#### DOE Bioenergy Technologies Office (BETO) 2021 Project Peer Review

Advanced Algal Biofoundries for the Production of Polyurethane Precursors

> March 11, 2021 Technology Area Session

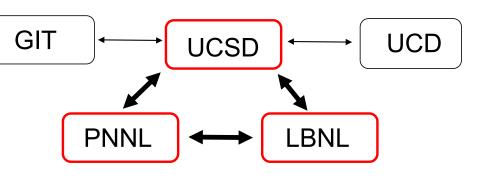
Stephen Mayfield UC San Diego Nathan Hillson (LBL) & Jeremy Zucker (PNNL)

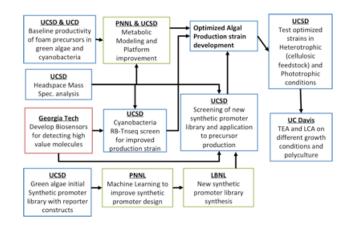
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## **Project Overview**

- Mission of project: Develop scalable, high-yield algae production platforms capable of producing polyurethane precursors for the sustainable manufacturing of bio-based, biodegradable, and recyclable foams and plastic products
- Key Academic Partners: UC San Diego, PNNL, LBL, UC Davis, & GT
- Cost Share Partners: Algenesis Materials, Reef, and Arctic Foam

## 1 – Management



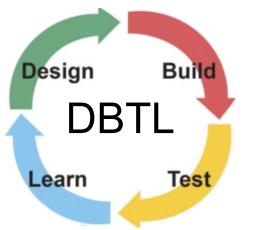


#### Key Tasks and Responsibility:

- 1. Perform multiple rounds of DBTL to optimize synthetic nuclear promoters for *Chlamydomonas* (PNNL, LBL, UCSD)
- 2. Metabolic modeling (PNNL) & subsequent engineering (UCSD & UCD) to optimize chemical production under heterotrophy or phototrophy
- 3. Develop & assess baseline production strains (UCSD & UCD)
- 4. Generate biosensors (GIT) and MS-based (UCSD) high-throughput screening systems
- 5. Scaled production (UCSD) & TEA/LCA assessments (UCD)

### 2 – Approach

Improve Synthetic Algal Nuclear Promoters



Perform 2+ rounds of DBTL:

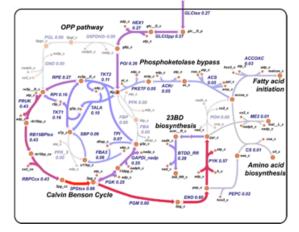
**D: PNNL** designs library of promoters based on experimental data from **UCSD** 

B: LBNL synthesizes & clones library

**T: UCSD** tests promoter strengths in algae

L: PNNL develop ML tools to analyze results for subsequent rounds

Predict ME Targets for Improved Production



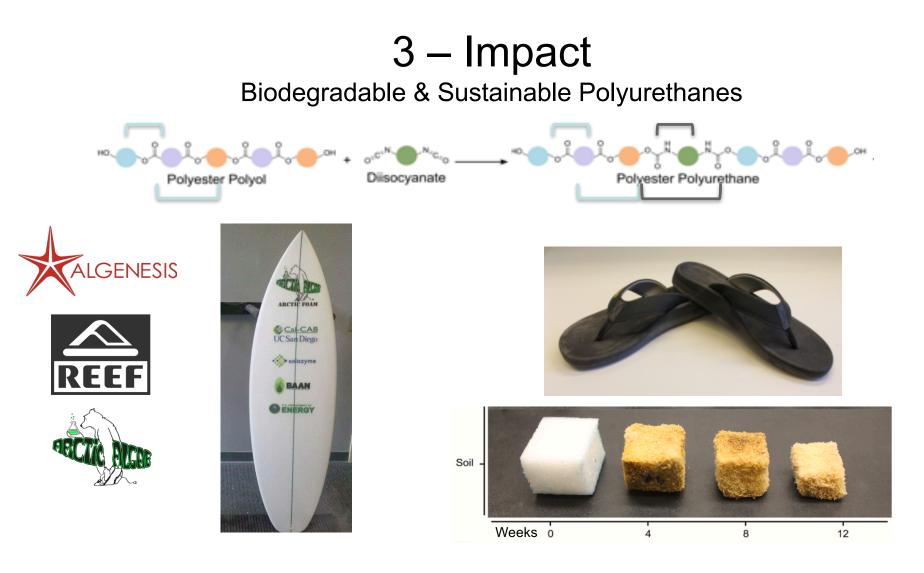
PNNL leverages metabolic models for cyanobacteria & algae to predict heterologous pathways, KOs, or over-expressions to optimize yields
UCSD & UC Davis tests these predictions & feeds back info to the models for further optimization.

#### **Scale Production**



**UCSD** scale production in both heterotrophic and autotrophic growth for TEA/LCA and to meet performance metrics.

Go/No-Go decision points = 1 gm/liter PU precursor



#### Synthetic promoter design

- **160bp promoters** trained on expression data from native promoter sequences
  - Neural network learned an embedding space mapping motifs and sequences to expression
  - AutoML learned RandomForest discriminator
- **260bp promoters** also contained predicted chromatin opening motifs in the upstream 100bp
  - Chromatin-opening motifs found empirically to be further from TSS
  - Motifs predicted from enrichment analysis of native expression data and native histone and RNAPol ChIP-Seq data.
- **Exploration**: designed low-confidence positive and negative promoters
- **Exploitation**: both methods used combinations of known high-expressing motifs
- > 1500 X 160-bp and 1500 X 260-bp long synthetic promoters were designed at PNNL
- Promoter libraries were synthesized by Twist via the LBNL ABL
- First round of libraries screened at UCSD and 2<sup>nd</sup> round designed and out for synthesis

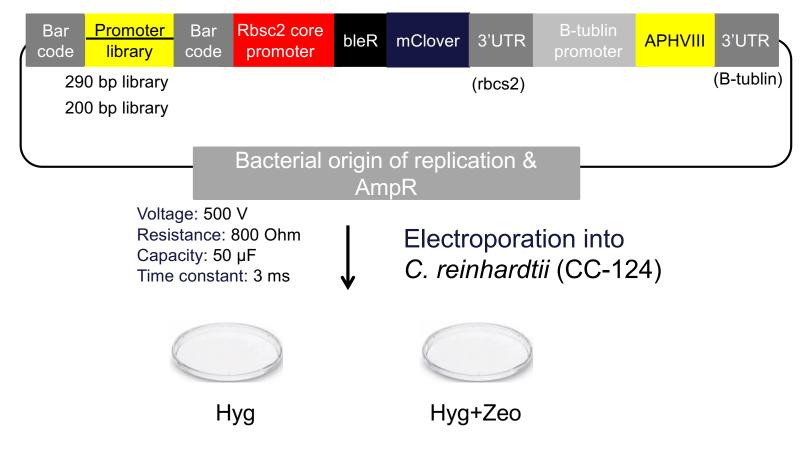
Promoter library construction

LBL added barcodes to Twist-synthesized promoters and cloned oligos into a 6778 bg reporter vector designed by UCSD DNA library has been delivered to UCSD ٠ (4539) XbaI and transformations into Chlamydomonas reinhardtii are underway. Left seq. 8xN 8xN Right seq. **RBCS2** Pro Synthetic Promoter Barcode primer site primer site Barcode

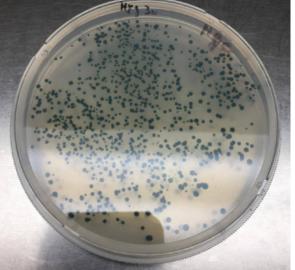
1500 290-bp and 1500 200-bp long synthetic promoters ordered

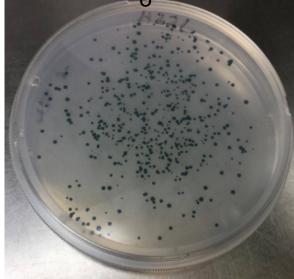
NdeI (184)

#### Reporter vector design

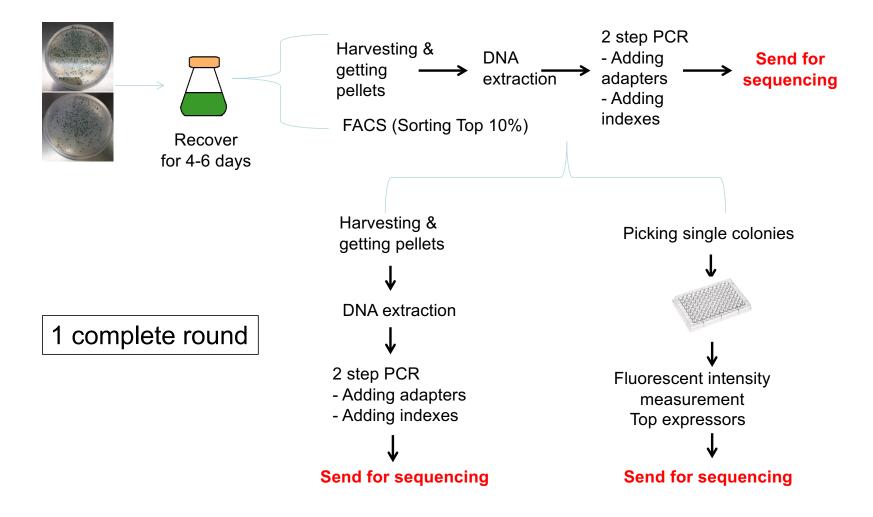


Library	Hyg	Hyg+Zeo
200 bp	~4000 colonies	~600 colonies
290 bp	~4000 colonies	~450 colonies
	Hyg	Hyg+Ze
	HF1 30	13231





5 replicate transformations were made



#### 200 bp library (Tap + Light)

<>	1	2	3	4	5	6	7	8	9	10	11	12
A	0.95372	1.02403	0.37941	0.08195	0.13417	0.40463	0.28867	0.96536	0.85335	0.57334	0.07666	0.75164
В	0.09664	0.87577	0.54517	1.48784	0.49818	0.64185	0.26716	0.61128	0.64637	0.64539	0.58224	0.46919
С	0.57324	0.64768	0.13062	0.66614	0.22241	1.02571	0.89963	0.42023	0.52139	0.32952	0.80015	0.41149
D	0.48674	0.24893	0.8184	0.85876	0.60651	0.91873	0.69128	0.88772	0.43604	0.38825	0.34852	0.4104
E	0.96837	0.97287	0.94873	0.63096	0.64033	0.7371	1.0717	0.76428	0.55084	0.56026	0.56043	0.57189
F	0.48871	0.84526	0.87743	0.28122	0.7871	0.57909	0.80794	0.56353	1.09065	0.64586	0.54583	0.6262
G	0.09356	0.32825	0.59998	1.13067	0.58181	0.6	0.88035	0.3768	0.35914	0.46659	0.39118	0.63168
Н	0.64894	0.61915	0.49459	0.65878	0.57559	0.41479	0.66962	0.65799	0.21425	0.55151	0.39487	0.60269

200 bp library (Tap + <u>Dark</u>)

$\diamond$	1	2						8	9	10	11	12
A	0.5557	0.53294	0.35469	0.09141	0.08944	0.37512	0.23739	0.75474	0.78011	1.21565	0.07495	0.47757
В					0.65454							
С					0.10791							
D					0.56498							
E	1.09312	1.35732	0.85387	0.52164	0.58951	0.59656	0.3477	0.96968	0.74225	0.75727	0.94672	0.75108
F	0.30109	0.45356	0.90955	0.1812	0.90095	0.49608	0.87134	0.41659	0.54724	0.53112	0.591	0.63898
G	0.11564	0.29795	0.68323	0.6428	0.38906	0.22245	0.53768	0.18266	0.27055	0.40303	0.32333	0.33541
Н	0.62643	0.51684	0.4616	0.45602	0.366	0.15916	0.64246	0.41879	0.14356	0.29363	0.23338	0.30068

#### Promoter assessment

- Separate Analyses for FACS-Sorted (enriched) and Unsorted Barcode Count Data
  - Survival Index Distribution (Gamma Distribution) Hyg (expression) / HygZeo (high expression)
    HygZeo Survival Probability (Binomial Distribution)
- Combined Analysis for FACS-Sorted and Unsorted Barcode Count Data
  - Fluorescence CDF Ratios (Non-Parametric Distribution) (protein accumulation)

$$\begin{aligned} H_i &\sim \Gamma\left(\alpha_i, \beta_i\right) & H_i &\sim B\left(n_i, p_i^H\right) & \int_0 p_{F_i}\left(f_i\right) df_i = C_{F_i}\left(x\right) \\ Z_i &\sim \Gamma\left(\gamma_i, \eta_i\right) & Z_i &\sim B\left(H_i, p_i^Z\right) & 0 \\ S_i &= \frac{Z_i}{H_i} & \Rightarrow Z_i &\sim B\left(n_i, p_i^H p_i^Z\right) & \frac{1}{m} \sum_i C_{F_i}\left(x^*\right) = 0.9 \end{aligned}$$

$$E_{i}\left[\ln\frac{Z_{i}}{H_{i}}\right] = E\left[\ln Z_{i}\right] - E\left[\ln H_{i}\right]$$
$$= \psi\left(\gamma_{i}\right) - \psi\left(\alpha_{i}\right) + \ln\left(\beta_{i}\right) - \ln\left(\eta_{i}\right)$$

$$\int_{f_{thresh}}^{\infty} p_{F_i}\left(f_i\right) df_i = p_i^Z \qquad \qquad \frac{Z_i Z_j^{FACS}}{Z_j Z_i^{FACS}} = \frac{1 - C_{F_i}\left(x^*\right)}{1 - C_{F_j}\left(x^*\right)}$$

x

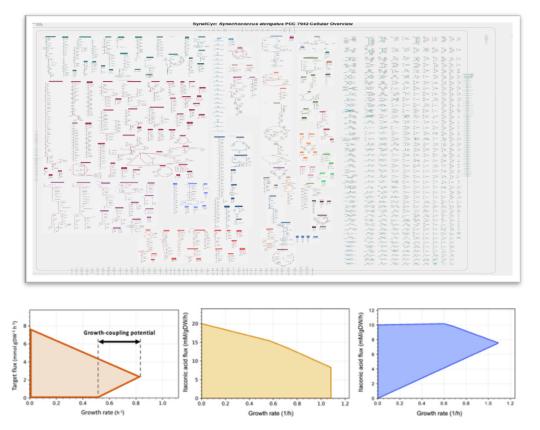
Prediction method

- Nucleotide and Motif-Based Promoter Sequence Embeddings
- 5 Separate Predictors Per Embedding
  - 2 Methods (Gamma and Binomial Distributions) each for Standard and FACS data
  - 1 Combined Method (Non-parametric CDF)
- Nonlinear Regressions with Deep Learning Trained on Analysis Results
  - Random Promoter Generation
  - Average Performance Across Predictors

$$E_i \left[ \ln \frac{Z_i}{H_i} \right] \qquad \qquad p_i^Z$$

 $d_{ij} \equiv \log (1 - C_{F_i}(x^*)) - \log (1 - C_{F_i}(x^*)) = \log Z_i - \log Z_i^{FACS} - (\log Z_j - \log Z_j^{FACS})$  $d_{ij} = -d_{ji}$  $\min_{\theta} \sum_{i,j} \|N(x_i;\theta) - N(x_j;\theta) - d_{ij}\|^2 + \epsilon \sum_i \|N(x_i;\theta)\|^2, \ \epsilon \ll 1$ 

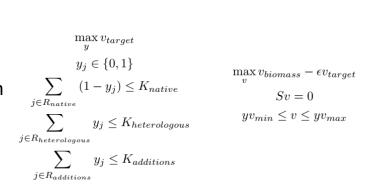
#### Metabolic Models (MMs)

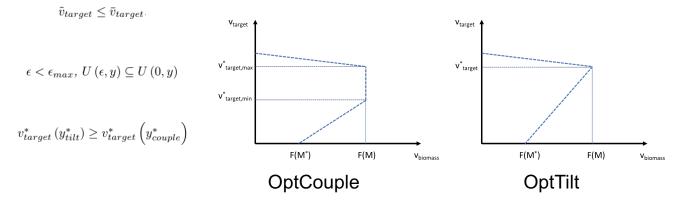


- Preliminary MMs have been coded for Synechococcus elongatus and C. reinhardtii, including essentiality and transcriptome data from UCSD.
- OptCouple, OptKnock, OptForce and OptTilt have been applied to these models to predict strains capable of improved production
- For example, 24 gene knockouts were predicted to improve diacid production in *S. elongatus.*

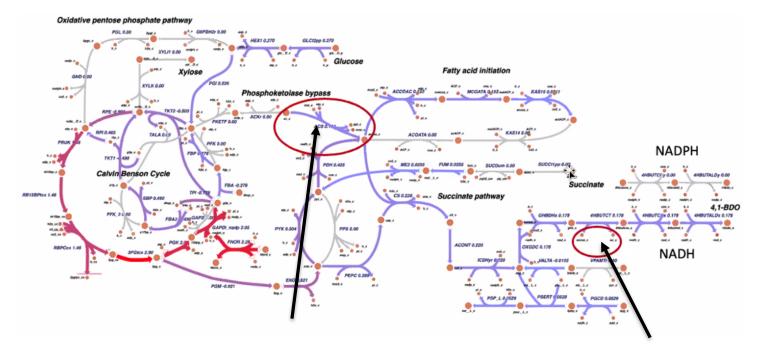
Cell Factory Design: New Theorem (PNNL)

- OptTilt beats OptCouple and OptKnock
- 'Tilting' Term
  - Generates growth-coupled solution
  - Guarantees optimality
  - Ensures maximal production



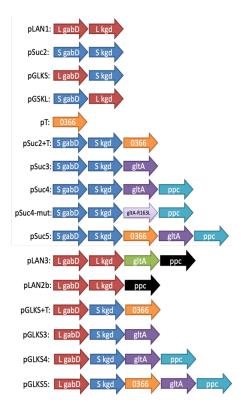


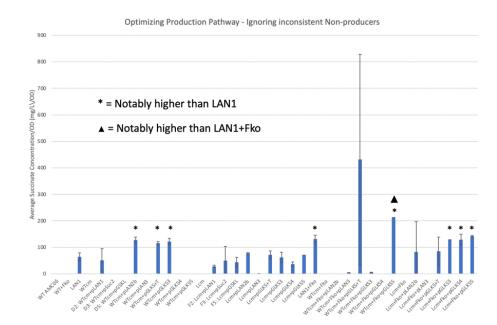
1,4-BDO Metabolic Model in cyanobacteria



Prediction is to increase acetate production to overcome acetate deficit at 2nd step in 1,4-BDO synthesis. Overexpression vector for ACS and strain currently being generated in *S. elongatus*.

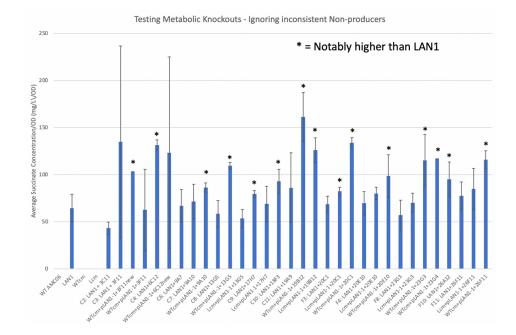
#### Succinate: Improved production vectors for cyanobacteria





Generated vectors with increased productivity over baseline production, but in a background strain dependent manner. Currently investigating the 5 SNPs that differ between the background strains.

#### Metabolic modeled mutants for succinate production in cyanobacteria



Over 30 KOs predicted to increase production. A number of knockouts increased production 2 - 3 fold. Currently combining multiple mutations and vector pathways into a single cell to test combined impacts.

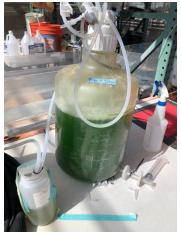
Phototrophic scaled production of succinic acid in cyanobacteria



LAN1 (baseline succinate production strain) grown at 20 L scale under <u>continuous light</u> <u>conditions indoors</u>

Succinate yields of:

- 178.8 mg/L
- or 336 mg/L/OD
- 2.7x improvement over smaller scale

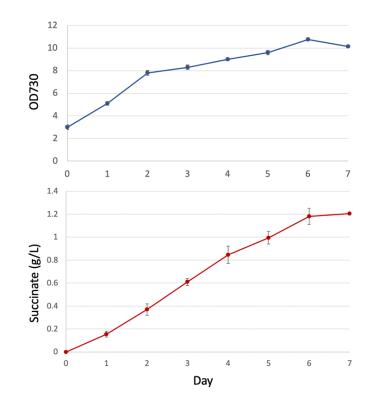


LAN1+sucD-KO grown at 20 L scale <u>in outdoor</u> greenhouse with natural light

Succinate yields of:

- 161 mg/L
- or 326 mg/L/OD
- Likely same as 2x less productive strain due to half the amount of light time

Heterotrophic production succinic acid in cyanobacteria



Strain: *S. elongatus* PCC 7942 that can consume glucose and produce succinate (NSI pTrc: *galP-zwf-gnd* spec<sup>R</sup>, NSIII pLlacO1: *gabD-kgd-ppc-gltA* gen<sup>R</sup>)

Light: 30 mmol photons/m<sup>2</sup>/s in the PAR range

Temperature: 30°C Production media: BG-11 + 50 mM NaHCO<sub>3</sub> + 10 g/L glucose

Every 24 h, 10% of the culture volume was removed, the pH was adjusted to 7.0 with 3.6N HCl and volume was replaced with production media containing 200 mM NaHCO<sub>3</sub>.

#### Over 1 g/L yield reached in 5 days = Go/NoGo milestone reached

Screening on glucose/xylose and complex corn stover hydrolysate substrate

		Mixotrophic on glucose	Heterotrophic on glucose	Indication of inhibition on xylose	Indication of inhibition on CSH
	IV-006	~	~		
	IV-031	~	~		
	IV-033	~	~		
	IV-055	>	>		
	IV-112	>			✓
	IV-113	~	~		
Income wind D. And Development	IV-118	~	~		
Imperial Valley isolates	IV-131	~	~		
	IV-132	~	~		
	IV-139	~	~		
	IV-157	~	~	~	
	IV-233	~			
	IV-238	~	~		
	IV-241	✓	✓	~	

	CCAP 11/41	~	~		
Chlamydomonas asymmetrica	UTEX 227	~	~		
	NIES 2207	~			
Chlamydomonas debaryana	UTEX 231	~	~	~	✓
Chlamydomonas pseudagloe	CPA WT	~	~		
Chlamydomonas pseudococcum	CPC	✓	✓	✓	✓

Chlorella vulgaris	CV 25	✓	✓	✓	
Desmodesmus armatus	DA 25	>			
(Chlorella sp.)	WHIT GREENS 7	~	~	~	
Parachlorella kessleri	PK 25	~	~		

Screening on pure glucose/xylose:

- 54 strains screened on CSH components separate glucose and xylose agar plates at 1% concentration
- 24 strains found to be capable to grow on glucose mixotrophically/heterotrophically
- No strain found to be capable to grow on xylose as sole carbon source; inhibition observed for a few strains

Screening on CSH (NREL) substrate:

- Mixotrophic/heterotrophic strains on glucose tested on CSH
- Goal: Confirm whether there is any toxicity visually observed on CSH (in a concentration equivalent to 1% glucose) compared to growth on pure 1% glucose
- No apparent toxicity observed for most of the strains

#### Next Steps

- Promoter DBLT:
  - PNNL: Analyze data from the five replicate transformations and generate 2nd library
  - LBNL: Synthesize & clone 2nd library
  - UCSD: Transform 2nd library into C. reinhardtii and assess promoter strengths using FACS and NGS.
  - If budget allows, perform a third round of DBLT
- Metabolic Modeling:
  - UCSD & UC Davis: Optimize & scale production strains and provide yield & omics data for production to PNNL
  - PNNL: Adjust models based on data from UCSD & UC Davis; predict heterologous, knock down, or over-expression alternatives for boosting production in both S. elongatus and C. reinhardtii
- Pilot scale production:
  - UCSD down select, optimize, and scale production strains and provide yield and omics data for TEA/LCA to UCD

#### Summary

- We set out to develop a scalable, high-yield algae production platforms capable of producing polyurethane precursors
- This was a collaboration between academic labs working on algae biotechnology (UCSD, UCD, GT) and the ABF labs of PNNL (computation) and LBNL (DNA foundry)
- At first, there were delays due to paperwork and communication glitches, but we eventually learned each other's languages and capabilities, and are moving forward together at full speed now
- We have had some good early successes on both creating synthetic promoters for algae, and metabolic modeling of succinic acid production in cyanobacteria
- We have achieved our Go/NoGo milestone of 1 gm/L succinic acid
- We have a pretty far way to go to achieve the FOA milestone of 20gm/L ... and that is
  probably still only half of the level required for commercial production but we are only 18
  months into the project ;-)

# Quad Chart Overview (Competitive Project)

#### Timeline

- Project start date 10/1/2019
- Project end date 6/30/2022

	FY20 Costed	Total Award
DOE Funding	(10/01/2019 – 9/30/2020)	(negotiated total federal share)
	\$859,559	\$2,000,000
Project Cost Share	\$301,610	\$570,000

#### Project Goal

Develop algae as a production platforms capable of producing polyurethane precursors for the sustainable manufacturing of bio-based, biodegradable, and recyclable foams and plastic products

#### End of Project Milestone

Determination of yield and cost of heterotrophic versus photosynthetic production of polyurethane precursors in cyanobacteria and algae production systems

#### **Project Partners\***

- Partner 1 PNNL, LBNL
- Partner 2 UCD, GT

Funding Mechanism DE-FOA-001916 Topic Area 2, Agile BioFoundry Industrial Partnership (ABF) 2018

\*Only fill out if applicable.

### **Additional Slides**

#### Responses to Previous Reviewers' Comments

- This project has not been peer reviewed previously
- Also provide highlights from any Go/No-Go Reviews

#### Publications, Patents, Presentations, Awards, and Commercialization

- CRADA signed between UCSD and ABF
- No Publications, Patents, or external Presentation to date