Associations between weather conditions during the first 45 days after feedlot arrival and daily respiratory disease risks in autumn-placed feeder cattle in the United States

N. Cernicchiaro,* D. G. Renter,*2 B. J. White,† A. H. Babcock,* and J. T. Fox*

*Department of Diagnostic Medicine/Pathobiology, †Department of Clinical Sciences, Kansas State University, Manhattan 66506

ABSTRACT: Data on associations between weather conditions and bovine respiratory disease (BRD) morbidity in autumn-placed feedlot cattle are sparse. The goal of our study was to quantify how different weather variables during corresponding lag periods (considering up to 7 d before the day of disease measure) were associated with daily BRD incidence during the first 45 d of the feeding period based on a post hoc analysis of existing feedlot operational data. Our study population included 1,904 cohorts of feeder cattle (representing 288,388 total cattle) that arrived to 9 US commercial feedlots during September to November in 2005 to 2007. There were 24,947 total cases of initial respiratory disease (animals diagnosed by the feedlots with BRD and subsequently treated with an antimicrobial). The mean number of BRD cases during the study period (the first 45 d after arrival) was 0.3 cases per day per cohort (range = 0 to 53.0), and cumulative BRD incidence risks ranged from 0 to 36% within cattle cohorts. Data were analyzed with a multivariable mixed-effects binomial regression model. Results indicate that several weather factors (maximum wind speed, mean wind chill temperature, and temperature change in different lag periods) were significantly (P < 0.05) associated with increased daily BRD incidence, but their effects depended on several cattle demographic factors (month of arrival, BRD risk code, BW class, and cohort size). In addition, month and year of arrival, sex of the cohort, days on feed, mean BW of the cohort at entry, predicted BRD risk designation of the cohort (high or low risk), cohort size, and the interaction between BRD risk code and arrival year were significantly (P < 0.05) associated with daily BRD incidence. Our results demonstrate that weather conditions are significantly associated with BRD risk in populations of feedlot cattle. Defining these conditions for specific cattle populations may enable cattle health managers to predict and potentially manage these effects more effectively; further, estimates of effects may contribute to the development of quantitative predictive models for this important disease syndrome.

Key words: bovine respiratory disease, feedlot, morbidity, weather

INTRODUCTION

Bovine respiratory disease complex (BRD) is the most common disease syndrome in commercial feedlots (Griffin et al., 1995; USDA, 2000). In the United States, the costs associated with BRD were estimated at $4 billion annually, which included the costs of treatment, prevention, and lost productivity (Griffin, 1997). There is evidence that ambient temperature affects feeder cattle metabolism and health, including BRD (MacVean et al., 1986; Ribble et al., 1995; Cusack et al., 2007). In addition, a recent survey of feedlot veterinarians in United States and Canada indicated that weather patterns were considered one of the most important factors for predicting morbidity and mortality of feeder cattle (Terrell et al., 2011). However, quantitative information on specific weather conditions and BRD morbidity in feeder cattle are extremely sparse. Ribble et al. (1995) found associations between fibrinous pneumonia and the hours of sunlight and maximum decline in temperature during the 4-d period after arrival processing. However, these authors indicated that a more thorough, multivariable assessment is necessary to better define how weather may affect BRD risk in
feeder cattle after controlling for potential confounding cattle demographic factors (Ribble et al., 1995).

An enhanced understanding of the effects of weather conditions on BRD morbidity may enable more targeted studies to evaluate how interventions for specific cattle populations might mitigate the effects of adverse weather conditions. Therefore, the objective of our study was to determine if daily BRD incidence risk for commercial feedlot cattle during the initial 45 d on feed was associated with weather variables in 3 different lag periods (1 to 2 d lag, 3 to 4 d lag, and 5 to 7 d lag) from the day when animals were initially diagnosed and treated for BRD, and then to evaluate if weather effects varied by cattle and feedlot demographic factors.

MATERIALS AND METHODS

Institutional Animal Care and Use Committee approval was not obtained because this study did not involve the use of animals; data were obtained from an existing database.

Feedlot Data

A data set compiled from a retrospective, operational cohort and individual animal health and performance data from 9 feedlots was used for this study. These data were retrieved from a feedlot management software program through a central database. The existing database included information collected routinely from multiple feedlots on lot (cohort) management characteristics, daily cumulative BRD incidence and overall mortality, and other health, performance, and demographic information. The data were compiled and standardized using a data mining program (Insightful miner 8.0, 2006, Insightful Corp., Seattle, WA), and then a confidential electronic database was created by using Microsoft Access (Microsoft Corporation, Redmond, WA). Aggressive procedures of data validation and error checking were performed on all animal health data (Babcock et al., 2009, 2010). Only feedlots and cohorts maintaining daily counts of BRD cases with morbidity classification were used for this study. These data were subsequently exported and reformatted in SAS (SAS Inst. Inc., Cary, NC) for analysis.

Our outcome, daily BRD incidence, involved cases of initial respiratory disease defined as animals diagnosed for the first time by feedlot personnel with BRD and subsequently treated with an antimicrobial. Population at risk was determined by subtracting cases from each day from the initial cattle count, and the risk period considered for this study consisted of the first 45 d on feed.

The data set was refined to include only cohorts of cattle arriving in September through November from 2005 to 2007, with a mean BW equal to or greater than 227 kg and equal to or less than 363 kg, and containing 40 to 340 animals per cohort at arrival. Mixed sex and Holstein cohorts also were excluded from the data set because of sparse data in these categories.

Cohort-level covariates of interest included mean arrival BW (categorized as follows: 227 to 271.9 kg, 272 to 317.9 kg, 318 to 363 kg), sex (steers and heifers), month of feedlot arrival (September to November), and year of arrival (2005 to 2007). In addition, respiratory risk code, assigned by feedlot employees based on a visual assessment of animals at arrival, BW, source, transport time, and other factors, was classified as high or low. Other covariates of interest included the number of cattle in the cohort (categorized in quartiles: <91, 91 to 138, 139 to 202, >202 cattle), days on feed (0 to 45 d), and the weather variables (described directly below) of primary interest in this study.

Weather Data

Weather information was obtained from weather stations nearest (<80 km) each feedlot. Data were downloaded from the National Oceanic and Atmospheric Administration website (NOAA, 2011). The impact of weather variables and events were assessed using 3 lag periods from the day of interest, which was the day of occurrence of a BRD case(s). The lag periods are referred to as 1 to 2 d lag (1 and 2 d before the day of interest), 3 to 4 d lag (3 and 4 d previously), and 5 to 7 d lag (5, 6, and 7 d previously) periods. Lag periods corresponding to days at the beginning of the feeding period when the entire lag period had not yet occurred were handled as missing values. Data were collected on mean temperature, mean wind chill temperature, temperature change, mean and maximum wind speed, total daily precipitation, and weather-related events (rain, freezing drizzle, and snowfall). Temperature change was calculated by taking the greatest maximum daily temperature of the lag period and subtracting the lowest minimum daily temperature of the lag period. Wind chill temperature was derived from mean daily temperature (T, degrees Fahrenheit) and mean daily wind speed (V, miles per hour) using the following equation: 35.74 + 0.6215T – 35.75 (V0.16) + 0.4275T (V0.16); from the National Oceanic and Atmospheric Administration, National Weather Service (NOAA, 2011). Those values were then transformed to the metric system [T in degrees Celsius and V in kilometers per hour (kph)]. Mean wind chill temperature was determined as the mean of daily wind chill temperature values over the lag period. Total precipitation was calculated as the sum of daily precipitation over the lag period. Mean temperature, temperature change, mean wind chill temperature, and total daily precipitation were divided into multiple categories of small increments (5°C for temperature variables, 6.35 mm for precipitation) based on categories used by the National Weather Service (NOAA, 2011) and then collapsed into a series of dummy variables to reduce the number of categories (Walter et al., 1987). Weather events (rain and freezing drizzle or snowfall)
were modeled as dichotomous (yes or no) variables repre-
resenting whether or not they occurred during the lag
period.

**Statistical Methods**

Associations between cattle demographics, weather
variables, and daily BRD incidence risk were analyzed
with a multivariable binomial regression model with a
Newton-Raphson and Ridging optimization (SAS Inst.
Inc.) using the Proc GLIMMIX procedure. The hierar-
chical structure of the data consisted of cattle cohorts
nested within feedlots. To account for clustering at the
feedlot level, a random intercept term for feedlot was
included in the model. The unit of observation was co-
hort with repeated measures for each day from 0 to
45 d on feed. The within-animal correlations resulting
from the repeated measurements within cohorts were
adjusted for in the hierarchical models either by using
an appropriate covariance structure (i.e., unstructured)
to model the correlation between residuals, by including
a random slope for the days on feed with an unstruc-
tured covariance structure to allow the correlations be-
tween measurements to change over time, or by adding
a multiplicative overdispersion parameter (residual-
type, R-side, random component; Brown and Prescott,
2006). The best-fitting model for dealing with repeated
measures was chosen based on the pseudo-Akaike’s in-
formation criterion and the pseudo-Schwarz’s Bayesian
information criterion.

The dependent variable for this analysis was daily
BRD incidence risk; thus, the outcome variable was
represented as the daily number of first BRD cases
(events)/daily population at risk (trials). Independent
variables included: month and year of arrival, BRD risk
code (high vs. low), cohort mean arrival BW category,
number of cattle in the cohort, days on feed, sex, and
weather variables. All continuous variables were cat-
egorized based on quartiles or meaningful biological
cutoffs to avoid violation of the linearity assumption.
Referent categories corresponding to the most frequent
categories (where the majority of observations were po-
 tioned) were chosen.

A correlation analysis was performed using the Pear-
son’s and the Spearman’s rank correlation statistics to
identify variables that may be collinear. If the value of
the correlation statistic between 2 independent vari-
ables was |0.80| or greater at a 5% significance level
\( P < 0.05 \), only one of the variables was selected for
inclusion in the multivariable model based on biological
plausibility or the completeness and quality of the data.

During the multivariable model building process,
only variables significant at the 10% level \( P < 0.10 \) in
the univariable screen were included in the main effects
model. Then, a manual backward elimination proce-
dure was conducted until only statistically significant
\( P < 0.05 \) main effect variables remained in the model.
All nonsignificant variables at the 5% level \( P < 0.05 \)
were removed from the multivariable model unless they
acted as confounding variables or were part of a signifi-
cant interaction term \( P < 0.05 \). Confounder variables
established a priori included sex, mean BW at arrival,
year and month of arrival, risk code, and cohort size;
these were included in all multivariable models. Other
variables were considered as confounders if they were
defined as a nonintervening variable that resulted in a
20% or greater change in the coefficient of a statisti-
cally significant variable when the potential confounder
was removed from the model (Dohoo et al., 2009). All
possible 2-way interactions between significant \( P < 0.05 \)
weather variables and between demographic and
weather variables were evaluated to determine their
level of significance by using manual forward selection.

Diagnostics of residuals from the final multivariable
models included the evaluation of the predicted values
of the random variables in the model or BLUP (Rob-
inson, 1991) and Pearson and deviance residuals for
observations at the sample level. Normal probability
plots and Shapiro-Wilk and Anderson-Darling tests for
normality were examined to assess the normality as-
sumption of the BLUP and general model fit. Graphical
indication of departures from normality or statistically
significant Shapiro-Wilk or Anderson-Darling statistics
\( P < 0.05 \) was used as a criterion to indicate lack of fit.
In addition, residual plots for the lowest level units were
visually examined to identify potential outliers and ob-
servations with undue influence on the model. Finally,
odds ratios (OR) and their respective 95% confidence
intervals (CI) were estimated for predictors included
in the final multivariable models. Differences in model-
adjusted means were used to display associations be-
tween demographic and weather variables included in
significant interactions in the final multivariable model.

**RESULTS**

Our study population included 1,904 cohorts of cattle
that arrived at 9 US commercial feedlots in the central
and south plains during the autumn (September to No-
vember) of 2005 to 2007. Mean (±SD) cohort size was
152 ± 70 (median = 139) with a minimum of 41 and a
maximum of 333 cattle. Seventy-two percent of cohorts
\( n = 1,373 \) were categorized as steers only, and 28%
\( n = 531 \) were composed of heifers. The population
included 288,388 total cattle, and there were a total of
24,947 initial cases of BRD over the 45-d evaluation
period, with a mean (±SD) of 13 ± 18 and a range of 0
to 140 cases per cohort. The overall mean (±SD) daily
incidence risk of BRD was 0.3 ± 0.9% (range = 0 to
36.1%); cumulative BRD incidence risks ranged from
0 to 83.0% within cohorts. The daily incidence risk of
BRD for each BW class of cattle is shown in Figure
1. The mean (±SD) number of BRD cases during the
study period (the first 45 d after arrival) was 0.3 ± 1.0
cases/d (range = 0 to 53.0).

When building the multivariable model, different
random effects and covariance pattern models were at-
ttempted, including the variable days on feed and its

\[ \text{RESULTS} \]

\[ \text{RESULTS} \]
transformations (e.g., weeks on feed) as random slope; however, these models did not converge or did not improve model fit. The best-fitting model for dealing with repeated measures (and the hierarchical structure of the data), based on information criteria and appropriate model convergence, included the variable days on feed as a fixed effect and a multiplicative overdispersion parameter (residual-type, R-side, random component) added in addition to a random intercept for feedlot.

Variables significantly \( (P < 0.05) \) associated with daily BRD incidence in the final multivariable model included month and year of arrival, days on feed, mean arrival BW class, sex, BRD risk code, size of the cohort, 3 to 4 d lag maximum wind speed, 5 to 7 d lag maximum wind speed, 3 to 4 d lag mean wind chill temperature, 5 to 7 d lag mean wind chill temperature, and 5 to 7 d lag temperature change (Table 1). Several 2-way interactions between weather variables (i.e., maximum wind speed, temperature change, and mean wind chill temperature) in different lag periods and demographic factors (i.e., month of arrival, BRD risk code, mean arrival BW class, cohort size) were significantly \( (P < 0.05) \) associated with daily BRD incidence (Table 1).

The arrival month modified the effect of maximum wind speed recorded in the 5 to 7 d lag on daily BRD incidence. For instance, cattle arriving in the months of September and October that were exposed to the highest category of maximum wind speed (≥32.2 kph) in the 5 to 7 d lag had significantly \( (OR = 1.47, P < 0.001) \) greater odds of BRD incidence than cattle exposed to the same wind speed in the 5 to 7 d lag in November.

The effects of maximum wind speed in the 3 to 4 d lag, mean wind chill temperature, and temperature change in the 5 to 7 d lag were all modified by BRD risk code. However, high-risk cattle showed significantly \( (P < 0.001) \) greater odds of BRD incidence than low-risk cattle across all categories of maximum wind speed in the 3 to 4 d lag (OR = 2.45 for <16.1 kph, OR = 3.05 for 16.1 to 32.2 kph, and OR = 3.19 for 32.3 to 48.3 kph). Similarly, high-risk cattle showed significantly \( (P < 0.05) \) greater odds of BRD incidence across greater categories of mean wind chill temperature (≥−6.6°C) in the 5 to 7 d lag compared with high-risk cattle exposed to the same categories of mean wind chill temperature in the 5 to 7 d lag (Figure 2).

The effects of the maximum wind speed in the 3 to 4 d lag and 5 to 7 d lag and by the temperature change in the 5 to 7 d period on daily BRD incidence were modified by mean arrival BW class. Overall, the impact of maximum wind speed in either the 3 to 4 d or 5 to 7 d lag was significantly \( (P < 0.05) \) greater for lighter-BW (227 to 271.9 kg) cattle than on their heavier-BW (318 to 363 kg) counterparts; however, these weather events did not seem to affect risk for medium-BW cattle (272 to 317.9 kg; Figure 3). The temperature change in the 5 to 7 d lag seemed to affect all BW classes in a similar manner. Lighter- and medium-BW cattle showed significantly \( (P < 0.05) \) greater odds of BRD incidence across all levels of temperature change compared with heavier-BW cattle exposed to the same temperature changes. However, the risk of BRD incidence appeared to decrease across all weight classes as the temperature change in the 5 to 7 d lag increased (Figure 3).

The effect of the mean wind chill temperature in the 5 to 7 d lag on the incidence of BRD depended on cohort size. However, medium (91 to 138 and 139 to 202 cattle) and larger cohorts (>202 cattle) had signifi-
Table 1. Final multivariable model\(^1\) demonstrating weather and cattle demographic factors associated with daily bovine respiratory disease (BRD) incidence during the first 45 d after arrival in autumn-placed commercial feedlot cattle

<table>
<thead>
<tr>
<th>Variable</th>
<th>OR(^2)</th>
<th>P-value</th>
<th>OR 95% CI(^3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>3 to 4 d lag(^4) maximum wind speed, kph</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt;16.1</td>
<td>ref(^5)</td>
<td>ref</td>
<td>ref</td>
</tr>
<tr>
<td>16.1 to 32.2</td>
<td>1.07</td>
<td>0.360</td>
<td>0.93 to 1.23</td>
</tr>
<tr>
<td>32.3 to 48.3</td>
<td>0.77</td>
<td>0.139</td>
<td>0.54 to 1.09</td>
</tr>
<tr>
<td>5 to 7 d lag(^4) maximum wind speed, kph</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt;32.2</td>
<td>ref</td>
<td>ref</td>
<td>ref</td>
</tr>
<tr>
<td>≥32.2</td>
<td>0.71</td>
<td>0.004</td>
<td>0.56 to 0.89</td>
</tr>
<tr>
<td>3 to 4 d lag(^4) mean wind chill, °C</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt;−17.8</td>
<td>1.30</td>
<td>0.400</td>
<td>0.70 to 2.42</td>
</tr>
<tr>
<td>−17.8 to −1.1</td>
<td>1.03</td>
<td>0.768</td>
<td>0.85 to 1.25</td>
</tr>
<tr>
<td>−1.0 to 4.4</td>
<td>0.65</td>
<td>0.001</td>
<td>0.51 to 0.85</td>
</tr>
<tr>
<td>&gt;4.4</td>
<td>ref</td>
<td>ref</td>
<td>ref</td>
</tr>
<tr>
<td>5 to 7 d lag(^4) mean wind chill, °C</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt;−9.4</td>
<td>0.92</td>
<td>0.854</td>
<td>0.37 to 2.26</td>
</tr>
<tr>
<td>−9.4 to −6.7</td>
<td>1.16</td>
<td>0.612</td>
<td>0.53 to 2.06</td>
</tr>
<tr>
<td>−6.6 to 1.7</td>
<td>1.07</td>
<td>0.595</td>
<td>0.83 to 1.38</td>
</tr>
<tr>
<td>1.8 to 7.2</td>
<td>1.07</td>
<td>0.587</td>
<td>0.83 to 1.39</td>
</tr>
<tr>
<td>&gt;7.2</td>
<td>ref</td>
<td>ref</td>
<td>ref</td>
</tr>
<tr>
<td>5 to 7 d lag(^4) temperature change, °C</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt;1.7</td>
<td>ref</td>
<td>ref</td>
<td>ref</td>
</tr>
<tr>
<td>1.7 to 4.4</td>
<td>0.82</td>
<td>0.028</td>
<td>0.69 to 0.98</td>
</tr>
<tr>
<td>4.5 to 10.0</td>
<td>0.66</td>
<td>&lt;0.001</td>
<td>0.56 to 0.78</td>
</tr>
<tr>
<td>10.1 to 12.8</td>
<td>0.77</td>
<td>0.050</td>
<td>0.59 to 1.00</td>
</tr>
<tr>
<td>Sex</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Steers</td>
<td>ref</td>
<td>ref</td>
<td>ref</td>
</tr>
<tr>
<td>Heifers</td>
<td>0.87</td>
<td>&lt;0.001</td>
<td>0.83 to 0.92</td>
</tr>
<tr>
<td>Month of arrival</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>September</td>
<td>ref</td>
<td>ref</td>
<td>ref</td>
</tr>
<tr>
<td>October</td>
<td>1.02</td>
<td>0.480</td>
<td>0.96 to 1.08</td>
</tr>
<tr>
<td>November</td>
<td>0.89</td>
<td>0.008</td>
<td>0.81 to 0.97</td>
</tr>
<tr>
<td>BW class, kg</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>227 to 271.9</td>
<td>1.27</td>
<td>0.006</td>
<td>1.07 to 1.50</td>
</tr>
<tr>
<td>272 to 317.9</td>
<td>1.43</td>
<td>&lt;0.001</td>
<td>1.23 to 1.68</td>
</tr>
<tr>
<td>318 to 363</td>
<td>ref</td>
<td>ref</td>
<td>ref</td>
</tr>
<tr>
<td>Cohort size, cattle</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt;91</td>
<td>ref</td>
<td>ref</td>
<td>ref</td>
</tr>
<tr>
<td>91 to 138</td>
<td>1.31</td>
<td>&lt;0.001</td>
<td>1.21 to 1.41</td>
</tr>
<tr>
<td>139 to 202</td>
<td>0.94</td>
<td>0.164</td>
<td>0.87 to 1.02</td>
</tr>
<tr>
<td>&gt;202</td>
<td>0.73</td>
<td>&lt;0.001</td>
<td>0.67 to 0.80</td>
</tr>
<tr>
<td>BRD risk code</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low</td>
<td>ref</td>
<td>ref</td>
<td>ref</td>
</tr>
<tr>
<td>High</td>
<td>3.68</td>
<td>&lt;0.001</td>
<td>3.22 to 4.20</td>
</tr>
<tr>
<td>Year of arrival</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2005</td>
<td>0.95</td>
<td>0.261</td>
<td>0.86 to 1.04</td>
</tr>
<tr>
<td>2006</td>
<td>0.76</td>
<td>&lt;0.001</td>
<td>0.69 to 0.84</td>
</tr>
<tr>
<td>2007</td>
<td>ref</td>
<td>ref</td>
<td>ref</td>
</tr>
</tbody>
</table>

\(^1\)Mixed-effects models with binomial distribution and random intercept for feedlot. Estimates for all categories (n = 45) of the variable days on feed and estimates for effects shown elsewhere were omitted in this table; these estimates are available from the authors on request.

\(^2\)OR = odds ratio.

\(^3\)OR 95% CI = odds ratio 95% confidence interval.

\(^4\)Lag periods = 1 to 2 d lag (1 and 2 d before the day of interest), 3 to 4 d lag (3 and 4 d previously), and 5 to 7 d lag (5, 6, and 7 d previously).

\(^5\)kph = kilometers per hour.

\(^6\)P-value of Wald test for all levels of categorical variables.
The effect of the mean wind chill temperature depended on the temperature change (both in the 5 to 7 d lag). Overall, the odds of BRD significantly \( (P < 0.05) \) increased as the mean wind chill temperature and the temperature change in the 5 to 7 d lag increased. However, for the lowest category of temperature change (<1.7°C), the effect of the mean wind chill temperature was greater, especially with wind chill temperatures of −9.4 to −6.7°C (Figure 5). The effect of the maximum wind speed on mean daily BRD morbidity risk depended on the mean wind chill temperature recorded during the previous 3 to 4 d (i.e., 3 to 4 d lag). The effect of wind chill temperature was significantly \( (P < 0.05) \) greater for the highest category of maximum wind speed (32.3 to 48.3 kph), although for all categories the risk of BRD incidence was greater under extreme categories of wind chill temperature (<−17.8 and −17.8 to −1.1°C; Figure 5). The association between daily BRD incidence and the maximum wind speed recorded during the previous 3 to 4 d (3 to 4 d lag) was modified by the temperature change registered in the previous 5 to 7 d (5 to 7 d lag). This interaction showed that temperature changes in the 5 to 7 d lag had a greater effect on lower categories of maximum wind speed (<16.1 and 16.1 to 32.2 kph) than in categories >32.2 kph (Figure 5).

The effect of BRD risk code on daily BRD incidence depended on the year of arrival; cattle designated as low risk showed similar odds of BRD incidence throughout the years, and these estimates were significantly \( (P < 0.001) \) less (OR = 0.32 for 2005, and OR = 0.26 for 2006) than for high-risk cattle in 2007. High-risk cattle in 2005 had significantly \( (OR = 1.13, P < 0.001) \) greater odds of daily BRD incidence than high-risk cattle in 2007; however, high-risk cattle in 2006 had significantly

\[ \begin{align*} \text{BW class} & \\
& - 227-271.9 \text{ kg} \\
& - 272-317.9 \text{ kg} \\
& - 318-363 \text{ kg} \\
\end{align*} \]

\[ \begin{align*} \text{3 to 4 d lag maximum wind speed, kph} & \\
& <16.1 \quad 16.1-32.2 \quad 32.3-48.3 \\
\end{align*} \]

\[ \begin{align*} \text{5 to 7 d lag maximum wind speed, kph} & \\
& <32.2 \quad >32.2 \\
\end{align*} \]
and wind speed are particularly stressful for groups of cattle that have not adequately acclimated to such conditions, with the most susceptible animals being younger, newly arrived cattle. If we add other potential stressors such as transportation, commingling, and handling to the stress caused by weather fluctuations, the adverse impact on cattle health could be severe.

Only cohorts arriving during autumn months (September to November) were included in this study to prevent confounding because of seasonality, an important consideration given that BRD risk factors vary among cattle arriving at North American feedlots in different seasons (Ribble et al., 1995). The overall in-

Figure 4. Model estimated mean daily bovine respiratory disease (BRD) incidence by cohort size and mean wind chill temperature in the 5 to 7 d lag in autumn-placed commercial feeder cattle during the first 45 d after feedlot arrival. Lag periods = 1 to 2 d lag (1 and 2 d before the day of interest), 3 to 4 d lag (3 and 4 d previously), and 5 to 7 d lag (5, 6, and 7 d previously). Error bars represent SE of least squares means.

Figure 5. Graphical representation of effects of weather variables included in significant interactions in the final multivariable model of mean daily bovine respiratory disease (BRD) incidence in autumn-placed commercial feeder cattle during the first 45 d after feedlot arrival. *Estimates not available. Lag periods = 1 to 2 d lag (1 and 2 d before the day of interest), 3 to 4 d lag (3 and 4 d previously), and 5 to 7 d lag (5, 6, and 7 d previously). Error bars represent SE of least squares means. kph = kilometers per hour.
creased risk for respiratory morbidity in cattle cohorts arriving in September and October compared with November arrivals might be due to the fact that in November cattle may have acclimated to the cold weather conditions or they may have been weaned longer than earlier cohorts. However, it is important to note that the effect of arrival month on the risk of BRD morbidity was modified by the maximum wind speed recorded in the 5 to 7 d lag. In the study by Ribble et al. (1995), conducted from September to December 1985 to 1988, cattle arriving in November had increased risk of fatal fibrinous pneumonia. Although our study reported morbidity rather than mortality, calves in our study that were morbid in September or October may have become mortalities in November. Ribble et al. (1995) stated that the increased mortality in November for all 4 study years could have been due to the lower mean daily temperatures and greater precipitation registered in that month. Synergistic effects between monthly variations in other weather characteristics with extreme wind speeds may explain the increased respiratory morbidity found in particular time periods in our study.

The association between BRD risk code and daily BRD incidence was modified by the arrival year of the cohort; however, low-risk cattle had BRD incidence risks that were fairly consistent among years and were significantly less than those of high-risk cattle. Commercial feedlots often use a risk code to subjectively predict the burden of BRD based on a visual evaluation of animals upon arrival, transport time, assessment of their source, and other factors (Lechtenberg et al., 1998); accurate prediction of disease risk may influence the implementation of interventions such as metaphylaxis (Nickell and White, 2010). Feedlots in our study used risk code to designate cohorts that did (high risk) or did not (low risk) receive metaphylaxis. Our results demonstrated that in high-risk cattle, there were differences in BRD incidence risks throughout the different years, with significantly decreased BRD incidence risk in 2006 compared with 2005 and 2007. The disparities based on a year effect may be due to many factors, including differences in feed or animal prices that ultimately affect BRD risk, or based on variation in management strategies that could affect BRD incidence risks; however, data on these practices are not always recorded. When the effect of BRD risk code was considered in concurrence with the effect of 3 to 4 d lag maximum wind speed or the 5 to 7 d lag mean wind chill temperature, high-risk cohorts showed greater BRD incidence risk than low-risk cohorts exposed to the same weather characteristics. Prearrival characteristics of low-risk cohorts still seem to be beneficial at maintaining their low BRD risk status, regardless of the weather conditions at arrival.

Lighter-BW cattle were at increased risk of respiratory morbidity compared with heavier-BW cattle across different categories of maximum wind speed in the 3 to 4 d and 5 to 7 d lags and of temperature change in the 5 to 7 d lag. Arrival BW is a rough proxy for animal age, and our results agree with previous authors who have indicated that lighter cattle may be more susceptible to respiratory diseases because of a less developed immune system compared with heavier-BW cattle (Sanderson et al., 2008). Thus, the stress related to adverse weather conditions may have a more pronounced effect in lighter, and likely younger, cattle.

The effect of cohort size on the incidence of BRD depended on the mean wind chill temperature in the 5 to 7 d lag. These data indicated that medium- and larger-size cohorts (>91 cattle) were associated with increased BRD incidence risk across all categories of wind chill temperature compared with smaller-size cohorts (<91 cattle). The size of the cohort may be a proxy for other characteristics related to procurement, management, or infrastructure of the feedlot system that influence BRD morbidity (e.g., exposure to pathogens, commingling, cattle source, distance traveled, personnel availability, pen size, attention to biosecurity). Unfortunately, in this study we did not have sufficient data to further evaluate these potential effects.

Although there was not an obvious trend, it seemed that, overall, an increased BRD risk was associated with greater maximum wind speeds and greater wind chill temperatures in the 3 to 4 d lag. Wind chill temperature is derived from mean daily temperature and mean daily wind speed; thus, its effect is embedded in the variable maximum wind speed, but it also relates to temperature. Given that these effects seem to be potentially important contributors to BRD, there is a need for a more detailed assessment into how specific wind speeds and temperatures affect BRD incidence. A clearer trend was found for the relationship between temperature change in the 5 to 7 d lag and maximum wind speed in the 3 to 4 d lag, where temperature changes in the 5 to 7 d lag showed greater effects on lower categories of maximum wind speed (<32.2 kph). Perhaps, one would expect that larger changes in temperature and greater wind speeds would increase the risk of BRD incidence, given that susceptible animals would be more prone to becoming ill when exposed to extreme weather conditions. However, poor weather conditions could affect the assessment of illness by feedlot personnel, which may explain why greater morbidity risks were found under moderate conditions for both temperature and wind speed. In addition, it is important to consider the scale and time of year at which these effects were measured; in other words, these weather conditions in autumn months and the scale at which they were categorized may not be considered extreme weather for cattle production systems. Moreover, an interaction involving temperature change and mean wind chill temperature in the 5 to 7 d lag did not show a clear pattern either; possibly the actual maximum and minimum temperatures affect BRD incidence instead of their difference and its relationship with wind speed (which is embedded in the variable wind chill). In observations made by MacVeal et al. (1986), Ribble et al. (1995), and more recently by Cusack et al. (2007),
the actual minimum and maximum values of temperature or wider ranges of ambient temperature were associated with an increased BRD morbidity. Because of strong correlations among several weather variables in these data, we evaluated the effect of variables accounting for the more general effects (e.g., maximum wind speed, overall temperature change).

Our study outcome was daily BRD cases that were treated with antimicrobials, which is logical from a cattle-accounting or record-keeping standpoint, as well as from a weather standpoint. However, diagnosis of BRD is subjective and may not be consistent among feedlots; thus, misclassification of the study outcome may occur. If weather events affect the distribution of manpower or the disposition of cattle and that is associated with identification of BRD cases, weather then might affect the accuracy of diagnosing daily BRD incidence. For instance, if certain weather conditions such as increased wind chill or extreme ambient temperatures make cattle experience BRD-like signs, or if feedlot personnel change management because of weather and that affects detection of disease, then disease estimates, based on perceived morbidity, could be biased. Moreover, from a practical standpoint, with severe weather conditions, personnel responsible for observing cattle may not examine as many animals or may not even observe the pens depending on how long these conditions last. In addition, in periods of cold, wet, and windy weather, cattle may congregate, making the assessment of illness more difficult. The current study was not designed to address these potential problems, but these findings could raise the question about potential misclassification arising from the knowledge of the weather characteristics. Despite these potential limitations, we have demonstrated that weather conditions are significantly associated with the observed incidence of BRD-treated cattle.

Given there are not only daily but also wider variations in weather patterns, we modeled weather variables using different lag periods to determine how daily BRD morbidity might be affected by weather events that happened up to 7 d earlier. Our future goal is to develop these models further so we could predict future BRD morbidity based on both current weather and available feedlot demographic data. Weather data were gathered from weather stations located within an 80-km radius from each feedlot; thus, data recorded from some stations may have been more representative of weather conditions experienced at the feedlot than others. Therefore, future studies may benefit from recording weather data using on-site systems.

A potential limitation of this study was the high correlation found among some of the weather variables and that the effect of some of these variables was embedded within other predictors (e.g., the reduction of temperature caused by precipitation could have been explained by subsequent temperature changes); this may have prevented us from providing more specific assessment of factors affecting daily BRD incidence. Future alternatives to explore these data could include the use of principle component analysis as well as a more comprehensive assessment of the lag phases of the weather variables. More research is needed to quantify how specific weather events and shifts in temperature over wider time periods throughout the feeding phase are associated with adverse health outcomes in specific populations of feedlot cattle; particularly because this study has provided initial evidence of the effects of weather. Furthermore, with increasing public concerns of animal welfare and climate change, future research on weather effects on health and production may be critical.

We have provided the first report of how weather effects, such as mean wind chill, maximum wind speed, and temperature change, in different time periods and different cattle populations appear to affect daily BRD incidence. Several other factors, such as region of origin and management of cattle prearrival, may have been embedded in these cattle demographic and weather variables, and these also may affect BRD morbidity in cattle after arrival at the feedlot. Unfortunately, these data are not always readily available in operational feedlot databases. Results from this study suggest that weather and demographic characteristics cannot be assessed independently in their association with BRD morbidity because their effects depend on other effects. A recent survey of health and well-being recommendations made by feedlot veterinarians in the United States and Canada indicated that weather patterns were considered the second most important factor, preceded by cattle health risk on arrival, for predicting morbidity and mortality (Terrell et al., 2011). Further defining the weather conditions associated with BRD in specific populations of feedlot cattle may enable feedlot managers and veterinary consultants to manage more effectively these effects by adjusting feedlot personnel or cattle management strategies. In addition, estimates of these effects may contribute to the development of quantitative predictive models for improved health and economic risk management.

**LITERATURE CITED**


