2023

Using drones to detect and quantify wild pig damage and yield loss in corn fields throughout plant growth stages

Bethany A. Friesenhahn

Lori D. Massey

Randy W. DeYoung

Michael J. Cherry

Justin W. Fischer

See next page for additional authors

Authors

Bethany A. Friesenhahn, Lori D. Massey, Randy W. DeYoung, Michael J. Cherry, Justin W. Fischer, Nathan P. Snow, Kurt C. Vercauteren, and Humberto L. Perotto-Baldivieso

Received: 25 April 2022 | Revised: 31 January 2023 | Accepted: 10 February 2023

DOI: 10.1002/wsb.1437

RESEARCH ARTICLE

WILDLIFE SOCIETY BULLETIN Open Access

Using drones to detect and quantify wild pig damage and yield loss in corn fields throughout plant growth stages

Bethany A. Friesenhahn[1] | **Lori D. Massey**[1] | **Randy W. DeYoung**[1] | **Michael J. Cherry**[1] | **Justin W. Fischer**[2] | **Nathan P. Snow**[2] | **Kurt C. VerCauteren**[2] | **Humberto L. Perotto-Baldivieso**[1]

[1]Caesar Kleberg Wildlife Research Institute, Texas A&M University-Kingsville, 700 University Blvd MSC 218, Kingsville, TX 78363, USA

[2]United States Department of Agriculture, Animal Plant and Health Inspection Service, Wildlife Services, National Wildlife Research Center, 4101 Laporte Ave, Fort Collins, CO 80521, USA

Correspondence

Bethany A. Friesenhahn, Caesar Kleberg Wildlife Research Institute, Texas A&M University-Kingsville, 700 University Blvd. MSC 218, Kingsville, TX 78363, USA.
Email: Bethany.friesenhahn@tamuk.edu

Funding information

National Feral Swine Damage Management Program, Grant/Award Number: AP20WSHQ0000C004

Abstract

Presently, there are an estimated 6.9 million wild pigs (*Sus scrofa*) in the U.S., which cause over US$1 billion in damage to agriculture, environmental impacts, and control costs. However, estimates of damage have varied widely, creating a need for standardized monitoring and a method to accurately estimate the economic costs of direct wild pig damage to agriculture. The goal of our study was to integrate remotely sensed imagery from drones and crop harvest data to quantify wild pig damage in corn fields. We used drones with natural color (red, green, blue) cameras to monitor corn fields at different growth stages in an agricultural matrix in Delta County, Texas, USA, during 2019–2020. We flew 36 drone missions and classified wild pig damage in 18 orthomosaics by a combination of manually digitizing and deep-learning algorithms. We compared estimates of damage from drone imagery to those derived from ground-based transect surveys, to verify pig damage. Finally, we compared damaged areas of fields to maps of collected real-time yields at harvest to estimate yield loss. All classified drone orthomosaics of pig damage had >80% overall accuracy for all growth stages. Ground transect surveys, which subsampled 2.6–4.1% of the field, were found to miss damage compared to the complete field coverage provided by drone imagery. Most damage occurred in latter growth stages, when corn ears were maturing, seed was most nutritious, and producers had already invested in the majority of annual crop inputs. Wild pigs damaged up to 9.2% of a single monitored field, which resulted in a mean loss of 3,416 kg of corn/ha and a direct cost to producers of US$17.18–48.24 per ha of damage. Drone imagery, when combined with spatially-explicit, harvest yield data, provides an accurate assessment of crop damage and yield loss due to wild pigs in the currency required for the cost-benefit evaluation of management actions.

KEYWORDS

crop damage, deep-learning, drones, harvest yield, *Sus scrofa*, wild pigs, wildlife damage management

Populations of wild or feral pigs (*Sus scrofa*), also known as wild boar, are globally widespread and represent a significant environmental and economic problem, even in their native range of Eurasia and North Africa (Barrios-Garcia and Ballari 2012). Currently, wild pigs are found on 6 of the 7 continents and have been considered one of the 100 World's Worst Invasive Alien Species (Lowe et al. 2000). Wild pigs were first introduced to the western hemisphere ~1220 CE during the colonization of the Hawaiian Islands by Polynesians (Wilmshurst et al. 2011, Hess et al. 2020) and to mainland North America in the 16th century by European settlers (Wood and Barrett 1979, West et al. 2009). Over the past 4 decades, the range of wild pigs has expanded into 35 states in the U.S., and the current population is estimated at 6.9 million, which has almost tripled since 1982 (Lewis et al. 2019). The recent proliferation and expansion of wild pigs is credited to both behavioral and anthropogenic factors (Seward et al. 2004, Bevins et al. 2014, Tabak et al. 2017). Wild pigs are highly adaptable, have an omnivorous diet, and high reproductive rates (Singer et al. 1984, Samiappan et al. 2018). Besides dispersing on their own, humans also translocate and release wild pigs due to their popularity with hunters (Seward et al. 2004, Bevins et al. 2014, Tabak et al. 2017, McCann et al. 2018, Fischer et al. 2020).

With range expansion of wild pigs comes the cost of billions of dollars in environmental and economic impacts, which is far greater than the hunting industry income they generate (Seward et al. 2004, Massei et al. 2011, Fischer et al. 2020). Multiple studies across the globe have reported the negative impact of wild pigs to agricultural crops (Seward et al. 2004, Herrero et al. 2006, Gentle et al. 2011, McKee et al. 2020). Wild pig damage to agriculture costs millions of U.S. dollars annually (Hill 1997, Pedrosa et al. 2015, McKee et al. 2020), resulting in lost revenue for agricultural producers (Hill 1997, Gong et al. 2009, Pedrosa et al. 2015).

Prior studies that quantified the spatial and temporal scale of wild pig damage and economic cost relied on producer surveys and ground sampling (Anderson et al. 2016, Engeman et al. 2018, Boyce et al. 2020). Assessment of wild pig damage using ground surveys is time consuming (Herrero et al. 2006, Poudyal et al. 2017, Boyce et al. 2020) and becomes difficult as plant growth impedes visibility and reduces the proportion of the field that surveyors can sample (Engeman et al. 2018). Accurate and efficient estimates of harvest loss due to wild pigs would enable financial compensation to producers through crop insurance claims (Michez et al. 2016, McKee et al. 2020). Such estimates would also provide the most accurate cost of wild pigs on the landscape.

Remote sensing approaches already used in precision agricultural practices at the farm and field scale (Bohon 2014, Rembold et al. 2015, Houborg and McCabe 2016, Garza et al. 2020, Weiss et al. 2020) could provide a more efficient method to monitor and assess wild pig damage. Remotely sensed data are widely available at the global (e.g., Planet Labs, Sentinel-2, Landsat satellite constellations) and national scale (National Agriculture Imagery Program), providing high spatial- and temporal-resolution data that can be used to assess, study, monitor, and map agricultural landscapes (Bohon 2014, Frotscher et al. 2016, Perotto-Baldivieso et al. 2020). At finer scales, drones can provide high-resolution data with natural color, multispectral, thermal, hyperspectral imagery, and high-definition video (Hodgson et al. 2016, Green et al. 2019, DiMaggio et al. 2020). Recent advances in drone-based imagery acquisition allows for deep-learning techniques with advanced software to classify and detect specific features or objects based on spectral, spatial, and structural patterns (Gustafson et al. 2018, Fischer et al. 2019).

Recent research has focused on drones and object detection technology to monitor timing and extent of wild pig damage at a field scale (Michez et al. 2016, Kuzelka and Surovy 2018, Rutten et al. 2018, Samiappan et al. 2018, Fischer et al. 2019). Approaches to train and fully automate classification of wild pig damage include crop height models (Michez et al. 2016, Kuzelka and Surovy 2018), vegetation indices calculated from multispectral drone imagery (Houborg and McCabe 2016, Fischer et al. 2019), and textural feature extractions (Samiappan et al. 2018, Fischer et al. 2019). Studies concluded that drone approaches were a useful tool to efficiently estimate wild pig damaged areas in crops, yet when it came to determining yield losses, an approximate estimate based on regional yield averages was used (Rutten et al. 2018). The timing and extent of wild pig damage and total losses in harvest yield are critical to a farmer's livelihood (Tzilkowski et al. 2002).

Producer and ground surveys may over or underestimate lost income (Rutten et al. 2018, McKee et al. 2020, Carlisle et al. 2021). As such, standardized and accurate methods of monitoring wild pig agricultural damage to estimate economic losses is needed. The goal of our study was to integrate drone approaches, crop harvest data, and crop phenology to quantify wild pig damage in corn (*Zea mays*) fields, which is a highly preferred crop by wild pigs (Schley and Roper 2003, Herrero et al. 2006, Michez et al. 2016, Fischer et al. 2019). Our objectives were to 1) evaluate the use of drones to detect wild pig damage early in the plant establishment stage, as well as when the corn is maturing, and 2) assess the relationship between wild pig damage and harvest yield data.

STUDY AREA

We conducted our study in northeastern Texas, USA, primarily in Delta County and a small southeast corner of Lamar County (Figure 1). Delta County is bordered by the North Sulphur and South Sulphur rivers, contains 720 km^2 of the Blackland Prairies ecoregion, with prime farmland covering 51–60% of the county (McCroskey 2016). Lamar County is bordered by the Red River on the north and North Sulphur River on the south and contains 2,380 km^2 of pasture and farmland, with scattered timber forests (Ludeman 2016). Soil texture ranges from deep clay to clay with a dark loam (Ludeman 2016, McCroskey 2016). The vegetation in the region includes hardwoods, such as oak (*Quercus spp.*), elm (*Ulmus spp.*), pecan (*Carya illinoinensis*), and mesquite (*Prosopis glandulosa*), and prairies and pastures with grasses such as Texas grama (*Bouteloua rigidiseta*), buffalograss (*Buchloe dactyloides*), and bunchgrass (*Festuca idahoensis*; McCroskey 2016). According to the 2017 Census of Agriculture for Delta County, there were 571 farms and ranches, covering an area of 58,200 ha, and 56% of that land was in farms used for crops (U.S. Department of Agriculture [USDA] 2017). Major crops in this region include corn, wheat (*Triticum*), soybeans (*Glycine max*), sorghum (*Sorghum bicolor*), forage or hay, and cotton (*Gossypium*; USDA 2017).

The climate in the region is warm and wet, with an annual average rainfall of 1,010 mm and elevation range of 122 to 152 m above sea level. The temperatures range from an average of −1°C in January to an average of 35°C in July (McCroskey 2016). The first freeze generally occurs in November and the last freeze in March, which allows for a 233 day growing season. Since weather conditions specific to our study area impacted data collection, it is important to point out that according to the National Oceanic and Atmospheric Administration Climate at a Glance

FIGURE 1 Corn fields in Delta County, Texas, USA, monitored for wild pig damage. Drones were used to capture imagery of each field at 100 m above ground level to detect and quantify wild pig damage at different corn growth stages. Fields 1, 2, 3, 9 and 14 were flown in 2019 and fields 1, 2, 3, 8, and 11 in 2020. Imagery from the National Agriculture Imagery Program (Texas Natural Resources Information System [tnris.org]). Accessed 25 September 2020.

records (https://www.ncei.noaa.gov/), from April 2019 to September 2020 Delta County experienced the fourth wettest 18-month period since 1945, receiving 2,324 mm of precipitation, compared to the 1901–2000 average of 1,671 mm. It is also important to note that intense aerial gunning efforts to remove wild pigs were carried out by Texas Wildlife Services in February and March of 2019 and 2020 throughout the study area, immediately prior to planting and continued removal efforts by trapping and ground shooting throughout the entirety of the growing season.

METHODS

Drone flights

We monitored a total of 10 corn fields ($n = 5$ in 2019 and $n = 5$ in 2020) ranging from 30 to 112 ha in size on 2 separate farms (Figure 1) with history of annual wild pig damage. We conducted drone flights April through August in 2019 and May through August in 2020 to monitor wild pig damage to corn. In 2019 we flew a DJI Phantom 4 Pro v.2 and in 2020 we flew a DJI Phantom 4 Pro v.2 RTK (DJI, Shenzhen, China). Both drone units had a mounted natural color camera (red, green and blue bands [RGB]) that collected images with a resolution of 20 megapixels. The DJI Phantom 4 Pro v.2 RTK had a D-RTK 2 Mobile Station that connected to the drone along with a built in

TABLE 1 Drone flight dates in different growth stages of monitored corn fields in Delta County, TX, USA, in 2019 and 2020.

Year	Field	Flight dates			
		Establishment	Vegetative	Blister-milk	Dent-mature
2019	1	1-April*	22-May 19-June	9-July[b]	13-August[b]
	2	1-April*	22-May 19-June	9-July[b]	13-August[b]
	3	1-April*	22-May 19-June	9-July[b]	13-August[b]
	9	2-April*	22-May	9-July*	26-July*
	14	3-April[a]	22-May 20-June	9-July*	23-August*
2020	1		6-May	16-July[b]	4-August[c]
	2		6-May		
	3		6-May	16-July[b]	
	8		6-May	16-July[b]	4-August[b]
	11		6-May	16-July*	4-August*

*Flights used for analysis of detecting wild pig damage in different corn growth stages.

[a]Heavy rain event made wild pig damage indistinguishable.

[b]Complete orthomosaics unable to be created.

[c]No harvest yield data.

GPS/GLONASS system (Global Positioning System/Global Navigation Satellite System), which accounted for real-time mapping corrections with horizontal accuracy of 2 cm or better (Page et al. 2022), optimized relative accuracy, and required less ground control points during flights (Garza et al. 2020, Taddia et al. 2020). We used Pix4D Capture (Pix4D S.A., Prilly, Switzerland) to conduct flights and collect imagery. Flight altitude was 100 m above ground level (AGL) at a speed of 3–5 km/h, −90∘ camera angle, with 80% image overlap and sidelap (DiMaggio et al. 2020). All flights took place on sunny, clear days with winds <16 km h^{-1} and were conducted between 0930 and 1430 to minimize shadows (DiMaggio et al. 2020, Page et al. 2022).

We conducted flights throughout 4 corn growth stages to determine if different types of crop damage could be detected and quantified from drone imagery (Table 1). The 4 corn growth stages are establishment, vegetative, blister-milk, and dent-mature (Nafziger 2009). Wild pig damage differs during distinct corn growth stages (Figure 2); wild pigs use their snout to root up seeds and seedlings during the establishment stage, then trample plants in the latter reproductive stages (R2 blister-milk and R6 dent-mature stages) once kernels are beginning to form and provide maximum nutritional value (Schley et al. 2008, Bleier et al. 2017, Boyce et al. 2020). Flights started in the establishment stage, occurring between 10–36 days after planting and then again in each of the following 3 growth stages. We flew 36 missions: 24 in 2019 and 12 in 2020. Out of those 36, 5 were in the establishment stage, 14 in the vegetative stage, 9 in the blister-milk stage, and 8 in the dent-mature stage of corn growth. We did not have flights during the establishment stage in 2020 due to weather and travel issues and restrictions due to a global pandemic.

Ground data collection

In 2019 and 2020, we assessed corn damage due to wild pigs using an established method of walking transects across a portion of each field (Engeman and Sugihara 1998, Engeman and Sterner 2002, Gilsdorf et al. 2004, Engeman 2017). Transect surveys are commonly used by wildlife damage management professionals and served as

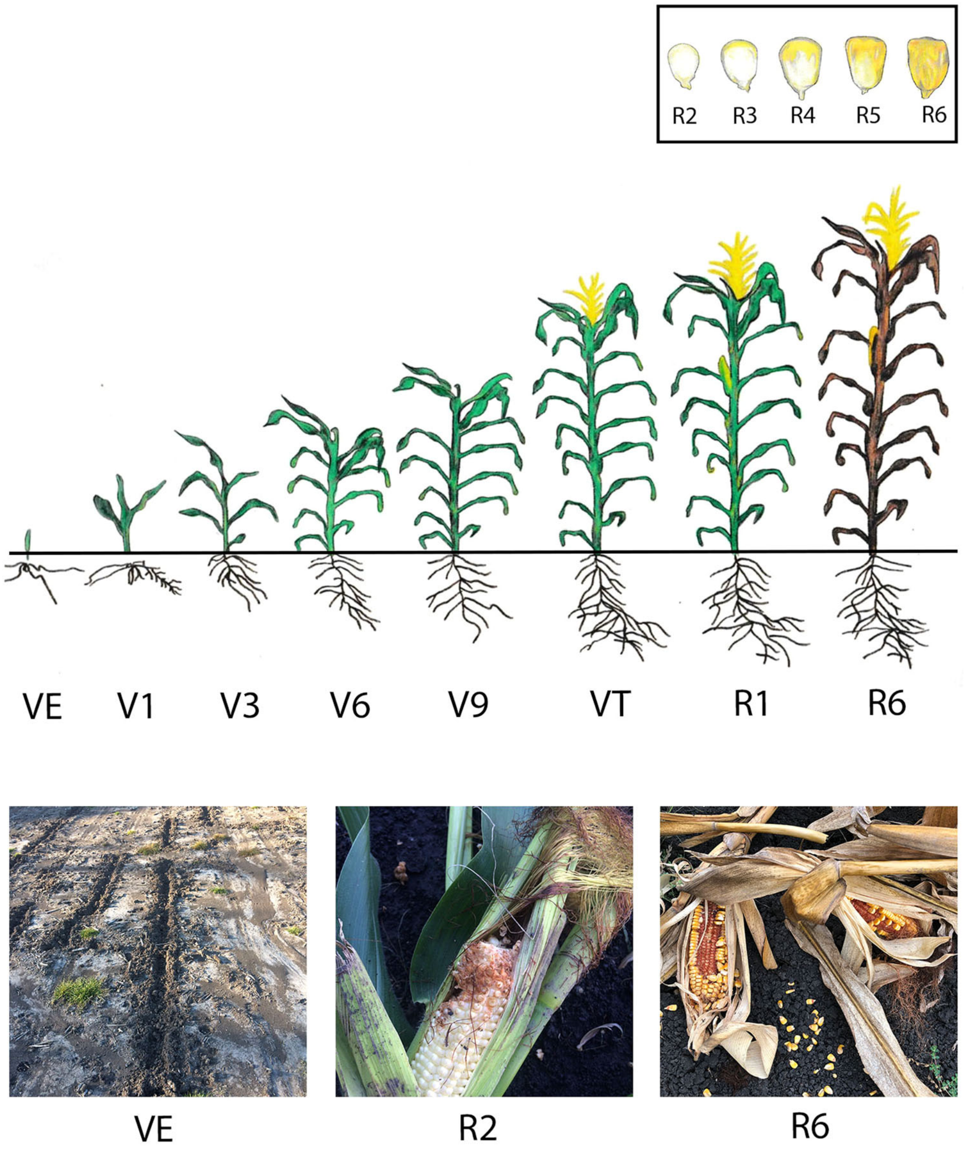

FIGURE 2 Corn growth stages from seed emergence (VE), vegetative stages (V) and kernel development once the plant reached the reproductive stages (represented by an R) in Delta County, Texas, USA during the spring and summer months of 2019 and 2020. Photos represent the type of wild pig damage to the plant at different growth stages (left to right): rooting up seeds and soil in the VE establishment stage, trampling and consumption of kernels in the R2 blister-milk stage and R6 dent-mature stage. Corn growth stages adapted from Pioneer (https://www.pioneer.com/us/agronomy/staging_corn_growth.html; Nafziger 2009).

a ground truthing validation of the drone imagery. We mapped out and walked transects that paralleled planted crop rows, each transect (hereafter, transect polygon) consisting of 12 rows wide (approximately 28 m) and spaced 225 m apart throughout each monitored field. To record wild pig damage in 2019, we used a measuring wheel to measure each segment of rooting damage and totaled the segments of damage at the end of each row during the establishment stage. We collected ground data using this method for 5 fields in 2019 in the establishment stage 16–20 days after drone flights due to weather conditions.

In the latter growth stages in 2019 and all ground surveys in 2020, we used a GPS (Bad Elf, West Hartford, CT, USA) and Collector app (Esri, Redlands, CA, USA) to mark polygons around areas of damaged corn plants observed within each transect. In 2019, we collected ground data within 2 days after drone flights during the vegetative, blister-milk, and dent-mature growth stages. In 2020, we collected ground data for 5 fields within 2 days after each flight, in the vegetative stage, blister-milk and dent-mature stages.

Harvest yield data

We acquired spatially indexed harvest yield data for 5 fields in 2019 and 2 fields in 2020. Harvest yield data were collected using a precision agriculture controller (CLAAS Lexion 750; CLAAS, Harsewinkel, Westphalia, Germany) and software (Climate Fieldview; The Climate Corporation, San Francisco, CA, USA) mounted on a combine to collect and map real-time yield data as the corn was being harvested. Grain cart scales were used before harvest and frequently during harvest to recalibrate yield and moisture sensors on the combine to maximize accuracy of yield data (Grisso et al. 2009). We downloaded yield data with Field Operations Viewer and used field operations device driver for Precision Planting 20/20 (Granular Inc., Ames, IA, USA) to obtain point data and quantify yield (we used the dry yield value). Harvest data were then imported into ArcMap 10.8 (Esri) as a point shapefile for further analysis.

Data analysis

Drone imagery processing

Imagery captured by the drone was processed in Pix4Dmapper (Pix4D S. A., Prilly, Switzerland), which enabled us to stitch overlapping images together to create 2-D orthomosaics and 3-D models of each flight (DiMaggio et al. 2020, Page et al. 2022). Pix4Dmapper uses the structure from motion algorithm to create 3-D photogrammetric meshes and 3-D point cloud datasets (X, Y, Z), generating a digital surface model (DSM) and digital terrain model (DTM; Kuzelka and Surovy 2018, DiMaggio et al. 2020, Page et al. 2022). The DSM represents height values of the vegetation canopy and the DTM depicts elevation values of the terrain (Jimenez-Jimenez et al. 2021). To calculate the height of the vegetation, we subtracted the DSM from DTM to get a normalized DSM (nDSM; Mayr et al. 2018, Page et al. 2022).

Classification of wild pig damage

The forms of damage and plant heights differ among corn growth stages (Figure 3). Therefore, we used different approaches to classify wild pig damage in the establishment stage and latter growth stages. For the establishment stage, we delineated wild pig damage using drone imagery at a nominal scale of 1:100. We used this method for 4 of the 5 fields in 2019. We could not use this method in 1 of the 5 fields because large amounts of rainfall in our study area made wild pig damage indistinguishable from tire tracks and planting equipment. Wild pig damage that we were able to identify and not distorted by heavy rainfall, were dark, straight lines of disturbed soil caused by wild pig rooting that followed the planted rows (Figure 3A,B). To estimate percentage of wild pig damage found within transect polygons during the establishment stage, we divided the total meters of damage by wild pigs by the total meters of the transect rows, per field (Engeman and Sterner 2002, Engeman 2017).

To quantify damage in the blister-milk and dent-mature stages, we used 2 fields from 2019 and one field from 2020 because these fields had orthomosaics for each of the stages and harvest yield data maps. We combined the

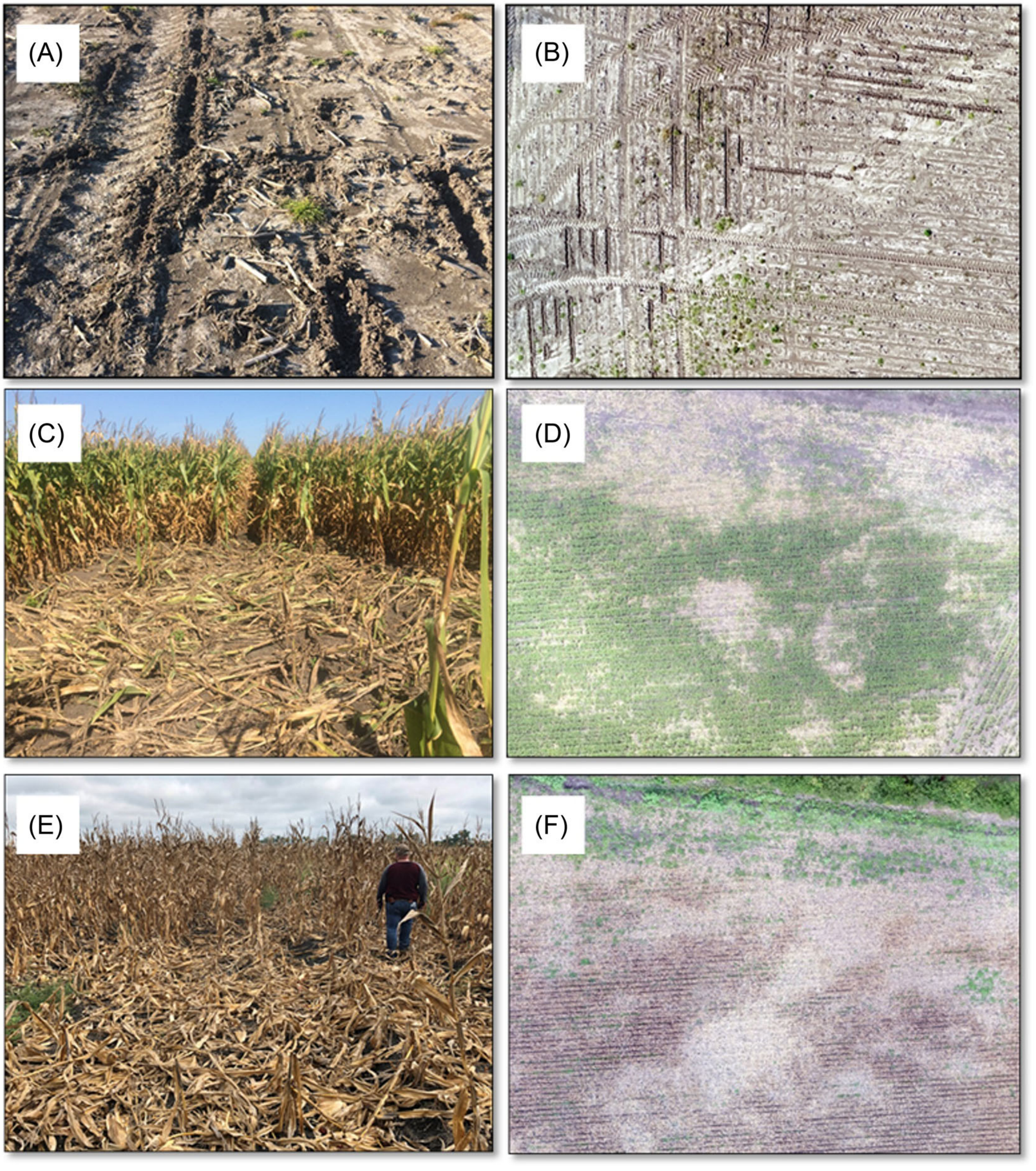

FIGURE 3 Images of different types of wild pig damage at different growth stages of corn taken during ground surveys and from drone flights in monitored corn fields in Delta County, Texas, USA, in 2019 and 2020. Wild pig rooting damage from ground level during the establishment stage (A) and from drone imagery at a scale of 1:100 (B). Wild pig damage by trampling plants from ground level during the blister-milk stage (C) and from drone imagery (D). Wild pig damage during the dent-mature stage, pictured from the ground (E) and from drone imagery (F).

drone RGB orthomosaic and the height raster nDSM data to train deep-learning models to identify damaged areas for the blister-milk (Figure 3C,D) and dent-mature stages (Figure 3E,F). We ran the deep-learning algorithm in ArcPro 2.7 (ESRI); this algorithm uses convolutional neural network models trained to recognize specific patterns in an image (Ferentinos 2018). The first step was to use the Train ISO cluster classifier tool, which performs an unsupervised classification (Lemenkova 2021) on the RGB orthomosaic and height raster nDSM, with a max number of classes/clusters set at 25. The Train ISO cluster classifier is machine learning based on color bands of the imagery, does not require ground survey data (Lemenkova 2021), and creates an ESRI Classifier definition file output, which contains all the parameters required for classification in the next steps. We then used the output, RGB orthomosaic, and nDSM to generate a classified raster with 25 classes using the Classify Raster tool. The 25-class raster and the RGB orthomosaic were used as input for the Export Training Data for Deep Learning tool, with the metadata format set on classified tiles. The output creates a folder containing images, labels, maps, and stats of the created training data or image chips identified in the drone imagery (2.9 cm^2; Page et al. 2022). We applied the Train Deep Learning Model tool (Esri 2022) to the RGB orthomosaic and image chips using the following parameters: max epochs (amount of times the dataset will be passed back and forth through the neural network) set at a default value of 20, model type was u-net pixel classification, batch size of training samples processed at a time is the default size of 2, backbone model is the default ResNet-34 (preconfigured model with more than 1 million images and is 34 layers deep), and validation percentage at a default value of 10 (10 percent of the training samples will be used to validate the model; ESRI 2022). Finally, we used the Classify Pixels Using Deep Learning tool with an input raster of the RGB orthomosaic and model definition of Esri Model Definition File and Deep Learning Model Package. The deep-learning model classified pixels based on training data and classified imagery which we then reclassified into 4 land cover classes: corn (undamaged), wild pig damaged corn, herbaceous, and bare (Figure 4). The above steps were summarized in a workflow created to assist other researchers planning to follow similar methods of classifying crop damage (Figure S1, available in Supporting Information).

To improve the accuracy of our classification for 3 fields during the blister milk and dent mature growth stages, we created 150 points for each observed class in the RGB orthomosaic: corn (undamaged), wild pig damaged corn, herbaceous, and bare (Figure S1). We extracted the height values for each one of the points from the nDSM layer, calculated mean height per land cover class, and reclassified the nDSM layer (Michez et al. 2016) into 4 land cover classes using the mean and standard error. We used the reclassified nDSM to correct land cover classes that had more than one cover type. We repeated this procedure for each field to account for variability in terrain, vegetation height, and flight quality (Fischer et al. 2019). We combined the classified imagery produced from deep-learning and the reclassified nDSM by using the Raster Calculator tool in ArcMap 10.8 (ESRI) to obtain a final classification for the imagery (Figure S1). To create a classified image that displayed all classified wild pig damage in one layer, we used the Raster Calculator tool to overlay the final classified image from the blister milk and dent-mature. This layer will be referenced as Combined Damage throughout the manuscript.

We assessed classification accuracy for each classified orthomosaic using a confusion matrix as described by Congalton (1991), Samiappan et al. (2018), and Fischer et al. (2019). We created 400 random points and we assigned a class (corn, damage, herbaceous, or bare) through visual observation of the drone imagery (2.9 cm pixel size) for each one of the points (Pulighe et al. 2016, Mata et al. 2018). We then extracted the raster pixel values from the final classified imagery to each random point. We compared field data and image classification values by constructing a confusion matrix (Table S1, available online in Supporting Information; Congalton 1991). Overall accuracy corresponds to the percent of the number of pixels correctly classified for all classes, producer's accuracy refers to the error of omission for each class (errors of exclusion or how well an area can be classified), and the user accuracy represents the error of commission (error of inclusion or the probability a pixel is correctly classified) for each class (Rutten et al. 2018, Fischer et al. 2019, Page et al. 2022).

Once this process was completed, we then multiplied the number of pixels per class by pixel area (8.41 cm^2) to estimate surface area and percentage of the transect polygons and field that wild pigs damaged. To verify wild pig damage within the transect polygon, we performed a t-test model in R (version 4.2.1, R Core Team 2019) to compare the percentage of damage in the final classified drone orthomosaic to the percentage of damage polygons marked from ground data collection. We used 2-way analysis of variance (ANOVA) in R (R Core Team 2019) to compare mean damage estimated from transect polygons and 100% drone coverage. The dependent variable was percentage of wild pig damage and the 2 independent variables were the method of damage estimation and stage of corn growth.

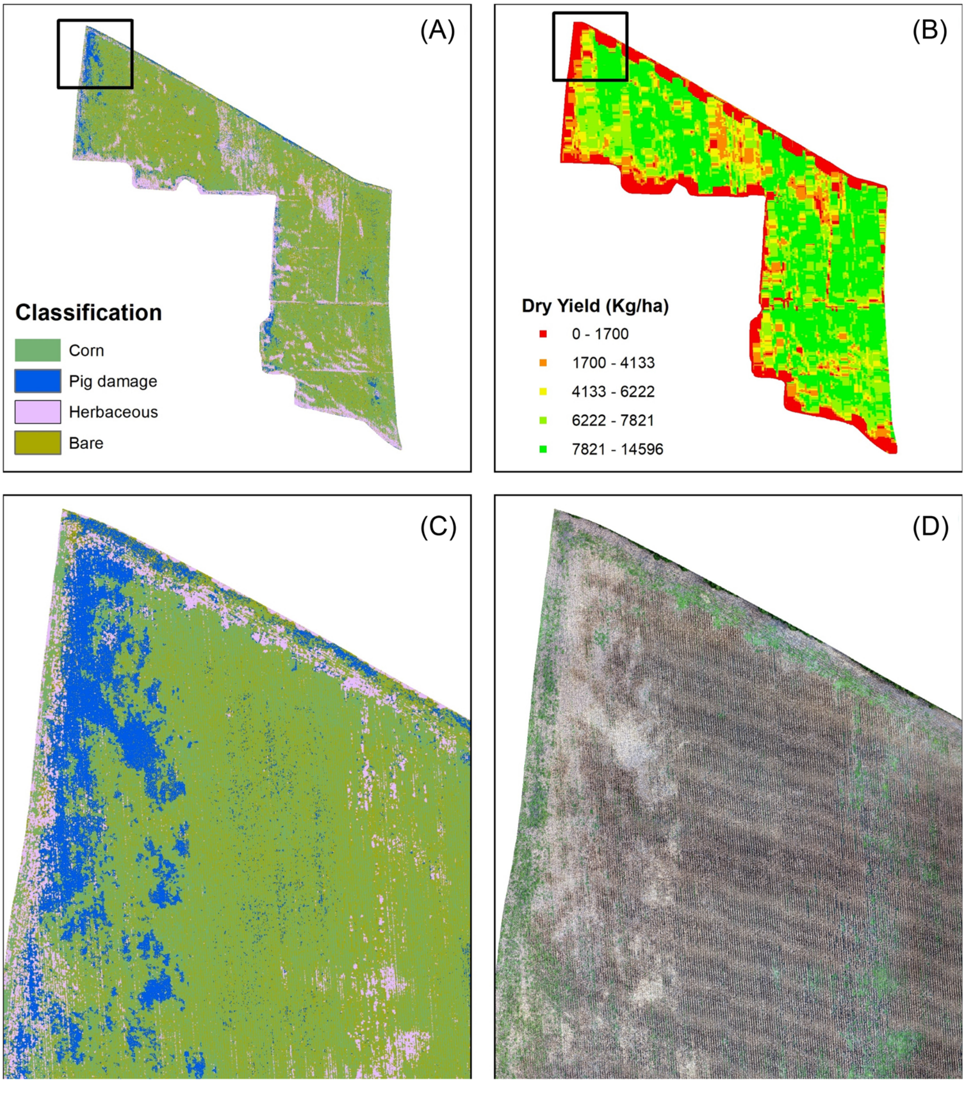

FIGURE 4 Geospatial data collected from field 14 for the study of wild pig damage to corn in Delta County, Texas, USA, in 2019. Classified image with 4 land cover classes (A), harvest yield (B), zoomed classification (C) and orthomosaic captured with drone (D).

For field validation, we estimated the cost of yield loss due to wild pig damage by using the Extract Multi-Values tool in ArcMap 10.8 (ESRI) to extract land cover classes at each harvest yield data point and averaged the dry yield by corn and wild pig damaged corn. This process was used for the final blister-milk, final dent-mature, and combined damage layers for each field. We calculated total loss as follows:

$$\text{Loss in yield} = \text{Corn mean yield} - \text{Damage mean yield} \tag{1}$$

$$\text{Cost} = \text{Loss in yield} * \text{Corn prices (price based on August of appropriate year)} \tag{2}$$

$$\text{Total Loss} = \text{Cost} * \text{Surface area of wild pig damage (ha).} \tag{3}$$

According to the US Department of Agriculture website (https://www.nass.usda.gov/Charts_and_Maps/Agricultural_Prices/pricecn.php), corn was priced at $0.16 per kg on 31 August 2019 and $0.12 per kg on 31 August 2020.

RESULTS

We were able to produce orthomosaics for 28 of the 36 drone missions flown. The final data set for analysis consisted of 18 orthomosaics: 4 during the establishment stage, 8 during the vegetative stage, 3 during the blister-milk stage, and 3 during the dent-mature stage. The remaining 10 orthomosaics were not included in analysis because image processing errors prevented development of a DSM or DTM, or because of gaps in image stitching. We were also unable to obtain harvest data for 3 of the 5 fields in 2020 due to the farmer using different harvesting equipment, which did not provide yield estimates.

From the nDSM in latter growth stages, we found that mean corn height ranged from 0.67 to 0.95 m and mean damage height ranged from 0.14 to 0.27 m (Figure 5). Overall accuracies of the image classification from the 3 fields in the blister-milk stage and dent-mature stage were all ≥80% (Table 2). Producer's accuracy averaged 92.0% for corn and 70.1% for wild pig damage, meaning a 92.0% probability that corn observed on the ground is correctly

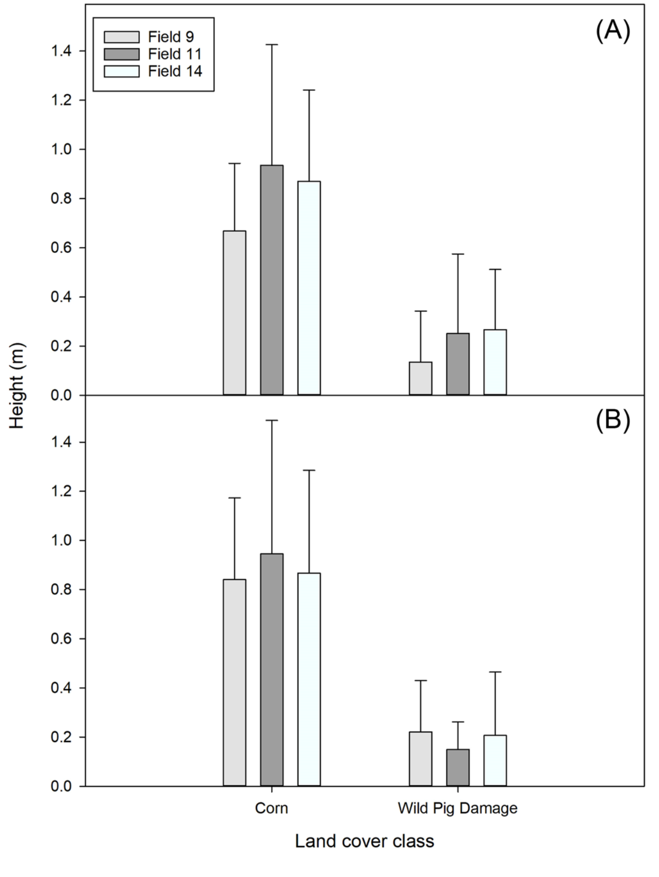

FIGURE 5 Mean heights and standard deviations of corn and wild pig damaged corn cover classes, derived from height rasters of fields 9, 11, and 14 in Delta County, Texas, USA, during the blister-milk (A) and dent-mature stages (B) of corn growth in 2019 and 2020.

TABLE 2 Overall accuracy, producer's accuracy (error of omission), and user's accuracy (error of commission) of the classification of corn and wild pig damage via drone orthomosaics during blister-milk, dent-mature growth stages, and combined damage of corn in Fields 9, 14, and 11 in Delta County, Texas, USA, during 2019 and 2020.

Year	Field	Stage	Overall accuracy[a]	Cover class	Producer's accuracy[b]	User's accuracy[c]
2019	9	Blister-milk	87.6%	Corn	93.9%	66.7%
				Damage	66.7%	91.0%
		Dent-mature	86.5%	Corn	91.3%	33.3%
				Damage	60.0%	87.6%
		Combined damage	80.0%	Corn	88.2%	97.0%
				Damage	73.3%	100.0%
	14	Blister-milk	87.4%	Corn	94.1%	91.0%
				Damage	50.0%	40.0%
		Dent-mature	88.0%	Corn	87.8%	92.6%
				Damage	75.0%	75.0%
		Combined damage	83.5%	Corn	90.6%	89.5%
				Damage	70.0%	58.3%
2020	11	Blister-milk	90.3%	Corn	93.4%	96.4%
				Damage	85.7%	66.7%
		Dent-mature	87.9%	Corn	96.0%	90.3%
				Damage	75.0%	60.0%
		Combined damage	88.4%	Corn	92.9%	95.0%
				Damage	75.0%	81.0%

[a]The proportion of the image classified correctly.

[b]The error of omission; probability a pixel on the ground was classified correctly.

[c]The error of commission; how often the class on the classified image will actually be correct on the ground or RGB orthomosaic.

classified, and 70.1% probability that wild pig damage observed on the ground is correctly classified. Mean user accuracies of the drone orthomosaics classification were 83.5% for corn and 73.3% for wild pig damage, meaning 83.5% of the pixels classified as corn were actually corn and 73.3% of the pixels classified as wild pig damage were actually wild pig damage.

There was no significant difference ($t = -0.38$, df = 9, $P = 0.71$) between wild pig damage verified from the ground data and classified imagery within the transect polygons. No damage was recorded within the transect polygon from ground survey data collection or from drone RGB orthomosaics in 2019 during the establishment stage. We did not identify wild pig damage during the vegetative stage in 2019 and 2020, so they were not classified. The values obtained on the ground within the transect polygons ranged from 0.58 to 0.93% (<0.01–0.03 ha) in the blister-milk stage and 1.57 to 3.81% (0.05 ha–0.16 ha) in the dent mature stage. The percentages of total area classified as wild pig damage within the transect polygons in drone RGB orthomosaics ranged from 1.01 to 1.57% (<0.01–0.05 ha) in the blister-milk stage ($n = 3$) and 1.30 to 3.12% (0.01–0.13 ha) in the dent mature stage ($n = 3$; Table 3).

The 2-way ANOVA test showed that the amount of damage found was significantly different based on the corn growth stage ($F_{(2,25)} = 30.996$, $P < 0.001$), yet overall the method used to estimate damage showed no statistically

TABLE 3 Percentage of wild pig damage to corn fields within transects identified during ground surveys and classified from drone orthomosaic imagery for Fields 9 and 14 in 2019 and Field 11 in 2020 in Delta County, Texas, USA, compared to the total percentage of the field classified as wild pig damage from the UAV orthomosaics.

Year	Field	Field (ha)	Transect (ha)	Stage	Ground transect %	Drone transect %	Drone 100% coverage
2019	9	21 ha	0.69 ha	Blister-milk	0.58%	1.01%	2.43%
	9			Dent-mature	1.74%	1.30%	1.95%
	14	112 ha	4.30 ha	Blister-milk	0.93%	0.93%	1.02%
	14			Dent-mature	3.81%	3.12%	4.12%
2020	11	59 ha	3.18 ha	Blister-milk	0.63%	1.57%	3.25%
	11			Dent-mature	1.57%	1.88%	2.73%

significant difference ($F_{(2,25)} = 2.943$, $P = 0.07$). Damage detected from 100% field coverage by drone detected 100% more damage than transect polygons during the establishment stage in 3 of the 4 fields. Drone-based estimates of wild pig damage during the establishment stage consisted of 2,454 m (0.47% of the field) in field 1, 137 m (0.02% of the field) in field 2, and 3 m (<0.01% of the field) in field 3. Yet, no wild pig damage was detected in field 9 during the establishment stage, which was what we saw in the transect polygons. Most damage was found during the blister-milk stage, where drone classified damage averaged 1.22 ha ($\bar{x}$ = 2.77% of the field) and 2.51 ha ($\bar{x}$ = 3.03% of the field) in the dent-mature stage, respectively. The 100% field coverage by drone detected 38% more damage than the transect polygon estimates.

Total wild pig damage based on drone imagery found within the fields ranged from 4.0 to 9.2% (0.98–10.28 ha). Average yield of corn was 6,948.64 kg/ha and average yield of wild pig-damaged areas was 3,766.41 kg/ha in fields 9, 11, and 14 (Table 4). Area lost in Field 9 in 2019 was 0.98 ha with a yield loss of 2,616.77 kg/ha, so total loss was 2,564.43 kg of corn valued at $410.31. Area lost in Field 14 in 2019 was 10.28 ha with a yield loss 3,439.65 kg/ha, so total loss was 35,359.61 kg of corn valued at $5,657.54. Area lost in Field 11 in 2020 was 2.37 ha with a yield loss of 3,489.86 kg/ha, so total loss was 8,270.96 kg of corn valued at $992.52. Thus, total loss of income due to wild pig damage estimated at $19.54 per ha in Field 9 and $50.51 per ha in Field 14 in 2019 and $16.82 per ha in Field 11 in 2020 (Table 4).

DISCUSSION

Our aim was to give producers the means to conduct economic cost-benefit analyses of wild pig damage to agriculture using drone technology and custom workflows. Our study obtained accurate, real-time harvest data that verified yields in areas that had damaged corn plants and in areas with undamaged corn plants. Previous studies estimated the total field yield by either ground sampling and estimating potential yields (Pandav et al. 2021) or averaging yields from state-wide and county statistics (Foster 2021), both of which can be less accurate due to the diversity of agricultural field conditions, crop varieties, and weather conditions. Studies that used averaged yields and quantified damage based on ground estimates and producer surveys estimated a 0.93% to 1.28% yield loss, which corresponds with our 1.04% yield loss (Foster 2021). Areas of our monitored fields that experienced wild pig damage showed a noticeably lower yield, which was expected, resulting in thousands of dollars in income loss to producers in our study area. Yet, comparing the price of loss varies due to the fluctuating prices of the grain market and the variability of different regions in terms of crop yield potential, which makes it difficult to compare our findings to those of others. Although we were able to quantify direct damage to corn caused by wild pigs, there are

TABLE 4 Estimated area (ha) and average yield (kg/ha) of corn and damage ($USD) caused by wild pigs in Fields 9, 14, and 11 during the blister-milk stage, dent-mature stage, and final classified raster (Combined Damage) in Delta County, Texas, USA, during 2019 and 2020.

Year	Field	Field area (ha)	Stage	Cover class	Cover class total ha	Yield (kg/ha)	Total loss[a]
2019	9	21 ha	Blister-milk	Corn	13.20		
				Damage	0.51		$213.53
			Dent-mature	Corn	7.89		
				Damage	0.41		$171.66
			Combined damage	Corn	15.15	6,138.64	
				Damage	0.98	3,521.87	
				Loss	0.98	2,616.77	$410.31
	14	112 ha	Blister-milk	Corn	73.29		
				Damage	1.14		$627.39
			Dent-mature	Corn	50.63		
				Damage	4.61		$2,537.10
			Combined damage	Corn	49.51	6,841.64	
				Damage	10.28	3,401.99	
				Loss	10.28	3,439.65	$5,657.54
2020	11	59 ha	Blister-milk	Corn	51.80		
				Damage	1.92		$804.06
			Dent-mature	Corn	38.23		
				Damage	1.61		$674.24
			Combined damage	Corn	49.07	7,864.70	
				Damage	2.37	4,374.80	
				Loss	2.37	3,489.86	$992.52

[a]Total loss of income due to wild pig damage.

also indirect costs more difficult to enumerate (Carlisle et al. 2021). For instance, wild pigs rooting up soil in agricultural areas results in damage to farming equipment, and more time and money needed to fix damaged fields prior to planting. Moving forward, indirect costs should be considered when estimating wild pig damage to agriculture.

Our results revealed that the severity of damage by wild pigs to corn is temporally dynamic with corn growth stages. Wild pig damage is most visually obvious during the establishment stage, but the scale of damage at this stage was minimal in terms of lost yield. There was no damage during the vegetative stage, when the plants were less nutritious. Damage peaked during the latter growth stages (blister-milk and dent-mature), when corn provided higher caloric content and cover for thermoregulation and safety (Schley et al. 2008, Bleier et al. 2017, Paolini et al. 2018, Boyce et al. 2020). The damage we observed was similar to previous studies done by producer surveys and ground data collection, with <5.0% of the field area damaged by wild pigs (Anderson et al. 2016, Engeman et al. 2018). In our monitored fields, the percentage of total direct damage to crop fields was similar to previous studies using drones estimating damage and loss of crops due to wild pigs (averaging less than <10%; Samiappan et al. 2018, Fischer et al. 2019, Foster 2021). However, Rutten et al. (2018) found a higher average loss (17.2%) to corn fields due to wild pig damage than we did. Damage may have been more prevalent if there were no removal efforts in our study area (Engeman et al. 2018), but we were unable to evaluate the direct effects of management efforts in this study. Future studies should consider how removal efforts and wild pig abundance throughout each growth stage affects timing and extent of damage (Boyce et al. 2020).

We did not find a statistically significant difference between methods used to estimate damage. The lack of a difference may be due to the smaller sample size we had for this study, resulting in low power to detect a difference (Type II error; Dowdy and Weardon 1991, Reidy et al. 2008, Thiese et al. 2016). However, we observed that when we assessed damage with a 100% field coverage, we obtained ~40% more damage than transects alone. Ground surveys captured a small portion of the field area, which alone may not be sufficient to estimate wild pig damage due to the function of the proportion of the field surveyed. Wild pig damage tends to be clumped and patchily distributed, more commonly near sensitive areas such as field edges near cover or drainage ditches (MacGowan et al. 2006, Boyce et al. 2020, Foster 2021). Overall, the relatively rare occurrence of wild pig damage would require ground survey coverage over much of a field, especially sensitive areas, to accurately estimate damage. Other studies also relied on producer surveys to quantify damaged areas by wild pigs, which can be biased and often overestimated (Anderson et al. 2016, Pandav et al. 2021). Drones allow users to map out the entire field in a time-efficient manner and have the capability of accurately detecting wild pig damage in all growth stages.

We were able to develop imagery analysis workflows to successfully detect damage in all corn growth stages. The approach of machine learning, classifying pixels from RGB mosaics and height rasters, differentiated damaged vs. undamaged corn plants in the blister-milk and dent-mature growth stages with overall accuracies ≥80%, similar to previous studies (Michez et al. 2016, Kuzelka and Surovy 2018, Garcia Millan et al. 2020). Using corn plant height during the blistering and dent mature stages allowed us to differentiate wild pig damage from damage caused by water or wind. The corn that was damaged by wild pigs was trampled and flat along the soil surface, versus corn plants that endure water and wind damage resulting in stunted heights, delayed emergence, and root lodging (Shrestha et al. 2013, Lindsey et al. 2021). The nDSM height raster can be used to detect damage in latter growth stages of other crops such as sorghum, wheat, or hay fields that display a distinct height difference between healthy plants and wild pig damaged plants (Kuzelka and Surovy 2018). However, pixel classification in drone imagery may underestimate wild pig damage due to errors derived from orthomosaic stitching and classification processes (Michez et al. 2016, Samiappan et al. 2018, Fischer et al. 2019). Other approaches that have proven efficient include fully automated object- and feature-based classifications, taking advantage of the unique pattern of wild pig damage (Rutten et al. 2018, Samiappan et al. 2018, Fischer et al. 2019).

The fields we monitored were of larger scale (from 30 ha to 112 ha) than previous studies (from 2 ha to 37 ha; Michez et al. 2016, Samiappan et al. 2018, Fischer et al. 2019). The ability to monitor fields at a relevant scale for producers was advantageous but introduced additional logistical constraints. Because each drone orthomosaic was unique based on vegetative state or weather conditions during the flight, training data for image classification were unique per individual field (Fischer et al. 2019). Flight times required more planning to ensure consistent weather conditions (winds <16 km/h; <10% cloud cover) for the duration of the mission to acquire accurate and high-quality imagery for generating orthomosaics (Wierzbicki et al. 2015). Furthermore, we timed the flights and field assessments to correspond as closely as possible, but sometimes experienced inclement weather, which resulted in some delays. Timing of drone flights 2–5 days after wild pig damage occurs was crucial to positively identify wild pig damage from other types of damage due to the heavy amount of rainfall in our study area. For instance, rainfall or other weather conditions may distort the damaged areas or knock over mature plants. Previous studies have noted similar constraints (Boyce et al. 2020), and these issues become magnified as the size of the area increases. The largest delay of 16–20 days was during the establishment stage, where we also observed either little damage or were unable to use the data due to heavy rainfall. For the remaining stages, we completed surveys within 2 days, sometimes sooner. Additional damage can occur during any lags between measurements, but we note that there was no difference between our ground-based assessments and the drone-based assessment of damage.

RESEARCH IMPLICATIONS

Wild pig damage to corn was found throughout the growing season at different growth stages, with most damage and crop loss occurring during the latter growth stages where the corn plants are maturing and provide cover. Drones covered >95% more area than ground surveys, allowing us to detect and estimate damage that would be missed from transects due to the clumpy distribution of wild pig damage. Drone technologies are advancing quickly and becoming a more common practice in the wildlife and agricultural industry. Drones can be a great tool for landowners and producers to accurately estimate wild pig damage and crop yield loss, and to receive compensation for their lost income.

ACKNOWLEDGMENTS

We are grateful to the staff of USDA APHIS Texas Wildlife Services and private landowners in Delta County, Texas, USA, for their cooperation which allowed us to carry out this project. We thank J. Baumgardt and A. Foley for the comments and suggestions and the 2 anonymous reviewers who helped improve this manuscript. We thank M. Page and R. Combs, who contributed to data collection, and V. Cavazos for assistance in developing manuscript figures. This is manuscript number No. 22-114 from the Caesar Kleberg Wildlife Research Institute at Texas A&M University-Kingsville. This study was supported by the USDA APHIS Wildlife Services National Feral Swine Damage Management Program Project No. AP20WSHQ0000C004 and The Rotary Club of Corpus Christi Harvey Weil Sportsman Conservationist Award.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

ETHICS STATEMENT

No animals were handled or disturbed as part of the drone research and therefore no Institutional Animal Care and Use Committee protocol was required. All drone operations were conducted by pilots that had their FAA Part 107 permit, followed Federal Aviation Administration (FAA) regulations, and were approved by TAMUK Office of Risk Management.

ORCID

Bethany A. Friesenhahn http://orcid.org/0000-0002-3291-6043
Humberto L. Perotto-Baldivieso http://orcid.org/0000-0001-7700-7110

REFERENCES

Anderson, A., C. Slootmaker, E. Harper, J. Holderieath, and S. A. Shwiff. 2016. Economic estimates of feral swine damage and control in 11 US states. Crop Protection 89:89–94.

Barrios-Garcia, M. N., and S. A. Ballari. 2012. Impacts of wild boar (*Sus scrofa*) in its introduced and native range: a review. Biological Invasions 14:2283–2300.

Bevins, S. N., K. Pedersen, M. W. Lutman, T. Gidlewski, and T. J. Delberto. 2014. Consequences associated with the recent range expansion of nonnative feral swine. BioScience 64:291–299.

Bleier, N., I. Kovacs, G. Schally, L. Szemethy, and S. Csanyi. 2017. Spatial and temporal characteristics of the damage caused by wild ungulates in maize (*Zea mays* L.) crops. International Journal of Pest Management 63:92–100.

Bohon, R. K., Jr. 2014. Comparing Landsat7 ETM+ and NAIP imagery for precision agriculture application in small scale Farming: a case study in the south eastern part of Pittsylvania County, VA. Thesis, University of Southern California, Los Angeles, USA.

Boyce, C. M., K. C. VerCauteren, and J. C. Beasley. 2020. Timing and extent of crop damage by wild pigs (*Sus scrofa* Linnaeus) to corn and peanut fields. Crop Protection 133:105131.

Carlisle, K. M., N. Didero, S. McKee, J. Elser, and S. A. Shwiff. 2021. Towards a more comprehensive understanding of wild pig (*Sus scrofa*) impacts on agricultural producers: insights from a Texas case study. Crop Protection 150:105793.

Congalton, R. G. 1991. A review of assessing the accuracy of classification of remotely sensed data. Remote Sensing of Environment 37:35–46.

DiMaggio, A. M., H. L. Perotto-Baldivieso, J. Alfonso Ortego-S., C. Walther, K. N. Labrador-Rodriguez, M. T. Page, J. de la Luz Martinez, S. Rideout-Hanzak, B. C. Hedquist, and D. B. Wester. 2020. A pilot study to estimate forage mass from unmanned aerial vehicles in a semi-arid rangeland. Remote Sensing 12(15):p2431.

Dowdy, S., and S. Weardon. 1991. Statistics for research. Second edition. John Wiley and Sons, New York, New York, USA.

Engeman, R. M. 2017. Estimating feral swine damage to row crops just after planting. In: General Procedural Guide for WS operations to Implement Practical Damage Estimation. Wildlife Services Tech Note, Part of the WS Damage Assessment Series. USDA-APHIS, Wildlife Services National Wildlife Research Center, Ft. Collins, Colorado, USA.

Engeman, R. M., and R. T. Sterner. 2002. A comparison of potential labor-saving sampling methods for assessing large mammal damage in corn. Crop Protection 21:101–105.

Engeman, R. M., and R. T. Sugihara. 1998. Optimization of variable area transect sampling using Monte Carlo simulation. Ecology 79:1425–1434.

Engeman, R. M., J. Terry, L. R. Stephens, and K. S. Gruver. 2018. Prevalence and amount of feral swine damage to 3 row crops at planting. Crop Production 112:252–256.

ESRI. 2022. Train deep learning model: image analyst. https://pro.arcgis.com/en/pro-app/latest/tool-reference/image-analyst/train-deep-learning-model.htm. Accessed 28 Nov 2022.

Ferentinos, K. P. 2018. Deep learning models for plant disease detection and diagnosis. Computers and Electronics in Agriculture 145:311–318.

Fischer, J. W., K. Greiner, M. W. Lutman, B. L. Webber, and K. C. VerCauteren. 2019. Use of unmanned aircraft systems (UAS) and multispectral imagery for quantifying agricultural areas damaged by wild pigs. Crop Protection 125:104865.

Fischer, J. W., N. P. Snow, B. E. Wilson, S. F. Beckerman, C. N. Jacques, E. H. VanNatta, S. L. Kay, and K. C. VerCauteren. 2020. Factors and costs associated with removal of a newly established population of invasive wild pigs in Northern U.S. Scientific Reports 10(1):11528.

Foster, D. H. 2021. Estimation of wild pig damage to corn production in the Mississippi Alluvial Valley. Thesis, Mississippi State University, Mississippi State, USA.

Frotscher, K., R. Schacht, L. Smith, and E. Zillmann. 2016. Planet Labs' monitoring solution in support of precision agriculture practices. Pages 1–11 *in* Proceedings of the 13th International Conference of Precision Agriculture. International Society of Precision Agriculture, 13 July–4 August 2016, St. Louis, Missouri, USA.

Garcia Millan, V. E., C. Rankine, and G. Arturo Sanchez-Azofeifa. 2020. Crop loss evaluation using digital surface models from unmanned aerial vehicles data. Remote Sensing 12(6):981.

Garza, B. N., V. Ancona, J. Enciso, H. L. Perotto-Baldivieso, M. Kunta, and C. Simpson. 2020. Quantifying citrus tree health using true color UAV images. Remote Sensing 12(1):170.

Gentle, M., S. Phinn, and J. Speed. 2011. Assessing pig damage in agriculture with remote sensing. Bureau of Rural Sciences Australian Pest Animal Management Program Final Report, University of Queensland, Brisbane, Australia.

Gilsdorf, J. M., S. E. Hygnstrom, K. C. VerCauteren, E. E. Blankenship, and R. M. Engeman. 2004. Propane exploders and electronic guards were ineffective at reducing deer damage in cornfields. Wildlife Society Bulletin 32:524–531.

Gong, W., J. Sinden, M. Braysher, and R. Jones. 2009. The economic impacts of vertebrate pests in Australia. Invasive Animals Cooperative Research Centre, Canberra, Australia.

Green, D. R., J. J. Hagon, C. Gomez, and B. J. Gregory. 2019. Using low-cost UAVs for environmental monitoring, mapping, and modelling: examples from the coastal zone. Pages 465–501 *in* R. R. Krishnamurthy, M. P. Jonathan, S. Srinivasalu, and B. Glaeser, editors. Coastal management: global challenges and innovations, Academic Press, Elsevier, London.

Grisso, R. D., M. Alley, and P. McClellan. 2009. Precision farming tools: yield monitor. Virginia Cooperative Extension Publication 442–502.

Gustafson, K. B., P. S. Coates, C. L. Roth, M. P. Chenaille, M. A. Ricca, E. Sanchez-Chopitea, and M. L. Casazza. 2018. Using object-based image analysis to conduct high-resolution conifer extraction at regional spatial scales. International Journal of Applied Earth Observation and Geoinformation 73:148–155.

Herrero, J., A. Garcia-Serrano, S. Couto, V. M. Ortuno, and R. Garcia-Gonzalez. 2006. Diet of wild boar *Sus scrofa L.* and crop damage in an intensive agroecosystem. European Journal of Wildlife Research 52:245–250.

Hess, S. C., N. H. Wehr, and C. M. Litton. 2020. Wild Pigs in the Pacific Islands. Pages 403–421 *in* K. VerCauteren, J. Beasley, S. S. Ditchkoff, J. J. Mayer, G. J. Roloff, and B. K. Strickland, editors. Invasive Wild Pigs in North America: Ecology, Impacts, and Management. CRC Press, Boca Raton, Florida, USA.

Hill, C. M. 1997. Crop-raiding by wild vertebrates: the farmer's perspective in an agricultural community in western Uganda. International Journal of Pest Management 43:77–84.

Hodgson, J. C., S. M. Baylis, R. Mott, A. Herrod, and R. H. Clarke. 2016. Precision wildlife monitoring using unmanned aerial vehicles. Scientific Reports 6:22574.

Houborg, R. and M. F. McCabe. 2016. High-resolution NDVI from Planet's constellation of earth observing nano-satellites: a new data source for precision agriculture. Remote Sensing 8(9):768.

Jimenez-Jimenez, S. I., W. Ojeda-Bustamante, M. de Jesus Marcial-Pablo, and J. Enciso. 2021. Digital terrain models generated with low-cost UAV photogrammetry: methodology and accuracy. International Journal of Geo-Information 10(5):285.

Kuzelka, K., and P. Surovy. 2018. Automatic detection and quantification of wild game crop damage using an unmanned aerial vehicle (UAV) equipped with an optical sensor payload: a case study in wheat. European Journal of Remote Sensing 51:241–250.

Lemenkova, P. 2021. ISO cluster classifier by ArcGIS for unsupervised classification of the LANDSAT TM image of Reykjavik. Bulletin of Natural Sciences Research 11:29–37.

Lewis, J. S., J. L. Corn, J. J. Mayer, T. R. Jordan, M. L. Farnsworth, C. L. Burdett, K. C. VerCauteren, S. J. Sweeney, and R. S. Miller. 2019. Historical, current, and potential population size estimates of invasive wild pigs (*Sus scrofa*) in the United States. Biological Invasions 21:2373–2384.

Lindsey, A. J., P. R. Carter, and P. R. Thomison. 2021. Impact of imposed root lodging on corn growth and yield. Crop Ecology and Physiology 113:5054–5062.

Lowe, S., M. Browne, S. Boudjelas, and M. De Poorter. 2000. 100 of the world's worst invasive species: a selection from the global invasive species database. Invasive Species Specialist Group, Species Survival Commission, World Conservation Union (IUCN), Auckland, New Zealand.

Ludeman, M. M. 2016. Handbook of Texas online: Lamar County. <http://www.tshaonline.org/handbook/online/articles/hcl01>. Accessed 19 Jan 2021.

MacGowan, B. J., L. A. Humberg, J. C. Beasley, T. L. DeVault, and M. I. Retamosa. 2006. Corn and soybean crop depredation by wildlife. Department of Forestry and Natural Resources Publication FNR 265-W, Purdue University, West Lafayette, Indiana, USA.

Massei, G., S. Roy, and R. Bunting. 2011. Too many hogs? A review of methods to mitigate impact by wild boar and feral hogs. Human-Wildlife Interactions 5:79–99.

Mata, J. M., H. L. Perotto-Baldivieso, F. Hernández, E. D. Grahmann, S. Rideout-Hanzak, J. T. Edwards, M. T. Page, and T. M. Shedd. 2018. Quantifying the spatial and temporal distribution of tanglehead (*Heteropogon contortus*) on South Texas rangelands. Ecological Processes 7:2.

Mayr, M. J., S. Malß, E. Ofner, and C. Samimi. 2018. Disturbance feedbacks on the height of woody vegetation in a savannah: a multi-plot assessment using an unmanned aerial vehicle (UAV). International Journal of Remote Sensing 39:4761–4785.

McCann, B. E., T. J. Smyser, B. S. Schmit, R. A. Newman, A. J. Piaggio, M. J. Malek, S. R. Swafford, R. A. Sweitzer, and R. B. Simmons. 2018. Molecular population structures for feral swine in the United States. Journal of Wildlife Management 82:821–832.

McCroskey, V. K. 2016. Handbook of Texas online: Delta County. <https://tshaonline.org/handbook/online/articles/hcd05>. Accessed 19 Jan 2021.

McKee, S., A. Anderson, K. Carlisle, and S. A. Shwiff. 2020. Economic estimates of invasive wild pig damage to crops in 12 US states. Crop Protection 132:105105.

Michez, A., K. Morelle, F. Lehaire, J. Widar, M. Authelet, C. Vermeulen, and P. Lejeune. 2016. Use of unmanned aerial system to assess wildlife (*Sus scrofa*) damage to crops (*Zea mays*). Journal of Unmanned Vehicle Systems 4:266–275.

Nafziger, E. 2009. Corn. Pages 13–26 *in* Illinois agronomy handbook. University of Illinois Extension, Urbana, Illinois, USA.

Page, M. T., H. L. Perotto-Baldivieso, J. A. Ortega-S., E. P. Tanner., J. P. Angerer, R. C. Combs, A. M. Camacho, M. Ramirez, V. Cavazos, H. Carroll, et al. 2022. Evaluating mesquite distribution using unpiloted aerial vehicles (UAVs) and satellite imagery. Rangeland Ecology & Management 83:91–101.

Pandav, B., L. Natarjan, A. Kumar, A. A. Desai, and B. Lyngkhoi. 2021. Household perceptions and patterns of crop loss by wild pigs in north India. Human-Wildlife Interactions 15:56–65.

Paolini, K. E., B. K. Strickland, J. L. Tegt, K. C. VerCauteren, and G. M. Street. 2018. Seasonal variation in preference dictates space use in an invasive generalist. PLoS ONE 13(7):e0199078.

Pedrosa, F., R. Salerno, F. V. B. Padhilha, and M. Galetti. 2015. Current distribution of invasive feral pigs in Brazil: economic impacts and ecological uncertainty. Brazilian Journal of Nature Conservation 13:84–87.

Perotto-Baldivieso, H. L., S. Tapaneeyakul, and Z. J. Pearson. 2020. Using geospatial technologies in wildlife studies. *In* N. J. Silvy, editor. Application of spatial technologies in wildlife research. Wildlife Techniques Manual. Eighth Edition. Volume I: Research. Johns Hopkins University Press, Baltimore, Maryland, USA.

Poudyal, N. C., C. Caplenor, O. Joshi, C. Maldonado, L. I. Muller, and C. Yoest. 2017. Characterizing the economic value and impacts of wild pig damage on a rural economy. Human Dimensions of Wildlife 22:538–549.

Pulighe, G., V. Baiocchi, and F. Lupia. 2016. Horizontal accuracy assessment of very high resolution Google Earth images in the city of Rome, Italy. International Journal of Digital Earth 9:342–362.

Reidy, M. M., T. A. Campbell, and D. G. Hewitt. 2008. Evaluation of electric fencing to inhibit feral pig movements. Journal of Wildlife Management 72:1012–1018.

Rembold, F., M. Meroni, F. Urbano, A. Royer, C. Atzberger, G. Lemoine, H. Eerens, and D. Haesen. 2015. Remote sensing time series analysis for crop monitoring with the SPIRITS software: new functionalities and use examples. Frontiers in Environmental Science 3:46.

R Core Team. 2019. R: a language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria.

Rutten, A., J. Casaer, M. F. A. Vogels, E. A. Addink, J. V. Borre, and H. Leirs. 2018. Assessing agricultural damage by wild boar using drones. Wildlife Society Bulletin 42:568–576.

Samiappan, S., J. M. P. Czarnecki, H. Foster, B. K. Strickland, J. L. Tegt, and R. J. Moorhead. 2018. Quantifying damage from wild pigs with small unmanned aerial systems. Wildlife Society Bulletin 42:304–309.

Schley, L., M. Dufrene, A. Krier, and A. C. Frantz. 2008. Patterns of crop damage by wild boar (*Sus scrofa*) in Luxembourg over a 10-year period. European Journal of Wildlife Research 54:589–599.

Schley, L., and T. J. Roper. 2003. Diet of a wild boar *Sus scrofa* in western Europe, with particular reference to consumption of agricultural crops. Mammal Review 33:43–56.

Seward, N. W., K. C. VerCauteren, G. W. Witmer, and R. M. Engeman. 2004. Feral swine impacts on agriculture and the environment. Sheep & Goat Research Journal 19:34–40.

Shrestha, R., L. Di, G. Yu, Y. Shao, L. Kang, and B. Zhang. 2013. Detection of flood and its impact on crops using NDVI—Corn case. Pages 200–204 *in* Proceedings of the Second International Conference on Agro-Geoinformatics. 12–16 August 2013, Fairfax, Virginia, USA.

Singer, F. J., W. T. Swank, and E. E. C. Clebsch. 1984. Effects of wild pig rooting in a deciduous forest. Journal of Wildlife Management 48:464–473.

Tabak, M. A., A. J. Piaggio, R. S. Miller, R. A. Sweitzer, and H. B. Ernest. 2017. Anthropogenic factors predict movement of an invasive species. Ecosphere 8(6):e01844.

Taddia, Y., F. Stecchi, and A. Pellegrinelli. 2020. Coastal mapping using DJI Phantom 4 RTK in post-processing kinematic mode. Drones 4:9.

Thiese, M. S., B. Ronna, and U. Ott. 2016. P value interpretations and considerations. Journal of Thoracic Disease 8: E928–931.

Tzilkowski, W. M., M. C. Brittingham, and M. J. Lovallo. 2002. Wildlife damage to corn in Pennsylvania: farmer and on-the-ground estimates. Journal of Wildlife Management 66:678–682.

United States Department of Agriculture [USDA]. 2017. 2017 Census of Agriculture: Delta County Texas. <https://www.nass.usda.gov/Publications/AgCensus/2017/OnlineResources/County_Profiles/Texas/cp48119.pdf>. Accessed 19 Jan 2021.

Weiss, M., F. Jacob, and G. Duveiller. 2020. Remote sensing for agricultural applications: a meta-review. Remote Sensing of Environment 236:111402.

West, C. B., A. L. Cooper, and J. B. Armstrong. 2009. Managing wild pigs: a technical guide. Human-Wildlife Interactions Monograph 1:1–55.

Wierzbicki, D., M. Kedzierski, and A. Fryskowska. 2015. Assessment of the influence of UAV image quality on the orthophoto production. International Archives of the Photogrammetry, Remote Sensing & Spatial Information Sciences, Conference on Unmanned Aerial Vehicles in Geomatics, 30 Aug–02 Sep 2015, Toronto, Canada.

Wilmshurst, J. M., T. L. Hunt, C. P. Lipo, and A. J. Anderson. 2011. High-precision radiocarbon dating shows recent and rapid initial human colonization of east Polynesia. Proceedings of the National Academy of Sciences 108:1815–1820.

Wood, G. W., and R. H. Barrett. 1979. Status of wild pigs in the United States. Wildlife Society Bulletin 7:237–246.

Associate Editor: M. Byrne.

SUPPORTING INFORMATION

Additional supporting material may be found in the online version of this article at the publisher's website.

How to cite this article: Friesenhahn, B. A., L. D. Massey, R. W. DeYoung, M. J. Cherry, J. W. Fischer, N. P. Snow, K. C. VerCauteren, and H. L. Perotto-Baldivieso. 2023. Using drones to detect and quantify wild pig damage and yield loss in corn fields throughout plant growth stages. Wildlife Society Bulletin 47:e1437. https://doi.org/10.1002/wsb.1437