AI in agriculture:
Opportunities and Challenges of Unmanned Aircraft Systems in Research and Precision Management

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The Opportunity

The growing availability of data present an opportunity to improve the resilience and efficiency of food and agricultural production on a scale *unimaginable* even one decade ago.


The Challenge

We are drowning in information, while starving for wisdom. The world henceforth will be run by synthesizers, people able to put together the right information at the right time, think critically about it, and make important choices wisely.

Vertex Computer Systems, after Centurion 2015, Analytics Maturity Model
Texas A&M AgriLife UAS Program
Objectives and Applications

- Genotype performance evaluation
- Earliness, Yield
- Disease/insect resistance/tolerance
- Stress tolerance (e.g. drought, heat, salt)

- Irrigation
- Fertilizer
- Weeds
- Growth regulator
- Disease / Insects
- Harvest advisors
Plants as “Biological Sensors”

Plant Height, Canopy Cover, Canopy Volume, NDVI, ExG, Other Vegetative Indexes

Weather, soil type, soil moisture, management (seeding rate, planting date, nutrition)
Location: Driscoll, Texas
Field size: ~100 acre
Grid size: 10m x 10m

UAV data (250,000/acre)
• Plant Height
• Canopy Cover
• Canopy Volume
• ExG, NDVI
• Other RGB or MS VI as needed

Ground data (validation), Yield (machine harvest), Sentinel II signals
Extraction of Growth Parameters (level 2)
PHY 499 WRF, Corpus Christi, TX. 2016

Canopy Cover (%)

Rate
1) Early Relative Growth Rate
2) Late Relative Growth Rate
3) Early Half-Max Rate
4) Late Half-Max Rate
5) Maximum Growth Rate
6) Maximum Height (from sigmoid)

Timing
7) Early Half-Max Date
8) Early Half-Max Duration
9) Late Half-Max Date
10) Late Half-Max Duration
11) Max Growth Rate Date
12) Half-Max Duration
Our Strengths & Competitive Advantages
(boxes in maroon)

Texas A&M AgriLife & Purdue
UAVs, Simulation Models, Satellites,
Robotics, Genomics, Soils, Weather

Big Data

Connectivity 5G, IoT

Cloud Computing Analytics

Machine learning

Big Data Management and Analytics
• Microsoft
• Amazon
• Google
• Oracle

Texas A&M System

Modeling
Data Mining
Optimization
Simulation

Artificial Intelligence
Machine Learning
Neural Networks
Pattern Recognition

Statistics
Data Clustering
Regression Analysis
Risk and Uncertainty

Predictive, Prescriptive Management Tools
The Unreasonable Effectiveness of Data

- Eugene Wigner (1960) - *The Unreasonable Effectiveness of Mathematics in the Natural Sciences*
  - \( F = ma \)
  - \( e = mc^2 \)

- Halevy et al. (2009) – *The Unreasonable Effectiveness of Data*
  - Fairly simple machine learning algorithms performs almost identically well on a complex problem of natural language disambiguation once they were given enough data

(Banko and Brill, 2001)
UAS based HTP System Development

RGB

LiDAR DSM

VNIR

Hyperspectral

SWIR


UAS based HTP -> Consistent & Reliable Observations
geospatial data products

Level 0
- RGB Raw Images
- Multispectral Raw Images
- Hyperspectral Image Cube
- LiDAR Ranges

Level 1
- Orthomosaic
- DSM
- 3D PC

Level 2
- Canopy Height
- Canopy Cover
- Canopy Volume
- NDVI
- Greenness Index

Level 3
- Plot Level Summary
UAS based HTP workflow v0

L0 → L1 → L2 → L3 → Growth parameters → AI Model → Target Variable

\[ y = 1.0165x + 0.0007 \]
\[ R^2 = 0.7044 \]
UAS based HTP workflow v1

L0 → L1 → L2 → L3 → Growth parameters → AI Model → Target Variable

ExG

CH

Concatenated Feature Vector

Hidden Layer

Input Layer

Output Layer

Error Signal

Estimated Yield

Function Signal
Artificial Neural Network

Training $R^2 : 0.9342$

Testing $R^2 : 0.8961$

All $R^2 : 0.9245$

Convolution Neural Network

Training $R^2 : 0.9313$

Testing $R^2 : 0.9215$

All $R^2 : 0.9279$

4,800 data points
UAS based HTP workflow v3,4,5...

More Information
Integration of UAS HTP and Satellite RS for Precision Agriculture

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Phenotypes derived from UAS

Satellite Remote Sensing Data (MS, HS, LiDAR, ...)

Crop & Soil Productivity Simulation Models

Digital Twins

Machine Learning – Artificial Intelligence

Prescriptive in-season management & yield estimation

Plant Height, Canopy Cover, Canopy Volume, NDVI, ExG

Prescriptive in-season management & yield estimation