Using Unoccupied Aircraft System (UAS) to Assess Crop Damage by Wild Pigs in Alabama

by

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Abstract

Agriculture is essential for human sustenance and global economies, cultures, and societies. However, wildlife damage to crops can significantly diminish productivity, necessitating effective mitigation strategies. Among the most destructive species are wild pigs (*Sus scrofa*), renowned for their severe impact on row crop damage through consumption, rooting, and trampling. In our study, we assessed the extent of wild pig damage to row crop fields in southern Alabama, USA. We utilized aerial imagery collected via unoccupied aircraft systems (UAS) and developed detection models using deep learning algorithms to quantify damage. Additionally, we evaluated the economic ramifications of wild pig damage on row crops and analyzed surrounding landscape elements as potential predictors of field predation by wild pigs. We successfully developed detection models with over 90% accuracy for corn and peanut crops. However, our attempts to develop a similar model for cotton proved infeasible due to flying at too high of an altitude, resulting in a ground sampling distance (GSD) with a resolution that was too large. Corn experienced more frequent damage compared to peanuts and the average amount of damage was greater for damaged corn fields (0.12 ha, 6.28% overall field damage) than damaged peanut fields (0.08 ha, 0.38% overall field damage). However, the cumulative losses were greater for peanut (n = 23 fields, $5,675.18, averaged $16.13/ha across damaged fields) than corn (n = 6 fields, $3,164.05, $49.21/ha). Furthermore, crop type, distance to water, and landscape patch density were significant contributors to the likelihood of wild pig-induced damage. Our findings offer valuable insights for policymakers, landowners, and wildlife managers striving to combat the challenges posed by wild pig predation in agricultural landscapes. By integrating ecological understanding with practical management strategies, we can effectively address the adverse impacts of wild pig predation and sustain agricultural productivity.

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Chapter 1: Using UAS to classify and measure the amount of wild pig damage to agricultural fields in Alabama

ABSTRACT:

Wild pigs (*Sus scrofa*), an invasive species, pose a significant threat to United States agriculture. Despite extensive research on wild pig damage, a gap exists in reliable and accessible methods for quantifying such damage in row crop fields, particularly in short-standing crops like peanuts. Our study addresses this gap by utilizing unoccupied aircraft system (UAS)-collected imagery to develop deep learning algorithms for estimating row crop damage caused by wild pigs and resulting financial losses. Using a UAS, we quantified wild pig damage in corn, cotton, and peanut fields on 15 private agricultural production farms in southwest and southeast Alabama during 2021 and 2022. Ground-truthing, validated by a handheld GPS unit, confirmed wild pig damage. Deep learning algorithms, developed in ArcGIS Pro 2.9 using orthomosaics from six damaged corn fields and 22 damaged peanut fields, successfully delineated damaged areas. While corn and peanut models demonstrated accuracy >90%, the altitude at which we collected data resulted in imagery that was too coarse for the development of a model for cotton. The average area of corn damage was 0.12 ha, with 6.28% average damage per field that contained damage. Peanut fields exhibited smaller areas of damage (0.08 ha) and a lower percentage of damage across damaged fields (0.38%). However, across 28 damaged fields, the total loss to producers within our study amounted to USD $5,675.18 (averaged $16.13/ha across damaged fields) for peanuts and $3,164.05 (averaged $49.21/ha across damaged fields) for corn. Our integrated approach, utilizing UAS imagery data and trained models, proves effective in detecting and quantifying wild pig damage, contributing to accurate assessments of economic losses endured by producers.

INTRODUCTION

Wild pigs (*Sus scrofa*) are a prolific invasive species with a global presence, excluding only Antarctica (Long 2003). Being one of the most widely distributed mammals in the world (Massei and Genov 2004), wild pigs present a significant threat to agriculture within their native Eurasia and North Africa (Barrios-Garcia and Ballari 2012) and non-native range, including North America (Mayer and Brisbin 2009). Particularly abundant in the southeastern region of the United States (McKee et al. 2021), wild pigs consume a variety of crops, including peanut (*Arachis hypogaea*), corn (*Zea mays*), and cotton (*Gossypium* spp.), closely followed by wildlife food plots, wheat (*Triticum* spp.), pecans (*Carya illinoensis*), hay/pasture, blackberries (*Rubus* spp.), sorghum (*Sorghum* spp.), and oats (*Avena sativa*; Mengak 2012) resulting in significant loss in crop production. Although estimates vary widely, a conservative evaluation of wild pig damage to agriculture in the United States is over USD $1 billion annually (Pimental 2007, McKee et al. 2020, Carlisle et al. 2021) mainly from direct consumption or trampling of crops (Figure 1.1). For example, Anderson et al. (2016) projected estimates based on data from 10 states and found a total crop loss of $190 million across only six crop types. Similarly, Engeman et al. (2018) conducted an assessment during planting in Alabama, identifying damaged soil and measuring damaged row length for corn, peanut, and cotton. Their findings indicated an estimated loss value of $16,770.84 across seven fields. Notably, Engeman et al. (2018) theorized a preference for peanuts over other crops, noting a 40% damage rate in peanut fields compared to 15.4% for cotton and 21.9% for corn.

While wild pigs cause direct financial damage by destroying crops, they also cause indirect losses such as lost opportunity and time/labor costs (Carlisle et al. 2021). Moreover, their rooting damages machinery (Frederick 1998); Mengak (2012) found that producers in Georgia spend approximately $2.2 million annually repairing equipment damaged by wild pigs, totaling $98.8 million in crop loss and associated expenses. In Mississippi, Tegt and Strickland (2018) surveyed 803 individuals via mail and online surveys, revealing a total reported expenditure of $667,000 on equipment repair, labor, and population control, with an average of $14.05–15.61 per hectare, resulting in a statewide loss of $60–67 million. Similarly, in Louisiana, Tanger et al. (2015) identified $1.2 million spent on infrastructure damage and increased production costs due to wild pigs, culminating in $74 million in losses. Poudyal et al. (2017) estimated that control and eradication efforts in Tennessee cost $2.09 million in 2015 alone, resulting in $28 million spent on mitigating wild pig damage.

Although numerous attempts have been made to estimate agricultural damage caused by wild pigs, achieving accurate assessments remains challenging. Shortcomings arise from the need to simplify damage calculations despite potentially impactful nuances such as the flexible ecology of wild pigs, weather, farm conditions, and crop prices that can greatly impact estimations (Bengsen et al. 2014). Landowner surveys are frequently used to estimate damage and financial loss; however, surveys are susceptible to biases (Bengsen et al. 2014), including respondent's ability to accurately assess the amount of damage and the artificial inflation of reported losses due to non-response bias—individuals unaffected by damage are less likely to participate (Garshelis et al. 1999). Furthermore, inherent biases, such as sampling errors and the absence of ground-truthing, can introduce uncertainties in estimations (Kuželka and Surový (2018). Bias disparities may lead to damage being either overrepresented or underrepresented in broad depictions, making it challenging to confidently attribute observed damage to wild pigs (Samiappan et al. 2018). An illustrative example was provided by Pandav et al. (2021), where landowner surveys reported perceived losses significantly higher than actual losses in wild pig damage to wheat. The measured damage resulted in an average of 58.8 kg per farm, whereas the perceived/reported damage was 520 kg per farm. Landowner surveys inherently harbor biases that can skew results.

Alternative approaches have been used to measure crop damage caused by wild pigs to address possible sources of bias. For example, Chavarria et al. (2007) used handheld GPS units to estimate rooted area via line-transects, calculating the simple polygon area by multiplying the longest length by the width's center point. However, this simplified approach led to overestimation due to wild pigs creating damage in irregular shapes, inadvertently conflating damaged and non-damaged areas. Advancing upon previous methods, Felix et al. (2014) more accurately mapped the entire rooted area without simplifying polygons, incorporating rooting age and severity while recording re-rooting events. However, this method was prone to observer error due to its high cost and labor requirements. Considering the substantial time and resources demanded by line-transect methods, Thomas et al. (2013) studied the trade-offs between sampling intensity (transect spacing), and estimation accuracy. Thomas et al. (2013) determined the Total Length Method to be optimal (consistently low relative root mean squared error, RRMSE), where the sum of damaged lengths along each transect were divided by the total length. Ideally, 5-m intervals minimized labor while producing acceptable estimates. However, Thomas et al. (2013) noted even their best method achieved only 66% accuracy. Recognizing infield observers' limitations (e.g., labor-intensiveness, potential for data collection-related damage, resource requirements), Salamí et al. (2014) and Michez et al. (2016) highlighted the increasing value of remote sensing and proposed a promising alternative: unoccupied aircraft systems.

Unoccupied aircraft systems (UAS) and unoccupied aerial vehicles (UAV or drones) have been used recently to measure crop damage, utilizing quickly deployable, remotely controlled aircraft to capture high-resolution imagery data. Already used in other agricultural sectors such as precision agriculture, pesticide dispersal, seed mapping, and crop production management (Watts et al. 2010), UAS are recently being recognized for their expanded use in estimating wild pig damage within agriculture. The time-saving advantages of using UAS-collected imagery are evident. For instance, Anderson (2020) noted that the volume of data gathered through UAS surpassed what could have been achieved within the same timeframe using ground-based methods. Further, Michez et al. (2016) found that UAS-based methods required only 10–25% of the time compared to their ground approach (0.5–1.3 man-hours/ha versus 5.1 man-hours/ha) when recording the number of damaged corn stalks. Similarly, Kuželka and Surový (2018) highlighted a significant contrast in data collection time between UAS (150 min) and infield assessment involving GPS-delineated damaged areas (26 hours) for the same 5-ha field.

While the time-saving benefits are apparent, ongoing research is still refining the optimal utilization of UAS for row crop damage identification. For example, using crop height models, researchers like Michez et al. (2016), Kuželka and Surový (2018), and Friesenhahn et al. (2023) were able to differentiate between damaged and healthy tall-standing vegetation such as corn and wheat. Michez et al. (2016) and Kuželka and Surový (2018) used light detection and ranging (LiDAR) laser scanning to generate digital 3D renderings of their study areas in Belgium and Czech Republic, respectively, utilizing image texture differentiation. While Michez et al. (2016) found both UAS-based methods tested (operator delineated and height threshold) slightly underestimated damage compared to ground-based approaches, the difference was not significant. In a wheat-focused study, Kuželka and Surový (2018) achieved high accuracy (97%

and 95%) comparing their ground-based method (representing height differences through digital surface method) and UAS-based (3D point cloud of field surface). In comparison, Friesenhahn et al. (2023) used deep learning algorithms and unsupervised classification for corn fields in Texas, yielding 80% overall accuracy. However, the utilization of height differences between healthy and damaged crops might not be applicable for crops that mature at lower levels (e.g., peanuts) or for wind-blown crops that have been flattened (Kuželka and Surový 2018).

Straying from using height disparities as the primary damage indicator, Samiappan et al. (2018) estimated infield corn damage using visible data and textural analysis of UAS-collected imagery coupled with support vector machines. However, their outcomes underestimated damage with 65–78% accuracy due to classification errors and fixed-wing aircraft rotation (e.g., roll, yaw, pitch) during image capture, aligning with Engeman et al. (2016) findings that off-nadir (90°) sensor angles can decrease accuracy. Departing from pixel-centric methods, both Michez et al. (2016) and Rutten et al. (2018) implemented object-based classification, categorizing pixels with similar spectral and shape characteristics as reference training samples. In their prediction classifier within corn fields, Rutten et al. (2018) achieved a model performance of 84.5%. Using multispectral imagery in addition to RGB, Fischer et al. (2019) achieved accuracies ranging from 74–98% with a slightly lower range of 72–94% with RGB imagery alone. However, other studies (Boyce et al. 2020, Dobosz et al. 2023, Engeman et al. 2016) suggest that the addition of multispectral imagery does not significantly improve accuracy, if at all, and incurs additional costs for specialized sensors.

Conventional infield and landowner survey methods may inadequately capture accurate depictions of crop damage and its income-related impact (Rutten et al. 2018, McKee et al. 2020, Carlisle et al. 2021, Friesenhahn et al. 2023). A pressing need exists for a standardized approach to consistently and comprehensively identify and quantify wild pig damage. Consequently, the objectives of this study were twofold: to use UAS-collected imagery for creating deep learning algorithms that estimate wild pig row crop damage with applicability across diverse study sites and sustained high precision, and to estimate the amount of damage caused by wild pigs and resulting financial loss to producers.

STUDY AREA

Our research was conducted under the auspices of the Alabama Soil and Water Conservation Committee (SWCC) Feral Swine Control Program and was therefore restricted to pre-determined focal areas within Alabama. Specifically, our study was conducted at 15 privately-owned farms located in the Lower Coastal Plain (LCP, Baldwin and Escambia counties) and Wiregrass (WIRE, Houston, Henry, and Geneva counties) regions of Alabama (Figure 1.2). Study regions were characterized by a considerable extent of row crop, with peanuts, cotton, and corn being the primary crops. Mean annual rainfall during 2021–2022 was 138.1 cm in Houston, 136.1 cm in Henry, and 146.0 cm in Geneva counties (National Oceanic and Atmospheric Administration 2023). In terms of landscape structure, the WIRE region was comprised of row crop/pasture/hay (36% of land area), forest (33%), human development (7.1%), and water/wetland (16%; Dewitz and Geological Survey 2021) with primarily loamy sand with the Bibb-Osler-Kinston soil complex (United States Department of Agriculture 2023). Within the LCP region, mean annual rainfall during 2021–2022 measured 158.2 cm in Baldwin and 154.2 cm in Escambia (National Oceanic and Atmospheric Administration 2023). The LCP region was primarily composed of forest (40%), water/wetland (30%), row crop/pasture/hay (15%; Dewitz and Geological Survey 2021). The primary soil types in LCP included fine sandy loam, Bibb, Benndale-Orangeburg complex, and Hyde-Bayboro-Muck soils (United States Department of Agriculture 2023).

Within each focal area, farms had to meet specific criteria for inclusion in this study. First, farms needed to be situated within the designated project area in the southeast (WIRE) and southwest (LCP) regions. Secondly, farms must have had a history of wild pig presence or ongoing sightings. Lastly, it was essential for the producers to grant permission for us to conduct UAS flights throughout the growing season to gather data. We established connections with landowners through the SWCC Feral Swine Control Program and subsequently collaborated with additional landowners referred by those within the farming network. Given the constraints of available fields meeting our criteria, we focused on assessing as many fields as possible within each of the two study regions without a specific effort to balance between the two. Some producers actively participated in the SWCC Feral Swine Control Program, which focused on the removal of wild pigs to mitigate damage through utilization of a combination of trapping by United States Department of Agriculture (USDA) Wildlife Services, removal efforts by landowners themselves, or a combination of both. As such, removal efforts varied greatly among farms, from essentially no removal activities to active removal by trained professionals. Therefore, we did not know the population density or removal rate of our farms. However, approximations of densities based on a predictive model by Lewis et al. (2017) estimate 6–8 pigs/km^2 in our study regions.

METHODS

Field selection

After identifying farms, we conducted in-person meetings with producers to identify crop fields damaged by wild pigs and those vulnerable during the growing season based on historical observations. Our focus was on prevalent regional row crop types—corn, cotton, and peanuts. Peanuts were predominant in the LCP region, while WIRE had a more balanced distribution between cotton and peanuts. Corn was the least abundant crop in both areas. The availability of suitable fields and landowner cooperation influenced field selection, averaging two per farm. The proximity (range 0.11–5.17 km ± 1.5 km) of surveyed fields on the same farm was due to the tendency of wild pigs to damage multiple fields in their vicinity, like results found by Schley et al. (2008).

When field sizes were <9 ha, we conducted UAS flights across the entire field to ensure comprehensive detection. For fields >9 ha, we were limited in flight times primarily due to the battery life of the UAS. Interrupting UAS operations for battery replacement posed logistical challenges, including UAS and sensor overheating, disruption in flight programming continuity, changes in lighting conditions, and inconsistent flight patterns due to global positioning system (GPS) recalibration, which frequently diminished image quality and consistency. Therefore, we typically limited flight times and areas to one battery (approximately <14 min and/or <9 ha; dependent on weather and field shape). In such cases, we met with the producers to identify areas with the highest probability of receiving damage or areas where we observed signs of wild pig activity at the time of field selection. In addition, we investigated sections of the field not covered by our predetermined flight path, conducting on-foot inspections and manual post-mission UAS flights for crop health assessment. We also engaged in consultations with the landowner, Wildlife Services personnel, and other individuals involved in land management to ensure we captured all damage present. In the event of damage in unflown areas, we conducted supplementary flights to ensure comprehensive coverage and adjusted future flight paths accordingly to fully encompass damage. Regular communication with producers ensured that any additional field areas with damage were included in our observations, providing confidence that our coverage was exhaustive and that no damage in our observed fields occurred outside our flight areas.

Imagery collection and processing

During the 2021 and 2022 growing seasons, we used a Phantom 4 Pro V2.0 (DJI, Nanshan, Shenzhen, China) UAS, equipped with a natural light Red-Green-Blue (RGB) sensor (Table 1.1). We collected imagery throughout the growing season which typically occurred from April–November. We flew each field (n = 27 in 2021, n = 33 in 2022) within a week of planting and subsequently every 2–3 weeks until harvest. Flights were preprogrammed to follow a transverse pattern within a designated polygon (i.e., field or field section) with flight times between 1000 hours through 1400 hours CST. Transects were aligned parallel to the field edge and spaced to ensure adequate image overlap (80% in all directions) and minimize turns and flight duration. To achieve consistent flight patterns, we used Pix4Dcapture (Pix4D, Prilly, Switzerland), a UAS flight planning app, to preprogram flights with specified transects at an altitude of 100 m above ground level (AGL; Figure 1.3).

To ensure spatial accuracy and consistency in aerial imagery processing, we established three to four ground control points (GCPs) at the perimeter corners of each field (Figure 1.3). GCPs consisted of white-painted 0.3 m x 0.3 m sheets of treated plywood with a black "X" painted across the top-facing side like methods by Anderson (2020). GCPs were staked at two corners into the ground using 0.4–0.7-m rebar stakes with a 90° angle on the upper end that laid flush with the ground. The GCPs remained in the field throughout the growing season. Using a Trimble R2 Global Positioning Systems (GPS) Receiver (Sunnyvale, California, USA), we accurately measured the coordinates (with a precision of 1 cm x 1 cm) for the center point of each GCP. Measurements were recorded only when the receiver's precision was <2 cm. The Trimble R2 leverages GNSS (Global Navigation Satellite System) surveying in real-time kinematic positioning (RTK) with ProPoint GNSS technology and a high-capacity receiver for enhanced performance and precision. We cannot disclose the exact coordinates of the GCPs due to landowner privacy concerns. By correlating the on-site locations of the GCPs with their corresponding coordinates in the aerial imagery during post-processing, we maintained consistency and accuracy across multiple flights.

Infield damage measurements

We used a handheld Nomad TDS GPS unit (Trimble, Sunnyvale, California) for infield damage measurement. In 2021, a single observer was used, while in 2022, two observers collaborated. After each flight, we physically walked the perimeter of damaged areas, tracked boundaries with the GPS unit, and recorded occurrence dates, establishing virtual damage polygons. In highly damaged fields, we recorded approximately 20 instances randomly chosen across the entire field and noted additional damage was present. Our decision aimed at efficiency, as collecting >20 measurements was time-consuming and redundant as we conducted infield measurements to understand how wild pig damage was portrayed in aerial imagery in subsequent computer-based analyses. Since the amount of damage to individual plants by wild pigs can be highly variable, the damage observed in each polygon was classified into one of three severity categories: low (1–33% damaged), medium (34–75%), or high (76–100%) based on ocular estimation of the percentage of plants rooted, trampled, consumed, or otherwise damaged by wild pig activity. We differentiated wild pig damage from that of other sources such as erosion or other wildlife species due to wild pigs' distinct rooting habits, characterized by soil layer disruption caused by their snouts. We also considered additional signs such as spoors and scat for verification purposes. Ground-truthed data, which involved validating and confirming observed information, was essential in creating training samples for model building and model verification. Training samples, represented as polygons and comprised of paired input data (i.e., pixel values in imagery) and corresponding output labels (i.e., wild pig damage), served as inputs for the model during the training phase. Training samples taught the machine learning model by providing examples of the features and patterns necessary to recognize and classify future imagery.

Image analysis

Imagery data were orthorectified using Pix4Dmapper (Pix4D, Prilly, Switzerland) to generate an orthomosaic image, which used a minimum of 1,000 key points (identifiable characteristic point) to remove potential distortions (e.g., sensor tilt, topographic relief). The Digital Surface Model (DSM) was instrumental in preserving distances, ensuring the accuracy of area and distance measurements in calculations using the orthomosaic. GCPs served as reference points during the orthomosaicking process, ensuring spatial accuracy and alignment of the imagery. In Pix4Dmapper, the GCPs were imported, and their precise coordinates were entered into the software. For each GCP, we used five individual images from the flight where each was visible. Within these images, we identified the center of the GCPs and assigned the known ground coordinates through the “Basic GCP/MTP Editor” tool. This method enabled the correction of any distortions and precise alignment of the images within the geographic coordinate system. The process involved aerial triangulation, allowing Pix4Dmapper to adjust the position and orientation of each image relative to the control points for optimal accuracy. After the initial GCP processing, the photogrammetry software generated an orthomosaic by stitching the aligned images together, correcting for topographic relief, and creating a seamless, georeferenced output. This resulted in an orthomosaic with high spatial accuracy, suitable for quantitative analysis and further interpretation in scientific research.

We used ArcGIS Pro 2.9 (Esri 2021) for image preparation and analysis. For optimal model performance, we exclusively utilized high-quality imagery in our model training dataset, ensuring the inclusion of the most representative instances of wild pig damage. High quality imagery included a low (<3 cm) ground sampling distance resolution, limited (<40%) cloud cover, and clear features (i.e., non-blurry/distorted). Moreover, we used imagery near crop maturity to allow for the most representative training samples. For corn, this was typically the post-tassel stage (June–August) while peanut was in the post-R2 stage (start of peg formation), approximately July–September. From this imagery, we identified our area of interest (AOI, the field or field section) and used a polygon filter to remove portions of the mosaic outside the field boundaries. We then removed the fourth alpha band from the RGB imagery as it did not contain pertinent information within this system.

In creating training data, we delineated individual damage samples, and verified with ground-truthing to teach the model how to identify wild pig damage through imagery. We then exported the training files with a 270° rotation angle for varied alignment. Variation was crucial for the computer algorithm to accurately identify wild pig damage across diverse orientations, enhancing the model's ability to detect and quantify damage in different landscapes and conditions. Using the "Train Deep Learning Model" tool, we trained the Mask R-CNN (MRCNN) model to identify damage in fields, utilizing established training samples and the underlying orthomosaic. MRCNN was chosen for its capability to construct high-quality segmentation masks (pixel-level labeling of an image) and bounding boxes, precisely isolating pixel values, such as damage caused by wild pigs (Table 1.2). Detailed segmentation enhanced accuracy in identifying and quantifying damage, particularly valuable in discerning fine-grained patterns in agricultural landscapes affected by wild pig activities. MRCNN is simple to train, flexible, and runs relatively quickly at five frames per second (He et al. 2018). We used ResNet-50 as the model's core architecture (i.e., backbone), containing 50 neural network layers. Each layer within the convolutional neural network contains data that, when stacked with other layers, teaches the model to identify unique and intricate patterns. As He et al. (2016) detailed, there is a delicate balance between having enough layers to accurately teach the model, while having too many layers may oversaturate and degrade accuracy. Further, more layers require increased processing time and power while not necessarily increasing the model's performance. Therefore, we chose 50 layers as the optimal number due to a low error rate (6.71%) and relatively quick processing time, increasing overall efficiency (He et al. 2016). We imposed a maximum of 20 epochs (complete cycle through the entire training dataset during the training of the model) for iterating through the dataset (default value), with 90% of the data utilized for training purposes and the remaining 10% withheld from training and allocated for later verification (default value). We opted to allow the model to take into account for the weights and biases for the ResNet-50 backbone, by allowing the model to freeze. Freezing a deep learning model's training when it is no longer improving offers several benefits. It prevents overfitting, which helps the model generalize better to new data (Aji and Herdiana 2023). It also conserves computational resources by stopping the training process when further improvements are unlikely. This approach can maintain the model's consistent performance and stability while streamlining the development process by focusing on other aspects like hyperparameter tuning.

To apply the trained model to new imagery, we utilized the "Detect Objects Using Deep Learning" tool. Parameters were configured with a padding size of 10% of the pixel size (e.g., 256-pixel size = 26-pixel padding) to provide additional context around image chips and enhance edge detections, a 10% threshold for detection sensitivity to balance true positive detections while minimizing false positives, and a maximum overlap ratio of 5% for the "Non Maximum Suppression" tool to eliminate redundant detections and ensure each object is represented by a single confident detection. Computer-detected damage detections were categorized as True Positive, False Positive, True Negative, or False Negative based upon ground-truthed GPS data.

To assess overall model accuracy, we used the tool “Compute Accuracy for Object Detection” and determined model precision (Table 1.3) which quantifies performance of the model’s correct identification and localization of objects within an image. Precision rate is a measure of the reliability of the predictive classification model and is a fundamental performance metric in evaluating classification models, signaling the model’s ability to correctly identify positive damage detections among all its positive predictions. A high precision rate indicates the model adeptly identified damage without incorrectly identifying non-damage as positives. In similar applications, precision rates of >80% are commonly regarded as high, as illustrated by Friesenhahn et al. (2023; 80%), Kuželka and Surový (2018, 95–97%), and Rutten et al. (2018, 85%). The precision was calculated as Precision = (Number of True Positives) / (Number of True Positives + Number of False Positives). In this model precision percentage calculation, True Positives refer to instances where model-detections accurately identified wild pig damage (based on ground-truthing) while False Positives represent cases where the model incorrectly detected damage, determined not to be caused by wild pigs through ground-truthing.

To determine how well fitted the model was to our row crop imagery, we created training and validation loss graphs (Figure 1.3) which incorporated a learning curve for peanut and corn models. Learning curve graphs function as a diagnostic tool for evaluating the learning behavior of the developed models. The learning curve consists of the training curve, indicating the model's learning progress, and the validation curve, reflecting the model's performance on unseen data. A well-fitted model was characterized by both curves reaching a state of stability with minimal fluctuations, demonstrating a decrease in loss as the number of processed training samples increases. Additionally, a well-fit model was achieved when both curves were relatively close to each other. To numerically demonstrate the fitness of our model, we used a relative (generalized) gap, calculated as Gap = (Validation Loss – Training Loss) / Training Loss, where differences <5% signify a small gap in a well-fit model.

Estimating whole field damage

To calculate the percentage of damage across entire fields, we measured each field's area using imagery within ArcGIS Pro. After the model identified areas of wild pig damage and categorized them as feature class polygons, we aggregated the area of all confirmed damage detections (ground-truthed as true positives) within that field. Subsequently, we divided the total damaged area by the entire field's area (including outside our UAS flight area), resulting in the percentage of damage within each field. The standard error was calculated for field size, area damaged, and percentage of damage within a field.

In some instances, we conducted flights covering the entire field, ensuring that we detected all damage that was present. If flying the entire field was impractical, we surveyed the largest area feasible within one battery cycle (approximately <14 min and/or <9 ha) if no wild pig damage was noted elsewhere. If wild pig damage was detected beyond this coverage, we adjusted our flight area to include all damage, replacing batteries as necessary. For fields that exceeded our flight capacity in a single flight due to battery limitations, we maintained continuous monitoring of areas beyond our flight path which was done through physical checks, manual UAS flights, and regular communication with the producer. Our objective was to guarantee that all damage within the field was monitored. If any damage occurred outside our initial flight path, we extended the flight to encompass the entirety of the damage. Consequently, we had a high degree of confidence that all damage within the entire field was accurately assessed.

Economic impact

To estimate the financial impact of wild pig damage, we extrapolated the documented extent of wild pig damage within our studied fields and estimated the costs associated with farming row crops and yield earnings. To calculate costs of cultivating row crops, we multiplied the total model-detected hectares of damage for each field by the cost to produce each crop type per hectare. Costs considered various factors such as planting, fertilizer, and insecticide, as detailed in publications by the Alabama Cooperative Extension System (Runge et al. 2023). For irrigated corn in Alabama, the combined variable and fixed expenses cost \$3,442.98/ha; non-irrigated peanut cultivation cost of \$1,966.76/ha, while irrigated peanut production had a cost of \$2,664.52/ha (Runge et al. 2023). To calculate the lost yields and the resulting economic impacts, we relied on publicly available data (National Agricultural Statistics Service 2023, Runge et al. 2023) which provided information on average yield prices in Alabama (peanut = \$0.59/kg, corn = \$0.24/kg) and yields per hectare (peanut = 3,072 kg/ha, corn = 3,566 kg/ha) during our study years. We multiplied the total hectares damaged, as calculated by our model, by the average yield per hectare, then multiplied by the yield price producers would be earning at harvest with each crop type. We could then estimate from the damaged fields the total crop yield (kg) and the resulting value lost (USD \$) due to wild pigs. Incorporating the total yield value lost with the expenses associated with cultivating peanuts and corn per hectare, we determined the comprehensive cost to producers across our studied fields. Our integrated perspective emphasizes the substantial financial investments that producers make in both planting and cultivating crops. Moreover, when their fields endure damage from wild pigs, the lack of returns needed to counterbalance these expenses became apparent.

RESULTS

During the 2021 and 2022 growing seasons, we studied 60 fields or field sections ranging from 0.1–37.2 ha. On average, LCP fields measured 12.4 ha ± 8.04 ha while WIRE fields measured 19.6 ha ± 12.55 ha. We flew five whole fields and 55 field sections. We measured 1–4 fields on each of 15 farms, with the mean planting dates on May 16 (2022) and May 10 (2021) in WIRE, and May 27 (2022) and May 20 (2021) in LCP. In 2021, we conducted 146 flights, including cotton ($n = 38$), corn ($n = 13$), and peanut ($n = 95$). In 2022, we performed 154 flights, covering cotton ($n = 91$), corn ($n = 4$), and peanut ($n = 59$).

Model results

We selected high-quality imagery for the training dataset to improve our model's accuracy and efficiency, encompassing samples from 23 peanut fields and six corn fields. We focused on capturing clear examples of wild pig damage within these images to provide the model with precise and accurate representations for training. By using imagery from the crop maturity periods (peanut = 7 July–26 September; corn = 15 June–5 August), we improved the model's ability to distinguish between damaged areas (such as disturbed soil and vegetation) and healthy crops. This choice enabled the model to harness the unique spectral signatures for training and future identification. Earlier in the growing season, disturbed soil may arise from both wild pig rooting and row planting techniques, resulting in overlapping spectral signatures. Consequently, we focused solely on imagery showcasing disturbances specifically caused by wild pig rooting. Additionally, we excluded images with less-than-optimal lighting conditions (e.g., <40% cloud cover) or those that were blurry or distorted due to environmental factors like high humidity or wind, to maintain the quality of our training data.

Our strategy facilitated a more nuanced learning process, allowing the model to discern intricate patterns and variations associated with different damage levels across diverse landscapes and environmental conditions while limiting the number of false positives. Detection results were also visually verified with manually delineated samples. As a result, our corn model attained an overall accuracy of 91.7% and 91.8% accuracy for the peanut model (Table 1.3). For the corn model, we utilized 6,194 training samples (58–4,523 per field ± 1288.9, mean area = 1.33 m^2), while the peanut model was trained with 38,948 samples (16–23,567 per field ± 7674.7, mean area = 0.38 m^2). However, we found developing a model for cotton presented significant challenges due to the ground sampling distance (GSD) achieved within imagery. While creating training samples, we encountered difficulties in outlining distinct damage within the field, even while referencing ground-truthed GPS polygons, resulting in inferior training sample quality. Difficulties were confounded with a lack of distinction between the appearance of wild pig damage and tilled rows that occurs during cotton planting. Consequently, the model struggled to differentiate pig damage from tilled rows or other exposed soil not attributable to wild pigs due to. Therefore, we opted not to pursue the creation of the cotton model.

However, we found our training and validation loss graphs for peanut and corn (Figure 1.4) were well-fit to the imagery as we saw limited fluctuations with increasing number of batches of imagery processed. Moreover, both the training and validation lines were relatively close to each other for both peanut and corn models, another signal of a well-fit model. We found small (<5%) relative gaps for both models (peanut = 1.79%, corn = 0.49%), further indicating the models were well fit to the imagery.

Economic impacts

Using our calculated quantities of wild pig damage (accumulating 0.12 ha of damage in corn and 0.16 ha in peanut; Table 1.3), we determined that corn producers incurred a total loss of $3,164.05 across our six studied damaged fields (total area 64.3 ha), averaging $527.34 per field (range $30.07–$2,169.06 ± $748.72) or $49.21/ha. Considering the mix of irrigated and non-irrigated peanut fields, we averaged the cultivation costs associated with both farming techniques for an average of $2,314.05/ha to be used in calculations. Within the 23 studied damaged peanut fields (total area 351.9 ha), we found an overall loss of $5,675.18, averaging $246.75 per field (range $2.57–$3,478.11 ± $702.32) or $16.13/ha. The total cost/loss incurred by producers encompasses both variable and fixed planting expenses and the monetary value of yield losses at harvest (Table 1.4). It is important to note that these figures exclusively represent the direct losses resulting from damage and yield reduction; they do not encompass the expenses associated with mitigation efforts (e.g., damage to farming equipment, fencing, scare devices, removal, personnel time), which can be considerable (Carlisle et al. 2021).

DISCUSSION

Our research highlights the potential of UAS technology to accurately estimate wild pig damage and provide reliable estimations of associated economic losses. The accuracy of detection models significantly impacts their practical applicability, and our study achieved notable accuracies (>90%). Our rates surpass the accuracies of Samiappan et al. (2018; 65–78%) and Friesenhahn et al. (2023; >80% overall accuracy). In comparison, Rutten et al. (2018) reported higher accuracies (95.71–96.45%), like Kuželka and Surový (2018; 95–97%), but their results overestimated damage by 0.5–12.6% due to inaccurate georeferencing. Lower accuracies in previous studies may be attributable to challenges in stitching orthomosaics, alignment errors in aerial imagery, the absence of Ground Control Points (GCPs), processing complications, GPS ground-truthing misalignment, or classification procedures (Fischer et al. 2019, Friesenhan et al. 2023, Kuželka and Surový 2018, Samiappan et al. 2018). Our greater accuracy rates compared to some other studies may have been due to the use of GCPs for precise georeferencing and robust classification procedures, which enhanced model accuracy.

We enumerated wild pig damage in damaged row crop fields, indicating an overall average of 6.25% damage in corn fields and 0.38% in peanuts in southern Alabama. In contrast, both Anderson et al. (2016) and Engeman et al. (2018) reported lower corn damage (0.93% and 1.01%, respectively) and higher peanut damage (6.17% and 8.857%) in Alabama. However, Anderson et al. (2016) relied on landowner opinions, potentially introducing bias toward higher estimations (Friesenhan et al. 2023). Furthermore, Engeman et al. (2018) collected data immediately post-planting through ground surveys, which may yield different results compared to our focus on crops at maturity. In corn, Friesenhahn et al. (2023) found less damage (<5%) in Texas than our study, while Rutten et al. (2018) reported higher damage (17.2%) in Belgium, with a broad range (0.36–45.11%), likely influenced by a single field with significant damage. Fischer et al. (2019) reported variable damage (0.04–5.70%) in corn fields, aligning more closely with our findings. Notably, our estimations may be low due to ongoing wild pig removal and harassment throughout our study, which could potentially reduce damage within the fields we examined.

Our economic evaluation of wild pig damage in row crop fields is comparable to Friesenhan et al. (2023) when focusing on yield loss alone, as they reported $14.08/ha in corn damages in Texas. When considering only yield loss, our estimations are slightly higher at $25.49/ha (corn) and $7.71/ha (peanut). However, by incorporating planting costs for each crop, our damage estimations increased to $64.33/ha (corn) and $16.13/ha (peanut).

Previous methodologies, often reliant on producer and ground surveys, are susceptible to biases that could introduce inaccuracies in evaluating harvest and income loss. Such techniques can lead to both over- and underestimations and, in some cases, inadvertently cause additional damage during data collection (Carlisle et al. 2021, Kuželka and Surový 2018, McKee et al. 2020, Rutten et al. 2018). Ground-based surveys, as exemplified by Boyce et al. (2020), estimated damage averaging $2.02/ha for corn and $1.40/ha for peanuts. However, their method covered less than 10% of field areas due to the extensive resources required for observations, potentially leading to underestimations. Contrastingly, Engeman et al. (2018) observed damages of $21.11/ha for corn and $254.28/ha for peanuts in Alabama. Yet, excluding an outlier in Engeman et al. (2018) aligns their averages more closely with ours for peanuts at $10.50/ha. Producer surveys also present disparities, as their dependence on landowner opinions introduces potential discrepancies. Moreover, landowner surveys do not allow for precise estimations on a temporal or spatial scale. For instance, based on 172 landowner surveys in Alabama, Anderson et al. (2016) estimated wild pigs caused $1,949 total statewide damages to corn and $15,841 to peanuts. However, they relied entirely on producers' personal estimations of the number of acres damaged and the hypothetical yield loss due to the damage throughout the entire growing season. Validation of these estimations is lacking, undermining the reliability of producer surveys. In contrast, UAS-based estimations offer the opportunity for precise calculations, allowing the assessment of the accuracy of the methodology without resorting to speculations.

Our deep learning algorithmic modeling approach demonstrated superior performance in addressing georeferencing issues and detecting whole-object damage. Pixel-based classification can result in overestimation (Kuželka and Surový 2018) of damage or underestimation (Fischer et al. 2019, Michez et al. 2016, Samiappan et al. 2018) due to errors in orthomosaic stitching and classification processes (Friesenhahn et al. 2023). Alternative methods (Samiappan et al. 2018, Rutten et al. 2018, Fischer et al. 2019) utilize grouping pixels with similar spectral and shape characteristics, but encounter challenges in cross-field application, a limitation our model overcomes with its versatility across fields with similar topography. Other alternatives include height models, which distinguish damage based on crop height, and have shown effective for corn (Friesenhahn et al. 2023, Dobosz et al. 2023) and wheat (Kuželka and Surový 2018). Nonetheless, both Dobosz et al. (2023) and Kuželka and Surový's (2018) reported very low accuracy (<50%) for small damage areas (<12 m^2). Along with Johenneken et al. (2020), they all identified common omissions on damage borders and small areas, resulting in significant underdetections across entire fields. Their methods also encountered challenges in accurately classifying irregularly shaped damage, a notable issue given the irregular nature of many wild pig rooting incidents. In contrast, our corn and peanut models did not encounter these issues with irregularly shaped or small-sized damage. Models efficiently detected observations down to 0.1 m^2; the average size of our detections was <2 m^2 (corn = 1.33 m^2, peanut = 0.38 m^2), exemplifying the significance of detecting a wide range of damage sizes for accurate assessments.

We found that using imagery data acquired at or around crop maturity provided the most efficient training data for our models and aligned with periods of heightened wild pig damage. Our conclusions concurred with the findings of Boyce et al. (2020), Friesenhahn et al. (2023), and Kuželka and Surový (2018), who identified a significant peak in consumption by wild pigs during the mature stages of crop development, phases characterized by the crop's nutritional richness and provision of cover for safety and shade. Our models identified the spectral signature of rooted soil in conjunction with damaged or trampled crops as the most discernible, prompting us to use imagery captured later in the growing season for model training. Imagery collected earlier in the season (around April–June) did not always effectively represent wild pig damage in a manner that the model could definitively detect and quantify. Therefore, we propose that future best practices for imagery collection focus on the latter part of the growing season (June–September in Alabama) to ensure the acquisition of high-quality training samples while minimizing time spent in the field for data collection.

Additionally, unlike height models, our model structure applied to both tall- and short-standing crops, using unique pixel values, shape, texture, surrounding pixels, and contextual clues. For instance, weeds, stimulated by wild pig rooting, can serve as context clues for damage identification, similar to methods by Samiappan et al. (2018). Combining these aspects, we could better train our model to identify damage correctly. Integrating UAS technology and computer algorithmic models, our research presents a versatile and field-adaptable solution, offering a valuable tool for accurate wild pig damage assessment across crops and landscapes.

Our attempts to construct a model for cotton encountered challenges centered around the GSD, specifically during the formulation of training samples. Although the cotton plant itself was not the primary target for wild pig consumption, it incurred damage as pigs rooted for newly planted seeds or remnants from the previous year's peanuts. Because our flights were flown at 100 m altitude, resulting in a GSD of >2.5 cm, the resulting resolution was too coarse and we were unable to discern damage at the necessary fine scale (Mathews et al. 2023) given the typical range of cotton stem diameters is 0.7–1.60 cm (Zong et al., 2012). The irregular branched growth patterns of cotton, which left ground views exposed even at maturity, posed additional challenges that were difficult to determine given our spatial resolution. Furthermore, the conventional tilled row technique in cotton planting closely mimicked wild pig rooting patterns, complicating the task of distinguishing between healthy and damaged crops as underlying soil is visible through the crops at maturity. For future research, it is recommended to carefully consider the required resolution and opt for lower flight altitudes to enhance image resolution, particularly when monitoring smaller objects. As discussed by Matthews et al. (2023), one approach to determine the necessary spatial resolution is to divide the smallest object size (i.e., 0.7 cm) by four. In our study, flying at substantially lower altitudes would have significantly improved our GSD. Despite our efforts using ground-truthed data, these collective factors impeded progress beyond the training stage, as discrete training samples, essential for effective model comprehension, were challenging to obtain. Our findings are congruent with Engeman et al. (2018) and emphasize the complexity of developing accurate models for crops like cotton and show the importance of continued advancements in image processing and machine learning techniques.

Further obstacles arose, similar to Friesenhahn et al. (2023), Fischer et al. (2019), and Kuželka and Surový (2018), as we encountered difficulties in distinguishing between exposed soil in thinning canopies, machinery tracks, and areas affected by water erosion, resulting in false positives. While increasing and diversifying the training samples might alleviate some false positives, complete elimination is unlikely. We achieved notable accuracies while addressing issues from previous studies, including utilizing whole-object detection, orthomosaic stitching, and classification procedures. Avoiding subjective assessments inherent in ground-based and producer surveys that introduce biases and inaccuracies, our use of UAS-based estimations offers a precise alternative that is versatile across various crops and landscapes.

Research implications

Unoccupied aircraft system technologies are rapidly gaining traction across various disciplines. In our study, we explored an alternative application of UAS and associated computer algorithms like work by Rai and Flores (2021) in identifying sunflowers and Arnold (2023) in locating dams. Our research revealed the potential for these technologies to detect wild pig damage, opening avenues to numerous applications across disciplines. Coupling the use of UAS with the structure of our models, deep learning algorithms can be utilized for limitless applications such as the detection of individual tree species (Khalid and Shahrol 2021), plastic pollution in rivers (Haris et al. 2023), car density in parking lots (Kaya et al. 2023), archaeological features (e.g., shell rings; Davis et al. 2021), and more. UAS and deep learning algorithms emerge as invaluable tools for landowners and producers, requiring minimal financial investment and time. Their capability to provide precise estimations of wild pig damage (Figure 1.5), along with the resulting yield and financial losses, facilitates accurate damage mitigation and income loss compensation. Assessing damage in agricultural settings, especially for crops like corn that exceed the observer's line of sight, can be laborious and time-consuming, and landowner surveys often introduce significant biases. UAS offers a comprehensive perspective, saving time and preventing further field damage by passively collecting data. The increasing prevalence of UAS in natural resource management and precision agriculture is noteworthy (Gaston et al. 2008, Salamí et al. 2014, Michez et al. 2016, Anderson 2020). Unlike manned aircraft, UAS offer the advantage of quick deployment, enabling the capture of temporal and spatial changes. Moreover, the enhanced spatial resolution and ability to incorporate additional sensors are revolutionizing ecological investigations conducted with UAS.

Previous UAS-based approaches have often underestimated damage, primarily due to inaccuracies in orthomosaics (with errors increasing significantly in the absence of GPS ground references (Martínez-Carricondo et al. 2018) and classification procedures (Fischer et al. 2019). Nevertheless, ongoing and future research endeavors aim to establish optimal practices for harnessing this emerging technology while reducing errors and inaccuracies. Our research contributes to ongoing efforts by providing insights that enhance the accurate quantification of crop damage, which improves decision-making in wild pig damage management, facilitating the implementation of techniques designed to mitigate the impact of wild pig damage efficiently.

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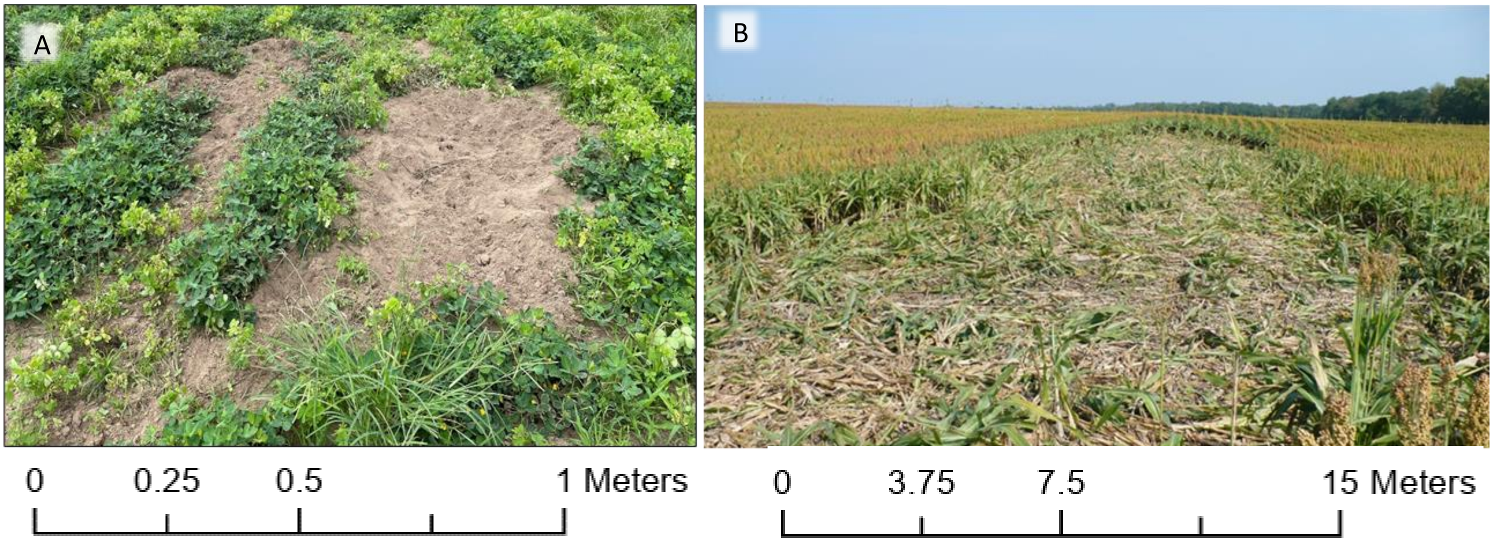

Figure 1.1. Evidence of wild pig (*Sus scrofa*) activity in the study areas. Panel A displays the effects of wild pig rooting in peanut (*Arachis hypogaea*), characterized by soil disturbance and vegetation damage. Panel B illustrates signs of wild pig trampling in corn (*Zea mays*), indicated by soil compaction and vegetation flattening.

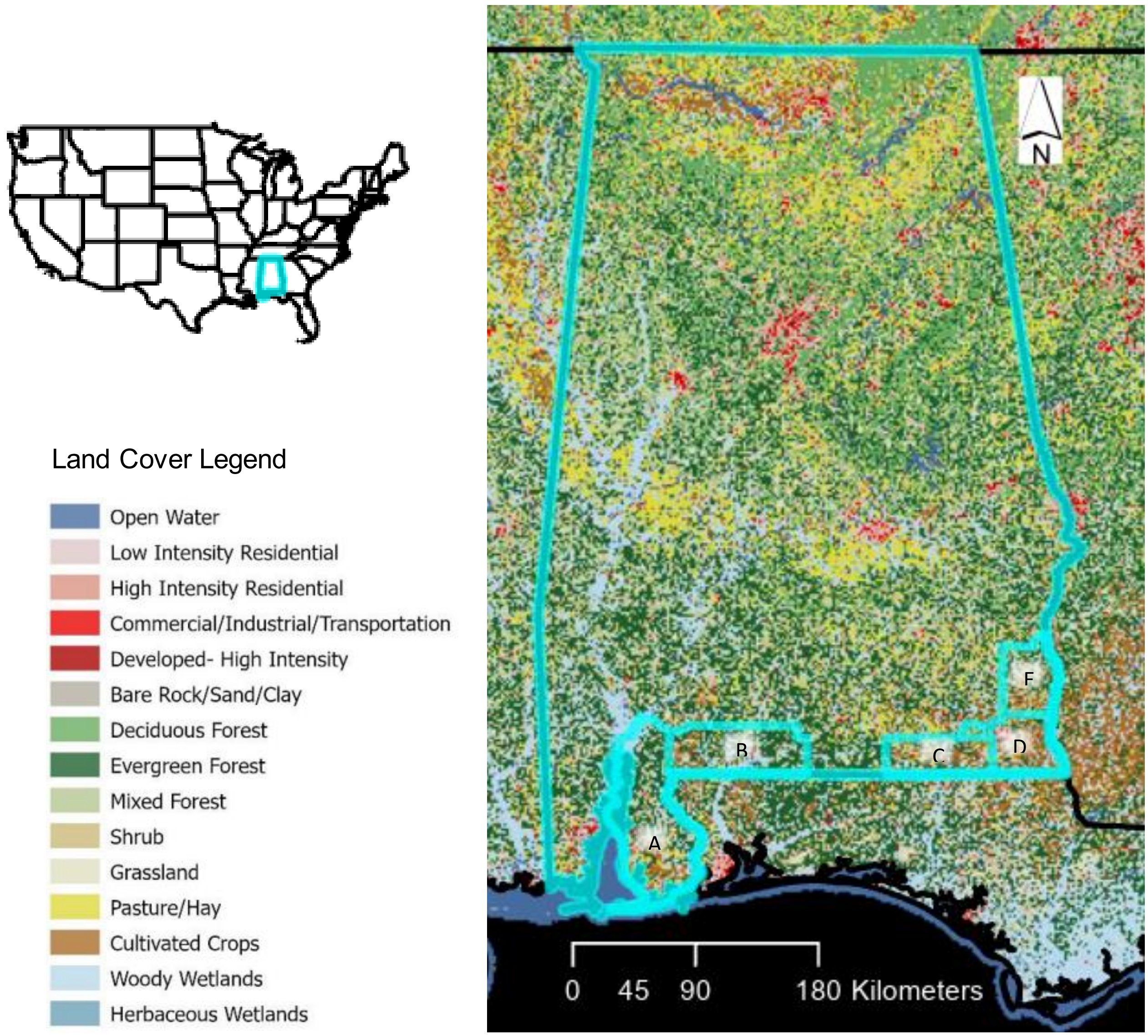

Figure 1.2. Map of Alabama, USA showing the locations of the study areas across the state. The map highlights the specific counties of Baldwin (A), Escambia (B), Geneva (C), Houston (D), and Henry (E), where the study areas are situated.

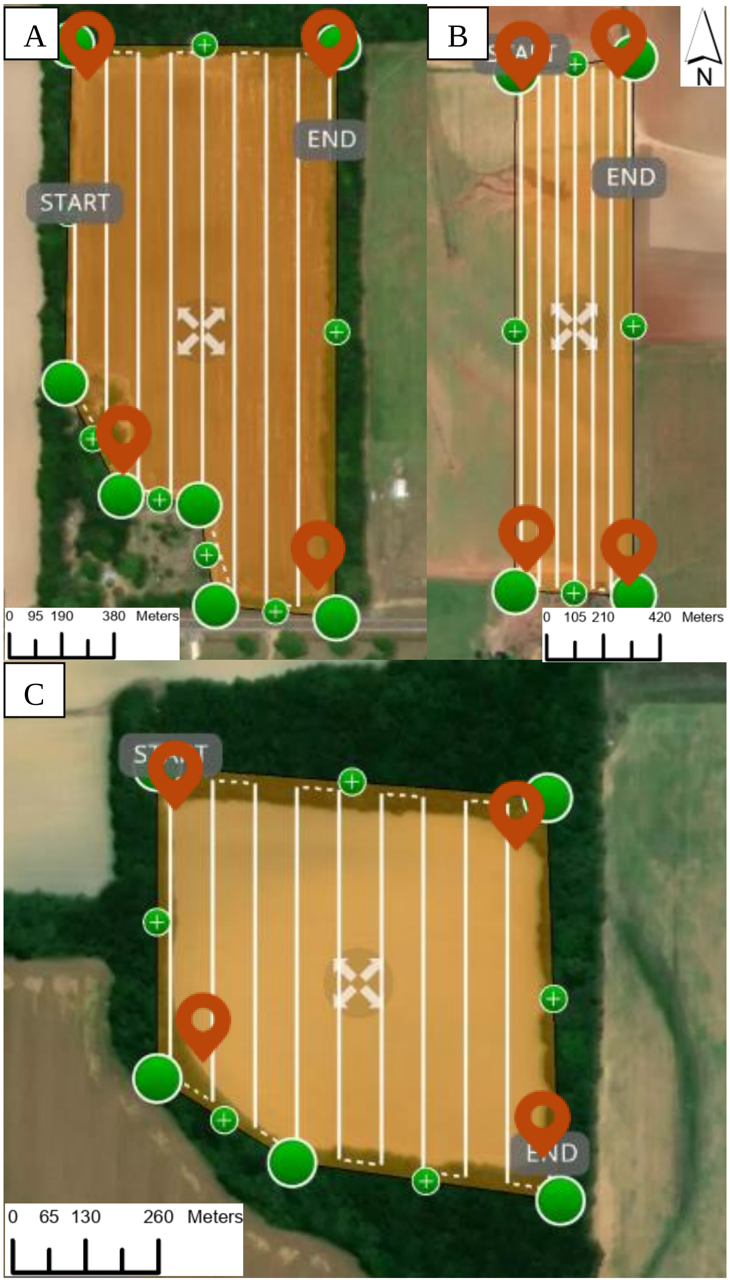

Figure 1.3. Examples of preprogrammed flight areas, transects, and ground control point locations across three fields. Panels A, B, and C display the designated flight paths and transect lines (80% image overlap) for each field, with ground control points marked by red pins for reference and calibration.

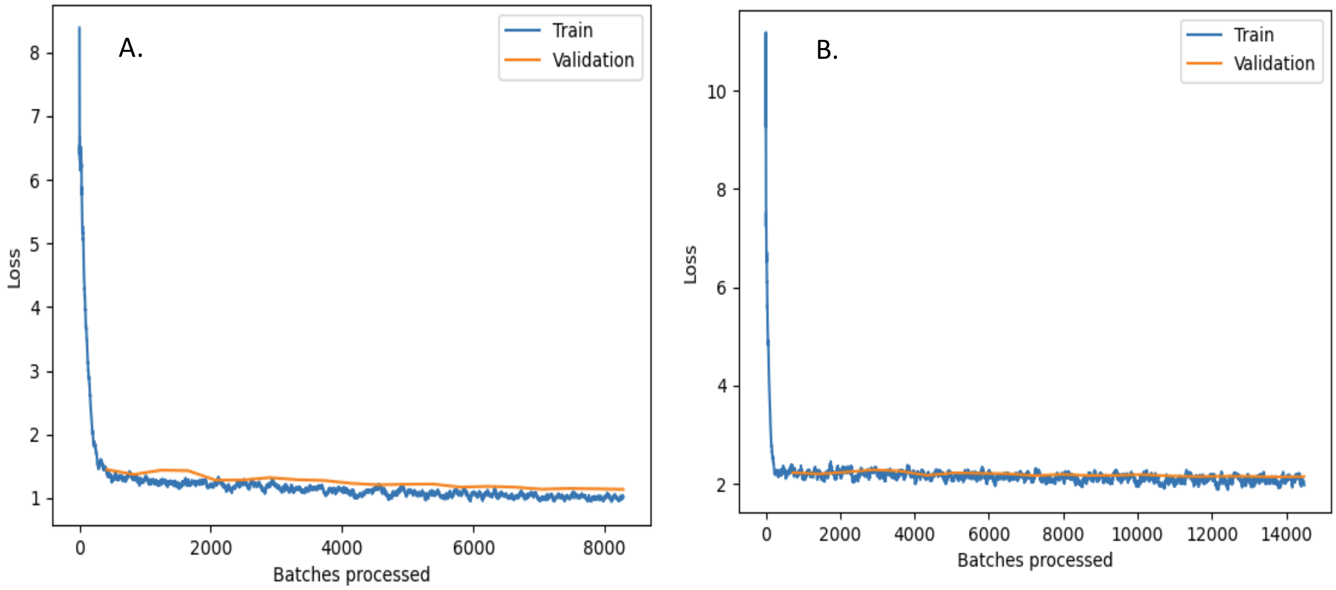

Figure 1.4. Training and validation loss graphs for computer model development. Panels A and B represent loss graphs for peanut and corn fields, respectively. The Y-axis denotes the loss, a measure of model performance, with lower values indicating increased accuracy. The X-axis corresponds to the batches processed during training, reflecting the model's learning progression. These graphs were generated during the development of a computer model to detect wild pig damage in row crop fields in Alabama, USA, 2021–2022.

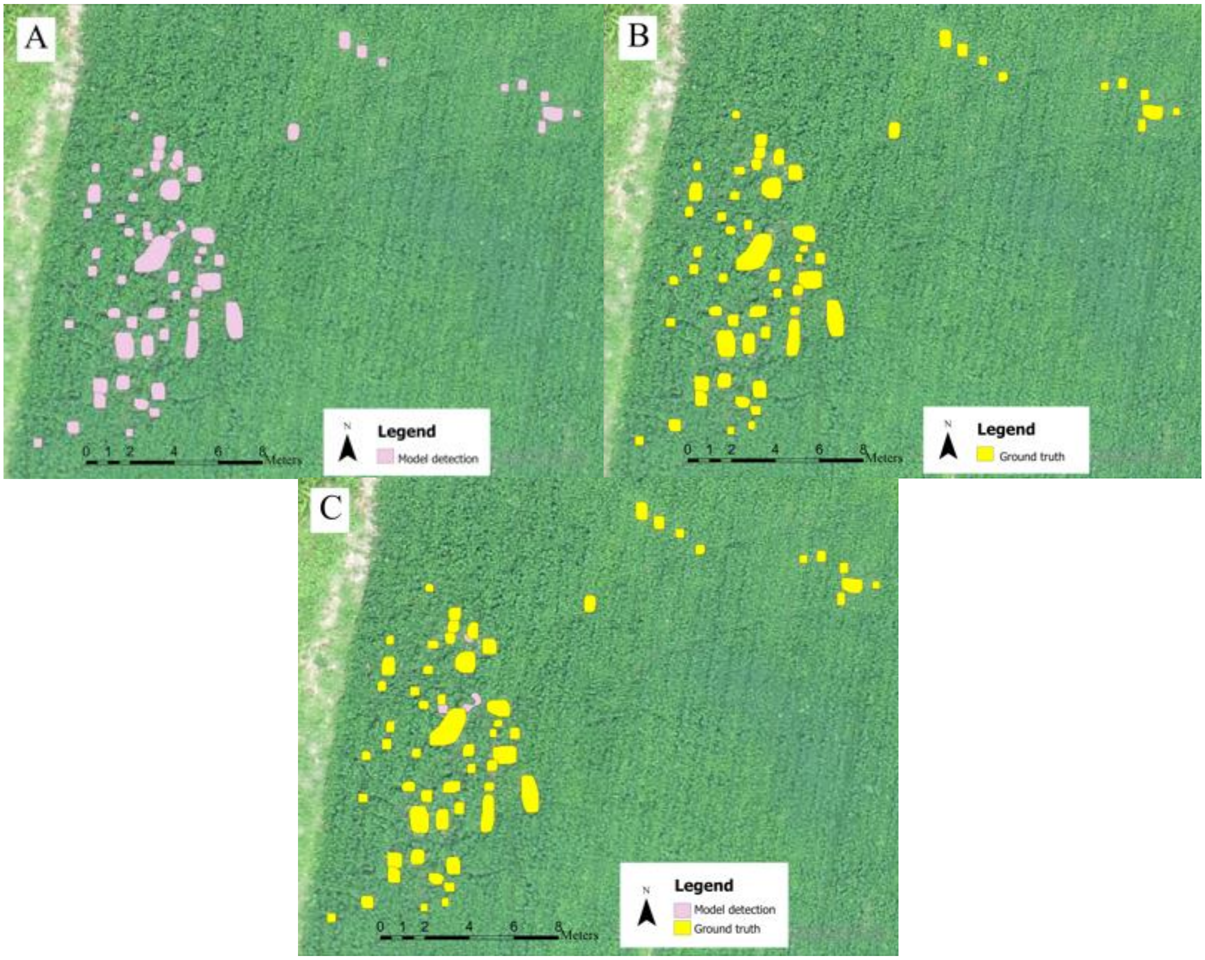

Figure 1.5. Example imagery of wild pig damage, showcasing comparisons between trained model detections and ground-truthed data. The figure demonstrates the model's accuracy in correctly identifying wild pig damage, highlighting areas where the model's predictions closely align with the ground-truthed observations.

Table 1.1. Description of DJI Phantom 4 Pro V2.0 with integrated visible wavelength red, green, blue (RGB) camera.

Parameter	Value
Field of view	84° 8.8 mm/24 mm
Image size	5472 x 3648 pixels
Spatial resolution	1 cm/pixel 100 m altitude
Effective pixels	20 M
Focal length	24 mm

Table 1.2. Summary of model parameters and descriptions.

Parameter	Value	Description
Max epochs	20	The maximum number of complete iterations through the neural network for the dataset in a single cycle.
Model type	MRCNN	Applied for instance segmentation, which precisely delineates objects within an image, and utilizes metadata as input for training data.
Batch size	2	Number of training samples that are processed at a single time.
Chip size	256 pixels	Fixed dimensions (width and height in pixels) of smaller portions of a larger raster dataset.
Backbone	ResNet-50	Contains >1 million images and is 50 layers deep.
Validation %	10	The percentage of training samples withheld from the training process and reserved for model validation.
Stops	When model stops improving	Model training can be halted early if there is no improvement in performance, even if fewer than 20 epochs have been completed.
Freeze model	Not frozen	Allows for weights and biases for the backbone to be altered to fit the training samples. Takes longer unfrozen, but typically provides better results.
Rotation	270°	Enabling varied orientations of future detections. By using angles that are not divisible by 90°, we introduce greater variation within samples during the training cycle.

Table 1.3. Mean field size (ha), estimated wild pig damage (ha), percentage of field damaged by wild pigs, and model precision by crop type and study area (LCP = Baldwin and Escambia counties, WIRE = Houston, Henry, and Geneva counties), Alabama, USA, 2021–2022. Percentage of the field damaged was based on the whole field with confirmed wild pig damage. Calculation of model precision was the percentage of correctly identified positive damage detections among all positive predictions. Presented numbers are based solely on fields with confirmed wild pig damage.

Study area	Crop	n	Field size		Area damaged		% damaged		Model precision	
			$\bar{x}$	SE	$\bar{x}$	SE	$\bar{x}$	SE	$\bar{x}$	SE
LCP	Peanut	14	11.7	2.45	0.03	0.01	0.30%	0.001	90.9%	0.02
	Corn	6	10.7	3.35	0.12	0.08	6.28%	0.04	91.7%	0.02
WIRE	Peanut	8	17.1	4.67	0.13	0.11	0.45%	0.003	92.7%	0.03

Table 1.4. Mean area (ha) damaged in crop fields by wild pigs, resulting crop yield lost (kg), value of lost yield (USD \$), and total loss to the producer (USD \$), including lost yield and cultivation costs of damaged area) of fields experiencing wild pig damage by crop type. Damaged fields were located in studied corn (n = 6) and peanut (n = 23) fields across Baldwin, Escambia, Houston, Henry, and Geneva counties, Alabama, USA, 2021–2022. Yield loss estimations and their corresponding economic values were derived from average crop yields data (National Agricultural Statistics Service 2023). Value lost and producer loss calculations were based on average crop prices and associated planting costs (Runge et al. 2023). Presented numbers are based solely on fields with confirmed wild pig damage.

	Corn			Peanut		
	$\bar{x}$	SE	Total	$\bar{x}$	SE	Total
Area damaged	0.12	0.19	0.72	0.08	0.16	1.28
Yield lost	208.15	651.66	2322.34	490.96	1397.42	11292.10
Value lost	113.03	160.48	678.18	117.90	335.59	2711.73
Total loss to producer	527.34	748.72	3164.05	246.75	702.32	5675.18

Chapter 2: Landscape characteristics in predicting wild pig damage to agricultural fields in Alabama

ABSTRACT:

Wildlife-induced crop damage poses a significant challenge to agricultural productivity in the United States. Wild pigs (*Sus scrofa*) are known for their propensity to cause damage on row crops through rooting, trampling, and consumption. Our objectives were to determine if specific landscape elements could serve as predictors of field susceptibility to wild pig crop damage. Conducted in the Lower Coastal Plain and Wiregrass regions of southern Alabama, USA, we monitored 27 fields in 2021 and 33 fields in 2022 from planting (approximately May) to harvest (approximately September–November) for wild pig damage. Utilizing unoccupied aircraft systems (UAS) complemented by ground-truthing, we binarily marked each field as "damaged" or "undamaged" throughout the growing season. Surrounding landscape features within a 500-meter buffer around each field were digitized and categorized into five categories woody, row crop, pasture/hay, human development/road, water/wetland) using ArcGIS Pro. Analysis in R, utilizing the 'landscapemetrics' package, aimed to identify patterns within damaged fields that could serve as predictors of damage. Of the 60 fields observed, 44 were found to be damaged, with all corn fields (6 of 6) affected, alongside numerous peanut (24 of 28) and some cotton fields (14 of 26). Notably, crop type, distance to water, and landscape patch density emerged as significant contributors to the likelihood of wild pig-induced damage based on generalized linear models. Our research findings provide valuable guidance for policymakers, landowners, and wildlife managers endeavoring to address the challenges posed by wild pig predation in agricultural landscapes by integrating ecological insights with practical management strategies.

INTRODUCTION

Agriculture plays a vital role in sustaining human life and driving economies worldwide, with an annual valuation in the United States alone exceeding $256 billion (United States Department of Agriculture 2021). Agriculture's significance extends beyond mere sustenance, influencing economies, cultures, and societies globally. However, agriculture faces a persistent challenge: wildlife-induced crop damage. Wildlife intrusion upon cultivated lands impacts food security, economic stability, and ecological balance. Therefore, assessing wildlife crop damage emerges as an integral component of wildlife management strategies. Among the wildlife species causing agricultural damage, wild pigs (*Sus scrofa*) alone produce over $1 billion in damages across the United States (Pimental 2007, McKee et al. 2020, Carlisle et al. 2021), particularly in the southeastern United States, where they have well-established populations (McKee et al. 2021).

Wild pigs are attracted to areas abundant in row crops over natural food sources, given their preference for nutritionally rich crops like corn (*Zea mays*; Herrero et al. 2006). Engeman et al. (2018) noted wild pigs tend to congregate in agricultural landscapes in Alabama, with densities near croplands up to four times higher than in non-cropland areas. Similarly, White et al. (2018) observed wild pigs traveling significant distances (5.8–8.05 km) daily to crop fields during peak harvest seasons in California. Paolini et al. (2018) found wild pigs tend to avoid cornfields during the early growing season when proximal to wetlands. Wild pigs presumably adhere to wetland areas due to easy access to food resources and cover (Gaston et al. 2008, Paolini et al. 2018, Boyce et al. 2020), reducing the need to travel to cornfields during these times. Because hunting pressure requires wild pigs to stay in areas with cover (Gaston et al. 2008), early stages of corn and cotton do not offer the safety required. Further along in the growing season (i.e., late growing season and fallow season), when resources become limited in wetland areas and mature corn and cotton stalks can act as cover, wild pigs had a high preference for corn (Paolini et al. 2018). However, in areas that had lower amounts of wetland, corn was selected for during all seasons (Gaston et al. 2008, Paolini et al. 2018, Boyce et al. 2020). Likewise, Thurfjell et al. (2009) found during the summer months in Sweden, wild pigs spent more time in open agricultural fields when the crops were mature as it provided both cover and food simultaneously.

Both ephemeral resources and permanent landscape features influence the movements of wild pigs. Water, crucial for thermoregulation, serves as an essential habitat element, particularly during hot summer months (Mayer and Brisbin 2009). Thurfjell et al. (2009) highlighted water as a preferred habitat year-round with wild pigs remaining within close proximity, as evidenced by Mersinger and Silvy (2007) in Texas where wild pigs were found on average within 46.2 m of water. Despite low availability (<0.1%) of riparian habitat (high elevation ephemeral ponds) in Ecuador, wild pigs exhibited a strong preference for these areas, emphasizing the significance of water sources (Coblentz and Baber 1987).

Landscape elements promoting safety, such as forest edges, may shape wild pig foraging behaviors, with studies indicating concentrated damage near forest boundaries (Geisser 1998, Meriggi and Sacchi 2001, Keuling et al. 2008, Thurfjell et al. 2009). For instance, Meriggi and Sacchi (2001) noted wild pig crop damage was concentrated near the forest edge in Italy. Likewise, Thurfjell et al. (2009) found wild pig damage in Sweden was located closer to forest edge (<54 m) than chance alone would predict based on random points. Wild pigs tend to stay close to cover from hunting pressure; foraging behavior may reflect the dangers of feeding in a wide-open field. Consequentially, smaller fields with more edge may receive increased damage as more points within the field are close to an edge. Larger fields, however, have a greater interior field area that wild pigs tend to avoid, resulting in a lower percentage of crop damage on average despite having more cumulative area.

Fragmented habitats often offer ideal conditions for wild pigs, balancing cover requirements with access to food and water resources. Proximity to diverse landscape elements allows for fulfilling various biological needs within a concentrated area. Previous research has identified a combination of landscape characteristics as the best indicator of field susceptibility to wild pig damage. Schley et al. (2008) showed damage was positively correlated with forest cover while negatively correlated with high proportions of agricultural land and anthropogenically fragmented (e.g., human density and roads) forest cover in Luxembourg. Furthermore, studies by Devault et al. (2007) and Cai et al. (2008) indicate that combining factors such as distance from streams (used as travel corridors) and forest edge (used as cover) to crop fields can be used to predict wild pig movement patterns.

Given the variations of the temporal, spatial, and extent of wild pig damage (Singer et al. 1984, Paolini et al. 2018), understanding depredation patterns of crop fields is crucial for effective management. Identifying crop susceptibility to wild pig damage based on surrounding landscape elements enhances mitigation strategies and reduces economic losses. Thus, our objective was to ascertain whether specific landscape features can serve as predictors of field susceptibility to wild pig crop damage.

STUDY AREA

Our study, conducted within the framework of the Alabama Soil and Water Conservation Committee (SWCC) Feral Swine Control Program, operated within predetermined focal areas across Alabama, USA. Our research took place on 15 privately-owned farms located in the

Lower Coastal Plain (LCP, Baldwin and Escambia counties) and Wiregrass (WIRE, Houston, Henry, and Geneva counties) regions (Figure 2.1). Our study areas were characterized by extensive row crop cultivation, with peanuts, cotton, and corn being the predominant crops. In the WIRE region, the mean annual rainfall during 2021–2022 varied, with Houston receiving 138.1 cm, Henry 136.1 cm, and Geneva 146.0 cm (National Oceanic and Atmospheric Administration 2023). Across these landscapes, the WIRE region was predominantly comprised of row crop/pasture/hay (35%), forest (33%), human development (7%), and water/wetland (16%; Dewitz and Geological Survey 2021) with loamy sand soil primarily featuring the Bibb-Osler-Kinston complex (United States Department of Agriculture 2023). Within the LCP region's two counties, mean annual rainfall during 2021–2022 measured 158.2 cm in Baldwin and 154.2 cm in Escambia (National Oceanic and Atmospheric Administration 2023). The LCP region predominantly consisted of forest (40%), water/wetland (30%), human development (8%) and row crop/pasture/hay (15%; Dewitz and Geological Survey 2021), with major soil types including fine sandy loam, Bibb, Benndale-Orangeburg complex, and Hyde-Bayboro-Muck soils (United States Department of Agriculture 2023).

Within each focal area, farms had to meet specific criteria for inclusion in the study. They had to be located within the designated project area in the southeast (WIRE) and southwest (LCP) regions and have a history of wild pig presence or ongoing sightings. Furthermore, producers had to grant permission for unoccupied aircraft systems (UAS) flights throughout the growing season to collect data. Collaboration with landowners was facilitated through the SWCC Feral Swine Control Program, with additional landowners referred by those within the farming network. Due to the constraints of available fields meeting the criteria, our focus was on assessing as many fields as possible within each study region, without specific efforts to balance between the two. Some producers were actively engaged in the SWCC Feral Swine Control Program, which involved the removal of wild pigs to mitigate damage through trapping by United States Department of Agriculture (USDA) Wildlife Services, landowner removal efforts, or a combination of both. Consequently, removal efforts varied significantly among farms, and we did not have information on population density or removal rates. However, approximations of densities based on a predictive model by Lewis et al. (2017) estimate 6–8 pigs/km^2 in our study regions.

METHODS

Field selection

Following the identification of farms, we engaged with producers to select fields affected by wild pig damage and those susceptible during the growing season based on historical observations. Our primary focus centered on prevalent regional row crop types, namely corn, cotton, and peanuts. While corn represented the least prevalent crop in both areas, peanuts were the most abundant in the LCP region, while WIRE exhibited a more balanced distribution between cotton and peanut. The selection of fields, averaging two per farm, was contingent upon the availability of suitable fields and cooperation from landowners. Because wild pigs may damage multiple fields within an area, fields on some farms were proximal to each other (range 0.11–5.17 km ± 1.5 km).

Subsequently, we monitored each selected field for wild pig damage from planting (approximately May) throughout the growing season until harvest (approximately September–November) in 2021 and 2022. We utilized a Phantom 4 Pro V2.0 (DJI, Nanshan, Shenzhen, China) UAS equipped with a natural light Red-Green-Blue (RGB) sensor flown at 100 m above ground level (AGL) to observe wild pig damage. Flight patterns were preprogrammed in traverse patterns using Pix4Dcapture (Pix4D, Prilly, Switzerland) with 80% image overlap (all directions) within the designated field boundary with flight times between 1000 hours through 1400 hours CST. Additionally, we manually flew a UAS to further investigate areas within a field that were presumed to be damaged by wild pigs. UAS monitoring efforts were supplemented by ground surveys to identify instances of wild pig damage, at which point the field was marked as "damaged." Fields that remained untouched by wild pig activity throughout our research period were classified as "undamaged." To verify damage was due to wild pigs, we ground-truthed instances and differentiated from other forms of damage, such as water erosion, machinery tire tracks, and non-wild pig crop damage, based on distinctive wild pig rooting characteristics. Additionally, we verified damaged areas by identifying spoors and scat, if present.

Analysis

We used ArcGIS Pro (Esri 2021) to generate vector coverages of landcover with a 500-m buffer around each field (Figure 2.2). We chose a 500 m buffer as it represented approximately half of a wild pig's average daily movement (Sparklin et al. 2009). Within each buffer we digitized landcover into five categories (woody, row crop, pasture/hay, development/road, and water/wetland) using information provided by the basemap “World Topographic Map” (5 cm resolution) available through ArcGIS Pro in combination with the high-resolution (30 cm) imagery from the USDA’s National Agriculture Imagery Program (NAIP; Table 2.1). We then converted each digitized vector coverage into a 5-m resolution raster for subsequent analysis. We used the 'landscapemetrics' package (Hesselbarth et al. 2019) in R (R Core Team 2020) to compute class- and landscape-level metrics that were used to possible variables to identify patterns within damaged fields that could serve as predictors of damage.

We selected a subset of metrics relevant to wild pig movements from an initial set of over 300 metrics based on prior knowledge of wild pig biology and ecology (VerCauteren et al. 2020). The variables analyzed included crop type (corn, peanut, or cotton) to determine whether certain crops were preferred due to nutritional or other benefits. Given our focus on row crop damage, we sought to understand if landscapes with a higher percentage of row crops experienced more damage due to the landscape providing abundant food resources or if increased row crop dispersed the consumption across fields, thereby reducing damage to individual fields. Often, wild pigs favor field edges due to the lack of cover within the field interior (Boyce et al. 2020). Therefore, we assessed field size in relation to damage to determine if smaller fields with more edge and less interior area experienced more frequent damage than larger ones. We also measured the distance from the field edge to the nearest water source, as water significantly influences wild pig movement (Thurfjell et al. 2009, Kay et al. 2017, Snow et al. 2017, Paolini et al. 2018, Gray et al. 2022), especially during the summer months during the growing season (Friesenhan et al. 2023). Research indicates that wild pigs use water sources such as streams as corridors (Kristiansson 1985), suggesting that landscapes with higher water cohesion may experience more frequent pig activity and, consequently, more damage to fields, Therefore, to further explore the impact water may have on field vulnerability, we examined water edge density and the cohesion of water across the landscape. We also calculated the distance from the field edge to the nearest human development, if present, as wild pigs tend to avoid areas with human presence (Schley et al. 2008, Kay et al. 2017, Lombardini et al. 2017, Boyce et al. 2020). Additionally, we considered the percentage of developed landscape, attempting to understand its impact on wild pig behavior. Fragmentation has produced various findings in prior research regarding its impact on wild pig movement (Thurfjell et al. 2008, Schley et al. 2008). While some fragmented landscapes provide food, water, and cover in close proximity, other forms of fragmentation such as road networks and large bodies of water can hinder wild pig movement. Therefore, we investigated the effect of landscape-level patch density on wild pig row crop predation in our study areas. Considering the importance of forested areas for wild pigs (Schley et al. 2008, Thurfjell et al. 2009, Lombardini et al. 2017, Boyce et al. 2020, Pandav et al. 2021, Yang et al. 2024), we investigated the effect of percentage of surrounding woody landscape. We also evaluated Shannon's diversity index based on class-level metrics to understand how overall landscape diversity may impact on wild pig field predation.

For the independent variable, fields were categorized as either "damaged" or "undamaged" for analysis. Since data were collected over two years for some fields, each year was treated as an independent entity, with the crop type grown during that year and damage received associated with the entry. For instance, if a field was surveyed in 2021 and was planted with cotton and remained undamaged and then in 2022 with peanuts but was damaged, we treated these as two separate entries for analyses, with their respective landscape elements and damage results segregated. To ensure comparability across diverse metrics calculated on different indices for non-categorical variables, we standardized the data using the 'scale' function in R, following methodologies by Lustig et al. (2015) and Long et al. (2010). This approach ensured that subsequent analyses produced comparable numbers, offering meaningful insights into landscape patterns and structures.

Once predictor variable metrics were standardized, we conducted univariate linear regression using the "lm" function on each where the response variable was field damage. Non-significant ($P \geq 0.05$) metrics were excluded from further analyses. We explored possible quadratic relationships using Likelihood-Ratio Test in the R package "lmtest." To assess potential multicollinearity, we used correlation matrices and the Variance Inflation Factor (VIF); we used VIF = 3 as a threshold valuable when assessing collinearity between variables (Dormann et al. 2013). Following metric refinement, we used generalized linear models (GLM) to explore and quantify the relationships between the retained landscape metrics and field damage using the "glmer" function (family = binomial). We used the binary dependent variable for damage while metrics were predictor variables. We used Akaike's Information Criterion adjusted for sample size (AIC_c) to rank competitive models (Akaike 1973). Post-analyses, we back-transformed the variable metrics to original indices for reporting.

RESULTS

We studied 27 fields in 2021 and 33 fields in 2022 between the LCP and WIRE regions where we delineated field damage binarily (either damaged or undamaged). Of these 60 fields, we found 16 were undamaged by wild pigs and 44 were ground-truthed to contain at least some wild pig damage. All corn fields were damaged (6 of 6) while many (24 of 28) peanut fields and some (14 of 26) cotton fields were damaged. Using the univariate models, we found seven metrics that differed between damaged and undamaged fields and were included in further analyses (Table 2.2). VIF scores of all remaining metrics were <2 and the correlation matrix showed no collinearity. No quadratic relationships were shown through the Likelihood-Ratio Test.

We found three plausible models based on AIC_c weight (w_i) ≥0.05, with five predictors included in the best models. We found the most important variables explaining the presence of wild pig damage included distance from field to water, landscape patch density, crop type, percentage row crop within the landscape, and the cohesion of water (Table 2.3). Our most supported model ($\Delta AIC_c = 60.7$) showed crop type, distance to water, and landscape patch density were the most influential factors to whether a field was predated by wild pigs.

We found that cotton fields were 0.072 (0.007–0.423; 95% C.L.) times as likely to be damaged as peanut fields ($P < 0.01$; Figure 2.3). For every 1 m increase in distance from field edge to the nearest water source, fields were 0.994 (0.988–0.998; 95% C.L.) times as likely to be damaged ($P < 0.02$). For every 1 patch increase per 100 ha in patch density, fields were 0.733 (0.535–0.903; 95% C.L.) times as likely to be damaged ($P < 0.02$). For every 1 percent increase in row crop across the landscape, fields were 0.831 (0.663–0.964; 95% C.L.) times as likely to be damaged ($P < 0.05$). For every 1 percent increase in the cohesion of water across the landscape, fields were 0.947 (0.887–0.993; 95% C.L.) times as likely to be damaged ($P < 0.05$). We found percentage of development and percentage of woody did not statistically significantly impact whether a field was more likely to be damaged ($P > 0.05$).

DISCUSSION

Our study revealed that crop type, distance to water sources, patch density, percentage row crop, and water cohesion influenced the susceptibility of fields to wild pig predation in southern Alabama. Our best predictive model identified crop type, distance to water, and patch density as the most significant predictors of field damage. Interestingly, we found that the percentage of development (roads, buildings, etc.) and woody area did not exert a significant impact on the likelihood of field damage by wild pigs.

Our research exhibits the variations and preferences in crop selection by wild pigs. We observed that all our corn fields experienced damage, while cotton fields were damaged less than peanut fields. Corn and peanuts offer nutritional resources, while cotton is not the target of wild pig consumption; instead, it is primarily damaged through trampling and rooting for volunteer plants from the previous year. Our findings align with similar research as Schley et al. (2008) noted higher-than-expected damage to corn, considering its prevalence in the landscape. Likewise, Paolini et al. (2018) illustrated wild pigs' preference for corn, with other crops like pecan, pea, and sorghum were only utilized when adjacent to wetlands that provided cover. In addition to the nutritional aspects, tall-standing crops like corn also offer shelter and aid in thermoregulation. Wild pigs, lacking efficient temperature control mechanisms, seek refuge in shaded and watery areas during high temperatures, reducing activity levels (Kay et al. 2017). In contrast, short-standing crops like peanuts may lack adequate daytime shelter, prompting wild pigs to exploit them at night, as observed by Lemel et al. (2003). However, the availability of corn during the day may contribute to increased damage, as wild pigs both consume and trample crops, as highlighted by Pandav et al. (2021). Notably, crop consumption often is not the primary cause of crop damage; Kristiansson (1985) found that only 5–10% of corn damage was due to consumption, with the remaining 90–95% attributed to trampling as wild pigs traversed the field. Therefore, tall-standing crops are especially vulnerable to damage by wild pigs. Our findings and prior studies emphasize the interplay between crop characteristics and susceptibility to damage. Understanding these dynamics is crucial for developing effective strategies to minimize losses and sustain agricultural productivity in wildlife-affected regions.

Similar to the significance of tall-standing crops for providing cover to wild pigs, access to water and wetlands is vital for thermoregulation. Our findings were anticipated and emphasized two key metrics illustrating the importance of water for wild pigs. The proximity of a field to the nearest water source and the cohesion of water across the landscape were both significant predictors of wild pig damage. The term cohesion of water in this context refers to how interconnected one body of water, such as a pond, river, stream, lake, or wetland, was to another within the landscape. Proximity to water and the ability to move between water sources are particularly crucial during hot summer months when extensive travel becomes challenging (Kristiansson 1985). Wild pigs utilize streams and water sources as safe travel routes, facilitating movement across landscapes (Rosenberg et al. 1997). Additionally, wild pigs concentrate movements near wetlands and riparian habitats, where foraging and wallowing sites are abundant (Choquenot 1993, Eckert et al. 2019). Various studies (Thurfjell et al. 2009, Kay et al. 2017, Snow et al. 2017, Paolini et al. 2018, Gray et al. 2022) demonstrate wild pigs' preference for spending time near water while other studies (Thurfjell et al. 2009, Boyce et al. 2020) show more specifically the importance of water in predicting wild pig damage to agriculture, corresponding to our results. We reiterate the biological importance of water for wild pigs as our findings suggest that fields situated near water sources experienced significantly more damage. For instance, our analysis suggests that a field located 200 m from a water source would carry an estimated 86% probability of experiencing damage, whereas a field situated 1,000 m away from water would exhibit a substantially reduced likelihood, approximately 4%. Our findings indicate a potential confounding effect for field damage based on the necessity for water and proximity to high-nutritional agricultural resources.

To assess the impact of landscape fragmentation on field damage, we used patch density as our representative metric. We observed that increasing patch density correlated with a higher likelihood of field damage. Thurfjell et al. (2008) similarly observed this trend in Sweden, where wild pigs showed a preference for landscapes with linear landscape elements such as areas between fields, rows of trees or bushes, walls, and ditches. Fragmented landscapes often offer multiple biologically significant attributes in proximity, increasing the appeal for wild pigs. For instance, in Barcelona, Castillo-Contreras et al. (2018) noted wild pigs' ability to adapt to fragmented landscapes due to increased resource availability and cover. Conversely, Schley et al. (2008) found a negative association between forest fragmentation and wild pig damage, although it did not emerge as a significant factor in their final predictive model ($P > 0.05$). Our insights could prove valuable in informing field planning and layout for crop planting as well as field design considerations.

We found that an increase in surrounding row crop increased the likelihood that a field would be damaged by wild pigs. Our findings align with a mix of results from previous literature, where some studies reported a decrease in damage while others, like our research, found an increase. For instance, Lombardini et al. (2017) observed that areas with a higher concentration of crops in central Italy corresponded to an elevated risk of damage. Snow et al. (2017) identified a positive correlation between wild pig presence, tracked via GPS collars, and the percentage of agricultural land across the continental United States. Similarly, Gray et al. (2022) noted that GPS-collared wild pigs tended to spend more time in areas with greater agricultural activity. However, contrasting findings exist in other studies. For example, Boyce et al. (2020) and Schley et al. (2008) reported a negative association between wild pig damage and agricultural field presence. Likewise, Kay et al. (2017) discovered that wild pig density and home range size showed a negative correlation with agricultural presence in the southern United States. An abundance of crops in an area may attract wild pigs, leading to their congregation and consequently increasing the likelihood of damage to those fields (Engeman et al. 2018). Conversely, if a row crop field is isolated within other landscape elements, wild pigs may spend less time there, thus reducing the likelihood of damage to that particular field. The overall landscape composition and other surrounding food availability can influence the appeal of a field to wild pigs.

In contrast to many studies investigating the impact of landscape structure on wild pig movements, we observed that the percentage of woody cover did not significantly increase the likelihood of field damage. While previous research (Schley et al. 2008, Thurfjell et al. 2009, Lombardini et al. 2017, Boyce et al. 2020, Pandav et al. 2021, Yang et al. 2024) noted the importance of forest and shrub areas for wild pig agricultural damage, our findings differed. Previous studies emphasized the role of nearby forests as quick escape routes for wild pigs foraging in open agricultural fields. For instance, Lombardini et al. (2017) noted that fields proximal to forests experienced the most damage, while Thurfjell et al. (2009) found that sampled damage occurred on average 54 m from a forest edge. However, our results echoed those of Gray et al. (2022), who found that forest edge density had minimal predictive significance regarding wild pig movements and behavior in Michigan. Despite observing a positive correlation (beta = 0.858) between the percentage of woody cover across the landscape and wild pig damage, it did not emerge as a significant predictor ($P > 0.05$) within our study area. Given the significant portion of forested terrain in our study areas (40% land area in LCP and 33% in WIRE), the presence of woody cover within our observed field buffers may not have strongly influenced wild pigs' selection of one field over another, as ample woody areas surrounded all fields. In contrast, studies (Thurfjell et al. 2009, Schley et al. 2008, Pandav et al. 2021, Lombardini et al. 2017) with lower percentages of forested area (7–30%) may induce wild pigs to rely more heavily on woody areas when options are limited which could elevate the likelihood of fields near forests being preyed upon in such areas. Reported dynamics suggest that the impact of woody cover on wild pig behavior may vary depending on the availability of alternative habitat options.

We discovered that human development similarly did not have a significant impact on whether a field was damaged by wild pigs. Previous studies (Schley et al. 2008, Kay et al. 2017, Lombardini et al. 2017, Boyce et al. 2020) have indicated a negative association between human presence (e.g., buildings, roads) and wild pig activity and damage. For example, Lombardini et al. (2017) utilized three human disturbance variables (human population density, field distance to primary roads, and field distance to protected areas) and found a negative correlation between human development and wild pig damage. However, predictors exhibited low importance (w <0.3) in a regression model and were not statistically significant ($P <0.05$), similarly demonstrated in our results. Wild pigs have a longstanding history within our study areas, which may have led to their acclimatization to human development and potentially now exhibit reduced fearfulness. Wild pigs frequently venture into gardens, domestic trash, and other areas adjacent to human dwellings (Lewis et al. 2020), indicating their comfort with human presence. Conversely, in regions with newer populations of wild pigs, such as Lombardini et al. (2017) study in Sardinia, Italy, humans may still present an unfamiliar threat, prompting wild pigs to avoid these areas whenever possible. Although we observed a slight positive association between percentage developed and damage (beta = 0.826), human development did not have a significant impact (P >0.05) on the susceptibility of a field being damaged in our study areas.

The selection of fields for our study was non-random, guided by their involvement in a previous study with different goals. Fields were chosen based on their history of wild pig activity and the anticipated likelihood of damage during the growing season, leading to biased selection. Additionally, the absence of precise data on wild pig densities across our study areas may influence our findings. However, based on a predictive density model by Lewis et al. (2017), it is estimated that wild pig density was 6–8 pigs/km^2 in our regions. Thus, caution is warranted in interpreting our results, as wild pig populations fluctuated but were not factored into our analysis. Consequently, our results may accurately reflect the specific fields within our study but may not be generalizable to the broader landscape due to the lack of random field selection and knowledge of wild pig density.

Management implications

Our investigation into the factors influencing wild pig predation on row crop fields in southern Alabama yields valuable insights with practical implications for both research and management strategies. The significant impacts of crop type, reliance on water sources, and patch density stress the most influential indicators when evaluating wild pig damage risks. Understanding key predictors can aid in the development of predictive models to forecast potential damage and prioritize management efforts. The observed differences in crop susceptibility highlight the importance of crop selection and landscape composition in mitigating wild pig predation. Management strategies should consider these preferences to implement targeted interventions that protect vulnerable crops and minimize damage. Access to water and wetlands emerged as critical factors influencing wild pig behavior and movement patterns. Incorporating water availability and wetland proximity, along with overall fragmentation, into landscape planning and management strategies can enhance the effectiveness of mitigation efforts. Moreover, our findings challenge conventional assumptions regarding woody cover and human development's impact on wild pig predation as the lack of significant influence from these elements suggests that alternative factors may drive wild pig behavior in agricultural landscapes. Further research is warranted to explore these complexities and refine our understanding of wild pig ecology. Our study affirms the importance of interdisciplinary collaboration between researchers, land managers, and stakeholders to develop integrated and educated management approaches. By incorporating ecological insights with practical management strategies, we can more effectively mitigate wild pig damage and sustain agricultural productivity in wild pig-affected regions. Our research offers valuable guidance for policymakers, landowners, and wildlife managers seeking to address the challenges posed by wild pig predation in agricultural landscapes.

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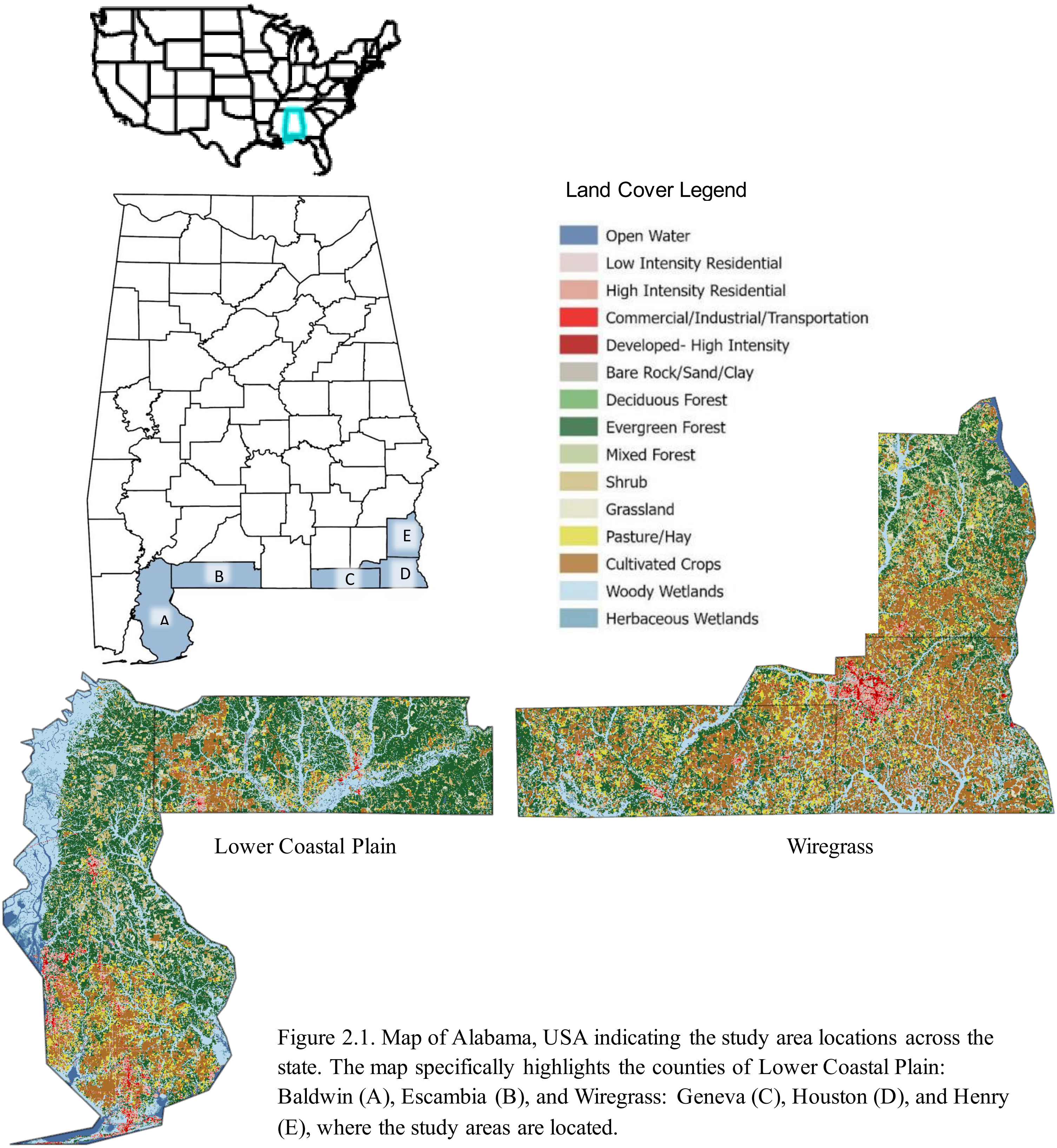

Figure 2.1. Map of Alabama, USA indicating the study area locations across the state. The map specifically highlights the counties of Lower Coastal Plain: Baldwin (A), Escambia (B), and Wiregrass: Geneva (C), Houston (D), and Henry (E), where the study areas are located.

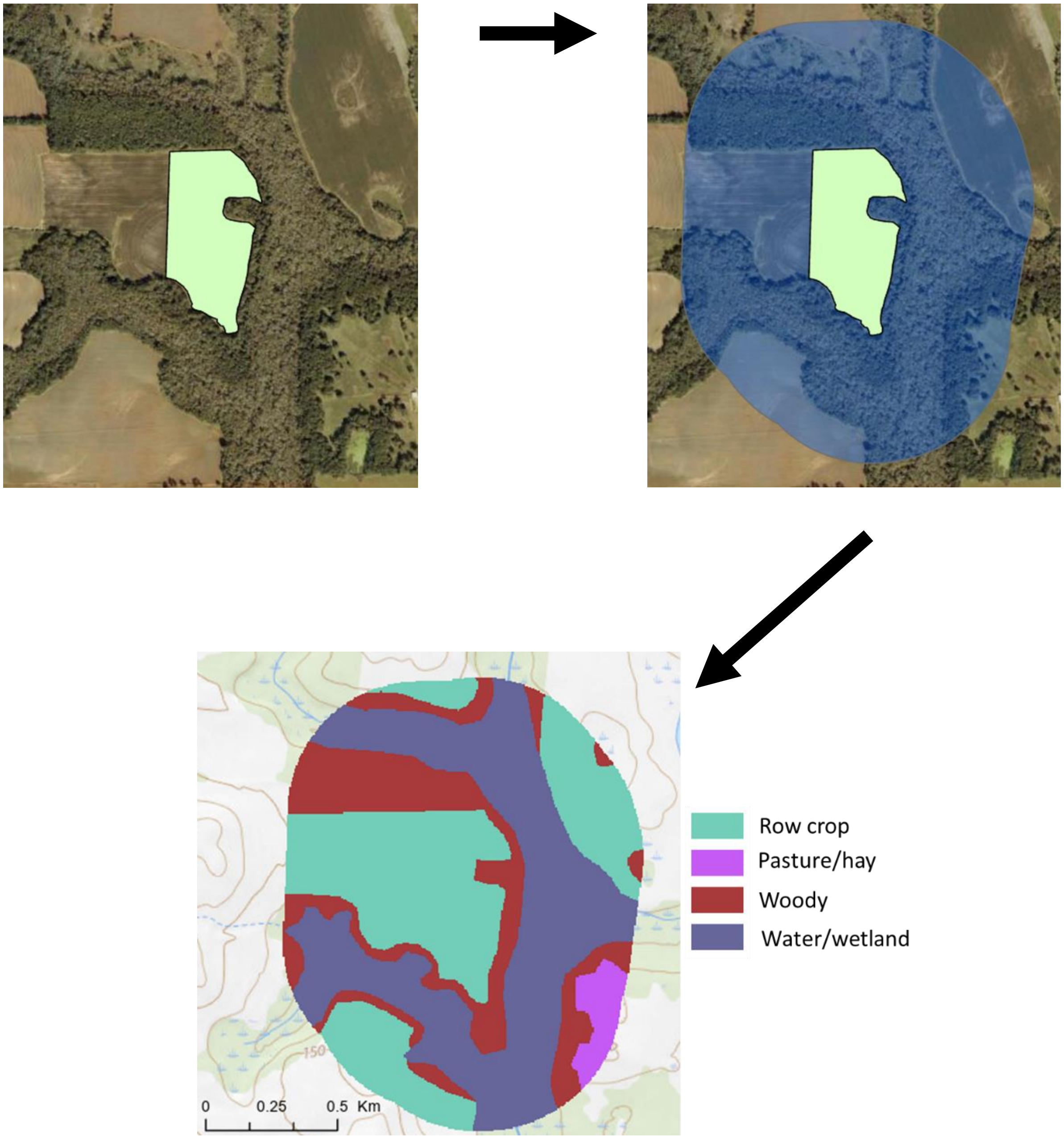

Figure 2.2. An example demonstrating the creation of a 500-m buffer zone around a field, followed by the classification of the buffer into distinct landscape elements, resulting in a raster file with a resolution of 5 meters.

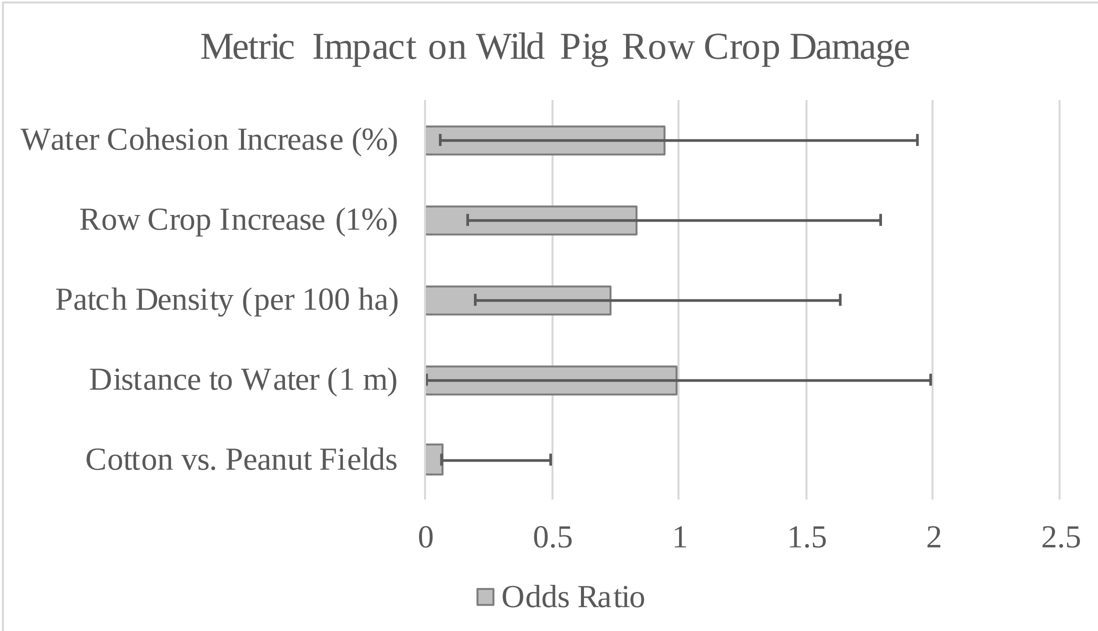

Figure 2.3. Results from a generalized linear model (GLM) showing the impact of various metrics on wild pig damage likelihood in row crop fields across the Wiregrass (Henry, Houston, Geneva co.) and Lower Coastal Plain (Baldwin, Escambia co.) regions of Alabama, USA. The chart presents the odds ratios with 95% confidence limits for each metric, highlighting the relative importance in predicting damage. Non-significant metrics such as percentage of development and woody cover were also examined.

Table 2.1. Overview of the basemaps used in the classification of landscape metrics in ArcGIS Pro. The table includes information about the recent NAIP imagery from Alabama and the ArcGIS basemap "World Topographic Map."

Basemap name	NAIP Imagery from Alabama	World Topographic Map
Data source	USDA NAIP	Esri
Data type	Imagery	Vector and raster
Spatial resolution	30 cm	0.5 m
Coordinate Reference System (CRS)	WGS 84	WGS 84
Data of data	2021	Continuously updated
Extent	Entire state of Alabama	Global

Table 2.2. Reported means and standard errors (*SE*) for metrics observed in fields damaged and undamaged by wild pigs in southern Alabama, USA, 2021–2022.

	Damaged		Undamaged	
Metrics	Mean	*SE*	Mean	*SE*
Distance from field edge to water source (m)	304.6	63.8	412.7	164.5
Patch density (number per 100 ha)	12.7	1.1	15.3	3.0
Percentage row crop	44	3.1	47.4	6.4
Percentage water cohesion	64.8	7.9	57.4	15.6
Percentage development	7.9	2.3	6.1	1.6
Percentage woody	34.7	4.1	40.3	6.7

Table 2.3. Candidate model selection results from relationship examination between landscape characteristics and row crop field susceptibility to being damaged by wild pigs in southern Alabama, USA. Presented are the models with Akaike's Information Criterion adjusted for sample size (AIC_c) weight (w_i) ≥0.05.

Model	Parameters	df	ΔAIC_c	w_i
113	Distance to water + patch density + crop	5	60.7	0.154
117	Percentage land row crop + distance to water + patch density + crop	6	61.8	0.086
114	Water cohesion + distance to water + patch density + crop	6	62.1	0.073

Appendix 1.1. UAS flight details for this study. Ground sampling distance (GSD) values correspond to both aerial images and finished orthomosaics.

Flight ID	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Date	8/24/22	9/7/21	9/7/21	9/7/21	8/4/21	8/3/21	8/3/21	8/3/21	8/3/21	8/5/21	8/24/22	8/24/22	9/8/21	9/26/22
Time start	11:43	11:15	11:43	11:59	10:58	11:43	11:53	11:21	11:01	11:30	10:34	11:33	10:44	13:01
Duration (min)	0:10	0:08	0:11	0:12	0:06	0:06	0:08	0:11	0:14	0:06	0:09	0:09	0:07	0:21
Location	LCP	LCP	LCP	LCP	LCP	WIRE	WIRE	WIRE	WIRE	LCP	LCP	LCP	LCP	WIRE
Crop type	P	P	P	P	P	P	P	P	P	P	P	P	P	P
GSD (cm/pixel)	2.80	2.86	2.83	2.83	2.80	2.80	2.80	2.87	2.87	2.88	2.77	2.76	2.80	2.77
Flight dimensions (m^2)	109992	7099	57154	44271	50870	42124	43052	12224	104451	74601	121869	93501	65509	207584
Wind (mph)	5	6	6	6	5	6	6	6	6	2	5	5	2	5
Humidity (%)	81	80	80	80	80	57	57	57	57	90	81	81	80	32

Flight ID	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29
Date	9/7/21	9/7/21	9/7/22	8/26/22	8/26/22	8/26/22	8/28/21	8/19/22	7/22/22	8/4/21	8/4/21	8/5/21	6/15/22	7/15/21	7/3/21
Time start	10:03	10:47	1:22	11:52	11:36	11:12	11:46	10:23	10:15	10:16	10:36	11:15	10:39	10:59	10:48
Duration (min)	0:10	0:07	0:13	0:08	0:06	0:05	0:09	0:08	0:09	0:07	0:10	0:08	0:08	0:14	0:07
Location	LCP	LCP	WIRE	LCP	LCP	LCP	LCP	WIRE	WIRE	LCP	LCP	LCP	LCP	LCP	LCP
Crop type	P	P	P	P	P	P	P	P	P	C	C	C	C	C	C
GSD (cm/pixel)	2.80	2.81	2.84	2.78	2.82	2.77	2.75	2.96	2.78	2.83	2.83	2.83	2.93	2.79	2.76
Flight dimensions (m^2)	114031	75933	116860	92357	75183	81467	97460	86910	131293	5043	8546	89939	104045	171057	45867
Wind (mph)	1	1	6	1	1	1	2	9	5	1	1	1	5	2	2
Humidity (%)	66	66	51	90	90	90	78	79	62	81	81	85	56	82	75

P, peanut; C, corn; WIRE, Wiregrass region (Houston, Henry, Geneva counties, Alabama, USA); LCP, Lower Coastal Plain (Baldwin, Escambia counties, Alabama, USA); GSD, ground sampling distance. Weather data was taken from Alabama A&M University (2023).

Supporting Information 2.1. Table presenting all tested landscape metrics utilized to predict wild pig row crop damage in southern Alabama, USA. Metrics were derived from FRAGSTATS (McGarigal and Marks 1995) and calculated in R using the package 'landscapemetrics'. Bold type indicates statistical significance ($P \leq 0.05$) at individual metric level, while an asterisk (*) denotes significance in final predictor model.

Metric	Name	Level	Type
Crop type	**Crop type***	-	-
Field_size	Field size	-	-
dist_wa_m	**Distance from field to water source***	-	-
dist_develop_m	Distance from field to development	-	-
area_mn	Mean of patch area	Class	Area and edge
cai_mn	Mean of core area index	Class	Core area
cohesion	Patch cohesion index (**water***)	Class	Aggregation
pland	Percentage of landscape for each class (**row crop*, development, woody**)		
condent	Conditional entropy	Landscape	-
contig_mn	Mean of contiguity index	Landscape	Shape
core_mn	Mean of core area	Landscape	Core area
dcad	Disjunct core area density	Landscape	Core area
dcore_mn	Mean number of disjunct core areas	Landscape	Core area
division	Landscape division index	Landscape	Aggregation
ed	Edge density (water)	Landscape	Area and edge
enn_mn	Mean of Euclidean nearest-neighbor distance	Landscape	Aggregation
ent	Marginal entropy	Landscape	-
frac_mn	Mean fractal dimension index	Landscape	Shape
gyrate_mn	Mean radius of gyration	Landscape	Area and edge
iji	Interspersion and juxtaposition index	Landscape	Aggregation
joinent	Joint entropy	Landscape	-
lpi	Largest patch index	Landscape	Area and edge
lsi	Landscape shape index	Landscape	Aggregation
mesh	Effective mesh size	Landscape	Aggregation
msidi	Modified Simpson's diversity index	Landscape	Diversity
msiei	Modified Simpson's evenness index	Landscape	Diversity
mutinf	Mutual information	Landscape	-
ndca	Number of disjunct core areas	Landscape	Core area
np	Number of patches	Landscape	Aggregation
pafrac	Perimeter-area fractal dimension	Landscape	Shape

para_mn	Mean perimeter-area ratio	Landscape	Shape
pd	**Patch density***	Landscape	Aggregation
pladj	Percentage of like adjacencies	Landscape	Aggregation
pr	Patch richness	Landscape	Diversity
prd	Patch richness density	Landscape	Diversity
relmutinf	Relative mutual information	Landscape	-
rpr	Relative patch richness	Landscape	Diversity
shape_mn	Mean shape index	Landscape	Shape
shdi	Shannon's diversity index	Landscape	Diversity
shei	Shannon's evenness index	Landscape	Diversity
sidi	Simpson's diversity index	Landscape	Diversity
siei	Simpson's evenness index	Landscape	Diversity
split	Splitting index	Landscape	Aggregation
ta	Total area	Landscape	Area and edge
tca	Total core area	Landscape	Core area
te	Total edge	Landscape	Area and edge