Key Advances and Remaining Knowledge Gaps in Remote Sensing for Precision Agriculture

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Challenges Facing Agriculture

- Need to feed and provide energy for an additional 1 billion people in 10 years using sustainable approaches
- Very little new land is available for new rainfed production
- Climate change threatens to alter rainfall patterns and crop yield potential
- Need to reduce agricultural impacts on water quality & greenhouse gases
Precision Agriculture

- A management practice applied at the right time and the right place in the right amount
- Field sub-region management
  - Nutrients
  - Drainage or Irrigation
  - Pests and Weeds
  - Tillage and Seeding
Precision Management

Optimal Resource Management

Implementation

Map Based or Real Time Approach

Data Collection

Information Management

Analysis and Diagnostics

Knowledge

Wisdom
The Electromagnetic Spectrum
Remote Sensing

- Bare soil reflectance
  - Soil organic carbon and water content
  - Iron oxides or carbonates

- Crop reflectance
  - Leaf area index
  - Crop growth stage
  - Crop color and leaf N status
  - Weeds and disease

- Thermal emission of energy
  - Surface temperature and crop water stress
Remote Sensing Applications

- Mapping crop variability
  - Crop growth, biomass, and yield
  - Crop phenology and evapotranspiration
  - Crop stresses due to nutrients, disease, weeds, and insects
- Mapping soil variability
- Targeted sampling
- Management zone delineation
- Ability to monitor changes over time
Remote Sensing Sugar Beets
(Seelan et al., 2003)
History of Remote Sensing
## Satellite Remote Sensing

<table>
<thead>
<tr>
<th>Satellite</th>
<th>Spectral Bands</th>
<th>Return Frequency</th>
<th>Suitability for PA</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Year)</td>
<td>(Spatial Resolution)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Landsat 1 (1972)</td>
<td>G, R, two IR (56x79 m)</td>
<td>18</td>
<td>L</td>
</tr>
<tr>
<td>AVHRR (1978)</td>
<td>R, NIR, two TIR (1090 m)</td>
<td>1</td>
<td>L</td>
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<tr>
<td>Landsat 5 TM (1984)</td>
<td>B, G, R, two NIR, MIR, TIR (30 m)</td>
<td>16</td>
<td>M</td>
</tr>
<tr>
<td>SPOT 1 (1986)</td>
<td>G, R, NIR (20 m)</td>
<td>2-6</td>
<td>M</td>
</tr>
<tr>
<td>IRS 1A (1988)</td>
<td>B, G, R, NIR (72 m)</td>
<td>22</td>
<td>M</td>
</tr>
<tr>
<td>ERS-1 (1991)</td>
<td>Ku band altimeter, IR (20 m)</td>
<td>35</td>
<td>L</td>
</tr>
<tr>
<td>JERS-1 (1992)</td>
<td>L band radar (18 m)</td>
<td>44</td>
<td>L</td>
</tr>
</tbody>
</table>
## Satellite Remote Sensing

<table>
<thead>
<tr>
<th>Satellite</th>
<th>Spectral Bands</th>
<th>Return Frequency (d)</th>
<th>Suitability for PA</th>
</tr>
</thead>
<tbody>
<tr>
<td>IKONOS (1999)</td>
<td>Panchromatic, B, G, R, NIR (1-4 m)</td>
<td>3</td>
<td>H</td>
</tr>
<tr>
<td>EO-1 Hyperion (2000)</td>
<td>400-2500 nm, 10 nm bandwidth (30 m)</td>
<td>16</td>
<td>H</td>
</tr>
<tr>
<td>QuickBird (2001)</td>
<td>Panchromatic, B, G, R, NIR (0.61-2.4 m)</td>
<td>1-4</td>
<td>H</td>
</tr>
<tr>
<td>EOS MODIS (2002)</td>
<td>36 bands in VIS-IR (250-1000 m)</td>
<td>1-2</td>
<td>L</td>
</tr>
<tr>
<td>RapidEye (2008)</td>
<td>B, G, R, Red edge, NIR (6.5 m)</td>
<td>5.5</td>
<td>H</td>
</tr>
<tr>
<td>GeoEye-1 (2008)</td>
<td>Panchromatic, B, G, R, NIR1, NIR2 (1.6 m)</td>
<td>2-8</td>
<td>H</td>
</tr>
<tr>
<td>WorldView-2 (2009)</td>
<td>P, B, G, Y, R, Red edge, NIR (0.5 m)</td>
<td>1.1</td>
<td>H</td>
</tr>
</tbody>
</table>
# Increasing Spatial Resolution of Imagery

<table>
<thead>
<tr>
<th>Year</th>
<th>Pixel size (m)</th>
<th>Type of Satellite/Resource</th>
<th>Spatial Resolution</th>
</tr>
</thead>
<tbody>
<tr>
<td>1960</td>
<td>1000</td>
<td>Geostationary satellites</td>
<td>≥5 km²</td>
</tr>
<tr>
<td></td>
<td>100</td>
<td>Polar orbiting meteorological satellites</td>
<td>≥1 km²</td>
</tr>
<tr>
<td></td>
<td>10</td>
<td>Regional-scale natural resources</td>
<td>≥1 Ha</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>Commercial satellites</td>
<td>≥1 m²</td>
</tr>
<tr>
<td></td>
<td>0.1</td>
<td>Local-scale natural resources</td>
<td>≥0.1 Ha</td>
</tr>
</tbody>
</table>
Pixel Size
Increased Homogeneity of Pixels
Limitations to Satellite Remote Sensing

- Coarse spatial resolution and infrequent repeat coverage for older satellite platforms
- Difficulty obtaining images when needed
- Interference from clouds
- Changes in irradiance on multiple passes
- Slow turn-around time due to image processing for calibration, corrections, and geo-rectification
- Cost ranges from $23 - $45/km²
Aerial Remote Sensing

- Airplanes
- Unmanned Aerial Vehicles
NDVI Classified image\(^5\) (ADC camera, August 27th, 2003).

Tasseled cap classified image\(^5\) (QuickBird, July 31th, 2003).

Yield map\(^5\) (October 16th, 2003).
Proximal Remote Sensing

- Sensors can be mounted on tractors, spreaders, sprayers or irrigation booms
  - GreenSeeker
  - Crop Circle
  - WeedSeeker
  - Infrared thermometers
- Allows real time site specific management of fertilizer, pesticides or irrigation
Data Interpretation

- Classification (Bauer, 2000)
  - Supervised, unsupervised, multi-temporal data sets, decision tree classifiers, neural network classification, guided clustering, fuzzy sets, contextual classifiers, and use of auxiliary information

- Pattern Detection (Civco, 2002)
  - Image differencing, cross correlation, chemometric analysis, principal component analysis, neural networks, object oriented classification (Walker, 2003), fuzzy set theory (Viscarra Rossel, 2006)

- Assess accuracy (Congalton, 1991; Foody, 2002)
  - Visual assessment, Area comparisons, Sampling strategies, Kappa statistic, Confusion matrix
Traditional Classification

Classification

- **NIR**
  - < 10%
  - > 10%
  - Water
  - Green
    - > 30%
    - < 30%

<table>
<thead>
<tr>
<th>RED</th>
<th>SWIR</th>
<th>RED</th>
<th>SWIR</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt; 30%</td>
<td>&lt; 40%</td>
<td>&lt; 30%</td>
<td>&lt; 40%</td>
</tr>
<tr>
<td>&gt; 30%</td>
<td>&gt; 40%</td>
<td>&gt; 30%</td>
<td>&gt; 40%</td>
</tr>
<tr>
<td>Urban (very likely)</td>
<td>Cereal (likely)</td>
<td>Urban (likely)</td>
<td>Cereal (very likely)</td>
</tr>
</tbody>
</table>

- **DEM**
  - < 800m
  - > 800m
  - Irrigated crops
  - Deciduous trees

- **Legend**
  - Water
  - Shrub
  - Forest
  - Rainfed crops
  - Grasslands
  - Irrigated
  - Soil
Fuzzy Classification

- class 1
- class 2
- class 3
- class 4

- class 1
- 70% class 1
- 15% class 2
- 10% class 3
- 5% class 4

Conventional set

Fuzzy set

membership grade

1

0

membership grade

1

0.5

0
Spectral Decomposition and Chemometrics

- Spectral Mixing Analysis (Huete, 1991)
- Principal Component Analysis
- Partial Least Squares Regression (Lindgren, 1994)
- Stepwise Multiple Linear Regression
- Multiple Regression Analysis
- Multivariate Adaptive Regression Splines
Spectral Mixing Analysis

Two pure classes (lines and dots) are mixed in the real images in different proportions

\[ \rho_{i,j,k} = \sum_{m=1}^{p} F_{i,j,m} \rho_{m,k} + e_{i,j,k} \]

where \( \rho \) is reflectance, \( m \) are end-members, \( k \) are bands, and \( i,j \) are pixels
Principal Component Analysis
Artificial Neural Networks

Output Layer
- weighting factors
- a summation function
- a transfer function
- scaling and limiting processes
- an output function
- an error function
- a back-propagated value/learning function

Input Layer

Neuron (hidden)

Pixel Accuracy Assessment

Non-Spatial Accuracy Test

Border Pixel Accuracy Important
Confusion Matrix

<table>
<thead>
<tr>
<th>Classification</th>
<th>Reference</th>
<th>Class 1</th>
<th>Class 2</th>
<th>Class 3</th>
<th>Class n</th>
<th>Total</th>
<th>User's Accuracy</th>
<th>Commission Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Class 1</td>
<td>$X_{11}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>$X_{1+}$</td>
<td>$X_{11}/X_{1+}$</td>
<td></td>
</tr>
<tr>
<td>Class 2</td>
<td></td>
<td>$X_{22}$</td>
<td></td>
<td></td>
<td></td>
<td>$X_{2+}$</td>
<td>$X_{22}/X_{2+}$</td>
<td></td>
</tr>
<tr>
<td>Class 3</td>
<td></td>
<td></td>
<td>$X_{33}$</td>
<td></td>
<td></td>
<td>$X_{3+}$</td>
<td>$X_{33}/X_{3+}$</td>
<td></td>
</tr>
<tr>
<td>Class n</td>
<td></td>
<td></td>
<td></td>
<td>$X_{nn}$</td>
<td></td>
<td>$X_{n+}$</td>
<td>$X_{nn}/X_{n+}$</td>
<td>$1-X_{nn}/X_{n+}$</td>
</tr>
<tr>
<td>Total</td>
<td>$X_{+1}$</td>
<td>$X_{+2}$</td>
<td>$X_{+3}$</td>
<td>$X_{+n}$</td>
<td></td>
<td>$\Sigma X_{ij}$</td>
<td></td>
<td>$1-X_{+1}/X_{+1}$</td>
</tr>
</tbody>
</table>

Producer's Accuracy

<table>
<thead>
<tr>
<th>Class 1</th>
<th>Class 2</th>
<th>Class 3</th>
<th>Class n</th>
</tr>
</thead>
<tbody>
<tr>
<td>$X_{11}/X_{+1}$</td>
<td>$X_{22}/X_{+2}$</td>
<td>$X_{33}/X_{+3}$</td>
<td>$X_{nn}/X_{+n}$</td>
</tr>
</tbody>
</table>

Omission Error

<table>
<thead>
<tr>
<th>Class 1</th>
<th>Class 2</th>
<th>Class 3</th>
<th>Class n</th>
</tr>
</thead>
<tbody>
<tr>
<td>$1-X_{11}/X_{+1}$</td>
<td>$1-X_{22}/X_{+2}$</td>
<td>$1-X_{33}/X_{+3}$</td>
<td>$1-X_{nn}/X_{+n}$</td>
</tr>
</tbody>
</table>

Omission errors involve underestimation of a class
Commission errors involve overestimation of a class
Accuracy Assessment

Statistics

- **Class accuracy:**
  - **User’s:**
    \[ A_{u,i} = \frac{X_{ii}}{X_{i+}} \]
  - **Producer’s:**
    \[ A_{p,i} = \frac{X_{ii}}{X_{+i}} \]

- **Commission error:**
  \[ E_{c,i} = \frac{X_{i+} - X_{ii}}{X_{i+}} \]

- **Omission error:**
  \[ E_{o,i} = \frac{X_{+i} - X_{ii}}{X_{+i}} \]

**Kappa Statistic for Classification Accuracy**

\[ \kappa = \frac{n\sum_{i=1}^{n}X_{ii} - \sum_{i=1}^{n}X_{i+}X_{+i}}{n^2 - \sum_{i=1}^{n}X_{i+}X_{+i}} \]
## Confusion Matrix

<table>
<thead>
<tr>
<th>DCNI</th>
<th>Leaf N</th>
<th>User's Accuracy</th>
<th>Commission Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>RB</td>
<td>High</td>
<td>Moderate</td>
<td>Low</td>
</tr>
<tr>
<td>High</td>
<td>19</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>Moderate</td>
<td>2</td>
<td>3</td>
<td>0</td>
</tr>
<tr>
<td>Low</td>
<td>2</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>None</td>
<td>0</td>
<td>1</td>
<td>9</td>
</tr>
<tr>
<td>Total</td>
<td>23</td>
<td>7</td>
<td>12</td>
</tr>
</tbody>
</table>

Producer's Accuracy: 0.83, 0.43, 0.17, 0.84, 0.70
Omission Error: 0.17, 0.57, 0.83, 0.16

Nigon, Rosen, Mulla et al., 2012
Estimate Biophysical or Biochemical Variables

Courtesy of Drs. V.C. Patil and K.A. Al-Gaadi, King Saud University
Spatial Pattern

Fragmentation
Connectivity
Shape
Size
Spatial Pattern is Complicated when Hyperspectral Data are involved!
Integration of Imagery in GIS
Statistical Advances

- Traditional statistics
  - Mean and dispersion
  - Histograms

- Spatial and non-traditional statistics
  - Spatial filtering (low and high pass kernel filters, Kalman filters, wavelets, etc)
  - Homogeneity, Contrast, Dissimilarity
  - Geostatistical analysis
Using Geostatistics to Correct Errors in RS Images

- Used when pixels are missing
  - Cloud cover or satellite malfunction
  
Spatial Modeling & Interpolation

\[ \gamma_{12} = \left( \frac{1}{2n(h)} \right) \sum_{i=1}^{n(h)} [z_{1,i} - z_{1,i+h}]x[z_{2,i} - z_{2,i+h}] \]

\[ Z_o^* = \sum_{i=1}^{N_1} \lambda_{1i} z_{1i} + \sum_{j=1}^{N_2} \lambda_{2j} z_{2j} \]

Cokriging \[\rightarrow\] Kriging

\[ \gamma(h) = \left( \frac{1}{2n(h)} \right) \sum_{i=1}^{n(h)} [z_i - z_{i+h}]^2 \]

\[ Z_o^* = \sum_{i=1}^{N} \lambda_i z_i \]

Kriged Phosphorus (ppm)
Cokriged Phosphorus (ppm)
Targeted Soil Sampling Strategy
Based on Bare Soil NIR Image
Applications of Remote Sensing in Precision Ag

- Crop growth stages, LAI, biomass, and yield
- Crop chlorophyll and nitrogen stress
- Crop ET and water stress
- Weed, insect and disease infestations
- Soil salinity, organic matter, moisture, etc
- Delineating management zones
- Precision conservation
## Crop Sensors

<table>
<thead>
<tr>
<th>Year</th>
<th>Innovation</th>
<th>Citation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1992</td>
<td>SPAD meter (650, 940 nm) used to detect N deficiency in corn</td>
<td>Schepers et al., 1992</td>
</tr>
<tr>
<td>1995</td>
<td>Nitrogen Sufficiency Indices</td>
<td>Blackmer and Schepers, 1995</td>
</tr>
<tr>
<td>1996</td>
<td>Optical sensor (671, 780 nm) used for on-the-go detection of variability in plant nitrogen stress</td>
<td>Stone et al. (1996)</td>
</tr>
<tr>
<td>2002</td>
<td>Yara N sensor (450-900 nm)</td>
<td>Link et al. (2002), TopCon</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Industries</td>
</tr>
<tr>
<td>2002</td>
<td>GreenSeeker (650, 770 nm)</td>
<td>Raun et al. (2002), NTech</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Industries</td>
</tr>
<tr>
<td>2004</td>
<td>Crop Circle (590, 880 nm or 670, 730, 780 nm)</td>
<td>Holland et al (2004), Holland</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Scientific</td>
</tr>
<tr>
<td>2002</td>
<td>CASI hyperspectral sensor based index measurements of chlorophyll</td>
<td>Haboudane et al. (2002; 2004)</td>
</tr>
</tbody>
</table>
Spectral Signatures

- Green Vegetation
- Brown vegetation
- Soil
Dominant factors controlling leaf reflectance

- Leaf pigments in the palisade mesophyll:
  - chlorophyll \( a, b \)
  - \( \beta \)-carotene, etc.

- Scattering in the spongy mesophyll

- Leaf water content

Primary absorption bands

- Chlorophyll absorption bands
- Atmospheric water absorption bands

Reflectance (%)

Wavelength, \( \mu m \)

Visible

Reflective infrared

Near-infrared

Middle-infrared

Atmospheric Transmission (%)
Visible Absorption Spectrum
The Red-NIR Reflectance Space

Peak vegetation

Soil Line

\[ y = 1.098x + 0.0265 \]

\[ R^2 = 0.985 \]
Satellite RS-based N Management of Rice in Northeast China

Village level

Field level

2010-6-3  2010-6-25  2010-7-14  2010-7-30

Deficient
Normal
Excessive

Courtesy of Dr. Y. Miao,
Beijing Agric. Univ.
Crop Sensor-based N Management Strategy (China)
(Li et al., 2009. Soil Science Society of America Journal 73:1566-1574)

N Rate

Winter Wheat Yield
Spectral Indices

- Canopy reflectance is affected by water, chlorophyll, canopy density and age, soil, etc
- Leaf water potential and leaf temperature
  - 1981 Crop Water Stress Index (Jackson)
- Leaf Area Index
  - 1974 NDVI (Rouse, 670 & 800 nm)
- Soil Adjusted Vegetative Index (670 & 800 nm)
  - 1994 MSAVI (Qi)
- Chlorophyll Absorption Ratio Index
  - 2000 MCARI (Daughtry, 550, 670 & 700 nm)
Crop Water Stress

High water Treatments (low temperatures)
Blue and green spots

Thermal Crop Water Stress Indices.
- Crop: Cotton
- Location: Arizona
- Sensor: Thermal scanners (helicopter)

Low water Treatments (high temperatures)
Yellow and orange spots.

Source: http://www.uswcl.ars.ag.gov
Types of Reflectance Spectra

- **Panchromatic reflectance**
  - An average over all wavelengths

- **Broad band or multispectral reflectance**
  - Reflectance at a few specific discrete wavelengths
  - B, G, R NIR portions of spectrum

- **Hyperspectral reflectance**
  - Reflectance at specific narrow band discrete wavelengths across a large continuous spectral range
Multi-spectral broad-band vegetation indices available for use in Precision Agriculture

<table>
<thead>
<tr>
<th>Index</th>
<th>Definition</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>GDVI</td>
<td>NIR-G</td>
<td>Tucker, 1979</td>
</tr>
<tr>
<td>NDVI</td>
<td>$(\text{NIR-R})/\text{(NIR+R)}$</td>
<td>Rouse et al., 1973</td>
</tr>
<tr>
<td>GNDVI</td>
<td>$(\text{NIR-G})/\text{(NIR+G)}$</td>
<td>Gitelson et al., 1996</td>
</tr>
<tr>
<td>SAVI</td>
<td>$1.5 \times [(\text{NIR-R})/\text{(NIR+R+0.5)}]$</td>
<td>Huete, 1988</td>
</tr>
<tr>
<td>GSAVI</td>
<td>$1.5 \times [(\text{NIR-G})/\text{(NIR+G+0.5)}]$</td>
<td>Sripada et al., 2005</td>
</tr>
<tr>
<td>OSAVI</td>
<td>$(\text{NIR-R})/\text{(NIR+R+0.16)}$</td>
<td>Rondeaux et al., 1996</td>
</tr>
</tbody>
</table>
Hyperspectral Data Cube

Nigon, Rosen, Mulla et al., 2012
Best Reflectance Wavelengths?
Thenkabail et al. (2000)

• The greatest information about plant characteristics with multiple narrow bands includes the longer red wavelengths (650-700 nm), shorter green wavelengths (500-550 nm), red-edge (720 nm), and NIR (900-940 nm and 982 nm) spectral bands
  – The information in these bands is only available in narrow increments of 10-20 nm, and is easily obscured in broad multispectral bands that are available with older satellites

• The best combination of two narrow bands in NDVI-like indices is centered in the red (682 nm) and NIR (920 nm) wavelengths, but varies depending on the type of crop, as well as the plant characteristic of interest
Hyperspectral narrow-band vegetation indices available for use in precision agriculture

<table>
<thead>
<tr>
<th>Index</th>
<th>Definition</th>
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</tr>
</thead>
<tbody>
<tr>
<td>SR1</td>
<td>NIR/Red = R_{801}/R_{670}</td>
<td>Daughtry et al., 2000</td>
</tr>
<tr>
<td>SR7</td>
<td>R_{860}/(R_{550} \times R_{708})</td>
<td>Datt, 1998</td>
</tr>
<tr>
<td>NDVI</td>
<td>(R_{800}-R_{680})/(R_{800}+R_{680})</td>
<td>Lichtenthaler et al., 1996</td>
</tr>
<tr>
<td>Green NDVI</td>
<td>(R_{801}-R_{550})/(R_{800}+R_{550})</td>
<td>Daughtry et al., 2000</td>
</tr>
<tr>
<td>(GNDVI)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NDI1</td>
<td>(R_{780}-R_{710})/(R_{780}-R_{680})</td>
<td>Datt, 1999</td>
</tr>
<tr>
<td>NDI2</td>
<td>(R_{850}-R_{710})/(R_{850}-R_{680})</td>
<td>Datt, 1999</td>
</tr>
</tbody>
</table>
Hyperspectral narrow-band vegetation indices available for use in precision agriculture

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<thead>
<tr>
<th>Index</th>
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</tr>
</thead>
<tbody>
<tr>
<td>MCARI</td>
<td>$(R_{700} - R_{670}) - 0.2(R_{700} - R_{550})(R_{700}/R_{670})$</td>
<td>Daughtry et al., 2000</td>
</tr>
<tr>
<td>TCARI</td>
<td>$3\times[(R_{700} - R_{670}) - 0.2\times(R_{700} - R_{550})(R_{700}/R_{670})]$</td>
<td>Haboudane et al., 2002</td>
</tr>
<tr>
<td>OSAVI</td>
<td>$(1 + 0.16)(R_{800} - R_{670})/(R_{800} + R_{670} + 0.16)$</td>
<td>Rondeaux et al., 1996</td>
</tr>
<tr>
<td>MSAVI</td>
<td>$0.5[2R_{800}+1-\text{SQRT}((2R_{800}+1)^2-8(R_{800} - R_{670}))]$</td>
<td>Qi et al., 1994</td>
</tr>
<tr>
<td>MCARI2</td>
<td>$\frac{1.5[2.5(R_{800} - R_{670}) - 1.3(R_{800} - R_{550})]}{\sqrt((2R_{800} + 1)^2 - (6R_{800} - 5\sqrt{R_{670}}) - 0.5)}$</td>
<td>Haboudane et al., 2004</td>
</tr>
</tbody>
</table>
Derivative Spectra

- Hyperspectral reflectance data are collected in nearly continuous narrow bands across a wide range of wavelengths.
- The derivative of hyperspectral reflectance data can be very useful at indicating portions of the spectrum where the slope of the reflectance curve changes rapidly.
- Derivative spectra reduce interference from soil.
Derivative Spectra

Nigon, Rosen, Mulla et al., 2012
Lambda-Lambda Plots

- Lambda-lambda plots involve calculating, for example, the $r^2$ coefficient for leaf N content at all hyperspectral reflectance bands.
- A graph of the $r^2$ coefficient for all possible combinations of band 1 on the x-axis and band 2 on the y-axis results in a lambda-lambda plot.
- The lambda-lambda plot is useful for identifying which combinations of two bands contain redundant information about N stress.
- Spectral bands or narrow band indices should be selected with low $r^2$ coefficients to eliminate redundancy and maximize information about crop characteristics (such as N stress).
Lambda-plot

Nigon, Rosen, Mulla et al., 2012
Temporal Analysis of Data

DATE 1 → INTERPRETATION

DATE 2 → MULTI-SEASONAL ANALYSIS

DATE 3 → MULTI-YEAR ANALYSIS

DATE 1 → INTERPRETATION

DATE 2 → INTERPRETATION
In-Season N Management

(From J. Schepers, 2005)
Properties of N deficient Plants

- Green reflectance increases
- Red reflectance increases & NIR reflectance decreases
- Differences in reflectance greatest between 550 – 600 nm, followed by red-edge (680 – 730 nm)

**Nitrogen Sufficiency Index (NSI)**

\[
\text{NSI} = \frac{\text{Leaf} N}{\text{Spectral index}} \times 100\%
\]
Hyperspectral Imaging for N Sufficiency in Maize

\[
CM = 56.74 + 6.48 \times R_{713} + 2.02 \times R_{953} + 8.42 \times R_{666} - 9.87 \times R_{695} - 0.75 \times R_{972} - 19.57 \times R_{554} + 16.68 \times R_{499} - 1.66 \times R_{934}
\]

Miao et al., Precision Agriculture 10:45-62, 2009
Promising Indices for Crop N Stress

Normalized Difference Index 2:

$$NDI2 = \frac{R_{850} - R_{710}}{R_{850} - R_{680}}$$
N stress in potato

Leaf N
NDI2

Nigon, Rosen, Mulla et al., 2012
LiDAR

- Light Detection and Ranging scans earth’s surface using a laser with visible radiation
- Provides a high resolution Digital Elevation Model (DEM) which can be processed in GIS with terrain analysis
  - Slope, curvature, flow accumulation, etc.
  - Stream power, topographic wetness, etc.
Precision Conservation in Critical Source Areas


- Two criteria:
- Accumulation of surface flow
- Hydrologic connection to surface waters
- GIS based LiDAR data used to identify CSAs
Example: Using Specific Catchment Area to Identify Critical Source Areas

Beauford Watershed (Blue Earth County)
Conclusions

- Precision agriculture dates back to the middle of the 1980’s
- Remote sensing applications in precision agriculture began with sensors for soil organic matter, and have quickly diversified to include satellite, aerial, unmanned aerial vehicles, tractors, spreaders, sprayers and irrigation booms
- Spatial resolution of aerial and satellite remote sensing imagery has improved from 100’s of m to sub-meter accuracy
Conclusions

- Wavelengths in use range from the ultraviolet to microwave portions of the spectrum
  - Red edge reflectance is increasingly available
  - LiDAR, fluorescence and thermal spectroscopy have advanced
- Spectral bandwidth has decreased with the advent of hyperspectral remote sensing
- A variety of useful spectral indices now exist for various precision agriculture applications
  - The best spectral indices for N stress are robust over crop species, variety and growth stage (with high $r^2$ and CV)
Conclusions

- Return frequency of satellite remote sensing imagery has improved dramatically
  - Timeliness, cloud interference and cost of imagery are still issues
- More research on remote sensing with unmanned aerial vehicles is needed to improve the timeliness of data collection
- Errors in geo-rectification and geometric correction from aerial platforms are becoming more important relative to image pixel size
Remaining Knowledge Gaps

- More emphasis is needed on chemometric methods of analysis to assess crop biophysical and biochemical characteristics.
- Spectral indices that simultaneously allow for assessment of multiple crop stresses (e.g., water, nitrogen and disease) are lacking.
- Higher spatial resolution of aerial remote sensing is needed for early detection of disease.
Remaining Knowledge Gaps

- Sensors are needed for direct estimation of nutrient deficiencies without the use of reference strips.
- There are many algorithms and spectral indices for management of crop N stress:
  - The utility of these seems to vary by year, crop type, variety and growth stage.
  - Simple, generalizable solutions are needed.
- Remote sensing needs to be better integrated with automated, online soil and crop management decision support systems.
Remaining Knowledge Gaps

- At present there is considerable interest in collecting remote sensing data at multiple times in order to conduct near real-time soil, crop and pest management.

- We have progressed from farming by soil, to farming by grid cell to farming by management zone and now the challenge is to manage individual plants in real-time.
Questions?

Acknowledgement: Some images were obtained from “Fundamentals of Satellite Remote Sensing” by Chuvieco and Huete (2010)