Remote sensed fuel moisture using leaf and imaging spectroscopy

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Spectroscopy

- **Imaging spectroscopy**
  - Also called hyperspectral imaging, hyperspectral remote sensing
  - “a new tool that can be used to map specific materials by detecting specific chemical bonds.” (http://speclab.cr.usgs.gov)

- **Leaf spectroscopy**
  - Used in field or laboratory
  - Understand the physical mechanism of estimating FMC using spectroscopy data

- Advantages of using spectroscopy data
  - Determination of the most sensitive spectral regions for specific mapping tasks
  - Analysis of specific absorption features

(Courtesy of ASD Inc.)
Remote sensing of fuel moisture content

FMC is a leaf mass based variable:

\[ FMC = \frac{FW - DW}{DW} \]

FMC is related to two leaf area based variables equivalent water thickness (EWT) and dry matter content (DMC):

\[ FMC = \frac{EWT}{DMC} \]

\[ EWT = \frac{FW - DW}{A} \]

\[ DMC = \frac{DW}{A} \]

- What are the spectral changes related to FMC variation?
  - Overall amplitude due to strong water absorption in the entire SWIR region
  - Overlapping absorption features of dry matter (lignin, cellulose, nitrogen, etc.)
- Both water and dry matter absorptions vary with FMC. Can we just use water indices (WI, NDWI, NDII) to estimate FMC?
A summary of studies on the spectroscopic estimation of leaf FMC

- **Methods:**
  - Spectral indices
  - Inversion of radiative transfer models (PROSPECT)
  - Partial least squares (PLS) regression
  - Genetic-algorithm partial least squares (GA-PLS) regression
  - Continuous wavelet analysis

- **Table: Spectroscopic estimation of leaf FMC**

- **Estimations are good for EWT but not good enough for FMC**
- **Water indices (designed for EWT), particularly for multiple species**
- **PROSPECT model inversion (hard to invert dry matter content)**

(Cheng et al., 2011)
Wavelet transform

- Allows for analysis of signals at various scales
- Converts a reflectance spectrum into a set of coefficients (wavelet features)

- *Discrete* (DWT) vs *Continuous* (CWT)

- Most vegetation studies use DWT, but the results are difficult to interpret

- CWT
  - Multi-scale decomposition
  - Emphasize spectral regions rather than individual bands
  - Takes advantage of continuous nature of spectroscopy data

CWT & DWT of a leaf reflectance spectrum (Blackburn & Ferwerda, 2008)
Continuous wavelet analysis (CWA)

CWT output of a reflectance spectrum (wavelet power scalogram)

Wavelet power scalograms

Linear correlation

Correlation scalogram

FMC
The correlation scalogram demonstrates the magnitude of linear correlation ($R^2$) between wavelet coefficients and leaf FMC across all samples. By applying a threshold (1%) to the $R^2$ scalogram, the features producing the highest correlations to leaf FMC are highlighted.

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- By applying a threshold (1%) to the $R^2$ scalogram, the features producing the highest correlations to leaf FMC are highlighted.

A leaf-level study for multiple species

Data sets contain leaf FMC and reflectance (400-2500 nm with 1 nm step) data

Simulated data
- Parameters estimated from a global leaf database
- Represent leaves from various species and growing conditions

60% of samples for calibration and 40% for validation

Goals:
- To evaluate CWA for estimating leaf FMC across a large collection of plant species
- To determine robust wavelet features for FMC estimation

<table>
<thead>
<tr>
<th>Data set</th>
<th>Sample size</th>
<th>Mean ± s.d.</th>
<th>Min</th>
<th>Max</th>
<th># of species</th>
<th>Origin</th>
</tr>
</thead>
<tbody>
<tr>
<td>LOPEX</td>
<td>325</td>
<td>240.47±193.18</td>
<td>9.43</td>
<td>1258.57</td>
<td>45</td>
<td>Broadleaf trees and crops in Ispra, Italy</td>
</tr>
<tr>
<td>PANAMA</td>
<td>265</td>
<td>143.60±52.44</td>
<td>32.31</td>
<td>418.20</td>
<td>47</td>
<td>Trees and lianas in tropical forests of Panama</td>
</tr>
<tr>
<td>PROSPECT</td>
<td>2495</td>
<td>177.14±107.22</td>
<td>36.51</td>
<td>1154.36</td>
<td>-</td>
<td>Simulated using PROSPECT-5 (Féret et al., 2011)</td>
</tr>
</tbody>
</table>


• Almost all feature regions occurred in the SWIR region (1300-2500 nm)
• Consistent feature regions were found across data sets
  • Five were common to the two measured ones (absorptions by water, cellulose and lignin, nitrogen)
  • Three were common to all data sets (water, cellulose and lignin)
What spectral information do these wavelet features represent?

- We can separate information into different scales.
- Higher scale features (in red) represent broader absorptions by water absorption.
- Lower scale features (in blue) represent narrower absorptions by dry matter (e.g., lignin, cellulose, nitrogen).
- Simulations did not capture the common dry matter features from measured data.

The wavelength position and scale of each feature are indicated by a vertical line and a Gaussian-shaped curve (wavelet function).
Predictions of FMC

- Feature combinations outperformed best features
- Close to 1:1 lines but some underestimations occurred at extremely high FMC values?
  - Lower RMSE values
  - Less underestimations

(Cheng et al., 2012)
Regression models across data sets

- Relationship between FMC and wavelet power
  - Generally log-linear for wide ranges
  - Linear when FMC<400% for LOPEX and 250% for PANAMA

- Point clouds overlapped most using feature (1733 nm, scale 4)
Transferability of regression models between data sets

- It is possible to transfer a model from simulations to measured data
- We may have to apply models based on feature combinations to individual data sets
Comparison of CWA to GA-PLS based on the LOPEX data set

Best FMC estimation using GA-PLS (Li et al., 2007): 
$R^2 = 0.893$, RMSE $= 68.5\%$.

FMC estimation using a combination of wavelet features: 
$R^2 = 0.89$, RMSE $= 63.66\%$.

Results for the two methods are comparable: 
- Close accuracy
- Overlapping spectral regions selected
Spectral indices for FMC

- Broad-band water indices for the LOPEX data set (Danson & Bowyer, 2004): $R^2 = 0.54$, RMSE = 179.3%, but it worked poorly for PANAMA data set

\[
\text{MSI} = \frac{R_{1600}}{R_{820}}
\]

\[
\text{NDWI} = \frac{(R_{860} - R_{1240})}{(R_{860} + R_{1240})}
\]

\[
\text{WI} = \frac{R_{900}}{R_{970}}
\]

- The spectral index for FMC has to be optimized

- Feret et al. (2011) provided optimal indices for EWT and DMC, but not directly for FMC:
  - EWT: \((R_{1062} - R_{1393})/(R_{1062} + R_{1393})\)
  - DMC: \((R_{1368} - R_{1722})/(R_{1368} + R_{1722})\)

(Cheng et al., 2011)
A canopy-level study using AVIRIS imagery

- Experiment was designed to examine the diurnal and seasonal variations in canopy water content
- Study area:
  - Irrigated Almond and pistachio orchards
- AVIRIS imagery
  - Pixel size: 8 m
  - Acquired twice in a day (11:00 and 15:00 PDT, June 30, 2011)
  - Images corrected for view angle effects
- Morning and afternoon FMC samples were combined together
- Preliminary results on FMC mapping using wavelet analysis and spectral indices

A false color composite image from AVIRIS (R: 860 nm, G: 650 nm, B: 550 nm)
Scales 1~3 were excluded (scale 3 produced noisy FMC maps)

Centre features:
- (2320 nm, scale 5)
- (2210 nm, scale 6)
- (2390 nm, scale 5) close to (2380 nm, scale 4) from the leaf study

All features were related to dry matter absorption and appeared at higher scales than those from the leaf study
Performance of wavelet features

- Higher correlations than common water indices
- Improved when combined with vegetation indices
- Linear correlation with FMC

<table>
<thead>
<tr>
<th>Spectral features</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>(2320, 5)</td>
<td>0.56</td>
</tr>
<tr>
<td>(2210, 6)</td>
<td>0.41</td>
</tr>
<tr>
<td>(2390, 5)</td>
<td>0.40</td>
</tr>
<tr>
<td>All wavelet features</td>
<td>0.58</td>
</tr>
<tr>
<td>NDII</td>
<td>0.31</td>
</tr>
<tr>
<td>NDWI</td>
<td>0.20</td>
</tr>
<tr>
<td>WI_970</td>
<td>0.17</td>
</tr>
<tr>
<td>WI_1180</td>
<td>0.21</td>
</tr>
<tr>
<td>All indices</td>
<td>0.47</td>
</tr>
<tr>
<td>All</td>
<td>0.66</td>
</tr>
</tbody>
</table>
Estimations using different spectral features

- Greater improvement in $R^2$ than in RMSE due to low variance in FMC data (mean=208.16%, s.d. =13.15%)
- Wavelet features helped improve the sensitivity of spectral responses to FMC variation. This is more obvious on FMC maps.
FMC Maps produced by using and adding wavelet features have broader ranges as shown by field data.

The improvement suggests the wavelet approach is promising and it can be integrated with the spectral index approach.

Morning FMC maps using different combinations of spectral features:
Afternoon FMC maps using different combinations of spectral features

- Spatial patterns are similar to those on morning FMC maps
- FMC was generally lower in the afternoon, representing diurnal FMC variation within four hours
Challenges of using imaging spectroscopy data

- Take advantage of full-spectrum information
  - Band-based or spectral region-based?
  - Learn from the transition from pixel-based to object-based for high spatial resolution imagery

- Fidelity of spectral data is important for the use of some absorption features

- Identification of robust spectral regions
  - Across different airborne or spaceborne instruments
  - Across different illumination conditions

The HyspIRI satellite mission:
- 380-2500 nm with 10 nm steps
- Revisit frequency of 19 days
- 60 m pixel size

(http://hyspcri.jpl.nasa.gov)
Conclusions

- Wavelet features are effective spectral metrics for the estimation of FMC across a wide range of leaf types.

- The wavelet approach demonstrated leaf FMC variation was sensitive to both broad-range water absorptions and narrow-range dry matter absorptions.

- Canopy FMC variation was sensitive to dry matter absorptions but the scales were higher than those at leaf level.

- The wavelet approach showed promise for mapping FMC over a large area using imaging spectroscopy data.
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Relationship between FMC and wavelet power