

**Unmanned Aerial Vehicle Monitoring of Forestry Best Management Practices: Feasibility,  
Potentiality, and Framework**

by

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## Abstract

This study explores unmanned aerial vehicles (UAVs) in the forestry sector and evaluates the feasibility and potential of UAVs for monitoring forestry best management practices (BMPs). The review of 58 studies from 2003 to 2021 found that rotary-wing UAVs were the most used and that RGB imaging was the most widely employed technology for data collection. The most common applications of UAVs in forestry included generating high-definition maps and models, conducting forest inventory and structure assessments, detecting forest health and diseases, and monitoring forest fire activities. The study comparing the performance of UAV-live feed and UAV-created map surveys with conventional surveys found that UAV-live feed surveys were as effective as conventional surveys in all major BMP categories (correlation coefficient = 0.98). UAV-created map surveys were less effective but provide an observation record that includes a map of the site. In conclusion, UAVs have the potential to greatly improve the quality of data collection in the forestry sector and are a feasible option to monitor forestry BMPs.

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## Chapter 1. Review of Unmanned Aerial Vehicles in Forestry: Global Perspective

### 1.1 Abstract

The latest advancements in unmanned aerial vehicle (UAV) technology have made them highly useful in various aspects of the forestry sector. UAVs provide a supplementary method for data collection that can fill gaps in information and improve the quality of data. This review of 58 studies from 2003 to 2021 examines the use of UAVs for various forestry applications, covering common UAV types, cameras, sensors, and their specific applications and the advantages and disadvantages of the use of UAVs along with a brief view into future areas of UAVs applications. The use of rotary-wing UAVs was prevalent (74%) in the reviewed studies, with RGB imaging being the most widely employed (63%) technology for data collection. The reviewed articles revealed that the most common applications of UAVs in forestry included generating high-definition two-dimensional orthomosaic maps and three-dimensional models, conducting forest inventory and structure assessments, detecting forest health and diseases, and monitoring forest fire activities. UAVs offer a high-spatial resolution, the ability to acquire geographic data on demand, the capability of traversing difficult terrain, and low operational costs. The trend is that UAVs are becoming smaller, lighter, more efficient with improved technology, and cheaper, increasing their potential in forestry.

## 1.2 Introduction

The importance of having accurate, up-to-date information about the composition, structure, distribution, and growth of forests must be considered when it comes to making informed decisions about sustainable forest management. This data is a key foundation for any decisions related to managing these resources (Torresan et al., 2017; Wulder et al., 2008).

Remote sensing technology can acquire high-resolution data of forests. It is applied in a variety of forestry-related applications, such as creating computer models of forested areas (Joshi et al., 2004), identifying different types of forests (Dalponte et al., 2008; Goodenough et al., 2003; Pal, 2005), forest structure estimation (Baines et al., 2020; Lim et al., 2003), and detecting changes in forested areas (Coppin & Bauer, 1996; Housman et al., 2018). Historically, remote sensing data could only be collected from satellites or manned aircraft (Melesse et al., 2007; Pinter Jr et al., 1990). The use of satellite imagery has become a popular choice for large-scale mapping and monitoring efforts due to its broad coverage capabilities. As reported by White et al. (2016), some satellite systems possess the capability of providing high-spatial resolution multispectral imagery. Despite the many advantages, it can be limited by cloud coverage and timing issues (Al-Wassai & Kalyankar, 2013; Rasid & Pramanik, 1993). Manned aircraft can provide high-resolution data, at a high cost (Dash et al., 2019; Wang et al., 2019). In contrast, unmanned aerial vehicles (UAVs) (also known as drones) have become increasingly popular in forestry over the past decade. With advancements and the rise of low-cost UAVs, it is now possible to collect high-resolution data on forest areas at a low cost (Diez et al., 2021). The utilization of UAVs in forestry can provide several advantages, such as the potential for acquiring data at any time, cost efficiency, flexibility in scheduling flights, a diverse selection of applications, and decreased hazards for human operators (Banu et al., 2016; Campos et al., 2019; Johnston, 2019; Torresan et

al., 2017).

Continuous developments of new UAVs and sensors have increased UAV-based remote sensing applications in forestry (Tang & Shao, 2015). It is important to note that UAVs should not be considered as a replacement for satellite or manned aircraft observations, as each technology has its strengths and limitations (Hassler & Baysal-Gurel, 2019). UAV and satellite imagery are often used together in many instances (Gevaert et al., 2015; Maimaitijiang et al., 2020). Currently, UAV use in forestry is at an exploratory stage and expanding rapidly (Alsammak et al., 2022; Shahbazi et al., 2014); however, there are still several difficulties related to UAV-based remote sensing such as the legality of UAV use (Colomina & Molina, 2014), limited flight endurance (Chen et al., 2018; McElwee, 2021; Shivgan & Dong, 2020), data degradation due to lighting conditions (Duffy et al., 2018), airspace restrictions, and difficulty to operate in severe weather conditions (Alsamarraie et al., 2022). This article aims to provide a comprehensive summary of the use of UAVs in forestry rather than exhaustively cover all research on the topic. The review focuses on using UAVs in forestry, including common types of UAVs, cameras and sensors, advantages, and disadvantages, and the future of UAVs in forestry.

### **1.3 Types of UAVs, cameras, and sensors**

UAVs have a long history, with early developments dating back to the 19th century. However, it was not until the 1950s that UAVs started to be primarily utilized for military purposes such as reconnaissance and surveillance (Banu et al., 2016). Recently, the utilization of UAVs has seen a substantial rise for diverse civilian applications, such as precision agriculture (Tsouros et al., 2019), disaster management (Erdelj et al., 2017), and forestry (Banu et al., 2016;

Tang & Shao, 2015). Other industries that have seen growth in UAV usage include construction (Elghaish et al., 2020), and mining (Ren et al., 2019). As UAV usage expands, a variety of different airframes have been developed. In forestry, rotary-wing and fixed-wing UAVs are the most common types used (Tang & Shao, 2015). Fixed-wing UAVs are known for their horizontal take-off and landing capabilities, longer flight times and more extensive coverage areas per charge (Lisein et al., 2013; Sankey et al., 2017). However, these UAVs cannot hover and require more space for take-off and landing than rotary-wing UAVs (Olson & Anderson, 2021). Recently, some fixed-wing UAVs have also been developed with vertical take-off and landing (VTOL) capabilities, which use a combination of fixed-wing flight and vertical propulsion systems such as propellers or jets. On the other hand, rotary-wing UAVs are known for their VTOL capabilities, ease of operation, stability during flight, and ability to hover. However, their flight time and coverage range are more limited than fixed-wing UAVs (Boon et al., 2017; Gini et al., 2014; Sankey et al., 2017).

UAV data collection in forestry uses standard red, green, and blue (RGB) cameras along with multispectral, hyperspectral, thermal, and light detection and ranging (LiDAR) sensors. RGB cameras create images by assigning three values to each pixel - red, green, and blue - representing the intensity of specific colours. Multispectral sensors record multiple (3-10) coarse bands of the electromagnetic spectrum (Hagen & Kudenov, 2013). Hyperspectral sensors are similar to multispectral sensors but differ in the size of the bands they capture. Hyperspectral sensors can detect thousands of narrow bands of light for each pixel in the image (Junttila et al., 2015). Thermal imaging sensors can obtain localized temperatures of objects using regions of electromagnetic radiation located within the electromagnetic spectrum's infrared segment (mid-infrared imaging and far-infrared imaging) (Hou et al., 2022). The application of LiDAR

technology using UAVs has vast applications in the forestry industry. LiDAR technology acquires ranging data by emitting light pulses, in the form of laser energy, and measuring the time interval between the emission and reception of the reflected energy (Dubayah & Drake, 2000; Peterson et al., 2007). The range to the target is determined by measuring the time it takes for the reflected energy from the target to reach the LiDAR sensor.

When applied to forests, LiDAR sensors can capture three-dimensional (3D) information of forests. This information includes details about forest structure, such as topography and distribution of tree crowns, providing a comprehensive view of the forest's composition. Moreover, LiDAR technology can also provide information from within the canopy, further enhancing the accuracy and comprehensiveness of the collected data (Popescu, 2007). Orthomosaic maps are often created using high-resolution RGB imagery captured by UAVs. Generating orthomosaic maps involves capturing multiple images from various perspectives and then using photogrammetric methods to stitch them together into a single, smooth representation. RGB cameras are also commonly used in machine learning for object recognition, phenology analysis, and identifying plant pathologies (Esposito et al., 2021). High-resolution digital surface models (DSM) and digital terrain models (DTM) have been used for the estimation of tree height (Waser et al., 2008). DSMs and DTMs can be generated through stereophotogrammetry using high-resolution RGB imagery or through LiDAR point cloud data analysis. LiDAR has successfully captured forest structure, mapped individual trees in forests, forest canopy mapping from below, calculated forest topography and infrastructure, etc. (Carson et al., 2004; Dassot et al., 2011). Species of trees can be identified with reasonable accuracy (cross-validation accuracies from 61.64% to 84.25% for pine species and classification accuracies from 78.36% to 92.54% for hardwood species) through the use of false-colour images that incorporate

multispectral and hyperspectral data (van Aardt, 2000). The analysis involves extracting the unique spectral characteristics of different tree species and utilizing this information to classify them.

#### **1.4 Review of UAVs in forestry**

Applications of UAVs in forestry were divided into seven categories based on the following research topics: (1) forest structure estimation and inventory, (2) forest health and diseases, (3) forest fire, (4) forest regeneration, (5) species classification and identification, (6) post-harvest soil erosion, and (7) other studies (areas with few studies that could not be categorized in the above topics). Reviews of the forestry UAV studies are below, along with summarization tables in the appendix (A1).

##### **1.4.1 Forest structure estimation and inventory**

Forest structure estimation and inventory refer to determining the characteristics of a forested area, such as such as determining the quantity, dimension, and type of trees present. The goal of forest structure estimation and inventory is to provide accurate and comprehensive information on the composition and structure of forested areas, which can be used for various management, conservation, and research purposes. Integrating UAVs into forest structure estimation and inventory has proven to be a valuable tool for overcoming the limitations associated with traditional remote sensing methods. The low temporal and spatial resolution, often experienced with remote sensing, can be mitigated by utilizing UAVs equipped with advanced technology such as RGB cameras or LiDAR sensors. These instruments allow researchers to estimate forest structures and gather comprehensive data on the composition and

structure of forested areas more accurately.

According to a study by Dandois and Ellis (2013), using overlapping UAV photos to create high-resolution, multispectral 3D datasets is an effective method for observing the structural and spectral dynamics of forest canopies in 3D. The study employed a rotary-wing hexacopter equipped with a digital camera to make observations of canopy phenology at a desired temporal resolution (leaf-on and leaf-off conditions). It was found that this method for constructing 3D forest measurements and maps was cost-effective and logistically efficient, with results comparable to those obtained using airborne LiDAR and conventional methods.

In a study by Fritz et al. (2013), an octocopter with a standard consumer-grade camera was evaluated for its ability to detect and reconstruct single trees in open stands automatically. The research, which took place in an old oak (*Quercus robur*) dominated forest in Germany, compared the results obtained from the UAV with those from a terrestrial laser scanner (TLS). The authors found a good correlation ( $r = 0.70$ ) between the radius of the stems extracted from the two data sources. They concluded that UAVs could be a cost-effective and efficient method for detecting individual trees in sparse forests when utilizing 3D point clouds generated through image matching.

In a study conducted in Belgium, Lisein et al. (2013) employed a fixed-wing UAV outfitted with a near-infrared-adapted camera to develop a photographic method for creating a canopy height model (CHM) of 200 ha mixed uneven-aged broadleaved stands. The research aimed to determine the accuracy of height measurements derived from a photo CHM compared to those obtained from a CHM generated using airborne laser scanning (ALS) data. The study found that the measurements from the cost-effective photo CHM were a reliable substitute for

the more expensive LiDAR data obtained from manned aircraft.

In a study by Getzin et al. (2014), a fixed-wing UAV was used to assess spatial gap patterns in forests of varying management in Germany. The study found that the UAV was highly influential in mapping small gaps and canopy structures and provided high-resolution images capable of detecting openings as small as one m<sup>2</sup>. The study was conducted at altitudes of 250m and examined ten 1-hectare forest plots.

Zarco-Tejada et al. (2014) conducted a study to evaluate the use of a low-cost fixed-wing UAV equipped with a modified consumer-grade RGB camera for colour-infrared detection in an olive (*Olea europaea* L.) orchard in Spain. The study aimed to determine the accuracy of UAV imagery for quantifying canopy height. The research found that the tree height values obtained from the consumer-grade cameras on the UAV were accurate ( $R^2 = 0.83$ ) when compared to more expensive miniaturized LiDAR systems for canopy height quantification.

Dandois et al. (2015) flew a hexakopter with a digital camera to collect aerial images to characterize forest canopy structure across three temperate deciduous forest sites in Maryland, USA. The authors aimed to understand how the quality of UAV structure from motion (SfM) point clouds and matrices change based on lighting, flight altitude, and image overlap. The study found no significant differences in observed height at different lighting levels, altitudes, and side overlaps. Additionally, the authors compared canopy parameters obtained from UAV-SfM remote sensing tools with canopy height measured from the conventional field-based survey as well as with high-resolution airborne LiDAR data and concluded that the UAV data was similar to airborne LiDAR and conventional field-based measurements under the optimal condition of clear lighting and high image overlap (>80%).

Puliti et al. (2015) used a fixed-wing UAV equipped with a near-infrared (NIR) camera to gather 3D variables in combination with ground reference data in the boreal forest of Norway. They aimed to evaluate the accuracy of the UAV-acquired data for mean height, dominant height, number of stems, basal area, and stem volume. They found that dominant height was the best-predicted variable ( $R^2 = 0.97$ ), while the number of stems was not a good predictor ( $R^2 = 0.60$ ). They concluded that UAV imagery was relatively accurate and comparable to other remotely sensed data, such as ALS, for providing forest inventory data at a local scale.

Zahawi et al. (2015) assessed extracting measures of canopy height, structural complexity, and canopy openness for restoration sites in Costa Rica. They used a rotary-wing hexakopter with a digital camera to collect aerial images. The authors noted that canopy height, above-ground biomass, and percent canopy openness were accurate ( $R^2 \geq 0.85$ ,  $R^2 \geq 0.81$ , and  $R^2 \geq 0.82$ , respectively) when compared with conventional field-based measurements.

Chianucci et al. (2016) conducted a study to examine the effectiveness of using a fixed-winged UAV equipped with a commercial RGB camera in pure beech stands in Italy to estimate forest canopy attributes. They found that estimates of leaf area index (L) from UAV images acquired with commercial digital cameras provided quick, cost-effective, and relatively accurate ( $R^2 = 0.70$ ,  $p$ -value  $< 0.01$ ) estimates when compared with those obtained from adopting either the planophile or the spherical leaf angle distribution.

Hassaan et al. (2016) used a rotary-wing UAV equipped with an RGB camera to acquire images and to count the number of trees in Pakistan. UAV and computer vision algorithms successfully identified trees with reasonable accuracy (72%) compared to conventional field-

based measurements. Hassaan et al. 2016 concluded that UAV and computer vision algorithms efficiently acquire images and count trees in an urban environment.

McNeil et al. (2016) examined the ability of UAVs to measure leaf angle by comparing leaf angle measurements taken from UAVs to those taken from conventional sources such as towers, ladders, buildings, and poles. They used a rotary-wing quadcopter with a 4K camera and a rotary-wing hexacopter with a compact camera. They found that the UAVs provided statistically similar results (t-test,  $p$ -value  $< 0.05$ ) to those obtained from conventional field-based methods.

According to a study by Wallace et al. (2016), the effectiveness of two technologies, ALS and SfM point clouds, were compared in determining absolute terrain height, horizontal and vertical arrangement of elements within the forest canopy, as well as details related to individual trees within a Tasmanian eucalyptus (*Eucalyptus globulus*) forest that has varying levels of canopy coverage in Australia. They used a rotary-wing octocopter equipped with a digital RGB camera. The study found that SfM and ALS accurately portrayed the upper forest canopy layer. However, they determined that the ALS method had better penetration of denser canopies and provided a more accurate estimate of the vertical distribution of vegetation.

Zainuddin et al. (2016) studied to quantify tree height using CHMs from high-resolution images captured by a rotary-wing UAV equipped with an RGB camera. They flew the UAV at an altitude of 50 m AGL in Malaysia's coconut (*Cocos nucifera*) forest. They found that tree height estimation using CHM was correlated with observations from the conventional field-based surveys ( $R^2 = 0.80$ ). However, they also noted that the UAV application in estimating height of coconut trees was more accurate than previous studies using the same technique.

Banu et al. (2017) evaluated the efficacy of a low-cost commercial rotary-wing UAV equipped with a digital camera in a mixed beech (*Fagus spp*) and durmast oak (*Quercus petraea*) stand in Romania for measuring tree height. The authors concluded that a low-cost commercial UAV effectively measured the dominant height of trees in a stand rather than individual tree heights. The difference between the results of the UAV-based and conventional field-based methods was below 1% of the canopy cover area.

Miller et al. (2017) examined the accuracy of low-cost UAVs in determining height and biomass in tropical monoculture plantations. UAV imagery was collected from the Agua Salud project in Panama using a rotary-wing hexakopter with a digital camera. The authors compared the height and biomass of five different species extracted from UAV imagery-based CHM and airborne LiDAR DTM-based CHM to data collected by conventional field-based survey and found that both CHMs strongly agreed with conventional field-based data for predicting the height of all species. However, the CHM from the airborne LiDAR DTM predicted heights and biomass more accurately than UAV imagery-based CHM on a per-species basis.

Mlambo et al. (2017) evaluated horizontal and vertical accuracy of SfM-derived UAV imagery for measuring height of individual trees. Aerial imagery was collected from two sites using two different UAVs. The one site in Meshaw, England, a fixed-wing UAV was used to collect imagery and compare the results with airborne LiDAR point cloud surface models. The other site in Dryden, Scotland, estimated tree height from SfM-derived imagery collected by a rotary-wing UAV and compared the results with ground-measured tree heights. Mlambo et al. 2017 found that the SfM method performed poorly ( $R^2 = 0.19$ ) for measuring heights in closed canopies; however, they suggested that UAVs can be used to provide a low-cost solution in

developing countries with sparse canopy cover (<50%).

In a study by Panagiotidis et al. (2017), high-resolution imagery captured by a rotary-wing UAV equipped with an RGB camera was used to extract heights and determine the local maxima and inverse watershed segmentation (IWS) to extract estimation of crown diameters. They found that there was a stronger agreement between conventional field-based measurements and estimation from images for heights (root mean square error (RMSE) % 11.42-12.62) than crown diameters (RMSE % 14.29-18.56). The study concluded that the overall accuracy for heights and crown diameters was acceptable, and that high-resolution imagery collected from UAVs effectively determined height and crown diameters.

Sankey et al. (2017) employed a rotary-wing octokopter fitted with a LiDAR sensor and hyperspectral camera and a fixed-wing UAV equipped with a multispectral sensor to classify and measure structural characteristics of individual canopies in ponderosa pine forests and ecotone vegetation in northern Arizona, USA. They found that UAV LiDAR data were effective in estimating individual tree height, crown diameter, total tree canopy cover, and tree density ( $R^2 = 0.90$ ,  $R^2 = 0.72$ ,  $R^2 = 0.87$ , and  $R^2 = 0.77$ , respectively), but it was challenging to characterize a densely vegetated forest site's canopy fully. The UAV images were found to help monitor changes in canopy cover and tree density and quantify the results of treatments. Additionally, they noted that the combination of UAV-based LiDAR and hyperspectral imagery was more effective (88% overall accuracy) in classifying multiple species and characterizing forest structure changes than either method alone.

Alonzo et al. (2018) used high-resolution imagery captured by a rotary-wing UAV equipped with a consumer-grade RGB camera through SfM to generate key forest inventory

parameters in the boreal forest of Alaska, USA. They found that SfM heights strongly agreed with conventional field-based measurements ( $R^2 = 0.94$ ), and SfM point cloud data significantly classified species at the crown scale (85% accuracy). Furthermore, the authors also mapped tree density, basal area, and above-ground biomass with errors of 3%, 2%, and -6%, respectively, using SfM point cloud data. Based on their finding, UAV SfM efficiently generated information on the density, basal area, biomass, and species composition of boreal forests.

Iizuka et al. (2018) deployed a rotary-wing UAV fitted with an RGB camera over a cypress (*Chamaecyparis obtusa*) forest in a mountainous area of Japan to construct a 3D model of forest structures. They used CHM to extract the maximum height of individual trees. Despite the challenges of limited ground visibility in a densely forested area, they found that tree heights were accurately estimated with an RMSE of 1.71 meters for observed tree heights ranging from 16 to 24 meters. They also discovered that individual tree diameter at breast height (DBH) was strongly correlated with canopy width ( $R^2 = 0.78$ ) and canopy area ( $R^2 = 0.79$ ) when DBHs ranged from 11 to 58 cm. Their results concluded that using a UAV was efficient for accurate spatial analysis of forest structure.

Jones et al. (2020) imaged a Mangrove (*Avicennia marina*) stand in south Australia using a rotary-wing UAV equipped with an RGB camera to estimate various parameters of tree structure. The authors found that conventionally measured tree height and UAV image-based tree height had a strong positive correlation ( $R^2 = 0.98$ ); however, image-based estimates of above-ground biomass were less accurate ( $R^2 = 0.54$ ) when compared with conventional-based estimates.

Karl et al. (2020) used a rotary-wing UAV equipped with a 20-megapixel RGB camera to

collect overlapping aerial images to construct 3-dimensional point clouds of willows (*Salix spp.*) to estimate canopy volume. Canopy volume estimated from the UAV imagery-based point cloud was highly correlated with conventional field-based measured volume ( $R^2 > 0.80$ ), and the authors concluded that UAV-collected imagery was an efficient method for measuring and monitoring riparian woody vegetation.

In Norway, Solvin et al. (2020) utilized RGB imagery collected from a rotary-wing UAV to develop a CHM of a dense stand of 15-year-old Norway spruce (*Picea abies L. Karst*). The CHM was used to estimate individual trees' total height, intra-annual height growth, and phenology. The authors found that the estimation of intra-annual growth ( $r < 0.24$ ) and phenology ( $r = -0.05$  for day05,  $r = 0.02$  for day95) were not accurate, whereas total tree height to the uppermost whorl was accurately estimated (RMSE = 0.93 m) when compared with manual measurements.

In 2021, SfM-based 3D point generation and processing techniques were used by Gülci et al. (2021) to estimate tree height and crown projection area in a stone pine (*Pinus pinea, L.*) plantation affected by winter storm damage. A rotary-wing UAV with a digital camera for the photogrammetric flight was used to evaluate the accuracy of height and crown projection area measurements of 105 stone pine trees using UAV-based SfM-derived 3D dense point clouds. The authors found no significant differences between the conventional field-based and SfM measurement-based methods for estimating height ( $p$ -value = 0.973) and crown projection area ( $p$ -value = 0.681). UAV imagery-based SfM measurements were as effective as conventional field-based methods.

## 1.4.2 Forest health and diseases

Forest health refers to the overall well-being of forests, including the health of individual trees and their communities and the ecological processes that sustain them. Forest disease can significantly impact tree health, resulting in loss of biodiversity, decreased carbon sequestration, and changes to ecosystem services. UAVs have shown promise in detecting and mapping diseases in forests. Studies have utilized UAVs with various cameras and sensors, including colour infrared, hyperspectral, thermal, and multispectral cameras, to monitor forest health and disease.

Lehmann et al. (2015) evaluated the efficacy of UAV-acquired colour infrared (CIR) images to provide sound remote sensing data and maps of inferred pest infestation levels to support forest management activities. The authors collected aerial images from two study sites in August 2013 using a rotary-wing UAV equipped with a CIR-modified digital camera. Study areas were occupied predominately with oak (*Quercus robur*), European hornbeam (*Carpinus betulus*), isolated beech trees (*Fagus sylvatica*), and several understorey species. The forests were infested by the oak splendour beetle (*Agrilus biguttatus*). The authors reported that the overall accuracy of classifying pests using UAV-based colour infrared imagery was more than 80%. This method was also found to be more efficient in terms of time and cost savings, with estimated savings of over 50% compared to conventional field-based methods.

Näsi et al. (2015) used an octocopter UAV equipped with a hyperspectral camera to determine the potentiality of UAV-based 3D hyperspectral imaging for mapping bark beetle (*Ips typographus* L.) damage in a mature Norway spruce (*Picea abies* L. Karst.) forest in southern Finland. The team utilized a dense point cloud generated from UAV-based imagery, which

yielded an accuracy of 74.7% in detecting bark beetle damage in individual trees. When the trees were separated into healthy, infected, and dead categories, the overall accuracy was 76% (Cohen's kappa = 0.60). Furthermore, when the trees were classified into two groups (healthy and dead), the overall accuracy increased to 90% (Cohen's kappa = 0.80).

Smigaj et al. (2015) explored the efficacy of a low-cost UAV-based thermal system for monitoring disease-induced canopy temperature rise. The authors used a fixed-wing UAV equipped with a longwave infrared camera and a NIR-modified compact digital camera in five research plots of scots pine (*Pinus sylvestris*) and lodgepole pine (*Pinus contorta*) representing a range of red band needle (*Dothistroma septosporum*) infection levels within the Queen Elizabeth Forest Park in Scotland. The authors found that when the disease progressed, there was a slight temperature increase ( $r = 0.53$ ,  $p\text{-value} = 0.001$ ) by using a NIR-modified digital camera.

Kulhavy et al. (2016) used a rotary-wing UAV equipped with a front and downward-looking RGB camera to evaluate the condition of 52 trees using a hazard rating system designed for an urban landscape. They compared UAV-based hazard ratings to the Council of Tree and Landscape Appraisers (CTLA) method, which evaluates tree condition based on six factors: trunk condition, growth, crown structure, insect and disease, crown development, and life expectancy. The study found a strong correlation between UAV-based hazard ratings and CTLA ratings for overall tree conditions ( $r = 0.97$ ;  $p\text{-value} < 0.001$ ).

Michez, Piégay, Lisein, et al. (2016) developed a methodological approach to evaluate the effectiveness of using multi-temporal hyperspectral UAV imagery collected during a single growing season to identify riparian forest species and assess health conditions. The authors used a fixed-wing UAV with two digital cameras in southern Belgium. Data from flights conducted in

the late growing season or during partial leaf-off conditions were best suited for classifying riparian tree crowns. Accuracy of tree classification was 79.5% (site 1) and 84.1% (site 2), and the classification of health conditions of alder (*Alnus glutinosa*) was 90.6%.

Dash et al. (2017) used a rotary-wing UAV to acquire time-series multispectral imagery of a 2.7 ha study site located in the Kinleith Forest in New Zealand to develop methods for monitoring physiological stress from a UAV platform. They found that the multispectral imagery obtained from the UAV was useful (weighted kappa = 0.69) in detecting and monitoring symptoms associated with a forest disease outbreak in mature plantation trees.

Abdalla et al. (2020) used a rotary-wing UAV to gather aerial imagery of a brown salwood (*Acacia mangium*) forest in Bogor, Indonesia, during the spring and summer to identify spectral characteristics of leaves, which were used to locate and identify unhealthy trees. The study found that healthy, unhealthy, and dead trees had distinct spectral RGB values. The researchers also noted that as the health of a tree deteriorates, RGB value increases.

### **1.4.3 Forest fire**

UAVs have become a valuable tool in forest fire management. UAVs equipped with thermal cameras and other sensing equipment can provide real-time data on the extent and progression of fires, enabling firefighters to respond quickly and effectively. In addition, UAVs can survey the damage caused by fire, providing crucial information for post-fire activities such as reforestation, rehabilitation, and risk assessment.

One of the early studies in the field of forestry that highlighted the importance of UAVs for forest fire monitoring was conducted by Ambrosia et al. (2003). The authors used a fixed-

wing UAV equipped with an AIRDAS scanner, flying the UAV at 945 meters above ground level (AGL) over a prescribed burn in El Mirage, California. The UAV imagery was transmitted via a satellite telemetry system to an Incident Command Center and the World Wide Web. The study found that fully geo-rectified imagery collection, telemetry, geo-processing, and delivery were accomplished in less than ten minutes once the UAV was on station at the fire site.

Additionally, Ambrosia et al. (2011) demonstrated the capabilities of NASA Ikhana UAV equipped with a multispectral sensor, onboard processing, and data visualization to provide fire intelligence to management teams. Their findings concluded that integrating UAV platforms with sensor, communications, and geospatial technologies provided near real-time intelligence for disaster management.

Aicardi et al. (2016) employed a sequence of DSMs obtained from ALS data and digital images captured by a fixed-wing UAV equipped with an RGB camera to identify changes in a secondary forest in the Aosta Valley region of Italy. The UAV-DSM was compared to the ALS-DSM that was acquired in 2008. The study found that snag fall dynamics and tree regeneration were detected with high accuracy and efficiency in both systems, allowing for easier and faster characterization of small-scale post-fire processes over large areas.

Ghamry et al. (2016) evaluated forest monitoring and fire detection strategies using a combination of UAVs and unmanned ground vehicles (UGVs). The authors conducted a simulation that involved three UAVs and three UGVs. Simulation results indicated that both UAVs and UGVs effectively monitor forest fires.

Samiappan et al. (2019) used a fixed-wing UAV platform to collect five-band multispectral imagery in February 2016 to create a photogrammetry-based DSM and

orthomosaic for object-based classification analysis. The study found that the UAV-based DSM can be a good representative for airborne LiDAR-based DSM ( $R^2 = 0.97$ ). Additionally, the study found that the UAV-based classification map had higher overall accuracy (78.6%) than the burned area reflectance classification (BARC) (57% overall accuracy) for the same region when compared to ground reference (GR) data. The study suggested that a UAV platform with a multispectral sensor can collect data timely to map the extent of burned areas.

Aurell et al. (2021) evaluated the effectiveness of using UAV-based sensors and samplers to characterize emissions from large wildland fires. A rotary-wing UAV equipped with 'Kolibri,' a battery-powered, remotely controlled instrument composed of sensors and samplers to take emission samples, was used. The study found that the results of the emissions obtained using UAV-based sensors and samplers were consistent with the range of published emission factors obtained in other studies.

Martinez et al. (2021) used LANDSAT 8 imagery and imagery collected from a quadcopter equipped with an RGB digital camera to evaluate the effectiveness of satellite and UAV surveys in quantifying vegetation recovery after post-fire treatments in a Mediterranean forest in Central Eastern Spain. The authors found poor agreement ( $R^2 = 0.03$ ,  $p$ -value  $> 0.05$ ) between LANDSAT 8-derived visible atmospherically resistant index (VARI) and vegetation cover measured conventionally. However, they found that UAV-derived VARI was a good proxy for vegetation cover conventionally measured in the field ( $R^2 = 0.84$ ,  $p$ -value  $< 0.05$ ). UAVs could detect variability in vegetation cover only when there was a noticeable difference (e.g., between burned and unburned areas); in contrast, comparing areas with similar VARIs was not helpful (e.g., when evaluating the effectiveness of treatment).

#### 1.4.4 Forest regeneration

Forest restoration involves the renewal of forests, which can help reduce the effects of deforestation and boost the ecological, social, and economic advantages of forests. Recently, the application of UAVs has become increasingly popular for contributing to forest regeneration efforts. UAVs equipped with remote sensing technology provide comprehensive imagery of forested areas, enabling accurate mapping and monitoring of forests. This information can be utilized to aid in forest restoration planning and decision-making, such as identifying reforestation locations and tracking the progress and well-being of newly planted trees. Furthermore, UAVs can assess the scope and intensity of fires, pests, or other hazards and support post-disaster forest restoration initiatives.

Almeida et al. (2019) used a UAV-based LiDAR system to study the effectiveness of a mixed-species restoration plantation in increasing AGB. They measured canopy height, gap fraction, and leaf area index using UAV-based LiDAR (Phoenix LiDAR sensor) and compared results to conventional field-based methods to measure AGB. Almeida et al. (2019) found that LiDAR-derived canopy height had the strongest correlation with AGB, with a coefficient of determination ( $R^2$ ) of 0.84 and a relative root mean squared error of 15.5%.

Fromm et al. (2019) examined the possibility of using convolutional neural networks (CNNs) on data derived from a rotary-wing UAV equipped with an RGB camera to detect conifer seedlings in recovering seismic lines in North-eastern Alberta's boreal forest. The authors reported that this method was highly accurate for large and medium seedlings, making it useful for evaluating restoration success, but it may need to be more accurate enough for identifying

small seedlings in operational use.

Puliti and Granhus (2020) used photogrammetric UAV data and data analytics to model stand-level forest management needs and costs. The authors compared UAV-based models to models derived from ALS data and forest management plans. UAV-based models were more correlated ( $r = 0.38$  to  $0.59$ ) with management needs and tending costs than the ALS-based models ( $r = 0.32$  to  $0.54$ ) and previous inventory data ( $r = 0.33$  to  $0.57$ ).

Nuijten et al. (2021) investigated using UAV-based digital aerial photogrammetry (DAP) for mapping vegetation structures in regenerating forests. Two UAVs with RGB cameras were used to collect imagery in Alberta, Canada, and processed using SfM algorithms. The authors found DAP heights of short-stature vegetation were consistently underestimated, but strong correlations ( $r > 0.75$ ) were found for juvenile trees, shrubs, and perennials.

#### **1.4.5 Species classification and identification**

Forest tree species classification and identification is a critical aspect of forestry management, as it provides essential information for ecological and biogeographical studies and sustainable forest management and conservation. UAVs have gained considerable attention for supporting forest tree species classification and identification efforts. UAVs equipped with multispectral or hyperspectral sensors can provide high-resolution images of forested areas, allowing for precise mapping and monitoring of forest tree species. This information can identify areas of high biodiversity, detect, and monitor tree species invasions, and map the distribution of endangered species.

Gini et al. (2014) researched using UAVs to monitor and classify vegetation. Both supervised and unsupervised classification methods of multispectral images collected by a quadrotor equipped with modified camera sensors were used. The unsupervised classification resulted in an accuracy of 50%, while the supervised classification was 80%. The study concluded that conducting classification using UAV data alone was insufficient but provided useful information for analysing and identifying different tree species.

Michez, Piégay, Jonathan, et al. (2016) used a fixed-wing UAV with two digital cameras, one of which was adapted for near-infrared acquisition to map three riparian invasive plant species: Himalayan balsam (*Impatiens glandulifera* Royle), giant hogweed (*Heracleum mantegazzianum*), and Japanese knotweed (*Fallopia sachalinensis*, *Fallopia japonica* (Houtt.) and hybrids). The authors found classification accuracy of 72%, 68%, and 97% for Himalayan balsam (*Impatiens glandulifera*), Japanese knotweed (*Fallopia sachalinensis*, *Fallopia japonica* (Houtt.) and hybrids), and giant hogweed (*Heracleum mantegazzianum*), respectively. It was suggested that UAV users consider the season, sun trajectory, and other factors influencing mapping accuracy.

Näsi et al. (2016) used a rotary-wing UAV to identify different species of trees in South-eastern Finland. Based on their observation, the authors concluded that UAV-based hyperspectral technology provided accurate geometric, radiometric, and spectral information for measuring the forest canopy's 3D geometry and spectral characteristics.

Bolch et al. (2021) evaluated the effectiveness of UAV imaging spectroscopy in monitoring invasive species in wetland habitats by comparing the mapping performance of a UAV-mounted imaging spectrometer to a manned aerial vehicle-mounted imaging spectrometer

(MAV). A Headwall Nano-Hyperspec sensor was mounted on a rotary-wing UAV, and a HyMap sensor was mounted on the MAV. Data was collected in the Sacramento-San Joaquin River Delta in California, USA. The authors generated classification maps using random forest models. The map-making model selected for the classification of the nano imagery had an overall accuracy of 94.1%, which outperformed the HyMap classifier, which had an overall accuracy of 85.7%.

#### **1.4.6 Post-harvest soil erosion**

Timber harvest activities including establishing roads, skid trails, and stream crossings can cause significant soil erosion and sedimentation. This can negatively impact water quality and harm forest ecosystems' health, reducing trees' growth and productivity. Effective monitoring and management practices are essential to minimize the impacts of post-harvest soil erosion.

Pierzchała et al. (2014) used a rotary-wing UAV equipped with an RGB camera to capture high-resolution aerial imagery and generate a detailed post-harvest terrain model of a 7-ha wide forest in western Norway. They used the UAV data to estimate post-harvest soil displacement and skid trail geometry. The study found that the DTM derived from UAV imagery had a total root mean error of 8.2 cm and that the profiles with the highest and lowest side slopes showed the most considerable differences in soil volumes per running meter. They concluded that UAVs were effective in estimating soil displacement from skid trails but recommended reducing the coverage area, flying altitude, and calibrating cameras precisely to improve accuracy.

Talbot et al. (2018) employed UAV-derived orthomosaics in combination with desktop-based line interception sampling to estimate the degree of soil disruption after logging. They conducted flights with two rotary-wing UAVs in six clearcut sites in south-eastern Norway. From the orthomosaic maps, they discovered variations in the extent of vehicle traffic at different sites (ranging from 787 m ha<sup>-1</sup> to 1034 m ha<sup>-1</sup>). They concluded that manually tracing and categorizing vehicle traffic using orthomosaics provided a more detailed record of site disruption with lower resource requirements based on their observation during research.

#### **1.4.7 Other studies**

Getzin et al. (2012) examined the utility of using UAV-based images to evaluate understory biodiversity. Fixed-wing UAV equipped with an RGB camera was flown over beech-dominated deciduous and mixed (coniferous and deciduous) forests in Germany. The authors noted that detailed spatial information on gap shape metrics resulted in a strong correlation between disturbance patterns and plant diversity ( $R^2$  up to 0.74).

Puttock et al. (2015) employed a hexacopter equipped with a consumer-grade RGB camera to collect high-resolution aerial imagery in south-west England's headwaters of the Tamar River catchment. UAV data was used to generate orthomosaic maps and DSM data products in an area where beavers (*Castor fiber*) had recently been reintroduced. Effectiveness of these products in characterizing the environmental impacts of beaver reintroduction was determined. The authors found that the utilization of UAV-generated orthomosaic maps and digital surface models (DSMs) can effectively identify the effects on ecosystem structure, including the presence of dams and accompanying ponds and alterations in vegetation structure caused by beaver tree felling activity.

Mokroš et al. (2016) evaluated the effectiveness of using a GNSS device (Geo Explorer 6000) and a UAV to estimate the volume of wood chip piles. A rotary-wing UAV fitted with an RGB camera was flown at the height of 20 m AGL with a flight path that included 80% front overlap and 60% side overlap. Mokroš et al. (2016) reported that the UAV-based method for volume calculation was highly correlated ( $r = 0.99$ ) with the GNSS device-based volume calculation.

Gülci et al. (2017) studied the advantages and disadvantages of UAVs in forestry. The authors used a rotary-wing UAV flown at 120 m altitude in Turkey and collected DSM data with a resolution of 9.64 cm and orthomosaic maps at 4.82 cm/pix resolution. They concluded that UAV-derived high-resolution imagery was useful for evaluating forest resources, roads, and stream channels.

Klosterman and Richardson (2017) employed a rotary-wing UAV fitted with an RGB camera to examine the correlation between leaf life cycle events of trees and digital image analysis metrics of those same trees in aerial UAV imagery. The authors reported that by using a UAV, it was possible to observe the full seasonal cycle of deciduous canopy development at a landscape scale, with a spatial resolution high enough to discern patterns at the level of individual trees.

Yong and Yeong (2018) conducted a study to develop a human object detection algorithm using UAV vision for forest surveillance. They employed a rotary-wing quadcopter fitted with a GoPro Hero 4 to capture visual information. Yong and Yeong (2018) found that using human object detection algorithms with UAV vision was successful (average precision

0.77) in locating both humans and forestry equipment.

Dugdale et al. (2019) integrated SfM photogrammetry acquired from a UAV with a process-based temperature model to understand the effects of tree shading on river temperature. A rotary-wing quadcopter equipped with an RGB camera was used to gather aerial imagery of the Girnock catchment in Scotland. The study found that SfM was effective in estimating true canopy elevation ( $R^2 = 0.96$ ). Additionally, the authors observed that models with SfM data and airborne LiDAR data performed similarly.

de Almeida et al. (2020) evaluated the effectiveness of using a UAV-based LiDAR system to monitor tropical forest succession by analysing canopy structural attributes. The team flew a rotary-wing UAV equipped with a Phoenix Scout system, which combines LiDAR and other sensors with inertial and georeferencing systems. The study was conducted over nine forested plots in Sarapiquí, Costa Rica. Forest age was found to be positively correlated with spatial heterogeneity ( $r = 0.83$ ) and gap fraction ( $r = 0.72$ ) and negatively with understory leaf area index (LAI) ( $r = 0.52$ ). The accuracy of above-ground biomass (AGB) estimates from LiDAR-derived variables (canopy height and leaf area height volume (LAHV)) were found to be high ( $r = 0.80$ ).

In the Summer of 2019, Thiel et al. (2020) flew a rotary-wing UAV over the Roda Forest in central Germany to map selective logging and monitor forest management without using ground control points (GCPs). This study found high rates of detected trees were achieved using UAV data and the object-based image analysis (OBIA) approach (precision = 97.5%; recall = 91.6%).

Adand and Ridzuan (2021) conducted a study that employed a UAV to map environmental mitigation measures along a proposed access road in a reserve forest in Bentong, Pahang, Malaysia. The authors found that using a UAV to create photogrammetry was more efficient than using a total station or conventional field-based techniques to survey environmental mitigation measures.

## **1.5 Discussion**

This review article provides a concise but comprehensive analysis of the current use of UAVs in forestry. The above text provides information regarding specific applications, types of UAVs, sensors, and cameras. With this knowledge, it is beneficial to understand the application of UAVs, the advantages, potential use, and limitations of this technology in the forestry field.

### **1.5.1 UAVs in forestry**

This review analysed 58 published articles from 2003 to 2021 which employed UAVs in forestry. The studies covered various applications and were conducted by different organizations in many countries. Through this review, it was found that most of the forestry research utilizing UAVs was carried out by academic institutions (50), followed by government agencies (7) and research centres (1) (Figure 1). Majority of the studies were conducted in Europe (30), followed by North America (19).

RGB imaging (63%) was the most widely used technology, followed by multispectral (19%), hyperspectral (8%), LiDAR (7%), and thermal technology (3%) (Figure 2). UAV-based RGB imaging has seen significant growth over the past decade. RGB cameras are often included as standard equipment when purchasing a UAV. Their low cost and optimal resolution make it a

popular choice for data collection to create high-resolution 2D orthomosaic maps and 3D models, determining vegetation indices such as VARI, green leaf index (GLI), and for machine learning techniques in forest inventory, forest structure estimation, object recognition, phenology (Dandois & Ellis, 2013; Esposito et al., 2021; Hassaan et al., 2016; Yong & Yeong, 2018; Zhao & Lee, 2020).

In the reviewed studies, 74% utilized rotary-wing UAVs, while 26% used fixed-wing UAVs (Figure 3). Higher usage of rotary-wing UAVs can be attributed to their greater maneuverability, lower cost, compactness, ease of use, and higher payload capacity (Boon et al., 2017; Tang & Shao, 2015). Most studies focused on forest structure estimation and inventory, followed by forest health and diseases, forest fire, forest regeneration, species classification and identification, and post-harvest soil erosion (Figure 4).

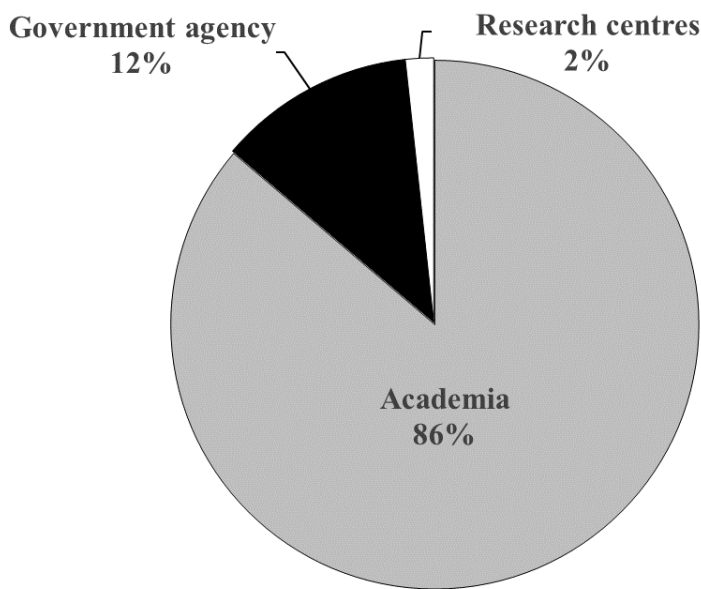


Figure 1: Various organizations that have conducted research in forestry using UAVs.

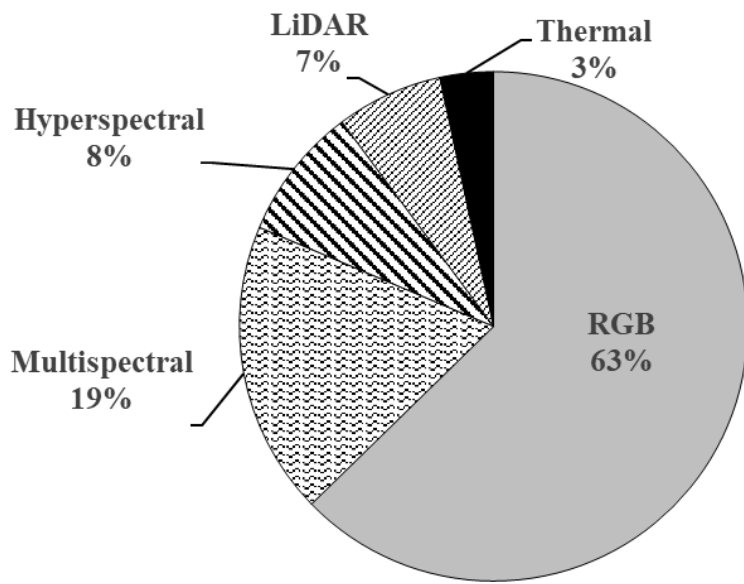


Figure 2: Percentages of forestry research studies by camera/sensors.

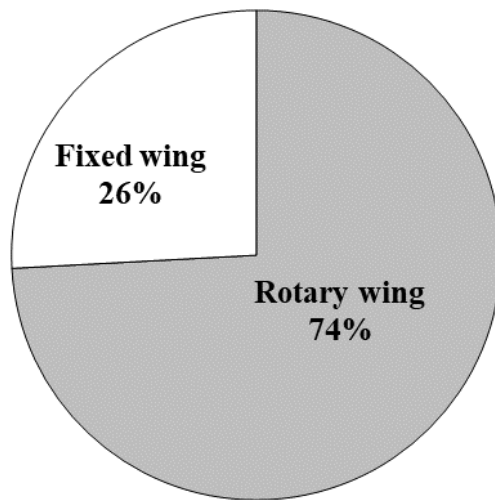


Figure 3: Percentages of forestry research studies by UAV type.

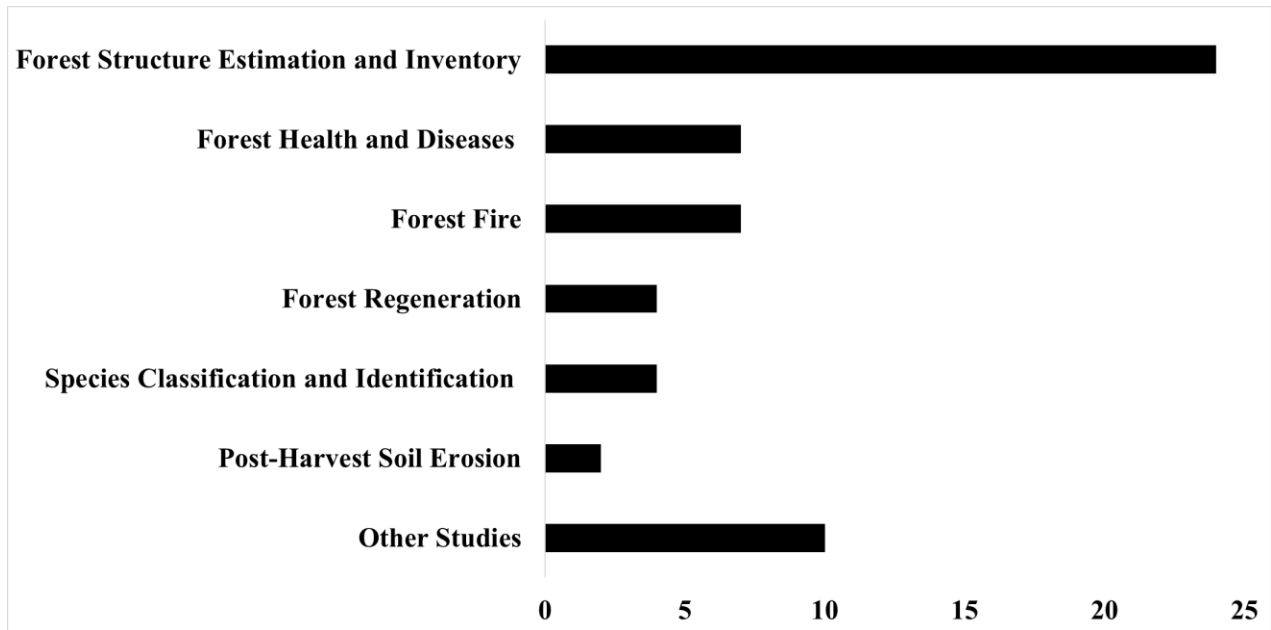


Figure 4: Number of studies by UAV application in forestry.

### 1.5.2) Advantages and limitations

UAV technology has been effectively used in a wide range of forestry applications. UAVs are a complementary option or replace existing spatial and conventional methods of data capture, filling gaps in information and improving the quality of forest data. Specific sensors, high spatial resolution, ability to acquire geographic data on demand, the capability to traverse difficult terrain, ability to fly in different trajectories, lower risk, cost-effectiveness, and ability to collect georeferenced imagery are all attributes that make UAVs suitable for remote sensing in forestry. However, many UAVs have short flight times, particularly with larger payloads, and UAV effectiveness can be greatly affected by the weather. Some limitations include limited area coverage compared to manned aerial vehicles and satellite-based mapping.

Regulations on UAV usage can limit the capabilities of UAV surveys, as rules vary by country and can include limitations on the line of sight, flight restrictions, and altitude limits.

Users must navigate these regulations, potentially seeking special exemptions or avoiding certain areas altogether. In addition, UAV pilots also need to think about the resolution needed, and there may need to be a compromise between resolution and flight altitude to obtain the needed data. Though there are some limitations, UAVs are constantly being improved. UAVs have become smaller, lighter, more efficient, and cheaper (Custers, 2016). Due to advancement, smaller UAVs can now use technology that they could not in the past. For example, attachment sizes (weight) have been decreasing, making more UAVs capable of utilizing new sensors (Pajares et al., 2013; Vergouw et al., 2016). These days, even small UAVs have efficient cameras and sensors, which can be very useful in forestry.

### **1.5.3) Future areas of research**

The advancements in sensor technology and machine learning analytics are poised to expand the use of UAVs in forestry, with the potential for a wide range of applications. While further exploration is needed in areas previously studied, new possibilities for UAV usage in forestry include monitoring the implementation of best management practices, mapping leaf area index and growth patterns, analysing forest health, assessing the effects of topography and climate on tree growth, studying carbon sequestration, monitoring storm damage, and conducting inspections and mitigation assessments.

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## 1.7 Appendix (A1)

Table 1: List of papers that used UAVs for forest structure estimation and inventory.

Investigator	Country	Study conducted by	Wing	Camera/Sensor	Major conclusions
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Dandois and Ellis (2013)	USA	Academia	Rotary	RGB	UAV-based method is a low-cost, streamlined method for producing 3D forest measurements and mapping products compared to LiDAR and conventional field-based methods.
Fritz et al. (2013)	Germany	Academia	Rotary	RGB	UAVs proved effective for detecting individual trees within forests.
Lisein et al. (2013)	Belgium	Academia	Fixed	Multispectral (RGB camera modified to capture NIR)	While photogrammetry holds promise for forest mapping and planning, there are numerous areas that require improvement.
Getzin et al. (2014)	Germany	Academia	Fixed	RGB	UAVs demonstrated exceptional efficiency in mapping small openings, repetitive patterns of openings, and the structure of the canopy.
Zarco-Tejada et al. (2014)	Spain	Research Centre	Fixed	Multispectral (RGB camera modified to capture NIR)	UAVs equipped with consumer-grade cameras demonstrated comparable accuracy to more expensive and complex LiDAR systems in determining canopy height.
Dandois et al. (2015)	USA	Academia	Rotary	RGB	UAV imagery provided accurate estimates of canopy height when compared to conventional field-based measurements and LiDAR
Puliti et al. (2015)	Norway	Academia	Fixed	Multispectral	UAV imagery is comparable to that obtained using other popular remote sensing data, such as ALS with

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high relative accuracy.

Zahawi et al. (2015)	Costa Rica	Academia	Rotary	RGB	UAV canopy height measurements had a strong correlation with conventional field-based measurements, but the correlation with canopy roughness was weaker.
Chianucci et al. (2016)	Italy	Academia	Fixed	RGB	UAV allowed for quick, affordable, and accurate assessment of forest canopy characteristics on a medium to large scale using a commercial digital camera.
Hassaan et al. (2016)	Pakistan	Academia	Rotary	RGB	Using a UAV along with computer vision techniques proved to be an effective method for capturing images and tallying trees in an urban setting.
McNeil et al. (2016)	USA and Estonia	Academia	Rotary	RGB	UAV surveys were as effective as conventional levelled digital photographs for mapping the distribution of leaf angles.
Wallace et al. (2016)	Australia	Academia	Rotary	RGB and Laser Scanning	SfM and ALS provided accurate representation of the upper forest canopy. However, ALS was able to penetrate the denser upper canopy more effectively and resulted more accurate estimates of vertical distribution of vegetation.

Zainuddin et al. (2016)	Malaysia	Academia	Rotary	RGB	CHMs derived from high-resolution images captured by a UAV can be used to accurately estimate tree height in dense canopy environments.
Banu et al. (2017)	Romania	Academia	Rotary	RGB	Low-cost commercial UAVs were successful in measuring dominant height of trees in a stand, but not at the level of individual trees.
Miller et al. (2017)	Panama	Academia	Rotary	RGB	The use of UAV imagery and LiDAR DTM to create Canopy Height Models (CHMs) was in strong alignment with field data for predicting tree species height. However, CHMs created from LiDAR DTM provided more accurate predictions of height and biomass on a per-species basis.
Mlambo et al. (2017)	Scotland, England	Academia	Fixed, Rotary	RGB	The SfM method did not perform well for measuring tree heights in closed canopy systems but can be a cost-effective solution in developing countries where canopy cover is sparse (less than 50%).
Panagiotidis et al. (2017)	Czech Republic	Academia	Rotary	RGB	UAV-collected high-resolution imagery was effective in measuring tree height and crown diameter.

Sankey et al. (2017)	USA	Academia	Rotary, Fixed	Multispectral, Hyperspectral, LiDAR	Using UAV-acquired multispectral data, a 3D point cloud of vegetation and bare earth was successfully generated. UAV images were also found to be efficient in determining canopy cover and density. Combining LiDAR and hyperspectral imagery resulted in even greater accuracy in identifying various species and characterizing forest structure.
Alonzo et al. (2018)	USA	Academia	Rotary	RGB	UAV SfM was found to be efficient in determining density, basal area, biomass, and species composition of boreal forests.
Iizuka et al. (2018)	Japan	Academia	Rotary	RGB	UAV was efficient for accurate spatial analysis of forest structures.
Jones et al. (2020)	Australia	Academia	Rotary	RGB	Tree height measured using conventional methods and UAV image-based point cloud had strong positive correlation.
Karl et al. (2020)	USA	Academia	Rotary	RGB	Point cloud estimates of canopy volume were found to be highly correlated with conventional estimates and more efficient in terms of time. UAV-collected images were also found to be effective in measuring and monitoring riparian woody vegetation.

Solvin et al. (2020)	Norway	Government agency	Rotary	RGB	While estimates of intra-annual growth and phenology were not found to be accurate using UAV imagery and CHM, total tree height to the uppermost whorl was accurately determined.
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Table 2: List of papers that used UAVs for forest health and diseases mapping.

<b>Investigator</b>	<b>Country</b>	<b>Study conducted by</b>	<b>Wing</b>	<b>Camera/Sensor</b>	<b>Major conclusions</b>
Lehmann et al. (2015)	Germany	Academia	Rotary	Multispectral (RGB camera modified to capture NIR)	The classification of pests using UAV-based colour infrared (CIR) images was found to be greater than 80% reliable, resulting in a savings of over 50% in terms of both time and financial cost for small to medium sized stands when compared to conventional field-based methods.
Näsi et al. (2015)	Finland	Government agency	Rotary	Hyperspectral	UAV was well suited for small-scale investigations of anomalous reflectance characteristics in trees.
Smigaj et al. (2015)	Scotland	Academia	Fixed	Thermal	UAV-based thermal system was able to notice temperature changes resulting from disease onset at sub-degrees.
Kulhavy et al. (2016)	USA	Academia	Rotary	RGB	UAV was an effective tool for urban tree hazard assessments and valuable for non-accessible or viewable areas from ground level.

Michez, Piégay, Lisein, et al. (2016)	Belgium	Academia	Fixed	Multispectral (RGB camera modified to capture NIR)	The quality of classification models using a cost-effective UAV-based approach was found to be comparable to that of multi-spectral and hyperspectral airborne imagery.
Dash et al. (2017)	New Zealand	Academia	Rotary	Multispectral	Multispectral imagery collected from the UAV was useful in detecting and monitoring tree disease symptoms (foliar discoloration).
Abdalla et al. (2020)	Indonesia	Academia	Rotary	Hyperspectral	Spectral value differences were attainable for differentiating healthy, sick, and dead trees.

Table 3: List of papers which used UAVs for forest fire.

<b>Investigator</b>	<b>Country</b>	<b>Study conducted by</b>	<b>Wing</b>	<b>Camera/Sensor</b>	<b>Major conclusions</b>
Ambrosia et al. (2003)	USA	Academia	Fixed	Thermal	UAV was useful for real-time remote sensing data to support disaster management.
Ambrosia et al. (2011)	USA	Academia	Fixed	Multispectral	UAV provided near-real-time intelligence to disaster management entities.
Aicardi et al. (2016)	Italy	Academia	Fixed	RGB	Multi-temporal, high-resolution DSMs generated by UAVs provided useful information for assessing post-disturbance dynamics.
Ghamry et al. (2016)	Canada	Academia	*	*	UAVs and UGVs were effective in monitoring and detecting forest fires.

Samiappan et al. (2019)	USA	Academia	Fixed	Multispectral	UAV data with high spatial resolution was found to produce more accurate classification maps than satellite data.
Aurell et al. (2021)	USA	Academia	Rotary	RGB	Using UAVs for emission sampling minimized the risk to personnel and equipment, allowed for flexible sampling locations, and ensured that representative fresh smoke constituents were captured.
Martinez et al. (2021)	Spain	Academia	Rotary	RGB	UAV surveys were effective to detect variability of vegetative cover between burned and unburned areas.

\* Was not stated in the article.

Table 4: List of papers that used UAVs for forest regeneration-related studies.

<b>Investigator</b>	<b>Country</b>	<b>Study conducted by</b>	<b>Wing</b>	<b>Camera/Sensor</b>	<b>Major conclusions</b>
Almeida et al. (2019)	Brazil	Academia	Rotary	LiDAR	UAV-based LiDAR was found to be effective in assessing the structure of forest restoration plantations and differentiating the results of silviculture techniques.
Fromm et al. (2019)	Canada	Academia	Rotary	RGB	The use of UAV imagery analyzed by artificial intelligence was found to be useful in detecting large and medium-sized conifer seedlings in regenerating sites with high accuracy.
Puliti and Granhus (2020)	Norway	Government agency	Rotary	RGB	UAV data were better at predicting tending need and cost compared to ALS data.

Nuijten et al. (2021)	Canada	Academia	Rotary	RGB	UAV-based digital aerial photogrammetry was effective to characterize short stature vegetation.
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Table 5: List of papers that used UAVs for forest species classification and identification-related studies.

Investigator	Country	Study conducted by	Wing	Camera/Sensor	Major conclusions
Gini et al. (2014)	Italy	Academia	Rotary	Multispectral	While the classification results obtained from UAV data were not entirely satisfactory, they were still useful for high-quality analysis and classification of different tree species.
Michez, Piégay, Jonathan, et al. (2016)	Belgium	Academia	Fixed	Multispectral (RGB camera modified to capture NIR)	The classification accuracy for Himalayan balsam ( <i>Impatiens glandulifera</i> Royle), and Japanese knotweed ( <i>Fallopia sachalinensis</i> , <i>Fallopia japonica</i> (Houtt.) and hybrids) did not meet the desired level of accuracy. However, the accuracy results for Giant hogweed ( <i>Heracleum mantegazzianum</i> ) were encouraging at 97%.
Näsi et al. (2016)	Finland	Government agency	Rotary	Hyperspectral	The use of UAV-based hyperspectral technology was found to provide accurate geometric, radiometric, and spectral information in a forested setting for measuring the 3D geometry and spectral characteristics of a

forest canopy.

Bolch et al. (2021)	USA	Academia/state	Rotary	Hyperspectral	The accuracy of a UAV-mounted Nano-Hyperspec was found to be higher than that a MAV-mounted imaging spectrometer but had some limitations in terms of coverage area when compared to the MAV.
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Table 6: List of papers that used UAVS for post-harvest soil erosion and displacement-related studies.

<b>Investigator</b>	<b>Country</b>	<b>Study conducted by</b>	<b>Wing</b>	<b>Camera/Sensor</b>	<b>Major conclusions</b>
Pierzchała et al. (2014)	Norway	Government agency	Rotary	RGB	UAV was effective in estimating soil displacement caused by skid trails.
Talbot et al. (2018)	Norway	Government agency	Rotary	RGB	Tracing and categorizing vehicle traffic from UAV orthomosaic maps provided more comprehensive records of site disturbance with lower resources inputs.

Table 7: List of some other additional studies that used UAVs for forest related research.

<b>Investigator</b>	<b>Country</b>	<b>Study conducted by</b>	<b>Wing</b>	<b>Camera/Sensor</b>	<b>Major conclusions</b>
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Getzin et al. (2012)	Germany	Academia	Fixed	RGB	UAV aerial images of canopy gaps were found to be efficient in assessing forest understorey floristic diversity. A strong relationship between disturbance patterns and plant diversity was detected.
Puttock et al. (2015)	England	Academia	Rotary	RGB	UAV-derived orthophoto and DSM, determined the extent of dams and associated ponds, as well as changes in vegetation structure due to beaver tree felling activity.
Mokroš et al. (2016)	Czech Republic	Academia	Rotary	RGB	UAV-based volume calculations were in strong agreement and more detailed than GNSS device-based volume calculations.
Gülci et al. (2017)	Turkey	Academia	Rotary	RGB	High-resolution images provided by a UAV were useful for assessing forest resources, forest roads, and stream channels.
Klosterman and Richardson (2017)	USA	Academia	Rotary	RGB	The use of UAVs enabled the observation of a complete picture of the seasonal cycle of deciduous canopy development at a landscape scale.
Yong and Yeong (2018)	Malaysia	Academia	Rotary	RGB	The use of human object detection algorithms with UAV vision was successful in localizing both human and wood cutting vehicles during forest surveillance.
Dugdale et al. (2019)	Scotland	Academia	Rotary	RGB	UAV was efficient in providing accurate and detailed spatial

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de Almeida et al. (2020)	Costa Rica	Academia	Rotary	LiDAR	representation of riparian tree cover and was as efficient as airborne LiDAR data. UAV-LiDAR systems were effective to improve forest recovery assessments and creating mechanistic carbon sequestration models.
Thiel et al. (2020)	Germany	Government agency	Rotary	RGB	High rates of detected trees were achieved using UAV data and an object-based image analysis approach.
Adand and Ridzuan (2021)	Malaysia	Academia	*	*	UAVs were found to be more efficient than total stations or other conventional techniques for creating photogrammetry to survey environmental mitigation measures.

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\* Was not stated in the article.

## Chapter 2. Evaluating the Feasibility and Potential of Unmanned Aerial Vehicles to Monitor Implementation of Forestry Best Management Practices in the Southeastern United States

### 2.1 Abstract

Timber harvest activities such as constructing roads, skid trails, and stream crossings have the greatest potential for erosion and sedimentation. Forestry best management practices (BMPs) monitoring serves as a tool to evaluate BMP implementation status. Conventional on-the-ground BMP monitoring has contributed substantially to assessing BMP implementation. However, conventional on-the-ground surveys can be time consuming. Unmanned aerial vehicles (UAVs) have been rapidly emerging as a new tool for local-scale monitoring. In this study, we evaluated the feasibility and potential of UAVs for monitoring forestry BMPs in the southeastern United States. By using BMP guidelines and implementation survey questions from Alabama, Georgia, and Florida, the performance of UAV-live feed surveys and UAV-created map surveys were compared with conventional on-the-ground surveys across major BMP categories on 30 study sites using the BMP survey for that state (10 sites in each state). We found that using a UAV for monitoring BMPs efficiently provided an overview of a timber harvest area from above. UAV-live feed surveys were as effective as conventional on-the-ground surveys across all major BMP categories. Specifically, the correlation coefficient ( $r$ ) between UAV-live feed and conventional on-the-ground surveys for all BMP categories, was 0.98 ( $p < 0.0001$ ) for detecting implemented BMPs and 0.94 ( $p < 0.0001$ ) for detecting when BMPs were not implemented but needed to be. UAV-created map survey results vs. conventional on-the-ground surveys were not as effective ( $r$  of 0.87 for detecting implemented BMPs and 0.49 for detecting BMPs not implemented but needed). Stream crossing BMP questions were the main issue impacting map surveys which was not an issue with the live feed surveys due to the

capability to evaluate the crossing at different camera angles. While UAV-created map surveys may be less effective, they provide an observation record that includes a map of the site. This project also developed a standardized framework for using UAVs to monitor forestry BMPs, including instructions and procedures for conducting UAV-live feed and map surveys. In conclusion, a UAV using the live feed function in the field is a feasible option to monitor forestry BMPs.

## 2.2 Introduction

Timber harvesting can negatively affect the environment, particularly regarding erosion and water quality. According to Worrell et al. (2011), timber harvesting can lead to increased erosion rates on forest roads, skid trails, and log landings. Erosion becomes sedimentation when it reaches waterways and can harm aquatic habitats and degrade water quality. The extent of the impact of timber harvesting depends on various factors, such as elevation, slope, soil type, ground cover, vegetation recovery rate, and harvesting system (Parajuli et al., 2022; Worrell et al., 2011).

To minimize these negative effects, states developed forestry best management practices (BMPs), which promote environmentally sound forestry practices. BMPs were created as a response to the Clean Water Act and are intended to protect water quality during and after forest operations such as timber harvesting, as outlined in a variety of sources, including the Alabama Forestry Commission (2019), Cristan et al. (2016), Rivera (2004), Sanders (2008), Schuler and Briggs (2000), VanBrakle (2010), and Warrington et al. (2017). Implementing BMPs based on site conditions reduces nonpoint source pollution (NPSP) and helps to protect water quality. Using BMP implementation rates as an indicator of water quality protection is logical since properly applied BMPs have been shown to reduce erosion and sedimentation (Cristan et al., 2016; Nolan et al., 2015; Schilling et al., 2007; Sun et al., 2004). However, their effectiveness is dependent on proper implementation. To ensure BMPs are being implemented effectively, states monitor forestry BMPs (Cristan et al., 2018). This process assesses the practical application of BMPs in the field and their effectiveness in protecting water quality (Indiana Department of Natural Resources, 2019). Monitoring can provide insight into the implementation status and

identify improvement areas. It can also help target educational and technical assistance programs for landowners and loggers needing to meet compliance standards (Ellefson et al., 2001).

Although BMP guidelines vary by state, they typically encompass multiple BMP categories such as forest roads, streamside management zones (SMZs), stream crossings, timber harvesting, waste disposal, and site preparation (Cristan et al., 2018; Shepard, 2006). The evaluation of BMP implementation in the southeastern United States is based on different indicators for each category, as outlined by the Southern Group of State Foresters (SGSF Water Resources Committee, 2006).

Conventional on-the-ground surveys (conventional surveys hereafter) are commonly used to assess the implementation of forestry BMPs, but they come with challenges, such as the time and effort required for proper fieldwork, site factors such as terrain and wetness of the site, and size of the area being surveyed. These challenges can make it difficult for foresters to cover the entire timber harvest area (Horcher & Visser, 2004). Remote sensing techniques involving unmanned aerial vehicles (UAVs) have been gaining popularity in monitoring and management activities in various fields (Samiappan et al., 2019; Yi & Sutrisna, 2021; Zwęgliński, 2020). UAVs provide advantages such as a wider coverage area and quicker data collection than conventional surveys (Adams et al., 2010). In the past, remote sensing was limited to satellite or manned aircraft (Melesse et al., 2007; Pinter Jr et al., 1990), but with the advent of UAVs, collecting high-resolution forest data has become more efficient and cost-effective (Diez et al., 2021). Despite advanced technology, UAVs are relatively simple to operate with only basic training required for efficient use, as Koh and Wich (2012) noted. These devices can be controlled manually using the live feed function or flown autonomously for mapping purposes.

Recent advancements in battery technology and sensor integration have made UAVs increasingly effective for a variety of applications, such as monitoring wildlife populations (Lyons et al., 2019), farm monitoring and pesticide spraying (Hafeez et al., 2022), pipeline monitoring (Ramalli et al., 2016), surveillance of construction sites (Yi & Sutrisna, 2021), post-disaster monitoring (Takano et al., 2021), etc. Major uses of UAVs in forestry are for forest structure estimation (Almeida et al., 2019; Alonzo et al., 2018; Goodwin et al., 2006), monitoring forest fires (Barrett et al., 2015; Ghamry et al., 2016; Merino et al., 2012), and mapping forest diseases (Dash et al., 2017; Housman et al., 2018; Smigaj et al., 2015). Despite the growing use of UAVs in forestry, no studies have been published to date that have used UAVs to evaluate the implementation of forestry BMPs. It is essential to understand the potential and limitations of using UAVs for this purpose and to determine if they can accurately assess BMP implementation compared to conventional methods. A comprehensive framework for planning and executing UAV missions for BMP assessment is also needed.

In this study, considering the case of the southeastern United States, we evaluated the efficacy of a UAV to assess forestry BMP implementation. Using BMP guidelines and BMP implementation survey questions from Alabama, Georgia, and Florida, we compared the effectiveness of UAV-live feed surveys and UAV-created map surveys with conventional surveys for different BMP categories. Additionally, we examined how different BMP survey questions and site conditions affect the performance of UAV-live feed surveys and UAV-created map surveys for evaluating BMP implementation. We also developed a standardized operational framework for using UAVs for monitoring forestry BMPs that includes various aspects related to UAV mission planning and execution for UAV-based BMP implementation monitoring and

discuss how UAVs can help establish evidence-based directives to address NPSP during and after timber harvesting.

## **2.3 Materials and methods**

### **2.3.1 Unmanned aircraft system (UAS)**

The UAS consists of a UAV, control system, and payload. Professional and enterprise UAVs offer more functionality but can be expensive. Stakeholders who want UAVs to assess forestry BMP implementation are typically foresters and loggers, and generally, these stakeholders prefer a UAV that will be easy to operate, comparatively cheap, and affordable. In this study, we selected a consumer-grade UAV, similar to what a forester or logger would use. The drone selected was the DJI Air 2S (<https://www.dji.com>) and had the following features: rotary-wing, ready-made, commercially available, equipped with a global positioning system (GPS) and inertial measurement unit (IMU) for navigation and control, and a red, green, and blue (RGB) camera for georeferenced photos and videos. Technology advancements have enabled smaller UAVs, such as the Air 2S, to become more efficient for mapping and surveying at a lower cost (Madawalagama et al., 2016). In addition, sensor sizes (weight) have also been decreasing, making smaller UAVs capable of carrying new sensors with advanced technology (Pajares et al., 2013; Vergouw et al., 2016).

The DJI Air 2S has a maximum flight time of approximately 31 min, maximum speed of 15 meters/second, and wind speed resistance of up to 10.7 meters/second. It has a 1" complementary metal oxide semiconductor (CMOS) sensor with a 20-megapixel camera that captures still images of 5472 x 36488 and 5.4K videos of 5472 x 3078 at 24/25/30 frames per

second (<https://www.dji.com/air-2s/specs>). The DJI Fly app (<https://www.dji.com/dji-fly>) was used to conduct the live feed surveys, while the Dronelink program and app (<https://www.dronelink.com>) were used for mapping.

### 2.3.2 Testing flight parameters

The size of the harvested area, altitude, overlap, image capturing strategy, spatial and temporal resolution, and processing specifics are key factors that influence the accuracy, duration, and cost of UAV map surveys (Seifert et al., 2019; Torresan et al., 2017). To create useful orthomosaic maps, a minimum of 70% overlap between images, both front and side, is recommended (Brookman-Amissah, 2022; Stöcker et al., 2020). Before flying the UAV, the Dronelink program was used to project hypothetical flight scenarios using different flight parameters and tract sizes (Table 8). Five test flights at various locations were conducted prior to conducting BMP surveys to gain insight into the advantages and disadvantages of these different flight parameters, allowing us to make any necessary adjustments before proceeding with the flights at the selected sites.

Table 8. Results from a hypothetical flight scenario using different combinations of flight parameters and tract sizes.

Acres	Altitude (ft)	Front/Side Overlap %	Batteries	Images
50	200	70/70	2	384
50	300	70/70	2	176
50	400	70/70	1	102
50	200	75/75	2	550
50	300	75/75	2	250
50	400	75/75	1	143
75	200	70/70	3	576
75	300	70/70	2	255

75	400	70/70	2	154
75	200	75/75	3	826
75	300	75/75	2	368
75	400	75/75	2	219
100	200	70/70	4	773
100	300	70/70	3	341
100	400	70/70	2	199
100	200	75/75	4	1105
100	300	75/75	3	493
100	400	75/75	2	277
150	200	70/70	5	1153
150	300	70/70	3	515
150	400	70/70	3	292
150	200	75/75	5	1652
150	300	75/75	4	740
150	400	75/75	3	416
200	200	70/70	7	1533
200	300	70/70	4	674
200	400	70/70	3	383
200	200	75/75	7	2201
200	300	75/75	4	979
200	400	75/75	4	552

### 2.3.3 Study sites

Study sites included recently completed timber harvests (less than 1 year) in Alabama, Georgia, and Florida. Thirty post-harvest sites (10 from each state) (Figure 5) were analyzed. All sites were within the Coastal Plain physiographic region.

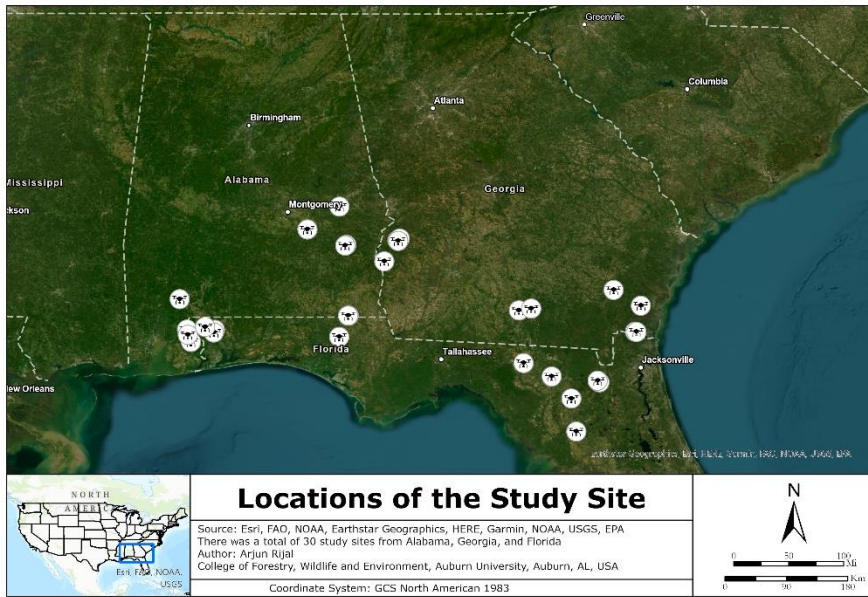


Figure 5. Study site locations.

### 2.3.4 BMP implementation surveys

BMP guidelines and implementation surveys were specific to each state. We used BMP guidelines and survey questions from each state for the sites specific to that state. The following BMP categories were assessed on each site (if applicable to the site): harvest area, forest roads, SMZs, stream crossings, and waste disposal. Skid trails were not a separate BMP category since skid trail BMPs fall within harvesting guidelines in Alabama and Florida and within harvesting and stream crossings in Georgia (Alabama Forestry Commission, 2007; Florida Forest Service, 2008; Georgia Forestry Commission, 2019).

BMP evaluations were completed by answering “yes,” “no,” or “not applicable (NA)” for questions regarding proper BMP implementation for each BMP category. A “yes” score was given when the practice was applied as specified in the state's BMP manual (indicating correct

implementation), and a "no" score was given when there was a significant deviation from practice specifications (indicating incorrect or lack of implementation). For BMPs not applicable to the site, "NA" was recorded on the evaluation form. The protocol developed by the SGSF Water Resources Committee was used to determine implementation rate, which is expressed as a percentage. For each BMP category, the sum of the number of "yes" answers was divided by the total number of applicable answers (yes/(yes + no)) (SGSF Water Resources Committee, 2006).

Conventional BMP surveys were done by walking the entire study site and the implementation status of BMPs were evaluated as this is the method that state forestry agencies use to conduct BMP implementation surveys. Like conventional surveys, UAV-live feed surveys were also completed in real-time; however, instead of walking the study site, the UAV was flown from a stationary location such as the logging deck, forest road, or roadside. Time, weather, airspace restrictions, site conditions during flight, and challenges/limitations were documented at each site. Different individuals were assigned to conduct the conventional and UAV-live feed surveys to ensure objectivity, which remained consistent across all sites.

The UAV-created map survey utilized high-resolution orthomosaic maps (Figure 6) created from UAV images. A flight plan was created using Dronelink and the UAV was flown autonomously using an altitude of 91.4 meters (300 feet) above ground level (AGL), speed of 7 m/s (16 mph), camera angle of 90 degrees, 70/70 percentage front and side overlap, and regular intervals of photo capture (every 2 seconds). The direction of the flight plan was selected based on minimizing flight duration. To ensure optimal image quality, UAV flights were conducted before midday to take advantage of favorable lighting conditions (Joyce et al., 2018). ArcGIS

Drone2Map (ArcGIS Drone2Map, 2022) was used for UAV imagery processing and visual inspection and ArcGIS Pro (Esri, 2022) was used for map layouts. We began by reviewing the entire site using an orthomosaic map from a wide-angle perspective (Figure 6). If we identified anything of interest on a specific area of the map, we examined individual images of that section in greater detail (Figure 7). Additionally, we utilized the digital surface model (DSM) and digital terrain model (DTM) created from the UAV data to examine terrain. The framework for the research is presented in Figure 8.



Figure 6. An orthomosaic map of a harvest site.

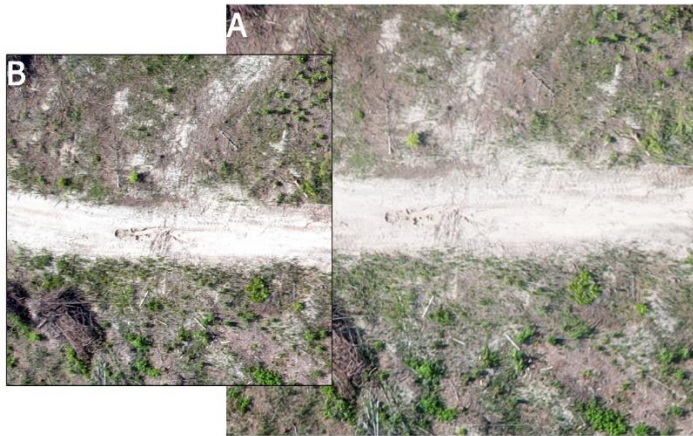


Figure 7. An orthomosaic map inspection for BMP evaluation showing a zoomed-in area of a forest road (A) and an individual UAV picture of the same area (B).

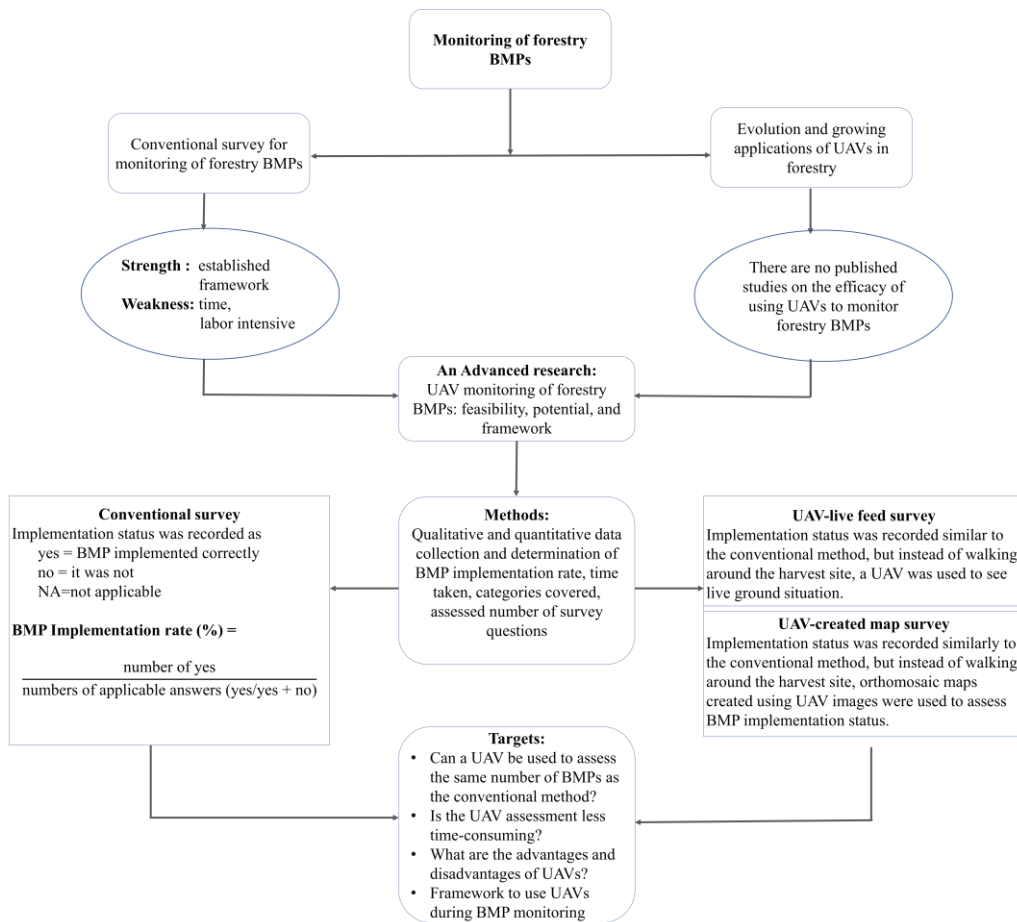


Figure 8. Research conceptual framework.

### **2.3.5 Statistical analysis**

Correlation ( $r$ ) for each BMP category was analyzed to determine the relationship between the responses of yes, no, and NA from conventional surveys with those obtained from UAV-live feed surveys and UAV-created map surveys. Analysis of Variance (ANOVA) and Tukey's HSD multiple comparisons were used when evaluating time differences between survey methods. Furthermore, we performed two-sample t-tests to compare BMP implementation percentages from UAV-live feed surveys and conventional surveys. Generalized regression was used to determine the variables influencing the duration of UAV-live feed surveys and UAV-created map surveys. Residuals were assessed for normality through the Shapiro-Wilk normality test. Statistical analyses were completed using JMP Pro 15 (SAS Institute, 2019) using an alpha level of 0.05.

## **2.4 Results**

Our study surveyed approximately 1074 ha (2655 acres) of harvested timber using UAV-live feed, UAV-created map, and conventional monitoring methods. Of the 30 study sites, 3 were less than 20 ha (50 acres), 14 were 20-40 ha (50-100 acres), 11 were 41-61 ha (101-150 acres), and 2 were over 61 ha (150+ acres). Eight sites were within special use airspace (alert zones) where UAVs could still be operated, but extra observation was needed during flight, while the rest were in uncontrolled Class G airspace where there were no flight restrictions.

### **2.4.1 Comparing UAV-based surveys with conventional surveys**

The average time for the UAV-live feed surveys to assess BMP implementation was 34.6 minutes, UAV-created maps averaged 305.9 minutes, and the conventional surveys took 105.9

minutes (Figure 9). UAV-live feed surveys resulted in significantly lower mean time to complete a survey than both the UAV-created map surveys ( $p < 0.0001$ ) and conventional surveys ( $p < 0.0001$ ). The UAV-created map surveys resulted in significantly more time than both other survey methods.

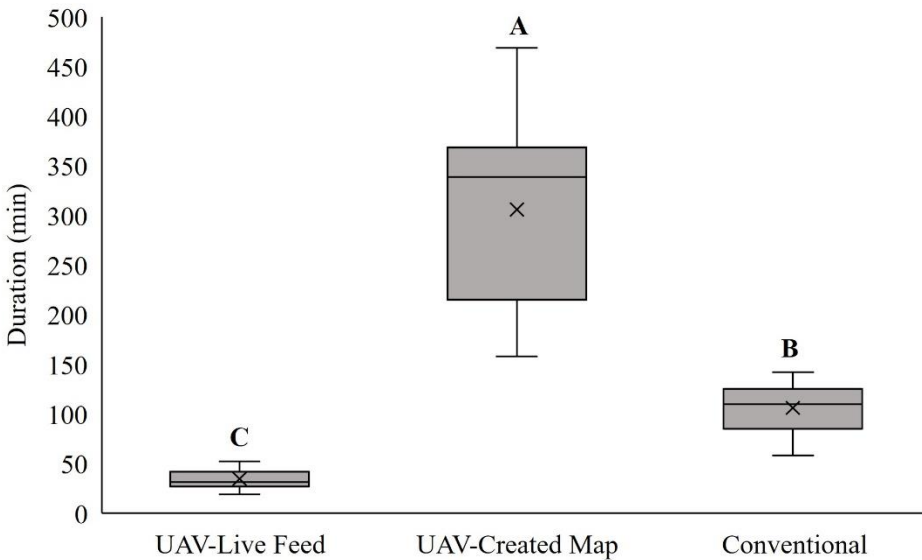


Figure 9. Comparison of duration of UAV-based surveys with the conventional survey. Survey methods followed by a different letter are significantly different at  $p \leq 0.05$  using Tukey’s HSD.

UAV-live feed surveys compared to conventional surveys indicated a strong agreement between the responses from the two survey methods for all BMP categories. The correlation coefficient ( $r$ ) for all BMP categories combined was 0.98 detecting when BMPs were implemented ( $p < 0.0001$ ), 0.94 detecting when BMPs were not implemented and needed to be ( $p < 0.0001$ ), and 0.99 detecting BMP questions which are not applicable for the site ( $p < 0.0001$ ) (Table 9). When examining the results of “yes,” “no,” and “NA” for each BMP category, the correlation suggests a strong positive relationship between UAV-live feed surveys and conventional surveys for all categories (0.90 - 1.00) (Table 9). Stream crossings showed the

lowest correlation (yes = 0.98, no = 0.90, and NA = 0.99) but still indicated a strong correlation between the UAV-live feed and conventional survey methods.

Responses from UAV-created map surveys compared to conventional surveys were not as highly correlated. The correlation for all BMP categories combined was 0.87 detecting implemented BMPs ( $p < 0.0001$ ), 0.49 detecting when BMPs were not implemented and needed to be ( $p < 0.001$ ), and 0.90 detecting BMP questions which are not applicable for the site ( $p < 0.0001$ ) (Table 10). Correlation values for stream crossing and SMZ BMPs not implemented “no” were not significant ( $p = 0.2696$  and  $p = 0.0927$ , respectively).

Table 9. Comparison between UAV-live feed and conventional surveys by BMP category and overall BMP records (r is the correlation coefficient).

Categories	Count(n)	Yes Records		No Records		NA Records	
		r	p-value	r	p-value	r	p-value
Harvesting	30	0.99	<0.0001	0.95	<0.0001	1.00	<0.0001
Roads	30	1.00	<0.0001	1.00	<0.0001	1.00	<0.0001
SMZs	18	0.99	<0.0001	0.91	<0.0001	1.00	<0.0001
Stream Crossings	10	0.98	<0.0001	0.90	0.0004	0.99	<0.0001
Waste	20	1.00	<0.0001	1.00	<0.0001	1.00	<0.0001
Overall	108	0.98	<0.0001	0.94	<0.0001	0.990	<0.0001

Table 10. Comparison between UAV-created map and conventional surveys by BMP category and overall BMP records (r is the correlation coefficient).

Categories	Count(n)	Yes Records		No Records		NA Records	
		r	p-value	r	p-value	r	p-value
Harvesting	30	0.67	<0.0001	0.41	0.0249	0.91	<0.0001
Roads	30	0.83	<0.0001	0.50	0.0050	0.82	<0.0001
SMZs	18	0.98	<0.0001	0.41	0.0927	0.99	<0.0001
Stream Crossings	10	0.91	0.0002	0.39	0.2696	0.84	0.0025
Waste	20	0.58	0.0070	0.50	0.0263	0.75	0.0001
Overall	108	0.87	<0.0001	0.49	<0.001	0.90	<0.0001

The overall BMP implementation percentage in the region was 93.83% from the UAV-live feed surveys and 92.88 % from the conventional surveys (Table 11). Individual BMP category implementation was also similar between the two methods. There was no significant difference between UAV-live feed surveys and conventional surveys in terms of BMP implementation rate of individual BMP categories and overall BMP implementation rate in the region ( $p \geq 0.05$ ). The UAV-created map survey was not compared due to the lower correlation between the conventional survey and UAV-created map survey as it would not be a good fit for assessing BMP implementation, particularly for detecting not implemented BMPs.

Table 11. BMP implementation percentage for the conventional and UAV-live feed surveys. No significant differences were found ( $p > 0.05$ ).

BMP Category	Conventional	UAV-live feed
	Percent (%)	
Harvesting	94.33	94.89
Roads	96.14	96.14
SMZs	95.57	97.42
Stream Crossings	68.87	74.06
Waste	95.42	95.42
Overall	92.88	93.83

#### 2.4.2 UAV flight factors

The duration of UAV-live feed surveys was significantly influenced by the number of BMP questions for a site ( $p < 0.0001$ ), site area ( $p < 0.0001$ ), presence of SMZ ( $p = 0.0058$ ) and presence of stream crossings ( $p = 0.0166$ ) (Table 12). Flight zone, gust speed (mph), and temperature (Fahrenheit) were not significant ( $p > 0.05$ ). Generalized regression analysis revealed that the survey area ( $p < 0.0001$ ) and gust speed ( $p = 0.0096$ ) were statistically significant factors affecting the autonomous flight duration for UAV-created map surveys (Table 13). Flight zone, temperature (in Fahrenheit), presence of stream crossings, and presence of SMZ

were not significant in affecting the UAV-created map surveys ( $p = 0.1257$ ,  $p = 0.15$ ,  $p = 0.371$ , and  $p = 0.6126$ , respectively).

Table 12. Factors influencing the duration of manual flight for UAV-live feed surveys.

Factors	Sum of Squares	F Ratio	Prob > F
Number of BMP Questions	542.58	89.43	<.0001
Area (acres)	247.33	40.77	<.0001
SMZ Presence	56.61	9.33	0.0058
Stream Crossings Presence	40.81	6.73	0.0166
Flight Zone	11.22	1.85	0.1877
Gust Speed (mph)	0.34	0.06	0.8164
Temperature (Fahrenheit)	0.18	0.03	0.8652

Table 13. Factors influencing the duration of autonomous flight for UAV-created map surveys.

Factors	Sum of Squares	F Ratio	Prob > F
Area (acres)	3282.95	43.99	<.0001
Gust Speed (mph)	595.09	7.97	0.0096
Flight Zone	188.51	2.53	0.1257
Temperature (Fahrenheit)	165.50	2.22	0.1500
Stream Crossings Presence	62.14	0.83	0.3710
SMZ Presence	19.67	0.26	0.6126

## 2.5 Discussion

### 2.5.1 UAVs for monitoring of forestry best management practices implementation

BMP guidelines and implementation varies based on state policy, site characteristics, and timber harvesting practices. To the best of our knowledge, no state has integrated UAVs into forestry BMP monitoring. This study served to demonstrate the feasibility of using UAVs for monitoring forestry BMP implementation using a consumer-grade UAV and compare the results with conventional surveys. Our findings align with previous research that suggests UAVs can be

an efficient and effective tool for monitoring and surveying in various fields, such as urban tree hazard monitoring (Kulhavy et al., 2016), marine trash detection (Liao & Juang, 2022), pipeline and environmental monitoring (Asadzadeh et al., 2022; Marathe, 2019), rail track extraction and monitoring (Singh et al., 2019), and rangeland monitoring programs (Gillan et al., 2020).

UAV real-time video and orthomosaic mapping provide an overview of a site quickly from its elevated point of view. Conventional surveys may be hindered by species present on the site, complexity of the site, such as terrain and water features, and size of the site, which can make surveys more field intensive and require more time for surveying. Aubert et al. (2021) found UAV surveys were more efficient in covering larger and more remote areas than conventional surveys. In this study, UAV-live feed surveys and UAV-created map surveys were more efficient than conventional surveys for general assessments to determine the number and location of stream crossings, SMZs, loading decks, skid trails, and roads. The UAV-live feed survey was just as efficient as the conventional survey in monitoring BMP implementation and took significantly less time to complete. However, the UAV-created map survey was not efficient in evaluating where BMPs should have been implemented and were not, and this method was also more time consuming than the other methods. In the UAV-created map survey, the UAV was flown autonomously at a continuous height to take pictures and create an orthomosaic map of the site, and this would be the best approach to get an overview of the site. The orthomosaic map was a high-resolution (2.7 cm) top-down representation of the whole study site; however, when zooming in close to the ground, the map becomes pixelated and had issues identifying BMP implementation compared to manual observation using the UAV-live feed method (Figure 10). Orthomosaic maps and nadir images from the autonomous flights can be

hindered by vegetation, particularly at stream crossings. This was problematic when identifying when a BMP was not implemented correctly, or if a BMP should have been implemented.

Whereas the UAV-live feed survey provides much higher resolution as the UAV can be lowered closer to the ground and the pilot can rotate camera angles (for oblique image) to have a high-resolution view of a specific area up close (Figure 11). The pilot can also take an image of this area in which that image will be georeferenced. Vacca et al. (2017) also compared oblique vs nadir UAV imagery for measurements of buildings and found that oblique UAV flights increased the achievable accuracy both in terms of the number of points in a point cloud, and in the measurements taken on the 3D models, with respect to the limited cost and the increase in time for surveying and image processing. The UAV-created map can be useful for determining if SMZs meet the BMP guideline specifications regarding width and canopy cover, along with determining if skid trails followed the sites' contours and evaluating slope of particular areas such as stream crossing approaches.

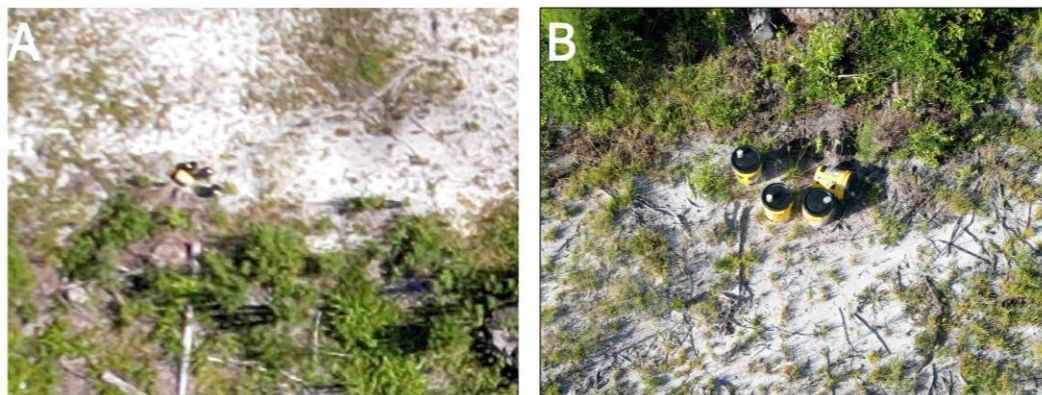


Figure 10. Example of waste disposal monitoring from UAV-created map survey (zoomed-in orthomosaic map, camera angle – vertical (90°) (A) and the UAV-live feed survey (altitude 30.5 meters (100 feet), camera angle – oblique) (B)

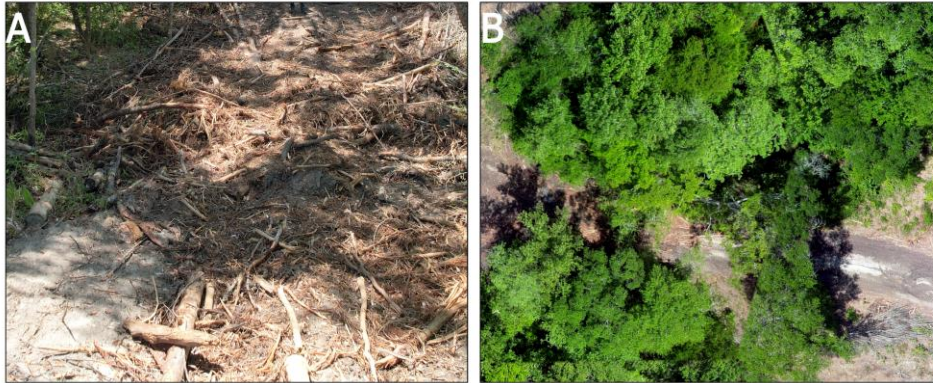


Figure 11. Example of stream crossing BMP evaluation from the UAV-live feed survey (camera angle-oblique) (A) and a zoomed-in orthomosaic map (B). The orthomosaic map does not show the BMP concern of a temporary crossing using logging debris and the logger not removing the debris after completion of the harvest that the UAV-live feed survey showed.

Furthermore, it is also feasible for images acquired to be reviewed by a trained person remotely, allowing for repeatable and quantifiable BMP implementation assessment and establishing a platform for an evidence-based BMP implementation monitoring report. The UAV-created map survey may require additional software for flight planning and imagery processing, but it provides a permanent record of observations to document the site through images and a map, which can be an advantage for foresters and forest industry companies (Aubert et al., 2021; Kelaher et al., 2019). An orthomosaic map prepared during a UAV-created map survey can be used to verify the number of loading decks, stream crossings, and roads and is also extremely useful for calculating the area covered by each BMP category for use in soil erosion estimation, site preparation, and planting. Moreover, ensuring responsible forest management and promoting sustainability are key considerations in the forestry industry. In the United States, third-party certification standards, such as the American Tree Farm System (ATFS), Sustainable Forestry Initiative (SFI), and Forest Stewardship Council (FSC), are widely adopted to support these goals (Schilling et al., 2021). These standards aim to implement BMPs during and after timber harvesting, with forest landowners and wood procurement entities

required to comply with the standards and undergo third-party audits to verify adherence. In order to facilitate these audits and maintain accurate documentation, imagery and videos from a UAV-live feed survey and an orthomosaic map from a UAV-created map survey can be extremely helpful. These tools offer visual evidence of BMP implementation and can be employed to verify compliance and provide documentation.

The number of questions assessed by UAV-live feed surveys were similar to those assessed by conventional surveys. However, in the case of UAV-created map surveys, especially for stream crossings, there were multiple questions that were not detected when compared to the UAV-live feed and conventional surveys. Cristan et al. (2018) and Phillips and Blinn (2004) noted that state BMP monitoring programs typically are standardized within a region, which makes results comparable to states within that region. Considering the advantages of UAVs in terms of feasibility and efficiency reported in this research, incorporating UAVs into state BMP monitoring programs could be a strategic move.

In other sectors, such as ecological monitoring (Mangewa et al., 2019; Marvin et al., 2014), community-based forest monitoring (Paneque-Gálvez et al., 2014), landslide monitoring (Rossi et al., 2018), etc., authors focused on the development of an integrated UAV-based monitoring system that generates real-time data and complementing that with conventional methods. Forestry BMP monitoring could also implement this type of approach. This could be particularly pertinent if the harvested area is large with decreasing time from walking the entire site. The UAV can detect critical areas and the person conducting the survey can traverse directly to those areas.

### **2.5.2 Factors and challenges using UAVs**

Studies have identified several benefits of using UAVs in natural resources management, including being less time-consuming than conventional survey methods, affordable, and easy to master (Berra, 2020; Liu & Wang, 2018; Mohan et al., 2017). Consistent with other studies, this study found that UAV-based forestry BMP monitoring was beneficial in terms of time.

The results of this study indicate that the average time taken to conduct UAV-live feed surveys was 34.6 minutes, whereas the average time taken for conventional surveys was 105.9 minutes and UAV-created map surveys was 305.9 minutes. UAV-created map surveys took less time in the field than conventional surveys but demanded much more time to process imagery in the office, resulting in increased total duration. The processing of UAV imagery includes creating orthomosaic maps and digital elevation models, with the duration of data processing dependent on the software used, the number of images, and the computer's processing power (Albuquerque et al., 2022; Pell et al., 2022). UAV imagery processing requires proper training with the UAV and the software programs (Albuquerque et al., 2022; Chabot & Bird, 2015; Koh & Wich, 2012). Several factors influenced UAV-live feed surveys, including the number of BMP survey questions and site characteristics, such as area (size) and the presence of SMZ and stream crossings. Although most of the influential factors were common, there were some differences between the factors affecting autonomous flight during UAV-created map surveys and manual flight during UAV-live feed surveys. While the presence of SMZs, stream crossings, and the number of questions impacted UAV-live feed surveys, they did not affect autonomous flight. This is because autonomous flight follows a pre-defined path at a constant altitude and camera angle, while the UAV-live feed surveys require the pilot to adjust the altitude and camera angle based on the survey requirements.

Weather conditions are one of the major factors which affect UAV-based surveys (Albeaino & Gheisari, 2021). The UAV used in our study was operated within the gust tolerance capacity specified in the UAV manual (up to 10.7 m/s). Furthermore, during UAV-live feed surveys, the pilot flew the UAV controlling the UAV speed according to gust speed and direction. This is one of the reasons why gusts did not significantly impact the manual flight duration of UAV-live feed surveys. In contrast, UAV-created map surveys involve autonomous flight on a pre-defined path and direction, and slightly high gusts can cause fluctuations in the UAV's speed and affect the flight path, which in turn can extend the survey duration as the UAV is compensating for the gusts and potentially being moved off the flight path. Temperature was found to have no significant effect on the UAV flight duration in our study. However, from our experience on hot days, it was not easy to see the UAV controller and tablet screens due to sunlight reflection. Overheating of the remote controller or tablet/phone can potentially be an issue. To prevent overheating, it is recommended to keep the controller and tablet/phone away from direct sunlight. When possible, seeking shade is a good precautionary measure and will also help with screen output visibility (Raoult et al., 2020). Li et al. (2021) investigated the effects of extreme temperatures on UAV battery life and flying performance. Their results showed that high temperatures (60+ °C) significantly impacted the battery life and discharge capacity, causing experimental lithium-ion batteries to crack after just five cycles of the charge/discharge process. On the other hand, low temperatures, such as -30°C, substantially decreased the UAV's flying and battery performance, resulting in shorter flight time. Furthermore, their study highlighted that low-temperature conditions had a more severe effect on the battery's performance than high-temperature conditions.

In the field, there may be environmental and logistics challenges. UAVs generally fly low enough not to be affected by cloud cover, but fog, rainfall, and high winds/gusts can impede operation. Weather can be a challenge in general which makes pre-flight planning important and includes checking the weather forecast prior to flight. There are apps that are designed specifically for assessing weather parameters for operating UAVs.

Flight plan layout for autonomous flights can impact flight duration and, consequently, the number of batteries required. UAVs tend to be more efficient in terms of time and battery usage when flying on a path with fewer turns and longer flight lines, which was also found in the study by Joyce et al. (2018). We found that we only needed one battery to survey 32.3 ha (80 acres) of a harvested site with a DJI Air 2S when flying on a rectangular flight plan with wind speeds less than 2.2 m/s (5 mph), altitude of 91.4 meters (300 feet) above ground level, and 70/70 imagery overlap. However, when we flew the same UAV on an irregular flight plan on a harvested site within the same wind speed, altitude, and imagery overlap, it took two batteries to survey the same area of the harvested site. Moreover, rectangular or square-shaped survey areas are generally preferred for producing high-quality orthomosaics (Joyce et al., 2018). This shape maximizes the area of accurately processed data, as mosaic products tend to be less precise at the edges where the overlap between images is reduced (Pell et al., 2022) (Figure 12). To ensure adequate overlap near the edges of the survey area for autonomous flight, we recommend designing a rectangular or square flight plan slightly larger than the region of interest.



Figure 12. Showing distortion in orthomosaic map around the edges.

In the United States, UAVs are regulated as aircraft by the Federal Aviation Administration (FAA) under the 14 Code of Federal Regulations, Part 107. For commercial use, an operator must pass a knowledge test and become an FAA-certified UAV pilot (FAA, 2022a). UAV flight restrictions are the main criteria in the FAA regulations (controlled airspace, special use airspace, etc.). Besides flight restrictions, there are limitations for maximum height (altitude) level and horizontal distances in terms of visibility and range. Regarding flying height, the maximum allowable height is 121.9 meters (400 feet) AGL (Aircraft, 2016). The FAA limits UAV weight to 24.9 kg (55 pounds) and prohibits its use around people not involved in its operation. The rules also prohibit the operator from flying the UAV from a moving vehicle. Waivers can be obtained through the FAA for weight and flying over people (FAA, 2022b). However, this is not a problem for forestry BMP monitoring as most timber harvests are in rural and remote areas.

Managing UAV data can be logistically difficult without cloud storage or large hard drives. UAV imagery and orthomosaic map files for one site can be several gigabytes (GB) in size and can be problematic if storing data for a long period without a plan. Similar problems were faced by researchers who had used UAVs in other sectors, such as UAV use in precision agriculture (Parra et al., 2021) and landscape and urban planning (Kleinschroth et al., 2022). However, if only flying the UAV for live feed surveys and not collecting imagery for orthomosaic maps, data storage will not be a problem unless live feed surveys are recording video of the survey.

Repairs and maintenance of UAVs can be challenging without expertise in this area. UAVs need to be kept clean from dust and debris. There is always the scenario of what if your UAV crashes and the most likely scenario is sending it back to the manufacturer for repair or replacement. Some UAV manufacturers offer insurance-type replacement plans for crashes, breakdowns, or lost (fly-away) UAVs. These scenarios can increase operating costs and lead to a loss of flying time (Martin et al., 2018; Paneque-Gálvez et al., 2014; Waibel et al., 2017). Previous research reported experiences with UAV malfunctions (Martin et al. (2018). Technological improvements have been shown to rapidly decrease these problems (Paneque-Gálvez et al., 2014).

The average survey durations reported in this study were specific to the study areas that were analyzed, the UAV and the flight parameters we used. It is important to note that various factors, such as state BMP guidelines, geographical location, harvest area, flight parameters, and

weather conditions can impact UAV-based surveys. Careful pre-planning and incorporating these factors can increase the rate success and efficiency of UAV-based monitoring.

### **2.5.3 Operational framework**

Since UAVs are a novel approach for forestry BMP monitoring, we developed a standardized operational framework based on test flights and our experience with UAV data collection for monitoring forestry BMP implementation. The operational framework incorporates detailed information and procedures for UAV-live feed and UAV-created map surveys to provide a reference for researchers, landowners, foresters, and loggers using or planning to use UAVs to monitor forestry BMP implementation. The UAV-live feed and a UAV-created map surveys have similar preliminary procedures, with only a few exceptions. Procedures for both survey types include 1) preparation for using and selecting a UAV; 2) pre-flight set-up and checks; and 3) conducting a UAV survey (Figure 13).

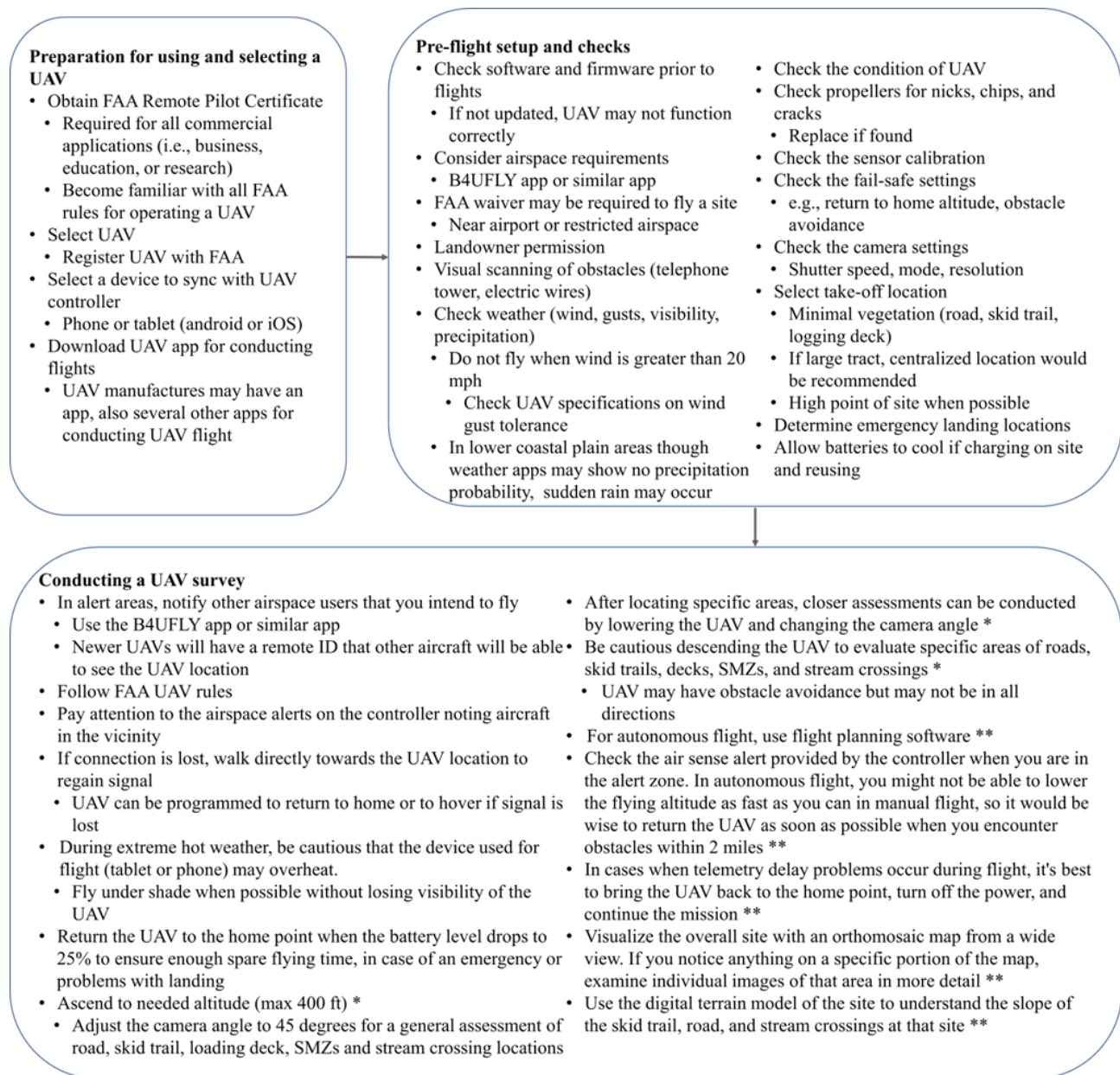


Figure 13. Operational Framework for UAV Monitoring of Forestry BMPs (\* refers only to UAV-live feed survey, \*\* refers only to UAV-created map survey, and where not noted, refers to both methods).

### 2.5.3.1 Preparation for using and selecting a UAV

Flying for commercial purposes in the United States necessitates the operator to pass a knowledge test and become an FAA-certified UAV pilot, which is mandatory before operating a UAV. It also requires registration of the UAV with FAA. Before flying, mark your UAV with

the registration number provided. Registration can be done through the FAA website (<https://www.faa.gov/>). In the United States, beginning September 16, 2023, all UAVs operating must have remote ID capability. So before buying a UAV, you also need to consider whether the UAV can provide identification and location information that other parties can receive during flight. Furthermore, before conducting fieldwork, it is crucial to communicate with landowners and forest managers about using UAVs. While obtaining permission is crucial, it is also crucial to respect the privacy of the property manager and keep their identity confidential.

Selecting a suitable UAV for your specific goals is crucial. When performing a BMP implementation monitoring survey, you should consider factors such as the UAV's availability, cost, and regulations. Some UAVs offered by certain companies may be restricted in the United States due to conflicts with national and local interests. It is essential to be aware of these restrictions when choosing a UAV for your survey. When selecting a UAV, it is essential to consider the camera quality. Many consumer-grade UAVs come with a standard RGB camera, while professional and enterprise UAVs may not come with any payloads, such as cameras or sensors. You may need to purchase additional hardware components to collect the desired data in these cases. The cost of a UAV can range significantly depending on its capabilities and technology level. Consumer-grade UAVs for forestry purposes may cost between \$300 and \$1500, while enterprise-level UAVs can cost more than \$5000. In general, UAVs with advanced guidance and control systems and additional sensor technologies tend to be more expensive.

In addition to a UAV, you will need a device such as a phone or tablet (running Android or iOS) to synchronize with the UAV controller. Some controllers, known as pro controllers,

feature a wide screen and advanced features that eliminate the need for an extra device. These pro controllers tend to be more expensive than regular controllers. To conduct flights, you will also need a flight app. Some UAV manufacturers offer their own apps for UAV flights, but these may not support autonomous flight planning. In this case, you can download a separate app that does support autonomous flight planning. There are a variety of flight planning apps available, some of which are free, while others require a small fee to download. These apps use user-defined inputs such as flying altitude, overlap, side lap, and sensor characteristics to create flight paths and calculate flight duration. Some common flight-planning apps include Dronelink, DroneDeploy, Pix4DCapture, and Litchi. These apps can help you predict how long it will take to complete a mission and determine how many batteries are necessary to cover the study area.

### **2.5.3.2 Pre-flight set -up and checks**

As UAV technology continues to evolve, it is becoming increasingly common for new firmware and app updates to be released. To ensure optimal performance during site visits, it is important to keep your UAV equipment up to date. In some forested areas, getting a reliable phone signal can be a challenge, so it may be necessary to travel to a location with better coverage to update your UAV. It is best to check for updates prior to going to the field.

Before flying a UAV, it is essential to check the rules and regulations related to UAV flights in the area; in the Southeast United States, particularly in southern Alabama and southern and western Florida, there are many military bases and training areas. Some areas fall into the alert area, and some fall into restricted areas. Therefore, check if you can fly UAVs in that area before heading to the site. This information will allow you to choose the right flying altitude or

apply for an FAA waiver if necessary. If a waiver is needed, you can apply to get airspace authorization through the Low Altitude Authorization and Notification Capability (LAANC).

Before flying a UAV survey, it is essential to examine the survey area for potential obstacles like power lines or trees that could impede the line of sight, signal, or damage the aircraft. Choosing an appropriate take-off location is crucial, such as a clear surface with minimal vegetation like a road, skid trail, or deck, and avoiding areas with ditches or bodies of water. Selecting a central location that offers a clear view of the entire area can be beneficial for large sites. Additionally, the UAV operator should have a designated emergency landing spot in case of unforeseen circumstances, such as low-flying manned aircraft or large birds.

Before commencing a UAV survey, ensuring that all equipment is functioning properly is imperative. This includes checking the UAV for updates, performing flight tests, calibrating the equipment, and setting fail-safe features such as return to home altitude and obstacle avoidance. It is also important to adjust camera settings like shutter speed, mode, resolution, and orientation to ensure high-quality data is collected. Double-checking these details can assist in preventing issues during the survey.

### **2.5.3.3 Safety and personal protective equipment for the use of UAV in forestry BMP**

When UAVs interact with people and/or other manned aircraft, there is a risk of causing lethal injuries, as noted in several studies (Koh et al., 2018; Moskowitz et al., 2018; Raoult et al., 2020). To minimize this risk, UAV operators must follow established safety protocols. Even when UAVs are not powered, the blades spinning in the wind can cause harm, making personal

protective equipment necessary (Raoult et al., 2020). Check propellers for nicks, chips, and cracks before a flight, and replace them when needed. UAV operations can pose challenges in certain environments, such as timber-harvested sites near wetland areas, sites with heavy shrub cover, or sites with a mobile substrate, like sand. In these cases, using a take-off pad can help prevent accidents, as UAVs can cause low pressures that attract foreign objects that could crash into the UAV (Raoult et al., 2020). To enhance safety, we suggest deploying clear signs that indicate the presence of UAVs. Additionally, when you are flying a UAV, it is wise to notify other airspace users of your intention to fly, operational flight plans, and on completion of your survey. The B4UFLY app (FAA, 2022a) can be helpful for this purpose.

#### **2.5.3.4 Conducting a UAV survey**

A UAV survey requires user-defined adjustments depending on the location to be surveyed. To begin a live feed survey using a UAV, start by ascending the UAV to the required altitude (not exceeding 400 feet). Then, adjust the camera angle to forty-five degrees to get a general overview of roads, skid trails, loading decks, special management zones, and stream crossing locations. Once specific areas have been identified, you can conduct a closer assessment by lowering the UAV and adjusting the camera angle. However, be careful when descending the UAV to inspect specific areas as the UAV may have obstacle avoidance, but it may not be in all directions. For a live feed survey using a UAV in and around the deck area, we recommend flying the UAV at an altitude of lower than 100 feet. This is particularly useful for identifying trash and oil containers, which logs, and woody debris may cover and are challenging to detect. Careful observation is necessary to ensure that these items are not missed.

One of the main challenges of using UAVs for both a UAV-live feed and a UAV-created map survey is the potential for adverse weather conditions, particularly rainfall. If you are conducting a UAV survey in the lower coastal plains, it is imperative to be aware that even if the weather app indicates only a small chance of precipitation, there is still the possibility of sudden rain. It is vital to remain vigilant, monitor the sky and cloud conditions while flying the UAV, and be prepared to quickly bring the UAV back to the take-off point if necessary.

While operating a UAV autonomously in an alert zone, it is crucial to constantly monitor the air sense alert the controller provides and keep an eye on the surroundings. If you encounter an obstacle, such as a helicopter or aircraft, the best action is to immediately return the UAV to its home location. The best course of action is to press the "return to home" button on the controller or app and swiftly decrease the altitude of the UAV when it gets above the home point.

The number and performance of batteries are crucial considerations in UAV operations. Actual battery life during flight is usually shorter than stated in the company's manual, which is based on ideal conditions without reserve power (Joyce et al., 2018). Additionally, batteries do not discharge evenly, and the discharge rate tends to increase rapidly when the battery reaches a certain level of discharge (Traub, 2016). Even though the UAV still has a small area to cover, it's recommended to return the UAV home when the battery level drops below 25%. Another battery can then be utilized to continue the flight. This provides enough spare flying time in an emergency or difficulty with landing. In addition, the distance from the takeoff site and wind speed should also be considered when determining the required battery backup level before

pressing the "return to home" button on the UAV. You can resume the UAV-live feed or the UAV-created map survey after changing the battery.

## **2.6 Conclusion and suggestions**

In this study, “yes,” “no,” or “not applicable” responses regarding proper BMP implementation were evaluated and compared for conventional surveys, UAV-live feed surveys and UAV-created map surveys. The results indicated that the UAV-live feed survey can be as accurate as conventional surveys for monitoring BMP implementation, indicating that UAVs can be used to monitor forestry BMPs. While the UAV-created map survey was less effective, it still offered valuable benefits for mapping of the harvest sites but is not recommended solely for forestry BMP monitoring. Assessing BMP implementation through UAV-live feed surveys provides significant time savings and details from the air that personnel on the ground may not see. This research focused on the southeastern United States using three-state BMP implementation surveys in their respective states, and there will need to be further studies in the northeast and western United States to determine practicality of using UAVs for BMP monitoring in these regions; however, these regions can incorporate similar approaches, but the state BMP guidelines from these regions will need to be evaluated with a UAV.

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