CASE STUDIES ON THE EFFECTS OF CLIMATE CHANGE ON WATER, LIVESTOCK AND HURRICANES

A Dissertation

by

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ABSTRACT

This dissertation investigates the agricultural impacts of climate change in three ways addressing water implications of mitigation strategies, feedlot livestock productivity vulnerability induced by climate change and dust and welfare effects of altered tropical storm frequency and intensity.

Even though mitigation alleviates GHG emissions and ultimate climate change, it also has externalities and can alter water quantity and quality. The first essay focuses on examining the water quality and quantity effects of mitigation strategies. This is done using quantile regression and sector modeling. The quantile regression result examined land use change and showed that an increase in grassland significantly decreases water yield with changes in forest land having mixed effects. In the sector modeling we find that water quality is degraded under most mitigation alternatives when carbon prices are low but is improved with higher carbon prices. Also water quantity slightly increases under lower carbon prices but significantly decreases under higher carbon prices.

The second essay examines the effects of climate change and dust on feedlot cattle performance plus the benefits of dust control adaption. A linear panel data model is used to see the relationship between climate and dust with cattle sale weight. We find that hotter temperatures and increased dust levels generally worsen cattle live sale weight. Dynamic programming is then used to estimate the benefits of dust control. The results show that dust control activity is beneficial. Additionally, climate change is found to be damaging and a factor that reduces dust control benefits.

The last essay applies a demand model to investigate the economic consequences of tropical storm strikes on the vegetable market in Taiwan. Findings are that tropical storm strikes raise vegetable prices and in turn cause consumer loss and producer gain. Also higher intensity storms generally have larger impacts than lower intensity storms. Finally possible climate change induced intensified tropical storms or increased storm frequencies were found to result in a more severe welfare loss.

DEDICATION

To my beloved mother, father and little brother.

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1. INTRODUCTION

Evidence has been amassed by the IPCC (2013) among others that accumulating GHG emissions have brought about increased temperature and altered precipitation patterns plus incidence of extreme temperature events. In particular scientists have observed that the global temperature has increased about 1.33°F during the 20th century and projected a further increase (IPCC 2013). Precipitation is also changing as are extreme events (IPCC 2012; 2013). Agriculture is affected by such temperature increases and also by associated alterations in incidence of pests and diseases, water supply, feed-grain production, availability and price, pastures and forage crop production and quality, and disease and pest distributions (Walthall et al. 2012). There are also impacts on animal mortality and morbidity, feed intake, feed conversion rates, rates of weight gain, milk production, conception rates and appetite alteration loss (Adams et al. 1998; Hansen et al. 2001; Huynh et al. 2005; Kerr et al. 2003; Kerr et al. 2005; Mader et al. 2009; Wolfenson et al. 2001).

To deal with these vulnerabilities from climate change, two fundamental response actions are considered: mitigation and adaptation. Mitigation activities aim to reduce GHG emissions to limit the extent of future climate change while the adaptation activities aim to improve performance under a changed climate moderating vulnerability. Such actions impact agriculture directly and indirectly, for example, affecting available water quantity and quality.

This dissertation investigates the three dimensions of the impacts of climate change and related actions. First, we address the external water effects of mitigation actions. Second, livestock vulnerability and effects on welfare from hotter temperatures, altered precipitation and changes in dust incidence are investigated. Third, we examine the market effects of altered tropical storm frequency and intensity. This is done through three related but independent essays as follows.

Essay 1 addresses water implications of agricultural mitigation strategies. Namely we will examine the "co-effect" or externality effects on water arising from a group of agricultural mitigation possibilities. Both literature review and empirical work are carried out in the U.S. Missouri River Basin.

Essay 2 discusses climate change and dust effects on feedlot livestock production considering the effects of temperature, precipitation and altered dust incidence. In this essay we first econometrically examine the impacts of temperature, precipitation and dust. Then we use an economic model to estimate and project costs of dust and climate change and to discuss the benefits of dust control. This study is done in the top 7 cattle producing states: Texas, Kansas, Nebraska, Iowa, Colorado, California, and Wisconsin.

Essay 3 investigates the economic consequences on a vegetable market caused by tropical storms. The Taipei vegetable market in Taiwan is analyzed to examine the price and welfare changes induced by tropical storms and possible climate change induced increases in tropical storm frequency and intensity.

2. ESSAY ONE: THE WATER IMPLICATIONS OF AGRICULTURAL AND FORESTRY GREENHOUSE GAS MITIGATION

2.1. Introduction

Greenhouse gas emissions (GHGEs) are a main contributor to climate change. Many international conventions or agreements propose mitigation policies to reduce those emissions, and some of these policies involve alterations in agricultural and forestry (AF) land uses, input usage rates, animal feeding practices, manure management and other items (for a more complete list see McCarl and Schneider (2001) or IPCC (2007)). Such measures will also have external influences on water quality and quantity.

Water quantity effects occur through alterations in direct irrigation water use plus alterations in the amount of water running off or infiltrating groundwater from AF lands (Reilly et al. 2003). Water quality effects occur when AF strategies alter erosion rates, input usage, and animal manure supplies in turn altering runoff of sedimentation, manure and chemicals along with their intrusion into both ground and surface water. Figure 1 presents a conceptual framework among GHGEs, climate effects, mitigation policies, and water implications. This essay will review and analyze water implications induced by the use of AF GHG mitigation efforts through both reviewing the literature and conducting a modeling based case study.

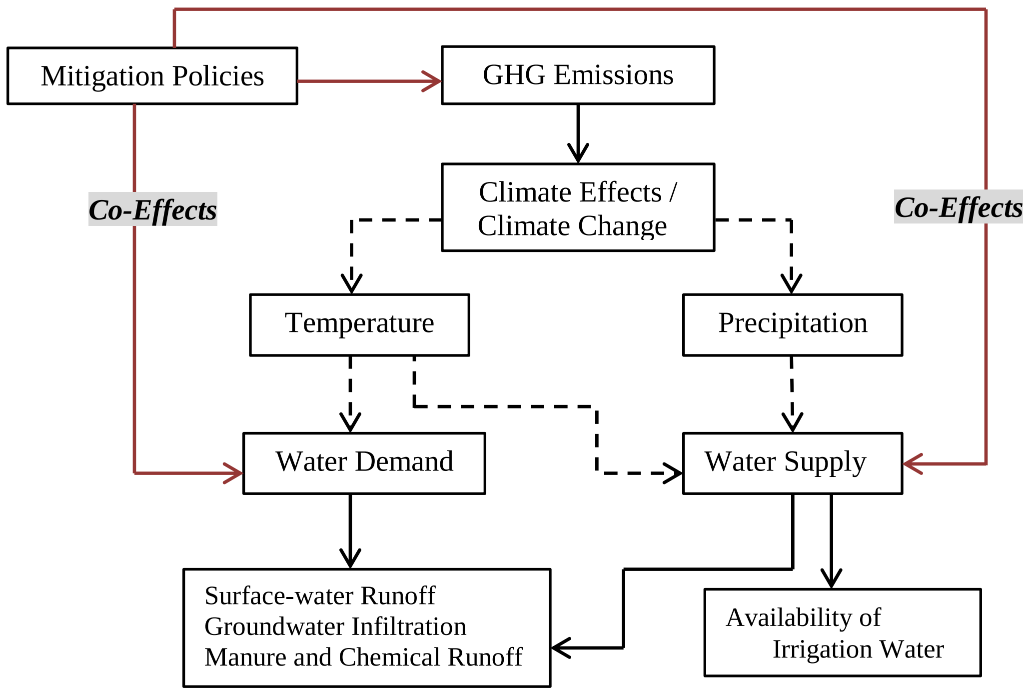

Figure 1 Conceptual Framework of Mitigation Policy on Water Implications

2.2. Literature Review

The literature suggests that the AF sector may participate in GHGE mitigation efforts in several fundamental ways (McCarl and Schneider 2000; United Nations Framework Convention on Climate Change 1997).

- First, AF may reduce emissions by manipulating crop, livestock or forest management plus by switching enterprise mix. AF activities release substantial GHG emissions (GHGE) in the forms of methane, nitrous oxide, and/or carbon dioxide (an estimated 30% of global emissions in IPCC (2007)) and have been argued to be responsible for about 25% of historical carbon releases to the atmosphere (Ruddiman 2003; Lal 2004).

- Secondly, AF may enhance its absorption of atmospheric carbon by creating or expanding carbon sequestered in sinks. This largely involves changes in tillage intensity, land use, deforestation, forest management and afforestation (Lal 2004; Murray et al. 2005).
- Thirdly, AF may provide products which substitute for GHGE intensive products like fossil fuels or building materials in turn displacing emissions from those sources (McCarl 2008).
- Finally, AF may develop and utilize technical advances that reduce emissions intensity per unit production and allow less land and possible input use to produce a given amount of production (Baker et al. 2013).

In this review mitigation strategies will be classified into six broad categories: land use change, crop management, animal management, bioenergy production, forest management, and technological progress. The impacts on water quantity and quality vary among these mitigation categories with the literature indicating a number of effects as reviewed by category below.

2.2.1. Land Use Change

Land use change involves transformation of the fundamental use of a parcel of land between growing crops, grass, forests or serving as a wetland (note we will not discuss changes to/from non-agricultural uses including urban uses). This can involve de-intensification, for example, cropland moving to grasslands, forests, wetlands or intensification vice versa. Also grassland can move into forests or wetlands or vice versa.

Under land use change water use/supply can be altered depending on the type of land use plus the resulting vegetation, irrigation status and soil/climate characteristics. For example, farms in Texas on average apply 0.8 acre-feet per acre water to produce sorghum but 1.7 acre-feet per acre water to produce corn (USDA 2010). Furthermore, Jackson et al. (2005) show that afforestation in many cases increases water use and decreases runoff relative to prior cropland use.

A number of studies have addressed water quantity implications of land use change. Leterme and Mallants (2011) simulate groundwater recharge under different land conversions in Beligum and show that groundwater recharge will increase if the land is converted to crops (maize) land but will decrease if the land is converted to grassland (meadow), coniferous forest or deciduous forests. Bhardwaj et al. (2011) indicate that water use is likely to increase if cropland is moving to energy crop production. Water runoff for lands is also altered by the conversion of lands to forests (Jackson et al. 2005; Sahin and Hall 1996; Schnoor et al. 2008). Frankenberger (2013) calculates the expected runoff from a 4-inch rainfall under four types of land use in Indiana: on a corn or soybeans cropped field the runoff was 3.9 inches, around 97%, while the runoff was between 12.5%-30% (0.5 inch-0.8 inch) on the forest, meadow, or turf grass.

Water quality is also affected by land use change. It is affected by erosion which is altered by GHG mitigation practices that alter soil disturbance (Binkley and Brown

1993; Clark et al. 2000; Fulton and West 2002; Watson 2000; Weller et al. 2003; Myers 1997). It is also affected by land use changes that alter rates of chemical or animal manure and in turn nutrient loading (Mayer et al. 2007; Schnoor et al. 2008; Van Dijk et al. 1996), plus by practices that alter water infiltration like buffer strips (Pionke and Urban 1985; Scanlon et al. 2007). The impacts on water quality may be ambiguous; for example, Pattanayak et al.(2005) show increased water quality under widespread afforestation while Jackson et al.(2005) review cases where water quality is degraded. Thus water quantity and quality impacts depend on region and prior land use/management.

2.2.2. AF Management

Mitigation via agricultural management involves pursuing more carbon sequestration or less GHG emissions by manipulating the way the AF enterprise is managed. Mitigation alternatives under AF management can be divided into four sub classes: cropping management, animal management, afforestation and forest management.

Cropping management involves such means as changes in tillage, crop mix, irrigation strategy, and fertilization amount along with other chemical use alterations. Water quantity will be affected by conservation strategies such as residue retention. Runoff is reduced for example when switching to conservation tillage from conventional tillage (Holland 2004), shifting from water-intensive crops such as rice to row crops (Watson 2008; Yagi et al. 1996), and improving irrigation efficiency to reduce the consumptive use of water (Perry 2007; Pfeiffer and Lin 2010).

In terms of water quality, sediment and chemical runoff are reducible with quality increased through mitigation oriented cropping management like altering chemical use, tillage and better managing residues (Beasley 1972; Bjorneberg et al. 2002; Moldenhauer et al. 1983; Ongley 1996; Rabotyagov et al. 2010). Furthermore, water or chemical infiltration to groundwater may be improved by deep tillage (Raper 2004) but can be reduced because of subsequent less intensive tillage (Pikul and Aase 2003).

Mitigation strategies related to animal management include manure management, animal breed improvement/choice, animal species choice, grazing land management and herd size. Principal effects on water quality involve the altered volume of animal nutrient loads and manure runoff. Fast removal of manure solids and more mechanical rather than water-based removal not only reduce water use but also improve water quality (MacLeod 2005); however, the application of the manure has the potential to increase nutrient runoff and degrade water quality (Kronvang et al. 2008). Additionally use of non-ruminant rather than ruminant animal species could reduce enteric fermentation, alter feed consumption, and alter the volume of manure per unit of meat product produced, and thus affect water quantity and water quality (Steinfeld et al. 2006). Grazing land management, including stocking rate alteration, fertilization, fire management improvement, brush management alteration and grass species alteration, and animal herd management also have water quantity and quality implications.

GHG mitigation producing forest manipulations include afforestation and forest management (rotation length extension, improved silvaculture and fire suppression) as discussed in Murray et al. (2005) and Wall (2008). In terms of water, afforestation of cropland would likely reduce the usage of chemical inputs and the incidence of erosion improving water quality (Fulton and West 2002), but generally increase the amount of water consumed due to increased use by trees (Jackson et al. 2005). Thus this action diminishes water quantity and perhaps enhances water quality depending on whether flows are greatly reduced. The afforestation of pastureland possibility would likely be neutral on erosion and nutrients but might well increase water consumption by the arguments above. Jackson et al. (2005) present a review of the literature relative to this. Altering rotation length would reduce sedimentation while fire management might increase sediment due to soil disturbance.

2.2.3. Bioenergy

Bioenergy can be a mitigation alternative when it replaces use of fossil fuels by providing net emissions lowering AF commodities in the form of liquid fuels or inputs to electricity and heat generation (McCarl 2008; McCarl and Schneider 2000). In judging the net emission effect one must consider the inputs used in producing, hauling and processing the bioenergy feedstock. The direct effects on water involve water direct use in bioenergy processing and production of the feedstock. In terms of processing, the Iowa Department of Natural Resources (2008) showed that aquifers can be depleted presenting a case where there was a drawdown of 17.1 feet in groundwater levels over 10 years due to ethanol facility use.

Feedstock sources include energy crops such as switchgrass, miscanthus, willow and poplar (Jha et al. 2009), conventional crops and their residues (de Fraiture et al. 2008; Renouf et al. 2008; Wilhelm et al. 2004) and animal wastes (National Academy of Sciences 2008). Raising or recovering these feedstocks can change chemical fertilizer and pesticide characteristics, water consumptive use, runoff volume and sediment/nutrient content.

2.2.4. Technological Progress

The final strategy involves technological progress. In particular, technological progress through means such as genetic improvement (via biotechnology or breeding) or precision farming can increase yields and alter water quantity and quality. This is particularly true when yield increases with the same mix of inputs and/or when yield is unchanged but input usage is reduced. Such actions can reduce GHG emissions either in total or in terms of emissions per unit of the products produced. For example, in the last decade in the United States corn yields have gone up substantially without any per acre increase in nitrogen fertilization. This occurred as a consequence of technological improvements in crop genetics, nutrient uptake efficiency, pesticide resistance, yield per acre, drought tolerance, pest susceptibility and nutrient application practices along with many other factors. Such developments can have both water quantity and quality impacts.

Quantity impacts occur if the technical developments cause a difference in the amount of water used although these can be positive or negative depending on water usage per acre and the stimulation of additional acres. Quality impacts occur if the technological development reduces input use or stimulates crops mix shifts to crops that use less fertilization or other inputs plus reduce erosion. The water quality effects depend on the particular practice that is being considered and the resultant change in the use of chemical inputs, tillage, etc. Baker et al. (2013) analyze the issue in a US setting showing mitigation and water effects. However, not much can be said about the interrelationship between technological progress and water use/quality because of the vast array of possibilities and their non-homogeneous water effects.

2.3. Material and Methods

To empirically examine the co-effects of select mitigation policies on water quality and quantity, a two stage analyses will be carried out. First, using a water quantity and quality data set from the Soil and Water Assessment Tool (SWAT) model (Srinivasan et al. 2010), quantile regression will be applied to investigate the effects from altered land use on water quantity and quality. Second, the Forest and Agricultural Sector Optimization Model with Greenhouse Gases (hereafter abbreviated as FASOMGHG) (Adams et al. 2009; Beach et al. 2010) is used to examine mitigation strategies adopted under alternative carbon prices and then is integrated with the earlier econometric results to investigate water implications. This section introduces the study areas, data and methods used.

2.3.1. *Quantile Regression Study Area*

The study area for the SWAT based empirical work using quantile regression is the Missouri River Basin, as shown in figure 2, which is the largest river basin in the continental U.S. and encompasses around 519,650 square miles.[1] The land cover shares in the Missouri River Basin are cultivated cropland 29%, grazing land 49% and forest 9% (USDA 2012). Most of the grazing land is located in the western and central parts of the basin while most of the forestland is located in west and in central Missouri. Additionally, 10% of the area comprises permanent pasture, hayland, water, wetland, horticulture and barren land, and the remaining 3% of the basin consists of urban areas (USDA 2012). In our SWAT data set, the Missouri River Basin is further represented by 29 sub-regions, which are defined by the U.S. Geological Survey (USGS 1980).[2]

The 2007 Census of Agriculture reported that the Missouri River Basin produced about $49 billion in agricultural sales, 45% of which is from crops and 55% from livestock. The principal crops grown in the basin are corn, soybeans (mainly in the eastern portion of the basin), and wheat (mainly in the western portion of the basin). Cow calf and feedlot production are the primary livestock enterprises. In 2007, about 15% of all U.S. crop sales and about 17% of all U.S. livestock sales arose from the basin, in particular, about 25% of all U.S. corn and soybeans, 40% of all wheat and 32% of all cattle sales (USDA 2012). As reported by USDA, in 2007 16% of cropland

[1] The Missouri River Basin includes all Nebraska and parts of Colorado, Iowa, Kansas, Minnesota, Missouri, Montana, North Dakota, South Dakota, and Wyoming, covering a total of 411 counties.
[2] The Missouri River Basin is defined following U.S. Geological Survey (USGS) water-supply paper 2294, <http://water.usgs.gov/GIS/huc.html>.

harvested in this area (around 13 million acres) is irrigated with commercial fertilizers and pesticides applied to 62 million and 60 million acres, respectively.

2.3.2. Data Description

The SWAT data set contains records on water runoff, water quality, land use, climate, irrigation water use, and land use change. SWAT contains data on hydrography, terrain, land use, soil, soil drainage-tile, weather, and management practices (Srinivasan et al. 2010). Both water runoff and water quality indicators are generated on a monthly basis for the 13,437 sub-basins in the Missouri River Basin over the 1990-2010 period. Based on Cude (2001) we select the following two water quality indicators: total nitrogen, including ammonia, nitrate and nitrite, in surface runoff and total phosphorus in surface runoff.

Figure 2 The Missouri River Basin

A subindex is needed to convert each water quality indicator into a relative quality rating, and then a single water quality index (WQI) is formed using these subindices. The literature shows several possible approaches to develop the single water quality index, including the weighted arithmetic mean function, the weighted geometric mean function, the minimum operator function and the unweighted harmonic square mean function (Cude 2001; House 1989; Swamee and Tyagi 2000).[3] We will use the unweighted harmonic square mean formula following Swamee and Taygi (2000). The formula is given by:

$$I = \left(\frac{1}{N} \sum_{i=1}^{N} S_i^{-2} \right)^{-0.5}, \tag{2.1}$$

where I is the single water quality aggregate index; N is the number of subindices; S_i is the ith subindex. The transformation formulae are provided in the Appendix, and the subindices are scaled between 10 (worst quality) and 100 (best quality).

All water related data are aggregated to the county-level. However, aggregation is problematic when a sub-basin is distributed across several counties. To overcome this we do an area weighted average calculation of the water data based on proportions of each sub-basin falling into each county. For example, sub-basin 1 is spread across three counties in Iowa, with 16.27% of it falling in Harrison, 2.12% in Pottawattamie, and 81.61% in Shelby. In turn when computing water quantity and quality for county Shelby

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[3] The weighted arithmetic mean function: $I = \sum_{i=1}^{N} W_i S_i$; the weighted geometric mean function: $I = \prod_{i=1}^{N} S_i^{W_i}$; the minimum operator function: $I = \min\left(S_1, S_2, S_3, \cdots\cdots, S_N\right)$.

we use 81.61% of the quantity and quality estimates from subbasin 1 plus shares form the other sub-basins falling into that county.

Land use is categorized in SWAT into the following groups: (1) acres for continuous dryland crops including corn, grain sorghum, soybean, spring wheat and winter wheat, (2) irrigated acres for continuous corn, soybean, winter wheat and irrigated corn after soybean, (3) rotation acres for soybean and corn, spring wheat and winter wheat (4) alfalfa and hay, (5) evergreen forest and deciduous forest, (6) grass range, and (7) urban area. Notice that land use is assumed to be time-invariant in the SWAT model simulation,[4] and figure 3 reports the proportion of land use described above in the Missouri River Basin by subbasin level, where the darker color the greater incidence of this land use. For example, the bottom left diagram (sketch (e)) presents the coverage ratio of grassland, and the darkest area shows areas where more than 50% of the land is covered by grass while the lightest area shows places where less than 10% of land is covered by grass. As shown in figure 3, most of the upper Missouri River Basin and about 75% of the counties in the middle Missouri River Basin are mainly covered by grass. The continuous crops including rotation crops are mainly planted in the northern upper Missouri River Basin, the eastern middle Missouri River Basin and the western lower Missouri River Basin (the top two left sketches: (a) and (c)) while alfalfa and hay are mainly grown in the lower Missouri River Basin (sketch (d)). On the other hand, the irrigated land for continuous corn, soybeans, winter wheat and irrigated corn after soybeans is mainly located in the southern middle Missouri River Basin (sketch (b)).

[4] Although land use is not change over time, the water runoff data is calibrated to real values.

In our analysis, we will mainly look at how land use changes between crop land, grassland and forest land affect water quality and quantity, and thus category one to four are aggregated into one broad category: crop land.

Monthly climate data summarizing temperature and precipitation averages and extremes from 1990 to 2010 were drawn from the National Oceanic and Atmospheric Administration (NOAA) Satellite and Information Service, National Climatic Data Center (NCDC).[5] Those data are reported from multiple weather stations and include: (1) number of days with greater than or equal to 0.1 inch, 0.5 inch and 1.0 inch of precipitation, respectively, (2) number of days with minimum temperature less than or equal to 0.0 °F and 32.0 °F, respectively; (3) number of days with maximum temperature greater than or equal to 90.0 °F, (4) total precipitation measured in millimeters, and (5) monthly mean temperature measured in °F.

As the NOAA data on each weather station contains latitude and longitude of its location, we can identify the county for each weather station and in turn form all climate variables as county-level averages across all contained stations.

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[5] < http://www.ncdc.noaa.gov/cdo-web/datasets>.

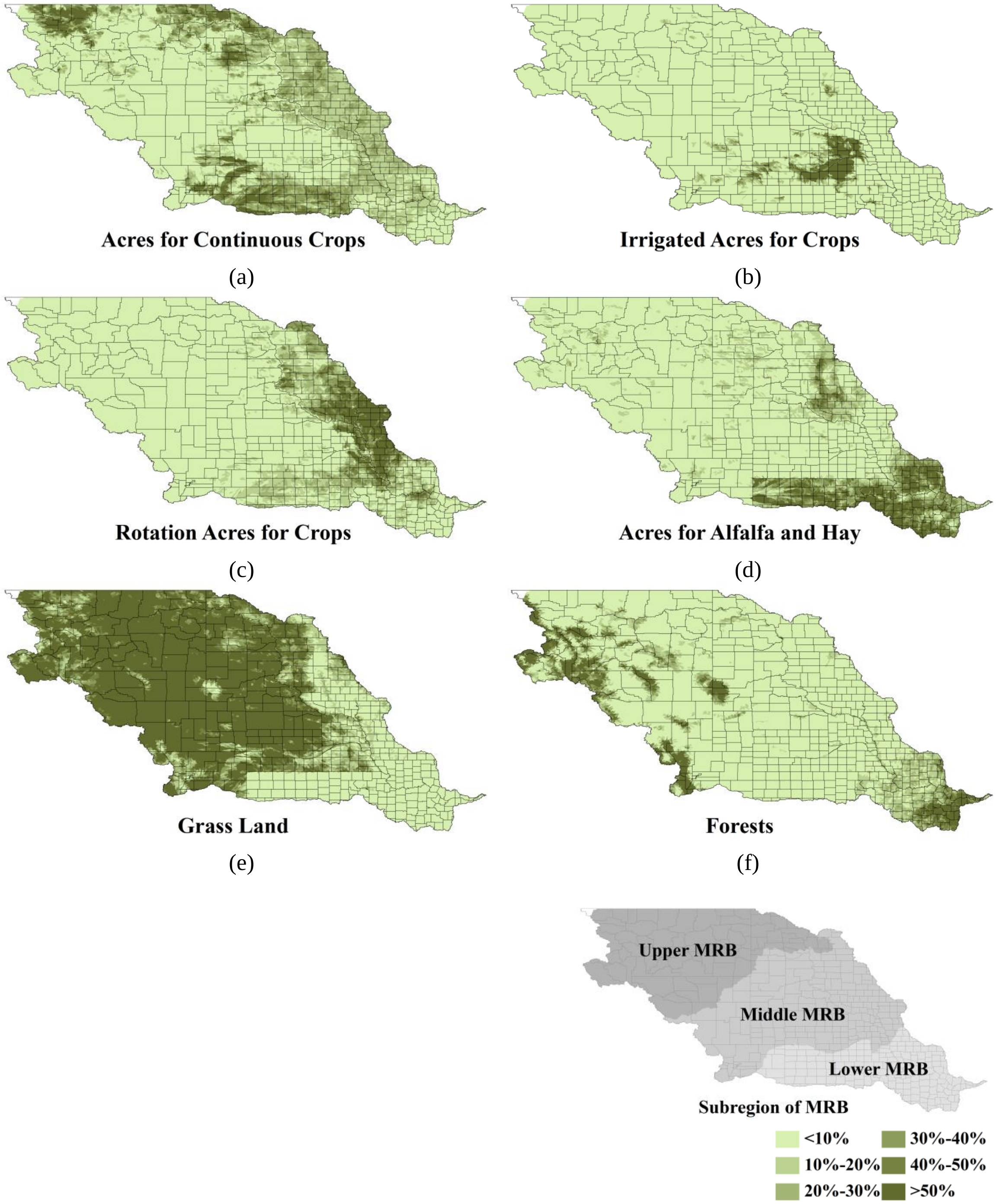

Figure 3 The Proportion of Each Land Use Type in the Missouri River Basin

Table 1 and table 2 report summary statistics and quantile statistics for the SWAT data set. The average water yield is around 7.2 mm, which is close to the value reported at the 75% quantile, meaning that 75% of the water yield observations in the Missouri River Basin are below the average. On the other hand, the average water quality index is around 19 while that at the 75% quantile is around 14. We have further checked that the observations reporting above average water quality only account for 11.17%, and around 50% of the observations exhibit the worst value for the water quality value (WQI=10).

To examine the interrelationship between land use and water quality we divide the sample into several subsets as shown in table 3. First we examine the differences in land use share between observations with the worst water quality (WQI=10) as opposed to those with better water quality (WQI>10). The average percentage of crop land use for the observations with the worst water quality is 53.8% while for those with better water quality it is 31.8%. On the other hand, grass land coverage in the areas exhibiting better water quality is 40.2% while it only averages 15.7% in the areas with the worst water quality.

The land coverage rates for the 50%, 75% and 90% quantiles of water quality are also reported in table 3. The coverage rates of crop land at the 50%, 75% and 90% quantiles are significantly lower while the amount of grass coverage is much higher. Therefore we expect that crop land would potentially worsen water quality while grass land would improve it.

We also observe from table 3 that the forest land coverage appears to be associated with a slight increase in water quality at the low quantiles but not at the highest. Furthermore, table 3 indicates urban coverage appears to worsen water quality. These relationships will be further examined in the econometric analysis.

Table 1 Summary Statistics in the Missouri River Basin

Variables	Mean	Std. Dev.	Max	Min
Water Yield	7.179	15.559	304.259	0
Water Quality[1]	19.016	21.787	100	10
Land Use (% of Total Acres)				
Urban	.038	.056	.702	6.30e-10
Agriculture	.426	.325	.962	0
Acres for Continuous Crops	.129	.119	.547	0
Irrigated Acres for Crops	.047	.139	.820	0
Rotation Acres for Crops	.121	.168	.718	0
Acres for Alfalfa and Hay	.129	.167	.640	0
Grass Land	.282	.311	.986	1.35e-09
Water	.012	.019	.171	1.23e-10
Forests	.079	.128	.755	4.07e-10
Climate Factors				
# of Days with >1.0 Inch of Precipitation	.519	.847	11	0
# of Days with ≤32.0 °F of Minimum Temperature	12.915	12.176	31	0
# of Days with ≥90.0 °F of Maximum Temperature	2.465	4.938	30	0
Total Precipitation (mm)	54.145	51.7561	1303.07	0
Monthly Mean Temperature (°F)	48.576	18.720	87.98	-12.1
El Niño (Dummy)	.238	.426	1	0
La Niña (Dummy)	.190	.393	1	0

Source: the SWAT model (2013).
Note: 1. Water quality is an index conducted by two indicators, total nitrogen and total phosphorus, and scaled from 10 (the worst water quality) to 100 (the best water quality).

Table 2 Quantile Statistics of Water Yield and Water Quality in the Missouri River Basin

Variables	Quantiles				
	10%	25%	50%	75%	90%
Water Yield	0.037	0.262	1.610	6.951	19.427
Water Quality[1]	10	10	13.232	13.983	45.556

Source: the SWAT model (2013).
Note: 1. Water quality is an index conducted by two indicators, total nitrogen and total phosphorus, and scaled from 10 (the worst water quality) to 100 (the best water quality).

2.3.3. Quantile Regression over Panel Data

The above analysis just examines the "average" marginal effects of land cover on water. We are also interested in the marginal effects. To obtain marginal estimate we use quantile regression. The quantile approach will yield information for different intervals of the distribution. For example, when estimating the 90% quantile of the data for water quantities, we get an estimate of the land usages associated with level of water quantity that is exceeded only 10% of the value with 90% of the observations being equal or smaller.

Quantile regression for panel data is specified by Koenker (2004) as:

$$y_{it} = \boldsymbol{X}_{it}^T \boldsymbol{\beta}_\tau + c_i + u_{it}, \tag{2.2}$$

where $c_i = \varphi(x_i) + v_i$ with $E(v_i \mid x_i) = 0$, which denotes a fixed effect analysis. For any $\tau \in (0,1)$, the conditional τth quantile of y_{it} is

$$Q_{y_{it}}(\tau \mid x_{it}) = c_i + X_{it}^T \beta_i, \tag{2.3}$$

Table 3 Summary Statistics in the Missouri River Basin Based on Water Quality Index

Variables	Mean	Std. Dev.	Max	Min
Land Use (% of Total Acres) When WQI[1] = 10				
Urban	.043	.056	.702	6.30e-10
Crop Land	.538	.322	.962	0
Grass Land	.157	.233	.986	1.35e-09
Water	.012	.017	.171	1.23e-10
Forests	.076	.120	.755	4.07e-10
Land Use (% of Total Acres) When WQI[1] > 10				
Urban	.034	.056	.702	6.30e-10
Crop Land	.318	.288	.962	0
Grass Land	.402	.329	.986	1.35e-09
Water	.012	.020	.171	1.23e-10
Forests	.081	.136	.755	4.07e-10
Land Use (% of Total Acres) When WQI[1] > 13.232 (the 50% Quantile)				
Urban	.034	.056	.702	6.30e-10
Crop Land	.316	.288	.962	2.22e-11
Grass Land	.403	.329	.986	1.35e-09
Water	.012	.020	.171	1.23e-10
Forests	.081	.136	.755	4.07e-10
Land Use (% of Total Acres) When WQI[1] > 13.983 (the 75% Quantile)				
Urban	.029	.049	.702	6.30e-10
Crop Land	.278	.294	.962	0
Grass Land	.398	.349	.986	1.35e-09
Water	.012	.021	.171	1.23e-10
Forests	.070	.132	.755	4.07e-10
Land Use (% of Total Acres) When WQI > 45.556 (the 90% Quantile)				
Urban	.025	.028	.492	6.30e-10
Crop Land	.330	.322	.962	0
Grass Land	.301	.330	.986	1.35e-09
Water	.019	.025	.171	1.23e-10
Forests	.040	.109	.755	4.07e-10

Source: the SWAT model (2013).
Note: 1. Water quality is an index conducted by two indicators, total nitrogen and total phosphorus, and scaled from 10 (the worst water quality) to 100 (the best water quality).

Following Koenker (2004), we can estimate model (2.3) for several quantiles simultaneously by solving the following minimization problem

$$\min_{(c,\beta)} \sum_{k=1}^{q}\sum_{i=1}^{n}\sum_{t=1}^{T} w_k \rho_{\tau k}\left(y_{it} - c_i - X_{it}^T \beta_{\tau_k}\right) + \lambda \sum_{i=1}^{n} |c_i|, \qquad (2.4)$$

where w_k is the weight controlling the relative influence of the associated quantiles τ_k, and $\rho_{\tau k}$ denotes the piecewise linear quantile loss function. Koenker (2004) named problem (2.4) the penalized quantile regression with fixed effects approach, and we can obtain the fixed effect estimators while $\lambda \to 0$.

2.3.4. Quantile Regression Results for Water Yield

The quantile regression estimation is implemented using the R open source *rqpd* package (Bache et al. 2013; Koenker 2004). The estimated coefficients relevant to the influence of land use and climate factors on water yield at different quantiles are reported in table 4.

As water yield is mainly influenced by precipitation,[6] we first analyze the marginal effects of precipitation. Total monthly precipitation exhibits positive effects on water yields for all quantiles, indicating water yields will be increased by increased precipitation. Also the marginal effect of precipitation on water yields is larger at the higher quantiles. For example, the marginal value for 100 mm precipitation at the 90% quantile is 0.2 while that at the 10% quantile is only 0.02, reflecting when it is dry more of the water is absorbed on land whereas when it is wet more runs off. On the other

[6] <http://water.usgs.gov/wsc/glossary.html#W>.

hand, we also include an extreme precipitation variable (the number of days with greater than one inch of precipitation) which is found to increase water yield, meaning the more intense the rainfall the more the runoff. The effects are greater at the lower quantiles with water yield at the 10% quantile will be increased by 7.1 mm but that at the 90% quantile will only be increased by 3.58 mm. Furthermore, the impacts of extreme precipitation events affect water yields more at the 25% and 50% quantile than other quantiles.

Monthly mean temperatures including the squared terms do not significantly influence water yield at most quantiles; however, extreme temperature events significantly influence water yield at all quantiles. The number of days with $\leq$ 32°F of minimum temperature has positive effect on water yield while the number of days with $\geq$ 90°F of maximum temperature has the opposite impact. Combining the above results indicates that the occurrence of lower temperature days might increase the water yield while the extremely higher temperature might decrease the water yield. It is because of water freezing in the lower temperature level and evaporation or vegetative evapotranspiration in the higher temperature level.

Table 4 Water Yield Panel Data Estimation Results

	Quantile Regressions					
	10%	25%	50%	75%	90%	OLS
Land Use (% of Total Acres)						
Urban	3.452	6.882	9.126	8.149	7.300	0.819
	(0.790)***	(1.635)***	(3.477)***	(5.014)	(8.915)	(1.714)
Urban^2	-4.144	-8.074	-10.227	-8.273	-4.763	12.875
	(1.770)**	(3.123)***	(6.155)*	(8.273)	(15.661)	(3.256)***
Crop Land	3.373	8.029	17.143	26.331	21.200	21.329
	(0.392)***	(0.768)***	(1.459)***	(3.925)***	(5.194)***	(0.565)***
Crop Land^2	-3.222	-8.146	-17.746	-26.825	-19.022	-18.018
	(0.353)***	(0.748)***	(1.503)***	(4.104)***	(5.974)***	(0.587)***
Grass Land	-2.887	-7.870	-18.276	-29.628	-28.720	-18.618
	(0.323)***	(0.711)***	(1.598)***	(4.235)***	(4.842)***	(0.516)***
Grass Land^2	3.477	8.718	19.822	32.898	33.114	23.661
	(0.367)***	(0.811)***	(1.888)***	(5.059)***	(5.484)***	(0.591)***
Forests	3.862	8.861	18.578	39.557	75.484	45.161
	(0.457)***	(1.073)***	(2.640)***	(5.266)***	(8.359)***	(0.739)***
Forests^2	-3.416	-7.679	-12.091	-30.176	-65.077	-38.965
	(1.279)***	(3.175)**	(7.874)	(12.321)**	(16.528)***	(1.389)***
Climate Factors						
# of Days with >1.0 Inch of Precipitation	-0.384	-0.823	-0.601	0.204	0.440	-4.405
	(0.120)***	(0.158)***	(0.172)***	(0.251)	(0.449)	(0.117)***
# of Days with >1.0 Inch of Precipitation^2	0.374	0.723	0.550	0.225	0.157	2.366
	(0.114)***	(0.150)***	(0.155)***	(0.166)	(0.206)	(0.031)***
# of Days with ≤32.0 °F of Minimum Temperature	0.008	0.017	0.030	0.047	0.279	0.249
	(0.003)**	(0.005)***	(0.008)***	(0.021)**	(0.062)***	(0.021)***
# of Days with ≤32.0 °F of Minimum Temperature^2	-0.0001	-0.0003	-0.001	-0.0005	-0.005	-0.002
	(0.0001)	(0.0001)**	(0.0002)***	(0.0005)	(0.002)***	(0.001)***
# of Days with ≥90.0 °F of Maximum Temperature	-0.011	-0.018	-0.036	-0.094	-0.214	-0.461
	(0.004)**	(0.007)**	(0.014)***	(0.026)***	(0.054)***	(0.030)***
# of Days with ≥90.0 °F of Maximum Temperature^2	-0.0001	-0.0001	0.001	0.002	0.004	0.010
	(0.0002)	(0.0002)	(0.0004)	(0.001)***	(0.001)***	(0.001)***
Total Precipitation (mm)	-0.0009	-0.017	-0.038	-0.038	0.0003	0.127
	(0.004)	(0.004)***	(0.004)***	(0.005)***	(0.010)	(0.002)***
Total Precipitation (mm)^2	0.0001	0.0004	0.001	0.001	0.001	0.0002
	(0.00004)**	(0.0001)***	(0.0001)***	(0.0001)***	(0.0001)***	(5.58e-06)***
Monthly Mean Temperature (°F)	0.001	-0.002	-0.001	-0.006	0.004	-0.054
	(0.002)	(0.004)	(0.006)	(0.011)	(0.023)	(0.015)***
Monthly Mean Temperature^2 (°F)	0.0001	0.0001	0.0001	0.0002	0.001	0.002
	(0.00003)*	(0.0001)**	(0.0001)	(0.0002)	(0.0003)**	(0.0002)***
El Niño (Dummy)	-0.030	-0.078	-0.120	-0.204	-0.493	-0.649
	(0.009)***	(0.013)***	(0.018)***	(0.033)***	(0.092)***	(0.083)***
La Niña (Dummy)	0.046	0.099	0.341	1.122	2.291	1.581
	(0.011)***	(0.017)***	(0.051)***	(0.136)***	(0.262)***	(0.089)***

Note: * p<0.1, ** p<0.05 and *** p<0.01; robust standard errors are reported in parenthesis.

El Niño (warm oceanic phase) and La Niña events are also considered in our analysis. NOAA indicates that winters are warmer and drier than average in the Missouri River Basin with El Niño while these are cooler and wetter than average with La Niña,[7] and the result shows that El Niño reduces water yield while the La Niña wetter years amplifies water yield at all quantiles. The marginal effects of El Niño and La Niña are greater at the higher quantiles.

Most of the land use factors have significant influences on water yield at all quantiles. Figure 4 to figure 6 depict the effects on water yield when the land use proportions of crop land, grassland and forest change. An increase in crop land share significantly increases water yield with decreasing marginal effects. All the quantiles show the highest impacts on water yield when the crop land use proportions are between 50% and 60%. Forest land has similar effects, but the highest yields happen when the forest land use proportions are between 55% and 80%. Grassland exhibits the opposite influence on water yield, that is, the increase of grassland use will decrease water yield with increasing marginal effect. As shown in figure 5, water yield will increase when the land use proportion of grassland at least exceeds 85%. Furthermore, urban land positively affects water yield but only at lower quantiles.

The influences of grassland and crop land on water yield exhibit similar magnitude but are opposite in effect. For example at the 50% quantile, other things being equal water yield will increase by around 4 mm if 50% of land is covered by crop while it is decreased about 4 mm if 50% of land coverage is grassland. At all the other

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[7] < http://oceanservice.noaa.gov/facts/ninonina.html >.

quantiles the amount of water yield generated by the 50% land coverage of crop land also roughly equals to that decreased by the 50% land coverage of grassland. On the other hand, forest land generates more water yield than crop land if we compare at the same land use proportion and the same quantile. Therefore the afforestation from grassland is expected to have greater benefits on water yield than the switch from grassland to crop land.

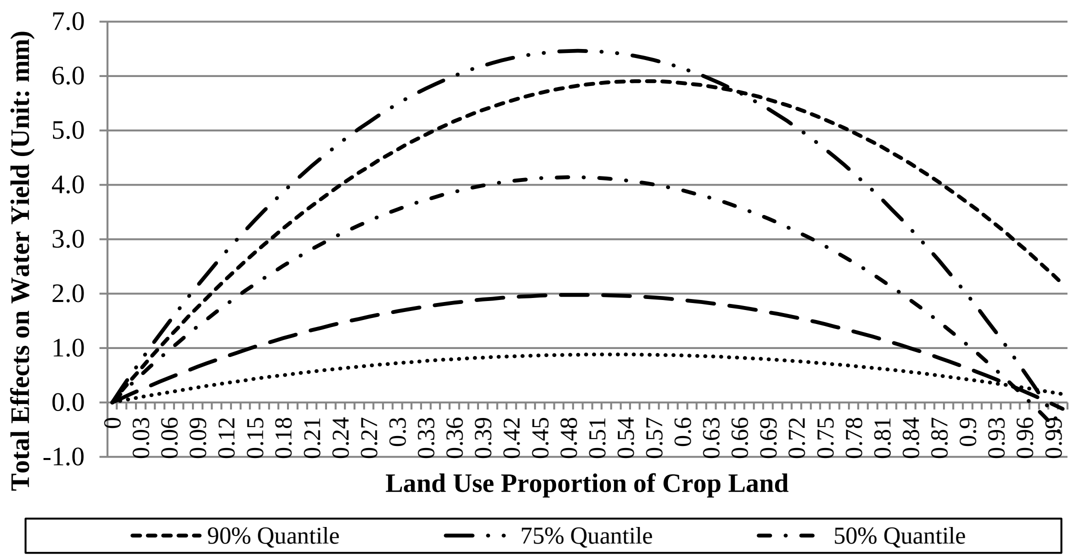

Figure 4 The Total Effects on Water Yield in Different Land Use Proportion of Crop Land

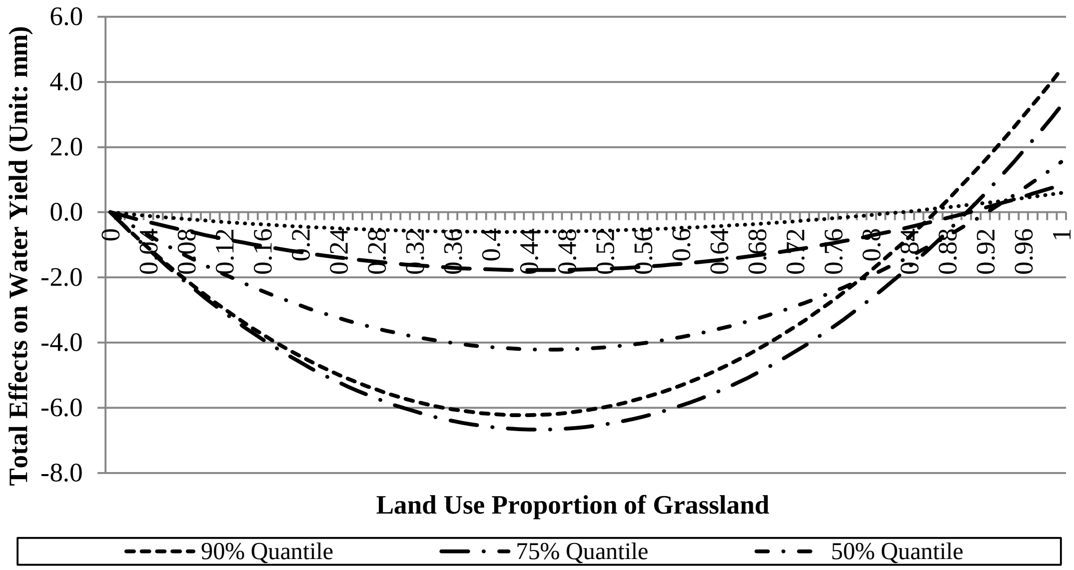

Figure 5 The Total Effects on Water Yield in Different Land Use Proportion of Grassland

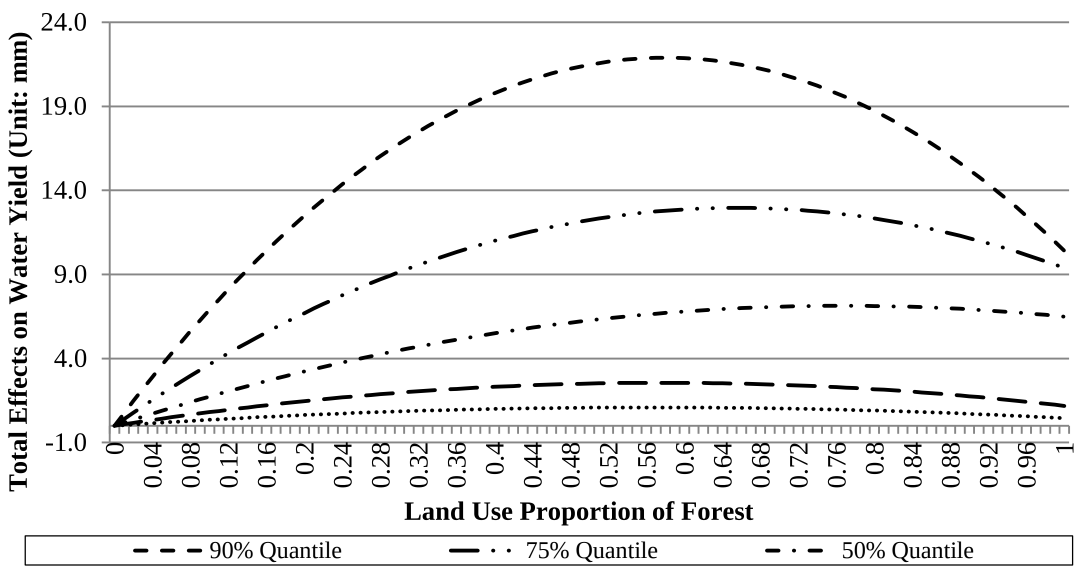

Figure 6 The Total Effects on Water Yield in Different Land Use Proportion of Forest

2.3.5. Quantile Regression Results for Water Quality

We also apply quantile regression to water quality estimating the effects of climate factors, land use variables and water yield. As specified earlier, water quality is measured by a water quality index based on total nitrogen and total phosphorus that ranges from 10 (the lowest quality) to 100 (the highest quality). There is no estimate at the 10% quantile since the water quality index is constructed with a truncated value 10 plus most of the observations at the 10% quantile are 10. Table 5 reports the results.

Most of the coefficients estimated have consistent signs; for example, if the forest land coverage is less than 70%, an increase in forest land use proportion significantly degrades water quality at the 50% and 90% quantile, as happens under an OLS estimate. Increasing forest land improves water quality in a heavily forested area (>80%). The coefficients for forest land effects at higher quantile are much greater than that at the lower quantiles, which means that an increase in forest land coverage will alter water quality more in relatively higher quality areas than in lower water quality regions. However, some quantile regression estimates have opposite results comparing to the OLS estimates. For example, the increase of grass land exhibits positive impacts on water quality at the 50% quantile while that estimated by OLS shows negative influences. El Niño and La Niña significantly improve water quality at the 90% quantile, which is consistent with the results from OLS; but El Niño and La Niña instead have significant negative effects on water quality at the 50% and 75% quantile. Therefore quantile regression provides a more complete characterization of the impacts on water quality.

Table 5 Water Quality Index Panel Data Estimation Results

	Quantile Regressions					
	10%	25%	50%	75%	90%	OLS
Water Yield	-	0.0002	-0.0003	-0.007	0.049	0.028
	-	(0.0002)	(0.001)	(0.004)*	(0.020)**	(0.006)***
Land Use (% of Total Acres)						
Urban	-	0.023	-1.550	-2.718	-26.323	-7.146
	-	(0.984)	(2.418)	(7.527)	(30.513)	(3.126)**
Urban^2	-	0.190	-0.889	0.906	-51.018	-18.631
	-	(1.741)	(5.381)	(5.561)	(50.042)	(5.937)***
Crop Land	-	-0.505	-2.640	0.975	-7.428	-2.213
	-	(1.624)	(1.449)*	(7.831)	(26.117)	(1.037)**
Crop Land^2	-	0.516	-0.408	-4.835	-38.580	-9.760
	-	(1.596)	(0.662)	(1.677)***	(26.104)	(1.075)***
Grass Land	-	-0.920	6.623	-1.156	-70.286	-17.173
	-	(1.452)	(1.858)***	(7.138)	(19.883)***	(0.947)***
Grass Land^2	-	5.324	-5.713	0.141	46.399	10.018
	-	(1.642)***	(0.822)***	(1.208)	(22.318)**	(1.086)***
Forests	-	0.541	-3.552	-5.407	-142.099	-59.158
	-	(1.608)	(1.687)**	(8.623)	(30.269)***	(1.373)***
Forests^2	-	-0.698	4.928	8.116	175.860	79.821
	-	(2.073)	(2.994)*	(4.642)*	(59.798)***	(2.543)***
Climate Factors						
# of Days with >1.0 Inch of	-	-0.001	-0.047	-0.203	-0.056	-1.407
Precipitation	-	(0.004)	(0.023)**	(0.061)***	(0.925)	(0.215)***
# of Days with >1.0 Inch of	-	0.001	0.019	0.034	0.022	0.528
Precipitation^2	-	(0.002)	(0.007)***	(0.017)**	(0.207)	(0.058)***
# of Days with ≤32.0 °F of	-	-0.002	-0.001	0.025	-0.696	-0.160
Minimum Temperature	-	(0.002)	(0.003)	(0.012)**	(0.178)***	(0.039)***
# of Days with ≤32.0 °F of	-	-0.0001	-0.0004	-0.003	-0.023	-0.010
Minimum Temperature^2	-	(0.0001)	(0.0001)***	(0.002)*	(0.005)***	(0.001)***
# of Days with ≥90.0 °F of	-	0.001	-0.004	-0.080	-0.171	-0.320
Maximum Temperature	-	(0.002)	(0.005)	(0.027)***	(0.184)	(0.055)***
# of Days with ≥90.0 °F of	-	-0.0001	-0.0005	-0.001	-0.018	-0.008
Maximum Temperature^2	-	(0.0001)	(0.0001)***	(0.001)**	(0.006)***	(0.002)***
Total Precipitation (mm)	-	-0.001	-0.006	-0.019	-0.421	-0.123
	-	(0.001)	(0.001)***	(0.006)***	(0.099)***	(0.004)***
Total Precipitation (mm)^2	-	0.0000	0.0001	0.00003	0.001	0.0001
	-	(0.0000)	(0.0000)***	(0.00002)*	(0.0003)***	(0.00001)***
Monthly Mean Temperature	-	-0.007	-0.033	-0.272	-3.891	-1.455
(°F)	-	(0.007)	(0.009)***	(0.162)*	(0.343)***	(0.028)***
Monthly Mean Temperature^2	-	0.0001	0.0003	0.003	0.031	0.014
(°F)	-	(0.0001)	(0.0001)***	(0.001)**	(0.003)***	(0.0004)***
El Niño (Dummy)	-	-0.001	-0.015	-0.011	1.259	0.405
	-	(0.004)	(0.006)**	(0.031)	(0.372)***	(0.150)***
La Niña (Dummy)	-	-0.003	-0.015	-0.039	1.069	0.646
	-	(0.005)	(0.007)**	(0.022)*	(0.363)***	(0.163)***

Note: * p<0.1, ** p<0.05 and *** p<0.01; robust standard errors are reported in parenthesis.

A number of other effects can be mentioned. The coefficient of water yield on water quality is significantly positive at the 90% quantile but negative at the 75% quantile. As reported in table 2, the value of water quality index at the 75% quantile is similar as that at the 50% quantile, and it implies that increasing water yield will improve higher water quality (WQI>90% quantile) but worsen lower water quality (WQI<75% quantile) perhaps due to runoff. The land use of urban area doesn't exhibit significant impacts on water quality, which conflicts with the study of Ahearn et al. (2005). An increase in the proportion of crop land will significantly degrade water quality at the 50% and 75% quantile. On the other hand, the increase of grass coverage will improve water quality at the 50% quantile but worsen water quality at the 90% quantile. This is consistent with what we observe in the summary statistics in table 3. The increase of forest land use will initially degrade water quality but improve water quality while the land coverage is higher than 80%.

Next we discuss the impacts from climate factors. Notice that the impacts depend on the current conditions since quantile regression includes the squared terms of some of the climate variables. The result shows that water quality will worsen as precipitation is reduced and be improved if precipitation increases. Extreme precipitation has positive impacts on water quality probably since precipitation has dilution and flushing effects. On the other hand, extreme temperature degrades water quality. This is likely because extreme lower temperature freeze water and slow down flows while extreme higher temperature causes higher evaporation or transpiration to reduce water flow and dilution; both lower water quality. The marginal effects from El Niño and La Niña have the opposite results between 50% and 90% quantile, and the absolute magnitude at the 90% quantile is larger than that at the 50% quantile.

2.3.6. Analysis of Water Implications of Mitigation Strategy Choice

We now turn toward examining the water implications of different degrees of mitigation strategy use. To do this we use the FASOMGHG model (Adams et al. 2005; Beach et al. 2010) to simulate mitigation strategy choices under alternative carbon prices and in particular land use choices. In turn the land use choices are plugged into quatile regression equations to project impacts on water quantity and quality. More precisely we use FASOMGHG to project how land coverage between cropland, grassland and forest is altered under use of several combinations of mitigation strategies and carbon prices relative to a baseline with no carbon price strategy. Then we used those results in the estimated quantile regressions to investigate the effects on water quantity and quality, holding other things equal.

FASOMGHG is used to simulate the land use change since it models choices of agricultural GHG mitigation possibilities including land use, forestry, agricultural and biofuel options across a variety of sequestration, emission reduction and biofuels-related possibilities (Adams et al. 2009).

FASOMGHG is a dynamic, nonlinear and price endogenous programming model of the U.S forest and agricultural sectors, that simulates forest and agricultural land allocation and management over time in a perfectly competitive set of markets (Adams et al. 2009; Alig et al. 1998; McCarl and Spreen 1980). This model represents agricultural crop and livestock production, livestock feeding, agricultural processing, log production, forest processing, carbon sequestration, CO2/non-CO2 GHG emissions, wood product markets, agricultural markets, GHG payments and land use (Adams et al. 2009), and it is developed to simulate intertemporal factor and commodity market equilibria that are the first order conditions resulting from maximizing inter-temporal economic welfare. The basic economic concepts are then presented by a mathematical structure starting from the following assumptions (Adams et al. 2009): (1) there are h commodities including row (primary) and processed (secondary) products produced by n firms, which use i inputs and j resources in k production processes, (2) the aggregate market is simulated by the optimization problem, which seeks to maximize the discounted sum of consumers' and producers' surpluses over time t and discount rate r (Adams et al. 1999), and (3) the optimization problem is subject to demand supply balances and resource restrictions.

Based on the above assumptions, the set of equations of FASOMGHG are presented as follows:

$$\max \sum_t \left\{ \left(\frac{1}{1+r} \right)^t \left[\sum_h \int_0^{Z_{ht}} P_{dht}\left(Z_{ht}\right) dZ_{ht} - \sum_i \int_0^{X_{it}} P_{sit}\left(X_{it}\right) dX_{it} \right] \right\}, \tag{2.5}$$

$$s.t. \qquad Z_{ht} \quad - \sum_n \sum_k c_{hnkt} Q_{nkt} \leq 0, \forall h, t, \tag{2.6}$$

$$- X_{it} \quad - \sum_n \sum_k a_{inkt} Q_{nkt} \leq 0, \forall i, t, \tag{2.7}$$

$$- \sum_k b_{jnkt} Q_{nkt} \leq Y_{jnt}, \forall j, n, t, \tag{2.8}$$

$$Z_{ht}, \;\; X_{it}, \;\; Q_{nkt} \geq 0, \forall h, i, k, n, t, \tag{2.9}$$

where Z_h, Q_{nk}, X_i and Y_{jn} refer to the consumed quantity of commodities, the level of production processes, the purchased quantities of inputs and the resource endowments, respectively, and the coefficients c_{hnk}, a_{ink} and b_{jnk} depict the quantitative relationships among these variables.

Broad GHG mitigation strategies covered in FASOMGHG include afforestation, forest management, agricultural soil carbon sequestration, fossil fuel mitigation from crop production, agricultural methane and nitrous oxide mitigation, and biofuel offsets (Adams et al. 2009). All mitigation activities are considered.

2.3.7. FASOMGHG Results

In simulating the land use change, choices under a number of alternative mitigation strategies individually and collectively are cumulated. These are as follows:

- afforestation;
- crop fertilization alternatives;
- crop tillage alternatives;
- direct land use change;
- crop management;
- livestock management;
- bioenergy management;
- forest management; and
- the joint use of all of the above strategies.

Runs are made under the use of each of these strategies with the amount of strategy stimulated by alternative carbon prices. Several hypothetical carbon prices are imposed: prices of $5, $10, $30 and $50 per metric ton CO_2 equivalent escalating at a 5% increase rate. Additionally the baseline scenario has a price of $0. The land use change is then simulated by comparing the alternative scenario with the baseline scenario.

The conterminous US is divided into 11 regions by FASOMGHG, and the simulated land use values of each mitigation policy are reported in regional level. The Missouri River Basin consists of parts of Corn Belt, Northern Plains and Rocky Mountains, and hence we do a weighted average calculation of the Missouri River Basin value based on proportions of each region falling into the Missouri River Basin, which is 10.90%, 45.72% and 43.38%, respectively.

The mitigation effects on water yield and water quality are reported in table 6, which also reports the land coverage proportion of crop land, grassland and forest land. All the values are reported for the period 2025 with years between 2025 and 2029. The land coverage of crops, grass and forests under baseline scenario are 31.35%, 37.02% and 19.84%, respectively. Here we only report and discuss the effects at the 50% quantile since the land use exhibits most significant impacts on water quality at the 50% quantile in the quantile regression analysis.

With carbon price of $5 at a 5% increase rate per year, all mitigation policies except for bioenergy management slightly increase as does crop land use comparing with the baseline scenario. Crop land use further increases with carbon price of $10 at a

5% increase rate per year. However, crop land use decreases at the higher carbon prices at $30 and $50. On the other hand, the grassland coverage moves in the opposite direction. Also when all mitigation policies are considered simultaneously, the grassland coverage increases under all price scenarios. Additionally, the forest coverage under most strategies decreases as the carbon price increases.

Under the lower carbon price scenarios, $5 and $10, water quantity is slightly increased by the mitigation strategies except when bioenergy and forest management are independently considered. The joint use of all mitigation strategies also exhibits a negative impact on water quantity. However, water quantity is decreased across the board when carbon prices of $30 and $50 are applied. The joint use of all the strategies at price $30 scenario reduces water yields by around 1.05 mm per acre. This result suggests that stronger incentives to have AF mitigating GHGEs will have adverse effects on water yield.

Generally mitigation via AF management has varied effects on water yield and water quality, depending on the carbon price. Considering all mitigation policies simultaneously decreases water yield but improves water quality.

2.4. Conclusions

This paper examines the water quality and quantity implications of using agricultural and forestry climate change mitigation strategies. To do this we first conduct a literature review then an empirical study in the Missouri River Basin investigating the effects from altered land use.

The literature review indicates that AF mitigation will impact water quality and quantity. In particular, many of the sequestration possibilities lessen water yield while increasing water quality. Also fertilization and animal management strategies have complex effects on altering water quality while having mixed effects on water quantity.

The first phase of the empirical study on the Missouri River Basin land use applied quantile regression over water data sets from the SWAT river basin simulation model. The result shows that an increase in grassland significantly decreases water yield with an increase in forest land having mixed effects. The second phase used the regression results in a mitigation policy simulation exercise. The consequent results showed that water quantities slightly increased under lower carbon price scenarios but significantly decreased under higher carbon price scenarios. On the other hand, the results showed that water quality is degraded under most mitigation alternatives except for the bioenergy and forest management when carbon price is low but with higher carbon price policies that water quality was improved.

Table 6 Effects on Water from Mitigation Policies for Period 2025

Mitigation Policies	Land Use Proportion of Crop Land (%)	Grassland (%)	Forests (%)	Effects on Water Yield (mm)	Effects on Water Quality
Baseline Scenario	31.35	37.02	19.84	-	-
Scenario of Carbon Price of $5 at a 5% Increase Rate Per Year					
Afforestation	31.47	36.97	19.67	0.0055	-0.0045
Crop Fertilization Alternatives	32.18	36.24	19.68	0.0767	-0.0430
Crop Tillage Alternatives	31.91	36.34	19.72	0.0616	-0.0332
Direct Land Use Change	32.17	36.23	19.68	0.0770	-0.0430
Crop Management	32.15	36.20	19.68	0.0738	-0.0428
Livestock Management	31.61	36.86	19.69	0.0094	-0.0101
Bioenergy Management	31.34	37.01	19.84	-0.0027	0.0003
Forest Management	32.81	37.72	17.29	-0.2708	0.0144
All the Above Strategies	32.79	37.70	17.25	-0.2745	0.0147
Scenario of Carbon Price of $10 at a 5% Increase Rate Per Year					
Afforestation	31.93	36.72	19.81	0.0213	-0.0212
Crop Fertilization Alternatives	31.93	36.71	19.83	0.0244	-0.0220
Crop Tillage Alternatives	31.66	36.81	19.86	0.0099	-0.0123
Direct Land Use Change	31.94	36.73	19.83	0.0242	-0.0218
Crop Management	31.64	36.87	19.81	0.0008	-0.0094
Livestock Management	31.93	36.72	19.75	0.0240	-0.0217
Bioenergy Management	31.36	37.03	19.82	0.0010	-0.0003
Forest Management	32.88	37.81	17.49	-0.2992	0.0182
All the Above Strategies	32.84	37.79	17.46	-0.3053	0.0192
Scenario of Carbon Price of $30 at a 5% Increase Rate Per Year					
Afforestation	27.65	46.38	17.63	-0.7200	0.3180
Crop Fertilization Alternatives	27.92	46.29	17.37	-0.7386	0.3139
Crop Tillage Alternatives	27.29	46.55	17.45	-0.7722	0.3339
Direct Land Use Change	27.97	45.92	17.23	-0.7554	0.3102
Crop Management	27.21	46.41	17.41	-0.7843	0.3351
Livestock Management	27.50	46.38	17.40	-0.7653	0.3268
Bioenergy Management	27.51	46.40	17.37	-0.7683	0.3271
Forest Management	29.75	46.07	15.03	-0.9547	0.3041
All the Above Strategies	28.97	47.57	14.72	-1.0494	0.3521
Scenario of Carbon Price of $50 at a 5% Increase Rate Per Year					
Afforestation	29.02	44.50	18.16	-0.5430	0.2425
Crop Fertilization Alternatives	28.50	44.77	17.73	-0.6423	0.2692
Crop Tillage Alternatives	28.05	45.35	17.93	-0.6482	0.2869
Direct Land Use Change	28.36	43.93	17.40	-0.6934	0.2661
Crop Management	28.00	45.47	17.92	-0.6530	0.2903
Livestock Management	28.38	45.22	17.58	-0.6733	0.2819
Bioenergy Management	27.96	45.45	17.69	-0.6888	0.2953
Forest Management	30.82	42.03	16.00	-0.7099	0.1893
All the Above Strategies	29.29	46.55	15.29	-0.9462	0.3184

3. ESSAY TWO: FEEDLOTS, CLIMATE CHANGE AND DUST- COST AND BENEFIT ESTIMATION

3.1. Introduction

The United States has a large cattle industry with many animals fed in feedlots. Dust is an issue in states where feedlots are common, and climate influences production and dust. The major climate influences on production involve heat/cold stress and drought (Gaughan et al. 2009; Howden et al. 2008). Thermal stress usually impairs immunological, physiological, metabolic or digestive functions of animals and in turn reduces animal production (Mader 2003; Nienaber and Hahn 2007). Also performance of animals varies between winter and summer particularly in colder areas. The United States Department of Agriculture (USDA) reported that in 2005 digestive problems, metabolic problems and weather issues accounted for around 25.9% of cattle deaths.[8] Therefore adaptation activities that reduce the vulnerability of livestock, including animal management and animal adaptation, are needed (Gaughan et al. 2009).

Feedlots are generally in drier areas with dust emissions arising from manure or animal activities and being a major cause of respiratory problems. In turn this increases animal morbidity and mortality. The USDA estimated that in 2005 1.11 million head of U.S. cattle and calves died from respiratory problems, amounting to about $680 million

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

in losses.[9] Dust suppression is thus an important industry issue (Cambra-López et al. 2010).

Previous climate change studies that examined livestock focused on temperature, precipitation and humidity impacts on livestock productivity (Davis et al. 2003; Gaughan et al. 2009; Howden et al. 2008) while in our study both climate and dust effects will be considered. This essay examines economic effects of both climate change and dust stimulated respiratory morbidity on feedlot cattle profitability. Additionally the economic consequences of possible dust control options will be explored.

To examine climate and dust impacts we will first estimate an econometric model that relates climate conditions and dust incidence to cattle weight. Then we will develop a dynamic programming model of livestock feeding and growth and solve it with and without climate change and dust control efforts to examine the costs and benefits of climate change and dust control.

3.2. Background

The United States ranks fourth globally in cattle production after India, Brazil and China. In 2012 the US accounted for 12.3% of global production (USDA 2012).[10] Within the US the top 7 states are Texas, Kansas, Nebraska, Iowa, Colorado, California and Wisconsin. During 2010, these 7 states had around 44% of the national cattle

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

[10] USDA (April 2012) Reports of "Livestock and Poultry: World Markets and Trade."

inventory, marketing more than half of the nation's beef and producing $30.1 billion in gross income or 58% of the national amount as shown in table 7.

Table 7 Statistics on Cattle Herd Size and Value in the 7 Largest States: January 1, 2010

	All Cattle and Calves		Cattle Only		Marketing[2]		Gross Income[3]
	Inventory	Total Value	Number Slaughtered	Total Live Weight[1]	Cattle	Calves	
	(Thousands)	(Million $)	(Thousands)	(Million lbs)	(Thousands)	(Thousands)	(Million $)
Texas	13,300	10,108	6,674	8,179	6,610	155.0	7,587
Kansas	6,000	4,740	6,517	8,347	5,309	1.5	6,547
Nebraska	6,300	5,355	6,938	9,109	5,678	85.0	7,207
Iowa	3,850	3,196	(D)[4]	(D)	2,344	102.0	2,929
Colorado	2,600	2,210	2,507	3,267	2,140	100.0	2,862
California	5,150	4,944	1,732	2,204	2,160	541.0	2,101
Wisconsin	3,400	3,536	1,744	2,292	792	415.0	883
U.S.	93,881	78,150	34,249	43,662	45,047	8,783	51,975

Source: available via <http://www.nass.usda.gov/Publications/Ag_Statistics/2011/Chapter07.pdf>, National Agricultural Statistics Service (NASS, 2011). [1] Excludes postmortem condemnations. [2] Includes custom slaughter for use on farms where produced and State outshipments, but excludes interfarm sales within the State. [3] Includes cash receipts from sales of cattle, calves, beef, and veal plus value of cattle and calves slaughtered for home consumption. [4] (D) means that data is withheld to avoid disclosure.

The USDA provides information on sources of death loss to cattle and calves, which indicates that respiratory problems cause the highest mortality of livestock. Table 8 shows the loss estimates in the top 7 cattle producing states for 2005 and 2010. Texas was estimated to lose about 142,500 head of cattle and calves valued at about $88 million in 2005, and 151,100 in 2010. Kansas had higher proportional losses from respiratory problems, estimated at 57.2% and 63.4% of cattle and calf deaths from all causes in 2005 and 2010, respectively. The main causes of respiratory problems are bacterial pathogens and viral infections (Edwards 2010), and dust is a carrier of viruses and bacteria thus being a major contributor to respiratory problems (Amosson et al.

2006; Harry 1978; Pearson and Sharples 1995). Dust causes not only respiratory problems but also aspiration pneumonia, heat stress and feed conversion efficiencies.

Table 8 Estimates of Losses of Cattle and Calves from Respiratory Problems

	% of Total Deaths from All Causes		Numbers of Total Deaths from Respiratory Problems (Head)		Values of Total Deaths from Respiratory Problems (1,000 Dollars)	
	2005	2010	2005	2010	2005	2010
Cattle						
U.S.	24.3%	25.9%	418000	448,910	405,417	428,002
Texas	18.1%	21.7%	54,500	67,184	49,709	59,727
Kansas	57.2%	63.4%	77,200	79,240	80,466	80,586
Nebraska	45.3%	39.1%	43,000	43,042	48,114	48,551
Iowa	41.5%	45.4%	27,000	31,759	29,133	34,840
Colorado	33.2%	39.1%	16,600	21,517	17,362	22,313
California	20.5%	26.9%	20,500	42,410	19,729	24,845
Wisconsin	14.1%	17.2%	9,200	12,889	8,811	12,231
Calves						
U.S.	29.7%	26.8%	692,000	604,989	274,697	214,699
Texas	32.6%	24.3%	88,000	70,500	35,859	24,957
Kansas	40.4%	33.7%	28,000	26,939	11,771	10,183
Nebraska	32.1%	22.0%	24,100	18,713	10,265	7,354
Iowa	29.1%	30.2%	32,000	28,735	12,591	10,345
Colorado	27.6%	28.4%	15,200	15,617	6,201	5,809
California	36.9%	43.8%	61,000	59,089	22,115	20,563
Wisconsin	32.2%	36.7%	45,000	51,338	22,022	21,716

Source: NASS USDA (2006; 2011).

Most of the dust in a livestock building is from feed (Honey and McQuitty 1979; Heber et al. 1988). On the other hand, large intensive feeding operations have dust mainly arising from manure, that is, cattle walking over dry and loose manure presenting on the corral surface generates most of the airborne dust (Amosson et al. 2006; Auvermann et al. 2000). In turn such emissions cause morbidity and mortality losses.

Considering the above facts, dust imposes costs on cattle producers and hence reduces feedlot revenue and profit.[11] Therefore dust suppression is a possible action that feedlot operators can employ to reduce costs by controlling sickness and reducing death rates. The proposed dust control strategies include manure harvest (Bretz et al. 2010; Auvermann et al. 2000) and water applications via trucks (Amosson et al. 2008), traveling guns (Amosson et al. 2007) and sprinklers (Amosson et al. 2006; Edwards 2010).

Climate change is another contributing factor and may influence future livestock production directly through fecundity and appetite (Frank et al. 2001; Mader et al. 2009; Nienaber and Hahn 2007) or indirectly through altered feed supplies (Reilly et al. 2002). Additionally drier and hotter conditions can increase dust emissions. Many of the feedlot areas are projected to face a drier and hotter climate potentially raising dust incidence and feed prices (Cook and Seager 2013; Coats et al. 2013; McCarl 2011; Seager et al. 2007; Seager et al. 2013) plus decreasing stocking rates (Mu et al. 2013). Therefore climate change may stress the industry in terms of productivity, feed costs, feeder cattle availability and dust incidence.

3.3. Literature Review

EPA defines six principle pollutants[12] under the 1990 Clean Air Act (Greenstone 2004).[13] Particulate matter (PM) is one main contributor to air pollution and is

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[11] < http://feedlotenvironmental.com/dust.html>.

[12] The six principle pollutants are carbon monoxide, lead, nitrogen dioxide, particulate matter, ozone, and

commonly measured using PM_{10} which indicates the average concentration of particulars on less than 10 micrometers (μm) during a day and $PM_{2.5}$ which is the average concentration of particulates of size less than 2.5 micrometers. Both primary and secondary standards[14] for PM_{10} were 150 μg/m^3 for a 24-hour average and those for $PM_{2.5}$ are 15.0 μg /m^3 for an annual average. The purpose of these standards is to indicate when there are conditions potentially dangerous to the health of human beings and animals in turn causing respiratory problems such as asthma, allergies, pneumonia and premature death.

Large confined cattle feeding operations emit large amounts of potentially airborne particulate matter (Sweeten et al. 1996). Sweeten et al. (1996) estimate that approximately 900 kg of dry manure are generated by an animal during a normal 150 day fattening period. A substantial amount of that dry manure becomes air-borne dust. Dust from animal feeding operations (AFO) has been found to adversely affect both animal and human health (Andersen et al. 2004; Donham 2000; Loneragan et al. 2001; MacVean et al. 1986).

Pearson and Sharples (1995) review the findings related to airborne dust concentrations in livestock buildings and the effects of dust on both workers and animals, indicating both workers and animals would suffer from dust induced respiratory

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sulfur dioxide.

[13] Also see the website: < http://www.epa.gov/air/criteria.html>.

[14] These two types of standards were phrased by EPA as follows: "***Primary standards*** set limits to protect public health, including the health of "sensitive" populations such as asthmatics, children, and the elderly. ***Secondary standards*** set limits to protect public welfare, including protection against decreased visibility, damage to animals, crops, vegetation, and buildings."< http://www.epa.gov/air/criteria.html#5>, June 2010.

problems. Cambra-Loṕez et al. (2010) review air pollution problems in livestock houses and argue that particulate matter control is a principal challenge for modern livestock production.

Numerous authors have discussed the economic losses caused by aerial pollution or the benefits of dust control (Amosson et al. 2006; 2007; 2008; Bretz et al. 2010; Morck et al. 1993; Sanderson et al. 2008; Smith 1998; Snowder et al. 2006). The most direct impact of dust is loss of productivity. For example, Morck et al. (1993) find that the average daily gain (ADG) of a calf experiencing a respiratory disease is 0.18 kg lower than that of a healthy calf and that the calf even has 0.33 kg lower ADG if it experienced the disease two or more times. Snowder et al. (2006) estimate an 8-kg difference between a healthy and a bovine respiratory disease infected calf over a 200-day feeding period amounting to a $13.90 economic loss.

A number of studies have investigated how climate factors affect livestock productivity. The overall climate impacts on livestock include alterations in: feed-grain production, availability and price; pasture and forage crop production and quality; animal health, growth and reproduction; disease and pest distributions; animal health; growth rate; mortality and morbidity; feed intake, appetitie loss, and conversion rates; milk production; and conception rates (Hansen et al. 2001; Huynh et al. 2005; Kerr et al. 2003; Kerr et al. 2005; Mader et al. 2009; Wolfenson et al. 2001)**.**

Adams (1998), Hahn (1995) and Mader et al. (2009) review evidence that animal mortality, feed conversion rates, rates of gain, milk production, conception rates and appetite are altered by hotter temperatures. Davis et al. (2003), Johnson (1987) and

Kadzere et al. (2002) indicate that a temperature-humidity index (THI) higher than around 72 results in declining animal performance. Mader et al. (2009) simulate beef cattle production under climate change and project that US beef cattle would need up to a 16% longer feeding period to grow from 350kg to 550kg during the summer and early fall (June 1 to October 31), with a year round average of a 4% to 5% longer period. However, they do not consider changes in the risk of mortality or morbidity during the feeding period.

Additionally studies have found that a change in the frequency and intensity of extreme events can reduce livestock productivity. For example, Hahn et al. (1997) note that the heat waves of 1995 and 1999 caused severe cattle losses in US states approaching 5,000 head each year.

Feed availability and quality will also be affected by climate change in terms of crops (Easterling III et al. 1993; Ehleringer et al. 2002; Morgan 2005) and forages. The forage effects involve changes in grass growth (Reilly et al. 2002), and changes in forage quality including the effects of higher concentrations of CO_2 on chemical content, nutritional value and digestibility (Adams et al. 1998; Allen Consulting Group 2005).

In terms of farm incomes Belasco et al. (2009) simulate the feedlot returns profitability distribution considering sale prices minus costs of feeder cattle, feed, veterinary and interest costs along with mortality rates. However, they do not consider dust induced morbidity rate. Our analysis will extend and unify the climate and profitability considerations addressed in these studies.

This analysis will examine the economic effects of climate and dust on cattle in feedlots plus possible dust control with and without climate change. 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. The benefits of dust control will be estimated by applying dynamic programming.

3.4. Data Description

The first effort herein involves estimation of the relationship between cattle finishing weight, dust and climatic factors. This will be done through econometric estimation with the dependent variable being average cattle live sale weight, and the independent variables include:

- dust level (PM_{10}),[15]
- temperature,
- precipitation,
- temperature-humidity index (THI) since high temperature and low humidity cause manure to become light and more easily emitted as dust (Amundson et al. 2006; Mayer et al. 1999),[16]
- price of feeder cattle and fed cattle,
- feed costs, and

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[15] 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.

[16] $THI = (0.8 \times T) + [(\%\, relative\ humidity/100)] \times (T - 14.3)] + 46.4$,
where $\%\, relative\ humidity = (6.1121) \times \exp\left\{\left(18.678 - \frac{T}{234.5}\right) \times \left(\frac{T}{257.14+T}\right)\right\}$, and T is temperature in °C.

- morbidity rates.

To carry out the estimation a monthly panel data set is assembled for the 7 largest cattle feeding states (Texas, Kansas, Nebraska, Iowa, Colorado, California and Wisconsin) from 1993 to 2010. This results in 216 potential observations for each state over time. However, there were only 132 observations for Iowa because of confidentiality concerns since 2004 and only 108 observations for Texas because of a lack of PM_{10} records since 2002, resulting in a total of 1320 observations.

Data sources and manipulations are described below:

- **Historical cattle price and weight:** Monthly cattle price and sale weight data are drawn from USDA National Agriculture Statistics Service Quick Stats.[17] The weight data used are the average monthly state commercial slaughter weight on a live animal basis. The price data are price received per hundred weight ($/Cwt). Both price and weight data are for cattle weighing more than 500 lbs. The cattle prices are transformed to a real 2010 basis using the consumer price index (CPI).[18]
- **Feeder cattle purchasing costs:** The purchase cost for feeder cattle is the price paid per hundred weight ($/cwt) and are obtained from the National Agricultural Statistics Service (NASS). These data are only available at the national level on a monthly basis.
- **Expenditures on feed:** To avoid confidential data disclosure USDA only reports total state expenditures on feed and the percent that feed is of the production

[17] <http://quickstats.nass.usda.gov/>.
[18] <http://www.bls.gov/data/inflation_calculator.htm>.

expenses. Generally the quantity of roughage/forage fed daily is approximately 1.5%-2.5% of a cow's body weight on a dry matter basis, depending on its age, class (dry, lactating, or gestation) or forage type (Burris and Johns 1996; Fluharty and Loerch 2013; Rasby et al. 1995). The dry matter of feeds is between 80%-92% based on the feed type, and hence we could estimate the amounts of roughage/forage a cow need per day. For example, a 900 lb cow which needs 2.25% dry matter intake will consume around 20 lbs of corn (containing 88% dry matter) plus 1lb of protein supplement per day. With corn (forage) at $6/ bu and corn meal (protein supplement) at $14.3/cwt in 2012, the feeding cost is thus estimated about $2 per day. Accordingly, for a cow placed at 550 lbs and finished at 1200 lbs spending 26 weeks in the feedlot, the 2012 total feeding cost is about $469 during the entire feeding period or averages $18 per week.

- **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).[19] Temperature is measured in degrees Fahrenheit and precipitation is in millimeters. Many studies have considered the influences of extreme events such as thermal stress or cold stress (Mader 2003; Nienaber and Hahn 2007; Tarr 2007). We include monthly maximum and minimum temperature data. The climatic data are transformed to a state level average using a cattle sale weighted average across the climate divisions demarcated by NOAA within each

[19] <http://www7.ncdc.noaa.gov/CDO/CDODivisionalSelect.jsp#>.

state. The weighting was done based on the proportion of cattle sales falling in each climate division. For example, around 98.19% of the cattle sold in Texas are raised in the first climate division, and hence the state level climatic data are obtained by weighting the data from that area by 98.19% and other areas accordingly. Table 9 reports the proportion of sales by climate division levels, and figure 7 shows the climate divisions in each state.

- **Historical dust level data (PM):** Dust as measured by PM_{10} (thoracic fraction which is less than 10 μm) are obtained from the EPA report, Emissions by Category Report-Criteria Air Pollutants and measured hourly in ug/m^3, and the PM_{10} reports can be found on an hourly, daily, or weekly basis and this varies by measurement site.[20] To develop a dust variable we first average the records to a monthly basis for each station and then average values across the stations in each climate division. Finally we aggregate the climate division PM_{10} level to a state PM_{10} level based on cattle sale proportion.

- **The projected climate conditions:** Projected climate change alterations in temperature and precipitation are drawn for the A1F SRES scenario from runs of the Hadley Centre Coupled Model (HADCM) for period 2020, 2050 and 2080 as reported on the IPCC website.[21]

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[20] <http://www.epa.gov/air/data/emcatrep.html?st~KS%20NE~Kansas%2C%20Nebraska>.

[21] Period 2020, 2050 and 2080 refer to the period 2010-2039, 2040-2069 and 2070-2099, respectively.

Table 9 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.

- **Empirical morbidity rate:** The morbidity rate for animals independent of dust losses is drawn from Sanderson et al. (2008). Based on their results when the initial animal weight is less than 550 pounds, the morbidity rates are specified as descending from 6.2% in the first week after placement to around 0.01% in the 12th week in the pattern given in table 10. When the placement weight is between 550 and 650 pounds, the morbidity rate is 2.4% in the first week after placement and decreases in the following weeks again as in table 10.

Table 11 contains summary statistics for the climatic and cattle performance data. The climate data are weighted averages over climate division based on the proportion of cattle sales in each climate division in each state. As shown in table 11, average cattle live sale weight in Texas is the lightest (1124 lbs) while that in Wisconsin is the heaviest (1291 lbs). Cattle grown in Nebraska and Wisconsin have the highest variation in live sale weights. The sale price of cattle in Wisconsin is lowest

($67.43/cwt) while that in Colorado is highest ($99.31/cwt). Basically Wisconsin and California produce the heaviest cattle but face the lowest prices.

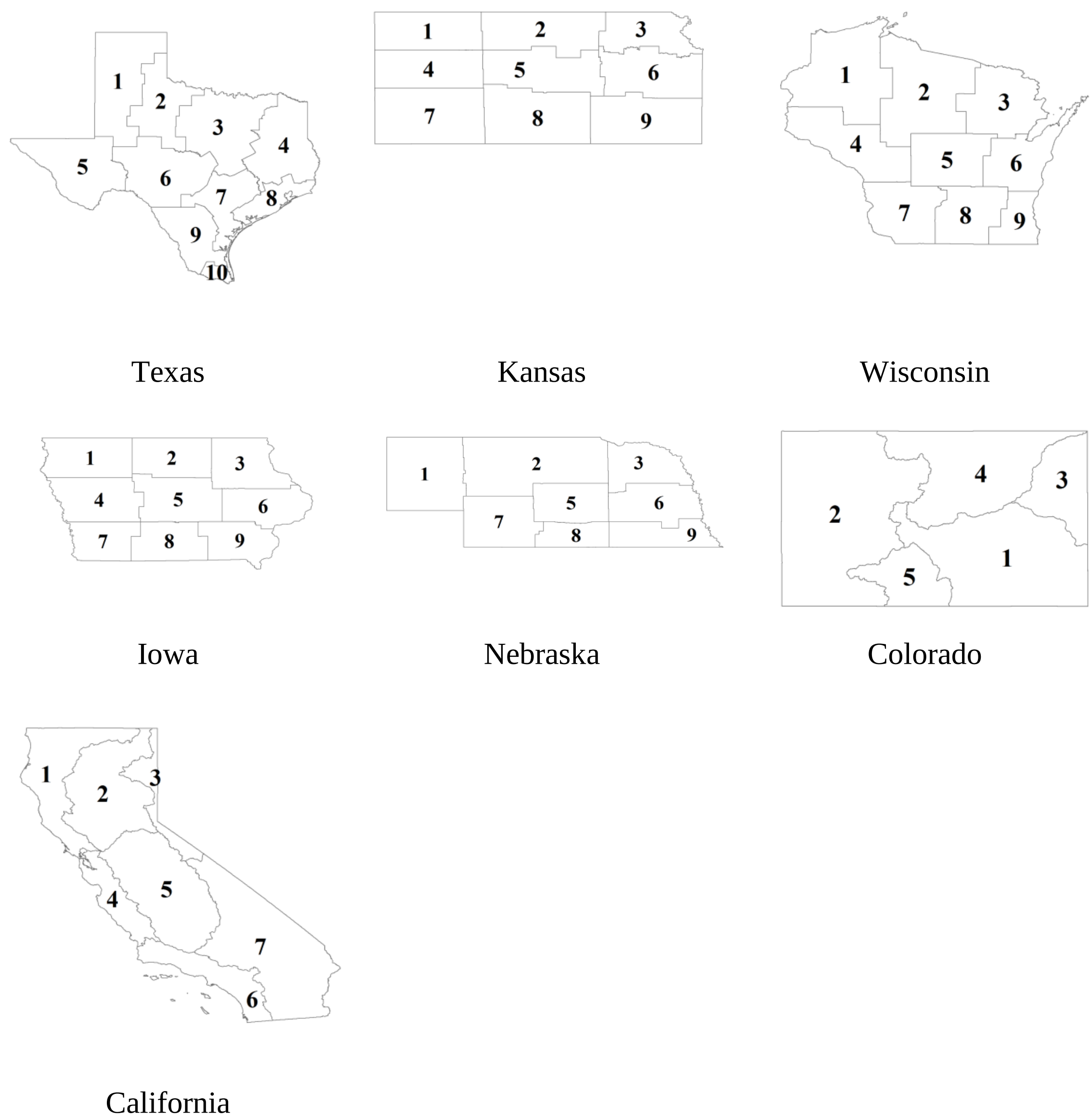


Figure 7 The Climate Divisions Demarcated by NOAA.

Table 10 Weekly Morbidity Rates from Respiratory Problem

Initial Weight Category [1]	Week1	Week2	Week3	Week4	Week5	Week6	Week7
<550 lbs	6.2%	2.6%	3.2%	1.4%	2.9%	2.2%	1.3%
550 lbs ~ 650 lbs	2.4%	2.3%	2.0%	1.7%	1.1%	1.2%	0.8%
>650 lbs	0.7%	0.6%	0.7%	0.3%	0.5%	0.2%	0.2%
	Week8	Week9	Week10	Week11	Week12	Week13~26 [2]	
<550 lbs	1.1%	0.01%	0.7%	0.3%	0.01%	0.0001%	
550 lbs ~ 650 lbs	0.3%	0.8%	0.4%	0.3%	0.4%	0.0001%	
>650 lbs	0.1%	0.15%	0.2%	0.1%	0.001%	0.0001%	

Note: 1. The rates is from Sanderson et al. (2008). 2. The morbidity rate almost descends to zero after 13th weeks.

Dust levels in Wisconsin and Nebraska are lowest among these seven states (8.58 ug/m^3 in Wisconsin and 11.75 ug/m^3 in Nebraska). California, Texas, Iowa and Kansas have the highest dust levels and exhibit the most variation. For the temperature-humidity index (THI), Texas and Colorado have the highest and lowest THI, respectively. The environment is considered comfortable when THI values are 70 or less following Kadzere et al. (2002), and the THI in Texas is the most likely to reach the upper threshold of environmental comfort level for cattle with maximum THI 69.79 reported. Figure 8 gives box-and-whisker plots of climate factors in each state. For example, the bottom left figure presents the distribution of average monthly temperature difference, which shows that the monthly temperature in California and Texas varies the most. The bottom right figure shows the distribution of average monthly precipitation, and Texas seems to have more extreme rainstorms than other states while California has much steady rainfall.

3.5. Methodology and Estimation

The basic estimation problem involves panel data estimation on how cattle sale weight is affected by the independent variables. The panel data set spans years and 7 cattle producing states. Then given that for each state i we have observations for month t on a set of independent variables (X_{it}) for T time periods, and the average live sale weight (W_{it}) can be estimated using the following linear panel data model:

$$W_{it} = X_{it}^{T}\beta + u_{it}, \tag{3.1}$$

where t represents month of sale during the time period from January 1993 to December 2010. W_{it} is a scalar, and X_{it} is a vector of the explanatory variables for state $i = 1, 2, \cdots, N$ and month $t = 1, 2, \cdots, T$.

The independent variables are

- climate data including monthly particulate matter level, temperature-humidity index, maximum temperature, minimum temperature and precipitation;
- seasonal dummies indicating spring, summer and fall which consist of March to May, June to August and September to November, respectively;
- state dummy variables;
- interaction terms between climatic variables and the state dummy variables;
- the lagged terms of both climatic variables for 2 months and all of the interaction terms.

The state dummy variables are included to capture spatial differences, as are interaction terms between climatic variables and states. We include the lagged terms since cattle growth is a dynamic progress and current live sale weight is affected by both current and previous climate conditions. This reduces the number of usable observations by 14 (2 lagged terms in 7 states), and the final number of observations in the regression is 1306.

Pooled ordinary least squares (POLS) is applied as in Wooldridge (2010), and the consistent POLS parameter, $\hat{\beta}$ and its asymptotic robust variance-covariance matrix of the extimator (VCE), $A\hat{v}ar\left(\hat{\beta}\right)$, could be written as

$$\hat{\beta} = (\boldsymbol{X}^T\boldsymbol{X})^{-1}\boldsymbol{X}^T\boldsymbol{W}, \tag{3.2}$$

$$A\hat{v}ar\left(\hat{\beta}\right) = (\boldsymbol{X}^T\boldsymbol{X})^{-1}\hat{\boldsymbol{S}}_{\boldsymbol{T}}(\boldsymbol{X}^T\boldsymbol{X})^{-1}, \tag{3.3}$$

In expression (3.3), the variance estimates, $\hat{\boldsymbol{S}}_{\boldsymbol{T}}$, are defined as in Newey and West (1987):

$$\hat{S}_T = \frac{NT}{NT-K}\left\{\boldsymbol{X}^T\hat{\Omega}_0\boldsymbol{X} + \sum_{j=1}^{m(T)}\left(1-\frac{j}{m(T)+1}\right)\left[\hat{\Omega}_j + \hat{\Omega}_j^T\right]\right\}, \tag{3.4}$$

where the variance estimates for no autocorrelation, $\boldsymbol{X}^T\hat{\Omega}_0\boldsymbol{X}$, are calculated using the White formulation:

$$\boldsymbol{X}^T\hat{\Omega}_0\boldsymbol{X} = \sum_{t=1}^{T}\sum_{i=1}^{N}\hat{u}_{it}^2 x_{it}^T x_{it} \tag{3.5}$$

and the $(K+1)\times(K+1)$ matrix $\hat{\Omega}_j$ is defined as:

$$\hat{\Omega}_j = \sum_{t=j+1}^{T}\sum_{i=1}^{N(t)}\hat{u}_{it}\hat{u}_{it-j}x_t^T x_{t-j} \tag{3.6}$$

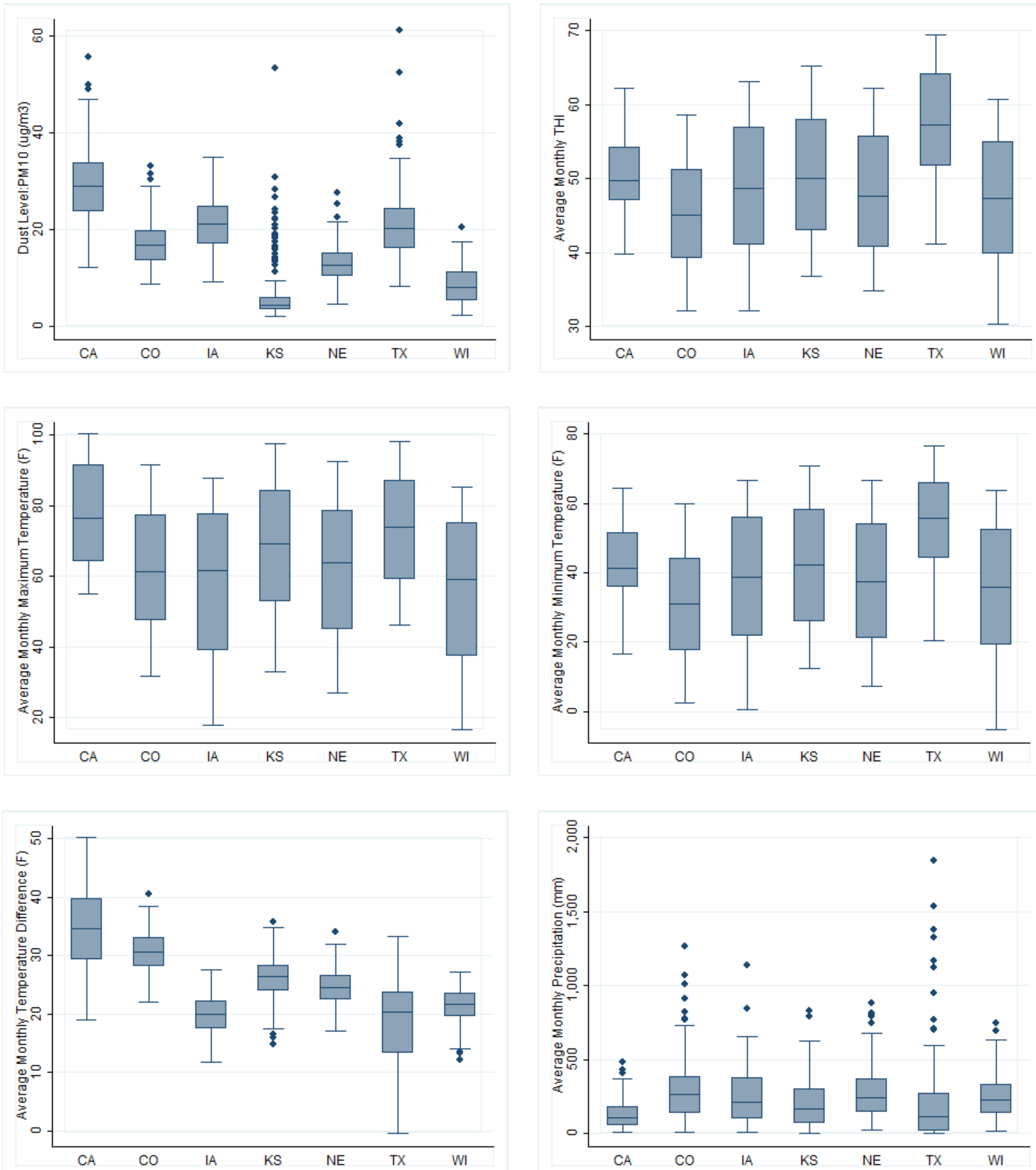
This estimator is called Driscoll and Kraay's covariance matrix estimator.

Table 11 Variable Summary Statistics for Monthly Data in Each State, 1993 to 2010

	State	Mean	Std. Dev.	Max	Min
Cattle Live Sale Weight (lbs)	Texas[2]	1124.30	29.96	1194	1068
	Kansas	1218.22	49.39	1322	1090
	Nebraska	1263.14	54.72	1380	1129
	Iowa[2]	1214.34	36.81	1306	1101
	Colorado	1250.90	50.72	1366	1129
	California	1272.57	40.27	1382	1200
	Wisconsin	1291.22	52.18	1379	1172
Cattle Price[1] ($/ cwt)	Texas[2]	91.12	10.78	120.05	73.81
	Kansas	93.93	9.05	123.07	78.39
	Nebraska	94.29	9.21	120.19	76.35
	Iowa[2]	88.93	9.83	118.88	72.72
	Colorado	99.31	13.38	132.16	77.59
	California	71.69	10.22	102.23	53.10
	Wisconsin	67.43	7.64	92.41	54.74
Dust Level PM_{10} (ug/m^3)	Texas[2]	20.79	7.38	51.24	8.29
	Kansas	16.11	7.79	58.61	2.34
	Nebraska	11.75	3.38	21.75	4.11
	Iowa[2]	19.73	5.98	37.00	9.93
	Colorado	17.75	3.99	31.68	8.79
	California	29.18	7.53	55.30	12.24
	Wisconsin	8.58	3.66	20.45	2.29
Monthly Maximum Temperature (°F)	Texas[2]	73.21	15.06	98.05	46.23
	Kansas	68.30	17.42	97.63	33.04
	Nebraska	61.69	18.90	92.49	27.13
	Iowa[2]	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 Minimum Temperature (°F)	Texas[2]	54.82	15.20	77.00	24.10
	Kansas	41.95	17.12	69.82	12.49
	Nebraska	37.09	17.69	66.04	7.14
	Iowa[2]	38.00	18.53	66.68	0.67
	Colorado	31.53	14.93	58.25	0.68
	California	42.97	9.60	66.05	21.61
	Wisconsin	34.65	18.35	63.70	-4.33
Monthly Temperature Difference (°F)	Texas[2]	18.39	6.64	29.84	0.10
	Kansas	26.34	3.53	34.93	14.00
	Nebraska	24.60	3.16	33.59	17.47
	Iowa[2]	19.81	3.48	28.31	11.26
	Colorado	30.63	3.62	41.68	21.96
	California	34.42	6.52	48.27	19.46
	Wisconsin	21.22	3.05	28.58	13.35
Temperature and Humidity Index	Texas[2]	56.95	7.98	69.79	42.06
	Kansas	50.49	8.20	64.88	37.05
	Nebraska	48.17	8.23	62.54	34.76
	Iowa[2]	48.63	8.63	62.92	31.98
	Colorado	45.50	6.73	31.98	58.11
	California	50.65	4.56	62.54	40.98
	Wisconsin	47.02	8.37	61.16	29.83
Monthly Mean Precipitation (mm)	Texas[2]	212.04	319.36	1693.79	0.30
	Kansas	209.19	164.77	972.72	2.78
	Nebraska	280.73	173.49	911.99	30.16
	Iowa[2]	243.11	178.28	923.58	12.97
	Colorado	294.76	207.11	1167.34	15.41
	California	124.54	85.96	463.16	7.97
	Wisconsin	257.53	163.69	877.30	15.03

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

[2] Data in Texas is from Jan. 1993 to Dec. 2001 because of missing records, and data in Iowa is from Jan. 1993 to Dec. 2003 because of data withheld.



Note: The boxes cover the interquartile range, and the upper (lower) whisker is at the upper (lower) quartile plus (minus) 1.5 times the interquartile range, or the maximum (minimum) value if it is smaller (larger). Data outside the whiskers are outliers and represented with dots.

Figure 8 Box-and-Whisker Plots of Monthly Climate Factors

3.5.1. Estimation Results of Linear Panel Data Model

In this section we present and discuss the results from several variants of the model on a state basis. Table 12 through table 14 report the estimation results for equation (3.1). Table 12 presents the basic model without distinguishing the effects across different states with alternative sets of climate variables. These results demonstrate that dust level (PM_{10}), at least during the one-month lagged period, has consistently negative impacts on cattle live sale weight. The absolute values of the PM_{10} parameter estimates are significantly amplified as we add more climatic variables moving from model (1) to model (4). Comparing model (3) with model (2), the addition of monthly minimum temperature causes dust to have a larger negative influence, and it also enlarges the monthly maximum temperature parameter estimates. Moreover, we find that monthly maximum temperature has positive impact on cattle live sale weights while the impact from monthly minimum temperature is negative when both monthly maximum and minimum temperature are included in model (3), and it outlines that the relative impacts might be captured more completely from the extreme conditions rather than from the average conditions. The opposite impacts from monthly maximum and minimum temperature will be further discussed below.

We have the most complex climate specification in model (4) where we add the temperature-humidity index and precipitation variables. That model shows positive parameter estimates for monthly maximum temperature and monthly minimum temperature changes. To more accurately identify the impacts of both monthly maximum temperature and monthly minimum temperature, we will later include the interaction terms of climatic variables and states. Also monthly minimum temperature and the temperature-humidity index have opposite effects on cattle live sale weight in model (4) in table 12.

Table 12 Estimate Results of Climate Variables on Cattle Weight: Basic Models

	Model 1: Dust Level (PM_{10}) Only	Model 2: Add Monthly Maximum Temperature	Model 3: Add Monthly Minimum Temperature	Model 4: Add Temperature -Humidity Index and Precipitation
Dust Level (PM_{10})	-0.546	-0.417	-1.314	-1.224
	(0.32)	(0.33)	(0.31)***	(0.31)***
One-month Lagged Dust Level (PM_{10})	-0.593	-0.606	-1.147	-1.322
	(0.24)**	(0.24)**	(0.26)***	(0.28)***
Two-month Lagged Dust Level (PM_{10})	-0.611	-0.898	-1.413	-1.272
	(0.30)*	(0.30)**	(0.30)***	(0.34)**
Monthly Maximum Temperature		-0.123	2.198	1.800
		(0.32)	(0.40)***	(0.44)***
One-month Lagged Monthly Maximum Temperature		-0.084	1.734	2.048
		(0.40)	(0.44)***	(0.45)***
Two-month Lagged Monthly Maximum Temperature		0.367	1.756	1.401
		(0.38)	(0.46)***	(0.51)**
Monthly Minimum Temperature			-2.786	6.351
			(0.34)***	(1.94)**
One-month Lagged Monthly Minimum Temperature			-1.723	-9.876
			(0.36)***	(2.46)***
Two-month Lagged Monthly Minimum Temperature			-1.578	5.582
			(0.35)***	(2.05)**
Temperature-humidity Index				-18.641
				(3.77)***
One-month Lagged Temperature-humidity Index				17.044
				(5.09)**
Two-month Lagged Temperature-humidity Index				-14.802
				(3.96)**
Monthly Mean Precipitation				-0.016
				(0.01)
One-month Lagged Monthly Mean Precipitation				-0.001
				(0.01)
Two-month Lagged Monthly Mean Precipitation				0.011
				(0.01)
Constant	1274.47	1267.08	1179.17	1694.75
	(8.82)***	(17.44)***	(15.66)***	(187.10)***
R-squared	0.04	0.05	0.28	0.29

Note: * p<0.1, ** p<0.05 and *** p<0.01; Driscoll and Kraay's standard errors are reported in parenthesis.

Table 13 Estimated Results of Climate Variables on Cattle Weight: Complete Model

Variables		Variables		Variables	
Dust Level		***Maximum Temperature***		***Precipitation***	
in Texas at t	-0.182 (0.53)	in Texas at t	0.106 (0.65)	Precipitation	0.003 (0.01)
in Texas at t-1	-0.720 (0.42)	in Texas at t-1	0.480 (0.62)	Precipitation $_{t-1}$	0.007 (0.01)
in Texas at t-2	0.020 (0.47)	in Texas at t-2	-0.320 (0.61)	Precipitation $_{t-2}$	0.008 (0.01)
in Kansas at t	-1.464 (0.72)*	in Kansas at t	2.267 (1.13)*		
in Kansas at t-1	0.235 (0.53)	in Kansas at t-1	0.734 (1.05)		
in Kansas at t-2	-1.715 (0.64)**	in Kansas at t-2	2.192 (1.10)*	***Season Dummy***	
in Nebraska at t	-5.988 (1.05)***	in Nebraska at t	4.804 (1.24)***	Mar.-May	0.410 (5.36)
in Nebraska at t-1	-5.786 (1.27)***	in Nebraska at t-1	4.471 (1.26)**	Jun.-Aug.	3.630 (8.00)
in Nebraska at t-2	-4.058 (1.19)**	in Nebraska at t-2	3.465 (1.34)**	Sep.-Nov	12.498 (7.36)
in Iowa at t	1.379 (0.98)	in Iowa at t	1.412 (1.49)		
in Iowa at t-1	0.222 (0.97)	in Iowa at t-1	0.776 (1.23)		
in Iowa at t-2	1.338 (1.33)	in Iowa at t-2	1.432 (1.68)	***State Dummy***	
in Colorado at t	1.911 (1.17)	in Colorado at t	0.964 (1.31)	Kansas	-2099.78
in Colorado at t-1	2.404 (1.13)*	in Colorado at t-1	-0.148 (1.06)		(514.13)***
in Colorado at t-2	0.357 (1.50)	in Colorado at t-2	1.219 (1.22)	Nebraska	-2722.53
in California at t	-0.651 (0.73)	in California at t	0.283 (0.91)		(778.97)**
in California at t-1	-0.388 (0.58)	in California at t-1	-0.193 (0.79)	Iowa	-1388.87
in California at t-2	-1.320 (0.76)	in California at t-2	1.441 (0.97)		(578.50)*
in Wisconsin at t	-4.104 (1.42)**	in Wisconsin at t	1.789 (1.20)	Colorado	-3430.11
in Wisconsin at t-1	-2.558 (1.05)**	in Wisconsin at t-1	-0.277 (1.10)		(989.84)**
in Wisconsin at t-2	-3.873 (1.36)**	in Wisconsin at t-2	0.998 (1.16)	California	-674.35
					(1314.61)
Temperature-humidity Index		***Minimum Temperature***		Wisconsin	-346.66
in Texas at t	5.789 (6.63)	in Texas at t	-3.307 (3.50)		(645.30)
in Texas at t-1	5.740 (5.60)	in Texas at t-1	-3.279 (2.96)		
in Texas at t-2	-3.322 (4.75)	in Texas at t-2	1.945 (2.46)	Constant	903.79
in Kansas at t	31.017 (10.83)**	in Kansas at t	-16.197 (5.61)**		(364.21)**
in Kansas at t-1	0.069 (8.73)	in Kansas at t-1	-1.963 (4.65)		
in Kansas at t-2	36.799 (10.05)**	in Kansas at t-2	-18.814 (4.90)***	R^2	0.65
in Nebraska at t	23.277 (16.19)	in Nebraska at t	-14.936 (7.86)		
in Nebraska at t-1	30.072 (11.10)**	in Nebraska at t-1	-19.001 (5.81)**		
in Nebraska at t-2	33.592 (14.42)**	in Nebraska at t-2	-18.482 (7.31)**		
in Iowa at t	4.193 (11.42)	in Iowa at t	-3.258 (6.10)		
in Iowa at t-1	20.193 (9.07)*	in Iowa at t-1	-10.225 (4.56)*		
in Iowa at t-2	19.343 (12.06)	in Iowa at t-2	-10.790 (6.33)		
in Colorado at t	13.913 (16.23)	in Colorado at t	-6.369 (7.93)		
in Colorado at t-1	50.474 (15.73)**	in Colorado at t-1	-23.583 (7.54)**		
in Colorado at t-2	43.581 (15.65)**	in Colorado at t-2	-20.187 (7.43)**		
in California at t	3.296 (16.48)	in California at t	-1.610 (7.93)		
in California at t-1	5.743 (15.72)	in California at t-1	-2.780 (7.47)		
in California at t-2	18.416 (20.53)	in California at t-2	-9.877 (9.70)		
in Wisconsin at t	3.789 (12.88)	in Wisconsin at t	-2.521 (6.18)		
in Wisconsin at t-1	1.364 (9.51)	in Wisconsin at t-1	-0.324 (4.63)		
in Wisconsin at t-2	10.791 (11.87)	in Wisconsin at t-2	-5.984 (5.82)		

Note: * p<0.1, ** p<0.05 and *** p<0.01; Driscoll and Kraay's standard errors are reported in parenthesis.

Table 14 Estimate Result Comparison of Monthly Maximum and Minimum Temperature from Different Models

		Model 2: Add Monthly Maximum Temperature	Model 3: Add Monthly Minimum Temperature	Complete Model
Monthly Maximum Temperature	Current Month in Texas	-1.714 (0.54)**	-0.709 (0.58)	0.106 (0.65)
	One-month Lagged in Texas	2.102 (0.74)**	0.721 (0.72)	0.480 (0.62)
	Two-month Lagged in Texas	-1.853 (0.54)**	-1.372 (0.58)*	-0.320 (0.61)
	Current Month in Kansas	1.401 (0.65)*	2.843 (1.05)**	2.267 (1.13)*
	One-month Lagged in Kansas	-2.279 (0.94)*	-0.365 (1.03)	0.734 (1.05)
	Two-month Lagged in Kansas	2.416 (0.56)***	1.307 (0.94)*	2.192 (1.10)*
	Current Month in Nebraska	2.573 (0.66)***	6.460 (1.06)***	4.804 (1.24)***
	One-month Lagged in Nebraska	-3.153 (0.94)**	1.668 (1.17)	4.471 (1.26)**
	Two-month Lagged in Nebraska	3.416 (0.60)***	2.487 (0.97)**	3.465 (1.34)**
	Current Month in Iowa	-0.025 (0.58)	1.624 (1.17)	1.412 (1.49)
	One-month Lagged in Iowa	-0.254 (0.80)	-1.247 (1.25)	0.776 (1.23)
	Two-month Lagged in Iowa	0.834 (0.53)	0.216 (1.40)	1.432 (1.68)
	Current Month in Colorado	0.574 (0.70)	0.707 (0.92)	0.964 (1.31)
	One-month Lagged in Colorado	-1.328 (1.06)	-0.961 (0.91)	-0.148 (1.06)
	Two-month Lagged in Colorado	1.669 (0.62)**	0.905 (0.94)	1.219 (1.22)
	Current Month in California	2.060 (0.67)**	2.527 (0.85)**	0.283 (0.91)
	One-month Lagged in California	-2.488 (0.88)**	-1.072 (1.06)	-0.193 (0.79)
	Two-month Lagged in California	3.035 (0.63)***	3.707 (0.85)***	1.441 (0.97)
	Current Month in Wisconsin	3.584 (0.61)***	5.229 (0.88)***	1.789 (1.20)
	One-month Lagged in Wisconsin	-3.770 (0.86)***	0.397 (0.98)	-0.277 (1.10)
	Two-month Lagged in Wisconsin	3.300 (0.54)***	3.937 (0.89)***	0.998 (1.16)
Monthly Minimum Temperature	Current Month in Texas		0.002 (0.50)	-3.307 (3.50)
	One-month Lagged in Texas		0.214 (0.42)	-3.279 (2.96)
	Two-month Lagged in Texas		0.681 (0.44)	1.945 (2.46)
	Current Month in Kansas		-2.231 (1.13)*	-16.197 (5.61)**
	One-month Lagged in Kansas		-1.038 (0.91)	-1.963 (4.65)
	Two-month Lagged in Kansas		0.256 (0.92)	-18.814 (4.90)***
	Current Month in Nebraska		-5.854 (1.09)***	-14.936 (7.86)
	One-month Lagged in Nebraska		-2.827 (1.13)**	-19.001 (5.81)**
	Two-month Lagged in Nebraska		-0.915 (1.02)	-18.482 (7.31)**
	Current Month in Iowa		-1.616 (1.08)	-3.258 (6.10)
	One-month Lagged in Iowa		0.715 (1.08)	-10.225 (4.56)*
	Two-month Lagged in Iowa		0.465 (1.60)	-10.790 (6.33)
	Current Month in Colorado		-0.218 (0.99)	-6.369 (7.93)
	One-month Lagged in Colorado		-0.246 (0.76)	-23.583 (7.54)**
	Two-month Lagged in Colorado		0.547 (0.92)	-20.187 (7.43)**
	Current Month in California		-1.226 (0.82)	-1.610 (7.93)
	One-month Lagged in California		-1.317 (0.79)	-2.780 (7.47)
	Two-month Lagged in California		-1.390 (0.88)	-9.877 (9.70)
	Current Month in Wisconsin		-4.355 (0.88)***	-2.521 (6.18)
	One-month Lagged in Wisconsin		-1.984 (0.69)**	-0.324 (4.63)
	Two-month Lagged in Wisconsin		-2.505 (0.88)**	-5.984 (5.82)

Note: * p<0.1, ** p<0.05 and *** p<0.01; Driscoll and Kraay's standard errors are reported in parenthesis.

Now we move to table 13, which reports estimation results of equation (3.1) with the state variables included. Since we include interaction terms between state and climate factors, we need to combine marginal effects to know the impacts of simple changes in climate factors. For example, the total PM_{10} effect in Kansas is a combination of the effects in $\beta_{PM_{10}}$ and $\beta_{PM_{10}\_KS}$, where $\beta_{PM_{10}}$ is the estimated coefficient of PM_{10} and $\beta_{PM_{10}\_KS}$ is the estimated coefficient of the interaction term of PM_{10} and state dummy which indicates Kansas. In this case the Wald test is applied to see if the parameter estimates are significantly different from zero.

We illustrate the estimated climate and dust effects on cattle mean live sale weight in table 15. The estimated results show that dust levels in both current and previous period have negative impacts on cattle live sale weight in Kansas, Nebraska, California and Wisconsin. The most damaging impacts of dust level are in Nebraska and Wisconsin, where the variations of cattle live sale weight are also highest (standard deviations are 54.72 lbs in Nebraska and 52.18 lbs in Wisconsin as shown in table 11). However, it is interesting that both the mean and variation of historical dust level in Nebraska and Wisconsin reported in table 11 are the lowest, but at this point we can't infer a confident conclusion because of limited information. The dust level in the other states (Texas, Kansas and Colorado) doesn't exhibit significant impacts on cattle live sale weight.

Table 14 details the parameter estimates of monthly maximum and minimum temperatures. Here we see the maximum temperature effects are mainly positive when adding the variable monthly minimum temperature. On the other hand, most of the significant parameter estimates of monthly minimum temperature exhibit negative impacts on cattle weight in model (3), which has a similar result in model (4). Therefore, the simultaneous consideration of both monthly maximum temperature and monthly minimum temperature yields the best performing model. Monthly minimum temperature has largely opposite effects from the maximum temperature, and it has dominant marginal impacts when there is a 1 °F increase in both monthly minimum temperature and monthly maximum temperature. Most of the influence from both monthly maximum and minimum temperatures in Kansas and Nebraska conform to our previous discussion, that is, opposite impacts (positive and negative, respectively). On the other hand, the estimated parameters of temperature-humidity index in Kansas, Nebraska, Iowa and Colorado indicate that cattle live sale weights are enhanced as THI increases.

3.5.2. Estimation of Climate Effects on Dust

Now we turn attention to estimation of the relationship between dust level and climate factors, especially precipitation. There are two reasons for addressing this. First, proposed dust control strategies such as water trucks, traveling guns and sprinklers seek to reduce dust level by using water, and this analysis can help to identify water effects through its estimation of the effects of precipitation. Second, this analysis gives us a means to project how climate change will affect dust emissions since there are no projected dust incidence change data under climate change.

Table 15 Estimated Climate Effects on Cattle Mean Weight

Variables	Texas	Kansas	Nebraska	Iowa	Colorado	California	Wisconsin
Dust Level (PM_{10})	-0.182	-1.647	-6.171	1.196	1.728	-0.834	-4.287
	(0.53)	(0.35)***	(1.07)***	(0.90)	(1.08)	(0.44)	(1.29)**
One-month Lagged Dust Level (PM_{10})	-0.720	-0.486	-6.506	-0.499	1.684	-1.108	-3.278
	(0.42)	(0.31)	(1.20)***	(0.85)	(1.13)	(0.36)**	(0.93)**
Two-month Lagged Dust Level (PM_{10})	-0.020	-1.735	-4.078	1.318	0.337	-1.340	-3.893
	(0.47)	(0.36)***	(1.03)***	(1.05)	(1.34)	(0.56)*	(1.23)**
Temperature-humidity Index	5.789	36.807	29.066	9.982	19.703	9.085	9.578
	(6.63)	(9.29)***	(14.59)*	(10.21)	(15.72)	(15.45)	(11.27)
One-month Lagged	5.740	5.810	35.812	25.933	56.214	11.483	7.105
Temperature-humidity Index	(5.60)	(7.86)	(10.99)**	(9.35)**	(15.20)**	(16.15)	(8.09)
Two-month lagged	-3.322	33.477	30.270	16.021	40.259	15.094	7.468
Temperature-humidity Index	(4.75)	(8.86)***	(13.39)*	(11.16)	(15.73)**	(20.88)	(9.99)
Monthly Maximum Temperature	0.106	2.373	4.910	1.518	1.070	0.389	1.894
	(0.65)	(0.84)**	(1.11)***	(1.52)	(1.07)	(0.62)	(0.97)*
One-month Lagged	0.480	1.214	4.952	1.256	0.332	0.288	0.203
Monthly Maximum Temperature	(0.62)	(0.87)	(1.16)***	(1.08)	(1.13)	(0.60)	(0.85)
Two-month Lagged	-0.320	1.872	3.145	1.112	0.899	1.121	0.678
Monthly Maximum Temperature	(0.61)	(0.81)*	(1.17)**	(1.51)	(1.03)	(0.65)	(0.98)
Monthly Minimum Temperature	-3.307	-19.504	-18.243	-6.565	-9.676	-4.918	-5.828
	(3.50)	(4.60)***	(7.01)**	(5.24)	(7.61)	(7.29)	(5.38)
One-month Lagged	-3.279	-5.242	-22.281	-13.504	-26.863	-6.059	-3.604
Monthly Minimum Temperature	(2.96)	(4.04)	(5.65)***	(4.73)**	(7.20)**	(7.61)	(3.81)
Two-month Lagged	1.945	-16.869	-16.536	-8.845	-18.242	-7.932	-4.069
Monthly Minimum Temperature	(2.46)	(4.30)***	(6.78)*	(5.87)	(7.47)*	(9.86)	(4.86)

Note: * $p<0.1$, ** $p<0.05$ and *** $p<0.01$; robust standard errors are reported in parenthesis.

In this dust regression we include precipitation, monthly maximum temperature, monthly minimum temperature, temperature-humidity index and their squared terms as the explanatory variables. The resultant estimates are reported in table 16. Additionally the marginal effects are reported since the regression includes the squared terms of variables. We also report the 5th and 95th percentile of the marginal effects to examine the full range of impacts.

Examining the results we see that precipitation exhibits significant suppressive effects on dust level in both 5th and 95th percentiles, and the result shows that increased precipitation (or water application as a control strategy) can have marked effects on dust suppression. For example, 0.3mm precipitation increase leads to a decrease of 0.028

units in the PM_{10} dust level, but the suppressive effects gradually decline as precipitation increases. We may reasonably conclude that precipitation/water can effectively decrease dust level and in turn enhance cattle weight gain at least in Kansas, Nebraska, California and Wisconsin.

Additionally we find that monthly maximum temperature significantly increases dust level for temperatures in the range of 31.36 °F to 93.03 °F. This effect is expected since temperature increase causes the manure layer to become drier and to generate more dust. Hence warming increases dust in the form of higher PM_{10} levels. Finally the effects of monthly minimum temperature and the temperature-humidity index are not significantly different from zero.

3.5.3. Projections Under Climate Change

Table 17 reports historical climate characteristics along with projected climates for 2080 and the difference between the historical and projected climates for summer (June) and winter (December) months. Since there are no projected dust data, we do a projection using the estimated parameters in table 16. The comparison shows that during summer time monthly maximum temperature is projected to increase more rapidly than monthly minimum temperature in all states except for California, while during winter time monthly minimum temperatures rise more than monthly maximum temperature in all states excluding Texas, where monthly minimum temperature falls by 10 °F. On the other hand, dust levels in Texas, Kansas, Nebraska and Wisconsin increase substantially during summer time and somewhat during winter time. In Iowa and California dust levels become more moderate during both summer and winter time. Besides, the dust level in Colorado increases in the summertime while it decreases in the wintertime.

Table 16 Estimation Results: Impacts of Climate Factors on Dust Level

Regression Results		Marginal Effects on Dust		
Variables	OLS	Variables	Inferring Points	Marginal Effects
Monthly Mean Precipitation	-0.0279	Monthly Mean Precipitation (mm)	580.41[1]	-0.002
	(0.0022)***			(0.001)*
Monthly Mean Precipitation^2	2.21e-05		24.94[2]	-0.027
	(2.31e-06)***			(0.002)***
Monthly Maximum Temperature	-0.0481	Monthly Maximum Temperature (°F)	93.03[1]	0.870
	(0.1168)			(0.051)***
Monthly Maximum Temperature^2	0.0049		31.36[2]	0.261
	(0.0008)***			(0.068)***
Monthly Minimum Temperature	5.1327	Monthly Minimum Temperature (°F)	65.42[1]	0.666
	(3.972)			(2.025)
Monthly Minimum Temperature^2	-0.0341		11.46[2]	4.350
	(0.1577)**			(3.622)
Temperature-humidity Index	-22.7228	Temperature-humidity Index	69.79[1]	0.7332
	(16.0243)			(2.021)
Temperature-humidity Index^2	0.1680		29.83[2]	-12.697
	(0.1030)			(9.910)
Constant	563.4408			
	(405.69)			
R-squared	0.42			

Note: * p<0.1, ** p<0.05 and *** p<0.01; robust standard errors are reported in parenthesis. 1. The inferring point is 95th percentile. 2. The inferring point is 5th percentile.

We can thus uncover the climate change effects on the cattle live sale weight by integrating the estimated climate effects from table 15 and table 16 with the projected shifts on climate in table 17. Because of the significance in the estimate of linear panel data model we mainly focus our discussion on Kansas, Nebraska and Wisconsin, where the dust levels are exacerbated during both summertime and wintertime. Other things being equal, the aggravated current month dust levels cause cattle to lose 22.23 lbs of sale weight in Kansas, 60.35 lbs in Nebraska and 31.17 lbs in Wisconsin during summer as well as to loss 3.77 lbs in Kansas, 14.32 lbs in Nebraska and 17.36 lbs in Wisconsin during winter. Also the increased temperatures reduce sale weights in the future as the projected minimum temperature changes induce negative impacts on weight gains with other things being equal. For example, the projected 17.62 °F increase in Kansas in June results cattle weight loss by about 344 lbs as well as a 8.19 °F increase in Nebraska in December generates around 149 lbs weight loss.

Next we apply climate change scenarios to project cattle weights by simulating the live sale weight estimates 5000 times varying the predicted error terms according to its distribution to obtain the confidence interval of the projected cattle live sale weights in each scenario during June and December (summer and winter time, respectively). Table 18 presents the simulated upper bound (97.5%), average (50%), and lower bound (2.5%) plus the historical maximum and minimum of cattle live sale weight.

We first examine the simulated results across the states. All three periods indicate that cattle in Colorado, California and Wisconsin perform better under climate change. This is perhaps because of feeding conditions where the terrain of Colorado is higher in altitude, over 70% cattle were fed in the mountain areas in California, and Wisconsin is more northern. Though the projected temperatures indicate a general increased warming under climate change, the impacts widely vary across the nation. The climate is likely to improve for agriculture in northern regions while it might be more detrimental in southern areas. Therefore the warmer climate in these three states might cause better cattle performance. On the other hand, cattle in Kansas historically gain under-average weights but perform relatively better under climate change, while cattle performance in Nebraska is getting comparative worse among the seven states.

We also compare summer with winter cattle performance. Historically cattle in Texas, Kansas and Wisconsin gain better live sale weights during summer time (base scenario). In the 2020, 2050 and 2080 period cattle in Kansas consistently perform better while cattle in Texas inversely perform worse during summer time. Note this is not reflective of a dust effect in Texas since that variable was insignificant but rather is a climate change effect. The reduced cattle performance in summer in Texas might be resulted from the thermal challenges in summer that reduce appetite and impair immunological and physiological functions as discussed in Mader et al (2009). Also, the difference between predicted cattle performance in summer and winter in Wisconsin approaches zero perhaps because of the more moderate climate conditions in winter under climate change.

Now let us compare cattle production under the three scenario periods. As shown in table 18, cattle during summer time in Kansas, Nebraska, Iowa and Colorado perform slightly better while cattle in Texas, California and Wisconsin maintain similar weights under climate change. Cattle weight gain during winter time in Texas, Nebraska and Iowa decreases while that in other four states remains unchanged under climate change.

As discussed earlier, the econometric results indicate that aggravated dust levels will worsen cattle live sale weight as shown in table 15, and that dust incidence will be aggravated by higher temperatures but suppressed by increases in precipitation as reported in table 16. Under climate change the dust level is projected to be aggravated in all states except for Iowa and California during summer time plus in Texas, Kansas, Nebraska and Wisconsin during winter time.

Table 17 Comparison of Historical and Projected Climate Factors

Month	Projected Values[1]	States						
		Texas	Kansas	Nebraska	Iowa	Colorado	California	Wisconsin
Jun.	Average Historical Values Between 1993 and 2010[1] (A)							
	Maximum Temperature (°F)	89.77	86.80	81.37	79.67	79.37	91.14	77.59
	Minimum Temperature (°F)	69.43	60.51	57.07	58.84	46.99	51.23	54.67
	Mean Precipitation (mm)	69.34	399.81	470.51	426.01	528.99	165.94	326.59
	Dust Level (ug/m^3)	23.24	18.98	12.87	21.83	17.42	31.44	9.76
	Projected Values in 2080[2] (B)							
	Maximum Temperature (°F)	105.31	106.77	96.42	96.75	93.96	91.11	87.96
	Minimum Temperature (°F)	70.11	78.13	71.97	74.05	59.48	60.80	67.51
	Mean Precipitation (mm)	47.73	69.41	92.06	105.12	41.23	7.91	120.65
	Dust level (ug/m^3)	35.68	32.49	22.65	21.48	29.17	26.07	17.03
	Difference Between Historical and Projected Values (C= B-A)							
	Maximum Temperature (°F)	+15.54	+19.97	+15.05	+17.08	+14.59	-0.03	+10.37
	Minimum Temperature (°F)	+0.68	+17.62	+14.90	+15.21	+12.49	+9.57	+12.84
	Mean Precipitation (mm)	-21.61	-330.40	-378.45	-320.89	+487.76	-158.03	-205.94
	Dust Level (ug/m^3)	+12.44	+13.50	+9.78	-0.35	+11.75	-5.37	+7.27
Dec.	Average Historical Values Between 1993 and 2010[1] (A)							
	Maximum Temperature (°F)	53.39	46.07	37.46	32.84	41.97	59.04	30.55
	Minimum Temperature (°F)	41.38	20.48	15.71	17.17	11.88	32.54	13.76
	Mean Precipitation (mm)	342.92	54.96	141.91	72.04	127.16	61.42	192.02
	Dust Level (ug/m^3)	14.87	13.00	10.08	15.18	18.28	24.96	7.24
	Projected Values in 2080[2] (B)							
	Maximum Temperature (°F)	53.39	49.22	36.99	34.99	36.12	54.96	29.44
	Minimum Temperature (°F)	31.25	30.34	23.90	23.75	21.84	39.93	19.07
	Mean Precipitation (mm)	22.13	24.13	36.87	50.65	34.38	100.62	59.19
	Dust Level (ug/m^3)	17.19	15.29	12.40	11.59	12.76	12.76	11.29
	Difference between Historical and Projected Values (C= B-A)							
	Maximum Temperature (°F)	0.00	+3.15	-0.47	+2.15	-5.85	-4.08	-1.11
	Minimum Temperature (°F)	-10.13	+9.86	+8.19	+6.58	+9.96	+7.39	+5.31
	Mean Precipitation (mm)	-320.79	-30.83	-105.04	-21.39	-92.78	+39.2	-132.83
	Dust Level (ug/m^3)	+2.32	+2.29	+2.32	-3.59	-5.52	-12.2	+4.05

Note: 1. The average values of climate factors are weighted based on the proportion of cattle sales in each climate division in each state. 2. The projected values of Tmax and Tmin are from the SRES of HADCM for 2080, and the projected dust level is obtained from the estimation reported in table 16.

Table 18 Projected Cattle Live Sale Weight from the A1F SRES of HADCM

Sale Month	Quantile	States						
		Texas	Kansas	Nebraska	Iowa	Colorado	California	Wisconsin
Base Scenario: Actual Average Sale Weight Between 1993 and 2010								
Jun	Minimum	1085	1136	1147	1120	1154	1210	1212
	Average	1122	1203	1234	1196	1218	1268	1297
	Maximum	1153	1268	1315	1237	1283	1353	1355
Dec	Minimum	1071	1090	1140	1111	1144	1210	1208
	Average	1106	1175	1234	1203	1213	1271	1290
	Maximum	1139	1252	1330	1255	1302	1352	1351
A1F Scenario: 2020 Projected Sale Weight for Period 2010-2039								
Jun	2.5%	1059	1120	1042	1121	1163	1192	1146
	50%	1112	1189	1109	1177	1233	1272	1215
	97.5%	1165	1257	1173	1230	1301	1349	1282
Dec	2.5%	1086	1096	1046	1113	1117	1222	1149
	50%	1132	1168	1101	1172	1205	1287	1214
	97.5%	1176	1239	1156	1230	1290	1350	1277
A1F Scenario: 2050 Projected Sale Weight for Period 2040-2069								
Jun	2.5%	1057	1154	1046	1142	1183	1189	1145
	50%	1111	1223	1113	1197	1253	1269	1214
	97.5%	1164	1292	1179	1252	1323	1348	1283
Dec	2.5%	1083	1094	1029	1106	1111	1219	1143
	50%	1129	1167	1084	1165	1198	1284	1208
	97.5%	1174	1239	1140	1224	1286	1349	1273
A1F Scenario: 2080 Projected Sale Weight for Period 2070-2099								
Jun	2.5%	1059	1190	1059	1169	1208	1190	1144
	50%	1112	1259	1126	1224	1278	1270	1213
	97.5%	1165	1327	1190	1278	1346	1347	1281
Dec	2.5%	1080	1094	1025	1102	1112	1218	1145
	50%	1126	1167	1080	1161	1200	1283	1210
	97.5%	1171	1238	1134	1218	1285	1346	1273

3.6. An Investigation of Dust Control

3.6.1. Dynamic Programming Model

In the previous section we found that aggravated dust level will worsen cattle performance, and that dust incidence will be aggravated by higher temperatures but suppressed by increases in precipitation. Here we analyze dust suppression benefits with and without climate change. This will be done using a dynamic programming model exploring the costs of dust plus the benefits of control with and without climate change. The farmer is assumed to maximize cattle sale weights by implementing dust control, and a sprinkler system is considered as the control method. Since cattle usually spend three to six months in the feedlot after placement and the farmers have to make many related decisions during the feeding period, a dynamic optimization approach is used.

To simplify our analysis, the model is structured as follows. An animal is assumed to have average body condition when placed on feed and fed for a specific number of weeks. It starts from an initial weight W_0. We have animal purchase costs C_p and feeding costs C_f which are stochastic. Other costs C_{nf} are also included. Treatment costs for dust related sick animals are C_t and certain. We will not consider the fixed cost of sprinkler installation in the dynamic program but will consider it ex post. The costs of water and energy are C_w. The morbidity rate in period t without dust control is v_{1t} and with dust control is v_{2t}. Additionally, h_t and w_t represent the health and weight states of cattle in period t, while z_t is the dust control policy. In turn the stochastic cost of an animal in period t is:

$$\tilde{u}(t) = -\tilde{C}_f w_t - C_{nf} - C_t(1-h_t) - C_w z_t, \tag{3.7}$$

where for an animal

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

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

The stochastic state equations are as follows:

$$h_t = \begin{cases} 0 & \text{with } v_{1t}^{(1-z_t)} v_{2t}^{(z_t)} \\ 1 & \text{with } 1 - v_{1t}^{(1-z_t)} v_{2t}^{(z_t)} \end{cases}, \tag{3.8}$$

$$w_{t+1} = w_t + A\hat{W}G_H h_t + A\hat{W}G_S \left(1 - h_t\right), \tag{3.9}$$

where $A\hat{W}G_H$ and $A\hat{W}G_S$ 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 the stochastic price is $\tilde{P}_T$. Based on the above the *Bellman's Equation* is:

$$V\left(w_t, h_t, t\right) = \max_{z_t} \left\{ u\left(w_t, h_t, t\right) + \beta EV\left(w_{t+1}, h_{t+1}, t+1\right) \right\}, \tag{3.10}$$

Equation (3.10) presents the dynamic maximization problem of the cattle feeders. β is the discount factor and $EV\left(w_{t+1}, h_{t+1}, t+1\right)$ is the expected value the feeding returns from the next period forward.

The optimal choice of dust control strategy in each planning period, $z_t^*\left(w_t, h_t, t\right)$, is the result of solving the maximization problem above and could be technically written as:

$$z_t^*\left(w_t, h_t, t\right) = \underset{z_t = 0,1}{\operatorname{argmax}} \left\{ u\left(w_t, h_t, t\right) + \beta EV\left(w_{t+1}\left(w_t, h_t, z_t\right), h_{t+1}\left(w_t, h_t, z_t\right), t+1\right) \right\},$$

(3.11)

3.6.2. *Dynamic Programming Results*

The dynamic program is set up with the following assumptions.

- The farmer makes his decision on sprinkler use once a week.
- The initial placement weight of cattle is 550 lbs, and the feeding period is fixed as 26 weeks.
- All animals are initially in good health.
- The average weekly weight gains of healthy cattle depend upon the production location (Texas, Kansas and etc.) and the regional climate conditions, which are based on the projected climate change results shown in table 18, and are reported in table 19.
- A sick animal suffering from respiratory problems will add weight at a rate of 0.924 pounds less per week less than a healthy animal based on the estimation result from Smith (1998).
- The feeding costs are approximated by the price of corn and the feed cost percent of production expenses, which are reported in table 19.
- Non-feeding cost is around \$2.17 per head per week, and the watering cost is estimated around \$0.02 per head per week based on Amosson et al. (2006).
- The purchase cost for feeder animals is assumed to be \$1.04 per hundred weight (\$/cwt) based on the price of feeder cattle from the National Agricultural Statistics Service (NASS).
- The sale price for fed animals is the average of the historical data from USDA National Agriculture Statistics Service Quick Stats (between 1993 and 2010).

- The one-time treatment cost for animals with respiratory problems is $11 per head based on the work of Sanderson et al. (2008), and we assume that cattle will fully recover in a week.
- The weekly morbidity rates of respiratory disease for a cow after being placed on feed are based on the work of Sanderson et al. (2008) and are assumed to be independent among weeks. These are reported in table 10, where only 550 lbs initial weight category is covered.
- We assume that the morbidity rate will be reduced by 50% if the farmer applies water to reduce dust.
- The dust control decision in next period is decided based on the cattle weight and the returns to the health state given the dust infection probabilities.

Figure 9 presents an example of the dynamic programming solution for the case of cattle in Nebraska in December for 2050 climate. It reports the values of cattle based on cattle live sale weight and health status. The result shows that an animal being healthy has a higher value as opposed to an animal that is sick. Figure 10 presents the range of values over the whole feeding periods depending upon the weight in both healthy and sick status. It shows how cattle values are cumulated in the dynamic programming solution.

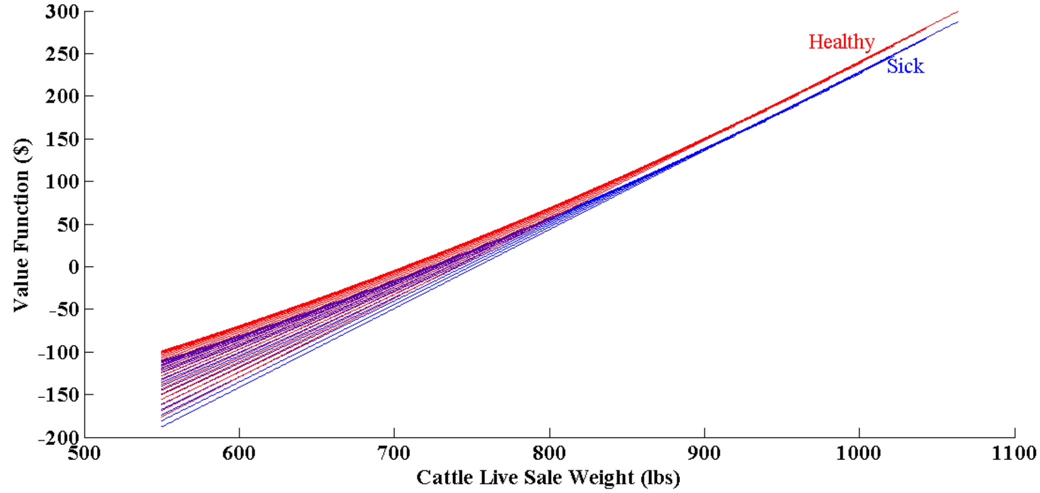


Figure 9 Value Function of Cattle in Nebraska in December of Period 2050

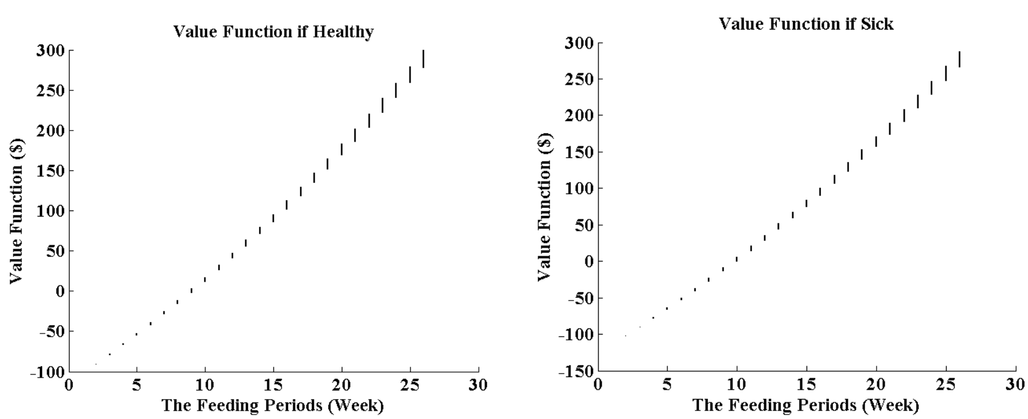
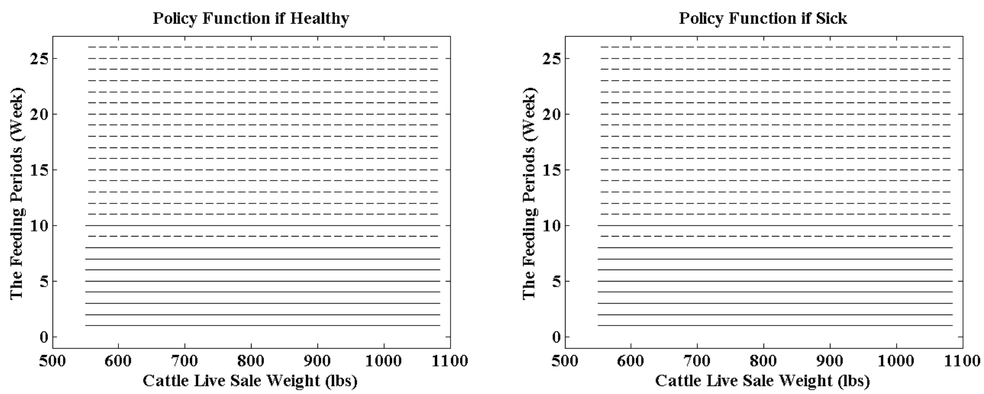


Figure 10 Value Function over the Feeding Periods

Figure 11 reports the policy functions over feeding weeks and shows that the optimizing feedlot operator will do dust control when animals are small in earlier weeks. It is because smaller animals are more likely to suffer from respiratory problems while mature animals have stronger resistance, which is also indicated in the weekly morbidity rates reported in table 10. However, the policies under both healthy and sick status are the same, meaning that the policies are independent from the health state. It might be because of the relative lower morbidity rates. We simulate the results 1000 times and then take an average. Figure 12 gives an example of the simulated weight pattern per animal during summer in Nebraska over the period 2040-2069.



Dashed Line: No Dust Control   Solid line: Do Dust Control

Figure 11 Policy Function over the Feeding Periods

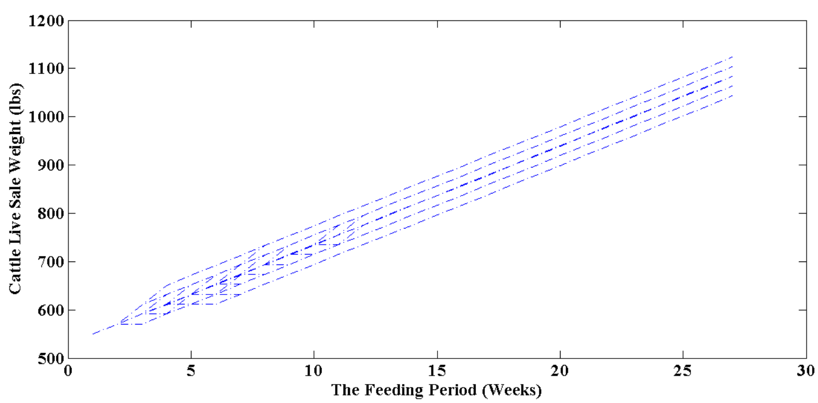


Figure 12 Simulated Weight Pattern During Summer in Nebraska over the Period 2040-2069

Table 19 presents the estimated individual animal values with and without optimal dust control by state. Scenario 1 represents performance under the current climate while scenario 2 and 3 reflect future projected climates over the period 2040-2069 and 2070-2099, respectively. Based on the econometrics results, we inferred the change in average weekly weight gain of healthy cattle (AWG_H) due to climate change. For example, the average weekly weight gain in Texas during summer is 22.00 lbs in the baseline scenario then is reduced to 21.58 lbs in scenario 2 and 21.62 lbs in scenario 3, respectively.

Basically the simulated optimization results show increased cattle value under dust control activities relative to no dust control activities under all scenarios, which return positive benefits. In the baseline scenario, the benefit of dust control gained during the summer time exceeds that gained during the winter time in all states except for California and Wisconsin. Texas, Kansas and Wisconsin have consistently greater benefits of dust control during winter time while Nebraska and California have these during summer. The dust control benefits in Iowa and California shifts between summer and winter in the two climate change scenarios.

Next we compare the benefits among the baseline scenario and the two climate change scenarios. The benefits during summer in Texas, Kansas, Nebraska and Iowa decrease from the baseline scenario to the climate change scenarios while that in Colorado and California decrease in the period 2050 but then increase in the period 2080. During winter time the benefits in all states except for Texas and Kansas decrease from the baseline scenario to the climate change scenarios.

The annualized benefits for an animal in each state are then calculated by aggregating the benefits during summer and winter. Texas, Kansas and Nebraska have the largest annualized benefits among the 7 states. The annualized benefits in all states except for Texas decline under the climate change scenarios, which show that climate change reduces dust control benefits. To conclude the benefits under dust suppression are consistently greater than those without any dust suppression activities. Also climate change is found to be costly.

3.7. Conclusions and Limitations

Dust and climate effects on cattle production and the benefits gained from dust control activities are investigated. Using econometrics we find that dust incidence significantly lowers cattle sale weight in most states. The climate analysis indicates that an increase in monthly minimum temperature reduces cattle sale weight while an increase in monthly maximum temperature has the opposite effects. An across the board increase in temperature exhibits a negative influence on cattle sale weight since the impacts from minimum temperature dominate those from maximum temperature. Estimation results also show that dust levels are increased by increased temperatures but suppressed by increases in precipitation. Hence the proposed dust control strategies such as water trucks, traveling guns and sprinklers can be expected to reduce dust levels.

Under climate change projections the econometric results show dust levels in Texas, Kansas, Nebraska and Wisconsin are substantially increased during summer and slightly increased during winter. In Iowa and California dust levels are reduced during both summer and winter. The dust level in Colorado is increased in the summer while it is reduced in the winter.

We also find that dust has effects on cattle live sale weight. For example, for the 2080 projection the dust levels reduce cattle sale weights by 22.23 lbs in Kansas, 60.35 lbs in Nebraska and 31.17 lbs in Wisconsin during summer as well as to reducing sale weights by 3.77 lbs in Kansas, 14.32 lbs in Nebraska and 17.36 lbs in Wisconsin during winter.

Cattle weights under climate change are predicted with dust effects including period 2020, 2050 and 2080, respectively. The results show that cattle have mixed performance effects with those in Colorado, California and Wisconsin having better winter performance but with summer performance declines in Nebraska, Iowa and Colorado and increases in Texas. In terms of dust control, a sprinkler system is assumed as a dust suppression strategy and the dust suppression benefits are estimated in the period 2020, 2050 and 2080. We found that the benefits under dust suppression are consistently greater than those without any dust suppression activities. Also climate change is found to be costly.

This work has a number of limitations. First, the data on dust and sale weight performance are rather aggregate but we could not find systematic wide spread localized data. Second, in examining climate change we did not consider extreme events such as drought, heat waves or number of days of consecutive days with extreme hot (cold) temperatures. Such factors can be considered in the further research to capture the impacts of extreme events on the livestock. Third, we do single equation estimate of climate and dust impacts on cattle weight by assuming strong exogenity, and system estimation will be considered in the future research to release the assumption. Fourth, it might be more realistic if daily dust control decisions were modeled in the dynamic programming model and future work could do this. Fifth, we fixed the length of the feeding period and this could be a variable in future work as feeding practice varies including feeding the animals longer to achieve a constant sale weight. Sixth, IPCC 2007 climate scenarios are applied in this essay and should be updated to newer ones (IPCC 2013) in future work. Finally dust mortality was not considered and consequently the dust control benefits might be underestimated.

Table 19 Simulated Benefits with and Without Dust Control

(Unit: $ or lbs / Per Head)

Variables		States						
		Texas	Kansas	Nebraska	Iowa	Colorado	California	Wisconsin
Feeding cost ($/pct)		22.07	18.40	17.17	19.00	21.70	14.47	17.67
Base Climate Scenario 1: Baseline								
Summertime								
AWG_H (lbs/Week)[2]		22.00	25.12	26.31	24.85	25.69	27.62	28.73
Cattle Value	No Dust Control	202.70	335.62	376.86	263.17	372.22	150.42	71.09
($/Head)	Dust Control	203.59	336.95	378.46	264.91	373.82	151.59	71.96
Benefit($/Head)		0.89	1.33	1.60	1.74	1.60	1.17	0.87
Wintertime								
AWG_H (lbs/Week)[2]		21.38	24.04	26.31	25.12	25.50	27.73	28.46
Cattle Value	No Dust Control	191.79	314.32	376.92	268.58	368.33	152.20	67.47
($/Head)	Dust Control	192.68	315.63	378.37	269.86	369.85	153.40	68.74
Benefit($/Head)		0.89	1.31	1.45	1.28	1.52	1.20	1.27
Annualized Benefit[3]		1.78	2.64	3.05	3.02	3.12	2.37	2.14
Climate Change Scenario 2: (over the period 2040-2069)								
Summertime								
AWG_H (lbs/Week)[2]		21.58	25.88	21.65	24.88	27.04	27.65	25.54
Cattle Value	No Dust Control	195.32	350.40	284.93	263.93	398.64	150.93	31.69
($/Head)	Dust Control	196.05	351.31	286.23	265.66	399.58	152.52	32.39
Benefit($/Head)		0.73	0.91	1.30	1.73	0.94	1.59	0.70
Wintertime								
AWG_H (lbs/Week)[2]		22.27	23.73	20.54	23.65	24.92	28.23	25.31
Cattle Value	No Dust Control	207.53	308.60	262.86	241.68	357.55	159.72	28.55
($/Head)	Dust Control	208.59	309.92	263.85	242.86	358.71	160.75	29.55
Benefit($Hhead)		1.06	1.32	0.99	1.18	1.16	1.03	1.00
Annualized Benefit[3]		1.79	2.23	2.29	2.91	2.10	2.62	1.70
Climate Change Scenario 3: (over the period 2070-2099)								
Summertime								
AWG_H (lbs/Week)[2]		21.62	27.27	22.15	25.92	28.00	27.69	25.50
Cattle Value	No Dust Control	195.98	376.04	294.70	282.89	417.06	151.74	30.99
($/Head)	Dust Control	196.79	376.85	296.10	283.76	418.94	152.62	31.94
Benefit($/Head)		0.81	0.81	1.40	0.87	1.88	0.88	0.95
Wintertime								
AWG_H (lbs/Week)[2]		22.15	23.73	20.38	23.50	25.00	28.19	25.38
Cattle Value	No Dust Control	205.31	308.11	259.67	239.24	358.89	159.40	29.25
($/Head)	Dust Control	206.46	309.91	260.78	240.21	360.04	160.16	30.35
Benefit($/Head)		1.15	1.80	1.11	0.97	1.15	0.76	1.10
Annualized Benefit[3]		1.96	2.61	2.51	1.84	3.03	1.64	2.05

Note: 1. Source: available via <http://www.nass.usda.gov/Publications/Ag_Statistics/2011/Chapter07.pdf>.
2. AWG_H represents the average weekly gain of healthy cattle from the results projected in the econometric part. We take the 50% quantile values.
3. The benefit estimation from DP assumes 26 weeks feeding periods, which is half of a year. Hence the annualized dust control benefit is obtained from the aggregation of the benefits during summertime and wintertime.

4. ESSAY THREE: CONSUMER RESPONSE TO TROPICAL STORM STRIKE-DEMAND ANALYSIS ON VEGETABLE PURCHASE IN TAIWAN

4.1. Introduction

Tropical storms (hurricanes, typhoons and cyclones) can be destructive and costly natural disasters. Associated strong winds, heavy rains and storm surges damage buildings, infrastructure, crops and individual welfare. For example, Pielke et al. (2008) estimate that such storms cause around $10 billion in annual losses in the continental United States. Additionally, the torrential rains brought by tropical storms usually cause flooding, which also cause serious damages and reduce property values (Bin and Landry 2013; Bin and Polasky 2004). Even low-intensity tropical storms can cause economic loss. For example, Burrus Jr. et al. (2002) estimate the average regional business interruption impacts caused by low-intensity tropical storms in the Wilmington, N.C. region, and find that the impact is equivalent to between 0.8 to 1.23% of annual regional output. They estimate the region incurs an annual $3.7 billion loss from all intensities of tropical storms.

Climate change might intensify tropical storms. Webster et al. (2005) point out that the number and proportion of tropical storms reaching categories 4 and 5 has almost doubled over the past 35 years with the largest impacts in the Northern Pacific, Indian, and Southwestern Pacific Oceans. The results are consistent with the hypothesis that the ocean will have more energy to convert to tropical cyclone wind as a result of warmer oceans as indicated in IPCC (2007). Emanuel (2005) projects that the destructiveness of tropical storms will increase by 40-50% under climate change scenarios associated with doubled CO_2. Knutson and Tuleya (2004) find that the occurrence of highly destructive tropical storms is likely to increase under global warming. However some studies present an opposite view, for example, Knutson et al. (2008) indicate that the increase of SSTs did not significantly affect tropical storm activities in the recent past. All of these conclusions are hampered by small sample sizes since accurate satellite records have only been available since 1970.

Many studies have investigated the economic consequences of amplified tropical storms under climate change. Webersik et al. (2010) employ Monte-Carlo simulation to measure the expected future loss in Japan and find that around US$60 per capita will be lost for the year 2085. Similarly, Esteban et al. (2009; 2010) examine the annual GDP loss resulted by the increase in tropical cyclone intensity induced by global warming in Taiwan and Japan. They find that the annual GDP loss in Taiwan is up to 0.7% and that in Japan is between 6% and 13% by 2085. Nordhaus (2010) examines the economic impacts of US tropical storms and concludes that global warming will increase average annual US tropical storm damages by $10 billion in 2005 dollars. Chen and McCarl (2009) simulate regional and aggregate welfare effects in the U.S. agricultural sector with and without tropical storm strike intensity and frequency changes concluding that the welfare loss will grow if storms are more frequent or severe.

This paper will examine the economic loss due to current and possible future incidence of tropical storm strikes in Taiwan considering effects on a wholesale vegetable market. This will be done by examining effects on consumer demand, market prices, revenue at the wholesale level and social welfare. We will also compare the welfare loss across different storm strike frequencies and intensities.

4.2. Study Area and Data Description

Taiwan is located in the western Pacific Ocean and during 1958 to 2011 was struck on average by 4.83 typhoons per year (tropical storm, which is the word preferred in North America will be used in the rest of this essay). Around 39% of those storms directly made landfall on Taiwan, and the other 61% storms passed by the offshore area but still brought rainfall and in turn damages. If we divide the period into 2 sub-periods, 1958-1984 and 1985-2011, we find an increasing number of strikes in the later period with the annual average rising from 4.19 to 5.48 per year. These strikes have been of varying intensity. In particular we examine this adopting three intensity categorization – weak, medium and strong.[22] Both weak and medium intensity strikes have been increasing with the average frequency per year in the latter period rising from 21.24% to 25.68% for weak storms and from 36.28% to 50.67% for medium ones. The tropical storm information is reported in table 20.

[22] According to the classification from <http://typhoon.ws/learn/reference/typhoon_scale>, weak intensity is 34-63 knots, medium intensity represents 64-100 knots, and strong intensity indicates 100 above knots in 10-minute sustained winds.

Tropical storms usually strike Taiwan on the eastern or south-western coasts, where around 77% of vegetables are produced.[23] Severe damages on vegetable production are usually induced causing a short-run shortage on vegetable products, which usually leads to temporary price increase. Of course, such short-run shock affects not only the market supply but also the consumer's consumptions.

Table 20 Numbers of Tropical Storm Striking Taiwan Between 1958 and 2011

	Full Period (1958-2011)		Period 1 (1958-1984)		Period 2 (1985-2011)	
Category	Numbers	Percentage (%)	Numbers	Percentage (%)	Numbers	Percentage (%)
Weak (34-63 knots)	62 (21)	23.75	24	21.24	38	25.68
Medium (64-100 knots)	116 (45)	44.45	41	36.28	75	50.67
Strong (>100 knots)	83 (36)	31.80	48	42.28	35	23.65
Total	261(102)		113		148	
Average	4.83/year		4.19/year		5.48/year	

Source: the Central Weather Bureau in Taiwan.

Data on tropical storm intensity, warning period and warning frequency are collected from the Central Weather Bureau in Taiwan and the digital typhoon website of Japan. The data cover the period in 1958-2011 and provide a total of 261 tropical storm observations.

[23] In 2009, the vegetable planted area in north of western Taiwan, south of western Taiwan, and eastern Taiwan are 23,633 ha., 116,734 ha., and 11,268 ha., respectively. This information is reported in the 2009 Agricultural Statistics Yearbook, which is available from <http://www.coa.gov.tw/view.php?catid=21690>.

Storm incidence involves both the immediate strike effects and more distant flooding damages. The Central Mountain Range of Taiwan runs from the north of the island to the south and provides a natural barrier from the intensive wind. About 73% of the tropical storms move westward across Taiwan, cropping rain in western Taiwan, where the main vegetable product regions are located. This rainfall can have a more severe influence on vegetables than the immediate strike effects on the western plains.

Thus rainfall data are also used to capture the impacts of tropical storms. Although the Central Weather Bureau records the precipitation hourly in several stations and reports the rainfall as daily accumulations, this study only uses the record from Alishan, which is the central mountain in Taiwan. However, the rainfall data are only available since 2003, and thus only 94 or 36% of total tropical storm observations are used in this study. The rainfall information incorporated with tropical storm information in period 2003-2010 is reported in table 21. These data show that the average amount of rainfall during a tropical storm period (114.67 mm) is much higher than that in non-tropical storm period (19.30 mm), and the variation of rainfall during a tropical storm period (208.23 mm) is also much greater than that in non-tropical storm period (41.33 mm).

In terms of vegetable prices and damages, daily transaction prices and quantity data for vegetable products are assembled from the Agriculture and Food Agency Council of Agriculture Executive Yuan (AFACAEY) on the first Taipei market. The data are available since 1996 and cover ninety-three commodities, which are categorized into four groups. These groups and their components are as follows:

- root vegetables including 31 commodities such as radishes, carrots, potatoes, onions, scallion, taros, bamboo shoot, lotus root, ginger, asparagus, etc.;
- green leafy vegetables including 24 commodities such as cabbage, Chinese mustard, celery, bok choy, lettuce, borecole, water spinach, Chinese spinach, basil, etc.;
- bulbs and tubers including 26 commodities such as cucumbers, eggplants, tomatoes, cauliflowers, bitter gourds, day lily, peas, kidney beans, etc.;
- mushrooms including 12 commodities such as button mushroom, king oyster, oyster mushroom, champignon, needle mushroom, etc.

Table 21 Summary Statistics of Rainfall Data in 2003-2010

	Observations	Mean	Std. Dev.	Min	Max
Non-tropical storm period	1279	19.30	41.33	0.1	811.5
Tropical storm period	143	114.67	208.23	0.4	1165.5
Rainfall < 130	106	18.21	22.15	0.4	107.5
130 < Rainfall < 200	7	154.07	14.33	131	170.0
200 < Rainfall < 350	13	264.42	43.59	203.5	347.5
Rainfall > 350	17	585.32	253.37	350	1165.5

Source: the Central Weather Brueau in Taiwan.

The price indices for these four groups are calculated as weighted-average based on proportions of transaction quantities within each group. Figure 13 contains plots of the market quantity index against the weighted market price index. There we see that the aggregate market data for all the categories except for mushrooms exhibit general downward sloping curve. Mushrooms seem have an upward sloping curve, and perhaps because the Taiwanese population has been exhibiting higher health consciousness in recent years and view several kinds of mushrooms as higher class ingredients.

Summary statistics on the vegetable category prices and quantities during storm strikes are shown in table 22 and table 23. Table 22 represents the summary statistics based on the day of landfall during the tropical storm period, and table 23 shows those statistics of the first and second announced warning day and the day before the warning day to see how the market reacts to tropical storm information.

We summarize the price and quantity of the four vegetable groups in two ways in table 22. The first way (Part I) includes all the observations based on the date of landfall, and the second (Part II) only includes the observations during the warning period, which have fewer observations. The figure shows the price of root vegetables, green leafy vegetables and bulbs and tubers increase two days before the day of landfall but then decrease while mushroom prices show the opposite tendency. Basically the quantities of the first three categories traded before the day of landfall follow the law of demand since the quantities decrease with increasing market prices. On the other hand, the quantities of the first three categories traded after the day of landfall seem to follow the law of supply since the market price and quantity change in the same direction.

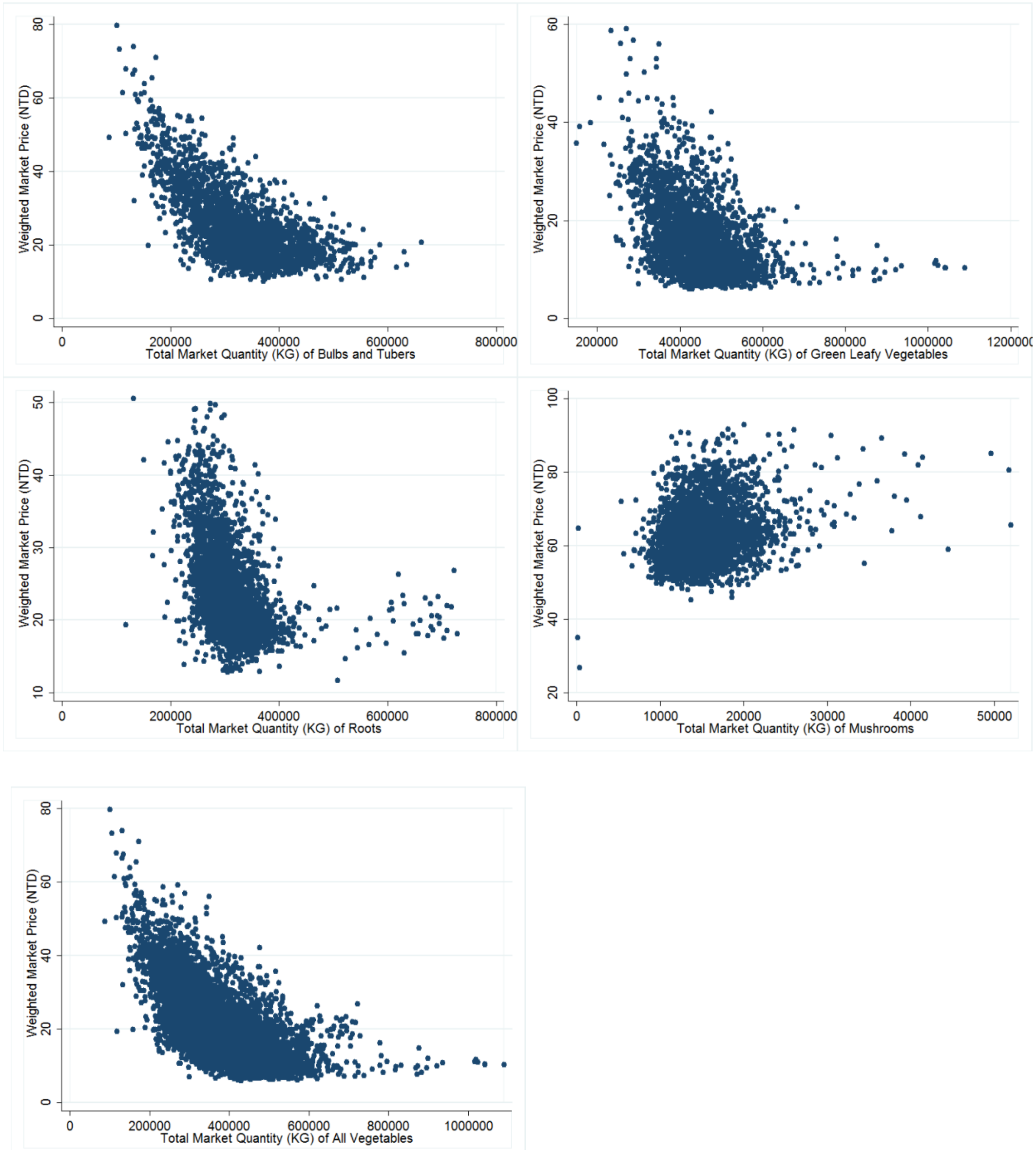


Figure 13 The Price and Quantity of Vegetables in Taiwan Market

The quantities reported in part II exhibit similar trends as that in part I; however, most of the prices in part II have the opposite tendencies, which show that the warning period affects the market. To capture market adjustments more accurately, we summarize the information based on the warning day in table 23 since warnings may be announced not on the actual day of landfall, but perhaps on the day before the day of landfall.

Table 23 reports the weighted average prices and total market quantities on the first day that the consumer receives a warning, the day after the first day of the warning announcement, and the day before the first day of the warning. The price of all groups increases when the warning announcement appears. The quantity of green leafy vegetables and bulbs and tubers keeps increasing, while that of root vegetables and mushrooms rises on the first day of the warning announcement, but then falls on the second day of the warning.

If we divide the data into groups reflecting storm intensity we can examine the market reacts when they receive warnings of different intensities. Both market prices and quantities rise given a warning of a strong storm, while under a medium warning the market prices and quantities slightly increase on the first day but then drop or remain level. However, the price and quantity information under the warning of weak tropical storm strike are chaotic, and it is difficult to conclude how the market reacts.

4.3. Empirical Model

To estimate welfare and price implications of storms for vegetables we use the differentiated-product discrete-choice demand model introduced by Berry (1994). This model resolves the common heterogeneity and endogeneity problems from the aggregate data. We apply discrete-choice concept by assuming that individual *i* makes his purchase decisions among different vegetables. In the aggregation all vegetables will be chosen since different consumers have different characteristics. Hence the aggregate demand of all vegetables is then estimated depending on the entire distribution of consumers. Assume that there are N vegetables in the vegetable market, and the utility of individual *i* for vegetable *j* at time *t* depends on the characteristics and the price of vegetable *j*. Individual *i* can observe all the product characteristics and all the decisions in the market; however, some characteristics and some decisions are difficult to observe in the data. Therefore the indirect utility of individual *i* obtained from consuming vegetable *j* at time *t*, U_{ijt}, is specified as:

$$U_{ijt} = X_{jt}\beta - \alpha p_{jt} + \xi_{jt} + \mu_{ijt}, \tag{4.1}$$

where X_{jt} is the observed characteristic of vegetable *j* at time *t*, ξ_{jt} is the unobserved characteristics of vegetable *j* at time *t*, and p_{jt} is the weighted aggregate market price of vegetable *j* at time *t*. Notice that β is the mean level parameter across individuals and products, and hence we denote

$$\delta_{jt} \equiv X_{jt}\beta - \alpha p_{jt} + \xi_{jt}, \tag{4.2}$$

Table 22 Summary Statistics for the Prices and Quantities of Four Groups During Tropical Storm Period in 1996-2010

Vegetables		The day before the day of landfall			The day of landfall	The day after the day of landfall	
		T-3	T-2	T-1	T	T+1	T+2
I. The observations based on the date of landfall							
Roots	Price (NT$/kg)	26.88 (6.13)	27.51 (6.64)	28.58 (7.15)	27.97 (6.65)	27.38 (6.32)	26.90 (6.20)
	Quantity (10^3kg)	283.13 (35.67)	282.10 (45.62)	258.54 (49.62)	285.39 (38.02)	284.00 (32.92)	281.60 (32.60)
Green Leafy Vegetables	Price (NT$/kg)	19.48 (6.55)	20.41 (7.48)	21.44 (7.69)	21.16 (7.20)	20.33 (7.03)	19.39 (6.65)
	Quantity (10^3kg)	389.68 (61.63)	383.26 (76.70)	363.07 (78.89)	397.31 (73.17)	390.04 (67.62)	379.67 (56.49)
Bulbs and Tubers	Price (NT$/kg)	25.07 (9.76)	25.91 (10.24)	27.50 (10.52)	26.85 (10.05)	26.17 (10.11)	24.68 (9.32)
	Quantity (10^3kg)	305.98 (82.70)	310.87 (91.21)	284.79 (84.48)	316.23 (71.29)	311.40 (67.64)	315.84 (72.68)
Mushrooms	Price (NT$/kg)	61.25 (7.23)	60.73 (6.41)	59.98 (7.59)	60.78 (6.52)	60.92 (6.81)	61.17 (6.68)
	Quantity (10^3kg)	13.79 (5.15)	13.68 (3.45)	13.72 (3.85)	13.81 (3.40)	13.70 (3.52)	13.23 (3.28)
II. The observations specified during the warning period							
	Observations		3	56	76	38	
Roots	Price (NT$/kg)	-	30.67 (11.36)	27.32 (6.19)	27.97 (6.65)	29.94 (7.01)	-
	Quantity (10^3kg)	-	273.57 (24.10)	283.51 (34.40)	285.39 (38.02)	253.93 (46.60)	-
Green Leafy Vegetables	Price (NT$/kg)	-	21.03 (11.20)	20.13 (6.97)	21.16 (7.20)	22.57 (7.42)	-
	Quantity (10^3kg)	-	333.35 (98.10)	389.22 (64.28)	397.31 (73.17)	356.40 (73.23)	-
Bulbs and Tubers	Price (NT$/kg)	-	23.36 (9.03)	26.27 (10.48)	26.85 (10.05)	28.78 (10.71)	-
	Quantity (10^3kg)	-	313.07 (38.73)	310.45 (71.95)	316.23 (71.29)	268.58 (74.82)	-
Mushrooms	Price (NT$/kg)	-	56.94 (1.90)	61.13 (6.61)	60.78 (6.52)	59.90 (8.81)	-
	Quantity (10^3kg)	-	13.99 (0.73)	13.29 (3.57)	13.81 (3.40)	13.24 (3.88)	-

Source: < http://amis.afa.gov.tw/>.
Note: 1. The values in the parenthesis are standard deviations.

Table 23 Summary Statistics for the Prices and Quantities of Four Groups in the First and Second Day of Warning Announcement in 1996-2010

		The day before the 1st day of warning (T-1)	The 1st day of warning (T)	The 2nd day of warning (T+1)	Strong Intensity			Medium Intensity			Weak Intensity		
					T-1	T	T+1	T-1	T	T+1	T-1	T	T+1
Groups	Obs.	76	74	41	12	12	10	45	40	23	19	17	5
Roots	Price	25.31	25.44	26.24	26.25	26.64	29.99	25.52	26.04	24.54	24.23	23.16	23.17
		(6.38)	(6.82)	(7.26)	(6.82)	(6.74)	(8.30)	(6.75)	(7.47)	(5.69)	(5.27)	(5.17)	(4.62)
	Quantity	191.81	200.99	203.74	193.29	208.30	213.29	194.12	201.33	198.64	185.41	189.87	196.60
		(29.26)	(34.30)	(32.11)	(28.22)	(39.98)	(18.16)	(33.17)	(36.84)	(36.49)	(18.27)	(19.73)	(10.90)
Green Leafy Vegetables	Price	17.89	18.92	20.62	19.05	20.29	23.18	18.37	19.64	20.10	16.01	16.77	16.93
		(5.97)	(6.20)	(6.29)	(5.71)	(6.02)	(7.87)	(6.19)	(6.40)	(5.58)	(5.42)	(5.72)	(5.77)
	Quantity	334.26	336.91	358.45	327.22	336.41	388.23	338.37	338.34	344.55	328.97	321.87	357.64
		(50.51)	(59.38)	(53.63)	(50.22)	(41.75)	(33.18)	(54.81)	(68.70)	(63.74)	(40.51)	(45.16)	(16.23)
Bulbs and Tubers	Price	25.56	26.72	28.62	28.11	29.19	34.97	26.58	27.89	26.21	21.54	22.87	25.76
		(9.62)	(10.19)	(10.18)	(7.21)	(8.20)	(12.38)	(10.48)	(10.90)	(8.32)	(7.86)	(9.78)	(11.92)
	Quantity	236.81	239.52	245.35	213.26	228.78	243.13	233.52	235.34	240.24	259.47	240.69	256.21
		(52.75)	(56.09)	(56.29)	(46.83)	(52.52)	(68.74)	(48.83)	(57.11)	(57.20)	(59.06)	(52.02)	(45.08)
Mushrooms	Price	60.77	61.58	62.24	65.96	67.23	69.74	60.38	61.47	59.40	58.38	57.93	58.17
		(6.85)	(6.04)	(7.46)	(8.66)	(7.26)	(7.37)	(6.45)	(5.16)	(5.33)	(4.78)	(4.82)	(6.99)
	Quantity	13.47	13.91	13.76	12.36	13.44	14.74	13.81	14.45	12.57	13.39	12.23	13.44
		(3.43)	(3.84)	(3.27)	(3.05)	(2.65)	(3.27)	(3.55)	(4.42)	(2.90)	(3.40)	(2.64)	(2.33)

Source: http://amis.afa.gov.tw/.
Note: 1. The values in parenthesis are standard deviations.
2. The prices and the quantities are reported in NT$/kg and 1000kg, respectively.

where δ_{jt} is called the "mean utility" for vegetable *j* at time *t* and ξ_{jt} is interpreted as unobserved quality correlated with market price p_{jt} and characteristics X_{jt} To specify the demand system completely, we assume that individual *i* will maximize his utility by choosing the consumption quantities among N vegetables plus another type of good, which is called "outside good" and denotes the non-purchase of any vegetables inside the market. Therefore individual *i* will divide his income on one of the vegetables plus the outside good, and we can calculate the aggregate market share of vegetable *j* at time *t* as:

$$s_{jt} = \frac{q_j}{M}, \forall j = 0, \cdots, N, \tag{4.3}$$

where $j = 0$ represents the outside good, and M is the observed total market size. Define y_{ijt} as an indicator with value 1 if individual *i* chooses vegetable *j* at time *t*, and hence the multinomial logit choice probabilities are

$$Prob\left(y_{ijt} = 1 \mid \beta, x_{j't}, \xi_{j't}, j' = 1, \cdots J\right) = \frac{exp\left(\delta_{jt}\right)}{\sum_{j'=1}^{J} exp\left(\delta_{j't}\right)}, \tag{4.4}$$

This is also defined as aggregate market share s_{jt}. At this aggregate market share level, the individual-level decision-making problem (Independence of Irrelevant Alternatives, IIA), is thus solved.

We would have the endogeneity problem because of the correlation between ξ_{jt} and p_{jt}, and hence an IV-based estimation approach is suggested by Berry (1994). Let predicted share $\tilde{s}_{jt} = \frac{exp\left(\delta_{jt}\right)}{1+\sum_{j'=1}^{J} exp\left(\delta_{j't}\right)}$, and the system of equations from matching actual share to predicted shares would be:

the predicted share of outside good:

$$\hat{s}_{0t} = \frac{1}{1+\sum_{j=1}^{J} exp\left(\delta_{jt}\right)}, \tag{4.5}$$

the predicted share of vegetable k:

$$\hat{s}_{kt} = \frac{exp\left(\delta_{kt}\right)}{1+\sum_{j=1}^{J} exp\left(\delta_{jt}\right)}. \tag{4.6}$$

The mean utility δ_{jt} of the outside good is assumed to be zero, which is necessary to identify the random estimators to complete the specification of the demand system. Taking logs and doing a log transposition we obtain

$$\delta_{jt} = \log \hat{s}_{jt} - \log \hat{s}_{0t}, j = 1, \cdots, J. \tag{4.7}$$

Hence we finally get the following logistic regression:

$$\log \hat{s}_{jt} - \log \hat{s}_{0t} = X_{jt}\beta - \alpha p_{jt} + \xi_{jt}, \tag{4.8}$$

where α and β are the coefficients and interpret as the marginal utility change induced by characteristics and market price.

Let q_j denote the quantity of vegetable j and Q denote the aggregate market quantity, the own-price elasticity and the cross-price elasticities can be calculated as follows:

own-price elasticity:

$$\begin{aligned}\varepsilon_{jjt} &= \frac{\partial q_{jt}/q_{jt}}{\partial p_{jt}/p_{jt}} = \frac{\partial q_{jt}/Q_t}{\partial p_{jt}}\frac{p_{jt}}{q_{jt}/Q_t} = \frac{\partial s_{jt}}{\partial p_{jt}}\frac{p_{jt}}{s_{jt}} \\ &= \alpha s_{jt}\left(1-s_{jt}\right)\frac{p_{jt}}{s_{jt}} = \alpha p_{jt}\left(1-s_{jt}\right),\end{aligned} \tag{4.9}$$

cross-price elasticity:

$$\begin{aligned}\varepsilon_{jkt} &= \frac{\partial q_{jt}/q_{jt}}{\partial p_{kt}/p_{kt}} = \frac{\partial q_{jt}/Q_t}{\partial p_{kt}}\frac{p_{kt}}{q_{jt}/Q_t} = \frac{\partial s_{jt}}{\partial p_{kt}}\frac{p_{kt}}{s_{jt}} \\ &= -\alpha s_{jt}s_{kt}\frac{p_{kt}}{s_{jt}} = -\alpha p_{kt}s_{kt}.\end{aligned} \tag{4.10}$$

Notice that all the price elasticities are based on market shares. This generates the same cross-price elasticity since the cross-price elasticity only depends on the market share and market price of vegetable *k*. It is the limitation of the differentiated-product discrete-choice demand model; however, we will not fix this unusual substitution pattern here.

To analyze the impacts of tropical storm strikes on consumers in the whole market, we would like to know the change in consumer's welfare, which can be measured from the change of indirect utility of individual *i*. The expenditure on vegetable consumption is usually a small proportion of the individual's total income, and the compensating variation is thus applied since it is quite equivalent to the change in Marshallian consumer surplus. With the assumptions that there are no changes in the unobserved characteristics of vegetable *j* at time *t*, ξ_{jt}, in the short run and there are no changes in the utility from the outside good (Nevo 2000), the change in Marshallian consumer surplus for individual *i* is approximated following De Jong et al. (2007) and given by:

$$\Delta E\left(CS_i^u\right)=\left(1/\alpha^*\right)\left(\ln\sum_j \exp\left(V_j^t\right)-\ln\sum_j \exp\left(V_j^s\right)\right) \tag{4.11}$$

where α^* is the coefficient obtained from equation (4.8), t is the time that tropical storm strikes, s is the time without tropical storm strikes, and V is the indirect utility of consuming vegetable j at time t or s.

Besides, in the short-run vegetable production is fixed and hence the market faces a perfect inelastic supply. Assuming all production costs remain unchanged, producers' surplus is then simply the sum of the revenues across four vegetable groups. Hence the total change in producer's welfare in the market will be given by:

$$\Delta E\left(PS\right)=\sum_j\left(R_j^t-R_j^s\right) \tag{4.12}$$

where R_j^t indicates the revenue from selling vegetable j during tropical storm strikes. Total welfare change due to tropical storm strike is thus the sum of the change in consumer surplus and the change in producers' surplus.

4.4. Estimation Results and Discussion

Following Berry (1994) the model will be estimated as a discrete choice model. In estimation mushrooms will be taken as the outside good, and consumer i is assumed to makes his choice among root vegetables, green leafy vegetables, and bulbs and tubers. Since it is difficult to identify the specific characteristics of these vegetables, a vegetable group dummy is used. The year dummies are used to capture changes of consumption behavior and the inflation, and the seasonal dummies capture seasonal impacts.

Furthermore, supply shock variables are needed to identify the demand, and hence the following instrumental variables are selected:

- Area damaged by tropical storms, including: damaged area of root vegetables, damage area of green leafy vegetables, and damage area of bulbs and tubers;
- Rainfall dummies, identifying three levels of occurrence: the cumulative precipitation is in the range of 130 mm and 200 mm, in the range of 200mm and 350mm, and greater than 350mm.

Notice that the interpretation of the utility change of individual *i* is in terms of dollars, and hence all the coefficients are divided by the coefficient of market price, α.

Table 24 reports the model estimation results. The coefficients denote the unit changes in utility, and all can be transformed into monetary units when divided by α. The marginal effect of market price on the utility of each individual *i* is -0.0188, which means that one dollar increase in vegetable prices will reduce the individual's utility by 0.0188 units. Later we will discuss the market price effects using price elasticity. Hence the value of -0.0188 will only be used to calculate the utility change caused by other variables in terms of dollars.

Compared with green leafy vegetables, the consumption of root vegetables and bulbs and tubers reduce the individual's utility by \$10.54 and \$8.36, respectively. Therefore, consumer *i* will prefer to choose green leafy vegetable to maximize his utility, and bulbs and tubers will be consumer *i*'s second choice. Furthermore, compared with purchasing vegetables in the fall season, the purchase in winter has less utility ($-\$9.78$) while that in summer has higher utility ($+\$2.04$) for consumer *i*.

Table 24 Vegetable Demand Estimation Results from 2SLS

	Coefficients	Stand Errors	t-values
Market price	-0.0188	0.0043	-4.32***
Root group dummy	-0.1981	0.0365	-5.43***
Bulb and Tuber group dummy	-0.1572	0.0367	-4.29***
Year Dummy_2003	-0.0941	0.0223	-4.22***
Year Dummy_2004	-0.0930	0.0164	-5.66***
Year Dummy_2005	-0.1324	0.0203	-6.53***
Year Dummy_2006	-0.1014	0.0118	-8.59***
Year Dummy_2007	-0.1134	0.0175	-6.47***
Year Dummy_2008	-0.1070	0.0175	-6.11***
Year Dummy_2009	-0.0369	0.0121	-3.06***
Year Dummy_2010	0.0263	0.0120	2.18**
Winter Season Dummy	-0.1839	0.0345	-5.32***
Spring Season Dummy	-0.0133	0.0421	-0.32
Summer Season Dummy	0.0383	0.0140	2.74***

Note: * p<0.1, ** p<0.05 and *** p<0.01.

As this paper uses daily data to estimate demand, the price elasticity is dynamic. To compare the price elasticities with and without tropical storm strike, we choose 8 and 9 days before the day of landfall as the non-tropical storm period and the days with tropical storm warning, including the day of landfall, as the tropical storm period. We calculate daily price elasticity and then take the average over the tropical storm period and the non-tropical storm period. Own-price elasticities, cross-price elasticities, and consumer surplus change from non-tropical storm period to tropical storm period are calculated and reported in table 25. We also report the price elasticities and consumer surplus changes under strong-, medium-, and weak-intensity tropical storm strike, respectively.

All own-price elasticities are less than unity, indicating that all three vegetable groups are price inelastic. The -0.3693 own-price elasticity of root vegetables indicates that there is a 36.93% reduction in root vegetable consumption if their price increases 1% during the non-tropical storm period. The absolute value of own-price elasticity of root vegetables is largest not only in the non-tropical storm period but also during the tropical storm period, implying that consumer *i* responses more to price changes for root vegetables relative to the other two vegetable groups. On the other hand, the price sensitivity of bulbs and tubers increases from -0.33 to -0.39, which is close to the price elasticity of root vegetables during tropical storm period, -0.41.

Furthermore, all three groups have larger own-price elasticity values during the tropical storm period, indicating that tropical storm strike makes the vegetable market more responsive to price changes, and strong storms generally have larger impacts than the lower intensity storms. Strong-intensity tropical storm strike makes all demands for vegetables more sensitive, a 10% difference for both green leafy vegetables and bulbs and tubers. The price elasticity change of root vegetables under weak-intensity tropical storm strike is comparable to that under medium-intensity tropical storm strike, and green leafy vegetables have similar result with root vegetables.

The cross-price elasticities represent the substitution relationships among the three groups, and tropical storm strikes generally slightly increase the substitution extent. Consumer *i* is likely to switch his consumption among vegetable groups during strong-intensity tropical storm strike period, suggesting that tropical storm intensity positively affects consumer *i*'s consumption behavior.

The consumer surplus change presents the consumer's welfare loss induced by tropical storm strike. The $-3.639 consumer surplus change reports that individual *i* will lose welfare at a rate of $3.639 per day during the tropical storm period. As reported in table 25, individual *i* will lose welfare at a rate of $5.94 per day if strong-intensity tropical storm strikes while he will only lose welfare of around $3.3 under medium- or weak-intensity storms. Considering the number of total households (7.7 million) and the 3-day tropical storm period, the consumer's welfare losses induced by each strong-, medium-, and weak-intensity tropical storm are NT$137.82 million, NT$76.68 million, and NT$77.76 million, respectively.

Table 25 also reports the producers' surplus change and the total welfare change between the non-tropical storm period and the tropical storm period. Generally vegetable producers as a whole will gain from tropical storm strike although those directly struck will not. This is not unexpected since both of the price and quantity of vegetables increase on the day of landfall, and the price of vegetables is even higher on the day after the day of landfall with the increase in price possibly compensating for the loss in quantity. However, it should be noticed that the market price and quantity used in this study are collected from the wholesale market, and hence equation (4.12) does not uncover farmer's welfare rather it captures welfare to the marketing chain including producers, transporters and wholesalers.

The daily producers' surplus changes of root vegetables, green leafy vegetables, and bulbs and tubers are gains of NT$0.34 million, NT$1.32 million, and NT$1.10 million, respectively. This result shows that the producers of green leafy vegetables have greatest gain from storm strikes, which is consistent even considering the changes in different storm intensities. If we compare the producers' surplus change among different storm intensities, both producers of green leafy vegetables and bulbs and tubers gain most under strong-intensity storms while the producers of roots gain most under medium-intensity storms. The overall change in producers' surplus is then aggregated, and it shows that the greatest producers' surplus gain is under strong-intensity storm strikes over against the other intensity storm strikes.

Considering both changes in consumer surplus and producers' surplus, the society losses an average of NT$ 25.76 million per day during storm strikes. The total country level welfare losses induced by each strong-, medium-, and weak-intensity tropical storm are NT$125.19 million, NT$67.71 million, and NT$72.87 million, respectively, during a 3-day tropical storm period. Applying the incidence and average annual frequency in table 20, the annualized total welfare loss increases from NT$389.56 million in the first period to NT$452.81 million in the second period. It indicates that the social welfare loss induced by tropical storms is larger in recent years, possibly reflecting from the greater intensity of recent storms possibly because of climate change.

Table 25 Average Price Elasticity and Welfare Change

Groups	All Tropical storms Before[1]	All Tropical storms After[1]	Strong Intensity Before[1]	Strong Intensity After[1]	Medium Intensity Before[1]	Medium Intensity After[1]	Weak Intensity Before[1]	Weak Intensity After[1]
Own-Price Elasticity								
Roots	-0.3693 (0.0781)	-0.4083 (0.0969)	-0.4107 (0.0931)	-0.4582 (0.0995)	-0.3706 (0.0834)	-0.4095 (0.0974)	-0.3428 (0.0424)	-0.3812 (0.0878)
Green Leafy Vegetables	-0.2208 (0.0854)	-0.2560 (0.0874)	-0.2247 (0.0679)	-0.3136 (0.1215)	-0.2317 (0.1003)	-0.2588 (0.0798)	-0.1998 (0.0627)	-0.2223 (0.0653)
Bulbs and Tubers	-0.3274 (0.1445)	-0.3905 (0.1716)	-0.3729 (0.1254)	-0.4738 (0.1781)	-0.3503 (0.1694)	-0.3970 (0.1753)	-0.2615 (0.0720)	-0.3371 (0.1481)
Cross-Price Elasticity [2]								
if k is Roots	0.1508 (0.0425)	0.1612 (0.0439)	0.1615 (0.0374)	0.1790 (0.0438)	0.1550 (0.0513)	0.1635 (0.0473)	0.1375 (0.0216)	0.1481 (0.0346)
if k is Green Leafy Vege.	0.1385 (0.0534)	0.1692 (0.0618)	0.1549 (0.0519)	0.2029 (0.0757)	0.1450 (0.0585)	0.1723 (0.0587)	0.1176 (0.0384)	0.1466 (0.0527)
if k is Bulbs and Tubers	0.1404 (0.0380)	0.1638 (0.0465)	0.1528 (0.0339)	0.2036 (0.0595)	0.1448 (0.0452)	0.1635 (0.0429)	0.1256 (0.0182)	0.1445 (0.0324)
Consumer Surplus Change Per Day[3]								
Individual	NT$-3.6390		$-5.9428		$-3.3062		$-3.3538	
Total Household[3]	NT$-28.52 million		NT$-45.94 million		NT$-25.56 million		NT$-25.92 million	
Producers' surplus Change Per Day[3]								
Roots	NT$0.34 million		NT$0.38 million		NT$0.48 million		NT$0.08 million	
Green Leafy Vegetables	NT$1.32 million		NT$2.01 million		NT$1.37 million		NT$0.89 million	
Bulbs and Tubers	NT$1.10 million		NT$1.83 million		NT$1.13 million		NT$0.66 million	
Total	NT$2.76 million		NT$4.21 million		NT$2.99 million		NT$1.63 million	
Total Welfare Change Per Day[3]	NT$-25.76 million		NT$-41.73 million		NT$-22.57 million		NT$-24.29 million	

Note: 1. Before represents non-tropical storm period, which is 8 and 9 days before the tropical storm landfall, and During represents tropical storm period.

2. Based on equation (4.10), the cross price elasticity ε_{jkt} only depends on the price and market share of group k, and hence we report the elasticities from the change of group k.

3. The change per day is reported in New Taiwan Dollars.

4. The number of total household in Taiwan is estimated to be average 7.73 million.

5. The values in the parenthesis are standard deviations.

Table 26 presents several scenarios with different increased tropical storm intensity and frequency. We arbitrarily assign these shifts since there is no simulated intensity or frequency information associated with the climate change scenarios. Since average annual storm strike is 4.19 in 1958-1984 and 5.48 in 1985-2011, the average annual strike without and with frequency change is assigned as 5 and 6, respectively.

Without frequency change, the annualized welfare losses are large for all the increased intensity scenarios. Consumers lose more welfare with losses rising up to $10 million dollars while producer's gain a little bit with the amount rising up to around NT$1 million dollars. Collectively society loses about NT $9 million. Both consumer's welfare and producer's welfare changes increase when strike frequency rises. For example, consumers lose around an additional $100 million dollars while producers gain additional NT$10 million dollars under scenario 6. This results a loss in annualized total welfare of NT$533.62 million, which exceeds the loss under current conditions. Thus the increase in frequency and intensity results in a more severe welfare loss for the society in the vegetable market.

4.5. Conclusions

This paper estimates effects of tropical storm strikes on the market for vegetables in Taiwan then analyzes the associated social welfare losses. Storm effects on demand are estimated by applying the differentiated-product discrete-choice demand model introduced by Berry (1994). The results suggest that the availability and resultant consumption of all vegetables is affected by strong-intensity tropical storm strikes. The whole society is estimated to lose NT$25.76 million per day under tropical storm strikes. The losses under strong-intensity tropical storm strikes rise to around NT$41.73 million per day while losses under medium-intensity strikes are NT$22.57 million per day and under weaker-intensity strikes this is NT$24.29 million per day. A sensitivity analysis on possible changes in storm frequency and intensity shows that consumers lose yet more welfare if climate change increases strikes with significant losses estimates under both frequency and intensity increases.

This study has some limitations. First it failed to analyze general forms of substitution between different vegetables. The model restricts the cross-price elasticity of each vegetable group *j* to only depend on the market share and market price of vegetable *k*. Second we only collected price and quantity information in one market (the first Taipei market), which is a wholesale market. The estimation would be improved if data from more markets were collected. Third, we could not find estimates of shifts in incidence and frequency of tropical storms in Taiwan under climate change rather doing an arbitrary sensitivity analysis and hence the analysis could be improved if such data were available. Fourth we used a discrete choice model and it may be better to use a more conventional commodity demand model.

Table 26 The Annualized Welfare Change of Tropical Storms with Difference Incidence and Frequency

	Intensity Shifts CDF under		Annualized Welfare Change	
	Weak	Medium	Without Frequency Change	With Frequency Change (Average increase by one)
Consumer's Welfare				
Current Scenario	23.75%	68.20%	NT$-481.90 million	-
Scenario 1	23.00%	68.00%	NT$-482.47 million	NT$-578.96 million
Scenario 2	22.00%	67.00%	NT$-485.47 million	NT$-582.56 million
Scenario 3	22.00%	65.00%	NT$-491.58 million	NT$-589.90million
Scenario 4	22.00%	66.00%	NT$-488.53 million	NT$-586.23 million
Scenario 5	21.50%	65.50%	NT$-490.03 million	NT$-588.03 million
Scenario 6	21.50%	65.00%	NT$-491.56 million	NT$-589.87 million
Producer's Welfare				
Current Scenario	23.75%	68.20%	NT$45.82 million	-
Scenario 1	23.00%	68.00%	NT$46.01 million	NT$55.22 million
Scenario 2	22.00%	67.00%	NT$46.40 million	NT$55.68 million
Scenario 3	22.00%	65.00%	NT$46.77 million	NT$56.12 million
Scenario 4	22.00%	66.00%	NT$46.58 million	NT$55.90 million
Scenario 5	21.50%	65.50%	NT$46.78 million	NT$56.13 million
Scenario 6	21.50%	65.00%	NT$46.87 million	NT$56.24 million
Total Welfare				
Current Scenario	23.75%	68.20%	NT$-421.24 million	-
Scenario 1	23.00%	68.00%	NT$-436.45 million	NT$-523.74 million
Scenario 2	22.00%	67.00%	NT$-439.07 million	NT$-526.88 million
Scenario 3	22.00%	65.00%	NT$-444.82 million	NT$-553.78 million
Scenario 4	22.00%	66.00%	NT$-441.84 million	NT$-530.33 million
Scenario 5	21.50%	65.50%	NT$-443.25 million	NT$-531.90 million
Scenario 6	21.50%	65.00%	NT$-444.69 million	NT$-533.62 million

5. CONCLUSIONS

This dissertation investigates the impacts of climate change in three ways addressing water effects of mitigation actions, livestock vulnerability and effects on welfare if tropical storm intensity is affected.

The first essay focuses on water implication of agricultural and forestry greenhouse gas mitigation efforts. The literature review indicates that AF mitigation will impact water quality and quantity. In particular many of the sequestration possibilities lessen water yield while increasing water quality. Also fertilization and animal management strategies have complex effects on water quality while having mixed effects on water quantity.

The empirical study result shows that an increase in grassland significantly decreases water yield with forestry having mixed effects. In turn using the regression results in a mitigation policy simulation exercise shows that water quantity slightly increases under lower carbon prices but it significantly decreases under higher carbon prices. On the other hand, water quality is degraded under most mitigation alternatives except for the use of bioenergy and forest management when carbon prices are low but improves under higher carbon prices.

The second essay examines climate change and dust issues in U.S. feedlots. We do an econometric investigation of the effects of dust and climate factors on cattle live sale weight finding that cattle sale weight is reduced by increased in dust and that the dust incidence will be aggravated by higher temperatures but suppressed by increases in precipitation. We then examine the benefits of dust control with and without the effects of climate change and find it beneficial across all cases examined. Additionally we find climate change to be consistently costly.

The third essay turns to the analysis of market response and welfare effects to tropical storm strikes in the context of vegetable purchases in Taiwan. The results show that tropical storm strikes raise vegetable prices, and that higher intensity storms generally have larger impacts than lower intensity storms. We find Taiwan consumers lose from storm strikes while producers gain with society in total losing. A sensitivity analysis shows that the intensifications in tropical storms or increases in storm frequency as might occur under climate change would enlarge social welfare losses.

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APPENDIX

In essay 2 a subindex is needed to convert each water quality indicator into a relative quality rating, and then a single water quality index (WQI) is formed using these subindices. All the subindex (SI) transformation formulae in equation (2.1) are adopted from Cude (2001).

Total Nitrogen (N)

$N \leq 3\ mg/L \qquad SI_N = 100(-0.4605N)$

$N > 3\ mg/L \qquad SI_N = 10$

Total Phosphorus (P)

$P \leq 0.25\ mg/L \qquad SI_P = 100 - 299.5P - 0.1384P^2$

$P > 0.25\ mg/L \qquad SI_P = 10$