Feedlots, Air Quality and Dust Control-Benefit Estimation under Climate Change

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1. *Introduction*

The United States Department of Agriculture (USDA) has reported that 1.11 million head of cattle and calves in U.S. died from respiratory problems, amounting to about $680 million in losses during 2005[1]. Losses from respiratory problems in Nebraska were estimated to about $58.4 million in 2005 and $55.8 million in 2010, while in Kansas respiratory problems are estimated to have caused 57.2 and 63.4 percent of total deaths from all causes reference. Dust is a major cause of respiratory problems, and large intensive feeding operations have large dust emissions from manure or animal activities that, in turn, cause higher morbidity and mortality. Losses caused by dust could be more extreme under climate change. Therefore there is no doubt that both currently and in a future with climate change that dust suppression is an important issue for the feedlot industry.

Large amounts of airborne particulate matter are emitted from intensive livestock feeding systems in dry and windy areas. Sweeten (1996) revealed that approximately 900 kg of dry manure are generated by an animal during a normal 150 day fattening period. A substantial amount of the dry manure becomes air-borne dust particles. Dust from confined animal feeding operations (CAFOs) is widely reported to adversely affect both animal and human health (Andersen et al., 2004; Donham, 2000, Loneragan et al., 2001; Mac Vean et al., 1986). The most direct impact of dust is loss of productivity. For example, Snowder et al. (1999) estimated an 8-kg difference between a healthy and a bovine respiratory disease infected calf over a 200-day feeding period amounting to $13.90 of economic loss per animal.

[1] http://usda.mannlib.cornell.edu/usda/current/CattDeath/CattDeath-05-05-2006.pdf.

There have been a number of studies that have investigated how climate factors affect livestock productivity, for example, Smith (1998), Hahn (1995, 2000), and Mader et al. (2009) have reviewed evidence that animal mortality, feed conversion rates, rates of gain, milk production, conception rates and appetite are altered by hotter temperatures. Mader et al. (2009) simulated beef cattle production under climate change projections and projected that US beef cattle would need up to 16% longer to grow from 350 to 550kg during the summer and early fall (June 1 to October 31), with a year round average of 4% to 5%. However, they did not consider changes in the risk of mortality and morbidity.

Belasco et al. (2009) simulated profitability risk considering sale prices, along with feeder cattle, feed, veterinary and interest cost costs along with mortality rates. However, they did not consider weather conditions and dust induced morbidity rate. Our analysis will extend and unify the climate and profitability considerations addressed in these studies.

This paper will report on estimates of the impacts of respiratory loss and climate change on cattle in CAFOs plus possible adaptation. This will be done in the context of United States case studies, in particular in the top 7 cattle producing states: Texas, Kansas, Nebraska, Iowa, Colorado, California, and Wisconsin. To do this a linear panel data model will be used in an effort to estimate the impacts of climate and associated dust on CAFO cattle. Bootstrapping will also be used to simulate upper and lower bounds on the climate change effects. Finally we will use dynamic programming to evaluate the benefits of reducing the respiratory problems.

2. *Estimation Approach*

The first step used herein in analyzing the dust control/climate change issue is to identify climate factors that influence cattle production. The climate factors used include the standard temperature and precipitation measures. Additionally since, high temperature and low humidity causes manure to become light and easily emitted (Amosson, 2006), we will include the dust level (PM_{10}) [2] to address our objective.

2.1 Linear Panel Data Model

Under the assumption that the feeding period is fixed, we estimate the average live sale weight (W_{it}) using the following linear panel data model:

$$W_{it} = \boldsymbol{X_{it}\beta} + \boldsymbol{Q_{it}\delta} + \boldsymbol{M_t\varphi} + \boldsymbol{S_i\gamma} + e_{it} \qquad (1)$$

where i indicates the states, t represents the month during the time period from January 1993 to December 2010. $\boldsymbol{X_{it}}$ is a 4×1 vector of independent variables including the following particulate matter level ($PM10_{it}$), monthly maximum temperature ($Tmax_{it}$), monthly minimum temperature ($Tmin_{it}$), and precipitation ($Precp_{it}$). $\boldsymbol{M_t}$ is a 11×1 vector of monthly dummies indicating a specific month while $M_t = 1$, and $\boldsymbol{S_i}$ is a 6×1 vector of state dummy variables to capture the spatial difference. $\boldsymbol{Q_{it}}$ is a 12×1 vector that includes the interaction terms of temperature and state, $Tmax\_S_{it}$ and $Tmin\_S_{it}$, which help to distinguish the impacts of temperatures among different states.

[2] PM refers to particulate matter and could be divided into several fractions, such as PM_{10} refers to thoracic fraction which is less than 10 µm or refers to respirable fraction which is less than 2.5µm.

Since cattle growth is a dynamic progress and current live sale weight is affected by both current and previous climate conditions, we modify equation (1) to include lagged terms of the climate variables as the following equation:

$$W_{it} = \boldsymbol{X_i\beta} + \boldsymbol{Q_i\delta} + \boldsymbol{D_h\varphi} + \boldsymbol{S_i\gamma} + e_{it} \qquad (2)$$

where $\boldsymbol{X_i}$ is a 12×1 vector that includes current terms and lagged terms of particulate matter level, monthly maximum temperature, monthly minimum temperature, and precipitation; $\boldsymbol{Q_i}$ is a 36×1 vector that includes current and lagged interaction terms of temperature and state. $\boldsymbol{D_h}$ is a 3×1 vector of seasonal dummy variables for the quarters of the year including spring (Mar.-May), summer (Jun.-Aug.), and fall (Sep.-Nov.), and $\boldsymbol{S_i}$ is a 6×1 vector that has the same indications as equation (1).

Next we use the estimated results from the linear panel data model and the projected climate values for the year 2080 under A1F SRES scenario from runs of the Hadley Centre Coupled Model (HADCM) to predict the live sale weights of cattle. Simultaneously we also employ bootstrap simulation to find the upper and lower bound of the projected cattle production.

2.2 Dynamic Programming

Finally dynamic optimization approach is used to find the value of dust control policies with and without climate change. The dynamic programming (DP) model will assume that farmers maximize the profits from animal feeding and have dust suppression alternatives. The model is structured as follows: animals are placed on feed and fed for a specific number of weeks starting from an initial weight W_0. Animal purchase costs C_p and feeding costs C_f are stochastic, other costs are C_{nf}, treatment costs for sick animals are C_t, and dust suppression sprinkler costs are C_w. The morbidity and mortality rates without dust control are v_1 and u_1, respectively. These reduce to v_2 and u_2 under dust suppression. Additionally, h_t, w_t, and z_t represents the period t health and weight state of cattle, plus the control policy. In turn the stochastic cost of an animal in period t is:

$$\tilde{u}(t) = -\tilde{C}_f - C_{nf} - C_t * (1 - h_t) - C_w * z_t \quad (3)$$

where $h_t = \begin{cases} 0 & \text{if sick} \\ 1 & \text{if healthy} \end{cases}$

$$z_t = \begin{cases} 0 & \text{if the sprinkler is off} \\ 1 & \text{if the sprinkler is on for dust control} \end{cases}$$

The state equations are as follows:

$$h_t = \begin{cases} 0 & \text{with } {v_1}^{(1-z_t)} \cdot {v_2}^{(z_t)} \\ 1 & \text{with } 1 - {v_1}^{(1-z_t)} \cdot {v_2}^{(z_t)} - {u_1}^{(1-z_t)} \cdot {u_2}^{(z_t)} \end{cases} \quad (4)$$

$$w_{t+1} = w_t + A\widehat{W}G_H * h_t + A\widehat{W}G_S * (1 - h_t) \quad (5)$$

where AWG_H and AWG_S represent the average weekly gain of healthy and sick animals, respectively.

At the end of the total planning period, the cattle can be sold at the stochastic average sale weight $\tilde{w}_T$ and stochastic price $\tilde{P}_T$, which we random draw from the estimation in the previous stage. Based on the above establishment, the *Bellman's Equation* is written as:

$$V(w_t, h_t, t) = \max_{z_t} E\{u(w_t, h_t, t) + \beta V(w_{t+1}, h_{t+1}, t+1)\} \qquad (6)$$

in which β is the discount factor.

The optimal choice of z in each planning period, $z_t^*(w_t, h_t, t)$, will solve the maximization problem above and could be technically written as:

$$z_t^*(w_t, h_t, t) = \text{argmax}_{z_t=0,1}\{u(w_t, h_t, t) + \beta V(w_{t+1}(w_t, h_t, z_t), h_{t+1}(w_t, h_t, z_t), t+1)\} \quad (7)$$

3. *Data Description*

Data needed for this empirical analysis include the price and weight of cattle plus data on climate factors. A comprehensive set of monthly data are collected for the 7 largest cattle feeding states (Texas, Kansas, Nebraska, Iowa, Colorado, California, and Wisconsin) from 1993 to 2010. Table 1 contains summary statistics. Data sources and manipulations are described as below:

- **Historical cattle price and weight:** Monthly price and sale weight data were drawn from USDA National Agriculture Statistics Service Quick Stats.[3] The weight data used are average monthly state commercial slaughtered weight on a live animal basis. The price data are price received per hundred weight ($/Cwt). Both price and weight data are for cattle weighing more than 500 lbs. The cattle prices were transformed to a real

[3] <http://quickstats.nass.usda.gov/>.

2010 basis using the consumer price index (CPI)[4].

- **Cattle feeding costs:** Feeding costs were drawn from reference.
- **Historical climatic data:** Monthly temperature and precipitation data for weather stations in the feeding areas were obtained from the National Oceanic and Atmospheric Administration (NOAA) Satellite and Information Service, National Climatic Data Center (NCDC).[5] Temperature is measured in degrees Fahrenheit and precipitation is in millimeters. Monthly maximum (Tmax) and minimum (Tmin) temperature data are used instead of monthly average temperature to reflect the relative impacts of extreme climate conditions. The climatic data were averaged in climate divisions demarcated by NOAA, and then a state level number was derived based on the proportion of cattle sales in that state falling in each climate division. For example, around 98.19% sale cattle are from the first climate division in Texas, and hence the state level climatic data were obtained by weighting the data from that area by 98.19%. Table 2 reports the proportion of sales in climate division levels, and figure 1 shows the climate divisions in each state.
- **Historical particulate matter recorded data (PM):** Particulate matter, in particular PM_{10}, were obtained from EPA, Emissions by Category Report-Criteria Air Pollutants and measured hourly in ug/m^3. Since the data were reported by station, we used cattle sale numbers to construct a state level weighted average[6] When there were missing values the average monthly PM_{10} level among the climate divisions was used.

[4] <http://www.bls.gov/data/inflation_calculator.htm>.
[5] <http://www7.ncdc.noaa.gov/CDO/CDODivisionalSelect.jsp#>.
[6] <http://www.epa.gov/air/data/emcatrep.html?st~KS%20NE~Kansas%2C%20Nebraska>.

- **The projected climate conditions:** Projected temperature and precipitation were drawn from the A1F SRES scenario from runs of the Hadley Centre Coupled Model (HADCM) for 2080 as reported on the IPCC website.
- **Empirical mortality rate and morbidity rate:** The mortality and morbidity rates were drawn from Sanderson et al. (2008). When the initial animal weight was less than 550 pounds, the morbidity rates were specified as descending from 6.2% in the first week after placement to around 0.01% in the 12th week. When the placement weight was between 550 and 650 pounds, the morbidity rate is 2.4% in the first week after placement and decreases in the following weeks.

4. Estimation Results

Table 3 reports the estimation results for equation (1) with different sets of independent variables: Model (A) only considers climate variables, Model (B) adds interaction terms of temperature and production region dummies, and Model (C) further includes monthly and production region dummy variables. All models indicate that increased PM_{10} significantly decreases sale weights. For example, as shown in Model (C), one unit of PM_{10} decreases sale weight by -2.69 pounds. These models also help to identify the effects of monthly maximum (Tmax) and minimum (Tmin) temperatures. Both have significant negative impacts on average live sale weight. However, including both Tmax and Tmin gives the opposite results (positive and negative, respectively), which indicates that warming has an ambiguous impact. However, we will not try to explain the reasons here until the following analysis using linear panel data model with considering lagged terms.

Table 4 contains the estimated results for the model with lagged terms as described in equations (2). We will again focus on Model (C) which fits the best. Here we find that, the total impacts from PM10 considering the effects over the total lag period are higher than the impacts when not considering lags. For example, Model (C3) shows that one more unit increase of PM10, $PM10_{t-1}$, and $PM10_{t-2}$ decrease the cattle production by around -1.29, -1.03, and -1.28 pounds, respectively.

Monthly maximum temperature and minimum temperatures present interesting results. Almost all the estimated results of Tmax, Tmin, and the interaction terms of Model (C) in Table 3 are significant. However, fewer terms are significant when we consider lagged terms. Temperatures of the previous periods significantly affect the cattle production only in Kansas, Iowa, and California while temperatures in the current period have significant impacts on cattle production in Kansas, Nebraska, Iowa, California and Wisconsin. Temperature in Texas and Colorado does not significantly affect cattle weight. It might be reasonable since cattle in a hotter area such as Texas panhandle might have higher capacity to deal with heat stress.

The next step we use the projected climate values in year 2080 to predict the live sale weight and the results from equation (2) will be used in this prediction. Since we do not have any projected PM_{10} data, an 10% increase in PM10 in year 2080 were assumed. For this increase, the mortality rate and morbidity rate were also assumed to increase by 5% increase in our analysis. The simulated upper bound and lower bound live sale weights were reported in Table 5.

Table 6 presents the estimated values of individual cattle under optimal dust control policies. In our analysis we only analyze the cattle marketed in June and December, and the results do not show quite different values between these two months. However, the cattle values estimated under higher (97.5% quantile) live sale weight are significant higher than that under lower (2.5% quantile) live sale weight in the same month. The live sale weight in dynamic programming is treated as the best situation we expect to achieve, and the costs of feeding cattle might be reduced because of the earlier achievement of the lower live sale weight under the optimal control policies. This demonstrated that an optimal control policy could help to reduce the risk of benefits even the future climate change scenario change the expected live sale weight.

5. *Conclusions*

In this paper, we investigated the dust control and climate change issue. Statistically we found that dust significantly lowers the cattle sale weight while monthly maximum and minimum temperatures have ambiguous effects. We did find that a dust mitigation strategy of using sprinklers reduces the impacts of dust. The extreme climate variables such as drought and heat waves could be also considered in the further research to capture the impacts of extreme events on the livestock.

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Table1. Variable Summary Statistics for monthly data in each state, 1993 to 2010

	State	Mean	Stand Error	Max	Min
Cattle Weight (lbs)	Texas	1167.42	51.32	1265	1068
	Kansas	1218.46	48.70	1322	1090
	Nebraska	1263.44	54.06	1380	1129
	Iowa	1214.63	36.07	1306	1101
	Colorado	1251.08	50.03	1366	1129
	California	1272.77	39.97	1382	1200
	Wisconsin	1291.47	52.02	1379	1172
Cattle Price[1] ($/ cwt)	Texas	91.95	9.25	120.05	73.81
	Kansas	94.01	8.99	123.07	78.39
	Nebraska	94.43	9.13	120.19	76.35
	Iowa	89.03	9.86	118.88	72.72
	Colorado	99.79	13.55	132.16	77.59
	California	71.84	10.09	102.23	53.10
	Wisconsin	67.52	7.58	92.41	54.74
PM_{10} (ug/m^3)	Texas	23.17	7.03	48.83	8.42
	Kansas	24.00	8.01	74.38	10.72
	Nebraska	31.41	8.89	65.23	12.27
	Iowa	26.62	6.08	44.13	14.12
	Colorado	22.23	3.80	39.16	12.43
	California	33.14	9.55	88.16	15.27
	Wisconsin	17.75	3.86	31.07	8.40
Monthly Max Temperature (F)	Texas	73.21	14.72	98.05	43.63
	Kansas	68.30	17.42	97.63	33.04
	Nebraska	61.69	18.90	92.49	27.13
	Iowa	57.81	20.47	87.81	18.07
	Colorado	62.16	16.23	91.63	31.80
	California	77.39	13.87	100.30	54.91
	Wisconsin	55.87	20.08	85.40	16.54
Monthly Min Temperature (F)	Texas	54.67	14.82	78.33	24.40
	Kansas	42.02	17.08	69.85	12.91
	Nebraska	37.18	17.71	65.51	7.10
	Iowa	37.90	18.57	67.12	0.99
	Colorado	31.66	14.94	58.01	-1.57
	California	42.64	9.55	64.70	21.24
	Wisconsin	34.65	18.46	65.02	-5.64
Precipitation (mm)	Texas	207.49	315.54	1839.43	0.04
	Kansas	203.89	162.04	875.52	1.82
	Nebraska	274.41	163.01	812.51	26.81
	Iowa	237.34	180.11	954.92	14.46
	Colorado	295.34	203.12	965.20	7.18
	California	126.72	85.17	477.88	13.12
	Wisconsin	257.97	161.58	851.11	20.70

Note: 1. the cattle prices were adjusted by the consumer price index (CPI) in 2010 to adjust for the effect of inflation.

Table2. Proportion of Cattle Sales in Different Climate Divisions

Climate Division	Texas	Kansas	Nebraska	Iowa	Colorado	California	Wisconsin
1	98.19%	4.67%	10.96%	32.42%	11.32%	3.81%	3.24%
2	0.11%	1.00%	5.05%	6.27%	0.13%	6.10%	2.39%
3	0.45%	1.28%	28.41%	12.88%	27.48%	0.72%	3.05%
4	0.27%	21.54%	0.00%	19.02%	61.06%	13.29%	17.53%
5	0.01%	7.02%	18.00%	6.03%	0.01%	22.87%	5.85%
6	0.30%	2.77%	16.70%	11.17%	-	3.88%	8.64%
7	0.19%	54.54%	8.04%	7.41%	-	49.33%	30.55%
8	0.05%	4.52%	10.83%	1.64%	-	-	25.41%
9	0.42%	2.66%	2.01%	3.16%	-	-	3.34%
10	0.01%	-	-	-	-	-	-

Note: The data is collected from 2002 and 2007 census data reported by USDA, and the climate divisions are demarcated by NOAA. The notation "-" means no such climate division in that state.

Table3. Estimated Results of Linear Panel Data Models without Including Lagged Terms

	Model A: Only Climate Variables			Model B: W/ Interaction Term		Model C: W/ All Variables		
	(A1)	(A2)	(A3)	(B1)	(B2)	(C1)	(C2)	(C3)
PM10	-0.12	-0.10	-1.35	-2.34	-2.22	-2.43	-2.57	-2.69
	[0.76]	[0.64]	[7.30]**	[11.91]**	[11.50]**	[11.79]**	[12.61]**	[13.31]**
Tmax	-0.28		3.28	-0.96		-0.89	-0.24	0.52
	[3.06]**		[13.90]**	[13.44]**		[2.76]**	[0.67]	[1.04]
Tmin		-0.74	-3.93		-1.42	0.61	0.93	0.58
		[7.66]**	[15.69]**		[18.50]**	[1.55]	[2.52]*	[1.55]
Precp	-0.01	0.001	0.002	-0.03	-0.03	-0.02	-0.02	-0.01
	[0.76]	[0.15]	[0.19]	[5.86]**	[5.52]**	[3.63]**	[3.04]**	[0.94]
Interaction Term								
Tmax_KS				0.87		2.01	2.15	2.65
				[14.73]		[4.41]**	[5.08]**	[2.86]**
Tmax_NE				1.40		3.85	4.32	2.57
				[21.40]**		[7.53]**	[8.55]**	[2.08]*
Tmax_IA				1.01		2.81	3.74	5.48
				[12.73]**		[4.56]**	[5.71]**	[4.47]**
Tmax_CO				1.40		3.07	3.39	2.01
				[20.51]**		[6.99]**	[8.07]**	[2.02]*
Tmax_CA				2.02		3.53	3.59	1.68
				[27.08]**		[7.41]**	[7.33]**	[2.69]**
Tmax_WI				1.80		4.78	5.75	3.58
				[26.39]**		[8.73]**	[9.66]**	[2.67]**
Tmin_KS					1.07	-1.65	-1.72	-2.79
					[12.13]**	[2.50]*	[2.80]**	[2.95]**
Tmin_NE					1.86	-3.70	-4.16	-3.06
					[18.45]**	[4.89]**	[5.61]**	[2.34]*
Tmin_IA					1.27	-2.46	-3.47	-5.95
					[11.22]**	[2.85]**	[3.88]**	[4.44]**
Tmin_CO					1.92	-2.78	-2.98	-2.32
					[16.06]**	[3.92]**	[4.40]**	[2.11]*
Tmin_CA					3.02	-2.49	-2.51	-1.72
					[23.55]**	[3.23]**	[3.13]**	[2.10]*
Tmin_WI					2.43	-4.33	-5.44	-3.81
					[23.47]**	[5.49]**	[6.47]**	[2.60]**
Monthly Dummy								
Feb.							-1.70	-0.21
							[0.30]	[0.04]
Mar.							-13.11	-10.30
							[2.05]*	[1.48]
Apr.							-59.14	-55.19
							[7.37]**	[5.95]**
May							-48.82	-42.84
							[5.09]**	[3.53]**
Jun.							-64.68	-56.55
							[5.80]**	[3.88]**
Jul.							-60.66	-50.46
							[4.91]**	[3.10]**
Aug.							-44.18	-34.17
							[3.68]**	[2.16]*

	Model A: Only Climate Variables			Model B: W/ Interaction Term		Model C: W/ All Variables		
	(A1)	(A2)	(A3)	(B1)	(B2)	(C1)	(C2)	(C3)
Sep.							-47.09	-38.60
							[4.33]**	[2.85]**
Oct.							-22.96	-17.66
							[2.65]**	[1.75]
Nov.							-20.50	-17.38
							[3.54]**	[2.69]**
Dec.							-33.50	-32.82
							[5.73]**	[5.78]**
State Dummy								
KS								12.34
								[0.43]
NE								71.44
								[2.12]*
IA								0.44
								[0.02]
CO								66.75
								[2.08]*
CA								114.14
								[4.83]**
WI								72.88
								[2.37]*
Constant	1262.34	1271.06	1204.50	1269.05	1277.70	1228.64	1199.51	1155.11
	[213.21]**	[269.57]**	[190.02]**	[244.01]**	[297.16]**	[145.21]**	[90.81]**	[47.19]**
R-squared	0.01	0.04	0.14	0.45	0.43	0.47	0.52	0.53

Note: * p<0.05 and ** p<0.01; t-values are reported in the square brackets.

Table4. Estimated Results of Linear Panel Data Models Including Lagged Terms

	Model A: Only Climate Variables			Model B: W/ Interaction Term		Model C: W/ All Variables		
	(A1)	(A2)	(A3)	(B1)	(B2)	(C1)	(C2)	(C3)
PM10	0.30	0.25	-0.68	-1.08	-1.04	-1.29	-1.29	-1.29
	[0.88]	[0.75]	[2.22]*	[4.48]**	[4.36]**	[4.99]**	[5.00]**	[5.26]**
$PM10_{t-1}$	-0.28	-0.16	-0.68	-0.98	-1.01	-0.99	-1.01	-1.03
	[0.72]	[0.42]	[1.94]	[3.60]**	[3.75]**	[3.48]**	[3.50]**	[3.69]**
$PM10_{t-2}$	-0.15	-0.21	-0.60	-1.27	-1.16	-1.13	-1.12	-1.28
	[0.46]	[0.67]	[1.90]	[4.66]**	[4.54]**	[3.86]**	[3.85]**	[4.76]**
Tmax	-0.46		1.43	-0.54		-0.32	-0.03	0.01
	[1.93]		[4.04]**	[1.61]		[0.76]	[0.07]	[0.01]
$Tmax_{t-1}$	0.21		1.65	-0.10		-0.98	-0.91	-0.94
	[0.53]		[3.62]**	[0.16]		[1.58]	[1.48]	[1.60]
$Tmax_{t-2}$	-0.11		1.50	-0.20		0.08	-0.19	-0.09
	[0.45]		[4.06]**	[0.51]		[0.18]	[0.41]	[0.19]
Tmin		-0.92	-2.15		-0.71	0.55	0.55	0.54
		[4.15]**	[6.08]**		[3.08]**	[1.54]	[1.55]	[1.55]
$Tmin_{t-1}$		0.44	-1.49		-0.16	0.47	0.48	0.43
		[1.29]	[3.83]**		[0.51]	[1.42]	[1.44]	[1.26]
$Tmin_{t-2}$		-0.48	-1.75		-0.50	0.38	0.36	0.31
		[2.18]*	[4.97]**		[2.10]*	[1.23]	[1.17]	[1.01]
Precp	-0.01	-0.01	-0.01	-0.02	-0.02	-0.01	-0.01	-0.01
	[0.74]	[0.44]	[0.86]	[2.55]*	[3.76]**	[1.97]*	[1.91]	[1.17]
$Precp_{t-1}$	0.001	0.01	0.01	-0.01	-0.02	-0.01	-0.01	0.001
	[0.06]	[0.46]	[0.51]	[0.76]	[2.70]*	[1.01]	[1.15]	[0.49]
$Precp_{t-2}$	0.001	0.01	0.01	0.28	-0.01	0.001	0.01	0.01
	[0.37]	[0.82]	[1.19]	[0.56]	[1.15]	[0.24]	[0.23]	[0.80]
Interaction Term								
Tmax_KS				0.28		1.55	1.32	2.56
				[0.56]		[1.63]	[1.38]	[2.43]*
$Tmax\_KS_{t-1}$				0.25		1.28	1.28	2.31
				[0.27]		[1.06]	[1.07]	[1.89]
$Tmax\_KS_{t-2}$				0.44		0.10	0.34	1.37
				[0.75]		[0.10]	[0.33]	[1.26]
Tmax_NE				0.92		3.29	3.03	2.63
				[1.84]		[2.84]**	[2.62]**	[2.01]*
$Tmax\_NE_{t-1}$				-0.48		0.87	0.95	0.76
				[0.52]		[0.62]	[0.69]	[0.53]
$Tmax\_NE_{t-2}$				1.04		0.56	0.77	0.33
				[1.85]		[0.47]	[0.63]	[0.24]
Tmax_IA				0.30		3.11	2.89	5.10
				[0.58]		[2.76]**	[2.58]**	[3.63]**
$Tmax\_IA_{t-1}$				0.74		0.88	0.84	1.34
				[0.82]		[0.62]	[0.59]	[0.91]
$Tmax\_IA_{t-2}$				0.15		0.45	0.82	2.98
				[0.27]		[0.41]	[0.73]	[2.17]*
Tmax_CO				0.73		1.02	0.83	1.38
				[1.25]		[0.95]	[0.78]	[1.20]
$Tmax\_CO_{t-1}$				-0.24		1.67	1.59	2.09
				[0.21]		[1.22]	[1.18]	[1.48]
$Tmax\_CO_{t-2}$				1.05		1.32	1.58	2.21
				[1.59]		[1.17]	[1.40]	[1.79]

	Model A: Only Climate Variables			Model B: W/ Interaction Term		Model C: W/ All Variables		
	(A1)	(A2)	(A3)	(B1)	(B2)	(C1)	(C2)	(C3)
Tmax_CA				1.38		2.50	2.50	0.80
				[2.60]**		[3.66]**	[3.63]**	[1.04]
$Tmax\_CA_{t-1}$				-0.88		0.64	0.68	1.40
				[0.96]		[0.62]	[0.64]	[1.40]
$Tmax\_CA_{t-2}$				1.79		2.70	2.70	1.13
				[3.29]**		[3.90]**	[3.88]**	[1.42]
Tmax_WI				1.53		2.80	2.55	2.90
				[3.24]**		[2.25]*	[2.06]*	[1.92]
$Tmax\_WI_{t-1}$				-0.58		1.98	2.12	2.22
				[0.67]		[1.22]	[1.31]	[1.37]
$Tmax\_WI_{t-2}$				0.90		1.41	1.65	1.74
				[1.73]		[1.13]	[1.31]	[1.23]
Tmin_KS					0.11	-1.76	-1.55	-2.68
					[0.24]	[1.74]	[1.53]	[2.55]*
$Tmin\_KS_{t-1}$					0.69	-1.12	-1.14	-2.47
					[0.88]	[1.05]	[1.06]	[2.17]*
$Tmin\_KS_{t-2}$					0.45	0.06	-0.14	-1.01
					[0.90]	[0.06]	[0.14]	[0.97]
Tmin_NE					1.00	-3.67	-3.43	-3.21
					[1.91]	[2.72]**	[2.55]**	[2.21]*
$Tmin\_NE_{t-1}$					-0.35	-0.71	-0.85	-0.60
					[0.38]	[0.45]	[0.53]	[0.35]
$Tmin\_NE_{t-2}$					1.39	-0.44	-0.59	-0.27
					[2.49]*	[0.32]	[0.43]	[0.18]
Tmin_IA					-0.01	-3.83	-3.68	-5.87
					[0.02]	[2.91]**	[2.81]**	[3.87]**
$Tmin\_IA_{t-1}$					1.46	0.17	0.23	-0.81
					[1.79]	[0.12]	[0.16]	[0.53]
$Tmin\_IA_{t-2}$					0.07	-0.83	-1.19	-3.25
					[0.14]	[0.72]	[1.01]	[2.38]*
Tmin_CO					1.08	-1.22	-1.01	-1.61
					[1.81]	[0.97]	[0.80]	[1.22]
$Tmin\_CO_{t-1}$					-0.40	-1.69	-1.66	-2.38
					[0.37]	[1.34]	[1.32]	[1.75]
$Tmin\_CO_{t-2}$					1.58	-1.07	-1.30	-2.02
					[2.45]*	[0.88]	[1.07]	[1.55]
Tmin_CA					1.25	-2.10	-2.09	-1.58
					[2.77]**	[2.71]**	[2.70]**	[2.04]*
$Tmin\_CA_{t-1}$					0.44	-2.27	-2.32	-1.45
					[0.75]	[3.16]**	[3.22]**	[2.01]*
$Tmin\_CA_{t-2}$					1.87	-1.52	-1.55	-1.11
					[4.35]**	[2.21]*	[2.25]*	[1.55]
Tmin_WI					1.81	-3.02	-2.82	-3.33
					[4.09]**	[2.26]*	[2.11]*	[2.10]*
$Tmin\_WI_{t-1}$					-0.58	-1.62	-1.81	-1.91
					[0.77]	[1.05]	[1.16]	[1.19]
$Tmin\_WI_{t-2}$					1.29	-1.70	-1.88	-2.06
					[2.76]**	[1.28]	[1.40]	[1.45]

	Model A: Only Climate Variables			Model B: W/ Interaction Term		Model C: W/ All Variables		
	(A1)	(A2)	(A3)	(B1)	(B2)	(C1)	(C2)	(C3)
Seasonal Dummy								
Mar.-May							-12.59	-11.02
							[2.26]*	[1.99]*
Jun.-Aug.							-11.04	-2.63
							[1.48]	[0.34]*
Sep.-Nov.							-2.54	4.01
							[0.40]	[0.62]
State Dummy								
KS								-85.59
								[2.05]*
NE								33.30
								[0.71]
IA								-80.72
								[1.93]
CO								-41.80
								[0.86]
CA								124.77
								[3.76]**
WI								-5.07
								[0.12]
Constant	1267.09	1278.20	1186.16	1272.50	1286.95	1218.18	1218.99	1212.63
	[171.91]	[227.02]**	[153.94]**	[193.35]**	[253.03]**	[97.11]**	[85.01]**	[48.34]**
R-squared	0.01	0.05	0.18	0.48	0.47	0.50	0.51	0.52

Note: * p<0.05 and ** p<0.01; t-values are reported in the square brackets.

Table5. Projected Cattle Live Sale Weight in year 2080

Sale Month	Quantile	States						
		Texas	Kansas	Nebraska	Iowa	Colorado	California	Wisconsin
Jan	2.5%	1098.04	1090.46	1135.05	1096.48	1070.76	1158.32	1153.22
	97.5%	1236.75	1287.57	1350.61	1244.09	1294.36	1300.33	1328.78
Feb	2.5%	1096.83	1088.79	1139.06	1099.57	1063.40	1168.25	1160.80
	97.5%	1235.53	1285.90	1354.61	1247.18	1287.00	1310.26	1336.36
Mar	2.5%	1087.08	1093.95	1139.00	1099.29	1069.18	1147.02	1159.28
	97.5%	1212.85	1275.17	1341.86	1251.92	1274.52	1320.76	1337.61
Apr	2.5%	1081.09	1107.25	1135.19	1100.06	1086.87	1143.52	1170.93
	97.5%	1206.86	1288.47	1338.05	1252.68	1292.21	1317.27	1349.26
May	2.5%	1076.04	1115.06	1133.75	1102.39	1111.39	1138.10	1174.09
	97.5%	1201.80	1296.29	1336.61	1255.02	1316.73	1311.84	1352.43
Jun	2.5%	1093.40	1150.87	1155.50	1121.75	1142.29	1146.72	1193.11
	97.5%	1196.38	1289.64	1344.74	1286.98	1339.03	1316.54	1361.49
Jul	2.5%	1094.56	1148.74	1161.39	1141.18	1145.00	1148.96	1198.81
	97.5%	1197.54	1287.51	1350.63	1306.41	1341.74	1318.78	1367.19
Aug	2.5%	1096.56	1147.00	1161.55	1151.06	1144.56	1150.33	1202.61
	97.5%	1199.54	1285.77	1350.79	1316.29	1341.30	1320.14	1370.99
Sep	2.5%	1091.44	1137.63	1160.41	1141.48	1146.71	1156.41	1196.06
	97.5%	1216.67	1284.07	1351.34	1314.61	1332.89	1330.63	1377.14
Oct	2.5%	1095.96	1135.43	1156.99	1120.00	1146.02	1147.79	1180.40
	97.5%	1221.20	1281.86	1347.92	1293.14	1332.20	1322.01	1361.49
Nov	2.5%	1097.14	1132.50	1150.16	1095.78	1131.20	1141.11	1160.78
	97.5%	1222.37	1278.94	1341.09	1268.92	1317.38	1315.33	1341.87
Dec	2.5%	1092.75	1097.51	1130.97	1090.97	1092.59	1152.31	1150.43
	97.5%	1231.46	1294.62	1346.53	1238.58	1316.20	1294.32	1326.00

Table6. Estimated Benefits of Optimal Policy in year 2080

	Sale Month	Upper Weight[a]	Benefits of Optimal Policy under Upper Weight	Lower Weight[a]	Benefits of Optimal Policy under Lower Weight
Placement weight is 550 lbs					
Texas	June	1196.38	456.88	1093.40	368.32
	Dec	1231.46	487.05	1092.75	367.76
Kansas	June	1289.64	537.09	1150.87	417.74
	Dec	1294.62	541.37	1097.51	371.85
Nebraska	June	1344.74	584.47	1155.50	421.73
	Dec	1346.53	586.01	1130.97	400.63
Iowa	June	1286.98	534.80	1121.75	392.70
	Dec	1238.58	493.17	1090.97	366.23
Colorado	June	1339.03	579.56	1142.29	410.36
	Dec	1316.20	559.93	1092.59	367.62
California	June	1316.54	560.22	1146.72	414.17
	Dec	1294.32	541.11	1152.31	418.98
Wisconsin	June	1361.49	598.88	1193.11	454.07
	Dec	1326.00	568.36	1150.43	417.36
Placement weight is 650 lbs					
Texas	June	1196.38	352.88	1093.40	264.32
	Dec	1231.46	383.05	1092.75	263.76
Kansas	June	1289.64	433.09	1150.87	313.74
	Dec	1294.62	437.37	1097.51	267.85
Nebraska	June	1344.74	480.47	1155.50	317.73
	Dec	1346.53	482.01	1130.97	296.63
Iowa	June	1286.98	430.80	1121.75	288.70
	Dec	1238.58	389.17	1090.97	262.23
Colorado	June	1339.03	475.56	1142.29	306.36
	Dec	1316.20	455.93	1092.59	263.62
California	June	1316.54	456.22	1146.72	310.17
	Dec	1294.32	437.11	1152.31	314.98
Wisconsin	June	1361.49	494.88	1193.11	350.07
	Dec	1326.00	464.36	1150.43	313.36

Note: a. upper and lower weight refer to the 97.5% quantile and 2.5% quantile of the predicted live sale weight under climate change scenario.

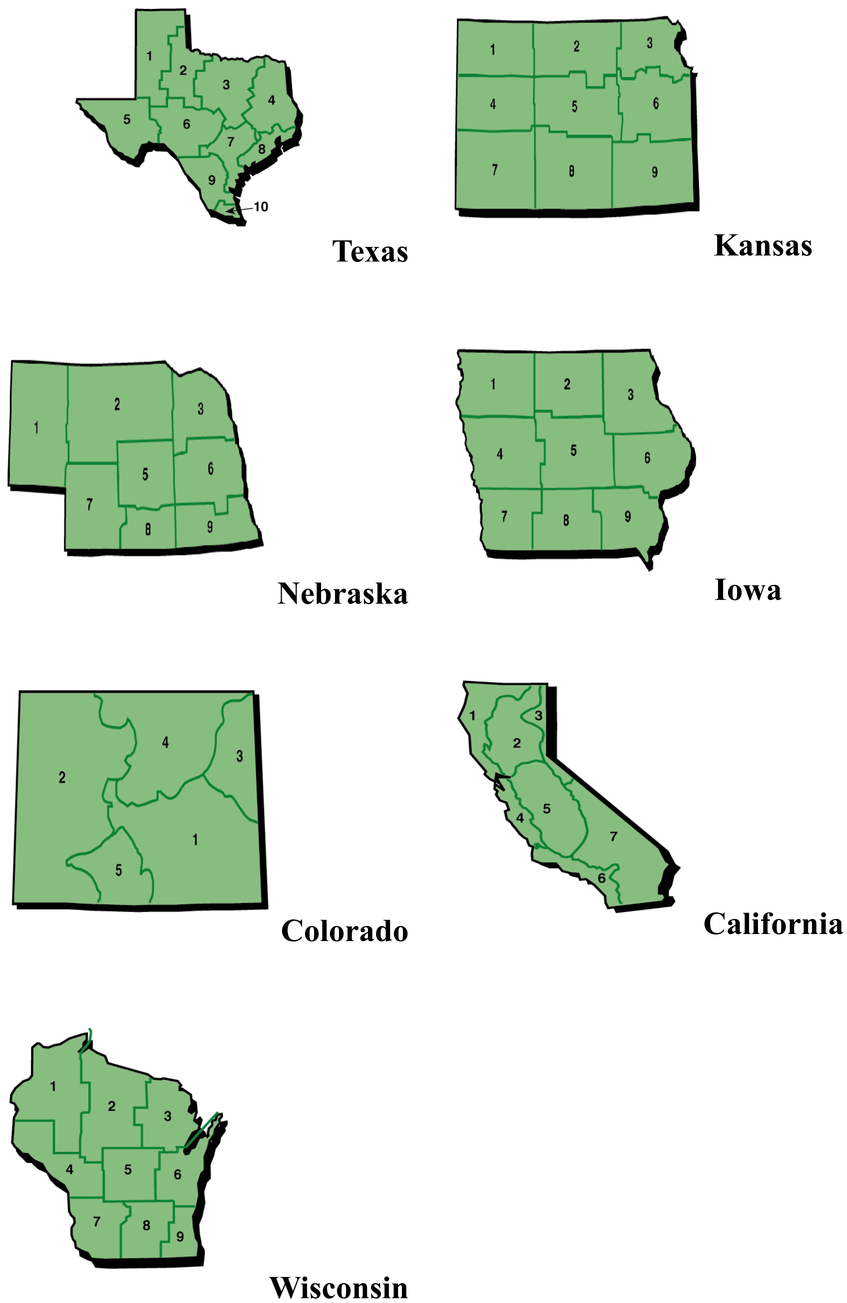

Figure 1. The climate divisions demarcated by NOAA.