### BGSTECH Lunch Seminar-V

## Nandkishor Dhawale,

PhD. Candidate and PASS research team member Department of Bioresource Engineering

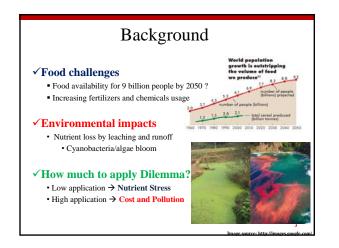
> Research Advisors Dr. Viacheslav I. Adamchuk Dr. Shiv O. Prasher

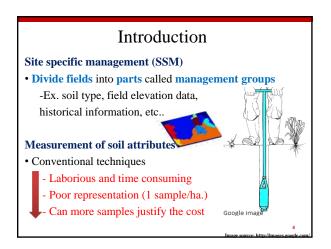
> > 11/05/2014

#### Topics of the talk

- 1. Background and Introduction
- Proximal Soil Sensing

   On-the Go Soil Sensing
   On-the-Spot Soil Sensing
- 3. Research Objectives
- 4. Highlighting Results on
  - i. Combining Soil Sensor Information
  - ii. Automated On-the-Spot Analyser
  - iii. Sensing with Soil Spectroscopy



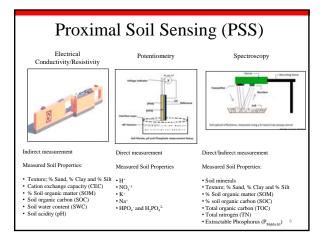


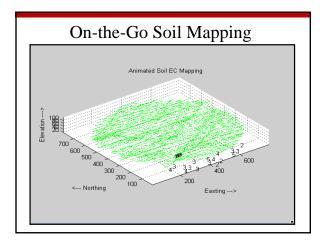
#### Proximal Soil Sensing (PSS)

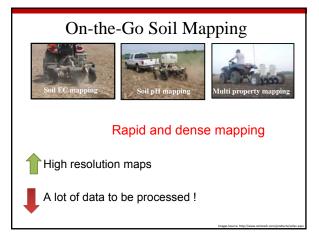
The term *PSS* is used when field-based sensors are used to obtain signals from the soil, placing the sensor's detector in contact with or close to (within 2 m) of the soil. (Viscarra Rossel and McBratney, 1998; Viscarra Rossel *et al.*, 2010).



With advancements in Global Navigation Satellite Systems (GNSS) such as the Global Positioning System (GPS), soil information can be collected at resolutions <1-2 cm horizontally and about a twice of it vertically.





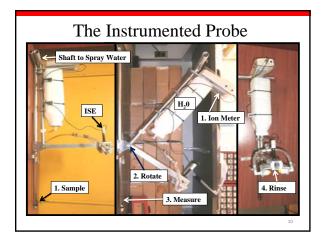


#### Disadvantages

• Soil distortion is created along the entire path travelled.

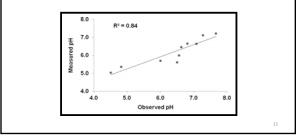
• Response time of the sensor can be a limiting factor on the time allowed for each measurement.

• What if field surface coverage does not allow for the continuous engagement between soil and parts of the sensor system.



#### Soil pH

Ten locations from seven plots, on the campus seed farm's research facility (McGill University, Macdonald Campus, Ste-Anne-de-Bellevue, QC, Canada) were chosen to conduct the field evaluation.



#### Soil NO<sub>3</sub>-Canola field divided into sixteen plots, which were treated with different levels of urea. Two months after planting, three random in-situ measurements were taken at a depth of 2-3 cm below soil surface. 3.9 heddetted, NO, mg L-1 2.5 ٠ 20 Variabili L5 â 1.0 ģ 1.8 1.5 2.8 2.5 3.6

eilNO<sub>2</sub> mg L<sup>4</sup>

159

100

58

Nhep

#### Disadvantages

• Need of operator.

• What if it is very crucial to collect soil samples or sensor based measurements without delays (on time) where data misinterpretation and financial losses are undesirable.

• Else if in harsh and hazardous environments, where health of human labour is at risk.

• What about exploring automation/robotic solutions?

13

# Mars Rovers List of well-known Mars Rovers 1. Sojourner, 1997-97 2. Spirit, 2003-10 3. Opportunity, 2004-12 4. Curiosity, 2011-present Soil Mapping System (None) Simpler than the Mars Rover. Affordable to a North American farmer. Robust to operate in uneven field surface conditions.



#### Challenges

Several challenges over choosing or developing a suitable.

• Platform of mobile vehicle, capable to operate in uneven field surface conditions.

- Platforms for soil sensor data acquisition.
- Strategies to collect multi soil information.
- Algorithm's to combine soil sensor information.
- Human safety and security.

All above keep the research plate burning hot in this discipline!

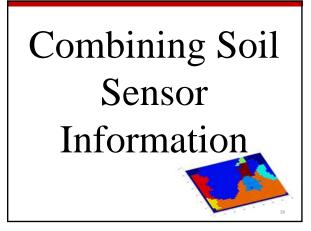
#### **Research Objectives**

The overall objective of this research is:

•To develop an Automated On-the Spot Analyser (OSA)

#### The specific objectives are:

1.To develop a methodology for the hierarchical clustering of high-density, multi-source, proximal-sensing soil data such as Field Elevation and Soil Electrical Conductivity. 2.To develop and evaluate a autonomous platform capable to determine  $H^+$  and  $NO_3^-$  ion activities on-the-spot. 3.Analysing the capabilities of advanced Vis/NIR/MIR spectroscopic instruments, for detecting differences in selected soil properties towards extending the suit of deployable sensors, on the platform.



#### **Present Choices**

Majority of known algorithms

≻Relate to Kmeans clustering.

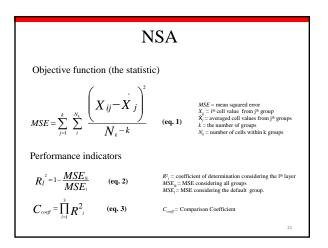
> Which calculates a distance matrix based on data and performs clustering over this new distance matrix and they doesn't consider the spatial distances.

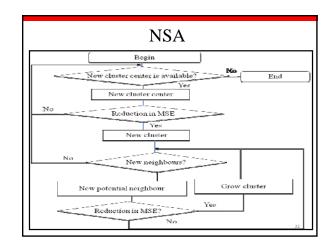
> The results depends on the selection of initial centroids and therefore not repeatable and requires cross validation.

> Complexity and frequently occurring discontinuities of certain management groups make this technology less appealing to potential users.

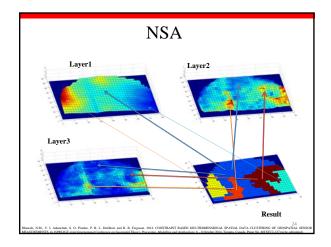
#### A New Algorithm Using Neighbourhood Search Analysis(NSA)

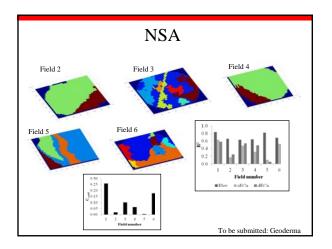
- 1. The default set of group is average of all data points and is called the default of the field.
- 2. Minimum new group size is defined considering a location with all eight immediate neighbours.
- 3. A new group can only initiate and grow if the new statistic is lower than the previous statistic, both, calculated over the old and new groups.

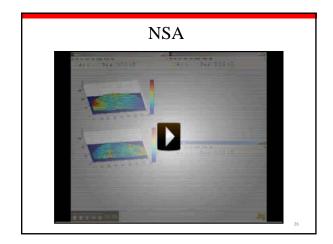




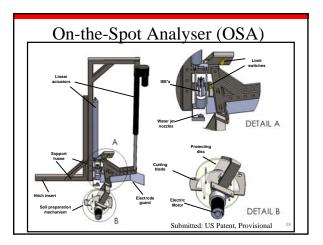
PROPERTIES	Field 1	Field 2				
LONGITUDE		Field 2	Field 3	Field 4	Field 5	Field 6
	-97.984	-98.255	-102.53	-97.572	-98.167	-98.356
LATITUDE	41.2747	40.8882	41.5547	42.1921	40.8427	42.4079
AREA, Ha	25.4	46.08	49.88	54.56	66.84	44.24
ield Elevation (El pparent Soil Elec om both layers sh eep (dECa) *	trical C		-	AG		y

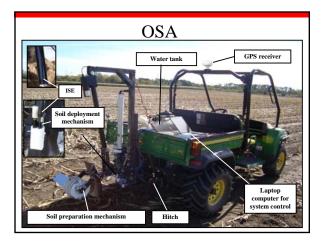


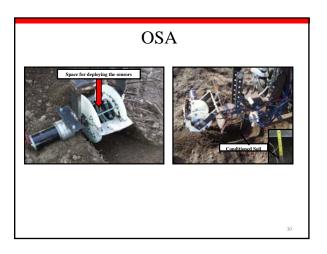


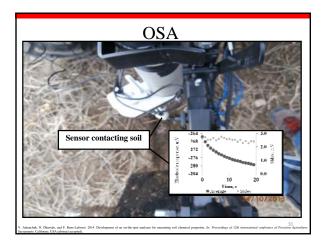


# Automated Soil Sensing Platform



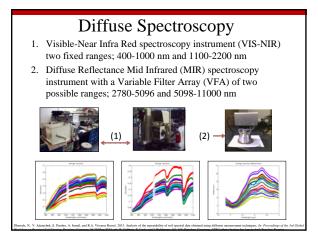








## Soil Sensing with Spectroscopy



#### Numerous Studies

- 1. Vis-NIR vs portable MIR using 282 soils.
- 2. Evaluating a portable MIR on 44 moist soils.
- 3. Ex situ, Vis-NIR using 86 soils.
- 4. Ex situ Vs In situ, using Vis-NIR using 20 soils.
- 1. Texture; % Sand and % Clay
- 2. Soil Organic Matter (SOM)
- 3. Soil Organic Carbon (SOC)
- 4. Soil Total Phosphorus (STP)

#### Methodology

Soil spectral data was collected in three replicates.

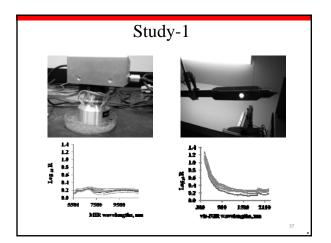
Spectral data was portioned into training and testing sets.

Calibrated models using testing set against laboratory measurements.

Models validated using leave-one-out cross validation on the training set and directly on the testing sets.

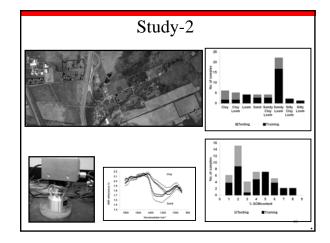
Performance indicators :

Coefficient of determination (R<sup>2</sup>), Root Mean Squared Error (RMSE), Standard Distribution of Errors (SDE), Mean Error (ME).



V	is-NIR	vs porta	ble MIF	λ	
18 19 19 19 19 19 19 19 19 19 19 19 19 19	leyina bas be				
Data set	Stats	Sand, %	Clay, %	SOC, 9	
Data set	Min	0	Clay, %	0.54	
	Min Max	0 86	4 74	0.54 3.91	
Data set Training	Min Max Mean	0 86 38	4 74 29	0.54 3.91 1.71	
	Min Max Mean SD	0 86	4 74 29 14	0.54 3.91 1.71 0.60	
	Min Max Mean	0 86 38	4 74 29	0.54 3.91 1.71	
	Min Max Mean SD	0 86 38 20	4 74 29 14	0.54 3.91 1.71 0.60	
	Min Max Mean SD Median	0 86 38 20 34	4 74 29 14 28	0.54 3.91 1.71 0.60 1.60	
	Min Max Mean SD Median Min	0 86 38 20 34 0	4 74 29 14 28 5	0.54 3.91 1.71 0.60 1.60 0.97	
Training	Min Max Mean SD Median Min Max	0 86 38 20 34 0 86	4 74 29 14 28 5 75	0.54 3.91 1.71 0.60 1.60 0.97 3.75	

Property, %	Data Set	No. of factors	R <sup>2</sup>	RMSE	SDE	ME
1	Training	5	0.64	12.14	12.17	0.05
Sand	Testing		0.52	10.33	10.52	1.20
	Training	4	0.61	8.86	8.88	-0.03
Clay	Testing		0.70	7.79	7.92	-0.25
	Training	6	0.63	0.37	0.37	0.00
SOC	Testing		0.54	0.41	0.42	-0.02
Property, %	Data Set	No. of factors	R <sup>2</sup>	RMSE	SDE	ME
	Training	15	0.74	10.40	10.40	0.14
Sand	Testing		0.72	12.73	12.40	2.95
	Training	7	0.79	6.57	6.58	-0.02
Clay	Testing		0.81	7.17	7.17	-0.50
	Training	12	0.62	0.38	0.38	-0.01
SOC	Testing		0.45	0.45	05	



		on Moi				
Sc	Performance Indicators					
Model calibration	Model validation	PLSR Factors	R <sup>2</sup>	RMSE	ME	SDE
	,	and				
An in provining	Cross validation	3	0.74	11.81	-0.03	11.07
Moist training	Cross validation	5	0.81	10.12	-0.04	10.15
Air-dry training	Air-dry test set validation	3	0.90	8.58	-2.10	8.41
Moist training	Moist test set validation	5	0.82	11.65	-4.30	10.89
Moist training	Air-dry test set validation	5	0.80	11.98	-3.70	11.53
And your second	Moist test set validation	3	0.88	10.26	2.34	10.0.
	% C	Clay				
Air-dry training	Cross validation	3	0.65	9.48	-0.93	9.52
Moist training	Cross validation	5	0.79	7.27	-0.03	7.29
Air-dry training	Air-dry test set validation	3	0.88	10.50	-5.35	9.14
Moist training	Moist test set validation	5	0.91	7.82	-2.57	7.43
Moist training	Air-dry test set validation	5	0.84	9.32	-2.63	9.05
Air-dry training	Moist test set validation	3	0.89	10.00	-3.37	9.55
	% S	OM				-
Air-dry training	Cross validation	6	0.54	1.42	0.00	1.43
Moist training	Cross validation	6	0.49	1.48	0.01	1.49
Air-dry training	Air-dry test set validation	6	0.58	1.17	0.72	0.93
Moist training	Moisttest set validation	6	0.62	1.21	0.84	0.87
Moist training	Air-dry test set validation	6	0.82	0.76	-0.46	0.61
Air-dry training	Moist test set validation	6	100	2.24		1.97

