Essays on weather changes and U.S. cattle industry

by

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B.S., Wayamba University of Sri Lanka, 2011
M.S., University of Wyoming, 2016

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

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Abstract

The U.S. cattle sector is the largest agricultural industry with the world's largest fed-cattle industry. Cattle production is highly specialized with cow-calf operations that graze pastureland and feedlot operations that focus on feeding grain-based diets to finish cattle for slaughter. Weather changes, forage availability, economies of size, and production practices create unique challenges across cow-calf production regions. Weather changes, in particular, can alter livestock production. In response, producers may adapt their production practices to changing natural and policy environments. This dissertation contains two chapters providing insights into how weather changes impact the cow-calf industry in the United States.

Essay 1 examines the weather impacts on location and production of the cow-calf sector between 1992 and 2017. Econometric models are estimated using county-level agricultural data from the Census of Agriculture-United States Department of Agriculture of 25 states. The selected sample of states held more than 88% of the national beef cow inventories. Key explanatory variables in this study are county-level seasonal average temperature and total precipitation from PRISM daily climate data. Results demonstrate that seasonal temperatures and total seasonal precipitation significantly impact county-level beef cow inventories and operational locations.

Essay 2 evaluates the impact of long-term weather changes on the cow-calf production decision using a dynamic panel estimator. By exploiting seasonal weather changes and using 67 years of state-level beef cow inventories, the study estimates the impact of seasonal weather on the U.S. cow-calf industry across 25 major cow-calf producing states. Results suggest that the U.S. cow-calf industry is indeed sensitive to weather. The results of an out-of-sample prediction assessment further suggest that adding seasonal weather information improves the prediction ability of state-level beef cow inventories.

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Dedication

To my amazing family, especially mom, dad, grandma, and aunties.

Chapter 1 - Introduction

In the U.S., cow-calf operations are focused on maintaining cow herds to raise calves. The operations primarily use land suitable for cattle grazing (McBride and Mathews, 2011). Increased consolidation in cow-calf operations has led to an increased average number per-farm beef cow, from 89 in 1987 to 110 in 2012 (McDonald and Hoppe, 2018). Resulting scale changes are due to technological development, improved disease control and reproduction, and feeding practices (Economic Research Service, 2018). Significant fluctuations in the number of beef cow inventories are a result of market conditions and weather changes. Extreme weather events can significantly affect beef cow production. Unfavorable weather conditions deteriorate pasture conditions and reduce pasture growth forcing livestock producers to use high-cost alternative feed-stuffs which increase their production costs. Further more, extreme weather may also reduce overall animal performance, including reduction in feed gain efficiency, breeding performance, and resistance to disease. However, the impact of weather on cow-calf production in the United States has received minimal research attention.

This study uses beef cow inventories as a proxy for production data. In contrast to crop yield data available in crop literature, analysis weather impacts here rely on beef cow inventory data. The inventory data used in this study is not directly equivalent to crop yield data. A more accurate proxy for production data would be average calf weight, but the information does not exist. The study captures the weather impacts on cow-calf industry indirectly through beef cow inventories.

Chapter 2, provides new empirical evidence of weather effects on location and production of the cow-calf industry, including multiple county-level measures for each season in 25 major cow-calf producing states between 1992 and 2017. The results show that seasonal temperatures and total seasonal precipitation significantly impact county-level beef cow inventories and operational locations. The results also reveal significant spatial patterns relative to positive correlations of beef cow inventories across counties.

By exploiting seasonal weather changes and using 67 years of state-level beef cow inventories as a proxy for cow-calf production, Chapter 3 provides the impact of seasonal weather on U.S. cow-calf production across 25 major cow-calf producing states. Results suggest that the U.S. cow-calf industry is indeed sensitive to weather and especially temperature. Results of an out-of-sample prediction assessment suggests that adding seasonal weather information improves the prediction ability of state-level beef cow inventories. This study also provides future beef cow inventory forecasts utilizing future weather forecasts. These findings provide insight to cow-calf producers on how to adjust for weather variations and future production planning.

Chapter 2 - Impact of Weather on Cow-Calf Industry Locations in the United States

2.1 Introduction

Cow-calf production in the United States is scattered across a wide geographic area. Production systems differ by region as well. For example, the central[1] region depends heavily on grasslands that advantageously provide an extended grazing period, whereas the northern[2] plains have the competitive advantage of size economies and production efficiencies (McBride and Mathews 2011). Weather changes, forage availability, economies of size, and production practices create unique challenges across cow-calf production regions.

This paper is the first to examine weather impacts on geographic locations of the cow-calf sector in the United States. Previous studies have quantified the effects of public policy, environmental regulation, technological advances, and market forces on spatial distribution of the livestock industry (Abdalla, Lanyon, and Hallberg 1995; Roe, Irwin, and Sharp 2002; Isik 2004; Herath, Weersink, and Carpentier 2005). Changes in the spatial structure of the cow-calf sector, however, have received relatively less attention. Even though crop modeling, urban economics, regional sciences, and livestock sectors have used spatial correlation between neighboring units, no quantitative evidence of spatial correlation in the cow-calf sector has been demonstrated (Anselin, Bongiovanni, and Lowenberg-Deboer 2004; Roe, Irwin, and Sharp 2002; Isik 2004; Norsworthy et al. 2014). The objective of this study is to examine how weather influences county-level cow-calf inventories and the production location in the United States.

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[1] Kansas, Missouri, Nebraska
[2] Minnesota, Montana, North Dakota, South Dakota, Wyoming

This study makes significant contributions to the literature because it considers weather changes to be an influential determinant of cow-calf sector location. The study extends the research of additional location determinants and emphasizes spatial correlation between neighboring cow-calf operations using a spatial lag parameter and an inverse distance matrix.

This paper proceeds as follows. The next section provides background information on the cow-calf sector in the United States. This is followed by sections outlining the conceptual, and econometric models, as well as description of the data and results. The article closes with conclusions, suggestions, and future research directions.

2.2 U.S. Cow-Calf Production

Increased consolidation has led to an increased average number of per-farm beef cows, from 89 in 1987 to 110 in 2012 (MacDonald and Hoppe 2018). During the same period, nearly 175,000 cow-calf operations dropped out of production; 80% of this decline was attributed to operations that maintained 1- 49 beef cows (Speer 2014). Scale changes in cow-calf operations are the expected consequence of transitioning from small-scale agricultural activities to large-scale, specialized production units (Isik 2004) due to technological development, improved disease control, reproduction, and feeding practices (Economic Research Service 2018). Meanwhile, significant fluctuations in the number of beef cow inventories are a result of market conditions and weather changes (Drouillard 2018). In addition, changes in industry structure, forage availability, and cost of transporting animals versus forage have caused geographic movement of the cow-calf sector in the United States (Shields and Mathews, Jr. 2003).

Because increased weather volatility has become crucial to agricultural production, a rich body of literature has previously addressed weather impacts on agricultural crops (Easterling et al.

1993; Chen et al. 2004; Schlenker and Roberts 2009; Lobell et al. 2013; Tack and Ubilava 2013; Chavas and Di Falco 2017; Tack, Lingenfelser, and Jagadish 2017; Ortiz-Bobea and Tack 2018; Kuwayama et al. 2018Chavas et al. 2019;). Cow-calf operations in the United States are characterized by weather, environmental conditions, breeds, management and feeding practices (Drouillard 2018). Therefore, the effect of rising temperatures on cow-calf operations has become a subject of increased interest due to the direct impact on production costs, resource availability, market prices, welfare, and food security of the sector (McCarl and Hertel 2018).

Cows are usually pasture-raised year-round (MacDonald and Hoppe 2018), thus fulfilling nearly two-thirds of their forage requirements with hay or silage. However, variations in average temperature and precipitation affect pasture forage conditions. For example, extended drought reduces pasture and forage availability, forcing farmers to supplement hay in the summer instead of winter, which consequently increases the production cost due to higher transportation costs and feed prices (Kemper et al. 2012).

Extreme weather events cause agricultural producers to take drastic actions. From the years 2006 to 2012, the national beef cow inventory decreased by 8% as a result of increased feed prices and prolonged drought in the southern[3] plains (Larson 2012). In addition, increased weather volatilities can trigger cattle movement across county boundaries as producers search for optimal weather conditions. Therefore, increased understanding of how weather changes impact the spatial structure of cow-calf locations and production in the United States is essential.

Most livestock production models have examined how public policy, environmental stringencies, technological advances, relative prices, and social factors have impacted the spatial distribution (Abdalla, Lanyon, and Hallberg 1995; Eberts and McMillen 1999; Hubbell and Welsh

[3] Texas and Oklahoma

1998; McBride and Key 2003; Roe, Irwin, and Sharp 2002; Isik 2004; Herath. Weersink, and Carpentier 2005). A few studies have also examined the impact of weather on livestock production. Klinedinst et al. (1993) predicted the direct effects of global warming on dairy production. Mark and Schroeder (2002) analyzed the effects of weather variability on daily weight gain in fed cattle including profit implications. Results confirmed that temperature variability, heat stress, and precipitation influence cattle feeding performance and profits. Frank et al. (2009) hypothesized that changes in warm-season (i.e. June to October) have advantages and disadvantages for the production of confined swine, beef, and dairy cattle. Rojas-Downing et al. (2017) examined specific climate change adaptation and mitigation strategies in the livestock sector. These studies, however, did not explicitly control for weather changes that may influence the location of the cow-calf sector.

2.3 Conceptual Model

Factors such as high output prices, sufficient feed supply, a trained workforce, availability of land, and seasonal weather changes may make a particular county more desirable for cow-calf production.

We develop a general firm-level location and inventory model to reflect the spatial structure of cow-calf location and production. Input availability and distance to the output market determine the location of cow-calf operations. The distance between two places (i.e., firm location and output market location) (x_i, y_i) and (x_k, y_k) and the Euclidean distance formula is

$$d_{ik} = \sqrt{(x_i - x_k)^2 + (y_i - y_k)^2} \quad (1)$$

where d_{ik} is the distance from the firm i's location and and the output market k. The same distance relationship could be derived for the distance between firm location and input market (Isik 2004). If m_{ij} is the Euclidean distance between firm i and input market j, then

$$m_{ij} = \sqrt{\left(x_i - x_j\right)^2 + (y_i - y_j)^2} \quad (2)$$

The production of firm i (total number of calves) is given by $Q_i = f(S_i, \delta_i, \theta_i; e)$ a stochastic production function where output depends on input vector S_i, firm-specific factors affecting production δ_i , weather conditions θ_i, and a random variable e. First order and second order conditions are assumed to be $f_{S_i} > 0$ and $f_{SS_i} < 0$.

If ϑ is the unit distance transport rate on the product Q and γ_j is the unit distance transport rate for input j, the profit of firm i is

$$max_{w\geq 0}\pi_i = (P - \vartheta d_{ik})Q_i - \sum_{j=1}^{J}(w_j + \gamma_j m_{ij})S_{ij} - c(x_i, y_i) \quad (3)$$

where P is output price, S_{ij} is the firm i input from input market j, w_j is the input price, and $c(x_i, y_i)$ is the fixed costs of a firm at (x_i, y_i) (Isik 2004). Per farm profit is a function of input and output prices and quantities, and profit is a random variable due to the uncertainty of prices and quantities.

Cow-calf operator i maximizes expected utility, EU_i:

$$EU_i = E[U_i(w_0 + \pi_i|(x_i, y_i)] \quad (4)$$

where w_0 is initial wealth and π_i is profit. The choice variables in equation (4) are the firm's input levels (S_{ij}) and the firm's location (x_i, y_i). First order conditions are

(5) $$\frac{\partial EU}{\partial S_{ij}} = EU_w\left[(P - \vartheta d_{ik})f_{S_{ij}} - (w_j - \gamma_j m_{ij})\right] = 0$$

(6) $$\frac{\partial EU}{\partial x_i} = EU_w\left[(-\vartheta d_{ik})f(.) - \gamma_j m_{ijx_i}S_{ij} - c_{x_i}\right] = 0$$

(7) $$\frac{\partial EU}{\partial y_i} = EU_w\left[\left(-\vartheta d_{iky_i}\right)f(.) - \gamma_j m_{ijy_i}S_{ij} - c_{y_i}\right] = 0$$

According to first order conditions, firm i locates its business where expected utility is highest:

(8) $$\arg max_{(x_i,y_i)}\, EU(W_0 + \pi_i\left(P, S, w, c\middle|(x_i, y_i)\right))$$

After approximating the supply of beef cows by a county's inventory of all beef cows, the optimal output can be defined as $Q_i^* = f\left(S_{ij}^*, \delta_i, \theta_i\middle|(x_i^*, y_i^*)\right)$.

Using this conceptual framework and spatial econometric methods, we test the hypothesis, does weather impact location and inventories of cow-calf operations? In our empirical setting, we first estimate the magnitude of weather effects and then present estimated impacts.

2.4 Empirical Model

When data are spatially correlated, spatial econometrics techniques are needed to fully control variance and spatial relationships (Kpczewska, Kudla, and Walczyk, 2015). The three primary types of spatial specifications are spatially lagged dependent variable, spatially autocorrelated error, and spatial Durbin model, which includes spatially lagged dependent variable and spatial lags of independent variables (Vega and Elhorts 2013). However, because the best-fit model must be determined but comparisons of spatial models are not yet well developed, spatial model selection requires economic theory or the appropriate context (Vega and Elhorts 2013; Kpczewska, Kudla, and Walczyk 2015).

Spatial models can control spatial relationships in spatial units. In recent spatial econometrics literature, the widely used criteria for spatial model selection is AIC, significance of all coefficients, and significance of the spatial terms[4] (Kpczewska, Kudla, and Walczyk 2015; Song et al. 2017). Pseudo R-squared and AIC criteria is also used for non-panel spatial models. This research initially utilized the aspatial model specification and then extended the analysis to spatial specifications. Results showed that the best-fit model for U.S. county-level cow-calf operations is the spatial lag model.

The empirical model determines weather impacts on the spatial distribution of cow-calf operations. The estimation approach is based on spatial econometrics, because it accounts for spatial autocorrelation due to localization economies. Localization economies, which are external to individual firms but internal to the cow-calf sector can enhance the performance of cow-calf operations (Eberts and McMillen 1999; Roe, Irwin, and Sharp 2002). For example, well-developed road systems and proximity to auction markets improve nearby cow-calf operation functionality.

The omission of spatial correlations, however, leads to model misspecification, thereby decreasing robustness and creating misleading information (Anselin 1988)[5]. Moreover, if panel

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[4] Spatial terms can be spatial lag, spatial error, and spatial lags of independent variables.

[5] The presence of spatial autocorrelation is measured by Moran's I statistics, and the null hypothesis of Moran's I test for regression residuals is the absence of spatial autocorrelation. Test statistics are significant at the 1% level for all models. However, the presence of spatial autocorrelation does not specify the form of a spatial relationship.

data contains spatial relationships, estimated coefficients of a spatial model are biased and inefficient due to omitted variables. This study used a spatial autocorrelation parameter and a spatial weight matrix to capture spatial interactions between county-level cow-calf operations. Beef cow production may be simultaneously determined among counties, leading to endogeneity concerns and biased parameter estimations.

Spatial interaction among the dependent variable for time t can be stated as

(9) $$y = \rho W y + \alpha l_N + X\beta + \epsilon$$

where y is the $N \times 1$ vector of the endogenous beef cow inventories, ρ is the scalar spatial lag coefficient, W is the spatial weight matrix, $l_N$is the $N \times 1$ vector associated with the constant term α, X is the $N \times K$ matrix of exogenous variables, β is the $K \times 1$ parameter vector to be estimated, and ϵ is the vector of normally distributed errors.

2.4.1 Spillover effects

Because spatial econometric analysis does not directly utilize point estimates to test whether spillovers exist as parameter estimates (Claeys, Moreno, and Suriñach 2012; Vega and Elhorts 2013; Kpczewska, Kudla, and Walczyk 2015), equation (9) can be rewritten to obtain the direct and spillover effects:

(10) $$y = (I - \rho W)^{-1}\alpha l_N + (I - \rho W)^{-1}X\beta + (I - \rho W)^{-1}\epsilon$$

The marginal effect of all the variables must also be derived. Total marginal impacts can be categorized as direct impacts and indirect impacts. For example, for the expectation of $y, E(y)$, the partial derivative of $E(y)$ with respect to jth explanatory variable can be stated as

$$\left[\frac{\partial E(y)}{\partial x_{1j}} \cdots \frac{\partial E(y)}{\partial x_{Nj}}\right] = (I - \rho W)^{-1} \beta_j \tag{11}$$

Diagonal elements of equation (11) provide direct impacts, whereas off-diagonal elements reveal the spillover effects.

The spillover effects were assumed to be proportional to the inverse distance between counties and assigned weights using inverse distance function $w_{ij} = 1/d_{ij}$, where d_{ij} is the centroid-to-centroid distance in miles between county i and j. As stated in the literature (Roe, Irwin, and Sharp 2002; Isik, 2004), the models were estimated using upper distances of 50, 100, 200, and 300 miles. The upper distance with 200 miles reported the smallest AIC statistics for all estimated models.

Spatial panel models can be used to control for relationships over time and spatial units. Spatial lag of the dependent variable $\rho W y$ is defined as a global spatial spillover. Moreover, lag dependent variables may express a long-term steady relations in a temporal dimensions (Kopczewska, Kudla, Walczyk 2015). A maximum likelihood was used to estimate (9), where the likelihood function corresponds to the normal distribution and variables used in the analysis are summarized in Table 2.1. Each element of W represents the proximity between two observations i and j. The common specification of the weighting matrix W is $W_{ij} = 1$ if two counties share a border, and 0 otherwise. The spatial lag term is often treated as endogenous and following the literature (Elhorst 2003; Claeys, Moreno, Surinach 2012) we used maximum likelihood methods to estimate equation (9). Including a spatial lag dependent variable from the same time period can cause simultaneity effect and this can be overcome by using direct, indirect and total effects for final interpretation (Kopczewska, Kudla, Walczyk 2015).

The following assumptions on weighting matrix are maintained: (a) Weighting matrix is nonnegative; (b) weighting matrix is non-nilpotent; (c) diagonal componentsm of weighting matrix are zero; (d) weighting matrix is normalized so that spectral radius is one (Hillier and Martellosio, 2013). In practical applications, assumptions from (a) through (c) are always satisfied. Under the assumption of nonnegativity of spatila weighting matrix, non-nilpotency is simply means that no permutation of the spatial units that could cause autiregressive process unilateral (Martellosio, 2011; Hillier and Martellosio, 2013). The necessary and sufficient condition for parameter space is that the matrx $S := I - \lambda W$ is nonsingular (Lee 2004; Kelejian and Prucha 2010). The factors affecting beef cow inventories were further examined by controlling for county characteristics. The baseline estimation equation is

$$y = \beta V + \delta X + \varepsilon \tag{12}$$

where y is the natural log of county-level beef cow inventories, V is a vector of weather variables, and X is a vector of control variables. The weather variables were highly correlated with each other. Multicollinearity, however, inflates the standard errors and prevents the determination of explanatory variable importance (Ayyangar 2007). The mean of variance inflation factor of the regression was 66.65, so the lasso[6] approach was used to select the best explanatory variables. Results of the full model, including all weather variables, are described in results section.

[6] Variable selection methods, such as the elastic net approach and ridge regression, perform better when some conditions are present (Zou and Hastie, 200). This study initially used the elastic net approach with cross validation and alpha values beginning at $\alpha = 0.01$ and continuing in 0.01 increments. As with the lasso approach, MSPE with the $\alpha = 1$ was recorded least.

2.5 Data

This study utilized county-level agricultural data from the Census of Agriculture -United States Department of Agriculture (USDA) for 25 states[7]. As of 2017, these states held more than 88% of the national beef cow inventories (Livestock Marketing Information Center 2019). Because the US Department of Agriculture database only provides data from 1997, older census data were collected from Haines (2004). States with more than 300,000 beef cow inventories were selected as the sample for econometric analysis, and the dependent variable was the natural logarithm of a county's total beef cow inventory.

Key explanatory variables in this study were total precipitation and seasonal weather variables based on PRISM daily climate data. Following the literature, the gridded climate data were aggregated to develop county-level seasonal weather measures. Instead of a traditional calendar-based, quarterly definition of seasonality, however, this study defined the timeline of seasons based on the relative impact of the cow-calf life cycle and production. Because most producers breed cows to calve in the spring to take advantage of spring grass growth, weather conditions in the first season, January through March, are crucial to beef cow inventories (Penn State University 2017). The second season, April through July, is defined as the growing season because it is the period of maximum pasture growth (Smoliak 1986; Yu et al. 2019). Weather during the growing season most significantly impacts pasture growth, and consequently, the availability of pasture. This impacts beef cow inventories because pasture is the main feedstuff

[7] Alabama, Arkansas, California, Colorado, Florida, Georgia, Idaho, Illinois, Iowa, Kansas, Kentucky, Louisiana, Missouri, Mississippi, Montana, Nebraska, New Mexico, North Dakota, Oklahoma, Oregon, South Dakota, Tennessee, Texas, Virginia, Wyoming

source of the cow-calf sector. Many producers utilize the third season, August and September, as a second or alternative calving season (BEEF 2018). The fourth season, October through December, typically involves spring-calving and the weaning of fall-weaning herds, as well as the time when most producers sell their calf crop. The description of seasons can be found in the appendix (Table A.1). Seasonal cumulative precipitation variables were created by summing across daily precipitation values. Temperature was measured in degrees Celsius, and precipitation is measured in millimeters.

This study included the county-level feed cost per cow, which is the ratio of total feed costs of a county to the number of beef cows in that county. This variable was consistent with similar studies (Isik 2004). Data for county-level total feed cost were obtained from the USDA census.

The Conservation Reserve Program (CRP), a land conservation program administered by the Farm Service Agency (FSA), works with farmers to remove land from crop cultivation in exchange for a yearly rental payment. This program is the most extensive private-lands conservation program in the United States (FSA, USDA). CRP impacts cattle production because it restricts all cropping activities, resulting in less forage areas and higher feed prices. However, emergency haying and grazing on CRP land has occasionally been authorized during natural disasters to support livestock producers. This study utilized county-level CRP acres and data obtained from FSA.

The correlation of irrigation and climate variables is also helpful for this research. For example, drought impacts are minimal in highly irrigated counties but, omission of the irrigation variable can result in biased coefficient estimates (Schlenker and Roberts 2009). To account for the irrigation effect, this research included the percentage of irrigated land; the variable, which was the ratio of total agland to total irrigated agland, was used as a proxy for county-level irrigation since direct data on pasture irrigation was not available. The data were collected from USDA census.

Because population growth reduces the amount of land available for livestock operations, this study also included the variable population density to capture the influence of urban pressure, as is consistent with the literature (Roe, Irwin, Sharp 2002; Ortiz-Bobea 2019). County-level population and land acres were collected from the U.S. Census Bureau.

2.5.1 Stability of weather over time

As described in the literature, this study estimated the panel variation of weather data. Alternative panel analysis confirmed that variation in weather effects lack joint significance over time (Table A.3). This finding is important for our final identification when weather effects corresponding to different time periods remain constant. The high correlation for seasonal weather variables over time could explain this stability (Ortiz-Bobea 2019). All individual panel models included state-fixed effects and year-fixed effects to control unobserved heterogeneities.

2.5.2 Prediction evaluation

An out-of-sample exercise was implemented to further examine the importance of weather effects in the analysis. Prediction evaluation utilized 80% of randomly selected data and then predicted the remaining 20%. Two model specifications (preferred model specification and model without weather variables) were run, and beef cow inventories were predicted. Based on the results of the root mean square error (RMSE), the preferred model predictions had the least prediction error compared to the baseline model (Table A.4). Overall, a comparison of the prediction accuracy measures suggested that adding a weather component improves the out-of-sample prediction.

2.6 Results

This section presents the estimation of spatial lag model given in equation (12). Table 2.1 presents summary statistics for estimated parameters. The spatial lag model of county-level beef cow inventory was estimated to emphasize weather impacts when determining the location of cow-calf output. The spatial lag model revealed the importance of localization economies for the spatial structure of the cow-calf sector. Positive and statistically significant spatial lag variables indicated the correlation of beef cow inventories between counties and positive spillovers among cow-calf operations in neighboring counties.

2.6.1 Impact of weather variables

The influence of weather is complex and varies over time and space (Chavas et al. 2019). Although weather has a significant effect on cow-calf operations, the impacts of weather on beef cow inventories are poorly understood. Because weather effects can be linear or nonlinear, the final model of the study contained selected linear and non-linear weather effects.

In accordance with the literature, equation (12) was estimated with a non-panel aspatial linear model (OLS), panel model, spatial lag of the dependent variable, and error spatial autocorrelation; all explanatory variables lagged spatially. Estimation results (Table 2.2) confirmed that the model with spatial lag dependent provided the best estimates.

Table 2.2 also shows alternative estimated results for equation (12). Columns (2) and (3) report the estimation results using ordinary least squares method and panel data controlling for state fixed effects, respectively, without controlling for spatial correlation. Columns (4) and (5) highlight only the spatial lagged model with the spatial lagged dependent variable and spatial error, respectively. Column (6) shows both independent and dependent spatial lags. There are some advantages of using spatial components in the model. For example, if the panel data contains spatial interdependence and the final model is being specified as aspatial , this may result in biased and inefficient coefficient estimates because of omitted variables. Inclusion of fixed effects in the models is known to increase the fit of the model but decreases the significance of variables of interest (McKinnish 2000). Further FE can control for time invariant and unobserved heterogeneities, but at the same time remove a great part of data variation which may result in no impact of variables of interest (Kopczewska, Kudla, Walczyk 2015). Spatial lag measures the correlation of county-level beef cow inventories. A positive and significant coefficient estimate of the spatial lag parameter confirms that important spillover effect; a higher positive value of ρ indicates an increase in beef cow inventory in county i will be followed by an increase in beef cow inventories in neighboring counties. Because the spatial lagged dependent model was selected as the best model, comparisons of the direct impact estimates, the indirect impact, and the total impact estimates are presented in the appendix (Table A.2). The direct impact estimates of non-spatially lagged variables were similar to the model averaged estimates (Lesage and Fischer 2008). Study results revealed that the coefficients for average seasonal weather are positive and, similarly, the coefficients for nonlinear seasonal weather variables captured by squared terms of seasonal average weather variables are mostly negative and significant. The magnitude of nonlinear weather was lower than the seasonal averages, suggesting that seasonal weather is a primary determinant of county-level cow-calf inventories. Seasonal total precipitation measures were shown to significantly impact cow-calf inventories. Specifically, first season and third season total precipitation measures negatively impacted inventories, as is consistent with the biological cycle of cow-calf production, because additional resources are required to maintain animal comfort during months with primarily cold weather. In contrast, pooled regressions usually give higher weather impacts.

The impact of all climate variables was then calculated from the marginal effect derived from the spatial lag model, and weather impacts were decomposed to determine the impact and contribution of individual weather variables on county-level beef cow inventories (Table 2.3). Changes in growing-season weather were shown to have more significant impacts overall. For example, one unit increase in growing season average temperature increases the beef cow inventories nearly by 4.47%. This is as expected. Previous climate literature has also found positive impact of daily average temperature on either yield or land values which is parallel to beef cow inventories. Moreover, the impacts of changes in temperature variables were more severe than seasonal precipitation changes. The benefits of seasonal average temperatures were intuitively based on the biological cycle of cow-calf production and feed availability, thus emphasizing the importance of seasonal weather on cow-calf production and industry location.

In contrast to county-level crop yield data available in crop literature, weather impacts here rely on county-level beef cow inventory data. The inventory data used in our analysis is not directly equivalent to crop yield data. A more accurate proxy for yield in the situation faced by cow-calf operations would be average calf weight by county, but current county-level calf weight information does not exist. Overall, we find the weather impact on the cow-calf sector to be pointedly different than designated in crop literature.

2.6.2 Impact of feed cost, land availability, and urbanization

Feed costs negatively impact production levels over time. Although CRP acres seem to determine cow-calf location and production, this variable was not found to be statistically significant. The impact of county population density was shown to be negative and significant, indicating that counties with high population density are likely to have decreased beef cow inventories. In addition, the percentage of irrigated land acres did not significantly affect inventories, suggesting that the location of cow-calf operations is not sensitive to the availability of irrigated land.

2.7 Conclusions

Although abundant literature examines economic activities related to greenhouse gas emissions and climate change, few economic studies have linked changes in weather to livestock production in the United States (Mendelsohn and Neumann 1999). This research used the applied estimation strategy of spatial panel modeling to analyze the effects of weather on geographic locations of cow-calf operations. Statistically significant effects confirmed that weather significantly impacts cow-calf industry production and location. Estimated coefficients of weather variable values were small, which was consistent with recent climate literature (Ortiz-Bobea 2019). Small magnitudes of weather variables from the panel study from 1992 may reflect producer adaptations to weather. The data also suggest that average temperature and total seasonal precipitation may contribute to the preferred locations of cow-calf operations. Because changes in production resulting from weather changes ultimately affect operational profits, cow-calf producers must understand how these weather changes influence their production decisions and risk-mitigating practices.

The results show that local economic conditions such as feed costs and socio-economic factors such as population density considerably impact cow-calf location and production. However, the results lacked significant correlation between irrigation and county-level beef cow inventories. Localization economies are also important determinants of location and production of the cow-calf sector. Beef cow inventories were positively correlated across county boundaries. When similar types of businesses locate in close proximity, they attract input and output markets, quality labor, extension services, and other production factors. These significant spatial patterns are important for sector specific development and concentration. Understanding the importance of the spatial location of cow-calf operations may help policymakers formulate effective policies to facilitate sector development. This analysis, which explicitly focused on the effect of weather when determining the location of cow-calf operations, could be useful to policymakers regarding disaster assistance in times of economic loss.

Future research could examine the impact of weather variables, such as drought, on location and production determination. In addition, future research could focus on producer adaptation and adaptation costs related to weather changes. Consideration of changes in production levels over a long period across counties could increase understanding of weather dynamics, and an extended period of weather variables may help capture county-level inventory changes. In addition, controlling for county-level economic losses due to weather changes would allow future studies to investigate the causal effects of weather.

Tables

Table 2.1 Summary statistics

Variables	Mean	S.D.	Observations
Season 1 average temperature (^oC)	5.17	5.67	4,584
Growing season average temperature (^oC)	19.46	3.41	4,584
Season 3 average temperature (^oC)	7.95	4.87	4,584
Season 1 total precipitation (mm)	215.34	152.46	4,584
Growing season total precipitation (mm)	372.37	171.47	4,584
Season 2 total precipitation (mm)	166.46	105.61	4,584
Season 3 total precipitation (mm)	215.69	136.88	4,584
Feed cost	1.90E+07	5.65E+07	4,584
CRP acres	11077.12	21735.52	4,584
Population	67894.37	197620.10	4,584
Percentage of irrigated acres (%)	0.16	0.65	4,584

Table 2.2 Parameter estimation results

Variables	OLS	Panel	Restricted model: Spatial lag	Restricted model: Spatial error	Full Model
Season 1 average temperature	0.0613	0.0306	0.0026	-0.0019	-0.0012
	[0.0091]	[0.0095]	[0.0028]	[0.0039]	[0.0037]
Growing season average	-0.0168	0.2803	0.0469	0.0831	0.0655
temperature	[0.0532]	[0.0544]	[0.0172]	[0.0216]	[0.0211]
Season 3 average temperature	-0.0678	-0.0412	0.0108	0.0012	0.0043
	[0.0173]	[0.0186]	[0.0073]	[0.0089]	[0.0086]
Season 1 average temperature^2	-0.0011	-0.0011	-0.0006	-0.0007	-0.0004
	[0.0006]	[0.0006]	[0.0002]	[0.0002]	[0.0002]
Growing season average	-0.0023	-0.0095	-0.0008	-0.0019	-0.0016
temperature^2	[0.0014]	[0.0015]	[0.0004]	[0.0005]	[0.0006]
Season 2 average temperature^2	0.0028	0.0019	0.0001	0.00004	0.00002
	[0.0003]	[0.0003]	[0.0001]	[0.0001]	[0.0001]
Season 3 average temperature^2	0.0016	0.0024	-0.0007	-0.0003	-0.0003
	[0.0009]	[0.0009]	[0.0004]	[0.0004]	[0.0005]
Season 1 total precipitation	-0.0011	-0.0007	-0.0001	-0.0002	-0.0001
	[0.0001]	[0.0001]	[0.00003]	[0.00004]	[0.00004]
Growing season total	0.0002	0.00004	0.0001	0.0001	0.00001
precipitation	[0.0001]	[0.0001]	[0.00002]	[0.00004]	[0.00004]
Season 2 total precipitation	-0.0005	0.0002	0.0001	0.0001	0.0001
	[0.0002]	[0.0001]	[0.00004]	[0.00005]	[0.00005]
Season 3 total precipitation	-0.0012	-0.0006	-0.0001	-0.0001	-0.00004
	[0.0001]	[0.0001]	[0.00003]	[0.00005]	[0.00005]
Feed cost per cow	-0.00003	-0.00003	-8.55E-06	-8.45E-06	-8.91E-06
	[2.11E-06]	[1.90E-06]	[6.74E-07]	[6.91E-07]	[7.00E-07]
CRP acres	3.51E-06	3.19E-06	-1.56E-07	-1.69E-07	3.30E-07
	[6.55E-07]	[5.83E-07]	[4.29E-07]	[4.60E-07]	[5.03E-07]
Population density	-0.0007	-0.0006	-0.0010	-0.0001	-0.0010
	[0.0001]	[0.0001]	[0.0001]	[0.0001]	[0.0001]
Percentage of land irrigated	0.3137	0.3054	-0.0078	-0.0057	0.0017
	[0.0668]	[0.0677]	[0.0252]	[0.0256]	[0.0255]
Spatial lag of y			0.8910		0.7010
			[0.0369]		[0.0827]
Spatial error				0.9466	0.8503
				[0.0217]	[0.0556]
Feed cost per cow.splag					0.00003
					[8.99E-06]
CRP acres.splag					-0.0001
					[4.75E-06]
Population density.splag					0.0035
					[0.0011]
Percentage of land					0.2630
irrigated.splag					[0.8413]
Observations	4,584	4,584	4,584	4,584	4,584
AIC	11,576.47	9,887.85	3,004.92	3,062.29	3,121.37

Note: Standard errors are in the brackets.

Table 2.3 Weather impact decomposition

Variables	**Impact (%)**
Season 1 temperature	0.14
Growing season temperature	4.47
Season 2 temperature	0.01
Season 3 temperature	0.94
Season 1 total precipitation	-0.01
Growing season total precipitation	0.01
Season 2 total precipitation	0.01
Season 3 total precipitation	-0.01

Note: Direct impacts percent are computed as $100 * (\exp(\partial X\beta) - 1)$, where $\partial X\beta$ are changes in county-level beef-cow inventories driven by changes in weather variables.

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Chapter 3 - Long Term Effects of Weather on Cow-Calf Production

3.1 Introduction

The success of agricultural farming is uniquely sensitive to changes in climate (Di Falco et al., 2014). Global warming is expected to produce hotter daily maximum and lengthy winter periods in many regions of the world, and these climate changes create production challenges and significant production losses throughout all cow-calf production regions in the United States (Belasco, Cheng, and Schroeder, 2015). Many studies have focused on cattle price prediction, cattle market price volatility, and market price volatility impact on livestock risk management, while other studies have analyzed weather risks in cattle production. For example, previous studies have examined the impacts of extreme weather on fed-cattle profits, economic losses from heat stress, climate change consequences for livestock production, and livestock performance (St-Pierre, Cobanov, and Schnitkey, 2003; Nardone et al., 2010; Gauly et al., 2013; Belasco, Cheng, and Schroeder, 2015). To our knowledge, this is the first paper to evaluate the impacts of long-term seasonal weather changes on cow-calf production in the United States.

This article estimates the effects of seasonal weather on beef cow production using state-level beef cow inventories from 25 major cow-calf producing states from the years 1951 through 2017.[8] This study significantly contributes to the literature because it considers seasonal weather changes to be an important determinant of cow-calf inventories nationally and regionally. Out-of-sample forecasting evaluations recommend incorporating weather information for inventory

[8] State-level beef cow inventories are the best publicly available data aggregation level; the recorded numbers dated back to 1920. The terms, production and inventories, are used interchangeably throughout this article.

forecasts, and future forecasting of beef cow inventories uniquely reveals how seasonal weather changes impact the cow-calf industry in the United States.

This analysis initially shows how seasonal weather significantly affects state-level beef cow inventories and then documents the impacts of breeding season weather on cow-calf inventories. This paper also shows how seasonal weather effects vary across geographical locations. The study results contribute to the literature in three ways. First, the study broadens understanding of seasonal weather effects on the U.S. cow-calf sector. Second, the study emphasizes the importance of breeding season weather on cow-calf operations to encourage necessary adaptation practices, and third, this study geographically expands weather effects on exposure risks of cow-calf production. Depending on the geographical location, the risk of exposure to adverse climate conditions can vary.

3.2 Overview of the U.S. Cow-Calf Sector

Beef cows can be classified as a capital good and a consumption good (Aadland and Baily, 2001). The U.S. beef industry is a lucrative component of the agricultural sector, totaling $67.1 billion in 2018, which accounted for approximately 18% of the total agricultural cash receipts (ERS, 2019). Cow-calf production is the first stage of beef cattle production; cattle operations maintain cowherds and raise calves until weaning when they are 7 to 8 months old. Ideally, cowherds calve one calf per cow each year. The estimated total beef cow inventory in 2018 was 31.7 million, but cow-calf inventory numbers fluctuate from year to year due to drought, market conditions, renovation of previously unproductive land, and shift in land use towards more profitable crops (Drouillard, 2018; Field, 2017). Nearly 80% of cow-calf producers own less than 50 cows and control less than 30% of the total national beef cow inventory (LMIC, 2015).

Although producers adjust production depending on cattle market prices, biological constraints (i.e. lenthy calving period) in cow-calf production often prevent prompt responses to increased cattle prices.

Cow-calf operations typically use pasture raising to fulfill two-thirds of forage requirements (McDonald and Hoppe, 2018), meaning the success and efficiency of cow-calf operations heavily depend on weather conditions (ERS, 2019). Deviation of average temperature and precipitation affect both the quantity and quality of pastures (Gauly et al., 2012). For example, extended drought reduces pasture forage availability, forcing farmers to utilize alternative feedstuffs (Kemper et al., 2012). Moreover, the northern region [9]of the United States has to depend on supplemental feedstuffs during the winter, whereas the southern region [10] benefits from year-round grazing (McBride and Mathews, 2011). Feed costs account for 60%–70% of total livestock production costs (Lawrence et al., 2008). Increased feed costs ultimately increases consumer prices at the retail level. Experience has shown that weather changes have caused increasing feed costs in the U.S. livestock sector (Larson, 2012; Kemper et al., 2012). According to the Kansas Farm Management Association (KFMA), between 2012 and 2016, the average feed cost per cow was $365, while in 2017, the estimated total feed cost per cow was $387.67 per year.

Although the literature includes many studies that have researched the impacts of weather on agriculture (Schlenker and Roberts, 2009; De Salvo, Raffaelli, and Moser, 2013; Lobell et al., 2013; Tack and Ubilava, 2013; Tack, Lingenfelser, and Jagadish, 2017; Chavas and Di Falco, 2017; Rojas-Downing et al., 2017; Chavas et al., 2019), only a few studies have examined weather effects on the livestock sector (Klinedinst et al., 1993; Mark and Schroeder, 2002; Frank et al.,

[9] Illinois, Indiana, Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, South Dakota

[10] Alabama, Arkansas, Florida, Georgia, Kentucky, Louisiana, Mississippi, Tennessee, Texas, Virginia

2009; Nardone et al., 2010; Gauly et al., 2012; Belasco, Cheng, and Schroeder, 2015; Rojas-Downing et al., 2017). Moreover, animal science literature has explored the physiological effects of heat stress on livestock (Lippke, 1975; Hahn et al., 2001; Mader, 2003; Mader, Davis, and Brown-Brandl, 2006), but the effect of seasonal weather on beef cow inventories in the U.S. cow-calf sector has not been fully researched. As climate impacts increase, weather becomes an increasing influential factor for producers; therefore, this study utilized state-level data to estimate weather impacts on cow-calf production.

3.3 Conceptual Framework

Following the conceptual framework by Marsh (1999), the supply relationship for beef cow herds can be assumed by

$$y_i = C_b - D_b \tag{1}$$

where y_i is the beef cow inventory, C_b is available beef cow inventories, and D_b is inventory demand. Following Reutlinger (1966), the conceptual model for beef cow inventory demand is

$$D_b = I_{t+1} - I_t \tag{2}$$

where I denotes the beef cow inventory. Positive investments in beef cow inventories occur when yearling heifers nearing breeding age are retained, while negative investments are due to the death of mature cows or culled cows (Aadland and Bailey, 2001). If the beef cow industry is competitive, derived demand for beef cow inventories is I_d:

$$I_d = E(P_0) + \rho X + \theta_i^p + \theta_i^n \tag{3}$$

where $E(P_0)$ is expected cattle price, X is a vector of inputs, θ_i^p is weather changes that cause increased inventories at cow-calf operations, and θ_i^n is weather changes that cause decreased inventories. The relationship between derived demand function and actual production can be stated as follows:

$$I_{t+1} - I_t = \beta(I_d - I_t) \tag{4}$$

The demand for change inventory (equation 2) can be re-written as,

$$D_b = \beta_0(E(P_0) + \rho X + \theta_i^p + \theta_i^n) - \beta I_t \tag{5}$$

Conceptually, available beef cow inventories are a function of beef cow inventory I_t. If a is the beef cow replacement rate, then the available beef cow inventory is

$$C_b = aI_a \tag{6}$$

The market supply equation of beef cows is

$$y_i = aI_a - \{\beta_0 E(P_0) + \rho X + \theta_i^p + \theta_i^n\} - \beta I_a \tag{7}$$

Since the coefficient of the price is expected to be positive, the respective price elasticity for beef cow supply is expected to be negative. The first-order condition with respect to weather changes yields

$$\frac{dy_i}{d\theta_i} \gtreqless 0 \tag{8}$$

The first-order condition indicates that significant weather changes increase or decrease beef cow inventories, depending on the specific weather condition, ceteris paribus. However, seasonal weather impacts on beef cow inventories may not always be negative, and unique seasonal weather conditions could increase beef cow inventories. For example, if the first-order condition is Season 4 minimum temperature, then a positive relationship would be expected between beef cow inventories and Season 4 minimum temperature ($\frac{dy_i}{d\theta_i} > 0$[11]) due to a priory expectation of increased extreme minimum temperature, which increases beef cow inventories.

3.4 Data and Variable Construction

This study used annual state-level beef cow inventory data from the Livestock Marketing Information Center (LMIC) for 25 states[12] that held 88% of the total national beef cow inventories in 2017. The data included annual beef cow inventories and weather data from 1951 to 2017[13]. Following the literature, this study explored several weather models, including seasonal averages and nonlinear effects. However, as evidenced by the in-sample model-fit measures, the seasonal extreme weather model fit better with the data considered in this analysis.

Seasonal weather variables based on PRISM daily climate data for minimum and maximum temperatures proxied weather changes. Because beef cow inventory data are typically recorded as of January 1 each year, this research utilized lagged weather variables that are more appropriate with the recorded beef cow inventory numbers. Temperature and rainfall can vary depending on time and space (Chavas et al., 2019), so this study constructed seasonal[14] minimum and maximum temperatures and respective cumulative precipitation measures, including three lags according to the biological production cycle of a beef cow, to measure weather impacts on state-level beef cow inventories. A preliminary analysis revealed that these weather variables have a

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[11] θ_i is the season 4 minimum temperature

[12] Alabama, Arkansas, California, Colorado, Florida, Georgia, Idaho, Illinois, Iowa, Kansas, Kentucky, Louisiana, Mississippi, Missouri, Montana, Nebraska, New Mexico, North Dakota, Oklahoma, Oregon, South Dakota, Tennessee, Texas, Virginia, and Wyoming

[13] Panel unit root test using an Im-Pesaran-Shin test on the balanced panel rejects the null hypothesis that panels contain a unit root in favor of the alternative that panels represent stationary process.

[14]Season1= January through March. Season 2= April through June. Season 3= July through September. Season 4= October through December

high level of collinearity, potentially causing unreliable coefficients estimates. Feature selection criteria[15] was used to select the most important attributes among a list of explanatory weather variables to explain the state-level beef cow inventories. The final model did not have seasonal precipitation variables as their explanatory power of long-term state-level beef cow inventories are lower compared to temperature variables. Although nonlinear terms are often included in weather variables to capture nonlinear weather effects, this study did not include any nonlinear weather variables because no nonlinearity[16] was detected between weather variables and state-level beef cow inventories. Table 3.1 lists the descriptive statistics of all explanatory variables.

3.5 Estimation Strategy

This section describes the econometric model used to determine if weather changes significantly affect state-level beef cow inventories, the main hypothesis of this research. The dependent variable was specified as total beef cow inventory number, y_{it}, for state i and year t, and a logarithmic transformation was used since state inventory numbers differ by states.

$$\ln(y_{it}) = \beta_0 + \theta T + \beta X_{i(t-l)} + \sum_{k=1}^{3} \delta_{i(t-k)} y_{i(t-k)} + \mu_i + \varepsilon_{it} \tag{9}$$

where T denotes linear time trends that capture changes in technology over time. Likelihood ratio tests were used to identify two distinct time trends: T_1 = 1984 and T_2 = 1989. $X_{i(t-l)}$ is a vector of lagged seasonal minimum and maximum temperatures, and ε_{it} denotes random errors. Lagged weather variables were considered since contemporaneous weather effects are less likely to impact current beef cow inventories due to the multiyear nature of production.

[15] Least Absolute Shrinkage Operator (LASSO)
[16] We used partial residual plots to detect the non-linearity

Past productivity of cow-calf operations, therefore, is a key factor in determining current production. $y_{i(t-k)}$ is a vector with lagged dependent variables that captured past productivity.

This study included state fixed effects to control for unobserved heterogeneities; hence, identification resulted from the correlation between seasonal weather changes and state-level beef cow inventories. Standard errors were clustered at the state level. However, because producers often seek to increase their profits by improving managerial skills and productivity over the years, this study implemented an estimation strategy to control for past production even though the estimated parameters could be biased due to the inclusion of lagged dependent variables, i.e. Nickell bias (Nickell, 1981). Since we have a large T, this can substantially reduce incidental parameter bias. Lagged dependent variables are interpreted as the dynamics of partial adjustment towards a long run equilibrium. The overall objective was to investigate the causal relationship between beef cow inventories and weather changes. Moreover, the covariance of weather variables and lagged dependent variables was small. This study also utilized a long panel and the subsequent fixed-effects approach to help mitigate endogeneity. Estimation results of the Arellano-Bond estimator are provided in the appendix (Table B.1).

3.6 Estimation Results

Study results suggest that average changes in state-level beef cow inventories in response to changes in seasonal temperatures could be negative or positive (Table 3.2). In addition, as shown in Table 3.2, lagged beef cow inventories [17]have statistically significant effects on current beef cow inventories, thereby confirming the dynamic nature of cow-calf operations.

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[17] The total effect of lagged dependent variables is less than one thus, does not have a unit root issues in the system. Lagged dependent variables are important in the analysis due to multiyear biological nature of beef cows.

Although the time trend variables (T_1, T_2) exhibited statistical significance, the effects varied depending on the time period. Parameter estimates for T_1 (time trend after 1984) positively impacted state-level beef cow inventories, whereas, T_2 (time trend after 1989) negatively impacted, or decreased, beef cow inventories. These results suggest that, when controlling for weather, the rate of inventory growth decreased after 1989, potentially due to structural changes and low prices in the U.S. cattle industry during the mid and late 1980s (Aadland and Bailey, 2001). The resulted market changes may have also been the reason two distinct time trends were observed around mid and late 1980s.

Extended drought and hot summers deteriorate pasture conditions and affect pasture growth, forcing producers to use alternative feed-stuffs. However, extreme heat and prolonged winters reduce feed conversion efficiency in cattle and increase the animal mortality rate (Hahn, 1985; Belasco, Cheng, and Schroeder, 2015; LPELC, 2019). Consequently, weather variations cause farmers to reduce cow herds due to limited water supplies and high costs of alternative feed (Kemper et al., 2012). Impact calculations were estimated (Table 3.3) to understand the economic impacts of seasonal weather variables. As expected, estimated impacts of seasonal weather ranged from 0.10 to -0.40. For example, increase in temperatures throughout winter months could ease the cold discomfort of beef cows as evidenced by positive impacts of season 4 minimum temperature. Season 1 lagged minimum temperature and Season 3 lagged maximum temperature, negatively impacted beef cow inventories, confirming that seasonal weather significantly influences state-level beef cow inventories.

The estimated seasonal weather effects closely aligned with external impacts reported in the literature. In addition to new empirical evidence of weather impacts, the dynamics of output and input price expectations determine the beef cow supply. Following previous literature, this study compared weather impacts with input and output price impacts. The literature provides evidence of positive and negative output price impacts, with negative output price impacts ranging from -0.10 to -1.225 (Reutlinger, 1966; Marsh, 1994) and positive output price impacts ranging from 0.30 to 0.60 (Foster and Burt, 1992; Marsh, 1999; Aadland and Bailey, 2001). Input price impacts have been shown to range from 0.01 to -0.8 (Marsh, 1999; Marsh, 1999; Aadland and Bailey, 2001). Parameter estimate values in Table 3.3 were consistent with parallel average output and input price impacts from the literature.

3.7 Sensitivity Analysis

This section includes two additional analyses: estimations that control for breeding-season weather and estimations that control for geographic locations of cow-calf production.

3.7.1 Effect of Breeding Season Weather on Cow-Calf Operations

Breeding performance impacts the profitability of a cowherd, especially calf-crop percentage and calf weaning weight (Gadberry et al., 2015). Calf-crop percentage depends primarily on management during the breeding season, reproduction, and weaning weight (Rasby, 2015). High temperature and humidity most significantly influence the reproductive performance of beef cows (Selk, 2019). In fact, potential heat stress during the early stages of pregnancy can cause reduced pregnancy rates, conceptus development, and fetal degeneration (Biggers et al., 1987). Similarly, severe winters can cause late breeding and fall out from the calving season (Meteer, 2019), while cold weather has been shown to increase maintenance requirements and feed intake (Peel, 2019). Wet weather (i.e., rain or wet conditions) creates a wet hair coat on cattle that must be controlled to maintain animal comfort which requires additional feed energy resulted in higher feed intake. Notably, during winter, producers have to increase both the quantity and quality of feed for cows to avoid adverse impacts on pregnancy and lactation (Peel, 2019).

Compared to fall calving, spring calving predominantly occurs in the northern states to avoid severe winter weather and to allow new calves to graze on summer pasture. Fall calving is advantageous, however, because older, larger calves are sold at weaning. Southern states may use both spring and fall calving seasons (McBride and Mathews, 2011). To our knowledge, breeding-season weather and its quantitative impacts on cow-calf inventory have not been investigated. The econometric model in this study can quantify seasonal weather effects on potential changes in inventory.

Considering the impacts of breeding-season weather on cow-calf operations, extreme weather variables of the breeding season were constructed using lagged minimum and maximum temperatures, demonstrating that extreme temperatures significantly impact the breeding performance of beef cows (Selk, 2019). The supply of feeder calves, approximated in this study using state inventories of all beef cows, was shown to expand as reproductive efficiency increased. The reproductive efficiency of a cow-calf herd is defined as the ratio of the total number of pounds of calf weaned to the number of cows exposed in the breeding season (Gadberry et al., 2015). This study used two widely defined breeding seasons: May–June (spring calving) and November–December (fall calving).

State-level cow-calf inventory was modeled as a function of two breeding seasons, minimum and maximum temperatures, and cumulative precipitation of the breeding season:

$$\ln(y_{it}) = \beta_0 + \beta_1 T + \beta_2 prec_{it} + \beta_3 TMin_{ij(t-1)} + \beta_4 TMax_{ij(t-1)} + \mu_i + \varepsilon_{it} \quad (10)$$

where $\ln(y_{it})$ is log beef cow inventory of state i in year t, and linear time trends T capture changes in technology. Two temperature variables were denoted for two breeding seasons

j: $TMin_{ij(t-1)}$ and $TMax_{ij(t-1)}$. Breeding season minimum and maximum temperatures were the average minimum and maximum temperatures for the two breeding seasons, which provided extreme temperate effects of the breeding season on beef cow inventories. In addition, cumulative precipitation variables were constructed for two breeding seasons by summing across daily precipitation. Because breeding occurs only once a year, one-year lagged weather variables determined the impacts of breeding-season weather on beef cow inventories.

Table 3.4 shows the estimated results for equation (10). As shown, a one-unit increase in lagged minimum temperature in May and June (i.e., spring calving with calving February–April) reduced beef cow inventories by nearly 2.76%, suggesting that extreme temperatures in November and December (i.e., fall calving) negatively affect state-level beef cow inventories. In addition, the impacts of breeding-season weather were more significant than traditional seasonal weather (Table 3.4), with impact estimates between 2.70% and -2.70%. No significant impact of cumulative precipitation was found in any calving season.

3.7.2 Geographical Variation in Cow-Calf Inventories

Cow-calf operations are active in every state in the United States. However, climate conditions, environmental factors, animal phenotypes, and management practices uniquely determine the type of production system (Drouillard, 2018). Although geographical diversity and climate conditions affect feed costs, some producers advantageously utilize year-round grazing, while other producers must implement alternative feed-stuffs during winter due to prevalent snow cover on grazing land (McBride and Mathews, 2011). This study utilized individualized models to identify weather differences in major production regions[18].

Table 3.5 shows alternative estimated results for equation (9), and Table 3.6 provides respective impact estimations. When controlling for geographical variation, estimation results for the northern states suggest that Season 1 lagged minimum temperature negatively impacted beef cow inventories (-0.10%) (Table 3.6, column 2). Hence, a one-unit increase in Season 1 lagged minimum temperature decreased beef cow inventories by 0.1%. However, no other significant weather impacts were identified for alternative geographic classification of northern states. In comparison, significant negative impacts of Season 1 lagged minimum temperature were observed for beef cow inventories in the southern states. A one-unit increase in Season 1 lagged minimum temperature reduced beef cow inventories by 0.40%. The difference suggests that existing high temperatures in breeding season in southern states significantly negatively impacts beef cow inventories. Further, lagged Season 3 maximum temperature and lagged Season 4 minimum temperature significantly impacted southern beef cow inventories. Overall, temperature impacts were more significant in the southern states than the northern states.

3.8 Evaluation of the Forecasting Ability

This study also used a 46-year sample (1951–1996) to evaluate the forecasting performance of each model and examine the importance of including weather information on out-of-sample predictions. Although the selected sample length was ad hoc, sample length remained constant. In making an annual forecast, this study included three alternative forecasting models to update

[18] Northern: Colorado, Idaho, Illinois, Iowa, Kansas, Missouri, Montana, Nebraska, North Dakota, Oregon, South Dakota, Wyoming; Sourthern: Alabama, Arkansas, California, Florida, Georgia, Kentucky, Lousiana, Mississippi, New Mexico, Oklahoma, Tennessee, Texas, Virginia

horizons: each year, 10 years ahead, and 20 years ahead. For example, when making a one-step-ahead forecast, the model was initially estimated using the 1951–1996 time period, and then beef cow inventories for 1997 were forecasted. The model was reestimated for the 1952–1997 period, and then beef cow inventories for 1998 were forecasted, continuing until the last forecast was complete. For 10-year updating, the model was estimated using the 1951–1996 sample period and then made 10 years of forecasting (1997–2006). After using the model to make the first 10 years forecast, the model parameters were reestimated using the 1961–2006 period and subsequently forecasted 2007–2016 beef cow inventories, continuing until the last forecast was complete. The 20-year updating procedure was similar to the 10-year updating.

Table 3.7 presents the forecasting evaluations. Based on the results of root mean squared error (RMSE), the model with seasonal weather had the least prediction error for all three forecasting horizons, followed by the AR(3) model[19]. Naïve[20] forecasting had the highest RMSE values for all three forecasting horizons. Overall, a comparison of forecasting accuracy measures suggests that adding weather information improves the forecasting ability of state-level beef cow inventories.

This study used the Ashley, Granger, Schmalensee (AGS) method (Table 3.8) to compare RMSEs of alternative forecasts. The AGS method provides a statistical test to compare the significance of differences between forecasting errors of two competing forecasts (Bradshaw and Ordern, 1990; Kastens and Brester, 1996). The regression used to estimate AGS statistics is

$$A_t = \gamma_0 + \gamma_1 (E_t - E_{mean}) + \epsilon_t \tag{11}$$

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[19] AR(3) model includes lagged beef cow inventory information.

[20] Naïve forecasting uses only the last year information to predict current year beef cow inventories and presumes no change from the prior year.

where A_t is the difference between forecast error of low RMSE forecast subtracted from competing forecast errors, E_t is the sum of forecasting error, E_{mean} is the sample mean of E_t, and t is white noise. Following Kastens and Brester (1996), this study obtained the absolute value for the error sample mean to avoid negative sample mean. Estimation criteria was if γ_0 and γ_1 estimates were positive, a F-test for joint hypothesis $\gamma_0 = 0$ and $\gamma_1 = 1$. If either γ_0 or γ_1 was negative and significant, the test was inconclusive. If an estimate was negative and insignificant, the appropriate test was an upper tail t-test (Bradshaw and Ordern, 1990; Kastens and Brester, 1996). Results of the AGS analysis confirmed that, compared to the seasonal weather model, the majority of naïve and AR(3) models' forecasting errors were significantly different, and the seasonal weather model performed more accurately than the other models considered in this study.

Forecast improvement was also tested over time (Table 3.9) by regressing the absolute value of forecast errors on a time trend as follows:

$$|e| = \delta_0 + \delta_1 Trend_t + \varepsilon_t \tag{12}$$

where $|e|$ is absolute forecast error. The null hypothesis is $\delta_1 = 0$, meaning that no time improvement was present. If $\delta_1 < 0$, then forecast improved over time. Results suggest that time improvement only occurred in the 20-steps-ahead forecast with the naïve model (Table 3.9).

3.8.1 State-Level Beef Cow Inventories as Forecasts

Forecasts are useful for decision making and risk management, as well as resource allocation (Tomek, 1997; Manfredo and Sanders, 2004). Cattle producers react to high/low prices by adjusting the numbers in their breeding herds (Bently and Shumway, 1981). Although forecasting cattle prices using options contracts, futures markets, and basis forecasting is common in practice (Martin and Garcia, 1981; Liu et al., 1994; Tomek, 1997; Manfredo and Sanders, 2004;

Tonsor, Dhuyvetter, and Mintert, 2004), production forecasts using weather information is novel. This study forecasted state-level beef cow inventories using the estimated coefficients in equation (9) to help producers identify optimal herd size in response to weather changes. The long biological time gap between cow breeding, calf weaning, and marketing is nearly two years, making it difficult for producers to plan herd size. In addition, market prices vary depending on demand, and supply signals and supply forecast indicate price volatility (Bacon, Trapp, and Koontz, 1992). Hence, beef cow forecasting could help producers determine profitable herd sizes and increase understanding of weather impacts on beef cow inventories in the next 10 years, resulting in better economic decisions.

3.8.2 Prediction Accuracy Comparison

This study compared the forecast from final model (equation 9) to U.S. Department of Agriculture (USDA) annual agricultural projections from 2005 to 2016 to evaluate prediction accuracy. For the seasonal weather model and AR(3) model, 1958–2004 was the first period of parameter estimation with 10-steps-ahead forecasts. After the first 10 years of forecasts (2005–2014), the model parameters were reestimated using 1959–2005, and then forecasts were conducted for the next 10 years (2006–2015). Analysis included the RMSE for USDA, seasonal weather model (equation 9), AR(3), and naïve model, which used the previous year's beef cow inventories as the current year's inventory numbers. Collectively, this testing procedure evaluated the ability to forecast beef cow inventories using three distinctive model specifications.

Results confirmed that, until six years ahead, USDA cow-calf inventories have the least RMSE, followed by the seasonal weather model (Figure 3.1). After six years, USDA forecasting errors were higher than the other three models. The seasonal weather model most accurately projected long forecasting horizons.

3.8.3 Prediction Simulation

This study utilized weather forecasts from U.S. Geological Survey (USGS) national weather prediction data from 2020 to 2028 to simulate changes in future weather conditions. Beef cow forecasts from the USDA agricultural projections for the same period were used for the 2028 report. Because the USDA agricultural projection report does not include individual state-level beef cow inventories, however, this study used weather and beef cow forecasts to recalculate future weather impacts on state-level beef cow inventories. The state-level beef cow inventory share used to calculate future state-level beef cow inventories was the ratio of observed state-level beef cow inventory numbers from LMIC in 2017 which is the last year of data used in this study to the USDA-projected total national beef cow inventory in the same year. Consistent share numbers were maintained throughout the sample period.

Figure 3.2 shows the average USDA agricultural projections for state-level beef cow inventories and predicted beef cow inventories using seasonal weather information from 2018 to 2028. Forecasts that used the seasonal weather model tended to underpredict beef cow inventories compared to USDA predictions. However, the forecasting accuracies of both forecasting models were not measured because none of the beef cow inventory numbers were yet observed. Compared to previous 10-year beef cow inventories for the 25 states in this study, predicted 10-year-ahead values showed, on average, a 10% reduction in national beef cow inventories based on predicted seasonal weather changes.

3.9 Conclusions

This study estimated the effects of seasonal weather on state-level beef cow inventories and examined the impact of breeding-season weather on state-level beef cow inventories and geographical cow-calf production. Study results affirmed the importance of incorporating weather information in models for state-level cow-calf inventory analysis and production forecasting. Estimation results suggest that lagged minimum and maximum temperatures significantly affect state-level beef cow inventories. Increases in temperature during cold months (i.e. season 4) increase beef cow inventories, while increased temperatures in warm months (i.e. season 3) decrease beef cow inventories. These estimates can be used to understand economic impacts on the cow-calf industry. For example, a decreased beef cattle supply ultimately affects domestic beef prices, meaning consumers encounter high beef prices as a result of a negative supply response. Moreover, this analysis captured the dynamic nature of cow-calf operations, evidenced by significant production lags.

Research results also showed that weather impacts during the breeding season are substantially greater than seasonal weather impacts on cow-calf production. Significant breeding-season weather estimates suggest that weather stress during breeding season significantly affects the production of cow-calf operations. These estimated breeding-season weather impacts can be used to improve the reproductive performance of beef cows since reproductive performance and subsequent profitability of cow-calf operations are closely tied to weather conditions. Moreover, study findings confirmed that weather impacts on beef cows are geographically distinct. Results of geographically separated weather impacts on cow-calf operations highlighted the importance of geographical weather analysis for beef cow inventories.

This study also utilized weather information to forecast beef cow inventories. Using RMSEs of the main model (equation 9) and other competing models, the model with weather information provided more accurate forecasts than the naïve forecasting and AR(3) models. In addition, the seasonal weather models produced the lowest RMSEs with significantly superior performance. These results prove that the inclusion of weather information is beneficial for out-of-sample forecasting. This research also provided new empirical evidence proving that seasonal weather is essential for determining state-level beef cow inventories by advantageously considering a longer time period across states to capture weather dynamics.

Future research would benefit from controlling adverse weather adaptation behavior of cow-calf producers. In addition, this study focused only on the U.S. cow-calf industry, but spatially variable, negative weather impacts in U.S. competitors such as Canada, Australia, and New Zealand could negatively impact international beef prices. Future work should consider weather impacts on the global beef and cattle trade.

Tables

Table 3.1 Summary Statistics

Variables	Mean	Min	Max	S.D
Beef cow inventory	1164.84	190	6895	957.63
L1. Beef cow inventory	1165.71	190	6895	959.10
L2. Beef cow inventory	1167.15	190	6895	961.10
L3. Beef cow inventory	1169.09	190	6895	963.47
L3.Season 1 min temperature	-3.01	-20.46	11.45	6.10
L1.Season 3 max temperature	29.48	21.75	37.35	2.73
L2.Season 3 max temperature	29.47	21.75	37.35	2.74
L3.Season 3 max temperature	29.47	21.75	37.35	2.74
L3.Season 4 min temperature	0.86	-11.93	14.86	5.30
L1.Min temp spring calving	12.41	2.74	21.44	4.66
L1.Max temp spring calving	26.25	16.70	34.18	3.71
L1.Min temp fall calving	-1.72	-17.50	15.73	5.75
L1.Max temp fall calving	10.57	-7.85	26.07	6.19
L1.Precip spring calving	259.47	14.00	776.88	119.19
L1.Precip fall calving	203.67	13.38	758.28	127.56

Note: all the temperature measures are in Celsius and precipitation measures are in millimeters
L1, L2, and L3 are lag1, lag2, and lag3 respectively

Table 3.2 Effect of the seasonal weather on beef cow production

Variables	Estimate
L3.Season 1 min temperature	-0.30***
	(0.00)
L1. Season 3 max temperature	-0.40***
	(0.00)
L2.Season 3 max temperature	-0.30*
	(0.00)
L3.Season 3 max temperature	-0.10
	(0.00)
L3.Season 4 min temperature	0.10
	(0.01)
L1. Ln of beef cow inventory	1.11***
	(0.03)
L2.Ln of beef cow inventory	-0.15**
	(0.04)
L3.Ln of beef cow inventory	-0.04
	(0.03)
T1	0.03***
	(0.00)
T2	-0.02***
	(0.00)
Constant	0.00
	(0.000)
N	1600

Note: All weather coefficients are multiplied by 100 for clarity.
*,**,*** Statistical significance at the 10,5,and 1% levels, respectively
L1, L2, and L3 are lag1, lag2, and lag3 respectively

Table 3.3 Impact estimation- seasonal weather model

Variables	Impact (%)
L3.Season 1 min temperature	-0.30
L1.Season 3 max temperature	-0.40
L2.Season 3 max temperature	-0.30
L3.Season 3 max temperature	-0.10
L3.Season 4 min temperature	0.10

Note: Total impacts in percent are calculated as $100(\exp(\Delta X\beta) - 1)$
L1, L2, and L3 are lag1, lag2, and lag3 respectively

Table 3.4 Effect of the breeding season weather on beef cow production

Variables	Estimate	Impact (%)
L1.Min temp spring calving	-2.80**	-2.76
	(0.01)	
L1.Max temp spring calving	-0.70	-0.70
	(0.01)	
L1.Min temp fall calving	2.70***	2.70
	(0.01)	
L1.Max temp fall calving	-2.20***	-2.20
	(0.01)	
L1.Precip spring calving	0.00	0.01
	(0.00)	
L1.Precip fall calving	0.00	-0.01
	(0.00)	
Constant	0.00	
	(0.00)	
N	1600	

Note: All weather coefficients are multiplied by 100 for clarity.
*,**,*** Statistical significance at the 10,5,and 1% levels, respectively
L1, L2, and L3 are lag1, lag2, and lag3 respectively

Table 3.5 Geographic variation in weather impacts on beef cow production

Variables	Northern	Southern
L3.Season 1 min temperature	-0.10*	-0.40***
	(0.00)	(0.00)
L1.Season 3 max temperature	0.00	-0.30**
	(0.00)	(0.00)
L2. Season 3 max temperature	-0.10	0.00
	(0.00)	(0.00)
L3. Season 3 max temperature	0.10	0.40***
	(0.00)	(0.00)
L3. Season 4 min temperature	0.00	0.40***
	(0.00)	(0.00)
L1. Ln of beef cow inventory	1.18***	1.22***
	(0.04)	(0.03)
L2. Ln of beef cow inventory	-0.14***	-0.16***
	(0.05)	(0.05)
L3. Ln of beef cow inventory	-0.04	-0.06*
	(0.04)	(0.03)
T1	0.04***	0.03***
	(0.01)	(0.01)
T2	-0.03***	-0.02**
	(0.01)	(0.01)
Constant	0.05*	0.02
	(0.03)	(0.04)
N	768	832

Note: All weather coefficients are multiplied by 100 for clarity.
*,**,*** Statistical significance at the 10,5,and 1% levels, respectively
L1, L2, and L3 are lag1, lag2, and lag3 respectively

Table 3.6 Impact estimation

Variables	Northern(%)	Southern(%)
L3.Season 1 min temperature	-0.10	-0.40
L1.Season 3 max temperature	0.01	-0.30
L2. Season 3 max temperature	-0.10	0.01
L3. Season 3 max temperature	0.10	0.40
L3. Season 4 min temperature	0.01	0.40

Note: L1, L2, and L3 are lag1, lag2, and lag3 respectively

Table 3.7 Forecasting evaluations

	RMSE		
Model	1 step	10 steps	20 steps
Naive(no change)	0.18	0.57	0.99
AR(3)	0.18	0.47	0.67
Seasonal weather	0.17	0.47	0.66

Table 3.8 AGS tests for the significance

Forecast	Naive vs Seasonal Weather	AR(3) vs Seasonal Weather
One step ahead	0.07*	0.94
Ten steps ahead	0.00***	0.00***
Twenty steps ahead	0.00***	0.00***

Note: *,**,*** Statistical significance at the 10,5,and 1% levels, respectively

Table 3.9 Time improvement test

	RMSE		
Model	1 step	10 steps	20 steps
Naive(no change)	0.06***	0.02	-0.32***
AR(3)	0.05**	0.18***	0.58***
Seasonal weather	0.01	0.14***	0.56***

Note: *,**,*** Statistical significance at the 10,5,and 1% levels, respectively

Figures

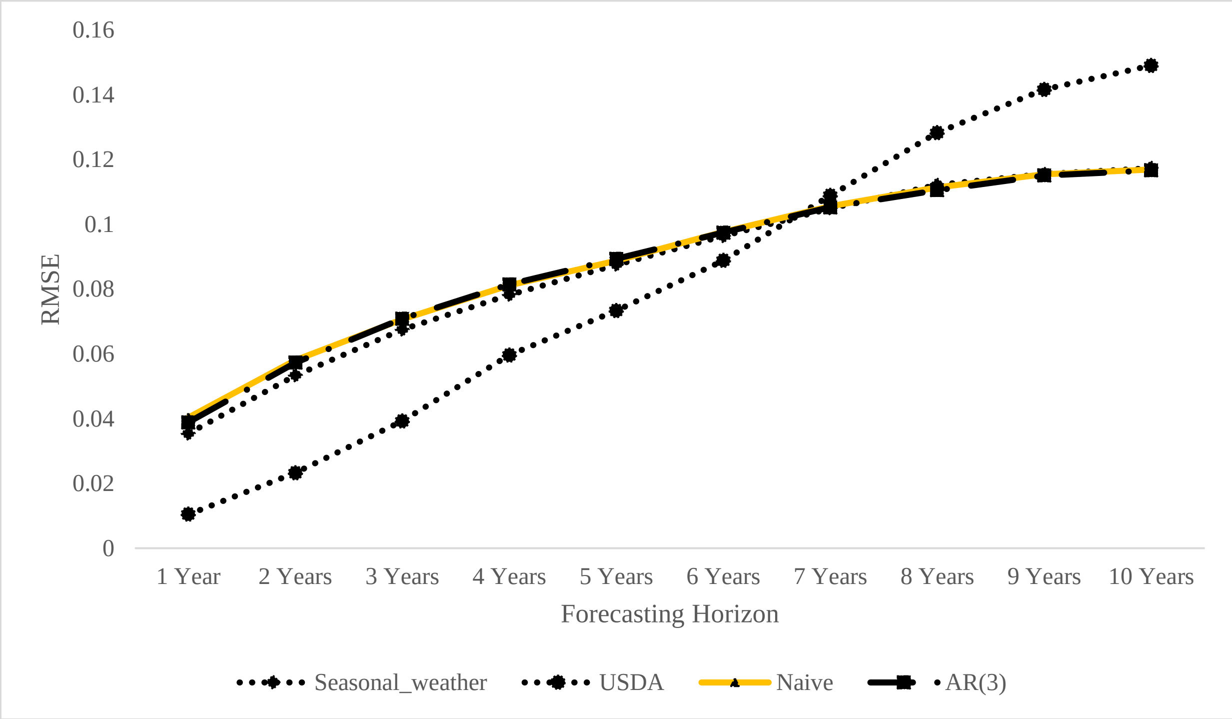

Figure 3.1 Prediction Accuracy Comparison

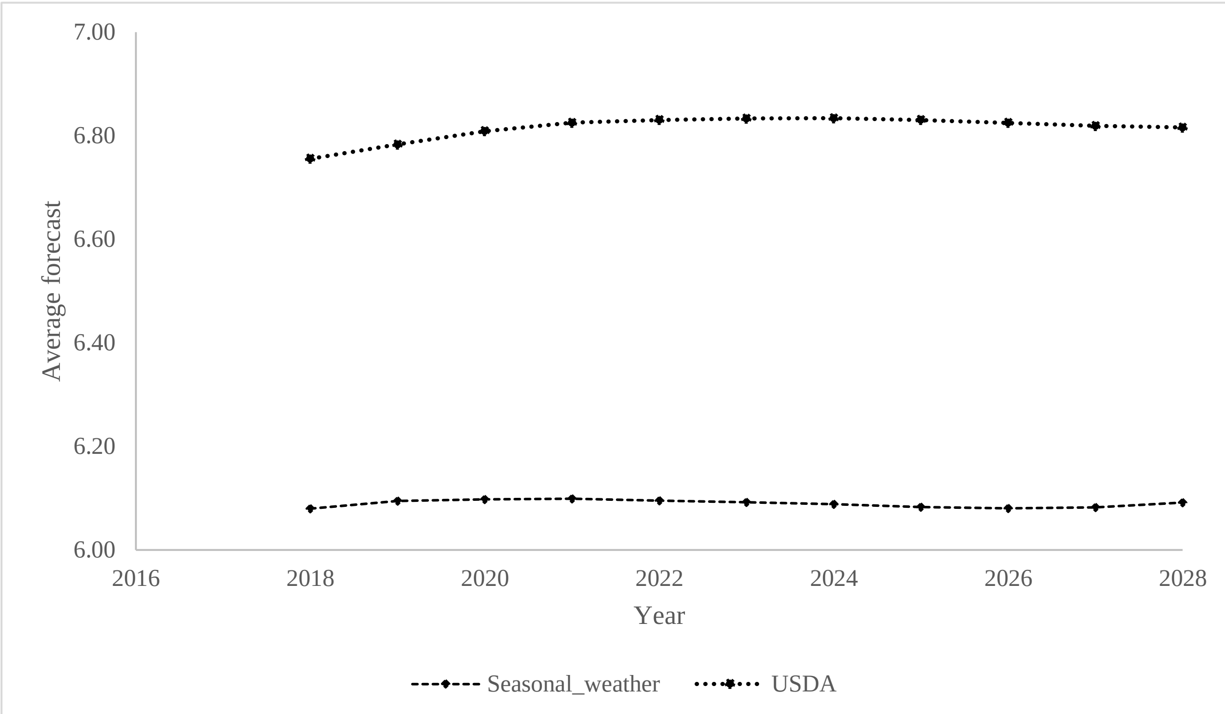

Figure 3.2 Beef-cow Forecast Comparison

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Appendix A - Appendix to Chapter 2

Table A.1 Description of seasons

Season	Time line
Season 1	January - March
Growing Season	April - July
Season 2	August – September
Season 3	October – December

Table A.2 Direct, indirect, and total effects calculation for spatial lag dependent model

Variables	Direct	Indirect	Total
Season 1 average temperature	0.0027	0.0065	0.0091
	[0.0028]	[0.0070]	[0.0097]
Growing season average	0.0478	0.1150	0.1627
temperature	[0.0175]	[0.0525]	[0.0671]
Season 3 average temperature	0.0110	0.0267	0.0376
	[0.0074]	[0.0194]	[0.0264]
Season 1 average temperature^2	-0.0006	-0.0015	-0.0021
	[0.0002]	[0.0006]	[0.0007]
Growing season average	-0.0008	-0.0020	-0.0029
temperature^2	[0.0005]	[0.0012]	[0.0016]
Season 2 average temperature^2	0.0001	0.0001	0.0002
	[0.0001]	[0.0002]	[0.0003]
Season 3 average temperature^2	-0.0007	-0.0017	-0.0024
	[0.0004]	[0.0011]	[0.0014]
Season 1 total precipitation	-0.0001	-0.0003	-0.0004
	[0.00003]	[0.0001]	[0.0001]
Growing season total precipitation	0.0001	0.0002	0.0003
	[0.00003]	[0.0001]	[0.0001]
Season 2 total precipitation	0.0001	0.0003	0.0004
	[0.00004]	[0.0001]	[0.0002]
Season 3 total precipitation	-0.0001	-0.0001	-0.0002
	[0.00004]	[0.0001]	[0.0002]
Feed cost per cow	-8.72E-06	-0.00002	-0.00003
	[6.88E-07]	[6.25E-06]	[6.49E-06]
CRP acres	-1.59E-07	-3.82E-07	-5.41E-07
	[4.38E-07]	[1.05E06]	[1.49E-06]
Population density	-0.0001	-0.0024	-0.0034
	[0.0001]	[0.0007]	[0.0007]
Percentage of land irrigated	-0.0080	-0.0193	-0.0274
	[0.0257]	[0.0619]	[0.0875]

Note: Standard errors are in the brackets.

Table A.3 Alternative panel analysis estimates for weather variables

Variables	**1992-2002 Panel**	**2007-2017 Panel**
Season 1 average	-0.0066	0.0038
temperature	[0.0041]	[0.0054]
Growing season average	0.0168	0.0058
temperature	[0.0248]	[0.0230]
Season 3 average	-0.0405	0.0276
temperature	[0.0146]	[0.0118]
Season 1 average	0.0006	-0.0007
temperature^2	[0.0003]	[0.0003]
Growing season average	-0.0002	-0.0009
temperature^2	[0.0006]	[0.0008]
Season 2 average	0.0004	-0.0002
temperature^2	[0.0001]	[0.0001]
Season 3 average	0.0018	-0.0013
temperature^2	[0.0008]	[0.0006]
Season 1 total precipitation	-0.0001	-0.00003
	[0.00004]	[0.0001]
Growing season total	0.0001	-0.00004
precipitation	[0.00004]	[0.00003]
Season 2 total precipitation	0.0001	0.00003
	[0.00001]	[0.0001]
Season 3 total precipitation	0.00001	-0.00003
	[0.0001]	[0.0001]
Observations	2,292	2,292

Note: Standard errors are in the brackets.

Table A.4 Prediction evaluations

Model	**MAPE**	**MAE**	**RMSE**
Baseline prediction (no weather)	1.28	0.73	0.94
Spatial Lag Prediction	0.8	0.56	0.72

Appendix B - Appendix to Chapter 3

Table B.1 Effect of the seasonal weather on beef cow production- Arellano-bond estimation

Variables	Estimate
L3.Season 1 min temperature	-0.30***
	(0.00)
L1.Season 3 max temperature	-0.40***
	(0.00)
L2.Season 3 max temperature	-0.40***
	(0.00)
L3.Season 3 max temperature	-0.10
	(0.00)
L3.Season 4 min temperature	0.10
	(0.00)
L1.Ln of beef cow inventory	1.08***
	(0.03)
L2.Ln of beef cow inventory	-0.15***
	(0.04)
L3.Ln of beef cow inventory	-0.03
	(0.02)
T1	0.03***
	(0.01)
T2	-0.02***
	(0.01)
Constant	0.84***
	(0.08)
N	1600

Note: All weather coefficients are multiplied by 100 for clarity.
*,**,*** Statistical significance at the 10,5,and 1% levels, respectively
L1, L2, and L3 are lag1, lag2, and lag3 respectively