Research Paper

Using a Six Sigma Fishbone Analysis Approach To Evaluate the Effect of Extreme Weather Events on \textit{Salmonella} Positives in Young Chicken Slaughter Establishments

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MS 16-173: Received 26 April 2016/Accepted 15 August 2016

\textbf{ABSTRACT}

A six sigma fishbone analysis approach was used to develop a machine learning model in SAS, Version 9.4, by using stepwise linear regression. The model evaluated the effect of a wide variety of variables, including slaughter establishment operational measures, normal (30-year average) weather, and extreme weather events on the rate of \textit{Salmonella}-positive carcasses in young chicken slaughter establishments. Food Safety and Inspection Service (FSIS) verification carcass sampling data, as well as corresponding data from the National Oceanographic and Atmospheric Administration and the Federal Emergency Management Agency, from September 2011 through April 2015, were included in the model. The results of the modeling show that in addition to basic establishment operations, normal weather patterns, differences from normal and disaster events, including time lag weather and disaster variables, played a role in explaining the \textit{Salmonella} percent positive that varied by slaughter volume quartile. Findings show that weather and disaster events should be considered as explanatory variables when assessing pathogen-related prevalence analysis or research and slaughter operational controls. The apparent significance of time lag weather variables suggested that at least some of the impact on \textit{Salmonella} rates occurred after the weather events, which may offer opportunities for FSIS or the poultry industry to implement interventions to mitigate those effects.

Key words: Process control; \textit{Salmonella}; Weather; Young chicken slaughter

The Food Safety and Inspection Service (FSIS) is the public health regulatory agency within the U.S. Department of Agriculture responsible for ensuring that the nation’s commercial supply of meat, poultry, and egg products is safe, wholesome, and correctly labeled and packaged. As part of that mission, FSIS conducts verification testing for pathogens of public health significance, including \textit{Salmonella}, which is a leading cause of foodborne illness (20) and deaths from poultry-related illness (16). Although ordinary cooking and preparation of raw product is generally considered sufficient to destroy \textit{Salmonella} (1, 2), its presence on raw products continues to cause illness when products are not cooked properly or by cross-contaminating other foods during handling and preparation. Therefore, FSIS has established public health–related performance standards for \textit{Salmonella} on poultry (young chicken and young turkey) carcasses and has proposed performance standards for \textit{Salmonella} on chicken parts and not ready-to-eat comminuted poultry (chicken and turkey) to encourage industry efforts to reduce its prevalence in these products (4). These performance standards are designed to assess process control within an establishment by setting the maximum percent positive for samples collected at that plant in a given time period (for a given product). The percentage of positives that are allowed under these performance standards are designed to reduce public exposure to the pathogen and help the agency meet the Healthy People 2020 goal set by the U.S. Department of Health and Human Services (11).

Historically, FSIS has used a variety of discrete operational measures to assess progress around many of its pathogen-related public health goals. For example, the percent of regulated establishments meeting a performance standard based on internal verification sampling results of FSIS is a typical measure to evaluate progress in reducing public exposure to \textit{Salmonella}. The percent of scheduled samples collected and analyzed are additional examples of operational measures using internal data. FSIS also uses external data, such as illness data from the U.S. Department of Health and Human Services Centers for Disease Control and Prevention, to estimate the numbers of illnesses attributed to FSIS-regulated products. These external measures are more complex and difficult to link to FSIS actions. However, such measures are vital to evaluate the ultimate public health impact of FSIS policies.
Discrete operational measures are important for program evaluation purposes and also as a driver for change. For example, a risk assessment conducted by the agency (8) showed that publicly posting the names of establishments failing the young chicken carcass performance standard (Category 3 establishments) for Salmonella had a significant effect on reducing the number of establishments failing over time. However, evaluating operational measures only as discrete measures did not allow for the understanding of the interaction and interrelations of measures, both within and across particular kinds of FSIS-regulated products.

To address the issue of the interaction and interrelations of measures, the authors developed a first-generation six sigma “define, measure, analyze, improve, and control” process, which adapted fishbone diagrams to look at the interdependencies of a wide range of variables, including historical discrete operational measures, beginning with FSIS young chicken carcass pathogen sampling data from September 2011 through July 2015. Six sigma is a recognized approach for assessing data such as this and has been used in other published studies (14), and fishbone analysis is becoming widely used in public health (7, 12, 18). The model described in this article incorporated both internal and external data to help understand what the significant drivers of the levels of Salmonella are on young chicken carcasses. Future versions of this model will be used to assess where policies or actions can be modified or introduced to further reduce those levels.

MATERIALS AND METHODS

The described six sigma fishbone modeling process was based on a machine learning algorithm and is built in SAS, Version 9.4 (SAS Institute Inc., Cary, NC), which looked at nationally aggregated data for young chicken carcass samples collected at FSIS-inspected slaughter establishments by production volume quartiles with a primary focus on the bottom and top volume quartiles (quartiles 1 and 4, respectively), as well as data from external data sources, such as the National Oceanographic and Atmospheric Administration (NOAA) and Federal Emergency Management Agency (FEMA).

Data included. The base data set used included verification sampling results from January 2012 through April 2015. Specifically, it included details on results, such as Salmonella and Salmonella serotype percent positive, moving window performance category counts and percentages, monthly sample counts, as well as plant operations information, such as establishment counts for types of slaughter and inspection methods. The data was also aggregated and subdivided by product type, year, month, and slaughter volume quartile. For purposes of this article, the product (P) was always young chicken carcasses, the year (Y) and month (M) was the corresponding year and month of the sample taken, and the quartile (Q) was the national slaughter volume quartile the establishment was in for that year and month. For example, PYMQ4 was the highest young chicken carcass slaughter volume quartile for that year and month, while PYMQ1 was the lowest.

Young chicken carcass results were chosen for this article for a number of reasons. First, FSIS has a long period of available testing data for this product. Second, it represents the source product for all other chicken products, such as chicken parts and comminuted chicken, which will be included in later iterations of the model. External sampling data, for example, from industry or other agencies, such as the Agricultural Marketing Service, was not included, because it was neither readily available, nor has the amount of detail: for example, antimicrobial resistance information, which was desired for the overall purposes of this study.

In addition, this article investigates the impact of environmental factors on the sampling results, and slaughter is the closest point in production to the preharvest arena in which these factors should be strongest. NOAA collects National Weather Service weather station data and other sources and prepares climatological and weather databases. For purposes of the model, we used the national monthly series for cooling degree days (CDD), which measures daily temperatures above 65°F (ca. 18°C). Other measures included heating degree days, precipitation and stress indices, such as the Palmer Drought Severity Index (15). CDD and heating degree days are recognized measures for weather-related temperatures and are expected to change over time (17). Finally, state level data from FEMA, for fires, floods or mudslides, severe storms, tornadoes, hurricanes, and drought events were collected and aggregated by month for inclusion in the model.

One note on a recent study performed on the potential effects of antimicrobial carryover on FSIS verification samples: Gamble et al. (9) have concluded that sanitizer carryover may have an effect on FSIS verification Salmonella results in young chicken establishments. For the purposes of this study, the authors do not believe this has any significant effect on the results, because the Gamble study was conducted under laboratory conditions that do not reflect actual in-plant conditions or practices under which FSIS samples are collected. Based on this reasoning, FSIS and the authors are confident that the FSIS testing results, overall, reflect accurate outcomes.

Data preparation. The first step in the overall process was to develop code in SAS to pull and clean the various pieces of data from a variety of FSIS sources and compile the base data set to feed into the model. Slaughter volume quartiles were calculated by placing a slaughter establishment into its quartile according to overall (industry-wide) number of carcasses slaughtered for each month, which means that there were potentially a varying number of establishments in each quartile, depending on production volume and number of active establishments, for each month. Note that there were seasonal producers, typically in the lowest volume quartiles, which could result in an artificial shift of higher production establishments into lower volume quartiles when these seasonal producers were in the off-season. One means of counteracting this would have been to assign establishments on an annual or moving year basis, but this would have been computationally intense, especially with the large number of active and inactive establishments in the lowest production volumes. Calculating on a monthly basis and establishing monthly quartiles in which the number of active seasonal producers in the lowest quartile may have been low, while those in the highest quartile were not distorted by redistribution, were deemed the best compromise solutions. Finally, the data from NOAA and FEMA were also compiled from the respective Web sites and cleaned in SAS.

Overall model design. Figure 1A shows the basic design of the overall layered model with root causes on the left and sample outcomes on the right. The model layers are color coded to correspond to model backcast output figures included later in the article. The percent positive for Salmonella in FSIS verification testing was the primary dependent variable that measured the
FIGURE 1. Model construct showing (A) model layers, (B) constructed humidity, and (C) lagged FEMA disaster declarations.
sample testing outcomes. The purpose of the investigation was to determine the root causes, i.e., the explanatory variables that led to the positive sample result that could then be used as a “background noise filter” for the overall model. For example, the moving window was designed as both an explanatory variable for Salmonella and a dependent variable for operational measures. In addition, the serotype measures were the percent positive for specific serotypes of Salmonella, such as Salmonella serotypes Enteritidis, Infantis, and Typhimurium. These serotype series were also dependent on operational root causes and served as explanatory measures for the emulated moving window performance categories and overall Salmonella percent positive. Operational characteristics included establishment counts by month of slaughter and inspection type. Further, environmental measures included NOAA and FEMA measures for weather and disasters.

Modeled dependent measures are shown in the rectangular boxes in Figure 1A— with Salmonella direct path root causes being the subject of this article. Root causes could also have indirect effects, such as weather effects on performance and performance effects on percent positive. The modeled decision systems also incorporated such effects, but that complexity is beyond the scope of this article.

Overall, the models were constructed to include underlying layers. For example, the weather model included the base operational model, and the disaster model, in turn, included the weather model. In this manner, the models tested the explanatory power of each layer’s explanatory variables to improve over the prior layer. Model comparisons were based on scoring by using only explanatory variables, while outliers, maximum observations, and prior month estimations were excluded. Total scores by model and quartile were compared with actuals. As such, the model estimation process specifically consisted of three steps in which selected variables were progressively added to the model and checked for statistical impact, and the model overall fit was measured by $R^2$ with an overall fit goal of at least 0.85. The models were then estimated using SAS ordinary least-squares regression with a stepwise selection of variables. Each estimation step included serial correlation and several outlier check flags. The impacts of the explanatory variables (i.e., excluding outlier flags) for each model step were summarized and carried forward as a variable in the next step. Each successive model step test used new additional variables as replacements for the prior model’s outliers and errors as long as they were significant.

Identifying variables. A six sigma process was used to focus on identifying key process input variables for each layer to measure and further investigate, which required that each significant root cause was scientifically plausible and not just a random statistical pattern. To achieve this, relationships were constrained to be positive, i.e., where variables rise or fall together or negative, when dependent and explanatory levels changed in an inverse relationship, based on six sigma team input from subject matter experts. For example, in the base model layer, performance Category 3 means that an establishment has failed the Salmonella performance standard. Its effect was constrained to be positive, because Category 3 was defined as “standard failure” when the establishment had positive Salmonella sample test results. Category 1 indicates that an establishment has passed with positives at or below half the performance standard. Its effect was constrained to be negative as an inverse relationship to passing tests, meaning a lower Salmonella percent positive.

Statistical tests provided an objective assessment of identified variables that included all the “complex” constructions and each underlying individual measure. The groups included 18 explanatory variables for the base model, 36 for the weather, and 40 for the disaster layer. The stepwise regression at each layer (see the following) identified statistically significant (SLSTAY = 0.15) variables that were checked for sign and then relevant ones were carried forward. Correlations between the explanatory variables and Salmonella were reviewed to determine sign and strength to be expected for the regression coefficients. A cross-correlation matrix reviewed the interrelations between the independent variables. Correlations with more than a 0.30 were used to determine if interaction variables were needed. The program then tested all the regression coefficients for their expected sign and dropped those that did not have the same sign as found in the correlation.

Base model layer. The base model was estimated using ordinary least squares with iterations of stepwise regression (SAS “Proc Reg”), error computation, and sign constraint checks. This layer specifically included monthly aggregates for slaughter and inspection type counts and moving window performance category percentages. Serotype flags and pulsed-field gel electrophoresis counts were omitted due to sparse observations. Repeated iterations were used to overcome the stepwise limitation by removing multicollinearity that occurred when statistically weaker measures that had inappropriate negative signs were collinear with one or more dominant independent measures. If an overall fit ($R^2$) of 0.85 could not be achieved, then the model proceeded to the next layer, retaining the base model layer variables (BaseExplained).

Weather model layer. The same process as previously mentioned was used, this time including the BaseExplained and normal (30-year averages) and difference grouped continental U.S. NOAA aggregated weather measures. If an overall fit of 0.85 could not be achieved, then the model proceeded to the next layer, retaining the weather model layer variables (WeatherExplained). If none of the weather variables were significant, then the weather model step results only included the BaseExplained.

External data sources were examined to find potential root causes related to warmth, such as environmental measures available from NOAA. A measure for humidity was constructed by multiplying hot (CDD) × wet (precipitation). The “normal” and “differences” of the actual from the normal values and the distributed three-period “lags” on the difference were computed for each variable.

The time series model included seasonal measures designed as Koyck patterns for use in a time series and as a comparison to weather normal impact, which showed a sawtooth pattern in the first quartile with recurring peaks in August. Interactions between seasonality and time were also included. This approach was chosen rather than a ×12 seasonal decomposition because the data only included 40 periods and seasonality was not stationary. The time series model demonstrated the seasonal pattern differences by volume quartile for comparison to the base and weather models.

Test measures included normal and differences from normal for humidity (see Fig. 1B). Not shown are similar measures for CDD, heating degree days, and precipitation. In addition, changes in weather effects were tested by using interactions, such as CDDTime (i.e., CDD × time). Models were estimated at the individual measures level, e.g., CDD, and significant measures were used to compute the impacts on Salmonella percent positive. The impacts were then aggregated up to the group level for normals and differences.
Table 1. Example of severe storms and extreme events distributed lag computation

<table>
<thead>
<tr>
<th>Variable</th>
<th>Formula</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fire_1</td>
<td>Fire + Wildfire + lag(Wildfire)</td>
</tr>
<tr>
<td>Floods_1</td>
<td>Flooding + lag(Flooding) + 1/2 × lag2(Flooding)</td>
</tr>
<tr>
<td>Storm2_1</td>
<td>Storm2 + 1/2 × lag(Storm2)</td>
</tr>
<tr>
<td>Hurricanes_1</td>
<td>1/2 × TropicalDepression + HurricaneIsaac_l + 2 × HurricaneIrene_l + 3 × HurricaneSandy_l</td>
</tr>
<tr>
<td>Tornado2_1</td>
<td>Tornado2 + 1/2 × lag(Tornado2)</td>
</tr>
<tr>
<td>Winter2_1</td>
<td>Winter2 + 1/2 × lag(Winter2)</td>
</tr>
</tbody>
</table>

**Disaster model layer.** The process was once again performed, this time including WeatherExplained and disaster impact groups for severe and extreme weather variables as long as they were significant. Once the $R^2$ result could no longer be improved, the final results were assessed.

The disaster model included disaster declarations from FEMA as additional environmental root causes. The state-level data from FEMA, for fires, floods and mudslides, severe storms, tornados, hurricanes, and drought events were used to construct intensity and duration measures with lags (see Table 1), as a distributed lag linear time series model with the larger the event, the longer it persisted. Using pulse dummy variables in SAS is a common technique for time series analysis and forecasting (25).

Hurricanes surged between August 2012 and April 2013 (see Fig. 1C), with peaks in October 2012 and January 2013. Storms varied throughout the period, with the peak in September and October 2013 being roughly twice the average. Floods, tornados, and fires are also depicted. The monthly FEMA data was gathered at the state level, whereby state summary counts by disaster type provided a measure of severity as to how many states were affected by each disaster event. Severity was also measured by counting key words associated with particular events, e.g., storms that also included straight-line winds and floods were more severe storms than events with fewer key word descriptions. Distributed lags were used to create pulse variables related to the storm duration and aftermath. The “severe” grouping included fires, floods, storms, and winter storms. The “extreme” grouping included wildfires, tornados, tropical depressions, and hurricanes.

Lags were further applied to pulse variables to test for cleanup and recovery delays following the storms. In addition, constraints were applied in the model to FEMA measure relationships based on the hypothesized positive relationship between heat-precipitation-humidity and pathogen environmental presence.

**RESULTS AND DISCUSSION**

The core measure for the overall model was the average Salmonella percent positive over time with the behavior of the pathogen being what the model was designed to help explain. Over the time frame of the included data, the percent positive in the lowest slaughter volume quartile, PYMQ1 was above average and separated from the more tightly grouped PYMQ2, PYMQ3, and PYMQ4 quartiles (see Fig. 2). This degree of separation is not as distinct using the three hazard analysis and critical control point size categories (not shown), which is based on the number of employees. The lowest slaughter volume establishments typically operate with a larger amount of manual, seasonal, or intermittent processing. In comparison, the larger volume establishments typically operate more consistently and with a higher degree of automation.

To better assess performance and calculate prevalence, FSIS began using a continuous sampling methodology instead of a set-based method for poultry carcasses in May of 2015 and started using moving windows to assess and Web post regulated establishment performance in June 2016. As a measure of this performance, starting in 2006, FSIS began placing establishments into one of three performance categories according to the consistency of their process control, with Category 1 being the best performers (3). The data used for this model was from calendar years September 2011 through July 2015, because late 2011 to date represents the time frame the agency has most reliably collected information for all of the variables used in the model and allowed for the computation of lags and moving windows to begin in January 2012. The older set-based data were reformatted to emulate the same moving window-based approach the agency now uses. Although this is a limitation to the older data, because of nonuniform sampling across establishments and time, this will smooth out as the agency takes samples under its new approach and will be taken into account as additional data are added to the model in future phases.

It can be hypothesized that there was something different happening in PYMQ1 than in PYMQ2 and PYMQ4. The easiest explanation is that production practices were at the core of this difference. To obtain these production differences and to test that hypothesis, variables that were equal across all slaughter volume quartiles needed to be filtered out. These equal variables can be considered as background “noise,” and once they have been removed, the differences that could be attributed to production or other variables could then be assessed. This article does not attempt to test that overall hypothesis but demonstrates how the basic background noise was filtered out of the overall process.

There also appeared to be a seasonal variability in Salmonella positive rate, especially for PYMQ1 (see Fig. 2). Salmonella rates are known to be impacted by conditions affecting live poultry before slaughter. It is widely documented that temperature (6, 19, 21, 22) and weather conditions (23) can contribute to increased Salmonella in live birds. Therefore, the impact of including weather-related data sets as potential explanatory variables of Salmonella on the slaughtered carcasses that FSIS tested during the included time frame was investigated.

To assess the impact of the individual variables, the discrete operational measures built into the model were organized into a fishbone design with root causes for individual operational and environmental factors (5). The
base operational layers were defined to include measurement (pathogen control performance categories), materials (sero-types), machines, (slaughter types), and methods (inspection types). The environmental measures separated normal from abnormal weather and extreme from severe disaster events. Future versions of the model will include other branches and root cause measures as the ongoing define, measure, analyze, improve, and control process continues.

When the base operations, weather, and disaster model results for PYMQ1, as well as the upper trend and time series were compared (see Fig. 3A), there again appeared to be a seasonal variability in the Salmonella-positive rate. The weather backcast performance model demonstrated a better fit to the actuals than the base operational model. The disaster model, which included the weather model, identified reasons for the spikes in Salmonella percent positives occurring in October 2012 and January 2013 that were unexplained by the other model layers.

The weather impact chart showed that PMYQ1 was impacted by weather normals (see Fig. 3B). The actual differences from normal varied in amplitude and in 2015 occurred earlier in the season than both the normals and the usual September peak. The results also showed disaster impacts on PMYQ1, including impacts from hurricanes (e.g., Sandy) and storms (see Fig. 3C).

PMYQ4 results showed that weather performance improved the fit to the actuals over the base operational model (see Fig. 4A). The disaster model further improved over the weather model. The results showed the negative effects of drought (see Fig. 4B), as well as the impacts of fire and severe storms on Salmonella percent positive in PMYQ4 (see Fig. 4C).

Both PMYQ1 and PMYQ4 were impacted by weather and disasters but differently. PMYQ1 was mainly impacted by weather normals, hurricanes, such as Sandy, and severe storms. PMYQ4 was mainly impacted by drought, severe storms in 2012, and recurring summer fires.

Overall, in PMQ1, the base operational model $R^2$ was 0.16 and the $t$ value for the base operational overall model was 2.88. The weather model $R^2$ increased to 0.46 and the $t$ value to 5.82, while the disaster model improved slightly to an $R^2$ of 0.65 and a $t$ value of 8.41. In PMQ4, the base operational model $R^2$ was 0.43 and $t$ value 5.46, and the weather model $R^2$ increased to 0.65 and the $t$ value to 8.41, while the disaster model $R^2$ increased to 0.69 and the $t$ value to 9.15. These results confirmed the substantial fit improvement by including weather and disasters for these volume quartiles. For PMQ2 (not shown), the weather and disaster models did not improve over the base. For PMQ3 (not shown), the weather model improved over the base, but
FIGURE 3. Model results for first slaughter quartile (PYMQ1), showing (A) comparison of back models, (B) relative weather impacts, and (C) relative disaster impacts on Salmonella percent positive.
FIGURE 4. Model results for fourth slaughter quartile (PYMQ4), showing (A) comparison of back models, (B) relative weather impacts, and (C) relative disaster impacts on Salmonella percent positive.
the disaster remains unchanged. None of the models in any quartile, based on national monthly aggregates, achieved the goal of 0.85 $R^2$, indicating there was further room for improvement. An overall model to compare to the volume quartile models was not developed, as the authors’ interest was intentional to specifically focus on differences across quartiles rather than an overall result.

In the base operational layer, internal data alone were used to look at the interaction of Salmonella control performance, types of plant operations, and pathogen sampling data, grouped by slaughter volume quartile. FSIS had previously identified an annual seasonal variation in the incidence of Salmonella-positive results. Seasonality, based on FSIS data, was more pronounced in the lowest slaughter volume quartile (PYMQ1), as illustrated in the September peaks in the time series model on Figure 3A. Similar patterns have been noted in the literature (24).

The second weather layer model tested environmental explanations for seasonal variations. Weather is a known factor in the prevalence of Salmonella (10) because environmental factors, such as temperature and humidity, directly impact the survival and growth rates of Salmonella. Weather patterns could also affect Salmonella prevalence by impacting movement of pathogen vectors (e.g. rodents and migratory fowl), by increasing physiological stress on poultry during growing and transport to slaughter and by altering management practices at poultry farms. The apparent significance of time lag weather variables suggests that at least some of the impact on Salmonella rates occurred after the weather events, which may offer opportunities for FSIS or the poultry industry to implement interventions to mitigate those effects.

Extreme weather events are also known to regionally impact Salmonella (13). The results of the disaster layer model showed that weather and disaster events helped explain the Salmonella percent positives in all slaughter volume quartiles in young chickens at the nationally aggregated level. Model results showed that spikes in Salmonella percent positive in both the highest and lowest volume quartiles were explained by weather and disasters but with different impacts by type of weather and disaster in individual quartiles. It is expected that these impacts will be easier to isolate with disaggregated data at the geographic level.

The previously described results have demonstrated the benefit of the layering fishbone modeling approach. There are two primary benefits from this process:

(i) The model identified periods when the observed pathogen sampling results do not appear to be explained by the known associated root causes. These “flags” provide opportunities to investigate and identify additional causes associated with pathogen prevalence in sampled products and develop measurements and collection processes to enhance operational analysis.

(ii) The model identified root causes that significantly impacted Salmonella as observed in sampling results and estimated the relative magnitude of each root cause’s contribution. This information can be used to identify significant factors that might be influenced by new or modified operational factors or policies.

As shown, backcast performance by model varied by volume quartile as the lower volume quartiles (PYMQ1 through PYMQ3) were more closely related to weather and disasters, while the highest volume quartile (PYMQ4) were less related to these measures. These identified factors and estimates of their association with pathogen sampling results can help to ensure that inspection policies are targeted at operational factors that are likely to produce the desired result of reducing pathogens in sampled products. For example, understanding that weather and disasters more directly impact the Salmonella percent positive in lower volume establishments is valuable for these establishments to understand so that mitigations can be put in place around anticipated weather events. Conversely, investigating and better understanding factors that overshadow these weather and disaster events in the largest establishments can lead to the development of more effective policies for this target population. This alone does not explain which variables most impacted the Salmonella percent positive in the larger volume establishments or test the possible hypothesis that production practices were responsible for the differences between PYMQ1 and the larger volume quartiles. It does show that weather and disaster events had an overall impact on Salmonella percent positive across all slaughter volumes and was a valuable “filter” to use in the layered model when assessing the impact of other variables.

To more fully understand the impacts of internal and external variables on Salmonella percent positive, more analysis must be conducted. Future versions of the model will focus fishbone analysis with broader operational measures and branches, as well as the weather- and disaster-related events at the regional and local (county or weather station) level. This will help further explore the significance of the impacts of these events under varying circumstances. Exploring the data at the corporate level could lead to identifying additional factors, especially in the largest slaughter volume establishments, where vertical integration of production and horizontal integration of corporate policies is widespread.

In conclusion, this model has clearly identified the benefit of including weather and disaster data into explaining Salmonella percent positives over time in young chicken slaughter establishments. Other research or analysis projects examining pathogen-related food safety issues and operational outcomes may benefit from including weather and disaster measures to account for variances, reduce noise, and enhance detection of other significant explanatory variables. Further, industry or policymakers can use this information in the development of strategies or policies to reduce the Salmonella percent positive.

REFERENCES