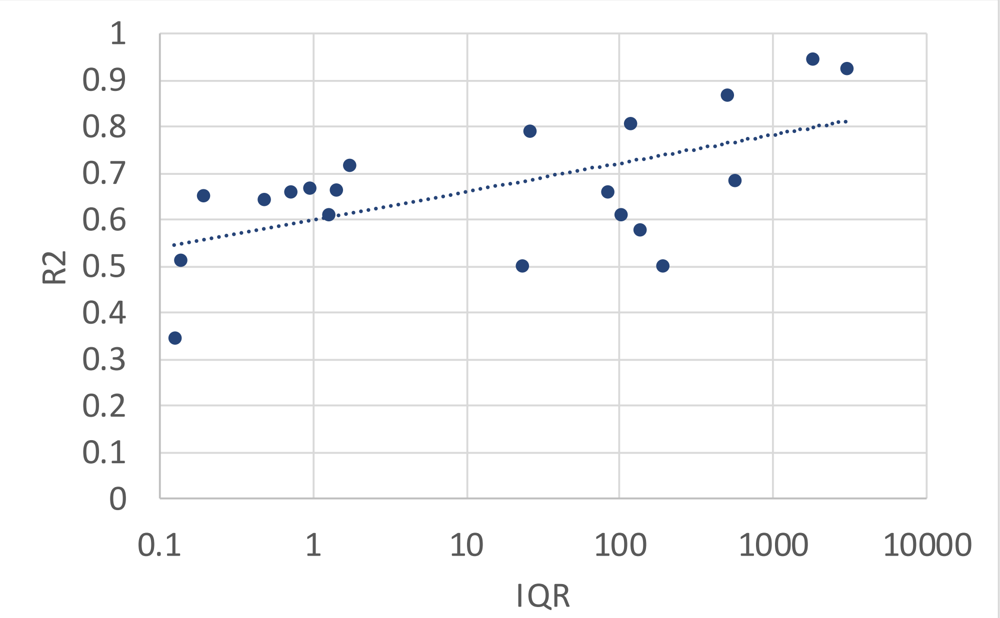
ELSEVIER

Regional transferability of mid-infrared diffuse reflectance spectroscopic prediction for soil chemical properties

Budiman Minasny [a,*], Grant Tranter [a], Alex. B. McBratney [a], Daniel M. Brough [b], Brian W. Murphy [c]

MEHLICH EXTRACTION

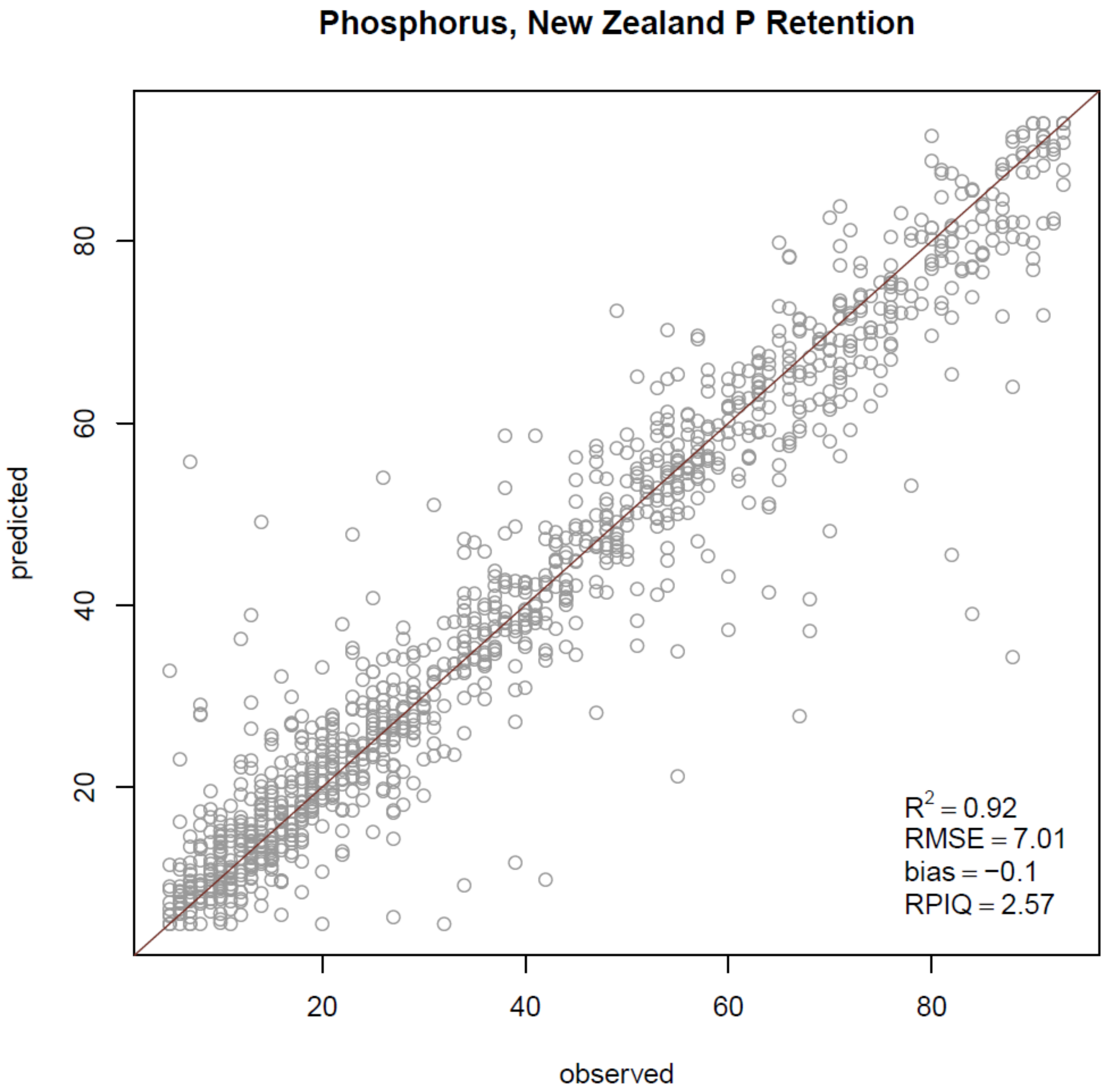
Properties	units	Accuracy	R2	RMSE
Calcium, Element Mehlich3 Extractable	mg/kg	B	0.928	1056.672
Aluminum, Element Mehlich3 Extractable	mg/kg	A	0.948	157.099
Magnesium, Element Mehlich3 Extractable	mg/kg	B	0.869	149.077
Barium, Element Mehlich3 Extractable	mg/kg	B	0.810	26.118
Silicon, Element Mehlich3 Extractable	mg/kg	C	0.688	122.599
Potassium, Element Mehlich3 Extractable	mg/kg	D	0.502	65.888
Iron, Element Mehlich3 Extractable	mg/kg	C	0.582	42.124
Sodium, Element Mehlich3 Extractable	mg/kg	C	0.614	102.009
Manganese, Element Mehlich3 Extractable	mg/kg	C	0.663	32.772
Strontium, Element Mehlich3 Extractable	mg/kg	C	0.793	9.918
Phosphorus, Element Mehlich3 Extractable	mg/kg	D	0.502	13.779
Copper, Element Mehlich3 Extractable	mg/kg	C	0.718	0.858
Zinc, Element Mehlich3 Extractable	mg/kg	C	0.665	0.697
Arsenic, Element Mehlich3 Extractable	mg/kg	C	0.611	0.790
Lead, Element Mehlich3 Extractable	mg/kg	C	0.671	0.432
Cobalt, Element Mehlich3 Extractable	mg/kg	C	0.662	0.308
Nickel, Element Mehlich3 Extractable	mg/kg	C	0.647	0.290
Cadmium, Element Mehlich3 Extractable	mg/kg	C	0.654	0.061
Chromium, Element Mehlich3 Extractable	mg/kg	D	0.516	0.046
Molybdenum, Element Mehlich3 Extractable	mg/kg	D	0.346	0.045



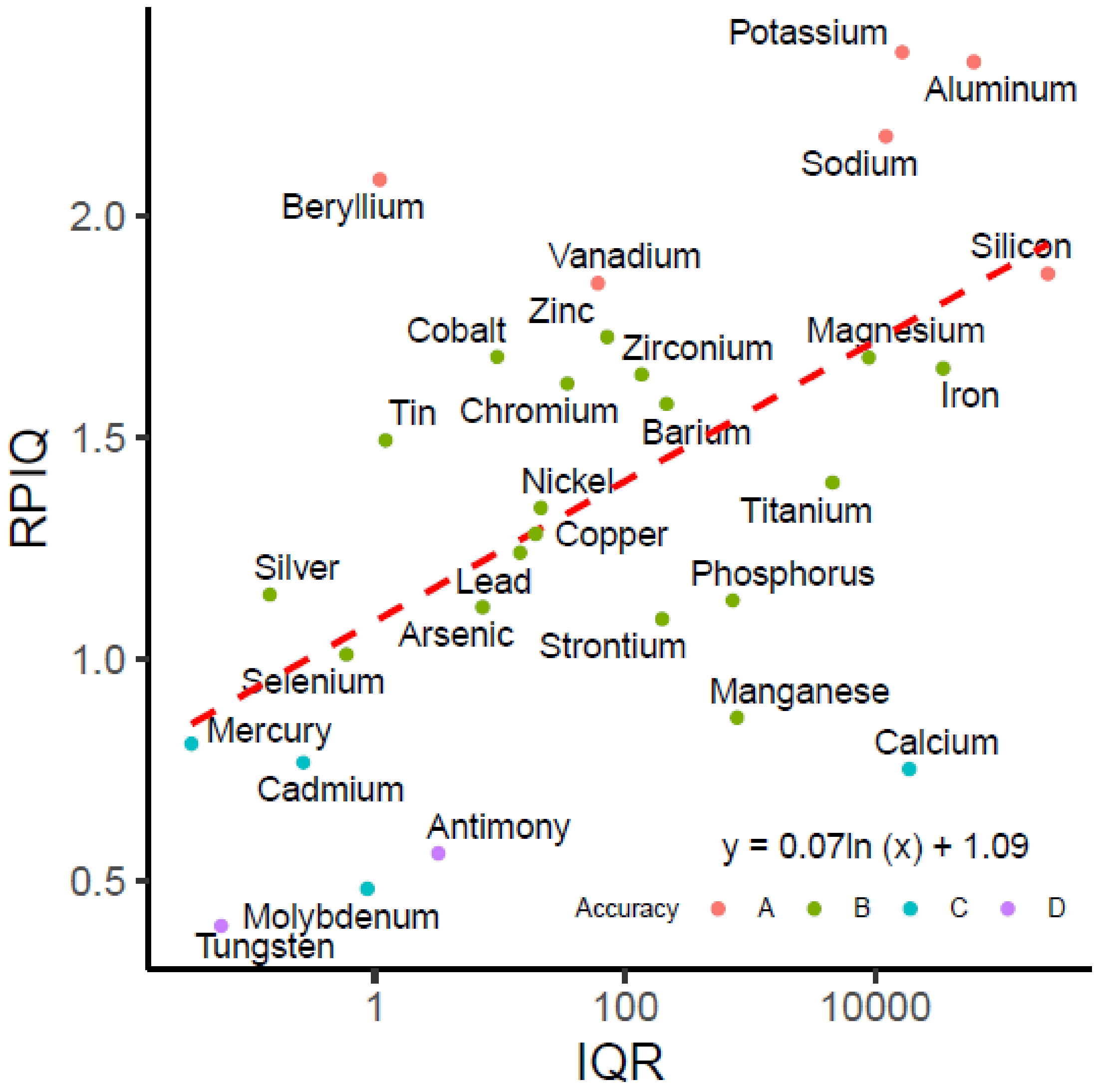
Interquartile range (ppm)

PHOSPHORUS

Properties	units	Accuracy	R2	RMSE
Phosphorus, P Retention	**%**	**A**	**0.928**	**6.750**
Phosphorus, Water Soluble	mg/kg	D	0.387	0.130
Phosphorus, Bray-1 Extractable	mg/kg	C	0.590	12.902
Phosphorus, Olsen Extractable	mg/kg	D	0.562	7.499
Phosphorus, Mehlich3 Extractable	mg/kg	D	0.524	12.842



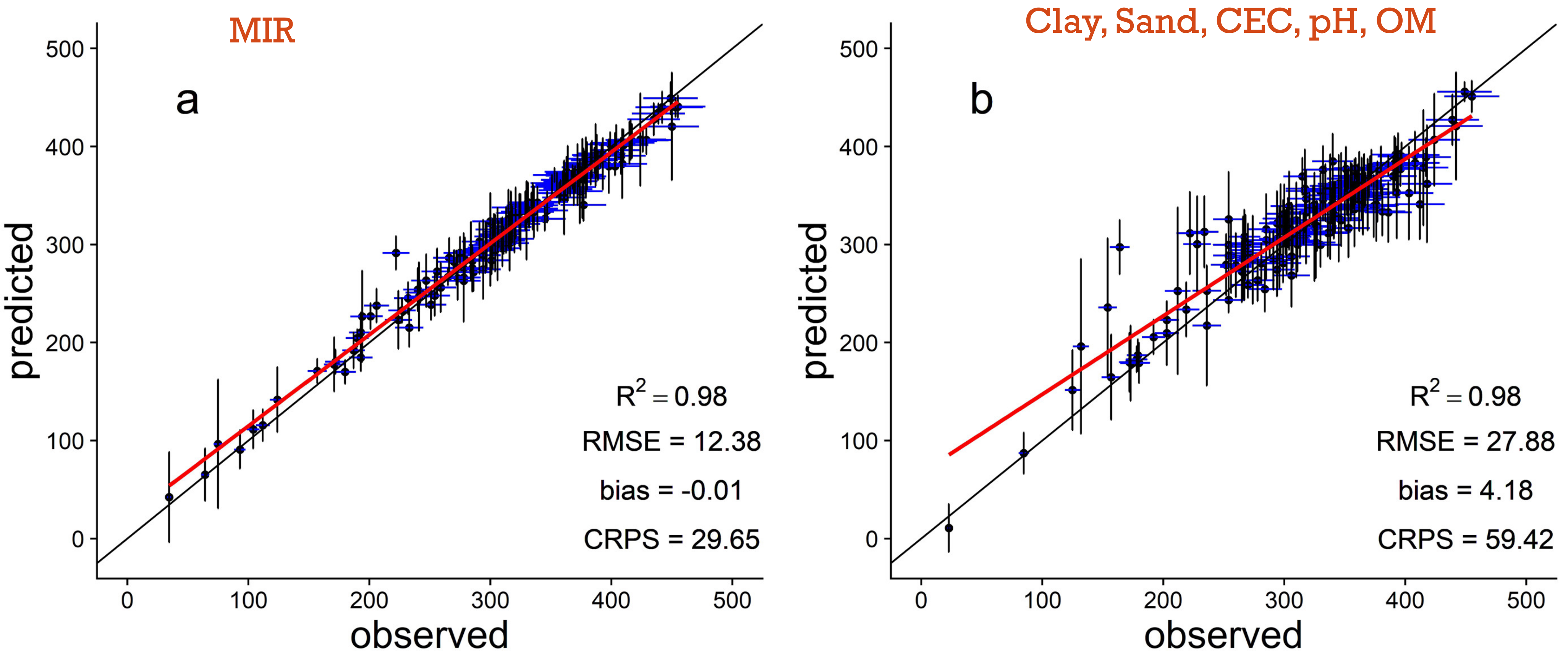
ELEMENTAL CONCENTRATION



Properties	units	Accuracy	R2	RMSE
Silicon, Major Element	mg/kg	A	0.881	20295.514
Aluminum, Major Element	mg/kg	A	0.898	5960.448
Potassium, Major Element	mg/kg	A	0.864	2030.995
Sodium, Major Element	mg/kg	A	0.887	1701.090
Vanadium, Trace Element	mg/kg	A	0.876	9.374
Beryllium, Trace Element	mg/kg	A	0.875	0.166
Iron, Major Element	mg/kg	B	0.918	5014.026
Calcium, Major Element	mg/kg	B	0.980	4080.728
Magnesium, Major Element	mg/kg	B	0.880	1718.701
Titanium, Major Element	mg/kg	B	0.871	811.615
Phosphorus, Major Element	mg/kg	B	0.793	167.815
Barium, Trace Element	mg/kg	B	0.784	42.430
Strontium, Major Element	mg/kg	B	0.823	47.362
Zirconium, Major Element	mg/kg	B	0.811	23.189
Zinc, Trace Element	mg/kg	B	0.815	13.753
Strontium, Trace Element	mg/kg	B	0.831	16.493
Chromium, Trace Element	mg/kg	B	0.840	6.625
Nickel, Trace Element	mg/kg	B	0.795	5.236
Copper, Trace Element	mg/kg	B	0.802	4.819
Lead, Trace Element	mg/kg	B	0.760	3.565
Cobalt, Trace Element	mg/kg	B	0.829	1.955
Tin, Trace Element	mg/kg	B	0.792	0.238
Manganese, Major Element	mg/kg	C	0.654	233.732
Selenium, Trace Element	ug/kg	C	0.682	176.124
Manganese, Trace Element	mg/kg	C	0.658	173.976
Mercury, Trace Element	ug/kg	C	0.692	16.416
Arsenic, Trace Element	mg/kg	C	0.713	1.953
Molybdenum, Trace Element	mg/kg	C	0.609	0.434
Cadmium, Trace Element	mg/kg	C	0.647	0.093
Silver, Trace Element	mg/kg	C	0.708	0.039
Antimony, Trace Element	mg/kg	D	0.458	0.148
Tungsten, Trace Element	mg/kg	D	0.442	0.029

GEOCHEMICAL CONCENTRATION

- **Total Silica**



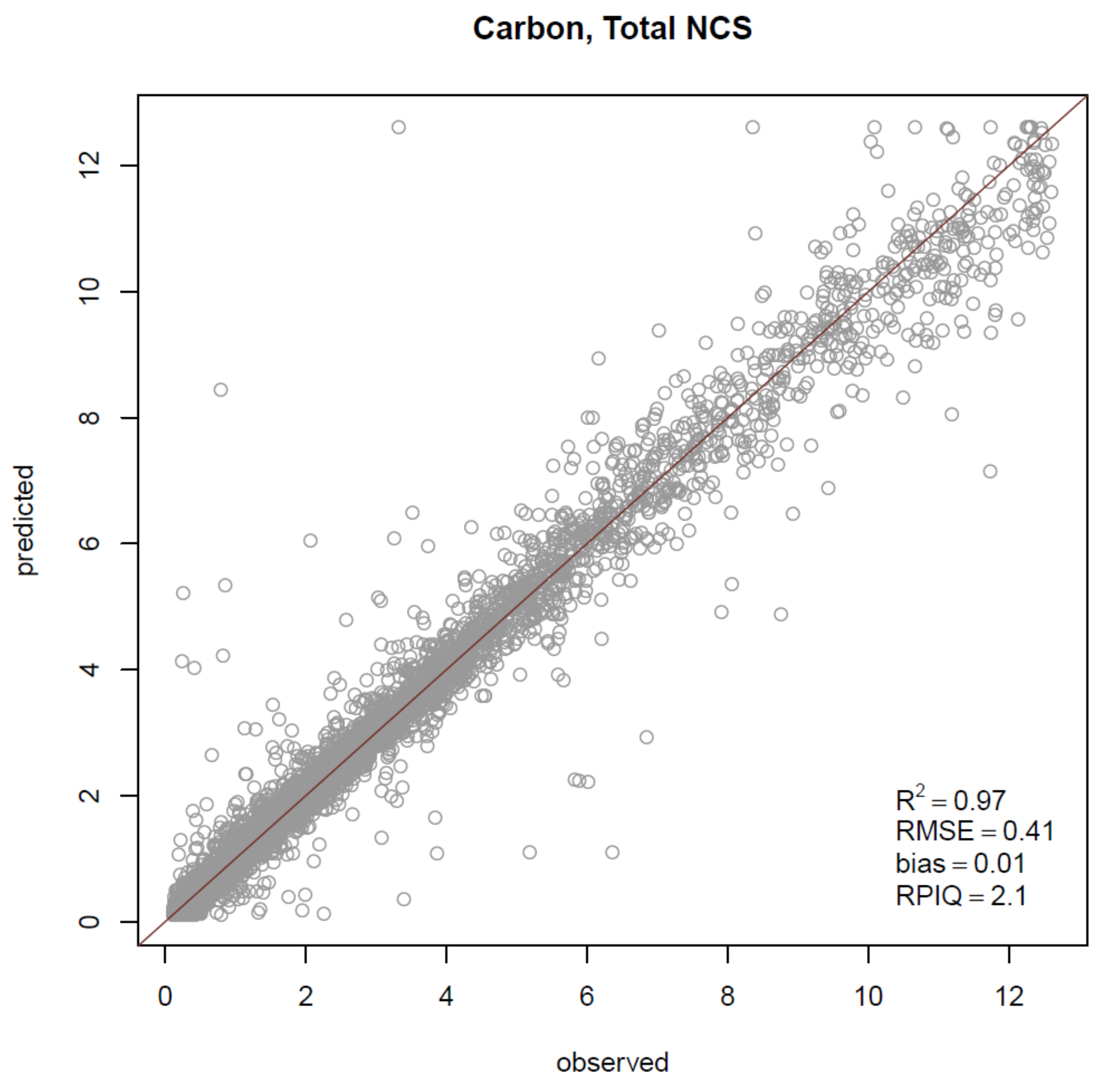
Landré, A., Saby, N.P.A., Barthès, B.G., Ratié, C., Guerin, A., Etayo, A., Minasny, B., Bardy, M., Meunier, J.D. and Cornu, S., 2018. Prediction of total silicon concentrations in French soils using pedotransfer functions from mid-infrared spectrum and pedological attributes. *Geoderma*, *331*, pp.70-80.

SATURATION EXTRACT

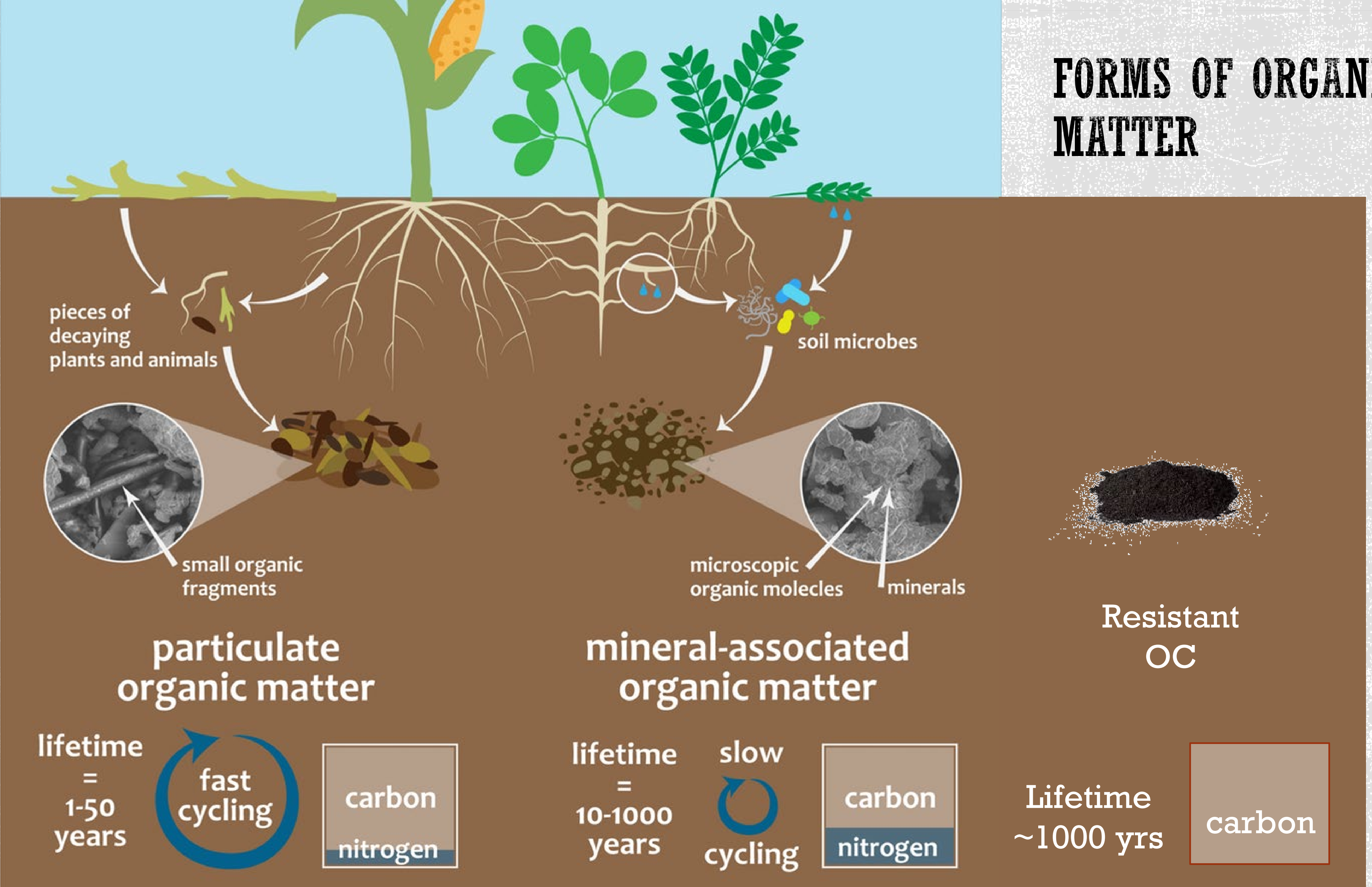
Properties	units	Accuracy	R2	RMSE
Electrical Conductivity, Saturation Extract	dS/m	C	0.685	2.065
Electrical Conductivity, Predict, 1:2 (w/w)	dS/m	D	0.783	0.887
Acetate, Saturation Extract	mmol(-)/L	D	0.290	0.151
Bicarbonate, Saturation Extract	mmol(-)/L	C	0.628	1.003
Bromide, Saturation Extract	mmol(-)/L	D	0.079	0.026
Calcium, Saturation Extract	mmol(+)/L	C	0.645	5.602
Chloride, Saturation Extract	mmol(-)/L	D	0.675	13.132
Fluoride, Saturation Extract	mmol(-)/L	D	0.195	0.085
Magnesium, Saturation Extract	mmol(+)/L	C	0.668	8.818
Nitrate, Saturation Extract	mmol(-)/L	D	0.392	2.168
Nitrite, Saturation Extract	mmol(-)/L	D	0.286	0.458
Ammonium, Saturation Extract	mmol(+)/L	D	0.364	0.405
Potassium, Saturation Extract	mmol(+)/L	D	0.408	0.454
Sodium, Saturation Extract	mmol(+)/L	D	0.703	17.386
Sulfate, Saturation Extract	mmol(-)/L	C	0.653	18.416

SOIL ORGANIC MATTER

Properties	units	Accuracy	R^2	RMSE
Carbon, Total	% wt	A	0.97	0.42
Organic C	% wt	A	0.93	0.65
C, $KMnO_4$ extract	mg kg^{-1}	A	0.92	84.47
Nitrogen, Total	% wt	B	0.90	0.08
Sulfur, Total	% wt	D	0.64	0.10
Carbon, hpom	% wt	B	0.90	0.18
Nitrogen, hpom	% wt	C	0.71	0.03
Sulfur, hpom	% wt	C	0.72	<0.01
ß-Glucosidase	mg kg^{-1} hr^{-1}	B	0.81	32.78

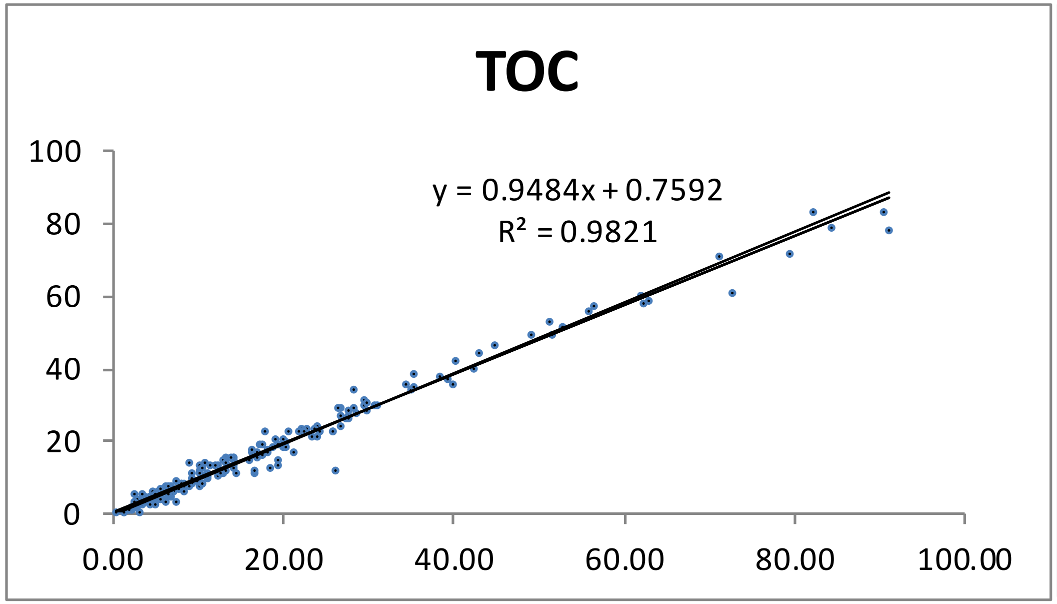


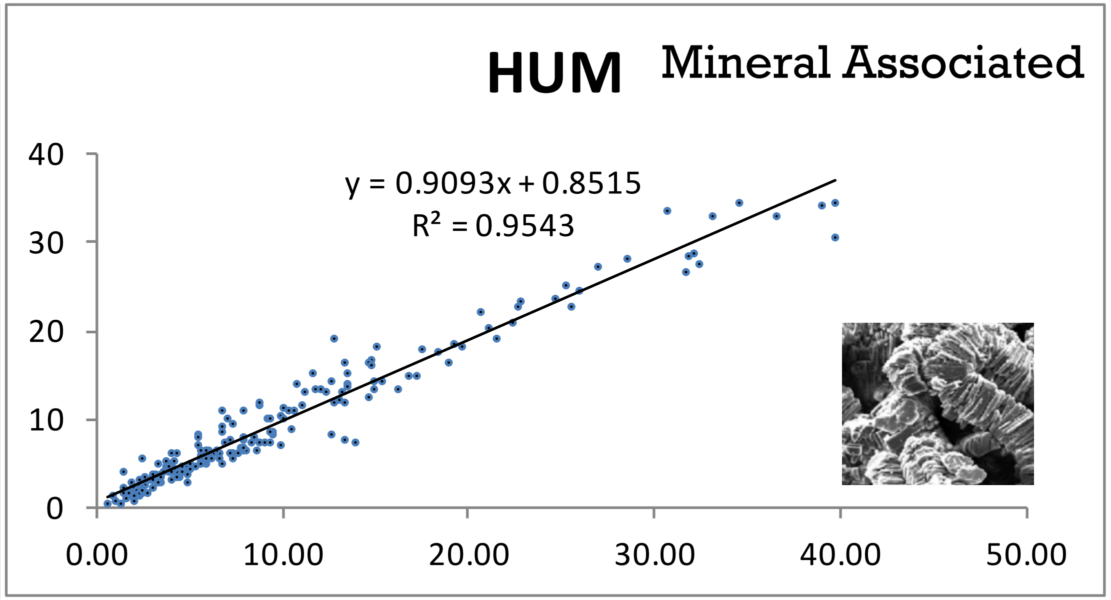
FORMS OF ORGANIC MATTER

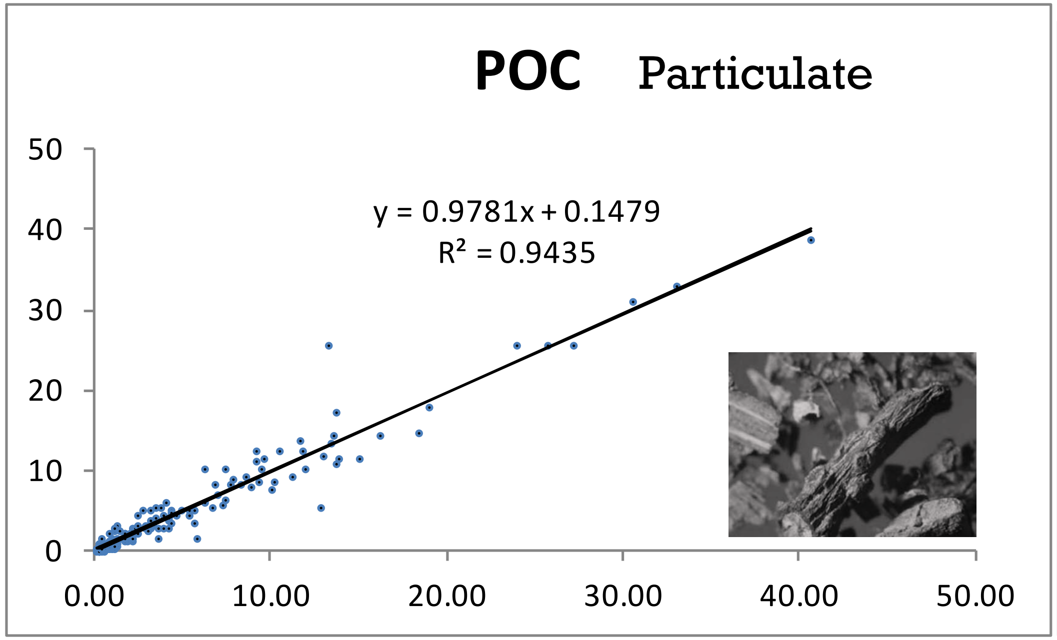


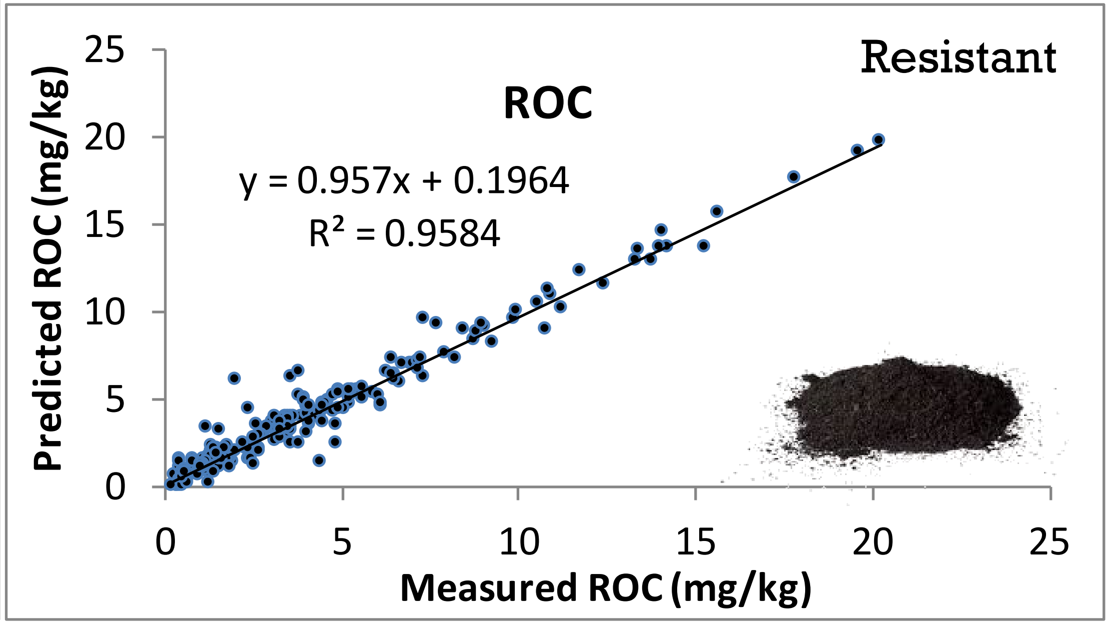
https://www.nrel.colostate.edu/investigator/francesca-cotrufo-homepage/francesca-cotrufo-research/

Soil Carbon fractions (Australian Sites)









SOIL PHYSICAL PROPERTIES

Proposition

- Properties based on the soil solid composition and surfaces can be predicted well predicted
- Properties based on pore-space relationships cannot be well predicted

European Journal of Soil Science, 2008

doi: 10.1111/j.1365-2389.2008.01058.x

Using soil knowledge for the evaluation of mid-infrared diffuse reflectance spectroscopy for predicting soil physical and mechanical properties

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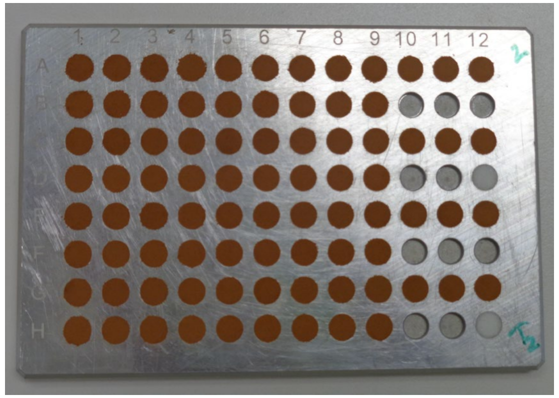
[b]*Department of Environment and Climate Change, Cowra, New South Wales 2794, Australia*

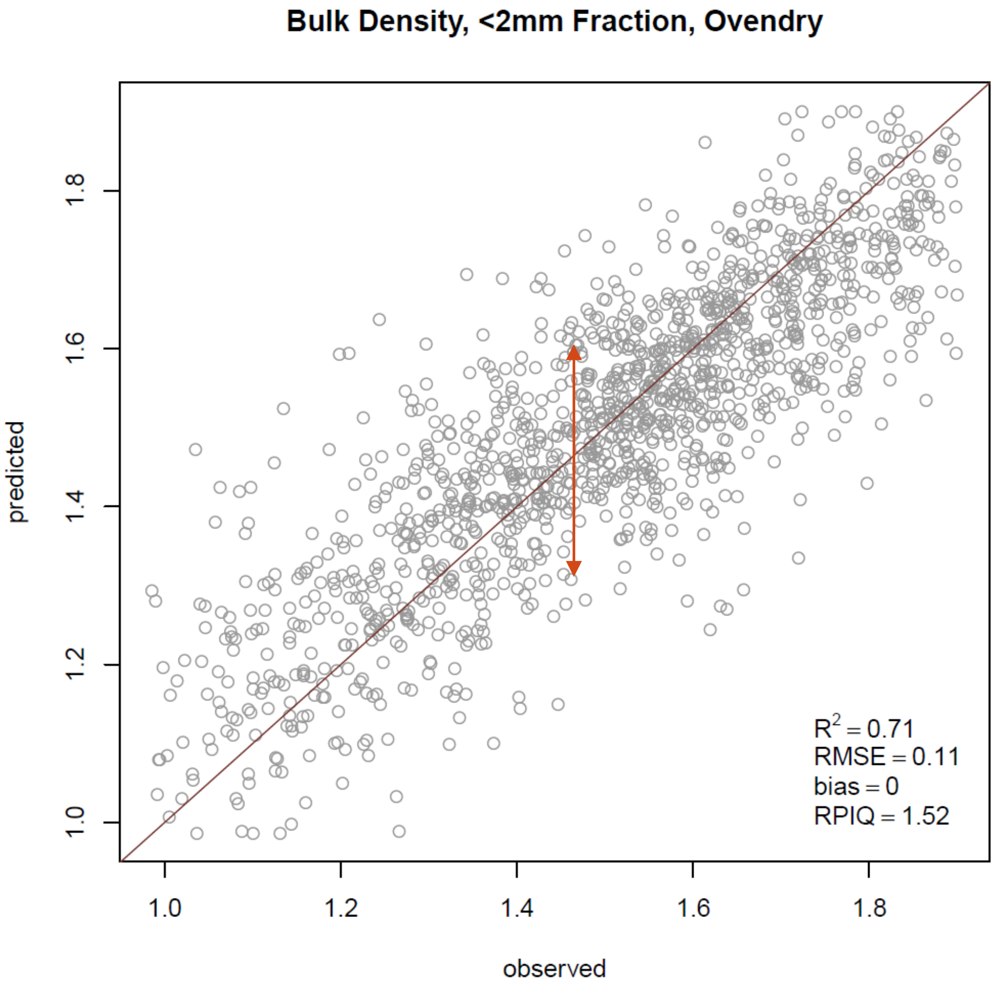
AGGREGATE & BULK DENSITY

Properties	units	Accuracy	R2	RMSE
Aggregate Stability, 0.5-2mm Aggregates	% wt	C	0.656	18.331
Bulk Density, <2mm Fraction, 1/3 Bar	g/cc	C	0.683	0.106
Bulk Density, <2mm Fraction, Ovendry	g/cc	C	0.694	0.114
Bulk Density, Core, <2 mm fraction, Field Moist	g/cc	C	0.616	0.212

Field

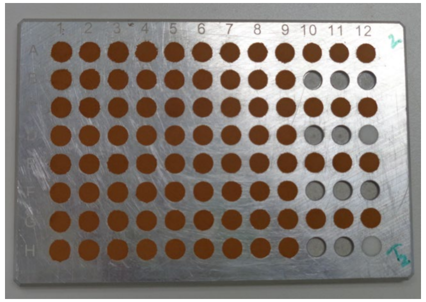


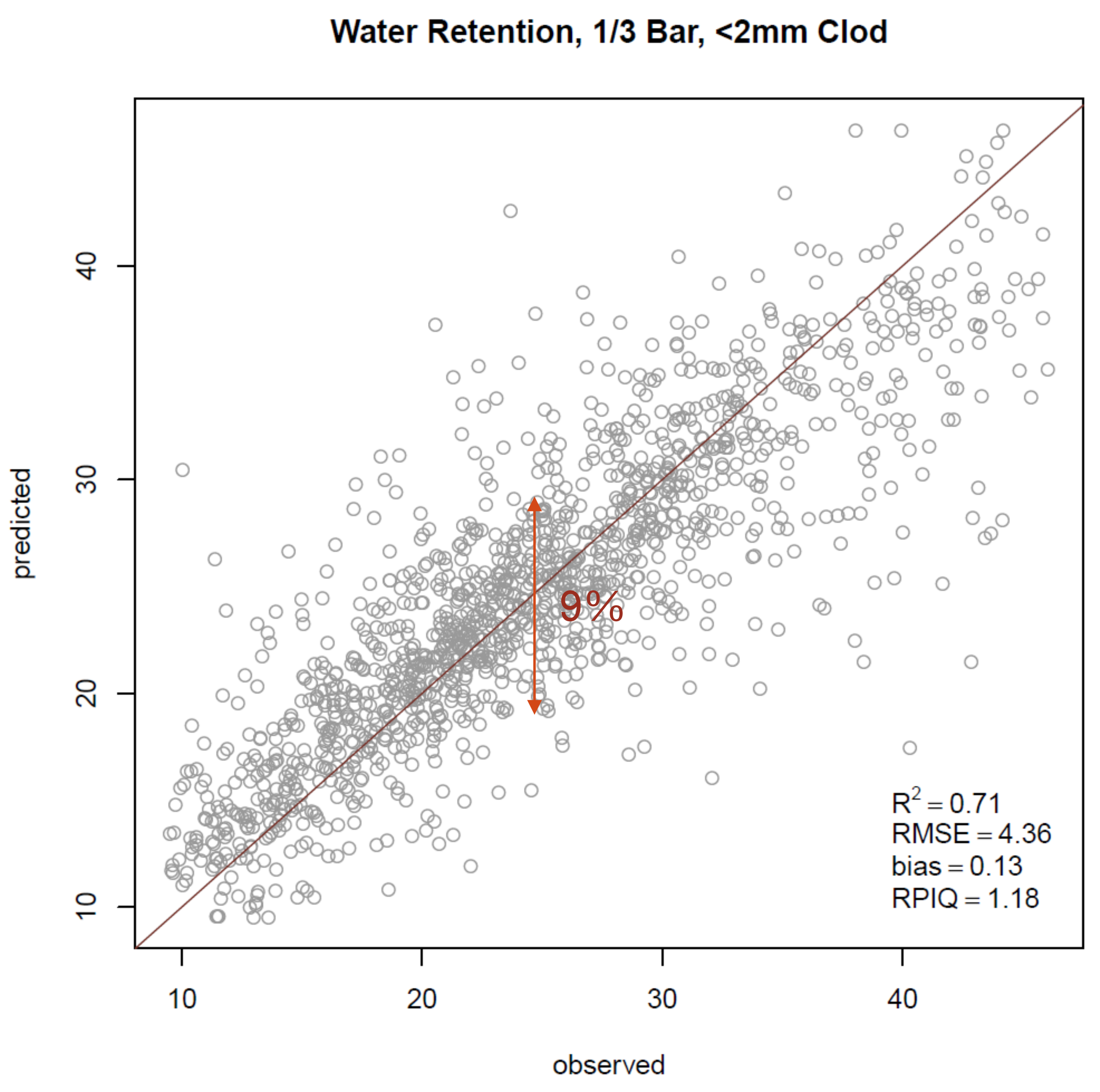
MIR Lab analysis

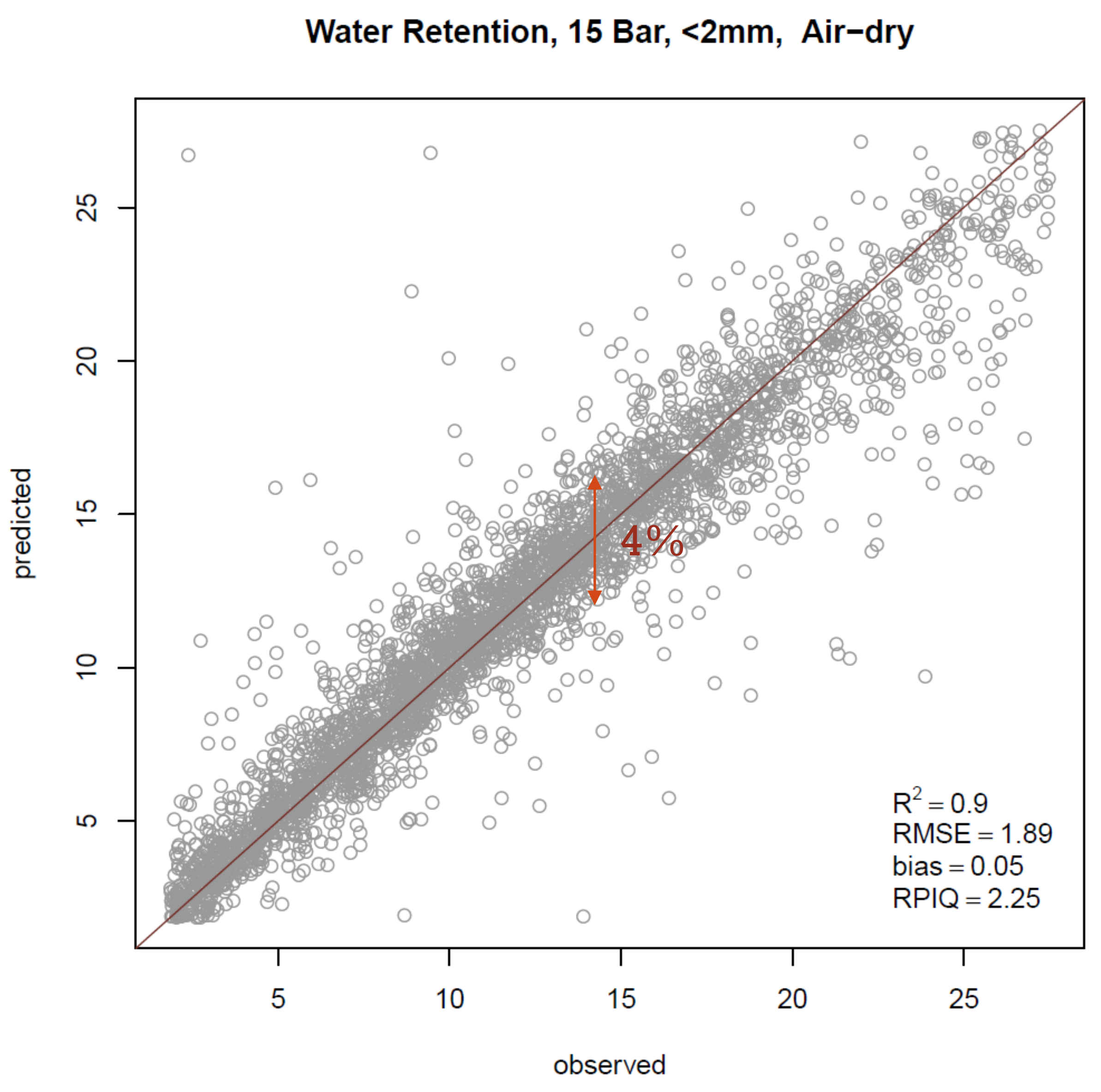


WATER RETENTION

Properties	units	Accuracy	R2	RMSE
Water Retention, 0.06 Bar, <2mm **Clod**	% wt	C	0.587	4.594
Water Retention, 1/10 Bar, <2mm Clod	% wt	C	0.694	6.287
Water Retention, 1/3 Bar, <2mm Clod	% wt	C	0.715	4.287
Water Retention, 0.06 Bar, <2mm **Sieve**	% wt	A	0.808	4.971
Water Retention, 1/10 Bar, <2mm Sieve, Air-dry	% wt	A	0.836	4.489
Water Retention, 1/3 Bar, <2mm Sieve	% wt	A	0.892	3.205
Water Retention, 1 Bar, <2mm Sieve, Air-dry	% wt	A	0.912	2.408
Water Retention, 2 Bar, <2mm Sieve, Air-dry	% wt	A	0.905	2.278
Water Retention, 5 Bar, <2mm Sieve, Air-dry	% wt	A	0.864	2.585
Water Retention, 15 Bar, <2mm, Air-dry	% wt	A	0.907	1.854
Volumetric water content at 1/3 Bar	% vol	C	0.653	4.327
Volumetric water content at 15 Bar	% vol	B	0.851	3.493
Field Water Content, <2mm	% wt	B	0.755	4.569
Field Water Content, Core	% wt	C	0.681	25.177




Water Retention, 1/3 Bar, <2mm Clod
predicted
observed
10
20
30
40
9%
$R^2 = 0.71$
RMSE = 4.36
bias = 0.13
RPIQ = 1.18


Water Retention, 15 Bar, <2mm, Air−dry
predicted
observed
5
10
15
20
25
4%
$R^2 = 0.9$
RMSE = 1.89
bias = 0.05
RPIQ = 2.25

SOIL QUALITY INDICATORS

Biological	Chemical	Physical
Microbial Biomass	pH	Rooting Depth
Mycorrhiza populations	CEC	Stoniness
Particulate Organic Matter	Heavy Metals	Texture
Respiration	EC	Aggregate Stability
Potential N mineralization	Organic C & N	Slaking Index
Fatty Acid profiles	Extractable macronutrients	Water holding capacity
Soil enzymes	Total elements, Micronutrients	Bulk Density
	$CaCO_3$	Infiltration
	P retention	Penetration resistance

Poorly estimated, reasonably estimated, Well Estimated

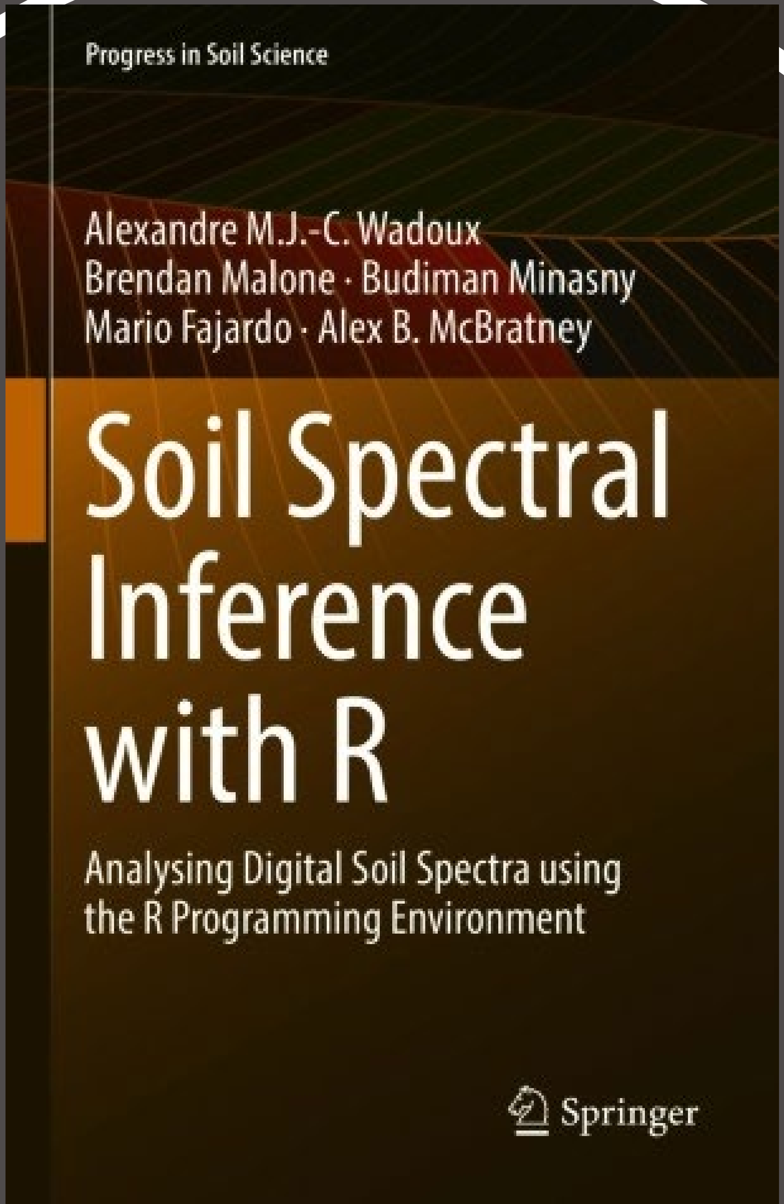
Quantitative Evaluation of Soil Functions: Potential and State

	inherent soil & site conditions										affected by soil management							
	hydrol		site			soil					physics				chem.		biol.	
SOIL & SITE ATTRIBUTES	water balance (vegetation period)	depth to groundwater	temperature	slope aspect	slope gradient	soil depth (rootable)	texture	mineralogy	$CaCO_3$	coarse fragments	bulk density	air capacity	plant available water	hydraulic conductivity	SOC	pH	earthworm abundance	species diversity
SOIL FUNCTIONS																		
Production (fertility)																		
Nutrient cycling – mobilization & buffering																		
Carbon storage															X			
Water storage & filtering											X							
Habitat for biological activity																		X

https://www.frontiersin.org/articles/10.3389/fenvs.2019.00164/full

SUMMARY

- MIR offers a rapid and highly accurate measurement of many soil physical and chemical properties
- Properties related to soil mineral components and surface chemistry can be well predicted (infrared-responsive chromophores)
- Properties related to soil solution (extraction) chemistry cannot be well predicted.
- Properties based on soil solid composition and surfaces can be predicted well predicted.
- Properties based on pore-space relationships cannot be well predicted. However MIR can be used as a better alternative to PTFs



JUST PUBLISHED

- Soil Spectral Inference with R
- Springer (2020)

Training course hosted by FAO! coming soon!

ACKNOWLEDGEMENT

Indonesian Center for Agricultural Land Resources Research and Development(ICALRD)

United States Department of Agriculture

Natural Resources Conservation Service

Soil and Plant Science Division

National Soil Survey Center

Kellogg Soil Survey Laboratory


THANKS FOR YOUR
ATTENTION