Food and Agriculture Organization of the United Nations

GLOSOLAN
Soil spectroscopy training workshops

# THE ROLE OF SPECTROSCOPY IN PROMOTING PRECISION AGRICULTURE SOLUTIONS


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Online webinars

GLOBAL SOIL PARTNERSHIP

# OUTLINE

- Basic principles of spectroscopy
- Field spectroscopy and methods for mitigating effects of external factors
- Multi-sensor data fusion approach
- Philosophy of precision agriculture
- Multi-sensor data fusion in precision agriculture
- Adoption of precision agriculture solutions
- Conclusions

# BASIC PRINCIPLES OF SPECTROSCOPY

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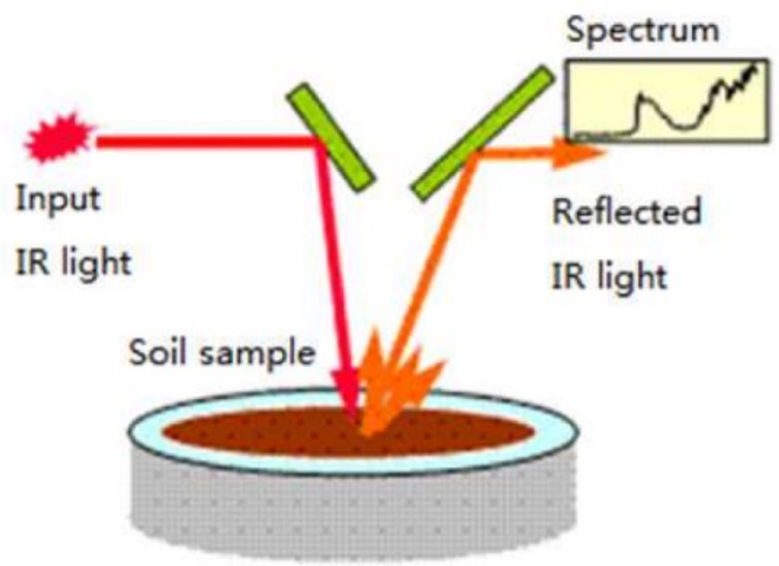
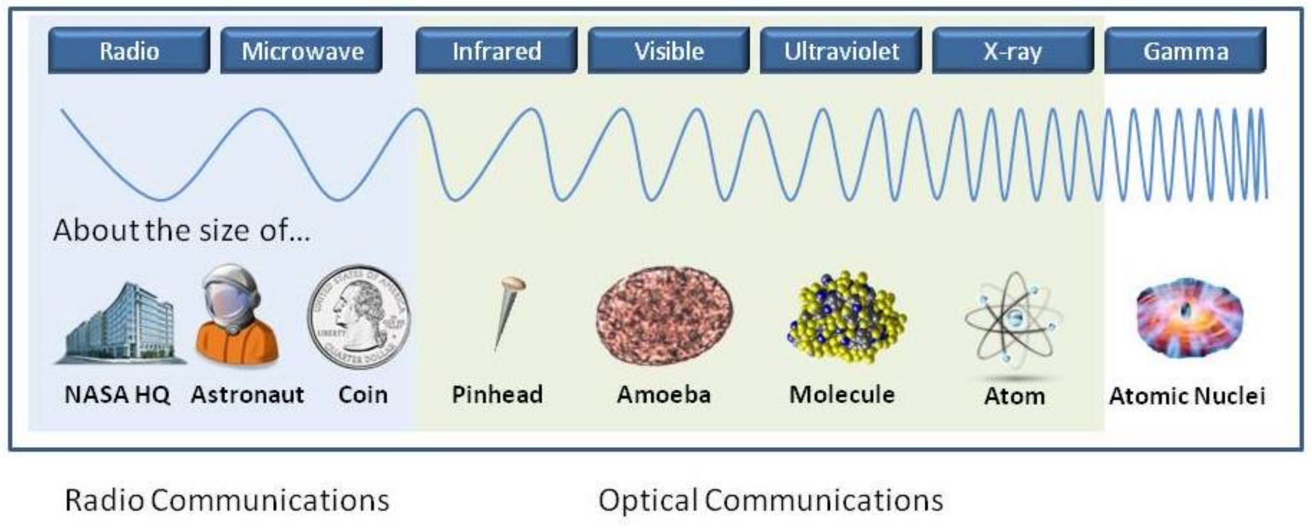
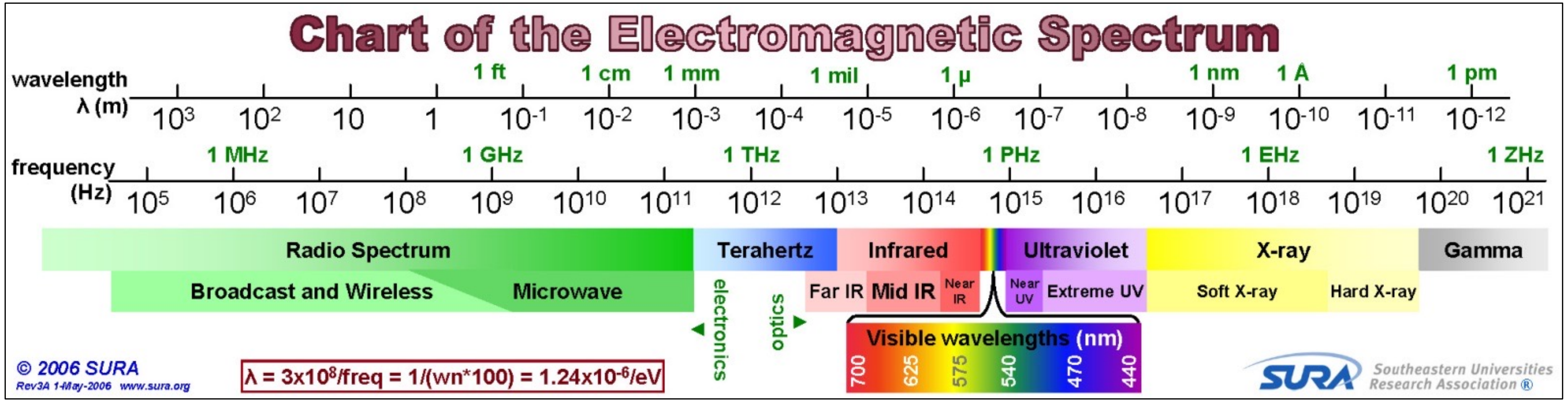
# BASIC PRINCIPLES OF SPECTROSCOPY - ELECTROMAGNETIC WAVE RANGE

- Visible (Vis): 390 – 750 nm – Human eyes sees
- Near infrared (NIR): 750 – 2500 nm
- Mid infrared (MIR) : 2500 – 25000 nm

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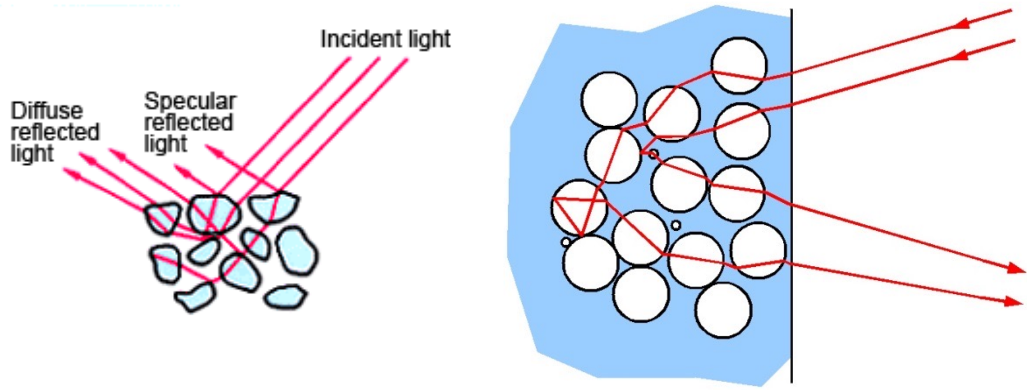
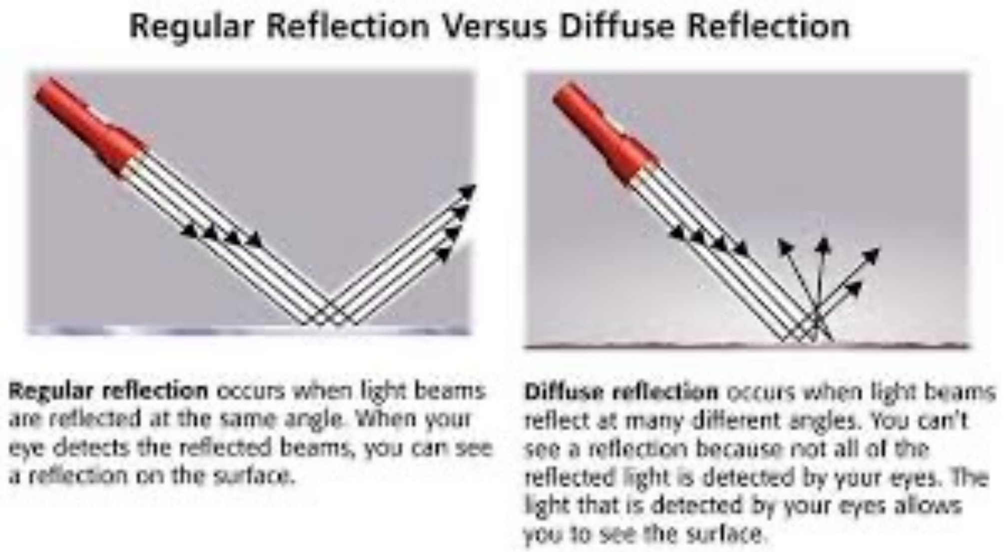
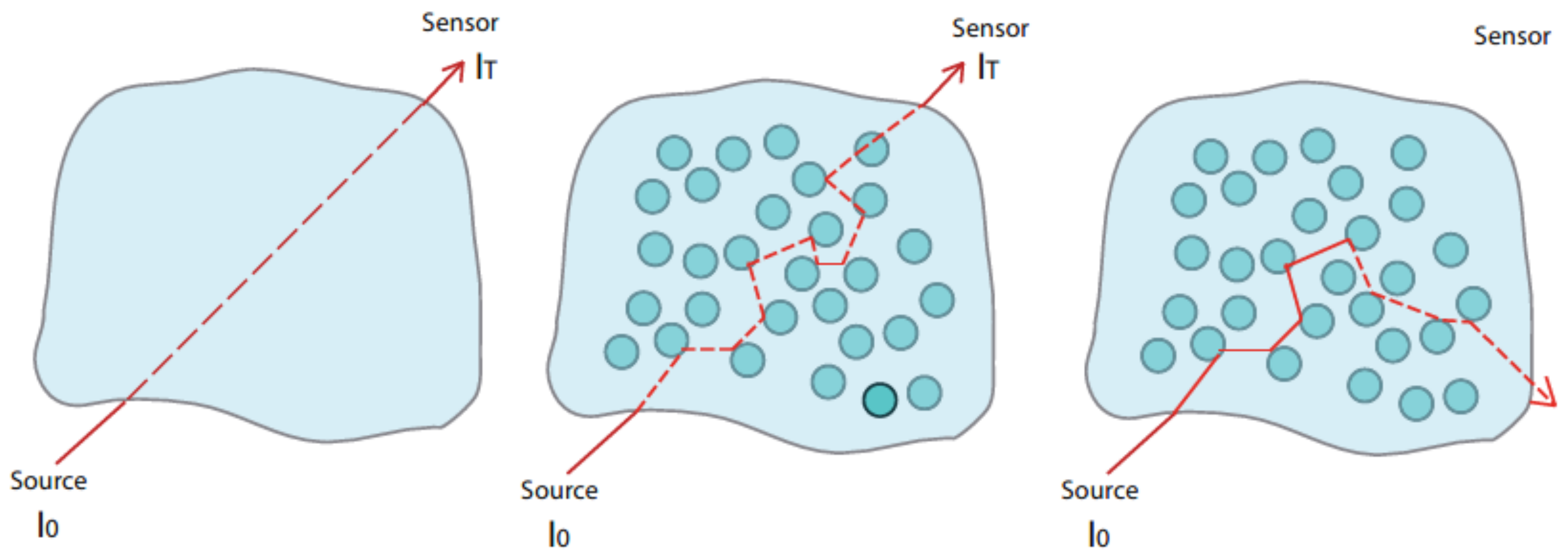
# BASIC PRINCIPLES OF SPECTROSCOPY – PHYSICAL PRINCIPLES

- Reflection (R)
- Absorption (A)
- Transmission (does not exist in soils).

Absorbance = log(1/R)




$A(\lambda) = \mu a(\lambda) \, . \, l$    $. \, fm(\lambda, \mu s(\lambda))$    $+ \, fa(\mu s(\lambda), \lambda, l)$

a. Beer-Lambert Law    b. Multiplicative effect    c. Additive effect

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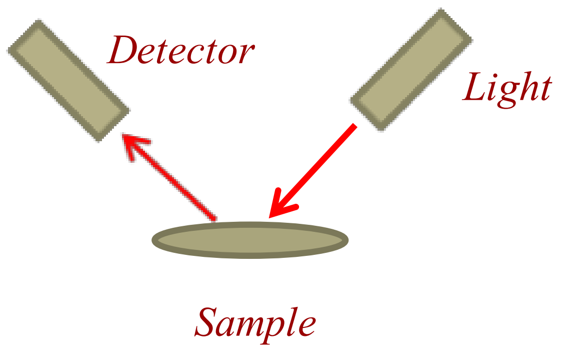
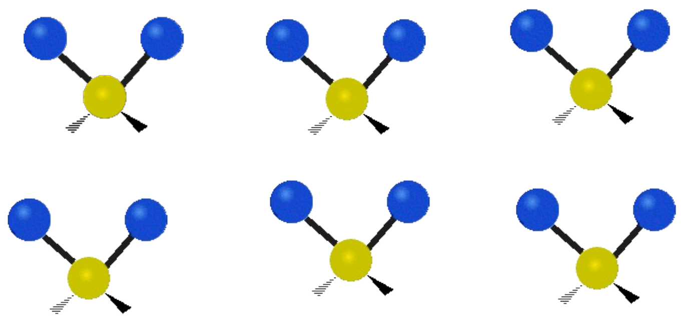
*Gobrecht (2015), Montpelier, France*

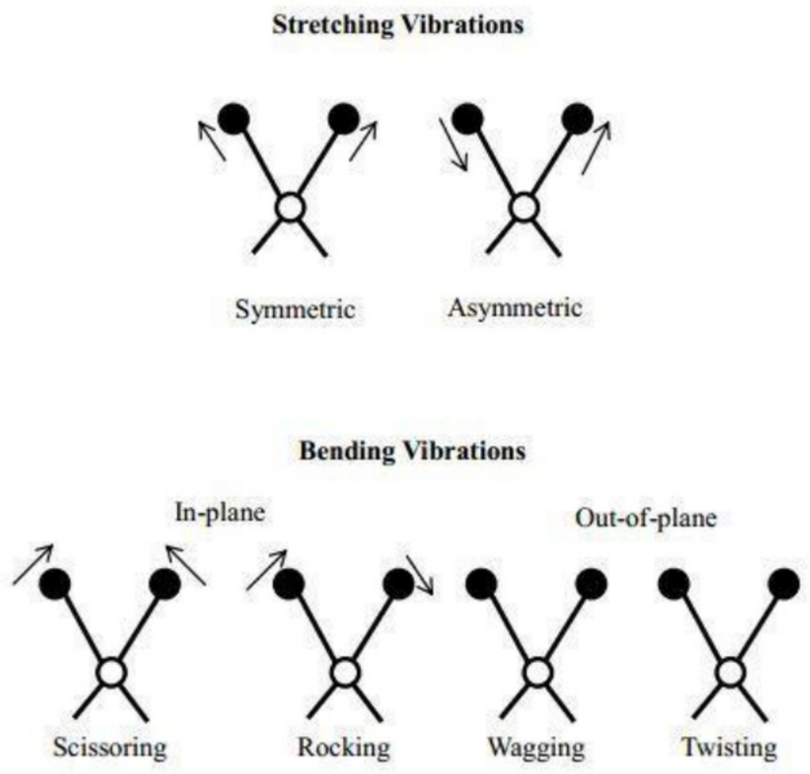
# BASIC PRINCIPLES OF SPECTROSCOPY - MOLECULE VIBRATIONS




**Chemical principles of spectroscopy**



Molecule vibration
⇓
Energy absorption




- **Molecule vibrations** are of different modes: bending, stretching, twisting, wagging, rocking,..
- **Molecules:** CH, CH2, C=O, N-H, C-N, O-H,…

# MOLECULE VIBRATIONS – HARMONIC OSCILLATION

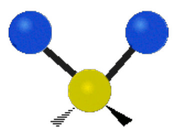

Molecule vibration
↓
Energy absorption

Harmonic oscillation (Herzberg, 1950): *Potential energy of a vibrating system (V) at any given time is a quadratic function of displacement of the atom involved.*

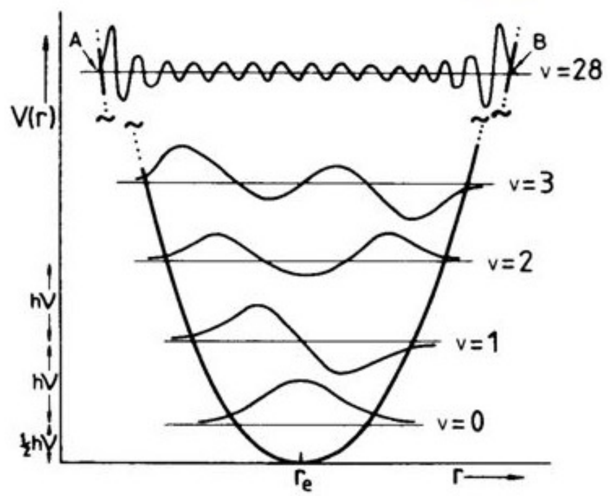
$$V = \frac{1}{2}kx^2$$

*Where: x is displacement of atoms from their equilibrium position; k is restoring force constant*

$$E = \frac{h}{2\pi}\sqrt{\frac{k}{\mu}}$$



*Where: E is vibrational energy; h is Planck's constant, k is force constant of bond between two atoms (bond strength); and μ is the reduces mass = m1m2/m1+m2*




Plot of $V(r)$ against $r$ for the harmonic oscillator model for vibration. A few energy levels and wave functions are shown.

J. Michael Hollas, *Modern Spectroscopy*, John Wiley & Sons, New York, 1992.

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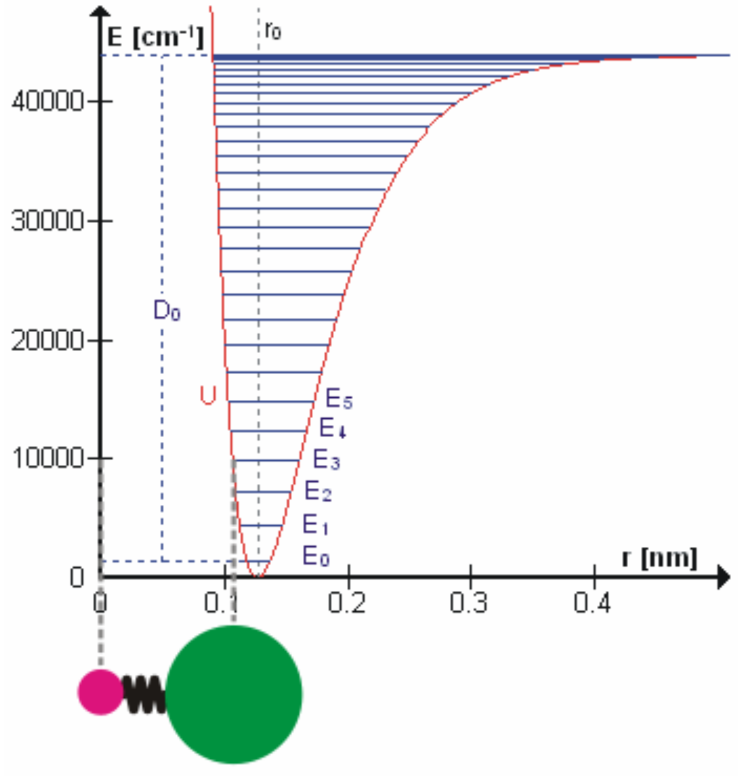
# MOLECULE VIBRATIONS – ANHARMONIC OSCILLATION

*Anharmonic oscillation*

$$V = k_1x^2 + k_2x^3 + k_3x^4 + \ldots..$$




***NIR spectroscopy***: *Overtones and combinations*

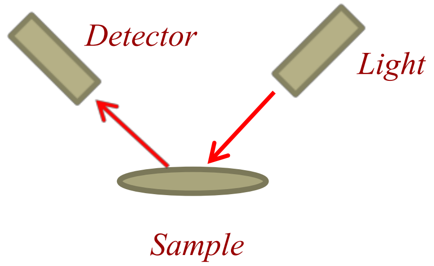
***MIR spectroscopy:*** *Fundamental vibrations*

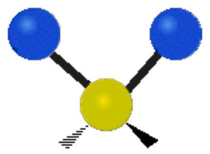
*Frequencies of a* ***overtone band*** *are approximately equal to integer multiples of frequency of fundamental vibrational band (e.g., a x b) in MIR (e.g., CH, NH, and OH).*

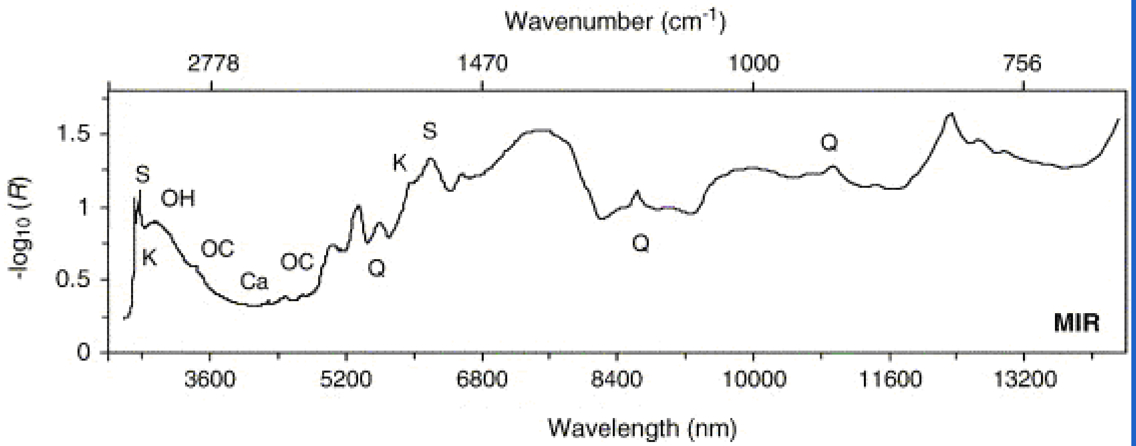
*Frequencies of a* ***combination band*** *is approximately the summation of frequencies of fundamental vibrational bands (e.g., a + b + c) in MIR that make up this combination.*

*A, b, c are wavelength frequencies.*

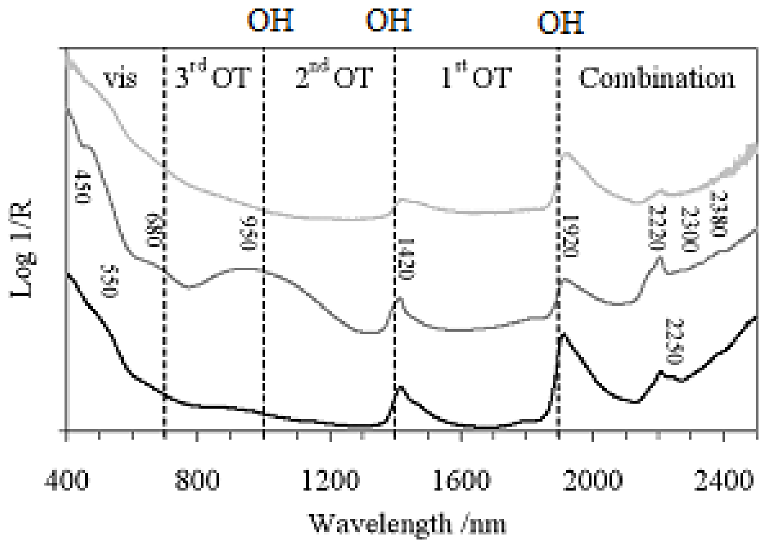
# REFLECTANCE SPECTROSCOPY






***MIR spectroscopy:*** *Fundamental vibrations of molecules*




*Overtones (a x b) and combinations (a + b + c) of different fundamental frequencies in MIR*

***NIR spectroscopy:*** *Overtones and combinations of fundamental vibrations in MIR*

$$E = \frac{h}{2\pi}\sqrt{\frac{k}{\mu}}$$

*Where: E is vibrational energy; h is Planck's constant, k is force constant of bond between two atoms (bond strength); and μ is the reduces mass = m1m2/m1+m2*

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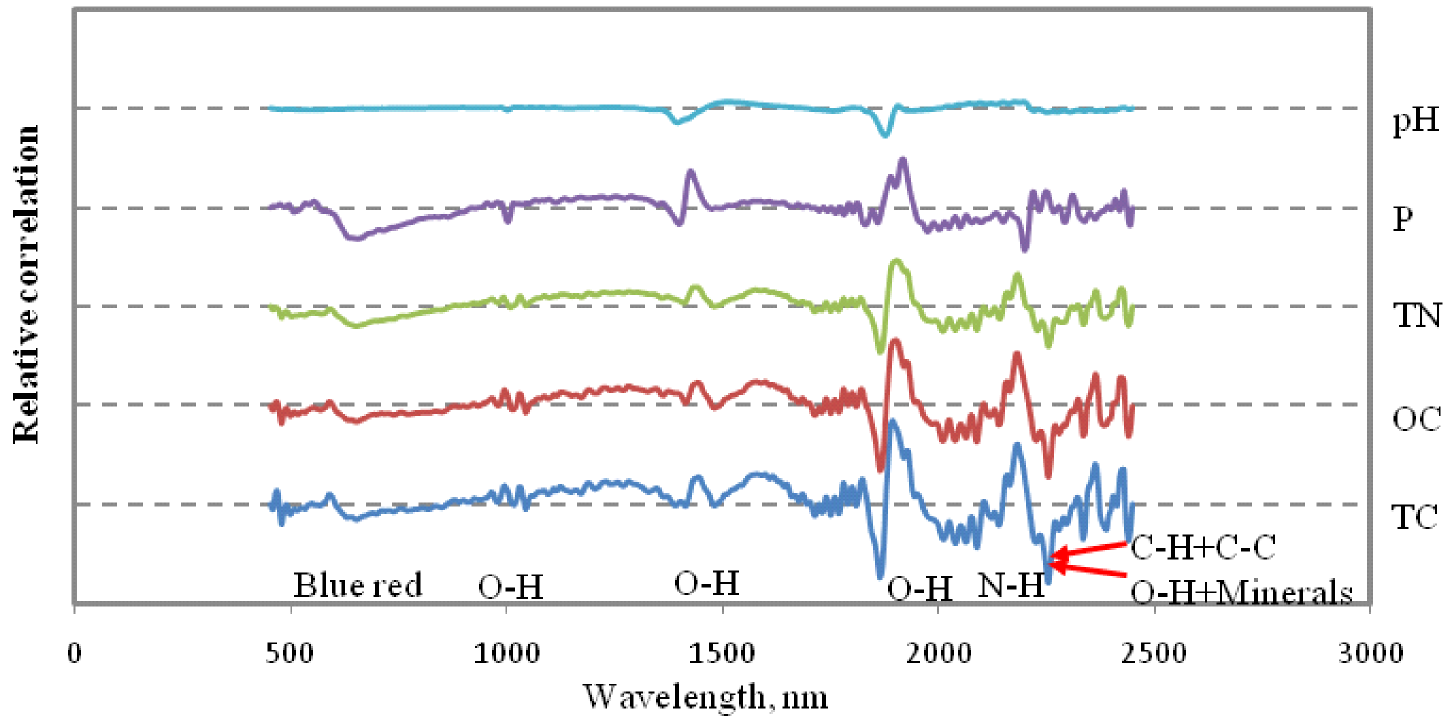
① **Direct spectral responses:**

Organic carbon/N, Water, Clay, Mineralogy

② **Indirect spectral responses:**

P, pH, Mg, Ca, Na, CEC, K, PI




**Soil fertility and chemical properties**

*After: Mouazen et al. (2010), Geoderma*

*Stenberg et al. (2010) – Advances in Agronomy*

| Soil sensors | | | Soil properties | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Physical | | | | Chemical | | | Mechanical | | Primary macronutrients | | | micro nutrients |
| Sensor category | Sensor name | Measu-rment. | MC | Soil texture (sand (S), silt (Si) and clay (C) | OMC or TC/OC | Soil variability | pH | CEC, Ca, Mg | Salinity or $Na^+$ | Draught, PR | Shear strength, Cohesion, Friction | Nitrogen; total (TN), or nitrate ($NO_3^-$) | P or fertility indicator | K | Fe, S, Mn, Cu, Zn |
| Reflectance based sensors | ***Visible & near infrared*** | Lab | xxxx | xxx (C), xx (SI, S) | xxxx | - | xxx/xx | xxx | 0 | - | - | xxxx (TN) | xx | x | xxx-xx |
| | | *In situ* | xxxx | xx (C), 0 (Si, S) | xxx | - | xx | xx | 0 | - | - | xxx (TN) | xx | x | - |
| | | On-line | xxx | xx (c) | xxx | - | xx | xx | - | - | - | xxx (TN) | xx | - | - |
| | ***Mid-infrared*** | Lab | 0 | xxxx (C, S) xxx (Si) | xxxx | - | xxx | xxx | 0 | - | - | xxxx (TN) | xx | 0 | - |
| Conductivity, resistivity, and permittivity based sensors | ***Electromagnetic induction*** | *In situ* | x | x (C and Si), 0 (S) | 0 | xxxx | 0 | xx | xxx-xxxx | - | - | x ( $NO_3^-$) | - | - | - |
| | | On-line | xx | x | x | xxxx | 0 | xx | xx | | | x ( $NO_3^-$) | | | |
| | ***Electrical resistivity*** | *In situ* | x | 0 | 0 | xxxx | 0 | - | xxx | - | - | - | - | - | - |
| | | On-line | x-xx | x | x | xxxx | x | x | xxx | | | | | | |
| | ***Ground penetrating radar*** | *In situ* | xxx | xxx | - | xxxx | - | - | xx | - | - | - | - | - | - |
| | | On-line | xxx | - | - | xxxx | - | - | - | - | - | - | - | - | - |
| | ***Time domain reflectometry*** | Lab | xxxx | - | - | - | - | - | - | - | - | - | - | - | - |
| | | *In situ* | xxxx | | | | | | | | | | | | |
| | ***Frequency domain reflectometry*** | Lab | xxxx | | | | | | | | | | | | |
| | | *In situ* | xxxx | - | - | - | - | - | - | - | - | - | - | - | - |
| | | On-line | xxxx | | | | | | | | | | | | |
| Passive radiometric based sensors | Gamma-ray or radiometrics | On-line | - | xx | - | - | x | - | - | - | - | xxx | xxx | xxx | xxx |
| Strength based sensors | Penetrometer, tine | *In situ* | - | - | - | - | - | - | - | xxxx | - | - | - | - | - |
| | | On-line | - | - | - | - | - | - | - | xxxx | - | - | - | - | - |
| | Triaxial, shear box | Lab | | | | | | | | | | | | | |
| | Torsion, shear vane | *In situ* | - | - | - | - | - | - | - | - | xxxx | - | - | - | - |
| | | | - | - | - | - | - | - | - | - | xxxx | - | - | - | - |
| Electro-chemical based sensors | Ion-selective electrodes | *In situ* | - | - | - | - | xxxx | - | - | - | - | xxxx ( $NO_3^-$) | xxx | xxx | - |
| | | On-line | - | - | - | - | xxxx | - | - | - | - | xxx ( $NO_3^-$) | xxx | xxx | - |
| | Ion-selective field-effect transistors | *In situ* | - | - | - | - | xxxx | - | - | - | - | xxxx ( $NO_3^-$) | xxx | xxxx | - |
| | | On-line | - | - | - | - | xxxx | - | - | - | - | xxxx ( $NO_3^-$) | xxx | xxxx | - |

*After Kuang et al. (2012), Advances in Agronomy*

–, not measurable or not mentioned in the literature; 0, measurable with very low accuracy ($R^2 < 0.50$); x, measurable with low accuracy ($R^2$ = 0.50–0.66); xx, measurable with medium accuracy ($R^2$ = 0.66–0.81); xxx, measurable with high accuracy ($R^2$ = 0.82–0.90); xxxx, measurable with very high accuracy (R2 > 0.90).

# FIELD SPECTROSCOPY AND METHODS FOR MITIGATING

# EFFECTS OF EXTERNAL FACTORS

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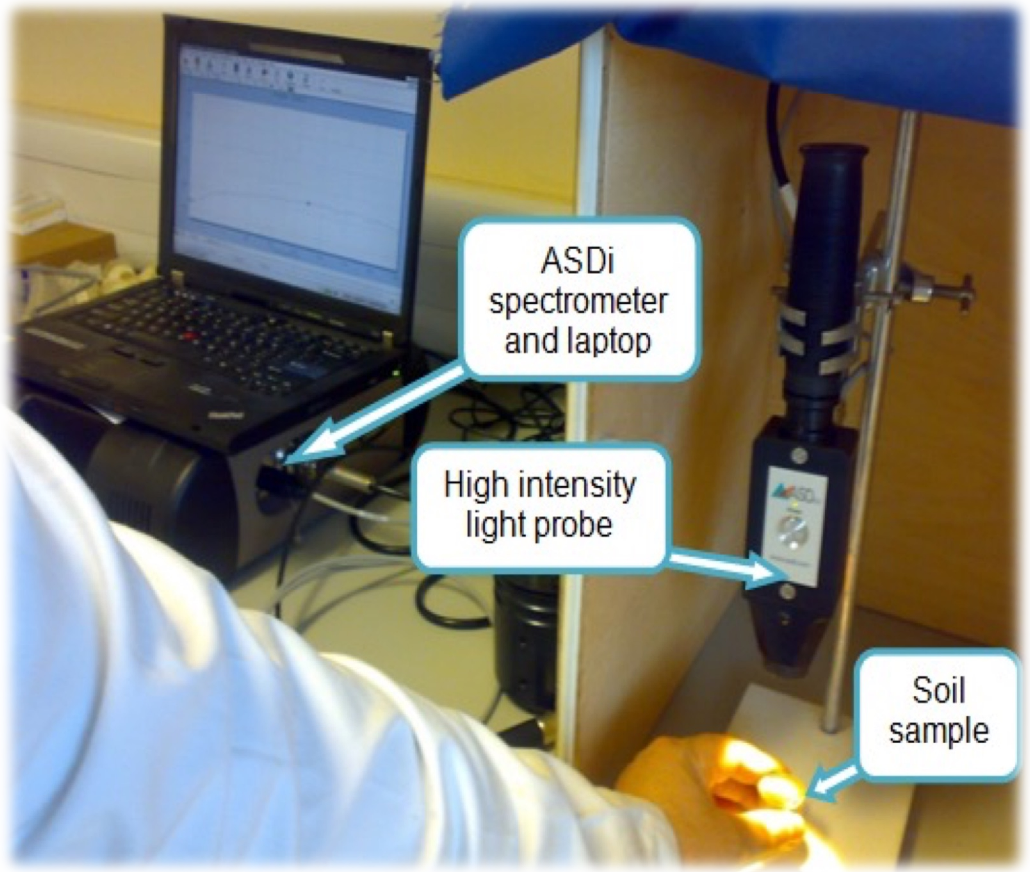
# DEFINITION OF FIELD SPECTROSCOPY

The use of spectroscopy for scanning fresh soil samples (disturbed and non-disturbed), either in the laboratory or *in situ* (portable and on-line).

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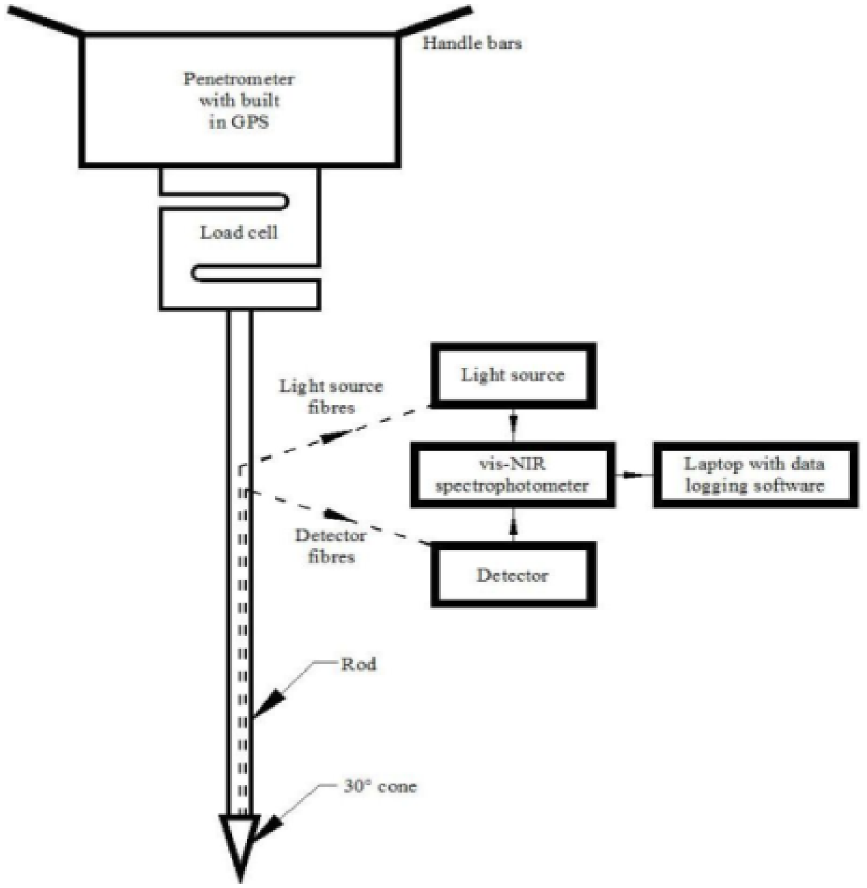
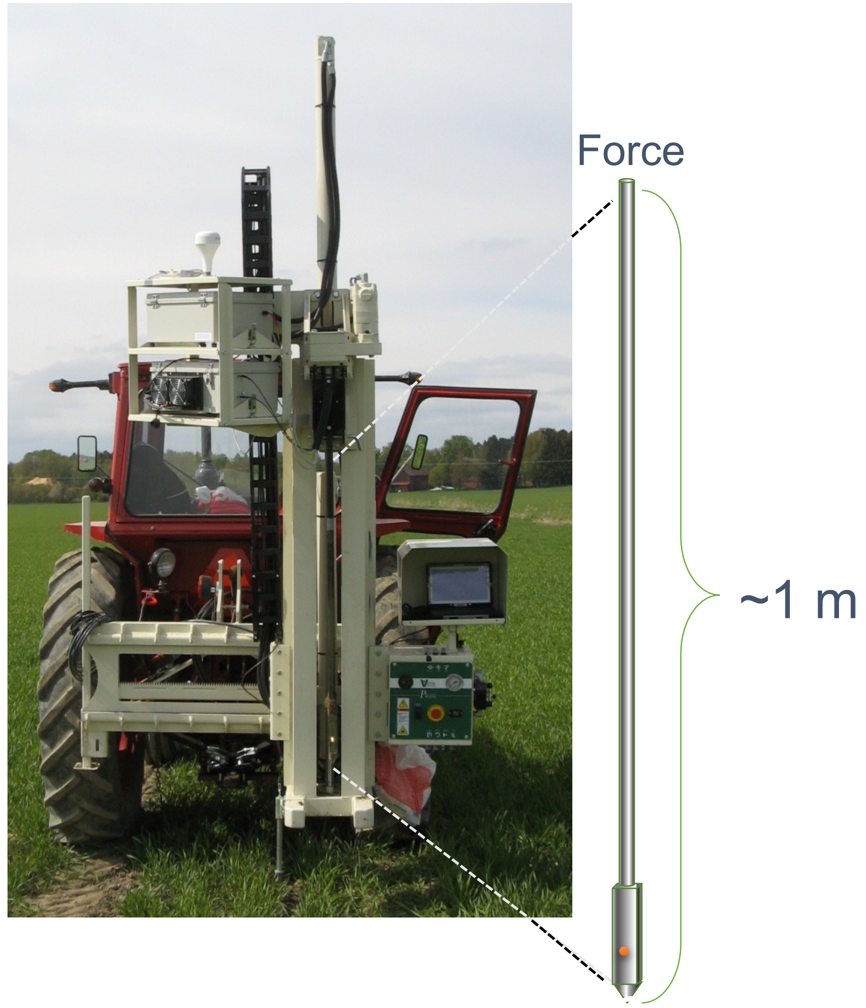
# PORTABLE VIS-NIR FIELD SPECTROSCOPY



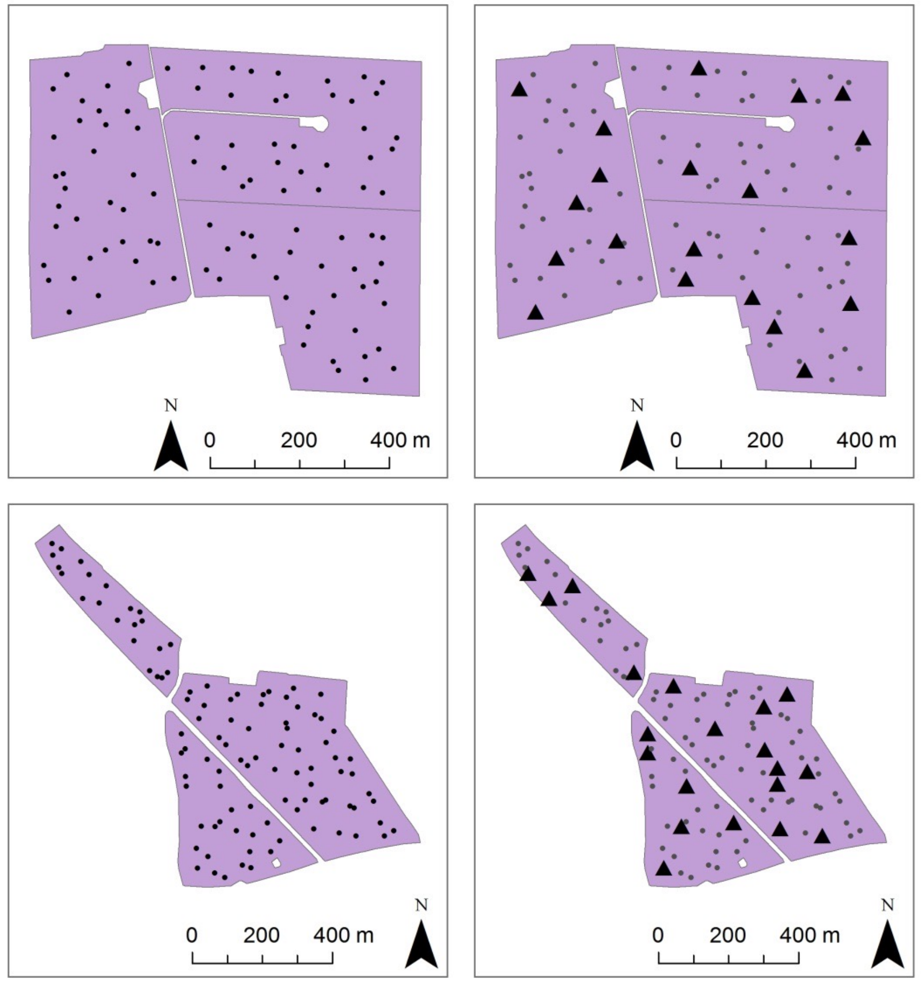

*Quraishi and Mouazen (2013) Soil & Tillage Research*

# MOUNTED STOP – MEASURE – GO VIS-NIR FIELD SPECTROSCOPY




100 readings ~ 2 /ha

20 reference readings for calibration

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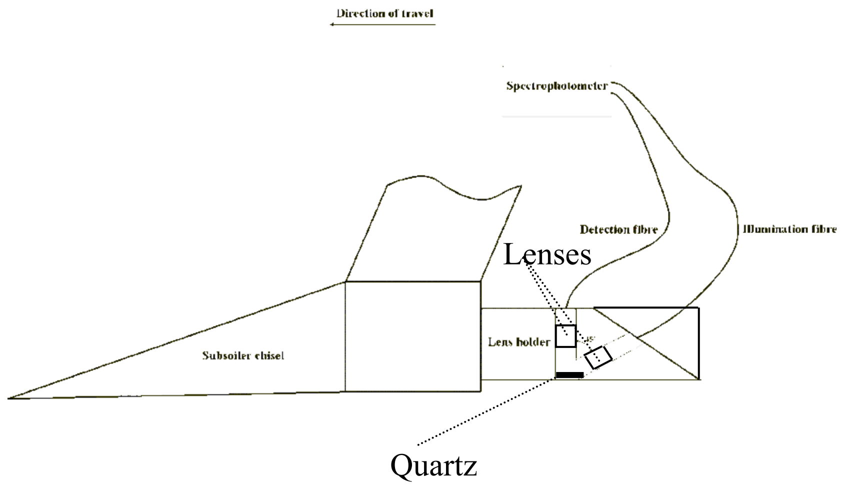
*Wetterlind, et al. (2015). EJSS, doi: 10.1111/ejss.12228*

# TRACTOR MOUNTED ON-LINE FIELD VIS-NIR SPECTROSCOPY





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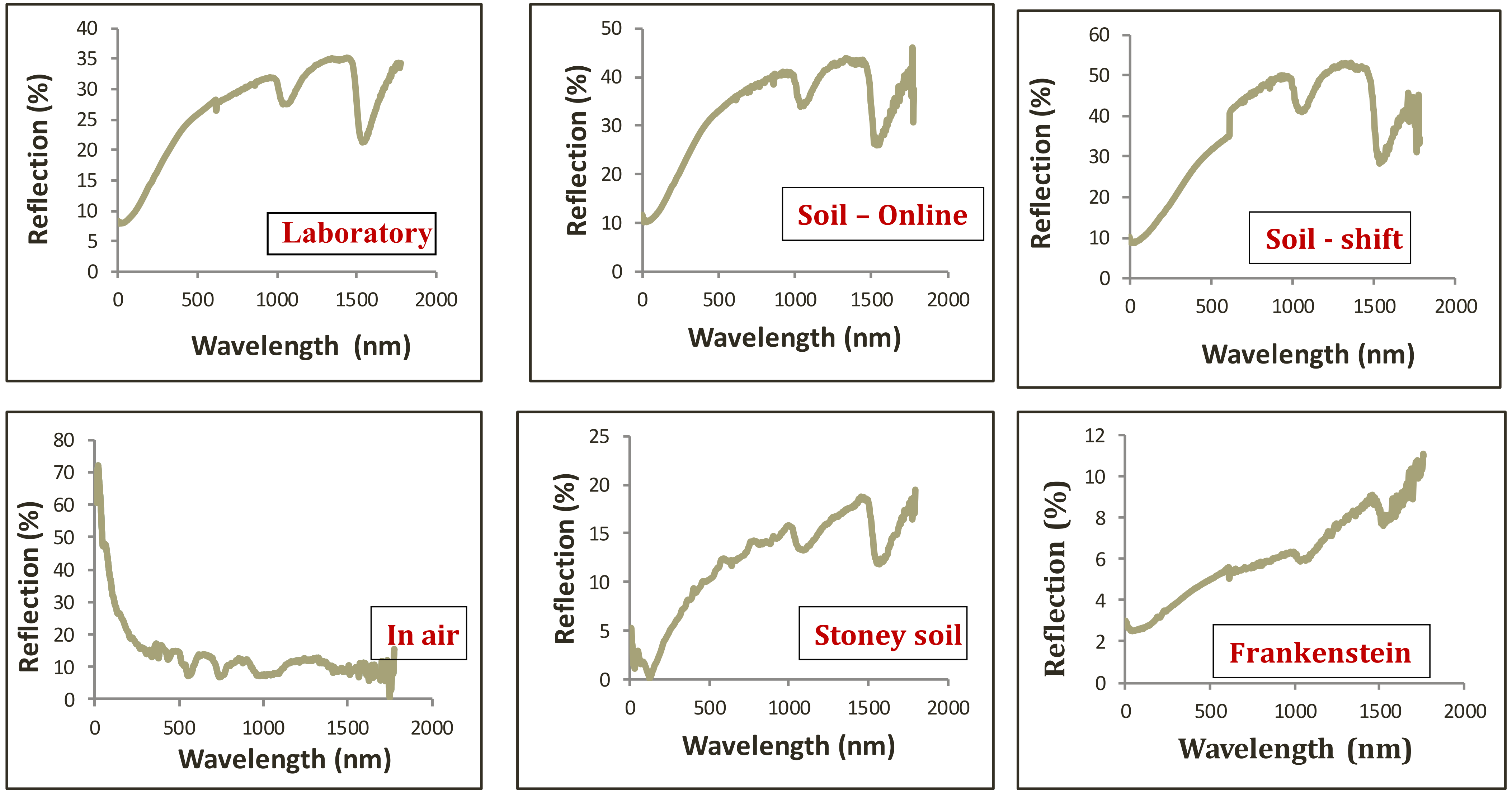
*After: Mouazen, 2006 - International patent, World Intellectual Property Organization*

# FACTORS AFFECTING NIR FIELD SPECTROSCOPY – ON-LINE SENSING

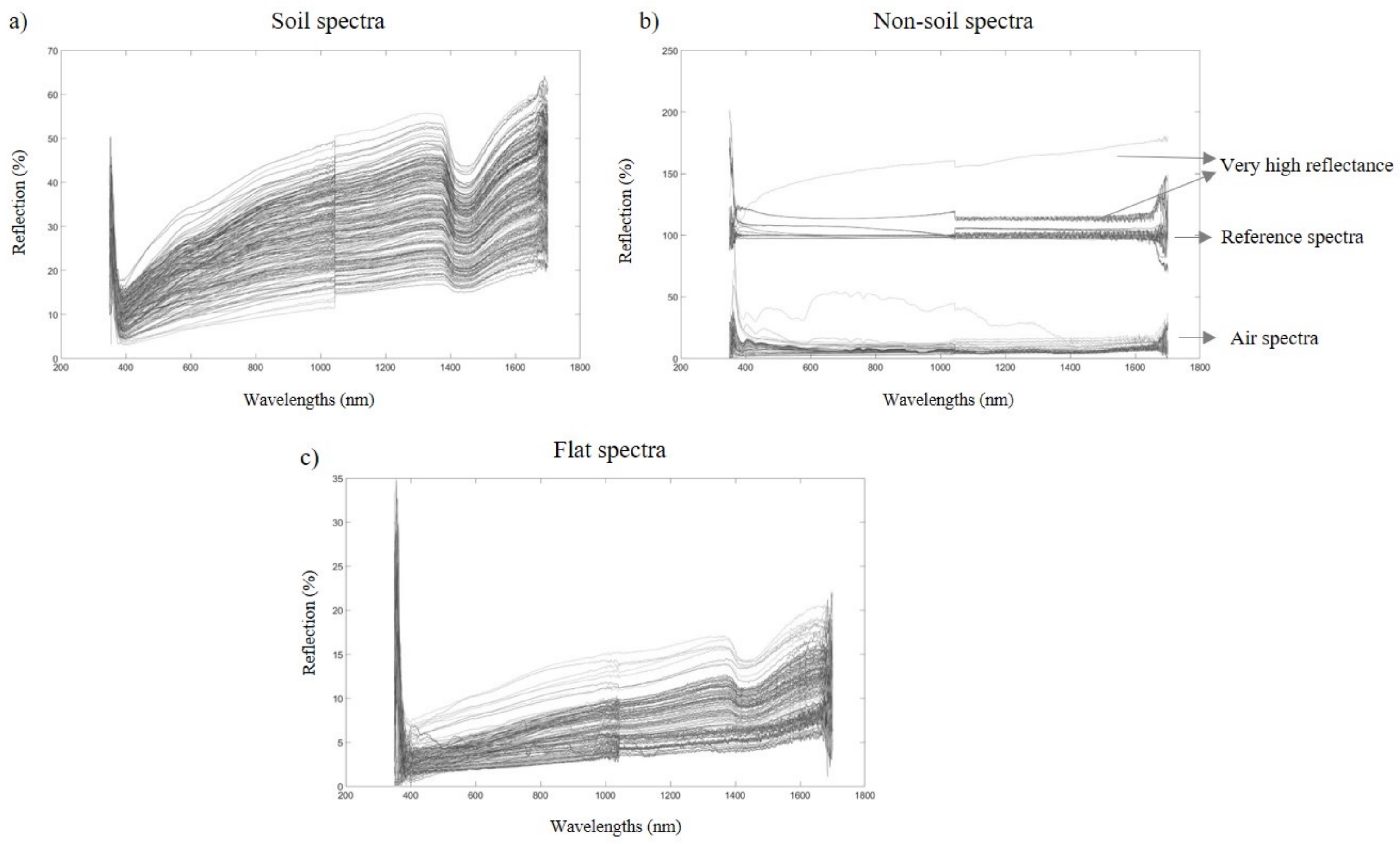
- Moisture content.
- Roots, stones, plant residue etc.
- Ambient light.
- Variation in soil-to-sensor distance & angle (on-line sensing).
- Surface roughness.
- ………..

# SOIL SPECTRA & NOISE

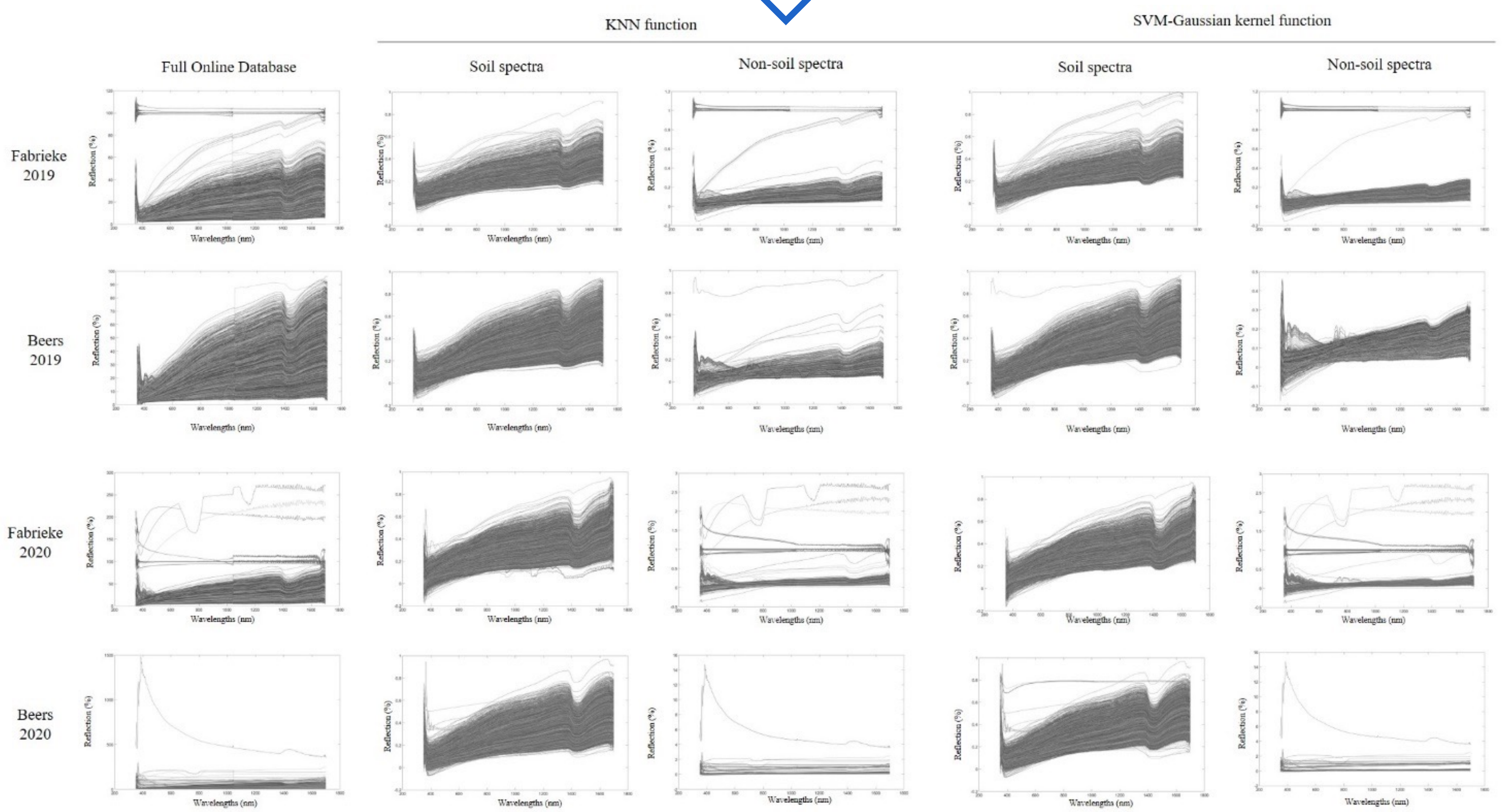


*After: Guerrero et al. (2022); Computers & Electronic in Ag*

# SPECTRA FILTERING



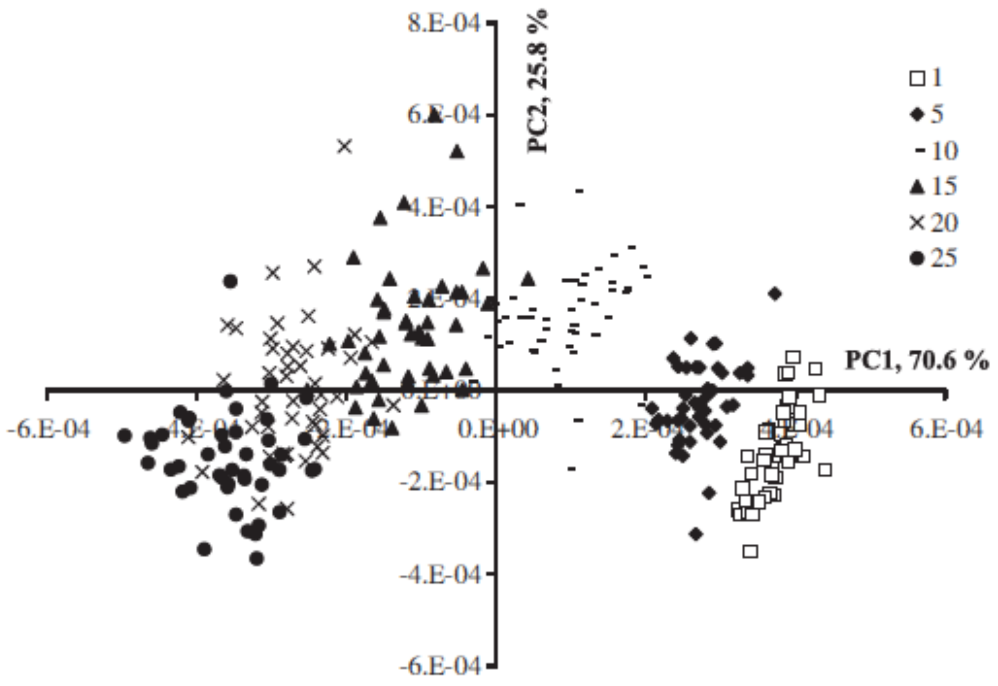

| Algorithm | Method | Database 1 | | Database 2 | |
|---|---|---|---|---|---|
| | | Cross-Validation | Independent Validation | Cross-Validation | Independent Validation |
| **Similarity metrics** | Pearson correlation | 73.6 | -- | 71.0 | -- |
| | Spearson correlation | 68.4 | -- | 71.0 | -- |
| | Euclidian distance | 45.2 | -- | 49.5 | -- |
| | Cosine distance | 75.2 | -- | 76.1 | -- |
| | Principal component analysis | 49.6 | -- | 54.6 | -- |
| | | | | | |
| **Machine learning** | Linear discriminant analysis | 74.6 | 73.4 | 34.1 | 35.02 |
| | Support vector machine with linear kernel | 58.5 | 42.8 | 49.4 | 62.1 |
| | **Support vector machine with Gaussian kernel** | **98.3** | **98.6** | **81.4** | **82.03** |
| | **K-nearest neighbors** | **98.5** | **98.6** | **78.4** | **81.57** |

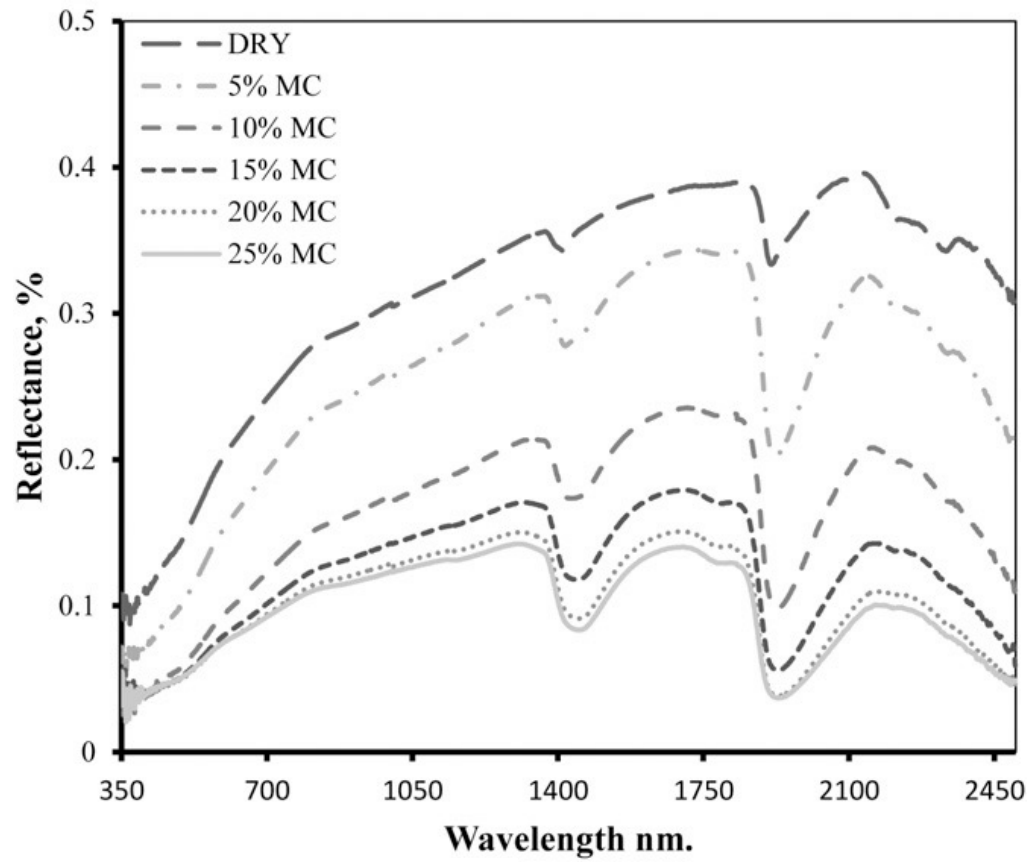


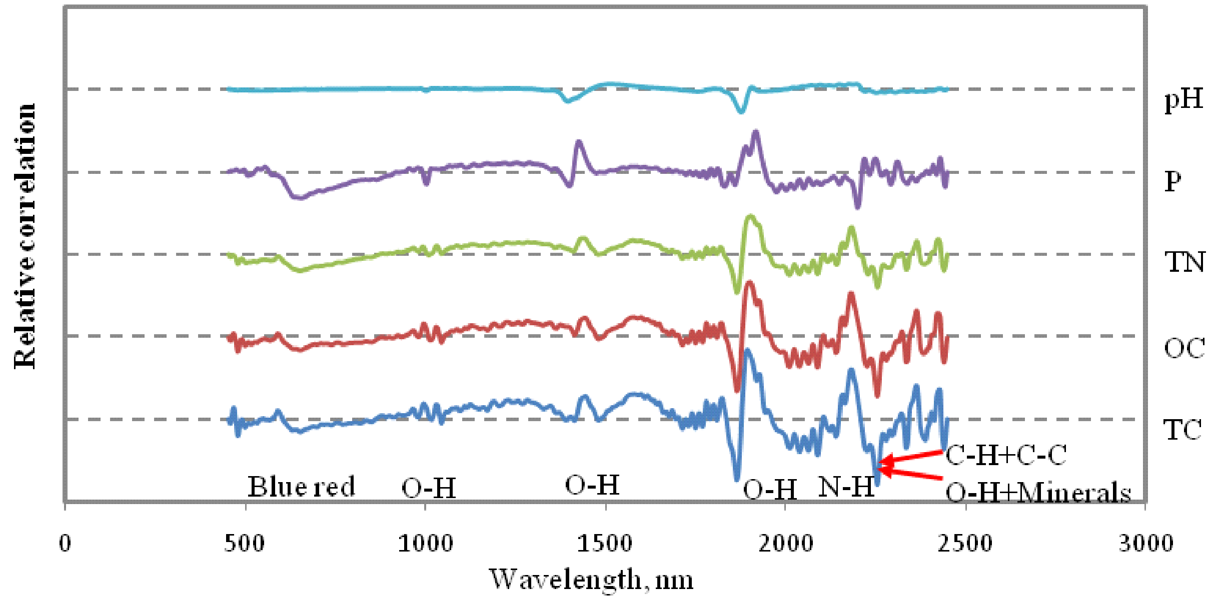

| | | Nr. of samples of Full Database | Nr of samples predicted within field range | % of correct prediction | Nr of sample of KNN | Nr of samples predicted within field range bu KNN | % of correct prediction by KNN | Nr. of sample of SVM-GK | Nr of samples predicted within field range by SVM-GK | % of correct prediction by SVM-GK |
|---|---|---|---|---|---|---|---|---|---|---|
| **pH** | Fabrieke 19 | 5842 | 4961 | **84.92** | 3520 | 2365 | **67.19** | 2691 | 1959 | **72.80** |
| | Beers 2019 | 6621 | 5876 | **88.75** | 4781 | 4490 | **93.91** | 4239 | 4020 | **94.83** |
| | Fabrieke 20 | 7123 | 3977 | **55.83** | 4155 | 2599 | **62.55** | 3375 | 2012 | **59.61** |
| | Beers 2020 | 9199 | 6665 | **72.45** | 6531 | 4275 | **65.46** | 5316 | 3745 | **70.45** |
| | | | | | | | | | | |
| **K** | Fabrieke 19 | 5842 | 5598 | **95.82** | 3520 | 3512 | **99.77** | 2691 | 2683 | **99.70** |
| | Beers 2019 | 6621 | 6243 | **94.29** | 4781 | 4777 | **99.92** | 4239 | 4234 | **99.88** |
| | Fabrieke 20 | 7123 | 6491 | **91.13** | 4155 | 4092 | **98.48** | 3375 | 3329 | **98.64** |
| | Beers 2020 | 9199 | 8997 | **97.80** | 6531 | 6521 | **99.85** | 5316 | 5305 | **99.79** |

# EFFECT OF MOISTURE CONTENT

- Soil become darker with increased moisture.
- Water absorption bands are at 950, 1450 and 1950 nm.
- Principal component analysis can group soils into different moisture groups



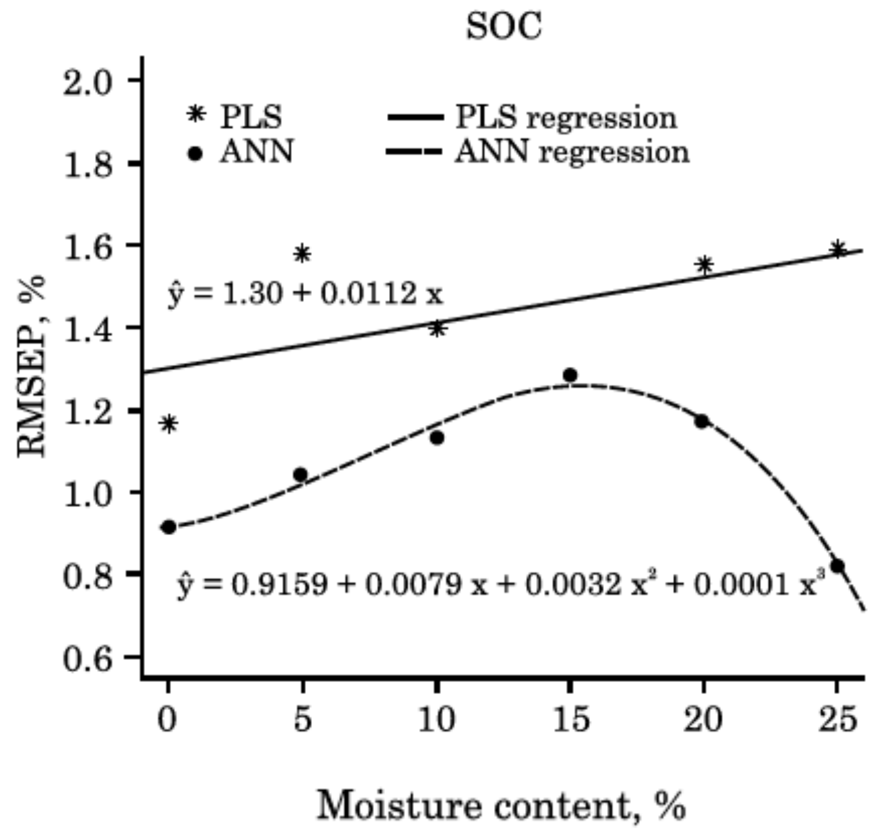



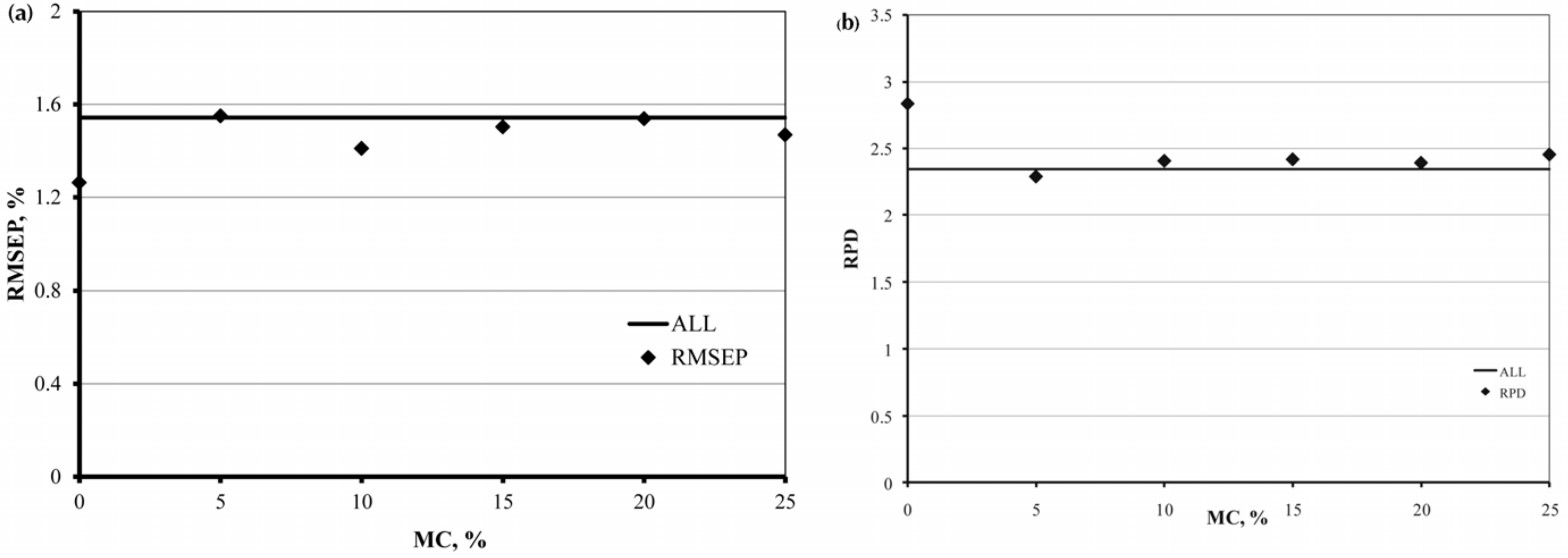




*After: Mouazen et al. (2006); Tekin et al. (2012) – SSSAJ*

# WAYS TO REMOVE THE EFFECT OF MOISTURE CONTENT

1. Grouping of samples into different moisture ranges & develop moisture range specific calibration models.




After: Mouazen et al. (2006); Tekin et al. (2012) – SSSAJ

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# WAYS TO REMOVE THE EFFECT OF MOISTURE CONTENT

**2. Spectra transformation**

- Direct standardisation (DS)
- Piecewise direct standardisation (PDS)

**3. Correcting orthogonality**

- External Parameter Orthogonalization (EPO)
- Orthogonal signal correction (OSC)

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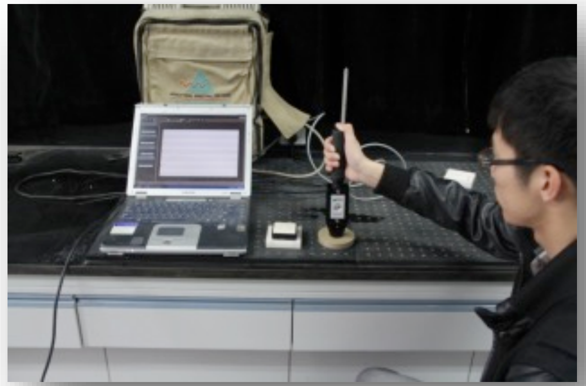
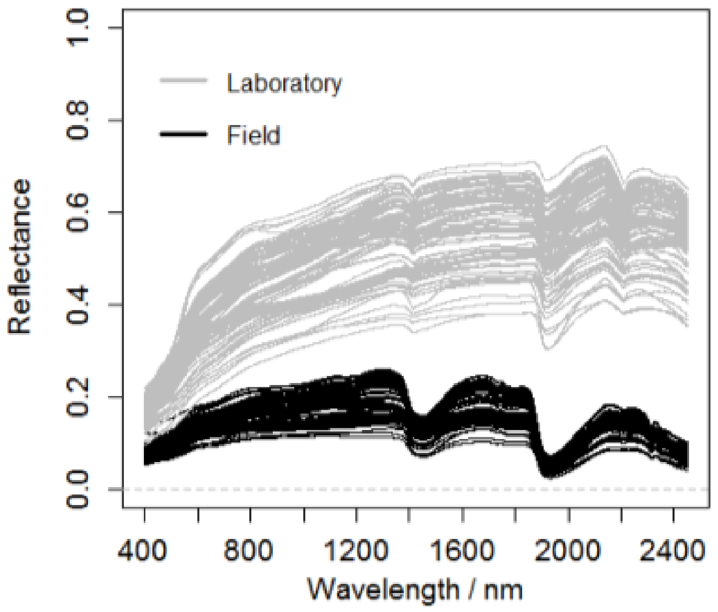
*After: Ji et al. (2015) – European Journal of Soil Science*

# DIRECT STANDARDISATION – *SPECTRA TRANSFORMATION*

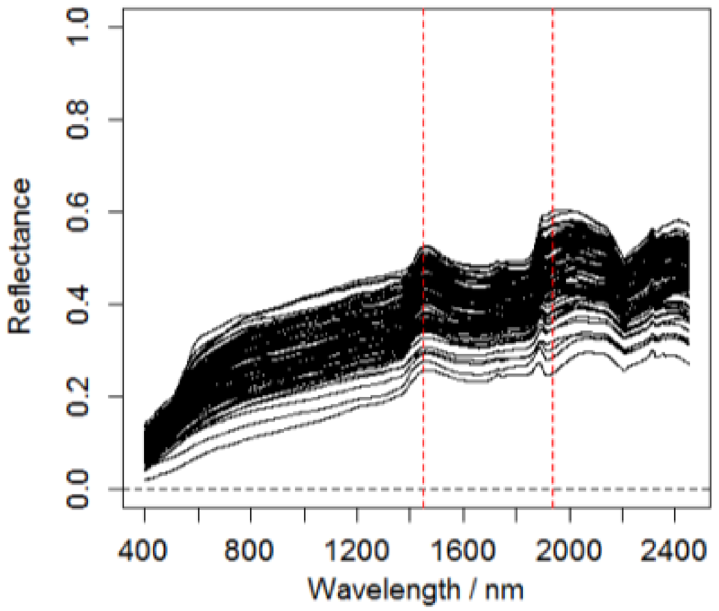
*Wet scanning*



*Dry scanning*




*Wet & dry spectra*




*Created spectra*

PLSR or ANN, RF

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*After: Ji et al. (2015) – European Journal of Soil Science*

# DIRECT STANDARDISATION – RESULTS

| Method | Calibration Dataset （N=70） | $t$* | Validation Dataset （N=34） | $R^2$ | RMSE /$\log_{10}$ (OC %) | RPD |
|---|---|---|---|---|---|---|
| Original | Lab 70 | / | Lab 34 | 0.86 | 0.099 | 2.31 |
| | Field 70 | / | Field 34 | 0.78 | 0.119 | 1.91 |
| Direct Standardization | Field 70_DS | 50 | Field 34_DS | 0.83 | 0.102 | 2.24 |

RMSE = root mean square error; RPD is ration of prediction deviation = SD/RMSE

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*After: Ji et al. (2015) – European Journal of Soil Science*

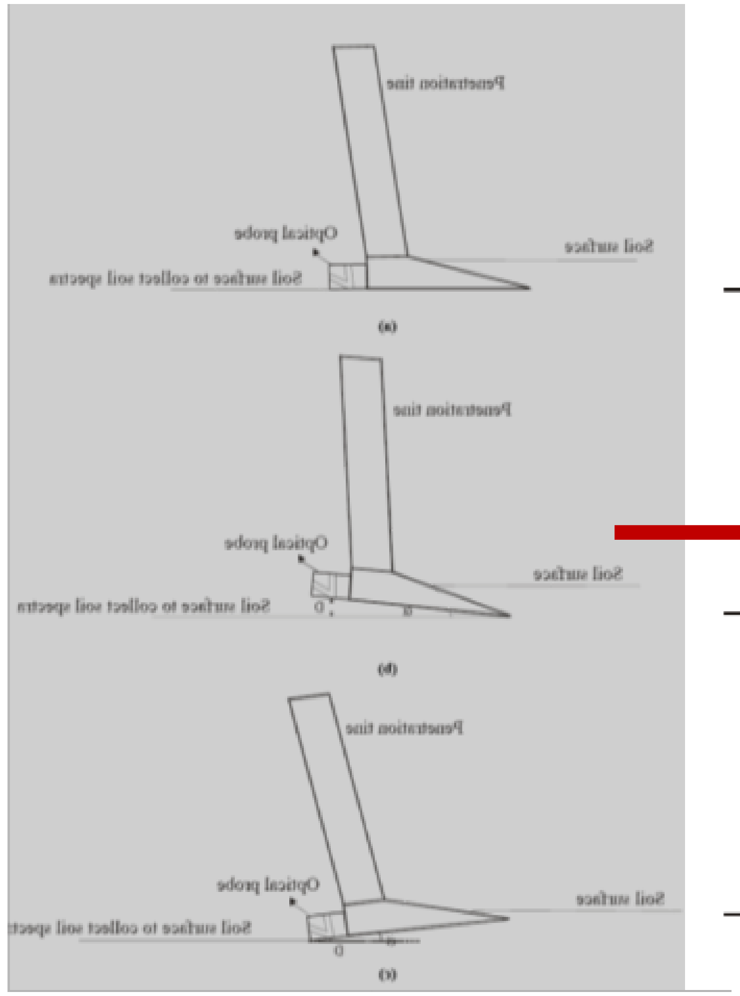
# CORRECTION FOR MC + LINEAR AND NONLINEAR REGRESSION METHODS – OC

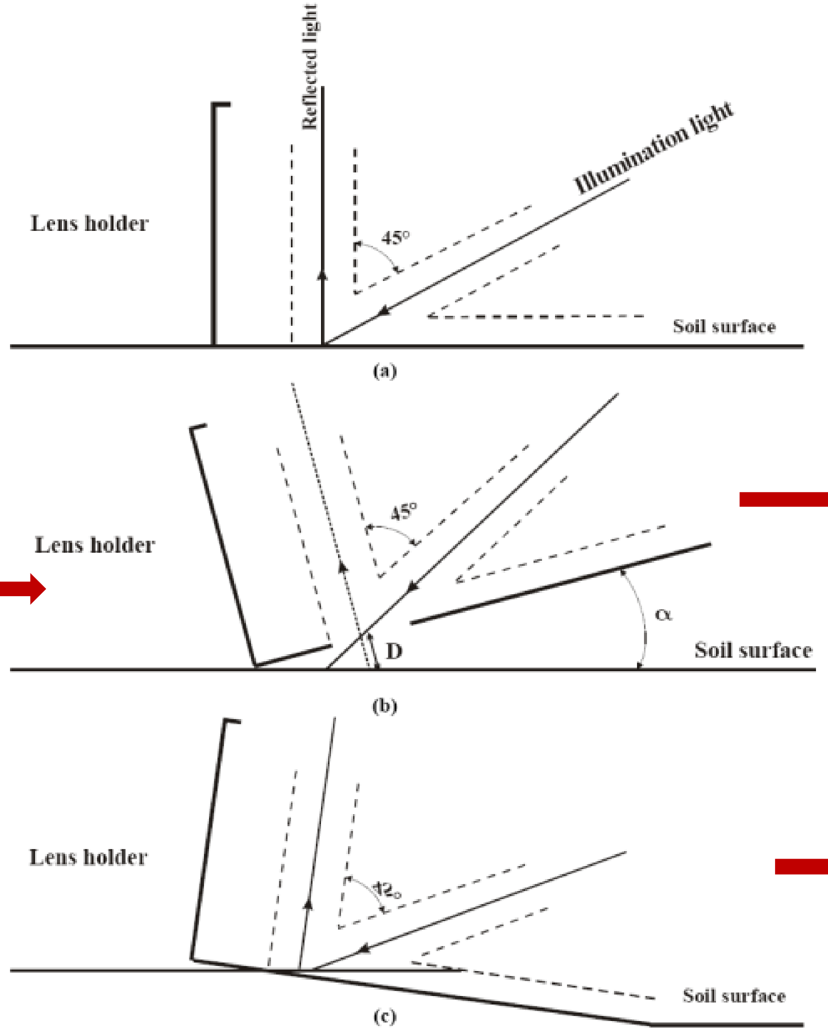
- Dataset specific
- Property specific
- Nonlinear models perform better
- Spectra transformation algorithms (e.g., DS and PDS) are less accurate than the algorithms for correcting orthogonality (EPO and OSC) – eliminate redundant info.
- Trial and error
- Spectra correction was not useful for SVM

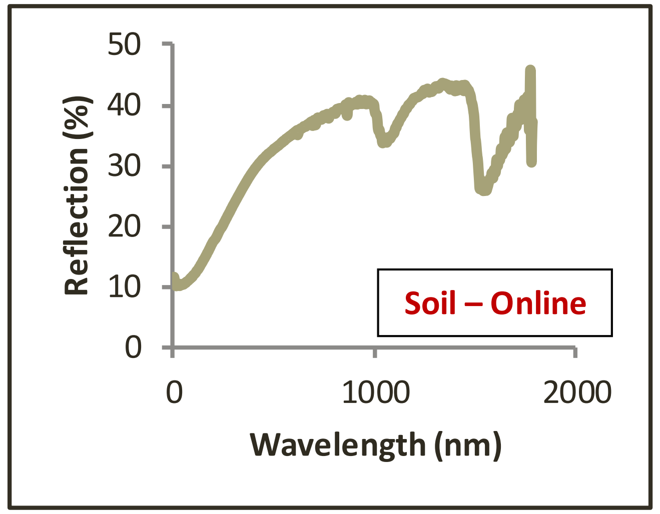
| Regression | Method | Cross-validation (260 S.) | | | | | On-line prediction (112 S.) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | $R^2$ | RMSE | MAE | RPD | RPIQR | $R^2$ | RMSE | MAE | RPD | RPIQR |
| PLS | NC | 0.88 | 0.55 | 0.42 | 2.84 | 1.15 | 0.58 | 1.65 | 1.22 | 1.56 | 0.38 |
| | DS | 0.59 | 1.00 | 0.72 | 1.57 | 0.63 | 0.26 | 2.19 | 1.38 | 1.17 | 0.29 |
| | EPO | 0.86 | 0.58 | 0.45 | 2.70 | 1.09 | 0.58 | 1.65 | 1.17 | 1.56 | 0.38 |
| | PDS | **0.83** | **0.65** | **0.50** | **2.40** | **0.97** | **0.60** | **1.61** | **1.13** | **1.59** | **0.39** |
| | OSC | **0.86** | **0.59** | **0.45** | **2.63** | **1.07** | **0.61** | **1.59** | **1.13** | **1.62** | **0.40** |
| SVM | NC | **0.99** | **0.14** | **0.13** | **11.41** | **4.62** | **0.63** | **1.55** | **0.77** | **1.66** | **0.41** |
| | DS | 0.41 | 1.19 | 0.51 | 1.31 | 0.53 | -0.10 | 2.68 | 1.31 | 0.96 | 0.24 |
| | EPO | 0.94 | 0.37 | 0.21 | 4.24 | 1.72 | 0.59 | 1.64 | 0.74 | 1.57 | 0.38 |
| | PDS | 0.94 | 0.38 | 0.21 | 4.12 | 1.67 | 0.59 | 1.63 | 0.71 | 1.58 | 0.39 |
| | OSC | 0.94 | 0.38 | 0.22 | 4.13 | 1.67 | 0.56 | 1.70 | 0.68 | 1.51 | 0.37 |
| RF | NC | 0.96 | 0.31 | 0.17 | 5.12 | 2.07 | 0.62 | 1.58 | 0.72 | 1.63 | 0.40 |
| | DS | 0.77 | 0.75 | 0.47 | 2.08 | 0.84 | 0.01 | 2.54 | 1.38 | 1.01 | 0.25 |
| | EPO | 0.96 | 0.32 | 0.18 | 4.93 | 1.99 | 0.62 | 1.58 | 0.74 | 1.62 | 0.40 |
| | PDS | **0.97** | **0.28** | **0.16** | **5.67** | **2.30** | **0.71** | **1.38** | **0.64** | **1.86** | **0.46** |
| | OSC | **0.97** | **0.27** | **0.16** | **5.76** | **2.33** | **0.71** | **1.38** | **0.66** | **1.85** | **0.45** |
| M5Rules | NC | 0.87 | 0.57 | 0.34 | 2.76 | 1.12 | 0.73 | 1.33 | 0.68 | 1.93 | 0.47 |
| | DS | 0.15 | 1.44 | 0.90 | 1.09 | 0.44 | -0.08 | 2.65 | 1.34 | 0.97 | 0.24 |
| | EPO | 0.90 | 0.50 | 0.32 | 3.12 | 1.26 | 0.67 | 1.47 | 0.75 | 1.74 | 0.43 |
| | PDS | **0.95** | **0.35** | **0.24** | **4.44** | **1.80** | **0.74** | **1.29** | **0.67** | **1.99** | **0.49** |
| | OSC | **0.92** | **0.43** | **0.28** | **3.65** | **1.48** | **0.82** | **1.09** | **0.57** | **2.36** | **0.58** |

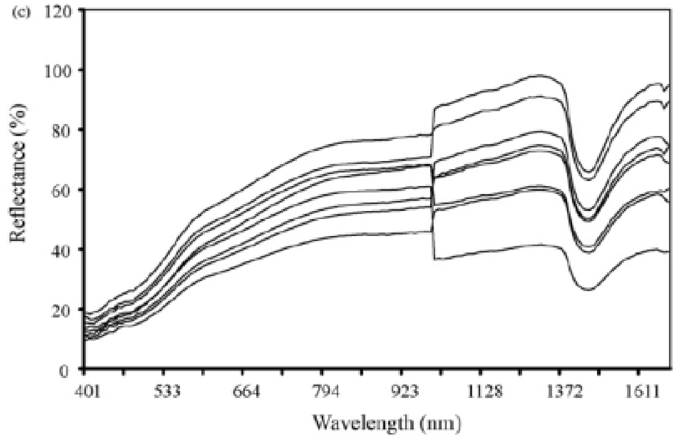
*After: Munnaf and Mouazen, 2022 – CATENA*

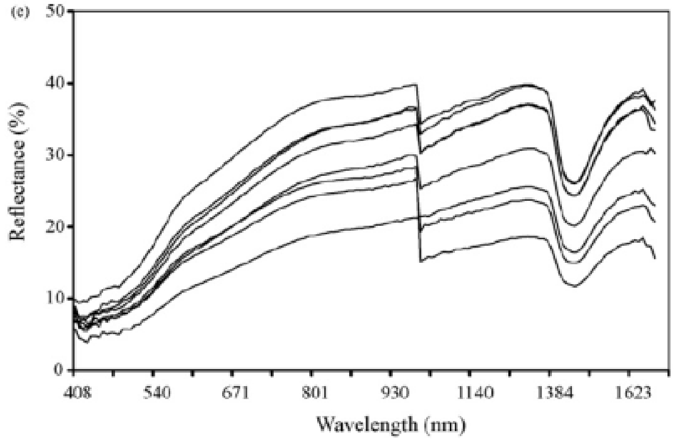
# INFLUENCE OF SOIL-TO-SENSOR DISTANCE AND ANGLE



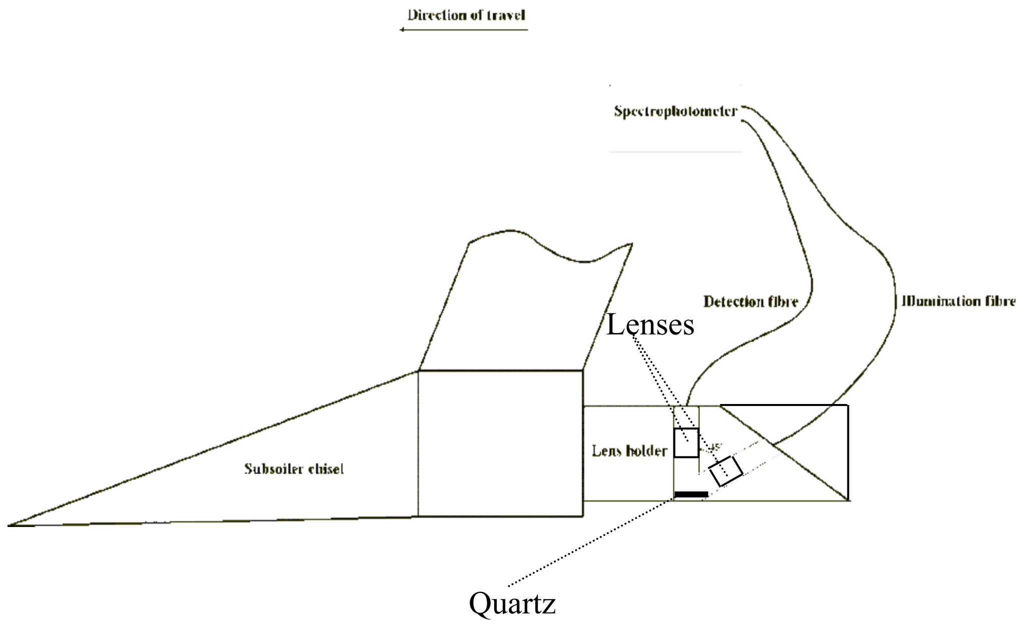




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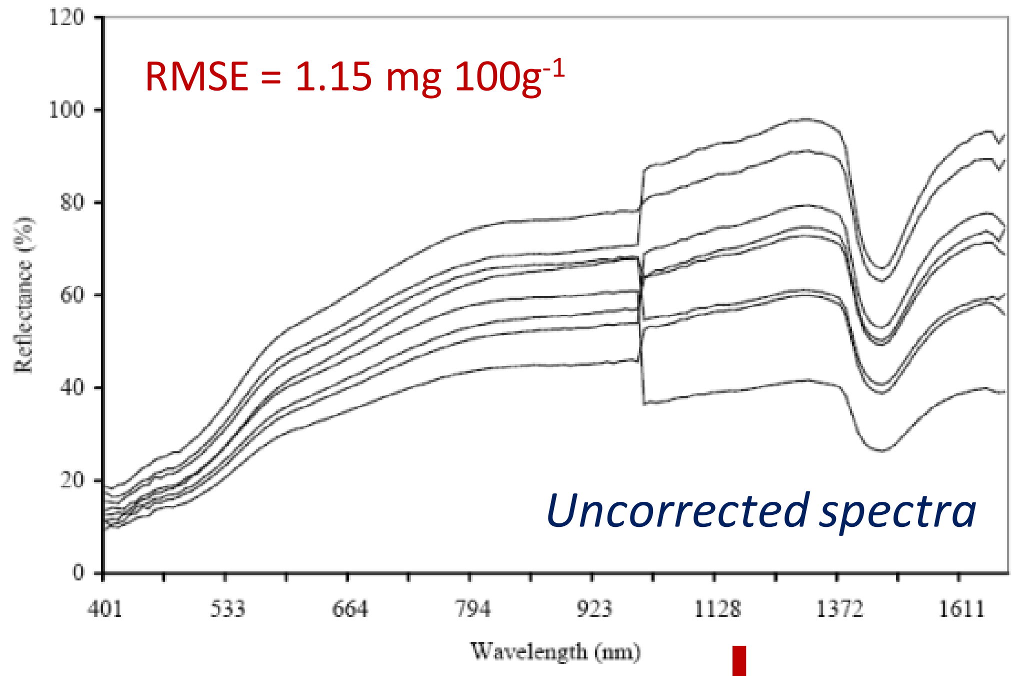
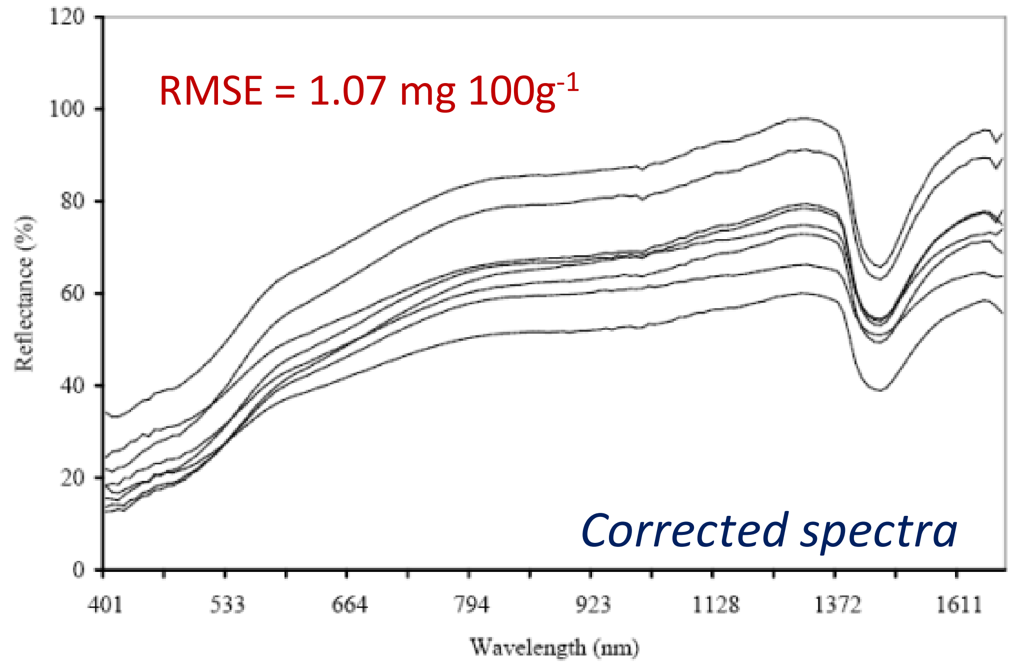
*After: Mouazen et al. (2009) – Soil & Tillage Research*

# CORRECTING SPECTRA TO REMOVE SOIL-TO-SENSOR DISTANCE EFFECT

Correcting soil spectra leads to improve accuracy of phosphorous measurement (e.g., smaller root mean square error (RMSE).




After: Mouazen et al. (2009) – Soil & Tillage Research

# MULTI-SENSOR DATA FUSION

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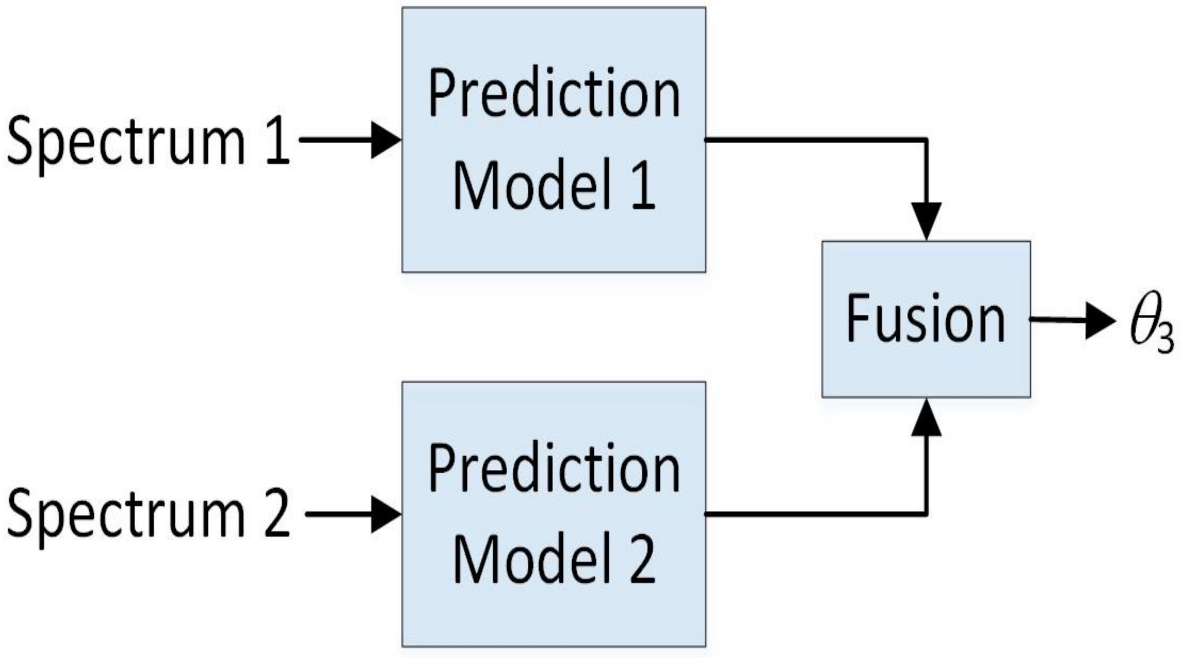
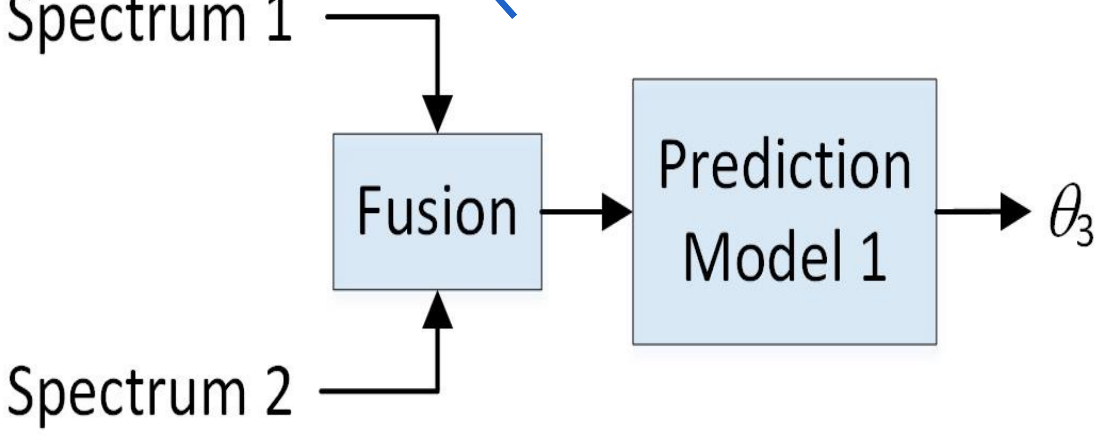
# MULTI-SENSOR DATA FUSION

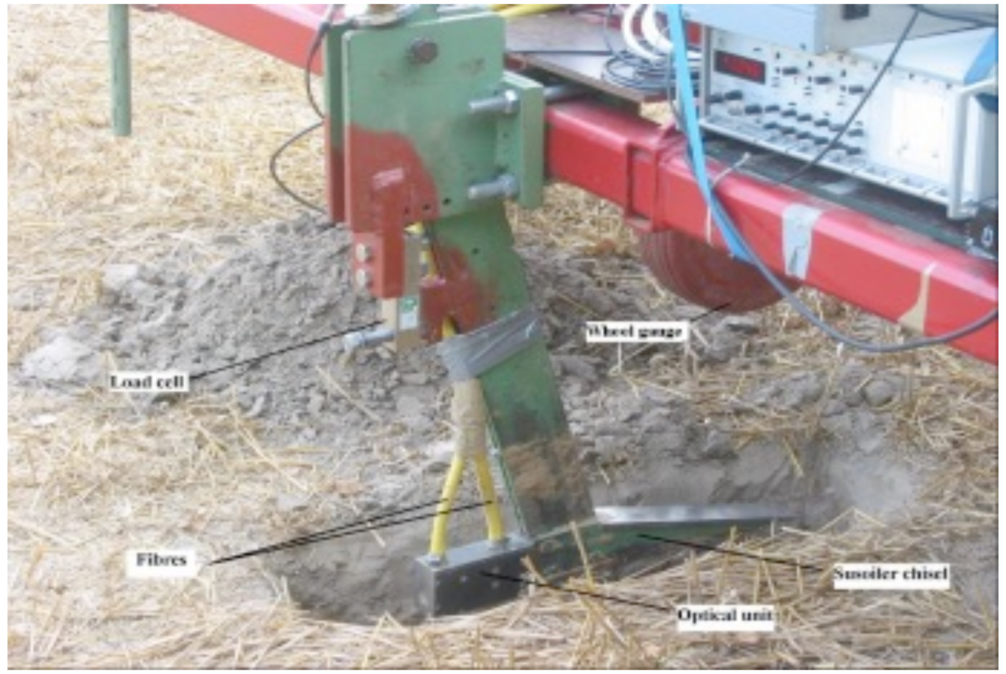
All available information is fused before prediction




(a)




(b)




$$BD = \left( \sqrt[3]{\frac{D + 21.36MC - 73.9313d^2}{1.6734}} \right) \times (1.255 - 0.772MC)$$

(c)

(a) Fusion after prediction

(b) Prediction after fusion [spectral fusion-concatenation, outer product analysis (OPA), or PCA and LV]

(c) prediction of a new attribute e.g., bulk density (BD)

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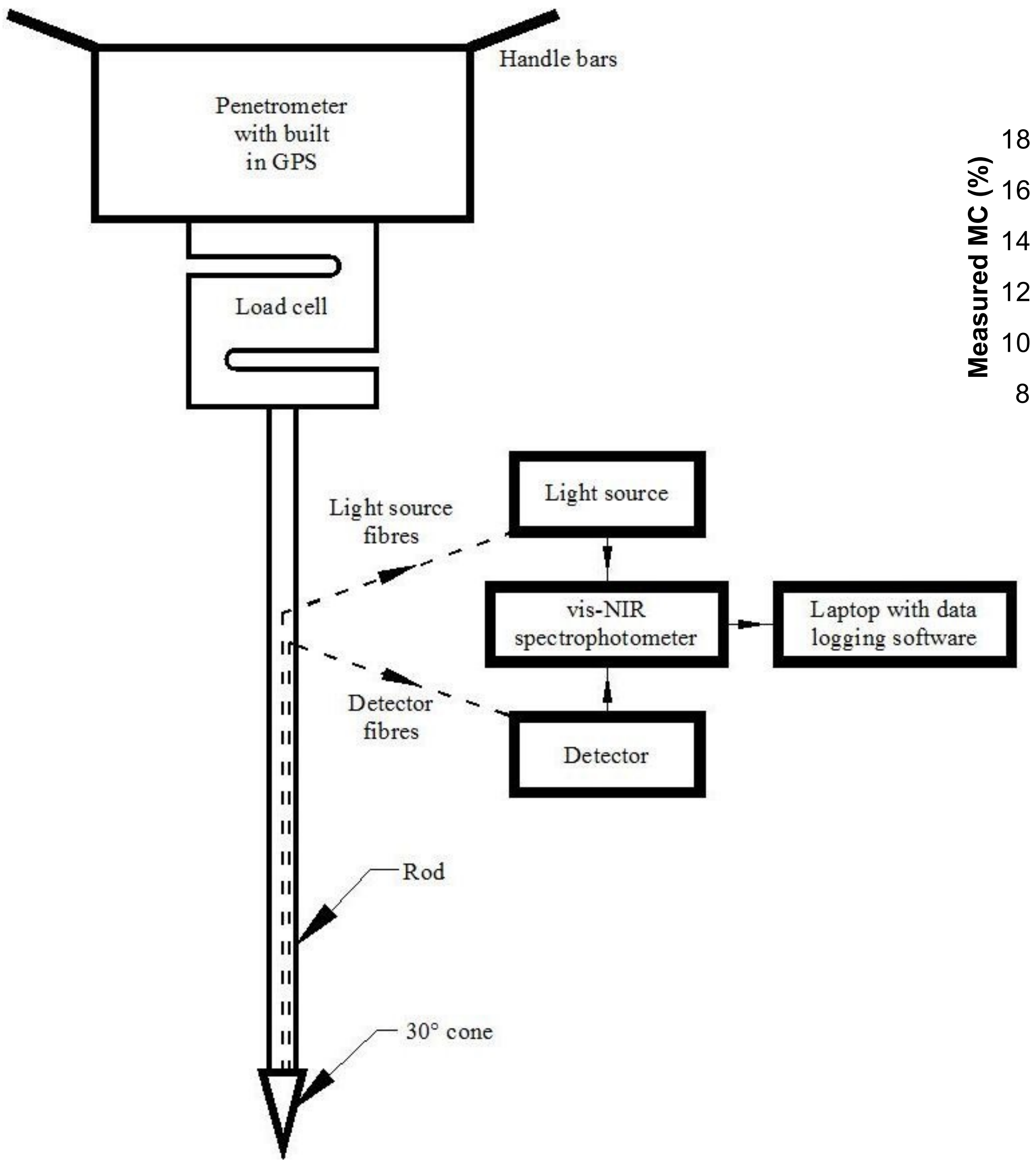
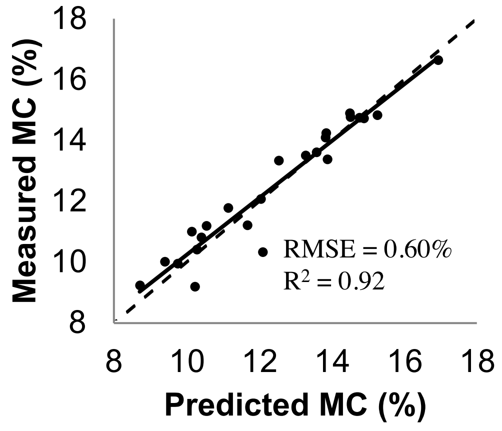
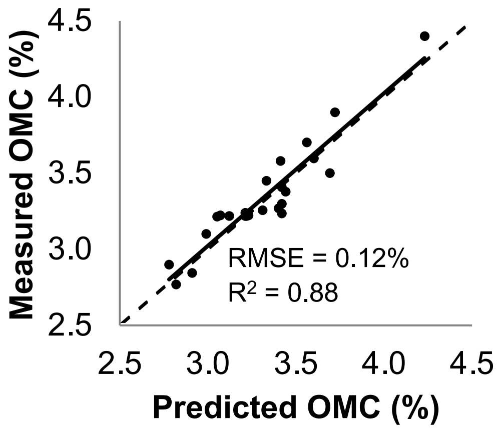
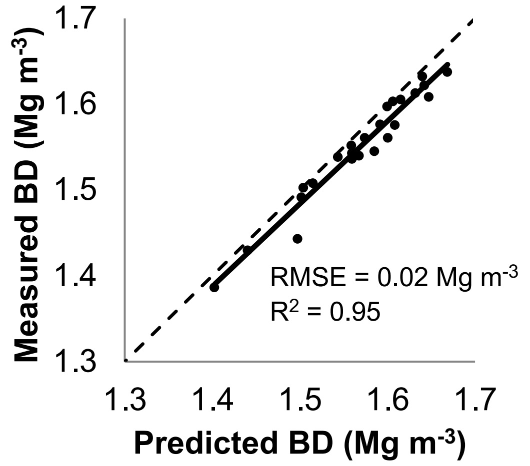
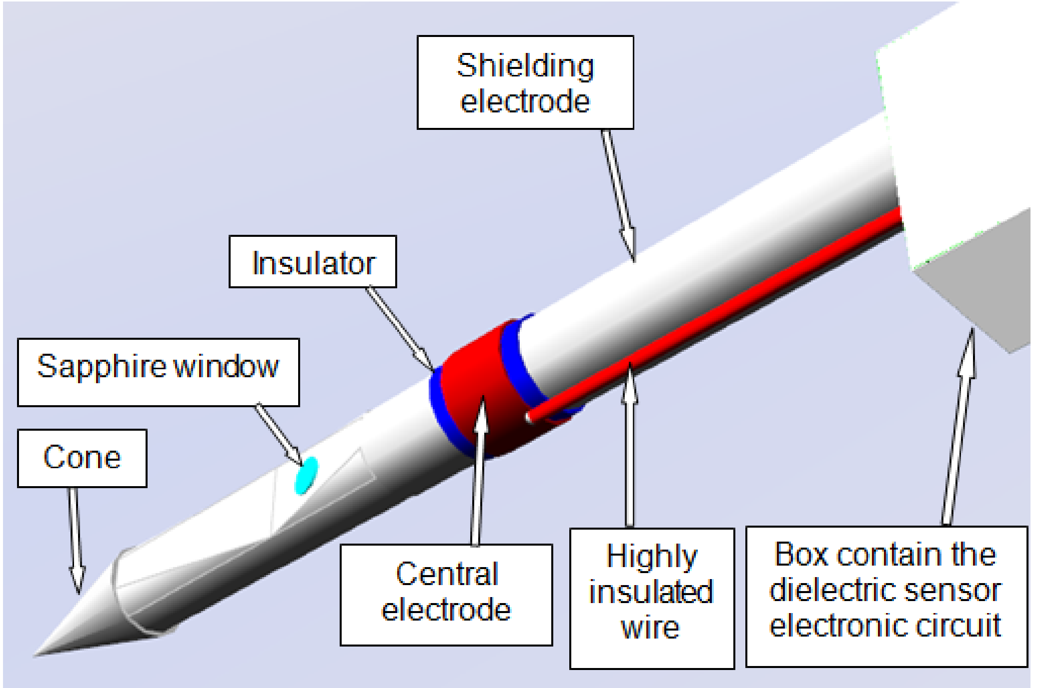
# MULTI-SENSOR ‘PORTABLE’ KIT

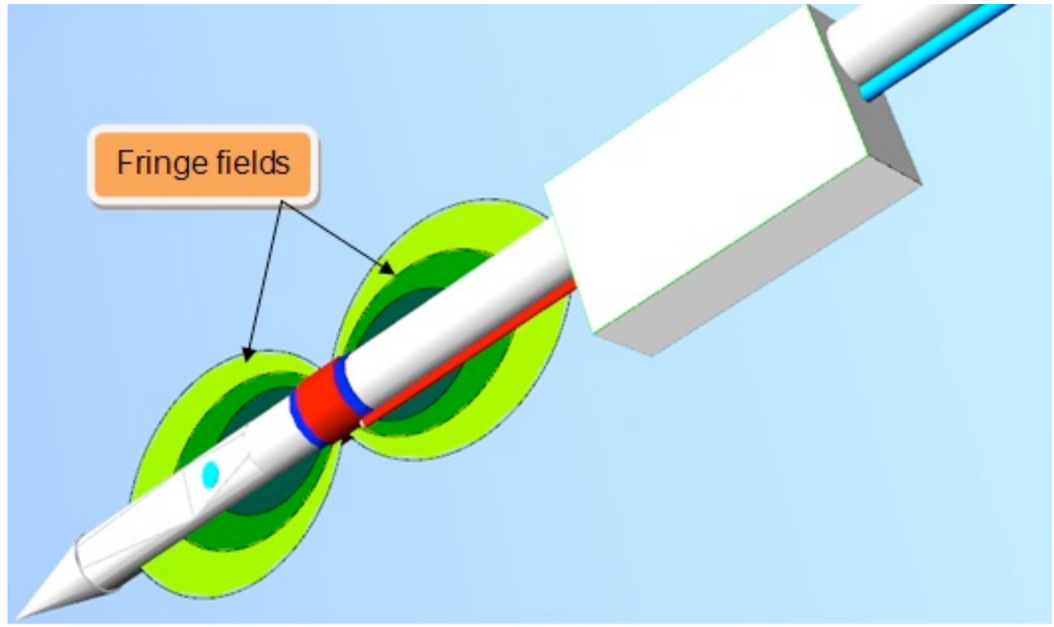


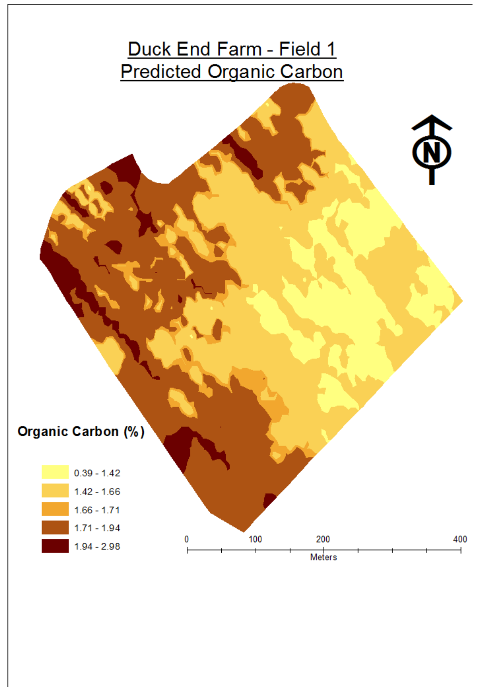



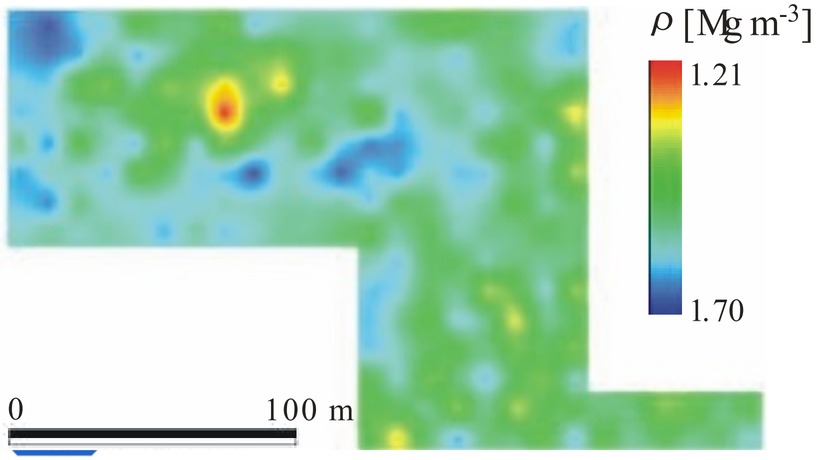

*After: Quraishi and Mouazen (2012), Soil & Tillage Research*
*Al Asadi and Mouazen (2014), Soil & Tillage Research*

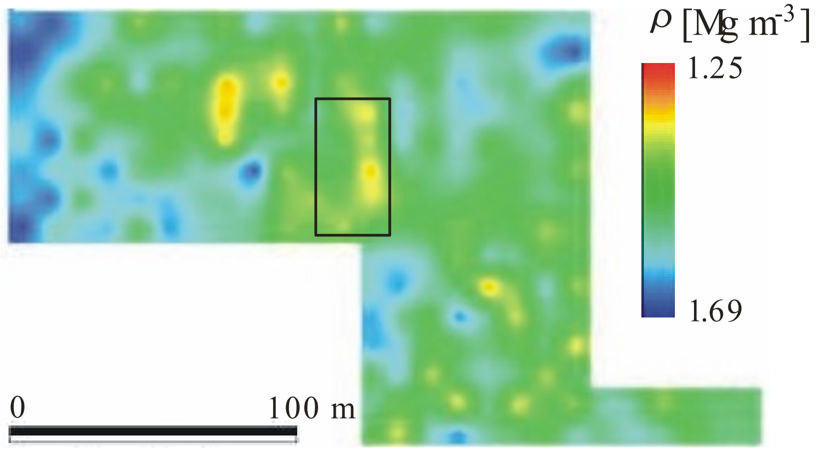
# INNOVATIVE MULTI-SENSOR 'ON-LINE' KIT

- High resolution data (1500 – 2000 readings per ha).
- Any depth between 5 – 50 cm.
- Can be fit onto different soil equipment e.g., tillage, planters & seeding machine.
- Particularly successful for organic carbon, moisture, total nitrogen, clay and organic matter.
- Less accurate for pH, phosphorous, calcium cation exchange capacity and magnesium.

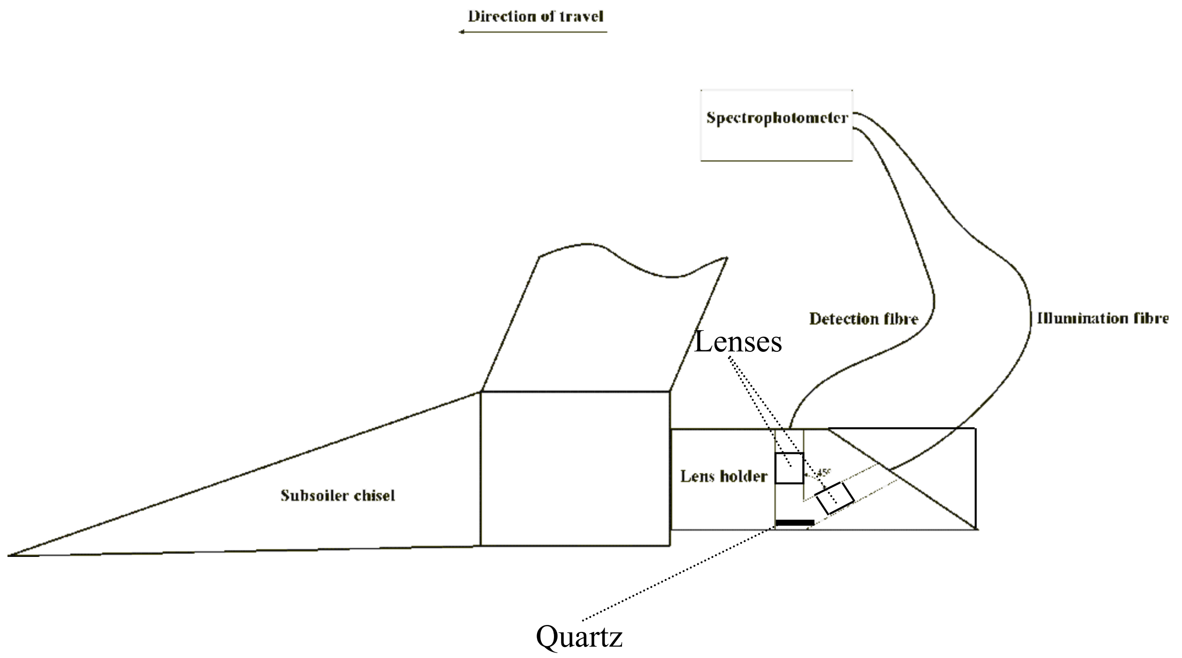




$$BD = \left( \sqrt[3]{\frac{D + 21.36MC - 73.9313d^2}{1.6734}} \right) \times (1.255 - 0.772MC)$$




Bulk density maps




On-line multi-sensor platform (Mouazen, 2006)

Mouazen, A.M. (2006). Soil Survey Device. International publication published under the patent cooperation treaty (PCT). World Intellectual Property Organization, International Bureau. International Publication Number: WO2006/015463; PCT/BE2005/000129; IPC: G01N21/00; G01N21/00.

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# PHILOSOPHY OF PRECISION AGRICULTURE

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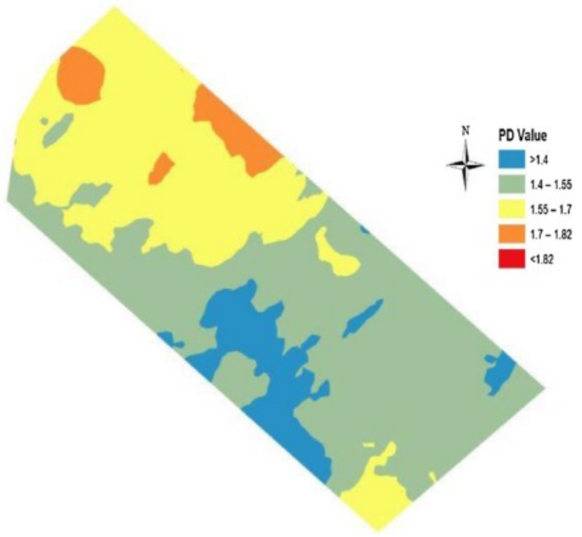
# MANAGING WITHIN FIELD VARIABILITY

Precision agriculture aims at managing spatial and temporal variabilities (at field / subfield level) by applying the right farm product (fertilisers, water for irrigation, pesticides, seeds) in the right amount, right place and the right time, using the right technologies and practices.

**The 5R principles**

- Right Product
- Right Time
- Right Rate
- Right Place
- Right technology




Considerable variability


No variability

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*After: Shamal et al., (2016). Soil and Tillage Research.*

# PRECISION AGRICULTURE SOLUTIONS

- Variable rate (site specific) applications.
- Auto-steering, and controlled traffic farming.
- Robotics.

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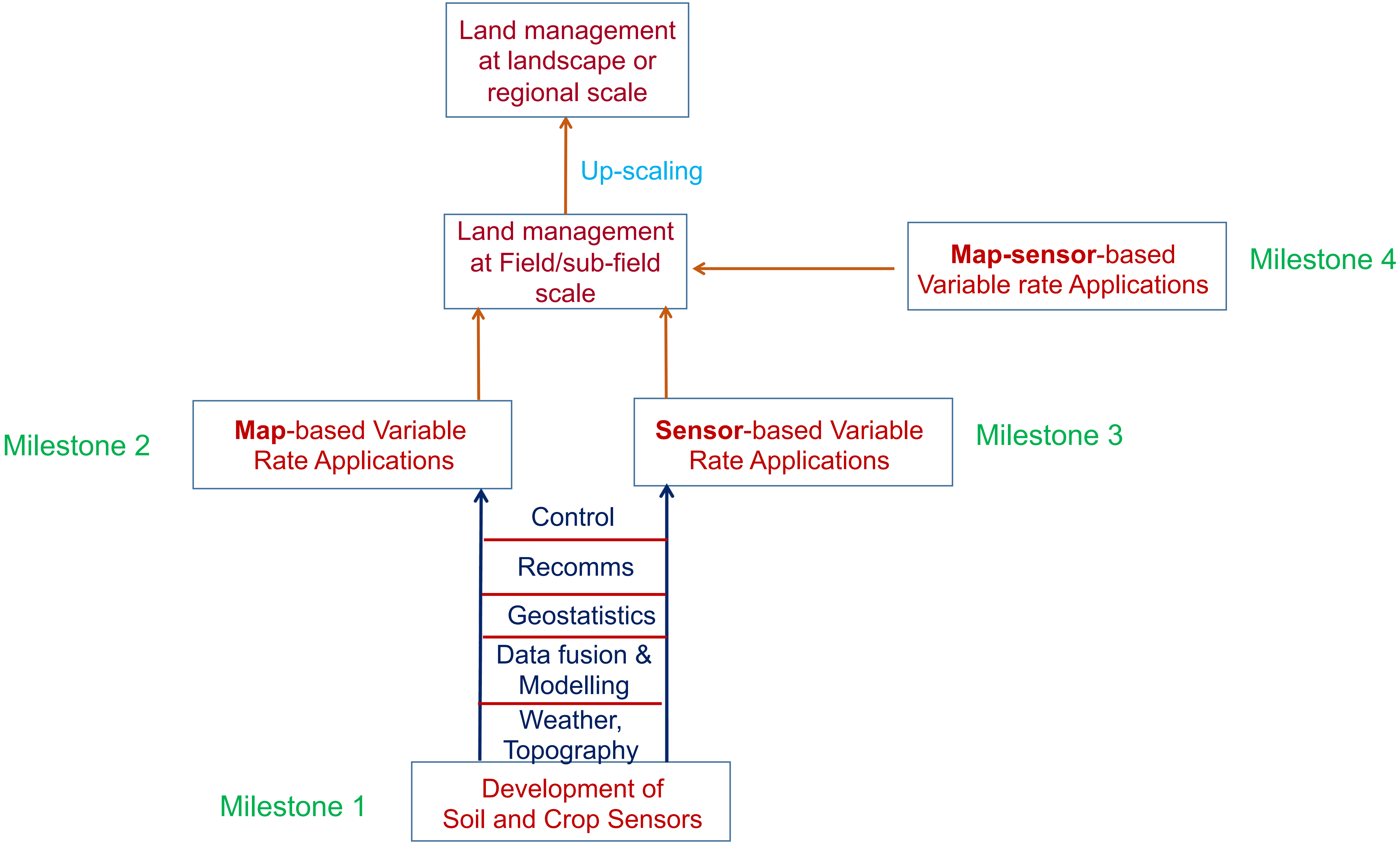
# PHILOSOPHY OF PRECISION AGRICULTURE

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# MULTI-SENSOR DATA FUSION IN PRECISION AGRICULTURE

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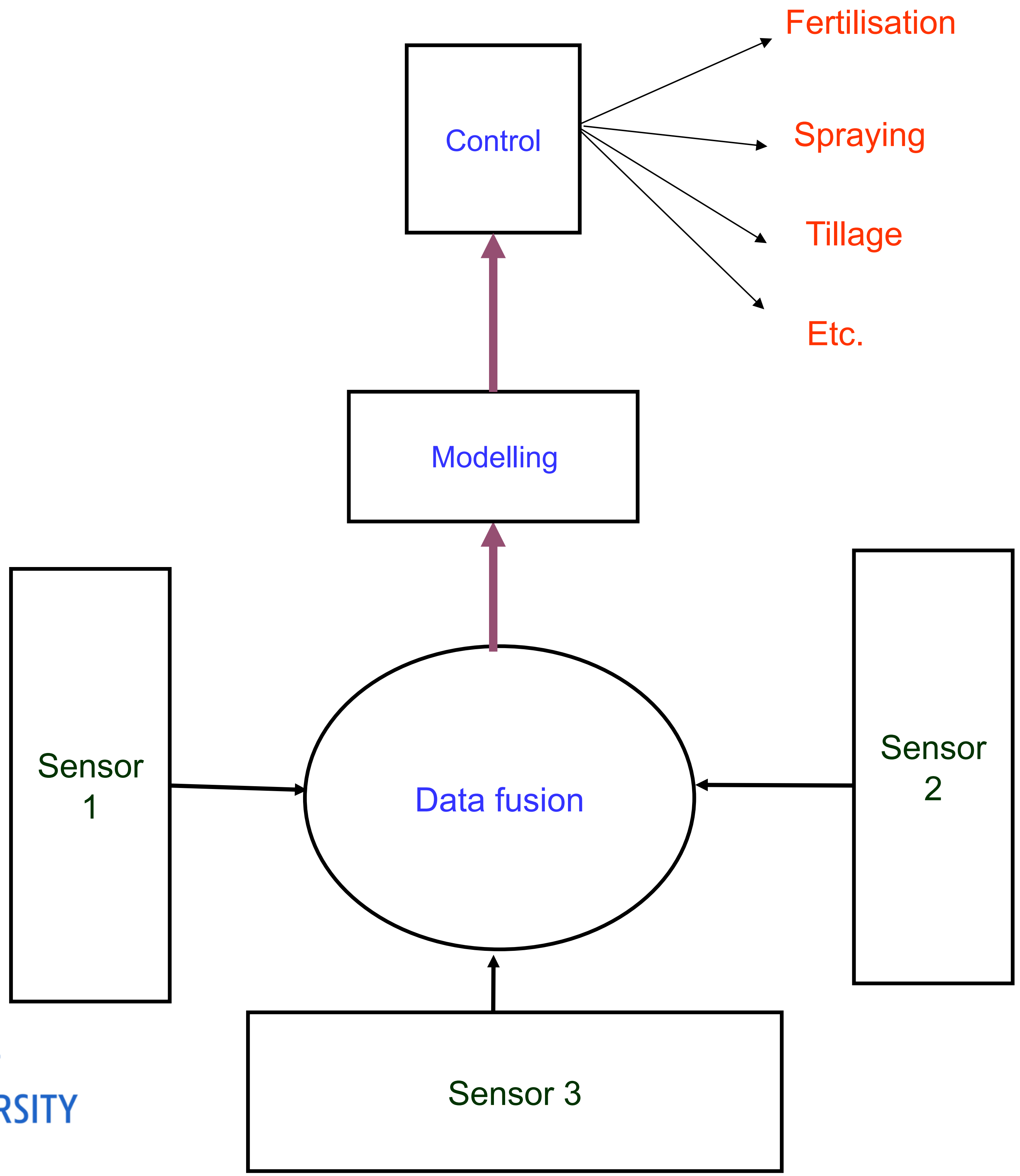
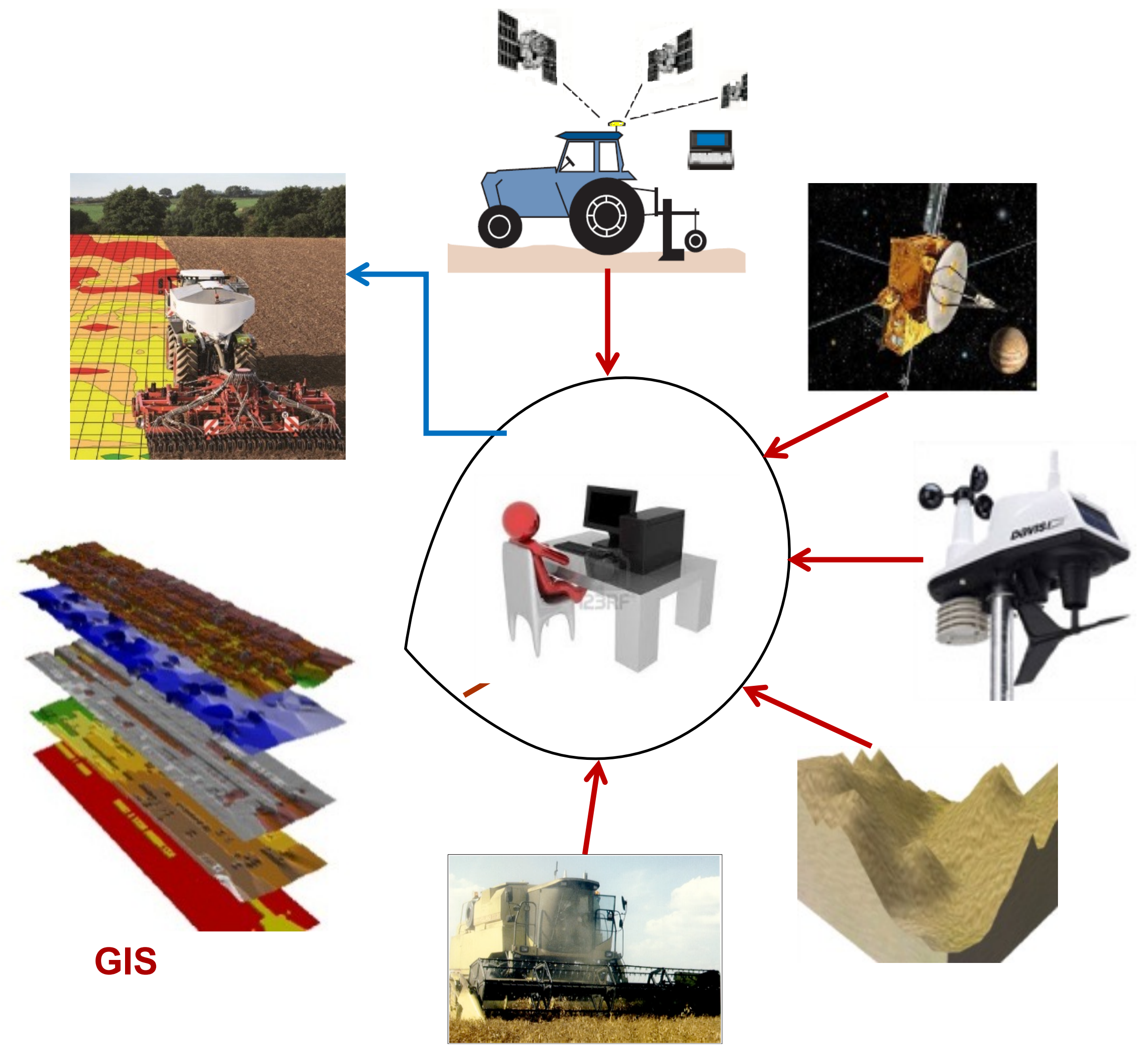
# MULTIPLE SENSORS & DATA FUSION




Multiple sensors & data fusion in PA

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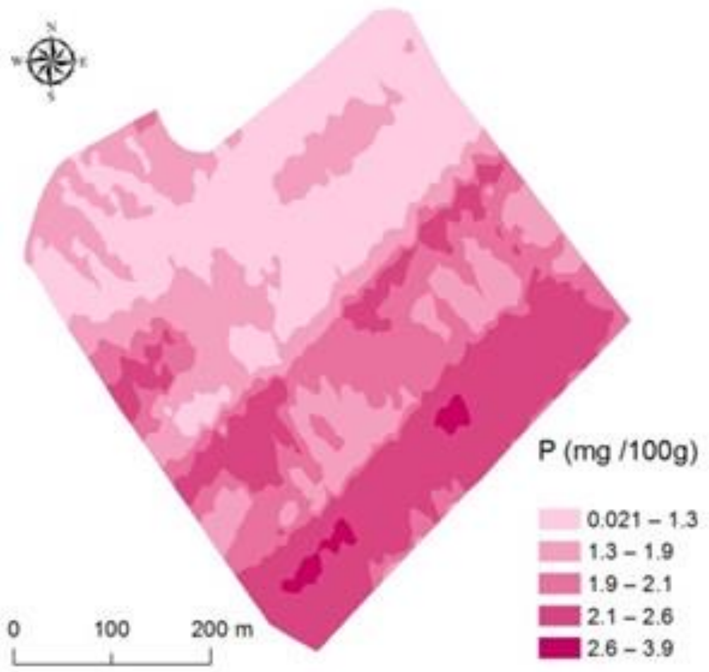
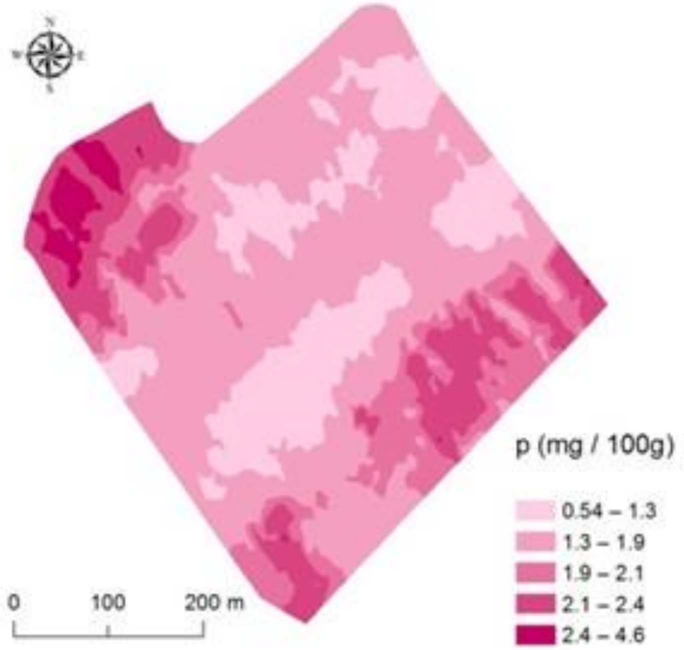
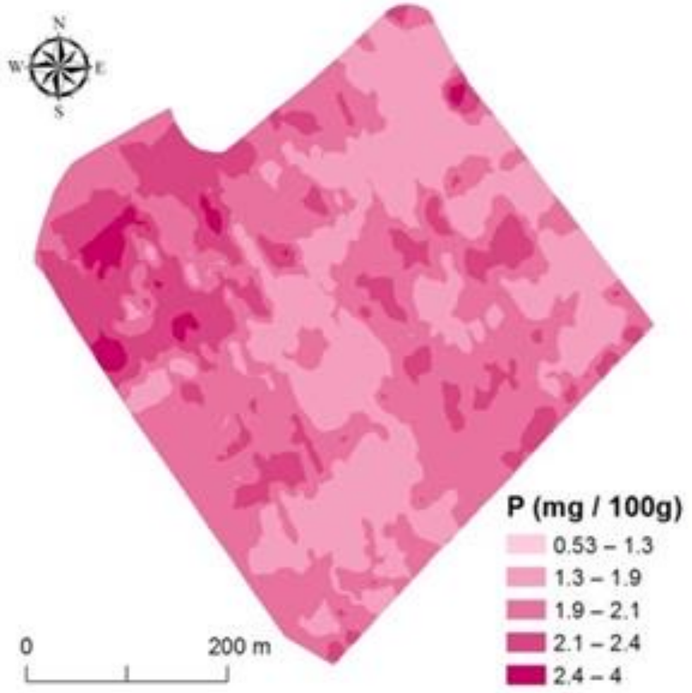
# MAP-BASED SITE SPECIFIC P FERTILISATION



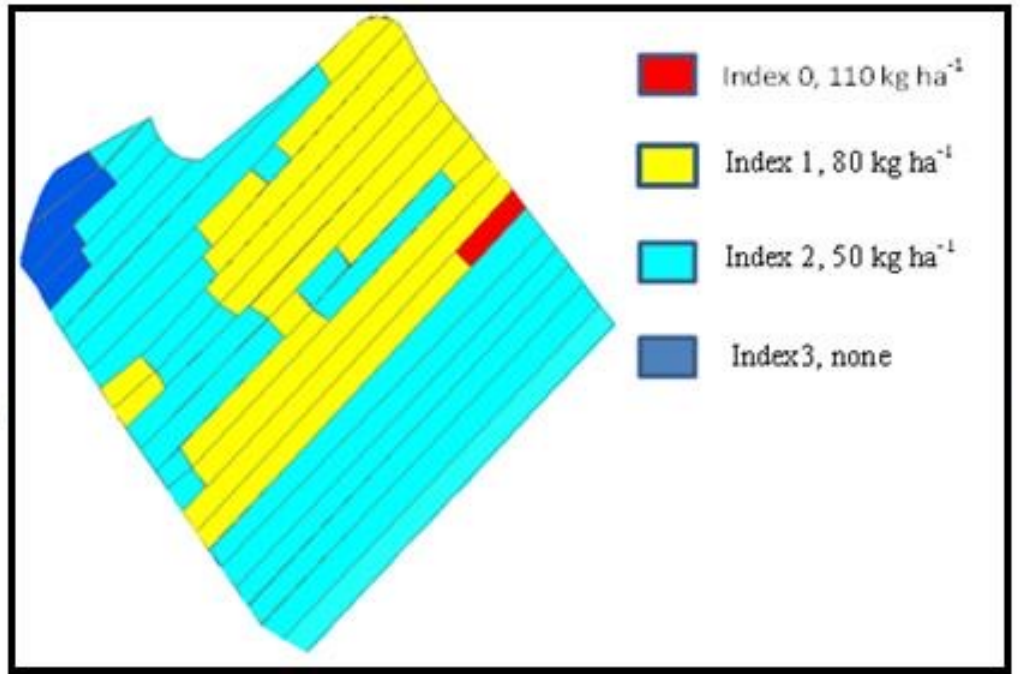

2011




2012




2013

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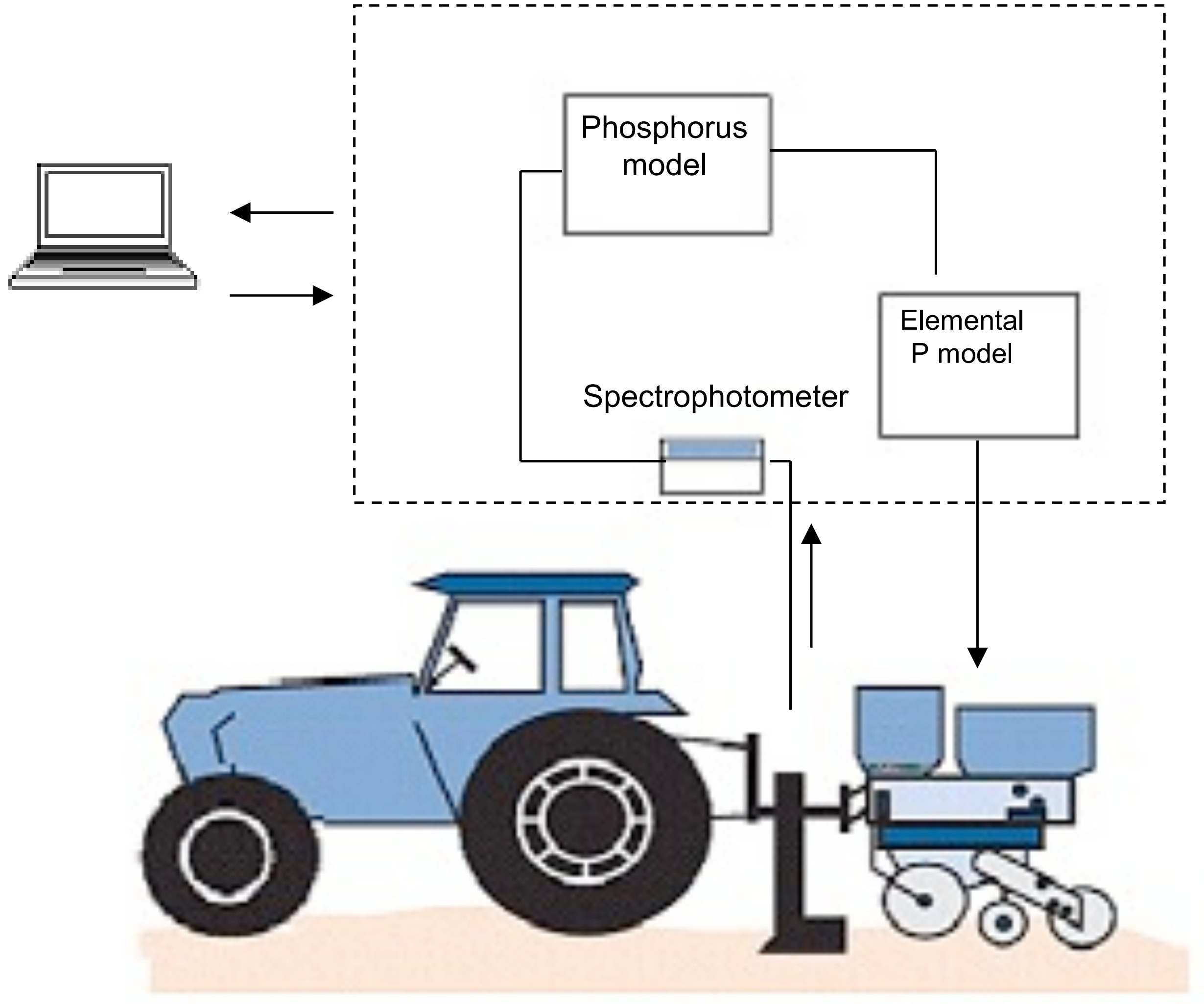
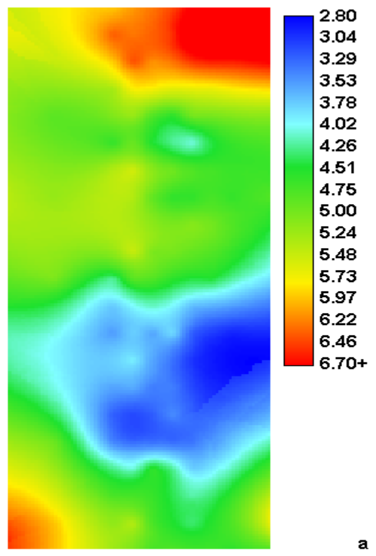
*After: Mouazen et al. (2015), Soil & Tillage Research*

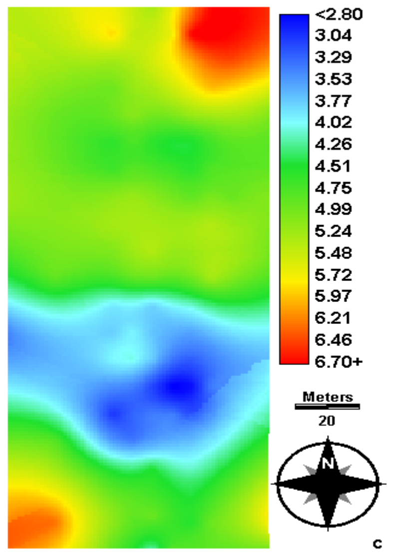
# SENSOR-BASED SITE SPECIFIC P FERTILIZATION








Lab measured P




On-line measured P

*After: Maleki et al. (2008), Biosystems Engineering*

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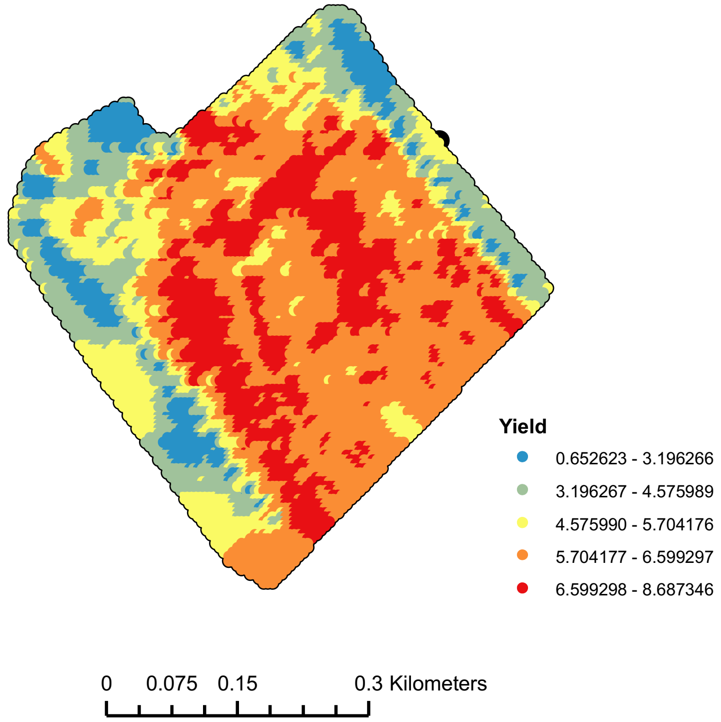
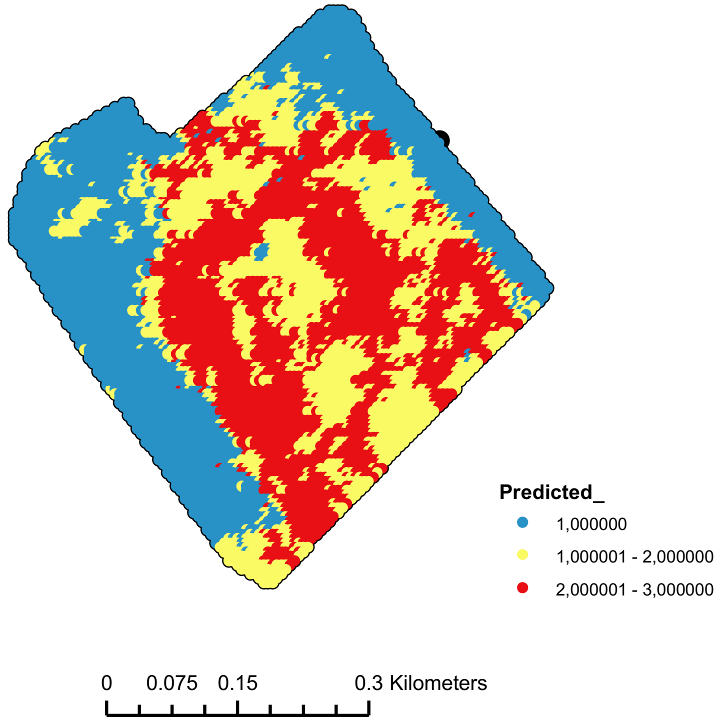
# MULTI-SENSOR & DATA FUSION FOR YIELD PREDICTION


+

+


Measured




Predicted

| Actual yield Isofrequency Class | Network Prediction (%) | | |
|---|---|---|---|
| | Low | Medium | High |
| *SKN* | | | |
| Low | 91.3 | 6.96 | 1.74 |
| Medium | 10.87 | 64.35 | 24.78 |
| High | 1.54 | 16.98 | 81.48 |
| *CP-ANN* | | | |
| Low | 90.09 | 9.29 | 0.62 |
| Medium | 9.57 | 69.86 | 20.58 |
| High | 2.11 | 24.40 | 73.49 |
| *XY-F* | | | |
| Low | 87.91 | 11.21 | 0.89 |
| Medium | 5.76 | 85.15 | 9.09 |
| High | 2.11 | 38.67 | 59.21 |

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*After: Pantazi et al. (2016), Computers and Electronics in Agriculture*

# MULTI-SENSOR & DATA FUSION FOR QUANTIFYING YIELD LIMITING FACTORS


+

+


Non-linear parametric modelling

**Calculated individual contribution to NDVI**

| | 2013 | | 2015 | |
|---|---|---|---|---|
| **Input** | May | June | April | May |
| **TC (%)** | 10.25 | 16.46 | 5.86 | 3.52 |
| **K (cmol kg$^{-1}$)** | 9.82 | 3.19 | 5.90 | 4.12 |
| **P (mg kg$^{-1}$)** | 6.00 | 12.33 | 31.31 | 0.00 |
| **pH** | 2.69 | 0.91 | 3.21 | 0.00 |
| **MC (%)** | 1.71 | 1.39 | 2.31 | 2.83 |
| **TN (%)** | 0.45 | 1.14 | 0.23 | 0.88 |
| **Total (SERR)** | 30.92 | 35.42 | 48.59 | 11.35 |

**Calculated individual contributions to yield**

| Input | 2013 | 2015 |
|---|---|---|
| **K (cmol kg$^{-1}$)** | 7.66 | 0.23 |
| **P (mg kg$^{-1}$)** | 4.28 | 1.96 |
| **TC (%)** | 3.99 | 3.23 |
| **pH** | 3.51 | 1.45 |
| **TN (%)** | 1.56 | 4.46 |
| **MC (%)** | 0.00 | 1.18 |
| **Total (SERR)** | 21.00 | 12.51 |

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# MULTI-SENSOR & DATA FUSION FOR QUANTIFYING YIELD LIMITING FACTORS


+

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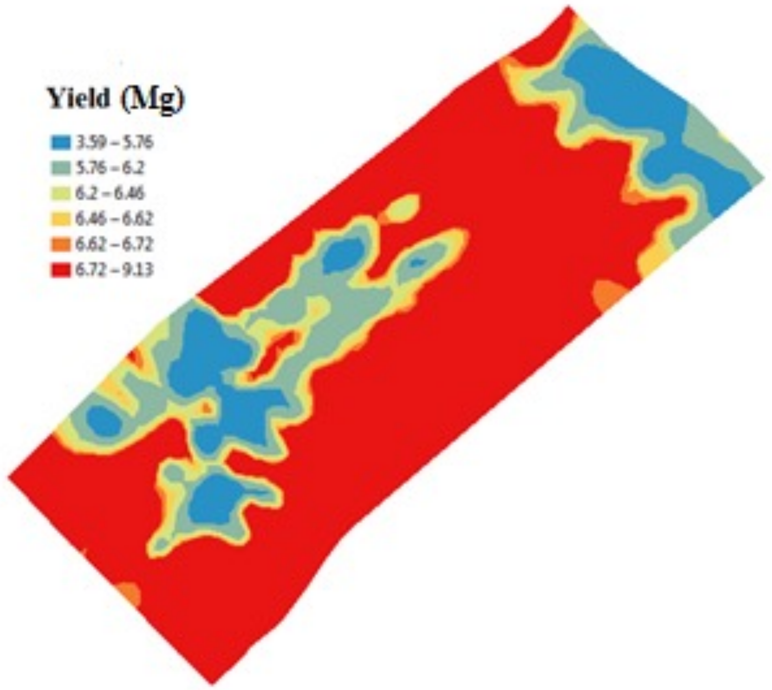
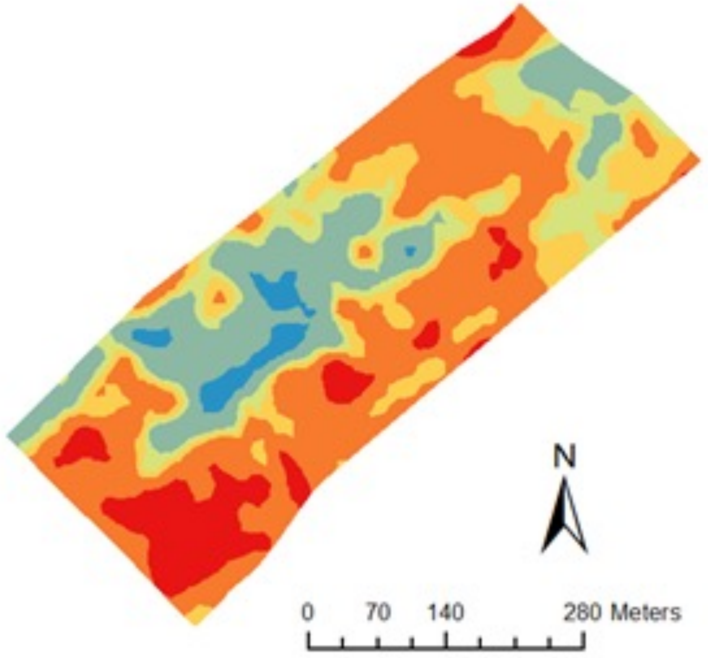
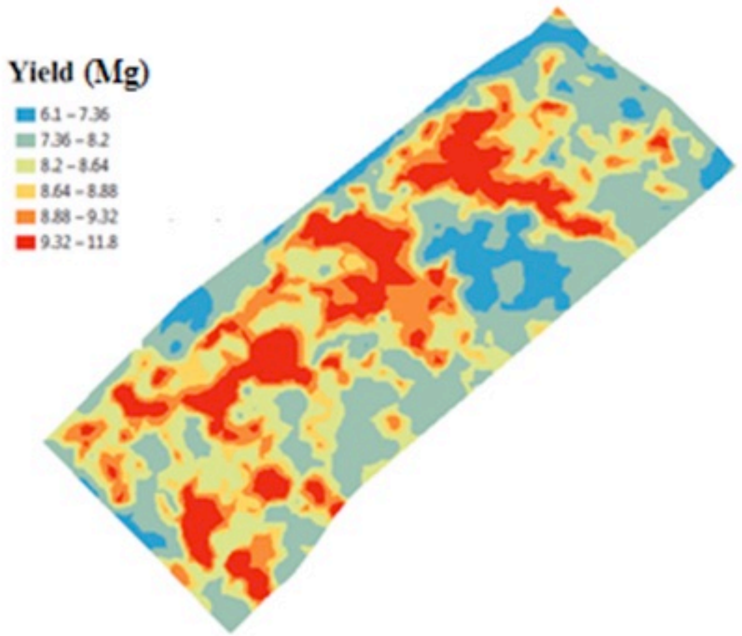


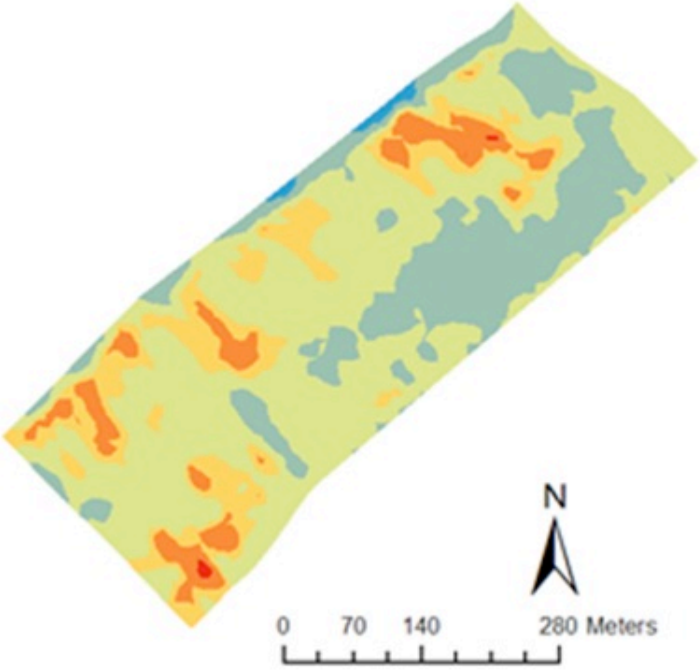

Predicted




Measured




Predicted




Measured

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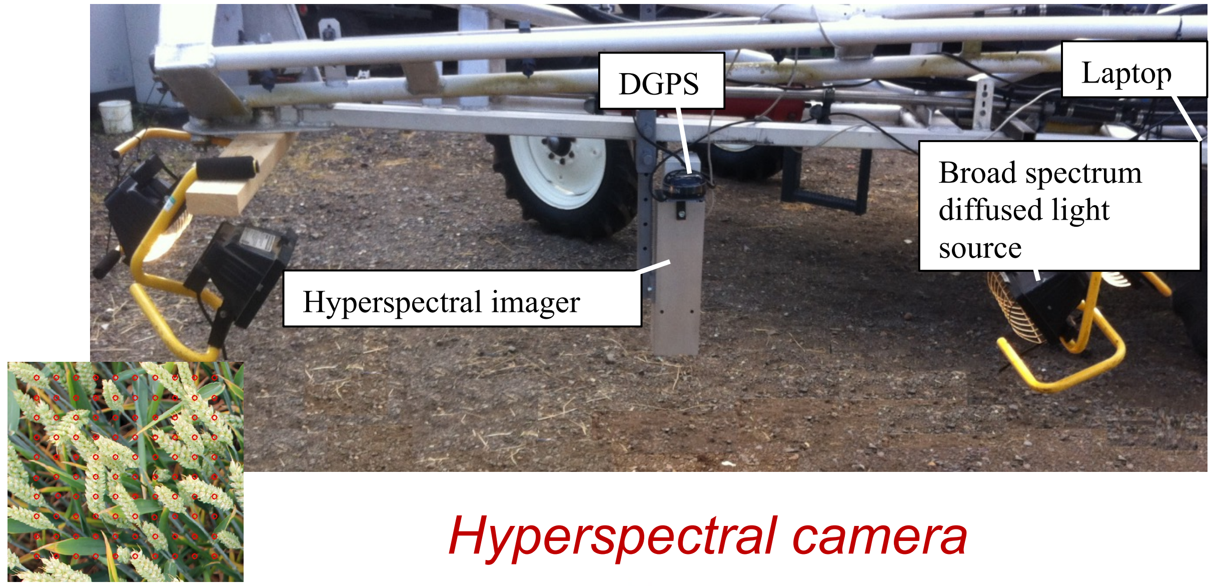
# MULTI-SENSOR & DATA FUSION FOR SITE SPECIFIC FUNGICIDE APPLICATION


*Soil sensor*

+

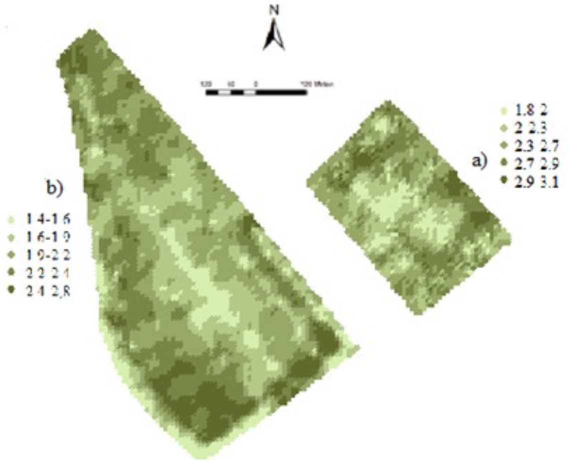


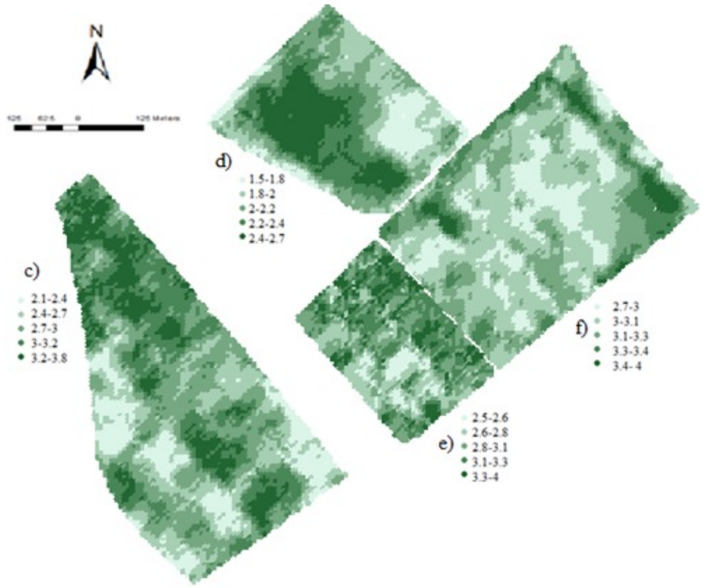

*Hyperspectral camera*

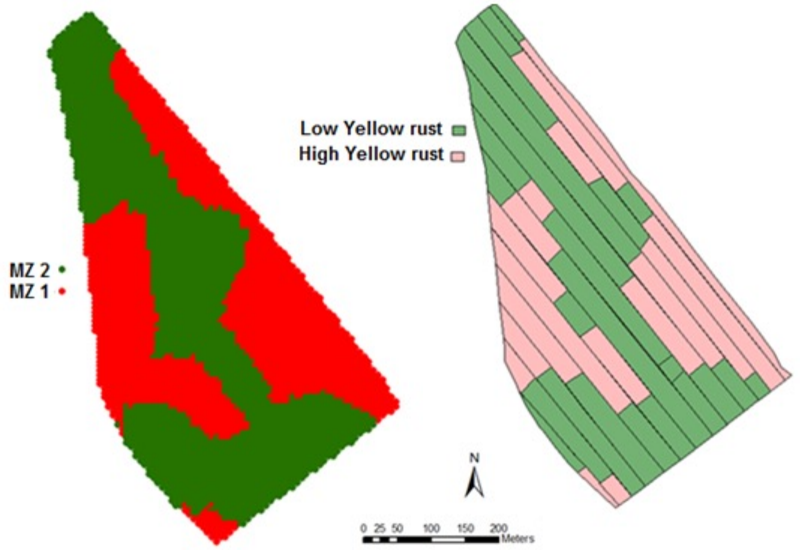
+

*NDVI*

*Yellow rust*




*MZ for VR fungicide*

**£35.31 per ha profit by VR fungicide application**

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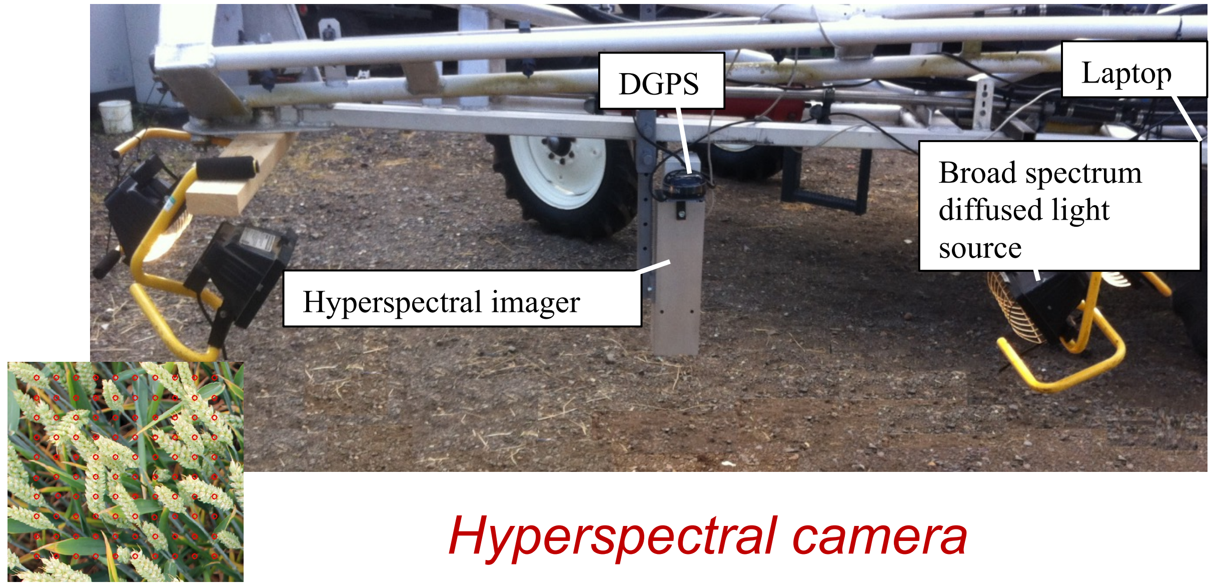
*After: Whetton et al. (2017), Computers and Electronics in Agriculture*

# MULTI-SENSOR & DATA FUSION FOR SELECTIVE HARVEST


+

*Soil sensor*

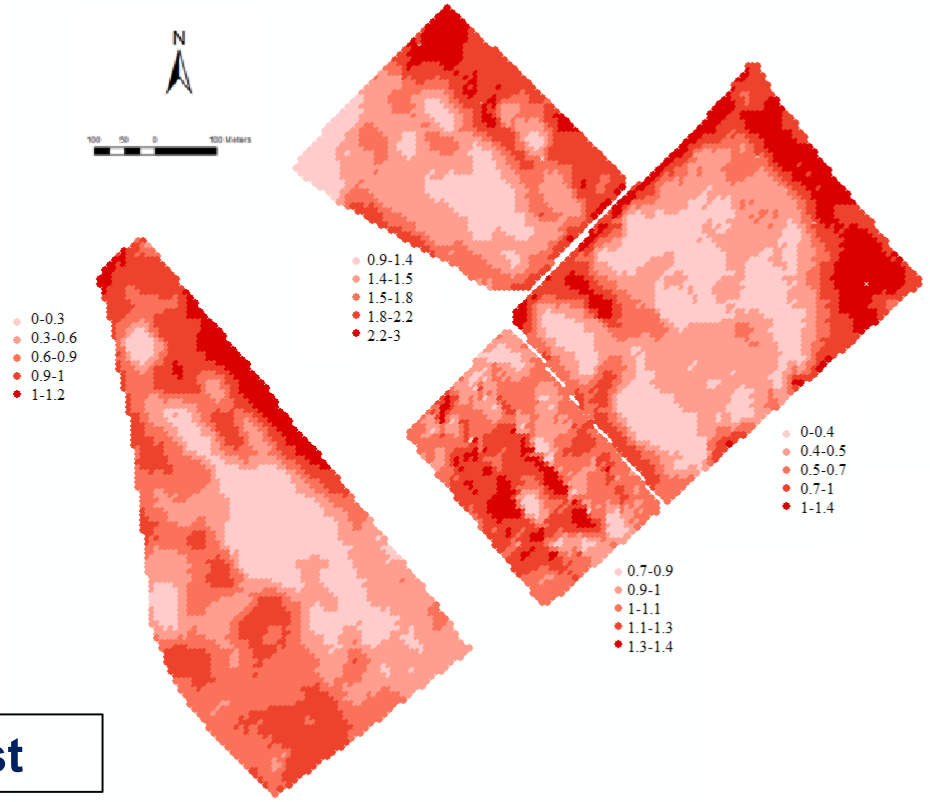


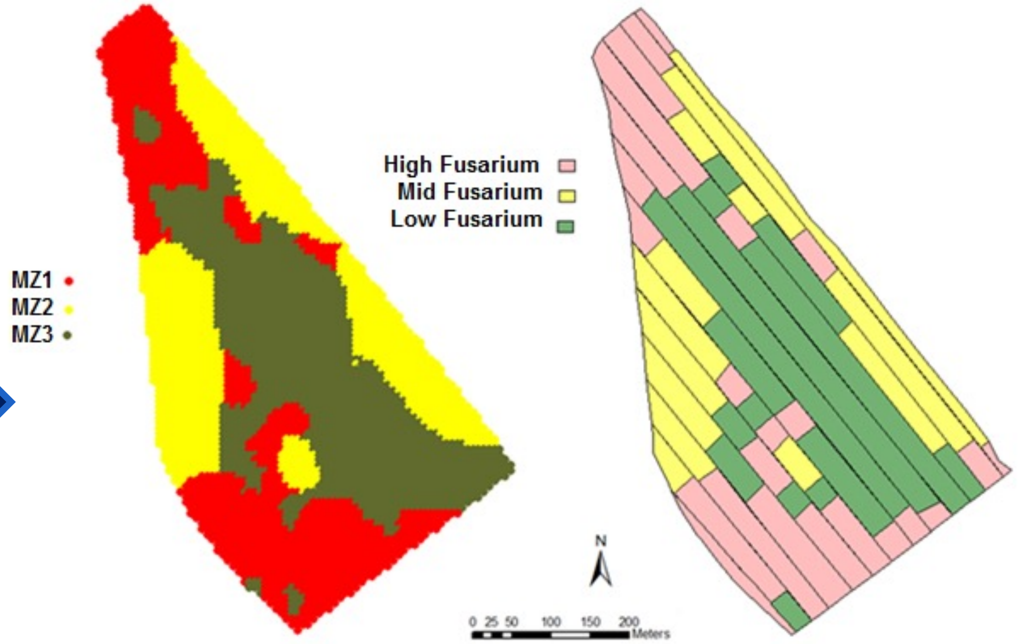

+

*Hyperspectral camera*

*NDVI*

*Fusarium*




*MZ for selective harvest*

**£48.04 per ha profit by selective harvest**

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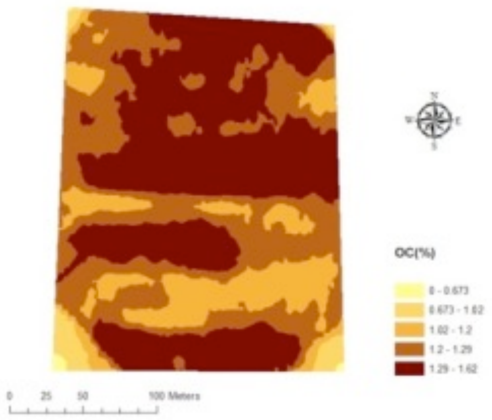
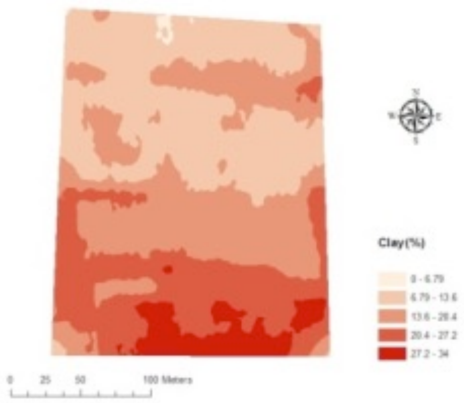
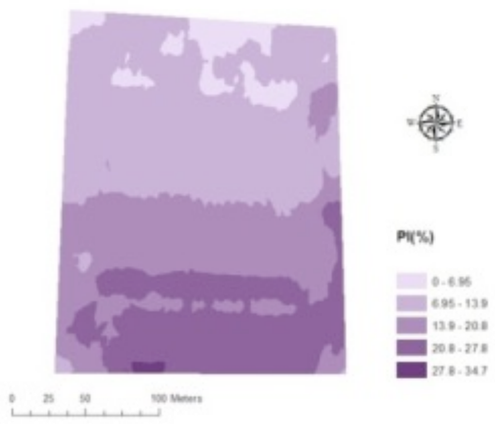
*After: Whetton et al. (2017), Computers and Electronics in Agriculture*

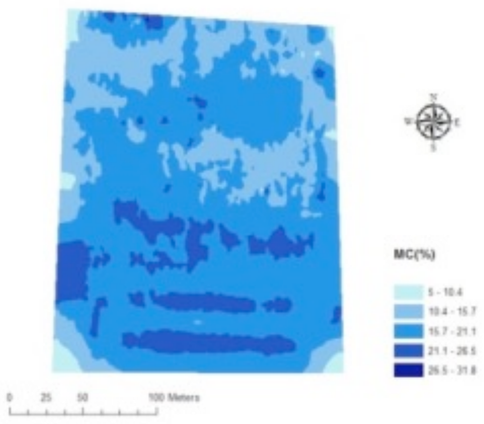
# MULTI-SENSOR & DATA FUSION FOR SITE SPECIFIC IRRIGATION

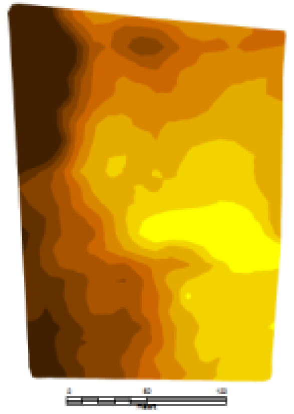
+



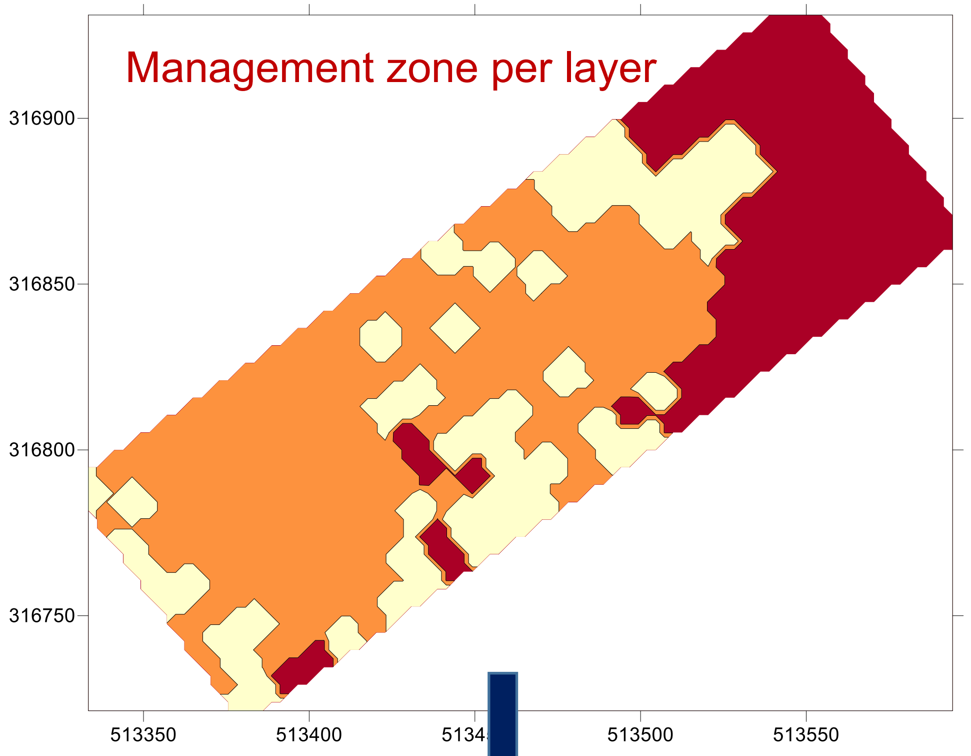



Fusion of 5 layers on soil properties




After: Mouazen et al. (2014) – Soil & Tillage Research

# MULTI-SENSOR & DATA FUSION FOR COMPACTION MANAGEMENT

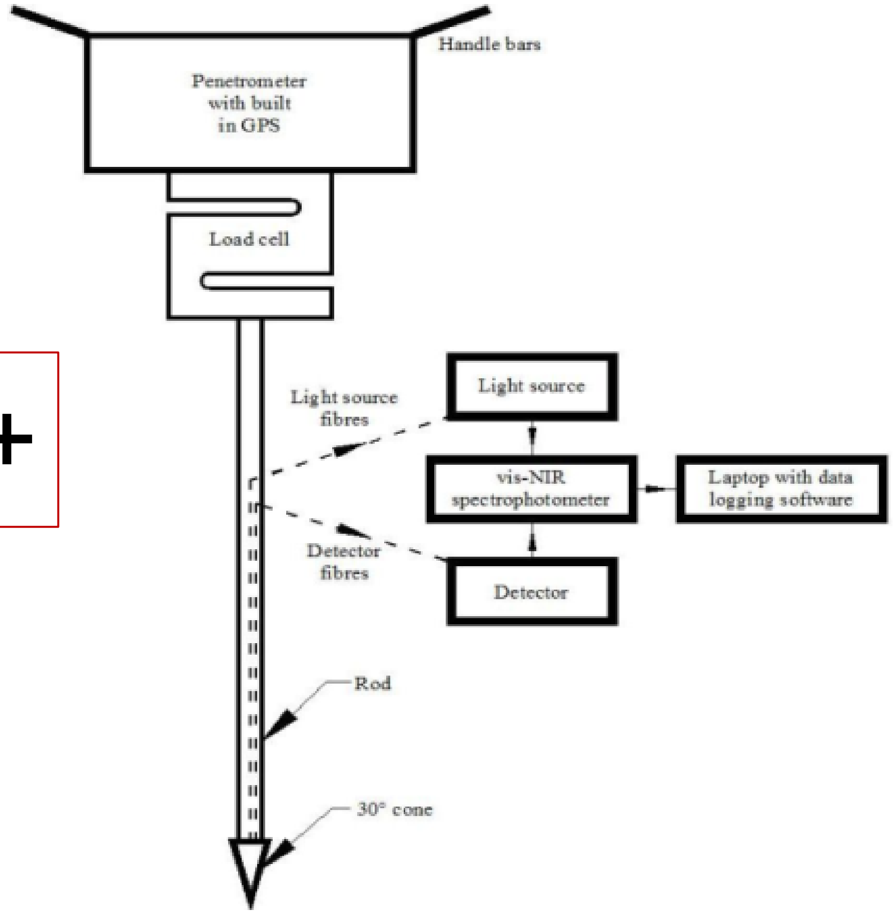



| d-Clus | 10-1 | 10-2 | 10-3 |
|---|---|---|---|

EMI

+

Penetrometer




Multi linear regression

Calculate BD & clay content per cluster

BD = f(PR, ECa, MC) per layer

Renger (1970):

Packing Density = BD + 0.009 Clay (%)

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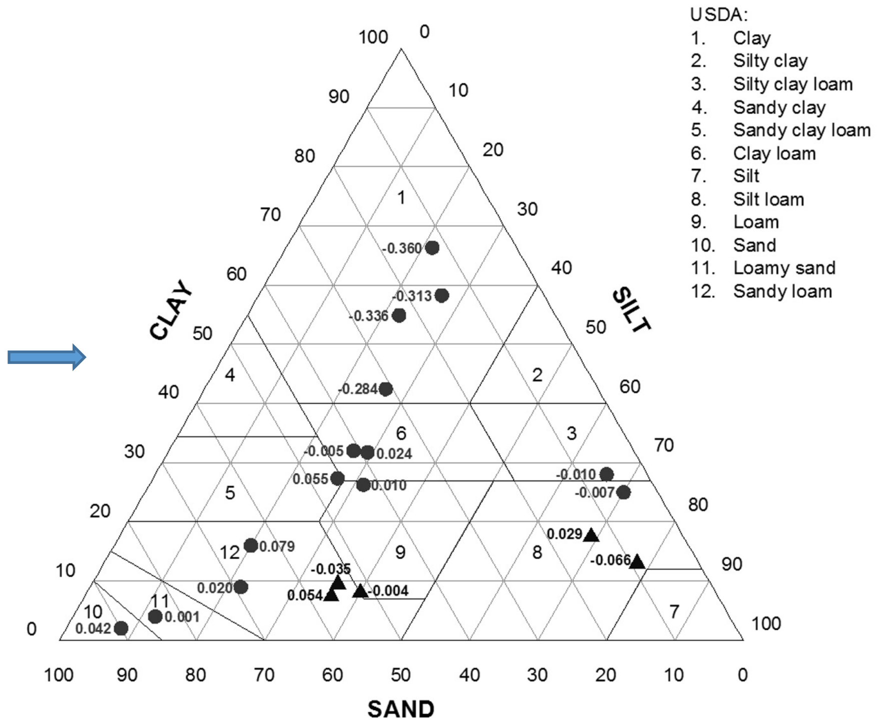
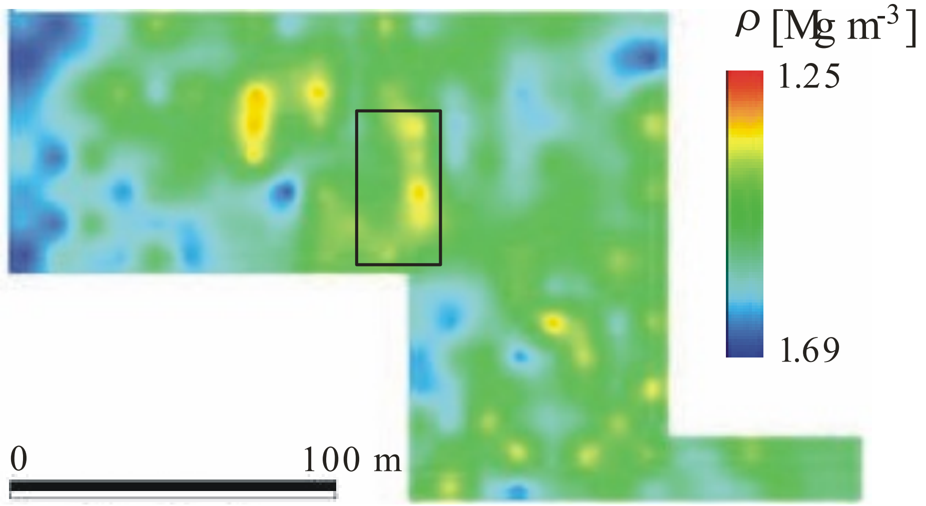
# MULTI-SENSOR & DATA FUSION FOR SITE SPECIFIC TILLAGE


$$BD = \left(\sqrt[3]{\frac{D + 21.36MC - 73.9313d^2}{1.6734}}\right) \times (1.255 - 0.772MC)$$




② Sensor-based

① Map-based

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*After: Mouazen and Ramon (2006) & (2010), Soil & Tillage Res*

*Quraishi and Mouazen (2012), Soil & Tillage Res*

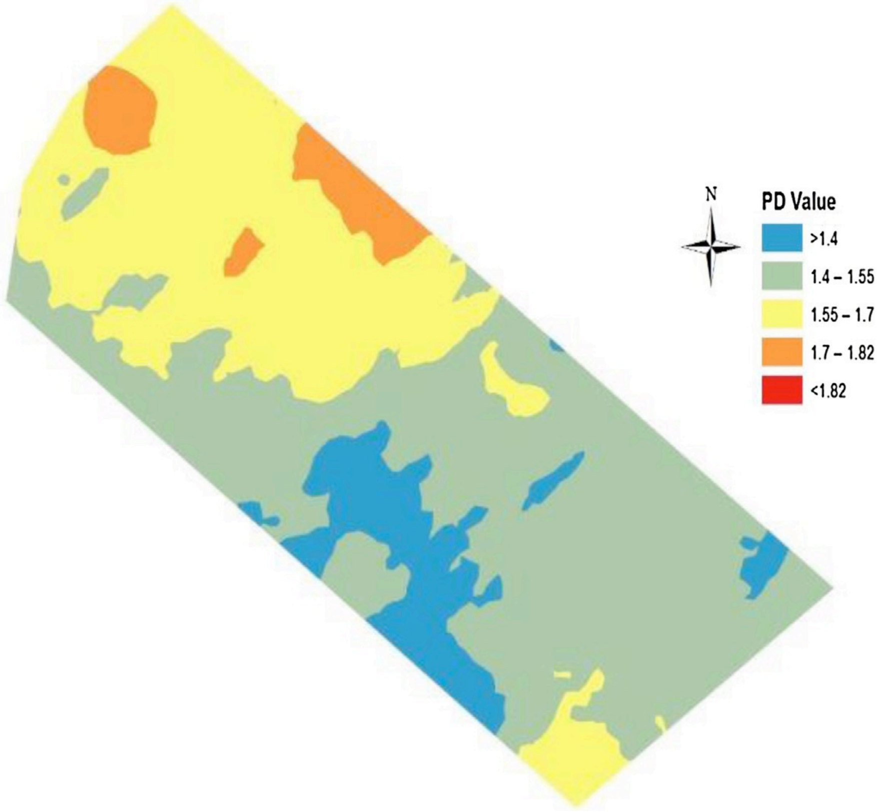
# MULTI-SENSOR & DATA FUSION FOR SITE SPECIFIC TILLAGE

Packing Density = BD + 0.009 Clay (%)

| PD value | Crop growth condition |
| --- | --- |
| < 1.40 | Below optimum range |
| 1.40-1.55 | Lower optimum range |
| 1.55-1.70 | Upper optimum range |
| 1.70-1.82 | Lower limiting range |
| > 1.82 | Upper limiting range |

- **50% reduction in energy consumption**
- **66-78% reduction in $CO_2$ emission**






*After: Shamal et al. (2016), Soil & Tillage Research*

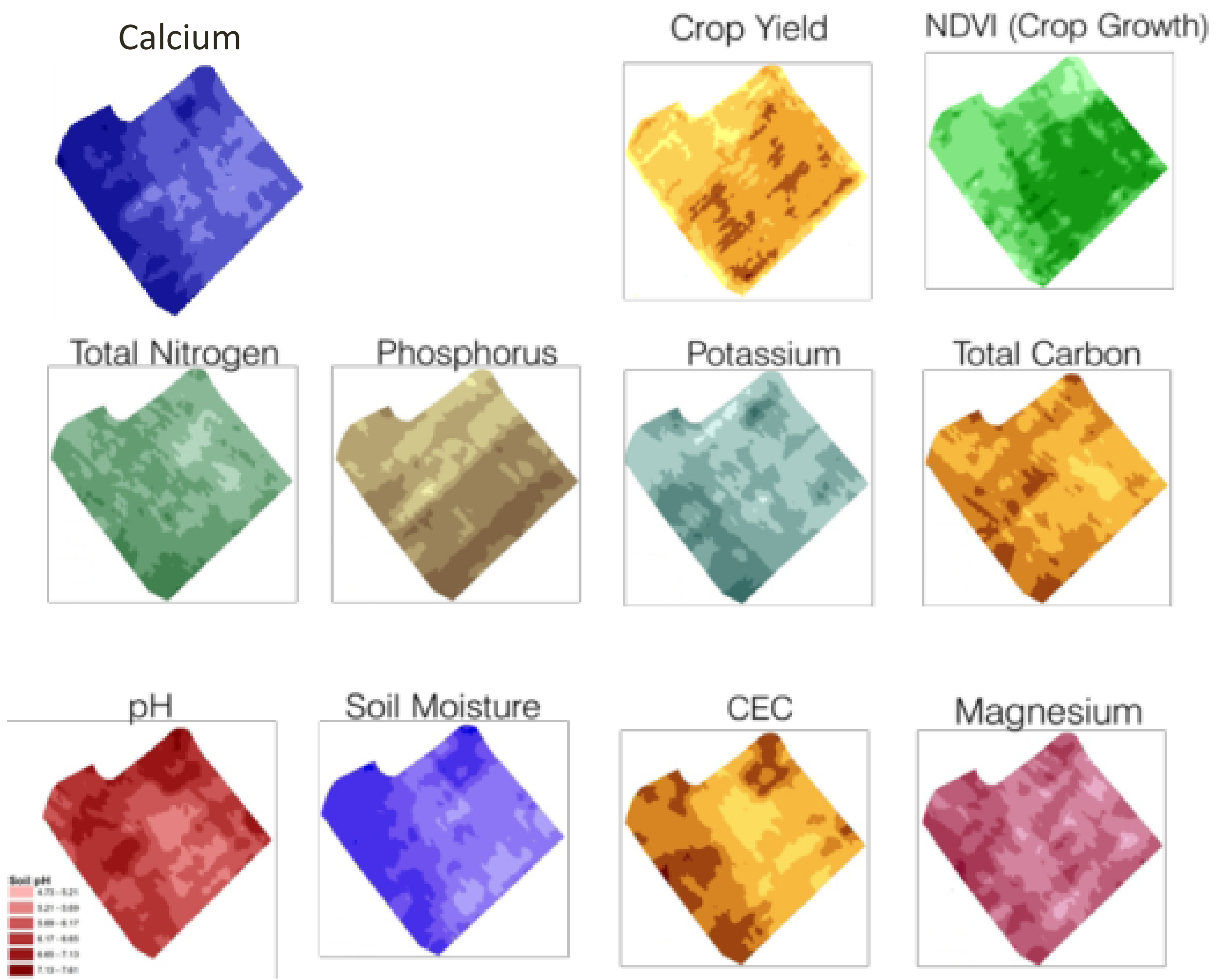
# MULTI-SENSOR & DATA FUSION FOR VR N FERTILISATION

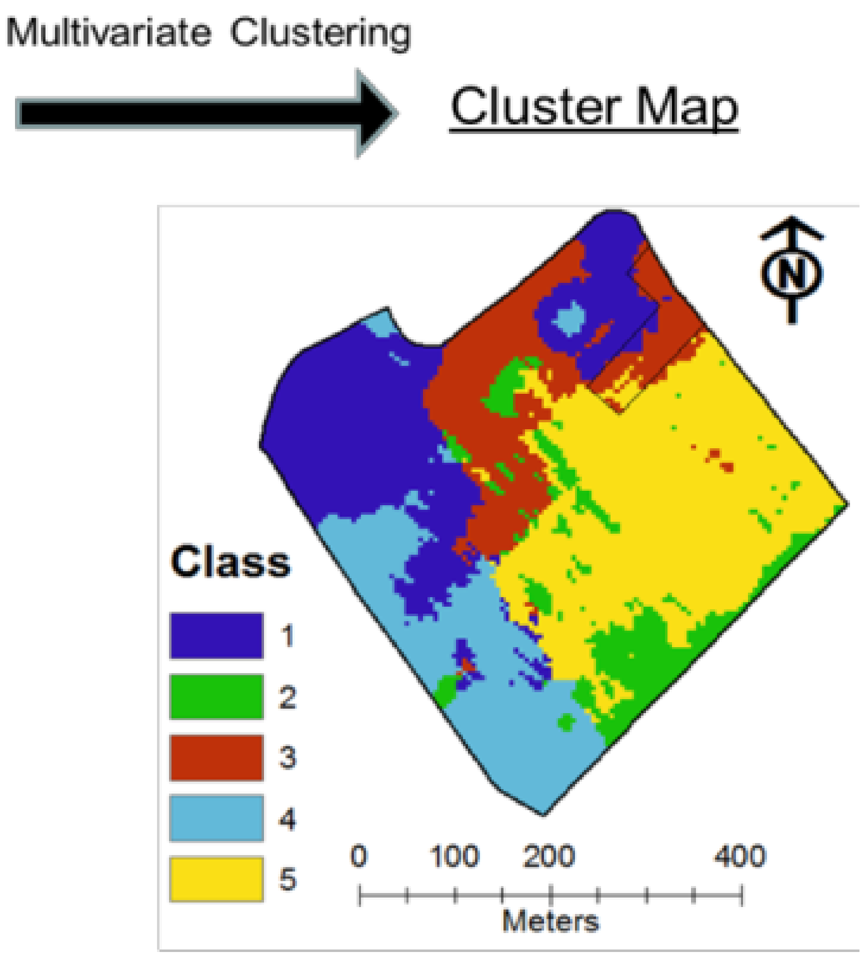
- Common Raster Grid Creation
- Data Fusion by Clustering
- Mapping


+

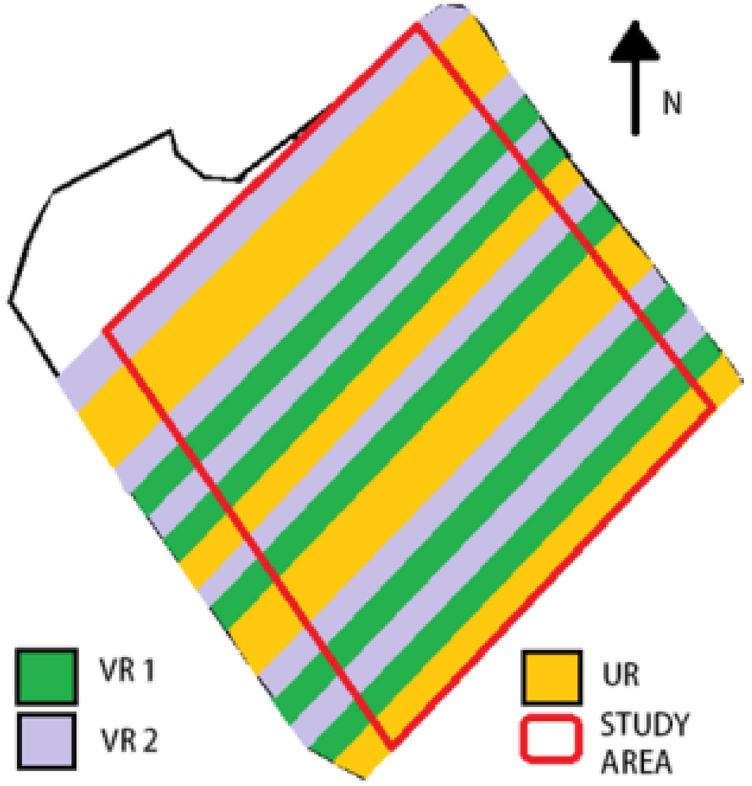
+

+


**Fertility zone map**




**N application map**

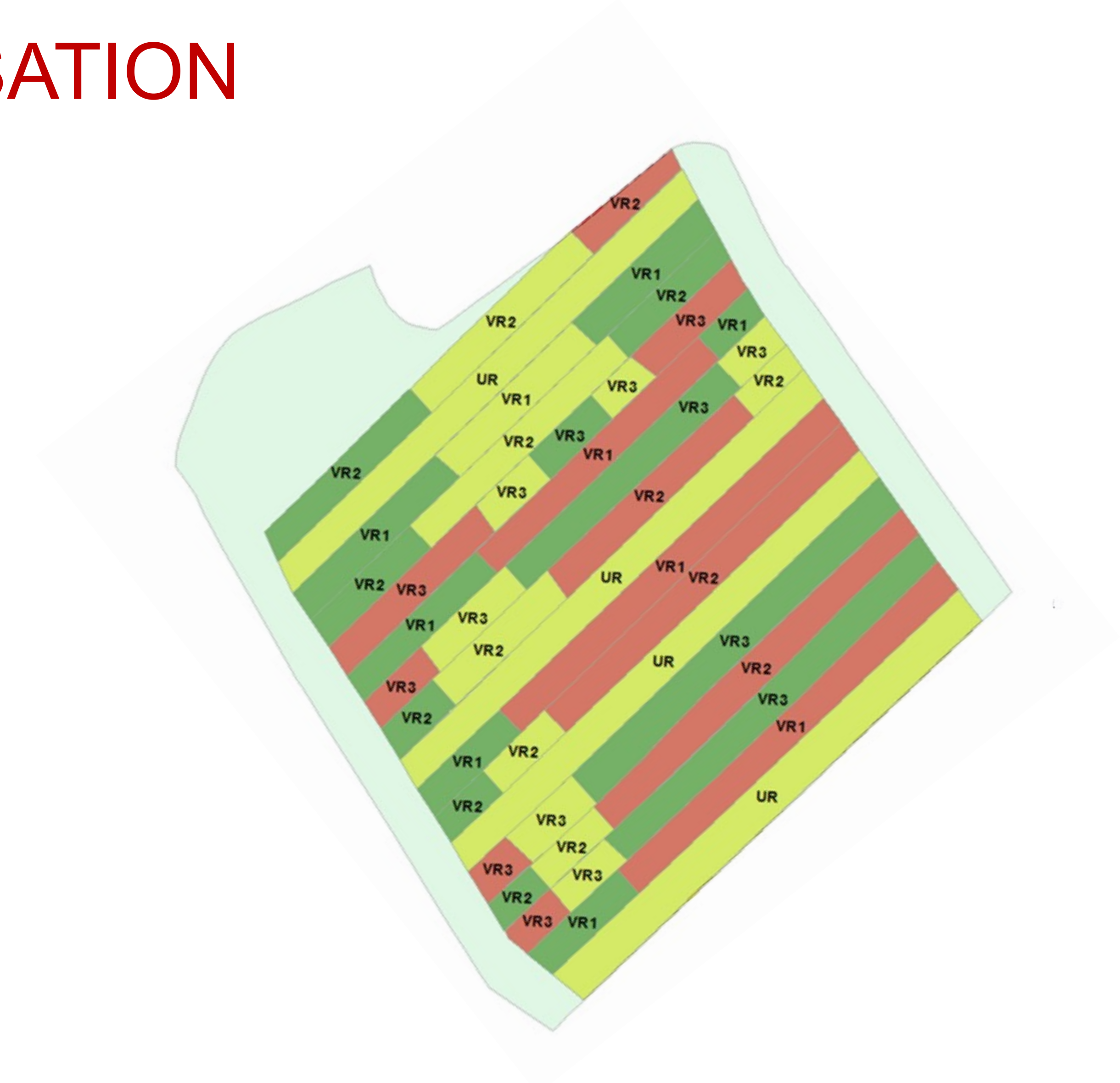


*After: Halcro el al. (2013) – 3rd International Workshop on PSS*
*Nawar et al. (2017) – Advances in Agronomy*

# COST-BENEFIT ANALYSIS OF VR N FERTILISATION

| | N fertilisation |
|---|---|
| Projected net benefit to farmer per ha per year (**innovative IVR-UR**) | **£49.8** |
| Projected net benefit to farmer per ha per year **(innovative IVR-TVR)** | **£25** |

**£72.8 per ha extra profit to farmer for N, P and lime**



UR – Uniform rate
TVR – Traditional variable rate (NDVI)
IVR – Innovative variable rate (on-line soil data & NDVI)

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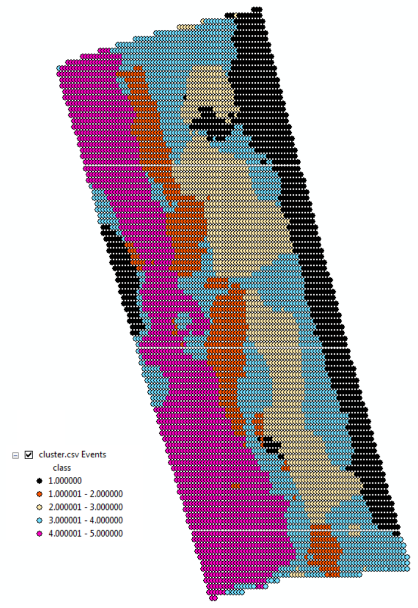
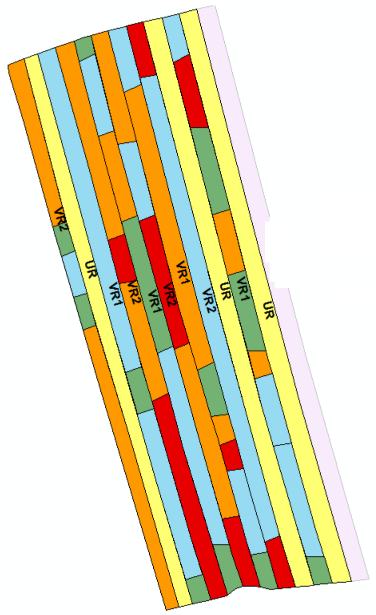
*FarmingTruth – ESA – Unpublished data*

# PROFITABILITY - VR N FERTILISATION






| Field | Profitability IVR vs UR (€) | | Profitability IVR vs TVR (€) | | Fertiliser use IVR vs UR (€) | | Fertiliser use IVR vs TVR (€) | |
|---|---|---|---|---|---|---|---|---|
| | 2014 | 2015 | 2014 | 2015 | 2014 | 2015 | 2014 | 2015 |
| UK* | 24 | 46.56 | 15.6 | 22.2 | -0.07 | -0.52 | 10.94 | 3.18 |
| Germany | - | 98.81 | - | 39.21 | - | -10.91 | - | -21.81 |
| Turkey** | 304.5 | 355.17 | - | 50.55 | - | -1.16 | - | - |

* VR N application in Fields in UK and Germany
** VR N, P & K in Field in Turkey

UR – Uniform rate
TVR – Traditional variable rate (NDVI)
IVR – Innovative variable rate (on-line soil data & NDVI)

# ENVIRONMENTAL ANALYSES OF N FERTILISATION (£)

| Impact | Receptor | Unit indicator | Cost | | Annual non-market benefit per sensor |
|---|---|---|---|---|---|
| | | | **Value** | **Unit** | |
| **Climate change impact** | Atmosphere | $CO_2e$ | 58 | £ $t^{-1}$ | 98,832 |
| | | $N_2O$ | 17,727 | £ $t^{-1}$ | |
| **Air quality regulation** | Atmosphere | $NH_3$ | 1,933 | £ $t^{-1}$ | 11,565 |
| **Environmental water quality regulation** | Rivers, canals | $NO_3$-N | 180 | £ $t^{-1}$ | 14,919 |
| | Freshwater lakes | P | 1,573 | £ $t^{-1}$ | |
| | Transitional water | $NO_3$-N | 10 | £ $t^{-1}$ | 829 |
| **Drinking water regulation** | Drinking water | $NO_3$-N | 192 | £ $t^{-1}$ | 15,913 |
| | | | | **Total benefit per sensor per year** | **142,058** |

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*FarmingTruth – ESA – Unpublished data*

# MULTI-SENSOR & DATA FUSION FOR SITE SPECIFIC MANURE APPLICATION

**KINGs**

**VR1:**

Low Fertility = (green)
Medium Low Fertility = (orange)
Medium High Fertility = (red)
High Fertility = (light blue)

**ROBIN HOOD**

**VR2:**

Low Fertility = (light blue)
Medium Low Fertility = (red)
Medium High Fertility = (orange)
High Fertility = (green)

**UR:** All fertility zones = (yellow)

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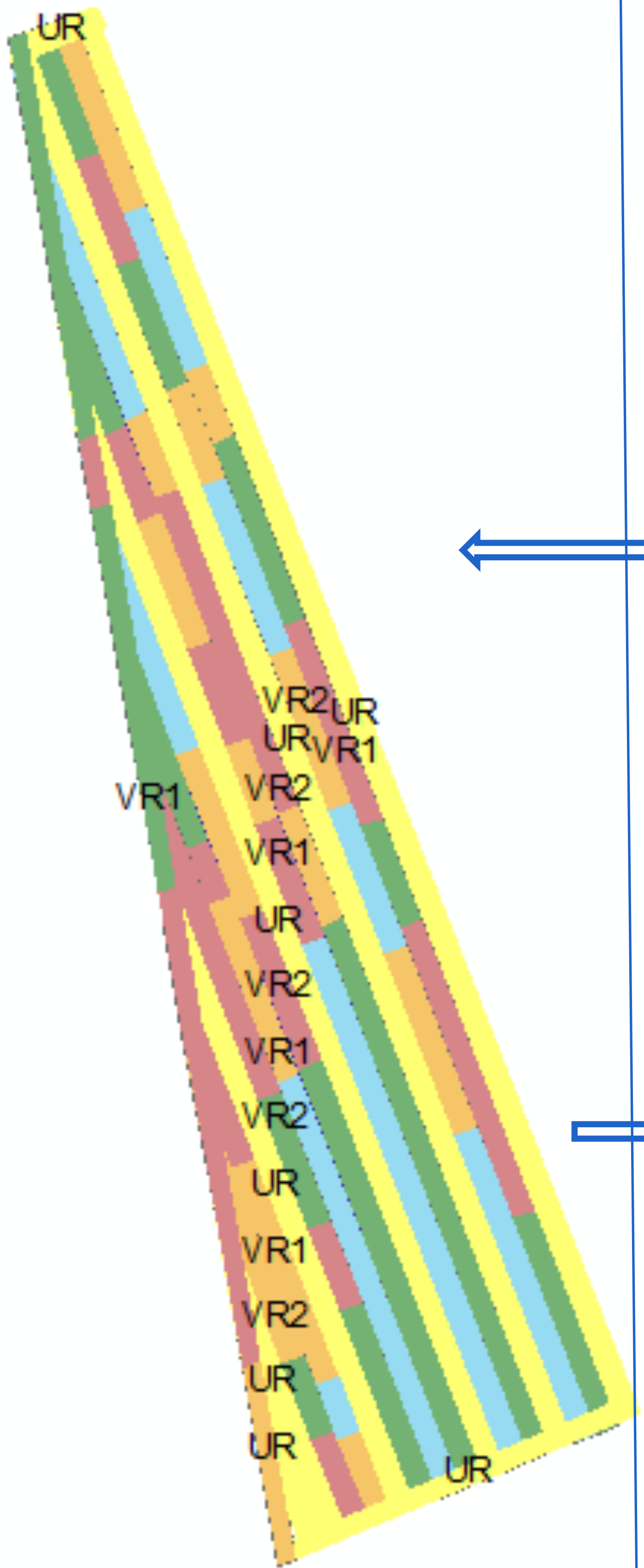
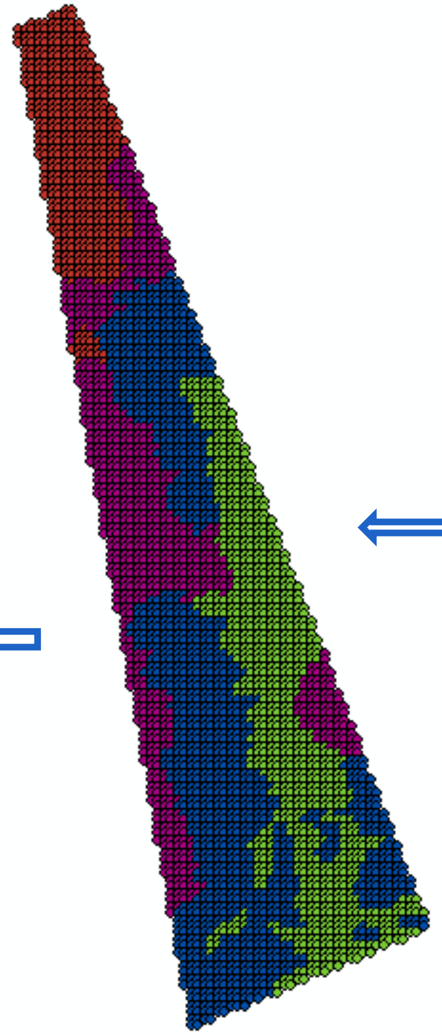



*After: Zhang et al. (2020) Soil & Tillage Research*




# ECONOMIC AND ENVIRONMENTAL PROFIT FOR MANURE APPLICATION

| TREAT | AREA (Ha) | Manure t/ha | COST PER HECTARE (EUR) | YIELD (T/Ha) | Output (EUR) | PROFIT PER HECTARE (EUR) | COMPARISON PER HECTARE (EUR) | PROFIT PER TREATMENT (EUR) | SIMULATION PROFIT PER FIELD (EUR) |
|---|---|---|---|---|---|---|---|---|---|
| UR | 3.40 | 35 | -16.50 | 12.52 | 1903.04 | 1919.54 | ------ | 6523.55 | 18392.29 |
| Kings VR1 | 3.14 | 36.9 | -13.24 | 12.81 | 1946.36 | 1959.60 | 40.06 | 6156.83 | 18776.14 |
| R. Hood VR2 | 3.04 | 32.52 | -23.94 | 12.71 | 1931.92 | 1955.86 | 36.32 | 5948.24 | 18740.32 |

⇧ **Yield 1.5 – 2.3 %** ⇧ **Profit 1.9 – 2.1 %**

| TREAT | Area (Ha) | Total N per entire area (kg/ha) | N applied (kg/ha) | Comparison (kg/ha) | Simulated N Kg / field | Comparison simulated N (kg/field) | | Total P per entire area (Kg/ha) | P applied (Kg/ha) | Comparison (kg/ha) | Simulated P Kg / field | Comparison simulated P (kg/field) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| UR | 3.40 | 983.87 | 289.50 | | 2773.88 | | | 178.42 | 52.50 | | 503.03 | |
| Kings VR1 | 3.14 | 925.96 | 294.71 | 5.21 | 2823.84 | 49.96 | | 170.07 | 54.13 | 1.63 | 518.65 | 15.61 |
| | | | | | | | | | | | | |
| R. Hood VR2 | 3.04 | 844.22 | 277.59 | -11.91 | 2659.78 | -114.09 | | 148.35 | 48.78 | -3.72 | 467.38 | -35.65 |

⇧ **Kings N 1.8 %**
**P 3.1 %**

⇩ **R. Hood N - 4.1 %**
**P - 7.1 %**

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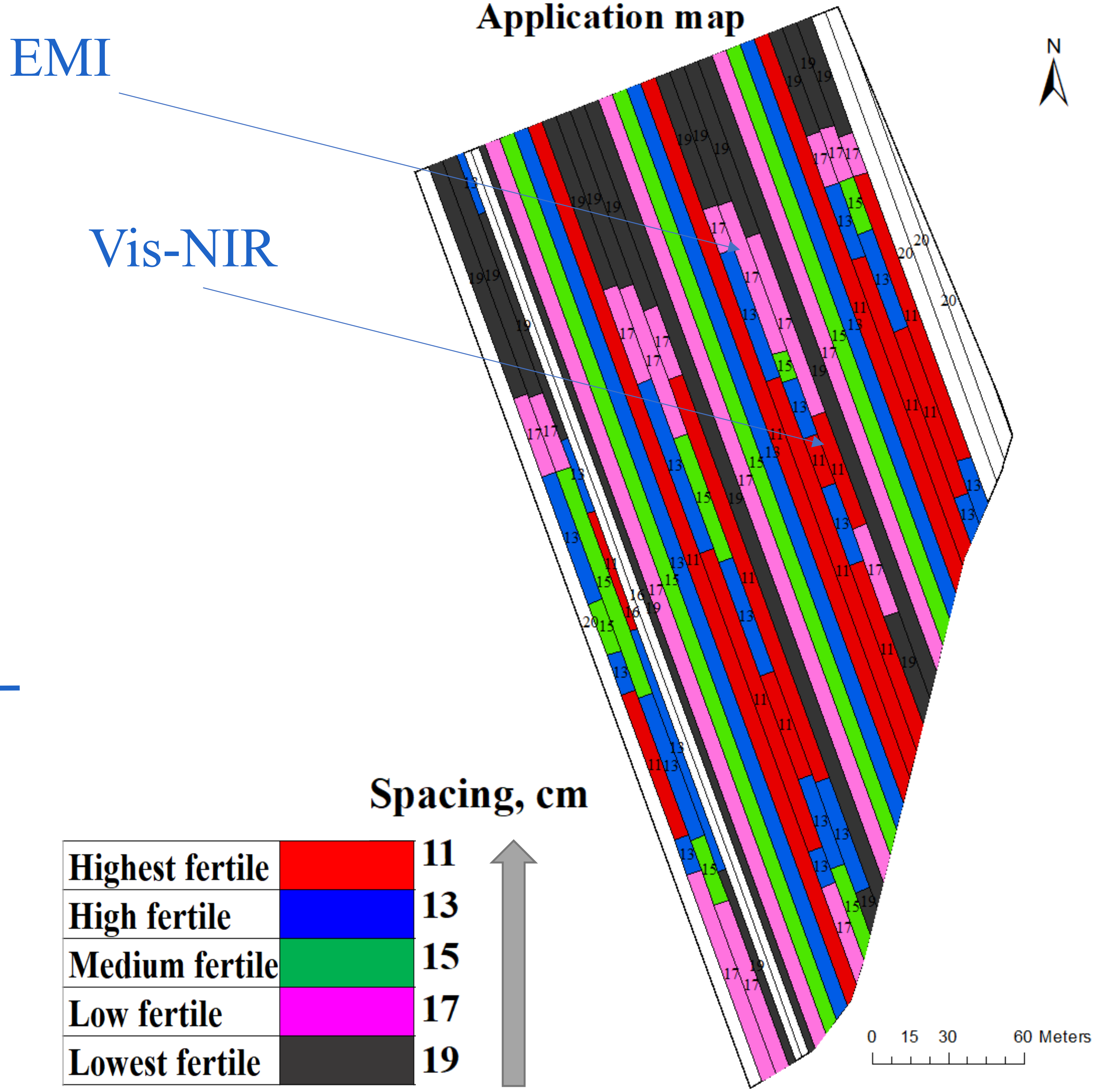
*After: Zhang et al. (2020) Soil & Tillage Research*

# MULTI-SENSOR & DATA FUSION FOR SITE SPECIFIC POTATO SEEDING



*After: Munnaf et al. (2020) Soil & Tillage Research*

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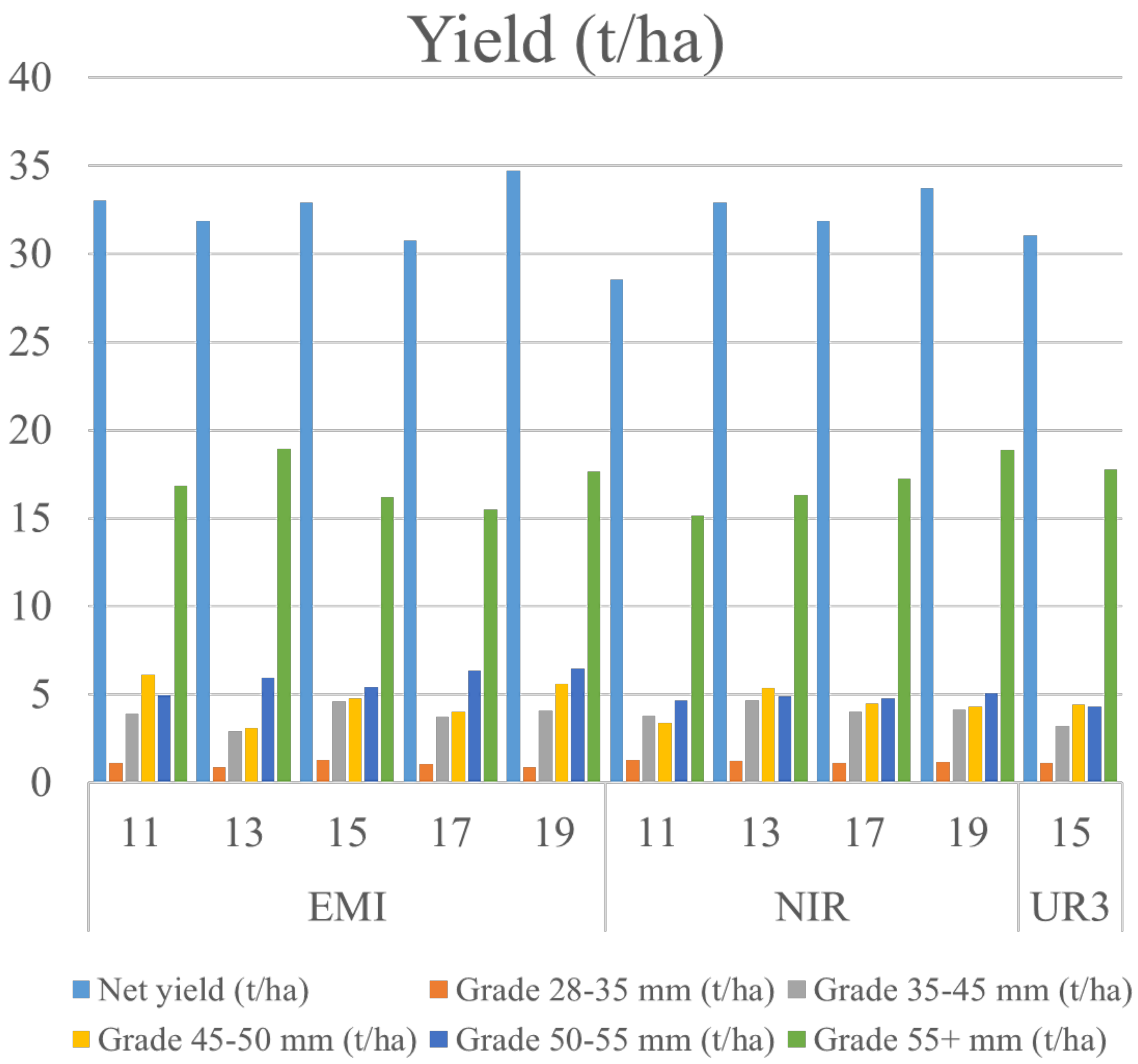
# COST-BENEFITS ANALYSIS FOR SITE SPECIFIC POTATO SEEDING




| Treatment | Cost (€/ha) | Yield (t/ha) | Revenue (€/ha) | Net Profit (€/ha) | Relative profit (€/ha) |
|---|---|---|---|---|---|
| UR | 2200 | **31.06** | 6728 | 4528 | - |
| Vis-NIR | 2186 | **31.89** | 7181 | 4995 | **467** |
| EMI | 2205 | **32.42** | 7152 | 4947 | **419** |

⇧ ***Yield* 2.62%**

⇩ ***Cost* 0.6%**

⇧ ***Profitability* 10.32%**

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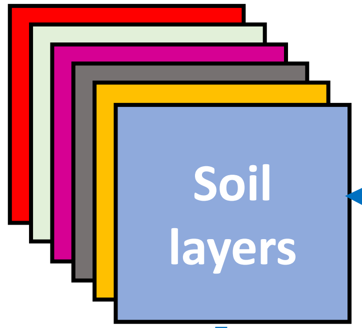
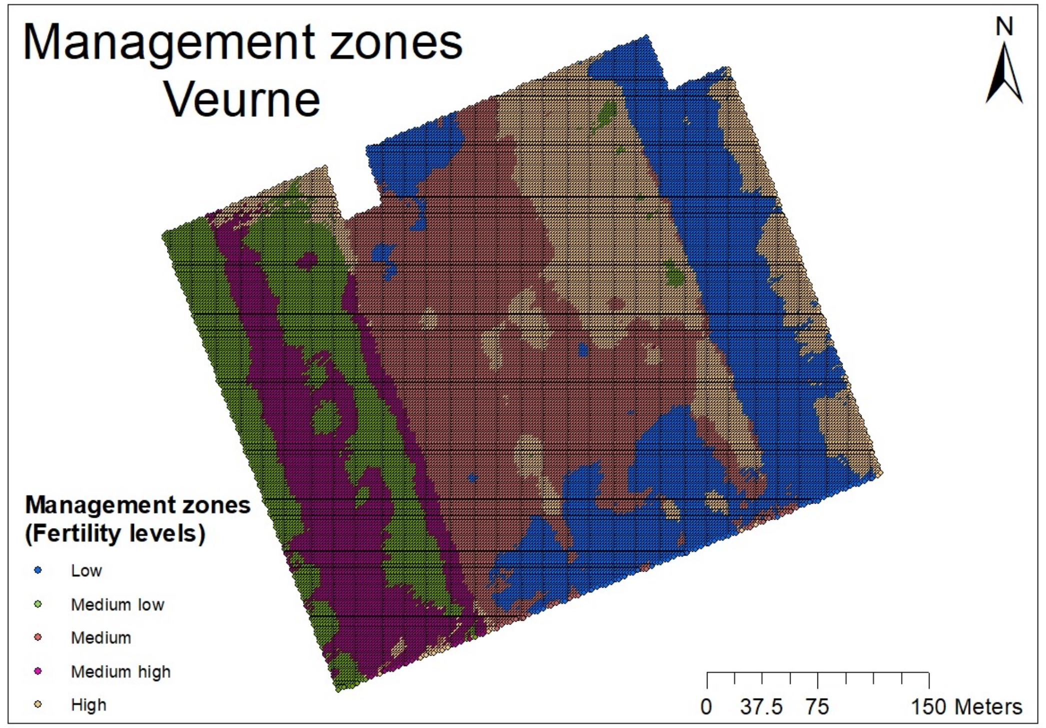
*After: Munnaf et al. (2020) Soil & Tillage Research*

# MAP-SENSOR-BASED VARIABLE RATE N FERTILIZATION

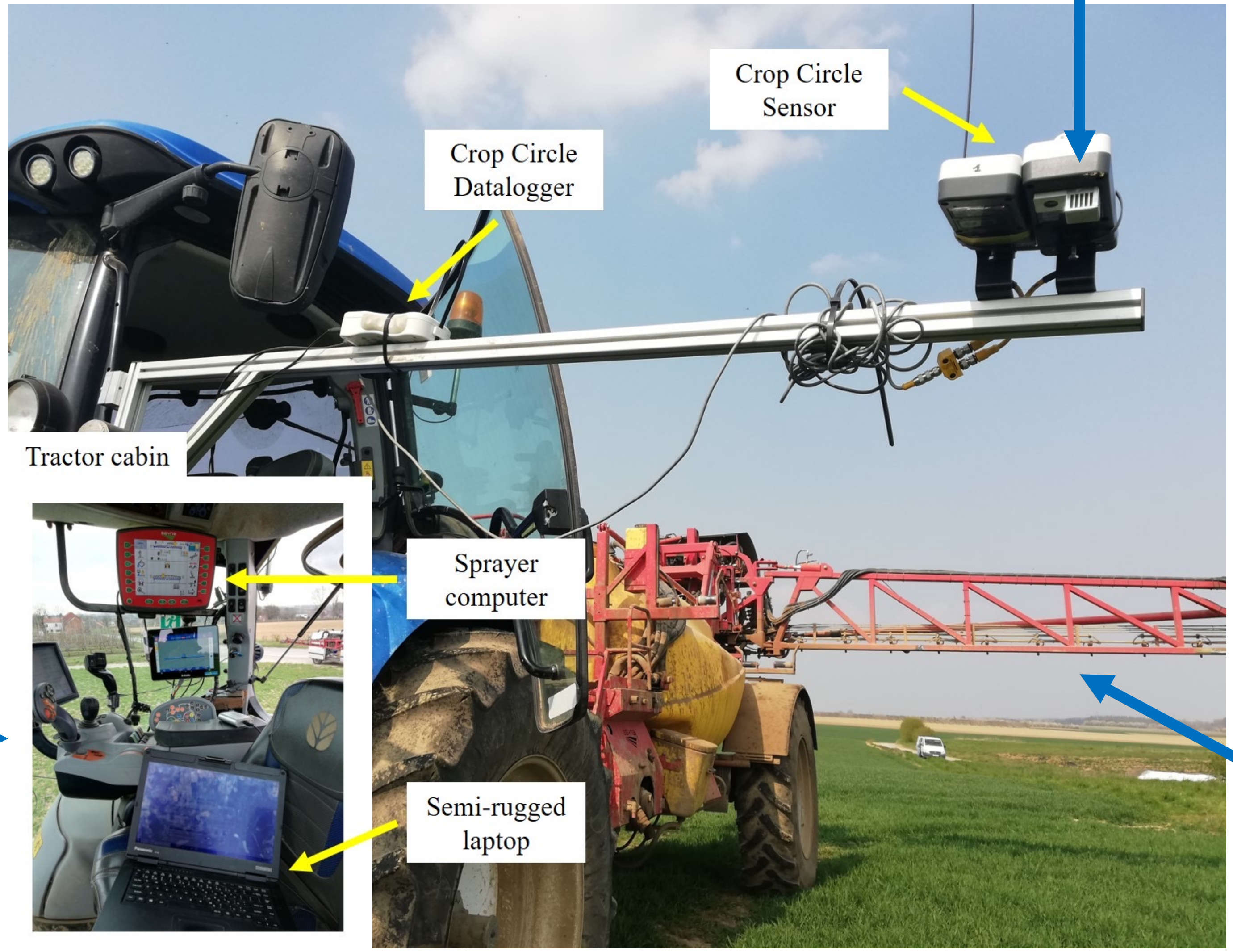
**Management zone maps**








**Real time NDVI measurement**




**VR N application**

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# COST-BENEFITS ANALYSIS FOR MAP-SENSOR-BASED VR N FERTILISATION

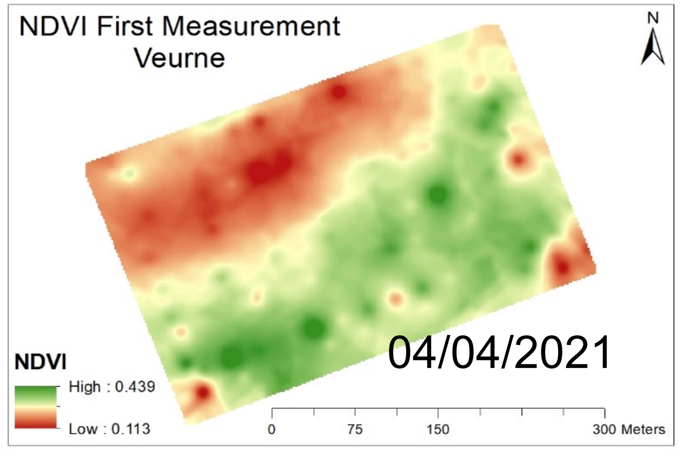
## A case study for Wheat

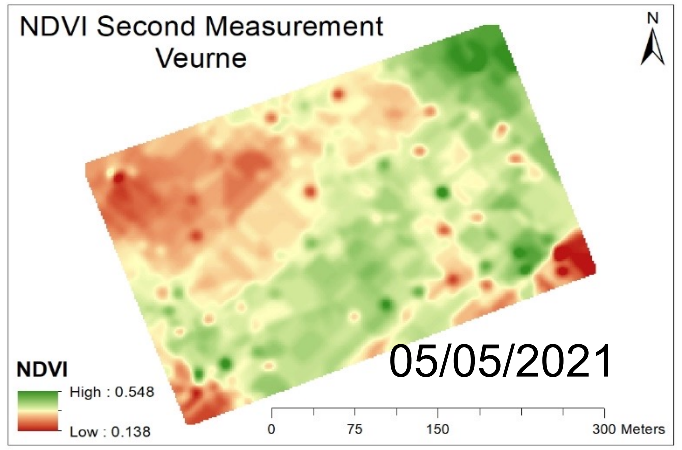
| Treatment | Area (ha) | First application (l/ha) | Second application (l/ha) | Cost of fertilizer (€/ha) | Yield (t/ha) | Profit (€/ha) | Comparison between treatment (€/ha) | Amount of fertilizer per hectare (l/ha) | Comparison per treatment (l/ha) |
|---|---|---|---|---|---|---|---|---|---|
| **URNF** | 6.72 | 1650.60 | 825.29 | 477.5 | **9.77** | 2453.5 | --- | 368.60 | --- |
| **VRNF** | 6.16 | 1503.52 | 720.19 | 428.9 | **9.54** | 2433.1 | **-20.37** | 361.17 | **-7.43** |

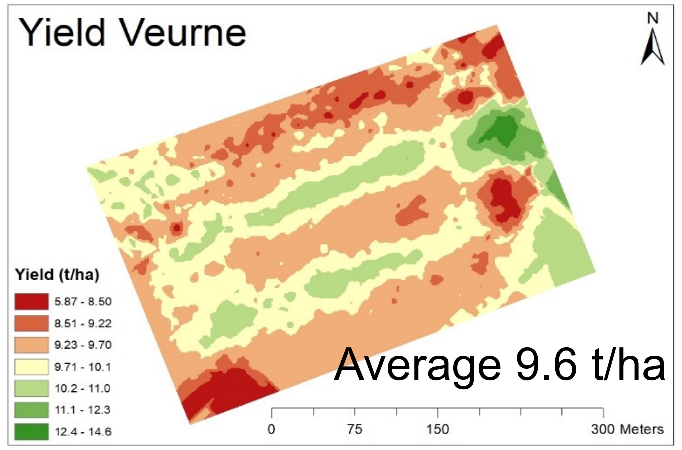
Almost same yield with URNF and VRNF

VRNF loses 20.37 €/ha

VRNF saved 7.43 l/ha N

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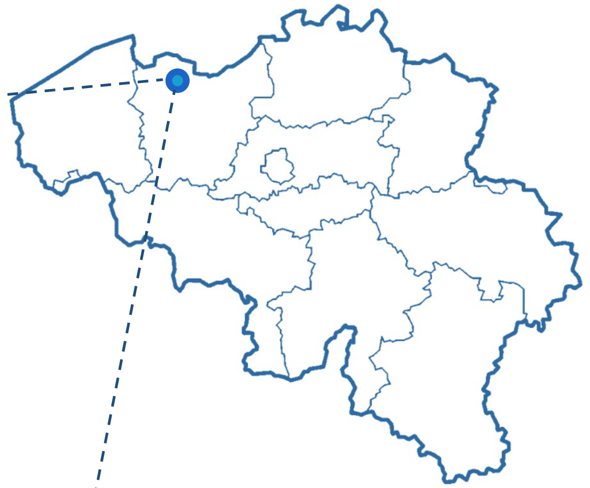
# SENSOR-BASED SITE SPECIFIC SEEDING OF MAIZE



On-line vis-NIRS sensing platform to measure a soil fertility index

Kverneland Optima Rigid e-Drive

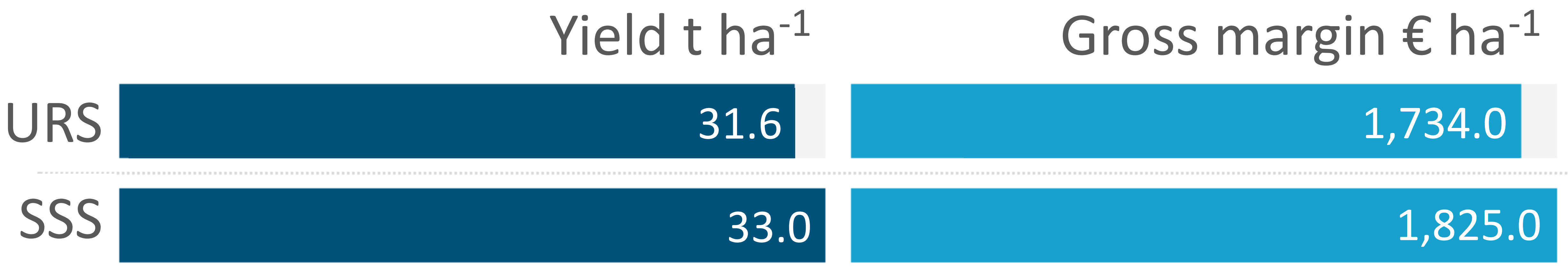
1 field in Melle region
(50◦59′10.5″N 3◦49′04.1″E)
Bottelare 5 ha
**Silage Maize**
Hybrid of SY Talisman
16th of June 2021

# COST-BENEFITS ANALYSIS FOR SENSOR-BASED SITE SPECIFIC MAIZE SEEDING

Sensor based SSS improves silage production and gross margin compared to URS

91

€ ha$^{-1}$ gross margin increasing with saving seed cost of 7 € ha$^{-1}$



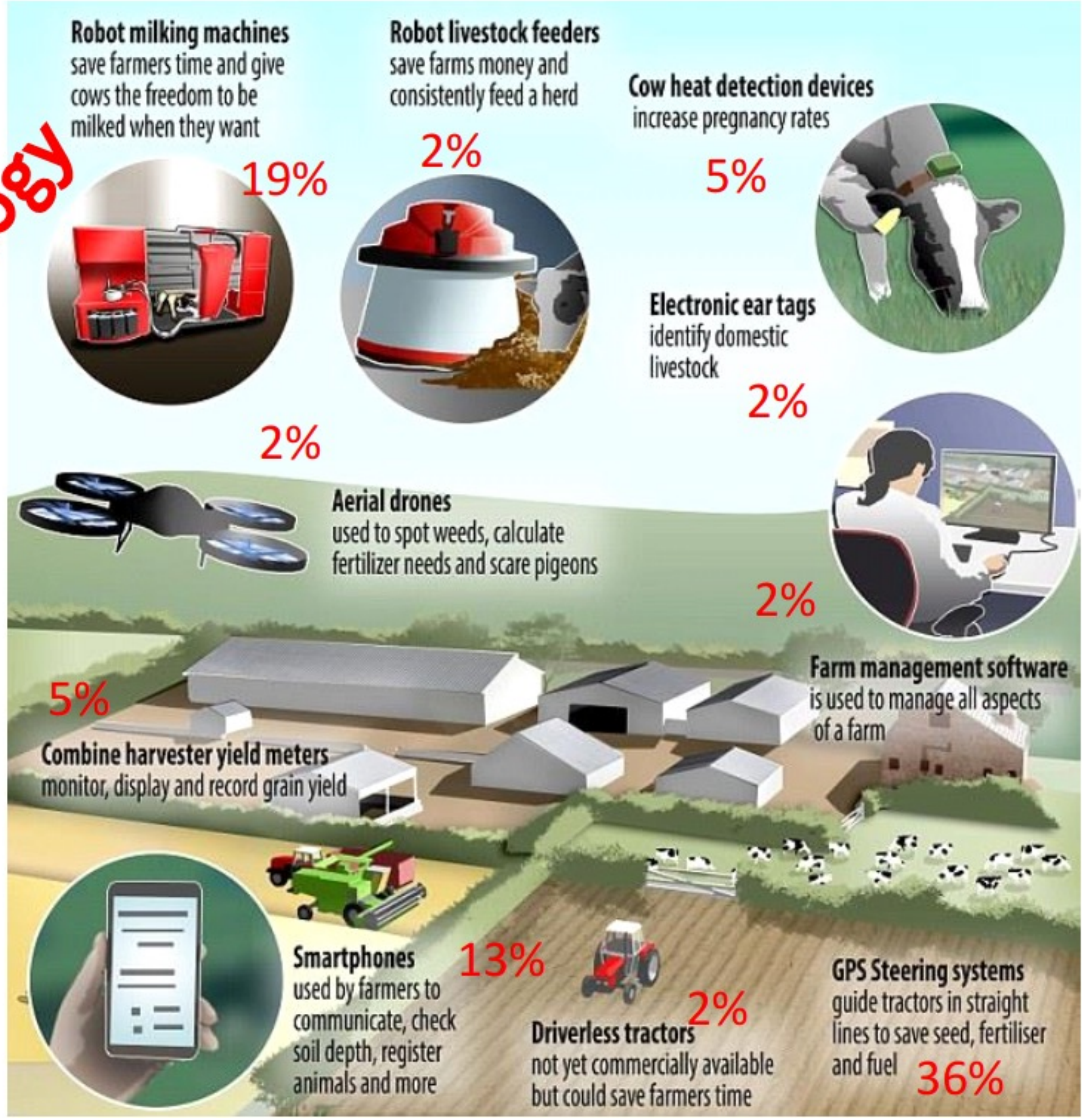

Yield improved by SSS is not significant (P = 0.18)

# LOW ADOPTION OF PA - *PROBLEMS*

**Low adoption rates, due to:**

- Few proven economic and environmental benefits.
- Technology is expensive.
- Complex technology.
- Social issues - farmers are reluctant for change.
- Lack of training and demonstration.
- Availability of subsidies

Top Ten Favorite Technology

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# CONCLUSIONS

- On-line vis-NIR spectroscopy within a multi-sensor framework holds great potential in precision agriculture.
- Needs for methods and algorithms to remove influences of external factors.
- Needs for high data processing capacity, big data management in cloud platforms.
- Implementation of real-time control (sensor-based or map-sensor-based) of inputs when appropriate.
- Potential for increase profitability, reduce environmental impacts and waste.
- Efforts to convince farmers to adopt precision agriculture practices.

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