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Tools and Technology

Quantifying Damage From Wild Pigs With Small Unmanned Aerial Systems

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ABSTRACT Wild pig (*Sus scrofa*) population expansion and associated damage to crops, wildlife, and the environment is a growing concern in the United States. The destructive rooting behavior of wild pigs indicates where they have foraged and their general presence on the landscape. We used aerial imagery with a small unmanned aerial system to assess damage of corn (*Zea mays*) fields by wild pigs in the Mississippi Alluvial Valley of Mississippi, USA, during the 2016 growing season. Images were automatically classified using segmentation-based fractal texture analysis and support vector machines. We assessed the accuracy of automated classification with 5,400 Global Positioning System ground reference points collected in the fields. Classification accuracies for identification of damaged and nondamaged areas were between 65% and 78%. In general, automated classification underestimated the area of damage present within fields. Kappa values ranged from 0.26 to 0.51, on a scale of 0.0–1.0. Small unmanned aerial systems overcome limitations of existing methods because they can survey an entire field rapidly and without significant field labor.

KEY WORDS corn, damage assessment, human–wildlife conflict, Mississippi, small unmanned aerial systems, *Sus scrofa*, wild pigs, *Zea mays*.

Wild pigs (*Sus scrofa*) were introduced to North America in the 1500s. Natural dispersal, colonization, and illegal translocation have caused populations to expand significantly throughout the southeastern United States and other areas in North America (Gipson et al. 1998). Wild pigs are considered a significant ecological threat that far surpasses damages posed by other invasive vertebrates; accordingly, wild pigs are listed as one of the greatest concerns by wildlife managers and biologists (Ditchkoff and West 2007). Negative effects of wild pigs are numerous and detailed in review articles (Barrios-García and Ballari 2012, Bevins et al. 2014), but one economic consequence that results in human–wildlife conflict is damage to agricultural lands (Schley et al. 2008, Barrios-García and Ballari 2012). In Mississippi, USA, like other regions where corn (*Zea mays*) is grown, wild pigs are a nuisance, causing damage to plants from seeding through maturity (Mackin 1970, Herrero et al. 2006, Schley et al. 2008).

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Previous studies to determine economic loss due to wild pigs relied on scientific measures such as self-reporting questionnaires to approximate damage costs and radiotelemetry to track wild pig movement and measure habitat selection (Hayes et al. 2009; Hartley et al. 2012, 2015; Anderson et al. 2016). Although sound, these approaches possess inherent biases such as sampling error and lack of visual investigation. Such research gaps prompted an appeal in the literature for more precise and efficient methodology for determining the true extent of wild pig damage (Felix et al. 2014, Engeman et al. 2016). Current estimates of wild pig damage are mixed. Pimental (2007) estimated an annual combined cost of US$1.5 billion for damage and control. However, this value assumed a nationwide total of 5 million wild pigs. Seven years later, Mayer (2014) estimated there were approximately 6.3 million wild pigs in the United States. At a cost of US$300/wild pig, this could mean the cost of control and damage is now closer to US $1.9 billion annually (Pimental 2007).

Beyond merely detecting damage, it is more informative to determine the extent of damage in areas frequently selected by wild pigs. Two common geospatial techniques include quadrats and line-intercept sampling, although exact methods of precisely measuring damage are also utilized

(Engeman et al. 2016). These methods require potentially high levels of field-data collection effort; therefore, Engeman et al. (2016) suggested remote sensing methods were more desirable. Remotely sensed images require a certain amount of ground verification to train pattern recognition software in an effort to automate detection of wild pig damage. However, once accurate algorithms are built, automating damage assessment through pattern recognition techniques will reduce time and effort needed for assessment of wild pig damage (Engeman et al. 2016). Remote sensing methods also address the need for temporal evaluation because less effort to collect data can allow for more frequent collection (Felix et al. 2014). These methods overcome obvious challenges in assessing interior damage to mature corn because of the obscured view (Mackin 1970). Finally, remote sensing offers the capability to capture landscape information from surrounding areas, which can assign more meaningful context to damage assessments (Felix et al. 2014).

Engeman et al. (2016) suggested pattern recognition as a useful technique for identifying wild pig rooting damage. Texture, a component of pattern recognition analysis, enables discrimination between classes of interest and removes the need to purchase a more costly multispectral sensor. Particularly with land-cover classification problems, texture within an image can compensate for the lack of spectral bands. A standard practice is to use Gabor filters and gray-level co-occurrence matrix (Marceau et al. 1990, Dunn and Higgins 1995). These methods are effective texture-extraction methods for land cover applications using imagery with low spatial resolution (Samiappan et al. 2017). For high-resolution imagery, such as is generally collected by small unmanned aerial systems (UAS), these methods require significant computational resources, making them less efficient. Samiappan et al. (2017) demonstrated that texture extraction using segmentation-based fractal texture analysis (SFTA; Costa et al. 2012) can achieve similar results with less computation. Our objective was to assess the ability of a small UAS to estimate damage caused by wild pigs in production corn fields. Specific goals of this study were to apply SFTA to UAS-collected imagery to 1) reliably automate detection of wild pig damage and 2) accurately estimate the area of damage from classification maps using threshold and histogram analysis.

STUDY AREA

The study area was located in the Mississippi Alluvial Valley, an area in northwestern Mississippi between Mississippi and Yazoo rivers (Fig. 1). We chose 5 production corn fields in Bolivar, Leflore, and Sunflower counties ranging in size from 4.57 ha to 36.67 ha. We selected fields with mild (<0.5 ha) to substantial (≥0.5 ha) levels of pig damage, verified by visual inspection.

METHODS

Data Collection

We conducted UAS operations with a Lancaster V4 (Precision Hawk, Raleigh, NC, USA) fixed-wing aircraft. The aircraft carried a 14.2-megapixel, 1S2 point-and-shoot digital camera (Nikon USA, Melville, NY, USA) to collect visible (i.e., RGB) imagery in 3 bands. Bands were centered at approximately 450 (blue), 550 (green), and 650 (red) nm. We conducted flights on 29 June and 5 August, 2016, at 120-m altitude, resulting in a ground-sampling distance of 1 cm/image pixel. Flight lines resulted in imagery with 70% side and in-track overlap between successive images. Individual overlapping images were stitched together (i.e., mosaicked) to create a larger, continuous image using image processing software (AgiSoft, LLC, St. Petersburg, Russia).

We dispatched a field crew on 30 June and 9 August, 2016, corresponding with the aforementioned flights to provide ground-truth data that could be used to validate image analysis. At the time of the first collection, corn was between R1 (silking) and R4 (dough) growth stages, when the corn kernel was still tender and full of sugars. The second sampling trip occurred once the corn reached full maturity and the kernel had completely hardened. A substantial portion of the damage occurred immediately after planting, when wild pigs rooted up freshly planted corn seed. This type of damage caused weeds to grow in areas where the corn seed was depredated, leaving an easily noticed identifiable pattern. Wild pig damage on mature corn consisted of numerous trampled stalks, which the field crew also identified. The field crew documented areas of damage with field notes and photographs. Additionally, the field crew recorded locations of damaged patches with a Geo 7X Global Positioning System (GPS) unit (Trimble, Sunnyvale, CA, USA), capable of centimeter-level accuracy with virtual reference station connectivity, or when postcorrected (Fig. 2). The field crew collected GPS coordinates for 5,400 points of damage to measure the extent of wild pig–damaged areas in each field for accuracy assessment with UAS-collected imagery.

Image Classification

Healthy, uniform crop structure exhibits a unique texture pattern when compared with the regions with damaged or missing plants. Visual inspection of the imagery revealed unique texture characteristics between healthy and damaged regions. Textural differences in appearance were mainly differences in roughness, granulation, and regularity. We computed the SFTA on a subimage of size $k \times k$ pixels that produced a feature vector that uniquely represented regions such that feature vectors extracted from dissimilar regions were distinguishable from each other, while similar regions were indistinguishable. We can distinguish healthy regions with the SFTA feature vector because they exhibit a different pattern distinguishable from damaged regions (Fig. 3).

Support Vector Machine (SVM; Burges 1998) classifiers have previously been effective for classifying land cover types in remotely sensed imagery (Mountrakis et al. 2011). Initial testing with UAS imagery showed SVM classifiers produced superior results to alternatives (e.g., naïve Bayes and maximum likelihood classifiers). The supervised pattern-classification process consisted of 2 phases—training and testing. In the training phase, we presented SFTA vectors for ground-verified examples of healthy regions and damaged

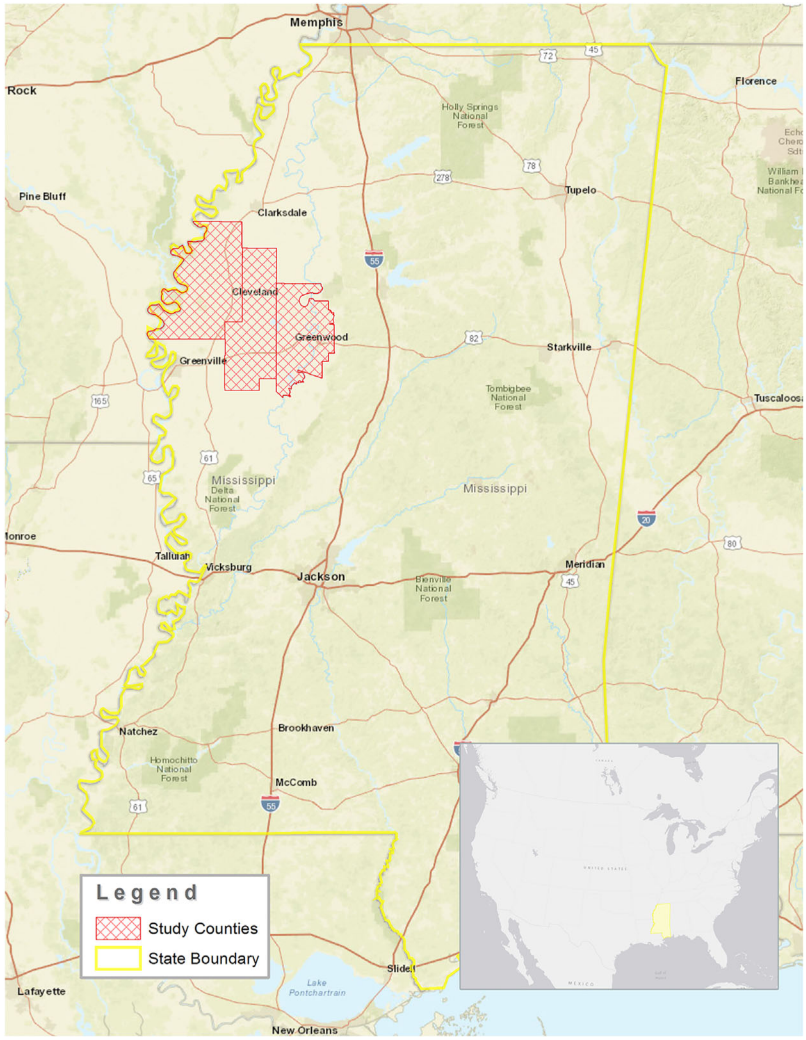

Figure 1. Area of study shown in relation to the state of Mississippi, and the United States of America.

regions so the SVM classifier could learn the patterns and build a mathematical model that characterized training examples. The training subimages for both healthy (H) and damaged (D) classes were randomly selected from both healthy and damaged regions (as determined from ground reference information, photographs, and field notes) found in the UAS images. This ensured a representative sample from both classes, distributed across the study site. From each of the 5 study fields, we used <1% of the pixels for training the supervised classifier (~25,000 samples from each class). The selection of training samples and accuracy assessment of the classification process were aided by the ground reference information. We presented new imagery to the SVM classifier so the SVM could identify healthy and damaged regions automatically in the testing phase. The SFTA texture features were linearly scaled to a range of −1.0–1.0 to normalize the difference between the numerical values of the features. We used a grid search algorithm to calculate the optimal SVM classifier parameters (Penalty C and Gamma γ; Chang and Lin 2011). We used open-source Library for Support Vector Machines (LibSVM) library to train and test the SVM classifier (Chang and Lin 2011). Finally, we used MATLAB (Mathworks, Natick, MA, USA) with LibSVM toolbox to perform the classification.

Accuracy Assessment

We loaded the classification map, image mosaic, and GPS coordinates of the ground reference information into ArcGIS (v. 10.3; ESRI, Redlands, CA, USA) and calculated accuracy estimates after the classification process. We determined performance of the classification algorithm with respect to 1) Kappa accuracy (κ), 2) overall accuracy, 3) commission error, 4) omission error, and 5) confidence intervals. These parameters provide a good understanding of the efficacy of the SVM classifier. The Kappa (κ) statistic is a discrete multivariate technique frequently used in remote sensing to measure agreement between ≥2 classifiers (Viera and Garrett 2005). We used a confusion matrix to interpret the classification accuracy (Stehman 1997). Overall accuracy is the sum of the diagonal elements divided by the total sum of the matrix. The overall accuracy is the percentage of samples that were correctly classified. The commission error, estimated from nondiagonal elements of a confusion matrix, represents samples that belong to H class but were classified

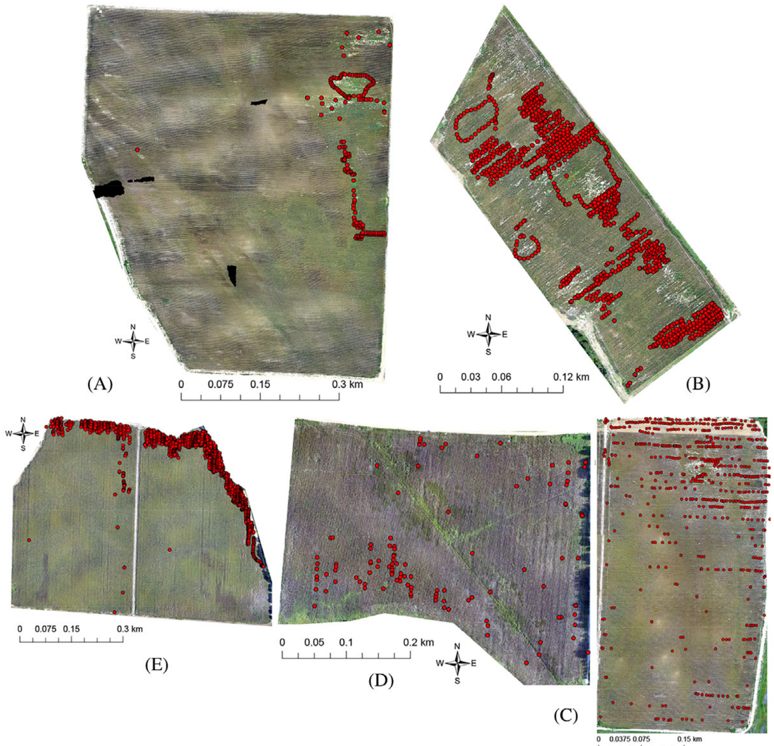

Figure 2. Aerial images of production corn fields collected with unmanned aerial systems on 29 June and 5 August 2016, shown with locations of Global Positioning System coordinates collected on 30 June and 9 August 2016, for ground-truth assessment (red dots) of damage from wild pigs in Mississippi, USA. Letters correspond to fields as referenced in Tables 1 and 2.

as belonging to the D class. The omission error represents the samples that belong to D class but were classified as H class. The 95% confidence interval reported with κ provides a range of positive and negative values that act as good estimates of the unknown population parameter.

RESULTS

Overall classification accuracies for pig damage were between 65% and 78% (Table 1). Errors of omission were more common than errors of commission, meaning that when the classifier was incorrect, it was more likely to label damaged areas as healthy, rather than labeling healthy areas as damaged. Kappa values ranged from 0.26 to 0.51, with 0.40 being a benchmark for moderate agreement for this type of analysis (Viera and Garrett 2005). This means a reasonably accurate assessment of damage was produced; however, damage extent was likely underestimated (Table 2).

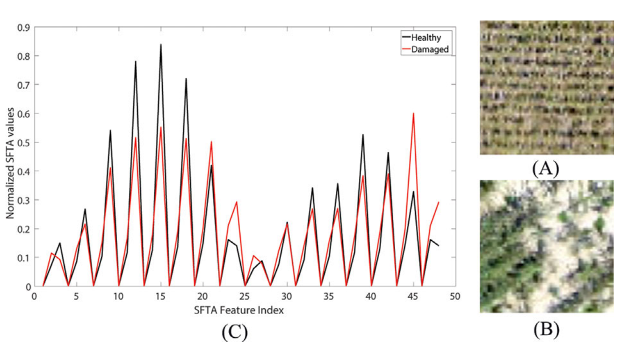

Figure 3. Subimages taken from unmanned aerial systems imagery of production corn fields showing differences in texture of healthy, uniform crop (A) and crop damaged by wild pigs (B) in Mississippi, USA, during 2016. Segmentation-based fractal analysis was used to create feature vectors for both classes (C) and differentiate between the 2 classes within the imagery.

The processing time for the analysis was approximately 15 min/km^2 of land imaged, on a moderately robust computing system. As a result of computational efficiency, it is likely that computational speed would not be dramatically slower for a computer of lesser power; it is not certain if a more powerful computer would produce a result in less time. Thus, it is likely that future users will not be challenged to find computing systems capable of the same analysis.

DISCUSSION

Segmentation-based fractal texture analysis of UAS-collected imagery automated detection, but underestimated area estimates of wild pig damage. The majority of underestimation error was the result of classification error. Classification error resulted from both data collection and data processing. Roll, pitch, and yaw of the aircraft during image collection introduces error that must be taken into account during mosaic creation. Without consideration for this distortion, results similar to Engeman et al. (2016) are likely (i.e., underestimation of damaged area due to off-nadir views). Some error was also due to discrepancy between the accuracy of the GPS used to collect ground-reference data and mosaicked UAS images. Discrepancy in accuracy can mean that placement of the reference GPS point was slightly off

Table 1. Accuracy assessment of classified unmanned aerial systems imagery was conducted with a confusion matrix listing the percentages of areas classified as healthy (H) and damaged (D) within each study site. The matrix also generated percentages of errors of omission (OE) and commission (CE), an overall accuracy (OA), and a kappa (κ) statistic confidence interval (CI). The confusion matrix evaluated the accuracy of the structured vector machine classifier with regard to its ability to automate detection of wild pig damage in production corn fields in Bolivar, Leflore, and Sunflower counties, Mississippi, USA, during the 2016 growing season.

Class	Field A	Field B	Field C	Field D	Field E
H (%)	40.8	61.4	71.4	64.4	61.1
D (%)	83.7	88.2	75.0	67.9	78.9
OE (%)	40.8	38.5	28.5	35.5	38.8
CE (%)	16.2	11.7	25.0	32.0	21.1
OA (%)	70.7	77.7	73.4	65.9	64.9
κ (with CI)	0.26 (±0.01)	0.51 (±0.01)	0.46 (±0.01)	0.31 (±0.01)	0.27 (±0.01)

from the actual location within the image when ground-reference data and mosaicked UAS images were combined. If the GPS ground-truth damage point appears just outside of an area classified as damage on the image, the accuracy assessment would classify this as an error of omission, when in reality it is an alignment issue between the GPS points and the image. Although other studies (e.g., Felix et al. 2014) have utilized high-precision GPS to conduct survey of pig damage, these data were not combined with high-resolution aerial imagery in this manner.

Image mosaicking relies on finding tie points (i.e., the same object appearing in both images) in overlapping images. These tie points, along with automated geotagging of images by the UAS during collection, facilitated stitching of snapshots into a continuous image by the mosaicking software. More tie points lead to more coherent and uniform stitching. In production corn fields, finding good tie points can be challenging because there are limited unique features within the image that serve as tie points. As a result, mosaicking artifacts in the imagery can be a major source of error for identifying and estimating the damages caused by wild pigs (Fig. 4). These errors can (but do not always) lead to errors of commission or omission because they create error in the imagery. Decreasing presence of mosaicking artifacts will improve classification accuracy; however, this process can be tedious and more of an art than a science. Marking of fields to create unique features that serve as tie points (e.g., poles, field flags) and decreasing the distance between flight lines can proactively reduce image mosaicking artifacts in the data collection phase. The availability of a near infrared band might also increase the classification accuracy by increasing the potential to discriminate between soil and crop; however, this would require a multispectral sensor rather than the visible sensor used in this study.

Table 2. Estimated area of study corn fields damaged by wild pigs in Bolivar, Leflore, and Sunflower counties, Mississippi, USA, during the 2016 growing season. Damage estimates were approximated from automated classification of unmanned aerial systems imagery.

Field	Damaged areas (ha)	Total area (ha)
A	0.34	36.67
B	0.13	4.57
C	0.54	15.82
D	0.39	16.67
E	2.10	36.50

There is clear room for improvement in use of UAS for automated detection of wild pig damage; however, these results show promise for future endeavors and more accurate economic estimation of wild pig damage. This approach provides an objective technique to quantify damage and removes potential bias from self-reporting landowners or human observers. Furthermore, UAS-collected imagery samples the entire field of interest, rather than subsampling along transects. The methodology used in this study also

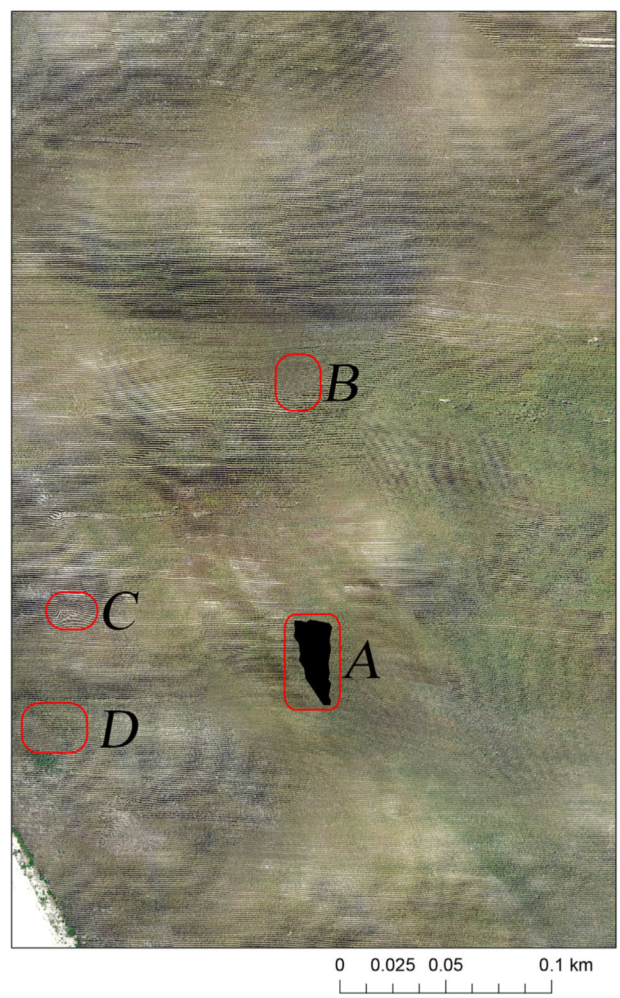

Figure 4. Mosaicking artifacts in aerial imagery collected with unmanned aerial systems over production corn fields in Mississippi, USA, during 2016 that lead to classification errors during automated classification of wild pig damage. Multiple errors appear including missing data (A), image quality mismatch (B), tie-point mismatch (C), and image orientation mismatch (D).

addresses research gaps identified in literature, including use of pattern recognition and precision (Felix et al. 2014, Engeman et al. 2016).

A small UAS is an efficient alternative to conducting wild pig damage surveys when compared with the time needed to do extensive in-field or landowner surveys, or per unit costs of telemetry collars (Tzilkowski et al. 2002, Felix et al. 2014). Easy-to-pilot, off-the-shelf systems can be obtained for ≤US $500. Mosaicking can be done by any of a handful of cloud-based processing services that charge varying fees per land unit, per flight, or on a monthly basis; some are as low as $30/month. As legal hurdles for use of UAS are lowered, this tool will become more accessible to researchers and landowners. Additionally, small UAS can be used to create temporal data sets to more effectively monitor the size and age of damaged areas.

The expansion of wild pigs throughout North America makes cost-effective, reliable techniques for discovery and measurement of pig-related damage a necessity. Using an inexpensive and widely available tool, we detected wild pig damage through an automated image processing methodology, which will enable wildlife biologists and agricultural producers to estimate damage for greater areas than previously possible. Wildlife biologists charged with reduction of human–wildlife interactions can use the process described herein to determine where wild pigs occur and enact remediation techniques as quickly as possible. Agricultural producers can use these technologies to determine how much damage has occurred to make cost-effective decisions regarding whether or not to take remediative action. Lastly, these techniques will help researchers more efficiently quantify pig damage by reducing labor costs for ground-based technician support. In summary, small UAS represent a new option for damage assessment and are becoming more viable as legal hurdles are reduced, costs come down, and scientists find more applications for their use.

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