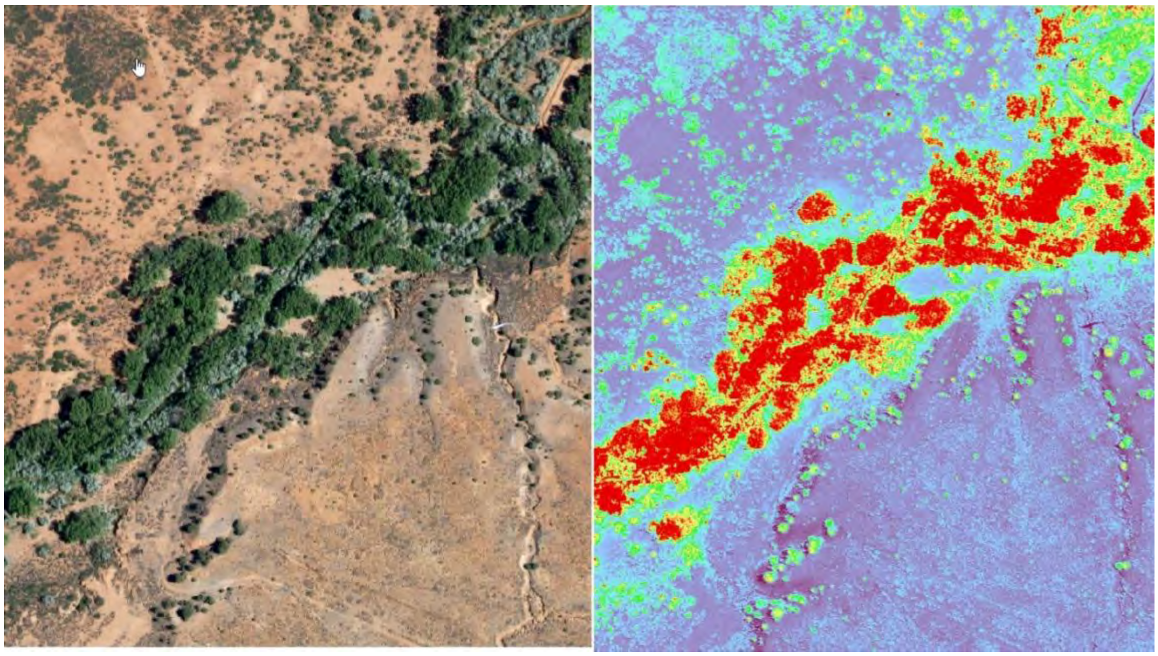
A Review of Drone-Assisted Ecological Monitoring for Riparian Ecosystems



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Acronyms

UAS	Unmanned aerial system
NMFWRI	New Mexico Forest and Watershed Restoration Institute
GRGWA	Greater Rio Grande Watershed Alliance
RS	Remote sensing
NAIP	National Agriculture Imagery Program
USGS	United States Geological Survey
UAV	Unmanned aerial vehicle
RPA	Remote piloted aircraft
RGB	Red, green, blue
NIR	Near infrared light
NDVI	Normalized difference vegetation index
LIDAR	Light detection and ranging
DBH	Diameter at breast height
ALS	Airborne laser scanning

Summary

The main objective of this review is to identify potential areas for unmanned aerial system (UAS), or drone, use in data collection and site characterization for Bosque ecological monitoring in the Greater Rio Grande watershed in New Mexico. This overview is meant to assist staff in assessing appropriate applications of drones in monitoring projects. A google scholar search for relevant articles was done using key words – i.e. drone, canopy, wetland, and aerial. A total of 33 articles were read. They are summarized below based on topic area. In addition, this review provides an introductory background to drones, imagery types, and processing protocols for those new to the field.

Introduction

The New Mexico Forest and Watershed Restoration Institute (NMFWRI) has partnered with the Greater Rio Grande Watershed Alliance (GRGWA) since 2011 to provide pre- and post-treatment monitoring of restoration sites throughout the Rio Grande watershed in New Mexico. The majority of projects have focused on invasive tree removal, particularly focused on Russian Olive (ELAN), Siberian Elm (ULPU), and salt cedar (TARA). Some projects have focused on invasive grass removal and Pinon-Juniper thinning for grass regeneration. These GRGWA-sponsored projects have taken place on public, private, and Tribal lands. NMFWRI is contracted through GRGWA to assess the project success through pre-treatment monitoring and 5-10-year post-treatment monitoring.

The utilization of drones and aerial imagery in ecological monitoring has the potential to assist or augment the data collection process for these projects. Remote sensing (RS) protocols have been used previously in NMFWRI's riparian projects, particularly during the 2020 COVID-19 pandemic due to difficult logistics for on-the-ground work. Historical and current National Agriculture Imagery Program (NAIP) imagery and software were used to assess sites for vegetation changes.

The goal of this review is to evaluate the efficacy of drone-use for NMFWRI's riparian monitoring projects. Articles from the growing field of unmanned aerial vehicle (UAV) assisted ecological monitoring were selected based on relevance to NMFWRI activities and include: invasive species monitoring, wetland restoration, fuels, and canopy characterization.

Overview of Unmanned Aerial Systems, Imagery Types, and Processing

Remote sensing is defined by the US Geological Survey (USGS) as "the process of detecting and monitoring the physical characteristics of an area by measuring its reflected and emitted radiation at a distance". This method uses a variety of technology including drones, satellites, airplanes, and sonar.

Drones are machines that fly without a human pilot. Other terms used to describe these types of machinery include unmanned aerial system (UAS), unmanned aerial vehicle (UAV), and remotely piloted aircraft (RPA). Some institutions are adopting gender-neutral terminology and using ‘uncrewed’ instead of ‘unmanned’. The table below from JOUAV describes the different types of drones and their uses.

Drone type	***Advantage***	***Disadvantage***	***Use***
Multi-rotor drones	• Easy to control and maneuver • VTOL and hover flight • Often lower price • Portability	• Limited flying time • Small payload capabilities • Less stability in the wind • Lower flight speeds	• Aerial photography • Aerial inspection • Landing surveying • Agriculture
Fixed-wing drones	• Longer flight time • Can carry a heavier payload • Greater stability in the wind • Higher flight speeds	• More training needed • No VTOL/hover • Expensive • Difficult to land, more places needed	• Aerial mapping • Utility inspection • Surveillance • Agriculture
Single-rotor helicopter drones	• VTOL and hover flight • Long endurance (with gas power) • Heavier payload capability	• More dangerous • Harder to fly, more training needed • Expensive	• Aerial LiDAR laser scanning
Fixed-wing hybrid VTOL drones	• VTOL and hover • Long-endurance flight • Fast speed • Heavier payload capability	• More training needed • Expensive	• Aerial mapping • Utility inspection • Surveillance • Agriculture • Search and rescue

Table 1: Types of drones sourced from https://www.jouav.com/blog/drone-types.html.

For monitoring, imagery is the main output of drones, satellites, and airplanes that are equipped with cameras. There are different types of imagery and cameras that collect imagery at different wavelengths. RGB or visible light capture standard color photos the way the human eye would see. Multispectral imagery captures specific, narrow bands of light that include RBG and near infrared light (NIR); this type of imagery is used for normalized difference vegetation index (NDVI). Hyperspectral imagery increases the number of specific bands from multispectral to allow for more detail and can be used to differentiate plant species. Thermal imagery detects heat radiation instead of reflected light and is used to measure temperature and moisture. Light Detection and Ranging (LiDAR) uses pulses of laser light to measure distances between the machine and the ground or the object (i.e. a tree).

Type of Imagery	*Method*	*Typical Uses*
RGB/Visible	Reflection of visible light	Tracking changes, plant health
Multispectral	Specific, narrow bands of reflection of visible light and near infrared light	Normalized difference vegetation index (NDVI)
Hyperspectral	Large number of specific narrow bands of reflection of visible light and near infrared light	Differentiating plant species
Thermal	Heat radiation	Detecting moisture, measuring temperature
LiDAR	Pulsed infrared laser light	Canopy and tree heights, elevation

Table 2: Types of imagery.

Once imagery is collected, computer processing is necessary to extract the desired data output. There is a wide range of software's, algorithms, statistical processes that can be used for post-processing and which to use depends on price, accessibility, type of input, time, and accuracy.

Photogrammetry is the method of determining measurements from a photo, often many overlapping photos. Structure-from-Motion (SfM) is the main technique used. Outputs are georeferenced to place the model or image in correct place. Using this method, a 3D model or an orthomosaic (many photos pieced together, often 2D) of an area can be created and used for analysis. LiDAR is separate technology from photogrammetry, but have been used in conjunction to increase resolution (Agisoft Metashape, 2025).

Image segmentation is the process in which objects are identified within a photo. Semantic segmentation is the most common, where each pixel is assigned a class. While it is time consuming, some methods use manual segmentation where a person manually identifies features in an image. Most methods use either machine learning or deep learning, with deep learning increasingly used. Machine learning is the traditional method that uses less computational power and more human experts to guide the algorithm. Deep learning is a subset of machine learning and also requires training – but instead of a human defining features the network automates learning thus allowing it to solve more complex problems and process complicated imagery (Yu et al, 2023; Janiesch et al, 2021).

Software Name	*Type*	*Best For*	*Cost & Accessibility*	*Key Features*
OpenDroneMap (ODM) / WebODM	Photogrammetry (Open-Source)	Users comfortable with working in a coding environment.	Free for the command-line version.	Creates high-quality orthomosaics and point clouds. Free for users who are comfortable with command-line format.
Agisoft Metashape	Photogrammetry (Commercial)	Researchers, professionals.	High cost for a professional license.	Most common software used for photogrammetry. High accuracy and requires more computing power.
Pix4Dmapper	Photogrammetry (Commercial)	Researchers, professionals.	High cost with different tiers.	User-friendly with automated workflows, high accuracy. Requires more computing power.
DroneDeploy	Photogrammetry / GIS (Commercial)	Users who may not have computing power.	Subscription-based. More affordable compared to Agisoft.	An all-in-one, cloud-based platform so it will not tax your computing power.
Maps Made Easy	Photogrammetry (Commercial)	Occasional users.	Pay-as-you-go credit system. Cost-effective for small or infrequent projects.	Simple, cloud-based processor. One of the more affordable options for generating orthomosaics and digital models.
QGIS (Quantum GIS)	GIS (Open-Source)	Researchers, students, community organizations looking for open-source options.	Free.	Open-source GIS software. Can process drone outputs and has a library of plugins for a wide range of tasks.
ArcGIS Pro	GIS (Commercial)	Researchers and professionals.	High cost. Can acquire cheaper license for educational institutions.	Most commonly-used GIS software. It has tools for most image processing steps, including working with 3D point clouds.
eCognition	Image segmentation (Commercial)	Researchers and professionals.	High cost. Lower cost for education institutions.	Specializes in object-based image analysis.
Python	Image segmentation (Open-source)	Users comfortable with working in a coding environment.	Free.	Open-source and with online resources to help users perform image analysis. See OpenCV, scikit-image, PyTorch.

Table 3. Types of software for image processing and their costs.

Applications of UAV in Riparian Ecological Projects

Ecological monitoring using drones has been utilized in many contexts – forests, tidal marshes, grasslands, agricultural fields, and more. In restoration ecology, drone-use has been less widespread compared to other fields (Robinson, 2022). During this time of adoption, standardization of protocol, access to equipment and software, and human knowledge has been increasing yet all of the above are still limitations cited in literature (Robinson, 2022; Singh, 2024). While the focus of this review is riparian restoration ecology applications, papers from other ecosystems are cited as they are relevant due to limited research papers on this specific topic. Below, invasive species monitoring, wetland restoration, fuels, and canopy structure are summarized briefly to show where current applications have been successful.

Invasive Species Monitoring

The significant and widespread impact of invasive species on ecosystems globally has affected water availability, persistence of native species, and ecosystem function. Invasive species monitoring is a potential application of UAVs in riparian settings due to its flexibility, cost-efficiency, and ability for greater temporal data collection as compared to crewed and satellite remote sensing (Lehman, 2017; Singh, 2024). The level of detail in satellite imagery can be limiting, making drones a cost-effective way to monitor plant invasions. Increasingly, studies have shown the efficacy of using drones to assess invasive plants in an ecosystem (Singh, 2024).

Woody invasive plants like Russian olive and Siberian elm in the Rio Grande are common target species for removal. One monitoring goal during post-treatment monitoring is detection of re-sprouts. Limited research has been done in this area. For early-detection of invasions, authors note the difficulty of monitoring young seedlings due to canopy cover (Lehman, 2017). One study showed feasibility of using UAV monitoring for early-detection of seedling growth in open-canopy environments (Dash, 2019), but limited research has been done in different levels of closure canopy forests. LiDAR's ability to penetrate through canopy could address this issue and is demonstrated in Singh et al 2015, but potentially cost-prohibitive and explains limited research using this method.

One study provided an example of using drone-acquired RGB photos to create 3D point clouds and 2D super pixels to distinguish overstory and understory vegetation (Li et al, 2020). This would potentially provide a more cost-effective methodology compared to LiDAR, but is a relatively untested and requires high-quality imagery with >80% overlap in imagery which is time and energy intensive.

A crucial aspect of remote sensing for invasive species monitoring is image segmentation for isolation and identification of plant species. Studies utilized a wide variety of combinations of imagery types and processing models that vary in optimizing accuracy, efficiency, and cost (Dong et al., 2025; Gautam et al., 2025; Papp et al., 2021). Two studies used more detailed-imagery types (multispectral, hyperspectral, LiDAR) along with intensive deep learning models which yielded high accuracy of species identification (Dong et al., 2025; Papp et al., 2021).

Because of the high variety in environment, target plant species, access to software, equipment, and human know-how, there is a lack of standardization and useful protocol to be extracted from the current available literature on invasive species, particularly in early-detection of small seedlings and understory vegetation.

Wetland Restoration

Wetland restoration success has been measured through vegetation indices and changes in evapotranspiration rates. Two studies did not use drones and used satellite imagery to demonstrate changes in vegetation in response to restoration treatments in riparian areas, but noted limitations including 1) inability to distinguish between native and invasive species, 2) no control over collection timing, and 3) annual changes in water budget and other activities like grazing (Silverman et al., 2019; Vanderhoof & Burt, 2018).

Dronova et al. provides a recent review of drone application in wetland monitoring. The authors note that while RBG and multispectral imagery dominates, LiDAR, hyperspectral, and thermal sensors will become more prevalent as the cost for greater data-rich imagery decreases. Vegetation mapping was the most prevalent method of the papers reviewed, with mapping change over time being the least prevalent (Dronova et al., 2021).

Fuels

Due to damming and flood control along the Rio Grande paired with the introduction of exotic plant species, the Bosque forest ecosystem has seen an increase in hazardous fuels and incidence of wildfires (Ellis, n.d.; Finch & Deborah M, 2008). Hazard fuels measurements include canopy cover and surface fuels. In general, estimating fuel load in the tree canopy with remote sensing has been shown to be more accurate compared to surface fuels, due to sensors' inability to penetrate dense forest canopies (Abdollahi & Yebra, 2025).

Studies have shown proven ability of UAV collected imagery to accurately quantify canopy fuels, but all reviewed papers have utilized different protocols (Arkin et al., 2023; Chávez-Durán et al., 2024; Shin et al., 2018). Chávez-Durán et al. demonstrated an effective protocol using RBG imagery, while Arkin et al. utilized LiDAR data. Both studies used Agisoft and CloudCompare softwares for point-cloud generation. Concerns with processing include overlapping, dense canopies particularly in mixed forests (Chávez-Durán et al., 2024). Shin et al. found that canopy bulk density collected via UAV multispectral imagery was not correlated with field measurements but mentioned that LiDAR has accurately estimated canopy bulk density in other studies, such as the study by Arkin et al.

For understory fuel measurements, a wide-array of methods have been used indicating that a standard protocol has not been developed or that custom protocols are needed for specific locations. Two studies utilized close-range methods for quantification (Cova et al., 2023; Zhang et al., 2022) and other studies' environments were relatively open-canopy (Herzog et al., 2022; Penglase et al., 2023; Shrestha et al., 2021; Sos et al., 2023). Point clouds were derived from RBG imagery in three cases (Cova et al., 2023; Penglase et al., 2023; Sos et al., 2023) and in the other half used LidAR/laser scanning (Herzog et al., 2022; Shrestha et al., 2021; Zhang et al., 2022). Image processing varied from utilization of Agisoft, ArcGIS Pro, Python, R, and voxel creation.

An emerging new method for addressing some of the drawbacks of current imagery processing for fuels is the use of voxels – volumetric pixels that can account for movement like wind, fire (Cova et al., 2023; Enterkine et al., 2025; Lecigne et al., 2018; S. Eusuf et al., 2020). While still new and requires further refinement, this method may assist in providing more accurate results from RS-collected imagery for fuels management.

Canopy Structure & Forest Inventory

Drone collected data has been widely confirmed of its accuracy in estimating canopy cover and tree heights (Islami et al., 2021). Diameter-at-breast-height (DBH) has been utilized in some studies, but remains context-dependent for its accuracy and is generally difficult due to canopy cover. Flight height is an important consideration and it is recommended to test accuracies at different heights. Reviewed papers typically used laser scanning (airborne laser scanning [ALS] or LiDAR) to achieve their results (Goodbody et al., 2017, 2019; White et al., 2016).

Considerations and Best Practices

In published literature reviews on the subject of drone-use for ecological monitoring, authors noted important considerations for future projects. A vast majority of papers they reviewed did not adequately report the technological specifications, hindering replicability. Sensor calibration, drone platforms, image processing methods were often not reported or discussed in enough detail. Regarding invasive species monitoring in particular, Singh et al also notes the lack of larger, regional studies considering the widespread impact of the issue – partially due to propulsion limitations and compatibility issues with satellite imagery (Singh, 2024).

In Ecke et al's review of forest health monitoring, they outline six gaps to be addressed: 1) hyperspectral and LiDAR should be used more, and in conjunction; 2) more re-visits and long-term monitoring; 3) early stress detection is important; 4) technical and regulatory barriers should be addressed; 5) multisource monitoring would benefit from standardization; 6) overreliance on commercial software may be a weakness in knowledge transfer (Ecke et al., 2022).

The main themes of reproducibility, data sharing, cost barriers, and the technical expertise required to perform these studies were echoed through many of the papers reviewed.

Application to NMFWRI Monitoring

Applying drone technology to NMFWRI's monitoring program requires careful consideration of several factors. First, replicability across diverse landscapes. Riparian monitoring locations have incredibly varying canopy coverage, from 0% to 100% coverage. When designing a data collection protocol via UAV, it is crucial to account for how these differences might affect the types and quality of data that can be acquired.

Second, potential for landscape-level data collection. Current plot collection is focused on multiple tenth of an acre plots across a project. It is possible that drone-collected landscape data could provide larger context for plot data or fill in gaps. This could also be an opportunity for collaboration with other land managers and organizations.

Third, human and technological capacity. From protocol creation to image analysis, this process is intensive both in human specialization and technology requirements. To ensure sustainability, the program should consider the training, certification, space, and cost of such investments long-term.

Overall, UAV-assisted monitoring shows great potential for projects along the Rio Grande in New Mexico. For those considering remote sensing, it is suggested to carefully develop protocols that consider the varying landscape, explores regional opportunities, and aims to keep the barrier to utility low by minimizing requirements for highly specialized human expertise and expensive technology.

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