

Remote Sensing Methodology for Unmanned Aerial Systems

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1 INTRODUCTION

Unmanned aerial systems (UASs) have rapidly developed into a promising tool for remote sensing applications across a wide range of disciplines, from archeology to wildlife conservation. They can be designed and customized to fulfill a spectrum of characteristics and capabilities, such as low-altitude flying, long endurance, high maneuverability, and automated flight controls. But the UAS is simply the platform from which the target data are acquired. Unfortunately, with the multitude of UASs and combinations of sensing equipment, it can be a daunting challenge to determine the correct or cost-effective solution. The development of a thorough project methodology is an effective tool for addressing this challenge.

Section 2 of this chapter provides a guide to developing an effective methodology for UAS-based applications. Section 3 identifies several core attributes across three major types of remote sensing applications to guide the development of a methodology and influence equipment choices. Finally, in

Section 4, imaging equipment attributes are discussed to provide guidance in their selection. While there are a multitude of different types of UASs and sensors, the chapter will utilize small UASs (<55 lb) and optical-based remote sensing as an example, although the overarching message is applicable for any UAS and sensing technique.

2 UAS REMOTE SENSING METHODOLOGY

It is far too easy for an application or project to be proposed with a UAS without a clear concept of the necessary methodology to address the problem. While public interest has fostered technological innovation, literature has been sparse of general methodology approaches for the unique challenges of UASs. Instead, UAS research is saturated with specific application with specialized workflows and methodologies unique for the immediate application. It has become necessary to promote methodology for the development of new applications and mature UASs.

An important challenge for the UAS project developers is to translate layman statements such as “Let’s use a drone to improve land management practices” into “Let’s use a remote sensing platform carrying radiometrically calibrated optical imagers in the visible and near-infrared (NIR) spectra for the bare ground classification of a 10 square mile area with a desired optical resolution to discern the endemic population of Meadowfoam (*Limnanthes alba*).” The first statement is a wishful goal; the second introduces the

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methodology necessary to ensure a successful application and that the initial development and equipment purchases will lead to an effective solution.

An effective methodology defines the end goal, the activity, the implementation of the activity, the measurement of progress, and the success of the project. It provides a guideline for solving the targeted problem with specific tasks, components, and metrics. An incomplete or poorly defined project methodology can lead to development delays, spiraling costs, purchases of incorrect equipment, or complete project failure. In practice, many project developers find it useful to formulate a project methodology in terms of a series of questions such as the following (as adapted from Bhatta (2013)):

- What is the purpose of the project?
- What is the stated goal of the project?
- Is the goal quantitative or qualitative?
- Does this project utilize the scientific method or the technological method?
- What objects or events are the desired outcomes related to?
- Are there specific relationships found within the object or event of interest that can be utilized or must be taken into consideration?
- What data are necessary to address the problem?
- How should the data be collected?
- What procedures should be used to analyze the data?
- Are there available models/procedures sufficient to analyze the data?
- Does it require developing new models/procedures?
- What efforts must be undertaken to ensure the validity and reliability of the project?
- What ethical issues need to be addressed?

Addressing the questions above and/or other clarifying questions about the proposed project is designed to help form connections between goal and implementation and identify specific methods that will enable the successful completion of the application or the project.

The first step in any project is to understand the goal with the intended purpose of narrowing down the language to actionable items. Simple classifications such as separating the goal between quantitative goals and qualitative goals are often useful in this regard. This step often requires a thorough understanding of the desired goal that may not always align with the wording of the stated goal. For example, a project with a purpose of “improving crop yield” utilizes language that implies a qualitative goal, but in practice would require quantitative goals such as “improve yield by 5%,” which implies accurate measurements to be achievable.

The method or body of techniques of the project is another example of a way to provide guidance to the development of an effective methodology. For UAS remote sensing applications, the scientific method and the technological or engineering method are the most common. Whereas the scientific method strives to advance knowledge, the technological method addresses specific problems or issues. If the scientific method is about *knowing*, then the technological method is about *applying* (Bhatta, 2013). The two methods may overlap at times and utilize similar approaches and equipment, but the differences play a role in the development of a UAS remote sensing methodology.

The scientific method can be described as a set of techniques based on empirical and measurable evidence with principles of reasoning and inquiry to arrive at new knowledge. It is a cycle of observations, refining hypotheses, and testing, until a thoroughly vetted understanding can be presented as knowledge. Environmental research UAS applications typically fall under this category and assume that the technical capability of the UAS-based remote sensing is sufficient. In contrast, the technological method is an application of research, directed at a specific target goal or a desired state. In this approach, the enabling technical capability is the target end goal. Validation and testing become methods to measure progress rather than part of the implementation. In some projects, both methods may be employed, such as answering a scientific inquiry while developing the underlying technical capability. Clarifying the goals and the methods of the project can help put realistic targets and progress metrics within the context of the project end goals, and prevent cost-control problems from inadequate detail planning.

Examining the relationships of the desired objects and events of the goal is another aspect of forming a methodology. Keeping track of strong correlations and dependencies can be valuable. In some cases, the target goal, for example, “measuring chlorophyll content,” might show a positive correlation with a reflectance ratio calculation known as normalized difference vegetation index (NDVI; Jones and Vaughan, 2010). Thus, utilizing NDVI might be an effective method. However, a thorough methodology may identify that NDVI also shows a strong correlation with a leaf area index (Jones and Vaughan, 2010), which may complicate the desired goal measurements if the influences of the two correlations cannot be separated.

Understanding the goals and ways that the desired data can be collected provides some guidance for equipment, software, and workflow requirements, but selecting the right pieces can still be a significant challenge. There are a wide variety of platforms, sensor packages, software solutions at an equally wide range of costs, and capabilities already

commercially offered, but even still many researchers and developers end up implementing their own custom solutions (Stark, Smith, and Chen, 2013). This application-centric approach, choosing equipment based on the specific requirements of the application, is common, given the narrow and specialized applications proposed. However, this drives up costs and delays projects when incorrect equipment is purchased or developed.

Once the project's data goal is selected, the data must be collected. Data collection strategies vary significantly based on equipment, although there are plenty of examples of the use of modified equipment (Chabot and Bird, 2012; Jang and Kim, 2008; Jensen, Baumann, and Chen, 2008). However, one of the major challenges for remote sensing applications of UASs is the lack of standardized processing procedures. As many developers and researchers have discovered, specialized workflows are often necessary to process their data. Unfortunately, this poses problems in addressing whether or not the results of the project were valid and reliable. It is not an uncommon problem however, especially for remote sensing operations where different data generating processes can create data that may not be comparable with other sources (Trishchenko, Cihlar, and Li, 2002). Sections 3 and 4 provide guidance on selecting what type of data should be collected and how to collect it.

Ethical and legal issues are significant topics that require addressing with an effective methodology. The current legal environment, especially in the United States, is particularly challenging to traverse. However, it is important that UAS applications are developed with the legal restrictions and limitations in mind and understand how they may affect the data collection process and feasibility of the proposed goal. A challenge may arise from addressing privacy concerns. A common technique is to employ a "Privacy by Design" approach (Cavoukian, 2009), incorporating privacy considerations into the technology and methodology that addresses it at all stages: data collection, data management, data dissemination.

3 CORE CONCEPTS IN UAS REMOTE SENSING APPLICATIONS

In the following section, several core concepts are identified to provide guidance in the selection of the necessary data requirements and its influence on UAS and sensor selection. While there are many unique solutions in UAS remote sensing applications, there are some common equipment and workflow implementations that are useful to refer to when analyzing the data goal for a proposed project.

UAS remote sensing applications can be grouped by data goals into three major categories: detection or counting applications, identification or localization applications, and analysis applications. Detection or counting applications are focused on detecting or counting targets. Unlike the other types of applications, the data in these applications are in the form of contrasts, such as person versus not-person. Identification or localization applications are focused at understanding the contextual information associated with a target. Rather than looking for a herd of cattle, the size and location of the herd is vital to the application. Analysis applications require further investigation of the data and contextual information to create calibrated and meaningful or actionable information, although these applications can be very complex to establish. In general, the increasing complexity of the application is proportional to the costs, both in time and money.

3.1 Detection/Counting Applications

The detection or counting of targets is a common and valuable wide-area monitoring UAS application. Conceptually, the goal of such applications is simple: to find the existence of the desired target. The significant challenge is to determine the optimal way to separate the target from the rest of the scene, either of which could be static or moving. The target is the primary goal, thus the accuracy of the separation or classification is paramount to success rather than the accuracy of the image or other measurements. The separation or classification of the target can be accomplished in any variety of ways by focusing on finding specific characteristics such as color, texture, or shapes that are unique for the target. Additional contextual information, such as location, time of day, or *a priori* knowledge, may also be valuable for improving the accuracy, and could require the use of data fusion techniques or statistical modeling to reduce errors. However, in contrast to the accuracy requirement of the detection, the collection of the characteristic or contextual information is reliant on precision or the repeatability or reproducibility of the collection of the information. This is an important distinction to make because it may affect equipment choice. For example, if the goal is to find hogs on property (Hirsch, 2013), a thermal camera is an effective tool, but the temperature measurement of the hog is not of value, only the contrast of hot and cold. A lower cost precise thermal imager may be utilized rather than a more expensive accurate thermal imager.

Identifying the characteristics or contextual information necessary for detection influences equipment selection. Many characteristics such as texture and shape often require a high spatial resolution to discern small features. Contextual

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information, such as location, size, and depth, can be inferred from motion determined from images with a high temporal resolution such as individual frames in a video. Automated low-level control found in many cameras and video systems such as color balance, autofocus, aperture, and shutter speed control can be effective at maintaining the visibility of the image for characteristics to be discerned.

The time sensitiveness of the application also plays a role in the equipment selection, more so in detection and counting applications than the others (Doherty and Rudol, 2007). Often an immediate reaction is desired at the detection of a target, such as returning home or changing search patterns. This level of visual feedback into the system often requires real or near real-time communication and systems with a high frame rate are best suited (Peschel and Murphy, 2013). The desire to have an independently operated imaging system often requires the same level of visual feedback as well. For these reasons, video systems are more common for detection and counting applications where immediate visual feedback is prioritized over image quality and resolution.

The processing of the data can be automated or manually done with a human operator. Automated machine vision algorithms have been utilized and demonstrated widely, although human operator monitoring are commonplace. Search and rescue operations, especially, are staffed with human operators due to scene complexity and ease of implementation (Woods *et al.*, 2004).

However, there are specific challenges to detect and counting applications. For automated machine vision systems, the data processing increases significantly with image resolution, but too low of a resolution limits the ability to discern details such as texture. Human operators who monitor real-time video also have a number of challenges, as documented by studies on human factors for search and rescue operations with tele-operated robotics (Murphy, 2004). Operator fatigue and sensory overloads are common issues that lead to decreased detection and counting accuracy (Freed, Harris, and Shafto, 2004). Long operations may be limited by UAS platform capabilities, proper selection of the desired platform is another key for success (Stark, Smith, and Chen, 2013). In addition, the data bandwidth of the video system is often much greater than the rate of detection, leading to a significant amount of wasteful redundant data. From that challenge, it is important to recognize the value of optimal path planning and optimal sensing strategies (Chao and Chen, 2012).

3.2 Identification/Localization Applications

In many situations, the characteristic or contextual information of a target is a part of the data goal. This transforms the

application into an identification or localization application, where instead of asking “is it there?” the question is “what is it?” Characteristic or contextual information commonly includes location and surroundings, but may also include size, time, color, or texture. These attributes often require a higher spatial resolving capability of imagery, though not necessarily always a faster temporal resolution. The addition of this information enables the classification or identification of a number of items such as plants, animals, vehicles, or sustained damage. However, the challenge of classification introduces the need for repeatability and consistency from image to image.

A wide variety of sensor equipment can be utilized for identification or localization applications. Video systems can be utilized effectively as described in firefighting efforts (Ambrosia *et al.*, 2003; Hinkley and Zajkowski, 2011). Digital cameras can often provide a higher resolution and many are affordable solutions where real time is not necessary. Other specialized equipment such as thermal imagers, multispectral imagers, or hyperspectral imagers are also effective equipment though are often a costly investment. Remote sensing applications may also utilize nonimaging sensors for air quality measurements and the inclusion of localization data enables the creation of detailed spatial maps.

Whereas some detection applications can be accomplished without specialized equipment, identification and localization applications often require contextual information to be stored during image collection and additional processing to fully utilize it. UAS payloads may employ camera systems with embedded Global Positioning Systems (GPSs) to record image locations. Photogrammetry software such as Pix4D (Pix4D SA, www.pix4d.com) and Ensomosaic UAV (MosaicMill Inc., www.mosaicmill.com) are commonly a part of the workflow.

The tracking of moving targets is another common UAS application that combines the challenge of object identification and localization (Ren and Beard, 2004). Challenges such as multiobject tracking may require the use of real-time data downlinks or significant onboard computing power. As with detection and identification applications, the use of auxiliary processing and data fusion algorithms may be useful for improving results at the expense of cost and complexity.

3.3 Analysis Applications

Analysis applications are typically complex and require significant development and a strong methodology. While identification applications ask “what is it?” analysis applications are designed around the question “what does it mean?” In essence, they are designed for the purpose of

transforming remote sensing data into meaningful or actionable intelligence. The counting application will return with the information that there are 12 trees in the grove. The identification application will return with the location and size of each tree. The analysis application will generate the data to make estimations on the health of the trees and how much fruit will be produced.

In analysis applications, often the data produced is not the image, but rather a 2D map of the optical sensor measurements. As such, sensor calibration, radiative transfer models, ground control points, and bias corrections are standard elements of the analysis application workflow in an effort to relate sensor measurements to physical features. Commercially available point and shoot digital cameras may not always be well suited for these applications as they typically lack the ability to record sensor measurements. Multispectral cameras and hyperspectral imagers are commonly implemented and have demonstrated effectiveness in agricultural applications such as crop monitoring (Berni *et al.*, 2009) and environmental applications such as invasive weed monitoring (Rasmussen *et al.*, 2013).

The value of calibrated imaging equipment can be interpreted in the spectral reflectance of grass, dry grass, and brown sandy loam (Figure 1) (Baldrige *et al.*, 2009). Live vegetation, including grass, has a distinctive pattern of

spectral reflectance or the amount of light that is reflected. Vegetation typically appears green to the human eye because it reflects more light in the green spectrum (0.53–0.58 μm) than red or blue. Most vegetation is also highly reflective in the near-infrared spectrum that is in the range of 0.7–1.0 μm , beyond what the human eye can see. An imaging system that can measure the reflectance of an object at multiple wavelengths would be able to very clearly determine the difference between grass and dry grass, which has a different spectral signature as depicted in Figure 1. However, if a sensor was uncalibrated and suffered from an unknown bias, the different materials may be separated, but not identified. The following section examines this issue in more detail.

4 UAS IMAGING EQUIPMENT

The development of an effective UAS remote sensing methodology requires knowledge of various equipment available and their capabilities. Rather than focusing on specific technological metrics, the following discussion focuses on the common qualities of selected imaging equipment types. Without specifying existing imaging resolutions or shutter speeds, it is still valuable to examine the different defining

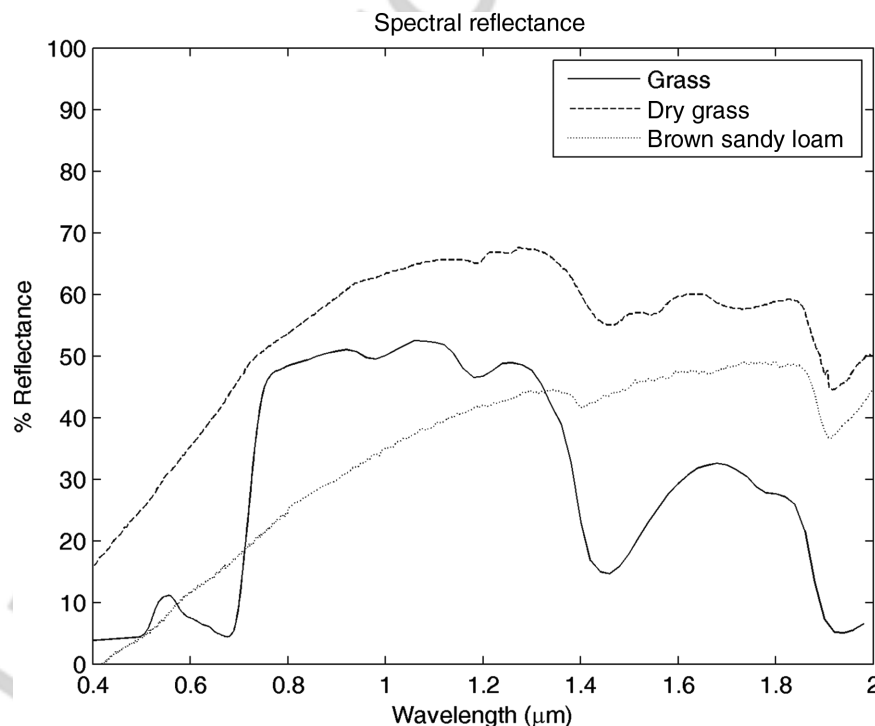


Figure 1. Spectral reflectance of grass, dry grass, and brown sandy loam (Baldrige *et al.*, 2009).

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aspects and how they dictate the remote sensing workflows and best practices. The following section examines common UAS payloads such as video systems, digital cameras, and calibrated digital imagers with a discussion of the implementation strategies and methodology development. Additional equipment, such as thermal imagers, have been found to be significantly useful (Stark, Smith, and Chen, 2014), but are outside the scope of this section.

4.1 Video Systems

Video systems can be a simple payload to integrate into a UAS. It can be as simple as affixing a small HD video recorder to the UAS but also as advanced as a remotely operated gimbaled video system with real-time communication and control. The wide range in capabilities does enable project developers the ability to decide on the best system, balancing performance and cost with functionality.

Image quality and resolution vary significantly with quality and price, although, in general, they are not at the same level as digital cameras. However, the key aspect of video systems is the high frame rate rather than optical quality. For human viewers of live or recorded video, the implied motion visible from the rapid progression of frames provides significant contextual information such as movement direction, relative size and orientation of visible objects, and object depth that are difficult to discern from still imagery at lower frame rates.

With machine vision algorithms and automated processing, the high frame rate enables superior object tracking and coverage area with faster moving vehicles. The use of a controllable gimbal system provides improved situational awareness for human operators (Peschel and Murphy, 2013), a valuable capability for search and rescue operations, although at the cost of added complexity. While video systems typically have a lower image resolution than digital cameras, the use of a narrow field of view lens or a controllable zoom lens can enable a similar high spatial resolution at the tradeoff of a smaller viewing area.

Implementation of video systems into a project workflow is straightforward. Typically, they do not require preflight calibration or image correction as the information goal is to obtain visual references of objects or of characteristic information. Setting up ground control points can be utilized for postprocessing georeferencing. Depending on the desired autonomy, video processing can be done onboard or on the ground, though typically the computer power is greater on the ground.

4.2 Digital Cameras

Digital cameras are effective for many UAS operations that require high spatial resolution but do not require immediate visual feedback or a high frame rate. Many cameras, even those that are commercially available, have advanced automated features such as automatic focus, color balance, white balance, and image stabilization that ensure excellent pictures are generated. Overall, digital cameras provide excellent resolution for quantitative measurements of many characteristics such as small features and object texture, making them ideal for identification or localization applications. The additional contextual information, such as known ground control points or recording the position the picture was taken in, can enable accurate spatial measurements as well. With a sufficient coverage, a mosaic can be generated from the set of pictures over the targeted area (Figure 2). Combined with the contextual information, this enables high-resolution georectified orthophotos that can be used for applications such as mapping fire damage (Hinkley and Zajkowski, 2011) and rangeland management (Laliberte *et al.*, 2010). In the example orthophoto, the discoloration of soil is apparent in the area surrounding the water tower located on the right side of the orthophoto, which was caused by sediment leakage.

The pictures generated can also be used with a photogrammetry technique of generating 3D surface models from aerial images (Figure 3). Utilizing sufficiently overlapping pictures, image points from a structure-from-motion (SfM) algorithm are matched together to generate pixel depths and stitched together to form a digital surface model. These digital surface models have been presented as both accurate

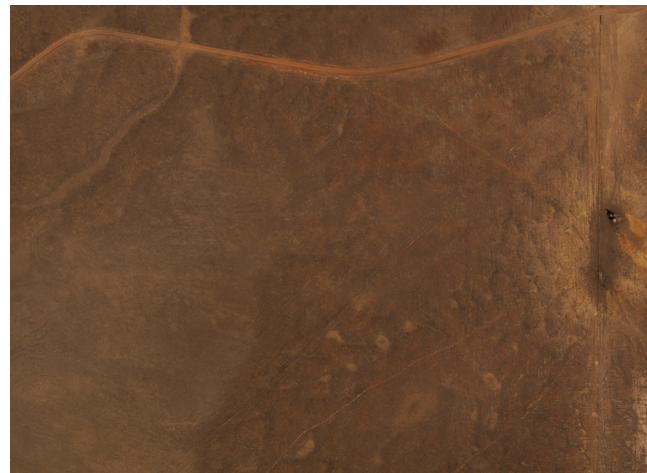


Figure 2. Example orthophoto.

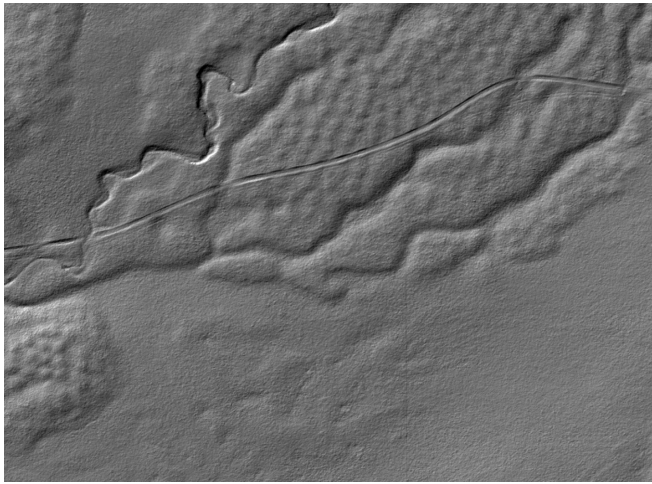


Figure 3. Example digital surface model (hillshaded for clarity).

and precise (Rock, Ries, and Udelhoven, 2011) enough to be utilized for applications such as modeling river topology (Javernick, Brasington, and Caruso, 2014) and mapping ice flows (Whitehead, Moorman, and Hugenholtz, 2013). In Figure 3, the digital surface model depicts the abundance of sediment mounds that characterize the formation of the seasonal vernal pools in the Merced Vernal Pool and Grassland Reserve.

While digital cameras have a number of advantages, they are less suited for applications where immediate responses or quantitative spectral measurements are needed. The automated features that enable high-quality pictures obscure accurate reflectance radiation measurements by dynamically adjusting color, light, and introducing artifacts through lossy compression.

4.3 Calibrated Digital Imagers

Quantifiable spectral measurements are a powerful analytical tool and the basis for most satellite remote sensing applications. While satellites suffer from low spatial resolution, low temporal resolution, and atmospheric interference, UASs can be utilized to counter these issues.

Calibrated systems are designed to provide accurate radiometric measurements, typically of the radiation emanating from the surface (Jones and Vaughan, 2010). Rather than looking at images in terms of colors, images are comprised of the intensity of energy received at particular wavelengths. Whereas a red object may appear slightly pink or orange depending on the time of day, camera orientation, or camera settings, a calibrated system is designed to isolate only the

reflectance of an object and provide a consistent measurement across multiple settings and viewings.

4.3.1 Digital cameras as calibrated imagers

Digital cameras can be utilized as radiometrically calibrated imagers, although additional procedures are required for calibration. In Figure 4, an example workflow for using digital cameras as calibrated digital imagers is depicted. Field data collection is often a necessity for most workflows for radiometric calibration. Camera identification is also a process done prior to the flight operation, although this may not be necessarily prior to each flight. Lens calibration calibrates for the optical qualities. Flat-field calibration provides for adjustments from nonuniform image collection (vignetting, nonlinear response, and dead pixels). Spectral sensitivity enables radiometric data to be collected for spectral signature matching, which often requires ground control points and spectral control points. The data processing workflow includes the integration of metadata for spatial processing and raw band separation to adjust for band-to-band registration.

Digital cameras can also be modified to measure reflectance at the near-infrared spectrum. The CMOS- and CCD-based imaging sensors used for commercial cameras are also sensitive to the NIR spectrum, although normally NIR blocking filters are installed for regular pictures. Removal of this filter restores the NIR sensitivity, although it can be mixed with the red light spectrum. The installation of a NIR pass filter such as Hoya R72 (Hoya Filters, hoyafilters.com) blocks out the red spectrum to enable NIR measurements. Other solutions utilize a red notch filter, blocking only visible red while allowing visible blue and green and NIR (LDP LLC, www.maxmax.com). On some cameras, the blue channel is also marginally sensitive for NIR. In those cases, it is possible to install a blue notch filter. This has the intended effect of blocking the visible blue wavelengths on the blue channel while still allowing the NIR wavelengths to be measured on the blue channel.

4.3.2 Multispectral and hyperspectral imagers

Imaging equipment that specialize in measuring the reflected radiation at specific wavelengths are either considered multispectral or hyperspectral imagers. Multispectral imagers are typically only a handful of selected wavelengths, while hyperspectral generate upward of 60 channels of selected wavelengths, typically at much narrower bands than multispectral.

Advances in technology have led to the feasibility of the use of multispectral imagers such as those developed by Tetracam (Tetracam Inc., www.tetracam.com) and

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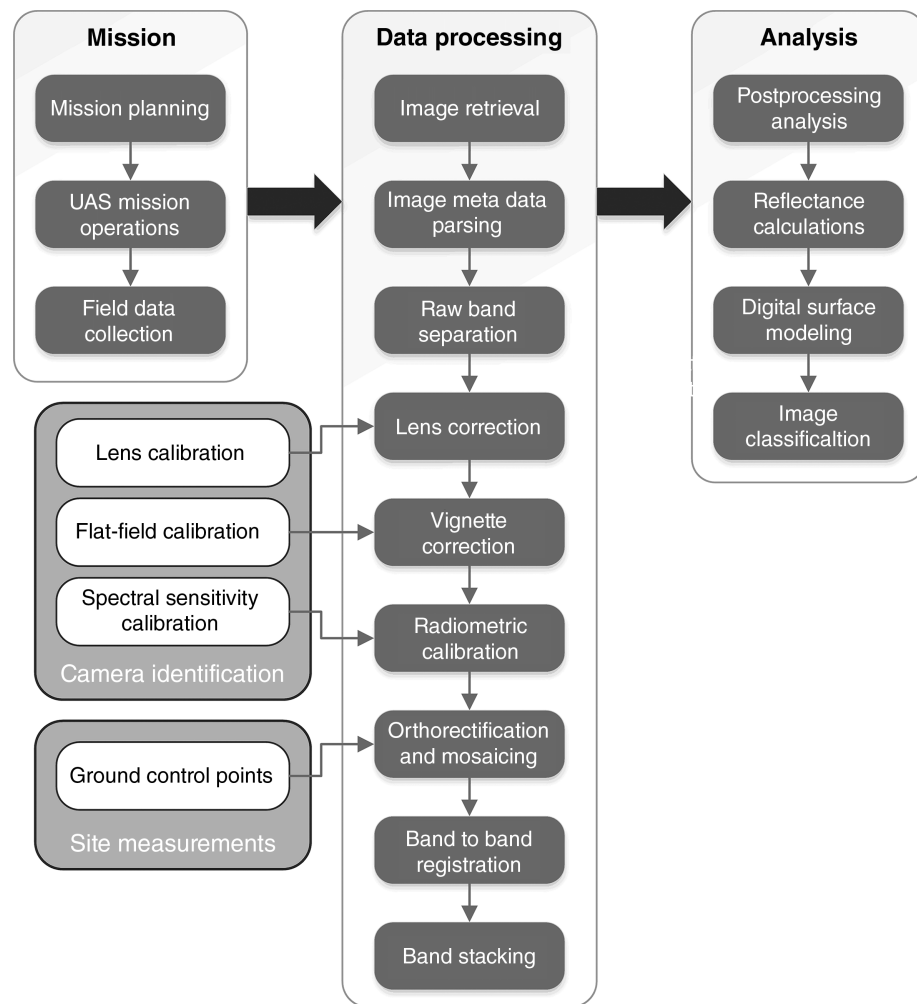


Figure 4. UAS analysis workflow for converted digital cameras.

MicaSense (MicaSense Inc., www.micasense.com). For applications that rely on spectral signatures of targets, often these systems are a necessity. A variety of agricultural applications such as crop water stress (Zarco-Tejada *et al.*, 2013) and identifying citrus greening disease (Garcia-Ruiz *et al.*, 2013) have demonstrated the effectiveness of these systems for both multispectral and hyperspectral imaging.

Many of the implementation strategies of calibrated digital cameras can be similarly applied to these calibrated imagers. As with other optical systems, corrections such as background noise, radial distortion, and vignetting are required for accurate radiometric measurements (Del Pozo *et al.*, 2014). Multispectral sensors, based on CMOS or CCD sensors, utilize a wide range of spectral sensitivity of sensors and optical bandpass filters such as those commercially sold

by Andover (Andover Inc., www.andover.com) or Edmund Optics (Edmund Optics Inc., www.edmundoptics.com). The advantage of these specialized sensors is the quality of the spectral measurements. While calibrated camera systems have broadband spectral responses, the specialized imagers are capable of measuring specific spectrum as described in the following section.

4.3.3 Spectral sensitivity

An understanding of spectral sensitivity is an important quality for proper measurement of reflected radiation. For optical imaging systems, a simplified model of the measured light radiation for each channel or band can be described as the integration of the camera's sensitivity, scene illumination, and the scene's reflectance over the spectral range as shown

in the following equation:

$$I_{k,x} = \int_{\lambda_{\min}}^{\lambda_{\max}} C_k(\lambda) L(\lambda) R_x(\lambda) d\lambda$$

where k is the channel, x is the spatial position, I is the measured intensity, $C_k(\lambda)$ is the imager sensitivity for band k , $L(\lambda)$ is the spectral power distribution of the illuminate, and $R_x(\lambda)$ is the spatial reflectance of point x . $C_k(\lambda)$ of the imager sensitivity can be measured or estimated through a variety of means (Jiang *et al.*, 2013). The illumination can be measured or estimated with existing solar models. The goal for most analysis application involves solving $R_x(\lambda)$ given $I_{k,x}$, which is a challenge due to the low intrinsic dimensionality. However, the solution for $R_x(\lambda)$ can be approximated when the camera sensitivity is sufficiently narrow, as with multi-spectral or hyperspectral imaging sensors.

When the channels or bands are not sufficiently narrow, a common solution utilizes colored panels or objects with a known spectral response. To calibrate scene illumination, *in situ* measurements either concurrently with the imagery or immediately prior or after are used (Clemens, 2012). The calibration of the imager with known reflectance values ensures an accurate ratio between bands rather than accurate radiation measurements.

Although the intended effect of calibrated imagers is to provide satellite-like measurements of particular wavelengths, in practice the differences in spectral sensitivity of the imagers pose a challenge for a unified data set. The following plots of the spectral sensitivity of a Canon 600D digital camera (Figure 5), Tetracam Mini-MCA6 (Figure 6),

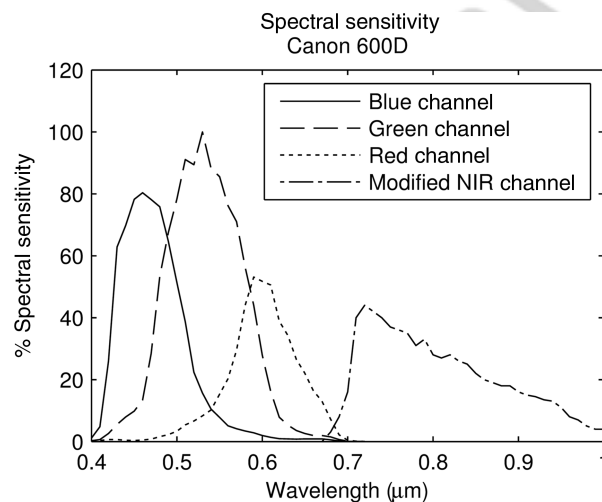


Figure 5. Spectral sensitivity for a Canon 600D camera. Modified NIR channel on a second camera (Jiang *et al.*, 2013).

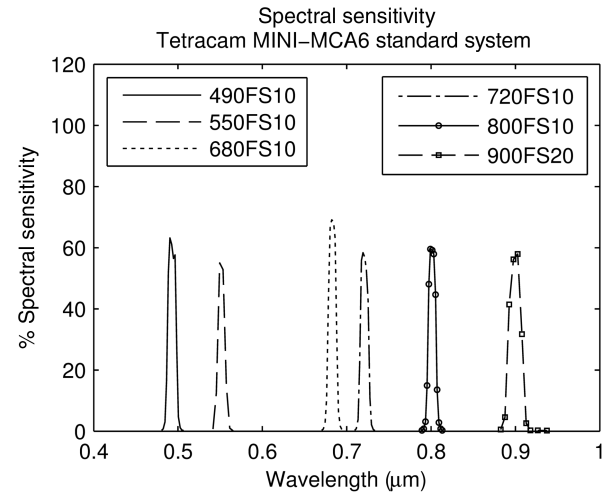


Figure 6. Spectral sensitivity of standard filters of a Tetracam Mini-MCA6 Standard System. (Reproduced with permission from Tetracam, 2016. © Tetracam Inc.)

and the Landsat 8 Satellite (Figure 7) depict the significant variation. For common calculations such as NDVI, the differences in spectral sensitivities of the imaging systems can have significant differences in the final calculations even with satellite systems (Trishchenko, Cihlar, and Li, 2002). As these differences play a large role in the accuracy of the data, care should be taken in the proper selection of the sensor sensitivity to the desired data goal.

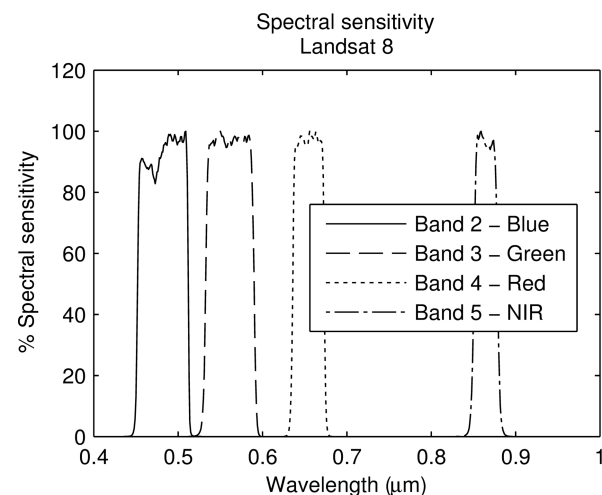


Figure 7. Spectral sensitivity of Landsat 8 (NASA, http://landsat.gsfc.nasa.gov/?page_id=7195).

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5 CONCLUSION

The use of UASs as a remote sensing tool has a number of significant advantages to complement existing technology and methodology. However, as new capabilities are developed, there is a need for describing how to utilize and capitalize them efficiently. As more and more applications are developed and described, UAS methodology will mature and effective projects will be the norm. For many applications, such as those based around detection or identification applications, existing technology is capable. While it is tempting to use UASs as a direct replacement for satellites for analysis applications, there are additional challenges that need to be addressed, especially toward accurate spectral measurements. However, the future is bright for UAS remote sensing applications, and sooner than later the use of UASs will become regular and mature.

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Abstract:

The use of unmanned aerial systems (UASs) for remote sensing applications has increased significantly over the last decade. As more and more applications are developed and documented, the need for a guide for the development of a UAS remote sensing methodology has become apparent. A well-developed methodology is critical for the success of the project as it defines with clarity the end goal, the implementation, and the data collection strategy and provides metrics for success and project completion. Failure to accurately develop a methodology can lead to significant development delays, spiraling costs, or complete project failure. In this chapter, a guide to developing UAS remote sensing methodology is presented, focusing specifically on common UAS applications and payload equipment.

Keywords: data collection strategy; multispectrum; payload; remote sensing methodology; UAS-based remote sensing.