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# Taking a closer look at invasive alien plant research. A review of the current state, opportunities, and future directions for UAVs.

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**Keywords**

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**Abstract**

1. The development and proliferation of unmanned aerial vehicles (UAV) in recent years presents a new data collection opportunity for invasive alien plant (IAP) research. The flexibility and cost-efficiency of these craft offers a valuable solution where high-spatial or high-temporal resolution remotely sensed data is required.

2. In this paper we review all published studies using UAV for remote data collection in IAP research.
3. We have systematically identified the taxonomy and habitat characteristics of the system studied, classified the UAV configuration, analytical methods, and the limitations of each study.
4. We used this synthesis to identify research gaps, suggest directions for future research, and identify opportunities for practical application of the technology.

## 1.Introduction

Translocated plants present due to intentional or accidental introduction as a result of human activity are referred to as alien plants (Richardson et al 2000). The globalisation of trade and the ubiquity of human travel and migration has resulted in the large-scale distribution of alien plants across the Earth (Kueffer, 2017; Meyerson and Mooney, 2007). A subset of alien plants reproduce freely in their new environment, outcompete, and replace existing vegetation (Richardson et al 2000). These species are of concern as they can invade indigenous vegetation impacting biodiversity and ecosystem services (Simberloff et al., 2013; Vaz et al., 2018b) and are recognised as a major component of human-induced environmental change (Hulme, 2003). Invasive alien plants (IAP) often benefit from a different evolutionary history than the recipient biotic community (Kueffer, 2017; Saul and Jeschke, 2015) and many IAP exhibit traits that are not present in native communities (Richardson et al 1990) affording them a competitive advantage. Without effective management, IAPs will continue to threaten biodiversity and ecosystem function and must be controlled (Hulme, 2003). Effective management must be supported by appropriate methods for detection and monitoring (Richardson and Rejmánek, 2011). Traditional methods including observer-based surveys are expensive, can be error prone, and are difficult challenging terrain (Dash et al., 2017a). As a result, new modes of detection and monitoring are required.

Remote sensing has matured to provide practical management tools in many domains. Previous reviews of IAP research using remote sensing have reviewed the properties of the datasets (Huang and Asner, 2009), the analytical methods used (Bradley, 2014), and discussed the future applications of remote sensing of plant invasions (Niphadkar and Nagendra, 2016). Others have summarised research relating to a single species (Thamaga and Dube, 2018) or aspects of a management approach (Juanes, 2018). The evolution of remote sensing based IAP research has also been reviewed and used to suggest directions for future studies, technological developments, and planned remote sensing missions (Vaz et al., 2018a). Techniques that provide data at an appropriate scale will enable the development of myriad applications suitable

for IAP research. Uses range from the earliest detection of plant invasions to monitoring historical trends in spread at a global or continental scale.

Unmanned aerial vehicles (UAV) are recently emergent remote sensing platforms. These robotic craft offer automated movement and navigation and can carry a range of sensors to acquire data with finer spatial and temporal resolution than ever before. Furthermore, UAVs are now available with limited financial investment (Manfreda et al., 2018) and the technological barrier to entry is lower than traditional platforms (Dash et al., 2016; Heaphy et al., 2017). Their versatility, adaptability, and flexibility compared to more established alternatives means that they will continue to provide a vital data source for IAP research. UAVs also provide safe access to dangerous, or difficult to reach locations where data collection is required (Manfreda et al., 2018; Rivas-Torres et al., 2018; Watts et al., 2012). Moreover, the capacity for data collection under cloudy conditions, that can preclude data capture from orbital satellites and many manned aircraft, is a significant advantage. This is particularly important in tropical and maritime areas where successful collection of cloud-free satellite imagery may be as low as 20% of the total overpass rate (van der Wal et al., 2013).

There are many benefits of using UAVs for data acquisition, but several limitations remain that require research effort to overcome. These include constraints in areal coverage as the range that can currently be covered efficiently by UAVs is relatively small. Therefore, UAV data are frequently augmented with data from other platforms to provide insight over larger areas. The immaturity of the UAV domain is also an impediment with legislation, data processing pipelines, and sensor sophistication all lagging the pace of development and demand for UAV data.

The favourable properties of UAV-borne remote sensing systems mean that they have been successfully, and repeatedly, used for data collection (Manfreda et al., 2018; Pajares, 2015) for a wide range of applications (Baena et al., 2018; Dandois and Ellis, 2013; Dash et al., 2017b; Goodbody et al., 2016; Kachamba et al., 2016; Morley et al., 2017; Puliti et al., 2015; Wallace et al., 2012). Several reviews have summarised aspects of UAV research in a range of contexts including environmental monitoring (Manfreda et al., 2018), forestry (Torresan et al., 2016), ecology (Anderson and Gaston, 2013), and other domains (De Roos et al., 2018; Singh and Frazier, 2018). However, no review has yet addressed the application of UAV data to support IAP research even though these data are well suited to this application. We sought to develop a clear understanding of the current state of knowledge and to identify research needs to guide further development of UAVs as a tool for IAP research and management.

In this paper, we reviewed the research on UAV deployment for collection of remotely sensed data for IAP research. We illuminate current trends and identify additional research that would aid progress. Specifically, we provide information on the characteristics of the study system, analytical methods, technical configuration, and limitations of all studies. This was completed through a comprehensive review of studies on the topic and the authors' knowledge in this area from previous experience.

## 2. Methods

We collated research into IAP remote sensing and on the use of UAVs in the context of IAPs. This was achieved through a series of nested search queries in the Scopus and ISI web of science databases. The results were cross-referenced against Google Scholar to identify any studies missed initially. The search strings used featured a selection of terms compiled by the authors, and with reference to the techniques of Vaz (2018a). This identified studies containing these terms in the keywords, title, or abstract. Following a review of the first ten records returned within each query the search terms were updated to include several new or alternative terms (Table S1). The initial query was designed to return all IAP studies found within the databases. Subsequently, two further queries were designed to 1) restrict the IAP research to only those studies that employed remote sensing of any kind, and 2) to identify which of these studies used UAVs for data collection. Only English language peer-reviewed articles were included. The search timeframe was from the beginning of database records to the search date in 20 April 2019. A small number of articles were eliminated from the dataset as they were not relevant to the aims of this review.

The full text of each UAV-based IAP study was reviewed to enable categorisation following a procedure adapted from Vaz et al. (2018a). Studies were categorised according to (A) the taxonomy of the IAP and characteristics of the habitat under invasion, (B) properties of the UAV data collection in the study, (C) the analytical methodology followed, and (D) the limitations identified (Table 1).

## 3. Literature Review

A total of 309 IAP records were returned when all remote sensing platforms were considered; only 24 of these featured UAV as a data collection platform. The first IAP studies using remote sensing were published in 1999. Thereafter, there was a steady annual increase in studies throughout the early 2000s, which stabilised during the latter part of the decade, before

increasing substantially in 2017 and 2018 (Figure 1). This pattern is consistent with the findings of a previous meta-analysis (Vaz et al., 2018a) and includes two distinct phases. The first, between 2003 and 2007, was due to growing awareness of IAP issues and increased availability of analysis ready remotely sensed data. The second increase between 2016 and 2018 is attributable to the emergence of UAVs as a tool for IAP research and further heightening of awareness of IAP impacts.

The earliest study using a UAV for IAP was published in 2010 (Figure 1). There were no further studies published until 2016 and then a substantial increase between 2016 and 2018. This coincided with the widespread availability of high-quality, reliable commercial UAVs. The comparative abundance of UAV related studies in other domains (Manfreda et al., 2018) indicates the novelty of the application of UAV remote sensing to IAP studies. Clearly, there is significant scope within this domain for further research.

Studies using UAVs for IAP research have originated throughout the world (Figure 2). The largest number of studies (5) originated in the USA with multiple studies from China (3), Czech Republic (3), Chile (2), and South Africa (2). Single studies have originated in other countries including Brazil, Australia, Canada, Belgium, and New Zealand.

### 3.1 Taxonomic and habitat characterisation of UAV-based IAP research

We reviewed the species and growth form of the target IAP in the published UAV studies. Herbaceous plants were most commonly targeted comprising 40% of studies. This was followed by studies targeting shrubs (20%), trees (20%), a combination of trees and shrubs (10%), and two studies (8%) targeting succulent plants. The predominance of studies targeting herbaceous plants mirrored the all-platform remote sensing studies where 49% of studies focussed on herbaceous IAPs (Vaz et al., 2018a). There are also striking differences in the target IAP form between studies using all platforms and those that use UAVs. When all platforms were considered 44% of studies were concerned with trees (Vaz et al., 2018a) whereas for UAV studies the equivalent proportion was 20%. Earlier all-platform studies focussed on trees to facilitate the early development of classification methods using the coarser spatial resolution imagery available (Vaz et al., 2018a). Of the tree-focussed UAV-based IAP studies one addressed the detection of juvenile trees (Dash et al., 2019), while another was concerned with an understory tree frequently hidden by the surrounding canopy (Perroy et al., 2017). The very high-resolution data available from UAVs enables focussing on smaller, and often more difficult to

detect species. This is reflected by the larger proportion of shrub and herb studies in the UAV specific literature (20% and 10%) compared to the all-platform literature (3.1% and 1.5%).

The wide range of host environments is a testament to the flexible nature of UAVs and the variety of threatened environments. The pattern of environments studied is somewhat similar to the overall trend in studies using other remote sensing platforms (Huang and Asner 2009). The earliest study using UAVs for IAP took place in an agricultural setting (Bryson et al. 2010) where the spread of IAPs can reduce productivity. Several studies have been undertaken in mixed landscapes where land uses included agricultural areas as well as forest or shrubland (Müllerová et al. 2016, 2017; Dvořák et al. 2015; Alvarez-Taboada, Paredes, and Julián-Pelaz 2017; de Sá et al. 2018). The management of invasions into vulnerable wetland ecosystems remains a focus of UAV studies in a similar manner to other remote sensing platforms. Studies in wetland environments using UAVs have originated from groups in the USA (Zaman, Jensen, and McKee 2011; Lishawa et al. 2017) and Canada (Hill et al. 2017). These focussed on the detection of reed species (*Typha spp.* and *Phragmites spp.*) and the herb *Iris pseudacorus* L.. Due to the relative ease of separability of reed species in some wetland environment the classification accuracy reported was high and UAV-based detection and mapping has been operationalised for monitoring management activities (Lishawa et al. 2017).

IAP studies have also been located in arid, or semi-arid, environments of South Africa (Mafanya et al. 2017, 2018) and the Brazilian savanna. In the Brazilian savannah dominated by grasses and monocotyledons UAVs have been used for detection and mapping of *Acacia mangium* (Lehmann et al. 2015). The spectral and structural properties of the target tree allowed accurate separation from the indigenous shrubs and small trees present. Other habitats that have hosted UAV-based IAP studies include riverbanks and mountainous areas. The IAP *Fallopia japonica* has been mapped along the banks of two river systems in France using multi-date UAV data (Martin et al. 2018). Detection of IAP using UAVs has also been extended to mountainous areas (Wu et al. 2019) where data collection can often be complicated by shading and challenging weather. Given the high density of IAPs in cities (Gaertner et al., 2016) and their increased vulnerability to new invasions (Hulme, 2009), it is notable that there are no UAV-based studies in urban areas. This is due to stricter restrictions on low-flying UAV flights in many urban jurisdictions due to safety and privacy concerns. The study environment has a major influence on the ease of separation of the target from indigenous species. Detection accuracy is highest where the spectral or structural characteristics of the IAP are significantly different from the vegetation of

the host community. In forested areas the presence of the IAP in the overstorey canopy also leads to greater higher detection accuracy.

### 3.2 Characterising UAV data collection in IAP research

UAV systems can be characterised according to the configuration of the wing that provides uplift to the airframe; these are typically separated into fixed-wing and rotary-wing craft. Fixed-wing craft have a simpler structure with efficient aerodynamics that can be configured to provide longer flying times at faster speeds. Because of the required continuous airstream, fixed-wing craft cannot remain stationary and are not suited for detailed inspection work. They also require space for take-off and landing and so can be difficult to deploy in some environments. Rotary-wing craft have more complex mechanical and electronic configurations resulting in better manoeuvrability, fine control, and resilience to turbulent air. They can take-off and land vertically but typically cannot stay airborne for longer periods due to battery limitations.

UAV-based IAP studies are divided between fixed-wing (50%) and rotary-wing (50%) platforms. There is a clear trend showing that older UAV studies used fixed-wing craft and that rotary-wing craft have become more common in recent years. This is likely caused by the ubiquity of reliable and low-cost rotary-wing craft since 2016 from commercial providers such as DJI (DJI Ltd., Shenzen, China).

The choice of craft deployed is usually a compromise between budget, the size of the area of interest, and the sensors required. Both platforms can provide very high-resolution imagery, the mean ground sampling distance (GSD) reported in the reported UAV studies was 4 cm for fixed-wing craft and 6 cm for rotary-wing craft. These means are skewed by a single rotary-wing study that used unusually coarse imagery (GSD = 18 cm) (Wu et al., 2019), excluding this study, the average GSD collected with rotary-wing craft was 4 cm. Only rotary-wing craft have been deployed with a laser scanner (Dash et al., 2019) or hyperspectral cameras (Lopatin et al., 2019), but multispectral and RGB cameras have been used with both craft types. This is due to the greater flexibility, stability, and capacity for lower velocity flight of the rotary-wing craft. The more controlled vertical take-off and landing also offers greater protection for expensive sensors.

Apart from a single study (Dash et al., 2019) all IAP studies that use UAVs have used passive sensors (Table 2). This is probably because of the increased cost, complexity, size, and weight of miniaturised active sensors. Six studies used RGB imagery (Bryson et al., 2010; Hill et al., 2017; Mafanya et al., 2018, 2017; Perroy et al., 2017; Wu et al., 2019) with the remainder using

multispectral imagery with bands frequently including the near-infrared and red edge. Only two studies (Kattenborn et al., 2019; Lopatin et al., 2019) used UAV-borne hyperspectral imagery but this will likely increase as miniaturised hyperspectral cameras become more accessible. A range of consumer-grade RGB cameras have been used (Table 2) and modifying consumer-grade cameras by replacing the inbuilt filter to capture broadband near-infrared data has been popular (Table 2). Narrowband multispectral cameras have been used in a small number of studies (Dash et al., 2019; de Sá et al., 2018; Peña et al., 2013), these sensors have a finer spectral resolution offering differentiation of IAP in more complex environments. Models used to date include the Sentera Double 4k (Senterra LLC, Houston TX, USA) and the TetraCam (Tetracam Inc, Chatsworth CA, USA). Other cameras such as the MicaSense RedEdge (MicaSense, Seattle WA, USA) and its successors have been used in UAV research (e.g. Dash et al., 2018, 2017b) including IAP studies (Samiappan et al., 2017b).

The GSD provided by sensors onboard UAV platforms is related to data collection altitude. At higher altitudes, the swath width collected is larger and so a larger area is covered by each image. The area covered by each pixel is larger at higher altitudes and so the minimum size of the object that can be resolved will be larger. The size of the target plant at the life stage of interest must carefully considered when selecting the sensor and altitude used.

The UAV-based IAP research has generally used very high-resolution imagery collected from low altitudes (mean altitude = 105 m a.g.l). This is the finest resolution imagery available for IAP research with conventional aerial imagery (typically 0.1 - 0.5 m) and satellite imagery (typically 0.5 - 250 m) being considerably coarser (Figure 3). This means that detection of small herbaceous plants (Lishawa et al., 2017), understory trees (Perroy et al., 2017), and immature trees (Dash et al., 2019) are possible. The maximum reported altitude used for UAV data collection was 160 m agl (Mafanya et al., 2018). Higher altitudes can be achieved from UAVs and regularly are where photogrammetric methods are used over forest canopies (Goodbody et al., 2019; Puliti et al., 2019). A coarser resolution can be advantageous to the image matching process, but legislative restrictions aimed at protecting commercial air space limit operational altitude used.

The maximum range of most UAVs is limited by battery capacity restricting the area surveyed in a single flight. With repeated surveys large areas can be covered but this can be time and cost prohibitive. Furthermore, changes in atmospheric and lighting conditions can reduce the consistency of the data collected during subsequent flights. Progress in forest resource

assessment has developed sampling methods that link UAV data to other data sources (Puliti et al., 2017). This has now been extended to IAP research where initial methods have been developed for extrapolating UAV derived findings to large areas using satellite imagery (Kattenborn et al., 2019). Further research is required to enable UAV data to progress this as the optimal methods and data source will vary according to the local conditions, satellite data availability, and the properties of the target plant.

The average size of the area assessed using UAV for IAP detection was 246 ha (range = 1.4 ha -- 1450 ha). This varied according to UAV configuration between rotary-wing craft (mean = 200 ha) and fixed-wing craft (mean = 310 ha). In some scenarios, this is a suitable operational scale but in other contexts, this is not large enough and UAV data must be augmented. As UAV technology advances and modern communications systems enable safer working practices, we expect these areas to increase. This will be facilitated by improvements in power source, lighter aircraft with greater payload capacity, and increased range of radio control systems.

### 3.3 Analytical Methodology and Study Characterisation for UAV-based IAP research

#### 3.3.1 Analytical approaches

Image classification can be separated into pixel-based and object-based image analysis (OBIA) depending on whether individual pixels or groups of pixels (objects) within the image are considered the fundamental unit of classification (Dronova, 2015; Li et al., 2014). Since the earliest remote sensing studies, pixel-based image analysis has been the mainstay of automated image classification (Duro et al., 2012), although more recently OBIA has become increasingly popular (Blaschke, 2010). Several studies have compared the two methods (Castillejo-González et al., 2009; Cleve et al., 2008; Duro et al., 2012; Whiteside et al., 2011; Yu et al., 2006) and have frequently found OBIA to be more accurate (Xu et al., 2017); but this is not true in all cases (Duro et al., 2012). A UAV-based IAP study (Mafanya et al., 2017) compared both methods and found that the accuracy of was similar. However, the OBIA method tested was found to accurately map both small and large clumps of the target plant and the authors recommended this approach (Mafanya et al., 2017). The UAV studies concerned with IAP are quite evenly split between pixel-based (45%) and object-based (55%). Studies using both methods report high classification accuracy and there is no clear difference between the two. Manual image interpretation provides an alternative to automated image classification. The amount of imagery that can be interpreted and therefore the area that can be manually processed is limited by the endurance of the human

interpreter. Nevertheless, manual interpretation provides a useful approach for IAP detection in targeted studies, especially where scene complexity is high (Perroy et al., 2017).

Regardless of the type of image classification used, an algorithm for classifying the fundamental analytical unit is required to output maps. These algorithms can be supervised or unsupervised and a wide range of parametric and non-parametric classification algorithms have been developed (Lu and Weng, 2007; Phiri and Morgenroth, 2017). Both algorithm types have been successfully applied in published studies but non-parametric methods such as support vector machines (SVM), random forests (RF), and artificial neural networks (ANN) have become popular. The key advantages of these approaches are freedom from assumptions about the distribution of the underlying dataset and evidence for improved classification performance in more complex landscapes (Lu and Weng, 2007; Phiri and Morgenroth, 2017; Rodriguez-Galiano et al., 2012).

In UAV-based IAP studies classification procedures range from simplistic rule-based thresholding (Lishawa et al., 2017; Peña et al., 2013) to statistical learning approaches (Müllerová et al., 2017b; Samiappan et al., 2017b). The most commonly used classifier RF (Breiman, 2001) was used in 33% of studies. This algorithm has been shown to be highly flexible and capable of producing accurate results in many domains (Dash et al., 2017a, 2015; Mellor et al., 2013). The next most popular algorithm (SVM) was used in 17% of studies. Rule-based spectral classification was a popular approach and a single study has trialled classification based on machine vision (Bryson et al., 2010). Maximum Entropy One-Class Classification has also been trialled (Kattenborn et al., 2019; Lopatin et al., 2019). This approach has the advantage of only requiring the analyst to identify a single class “positive” sample to train the algorithm, saving considerable field or manual interpretation time. Future research will benefit from the development of new methods using deep-learning algorithms that will become powerful tools for IAP detection using the spectral and textural properties of UAV imagery.

### 3.3.2 Analytical software

We reviewed the processing software used to assist method development for future studies. Two types of software are typically required for processing UAV imagery 1) pre-processing software that provides geo-rectification, ortho-mosaicing and bundle adjustment outputting analysis-ready data, and 2) analysis software for segmentation and image classification.

Pre-processing of UAV imagery has recently advanced through the development of commercial software that produce 3D point clouds, digital surface models (DSM), and enable orthomosaicing of UAV imagery using dense overlapping imagery. This technique allows 3D reconstruction of a scene using 2D images through feature detection, image matching, and bundle block adjustment (Mafanya et al., 2017; Wang et al., 2014). Ground control points (GCP) identified by the user can also be integrated with the geotagged raw UAV imagery to provide a georectified orthomosaic suitable for image classification (Mafanya et al., 2017). Two software packages are widely used in the UAV-based IAP research, with Photoscan (Now renamed Metashape) (Agisoft LLC, St Petersburg, Russia) the most popular followed by Pix4D (Pix4D S.A., Lausanne, Switzerland). The popularity of Photoscan is due to the lower price, ease of scripted batch processing, and superior performance over vegetated areas (Sona et al., 2014). Open source alternative (e.g. https://www.opendronemap.org/) also offer high quality pre-processing of UAV data free of charge.

Following generation of analysis-ready imagery, software is required for subsequent image classification. For automated classification, the most popular software is eCognition (Trimble LLC, Sunnyvale CA, USA). which provides a user interface for the OBIA methods initially proposed in the 1970s (Kettig and Landgrebe, 1976). Although numerous other commercial OBIA software exists, these have not been used in UAV-based IAP research. Several studies have made use of open source programming languages such as R (R Core Team, 2018) (Dash et al., 2019; Lopatin et al., 2019) and Python (Python Software Foundation, 2018).

**3.3.3 Field sampling**

Field sampling is an important part of remote sensing research as these data are used to train classifiers and validate classification outputs. Various strategies have been proposed for the collection of a field sample which is a significant expense and, if not carefully designed, can introduce bias (Cacho et al., 2006; Kaplan et al., 2014). Some studies have sought to minimise or eliminate ground-based data collection from their study design (Kattenborn et al., 2019; Lopatin et al., 2019; Piiroinen et al., 2018). Whilst more cost-effective without an appropriate field sample the error rates of the methods examined cannot be quantified. This is exacerbated for IAPs that are difficult to detect using remotely sensed imagery alone as even the most careful manual image interpretation can include substantial errors.

The majority (90%) of UAV-based IAP research included ground sampling and a range of sampling strategies were employed. Probability-based field sampling is deemed to be best

practice (Olofsson et al., 2014; Watt et al., 2015) but only a minority (23%) of UAV-based IAP research used these approaches. The most popular probability-based approach used was stratified sampling using pre-existing remotely sensed data (de Sá et al., 2018; Mafanya et al., 2017; Müllerová et al., 2016; Wu et al., 2019). This improves sampling efficiency whilst ensuring an unbiased sample with a known probability of inclusion in the field sample. Most studies used selective sampling targeting specific plants or land use types.

The sampling unit used in UAV-based IAP research was most commonly point (Alvarez-Taboada et al., 2017; Mafanya et al., 2017; Müllerová et al., 2016) or individual plant sampling (Dash et al., 2019; Perroy et al., 2017). Other studies incorporated sampling of plant traits (de Sá et al., 2018; Peña et al., 2013). Supplementary data can provide context on the host growing environment (Dash et al., 2019; Perroy et al., 2017). One innovative study quantified the target plant's growing environment using hemispherical photographs enabling the detectability of an understorey IAP to be linked to the surrounding canopy development (Perroy et al., 2017).

In modern studies, the collection of global navigation satellite system (GNSS) data is common practice. Within the UAV-based IAP research, GNSS data were recorded in 88% of studies where a field sample was collected. Both recreational-grade and specialist survey-grade GNSS equipment were used. Recreational-grade data were commonly used (Dvořák et al., 2015; Hill et al., 2017; Lehmann et al., 2015; Müllerová et al., 2016) and have a reported accuracy of approximately 10 m. These data are faster to collect and require less specialist equipment and software. Several studies used survey-grade equipment with positional correction made through post-processing or through real-time kinematic (RTK) methods (Dash et al., 2019; de Sá et al., 2018; Mafanya et al., 2017; Martin et al., 2018; Perroy et al., 2017; Samiappan et al., 2017b, 2017a). This provides accuracy of less than 1 m minimising positional errors in the field sample.

In addition to positional data, information on plant traits can provide useful information to characterise invasions and the causes of variable detection success. Plant traits that have been collected in UAV-based IAP studies included target plant dimensions (Dash et al., 2019; Lehmann et al., 2015; Perroy et al., 2017), flower counts (de Sá et al., 2018), and identification of the onset of seed production (Dash et al., 2019).

### 3.4 Study and Operational Limitations Identified

Study limitations identified in UAV-based IAP research identified were collated and classified (Table 1). This provided suggestions for future research direction and a comparison with

limitations identified in the all-platform IAP research. The most commonly cited limitations in the UAV-based IAP literature were operational and technical constraints with almost all studies (95%) citing these. The most frequently reported was limited flight time and resulting difficulties in acquiring data over larger areas. This limitation is caused by constraints on the operational range due to battery performance, payload weight, and craft configuration (Alvarez-Taboada et al., 2017; Dash et al., 2019; Mafanya et al., 2018; Martin et al., 2018).

The area range of UAV data collection is also limited by legal restrictions that prevent operation beyond the visual line of sight (BVLOS) of the pilot or restrictions on flight altitudes. In forests, this is problematic as trees disrupt the line of sight to the craft (Perroy et al., 2017). This is exacerbated by altitude restrictions designed to exclude UAVs from commercial airspace. Furthermore, legal restrictions around where UAVs can operate prevent their use in some of the most sensitive areas for IAP research. Urban areas are often under the greatest pressure from IAPs and are the focus of considerable monitoring and management activity (Pyšek, 1998; Pyšek and Hulme, 2005). Unfortunately, UAV use in this environment is strictly regulated if allowed at all (Müllerová et al., 2017a). The impact of adverse weather conditions on UAV operation and data collection is also an operational constraint (Martin et al., 2018) as they cannot operate in heavy winds and data collection during precipitation is not feasible.

Due to the operational limitation of data collection altitude and the miniaturisation of the onboard sensors, the swath covered by a single UAV image is relatively small. Therefore, many images are required to cover a study area leading to high computation requirements and extended processing times (Mafanya et al., 2017; Müllerová et al., 2016). Other common technical limitations raised include GNSS accuracy of both field survey and UAV positioning (de Sá et al., 2018; Hill et al., 2017; Lehmann et al., 2015; Mafanya et al., 2017), the inability of passive UAV sensors to penetrate non-target canopy to identify IAPs in the understory (de Sá et al., 2018; Mafanya et al., 2017; Müllerová et al., 2017b; Perroy et al., 2017; Wu et al., 2019), and the lack of established software for analysis of UAV data without expert user input (Lehmann et al., 2015; Martin et al., 2018; Perroy et al., 2017).

The high cost of emerging technologies often limits research uptake and must be considered when recommending practical solutions. Costs can accrue through the initial financial outlay for purchasing hardware, purchasing software, data storage and computing hardware, and through labour-intensive activities such as field measurement. Fortunately, the purchase cost of UAVs has decreased in recent years inversely to their sophistication. Most early studies used custom-

built craft, and these are prohibitively expensive for most practical applications (Lehmann et al., 2015). More recently most studies have transitioned to using standard commercial UAVs for data collection bridging the gap towards practical solutions.

The price of the miniaturised UAV sensors has been noted as a constraint. Laser scanning systems offer accurate vegetation characterisation and a method for detecting IAPs in the understory. However, purchasing and operating these systems is expensive limiting current uptake (Martin et al., 2018; Perroy et al., 2017). In a similar manner, the finer spectral resolution of hyperspectral cameras is favourable for differentiating IAPs (Martin et al., 2018; Müllerová et al., 2017a) but they remain prohibitively expensive. Cost limitations mean that many studies have used modified consumer-grade cameras rather than specialised narrowband multispectral sensors. This has led to issues with spectral differentiation (Lishawa et al., 2017), blurring and distortion (Lehmann et al., 2015; Müllerová et al., 2017a), and issues caused by changing illumination during data collection (Dvořák et al., 2015). However, it should be noted that converting to purpose built multispectral cameras does not guarantee that image quality issues will be resolved.

Using UAVs in IAP research can lead to reduced field measurement. This is beneficial as costs are reduced, technicians are less exposed to danger, and damage or disturbance to indigenous ecosystems is minimised. However, at least during method validation, ground-based field datasets remain important. The limitation caused by a lack of an adequate field sample or training dataset has been noted (Michez et al., 2016), but others have sought to develop methods to eliminate the need for a ground-based field dataset (Lopatin et al., 2019). Depending on the specifics of study design and the purposes of the study, research without a robust field dataset may be deemed to be less reliable.

No UAV-based IAP study identified spatial resolution as a limitation. This contrasts with the all-platform research where studies published since 2000 consistently identified spatial resolution as a limitation (Vaz et al., 2018a). This suggests that this technology has solved the issue of spatial resolution in IAP research. However, very high-resolution imagery is not always advantageous for image classification as it can mask the distinctive spatial properties of the object of interest when using OBIA (Müllerová et al., 2016). This can happen when the plant traits that are useful for detection, such as branching patterns or leaf architecture are saturated by noise resulting from the very high-resolution imagery. Approaches using deep learning methods may resolve these issues and are an active area of research in UAV-based IAP research. The temporal resolution of

the imagery available is less of a limitation in UAV-based IAP research than in the general remote sensing research. UAV deployment flexibility and their capacity for data collection under overcast conditions means that the return frequency can be higher. However, additional data collection incurs significant financial costs, and this may be prohibitively expensive. Spectral resolution remains a significant limitation for UAV-based studies. This is most common in studies using modified consumer-grade cameras (Dvořák et al., 2015; Lehmann et al., 2015; Lishawa et al., 2017; Müllerová et al., 2017a) although has also been noted for multispectral imagery (Peña et al., 2013).

## 4. Discussions

### 4.1 Overall trends emerging

The application of UAVs for IAP research is expanding rapidly throughout the world. These studies have adapted methods from other remote sensing platforms to the new opportunities provided by the proliferation of UAVs. Although the traditional limitations of spatial and temporal resolution have been solved, others remain, and ongoing research must seek solutions to these. Several of the limitations identified require advances in hardware to resolve. For example, if legal restrictions are loosened, the areal coverage of UAV data will be solved through improving battery performance and craft design. The data processing pipelines to produce analysis-ready data and to automatically detect IAP in UAV imagery is currently a bottleneck to further research. We have scanned emerging technologies to highlight solutions that might overcome the identified limitations.

### 4.2 Emerging technologies that can reduce the impact of the identified limitations

The most frequently cited limitation to UAV-based IAP research was the data collection longevity. Innovation in the UAV sector is rapid and several new-to-market, or near-market innovations may overcome current limitations. These include craft with better aerodynamic efficiency, including vertical take-off and landing (VTOL) that combine the flexibility of rotary-wing and the efficiency of fixed-wing craft. These are now commercially available (e.g. https://www.altiuas.com) and reportedly offer up to 20 hours flight time, a substantial improvement on widely used rotary-wing systems that offer around 20-30 minutes. The power sources used must advance as the batteries currently used are at their performance limit and so flight times have not kept pace with other system aspects. The commercialisation of alternative power sources such as hydrogen fuel cells could considerably improve performance (McConnell, 2007). Several studies have configured hydrogen fuel cell UAVs (Okumus et al., 2017; Ward and Jenal, 2010) and reported a flight endurance of more than 24 hours when carrying up to 3 kg (Swider-Lyons et al., 2011). Hybrid

power systems using a combination of petroleum-based fuel and batteries offer an alternative and are now available (e.g. https://skyfront.com/). In-flight battery charging by wireless power transmission is also being developed (e.g. Simic et al., 2015). Improved power provision will facilitate the emergence of longer-range UAV and overcome the major limitation identified in the UAV-based IAP research.

Legislation governing UAV operation remains a significant challenge in many regions. Legal frameworks governing UAV use have been developed since the early 2000s and vary considerably in operational restrictions (Stöcker et al., 2017). The major legislative changes needed to address the limitations identified are the permission of BVLOS operation and relaxation of the maximum operating altitude. Technological advances including automated collision avoidance systems will contribute to increasingly safe operation and should promote relaxation of the legal restrictions. There is a push towards unmanned traffic management systems (UTMS) (Jiang et al., 2016) to better control UAV traffic and the advent of mandatory automatic dependence surveillance-broadcast (ADS-B) transmitters onboard UAVs should encourage relaxation of restriction on BVLOS operation.

Computing power has increased exponentially over the last decade and both storage and computational capacity are becoming cheaper. Therefore, the costs of compute intensive pre-processing and analytical aspects of UAV-based IAP research are decreasing. Meanwhile, the need for conventional computing is likely to be reduced by the further development of machine vision methods that enable close to real-time detection without the requirement for pre-processing (Bryson et al., 2010). This may enable automatic adjustment of search patterns for a more targeted search, improving the probability of detection of rare or partially obstructed IAP. Removing the need for input from an analyst and complex pre-processing means that one of the key technical limitations identified will be eliminated.

Several studies identified GNSS accuracy as a limitation. The negative effects of this limitation can be reduced through using survey-grade GNSS systems with sufficient occupancy to provide a high accuracy positional fix. Recent developments, including the launch of the European Union's Galileo Navigation System, will improve GNSS accuracy and complement alternative systems such as the Global Positioning System (GPS) and the Global Navigation Satellite System (GLONASS). However, poor GNSS accuracy from field data collection under dense vegetation remain problematic.

The cost of sensor and UAV hardware will reduce as the market for these technologies matures. Researchers can speed development by identifying the best and most cost-effective solutions that are relevant for IAP research. Despite their proven utility, the cost of both hyperspectral sensors and laser scanners have been highlighted as prohibitively expensive. The advent of lower cost "snapshot" UAV hyperspectral systems and their application to natural resource monitoring will go some way to addressing the cost limitation (Aasen et al., 2015; Saarinen et al., 2018; Yue et al., 2018; Zhong et al., 2018). These systems are also easier to use than traditional push-broom sensors, particularly when mounted on UAVs where positional data may be less accurate (Adão et al., 2017).

Laser scanning systems provide the most accurate depiction of vegetation structure and terrain characteristics available and can be valuable for IAP research. Systems that provide high-quality solutions for UAVs are becoming more ubiquitous and show promise. Unfortunately, the price of survey-grade units remains expensive, but following developments in other domains it is likely that costs will decrease as they become more widespread. The emergence of laser scanning systems that can also collect spectral data (Wang et al., 2018) offers an exciting tool for IAP research through the provision of highly detailed structural and spectral data from a UAV potentially enabling IAP detection in highly complex environments.

## 4. Conclusions

We have reviewed the current state of the studies using UAV for IAP research. Our review of this rapidly developing field has identified a wide range of studies in varied biological systems throughout the world. We have summarised the limitations identified in the current research and identified emerging solutions that can help to mitigate the impact of these limitations. In this manner, we have identified niches for additional research that can further develop UAVs as a tool to support IAP research and management.

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## 6. Data availability

The search terms used to extract all records summarised in this review are included as supplementary materials. This data has also been published online and can be accessed at the following DOI 10.6084/m9.figshare.9758720.

## 7. Author contributions

JPD conceived of this review, carried out all analysis, and wrote the original draft of the manuscript. All other authors reviewed, edited, and made contributions to the text of the final version.

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***Table 1. Categories used for the description of the UAV-based invasive plant studies.***

| ***Category*** | ***Description*** |
|---|---|
| ***A. Taxonomic and Habitat Characterisation*** | |
| Species | The name of the species studied as listed in The Plant List (at http://www.theplantlist.org/) |
| Growth form | The growth form of the species: herbaceous, shrubs, trees, succulents or ferns |
| Habitat | Targeted habitats classified based on the habitat classification scheme from IUCN (at: http://www.iucnredlist.org/) |
| ***B. Characterising UAV Data Collection*** | |
| UAV type | The type of UAV used (Fixed-wing or rotary-wing) |
| Sensor type | The type (active / passive), model and properties of the sensor used |
| GSD | The ground sample distance (GSD) of the imagery collected |
| Altitude | The reported data collection altitude used in the study. |
| Area coverage | The area covered by the UAV data. |
| ***C. Analytical Methodology and Study Characterisation*** | |
| Image analysis type | The type of image analysis for detection (pixel-based / object-based / phenological / hybrid) |
| Classification autonomy | Level of image classification autonomy used (supervised / unsupervised) |
| Processing software | Processing software used |
| Ground sampling | Characteristics of the ground sample collected (if any) |

***D. Study and Operational Limitations***

| | |
|---|---|
| Operational constraints | Operational constraints due to available technologies or other factors limiting the capacity to collect relevant data. |
| Technical constraints | Technical and methodological approaches are the major limitations (e.g. sensor capability, data storage, computational power, processing time) |
| Cost | Costs of data acquisition, equipment, or processing are too expensive |
| Field validation | Results can only be seen as accurate if proper field calibration or validation is done |
| Spectral resolution | The spectral resolution of the available data is insufficient to get accurate results |
| Spatial resolution | The spatial resolution of the available data is insufficient to get accurate results |
| Temporal resolution | The temporal resolution of the available data is insufficient to get accurate results |

**Table 2. Properties of the cameras used in UAV-based IAP research**

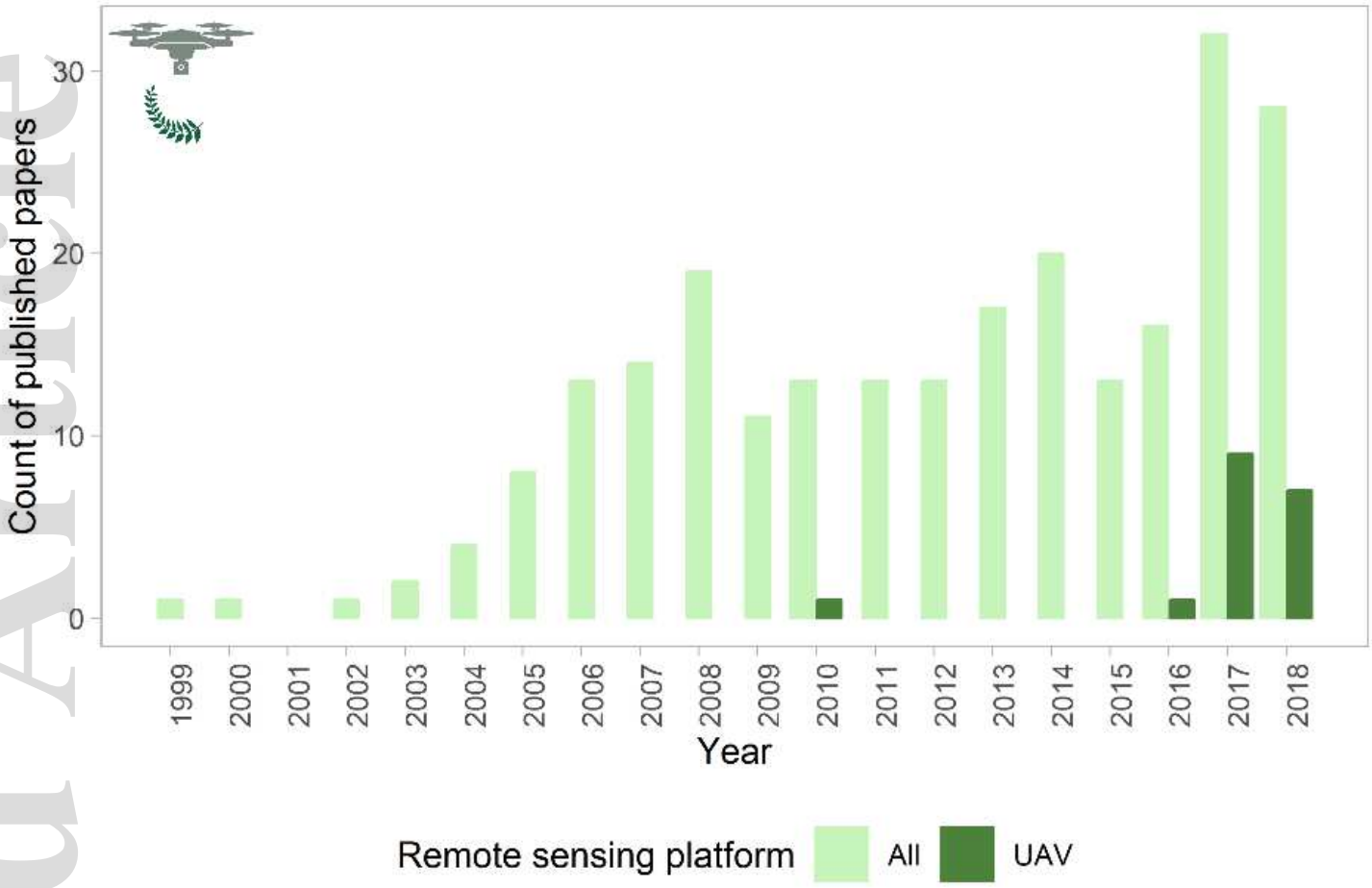
| Sensor type | Manufacturer | Model | Spectral resolution | Spectral Range | Spatial resolution | Weight | Source |
|---|---|---|---|---|---|---|---|
| Hyperspectral | Gamaya | OXI VNIR-40 | 40 bands | 450-950 nm | 2MP | 250 g | (Kattenborn et al., 2019; Lopatin et al., 2019) |
| Multispectral | Sentera | Double-4K | 5 bands | 416 – 760 nm | 12.3 MP | 80 g | (Dash et al., 2019) |
| Multispectral | TetraCam | Mini-MCA-6 | 6 bands | 450 - 900 | 1.3MP | 700 g | (Peña et al., 2013) |
| Multispectral | MicaSense | RedEdge | 5 bands | 470- 860 nm | 1.3 MP | 150 g | (Samiappan et al., 2017b, 2017a) |
| RGB* | Canon | Powershot S100 | 4 bands | 470 – 670 nm | 12.1 MP | 198 g | (Dvořák et al., 2015; Lishawa et al., 2017; Mafanya et al., 2017; Müllerová et al., 2016) |
| RGB* | Ricoh | GR3 | 4 bands | 470 – 670 nm | 24.2 | 257 g | (Michez et al., 2016) |
| RGB | DJI | FC350 | 3 bands | 470 – 670 nm | 12.4 MP | | (Hill et al., 2017; Perroy et al., 2017; Wu et al., 2019) |
| RGB | Canon | G9X | 3 bands | 470 – 670 nm | 20.2 MP | 209 g | (Lishawa et al., 2017) |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| RGB* | Canon | PowerShot SD780 IS | 4 bands | 470 nm | – | 670 | 12.1 MP | 133 g | (Lehmann et al., 2015) |
| RGB | Canon | IXUS 220 HS | 3 bands | 470 nm | – | 670 | 12.1MP | 141 g | (Alvarez-Taboada et al., 2017) |
| RGB* | Canon | PowerShot ELPH 300HS | 3 bands | 470 nm | – | 670 | 12.1 MP | 141 g | (Alvarez-Taboada et al., 2017) |
| RGB+* | Sony | Alpha A5100 | 3 bands | 470 nm | – | 670 | 24 MP | 399 g | (Dvořák et al., 2015) |
| RGB* | Canon | IXUS/ ELPH | 3 bands | 470 nm | – | 670 | 10 MP | 155 g | (de Sá et al., 2018) |
| RGB | Sony | NEX-7 | 3 bands | 470 nm | – | 670 | 24 MP | 353 g | (Mafanya et al., 2018) |
| RGB*$ | Sony | Alpha 7 | 3 bands | 470 nm | – | 670 | 24 MP | 769 g | (Martin et al., 2018) |
| RGB | Canon | 100D | 3 bands | 470 nm | – | 670 | 18 MP | 407 g | (Kattenborn et al., 2019; Lopatin et al., 2019) |
| RGB | Canon | EOS 5D | 3 bands | 470 nm | – | 670 | 12.8 MP | 810 g | (Wan et al., 2014) |

[*] Camera filter modified to record near-infrared. In many instances this is achieved by removal of the built-in IRcut filter and the addition of an alternative (e.g. Hoya R72) filter.

[+] Additional lens (Sony E-20) used

[$] Additional FE 35mm f/2.8 Zeiss lens (281 g)

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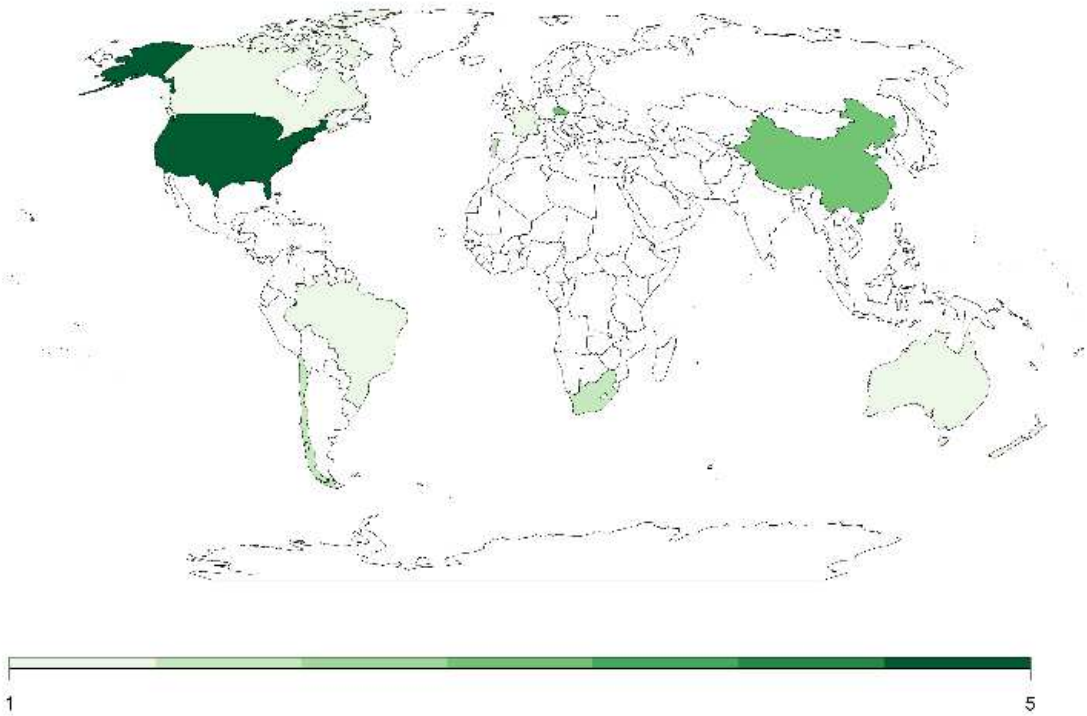


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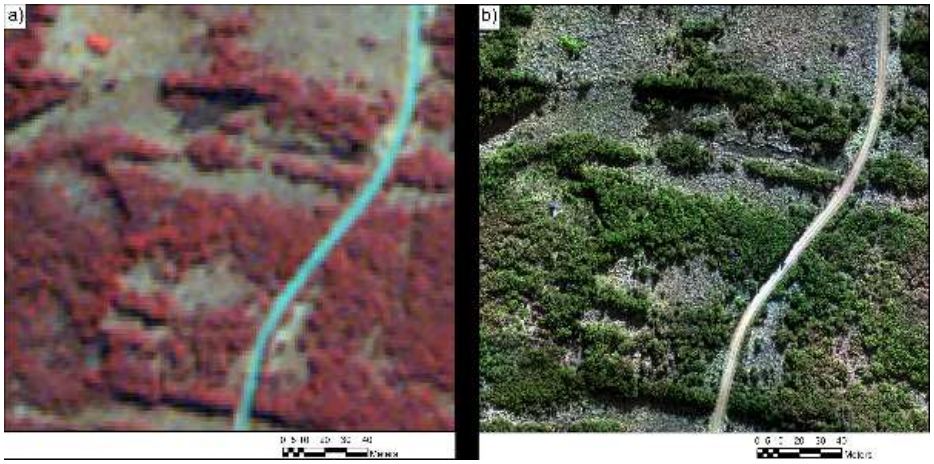


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