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Predicting Time Cattle Spend in Streams to Quantify Direct Deposition of Manure

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Abstract

Current methods to predict bacterial loads into streams resulting from direct deposition of manure by livestock do not consider factors that influence livestock behavior. Data from three studies that monitored spatial behavior of cattle through GPS were used to develop a new method with increased temporal resolution and consideration of environmental factors to predict the time that cattle spend in streams. Information on relative location of the cattle to the pasture stream was used to calculate the number of hours a cow spent in the stream, and from that the load of bacteria deposited directly into the stream. Ultimately, four empirical equations were developed based on the pasture geometry and shaded area, and each varied as a function of the daily minimum temperature. The models were applied to the Duck Creek watershed, Iowa, (at USGS Station 05422560) to demonstrate the variation in temporal resolution when compared to standard monthly load allocation methods. Three of four models estimated fewer days of E. coli load exceeding the water quality standard than days predicted using conventional methods. While the models do not capture the entire range of cattle spatial behavior, results suggest that the models can be used as a more detailed means of calculating bacterial loads. Daily load estimations averaged over a month can be used to populate current predictive tools as an alternate to the less representative estimation method on which the current modeling tools rely.

Keywords

Animal Science, Cattle manure, Grazing, Pasture, Pathogen indicator, Water quality, Regression models, Direct deposition

Disciplines

Agriculture | Animal Sciences | Bioresource and Agricultural Engineering | Water Resource Management

Comments

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PREDICTING TIME CATTLE SPEND IN STREAMS TO QUANTIFY DIRECT DEPOSITION OF MANURE

S. B. Brown, C. D. Ikenberry, M. L. Soupir, J. Bisinger, J. R. Russell

ABSTRACT. *Current methods to predict bacterial loads into streams resulting from direct deposition of manure by livestock do not consider factors that influence livestock behavior. Data from three studies that monitored spatial behavior of cattle through GPS were used to develop a new method with increased temporal resolution and consideration of environmental factors to predict the time that cattle spend in streams. Information on relative location of the cattle to the pasture stream was used to calculate the number of hours a cow spent in the stream, and from that the load of bacteria deposited directly into the stream. Ultimately, four empirical equations were developed based on the pasture geometry and shaded area, and each varied as a function of the daily minimum temperature. The models were applied to the Duck Creek watershed, Iowa, (at USGS Station 05422560) to demonstrate the variation in temporal resolution when compared to standard monthly load allocation methods. Three of four models estimated fewer days of* E. coli *load exceeding the water quality standard than days predicted using conventional methods. While the models do not capture the entire range of cattle spatial behavior, results suggest that the models can be used as a more detailed means of calculating bacterial loads. Daily load estimations averaged over a month can be used to populate current predictive tools as an alternate to the less representative estimation method on which the current modeling tools rely.*

Keywords. *Cattle manure, Grazing, Pasture, Pathogen indicator, Water quality, Regression models, Direct deposition.*

Of Iowa's 901 assessed streams and rivers in 2012, 55% were considered to be impaired and 23% were considered potentially impaired according to the USEPA's water quality standards (USEPA, 2013). There were 606 causes of impairment reported for the 2012 cycle, 45.7% of which were due to elevated levels of the fecal indicator organism (FIO) *Escherichia coli* (USEPA, 2013). Increased concentrations of FIOs correlate to an increased likelihood of pathogenic contamination in a body of water (Payment et al., 2000). Frenzel and Couvillion (2002) showed that this contamination can result in compromised human health and waterborne disease outbreaks if the water is used for consumption or recreation.

Section 303(d) of the Clean Water Act of 1972 requires states to compose a list of impaired water bodies and to establish Total Maximum Daily Loads (TMDL) for these waters. The TMDL for a watershed is defined as the maximum amount of pollutant received by a body of water such that the water quality standards are still met. A TMDL can be comprised of two forms of contaminant sources: point and nonpoint sources, plus a margin of safety. Physically measuring pollutant concentration in these nonpoint sources for sufficient TMDL analysis is financially and temporally impractical, and therefore on a watershed scale, water quality models are often used to simulate the impacts of land management practices on water quality. For example, the Soil and Water Assessment Tool (SWAT) has been used in conjunction with geographic information system (GIS) to generate watershed simulations for the purpose of water quality modeling and TMDL establishment (Santhi et al., 2001; Munoz-Carpena et al., 2006; Gassman et al., 2007; Jha et al., 2010). Accordingly, with more accurate model inputs that yield more accurate outputs, there can be theoretically better load allocation. Direct deposition of cattle manure into streams is technically classified as a nonpoint source according to EPA classifications (USEPA, 1994); however, it is treated as a point source of FIOs when inputting the data into water quality models. Two tools are publically available for predictive calculation of bacterial loading from grazing cattle into streams. The Bacterial Indicator Tool (BIT) was designed by the USEPA and is executed through Excel (USEPA, 2000) and the Bacterial Source Load Calculator was developed at Virginia Polytechnic Institute and State University and runs via Visual Basic for Applications (VBA) in Excel (Zeckoski et al., 2005). Both tools are designed to simulate the bacterial contribution from wildlife and grazing livestock into water bodies. These tools, however, have a potentially significant limitation in that the amount of time livestock spend in the stream is

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predicted through an estimated ratio that is applied across an entire month. The ratio estimation falls upon the user because limited information is available regarding the spatial tendencies of cattle in or around streams (Zeckoski et al., 2005). Furthermore, the tools do not utilize the factors thought to influence cattle behavior including weather conditions, pasture-stream geometry, pasture shade, pasture vegetation, or management practices such as restricting pasture access or providing water outside the stream corridor (Sheffield et al., 1997; Haan et al., 2006; Haan et al., 2010; Schwarte et al., 2011; Bear et al., 2012).

Because direct deposition of manure has a high impact on water quality (Line, 2003), errors produced by assuming a constant monthly FIO load to streams have potential to greatly over or underestimate the bacterial load due to grazing systems in TMDLs, especially on short timescales. Accordingly, watershed modeling tools need refinement for accurate prediction of direct deposition to streams. The first objective of this study was to develop empirical equations to estimate the amount of time that a cow spends in the stream on a daily time step as a function of environmental and pasture-related factors, a value termed cattle hours. The second objective was to modify the cattle-related portion of the BIT to produce data for input into watershed scale water quality models. This new tool, termed the In Stream Deposition Calculator (ISDC), would execute the developed model equations.

MATERIALS AND METHODS

The methodology described herein was designed to use available data to develop equations that predict the amount of time that cattle spend in a stream on a daily time step. Parameters available for model development were characteristics of the pasture including pastureland area, area within varying proximities to the stream, shaded area, and off-stream water sources, as well as environmental factors such as temperature, and, in some cases, precipitation. These equations were incorporated into the ISDC, which uses the cattle hour estimation to predict the *E. coli* load into the stream for a given day. The developed equations were analyzed for significance of daily variation, differences between resulting estimations among models, and the impact of averaging outputs over the month as a means of producing monthly estimates for current tools.

DATA SOURCES

The data for model development were collected from three different studies conducted from 2007 to 2010 at Iowa State University's Rhodes Research Farm in central Iowa (Schwarte et al., 2011; Bisinger and Russell, 2012) and at Iowa State University's McNay Research Farm and on four private farms in southern Iowa (Bear et al., 2012). Each study aimed to evaluate the spatial and temporal distribution of cattle with GPS-equipped collars. On-site weather data was also collected using a data-logging HOBO weather station (Onset Comp. Co., Bourne, Mass.). One to three adult beef cows were selected per pasture and collared to represent the behavior of the herd for two weeks either monthly (Schwarte et al., 2011; Bisinger and Russell, 2012) or in the spring, summer, and fall (Bear et al., 2012). Although grazing management varied between different pastures, only pastures with unrestricted access to the stream were considered. These farms and pastures are listed in table 1, as well as the year and number of collars used to collect data.

All three studies reported GPS location of the collar and weather data for each point in time collected. Data collection was taken continuously and automatically every 10 min. The latitude and longitude coordinates were analyzed using ArcGIS 9.1 and 9.2 (ESRI, Redlands, Calif.) to determine the location of the collared cow relative to the stream. In this project, cattle hours in the stream (CHS) were classified by considering points that were in or within 5 m of the stream ("stream"), and between 5 and 30 m of the stream ("streamside"). The combination of these two classifications was also considered ("stream + streamside"). The minimum range was chosen in part to account for the accuracy of the GPS technology, which was reported with a mean horizontal error of 7.7 m (Haan, 2010).

All three studies were designed for analysis such that a predictive probability could be produced, generating a curve of probabilities that a cow would be in a given pasture zone at a specific temperature (Schwarte et al., 2011; Bear et al., 2012; Bisinger and Russell, 2012). For this study however, to quantify the hours per day spent in the stream instead of a probability based on temperature, the time interval between data collection was multiplied by the number of instances that the collar was considered in the stream or streamside. This calculation estimated the number of cattle hours for a specific collar, location, and day.

The type of weather data collected varied across the three studies but ambient temperature was included at each site. To supplement the on-site weather data collected in each study, daily weather information from the nearest weather station was imported from the Iowa Environmental Mesonet National Weather Service (NWS) Cooperative Observer Program (Iowa Environmental Mesonet, 2012). Gathered NWS weather information included maximum temperature, minimum temperature, and precipitation for the stations nearest each of the farms. This inclusion was

Table 1. Data sources for model development.

Study	Farm, Pasture	Off-stream Water	Year	No. of Collars[a]
Bisinger and Russell, 2012	Rhodes, 1	Yes	2010	2
	Rhodes, 2	No	2010	2 to 3
	Rhodes, 4	Yes	2010	2
	Rhodes, 5	No	2010	2 to 3
Schwarte et al., 2011	Rhodes, 2	No	2008 2009	1 1
	Rhodes, 5	No	2008	1
Bear et al., 2012	McNay Farm A	No	2007	2
	McNay Farm C	Yes	2007 2008	1 1
	McNay Farm D	No	2007 2008	1 2
	McNay Farm E	Yes	2007	2

[a] GPS data sources utilized in this study for model development.

Table 2. Pasture factors and shade factors for the various pastures.

Farm, Pasture	Pastureland Total Area (ha)	Pastureland Area within 30 m of the Stream (ha)	Pastureland Pasture Factor Ratio [a]	Shaded Land Area of Shade within 10 m of the Stream (ha)	Shaded Land Shade Factor Ratio [b]
Rhodes, Past. 1, SM [c]	4.11	0.85	0.21	0.01	0.003
Rhodes, Past. 2, SM	4.03	0.83	0.21	0.01	0.002
Rhodes, Past. 2, LG	11.99	0.83	0.07	0.01	0.001
Rhodes, Past. 4, SM	4.09	0.80	0.20	0.06	0.015
Rhodes, Past. 5, SM	4.09	0.90	0.22	0.05	0.012
Rhodes, Past. 5, LG	11.97	0.90	0.08	0.05	0.004
McNay Farm A	125.2	26.22	0.21	7.46	0.060
McNay Farm C (2007)	92.2 [d]	3.46 [d]	0.21	1.28	0.014
McNay Farm C (08-09)	29.2 [d]	4.09 [d]	0.14	1.60	0.056
McNay Farm D	21.3	4.72	0.23	1.15	0.054
McNay Farm E	13.5	2.84	0.21	0.89	0.066

[a] Pasture Factor Ratio (PF_{ratio}) = area within 30 m of the stream/total area.

[b] Shade Factor Ratio (SF_{ratio}) = shaded area within 10 m of the stream / total area.

[c] Pastures in the Rhodes Research Farm (latitude 42°00’ N, longitude 93°25’ W) rotated biweekly between restriction of pasture area to a riparian paddock (SM) and access to the entire pasture (LG).

[d] Values based on an average between the farm’s pastures.

necessary to account for potential differences in collection methods and to add precipitation as an independent variable. Weather station data is also the most accessible source of weather information for most model users due to high costs and difficulties associated with collecting site-specific data.

Table 3. Variables available from data and considered in later analysis.

Examined Independent Variables	Examined Dependent Variables
• Presence or lack of off source water • Maximum temperature, on-site, °C • Minimum temperature, on-site, °C • Average temperature, on-site, °C • Maximum temperature, weather station, °C • Minimum temperature, weather station, °C • Average temperature, weather station, °C • Precipitation, weather station, mm • Total pasture area, acres • Pasture Factors (area of pastureland within *n* meters), ArcGIS, acres o 30 m of the stream o 25 m of the stream o 15 m of the stream o 10 m of the stream • Shade Factors (area of shade within *n* meters), ArcGIS, acres o 30 m of the stream o 25 m of the stream o 15 m of the stream o 10 m of the stream • Various ratios of streamside area • Various ratios of shaded area	• Cattle hours (Stream), h/day/cow • Cattle hours (streamside), h/day/cow • Cattle hours (stream + streamside), h/day/cow

In total, data were utilized from 11 distinct pastures, listed in table 2. Each of the pastures belonged to the five farms researched in the Bear study and the one farm in the Bisinger and Schwarte studies described in table 1. Pasture geometry was summarized into factors including and based on total pasture size. The term geometry is used to emphasize the shape of the pasture in relation to the stream. For example, cattle may behave differently in a long pasture with a stream along the length, than in a long pasture with a stream perpendicular to the length. Pasture factors represent the area within a certain distance of the stream, and shade factors represent the area of shade within a certain distance of the stream. Ratios of pasture factors and shade factors to the total area were also considered. All pasture and shade factors were calculated through aerial photos and ArcGIS software, as described by Bear et al. (2012).

Table 3 lists the information which was analyzed by SAS JMP statistical software (SAS, Cary, N.C.) and Excel. Initial dependent variables included: cattle hours (stream, hours), cattle hours (streamside, hours), and cattle hours (both stream and streamside, hours). Initial independent variables included: daily maximum temperature (on site, °C), daily minimum temperature (on site, °C), daily average temperature (on site, °C), daily maximum temperature (weather station, °C), daily minimum temperature (weather station, °C), daily average temperature (weather station, °C), daily precipitation (weather station, mm), pasture factors (acres), shade factors (acres), and ratios of pasture and shade factors (unitless). Data were not considered if a collar mechanically failed or was installed at any point during that day. Even after excluding these days, points from the years and collars listed in table 1 represented a total of 712 days of data.

Prior to developing the model, analysis was conducted to identify the best combination of variables from the extensive data that was available. First, multivariate correlation of the three dependent variables to the independent variables was performed in SAS JMP 10 to determine the most appropriate dependent variable. Next, a standard least squares stepwise fit was used to analyze the input parameters for the selected dependent variable. Independent variables were fit to the dependent variable and were selected for inclusion in the model based on resulting p-values. With respect to encompassing weather in the models, only weather station data were considered further for practicality and availability of data for future users.

To accommodate noncontinuous parameters including presence of off-stream water and pasture geometry, data were separated based on these parameters and used to develop unique models that apply to specific pasture characteristics. Tested subsets of data included dividing data by presence or lack of off-stream water, pasture factor, pasture factor ratio, shaded area within 10 m of the stream, shade factor ratio, and combinations thereof. This approach was used so that a model could be selected based on the site characteristics defined by a user.

To fit models to the large spread of data within a subset, an averaging technique was developed and implemented. This technique involved separating cattle hour data points by sorting minimum daily temperature measured by a weather station (MINws) by decreasing temperature. Within each range of temperature shown below, the cattle hours and temperatures were averaged and plotted against minimum daily temperature. Minimum daily temperature was chosen as a result of statistical correlations described below in table 4.

$20°C < MINws \leq 24°C$
$16°C < MINws \leq 20°C$
$12°C < MINws \leq 16°C$
$8°C < MINws \leq 12°C$
$4°C < MINws \leq 8°C$
$0°C < MINws \leq 4°C$
$-4°C < MINws \leq 0°C$
$MINws \leq -4°C$

Model Assessment

Because a large spread of CHS data exists within each temperature range, the models may inherently over- or underestimate times when cattle behave atypically. To evaluate model performance, a comparison between total observed hours and predicted hours was performed for each model on pastures that correspond to that model. The results for the four models were analyzed to determine if any model was under- or over-predicting cattle hours of the same dataset. A two-tailed t-test was used to determine if there were statistically significant differences between observed and predicted CHS for each of the models.

In addition to the analysis of daily CHS predictions, the average of the daily estimations over respective months was assessed. The motivation for this analysis was to determine if the predicted monthly averages could be used in current bacterial load tools which require a single input per month for the percentage of time spent in the stream. This value would eliminate the need for a user's potentially inaccurate estimate of the monthly time cattle spend in the stream. All of the days analyzed in model development were separated by month and the models were used to predict the daily cattle hours. Both predicted and observed daily cattle hours were averaged and compared. For all months except October and November, there were over 100 days analyzed between the three studies. Average cattle hours for October and November were based on 88 and 24 days of data, respectively, and days only until the end of Iowa's water recreation season, 15 November, were considered. GPS data collection did not extend past November and therefore the models are not representative for days outside of the recreation season.

Table 4. Significant variables resulting from the stepwise fit of independent variables to cattle hours (stream).

Parameter	P-value [a]
Minimum station temperature	< 0.001
Precipitation (station)	0.00308
PF_{Total} [b]	< 0.001
PF_{30} [c]	< 0.001
SF_{10} [d]	< 0.001

[a] P-Value Threshold: 0.05.

[b] Total pasture area (acres).

[c] PF_n is the Pasture Factor (PF), or the area within n meters of the stream (ha).

[d] SF_n is the Pasture Factor (SF), or the shaded area within n meters of the stream (ha).

Results and Discussion

Model Development

Initial tests indicated that the cattle hours (stream) variable was more strongly correlated to various parameters than were cattle hours (streamside) or cattle hours (stream + streamside). The average r-values for the combined parameters' correlation to the dependent variables CHS, CHSS, and CHS+SS were 0.16, -0.06, and -0.00, respectively. A stepwise fit of potential parameters to cattle hours (stream) in SAS JMP 10 indicated correlation of the following variables to CHS:

As detailed in table 4, variables with a $P < 0.05$ included minimum temperature (weather station), precipitation, total area of pastureland, area of pastureland within 30 m of the stream, and shaded area within 10 m of the stream. The pasture geometry variables suggest that the total pasture area and area within 10 m of the stream are correlated with CHS. However, to normalize data to accommodate future applications to pastures of different sizes, PF_{ratio} instead of PF_{total} or PF_{10} was considered further.

Bisinger and Russell (2012) concluded mathematically and through observation that shade is a contributing factor to cattle spatial behavior. Additionally, shade (SF_{10}) was correlated to cattle hours according to the stepwise fit results. The averaging technique was applied and R^2 values were considered for subsets of data based on SF_{10} and SF_{ratio} to normalize data. Only the subset of data $SF_{10} <$ 0.405 ha (1.0 acres) exhibited an R^2 equal to 0.99, while all subsets $SF_{10} >$ 0.405 ha were below an R^2 of 0.48. Applying the averaging technique to data subsets of SF_{ratio} resulted in models that were more consistently representative of measured cattle hours between ranges of pasture characteristics.

Overall, it was determined that models predicting cattle hours would most appropriately be defined by daily minimum temperature, land area near the stream relative to pasture size (PF_{ratio}), and shaded area near the stream relative to pasture size (SF_{ratio}). To develop the final models, the averaging technique was applied to each of four subsets of data defined by the following classifications of pasture: PF_{ratio} less than and greater than 20% and SF_{ratio} less than and greater than 1%. Accordingly, four unique models were developed, each applying to a specific range of pasture characteristics and varying with minimum daily temperature in degrees Celsius as the independent variable. These models are shown in figure 1 and defined in table 5.

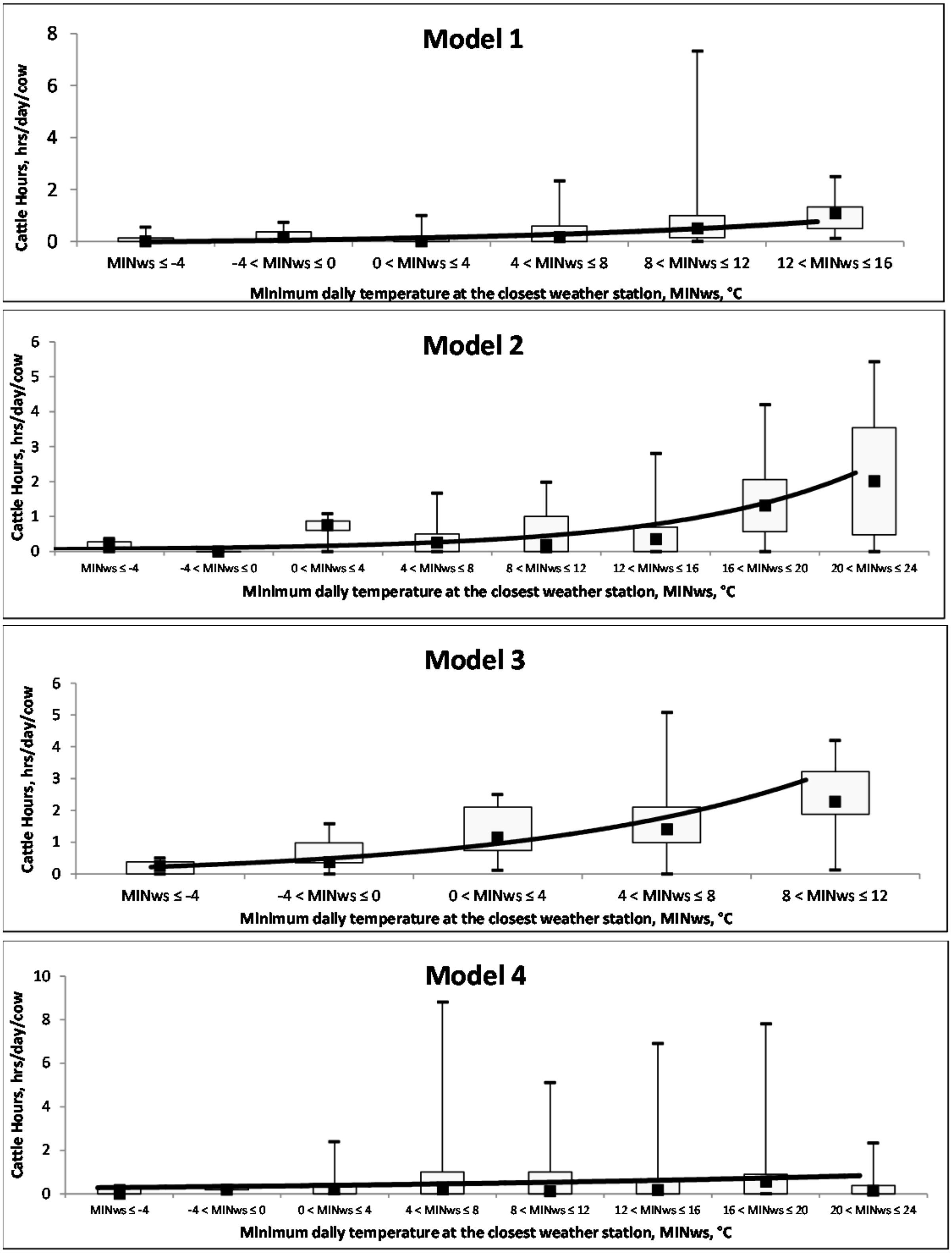

Figure 1. The four models (defined in table 5) predict the number of hours spent in the stream by one cow in one day as a function of minimum daily temperature. The data is represented through box and whisker plots and the model equation is illustrated as the continuous exponential trendline developed through the averaging technique. The appropriate model is chosen based on pasture characteristics.

The R^2 values listed in table 5 refer to the fit between the exponential trendline and the averaged cattle hour value for each temperature range. Therefore, these values do not necessarily reflect the usability of the models. However, the shape and sensitivity of the models is important. For example, models 1 and 4 are relatively flat and therefore are likely do not capture high CHS. Accordingly, those using the models for pastures with both low PF_{ratio} and

Table 5. Model classifications and definitions.

Pasture Discretization	Shade Discretization	Model Number	Averaged Equation[a]	$R^{2[b]}$
$PF_{ratio} < 0.2$	$SF_{ratio} < 0.01$	1	$y = 0.090\ e^{0.11x}$	0.91
$PF_{ratio} < 0.2$	$SF_{ratio} \geq 0.01$	2	$y = 0.090\ e^{0.15x}$	0.38
$PF_{ratio} \geq 0.2$	$SF_{ratio} < 0.01$	3	$y = 0.120\ e^{0.15x}$	0.94
$PF_{ratio} \geq 0.2$	$SF_{ratio} \geq 0.01$	4	$y = 0.329\ e^{0.042x}$	0.46

[a] y = cattle hours in the stream (h/day/cow),x = the daily low temperature (°C).

[b] R^2 corresponds to the exponential trendline fit to the averaged values determined with the averaging technique.

SF_{ratio} or both high PF_{ratio} and SF_{ratio} should take precaution that estimations may underpredict bacteria loads. Of the four final models, models 2 and 3 exhibit the greatest sensitivity to temperature. These results suggest a higher tendency of cows to spend time in streams on a hot day when, in pastures of large areas away from the stream, shade is more concentrated near the stream (model 2 parameters) and in pastures with a higher percentage of the land near the stream despite having less shade concentrated near the stream (model 3 parameters).

The averaging technique produced trends that reasonably fit the spread of the data. However, the final models of figure 1 and table 5 still cannot accurately reflect the range of CHS for any given minimum daily temperature. Particularly illustrated through the box and whisker plots of model four in figure 1, there is a high variability in CHS that was not captured when utilizing the considered variables. Awareness of this high level of potential error is especially critical when modeling pastures with a large cattle population because the total hours spent in the stream is a multiplicative result of CHS per cow and the number of cows, multiplying any error associated with CHS estimation.

MODEL ASSESSMENT

Analyzing observed and predicted cattle hours for each of the four models produced the results shown in figure 2. Each of the first three models had an absolute percent difference between observed and predicted CHS that is less than 5.5%. However, model 4 under-predicted CHS by 18.0%, which could be caused by the small variation in CHS with temperature that is shown in figure 1. Nevertheless, a two-tailed t-test indicated that there is no significant difference between observed and predicted CHS for each of the models.

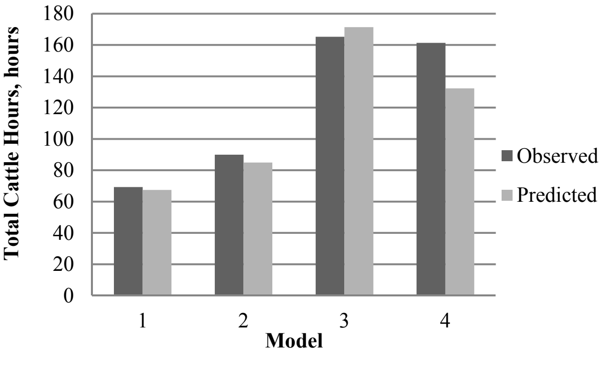

Figure 2. Comparison of observed and models' predictions of CHS. Models performed estimations only on pastures with pasture characteristics that correspond to that model.

Because daily cattle hour predictions may not be as valuable to modelers using current bacterial load tools, average monthly cattle hours were also evaluated. The dataset was composed of all daily cattle hours within a month for all pasture characteristics. The results of monthly averaging are shown in table 6. The averaged model-predicted CHS could be used as inputs for tools such as the BIT, offering a more representative method of estimating the time that cattle spend in streams for a given month. This procedure is particularly applicable to the months of June through September.

MODEL ANALYSIS AND IMPLEMENTATION

The In Stream Deposition Calculator (ISDC) was designed to output the daily bacterial load deposited directly into a stream by cattle through calculations that employ the estimated number of hours a cow spends in the stream. It uses the BIT (U.S. EPA, 2000) as a platform for design and function. The ISDC, executed through Excel, operates on multiple sheets of Excel, with the entire file representing a single subwatershed. However, the models are not limited to the subwatershed scale and can be applied to other land such as a single pasture or field.

After the development of the models and the ISDC, a test was executed to analyze the variability in daily bacterial loads compared to the average predicted loads of the current tools. This test utilized data for Duck Creek, Iowa (USGS Station 05422560). Available data included stream flow (cfs), number of cattle on pasture, and the daily temperatures (°C) calculated through a Thiessen Polygon of three nearby weather stations between 1 May 2008 and 15 November 2008. Each of the four models was executed using these data for the purpose of illustrating differences between models and therefore potential consequences of pasture characteristics on cattle hour estimations.

The FIO of interest for this illustration was *Escherichia coli.* The bacterial load was graphically and numerically compared to the loading capacity, which was calculated as the product of the water quality standard (WQS) of 235 cfu/100 mL and the daily stream flow measured at the USGS gauging station 05422560. Cattle hours for each day were predicted by each model. *E. coli* load was calculated using the model-predicted cattle hours in streams, the average manure production of 46 $lb_{manure\ (wet\ basis)}$/cow/day, and manure *E. coli* concentration (*ASAE Standards*, 1998). This approach assumes that deposition in the stream is proportional to the percentage of the day that cattle are in

Table 6. Monthly cattle hours, observed and predicted.[a]

	Observed CHS, Averaged	Predicted CHS, Averaged	Difference (%)
May	0.88	0.60	31.8
June	0.70	0.81	-15.7
July	0.99	0.99	0.0
August	0.85	0.90	-5.9
September	0.51	0.56	-9.8
October	0.57	0.36	36.8
November	0.17	0.27	-58.8

[a] All CHS are reported in hours per day per cow and averaged over the month.

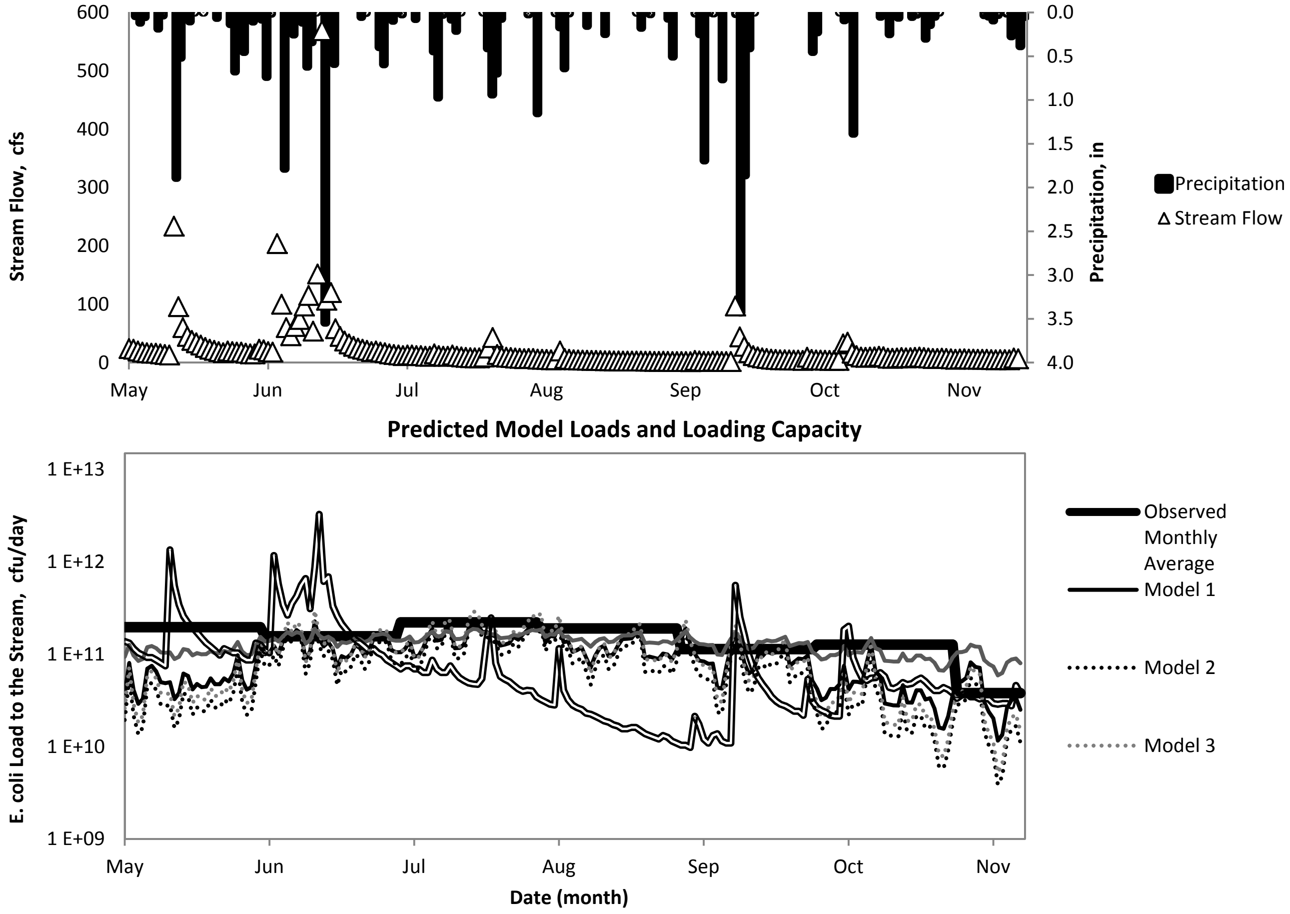

Figure 3. Loads of *E. coli* predicted by each of the four models and the monthly average of the model predictions that represents the prediction method of current tools. Results are based on 2008 data from Duck Creek (USGS Station 05422560, drainage area of 16.1 square miles, 130 cattle). This analysis assumes no other sources of bacteria are present.

the stream. This assumption is justified by findings of Haan et al. (2010) which showed that the observed rate of cattle defecation does not vary with location within the pasture.

Current modeling tools predict cattle hours and resulting bacteria loads as constant monthly values. To illustrate the potential significance of daily variation of time spent in streams, the monthly average was included in figure 3. Here, the monthly average represents a typical output of current tools' estimations of cattle hours. These values of CHS per cow were constant for each day within the correlated month, illustrating a typical estimated output of bacterial load from livestock by the BIT and the Bacterial Source Load Calculator. It is important to note that these predicted *E. coli* loads are presented for the purposes of relative comparison and field data do not exist to test these predictions.

In addition to comparing bacteria loads predicted by the daily models and current monthly average tools, implications for in-stream water quality were also examined. Predicted bacteria loads using the monthly average and daily model predictions were compared with the WQS loading capacity, shown in figure 3. The WQS loading capacity is defined by the product of the WQS and the stream flow. A violation of the WQS occurs on days in which the predicted load exceeds the loading capacity. The number of days with predicted violations was summarized in figure 4 for each model as well as the monthly average method.

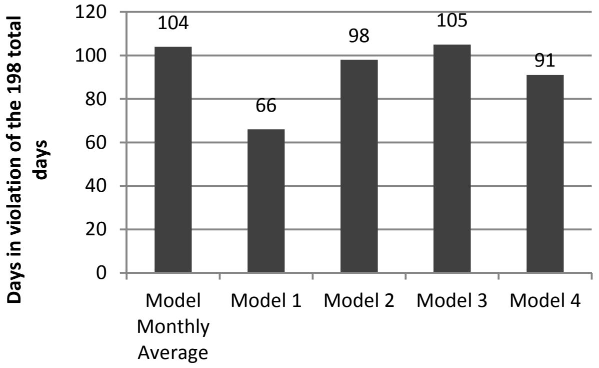

Figure 4. Number of days in which predicted *E. coli* load exceeded the WQS loading capacity for 1 May 2008 through 15 November 2008.

Figures 3 and 4 illustrate differences between the models and the current tool outputs. Figure 3 demonstrates a significant variation in daily load of bacteria into the stream relative to the current tools' method of having a single estimation for a month. This variation resulted in a decreased number of water quality standard violations in three of the four models compared with the existing monthly average methods, shown in figure 4.

Figure 4 also illustrates the impact of pasture characteristics on the cattle hours and therefore on water quality predictions. The number of days in which the predicted *E. coli* load exceeded the WQS ranged from 66 days (Model 1) to 105 days (Model 3) of 198 total observed days. Predicted bacteria loads are clearly sensitive to model selection, showing that the models are appropriately sensitive to the selected variables. The number of exceedances of the water quality standard can be influenced by pasture characteristics because stream water quality is strongly affected by direct deposition of livestock manure (Line, 2003).

SUMMARY AND CONCLUSION

The objectives of this study were to create empirical equations that improve estimation of the time a cow spends in a stream on a given day, termed cattle hours (CHS) and to design a tool to predict manure and bacteria loads deposited directly into the stream based on cattle hour calculations. This approach can improve the consideration of important factors in water quality modeling of pastureland containing cattle and streams. Additionally, it may be used to assess the impacts of landuse changes such as integrating livestock into farmland.

The parameters found to most accurately and consistently describe the time cattle spend in a stream were minimum daily temperature, the ratio of land area within 30 m of the stream to total pasture area, and the ratio of shaded area within 10 m of the stream to total pasture area. Four models were developed, each applying to pastures of certain combinations of the characteristics above and varying with minimum daily temperature. Models were incorporated into the In Stream Deposition Calculator (ISDC), which used the Excel-based Bacterial Indicator Tool (BIT) developed by the U.S. EPA as a template. The ISDC outputs bacterial load estimations based on cattle hour predictions by each model. The equations can be utilized directly through the ISDC to calculate bacterial load deposition or as a means of generating predictions for input into current tools. If the later, a modeler could chose the equation appropriate for a pasture of interest, use temperature data to calculate the predicted time spent in the stream daily, and average these daily cattle hours over a month to determine the average monthly time spent in streams, the required input value of current tools.

Results indicated that the developed models increase the temporal resolution of the time cattle spend in streams. Because cattle deposition has been shown to be uniform in and out of streams, the improved prediction of time in streams should theoretically yield improved *E. coli* load predictions when compared to estimations produced with existing available tools. However, bacterial data do not exist at this time to test this theory.

The models can over- or underestimate hours spent in streams on days when cattle behavior is not fully explained by model parameters (temperature, pasture geometry, and relative area of shade). Nevertheless, the models can be used as a more detailed method of determining the monthly input values required by the current bacterial load estimation tools. While the ISDC provides increased prediction resolution and a more representative method of predicting time spent in the stream, further research is recommended to investigate the behavior of cattle as it relates to time spent in streams across a wider range of pasture characteristics, climates, geographical regions, and cattle breeds. Currently, there is insufficient evidence to determine the degree of applicability of the models to other areas of the country and other breeds. Investigation of these environmental and breed differences could define the applicability of the models to farmland characteristics other than those studied.

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