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The Future of Unmanned Aerial Systems (UAS) for Monitoring Natural and Cultural Resources

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ABSTRACT

Aerial imagery and photogrammetric techniques that have long been used to monitor natural and cultural resources are undergoing innovative transformation with the increased availability of low-cost unmanned aerial systems (UAS) and software for Structure-from-Motion (SfM) image processing. Cultural resources of historic buildings, gardens and monuments, along with natural resources such as inland freshwater wetlands that are small in size (e.g., < 0.5 ha), composed of diverse aquatic plant species and temporaly variable in soil mosture/open water, present challenges to managers tasked with detection, delineation and monitoring using remotely sensed data. Traditional image data sources of medium (10 to 30-m pixels) and high (1 to 5-m pixels) spatial resolution satellite images, large-scale (1:10,000 and greater) airborne film format aerial photographs and digital camera imagery (0.5 to 1-m pixels) present limitations for detailed resource monitoring due to relatively coarse spatial and temporal resolution. The capability to respond quickly and capture imagery with pixel sizes in the range of a few centimeters is needed to accommodate variable weather conditions, rapid phenological changes and unexpected disturbances. Such systems are required to obtain optimal aerial imagey tailored for specific resource applilcations. Off-the-shelf, portable UASs fitted with video cameras now permit users to collect high quality imagery within minutes of launch and processing capability on-site for near real time 3D data extraction and visualization for quick decision making. Researchers at the University of Georgia's Center for Geospatial Research (CGR) have explored the use of small UAS quadcopters for mapping wetlands, assessing woody debris biomass in forests, creating 3D visualizations of historical buildings and documenting seasonal changes in botanical gardens. This paper will describe methods used to acquire aerial images with DJI Phantom 2 Vision and Vision+ quadcopters to create image mosaics, 3D point clouds and image models used to monitor natural and cultural resources. Finally, future directions will be addressed with an eye towards advances for resource monitoring.

1. INTRODUCTION

The mapping and monitoring components of natural resource management is critical for inventory and assessment of ecological health related to natural disturbances and human impacts. Aerial images provide synoptic views of forest canopies, aquatic vegetation in coastal and inland wetlands, grasslands, rangelands and desert ecosystems in valuable conservation lands (Bogucki & Gruendling, 1978; Carter et al., 1979; Remillard & Welch, 1992, 1993). Likewise, aerial images are invaluable as documentation of cultural heritage structures and land features (Baltsavias et al., 2006; Lonnqvist & Stefanakis 2009; Höhle, 2013). The integration of remote sensing, photogrammetry and spatial information systems are then used to transform aerial views of natural and cultural resources to quantitative data suitable for geospatial analysis, predictive modeling and actionable decision making (Welch et al., 1992; Colosi et al., 2009).

1.1. U.S. national programs of aerial images used for natural resources

The use of aerial photographs to monitor agricultural resources of the United States was initiated in 1937 by the U.S. Department of Agriculture's Agricultural Stabilization and Conservation Service (USDA-ASCS) and continued to the early 1940s (Lillesand et al., 2015). Although the 1:20,000-scale, black-and-white (BW) stereo photographs were intended for efficient measurement of farmland acreage (USDA, 2015a), their value was soon recognized as a source for mapping additional resources including forests, stream/river networks and topography. Over the ensuing 60 to 70 years, managers tasked with detecting and mapping natural resources relied on vertical aerial imagery acquired from cameras attached to aircraft and targeting coastlines, forest tracts, grasslands, wetlands and water bodies (Colwell, 1997; Tiner, 1984, 1997, 2009; Wilen & Bates, 1995).

Since 1980 in the U.S., there have been several national programs for acquiring aerial photographs for natural and cultural resource monitoring. High resolution film and paper photographs, and more recently, digital orthoimages acquired by the USGS and USDA, are traditionally the main data sources for mapping in the U.S. at 1:24,000 scale (USGS, 2015a) Limitations for resource mapping, however, result from these programs being multipurpose and multi-agency collaboration for funding dictating specifications of film type, scale and season of image acquisition according to the aim of each mapping project. For example, aerial photographs were largely acquired during leaf-off conditions by the USGS National High Altitude Aerial Photography (NHAP) program from 1980 to 1989 (1:80,000 scale BW and 1:58,000 CIR) and the National Aerial Photography Program (NAPP) (1:40,000 scale BW and CIR) in the1990s, to facilitate topographic mapping (USGS, 2015b, 2015c). The responsibility for national aerial photographs shifted to the USDA Farm Service Agency (FSA) Aerial Photography Field Office (APFO) in the early 2000s and the National Agricultural Imagery Program (NAIP) resulted in first film and then digital aerial photographs acquired during the growing season in leaf-on conditions for largely agricultural monitoring applications (USDA, 2015b). In order to promote the use of these images for agricultural applications, NAIP products are generally available as 1-m color mosaics subset by county. Although small features such as wetland vegetation can be identified in the color imagery, large-scale color infrared film on the order of 1:8,000 to 1:20,000 scales or digital images with pixel sizes < 1-m are needed to detect small inland wetlands < 0.5 ha in size, distinguish vegetation species and delineate upland-wetland boundaries (Bogucki et al., 1980; Welch et al., 1995, 1999; Teng, 1997; Tiner, 1997; Madden, 2004). C-ASTRAL

1.2. Systematic-repetative and targeted satellite imagery

For over 40 years, synoptic, systematic and repetitive coverage of Earth resources by medium-resolution (i.e., 80-m and 30-m pixel sizes) multispectral images has been achieved by satellite programs such as the U.S. Landsat program in continuous operation since 1972 (USGS, 2015d). These images have been used extensively to map natural resources and are especially suitable for mapping extensive coastal marshes and large wetland areas such as the Everglades and Chesapeake Bay with automated classification techniques (Klemas et al., 1975; Butera, 1983; Ackleson & Klemas, 1987; Jensen et al., 1995; Baker et al., 2006). Limitations of using satellite images for vegetation mapping include constraints of spatial and/or temporal scale of these images. For example, Landsat is designed to have sun-synchronous orbits such that sensors capture images of any given location at the same time of day during each 16-day orbital revisit, crossing the Equator in the north to south direction at 9:45 am local time for Landsat-4, -5 and -7 and 10:00 am for Landsat -8 (Jensen, 2007; Lillesand et al., 2015). The multispectral imagery covers a 185 by 185-km area for each scene at a nominal spatial resolution of 80-m for the Landsat-1, -2 and -3 Multispectral Sensor (MSS), 30-m pixel size for optical bands of Landsat -5 Thematic Mapper (TM) and -7 Enhanced Thematic Mapper Plus (ETM+), and the most recent Landsat-8 Operational Land Imager (OLI) multispectral bands of 30-m with a single 15-m OLI panchromatic band (USGS, 2015d). These data document a 40-year history of global land cover with the entire archive opened for free and access since December of 2008.

With the need for satellite imagery of high spatial resolution to map smaller natural and cultural features, multispectral digital images were acquired by commercial satellites for targeted locations (i.e., acquired opportunistically instead of systematically and synoptically) since 1999 at pixel sizes on the order of < 5-m pixel size (DigitalGlobe, 2015a). Commercial satellite companies in the U.S., such as ORBIMAGE, Space Imaging, DigitalGlobe and GeoEye, began acquiring panchromatic images at 0.41 to 1-m spatial resolution and multispectral images at 1.64 to 4-m for smaller footprint areas (e.g., image swaths of 18 km) and on a tasked-basis for locations of interest (Petrie & Stoney, 2009; DigitalGlobe, 2015b). Although offering stereo imagery, high spatial resolution and the ability to task the satellite to acquire imagery of particular locations via pointable sensors with 1- to 2-day revisit times, the spaceborne platform orbits at altitudes of 450 to 770 km. For instance, WorldView-3 launched in 2014 at 617 km allows imagery of 31-cm panchromatic and 1.24 m multispectral spatial resolution to be acquired (DigitalGlobe, 2015b). Imagery acquired from space requires atmospheric corrections due to clouds, haze and smoke that effectively reduces contrast and/or blocks features of interest. The high spatial resolution imagery available from commercial satellites is well suited for resource mapping, and especially for updating existing wetlands maps (Dahl et al., 2009; FGDC, 2009; Maxa & Bolstad, 2009). Limitations, however, include the time and expense that is required to order/schedule the data acquisition in cloud-free conditions, availability of archived data and need to purchase imagery under license agreements and thereby reduce data collaboration.

1.3. Contracted airborne imagery

Aerial photographs from film cameras and digital imagery from airborne multispectral and hyperspectral sensors that are contracted on a project basis from photogrammetric firms offer greater flexibility in flying heights (i.e., potential higher spatial resolutions and larger scales) and timing for data acquisition in particular seasons, days or times of the day (Jensen et al., 1984; Christensen et al., 1988; Remillard and Welch, 1992; Welch et al., 1992, Hirano et al., 2003). Drawbacks again are the expense of customized flights of airborne image data, the need to wait for ideal weather conditions and minimum flying heights for aircraft of approximately 300 m for fixed wing airplanes and 150 m for helicopters (Welch et al., 1999).

In spite of the plethora of traditional aerial imagery that are readily available at a variety of scales and formats for resource mapping, the potential for unmanned aerial systems (UAS) to revolutionize mapping was instantly recognized by mangers, scientists, surveyors, engineers, foresters, farmers, private practioners and policy makers. In response to miniaturization and improvements of electronic components, batteries and navigation controls, a number of unmanned fixed-wing airplanes and rotary-wing helicopters are readily available for mounting small sensors and remotely collecting Earth surface data (Madden et al., 2015).

2. UAS FOR FLEXIBLE DATA ACQUISITION AT HIGH SPATIAL AND TEMPORAL RESOLUTIONS

In the late 1990s and early 2000s, educators and resource managers interested in exploring the use of low-cost remotely controlled aircraft (RCA), also known as remotely piloted vehicles (RPVs) and unmanned aerial vehicles (UAVs), often resorted to building their own from off-the-shelf components (Nyquist, 1997; Hardin & Jackson, 2005). Although Do-It-Yourself (DIY) kits and instructions remain popular, unmanned aerial systems (UAS), are now readily available for purchase online or in electronics, hobby and toy stores (Austin, 2010; Neitzel & Klonowski, 2011; DIY Drones, 2015). These multicomponent systems include the small aircraft, along with hardware and software supporting video/still image capture, navigation and controller starting at costs less than 50 Euros (Simplebotics, 2015). Overviews of UAS theory, practice, components and mission control are provided by Beard and MacLain (2012), Fahlstrom & Gleason (2012), Gupta et al. (2013), Colomina & Molina (2014), among others. Applications of UAS for natural resource inventory and monitoring include use in forestry, wildlife, wetlands and rangeland monitoring (Abd-Elrahman et al., 2005; Dunford et al., 2009; Watts et al., 2010; Laliberte & Rango, 2011; Laliberte et al., 2011; d'Oleire-Oltmanns et al., 2012; Getzin et al., 2012; Bird & Chabot, 2013; Madden et al., 2015).These UAS applications have used both fixed- and rotary-wing unmanned aircraft equipped with a variety of sensors, data recorders and navigation devices contributing to the excitement of accessible UAS technology in diverse disciplines related to resource assessment (Stefanik et al., 2011; Watts et al., 2012; Anderson & Gaston, 2013).

In general, fixed-wing UAS have greater ability to glide over relatively large areas over longer flight times and navigating to pre-programed waypoints. Their simple, aerodynamic design makes these systems ideal for large survey missions such as mapping expansive forest tracts, agricultural fields, coastal marshes and large, nontidal marshes and swamps on the order of square kilometers in size. Equipped with instruments such as GPS, Inertial Measurement Unit (IMU), barometer, sonar and magnetic compass, the platform's inertial navigation system (INS) calculates the position, velocity, and orientation of the UAS and provides feedback to further calibrate the GPS (Wendel et al., 2006). A barometer provides information on aircraft vertical movement (Bristeau et al., 2010), while a magnetic compass acts as a fail-safe strategy when readings from other positioning systems are not available. Sonar provides accurate estimation of height above ground needed for automatic takeoff and landing capability (Johnson & Schrage, 2004). Thus, fixed-wing UAS with an INS are well-suited to follow pre-planned flight paths when it is important for imagery to be flown along traditional fight lines providing vertical and/or oblique imagery to be captured at specific flying heights (i.e., nominal scales) with enough sidelap to ensure there are no gaps in coverage. This is especially important when the sensor is capturing frames and straight flight lines are required.

The launch of some high-end systems, such as the BRAMOR gEO (C-ASTRAL Aerospace Ltd.) that costs over 50,000 Euros is facilitated by using a launching mechanism that catapults the aircraft from a moving vehicle or from a fixed platform with a launcher and lands with a parachute (Figure 1, C-ASTRAL, 2015). During flights, local weather conditions may affect fixed wing aircraft performance with wind potentially buffeting the plane and resulting imagery being blurred, distorted by excessive tip, tilt and crab, or acquired at flying heights and along flight lines deviating from the planned mission. Landing a fixed-wing UAS can be even more difficult to perform without crashing and damaging suspended payloads such as cameras, LiDAR or other larger instruments. Because a high degree of skill is often needed for takeoff and landing of UAS, new operators may wish to practice with flight simulating software (for example, Syndrome (2015), Heli-X (2015) and AeroSIM^{RC} (2015) Radio Control Training Simulators that interface with the many controllers used by fixed- and rotary-wing UAS. Practice using the controller is especially helpful for learning take-off, flying and landing steering which is in opposite directions depending on whether the aircraft is

Figure 1: Fixed-wing BRAMOR gEO (C-ASTRAL Aerospace Ltd.) aircraft provides survey-grade data products for study areas of 10s of km^2 of resource mapping.

going away from or towards the operator. The eBEE fixed-wing UAS (SenseFly) is a popular survey-grade system used for resource monitoring at 3 cm horizontal and 5 cm vertical accuracy (Sensefly, 2015). This aircraft provides the advantages described above of fixed-wing UAS performance, but the ability for the operator to "throw it in the air" makes this UAS easier to launch and operate (Figure 2a). The current cost of the eBEE system is approximately 40,000 Euros, making it an affordable survey-grade system that may be costly for resource managers.

Rotary-wing systems, on-the-other-hand, are aircraft equipped with spinning blades or rotors ranging from one (appearing similar to a typical full-scale helicopter) to multiple rotors, typically four or more). The multi-rotor systems allow the operator to hover and maneuver the aircraft in an unstructured flight path, especially when the operator uses First Person Viewer (FPV) navigation. In this way, the operator on the ground uses a controller that includes a screen capable of displaying the view "seen" by the UAS. In other words, the operator is effectively the eyes of the aircraft and can adjust the position of the UAS accordingly to ensure the area of interest is being imaged. Capturing video in this way may not be optimal for performing traditional photogrammetric flight missions to acquire near-vertical (< 3 degrees of tilt) imagery. However, the ability to hover and rapidly change direction and altitude may be desired when the objective is to follow a dynamic target or process (e.g., following moving wildlife, objects flowing downstream or irregular coastlines). This relatively unstructured flight plan may also be used to collect bird's-eye-view imagery at low altitudes that can be used to provide ground truth video/stills of ultra-high resolution depicting features required to identify vegetation species such as canopy structure (e.g., evenness, height, color/texture and pattern), branch arrangement (opposite or alternate), leaf type (simple or compound), leaf size/shape/color, bark texture, etc. Such imagery may provide information on resource context and factors that with potential negative effects on resources, such as proximity to human influences, pollutants or exotic invasive plants or animals. Drawbacks to UAS with multi-rotor systems include their relatively high power consumption and, consequently, shorter flight times. Battery-powered quadcopters, such as the DJI Phantom Vision Plus, for example, have a maximum flight time of 15 to 20 minutes per battery pack (Figure 2b).

Multi-rotor systems are generally easier to operate because they typically launch from a stationary position on, ideally, a hard and flat surface and the UAS pilot has precise control of small movements of the aircraft. Essentially pressing "up" and "down" buttons allow the aircraft to achieve vertical takeoff and landing (VTOL) and versatility in where the UAS can be launched. Multi-rotor systems can be launched and landed on very small areas such as a narrow dock, boat or even directly from the operator's hands. The ability to hover and rotate the UAS from a stable position also allows the camera to view and record a continuous 360° view of an area, which is especially useful for

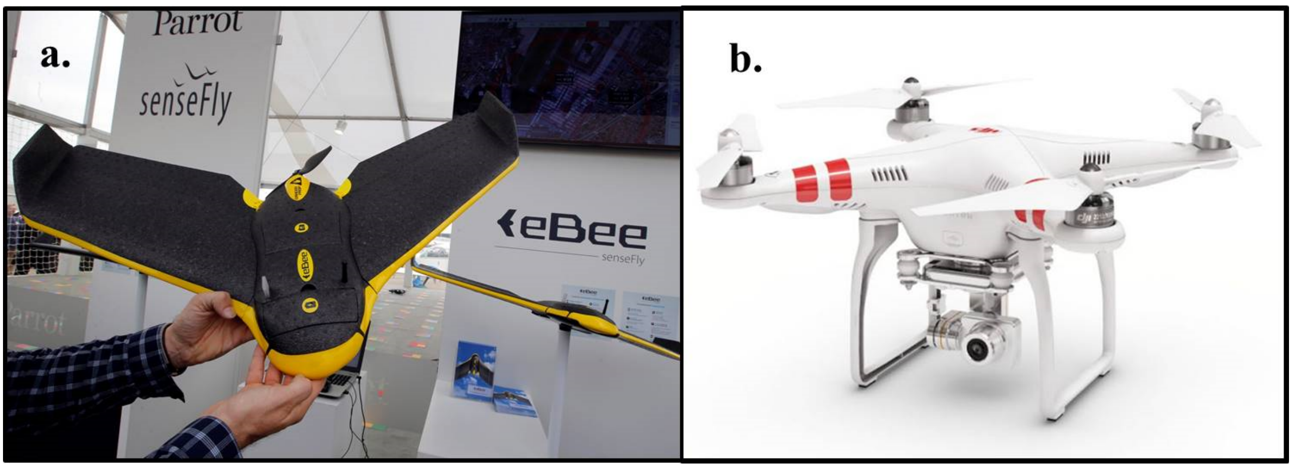

Figure 2a: Fixed-wing eBee (SenseFly) aircraft, and 2b: Rotary-wing Phantom 2 Vision Plus (DJI) quadcopter used for image acquisition and resource mapping.

reconnaissance of the condition of a natural resource to determine if the desired phenological stage has been realized (e.g., if there is adequate loss of leaves in the fall to expose the understory or bare earth) or respond to damage by natural disaster or human impact. Navigation and control of multi-rotor UAS may also benefit from an INS to support automated flight along preplanned flight lines and for the aircraft to automatically fly back to its "home" location when the battery power is low.
Both fixed-wing and multi-rotor UAS equipped with INS permit a skilled UAS pilot to fly under scenarios that conventional airborne and orbital image acquisition systems cannot. Rotary-wing systems, for example, can be flown in hard-to-reach places such as close to or under tree canopies. Using a combination of FPV with a heads-up display on a laptop, tablet or mobile phone and line of sight view from the pilot and spotter (i.e., an additional person observing the UAS flight) on the ground, images of specific locations can be achieved quickly to take advantage of ideal weather conditions or respond immediately after an event has occurred. When planning UAS missions over natural areas, however, system limitations should be considered, including the flight range which is influenced by battery life and, if remote controlled, by communication between the transmitter and the receiver. The range of remote control varies by model from hundreds of meters to several kilometers. Regulations for UAS operation may also require the pilot to maintain line-of-sight of the aircraft. When preplanned, autonomous flight systems are utilized and regulations permit, remote control range is not limited and the INS of the aircraft is used to fly to specific locations designated as waypoints, collecting data along the route and changing direction to navigate to the next location, independent of operator intervention during the flight.

3. STRUCTURE FROM MOTION AND MULTIPLE IMAGE MATCHING

Reconstructing 3D geometry of objects of interest, including the generation of point clouds, employs image processing concepts dating back to the 1950s. In traditional stereo photogrammetry, a series of overlapping, offset images, but *a priori* knowledge of scene geometry, camera parameters, camera orientation and ground control point (GCP) targets are required. We used Structure-from-Motion (SfM), which does not require ground control, reference targets, or a priori knowledge of the camera exposure locations and attitudes to resolve 3D structure from overlapping images (Dellaert et al., 2000; Westoby et al., 2012). Instead, the geometry of the camera/scene parameters is solved automatically with very little user interaction. The approach originated in the computer vision community and incorporates automatic feature-matching algorithms using multiple overlapping images (Westoby et al., 2012). SfM incorporates simultaneous, highly redundant and iterative bundle adjustment procedures to automatically extract features. Very accurate point matching between photographs can be achieved and a dense RGB-encoded point cloud extracted for resource monitoring (Mancini, 2013). SfM works best with highly overlapping images capturing the 3D structure of a scene viewed from a wide array of positions. It also works with images derived from a moving sensor, such as frames captured from video.
Although internally consistent, models derived from SfM typically lack scale and orientation provided by GCPs and 3D point clouds are generated in a relative image-space coordinate system. Although solutions based on relative coordinates are often satisfactory for many applications, data can be scaled using a known distance or ruler imaged in a scene. If more rigorous representations are required for analysis and repeatability, data must be aligned to a real-world, object-space coordinate system. A multidimensional data adjustment can be achieved by 3D similarity transform using a few GCPs measured after the model is complete. The corresponding processing workflow requires known control points and the definition of direction and dimension. In addition, control points can be inserted by integrating 3D points measured on photos into the model solution. Several software solutions exist to process a series of images and generate a point cloud dataset: cloud based (Autodesk 123D Catch), open source (Visual SfM/CMVS/ Meshlab, Insight3D), and commercial (Agisoft PhotoScan, Eos

Systems PhotoModeler, University of Stuttgart SURE) (Madden et al. 2015). Examples below demonstrate the SfM workflow for 3D point clouds, digital surface models and microterrain extraction for building, vegetation and geomorphic structure representation.

4. APPLICATION OF UAS IMAGERY WITH STRUCTURE-FROM-MOTION TO CREATE 3D MODELS OF NATURAL AND CULTURAL RESOURCES

Researchers at the Center for Geospatial Research (CGR) within the Department of Geography at the University of Georgia have used DJI Phantom 2 Vision and Phantom 2 Vision Plus quadcopters to collect imagery using both operator-controlled FPV and automated navigation to preplanned waypoints, depending on the objective of the mission. Images acquired of the Georgia State Botanical Garden, for example, demonstrate the advantage of using a multi-rotory UAS to document seasonal changes in a cultural landscape. The flexibility of the UAS allowed the operator to take advantage of optimal flying conditions (i.e., calm winds and clear skies) synchronized with the planting schedule and plant phenology of the gardens. The UAS could be unpacked and launched within 10 minutes of arrival at the gardens. Upon reaching an altitude of approximately 100 m, the operator controlled the quadcopter to hover and used FPV to turn the aircraft with the camera pointing at an oblique angle in 360 degrees to record video of the landscape. Individual frames were selected to depict aerial views of the botanical gardens all seasons (Figure 3). This simple application provided managers with a vantage point they had never had before and the imagery allows them to better plan planting and maintenance, inspect infrastructure and evaluate visitor experience. Multiple overlapping frames also were selected from the video for input to PhotoScan (AgiSoft, Inc.) for SfM processing to produce 3D point clouds and image models of the gardens for unique geovisualizations (Figure 4).

Figure 3: Bird’s-eye-view of the Georgia State Botanical Gardens acquired with a rotary-wing Phantom 2 Vision Plus (DJI) quadcopter used for image acquisition and resource mapping.

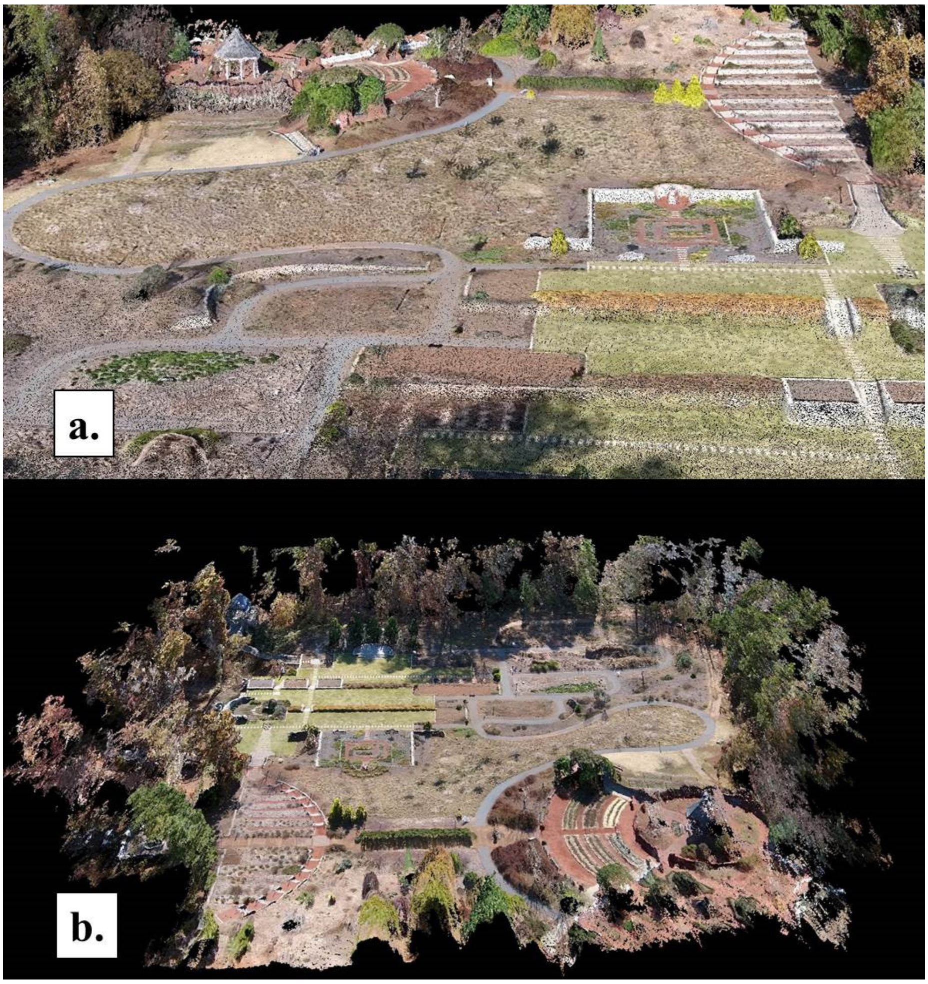

Figure 4: a) 3D point cloud of the Georgia State Botanical Gardens and b) geovisualization.

Images acquired of the Abbey of the Holy Cross in Cañon City, Colorado, demonstrate the advantage of using a multi-rotary UAS to document heritage buildings and gardens in a cultural landscape. Built in 1866 of Gothic Revival style as a monastery, the Abbey was subsequently used as a boarding school for boys and a winery, and is now listed on the U.S. National Register of Historical Places. Navigation by FPV was used to turn the Phantom 2 Vision Plus quadcopter to position a RGB camera pointing at an oblique angle and record video of the cultural landscape along roughly parallel flight lines. Although the flight mission will vary depending on the physical configuration of the ground features of interest, we typically fly video along at least three flight lines with the camera tilted at different angles to obtain multiple views of the abbey. Occlusions in the resulting products are minimized by flying low oblique video in two to four directions to ensure all surfaces are visible in multiple overlapping images (Figure 5). In practice, the UAS imagery is collected and preliminary processing is performed on a laptop in the field. The first pass performs a low or medium density point matching and low density point cloud. This logic check and data completeness verification requires about 1 hour of processing. If the resulting point cloud is not complete (e.g., there are gaps) the video can be reflown without the added expense of traveling to the site for a second time. If the preliminary pass is satisfactory, all of the data can be transferred to the CGR for further process. Second pass processing by PhotoScan includes high accuracy point matching and the creation of a high density point cloud. This step can take from 12 to over 24 hours on server platforms and with processing in batch mode. Point matching refinement is based on lens distortion and removes the barrel distortion caused by typical cameras of wide angle and short focal length.

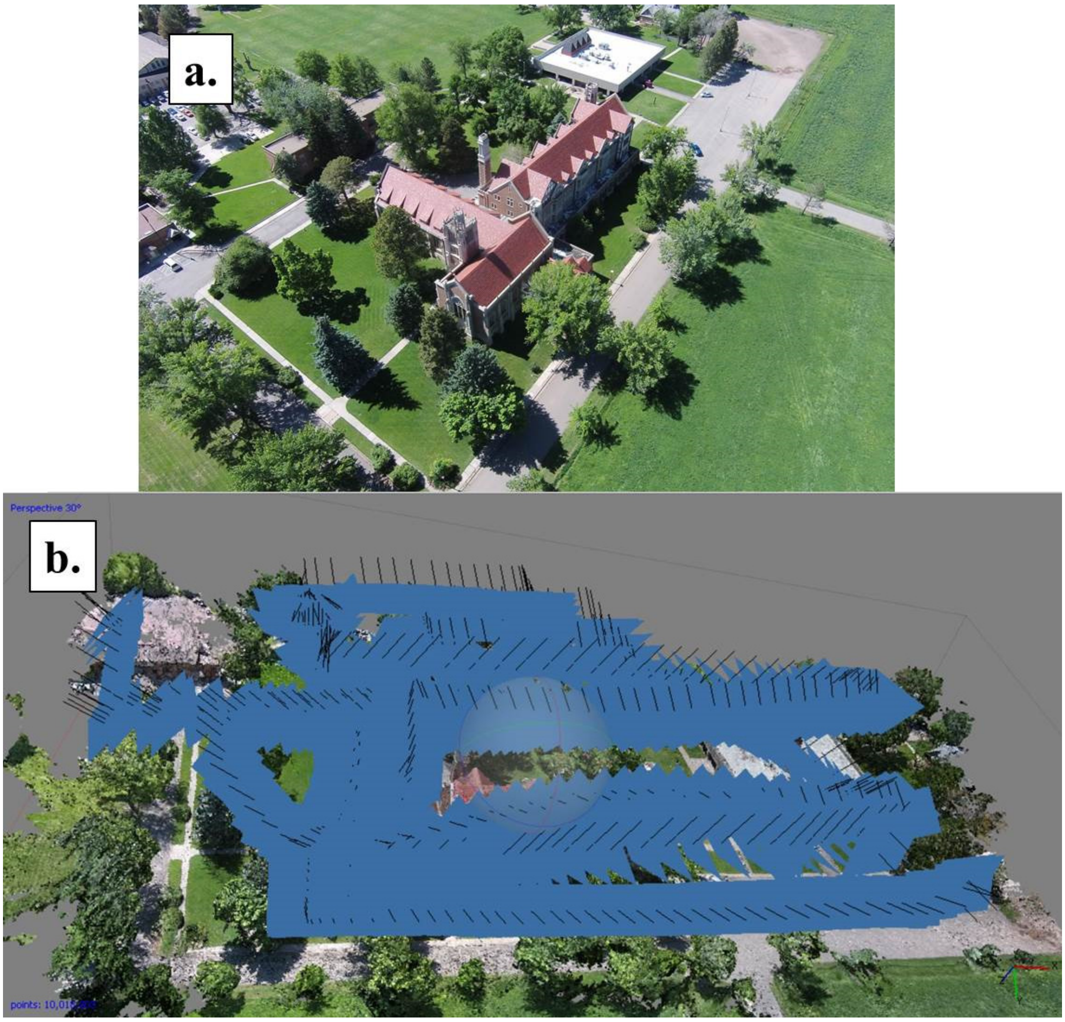

Figure 5a) Frame selected from the UAS video the Colorado Abbey, and 5b) blue lines indicate 418 frames extracted from video collected at multiple angles along multi-directional flight lines.

A total of nine ground control points (GCPs), namely well-distributed corners of sidewalks surrounding the Abbey, were identified in Google Earth and X, Y and Z coordinates extracted from high-resolution DigitalGlobe imagery in Google Earth for all GCPs (Figure 6a). To avoid having to input the locations of the 9 GCPS on each of the 418 images as required by PhotoScan to rectify the images individually, a point cloud consisting of 10.6 million points was created in PhotoScan, scaled *a priori* in LAS Tools and then transformed in Quick Terrain Modeler (QTModeler by Applied Imagery) by measuring the 9 GCPs once (Applied Imagery, 2015). The QTModeler software transformed the point cloud to an accuracy of 0.34 m in XY, 0.30 m in Z and 0.45 m in XYZ (Figure 6b). This level of 3D point cloud accuracy is suitable for most natural and cultural resource applications. The products of PhotoScan are generally of excellent quality and we understand a scaling capability will soon be added to the upcoming Beta version.

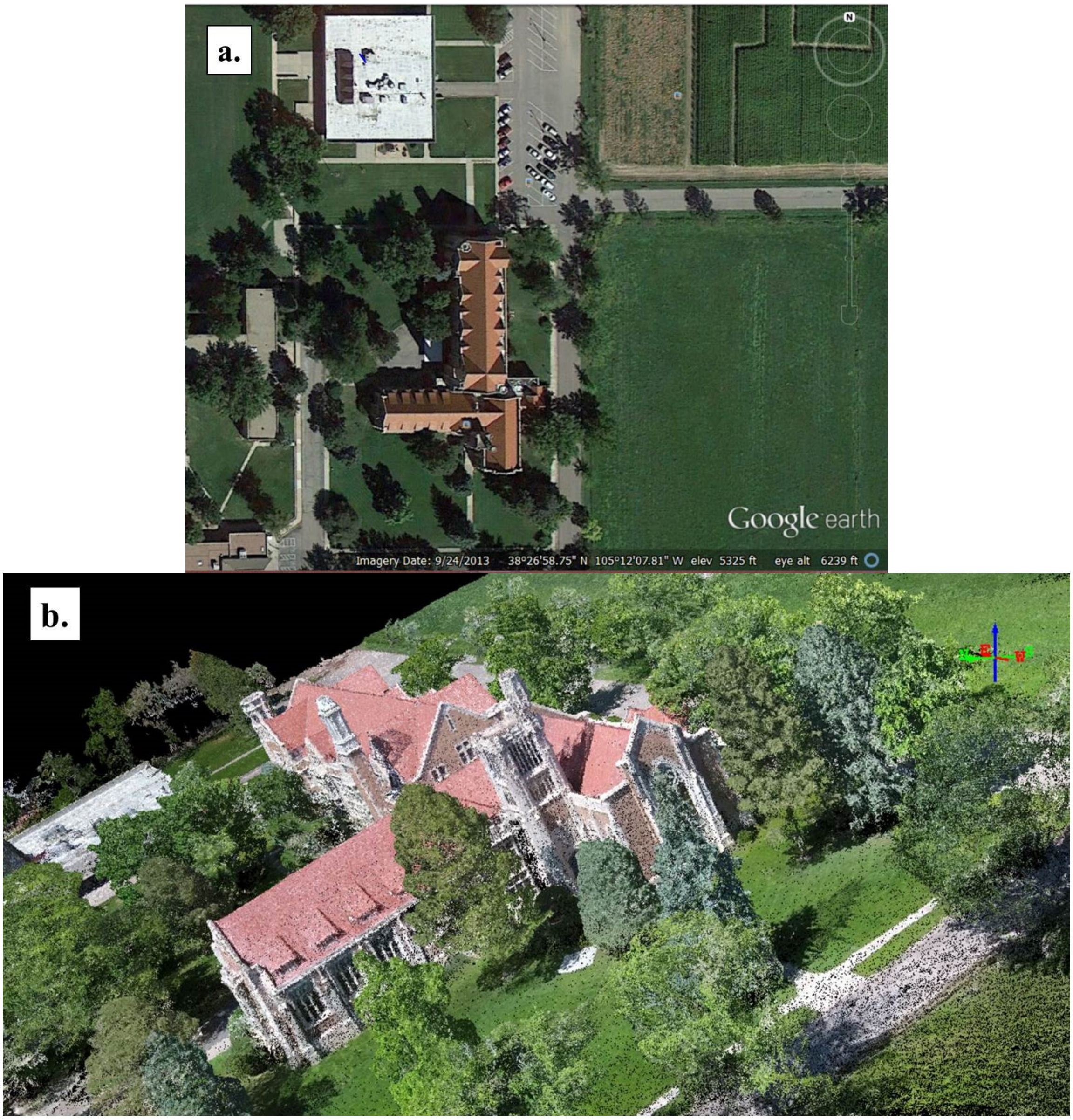

Figure 6a) Control obtained from Google Earth is sufficient for transforming 3D models to approximately +/- 0.3 to 5 m., and 6b) the resulting RGB 3D point cloud.

5. FUTURE DIRECTIONS OF UAS

Future directions in UAS include improvements in system components, beginning with the UAS sensor payload and factors that permit payload options. Although sensor requirements depend on the mission of the flight and project objectives, advances in sensors and system components can also create new opportunities for innovative UAS applications. In some cases, images collected in the visible region of the electromagnetic spectrum by nonmetric cameras are sufficient to perform simple tasks such as general delineation of natural resources or cultural landscapes, buildings and objects. In this context, point-and-shoot red–green–blue (RGB) cameras or mobile phones operating under factory default settings are sufficient payloads for fixed and rotary-wing UAS. Currently, the software and/or hardware of these cameras may be modified to acquire images in the near infrared (NIR) portion of the spectrum, allowing the monitoring of plant vigor and health. There are some multispectral sensors that offer native G, R, NIR capabilities or allow for the selection of particular wavelength ranges or bands for image acquisition (e.g., Tetracam Mini-MCA).

Advancements in the miniaturization of electronics also have produced hyperspectral sensors that can be mounted on UAS to collect data using tens to hundreds of narrow wavelength intervals. The hyperspectral bands can then be used to produce fine-scale spectral reflectance curves characterizing biophysical properties and chemical composition of vegetation, water and soil (Berni et al., 2009; Burkart et al., 2014; Duan et al., 2014). Further radiometric and geometric analysis of hyperspectral imagery acquired by UAS are required to ensure the accuracy of multidimensional data cubes and permit multi-sensor data fusion (Hruska et al., 2011; Turner et al., 2014).

Non-optical sensors, including thermal infrared and microwave, also have been used for land cover characterization and miniaturized sensors suitable for mounting on UAS can make significant contributions, especially for wetlands, forest, grasslands and agricultural mapping projects. Thermal infrared sensors have been used in the identification of spatial variability in water temperature and seeps, with implications to monitoring biotic responses to changes in temperature and variability in salinity levels (Lega & Napoli, 2010). Microwave-based systems have been used to monitor water under canopies and flood levels and to investigate soil moisture (Acevo-Herrera et al., 2010). Further, vegetation structure has been investigated by using data collected by LiDAR systems mounted on UAS (Wallace et al., 2012) with great potential for wetland studies. Significant strides in sensor development have allowed the engineering of smaller and lighter sensor systems that can be used as payload of small aircraft. Examples of these systems include the Micro-Hyperspec™ hyperspectral sensor by Headwall, the Tamarisk 640 thermal sensor by DRS Technologies, and the HDL-32E LiDAR by Velodyne.

Battery weight and maximum time a charge is held greatly limits UAS missions. In low-cost systems, rotary-wing aircraft such as the DJI Phantom 2 Vision Plus equipped with an 11.1 volt lithium-polymer battery typically holds a charge for a maximum of 25 minutes. Advances in battery performance and power management, therefore, will extend flights and greatly enhance UAS function. Future directions include the development and incorporation of solar powered battery components of UAS, as well as wireless sensor networks to simultaneously collect field data that can be related to image data (Malaver, 2015).

6. CONCLUSIONS

As the users of UAS in diverse applications and discipline related to natural and cultural resources, continue to increase, adjectives such as “revolutionize” are appropriately used to describe the impacts of UAS. Even researchers in the fields of photogrammetry, remote sensing and SIS who are intimately familiar with data provided by “views from above” find the excitement surrounding UAS refreshing. Low-cost systems of small size and simple to operate have brought an emerging technology into the hands of anyone willing to risk a UAS crash. There is no question that the toy-like nature of a quadcopter appeals to the scientist and the hobbyist, alike. The sound of the quadcopter taking flight can draw a crowd and viewing video captured by a UAS for the first time remains a memorable experience. Indeed, a UAS packed in a case and recently taken through an airport created quite a stir, not because of the concern for security, but because so many agents wanted to how it operated. Although some may argue the image data collected by the majority of UAS are not of sufficient quality to meet photogrammetric standards, we have demonstrated it is possible to follow a workflow that results in multiview imagery suitable for SfM processing and the creation of 3D point clouds of sufficient geometric accuracy for the monitoring of natural and cultural resources.

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