ON THE USE OF DRONE TECHNOLOGY TO MONITOR TAMARAW POPULATONS AND ITS HABITAT IN MINDORO

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This document aims at briefly presenting the drone technology as of today's development and use in ecology, the different options and possible use for monitoring tamaraw population in Mindoro, or other aspects of its conservation. It is addressed to concerned organizations, stakeholders or authorities involved in the conservation of the species. The text intends to guide decision makers on the relevance of this technology prior to engage money and manpower on this technology in the field.

Introduction

Drones have been used for a long time in different fields of science such as geology and geography. It is nowadays more and more used for ecological studies and is considered as a very appealing and promising tool for animal population monitoring. After 10-15 years of experience, reports and online materials allow us to evaluate the pertinence of this technology in the context of the tamaraw and to highlight the many points to be taken into consideration prior to engage into it.

I. Introduction to the drone technology

A. Different types of drones and associated cameras

The **Unmanned Aerial System** (UAS) is commonly a called drone by lay people, even though the two a somewhat different technically speaking. UAS can be divided into three main components, (*i*) the **Unmanned Aerial Vehicle** (UAV), which is sometimes the so-called drone; (*ii*) the **ground-based controller system**; and (*iii*) the **communication, command and control system**. When used to monitor wildlife, we usually fit the UAV with a **sensor**, most often a standard or thermal camera. Each of these components can vary depending on the study needs and goals.

<u>Unmanned Aerial Vehicle - UAV</u>

The UAV has a broad range of models depending on their applications, and vary markedly in size, weight, airframe type, power sources, etc. Currently, two main airframe types are available to the public: (1) fixed wings and (2) rotor-based vehicles.

1) **Fixed wings** usually are larger and heavier models. They have a bigger payload, usually reaching up to 50 kg. They have different power sources, ranging from electric batteries to fuel or even solar panels. The most important advantages of fixed winged UAV are the large

survey area they can cover, their relatively long autonomy – usually < 2 hours though ([1]) – and the higher altitude they can reach compared to rotor-based vehicles. On the other hand, they usually need a launching ramp (even though some models can be launched by hand) and, importantly enough, an open and flat area for landing.

Most of the studies that used these airframe types prefer small sized UAV (300-500 mm) over large areas and at high altitudes, as could be seen in Table.1 (over 100-meter height and 35.2 km2 area, but generally not more than 2 km2) [2,3, 4, 5].

2) **The rotor-based vehicles** are the predominant models used for environmental monitoring. They are usually smaller and more economic than fixed-wing UAV. They do not need open areas to take off and land, and can maintain a stationary position in flight to take photos in several directions. They are usually powered by electric batteries. These batteries can't be heavy due to the lower payload allowed and, consequently, their lifetime is substantially shorter than in the fixed wings UAV, typically less than 30 mins (Wang et al., 2019). Rotor-based UAV hence travel shorter distance, and cover areas of usually less than 1 km2 (Table 1) than their wing-based counterpart. In addition, they usually fly at lower altitude, allowing them to take more detailed data with the same sensor. The number of rotor ranges between one and eight rotors, which affects its size and payload.

Group	Species or items detected	UAS Model	Sensor	Data type	Surveyed area (km^2)	Flight height (m)
Terrestrial mammals	Roe deer (*Capreolus pygagrgus)*	Falcon-8 (fixed-wing, electric)	FLIR Tau640 thermal imaging camera	Thermal image	0.71	30-50
	Elephants (*Loxodonta Africana)*	Gatewing 100 (fixed-wings, electric) Custom-made 750 mm, carbon folding	Ricoh GR3 still camera	RGB image	13.79	100-600
	Cow (*Bos taurus*)	Y6-Multirotor (Hexacopter, electric)	FLIR Tau 2 LWIR thermal imaging camera	Thermal image	<1.0 *	80-120
	Koalas (*Phascolarctos cinerus)*	S-800 evo (hexacopter, electric)	Mobius RGB camera + FLIR Tau2-640 Thermal imaging camera	RGB image + thermal video	0.01 *	20-60
	Red deer (*Cervus elaphus*), roe deer (*Capreolus capreolus*) and wild boar (*Sus scrofa*)	Skywalker X-8 (fixed-wings, electric)	IRMOD v640 thermal imaging camera	Video	~1.0 *	149-150
Aquatic and amphibius animals	Dugongs (*Dugong dugon*)	Scan-Eagle (fixed-wing, fuel)	Nikon D90 SLR camera + fixed video camera	RGB image + RGB video	1.3	152-304
	American alligators (*Alligator mississippiensis*) and Florida manatees (*Trichechus manatus*)	1.5-m wingspan MLB Foldbat (fixed-wing, fuel)	Canon Elura 2	RGB video	1.3	100-150
	Leopard seals (*Hydrurga leptonyx*)	APH-22 (hexacopter, electric)	Olympus E-P1	RGB image	<1.0 *	45
	Humpback whales (*Megaptera novaeangliae*)	ScanEagle (fixed-wings, fuel)	Nikon D90 12 megapixels digital SLR camera	RGB image	35.2	732
	Blacktip reef shark (*Carcharhinus melanopterus*) and pink whiprays (*Himantura fai*)	DJI-Phantom 2 (quadracopter, electric)	GoPro Hero 3	RGB video	0.0288	12
	Gray seals (*Halichoerus Grypus*)	SenseFly eBee (fixed wings, electric)	Canon S110 + FLIR Tau 2-640 thermal imaging camera	RGB image + thermal image	0.16*	250

Birds	White ibises (*Eudocimus albus*)	1.5-m wingspan MLB Foldbat (fixed-wing, fuel)	Canon Elura 2	RGB video	1.3	100-150
	Black headed gulls (*Chroicocephalus ridibundus*)	Multiplex Twin Star II model (fixed-wings, electric)	Panasonic Lumix FT-1	RGB image	0.0558	30-40
	Frigatebird (*Fregata ariel*), Crested tern (*Thalasseus bergii*) and royal penguins (*Eudyptes Schlegeli*)	3D Robotics (octocopter, electric)	Canon EOS M	RGB image	<1.0 *	75
	Gentoo pinguins (*Pygoscelis papua*) and chinstrap penguin (*Pygoscelis antartica*)	APH-22 (hexacopter, electric)	Olympus E-P1	RGB image	<1.0 *	45
	Cavasbacks (*Aythya valisineria*), Western/Clark's grebes (*Aechmorphous occidentalis/clarkii*) and double-crested cormorants (*Phalacrocorax auritus*)	Honeywell RQ-16 T-Hawk (Hexacopter, fuel) and AeroVironment RQ-11A (fixed-wigs, electric)	Canon PowerShot SX-230, SX-260, GoPro Hero3 and Canon PowerShot S100	RGB image	<1.0 *	45-76
Insects	Butterflies (*Libythea celtis)*	Phantom 2 Vision+ (quadracopter, electric)	GoPro Hero 3	RGB image	0.000016	4
	Bicknell's and Swainson's thrushes (*C. ustulatus*)	Sky Hero Spider X8 (octocopter, electric)	Radio transmitter (Avian NanoTag model NTQB-4-2, Lotek Wireless Inc., Newmarket, Ont., Canada)	Radio-tracking data	<1.0 *	50
	Noisy miner (*Manorina melancephala*)	Unmentioned (hexacopter, electric)	Radio transmitter (Avian NanoTag model NTQB-4-2, Lotek Wireless Inc., Newmarket, Ont., Canada)	Radio-tracking data	<1.0 *	50

*Indicates values estimated from the study

Table 1: UASs studies charts. Represented the animal species and the specs of the UASs from different studies Detected animal species and employed unmanned aerial systems (UASs) determined via a literature review ([1].

Ground based controller system

Broadly speaking, control systems fall into two types: (1) human-operated controls or (2) autonomous-operated controls.

1) **Human-operated controls**: A certified UAV pilot controls the trajectory, altitude, speed and rest of the parameters manually with remote control;

2) **Autonomous-operated controls**: The UAV follows the flying parameters as it was programmed previously. The presence of a certified pilot while the UAV is functioning is however needed, who supervises and modifies the flying parameters if necessary;

Communicating, command and control system

It is used to command and control the UAV, to receive the telemetry data (on the status of the aircraft), and to control its instruments.

Sensor*s*

Most wildlife studies with UAS have used two types of data: (1) optical and/or (2) microwaves [1].

1) Optical: In wildlife monitoring, red, green, blue (RGB) sensor models has been widely used: It is an additive colour model where the primary colours, red, green and blue, mixed to compound the array of colours of the visible light. These kinds of cameras are generally smaller and cheaper than microwaves cameras but have a higher resolution (8 to 24) megapixel [1]. It has been used to detect wild animals in open lands or marine environments [2].

2) Microwaves: Another option used in wildlife monitoring has been infrared cameras. These cameras detect the difference in temperature between the animals and the landscape. This technology is more expansive than the optical option, and its resolution is coarser (<0.21 megapixels). Its main use has been to detect animals in forested or other high-vegetation areas [6,7,8], and for nocturnal and crepuscular animals [5].

B. Regulation and importation, travelling with it

Flying UAV is legal in the Philippines. The competent governmental organism is the Civil Aviation Authority of the Philippines (CAAP).

Prohibitions (Reference: *Civil Air Regulations part 11.11-1)* [9]No flying over populated area [*11.11.2, paragraph (a)*]

- Example: flying over gathering of people in an event:
  - Stay clear of populated area [*11.11.3, paragraph (b)*]
- Example: flying over housing subdivision:
  - No flying at 400 feet and above [*11.11.3, paragraph (a*)]
  - No flying within 10 kms radius of any airport [*11.11.3, paragraph (a*)]
  - No flying over controlled or prohibited airspace [*11.11.3, paragraph (c)*]
- Examples: Aircraft approach and take off route, military camps, presidential palace

- No commercial drone operation without an RPA controller Certificate [*11.11.4, paragraph (a)*]
- Flying drones weighing more than 7 kgs require an RPA controller certificate [*11.11.4, paragraph (b)*] and it requires drone registration at CAAP [*11.11.5, paragraph (b)*]
- Drones with a gross weight of 150kgs and above are required to obtain a Special Certificate of Airworthiness (SCA) or an Experimental Certificate (EC) [*Phil. Civil Air Regulation part 5*]
- RPA Controller doing non-commercial operations may operate only within Visual Line of Sight [*11.11.7.2*]
- No night flying [*11.11.7.3*]
- Drone flying display or air show requires permit from CAAP [*11.11.7.4*]
- UAV/RPAS Controllers (Pilot) (Reference: *Civil Air Regulations part 11.11-1*) [9]:
- RPA Controller Certificate is required when flying a drone for commercial operations [*11.11.4**,** paragraph (a)*]

- RPA Controller Certificate may be obtained from CAAP office at Old MIA road Pasay City after passing written & practical exams
  - All RPA Controllers doing non-commercial operations are prohibited to operate an RPA at night unless authorized by the Authority [*11.11.7-3, paragraph (a)*]
  - *PCAR 2.13.10 – Validation of Foreign RPA Controller Certificate, License or Authorization.* Note: This new provision provides a mechanism for foreign companies that possess a current and existing certificate or authorization from their country to be validated in order to operate in the Philippines.

Travel restrictions should also be taken into consideration. Entering the country with a UAV bought abroad requires an "Import Bond" stating that the UAV equipment will not be resold. It will also need an "Import Clearance" from the CAAP [9].

C. Range of price

Here we are presenting some examples of the costs associated with UAS projects to monitor wildlife and the environment. Table 2 presents a project with a lemur species (*Propithecus tattersalli*) in Madagascar. Even with the obvious differences between lemur species and wild cattle species, the equipment requirements could be similar, as thermal imaging is indicated for rough terrains with patches of forest, like Mts. Iglit-Baco Natural Park (MIBNP) is. This table compares the cost associated with a transect survey and a UAS survey. The costs of a drone survey are quite stable if we increase the area covered, while with transects, they increase as the hours of work and supplies needed also increase. This cost does not include the previous work to establish a correct design and protocol for the area and animal surveyed.

Table 3 presents the range of prices of different kinds of sensors. Before a proper assessment of the needs to survey tamaraw in MIBNP, it is difficult to define what the appropriate devices are, but probably it will range between Near Infrared (NIR) and thermal imaging due to the difficulties of the terrain and the different habitats within the natural Park.

	Walking transects		Improved UAV transects	
Supplies	Range finder	200	–	–
	Data recording (notebooks)	100	–	–
	–	–	UAV (Phantom 4 Pro)[1]	1,500
	–	–	Thermal camera (640×512 pixels)[2, 3]	3,500
	–	–	1-TB hard drive for image storage	100
	–	–	UAV extras (batteries, propellers, case, insurance, etc.)	1,000
	–	–	Solar battery charger[4]	1,000
Permits	Foreign researcher	350	Foreign researcher	350
	–	–	UAV flight permit	380
Set-up	Cut transects[5]	15/km	–	–
Local Malagasy field assistant	5 assistants + food	3/km	1 assistant + food	0.05/km
Data entry and processing	90 person-hours (272.2 km, 90 h)	3.3/km	–	–
	–	–	OBIA software (eCognition)[6]	0
Cost per distance[7]				
250 km		5,925		7,843
500 km		11,200		7,855
750 km		16,475		7,868
1,000 km		21,750		7,880

Estimates are based on 16 transects across five forest fragments (survey effort = 291.34 km). Expected survey costs were then scaled for possible surveys with distances ranging from 250 to 1,000 km. Principal investigator (PI) time commitment/salary are not included in cost estimates for any of the methods given high variance in those costs depending on experience level of the PI. UAV monitoring is cost effective after 341 km of survey effort. [1] DJI, Shenzhen, China. [2] FLIR Systems, Wilsonville, OR, USA. [3] Pix4D recommends using a minimum 640 × 480 thermal sensor for mapping purposes. [4] Goal Zero, Bluffdale, UT, USA. [5] Each walking transect took one day to cut through forest (27.2 km of trails cut). Labour costs for local assistants are based on current market rates as set by non-profit research partner Fanamby. [6] We assumed that OBIA (object-based imagery analysis) software (e.g., eCognition) was available at no charge through research universities. [7] Estimates are calculated by taking the supplies, permits, set-up and local assistant and data processing costs and scaling by kilometre surveyed, based on costs in USD (2018 and not accounting for inflation). Expenses ubiquitous across methods (transport to and from site) are not included.

Table 2: Cost estimates (USD) for walking and possible UAV monitoring programmes for golden-crowned sifakas (*Propithecus tattersalli*) in Madagascar's Daraina region [10]

Instrument.		Type of Sensor	Spatial Resolution	Spectral Resolution	Weight	Costs
Imaging sensors	Visible RGB	Passive	Very high 1–5 cm/pixel	Low (3 bands)	Low <0.5 kg	Low $100–1000
	Near Infrared (NIR)	Passive	Very high 1–5 cm/pixel	Low (3 bands)	Low <0.5 kg	Low $100–1000
	Multispectral	Passive	High 5–10 cm/pixel	Medium (5–12 bands)	Medium 0.5–1 kg	Medium $1000–10,000
	Hyperspectral	Passive	High 5–10 cm	High (> 50–100 bands)	Medium 0.5–1 kg	High $10,000–50,000
	Thermal	Passive	Medium 10–50 cm/pixel	Low 1 band	Medium 0.5–1 kg	Medium $1000–10,000
Ranging sensors	Laser scanners (LiDAR)	Active	Very high 1–5 cm/pixel	Low 1–2 bands	High 0.5–5 kg	High $10,000–50,000
	Synthetic Aperture Radars (SAR)	Active	Medium 10–50 cm/pixel	Low 1 band	High >5 kg	Very high >$50,000
Other sensors and devices						
Atmospheric sensors		Temperature, Pressure, Wind, Humidity				
Chemical Sensors		Gas, Geochemical				
Position systems		Ultrasound, Infrared, Radio Frequency, GPS				
Other devices		Recorder device/microphones				
Sampling Devices		Water, Aerobiological, Microbiological Sampling				
Other devices		Cargo, Spraying, Seed spreader				

Table 3: Summary classification of sensors and devices that can be coupled on drones [11]

II. Some examples of using drone technology for wildlife population monitoring or ecological studies; experiences and feedbacks

This technology has been used in different species of large mammals, like roe deer [8], orangutans [12] [45], African elephants [2], wildebeests [13], elephants [14], koalas, deer, kangaroos [7], red deer, roe deer, and wild boar [5].

A. Large mammals in open landscapes

- Martin Israel [15] used a self-made UAV with a thermal infrared camera to detect roe deer (*Capreolus capreolus*) fawns in farm meadows. The motivation was to avoid accidents. To do so, he calculated the optimal field of view angle, the maximum pixel size to detect the animals. The UAV followed a designed flying path in a stop-and-go mode taking pictures in every waypoint. 70.77 ha were scanned, 44.2 ha of them in 22 flights at a flight altitude of 50 m, and 26.6 ha in 28 flights at 30 m. With the first altitude, more fawns were missed, but no information about failure in detection was provided.
- Vermulen et al. [2] used the Gatewing ×100™ equipped with a Ricoh GR III camera testing animal reaction to the UAS. Visibility on the images was tested as well. 100 meters height was the elevation where animals didn’t show a reaction, but only elephants were easily visible and not medium or small-sized animals. They implemented an aerial strip sample count along four transects, each of them overflown twice and previously surveyed by foot. The animals were counted manually through the images. 2.47 elephants per square kilometre were estimated with a coefficient of variations of 36.10 %.

B. Large mammals in rough landscape and forest

- Gonzalez et al. [7] tested UAS to detect Koalas at different altitudes, while people were counting animals on the ground. They used an airborne system consisting of a multirotor UAV (S800 EVO Hexacopter), navigation system, thermal camera (Tau 2-640), gimbal system and video transmitter. Then, for the ground segment, they used software installed in a laptop, the datalink and video receivers for remote displaying and recording, plus an aerial platform. To analyse the data, they used a pixel-based method, using the wildlife heat signature that creates a good contrast between the background and the target wildlife; and an object-based method, using multiple templates reflecting changes in size, shape and colour of the object. Results showed no false-positive at 20- and 30-meter altitude above ground, 1.5 of average false positive at 60 meters for every 5 to 6 detection, and not reliable results above this elevation.

- Witczuk et al. [5] conducted a study to explore the feasibility of a UAV and TIR imaging system for detecting ungulate in forests. The main points of the study were: 1) assess if quality/resolution of aerial thermal images is sufficient for the identification of ungulate species; 2) check its performance in different forest types/canopy cover classes and at different times of the day; 3) assess the risk of double counting; 4) assess the efficiency of the method in the field. They used two different UAVs models (fixed-8 wing AVI-1 aeroplane for daylight and fixed-wing Skywalker X8 Flying Wing with LED lights for night time). UAVs were equipped with a thermal infrared camera IRMOD v640. They used parallel transects along the long side of a rectangle. They flew four flights in daylight and one at night at an average altitude of 149 meters.

Their conclusions were: 1) Species identifications were ambiguous; 2) If the ground is totally obscured by the canopy, UAV thermal surveys are not recommended and the best time of the day is influenced by the thermal difference between animal and background, and the activity pattern of the animal (e.g. avoiding the time of resting in dense forest); 3) Double counting is an important risk if transects patterns are not properly designed; 4) sensor resolution could determine importantly the efficiency of the method.

C. Discussion on relevancy of results and comparison to other methods

The use of UASs for wildlife monitoring is a quite new methodology, and thus, there are still little background studies. Besides, most of them are focused on the detection probabilities and their influencing factors [1].

<u>Image analysis.</u>

For the image analysis, a determination of the optimal number of pixel-per-animal is crucial and difficult. It depends principally on the body size of the targeted animals and its contrast in temperature with the landscape, the image quality, other confounding features and flight altitude, but must occupy at least 2 pixels to recognize [1].

In most of the studies, the animal shape covers between 22 and 79 pixels, but, as was stated above, it varies strongly, depending on the height of the flight of the UAS. An insightful example is the work by Israel [8], who found out that a roe deer (*Capreolus capreolus*) can be detected with a FLIR Tau640 thermal camera at a flying altitude of 166 meters (the animal occurs in two pixels). However, he recommends a flight altitude of 30 meters to avoid missing animals (22 pixels occupied by a single roe deer).

This optimal distance is at the balance between the image resolution, animal disturbance and cover efficiency, and the presence of other animals, among others [1]. Note that the discrimination between animals has been poorly tested in the bibliography [16].

Methods for detecting animals

We can divide the most relevant methodologies to process the imagery in two: Automated and semi-automated counts of animals; and manual counts. Automated and manual of both methodologies processing of pictures were reported to be generally highly correlated when the survey takes place in small and homogeneous areas, achieving an overall accuracy of >70% [1]. When the complexity of the area increases, the accuracy decreases dramatically, down to detected fraction of a species in the area surveyed near to 0% [17, 18]. For instance, Rey et al. (2017) working on large mammals in the African savannah reported 3-20 false positives for for each true positive could be expected at a recall rate (true positive rate from the total population) of 80% [19, 1].

Several factors were found to greatly affect the detection probability of animals on the photographs. Some of them are related to the ecology of the animal (*e.g.* group size, animal activity pattern), and others to the environmental and technical factors (vegetation composition and structure, lighting conditions, flight speed). To avoid such situations, higher resolution imagery and the use of double observer estimator of abundance have been employed [20].

The most important methodologies are the following:

- Pixel-based methods.

The histogram thresholding analyses have been widely used for image classification mainly because of its implementation simplicity [21, 1]. It needs previous work to identify the species-specific threshold [21]. This methodology has achieved good results with low-resolution and RGB imagery, similar to human counts [22], but it quickly loses efficiency when the difference in pixel values between species and/or surface is small, a situation that is frequently encountered in heterogeneous landscapes [1].

- Object-based methods.

It has been widely used, like the pixel-based methods. It uses the higher resolution of the new sensors to include other characteristics, like the shape or texture, to build a more accurate algorithm for automatic counting and machine learning [1], allowing better discrimination in heterogeneous landscapes. In general, these different algorithms have produced more accurate results than manual counts [17].

- Deep learning.

Convolutional Neural Network (CNN) is a new development of deep learning algorithms. It has been used to detect large animals with higher accuracy than traditional machine learning algorithms, like EESVM (80% correct detections for a precision of 30% [19] vs. 75% correct detections for a precision of 10% [23]) [1]. These models usually use the pixel information to classify between classes like “animal” and “background”. CNN allows extracting particular expressions of the image through a learning process [19].

The major limitations of machine learning methods are the extremely large datasets needed for the training to get reliable results [24] and the difficult balance between recall rates and false positives, as the conditions might vary between data sheets (e.g., different years with different weather, changes in hardware, etc.) [19].

All these methodologies are in a phase of development. To partially solve these problems, Wang et al. [1] have suggested combining automated methods with manual counting.

Statistical analysis of the data

UAV is just a tool to collect information, but it needs statistical development for any population monitoring program. It means that before making any decision, the objectives and possible results need to be clear. Any monitoring design will need to deal with two factors, among others: spatial variation and detectability. The study area needs to be sampled in a manner that is possible to make inferences about the whole area of interest. Then, the data collection needs to permit the estimation of the detectability rate for the selected count statistic [25].Different approaches can be taken (double count, distance sampling, capture-recapture…). In all of them, the researcher will face the same difficulties as if he was using any other data gathering methodology. Due to that, these statistical methodologies need to be clear before building the rest of the design.

Use for other ecological research topics

Outside wildlife monitoring, the UAS has been used in different fields of ecology most often to characterize the landscape and habitats. Some examples of that are investigations about the influence of wildlife on their habitat and the ecosystem they can be found (e.g. beavers) [26, 27]; map vegetation at an intermediate scale, less coarse than with satellite imagery [28, 29, 30, 31]and also with invasive vegetation species [32, 11]; even for projects planting seeds for habitat restoration [33].

Interestingly, this quite new technology has been used to deal with wildlife conflict [8, 34, 35]; providing new anti-poaching tools [14] and anti-illegal logging [11]; mapping spatial epidemiology, providing information on the spatial pattern of hosts [36]and vectors [37].

III. Exploring the use of drones and its relevance for monitoring tamaraw population in MIBNP

As stated above, the literature about the use of UAV to monitor wildlife is rapidly growing. The use of this technology is still under development, and its implementation in new fields of research is on-going, and somewhat experimental. In MIBNP, alternative tamaraw population monitoring methodologies are being tested, and the use of this technology remains an option to be evaluated. With regards to the literature, tamaraw population monitoring (abundance, density), studies about animal movements, group size or wildlife conflicts with IPs could be field of research for possible testing of this technology. To be successful, the possibility of detecting and distinguishing the species needs to be tested and validated beforehand. Unlike with the traditional annual point count, assessing sex, age structures or tamaraw groups' composition might not be possible with UAV technology.

Important considerations

Most of the wildlife monitoring projects through UAV so far are centred on testing methodologies, their accuracy, and their benefits and constraints. Therefore, at this stage there is no existing turnkey solution or customized protocol that could be implemented for tamaraw population monitoring. In other words, evaluating the use of drone technology in Mindoro and MIBNP would be an exploratory process with no certainty on its effectiveness at the end.

Furthermore, testing and developing drone technology requires taking into account and evaluating several parameters, such as:

- ✓ Legal regulation: There is not a common legal frame for using this technology among countries. The UAV flying regulations through different sites (human settlements, government installations, etc.) needs to be considered prior to any project. Also, other aspects can collapse with this technology, as the privacy of the people overflown and recorded by these devices.
- ✓ Direct impacts on wildlife: Animals can suffer different impacts from this technology that needs to be evaluated, not only for the focus species but the other species that share tamaraw's habitat.
- ✓ Geomorphology and habitat types: There are different challenges in collecting and analysing the data in different types of terrain (e.g., flat or mountainous areas) or vegetation (e.g., grassland, dense forest, cloud forest, etc.).
- ✓ Size of the focus species and the rest of animals sharing its space: Bigger animals are easier to detect at higher elevation from the ground and/or if there are not similar animals in size.
- ✓ People's reaction to this technology: It can cause conflict with local communities.
- ✓ etc.

Tentative process to evaluate the relevance of drone technology for tamaraw population monitoring

As a consequence of the above points, the implementation of this technology in Mindoro for tamaraw would require several steps of testing, which should be running in parallel most of the time. The expertise required for each step needs to be carefully considered.

First, the UAV and sensor models, and their calibrations (e.g., height of flight to obtain reliable images of the animals without disturbing them; angle of the camera to better detect the animals and cover the surface) needs to be defined. All these need to take into account the vegetation coverages/types and the ground disruptions (e.g., creeks, cliffs, V-shaped valleys), among other things.

The second step is to define the design of the fieldwork. This includes, among others, the best time of the day and season of the year to carry out the survey. If thermal imagery is used, the time of the day is vital to find the higher difference in temperature between the animal and its background, but also when it is not resting or hiding in difficult places to detect. Seasonality is important, not only because of the possible difference between the body temperature of the animal and surrounding but because of the weather itself.

This technology cannot be used with medium to strong winds or with rain. All these aspects highlight the need to base the sampling period only on the best design to obtain the most reliable data (weather and climate, ecology of the animal…), and less on other technical consideration (availability of experts, calendar or schedule of the fieldworkers…). If these two aspects are not gathered, the use of this technology shouldn't be an option.

The trajectory of the device should avoid as much as possible double-counting, covering the whole area at the same time. This re-observation of the same individuals will depend on the movement of the animals, but also on transect length (longer transects takes more time to flight) or the angle of the camera [5].

The data pre-processing needs to be tested. As it was explained in another section, there are several options to analyse the images obtained by the UAS. If the AI (eg., CNN) is used, prior training is needed, processing a relevant number of different photos from the animal trying to replicate as much as possible the environmental conditions and the angles of the photos, and representing the different habitat types. All these options should be evaluated and compared with other population abundance estimation methods, for which the accuracy of the methodology has already been measured (e.g., transects by foot, point count).

Properly testing and evaluating the following parameters shall help to avoid usual pitfalls. Duffy et al. [38] highlights some of them:

- ✓ Pre-flight planning: It is used to make optimal planning of where and when it is safe to fly, identify safe locations for take-off and land, and follow the government regulations.
- ✓ Flight operation: It is suggested to have one pilot-in-command and a 'spotter/ground control station operator' to assist.
- ✓ Weather and local consideration: Some accessories, like the anemometer, could be a clue for the safety of the UAS.
- ✓ Dust, Damage and Redundancy: The environment can damage the device, affecting its performance.
- ✓ Data quality: Shadows and light angles can interfere with the accuracy of the data, as well as the movements caused by the wind.
- ✓ Battery: They can be the most hazardous component of the UAS. Lithium polymer (LiPo) batteries are highly recommended.

Finally, the important parameters to take into account in planning a sampling design using UAV technology are the biological factors and the ground context. If technical matters, related to UAV use, become the main constraining factors, then this technology shall not be considered as an option.

Tentative list of pro and cons (not elaborated above)

Advantages:

- ✓ Access to dangerous or impossible areas or terrains for humans, enabling a better coverage of the study area compared to line transects design.
- ✓ Accuracy in replications of the study.
- ✓ A great flexibility for carrying different types of sensors and devices.
- ✓ Less invasive, non-hazardous, repetitive and reliable monitoring technique to monitor wildlife [11].
- ✓ Less physically demanding than foot surveys and field work.
- ✓ It can be less costly than physical fieldwork.
- ✓ Multiple uses.

Disadvantages:

- ✓ It is sensitive to weather condition. It cannot fly under rain or moderate to strong winds [39, 40].
- ✓ Hostility from the local people (It can be even shot down) [41].
- ✓ It can stress the animals, especially flying at the wrong height or if they are large or noisy [42, 43].
- ✓ Possible double-counting if an animal moves to other surveyed areas inside the study area, or during the survey period.
- ✓ Need permits, while regulations can hinder its range of uses or possible study designs
- ✓ The study design is dependent on the battery life and flight duration capacity
- ✓ The data collected is limited to the type of sensor installed.
- ✓ If low flight is required, the reliability of the device is low, which could end up in accidents [1].

Furthermore, the analysis of the data collected is still facing many challenges:

- ✓ Even if deep learning algorithms have shown higher reliability than pixel-based or object-based methodologies, the accuracy of animal recognition and classification is still low when large datasets are analysed [19,44].
- ✓ Difficulty from the deep learning models to discriminate animals when they are aggregates [4].
- ✓ Most of the studies carried out until today are focused on assessing the detectability of the animals through this methodology only [4].
- ✓ The analysis of the data requires modern, robust and computationally intensive methods [11].

Exploring its use for other aspects related to tamaraw conservation

In MIBNP, the planned phase-out of the annual grassland burning for counting purpose will probably result in a change of the habitat structure (forest and scrublands expansion). These changes in the vegetation cover needs to be monitored. Satellite imagery could be used for medium to large scale monitoring), but purchasing such data material can be costly and too coarse.

Ground-based surveying can produce useful data but require time for fieldwork and thorough protocol that must be respected (accessibility of site at all time and coordination with IPs). UAS can offer fine-scale monitoring, easy to replicate on a regular basis. Good skills would enable to build a Digital Surface Models (DSM) [26].

In the surroundings of the No Hunting Agreement in MIBNP, the use of UAS could help assess habitats suitability and investigate the possible areas of expansion of the tamaraw.

An interesting use of drones could be to address anti-poaching/illegal activities within and at the border of the Core Zone of Monitoring. The UASs have been used already to localize poachers or investigate their movements, illegal loggings, or other activities against the law ([14, 11].

IV. Discussion and recommendation

This paper shows that the use of drone technology to monitor wildlife population is still at its early stage of development, with many pitfalls on the way and no turnkey solution available to be applied right away.

In addition, this quick review highlights that UAV are just another new sampling technique, which, for comparison, stands to the same level than counting animal from vantage points, but can indeed do it quicker and with much less human resources needed. If the goal is to estimate population abundance, one will need the number of detected animals from the generated pictures or videos. However, flying the study area with a drone will not return the number of tamaraws; drone sampling must be coupled with a population abundance estimator, which has to be prior generated and evaluated through other methods (double counts, distance sampling, capture-recapture…).

In other words, the limitation are exactly the same as counting from the ground, albeit the average detection rate that could be higher than other methods such as point count or distance sampling. But it is barely expected to be 1. It faces the same issue of detectability and double count. These difficulties are not removed by using drones and must be addressed during the data analysis process whatsoever.

The data analysis process is a constant of any census method. For instance, UAV technology doesn’t stop at flying the drone over the study area. And we must not confound the extraction of relevant information from photographs or videos, which is already a tedious phase, with the real statistical treatment that these data must undergo afterwards. Drone technology can generate a huge amount of data, tedious to analyse and requiring specific skills and capacities (AI for instance). Overlooking the analysis phase and the quality of data management might obliterate all the effort and resources deployed to conduct drone survey in the field.

Finally, and even more than with other methods, it is important to ask basic questions before to engage in using drone technology:

- ✓ What information do we want to get?
- ✓ Do we have any other existing relevant methods in hand that enables us to get this information already?
- ✓ If yes, in which proportion we expect drone technology to provide better results?
- ✓ What kind on data do we seek to generate?
- ✓ Do we have the resource and capacities to analyse these data?
- ✓ Do we want to use drone technology only ones to address a specific biological question (population abundance, distribution), or do we intend to use it on a regular basis?

In the case of the tamaraw, in MIBNP, it is recommended to undergo an evaluation and testing process in order to measure the trade-off between developing the drone technology with the probability that it is not relevant after all, and other options. It raises several questions that must be addressed to help prepare the evaluation process and prior to conduct the testing phase:

a) How long it would take to test and establish an effective method?

b) How much would it cost to do it?

c) How much would cost the implementation of regular operations afterwards (in comparison to annual count and transect operation); is it cost effective?

d) Will it provide more accurate results than other methods?

e) Can it replace other monitoring methods or shall it only complement existing ones?

f) Are the skills and qualification available to conduct the testing phase?

g) Is it worth engaging in it in MIBNP or shall we focus / strengthen /explore other options?

Conclusion

Despites its appealing aspect and apparent facility, drone technology is not the new technological magical tool that will revolutionize the life of conservationist and decision makers. Using UAV is a way of sampling the species population of interest over a specific study area, no more. As any type of scientific approach and field intervention, it requires a thorough thinking and evaluation process in order to harness its potential and avoid pitfalls or disappointment. Such process must also avoid engaging precipitated financial expenses based on poor assumptions or insufficient preparation.

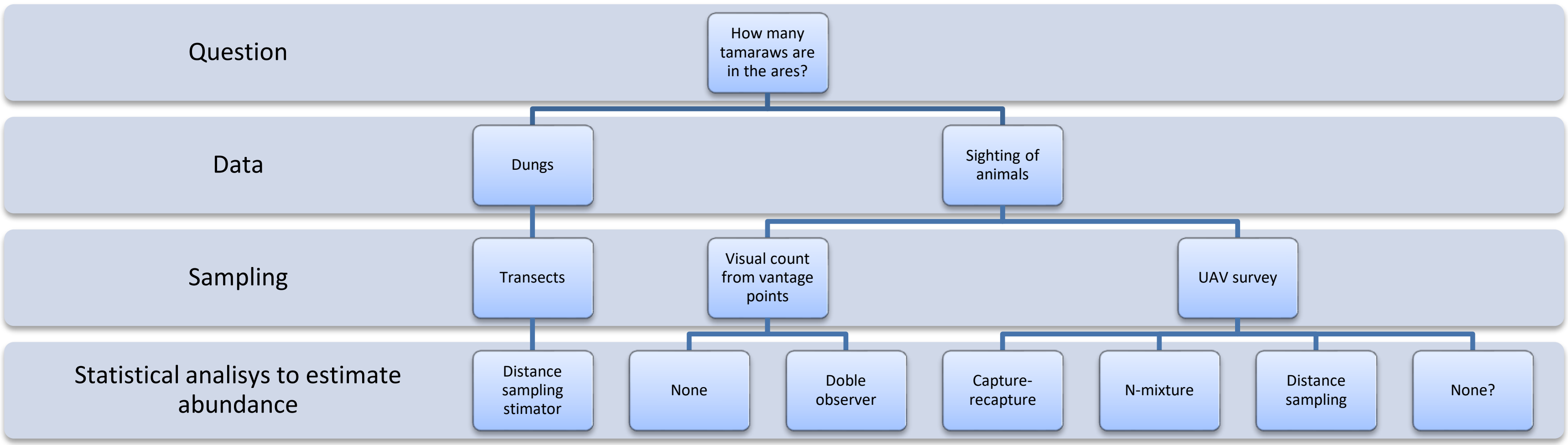

Fig1: As it is explained in this diagram, the use of UAV is only a methodology of sampling, and as such, it won't give the number of animals we have in an area. The data gathered by the drone will need to use pre-existing statistical analyses, and consequently, will face the same constraints and problems as other sampling methodologies, but with less bibliography and former studies to give consistency to the results. These statistical methodologies should be decided previous the design of the protocol for the fieldwork, as it needs to be in accordance with the requirements for the analysis. The sampling methodologies currently used in MIBNP are transects and visual count from Vantage points.

BIBLIOGRAPHY

1. Wang, D., Shao, Q., & Yue, H. (2019). Surveying wild animals from satellites, manned aircraft and unmanned aerial systems (UASs): A review. *Remote Sensing*, *11*(11), 1308.
2. Vermeulen, C.; Lejeune, P.; Lisein, J.; Sawadogo, P.; Bouche, P. Unmanned aerial survey of elephants. PLoS ONE 2013, 8, e54700. [CrossRef] [PubMed]
3. Hodgson, A., Kelly, N., & Peel, D. (2013). Unmanned aerial vehicles (UAVs) for surveying marine fauna: a dugong case study. *PloS one*, *8*(11), e79556.
4. Hodgson, A., Peel, D., & Kelly, N. (2017). Unmanned aerial vehicles for surveying marine fauna: assessing detection probability. *Ecological Applications*, *27*(4), 1253-1267.
5. Witczuk, J.; Pagacz, S.; Zmarz, A.; Cypel, M. Exploring the feasibility of unmanned aerial vehicles and thermal imaging for ungulate surveys in forests - preliminary results. Int. J. Remote Sens. 2017, 1–18. [CrossRef]
6. Seymour, A.C.; Dale, J.; Hammill, M.; Halpin, P.N.; Johnston, D.W. Automated detection and enumeration of marine wildlife using unmanned aircraft systems (uas) and thermal imagery. Sci. Rep. 2017, 7, 10. [CrossRef]
7. Gonzalez, L.F.; Montes, G.A.; Puig, E.; Johnson, S.; Mengersen, K.; Gaston, K.J. Unmanned aerial vehicles (uavs) and artificial intelligence revolutionizing wildlife monitoring and conservation. Sensors 2016, 16, 97. [CrossRef]
8. Israel, M. A uav-based roe deer fawn detection system. In Proceedings of the International Conference on Unmanned Aerial Vehicle in Geomatics, Gottingen, Germany, 14–16 September 2011; pp. 51–55.
9. Philippine Drone Association. (2017). *Drone Laws in Philippines*. https://philippinedroneassociation.org/drone-laws-in-philippines/#uas-regulator
10. Semel, B. P., Karpanty, S. M., Vololonirina, F. F., & Rakotonanahary, A. N. (2020). Eyes in the sky: Assessing the feasibility of low-cost, ready-to-use Unmanned Aerial Vehicles to monitor primate populations directly. *Folia Primatologica*, *91*(1), 69-82.
11. Jiménez López, J., & Mulero-Pázmány, M. (2019). Drones for conservation in protected areas: present and future. *Drones*, *3*(1), 10.
12. Koh, L.; Wich, S. Dawn of drone ecology: Low-cost autonomous aerial vehicles for conservation. Trop. Conserv. Sci. 2012, 5, 121–132. [CrossRef]
13. Torney, C.J.; Dobson, A.P.; Borner, F.; Lloydjones, D.J.; Moyer, D.; Maliti, H.T.; Mwita, M.; Fredrick, H.; Borner, M.; Hopcraft, J.G.C. Assessing rotation-invariant feature classification for automated wildebeest population counts. PLoS ONE 2016, 11, e0156342. [CrossRef] [PubMed]
14. Olivares-Mendez, M.A.; Fu, C.H.; Ludivig, P.; Bissyande, T.F.; Kannan, S.; Zurad, M.; Annaiyan, A.; Voos, H.; Campoy, P. Towards an autonomous vision-based unmanned aerial system against wildlife poachers. Sensors 2015, 15, 31362–31391. [CrossRef]

15. Israel, M. A uav-based roe deer fawn detection system. In Proceedings of the International Conference on Unmanned Aerial Vehicle in Geomatics, Gottingen, Germany, 14–16 September 2011; pp. 51–55.

16. Hodgson, J. C., & Koh, L. P. (2016). Best practice for minimising unmanned aerial vehicle disturbance to wildlife in biological field research. *Current Biology*, *26*(10), R404-R405.

17. Torney, C.J.; Dobson, A.P.; Borner, F.; Lloydjones, D.J.; Moyer, D.; Maliti, H.T.; Mwita, M.; Fredrick, H.; Borner, M.; Hopcraft, J.G.C. Assessing rotation-invariant feature classification for automated wildebeest population counts. PLoS ONE 2016, 11, e0156342. [CrossRef] [PubMed]

18. Longmore, S.N.; Collins, R.P.; Pfeifer, S.; Fox, S.E.; Mulero-Pazmany, M.; Bezombes, F.; Goodwin, A.; Ovelar, M.D.; Knapen, J.H.; Wich, S.A. Adapting astronomical source detection software to help detect animals in thermal images obtained by unmanned aerial systems. Int. J. Remote Sens. 2017, 38, 2623–2638. [CrossRef]

19. Kellenberger, B.; Marcos, D.; Tuia, D. Detecting mammals in uav images: Best practices to address a substantially imbalanced dataset with deep learning. Remote Sens. Environ. 2018, 216, 139–153.

20. Smyser, T.J.; Guenzel, R.J.; Jacques, C.N.; Garton, E.O. Double-observer evaluation of pronghorn aerial line-transect surveys. Wildl. Res. 2016, 43, 474–481. [CrossRef]

21. Otsu, K., Pla, M., Duane, A., Cardil, A., & Brotons, L. (2019). Estimating the threshold of detection on tree crown defoliation using vegetation indices from UAS multispectral imagery. *Drones*, *3*(4), 80.

22. Seymour, A.C.; Dale, J.; Hammill, M.; Halpin, P.N.; Johnston, D.W. Automated detection and enumeration of marine wildlife using unmanned aircraft systems (uas) and thermal imagery. Sci. Rep. 2017, 7, 10. [CrossRef]

23. Rey, N.; Volpi, M.; Joost, S.; Tuia, D. Detecting animals in African savanna with uavs and the crowds. Remote Sens. Environ. 2017, 200, 341–351. [CrossRef]

24. Zhu, X.X.; Tuia, D.; Mou, L.; Xia, G.S.; Fraundorfer, F. Deep learning in remote sensing: A comprehensive review and list of resources. IEEE Geosci. Remote Sens. Mag. 2018, 5, 8–36. [CrossRef]

25. Pollock, K. H., Nichols, J. D., Simons, T. R., Farnsworth, G. L., Bailey, L. L., & Sauer, J. R. (2002). Large scale wildlife monitoring studies: statistical methods for design and analysis. *Environmetrics: The official journal of the International Environmetrics Society*, *13*(2), 105-119.

26. Puttock, A. K., Cunliffe, A. M., Anderson, K., & Brazier, R. E. (2015). Aerial photography collected with a multirotor drone reveals impact of Eurasian beaver reintroduction on ecosystem structure. *Journal of Unmanned Vehicle Systems*, *3*(3), 123-130.

27. Michez, A., Morelle, K., Lehaire, F., Widar, J., Authelet, M., Vermeulen, C., & Lejeune, P. (2016a). Use of unmanned aerial system to assess wildlife (Sus scrofa) damage to crops (Zea mays). *Journal of Unmanned Vehicle Systems*, *4*(4), 266-275.

28. Fraser, R. H., Olthof, I., Lantz, T. C., & Schmitt, C. (2016). UAV photogrammetry for mapping vegetation in the low-Arctic. *Arctic Science*, *2*(3), 79-102.

29. Marcaccio, J. V., Markle, C. E., & Chow-Fraser, P. (2016). Use of fixed-wing and multi-rotor unmanned aerial vehicles to map dynamic changes in a freshwater marsh. *Journal of Unmanned Vehicle Systems*, *4*(3), 193-202.

30. Olsoy, P. J., Shipley, L. A., Rachlow, J. L., Forbey, J. S., Glenn, N. F., Burgess, M. A., & Thornton, D. H. (2018). Unmanned aerial systems measure structural habitat features for wildlife across multiple scales. *Methods in Ecology and Evolution*, *9*(3), 594-604.

31. Michez, A., Lejeune, P., Bauwens, S., Herinaina, A. A. L., Blaise, Y., Castro Muñoz, E., ... & Bindelle, J. (2019). Mapping and monitoring of biomass and grazing in pasture with an unmanned aerial system. *Remote Sensing*, *11*(5), 473.

32. Michez, A., Piégay, H., Jonathan, L., Claessens, H., & Lejeune, P. (2016b). Mapping of riparian invasive species with supervised classification of Unmanned Aerial System (UAS) imagery. *International Journal of Applied Earth Observation and Geoinformation*, *44*, 88-94.

33. Stone, E. Drones Spray Tree Seeds from the Sky to Fight Deforestation. Available online: https://news.nationalgeographic.com/2017/11/drones-plant-trees-deforestation-environment/?user.testname=none(accessed on 21 March 2021)

34. Hahn, N.; Mwakatobe, A.; Konuche, J.; de Souza, N.; Keyyu, J.; Goss, M.; Chang'a, A.; Palminteri, S.; Dinerstein, E.; Olson, D. Unmanned aerial vehicles mitigate human–elephant conflict on the borders of Tanzanian Parks: a case study. Oryx 2017,51, 513–516. [CrossRef]

35. Michez, A.; Morelle, K.; Lehaire, F.; Widar, J.; Authelet, M.; Vermeulen, C.; Lejeune, P.; Michez, A.; Morelle, K.; Lehaire, F.; et al. Use of unmanned aerial system to assess wildlife (Sus scrofa) damage to crops (Zea mays). J. Unmanned Veh. Sys2016,4, 266–275. [CrossRef

36. Barasona, J. A., Mulero-Pázmány, M., Acevedo, P., Negro, J. J., Torres, M. J., Gortázar, C., & Vicente, J. (2014). Unmanned aircraft systems for studying spatial abundance of ungulates: relevance to spatial epidemiology. *PloS one*, *9*(12), e115608.

37. Foxx, C. Drones scatter mosquitoes to fight diseases. Available online: https://www.bbc.co.uk/news/technology-42066518 (accessed on 21 March 2021)

38. Duffy, J. P., Cunliffe, A. M., DeBell, L., Sandbrook, C., Wich, S. A., Shutler, J. D., ... & Anderson, K. (2018). Location, location, location: considerations when using lightweight drones in challenging environments. *Remote Sensing in Ecology and Conservation*, *4*(1), 7-19.

39. Hollings, T., Burgman, M., van Andel, M., Gilbert, M., Robinson, T., & Robinson, A. (2018). How do you find the green sheep? A critical review of the use of remotely sensed imagery to detect and count animals. *Methods in Ecology and Evolution*, *9*(4), 881-892.

40. Linchant, J., Lisein, J., Semeki, J., Lejeune, P., & Vermeulen, C. (2015). Are unmanned aircraft systems (UAS s) the future of wildlife monitoring? A review of accomplishments and challenges. *Mammal Review*, *45*(4), 239-252.

41. Sandbrook, C. (2015). The social implications of using drones for biodiversity conservation. *Ambio*, *44*(4), 636-647.

42. Mulero-Pázmány, M., Jenni-Eiermann, S., Strebel, N., Sattler, T., Negro, J. J., & Tablado, Z. (2017). Unmanned aircraft systems as a new source of disturbance for wildlife: A systematic review. *PloS one*, *12*(6), e0178448.

43. SARDÀ-PALOMERA, F. R. A. N. C. E. S. C., Bota, G., Viñolo, C., Pallarés, O., Sazatornil, V., Brotons, L., ... & Sardà, F. (2012). Fine-scale bird monitoring from light unmanned aircraft systems. *Ibis*, *154*(1), 177-183.

44. Madec, S., Jin, X., Lu, H., De Solan, B., Liu, S., Duyme, F., ... & Baret, F. (2019). Ear density estimation from high resolution RGB imagery using deep learning technique. *Agricultural and forest meteorology*, *264*, 225-234.