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Effect of Heat Fluxes on Ammonia Emission from Swine Waste Lagoon Based on Neural Network Analyses

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ABSTRACT

Understanding factors that affect ammonia emissions from swine waste lagoons or any animal waste receptacles is a necessary first step in deploying potential remediation options. In this study, we examined the various meteorological factors (i.e., air temperatures, solar radiation and heat fluxes) that potentially affect ammonia emissions from swine waste lagoon. Ammonia concentrations were monitored using a photoacoustic gas analyzer. The ammonia emissions from the lagoon were monitored continuously for a 24 h cycle, twice a week during a winter month at a height of 50 cm above the lagoon surface. Meteorological data were also monitored simultaneously. Heat fluxes were tabulated and correlated to the averaged ammonia concentrations (range of zero to 8.0 ppmv). Multi-layer Perceptron (MLP) neural network predictive model was built based on the most important meteorological parameters. The results from MLP neural networks analysis show that ammonia emissions from the swine waste lagoon were affected by heat fluxes such as net solar radiation, sensible heat and latent heat of vaporization. Thus it is important to consider environmental conditions (i.e., meteorological parameters such as solar radiation, latent heat and etc.) in formulating management or abatement strategies for reducing ammonia emissions from swine waste lagoons or any other air pollutant emissions from livestock waste receptacles.

Key words: Ammonia, swine waste lagoon, emission, heat fluxes, artificial neural network

INTRODUCTION

Anaerobic lagoons are effective and low-cost bioreactors to treat animal manure but they are also responsible for emissions of numerous atmospheric pollutants including NH_3, greenhouse gases and odorous compounds such as skatoles. These pollutants are most prevalent and controlled by the interactions of the atmospheric conditions, biochemical and physical processes occurring at lagoon interfaces. Sulfides and Volatile Organic Compounds (VOCs) such as skatole, cresol and indole, are thought to be important chemical constituents of offending odors to humans and a cause of discomfort and disease in the environment within and near concentrated animal feeding operations (Cole *et al*., 2000). Thus, any study on Confined Animal Feeding Operations (CAFOs) from swine operations needs to address the issue of anaerobic lagoons as a source of atmospheric pollutants and the potential for devising emission reduction techniques (Loughrin *et al*., 2006). Despite their

relatively small size, compared to lakes or estuaries for instance, these lagoons exhibit a considerable amount of complexity when interacting with the atmospheric conditions. This complexity is reflected in the interactions that take place between the atmospheric boundary layer, stratification of the lagoon and the seasonal changes. Wind stress can drive lagoon surface circulation and stir the upper layers leading to a mixing of solid matter which contributes to the enhancement or reduction of ammonia and VOCs emissions to the atmosphere. Biochemical anaerobic reactions are a key element to the production of above mentioned compounds. The biochemical processes can produce enough internal thermal energy and temperature gradients to modify the lagoon's vertical temperature profiles through heat diffusion and convective motion. Therefore, any study aiming at mitigating its impact on atmospheric pollution needs to clarify the effect of heat fluxes on the production of these pollutants.

Recently, there is an increased demand to understand in detail the processes that control evaporation and emissions from fetch-limited water bodies and waste lagoons (Tanny *et al.*, 2008; Jacobs *et al.*, 2008; Quintanar *et al.*, 2009; Ham, 1999). At the atmosphere-lagoon interface a number of physical, chemical and biological processes are at work which can limit or enhance mass and energy fluxes, emissions of CH_4, CO_2, NH_3, sulfides and VOCs such as skatole, cresol and indole (Loughrin *et al.*, 2006; Lovanh *et al.*, 2009). These compounds are important contributors to the local atmospheric burden and can represent a health hazard for human operators and the public living in the vicinity of CAFOs, especially ammonia (Loughrin *et al.*, 2006; Cole *et al.*, 2000; Lovanh *et al.*, 2009).

Ammonia emission and its subsequent deposition can be a major source of pollution, causing nitrogen enrichment, acidification of soils and surface waters, aerosol formation, photochemical air pollution, reduced visibility, ecosystem fertilization, global warming and stratospheric ozone depletion. A number of studies have evaluated the effects of nitrogen deposition. Significant excess nitrogen deposition has occurred in the eastern coastal areas of the United States (Paerl, 1995). A particular area of concern is the coastal rivers and their estuaries. This excess nitrogen can result in toxic and non-toxic phytoplankton blooms which can lead to fish kills and reductions of 'clean water' species (Paerl, 1995). Furthermore, the atmospheric deposition constitutes a large part of the overall load in these waters and is therefore an important source for fixed nitrogen (Spokes *et al.*, 2006). Soil acidification is another problem. Van Breemen *et al.* (1982) identified the deposition of ammonium sulfate ($(NH_4)_2SO_4$) as the main cause of soil acidification in the Netherlands. Research conducted by Barthelmie and Pryor (1998) in the Lower Fraser Valley, British Columbia, Canada showed that NH_3 and NH_4^+ species and emissions play a particularly critical role in visibility degradation. Fine particulate aerosols have also been linked to human respiratory health problems. Studies suggest that the smaller the particle the greater the potential health effect. For example, Lippmann (1998) found fine particles ($PM_{2.5}$) to be more toxic than coarse particles (PM_{10}-$PM_{2.5}$). Donaldson and MacNee (1998) examined ultra-fine particles (<100 nm) and found that toxicity increases as particle size decreases.

There have been many studies involving the evaluation of anaerobic lagoon performance for treatment of wastes from CAFOs and reduce unwanted air pollutants in the United States and around the world (Westerman *et al.*, 1990; Bicudo *et al.*, 1999; Wesley *et al.*, 2000; Leung and Topp, 2001; Warnick *et al.*, 2001; Ham, 2002; Natvig *et al.*, 2002; McGarvey *et al.*, 2004; Szogi *et al.*, 2006). The content and/or the effluent from these lagoons are usually land-applied and, in some cases, discharged to surface water. However, the direct discharge of wastes to surface water without further treatment practice is no longer allowed in the U.S. Although these anaerobic

lagoon systems are able to reduce organic matters, nutrients and other heavy metals (McGarvey *et al*., 2004), their efficiency is dependent on seasonal variability and other environmental conditions. This is very critical in improving the management of these open lagoons and/or when considering alternative treatment systems for these wastes. As more modern and different livestock operation practices are changing, the demands and requirements of the efficacy of these lagoons are also changing. In regard to ammonia emissions, it is essential to be able to characterize the important environmental factors that affect the ammonia emission from these swine waste lagoons. Thus the objective of this study was to examine the effect of photochemical processes such as heat fluxes on the ammonia emission profile from an anaerobic swine lagoon using artificial neural networks (NNs) as a case study for adopting better management strategies and designing alternative remediation options.

MATERIALS AND METHODS

Neural networks: The theory of neural computing was first introduced by McCulloch and Pitts (1943) and further developed by Rosenblatt (1962). Neural Networks (NN) were inspired by the learning process of the human brain where neurons receive, pass and process information through input, hidden and output layers, respectively. The strongly connected network of neurons captures a global coherent behavior of the phenomena of interest (Robert *et al*., 1998). NNs are commonly used for classification, pattern recognition, decision making, knowledge data bases for stochastic information, optimization computations and robot control (Kohonen, 1988).

Data is initially introduced into the network through a set of input nodes. Input variables are weighted and their sum is altered by a transfer function at each neuron in the hidden layers. Although transfer functions can be categorized as linear, threshold and Sigmoidal, the most commonly used are the Sigmoidal functions because they introduce nonlinearity into the problem. Next, outputs from neurons at a given layer become inputs for neurons at consecutive layers and this process continues until the final information is passed through to the output layer. While NNs can be classified into three categories based on their architecture, the most commonly used are feed-forward NNs which only allow information to flow in the input-to-output direction, thus downstream layers do not affect upstream layer since there is no feed-back loop. Only feed-forward NNs are considered for the scope of this study.

Developing a NN usually involves parsing available data into training and testing sets. The training set, usually consisting of the majority of the data, is used to form the NN connection topology, also known as the "learning/training" phase. The NN learning processes aims to find a set of weights that minimize an appropriate error function in order to minimize the difference between the network outputs and the known outputs (Lavine *et al*., 2009). In this regard, three metrics are considered: (1)-(3) to evaluate the quality of the model predictions. The Mean Square Error (MSE), Mean Absolute Error (MAE) and Standard Deviation (SD) are often used as to reflect the quality of the model predictions:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left|y_i - \widehat{y_1}\right|^2 \quad (1)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|y_i - \widehat{y_1}\right| \quad (2)$$

$$SD = \sqrt{\frac{\sum_{i=1}^{N}\left|y_i - \widehat{y_i}\right|^2 - MAE}{N-1}} \quad (3)$$

where, $\hat{y}$ is the output value, y_i is the measured value and N is the number of data points. The error functions are then computed between the test subset and model predictions to determine the NN's predictive accuracy.

Neural Network learning processes can be classified as supervised and unsupervised. In supervised learning a function is inferred from the training data subset, therefore it can be seen as incorporating an external guide that dictates the desired response of the input signal to the output. It does not take place simultaneously with the operational phase. In contrast, unsupervised learning is based only on local information within the data and uses no external guide. It corresponds to conditions where there is no information about the classification of the data being used in the learning process and where the NN must organize the patterns into clusters (Likhovidov, 1997). Contrary to supervised learning, unsupervised learning method does take place during the operational phase.

A commonly used learning rule for multi-layered feed-forward NNs (discussed below) which are the most commonly used NNs, is known as the back-propagation algorithm (KrishnaKumar, 1993). Tan *et al.* (2006) described it in terms of forward and backward phases associated with each iteration. In the forward phase the neuron output values are determined based on the weights from the previous iteration. In the backward phase a formula is applied to update the weights at the n+1 layer before the weights at layer n. The weight update equation can be expressed as:

$$w_j \leftarrow w_j - \lambda\frac{\partial E(w)}{\partial w_j} \quad (4)$$

where, w_j is the weight associated with the jth attribute of a set of weights which is given by w and E is the error function for a set of weights.

EXPERIMENTAL SET UP AND METEOROLOGICAL MEASUREMENTS

The research site was a farrowing farm containing approximately 2,000 sows located in Logan County in South Central Kentucky. At the farm, an anaerobic lagoon of 65×65 m and 3 m in depth is used to treat wastewater from four houses located around 100 m away from the lagoon bank. Most of the surrounding land is used for producing crops.

Meteorological data were collected for the entire month of February, 2009. Only days with mostly clear sky conditions and no precipitation were chosen to be studied in order to improve on net radiation estimates. Measurements were made on two floating stations that carried instrumentation. Each station recorded temperature, relative humidity and wind speed at 0.5 and 1.5 m above the lagoon surface. For this study, only data from 0.5 m level were used. Ammonia emissions were measured 0.5 m above the lagoon's surface. Measurements from these two stations were used to account for systematic errors and data quality control. To maximize the amount of fetch to around 60 m, the stations were deployed around the center of the lagoon. It is previously stated that the lowest level of thermometer and hygrometer placement was 0.5 m above the water surface. As a result, for the 65×65 m lagoon, this provides 60:1 for the shortest and about 90:1 for

the longest fetch-to-height ratio. For a variety of conditions of fetch-to-height ratios, Stannard (1997) has shown that ratio of 60:1 can give a Bowen ratio that is about 80% equilibrated. In this data collection and research effort the Stannard (1997) criteria were used. This criterion was also successfully applied by the authors to similar research studies (Loughrin *et al*., 2011; Quintanar *et al*., 2009).

Included in the meteorological measurements were lagoon surface temperature and subsurface (0.3, 0.6, 1.0 m and lagoon bottom) temperature measurements. Gas measurements and meteorological data were collected every 5 min. In addition, a surface weather station was installed about 20 m away from the southwest corner of the lagoon to measure meteorological conditions.

Meteorological instrumentation: In this study a series of meteorological variables were measured so that meteorological fluxes could be estimated by applying widely used methods. Meteorological variables include temperature, relative humidity, barometric pressure, wind speed and direction and solar radiation. Two rafts constructed from several PVC pipes carried weather stations (APRS World, Winona, MN) with relative humidity-temperature sensors and anemometers at 0.5 and 1.5 m above the lagoon surface. The resolution of the anemometers was around 0.1 m sec^{-1} with an accuracy of 0.4 m sec^{-1} and a minimum measurable wind speed of 0.5 m sec^{-1}. With a response time of 50 seconds, the temperature sensors had a measurement range of -26 to 70°C and an accuracy of 0.5°C. The non-condensing humidity sensors had an accuracy of ±2% and a measurement range of 3-100% relative humidity. The humidity sensors had a linearity of ±0.5%, a hysteresis of 1% and a response time of 25 sec. A waterproof cable connected the weather stations on the rafts to a solar-powered data collection system on the bank of the lagoon that recorded data every 5 min. To ensure that the data was collected at the same location on the lagoon's surface for each day, both rafts were secured approximately at the center of the lagoon with anchors and cables attached to the lagoon bank at two positions. HOBO U22 Pro v2 temperature sensors (Onset Comp.) recorded water temperatures every 5 min at the lagoon surface as well as at depths of 0.3, 0.6 and 0.9 m below the surface of the lagoon. These sensors had an accuracy of 0.2°C, a measurement range of -26°C to 70°C and a resolution of 0.02°C at 25°C.

A HOBO weather station (H21-001, Onset Computer Inc., Bourne, MA) equipped with a cup anemometer at 3 m above the ground, a barometer, temperature and relative humidity sensors and a silicon pyranometer (spectral range of 300 to 1,100 nm) positioned at 2 m above the ground was located approximately 20 m from the lagoon. As in Quintanar *et al*. (2009) to test for the soundness of the data, the land station data were compared with the data from the stations on the lagoon.

These data were used in-conjunction with well-known methods (Stull, 1988; Brutsaert, 2005) to estimate latent, sensible and lagoon storage heat fluxes. For this study net radiation was estimated using the approach developed by Brutsaert (2005) and presented in Quintanar *et al*. (2009). It is successfully applied in several previous studies (Loughrin *et al*., 2011, 2012). Others in the past also estimated net radiation in the absence direct observations (De Jong *et al*., 1980; Linacre, 1968; Novak *et al*., 2000; Wang and Liang, 2008).

AMMONIA MEASUREMENTS

Ammonia emissions were monitored using a Photoacoustic Gas Analyzer (Innova model 1412, Innova Air Tech Instruments A/S, Denmark). The Innova 1412 multi-gas analyzer used a 1 sec sampling integration time and fixed flushing time: 2 sec for the chamber and 3 sec for the tubing.

The required time to complete one sampling cycle was approximately 70 sec for ammonia and three other greenhouse gases. The response time of the analyzer to step changes in gas emissions was tested. Ammonia emissions were monitored at 0.5 m (to match meteorological measurements) above the lagoon surface over one month period. A pulley system was used to deploy Teflon tubing (10 m) over the lagoon for the gas sampling. The gas analyzer was housed in a trailer near the lagoon.

SENSIBLE AND LATENT HEAT FLUXES USING BOWEN RATIO ESTIMATES

Neglecting the local advection term of heat and moisture (Philip, 1987; Arya, 2001; Brutsaert, 2005) and the storage term of a very thin upper layer at the lagoon surface term then the energy balance at the surface can be written as:

$$R_N - G = H + L_e E \tag{5}$$

where, R_N is net radiation at the surface, G represents the energy flux into the lagoon, H is sensible heat flux L_e is the latent heat of vaporization and E, the evaporation rate. The sign convention adopted here is that radiative energy density fluxes are positive towards the lagoon surface (e.g., $R_N > 0$ at midday) while G, H and L_e E are positive away from it. While this is not a universally adopted convention it is one that has often been used in textbooks and the literature (Arya, 2001; Oke, 1987; Brutsaert, 2005; Ohmura, 1982).

The heating term G is computed integrating over the whole depth of the lagoon (Arya, 2001; Brutsaert, 2005):

$$G(t) = \int \frac{\partial}{\partial t}(\rho C_w T)dz \tag{6}$$

where, ρ (kg m^{-3}) is water density, C_w (J K^{-1} kg^{-1}) is specific heat and T(K) represents the vertical distribution of temperature of the water column. A trapezoidal rule is used to compute the integral term in Eq. 6 in finite form given a number of discrete temperature measurements along the vertical (Komzsik, 2007). Assuming that the lagoon area is constant with depth (Rodriguez-Rodriguez and Moreno-Ostos, 2006; Wetzel and Likens, 2000) and that ρ and C_w are constants, Eq. 6 can be approximated as:

$$G = \frac{\rho C_w}{2\Delta t}\sum_{i=1}^{N}\delta_i(\Delta T_{i-1} + \Delta T_i) \tag{7}$$

where, ΔT_i is the change of temperature of the i-th temperature sensor in the water column in a time step Δt. T_0 represents the surface or skin temperature of the lagoon surface. N is the number of thermal sensors below the surface. The term Δ_i is the depth of the i-th layer where, the temperature is taken to be $\frac{1}{2}(T_{i-1}+T_i)$ at its center.

In the absence of direct measurements of R_N, the method of Brutsaert (2005) was followed. In this case, the net radiation term is further decomposed as:

$$R_N = R_S(1-\alpha S) + \varepsilon_S R_{LD} - R_{LU} \tag{8}$$

where, R_S is the global short-wave radiation, α_S is the albedo of the water surface, R_{LD} is the incoming long-wave radiation, ε_S is the emissivity of the lagoon surface and R_{LU} is the outgoing long-wave radiation from the surface. The latter is estimated as:

$$R_{LU} = \varepsilon_S \sigma T_S^4 \tag{9}$$

where, σ is the Boltzmann constant and T_S is the absolute temperature of the lagoon surface. The R_{LD} term is expressed as:

$$R_{LD} = \varepsilon_{AC} \sigma T_A^4(z_1) \tag{10}$$

where, ε_{AC} is the atmospheric emissivity and T_A is atmospheric temperature at z_1(0.5 m). For clear day conditions, the ε_{AC} term is represented as:

$$\varepsilon_{AC} = A\left(\frac{e(z_2)}{T_A}\right) \tag{11}$$

with $e(z_2)$ the estimated vapor pressure at height z_2 (1.5 m), B = 1/7, A = 1.16 for the warm season measurements and A=1.28 for the cool season measurements. Crawford and Duchon (1999) provided a methodology for estimating the A term that accounts for seasonal variations. Thus, the method of Crawford and Duchon (1999) was used to calculate A. Using flux-gradient techniques to approximate the turbulent sensible and latent heat fluxes and assuming equality of eddy diffusivities for heat and moisture (Stull, 1988) Bowen ratio can be expressed as:

$$B = \gamma \frac{T(z_2) - T(z_1)}{e(z_2) - e(z_2)} \tag{12}$$

where, γ is the so called psychrometric constant computed as $(C_P\ P(z_M))/(0.622\ L_e)$, where C_P is the specific heat of air at constant pressure, $e(z_1)$ and $e(z_2)$ are the water vapor pressures at z_1 and z_2 and z_M is the arithmetic mean of z_1 and z_2. $T(z_1)$ and $T(z_2)$ are temperature measurements at z_1 and z_2 (Brutsaert, 2005).

Using Eq. 5 and 9 expressions for H and L_eE are obtained as:

$$H = (R_N - G)\frac{B}{1+B} \tag{13}$$

$$L_eE = (R_N - G)\frac{B}{1+B} \tag{14}$$

To obtain the correct magnitudes and signs for the energy fluxes, Bowen ratio estimates are subjected to two quality tests as suggested by Ohmura (1982) and further developed by Perez *et al.* (1999) and Guo *et al.* (2007).

Test 1: Here, the flux-gradient relations between H and the temperature gradients ($\Delta T = T(z_2)-T(z_1)$) and L_eE and the water vapor pressure gradients ($\Delta e = e(z_2)-e(z_1)$) are used. Points that violate the following inequality are discarded:

$$\frac{\Delta_e}{L_e E} = \left(\frac{1+B}{(R_N - G)}\right)\Delta_e < 0 \quad (15)$$

Test 2: In order to avoid unphysical values of latent and sensible heat fluxes, Bowen ratio values that fall in the interval, -2.0<B<-0.5, are rejected (Ohmura, 1982; Brotzge and Crawford, 2003).

RESULTS AND DISCUSSION

Data and parameters description: The data used in this study were obtained from a swine waste lagoon at a farrowing farm containing approximately 2,000 sows located in Logan County in South Central Kentucky. Ammonia concentrations at the surface of the lagoon along with meteorological data surrounding the lagoon were obtained and analyzed for a one month period (February). These parameters consisted of air temperatures above the lagoon (temperatures at 1.5, 0.5 m and surface of lagoon), pH (6.8 to 7.4), moisture, pressure, wind speeds and relative humidity.

The North American Regional Reanalysis (NARR) (Mesinger *et al*., 2006) data were used to characterize the general meteorological synoptic conditions for the month of February for the Logan County region. Kentucky was under the influence of a large high pressure system on the first week of February, 2009. The average pressure was 1033 mb. For the most part, the entire day was clear with no precipitation and light winds (8 km h^{-1} from the south). During the second week of February, Kentucky was under a high pressure system with a pressure around 1025 mb and no precipitation. Skies were also clear early in the morning but became mostly cloudy throughout the day. Winds are from the Southwest at around 19 km h^{-1}. A cold front started to push through Kentucky at the end of the second week of February. The pressure was around 1026 mb. The winds were generally from the southwest at 8 km h^{-1}. The skies were mostly cloudy in the early morning but the clouds broke up throughout the day becoming clear by the night. On the third week of February, a warm front was located south of KY. The pressure was 1023 with mostly clear skies for most of the day. Winds were around 16 km h^{-1} out of the south. Two highs were located over Nebraska and Arkansas/Mississippi with some ridging over Kentucky during this time period. The pressure was around 1020 mb with cloudy skies early in the morning and becoming clear with no precipitation. Winds were from the west at 9 km h^{-1}. In summary, except for brief instances, all days analyzed in this study can be approximated as clear days for radiation computations.

The analysis was completed for clear day conditions using time series of hourly meteorological variables for the 28 day in February of 2009 (hereafter referred to as 28 day ensemble). Median temperatures vary between 5 and 6°C early in the morning (2 am local time) and later in the evening (8 pm local time). The data also show a diurnal maximum of 13°C. Upper quartiles were about 5 to 8°C above median values while lower quartiles were about 5 to 7°C smaller and follow a diurnal cycle as well. The data show a wide range of variations as temperatures fluctuated between -10 to 20°C. Similar time series for air temperatures from the HOBO station (not shown) exhibited a very similar pattern except that temperatures at 0.5 m were slightly higher.

The median wind speeds show small values of 0.7 m sec^{-1} in the early morning (2 am local time) and in the evening (8 pm local time). While it increased up to 3.2 m sec^{-1} between 11 am and 12 noon. Wind speed was reach up to 9.5 m sec^{-1} for the 28 day ensemble. The position of the medians also indicate that wind speed data are skewed towards higher values early in the morning while they are skewed towards lower values during the afternoon hours.

The median solar radiation peaked at 11 am with a value of 542 W m^{-2}. The rather large spread in the data, particulary around noon, was brought about by the presence of clouds. The available energy flux (R_N-LS) for the 28 day ensemble at the surface as given by the difference between net solar radiation and lagoon heating computed as previously discussed (cf. Eq. 5 and 8). Median values reached up to 542 W m^{-2} at 11 am with fluctuations of about 600 W m^{-2} around this median values. Larger values of R_N-LS than those observed for solar radiation were due to higher atmospheric emissivities and rather small outgoing longwave radiation contributing to increase the available energy at the surface.

The 28 day ensemble of latent heat flux (L_eE) with median values of about 433 W m^{-2} at 1300 h and with lower values both early morning and late at night of about 100 W m^{-2}. The 28-day ensemble of sensible heat flux (H) with median values reaching about 278 W m^{-2} at noon and with smaller values of about 100 W m^{-2} during early morning and late evening. Medians show a spread of about 300 W m^{-2} around noon. It is noted that values of H were significantly smaller by a factor of 1.5 than those of L_eE indicating that available energy at the lagoon surface was used mainly for evaporation to the atmosphere. These results are consistent with the lagoon being a source of heat and moisture to the drier February atmosphere.

Ammonia emissions from the swine lagoon were monitored using a photoacoustic gas analyzer. A pulley system was utilized to monitor the ammonia concentrations above the lagoon surface at 0.5 m and at a distance of 10 m from the bank of the lagoon. The ammonia concentrations were monitored continuously for twenty-four hours at a time, at least twice a week for the duration of the month of February. The ammonia concentrations were then averaged and normalized to a twenty-four hour cycle to account for the diurnal effect. The averaged ammonia concentrations ranged from zero to about 8.0 ppmv over the study period.

Parameters selection: Although there were few parameters obtained for this study, most of these were used to tabulate heat fluxes based on Bowen Ratio method (Bowen, 1926; Stull, 1988). In order to determine inconspicuous relationships between potential NN input parameters (Table 1) in relation to the target ammonia concentration levels, parameters which exhibit Pearson's correlation coefficients greater or equal to 0.9 with respect to the target variable were removed. In this regard, only 1.5 m ($T_{1.5}$) was eliminated from the data set as its respective correlation coefficient exceeded 0.99. Native parameter ranking algorithms in the STATISTICA 7.0 software package (Statsoft, Tulsa, OK) were then used to indicate which NN input parameters were the most "influential" on ammonia levels. Several additional parameter selection algorithms such as

Table 1: Input variables ranking

Variable	K-predictors (F-value)	Boosting tree (rank)	Random forest (rank)
Surface temp (T_s)	25.93	92	79
Temp at 0.5 m ($T_{0.5}$)	45.78	100	100
Temp at 1.5 m ($T_{1.5}$)	1.26	31	29
Net radiation (R_n)	9.62	75	87
Lagoon heating (G)	11.38	44	42
Sensible heat (H)	4.29	72	52
Latent heat (L)	15.29	85	63
R_n-G	2.58	41	33

K-predictors in STATISTICA and sequential-forward selection in WEKA 3.6(http://www.cs.waikato.ac.nz/ml/index.html) were also implemented. However, the best NN model performances resulted by using the five highest ranking parameters under the Boosting Tree (Freund *et al*., 2003) and Random Forest (Stoppiglia *et al*., 2003) algorithms in STATISTICA 7.0. Based on the rankings shown the last two columns of Table 1, Surface Temp (T_s), Temp at 0.5 m ($T_{0.5}$), Net Radiation (R_n), Sensible Heat (H) and Latent Heat (L) were deemed important in predicting ammonia emissions from swine waste lagoon and therefore selected as input variables for simulating NN models.

Development and validation of the predicted model: The MLP neural network involves multiple fully connected layers. Except for the input nodes, each node is a neuron with a non-linear activation function. MLP neural networks utilize a supervised learning mechanism with back propagation for training. MLP is a modification of the standard linear perceptron able to distinguish data that is not linearly separable (Cybenko, 1989).

The dataset from Table 1 consisted of 305 measured instances which correlated with the ammonia concentrations. The 75 and 25% of the measurements were respectively used to train and test the MLP neural network models. In all, 1000 single hidden-layer neural networks were trained. The number of neurons in the hidden layer varied from 3 to 15 (Table 2). Table 2 summarizes the 5 best performing neural networks. The Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm was used to minimize sum of squared error (SSE)-which measures the MLP newural network accuracy-while building each neural network model (Gilbert *et al*., 2006). Multiple non-linear hidden and output activation functions, including identity, logistic, tanh and exponential, were used over the hidden and output neurons (not shown on table). The MLP neural networks successfully identify the non-linear relationship between the process variables as demonstrated with the low training errors shown in Table 2. The iteration number of the BFGS algorithm ranged between 86 and 241. Based on the native training and test errors, it appears that the MLP neural network with 7 hidden nuerons (MLP 5-7-1) performed best with the selected input variables and an exponential output activation function.

Figure 1 and 2 show the normalized observed values in the test data set versus the corresponding MLP 5-7-1 predicted values of ammonia emissions from swine waste lagoon. Furthermore, resulting error measured for this specific MLP included: MAE of 0.018, MSE of 0.001 and SD of 0.031. Besides the temperature input variables, the various heat fluxes appear to have a major effect on simulating the ammonia emissions from swine lagoon. Most ammonia emission patterns (the highs and lows) were clearly recognized by the model with a few exceptions of extreme high experimental observed values. A reason for the discrepancy may have been because of noise in the data sampled.

Table 2: Multi-layer perceptron (MLP) neural networks using five input variables of importance for ammonia

MLP structure	Training error	Test error	Train algorithm
MLP 5-13-1	0.001724	0.000725	BFGS89
MLP 5-6-1	0.001983	0.001009	BFGS86
MLP 5-7-1	0.001394	0.000875	BFGS241
MLP 5-15-1	0.001586	0.001586	BFGS97
MLP 5-15-1	0.001868	0.000892	BFGS 153

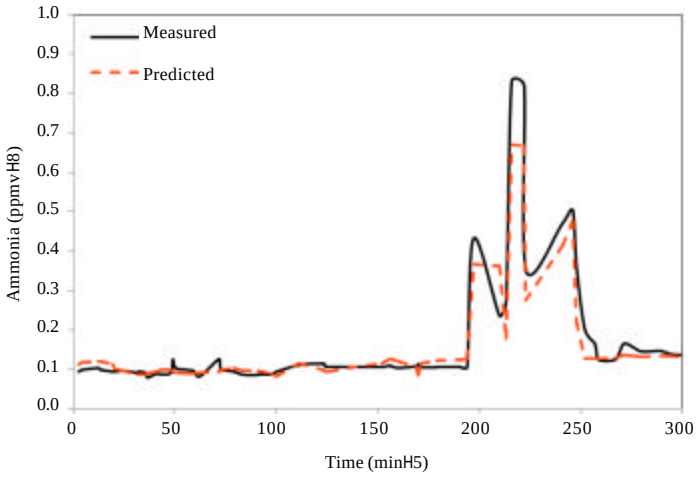

Fig. 1: Measured and MLP neural network predicted ammonia concentrations. Each point on the temporal axis represents a 5 min interval

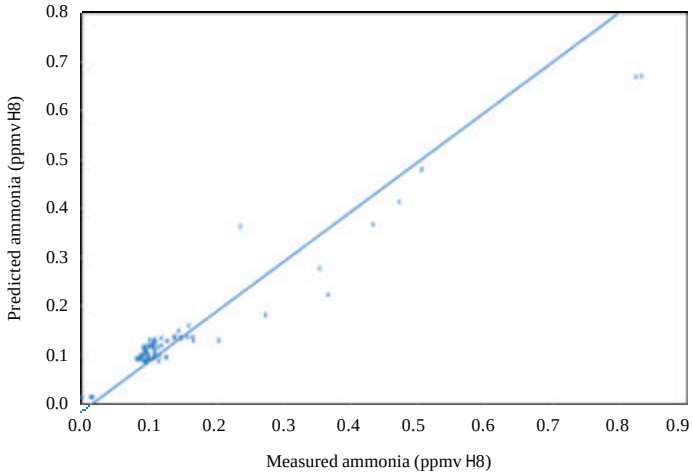

Fig. 2: Correlation between measured and predicted ammonia levels. Solid line indicates a 45-degree line (one-to-one correspondence). Each experimental datum point represents average concentration over 5 min sampling periods (n = 300)

CONCLUSION

An artificial neural network analysis was carried out to examine the effect of heat fluxes on the emission of ammonia from a swine waste lagoon. Based on the results, incorporating various heat fluxes such as net solar radiation, sensible heat and latent heat of vaporization improves the accuracy of the Multi-layer Perceptron (MLP) neural networks predictive model on ammonia emissions. Therefore, it could be concluded that heat fluxes do affect the emission of ammonia from swine lagoon. Thus it is important to consider environmental conditions (i.e., meteorological parameters such as solar radiation, latent heat and etc.) in formulating management or abatement strategies for reducing ammonia emissions from swine waste lagoons or any other air pollutant emissions from livestock waste receptacles.

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REFERENCES

Arya, S.P., 2001. Introduction to Micrometeorology. Academic Press, San Diego, USA.

Barthelmie, R.J. and S.C. Pryor, 1998. Implications of ammonia emissions for fine aerosol formation and visibility impairment: A case study from the lower fraser valley, British Columbia. Atmos. Environ., 32: 345-352.

Bicudo, J.R., L.M. Safley and P.W. Westerman, 1999. Nutrient content and sludge volumes in single-cell recycle anaerobic swine lagoons in North Carolina. Trans. ASAE, 42: 1087-1093.

Bowen, I.S., 1926. The ratio of heat losses by conduction and by evaporation from any water surface. Phys. Rev., 27: 779-787.

Brotzge, J.A. and K.C. Crawford, 2003. Examination of the surface energy budget: A comparison of eddy correlation and Bowen ratio measurement systems. J. Hydrometeorol., 4: 160-178.

Brutsaert, W., 2005. Hydrology: An Introduction. Cambridge University Press, New York, ISBN-13: 9780521824798, Pages: 605.

Cole, D., L. Todd and S. Wing, 2000. Concentrated swine feeding operations and public health: A review of occupational and community health effects. Environ. Health Perspect., 108: 685-699.

Crawford, T.M. and C.E. Duchon, 1999. An improved parameterization for estimating effective atmospheric emissivity for use in calculating daytime downwelling longwave radiation. J. Applied Meteorol., 38: 474-480.

Cybenko, G., 1989. Approximation by superposition of a sigmoidal function. Math. Control Signal Syst., 2: 303-314.

De Jong, R., C.F. Shaykewich and A. Reimer, 1980. The net radiation flux and its prediction at Pinawa, Manitoba. Agric. Meteorol., 22: 217-225.

Donaldson, K. and W. MacNee, 1998. The Mechanisms of Lung Injury Caused by PM10. In: Issues in Environmental Science and Technology, Hester, R.E. and R.M. Harrison (Eds.). Royal Society of Chemistry, Cambridge, UK., pp: 21-32.

Freund, Y., R. Iyer, R. E. Schapire and Y. Singer, 2003. An efficient boosting algorithm for combining preferences. J. Mach. Learning Res., 4: 933-969.

Gilbert, J.C., C. Lemarechal and C.A. Sagastizabal, 2006. Numerical Optimization: Theoretical and Practical Aspects. Springer, New York, ISBN-13: 9783540354475, Pages: 508.

Guo, X., H. Zhang, L. Kang, J. Du, W. Li and Y. Zhu, 2007. Quality control and flux gap filling strategy for Bowen ratio method: Revisiting the Priestley-Taylor evaporation model. Environ. Fluid Mech., 7: 421-437.

Ham, J.M., 1999. Measuring evaporation and seepage losses from lagoons used to contain animal waste. Trans. ASAE, 42: 1303-1312.

Ham, J.M., 2002. Seepage losses from animal waste lagoons: A summary of a four-year investigation in Kansas. Trans. ASAE, 45: 983-992.

Jacobs, A.F., B.G. Heusinkveld, A. Kraai and K.P. Paaijmans, 2008. Diurnal temperature fluctuations in an artificial small shallow water body. Int. J. Biometeorol., 52: 271-280.

Kohonen, T., 1988. An introduction to neural computing. Neural Networks, 1: 3-16.

Komzsik, L., 2007. Approximation Techniques for Engineers. CRC, Taylor and Francis, Boca Raton, FL., USA.

KrishnaKumar, K., 1993. Optimization of the neural net connectivity pattern using a backpropagation algorithm. Neurocomputing, 5: 273-286.

Lavine, M., G.C. Hegerl and S. Lozier, 2009. Discussion of reified Bayesian modelling and inference for physical systems by Michael Goldstein and Jonathan Rougier. J. Stat. Planning Inference, 139: 1243-1245.

Leung, K. and E. Topp, 2001. Bacterial community dynamics in liquid swine manure during storage: Molecular analysis using DGGE/PCR of 16S rDNA. FEMS Microbiol. Ecol., 38: 169-177.

Likhovidov, V., 1997. Variational approach to unsupervised learning algorithms of neural networks. Neural Networks, 10: 273-289.

Linacre, E.T., 1968. Estimating the net-radiation flux. Agric. Meteorol., 5: 49-63.

Lippmann, M., 1998. The 1997 US EPA Standards for Particulate Matter and Ozone. In: Issues in Environmental Science and Technology, Hester, R.E. and R.M. Harrison (Eds.). Royal Society of Chemistry, pp: 75-79.

Loughrin, J.H., A.A. Szogi and M.B. Vanotti, 2006. Reduction of malodorous compounds from a treated swine anaerobic lagoon. J. Environ. Qual., 35: 194-199.

Loughrin, J.H., A.I. Quintanar, K.L. Cook, N.C. Lovanh, R. Mahmood and E. Becerra-Acosta, 2012. Seasonal variation in heat fluxes, predicted emissions of malodorants and wastewater quality of an anaerobic swine waste lagoon. Water Air Soil Pollut., 223: 3611-3618.

Loughrin, J.H., A.I. Quintanar, N.C. Lovanh and R. Mahmood, 2011. Heat flux measurements and modeling of malodorous compounds above an anaerobic swine lagoon. Water Air Soil Pollut., 217: 463-471.

Lovanh, N., J.H. Loughrin, K. Cook, M. Rothrock and K. Sistani, 2009. The effect of stratification and seasonal variability on the profile of an anaerobic swine waste treatment lagoon. Bioresour. Technol., 100: 3706-3712.

McCulloch, W.S. and W. Pitts, 1943. A logical calculus of the ideas immanent in nervous activity. Bull. Math. Biophys., 5: 115-133.

McGarvey, J.A., W.G. Miller, S. Sanchez and L. Stanker, 2004. Identification of bacterial populations in dairy wastewaters by use of 16S rRNA gene sequences and other genetic markers. Applied Environ. Microbiol., 70: 4267-4275.

Mesinger, F., G. DiMego, E. Kalnay, K. Mitchell and P.C. Shafran *et al*., 2006. North American regional reanalysis. Bull. Am. Meteorol. Soc., 87: 343-360.

Natvig, E.E., C.S. Ingham, H.B. Ingham, L.R. Cooperband and T.R. Roper, 2002. *Salmonella enterica* serovar Typhimurium and *Escherichia coli* contamination of root and leaf vegetables grown in soils with incorporated bovine manure. Applied Environ. Microbiol., 68: 2737-2744.

Novak, M.D., W. Chen and M.A. Hares, 2000. Simulating the radiation distribution within a barley-straw mulch. Agric. Forest Meteorol., 102: 173-186.

Ohmura, A., 1982. Objective criteria for rejecting data for Bowen ratio flux calculations. J. Applied Meteorol., 21: 595-598.

Oke, T.R., 1987. Boundary Layer Climates. Routledge, New York, Pages: 435.

Paerl, H.W., 1995. Coastal eutrophication in relation to atmospheric nitrogen deposition: Current perspectives. Ophelia, 41: 237-259.

Perez, P.J., F. Castellvi, M. Ibanez and J.I. Rosell, 1999. Assessment of reliability of Bowen ratio method for partitioning fluxes. Agric. Forest Meteorol., 97: 141-150.

Philip, J.R., 1987. A physical bound on the Bowen ratio. J. Applied Meteorol., 26: 1043-1045.

Quintanar, A.I., R. Mahmood, J.H. Loughrin, N. Lovanh and M.V. Motley, 2009. A system for estimating Bowen ratio and evaporation from waste lagoons. Applied Eng. Agric., 25: 923-932.

Robert, C., C. Guilpin and A. Limoge, 1998. Review of neural network applications in sleep research. J. Neurosci. Methods, 79: 187-193.

Rodriguez-Rodriguez, M. and M. Moreno-Ostos, 2006. Heat budget, energy storage and hydrological regime in a coastal lagoon. Limnologica, 36: 217-227.

Rosenblatt, F., 1962. Principles of Neurodynamics: Perceptrons and the Theory of Brain Mechanisms. Spartan Books, Washington DC., Pages: 616.

Spokes, L., T. Jickells, K. Weston, B.G. Gustafsson and M. Johnsson *et al.*, 2006. MEAD: An interdisciplinary study of the marine effects of atmospheric deposition in the Kattegat. Environ. Pollut., 140: 453-462.

Stannard, D.I., 1997. A theoretically based determination of Bowen-ratio fetch requirements. Boundary-Layer Meteorol., 83: 375-406.

Stoppiglia, H., G. Dreyfus, R. Dubois and Y. Oussar, 2003. Ranking a random feature for variable and feature selection. J. Machine Learning Res., 3: 1399-1414.

Stull, R.B., 1988. An Introduction to Boundary Layer Meteorology. Springer, New York, ISBN: 9789027727695, Pages: 666.

Szogi, A.A., M.B. Vanotti and A.E. Stansbery, 2006. Reduction of ammonia emissions from treated anaerobic swine lagoons. Trans. ASABE, 49: 217-225.

Tan, P.N., M. Steinbach and V. Kumar, 2006. Introduction to Data Mining. Pearson Education, USA.

Tanny, J., S. Cohen, S. Assouline, F. Lange and A. Grava *et al.*, 2008. Evaporation from a small water reservoir: Direct measurements and estimates. J. Hydrol., 351: 218-229.

Van Breemen, N., P.A. Burrough, E.J. Velthorst, H.F. van Dobben, T. de Wit, T.B. Ridder and H.F.R. Reijnders, 1982. Soil acidification from atmospheric ammonium sulphate in forest canopy throughfall. Nature, 299: 548-550.

Wang, K. and S. Liang, 2008. An improved method for estimating global evapotranspiration based on satellite determination of surface net radiation, vegetation index, temperature and soil moisture. J. Hydrometeor, 9: 712-727.

Warnick, L.D., L.M. Crofton, K.D. Pelzer and M.J. Hawkins, 2001. Risk factors for clinical salmonellosis in Virginia, USA cattle herds. Preventive Vet. Med., 49: 259-275.

Wesley, I.V., S.J. Wells, K.M. Harmon, A. Green, L. Schroeder-Tucker, M. Glover and I. Siddique, 2000. Fecal shedding of *Campylobacter* and *Arcobacter* spp. in dairy cattle. Applied Environ. Microbiol., 66: 1994-2000.

Westerman, P.W., L.M. Safley and J.C. Barker, 1990. Lagoon Liquid Nutrient Variation Over Four Years for Lagoons with Recycle Systems. In: Agricultural and Food Processing Waste, Reddi, L.N. (Ed.). American Society of Agricultural Engineers, USA., pp: 41-49.

Wetzel, R.G. and G.E. Likens, 2000. Limnological Analyses. 3nd Edn., Springer, New York, USA., ISBN-13: 978-0387989280, Pages: 429.