Quantifying Biomass Feedstock Variability Using the DOE Bioenergy Feedstock Library

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• DOE has recognized the importance of supporting expansion of the US bioenergy industry.

• Biomass resource assessments identified over 1 billion tons of potentially available biomass in contiguous US by 2030.

• The physical and chemical variability and the sources of that variability will have a huge impact on logistics.

Raw biomass is NOT a biorefinery feedstock!
Variability Impacts Cost

- Variability in feedstock quality can be extreme.
- Understanding variability is necessary to establish a valuation system for bioenergy feedstocks.
- Feedstock variability impacts financial risk

Variability exists due to a number of confounding factors.

- Each 1% increase in ash increases cost ~$2.25/ton
  - Replacement
  - Disposal
  - Wear and tear
  - Buffering capacity

~2300 samples Ranging from 2 to >40%
Bioenergy Feedstock Library

- Collaboration with DOE Regional Feedstock Partnership
  - Store, Track, and Analyze samples

Tracking all information associated at every step in sample life cycle
Library Overview

- 35,000 unique sample
  - 90 feedstock types
  - 38 states in US
  - 3 countries

- >100 collaborating universities, feedstock supplier, National labs, and industrial partners

- 3321 samples with analytical data publically available.
  - Chemical
  - Physical
  - Conversion

[Link to Bioenergy Library Website]

![Bioenergy Feedstock Library Table]

<table>
<thead>
<tr>
<th>Attribute</th>
<th>#Entries</th>
<th>Min Value</th>
<th>Max Value</th>
<th>Mean</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lignin (%)</td>
<td>242</td>
<td>15.72</td>
<td>21.79</td>
<td>19.46</td>
<td>1.08</td>
</tr>
</tbody>
</table>

[Frequency Graph]
Application of Library Variability

- Regional Feedstock Partnership quality parameter data.
- Sources of Variability
  - Crop years
  - Feedstocks
  - Harvesting conditions
  - Field Treatments
- How does this help us answer large scale questions about feedstock variability?

<table>
<thead>
<tr>
<th></th>
<th>#’s</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crop Years</td>
<td>5</td>
</tr>
<tr>
<td>Feedstocks</td>
<td>5</td>
</tr>
<tr>
<td>States</td>
<td>21</td>
</tr>
<tr>
<td>Samples</td>
<td>1937</td>
</tr>
</tbody>
</table>
Drought Study

- 3 Feedstocks
  - Corn Stover
  - Native Mixed Grass
  - Miscanthus x giganteus

- 3 Locations
  - Iowa
  - Missouri
  - Nebraska

**Drought effects on Physical Yields and Quality Measurements.**

## Drought Study Cont.

<table>
<thead>
<tr>
<th>Feedstock</th>
<th>Location</th>
<th>Year</th>
<th>n</th>
<th>TEY (L Mg(^{-1}))</th>
<th>Dry Biomass (Mg ha(^{-1}))</th>
<th>TEY (L ha(^{-1}))</th>
</tr>
</thead>
<tbody>
<tr>
<td>Corn Stover</td>
<td>Iowa</td>
<td>2010</td>
<td>11</td>
<td>334 (7)</td>
<td>3.0 (1.4)</td>
<td>990 (471)</td>
</tr>
<tr>
<td>Corn Stover</td>
<td>Iowa</td>
<td>2012</td>
<td>11</td>
<td>300 (8)</td>
<td>3.7 (1.1)</td>
<td>1125 (325)</td>
</tr>
<tr>
<td>Mixed Grasses</td>
<td>Missouri</td>
<td>2010</td>
<td>18</td>
<td>250 (12)</td>
<td>2.5 (0.6)</td>
<td>635 (146)</td>
</tr>
<tr>
<td>Mixed Grasses</td>
<td>Missouri</td>
<td>2012</td>
<td>14</td>
<td>216 (17)</td>
<td>1.2 (0.6)</td>
<td>259 (119)</td>
</tr>
<tr>
<td>Miscanthus</td>
<td>Nebraska</td>
<td>2010</td>
<td>12</td>
<td>342 (5)</td>
<td>27.7 (3.2)</td>
<td>9495 (1159)</td>
</tr>
<tr>
<td>Miscanthus</td>
<td>Nebraska</td>
<td>2012</td>
<td>12</td>
<td>292 (5)</td>
<td>23.7 (1.8)</td>
<td>6912 (545)</td>
</tr>
</tbody>
</table>

**Conclusions:**
- Corn Stover yields not affected by drought but quality was impacted.
- Mixed grasses and Miscanthus decreased significantly both yield and quality.
- Miscanthus affects of drought were much more significant than field nitrogen treatments.
• Quality variability is an important factor in the success of the bioeconomy.

• Library is a useful sample tracking and management tool for project level management.

• The ubiquitous data collected across multiple projects can be used in aggregation to help understand scope and sources of feedstock variability.

• Publically available tool meant to help not only INL research but bioenergy researchers everywhere.
Acknowledgements

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• Those who were authors or contributed to data:

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  **University of Nebraska-Lincoln:** Matthew Sousek, Roch Gaussoin

  **University of Illinois:** Thomas Voight, Emily Thomas, Andy Wycislo, DoKyoung Lee

  • Collaborators mentioned: Krystel Castillo (University of Texas at San Antonio), Emily Heaton (Iowa State University), and Danielle Wilson (Iowa State University), Oakridge National Laboratory.

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Questions?
NIR Model Development

• Proximate/Ultimate rapid characterization

• Development of NIR models that can handle variability:
  – Feedstock (including different cultivars)
  – Location
    • Matrix effects of different locations within one type of feedstock can affect analyte concentrations
  – Crop Year/ Harvest Season
    • As seen in the drought study harvest year can effect multiple physical and chemical components in feedstocks

• High throughput and rapid screening techniques are necessary to quickly characterize samples

<table>
<thead>
<tr>
<th>Feedstock</th>
<th># of States</th>
<th># of Years</th>
<th>Total # Samples</th>
<th>Range: %Ash</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mixed Grasses</td>
<td>2</td>
<td>5</td>
<td>43</td>
<td>4-11</td>
</tr>
<tr>
<td>MIS (Miscanthus)</td>
<td>5</td>
<td>5</td>
<td>30</td>
<td>1-7</td>
</tr>
<tr>
<td>SG (Switchgrass)</td>
<td>5</td>
<td>5</td>
<td>38</td>
<td>1-12</td>
</tr>
<tr>
<td>SOR (Sorghum)</td>
<td>7</td>
<td>5</td>
<td>40</td>
<td>3-12</td>
</tr>
<tr>
<td>EC (Energy Cane)</td>
<td>5</td>
<td>4</td>
<td>48</td>
<td>1-8</td>
</tr>
<tr>
<td>WIL (Willow)</td>
<td>1</td>
<td>1</td>
<td>32</td>
<td>1-4</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>18</strong></td>
<td><strong>6</strong></td>
<td><strong>233</strong></td>
<td><strong>1-12</strong></td>
</tr>
</tbody>
</table>
**NIR Model Results**

**Model Merits**

<table>
<thead>
<tr>
<th>Metric</th>
<th>Common</th>
<th>Advanced</th>
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</thead>
<tbody>
<tr>
<td>RMSEC</td>
<td>0.92</td>
<td>0.65</td>
</tr>
<tr>
<td>RMSECV</td>
<td>1.01</td>
<td>0.88</td>
</tr>
<tr>
<td>$R^2$ Cal</td>
<td>0.89</td>
<td>0.95</td>
</tr>
<tr>
<td>$R^2$ CV</td>
<td>0.84</td>
<td>0.91</td>
</tr>
</tbody>
</table>

**Conclusions:**
Using advanced spectral preprocessing techniques a PLS model was built to predict ash content that could handle feedstock, temporal, and spatial variabilities.
Collaboration Opportunities

• The goals of the Library team are to establish collaborations so that disparate data can be brought together in a single management framework to perform similar studies too large for a single institution.

• Examples:
  – University of Texas at San Antonio: Krystel Castillo
    • Using the publically available library data to answer nationwide questions about chemical and physical differences based on the feedstock type and storage conditions.
  – Iowa State University: Emily Heaton & Danielle Wilson
    • Biomass Crop Production Lab will be using our library to manage their own field experiments and track data
    • Collaboratively we will be analyzing the samples from these studies for chemical and physical properties.
  – INL: Logistical Supply Chain Model Inputs
    • As the data in the library grows it has become a resources for supplying real data for simulations for logistical supply chain modeling efforts.
    • Energy inputs for processing samples can be linked to quality properties of the samples for a larger picture.