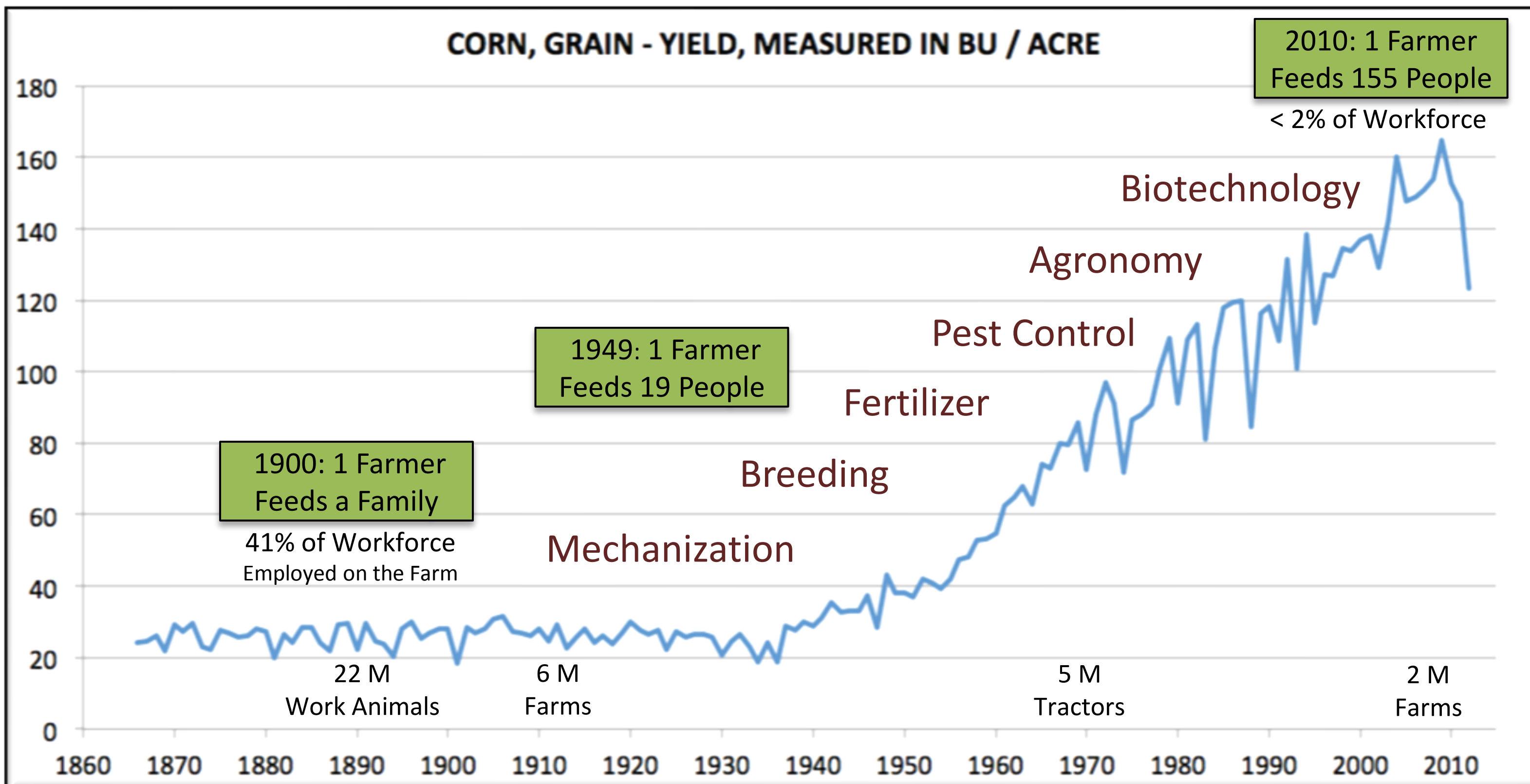
Accelerating Bioenergy Crop Development

Next Generation Phenotyping: Biology x Engineering x Computer Science

Bioenergy Crops – Fueling the Future

- **The Opportunity:** Unlocking Agricultural Genetic Potential
- **The Breakthrough:** High Throughput Phenotyping Systems
- **Program Straw Model:** We Can Do It Better

20th Century: The Green Revolution



21st Century: Knowledge Farming

1900 — *50 years* — 1950 — *40 years* — 1990 — *20 years* — 2010 — 21st Century

1900	1950	1990	2010	21st Century
Mechanized Farming	*Green Revolution*	*Biotechnology 2nd Green Revolution*	*Precision Agriculture*	***Knowledge Farming*** *(Data – Rich)*
Agronomy	Breeding	Agronomic Traits	Yield Monitors	**Integrated 'omics**
Tractors & Tillage	Hybrids	Quality Traits	GPS/GIS	Genomics
Fertilizer	Crop Protection Chemistry	Genetics	Auto Guidance Navigation	Proteomics
	Irrigation	Molecular Breeding	Variable Rate Technology	Metabolomics
		Markers	Soil Sampling	Transcriptomics
			Data Collection	Phenomics
				Digital Ag
				High Performance Computational Analytics
				Real Time Sensing
				Remote & Proximal Imaging Systems
				Autonomous Robotics and UAS

"A major challenge for crop production in the 21st Century is how to predict crop performance as a function of genetic architecture."

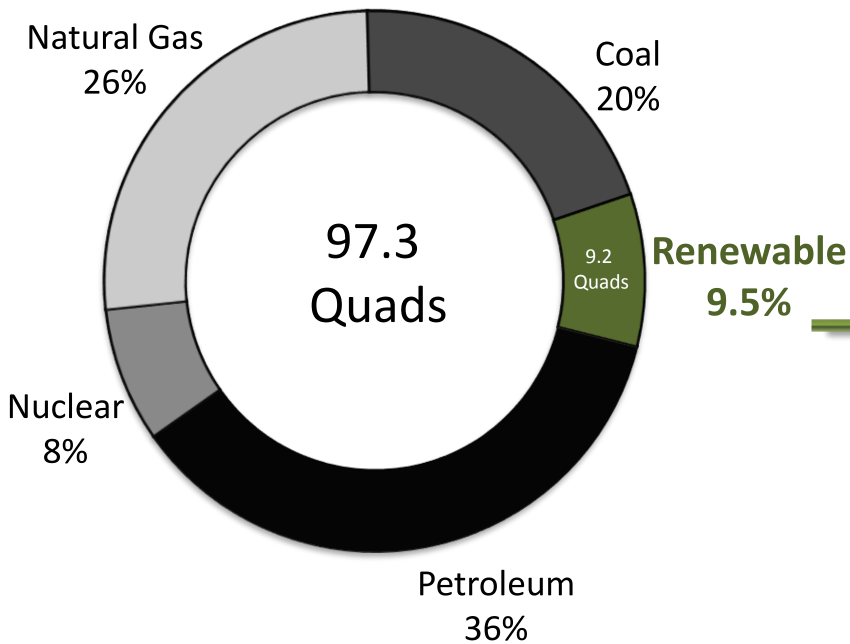
ANALOG — *41 percent of labor force worked in agriculture (1900)*

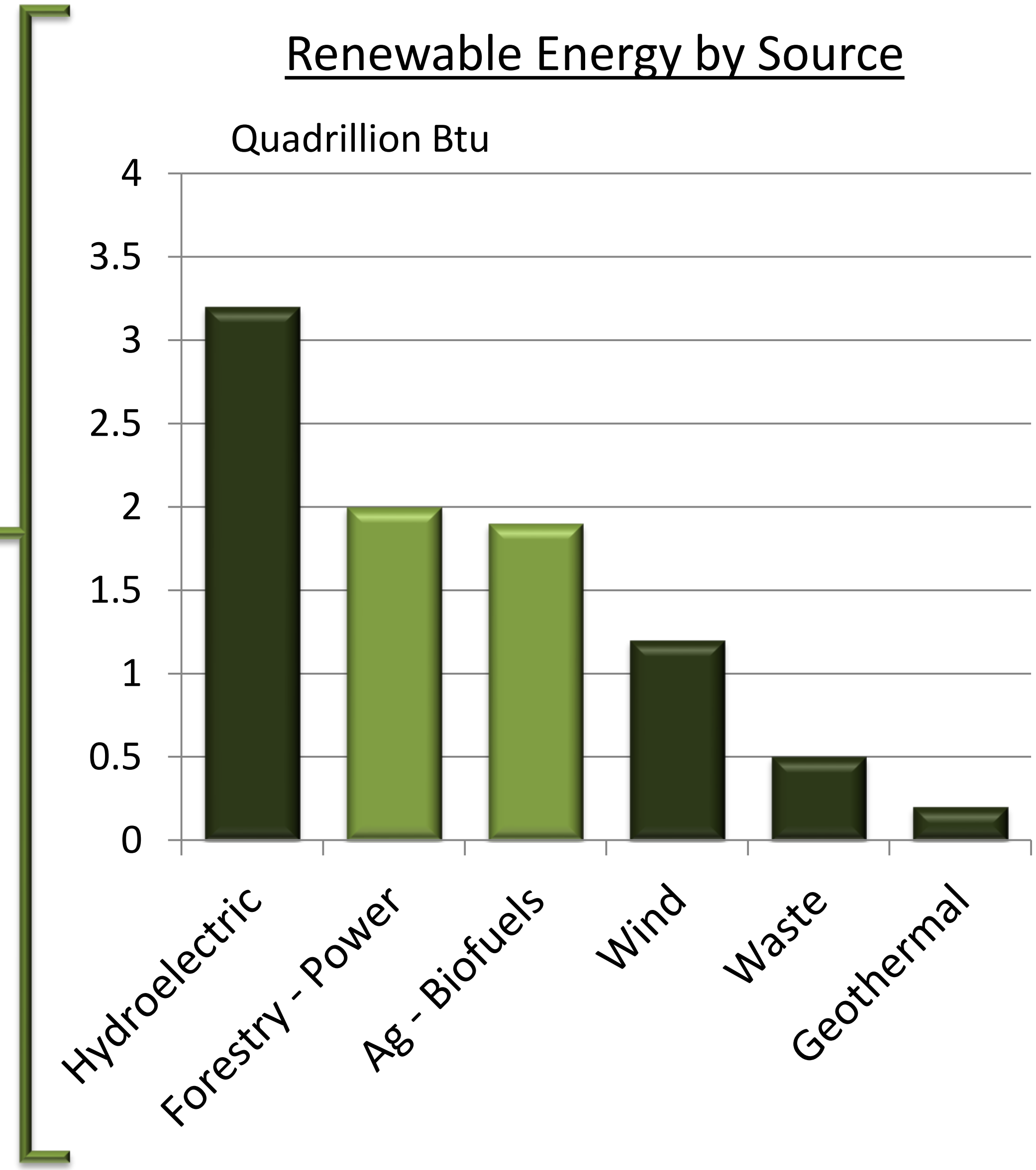
DIGITIZATION — *1.9 percent of labor force worked in agriculture (2000)*

DATAFICATION

Agriculture and Forestry are Important Renewable Resources

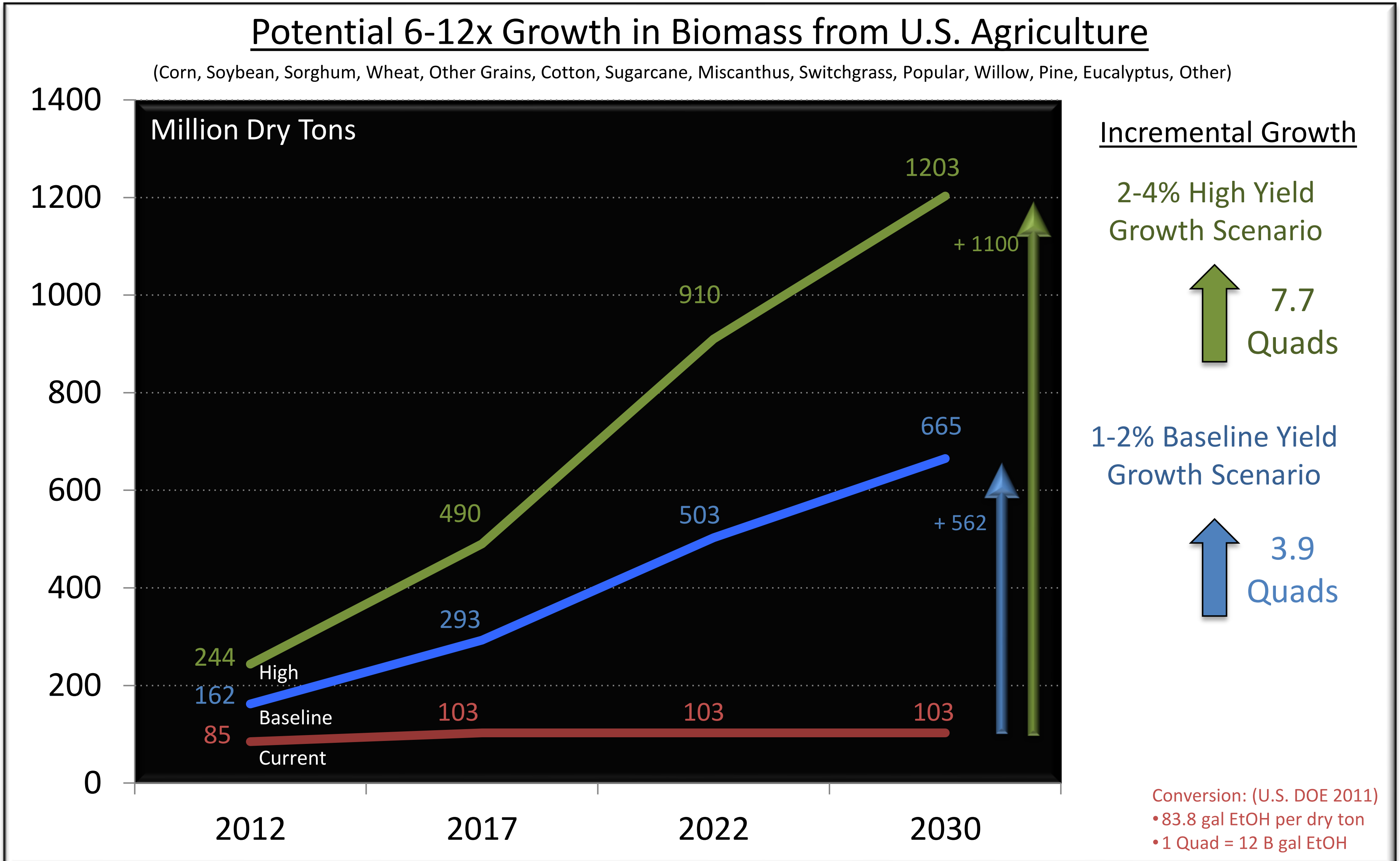
U.S. Total Primary Energy Consumption 2011





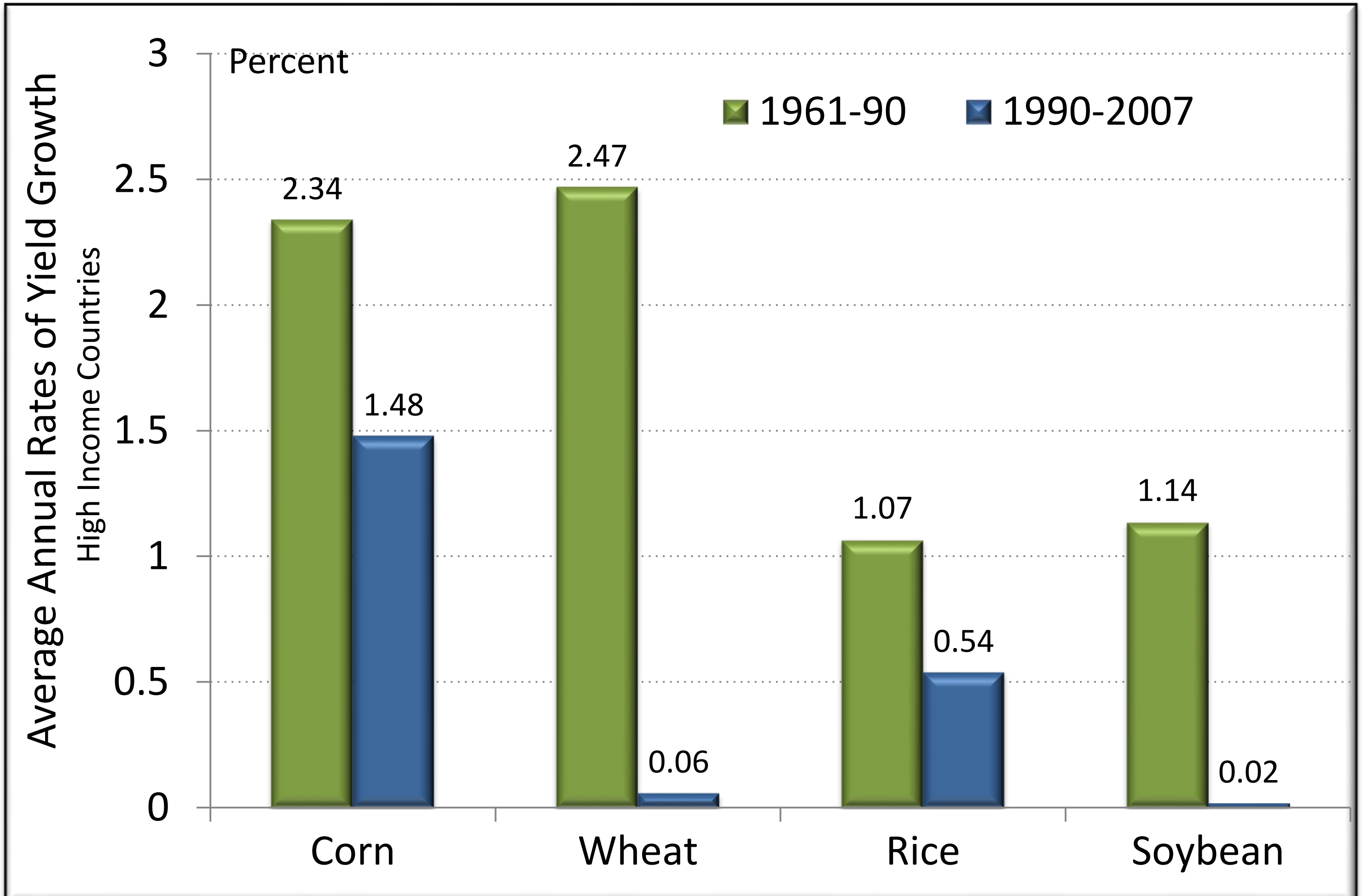
U.S. Energy Information Administration. *Annual Energy Review 2011*. September 27, 2012.

U.S. has the capability to deliver billion-ton feedstock for bioenergy in addition to food and export



U.S. Department of Energy. 2011. *U.S. Billion-Ton Update: Biomass Supply for a Bioenergy and Bioproducts Industry*. ORNL.

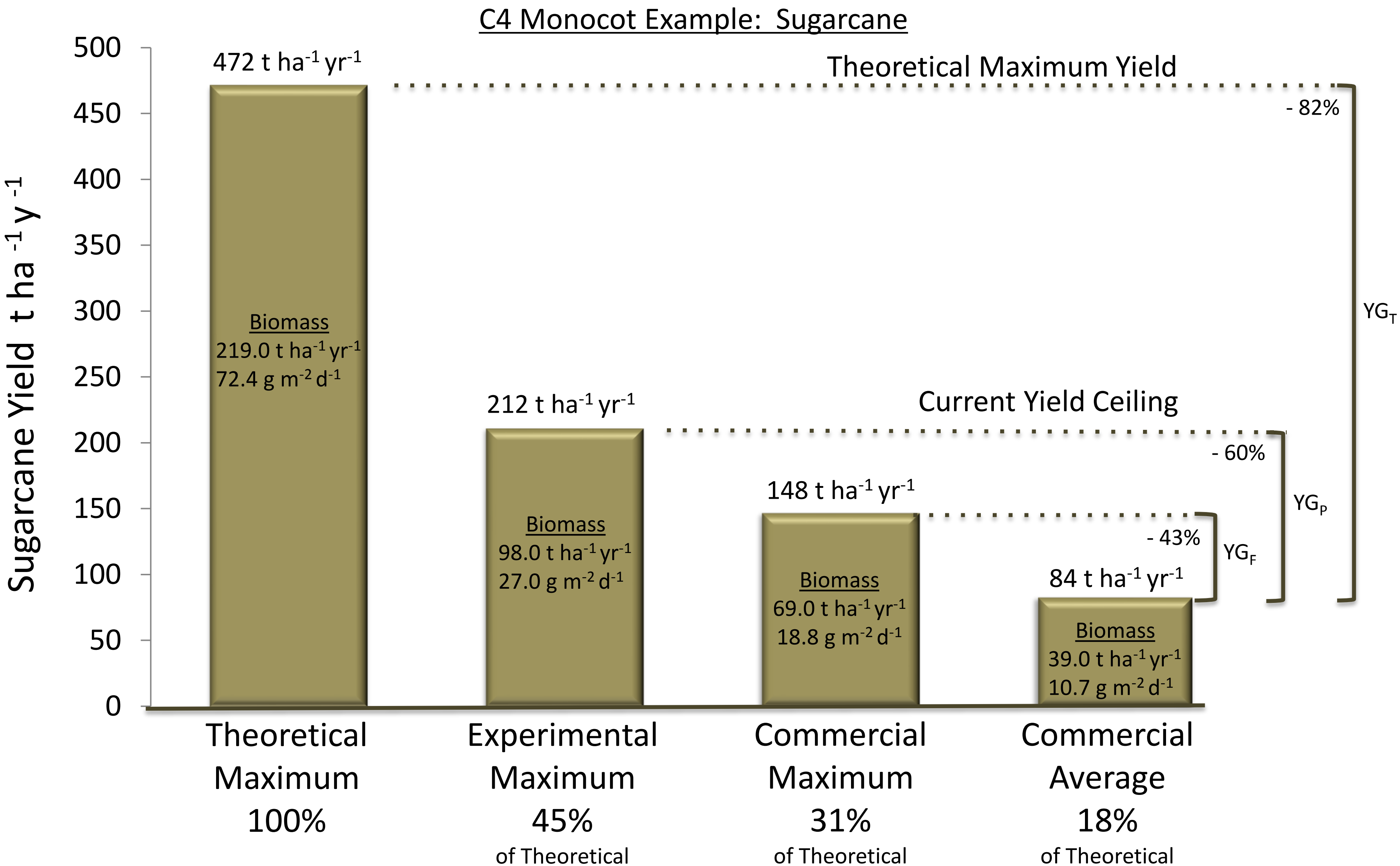
However, we are off the pace, evidenced by declining rates of genetic gain and suboptimal investments in bioenergy crops



"Rates of improvement in yield for many cropping systems are below the 1.16-1.31%/y^{-1} rates required to meet projected demand for crops." Hall et.al.

- FAOSTAT 2009
- *Prognosis for genetic improvement of yield potential of major grain crops*. A. J. Hall, R. A. Richards, Field Crops Research, 143 (2013) 18-33.

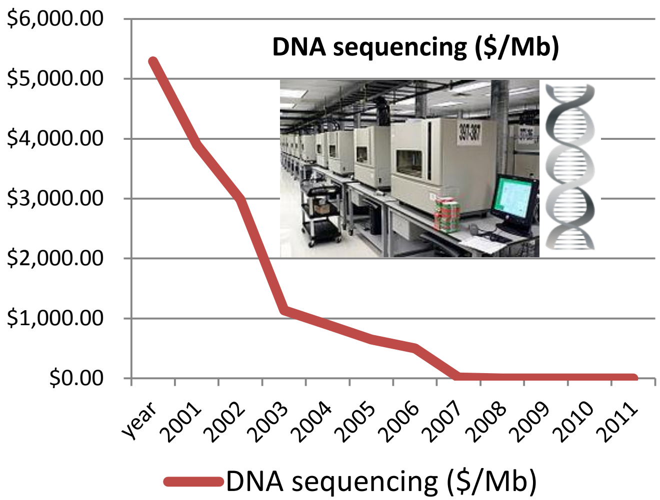
Our greatest opportunity to increase the supply of agricultural feedstock's is in closing the yield gap



USDA, ARS, US Pacific Basin Agricultural Research Center and Hawaii Agricultural Research Center

Our greatest opportunity to close the yield gap and develop better feedstock is advanced crop phenotyping

Sequencing is No Longer a Bottleneck



Achieved Automated Plant Imaging

Single Plant Green House Systems

Field Phenotyping in its Infancy… not continuous, automated or fast

ARPA-E Program Aspirations

Advanced Bioenergy Crop Phenotyping is the Catalyst

Reduced Energy Imports

Improve Genetic Gain and Grower Adoption

200 – 400% Increase

+4 to 8 Quads

2 Quads

Current Ag Based

Improved Energy Efficiency

Decrease Use of Fuel, Fertilizer, Water, Chemicals

25% Reduction

1.7 Quads

Current

Reduced GHG Emissions

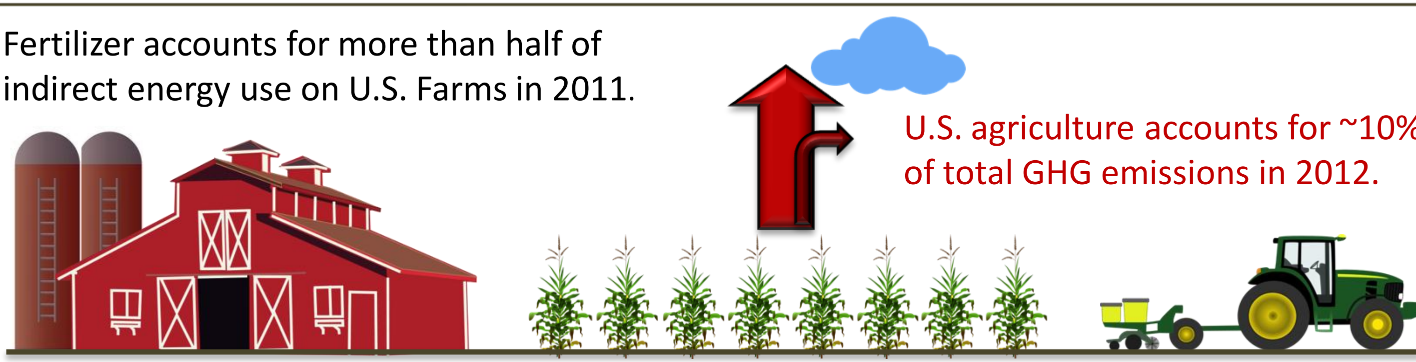
Decrease Greenhouse Gas and Increase Carbon Capture

25% Reduction

10% GHG

Current

Fertilizer accounts for more than half of indirect energy use on U.S. Farms in 2011.



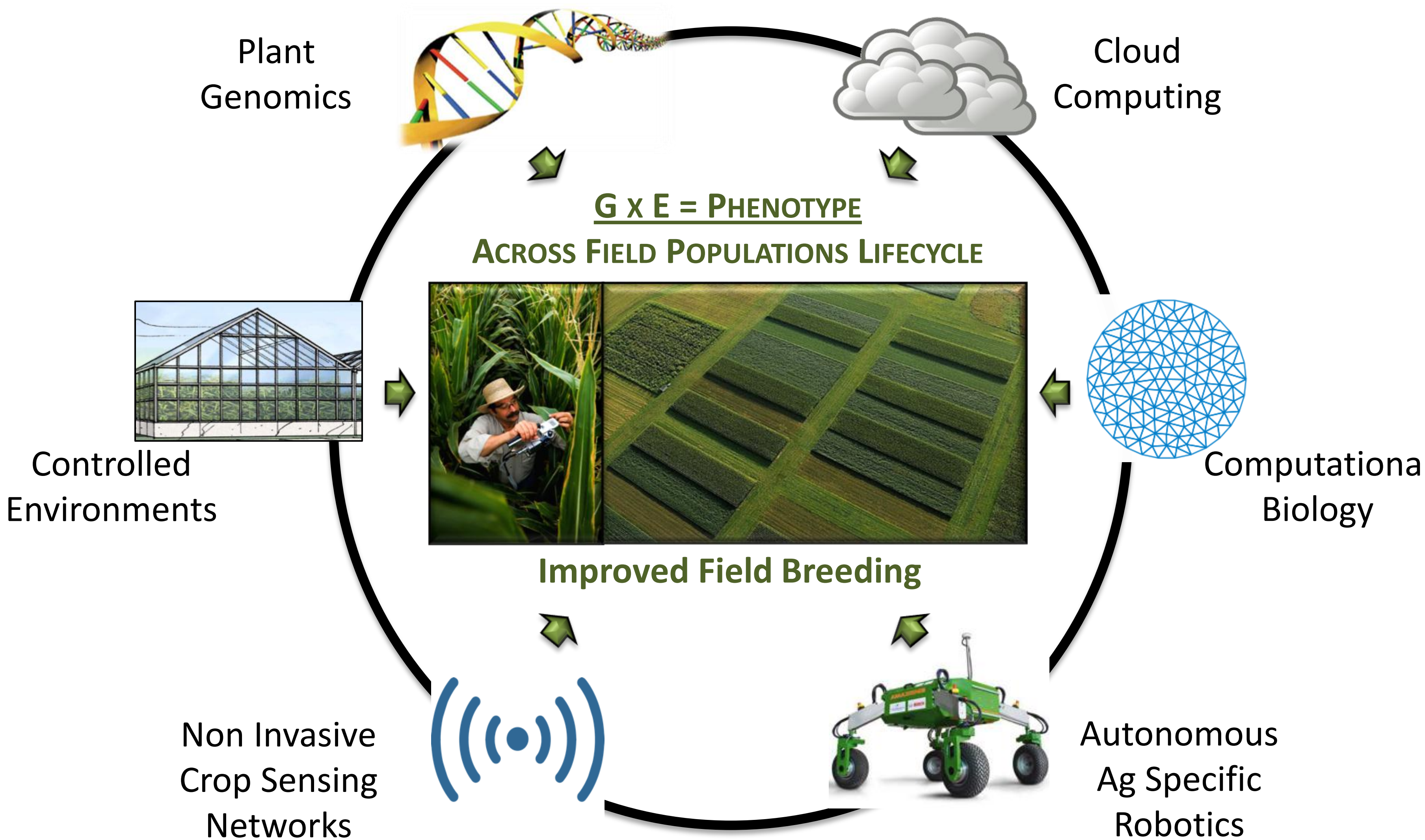
U.S. agriculture accounts for ~10% of total GHG emissions in 2012.

EPA: Sources of U.S. Greenhouse Gas Emissions 2012

ARPA-E Program Vision

Systematic Integrated Technologies Provides Platform for Innovation

BIOLOGISTS, ENGINEERS AND COMPUTER SCIENTISTS



Advanced Phenotyping

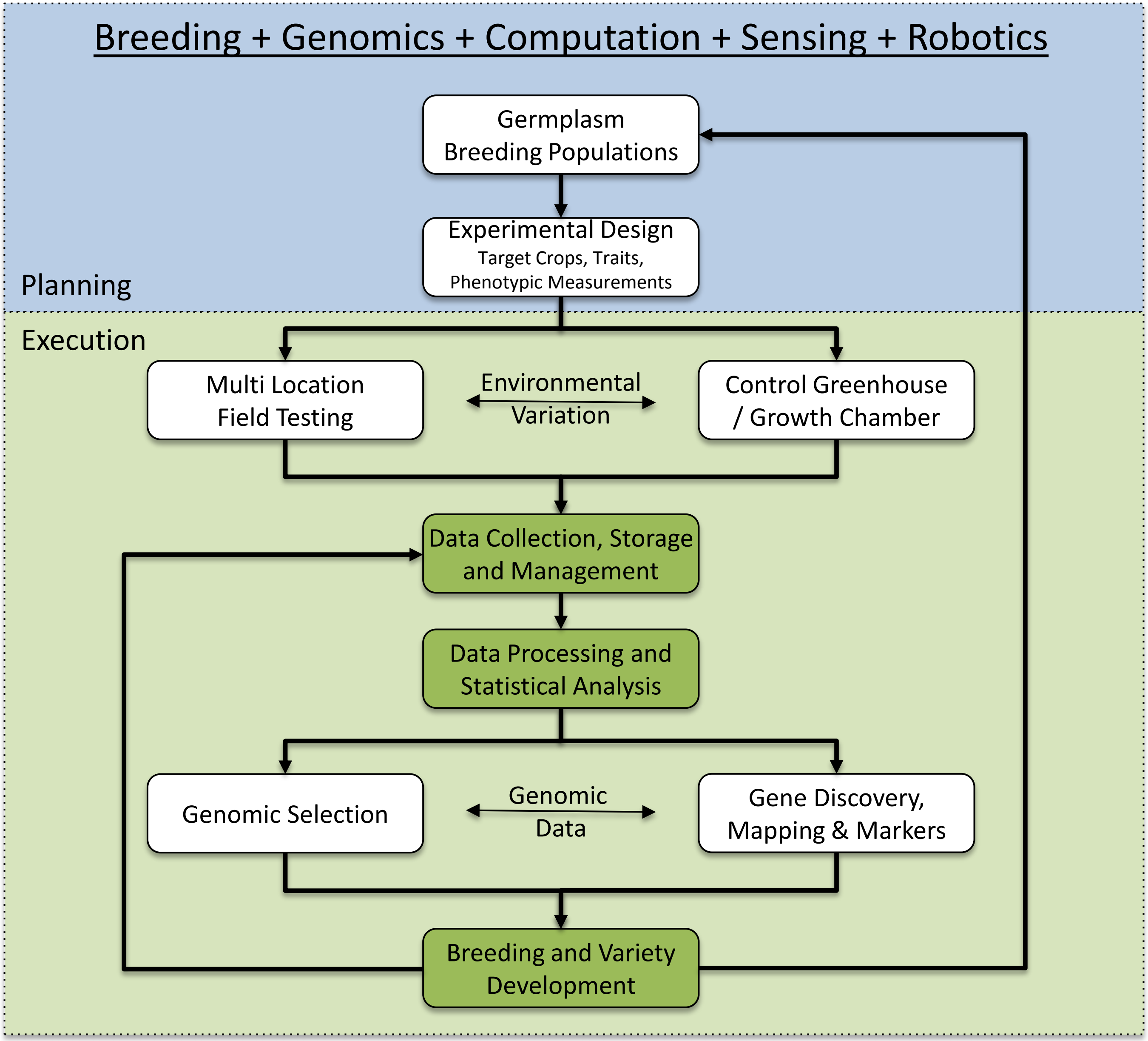
Increase accuracy, precision and throughput while reducing costs and minimizing labor

<u>G x E = Phenotype</u>

Across Field Populations Lifecycle

Advanced Phenotyping Workflows

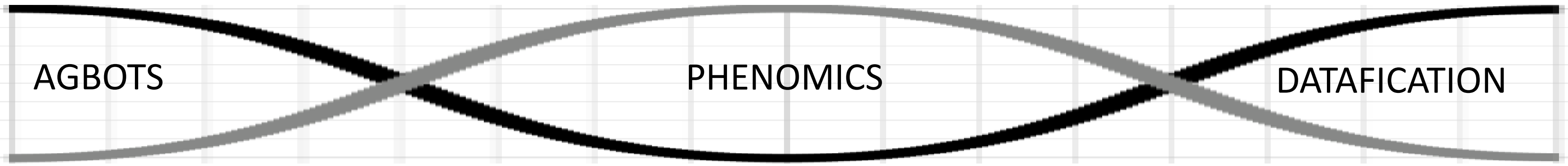
Objective: Increase accuracy, precision and throughput while reducing costs and minimizing labor



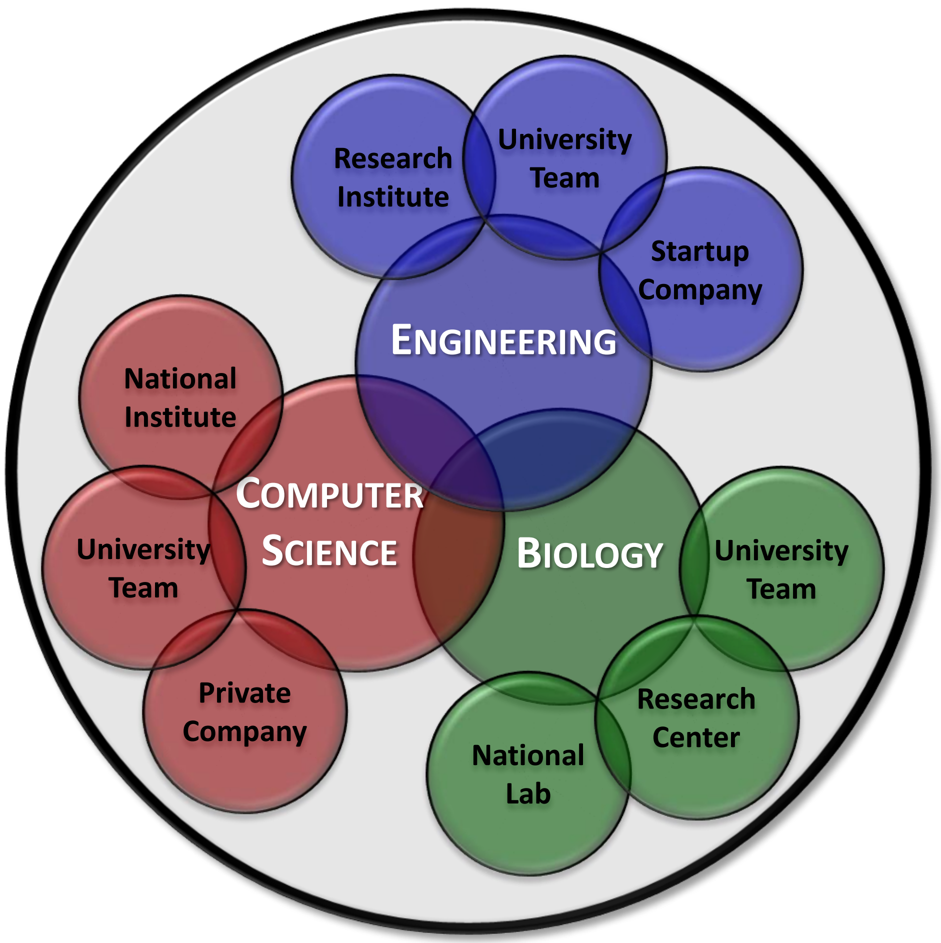
Cobb, DeClerck, Greenberg, Clark, McCouch; Theor Appl Genet (2013)126:867-887

ARPA-E Advanced Phenotyping Program: Collaboration

Straw Model for Breakout Group Discussion



Example: Team Network Building Across Technology Communities



ARPA-E Advanced Phenotyping Program: Targets

Straw Model for Breakout Group Discussion

- Target Bioenergy Crop: C4 grass (e.g. sorghum) with agronomic significance for biomass, compatible with current agronomic practices and learnings transferable to other crop platforms.
- Geographic Location: Testing across three regions with a minimum of 12 locations per region.
- Genetic Gain: Advance germplasm with 2-4% yield gain.
- Plant Genetic Analysis: High-resolution genotypes for germplasm analysis. GxPxE associations.
- Field Sample Frequency: Acquisition rate 4x/day, 1x/wk, over 1 acre (~1,200 plots/acre, plot size 1m x 3m).
- Phenotypic Measurements: Plant volume and height (stereoscopic cameras, LIDAR), lignocellulosic and sugar/carbohydrate composition and accumulation (NIR), photosynthetic rates (HSI) and new sensor technologies.

- Robotic Platform: Autonomous ground robot, $\geq$ 2 mph or $\leq$ 1.5 hrs/acre; fixed atmospheric sensors (temp, insolation, RH). Anticipate more than one platform will be required for entire crop lifecycle.
- On-board Processing: Robot equipped for image processing and generation of reduced data. Processed data sent via wireless network to collection point, or downloaded 1x/day after the robot returns to base.
- Hardware Cost Objective: Prototype systems comparable to automated greenhouse phenotyping systems (eg. Lemnatek, Qubit) with capacity to reduce costs one order of magnitude for commercial units.

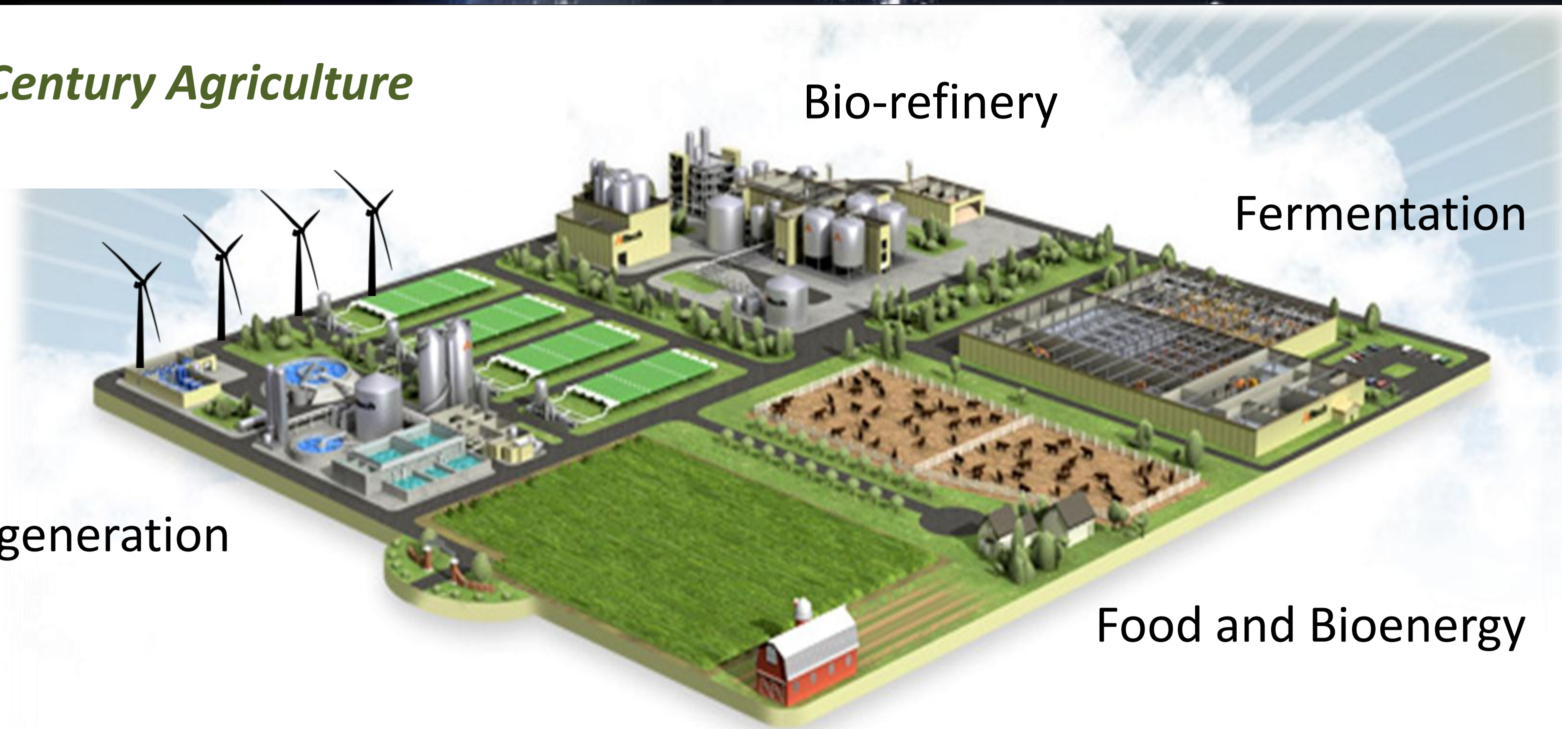
- Data Analysis: Turnaround 48 hours from collection of phenotypic measurements for breeder review.
- Accuracy: Achieve 5% accuracy against control measurements.
- Data Management: iPlant and KBase data portals to coordinate standards, shared analytics and machine learning tools. Open and closed architectures supported, however, analytic "black boxes" should be shared, while individual analysis tools/code may remain proprietary.

ARPA-E Advanced Phenotyping Program: Timeline

Straw Model for Breakout Group Discussion

Objectives	2014	2015	2016	2017
• Biology • Engineering • Computer Science • Technology to Market	Q2: Workshop Q3: Release FOA Q4: Kickoff	Ramp up teams. Select breeding populations, markers and implement field trials. Establish model systems for engineering robotic platforms. Demonstrate data management tools functionality. Validate sensing and analytics tools. Develop algorithms for image processing, feature extraction and phenotype identification.	Test prototype robotic and sensors platforms in breeding field trials. Analyze phenotypic measurements and correlate sensing technologies to environmental variation. Associate plant phenotypes with genotypes x environments. Screen breeding population and advance parental lines with improved performance.	Identify at least 3 traits/genes and markers of commercial interest. Launch commercial ready prototypes: - Robotic/sensing platform - Predictive software - Bioenergy germplasm Run field challenge with robotic/sensor platforms. Validate breeding material with 2-4% yield improvement. Secure commercial partners for phase II.

21st Century Agriculture



Mixed Breakout Sessions 2 – 3:30

	First	Last	Organization
Group A Brad Zamft & Justin Manzo	David	Allen	NIST
	Chid	Apte	IBM Research
	John	Burke	USDA-ARS
	Mike	Dentinger	Trimble
	Brad	Fabbri	Monsanto
	Michael	Gore	Cornell
	Robert	Pless	Washington University
	Jesse	Poland	Kansas State Univ./Dept. of Plant Pathology
	Bill	Rooney	Texas A&M University
	Curt	Salisbury	SRI International
	Corinne	Scown	Lawrence Berkeley National Laboratory
	Tim	Tsplinkski	Oak Ridge National Laboratory
	Liya	Wang	Cold Spring Harbor Laboratory
	Carl	Wellington	Carnegie Mellon National Robotics Engineering Center

Group B Paul Albertus & David Lee	Ed	Buckler	USDA ARS Cornell
	Jeffrey	Cruz	Michigan State University
	Steve	DiAntonio	Carnegie Mellon University
	Jorge	Heraud	Blue River Technology
	David	LeBauer	University of Illinois
	Hector	Martin	Lawrence Berkeley National Laboratory
	John	McKay	Colorado State University
	Todd	Mockler	Donald Danforth Plant Science Center
	John	Mullet	Texas A&M University
	Bruce	Orman	Pioneer
	Laxmi	Parida	IBM Research
	Sanjiv	Singh	Carnegie Mellon Robotics
	Scott	Staggenborg	Chromatin
	Avideh	Zakhor	UC Berkeley

Group C Kacy Gerst & David Guarrera	Phil	Benfey	Duke University/Biology
	Carl	Bernacchi	University of Illinois
	Matthew	Colgan	Blue River Technology
	Guilherme	DeSouza	University of Missouri
	Alexis	Johnson	Ayasdi
	Levente	Klein	IBM
	Ramesh	Nair	Chromatin
	Stephen	Nuske	Carnegie Mellon University
	Joshua	Peschel	University of Illinois
	Gary	Peter	University of Florida
	Edwin	Reidel	Lemnatec
	Jeremy	Schmutz	HudsonAlpha Institute
	Jianming	Yu	Iowa State
	Steve	Thomas	U. S. Department of Energy
	Jeff	White	USDA ARS Arizona