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A meta-analysis and review of unmanned aircraft system (UAS) imagery for terrestrial applications

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ABSTRACT
Over the past decade, the remote-sensing community has eagerly adopted unmanned aircraft systems (UAS) as a cost-effective means to capture imagery at spatial and temporal resolutions not typically feasible with manned aircraft and satellites. The rapid adoption has outpaced our understanding of the relationships between data collection methods and data quality, causing uncertainties in data and products derived from UAS and necessitating exploration into how researchers are using UAS for terrestrial applications. We synthesize these procedures through a meta-analysis of UAS applications alongside a review of recent, basic science research surrounding theory and method development. We performed a search of the Web of Science (WoS) database on 17 May 2017 using UAS-related keywords to identify all peer-reviewed studies indexed by WoS. We manually filtered the results to retain only terrestrial studies (n = 412) and further categorized results into basic theoretical studies (n = 63), method development (n = 63), and applications (n = 286). After randomly selecting a subset of applications (n = 108), we performed an in-depth content analysis to examine platforms, sensors, data capture parameters (e.g. flight altitude, spatial resolution, imagery overlap, etc.), preprocessing procedures (e.g. radiometric and geometric corrections), and analysis techniques. Our findings show considerable variation in UAS practices, suggesting a need for establishing standardized image collection and processing procedures. We reviewed basic research and methodological developments to assess how data quality and uncertainty issues are being addressed and found those findings are not necessarily being considered in application studies.

1. Introduction
Recent advances in unmanned and autonomous systems technology have provided researchers with a cost-effective means to capture imagery and other geospatial data at spatial and temporal resolutions not feasible with manned or satellite acquisitions.
The remote-sensing community has eagerly adopted these dynamic and flexible unmanned aircraft systems (UAS) and integrated them into applications across a wide variety of diverse disciplines including precision agriculture (Zhang and Kovacs 2012), conservation biology (Linchant et al. 2015), ecology (Anderson and Gaston 2013), forestry (Howell, Singh, and Smart 2018), and archeology (Mesas-Carrascosa et al. 2016). However, the rapid growth in the number of remote-sensing applications using UAS technology has outpaced our understanding of the relationships between data collection methods and data quality (Dandois, Olano, and Ellis 2015), thereby causing uncertainties in UAS data and products. These uncertainties call the accuracy, precision, and standards in products derived from UAS data into question, thereby creating barriers to widespread use. Therefore, it is an opportune time to review how researchers are using UAS data and products for terrestrial remote-sensing applications, particularly with respect to the procedures surrounding image data capture, processing, and analysis. It is also constructive to crosscheck these procedures with recent and concurrent developments in basic theory and methods to ensure the most up-to-date and scientifically advanced procedures for UAS image capture and processing are being adopted into UAS application studies.

The objective of this study is to synthesize the techniques and procedures used in UAS application studies through a meta-analysis of terrestrial remote-sensing applications. We want to understand: (1) which platforms and sensors are commonly used by the remote-sensing community and why specific equipment may be adopted, (2) how researchers are approaching the unique challenges of geometric and radiometric correction of imagery captured from UAS, and (3) how traditional workflows are being adapted to produce useful data products from UAS imagery. Through this meta-analysis, we also identify knowledge gaps and review developments in UAS remote-sensing theory and methods, specifically in the past 5 years, to determine how the science of UAS imagery capture and processing has progressed and whether those developments are being incorporated into application studies. While imagery is not the only type of geospatial data collected via UAS (e.g. Hemingway et al. 2017), it remains the most common type of data captured for remote-sensing applications (Mathews and Frazier 2017), so we focus specifically on digital image capture, processing, and analysis in this study.

It should be noted that we use the term unmanned aircraft system and the acronym UAS throughout the paper to refer to all types of unmanned and autonomous systems. The term unmanned aerial vehicle and the acronym ‘UAV’ along with several others (e.g. uninhabited aerial vehicle, personal aerial mapping system, remotely piloted airborne systems, drone, etc.) are widely used in the remote-sensing literature. However, the term ‘system’ recognizes UAS are systems of complementary technologies designed to achieve a specific purpose of air surveys (Colomina and Molina 2014), not simply vehicles or platforms that can be piloted remotely (Finn and Wright 2012). The system includes a platform or aircraft, the ground control system, and the communication system that provides a data link between the platform and the ground control station (Figure 1). Many institutions across the world, including the U.S. Department of Defense, the U.S. National Science Foundation, and the U.K. Civil Aviation Authority have all adopted the term UAS.
2. Meta-analysis framework

2.1. Article selection protocol

We performed a search of the Web of Science (WoS) database on 17 May 2017 using the following search criteria: <unmanned aircraft> in [Title] OR <unmanned aerial> in [Title] OR <UAS> in [Title] OR <UAV> in [Title] OR <Drone> in [Title] using a date range <from 1900 to 2017> in [Timespan]. We also tested the inclusion of the term <remotely piloted aircraft> OR <RPA>, but it did not alter the results. This search produced 4,235 results in WoS, and we crosschecked this list against other search engines (e.g. Google Scholar) to ensure we were not omitting relevant studies. Next, we filtered the initial result by document type to include only peer-reviewed articles (3,510), conference proceedings papers (170), research letters (65), and book chapters (4), which reduced the number of results to 3,575. We further filtered this list by the category of research to remove papers dealing specifically with the engineering and manufacturing of the platforms themselves and also omitted studies in WoS categories that were unrelated to unmanned aircraft (e.g. genetics/heredity) yet had been captured by our search terms acronyms. For example, the acronym UAS also stands for Upstream Activator Sequence (among other definitions) in the medical literature. Excluding these categories reduced our number of results to 1,696. Lastly, we performed manual filtering of the 1,696 records to remove articles not related to terrestrial remote sensing (e.g. atmospheric sampling, wildlife counts, traffic surveillance, marine studies, etc.). Our final list included 412 English language articles related to UAS remote sensing in terrestrial research (Figure 2).

Next, we assigned each article to one of three categories: theory (basic science), methods, or applications using the title and, in cases where more information was needed, the abstract. Articles coded as ‘theory’ had as their primary focus: the
development of remote sensing and photogrammetric fundamentals for the platform, sensors, or imagery acquired via UAS. Articles coded as ‘methods’ had as their primary focus the development of new algorithms or techniques for remote-sensing applications derived from imagery acquired via UAS. Articles coded as ‘applied’ has as their primary focus the application of already-established UAS methods and techniques to study a particular parameter (e.g. crop health, erosion, biomass, etc.). While coding articles in this manner can be somewhat subjective due to overlapping objectives, this classification provided us an ample categorization to perform both a meta-analysis of existing application studies alongside a review of current theoretical and methodological developments. After coding, we categorized 63 articles as theory, 63 as methods, and 286 as applied. We randomized the 286 applied articles and selected the first 110 records in the list for full-text, meta-analysis. After reviewing the list, we removed two articles that were not sufficiently relevant, creating a final list of 108 application articles (38%) for in-depth content analysis.

Figure 2. Graphic representation of the systematic procedure for selecting terrestrial, unmanned aircraft systems-based studies from the Web of Science database.

Records identified through Web of Science search 
(n = 4,235)

Records after filtering for document type 
(n = 3,575)

Records after filtering for WoS categories 
(n = 1,696)

Records after manual filtering 
(n = 412)

Descriptive statistics for all studies 
(n = 412)

Record characterization: theory, methods, applied 
(n = 63, 63, 286)

Random selection/meta-analysis of applied texts 
(n = 108)

Review of theory/method studies 
(n = 126)
2.2. Content meta-analysis

For the meta-analysis, we documented various parameters from the 108 articles that are fundamental to UAS image applications in terrestrial research (Table 1). After cataloging the parameters for each study in a spreadsheet, we performed exhaustive data cleaning and verified numbers in the selected parameters (e.g. overlaps, altitude etc.) and units (e.g. area in m versus ha, spatial resolution in cm and m, etc.) to ensure data quality and correctness. When necessary, data transformations were performed to account for skewness and foster interpretation of data patterns. Lastly, we performed exploratory analyses using boxplots, scatterplots, and simple correlation to determine if any trends were evident in the use of certain parameters for UAS applications in terrestrial research.

We were primarily interested in determining how digital images are being acquired, including which platforms and sensors are selected and what parameters (e.g. percentage image overlap, flying altitudes, spatial resolutions, etc.) are being applied. We also analyzed whether and how studies performed radiometric calibration/correction prior to image collection or after during post-processing as well as whether and how studies performed geometric correction or georeferencing (e.g. direct or indirect, number of ground control points (GCPs)/unit area on the ground, etc.). Lastly, we reviewed how studies have analyzed UAS data and what types of software are being used for these tasks. Woven throughout the meta-analysis results, we review the recent theory and method developments within terrestrial applications of UAS remote sensing to contextualize the findings and shed light on how we might improve UAS image capture and processing workflows moving forward.

Table 1. Parameters cataloged in the meta-analysis.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Publication name</td>
<td>Sources include refereed journals and conference proceedings</td>
</tr>
<tr>
<td>Disciplinary topic</td>
<td>Example includes forestry, grassland, land use change etc.</td>
</tr>
<tr>
<td>Term/acronym used</td>
<td>Examples include unmanned aerial vehicle (UAV), unmanned aerial/aircraft system (UAS) drone, personal aerial mapping system (PAMS), and uninhabited aerial vehicle (UAV)</td>
</tr>
<tr>
<td>Study area location</td>
<td>Geographical location and coordinates of study area</td>
</tr>
<tr>
<td>Study area size</td>
<td>Size of study area in hectares</td>
</tr>
<tr>
<td>Platform</td>
<td>Manufacturer, make, and model</td>
</tr>
<tr>
<td>Platform type</td>
<td>Examples include fixed wing, rotor, glider, and kitewing</td>
</tr>
<tr>
<td>Sensor</td>
<td>Manufacturer, make, and model. Examples include RGB cameras, visible, infrared, thermal, and hyperspectral sensors</td>
</tr>
<tr>
<td>Software</td>
<td>Software used for imagery collection and processing</td>
</tr>
<tr>
<td>Flight speed</td>
<td>Measured in ms⁻¹</td>
</tr>
<tr>
<td>Flight altitude</td>
<td>Measured in m</td>
</tr>
<tr>
<td>Image spatial resolution</td>
<td>Distance between two consecutive pixel centers measured on the ground</td>
</tr>
<tr>
<td>Number of images</td>
<td>Total number of images collected during flight campaign</td>
</tr>
<tr>
<td>Image overlap</td>
<td>Percentage of forward and side overlap</td>
</tr>
<tr>
<td>Radiometric correction procedures</td>
<td>Including brightness/illumination and distortion corrections as well as sensor calibration</td>
</tr>
<tr>
<td>Geometric correction procedures</td>
<td>Procedures followed for accurate geolocation of images in an x,y,(z) coordinate system</td>
</tr>
<tr>
<td>Ground control point (GCPs)</td>
<td>Number of GCPs collected</td>
</tr>
<tr>
<td>root mean square error</td>
<td>Measured in m for geometrically corrected imagery</td>
</tr>
<tr>
<td>Data processing methods</td>
<td>Methods used to process data for analysis. Examples include classification, index calculations (e.g. NDVI), etc.</td>
</tr>
<tr>
<td>Analytical techniques</td>
<td>Applied statistical analysis</td>
</tr>
</tbody>
</table>
3. Results and findings

3.1. Basic characteristics of UAS studies

The 412 papers identified from the WoS search related to terrestrial UAS remote sensing were published between 2000 and 17 May 2017 in 131 different journals/publications, indicating the wide breadth of research across disciplines utilizing UAS. The MDPI journal Remote Sensing published the largest number of articles (82), while the International Journal of Remote Sensing published 53 articles, the journal Applied Remote Sensing published 17 articles, and Remote Sensing of Environment published six. The trend in publication has increased steadily each year with growth in the number of articles published each year since 2010 (Figure 3(a)). It is reasonable to assume this growth will continue through 2017, with 104 articles already published by the date of the WoS search. Citation information from WoS shows that the average number of times

![Figure 3](image-url)
each article has been cited is 11.2, with a minimum of 0, a maximum of 186 (Zarco-Tejada, González-Dugo, and Berni (2012) published in Remote Sensing of Environment), and a median of two. We assigned general topics to each of the 108 studies (e.g. precision agriculture, geomorphology, forestry, land cover change, coastal ecosystems, etc.). Agriculturally related applications accounted for about 30% of articles followed by geomorphology (~17%) and forestry (13%) (Figure 3(b)).

We mapped study locations from the 108 papers and found that UAS have been applied in terrestrial research across the world with primary clusters of activity in Europe, East Asia, and North America (Figure 4). Given the recent change in regulations governing the use of UAS in the U.S. (Part 107 FAA regulations), we anticipate an increase in the proportion of studies undertaken there in the future. Other notable areas include Antarctica, where UAS have been used to map moss bed vegetation (Turner, Lucieer, and Wallace 2014) and sub-Saharan Africa, where they have been used for archaeological mapping of the Olduvai Gorge (Jorayev et al. 2016). Overall, the studies we selected for meta-analysis covered a broad geographic extent and a wide range of topics.

3.2. Meta-analysis findings

3.2.1. Platforms and sensors
Most studies (65%) used a rotor-style, vertical take-off and landing (VTOL) platform. Only 30% of studies reported using a fixed-wing or glider style platform, and just three that we reviewed used a kitewing. Several studies did not provide any details on the platform utilized. The most commonly used platform was the DJI Phantom, which is a recreational type platform that can be purchased for around $1,000–2,000 and outfitted with sensors for under $5,000. Other popular choices were MikroKoptor rotor platforms, Microdrone GmbH models including the md4-200 and md4-1000 series, and the SenseFly eBee fixed-

![Worldwide distribution of study sites mapped from information provided in the 108 studies analyzed for in-depth content analysis.](image-url)
wing platform. Several studies noted that a custom platform was built specifically for the research project or program.

Since cost is a major consideration for researchers undertaking UAS research, we approximated costs for commercial, off-the-shelf (COTS) platforms through internet-based research and other resources. Three natural price groupings emerged: (1) low-cost platforms (< $2,000 USD) such as the DJI Phantoms, which were used in about 38% of the studies analyzed; (2) mid-cost platforms ($5000–10,000 USD), primarily the MikroKoptor® suite, which were used in about 20% of the studies analyzed; and (3) high-cost platforms (> $20,000, and up to $80,000 USD), often fully autonomous with integrated autopilot and ground control systems, which were used in about 44% of studies analyzed.

A notable finding was the lack of mid-priced options available to researchers. We did not note many platforms in the $10,000–20,000 range aside from the MikroKoptor® suite of products (starting ~$7000 USD). There is a considerable price increase for fully autonomous, fixed-wing platforms with integrated autopilot, ground control, and image processing capabilities. Yet, we found that almost half (44%) of studies were using these sophisticated systems. It should be noted that in some instances, we were not able to identify platform prices based on the information provided in the text, and our price analysis also does not include prices for custom-built platforms for which data could not be derived. However, custom-built options typically cost many thousands or hundreds of thousands of dollars and so would likely fall into the high-cost category.

Studies overwhelmingly utilized off-the-shelf, digital RGB cameras either alone, or in combination with another sensor such as a thermal infrared or multispectral sensor. Canon cameras were a popular choice: 44 of the 108 studies (41%) utilized a Canon camera with the 500 series, IXUS, and the S series being mentioned often. The popularity of Canon cameras may be due to the ability to incorporate custom scripts with the Canon Hackers Development Kit (e.g. intervalometer for image capture). Seventeen studies used a Sony camera while fives studies each used an Olympus, Ricoh, and Panasonic cameras. Two studies used a GoPro. Multispectral cameras, such as Tetracam, were used in six studies, thermal cameras were used in two, and a few instances had unspecified ‘infrared’ or hyperspectral sensors. Most studies captured imagery with nadir- or near nadir-facing cameras, only a handful of studies noted they captured oblique imagery. Interestingly, many studies aiming to produce a 3D point cloud using the structure from motion (SfM) stated that images were captured at nadir. While nadir overlap is the basis for traditional photogrammetric processing, studies have found SfM may perform better if off-nadir images are incorporated (Smith and Vericat 2015).

### 3.2.2. Altitude and spatial resolution

Decisions regarding flying altitude (along with camera focal length settings) impact image spatial resolution. Since these decisions are often motivated by study aims, they are an important parameter to include when reporting findings. Correspondingly, more than three-fourths of the studies analyzed reported both altitude and spatial resolution, including several studies (~21%) that captured UAS imagery at multiple altitudes and spatial resolution. The remaining studies either did not report altitude (~13%), spatial resolution (~14%), or both (~8%). Among the studies that did provide
details on altitude and resolution, there were some interesting trends. More than 80% acquired data at spatial resolutions between < 1 and 50 cm and altitudes between 5 and 250 m (Figure 5). Most studies captured imagery at resolutions less than 20 cm, but there were some extreme outliers. For example, Ambrosia et al. (2003) captured real-time thermal UAS imagery to study fire at an altitude of 945 m with a spatial resolution of 2.5 m (the coarsest resolution we noted). Cunliffe, Brazier, and Anderson (2016) was among a few studies to acquire ultra-fine resolution (< 0.01 m) imagery to quantify biomass and carbon stocks in semi-arid rangelands.

The distance between a sensor and object determines spatial resolution; therefore, the lower the altitude of a flight, the higher the spatial resolution of an image. Flight altitude also depends on the capture time of a sensor, which was rarely mentioned in studies as influencing altitude choice. For example, a fixed-wing platform carrying a Tetracam sensor may require a higher flying altitude compared to a VTOL platform since the Tetracam requires approximately 2.5 sec to capture an image. Fixed-wing platforms are not typically able to fly low and slow enough to achieve sufficient overlap with this type of sensor.

With UAS image capture is still in its nascence, standards for altitude and resolution according to different applications have not yet been solidified. Additionally, compared to manned aircraft and satellite acquisitions in which nominal resolution is fixed, the flexibility afforded by UAS for researchers to choose their own resolutions means decisions surrounding these parameters remain varied. We reviewed several studies that specifically tested multiple altitudes with the aim of investigating optimal image

Figure 5. Relationship between flight altitude and spatial resolution based on 91 articles that reported values. Note: for clarity, we excluded one observation in which imagery was collected at an altitude of 945 m with a spatial resolution of 2.5 m.
resolutions for targeted applications (Torres-Sánchez et al. 2014; Holman et al. 2016; López-Granados et al. 2016). However, in general, most studies did not provide any justification or support for the flying altitude selected. A few studies mentioned factors that controlled flight altitude, such as flight regulations established by the aviation authority of the country where data were being collected (Laliberte, Winters, and Rango 2011), power consumption, climatic conditions (e.g. wind speeds and temperature) (Goebel et al. 2015), the height of the studied object (Perroy, Sullivan, and Stephenson 2017), and/or UAS configurations (Verger et al. 2014). However, the general lack of information provided in studies surrounding altitude may result from limited empirical studies that suggest standards or best practices.

Flying altitude also impacts the spatial resolution of acquired imagery, but we noted that studies rarely discussed consideration of an optimal resolution for the study objective. For example, remote-sensing researchers have long recognized the importance of selecting an appropriate minimum mapping unit (MMU) for land cover studies (Saura 2002). MMU is the area of the smallest entity to be mapped as a discrete object, and selection of MMU determines the detail conveyed through interpretation (Lillesand and Kiefer 1994). Considering MMU in decisions regarding spatial resolution may help researchers balance accuracy with data volume and processing costs to determine the most appropriate resolution for output products. Since many UAS data processing platforms (e.g. Pix4D) include built-in capabilities for determining spatial resolution, it is fairly simple to include a priori considerations of MMU in the workflow.

3.2.3. Forward and side image overlaps

There are important differences between image overlap procedures for UAS data capture and traditional photogrammetric processing, yet most studies (> 55%) did not include this parameter in their reporting. A few (five) reported side overlap but not forward (Figure 6). From the studies that did report on image overlap, the data reveal a noticeable difference between forward and side overlaps from established photogrammetric standards. Most studies exceeded 75% forward overlap. However, we observed high variability in the percentage of side overlap ranging from 20 to 90%. For example, Ajayi et al. (2017) used more than 50% forward and between 15 and 20% side overlap to create an elevation model, while López-Granados et al. (2016) used 30% side overlap to create an orthomosaic. While typical forward and side overlaps in traditional airborne photogrammetry are 25–30% (Stow, Coulter, and Baer 2003), literature on UAS imagery collection recommends above 70% forward overlap and 50–60% side overlap for most cases (Su et al. 2016), although percentages vary according to terrain type. However, these suggested overlaps may not apply in cases where only a single swath of imagery is needed (Zarco-Tejada, González-Dugo, and Berni 2012), or considerable overlap is not needed to produce the desired output data product.

Many of the studies we analyzed adopted the SfM workflow, and typically those algorithms need a large number of overlapping images to identify key points for creating 3D point clouds for surface models. Dandois, Olano, and Ellis (2015) found that optimal overlaps for creating SfM models were 60% forward and 60–80% side overlaps. High percentages of forward and side overlap increase the number of swaths/images needed to canvas the study area thereby increasing the flight duration, which has implications for power supply and on-board data storage. Thus, operators
may choose to reduce overlap to shorten flight times and data volumes. However, in these cases, studies should note any potential impacts to accuracy. Terrain characteristics also affect overlap percentages (e.g. flat terrain such as agriculture fields may require higher overlaps to extract matching points for 3D point cloud). We did not find any studies that explicitly mentioned terrain in their overlap decisions, but many studies we analyzed focused on agriculture, vegetation, and forest plots that typically have relatively flat topography. Lastly, we noted that very few studies reported the file format of collected imagery, limiting our ability to analyze this component statistically. RAW file format is considered superior to other formats (e.g. JPEG) because it does not compress information and can be used to produce higher quality images after image processing, but capturing RAW data is more time intensive compared to other formats such as JPEG, which may be another consideration in reducing image overlaps.

3.2.4. Radiometric calibration and correction
Even though certain atmospheric effects may be reduced when capturing UAS imagery at low altitudes, data are still prone to atmospheric absorption and scattering effects, particularly in the visible and near infrared portions of the electromagnetic spectrum. While only about 25% the studies we analyzed mentioned radiometric corrections, several of the methodological and basic science studies we reviewed noted the importance of calibrating sensors prior to collecting data to correct for any atmospheric contributions to the measured signal (Laliberte et al. 2011; von Bueren et al. 2015; Zarco-Tejada, González-Dugo, and Berni 2012). Surface reflectance calibration methods
included correcting effects using the empirical line method (von Bueren et al. 2015), using on-ground spectral targets (Laliberte, Winters, and Rango 2011), and calibrating light sources in vivo to develop algorithms for radiometric correction (Zarco-Tejada, González-Dugo, and Berni 2012).

Other radiometric quality issues may arise from the sensors themselves or platforms that require calibration or correction. Lens imperfections and uneven illumination due to camera tilt can result in pixels along the edge of an image receiving less light than those near the centre, a phenomenon known as vignetting. These differences in image brightness values can propagate as errors into classifications or vegetation indices if not corrected prior to image analysis. Similarly, certain cameras create ‘fish eye’ effects where pixel sizes are distorted away from centre. Vignette removal techniques have successfully been adopted in several recent UAS studies to mitigate these effects (Lelong et al. 2008; Schirrmann et al. 2016; Verger et al. 2014), while other studies have relied on the lens calibration removal tools built into software packages such as Agisoft Photoscan (De Reu et al. 2016; Turner, Lucieer, and Wallace 2014; Lucieer, De Jong, and Turner 2014). However, recent research has suggested that traditional approaches implemented through commercial software may not effectively deal with the inconsistencies in hue and illumination in UAS imagery, and more sophisticated dodging algorithms are needed (Li et al. 2016). In addition to vignetting effects, there can also be radial, tangential, and/or decentering distortions caused by misalignment of the physical elements in a lens. In a study focused on co-registration of images from multiple sensors, Turner, Lucieer, and Wallace (2014) used the Brown-Conrady model to account for these lens misalignment distortions in a Tetracam mini-MCA sensor, which may be an option for future UAS studies.

Several studies relied on image clipping or removal to overcome distortions whereby highly distorted images are omitted from the post-processing stages or only usable portions of images are included. This process can be time consuming if done manually, but Sieberth, Wackrow, and Chandler (2016) recently developed an automatic filtering process for detecting blurred images resulting from camera movement during UAS image acquisition. Edge distortions can also be resolved by capturing high forward and side overlaps, thus allowing the image portions with the highest distortions to be clipped out or omitted from analysis. However, our analysis found that while most studies are capturing large forward overlaps, some only capture 20–30% side overlap (Figure 6), which may not be sufficient to eliminate certain distortions. Studies also noted removing images to compensate for other radiometric effects such as shadows (Woodget et al. 2015; Cummings et al. 2017) or only capturing images during mid-day (Mathews and Jensen 2013; Husson, Ecke, and Reese 2016; Gómez-Candón et al. 2016). However, even during mid-day flights with high solar elevation angles, bidirectional reflectance effects are pronounced in UAS imagery due to low flying altitudes and large fields of view (Lelong et al. 2008). Most studies do not correct for these effects (Lelong et al. 2008; Verger et al. 2014; Schirrmann et al. 2016), but Hakala, Suomalainen, and Peltoniemi (2010) found that accurate bidirectional reflectance factor measurements can be taken with off-the-shelf cameras commonly used in UAS studies as long as sufficient image calibration is performed including having a reference target visible in all images and measuring reflectance parameters with high accuracy.
Off-the-shelf digital cameras can also introduce uncertainties because manufacturers often do not usually specify the wavebands comprising each image channel (Mathews 2015). Several studies performed their own camera calibration using either a Spectralon® panel or hand-painted calibration targets placed in the field (Laliberte, Winters, and Rango 2011; López-Granados et al. 2016; Peña et al. 2013; Capolupo et al. 2015; Mathews 2015). In sum, it is incumbent upon researchers to determine what level of radiometric processing is sufficient for their aims, but researchers should also recognize that UAS imagery are subject to a range of atmospheric and radiometric effects that may impact accuracy. Studies have recently begun devoting more attention to the issue of radiometric quality assessment for UAS imagery (Kedzierski and Wierzbicki 2015), but this is an area that deserves more attention.

### 3.2.5. Georeferencing and geometric correction

With some exceptions (Turner, Lucieer, and Wallace 2014; Eling, Klingbeil, and Kuhlmann 2015), UAS are not usually equipped with sufficient on-board Global Navigation Satellite System (GNSS) receivers to enable direct control of imagery through camera positions. Therefore, geometric correction is often necessary during image processing, yet only 66 of the 108 (61%) studies we analyzed explicitly mentioned georeferencing and provided details regarding how georeferencing was performed. One area where we noted large discrepancies was in the number of GCPs used for georectification. Based on the information provided by the 66 studies reporting geometric correction, we analyzed the relationship between the number of GCPs captured per unit area, and we did not identify any discernible relationship between the number of GCPs and the size of the study area (Figure 7(a)). This relationship did not improve when accounting for image resolution. While some variability in the number of GCPs needed is expected based on topographic differences, only a few studies provided terrain descriptions (Laliberte et al. 2011) that would permit normalization of our findings.

Thirty-seven of the 66 studies that mentioned georeferencing also included an assessment of image registration accuracy by reporting root mean square error (RMSE). We identified a weak but negative relationship between RMSE and the number of GCPs collected per hectare (Figure 7(b)). As the number of GCPs per hectare increased, the accuracy of the registration also increased, evidenced by decreasing RMSE. However, very few studies indicated whether their decisions regarding GCP placement and numbers were empirically or theoretically based. Mesas-Carrascosa et al. (2017) note a lack of standards with respect to GCP collection and distribution for UAS studies, yet a review of several recent UAS studies focused on GCPs demonstrates there are disparities within the literature. In general, studies have found that accuracy improves as the number of GCPs increases (Agüera-Vega, Carvajal-Ramírez, and Martínez-Carricondo 2017a; Agüera-Vega, Carvajal-Ramírez, and Martínez-Carricondo 2017b; Mesas-Carrascosa et al. 2015; Reshetyuk and Mårtensson 2016), which is corroborated by our findings (Figure 7(b)), but the specific numbers vary. For example, Agüera-Vega, Carvajal-Ramírez, and Martínez-Carricondo (2017b) found that optimal RMSE was obtained using 15 GCPs across a 17.64 ha study area with varying terrain (2.80 × 10⁻⁶ GCPs per pixel) while Mesas-Carrascosa et al. (2015) found that five GCPs was sufficient across a 1.12 ha crop field for varying flying altitudes.
Several studies noted there may be a critical threshold for the GCP number or density beyond which accuracy does not increase (Tonkin and Midgley 2016; Gindraux, Boesch, and Farinotti 2017). Specifically, Gindraux, Boesch, and Farinotti (2017) found that the accuracy of digital surface models (DSM) generated from UAS imagery increases asymptotically with increasing GCPs until a density of around 10–20 GCPs per km$^2$ (about 3–5 × 10$^{-8}$ GCPs per pixel) is reached. Additional GCPs beyond that density did not improve DSM accuracy in their study. In our analysis, we found that GCP densities were typically several orders of magnitude coarser than the value suggested by Gindraux, Boesch, and Farinotti (2017), signaling that studies may be using considerably fewer GCPs than needed to achieve optimal geometric accuracies. Most studies we analyzed used in the range of 1 × 10$^{-5}$–1 × 10$^{-6}$ GCPs per pixel. It should be noted though that there are situations in which precise georegistration may not be necessary (e.g. relative change studies). The placement of GCPs is laborious, and in some cases impossible, so the trade-offs between the time required to place and geo-locate GCPs across a study area extent, and (b) GCP ha$^{-1}$ of study area versus the root mean square error (RMSE) of georectification accuracy. The grey area represents the 95% confidence level interval for predictions from a linear model. Sixty-three studies provided information on ground control points, and 37 provided RMSE values. Variables were log transformed to account for skewness and allow interpretation of data patterns.

Figure 7. Relationship between (a) the number of ground control points (GCPs) and the study area extent, and (b) GCP ha$^{-1}$ of study area versus the root mean square error (RMSE) of georectification accuracy. The grey area represents the 95% confidence level interval for predictions from a linear model. Sixty-three studies provided information on ground control points, and 37 provided RMSE values. Variables were log transformed to account for skewness and allow interpretation of data patterns.
area needs to be weighed against the benefits of accurate georegistration. To overcome these issues, new options for GCPs are increasingly available. For example, portable and reusable GCPs that simultaneously serve as a GNSS receiver have recently come available to mitigate some of the effort associated with GCP placement and measurement. Researchers have also been investigating methods for automated GCP identification (James et al. 2017) and image-to-image registration (Yang and Chen 2015), but we came across few instances where internal orientation parameters from the camera were used for direct image georeferencing (Wallace et al. 2016; Li et al. 2017). However, studies are increasingly searching for direct georeferencing options (Carbonneau and Dietrich 2017), and we anticipate an uptick in these workflows in the future.

GCP distribution may also affect georectification accuracy. Mesas-Carrascosa et al. (2015) tested two distributional variations (a traditional photogrammetric distribution of four GCPs placed at the corners and a second distribution with a fifth GCP in the centre) and reported a better distribution of errors for the 5-GCP configuration. However, traditional photogrammetric-based distributions such as this may not be appropriate for UAS-captured imagery unless suitable camera orientation data from on-board GNSS and inertial navigation system are available (James et al. 2017). Gindraux, Boesch, and Farinotti (2017) found that their DSM accuracy declined as distance from a GCP increased, at a rate of just under 0.1 m/100 m, providing evidence that an even distribution of GCPs across a relatively flat study area may improve results. Shahbazi et al. (2015) also support findings that DSM accuracy is highest when GCPs are distributed evenly across the study area and visible on multiple images (e.g. in overlapping flight paths).

Lastly, we found that many studies interchanged the terms GCPs, tie points, and key points. GCPs are points on the surface of the Earth with known geographic coordinates and elevation values that are used to georeference an image to a coordinate system. In contrast, key points are corresponding points in overlapping images, and identifying these points is a necessary first step in the photogrammetric workflow for aerial triangulation and block adjustment to compute projection centre positions and the orientation of each image. Software systems (e.g. Agisoft Photoscan) usually generate key points automatically during image processing, but objects such as highly reflective targets can be manually placed in the field prior to data collection to aid in this process. Tie points are 3D coordinates generated from a set of key points that can be visually identified in an image, but they have arbitrary scale and orientation. Thus, GCPs provide external control for tie points in the bundle adjustment process by defining a datum and constraining the scale to a real-world projection (James and Robson 2014). It should also be noted that proprietary UAS software often do not provide details on the ‘built-in’ geometric and radiometric processing algorithms, making it difficult for users to report the accuracy of their results. In these cases, acknowledging that processing relied on software capabilities will help contextualize UAS findings.

3.2.6. Data products and applications
Innovation and improvement in UAS data acquisition and processing have shifted attention in the remote-sensing community from the historical landscape scale studies to more localized, pixel- and object-based analyses. With smaller study extents and higher resolution imagery, researchers have also begun devoting more attention to
processing and output products. In particular, we found that a considerable number of studies are using the SfM workflow to create 3D surface models and orthomosaics. SfM is attractive to researchers because it provides a low-cost alternative to lidar (light detection and ranging) with reliable accuracies for certain applications (Fonstad et al. 2013; Dandois and Ellis 2013). For example, Fonstad et al. (2013) found that SfM derived z-values explained 97% of the variance in aerial lidar z-values while capturing topographic structure in higher detail, and Dandois and Ellis, (2013) found that SfM-generated canopy height models correlated strongly ($r = 0.87$) with those produced from aerial lidar. Applications of SfM outputs range from assessing forest structure (Wallace et al. 2016) to mapping aquatic vegetation (Husson, Ecke, and Reese (2016) to reconstructing gully topography (Stöcker, Eltner, and Karrasch (2015) and landslide displacement (Lucieer, De Jong, and Turner 2014). Studies overwhelmingly used the Agisoft Photoscan software platform to create digital surface models and orthomosaics for eventual classification and analysis with Pix4D Mapper and ArcGIS also being implemented in a handful of studies. We noted from our analysis that object-based image analysis (OBIA) has emerged as a popular analysis technique for UAS imagery (Laliberte, Winters, and Rango 2011; Husson, Ecke, and Reese 2016; López-Granados et al. 2016), likely due to the very high spatial resolution of the images produced from UAS.

As stated previously, agricultural studies were, by far, the most common applications (Figure 3) with many studies attempting to estimate biophysical and biochemical crop parameters from UAS imagery. For instance, Schirrmann et al. (2016) used Pearson correlation, principal components analysis, and linear regression to monitor Nitrogen content of wheat crops, and Di Gennaro et al. (2016) monitored the early onset of grapevine leaf stripe disease in a vineyard using multi-temporal, high resolution NDVI images. Based on trends we noted in the literature, we anticipate an increase in applications using multi-sensor image fusion in the future. There are some difficulties to collecting these data since even the small distances between the sensors on board a UAS can lead to geometric misalignments in the images due to the low flying altitudes. However, Turner, Lucieer, and Wallace (2014) successfully integrated data from three sensors simultaneously on board a UAS (RGB, multi-spectral, and thermal infrared cameras) and developed a workflow to produce sufficiently accurate georectified mosaics of the three image types. Moving forward, capitalizing on the benefits of multiple sensors simultaneously will allow researchers to identify subtle differences in vegetation health.

4. Remaining challenges and future directions

While widespread use of UAS technology has clearly fostered the adoption of remote-sensing techniques across a wide range of disciplines (Figure 3(b)), our findings demonstrate there is considerable variation in whether and how established standards and procedures are implemented in studies. The applications we reviewed seldom engaged with basic scientific developments for UAS image processing that have been occurring within the remote-sensing community, and widespread publication and dissemination of findings that do not follow established processing standards will continue to propagate uncertainties connected to UAS data. There is no lack of basic science research related to UAS remote sensing (we identified 126 basic science studies, 28 of which were
published in 2017), but circulating these developments to the diverse, multi-disciplinary set of researchers engaged in UAS applications will be an ongoing challenge.

We noted several areas for future focus during our meta-analysis including the need for guidelines and/or standardized procedures for selecting appropriate image resolutions. While setting absolute limits for resolution may not be practical, identifying the relationship between minimum mapping unit and mapping accuracy among different applications (e.g. crop health, disaster relief, large-scale topographic surveys, etc.) may help researchers make informed decisions that balance accuracy with data storage and computational costs. Second, we recognized a lack of standardized procedures for georeferencing and geometric correction. While the literature on this topic is not in full agreement, many of the more recent studies suggest considerably more GCPs be used than the densities we noted were being adopted. Simply reporting RMSE is one way for studies to address some of the uncertainties in terms of GCPs and geometric errors. Lastly, very few studies acknowledged that UAS imagery may have radiometric distortions or atmospheric effects, which is concerning in terms of data quality and the accuracy of subsequent analyses. Moving forward, discussions surrounding the impact of these uncertainties in data products would be fruitful.

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