

Modeling the Role of Weather Patterns and Grain Quality in On-Farm Engulfments and Entrapments



Gretchen A. Mosher^{1,*}, Elzerie Derry¹, Mateus Pizarro²,
Yan Jiang¹, Cheryl Beseler³

¹ Department of Agricultural and Biosystems Engineering, Iowa State University, Ames, Iowa, USA.

² Department of Technology, Missouri Southern State College, Joplin, Missouri, USA.

³ Department of Environmental, Agricultural and Occupational Health, University of Nebraska Medical Center, Omaha, Nebraska, USA.

* Correspondence: gamosher@iastate.edu

HIGHLIGHTS

- Maximum high temperature and maximum relative humidity were found to be important in predicting corn moisture.
- Year, state, and maximum relative humidity were found to be important in predicting engulfment and entrapment.
- Findings warrant further investigation to examine exactly what is changing and impacting corn moisture and engulfment and entrapment incidents.

ABSTRACT. *Despite the clear hazard of out-of-condition grain, limited research has explored the role of specific indicators of grain condition and their impact on the rate of grain entrapments and engulfments. This project focuses on corn because it is the primary crop involved with documented grain entrapments and engulfments. The primary aim of the project was to identify significant factors associated with the moisture of harvested corn and to analyze the relationship between these factors and the occurrence of engulfment and entrapments. First, it was found that both year and state were associated with corn moisture. Further, the relationship between corn moisture and weather variables in the U.S. Corn Belt was investigated. It was found that both maximum high temperature and relative humidity predict corn moisture. A secondary goal was to measure the relationship between selected weather factors, the moisture of commodity corn, and on-farm and commercial entrapment and engulfment incidents in the U.S. Corn Belt. Year, state, and maximum relative humidity were found to be important in predicting the occurrence of engulfments and entrapments. Future work should examine other quality factors using modeling, including test weight, total damage, foreign material, and more detailed weather data to consider several prediction alternatives.*

Keywords. *Confined spaces, Grain bin safety, Grain quality.*



The authors have paid for open access for this article. This work is licensed under a Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International License <https://creativecommons.org/licenses/by-nc-nd/4.0/>

Submitted for review on 22 November 2024 as manuscript number JASH 16260; approved for publication as a Research Article by Community Editor Dr. Michael Pate of the Ergonomics, Safety, & Health Community of ASABE on 12 August 2025.

Citation: Mosher, G. A., Derry, E., Pizarro, M., Jiang, Y., & Beseler, C. (2025). Modeling the role of weather patterns and grain quality in on-farm engulfments and entrapments. *J. Agric. Saf. Health*, 31(4), 299-310. <https://doi.org/10.13031/jash.16260>

The agricultural industry is widely recognized as one of the most hazardous industry, for workers, based on the rate of total recordable cases of fatal and non-fatal injuries in 2023 (Bureau of Labor Statistics, 2024a,b). Hazards present both on the farm and within the commercial grain handling industry include grain handling safety, specifically, grain entrapment and grain engulfment (Gorucu et al., 2022; Cheng et al., 2023). Grain entrapment is a situation where an individual is partially submerged in grain but cannot remove themselves, while grain engulfments occur when individuals are completely buried in the grain (Issa et al., 2017). Both types of incidents are categorized as confined space hazards. A confined space is any space large enough to be entered by an individual and for work to be performed with limited means for entry or exit that is not designed for continuous occupancy (OSHA, 2011). There are currently approximately 2 million farms in the United States (USDA ERS, 2024), but routine surveillance to quantify the number of injuries, specifically injuries from a single hazard category, such as confined space, is rare (Faust et al., 2023).

Further, from 1964 through 2010, Riedel and Field (2013) estimated that 70% of entrapments occurred on farms that are exempt from OSHA requirements. The majority of documented confined space-related injuries and fatalities involve the storage and handling of grain and grain by-products (Issa et al., 2016). Entrapment and engulfment while working inside a grain storage structure account for 62% of documented cases, with the remaining cases being falls and entanglements. In 2022 there were no fewer than 42 grain-related entrapments (Cheng et al., 2023). This was nearly a 45% increase from 2021 and the highest number of grain entrapments in over a decade.

Further, tracking and quantifying confined space incidents is difficult, as noted by Leigh et al. (2014), who observed that over 80 percent of agricultural injuries and illnesses were missed by existing surveillance methods at the time their data were analyzed. National financial support for several surveillance methods ended in 2015. Although other sources have been developed to address surveillance gaps, the focus of these efforts was not solely surveillance and these efforts do not replace previous surveillance efforts (Faust et al., 2023). Despite the clear hazard of confined space incidents, limited analysis has investigated the factors that predict and characterize the reasons for these events. One of these factors is out-of-condition grain, characterized primarily by moisture content.

It is well known that managing the condition of grain has critical implications on the safety of grain handlers (Mosher et al., 2012). Out-of-condition grain has been identified as a primary causal factor in grain engulfments and entrapments (Freeman et al., 1998; Kingman and Field, 2005). Flowing grain entrapments, avalanche entrapments, bridging entrapments, and vacuum or conveyor-related entrapments are all related to out-of-condition grain (Issa et al., 2022).

Typically, a person enters a bin to resolve a grain quality problem, address a grain flow problem caused by spoiled grain, clean out spoiled grain, or try to rescue a trapped person (Issa et al., 2017). According to Issa et al. (2016), corn is the primary crop involved with documented grain entrapments and engulfments (USDA, 2022). Previous research has found a strong correlation between the number of farms with grain storage structures and the number of confined space incidents such as engulfments and entrapments within a given location (Issa et al., 2016).

To prevent engulfments and entrapments, several tasks may be undertaken to prevent crusted surfaces from forming on grain. These include the prevention of roof leaks in the storage facility, appropriate management of headspace conditions in the storage bin, and

holding grain at the correct storage temperature. Individuals should never enter a grain storage bin when flowing grain is loaded or unloaded or when crusted surfaces or vertically crusted columns of grain are prevalent. Yet, anecdotal and research data report that individuals often enter grain storage bins during these conditions (Mosher et al., 2014; Walker, 2010).

Limited research has examined the role of specific indicators of grain condition, and even less research has explored the potential of using these data to predict on-farm engulfments and entrapments. This research aimed to identify and empirically model several variables that are hypothesized to impact the condition of grain, thereby increasing the number of on-farm engulfments and entrapments. Because of the availability of data (or lack thereof) and because the project was an initial investigation, the analysis approach examines broadly defined variables, including regional and state-specific weather variables. Yet, many widely held assumptions about the preservation of grain quality have not been empirically validated, including the relationship between weather conditions and the quality of grain post-harvest. For this reason, the goal of this project was to identify and quantify significant factors to predict on-farm engulfments and entrapments. This project focused specifically on corn because the majority of farm engulfments and entrapments involve corn (Issa et al., 2016). Firstly, factors thought to predict corn moisture were identified and modeled. Then, factors predicting entrapments and engulfments were identified and modeled. Differences between years and states, the moisture of corn, and weather variables were examined. The models addressed two aims: (1) The identification of significant factors associated with the moisture of harvested corn, and (2) the measurement of the relationship between corn moisture, selected weather factors, states and years, and the occurrence of on-farm entrapment and engulfment incidents in the U.S. Corn Belt.

A primary project goal was to analyze variables that have not previously been analyzed together to predict the incidence of grain engulfments and entrapments. Specifically, the introduction of quality traits and weather data into the safety modeling equation was innovative. A central hypothesis of this work was that when grain remains in good condition, there is less reason or need to enter a grain bin. Anecdotally, it is known that crop years with wet, cold, and late harvests tend to result in larger numbers of grain engulfments and entrapments. Factors related to weather patterns and crop conditions are not usually controllable by agricultural producers, but their impact can have direct effects on the safety hazards presented by harvested and stored crops. The importance of managing the moisture content of corn has been well-researched. Moisture is arguably the most important quality attribute to be managed during post-harvest storage. High grain temperatures and high moisture content lead to the new presence of storage molds, kernel damage, changes in gases within the grain mass, and the disappearance of viable field molds (Reed et al., 2007). Moisture content also has a large economic impact because moisture content directly influences market price (Sadaka and Rosentrater, 2022). Test weight is another widely used indicator of grain quality and serves as a measure of bulk density (Manis and Sharpe, 2022).

Although post-harvest management can mitigate some risks, in years where weather conditions are extreme, the quality of the grain loaded into the storage bin may be poor from the beginning, resulting in hazards unexpected by producers and handlers (Mosher et al., 2012; Branstad-Spates et al., 2023; Castano-Duque et al., 2022). Understanding factors that influence the rate of engulfments and entrapments on an annual basis could potentially provide safety and quality practitioners and educators with more focused messaging in years where stronger safety messaging is warranted.

Materials and Methods

Variables

Data on injuries and fatalities for the years 2017 to 2021 were used from the Purdue Agricultural Confined Space Incident Database (PACSID), which provides data on engulfments and entrapments at the state level, coded using a standard process (Cheng et al., 2023). The database does not distinguish between engulfment and entrapment incidents. Purdue University's Agricultural and Biological Engineering Department has managed this database since 1977 (Issa et al., 2016). This website is supported by a U.S. Department of Labor, OSHA Susan Harwood Training Grant. Reported cases are separated into entrapments, falls, poisonings, entanglements, and others. Engulfment data were combined with entrapment data for analysis. Entrapment cases were separated by state. Fourteen states had at least one entrapment case between 2017 and 2021: Arkansas, Illinois, Indiana, Iowa, Kansas, Kentucky, Louisiana, Minnesota, Nebraska, North Dakota, Ohio, South Dakota, Texas, and Wisconsin. The entrapment and engulfment data were not separated into crop reporting districts, as the specific location of incidents were not available for the full data set. There were 77 entrapment cases documented across the 14 states between 2017 and 2022. The number of incidents was used as the dependent variable in the models. Grain engulfment and entrapment data, grain quality data at harvest, weather data, and data on total bushels of corn produced by each crop reporting district were used in the analysis. Quality indicators examined included quality attributes of grain, such as moisture content, as well as field and climate information including total bushels of corn produced, relative humidity, temperature, and rainfall.

Farmers' Independent Research of Seed Technology (FIRST) was used to obtain information about the quality of grain at harvest. Variables collected by FIRST include test weight, moisture, protein, oil, yield in acres per bushel, damage, and toxin presence, with all of these reported by crop reporting district within each state. After preliminary analyses found that moisture had the strongest relationship with engulfments and entrapments, no further analysis was completed on other variables, and only moisture data was utilized in this analysis. Moisture data were reported separately by crop reporting districts within each state. The mean of corn moisture by state from each crop reporting district examined archive information from 9 states, including Illinois, Indiana, Iowa, Kansas, Minnesota, Nebraska, North Dakota, South Dakota, and Wisconsin. Sixty-one entrapment and engulfment cases were represented in these data.

Weather data were obtained from the Environmental Mesonet at Iowa State University, with weather stations aligned with crop reporting districts. Weather data means were drawn from each state and each state's corresponding crop reporting district. Monthly weather summaries from 2017 to 2021 included overall mean, mean minimum, and mean maximum values for precipitation, high and low temperatures, and relative humidity. These data were averaged for each month, and then those values were averaged for each year.

Data on total bushels of corn produced by each crop reporting district was used as an offset variable to provide a denominator due to differences in corn production by each district. This allowed researchers to mitigate and remove the probability that states with higher corn production would observe greater numbers of engulfments and entrapments. These data were obtained from the 2017 Census from the National Agricultural Statistics Service, which is part of the USDA.

Data Analysis

Factors Predicting Corn Moisture

Initially, to determine whether corn moisture varied across the nine states and five years, an analysis of variance model was used. Both variables, year and state, were used in the analysis of variance model to explain corn moisture, separating out differences by year. Pairwise comparisons were undertaken. To control for Type I error across multiple comparisons, Tukey's method was used. These outputs are shown in table 1.

In considering how to model weather, grain quality, and engulfment and entrapment variables, two aspects were important: the accuracy of prediction variables and the simplicity of the models. Because of the number of highly correlated variables in the two models, a statistical technique known as elastic net was used for data reduction and selection of predictive variables (Zou and Hastie, 2005). Elastic net addresses the limitations of Lasso (L1) and Ridge (L2) penalties. Ridge regression has acceptable prediction performance, but it keeps all predictors in the model. While methods exist to reduce the model, results are variable, as discussed by Zou and Hastie (2005). Elastic net modeling also addresses limitations of the Lasso (L1) technique, which was developed to simultaneously reduce and select variables in the model (Zou and Hastie, 2005).

Yet, in some scenarios, particularly those where pairwise correlations among variables are very high, Lasso lacks the ability to group the most important variables in a model (Zou and Hastie, 2005). To produce an appropriately reduced model and retain the most significant predictive variables, elastic net was used. Elastic net models can be used for data reduction and are not sensitive to collinearity. Further, an elastic net model was able to capture and retain all of the important variables in or out of the model together (Zeng and Xie, 2008; Hans, 2011), similar to a large fishing net that retains all of the "big fish," but lets the smaller fish out (Zou and Hastie, 2005).

With the two models in this project, the idea of using an elastic net model was considered to address the highly correlated weather variables. These highly correlated variables, along with the algorithm used as part of elastic net, constrains the parameters and force each to zero, without considering collinearity, as was the case in a conventional linear regression model. Accordingly, some variables never get to zero, while variables that contain similar information to another variable but less information that is important to the model, are the first to go to zero.

Therefore, for the first model, which analyzed 12 weather variables with corn moisture, a linear elastic net regression model was used. The standardized corn moisture variable is the outcome, and the 12 standardized weather variables are the predictors. The penalized regression parameter (α) was set at 0.5 to balance the LASSO and Ridge penalties. No intercept was specified, and coefficients within one standard error of the lambda tuning parameter were considered influential. The output from the elastic net model is shown in table 2. Following the variable selection, selected coefficients were refitted using linear regression, shown in table 3.

Factors Predicting Engulfment and Entrapment

Due to collinearity among the variables, an elastic net regression model with a Poisson log link function was used to predict the likelihood and potential risk to workers of engulfment or entrapment. Poisson distributions were used for counts of events, and log link functions were used to predict the mean number of events. The model was constructed and analyzed as in the corn moisture model described above with standardized variables, with

alpha = 0.5 for elastic net specification, no intercept, an offset variable to act as a denominator for the count outcome, and variables selected based on being within one standard error of lambda. The total bushels of corn produced by each state were used as an offset variable. The selected variables were refit in a generalized linear regression model with a Poisson link function and offset. All data analysis was completed in R version 4.2.2 using the glmnet package.

Results

Factors Predicting Corn Moisture

The ANOVA model showed that, when considered separately, both state and year were associated with corn moisture (state: $F [(8, 118)] = 3.13$, $p = 0.003$; year: $[F(4, 122)] = 13.4$, $p<0.0001$). When both variables were included in the model, the effect sizes increased as seen in table 1.

The R^2 value for the state model was 17.5%, for the year model 30.6%, and for both together 47.6%, indicating that they were independently explaining additional variance. In examining the pairwise analysis comparing states, corn moisture was higher in Illinois and Wisconsin compared to Kansas ($p<0.05$). A graph of corn moisture content versus state for each year can be found in figure 1. Differences in corn moisture were seen by year, and there were also differences in corn moisture by state. Corn moisture was higher in 2019 than in any of the other years, and it was statistically different from all other years. No interactions were present.

Table 1. ANOVA of year and state with corn moisture.

Parameter	F-statistic	p-value
State	4.76	<0.0001
Year	16.3	<0.0001

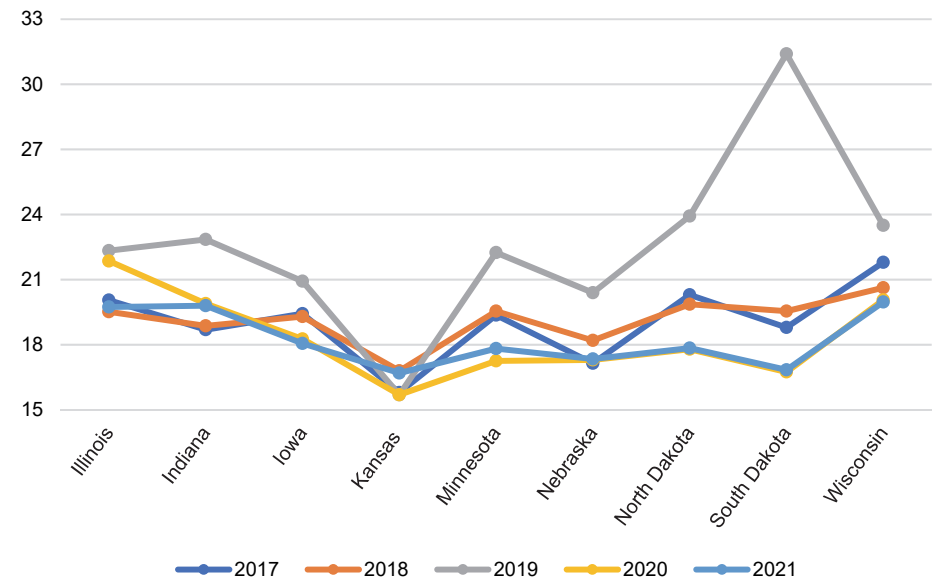


Figure 1. Mean corn moisture in each state for the years 2017–2021.

Table 2. Elastic net coefficients of weather variables to predict corn moisture.

Weather Variable	Elastic Net Coefficient
Minimum precipitation	0.0000
Maximum precipitation	0.0000
Mean precipitation	0.0000
Minimum high temperature	0.0000
Maximum high temperature	0.1220
Mean high temperature	0.0000
Minimum low temperature	0.0000
Maximum low temperature	0.0000
Mean low temperature	0.0000
Minimum relative humidity	0.0000
Maximum relative humidity	11.2702
Mean relative humidity	0.0000

Table 3. Refitted linear regression predictor of corn moisture.

Parameter	Estimate	Standard Error	p-value
Maximum High Temperature	-0.0471	0.0612	0.443
Maximum Relative Humidity	29.5653	6.5556	<0.0001

The elastic net model with its 12 weather variables identified only two important features that predicted corn moisture: maximum high temperature and maximum relative humidity. When refitted using a linear model, the relative humidity variable slope coefficient for maximum high temperature and for maximum relative humidity is shown in table 3.

Factors Predicting Engulfment and Entrapment

All 15 variables were entered into the elastic net model predicting engulfment and entrapment incidents. Table 4 presents the elastic net coefficients selected at the lambda threshold. Of the 15 variables (12 weather variables, corn moisture levels, state, and year) analyzed, the elastic net Poisson model identified three variables with non-zero coefficients: year, state, and maximum relative humidity. Importantly, corn moisture content was not selected, probably because maximum relative humidity explained corn moisture (and captured it into its “elastic net” along with maximum high temperature). The refitted Poisson linear regression model showed year, state, and maximum relative humidity to be statistically significant (table 5). Specifically, increased levels of maximum relative humidity levels showed a positive relationship with the number of engulfment and entrapment events. That the elastic net model failed to select any other variables indicates limited predictive values for those variables in this context, which is an important finding.

Table 4. Elastic net coefficient of model variables to predict engulfments and entrapments.

Modeled Variable	Elastic Net Coefficients
Year	0.03542
State	-0.03278
Minimum precipitation	0.00000
Maximum precipitation	0.00000
Mean precipitation	0.00000
Minimum high temperature	0.00000
Maximum high temperature	0.00000
Mean high temperature	0.00000
Minimum low temperature	0.00000
Maximum low temperature	0.00000
Mean low temperature	0.00000
Minimum relative humidity	0.00000
Maximum relative humidity	0.28634

Table 5. Refitted linear regression predictor of engulfsments and entrapments.

Parameter	Estimate	Standard Error	p-value
Year	-0.0104	0.0005	<0.0001
State	0.0537	0.0213	0.0118
Maximum Relative Humidity	2.6774	1.2739	0.0356

Discussion

The two sets of models produced results that show several insightful findings. Initial results from the elastic net model examining factors predicting corn moisture showed that maximum high temperature and relative humidity emerged as the only significant predictors. Maximum relative humidity explained nearly all of the variance in corn moisture ($R^2=97.6\%$) and was the only significant weather predictor of corn moisture in the refitted linear regression model. This result was not unexpected, given the large difference between the elastic net coefficient values of maximum high temperature and maximum relative humidity in the elastic net model. The relationship between the relative humidity and the moisture of corn in the storage bin is sometimes explained partially by equilibrium moisture content (Jones, 2018). In this case, equilibrium moisture content does not appear to be in play as the moisture content values used in the model were collected at harvest, before the corn was deposited into the storage bin. Grain held in a storage bin will eventually come to an equilibrium moisture content based on the relative humidity within the bin, as noted by Jones (2018) and others. Yet, the stored corn still requires post-harvest management. When actions related to aeration and temperatures are not taken, “hot spots” may develop and slow or block movement of corn during load-out. It is these blockages that often provide the reason for individuals to get into the bin, and several factors influence these actions (Jiang, 2024).

The magnitude of the high relative humidity effect may also be masking the effects of other weather variables in the elastic net model, including temperatures and precipitation. The high correlation of temperatures, precipitation, and relative humidity could have been interpreted by the elastic net model as redundant variables. Previous research has shown that field drying of mature corn grain is primarily influenced by temperature, humidity, and rainfall (Nielsen, 2018), so the influence of these factors was not unexpected. Generally, warmer temperatures and lower humidity allow for rapid field drying of corn grain. The selection of high temperature values as a non-zero variable in the elastic net model contradicts conventional and scientific wisdom, but the contradiction does add evidence to the hypothesis that the elastic net modeling analyzed high temperatures and high relative humidity values as redundant variables.

The finding suggests that there is potentially a surrogate variable or variables that vary by year that are influencing corn moisture at the state level and that are changing from year to year. Climate conditions, safety messaging, planting and harvest dates, and other growing conditions all vary between states and between years. All of these factors have the potential to influence corn moisture and its management, along with its connection with safety as well. One example of something that does not change substantially from year to year in each state is soil composition, which has played a significant role in grain quality at harvest and toxin development in Midwest corn (Branstad-Spates et al., 2023). Accordingly, although soil composition does not seem to play a direct role in corn moisture, it potentially could play an indirect role.

Variability of corn moisture levels was evident across states and by years. The corn moisture levels by state and year seem to play a role in the larger model that predicts engulfment and entrapment incidents, but the specifics of that role are not clear from this data analysis. These findings warrant further investigation to examine exactly what is changing on a state level and on a yearly basis to impact corn moisture. Additionally, the sampling method and when the moisture sample was taken are factors that need further investigation. Moisture values used in this research were assumed to be measured at harvest, but the exact time of measurement was unknown. Future research would benefit from more specific data on how and when the moisture samples were collected to validate this unexpected finding.

In the full 15-variable elastic net predictive model, year, state, and maximum relative humidity were all found to be non-zero variables in predicting engulfments and entrapments. While other weather variables were included in the initial elastic net model, they did not contribute meaningfully to the prediction and were not retained in the refitted model. Refitted Poisson modeling showed that year had the most statistically significant p-value of the three predictors. One interpretation of the significance of the year variable is that the finding reflects differences in yearly moisture levels and weather patterns. It is also possible that the elastic net model grouped weather and moisture variables as strongly correlated variables. Given that maximum relative humidity was a significant predictor, the possibility that maximum relative humidity is acting as a proxy for corn moisture is also possible, with the elastic net model interpreting the two variables as highly correlated and therefore, redundant.

This finding warrants further investigation to determine if the model is selecting maximum relative humidity as the significant predictor of corn moisture. If this was the case, the anecdotal and historic linkages between corn moisture and the number of engulfment and entrapment incidents could be confirmed empirically. Future research is needed to examine more detailed and geographically specific data on rainfall, relative humidity, and other weather data. Improved information about crop quality data, including test weight, mold or toxin presence, and total damage would also improve the predictive power of the model.

A final variable that was not modeled but that influences producer and handler behavior is seasonal safety messaging. Safety educators communicate with farmers and grain handlers through meetings, social media, radio, and print campaigns, which may vary from state to state and year to year. The influence of these messages has not been directly measured. States have varying needs for safety communications depending on their main agricultural practices and crops. Safety communication also varies from year to year due to different storage conditions, harvest conditions, and crop conditions, all of which may increase worker safety risk. There is much potential for extension professionals to collaborate more with agricultural media concerning farm life and agricultural seasonal grain handling safety messages (Heiberger and Evans, 2017). There is a need to strengthen the practice of farm safety communications to advocate for the occupational safety of producers and grain handlers (Evans and Heiberger, 2015).

A key limitation of the analyses performed as part of this project was data availability. Although the moisture levels collected were assumed to be moisture levels at harvest, researchers were unable to validate this. Further, information on the location of the engulfment and entrapment event or characteristics of the storage bin was not publicly available. Further, the duration of storage for the grain involved in an engulfment or entrapment event would also be helpful in establishing a causal relationship. These data were not available to researchers. Information on the duration of storage and on the characteristics of the

storage bin is dependent on producers, their record-keeping practices, and their willingness to share relevant information with researchers (Pennings et al., 2002).

Although the information is a great resource, data contained in the Purdue Agricultural Confined Space Incident Database (PACSID) are not a complete list of all entrapment and engulfment cases that occurred from 2017 to 2021. The database contains cases that were reported, documented, and confirmed as not duplicative, but is not, and does not claim to be, a full list of events.

It is estimated that the U.S. government undercounts the number of injuries and illnesses in the agricultural industry by 77.6% (Leigh et al., 2014). Agricultural occupational injury costs were estimated at \$4.57 billion in 1992 (Leigh et al., 2001). However, these high-cost issues receive little public attention and limited resources. The research team believed there was more of a relationship between weather, grain quality, and engulfments/entrapments than what the data could validate, but the available data potentially raised more questions about engulfment and entrapment incidents than it answered. Clearly, improved data sources and additional research on the why behind these incidents are warranted.

This research called into question previous assumptions made about the causal pathways of engulfment and entrapment, yet it provides a solid basis for further research. Future work will examine other quality factors, including damage and foreign material, more geographically descriptive weather variables, and post-harvest drying. Future analyses will also consider a stochastic risk modeling approach to consider several prediction alternatives. More accurate data on the number and characteristics of storage bins in each crop reporting district would also improve the accuracy and precision of the model estimates.

Conclusions

Findings from this research provide useful information to prepare producers, their families, on-farm workers, and grain handlers for an increased likelihood of engulfment or entrapment hazards in years when significant predictive factors are present. This project found year, state, and maximum relative humidity to be significantly associated with corn moisture, suggesting that weather variables that occur in each state and in each year play a role in corn moisture. Year, state, and maximum relative humidity were all found to be significant factors in predicting engulfment and entrapment.

Two implications emerge from the initial modeling of weather, quality, and safety incident variables. First, data sources to support appropriate modeling are needed, either through periodic surveillance or via qualitative methods such as interviewing. Other advanced statistical, technological, and computer vision tools are currently under investigation to determine the feasibility of adding relevant data to the model for researcher and practitioner use. The second primary implication is that although out-of-condition grain does play a role in predicting engulfment and/or entrapment incidents, the relationship includes several other contributing variables in grain quality and stored grain condition, weather, and management, as noted here and by other researchers (Jiang, 2024). The role of these variables and their ability to predict severe safety events such as engulfment and entrapments offers future researchers many angles by which to approach their research.

Finally, understanding factors that increase the probability of out-of-condition corn and that are more highly associated with engulfment and entrapments could potentially provide safety and quality practitioners and educators with more focused messaging in years where

a stronger safety warning is warranted. Agricultural practitioners must do a better job measuring these variables to improve the ability to predict grain entrapment and engulfment.

Acknowledgments

Funding from the Central States Center for Agricultural Safety and Health through a National Institutes of Occupational Safety and Health (NIOSH) Agriculture, Forestry, and Fishing Grant (U54 OH010162) and a USDA/NIFA Critical Agricultural Research and Extension Grant (Award # 20226800837105) is gratefully acknowledged. Input and feedback provided by reviewers strengthened and clarified several aspects of the manuscript, which is appreciated by the authors.

References

- Branstad-Spates, E. H., Castano-Duque, L., Mosher, G. A., Hurburgh, C. R., Owens, P., Winzeler, E.,... Bowers, E. L. (2023). Gradient boosting machine learning model to predict aflatoxins in Iowa corn. *Front. Microbiol.*, 14. <https://doi.org/10.3389/fmicb.2023.1248772>
- Bureau of Labor Statistics. (2024a). Fatal work injury rates (1) per 100,000 full-time equivalent workers by selected occupations, 2021-2023. Retrieved from <https://www.bls.gov/news.release/cfoi.t04.htm>
- Bureau of Labor Statistics. (2024b). Incidence rate and number (thousands) of nonfatal occupational injuries and illnesses by selected industry, private industry, 2022-2023. Retrieved from <https://www.bls.gov/news.release/osh.t02.htm>
- Castano-Duque, L., Vaughan, M., Lindsay, J., Barnett, K., & Rajasekaran, K. (2022). Gradient boosting and bayesian network machine learning models predict aflatoxin and fumonisin contamination of maize in Illinois – First USA case study. *Front. Microbiol.*, 13. <https://doi.org/10.3389/fmicb.2022.1039947>
- Cheng, Y. H., Nour, M. M., Field, W. E., Ambrose, K., & Sheldon, E. (2023). 2022 Summary of confined space-related injuries and fatalities. Purdue University.
- Evans, J. F., & Heiberger, S. (2015). Fitting farm safety into risk communications teaching, research and practice. *J. Appl. Commun.*, 99(3), 68-80. <https://doi.org/10.4148/1051-0834.1060>
- Faust, K., Casteel, C., Gerr, F., Cavanaugh, J. E., Boonstra, D. E., Anthony, T. R.,... Ramirez, M. (2023). Development of a checklist to identify injury hazards on row crop farms in the Midwestern United States. *J. Agric. Saf. Health*, 29(1), 15-32. <https://doi.org/10.13031/jash.15269>
- Freeman, S. A., Kelley, K. W., Maier, D. E., & Field, W. E. (1998). Review of entrapments in bulk agricultural materials at commercial grain facilities. *J. Saf. Res.*, 29(2), 123-134. [https://doi.org/10.1016/S0022-4375\(98\)00008-5](https://doi.org/10.1016/S0022-4375(98)00008-5)
- Gorucu, S., Pate, M. L., Fetzter, L., & Brown, S. (2022). Farmers' perceptions of grain bin entry hazards. *J. Agric. Saf. Health*, 28(1), 19-30. <https://doi.org/10.13031/jash.14662>
- Hans, C. (2011). Elastic net regression modeling with the orthonormal prior. *J. Am. Stat. Assoc.*, 106(496), 1383-1393. <https://doi.org/10.1198/jasa.2011.tm09241>
- Heiberger, S., & Evans, J. F. (2017). New extension approaches to serving agricultural media in advancing farm-life safety communications. *J. Ext.*, 55(6). <https://doi.org/10.34068/joe.55.06.44>
- Issa, S. F., Cheng, Y.-H., & Field, W. (2016). Summary of agricultural confined-space related cases: 1964-2013. *J. Agric. Saf. Health*, 22(1), 33-45. <https://doi.org/10.13031/jash.22.10955>
- Issa, S. F., Field, W. E., Schwab, C. V., Issa, F. S., & Nauman, E. A. (2017). Contributing causes of injury or death in grain entrapment, engulfment, and extrication. *J. Agromed.*, 22(2), 159-169. <https://doi.org/10.1080/1059924X.2017.1283277>
- Issa, S.F., Gaither, D. Raza, M.M.S., Lee, J., and Field, W.E. (2022). Removing out-of-condition grain: An exploration and documentation of existing strategies. *Journal of Agricultural Safety and Health*, 28(4), 245-259. Doi: <https://doi.org/10.13031/jash.14897>.

- Jiang, Y. (2024). Risk assessment of grain bin engulfment and entrapment using fault tree analysis and fuzzy fault tree analysis. MS thesis. Iowa State University.
- Jones, C. L. (2018). Aeration management: Knowing when to run aeration fans. BAE-1116. Oklahoma State University Cooperative Extension Service.
- Kingman, D. M., & Field, W. E. (2005). Using fault tree analysis to identify contributing factors to engulfment in flowing grain in on-farm grain bins. *J. Agric. Saf. Health*, 11(4), 395-405. <https://doi.org/10.13031/2013.19718>
- Leigh, J. P., Du, J., & McCurdy, S. A. (2014). An estimate of the U.S. government's undercount of nonfatal occupational injuries and illnesses in agriculture. *Ann. Epidemiol.*, 24(4), 254-259. <https://doi.org/10.1016/j.annepidem.2014.01.006>
- Leigh, J. P., McCurdy, S. A., & Schenker, M. B. (2001). Costs of occupational injuries in agriculture. *Public Health Rep.*, 116(3), 235. Retrieved from <https://journals.sagepub.com/doi/pdf/10.1093/phr/116.3.235>
- Manis, J. M., & Sharpe, J. (2022). Chapter 8 - Sampling, inspecting, and grading. In K. A. Rosentrater (Ed.), *Storage of cereal grains and their products* (5th ed., pp. 247-259). Woodhead Publishing. <https://doi.org/10.1016/B978-0-12-812758-2.00012-X>
- Mosher, G.A., Keren, N., Freeman, S.A., and Hurburgh, C.R. (2014). Development of a safety decision-making scenario to measure worker safety in agriculture. *Journal of Agricultural Safety and Health*, 20(2), 91-107. Doi: <https://doi.10.13031/jash.20.10358>
- Mosher, G. A., Keren, N., Freeman, S. A., & Hurburgh, C. R. (2012). Management of safety and quality and the relationship with employee decisions in country grain elevators. *J. Agric. Saf. Health*, 18(3), 195-215. <https://doi.org/10.13031/2013.41957>
- Nielsen, R. L. (2018). Field dry down of mature corn grain. Corny News Network Purdue University. Retrieved from <https://www.agry.purdue.edu/ext/corn/news/timeless/GrainDrying.html>
- OSHA. (2011). 29 CFR 1910.146(b): Permit-required confined spaces. Washington, DC: Occupational Safety and Health Administration. Retrieved from https://www.osha.gov/pls/oshaweb/owadisp.show_document?p_table=STANDARDS&p_id=9797
- Pennings, J.M.E., Irwin, S.H., & Good, D.L. (2002). Surveying farmers: A case study. *Applied Economic perspectives and policy*, 24(1), 266-277. Doi: <https://doi.org/10.1111/1467-9353.00096>
- Reed, C., Doyungan, S., Ioerger, B., & Getchell, A. (2007). Response of storage molds to different initial moisture contents of maize (corn) stored at 25°C, and effect on respiration rate and nutrient composition. *J. Stored Prod. Res.*, 43(4), 443-458. <https://doi.org/10.1016/j.jspr.2006.12.006>
- Riedel, S. M., & Field, W. E. (2013). Summation of the frequency, severity, and primary causative factors associated with injuries and fatalities involving confined spaces in agriculture. *J. Agric. Saf. Health*, 19(2), 83-100. <https://doi.org/10.13031/jash.19.9326>
- Sadaka, S., & Rosentrater, K. A. (2022). Chapter 9 - The significance of moisture and its measurement in cereal grains and grain products. In K. A. Rosentrater (Ed.), *Storage of cereal grains and their products* (5th ed., pp. 261-292). Woodhead Publishing. <https://doi.org/10.1016/B978-0-12-812758-2.09002-4>
- USDA ERS. (2024). Food grains sector at a glance. USDA. Retrieved from <https://www.ers.usda.gov/data-products/charts-of-note/chart-detail?chartId=108629>
- USDA Economic Research Safety. (2022). Farming and farm income. Retrieved from <https://www.ers.usda.gov/data-products/ag-and-food-statistics-charting-the-essentials/farming-and-farm-income>
- Walker, G.W. (2010). A safety counterculture challenge to a "safety climate". *Safety Science*, 48(3), 333-341. Doi: <https://doi.org/10.1016/j.ssci.2009.10.007>
- Zeng, L., & Xie, J. (2008). Regularization and variable selection for data with interdependent structures. Department of Statistics Purdue University. Retrieved from https://www.stat.purdue.edu/~doerge/BIOINFORM.D/FALL08/gLar_wnar_zeng043008.pdf
- Zou, H., & Hastie, T. (2005). Regularization and variable selection via the elastic net. *J. R. Stat. Soc. Ser. B: Stat. Methodol.*, 67(2), 301-320. <https://doi.org/10.1111/j.1467-9868.2005.00503.x>