BERKELEY LAB

U.S. DEPARTMENT OF ENERGY

UNIVERSITY OF CALIFORNIA

Mixed feedstock conversion screening to develop and scale efficient integrated processing through product transformation

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March 8, 2017

Feedstock Conversion Interface Consortium

Objective

Developing a predictive model to de-risk bio-based production, expand location choices

What feedstocks are available? How much will they cost?

What treatment and process parameters should we use?

- **Identify and Optimize Traditional Pretreatment Methods**
- **Biomass Mixture Compositions**

Integrate with Least cost Formulation (INL) and Techno-Economic Analysis (SNL)

BETO MYPP:

By 2017, validate efficient, low-cost, and sustainable feedstock supply and logistics systems that can deliver feedstock at or below $84/dry ton (2014$)

By 2022, …supply 285 million dry tons per year to support a biorefining industry (i.e., multiple biorefineries) utilizing a diversity of biomass types.

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Quad Chart Overview

Timeline

- Project Start Date: 10/1/2014
- Project End Date: 9/30/17
- 66% complete (paused 12/16)

Barriers

Ft-I. Overall Integration and Scale-Up

Ct-A, Feedstock Variability

Ct-D. Efficient Pretreatment

Budget

	Total Costs <FY15	FY 15 Costs	FY 16 Costs	Total Planned Funding (FY 17-)
DOE Funded	0	160,000 (LBNL) 95,000 (SNL)	220,00 (LBNL) 35,000 (SNL)	220,000 (LBNL) (paused) 15,000 (SNL) (paused)
Project Cost Share (Comp.)*	0	0	0	0

Partners

- SNL (20%)
  - Blake Simmons (now at LBNL)
  - Murthy Konda
  - Seema Singh (since FY 2017)
- INL (20%)
  - Allison Ray
  - Chenlin Li (at LBNL until 2015)
  - Damon S. Hartley

1 – Overview

1. INL

Least Cost Modeling, Feedstock blends supply and characterization

2. LBNL

Perform lab-scale deconstruction

3. LBNL

Build and Validate the predictive model

4. LBNL

Apply Predictive Model (High Solids Deconstruction and Fermentation)

5. LBNL

Rheological studies to determine behavior of mixed feedstocks at high solids loading

6. SNL

TEA model comparing IL with DA

7. LBNL

Scale up (100L) deconstruction tests

8. LBNL

Scale up (2L) hydrolysate fermentation

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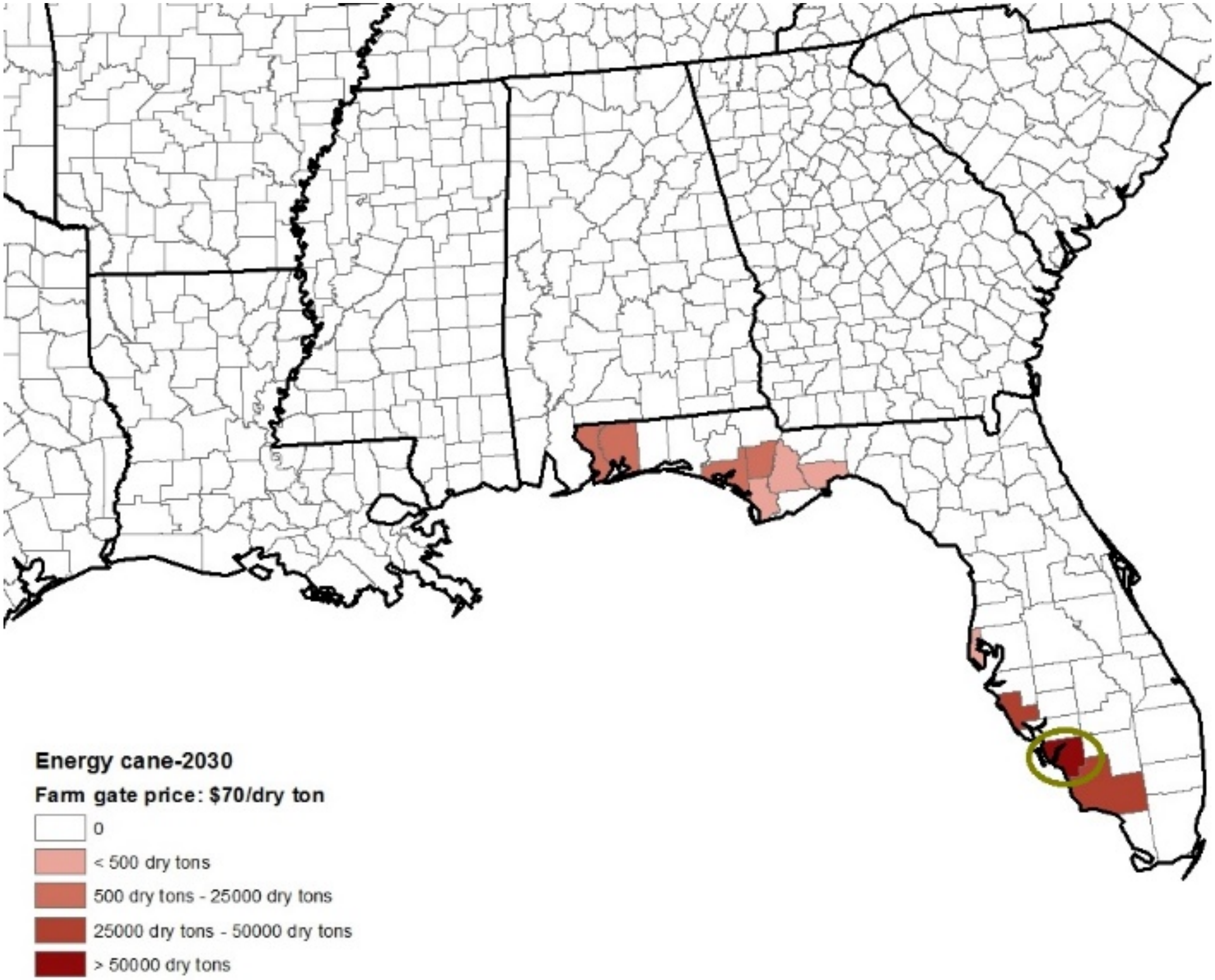
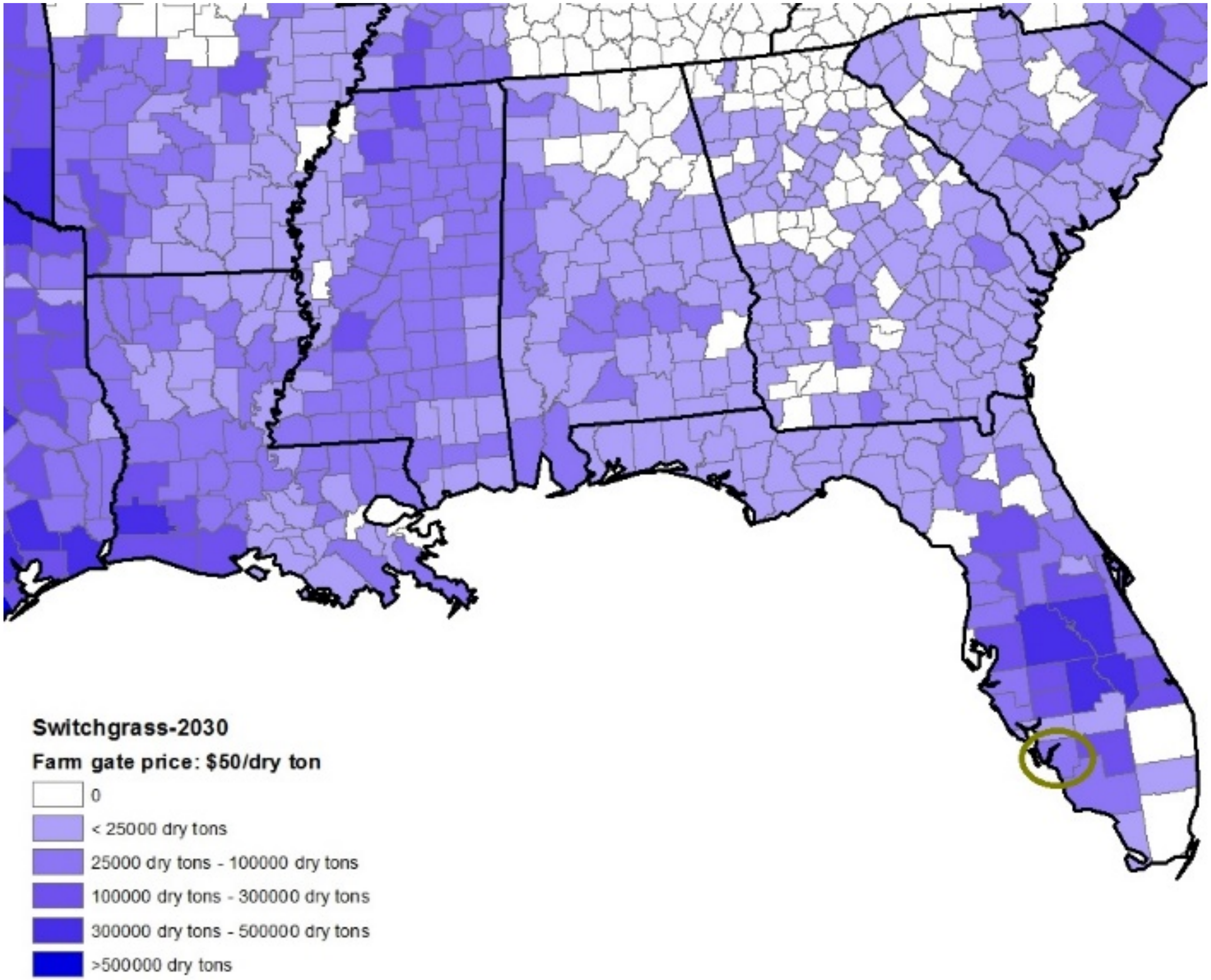
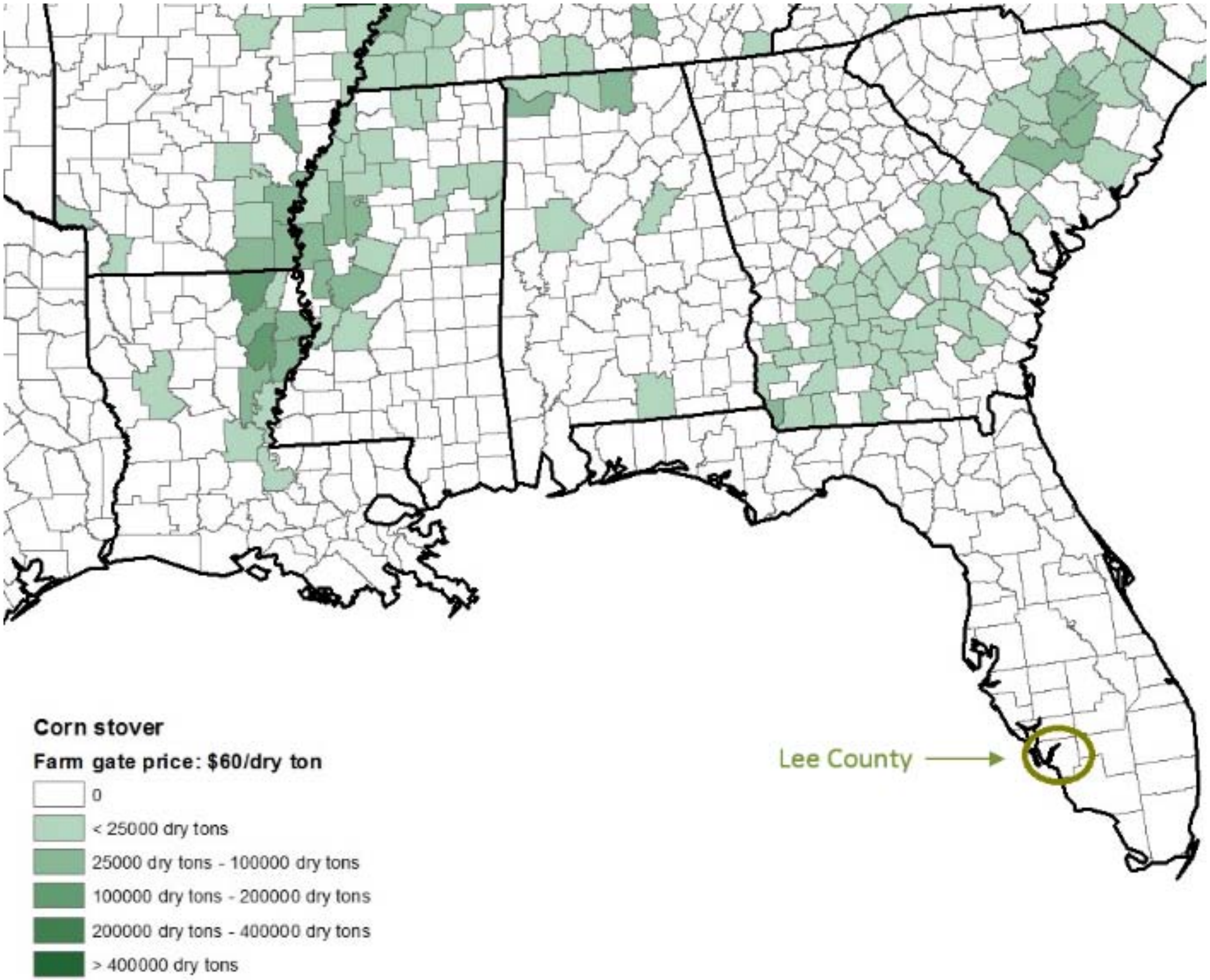
2 – Approach: LCF for Energy Cane availability



2 – Approach: LCF for Switchgrass availability



2 – Approach: LCF for Corn Stover availability



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2 – Approach: Experiments

Test Factors:

- 3 pretreatments (dilute alkali, dilute acid, and ionic liquids)
- Temperatures scaled, 1 – 100% (140 to 180°C; 55 to 120°C; 120 to 160°C)
- Times scaled, 1 – 100% (5 to 60 minutes, 1 to 24 hours, 1 to 3 hours)
- Mixtures with ratios of 3 feedstocks (energy cane, corn stover, switchgrass)

Challenges in obtaining a good model:

Several lab-scale deconstruction tests were required

Data need to be varied, low and high yields required

Applicable only for the feedstocks tested, mid FY16 replaced energy cane with wheat straw

Critical success factors: More deconstruction data, scale-up studies

2 – Approach: Experimental Design, SAS JMP®

Whole plots	PT	Temp%	^0C	Time %	Min	CS	SG	EC
1	IL	1	120	39	106.8	0	1	0
1	Ac	1	140	100	60	0.3	0.4	0.3
1	Al	1	55	100	1440	0	0	1
1	Al	1	55	39	589	0	0.5	0.5
1	Al	1	55	100	1440	0	1	0
1	IL	1	120	100	180	0	0	1
2	Ac	100	180	1	5	0	0.6	0.4
2	Ac	100	180	60	38	1	0	0
2	Al	100	120	1	60	0	1	0
2	Al	100	120	1	60	1	0	0
2	Al	100	120	1	60	0	0	1
2	IL	100	160	1	60	0	0	1
3	IL	39	135	100	180	0.5	0.5	0
3	Ac	39	155	1	5	0	0	1
3	IL	39	135	1	60	1	0	0
3	Al	39	80	1	60	0.3	0.4	0.3
3	Ac	39	155	1	5	0.4	0.6	0
3	Al	39	80	100	1440	1	0	0
4	Ac	80	172	80	49	0	1	0
4	IL	80	152	80	156	1	0	0
4	IL	80	152	80	156	0	1	0
4	IL	80	152	1	60	0.5	0	0.5
4	Al	80	107	80	1159	0.2	0.4	0.4
4	Ac	80	172	80	48.8	0	0	1

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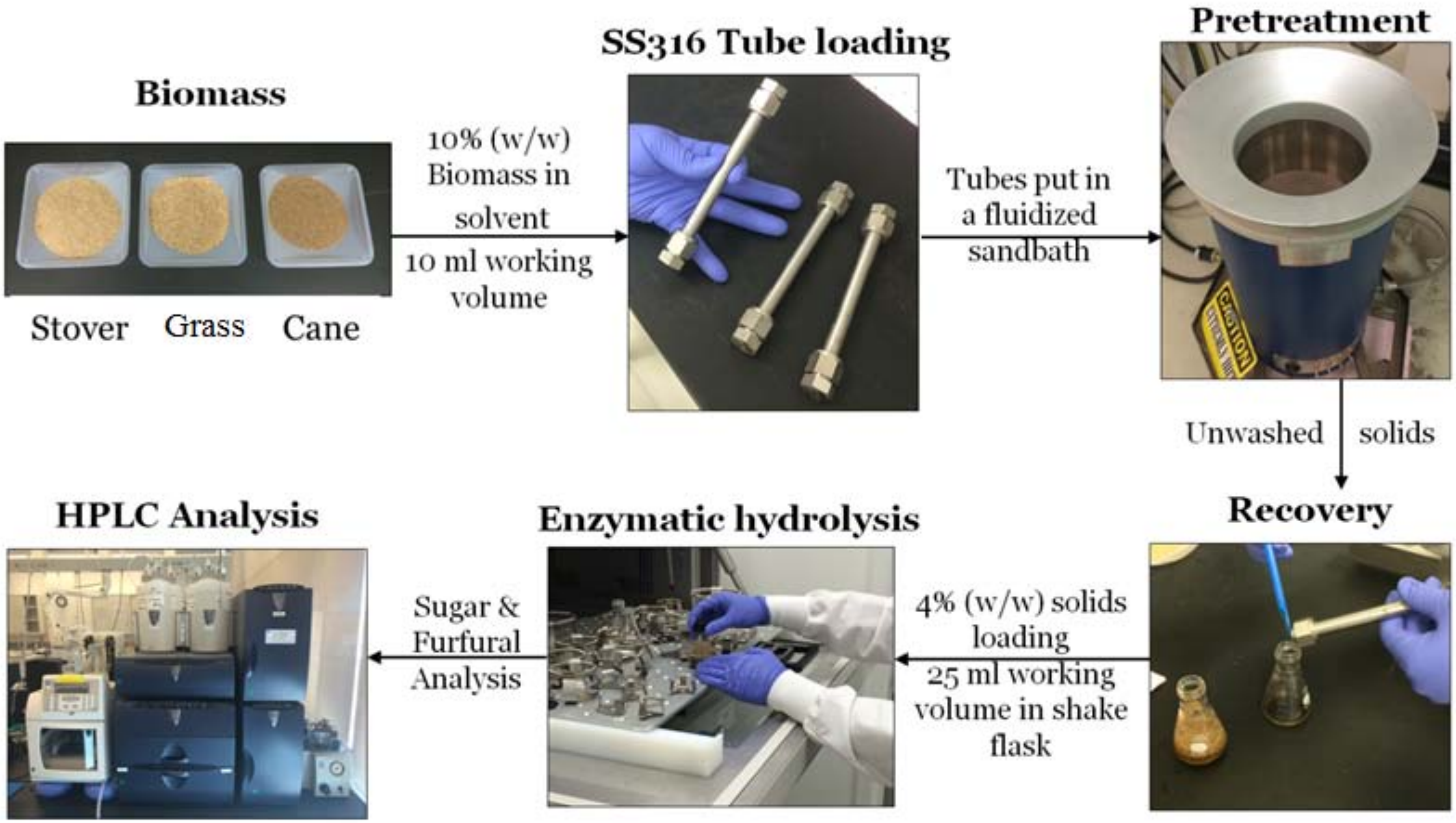
2 – Approach: Deconstruction

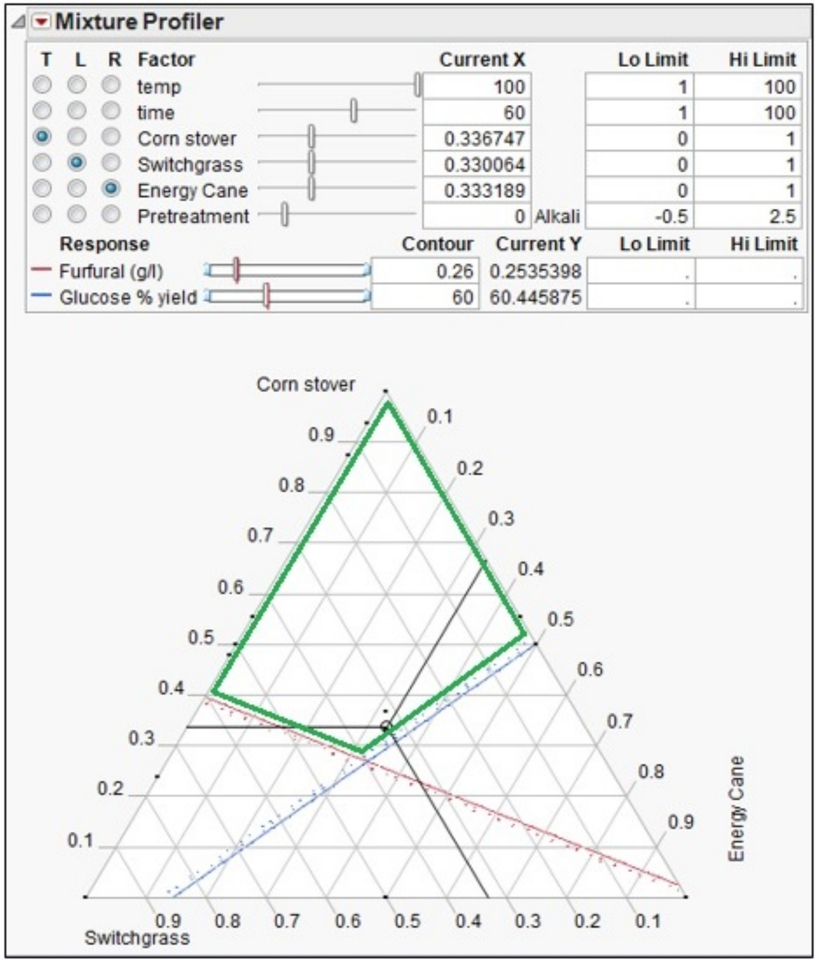


3 – Technical Accomplishments: Model

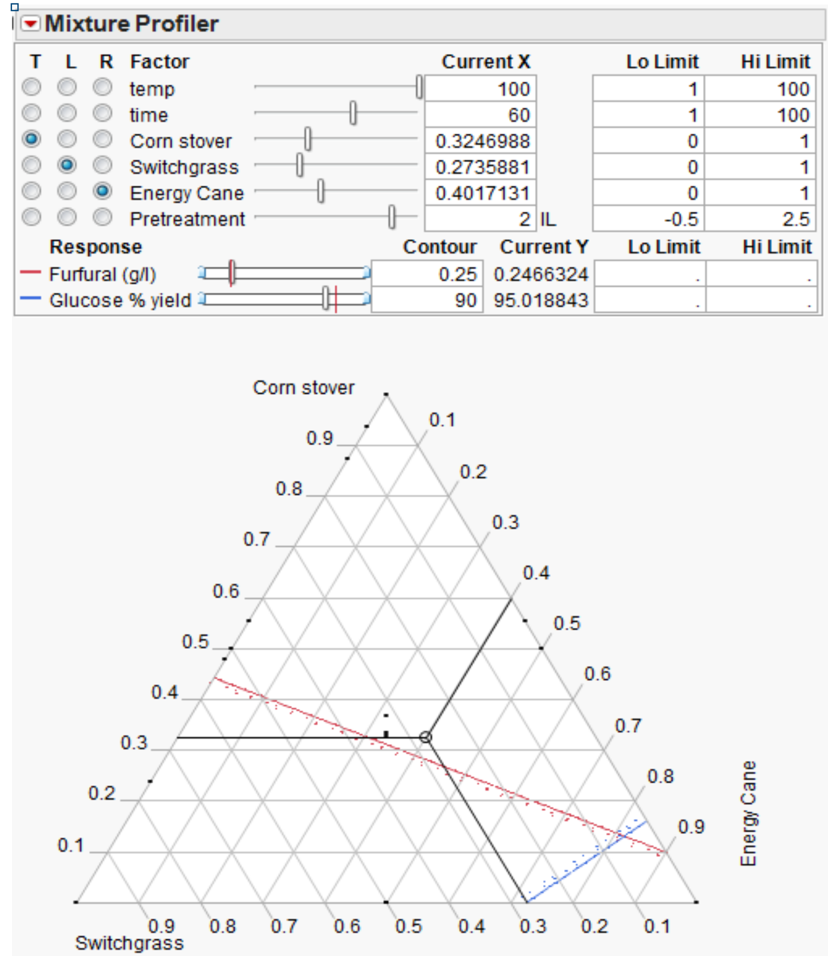
Factor	Coefficients	Standard Error	t-ratio	Prob>[t]
Energy Cane	66.76	3.80	17.57	<0.0001
Switchgrass	73.62	4.02	18.32	<0.0001
Corn Stover	79.95	3.95	20.24	<0.0001
Alkali Pretreatment	-10.37	2.84	-3.65	0.0005
Acid Pretreatment	-5.59	2.92	-1.91	0.0599
Temperature (1, 100)	3.30	2.68	1.23	0.2221
Time (1, 100)	2.43	3.00	0.81	0.4206

3 – Approach: Data Interpretation with Ternary Plots

Profile for predetermined yields and optimal biomass mixture envelopes

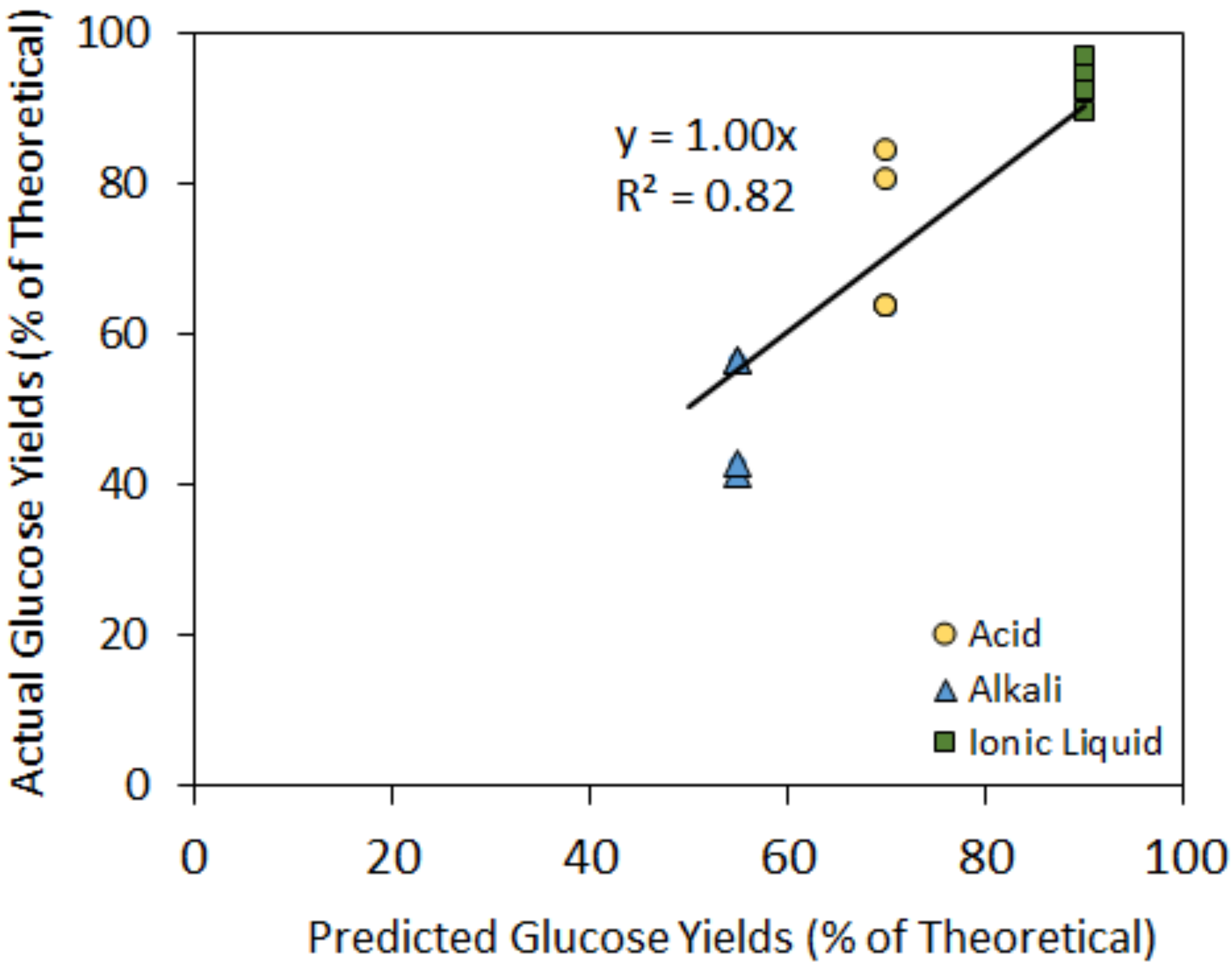


Dilute Alkali



Ionic Liquid

3 – Technical Accomplishments: Model Validation



3 - Technical Accomplishments: Summary

- Acid pretreatment of mixtures was leading to furfural generation due to uneven severities for feedstocks with different recalcitrance
- Ionic liquids were producing 90%+ (of theoretical) sugar yields in most cases leading to a distorted model
- Lower enzyme loadings were narrowing feedstock envelopes and leading to a drop of about 10% (of theoretical) sugar yield
- Validation of model was necessary

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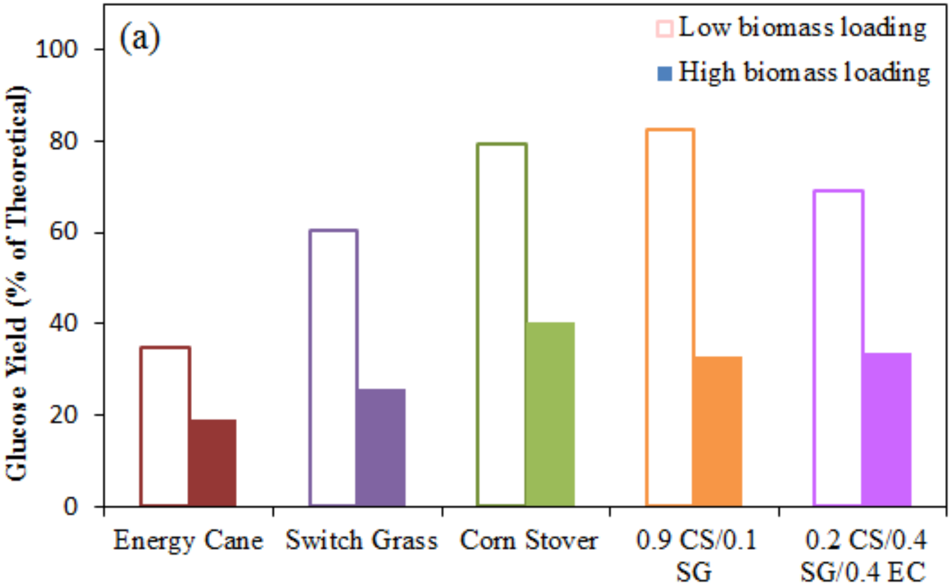
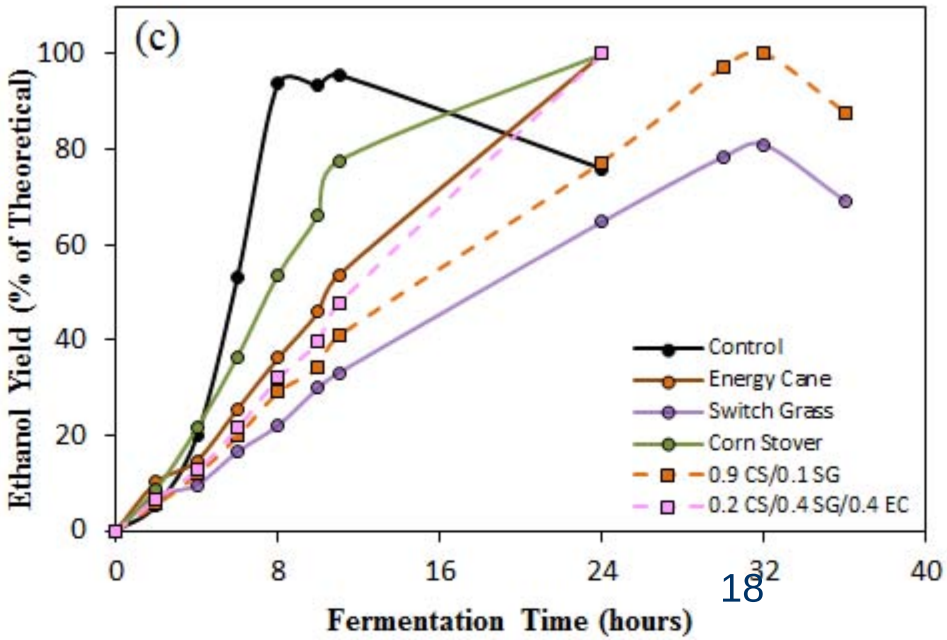
3 – Technical Accomplishments: Fermentation

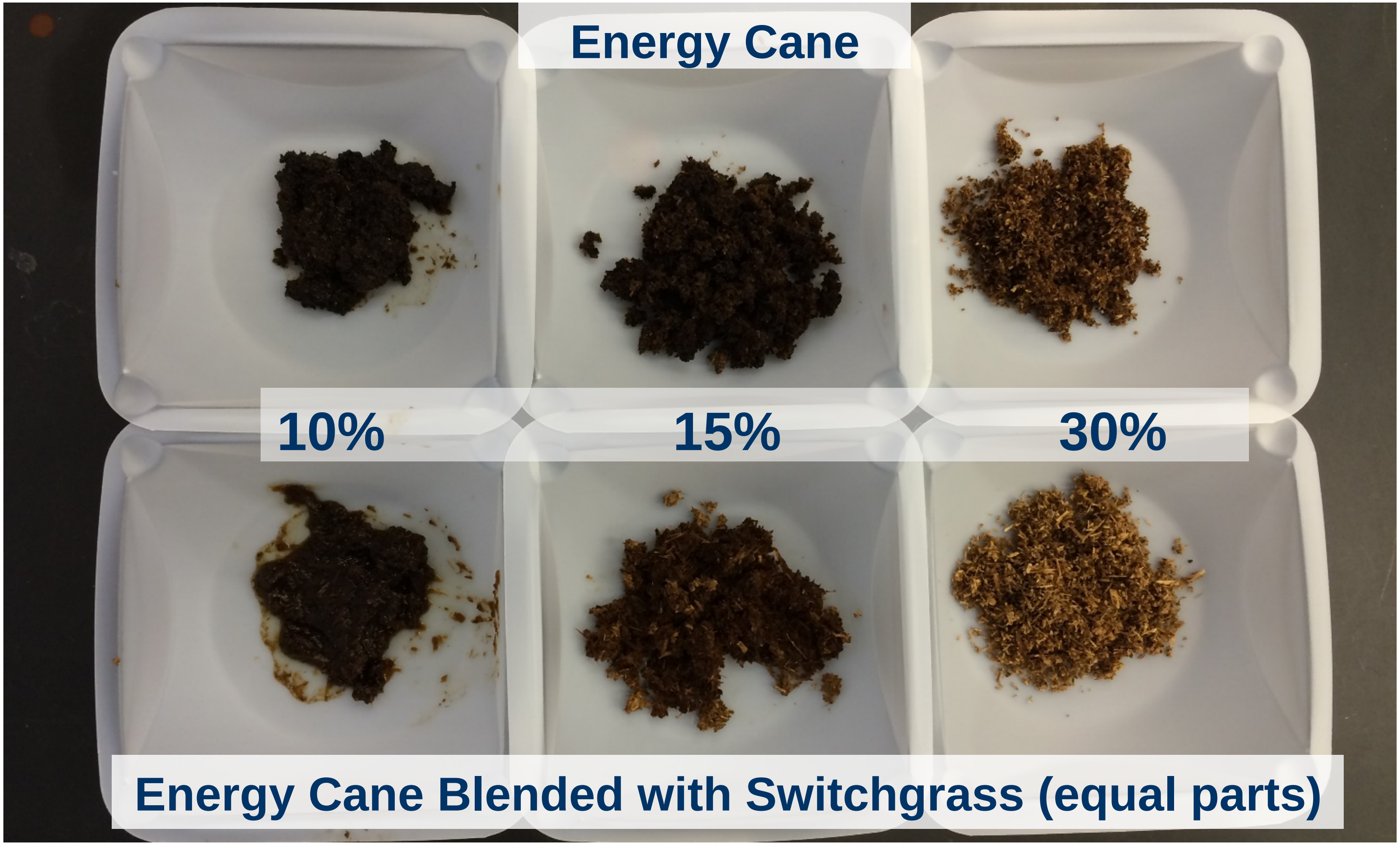


- Corn stover hydrolysate converted rapidly to ethanol
- Switchgrass hydrolysate was not only slow in converting, it yielded only 80% ethanol
- Mixed feedstock with only 20% corn stover led to 100% ethanol yield

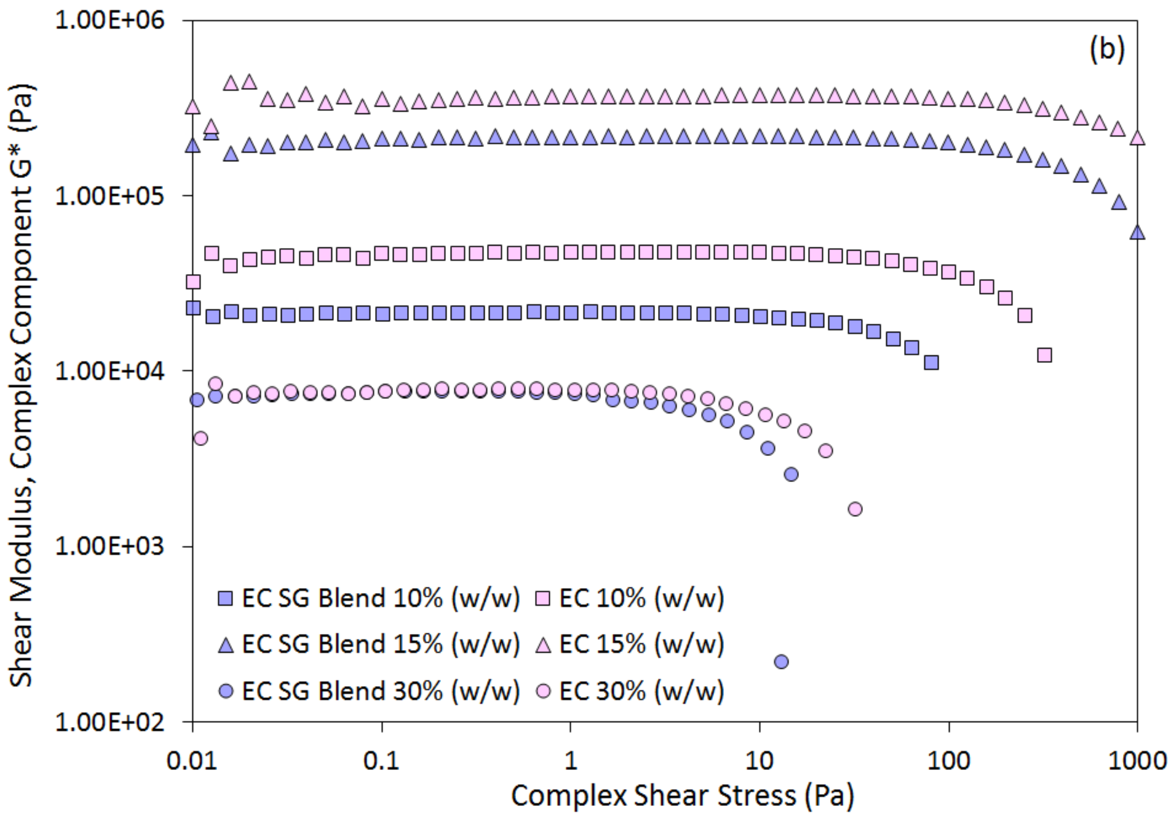
- Energy Cane was most recalcitrant
- Mixture of energy cane (40%) and switchgrass (40%) performed better than either single feedstocks when mixed with 20% corn stover
- High solids loading alkali pretreatment led to lower yields but with similar trends



2 – Approach: Rheology with Solid loading

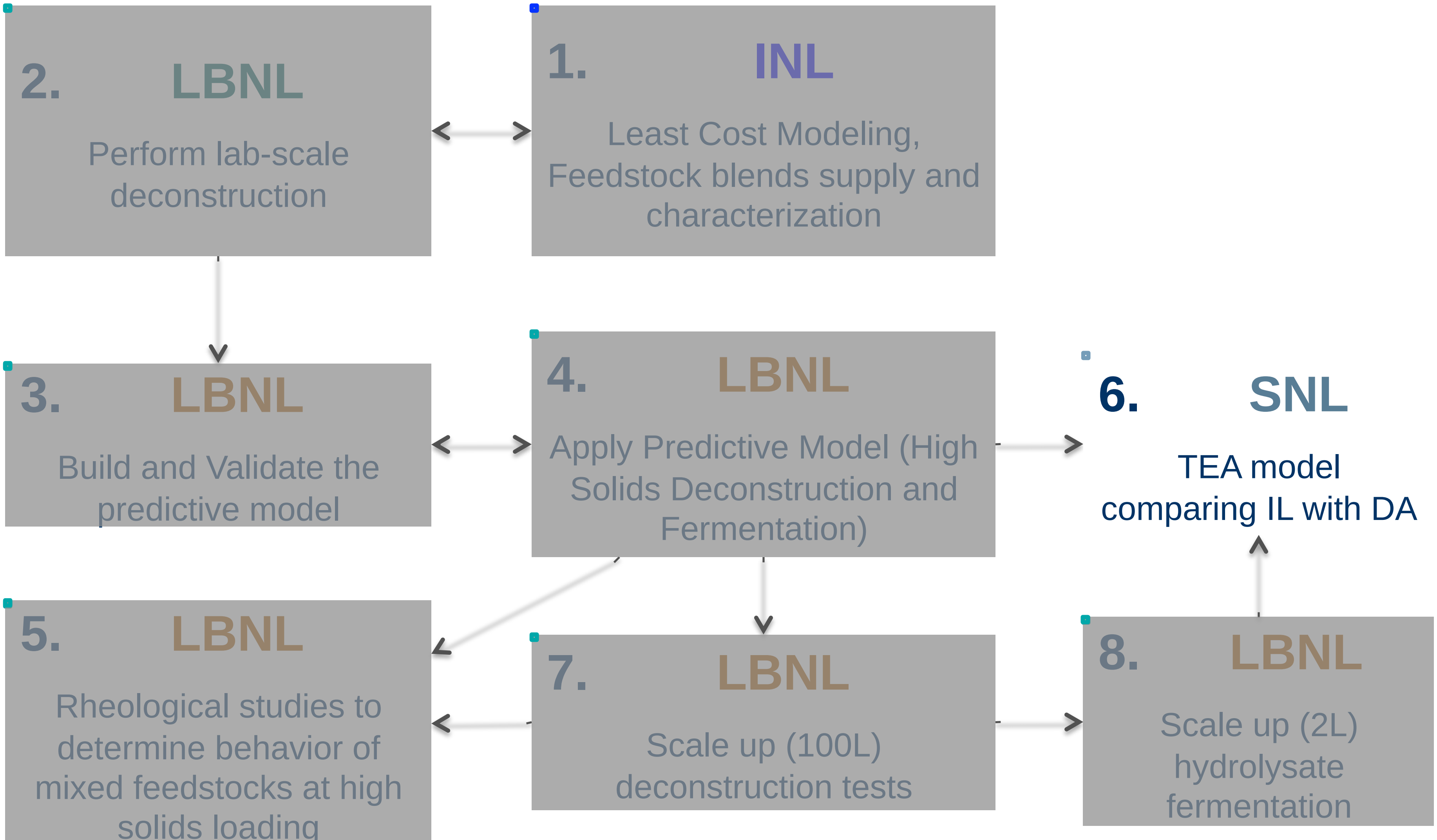


2 – Technical Accomplishments: Rheology Variation



- Mixed feedstocks behave differently at lower solid loading, potential to blend feedstocks to obtain better processing conditions
- The difference in rheological behavior not pronounced at high solids loading

1 – Overview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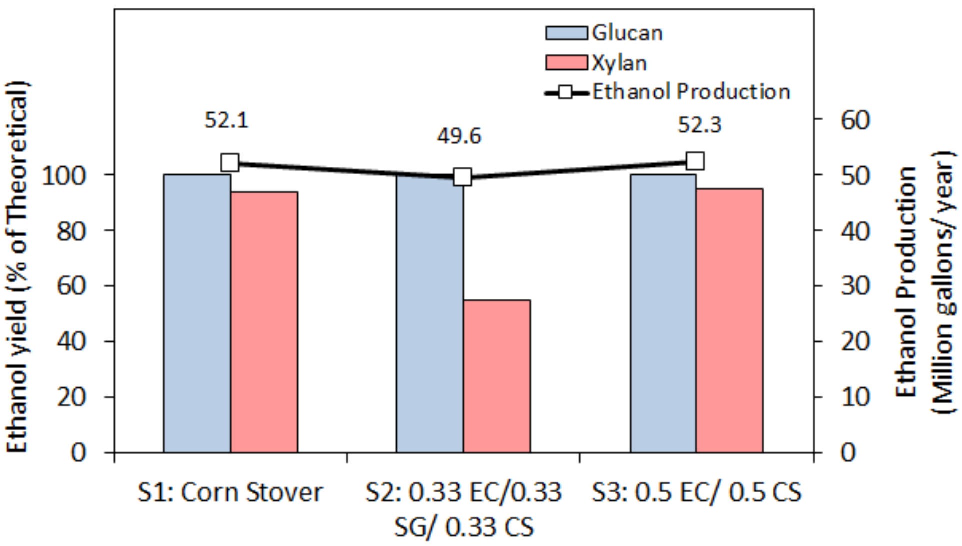
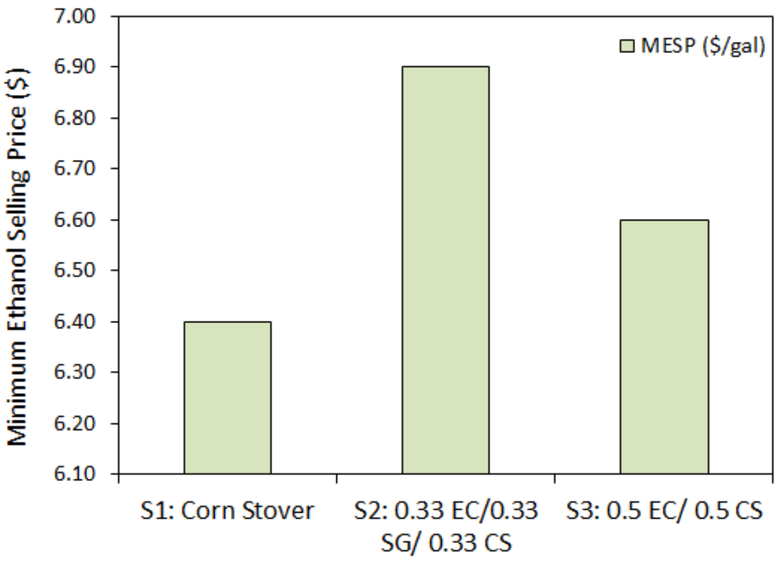
3 – Technical Accomplishments: TEA





- TEA indicated that feedstock cost does not always determine MESP; xylose yield and conversion can overcome the low cost feedstock pricing
- S3 scenario is a feedstock with 50% corn stover and more expensive than S2, but the MESP from S3 scenario is better

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4 – Relevance

- Goal: Developing a predictive model to de-risk bio-based manufacturing, expand biorefinery location choices
- Directly supporting BETO's goal: *Enable sustainable, **nationwide production of biofuels** that are compatible with today's transportation infrastructure...*
- Addresses BETO's 2017 performance goals:

i. ... validate efficient, low-cost, and sustainable feedstock supply and logistics systems..... at or below $84/dry ton (2014$)

ii. ... the industry could operate at 245 million dry ton per year scale

iii. ... determine the impact of advanced blending and formulation concepts on available volumes

- Project metrics and technical targets were driven by TEA
- Scale-up studies will not only validate the model, but also make tech-transfer smoother

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4 – Relevance

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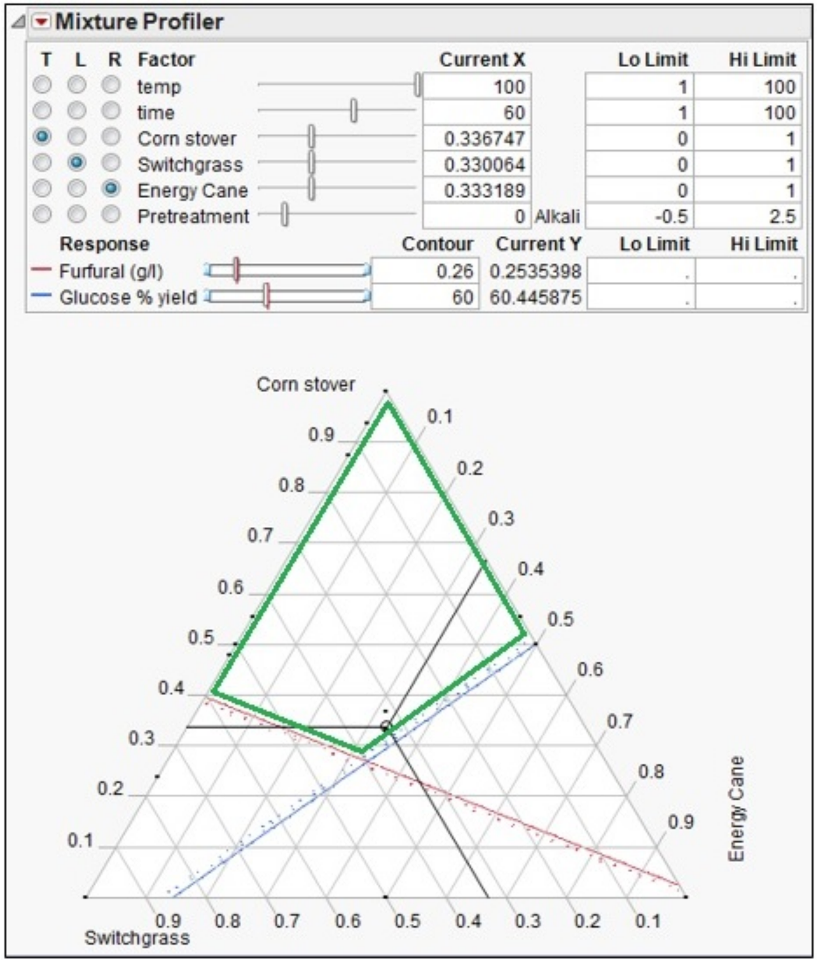

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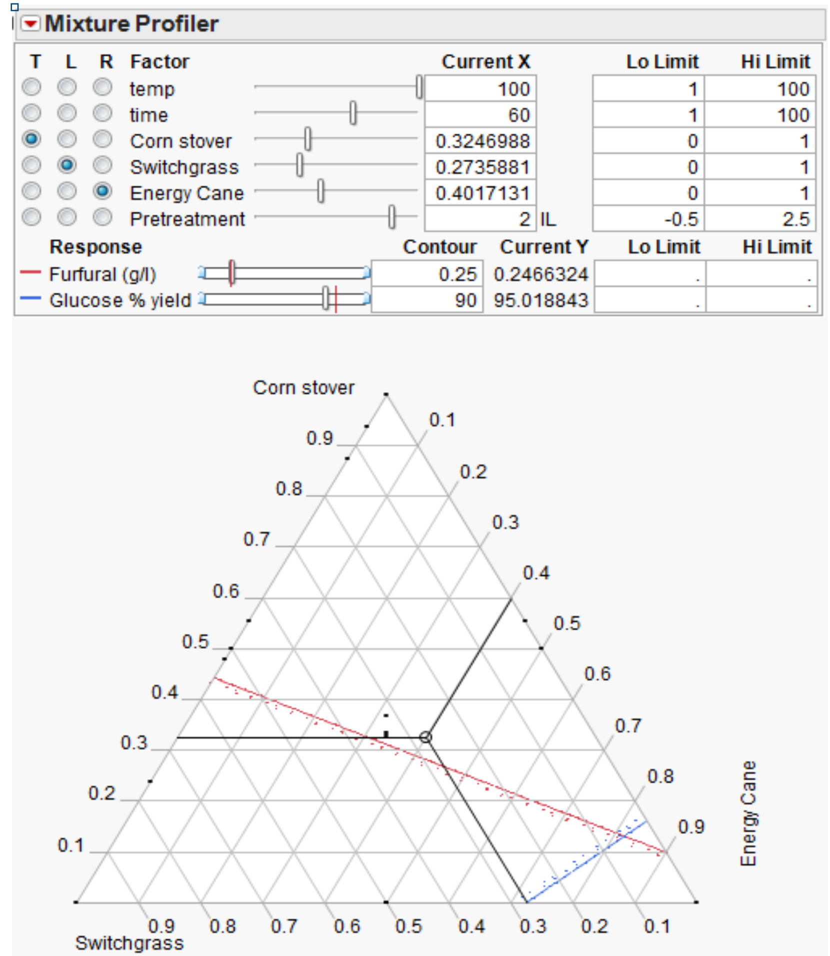


Ionic Liquid

5 – Future Work

- Compare loose feedstock with formatted versions (briquettes), perform energy density studies
- Include bio-compatible ILs, e.g. Cholinium Lysinate
- Scale-up dilute alkali pretreatment (100L) at high solids loading (30% w/w)
- Perform fermentations in 2L bioreactors
- More deconstruction tests at the lab-scale…

Summary

1. **Overview:** Predictive modeling provided insights into blending biomass feedstocks
2. **Approach:** Deconstruction tests and associated analytics can inherently bring some variability in data; validation and scale-up tests were necessary
3. **Technical Accomplishments:** Identified feedstock mixtures that can be successfully converted with a high ratio of recalcitrant feedstocks
4. **Relevance:** Feedstock variability can exist even in a single type. Predictive modeling can help address this variability in real time
5. **Future work:** More scale-up and more lab-scale tests

Summary

- All project goals and milestones were achieved until the end of FY16, developed wheat-straw based model
- Developed a predictive model to identify biomass blends that can utilize recalcitrant feedstocks
- Feedstock mixture with a 20% corn stover led to high sugar yields and was converted 100% to ethanol
- IL treatment provided highest sugar yields
- Alkali pretreated hydrolysates were successfully converted to ethanol
- Single feedstocks and biomass blends were observed to be rheologically similar at high solids loading

Additional Slides

Publications, Patents, Presentations, Awards, and Commercialization

Publication:

A. Narani, P.C. Coffman, J. Gardner, N.V.S.N. Murthy Konda, Chyi-Shin Chen, F. Tachea, C. Li, A. E. Ray, D. S. Hartley, A. Stettler, B. Simmons, T. Pray, and D. Tanjore

“Predictive modeling to de-risk bio-based manufacturing by adapting to variability in lignocellulosic biomass supply” Submitted to Energy and Environmental Sciences

Publications, Patents, Presentations, Awards, and Commercialization

Presentations:

A. Narani, P. Coffman, F. Tachea, C. Li, T. Pray, and D. Tanjore. Predictive Modeling and Rheological Characterization of Mixed Feedstocks. AIChE Annual Meeting. November 8-13, 2015, Salt Lake City, UT.

A. Narani, P. Coffman, J. Gardner, N.V.S.N. Murthy Konda, K. L. Kenney, V. Thompson, G. L. Gresham, C. Li, B. Simmons, D. Klein-Marcuschamer, T. Pray, and D. Tanjore. Predictive Modeling Can De-Risk Bio-Based Production. Oral Presentation for SIMB Symposium on Biotechnology for Fuels and Chemicals. April 27-April 30, 2015, San Deigo, CA.

Publications, Patents, Presentations, Awards, and Commercialization

Posters:

J. Gardner, G. Yang, P. Coffman, A. Narani and D. Tanjore. Predictive Modeling Can De-Risk Biobased Production, Poster Presentation, BERC Innovation Expo, October 16, 2014, Berkeley, CA.

J. Gardner, D. Tanjore, C. Li, J. Wong, W. He, K. Sale, B. A. Simmons and S. Singh. Rheological Characterization of 1-Ethyl-3-Methylimidazolium Acetate and Lignocellulosic Biomass mixtures. Poster Presentation for Joint BioEnergy Institute Retreat, Aug 26-28, 2013, Sonoma, CA.

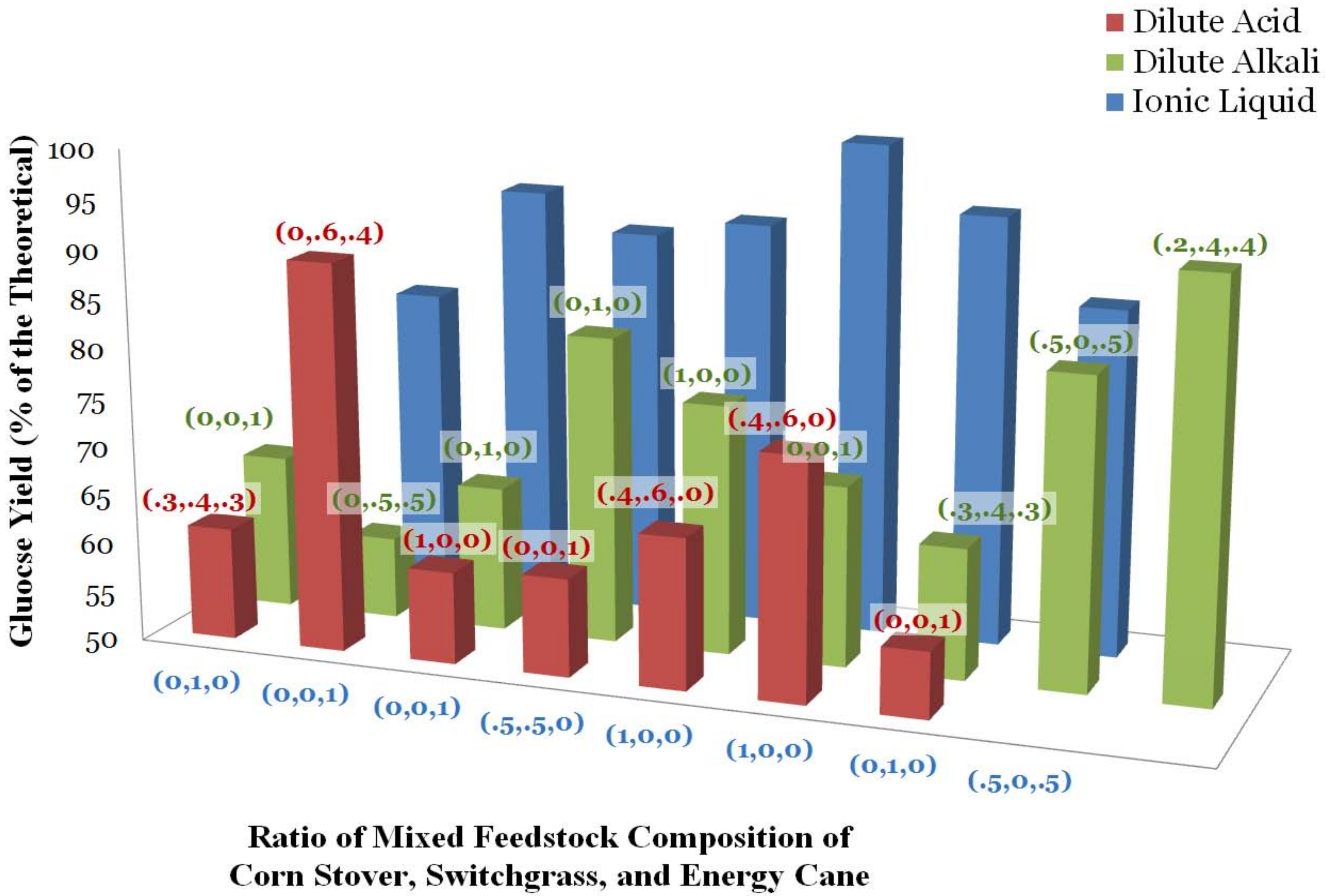
Predictive Modeling Defined

"*Predictive modeling is a mathematical algorithm that predicts target variable from a number of factor variables.*" - 56th Annual Canadian Reinsurance Conference

Day to day example of Predictive modeling

Has been applied in other renewable sectors: wind and solar

Data Interpretation through Excel can be Limiting



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