AN OPTIMAL APPLICATION OF SWINE EFFLUENT IN TEXAS AND OKLAHOMA PANHANDLES DETERMINED BY BAYESIAN STOCHASTIC DYNAMIC PROGRAMMING

By

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IN TEXAS AND OKLAHOMA PANHANDLES

DETERMINED BY BAYESIAN STOCHASTIC

DYNAMIC PROGRAMMING

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TABLE OF CONTENTS

Chapter Page

I. INTRODUCTION ... 1
Background ... 1
Problem ... 6
Study's Objectives, Hypotheses, and Justification ... 12
Objectives ... 12
Justification of the Study ... 13
Assumptions of the Study and Data Sources ... 14
Study Assumptions ... 14
Data Sources ... 16
II. LITERATURE REVIEW ... 18
Swine Effluent Application ... 18
Ammonia Volatilization Issues ... 18
Ammonia Volatilization Models ... 19
Application of Dynamic Programming (DP) in Agricultural Decision ... 21
The Incorporation of Weather Forecast through the Bayesian method ... 23
Application of Bayesian Stochastic Dynamic Programming to the Decision Making ... 24
III. METHODOLOGY ... 27
Conceptual Framework ... 27
Representative Application Situation ... 28
Ordinary Stochastic Dynamic Programming Problem (SDP) ... 30
Incorporation of Weather Forecast ... 32
Procedure ... 33
Simulation of Ammonia Volatilization for Historical Weather Data ... 35
Simulation of Ammonia Volatilization for Forecast Weather Data ... 46

Chapter Page

Step 1: Computation of Prior Probability Distribution of Ammonia Loss 53

Step2: Calculation of the Joint Forecast Loss and Actual Loss Probability Matrix 57

Step 3: Deriving the Probability of a Forecast for Each Level of Ammonia Loss 64

Step 4: Derivation of the Bayes Posterior Probability Distribution for Each Level of Forecast Nitrogen Loss 68

Step 5: Estimation of Expected Ammonia Loss in terms of Forecast Data 71

Step 6: Stochastic Process of Deriving the Probability of the Next Forecast Loss given the Forecast of Current Ammonia Loss 71

Optimization Model 77

Value of Weather Forecasts 79

IV. FINDINGS 82

Validation of Mechanistic Model and Input Data Estimation 82

Econometric Estimation for the Differences in Simulated Cumulative N Volatilization 83

Bayesians Stochastic Dynamic Optimization Results 83

Method 3: Ammonia Volatilization without Using Forecast Information 97

Economic Value of Weather Forecasts 101

V. CONCLUSIONS AND RECOMMENDATION 106

Summary 106

Conclusions 107

Recommendations 108

BIBLIOGRAPHY 109

APPENDIXES 112

APPENDIX A-TRANSITION PROBABILITY MATRIC OF AMMONIA VOLATILIZATION 113

APPENDIX B-BAYESIAN STOCHASTIC DYNAMIC PROGRAMMING OPTIMIZATION 131

LIST OF TABLES

Table Page

Table I-1. Nitrogen Excretion from Swine per Year by the Stage of Production 3

Table I-2. Mean and Range of Hourly Temperature, Wind Speed, Humidity, and Solar Radiation for April 1-May 15, 1994-2010........ 8

Table I-3. Summary Statistics of Average N Volatilization follows Effluent Application for April 1-May 15, 1994-2010 by Wu's model 9

Table I-4. The prices of urea with 44-46% nitrogen for 2006-2010 17

Table III-1. Example for Two Period Problem of Ammonia N Volatilization for Ordinary Stochastic Dynamic Programming Model........ 32

Table III-2. The Statistical Results for the Differences in Cumulative N Volatilization by Six-hour and Five-day periods 37

Table III-3. The Statistical Results for the Differences in Cumulative N Volatilization by Twelve-hour Daytime-only and Five-day periods 37

Table III-4. The Parameter Estimates of the Differences in Simulated Cumulative N Volatilization after 192 Hours for Six-Hour Application Periods by Time and Date of Application Using Hourly Recorded Mesonet Data at Goodwell Oklahoma from 1994 to 2010 as Estimated with GLM Procedure in SAS 38

Table III-5. The Parameter Estimates of the Differences in Simulated Cumulative N Volatilization after 192 Hours for Twelve-hour Daytime-only by Date of Application Using Hourly Recorded Mesonet Data at Goodwell Oklahoma from 1994 to 2010 as Estimated with GLM Procedure in SAS........ 39

Table III-6. The Statistical Comparison of Ammonia Volatilization by Times of Application for Six-hour Day or Night Application Method Estimated with GLM Procedure in SAS........ 40

Table III-7. The Statistical Comparison of Ammonia Volatilization by Periods of the Post-planting Season for Six-hour Day or Night Application Method as Estimated with GLM Procedure in SAS 41

Table III-8. Least Squares Means of Cumulative N Volatilization after 192 Hours by Time of Application for Six-hour Day or Night Application Method Estimated with the GLM Procedure in SAS........ 42

Table		Page

Table III-9. Least Squares Means of Cumulative N Volatilization after 192 Hours by Periods of Application for Six-hour Day or Night Application Method Estimated with GLM Procedure in SAS.................. 43

Table III-10. The Statistical Comparison of Ammonia Volatilization by Periods for Twelve-hour Daytime-only Application Method as Estimated with GLM Procedure in SAS.. 44

Table III-11. Least Squares Means of Cumulative N Volatilization by Period for Twelve-Hours Daytime Application Method as Estimated with GLM Procedure in SAS.. 45

Table III-12. Summary Statistic for Correlation Coefficients of Solar Radiation and Climate Variables.. 47

Table III-13. Parameter Estimates for the Solar Radiation Estimated with GLM Procedure in SAS.. 49

Table III-14. Frequency Distribution of Simulated Ammonia Volatilizations after 192 Hours for the Twelve-hour Daytime-only Application by Five Day Period Using Hourly Recorded Mesonet Weather Data at Goodwell, Oklahoma from 1994 to 2010.. 54

Table III-15. The Prior Probability Distribution of Ammonia Losses for the Twelve-hour Daytime-only Application by Five Day Period from April 1 to May 15.. 56

Table III-16. The Probability Matrix of Ammonia Loss by Class Means Level of Loss for Applications during Time *k* 59

Table III-17. The Frequency Matrix of Ammonia Loss by Class Means Level of Loss for Applications during April 1 to 5 for the Twelve-hour Daytime-only Application Method... 61

Table III-18. The Probability Matrix, $\Pr(Z^i \mid L^s)$, of Ammonia Losses by Class Means Level of Loss for the Applications during April 1 to 5 for the Twelve-hour Daytime-only Application Method 63

Table III-19. The Probability of Forecast Ammonia Losses, $\Pr(Z^i)$, for Each Class Means Level of Forecast Predicted Loss for Applications during Time *k*.. 65

Table III-20. The Probability of the Occurrence of Ammonia Losses for Each Class Level of Forecast Predicted Loss for the Applications during April 1 to 5 for the Twelve-Hour Daytime-only Application Method.. 67

Table III-21. The Posterior Probability and the Expected Ammonia Loss for Each Class Means Level of Forecast Predicted Loss for the Applications during Time *k* 69

Table Page

Table III-22. The Posterior Probability and the Expected Ammonia Loss for Each Class Means Level of Forecast Predicted Loss for the Applications during April 1 to 5 for the Twelve-Hour Daytime-only Application Method ... 70

Table III-23. Markov Transition Probability Matrix Moving from Application Time *k* =1 to Application Time *k*+1 Given Decision *d*... 74

Table III-24. Markov Transition Probability of Forecast Ammonia Losses Moving from Applications during Twelve-hour Daytime of April 1 to the Next Day (April 2)... 76

Table IV-1. The Optimal Action Obtained from the BSDP model for the Twelve-hour Daytime-only Application Method ... 86

Table IV-2. The Total Expected Ammonia Volatilization from Swine Effluent Application for Each Class Range of Forecast Loss Obtained under BSDP Model ... 89

Table IV-3. The Range of Total Expected Ammonia Volatilization from Swine Effluent Application for Each Class Range of Weather Forecast of Period 1 (April 1) ... 92

Table IV-4. The Mean Average Days of Completing All Application for Each Class of Initial Forecast Ammonia Loss... 94

Table IV-5. Prior Probability of Ammonia Loss for Each Class of Weather Conditions for Application Made During April 1-5... 98

IV-6. Expected Ammonia Loss (lb./acre) from Applications Made during Each Six-hour of the Day by Each Five-day Period ... 100

Table IV-7. Expected Ammonia Loss for Covering a 128-Acre Corn Field from Applications during Each Five-day Period under the Twelve-hour Daytime-only Application Method... 101

Table IV-8. The Expected Cost of Nitrogen Fertilizer for 128 Acres of a Corn Field under Two Application Methods ... 105

Appendix Table 1. Markov Transition Probability of Forecast Ammonia Losses Moving from One Day to the Next for the Twelve-hour Daytime Application During April 1 to April 5 ... 114

Appendix Table 2. Markov Transition Probability of Forecast Ammonia Losses Moving from Twelve-hour between Application of April 5 and April 6... 115

Appendix Table 3. Markov Transition Probability of Forecast Ammonia Losses Moving from One Day to the Next for the Twelve-hour Daytime Application During April 6 to April 10 ... 116

Table Page

Appendix Table 4. Markov Transition Probability of Forecast Ammonia Losses Moving from Twelve-hour between Application of April 10 and April 11 117

Appendix Table 5. Markov Transition Probability of Forecast Ammonia Losses Moving from One Day to the Next for the Twelve-hour Daytime Application During April 11 to April 15 118

Appendix Table 6. Markov Transition Probability of Forecast Ammonia Losses Moving from Twelve-hour between Application of April 15 and April 16 119

Appendix Table 7. Markov Transition Probability of Forecast Ammonia Losses Moving from One Day to the Next for the Twelve-hour Daytime Application During April 16 to April 20 120

Appendix Table 8. Markov Transition Probability of Forecast Ammonia Losses Moving from Twelve-hour between Application of April 20 and April 21 121

Appendix Table 9. Markov Transition Probability of Forecast Ammonia Losses Moving from One Day to the Next for the Twelve-hour Daytime Application During April 21 to April 25 122

Appendix Table 10. Markov Transition Probability of Forecast Ammonia Losses Moving from Twelve-hour between Application of April 25 and April 26 123

Appendix Table 11. Markov Transition Probability of Forecast Ammonia Losses Moving from One Day to the Next for the Twelve-hour Daytime Application During April 26 to April 30 124

Appendix Table 12. Markov Transition Probability of Forecast Ammonia Losses Moving from Twelve-hour between Application of April 30 and May 1 125

Appendix Table 13. Markov Transition Probability of Forecast Ammonia Losses Moving from One Day to the Next for the Twelve-hour Daytime Application During May 1 to May 5 126

Appendix Table 14. Markov Transition Probability of Forecast Ammonia Losses Moving from Twelve-hour between Application of May 5 and May 6 127

Appendix Table 15. Markov Transition Probability of Forecast Ammonia Losses Moving from One Day to the Next for the Twelve-hour Daytime Application During May 6 to May 10 128

Appendix Table 16. Markov Transition Probability of Forecast Ammonia Losses Moving from Twelve-hour between Application of May 10 and May 11 129

Table | Page

Appendix Table 17. Markov Transition Probability of Forecast Ammonia Losses Moving from One Day to the Next for the Twelve-hour Daytime Application During May 11 to May 15 130

LIST OF FIGURES

Figure		Page
Figure I-1.	Acres of Harvested Corn in Texas Panhandle, 2001 – 2010	1
Figure I-2.	Acres of Irrigated Harvest Corn in Oklahoma Panhandle, 2001-2008	2
Figure I-3.	The Validation of The Ammonia Volatilization Model at Goodwell, Oklahoma in May, July, September, and March of 1998 and 2000	5
Figure I-4.	The Sensitivity of Cumulative Distribution of Hourly Ammonia Volatilization to Temperature and Wind Speed	5
Figure I-5.	The Average Cumulative N Volatilization after 192 Hours Following an Application (lbs/acre) by Hour of Application for April 1-May 15, 1994-2010	10
Figure III-1.	Schematic for Pivot Irrigation System	29
Figure III-2.	Flow Diagram Representing the Study	34
Figure III-3.	The comparison of cumulative N volatilization at 192 hours after application estimated from historical and forecast weather data for April 1-May 15, 2005-2010	52
Figure IV-1.	The Probability Distribution of Application Period for Completing the Application of Swine Effluent Given 150 lbs of Nitrogen per Acre	96
Figure IV-2.	Total Expected Ammonia Loss for Covering a 128-Acre Corn Field Obtained from With and Without Weather Forecast for Two Application Methods	102
Figure IV-3.	The Comparison of Nitrogen Fertilizer Cost per 128 Acre Corn Field between Application Methods	103
Appendix Figure 1.	The Excel Spreadsheet of Input Data Entry for Bayesian Stochastic Dynamic Programming Optimization	132
Appendix Figure 2.	The Dynamic Programming Routine for Optimization Application for Six-hour Day and Night Times Application Method	133

Figure | Page

Appendix Figure 3. The Dynamic Programming Routine for Optimization Application for Twelve-hour Daytime-only Application Method.......... 134

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I.

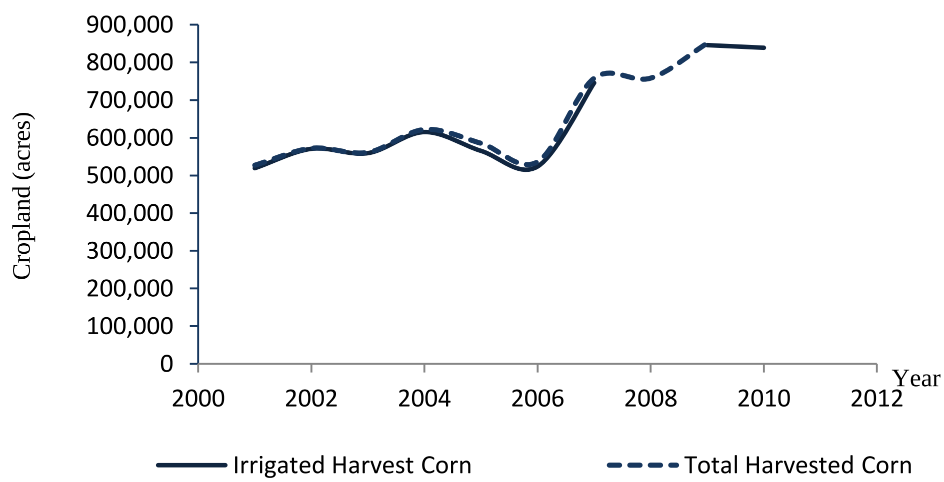
CHAPTER I

INTRODUCTION

Background

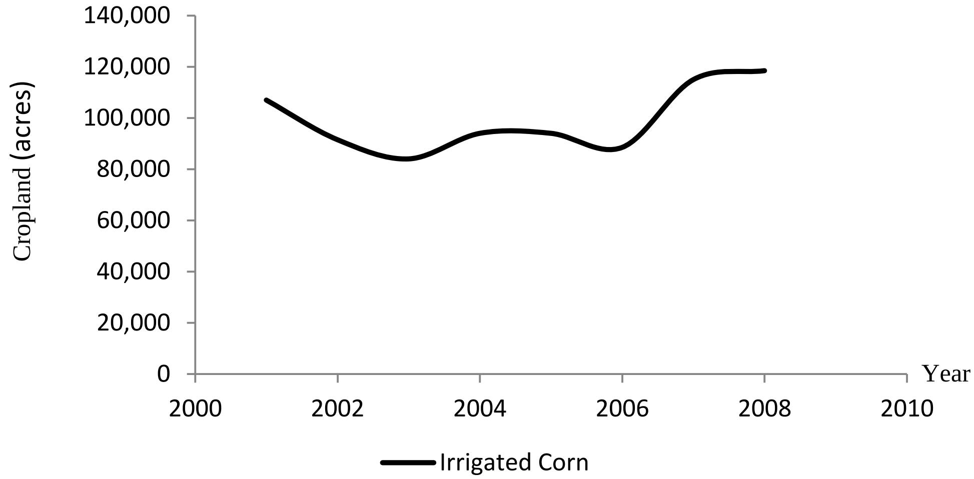
The acreage of corn in the Texas and Oklahoma Panhandles has been increasing during the past several years. The total acres of harvested corn, irrigated and non-irrigated, in the Texas Panhandle increased from 527,000 acres in 2001 to 858,000 acres in 2010. The acreage of irrigated corn increased from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

Figure I-1. Acres of Harvested Corn in Texas Panhandle, 2001 – 2010



Source: National Agricultural Statistics Service, 2011.

Figure I-2. Acres of Irrigated Harvest Corn in Oklahoma Panhandle, 2001- 2008



Source: National Agricultural Statistics Service, 2011.

Over the past several years, the number of confined animal feeding operations (cattle, and swine) in the Texas and Oklahoma Panhandle areas have also increased in both number of animals and in the size of firm. Since year 1991, the number of swine operations in the Oklahoma Panhandle have increased following the removal of restrictions on corporate farms in Oklahoma Senate Bill 518 (Regno et al., 2002). In the year 2010, the swine population in Oklahoma was 2,350,000 head (NASS, 2011). The crop and livestock operations 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 top 20% of animal waste producing areas (Green Media Toolshed, 2011). The current swine population in Oklahoma, 2,350 thousand head (NASS, 2011), can produce up to 30 thousand tons of nitrogen per year. Table I-1 shows an approximate amount of nitrogen excretion per year in Oklahoma computed based on the proportion number of swine in each production stage (NRCS, 1998).

Table I-1. Nitrogen Excretion from Swine per Year by the Stage of Production

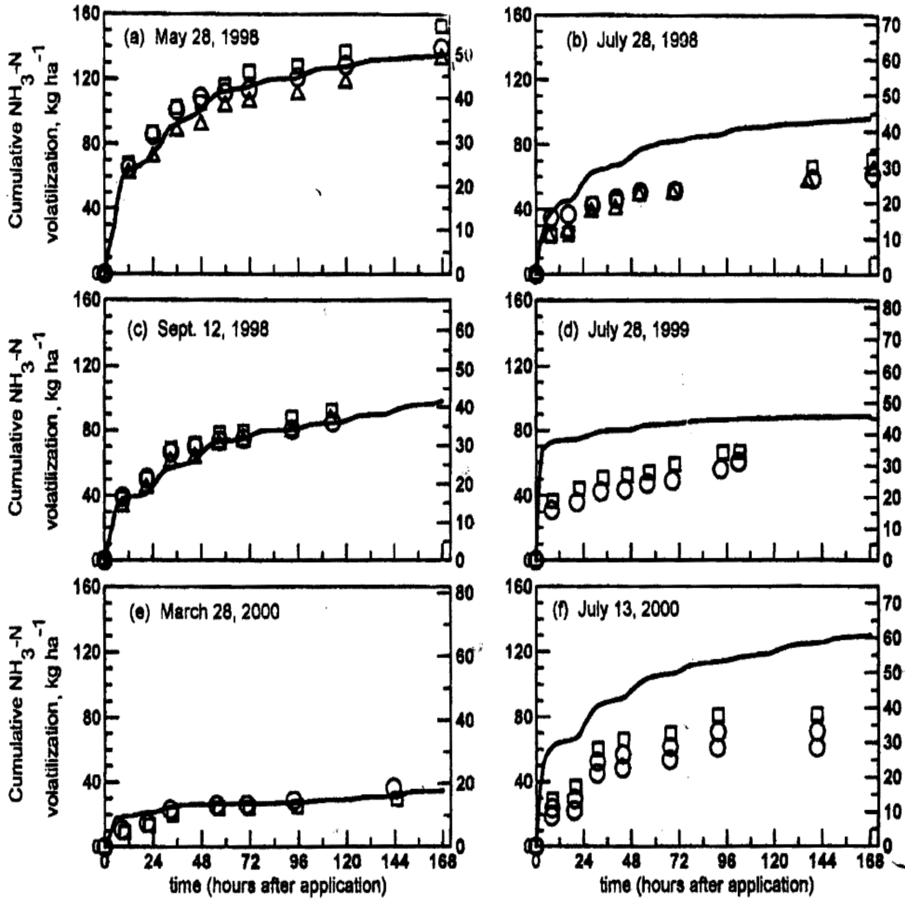
Production Stage	Weight (lb/head)	Nitrogen Produces[a] (lb/head/year)	Swine Number and Nitrogen Produced by Production Stage					
			Proportion of Head[b]	Number (1,000 Head)	Nitrogen (lb/year)	Proportion of Head [b]	Number (1,000 Head)	Nitrogen (lb/year)
Nursery pig	35	7.3	10	235	1,715,500	15	353	2,573,250
Growing pig	65	11	20	470	5,170,000	15	352	3,877,500
Finishing pig	200	33	20	470	15,510,000	30	705	23,265,000
Gestating sow	275	26	20	470	12,220,000	10	235	6,110,000
Sow	375	37	20	470	17,390,000	20	470	17,390,000
Boar	350	33	10	235	7,755,000	10	235	7,755,000
Total			100	2,350	59,760,500 (29,880.25)[c]		2,350	60,970,750 (30,485.375)[c]

Notes:
[a] The excretion value of nitrogen based on the livestock waste facilities handbook, MidWest Plan Service, NRCS. 1998.
[b] The proportion of swine in each production stage to the total number of swine population in Oklahoma for year 2010, 2,350 thousand head (NASS, 2011).
[c] Total amount of nitrogen excreted in tons per year .

The benefit of animal manure is from the nutrients available for plant growth such as nitrogen, phosphorus, potassium, and organic matter. The percent availability of N varies from 30 to 80 percent depending on the source of the manure and application strategy. Plant available nutrients in swine effluent can range from 30 to 50 percent during the first year following application (Zhang, 2009). However, lack of management and improper over use of animal manure could harm an environment in areas such as soil, water, and air quality. Nitrogen in swine effluent is mostly in the ammonium form ($NH_4 - N$) which can be volatilized during storage and application. Typically, the lagoon effluent in the Panhandles is applied to cropland through irrigation systems, thus subject to volatilization loss during and/or after the field application.

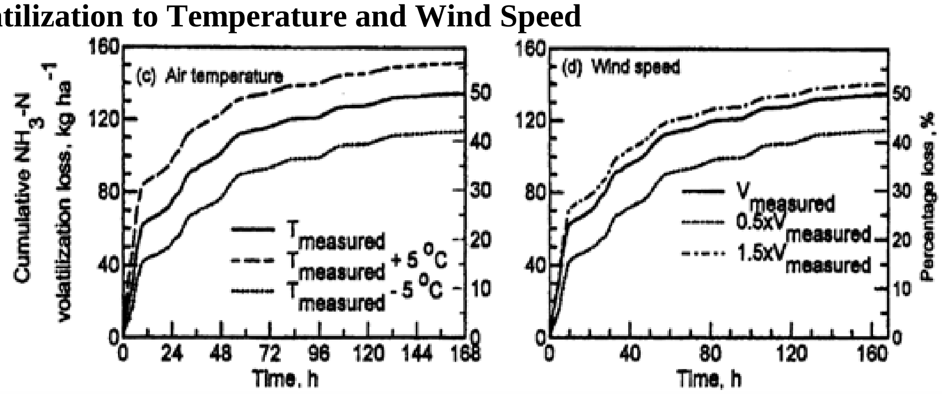
Wu et al. (2003a) developed a mechanistic model to simulate water infiltration and ammonia volatilization (NH_3) during and after the irrigation event. In the study, Wu et al. (2003a) used the mechanistic model to estimate the rate of ammonia volatilization and the cumulative amount of N loss from the swine effluent in the state of Oklahoma during an application based on hourly Mesonet weather data. The model uses hourly temperature, solar radiation, humidity, and wind speed values for up to 192 hours after the event to simulate the amount of N loss. Researchers found ammonia losses were higher during May and July than during March. The validation of the ammonia volatilization model is shown in Figure I-3. The sensitivity of cumulative ammonia loss to temperatures and wind speed also can be seen in Figures I- 4.

Figure I-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 I-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.

Problem

Figure I-4 shows that the changes in temperature and wind speed affect the level of simulated cumulative N volatilization over a period of one week following application (168 hours). The application of lagoon effluent during times followed by high wind, high temperatures, and low humidity will have increased ammonia N volatilization. The climate factors, temperature, wind speed, solar radiation, and humidity are varied though the time of the day, and 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 more favorable weather conditions do not occur, the producer incurs a loss of corn grain yield or must apply a more expensive commercial fertilizer. The loss of nitrogen can be expensive. If producers compensate for the nitrogen loss by adding more effluent, it may contribute to excessive applications of phosphorus. Attempts to compensate for the nitrogen loss can also result in excessive runoff of nutrients to streams and lakes and ultimately to the Gulf of Mexico. Sawyer et al.(1943) reported that the nuisance algal bloom and aquatic weeds in the shallow downstream areas of the Madison lakes, Waubesa and Kegonsa lakes were generated from excessive nitrogen and phosphorus applications and subsequent runoff. As a result, the management practices of swine effluent application to cropland should be considered.

The problem of evaluating the amount of N volatilization 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 also on the air temperature, wind speed, relative humidity, and solar radiation that occur for up to eight days (192 hours) 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 the month that the application occurs. Unfortunately, they do not really help the producer determine if the current time is really the best time to apply or not. Initially, the favorable weather was expected to occur at night and/or early morning, but our preliminary estimates (shown in Table I-2) indicate that the range of values for temperature, wind speed, relative humidity, and solar radiation are highly variable throughout the day. Table I-2 presents the mean average of hourly temperature, wind speed, relative humidity, and solar radiation obtained from Mesonet. The range of cumulative N volatilization after 1 hour, 24 hours, and 192 hours by hour of application using the data for April 1- May 15, 1994-2010 is also presented in Table I-3.

Table I-2. Mean and Range of Hourly Temperature, Wind Speed, Humidity, and Solar Radiation for April 1-May 15, 1994-2010

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

Note: The average temperature, wind speed, relative humidity, and solar radiation obtained from Mesonet, Oklahoma at Goodwell station

Table I-3. Summary Statistics of Average N Volatilization follows Effluent Application for April 1-May 15, 1994-2010 by Wu's model

Hours	Application Time	1 hour after application (lbs/acre)[a]					24 hour after application (lbs/acre)					192 hour after application (lbs/acre)				
		Mean	SD	Min	Max	% [b]	Mean	SD	Min	Max	%[b]	Mean	SD	Min	Max	%[b]
1	1:00	1.0	1.1	0.03	12	0.7	18.0	11.0	1.1	53	12.0	58.3	12.2	21.3	85	38.9
2	2:00	0.9	0.9	0.03	6	0.6	18.1	11.1	1.1	53	12.1	58.5	12.2	21.4	85	39.0
3	3:00	0.8	0.7	0.03	5	0.5	18.2	11.2	1.2	54	12.1	58.8	12.3	21.5	87	39.2
4	4:00	0.7	0.7	0.03	5	0.5	18.4	11.4	1.2	55	12.3	59.1	12.4	21.6	87	39.4
5	5:00	0.7	0.7	0.02	6	0.5	18.7	11.7	1.2	57	12.4	59.6	12.5	21.6	88	39.7
6	6:00	0.8	0.7	0.04	5	0.5	19.0	12.0	1.2	58	12.7	60.1	12.7	21.7	89	40.1
7	7:00	1.1	1.1	0.07	8	0.8	19.5	12.4	1.2	61	13.0	60.7	12.9	21.8	91	40.5
8	8:00	1.8	1.7	0.06	15	1.2	20.1	12.8	1.1	64	13.4	61.3	13.1	21.8	92	40.8
9	9:00	2.5	2.4	0.07	19	1.7	20.6	13.2	1.1	65	13.8	61.7	13.3	21.9	94	41.1
10	10:00	3.2	3.1	0.09	21	2.1	21.1	13.6	1.1	65	14.1	62.1	13.5	21.9	95	41.4
11	11:00	3.8	3.8	0.08	22	2.5	21.6	13.8	1.1	66	14.4	62.3	13.6	22.0	96	41.5
12	12:00	4.4	4.4	0.10	22	3.0	22.0	13.9	1.0	70	14.6	62.4	13.7	22.0	97	41.6
13	13:00	5.0	5.0	0.06	27	3.3	22.2	13.9	1.1	72	14.8	62.4	13.8	22.1	97	41.6
14	14:00	5.4	5.3	0.09	28	3.6	22.4	13.7	1.1	71	14.9	62.2	13.8	22.2	97	41.4
15	15:00	5.6	5.4	0.10	28	3.7	22.2	13.4	1.1	70	14.8	61.7	13.7	21.5	96	41.1
16	16:00	5.4	5.1	0.10	27	3.6	21.7	12.9	1.1	67	14.5	60.9	13.5	20.7	94	40.6
17	17:00	4.7	4.4	0.13	24	3.2	20.9	12.2	1.1	65	13.9	59.9	13.2	20.0	92	39.9
18	18:00	3.3	3.1	0.10	20	2.2	19.7	11.4	1.1	58	13.2	58.6	12.9	19.4	90	39.1
19	19:00	2.2	2.2	0.09	18	1.5	18.8	10.9	1.1	53	12.5	57.7	12.6	19.1	88	38.4
20	20:00	1.8	2.1	0.07	19	1.2	18.5	10.8	1.1	52	12.3	57.4	12.5	19.0	87	38.2
21	21:00	1.6	2.0	0.05	19	1.1	18.4	10.8	1.1	53	12.2	57.3	12.5	19.0	87	38.2
22	22:00	1.5	1.9	0.04	19	1.0	18.3	10.9	1.1	53	12.2	57.2	12.5	19.0	87	38.2
23	23:00	1.4	1.8	0.03	19	0.9	18.2	10.9	1.1	53	12.2	57.3	12.5	19.0	87	38.2
24	0:00	1.2	1.5	0.04	17	0.8	18.1	11.0	1.1	53	12.0	58.2	12.1	21.3	85	38.8

[a] The average cumulative N volatilization at hour following the time of application, which were estimated by using the mechanical model (Wu et al, 2003).
[b] mean percent lost of cumulative N volatilization from 150 pound of nitrogen.

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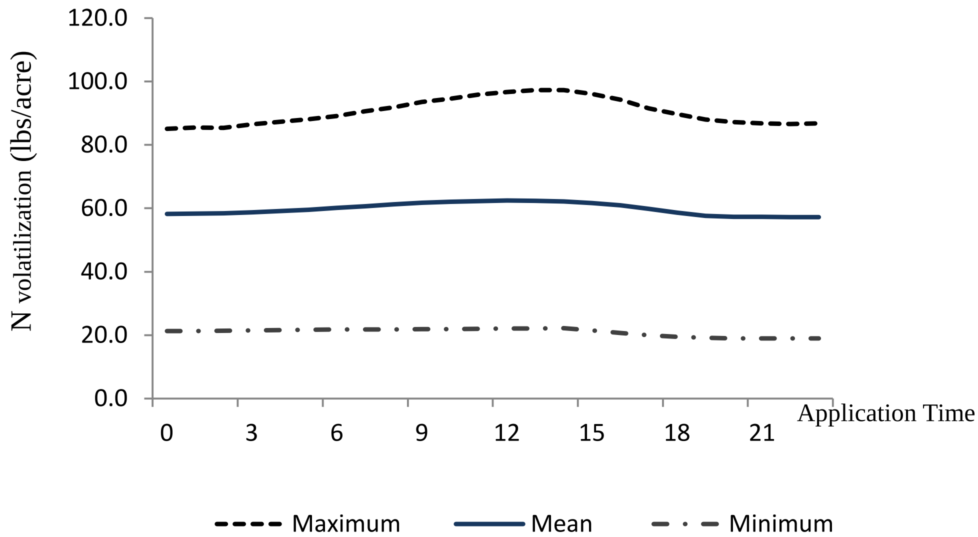
Figure I-5. The Average Cumulative N Volatilization after 192 Hours Following an Application (lbs/acre) by Hour of Application for April 1-May 15, 1994-2010



A visual view of this statistical data (figure I-5) indicates 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. It was initially hypothesized that the swine effluent model would identify the favorable application time based upon the historical weather data. On the other hand, our results show the minimum loss values after 192 hours are less than 37 percent of the mean losses. With a five year average price per pound of urea nitrogen fertilizers for periods 2006-2010 (National Agricultural Statistics Service, 2011), the difference between the minimum and the mean loss is about \$19.50 per acre while the difference between the minimum and the maximum N loss is almost \$34.80 per acre. Figure I-5 above implies there is considerable variation around the mean, and the range of hourly weather conditions (Table I-2) also confirms there is considerable variability in the weather from one day to the next. The preliminary analysis points out that the historical data alone is insufficient for the purpose of achieving the problem described above. However, Figure I-5 indicates that the producers might be able to use forecast information to identify a favorable five to eight day window to determine the time for effluent application.

An application of Bayesian methods can be used to include forecast information into the decision-making process to improve an accuracy of the outcome under uncertainty. Buchanan (1982) explains how forecasts are incorporated into the investor's decision under the Bayesian methods. The author discussed that the likelihood of the forecast inflation rate can help to increase the money outcome. Under this method, the expected value of the outcome is estimated by considering the prior and the posterior probabilities of the inflation rate, which occur in each state of nature. Currently, Mesonet provides hourly weather forecasts of temperature, wind speed, humidity, and solar radiation 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. A research question is, "What is the value of using forecast information to reduce the uncertainty associated with weather in the eight days (192 hours) following an effluent application in the Panhandle?" The Mesonet weather forecast data could be used to provide the producer with an estimate of the amount of ammonia N 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 our study is that the probability of obtaining a more perfect time for swine effluent application in the following period can be derived from historical weather data and forecast weather data. Under an uncertain condition, the BSDP method incorporates weather forecasts into producers' decisions in the context of a probabilistic framework, which can increase the accuracy of the expected ammonia loss. The optimal application giving the nitrogen of 150 pound per acre for the 45 days application horizon can be determined by stochastic dynamic programming optimization (SDP).Thus, the Bayesian formulation was applied to the SDP model to determine the best 48 potential hours for a 128 acre effluent application.

Study's Objectives, Hypotheses, and Justification

Objectives

1. To determine the most efficient time to apply swine effluent through a central pivot irrigation system for covering an entire corn field (128 acres) during the post-planting season from April 1 to May 15.
2. To determine the economic value of including weather forecasts into the producer's decision for two application methods.
    - Six-hour day and/or night time application method; and
    - Twelve-hour-daytime-only application method.
3. To illustrate the economic benefit of the optimal application between the two alternative methods:
    - Six-hour day and/or nighttime application method; and
    - Twelve-hour daytime-only application method.

Justification of the Study

In the study, Bayesian Stochastic Dynamic Programming (BSDP) will be used to determine the optimal time of swine effluent application for corn producers. The producers face with the decision of whether to apply the effluent at the current time or wait for more favorable time during the post-planting season. To aid in the application with the restriction of effluent nitrogen required for plant growth, the producers may use weather forecasts that are available on the Mesonet site as basic information for decision making. This forecast information can be applied through the Bayesian method. Although this method is a complex process, there is an economic benefit to the producer. The forecast value can evaluate in terms of nitrogen cost which the producers need to purchase for compensating the loss of nitrogen from the effluent application.

The Oklahoma Mesonet currently posts 3.5 day (84 hours) forecasts of hourly temperature, wind speed, humidity, and solar radiation. The Mesonet has also developed a special program (called Fire Prescription Planner) that incorporates the forecast data with the fire control. This program provides a model for a weather-based decision, which aids farmers and/or ranchers in the area of specific ranges of values for fire danger and smoke dispersion variables (Mesonet, 2011). Thus, a process of using weather forecast data to estimate ammonia loss from a current effluent application can also be added to the Oklahoma Mesonet site. The Mesonet program could supply three useful pieces of information to the producer. The first would use forecast weather to estimate ammonia loss occurring over the next 192 hours after a current application. The second would be an estimate of ammonia loss from an application made 192 hours previously using actual weather data since the time of application. Thirdly, the program would show the forecast of ammonia loss made 192 hours previously. The second and third items provide a measure of forecast accuracy in estimating ammonia loss.

Assumptions of the Study and Data Sources

Study Assumptions

In each production year, corn producers in Panhandle areas were assumed to apply the swine effluent to a 128 acre corn field during the post-planting period, April 1- May 15. A ¼ mile central pivot sprinkler irrigation system is commonly used by producers to apply the effluent. For corn yields of 200 bushels per acre, the 240 pounds of nitrogen is required per acre. Out of this amount, the producer applies 150 pounds of N from the swine effluent application. The producer will add the remaining 90 pounds plus an additional N to replace the nitrogen loss from effluent application by using commercial nitrogen fertilizer (J.G. Warren, December 2011). The effluent is combined with fresh water and applied through a center pivot sprinkler irrigation system. There is approximately one acre inch of water applied during effluent application. It is assumed that 48 hours are required to complete the irrigation of effluent to cover a 128 acre corn field with the rate of 150 pounds of nitrogen. Since the producer uses the nitrogen from these two sources, swine effluent and commercial fertilizer, the costs on water and diesel would remain the same and do not affect the producer revenue.

Without considering weather forecasts, the producer is assumed to apply the effluent as soon as possible after planting (first 48 hours) to avoid the expected high temperatures in the later periods. The level of ammonia volatilization that occurred from the lagoon effluent application was expected to vary by times of the day and periods of application. Hence, the objective of the producer is to find the most efficient time for effluent application with gives the minimum amount of ammonia volatilization. In the study, we assume that there were two application methods for operating center pivot sprinkler systems; one is the six-hour day and/or night application method. With this method, the producer continuously operated the irrigation system for six hours at each time of application. The alternative method is to continuously operate the irrigation system for 12 hours during only the daytime. It is assumed these two application strategies do not affect the crop yield growth. The labor cost for turning on and off the irrigation system was not considered in this study. It is also assumed that the field was irrigated prior to planting.

It was assumed that the producer could observe weather forecasts on temperature, wind speed, humidity, and solar radiation for the current hour and for 192 hours ahead from the Mesonet sites. Under the six-hour day and/or night time application method, the producer was assumed to make his/her decision every six hours based on observed weather forecasts. For the twelve-hour daytime-only application, the producer made the decision at every morning of the day (i.e., at 6:01 am). Further, the cost of nitrogen fertilizer which the producer purchased for compensating the amount of nitrogen lost from effluent application was used to determine the value of forecasts. In the study, the nitrogen cost was assumed to be equal to five-year average price of nitrogen fertilizer in the urea form ($/lbs). Also, there was no transportation cost added to the effluent cost because we assume that the effluent was only used on farm.

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 hourly weather data were gathered for April 1- May 23 for each year. These seventeen years of daily-hourly weather data were used in estimating the cumulative N volatilization (192 hours or 8 days 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 18,000 estimates of simulated nitrogen losses. The simulated N losses were used to compute the probability distributions of actual ammonia loss (the prior probability). The archive of the forecast weather on temperature, wind speeds, and relative humidity were available at the meteorological consulting company, Weatherbank, Inc., in Edmond, Oklahoma (Eric Freier, 30 May 2011). This forecast weather was for Guymon (National Weather Service), Texas county and available only from years 2005-2010. The six years of forecast data were used to estimate the nitrogen losses using Wu's model (2003a).

With the loss of nitrogen from effluent application, the producer will need to purchase the commercial fertilizer to compensate this loss. In the study, the prices of nitrogen fertilizer in the form of urea (44-46% N) were used as the compensated cost. The five-year average price of nitrogen fertilizer from 2006-2010 (shown in Table I-4) is \$0.50 per pound. (National Agricultural Statistics Service, 2011).

Table I-4. The prices of urea with 44-46% nitrogen for 2006-2010

Year	Price per ton ($)	Price per pound ($)
2006	362	0.39
2007	453	0.49
2008	552	0.60
2009	486	0.53
2010	448	0.49
Average Price	**460.20**	**0.50**

II.

CHAPTER II

LITERATURE REVIEW

Swine Effluent Application

Metcalfe et al. (2001) conducted a survey of the swine producers in Oklahoma to investigate the land application and the handling practices of swine waste. Researchers reported that the two irrigation methods, irrigation guns and pivot irrigation systems, were the common application methods in the area. The irrigation guns and the pivot irrigation were used for 52% and 39% of the manure application to the cropland, respectively. They found 28% of the lagoon effluent was applied to the cropland during the spring season, 53% applied during summer, 19% applied during fall, and 2% applied during the winter.

<u>Ammonia Volatilization Issues</u>

Much of the nitrogen in anaerobically digested swine effluent is generally in the ammonium form (NH_4^-), which can convert to ammonia gas, NH_3, and volatilize to the air during or after field application (Liu et al., 1997). Several researchers have studied the volatilization of nitrogen from liquid manure during and after application. Warren (2001) reported that 23 to 48 percent of NH_3 from liquid manure was lost to the air within a few days after field application of fallow cropland in the Oklahoma Panhandle area. The height of the wheat and/or corn canopy has a significant effect in reducing the NH_3 volatilization. Safley et al. (1992) found the ammonia volatilization from swine effluent application during sprinkler irrigation varied from 13.9 - 37.3 percent.

Further, previous researchers have identified the factors that affect the level of ammonia N volatilization. Apsimon et al. (1987) reported 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 day. Yang et al. (2003) reported that 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. This NH_3 volatilization dropped to 6.1 µg N $m^{-2}s^{-1}$ on the fifth day following the application.

Ammonia Volatilization Models

Ham (2010) has developed a mechanistic model to measure ammonia emission from cattle pens in the Texas Panhandle and in the northeast Colorado area (Greeley County). The model used hourly weather data (temperature and wind speed), soil chemistry and roughness as the input variables to estimate the amount of NH_3 flux using a convective transport equation. The researcher found the emission amount of NH_3 flux is highly correlated with temperature at the pen surface, and the amount of midday flux was increased by 30 percent when the soil pH increased from 7.6 to 7.8. The results also show that the level of NH_3 flux in the lower wind speeds and temperatures in the area of northeast Colorado was on average 27% lower than fluxes measured in the Texas Panhandle.

Wu et al. (2003a) developed a mechanistic model to use in simulating the 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 ammonia transport and transformation of ammonia N in the soil profile during and after an application. This simulation model used hourly climate measure of temperature, wind speed, humidity, and solar radiation to estimate the loss of ammonia N over a period of 192 hours after application. The model estimated the ammonia N concentration profile based on the ammonia transport and transformation. The model included sub-models that simulated water flow, heat flow, and the transport and transformation of ammonia N in the soil profile. The water and heat flow models provided information on soil moisture and temperature, which were needed for the calculation of parameters in the transport and transformation models. The rate of ammonia volatilization from the soil surface was determined by the concentration of ammonia N in the soil surface. Because of the complexities of the processes involved, the transport and transformation model was derived based on the following six assumptions;

1. the soil pH was not affected by the current application of liquid manure (swine effluent);
2. the transformation reactions among the ammonia N species reached equilibrium instantaneously;
3. the mineralization of organic N, and the immobilization and nitrification processes were insignificant N pathways compared to the volatilization loss for the short time of interest;
4. the adsorption-desorption reactions followed linear equilibrium isotherms;

5. the convective movement of soil air was insignificant; therefore, the transport of gaseous ammonia in soil was controlled by diffusion; and
6. the transport of aqueous ammonia N was controlled by the convection-dispersion process.

Wu et al. (2003b) also developed the sub-model 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. In the study, researchers found that the model gave an acceptable estimation of the ammonia volatilization when compared to the field experiment data. The validation of the model was previously mentioned in Figure 4. Consequently, the mechanistic model (Wu et al., 2003a) is used in our study to estimate the rate of ammonia volatilization and by the cumulative amount of N volatilization loss from the swine effluent application based on historical and forecast hourly weather data.

Application of Dynamic Programming (DP) in Agricultural Decision

Burt and Allison (1963) have explained the formulation of dynamic programming (DP) in farm management decisions. They examined the optimal decision of farmers in the Great Plains area, and the state of Kansas using the DP to justify the optimal choice between planting continuous wheat, or leaving the land fallow. The study assumed that the soil moisture would be accumulated when farmers left the field fallow and planted wheat in another year. The acre-inches of soil moisture at the root zone for each planting time were identified as a state variable which was divided into five levels. The results suggested that the farmers should leave the land fallow to accumulate the moisture for another year when the soil moisture is less than 2 inches. The results also showed the long-run expected return per year under optimal policy ($25.60) was higher than the continuous wheat ($22.56), and alternating fallow and wheat ($19.45). Epperson et al. (1993) have examined the optimal irrigation thresholds for six maize irrigation strategies in the state of Georgia using dynamic programming (DP). Six possible thresholds were given for each of five maize growth vegetative stages. Researchers reported that the use of DP improved farm average net returns of all irrigation strategies at each growth stage. Further, the irrigation water consumption was reduced when DP was employed as compared to fixed irrigation thresholds; especially for strategy 1 (varied depth trigger), strategy 3 (deep depth trigger), and strategy 4 (water- holding capacity). The mean water application for strategies 1, 3, and 4 were only 8.38, 6.02, and 8.92 cm while the water applications for the fixed irrigation required up to 24.03, 23.91, and 25.35 cm, respectively.

Previous researchers have utilized a stochastic dynamic programming (SDP) to determine the optimal timing of irrigation under risky conditions. Zavaleta et al. (1980) determined the optimum irrigation strategies and the effect of fuel curtailment under dynamic and stochastic environment using the stochastic open-loop feedback control. The authors reported that the use of irrigation water applied on the grain sorghum field under the stochastic case (random climatic values and uncertain energy curtailments) had a higher mean value than the perfect knowledge case, i.e., the producer knew the weather pattern of rainfall, solar radiation, and temperature. The water used in irrigation under the stochastic case was increased by 20-30% during periods 3 through 8. Such studies lead to the question of whether incorporation of forecast data could lead to more efficient resource use.

The Incorporation of Weather Forecast through the Bayesian method

Previous researchers have applied the Bayesian method to improve the decision making. This method can help to reduce the uncertainty of the outcome by including available forecast information into the decision. Cai et al. (2009) have investigated the accuracy of weather forecasts for estimating the reference evapotranspiration (ET_0). In their study, the 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. Moreover, the simulation of the soil water balance for wheat production using the ET_0 from weather forecast messages was sufficiently accurate when compared to the observed values. Also, Baquet et al. (1976) have evaluated the economic value of frost forecast information to orchard producers in Jackson County, Oregon. The authors incorporated the Bayesian method (i.e., using prior, and forecast information) into the producer's decision to determine an appropriate frost protection strategy. Researchers found that the average daily value of a frost forecast was $5.39 per acre when the orchard producer used prior probabilities of the nighttime temperature provided by the U.S. Weather Service. In a Bayesian format, the forecast value was increased to $8.57 per day per acre. The value of $3.18 per day per acre ($8.57 -$5.39) was contributed from including the prior probabilities and frost forecast information in the decision making of orchardists.

Application of Bayesian Stochastic Dynamic Programming to the Decision Making

The Bayesian stochastic dynamic programming (BSDP) was used to investigate the performance of the Skagit Hydropower System, SHS, (Kim et al., 1997). In the study the seasonal flow forecasts were incorporated into decision making to find the optimal release policies to supply the energy to the residents in the Seattle area. The researchers compared the average annual gains generated from energy production using the BSDP model with other alternative stochastic dynamic programming models. The three alternative models include: 1) Deterministic dynamic programming (DDP); 2) Stochastic dynamic programming with no hydrologic state variable (SDP-N) and; 3) Stochastic dynamic programming that incorporated only the current month's inflow as a hydrologic state variable (SDP-Q). Researchers reported that the optimal release policies that included the seasonal flow forecasts for the snowmelt season as the hydrologic state variable (BSDP) resulted in a higher average annual gain than other SDP models for all given sets of factors. These factors included a reservoir capacity, a portion of SHS energy demand, and the energy price ratios.

Mjelde et al. (1988) have also determined the value of seasonal climate forecasts in a dynamic agricultural production system (corn production) in East-Central Illinois. Researchers found that the effects of forecasts on decision making were sensitive to forecast characteristics and economic conditions—i.e., interest rate, input cost, and output price. The results showed an expected net return received from using information on the climate forecasts was higher than the return based on only historical prior knowledge. With known climate forecasts, producers can reduce their input use and lower the cost of production over the crop year. Further, the timeline information affected the value of forecasts; the expected value of the late spring forecast with a corn price of $2.83 per bushel was $3.39 per acre per year when forecasts was received in the fall. On the other hand, the expected value was only $3.01 per acre per year for forecasts received in early spring. This indicates that a less accurate forecast received earlier may have greater value than the more accurate forecast received just prior to the time of decision.

Wilks et al. (1997) have utilized Bayesian Stochastic Dynamic Programming (BSDP) to determine the optimal daily irrigation for lettuce in a humid climate, New York State, using precipitation forecasts. Researchers reported that the daily irrigation was unnecessary during the growing period, 62 days (1 May through 15 July) when the probability of next day rainfall was high. However, the daily irrigation was required with the probability of the next day rainfall, regardless of today's forecast, was zero. Also, the economic value to the producer from using a two day precipitation forecast (day-1 and day-2) was higher than using only the 50 percent available-water criterion. These economic values (using day -1 and day -2 forecasts) were $900 per hectare for a large farm operation, and $1,000 per hectare for a family farm operation.

Gowing et al. (2001) have applied the BSDP to determine real-time scheduling of supplemental irrigation for potatoes over the wet, average, and dry years using rainfall weather forecasts. They reported that the irrigation decision made without considering weather forecasts (SDP) resulted in a higher irrigation cost than when using weather forecasts (BSDP). In the wet year (1992), the water use was reduced by 44.8 and 72.4 percent at a highest and lowest irrigation cost when the producer included weather forecasts into the decision process. The profit from irrigation using weather forecast data (BSDP) was also higher than the profit obtained from irrigation without weather forecast

(SDP) in the average year. Overall, the previous research indicates that there might be the potential use of forecast information in decision making to improve the benefit of the producer in many agricultural fields.

III.

CHAPTER III

METHODOLOGY

Conceptual Framework

The climatic conditions, i.e., temperature, wind speed, relative humidity, and solar radiation at the time of application and for 192 hours (8 days) following the application are factors that affect the amount of ammonia volatilization. Therefore, the operating time of the irrigation system is important for producers to meet crop nutrient requirement and improves their benefits.

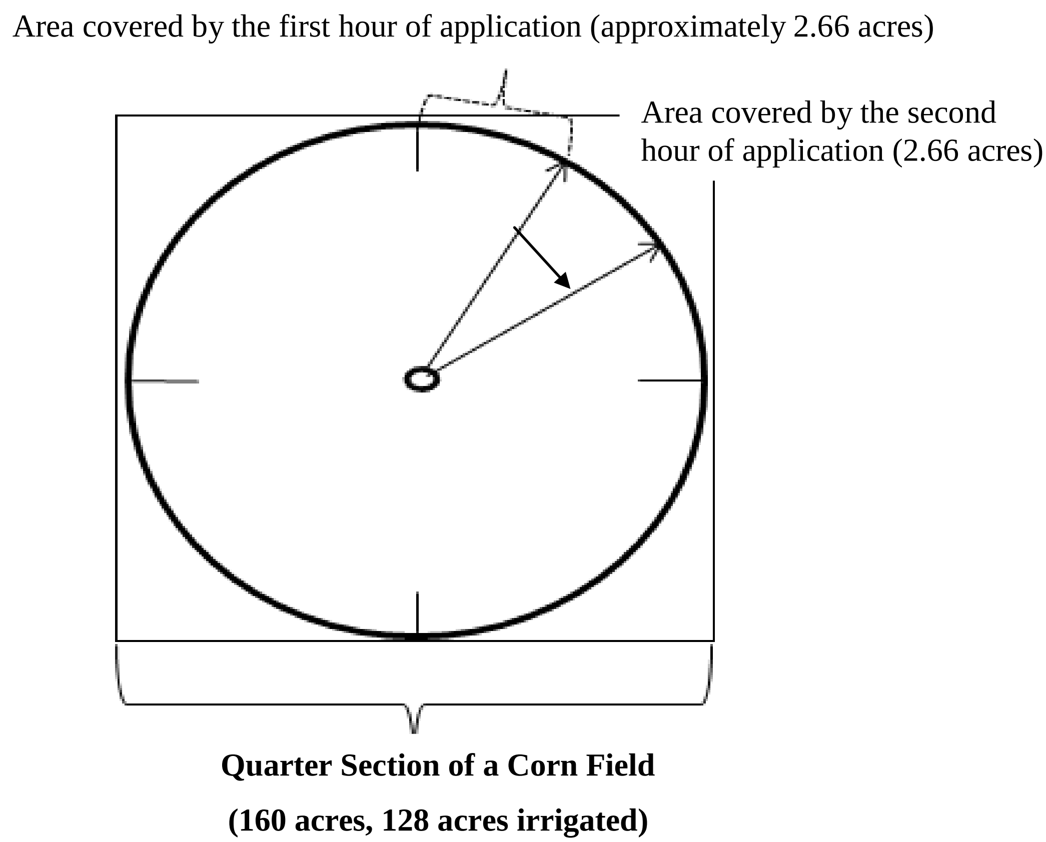
The operation of center pivot sprinkler irrigation for spreading the lagoon effluent in the Panhandle area can be explained as follows. Hourly weather data for both forecast and actual weather data were used to simulate ammonia loss over the 45 day period from April 1 to May 15. Conceptually, it would be possible to start and stop the application on an hourly basis. However, it was assumed the producer would be unlikely to start and stop the pivot operation for less than a six-hour period. Another problem was related to the limited number of weather forecasts for infrequent low or high ammonia loss events. This caused a problem in constructing the Markov transition matrices. The method used to approach both problems was to pool data by time period over several days. Regression analysis was used to test whether the length of aggregation period was such that the mean ammonia loss from one period was significantly different from the mean of the next period.

Representative Application Situation

The typical field application of lagoon effluent to corn in the Panhandle area occurs from April to the middle of June, approximately around 15 days after planting (J. Wu, 12 May 2011). In this region, the producers commonly use sprinkle and/or furrow irrigation systems to apply the swine effluent. The effluent is combined with fresh water and applied through a center pivot sprinkler irrigation system. The center pivot system is assumed to have a pumping capacity of 2,460 liters per minute (650 gallons/min.) and a radius of 500 meters in length. The irrigation system is operated as a circle (J.G. Warren, December 2010). For 200 bushels of corn yield growth per acre, the producer needs to apply 240 pounds of nitrogen. These amounts are obtained from two nitrogen sources, swine effluent and commercial fertilizer (J.G. Warren, December 2011). The producer applies 150 pounds nitrogen through the lagoon effluent application, and adds the 90 pounds of commercial N fertilizer.

The level of ammonia N volatilization from the effluent application can be affected by the temperatures, relative humidity, and wind speed (Zupancic, 1999). Thus, the amount of N volatilized in each segment of a quarter section corn field is affected by the weather conditions occurring during and after each application time. For instance, the volatilization loss of N in the first segment of the field depends on the weather conditions occurring in the 192 hour period beginning at the time of application and continuing for the next 192 hours. The volatilization of ammonia N from the second segment will depend on the weather conditions beginning at that hour of application. Figure III-1 illustrates field coverage divided into one-hour segments.

Figure III-1. Schematic for Pivot Irrigation System



The application horizon for swine effluent, April 1-May 15, was divided into periods following the two application strategies that are:

1. 180 periods for the six-hour day and/or night application method; and
2. 45 periods for the twelve- hour daytime-only application method.

For the method 1 above, the producer must find 48 hours (not necessarily continuous), eight application times (6 hours/application) of favorable weather in order to apply the effluent to a 128 acre pivot irrigated field. With method 2, the producer needs to make four applications (12 hours/application) out of the 45 hour periods. The above problem requires that the producer be able to recognize whether the current time is optimal for an application or whether it is better to wait for another time. The solution for the most efficient time can be found by applying the stochastic dynamic programming (SDP) to the problem.

Ordinary Stochastic Dynamic Programming Problem (SDP)

A simple example can be used to illustrate the application of SDP to the solution of the current problem. Suppose the producer had two periods in which to apply the effluent and exact weather conditions are unknown until the beginning of each period. However, assume the range of weather conditions is known and definite with known probabilities on each day. The exact amount of ammonia loss from an application at each weather condition is assumed to be known. The probability of each type of weather occurrence and the amount of ammonia volatilization associated with each weather condition can be used in decision making. The producer's objective function with the minimum of the total expected N volatilization can be defined as

$$(1) \qquad \textit{Minimize} \quad L^{s}_{p=1,d} + \sum_{s=1}^{5} (\Pr(L^{s}) * \bar{L}^{s})_{\ p+1,d}$$

where, L^{s}_{p} is the ammonia N volatilization that occurs from the weather condition s (S=1, 2, …, 5) in period p (p=1), $\Pr(L^{s})_{p}$ is the probability of each type of weather occurrence, and d is the choice variable which takes a value of one when the producer decides to apply, and d = 2 when the producer decides to wait for next period (p=2).

If the weather conditions, the amount of ammonia lost, and the probabilities of each day weather condition for each period are given in Table III-1, the problem can be solved by using SDP optimization. When the season begins, the expected losses for effluent applied in periods 1 and 2 are 24.2, and 33.44 lbs/acre, respectively. SDP can be used to reflect the producer's actions upon finding out the actual weather condition in period 1. The SDP problem can be solved for the optimal application decision by starting from the last period and moving backward to the first period. Begin with period 2. If the producer arrives in period 2 and has not applied the effluent, the producer must apply the effluent regardless of the weather. Before actually knowing the weather in period 2 the producer can determine the expected ammonia loss as 33.44 lbs/acre calculated by multiplying the probability of each weather condition by the amount of loss if that weather condition occurs. This expected loss can then be used to help in decision making for period 1. Assume the producer is at the beginning of period 1 and simply observes the weather that exists at that time. Given the weather that is occurring in period 1, the producer will compare the loss from the actual weather in period 1 with the expected loss from waiting until the second period. If the loss from the first period is greater than the expected loss from waiting, the producer waits. For example, if the weather in period 1 is very bad and the producer applies, the producer will lose 80 lbs/acre. This amount of N lost is higher than expected by applying in the next period (33.44 lbs/acre), so the producer should wait. The optimal decision for each additional state of weather in period 1 is determined the same way. The optimal decisions are to apply in period 1 if the weather is average or above and wait until period 2 if the weather is below average or bad.

Table III-1. Example for Two Period Problem of Ammonia N Volatilization for Ordinary Stochastic Dynamic Programming Model

Day Type of Weather Condition	Probability		N lost for Each Weather Condition	Expected loss occurring in period 1	Expected loss occurring in period 2
	Period 1 (*Pr*1)	Period 2 (*Pr*2)			
Very Good	0.10	0.07	2	(0.10*2) = 0.20	(0.07*2) = 0.14
Above Average	0.20	0.23	10	2.00	2.30
Average	0.30	0.25	20	6.00	5.00
Below Average	0.20	0.25	40	8.00	10.00
Very Bad	0.10	0.20	80	8.00	16.00
Total Expected Loss (lbs/acre)				**24.20**	**33.44**

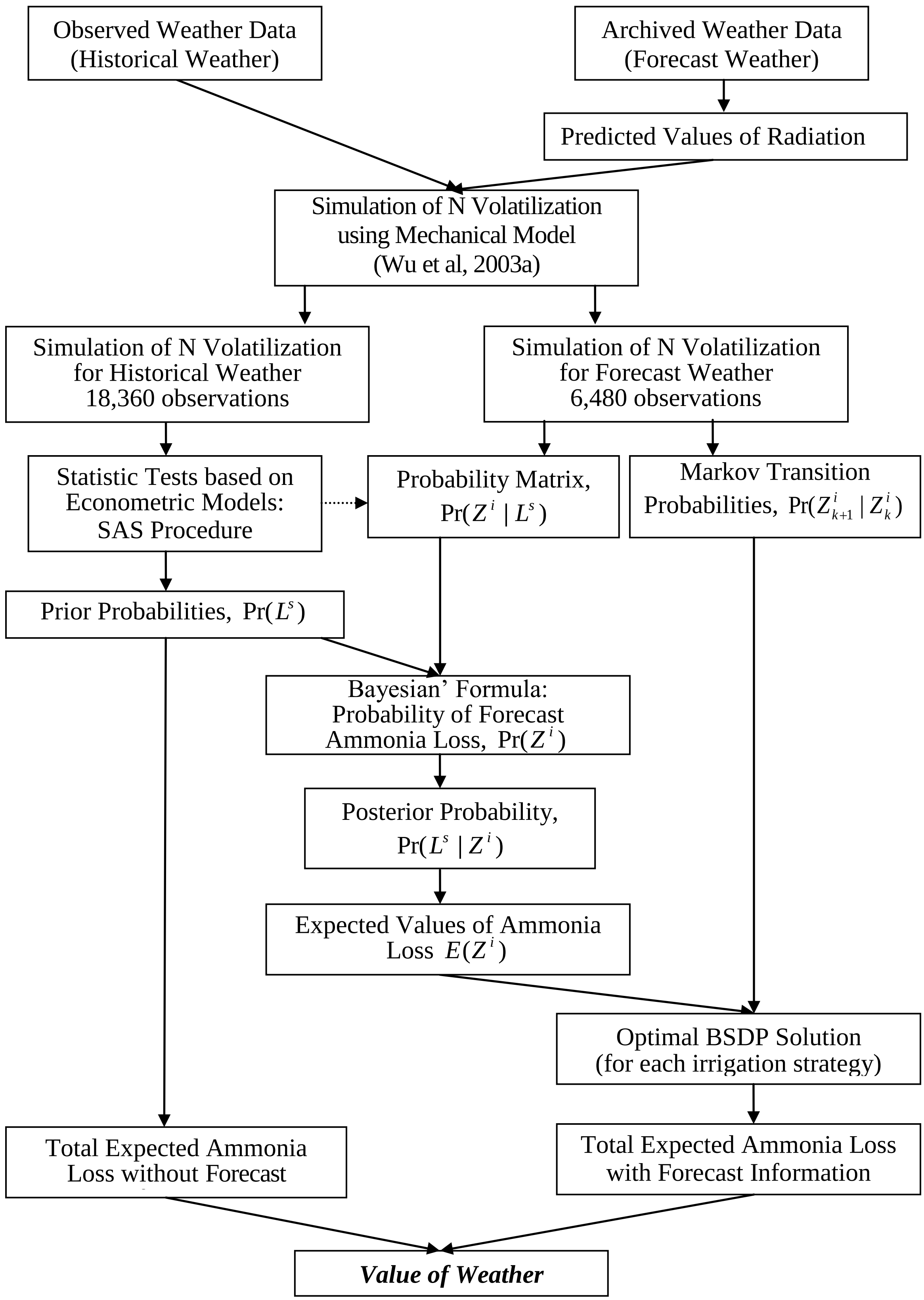
Incorporation of Weather Forecast

Unfortunately, the producer cannot estimate the ammonia loss from an application until 192 hours later unless the forecast information is used. The major benefit from incorporating weather forecasts in the decision making is to decrease the variance of the ammonia lost from unknown weather. This can reduce the total expected amount of ammonia volatilization over the planting season. Bayesian methods were applied to the study to increase the accuracy of the expected amount of ammonia volatilization. This method uses the estimated N losses from using weather forecasts in the Wu model along with the losses from historical weather data (actual weather) to estimate probability distributions of ammonia losses. The distributions include the joint probability of forecast ammonia loss and the actual loss, the probability of forecast occurrence, and the posterior probability. All of these probabilities were used to estimate the expected ammonia volatilization for each period of application, and applied to stochastic dynamic optimization (SDP). The probability distributions were computed in an Excel spreadsheet, which will be clearly asserted in the methodological section.

Procedure

A diagram representing the model of this study is shown in Figure III-2. Several steps were preformed to achieve the study's objectives. The first component of the steps is data collection and econometric estimation of the forecast solar radiation, which was not available. A second component is the simulation of ammonia volatilization and statistical analysis to test for differences in the mean levels of ammonia volatilization by time and period of application. This was done to allow aggregation of hourly and daily simulations. The third step involved the calculation of probability distributions and the expected amount of ammonia losses under the Bayesian Approach. The final step is to determine the optimal time of effluent application over the application horizon using Bayesian stochastic dynamic programming (BSDP), and illustrate the value of weather forecast.

Figure III-2. Flow Diagram Representing the Study



Simulation of Ammonia Volatilization for Historical Weather Data

The input data for Wu's model for hourly air temperature, wind speeds, relative humidity, and solar radiation for April 1 through May 15 between periods 1994 to 2010 were obtained from Goodwell, Oklahoma's Mesonet site. This data was used to estimate the cumulative amount of N volatilized up to 192 hours after application. The simulation gave more than 18,000 observations of the estimated N volatilization from the set of historical weather data.

Econometric Estimation of Simulated Ammonia N Volatilization

The simulated ammonia volatilization obtained from Wu's model was applied to an econometric model to perform statistical tests for significant differences in the amount of ammonia N volatilization. This was done to permit aggregation of hourly and daily measurements into groups. The mean levels of loss were assumed to be influenced by three main factors—the times of day that the application was made, the period of the month, and the interaction between the hour of application and time period during the application window. These assumptions were tested by using the GLM procedure in SAS. Several models were estimated with the intent to determine if there were significant differences in the amount of ammonia volatilization from an application made at one hour of the day as compared to the next hour. When there were no significant differences, the data were aggregated. Both five and seven day periods were considered. The total amount of N volitalized after 192 hours was regressed against discrete variables representing the time of day that application was made and the time period. The response function of the mean ammonia N loss was defined as

$$(2) \qquad L_{kpt} = \mu_0 + \sum_{k=1}^{K} \mu_k AT_{kt} + \sum_{p=1}^{P} \partial_p Pd_{pt} + \sum_{p=1}^{P} \sum_{k=1}^{K} \eta_q (AT * Pd)_{kpt} + \varepsilon_{kpt}$$

where L_{kpt} is the mean level of ammonia losses occurring during an application at time k (k =1,… K) in period p (p = 1,…, P) in year t, AT_{kt} and Pd_{pt} represent the dummy variables for time and period of application, respectively, $\mu_0\ \mu_k, \partial_p, and\ \eta_q$ are the parameters to be estimated, and $\varepsilon_{kpt} \sim N(0, \sigma_\varepsilon^2)$ is the random error term. The random error term is assumed to be independent and normally distributed.

The parameter estimates were used to determine periods with similar means that could be grouped. The statistical tests were performed under following null hypotheses:

1. The hypotheses testing for significance by times of the day are:

$$H_0 : \mu_k = 0$$
$$H_1 : \mu_k \neq 0$$

2. The hypotheses testing for significance by periods of the season are:

$$H_0 : \partial_p = 0$$
$$H_1 : \partial_p \neq 0$$

3. The hypotheses testing for significance of interaction terms between time and period are:

$$H_0 : \eta_q = 0$$
$$H_1 : \eta_q \neq 0$$

The coefficients of mean differences in ammonia loss between hours of the day and periods (days) of application are expected to be zero. The coefficients of the interaction term were not significantly different from zero. Analysis of the results in terms of significant differences indicated most of the variation could be captured by dividing the day into four, six-hour application periods, and by dividing a six-week window into nine, five-day periods. The four six-hour application periods were midnight to 6:00 am, 6:00 am to 12:00 noon, 12:00 noon to 6:00 pm, and 6:00 pm to midnight. The parameter estimates of the three main effects for two application methods, six-hour-day and night application, and twelve-hour daytime-only, are reported in Tables III-2 and III-3, respectively.

Table III-2. The Statistical Results for the Differences in Cumulative N Volatilization by Six-hour and Five-day periods

Variable	df	F-value	*p-value*
Time (6 hours, 4 applications/day)	3	133.47	<.0001
Period (5 day periods)	8	783.00	<.0001
Time x Period	24	0.40	0.9963

Note: These results indicate that the interaction terms between time and period variables are not significantly different from zero at the 1 percent significance level.

Table III-3. The Statistical Results for the Differences in Cumulative N Volatilization by Twelve-hour Daytime-only and Five-day periods

Variable	df	F-value	*p-value*
Period (5 days, 9 periods)	8	368.91	<.0001

The *p-values* of the interaction terms for the six-hour day and night application method is 0.996 which is not significantly different from zero. As a result, the interaction terms were removed from each estimation model, and equation 1 becomes;

(2)' $$L_{kpt} = \mu_0 + \sum_{k=1}^{K} \mu_k AT_{kt} + \sum_{p=1}^{P} \partial_p Pd_{pt} + \varepsilon_{kpt}$$

After the interaction term was removed from the model, the remaining variables were used to estimate for the different levels of mean ammonia N volatilization by time and period using class statement in GLM procedure (SAS Institute Inc, 2003). The parameter estimates for the six-hour day and night application strategy are reported in Table III-4.

Table III-4. The Parameter Estimates of the Differences in Simulated Cumulative N Volatilization after 192 Hours for Six-Hour Application Periods by Time and Date of Application Using Hourly Recorded Mesonet Data at Goodwell Oklahoma from 1994 to 2010 as Estimated with GLM Procedure in SAS

Variable	Parameter	Parameter Estimate[b]	Standard Error	t-value	*p*-value
Intercept[a]	μ_0	69.769	(0.2859)	244.03	<0.0001
Time Dummy Variables					
12:01 – 6:00 am	μ_1	1.564	(0.2334)	6.70	<0.0001
6:01 am-12:00 pm	μ_2	4.244	(0.2334)	18.18	<0.0001
12:01-6:00 pm	μ_3	3.444	(0.233)	14.75	<0.0001
Period Dummy Variables					
April 1-5	∂_1	-21.82	(0.350)	-62.31	<0.0001
April 6-10	∂_2	-19.51	(0.350)	-55.70	<0.0001
April 10-15	∂_3	-12.62	(0.350)	-36.05	<0.0001
April 16-20	∂_4	-13.77	(0.350)	-39.31	<0.0001
April 21-25	∂_5	-14.64	(0.350)	-41.82	<0.0001
April 26-30	∂_6	-14.35	(0.350)	-40.98	<0.0001
May 1-5	∂_7	-9.96	(0.350)	-28.46	<0.0001
May 6-10	∂_8	-3.75	(0.350)	-10.71	<0.0001

[a] Represents expected loss from an application between May 11-15 from 6:00 pm to midnight.
[b] Estimated from 18,359 observations.

All parameter estimates for the dummy variables for the three applications (i.e., midnight to 6:00 am, 6:00 am to 12:00 noon, 12:00 noon to 6:00 pm) and eight periods are statistically significant at the 1 percent level. The signs of the parameters were as expected. The mean levels of ammonia volatilization increased during day of application period. The mean losses from applications made between 6am and 6pm were significantly greater than applications made between 6pm and midnight. However, the differences between the means were still less than 4.3 lbs of N per acre. In the case of the twelve-hour daytime-only application method, the parameter estimates of period dummy variables are reported in Table III-5.

Table III-5. The Parameter Estimates of the Differences in Simulated Cumulative N Volatilization after 192 Hours for Twelve-hour Daytime-only by Date of Application Using Hourly Recorded Mesonet Data at Goodwell Oklahoma from 1994 to 2010 as Estimated with GLM Procedure in SAS

Variable	Parameter	Parameter Estimate[b]	Standard Error	t-value	*p*-value
Intercept[a]	μ_0	73.96	(0.366)	210.08	<0.0001
Period Dummy Variables					
April 1-5	∂_1	-22.16	(0.518)	-42.76	<0.0001
April 6-10	∂_2	-20.15	(0.518)	-38.87	<0.0001
April 10-15	∂_3	-12.91	(0.518)	-24.91	<0.0001
April 16-20	∂_4	-13.97	(0.518)	-26.96	<0.0001
April 21-25	∂_5	-14.98	(0.518)	-28.90	<0.0001
April 26-30	∂_6	-14.75	(0.518)	-28.46	<0.0001
May 1-5	∂_7	-10.60	(0.518)	-20.45	<0.0001
May 6-10	∂_8	-4.05	(0.518)	-7.82	<0.0001

[a] Represents expected loss from an application between May 11-15 from 6:00 am to 6:00 pm.
[b] Estimated from 9,179 observations.

The *p*-values for dummy variable of periods 1-8 are smaller than 0.0001 and have negative signs. These indicate the mean level of ammonia N volatilization of the periods 1-8 are statistically lower than period 9. The mean ammonia loss is increasing over time from period 1 (April 1-5) through period 9 (May 6-10). Historical weather records indicate the first 10 days of April are the most favorable for effluent application and the period from May 6-10 are the least favorable for effluent application.

The results above show there are significant differences in ammonia volatilization for 12-hour daytime only by period of application as compared to the application made from May 11-15 which is incorporated in the intercept. Hence, the pair-wise comparison method was performed to test for a significant difference of ammonia loss between each pair of applications (i.e., ∂_1 vs ∂_2, etc.) using PDIFF option in GLM procedure (SAS Institute Inc, 2003).This method compares the mean level of ammonia losses occur between two different applications at a time. Under the null hypothesis, the parameters of dummy variables for each two applications are assumed to be equal (μ_1=μ_2, μ_2=μ_3, etc.), as well as the parameters of the nine periods ($\partial_1 = \partial_2, \partial_2 = \partial_3$, etc.). Tables III-6 and III-7 present the statistical results of the comparison of ammonia N volatilization between the four six-hour applications and nine periods. All parameters in the statistic tests were considered at α = 1% level.

Table III-6. The Statistical Comparison of Ammonia Volatilization by Times of Application for Six-hour Day or Night Application Method Estimated with GLM Procedure in SAS

Application time	*p-value*			
	12:01- 6:00 am	6:01am-12:00 pm	12:00-6:00 pm	6:01pm-12:00am
12:01- 6:00 am		<.0001	<.0001	<.0001
6:01 am-12:00 pm	<.0001		0.0006	<.0001
12:01-6:00 pm	<.0001	0.0006		<.0001
6:01 pm-12:00 am	<.0001	<.0001	<.0001	

Table III-7. The Statistical Comparison of Ammonia Volatilization by Periods of the Post-planting Season for Six-hour Day or Night Application Method as Estimated with GLM Procedure in SAS

Period of Application	*p-value*								
	1	2	3	4	5	6	7	8	9
1		<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
2	<.0001		<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
3	<.0001	<.0001		<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
4	<.0001	<.0001	<.0001		0.012	0.0957	<.0001	<.0001	<.0001
5	<.0001	<.0001	<.0001	0.012		0.3977	<.0001	<.0001	<.0001
6	<.0001	<.0001	<.0001	0.0957	0.3977		<.0001	<.0001	<.0001
7	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001		<.0001	<.0001
8	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001		<.0001
9	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	

Note: The shaded portion of Table III-7 shows there are insignificant differences of the cumulative N losses after 192 hours for the application between those three periods (at 1% level).

Results report that there are significant differences in ammonia volatilization between times of the day and periods of application. The mean levels of ammonia loss were also found to be different from one period to another; except for periods 4-6. The loss occurs from application during period 4 is found to be insignificantly different from periods 5 and 6. Also, the loss that occurred from application during period 5 was not significantly different from that in period 6. Tables III-8 and III-9 present the least square means of ammonia volatilization for six-hour day or night application method.

Table III-8. Least Squares Means of Cumulative N Volatilization after 192 Hours by Time of Application for Six-hour Day or Night Application Method Estimated with the GLM Procedure in SAS

Time of Application	LSMEANS (lbs/acre)	*p*-value
12:01 am-06:00 am	59.07	<0.0001
06:01 am-12:00 pm	61.75	<0.0001
12:01pm-06:00 pm	60.95	<0.0001
06:01 pm-12:00am	57.50	<0.0001

Table III-9. Least Squares Means of Cumulative N Volatilization after 192 Hours by Periods of Application for Six-hour Day or Night Application Method Estimated with GLM Procedure in SAS

Period of Application		LSMEANS (lbs/acre)	*p*-value
Period	Date/Month		
1	April 1-5	50.26	<0.0001
2	April 6-10	52.58	<0.0001
3	April 11-15	59.46	<0.0001
4	April 16-20	58.32	<0.0001
5	April 21-25	57.44	<0.0001
6	April 26-30	57.73	<0.0001
7	May 1-5	62.12	<0.0001
8	May 6-10	68.33	<0.0001
9	May 11-15	72.08	<0.0001

For the twelve-hour daytime-only application method, the results also suggest that there the significant differences in mean ammonia volatilization by period of application. However, the N volatilization that occurred from application during period 4 was not significantly different from that in periods 5 and 6. And the volatilization that occurred from applications in period 5 was not significantly different from an application in period 6. The comparison of ammonia volatilization by periods of application for twelve-hour daytime-only application method is reported in Table III-10. The least square means of cumulative ammonia N volatilization after 192 hours after application for the twelve-hour daytime application are also reported in Table III-11.

Table III-10. The Statistical Comparison of Ammonia Volatilization by Periods for Twelve-hour Daytime-only Application Method as Estimated with GLM Procedure in SAS

Period of Application	*p-value*								
	1	2	3	4	5	6	7	8	9
1		<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
2	<.0001		<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
3	<.0001	<.0001		0.01	<.0001	<.0001	<.0001	<.0001	<.0001
4	<.0001	<.0001	0.01		0.053	0.134	<.0001	<.0001	<.0001
5	<.0001	<.0001	<.0001	0.053		0.660	<.0001	<.0001	<.0001
6	<.0001	<.0001	<.0001	0.134	0.660		<.0001	<.0001	<.0001
7	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001		<.0001	<.0001
8	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001		<.0001
9	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	

Note: The shaded portion of Table III-10 shows there are insignificant differences for the cumulative N losses after 192 hours for the application between those three periods (at 1% level).

Table III-11. Least Squares Means of Cumulative N Volatilization by Period for Twelve-Hours Daytime Application Method as Estimated with GLM Procedure in SAS

Period of Application		LSMEANS (lbs./acre)	*p*-value
Period	Date/Month		
1	April 1-5	51.80	<0.0001
2	April 6-10	53.81	<0.0001
3	April 11-15	61.05	<0.0001
4	April 16-20	59.99	<0.0001
5	April 21-25	58.99	<0.0001
6	April 26-30	59.21	<0.0001
7	May 1-5	63.37	<0.0001
8	May 6-10	69.91	<0.0001
9	May 11-15	73.96	<0.0001

Overall, the results indicate the amount of ammonia N volatilized increases from the beginning to the end of the application period. Also, applications made between 6:00pm and midnight had lower losses than other times of the day. This gives the support to our study's assumption about the number of application periods over the planting horizon. The season in the study was categorized into periods based on the estimated results above. Under the six-hour application method, the planting horizon was divided into 180 periods which the effluent can be applied during both day and night times. For the twelve-hour daytime application method, the producer is assumed to operate the sprinkler irrigation system only during the daytime from 6:01 am through 6:00 pm. Thus, there are 45 periods under the twelve-hour daytime-only application method. Further, the results obtained from this section were used as the initial assumption for computing the probability distributions of ammonia volatilization, which will be applied to the Bayesian stochastic dynamic framework

Simulation of Ammonia Volatilization for Forecast Weather Data

In similar approach to simulation with historical weather data, an archive of the forecast weather on temperature, wind speeds, and relative humidity for April 1- May 15 from 2005 through 2010 was obtained from the meteorological consulting company, Weatherbank, Inc. (Eric Freier, 30 May 2011). This data was used to estimate the cumulative N volatilization at 192 hours after an application. However, the estimates of solar radiation for forecast weather data are not available either from the Weatherbank, Inc. (Eric Freier, 30 May 2011) or in the published forecast of the Mesonet site. Thus, a statistical analysis was performed to estimate this forecast variable to use in Wu's simulation model. The steps of estimating the predicted values of solar radiation are explained as follows.

Estimation of Predicted Solar Radiation

The first step is to find the relationship between the climatological variables that are available on the Mesonet site. These variables include solar radiation, temperature, percentage of relative humidity, percentage of cloud cover, and possible maximum sunshine. The actual solar radiation or global solar radiation is the total amount of sun's energy that reaches to the earth's surface at any particular time. The amount of radiation reaching the ground is generally less than the amount of energy measured at the top of the earth's atmosphere (Griffiths et al., 1980). The radiation at the top of the atmosphere can be diffused, absorbed, and/or scattered during travel through the earth's atmosphere to the surface. The diffusion and scattering can be caused by the amount of water vapor, cloud, dust, and air molecules (EERE, 2011). The assumption was made that the relation between "forecast" solar radiation and forecast temperature, degree of cloudiness, and wind speed would be the same as between measured solar radiation, measured temperature, wind speed, and degree of cloudiness. An econometric model was used to investigate the relationship among those climate variables. This estimation was done based on the historical weather data. Table III-12 reports the results of the correlation coefficients for solar radiation.

The parameter estimates report that there is the negative correlation between the actual solar radiation and the percentage of humidity ($P \leq 0.0001$). There is also the negative correlation between the actual solar radiation and the percentage of cloud cover ($P \leq 0.0001$). These imply the presence of humidity and/or a cloudy day cause less solar radiation from the top of the earth's atmosphere reached to the ground.

Table III-12. Summary Statistic for Correlation Coefficients of Solar Radiation and Climate Variables

Variable	Pearson Correlation Coefficients				
	Clear Day Radiation	Actual Solar Radiation	Humidity (%)	Cloud Cover (%)	Possible Maximum Sunshine (%)
Clear Day Solar Radiation	1.000*	0.618*	-0.115*	0.001	-0.001
Actual Solar Radiation		1.000*	-0.291*	-0.234*	0.234*
Humidity (%)			1.000*	0.436*	-0.436*
Cloud Cover (%)				1.000*	-1.000*
Possible Maximum Sunshine (%)					1.000*

* indicates there is a significant correlation among the variables at 1% significant level

Based on the significant correlations among the climate variables, a regression model was developed to find the estimators for predicting the values of forecast solar radiation. The regression model was estimated as follows

(3) $$SR_{ijt} = a_1 RH_t + a_2 (1 - PMSun)_t + \sum_{i=1}^{I=14} \beta_i H_{it} + \sum_{j=1}^{J=6} \delta_j W_{jt} + \varepsilon_{ijt}$$

where SR_{ijt} is the ratio of the difference between clear day solar radiation and the actual solar radiation to the amount of clear day solar radiation (i.e., the proportion of the radiation prevented from reaching to the soil surface) at hour *i* of week *j* in year *t*, *RH* represents the percentage of relative humidity, *PMSun* represents the percentage of possible maximum sunshine, H_{it} , and W_{jt} are indicators for hourly and weekly dummy variables, respectively, $\varepsilon_{ijt} \sim N(0, \sigma_{\varepsilon}^2)$ is the random error term. Solar radiation at the top of the atmosphere was calculated by using a formula supplied by the Mesonet group (J.D. Carlson, June 2, 2011). The parameters a_1, a_2, β_i, and W_j were estimated using GLM procedure in SAS (SAS Institute Inc, 2003)—we expect the parameters a_1, and a_2 to be positive, which indicates the less amounts of solar radiation can reach to the soil surface when the percentages of relative humidity and cloud cover are high. The parameter estimates for the ratio of the difference between clear day solar radiation and the actual solar radiation are reported in Table III-13.

Table III-13. Parameter Estimates for the Solar Radiation Estimated with GLM Procedure in SAS

Variable	Parameter	Parameter Estimate	Standard Error	t-value	*p-value*
Humidity (%)	a_1	0.122	(0.0355)	3.43	0.0006
1-%Maximum Sunshine	a_2	0.349	(0.0181)	19.22	<0.0001
<u>Hourly Dummy Variables</u>					
6:00 am.	β_1	0.271	(0.0298)	9.09	<0.0001
7:00 am.	β_2	0.146	(0.0289)	5.04	<0.0001
8:00 am.	β_3	0.070	(0.0280)	2.49	0.013
9:00 am.	β_4	0.024	(0.0269)	0.87	0.383
10:00 am.	β_5	0.019	(0.0251)	0.77	0.442
11:00 am.	β_6	0.024	(0.0237)	1.03	0.302
12:00 pm.	β_7	0.039	(0.0226)	1.71	0.087
1:00 pm.	β_8	0.051	(0.0220)	2.32	0.020
2:00 pm.	β_9	0.068	(0.0215)	3.16	0.001
3:00 pm.	β_{10}	0.084	(0.0213)	3.92	<0.0001
4:00 pm.	β_{11}	0.118	(0.0212)	5.57	<0.0001
5:00 pm.	β_{12}	0.194	(0.0212)	9.16	<0.0001
6:00 pm.	β_{13}	0.296	(0.0213)	13.94	<0.0001
7:00 pm.	β_{14}	0.505	(0.0220)	22.98	<0.0001
<u>Weekly Dummy Variables</u>					
Week 1	δ_1	0.067	(0.0173)	3.89	0.0001
Week 2	δ_2	0.048	(0.0166)	2.89	0.0038
Week 3	δ_3	0.057	(0.0166)	3.45	0.0006
Week 4	δ_4	0.075	(0.0165)	4.50	<0.0001
Week 5	δ_5	0.078	(0.0167)	4.62	<0.0001
Week 6	δ_6	-0.043	(0.0166)	-2.57	0.010

Note: Number of observations 4210

The parameter estimates for the weekly dummy variables, weeks 1- 5, were statistically and significantly different from week 7 at the 1 percent level and have the positive signs. This indicates there are higher percentages of relative humidity and cloud cover during week 1 through week 5 than in week 7. However, the percentages of relative humidity and cloud cover during week 6 were not significantly different from those in week 7. The results also show the parameter estimates for the hourly dummy variables were positive and significant at the 1 percent level; except for the dummy variables for 08:00 am - 01:00 pm. The results indicate there are higher percentages of relative humidity and cloud cover during 06:00 - 07:00 am, and during 03:00-07:00 pm portions of the day $(P \leq 0.0001)$, especially during week 1-5 (April 1- May 5). This implies that there was a smaller proportion of the solar radiation at the top of the earth's atmosphere that reached the soil surface during the hours between 06:00-07:00 am, and the hours between 03:00-07:00 pm each day than during the hours between 8:00 am and 2:00 pm. This is especially true during weeks one through five than in week six. $(P \leq 0.0001)$.

The parameter estimates (reported in Table III-13) were used to predict the values of the ratio of the difference between clear day solar radiation and the solar radiation of forecast weather data. The values of forecast solar radiation were then derived by rearranging terms of equation (3), which gave

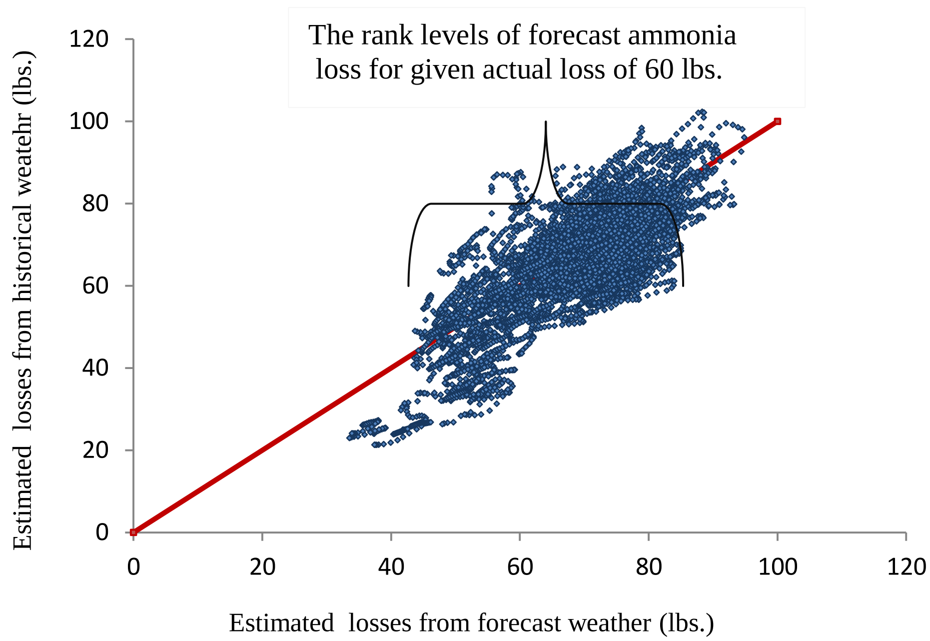
$$(3)' \qquad FSR_{ijt} = CDSR_{ijt} - \left[\left(a_1 RH_{ijt} + a_2 (1 - PMSun)_{ijt} + \beta_i H_{it} + \delta_j W_{jt}\right) * CDSR_{ijt}\right]$$

where FSR_{ijt} is the forecast solar radiation at hour *i* of week *j* in year *t*, $CDSR_{ijt}$ is the clear day solar radiation measure at the same hour, *RH* and *PMSun* represent the percentage of relative humidity and possible maximum sunshine, respectively, H_{it} is the dummy variable for hour *i* , and W_{jt} is an indicator for weekly dummy variables. The parameters

a_1, a_2, β_i, and W_j are obtained under the estimation of equation (3). The predicted values of solar radiation were then combined with other climate forecast data that occured at the same time period to simulate the ammonia N volatilization using Wu's model (2003a). There were 6,480 observations of N loss estimated from the set of forecast weather data.

While the statistical analysis results of historical weather data, reported in Table III-4, shows there is a variation of ammonia loss by the time of application, the hourly weather forecast data are also available on the Mesonet sites. As a result, the likelihood of forecast weather occurrence in terms of ammonia loss would become relevant information for the producer to determine the time for spreading the effluent. Figure III-3 presents the comparison of cumulative N volatilization at 192 hours after application estimated from historical and forecast weather data for period 2005-2010. A visual view from Figure III-3 indicates there were the frequencies of forecast ammonia losses that fell below and/or above the level of ammonia losses estimated for given actual weather at the same time period. For instance, when the actual of ammonia loss was 60 lbs, the forecast ammonia losses were between 40-90 lbs.

Figure III-3. The comparison of cumulative N volatilization at 192 hours after application estimated from historical and forecast weather data for April 1-May 15, 2005-2010



These results indicate that the volatilization of ammonia nitrogen is random and contingent on the weather conditions, which implies Bayesian methods could provide a means to incorporate forecast information into decision making. However, there are several steps required to implement the Bayesian methods into the stochastic dynamic programming (SDP) model to determine the best time of effluent application. The steps to incorporate the simulated ammonia losses from forecast weather data to the problem of effluent application includes;

1. Construct the prior probability distribution of ammonia losses estimated from the historical (actual) weather data for April 1-May 15, 1994-2010;
2. Determine the joint probability distribution of forecast ammonia loss and the actual loss for each class mean level of the weather conditions. This probability was constructed as the probability matrix by using the simulated ammonia losses from forecast weather data for only years 2005-

2010, as well as the estimated losses from the actual weather data from the same period;

3. Calculate the probability of forecast ammonia loss for each class mean level of forecast predicted loss;
4. Determine the posterior probability distribution of ammonia loss for each class mean level of loss. This probability was calculated by using the three probability distributions obtained from the previous steps (1-3);
5. Estimate the expected ammonia loss for each class mean level of forecast weather conditions;
6. Derive the Markov Transition matrix stating the probability of the forecast for the next period conditional upon the currently received forecast.

The steps of revising the past weather and forecasts information in the producer's decision can be described as follows.

Step 1: Computation of Prior Probability Distribution of Ammonia Loss

The prior distribution is the probability of actual ammonia loss that occur at each class mean level of loss during each period of application. The computation was performed by summarizing the ammonia losses simulated from historical weather data into the class mean ranges. In the study, the simulated losses were categorized into 14 classes with an increment of a six pound class per-acre of loss (18-23.99, 24-29.99, etc.). The next step is to find the frequency of the losses that fall into each category. Table III-14 shows the frequency distribution of simulated ammonia losses by five-day period from April 1 to May 15 for the twelve-hour daytime-only application method.

Table III-14. Frequency Distribution of Simulated Ammonia Volatilizations after 192 Hours for the Twelve-hour Daytime-only Application by Five Day Period Using Hourly Recorded Mesonet Weather Data at Goodwell, Oklahoma from 1994 to 2010

Loss Level	Class Range of Loss (lbs/acre)	Class means, $\bar{L}$ (lbs/acre)	Simulated N Losses Occurred from Applications Made between 6:01 am to 6:00pm by Five Day Period at Each Class Range of Loss						
			April 1-5	April 6-10	April 11-15	April 16-30[a]	May 1-5	May 6-10	May 11-15
1	18-24	21	52	48	0	0	0	0	0
2	24-30	27	26	12	12	39	0	0	0
3	30-36	33	36	87	6	116	0	0	0
4	36-42	39	97	59	75	64	0	0	0
5	42-48	45	156	66	135	191	34	0	4
6	48-54	51	148	245	69	512	167	8	22
7	54-60	57	198	172	179	654	228	123	30
8	60-66	63	204	135	154	653	227	226	89
9	66-72	69	55	99	141	371	177	271	263
10	72-78	75	46	37	139	308	68	221	313
11	78-84	81	2	28	73	129	80	98	180
12	84-90	87	0	26	37	23	30	56	82
13	90-96	93	0	6	0	0	9	16	33
14	96-102	99	0	0	0	0	0	1	4
Total Number of Observation			1,020	1,020	1,020	3,060	1,020	1,020	1,020

[a] According to our statistical results, the simulated ammonia loss data of the five day periods for April 16 to 30 were aggregated into only 1 group.

The frequency of losses shown in Table III-14 was then used to compute the historical prior probability of actual ammonia loss that occurs at each class mean level for each 5 day period. The prior probability can be calculated as follows;

(4) $$\Pr(L^s)_{kp} = \frac{A_{kp}^s}{n_{kp}}$$

where $\Pr(L^s)_{kp}$ is the prior probability of ammonia loss occurs during application time k in period p that fall in the class mean loss of s ($s = 1, 2, \ldots, S$; S=14), A_{kp}^s is the frequency or number of times that actual ammonia loss occurs in the class mean loss of s, and n_{kp} is the total number of simulated N losses in the same time period (shown in the shade portion of Table III-14 above). For example, the prior probability of loss occurs at class mean loss of 18-24 lbs/acre (Table III-15) from applications made during the first five day period, April 1-5, is 0.051 (52 ÷ 1020). Table III-15 reports the prior probability for each class mean level of ammonia loss by 5 day period for the twelve-hour daytime-only application method. The prior probabilities for the six-hour day and night time application method were done following the same process.

Table III-15. The Prior Probability Distribution of Ammonia Losses for the Twelve-hour Daytime-only Application by Five Day Period from April 1 to May 15

Loss Level	Class Range of Loss (lbs/acre)	Class means, $\bar{L}$ (lbs/acre)	Prior Probability of Loss, *Pr*(*L*), at Each Class Range of Loss from Applications Made between 6:01 am to 6:00pm by Five Day Period						
			April 1-5	April 6-10	April 11-15	April 16-30	May 1-5	May 6-10	May 11-15
1	18-24	21	0.051	0.047	0	0	0	0	0
2	24-30	27	0.026	0.012	0.012	0.013	0	0	0
3	30-36	33	0.035	0.085	0.006	0.038	0	0	0
4	36-42	39	0.095	0.058	0.074	0.021	0	0	0
5	42-48	45	0.153	0.065	0.132	0.062	0.033	0	0.004
6	48-54	51	0.145	0.240	0.068	0.167	0.164	0.008	0.022
7	54-60	57	0.194	0.169	0.175	0.214	0.224	0.121	0.029
8	60-66	63	0.200	0.132	0.151	0.213	0.223	0.222	0.087
9	66-72	69	0.054	0.097	0.138	0.121	0.174	0.266	0.258
10	72-78	75	0.045	0.036	0.136	0.101	0.067	0.217	0.307
11	78-84	81	0.002	0.027	0.072	0.042	0.078	0.096	0.176
12	84-90	87		0.025	0.036	0.008	0.029	0.055	0.080
13	90-96	93		0.006	0	0	0.009	0.016	0.032
14	96-102	99		0	0	0	0	0.001	0.004
	Sum Total		1.000	1.000	1.000	1.000	1.000	1.000	1.000

Note: The prior probability of losses for each class mean level of each 5 day period from applications during April 16 to 30 is the same based on the statistical analysis results.

Step2: Calculation of the Joint Forecast Loss and Actual Loss Probability Matrix

The first step to construct the joint probability matrix is to classify the simulated N losses from forecast weather data (for April 1- May 15, 2005-2010) into classes with an increment of an eight pound class per-acre of loss--0-7.99, 8-15.99, …, and 80-87.99. There were 11 classes chosen for the forecast ammonia loss. The simulated N losses from historical weather data for April 1- May 15, 2005-2010 were also categorized into 14 classes with an increment of a six pound class per-acre of loss--18-23.99, 24-29.99, etc. Eight pound classes were used for the forecast data because the forecast data period 2005-2010 was shorter than the actual weather data period 1994-2010. These two data sets were used to compute the joint probability of forecast loss Z^i and the actual loss L^s for each class mean level of loss, $\Pr(Z^i \mid L^s)$. The step was done by counting the frequency of ammonia losses that occurred at each class mean level during each application time. This was readily accomplished by aligning the nitrogen loss occurring from the actual weather data with the nitrogen loss from the forecast weather data by the same year, day of year, and hour of application. The Excel pivot table was then used to obtain the frequency distribution of forecast loss for each class of nitrogen loss estimated from actual weather data. For example, level 8 in Table III-16 represents actual loss levels from 60 to 66 lbs/acre for one of application periods. These losses were estimated to occur given the actual weather occurred during the forecast period to probability of the forecast given the actual ammonia loss. Assume there are the total of n_{kp} estimated losses from the actual weather during the application time *k* in period *p*, and that A^s observations fell in the class means of loss L^s. During the forecast period for an application time *k* in period *p*, there are F_s^i observations of estimated forecast ammonia loss that fall in the same class range of the given actual loss L^s. The joint probability of forecast loss Z^i given the actual loss L^s during application time *k* in period *p*, denoted by $\Pr(Z^i \mid L^s)_{kp}$, can be calculated as follows;

$$\Pr(Z^i \mid L^s)_{kp} = \left(\frac{F_s^i}{A^s}\right)_{kp} \tag{5}$$

The tabulations were done for all classes of the forecast weather predicted losses. A schematic of the frequency distribution matrix is presented in Table III-16.

Table III-16. The Probability Matrix of Ammonia Loss by Class Means Level of Loss for Applications during Time *k*

Loss Level	Forecast, Z^i	1	2	3	4	5	6	7	8	9	10	11	Sum
Actual, L^s	Class Range of Loss (lbs/acre)	Probability Distribution of Forecast Losses for the Level of Loss from Actual weather											Sum
		0-8	8-16	16-24	24-32	32-40	40-48	48-56	56-64	64-72	72-80	80-88	
1	18-24	F_1^1 / A^1	F_1^2 / A^1	F_1^3 / A^1	F_1^4 / A^1	F_1^5 / A^1	F_1^6 / A^1	F_1^7 / A^1	F_1^8 / A^1	F_1^9 / A^1	F_1^{10} / A^1	F_1^{11} / A^1	1
2	24-30	F_2^1 / A^2	F_2^2 / A^2	F_2^3 / A^2	F_2^4 / A^2	F_2^5 / A^2	F_2^6 / A^2	F_2^7 / A^2	F_2^8 / A^2	F_2^9 / A^2	F_2^{10} / A^2	F_2^{11} / A^2	1
3	30-36	F_3^1 / A^3	F_3^2 / A^3	F_3^3 / A^3	F_3^4 / A^3	F_3^5 / A^3	F_3^6 / A^3	F_3^7 / A^3	F_3^8 / A^3	F_3^9 / A^3	F_3^{10} / A^3	F_3^{11} / A^3	1
4	36-42	F_4^1 / A^4	F_4^2 / A^4	F_4^3 / A^4	F_4^4 / A^4	F_4^5 / A^4	F_4^6 / A^4	F_4^7 / A^4	F_4^8 / A^4	F_4^9 / A^4	F_4^{10} / A^4	F_4^{11} / A^4	1
5	42-48	F_5^1 / A^5	F_5^2 / A^5	F_5^3 / A^5	F_5^4 / A^5	F_5^5 / A^5	F_5^6 / A^5	F_5^7 / A^5	F_5^8 / A^5	F_5^9 / A^5	F_5^{10} / A^5	F_5^{11} / A^5	1
6	48-54	F_6^1 / A^6	F_6^2 / A^6	F_6^3 / A^6	F_6^4 / A^6	F_6^5 / A^6	F_6^6 / A^6	F_6^7 / A^6	F_6^8 / A^6	F_6^9 / A^6	F_6^{10} / A^6	F_6^{11} / A^6	1
7	54-60	F_7^1 / A^7	F_7^2 / A^7	F_7^3 / A^7	F_7^4 / A^7	F_7^5 / A^7	F_7^6 / A^7	F_7^7 / A^7	F_7^8 / A^7	F_7^9 / A^7	F_7^{10} / A^7	F_7^{11} / A^7	1
8	60-66	F_8^1 / A^8	F_8^2 / A^8	F_8^3 / A^8	F_8^4 / A^8	F_8^5 / A^8	F_8^6 / A^8	F_8^7 / A^8	F_8^8 / A^8	F_8^9 / A^8	F_8^{10} / A^8	F_8^{11} / A^8	1
9	66-72	F_9^1 / A^9	F_9^2 / A^9	F_9^3 / A^9	F_9^4 / A^9	F_9^5 / A^9	F_9^6 / A^9	F_9^7 / A^9	F_9^8 / A^9	F_9^9 / A^9	F_9^{10} / A^9	F_9^{11} / A^9	1
10	72-78	F_{10}^1 / A^{10}	F_{10}^2 / A^{10}	F_{10}^3 / A^{10}	F_{10}^4 / A^{10}	F_{10}^5 / A^{10}	F_{10}^6 / A^{10}	F_{10}^7 / A^{10}	F_{10}^8 / A^{10}	F_{10}^9 / A^{10}	F_{10}^{10} / A^{10}	F_{10}^{11} / A^{10}	1
11	78-84	F_{11}^1 / A^{11}	F_{11}^2 / A^{11}	F_{11}^3 / A^{11}	F_{11}^4 / A^{11}	F_{11}^5 / A^{11}	F_{11}^6 / A^{11}	F_{11}^7 / A^{11}	F_{11}^8 / A^{11}	F_{11}^9 / A^{11}	F_{11}^{10} / A^{11}	F_{11}^{11} / A^{11}	1
12	84-90	F_{12}^1 / A^{12}	F_{12}^2 / A^{12}	F_{12}^3 / A^{12}	F_{12}^4 / A^{12}	F_{12}^5 / A^{12}	F_{12}^6 / A^{12}	F_{12}^7 / A^{12}	F_{12}^8 / A^{12}	F_{12}^9 / A^{12}	F_{12}^{10} / A^{12}	F_{12}^{11} / A^{12}	1
13	90-96	F_{13}^1 / A^{13}	F_{13}^2 / A^{13}	F_{13}^3 / A^{13}	F_{13}^4 / A^{13}	F_{13}^5 / A^{13}	F_{13}^6 / A^{13}	F_{13}^7 / A^{13}	F_{13}^9 / A^{13}	F_{13}^9 / A^{13}	F_{13}^{10} / A^{13}	F_{13}^{11} / A^{13}	1
14	96-102	F_{14}^1 / A^{14}	F_{14}^2 / A^{14}	F_{14}^3 / A^{14}	F_{14}^4 / A^{14}	F_{14}^5 / A^{14}	F_{14}^6 / A^{14}	F_{14}^7 / A^{14}	F_{14}^{10} / A^{14}	F_{14}^9 / A^{14}	F_{14}^{10} / A^{14}	F_{14}^{11} / A^{14}	1

Assume the period was for April 1 to 5. The estimated losses from the actual and forecast weather data are used to construct a frequency distribution of forecast ammonia losses for a level of actual N loss. The next step is to find the distribution of all ammonia losses generated from forecast weather data for April 1 to 5 when the actual losses were between 60-66 lbs/acre. Table III-17 reports the frequency distribution for April 1 to 5 for the twelve-hour daytime-only application method.

Table III-17. The Frequency Matrix of Ammonia Loss by Class Means Level of Loss for Applications during April 1 to 5 for the Twelve-hour Daytime-only Application Method

Loss Level	Forecast, Z^i	1	2	3	4	5	6	7	8	9	10	11	Sum
Actual, L^s	Class Range of Loss (lbs/acre)	0-8	8-16	16-24	24-32	32-40	40-48	48-56	56-64	64-72	72-80	80-88	
1	18-24				2	23	1						26
2	24-30					7	4						11
3	30-36						3						3
4	36-42						34	1					35
5	42-48					1	38	13	2				54
6	48-54						23	17	1				41
7	54-60							16	23	2			41
8	60-66							**6**	44	21			**71**
9	66-72							6	13	8			27
10	72-78								12	13			25
11	78-84								2				2
12	84-90												
13	90-96												
14	96-102												

The frequency distribution in each row is converted to a probability distribution by dividing by the total observation for each row. For instance, the joint probability distribution of the forecast ammonia loss of 48-56 lbs/acre and the given actual loss of 60-66 lbs/acre is equal to 0.085 (6÷71). A schematic of the probability matrix of ammonia losses for this first 5 day period (April 1 to 5) is presented in Table III-18. The joint probability obtained follows equation (5) was used to compute the probability of occurrence of the forecast N loss, which will be described in the following section.

Table III-18. The Probability Matrix, $\Pr(Z^i \mid L^s)$, of Ammonia Losses by Class Means Level of Loss for the Applications during April 1 to 5 for the Twelve-hour Daytime-only Application Method

Loss Level	Forecast, Z^i	1	2	3	4	5	6	7	8	9	10	11	Sum
Actual, L^s	Class Range of Loss (lbs/acre)	Probability Distribution of Forecast Losses for the Level of Loss from Actual weather											
		0-8	8-16	16-24	24-32	32-40	40-48	48-56	56-64	64-72	72-80	80-88	
1	18-24				0.0769	0.885	0.038	0	0	0			1
2	24-30					0.636	0.364	0	0	0			1
3	30-36					0	1.000	0	0	0			1
4	36-42					0	0.971	0.029	0	0			1
5	42-48					0.018	0.704	0.241	0.037	0			1
6	48-54						0.561	0.415	0.024	0			1
7	54-60							0.390	0.561	0.049			1
8	60-66							0.085	0.620	0.296			1
9	66-72							0.222	0.481	0.296			1
10	72-78								0.480	0.520			1
11	78-84								1.000	0			1
12	84-90												
13	90-96												
14	96-102												

Step 3: Deriving the Probability of a Forecast for Each Level of Ammonia Loss

The revision of the past information in terms of the likelihood of occurrence can help to improve the accuracy of the outcome (Buchanan, 1982). The probability of forecast for the *i*th loss, $\Pr(Z^i)$, is shown in the last row of Table III-19 below. The probability of forecast occurrence for each class level of loss can be calculated as

(6) $$\Pr(Z^i)_{kp} = \sum_{s=1}^{S} \Pr(Z^i \mid L^s)_{kp} * \Pr(L^s)_{kp}$$

where $\Pr(Z^i \mid L^s)_{kp}$ is the joint probability of forecast loss Z^i and the actual loss L^s occurring during application time *k* in period *p* (as defined in Tables III 16), $\Pr(L^s)_{kp}$ is the prior probability vector of ammonia loss from actual weather occurring at each class mean level of loss during time period *p*, $\Pr(Z^i)_{kp}$ is a prior probability weighted sum of the joint probability of forecast ammonia loss Z^i and the actual loss L^s for *i*th forecast predicted loss. Table III-19 presents the tabulation for computing this probability of forecast ammonia, $\Pr(Z^i)_{kp}$.

Table III-19. The Probability of Forecast Ammonia Losses, $\Pr(Z^i)$, for Each Class Means Level of Forecast Predicted Loss for Applications during Time *k*

Loss Level	Forecast, Z^i	1	2	3	4	5	6	7	8	9	10	11	Sum
Actual, L^s	Class Range of loss (lbs/acre)	0-8	8-16	16-24	24-32	32-40	40-48	48-56	56-64	64-72	72-80	80-88	
1	18-24	$(F_1^1/A^1)*\Pr(L^1)$	$(F_1^2/A^1)*\Pr(L^1)$	.	.	.	.	.	.	.	.	$(F_1^{11}/A^1)*\Pr(L^1)$	
2	24-30	$(F_2^1/A^2)*\Pr(L^2)$	$(F_2^2/A^2)*\Pr(L^2)$	.	.	.	.	.	.	.	.	$(F_2^{11}/A^2)*\Pr(L^2)$	
3	30-36	$(F_3^1/A^3)*\Pr(L^3)$	$(F_3^2/A^3)*\Pr(L^3)$	.	.	.	.	.	.	.	.	$(F_3^{11}/A^3)*\Pr(L^3)$	
4	36-42	.	.	.	.	.	.	.	.	.	.	.	
5	42-48	.	.	.	.	.	.	.	.	.	.	.	
6	48-54	.	.	.	.	.	.	.	.	.	.	.	
7	54-60	.	.	.	.	.	.	.	.	.	.	.	
8	60-66	.	.	.	.	.	.	.	.	.	.	.	
9	66-72	.	.	.	.	.	.	.	.	.	.	.	
10	72-78	.	.	.	.	.	.	.	.	.	.	.	
11	78-84	.	.	.	.	.	.	.	.	.	.	.	
12	84-90	.	.	.	.	.	.	.	.	.	.	.	
13	90-96	.	.	.	.	.	.	.	.	.	.	.	
14	96-102	$(F_{14}^1/A^{14})*\Pr(L^{14})$	$(F_{14}^2/A^{14})*\Pr(L^{14})$	.	.	.	.	.	.	.	.	$(F_{14}^{11}/A^{14})*\Pr(L^{14})$	
Probability of Forecast		$\Pr(Z^1)$	$\Pr(Z^2)$	.	.	.	.	.	.	.	.	$\Pr(Z^{11})$	1

Note: 1) $\Pr(L^s)$ is the prior probability of ammonia loss for each class of actual loss as computed follows equation (4).

2) The probability of losses for each class mean of forecast loss is shown in the shaded portion, and the sum of probabilities of all class levels must be equal to one.

For example, the probability of receiving a forecast with a predicted loss of 24-32 lbs/acre from applications during April 1-5 is equal to 0.004. Table III-20 reports the probability of forecast loss occurrence for each *i*th class of forecast predicted loss for applications during April 1 to 5 for the twelve-hour daytime-only application method.

Table III-20. The Probability of the Occurrence of Ammonia Losses for Each Class Level of Forecast Predicted Loss for the Applications during April 1 to 5 for the Twelve-Hour Daytime-only Application Method

Loss Level	Forecast, Z^i	1	2	3	4	5	6	7	8	9	10	11	Sum
Actual, L^s	Class Range of Loss (lbs/acre)	0-8	8-16	16-24	24-32	32-40	40-48	48-56	56-64	64-72	72-80	80-88	
1	18-24				0.004	0.045	0.002	0	0	0			
2	24-30					0.016	0.009	0	0	0			
3	30-36					0	0.035	0	0	0			
4	36-42					0	0.092	0.003	0	0			
5	42-48					0.0028	0.108	0.037	0.006	0			
6	48-54						0.081	0.060	0.004	0			
7	54-60							0.076	0.109	0.009			
8	60-66							0.017	0.124	0.059			
9	66-72							0.012	0.026	0.016			
10	72-78								0.022	0.024			
11	78-84								0.002				
12	84-90												
13	90-96												
14	96-102												
Probability of Forecast					0.004	0.064	0.327	0.205	0.293	0.108			1.000

Note: 1) $\Pr(L^s)$ is the prior probability of ammonia loss for each class of actual loss as computed follows equation (4).
2) The probability of losses for each class mean of forecast loss is shown in the shaded portion, and the sum of probabilities of all class levels must be equal to one.

Step 4: Derivation of the Bayes Posterior Probability Distribution for Each Level of Forecast Nitrogen Loss

The posterior probability is the conditional probability of actual ammonia loss when a forecast of ammonia loss is received, denoted by $g(L^s \mid Z^i)_{kp}$. The posterior probability distribution for each class mean level of forecast predicted loss can be calculated as;

(7) $$g(L^s \mid Z^i)_{kp} = \frac{\Pr(Z^i \mid L^s)_{kp} * \Pr(L^s)_{kp}}{\Pr(Z^i)_{kp}}$$

where, $g(L^s \mid Z^i)_{kp}$ is the posterior probability of actual ammonia loss L^s_{kp} during application time *k* in period *p* given the forecast loss Z^i, $\Pr(L^s)_{kp}$ is the prior probability distribution calculated from the losses with actual weather in the same time period, $\Pr(Z^i \mid L^s)_{kp}$ is the joint probability of loss from weather forecasts Z^i and actual ammonia loss L^s, and $\Pr(Z^i)_{kp}$ is the probability of occurrence of a forecast ammonia loss Z^i. That is for forecast class *i*, the individual posterior probabilities are obtained by dividing each element (g_{si}) in column *i* of the joint conditional matrix, $\Pr(Z^i \mid L^s)_{kp} * \Pr(L^s)$, by its' column total, $\Pr(Z^i)_{kp}$. Table III-21 presents the scheme for calculating the posterior probability for each class mean level of ammonia loss. Table III-22 also reports the posterior probabilities and the expected amount of ammonia losses for each class level of forecast predicted loss for applications during April 1 to 5 for the twelve-hour daytime-only application method.

Table III-21. The Posterior Probability and the Expected Ammonia Loss for Each Class Means Level of Forecast Predicted Loss for the Applications during Time *k*

Loss Level	Forecast, Z^i	1	2	3	4	5	6	7	8	9	10	11
Actual, L^s	Class Range of Loss (lbs/acre)	0-8	8-16	16-24	24-32	32-40	40-48	48-56	56-64	64-72	72-80	80-88
1	18-24	$(F_1^1/A^1)*\Pr(L^1)/\Pr(Z^1)$	$(F_1^2/A^1)*\Pr(L^1)/\Pr(Z^2)$	.	.	.	.	.	.	.	.	$(F_1^{11}/A^1)*\Pr(L^1)/\Pr(Z^{11})$
2	24-30	$(F_2^1/A^2)*\Pr(L^2)/\Pr(Z^1)$	$(F_2^2/A^2)*\Pr(L^2)/\Pr(Z^2)$	.	.	.	.	.	.	.	.	$(F_2^{11}/A^2)*\Pr(L^2)/\Pr(Z^{11})$
3	30-36	$(F_3^1/A^3)*\Pr(L^3)/\Pr(Z^1)$	$(F_3^2/A^3)*\Pr(L^3)/\Pr(Z^2)$	.	.	.	.	.	.	.	.	$(F_3^{11}/A^3)*\Pr(L^3)/\Pr(Z^{11})$
4	36-42	.	.	.	.	.	.	.	.	.	.	.
5	42-48	.	.	.	.	.	.	.	.	.	.	.
6	48-54	.	.	.	.	.	.	.	.	.	.	.
7	54-60	.	.	.	.	.	.	.	.	.	.	.
8	60-66	.	.	.	.	.	.	.	.	.	.	.
9	66-72	.	.	.	.	.	.	.	.	.	.	.
10	72-78	.	.	.	.	.	.	.	.	.	.	.
11	78-84	.	.	.	.	.	.	.	.	.	.	.
12	84-90	.	.	.	.	.	.	.	.	.	.	.
13	90-96	.	.	.	.	.	.	.	.	.	.	.
14	96-102	$(F_{14}^1/A^{14})*\Pr(L^{14})/\Pr(Z^1)$	$(F_{14}^1/A^{14})*\Pr(L^{14}))/\Pr(Z^2)$	.	.	.	.	.	.	.	.	$(F_{14}^{11}/A^{14})*\Pr(L^{14})/\Pr(Z^{11})$
Expected N Loss		$E(Z^1)$	$E(Z^2)$	.	.	.	.	.	.	.	.	$E(Z^{11})$

Note: 1) The shaded portion of Table III-21 shows the expected amount of ammonia N losses, $E(Z^i)$ for each class mean of forecast predicted loss.
2) The value of expected losses was computed from equation (8) below.

Table III-22. The Posterior Probability and the Expected Ammonia Loss for Each Class Means Level of Forecast Predicted Loss for the Applications during April 1 to 5 for the Twelve-Hour Daytime-only Application Method

Loss Level	Forecast, Z^i	1	2	3	4	5	6	7	8	9	10	11	Sum
Actual, L^s	Class Range of Loss (lbs/acre)	0-8	8-16	16-24	24-32	32-40	40-48	48-56	56-64	64-72	72-80	80-88	
1	18-24				1.000	0.703	0.006	0	0	0			
2	24-30					0.253	0.028	0	0	0			
3	30-36					0	0.108	0	0	0			
4	36-42					0	0.282	0.013	0	0			
5	42-48					0.044	0.328	0.180	0.019	0			
6	48-54						0.248	0.294	0.012	0			
7	54-60							0.371	0.373	0.876			
8	60-66							0.083	0.425	0.547			
9	66-72							0.058	0.089	0.148			
10	72-78								0.074	0.217			
11	78-84								0.007				
12	84-90												
13	90-96												
14	96-102												
Probability of Forecast					21.00	23.58	42.86	54.03	61.81	65.97			

Note: 1) The shaded portion of Table III-22 shows the expected amount of ammonia N losses, $E(Z^i)$ for each class mean of forecast predicted loss.
2) The value of expected losses was computed follows equation (8)

Step 5: Estimation of Expected Ammonia Loss in terms of Forecast Data

The expected amount of ammonia loss for each class mean of the forecast weather can be estimated based on the known posterior probabilities in equation (7) above; that is

(8) $$E(Z^i)_{kp} = \sum_{s=1}^{S} [\bar{L}^s * g(L^s \mid Z^i)]_{kp}$$

where $E(Z^i)_{kp}$ is the expected ammonia loss from applying the effluent following a given forecast weather condition i in place during application time k in period p, $\bar{L}^s$ is the midpoint of actual ammonia loss in class s (lbs/acre), and $g(L^s \mid Z^i)_{kp}$ is the posterior probability. The shaded portion of Tables III-21 and III-22 present the expected amount of ammonia loss for each class mean of forecast weather.

The calculations above allow the producer to estimated loss $E(Z^i)_{kp}$ on each date (period and time of application). However, the producer also needs information on the likelihood of the next forecast given that forecast $E(Z^i)_{kp}$ has been received for the SDP optimization model.

Step 6: Stochastic Process of Deriving the Probability of the Next Forecast Loss given the Forecast of Current Ammonia Loss

The view of estimated ammonia losses from forecast weather data (in Figure III-3) also indicates there is a small deviation between the amounts of ammonia lost from an application made from one hour to the next. This suggests that the amount of losses occurs under weather conditions in the future applications (six hours or 12 hours later) are unlikely to change greatly from the lost obtained in the current application. In other words, the probability of loss occurrence in the future period is related to the loss in the current period. The Markovian property states that for any given present state, the conditional probabilities of the future state is determined by only the present and are independent of the past (Buchanan, p.189-195,1982). The expected ammonia loss for each class mean of forecast weather in the future application is assumed to be given by the future forecast probability. The expected ammonia loss follows a Markovian stochastic process. The mean levels of forecast ammonia loss can be used as a second state variable to identify the probability of ammonia loss and the movement from one period to the next. The transition probability of the expected loss moving from one period to the next is defined as

$$\Pr(Z_{k+1}^{i} \mid Z_{1}^{i}, Z_{2}^{i}, \ldots, Z_{K}^{i}) = \Pr(Z_{k+1}^{i} \mid Z_{k}^{i}) \tag{9}$$

where $\Pr(Z_{k+1}^{i} \mid Z_{k}^{i})$ is the probability of occurrence of *i*th ammonia loss for the application during time *k+1* given the *i*th loss in application time *k*. This conditional probability describes the Markov process of forecast ammonia loss which moving from state *i* in application time *k* to the *i*th state in the next application, *k* + 1.

The transition probability matrix was computed using the empirical probability distribution function. The first step is to classify the state variable of the current stage and the next stage into 11 classes with an increment of eight pound class per acre of loss--0-7.99, 8-15.99, …, and 80-87.99. The next step is to align the nitrogen loss which occurred in the first period of application (e.g., midnight to 6:00 am) with the nitrogen loss from the forecast weather data in the next period (e.g., 6:00am to 12:00 noon). Then use the Pivot table in Excel to obtain the probability distribution of forecast ammonia loss for each class mean of forecast weather in the future application. Assume the producer makes a decision choice d in current time k corresponding to a certain level of ammonia loss. The choice variable d takes a value of one when the producer decides to apply, and $d = 2$ when the producer decides to wait for the later time. Also, there is the probability distribution of ammonia loss that occurs in each state Z_{k+1}^{i} ($i = 1, 2, \ldots, 11$) of the next application ($k+1$). The transition probability of forecast ammonia loss from one application to the next is defined as

$$\text{(10)} \qquad \Pr(Z_{k+1}^{F} = Z_{k+1}^{i} \mid Z_{K}^{i} = Z_{k}^{i}, d) = p_{k_k, k+1}^{i}(d)$$

where,

$$0 \le p_{k,k+1}^{i} \le 1, \quad and$$

$$\sum_{i=1}^{I=11} p_{k,k+1}^{i}(d) = 1$$

The scheme of the transition probabilities can be shown as Table III-23. The sum of transition probabilities for each state of nature in each period (sum across the row) must be equal to 1. However, there is a different transition matrix for each period of application relative to the decisions made. All probabilities may not exist in all states, depending on the times and periods of the application. This is because the weather becomes warmer from April through May 15.

Table III-23. Markov Transition Probability Matrix Moving from Application Time *k* =1 to Application Time *k*+1 Given Decision *d*

State Z^{i}_{k+1}		1	2	3	4	5	6	7	8	9	10	11	Sum
State Z^{i}_{k}	Forecast Mean Loss (lbs/acre)	0-8	8-16	16-24	24-32	32-40	40-48	48-56	56-64	64-72	72-80	80-88	
1	0-8	$p_{11}(d)$	$p_{12}(d)$	$p_{13}(d)$	$p_{14}(d)$	$p_{15}(d)$	$p_{16}(d)$	$p_{17}(d)$	$p_{18}(d)$	$p_{19}(d)$	$p_{110}(d)$	$p_{111}(d)$	1
2	8-16	$p_{21}(d)$	$p_{22}(d)$	$p_{23}(d)$	$p_{24}(d)$	$p_{25}(d)$	$p_{26}(d)$	$p_{27}(d)$	$p_{28}(d)$	$p_{29}(d)$	$p_{210}(d)$	$p_{211}(d)$	1
3	16-24	$p_{31}(d)$	$p_{32}(d)$	$p_{33}(d)$	$p_{34}(d)$	$p_{35}(d)$	$p_{36}(d)$	$p_{37}(d)$	$p_{38}(d)$	$p_{39}(d)$	$p_{310}(d)$	$p_{311}(d)$	1
4	24-32	$p_{41}(d)$	$p_{42}(d)$	$p_{43}(d)$	$p_{44}(d)$	$p_{45}(d)$	$p_{46}(d)$	$p_{47}(d)$	$p_{48}(d)$	$p_{49}(d)$	$p_{410}(d)$	$p_{411}(d)$	1
5	32-40	$p_{51}(d)$	$p_{52}(d)$	$p_{53}(d)$	$p_{54}(d)$	$p_{55}(d)$	$p_{56}(d)$	$p_{57}(d)$	$p_{58}(d)$	$p_{59}(d)$	$p_{510}(d)$	$p_{511}(d)$	1
6	40-48	$p_{61}(d)$	$p_{62}(d)$	$p_{63}(d)$	$p_{64}(d)$	$p_{65}(d)$	$p_{66}(d)$	$p_{67}(d)$	$p_{68}(d)$	$p_{69}(d)$	$p_{610}(d)$	$p_{611}(d)$	1
7	48-56	$p_{71}(d)$	$p_{72}(d)$	$p_{73}(d)$	$p_{74}(d)$	$p_{75}(d)$	$p_{76}(d)$	$p_{77}(d)$	$p_{78}(d)$	$p_{79}(d)$	$p_{710}(d)$	$p_{711}(d)$	1
8	56-64	$p_{81}(d)$	$p_{82}(d)$	$p_{83}(d)$	$p_{84}(d)$	$p_{85}(d)$	$p_{86}(d)$	$p_{87}(d)$	$p_{88}(d)$	$p_{89}(d)$	$p_{810}(d)$	$p_{811}(d)$	1
9	64-72	$p_{91}(d)$	$p_{92}(d)$	$p_{93}(d)$	$p_{94}(d)$	$p_{95}(d)$	$p_{96}(d)$	$p_{97}(d)$	$p_{98}(d)$	$p_{99}(d)$	$p_{910}(d)$	$p_{911}(d)$	1
10	72-80	$p_{101}(d)$	$p_{102}(d)$	$p_{103}(d)$	$p_{104}(d)$	$p_{105}(d)$	$p_{106}(d)$	$p_{107}(d)$	$p_{108}(d)$	$p_{109}(d)$	$p_{1010}(d)$	$p_{1011}(d)$	1
11	80-88	$p_{111}(d)$	$p_{112}(d)$	$p_{113}(d)$	$p_{114}(d)$	$p_{115}(d)$	$p_{116}(d)$	$p_{117}(d)$	$p_{118}(d)$	$p_{119}(d)$	$p_{110}(d)$	$p_{1111}(d)$	1

In the study, there is different empirical transition probability matrix used for each specific application strategy. For the six- hour day and night application method (with 180 periods over the planting horizon), there were 45 transition probability matrices applied to the BSDP optimization model. The probability was used to identify the probability of loss moving from any current state to another. There were only 17 transition probability matrices uses in the optimization model under the twelve- hour daytime-only application (reported in Appendix A). Table III-24 presents the transition probability for each class mean level of losses that moving from application in the first twelve-hour application (6:00 am to 6:00 pm of April 1) to the next twelve-hour application (April 2). For instance, there is 90 percent chance that the producer will incur the loss between 32-40 lbs/acre in the next applications during twelve-hour of April 2 (6:00am to 6:00pm) if the producer obtained the loss between 32-40 lbs/acre in the current application, April 1.

Table III-24. Markov Transition Probability of Forecast Ammonia Losses Moving from Applications during Twelve-hour Daytime of April 1 to the Next Day (April 2)

State being in the next twelve- hour (April 2)		1	2	3	4	5	6	7	8	9	10	11	Sum
Current State (April 1)	Forecast N Loss (lbs/acre)	0-8	8-16	16-24	24-32	32-40	40-48	48-56	56-64	64-72	72-80	80-88	
1	0-8												
2	8-16												
3	16-24												
4	24-32				1	0	0	0	0	0			
5	32-40				0.050	0.900	0.050	0	0	0			1.000
6	40-48				0	0.089	0.835	0.076	0	0			1.000
7	48-56				0	0.106	0.106	0.426	0.362	0			1.000
8	56-64				0	0.011	0.022	0.133	0.634	0.200			1.000
9	64-72				0	0	0	0	0.296	0.704			1.000
10	72-80												
11	80-88												

Optimization Model

Formation of the Bayesian Stochastic Dynamic Programming Problem

The objective of the SDP model is to solve for the optimal decision of effluent application in each application period which gives the minimum amount of the total ammonia loss. The producer will compare the ammonia loss that occurs in the current period with the loss that he/she will receive in the future period. The expected losses obtained from the Bayesian formulas can be used as the producer expected cost from the decision made. There are eleven possible levels of ammonia loss that can occur in each period with the probability of $\Pr(Z^i)$ in this study. The loss in the future period is dependent on the probability of loss that moving from the current period as indicated by the Markov transition probability. The Bayesian stochastic dynamic programming (BSDP) model then used to determine the optimal action of the effluent application by considering the amount of nitrogen lost that follows from the current probability distribution. The model employs the eight-day weather forecasts to use as a secondary state variable to indicate the transition probability of ammonia loss. The BSDP optimization model attempts to visualize the value of including weather forecasts in the decision making. The producer's objective function under the BSDP model can be defined as

$$(11) \qquad Minimize \quad E(Z^i)_{k,d} + \sum_{k+1=2}^{K} p^i_{k,k+1}(d) * E(Z^i)_{k+1}$$

Subject to: $\qquad d = 1 \, or \; 2$

where $E(Z^i)_k$ is the expected ammonia loss (lbs/acre) from applying the effluent at the following receipt of a forecast of ammonia loss for the current application time *k*, $p^i_{k,k+1}(d)$ is the transition probability of ammonia loss moving from state *i* in the current period to *i*th loss level of the future period, *d* is the choice variable which takes the value of one if the producer decides to apply the effluent under the current forecast loss Z^i, and $d = 2$ when the producer waits for more favorable weather.

Two Alternative Methods for Swine Effluent Application

We tested two irrigation methods to apply the lagoon effluent. These two alternative methods are defined based on the starting hour of the sprinkler irrigation system and the duration of observing new weather forecasts. The two methods are a six-hour day and night application and twelve-hour daytime-only application. With the six-hour application method, the producer is assumed to make the decision every six hours based upon 198 hours observed weather forecasts (i.e., 6 hours plus 192 hours after an application). The producer applying in six-hour periods must make eight applications during the 180 possible periods to apply the effluent to the 128 acres corn field. Alternatively, the producer will make a decision each morning at 6:01 am after observing weather forecasts over the next 204 hours (i.e., 12 hours plus 192 hours after an application) when he/she operates the sprinkler irrigation only during twelve- hour daytime. Similarly, the producer must select four application periods out of 45 periods for this twelve-hour daytime-only method.

Solution of Bayesians Stochastic Dynamic Programming Models (BSDP)

The optimal solution of effluent application is determined using Dynamic Programming Application (Kennedy, 1986). The program is formulated as a Visual Basic Application combined with an Excel spreadsheet for the data entry (see Appendix B). The solution for each BSDP model is obtained by using backward recursion starting from the last period and moving backward to the beginning period. The optimal results list the optimal action under each possible weather condition at each stage or point in time, along with the expected amount of total N loss if the optimal actions are followed.

Value of Weather Forecasts

Expected Ammonia Loss from BSDP Optimization

The total amount of ammonia loss given in the solution of BSDP model is the total loss occurring from the decision made in the current period plus the losses that expected to occur from all future applications. There are different levels of total ammonia loss depending on weather conditions that are predicted to occur in the first period. In other words, the producer will incur the loss that corresponding to the probability of weather forecasts in the first period. Therefore, the total expected loss from applying the effluent to cover a 128 acre corn field can be calculated as the weighted sum of the total expected ammonia loss for all possible levels of initial forecast loss, that is

$$(12)\qquad Total\ \ Expected\ Loss = \sum_{i=1}^{I} \left\{ \left(E(Z^i)_{k,d} + \sum_{k+1=2}^{K} p^i_{k,k+1}(d) * E(Z^i)_{k+1} \right) * \Pr(Z^i)_{k=1,d} \right\}$$

In the study, the total expected amount of ammonia loss for the two application strategies will be estimated based on the optimal solution of each BSDP model.

Base Solution: Ammonia Loss without Using Forecast Information

With the ignorance of the weather forecasts, the producer is assumed to finish the effluent application to cover an entire field at the beginning of the planting season (first fourty-eight hours) because this will give the lowest expected loss. At a particular time of application, there is a set of ammonia losses that associated with all observed weather conditions. Suppose the weather conditions during the first period result in ammonia losses between $L^1, L^2, \ldots, L^s$, and the i*th* loss has whose probabilities follow the historical (prior) probability distribution *Pr* (L^s). The expected amount of ammonia loss incurred in this application period is

$$E(L)_k = \sum_{s=1}^{S} L_k^s * \Pr(L_k^s) \tag{13}$$

where $E(L)_k$ is the expected amount of ammonia loss (lbs/acre) from applying the effluent at given weather conditions in period k (k=1). This expected loss is calculated from multiplying the probability of each level of loss by the amount of ammonia loss. For this base application with the six-hour operation, the total expected amount of ammonia loss from the application to cover a 128 acre field is the sum of all expected losses from 8 applications during April 1-2. Under the twelve-hour-daytime-only application, the total expected loss without forecast information is equal to the sum of all expected losses from 4 applications during April 1- 4

Economic Benefit of Using Weather Forecasts

The economic benefit from using the weather forecast is the difference between the total expected losses obtained from the BSDP and the expected losses from application without using forecast information. This economic benefit can be evaluated in terms of the cost of nitrogen fertilizer which the producer will purchase to compensate of the loss of nitrogen from the effluent application. The monetary value of weather forecasts is the difference between cost of nitrogen that the producer incurs under the BSDP method and the cost from application schedules without using forecast information. The five-year average price of nitrogen fertilizer (shown in Table I-4, Chapter I) is used to evaluate the value of forecasts. The comparison of the forecast values between the two application methods are also illustrated in this study.

IV.

CHAPTER IV

FINDINGS

Validation of Mechanistic Model and Input Data Estimation

The first step of this study was to simulate the cumulative amount of ammonia N volatilization at 192 hours following effluent application using a mechanistic model developed by Wu.et al with actual hourly Mesonet weather data. (2003a). The model estimation was consistent with the field experimental data conducted at Oklahoma State University Panhandle Research Station, Oklahoma (Warren, 2001; Zupancic et al., 1999) as addressed in Chapter I. The temperature, wind speed, relative humidity, and solar radiation variables were used as input data for the simulation model. The Wu model requires hourly solar radiation as an input. However, estimates of solar radiation are not included in published forecasts. Econometric estimation was used to estimate this variable. The parameters of the solar radiation defined in equation 2 (Chapter III) were estimated using the GLM procedure in SAS. The results were reported in Table III-13 (Chapter III). Those results were used to predict the values of the solar radiation and applied to the Wu's model to simulate the ammonia volatilization for forecast weather data.

Econometric Estimation for the Differences in Simulated Cumulative N Volatilization

The assumptions of the significant differences in the amount of ammonia volatilization by six-hour of the day and periods of application were tested by using the GLM procedure in SAS. The results (reported in Table III-6 to III-9, Chapter III) indicate there are significant differences in mean levels of ammonia volatilization between each six-hour of the day period (April 1-5) to the next. As a result, the application horizon in the study was divided into 180 periods under the six-hour day or night application method. Out of these periods, the producer needs to find 8 favorable periods (48 hours) to apply the effluent to cover a 128 acre field. When the sprinkler irrigation system was operated only during twelve-hour daytime periods (6:00 am to 6:00 pm), the application horizon was divided into 45 periods. The 4 periods are required for the producer to make applications under this method. The prior distribution and posterior probability of ammonia volatilization were also computed based upon those reported results in Chapter III.

Bayesians Stochastic Dynamic Optimization Results

The objective of Bayesians stochastic dynamic programming (BSDP) is to solve for the optimal time of effluent application which minimizes the total expected ammonia volatilization such that the entire 128 acre field is covered. The analysis uses forecast weather conditions to indicate the random process of N volatilization which change relative to the weather that occurs during a 192 hour period following the application. The distribution of N volatilization was calculated using an empirical PDF method as described in a previous chapter. The total expected amount of ammonia volatilization is used to compare the economic benefit when the producer uses weather forecasts (BSDP model) and when the producer just begins application from April 1. (The April first date was established above as the most favorable application time based on historical records).

To evaluate the economic benefit of weather forecasts, the application method is defined in three ways: 1) the six-hour day or night application; 2) the twelve-hour daytime-only application; and 3) the base solution to always apply during the first forty-eight hours. The six-hour application period was arbitrarily assumed to be the shortest period for which the producer was willing to start and stop the pivot. The twelve-hour daytime-only period was used to test or measure the loss from forgoing nighttime applications. The third method is used when the producer does not incorporate weather forecast into his/her decision, and is used as the base solution. The optimal solutions for application strategies 1 and 2 were solved using backward recursion of dynamic programming (DP). The DP routine is run iteratively until the final solution for each period is reached. The final solution represents the minimum amount of total expected ammonia volatilization. This total loss is the expected loss obtained from the first action made in period 1, plus the expected loss for all future applications, which made to apply 150 lbs of nitrogen per acre to the entire corn field. Table IV-1 presents the sample of the optimal action for each period of the twelve-hour daytime application method, which is obtained from the BSDP model.

These optimal solutions reflect the producer's actions upon the stage or point in time and the number of applications remaining. At the first period (April 1) with the 4 applications remaining (no effluent has not been applied), the producer would apply if the forecast loss was less than 40 lbs/acre. After the first application has been made in period 1, the decision of the producer in the next period (April 2) follows the right side of Table IV-1. If there are 3 applications remaining, the producer decided to apply the effluent when the range of forecast loss was below 32-40 lbs/acre. After these two applications were made, the producer has 2 remaining applications need to be applied. When the producer arrived period 3 with 2 applications remaining, the producer will applied the effluent if the forecast loss was less than 32-40 lbs/acre as shown in left side of Table IV-1 (Contd). When the producer arrived at period 4 (April 4) and has one application that needs to be made, the producer decision follows the right side of Table IV-1 (Contd). The application would be made if the loss was less than 32-40 lbs/acre. On the other hand, if the producer arrived in period 42 (May 12) and has not applied any effluent, the producer must apply the effluent regardless of the weather. This is because of the limited time remaining. The optimal or only action when there is limited time to complete the remaining applications is defined as A* in table IV-1

Table IV-1. The Optimal Action Obtained from the BSDP model for the Twelve-hour Daytime-only Application Method

	Decision Made for Each Class of Forecast Loss by the Number of Remaining Application															
	4 Applications Remaining								3 Applications Remaining							
Range of Loss (lbs/acre)	24-32	32-40	40-48	48-56	56-64	64-72	72-80	80-88	24-32	32-40	40-48	48-56	56-64	64-72	72-80	80-88
Application Date/ Loss Level	4	5	6	7	8	9	10	11	4	5	6	7	8	9	10	11
April 1	A	A	W	W	W	W										
April 2	A	A	W	W	W	W			A	A	W	W	W	W		
April 3	A	A	A	W	W	W			A	A	A	W	W	W		
April 4	A	A	A	W	W	W			A	A	A	W	W	W		
April 5	A	A	A	W	W	W			A	A	A	W	W	W		
April 6		A	A	A	W	W	W			A	A	A	W	W	W	
April 7		A	A	A	W	W	W			A	A	A	W	W	W	
April 8		A	A	A	W	W	W			A	A	A	W	W	W	
April 9		A	A	A	W	W	W			A	A	A	W	W	W	
April 10		A	A	A	W	W	W			A	A	A	W	W	W	
.		.	.	.	.	.	.			.	.	.	.	.	.	
.		.	.	.	.	.	.			.	.	.	.	.	.	
.		.	.	.	.	.	.			.	.	.	.	.	.	
May 11					A	A	A	A					A	A	W	W
May 12					A*	A*	A*	A*					A	A	A	A
May 13					A*	A*	A*	A*					A*	A*	A*	A*
May 14					A*	A*	A*	A*					A*	A*	A*	A*
May 15					A*	A*	A*	A*					A*	A*	A*	A*

Note: 1) "A" defines the producer's decision of applying the swine effluent and "W indicates when the producer decided to wait for more favorable time.
2)The shade portion of Table IV-1 indicates no forecasts of those amounts were received on those dates.
3) * Indicates application required because of the limited time remaining.

Table IV-1 (Contd). The Optimal Action Obtained from the BSDP model for the Twelve-hour Daytime-only Application Method

	Decision Made for Each Class of Forecast Loss by the Number of Remaining Application															
	2 Applications Remaining								1 Applications Remaining							
Range of Loss (lbs/acre)	24-32	32-40	40-48	48-56	56-64	64-72	72-80	80-88	24-32	32-40	40-48	48-56	56-64	64-72	72-80	80-88
Application Date/ Loss Level	4	5	6	7	8	9	10	11	4	5	6	7	8	9	10	11
April 1																
April 2																
April 3	A	A	W	W	W	W										
April 4	A	A	A	W	W	W			A	A	W	W	W	W		
April 5	A	A	A	W	W	W			A	A	A	W	W	W		
April 6		A	A	A	W	W	W		A	A	A	W	W	W		
April 7		A	A	A	W	W	W			A	A	W	W	W	W	
April 8		A	A	W	W	W	W			A	A	W	W	W	W	
April 9		**A**	A	W	W	W	W			A	A	W	W	W	W	
April 10		A	A	W	W	W	W			A	A	W	W	W	W	
.		.	.	.	.	.	.			.	.	.	.	.	.	
.		.	.	.	.	.	.			.	.	.	.	.	.	
.		.	.	.	.	.	.			.	.	.	.	.	.	
May 11					A	A	W	W		.	.	.	.	.	.	
May 12					A	A	W	W					A	W	W	W
May 13					A	A	A	A					A	A	W	W
May 14					A*	A*	A*	A*					A	A	A	A
May 15					A*	A*	A*	A*					A*	A*	A*	A*

Note: 1) "A" defines the producer's decision of applying the swine effluent and "W indicates when the producer decided to wait for more favorable time.
2) The shade portion of this table indicates no forecasts of those amounts were received on those dates.
3) * Indicates application required because of the limited time remaining

In this study, there were six possible levels of loss observed to occur in the first period, which are given by the probability $\Pr(Z^i)$. Before the producer has received a forecast, the total expected loss incurred by the producer is equal to the probability weighted sum of total expected losses from all six possible levels of N losses in period 1. The total expected losses for six-hour day or night application and the twelve-hour daytime-only application methods are reported in Table IV-2. The value of 4,853 lbs.(the shaded portion in Table IV-2) represents the total expected amount of ammonia losses obtained when the sprinkle irrigation system was operated follows the six-hour day and night time strategy and the optimal decisions following record of forecast information are made. The expected loss is 5,779 lbs. if the effluent was applied only during the daytime and the optimal post forecast decisions are made. Although, the two application methods have included forecast information in the producer's decision, there is an advantage from employing the six-hour application method since it is more flexible and allows application during nighttime (6:00pm to midnight and midnight to 6:00 am periods). The difference of 926 lbs (5,779 -4,853) is the reduced amount of nitrogen losses when the producer has more choices to operate the center pivot sprinkler irrigation system during both day and night time.

Table IV-2. The Total Expected Ammonia Volatilization from Swine Effluent Application for Each Class Range of Forecast Loss Obtained under BSDP Model

		Six-hour day or night application				Twelve-hour daytime-only			
Loss Level*	Class Range of Loss, Z^i (lbs/acre)	Mean Days to Complete Application	Probability of Forecast, $\Pr(Z^i)$, in Period 1	Total Expected Loss (lbs), $E(Z^i)$	Weight Average of Expected Loss (lbs)	Mean Days to Complete Application	Probability of Forecast, $\Pr(Z^i)$, in Period 1	Total Expected Loss (lbs), $E(Z^i)$	Weight Average of Expected Loss (lbs)
1	0-8								
2	8-16								
3	16-24								
4	24-32	7.0	0.012	3,330	40	4.0	0.004	2,688	10
5	32-40	10.0	0.074	3,785	280	4.5	0.064	3,165	203
6	40-48	16.0	0.416	4,648	1,934	9.5	0.328	5,163	1,693
7	48-56	18.5	0.199	5,106	1,016	16.0	0.204	5,889	1,203
8	56-64	20.5	0.295	5,296	1,562	20.0	0.292	6,600	1,924
9	64-72	20.5	0.004	5,368	21	22.5	0.108	6,904	746
10	72-80								
11	80-88								
	Sum		1		4,853		1		5,779

Note: 1) There were eight applications required for six hour-day and night application method, and four applications required for the daytime application method.
2) The mean days to complete application were obtained from the thousand of simulations.
3) *There were only 6 possible levels of N loss observed to occur in the first period (April 1-5).

The dynamic programming provides only information on the optimal decision for each stage and state, and the value of nitrogen loss from all ways following the decisions. Simulation was used to validate the decision rules given by this BSDP model and to derive competition times if the optimal decisions were followed. The decision rules from the BSDP were tested for each initial weather forecast by one thousand simulations. The mean simulated values of nitrogen loss were essentially equal to the optimal values reported in dynamic programming model. These simulations were made in an Excel spreadsheet, and generated based on the transition probability of ammonia loss. Table IV-3 reports the range of total expected ammonia loss for each initial level of loss associated with the weather forecasts, which obtained from the thousand runs of simulations.

Results are heavily dependent upon the first forecast. If the forecast received on April 1 was very favorable, 24-32 lbs of N lost per acre (and would only be received one percent of the time), then the expected loss for completing all eight applications was 3,326 lbs given this forecast (Table IV-3). The range of the total expected ammonia losses for a quarter section range between 2,774 lbs. and 5,799 lbs (with 1.2 percent chance), when the producer applied effluent follows the six-hour application method. The expected nitrogen loss increases over the six-week period, so the presence of favorable application weather in the April 1-5 period is important. However, if the first forecast is for a loss of N between 64-72 lbs/acre (received 0.4 percent of the time), the optimal decision is to wait for a more favorable forecast, and the expected total loss of nitrogen upon receiving an unfavorable first forecast (64-72 lbs/acre) is 5,349 pounds with a range from 2,817 to 8,050 lbs for the entire 128 acre field. This is due to the weather conditions that become warmer from the beginning through the end of the season. When the effluent was applied only during twelve-hour daytime, the total expected ammonia losses are varied between 2,804- 9,216 lbs if the forecast received on April 1 was unfavorable, 64-72 lbs of N lost per acre (10.8 percent chance). The case where loss from following the twelve-hour daytime-only application is less than for the six-hour day and night method occurs only in the case of initial forecasts of loss less than 40 lbs per acre. These forecasts occur less than 8.6 and 6.8 percent of the time for the six and twelve hour application methods, respectively. There were too few observations to reliable estimate the Markov forecast transmission matrices in these cases.

Table IV-3. The Range of Total Expected Ammonia Volatilization from Swine Effluent Application for Each Class Range of Weather Forecast of Period 1 (April 1)

		Six-hour Day or Night Application Method					Twelve-hour Daytime-only Application Method				
Loss Level	Class Range, Z^i (lbs/acre)	Probability of Forecast	Means N Loss	SD N Loss	Min N Loss	Max N Loss	Probability of Forecast	Means N Loss	SD N Loss	Min N Loss	Max N Loss
1	0-8										
2	8-16										
3	16-24										
4	24-32	0.012	3,326	32	2,774	5,799	0.004	2,688	0	2,688	2,688
5	32-40	0.074	3,773	54	2,865	7,234	0.064	3,129	14	2,771	6,885
6	40-48	0.416	4,683	73	2,813	7,590	0.328	5,147	38	2,771	8,698
7	48-56	0.199	5,070	70	2,817	8,000	0.204	5,849	51	2,771	9,216
8	56-64	0.295	5,322	67	2,898	7,815	0.292	6,588	40	2,771	8,872
9	64-72	0.004	5,349	61	2,817	8,050	0.108	6,941	32	2,804	9,216
10	72-80										
11	80-88										
		1.000	4,853*		2,774	8,050	1.000	5,779*		2,688	9,216

Note: 1) There were eight applications required for six hour-day and night application method, and four applications required for the daytime application method.
2) The total expected ammonia losses were obtained from the thousand runs of different simulations, which made in an Excel spreadsheet.
3) There were only 6 possible levels of N loss observed to occur in this first application period (April 1-5).
4) *Represents the weighted sum of the total expected ammonia loss for all possible levels of forecast loss calculated follows equation (12).

There is an average of 7 days to complete all application when the initial favorable 24-32 lbs/acre (level 4) is received and the producer operated the irrigation system with the six-hour day and night time application method. On the other hand, the producer required an average of 20.5 days to complete all application when the forecast loss was 64-72 lbs/acre. This is because of the producer extended his/her application to wait for more favorable weather. With the twelve-hour daytime application method, an average of 4 days was required to complete all applications when the favorable 24-32 lbs of N lost was received. A similar reliability problem occurs when infrequent very high forecast loss are received. Table IV-4 reports the mean days to complete all applications for each class of initial forecast loss for two application methods.

Table IV-4. The Mean Average Days of Completing All Application for Each Class of Initial Forecast Ammonia Loss

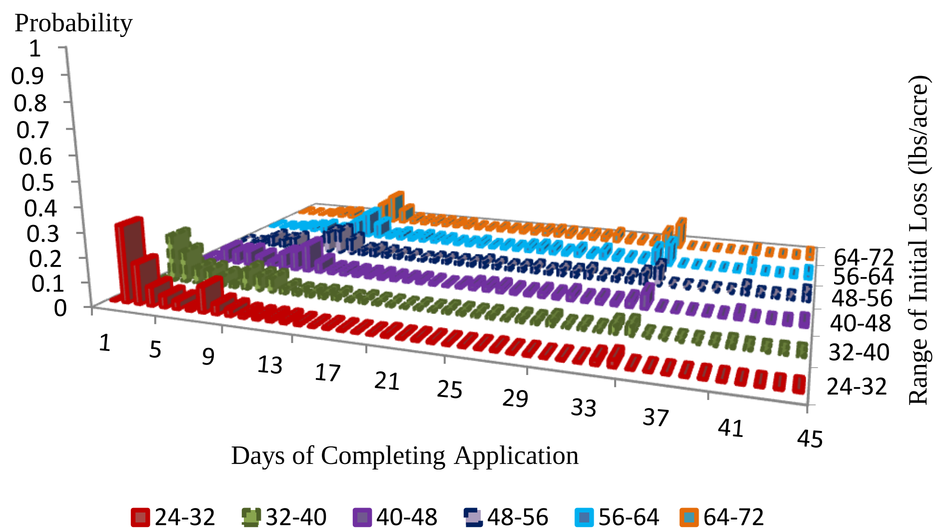
Loss Level	Forecast Class Range, Z^i, in Period 1	Six-hour Day or Night Application Method: Probability of Receiving Forecast	Mean Days to Complete All Application[b]			Twelve-hour Daytime-only Application Method: Probability of Receiving Forecast[a]	Mean Days to Complete All Application[b]		
			Means	Min	Max		Means	Min	Max
1	0-8	0				0			
2	8-16	0				0			
3	16-24	0				0			
4	24-32	0.002	7.0	2	45	0.001	4.0	4	4
5	32-40	0.018	10.0	2	45	0.016	4.5	4	30
6	40-48	0.120	16.0	3	45	0.096	9.5	5	44
7	48-56	0.171	18.5	3	45	0.161	16.0	5	44
8	56-64	0.287	20.5	3	45	0.241	20.0	5	44
9	64-72	0.307	20.5	4	45	0.345	22.5	6	44
10	72-80	0.086				0.128			
11	80-88	0.006				0.013			
				2	45			4	44

Note: 1) The probability of receiving forecast is the probability of occurrence in each class mean level of ammonia loss over the 45 days period.
2) The mean days to complete all application to cover 128 acre corn field for each class level of loss in the first period. These values were obtained from the thousand runs of simulation, which done in Excel spreadsheet.
3) There were only 6 possible levels of N loss observed to occur in this first application period (April 1-5).

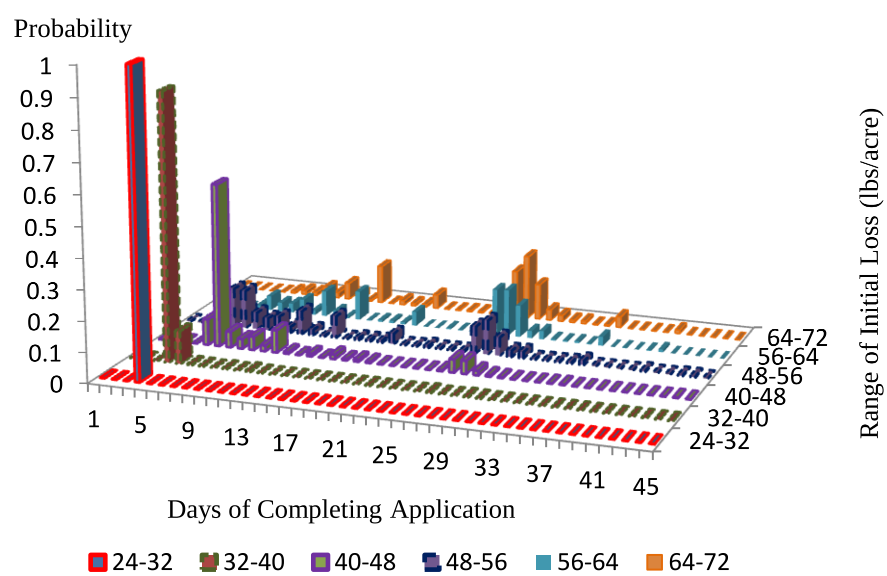
Figure IV-1 presents the probability distribution of the number of six-hour periods required to complete all applications for the 128 acre corn field following receipt of the initial forecast. A view from Figure IV-1 (a) shows in the rare event the producer receives the very favorable forecast of 32 lbs per acre or less (1.2 percent chance), the producer has 65 percent chance of completing all applications in 10 days. Conversely, only 16 percent of the time that the producer will complete all applications in 10 days when the unfavorable forecast between 64-72 lbs per acre of N lost is received (0.4 percent chance), the producer completed the applications at a later point in the planting season. When the producer received the most event forecast loss of 48 lbs or less (42 percent chance), the producer has 19 percent chance of completing all applications in these 10 days. Under the twelve-hour daytime-only application method, there is an 85-100 percent chance that the producer could complete all applications within 4 days when the initial favorable forecast of 40 lbs per acre or less was received (0.4 percent chance). However, mean application times extended from 16 to 22 days and actual times did reach the end of the season when the forecast loss in period 1 was between 40-48 lbs/acre or higher. Figure IV-1 (b) shows the distribution of the number of a period complete application under the twelve-hour daytime-only application method.

Figure IV-1. The Probability Distribution of Application Period for Completing the Application of Swine Effluent Given 150 lbs of Nitrogen per Acre

a) Six-hour day and night method (8 applications are required from 180 periods)



b) Twelve-hour daytime-only application method (four applications are required from 45 period)



Method 3: Ammonia Volatilization without Using Forecast Information

When weather forecasts are not included in the decision making, the producer was assumed to begin an application from the first day of planting season (April 1) and continued apply until complete all applications (48 hours). Under the six-hour day and night time application strategy, the producer started the pivot in the early morning of April 1 and stopped at midnight of April 2. When the producer applied the effluent only twelve-hour daytime, the pivot sprinkler irrigation was operated for 4 days from April 1 to April 4. The expected ammonia loss without using weather forecasts in each period is the sum product of the probability of each weather condition and the amount of N loss. Table IV-5 presents the prior probability of ammonia loss and the expected loss for each class of loss from applications during April 1-5.

Table IV-5. Prior Probability of Ammonia Loss for Each Class of Weather Conditions for Application Made During April 1-5

Loss Level	Class Range (lbs/acre)	Class Means Loss (lbs/acre)	Application Time of The Day				
			Six-hour Day or Night Application Method				Twelve-hour Daytime-only
			12:01-6:00am	6:01am-12:00pm	12:01-6:00pm	6:01pm-12:00am	6:01 am – 6:00 pm
1	18-24	21	0.047	0.036	0.067	0.071	0.051
2	24-30	27	0.023	0.035	0.016	0.035	0.026
3	30-36	33	0.041	0.035	0.035	0.051	0.035
4	36-42	39	0.157	0.078	0.112	0.190	0.095
5	42-48	45	0.114	0.157	0.149	0.104	0.153
6	48-54	51	0.212	0.143	0.147	0.206	0.145
7	54-60	57	0.212	0.200	0.188	0.182	0.194
8	60-66	63	0.143	0.216	0.184	0.102	0.200
9	66-72	69	0.051	0.053	0.055	0.049	0.054
10	72-78	75		0.047	0.043	0.006	0.045
11	78-84	81			0.004	0.004	0.002
12	84-90	87					
13	90-96	93					
14	96-102	99					
Total Expected loss (lbs)			794	839	820	763	1,659

Note: 1) The total expected loss for each six-hour application time computed as the sum product of the probability of each loss level in that application time and its respective means loss. This expected N was volatilized from an application to covers a 16 acre corn field.
2) The total expected loss for the twelve-hour daytime-only application is the volatilization from an application such that the 36 acres were covered.

With the constraint of fourty-eight hours to apply to all 128 acres, the total expected loss obtained from the base application with the six-hour day and night method is equal to the sum of the expected losses from applications made during six-hour time of April 1 and 2. The total expected loss of these two days is 6,432 pounds (3,216 lbs/day x 2 days). Table IV-6 reports the expected loss from applications made during each six-hour of each five-day period. When the producer applied the effluent only during the twelve-hour daytime, the total expected loss was 6,636 pounds (1,659 lbs/day x 4 days) for the 128 acre corn field. This total loss is the sum of the expected losses from 4 applications of April 1 to April 4. The expected ammonia loss from applications made during twelve-hour daytime of each five-day period is reported in Table IV-7. The results reported in Tables IV-6 and IV-7 also indicate that the level of ammonia losses tends to increase over the period of application from April 1 through May 15.

IV-6. Expected Ammonia Loss (lb./acre) from Applications Made during Each Six-hour of the Day by Each Five-day Period

Application Time	The Expected N Loss by Days of Application								
	April						May		
	1-5	6-10	11-15	16-20	21-25	25-30	1-5	5-10	11-15
12:01-6:00am	794	824	940	915	915	915	983	1,081	1,138
6:01am-12:00pm	839	866	983	957	957	957	1,020	1,124	1,188
12:01-6:00pm	820	859	969	942	942	942	1,006	1,114	1,178
6:01pm-12:00am	763	814	915	885	885	885	960	1,056	1,109
Total Expected Loss (lbs/day)	3,216	3,363	3,807	3,699	3,699	3,699	3,969	4,375	4,613

Note: The total expected loss is the sum of N losses from all six-hour application of the day. This total expected loss volatilized from applications in each day of each five-day periods such that the 64 acre corn field are covered.

Table IV-7. Expected Ammonia Loss for Covering a 128-Acre Corn Field from Applications during Each Five-day Period under the Twelve-hour Daytime-only Application Method

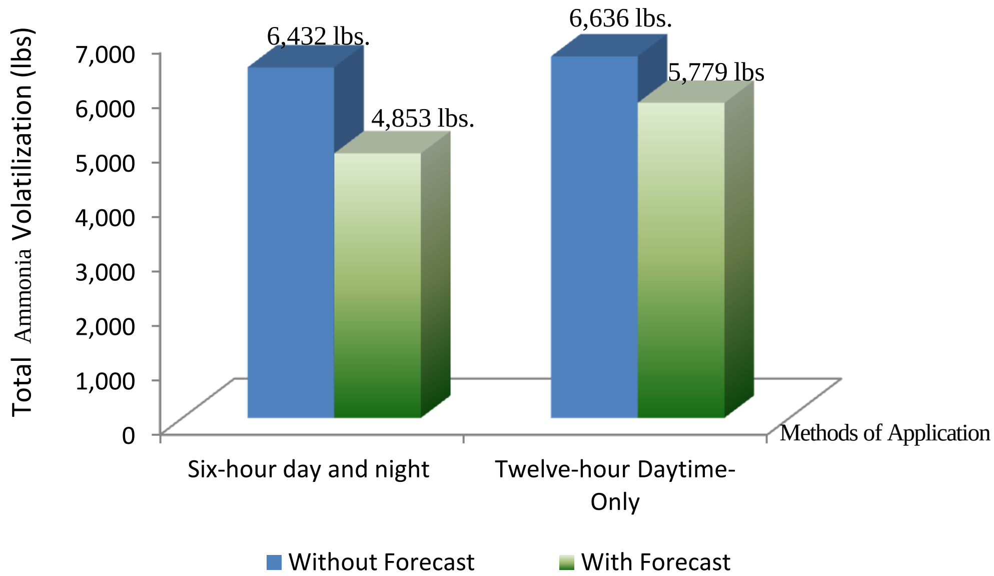
Application Time		Total Expected Loss from 128 acres (lbs)
Period	Month/Date	
1	April 1-5	6,636
2	April 6-10	6,900
3	April 11-15	7,808
4	April 16-20	7,600
5	April 21-25	7,600
6	April 25-30	7,600
7	May 1-5	8,104
8	May 5-10	8,952
9	May 11-15	9,464

[a] The expected loss occurring from twelve-hour daytimes application during particular day of each five-day periods such that the 32 acres were covered.

Economic Value of Weather Forecasts

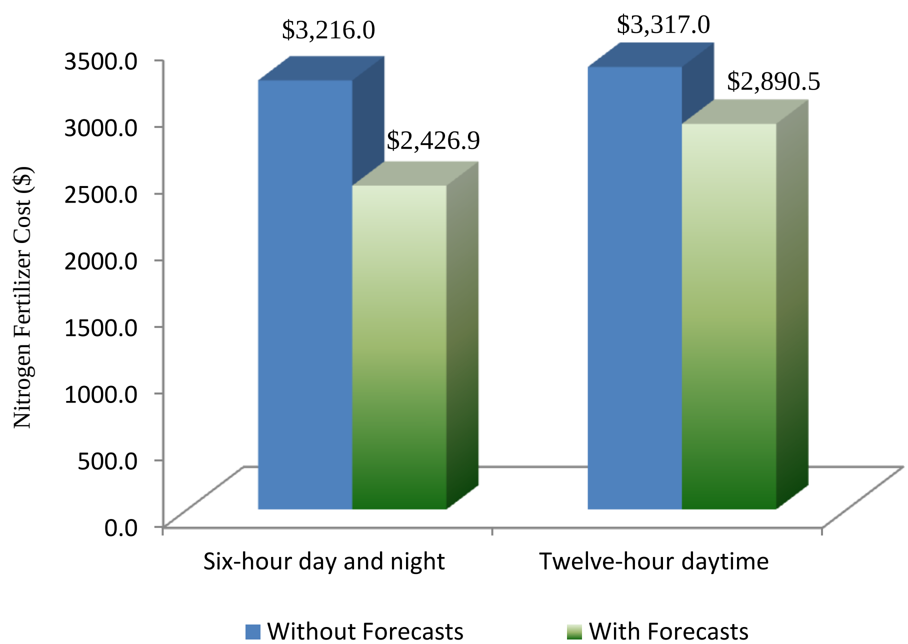
Figure IV-2 presents the comparison of nitrogen losses from effluent application using weather forecasts (BSDP model) and without using weather forecasts. The results report that the amount of nitrogen loss occurred from applications without using weather forecasts is higher than the loss obtained under the BSDP model. The nitrogen loss of 1,579 pounds (6,432 -4,853 lbs) were reduced when the producer applied the effluent upon the favorable weather forecasts using the six-hour day and night application method. In the case of the twelve-hour daytime-only method, the nitrogen losses was also reduced by 857 pounds (6,636 -5,779 lbs).

Figure IV-2. Total Expected Ammonia Loss for Covering a 128-Acre Corn Field Obtained from With and Without Weather Forecast for Two Application Methods



The amount of nitrogen loss can be converted to monetary values to the producer, which he/she can save from using the available information of weather forecasts. The monetary values were computed as the cost of commercial nitrogen fertilizer that the producer needs to purchase to apply to the corn field in order to have a sufficient amount of nutrient required (150 lbs/acre). With the nitrogen price is $0.50 per pound and weather forecasts were completely ignored, the producer incurs the cost of $3,216, and $3,317 for six-hour day and night application method and twelve-hour daytime-only method, respectively. The nitrogen costs are decreased to $2,427 if one includes the probability of weather forecasts to the decision making of effluent application by using the six-hour day or night application method. The cost from application using the twelve-hour daytime-only application method was also reduced to $2,891. Figure IV-3 shows the comparison of nitrogen fertilizer cost at the N price of $0.50 pound per acre for a quarter section of corn field between two alternative application methods.

Figure IV-3. The Comparison of Nitrogen Fertilizer Cost per 128 Acre Corn Field between Application Methods



The sensitivity analysis of the BSDP model results was also implemented to consider the effect of the increase in the price of the nitrogen commercial fertilize from \$0.25 to \$0.50 to \$0.75 per pound. Table IV-8 presents the summary of the expected nitrogen cost at each nitrogen price for the two application methods. With the five-year average price per pound of urea nitrogen fertilizer, \$0.50, the value of weather forecasts was \$789 per quarter section (\$3,216 - \$2,427). This value was gained when the producer making decision from observing the new weather forecasts every six hours. When the effluent was applied only during the daytime, the nitrogen cost was reduced by \$426 (\$3,317 - \$2,891). There is \$464 (\$2,891 - \$2,427) difference in the nitrogen cost when the producer determined the time of effluent application every six hours instead of every morning. When the nitrogen fertilizer price was increased from \$0.50 to \$0.75 per pound, the values of forecast increased to \$1,184 and \$640 per quarter section for the six-hour day and night and twelve-hour daytime-only application methods, respectively. These results suggest that the higher level of nitrogen fertilizer price could increase the value of weather forecasts.

Table IV-8. The Expected Cost of Nitrogen Fertilizer for 128 Acres of a Corn Field under Two Application Methods

Method of Application	Without Weather Forecast				With Weather Forecast			
	Expected Loss (lbs/quarter)	Nitrogen Cost per Quarter by Price of N ($/lbs)			Expected Loss (lbs/quarter)	Nitrogen Cost per Quarter by Price of N ($/lbs)		
		N = $0.25	N = $0.50*	N = $0.75		N = $0.25	N = $0.50*	N = $0.75
Six-hour Day/Night	6,432	1,608	3,216	4,824	4,853	1,214	2,427	3,640
Twelve-hour Daytime	6,634	1,659	3,317	4,976	5,779	1,445	2,891	4,336

Note: 1) The expected losses used for calculating the cost of nitrogen were obtained from the optimal solutions of the Bayesian Stochastic Dynamic Programming.
2) The cost of nitrogen fertilizer was computed as the value nitrogen lost from effluent application to cover a 128 acre corn field.
3) * Represents the five-year average price per pound of nitrogen in urea form (from 2006 to 2010).

CHAPTER VI

CONCLUSIONS AND RECOMMENDATION

Summary

The objectives of this study were to determine the most efficient time to apply swine effluent with minimum ammonia volatilization, and to evaluate the economic value of using weather forecasts. The lagoon effluent was assumed to be applied by a pivot irrigation system to a quarter section of a corn field (128 acres). Two application methods were composed. One is the six hour- day and night application, and another method is the twelve-hour daytime-only application. The application horizon was the 45 day period from April 1- May 15. Over the application period, the producer must determine the most efficient 48 hours to apply the effluent to the entire 128 acres at the rate of 150 pounds of nitrogen per acre. Bayesian Stochastic Dynamic Programming (BSDP) was used to find the optimal action of application when weather forecasts were included into the decision process. When the producer did not use forecast information, the lagoon effluent was assumed to be applied during the first fourty-eight hours of the planting season (i.e. April 1-4 upon the method of application). The total amounts of ammonia volatilization under BSDP models were used to compare with the losses from application without using forecasts. It was expected that the ammonia volatilization obtain under the BSDP models would be less than the amount of losses under the application without incorporating weather forecasts. The reduced amount of ammonia volatilization was used to illustrate the monetary value of weather forecasts. The comparison was made for both application methods: six-hour day and night time and twelve-hour daytime-only.

Conclusions

The statistic analysis was performed to test the hypotheses for significant differences of ammonia volatilization by the time of application using econometric model. The parameter estimates under the econometric models were consistent with the study's assumption. There was evidence of the difference in levels of ammonia volatilization by hours of the day and periods of application. The probability distributions of ammonia volatilization, used in the decision making, were computed under the empirical PDF approach based on the statistic results. Also, the transition probabilities were computed and used to indicate the Stochastic process of ammonia volatilization to use in the BSDP optimization model.

The comparison of the expected ammonia loss from optimal applications under the BSDP model with the application without using weather forecasts indicated that the amount of N volatilization can be reduced when the producer include forecasts into his/her decision. The total ammonia volatilization was reduced by 25% and 15 % under the six-hour application method and twelve-hour daytime-only method. The economic benefit gains of using weather forecasts were approximately $790 and $430 per quarter section of a corn field. This reduced cost of nitrogen fertilizer can be used to demonstrate the monetary value of weather forecasts (dollars/quarter section of corn field) to the producers. Additionally, the advantage of observing weather forecasts every six hours compared to the daily decision was almost $470 per quarter section of field higher.

However, this benefit was calculated without considering the additional cost of effluent application. Intuitively, a higher labor cost would be incurred if the producer operates the pivot sprinkler during both day and night times. This is because there is the cost of turning on and off the irrigation system.

Recommendations

The value of using weather forecasts indicated from the study would recommend the producers in the Panhandle areas to consider the forecast information to determine the most efficient time of effluent application. The results of this study give the guideline that the special program can be developed from using the Mesonet's forecast data to provide base information for the farmer's decision. This program can be written to read the forecast data and provides the estimates of nitrogen lost under each forecast weather conditions. However, the hourly forecast data of the Mesonet sites may be limited to eighty-four hours. Unfortunately, there was not enough time to test the value of limiting forecast data to 84 hours. However, the most of ammonia losses have occurred within the first 84 hours. The value of the 84 hour forecast should be determined.

In addition the Wu model does require further efforts to improve estimate of nitrogen losses under a crop canopy height because the length of canopy can affect the amount of N volatilization from the irrigation. Also, the cost of labor for operating the pivot sprinkler irrigation should be considered in the future research to determine the advantage between using the two application strategies, six-hour day and night application and twelve-hour daytime-only application.

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APPENDIXES

APPENDIX A-TRANSITION PROBABILITY MATRIC OF AMMONIA VOLATILIZATION

The transition probability is used to identify the probability of ammonia loss and the movement of loss from one period to the next. This probability was computed following the empirical probability distribution function. The computation was accomplished with the Pivot table in Excel spreadsheet. In this study, there were 45 transition matrices applied to the dynamic programming model under the six-hour day or night times application method (180 periods of application). There were only 17 transition probability matrices used in the optimization model for the twelve-hour daytime-only application method (45 periods of application). The transition probabilities of the expected loss moving from one period to the next for the twelve-hour daytime-only application method are reported in Table 1 through 17.

Appendix Table 1. Markov Transition Probability of Forecast Ammonia Losses Moving from One Day to the Next for the Twelve-hour Daytime Application During April 1 to April 5

State being in the next twelve- hour		1	2	3	4	5	6	7	8	9	10	11	Sum
Current State	Forecast N Loss (lbs/acre)	0-8	8-16	16-24	24-32	32-40	40-48	48-56	56-64	64-72	72-80	80-88	
1	0-8												
2	8-16												
3	16-24												
4	24-32				1	0	0	0	0	0			1.000
5	32-40				0.050	0.900	0.050	0	0	0			1.000
6	40-48				0	0.089	0.835.	0.076	0	0			1.000
7	48-56				0	0.106	0.106	0.426	0.362	0			1.000
8	56-64				0	0.011	0.022	0.133	0.634	0.200			1.000
9	64-72				0	0	0	0	0.296	0.704			1.000
10	72-80												
11	80-88												

Appendix Table 2. Markov Transition Probability of Forecast Ammonia Losses Moving from Twelve-hour between Application of April 5 and April 6

State being in the next twelve- hour		1	2	3	4	5	6	7	8	9	10	11	Sum
Current State	Forecast N Loss (lbs/acre)	0-8	8-16	16-24	24-32	32-40	40-48	48-56	56-64	64-72	72-80	80-88	
1	0-8												
2	8-16												
3	16-24												
4	24-32					1.000							1.000
5	32-40					0.600	0.400						1.000
6	40-48						0.656	0.344					1.000
7	48-56						0.169	0.785	0.046				1.000
8	56-64							0.077	0.410	0.513			1.000
9	64-72								0.217	0.633	0.150		1.000
10	72-80												
11	80-88												

Appendix Table 3. Markov Transition Probability of Forecast Ammonia Losses Moving from One Day to the Next for the Twelve-hour Daytime Application During April 6 to April 10

State being in the next twelve- hour		1	2	3	4	5	6	7	8	9	10	11	Sum
Current State	Forecast N Loss (lbs/acre)	0-8	8-16	16-24	24-32	32-40	40-48	48-56	56-64	64-72	72-80	80-88	
1	0-8												
2	8-16												
3	16-24												
4	24-32												
5	32-40					0.368	0.631						1.000
6	40-48						0.714	0.286					1.000
7	48-56						0.163	0.721	0.116				1.000
8	56-64							0.094	0.406	0.500			1.000
9	64-72								0.069	0.724	0.207		1.000
10	72-80										1.000		1.000
11	80-88												

Appendix Table 4. Markov Transition Probability of Forecast Ammonia Losses Moving from Twelve-hour between Application of April 10 and April 11

State being in the next twelve- hour		1	2	3	4	5	6	7	8	9	10	11	Sum
Current State	Forecast N Loss (lbs/acre)	0-8	8-16	16-24	24-32	32-40	40-48	48-56	56-64	64-72	72-80	80-88	
1	0-8												
2	8-16												
3	16-24												
4	24-32												
5	32-40						1.000						1.000
6	40-48						0.722	0.173	0.090	0.015			1.000
7	48-56						0.287	0.639	0.065	0.009			1.000
8	56-64						0.073	0.053	0.537	0.337			1.000
9	64-72								0.360	0.400	0.240		1.000
10	72-80						0.166	0.200		0.200	0.367	0.067	1.000
11	80-88												

Appendix Table 5. Markov Transition Probability of Forecast Ammonia Losses Moving from One Day to the Next for the Twelve-hour Daytime Application During April 11 to April 15

State being in the next twelve- hour		1	2	3	4	5	6	7	8	9	10	11	Sum
Current State	Forecast N Loss (lbs/acre)	0-8	8-16	16-24	24-32	32-40	40-48	48-56	56-64	64-72	72-80	80-88	
1	0-8												
2	8-16												
3	16-24												
4	24-32												
5	32-40												
6	40-48						1.000						1.000
7	48-56							0.828	0.171				1.000
8	56-64							0.010	0.978	0.011			1.000
9	64-72								0.047	0.952			1.000
10	72-80										1.000		1.000
11	80-88										0.166	0.833	1.000

Appendix Table 6. Markov Transition Probability of Forecast Ammonia Losses Moving from Twelve-hour between Application of April 15 and April 16

State being in the next twelve- hour		1	2	3	4	5	6	7	8	9	10	11	Sum
Current State	Forecast N Loss (lbs/acre)	0-8	8-16	16-24	24-32	32-40	40-48	48-56	56-64	64-72	72-80	80-88	
1	0-8												
2	8-16												
3	16-24												
4	24-32												
5	32-40												
6	40-48						0.444	0.556					1.000
7	48-56						0.053	0.719	0.228				1.000
8	56-64							0.307	0.693				1.000
9	64-72								0.160	0.520	0.320		1.000
10	72-80								0.250		0.750		1.000
11	80-88										0.600	0.400	1.000

Appendix Table 7. Markov Transition Probability of Forecast Ammonia Losses Moving from One Day to the Next for the Twelve-hour Daytime Application During April 16 to April 20

State being in the next twelve- hour		1	2	3	4	5	6	7	8	9	10	11	Sum
Current State	Forecast N Loss (lbs/acre)	0-8	8-16	16-24	24-32	32-40	40-48	48-56	56-64	64-72	72-80	80-88	
1	0-8												
2	8-16												
3	16-24												
4	24-32												
5	32-40												
6	40-48						0.364	0.636					1.000
7	48-56						0.135	0.573	0.292				1.000
8	56-64							0.112	0.531	0.357			1.000
9	64-72								0.049	0.707	0.244		1.000
10	72-80									0.343	0.571	0.086	1.000
11	80-88										1.000		1.000

Appendix Table 8. Markov Transition Probability of Forecast Ammonia Losses Moving from Twelve-hour between Application of April 20 and April 21

State being in the next twelve- hour		1	2	3	4	5	6	7	8	9	10	11	Sum
Current State	Forecast N Loss (lbs/acre)	0-8	8-16	16-24	24-32	32-40	40-48	48-56	56-64	64-72	72-80	80-88	
1	0-8												
2	8-16												
3	16-24												
4	24-32												
5	32-40												
6	40-48						0.400	0.600					1.000
7	48-56						0.158	0.526	0.316				1.000
8	56-64								0.525	0.475			1.000
9	64-72								0.053	0.816	0.131		1.000
10	72-80									0.455	0.545		1.000
11	80-88										1.000		1.000

Appendix Table 9. Markov Transition Probability of Forecast Ammonia Losses Moving from One Day to the Next for the Twelve-hour Daytime Application During April 21 to April 25

State being in the next twelve- hour		1	2	3	4	5	6	7	8	9	10	11	Sum
Current State	Forecast N Loss (lbs/acre)	0-8	8-16	16-24	24-32	32-40	40-48	48-56	56-64	64-72	72-80	80-88	
1	0-8												
2	8-16												
3	16-24												
4	24-32												
5	32-40												
6	40-48						0.538	0.462					1.000
7	48-56						0.400	0.500	0.100				1.000
8	56-64							0.088	0.842	0.070			1.000
9	64-72							0.007	0.149	0.731	0.113		1.000
10	72-80									0.676	0.324		1.000
11	80-88												

Appendix Table 10. Markov Transition Probability of Forecast Ammonia Losses Moving from Twelve-hour between Application of April 25 and April 26

State being in the next twelve- hour		1	2	3	4	5	6	7	8	9	10	11	Sum
Current State	Forecast N Loss (lbs/acre)	0-8	8-16	16-24	24-32	32-40	40-48	48-56	56-64	64-72	72-80	80-88	
1	0-8												
2	8-16												
3	16-24												
4	24-32												
5	32-40												
6	40-48						0.214	0.786					1.000
7	48-56							0.839	0.161				1.000
8	56-64							0.048	0.920	0.032			1.000
9	64-72							0.012	0.268	0.720			1.000
10	72-80									0.593	0.407		1.000
11	80-88												

Appendix Table 11. Markov Transition Probability of Forecast Ammonia Losses Moving from One Day to the Next for the Twelve-hour Daytime Application During April 26 to April 30

State being in the next twelve- hour		1	2	3	4	5	6	7	8	9	10	11	Sum
Current State	Forecast N Loss (lbs/acre)	0-8	8-16	16-24	24-32	32-40	40-48	48-56	56-64	64-72	72-80	80-88	
1	0-8												
2	8-16												
3	16-24												
4	24-32												
5	32-40												
6	40-48						0.520	0.480					1.000
7	48-56						0.414	0.483	0.103				1.000
8	56-64							0.031	0.536	0.433			1.000
9	64-72							0.031	0.198	0.521	0.250		1.000
10	72-80									0.100	0.900		1.000
11	80-88												

Appendix Table 12. Markov Transition Probability of Forecast Ammonia Losses Moving from Twelve-hour between Application of April 30 and May 1

State being in the next twelve- hour		1	2	3	4	5	6	7	8	9	10	11	Sum
Current State	Forecast N Loss (lbs/acre)	0-8	8-16	16-24	24-32	32-40	40-48	48-56	56-64	64-72	72-80	80-88	
1	0-8												
2	8-16												
3	16-24												
4	24-32												
5	32-40												
6	40-48							1.000					1.000
7	48-56							0.542	0.424	0.034			1.000
8	56-64							0.129	0.371	0.500			1.000
9	64-72								0.192	0.747	0.061		1.000
10	72-80								0.020	0.540	0.440		1.000
11	80-88												

Appendix Table 13. Markov Transition Probability of Forecast Ammonia Losses Moving from One Day to the Next for the Twelve-hour Daytime Application During May 1 to May 5

State being in the next twelve- hour		1	2	3	4	5	6	7	8	9	10	11	Sum
Current State	Forecast N Loss (lbs/acre)	0-8	8-16	16-24	24-32	32-40	40-48	48-56	56-64	64-72	72-80	80-88	
1	0-8												
2	8-16												
3	16-24												
4	24-32												
5	32-40												
6	40-48												
7	48-56							0.368	0.579	0.053			1.000
8	56-64								0.566	0.434			1.000
9	64-72								0.163	0.641	0.196		1.000
10	72-80									0.429	0.571		1.000
11	80-88												

Appendix Table 14. Markov Transition Probability of Forecast Ammonia Losses Moving from Twelve-hour between Application of May 5 and May 6

State being in the next twelve- hour		1	2	3	4	5	6	7	8	9	10	11	Sum
Current State	Forecast N Loss (lbs/acre)	0-8	8-16	16-24	24-32	32-40	40-48	48-56	56-64	64-72	72-80	80-88	
1	0-8												
2	8-16												
3	16-24												
4	24-32												
5	32-40												
6	40-48												
7	48-56								0.857	0.143			1.000
8	56-64							0.128	0.479	0.393			1.000
9	64-72								0.176	0.613	0.211		1.000
10	72-80									0.421	0.579		1.000
11	80-88												

Appendix Table 15. Markov Transition Probability of Forecast Ammonia Losses Moving from One Day to the Next for the Twelve-hour Daytime Application During May 6 to May 10

State being in the next twelve- hour		1	2	3	4	5	6	7	8	9	10	11	Sum
Current State	Forecast N Loss (lbs/acre)	0-8	8-16	16-24	24-32	32-40	40-48	48-56	56-64	64-72	72-80	80-88	
1	0-8												
2	8-16												
3	16-24												
4	24-32												
5	32-40												
6	40-48												
7	48-56							0.520	0.480				1.000
8	56-64								0.233	0.767			1.000
9	64-72								0.090	0.800	0.110		1.000
10	72-80								0.094	0.656	0.250		1.000
11	80-88												

Appendix Table 16. Markov Transition Probability of Forecast Ammonia Losses Moving from Twelve-hour between Application of May 10 and May 11

State being in the next twelve- hour		1	2	3	4	5	6	7	8	9	10	11	Sum
Current State	Forecast N Loss (lbs/acre)	0-8	8-16	16-24	24-32	32-40	40-48	48-56	56-64	64-72	72-80	80-88	
1	0-8												
2	8-16												
3	16-24												
4	24-32												
5	32-40												
6	40-48												
7	48-56								1.000				1.000
8	56-64								0.378	0.622			1.000
9	64-72								0.123	0.735	0.103	0.039	1.000
10	72-80									0.135	0.730	0.135	1.000
11	80-88												

Appendix Table 17. Markov Transition Probability of Forecast Ammonia Losses Moving from One Day to the Next for the Twelve-hour Daytime Application During May 11 to May 15

State being in the next twelve- hour		1	2	3	4	5	6	7	8	9	10	11	Sum
Current State	Forecast N Loss (lbs/acre)	0-8	8-16	16-24	24-32	32-40	40-48	48-56	56-64	64-72	72-80	80-88	
1	0-8												
2	8-16												
3	16-24												
4	24-32												
5	32-40												
6	40-48												
7	48-56												
8	56-64								0.551	0.449			1.000
9	64-72								0.068	0.651	0.226	0.055	1.000
10	72-80									0.197	0.724	0.079	1.000
11	80-88										0.824	0.176	1.000

APPENDIX B-BAYESIAN STOCHASTIC DYNAMIC PROGRAMMING OPTIMIZATION

The Dynamic Programming Application of J. Kennedy (1986) was used to solve the optimal solution for effluent application. The input data were generated in an Excel spreadsheet and applied to optimization application. Figure 1 shows the excel spreadsheet for data entry used in Dynamic Programming. Also, the optimization of the application for two alternative methods can be illustrated in Figure 2 and Figure 3.

Appendix Figure 1. The Excel Spreadsheet of Input Data Entry for Bayesian Stochastic Dynamic Programming Optimization

180 Stage 8 Applications Effluent Problem				**Maximum Applications #**		8		9	1	2	3	4	5	6	7	8	9	10	11
180	**Stages**			**Num Forcecasts**		11	1	1											
0	**Discount Rate %**			**Num of Markov Matric**		45	1	2											
S	**Determistic/Stochastic**			**Max No of States**		89	1	3											
N	**Constant Returns for All Stages?**			**Last Data Row**		29575	1	4	0	0	0	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00
N	**Presence of Decision Lables**						1	5	0	0	0	0.00	0.61	0.39	0.00	0.00	0.00	0.00	0.00
Stage	**State**	**Decision**	**Return**	**Next Stat**	**Probability**		1	6	0	0	0	0.00	0.00	0.76	0.24	0.00	0.00	0.00	0.00
180	1	1	-1000	89	1		1	7	0	0	0	0.00	0.00	0.00	0.50	0.50	0.00	0.00	0.00
180	2	1	-1000	89	1		1	8	0	0	0	0.00	0.00	0.00	0.00	0.68	0.32	0.00	0.00
180	3	1	-1000	89	1		1	9	0	0	0	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00
180	4	1	-1000	89	1		1	10											
180	5	1	-1000	89	1		1	11											
180	6	1	-1000	89	1		2	1											
180	7	1	-51.78	89	1		2	2											
180	8	1	-63.077	89	1		2	3											
180	9	1	-69.503	89	1		2	4											
180	10	1	-72.521	89	1		2	5	0	0	0	0.14	0.86	0.00	0.00	0.00	0.00	0.00	0.00
180	11	1	-83.109	89	1		2	6	0	0	0	0.00	0.10	0.85	0.06	0.00	0.00	0.00	0.00
	-1						2	7	0	0	0	0.00	0.00	0.17	0.69	0.14	0.00	0.00	0.00
179	8	1	-57.784	89	1		2	8	0	0	0	0.00	0.00	0.04	0.13	0.57	0.26	0.00	0.00
179	8	2	0	7	0.16		2	9	0	0	0	0.00	0.00	0.00	0.00	0.42	0.58	0.00	0.00
179	8	2	0	8	0.6		2	10											
179	8	2	0	9	0.24		2	11											

Appendix Figure 2. The Dynamic Programming Routine for Optimization Application for Six-hour Day and Night Times Application Method

KENNEDY FINITE DYNAMIC PROGRAMMING ROUTINE

Directory: Z:\

File Name: StocDP_SixH

Sheet: 8A180P

Begin to Store Results in Row: 29700

Load the Problem

Solve DP

Exit

Dynamic Programming Routine FDP
Copyright 1986 by J Kennedy
Solves Discrete Dynamic Finite Stage Problems
5 Stage 3 Ap Effluent Problem
Number of Stages 180
Discount Rate % 0
Stochastic Dynamic Programming Solution

Stage	State	Decision	Return	Nxt.State	Prob.
180	1	1	-1,000.00	89	1.000
180	2	1	-1,000.00	89	1.000
180	3	1	-1,000.00	89	1.000
180	4	1	-1,000.00	89	1.000
180	5	1	-1,000.00	89	1.000
180	6	1	-1,000.00	89	1.000
180	7	1	-51.78	89	1.000
180	8	1	-63.08	89	1.000
180	9	1	-69.50	89	1.000
180	10	1	-72.52	89	1.000
180	11	1	-83.11	89	1.000
0	-1	0	0.000		
179	8	1	-57.78	89	1.000
179	8	2	0.00	7	0.160
179	8	2	0.00	8	0.600
179	8	2	0.00	9	0.240
179	9	1	-72.59	89	1.000
179	9	2	0.00	8	0.271
179	9	2	0.00	9	0.694
179	9	2	0.00	10	0.035
179	10	1	-76.73	89	1.000
179	10	2	0.00	9	0.613

Stage	State	Decision	Stage Return	Expected Value
4	81	1	-21.00	-219.32
4	82	1	-33.01	-260.50
4	83	2	0.00	-298.21
4	84	2	0.00	-327.60
4	85	2	0.00	-338.86
3	59	1	-21.00	-162.36
3	60	1	-23.55	-163.61
3	61	2	0.00	-211.40
3	62	2	0.00	-227.07
3	63	2	0.00	-243.66
3	64	2	0.00	-248.92
3	70	1	-21.00	-194.28
3	71	1	-23.55	-195.50
3	72	2	0.00	-249.94
3	73	2	0.00	-268.10
3	74	2	0.00	-287.27
3	75	2	0.00	-293.36
3	81	1	-21.00	-227.11
3	82	1	-23.55	-228.30
3	83	2	0.00	-289.33
3	84	2	0.00	-309.88
3	85	2	0.00	-331.54
3	86	2	0.00	-338.41
2	71	1	-23.69	-187.12
2	72	2	0.00	-245.76
2	73	2	0.00	-267.61
2	74	2	0.00	-284.98
2	75	2	0.00	-290.80
2	82	1	-23.69	-219.02
2	83	2	0.00	-284.65
2	84	2	0.00	-309.33
2	85	2	0.00	-328.95
2	86	2	0.00	-335.52
1	81	1	-21.00	-208.12
1	82	1	-26.68	-236.61
1	83	2	0.00	-290.51
1	84	2	0.00	-319.14
1	85	2	0.00	-331.02
1	86	2	0.00	-335.52

Appendix Figure 3. The Dynamic Programming Routine for Optimization Application for Twelve-hour Daytime-only Application Method

KENNEDY FINITE DYNAMIC PROGRAMMING ROUTINE

Directory	E:\
File Name	ayTimeApps.x
Sheet	4Apps45P
Begin to Store Results in Row	4200

Load the Problem

Solve DP

Exit

Dynamic Programming Routine FDP
Copyright 1986 by J Kennedy
Solves Discrete Dynamic Finite Stage Problems
5 Stage 3 Ap Effluent Problem
Number of Stages 45
Discount Rate % 0
Stochastic Dynamic Programming Solution

Stage	State	Decision	Return	Nxt. State	Prob.
45	1	1	-1,000.00	45	1.000
45	2	1	-1,000.00	45	1.000
45	3	1	-1,000.00	45	1.000
45	4	1	-1,000.00	45	1.000
45	5	1	-1,000.00	45	1.000
45	6	1	-1,000.00	45	1.000
45	7	1	-1,000.00	45	1.000
45	8	1	-55.87	45	1.000
45	9	1	-72.85	45	1.000
45	10	1	-77.22	45	1.000
45	11	1	-77.17	45	1.000
0	-1	0	0.000		
44	8	1	-55.87	45	1.000
44	9	1	-72.85	45	1.000
44	10	1	-77.22	45	1.000
44	11	1	-77.17	45	1.000
44	19	1	-55.87	8	0.551
44	19	1	-55.87	9	0.449
44	20	1	-72.85	8	0.068
44	20	1	-72.85	9	0.651
44	20	1	-72.85	10	0.226
44	20	1	-72.85	11	0.055

Stage	State	Decision	Stage Return	Expected Value
45	1	1	-1,000.0 0	-1,000.00
45	2	1	-1,000.0 0	-1,000.00
45	3	1	-1,000.0 0	-1,000.00
45	4	1	-1,000.0 0	-1,000.00
45	5	1	-1,000.0 0	-1,000.00
45	6	1	-1,000.0 0	-1,000.00
45	7	1	-1,000.0 0	-1,000.00
45	8	1	-55.87	-55.87
45	9	1	-72.85	-72.85
45	10	1	-77.22	-77.22
45	11	1	-77.17	-77.17
44	8	1	-55.87	-55.87
44	9	1	-72.85	-72.85
44	10	1	-77.22	-77.22
44	11	1	-77.17	-77.17
44	19	1	-55.87	-119.36
44	20	1	-72.85	-145.76
44	21	1	-77.22	-153.57
44	22	1	-77.17	-154.38
43	8	1	-55.87	-55.87
43	9	1	-72.85	-72.85
43	10	2	0.00	-76.35
43	11	1	-77.17	-77.17
43	19	1	-55.87	-119.36
43	20	1	-72.85	-145.76
43	21	1	-77.22	-153.57
43	22	1	-77.17	-154.38
43	30	1	-55.87	-187.08
43	31	1	-72.85	-219.04
43	32	1	-77.22	-229.31
43	33	1	-77.17	-230.88
42	8	1	-55.87	-55.87
42	9	2	0.00	-72.71
42	10	2	0.00	-75.73
42	11	2	0.00	-76.50
42	19	1	-55.87	-119.36
42	20	1	-72.85	-145.56
42	21	2	0.00	-152.09
42	22	1	-77.17	-153.66
42	30	1	-55.87	-187.08

The stochastic optimization solves for an optimal solution in each application period. The stochastic process of the forecast ammonia losses moving from one period to the next follows the transition probability. The optimization takes approximately 45 minutes for each application method to find the optimal solution over the application horizon.

VITA

Chaowana Phetcharat

Candidate for the Degree of

Doctor of Philosophy

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Major Field: Agricultural Economics

Scope and Method of Study: The purpose of this study was to determine the most efficient time to apply swine effluent corn production in the Texas and Oklahoma Panhandle area. The effluent was assumed to be applied to a 128-acre corn field by a central pivot sprinkler irrigation system between April 1 and May 15. It was assumed that 48 hours were required to complete the application with the rate of 150 pounds nitrogen per acre. The mechanistic model developed by Wu et al. (2003a) was used to estimate the ammonia volatilization over the 192-hour period following application. Hourly weather forecast data were used in a Bayesian stochastic dynamic programming model to find the optimal time periods for effluent application. Markov transition matrices tracked the changes in forecast frequency from one day to the next. Total expected ammonia losses when applications were made with and without using weather forecasts were compared. The monetary values of the weather forecasts were estimated as the cost of additional nitrogen fertilizer to replace the nitrogen lost from nitrogen volatilization.

Findings and Conclusions: The simulated ammonia loss from the actual hourly weather data showed that 35% of ammonia applied would be lost when the application was made between April 1-5. The expected loss increased to 50% when the application was delayed until May 11-15. The expected nitrogen loss was reduced to 25% when the producer made an application only upon receiving a favorable weather forecast and was willing to operate the pivot for a six-hour period either day or night. If the producer applied effluent on a 12-hour day time only schedule but applied only after receiving a favorable forecast, the expected loss declined from 35 % to 30%. With nitrogen at $0.50 per pound, the value of the forecast information for a 128 acre corn field was $780 and $430 for the six-hour application and twelve-hour daytime-only application methods, respectively. There was a benefit of $463 for the 128-acre corn field from applying the effluent on a flexible six-hour day and/or night method as opposed to the 12-hour daytime only schedule. It is recommended the Wu model be incorporated into the Oklahoma Mesonet system using forecast weather data to provide producers with real time forecasts of nitrogen losses from effluent application.

ADVISER’S APPROVAL: Dr. Arthur Stoecker