THE POTENTIAL ECONOMIC BENEFIT OF UNMANNED AERIAL SYSTEMS IN AGRICULTURE

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Abstract

The use of small Unmanned Aerial Vehicles (UAVs) in remote sensing applications is being explored by a number of disciplines. One industry in particular – agriculture - has seen notable interest and exploration in the use of these types of systems to monitor crops. UAVs have potential to affect farming by reducing the amount of chemicals used, detect areas of less growth, pinpoint irrigation issues, and help in farm management decisions by providing yield estimates with high accuracy. After a review of the theory and science behind the data collection and processing, we estimate the dollar value of the data by looking to agronomic studies of remote sensing with satellites. The results suggest that UAVs will have a positive economic benefit in agriculture.

KEYWORDS: (UAV, UAS, Agriculture, Agronomics, Remote Sensing, Precision Agriculture, SFM)

JEL CODES: (Q15, Q16, O32)

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Literature Review

Introduction

Remote sensing techniques have a well documented history in precision agriculture and agronomics. Precision agriculture – or the science of getting the absolute highest yield out of the land – combined with remote sensing practices has potential to become the new way that farmers interact with their land. This hypothesis is based on the use of field state maps and Variable Rate Technology to pinpoint the application of chemicals.

Once data is collected and processed, the resulting images can be converted into computer files (SHP files) that can be read by farm equipment –and with variable rate technology the machine can use these files to apply fertilizer, pesticides, and herbicides to only the places that need treatment. Within precision agriculture, this practice is commonly referred to as site specific management, and allows farmers to take action with the data collected by remote sensing (Brisco, Brown , Hirose , McNairn , & Staenz. 1998).

Unmanned Aerial Vehicles (UAVs) are becoming increasingly popular as platforms for this type of sensing and appear to be the most compendious way to collect data. As a result, the current predicted value of the agriculture UAV industry is estimated at $75.6 billion before 2025. While this is an exciting number, the exact economics of how useful and profitable the technology will be to individual farmers is still unclear. To investigate this question, we will first look at the pests and diseases affecting the two most commonly grown crops in the United States, the benefit of remote sensing in agriculture, the procedure for collecting and processing data from remote sensing, an estimation of the economic advantages of UAVs compared to other platforms, and a cost benefit analysis of UAVs in three different scenarios.

Overview of Corn and Soybean Maturation

To understand the importance of remote sensing in agriculture and the benefit of using UAVs as a platform for sensing, we should first look into the growth stages of farm crops and what pests and diseases affect the crops at these stages of maturity. This will help us to understand the needs of farmers hoping to detect these ailments and treat them directly.

While remote sensing practices have potential in many different crops, we will look at only the two most commonly grown crops in the Untied States: corn and soybeans. In 2011, there were 84 million acres of corn and 74 million acres of soybeans harvested in the US (www.epa.gov, 2011). Since remote sensing is the most helpful after a plant emerges from the soil, we will focus on the post-germination stages of a plant's life. This is measured in stages starting at VE (emergence) and continuing based on the amount of leaves showing. For example, a corn plant showing one leaf would be at stage one or V1, with three leaves it would be at stage V3, and on until the plant is fully matured. Reproductive stages follow the growth stages and are notated in a similar way, but they mean different things for different plants and are referenced as R1, R2, and so on. At each stage or at every few stages the plant is susceptible to different pests, and there is potential for remote sensing data to be relevant in the process of preserving the crops (Pioneer, 2013).

Corn. In corn there are eight notable times at which the crops become susceptible to new threats during its growth process and six during their reproductive process, for a total of fourteen times at which new pests are appearing. These stages are VE, V3, V6, V9, V12, V15, V18, R1, R2, R3, R4, R5, and R6 – when the plant is fully matured and ready to be harvested. Some of the threats faced during the growth stages are the Brown Stink Bug (VE–V4), Goss's Wilt (VE–V6), Grape Colaspis (VE–V6), White Grub (V1 – V3), Wireworms (planting to V4) , slugs (VE–V4), eyespot (V6–V18), and Corn Rootworm V3–V18) (Pioneer, 2013).

The reproductive stages of corn start with silking at R1. During silking silk becomes visible on the outside of the husks. The silks are fertilized when falling pollen makes contact with them, and the ovule becomes a kernel. Blistering is stage two (R2) and occurs ten to fourteen days after R1. In this stage the kernel is developing, blistering out and beginning to fill with fluid. R3 is the milking stage and occurs twenty days after R1. During R3 the kernel turns yellow and the inner fluid is accumulating starch. In the fourth stage (R4) or the dough stage, the inner fluid and starch becomes a pasty consistency. In R5, the kernels begin to dent and dry, starting at the top of the cob. This typically happens forty days after silking. In the final stage, physiological maturity, the kernels are completely dry and husks and leaves are no longer green (Pioneer, 2012). The corn is now ready for harvest. During this reproductive cycle the crop is exposed to diseases and pests like Common Rust (V12 – R4), Corn Earworm (R1) , Corn Borers (R2), Stewart's Wilt (R2), Western Bean Cutworm (R2-R4), Anthracnose (R5 – R6), Ear Rot (R5 – R6), Stalk Rot (R5 – R6), Leaf Blight (R1–R4), Gray Leaf Spot (R1-R4), as well as many diseases and pests from the maturing stages (Pioneer, 2012).

Soy Beans. Soybean stages work in a similar way – except there is one less time at which new pests are introduced. Soy Beans have five main growth stages and eight reproductive stages for a total of thirteen stages at which new pests and diseases emerge. During the growth stages some of these problems include slugs (VE), Beal Leaf Beetle (V1-V3), Chlorosis (V4), White Mold (V4), Soybean Aphids (V4), Stem Canker (V5), Stem Borer (V5), Frogeye Leaf Spot (V5), and the Japanese Beetle (V5).

In the reproductive stages of soybeans R1 is the start of flowering, R2 brings full flowering to topmost nodes, R3 is when pods are beginning to form at one of the nodes, Stage R4 is when those pods are fully formed (2cm) at one of the nodes, R5 occurs when seeds begin to form within the fully developed pod, in R6 the seed is fully developed and fills the pod to capacity, stage R7 is realized when the pods begin to mature and change color, and in stage R8 the pod has reached full maturity and attained full mature color (Pioneer, 2012). During this reproduction process soybeans are susceptible to Soybean Aphids (R1), Soybean Cyst Nematode (R2), White Mold (R2), Root – Knot Nematode (V3), Bean Leaf Beetle (R4), Japanese Beetle (R5), Fusarium (R5), stink bug damage (R6), Brown Stem Rot (R6), Green Stem Syndrome (R7), Dectes Stem Borer (R7 – R8), and some of the other pests and diseases from the growth stages.

Introduction to Precision Agriculture and Remote Sensing. As we can see, there are many ways for a growing season to be compromised. Pests, weeds, irrigation issues, failing to plant or harvest at the right times, misapplication of fertilizer, and many other factors can contribute to loss of yield and consequent loss of profit for that year. In the United States, we experience an estimated $20 billion losses a year due to insect, disease, weed, and fertilizer and irrigation problems alone (USDA, 2005). Some of the common tools to manage these factors are inherited family wisdom, driving through the fields or sending scouts out to look for damaged crops, and spraying an entire field with chemicals to guard against pests and weeds.

In contrast to these traditional methods, precision agriculture is a practice that uses scientific methods in farming with the goal of maximizing yield. For example, some precision agriculture practices include using GPS navigation and mapping algorithms to ensure that the entire field is seeded when planting, using yield monitoring technology to predict the year's profit and make better trading decisions, and using Variable Rate Technology (VRT), or technology that allows for fertilizer and chemicals to be applied to only certain sections of a field. A common practice in precision agriculture is to monitor the farm by sections of the field instead of farming by the entire field. The smaller the sections, the more closely a farmer knows what is happening in his or her field, and the more precise their adjustments can be.

Another emerging technology in precision agriculture is remote sensing. Remote sensing is the practice of collecting data without being in direct contact with the subject of analysis. With this definition, we are constantly remote sensing with our ears, nose, and eyes. Our applications with these sensors vary across a number of activities. When we smell to determine taste, look to estimate size, or hear to understand the meaning of words, we are taking in the data from our sensors without being in contact with those stimuli. Remote sensing in agriculture uses the same principals, but the sensors are electronic and the results are usually in the form of pictures. However this data can be chemical levels, height readings, or a number of other outputs (Paine, David P., & James D. Kiser, 2012).

Remote Sensing in Agriculture. Remote sensing in agriculture has been around since 1927, when aerial photographs were used in determining whether cotton plants had contracted cotton root rot. This was done using a hot air balloon and pictures of the fields. Large areas were photographed and researchers were able to determine the health of the plants with just an aerial view (Tenkorang & Janmes Lowenberg-DoBoer, 2008). In 1978, the satellite Landsat began to take pictures for agricultural purposes, and between 1960 and the early 2000s about 5% of satellites launched were for agricultural applications (NASS, 2005 ; Tenkorang, 2008).

Satellite and airplane technology make remote sensing a viable option for large farming operations. Combining the images collected by these platforms with variable rate technology, machinery can be programmed to apply chemicals only to areas that need attention, saving money and reducing the amount of chemicals seeping into ground water. However, adoption of this promising technology is slow. Despite the $20 billion losses a year due to insect, disease, weeds, and fertility and irrigation problems, only 4% of field acreage in the United States was managed with the help of remote sensing in 2005 (USDA, 2005) and only 12% of agriculture retailers offered remote sensing solutions for crop management (Tenkorang, 2008). Part of this delay is likely due to the natural cycle of adopting new technologies, but there might be an increase of adoption in the near future as more companies emerge that are focused on collecting this technology and bringing it to farmers. One motivator of this increase in service-based farm management programs is the advance in Unmanned Aerial Vehicle (UAV) technology. UAVs allow for low cost rapid data collection and processing and are proving to be a competitor to satellites and planes as a platform for remote sensing in agriculture.

UAVs as Remote Sensing Platforms. The word "drone" is a blanket term for flying objects that are not what we consider 'usual' like a plane or helicopter, but by using the term UAV instead, we make several distinctions. First, the term "unmanned" tells us that the vehicle does not require a pilot, and instead is controlled using an autopilot. Second, "vehicle" allows us to understand that a UAV is just a platform for a variety of applications – just like a tank, car, and train can all be considered vehicles despite their obvious difference in applications.

Small UAVs (under 20 pounds) have several distinct advantages in the remote sensing field. First, they are cheap. An optimized, well-planned UAV that can carry out missions with flight times of an hour can cost as little as $5,000 but can go as high as $50,000 – although prices like these will certainly fall as competition increases. Compared to the cost of a full-scale plane or helicopter (roughly $200,000), the low end UAV comes at an extremely reasonable price, and the high end is still a quarter of the cost of a manned aircraft. Further, it costs around six cents each flight to charge a battery for UAV flights compared to the cost of fuel for full-scale platforms.

Secondly, cameras onboard UAVs can achieve a much higher resolution than conventional airplanes or helicopters. A UAV based camera can reach accuracy of one to three centimeters per pixel – compared to the meter per pixel accuracy of manned aircraft and satellite options. Finally, UAVs can be launched autonomously, meaning that an operator does not need any pilot background or training. From a tablet or smartphone, anybody can successfully run a UAV remote sensing mission using open source software like APM MissionPlanner or commercial software that comes with some UAV systems.

The output of these missions depends on the sensors attached to the UAV platform – but much can be achieved with a common digital camera. With a generic point and shoot camera, action camera, or even an iPhone duct taped to the bottom of a UAV, we can create 3D models, angularly and geographically correct maps, and texture meshes. In agriculture, these outputs can be useful in our pursuit of maximizing profits.

3D models show the exact geographic aspects of the land. They can be used to find the height of a crop – so in the example of corn, a farmer could tell the height of his or her corn row by row, and identify an area in his or her field that is shorter than the average and act on this knowledge.

Angularly and geographically accurate maps are maps that can represent the exact geographic location of a point displayed on the map, and all distances on the map represent the relative distances on the ground. This is useful because with the image output, we can now know the exact latitude and longitude of our underperforming corn area and treat it directly.

Texture meshes are 3D models that have a mosaic of stitched images laid over them. They provide us with the most useful output, since they are full color orthorectified mosaic of the area being surveyed. Orthorectification means that the mosaic of stitched images is angularly and geographically accurate. So in agriculture, we can use this to identify discoloration of a section in our field (possibly due to pests) and know the exact latitude and longitude to investigate.

In order to produce these outputs, we need to use an aerial platform to take pictures of an area with overlapping sections, and then import the resulting images to several types of post-processing software.

Data Collection and Post Processing

Data Collection. The first step in post processing is to load pictures into Structure From Motion (SFM) software (Verhoeven et al., 2013). The software requires that we have pictures of a given area from a camera that is changing positions, taking pictures at an interval, and captures the area being surveyed with pictures that have overlap and sidelap (common settings are sixty-five percent overlap and thirty-five percent side lap). This is necessary because the software needs to be able to match pixel points across pictures. The intervalometer settings rely on the height of the camera, the speed the camera is moving, the size of the sensor inside the camera, and the focal length - or the distance between the sensor and lens of the camera. The following equation explains the relationship between these factors and how to find the intervalometer frequency:

$$I = \frac{(1 - \%\,E)\,(Fmt)(PSR)}{17.6\,V}$$

Where:

I = Intervalometer setting in seconds

% E = Percent endlap in decimal form

Fmt = Photo size in inches (format) in the direction of flight

17.6 = Constant with the units of inch hour per mile second

V = Velocity of the aircraft in miles per hour

(Paine, 2012)

This equation shows us how many seconds must elapse between pictures in order to capture the terrain below in our specified overlap and sidelap. The equation takes our required overlap and sidelap, the camera's sensor size and focal length, and the speed of the aircraft and outputs a number of seconds that we need to pause in between pictures. Then the camera can be programmed to take a picture, wait 'I' seconds, and take another picture, and continue at this setting.

Another factor to consider in this process is the resolution necessary for the application. The higher resolution needed (less ground distance per pixel) requires a lower distance from the camera to the ground, meaning more passes and consequently a longer flight time is required to capture the same area.

For agricultural applications, we need to map areas of 200 hectares (the average farm size in the United States) at a resolution of one meter per pixel or better. In an example scenario, this means that if we use a camera with a focal length of 4.5mm and fly at a height of 45 meters at 3 meters per second, we could expect a resolution of 3cm per pixel and could map 200 hectares in about 60 minutes.

The limiting factor and only constant in the process is the flight time of the UAV. Flight times are determined by the efficiency of the UAV and the size of the battery. Larger batteries are heavier and reduce efficiency, but also carry more charge and can allow for longer flight times. Optimal battery size can be determined by how much weight the UAV can carry and how agile we prefer the UAV to be.

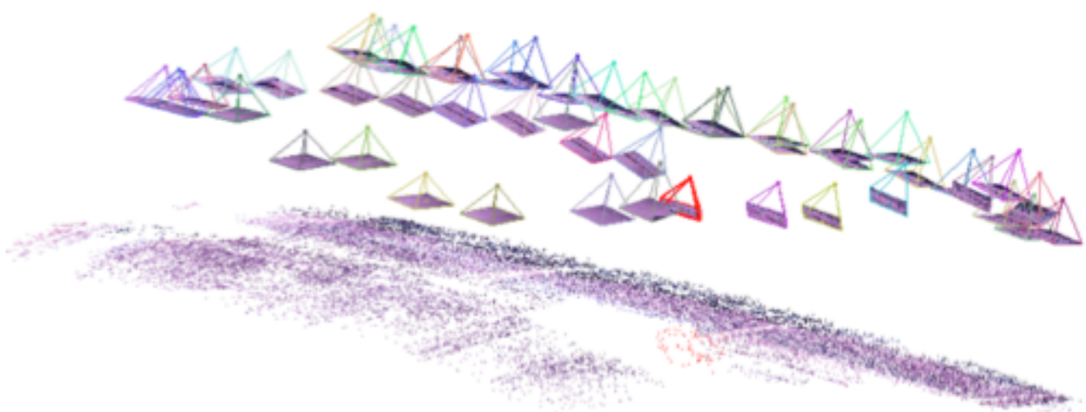
We can conclude with the realization that there is a give and take between distances covered and resolution achieved. Higher flight altitudes mean larger survey areas and less resolution, while lower altitudes mean higher resolution at the cost of less area covered.

Once these factors are considered, and the best optimization of resolution and area constricted by flight time is realized, the mission can be planned and executed – resulting in a series of pictures with the desired overlap and side lap. Now we can import these images into our Structure From Motion software and begin our post processing.

Data Processing. When a camera takes a picture, it is representing a 3D space in a 2D picture. In post processing, software is taking this 2D representation and converting it back into a 3D space by using basic trigonometric properties on known locations of pixel points on the sensor of a camera. The first step is to parse through the images and identify unique pixel points across images.

Structure From Motion. Structure From Motion or SFM is a type of software that processes images and creates angularly and geographically correct maps as well as 3D models. SFM software begins its process by calibrating the images. This will identify points in our images of the terrain that stand out, and then match those points across pictures (Verhoeven, 2013). To break this down, this means that it will scan the first image, identify points that are recognizable by the software, assign the point an address, then move to the next image, find recognizable points, and assign these points addresses. If these points on the subsequent image are identified as the same pixel point as a point on a previous image, then the addresses will be matched. The software will run through all of the images imported and carry through the same process. Now we have a database of points, and where they lie on the pictures – across all pictures that contain the same point.

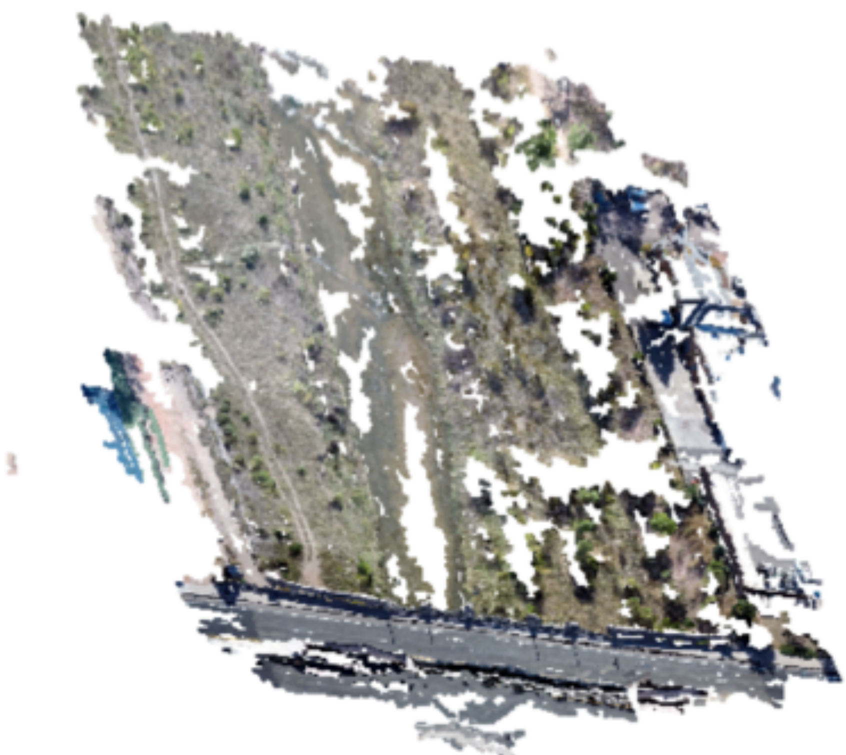
Sparse Point Clouds. Next, the SFM software constructs a sparse point cloud. A sparse point cloud is a visual representation of the calibration step, and shows us the points that were identified across pictures and their location on a local coordinate plane. This process takes the matched addresses of the points and determines their position on the camera's sensor at the position that the image was taken. Then, the points are triangulated on a local coordinate plane based on the position of the point on the sensor at different locations of the camera over the terrain (Verhoeven, 2013). This means that the software knows the position of a point on the camera's sensor at one location, and knows the location of the same point on the sensor at another location of the camera. These positions are triangulated and the pixel point is placed on the local coordinate plane. An example of this can be seen in the image below.



(Stockdale, 2014)

Sparse point clouds do not contain any useful data to humans, but images like the one above do help as a visual aid in understanding what the software is doing behind the scenes. The above image shows a field (on the bottom) being recreated with known pixel points. The floating objects are the pictures taken at different locations, and they are being processed to recreate the landscape (shown below them) in a three dimensional space.

Dense Point Clouds. Once the software is done constructing a sparse point cloud by triangulating known points on a camera sensor across camera locations, we can fill in some of the gaps using a process called multi-view reconstruction. This creates a dense point cloud by estimating points in between the known points. This process takes the points between known points found in SFM and estimates their location based on their relative distances to known points. So, the software will find points between known pixel points by estimating their location from each known point. This helps to give us more points that we can consider accurate points, and make a more accurate model. Once a dense point cloud is constructed, it looks like this:



(Stockdale,2014)

The dense point cloud is a more detailed and filled out version of the sparse point cloud. Detail is added when the estimation algorithms fill in the spaces in between known points, and the result is represented in a three dimensional space like above. This image by itself is difficult to interpret and not particularly helpful. However, we can begin to see the general shape and texture from these point clouds. Like the sparse point cloud this image is only useful as a visual aid in understanding the software process.

Orthorectified Images. The next step in the workflow is to create a mesh from these known and estimated points. The mesh is a 3D reconstruction of what the surface is known to look like. Once this is created we can take the final step of creating a texture layover. This takes the pictures themselves and stiches them together to create a mosaic, and lays this mosaic over the mesh, aligning known points on our model to the points in the pictures. Simply, it is the process of fitting a picture over a 3D surface to accurately account for changes in elevation and scale. The resulting image is finally something useful - an angularly accurate 3D representation of an area:

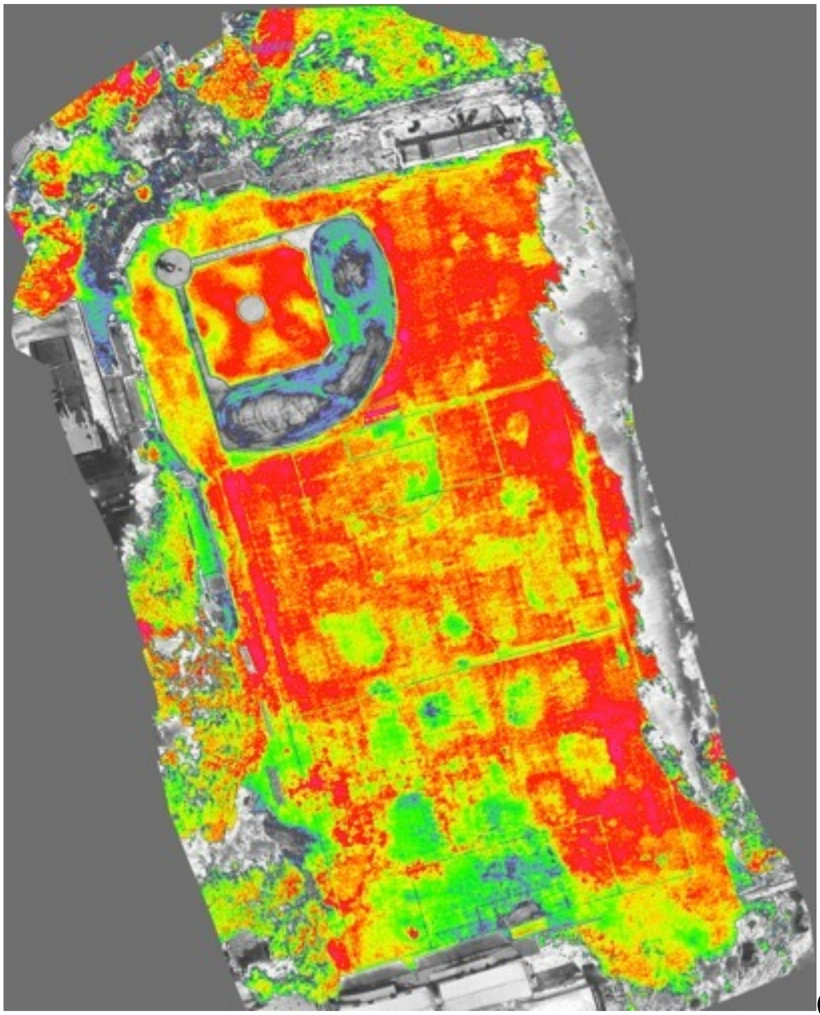
(Stockdale, 2014)

This map can be georeferenced as well, which allows us to take ground measurements and ground coordinates from our model. This particular image is of a section of river in Colorado Springs, CO. It is oriented so that the top faces north, and all relative angles and geographic locations are accurate. Without any more modification we can look at an image like this and see sections that are covered by trees, sections that are bare, where the river is, and areas of different color in the river suggesting depth or nutrient deposits.

Observations like these can help us to understand how an image like this might be used in a variety of applications like archeology, geology, energy management, wildlife conservation, land development, waste management, and many more. So far, most of the UAV research and development has been focused in agriculture, finding ways to save farmers money by locating problem areas, and treating them individually using variable rate technology rather than blanket spraying the entire field.

Using Remotely Sensed Data in Agriculture

Wavelength Reflectance and Vegetation Indices. Precision agriculture's focus on getting the absolute most out of the land year after year gives farmers a strong interest in the progress of commercial UAVs. By using specialized cameras farmers will be able to see their farms from above, observe exactly where their problem sections are by using vegetation indices, and program their variable rate machinery to treat these sections directly. UAVs can help in the process of producing maps like this one at highly accurate resolutions for a low cost and with a short turnaround time:



(Stockdale, 2014)

The above image is an angularly and geographically accurate map of a 1.5 hectare field in Claremont, CA. It was constructed using the SFM process mentioned above, but then modified to show relationships in the reflective properties of plants in certain wavelengths. These reflective properties show how healthy the plant is based on how light passes through or redirects back. In this case the closer the color is to '+1' on the included scale, the healthier the section is. When 'ground truthing', or checking to see if real life results are accurately captured in the image, we found that this image shows an extremely accurate representation of the health of the field.

In order to produce images like this, we manipulate light wavelengths and use the reflectance of the plants being surveyed. This means that we need to pull Near Infrared, Red, Green, and Blue wavelengths apart and use them to determine plant health (Lebourgeois, Bégué, Labbé, Mallavan, & Prévost 2010).

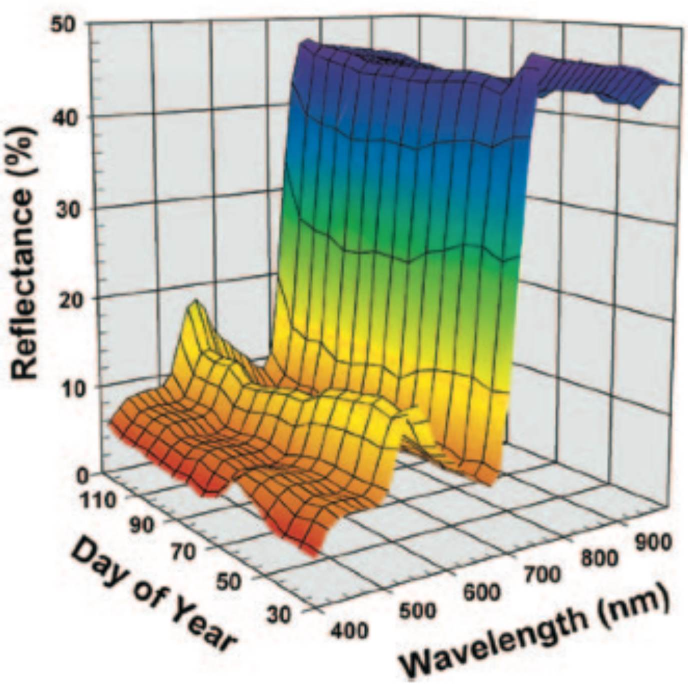
Agronomic studies have been carried out on this process and its benefit for the past forty years. The technology and theory rest on the fact that healthy plants with strong photosynthesizing cells reflect almost all infrared and green light – while absorbing most red, blue and yellow light as energy. Unhealthy plants have weaker cells that allow infrared light to pass through them. Additionally, they do not take in as much red, blue and yellow light, and instead reflect it back. So, we can manipulate the images by taking the wavelength strength and comparing it to other wavelength's magnitudes.

As collected by Pinter:

> "Green plant leaves typically display very low reflectance and transmittance in visible regions of the spectrum (i.e., 400 to 700 nm or Blue, Green, and Red) due to strong absorptance by photosynthetic and accessory plant pigments (Chappelle *et al.*, 1992). By contrast, reflectance and transmittance are both usually high in the near-infrared regions (Near Infrared, 700 to 1300 nm) because there is very little absorptance by subcellular particles or pigments and also because there is considerable scattering at mesophyll cell wall interfaces (Gausman, 1974; Gausman, 1977; Slaton *et al.*, 2001). This sharp dissimilarity in reflectance properties between visible and Near Infrared wavelengths underpins a majority of remote approaches for monitoring and managing crop and natural vegetation communities (Knipling, 1970; Bauer, 1975)."

These observations reinforce the idea that the reflectance of different wavelengths do in fact represent qualities of plants like chlorophyll concentration – which is responsible for the photosynthesis in plant cells. Plants that are under stress from a pest or weed will have lower chlorophyll levels, photosynthesize less, and absorb less red, blue and yellow light – instead reflecting those wavelengths back.

As a visual example, the image below shows the reflectance of a particular healthy section of vegetation. We can see that lower wavelengths (blue, green, red) reflect back much less than higher wavelengths (Near Infrared). We can also see that the reflective properties change over the course of this 120 day growing cycle and the plant naturally grows and dies:



(Pinter et al., 2003)

With this in mind, we can then begin to think about how we can turn a plant's reflective properties that represent health into quantitative measurements of how a certain section of the field is behaving. Spectral Vegetation Indices provide us a good option for collecting these measurements.

Vegetation Indices. Vegetation indices are ratios or linear combinations of reflectance in Green, Blue, Red, and Near Infrared (NIR) wavelengths (Moran, M.S., Inoue, & Barnes, 1997). For example, a vegetation index might be:

Near Infrared(NIR) – Green

This index gives us a measure of the NIR reflectance minus Green reflectance – or a measure to quantitatively assess the health of the section (McKinnon, 2012). Conceptually: we know a healthy plant is absorbing red, blue, and yellow light, and reflecting back green light. Healthy plants also reflect back almost all near infrared light – so by taking the magnitude of the total light being reflected back (NIR) and subtracting the magnitude of the green light being reflected back we can get a measure of how much total green light is being reflected back relative to the reflectance of all light reflecting back from the plant. The resulting value gives us an accurate measure of how healthy a plant is based on the amount of green light it is reflecting, and how much red, blue, and yellow light it is absorbing.

Other vegetation indices, like the Normalized Difference Vegetation Index (NDVI), will use a slightly different approach. Instead of just this first step, NDVI also requires that we divide this first index by NIR + Green, so our final equation looks like:

$$\frac{NIR - Visible\ (Green)}{NIR + Visible\ (Green)}$$

Both of these indices will give us a ratio that we can use to determine the health of a plant or section – but do so in different ways. Depending on the lighting, the time of year, the type of crop, or other factors, one might choose to use one vegetation index over another - but all give the same output: a decimal number representing the health of the plant surveyed (Lebourgeois, 2010). Vegetation indices like these and others are used when management goals require quantitative measurements of biomass, leaf area index, growth patterns, and section health. Vegetation Indices have a high correlation with green biomass and leaf area index of crop canopies (Pinter, 2003).

Types of Mapping Cameras. The sensors used on both satellites and planes are large multispectral sensors. These sensors can break our visible wavelengths into much smaller wavelengths to get specific colors. These colors can then be manipulated to show us new information, like in the case of NDVI showing us the health of farm field sections. These cameras also cost hundreds of thousands of dollars and weigh much more than a small UAV can carry.

A new solution is needed to detect these wavelengths if we are going to use UAVs to capture this type of data. Weight and flight time (and consequent area covered) are directly correlated – meaning that every gram onboard needs to be optimized to the application. Lifting a large sensor would mean a plummeting flight time, and the inclusion of many unnecessary parts. Modern UAV mapping has moved from these large sensors to modified digital cameras. These cameras are usually light point and shoot cameras, modified to see Near Infrared, with 4-5mm focal lengths and 12-16 megapixel resolution. This modification is done by simply removing the Infrared filter in the camera that usually helps to mimic our vision in the camera's vision (Verhoeven, 2013). Now the camera will see Near Infrared instead of the normal Red/Green/Blue wavelengths our human eyes see.

NIR images can be captured, matched, and processed with Red/Green/Blue images to show us vegetation indices – but this process requires two flights: one for the NIR camera, and one for the Red/Green/Blue camera. Thankfully, recent advancements have led to a new process that requires only one flight and one modified camera to find vegetation indices. This modification is to simply remove the Infrared filter and include a filter that blocks red wavelengths. So now the camera receives NIR/Green/Blue. Now we can proceed just as before using Green and NIR to show us plant health. Cameras like this are fully capable of vegetation mapping on these platforms, weigh around 200g, and cost roughly three hundred dollars. But are they comparable to the top of the line multispectral sensors found on satellites and advanced remote sensing aircraft for agricultural applications?

Lebourgeois and other authors found that modified point and shoot cameras could indeed be used for agricultural remote sensing. In their words: "Putting together several known solutions for radiometric corrections, we showed that a comprehensive image processing workflow was possible for real time crop monitoring using commercial digital cameras" (Lebourgeois, 2010). Their experiment used three modified consumer digital cameras to take aerial images. Then, researchers on the ground examined the plots for Leaf Area Index(LAI), Leaf Greenness(SPAD), and Chlorophyll Content(CC) – three tests for plant health (Lebourgeois, 2010). The ground tests and aerial images were compared for accuracy. The findings showed that modified digital cameras could produce results with sufficient accuracy for crop monitoring by correctly assigning higher vegetation index numbers to plants that were proven to be healthier with the ground testing methods.

Methods and Discussion

Impact of Remote Sensing on Loss Variables

Using quantitative methods like Vegetation Indices, we can continue towards increasing yield and lowering costs on a farm. Some of the more obvious ways are increasing yield by locating problem areas on a weekly (or more frequent) basis, saving money on chemicals by spraying specific problem sections rather than blanket application, watching the patterns of the fields over time to optimize planting in future years, reducing gas and labor costs needed to travel the fields to inspect crops on the ground, and obtaining better estimates of yield earlier in the season.

Unfortunately, extremely limited information on UAV use in agriculture is currently available for us to test these potential ways of saving. However, we can draw on agronomic remote sensing and vegetation index studies using satellites and manned aircraft to show us what we will be able to expect in terms of farm output with UAVs doing the remote sensing work.

Herbicide Variables. One area that has been researched is the economic benefit of site-specific management (SSM) and herbicide use. Studies using satellite imagery have analyzed the benefit of detecting where weeds are in a field and spraying only those sections instead of the entire field. In one example, NDVI satellite images were used to find weeds in a soybean field in Iowa. The images were run through a decision support system to identify what areas needed to be treated, resulting in a recommendation of spraying only 50% of the field. The remaining 50% did not contain any weeds, or did not show enough weed density to be worth spraying (Shaw, 2005). This information suggests that we can save about half of the money spent on herbicides per year. Shaw describes the calculated cost savings below:

> "Calculated cost savings using site-specific herbicide applications (SSHA) ranged from $92.24 per hectare to $104.76 per hectare in soybean. Scouting based on sampling at a 10m grid size resulted in an increased net gain of $77.17 compared with a 20m grid-sampling scheme." (Shaw, 2005)

His observations suggest that there is a large economic advantage to using remote sensing technology in weed detection, and that higher resolutions bring increased savings when sensing for weeds. In his experiment, Shaw found that there is a 50% increase in the amount of money saved on herbicide for a 50% decrease in farm section sizes.

Pesticide Variables. Similarly, variable rate machinery loaded with GIS maps of field conditions proved to reduce pesticide usage by 40% which both saved money and lessened the environmental impact of the chemicals (Dupont, J.K., Campenella, Seal, Willers, & Hood 2000; Pinter, 2003). Since pesticides cost an average of $80 per hectare, we could expect a $32 increase per hectare savings by using remote sensing techniques. Again this data was collected by satellite, and although the resolution was not stated, it was likely higher than 20m per pixel – meaning that there is potential for even higher savings at more accurate resolutions.

In this case, these results suggest two things. First, selective spraying does in fact save farms money in chemicals, and second, that a higher resolution image could lead to even more profitable spraying practices. These numbers were generated from satellite imagery which allowed for survey sections of 10m and 20m.

About the Data. Higher resolutions and smaller sections could allow for early season crop growth assessment, weed and insect monitoring, and fertilizer application monitoring (Shaw, 2005). However, higher resolutions from satellites come at higher costs. Currently, the cost to achieve higher resolution (1-5m) images of a 200 hectare farm (average farm size according to www.agday.org/media/factsheet.php) is $8,000 to $10,000 per new capture. Less accurate images cost less – down to $1,000 to $2,000 at the 20 to 30 meters per pixel accuracy. This means that in order to monitor crops every month, a farmer would have to order a new survey of their land at these prices for each capture. As Shaw acknowledges, the frequency of the monitoring needed to detect and resolve weed issues currently makes satellite imagery cost prohibitive.

Another study by Frank Tenkorang looked at many publically available papers on the economics of remote sensing and found that studies claimed to see benefits of remote sensing ranging from $222 per hectare to $5 a hectare. He conducted a study to estimate a more accurate number based on the currently available studies and found the average benefit of remote sensing to be $31.75 per hectare.

However, although Tenkorang discusses and criticizes the available studies for not explaining all of their methods, his estimate does not specify a certain crop, whether data was collected with a satellite or airplane, or what the resolution of the images were. Information like this is critical to the analysis of the potential benefit of remote sensing both in the costs of data collection and in assessing the augmented gains when using smaller sections. Problems like these likely explain why Tenkorang had difficulties in finding an estimate within a $200 per hectare range.

It is also important to remember that the estimates by Shaw and Pinter are only for the amount of money saved on herbicide and pesticide. Irrigation issues, planting efficiency, and other problems could also increase the total amount of money saved by remote sensing – and it is unclear if Tenkorang attempted to include these other factors in his research.

Most studies like Pinter's, and Shaw's use satellites as the primary platforms to collect data on farms. Satellites, while useful for large applications, are hard to use on demand and expensive to use for higher accuracies. Some of the drawbacks of satellites, like resolution, clouds blocking the ground, and frequency of captures, have been resolved by using manned aircraft. While the cost of hiring a pilot and plane is still high, data can be captured in a wider range of conditions, on demand, and with better resolution than a satellite. These advantages come at the cost of not being able to monitor as much area. Furthermore, processing times for manned aerial imaging are roughly 24 hours, compared to the 16 hours of processing needed for satellite images, although both of these time frames are acceptable for the use of weed and pest detection (Shaw, 2005).

UAVs offer a new solution to these problems – and potential for expansion on the actions available with the data. However, since the exact benefit of remote sensing is still unclear because of variation based on type of plant, region, resolution, etc., one good way to dissect this information and determine the usefulness of UAVs is to think of best, worst, and likely case scenarios.

Best, Worst, and Likely Case Scenarios

Best Case Scenario. In the best case scenario, we will take Shaw's and Pinter's findings (for herbicide: $100 per hectare savings at 20m sections and $150 savings at 10m sections; for pesticide: $32 per hectare savings at 20m sections) and scale them to resolutions easily attainable with a UAV using the same benefit increase we saw when halving the size of the survey section in herbicide savings.

From the herbicide data above, we see a roughly 50% increase in savings per hectare for every 50% decrease in section size. If we assume that this trend continues all the way down to the one meter per pixel level, then we expect the gain from using one meter per pixel accuracy to be $506 per hectare:

20 meters /2 = 10 meters -> $100 * .5 = $50 + $100 = $150

10 meters /2 = 5 meters -> $150 * .5 = $75 + $150 = $225

5 meters /2 = 2.5 meters -> $225 * .5 = $112.5 + $225 = $337.5

2.5 meters /2 = 1.25 meters -> $337.5 * .5 = $168.75 + $337.5 = <u>$506.25</u>

The process above takes the size of the section, halves it, then adds 50% of the savings at the previous section size to the current total savings to find the estimated savings at the specified section size. We work this logic all the way down to the one meter section size to find the estimated savings at this level. In this case the starting point is $100 from Shaw's herbicide study. With the same logic, pesticide savings at the one meter per pixel accuracy would be $162 per hectare:

20 meters /2 = 10 meters -> $32 *.5 = $16 + $32 = $48

10 meters /2 = 5 meters -> $48 * .5 = $24 + $48 = $72

5 meters /2 = 2.5 meters -> $72*.5 = $36 + $72 = $108

2.5 meters /2 = 1.25 meters -> $108 * .5 = $54 + $108 = $162

This process is similar to the herbicide savings calculations, but uses a starting point of $32 based on Pinter's experiment with pesticides. If we combine these two numbers, we get a total of $668 per hectare saved in chemicals. On a 200 hectare farm this is a $133,600 dollar per year estimated savings on chemicals alone.

To add some context to these numbers, we will first look at the costs and benefits of using satellite imagery to carry out our remote sensing missions. Using Pinter's and Shaw's estimates on a 200 hectare field, we find it would be cost effective to use low resolution (20 meter sections) satellite imagery ten times to monitor crops assuming each survey cost $2,000. We know this because the savings would be $100 of herbicide savings + $32 of pesticide savings = $132 per hectare. $132 * 200 hectares = a total of $26,400, less $20,000 spent on 10 remote sensing missions would show savings of $6,400 annually.

High resolution (1 meter sections) imagery that cost $10,000 each survey would be cost effective 12 times for the farmer to keep seeing returns on a 200 hectare field. We carry out a similar process to find this. If we save $506 in herbicide and $162 on pesticide at 1 meter section sizes, then we save a total of $668 per hectare. If this number is multiplied by 200 hectares, then we see an annual savings of $133,600 minus the cost of

1 meter resolution satellite imagery. This cost of $10,000 each survey would be profitable up to twelve times or a total cost of $120,000.

While satellite imagery might still be a useful tool, a UAV would allow for even further benefit. If a farmer chose to buy and operate a UAV, then process data in house, the total cost would be around $5,000 for the UAV, then $15 per survey using services like agribotix.com or precisionhawk.com. Assuming we want to survey our 200 hectare field 14 times during the season (one each time a new pest or disease emerges in corn), we will use $210 worth of survey processing a year.

This best case scenario would result in $128,390 in chemical savings for the farmer in the first year and $133,390 in subsequent years, or $667 per hectare. This is calculated as follows: $133,600(estimated benefit at 1 meter sections) - $5000(UAV cost) - $210(processing costs) = $128,390. Each subsequent year the calculation is the same but without the cost of the UAV. This estimate does not account for possible further savings through sensing for optimal irrigation, rotation patterns, sunlight patterns, yield prediction, optimal fertilizer placement, crop height at different stages, etc.

It is important to also mention that the relationship between number of surveys and benefit to yield is not yet known for any crop, so while a UAV would allow for unlimited surveys on demand, best farming practice might require surveys only eight times a season. In this case it would still be more cost effective to use a UAV, as long as the UAV or service costs less than $130,000 a year.

Worst Case Scenario. In the worst case scenario we would assume that the benefit of data does not scale to the image resolution, and that the benefit from remote sensing is as Tenkorang suggests: $32 per hectare. This scenario requires much less math.

On a 200 hectare farm, the estimated benefit would be $6,400 annually. We would also assume that this number does indeed capture all potential benefits of remote sensing on farms. Resolution would remain at one meter per pixel – but would not matter since in this scenario we do not assume that lower resolutions and smaller section sizes mean higher gains.

Tenkorang does already subtract the costs in his equation so the $32 number reflects only profit. His average cost per hectare is $5, or on a 200 hectare farm, $1000. We will add this cost back to the total gains since we are calculating our own cost making the total savings $7,400. When we subtract $5,000 for the full price of a UAV and $210 for a year's worth of surveys, we get $2,190. This is the amount we can expect to save using remote sensing with UAVs in the worst case scenario in the first year. In subsequent years we estimate a savings of $7,190, or $36 per hectare. With more expensive UAV setups this number could easily go negative for the first year, and might take several years to regain the overhead costs.

Likely Case Scenario. The likely scenario involves a bit more guesswork. It is likely that the benefit of remotely sensed data does scale to resolution and section sizes, but the exact diminishing or increasing returns is unclear. It is also likely that the benefit of remote sensing will vary depending on the crop being surveyed – but there is insufficient data on this assumption. So, to be conservative we will assume Tenkorang's $32 per hectare savings, but add $5 to it to cancel out his assumed cost – leaving us with $37 per hectare. We will take the $37 per hectare number and assume that the benefit of each 50% increase in resolution is met with a 30% increase in savings, and that Tenkorang's data came from an average resolution of 25 meters per pixel. The 30%

multiplier reflects the likely increase in savings with smaller sections, but is a more conservative estimated multiplier than 50%. When we process the savings using the same methods as before, but with $37 as our starting number and .3 as our multiplier, we end with an estimate of $106 per hectare:

25 meters /2 = 12.5 meters -> $37 * .3 = $11.1 + $37 = $48.1

12.5 meters / 2 = 6.25 meters -> $48.1 * .3 = $14.4.3 + $48.1 = $62.53

6.25 meters / 2 = 3.13 meters -> $62.53 * .3 = $18.76 + $62.53 = $81.29

3.125 meters / 2 = 1.56 meters -> $81.29 * .3 = $24.39 + $81.29 = $105.677

On a 200 hectare farm, this is a total benefit of $21,200. Subtract the startup cost of the UAV and data processing and our total is $21,200 - $5,000 - $210 = $15,990 for the first year, and $20,990 for subsequent years, or $105 per hectare. Again, more expensive UAV packages may lower the first year's gains – possibly to negative numbers, and several years would have to pass to regain the initial cost.

Cost Benefit Analysis of UAVs vs. Other Platforms

Now the question arises: is it worth it? These scenarios assume that the farmer has enough time, patience, and motivation to assemble a UAV, learn how to operate it, and routinely fly it. Is this hassle worth the potential benefit? The way that the UAV remote sensing industry is beginning to form would suggest that it is not.

Currently, large seed companies like Monsanto and Pioneer are contracting out their farm monitoring remote sensing programs to smaller companies (Janni, 2015).

Those smaller companies will travel to the subscriber's farm, perform the remote sensing flight, then process the data and provide farmers with code for their variable rate technology equipped machinery and vegetation index maps of their land. Farmers are then charged based on the amount of hectares surveyed (McKinnon, 2015). So, as long as this price per hectare is lower than (from our likely case) $105, the farmer should profit from this service. It would seem reasonable for the cost of surveying and data processing to be far lower than this price point – but the exact prices will need to settle in the market. In our worst case scenario, we would need the price of UAV remote sensing services to be less than $27 per hectare. Even with this number it seems reasonable to assume that UAV remote sensing services would be profitable for a farmer – but again, the market will determine standard pricing.

When we consider the 13 and 14 stages of crop maturation in soybeans and corn respectively, services like this become extremely competitive with satellite and airplane monitoring. If we reflect on the numbers we calculated before on the cost effectiveness of satellite remote sensing images ($26,000 - $2,000 * number of surveys at 20m sections and $133,600 - $10,000 * number of surveys at 1m sections) we notice that it would be a very slim margin of profit (if one exists), to monitor soybeans and corn at each stage of development using satellite imagery. Our analysis above suggests that there would be a much larger profit margin using UAV technology.

Other Considerations

Legal Aspect. Another facet to be considered is the legal environment surrounding the commercial use of unmanned vehicles. In February 2015, the FAA released a proposed set of regulations for UAVs. The regulations in summary are as follows:

Proposed Commercial UAV Regulations.

Operational Limitations	• Unmanned aircraft must weigh less than 55 lbs. (25 kg). • Visual line-of-sight (VLOS) only; the unmanned aircraft must remain within VLOS of the operator or visual observer. • At all times the small unmanned aircraft must remain close enough to the operator for the operator to be capable of seeing the aircraft with vision unaided by any device other than corrective lenses. • Small unmanned aircraft may not operate over any persons not directly involved in the operation. • Daylight-only operations (official sunrise to official sunset, local time). • Must yield right-of-way to other aircraft, manned or unmanned. • May use visual observer (VO) but not required. • First-person view camera cannot satisfy "see-and-avoid" requirement but can be used as long as requirement is satisfied in other ways. • Maximum airspeed of 100 mph (87 knots). • Maximum altitude of 500 feet above ground level. • Minimum weather visibility of 3 miles from control station. • No operations are allowed in Class A (18,000 feet & above) airspace. • Operations in Class B, C, D and E airspace are allowed with the required ATC permission. • Operations in Class G airspace are allowed without ATC permission • No person may act as an operator or VO for more than one unmanned aircraft operation at one time. • No careless or reckless operations. • Requires preflight inspection by the operator. • A person may not operate a small unmanned aircraft if he or she knows or has reason to know of any physical or mental condition that would interfere with the safe operation of a small UAS. • Proposes a microUAS option that would allow operations in Class G airspace, over people not involved in the operation, provided the operator certifies he or she has the requisite aeronautical knowledge to perform the operation.

Operator Certification and Responsibilities	• Pilots of a small UAS would be considered "operators".
	• Operators would be required to:
	    o Pass an initial aeronautical knowledge test at an FAA-approved knowledge testing center.
	    o Be vetted by the Transportation Security Administration.

	◦ Obtain an unmanned aircraft operator certificate with a small UAS rating (like existing pilot airman certificates, never expires). ◦ Pass a recurrent aeronautical knowledge test every 24 months. ◦ Be at least 17 years old. ◦ Make available to the FAA, upon request, the small UAS for inspection or testing, and any associated documents/records required to be kept under the proposed rule. ◦ Report an accident to the FAA within 10 days of any operation that results in injury or property damage. ◦ Conduct a preflight inspection, to include specific aircraft and control station systems checks, to ensure the small UAS is safe for operation.

(http://www.faa.gov/regulations_policies/rulemaking/media/021515_sUAS_Summary.pdf)

Discussion of Regulations. These proposed rules are somewhat limiting to the full potential of remote sensing UAVs – but are much more reasonable than the previous ban of any commercial use. Before these regulations were proposed, the FAA would not allow any commercial operations to be carried out with UAVs. Now we have hope that the FAA will understand the potential of the UAV market (estimated at $84 billion across all applications) and allow for more testing and commercial operations to continue.

For these proposed regulations, the specific points that limit the usefulness of UAVs start with the mandate to fly within visual line of sight – that is, the UAV cannot go past the point at which an operator can see it without any vision augmenting device. This is problematic because the furthest we could hope to maintain this visual link would be under a mile – making the thought of autonomously surveying farms of any reasonable size difficult legally. The second limitation is the 500ft above ground restriction. This allows us to still get good imagery at extremely high accuracies, but the higher UAVs are allowed, the more data per picture they can get, the faster they can travel, and the more area we can survey.

Another big restriction is the requirement of an ‘operator’ who will have to be trained and maintain a license. This means that the companies who provide remote sensing services will have to hire skilled labor at higher prices, which will be passed to the consumers and lower the overall benefit of UAV remote sensing.

Environmental Effects. If remote sensing can in fact reduce herbicide use by 50% and pesticide use by 40%, there is a large environmental aspect to consider as well. Reducing the chemical runoff into groundwater has been a large concern in farming communities – since all of the chemicals used in farming eventually end up going back into the soil and polluting groundwater. Being able to cut this problem in half would be an outstanding way to help preserve the land and water that farmers rely on – while simultaneously benefiting economically from chemical savings.

By using UAVs to carry out the remote sensing we further help to eliminate pollution on farms. Rechargeable batteries are far more environmentally friendly than the gas it takes to drive through the fields scouting for pests and diseases, or the fuel required by manned aircraft for remote sensing data. These environmental benefits alone might be important enough to make a case for the use of remote sensing and precision agriculture on farms – even in our worst case scenario.

Conclusions

Although the future of UAVs in remote sensing roles on farms is still unclear, studies in remote sensing with other platforms provide a strong argument for the adoption of tools like vegetation indices and variable rate technology. UAVs fill a unique space in the future of remote sensing practices because of their ability to quickly collect high resolution images of standard farm sizes on demand, and at prices far lower than current methods. It is reasonable to expect that in the next ten years we will see a number of companies begin service based programs that will be hired to monitor farmland using UAV technology. It is also reasonable that we can expect some farmers themselves to operate and process their own data due to the relatively low entry knowledge needed to set up and operate a UAV platform. Assuming that the use of UAVs continues to prove a profitable practice, legal issues will be the only hurdles in finding UAV remote sensing as standard technology on farms.

As we move closer to this point, more studies will certainly be carried out to estimate the exact benefit of higher resolution images, how accurate we need to be for optimal compatibility with variable rate technology equipment, and when/how often we need to survey for optimal monitoring of farmland. Once these factors are proven we can make a true analysis of the exact benefit of UAVs as remote sensing platforms.

With the information available today, we can see a promising future for UAVs and estimate their potential – but until the industry expands there can only be estimation. With the promise and excitement currently surrounding the technology, this expansion will likely occur rapidly – possibly more rapidly than farmers will be ready to adopt these advancements into their current practice. Hopefully further investigations on the potential economic benefit of UAVs will expedite the interest of farmers and potential crop monitoring companies.

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