Locating and identifying seed tree species for forest restoration in northern Thailand using an unmanned aerial vehicle

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Abstract: Rapid and reliable location of seed trees of required species, within forest, is essential, if global forest restoration targets are to be achieved, e.g. the Bonn Challenge (forest restored to 350 million ha by AD 2030). In dense forest, finding seed trees from the ground is laborious and inefficient, due to limited visibility and accessibility. In contrast, the use of quadcopters with high-resolution cameras, to view tree crowns from above, has become affordable and user-friendly. In this study, drone imagery, classical taxonomy (using leaf and crown characteristics) and image filtering were combined, to develop keys to distinguish 9 tree species, during monthly automated flights over regenerating evergreen forest in Chiang Mai Province, northern Thailand, from June 2018 to January 2019. Independent volunteer observers tested the keys' reliability, using images from a second, similarly aged validation plot. Overall, identification accuracy exceeded 50% for seven of the target species and over 70% for four species. However, identifiability varied with season, with reliability peaking (often at 100%) for most species, during their most distinctive phenophases. Consequently, development and use of aerial tree-identification systems will depend on building up databases of tree species characteristics, visible from drones, and their seasonal variability.

Key words: UAV, quadcopter, drone, tree species identification, keys, forest restoration, seed trees

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Introduction

In most countries, tree seed collection from remnant forest remains essential for forest restoration projects, but current methods of seed collection are primitive, inefficient, unpredictable and expensive. The possibility of observing trees from above, using remote sensing platforms, is therefore an attractive alternative (Sutton, 2001). Attempts to map species distributions by remote sensing have been made (Pouliot et al. 2002; Leckie et al. 2003; Gergel et al. 2007), but few such studies have been applied to tropical forests (Clark et al. 2005; Asner et al. 2008) and, even when combining hyperspectral and high-resolution satellite imaging, identifying trees to species level has proved to be both problematic and expensive (Read et al. 2003; Clark et al. 2004).

A potential simpler and less costly alternative is the use of high-resolution, digital, aerial photographs (Vooren & Offermans, 1985; Herwitz et al. 2000; Trichon & Julien, 2006; Gonzalez-Orozco et al. 2010; Morgan et al. 2010). Studies on the potential use of aerial photographs for tropical tree identification started in the early 1970's. Sayn-Wittgenstein et al. (1978) reported that species could be identified with a reasonable degree of success in Surinam. Since the 1990's, aerial photo survey techniques have advanced considerably (Brandtberg & Walter, 1998; Culvernor, 2002; Fenshman et al. 2002; Chubey et al. 2006). Trichon (2001) listed 12 Guianese trees, likely to be identifiable using aerial photographs. Trichon & Julien (2006) tested the accuracy the method and reported an overall identification success rate of 87%. In Ecuador, Gonzalez-Orozco et al. (2010) used similar techniques to identify tree species with identification accuracies ranging from 50% to 70%.

Previous research mostly used photographs from customized cameras, mounted on hot-air airships, helicopters and planes (Trichon et al. 2006; Morgan et al. 2010; Dandois et al. 2013). However, recent technological advances now allow the use of lightweight unmanned aerial vehicles (UAVs), flying close to forest canopies, as an alternative to satellites or airplanes (Koh & Wich, 2012; Anderson & Gaston, 2013; Getzin et al. 2012). Several studies have demonstrated that high-resolution imagery, acquired from UAVs, can be used to map invasive species (Michez et al. 2016), to monitor tropical forest recovery (Zahawi et al. 2015) and biodiversity (Paneque-Gálvez et al. 2014) and to aid community-based conservation and restoration initiatives (Baena et al. 2017; Onishi & Ise, 2018).

Therefore, the first objective of the study presented here was to develop taxonomic keys, to identify potential seed trees, for forest restoration projects, based on characteristics that can be distinguished in photographs taken by an off-the-shelf drone i.e. crown morphology (type, shape, texture), leaf characteristics (shape, arrangement), phenology (leaf fall/flush, flowering, fruiting, etc.) and image filtering (hue, saturation, brightness). The second objective was to test the usability and reliability of the keys.

Materials and methods

Study area

The study sites were in the upper Mae Sa Valley (latitude 18°51′29.38″N, longitude 98°50′53.60″E), in northern Thailand (1,360 m above sea level), about 30 km north-west from the city of Chiang Mai. The research was carried out in two restored forest plots, namely; 98.2 (the training plot) and 98.3 (the validation plot), each with an area of 0.64 ha (aged 20 years).

The forest in both of these plots had been restored by Chiang Mai University's Forest Restoration Research Unit (FORRU-CMU), in collaboration with local communities, using the framework species method starting in 1998. The framework species method of forest restoration was first conceived by Goosem & Tucker (1995) in Australia. It is the least intensive of the active forest restoration options, as it combines assisted natural regeneration with tree-planting, and it enhances natural seed dispersal mechanisms to bring about biodiversity recovery. The method involves planting trees of 20-30 so-called "framework" species, grown from locally collected seed. Framework tree species are those that are characteristic of the target forest ecosystem, which also have the following characteristics i) high survival when planted out in deforested sites, ii) rapid growth, iii) dense, spreading crowns that shade out herbaceous weeds and iv) early flowering, fruiting or the provision of other resources that attract seed-dispersing animals. The technique accelerates forest succession, maximizing the recovery rates of biomass, structural diversity, biodiversity and ecological functioning, within the limits imposed by prevailing climate and soil conditions (Elliott et al., 2013). For an in-depth study-site description and details of the restoration techniques applied, please refer to Elliott et al. (2019).

Mapping and ground truthing of selected species

In June 2018, digital aerial photographs were taken over the training plot (98.2), using the on-board RBG camera of a DJI Phantom 4 Pro drone, flying 100 m above ground. On the photographs, all visible tree crowns were marked and numbered, using a freehand marker in the Preview App (MacOS).

Ground truthing was then carried out, to locate and match tree crowns on the ground with those in the images. The tree species were identified from numbered tags that had been attached to the trees by a previous FORRU-CMU study that had employed a professional botanist to identify the tree species. For trees without such tags, voucher specimens were collected and compared with verified specimens in the Chiang Mai University (CMU), Herbarium. Nine framework tree species (*Artocarpus gomezianus* Wall. ex Trécul (Moraceae), *Castanopsis calathiformis* (Skan) Rehder & E.H.Wilson and *C. tribuloides* (Sm.) A.DC. (both Fagaceae), *Choerospondias axillaris* (Roxb.) B.L.Burtt & A.W.Hill (Anacardiaceae), *Ficus altissima* Blume (Moraceae), *Magnolia garrettii* (Craib) V.S .Kumar (Magnoliaceae), *Pinus kesiya* Royle ex Gordon (Pinaceae), *Prunus cerasoides* Buch.-Ham. ex D.Don (Rosaceae) and *Toona ciliata* M.Roem. (Meliaceae) were selected for the study. A total of 48 tree crowns of nine tree species were identified and used to develop keys in the training plot.

Digital aerial photographs

The GPS coordinates of all the target trees were recorded on the ground with a handheld GPS receiver and were then used to program autonomous drone flight plans, using the LITCHI application (flylitchi.com). A DJI Phantom 4 Pro drone was then flown along the autonomous flight paths, 50 m above the ground and photographs were taken at waypoints directly above each of the target trees, using the onboard RBG camera (5472 x 3078 pixels). In order to maintain uniform photo quality, the ISO camera setting was set to automatic, to maintain EV (exposure value) at zero. The same flights were replicated monthly from June 2018 to January 2019.

Development of tree species identification keys

The digital aerial photographs were analyzed to develop monthly tree species identification keys, based on crown and leaf characteristics, phenology and image filtering.

Seven crown properties and descriptors (Table 1) were used; modified and adapted from those proposed by Koelmeyer (1959), Trichon and Julien (2006) & Gonzalez-Orozco's (2010) (Fig. 1). Leaf properties and descriptors were modified and adapted from those of Gardner et al. (2007). Four of the most distinctive leaf properties were used to develop the leaf key (Table 2). Since, the UAV was flown close to the tree crowns (<30 m) and was equipped with a high-resolution camera, leaf characteristics, hitherto unobservable from conventional remote sensing platforms, could be recorded (Fig. 2).

The open-source, Java-based software, ImageJ (imagej.net/Welcome) was used for image filtering, by varying image hue, saturation and brightness (HSB), by trial and error, until crowns of each of the target species were isolated in the images. The upper and lower limits of 3 image variables that achieved maximum distinction of the crowns of the target species (indicated by the crowns turning red in ImageJ) were then recorded.

Key Validation

Key validation was performed by adapting and modifying the methods of Trichon & Julien (2006) and Gonzalez-Orozco et al. (2010). Eleven graduate students volunteered as 'photo-interpreters' for the validation process. Image J software and a folder consisting of one target crown key and two identified photographs for each species were preinstalled in the computers used for the validation process. Photographs for seven months (July 2018 to January 2019) were used for validation. The folder provided to each photo-interpreter comprised of photographs of nine species of all seven months, which were randomly mixed. Crowns of all the target tree species in each unidentified photograph were counted prior to validation. In order to identify tree species, photo-interpreters were directed to open the unidentified photographs in Microsoft Paint software and use the keys to locate target tree species. The photo-interpreters then drew a circle around each tree that they could identify as one of the 9 target species, using paint brush and then saved it in same folder. The results were reported and analyzed as % found (trees correctly identified as target species), % error of omission (missed trees of the target species) and % error of commission (trees misidentified as target species) after Gonzalez-Orozco et al. (2010).

Results

The keys for each species in their most distinctive months are presented in Table 4. Identification success rates, for all species, along with errors of omission and commission, are compared in Fig 3. Average overall identification success rates, using the keys developed by this project, across photographs over all months, ranged widely among species from 27.3 for *P. cerasoides* to 100% for *P. kesiya* (Fig. 3).

Tree species with identification accuracy of 100%

P. kesiya was the most distinguishable species, scoring 100% identification accuracy, in all months, with zero errors of omission and commission. The high identification accuracy for *P. kesiya* was because it had the most distinctive and largest crowns, compared to the other species. The whorls of needle leaves were very easy to distinguish from the rest of the forest canopy. The only other native *Pinus* species in northern Thailand (*P. merkusii*) was not present in the area, so the possibility of confusion between the two species did not arise. The volunteer photo-interpreters reported that they did not have to refer to the keys to find this species in the test photographs, since it was so distinctive. Gonzalez-Orozco et al. (2010) and Garzon-Lopez et al. (2012) reported a similar result for equally highly distinctive tree species such as palms.

Tree species with identification accuracy of 75% to 95%

C. axillaris was identified with an accuracy of 95%. The error of omission was therefore only 5% and the error of commission was zero. *M. garrettii* and *A. gomezianus* were both identified with an accuracy of 75% (errors of omission of 25%). The error of commission for *M. garrettii* was 7% and for *A. gomezianus,* 22%. Photo-interpreters reported that the relatively large leaves of *M. garrettii* and *A. gomezianus*, compared with the other species, made them distinguishable (Fig. 2). The high identification accuracy for these 3 species may also have been because they were the most abundant species in the plots. Gonzalez-Orozco et al. (2010) and Garzon-Lopez et al. (2012) also reported high accuracy of identification for common or abundant species.

Tree species with identification accuracy of 50% to 70%

F. altissima was identified with an accuracy of 67%, followed by *C. tribuloides* (61.1%) and *T. ciliata* (58.3%). The highest error of commission was for *F. altissima* (109%) followed by *T. ciliata* (56.1%) and *C. tribuloides* (52.1%). This meant that for only about half of the trees identified as *F. altissima* were actually that species. The error of omission was highest for *T. ciliata* at 42%, followed by *C. tribuloides* and *F. altissima* (Fig. 3). The high error of commission in case of *T. ciliata* was because most of the photo-interpreters misidentified it as be *C. axillaris*, since both species have large compound leaves. The low abundance of T. *ciliata* may also have contributed to its low identification success rate, in line with the findings of Gonzalez-Orozco et al. (2010) and Garzon-Lopez et al. (2012) for rare species.

Tree species with identification accuracy of 50% and below

C. calathiformis was identified at an accuracy of 45% (error of omission 55%) followed by *P. cerasoides* at 27% (error of omission 73%). Errors of commission were 146% for *P. cerasoides* and 43% for *C. calathiformis* (Fig. 3). This meant that for every *P. cerasoides* tree correctly identified, 5 additional trees were mistakenly assigned to the species, whereas for *C. calathiformis*, the ratio was 1:1. The rarity of *P. cerasoides* may have contributed to its low identification accuracy and very high % error of commission. The high % error of commission for *C. calathiformis* was because it was commonly confused with the similar congeneric, *C. tribuloides*.

Phenology and identification accuracy

Fig. 3 obscures the fact that tree-species distinctiveness varies seasonally, with some species being far more distinguishable in certain months during distinctive phenophases (usually leaf flushing, flowering etc.). At their most distinguishable phenophases 6 out of the 9 species tested were 100% identifiable with 0 commission error (Table 3). For example, the species with the lowest overall identification accuracy, *P. cerasoides*, became 100% identifiable in January when flowering, with 0 commission error. All *C. calathiformis* trees were also identified in July when flowering, but the number other trees wrongly assigned to the species also matched the number correctly identified, so the error of commission was 100%. However, this was the only problematic species. This outcome was similar to that reported by Trichon & Julien (2006) and Garzon-Lopez et al. (2012) who also found that trees species were more easily identified during particular phenophases.

Discussion

The development of pilot tree-species-identification keys, using digital aerial photographs from an off-the-shelf drone and based on crown and leaf characteristics and image filtering, makes this research original. We achieved an overall species-identification accuracy of 67%. Overall, errors of omission were 33% and errors of commission were 48%. The overall species identification accuracy of seven out of nine species tested exceeded 50%, whilst for four species (*P. kesiya*, *C. axillaris*, *M. garrettii*, *A. gomezianus*), it exceeded 70%.

Applications

Over the past few decades, the concept of tropical forest ecosystem restoration has been transformed from an idealistic notion into a global priority, with the UN calling for forests to be restored to 350 million ha of degraded land by 2030 (the Bonn Challenge, United Nations, 2014) and declaring 2021-30 as the “Decade on Ecological Restoration” (United Nations Environment Program, 2019). The achievement of such ambitious global goals will depend on a massive scaling-up of seed-collection programs. With most countries still lacking native seed supply chains, seed collecting of indigenous tree species in remnant forest remains essential, but current seed collection methods are primitive. Collectors search the dense forest canopy for ripe fruits, from below, with binoculars. Visibility is poor and only a small fraction of the forest canopy can be seen from footpaths. Even when a fruiting tree of a target species is spotted, the seeds may not be mature, necessitating a tedious return trip. Consequently, collectors tend to visit the same trees year after year, which narrows the genetic diversity of the planting stock. Conventional seed collection methods are, therefore, inefficient, unpredictable and expensive. The approach, described in this paper, has the potential to accelerate and increase the efficiency of seed collection programs, by mapping seed trees and reducing searching time. However, much remains to be done before such a system can be used reliably.

If the technique is used for studies of species distributions or for monitoring long term performance of species in forest restoration projects, errors of omission are important, but not for locating seed trees. Provided that sufficient numbers of trees, required to maintain genetic diversity of planting stock, are located, it does not matter how many others may have been missed. However, errors of commission are of more concern. For five of the species in this study, the number of trees, wrongly identified as the target species, exceeded the number correctly identified, meaning that seed collectors would be directed to trees of unwanted species more often than to those of the target species. Since the volunteer photo-interpreters had no prior knowledge of the species, keys or software, it is expected that such errors would decrease with further training.

Whilst, the reliability of the technique increases greatly when tree crowns enter their most distinctive phenophases (Table 3), it also means that the set-up period for drone-based tree identification systems, in any particular forest type, would be at least 1 year. Thereafter, monthly drone flights would be needed to locate sufficient numbers of all the target tree species, since the most distinctive phenophases of different species occur in different months. Once the GPS locations of target seed trees have been logged (from the drone photo EXIF data), seed collectors could be directed to them in the fruiting season, using hand- held GPS receivers. It may even be possible to check the ripeness of fruits of the target trees by descending the drones for closer inspection of target trees. Thus, seed collectors would minimize time wasted visiting trees with unripe fruit.

Limitations and challenges

The technique is limited to tree species with large distinctive crowns, visible in the upper layers of the forest canopy. In addition, it appears to be more suitable for abundant species than for rare ones (Trichon et al. 2006).

Inconsistencies in photograph quality and positioning were observed, which might influence identification accuracy. Photo quality issues may have been due to limitations of the DJI Phantom 4 Pro camera, weather and lighting variations. The auto-exposure settings of the camera often failed to maintain consistent photo brightness of the forest canopy, when lighting conditions changed during flights. Positioning issues may have been due to limitations of the drone's GPS receiver and the LITCHI app. All flights were undertaken with more than the recommended 10 GPS satellite connections. Image geometric distortion (Gonzalez-Orozco et al. 2010) sometimes made it difficult to identify crown perimeters towards the edges of the photographs. Topographic variation (Gonzalez-Orozco et al. 2010) also sometimes complicated the isolation of tree crowns in the photographs. Tree crown shapes vary within species and with tree age and position in the canopy (Richards, 1996; Brunig, 1974) and their reliability as taxonomic characteristics requires further investigation.

The weather was also a major limitation. The drone could not be flown when wind speed exceeded 24km/h, when it was raining or when mist covered the area. Since the study site was at >1,300 m above sea level and took place in the rainy season, such adverse weather conditions resulted in the postponement of several flights and increased costs for transport, labour, etc. Finally, short battery life limited the area that can be covered. For detailed photogrammetry flights, only about 0.72 ha can be covered within the 30 min life of a single battery.

Future steps

The pilot study, described in this paper, linked high-tech drone imagery and simple image processing, with the centuries-old concept of taxonomic keys, specifically to rapidly locate seed trees in order to scale-up seed collection to meet ambitious forest restoration targets. For the technique to become practicable, a databank of standardized species descriptions, based on characteristics observable from drones, must be established. We suggest that such characteristics are added to traditional species descriptions in future tree-species field guides, since most botanists are likely to use drones as standard field equipment, in the near future. The next step may be to use artificial intelligence, instead of manual inspection, to locate seed trees in drone imagery. Such automatic species-identification approaches are already being explored (Baena et al. 2017), including object-oriented technologies (Gonzalez-Orozco et al. 2010) and deep learning (Onishi & Ise, 2018).

Acknowledgements

This research work was partially supported by Chiang Mai University. We thank the Royal Government of Bhutan (RGOB), Bhutan Power Corporation Limited (BPC) and Thailand International Cooperation Agency (TICA) for sponsoring the first author's MSc degree program at Chiang Mai University, Thailand. In addition, we thank the Forest Restoration Research Unit, Chiang Mai University (FORRU-CMU) for a small project research grant to support field work and for use of the drone. We thank staff of FORRU-CMU for their help with field work and CMU Herbarium for species identifications. For helping to validate the model, we thank University Studies Abroad Consortium (USAC) student and the CMU Environmental Science Research Centre, the latter also for administrative support.

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Tables

Table 1. Characteristics used to classify tree crowns, adapted and modified from Koelmeyer (1959), Trichon and Julien (2006) & Gonzalez-Orozco's (2010).

Crown characteristics	Descriptors/classes	Description
Crown Type (CT)	Single	Crown entire without sub-division
	Multiple	A crown that has two or more sub-divisions within with each component resembling an individual crown
Vertical Crown Shape (VCS)	Slightly rounded, more rounded, hemispherical, pointed	Described based on intensity of curvature at the highest point of crown surface. Pointed > hemispherical > more rounded > slightly rounded
	Flat	Crown surface appears to be more or less horizontal
Horizontal Crown Shape (HCS)	Round, oval, elongated, star shaped, irregular	Described based on ratio of crown length: crown breadth: if 1:1 = round; if 1.5:1 = oval; if 2:1 = elongated; if crown shape does not follow above patterns, it is described as "irregular".
Crown Margin (CM)	Entire, crenulated, lobed	Entire - if the crown margin is more or less smooth without marked indentations; crenulated - if crown margin has indentations penetrating less than 25% towards to Centre; lobed - crown with deep indentations (>25%). towards its center
Foliage Texture (FT)	Smooth	Branches or any other lower elements concealed by dense compact foliage
	Rough	Branches or any other lower elements are distinguishable through the foliage
Crown Color (CC)	Green, yellow, red, brown, white, pink, blue	Shades of color or mixture of colors
Phenology	Leaf flush, Leaf fall (described as crown density of 0, 3/4, 1/2, 1/4, 1), flowering, fruiting	Phenophase at the crown level

Table 2. Leaf characteristics and descriptors used to delineate tree species. Adapted and modified after Gardner et al. (2007).

Leaf characteristics	**Descriptors**
Leaf Type (LT)	Simple or compound
Leaf Arrangement (LA)	Alternate, opposite, spiral, whorled, bundled, imparipinnate, paripinnate
Leaf Shape (LS)	Lanceolate, ovate, elliptic, oblong, needle-like, elliptic
Leaf Color (LC)	Green, pink, yellow, red, mixture of colors, shades of color

Table 3. Phenophases and identification accuracy

Species	**Month/Year**	**Phenophase**	**Identification Accuracy (%)**	**Performance class***	**Error of commission (%)**
Castanopsis calathiformis	July 2018	Flowering	100	Excellent	100
Prunus cerasoides	Jan. 2019	Flowering	100	Excellent	0
Choerospondias axillaris	Jan. 2019	Leaf fall	100	Acceptable	0
Toona ciliata	Aug. 2018	Leaf flushing	83	Marginal	25

**According to field trials reported by Elliott et al. (2003)*

Table 4. Key of species for the most identifiable months

	Artocarpus gomezianus	*Castanopsis calathiformis*	*Castanopsis tribuloides*	*Choreospondias axillaris*	*Ficus altissima*	*Magnolia garrettii*	*Pinus kesiya*	*Prunus cerasoides*	*Toona ciliata*
Crown									
Type (CT)	Single	Single	Single	Multiple	Single	Single	Multiple	Single	Multiple
Vertical Shape (VCS)	More rounded	More rounded	Slightly rounded	Flat	Flat	Rounded	More rounded	More rounded	Flat
Horizontal Shape (HCS)	Oval	Oval	Round	Elongated	Oval	Oval	Elongated	Elongated	Irregular
Margin (CM)	Crenulated	Entire	Entire	Entire	Entire	Entire	Entire	Entire	Entire
Foliage Texture (FT)	Rough	Rough	Smooth	Smooth	Smooth	Smooth	Rough	Smooth	Rough
Color (CC)	Dull green	Yellowish dull green	Bright green	Light green with yellow spots	Dark green with yellow spots	Dark green	Dark green with black spots	Branches visible with pink flowers	Dull green with yellow patches with visible branches
Leaves									
Type (LT)	Simple	Simple	Simple	Compound	Simple	Simple	Simple	Simple	Compound
Arrangement (LA)	Alternate spiral	Alternate spiral	Alternate spiral	Paripinnate	Alternate spiral	Alternate spiral	Bundled	Alternate spiral	Imparipinnate
Shape (LS)	Ovate	Elliptic	Lanceolate	Lanceolate with tapering end	Ovate	Elliptic	Needle-like	Ovate-oblong	Narrowly ovate with tapering end

Color (LC)	Glossy dark green		Glossy dull green and yellow		Leathery dark green		Light greenish yellow		Leathery dark green with prominent midrib		Leathery dark green and yellow		Leathery dark green		Yellowish-green		Dull green	
Image filters	*Low*	*High*	*Low*	*High*	*Low*	*High*	*Low*	*High*	*Low*	*High*	*Low*	*High*	*Low*	*High*	*Low*	*High*	*Low*	*High*
Hue	40	60	0	80-115	0	69	30-70	70-115	60	105	50-70	80-103	50-60	80-93	30	82-92	32-40	65-85
Saturation	0	54-64	0	65-101	49	255	40-58	80-115	20	65-113	0-50	81-145	50-80	120-135	20-50	68-88	30-60	112-255
Brightness	117-143	255	128-141	255	110	255	70-130	255	123	255	107-128	255	116-143	255	110	255	90-134	255
Max. ID success																		
Month	October		July		December		January, July, August, October		August, September,		November		All 9 months of study period		January		August	
Phenophase			Flowering		Leaf flush		Leaf flush (July), leaf fall (Oct)								Flowering		Leaf flush	
Identification Score	87.50%		100%		100%		100%		100%		100%		100%		100%		83.3%	
Error of commission	12.5%		100%		0%		(Jan, Jul, Aug, Oct) 0%		0%		0%		0%		0%		25%	