Ecological monitoring of arid rangelands using fixed-wing micro-UAVs (drones) in the MENA region

Dr David Gallacher, Zayed University, Dubai UAE Email: david.gallacher@zu.ac.ae
Mr Tamer Khafaga, Dubai Desert Conservation Reserve, Dubai UAE Email: tamer.khafaga@emirates.com

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Extended Abstract

Statement of the Problem

Arid rangelands throughout the Middle East / North Africa (MENA) region are currently managed without clear information of long term trends in vegetation, stocking rates, or ecological health. It is often stated that rangelands suffer from overgrazing and excess water extraction, but there is a lack of reliable historical data to support these claims. Data exists in well managed reserves such as the Dubai Desert Conservation Reserve (DDCR), but it is labor intensive and expensive to maintain a routine system of monitoring.

Recent years have seen the rapid emergence of low-altitude unmanned aerial vehicles (micro-UAVs) for civilian use. Dramatic developments in the platforms (drones) have been accompanied by the development of lightweight specialty sensors (e.g.; infra-red and multispectral cameras) and orthomosaic software. These new platform / sensor combinations present a dramatic new tool for the management of conservation zones as well as agricultural areas. Micro-UAVs have clear potential use for spatial ecology studies (Anderson and Gaston 2013) and for biodiversity assessments (Getzin, Wiegand, and Schöning 2012). They offer the potential of providing far more detailed information than previous technologies (from satellite and manned aircraft platforms) at a much lower cost (Walton et al. 2013), and with greater flexibility to gather information at specific times or frequencies. Aerial monitoring is now feasible at pixel resolutions that range from meters to millimeters, which brings imagery to a scale that is relevant to many ecological processes (Anderson and Gaston 2013).

This presentation will review how this emerging technology can be applied to better manage rangelands in the Middle East, and will draw on preliminary results from the author.

Significance and relevance of the work

The long-term aims of this project are to (1) reduce the cost of rangeland monitoring for organizations that are already doing this work manually, and (2) to provide a tool that non-specialists in the region can use, thus encouraging the gathering of much better information for land management decisions.

Applications of the technology for the Dubai Desert Conservation Reserve (DDCR) have been identified as follows:

- Habitat classification
- Animal population monitoring via aggregated sites (water / feeding sites) dispersed areas (open rangeland) and indirect methods (e.g.; lizard holes, carcasses)

- Animal condition monitoring. Mammalian body width is indicative of good health and/or pregnancy
- Plant monitoring, including estimations of biodiversity and biomass.
- Anthropogenic monitoring; evaluation of whether safari companies are compliant with regulations for operation within the DDCR.

Tools that are developed for the DDCR will be directly applicable to rangelands throughout the MENA region. The region is highly suited to aerial monitoring, since success of classifying individual plants to species level is inversely proportional to biodiversity within a size class (Féret and Asner 2012), and is improved when individuals are discretely separated by bare ground. Larger herbivores are rarely obstructed by trees. Privacy and safety regulations are of less concern in rangelands due to their remoteness and low human population densities (Laliberte 2012).

Description of research method

Preliminary research has been conducted using a DJI s1000 octocopter equipped with a 24MP RGB and a 3.2 MP multispectral camera, and a SenseFly eBee fixed-wing drone equipped with 12 MP RGB and multispectral cameras. Preliminary trials were conducted to identify the maximum ground sampling distance (related to drone altitude and camera resolution) required to be able to identify individual species with reasonable accuracy. Images were collected at 10 m intervals from 10 to 300m above animal and plant species. From this, trials will be conducted at selected altitudes, and species observation from resulting images will be checked for accuracy against ground-based data.

Results

At time of writing, observational data of known species taken from different altitudes has been collected, illustrating the viability of the technology. By the time of the conference presentation, results should include at least one structured study evaluating the reliability of the technology at a specific ground sampling distance.

Conclusions

Micro-UAVs have an enormous potential for improving rangeland management in the MENA region. However, much work still needs to be done to streamline processes and evaluate the enormous amount of data produced.

Introduction

Aerial photography of land surfaces is a rapidly developing field due to recent advances in unmanned aerial vehicles (UAVs). Civilian aerial platforms were until recently limited to orbital satellite and manned aerial vehicles (MAVs), although military photogrammetry has a long history involving kites, hot-air balloons, and many types of UAVs and remotely piloted aircraft (Watts, Amrosia, and Hinkley 2012). Many new low-altitude platforms are now available, causing sensor manufacturers to also produce new cameras specifically for mounting on UAVs. Robotic monitoring is now well established for large scale environmental issues and disasters, such as volcanos, tsunamis, and oil spills (Dunbabin and Marques 2012). UAV monitoring has clear potential use for spatial ecology studies (Anderson and Gaston 2013) and for biodiversity assessments (Getzin, Wiegand, and Schöning 2012).

Initial surveying and subsequent monitoring is one of the key tasks of a rangeland manager (Holechek, Pieper, and Herbel 2010). Effective conservation requires knowing what changes are taking place in the ecosystem, and whether observed changes require intervention. However, ecological monitoring is highly labor intensive of trained personnel, and thus expensive. Arid rangelands throughout the Middle East / North Africa (MENA) region are currently managed without clear information of long term trends in vegetation, stocking rates, or ecological health. It is often stated that these rangelands suffer from overgrazing and excess water extraction, but there is a lack of reliable historical data to support these claims. Adoption of UAV technology has the potential to reduce the cost of existing monitoring, as well as to encourage a much wider adoption of monitoring practices throughout the MENA region. Privacy and safety regulations for UAVs are less of a concern in rangelands due to their remoteness and low human population densities (Laliberte 2012).

Achieving this goal will require a meeting of hardware (platforms, sensors), software (automated image recognition) and interpretation (arranging data into meaningful information). The aim of this review is to identify the potential of UAVs for ecological monitoring in arid rangelands, and the research that is needed to realize the potential.

An overview of hardware (platforms and sensors) is provided, primarily to show that new platform / sensor configurations are still being developed. It would be premature to evaluate the cost-effectiveness of current configurations since price, usability, and applications are all in a state of flux. Two competing directions for UAV development that currently seem viable include:

- Semi-permanent platforms operating at a medium altitude (e.g.; 1-10 km), powered by solar and carrying several sensors.
- Swarms of low-altitude UAVs (e.g.; 100 m), each carrying a single sensor for a short (<1 hour) period.

Currently, however, the typical configuration is a single low-altitude battery powered UAV; either a fixed-wing or multirotor. Hence, research is needed to assist rangeland managers to get the most information from this hardware by applying appropriate sampling methods.

Platform classes

There is a confusing range of UAV classes currently available, necessitating a high learning curve for anyone entering this field (Watts, Amrosia, and Hinkley 2012). Platforms can be broadly categorized into four classes based on altitude, or by their mechanism of lift (Table 1).

The US military has its own UAV classification specific to its own needs and regulations (Watts, Amrosia, and Hinkley 2012). Early civilian photogrammetry developed from MAVs, typically operating at the lower end of their altitudinal range of 1 – 15 km. Satellites, which operate above 160 km altitude, advanced the field by providing large amounts of low-resolution data. UAVs now provide a new platform category in the 0-25 km altitude range. While the military have developed UAVs that operate throughout this range (Watts, Amrosia, and Hinkley 2012), airspace restrictions have resulted in the civilian market being divided into classes below and above commercial airspace. Micro-UAVs operating in the lower category are often capable of operating up to 1000 m, but are legally restricted in many jurisdictions to below 400 feet (122 m). Likewise, stratospheric UAVs are being planned for operation at around 20 km. Technological developments are occurring in all classes, but the greatest innovation is currently occurring in the near-ground and stratospheric altitude classes. Each of the platform categories fills a niche. Higher altitudes enable data to be gathered over a wider area, but with lower quality of data (Table 2).

A loose definition of a UAV is any aerial vehicle that operates without a human on board, but this would include paper planes and remote controlled aircraft. A more practical definition is a vehicle capable of autonomous cruising from one GPS coordinate to another. Many UAVs are also capable of landing at the launch point without human assistance, which is a legal requirement of multi-rotor UAVs in Europe and North America.

Stratospheric

Several companies have entered the race to provide stratospheric platforms (Table 1), with purported aims to extend Internet access across the developing world, as well as to better serve communication hotspots over cities. Solar UAVs are light and maneuverable, while the Stratobus airship is being designed as a platform capable of a 200 kg payload. Stratospheric projects have several advantages over satellites:

- Lower price
- Retrievable, hence can be maintained or upgraded, and will not become space junk
- Lower altitude, hence lower GSD (ground sampling distances) s and less atmospheric interference
- Short response time, to quickly respond to service gaps or peaks in data requirements

Such platforms are likely to remain outside the budget of rangeland managers in the near future, but will likely become available for rental, or for use across multiple government departments.

Commercial airspace

UAVs that operate within commercial airspace are usually launched by catapult and require the same clearance procedures as MAVs. Their larger size enables them to carry multiple, larger sensors. However, their product is undifferentiated from that of MAVs, and consequently most aerial imagery produced from this level is produced from the latter. In fact, a product was recently launched that attaches to the underside of a MAV wing and streamlines processing.[1]

Near-ground

There are currently two broad categories of near-ground UAVs; the multi-rotor micro UAV, capable of short flights at altitudes as low as 1 meter, and the fixed wing micro UAV, which operates from 80 m to the legal upper limit and is usually launched by hand. A third lighter-than-air (LTA) category is in development (Table 1). Micro UAVs are not currently permitted to be used for commercial purposes under US regulations, but LTA platforms bypass this restriction.

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[1] For details of the XCAM, see the WaldoAir Corporation website (waldoair.com).

Multi-rotor UAVs are more stable, thus improving the quality of images (Anderson and Gaston 2013) and have no minimum speed, but fixed-wing UAVs have longer flight times. Legally, most countries treat micro-UAVs as hobbyist aircraft, setting a maximum altitude limit and other requirements that may include flying only over private property, and remaining in line-of-sight of the operator. The cheapest multi-rotor models are available from retail outlets and are therefore highly accessible to anyone wanting to stream video from the sky. Concerns about privacy are warranted, yet easily overstated. Most people already have a high definition camera built into their phone, and aerial platforms exist that are not UAVs (kites, balloons, hobby craft).

By operating at the lowest altitude, micro-UAVs produce imagery with the least interference and the highest resolution GSD of all classes. This enables aerial monitoring at ecological scales that were previously impossible.

Sensors

Most micro-UAVs are limited by weight to carrying a single sensor, though this may change in the future, as many manufacturers are now designing specifically for the UAV market. All sensors except LiDAR measure a subset of the electro-magnetic spectrum. LiDAR sensors project a lazer beam and record its reflection, and are used for sensing three-dimensional structures. They have been widely used for determining topography and forest canopy heights. LiDAR sensors are now available at weights suitable for UAVs but their higher price remains a barrier.

Visible light / RGB

Sensors for visible light (380 – 750 nm) are widely available and have been miniaturized for the retail sector. These sensors record the intensity of the three wavelengths (red, green and blue) that human eyes are able to see. Micro-UAVs typically carry an off-the-shelf 10 to 24 megapixel mirrorless camera.

Multispectral and infra-red

Multispectral cameras record a small pre-set number of broad bands. In biology they are mainly used to measure photosynthetic activity by calculating the Normalized Difference Vegetation Index (NDVI), a contrast of red (670-680 nm) and near infra-red (750 – 850 nm) wavelengths (Cho et al. 2008). Heat sensors, or night vision cameras, operate at much longer wavelengths (8 – 15 µm) and can detect subtle differences in temperature, such as the presence of mammals or water flows. Miniature versions of both multispectral and infra-red sensors have recently become available for use in micro-UAVs. A description of their calibration and data processing workflow is described (Berni et al. 2009).

Hyperspectral

Hyperspectral sensors record a larger number of narrow bands from the visible through to the mid-infrared range of the electromagnetic spectrum (Vane and Goetz 1993). The most powerful record all radiation within a defined range (typically 0.4 – 2.5, or 0.4 – 0.9 µm) separated into 100 – 300 bands (Shippert 2003). These models are expensive, heavy, and their output is demanding of storage and computation. They are typically flown at high altitudes (20 km) over large areas, requiring further computation to correct for atmospheric, topographic, and time of day effects. High-end sensors are being produced with ever greater capacity (Ustin et al. 2004), but there is also a demand for lighter models with reduced functionality that can be marketed for precise agricultural purposes. Some current models can be mounted on UAVs capable of carrying payloads greater than 1 kg[2], but it must be noted that these models blur the distinction between hyperspectral and multispectral.

Hyperspectral information is highly dimensional since each radiation band is recorded for each pixel, creating an image cube[3]. It has been widely used for broad scale monitoring of weeds (He et al. 2011), and offers promise for monitoring drought, wildfire susceptibility, carbon storage, soil conservation, and vegetation change (Ustin et al. 2004). Although it is possible that specific bands might identify the presence of a molecule produced by a disease or condition, disease (Reynolds et al. 2011) and water stress (Kim et al. 2010; Weckler, Maness, and Stone 2004) is currently observed indirectly through a reduction in chlorophyll. Uptake of the technology has been limited by a typical data cost of at least US$60 000 (Lass et al. 2005), and analysis that requires expert knowledge and technical support (He et al. 2011). Several spectral libraries are publicly available to assist in the interpretation of data, with a focus on geological and anthropocentric features[4].

Within a species, hyperspectral images may produce a reliable estimate of total chlorophyll, the ratio of chlorophyll A to B, and carotenoids. Solar energy captured through these molecules is passed to chlorophyll A for conversion to chemical energy, hence Chlorophyll A may be considered the bottleneck molecule (Blackburn 2007). A review of 73 vegetation indexes to predict chlorophyll content concluded that index performance varied with species, but that the most reliable were red-edge[5] based, such as the red-edge position linear extrapolation (Cho and Skidmore 2006) and the Modified Red-Edge Inflection Point (Miller, Hare, and Wu 1990).

Sensing in 3D

Coarse three-dimensional structure, including plant canopy height, can be sensed either by LiDAR or by structure from motion (SfM) image processing. SfM requires the same object to be detected across multiple images taken at different angles. These images are then orthorectified into a composite, enabling the calculation of altitude points. SfM can be processed from images of any spectral range, though is most commonly applied to the visible spectrum. Field studies of tree canopies have indicated a reliability similar to LiDAR, at lower cost (Dandois and Ellis 2013).

Fine three-dimensional images can be generated from multiple, overlapping photographs taken with any sensor, enabling the production of topographic maps. Creating a three dimensional image of a plant or animal is far more difficult than for anthropogenic structures due to the more complex surface geometry. Use of hyperspectral data has produced some promising results for seedlings in laboratory conditions (Liang et al. 2013). Algorithms for 3D

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[2] For one company's examples of UAV mounted hyperspectral sensors, see PrecisionHawk (PrecisionHawk.com)

[3] An image cube is a conceptualization of data gathered, in which a two-dimensional image of a land surface contains several hundred data points for each pixel, rather than the three (red/green/blue) that are needed to represent visible light. Hence, the third dimension is the quantity of radiation received within each measured band at that pixel. For an example, see aviris.jpl.nasa.gov/data/image_cube.html

[4] ASTER Spectral Library, hosted by NASA, (speclib.jpl.nasa.gov); United States Geological Survey Spectral Library (speclab.cr.usgs.gov/spectral.lib04/spectral-lib04.html)

[5] Red-edge refers to the dramatic change in absorption between red and infra-red spectra. Red is absorbed by chlorophylls and other molecules during photosynthesis, while infra-red is reflected by cellular structures. The points at which this change begins and ends adds more information than the NDVI, which just measures the (normalized) difference between absorptive red and reflective infra-red.

construction are almost the same as for assembling an orthorectified terrain model, and so both services are typically offered by the same commercial software[6]. Care should be taken to not confuse software for 3D computerized images, and software to produce images or video for 3D monitors. The latter are stereoscopic, rather than true 3D images.

Video

Multirotor UAVs can record video, and also transmit a video signal 'live' to a ground station. Live video transmission enables multirotor micro-UAVs to be piloted manually, and thus respond to a moving animal or navigate a complex terrain (e.g.; surveying a cliff face or moving under a canopy).

Recorded video might be superior for estimating populations of some animals, since movement may make them more visible. Commercial and open-source software is available to detect and track a moving object within a video stream (Buchanan and Fitzgibbon 2006). This may make it possible to survey hard-to-find species by using the UAV to both 'flush' (frighten the animal from its cover) and record the species.

Applications for arid rangeland ecological monitoring

Aerial monitoring is now feasible for GSDs that range from meters to millimeters, which brings imagery to a scale that is relevant to many ecological processes (Anderson and Gaston 2013). Monitoring at the larger scale (1000 km^2 and more) will remain the domain of high altitude platforms for the foreseeable future (Thorp, French, and Rango 2013). Micro-UAVs operate at a scale of <10 km^2, thus enabling complete coverage of most farms, but most rangelands and conservation reserves in the MENA region are considerably larger, sometimes by several orders of magnitude[7]. Hence a UAV monitoring program will involve partial sampling, though at lower cost than it would take to pay a ground based observer to sample the same area.

Ecological monitoring by UAV could address six general areas:

- Plant biomass
- Plant biodiversity
- Animal population
- Animal fitness
- Anthropogenic influences
- Habitat zonation

The hyper-arid biome prevalent across the Arabian Peninsula is suited to monitoring by UAV for several reasons:

- Vegetation is dominated by woody shrubs with a low overlap of root zone, and an even lower overlap of canopy. Therefore it is relatively easy to identify individual plants.
- Ecological components are sparsely distributed across vast areas, making other forms of monitoring expensive (ground, satellite)

[6] Examples include Pix4D (pix4d.com) and Agisoft Photoscan (www.agisoft.ru). Autodesk 123D (www.123dapp.com/catch) is a free service for making 3D digital models from photographs, with links to a paid 3D printing service.

[7] For a map of conservation reserves recognized by the United Nations Environment Program, see the World Database on Protected Areas (www.protectedplanet.net)

- Field work can largely be performed by a non-specialist, allowing the trained ecologist to better allocate their time, and to perform data analysis offsite if desired. Traditional ground-based ecological surveys are normally performed by a postgraduate degree-holder.

It is now technically feasible for a nature reserve to contain a geographic database of each fixed item, including perennial plants and fixed animal artifacts (e.g.; burrows, tracks, nests). Repeated measures of each item would enable an assessment of change over time, both of biomass and of composition. Such a database would reduce the time required for on-ground verification, since a perennial plant need only be identified to species level once in its lifetime.

Plant biomass

Assessment of available forage within a habitat is inaccurate by satellite and expensive by ground operations (Walton et al. 2013), yet is a necessary aspect of livestock management. Options for assessment include the measurement of photosynthesis using a multispectral camera, green surface area using a visible camera, and plant volume using LiDAR. Currently the most promising of these is the multispectral camera to measure the NDVI (see above). However, no research has yet been done to correlate NDVI with measurements from destructive plant biomass sampling. This ground-truthing must be done for each of the main plant species within a reserve before the technique can be applied.

Plant biodiversity

Desert ecosystems are highly suited to biodiversity study through aerial monitoring. Success of classifying individual plants to species level is inversely proportional to biodiversity within a size class (Féret and Asner 2012), and is improved when individuals are discretely separated by bare ground.

Several options are available for remote classification to species level (Table 3) but none of these options currently approaches the accuracy of a ground survey performed by a trained botanist. The advantage of using UAVs is to be able to survey larger areas more quickly, and therefore to produce a moderately accurate biodiversity assessment at a much lower cost, and with a reduced reliance on highly trained field specialists. It should be possible to identify all trees and larger shrubs in the Arabian Peninsula to species level with close to 100% accuracy, but smaller species will be considerably more difficult.

Research and development is needed to automate the processing of drone images into a georeferenced database of perennial plants. Research is also needed to train pattern analysis software in plant recognition, and to validate their accuracy.

Animal population

Performing a complete population count of an animal species is rarely an option in arid rangelands due to the vast areas, and to animal movement. Nevertheless there are several possible approaches to estimating a population size.

- Perform a complete count of aggregation points, such as feed or water points, or high traffic areas.
- Conduct a transect survey (e.g.; 30 x 0.15 km2) over dispersed areas regularly, and determine a moving average.
- Perform a complete count of fixed artifacts related to the species (e.g.; burrow entrances of the lizard *Uromastyx aegypticus*).
- Use video from a low-flying UAV to flush animals from hiding.

Statistical techniques to estimate actual population from the above methods are well established. There is commercial and open-source software available that could be used to automate searching for and counting of individuals from the images. Research is needed into the accuracy of detection both by human eye, and by automated analysis, for each species of interest.

Animal fitness

Animal size can be determined from photographs or video at known GSDs. Body width of many species is correlated to pregnancy and body condition. The traditional method of scoring ungulates is to observe hip bone prominence, which can be photographed at ground level as an animal runs away. The same scoring method could be performed using UAV video footage, enabling more animals to be scored per day and with less disturbance to the animals.

No research is needed to verify the use of UAV video footage for scoring ungulates, since the method is the same as ground based methods already in use. To determine herd fitness from higher altitudes, however, requires research to correlate body width with fitness and pregnancy.

Anthropogenic influences

There are many applications that fall within this category, each requiring their own research and development to perfect the methods used. Three example techniques are given here:

- Line monitoring.
  Fence-lines must be routinely checked for breaks and dune burial. Roads within nature reserves must be checked to ensure users are keeping their vehicles to the assigned tracks. In both cases, a UAV could be programmed to routinely collect video footage along a set route, which could then be viewed at high speed.
- Disturbance transects.
  Assessing the amount of litter or damage from recreational driving can both be done through sample transects. Periodic evaluation would enable the impact of new management strategies to be tested.
- Heritage preservation.
  Archaeological sites can be digitally preserved in a three-dimensional orthorectified file, for future reference and to aid maintenance.

Habitat zonation

Traditionally, habitats have been defined only on the macro-scale that is available from satellite data, or less often from MAV generated data. By using UAVs it becomes viable to map habitats on a smaller scale, as well as develop localized contour maps and three-dimensional landscape images. Such work requires commercial software and specialized computers in addition to the airborne hardware. However the techniques are well established and routinely applied at the macro-scale.

Conclusion

UAVs offer much promise for ecological monitoring in arid rangelands. Many of the potential uses still require research and development to validate techniques and to improve their automation. Nevertheless there are some applications that can be applied immediately using off-the-shelf hardware and software. There is a very high learning curve in both the data collection, and the analysis and interpretation of results.

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Table 1. Airborne platforms, classified by altitude and lift mechanism

Altitude		Lift mechanism			
Category	Km	**Orbital**	**Fixed wing**	**Rotor**	**Lighter-than-air (LTA)**
Orbital	160+	Artificial satellites	-	-	-
Stratosphere	~20	-	Solar UAVs[1]	-	Balloon, airship[2]
Commercial airspace	2-15	-	Aircraft (MAVs and UAVs)	Helicopters	-
Near-ground	<1	-	Fixed wing micro UAVs	Multirotor micro UAVs	LTA Crop Monitor[3]

[1]: Current projects include internet.org, launched by Facebook and others in August 2013 (see internet.org), and Solara, launched April 2014 when Google purchased Titan Aerospace and replaced their stratospheric balloon project, Project Loon.
[2]: A current airship project by Thales Alenia Space was launched March 2014
[3]: A partnership between Aeros (aeroscraft.com) and Tetracam (www.tetracam.com) to develop an LTA platform for crop monitoring was announced April 2014.

Table 2. Increasing the altitude of a platform reduces data-collection cost per area, but impacts data collection in several ways.

Effect of increasing altitude	Description
+ Ground sampling distance (GSD)	GSD is the ground distance between the centers of two pixels. Satellite data typically has a resolution measured in meters, while micro-UAV data is typically measured in centimeters.
+ Area surveyed	Area is the product of flight distance traveled, pixel width of sensor, and GSD.
+ Atmospheric interference	Visible light images lose information disproportionately from the red end of the spectrum, and may be completely blocked by clouds. Specific hyperspectral bands are absorbed by atmospheric molecules, reducing interpretation.
- Topographic accuracy	Ground altitude estimates from satellite data is generally poor, but from a fixed-wing micro-UAV is often accurate to within 5 cm.
+ Initial cost of equipment	Generally, price increases with altitude
- Take-off / landing flexibility	Micro-UAVs can be launched anywhere, whereas MAVs and larger UAVs require a landing strip (Bryson et al. 2014).
- Data collection timing flexibility	Ability to select time of day and frequency to suit is a large advantage of micro-UAVs. MAVs are technically just as flexible but their higher cost per flight is a practical limitation, while satellite data often misses important time-windows (Berni et al. 2009).

Table 3. Techniques for classifying individual organisms to species level

Technique	Description
RGB color	Some species have a unique color within the visible range (e.g.; *Oryx leucoryx*), but even hyperspectral analysis is insufficient to identify individual species in most situations. Botanical reflectance may vary with the angle of the leaf (affected by wilting and time of day) and by phenology (e.g.; flowering).
RGB color variation	Might separate a sparse plant canopy from a dense one, or two similar animal species.
Multispectral indexes	Positive results in the literature tend to focus on large mono-specific vegetation patches and consistent conditions (e.g.; season), and results are inconsistent across scales (Ustin and Santos 2010). Differentiation may work better at the canopy level rather than the leaf level (Cho et al. 2008).
Hyperspectral indexes	Hyperspectal indexes can be derived directly from specific bands, or from ratios between them. The large amount of data available is probably sufficient to separate a small number of species (Sun et al. 2008)
2-dimensional size / shape	Commercial object-recognition software is available to detect shapes.
Height	(Zarco-Tejada et al. 2014).
3-dimensional shape	(Hung, Bryson, and Sukkarieh 2012). This measure is intuitively useful, but is computationally expensive and not necessarily accurate. Plant shape can be dramatically altered by grazing pressure and herbivore species mix. Accurate detection of shape is also affected by movement, reducing its value for animals, and vegetation in wind.
Shadow	Some tree species and animals have a distinct vertical structure, which is evident in their shadow (Hung, Bryson, and Sukkarieh 2012). This measure may be particularly useful for ground dwelling large birds such as the Houbara bustard or the Eagle Owl.
Topography / habitat	It is preferable to define a habitat by the species present, rather than the other way around. Nevertheless this measure could be used to influence a computerized prediction.
Nebkhas	Phytogenic mound (nebkhas) presence and structure
Distribution	A tree near the periphery of a cluster of *Prosopis cineraria* is more likely to be another *P. cineraria*, and a small brown animal near a herd of *Oryx leucoryx* is likely to be a juvenile of the species. Other species show dispersion rather than aggregation, which is equally predictive. Distribution may be used to improve animal count data by predicting the presence of hidden individuals (Martin et al. 2012).