Applications of UAVs in Precision Agriculture

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Outline

Three major topics will be discussed on this presentation related to UAVs in Precision Agriculture:

- **UAVs in Agriculture: Past, Present and Future**
- **Case studies highlighting potential uses of UAVs in Precision Agriculture**
- **Future perspectives and Take home messages**
UAVs in Agriculture

Past

UAVs platform design first…then collect data.

Present

UAVs platform + sensors
Integration of sensor and flight controller

Future

UAVs as an IoT (Internet of Things) device.
Why UAVs in Agriculture?

UAS can be relatively small and inexpensive:

- Affords flexibility – readily adapted to a particular mission
- Relatively low environmental footprint

Higher quality data product than other forms of remote sensing:

- Satellite advantages: higher resolution; increased flexibility; less susceptible to poor weather conditions; faster data update rate
- More thorough modeling than alternative precision agriculture collection methodologies

Kurt J. Carraway, Col (Ret), USAF
Case Studies: UAVs in Agriculture

• Case Study I:
  Evaluation of nitrogen status for field crops

• Case Study II:
  Monitoring seasonal plant growth changes

• Case Study III:
  Spatio-temporal evaluation of plant height

• Case Study IV:
  Early-season stand count determination
Example Case Study I: Evaluation of Nitrogen

NNI (Nitrogen Nutrition Index)

\[
\text{NNI} = \frac{\%N_a}{\%N_c}
\]

\[
\%N_c = a \times (W)^{-b}
\]

Requires N of pixels with NNI ~1 in the scene

Spatial variable rate (kg N ha\(^{-1}\))

Cilia et al. 2014
Example Case Study II: Monitoring seasonal crop growth

- Regression \( Y = X + e \)
- Vegetation indices (NDRE, NDVI, SAVI) and SfM on crop traits
- LAI, Biomass, Yield

Bendig et al. 2014
Example Case Study III: Spatio-temporal evaluation of plant height

Spatio-temporal evaluation of plant height in corn via unmanned aerial systems

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Example Case Study III: Spatio-temporal evaluation of plant height

Sampling methods are often destructive and labor intensive.

**Plant height** is a major indicator of plant growth.

UAVs: high **revisiting time** and ultra-high **spatial resolution** suitable for in-seasonal monitoring.

**Objective**

- Evaluate derived UAVs metric (plant height) versus ground-truth plant height and plant biomass.
Example Case Study III: Spatio-temporal evaluation of plant height

**Structure from Motion:** is a photogrammetry technique for 3-D reconstruction. It solves the **disparity** of a “target object” in two camera locations.

Target object = “top of the canopy”
Example Case Study III: Spatio-temporal evaluation of plant height

Workflow

Pre-flowering

Flowering

High

Low

Pre-flowering

Flowering
Example Case Study III:
Spatio-temporal evaluation of plant height

Area = 1.65 hectares
115 plots
Randomized Complete Block Design
Non-irrigated corn

FERTILIZATION
GAP-POPULATION
POPULATION
HYBRIDS

UAS DJI S800
Sony A5100 RGB
Topcon L1L2 Hiper Lite Station
Photoscan-Agisoft
ArcGIS 10.3.1
Example Case Study III: Spatio-temporal evaluation of plant height

2 growth stages were identified for UAS and field evaluation:
  2 weeks prior flowering - v14
  flowering – R1

Field sampling methodology:
  subplot area identification
  plants geo-location
  phenology
  plant height
  stalk diameter
  plant biomass
  ear weight
Example Case Study III: Spatio-temporal evaluation of plant height

- Plant biomass estimation

Pre flowering:
- $y = 0.71X$
- $R^2 = 0.63; P<0.05$
- $RMSE = 0.11\, m; n = 331$

Flowering time:
- $y = 0.90X$
- $R^2 = 0.79; P<0.05$
- $RMSE = 0.09\, m; n = 331$

22-24% 10%
Workflow

Orthomosaic and SfM reconstruction

Supervised classifier
Vegetation
Bare soil
Shadow

Bare soil
IDW
DTM

CSM

Estimated Plant Height

Ground-truth Plant Height

DTM (Digital Terrain Model) CSM (Crop Surface Model)
Example Case Study IV: Early-season stand count determination

Article
Early-Season Stand Count Determination in Corn via Integration of Imagery from Unmanned Aerial Systems (UAS) and Supervised Learning Techniques

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Example Case Study IV: Early-season stand count determination

Corn is sensitive to planting pattern and early-season uniformity.

- **Management**
  - Tillage system, rotation
  - Target plant population
  - N placement
  - Hybrid

- **Site-specific conditions**
  - Soil texture
  - Topography
  - OM

- **Achieved plant density**

- **Weather conditions**
  (planting-emergence)

- visual inspection on the ground
Example Case Study IV: Early-season stand count determination

Satellite and Aerial imagery
- Thorp et al

Proximal ground sensing
- Shertha et al

revisiting time spatial resolution
Example Case Study IV: Early-season stand count determination

Objective
Implement a workflow for quantifying early-season stand counts for corn by integrating the UAVs platform versatility and supervised learning

Workflow
Example Case Study IV: Early-season stand count determination
Sites location and data collection

<table>
<thead>
<tr>
<th>Fields</th>
<th>Previous Crop</th>
<th>Planting Date (DOY)</th>
<th>Growth Stage</th>
<th>Flight Day (DOY)</th>
<th>Flight Altitude (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Site 1</td>
<td>Soybean</td>
<td>116</td>
<td>v2</td>
<td>135</td>
<td>10</td>
</tr>
<tr>
<td>Site 2</td>
<td>Soybean</td>
<td>130</td>
<td>v2-v3</td>
<td>153</td>
<td>10</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Site 1</th>
<th>Site 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Data Set</td>
<td>Training</td>
</tr>
<tr>
<td>Images</td>
<td>94</td>
</tr>
<tr>
<td>Contours</td>
<td>17,608</td>
</tr>
</tbody>
</table>
Example Case Study IV: Early-season stand count determination

Better performance as the resolution of each pixel increases, 2.4 mm.
Future Perspectives

UAV as an IoT device

Platforms
- Automation (automated flight)
- Safe reliable operations (Industrial quality standards)

Sensors
- Multiple on board, integration (onboard/ground sensors)
- Standardized protocols

Data processing
- Microsoft Azure IoT Hub, Edge-Cloud

Information delivered
- Interactive, reactive (tactic) and strategic planning
Future Perspectives

Data collection

Data processing

Learning

Azure IoT Hub

Anomaly detection

Information delivery

Action required

Strategic planning
Take Home Messages

UAVs in the contexts of precision agriculture evolved significantly since early 2000s.

UAVs have been transformed from platform-design centered into a IoTs device (static data delivery mode into an actionable information delivery mode).

The synergic integration of UAVs and supervised learning disclosed potential for deriving early season information on crop performance under field conditions.

A successful implementation of UAVs IoT requires new business models, strong integration between computer science, modeling, engineers, and crop scientists.
Thank you!

Questions?

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