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Use of unmanned aircraft systems (UAS) and multispectral imagery for quantifying agricultural areas damaged by wild pigs

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ABSTRACT

Wild pigs (*Sus scrofa*) cause extensive damage to agricultural crops, resulting in lost production and income. A major challenge associated with assessing damage to crops is locating and quantifying damaged areas within agricultural fields. We evaluated a novel method using multispectral high-resolution aerial imagery, collected from sensors mounted on unmanned aircraft systems (UAS), and feature extraction techniques to detect and map areas of corn fields damaged by wild pigs in southern Missouri, USA. Damaged areas were extracted from orthomosaics using visible and near-infrared band combinations, an object-based classification approach, and hierarchical learning cycles. To validate estimates we also collected ground reference data immediately following flights. Overall accuracy of damage estimates to corn fields were similar among band combinations evaluated, ranging from 74% to 98% when using visible and near-infrared information, compared to 72%–94% with visible information alone. By including near-infrared with visible information, though, we found higher average kappa values (0.76) than with visible information (0.60) alone. We demonstrated that UAS are an appropriate platform for collecting high-resolution multispectral imagery of corn fields and that object-oriented classifiers can be effectively used to delineate areas damaged by wild pigs. The proposed approach outlines a new monitoring technique that can efficiently estimate damage to entire corn fields caused by wild pigs and also has potential to be applied to other crop types.

1. Introduction

Wild pig (*Sus scrofa*) populations in the U.S. have swelled to more than six million individuals and they have been documented in at least 41 states (U.S. Department of Agriculture, 2015; Snow et al., 2017). With increasing populations and densities of wild pigs come higher levels of damage to agricultural and natural resources (Barrios-Garcia and Ballairi, 2012; Bevins et al., 2017; Seward et al., 2004). Wild pig damage to agricultural crops and control costs in the U.S. each year is conservatively estimated to be $1.5 billion (Pimentel, 2007). Anderson et al. (2016) reported that U.S. producers of corn, soybeans, wheat, rice, peanuts, and sorghum in 10 southern states lost $190 million in crop production in 2014 due to wild pigs. Income lost to crop consumption, associated trampling, and control costs may be substantial to agricultural producers, especially when profit margins are small (Anderson et al., 2016). More accurate, cost-effective, and repeatable approaches for detecting and estimating damage caused by wild pigs are needed to fully understand these impacts to agricultural producers, support economic assessments, and document effectiveness of control measures.

Wild pigs have a very plastic diet and feed opportunistically on many plants and animals (Seward et al., 2004; Ditchkoff and Mayer, 2009; Barrios-Garcia and Ballairi, 2012). Wild pigs also exhibit seasonal and interannual preferences in diet, with agricultural crops often being preferred when available (Ditchkoff and Mayer, 2009; Morelle and Lejeune, 2015; Lombardini et al., 2017). Damage to crops begins immediately after planting (Engeman et al., 2018), persists through harvest (Schley et al., 2008), and includes consumption, rooting, and

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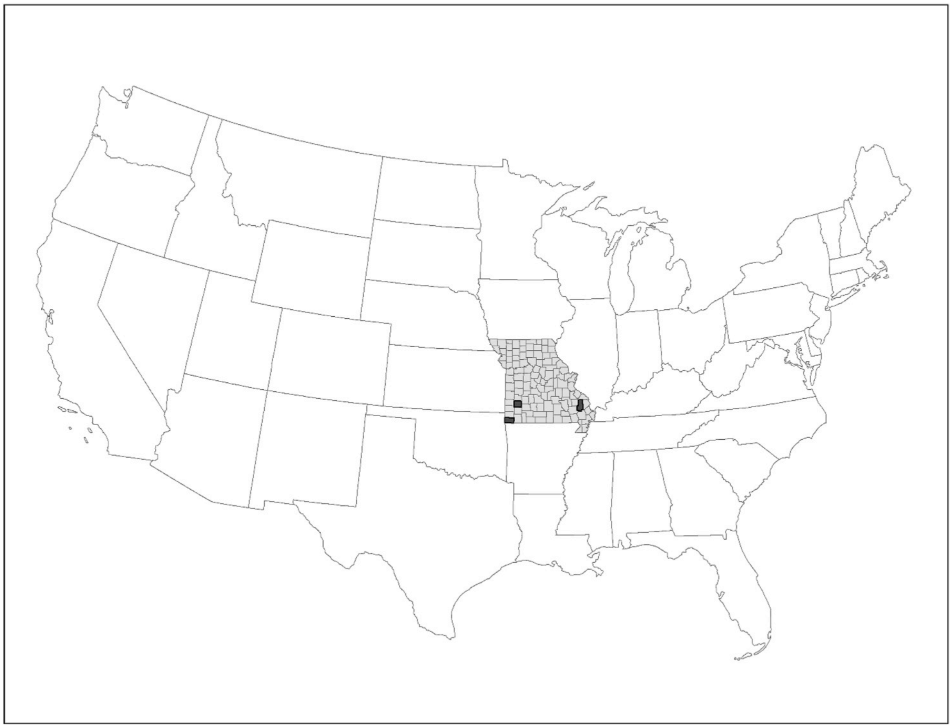

Fig. 1. Bollinger, Dade, and McDonald counties, southern Missouri.

trampling. The distance between crop fields and permanent vegetative cover is also a likely factor determining levels of crop loss (Schley et al., 2008; Morelle and Lejeune, 2015; Bobek et al., 2017).

Unmanned aircraft systems (UAS) outfitted with highly sensitive sensors are a relatively new technology with the ability to collect remotely sensed data at very high spatial (e.g. 5–10 cm) and temporal resolutions (e.g. daily or even hourly revisit times), thus they can assist with precision agriculture (Candiago et al., 2015; Christiansen et al., 2017; Hunt and Daughtry, 2018), rangeland monitoring (Laliberte et al., 2010; Laliberte et al., 2011; Sankey et al., 2018), forest mapping (Wallace et al., 2012; Getzin et al., 2014; Birdal et al., 2017), ecosystem monitoring (Habel et al., 2018), invasive species mapping (Samiappan et al., 2017), and detecting and monitoring pest infestations (Lehmann et al., 2015; Puig et al., 2015). Data collected by UAS have also been used recently to estimate damage to agricultural crops by wild pigs (Michez et al., 2016; Rutten et al., 2018; Samiappan et al., 2018). In particular, Michez et al. (2016) used a crop height model and manual ortho-photo delineation to estimate damage to corn. Kuzelka and Surovy (2018) used a similar crop height approach to delineate wild pig damage to wheat. Samiappan et al. (2018) used visible information and textural analysis classifiers to delineate damaged areas in corn fields.

Remotely sensed image classification historically relied on per-pixel based processing to classify and extract objects of interest, frequently using unsupervised and supervised algorithms and spectral information alone (Jensen, 1996; Lu and Weng, 2007). However, today's high-resolution satellite and UAS imagery has posed problems for these conventional classification techniques (Myint et al. 2006, 2011). New object-based classifiers use spectral, spatial, and iterative learning techniques to classify features (Quackenbush, 2004; Opitz and Blundell, 2008; Gustafson et al., 2018). Object-based classifiers quantify features based on specific properties, such as color, texture, shape, area, and scale (Opitz and Blundell, 2008; Miller et al., 2009; Momm and Easson, 2011). By using these properties the classifier is iteratively trained to classify and extract targeted outputs from remotely sensed data with highly accurate results (Miller et al., 2009; Myint et al., 2011).

We evaluated the ability of UAS, multispectral information, and feature extraction software for detecting and mapping wild pig damage to production corn fields. We proposed that the addition of near infrared information collected by UAS sensors could increase classification accuracy by adding additional information to further discriminate between soil, and damaged versus undamaged vegetation. Specifically, our objectives were to: 1) use object-based classification methods to precisely detect and extract areas damaged by wild pigs, and 2) compare accuracy of damage estimates using only visible information to those using visible and near-infrared information.

2. Methods

2.1. *Study sites*

We conducted our study in portions of Bollinger, Dade, and McDonald counties, Missouri, USA (Fig. 1). All UAS flights occurred over corn fields (n = 5), ranging in size from 2 to 25 ha. Corn and soybeans were the primary agricultural crops grown in the region and producers typically rotated crops on an annual basis. Topography within fields was generally flat, with gentle rolling river drainages in adjacent areas. Fields were chosen based on historical or existing damage from wild pigs and damage was visually verified prior to all UAS survey flights.

2.2. *UAS imagery acquisition*

Surveys to locate and quantify damage were conducted with a 3DR Solo multirotor UAS (3D Robotics, Berkeley, CA, USA) equipped with a RedEdge multispectral sensor (MicaSense Inc., Seattle, WA, USA). The RedEdge sensor captured reflectance data in 5 discrete spectral bands: blue, green, red, red edge, and near infrared, centered on 475, 560, 668, 717, and 840 nm, respectively. Front and side overlap between images was 75% and autonomous flight planning was conducted by Tower mission planning software (3D Robotics, Inc, Berkeley, CA, USA). All surveys were conducted at approximately 122m (400 ft) above ground level, which yielded a ground-sampling distance of 8.37 cm/pixel. We conducted two flights during the corn growing season: Flight 1 (8/1/17–8/3/17) and Flight 2 (8/29/17–8/31/17). Flight 1 was conducted when corn kernels were at the R4 growth stage or the dough stage. Flight

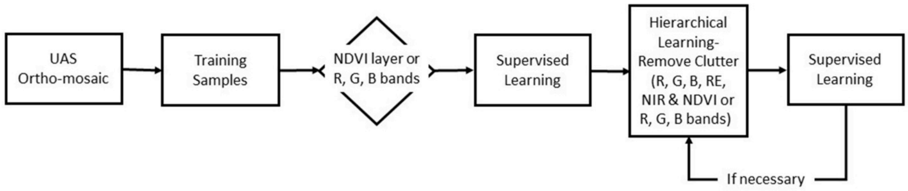

Fig. 2. Simplified flow diagram for Feature Analyst process to extract wild pig damage.

2 was conducted when corn was physiologically mature or directly before harvest. Ortho-mosaics were created using automated image matching software (Pix4D, Lausanne, Switzerland). We increased the spatial accuracy of ortho-mosaics by collecting ground control points (GCPs) prior to all UAS flights using a sub-meter global positioning system (GPS) unit (Trimble, Sunnyvale, CA, USA; 1-sec logging interval) and incorporated these GCPs into the mosaicking workflow. A Normalized Difference Vegetation Index (NDVI) layer was also created in Pix4D. Normalized Difference Vegetation Index is a vegetation index used to measure and monitor photosynthetically active vegetation, which in our case was to delineate healthy or non-damaged, uniform plant structure from damaged plants. The NDVI was calculated as NDVI = (NIR – Red)/(NIR + Red) where NIR and Red are the amount if near-infrared and red light reflected by vegetation.

2.3. *Automated feature extraction*

Areas damaged by wild pigs generally had unique spectral signatures and textural patterns, compared to areas of undamaged corn or other areas in fields. We used Feature Analyst (FA; Overwatch Systems Ltd, 2010), a machine learning add-in for ArcGIS (ESRI, Redlands, CA, USA), to automate extraction of damaged areas from ortho-mosaiced UAS imagery. Feature Analyst is a semi-automated, object-orientated software application that uses spectral and spatial information to classify and extract features of interest.

Extracting areas damaged by wild pigs from the UAS imagery using FA software was a hierarchical learning process consisting of three repeatable phases (Fig. 2): collecting training samples, supervised learning to 'train' and define target features, and clutter removal. We digitized 3 areas (i.e. polygons) of wild pig damage of varying size, shape, and color from each ortho-mosaiced field. These areas defined our training samples; they represented areas of wild pig damage for each field. To streamline the learning process we experimented with choosing training samples from only one field and then applying those sample properties to the other fields. This resulted in poor results for some fields and is consistent to the findings of Aksoy et al. (2010) and Olowokudejo and Piwowar (2013).

Initial supervised learning testing revealed that the NDVI layer generally worked best to broadly identify areas of damage and non-damage that we could then filter with FA hierarchical learning tools. We chose the 'natural feature' algorithm from the FA supervised learning tool, which functions to find individual features on the landscape. Feature analyst used contextual information (i.e. size, shape, and pattern) of pixels within and around our training samples to classify each pixel in the image. We limited our analysis to only include areas within field perimeters to reduce confusion during the classification process and processing time. Final outputs were filtered to only include damage areas $\geq$1 m^2 to reduce the number of small polygons scattered throughout the fields.

Initial output was a layer identifying areas matching the spectral and contextual signatures of the training samples. The output included correctly classified areas of damage, as well as false positives and missed features. We used the remove clutter option to "teach" FA what was correct and incorrect from the previous iteration of supervised learning. A second iteration of supervised learning was then run to refine the model, using both the NDVI layer as well as the 5-band multispectral

Fig. 3. Common example of wild pig damage to corn in southern Missouri, Aug 3, 2017.

UAS imagery to extract damaged areas. This process was repeated for each field.

We also wanted to test the above method for estimating wild pig damage when only using visible spectrum information (i.e. red, green, and blue bands), which is what most standard UAS sensors capture. The same training samples were used, but initial supervised learning only included visible information (Fig. 2). As before, this analysis only included areas within the perimeter of fields and outputs were filtered to include damage areas $\geq$1 m^2.

2.4. *Accuracy assessment*

In conjunction with UAS flights, a subset of in-field areas damaged by wild pigs were located and mapped with Trimble GPS units. Wild pigs trample and knock down standing corn stalks to gain access to high caloric kernels of corn (Fig. 3). These ground reference data were used to assess accuracy of wild pig damage estimates identified via the FA classification process.

We assessed accuracy of the final classification using a confusion matrix (Congalton, 1991) and stratified random sample schema. It has been demonstrated that 50 points per class is adequate for estimating the accuracy of land-use or land-cover classifications (Congalton, 1991). To estimate accuracy at the field level we used a sampling scheme of 100 hundred points per field or 50 points per class (i.e. damage and non-damage), resulting in 500 random points total for the five study fields. Each random point was overlaid on the FA classification, ortho-mosaic, and ground reference data and visually coded damage or non-damage. From the confusion matrix we calculated overall accuracy, producer's accuracy (error of omission), user's accuracy (error of commission), and Kappa coefficients. The Kappa coefficient is a measure of how well a classifier performed by accounting for the possibility of agreement occurring by chance (Congalton, 2001; Viera and Garrett, 2008). Kappa coefficients ranging from 0.41 to 0.60 indicated a moderate level of agreement with ground reference data. Kappa coefficients

Table 1
Summary of accuracy of Feature Analyst generated object classifications, which used 5 (blue, green, red, red edge, and near infrared) and 3 discrete spectral bands (blue, green, red) to delineate damage to corn fields in southern Missouri, USA, during 2017.

	Field 1		Field 2		Field 3		Field 4		Field 5	
	Producer's accuracy	User's accuracy	Producer's accuracy	User's accuracy	Producer's accuracy	User's accuracy	Producer's accuracy	User's accuracy	Producer's accuracy	User's accuracy
Damage[a]	96.1%	98.0%	100.0%	70.0%	98.0%	98.0%	100.0%	74.0%	100.0%	48.0%
Corn[a]	98.0%	96.0%	76.9%	100.0%	98.0%	98.0%	79.4%	100.0%	65.8%	100.0%
Overall accuracy[a]	97.0%		85.0%		98.0%		87.0%		74.0%	
Kappa[a]	0.94		0.70		0.96		0.74		0.48	
Damage[b]	90.7%	98.0%	100.0%	48.0%	97.5%	78.0%	100.0%	44.0%	100.0%	46.0%
Corn[b]	97.8%	90.0%	65.8%	100.0%	81.7%	98.0%	64.1%	100.0%	64.9%	100.0%
Overall accuracy[b]	94.0%		74.0%		88.0%		72.0%		73.0%	
Kappa[b]	0.88		0.48		0.76		0.44	0.46		

[a] Blue, green, red, red edge, and near-infrared spectral bands.
[b] Blue, green, red spectral bands.

Table 2
Estimated area of corn fields damaged by wild pigs, using semi-automated feature extraction techniques, during 2017 in southern Missouri, USA.

Bands	Field	Field area (ha)	Damaged area (ha)	Damaged area (%)
R,G,B, RE, NIR	Field 1	1.58	0.2	12.66%
	Field 2	13.99	0.19	1.36%
	Field 3	24.89	0.18	0.72%
	Field 4	23.89	0.07	0.29%
	Field 5	10.39	0.005	0.05%
	Total	74.74	0.645	3.02%
R,G,B	Field 1	1.58	0.09	5.70%
	Field 2	13.99	0.05	0.36%
	Field 3	24.89	0.13	0.52%
	Field 4	23.89	0.11	0.46%
	Field 5	10.39	0.004	0.04%
	Total	74.74	0.384	1.41%

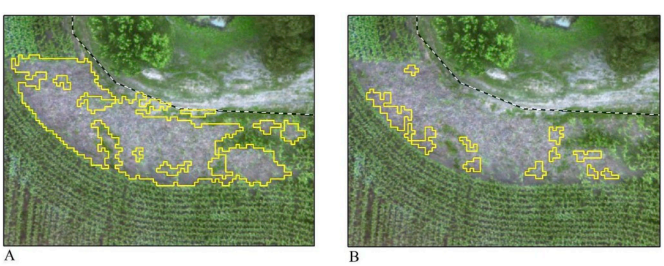

Fig. 4. Small portion of field 1 illustrating wild pig damage to corn and estimates of damage with Feature Analyst classification using (A) visible and near-infrared information (yellow) and only (B) visible information (yellow). The hashed black and grey line is the field boundary.

ranging from 0.61 to 0.80 indicated a substantial level of agreement.

3. Results

When incorporating both visible and near-infrared information into the FA classification, overall accuracies ranged from 74% to 98% (Table 1). User accuracies varied from 48.0% to 100% for the damage class and from 96.0% to 100% for the corn class (Table 1). Across all fields the kappa value was 0.76, which indicated a substantial level of agreement between the classification and ground reference sites.

Overall accuracies were slightly less when using only visible information (range: 72–94%; Table 1). User accuracies varied from 44.0% to 98.0% for the damage class and from 90.0% to 100% for the corn class (Table 1). Three fields in particular (i.e. 2, 4, and 5) all had low user's accuracy values for the damage class, meaning that only 44.0–48.0% of the areas identified as damage were actually damage. The overall kappa value across all fields was 0.60, which indicated a moderate level of agreement.

Estimates of total area damaged ranged from 0.05% to 12.66% for the FA classification which incorporated both visible and near-infrared information (Table 2). All percentage estimates of total area damaged were less when incorporating only visible information, except field 4, and ranged from 0.04% to 5.70%. Visual examination of both classifications compared to ground reference areas often revealed that the FA classification that incorporated both visible and near-infrared information more accurately included areas within damage site perimeters and mirrored ground reference damage boundaries compared to just the visible information classification which tended to underestimated damage (Fig. 4)

4. Discussion

Feature Analyst proved useful for delineating wild pig damage in corn fields. We tested many different combinations of FA functions via a trial-and-error process to determine which parameters were optimal for this application and needed to ultimately balance damage estimates between overestimation to underestimation. Once established though, only two cycles of hierarchical learning were needed to get detailed maps of damage sites. Initial testing revealed that damage training samples needed to extend all the way to the edge of damaged areas and that samples needed to include areas of the ortho-mosaic with differing image brightness. The arrival of afternoon clouds during most UAS flights led to mosaics that varied in image brightness and luminance. We also determined that using training sample characteristics from one field and applying those same characteristics to all fields led to poor results. Not all fields were planted with the same seed varieties or at the same growth stage, leading to different maturity dates and reflectance values. Subsequently, we identified training samples unique to each field and conducted our feature extraction at the field level.

Our approach, using UAS and multispectral information, proved useful for identifying areas in corn fields that were damaged by wild pigs. Four of five classified fields had substantial levels of agreement between ground reference data and the automated damage map. The one field with only a moderate level of agreement had little damage and was further along in the maturation process, making it a challenge to obtain representative training samples and also a thinning canopy which resulted in more exposed soil to the multispectral sensor which may have confused the FA tool. Accurately estimating damage caused by wild pigs, or any other wildlife, is difficult and time consuming (Engeman et al., 2018), especially in large fields and when crops grow beyond the height of the observer. The ortho-mosaics generated from the UAS provided a 'bird's-eye' view of fields that quickly and efficiently highlighted patterns of wild pig damage throughout the field. These results highlighted the utility of sensors that capture multispectral data, which can then be used to calculate numerous vegetation indices and improve the accuracy of mapping products.

Although inaccuracies in classification maps and estimated damage areas will exist for any UAS-based approach, we consider our method to be an objective, time-efficient, and accurate approach. Past studies, using visible or crop height information, have indicated that UAS-based imagery approaches underestimate damage caused by wild pigs (Michez et al., 2016; Samiappan et al., 2018). Some of this error was due to ortho-mosaic and classification procedures, while other error was due to alignment errors of ground reference data and damage maps. Initially we observed a slight shift in our ortho-mosaics, however this was removed by incorporating ground control points into the mosaicking process.

Estimates of area damaged by wild pigs (0.005–0.2 ha) were similar to estimates in Mississippi using UAS and segmentation-based fractal texture analysis (Samiappan et al., 2018), but considerably less than estimates in northern Belgium using UAS and geographic object-based image analysis (Rutten et al., 2018). This may be the result of wild pig elimination programs occurring across Missouri and much the U.S., which has presumably lowered wild pig densities (Centner and Shuman, 2015; U.S. Department of Agriculture, 2015). Future work includes estimating wild pig abundance near crop fields that have been damaged and establishing relationships between wild pig densities and amounts of damage (Davis et al., 2018).

Unmanned aircraft systems are an emerging technology and are quickly becoming ubiquitous in natural resource disciplines and precision agriculture industries (Anderson and Gaston, 2013; Christiansen et al., 2017; Hunt and Daughtry, 2018). In contrast to fixed-wing aircraft, UAS can quickly be deployed to capture the temporal nature of the feature(s) being mapped, which in our case was crop damage. Increased spatial resolution and easily interchangeable sensors are also transforming ecological investigations that use UAS. More accurately determining when and where crop damage occurs could lead to better management decisions regarding tools and techniques needed to reduce or minimize wild pig damage.

Wildlife damage to corn, and other crops, may be substantial and caused by a variety of wildlife species (i.e. white-tailed deer (*Odocoileus virginianus*), raccoons (*Procyon lotor*), black bear (*Ursus americanus*), plus many birds and rodents; Wywialowski 1996; Tzilkowski et al., 2002; Devault et al., 2007). We witnessed one corn field that appeared to be damaged by wild pigs, but was actually heavily damaged by raccoons. We excluded this field from our analysis, but acknowledge that this damage looked similar to wild pig damage and could confuse object-oriented classifications. Also complicating the classification process might be areas in fields that appear to be damaged by wildlife, but are actually areas damaged by unusually high winds, flooding, failed seed germination, or impacted by insects or heavy equipment. We recommend always complimenting image classifications with thorough site visits and ground referencing to accurately identify the wildlife species causing damage.

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