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Estimation of wildlife damage from federal crop insurance data

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Abstract

BACKGROUND: Wildlife damage to crops is a persistent and costly problem for many farmers in the USA. Most existing estimates of crop damage have relied on direct assessment methods such as field studies conducted by trained biologists or surveys distributed to farmers. In this paper, we describe a new method of estimating wildlife damage that exploits federal crop insurance data. We focused our study on four crops: corn, soybean, wheat, and cotton, chosen because of their economic importance and their vulnerability to wildlife damage.

RESULTS: We determined crop-raiding hot spots across the USA over the 2015–2019 period and identified the eastern and southern regions of the USA as being the most susceptible to wildlife damage. We estimated lower bounds for dollar and percent losses attributable to wildlife to these four crops. The combined loss across four crops was estimated at $592.6 million. The highest total estimated losses to wildlife were incurred by soybeans ($323.9 million) and corn ($194.0 million) and the highest percentage losses were estimated for soybeans (0.87%) and cotton (0.72%).

CONCLUSION: We believe the proposed method is a reliable way to evaluate geographic and temporal heterogeneity in damages for the coming years. Accurate information on damages benefits various management agencies by allowing them to allocate management resources to crops and regions where the problem is relatively severe. A better understanding of damage heterogeneity can also help guide research and development of new management techniques.

Keywords: crop damage; federal crop insurance; wildlife damage; fractional regression

1 INTRODUCTION

Wildlife damage to crops is a persistent and costly problem for many farmers in the USA. The last national survey of wildlife damage to US agriculture estimated $944 million in losses in 2001 (https://www.aphis.usda.gov/wildlife_damage/informational_notebooks/2012/Protecting_Agriculture_combined.pdf). Negative impacts include damage to planted acreage, consumption of final product, and destruction of infrastructure (e.g. irrigation equipment).[1–3] Losses due to wildlife are not limited to damage; they also include the costs of mitigation efforts. Farmers may install fences or use scare devices to inhibit access to production areas, or they may employ a variety of lethal and non-lethal removal techniques.[4–6]

Nationally, wildlife damage can vary substantially across space and time. There can be variation across different crops and regions, and even within relatively small, homogenous regions.[7] The spatial variation in damage by vertebrate pests can be described by a frequency distribution within a county; the relative frequency of 1-acre parcels with a given level of damage ranging from 0% to 100%. A body of literature[8] points to a non-uniform spatial distribution of damages: damage by house sparrows (*Passer domesticus*) to grain crops in parts of New Zealand had a positively skewed distribution[9] and rat damage to rice in the Philippines followed a log-normal distribution.[10] Negative exponential frequency distributions, with many sites experiencing little or no damage and a few sites seeing a high level of damage, have been reported for damage to sunflowers by birds in North and South Dakota[11] and damage to grapes by birds in Texas.[12] Feral pigs (*Sus scrofa*) in south-eastern Australia root up the ground and can change the species composition of native vegetation.[13] The frequency distribution of such ground rooting has a negative exponential distribution.[14]

Because of the distributional changes of wildlife populations across the country[15], crop damage can also vary across time. These changes largely reflect variations in habitat suitability and the ability of animals to adapt to these variations. Habitat suitability can change over short time scales due to weather and management (e.g. crop rotation, timber harvest), or long time scales due to succession. The loss of habitat quality and amount, and subsequent reductions in species' distributions, is increasing at unprecedented rates for the vast majority of wildlife.[16] Conversely, the range of certain species (primarily game species) has expanded in the recent years. Hunting has failed to control populations of white-tailed deer in many areas of the Midwest.[17] Wild pigs are currently experiencing global range expansion due to translocations by humans, natural dispersal, and favorable

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changes in environmental conditions.[18] Damages can also vary because of scare devices, repellents, and exclusion techniques put in place by farmers to protect high-value crops.[19,20]

Research on wildlife damage consists predominantly of individual studies on either a single species or multiple species impacting a single crop's final product.[21] A shortcoming of these studies is their limited focus. A multi-crop, multi-region analysis is important for several reasons. First, it allows resources to be allocated more efficiently. There are numerous state and federal wildlife agencies, as well as many university extension services, involved in management. Accurate information on damages benefits these various management agencies by allowing them to allocate management resources to crops and regions where the problem is relatively severe. Second, damage estimates can be used to evaluate large-scale management programs. Before management programs are implemented, damages can be estimated to serve as a baseline against which future damage can be compared. Finally, a better understanding of damage heterogeneity can help guide research and development of new management techniques.

Most existing estimates of crop damage have relied on direct assessment methods such as field studies conducted by trained biologists or surveys distributed to farmers. The advantage of well-designed field studies is that they can provide precise and accurate estimates of damages. However, they typically require careful, in-field evaluation of damages and doing this in a variety of production regions, especially in the same growing season, is difficult and costly. Surveys avoid some of the problems of field studies, but often suffer from other issues. Surveys can be distributed across many growing regions and can be repeated over time, but they are also costly. Large-scale mailings, data entry, and interpretation require substantial time and labor. Furthermore, survey responses are often based on a subjective evaluation by the responder and may suffer from a variety of biases. Hence using these direct methods to evaluate geographic and temporal heterogeneity in damages is uncommon as they require substantial resources and infrastructure. Indirect assessment methods, such as expert testimony, may also be used to assess crop damage. Estimates may be solicited from a single, authoritative expert or from a broad range of people concerned with the production of crop in an area to develop a consensus on the extent of loss.[22] But these indirect methods are by nature subjective and do not allow for exhaustive location-specific estimates of crop damage.

We focused our study on four crops: corn, soybean, wheat, and cotton. These crops were chosen because of not only their widespread production and economic importance, but also their vulnerability to wildlife damage. The USDA Census of Agriculture of 2018 estimates that the acreage planted for these four crops accounts for 75% of acreage planted and 74% of production in dollars of all field crops (USDA-NASS). Corn damage is caused by a variety of species, but some the most prolific are bears (Ursidae), white-tailed deer (*Odocoileus virginianus*), beavers (*Castor canadensis*), Canada geese (*Branta canadensis*), raccoons (*Procyon lotor*), blackbirds (Icteridae), sandhill cranes (*Grus canadensis tabida*), and wild pigs (*Sus scrofa*). Sandhill cranes turn to corn seeds as a source of food in the spring, when emerging seedlings alert the bird to the kernels underground.[23] Bears, deer, and birds prefer corn when it is just beginning to ripen and at its softest, in the milk or dough stages, which occur from July until mid-August.[24,25] Wild pigs also cause significant damage to the crop by using corn fields for both refuge and forage.[26] Corn is a preferred food source for raccoons, which also favor corn in its milk stage, but will continue to feed on the crop through harvest in October.[27,28] Deer damage is most commonly defoliation that limits light interception and increases weed pressure to reduce yield.[29] In spring, Canada geese can also cause serious damage to sprouting soybeans, and the largest soybean yield reductions result when feeding occurs during the first week after sprouting.[27] In their seed stages, wheat and cotton are of particular interest to a variety of birds, including blackbirds and Canada geese. Birds consume newly planted and sprouting seeds, trample crops, and contaminate fields with feces.[24,27,30,31]

The paper is organized as follows. In Section 2, we describe our data sources and our method of estimation. In Section 3, we present the model estimation results and establish heat maps of the intensity of crop damage by wildlife for four targeted crops. We also generate corresponding maps of monetary losses. In Section 4, we discuss our results and their implications, and we conclude in Section 5. All code is publicly available at https://github.com/anderaa/crop-insurance.

2 MATERIALS AND METHODS

Congress first authorized federal crop insurance as an experiment to address the effects of the Great Depression and crop losses seen in the Dust Bowl. In 1938, the Federal Crop Insurance Corporation (FCIC) was created to carry out the program. Congress enhanced the crop insurance program in 1980, 1994, 2000, 2014, and 2018 to encourage greater participation. Today, many banks, when making operating loans, require that farmers purchase crop insurance.[32] Under FCIC private-sector insurance companies sell and service the policies, while the United States Department of Agriculture's Risk Management Agency (USDA/RMA) approves the premium rates, administers premium and expense subsidies, approves and supports products, manages FCIC, and reinsures the companies. USDA/RMA also develops new crop insurance policy offerings, which may occur in collaboration with private-sector insurance companies (ERS https://www.ers.usda.gov/agriculture-improvement-act-of-2018-highlights-and-implications/crop-insurance/). Insurance policies are sold and completely serviced through 16 approved private insurance companies. Insurance companies' losses are reinsured by USDA, and their administrative and operating costs are reimbursed by the federal government.[33]

Crop insurance policies insure farmers for losses in excess of their guarantee. In the case of the most basic policy, catastrophic coverage (CAT), the farmer can receive a payment on losses in excess of 50% of normal yield, equal to 55% of the estimated market price of the crop (called 50/55 coverage). Coverage levels that are higher than CAT are called 'buy-up' coverage, and most farmers purchase buy-up policies because of the additional protection. In 2019, only 2.5% of policies sold were insured under catastrophic risk protection. A producer can 'buy up' the 50/55 catastrophic coverage to any equivalent level of coverage between 50/100 and 90/100 (i.e. up to 90% of 'normal' crop yield for selected crops and 100% of the estimated market price). The two main forms of crop insurance are yield-based and revenue-based. Yield-based insurance provides an indemnity when the actual yield falls below the coverage level. Revenue-based insurance provides an indemnity when the revenue (actual yield × price) falls below the guarantee (expected revenue × coverage level × price percentage). Policies typically consist of general crop insurance provisions, specific crop provisions, policy

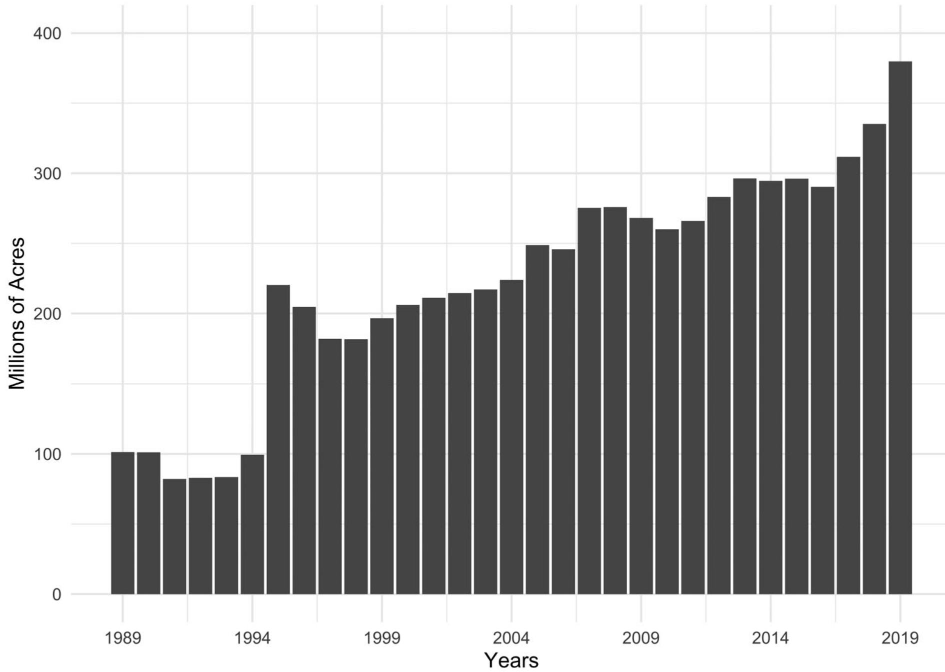

Figure 1. Insured area (millions of acres).

endorsements and special provisions. Individual plans are based on the insured's individual production or yield history, revenue or both. Area plans are based on information from the entire county, and use averages from surrounding agricultural producers as well. Additional plans of insurance are available in some states and counties (See https://www.rma.usda.gov/Policy-and-Procedure/Insurance-Plans for detail).

There has been steady progression in the number of acres covered by federal crop insurance since 1989 (Fig. 1). The large increase in the number of policies in 1995 and subsequent decrease in 1996 are due to mandatory enrollment requirements introduced by the Federal Crop Insurance Act of 1994 and their repeal in the Federal Agriculture Improvement and reform Act of 1996. The creation of CAT coverage in 1995 replaced the protection offered to crop producers under federal disaster programs in recent years. The increase in insured acres in 2007 was primarily due to the introduction of crop insurance policies for pasture, rangeland, and forage area (ERS). In 2018, US farmers planted

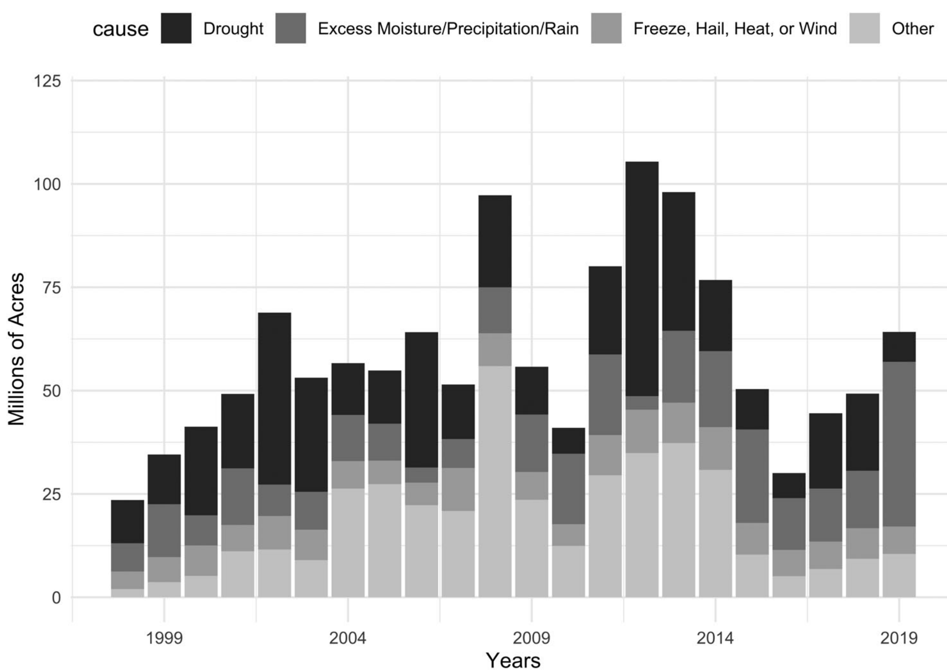

Figure 2. Acres claimed as lost – all causes of loss (millions of acres).

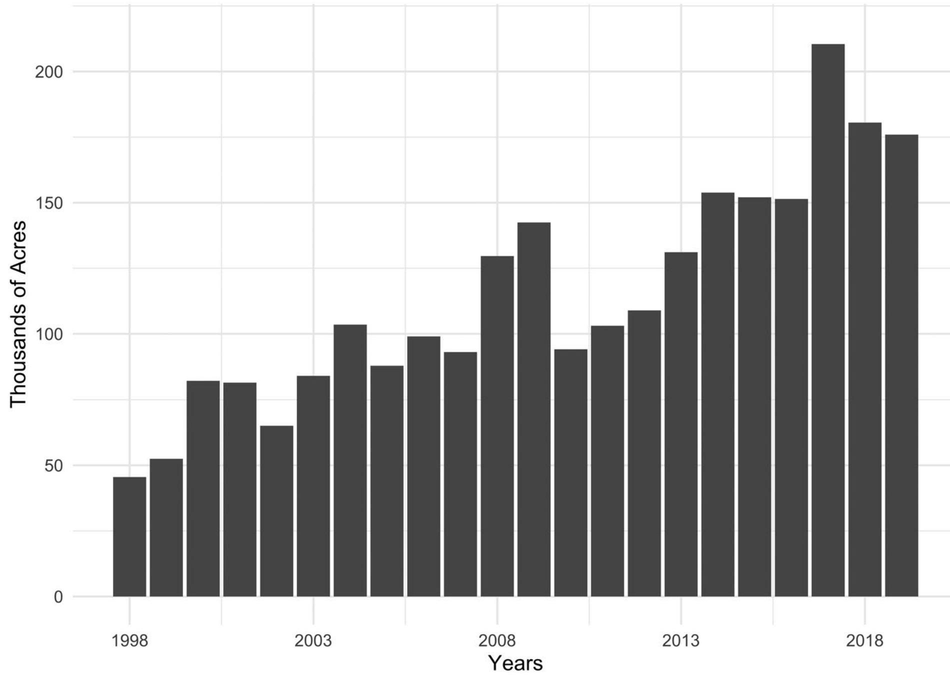

Figure 3. Acres claimed as lost to wildlife (thousands of acres).

240 million acres of the four crops targeted in our analysis. Crop insurance coverage for these same four crops totaled 208 million acres, indicating that 87% of planted acres had crop insurance coverage (AFBF https://www.fb.org/market-intel/majority-of-crop-acres-covered-by-crop-insurance). The fraction of acres for these four crops that are insured has plateaued in recent years, reflecting the trend in premium subsidies.[34]

There has been substantial variation in total indemnity payments since 1998 (Fig. 2). The maximum number of acres reported as lost was 105.4 million acres, of which 56.7 million were lost to drought. In most years, the majority of claims are triggered by weather events and show considerable randomness.

Wildlife claims, which account for a very small percentage of total claims, have increased substantially over the last two decades (Fig. 3). The increase in acres claimed as lost to wildlife can perhaps be explained by an increase in wildlife damages, but it may also be driven by temporal and spatial variation in the insured acreage, coverage levels, coverage types, and the projected yields and prices. The maximum number of acres reported as lost to wildlife was 210 500 acres in 2017.

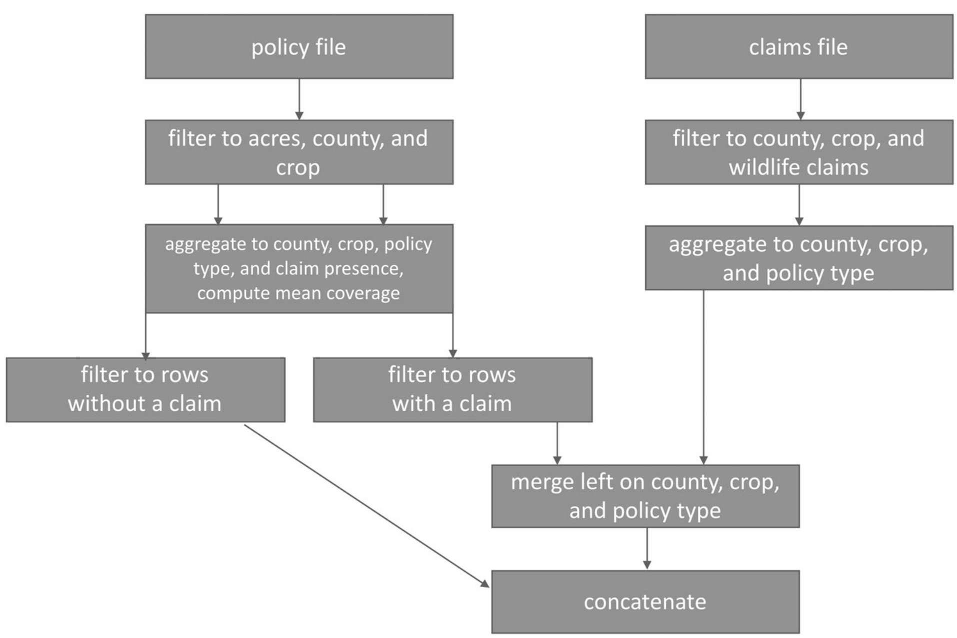

Figure 4. Data organization process.

We relied on two types of data files: the policy (or summary of business) file and the claim (or cause of loss) file. Both data files are aggregated for confidentiality purposes, but the level of aggregation is different for these two data sets. In the policy file, for a given county and crop, data are aggregated to the policy type and coverage level. Each row indicates the number of separate units (of that type and coverage level) that were sold, the number of acres covered, and the number of units that suffered a claim (for any cause of loss). In the claim file, for a given county and crop, data are aggregated at the policy type (combination of insurance plan type, e.g. yield-protection, revenue protection, and whether the policy is CAT or buy-up) and cause of loss level, but it lacks information on the coverage level. Rows are present only for policies that reported a claim and, notably, indicate the number of acres lost. The list of all variables in the policy and claim data sets can be found at https://www.rma.usda.gov/Information-Tools/Summary-of-Business/State-County-Crop-Summary-of-Business and https://www.rma.usda.gov/Information-Tools/Summary-of-Business/Cause-of-Loss, respectively. Our goal in organizing that data was to combine these two data sets to obtain a loss ratio (i.e. a ratio of lost acres to wildlife to insured acres) for each county and crop, while preserving as much detail about insurance coverage as possible.

After excluding observations in both files that lacked crop information and restricting the policy data set to policies expressed in acres, our first step was to split data in the policy file into rows with a claim and rows without a claim (Fig. 4). We then aggregated data in both resulting data sets by summing acres within each county/crop/policy type and calculating the average coverage level weighted by acres. Separately, we limited data in the claims file to wildlife-specific claims. We then aggregated by county/crop/policy type and merged the resulting data set with the data set we had constructed from the rows of the policy file that indicated a claim. Finally, we concatenated this merged data with the other data set we had created from the rows of the policy file that indicated no claims.

Because the claims data contains acres claimed as lost under each policy, we could compute the ratio of lost acres to total acres in the final, concatenated data set. Note that a specific county and crop combination may have had more than one row in this data set. The combination could have had different policy types (i.e. different insurance plans with CAT or buy-up). Additionally, for a given county/crop/policy type, some rows in the policy file contained a claim and some did not, which would result in the combination having two rows in the final data set.

We limited our sample to data from 2015 and 2019 to ensure a reasonable sample size and limit heterogeneity in reporting. All raw data are available for public download from https://www.rma.usda.gov/SummaryOfBusiness/ and https://www.rma.usda.gov/Information-Tools/Summary-of-Business/Cause-of-Loss.

Table 1. Descriptive statistics ($N = 116\ 844$)

Variable	Mean (SD)
Damage intensity	0.002 (0.026)
Catastrophic coverage	0.153 (0.360)
Mean coverage level	0.670 (0.118)
Not yield protection	0.543 (0.498)
Inverse mean area	0.020 (0.198)

Table 2. Estimation results (marginal effects)

Variable	Coefficients (SE)	
Mean coverage	0.010***	(0.001)
Not yield protection	−0.001***	(0.000)
Inverse mean area	0.000**	(0.000)
Catastrophic coverage	−0.002***	(0.000)
N	116 844	
Unique counties	2100	
Unique regions	4	
Unique commodity codes	4	

Robust standard errors in parentheses, ***$P < 0.01$, **$P < 0.05$, *$P < 0.1$.

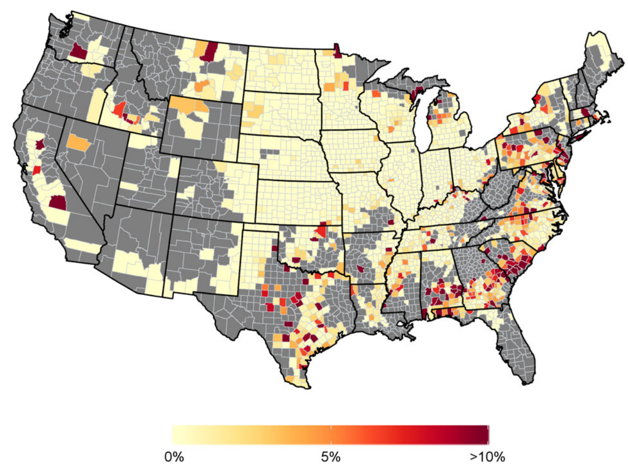

Figure 5. Average fraction of corn acres lost over the 2015–2019 period.

The primary objective of our analysis was to compare wildlife damage across geography and the four crops by synthetically holding insurance contract characteristics constant (insurance type and coverage level). Thus, the statistical model had to account for all known factors that affect the damage level or damage reporting. Our spatial level of analysis was the county. Within

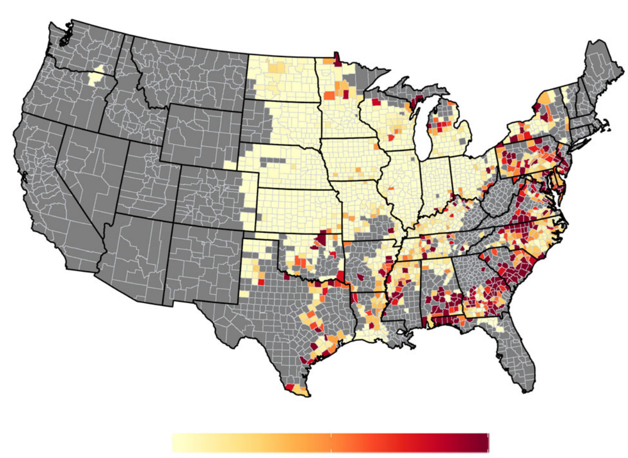

Figure 6. Average fraction of soybean acres lost over the 2015–2019 period.

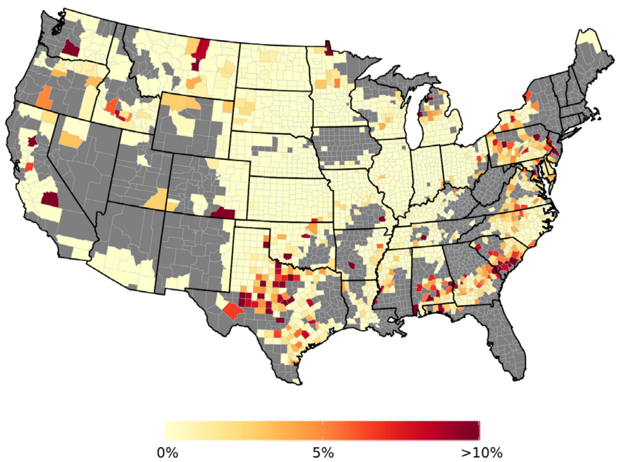

Figure 7. Average fraction of wheat acres lost over the 2015–2019 period.

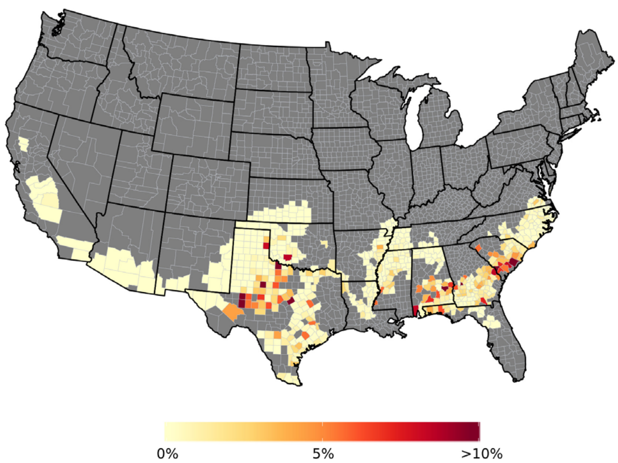

Figure 8. Average fraction of cotton acres lost over the 2015–2019 period.

a given county, damage levels can vary based on the type of crop grown. We also assumed that wildlife species vary across regions in the USA, and that this can influence the vulnerability of the crops studied within a region. A policyholder can file a claim if their estimated yield is less than the guaranteed yield defined by the policy. Hence, for the same level of damage, a farmer with more coverage is more likely to file a claim than a farmer with less coverage. Furthermore, the type of insurance policy may affect a policyholder's likelihood to report a claim. Finally, each observation represents an aggregation of policies with the characteristics previously described. Because wildlife damage is not uniformly distributed across acreage, the lower the mean insured acreage, the more likely it is the wildlife damage will reach the required threshold of loss in at least one of the insured parcels. A mathematical justification is shown in Appendix B. Additionally, previous research has shown that larger fields tended to have lower rates of crop damage.[35]

Because our units of observation were aggregations of similar policies at the county level, we used a fractional regression model (FRM)[36] where the response variable was the ratio between the acres lost to wildlife and the insured. The FRM only requires an assumption of a functional form that imposes the desired constraints on the conditional mean of the dependent variable such that:

$$|E\langle y = G(x\theta), \qquad (1)$$

where $G(\cdot)$ is some nonlinear function satisfying $0 \le G(\cdot) \le 1$. The model defined by Equation (1) may be consistently estimated by quasi maximum likelihood, which is fully robust and relatively efficient under the GLM assumption. Any cumulative distribution function can be specified for $G(\cdot)$[37], such as those commonly used to model binary data. The most widely used functions are the probit and logit functional forms.

We hypothesized that the average damage intensity (the ratio of lost acres to insured acres) in a given county over the period 2015–2019 depends on the mean coverage level, the type of coverage (catastrophic or not), the commodity insured interacted with the region of the county, the type of insurance plan, the inverse of the mean insured coverage, and the county. To model damage intensity in county *i*, crop *j*, and insurance plan type *k*, we estimated the following fractional regression model with a probit link:

$$E\left(DamageIntensity_{ijk}\right) = \Phi\left[\theta_0 + \beta_i + \gamma_j{}^{*}\rho_i + \delta_k + \theta_1 CAT_{ijk} + \theta_3 MeanCov_{ijk} + \theta_4 InvMeanAcres_{ijk}\right] \qquad (2)$$

where Φ is the normal CDF, θ_0 is a constant, β_i is the county fixed effect, ρ_i is the region fixed effect, γ_i is the crop fixed effect, and δ_k is the insurance plan type fixed effect. To account for the effect of having catastrophic coverage, we included a dummy variable, CAT_{ijk}, that equals 1 if the set of policies has catastrophic coverage. Finally, $MeanCov_{ijk}$, and $InvMeanAcres_{ijk}$ are continuous variables indicating respectively the mean coverage level and the inverse of the mean insured area for the policies aggregated in the observation. In the data set used for model estimation, mean *DamageIntensity* was ~ 0.002. (Table 1).

We estimated the statistical model using R Version 3.6.2 (www.r-project.org). We then synthetically standardized the level of insurance coverage across all counties and crops by setting the coverage level for all observations to 100% and the type of plan to 'yield

Table 3. Estimated national monetary losses (2017)

Crop	Total loss ($)	Total sales ($)	Percent loss
Corn	193 991 405	48 578 371 000	0.40
Soybeans	323 891 873	37 442 094 000	0.87
Wheat	27 045 970	6 805 866 000	0.40
Cotton	47 650 543	6 615 983 000	0.72

protection', which is the most common type of plan. We also set the inverse mean area to zero, its asymptotic limit. When a county and crop combination had multiple rows in the final data, we computed an overall insured area by summing insured acres across the rows. We then predicted the loss ratios by county and commodity combination and computed the number of lost acres implied by the ratio and the total acres associated with the combination. Finally, we additionally computed a monetary loss for each county based on the estimated loss ratio and total revenue for the county and crop as reported in the 2017 USDA/NASS Census of Agriculture (https://quickstats.nass.usda.gov).

Our procedure of synthetically standardizing the type and level of insurance is essentially an out-of-sample prediction problem. Thus, we evaluated variable inclusion using a k-fold cross-validation procedure in which we split the data into 50 folds, iteratively estimating on 49 folds and testing on one. The number of folds was set using Huberty's rule.[38] We then measured accuracy using mean squared error (MSE) averaged across the 50 validation folds (mean MSE = 0.025).

3 RESULTS

All coefficients are statistically significant at least at the 5% level (Table 2). As expected, all else being equal, damage ratios increase on average with mean coverage level and decrease with unit area or if the unit is insured under CAT. Damage ratios also decrease if it is not covered under yield protection crop insurance.

Figures 5–8 represent respectively the estimated average fraction of corn, soybean, wheat, and cotton lost to wildlife over the 2015 to 2019 period. The data used to generate these maps are available at https://github.com/anderaa/crop-insurance/tree/master/data. Current production value for the selected crops by county were obtained from NASS Quick Stats for the year 2017 (the most recent available census year at the time of writing). Figures A1–A4 in Appendix A represent 2017 sales by county for corn, soybeans, wheat, and cotton, respectively. Both corn and soybean production are relatively concentrated in the corn belt, upper Midwest, parts of the Great Plains and the Mississippi River region (particularly for soybeans): The state of Iowa was the leading producer of corn in 2017, followed by Illinois, Nevada, Minnesota, and Indiana. Illinois had the highest production of soybeans in 2017. Iowa is in second position, whereas Minnesota was third. Closing the top five were Nebraska and North Dakota. We also see counties with high soybean production along the Mississippi River. Wheat[4] production is concentrated in the Great Plains and the Northern Region of the USA. Kansas, North Dakota, and Washington were the leading wheat-producing states in 2017, followed by Montana and Oklahoma. Cotton[4] production is concentrated in the South and South-East, with four major producing states in 2017: Texas, Georgia, Mississippi, and Arkansas.

The main production regions for corn and wheat appear to be relatively spared, as wildlife damage is concentrated in the Southern and Eastern USA. Conversely, the southern soybean-producing counties (along the Mississippi River) overlap the area of highest wildlife damage, and the highest cotton producing counties appear to be located in the most intensely damaged areas.

We computed a monetary loss for each county by multiplying the estimated loss ratio and total revenue for the county and crop. Corresponding maps presenting the estimated monetary losses of corn, soybean, wheat, and cotton to wildlife in 2017 by county and state can be found in Appendix A (Figs A5–A12).

National monetary losses to wildlife for the four crops predicted by the model are presented in Table 3. The combined loss across four crops was estimated at $592.6 million. The highest total estimated losses to wildlife were incurred by soybeans ($323.9 million) and corn ($194.0 million) and the highest percentage losses were estimated for soybeans (0.87%) and cotton (0.72%).

4 DISCUSSION

Based on the claims filed to FCIC, we identified crop-raiding hot spots across the USA over the 2015–2019 period and identified the eastern and southern regions of the USA as being the most susceptible to wildlife damage. The higher susceptibly of crops in these regions may be due, in part, to smaller field and farm sizes (https://www.nass.usda.gov/Publications/Todays_Reports/reports/fnlo0220.pdf). Indeed, rural areas in these regions is interspersed with high quality wildlife habitat[35], whereas agriculture dominates the landscape in other regions like the Midwest corn belt. Interestingly, these regions are the stronghold of the wild pig population in the USA,[18,39] which are known to cause severe damage to agricultural crops.[40,41] Based on ground-based surveys of corn and peanut fields in South Carolina, the extent of forested and wetland areas surrounding crop fields was found to be the most important attributes positively associated with wild pig damage, whereas the amount of adjacent agricultural area and paved roads were associated negatively.[42] Future research should investigate the link between wildlife damage and wild pig presence.

We also estimated lower bounds for dollar and percent losses attributable to wildlife to the four main crops in the USA. The highest total estimated losses to wildlife were incurred by soybeans and corn. The highest percentage losses were estimated for soybeans and cotton.

There is a paucity of estimates of agricultural losses, in particular at the national level and they are commonly based on surveys with a limited sample size. The order of magnitude of these estimates converted to 2017 dollars matches our findings. The last national survey of wildlife damage to US field crops estimated $857 million in losses in 2001 (https://www.aphis.usda.gov/wildlife_damage/informational_notebooks/2012/Protecting_Agriculture_combined.pdf). Before that, based on responses to a survey of 13 310 farmers, the total estimated value of wildlife-caused losses to field crops in 1989 were estimated at $542 million.[43] In autumn 1993, the amount of wildlife-caused loss of ripening field corn in the top ten corn-producing states in the USA was quantified, and production loss for these states was valued at $156 million.[44] Production losses in percent have also been estimated at the regional scale. For example, based on a survey of 1500 producers of a specific region in Indiana, farmers indicated losses of 2% of total crop value for deer and raccoon.[35] In soybeans, crop value losses to deer and groundhogs were 2.8% and 1.7%, respectively. Wildlife caused the loss of 0.69% of the ten-state harvested production of corn for grain.[44]

Research has shown that crop insurance can encourage moral hazard – an increase in risk exposure because the farmer does not bear the full costs of that risk. For instance, moral hazard incentives lead insured farmers to use fewer chemical inputs.[45] Among winter wheat farmers, those who purchase revenue insurance tend to spend less on fertilizers.[46] Moral hazard can be problematic because it can be the source of endogeneity bias in the regression analysis. There are two ways in defining moral hazard in insurance markets: (i) *ex ante* and (ii) *ex post* moral hazard and we argue that neither are an issue in the case of wildlife damage. The first situation would arise if farmers experiencing wildlife damage were more likely to be insured. But we have seen that a vast majority of planted acres are covered by crop insurance. Crop insurance is purchased by agricultural producers to protect against either the loss of their crops due to natural disasters, such as hail, drought, and floods, or the loss of revenue due to declines in the prices of agricultural commodities. Wildlife claims account for a very small percentage of total claims (Fig. 2). Also, many banks, when making operating loans, require that farmers purchase crop insurance.[32] The second situation would arise if farmers were not less likely to engage in prevention if they are insured. For that matter, Section 1235 of the *Loss Adjustment Manual Standards Handbook* specifies that the first crop year loss resulting from severe wildlife damage will generally be considered unavoidable if the insured was unaware of the conditions at planting time. However, if it is determined that the insured was aware of the wildlife presence at planting time or later but did not follow appropriate recognized wildlife control measures that could be effectively used on agricultural acreages, some or all of the loss will be considered an uninsured loss. Hence, we can safely conclude that there is no basis for moral hazard in the case of wildlife damage and can reject allegations of endogeneity bias in the regression analysis.

We acknowledge that our approach does not perfectly capture the extent of wildlife damage in the four crops of interest. First, it is safe to assume that the accuracy at which crop insurance adjusters attribute crop damage to wildlife is low. Second, reliance on data that was aggregated for privacy reasons necessarily resulted in less-precise estimates. In particular, coverage levels were not available in the claims data set and had to be inferred. Additionally, when estimating damages, we did not consider uninsured acres or uninsurable damage. As for uninsured acreage, we have no reason to presume that the loss ratio for uninsured acres is lower or higher than for the insured acres. Hence, we could be over- or underestimating the average loss ratio for a given county. Third, although farmers absorb loss amounts too small to have triggered an insurance indemnity payment or that were considered uninsurable, there is no way to reliably determine a farmer's loss in this situation, because the number and size of these losses are not reported in the official statistics. Finally, we have seen that recurring wildlife damage with no appropriate recognized wildlife control measures is considered an uninsured loss. In cases such as these, RMA does not collect data on the cause of uninsurable damage.

For these reasons, the estimated spatial crop-raising intensities by crop types and the aggregate damages to wildlife presented here are conservative.

5 CONCLUSION

In this paper, we described a new method of estimating wildlife damage that exploits federal crop insurance data. Relying on crop insurance data has several advantages. First, it is available for public download on the USDA/RMA website. Second, the program insures more than 100 commodities and 127 000 county-crop programs. Because crop insurance premium support is size neutral, every eligible farmer, large or small, may purchase crop insurance. Third, the 2018 Farm Bill provides certainty and stability to the program, in particular by continuing its growth, providing avenues to expand farm safety net options for specialty crop producers, and ensuring increased program integrity (https://www.rma.usda.gov/en/Topics/Farm-Bill). Thus, we believe the proposed method will be a reliable way to evaluate geographic and temporal heterogeneity in damages for the coming years. Accurate information on damages benefits various management agencies by allowing them to allocate management resources to crops and regions where the problem is relatively severe. A better understanding of damage heterogeneity can also help guide research and development of new management techniques.

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6 APPENDIX A

6.1 Maps of crop sales by county and monetary loss by state

7 APPENDIX B

7.1 Justification for including average parcel size as an independent variable in the model

Let us consider the frequency distribution of crop damage within a given county as the relative frequency of 1-acre parcels with a particular level of damage ranging from 0% to 100%.

If crop damage is a continuous uniform distribution within the county (a, b), with $a \geq 0$, $b \leq 100\%$, and a population mean $\mu = \pi$ with $\pi < 100\%$, then the population standard deviation $\sigma_u \geq {}^{2\pi}/_{\sqrt{12}}$.

If crop damage is patchy, which can be represented by a dichotomous distribution with the same population mean $\mu = \pi$, then the population standard deviation $\sigma_d = \sqrt{\pi(1-\pi)}$.

It can easily be shown that $\sigma_d > \sigma_u$.

If we sample an area of size n acres in this county, the Central Limit Theorem tells us that the mean of the damage in that sample will tend to be distributed normally around the mean $\mu = \pi$ with a standard deviation ${}^{\sigma}/_{\sqrt{n}}$, where σ is the standard deviation of the crop damage distribution in the county. Let us assume the insurance threshold for the average loss on that parcel is T ($50\% \leq T < 95\%$). Then the probability for the landowner to

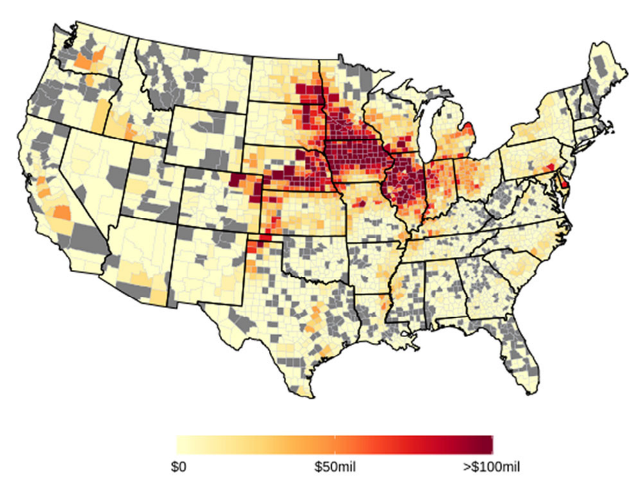

Figure A1. Corn sales in 2017 by county.

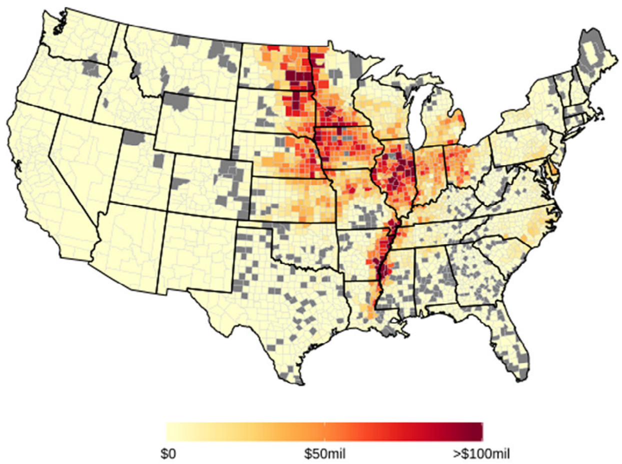

Figure A2. Soybean sales in 2017 by county.

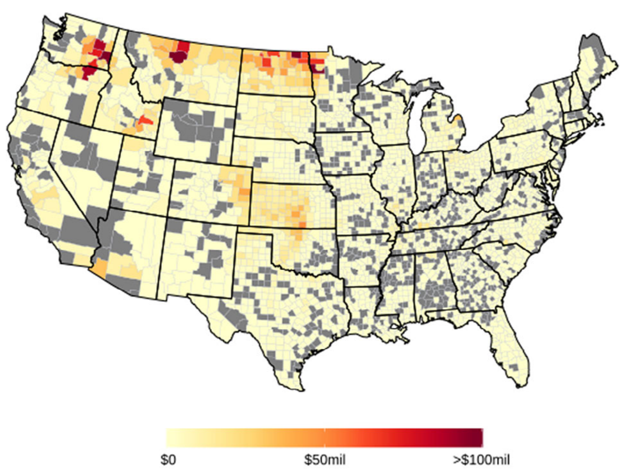

Figure A3. Wheat sales in 2017 by county.

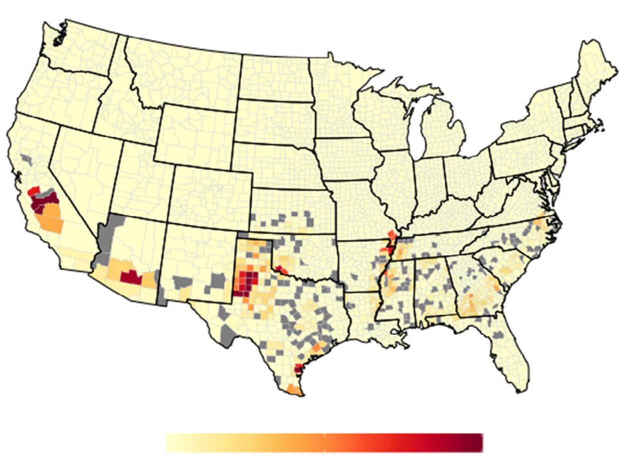

Figure A4. Cotton sales in 2017 by county.

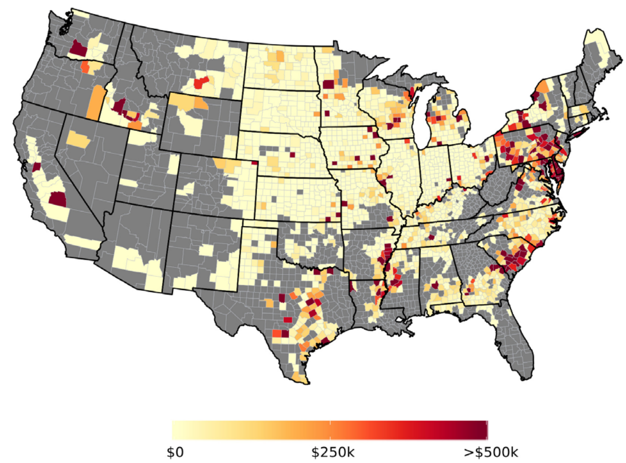

Figure A5. Corn monetary loss in 2017 by county.

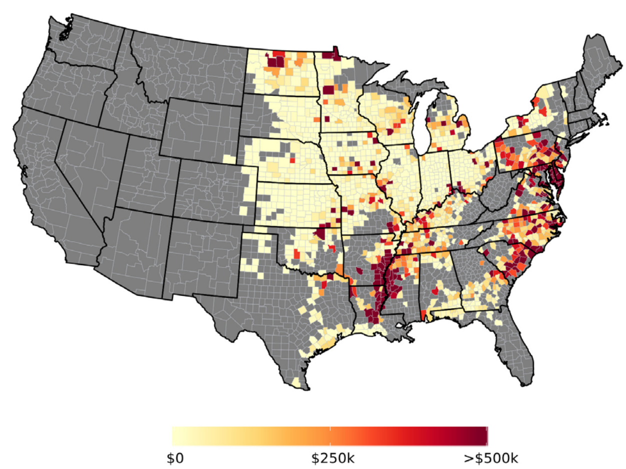

Figure A6. Soybeans monetary loss in 2017 by county.

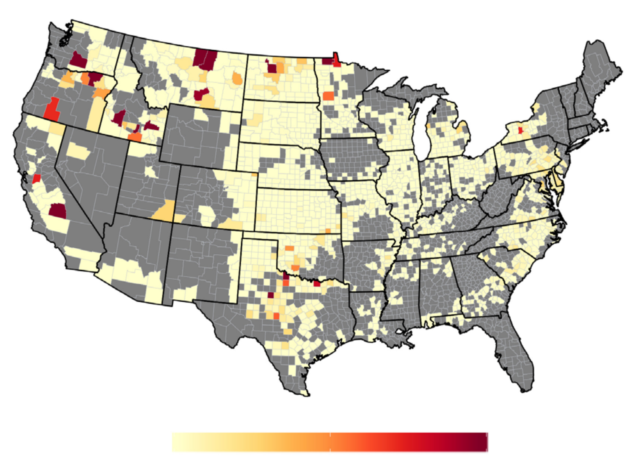

Figure A7. Wheat monetary loss in 2017 by county.

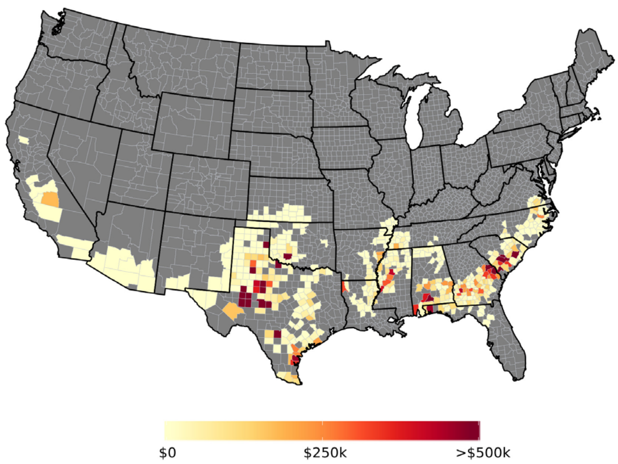

Figure A8. Cotton monetary loss in 2017 by county.

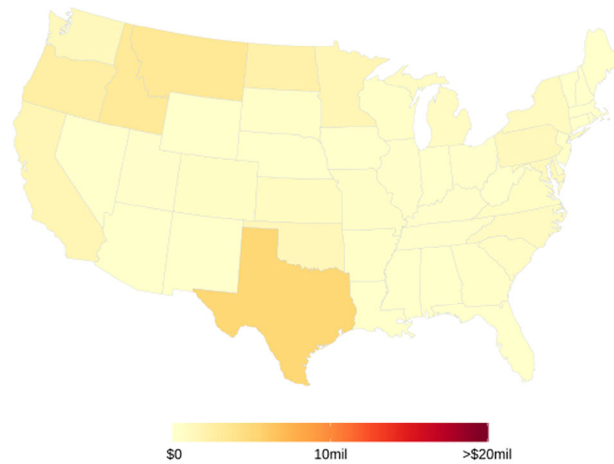

Figure A11. Wheat monetary loss in 2017 by state.

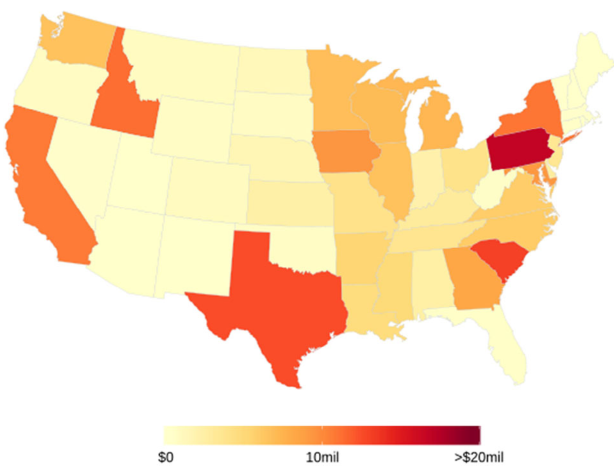

Figure A9. Corn monetary loss in 2017 by state.

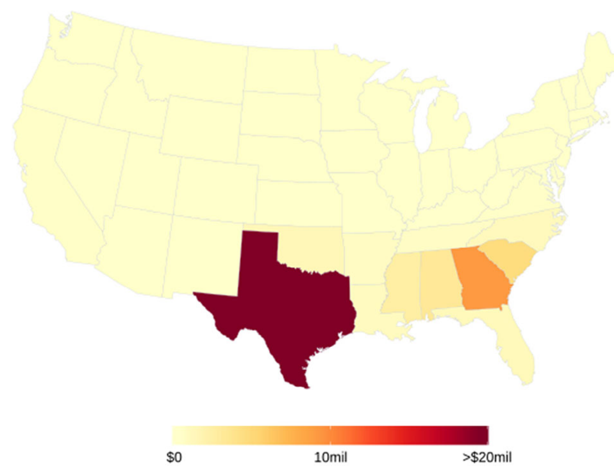

Figure A12. Cotton monetary loss in 2017 by state.

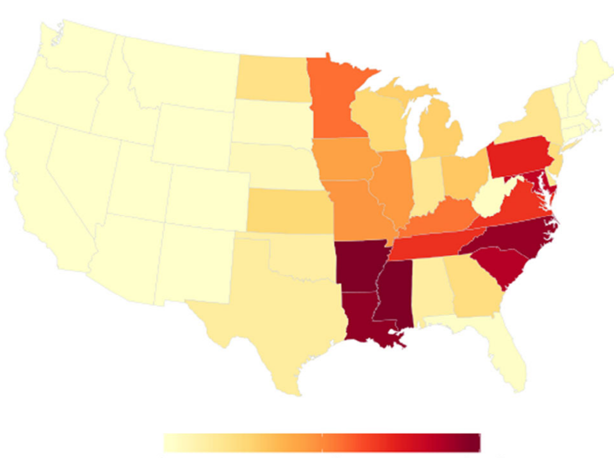

Figure A10. Soybeans monetary loss in 2017 by state.

declare a claim is $1 - CDF\left(\frac{T-\pi}{\sigma/\sqrt{n}}\right)$, where CDF is the cumulative density function of the standard normal distribution. When the parcel size is very large, then a claim will be filed only if the mean county damage π is greater than T. It can be shown that, all else being equal, even if the mean county damage π is less than T, a claim may be filed for that parcel and the probability to declare a claim increases when the parcel size decreases, and the parcel size effect increases when the skewness of the distribution increases (i.e. the patchier the damage distribution becomes).

REFERENCES

1 Conover MR, *Resolving Human–Wildlife Conflicts: The Science of Wildlife Damage Management*. CRC Press, Boca Raton, Florida (2001).
2 Messmer TA, Human–wildlife conflicts: emerging challenges and opportunities. *Hum-Wildl Confl* **3**:10–17 (2009).
3 Conover MR, Butikofer E and Decker DJ, Wildlife damage to crops: perceptions of agricultural and wildlife leaders in 1957, 1987, and 2017. *Wildl Soc Bull* **42**:551–558 (2018).

4 Garshelis DL, Sikes RS, Andersen DE and Birney EC, *Landowners' perceptions of crop damage and management practices related to black bears in east–central Minnesota*. Ursus, springer **219**:24 (1999).
5 VerCauteren KC, Lavelle MJ and Hygnstrom S, From the field: fences and deer-damage management: a review of designs and efficacy. *Wildl Soc Bull* **34**:191–200 (2006).
6 McManus JS, Dickman AJ, Gaynor D, Smuts BH and Macdonald DW, Dead or alive? Comparing costs and benefits of lethal and non-lethal human–wildlife conflict mitigation on livestock farms. *Oryx* **49**: 687–695 (2015).
7 Marchini S, Who's in conflict with whom? Human dimensions of the conflicts involving wildlife, in *Applied Ecology and Human Dimensions in Biological Conservation*. Springer, Berlin, pp. 189–209 (2014).
8 Hone J, Spatial and temporal aspects of vertebrate pest damage with emphasis on feral pigs. *J Appl Ecol* **32**:311–319 (1995).
9 Dawson DG, Estimation of grain loss due to sparrows (*Passer domesticus*) in New Zealand. *N Z J Agric Res* **13**:681–688 (1970).
10 Buckle AP, Rowe FP and Husin AR, Field trials of warfarin and brodifacoum wax block baits for the control of the rice field rat, *Rattus argentiventer* in peninsular Malaysia. *Int J Pest Manage* **30**:51–58 (1984).
11 Hothem RL, Otis DL. Bird Damage to Sunflower in North Dakota, South Dakota, and Minnesota, 1979–1981. Fish and Wildlife Technical Report (USA) (1988).
12 Johnson DB, Guthery FS and Koerth NE, Grackle damage to grapefruit in the lower Rio Grande Valley. *Wildl Soc Bull* **17**:46–50 (1989).
13 Alexiou PN, Effect of feral pigs (*Sus scrofa*) on subalpine vegetation at Smokers Gap, ACT. *Proceedings of the Ecological Society of Australia* **12**:135–142 (1983).
14 Hone J, Evaluation of methods for ground survey of feral pigs and their sign. *Acta Theriol* **33**:451–465 (1988).
15 Kernohan BJ and Gitzen RA, Analysis of animal space use and movements, in *Radio Tracking and Animal Populations*, ed. by Millspaugh JJ and Marzluff JM, Elsevier Science & Technology, San Diego, pp. 125–166 (2001).
16 Yackulic CB, Sanderson EW and Uriarte M, Anthropogenic and environmental drivers of modern range loss in large mammals. *Proc Natl Acad Sci* **108**:4024–4029 (2011).
17 VerCauteren K, Hygnstrom SE. *Managing White-Tailed Deer: Midwest North America*. Papers in Natural Resources. 380 (2011).
18 Lewis JS, Corn JL, Mayer JJ, Jordan TR, Farnsworth ML, Burdett CL *et al*., Historical, current, and potential population size estimates of invasive wild pigs (*Sus scrofa*) in the United States. *Biol Invasions* **21**: 2373–2384 (2019).
19 Curtis PD and Sullivan KL, *White-Tailed Deer. Wildlife Damage Management Fact Sheet Series*. Cornell Cooperative Extension, Ithaca, NY (2001).
20 Johnson HE, Fischer JW, Hammond M, Dorsey PD, Walter WD, Anderson C *et al*., Evaluation of techniques to reduce deer and elk damage to agricultural crops. *Wildl Soc Bull* **38**:358–365 (2014).
21 Gebhardt K, Anderson AM, Kirkpatrick KN and Shwiff SA, A review and synthesis of bird and rodent damage estimates to select California crops. *Crop Prot* **30**:1109–1116 (2011).
22 Van der Graaff N. Increasing the reliability of crop loss information: the use of indirect data, in *Crop Loss Assessment Methods; Supplement 3* (1981).
23 Lacy A, Cullen E, Barzen J, Schramm S and Crane GS, in *Protect Your Corn from Cranes*, ed. by University of Wisconsin–Extension, Cooperative Extension, Madison, WI (2013).
24 Johnson RJ, Timm RM. *Wildlife Damage to Agriculture in Nebraska: A Preliminary Cost Assessment* (1987). 3 - Third Eastern Wildlife Damage Control Conference.
25 Stowell LR, Willging RC. Bear damage to agriculture in Wisconsin, in *Fifth Eastern Wildlife Damage Control Conference*, p. 44 (1991).
26 Engeman RM, Terry J, Stephens LR and Gruver KS, Prevalence and amount of feral swine damage to three row crops at planting. *Crop Prot* **112**:252–256 (2018).
27 Dolbeer RA, Holler NR and Hawthorne DW, Identification and assessment of wildlife damage: an overview, in *The Handbook: Prevention and Control of Wildlife Damage: an Overview*, p. 2 (1994).
28 Beasley JC and Rhodes OE Jr, Relationship between raccoon abundance and crop damage. *Hum-Wildl Confl* **2**:248–259 (2018).
29 Hinton GC, Strickland BK, Demarais S, Eubank TW and Jones PD, Estimation of deer damage to soybean production in eastern Mississippi: perception versus reality. *Wildl Soc Bull* **41**:80–87 (2017).
30 Barzen JA, Ballinger Jr KE. Effective and sustainable prevention of avian damage to planted seeds through seed treatment, *Proceedings of the North American Crane Workshop*, **14**:89–100 (2018).
31 Ernst K, Elser J, Linz G, Kandel H, Holderieath J, DeGroot S *et al*., The economic impacts of blackbird (Icteridae) damage to sunflower in the USA. *Pest Manag Sci* **75**:2910–2915 (2019).
32 Shields DA, *Federal Crop Insurance: Background*. Congressional Research Service, Washington, DC (2015).
33 Shields DA, *Federal Crop Insurance: Background and Issues*. Congressional Research Service, Library of Congress, Washington, D.C. (2009).
34 Zulauf G, Schnitkey C, Coppess J and Paulson N, Premium Subsidy and Insured US Acres. *Farmdoc Daily* **8**:1–4 (2018).
35 MacGowan BJ, Humberg LA, Beasley JC, DeVault TL, Retamosa MI and Rhodes OE Jr, in *Corn and Soybean Crop Depredation by Wildlife. Purdue Extension FNR-265-W*, ed. by Purdue University. West Lafayette, IN (2006).
36 Ramalho EA, Ramalho JJS and Murteira JMR, Alternative estimating and testing empirical strategies for fractional regression models. *J Econ Surv* **25**:19–68 (2011).
37 Papke LE and Wooldridge JM, Econometric methods for fractional response variables with an application to 401(k) plan participation rates. *J Appl Economet* **11**:619–632 (1996).
38 Huberty CJ and Stephen O. *Applied MANOVA and Discriminant Analysis. Applied MANOVA and Discriminant Analysis. 2*. Wiley-Interscience, Aufl. Hoboken (2006).
39 Corn JL and Jordan TR, Development of the national feral swine map, 1982–2016. *Wildl Soc Bull* **41**:758–763 (2017).
40 Anderson A, Slootmaker C, Harper E, Holderieath J and Shwiff SA, Economic estimates of feral swine damage and control in 11 US states. *Crop Prot* **89**:89–94 (2016).
41 McKee S, Anderson A, Carlisle K and Shwiff SA, Economic estimates of invasive wild pig damage to crops in 12 US states. *Crop Prot* **132**: 105105 (2020).
42 Boyce CM, Vercauteren K and Beasley J, Timing and extent of crop damage by wild pigs (*Sus scrofa* Linnaeus) to corn and peanut fields. *Crop Prot* **133**:105131 (2020).
43 Wywialowski AP, Agricultural producers' perceptions of wildlife-caused losses. *Wildl Soc Bull* **22**:370–382 (1994).
44 Wywialowski AP, Wildlife damage to field corn in 1993. *Wildlife society bulletin* **24**:264–271 (1996).
45 Smith VH and Goodwin BK, Crop insurance, moral hazard, and agricultural chemical use. *Am J Agric Econ* **78**:428–438 (1996).
46 Mishra AK, Wesley Nimon R and El-Osta HS, Is moral hazard good for the environment? Revenue insurance and chemical input use. *J Environ Manage* **74**:11–20 (2005).

