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REVIEW ARTICLE

Applications of unoccupied aerial systems (UAS) in landscape ecology: a review of recent research, challenges and emerging opportunities

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Abstract
Context Unoccupied aerial systems/vehicles (UAS/UAV, a.k.a. drones) have become an increasingly popular tool for ecological research. But much of the recent research is concerned with developing mapping and detection approaches, with few studies attempting to link UAS data to ecosystem processes and function. Landscape ecologists have long used high resolution imagery and spatial analyses to address ecological questions and are therefore uniquely positioned to advance UAS research for ecological applications.
Objectives The review objectives are to: (1) provide background on how UAS are used in landscape ecological studies, (2) identify major advancements and research gaps, and (3) discuss ways to better facilitate the use of UAS in landscape ecology research.
Methods We conducted a systematic review based on PRISMA guidelines using key search terms that are unique to landscape ecology research. We reviewed only papers that applied UAS data to

Collection: Advances and Applications of Unoccupied Aerial Systems (UAS) Research in Landscape Ecology

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investigate questions about ecological patterns, processes, or function.
Results We summarize metadata from 161 papers that fit our review criteria. We highlight and discuss major research themes and applications, sensors and data collection techniques, image processing, feature extraction and spatial analysis, image fusion and satellite scaling, and open data and software.
Conclusion We observed a diversity of UAS methods, applications, and creative spatial modeling and analysis approaches. Key aspects of UAS research in landscape ecology include modeling wildlife microhabitats, scaling of ecosystem functions, landscape and geomorphic change detection, integrating UAS with historical aerial and satellite imagery, and novel applications of spatial statistics.

Keywords UAS · UAV · Drone · Ecosystems · Wildlife · Land change science · Landscape · Remote sensing

Abbreviations

AGB	Above ground biomass
API	Application programming interface
CACTI	Cacti index
CHM	Canopy height model
CNN	Convolutional neural networks
DEM	Digital elevation model
DLC	Disturbance and land change
DG	Direct georeferencing
DoD	DEMs of Difference
DUVES	Dune vegetation state
EM	Electromagnetic
EVI2	2-Band enhanced vegetation index
FAA	Federal Aviation Administration
GCC	Green chromatic coordinate
GCP	Ground control points
GNDVI	Green Normalized Difference Vegetation Index
GSD	Ground sampling distance
GNSS	Global navigation satellite system
GPP	Gross primary productivity
GUI	Graphical user interface
IG	Indirect georeferencing
LAI	Leaf Area Index
LAD	Leaf Area Density
LCI	Leaf Chlorophyll Index
Lidar	Light detection and ranging
minLoD	Minimum level of detection
MODIS	Moderate Resolution Imaging Spectroradiometer
MSAVI	Modified soil adjusted vegetation index
NDRE	Normalized difference red edge index
NDVI	Normalized difference vegetation index
NIR	Near infrared
OBIA	Object Based Image Analysis
OSAVI	Optimized Soil Adjusted Vegetation Index
PRISMA	Preferred Items for Systematic reviews and Meta-Analyses
PRI	Photochemical reflectivity index
PPK	Post processing kinematic
RMSE	Root mean square error
RGB	Red, blue, green bands
RTK	Real time kinematic
SIF	Solar induced fluorescence
SfM	Structure from Motion
STAC	SpatioTemporal Asset Catalogs
SWIR	Shortwave infrared index
SVM	Support vector machine
TIR	Thermal infrared
UAS	Unoccupied Aerial Systems
UAV	Unoccupied Aerial Vehicles
VIS	Visible band
VNIR	Visible-near infrared
WPE	Woody plant encroachment

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Introduction

Remote sensing data are a fundamental information source for landscape ecology research (Foody 2023). Early ideas about landscape patterns and spatial heterogeneity in ecology were informed by interpretation of aerial photography (Troll 1971), and many foundational papers showed the utility of high resolution (0.5–2 m) aerial photography for evaluating landscape patterns, fragmentation and historical land change

(O'Neill et al. 1988; Swetnam et al. 1999; Morgan et al. 2010). In the late twentieth century, medium resolution satellite data (30–50 m) became more widely available and used, offering several advantages for land cover mapping and change detection, namely increased spectral bands optimized for land cover and vegetation mapping, large footprints, and repeated observations over time (Rogan and Chen 2004). High resolution (1–3 m) multispectral aerial and satellite imagery have remained important data sources for characterizing landscape patterns and change (Ellis et al. 2006), and understanding how observed patterns are influenced by measurement scale (Wickham and Riitters 2019). More recently, ultra-high resolution (mm-cm resolution) imagery collected from small unoccupied aerial systems/vehicles (UAS/UAV; colloquially known as drones) has grown in popularity for use in environmental applications.

UAS have become an important tool in the environmental sciences allowing researchers to collect data on demand at very high resolution and with various sensors, at generally low costs and effort. Whereas satellite pixels are at a fixed resolution, the flexibility of UAS allow researchers to collect and analyze data at ecologically relevant units. UAS are capable of providing spectral and structural data at the scale of individual plants (Cunliffe et al. 2016; Sankey et al. 2017; Madsen et al. 2020) and at a scale suitable for improved wildlife detection and fine-scale species distribution models (Christie et al. 2016; Habel et al. 2018a). This resolution facilitates new research into plant and animal demographics, fine-scale impacts of natural disturbances, and linking landscape pattern and ecosystem function across scales.

Despite a rich history investigating landscape patterns and ecological processes from orbital satellite and aerial photography, landscape ecologists have been relatively slow to embrace UAS technologies. Over a decade ago Anderson and Gaston (2013) detailed the potential of UAS to revolutionize spatial ecology by allowing researchers to control and define the spatial, spectral and temporal characteristics of their remote sensing in ways that traditional satellite and aerial missions cannot. A rapid increase of UAS research has been observed in many fields related to landscape ecology, with recent systematic reviews in forestry (Guimarães et al. 2020), range management (Lyu et al. 2022), hydrology (Vélez-Nicolás et al. 2021), plant ecology (Sun et al. 2021), wildlife population monitoring and conservation (Christie et al. 2016; Elmore et al. 2023), earth and environmental sciences (Manfreda et al. 2018; Singh and Frazier 2018; Andresen and Schultz-Fellenz 2023) and biodiversity conservation (Nowak et al. 2019; Librán-Embid et al. 2020). However, the reasons for not observing similar growth of UAS research and applications in landscape ecology are unclear. One possible reason is a mismatch in spatial scales: landscape ecology studies tend to cover large geographical extents (1–100,000 km^2; Mayer and Cameron 2003), whereas UAS data collections often cover smaller areas (i.e., 1–100 hectares) due to constraints in flight distance, visual line of sight regulations and battery life. However, landscape ecologists have long explored patterns and ecological function at smaller spatial scales to study organism or ecological processes (Wiens and Milne 1989; Turner 2005), and there is continued interest in cross-scale inference of pattern and process (Wiersma and Schneider 2022). Small footprint UAS also provide sampling data at an intermediate scale, which help link field-based measurements with satellite data, increasing the opportunities for new landscape-scale ecological studies (Alvarez-Vanhard et al. 2021).

UAS remote sensing is still partially in the research and development phase, which may be another factor limiting widespread adoption for landscape ecology research. Yao et al. (2019) noted research practices are often developed through a "learn-by-doing" process, that signifies a lack of scientific consensus and standards for typical UAS remote sensing tasks like vegetation cover classification and change detection. A recent review of the UAS literature in plant ecology showed that much of the research output is generated by remote sensing scientists concerned with methodological questions about image classification, mapping and model accuracy, with few studies actually applying these approaches to address ecological questions (Sun et al. 2021). Sun et al. (2021) also identified few landscape-scale UAS studies and suggested that satellite data are more suitable for landscape research given the challenges of collecting and processing UAS data over large areas. However, there are signs that landscape ecologists are overcoming these challenges and integrating UAS technology into their studies. At the time of writing there were only 11 UAS papers published in the journal Landscape

Ecology, and 10 of these were published in the 2 years prior to this review (2022–2023). Perhaps we are now entering a phase where UAS data, image processing and modeling approaches are established enough to support widespread use in landscape-scale ecosystem science. Landscape ecologists, with a tradition of using high resolution remote sensing data to address ecological questions and a well-tested toolbox of spatial analysis techniques, are uniquely positioned to advance the science of UAS within an ecological framework.

The purposes of this review are to: (1) provide background on how UAS data are used in landscape ecological studies and the questions being addressed, (2) identify major advancements and research gaps, and (3) provide ideas and discussion to help better facilitate the use of UAS technologies in landscape ecology research. To systematically review and quantify recent trends and applications of UAS in landscape ecology literature, we formulated the following questions and sub-questions:

1. How have UAS data been applied to address key questions in landscape ecology regarding landscape structure and heterogeneity, and ecological patterns and processes?
    a. What are the major applications within the field?
    b. What types of data are used?
    c. What types of ecosystems are being studied?
    d. What types of models are used?
    e. Is there a commitment to open data and standardization?
2. Where are the major advancements and research gaps?

Methods

We conducted a systematic review following the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA; Page et al. 2021) protocol phases: (1) search terms and inclusion criteria; (2) screening titles and abstracts; and (3) analyzing and synthesizing eligible articles. We used Scopus (https://www.elsevier.com/products/scopus) as our primary search database and Google Scholar (https://scholar.google.com/) as a secondary search. We completed additional targeted searches within the following individual journals: Landscape Ecology, Ecosystems, Land, Landscape and Ecological Engineering, Ecological Applications, and Current Landscape Ecology Reports.

Search terms

Search terms included "UAV" OR "UAS" OR "sUAS" OR "drone" OR “aerial vehicle” OR “aerial systems” plus the following key terms: "landscape ecology" OR "landscape pattern" OR “landscape change” OR “landscape structure” OR “landscape dynamics”; "landscape metric*" OR “patch metrics”; “spatial ecology” OR “ecological pattern*” OR “ecological process” OR “ecological analysis”; "landscape fragmentation" OR "spatial heterogeneity" OR "habitat connectivity".

Landscape ecology is an interdisciplinary and inclusive field that shares many concepts with geography, plant and wildlife ecology, biogeography, geomorphology, and hydrology. Our search criteria were narrowly focused on keywords that set landscape ecology apart from these other fields, by highlighting the key concepts of landscape heterogeneity, spatial patterns and scale. We acknowledge that we likely excluded some important landscape ecology-adjacent research papers because of this narrow search criteria.

Criteria for inclusion

Our main criteria for inclusion were a clear “landscape” or “ecological” research application that included analysis of ecological patterns, processes, or function. In other words, the UAS data had to be analyzed in a way that attempted to provide insight into a species, ecosystem, or landscape and their function, patterns and processes. We filtered out papers concerned primarily with mapping techniques and methods as well as papers where the primary research questions were about the UAS technology itself rather than ecosystems or landscapes. We excluded any strictly urban or agricultural applications (i.e., crop mapping), with exception for studies of agropastoral landscapes or wildlife habitat studies in agricultural or urban landscapes. We only included papers published in peer reviewed journals (no theses, dissertations, or conference papers). The papers could be published any year up to our search period through August of 2023.

Metadata recorded

In addition to basic publication metadata (authors, title, year, journal, keywords), we collected information on study geography and spatial extent, aircraft and sensor details, flight details, derived image products and modeling approaches, use of satellite data, in-situ field methods, validation metrics and product accuracy, open-source code and data, and general application categories (Table 1). We classified the papers according to three general applications: vegetation (V), disturbance and land change (DLC), and wildlife (W) studies. Where applicable we also noted more specific landscape ecology applications, including land/vegetation change, spatial patterns, wildlife habitat modeling and distributions, plant demographics, ecosystem function and processes (i.e., phenology, evapotranspiration), restoration, and invasive species.

Data analysis and interpretation

We present the results of the literature review organized into the following sections: (1) Overall Results, where we provide descriptive statistics on the publication metadata, study geography, general type of UAS data use, (2) UAS Technology, where we describe trends in aircraft, sensors and geomatics, (3) Techniques and Methods, where we review derived products, modeling and spatial analyses, (4) Data Fusion, where we review and discuss image fusion and scaling with UAS, and (5) Open Data and Standards, where we review and discuss open science protocols.

Results and discussion

Of the 539 records returned in our initial search, we identified 161 papers that fit our criteria for review. These papers ranged in date from 2013–2023, with a large increase in the number of publications beginning around 2019 (Fig. 1). Papers were published across 78 different journals with the most common being Remote Sensing MDPI (20), Ecological Indicators (13), Landscape Ecology (11), Remote Sensing of Environment (8), Remote Sensing in Ecology and Conservation (7), and Science of the Total Environment (7).

Study locations were distributed across all continents, but were more densely clustered in Asia, North America, and Europe (Fig. 2). Studies were conducted in 45 different countries, and most were in China (33), followed by the United States (28), Australia (14), and Spain (8). The studies were generally well distributed across biomes, but with a higher tendency toward moderately dry and warm biomes like woodland/shrubland, temperate seasonal forest and tropical seasonal forest/savanna (Fig. 1). Study landscapes imaged using UAS ranged in size from 0.12 ha to 6,710 ha, with an average size of 192 ha (median = 10 ha); however, the spatial extent imaged was not reported in many of the papers reviewed. The number of study sites or distinct areas imaged with UAS per study ranged from 1–96, median = 1 and mean = 5. Nineteen of the 161 studies (about 12 percent) included more than 10 image sites.

We found that 75% of the studies reviewed used true color RGB (red, blue, green bands) cameras and true-color imagery, 15% visible-near infrared (VNIR) multispectral, 5% lidar, 3% thermal, 3% hyperspectral, and 1 used solar induced fluorescence (SIF). Twenty-four studies used more than one UAS sensor in their research (often a combination of RGB and multispectral), and 77 studies applied some type of fusion or scaling with satellite data. Seventy-one studies tracked landscape changes over time using multi-temporal UAS, and/or aerial photography and satellite data. Of the satellite data used for fusion or multitemporal analysis, Landsat satellites were the most popular (20) followed by Sentinel satellites (12), PlanetScope (6) and MODIS (5). Fifteen studies combined UAS with high resolution (< 2 m) aerial and satellite data.

Landscape ecology applications and themes

More than 50% of the papers reviewed had a disturbance and landscape change (DLC) application, and many of these papers investigated vegetation and morphological landscape changes in response to disturbances like wildfire (Fraser et al. 2017; Talucci et al. 2020; Viedma et al. 2020; Dashpurev et al. 2021; Reilly et al. 2021; Marsh et al. 2022; DaSilva et al. 2023), climate change (van der Sluijs et al. 2018;

Table 1 Table of metadata and data collected from papers reviewed, including the broad category, parameter and description of each

Category	Parameter	Description
Publication metadata	Authors	Populated from search database
	Title	Populated from search database
	Year	Populated from search database
	Journal	Populated from search database
	Source database	Populated from search database
Geography	Country	Country of study location
	Latitude/longitude	Geographical location and coordinates of study area
	Biome or ecosystem	Biome or ecosystem type reported in study area section
	Spatial extent of UAS data collection	Total size of UAS image collections
	Number of UAS image areas	Number of distinct sites with UAS image collections
UAS details	Platform	Aircraft or platform make and model
	Sensor 1 name	Make and model of sensor
	Sensor 1 spectral	Sensor type (i.e., RGB, multispectral, lidar)
	Sensor 1 altitude	Reported altitude
	Sensor 1 wind speed	Reported wind speed
	Sensor 1 GSD/resolution	Reported pixel resolution or ground sampling distance (GSD)
	Sensor 1 overlap	Percent overlap reported
	Sensor 1 calibration or normalization	Calibration or normalization methods if reported
	Sensor 1 georeferencing	If documented include details including RMSE, else "none"
Image products	Sensor 1 image products	Main products derived from UAS i.e., orthomosaic, NDVI
	Sensor 1 modeling/classification	Methods used to process image data
	Sensor 2,3,4, etc	Repeat the above if multiple UAS sensors
Multitemporal and fusion	Multitemporal? (Y/N)	Did the study contain multitemporal data? Yes or No
	Multitemporal info	Details about the time periods and number of repeat flights
	Data fusion or satellite scaling? (Y/N)	Yes or No
	Satellite data used	Satellite data used (i.e., Sentinel-2, Landsat 8)
	Structure from Motion (SfM), Canopy Height Model (CHM), or Digital Surface Model (DSM)?	Note which one was generated, else "none"
	Point cloud density	points/m2
Field data and validation	In situ field measures	Field data collected (i.e., plant height, area, volume and count)
	Field-based study design	Study design (i.e., 12 1×1 m quadrats)
	UAS products validated?	Yes or No
	Validation metric	How were the UAS products validated (i.e., regression, kappa)
	Reported accuracy	Reported accuracy values (i.e., R^2, RMSE)
Open science	Software UAS image processing	Software types used (i.e., Metashape, Pix4d)
	Open-source software used?	Open-source software types used
	Data availability/open data or code?	Are data available and hosted on website?
Application	Primary research application	Vegetation (V), wildlife (W), disturbance and land change (DLC)

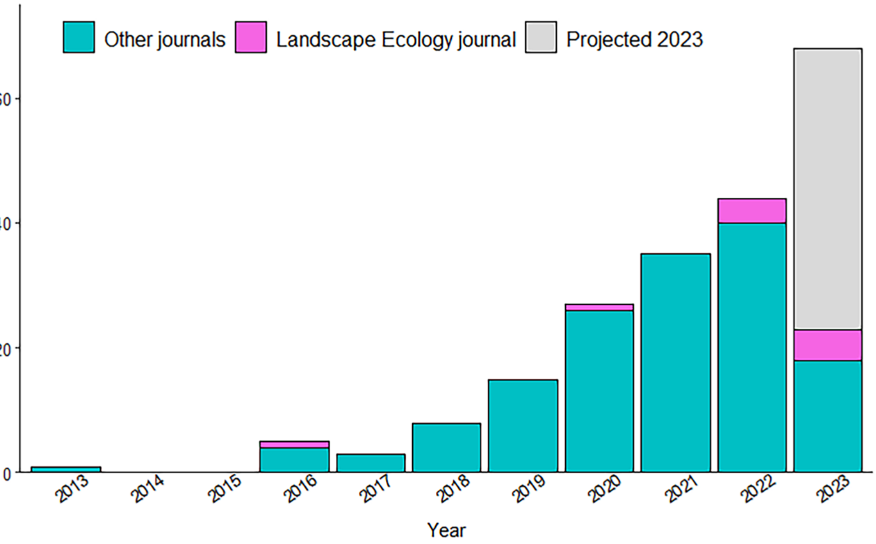


Fig. 1 Number of UAS papers in landscape ecology applications published per year. Papers published in the journal Landscape Ecology are in pink, and those published in all other journals are in turquoise. Note due to the timing of the literature search, 2023 only represents papers that were published through August 31, 2023. We projected the number of papers in 2023 (grey bar) using an exponential model ($y = 2.19e^{0.45x}$) fit with the data from 2016–2022

Orndahl et al. 2022; Steenvoorden et al. 2022; Tanguy et al. 2023) or anthropogenic land uses (Bregoli et al. 2019; Fenger-Nielsen et al. 2019; Iijima et al. 2021). Several studies used UAS data to evaluate vegetation and landscape change in response to restoration treatments (Laporte-Fauret et al. 2020, 2021; Broussard et al. 2022; Jiang et al. 2022; Peterson et al. 2023; Qiu et al. 2023; van Proosdij et al. 2023). Many of the DLC studies were also classified as Vegetation (V) application (62 classified as both DLC and V). Studies with vegetation applications that were not DLC were most often concerned with factors contributing to invasive species distributions (Zhu et al. 2019; Hensel et al. 2021; Chang et al. 2022; Nascente et al. 2022; Bishop and Errigo 2023; Zhou et al. 2023), ecosystem process and function (Faye et al. 2016; Klosterman et al. 2018; Ahongshangbam et al. 2020; Dixon et al. 2021; Simpson et al. 2022), and plant spatial patterns and landscape fragmentation (Fynn and Campbell 2019; Charton et al. 2021; Doughty et al. 2021; Wu et al. 2021; Blanchard et al. 2023). We reviewed 27 studies with wildlife applications, many with a sub-focus on detection of species and/or specific habitat components (Evans et al. 2016; Oosthuizen et al. 2020; Saqib et al. 2020; Hensel et al. 2021; Oleksyn et al. 2021; Thaker et al. 2022), and habitat and species distribution modeling (Habel et al. 2018a; Bao and Yang 2022; Barbosa et al. 2022; Shokirov et al. 2023).

Eleven UAS studies were published in the journal Landscape Ecology between 2016 and September 2023. These papers were broadly concerned with plant and wildlife ecology, specifically: (1) wildlife habitat suitability and species distribution modeling, and (2) linking vegetation spatial patterns to ecosystem processes. UAS data were used in wildlife research to define micro-habitat features important for butterfly larvae (Habel et al. 2016, 2022), aquatic insect distributions (Gerber et al. 2023), and marine species distributions in coastal habitats and their ecosystem functions (Schenone and Thrush 2022). UAS imagery was used for characterizing forest patterns to help explain genetic variation of rodents (Borja-Martínez et al. 2022), and for mapping phytochemicals of individual plants that serve as wildlife food sources (Olsoy et al. 2020).

Many of the UAS studies published in the journal Landscape Ecology explored spatial patterns of vegetation and vegetation changes, and the factors driving these patterns. These include analysis of vegetation and bare soil spatial patterns with RGB and lidar (Getzin et al. 2022), the influence of ungulates and livestock on vegetation productivity generated high resolution normalized difference vegetation index (NDVI) images (Velamazán et al. 2023), forest edge effects on structure and function (Blanchard et al. 2023), and analysis of vegetation patterns from interactions between lithology, aridity and soil water availability (Rodríguez-Lozano et al. 2023). Three papers were concerned with vegetation change from wildfire: Van Blerk et al. (2022) combined field and multispectral UAS

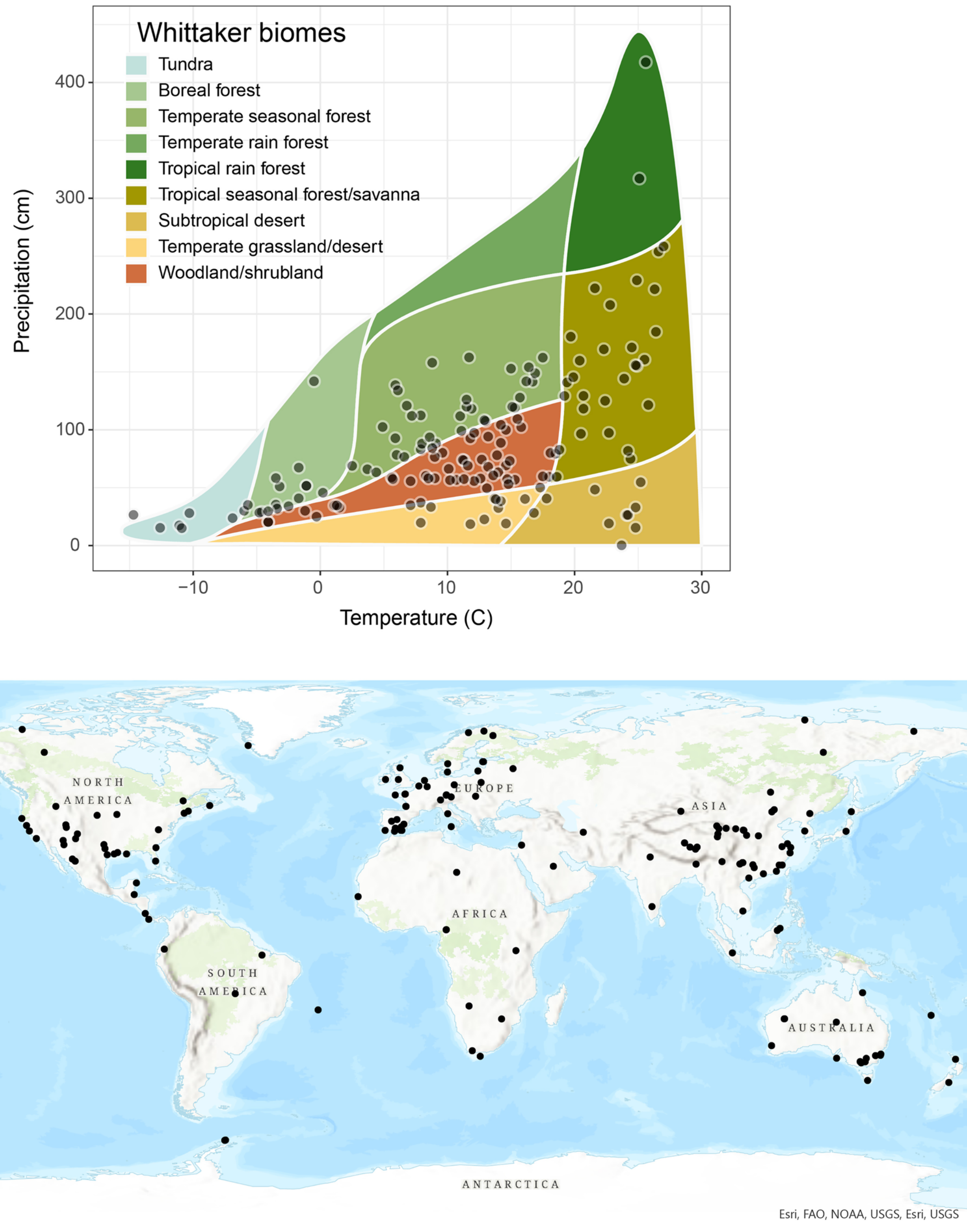


Fig. 2 Distribution of study locations across Whittaker biomes (top; Whittaker 1975) and globally (bottom)

measurements over three years to monitor post-fire shrubland recovery in response to altered rainfall seasonality at an experimental site. Bowman et al. (2023) used canopy height models (CHM) generated from lidar to define contemporary forest-sedgeland boundaries, and historical aerial photography to quantify past forest expansion and the effects of fire on vegetation dynamics. Sankey et al. (2024) used UAS multispectral data and Sentinel images to map wildfire severity and forest thinning impacts and quantify post-fire flood-driven sedimentation.

Aircraft, sensors and technology

Sensors and aircraft

When planning for data collection using UAS, it is imperative to begin by clearly defining the scientific questions to be answered and identifying the data needed to address these inquiries. Key considerations in determining the data requirements and appropriate sensor include recognizing the appropriate range of electromagnetic (EM) spectra, the minimum and maximum resolution needed for data products, frequency and timing of data collection, and data precision. UAS used in landscape ecology can be equipped with various sensors, having spectral sensitivity throughout the electromagnetic spectrum including RGB or visible spectrum cameras, thermal infrared, lidar, multispectral, hyperspectral, radar/radio wave, and gamma ray sensors, to name a few (Fig. 3). The data collected by these sensors can include imagery, elevation data, and spectral information, providing detailed insights into landscapes and ecosystems at scales from individual plants to entire biomes. Sensors can be active (such as lidar) or passive with fine spatial and temporal resolution which enables applications such as mapping, monitoring, surveying, and tracking.

Once a sensor is chosen, a suitable airframe is required to position the sensor near or over the target of interest. Knowing how much area needs to be covered helps determine whether a fixed-wing or rotary-wing is the most appropriate platform for the intended mission (Fig. 4). Quadcopters, or 4-rotor UAS, are extremely popular because they are inexpensive and easy to transport but are less stable in windy conditions compared to larger 6- or 8-rotor vehicles (Ahmed et al. 2022). These hexacopter and octocopter vehicles can support heavier payloads and are more stable in the air, although at the expense of battery life and smaller image areas. Fixed-wing UAS can traverse longer distances and cover larger areas than their rotary-wing counterparts before needing to be refueled or recharged, which may be preferred for landscape-scale research. Fixed-wing platforms

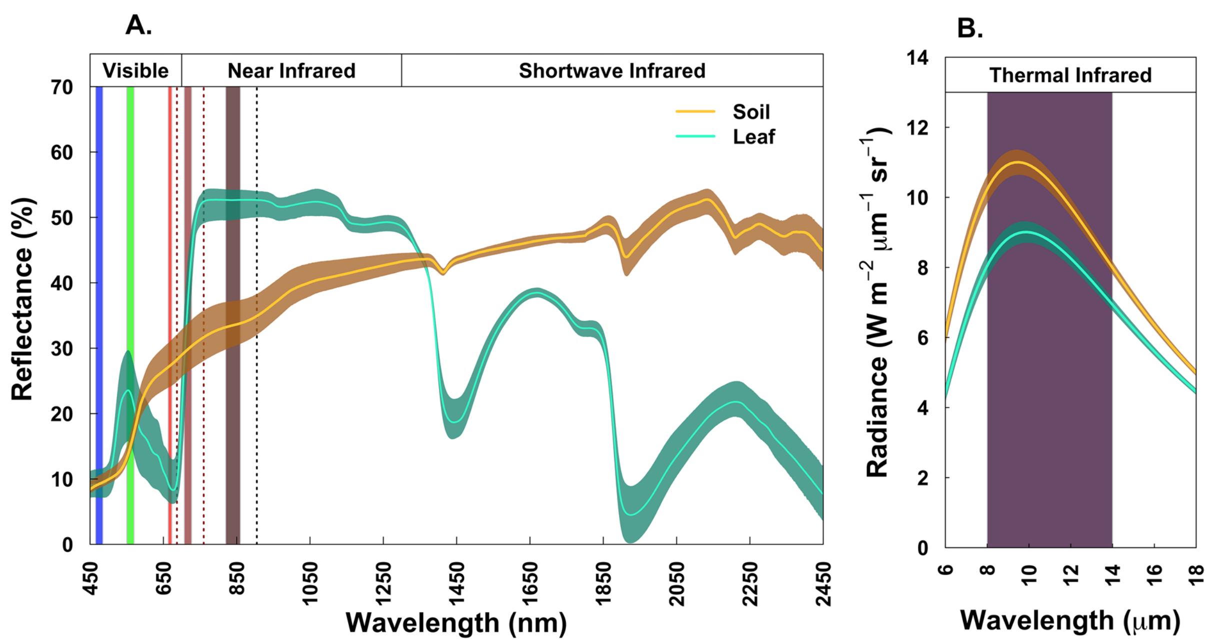


Fig. 3 A representative reflectance **A** and radiance **B** spectra for a healthy leaf and dry soil. Highlights show common UAS spectral bands blue (~475 nm; blue shading), green (~560 nm; green shading), red (~668 nm; light red shading), red edge (~717 nm; red shading), near infrared (~842 nm; dark red shading), and thermal infrared (8–14 µm; purple shading). Common SIF retrieval windows (680 nm and 760 nm) are shown as vertical dashed red lines. Common lidar emission wavelength (905 nm) is shown as a vertical dashed black line. Figure inspired by (Pierrat et al., 2025) and adapted to focus on unoccupied aerial systems applications

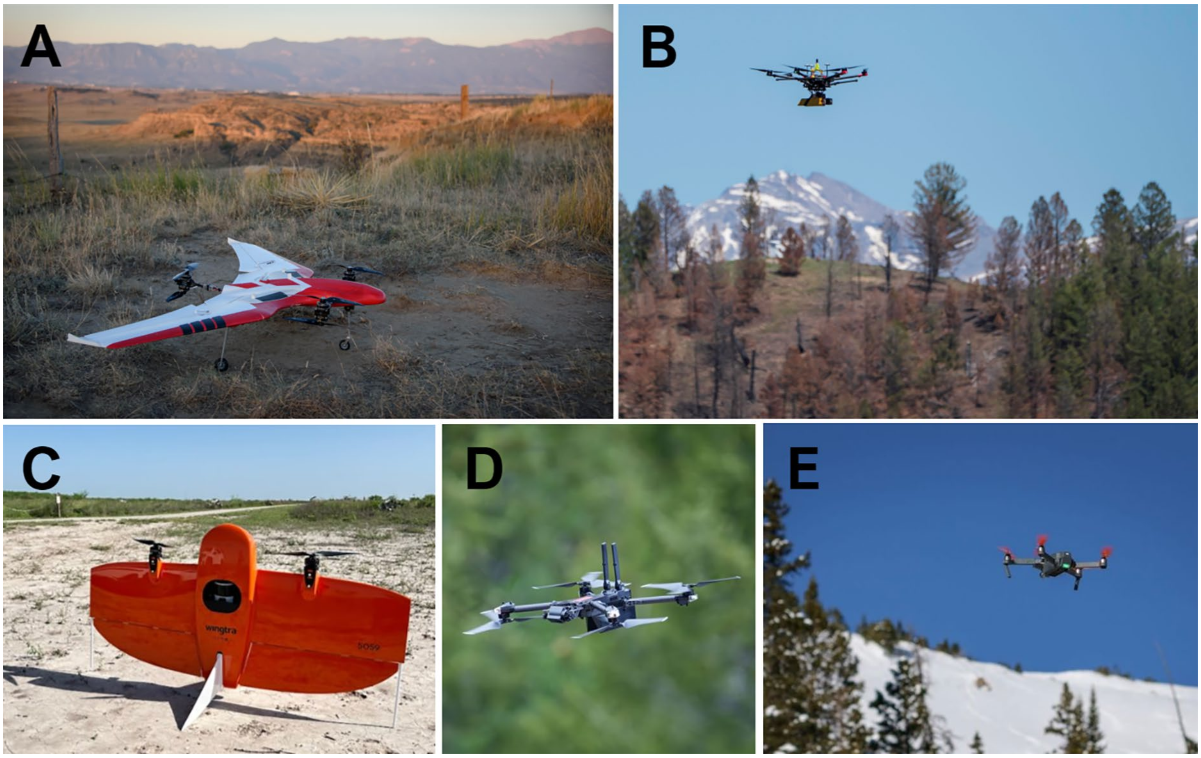


Fig. 4 Examples of various UAS platforms, sensors, and environments for collecting remote sensing data for scientific applications. These include but are not limited to fixed-wing **A**, **C** and rotary-wing UAS such as hexacopter **B** and quadcopter **D**, **E** platforms (Photos A, B, D, E by Mark Bauer, USGS; Photo C by Keith Williams, Wingtra, used with permission)

generally fly faster and are not as easy to maneuver compared to the more easily flown and transported rotary-wing UAS. Most of the studies reviewed used rotary-wing UAS in the form of quadcopters (4 rotors; 104 studies) hexacopters (6 rotors; 10 studies), and octocopters (8 rotors; 18 studies). Twenty-four studies used fixed-wing aircraft. Other UAS of note include kite (Madurapperuma et al. 2020) and blimp (Ruiz-García et al. 2020), both of which provide alternatives to motorized vehicles in areas where regulations prohibit them, or when UAS noise might impact wildlife.

Calibration and normalization

Landscape ecologists who seek to study patterns and processes across space, time, and remote sensing platforms require data with consistent scales and unit systems that can be quantitatively compared with one another (Moody and Woodcock 1995; Vogelmann et al. 2001; Padró et al. 2019). Normalization is the process of converting data to a common scale or range, eliminating differences in units, and calibration is the process of converting raw data from arbitrary values to physical units (e.g., radiance, reflectance, or temperature) and removing systematic bias that make the data useful for further scientific analysis (Sampath et al. 2023). Unlike the rigorous, well-documented calibration and validation standards for satellite and airborne remote sensing systems such as Landsat (Markham and Helder 2012) and Sentinel (Gascon et al. 2017), most UAS remote sensing places the responsibility of ensuring data quality into the hands of individual UAS manufacturers and customers, which can require substantial additional resources and post-processing workloads for users (Wyngaard et al. 2019; Tmušić et al. 2020). The ecological community continues to share and compare best practices, workflows, and recommendations towards the establishment of feasible and reliable calibration protocols (Cao et al. 2019; Koontz et al. 2022; Sampath et al. 2023).

The choice to calibrate or normalize UAS-derived data and the level of detail describing these methods is highly variable across landscape ecology literature. Post-processing workflows include camera lens calibration corrections to reduce geometric distortions such as fisheye distortions for improved vegetation mapping and habitat reconstruction (Habel et al. 2016; Dashpurev et al. 2021). Gray Card and ColorChecker reference materials may be used to color-balance or white-balance RGB imagery (Klosterman et al. 2018). Multispectral imagery is often radiometrically calibrated to physical units such as reflectance using reference panels and/or downwelling irradiance sensors. Radiometric calibration of multispectral data can enable the calculation of vegetation indices, land cover classification using published spectral libraries, and comparison with satellite-derived surface reflectance datasets (Doughty et al. 2021; Siewert and Olofsson 2021; Villoslada Peciña et al. 2021; Fernández-Guisuraga et al. 2022). Thermal infrared data can be calibrated to units of temperature which can inform permafrost terrain dynamics (van der Sluijs et al. 2018) and ecosystem respiration and evapotranspiration models (Kelly et al. 2021; Simpson et al. 2022). Hyperspectral data is typically calibrated to units of radiance or reflectance using lab-based measurements, atmospheric correction algorithms, and field-based reference materials to yield input features for models such as leaf area index and biomass (Räsänen et al. 2020), and species-level vegetation classification (Sankey et al. 2021c). Other studies reviewed had no mention of UAS data calibration.

Geolocation and georeference

Ecological processes are often measured using field observations combined with remote sensing data ranging from very-high (~1 cm) to coarse (~1 km) resolutions (Kerr and Ostrovsky 2003). Positional accuracy is important when comparing across scales and pixel resolutions, and for ensuring field-collected data are well registered with UAS imagery. For medium to low resolution satellite data, positional accuracy of half a pixel is commonly accepted (Congalton 2005; Storey et al. 2014; Pandžic et al. 2016). This criterion can be challenging to meet using very-high resolution UAS data where the pixel resolution is finer than potential global navigation satellite system (GNSS) positional errors. However, high resolution data does not always require high positional accuracy, and therefore, the level of accuracy is up to the researcher based on their objective and the UAS products (ASPRS 2024). Our review results indicate a wide range of georeferencing methods used to obtain and report on positional accuracy: 42.2% did not include any information on how the UAS data was georeferenced, 37.3% of the studies used ground control points (GCPs) and 20.5% of the studies used direct georeferencing (DG) with 6% of those applying post processing kinematic (PPK) and 4% applying real time kinematic (RTK).

The UAS GNSS provides DG assignment to the collected imagery. Consumer grade GNSS has an estimated low accuracy of ~5 m, making it suitable for projects using planimetric data and for scaling to medium to coarse resolution satellite imagery like Sentinel-2 or Landsat TM (Colomina and Molina 2014). PPK and RTK rely on higher precision satellite corrections from a multi-frequency static base station, which are then applied to the UAS GNSS data by matching observation timestamps, improving the accuracy to within centimeters (Padró et al. 2019; Syetiawan et al. 2020; Famiglietti et al. 2021; Zeybek 2021; Nesbit et al. 2022). Of the 15 reviewed studies that used PPK/RTK, 8 were lidar collections, 3 were multispectral collections, and 4 were RGB collections. Research indicates adding at least one GCP with a PPK/RTK solution could greatly improve RMSE under certain topography (Iizuka et al. 2022); however, Nesbit et al. (2022) found that 3 GCP's were recommended in addition to DG for their study within steep terrain.

The more traditional GCP, or indirect georeferencing (IG), continues to be the industry standard for high positional accuracy; however, the number and spatial distribution of GCPs is still debated among best practices (Singh and Frazier 2018). Our results showed a range in GCP distribution and geolocation methods, from 3 GCPs located with a low accuracy handheld GPS receiver over 0.1 hectare to around 50 GCPs located with an RTK rover over 15 hectares.

Techniques & methods

Landscape ecology papers reviewed used a wide array of image processing and modeling techniques to extract information from various UAS data sources. Of the papers reviewed, 47 studies used image classification algorithms to extract feature information, and these papers were nearly evenly split between pixel-based supervised classifications (23) and object-based image classifications (22), with the remaining 2 applying unsupervised classifications. Thirty-three studies relied on visual interpretation to manually extract information on features from the imagery. Thirty studies used lidar or SfM point cloud data as a primary product, 25 studies used an image derivative (spectral indices) as primary source of information, and 20 papers used custom modeling approaches.

True color, multispectral, hyperspectral, and thermal data and applications

UAS based products can be derived from a single image or an orthomosaic, a photogrammetrically orthorectified and mosaicked collection of images. Orthomosaics cover larger areas by stitching overlapping images and removing distortions for a seamless larger image. RGB digital cameras and multispectral instruments that include near infrared sensors continue to be widely used for vegetation classification mapping (Havrilla et al. 2020), ecosystem function modeling (Doughty et al. 2021), and characterizing ecosystem heterogeneity (Siewert and Olofsson 2021; Getzin et al. 2022) (Fig. 5). Havrilla et al. (2020) provided a novel application of UAS-based RGB data in the mapping of fine-spatial-scale variability in biocrust functional types and demonstrated that high spatial resolution observations alone were adequate to identify vascular plants, mineral soil, and multiple biocrust functional types within a complex ecosystem. Many studies have demonstrated that image derivatives and vegetation indices calculated from RGB imagery can be used to accurately map surface features, including the red green–blue vegetation index**,** the excess greenness Index and mean image brightness (Qian et al. 2021), the normalized difference greenness index, perpendicular vegetation index and normalized RGB band ratios; Laslier et al. 2019). Klosterman et al. (2018) tracked seasonal vegetation phenology using the green chromatic coordinate (GCC) calculated from multi-date RGB imagery. Image texture metrics calculated from single bands, indices or point clouds can also provide information on vegetation types and canopy structure (Olsoy et al. 2020; Räsänen et al. 2020; Bourgoin et al. 2020; Qian et al. 2021).

Multispectral sensors that include NIR and red edge bands tailored to measure vegetation properties like chlorophyll, biomass, canopy cover, and productivity, can help improve classification and characterization of green vegetation (Wang et al. 2022; Gano et al. 2024). With the addition of an NIR band, the most widely used spectral index remains NDVI, which provides an estimate of the greenness of individual plants and is commonly applied as a proxy for photosynthetic potential (Fig. 5; Polley et al. 2019; Belmonte et al. 2020; Charton et al. 2021; Doughty et al. 2021; Siewert and Olofsson 2021; Getzin et al. 2022; Pompa-García et al. 2022). For instance, Siewert and Olofsson (2021) used repeated UAS photography to reveal fine scale yet strong rodent impacts on Arctic ecosystem vegetation dynamics by using NDVI as a proxy for vegetation gross primary productivity

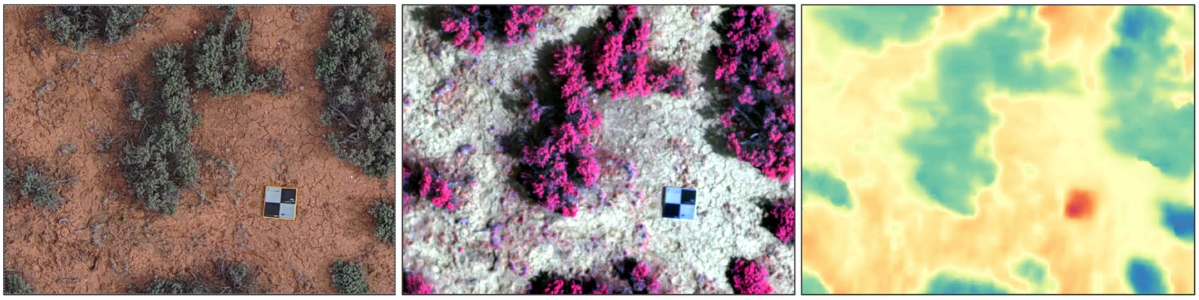


Fig. 5 Natural-color imagery captured using a Skydio X2D (Left), false-color composite of MicaSense Altum-PT multispectral images where pink indicates bright near infrared reflectance (Center), and MicaSense Altum-PT thermal imagery (Right) where blue indicates areas with cooler temperatures and red indicates areas with warmer temperatures at a dryland site mapped in May 2023 near Moab, Utah, USA

(GPP) and above ground biomass (AGB) within a change detection assessment. Additional derived indices from multispectral imagery have been explored to assess vegetation dynamics. Villoslada Peciña et al. (2021) used several indices including modified soil adjusted vegetation index (MSAVI) and a 2-Band enhanced vegetation index (EVI2) to estimate occurrence of plant community types, AGB, and topsoil moisture to assess the control of reindeers on woody plant encroachment (WPE). Bergmüller and Vanderwel (2022) used additional indices such as the normalized difference red edge index (NDRE) to predict tree mortality within a random forest model. In addition to NDVI And NDRE, Gallardo-Salazar et al. (2022) explored the Green Normalized Difference Vegetation Index (GNDVI), Leaf Chlorophyll Index (LCI) and Optimized Soil Adjusted Vegetation Index (OSAVI) to evaluate plant health based on field-measured dendroecological variables.

Hyperspectral instruments include coverage of the full solar spectrum from the visible (~350–750 nm; VIS) to the near infrared (~750–1400 nm; NIR) to the shortwave infrared (~1400 to 2500 nm; SWIR) (Fig. 3). The recent expansion of UAS-based hyperspectral instruments has driven the development of a remarkable variety of spectral traits used to characterize state and functional traits of individual species to entire ecosystems. Emerging spectral traits are moving beyond greenness to focus on functional traits such as nutrient status (e.g., foliar nitrogen content; Zhao et al. 2021), water content (e.g., canopy water index; Zhao et al. 2021), and pigment concentrations (e.g., carotenoids to chlorophyll content; Javadian et al. 2022; Zhao et al. 2021). A multitude of additional indices have been developed from multispectral and hyperspectral instruments to isolate species-specific structural or functional features, such as the dune vegetation state (DUVES; Talavera et al. 2022), burn severity index (Fraser et al. 2017), photochemical reflectivity index (PRI; e.g., Javadian et al. 2022), succulent delineation with the Cacti index (CACTI, Hartfield et al. 2022), and shortwave infrared index (SWIR; Norton et al. 2022). High spectral resolution instruments (spectral bands < 0.5 nm) centered around known atmospheric features (e.g., the oxygen A band at 760 nm; Fig. 3) are enabling additional novel applications, such as the measurement of solar-induced fluorescence (SIF), a direct measure of the light emitted by plants during photosynthesis, and thus a more direct proxy for plant physiological function (Zhang et al. 2022).

Thermal instruments measure longwave radiation emitted from surface materials at wavelengths directly proportional to their temperature (Figs. 3 and 5), and have been used on UAS platforms for a wide variety of applications, including to measure the surface temperatures of components of the surface soil (van der Sluijs et al. 2018; Zhang et al. 2020; Kelly et al. 2021), components of aquatic ecosystems (Dugdale et al. 2019; Casas-Mulet et al. 2020), and components of vegetation and plant canopies (Faye et al. 2016; Webster et al. 2018; Wang et al. 2019; Javadian et al. 2022; Simpson et al. 2022). Javadian et al. (2022) used UAS thermal images to show that taller and more clumped trees remained cooler and potentially less water stressed during periods of summer drought in a ponderosa pine-dominated forest. Sankey et al. (2021a) documented that UAS thermal images can be used to detect genetic trait-based differences in canopy temperature and evaporative cooling demand among genotypes of single cottonwood tree species. When combined with structure from motion (SfM, see Sect. "Lidar and structure-from-motion (SfM) point cloud applications") or lidar data, UAS-based thermal imagery has the capacity to provide information on three-dimensional patterns of heat within plant canopies. For example, Olsoy et al. (2023) combined high-resolution thermal imagery with SfM to model thermal emittance at the leaf-level and demonstrated that taller leaves had significantly cooler temperatures. These studies highlight the potential of UAS to overcome the time and expense limitations of on-the-ground measurements in the study of rapid changes in plant physiological function. Thermal UAS can be directly related to plant physiological function (e.g., stomatal conductance; Olsoy et al. 2024), with potential to upscale plant physiology measurements to spatial extents that match environmental gradients and management units. There has also been an expansion of high-resolution thermal imaging for characterization of surface temperature heterogeneity with implications for ecotherm niche modeling (Faye et al. 2016; Duffy et al. 2021).

Object based image segmentation and classification and regression

Object Based Image Analysis (OBIA) and segmentation are commonly used approaches for classification of high-resolution images (Blaschke 2010; Hossain and Chen 2019). OBIA approaches are well suited for UAS imagery because the segmentation exploits spectral, spatial and textural features, often allowing the extraction of ecologically meaningful objects like individual plant canopies and species (Fig. 6; Laliberte et al. 2011). For example, Olsoy et al. (2020) classified sagebrush canopies using structural features of shrubs with object-based image analysis and the support vector machine. The most appropriate scale for OBIA and segmentation remains a challenge, as a segmented feature at one scale can be homogeneous but heterogeneous when viewed at a different scale (Fig. 6; Hossain and Chen 2019). Small segment sizes result in large objects, including shrubs and trees, being segmented into multiple sub-objects (Fig. 6C). When segment size was too large, small objects including biocrusts, grass and bare soil were mixed in segments (Havrilla et al. 2020; Roser et al. 2022). Although it is feasible to use OBIA methods for change detection (St. Clair and Bishop 2019; Fallati et al. 2020), the size and shape of objects can be heavily influenced by image-specific properties (i.e., lighting angle, pixel size and radiometric resolution) which can create challenges for direct comparison across time. If the magnitude of change is small, a pixel-based change detection approach may be preferred (Siewert and Olofsson 2021).

Several machine-learning algorithms have been proposed for UAS image classification that can be applied both on individual pixels and segmented image objects. These include supervised classification models like decision trees (Sankey et al. 2019), and support vector machine (SVM) algorithms (Evans et al. 2022) to classify plant species and land cover types. When the target is a continuous variable (i.e., leaf area, vegetation fractional cover, biomass) machine learning regression models, such as support vector regression and gradient-boosting decision trees, can be applied to UAS images (e.g. Liu et al. 2021). Villoslada Peciña et al. (2021) used a random forest model to accurately predict above ground biomass from RGB, multispectral and SfM datasets, and random forest models to both classify plant communities and to predict soil organic carbon from multispectral vegetation indices and high resolution DSMs have been used ((Villoslada et al. 2022). Deep learning convolutional neural networks (CNNs) are emerging as a highly accurate classification approach suitable for ultra-high resolution imagery (Kattenborn et al. 2020; Schenone et al. 2021).

The large number of studies (33) that relied on visual interpretation for feature extraction was a surprising result. Visual interpretation and digitization from aerial imagery can be subjective and highly influenced by individual observers (Hearn et al. 2011). The choice of visual interpretation instead of more complex classification algorithms may be preferred when the sheer number and variety of features being mapped over a small area makes the time investment in machine-learning training less than ideal (Tanguy et al. 2023). The spatial detail of UAS imagery is appropriate for visual mapping based on color, texture and shape, and in some circumstances these maps are more accurate than automated classifications (Hamylton et al. 2020), however these approaches can be time consuming when mapping over large areas.

Lidar and structure-from-motion (SfM) point cloud applications

On-board UAS sensors such as digital cameras or more recent laser scanners have made earth system modeling for studies within agriculture, forestry, geomorphology and hydrology easier with the production of point cloud products (Liao et al. 2021). There are two main methods to generate point cloud 3D structures: (a) through the use of photogrammetric structure from motion (SfM) algorithms on overlapping digital images (e.g. Belmonte et al. 2021; Fernández-Guisuraga et al. 2022; Over et al. 2021) and (b) through light detection and ranging (lidar) laser scanning techniques (Kellner et al. 2019; de Almeida et al. 2020; Wallace et al. 2016). Details found within 3D structures provide novel datasets to derive landscape and vegetation characteristics from digital elevation models (DEM) and CHM, to above ground biomass (ABG) from point clouds (Dugdale et al. 2019; Sankey et al. 2021c; Cunliffe et al. 2022; Blanchard et al. 2023). Datasets derived from 3D point clouds provide the unique opportunity to assess spatially detailed, accurate shape information and standard geometries for landscape measurements (Fig. 7). Common uses

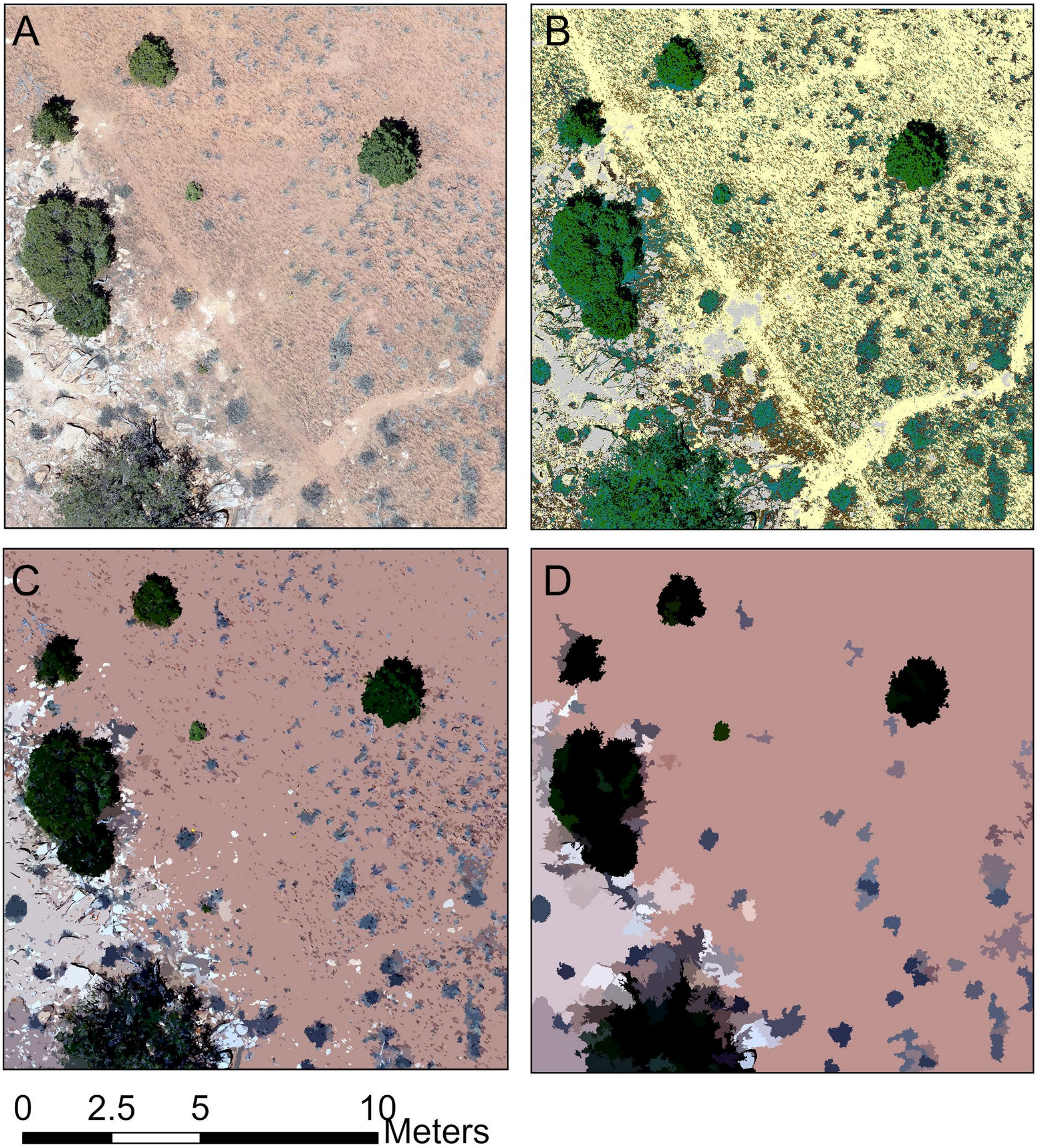


Fig. 6 Examples of a pixel-based classification compared to image segmentation. Original 0.5 cm RGB orthoimage **A**, classified 0.5 cm image **B**, segmented image with small objects **C** and segmented image with large objects **D**

of point cloud data include forest structure estimates and mapping geomorphological characteristics such as terrain (et al. 2020; de Almeida et al. 2020; Reilly et al. 2021; Chen et al. 2022). These derived datasets provide ways to collect monitoring inventory measurements, characterize plant canopy and conduct various assessments including geomorphological movement or vegetation change detection, and disturbance impacts on canopy height, biomass, biodiversity and carbon storage (Räsänen et al. 2020; Sagang

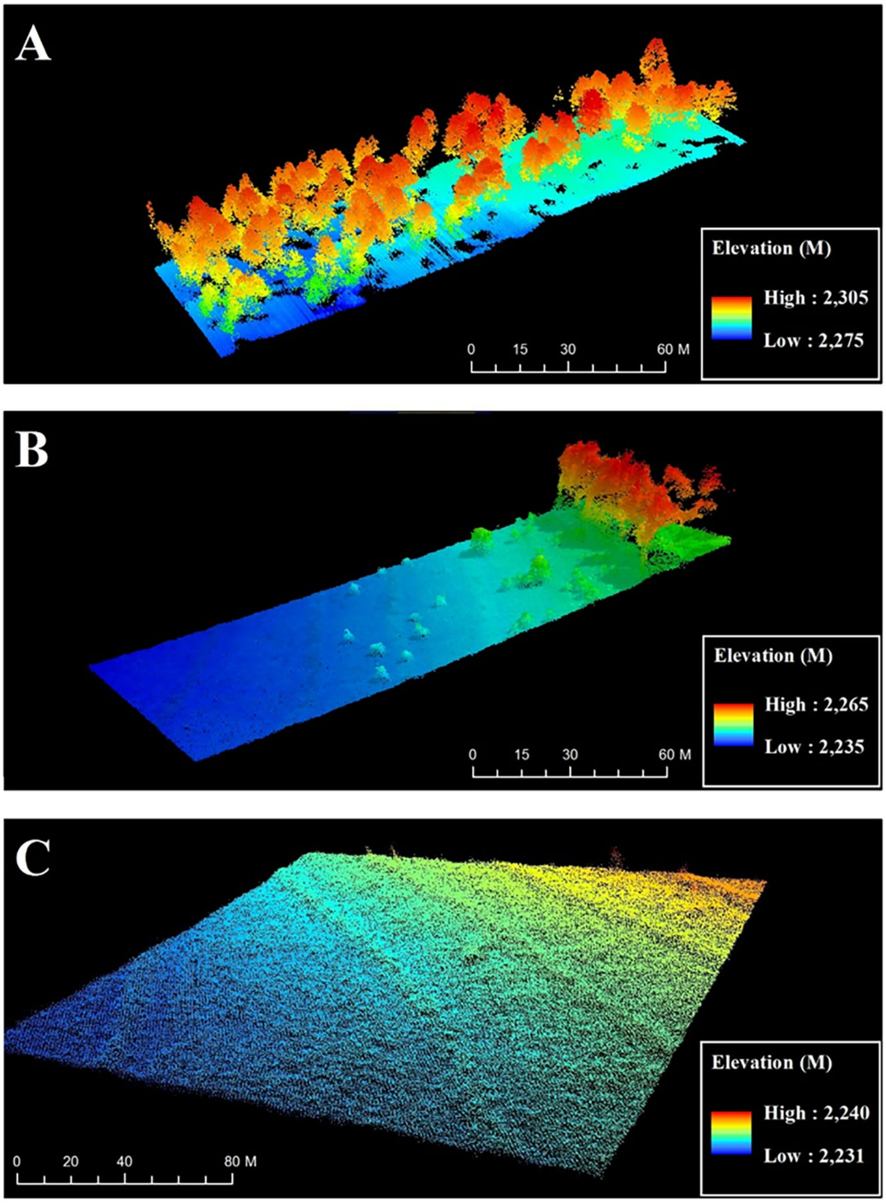


Fig. 7 Examples of three dimensional (3D) UAS lidar collected over a woodland/forest **A**, UAS SfM in ecotone **B** and UAS SfM in grassland **C**. Adapted from Sankey et al. (2017)

et al. 2022; Singh et al. 2023). Metrics such as crown area volume or crown surface area can be estimated for each canopy within the plot (Ahongshangbam et al. 2020), and repeated UAS lidar collections can be used to quantify monthly canopy height growth (Tang et al. 2023). Viedma et al. (2020) used lidar derived CHMs and various additional metrics such Leaf Area Index (LAI), Leaf Area Density (LAD) and crown volume to assess tree structure diversity within various burn severities and found areas with low burned severities had more diverse tree structures compared to moderate and high severity burns. Fernández-Guisuraga et al. (2022) instead used SfM to assess ecological competition and found that increased cover and height of surrounding shrub species impact pine sapling growth.

Hydrologic and geomorphic systems have long been a focus of landscape ecology research because they are highly dynamic in space and time and provide connectivity and movement of resources across ecosystems and landscapes (Butler 2001; Wiens 2002). Lidar and SfM enable the acquisition of high-resolution topography data (Passalacqua et al. 2015) suitable for precise spatial (< cm) geomorphic and land change analyses that can be measured at various temporal intervals (Andresen and Schultz-Fellenz 2023). These data support geomorphic feature extraction and morphological change detection between repeat SfM surveys (Wheaton et al. 2010; Milan et al. 2011; Passalacqua et al. 2015; Williams et al. 2020) across diverse environments and applications, including arctic landforms (Kartoziia 2019; Tanguy et al. 2023), tidal channels (Chen et al. 2022), coastal dunes (Hilgendorf et al. 2021; Laporte-Fauret et al. 2021), reef habitats (Jackson-Bué et al. 2021), riverscapes (Bertalan et al. 2018; Bregoli et al. 2019; Ikeda et al. 2020; Evans et al. 2022), and dune fields (Solazzo et al. 2018). These applications underscore the versatility of UAS technology in advancing our understanding of dynamic landscapes and their intricate changes over time.

UAS terrain change detection studies reviewed here primarily relied on raster DEMs of Difference (DoD) to model surface elevation changes (e.g., New DEM—Old DEM), generated from repeat SfM surveys (van der Sluijs et al. 2018; Hamshaw et al. 2019; Hilgendorf et al. 2021; Jackson-Bué et al. 2021; Evans et al. 2022). To address DEM uncertainties, error thresholds are typically employed during DEM differencing to filter reliable elevation change 'signals' from model 'noise' related to positional (e.g., registration) or surface representation errors (Wheaton et al. 2010; Passalacqua et al. 2015). The most common method for filtering propagated DEM errors was the minimum level of detection (minLoD) threshold, which can be applied uniformly across all cell values or determined probabilistically on a cell-by-cell basis (Wheaton et al. 2010; Brasington et al. 2012; van der Sluijs et al. 2018). Many UAS applications now use a cloud-based approach, specifically designed for 3D topographic change quantification between SfM point clouds (Backes et al. 2020; Andresen and Schultz-Fellenz 2023; DaSilva et al. 2023).

Spatial analyses and landscape pattern methods

Spatial pattern analyses, such as edge, patch density, and core area metrics, have been at the core of landscape ecology for decades (McGarigal et al. 2002). Historically, analyses of landscape- and patch-level metrics have used medium-resolution satellite imagery or aerial photography to define habitat patches (Saura 2004; Morgan and Gergel 2010; Haire and McGarigal 2010; Chambers et al. 2022). UAS provides the capacity to analyze spatial patterns of individual plants within landscapes, rather than of arbitrary pixels. A number of reviewed studies used landscape metrics to characterize vegetation and soil patterns from classified UAS imagery (Havrilla et al. 2020; Olsoy et al. 2020; Qian et al. 2021; Zhang and Zhang 2021; Villoslada Peciña et al. 2021; Singh et al. 2023; Velamazán et al. 2023), landscape change and habitat fragmentation (Fynn and Campbell 2019; Picone and Chemello 2023) and restoration impacts (Qiu et al. 2023). Spatial point pattern analysis, including extensions from points to polygons (Wiegand et al. 2006), is well-suited to analyze output from UAS-based OBIA (Xu et al. 2019). Such analyses have relevance for quantifying habitat structure and quality and present opportunities to connect spatial patterns to plant population and community dynamics. For example, environmental gradients can influence whether neighboring plants compete with or facilitate one another, ultimately determining levels of spatial dispersion in plant communities (Xu et al. 2015; Getzin et al. 2022). UAS-based approaches have the capacity to detect these patterns at the level of individual plants, enabling inference on feedbacks between plant spatial patterns and biotic and abiotic processes.

Field approaches/methods and validation methods

Various field-based measurements were used to validate UAS classifications across a variety of ecological applications. For example, in studies using UAS for vegetation and soil monitoring and classification (64.4% of studies), common field-based measurements included quadrat-and transect-based sampling of plant density and identity for herbaceous (Orndahl et al. 2022), and woody plant species (Bagaram et al. 2018; Talucci et al. 2020), as well as other plant biophysical measures including photosynthesis and stomatal conductance. Zhao et al. (2021), for example, collected ground-based leaf spectral data to validate UAS-derived hyperspectral classifications of leaf physiological traits in grassland monocultures. UAS applications for wildlife monitoring (20.0% of studies) commonly used ground-based animal surveys and capture. For example, Shokirov et al. (2023) used bird surveys to validate UAS lidar models for avian species richness and abundance in a restored woodland, and Habel et al. (2018b) used butterfly netting to collect ground data to validate UAS-based mapping of microhabitats of grassland butterflies in temperate grassland agricultural landscapes. Because most studies of disturbance and land use change (15.6% of studies) generally also focused on characterizing changes in vegetation and wildlife occurrence and distribution in response to change, field-based measurements were similar as in vegetation and wildlife studies (e.g., ground-based transects and surveys).

Metrics used for validation of UAS classifications ranged widely across studies. Of the 161 papers reviewed, 38.5% neither reported specific validation metrics nor included accuracy measures. Of the 61.5% of studies that reported validation metrics, 35.4% used regression and/or correlation analyses, 22.2% used ground control points and/or visual interpretation of imagery, 19.2% used confusion matrices and associated analyses (e.g., Kappa, overall accuracy), while 23.2% of studies reported use of various other methods.

As UAS classification approaches are increasingly used to quantify cover and to replicate ecological field measurements (e.g., abundance of rare plant species; Rominger and Meyer 2019), addressing measurement error in UAS imagery will become increasingly necessary. Some degree of error in UAS imagery is inescapable, from atmospheric conditions to overlapping canopies or incorrect classification (Brack et al. 2018). Wildlife ecologists have long grappled with these errors, including in counts of animals from UAS imagery, and have developed statistical methods that can disentangle measurement error from ecological information (Martin et al. 2012; Delisle et al. 2023). For example, Edwards et al. (2021) applied capture-mark-recapture models to count wintering Florida manatees (*Trichechus manatus latirostris*) in UAS imagery. Outside of wildlife ecology, models for imperfect detection remain underutilized in UAS analyses. Broader implementation of statistical approaches that acknowledge uncertainty in UAS imagery would likely improve the quality of ecological inference from these imperfect data.

Data fusion—scaling and integration

Of the 161 papers reviewed, 34 papers combined two or more datasets. Their primary objectives were to: (1) improve detection capabilities of individual and small objects (e.g., trees, graminoid biomass), (2) increase classification accuracies and subsequent model estimates, and (3) increase the temporal frequency of available images by leveraging two or more datasets. The data fusion studies most commonly combine UAS RGB images with SfM data or existing DEMs created from other data sources. Publicly available elevation data, such as the 10 m or 1 m resolution DEMs (USGS 2023), were commonly leveraged in UAS multispectral image processing and RGB image-derived classifications of target cover types. Less commonly fused datasets are UAS RGB images combined with manned airborne lidar or terrestrial lidar point cloud data, and subsequent lidar-derived vegetation CHM (Reilly et al. 2021). This is likely because of the increasingly common use of UAS RGB/multispectral image-derived SfM data, which can be used to generate DEMs and CHMs (Mayr et al. 2018; Shin et al. 2018; Sankey et al. 2019; et al. 2020, 2021; Bourgoin et al. 2020; Reilly et al. 2021; Evans et al. 2022). Even less common are UAS hyperspectral images fused with UAS lidar data (Sankey et al. 2017) and UAS lidar data combined with terrestrial lidar data (Swetnam et al. 2018; Sankey et al. 2021a; Shokirov et al. 2023). The data fusion studies typically report 5–20% increases in classification accuracies, although only a few studies quantitatively report the specific accuracy increases from data fusion (e.g., Sankey et al. 2017, 2019, 2021b).

The most common application of UAS data fusion is observed in vegetation analysis including forest cover changes, fragmentation, post-disturbance recovery, phenology, aboveground biomass, canopy temperature and physiological traits. Another common application of UAS data fusion has leveraged topographic and biophysical variables derived from various remote sensing data sources. For example, Iijima et al. (2021) leveraged a combination of InSAR and UAS data in detecting thermokarst landscapes and subsidence, whereas van der Sluijs et al. (2018) combined UAS photogrammetry and thermal imaging for examining permafrost terrain dynamics, thawing, and subsidence. Similarly, Luo et al. (2019) merged several types of remote sensing data (Landsat, ASTER, UAS, Radarsat-2) to derive predictor variables for soil moisture estimates. Casas-Mulet et al. (2020) combined UAS thermal and RGB images to detect cold-water patches in a river, whereas Sankey and Tatum (2022) fused UAS thermal images with UAS SfM data to extract tree canopy temperatures. In contrast, a few fusion studies have focused on urban landscapes, culturally important archeological sites, socio-ecological topics, and public health (Fang et al. 2021; Qin et al. 2022). An equally small fraction of the UAS studies leverage data fusion in wildlife, habitat, and food webs (Oosthuizen et al. 2020; Hasselerharm et al. 2021; Siewert and Olofsson 2021; Vinton and Larsen 2022; Krishnan et al. 2023). This leaves opportunities for further development of fusion methods and applications in these disciplines and subdisciplines.

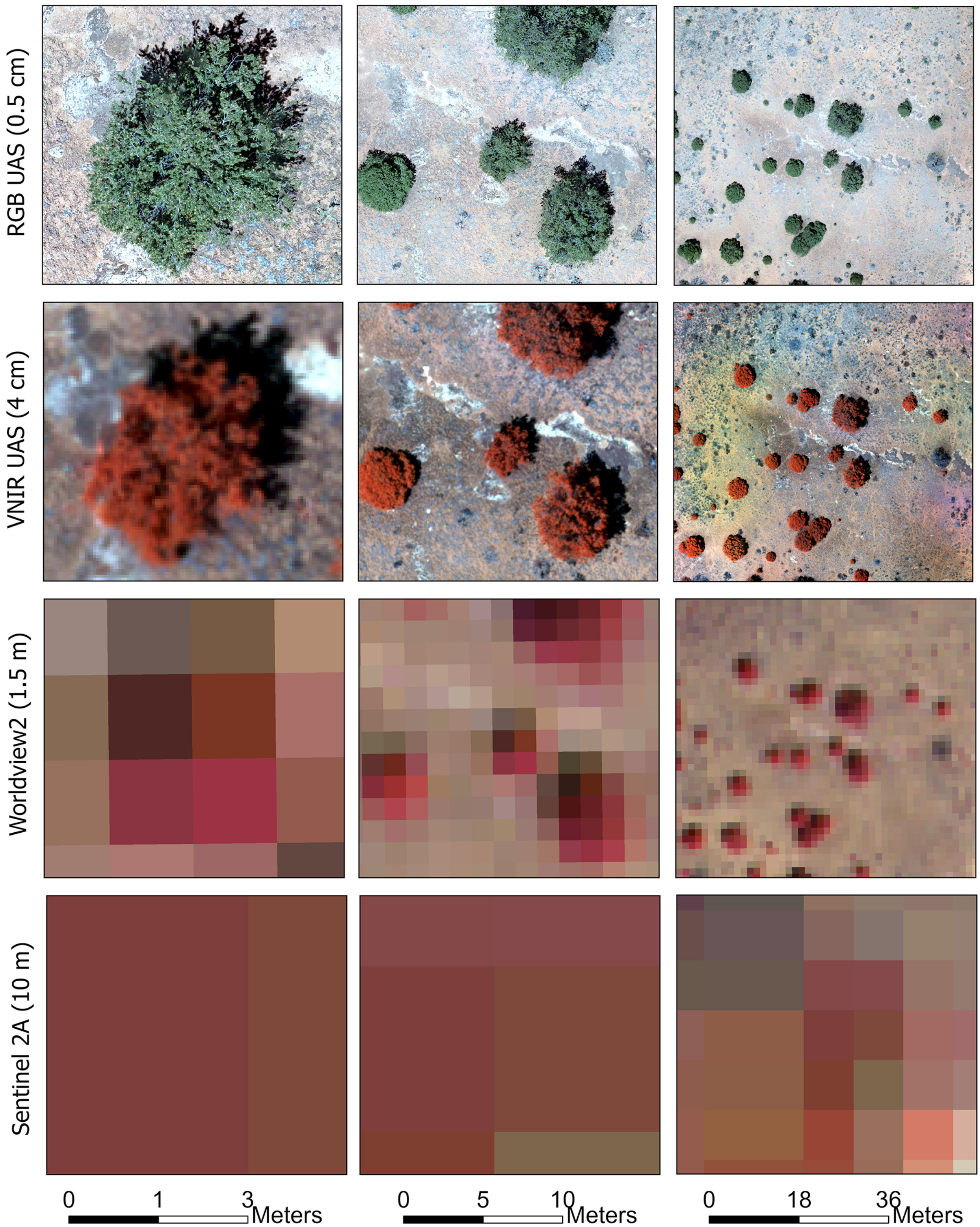
Several studies across disciplines leverage UAS data to extend the temporal scales of change detection analysis. For example, Chmielewski et al. (2020) and Bertalan et al. (2018) combine contemporary UAS data with historical manned aerial images. Despite the differences in spatial and spectral resolution, such combinations of multi-temporal datasets enable riparian, geomorphic, vegetation, and urban change detection over decadal time scales, often revealing finer-scale change processes that would not be possible to derive from satellite remote sensing. Because UAS technology and sensors became available only recently, multi-temporal UAS image analysis and change detection studies have been rare and typically cover shorter time scales (Evans et al. 2022; Sankey et al. 2024), but UAS data fusion with historical aerial images extend the temporal scales enabling much longer-term change detection.

Another observed trend is the spatial extension or scaling of analysis and image classification from smaller-extent UAS data to larger-extent satellite images (Fig. 8; Zhu et al. 2018; Marx and McFarlane 2019; Miranda et al. 2020; Alvarez-Vanhard et al. 2021). These studies, however, typically do not directly fuse the UAS data with satellite images or satellite-derived data products. There are numerous approaches to scale high resolution data to satellite (Markham et al. 2023), from direct scaling between UAS map data to satellite spectral indices (Siewert and Olofsson 2021; von Nonn et al. 2024) to subpixel fractional estimates (Riihimäki et al. 2019; Yang et al. 2021), and via training satellite image classifications. For example, by training coarser-resolution WorldView-2 satellite images with 15-cm resolution UAS multispectral images, Elkind et al. (2019) enabled invasive species detection over a much larger area than was imaged by the UAS multispectral sensor. Similarly, Solazzo et al. (2018) used smaller area UAS hyperspectral and multispectral images to train coarser-resolution WorldView-2 satellite data for 3D estimates of sand dune volume and sediment weight, and Page et al. (2022) used UAS RGB images and SfM-derived mesquite canopy height estimates to train a Sentinel-2A multispectral image classification via a random forest classification model. UAS data have been much more commonly linked with high resolution satellite data (WorldView-2, − 3, PlanetScope, Pleiades, Quickbird, and Sentinel-2A), than moderate resolution satellite images (i.e., Landsat, MODIS).

Open data and standards

Open data and open-source software can facilitate reproducibility of remote sensing data analysis, allowing potential reviewers to access data and test the codes being used in science, and remove dependencies on expensive, proprietary software (Rocchini et al. 2017). Freely accessible satellite imagery (i.e., Landsat, Sentinel) has led to rapid advances in remote sensing science in recent years; likewise access to freely available UAS imagery and associated ecological field data will likely facilitate new and innovative investigations and research applications. Open UAS data have been used to compare vegetation modeling approaches across different sites (Agapiou 2020) and are a potential source of training and validation data for broad-scale satellite-based machine learning models (Kattenborn et al. 2019; Schiefer et al. 2023). One way to maximize open UAS data is to use clear, standardized reporting of image collection and processing parameters documented via robust metadata. Likewise, implementing standardized data collection and analysis protocols can facilitate synthesis studies across different ecosystems and environmental conditions (Cunliffe et al. 2022).

In examining the prevalence of open science practices within the review, we focused on three primary questions: (1) How common is the use of open-source software? (2) Are researchers sharing raw and/or processed data? and (3) Are researchers sharing


RGB UAS (0.5 cm)
VNIR UAS (4 cm)
Worldview2 (1.5 m)
Sentinel 2A (10 m)
0 1 3 Meters
0 5 10 Meters
0 18 36 Meters

◂**Fig. 8** Illustration of different pixel resolutions and scales of UAS imagery and satellite imagery. The top row shows an RGB UAS image at 0.5 cm resolution displayed at scales ranging from tree crown to landscape (left to right), followed by a 4 cm resolution visible near infrared (VNIR) UAS image displayed as a false color composite (vegetation is red), a 1.5 m resolution Worldview2 (Maxar Technologies) false color composite satellite image and a 10 m resolution Sentinel 2A false color composite

analysis code that can be reproduced? We found that roughly half of the studies used some form of open-source software to analyze imagery. Most common open-source software is the R language (R core team 2021) and QGIS (QGIS.org 2024) (29.2% and 14.3% respectively). Other software used were CloudCompare (Girardeau-Montaut 2016; www.cloudcompare.org) (6.8%), Python (Van Rossum and Drake 1995) (4.3%), Google Earth Engine (Gorelick et al. 2017) (2.5%), and Orfeo ToolBox (Grizonnet et al. 2017). Only 2 of the studies used OpenDroneMap (ODM; WebODM Authors), an open-source photogrammetry toolkit to generate and process SfM data (Fig. 9).

Our findings indicate a low level of data sharing among the 161 studies analyzed (Fig. 9). Only 3 of 161 studies (1.8%) made their raw data available for download. Ten of 161 studies (6.2%) shared their UAS data products (e.g., orthomosaics, point clouds). Only 5 of 161 studies (3.1%) provided data that were derived from UAS data (e.g., NDVI values) in CSV format. Although some repositories such as Pangaea, Figshare, Zenodo, Oak Ridge Laboratory, and USGS ScienceBase were used for data sharing, a common approach was offering data "upon reasonable request." Privacy concerns were cited by a few authors as a reason for not posting data openly.

The sharing of processing and/or analysis code was slightly more common, but still limited. Twelve of 161 studies (7.4%) shared some kind of computer code (Fig. 9). No studies shared code for photogrammetric processing, indicating a reliance on graphical user interface (GUIs) based methods over programmatic approaches. Code was shared on web platforms like Github (https://github.com/), Figshare (https://figshare.com/), Zenodo (https://zenodo.org/), and directly from publishers. Many studies included software settings in their methods section (e.g., DaSilva et al. 2023), theoretically allowing for the reproduction of analysis, but without directly sharing executable code.

Standardization and accessibility for UAS data

Findings from this review suggest that there is substantial room for improvement in open science practices. The low rates of data and code sharing limit the potential for reproducibility, building upon previous work, and conducting synthesis studies. The low rate of data sharing is not surprising given the large size of raw data and processed products. This makes these data challenging to host in web repositories. Besides the data repositories mentioned in the literature, other UAS data repositories for data discovery and access include Open Aerial Map (https://openaerialmap.org/), GeoNadir (https://geonadir.com/), and OpenTopography (https://opentopography.org/). However, no single online repository has become more widely used compared to others. SpatioTemporal Asset Catalogs (STACs; https://stacspec.org/), are a json-based metadata specifications for describing any type of geospatial data. STACs specify a standard for metadata catalogs and data APIs. UAS data described using STAC could be stored in distributed cloud storage anywhere in the world and would be discoverable and accessible through the STAC browser (https://radiantearth.github.io/stac-browser) or standard API calls (Simoes et al. 2021).

In the larger UAS scientific world, common practices around data management are forming to facilitate data sharing. Wyngaard et al. (2019) discussed how to move from isolated and ad hoc efforts toward standardization of practice around data management. They identified 8 opportunities for standardization of UAS data collection and management that are relevant to the landscape ecology UAS community. These opportunities include: (i) Sensor use procedures, (ii) Operational practices, (iii) Analytics and Error correction procedures, (iv) Data and metadata data formats, (v) Data and metadata provenance practices, (vi) Data product levels, (vii) Data management and analytics tools, (viii) Data management education. Other efforts have focused on metadata and reporting recommendations for UAS data (Barbieri et al. 2023; Fremand 2023). The landscape ecology community could examine these initiatives and where applicable could implement and build upon them.

Policy, regulatory, and legal issues surrounding UAS operations may be a limitation for accessibility and use in certain areas. Development of UAS use in the military has led to serious security concerns with

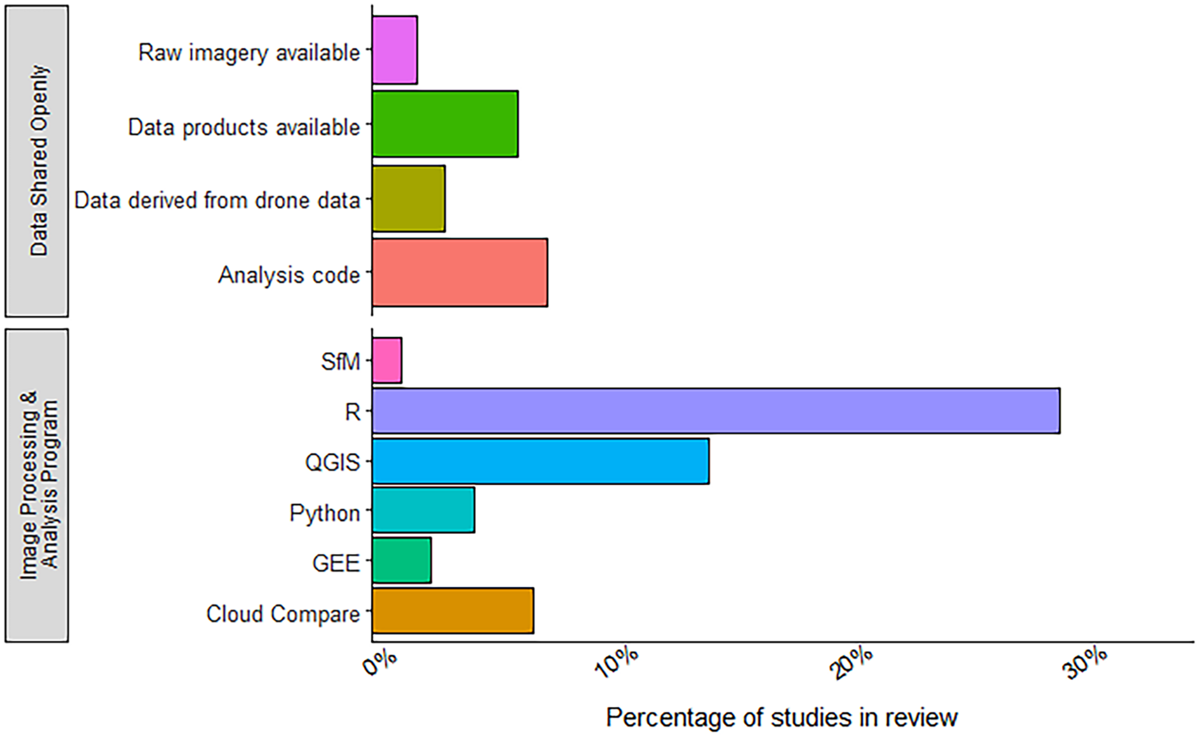


Fig. 9 Percentage of studies reviewed that shared data and code, or used open source software for image processing and analysis

data within military contexts (Cummings et al. 2007). It was not until the early 2000s that the US Federal Aviation Administration (FAA) started issuing certificates for use in a commercial setting. The policy and regulations are important for safe implementation of UAS in research (Rango and Laliberte 2010), although much of the legislation has lagged behind the rapid increase in technological advancements with UAS development (Stöcker et al. 2017). Many suggestions have been made for increased clarity in policy and security frameworks (Thangavelu et al. 2020; Robinson et al. 2022) but the current regulatory environment remains a challenge for more widespread implementation of UAS for landscape ecology research.

Summary of research trends and future opportunities

The current UAS literature is dominated by research papers seeking to advance remote sensing methods for feature detection, mapping, image classification and machine learning (Osco et al. 2021). Sun et al. (2021) noted a preponderance of UAS studies developing and testing methods for retrieving ecological parameters, with few attempting to answer ecological questions. We observed this imbalance in many papers that passed our initial keyword queries, but we were able to focus our review on the diverse and creative ways UAS data and analysis methods are being applied in ecological research. Many of the papers followed a tradition in landscape ecology of extracting information from remote sensing data to assess patterns and processes. As UAS mapping approaches mature we expect to see rapid growth in ecosystem science applications, and landscape ecologists are well positioned to inform research questions and analysis methods.

Several major themes and applications emerged from our review that define the state of UAS landscape ecology research. These include modeling wildlife micro-habitats, landscape and geomorphic change detection, integrating UAS with historical aerial and satellite imagery, and novel applications of spatial statistics for high-resolution imagery and scaling of ecosystem functions. The reviewed research covered a range of subjects from biodiversity conservation, vegetation succession, wildfire impacts, invasive species, range management, restoration, climate change impacts, habitat loss, and fragmentation.

Micro-habitat modeling with UAS demonstrates how high-resolution UAS data can often surpass field measurements (Wood et al. 2019) to provide important insights into species distributions and habitat spatial patterns at scales relevant to smaller animals and insects. Many of the concepts and approaches from macroecology are being explored with high resolution UAS data, including species thermal refugia (Milling et al. 2018), spectral heterogeneity and biodiversity (Polley et al. 2019), and UAS are useful for linking micro-habitats with mesoscale landscape structures (Barbosa et al. 2022).

Land change is identified as one of the most pressing environmental and policy issues being addressed by landscape ecologists (Mayer et al. 2016), especially global change type impacts of land use and climate. Half of the UAS studies reviewed addressed issues related to natural disturbances and land change at local-to-landscape scales. Terrestrial vegetation-related land change studies often integrated UAS with satellite data to evaluate impacts at landscape scales, while other studies focused on geomorphic change in streams, rivers, and wetlands tended to exploit the very-high resolution UAS data to characterize localized changes that have large ecological impacts. Change detection using UAS data can be difficult due to challenges aligning datasets as well as the influence of variable environmental conditions on multitemporal spectral signals (Yao et al. 2019). More importantly, given the recent technological development in UAS platforms and sensors, longer-term change detection studies using repeat UAS data have been rare and are just emerging (Sankey et al. 2024).

Scaling remains an active topic of study in landscape ecology (Markham et al. 2023), and ultra-high resolution UAS data provide new opportunities to examine scaling relationships. Research on statistical scaling methods from field-collected data to UAS (both image and point-based data) and from UAS to satellite, could help better integrate small-footprint UAS data into larger landscape-scale study designs. Many successful applications of scaling and data fusion were noted in our review, with some studies successfully integrating a wide range of remote sensing data sets, resolutions and scales to examine long-term landscape dynamics (i.e., Sagang et al. 2022). OBIA and image segmentation approaches are also widely applied for UAS image analysis, and OBIA lends itself to questions of scale given the hierarchical nature of image objects. OBIA can be used to address interactions between nested objects like individual plants, vegetation communities/habitats, and ecosystems (Hay and Castilla 2008; Barker and King 2012).

Spatial pattern analysis was widely used in UAS research designs, and many studies demonstrated that fragmentation and patch pattern metrics commonly applied to moderate-resolution satellite data provide ecological relevant information at much finer resolution when calculated from high-resolution UAS images. Spatial pattern analysis drives many research questions, but we also noted many studies examined functional roles of vegetation and wildlife from UAS. Relationships between species micro-habitats/distributions mapped from RGB orthomosaics can be used to infer multiple ecosystem functions (Shenone et al. 2021). Multispectral, lidar, and thermal-IR sensors support fine-scale assessment of ecosystem processes and function across terrestrial systems including canopy structure and temperature relationships (Webster et al. 2018), water stress (Javadian et al. 2022), edge effects on microclimates (Blanchard et al. 2023), evapotranspiration (Wang et al. 2019), and respiration (Kelly et al. 2021). As hyperspectral, TIR, and lidar UAS sensors become more accessible, with satellite data can be linked with UAS sensor data to examine temporal and spatial variability of ecosystem function across larger landscapes.

Conclusions

UAS is a rapidly evolving tool that is generating novel research questions and study designs in the field of landscape ecology. UAS expands upon the observation scales defined by satellite grain and extent, and allows researchers to control the resolution, scale, spectral information, and timing/frequency of their remote sensing data. UAS can function either as a main data source for mapping or modeling an ecological system (i.e., micro-habitat maps), or play an intermediate role by scaling field measures to satellite data. Although UAS data collection and processing can be technically and computationally challenging, hardware and software systems are developing rapidly and becoming easier to use. Image post-processing and analysis software, supported by cloud computing, could help to increase the performance and usability across all stages of the research. Thoroughly reporting of their UAS data collection procedures and research methods by researchers, and supporting of open science practices by sharing code, UAS imagery, and other data could help facilitate wider use of UAS for ecological applications.

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Declarations

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References

Agapiou A (2020) Vegetation extraction using visible-bands from openly licensed unmanned aerial vehicle imagery. Drones 4:27

Ahmed F, Mohanta JC, Keshari A, Yadav PS (2022) Recent advances in unmanned aerial vehicles: a review. Arab J Sci Eng 47:7963–7984

Ahongshangbam J, Röll A, Ellsäßer F, Hölscher D (2020) Airborne tree crown detection for predicting spatial heterogeneity of canopy transpiration in a tropical rainforest. Remote Sens. https://doi.org/10.3390/rs12040651

Alvarez-Vanhard E, Corpetti T, Houet T (2021) UAV & satellite synergies for optical remote sensing applications: a literature review. Sci Remote Sens 3:100019

American Society for Photogrammetry and Remote Sensing (ASPRS), 2024. ASPRS Positional Accuracy Standards for Digital Geospatial Data Edition 2, Version 2, https://publicdocuments.asprs.org/PositionalAccuracyStd-Ed2-V2 Accessed 10 May 2024

Anderson K, Gaston KJ (2013) Lightweight unmanned aerial vehicles will revolutionize spatial ecology. Front Ecol Environ 11:138–146.

Andresen CG, Schultz-Fellenz ES (2023) Change detection applications in the earth sciences using UAS-based sensing: a review and future opportunities. Drones 7:258

WebODM Authors, WebODM n.d. https://github.com/OpenDroneMap/WebODM/

Backes D, Smigaj M, Schimka M et al (2020) River morphology monitoring of a small-scale alpine riverbed using drone photogrammetry and LiDAR. Int Arch Photogramm Remote Sens Spat Inf Sci 43:1017–1024

Bagaram MB, Giuliarelli D, Chirici G et al (2018) UAV remote sensing for biodiversity monitoring: are forest canopy gaps good covariates? Remote Sens. https://doi.org/10.3390/rs10091397

Bao S, Yang F (2022) Influences of climate change and land use change on the habitat suitability of Bharal in the Sanjiangyuan district. Int J Environ Res Public Health China. https://doi.org/10.3390/ijerph192417082

Barbieri L, Wyngaard J, Swanz S, Thomer AK (2023) Making drone data FAIR through a community-developed information framework. Data Sci J 22:1–1

Barbosa RV, Jaud M, Bacher C et al (2022) High-resolution drone images show that the distribution of mussels depends on microhabitat features of intertidal rocky shores. Remote Sens. https://doi.org/10.3390/rs14215441

Barker R, King DJ (2012) Blanding's turtle (Emydoidea blandingii) potential habitat mapping using aerial orthophotographic imagery and object based classification. Remote Sens 4:194–219

Belmonte A, Sankey T, Biederman JA et al (2020) UAV-derived estimates of forest structure to inform ponderosa pine forest restoration. Remote Sens Ecol Conserv 6:181–197

Belmonte A, Sankey T, Biederman J et al (2021) UAV-based estimate of snow cover dynamics: optimizing semi-arid forest structure for snow persistence. Remote Sens 13:1036

Bergmüller KO, Vanderwel MC (2022) Predicting tree mortality using spectral indices derived from multispectral UAV imagery. Remote Sens 14:2195

Bertalan L, Novák TJ, Németh Z et al (2018) Issues of meander development land degradation or ecological value? The example of the Sajó River Hungary. Water Switz. https://doi.org/10.3390/w10111613

Bishop TB, Errigo IM (2023) Using sUAV imagery to map litter of invasive annual grass in dry environmental conditions. Ecol Indic 146:109755

Blanchard G, Barbier N, Vieilledent G et al (2023) UAV-Lidar reveals that canopy structure mediates the influence of edge effects on forest diversity, function and microclimate. J Ecol 111:1411–1427

Blaschke T (2010) Object based image analysis for remote sensing. ISPRS J Photogramm Remote Sens 65:2–16

Borja-Martínez G, Tapia-Flores D, Shafer ABA, Vázquez-Domínguez E (2022) Highland forest's environmental complexity drives landscape genomics and connectivity of the rodent Peromyscus melanotis. Landsc Ecol 37:1653–1671

Bourgoin C, Betbeder J, Couteron P et al (2020) UAV-based canopy textures assess changes in forest structure from long-term degradation. Ecol Indic 115:106386

Bowman DMJS, Ondei S, Lucieer A et al (2023) Forest-sedgeland boundaries are historically stable and resilient to wildfire at Blakes Opening in the Tasmanian wilderness world heritage Area, Australia. Landsc Ecol 38:205–222

Brack IV, Kindel A, Oliveira LFB (2018) Detection errors in wildlife abundance estimates from unmanned aerial systems (UAS) surveys: synthesis, solutions, and challenges. Methods Ecol Evol 9:1864–1873

Brasington J, Vericat D, Rychkov I (2012) Modeling river bed morphology, roughness, and surface sedimentology using high resolution terrestrial laser scanning. Water Resour Res. https://doi.org/10.1029/2012WR012223

Bregoli F, Crosato A, Paron P, McClain ME (2019) Humans reshape wetlands: unveiling the last 100 years of morphological changes of the Mara Wetland, Tanzania. Sci Total Environ 691:896–907

Broussard WP, Visser JM, Brooks RP (2022) Quantifying vegetation and landscape metrics with hyperspatial unmanned aircraft system imagery in a coastal Oligohaline Marsh. Estuaries Coasts 45:1058–1069

Butler DR (2001) Geomorphic process-disturbance corridors: a variation on a principle of landscape ecology. Prog Phys Geogr 25:237–238

Cao S, Danielson B, Clare S et al (2019) Radiometric calibration assessments for UAS-borne multispectral cameras: laboratory and field protocols. ISPRS J Photogramm Remote Sens 149:132–145

Casas-Mulet R, Pander J, Ryu D et al (2020) Unmanned aerial vehicle (UAV)-based thermal infra-red (tir) and optical imagery reveals multi-spatial scale controls of cold-water areas over a groundwater-dominated riverscape. Front Environ Sci. https://doi.org/10.3389/fenvs.2020.00064

Chambers S, Villarreal ML, Duane O et al (2022) Conflict of energies: spatially modeling mule deer caloric expenditure in response to oil and gas development. Landsc Ecol 37:2947–2961

Chang B, Kim I, Choi K et al (2022) Population dynamics of American bullfrog (*Lithobates catesbeianus*) and implications for control. Animals. https://doi.org/10.3390/ani12202827

Charton KT, Sclater VL, Menges ES (2021) Mapping spatially explicit vegetation gaps in Florida rosemary scrub using unmanned aerial vehicles. Ecosphere. https://doi.org/10.1002/ecs2.3470

Chen C, Zhang C, Schwarz C et al (2022) Mapping three-dimensional morphological characteristics of tidal salt-marsh channels using UAV structure-from-motion photogrammetry. Geomorphology. https://doi.org/10.1016/j.geomorph.2022.108235

Chmielewski S, Bochniak A, Natapov A, Wezyk P (2020) Introducing GEOBIA to landscape imageability assessment: a multi-temporal case study of the nature reserve "Kozki" Poland. Remote Sens. https://doi.org/10.3390/rs12172792

Christie KS, Gilbert SL, Brown CL et al (2016) Unmanned aircraft systems in wildlife research: current and future applications of a transformative technology. Front Ecol Environ 14:241–251

Colomina I, Molina P (2014) Unmanned aerial systems for photogrammetry and remote sensing: a review. ISPRS J Photogramm Remote Sens 92:79–97

Congalton RG (2005) Thematic and positional accuracy assessment of digital remotely sensed data. US Department of Agriculture General Technical Report WO-77, Washington

Cummings ML, Bruni S, Mercier S, Mitchell PJ (2007) Automation architecture for single operator, Multiple UAV command and control

Cunliffe AM, Brazier RE, Anderson K (2016) Ultra-fine grain landscape-scale quantification of dryland vegetation structure with drone-acquired structure-from-motion photogrammetry. Remote Sens Environ 183:129–143

Cunliffe AM, Anderson K, Boschetti F et al (2022) Global application of an unoccupied aerial vehicle photogrammetry protocol for predicting aboveground biomass in non-forest ecosystems. Remote Sens Ecol Conserv 8:57–71.

Dashpurev B, Wesche K, Jäschke Y et al (2021) A cost-effective method to monitor vegetation changes in steppes ecosystems: a case study on remote sensing of fire and infrastructure effects in eastern Mongolia. Ecol Indic. https://doi.org/10.1016/j.ecolind.2021.108331

DaSilva MD, Bruce D, Hesp PA et al (2023) Post-wildfire coastal dunefield response using photogrammetry and satellite indices. Earth Surf Process Landf 48:1845–1868

de Almeida DRA, Almeyda Zambrano AM, Broadbent EN et al (2020) Detecting successional changes in tropical forest structure using GatorEye drone-borne lidar. Biotropica 52:1155–1167

Delisle ZJ, McGovern PG, Dillman BG, Swihart RK (2023) Imperfect detection and wildlife density estimation using aerial surveys with infrared and visible sensors. Remote Sens Ecol Conserv 9:222–234

Dixon DJ, Callow JN, Duncan JMA et al (2021) Satellite prediction of forest flowering phenology. Remote Sens Environ. https://doi.org/10.1016/j.rse.2020.112197

Doughty CL, Ambrose RF, Okin GS, Cavanaugh KC (2021) Characterizing spatial variability in coastal wetland biomass across multiple scales using UAV and satellite imagery. Remote Sens Ecol Conserv 7:411–429.

Duffy JP, Anderson K, Fawcett D et al (2021) Drones provide spatial and volumetric data to deliver new insights into microclimate modelling. Landsc Ecol 36:685–702

Dugdale SJ, Malcolm IA, Hannah DM (2019) Drone-based structure-from-motion provides accurate forest canopy data to assess shading effects in river temperature models. Sci Total Environ 678:326–340

Edwards HH, Hostetler JA, Stith BM, Martin J (2021) Monitoring abundance of aggregated animals (Florida manatees) using an unmanned aerial system (UAS). Sci Rep 11:12920

Elkind K, Sankey TT, Munson SM, Aslan CE (2019) Invasive buffelgrass detection using high-resolution satellite and UAV imagery on google earth engine. Remote Sens Ecol Conserv. https://doi.org/10.1002/rse2.116

Ellis EC, Wang H, Xiao HS et al (2006) Measuring long-term ecological changes in densely populated landscapes using current and historical high resolution imagery. Remote Sens Environ 100:457–473

Elmore JA, Schultz EA, Jones LR, Evans KO, Samiappan S, Pfeiffer MB, Iglay RB (2023) Evidence on the efficacy of small unoccupied aircraft systems (UAS) as a survey tool for North American terrestrial, vertebrate animals: a systematic map. Environ Evid 12:3

Evans LJ, Jones TH, Pang K et al (2016) Spatial ecology of estuarine crocodile (*Crocodylus porosus*) nesting in a fragmented landscape. Sens Switz. https://doi.org/10.3390/s16091527

Evans AD, Gardner KH, Greenwood S, Still B (2022) UAV and structure-from-motion photogrammetry enhance river restoration monitoring: a dam removal study. Drones. https://doi.org/10.3390/drones6050100

Fallati L, Saponari L, Savini A et al (2020) Multi-temporal UAV data and object-based image analysis (OBIA) for estimation of substrate changes in a post-bleaching scenario on a maldivian reef. Remote Sens 12:2093

Famiglietti NA, Cecere G, Grasso C et al (2021) A test on the potential of a low cost unmanned aerial vehicle RTK/PPK solution for precision positioning. Sensors 21:3882

Fang Y, Que Q, Tu R et al (2021) How do landscape elements affect public health in subtropical high-density city: the pathway through the neighborhood physical environmental factors. Build Environ. https://doi.org/10.1016/j.buildenv.2021.108336

Faye E, Rebaudo F, Yánez-Cajo D et al (2016) A toolbox for studying thermal heterogeneity across spatial scales: from unmanned aerial vehicle imagery to landscape metrics. Methods Ecol Evol 7:437–446.

Fenger-Nielsen R, Hollesen J, Matthiesen H et al (2019) Footprints from the past: The influence of past human activities on vegetation and soil across five archaeological sites in Greenland. Sci Total Environ 654:895–905

Fernández-Guisuraga JM, Calvo L, Suárez-Seoane S (2022) Monitoring post-fire neighborhood competition effects on pine saplings under different environmental conditions by means of UAV multispectral data and structure-from-motion photogrammetry. J Environ Manag. https://doi.org/10.1016/j.jenvman.2021.114373

Foody GM (2023) Remote sensing in landscape ecology. Landsc Ecol 38(11):2711–2716

Fraser RH, Van der Sluijs J, Hall RJ (2017) Calibrating satellite-based indices of burn severity from UAV-derived metrics of a burned boreal forest in NWT. Canada Remote Sens 9:279

Fremand A (2023) UAV data management handbook. UK Polar Data Centre, Cambridge

Fynn IEM, Campbell J (2019) Forest fragmentation analysis from multiple imaging formats. J Landsc Ecol Repub 12:1–15

Gallardo-Salazar JL, Carrillo-Aguilar DM, Pompa-García M, Aguirre-Salado CA (2022) Multispectral indices and individual-tree level attributes explain forest productivity in a pine clonal orchard of Northern Mexico. Geocarto Int 37:4441–4453

Gano B, Bhadra S, Vilbig JM, Ahmed N, Sagan V, Shakoor N (2024) Drone-based imaging sensors, techniques, and applications in plant phenotyping for crop breeding: a comprehensive review. The Plant Phenom J 7(1):e20100

Gascon F, Bouzinac C, Thépaut O et al (2017) Copernicus sentinel-2A calibration and products validation status. Remote Sens 9:584

Gerber R, Piscart C, Roussel J-M et al (2023) Landscape models can predict the distribution of aquatic insects across agricultural areas. Landsc Ecol 38:2917–2929

Getzin S, Löns C, Yizhaq H et al (2022) High-resolution images and drone-based LiDAR reveal striking patterns of vegetation gaps in a wooded spinifex grassland of Western Australia. Landsc Ecol 37:829

Girardeau-Montaut D (2016) CloudCompare. EDF R&D Telecom ParisTech, Paris

Gorelick N, Hancher M, Dixon M, Ilyushchenko S, Thau D, Moore R (2017) Google earth engine: planetary-scale geospatial analysis for everyone. Remote Sens Environ 202:18–27

Grizonnet M, Michel J, Poughon V, Inglada J, Savinaud M, Cresson R (2017) Orfeo toolbox: open source processing of remote sensing images. Open Geospat Data Softw Stand 2:1–8

Guimarães N, Pádua L, Marques P et al (2020) Forestry remote sensing from unmanned aerial vehicles: a review focusing on the data, processing and potentialities. Remote Sens 12:1046

Habel JC, Teucher M, Ulrich W et al (2016) Drones for butterfly conservation: larval habitat assessment with an unmanned aerial vehicle. Landsc Ecol 31:2385–2395

Habel JC, Teucher M, Rödder D (2018) Mark-release-recapture meets species distribution models: identifying microhabitats of grassland butterflies in agricultural landscapes. PLoS ONE. https://doi.org/10.1371/journal.pone.0207052

Habel JC, Teucher M, Rödder D (2018) Mark-release-recapture meets species distribution models: Identifying microhabitats of grassland butterflies in agricultural landscapes.

PLoS ONE. https://doi.org/10.1371/journal.pone.0207052
Habel JC, Teucher M, Gros P et al (2022) The importance of dynamic open-canopy woodlands for the conservation of a specialist butterfly species. Landsc Ecol 37:2121–2129
Haire SL, McGarigal K (2010) Effects of landscape patterns of fire severity on regenerating ponderosa pine forests (*Pinus ponderosa*) in New Mexico and Arizona, USA. Landsc Ecol 25:1055–1069
Hamshaw SD, Engel T, Rizzo DM et al (2019) Application of unmanned aircraft system (UAS) for monitoring bank erosion along river corridors. Geomat Nat Hazards Risk. https://doi.org/10.1080/19475705.2019.1571533
Hamylton SM, Nurdin N, Carvalho RC et al (2020) Mangrove and sand cay dynamics on Australian and Indonesian low wooded islands: a 45 year comparison of changes from remote sensing. Estuar Coast Shelf Sci. https://doi.org/10.1016/j.ecss.2020.106912
Hartfield K, Gillan JK, Norton CL et al (2022) A novel spectral index to identify cacti in the sonoran desert at multiple scales using multi-sensor hyperspectral data acquisitions. Land 11:786
Hasselerharm CD, Yanco E, McManus JS et al (2021) Wildlife-friendly farming recouples grazing regimes to stimulate recovery in semi-arid rangelands. Sci Total Environ. https://doi.org/10.1016/j.scitotenv.2021.147602
Havrilla CA, Villarreal ML, DiBiase JL et al (2020) Ultra-high-resolution mapping of biocrusts with unmanned aerial systems. Remote Sens Ecol Conserv 6:441–456
Hay GJ, Castilla G (2008) Geographic object-based image analysis (GEOBIA): A new name for a new discipline. Object-based image analysis: spatial concepts for knowledge-driven remote sensing applications. Springer, Cham, pp 75–89
Hearn SM, Healey JR, McDonald MA et al (2011) The repeatability of vegetation classification and mapping. J Environ Manage 92:1174–1184
Hensel MJS, Silliman BR, van de Koppel J et al (2021) A large invasive consumer reduces coastal ecosystem resilience by disabling positive species interactions. Nat Commun. https://doi.org/10.1038/s41467-021-26504-4
Hilgendorf Z, Marvin MC, Turner CM, Walker IJ (2021) Assessing geomorphic change in restored coastal dune ecosystems using a multi-platform aerial approach. Remote Sens 13:1–34
Hossain MD, Chen D (2019) Segmentation for object-based image analysis (OBIA): a review of algorithms and challenges from remote sensing perspective. ISPRS J Photogramm Remote Sens 150:115–134
Iijima Y, Abe T, Saito H et al (2021) Thermokarst landscape development detected by multiple-geospatial data in Churapcha Eastern Siberia. Front Earth Sci. https://doi.org/10.3389/feart.2021.750298
Iizuka K, Ogura T, Akiyama Y et al (2022) Improving the 3D model accuracy with a post-processing kinematic (PPK) method for UAS surveys. Geocarto Int 37:4234–4254
Ikeda H, Iimura K, Komura S et al (2020) Vegetation transition and coarse sediment movement after gravel bar restoration with two meandering lanes in a steep river. J Hydro-Environ Res 30:25–34
Jackson-Bué T, Williams GJ, Walker-Springett G et al (2021) Three-dimensional mapping reveals scale-dependent dynamics in biogenic reef habitat structure. Remote Sens Ecol Conserv 7:621–637
Javadian M, Smith WK, Lee K et al (2022) Canopy temperature is regulated by ecosystem structural traits and captures the ecohydrologic dynamics of a semiarid mixed conifer forest site. J Geophys Res Biogeosci. https://doi.org/10.1029/2021JG006617
Jiang J, Johansen K, Tu Y-H, McCabe MF (2022) Multi-sensor and multi-platform consistency and interoperability between UAV, planet cubesat, sentinel-2, and landsat reflectance data. Giscience Remote Sens 59:936–958
Kartoziia A (2019) Assessment of the ice wedge polygon current state by means of UAV imagery analysis (Samoylov Island, the Lena Delta). Remote Sens. https://doi.org/10.3390/rs11131627
Kattenborn T, Lopatin J, Förster M et al (2019) UAV data as alternative to field sampling to map woody invasive species based on combined Sentinel-1 and Sentinel-2 data. Remote Sens Environ 227:61–73
Kellner JR, Armston J, Birrer M et al (2019) New opportunities for forest remote sensing through ultra-high-density drone lidar. Surv Geophys 40:959–977
Kattenborn T, Eichel J, Wiser S et al (2020) Convolutional neural networks accurately predict cover fractions of plant species and communities in unmanned aerial vehicle imagery. Remote Sens Ecol Conserv 6:472–486
Kelly J, Kljun N, Eklundh L et al (2021) Modelling and upscaling ecosystem respiration using thermal cameras and UAVs: application to a peatland during and after a hot drought. Agric For Meteorol. https://doi.org/10.1016/j.agrformet.2021.108330
Kerr JT, Ostrovsky M (2003) From space to species: ecological applications for remote sensing. Trends Ecol Evol 18:299–305
Klosterman S, Melaas E, Wang JA et al (2018) Fine-scale perspectives on landscape phenology from unmanned aerial vehicle (UAV) photography. Agric for Meteorol 248:397–407
Koontz MJ, Scholl VM, Spiers AI et al (2022) Democratizing macroecology: integrating unoccupied aerial systems with the national ecological observatory network. Ecosphere 13:e4206
Krishnan BS, Jones LR, Elmore JA, Samiappan S, Evans KO, Pfeiffer MB, Iglay RB (2023) Fusion of visible and thermal images improves automated detection and classification of animals for drone surveys. Sci Rep 13:10385
Laliberte AS, Goforth MA, Steele CM, Rango A (2011) Multispectral aircraft: image processing workflows and remote sensing from unmanned applications for rangeland environments. Remote Sens 3:2529–2551
Laporte-Fauret Q, Lubac B, Castelle B et al (2020) Classification of Atlantic coastal sand dune vegetation using in situ, UAV, and airborne hyperspectral data. Remote Sens. https://doi.org/10.3390/rs12142222
Laporte-Fauret Q, Castelle B, Michalet R et al (2021) Morphological and ecological responses of a managed coastal sand dune to experimental notches. Sci Total Environ. https://doi.org/10.1016/j.scitotenv.2021.146813

Laslier M, Hubert-Moy L, Corpetti T, Dufour S (2019) Monitoring the colonization of alluvial deposits using multitemporal UAV RGB-imagery. Appl Veg Sci 22:561–572
Liao J, Zhou J, Yang W (2021) Comparing LiDAR and SfM digital surface models for three land cover types. Open Geosci 13:497–504
Librán-Embid F, Klaus F, Tscharntke T, Grass I (2020) Unmanned aerial vehicles for biodiversity-friendly agricultural landscapes—a systematic review. Sci Total Environ. https://doi.org/10.1016/j.scitotenv.2020.139204
Liu Z, Guo P, Liu H et al (2021) Gradient boosting estimation of the leaf area index of apple orchards in UAV remote sensing. Remote Sens 13:3263
Luo W, Xu X, Liu W et al (2019) UAV based soil moisture remote sensing in a karst mountainous catchment. CATENA 174:478–489
Lyu X, Li X, Dang D et al (2022) Unmanned aerial vehicle (UAV) remote sensing in grassland ecosystem monitoring: a systematic review. Remote Sens 14:1096
Madsen B, Treier UA, Zlinszky A et al (2020) Detecting shrub encroachment in seminatural grasslands using UAS LiDAR. Ecol Evol 10:4876–4902
Madurapperuma B, Lamping J, Mcdermott M et al (2020) Factors influencing movement of the manila dunes and its impact on establishing non-native species. Remote Sens. https://doi.org/10.3390/rs12101536
Manfreda S, McCabe MF, Miller PE et al (2018) On the use of unmanned aerial systems for environmental monitoring. Remote Sens 10:641
Markham BL, Helder DL (2012) Forty-year calibrated record of earth-reflected radiance from landsat: a review. Remote Sens Environ 122:30–40. https://doi.org/10.1016/j.rse.2011.06.026
Markham K, Frazier AE, Singh KK, Madden M (2023) A review of methods for scaling remotely sensed data for spatial pattern analysis. Landsc Ecol 38:619–635
Marsh C, Krofcheck D, Hurteau MD (2022) Identifying microclimate tree seedling refugia in post-wildfire landscapes. Agric For Meteorol. https://doi.org/10.1016/j.agrformet.2021.108741
Martin J, Edwards HH, Burgess MA et al (2012) Estimating distribution of hidden objects with drones: From tennis balls to manatees. PLoS ONE 7:e38882
Marx A, McFarlane D (2019) Combining unmanned aerial systems and satellite data to monitor phenological changes in tropical forests: a case study from Costa Rica. Case Stud Environ. https://doi.org/10.1525/cse.2018.001842
Mayer AL, Cameron GN (2003) Consideration of grain and extent in landscape studies of terrestrial vertebrate ecology. Landsc Urban Plan 65(4):201–217
Mayer AL, Buma B, Davis A et al (2016) How landscape ecology informs global land-change science and policy. Bioscience 66:458–469
Mayr MJ, Malß S, Ofner E, Samimi C (2018) Disturbance feedbacks on the height of woody vegetation in a savannah: a multi-plot assessment using an unmanned aerial vehicle (UAV). Int J Remote Sens 39:4761–4785
McGarigal K, Cushman SA, Neel MC, Ene E (2002) FRAGSTATS: spatial pattern analysis program for categorical maps. University of Massachusetts, Amherst
Milan DJ, Heritage GL, Large ARG, Fuller IC (2011) Filtering spatial error from DEMs: implications for morphological change estimation. Geomorphology 125:160–171
Milling CR, Rachlow JL, Olsoy PJ et al (2018) Habitat structure modifies microclimate: an approach for mapping fine-scale thermal refuge. Methods Ecol Evol 9:1648–1657
Miranda V, Pina P, Heleno S et al (2020) Monitoring recent changes of vegetation in Fildes Peninsula (King George Island, Antarctica) through satellite imagery guided by UAV surveys. Sci Total Environ. https://doi.org/10.1016/j.scitotenv.2019.135295
Moody A, Woodcock CE (1995) The influence of scale and the spatial characteristics of landscapes on land-cover mapping using remote sensing. Landsc Ecol 10:363–379
Morgan JL, Gergel SE (2010) Quantifying historic landscape heterogeneity from aerial photographs using object-based analysis. Landsc Ecol 25:985–998
Morgan JL, Gergel SE, Coops NC (2010) Aerial photography: A rapidly evolving tool for ecological management. Bioscience 60:47–59
Nascente JC, Ferreira ME, Nunes GM (2022) Integrated fire management as a renewing agent of native vegetation and inhibitor of invasive plants in vereda habitats: diagnosis by remotely piloted aircraft systems. Remote Sens. https://doi.org/10.3390/rs14041040
Nesbit PR, Hubbard SM, Hugenholtz CH (2022) Direct georeferencing UAV-SfM in high-relief topography: accuracy assessment and alternative ground control strategies along steep inaccessible rock slopes. Remote Sens 14:490
Norton CL, Hartfield K, Collins CDH et al (2022) Multi-temporal LiDAR and hyperspectral data fusion for classification of semi-arid woody cover species. Remote Sens 14:2896
Nowak MM, Dziób K, Bogawski P (2019) Unmanned aerial vehicles (UAVs) in environmental biology: a review. Eur J Ecol 4:56–74
O'Neill RV, Krummel JR, Gardner RH et al (1988) Indices of landscape pattern. Landsc Ecol 1:153–162
Oleksyn S, Tosetto L, Raoult V, Williamson JE (2021) Drone-based tracking of the fine-scale movement of a coastal stingray (*Bathytoshia brevicaudata*). Remote Sens 13:1–24
Olsoy PJ, Forbey JS, Shipley LA et al (2020) Mapping foodscapes and sagebrush morphotypes with unmanned aerial systems for multiple herbivores. Landsc Ecol 35:921–936
Olsoy PJ, Zaiats A, Delparte DM et al (2024) High-resolution thermal imagery reveals how interactions between crown structure and genetics shape plant temperature. Remote Sens Ecol Conserv 10:106–120
Oosthuizen WC, Krüger L, Jouanneau W, Lowther AD (2020) Unmanned aerial vehicle (UAV) survey of the Antarctic shag (*Leucocarbo bransfieldensis*) breeding colony at Harmony Point, Nelson Island, South Shetland Islands. Polar Biol 43:187–191
Orndahl KM, Ehlers LPW, Herriges JD et al (2022) Mapping tundra ecosystem plant functional type cover, height, and aboveground biomass in Alaska and northwest Canada using unmanned aerial vehicles. Arct Sci 8:1165–1180

Over, J.R., Ritchie, A.C., Kranenburg, C.J., Brown, J.A., Buscombe, D., Noble, T., Sherwood, C.R., Warrick, J.A., and Wernette, P.A., 2021, Processing coastal imagery with Agisoft Metashape Professional Edition, Version 1.6—Structure from motion workflow documentation: U.S. Geological Survey Open-File Report 2021–1039, 46 p., https://doi.org/10.3133/ofr20211039

Padró J-C, Muñoz F-J, Planas J, Pons X (2019) Comparison of four UAV georeferencing methods for environmental monitoring purposes focusing on the combined use with airborne and satellite remote sensing platforms. Int J Appl Earth Obs Geoinformation 75:130–140

Page MJ, McKenzie JE, Bossuyt PM et al (2021) The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ 372:n71

Page MT, Perotto-Baldivieso HL, Ortega-S JA et al (2022) Evaluating mesquite distribution using unpiloted aerial vehicles and satellite imagery. Rangel Ecol Manag 83:91–101

Pandžic M, Mihajlovic D, Pandžic J, Pfeifer N (2016) Assessment of the geometric quality of sentinel-2 data. Int Arch Photogramm Remote Sens Spat Inf Sci 41:489–494

Passalacqua P, Belmont P, Staley DM et al (2015) Analyzing high resolution topography for advancing the understanding of mass and energy transfer through landscapes: a review. Earth-Sci Rev 148:174–193

Peterson EA, Carne L, Balderamos J et al (2023) The use of unoccupied aerial systems (UASs) for quantifying shallow coral reef restoration success in Belize. Drones. https://doi.org/10.3390/drones7040221

Picone F, Chemello R (2023) Seascape characterization of a Mediterranean vermetid reef: a structural complexity assessment. Front Mar Sci. https://doi.org/10.3389/fmars.2023.1134385

Pierrat Z, Magney T, Richardson WP, Runkle BRK, Diehl JL, Yang X, Woodgate W, Smith WK, Johnston MR, Ginting YRS, Koren G, Albert L, Kibler CL, Morgan BE, Barnes M, Uscanga A, Devine C, Javadian MΔ, Meza K, Julitta T, Tagliabue G, Dannenberg MP, Antala M, Wong CYS, Santos ALD, Hufkens K, Marrs JK, Stovall AEL, Liu Y, Fisher JB, Gamon J, Cawse-Nicholson K (2025) Proximal Remote Sensing: An essential tool for bridging the gap between high resolution ecosystem monitoring and global ecology. [Tansley Review] Proximal Remote Sensing: An essential tool for bridging the gap between high resolution ecosystem monitoring and global ecology. New Phytologist (accepted). https://doi.org/10.1111/nph.20405

Polley HW, Yang C, Wilsey BJ, Fay PA (2019) Spectral heterogeneity predicts local-scale gamma and beta diversity of mesic grasslands. Remote Sens. https://doi.org/10.3390/rs11040458

Pompa-García M, Martínez-Rivas JA, Valdez-Cepeda RD et al (2022) NDVI values suggest immediate responses to fire in an uneven-aged mixed forest stand. Forests. https://doi.org/10.3390/f13111901

QGIS.org, 2024. QGIS Geographic Information System. QGIS Association. http://www.qgis.org

Qian D, Li Q, Fan B et al (2021) Characterization of the spatial distribution of plateau pika burrows along an alpine grassland degradation gradient on the Qinghai-Tibet Plateau. Ecol Evol 11:14905–14915

Qin F, Fukamachi K, Shibata S (2022) Land-Use/landscape pattern changes and related environmental driving forces in a dong ethnic minority village in Southwestern China. Land. https://doi.org/10.3390/land11030349

Qiu Y, Xu Z, Xu C, Holmgren M (2023) Can remotely sensed vegetation patterns signal dryland restoration success? Restor Ecol. https://doi.org/10.1111/rec.13760

R Core Team (2021) R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna

Rango A, Laliberte A (2010) Impact of flight regulations on effective use of unmanned aircraft systems for natural resources applications. J Appl Remote Sens 4:043539

Räsänen A, Aurela M, Juutinen S et al (2020) Detecting northern peatland vegetation patterns at ultra-high spatial resolution. Remote Sens Ecol Conserv 6:457–471

Reilly S, Clark ML, Bentley LP et al (2021) The potential of multispectral imagery and 3d point clouds from unoccupied aerial systems (UAS) for monitoring forest structure and the impacts of wildfire in mediterranean-climate forests. Remote Sens 13:3810

Riihimäki H, Luoto M, Heiskanen J (2019) Estimating fractional cover of tundra vegetation at multiple scales using unmanned aerial systems and optical satellite data. Remote Sens Environ 224:119–132

Robinson JM, Harrison PA, Mavoa S, Breed MF (2022) Existing and emerging uses of drones in restoration ecology. Methods Ecol Evol 13:1899–1911

Rocchini D, Petras V, Petrasova A et al (2017) Open data and open source for remote sensing training in ecology. Ecol Inform 40:57–61

Rodríguez-Lozano B, Rodríguez-Caballero E, Martínez-Sánchez JF et al (2023) Lithology modulates the response of water limited Mediterranean ecosystems to aridification. Landsc Ecol 38:3115–3132

Rogan J, Chen D (2004) Remote sensing technology for mapping and monitoring land-cover and land-use change. Prog Plan 61:301–325

Rominger K, Meyer SE (2019) Application of UAV-based methodology for census of an endangered plant species in a fragile habitat. Remote Sensing 11(6):719

Roser A, Enterkine J, Requena-Mullor J et al (2022) Drone imagery protocols to map vegetation are transferable between dryland sites across an elevational gradient. Ecosphere. https://doi.org/10.1002/ecs2.4330

Ruiz-García D, Adams K, Brown H, Davis AR (2020) Determining stingray movement patterns in a wave-swept coastal zone using a blimp for continuous aerial video surveillance. Fishes 5:1–13

Sagang LBT, Ploton P, Viennois G et al (2022) Monitoring vegetation dynamics with open earth observation tools: the case of fire-modulated savanna to forest transitions in Central Africa. ISPRS J Photogramm Remote Sens 188:142–156

Sampath A, Shrestha M, While M, Scholl VM (2023) Guidelines for calibration of uncrewed aircraft systems imagery. US Geological Survey, Virginia

Sankey T, Tatum J (2022) Thinning increases forest resiliency during unprecedented drought. Sci Rep 12:9041

Sankey T, Donager J, McVay J, Sankey JB (2017) UAV lidar and hyperspectral fusion for forest monitoring in the southwestern USA. Remote Sens Environ 195:30–43
Sankey TT, Leonard JM, Moore MM (2019) Unmanned aerial vehicle—based rangeland monitoring: examining a century of vegetation changes. Rangel Ecol Manag 72:858–863
Sankey JB, Sankey TT, Li J et al (2021a) Quantifying plant-soil-nutrient dynamics in rangelands: fusion of UAV hyperspectral-LiDAR, UAV multispectral-photogrammetry, and ground-based LiDAR-digital photography in a shrub-encroached desert grassland. Remote Sens Environ 253:112223
Sankey T, Hultine K, Blasini D et al (2021b) UAV thermal image detects genetic trait differences among populations and genotypes of Fremont cottonwood (*Populus fremontii*, *Salicaceae*). Remote Sens Ecol Conserv 7:245–258
Sankey TT, Leonard J, Moore MM et al (2021c) Carbon and ecohydrological priorities in managing woody encroachment: UAV perspective 63 years after a control treatment. Environ Res Lett 16:124053
Sankey TT, Tango L, Tatum J, Sankey JB (2024) Forest fire, thinning, and flood in wildland-urban interface: UAV and lidar-based estimate of natural disaster impacts. Landsc Ecol 39:58
Saqib HSA, Chen J, Chen W et al (2020) Local management and landscape structure determine the assemblage patterns of spiders in vegetable fields. Sci Rep 10:15130
Saura S (2004) Effects of remote sensor spatial resolution and data aggregation on selected fragmentation indices. Landsc Ecol 19:197–209
Schenone S, Thrush SF (2022) Scaling-up ecosystem functions of coastal heterogeneous sediments: testing practices using high resolution data. Landsc Ecol 37:1603–1614
Schenone S, Azhar M, Ramírez CAV et al (2021) Mapping the delivery of ecological functions combining field collected data and unmanned aerial vehicles (UAVs). Ecosystems 25:948
Schiefer F, Schmidtlein S, Frick A et al (2023) UAV-based reference data for the prediction of fractional cover of standing deadwood from Sentinel time series. ISPRS Open J Photogramm Remote Sens 8:100034
Shin P, Sankey T, Moore MM, Thode AE (2018) Evaluating unmanned aerial vehicle images for estimating forest canopy fuels in a ponderosa pine stand. Remote Sens 10:1266
Shokirov S, Jucker T, Levick SR et al (2023) Habitat highs and lows: using terrestrial and UAV LiDAR for modelling avian species richness and abundance in a restored woodland. Remote Sens Environ. https://doi.org/10.1016/j.rse.2022.113326
Siewert MB, Olofsson J (2021) UAV reveals substantial but heterogeneous effects of herbivores on Arctic vegetation. Sci Rep. https://doi.org/10.1038/s41598-021-98497-5
Simoes R, Camara G, Queiroz G et al (2021) Satellite image time series analysis for big earth observation data. Remote Sens 13:2428
Simpson JE, Holman FH, Nieto H et al (2022) UAS-based high resolution mapping of evapotranspiration in a Mediterranean tree-grass ecosystem. Agric For Meteorol. https://doi.org/10.1016/j.agrformet.2022.108981
Singh KK, Frazier AE (2018) A meta-analysis and review of unmanned aircraft system (UAS) imagery for terrestrial applications. Int J Remote Sens 39:5078–5098
Singh A, Wagner B, Kasel S et al (2023) Canopy composition and spatial configuration influences beta diversity in temperate regrowth forests of Southeastern Australia. Drones. https://doi.org/10.3390/drones7030155
Solazzo D, Sankey JB, Sankey TT, Munson SM (2018) Mapping and measuring aeolian sand dunes with photogrammetry and LiDAR from unmanned aerial vehicles (UAV) and multispectral satellite imagery on the Paria Plateau, AZ, USA. Geomorphology 319:174–185
St. Clair SB, Bishop TB (2019) Loss of biotic resistance and high propagule pressure promote invasive grass-fire cycles. J Ecol 107:1995–2005
Steenvoorden J, Limpens J, Crowley W, Schouten MGC (2022) There and back again: forty years of change in vegetation patterns in Irish peatlands. Ecol Indic. https://doi.org/10.1016/j.ecolind.2022.109731
Stöcker C, Bennett R, Nex F et al (2017) Review of the current state of UAV regulations. Remote Sens 9:459
Storey J, Choate M, Lee K (2014) Landsat 8 operational land imager on-orbit geometric calibration and performance. Remote Sens 6:11127–11152
Sun Z, Wang X, Wang Z et al (2021) UAVs as remote sensing platforms in plant ecology: review of applications and challenges. J Plant Ecol 14:1003–1023
Swetnam TW, Allen CD, Betancourt JL (1999) Applied historical ecology: using the past to manage for the future. Ecol Appl 9:1189–1206
Swetnam TL, Gillan JK, Sankey TT et al (2018) Considerations for achieving cross-platform point cloud data fusion across different dryland ecosystem structural states. Front Plant Sci. https://doi.org/10.3389/fpls.2017.02144
Syetiawan A, Gularso H, Kusnadi GI, Pramudita GN (2020) Precise topographic mapping using direct georeferencing in UAV. IOP Conf Ser Earth Environ Sci 500:012029
Talavera L, Costas S, Ferreira Ó (2022) A new index to assess the state of dune vegetation derived from true colour images. Ecol Indic. https://doi.org/10.1016/j.ecolind.2022.108770
Talucci AC, Forbath E, Kropp H et al (2020) Evaluating post-fire vegetation recovery in Cajander Larch forests in Northeastern Siberia using UAV derived vegetation indices. Remote Sens. https://doi.org/10.3390/RS12182970
Tang X, You H, Liu Y et al (2023) Monitoring of monthly height growth of individual trees in a subtropical mixed plantation using UAV data. Remote Sens. https://doi.org/10.3390/rs15020326
Tanguy R, Whalen D, Prates G et al (2023) Permafrost degradation in the ice-wedge tundra terrace of Paulatuk Peninsula (Darnley Bay, Canada). Geomorphology. https://doi.org/10.1016/j.geomorph.2023.108754
Thaker M, Amdekar MS, Mohanty NP et al (2022) An expanding cityscape and its multi-scale effects on lizard distribution. Front Conserv Sci. https://doi.org/10.3389/fcosc.2022.839836
Thangavelu S, Janczewski L, Peko G, Sundaram D (2020) A Dynamic security-dedicated approach to commercial drone vulnerabilities, threat vectors and their mitigation. IEEE, Piscataway, pp 1054–1059

Tmušić G, Manfreda S, Aasen H et al (2020) Current practices in UAS-based environmental monitoring. Remote Sens 12:1001
Troll C (1971) Landscape ecology (geoecology) and biogeocenology—a terminological study. Geoforum 2:43–46
Turner MG (2005) Landscape ecology: what Is the state of the science? Annu Rev Ecol Evol Syst 36:319–344
U.S. Geological Survey (2023) 1 meter digital elevation models (DEMs) - USGS national map 3DEP downloadable data collection. US Geological Survey, Virginia
van Blerk JJ, West AG, Smit J et al (2022) UAVs improve detection of seasonal growth responses during post-fire shrubland recovery. Landsc Ecol 37:3179–3199
van Proosdij D, Graham J, Lemieux B et al (2023) High sedimentation rates lead to rapid vegetation recovery in tidal brackish wetland restoration. Front Ecol Evol. https://doi.org/10.3389/fevo.2023.1112284
van der Sluijs J, Kokelj SV, Fraser RH et al (2018) Permafrost terrain dynamics and infrastructure impacts revealed by UAV photogrammetry and thermal imaging. Remote Sens. https://doi.org/10.3390/rs10111734
Van Rossum G, Drake FL (1995) Python reference manual. Centrum voor Wiskunde en Informatica, Amsterdam, pp 1–52
Velamazán M, Sánchez-Zapata J, Moral-Herrero R et al (2023) Contrasting effects of wild and domestic ungulates on fine-scale responses of vegetation to climate and herbivory. Landsc Ecol 38:3463
Vélez-Nicolás M, García-López S, Barbero L et al (2021) Applications of unmanned aerial systems (UASs) in hydrology: a review. Remote Sens 13:1359
Viedma O, Almeida DRA, Moreno JM (2020) Postfire tree structure from high-resolution LiDAR and RBR sentinel 2A fire severity metrics in a pinus halepensis-dominated burned stand. Remote Sens 12:1–21.
Villoslada M, Sipelgas L, Bergamo TF et al (2022) Multisource remote sensing data reveals complex topsoil organic carbon dynamics in coastal wetlands. Ecol Indic. https://doi.org/10.1016/j.ecolind.2022.109329
Villoslada Peciña M, Bergamo TF, Ward RD et al (2021) A novel UAV-based approach for biomass prediction and grassland structure assessment in coastal meadows. Ecol Indic 122:107227
Vinton MA, Larsen A (2022) Landscape variability underpinning the social-ecological system in the Nebraska Sandhills. Gt Plains Res 32:69–81
Vogelmann JE, Howard SM, Yang L et al (2001) Completion of the 1990's National land cover data set for the conterminous United States. Photogramm Eng Remote Sens 67:650
von Nonn J, Villarreal ML, Blesius L et al (2024) An open-source workflow for scaling burn severity metrics from drone to satellite to support post-fire watershed management. Environ Model Softw 172:105903
Wallace L, Lucieer A, Malenovský Z, Turner D, Vopěnka P (2016) Assessment of forest structure using two UAV techniques: a comparison of airborne laser scanning and structure from motion (SfM) Point Clouds. Forests 7. https://doi.org/10.3390/f7030062
Wang S, Garcia M, Bauer-Gottwein P et al (2019) High spatial resolution monitoring land surface energy, water and CO2 fluxes from an unmanned aerial system. Remote Sens Environ 229:14–31
Wang N, Guo Y, Wei X, Zhou M, Wang H, Bai Y (2022) UAV-based remote sensing using visible and multispectral indices for the estimation of vegetation cover in an oasis of a desert. Ecol Ind 141:109155
Webster C, Westoby M, Rutter N, Jonas T (2018) Three-dimensional thermal characterization of forest canopies using UAV photogrammetry. Remote Sens Environ 209:835–847
Wheaton JM, Brasington J, Darby SE, Sear DA (2010) Accounting for uncertainty in DEMs from repeat topographic surveys: improved sediment budgets. Earth Surf Process Landf J Br Geomorphol Res Group 35:136–156
Whittaker RH (1975) Communities and ecosystems, 2nd edn. Macmillan, New York
Wickham J, Riitters K (2019) Influence of high-resolution data on the assessment of forest fragmentation. Landsc Ecol 34:2169–2182
Wiegand T, Kissling WD, Cipriotti PA, Aguiar MR (2006) Extending point pattern analysis for objects of finite size and irregular shape. J Ecol 94:825–837
Wiens JA (2002) Riverine landscapes: taking landscape ecology into the water. Freshw Biol 47:501–515
Wiens JA, Milne BT (1989) Scaling of 'landscapes' in landscape ecology, or, landscape ecology from a beetle's perspective. Landsc Ecol 3:87–96
Wiersma YF, Schneider DC (2022) Microlandscape experiments: are they useful for scale, scaling, and cross-scale inference? Curr Landsc Ecol Rep 7:116–127
Williams RD, Bangen S, Gillies E et al (2020) Let the river erode! enabling lateral migration increases geomorphic unit diversity. Sci Total Environ 715:136817
Wood CL, Sokolow SH, Jones IJ et al (2019) Precision mapping of snail habitat provides a powerful indicator of human schistosomiasis transmission. Proc Natl Acad Sci U S A 116:23182–23191
Wu S, Wang J, Yan Z et al (2021) Monitoring tree-crown scale autumn leaf phenology in a temperate forest with an integration of PlanetScope and drone remote sensing observations. ISPRS J Photogramm Remote Sens 171:36–48
Wyngaard J, Barbieri L, Thomer A et al (2019) Emergent challenges for science sUAS data management: fairness through community engagement and best practices development. Remote Sens 11:1797
Xu C, Holmgren M, Van Nes EH et al (2015) Can we infer plant facilitation from remote sensing? a test across global drylands. Ecol Appl 25:1456–1462
Xu J, Gu H, Meng Q et al (2019) Spatial pattern analysis of *Haloxylon ammodendron* using UAV imagery—a case study in the Gurbantunggut Desert. Int J Appl Earth Obs Geoinformation 83:101891
Yang D, Morrison BD, Hantson W et al (2021) Landscape-scale characterization of Arctic tundra vegetation composition, structure, and function with a multi-sensor unoccupied aerial system. Environ Res Lett. https://doi.org/10.1088/1748-9326/ac1291
Yao H, Qin R, Chen X (2019) Unmanned aerial vehicle for remote sensing applications—a review. Remote Sens 11:1443

Zeybek M (2021) Accuracy assessment of direct georeferencing UAV images with onboard global navigation satellite system and comparison of CORS/RTK surveying methods. Meas Sci Technol 32:065402

Zhang W, Zhang J (2021) Scaling effects on landscape metrics in alpine meadow on the central Qinghai-Tibetan Plateau. Glob Ecol Conserv. https://doi.org/10.1016/j.gecco.2021.e01742

Zhang W, Yi S, Qin Y et al (2020) Effects of patchiness on surface soil moisture of alpine meadow on the northeastern qinghai-tibetan plateau: implications for grassland restoration. Remote Sens 12:1–15.

Zhang X, Zhang Z, Zhang Y et al (2022) Influences of fractional vegetation cover on the spatial variability of canopy SIF from unmanned aerial vehicle observations. Int J Appl Earth Obs Geoinform. https://doi.org/10.1016/j.jag.2022.102712

Zhao Y, Liu X, Wang Y et al (2021) UAV-based individual shrub aboveground biomass estimation calibrated against terrestrial LiDAR in a shrub-encroached grassland. Int J Appl Earth Obs Geoinform. https://doi.org/10.1016/j.jag.2021.102358

Zhou Y, Qiu C, Li Y et al (2023) Integrating UAV data to explore the relationship between microtopographic variation and Spartina alterniflora expansion during its early invasion. Ecol Indic. https://doi.org/10.1016/j.ecolind.2023.110633

Zhu W, Li S, Zhang X et al (2018) Estimation of winter wheat yield using optimal vegetation indices from unmanned aerial vehicle remote sensing. Nongye Gongcheng XuebaoTrans Chin Soc Agric Eng 34:78–86

Zhu X, Meng L, Zhang Y et al (2019) Tidal and meteorological influences on the growth of invasive Spartina alterniflora: evidence from UAV remote sensing. Remote Sens. https://doi.org/10.3390/rs11101208

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