Drones in Agriculture: An Overview of Current Capabilities and Future Directions

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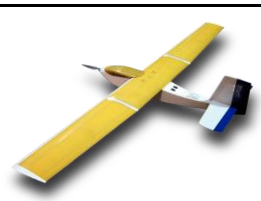
Abstract:
The Utah Water Research Laboratory at Utah State University has been active for more than a decade in the development and deployment of small, unmanned aerial systems (UAS, or "drones") for use in remote sensing in support of research and management applications in agriculture and natural resources. This document summarizes the current state of drone technology for agricultural uses, including crop health monitoring and farm operations. The current regulatory framework, as developed and enforced by the Federal Aviation Administration, and its implications for agricultural applications will be discussed. Anticipated future directions for the technology in agriculture are also outlined, and many examples will be given of products that are made possible through the use of UAS in agriculture.

Current Technologies in Agriculture
Multiple drones or UAV devices are available in the market for agricultural purposes, and some of them are already being used in Utah farmland. Because drones are available, it is important to determine their capabilities. The table below show the typical drones types available.

Typical Drones available in the Market

Type	**Flight time / Area per flight**
Quadcopter 	• Flight time: 30 mins • Area: 160 acres
Fixed Wing 	• 30 min to 1:30 hours • Area: 300 to 9600 acres

The camera sensors are key to the quality of maps produced by the drones. In general, low cost sensors that capture red-green-blue (RGB) and near-infrared (NIR) pictures are not necessarily calibrated for agricultural purposes. These cameras are intended for human portraits and nature photography and video, thus they are calibrated to capture light that describes these scenes. These types of sensors are found in Go-Pro, Canon, Sony, and any other camera brand found in a photography shop. Agricultural type cameras have specialized filters that make them more expensive. Examples of specialized cameras for agriculture are the Micasense Red-Edge[1], and Parrot Sequoia[2]. These cameras are lightweight and specifically designed for UAV power support.

Another major key in UAV use is the location accuracy on the ground of the pixels captured by the camera mounted in the drone. Like available agricultural equipment, UAVs have incorporated GPS, which records the location of the UAV while in flight. Nevertheless, the accuracy of the GPS device can be +/- 10 ft, which means the device could locate the UAV images out in the road or in next field. If the results of the UAV are for more than simple visual inspection, investing in GPS ground targets, such as the ones provided by Propeller,[3] or ground mats can provide a solution to the problem.

One of the map products that can be obtained using commercial UAVs is the Normalized Difference Vegetation Index (NDVI) or similar. The NDVI is an index that indicates the overall health of a plant. If the NDVI values is close to 1.0, vegetation is expected to be healthy, but for values close to 0.0, the map is showing bare soil or stressed vegetation. Different cameras will give different values of NDVI for the same field and flight time, which could mislead the user of the UAV NDVI map. Agricultural cameras, however, can provide a standard NDVI that is comparable with other agricultural cameras such as those in satellites.

UAVs tends to be time and money intensive because of the multiple conditions required for its use: FAA regulations, UAV flight by a licensed pilot, and processing capabilities to obtain the RGB or NDVI map. FAA regulations limit UAV flights to an elevation of 400 ft. and to ~1.8 miles (visual line of sight). The FAA also requires all UAV flights that benefit commercial applications (e.g. agriculture) to use a licensed UAV pilot. UAV flight data must be transferred into a cloud solution or a local powerful computer for processing. Cloud solutions tend to require an annual fee, and computer solutions often require a fee or a license.[5]

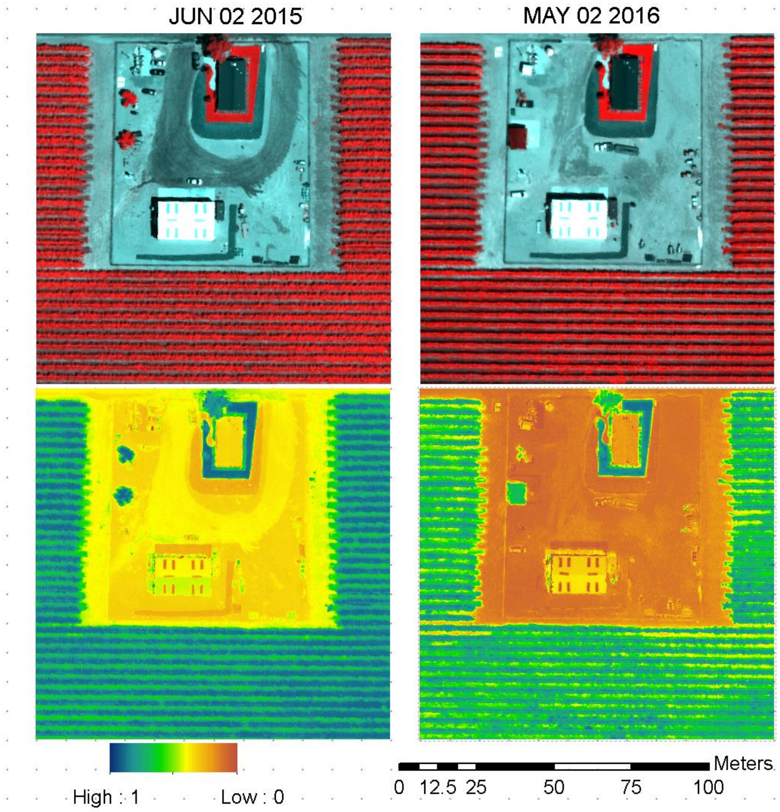


Fig 1. Example of NDVI differences (bottom row) between RGB and long pass NIR filters (left column, 2015) and RED and NIR spectral filters (right column, 2016) for a vineyard location in California (top row). Bare soil locations (such as road and vine interows) and vine canopies in 2015 have higher NDVI values (~0.30) and (0.7-1.0) than NDVI values estimated using Landsat filters used in 2016 (~0.10 and 0.5-0.9) for bare soil and vine canopy respectively. Source: AggieAir, 0.10m/pixel, [4]

The challenges may be daunting, but costs of UAV use in agriculture can be reduced if water canal companies and irrigation districts, rather than individual producers flying their own fields, acquire and operate the UAVs, and an industry-scale fixed wing UAV with scientific cameras can provide map products beyond NDVI. Reducing the costs of UAV use in agriculture and providing actionable scientific-grade remote sensing data products for agriculture have been the vision and the work of the Utah Water Research Laboratory at Utah State University over the past decade in developing AggieAir[6] (www.aggieair.usu.edu).

AggieAir in Agriculture:

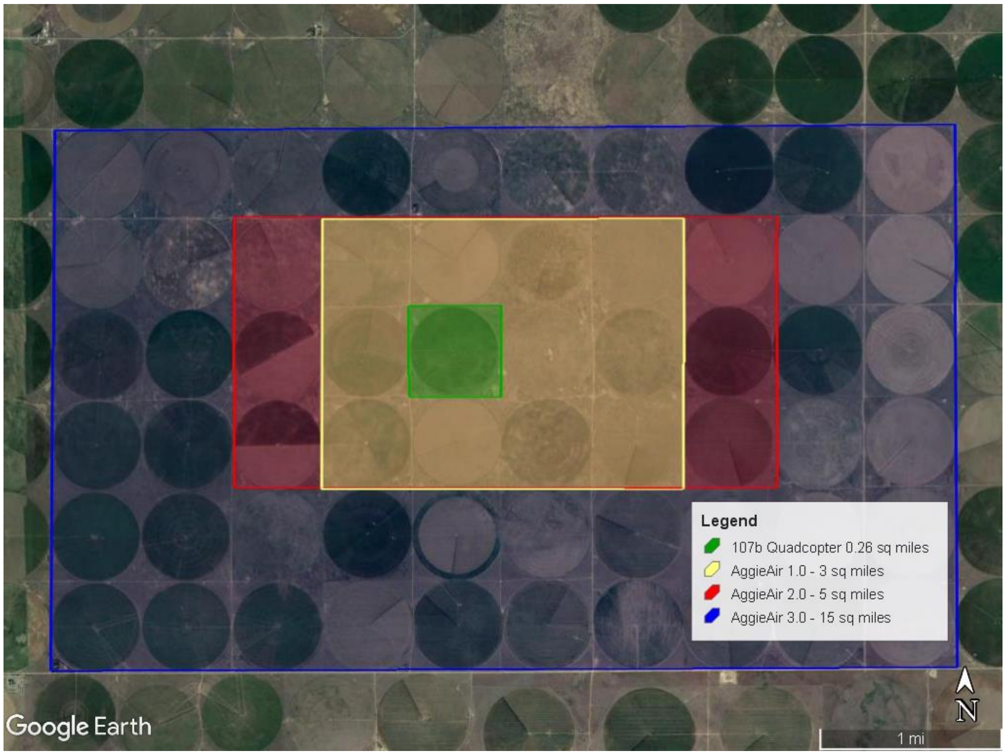


Fig. 2. Example of existing UAV solutions in US agriculture. Each center pivot in the image is 0.5 miles in diameter. Current FAA rules limit the UAV solutions (green square, quadcopters, 0.26 sq. miles - 1 land unit in ~35 minutes/single charge at 400 ft. AGL-above ground level). Removing flight elevation and distance restrictions, industrial UAVs such as AggieAir fixed wings can provide increasing coverage under 3 hrs. of flight (blue square, 15 sq. miles/single charge at 400m AGL), AggieAir 3.0 - Blujay. Source: AggieAir [5].

- **Evapotranspiration and Soil Moisture**

From an irrigation management perspective, two major components are necessary to estimate water irrigation needs at the land unit level: evapotranspiration (ET) and soil moisture (SM).[7] ET is the amount of water that the crop uses based on the water available in the root zone, the plant type, and the weather and seasonal conditions. SM is the amount of water retained in the root zone, and it varies spatially depending on soil type, amount of organic matter, and depth.[7] These two components allow for estimation of irrigation water needs through water balance accounting.[7–9] As indicated by the available ET models in scientific literature,[19–25] estimating ET using UAV technology requires, in addition to selected Red and NIR spectral filters,[10,11] incorporation of a temperature camera sensor along with local weather station information. Figure 3 shows an ET estimation map[7] across a vineyard field in California. This ET map was estimated using an AggieAir UAV carrying spectral scientific optical and temperature cameras at 0.15m/pixel (0.5 ft./pixel) resolution.[4] The ET information can be then aggregated to irrigation valve zones that the irrigation technology can support.[10,11]

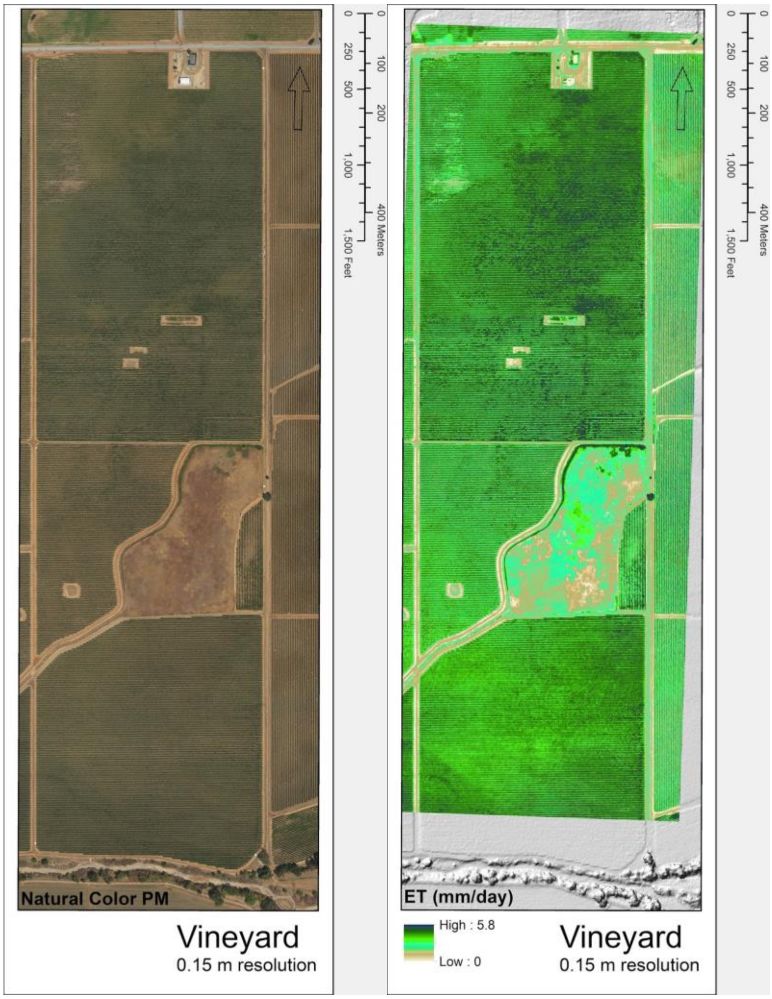


Fig 3. Example of AggieAir RGB (left) and estimation of Evapotranspiration, ET in inches/day or mm/day (right) for vineyards in CA. resolution: 4 inch/pixel, area 300 acres, Source: AggieAir[4].

Initial efforts to estimate SM have been related with the use of data mining models, and optical and temperature imagery have been successful but require a network of soil moisture probes.[16] Other efforts relate to specialized shortwave cameras and physical modeling of soil characteristics.[17] Still, soil moisture estimation using UAVs is an area under intense investigation.

- **Crop Nutrient Monitoring**

A major economic input for any agricultural season is the application of fertilizers (e.g., nitrogen, phosphate, potash), and micronutrients (e.g., sulphur, magnesium, zinc). Fertilizer is applied by on-ground equipment (tractor powered sprayers or pressurized irrigation systems)[18] or by manned aircraft.[19] The latter is the most preferred by producers with multiple and large land units. They generally use a single application rate for all fields being sprayed because changing wind speed and direction conditions during fertilizer application and the elevation of the aircraft make more precise application impossible. Ground equipment application is used as a complement to aerial spraying to maintain stable crop nutrient status across the irrigation season. UAV estimation of crop nutrient status can directly benefit the application rate recommendations by producer or agronomist consultant by including the entirety of the field. Research efforts indicate that it is possible to perform the monitoring with scientific UAVs and specialized camera sensors such as optical and thermal cameras,[20,21] along with specialized optical filters such as Red Edge or hyperspectral cameras.[22–24]

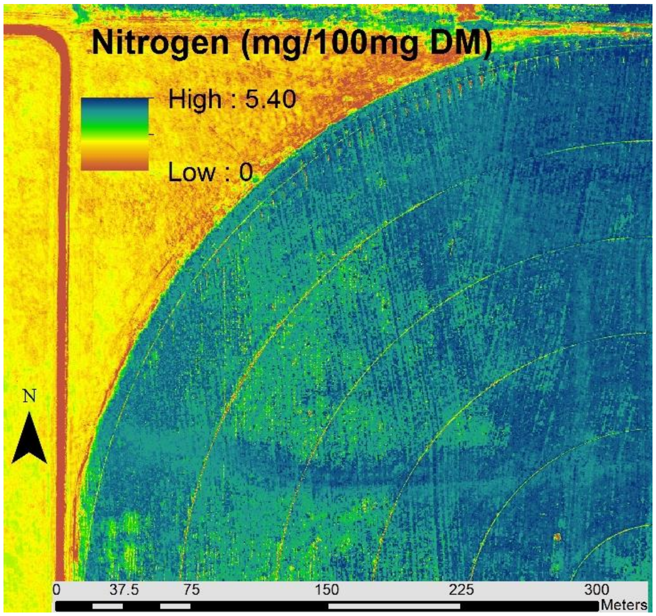


Fig. 4 Example of Estimation of Nitrogen Content for Oats (mg/100mg DM), Location: Scipio, UT, resolution: 6 inch/pixel using AggieAir[4]

- **Yield and Biomass Analysis**

An analysis can be performed with UAVs that has no equivalent in satellite sensors: a three-dimensional representation of surface conditions, also known as digital elevation models (DEMs). While no scientific sensors are required to produce DEMs, pixel location accuracy is necessary to relate the biophysical conditions (yield or biomass volume) with the height conditions, as well as time series analyses. Solutions in agricultural equipment as Real Time Kinematic or RTK-GPS accuracy (inches) ground control points can achieve high precision with error tolerances of +/-2 inches in x and y coordinates and +/- 0.5 ft. in z coordinates. Ground control points increase the costs of UAV flight planning, but they are an important component for row crops (orchards, vines) and early stages of commodity crops (wheat, corn, barley, etc.). Current UAV on-board GPS measurements do not provide enough accuracy yet in position and UAV inclination to replace ground control points, making the use of ground control points necessary.

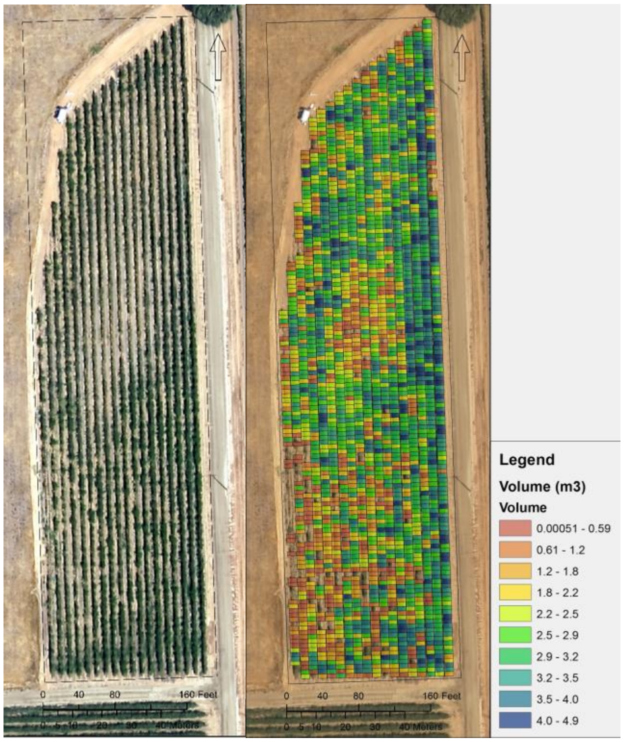


Fig. 5 Example of vine canopy volume estimation for canopy trimming. Source: AggieAir[4]

Summary

When choosing a UAV solution, the producer must be aware of the required investment in terms of the money and time necessary for the flights and for processing the data captured by a UAV. For this reason, we recommend UAV use at the water canal company or irrigation district level, which in turn minimizes individual efforts and investment to obtain data for each field. In addition, partnerships with a local research organization can provide more information from the UAV data than just NDVI (as in the examples for ET, SM, nitrogen, and others from AggieAir) because of new investigations that can extend the uses of UAVs.

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