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Farm vehicle crashes on public roads: Analysis of farm-level factors

Matthew McFalls MPH[1] | Marizen Ramirez MPH, PhD[1] | Karisa Harland MPH, PhD[2] | Motao Zhu MD, MS, PhD[3] | Nichole L. Morris PhD[4] | Cara Hamann MPH, PhD[5] | Corinne Peek-Asa PhD, MPH[6]

[1] Division of Environmental Health Sciences, School of Public Health, University of Minnesota, Minneapolis, Minnesota, USA

[2] Department of Emergency Medicine, University of Iowa Carver College of Medicine, Iowa City, Iowa, USA

[3] The Center for Injury Research and Policy, Abigail Wexner Research Institute at Nationwide Children's Hospital, Columbus, Ohio, USA

[4] Road Safety Institute, University of Minnesota, Minneapolis, Minnesota, USA

[5] Department of Epidemiology, College of Public Health, The University of Iowa, Iowa City, Iowa, USA

[6] Department of Occupational and Environmental Health, The University of Iowa, Iowa City, Iowa, USA

Correspondence
Matthew McFalls, MPH, Division of Environmental Health Sciences, School of Public Health, University of Minnesota, 420 Delaware St. SE, Mayo Mail Code (MMC) 807, Minneapolis, MN 55455-0381, USA.
Email: mcfal012@umn.edu

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Abstract

Purpose: Rural public roads experience higher crash fatality rates than other roadways, with agricultural equipment adding greater risk of injury and fatality. This study set out to describe farmers' experiences with farm equipment crashes and predictors of crashes at the farm level.

Methods: A survey of farm operators was conducted in 9 Midwestern states (IL, IA, KS, MN, MO, NE, ND, SD, and WI) in collaboration with the US Department of Agriculture's National Agricultural Statistical Service.

Findings: From 1,282 farms operating equipment on public roads in 2013, 7.6% of farmers reported that equipment from their farm had ever been in a crash (n = 97). Crashes occurred most often in June-August (44.0%) and were most often reported as being during the daytime (71.3%), on dry roads (79.4%), or in clear weather (71.4%). While most farmers responded that they were driving the farm equipment at the time of the crash (52.0%), nearly half of crashes involved their employees as the driver (48.0%). Crashes often went unreported to law enforcement (28.6%).

Conclusion: To illustrate crash probabilities for farms with different profiles, we included farm acreage, crop farming, vehicle horsepower, annual miles driven, and the total number of farm vehicles driven on public roads in a predictive model. Large crop farms of 241+ acres, those who drove farm vehicles 1,430+ miles per year, and those with 20 or more farm vehicles had the highest probability of crash of 0.14.

KEYWORDS
agricultural equipment, farm survey, farm vehicle crashes, rural road safety, traffic safety

INTRODUCTION

Farm vehicle crashes on public roadways are a major source of occupational injury and fatality for farmers and are a safety concern for all roadway users, with crashes often involving passenger vehicles.[1,2] These crashes contribute to the disproportionately high rate of traffic fatalities in rural areas over urban areas, although with increased urbanization, many farm vehicle crashes also occur near towns and cities.[3–5] Large farm equipment moving slower than the speed of traffic may be an unexpected encounter for many roadway users, evidenced by most crashes occurring as a rear-end collision from another vehicle.[4,6] Consequently, with often greater size and speed differentials with other vehicles, passengers of nonfarm vehicles are more likely to be injured in crashes than the farm vehicle driver.[4]

Many studies of farm equipment crashes use motor vehicle crash reports and have found seasonality, nighttime driving, farm-to-market routes, narrow roads, increasing urbanization, higher traffic volume, and higher speed limits to be factors in crashes.[3,6,7] Crashes are likely related to drivers' ability to perceive the size and speed of farm equipment, and states with stronger policies for the lighting and marking of farm equipment have reduced crash rates.[4,8] Motor vehicle crash reports, however, contain no detail from the level of the farm, resulting in mostly case-only studies that do not examine how farms or their operational characteristics influence the probability of a crash.

Few studies have surveyed or interviewed farmers for their perspectives on rural roadway safety, with only 2 US studies published over a decade ago.[2,9] A 2009 study surveyed farmers in North Carolina, finding that farms with younger drivers, nonfamily hired help, non-English-speaking drivers, and public road conflict were more likely to be present among farms who experienced crashes.[2] This was the only prior study found to ask farmers about their experiences with a crash. A 2003 study, also in North Carolina, examined farmer perceptions of roadway safety, finding that while most respondents took safety precautions with their tractors on rural roadways, most felt unsafe driving and that rural roads were becoming increasingly dangerous to drive on.[9]

Predictive modeling has potential in public health to identify factors in combination that contribute to a higher likelihood of an outcome, aiding in targeted interventions, policy, or the development of screening tools.[10–12] Exploratory studies can also use predictive modeling to identify potential risk factors for an outcome. Predictive models can be developed from a data set of candidate predictors and a known outcome, assessed for accuracy of the predictions, and used to calculate the probability of an outcome across different levels of variables in the model. This method has previously been applied to a case only study of farm vehicle crash reports to explore how environmental, vehicle, and driver factors may predict injury or death in a farm vehicle crash.[11] To our knowledge, this approach has not yet been used to identify predictors of a farm vehicle crash, which is fundamental to primary prevention and to identify future areas of focused study.

This study explored predictors of a farm equipment crash from a survey of farmers in 9 Midwestern states, developing a predictive model for farm equipment crashes. Predicted probabilities from the model were calculated and displayed across farm profiles with the highest and lowest probabilities of crash. In addition, farmer descriptions of the crash event were characterized by factors of the drivers and vehicles involved, as well as environmental factors, such as road, visual, and weather conditions.

METHODS

Data source

A cross-sectional survey of farmers in 9 Midwestern states served as the data source for this study. The Farm Equipment Roadway Use Survey was developed in 2013 by the University of Iowa Great Plains Center for Agricultural Health and administered through the US Department of Agriculture's National Agricultural Statistics Service (NASS). Farms were sampled from tax records in Illinois, Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, South Dakota, and Wisconsin. Weighted sampling of farms was in proportion to the number and size of farms in each state. Farm size was defined by 3 strata of a farms' annual value of sales, from the 2007 Census of Agriculture: small farms ($0-99k), medium farms ($100-499k), and large farms ($500k or above).[13] One individual, the farm owner or operator (farmer), was asked to complete the survey per farm. Survey responses were collected by phone or mail by NASS surveyors.

Variable definitions

Crash outcome

Survey responses about the crash outcome were limited to farmers who reported that their farm's equipment was driven on a public road in 2013. The dependent variable, history of a farm equipment crash on a public road, was based on a "Yes" response to the question, "Has any of your farm equipment ever been in an accident or crash while being driven on a public road?"

Predictors

Farmer characteristics
Respondents reported their age in years, gender (male or female), race (White, Black/African American, American Indian or Alaskan Native, Asian, Native Hawaiian, or Other Pacific Islander), and education (less than high school, high school graduate, some college, technical school training or associates degree, college degree, graduate degree). In addition, respondents were asked (yes or no) if their farm had any history of citations (for any driver) while driving the farm's equipment on a public road.

Farm characteristics
Farms were kept in their original sampling strata by value of sales, as small ($0-99k), medium ($100-499k), and large farms ($500k or above).[13] Farms were further defined by their size in acreage, reported in total number of acres on the survey. The type of farm was reported on the survey as crops, livestock, or both.

Farm equipment utilization

Respondents reported use of their farm equipment on public roads in a matrix-style questionnaire that binned exposure by season. For each of 4 seasons (January-March, April-May, June-August, and September-December), respondents were asked to report the type of equipment driven (tractors, self-propelled sprayers and combines/harvesters, towed implements, all-terrain vehicles, or other equipment), the number of each type driven, and the total miles driven by all equipment of that type. Annual farm vehicle miles were calculated from this matrix by summing the miles reported for all 4 seasons for tractors, self-propelled equipment, and other equipment, excluding all-terrain vehicles (ATVs). The total number of farm vehicles in use annually was calculated by summing the same categories across all 4 seasons. Towing miles and equipment numbers were calculated separately by the same procedure. A separate question asked for the age and horsepower of a farm's most frequently used farm vehicle.

Crash characteristics

If farmers reported a history of a crash, they were asked to respond to the follow-up question "How many roadway accidents or crashes have ever occurred on a public road with equipment from your farm?" to determine the number of crashes in their farm's history. This was followed by questions asking farmers to report the circumstances of only their most severe crash. Farmers were asked to select all that applied on the nature of the most severe crash, specifically: (1) others involved (another farm vehicle, passenger vehicle, commercial vehicle, bicycle, motorcycle, pedestrian, and animal); (2) whether the farm owner or another driver was operating the farm equipment at the time of the crash; (3) the number of passengers in the farm equipment; (4) years of experience of the farm equipment driver; (5) driver conditions of farm or other vehicle (ran stop sign or light, followed too close, wrong side of road, overcorrecting, aggressive/reckless driving, influence of drugs/medication/alcohol, or fatigue/sleepiness); (6) if either driver was distracted; (7) which driver was at fault; (8) if anyone was hurt in the crash; and (9) if the crash was reported to law enforcement. Environmental questions asked the year, time of year, weather conditions (clear, partly cloudy, cloudy, rain or mist, sleet/hail/freezing rain/drizzle, fog or smoke, snow, severe winds), visual conditions or obstructions (daylight, dawn or dusk, dark or nighttime, glare, parked or moving vehicles, trees or crops, buildings), and road conditions (dry, wet, snow/slush/ice, oil, water, sand/mud/dirt, rut/holes/bumps, flat, hilly, animals in roadway, inadequate shoulder, curve, straight). The survey also asked farmers to select the type(s) of equipment involved in the crash, including tractors or other self-propelled equipment, as well as towed implements or farm machinery. For self-propelled farm equipment, questions were asked regarding the age of the equipment, whether headlights or taillights were in use (or not equipped), and whether a slow moving vehicle (SMV) emblem was mounted at the time of the crash.

Descriptive analysis

Farms were compared by crash status across individual, farm, and equipment variables with chi-squared tests. Survey weights were applied to calculate weighted proportions for each of the independent variables. Farmer age was categorized as 18-44, 45-64, and 65 and over. Education was dichotomized as "Up to high school" or "Some college or higher." Tertile categories were created for farm acreage (0-240, 241-700, and 701+ acres), annual farm vehicle miles (0-420, 421-1,429, and 1,430+ miles), towing miles (0-12, 13-515, and 516+ miles), number of farm vehicles (0-4, 5-11, and 12+ vehicles), and number of towed implements (0-1, 2-6, and 7+ towed implements). Crash event variables were described separately for the crash group. The total number of crashes was summed across farms in the crash group.

Predictive model

Candidate predictor variables were informed by the descriptive analysis and included farmer age, education, acreage (in tertiles), crop farming, farm vehicle horsepower, farm vehicle miles (in tertiles), and the number of vehicles in use. Farmer gender, race, and past citations were excluded due to low variance. Towed equipment miles and number were excluded due to collinearity with vehicle miles and number of vehicles. Backward selection with logistic regression was used to narrow down candidate variables from the full model. This process ran the full model and deleted variables stepwise if they were above a significance threshold of $P = .20$. The variables for crop farms and vehicle miles were manually added back into the model based on a priori knowledge and improvements to model calibration and discrimination performance.[14]

To assess the performance of the model, calibration plots were used to assess agreement between the observed outcomes and predictions of the model. Model discrimination was assessed by the area under the curve (AUC). The model was internally validated by k-fold cross-validation ($k = 10$), to calculate an optimism-adjusted AUC with bootstrapped confidence intervals. Multiple imputation by chained equations was used to impute values for all variables with missing data, with 10 imputations, to consider possible bias in prediction from variables missing at random.[15] All analyses were conducted in Stata/MP 16.[16]

RESULTS

Of 1,668 survey responses, 1,282 farm operators (76.9%) met the inclusion criteria of driving farm equipment on a public road in 2013 and were included in the analysis. Of those included, respondents were predominantly male (95.7%) and White (99.5%), with a mean age of 58.1 years. The 386 respondents excluded (ie, did not drive farm equipment on the road) included a higher proportion of female farm operators (26.1%) and had a higher mean age of 65.3 years ($P<.05$). Excluded farmers more often reported a single type of land use, either crops or

TABLE 1 Owner/operator, farm, and equipment use characteristics by farm equipment crash history on public roadways

Variable		Total	Crash group (N = 97)	Weighted %	95% CI
Owner/operator					
Gender	Male	1,206	94	7.2	[5.3, 9.8]
	Female	54	1	2.6	[0.3, 17.6]
Age	18-44	181	15	9.3	[5.4, 15.5]
	45-64	666	48	5.9	[4.2, 8.1]
	65 and over	384	28	7.0	[4.1, 11.5]
Education	Up to high school	463	36	7.5	[5.3, 10.7]
	Some college or higher	794	59	6.7	[4.7, 9.5]
Citations while operating farm equipment	Past citation	22	3	16.9	[4.7, 45.3]
	No past citations	1,240	94	7.0	[5.1, 9.4]
Farm					
Annual value of sales	S: $0-$99k	367	18	4.9	[2.9, 8.3]
	M: $100-$499k	720	52	713.7	[5.0, 10.2]
	L:$500k	195	27		[9.6, 19.2]
Acreage tertile	0-240 acres	416	16	2.9	[1.4, 6.3]
	241-700 acres	415	39	11.3	[6.5, 18.9]
	701+ acres	403	39	10.5	[7.5, 14.5]
Land use (farm type)	Crops only	504	36	7.0	[5.1, 9.4]
	Livestock only	172	7	3.7	[1.9, 6.9]
	Both	579	53	9.0	[6.4, 12.5]
Farm equipment					
Annual vehicle miles driven (tertiles)	0-420 miles	373	14	4.2	[2.2, 7.9]
	421-1,429 miles	3733	34	9.4	[7.3, 12.2]
	1,430+ miles		48	10.1	[6.3, 16.0]
Number of vehicles (tertiles)	0-4 vehicles	425	22	4.6	[2.7, 7.8]
	5-11 vehicles	406	29	7.8	[5.2, 11.7]
	12+ vehicles	375	43	11.4	[7.1, 17.9]
Annual towing miles (tertiles)	0-12 miles	390	22	4.0	[2.3, 7.1]
	13-515 miles	356	22	710.7	[3.7, 12.7]
	516+ miles	373	42		[8.6, 18.3]
Number of towed implements (tertiles)	0-1 towed implements	479	30	4.1	[2.5, 6.8]
	2-6 towed implements	375	15	5.9	[3.0, 11.4]
	7+ towed implements	352	49	15.0	[11.3, 19.6]
Age of most used vehicle	0-17 years	601	40	7.8	[5.6, 10.7]
	18+ years	603	52	6.6	[3.9, 11.1]
Size of most used vehicle	14-100 hp	400	21	4.2	[2.5, 7.1]
	100+ hp	800	72	10.1	[8.0, 12.8]

livestock (77.6% vs 53.9%), as well as a higher proportion of livestock-only farms (31.4% vs 13.7%) and small acreage farms (63.5% vs 32.5%) ($P < .05$).

Farm and vehicle characteristics by crash group

Of the 1,282 farmers included, 97 farmers (7.6%) reported a history of their farm equipment crashing on a public road at any time during their farming experience (Table 1). Of these farmers, 17 (13.9%) reported multiple crashes in their farms' history, totaling 119 crashes reported by farmers in the study. Respondents' age, gender, education, and history of citations while driving farm equipment did not differ by crash history. Differences were observed by size of the farm: 13.7% of farmers in large farms ($500k or higher) had crashes, compared to 4.9% of smaller farms ($0-99k) ($P < .05$). By acreage, 11.3% of medium farms (241-700 acres) and 10.7% of farmers in large farms (over 700 acres) had crashes, compared to 2.5% of smaller farms (0-240 acres) ($P < .05$). Farmers in crop farms (7.0%) and farms with both crops and livestock (9.0%) had a higher proportion of crashes than farms with livestock only (3.7%) ($P < .05$). In the 2 highest tertiles of annual vehicle mileage (over 420 miles), 9.8% of farmers had crashes, while in the lowest tertile (420 miles or less), 4.2% of farms had crashes ($P < .05$). Where farmers' most frequently used a farm vehicle of 100 horsepower or greater,

TABLE 2 Characteristics of the most severe crash, among farmers reporting a farm equipment crash history

Variable		n	Total	Weighted %
Crash events and outcomes				
Multiple crashes	Yes	17	97	13.9
Nature of most severe crash	Ran off road	13	95	11.9
	Rollover	4		3.6
	Head on	3		2.6
	Rear-ended	28		28.1
	Sideswipe	19		27.6
	Broadside collision	7		5.6
	Hit while turning	12		12.2
	Other	9		8.9
Anyone hurt	Yes	17	96	16.0
Fault	Farm equipment driver	13	73	18.7
	Other driver	58		79.0
	Both farm and other driver(s) involved	2		2.3
Reported to law enforcement	Yes	67	94	71.4
Crash factors				
Time of year	Jan-Mar	8	88	9.1
	Apr-May	14		20.4
	June-Aug	37		44.0
	Sept-Dec	29		26.4
Weather conditions	Clear	66	95	71.6
	Partly cloudy to cloudy	8		6.2
	OtherNo weather factors reported	8		9.3
		14		12.9
Visual factors	Daylight	65	95	71.3
	Dawn or dusk	9		10.2
	Dark/night	11		10.7
	No visual factors reported	10		7.8
Road surface	Concrete	78	95	77.3
	Gravel	14		20.6
	Dirt/other	4		2.2
Road conditions	Dry	73	95	79.4
	Wet or other conditions	22		20.6

10.1% had a crash, compared to 4.2% of farmers where the vehicle was under 100 horsepower ($P < .05$).

Crash characteristics

The 97 respondents who reported farm equipment crashes most commonly reported the most severe crash as occurring in either June-August or the growing season (44.0%) or September-December or harvest season (26.4%) (Table 2). Crashes were most commonly reported as occurring during clear weather (71.6%), in daylight (71.3%), and with dry road conditions (79.4%). More than half of crashes involved either a rear-end collision (28.1%) or sideswipe (27.6%). When another vehicle was involved, farmers most often reported that only the driver of the other vehicle was at fault (79.0%).

The farm vehicles involved were typically a tractor (79.0%), and often towing was involved (45.0%) (Table 3). A passenger vehicle was most often involved in the crash (53.0%), while only 14.0% of crashes involved no other vehicle. The respondent was the driver in just over half of crashes (50.2%), and in the remaining crashes, the farm vehicle driver was a paid (26.4%) or unpaid worker (23.4%). In nearly one-quarter of crashes, the farm vehicle had passengers in addition to the driver (24.9%). Driver distraction of any driver (farm or nonfarm vehicle driver) was reported as a factor in 15.6% of crashes.

Predictive model

The backward selection resulted in an initial model that included acreage, horsepower, and number of farm vehicles, with an AUC of 0.66. Crop use and vehicle miles were added to reach a final model,

TABLE 3 Farm equipment and individuals involved in the most severe crash reported among farmers reporting a farm equipment crash history

Variable		n	Total	Weighted %
Vehicles and equipment involved				
Owner/operator equipment involved	Tractor < 100 hp	30	86	35.5
	Tractor > = 100 hp	35		43.5
	Towed implement	43		45.0
	Other equipment	9		4.2
Age of equipment at time of crash	< 15 years	35	60	56.0
	15 years or more	25		44.0
SMV emblem	Yes	80	90	86.0
Other vehicle involved	Other farm equipment	6	96	5.6
	Commercial vehicle	58		11.7
	Passenger vehicle	12		53.4
	Other vehicle	15		15.3
	No other vehicle involved			14.0
Individuals involved				
Driver of farm equipment	Owner/operator	51	94	50.2
	Paid worker	24		26.4
	Unpaid worker	19		23.4
Passengers in farm vehicle	Other passengers	23	93	24.9
	None	70		75.1
Driver (of farm vehicle) experience	< 5 years	16	91	17.8
	5 years or more	75		82.2
Driver conditions (any driver involved)	Followed too closely	15	95	15.3
	Wrong side of road/wrong way	7		9.6
	Overcorrecting/oversteering	13		11.6
	Aggressive/reckless, includes speeding	23		21.5
	Drugs/medicine/alcohol	6		7.1
	Fatigue/sleepiness	4		6.7
	Ran stop sign/light	1		0.7
Driver distraction (any driver involved)	Yes	18	95	15.6

which improved the AUC to 0.69. This model was found to have good fit (Hosmer-Lemeshow $P = .81$) and calibration. The cross-validated AUC to adjust for optimism was 0.67 (bootstrap 95% CI: 0.58-0.72). Predicted probabilities from the model showed a gradient of crash probability across farm profiles (Table 4). At the high end, farmers in a large crop farm, driving 1,430 or more annual miles, with 20 farm vehicles, have a 0.14 crash probability. By comparison, farmers in a smaller crop farm, driving under 420 annual miles, with 4 farm vehicles, have a 0.02 crash probability.

DISCUSSION

This is one of the first and most recent surveys of farmers' experiences with roadway crashes involving their agricultural equipment, and it is the first to report the lifetime prevalence of a farm equipment crash among farmers.[2] In our sample of 1,282 farmers in 9 Midwestern states, farmers had the highest probability of a crash if they were large operations with higher utilization of public roadways. Crop farms, even when holding farm size and roadway use constant, were more likely to report a crash than livestock farms. Although not entirely surprising, predicting crashes from a farm's size, roadway use, and land use adds to a scant body of research involving the use of predictive models. Just one previous study of farm-level characteristics and crashes found low farm income to be associated with lower crash risk.[2] Many more descriptive crash case studies have been conducted, however. Notably, our study of farmers' descriptive reports of the crash events corroborated many observations of farm equipment crashes from motor vehicle crash reports, with the exception of seasonality—in this study, farmers reported more crashes in the growing season than the harvest season.[4,17,18] These findings set the stage for future research on farm-level risk factors for crashes while suggesting areas of focused outreach to prevent farm equipment crashes.

In the predictive model, farm vehicle mileage and number of vehicles were found to be strong predictors of crash history. In combination with medium or large crop farms, these variables produced the highest crash probabilities from the model, possibly establishing one clear scenario for further investigation. The model also illustrates scenarios where farms of differing characteristics have similar crash probabilities. For example, where vehicle utilization is low, a large livestock farm

TABLE 4 Selection of predicted crash probabilities from the final crash prediction model

Acreage tertile	Crop farm	Annual vehicle mileage[a]	# farm vehicles[b]	Probability of crash (%)[c]	95% CI
T3: 700+ acres	Yes	High	High	14.2	[8.9, 18.7]
T2: 241-700 acres				13.8	[8.0, 19.5]
T1: 0-240 acres				6.3	[1.3, 11.4]
T3: 700+ acres	Yes	Low	Low	4.6	[1.5, 7.7]
T2: 241-700 acres				4.6	[1.7, 7.4]
T1: 0-240 acres				2.0	[0.0, 3.6]
T3: 700+ acres	No	High	High	8.3	[1.3, 15.3]
T2: 241-700 acres				8.3	[0.9, 15.6]
T1: 0-240 acres				3.7	0.0, 7.9]
T3: 700+ acres	No	Low	Low	2.6	[0.0, 5.3]
T2: 241-700 acres				2.6	[0.0, 5.2]
T1: 0-240 acres				1.1	[0.0, 2.4]

[a]Highest and lowest tertiles of vehicle mileage.
[b]High (20 farm vehicles), low (4 farm vehicles).
[c]Holding farm vehicle horsepower constant, at the sample mean (150 hp).

may have a similar crash probability as a small crop farm. Adding these contours to the model's predictions has been used previously in both clinical and public health applications.[11,19] This approach may help to identify farm profile types that are front-runners for future research, based on a high crash probability, either among all farms or within a certain subset of operational characteristics.

The predictive model was not designed for causal inference, although future causal studies may focus on variables identified through this process. Farm equipment crashes are an understudied phenomenon in motor vehicle safety research, and this predictive model presents a practical first step for hypothesis generation as to the risk or protective factors of farm equipment crashes.[11] Many predictors (such as a farm's size and crop use) in the model would be difficult to modify but could hint at areas for further exploration, particularly for farms with a high probability of crashes. For example, with greater mileage and number of farm vehicles, farmers may have a more consistent need to use roads in adverse weather or night conditions, which often have been found to be factors in crashes.[6,17,20] This could also suggest greater exposure to traffic, higher speed limits, or driving routes that increase crash risk.[7] With a larger fleet of vehicles driving more often, farms may also need more employees to operate equipment, adding to crash risk with younger, seasonal, or otherwise less experienced drivers.[2,17] By nature of higher acreage, farms may intersect more often with public roads, resulting in greater exposure to traffic during daily operation. Crop farming and vehicle horsepower may suggest larger and irregularly shaped tractors, sprayers, and combines, impeding the visibility of passing motorists, often a factor in crashes.[4,6] These vehicles may be slow moving and in some cases wider than a typical highway lane, increasing potential for a rear-end or sideswipe collision.[4,6,17,20]

Focusing on the crash event, descriptions from farmers were largely consistent with previous literature from motor vehicle crash reports. They highlight that farm equipment crashes are relatively rare, with 7.6% of farmers reporting a crash in their farm's history, and only 1.3% of all farmers reported having more than one crash in their history—which likely spans many years given the mean farmer age of 58.1 years. The most frequent crash circumstances were consistent with the literature—they most often occurred during the day, in clear weather, and on dry roads.[4,6] Most crashes had another vehicle involved, and most often the other vehicle was a passenger vehicle. More than half of crashes consisted of rear-end or sideswipe collisions as often found in case-only studies of farm equipment crashes.[6,20] Notably, the June-August summer season had the most crashes, rather than the harvest season as found in the literature.[4,17,18] This finding is limited by a small number of crashes and could be a point of further research.

Further applications of this study to public health could help inform research, prevention, and outreach efforts in rural roadway safety. The variables in the predictive model may be obtained through public resources or surveyed from farmers directly, to aid in a focused search strategy for farms that are more likely to experience a farm equipment crash. This could lend to more efficient sampling and recruiting of farmers to participate in research or a farm equipment safety intervention. Communities with farms that fit the high crash-risk profiles found in this study may also be identified for community-level or driver interventions, as most crashes with farm equipment are found to be the fault of the nonfarm vehicle driver.[4] Crash probabilities may further provide useful illustrations in risk communication to farms or communities as a part of public health outreach, as has previously been shown by Ranapurwala et al. with modeling risks of injury or death in a farm equipment crash.[11] Lastly, future studies may also benefit from surveying farmers on experiences with farm equipment crashes, in order to corroborate or expand on findings from motor vehicle crash reports.

This study has several limitations. As a cross-sectional survey, farm characteristics were assessed as of present-day factors, while crashes could occur at any point in a farm's history. By surveying farmers about a past event, details of the crash and its circumstances are subject to recall bias. Relatively, few crashes were present in the sample, limiting descriptions. In the predictive model, vehicle mileage may be prone to measurement error, although vehicle mileage may be well documented as part of farm business operations.[21] The internally cross-validated AUC of 0.67 suggests moderate discrimination between farms with and without a crash, although external validation is needed to test the model's reproducibility and generalizability to farms outside of the sample.[22] The predictive performance of the model may have been limited by the nature of farm equipment crashes, which are affected by a multitude of potential risk factors related to roadway usage, weather, the rural/urban environment, individual driver characteristics, and surrounding motor vehicle policies which were not collected.[4,6–8,17,18] Further addition of these variables could improve the precision of a farm-level model of crashes.

In 2017, rural areas accounted for 46% of all traffic fatalities while only accounting for 30% of total vehicle miles traveled.[23] Crashes on rural roadways are more likely to result in injury or fatality when farm equipment is involved, which makes these events important to study beyond the traditional data sources of motor vehicle crash data. This study was able to modestly predict farm equipment crashes using farm-level variables relating to a farm's size, land use, and utilization of public roads, which may help to focus research or prevention efforts. By drawing on farmer perspectives to study rural road safety, this study found that crash characteristics, including the time of day, weather, and road conditions, were largely consistent with motor vehicle crash data, while adding that farmers reported more crashes in the summer rather than fall season. Future research may focus on developing stronger prediction models as well as surveying farmers for possible points of intervention to prevent crashes.

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DISCLOSURES

The authors have no conflicts of interest to declare.

ORCID

Matthew McFalls MPH https://orcid.org/0000-0001-9487-4507
Marizen Ramirez MPH, PhD https://orcid.org/0000-0002-0830-9841
Karisa Harland MPH, PhD https://orcid.org/0000-0001-9482-8447
Motao Zhu MD, MS, PhD https://orcid.org/0000-0001-5639-4801
Nichole L. Morris PhD https://orcid.org/0000-0002-1296-9068
Cara Hamann MPH, PhD https://orcid.org/0000-0001-8916-7285
Corinne Peek-Asa PhD, MPH https://orcid.org/0000-0001-9472-2538

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