How Would Google Farm?

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How would Google farm?

The race to feed 9 billion people through the Internet of Agriculture and analytics.

BY (L-R) ALEX THOMASSON, GABE SANTOS AND ATANU BASU

A solution to world hunger might be found on the streets of Mountain View, Calif., and Austin, Texas. We’re talking about Google’s self-driving cars, now being test driven, and the technology behind them.

Although semi-autonomous farm equipment has existed for several years, the link between the tech giant and feeding the masses has more to do with sensors, data and analytics and less to do with just machines. In the decades to come, the intersection of these informational technologies will become increasingly crucial to feeding the world.

The need to rethink food production has never been more urgent. Anticipated population gains in developing countries and shifting demographics, particularly the expansion of the middle class, provide the biggest clues to what is coming. World population is predicted to grow from 7 billion today to 9.6 billion by 2050 and plateau at around 11 billion in 2100. That’s a lot more hungry mouths.

Clearly, the demand side of the equation is daunting; the supply side also looks problematic. Urbanization, road construction and potential climate effects reduce the amount of arable land available for farming. Taken together, these issues will require that food production per acre of land be doubled to meet the burgeoning demand by the end of this century.

Current agricultural technologies offer little hope for a solution. Growth in agricultural productivity is declining worldwide, according to the U.S. Department of Agriculture. Growth in productivity of grains and oilseeds, for example, averaged 2.4 percent per year from 1970 to 1990. But between 1990 and 2010, productivity growth fell to 1.6 percent annually, and the downhill slide is continuing. By 2021, it’s expected to be down to 1.5 percent.

Farmers in recent years have used new technologies in an attempt to increase crop yields while using fewer resources. But those technologies have been adopted piecemeal, resulting in less-than-desired outcomes. That’s where Google comes in.

WHAT DOES GOOGLE HAVE TO DO WITH FARMING?

Google’s big leap forward in the race to autonomous cars is its success at developing a fully integrated system. That system relies not only on sensors, but also on data — static and dynamic, and in many forms — along with algorithms from different scientific disciplines. If we are to meet the challenges of feeding an expanding global population, then adopting an integrated approach that takes into account advances in informational technologies and complementary scientific disciplines to improve crop productivity is essential.

Google’s blueprint for transforming our mobility is predicated on sensors, data and software. Like a human driver, the computer-driven car is designed to detect the driver’s location, understand what’s happening around the driver, predict what might happen next, prescribe what to do, and then implement this prescription. At the same time, Google must design cars with the capability to navigate varied and complicated scenarios and obstacles, including pedestrians and cyclists.

Crop production operates under a similar system of varied field and plant

"Waymo stands for a new way forward in mobility."

"Waymo began as the Google self-driving car project in 2009. Today, we’re an independent self-driving technology company with a mission to make it safe and easy for everyone to get around—without the need for anyone in the driver’s seat."
The Technology

• AI-based Control System
  – Onboard
  – Remote
• GNSS (RTK)
• IMU
• Road Map
• LIDAR (Velodyne 64-beam)
The AI

• "Experience" = Massive Amounts of Data
• Examples
  – Maneuvering through construction zones
  – Moving over for emergency vehicles
• Observed real-world situations are fed into system for training
• "Tensor Processing Units"
• Deep learning
Cotton Plant NDVI Map

Cotton Plant Height Map

mapping data.txt Events

NDVI
- 0.5037 - 0.6297
- 0.6298 - 0.6674
- 0.6675 - 0.6902
- 0.6903 - 0.7066
- 0.7067 - 0.7201
- 0.7202 - 0.7316
- 0.7317 - 0.7410
- 0.7411 - 0.7566

mapping data.txt Events

PLANT_HEIG
- 17.3 - 52.2 cm
- 52.3 - 71.0 cm
- 71.1 - 81.5 cm
- 81.6 - 91.4 cm
- 91.5 - 109.4 cm

Ruixiu Sui, former Postdoc and Research Professor, now Res. Eng. with USDA-ARS Mississippi
Deep Learning

- Typically based on artificial neural networks (ANNs)
Food/Fiber Demand

- Rising Population

- Rising Standard of Living
Food/Fiber Supply

- Farm Profitability
- Limited Arable Land
- Urbanization
- Climate Effects
Agricultural Trends

• Breeding gains in grain and oilseed yield
  – 1970 – 1990  2.4% per year
  – 1990 – 2010  1.6% per year
  – 2021 (expected)  1.5% per year

• Precision agriculture can help, but technology adoption has been piecemeal
Commonalities between Driving and Farming

• Sensors
  o Car
    o GPS
    o IMU
    o LIDAR
  o Farm
    o GPS
    o Crop Sensors
    o Etc.
Commonalities between Driving and Farming

• Data
  o Car
    o Map
    o Surroundings (static and dynamic)
  o Farming
    o Topography
    o Soil Type
    o Soil Fertility
    o Soil Moisture
    o Etc.
Commonalities between Driving and Farming

• Algorithms
  o Car
    o Navigate according to map
    o Identify obstacles
    o Predict what might happen
    o Prescribe what to do
    o Implement prescription
  o Farming
    o Agronomy, Physiology, Soil Science, Economics, etc.
    o Predict what might happen
    o Prescribe what to do
    o Implement prescription
We want to increase yield/profit per acre

- Doing this requires considering the fundamental equation,
  \[ P = G + E + G \times E \]
  - \( P \): phenotype such as crop yield, growth rate, drought tolerance, etc.
  - \( G \): genotype such as crop type and variety
  - \( E \): environment such as weather and field characteristics

We can affect \( G \) (genotype)

- Through breeding
  - **phenotypes** are measured
  - plant selections are made
  - genetics may be modified
- High-throughput phenotyping (HTP)
  - sensors on robots or UAVs (drones)
  - enable vastly more plant phenotypes and genetic variation to be analyzed
  - increase rate at which \( G \) can be affected

We can affect \( E \) (plant environment)

- By improving field characteristics through farm operations
  - Advances in GPS, sensors, and automation enable precise application of crop inputs (seed, water, fertilizer, etc.)
  - Further improvements in **precision agriculture** (PA) depend on
    - development of prescriptive analytics
    - to account for spatial and temporal variation in field characteristics
In the early days of precision agriculture, we noted:

“For precision agriculture to be successful, three things are required:

1. accurate site-specific data about field conditions
2. an understanding of relationships between the data and economic environmental benefits
3. the ability to vary inputs by location

Monitor Weight versus Scale Weight

\( n = 138 \)

\[ y = 1.00x \]

\( R^2 = 0.99 \)

Scale Weight (lb) vs. Monitor Weight (lb) graph with a linear relationship and high R-squared value.
Traditional Sensing in Precision Agriculture

- GPS
- Soil mapping
Recent Advances in Sensing for Precision Agriculture

- Plant reflectance
- Weed detection
- Soil electrical conductivity
- Etc.
Phenotyping

- Platforms
  - Remote
  - Ground-based
- Numerous phenotypes
The Internet of Things (IoT)

- Numerous sensors on linked farm equipment
- On-farm wireless sensor networks
Traditional Farm Analytics

- Management zones
Spatially Applied Crop Models
Big Data Methods

- Traditional artificial intelligence
  - neural networks
  - fuzzy logic
- Deep learning

Can we get to single-plant level?
Autonomy

• Autosteer
Autonomy

- Autospray
Autonomy

- Variable-rate planting
- Seed singulation
Autonomy

• Variable-rate irrigation
• Etc.
Robotics

- Field robots
  - Tractors
  - Sprayers
  - Pickers
What is needed now?

• What do we have?
  o Plenty of sensors and data
  o Good analytics concepts
  o Good input automation

• What do we still need?
  o Reliable data
  o Data infrastructure
  o Asking the right questions
Data reliability

- Yield maps
  - Data cleaning
  - Calibration
- UAV remote sensing
  - Radiometric calibration
  - Height calibration
Structure Design
Thermal calibration tiles

10×10 pixels at 50m
Why do we need a mobile GCP

https://www.ugcs.com/en/page/pro4pros
Wireless System Network

UAV

GCP 1

GCP n

Main control terminal

Laptop Monitoring

Xbee

sbRIO9627

Xbee

Xbee

Xbee
Controllers

Main controller terminal

Integrated GCP controller

Embedded control board on the UAV
Results

UAV Image Calibration


$R^2 = 0.98$

RMSE = 1.8


$R^2 = 0.98$

RMSE = 1.5

RMSE = 6

RMSE = 2.4
Results

UAV Plant Height Calibration

<table>
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<tr>
<th>Date</th>
<th>Uncalibrated (m)</th>
<th>Calibrated (m)</th>
<th>Blurriness</th>
<th>Improvement (%)</th>
<th>R²</th>
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<tr>
<td>05/24</td>
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<tr>
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<td>0.12</td>
<td>0.35</td>
<td>17%</td>
<td>0.88</td>
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<td>07/25</td>
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<td>0.26</td>
<td>0.42</td>
<td>12%</td>
<td>0.62</td>
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</tbody>
</table>

Estimated_06/29 vs. Ground Truth_07/09

\[
y = 0.9874x + 0.1288 \\
R^2 = 0.8349
\]

\[
y = 0.9294x + 0.1656 \\
R^2 = 0.8372
\]
Infrastructure Issues

• **Volume**
  – As-applied and prescription data
    • Spraying – 0.3 Mb/acre
    • Planting – 5.5 Mb/acre
    • Yield data – 4.2 Mb/acre
    • Soil/Fertility data – 0.6 Mb/acre
    • Prescription files – 0.01 Mb/acre
  – UAV images – 33 Mb/acre
Asking the right questions

• Assume we can apply
  o Any needed input
  o Any time we want
  o In any amount we want
  o At the single-plant level

• How do we make that decision?
  o The three main ingredients are there
  o But we must structure the extremely complex data in a way that deep learning can provide answers.
Farm Decision-Making

Terry Griffin, Ph.D.
Cropping Systems Economist
Kansas State University
Where are we going?

- Rapid genetic gains
  - Modern breeding and genetics
  - High-throughput phenotyping
- Transitioning phenotyping methods to broad-acre applications
  - Develop repeatable, important, practical phenotypes
  - Transition to broad-acre farming systems
- Approach single-plant management
What capabilities do we have today?

• Data
  o Sensors
  o High-throughput phenotyping techniques
  o IoT
  o Sensor platforms
  o Wireless networks
  o Cloud-based processing and storage
• Advanced artificial intelligence
• Real-time application capabilities
What capabilities will we have in 5 years?

- Better data infrastructure
- Better technologies for highly precise application
What capabilities will we have later?

• Ability to formulate management problems optimally
• Capability to apply all inputs when, where, and in the amounts that are optimal
Google?

- We will farm like Google would do it.