An Optimal Application of Swine Effluent in Texas and Oklahoma Panhandle Determined by Bayesian Stochastic Dynamic Programming

Chaowana Phetcharat, Art Stoecker, Jeffory A. Hattey,
Jason G. Warren, Jeffrey D. Vitale, and Seong C. Park
Oklahoma State University

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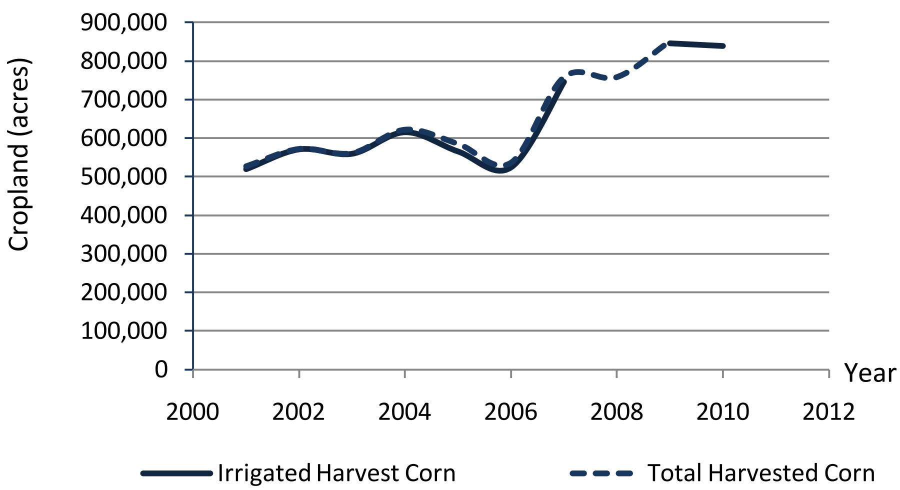
Contact Information:
Chaowana Phetcharat
557 Agr.Hall, Department of Agricultural Economics
Oklahoma State University, Stillwater, OK 74078-6026
Email: phetcha@okstate.edu

Introduction

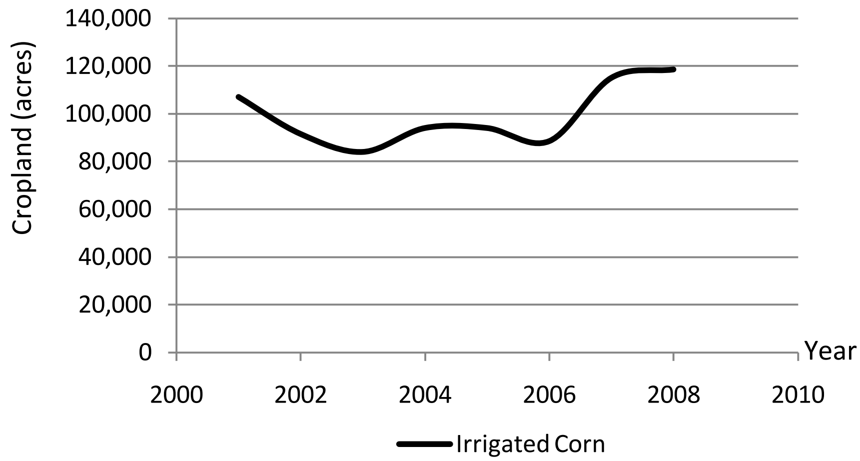
The acreage of corn in Texas and Oklahoma Panhandles has been increasing during the past several years. The total acre of harvested corn in Texas Panhandle increased from 527,000 acres in 2001 to 858,000 acres in 2010. The acreage of irrigated corn increased from approximately 519,000 acres in 2001 to almost 840,000 acres in 2010 (shown in figure 1). In the same time period, the acreage of irrigated harvested corn in Oklahoma Panhandle increased from 107,000 acres in 2001 to 118,500 acres in 2008 (shown in figure 2). The total acres of harvested corn (irrigated and non-irrigated) increased to 145,000 acres in year 2010 (NASS, 2011).

Figure 1. Acres of harvested corn in Texas Panhandle, 2001 – 2010



Source: National Agricultural Statistics Service, 2011.

Figure 2. Acres of irrigated harvest corn in Oklahoma Panhandle, 2001- 2008



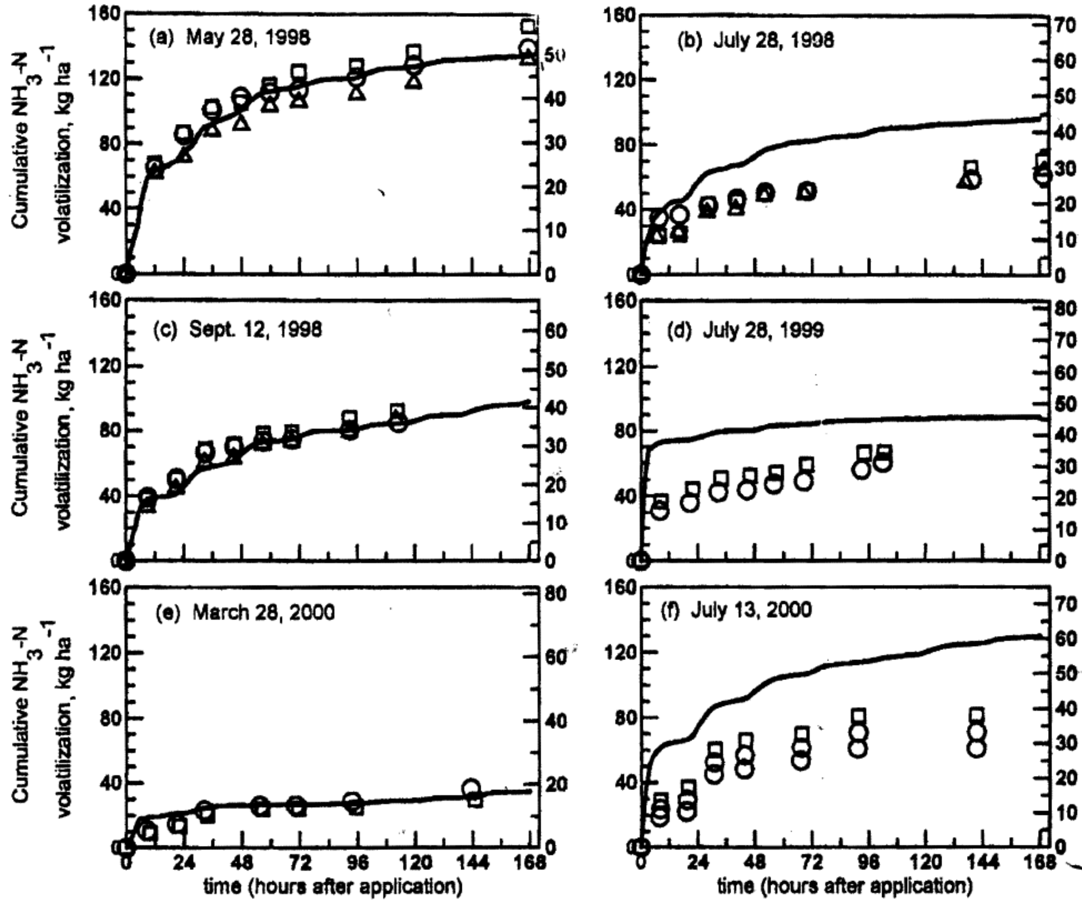
Source: National Agricultural Statistics Service, 2011.

The number of confined animal feeding operations (cattle, and swine) in Panhandle area have also increased in both number of animals and in the size of firm over the past several years. Since year 1991, the number of swine operations in Oklahoma Panhandle have increased following the removal of restrictions on corporate farms [Oklahoma Senate Bill 518]. The swine population in Oklahoma was almost 2,300,000 head in 2009 (NASS, 2011). The crop and livestock sectors have become major sources of regional growth bringing monetary benefits to residents. However, the confined livestock operations have created large quantities of animal waste in dry and liquid forms. The two states, Texas and Oklahoma, are among the highest 20% of animal waste producing areas (http://www.scorecard.org/env-releases/aw/). Animal manure contains plant nutrients such as nitrogen, phosphorus, and potassium and organic matter. The percent of N availability varies from 30 to 80 percent depending on the source of manure. The nutrients in swine effluent available for plant uptake range between 30- 50 percent during the first year of application (Zhang, 2009). However, improper use and lack of management of animal manure could harm the environment in areas such as soil, water, and air quality.

Specially, most of the nitrogen in swine effluent is in the ammonium form ($NH_4 - N$) which can be volatilized during storage and application. The effluent in Panhandles is mostly applied to cropland through irrigation systems. This could be subject to volatilization loss during and/or after the field application. Several researchers have studied the volatilization of liquid manure during and after application. Warren (2001) reported that 23 to 48 percent of NH_3 from liquid manure can be lost to the air within a few days after field application on fallow cropland in Oklahoma Panhandle area. Previous researchers have reported that several factors, including low humidity, high temperatures, and high wind speeds substantially increase the level of ammonia (N) volatilization. Apsimon et al. (1987) found that the amount of NH_3 flux from ground to the atmosphere following liquid manure application was high during conditions of low humidity, high winds, and high temperatures. The level of NH_3 flux was high during the first day of application and its volatilization speed rapidly declined over the following days. The level of NH_3 flux after cattle slurry was sprayed on the surface was 110 μg N $m^{-2}s^{-1}$ during the first day of application. The NH_3 volatilization dropped to 6.1 μg N $m^{-2}s^{-1}$ on the fifth day following the application (Yang et al, 2003).The loss of nitrogen is expensive. If producers compensate for the nitrogen loss by adding more effluent, it contributes to excessive applications of phosphorus. Attempts to compensate for the nitrogen loss can also result in excessive runoff of nutrients to streams and lakes. On the other hand, applying too little manure can reduce crop yields.

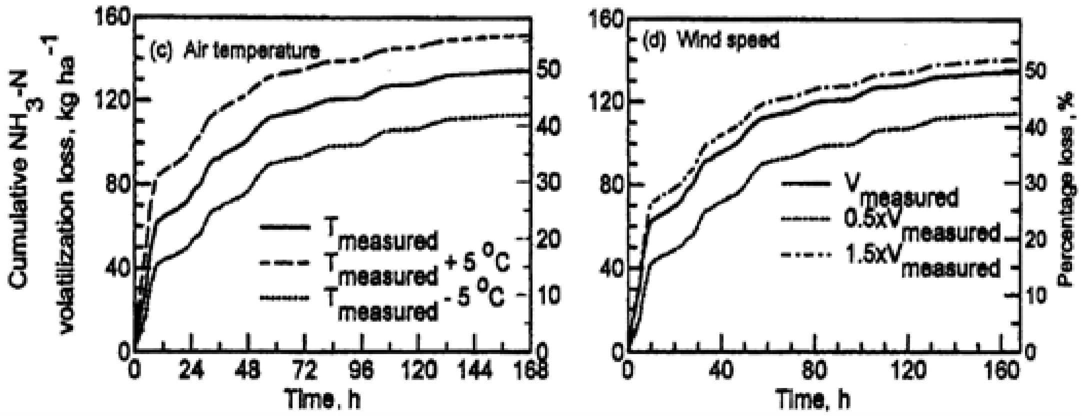
Wu et al. (2003a) developed a mechanistic model to simulate water infiltration and ammonia volatilization (NH_3) during the irrigation event. The model was designed to simulate the evaporation and ammonia volatilization from the soil surface, and also the transport and transformation of ammonia N in the soil profile during and after application. The model uses hourly temperature, solar radiation, humidity, and wind speed values for up to 192 hours after the event to create an ammonia N concentration profile based on the ammonia transport and transformation. The model includes sub-models that simulate water flow, heat flow, and the transport and transformation of ammonia N in the soil profile. The water and heat flow models provide information on soil moisture and temperature that is needed for the calculation of parameters in the transport and transformation model. Then, the rate of ammonia volatilization from the soil surface is determined by the concentration of ammoniacal N in the soil surface. The sub-models were also developed to calculate the ammonia volatilization and water evaporation from the sprinkler droplet. The model was derived from the mass and energy balance in a droplet based on observed changes in the ammonia concentration during the flight of the droplets from the sprinkler to the soil surface. Researchers found ammonia losses were higher during May and July than during March. The validation of the ammonia volatilization model is shown in figure 3. Figure 4 also shows the sensitivity of cumulative ammonia loss to temperatures and wind speed.

Figure 3. The validation of the ammonia volatilization model at Goodwell Oklahoma in May, July, September, and March of 1998 and 2000



Source: Wu, J., D.L. Nofziger, J.G. Warren, and J.A. Hattey. 2003a. "Modeling Ammonia Volatilization from Surface Applied Swine Effluent." *Soil Sci. Soc. America J.* 67(1): 1-11.

Figure 4. The sensitivity of cumulative distribution of hourly ammonia volatilization to temperature and wind speed



Source: Wu, J., D.L. Nofziger, J.G. Warren, and J.A. Hattey. 2003a. "Modeling Ammonia Volatilization from Surface Applied Swine Effluent." *Soil Sci. Soc. America J*. 67(1): 1-11.

In the study, Wu et al. (2003a) used the mechanistic model to estimate the rate of ammonia volatilization and the cumulative amount of N loss from the swine effluent during an application based on hourly Mesonet weather data. As stated above, application of lagoon effluent during times of high wind and temperatures and low humidity increases the amount of ammonia N volatilization. The wind, temperature, solar radiation, and humidity also vary through the most favorable times are expected to occur at night. At the beginning of the time window for application, a producer must determine whether to apply effluent under current conditions or wait until conditions are more favorable. If an application is postponed and the more favorable weather condition does not occur, the producer incurs a loss of corn gain yield or must apply a more expensive commercial fertilizer. The problem of evaluating the amount of N loss from applying at any point in time is much more complicated than assumed in the simple example above. This is because the actual N loss depends not only on the current weather but on climatic factors i.e. air temperature, wind speed, relative humidity, solar radiation, and rainfall that occur for up to eight days following the application. Simple simulation using historical weather data can help in determining whether there are significant differences in ammonia losses by the hour of the day or the time of month the application occurs. Unfortunately, they do not really help the producer determine the current time is really the best time to apply or not.

The above problem requires that the producer be able to recognize whether at the current time is optimal for an application or whether it is better to wait for another time. Past research has utilized Bayesian stochastic dynamic programming (BSDP) to determine the optimal timing of agricultural decisions under risky conditions. Bayesian method can be used to reduce an uncertainty of the outcome by incorporating the additional information of the weather forecast to the problem. The choice of the best time to apply irrigation effluent is not greatly different from the optimal timing of irrigation events. Cai et al. (2009) have investigated the accuracy of weather forecasts for estimating the reference evapotranspiration (ET_0). In their study, weather forecast of daily temperatures, wind grade, and solar radiation were used to estimate the parameters of the reference evapotranspiration (ET_0) equation for wheat in China. The authors concluded that the reference evapotranspiration (ET_0) prediction from weather forecast data could be used for making real time irrigation schedules. The simulation of the soil water balance for wheat production using the ET_0 from weather forecast messages was also sufficiently accurate when compared to the observed values.

Gowing et al. (2001) used Bayesian Stochastic Dynamic Programming (BSDP) to determine real-time scheduling of supplement irrigation for potatoes over the wet, average, and dry year using rainfall weather forecasts. They reported that the irrigation decision using weather forecasts in the wet year (1992) resulted in a higher profit than irrigation without considering the weather forecasts (SDP). The profit from the irrigation with weather forecast (BSDP) was also more than the profit form irrigation without weather forecast (SDP) in the average year. The profits for BSDP were higher than SDP in dry years. Wilks et al. (1997) also determined the optimal daily irrigation for lettuce in a humid climate, New York State, using precipitation forecasts. They reported that the daily irrigation decision was unnecessary during the growing period, 62 days (1 May and 15 July) when the probability of next day rainfall was height. In contrast, the daily irrigation was required when the probability of the next day's rainfall was zero regardless of today's forecast rainfall. The economic value from using both days' precipitation forecasts (day-1 and day-2) was higher than using only the 50 percent of water available criterion. The results also show that economic value from using one and two day forecasts were $900 for a large farm operation, and $1,000 per hectare for a family farm operation.

A research question is, "What is the value of using forecast information to reduce the uncertainty associated with weather in the two to five days following an effluent application in the Panhandle?" Mesonet provides hourly weather forecasts of temperature, humidity, wind speed, and solar radiation (percent of cloud cover) for the current day and for 3.5 days ahead. While the producer can observe the current weather, a substantial portion of the ammonia loss also depends on the weather which occurs up to eight days following the application. The Mesonet weather forecast data could be used to provide the producer with an estimate of the amount of ammonia that will volatilize during and following the application over a 3.5 day period. The decision of the producer is then to apply the effluent given the expected loss from the current forecast or wait until a later date with a more favorable forecast. A hypothesis in this study is that the probability of obtaining a more perfect time to apply the swine effluent in the next period can be derived from historical weather data and forecast weather data. The revision of historical and forecast weather could improve the accuracy of the producer decision.

The objectives of this study are to;

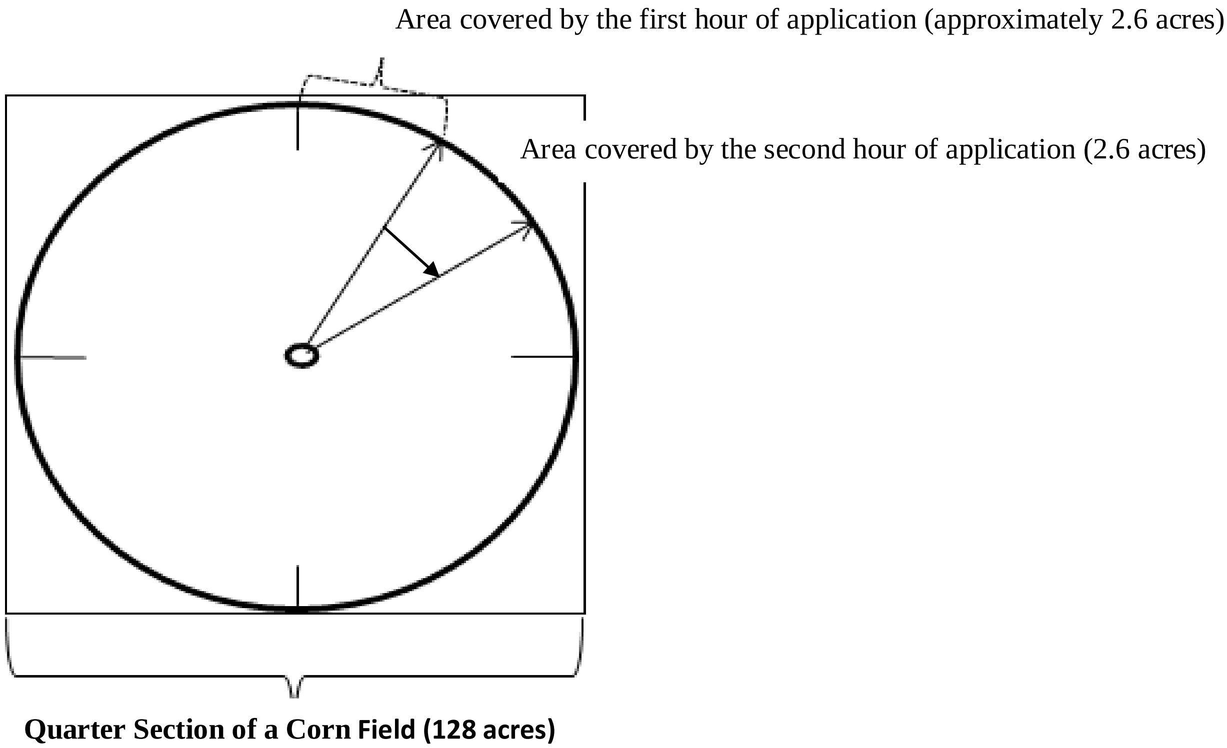
(1) Determine the most economically efficient time to apply swine effluent through an irrigation system during the post-planting season, and

(2) Estimate the economic benefits of the producer's decision from adopting optimal application schedules.

Representative Application Situation

Corn in the Panhandle area is planted from late March through the middle of May (National Agricultural Statistic, 2008), and the field application of effluent occurs from April to middle of June (J. Wu, 12 May 2011). In this region, sprinkle and furrow irrigation systems are used to apply the lagoon effluent. The swine effluent is commonly mixed with fresh water and applied through a center pivot sprinkler irrigation system. The system in this study is assumed to have a pumping capacity of 2,460 liters per minute (650 gallons/min.) with 500 meters in length of circle radius (¼ mile central pivot coverage). For 250 bushel of corn yield growth, the producers would need to apply 168 kilogram of N per hectare to meet plant nutrient require (J. G. Warren, December 2010). Technically, the irrigation system will require around 49 hours to complete an application for a quarter section corn field (approximately 128 acres). This sprinkler irrigation system is operated as a circle. In addition to previous research, the temperatures, relative humidity, and wind speeds could affect the level of ammonia N volatilization (Zupancic, 1999). Hence, the amount of N volatilized in each segment of a quarter section corn field stated above is varied by the weather condition occurring at and after each application time. For instance, the volatilization loss of N in the first segment of land depends on the weather conditions occurring in the 192 hours following the time of application. The volatilization of ammonia N from the second segment will depend on the weather conditions beginning at that hour of application. Figure 5 illustrates field coverage into one-hour segments.

Figure 5. Schematic for pivot irrigation system



In this study, the planting period of effluent application from April 1-May 15 was divided into eight periods. Out of these periods, the producer must find 49 hours (not necessarily continuous) that initiate a five day window of favorable weather in order to apply the effluent to a 128 acre pivot irrigated field.

Data Sources

The hourly weather data for air temperature, wind speeds, relative humidity, and solar radiation observed at the Goodwell, Mesonet station, in Texas county, Oklahoma, were collected for the years 1994 through 2010. The weather data were gathered for April 1- May 15 for each year. These sixteen years of daily-hourly weather data were used to estimate the amount of cumulative N loss (8 days, or 192 hours after the event) for each hour time step of the application using the mechanical model developed by Wu et al. (2003a). This generated more than 15,000 estimates of simulated nitrogen losses. The simulated N losses were used in computing the probability distributions of ammonia loss (the prior probability). Similarly, the archive of the forecast weather on temperature, wind speeds, relative humidity, and solar radiation was provided by the meteorological consulting company, Weatherbank, Inc., in Edmon, Oklahoma (Eric Freier, 30 May 2011). These forecast weather was for Guymon (National Weather Service), Texas county. Nitrogen losses from the forecast weather were estimated only from years 2005-2010 using the mechanical model (Wu et al, 2003a). These 6,500 estimates of cumulative N losses were used along with the N losses from actual weather data that occurred during the same time period. This comparison was used to compute the conditional probability of ammonia loss from the forecast data given the ammonia loss from actual weather data, $P(Z_{i,c}^{F} \mid L_{i,s})$. The two probabilities were then applied to the Bayesian method for determining the best time to apply the swine effluent.

The statistical data obtained from Mesonet were the hourly means for temperature, wind speed, relative humidity, and solar radiation for each hour from April 1- May 15, 1994-2010 as shown in Table 1. The range of values indicates that temperature, wind speeds, relative humidity, and solar radiation are highly variable throughout the day.

Table 1. Mean and range of hourly temperature, wind speed, relative humidity, and solar radiation for April 1-May 15, 1994-2010

Hour of the day	Application Time	Air Temperature (C)[a]			Relative Humidity (%)			Wind Speed (m/s)			Solar Radiation (W/M^2)		
		Mean	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max
1	0:00	10.01	-7.2	25.0	67.31	10	100	5.78	0.4	18.3	2.9	0.0	146.8
2	1:00	9.36	-7.8	23.9	69.89	11	100	5.71	0.1	20.6	0.8	0.0	38.3
3	2:00	8.77	-8.3	22.8	71.99	11	100	5.58	0.4	19.7	0.0	0.0	0.3
4	3:00	8.24	-8.3	22.2	73.48	13	100	5.48	0.7	18.0	0.0	0.0	0.0
5	4:00	7.74	-8.9	21.7	74.86	10	100	5.35	0.4	18.0	0.0	0.0	0.0
6	5:00	7.33	-9.4	20.6	75.75	18	100	5.26	0.1	18.1	0.8	0.0	11.0
7	6:00	7.37	-9.4	20.6	75.91	13	100	5.28	0.7	18.6	39.7	0.0	170.0
8	7:00	9.37	-7.8	22.8	70.54	12	100	5.81	0.4	17.5	176.1	4.0	359.0
9	8:00	12.04	-6.1	27.2	61.36	10	100	6.77	0.4	18.9	354.0	4.0	604.5
10	9:00	14.38	-6.1	29.4	53.48	6	100	7.18	0.9	20.6	529.7	13.0	816.1
11	10:00	16.32	-6.1	32.8	47.27	6	100	7.19	0.7	22.8	675.6	15.0	986.9
12	11:00	17.86	-5.6	35.0	42.62	4	99	7.19	0.8	21.5	780.0	13.0	1196.9
13	12:00	19.11	-4.4	35.6	38.96	3	99	7.20	0.4	22.5	823.2	11.0	1265.7
14	13:00	20.11	-3.3	36.7	36.12	3	100	7.25	0.9	21.0	810.9	0.0	1275.0
15	14:00	20.80	-3.3	38.9	34.34	3	100	7.40	1.3	19.7	740.8	0.0	1198.0
16	15:00	21.15	-3.3	38.3	33.15	3	100	7.50	0.9	18.9	627.5	0.0	1007.0
17	16:00	21.11	-2.8	37.8	33.12	3	99	7.53	0.8	19.3	469.9	0.0	886.0
18	17:00	20.55	-3.3	37.2	34.34	3	99	7.51	0.7	17.0	300.3	0.0	713.0
19	18:00	19.13	-3.9	35.0	37.88	3	100	6.80	1.0	18.8	136.5	1.0	559.1
20	19:00	16.19	-4.4	33.9	46.03	5	100	6.08	0.9	19.7	26.8	0.0	494.8
21	20:00	13.81	-6.1	28.9	53.18	7	100	5.87	0.4	19.2	11.6	0.0	482.3
22	21:00	12.58	-6.7	26.7	57.77	8	100	5.91	0.7	16.5	9.4	0.0	396.6
23	22:00	11.70	-6.7	26.7	61.21	9	100	5.88	0.5	17.0	7.5	0.0	325.5
24	23:00	10.84	-7.2	25.6	64.54	10	100	5.77	0.4	17.0	5.4	0.0	248.1

a This is the average temperature, wind speed, relative humidity, and solar radiation obtained from Mesonet, Oklahoma at Goodwell station

Method

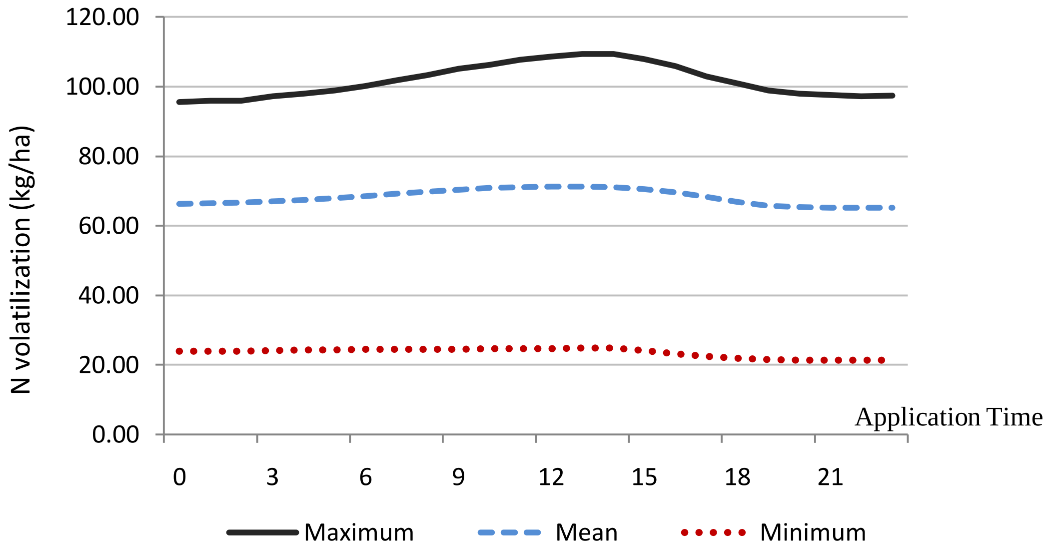
The range of ammonia losses after one hour, 24 hours, 168 hours, and 192 hours by hour of application using the data for April 1- May 15, 1994-2010 are shown in Table 2. A visual view of the data (figure 6) indicates that the mean nitrogen losses by the 192'nd hour are nearly the same regardless of the hour of application. The mean losses average 38 to 42 percent of the nitrogen applied. As noted above, spring is the time of the year when ammonia losses were the smallest. However, the minimum losses after 192 hours are less than 35 percent of the mean losses. With the cost of $0.53 per pound of N (in urea form), i.e., the four-year average price from 2007-2010 (NASS, 2011), the difference between the minimum and mean loss is about $21.60 per acre while the difference between the minimum and maximum N loss is almost $39.86 per acre. Table 2 above shows there is considerable variation around the mean. Furthermore, the range of hourly temperature, wind speed, relative humidity, and solar radiation shown in Table 1 confirms that there is considerable variability in the weather from one day to the next. The preliminary analysis points out the need for producers to be able to identify a favorable five to eight day window for application.

Table 2. Summary statistic of average cumulative N volatilization following the swine effluent for April 1-May 15, 1994-2010 by Wu's model

Hours of the day	Application Time	1 hour after application (kg/ha)[b]					24 hour after application (kg/ha)					192 hour after application (kg/ha)				
		Mean	SD	Min	Max	Mean % lost	Mean	SD	Min	Max	Mean % lost	Mean	SD	Min	Max	Mean % lost
1	0	1.4	1.7	0.0	19.0	0.8	20.9	12.5	1.2	59.7	12.4	66.4	13.2	23.9	95.6	39.5
2	1	1.1	1.2	0.0	13.5	0.7	20.8	12.5	1.2	59.6	12.4	66.5	13.2	23.9	96.0	39.6
3	2	1.0	1.0	0.0	7.1	0.6	20.9	12.6	1.3	60.0	12.4	66.7	13.3	24.0	96.0	39.7
4	3	0.9	0.9	0.0	7.6	0.5	21.0	12.8	1.3	60.6	12.5	67.0	13.4	24.1	97.2	39.9
5	4	0.8	0.8	0.0	6.0	0.5	21.3	13.0	1.3	62.0	12.7	67.4	13.5	24.2	98.0	40.1
6	5	0.8	0.8	0.0	6.6	0.5	21.6	13.3	1.3	63.6	12.8	67.9	13.7	24.3	99.0	40.4
7	6	0.9	0.8	0.1	6.0	0.5	22.0	13.6	1.3	65.1	13.1	68.5	13.9	24.4	100.1	40.8
8	7	1.3	1.2	0.1	9.0	0.8	22.6	14.1	1.3	68.1	13.4	69.2	14.1	24.5	101.8	41.2
9	8	2.0	1.9	0.1	16.5	1.2	23.2	14.6	1.2	71.6	13.8	69.9	14.3	24.5	103.2	41.6
10	9	2.9	2.8	0.1	20.9	1.7	23.9	15.1	1.2	73.0	14.2	70.4	14.6	24.6	105.2	41.9
11	10	3.7	3.6	0.1	23.4	2.2	24.5	15.5	1.2	72.7	14.6	70.8	14.8	24.6	106.3	42.2
12	11	4.4	4.4	0.1	24.4	2.6	25.0	15.8	1.2	73.9	14.9	71.1	14.9	24.7	107.7	42.3
13	12	5.2	5.2	0.1	25.2	3.1	25.5	16.0	1.2	78.1	15.2	71.3	15.1	24.8	108.7	42.4
14	13	5.8	5.9	0.1	30.0	3.5	25.8	16.0	1.2	80.6	15.4	71.3	15.1	24.8	109.4	42.4
15	14	6.4	6.3	0.1	30.9	3.8	26.0	15.7	1.2	79.4	15.5	71.0	15.1	24.9	109.3	42.3
16	15	6.6	6.4	0.1	32.2	3.9	25.8	15.3	1.2	78.1	15.4	70.5	15.0	24.1	108.0	42.0
17	16	6.4	6.2	0.1	35.0	3.8	25.3	14.7	1.2	75.6	15.0	69.6	14.8	23.2	106.0	41.4
18	17	5.6	5.2	0.1	27.4	3.3	24.3	13.9	1.3	73.0	14.5	68.4	14.4	22.4	102.9	40.7
19	18	4.0	3.7	0.1	21.9	2.4	22.9	13.0	1.3	65.2	13.6	66.9	14.1	21.8	100.9	39.8
20	19	2.6	2.6	0.1	19.7	1.6	21.8	12.4	1.2	60.1	13.0	65.8	13.7	21.5	98.8	39.1
21	20	2.1	2.4	0.1	21.5	1.3	21.4	12.3	1.2	59.2	12.7	65.4	13.7	21.3	98.0	38.9
22	21	1.9	2.2	0.1	21.4	1.1	21.2	12.3	1.2	59.5	12.6	65.3	13.7	21.3	97.5	38.9
23	22	1.7	2.1	0.0	21.2	1.0	21.2	12.3	1.2	60.0	12.6	65.2	13.7	21.3	97.3	38.8
24	23	1.5	2.0	0.0	21.8	0.9	21.1	12.4	1.2	60.0	12.5	65.2	13.7	21.3	97.5	38.8

[b] The average cumulative N volatilization occurring at each application time which were estimated from the mechanical model (Wu et al, 2003a)

Figure 6. The average cumulative N volatilization after 192 hours by hour of application for April 1-May 15, 1994-2010



The Mesonet currently posts hourly 3.5 day forecasts weather for each of the Mesonet sites in Oklahoma. Bayesian methods could provide a means to incorporate these forecasts into decision making. In the analysis, the historical weather condition and weather forecast were taken into the Bayesian methods to determine the best time to apply the swine effluent which will be explained in the following section.

Use of Bayesian methods to include forecasts in the Decision Model

Let L_i be the expected ammonia loss from an application with the weather condition (temperature, wind speed, etc.) beginning at time *i*. And $Z_{i,}^{F}$ is ammonia loss estimated from using forecast weather in place at time *i*. The probability of ammonia loss L_i given forecast loss Z_i^F can be calculated as

(3) $$g(L_i \mid Z_i^F) = \frac{P(L_i) * P(Z_i^F \mid L_i)}{P(Z_i^F)}$$

$$P(Z^F) = \sum_{i=1}^{I} P(Z_i \mid L_i) * P(L_i)$$

where

- $P(L_i)$ is the prior probability of ammonia loss L with the weather condition at time i ,
- $P(Z_i^F \mid L_i)$ is the conditional probability of the forecast loss Z_i^F given actual ammonia loss L_i,
- $g(L_i \mid Z_i^F)$ is the conditional probability of actual ammonia loss L_i when the forecast of ammonia loss Z^F is received.
- $P(Z_i^F)$ is the probability of occurrence of the forecast ammonia loss of Z_i^F .

The Bayesian method is to calculate the probability matrix $P(Z_i^F \mid L_i)$. The first step in calculating the matrix was to divide the mean ammonia losses estimated from forecast weather into rank intervals. In our study, the mean losses were divided into 13 classes with an increment of five kilogram class per-hectare of ammonia loss (30-34.99, 35-39.99, etc.). The frequency of ammonia losses was calculated from the actual weather in the same period. The tabulation was done for all classes of the forecast weather predicted losses.

Estimation of Prior Probabilities of Ammonia Loss by Time of Month

The prior probability is the probability of ammonia loss occurring in each class mean loss. To compute this probability, the ammonia losses from the historical actual weather for April 1- May 15, 1994-2010 were first estimated using the mechanical model (Wu et al, 2003a). Then, summarized the simulated losses as the rank interval with the five kilogram class per-hectare of loss (20-24.99, 25-29.99, etc.). The prior probabilities of ammonia loss in each class mean were calculated as follows

(4) $$P(L_s) = \frac{A_s}{n}$$

where $P(L_s)$ is the prior probability of ammonia loss falling in the class mean loss of *s*. A_s is the frequency or number of times that ammonia loss occurs in the class mean *s*, and *n* is the total number of simulated N losses. There were eighteen classes of ammonia loss in this study. The prior probabilities of ammonia loss at each class mean are shown in Table 3.

Table 3. The prior probabilities of ammonia loss in each mean class

Rank Interval	Class Range (kg/ha)	Frequency	Prior Probability *P(L)*
1	20-25	82	0.005
2	25-30	156	0.009
3	30-35	236	0.013
4	35-40	317	0.017
5	40-45	352	0.019
6	45-50	624	0.034
7	50-55	872	0.048
8	55-60	2036	0.112
9	60-65	2388	0.131
10	65-70	2749	0.151
11	70-75	2508	0.138
12	75-80	2121	0.117
13	80-85	1632	0.090
14	85-90	1097	0.060
15	90-95	653	0.036
16	95-100	248	0.014
17	100-105	79	0.004
18	105-110	18	0.001
Sum Total		18,168	1.000

Accuracy of using Weather Forecasts to Estimate Ammonia Loss

The 192 hour weather forecasts of temperature, humidity, solar radiation, and wind speed were used to simulate ammonia losses by the mechanistic model (Wu et al, 2003a). The simulated losses from the forecast weather data were used with the losses from the actual losses for April 1- May 15 from 2005 through 2010 to compute the probability matrix, $P(Z_i^F \mid L_i)$. These actual losses were estimated to occur given the actual weather that occurred during the forecast period to probability of the forecast given the actual ammonia loss. The probability matrix is shown in Table 4.

Table 4. The conditional probability of the forecast loss given actual ammonia loss

Class Means of Actual Ammonia loss	Class Means of Ammonia Loss Estimated from Forecast Weather (kg/ha)												
	30-35	35-40	40-45	45-50	50-55	55-60	60-65	65-70	70-75	75-80	80-85	85-90	90-95
20-25	0.196	0.353	0.451	0	0	0	0	0	0	0	0	0	0
25-30	0	0.325	0.375	0.200	0.088	0.013	0	0	0	0	0	0	0
30-35	0	0	0.074	0.231	0.537	0.157	0	0	0	0	0	0	0
35-40	0	0	0.007	0.158	0.596	0.240	0	0	0	0	0	0	0
40-45	0	0	0.085	0.316	0.424	0.158	0.017	0	0	0	0	0	0
45-50	0	0	0.027	0.365	0.316	0.217	0.076	0	0	0	0	0	0
50-55	0	0	0.002	0.140	0.271	0.235	0.211	0.114	0.026	0	0	0	0
55-60	0	0	0	0.035	0.103	0.193	0.208	0.172	0.208	0.077	0.004	0	0
60-65	0	0	0	0.008	0.036	0.077	0.218	0.258	0.215	0.159	0.028	0	0
65-70	0	0	0	0.005	0.020	0.042	0.188	0.252	0.264	0.170	0.058	0.001	0
70-75	0	0	0	0	0.011	0.022	0.080	0.225	0.321	0.256	0.084	0.001	0
75-80	0	0	0	0	0	0.016	0.018	0.060	0.265	0.269	0.269	0.078	0.024
80-85	0	0	0	0	0	0.018	0.030	0.137	0.278	0.288	0.190	0.050	0.008
85-90	0	0	0	0	0	0.046	0.010	0.030	0.162	0.279	0.239	0.203	0.030
90-95	0	0	0	0	0	0	0	0	0.034	0.222	0.393	0.274	0.077
95-100	0	0	0	0	0	0	0	0	0	0.278	0.111	0.278	0.333
100-105	0	0	0	0	0	0	0	0	0	0	0	1.000	0

Method of Calculation of Bayes Posterior Probabilities

The posterior probability is the conditional probability of actual ammonia loss when the forecast is received, denoted by $g(L_i \mid Z_i^F)$. The posterior probability at particular class interval of forecast predicted loss was calculated following equation (3) above. The posterior probabilities and the expected amount of N loss for each class mean of forecast weather predicted loss are shown in Table 5.

Table 5. The conditional probability of actual ammonia loss when the forecast is received, *g (L|Z)*

Class Means Of Actual N loss (kg/ha)	Means of Actual N loss in each class	Class Means of Ammonia Loss Estimated from Forecast Weather (kg/ha)												
		30-35	35-40	40-45	45-50	50-55	55-60	60-65	65-70	70-75	75-80	80-85	85-90	90-95
20-25	22.5	1	0.36	0.23	0	0	0	0	0	0	0	0	0	0
25-30	27.5	0	0.64	0.36	0.04	0.01	0.00	0	0	0	0	0	0	0
30-35	32.5	0	0	0.11	0.08	0.10	0.03	0	0	0	0	0	0	0
35-40	37.5	0	0	0.01	0.07	0.15	0.06	0	0	0	0	0	0	0
40-45	42.5	0	0	0.18	0.16	0.12	0.04	0.00	0	0	0	0	0	0
45-50	47.5	0	0	0.10	0.33	0.15	0.10	0.02	0	0	0	0	0	0
50-55	52.5	0	0	0.01	0.17	0.18	0.15	0.09	0.04	0.01	0	0	0	0
55-60	57.5	0	0	0	0.10	0.16	0.29	0.21	0.13	0.11	0.05	0.00	0	0
60-65	62.5	0	0	0	0.03	0.07	0.13	0.26	0.23	0.14	0.12	0.04	0	0
65-70	67.5	0	0	0	0.02	0.04	0.08	0.26	0.26	0.20	0.15	0.08	0.00	0
70-75	72.5	0	0	0	0	0.02	0.04	0.10	0.21	0.22	0.20	0.11	0.00	0
75-80	77.5	0	0	0	0	0	0.02	0.02	0.05	0.15	0.18	0.31	0.21	0.22
80-85	82.5	0	0	0	0	0	0.02	0.02	0.08	0.12	0.15	0.17	0.10	0.06
85-90	87.5	0	0	0	0	0	0.04	0.01	0.01	0.05	0.10	0.14	0.28	0.14
90-95	92.5	0	0	0	0	0	0	0	0	0.01	0.05	0.14	0.22	0.22
95-100	97.5	0	0	0	0	0	0	0	0	0	0.02	0.01	0.09	0.36
100-105	102.5	0	0	0	0	0	0	0	0	0	0	0	0.10	0
Expected loss at each class of forecast ammonia loss		**22.50**	**25.68**	**32.12**	**46.59**	**48.71**	**57.55**	**63.32**	**67.51**	**71.13**	**75.08**	**80.04**	**88.27**	**89.62**

Formation of the Bayesian Stochastic Dynamic Programming Problem

The Bayesian formulas were then applied to the producer decision to determine the best time for applying the lagoon effluent. The producer will compare the expected ammonia loss from applying at the current weather condition with the expected loss from applying in the next period. When the prior probability distribution, the probability of forecast occurrence, the posterior probability, and the expected loss from applying the effluent at the current period are known, the producer's objective function over the two periods can be simplified as

(5) $$Minimize\ \ E(L_{i,j,d}) + \{\sum_{i=1}^{I} P(Z_i^F) * E(L_{i,j+1,d})\}$$

Subject to:

$$E(L_i) = \sum_{i=1}^{I} \bar{L}_i + g(L_i \mid Z_i^F)$$

$$g(L_i \mid Z_i^F) = \frac{P(L_i) * P(Z_i^F \mid L_i)}{P(Z_i^F)}$$

$$d \ = 1 or\ 2$$

where

- $E(L_i)$ is the expected ammonia loss (lbs/acre) from applying the effluent at given forecast weather condition in place at time i ,
- $P(Z_i^F)$ is the probability of occurrence of the forecast ammonia loss of Z_i^F ,
- $\bar{L}_i$ is the means of actual ammonia loss in at any particular class,
- $g(L_i \mid Z_i^F)$ is the conditional probability of actual ammonia loss L_i when forecast $Z_{i,}^F$ is received.

- d is the choice variables. $d = 1$ if the producer decides to apply the effluent under any forecast weather circumstance. And $d = 2$ when the producer decides to wait for more favorable weather in the next period ($j+1$).

In the study, the planting period of corn (April 1-May 15) was divided into eight five-day periods. In multiperiod case, the producer's objective is to minimize the total ammonia loss over the planting season. Hence, the producer will compare the expected ammonia losses given a forecast for the next 192 hours to the expected ammonia losses occurring over the remaining future periods.

Evaluating Economic Benefit from Adopting an Optimal Decision

The optimal solution for the best time to apply the swine effluent was determined using the Bayesian stochastic decision formulation in an Excel spreadsheet. The solution was solved for each time period starting from the end of the season and moving backward to the beginning of the season. The producer will employ the optimal schedules when the total expected amount of cumulative N loss over the planting season is reduced from applying the effluent during without forecast weather information. The economic benefit then can be evaluated in terms of the nitrogen fertilizer cost reduction.

Results and Discussion

Bayesian Stochastic Dynamic Solution

The optimal solution for selecting the best time to apply the swine effluent using Bayesian Stochastic Dynamic was solved using the formulation in Microsoft Excel spreadsheet. In our study, the season was divided into eight five-day periods. The solution was solved for each period by starting from the last period and moving backward to the first period. The producer must decide whether to take an action to apply the effluent at the current time or wait for the next period. The decision is determined by comparing the expected loss from applying at the current time with expected loss from applying in the next period. Results shown in Table 6 indicate that the producer decides to apply the effluent at the current forecast when the expected loss was less than the expected loss from waiting. At the end of the season (period 8) if the producer has not yet applied the effluent it must be applied. The total expected loss in period 8 is 68.11 kg/ha, calculated from multiplying the probability of each level of loss by the amount of the loss. Knowledge of the expected loss in period 8 is then used to help in producer's decision making in period 7. For example if the producer is in period 7 and receives a forecast that the expected N loss from applying is 22.5 kg/ha, then the producer would apply because this is less than the expected loss of 68 kg/ha from applying in period 8. In looking at the options for Period 7 in Table 6 the producer would apply given any forecast loss less than 68 kg/ha and wait given any forecast with a loss higher than 68 kg/ha. The lower part of the column for period 7 can now be filled. When the producer is in period 6, then expected loss from applying in period 7 has declined to 58.48 kg/ha which is less than expected loss from waiting until period 8. The decisions for each weather forecast in periods 1-6 were determined the same way.

Table 6. Summary of optimal solution

The Forecast Given Loss (kg/ha)	Expected N loss (kg/ha)	Probability of Forecast	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7	Period 8
30-35	22.5	0.00	22.5	22.5	22.5	22.5	22.5	22.5	22.5	22.5
35-40	25.7	0.00	25.7	25.7	25.7	25.7	25.7	25.7	25.7	25.7
40-45	32.1	0.01	30.7	32.1	32.1	32.1	32.1	32.1	32.1	32.1
45-50	46.6	0.04	30.7	34.6	39.1	44.2	46.6	46.6	46.6	46.6
50-55	48.7	0.07	30.7	34.6	39.1	44.2	48.7	48.7	48.7	48.7
55-60	57.6	0.08	30.7	34.6	39.1	44.2	50.4	57.6	57.6	57.6
60-65	63.3	0.11	30.7	34.6	39.1	44.2	50.4	58.5	63.3	63.3
65-70	67.5	0.15	30.7	34.6	39.1	44.2	50.4	58.5	67.5	67.5
70-75	71.1	0.20	30.7	34.6	39.1	44.2	50.4	58.5	68.1	71.1
75-80	75.1	0.18	30.7	34.6	39.1	44.2	50.4	58.5	68.1	75.1
80-85	80.0	0.10	30.7	34.6	39.1	44.2	50.4	58.5	68.1	80.0
85-90	88.3	0.04	30.7	34.6	39.1	44.2	50.4	58.5	68.1	88.3
90-95	89.6	0.01	30.7	34.6	39.1	44.2	50.4	58.5	68.1	89.6
Total of Expected Loss		(kg/ha)	**27.3**	**30.7**	**34.6**	**39.1**	**44.2**	**50.4**	**58.5**	**68.1**

The expected ammonia losses at any given weather condition from apply the effluent during average time (without using weather forecast) are reported in Table 7.

Table 7. The frequency distribution of expected N volatilization in the Oklahoma Panhandle from Swine Effluent Applications from April 1 through May 15.

The Actual Given Loss (kg/ha)	Class Mean of Actual Loss (kg/ha)	Probability of Loss	Expected Loss (kg/ha)
20-25	22.5	0.00	0.10
25-30	27.5	0.01	0.24
30-35	32.5	0.01	0.42
35-40	37.5	0.02	0.65
40-45	42.5	0.02	0.82
45-50	47.5	0.03	1.63
50-55	52.5	0.05	2.52
55-60	57.5	0.11	6.44
60-65	62.5	0.13	8.21
65-70	67.5	0.15	10.21
70-75	72.5	0.14	10.01
75-80	77.5	0.12	9.05
80-85	82.5	0.09	7.41
85-90	87.5	0.06	5.28
90-95	92.5	0.04	3.32
95-100	97.5	0.01	1.33
100-105	102.5	0.00	0.45
	Total Expected Loss		**68.11**

Economic Benefit from Adopting an Optimal Decision

As stated earlier, the economic benefit from choosing the best time for effluent application can be evaluated in terms of minimizing the total expected ammonia loss over the planting season. In this study, we compared the cost of commercial fertilizer that the producer uses for compensate the lost of nitrogen from swine effluent application. It was done by comparing the expected N loss for given forecast at the current time with the expected N loss from waiting until the next period. The prices of nitrogen fertilizer in urea form (44-46% N) from 2007-2010 are shown in Table 8.

Table 8. The prices of urea with 44-46% nitrogen for 2007-2010

Year	Price per ton ($)	Price per pound ($)
2007	453	0.49
2008	552	0.60
2009	486	0.53
2010	448	0.49
Average Price		**0.53**

The results presented in Table 9 show the optimal schedules using weather forecast information to apply in any period when the current forecast predicts a lower loss than the expected loss from waiting until the next period. This optimal schedule reduced the amount of N loss from 60.62 lbs/acre to 24.27 lbs/acre in period 1 when the producer incorporated weather forecast to his/her decision. On a quarter section of pivot irrigated corn (128 acres), the producer could reduce the cost of commercial nitrogen to compensate for lost nitrogen by almost $2,500 ($4,112.46-$1,646.30). Similarly, the economic value of weather forecast for other periods can be identified as this reduced cost of N volatilization that the producer will need to compensate by commercial fertilizer.

Table 9. The comparison of the nitrogen cost from effluent application under optimal time and average time

Planting Period	Expected Loss with Forecast Information			Expected Loss without Forecast Information		
	Expected Loss (lbs/acre)[1]	Cost Per Acre ($)[2]	Cost Per Quarter Section ($)	Expected Loss (lbs/acre)	Cost Per Acre ($)	Cost Per Quarter Section ($)
1	24.27	12.86	1,646.30	60.62	32.13	4,112.46
2	27.33	14.48	1,853.80	60.62	32.13	4,112.46
3	30.81	16.33	2,090.15	60.62	32.13	4,112.46
4	34.79	18.44	2,360.33	60.62	32.13	4,112.46
5	39.35	20.85	2,669.21	60.62	32.13	4,112.46
6	44.82	23.75	3,040.42	60.62	32.13	4,112.46
7	52.05	27.59	3,531.12	60.62	32.13	4,112.46
8	60.62	32.13	4,112.46	60.62	32.13	4,112.46

Note:

1. The expected N loss was converted to pound per acre.
2. Value of swine effluent was calculated as the value of nitrogen in the form of urea. This average price of nitrogen was $0.53 per pound (the four years average price, 2007-2010).

Conclusion

The results of this study suggest that corn producers in Panhandle area can increase their economic benefits from using forecast information to determine the time to apply the swine effluent. The forecast information can help to reduce the uncertainty associated with weather conditions, and this has economic benefits in the form of reduced ammonia volatilization. The amount of ammonia volatilizations from using forecast information are expected to be less than the amount of volatilizations from randomly applies. The monetary value of forecast could indicate by the reduced cost of commercial fertilizer from the cost without using forecast information.

In our results, the expected ammonia loss and the cost of commercial fertilizer ($/acre) in each period were reduced when the producer incorporated weather forecasts to his/her decision making. Hence, the forecast information would be a potential factor that the farmers in

Panhandles should consider for their management practice of swine effluent application. However, the current study is not finished. It remains to determine the value of using forecast methods to spread the effluent over the entire 128 acres field. This practice would improve the benefit of the producers in the areas.

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