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REVIEW

Systematic review and best practices for drone remote sensing of invasive plants

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Abstract

1. Drones have emerged as a cost-effective solution to detect and map plant invasions, offering researchers and land managers flexibility in flight design, sensors and data collection schedules. A systematic review of trends in drone-based image collection, data processing and analytical approaches is needed to advance the science of invasive species monitoring and management and improve scalability and replicability.
2. We systematically reviewed studies using drones for plant invasion research to identify knowledge gaps, best practices and a path toward advancing the science of invasive plant monitoring and management. We devised a database of 33 standardized reporting parameters, coded each study to those parameters, calculated descriptive statistics and synthesized how these technologies are being implemented and used.
3. Trends show a general increase in studies since 2009 with a bias toward temperate regions in North America and Europe. Most studies have focused on testing the validity of a machine learning or deep learning image classification technique with fewer studies focused on monitoring or modelling spread. Very few studies used drones for assessing ecosystem dynamics and impacts such as determining environmental drivers or tracking re-emergence after disturbance. Overall, we noted a lack of standardized reporting on field survey design, flight design, drone systems, image processing and analyses, which hinders replicability and scalability of approaches. Based on these findings, we develop a standard framework for drone applications in invasive species monitoring to foster cross-study comparability and reproducibility.
4. We suggest several areas for advancing the use of drones in invasive plant studies including (1) utilizing standardized reporting frameworks to facilitate scientific research practices, (2) integrating drone data with satellite imagery to scale up relationships over larger areas, (3) using drones as an alternative to in-person ground surveys and (4) leveraging drones to assess community trait shifts tied to plant fitness and reproduction.

KEYWORDS

climate zones, flight and survey designs, non-native, remote sensing, unmanned/uncrewed/unpiloted aircraft systems

1 | INTRODUCTION

Invasive species continue to be one of the world's most pressing ecological concerns with impacts for both natural ecosystems and human well-being (Blackburn et al., 2011). Among their many threats, invasive species are a leading cause of extinction for other species (Clavero & García-Berthou, 2005), jeopardize ecosystem services (Paini et al., 2016) and can even alter disturbance regimes (Vitousek, 1990). Climate change is not only fostering the spread of invasive species but also impeding control mechanisms, rendering management strategies less effective (Hellmann et al., 2008). As global efforts intensify to protect terrestrial and marine areas for biodiversity protection under a changing climate, it is becoming even more crucial to understand how invasive species will utilize ecological niches, potentially altering key resources needed for other species to survive. Additionally, it is important to consider how climate change will alter these niches and potentially create new pathways for invasions.

Over the past several decades, satellite and airborne remote sensing have been important tools for systematic monitoring of invasive species (Huang & Asner, 2009). Programmes such as Landsat, MODIS and Sentinel have provided users with moderate to coarse resolution imagery at no cost, leading to hundreds of published studies on invasive species. Yet, invasive plants often exist interspersed within a matrix of other vegetation, making clear detection with moderate resolution imagery difficult (Frazier & Wang, 2011; Singh & Gray, 2020). High-resolution satellite imagery available through commercial providers can be costly and cumbersome to work with (Frazier & Hemingway, 2021), and airborne platforms are often inaccessible to researchers. Within these limitations, the environmental research community has eagerly adopted drones, or unpiloted aircraft systems (UAS), as a cost-effective means to capture remote sensing imagery (Singh & Frazier, 2018). Drones put data capture capabilities into the hands of users and offer flexibility in terms of sensors, flight design and spatial and temporal data collection schedules. The invasive species community has adopted them with vigour because they can be used to capture data at the high resolutions needed for species identification and permit monitoring in locations that cannot be visited in person. A review in 2019 identified 24 studies utilizing drones for invasive species research (Dash et al., 2019). Since then, many more studies have been published, prompting the need for an updated analysis of the state of the art that critically examines how these platforms are being used and whether findings are replicable.

If drone technologies are to have widespread impact on how invasive plant species are detected, mapped, monitored and managed, then a systematic review of the technical aspects of image collection and processing is needed alongside a conceptual review of the innovative analytical approaches being used to advance the science of invasive species monitoring and management. This review aims to (1) evaluate the trends and state of the art in terms of drone data capture, image processing and analysis techniques; (2) assess which species, plant characteristics and ecosystems are particularly suitable for drone-based studies based on extant findings; and (3) discuss the identified challenges for using drone remote sensing in invasive plant research as well as potential opportunities for scalability and replicability of drone applications in this field. In culmination, we (4) provide a list of best practices for using drone technology in invasive plant species research and discuss how these best practices align with benchmark reporting standards established in other disciplines.

2 | METHODS

2.1 | Literature search and data extraction

We performed a systematic search of the Scopus database on 04 December 2023 based on the title, abstract and keywords using the following search criteria to capture the range of terms regularly used in the literature (Rogers et al., 2022): "Remote sensing" AND "Invasive*" OR "exotic*" OR "alien*" OR "non-native" OR "non-native" AND "drone" OR "UAS" OR "UAV" OR "unmanned aerial*" OR "uncrewed" OR "*piloted*". We included all dates (1960–2023) and publication types (e.g. research and review articles, theses, reports, conference proceedings). The initial search returned 240 items. We manually screened all abstracts to remove unrelated entries and those not published in English. We also cross-checked the list against prior reviews (Dash et al., 2019; Müllerová, 2019) and other search engines (e.g. Google Scholar). The final list comprised 103 documents for analyses, which included 76 research articles, 22 conference proceedings, one book chapter and four graduate theses (see Supplemental Material for ROSES diagram [Figure S1] and list of publications).

2.2 | Content analysis

We developed a database of standardized reporting items that aligns with existing best practices for drone studies (James et al., 2019; Tmušić et al., 2020) and captures relevant details for invasive species. The list includes 28 reporting parameters including study area characteristics, field and drone survey design, equipment specifications, flight parameters, data processing, software and other details (Table S1). We coded the information presented in each study to the database and also inferred climate zone, ecosystem and biophysical attributes of the study area for each article when these characteristics were not reported. For each species, we catalogued their respective life histories, growth forms, foliage seasonality, monospecific stand formation and niche specialization as biological attributes using the United States Department of Agriculture (USDA) PLANTS database (United States Department of Agriculture, 2022) and the Global Invasive Species Database from the Center for Agriculture and Bioscience International (Center for Agriculture and Bioscience International, 2022; Poorter & Browne, 2005). To resolve conflicts on synonyms of plant scientific names, we referenced the taxonomic backbone of the Global Biodiversity Information Facility

(Poelen, 2022) through the R package Taxisize (Chamberlain & Szöcs, 2013). The reporting protocol permits comparison across studies and ensures replicability across geographies.

We calculated descriptive statistics on the coded parameters to assess the frequency of studies reporting each database parameter. We determined evident trends in the use of equipment and methods for drone remote sensing in invasive plant research and compared emerging trends with the established benchmark reporting standards. We summarized the trends in the context of invasive species research and discussed the challenges of using drones to study invasive plant studies. Lastly, we presented opportunities for improving the state of the science.

3 | RESULTS FOR TRENDS IN DRONE REMOTE SENSING OF INVASIVE PLANTS

Results related to the trends using drones for invasive species research along with findings on the key reporting parameters according to Table S1 are detailed in the sections below. Based on these findings, we synthesized a set of reporting best practices for researchers to use as a guide when working with drones for invasive species studies (Figure 1). At the beginning of our results, we present this guide for best practice use of drones to monitor invasive plants.

3.1 | Study areas and characteristics

The number of studies published has generally increased since 2009 (the first publication appeared in 2009), with a peak in 2021 (Figure 2). At the time of review, studies had been undertaken across 27 countries (Figure 3a), in 14 ecosystems (Figure 3b) and all five Level 1 Köppen–Geiger climate zones (Beck et al., 2018; Figure 3c). Most studies were conducted in the Global North, primarily North America (31% of those reviewed) and Europe (31%), with a handful conducted in Latin America and the Caribbean (12%), Asia (12%), Australia/New Zealand (8%) and Sub-Saharan Africa (4%) (Figure 3a). The geographic bias of studies in Europe and North America means that continental and temperate climate zones are well represented, while tropical and arid/semi-arid regions are less studied (Figure 3c). Given differences in species between biomes, the external validity of image classification procedures or species discrimination methods may not be generalizable across regions. For instance, mapping plant invasions in tropical forests can be challenging due to the higher floristic diversity compared to continental and temperate zones. The

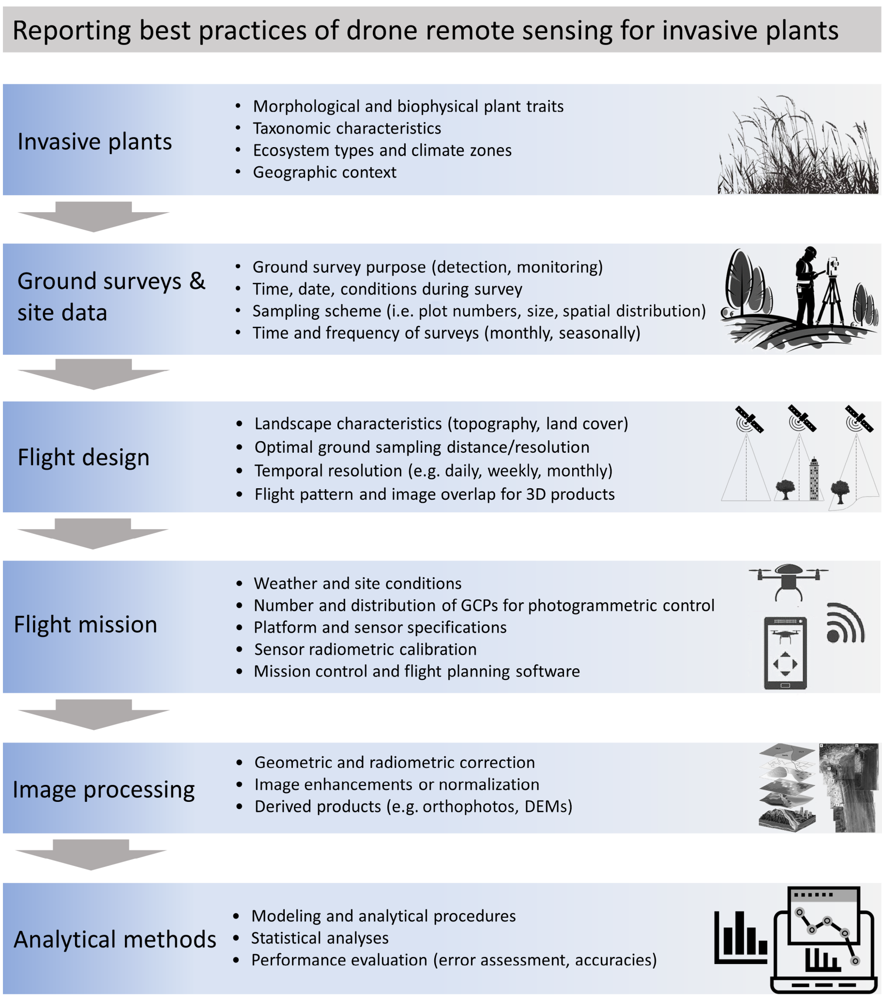

FIGURE 1 Best practices and workflow for documenting parameters of drone-based mapping, monitoring and measuring of plant invasions to ensure scalability and reproducibility across geographies. These best practices build from prior recommendations (Abdullah, 2021; James et al., 2019; Mathews et al., 2023).

value of drones for studying invasive plant species in tropical climates may therefore be missing from the existing knowledge base.

Collectively, the 103 articles reviewed surveyed 163 study sites, with the majority (about 74%) focusing on a single site, while the rest surveyed multiple (2–8) sites. Likewise, most studies focused on a single species (68%; excludes instances where the plant was not identified to the species level) while the rest focused on two to eight species. The total area studied ranged from 0.01 ha (Brooks et al., 2021) to 2733 ha (Li et al., 2019). Wetlands were the dominant ecosystem type studied (16% of studies), followed by grasslands (13%), forests (13%), estuaries and other coastal ecosystems (11%) and agricultural or mixed agriculture-forest (10%) systems. Glaciers, built-up areas and other modified environments were rarely studied (3%).

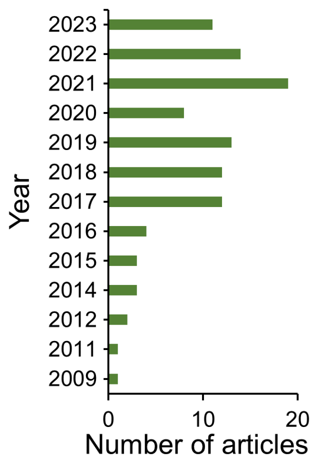

FIGURE 2 Number of articles published per year on the use of drones for studying plant invasions. *Note:* 2023 data only includes studies published through December 4.

3.2 | Invasive plant attributes

The biochemical substances in plant leaves and stems (e.g. chlorophyll-*a* and *b*, carotenoids, xanthophyll, total nitrogen, leaf moisture content) that drive their spectral reflectance are inherently linked to their taxonomy. Therefore, providing taxonomic details of both the invasive and native vegetation is important for remote sensing (Asner & Martin, 2009). Overall, 110 taxa representing five taxonomic groups (monocot, dicot, gymnosperms, ferns and algae) and 91 genera were studied. Of the studies reviewed, 86% described the focal invasive plants to the species level (including hybrid species), while 13% had genus-level identifications. The majority of plants studied were angiosperms, likely due to their distinct spectral characteristics during the flowering phase, which facilitates remote observation (Figure 4a). The most studied flowering plants were dicots (62% of taxa) and frequently included Japanese knotweed (*Reynoutria japonica*) and Bitter vine (*Mikania micrantha*). Monocots comprised about 28% of taxa and included Common reed (*Phragmites australis*) and Saltmarsh cordgrass (*Spartina alterniflora*). Only five gymnosperms, including Monterey pine (*Pinus radiata*) and Eastern red cedar (*Juniperus virginiana*), and three fern taxa, including Southern bracken (*Pteridium arachnoideum*), Drooping forked fern (*Dicranopteris flexuosa*) and Giant salvinia (*Salvinia molesta*), were studied. Gymnosperm studies were limited to non-forest ecosystems (e.g. glacier forelands, grasslands) where the coniferous evergreen tree morphology is visually distinguishable. Ferns also have visually distinguishable biophysical traits and morphology including bristle surface, thick mat composition, perennial and evergreen foliage with thick, leathery texture that support drone-based detection and mapping. Invasive algae were the least studied taxa.

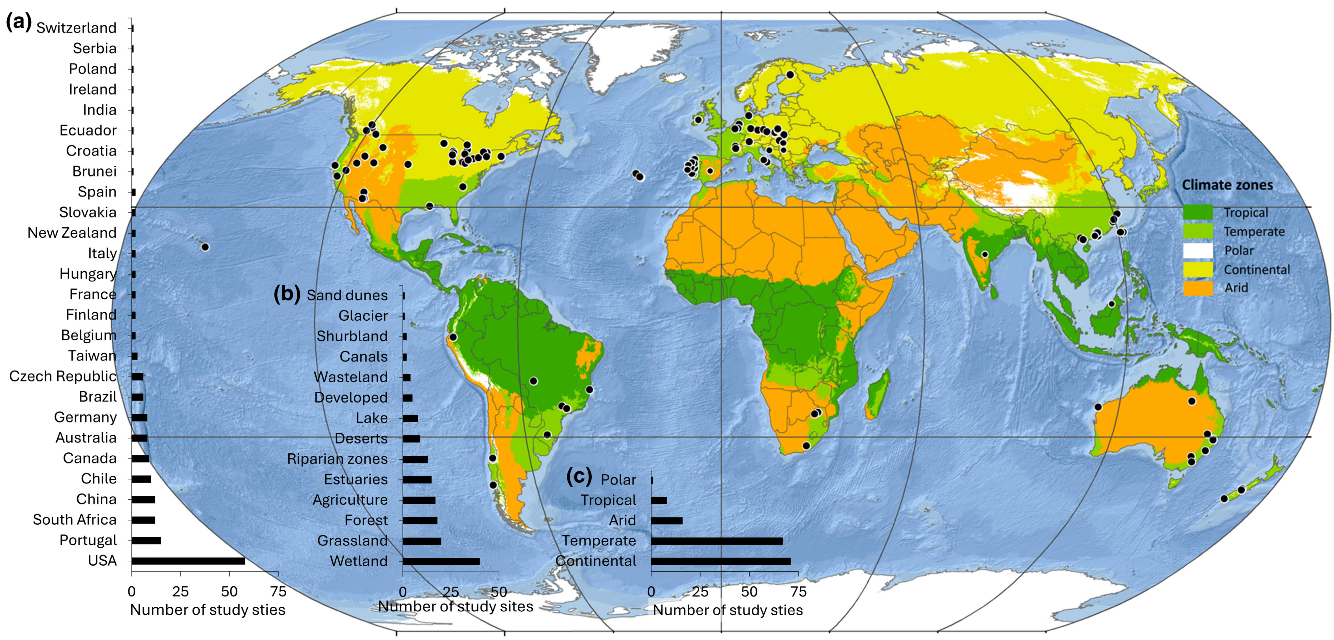

FIGURE 3 Köppen–Geiger climate zones overlaid with the locations (black dots) of drone-based invasive plant studies including (a) the number of study sites per country, (b) ecosystem types and (c) Köppen–Geiger climate zones (Beck et al., 2018).

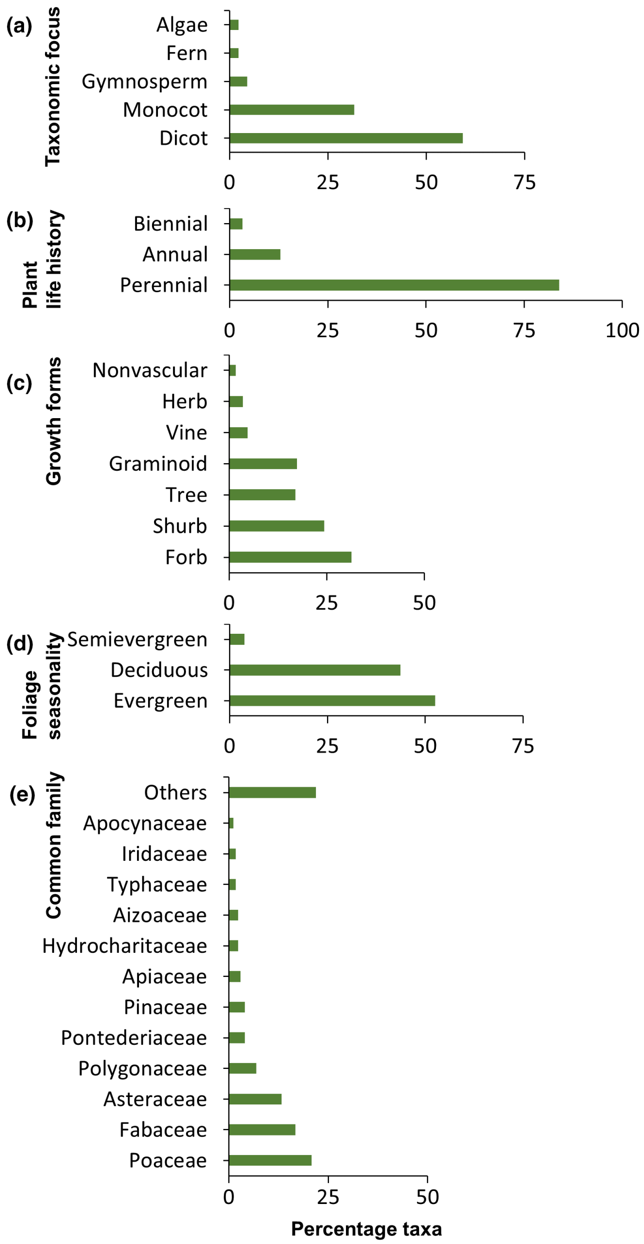

FIGURE 4 Trends in drone-based studies of invasive plants based on the biological features of the focal species and the characteristics of surveyed sites: (a) Representation of different taxa with respect to major plant taxonomic groups, (b) plant life histories, (c) plant growth forms, (d) foliage seasonality (e) and invasive plant families studied. The 'Others' category includes families with fewer than two plant taxa.

Invasive perennials (83 taxa) were more studied than annuals (14 taxa), with evergreens being the most studied perennial. Plants with multiple life histories were less often studied (10 species; Figure 4b). Forbs and shrubs (44 and 33 taxa, respectively) followed by graminoids (23 taxa) were the most extensively studied growth forms while non-vascular plants, vines and plants with mixed growth forms were among the least studied (Figure 4c). Morphological and seasonal characteristics of forbs (i.e. conspicuous flowers), shrubs (i.e. broad leaves) and graminoids (i.e. narrow leaves with high foliage density) make them distinctive from the surrounding native vegetation and easier to identify when using sensors with lower spectral resolution, like most off-the-shelf visible imaging (RGB) cameras used on drones. Structural characteristics of invasive plants such as their spatial arrangement (e.g. independent vs. aggregated units) also help discriminate them from the native vegetation (Niphadkar & Nagendra, 2016). Structurally distinct tree crowns, such as broad-leaved exotic species invading needle-leaved coniferous forests, can be detected with optical sensors. An overwhelming proportion of plant taxa studied form dense, monospecific stands (100 of the 110 taxa). The number of niche generalists (66) plant taxa studied exceeded that of niche specialists (45). The reviewed studies focused on three types of foliage seasonality: Most were about evergreen species (48%), followed by deciduous species (38%) and a handful on semi-evergreen species (1%) (Figure 4d). We tallied 45 plant families where Family Poaceae ('grass' family) accounted for the greatest number of studies (19%), followed by Fabaceae (Legume family, 14%) and Asteraceae (daisy family, 12%). The same pattern was evident in terms of the number of plant taxa studied per family where Poaceae included the greatest proportion of plant taxa (17%) followed by Fabaceae (15%) and Asteraceae (14%) (Figure 4e).

3.3 | Field survey design

3.3.1 | Site characterization

Adequate site characterization is key to ensuring methods and findings are replicable to different environments, and basic attributes of the focal species including morphological characteristics, plant growth patterns and habitat requirements inform sensor selection, survey design and flight missions. At the microhabitat scale (i.e. less than 10 m^2), reported variables should include soil type and texture, water availability, relative nutrient concentrations and resource distribution, which have been identified as critical drivers of plant invasions (Bakker & Berendse, 1999; Kolb et al., 2002; Wedin & Tilman, 1996) but could also complicate drone detection. At site scales (i.e. 10s of km^2), topographic characteristics that influence plant invasions, such as soil moisture and water availability as well as distinct growth patterns of vegetation characteristics attributable to both slope and aspect, should be reported as drones can acquire such fine-scale features with sufficient detail (Roundy et al., 2018). At the landscape scale (i.e. 10s to 100s km^2), land cover heterogeneity, disturbance regime and the nature of dispersal corridors are also important determinants of plant invasions and should be reported or described. Landscapes prone to frequent disturbances of both natural and anthropogenic (e.g. fire-maintained grasslands, riparian zones, roadsides, nature trails) often suffer heightened risks of plant invasions (Jauni et al., 2015; Pauchard et al., 2009). Floristic diversity at all scales can complicate detection by drones and should be reported to the highest achievable level. These details can help other users strategically modify and adapt methodologies for drone-based detection and mapping of plant invasions.

3.3.2 | In situ surveys

Many studies collect in situ reference data to be used during image calibration or for training/testing a classification algorithm. A detailed description of survey design including plot size, shape, number and configuration within the study area as well as the data collected, such as species presence/absence, percent cover or stem density, is needed. Ground surveys should coincide with the timing of the drone flight to ensure the growth stage and environmental conditions are consistent, with dates and times of data collection reported. In the studies we reviewed, field survey information was sometimes provided (Brooks et al., 2021; Marzialetti et al., 2021; Wang et al., 2021), but details were often omitted or not described in sufficient detail to allow replication. Most field studies focused on capturing the presence/absence or percent cover of the focal species, either in plots or as points. For any sampling scheme, it is critical to measure and report the geolocation accuracy of the plot or point survey locations with respect to the accuracy of the imagery. For instance, if plot locations are captured with a spatial accuracy of +/− 0.1 m, but the image resolution is 0.05 m with an estimated error of +/− 0.2 m, then the spatial error in the geolocation of the sampling plots may negate their use.

3.3.3 | Drone-based surveys

Capturing ground reference data with drones can be more time and cost-effective (Kaartinen et al., 2015; Kattenborn et al., 2019) than conducting in-person surveys. Extracting useful information from drone imagery often requires expert input and knowledge of the site; however, the high spatial resolution that can be captured with drones does facilitate direct visual interpretation with less reliance on field observations than is typically required for coarser resolution conventional aerial and satellite imagery (Hill et al., 2017). Several studies we reviewed collected reference data directly from drone images, and then used those labelled locations to train a classification (Sandino et al., 2018). In other cases, drones were used to capture fine-scale reference data, which were then labelled and upscaled to be used as training data for classifying coarser resolution satellite imagery (Kattenborn et al., 2019). Since drone imagery can have intrinsic errors and uncertainties, they may not always be a reliable alternative to in-person ground surveys for collecting reference data (Fraser & Congalton, 2019). When used in conjunction, drone and in-person surveys can help rectify observer bias and offer robust solutions for generating high-accuracy reference data.

3.4 | Drone system

3.4.1 | Platforms

Overall, more than 80% of studies reported details on the platform, with more than half of those using a drone from the DJI company (Figure 5a). The DJI Phantom, which is a ready to use, quadcopter that retails for around US $4,500, was the most popular make/model (just over 30% of studies used this drone) followed by the Sensefly eBee (~11%), which is a fixed-wing aircraft that retails for around US $15,000. It is worth noting that some institutions do not permit the use of DJI platforms due to data privacy issues, which may impact adoption.

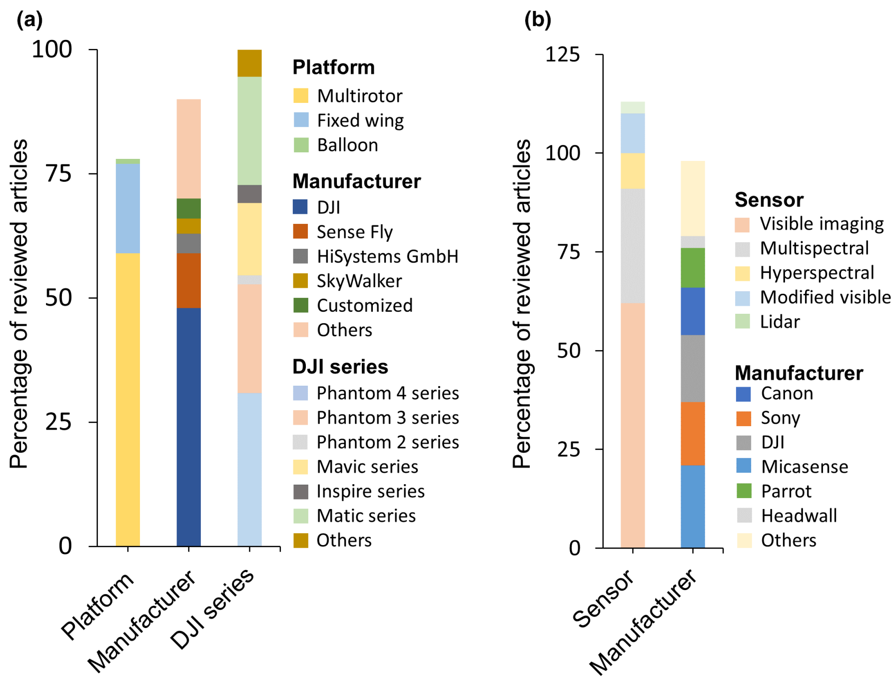

FIGURE 5 (a) Platform type, manufacturer and most used DJI models, and (b) sensor types and manufacturers.

3.4.2 | Sensors

Most studies provided very few details on the sensor, aside from the manufacturer and make (75% of studies reported), even though sensor selection is paramount for vegetation mapping since the spectral and textural details depend on the sensor properties (Dian et al., 2015; Peña-Barragán et al., 2011). We did note that rationale was rarely provided for sensor choice in the context of the science objective or application. Studies used a range of off-the-shelf sensors from Canon, Sony, DJI, Micasense and other manufacturers (Figure 5b). Some studies utilized multiple sensors to compare mapping or analysis techniques across sensors (Brooks et al., 2022; Chabot et al., 2017). Spectral resolution determines the number and bandwidths to which a sensor is sensitive. Sensors with higher spectral resolution (i.e. more bands) can more effectively differentiate plant species and traits (Bolch et al., 2020; Niphadkar & Nagendra, 2016). However, three-band, visible imaging (i.e. RGB) cameras are sufficient for creating orthomosaics and 3D point clouds, and we found these were used most often (61% of studies) despite their limited ability to discriminate species. Many studies used a sensor with a near infrared (NIR: 770–890 nm) or red edge band (670–780 nm), which are more sensitive to physiological and biochemical properties (e.g. chlorophyll, nitrogen, water content) and can help discriminate species (Tay et al., 2018; Weisberg et al., 2021). Hyperspectral sensors capture tens to hundreds of spectral bands and are extremely powerful for species discrimination and phenology. However, they are more expensive than multispectral sensors, and so their use remains rare, and their full potential has yet to be realized. Their use was reported in only nine studies we reviewed (Bolch et al., 2021; Kattenborn et al., 2019; Lopatin et al., 2019; Mitchell et al., 2012; Papp et al., 2021).

3.4.3 | Sensor calibration

Radiometric calibration is an important step for drone remote sensing because it helps ensure the sensor is capturing accurate reflectance measurements that can ultimately be translated into biophysical or chemical properties of the plant, such as chlorophyll or water content. Sensors on satellites, such as Landsat's Operational Land Imager (OLI), are calibrated by the manufacturer or agency, but this step needs to be performed by the user for most drone-based sensors (Frazier et al., 2021; Singh & Frazier, 2018). Since most camera manufacturers do not specify the wavebands comprising each image channel (Mathews, 2015), camera calibrations are highly recommended. Yet just under 6% of the studies we reviewed articles mentioned calibration, and there was typically very little description of how calibration was accomplished (Michez et al., 2016; Wijesingha et al., 2020). Calibration can be achieved with a highly reflective white reflectance panel designed to give near-perfect diffuse reflectance (Singh, 2021) from which image reflectance values can be standardized and adjusted. For example, Weisberg et al. (Amarasingam et al., 2023; Weisberg et al., 2021) and Amarasingam et al. (2023) used a Micasense calibrated reflectance panel to convert camera digital numbers to reflectances using the empirical line approach (Smith & Milton, 1999), while Papp et al. (2021) used a polytetrafluoroethylene reflectance panel to calibrate the hyperspectral imager used in their study. Other studies used a downwelling light sensor (DLS) mounted on top of the aircraft to capture sun angle and illumination information and used this in combination with data from a reflectance panel to adjust image reflectance (Chabot et al., 2018; Roca et al., 2022).

3.5 | Mission planning and execution

3.5.1 | Mission control and flight planning software

About 28% of studies named mission control software, but fewer provided an explanation for mission control software selection (Figure 6a). The most commonly used software was Pix4D Capture (10 studies; Brooks et al., 2021; Lam et al., 2021), which is an open-access application designed to plan and execute flight missions that is compatible with a wide range of drones and sensors. DroneDeploy, which shares similarities with Pix4DCapture, was used in three studies (Gonçalves et al., 2022; Kellaris et al., 2019). Other software included eMotion (Akandil et al., 2021), which is specifically designed for senseFly's fixed-wing drones, and ArduPilot (Mafanya et al., 2017; Samiappan, Turnage, Hathcock, & Moorhead, 2017), an open-source software with high versatility designed for small drones that is popular in both industrial and research applications (Colomina & Molina, 2014).

3.5.2 | Flight details

Several categories of flight details should be reported in any drone study. Flight compliance ensures air traffic safety, helps identify operational restrictions and safeguards both privacy and national security. Five studies mentioned compliance with federal, state and/or local regulations (Baron & Hill, 2020; Brooks et al., 2021; Hill et al., 2017). The lack of reporting does not necessarily mean studies did not comply, only that they did not report their procedures. Reporting flight compliance adds credibility and legitimacy to a study and also helps future users address location-specific regulatory concerns. Weather and site conditions including wind, precipitation, temperature and atmospheric haze can affect image quality and therefore the ability to discriminate invasive species but were only reported in about 30% of studies (Figure 6a; Gao et al., 2021; Kellaris et al., 2019), with studies most reporting that flights were performed on cloud-free days with low winds, which are ideal conditions (Casas et al., 2021; Tian et al., 2022; Weisberg et al., 2021). Several studies mentioned capturing images under overcast conditions but did not specify the rationale (Chabot et al., 2017; Perroy et al., 2017; Qian et al., 2020). Overcast conditions can minimize image shadow but will impact

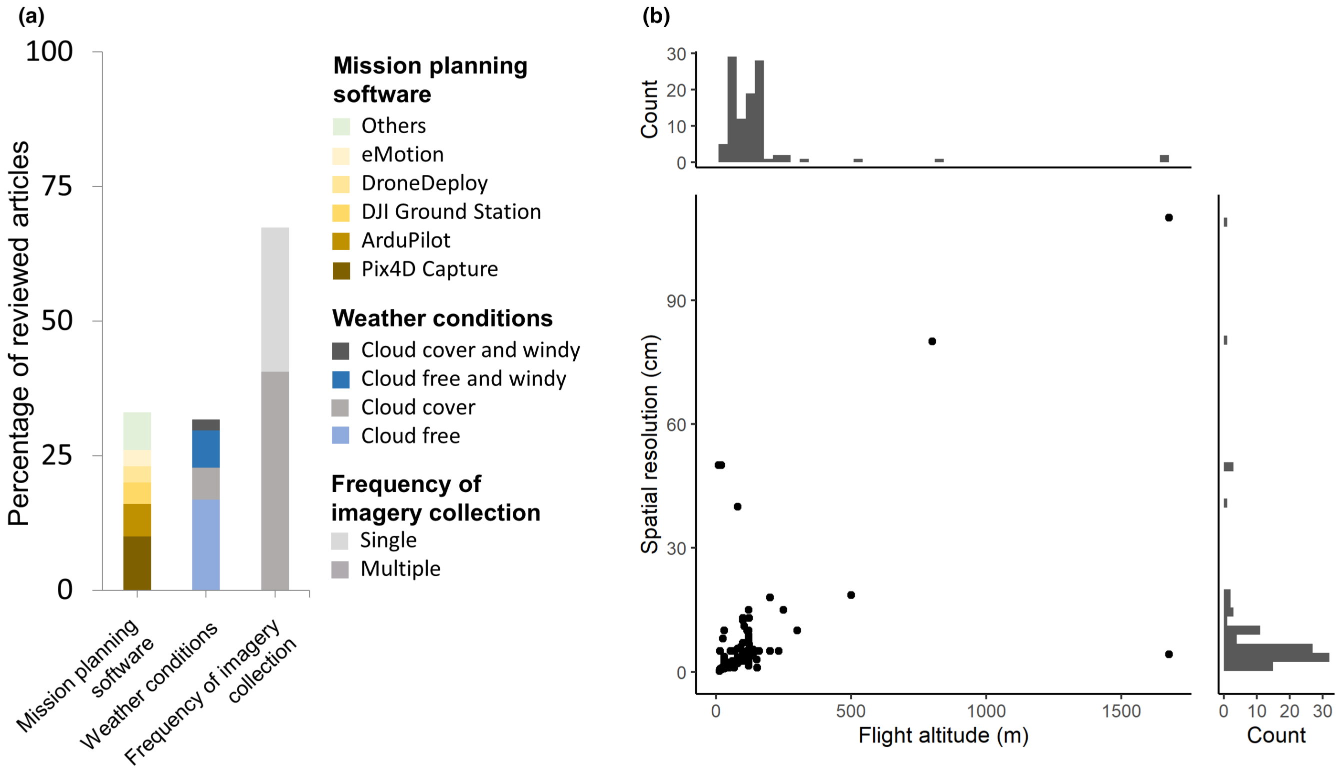

FIGURE 6 (a) Percentage of reviewed articles that reported the mission planning software, weather conditions during flight and the frequency (single or multiple flights) of imagery collection, and (b) the relationship between flight altitude and spatial resolution based on the articles that reported values.

reflectance, which is not recommended when data are to be used for biophysical measurements such as inferring biological traits from images and using those traits to infer the 'invasiveness' of a species (Hovick et al., 2012). Bidirectional reflectance effects, in which light is scattered in many directions, are pronounced issues in drone imagery (Lelong et al., 2008) and can particularly impact studies of invasive trees in forests where canopy structure is complex. These reflectance effects can create spurious seasonality signals in phenology studies and impact vegetation indices like NDVI (i.e. normalized difference vegetation index; Nagol et al., 2015), which are frequently employed. However, we found no reference to these effects in the reviewed studies, suggesting they may be overlooked by users. Other important site factors can include tidal cycles, which can obscure or occlude invasive aquatic vegetation in coastal environments (Casas et al., 2021; Tian et al., 2022). About 73% of articles reported the flight altitude, which ranged from 10 to 1700 m (Figure 6b). In most cases, the flight ceiling remained below 125 m, and flights exceeding 200 m were rare (Samiappan, Turnage, Hathcock, Casagrande, et al., 2017; Wu et al., 2019), possibly because most focal species were smaller shrubs and grasses. About one-fourth (23%) of studies reported flight speed, which ranged from 1 to 18 m/s (Nascente et al., 2022; Tian et al., 2022). Flight patterns were rarely reported (11%), but most followed a single grid/parallel lines (Perroy et al., 2017), double grid (Wijesingha et al., 2020) or zig-zag (Gonçalves et al., 2022) formation.

3.5.3 | Image capture

High image overlap (both forward and side) is critical for generating 3D models and orthomosaics from drone imagery (Frazier & Singh, 2021), which were widely used in the studies reviewed. Overlapping images provide multiple perspectives of the ground features, which permit image matching for generating 3D reconstructions. Image overlap was reported in 52% of studies, but there was high variability in the amount of overlap, ranging from 20% to 90% (Bolch et al., 2021; Lopatin et al., 2019; Wang et al., 2021). The most common overlap was 80% for both forward and sidelap (Casas et al., 2021; Lam et al., 2021; Weisberg et al., 2021), which adheres to recommendations for at least 70% forward and 40% sidelaps (Singh & Frazier, 2018; Su et al., 2016; Figure S2). About 5% of articles reported trigger cadence, which is the time interval between consecutively captured images (Kedia et al., 2021) and partially dictates overlap. About 30% reported the total number of images, which ranged upward of 10,000. Ground sampling distance, or GSD, reported in 27% of studies, is a metric of the nominal spatial resolution of the imagery expressed in units of linear distance per pixel (m or cm/pixel) and is influenced by factors such as the flight altitude, sensor focal length and sensor resolution. A smaller GSD indicates higher spatial resolution, facilitating detection of smaller plants or leaves. GSD ranged from 1.5 mm (Hung et al., 2014) to just over 40 cm (Papp et al., 2021), but most studies reported a GSD less than 10 cm (median: 5 cm), which is in line with other fields (Singh & Frazier, 2018). It should be noted that GSD does not always equal the spatial resolution at which analyses are performed since the image can be resampled to alter the spatial resolution. Approximately 17% of studies captured images from multiple sensors at different GSDs, and these were often resampled to match the higher spatial resolution before utilizing them for mapping or monitoring invasive plants (Figure 6b). However, this process of downsampling images is not considered a best practice (Markham et al., 2023). A trade-off between spatial resolution and mapping accuracy should be established to improve computational efficiency. However, only a single study discussed testing multiple spatial resolutions (Lopatin et al., 2019).

3.5.4 | Temporal and radiometric resolution

Temporal resolution is the frequency of image capture and was reported in 84% of studies. Capturing imagery at multiple time intervals enables monitoring phenological changes and responses of invasive and native species to different environmental conditions or treatment interventions. Although most studies only captured data from a single time period (49%), about 34% of studies implemented multiple flights across different time periods, and some studies exceeded 10 flights (Jay, Assistant-Research, Lawrence, & Keith, n.d.; Zhu et al., 2019). The remaining studies did not provide information on temporal resolution. To capture phenology changes of invasive species across a growing season, a time series of images is needed, yet only 12 studies captured five or more time periods of imagery. An example is Silva et al. (Silva et al., 2014), who created five image composites over the span of a year to monitor postfire canopy recovery and invasion in a grassland. Radiometric resolution refers to a sensor's sensitivity to radiant energy and is typically measured in bits. Images captured with higher radiometric resolution can better differentiate amounts of reflected or emitted energy, which can help with early detection of invasive species or qualify subtle differences or changes. Radiometric resolution was infrequently reported (9%), but ranged from 8 bits (Alvarez-Taboada et al., 2017) to 24 bits (Mafanya et al., 2018).

3.5.5 | Photogrammetric control

Photogrammetric control involves establishing a geographic reference for images, and typically, it involves the use of ground control points (GCPs), although direct georeferencing uses only camera locations and can also provide accurate georeferencing (Carbonneau & Dietrich, 2017) in some situations. The use of GCPs and the precise capturing of their geographic coordinates using Global Navigation Satellite System (e.g. GPS) typically improves accuracy though (Jurjević et al., 2020; Padró et al., 2019). Only 20% of studies reported the details of using GCPs for photogrammetric control although many more were inferred to have used these. GCP materials included plastic discs (Kedia et al., 2021), orange safety cones (Baron & Hill, 2020), black and white checkered boards (Wijesingha et al., 2020), compact discs (Lehmann et al., 2017), white panels (Samiappan, Turnage, Hathcock, & Moorhead, 2017) and even natural features (Nascente et al., 2022). However, very little justification for the number, type or location was provided, which aligns with other findings (Mesas-Carrascosa et al., 2017). General consensus is that mapping accuracy improves with more GCPs (Agüera-Vega et al., 2017; Reshetyuk & Mårtensson, 2016; Thomas et al., 2020), particularly for areas of high terrain variability (Thomas et al., 2020), but gains in accuracy level off after about 10–20 GCPs per km^2 (Gindraux et al., 2017). Studies reported using a minimum of six GCPs (Perroy et al., 2017) up to a maximum of 38 (Meyer et al., 2023). The use of post-processed kinematic (PPK) or real-time kinematic (RTK) global navigation satellite system (GNSS) can help capture the locational precision of GCPs needed to reference high spatial resolution drone imagery, and about 28% of studies reported using RTK- or PPK-GNSS for this purpose. Of note, Bolch et al. (Bolch et al., 2021) used a Trimble Geo7X RTK kit with a Zephyr-3 antenna to record GNSS locations to conduct a differential correction using GPS Pathfinder Office to improve positional accuracies for monitoring aquatic plant invasions in the Sacramento-San Joaquin River Delta, and Koco et al. (2021) surveyed Goldenrod-invaded areas using a GNSS-RTK GPS unit with an accuracy of <2 cm in Slovakia. If high accuracy GNSS is not available, upscaling the image GSD can help overcome positional errors (Gränzig et al., 2021). No studies reported using advanced methods for photogrammetric control such as automated GCP identification (James et al., 2017) or image registration (Yang & Chen, 2015) methods, or all-in-one, portable GCPs (such as from AeroPoints™) that simultaneously serve as a GNSS receiver (Frazier & Singh, 2021).

3.6 | Image processing

3.6.1 | Radiometric correction

Drone images are prone to radiometric anomalies due to atmospheric impedance (i.e. light absorption and scattering) as well as sensor calibration errors and noise from inconsistent brightness across scenes and the complexity of light interaction at the individual leaf scale. This noise can ultimately impact analyses performed on the data (Rogers et al., 2020). Radiometric correction minimizes these anomalies and allows biophysical and biochemical properties to be extracted from reflectance signatures. However, only 18% of studies indicated radiometric corrections were completed during image post-processing. Manfaya et al. (2018) provide a framework for radiometrically calibrating images to physical units of reflectance for mapping of invasive alien plants in semi-arid woodlands that includes designing calibration targets, checking scene illumination uniformity, converting digital numbers in orthomosaics to units of reflectance and assessing accuracy using in situ mean reflectance measurements. Other approaches included field-deployed reflectance calibration targets (Baron & Hill, 2020; Bolch et al., 2021; Papp et al., 2021), the empirical line method (Mafanya et al., 2018; Smith & Milton, 1999; Weisberg et al., 2021), a sun irradiance or incident light sensor (Baron & Hill, 2020; Jochems et al., 2021; Kedia et al., 2021) or a combination of these approaches (Chabot et al., 2018). While we did not encounter any studies that used pseudo-invariant features (i.e. ground features with minimal spectral change from one image acquisition date to the next) to perform relative normalization of multi-date images, this is a technique that has been implemented successfully for high spatial resolution Planetscope imagery (Tu et al., 2022). Colour thresholding and de-speckling can be implemented prior to mapping to improve noise (Baron et al., 2018), while clipping images, especially along the edges, can remove highly distorted areas. Moving windows can also be used to minimize radiometric noise (Lopatin et al., 2019) and address sensor calibration errors (Baron & Hill, 2020). If left uncorrected though, radiometric errors can propagate into classification and subsequent analyses.

3.6.2 | Geometric correction and referencing

Geometric correction rectifies images to a standard map projection and aligns the image with geographic coordinates. Only 40% of studies indicated geometric corrections were performed using either direct or indirect approaches. Direct georeferencing relies on the information from the IMU and GNSS onboard the drone, while indirect methods use GCPs with PPK techniques (Padró et al., 2019). Studies analysing the impact of georeferencing methods on improving mapping and monitoring of plant invasions were rare; indirect approaches generally result in higher georeferencing accuracy but can be costly and laborious, particularly in areas of complex terrain or sites with poor accessibility (Grayson et al., 2018; Padró et al., 2019; Thomas et al., 2020). Direct approaches are more likely to suffer larger horizontal and vertical errors (Jurjević et al., 2020) due to sensor-triggered uncertainties or offsets between the sensor and module position (Ekaso et al., 2020). With traditional, satellite-based remote sensing, georeferencing has typically aimed for sub-pixel geometric errors (Wolfe et al., 2002). However, this level of precision is much more difficult to achieve when the GSD is less than 10 cm. More typically, geometric errors are on the order of several pixels. For example, Granzig et al. (2021) used direct georeferencing with an average error of 2.87 pixels to map common gorse (*Ulex europaeus*) invasions, while Kellaris et al. (2019) used indirect georeferencing to achieve a spatial accuracy of +0.5 m but for imagery with a spatial resolution of less than 0.05 m. Co-registering georeferenced drone imagery to other high-resolution remotely sensed imagery can further improve georeferencing accuracies (Padró et al., 2019; Zhuo et al., 2017), but we did not find this approach among the studies we reviewed.

3.6.3 | Image processing procedure

Most studies employed a structure for motion workflow (Snavely et al., 2008) in which overlapping images are processed into 3D point clouds, digital elevation models and orthomosaics, which can ultimately be used as inputs for classification procedures (Mathews, 2021). While SfM was widely used in the studies we reviewed, the steps were rarely documented, which stymies replication efforts. Studies most often used Agisoft Metashape or Pix4DMapper software, but SimActive's Correlator3D and Bentley Acute3D ContextCapture Center were also used.

3.6.4 | Processed products and derived variables

The primary data products developed included digital elevation models (DEM), digital surface models (DSM), canopy height models (CHM) and orthomosaics. Secondary data products, which are derived from the orthomosaics and include products such as vegetation indices like NDVI, SAVI (soil adjusted vegetation index) and the green difference vegetation index (Lehmann et al., 2017; Samiappan, Turnage, Hathcock, & Moorhead, 2017; Zhou et al., 2018) were mentioned in about 30% of studies. Vegetation indices are advantageous because they minimize atmospheric impedance, canopy geometry and shading and the effects of soil background on canopy reflectance. They also enhance the variability of spectral reflectance of target vegetation over individual spectral bands and can advance both efficiency and accuracy in invasive plant mapping. However, a justification for the choice of vegetation indices and the reasons for their inclusion (i.e. seasonality, phenology, environmental context, etc.) should be specified. Texture layers derived from a grey level co-occurrence matrix (GLCM) were also created to compensate for the lack of spectral resolution (Samiappan, Turnage, Hathcock, & Moorhead, 2017) and facilitate mapping (Li et al., 2019; Wu et al., 2019; Zhu et al., 2019).

3.7 | Analyses and error assessment

3.7.1 | Analytical methods

The analytical objective of many studies we reviewed was technically focused and involved testing or proving the validity of an image classification method or workflow to map or detect invasive species. These studies almost always used machine learning or deep learning methods such as random forest, support vector machine or convolutional neural networks to classify images. Other related foci included testing different vegetation indices or structural layers (i.e. DSM or CHM) to improve classifications (Kedia et al., 2021; Lopatin et al., 2019; Martin et al., 2018; Müllerová et al., 2017; Wijesingha et al., 2020). For example, Kedia et al. found the inclusion of canopy structural information from the DSM and CHM improved overall classification accuracy for multiple invasive species by 13%, while Marzialetti et al. (2021) found the inclusion of the DSM improved mapping accuracy of golden wreath wattle (*Acacia saligna*) by more than 3%. Other studies incorporated aspects such as the timing of data collection (Müllerová et al., 2017) or inclusion of textural layers (Samiappan, Turnage, Hathcock, Casagrande, et al., 2017) to improve their machine learning classification accuracies.

An important part of image classification is accuracy assessment, which is often accomplished via a confusion matrix and associated metrics (e.g. precision, recall) in which the classified data are compared against a ground reference (Congalton & Green, 2019). We noted that most studies reported only their overall accuracy, which can be problematic if used as the only measure of validity when there is an imbalance in class coverage. Some studies did include the full matrix and associated metrics (Sandino et al., 2018), which is helpful to understand where class confusion is occurring.

Less than 20% of studies had an ecologically focused objective, such as estimating above-ground biomass (Tian et al., 2022), determining environmental drivers of growth potential (Zhu et al., 2019) or tracking re-emergence of species after disturbance (Nascente et al., 2022). Similarly, studies using drones to detect early emergence, project future spread and understand the drivers of invasion were rare. These more challenging topics that go beyond mapping the presence or spatial patterns of a plant and contribute to understanding the processes of invasion have received less attention not only in drone studies but also in plant invasion remote sensing research more broadly (Müllerová et al., 2023). Thus, there continues to be a large gap between what is possible to achieve using drones for invasive species research and what is being performed in studies.

4 | DISCUSSION

4.1 | Best practices for drone remote sensing of invasive plants

Based on our review, we identified several areas that, if addressed, could lead to more robust scientific advances in the use of drones to study invasive species. First, we noted a lack of benchmark reporting standards, which has led to irregular reporting of study parameters, hindering replicability. Of the papers we reviewed, most reported a small fraction of the items in Table S1 (see Table S3 for percentages), and almost all neglected to perform basic image processing steps considered fundamental within the remote sensing community (Jensen, 2015). For instance, one-fifth of studies did not mention the drone platform that was used, one-fourth did not report the sensor that was used and only two-fifths discussed how the images were ground referenced. These are basic details that are key for assessing the accuracy of any products or results and, in the case of georeferencing, can mean considerable spatial errors were injected into analyses. They are also critical for replicating methods and findings, which is key for scientific advancement. The lack of attention to radiometric calibration was also noteworthy. Many studies used uncalibrated sensors with unknown band intervals and/or uncorrected imagery to compute spectral indices (e.g. NDVI). If biophysical parameters are to be extracted from the data (e.g. leaf area index, chlorophyll, biomass, etc.), or if measurements from one image are to be compared to information extracted from another image captured at a different location or time, then it is imperative to calibrate sensors or correct data for other radiometric effects that might be impacting the imagery (Jensen, 2015). Similarly, if training data are to be extended through time and/or space for image classification, then radiometric correction is necessary (Song et al., 2001). To help overcome these reporting challenges and bolster the replicability of drone-based studies for advancing invasive species research, we developed a set of best practices (Figure 1) that build from prior recommendations (Abdullah, 2021; James et al., 2019) and address all aspects of the data capture and processing including flight design, platform and sensor selection, reporting of data processing and analysis parameters.

A second challenge is the lack of studies attempting to scale up from small, plot-level studies to larger landscape-level or regional extents (Bergamo et al., 2023) or to replicate methods across species or geographies. Of the studies we reviewed, 49% involved a single data collection event at a location that could be imaged in a single flight. The median study area size was about 12 ha, which is quite small considering that invasive species are problematic at regional to global scales and are considered a global change element themselves (Hobbs & Mooney, 2005). If drone use for invasive plant research is to be transformative, advances cannot remain limited to the spatial and thematic scopes we observed in this review. Battery capacity has been cited previously as a limiting factor for drones in invasive species research because it restricts the maximum area that can be canvassed by a single flight (Dash et al., 2019), and it remains a concern. Fusion of drone imagery with other satellite imagery may be one way to scale up methods and impact. Drones can potentially be used to determine the spectral signature of the species in a section of a Landsat or Sentinel image, and then that information is scaled to the rest of the area. In this way, drones could be used to capture training data for learning algorithms applied to much larger swaths of moderate resolution imagery (Gränzig et al., 2021; Kattenborn et al., 2019; Martínez-Sánchez et al., 2019). An affordable, miniature sensor for drones that captures similar optical wavebands as either Landsat or Sentinel-2 would be extremely beneficial to the remote sensing community in pursuit of this goal.

Lastly, we noted a lack of studies focused on quantifying the impacts of invasive species on the native communities or surrounding environment. The studies we reviewed mainly provided a proof of concept for classification and mapping with a machine or deep learning technique rather than leveraging drones to gain a better understanding of invasion ecology or environmental impacts. Without reproducible and replicable frameworks, these 'one off' studies add little to advancing the state of knowledge and solving the grand environmental challenge of invasive species.

4.2 | Opportunities to advance drone remote sensing of invasive plants

There are numerous opportunities to advance drone capabilities in invasive species studies, and we detail these below with suggestions for how future work might move the field forward.

4.2.1 | Reproducible and replicable frameworks

Many remote sensing studies cannot be independently recreated and validated (Kedron & Frazier, 2022), and we noted reproducibility and replicability (R&R) issues are prevalent in drone-based invasive species research as well. Most studies did not provide sufficient details to enable another researcher to replicate the steps in another time or place, and very few provided the data and code to enable reproduction. Given the small spatial extent of most drone-based remote sensing studies (<0.1 km^2), it is crucial that steps are taken to ensure that methods and findings replicate to new geographical areas or different species to help advance science. The reference guide for best practices and reporting standards that we developed (Figure 1) can help foster a culture of R&R for drone-based invasive species research. Additionally, establishing norms and platforms for sharing drone data and code will help foster R&R (Kedron & Frazier, 2022).

4.2.2 | Time-series observations

The flexibility of drones permits time-series monitoring for phenology and spread as well as recovery/invasion after disturbance events (e.g. floods, fire) or to assess the efficacy of intervention measures (e.g. herbicide treatments, controlled burns, mechanical removal). As phenophases differ between native and invasive plants, collecting multi-date imagery and employing time-series analyses can help exploit these temporal phenological distinctions for detection and mapping (Becker et al., 2013; Evangelista et al., 2009). While several studies have tapped into seasonal imagery for mapping and monitoring plant invasions, there is an opportunity to leverage drones even further to understand invasive plant phenology and identify signatures of invasive plant growth (as well as health and diseases) that will make them more distinguishable from native vegetation (Zhu et al., 2019).

4.2.3 | Better integration with satellite imagery

Scaling up methods to the larger areas needed to tackle invasive species problems will require better integration with satellite data. While fusing multiple streams of remote sensing data to study invasive species has been established (Asner et al., 2008), combining drone images with satellite imagery is not yet fully developed, particularly because this type of fusion remains challenging due to the varying spatial and temporal resolutions (Zhang, 2010). Overcoming these scale challenges could unlock the rich archive of long-term satellite imagery for studying plant invasions but at spatial and temporal resolutions that have not heretofore been possible.

4.2.4 | Augmenting ground surveys

The continued reliance on ground-collected data to train and validate classification models hinders the potential scope of studies and demands high labour and time costs. Leveraging drones across a greater portion of the workflow, including site surveillance, reference data collection and validation could reduce costs and foster up-scaling of methods. Drones outfitted with hyperspectral sensors could also contribute signatures to spectral libraries, furthering plans for a global information system of invasive species put forth more than two decades ago (Ricciardi et al., 2000), and the Global Invasive Species Information Network (GISIN) that was launched in 2004 (Simpson & Sastroutomo, 2004).

4.2.5 | Estimating biophysical traits

We noted some work to estimate plant functional traits from drones including plant height (using CHMs), as well as leaf chlorophyll and nitrogen content (Jay et al., 2019). Scientists largely agree there is a set of key plant traits that have a stable and strong predictive response to ecosystem functions (Homolová et al., 2013) that can be leveraged to investigate ecosystem response to plant invasions. Large-scale remote sensing of these traits is still in its infancy, but there is a good opportunity to explore how drones can be used as an intermediary platform to measure traits such as leaf mass per area, leaf water content and wood density, and then scale these traits up to larger scales using satellite-based platforms. Other structural metrics such as leaf morphology, branching patterns and canopy architecture (Dvořák et al., 2015) would also be valuable. Lidar sensors can also be used for these purposes (Almeida et al., 2019), but they are still prohibitively expensive for most drone studies.

Invasive species may present unique plant chemical compositions (e.g. chlorophyll, carbon and nitrogen content in the foliage) and physiological parameters (e.g. leaf photosynthetic rates, biomass accumulation) that contrast against native flora. Such unique chemical signatures in above-ground biomass can be detected via hyperspectral sensors (Ge et al., 2008; Große-Stoltenberg et al., 2018; He et al., 2011). In addition, greater spectral and spatial resolution inherent to drone imagery compared to spaceborne sensors can effectively capture floral characteristics (e.g. flower colour, shape and texture) that help discriminate invasive plants from their native counterparts (de Sá et al., 2018; Müllerová et al., 2017). The flexibility to schedule repeat flights can also help document phenologically relevant traits—such as flowering duration, leaf lifespan, whole plant longevity—which can heighten invasive plant detection (Müllerová et al., 2017; Thenkabail et al., 2018).

4.2.6 | Going beyond plant detection

Most studies we reviewed focused on plant detection, but drones can also be used to assess impacts of plant invasions on soil quality, hydrology, forest canopy structure, native plant health and native biodiversity. Monitoring the symptoms of impact early in an invasion can help guide interventions, and drones are suited to detect subtle changes in leaf pigmentation, water stress or other manifestations of deteriorating health in native vegetation that may signal demise and may not be detectable from conventional remote sensing platforms (Pontius et al., 2020). Drones can also assist in identifying determinants of plant invasions including canopy openness, water stress, landscape complexities and taxonomic and functional properties of resident communities. These factors were rarely studied in the papers we reviewed and are an underexplored use of drones. Beyond imagery and data capture, drones can also be used for interventions such as high-precision pesticide applications (Vergouw et al., 2016) or to re-seed areas with native varieties following disturbances such as fire or floods.

4.2.7 | Forecasting distributions under climate change

Climate change complicates conservation efforts by shifting habitat boundaries and altering community composition. Not only must scientists understand the current bounds and potential ranges of invasive species but they must also forecast how those bounds will change in the future to predict and prevent future invasions. Since drones can provide fine-scale environmental data to correlate with habitat conditions and biotic interactions, species–habitat relationships can be linked with climate data to forecast future distributions. One hurdle to overcome will be the resolution mismatch between the fine-scale data obtainable through drones and the coarser resolutions (>1 km) that presently characterize climate data sets.

5 | CONCLUSIONS

In conclusion, this review underscores the critical need for standardized reporting practices within drone-based studies to address key challenges in invasive plant research. The absence of benchmark reporting standards and the limited spatial and thematic scopes of many studies impede both the reproducibility and generalizability of research findings. To address these challenges, we propose a set of best practices aimed at enhancing the robustness and reproducibility of drone approaches in invasive plants research. These practices encompass all aspects of data capture and processing, including flight design, platform and sensor selection and reporting parameters.

This review highlights several opportunities to advance drone capabilities in studying plant invasions. These opportunities include the development of reproducible and replicable frameworks, leveraging time-series phenological observations and monitoring distribution changes of invasive plants, better integration with satellite imagery and augmenting ground surveys through drone technology. Additionally, there is potential for estimating biophysical traits and detecting unique plant chemical compositions using hyperspectral sensors mounted on drones.

Moving forward, researchers should focus on advancing drone technologies and methodologies to address the complex challenges posed by invasive plant species. By adopting standardized reporting practices, embracing innovative research approaches and leveraging the capabilities of drone technology, we can gain deeper insights into invasive species ecology and develop effective strategies for their management and control. Ultimately, these efforts are expected to contribute to the preservation of native ecosystems and the protection of biodiversity in the face of environmental change.

AUTHOR CONTRIBUTIONS

Dr. Kunwar K. Singh conceived the ideas and together with Drs. Thilina D. Surasinghe and Amy E. Frazier designed the methodology. The three authors reviewed an equal number of articles, collected the data and Dr. Kunwar K. Singh analysed the data and developed graphics. All three authors led the writing of the manuscript, and later edited, and revised the manuscript together. All authors contributed critically to the drafts and gave final approval for publication.

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CONFLICT OF INTEREST STATEMENT

The authors declare that there is no conflict of interest.

PEER REVIEW

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DATA AVAILABILITY STATEMENT

We openly shared all data extracted from the reviewed articles on Zenodo at the following link: https://doi.org/10.5281/zenodo.10971597 (Singh et al., 2024).

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

Table S1. Reporting parameters and definitions across eight key categories: study area, plant attributes, field survey design, drone system, flight survey design, image processing and analyses.

Table S2. List of invasive plants (alphabetically) by country that were studied using drone-captured images.

Table S3. Catalogued parameters under eight categories discussed and the percent of studies that described each parameter in the reviewed studies.

Figure S1. The ROSES flowchart depicts the systematic review of drone remote sensing studies on invasive plants, outlining the entire process from searching and screening to coding, data extraction, critical appraisal and synthesis.

Figure S2. Distribution of reported forward and side overlaps for drone-captured imagery. Red lines show recommended overlaps of 75% (forward) and 40% (side), and black dots represent outliers.

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