

PREDICTION OF INDOOR CLIMATE AND LONG-TERM AIR QUALITY USING THE BTA-AQP MODEL: PART II. OVERALL MODEL EVALUATION AND APPLICATION

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ABSTRACT. *The objective of this research was to develop a building thermal analysis and air quality predictive (BTA-AQP) model to predict indoor climate and long-term air quality (NH₃, H₂S, and CO₂ concentrations and emissions) for swine deep-pit buildings. This article presents part II of this research, in which the performance of the BTA-AQP model is evaluated using typical meteorological year (TMY3) data in predicting long-term air quality trends. The good model performance ratings (MAE/SD < 0.5, CRM ≈ 0; IoA ≈ 1; and NSEF > 0.5 for all the predicted parameters) and the graphical presentations reveal that the BTA-AQP model was able to accurately forecast indoor climate and gas concentrations and emissions for swine deep-pit buildings. By comparing the air quality results simulated by the BTA-AQP model using the TMY3 data set with those from a five-year local weather data set, it was found that the TMY3-based predictions followed the long-term mean patterns well, which indicates that the TMY3 data could be used to represent the long-term expectations of source air quality. Future work is needed to improve the accuracy of the BTA-AQP model in terms of four main sources of error: (1) uncertainties in air quality data, (2) prediction errors of the BTA model, (3) prediction errors of the AQP model, and (4) bias errors of the TMY3 and its limited application.*

Keywords. *Air quality predictive model, Long-term mean, Modeling, Typical meteorological year.*

The overall goal of this research was to develop a building thermal analysis and air quality predictive (BTA-AQP) model to quantify long-term indoor climate and air quality (NH₃, H₂S, and CO₂ concentrations and emissions) for swine deep-pit buildings. In the companion article forming part I of this study (Sun and Hoff, 2010), it has been demonstrated, based on statistical evaluation measures and graphical presentations, that the developed BTA model was capable of predicting indoor climate and building ventilation rate in swine deep-pit buildings and could provide accurate estimates of significant input variables for the AQP model.

Part II of this study, detailed in this article, deals with the development and evaluation of the BTA-AQP model under typical weather conditions (TMY3). The proposed modeling technology was intended to perform long-term simulation of source air quality in a rapid, economical, reliable, and accurate way in order to significantly reduce expensive and time-consuming field measurements. Therefore, the BTA-AQP model could be used by livestock producers to extrapolate annual air emission inventories, by research scientists to obtain a diurnal and seasonal air quality database for science-based setback distance determination, and by state and

federal regulatory agencies to make relevant environment policy decisions.

MATERIALS AND METHODS

LONG-TERM AIR QUALITY PREDICTION METHOD

Long-term air quality predictions can be separated into three components, as shown in figure 1: the building thermal analysis (BTA) model, the air quality predictive (AQP) model, and a typical meteorological year (TMY3) database (NSRDB, 2008). Specifically, a lumped capacitance model (BTA model) was developed to study the transient behavior of indoor air temperature and ventilation rate according to the thermo-physical properties of a typical Iowa swine building, a typical setpoint temperature scheme, a typical fan staging scheme, transient outside temperature, and the heat fluxes from pigs and supplemental heaters. The obtained indoor room temperature and ventilation rate combined with animal growth cycle, in-house manure storage level, and typical meteorological year (TMY3) data were fed into the generalized regression neural network (GRNN) air quality predictive model to calculate hourly NH₃, H₂S, and CO₂ concentrations and emission rates. The corresponding monthly and average annual air quality values were then obtained based on the hourly predictions. The TMY3 data used for this research project consist of representative hourly solar radiation and meteorological values for a one-year period in Des Moines, Iowa, about 100 km away from the swine deep-pit finishing facility where field data were collected (calendar year 2003 data collection). Animal growth cycle includes pig number and average pig weight in the room, which were used to estimate total animal units (AU). The total AU was obtained by dividing the total pig weight by 500 kg animal live weight.

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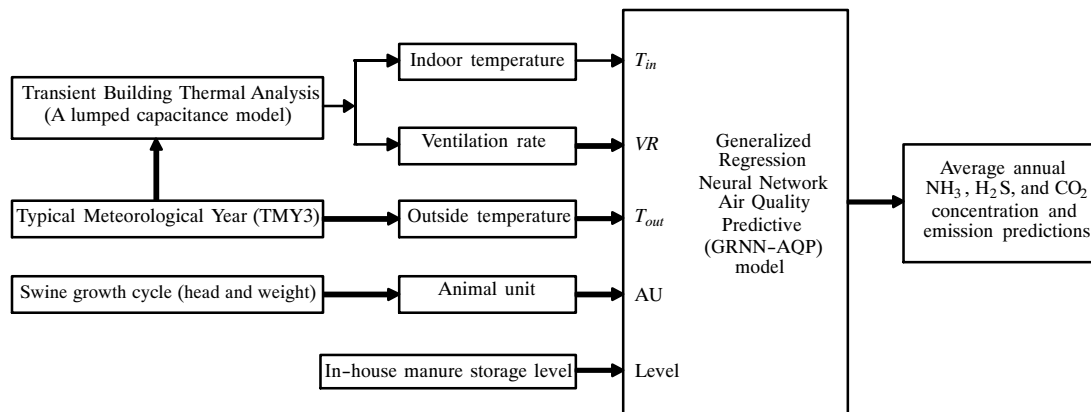


Figure 1. Schematic of the BTA-GRNN-AQP model: T_{in} = indoor temperature ($^{\circ}\text{C}$), VR = ventilation rate ($\text{m}^3 \text{s}^{-1}$), T_{out} = outside temperature ($^{\circ}\text{C}$), AU = animal unit, and $Level$ = in-house manure storage level (m).

In-house manure storage level was considered as an additional input variable representing a deep-pit system for the AQP model.

DESCRIPTION OF FIELD GAS MEASUREMENTS

Field monitoring was conducted for 15 months between January 2003 and March 2004, with the one-year monitoring in 2003 used in this research for model prediction comparison. Details of the field monitoring and overall procedures used can be found in Heber et al. (2006). Two identical deep-pit swine finishing buildings located in central Iowa were monitored. Each building was 60 m long and 13 m wide, which can house 960 finishing pigs from ~20 to 120 kg. Slurry was collected in a 2.4 m deep pit below a fully slatted floor and was stored for one year. Once a year in the fall, the under-floor deep pit was emptied and the slurry was injected to nearby cropland as a fertilizer source.

The real-time gas concentrations and emission rates, environmental data, and building ventilation rate were measured by a mobile emission laboratory (MEL) that included a gas sampling system (GSS), a computer-based data acquisition system, gas analyzers, environmental instrumentation, standard gas calibration cylinders, and other supplies. Gas concentrations from multiple sampling locations within the swine building were quantified with a chemiluminescence NH_3 analyzer (model 17C, Thermal Environment Instruments, Franklin, Mass.), a pulsed fluorescence SO_2 detector (model 45C, Thermal Environment Instruments, Franklin, Mass.), and two photoacoustic infrared CO_2 analyzers in the range from 0 to 2,000 and 10,000 ppm (model 3600, Mine Safety Appliances Co., Pittsburg, Pa.). A three-way solenoid system was used to automatically switch between 12 measuring locations with 10 min sampling intervals and sequentially delivered gas from each location to the gas analyzers. Therefore, gas samples were taken during twelve 120 min measurement cycles per day. Details of the monitoring method and QA/QC can be found in Heber et al. (2006). Climate parameters (temperature, relative humidity, and static pressure) and total building ventilation rate were also simultaneously monitored. Gas emission rates were determined by multiplying fan airflow rate by representative gas concentration differences between inlet and outlet for all fans operating at any given time. The maximum estimated uncertainty in ventilation rate and gas concentrations were $\pm 7.2\%$ (Hoff et al., 2009) and $\pm 5.0\%$, respectively. These individual uncertain-

ties resulted in an average uncertainty in emission rate of about $\pm 9.0\%$.

AIR QUALITY DATABASE AND INITIAL DATA ANALYSIS

The BTA-AQP model development was based on source air quality measurements, which included real-time gas concentrations and emission rates, indoor and outdoor environmental data (indoor, inlet, and exhaust temperature and relative humidity, outdoor temperature, relative humidity, wind speed, wind direction, solar energy, and barometric pressure), pig size and density (animal units), and building ventilation rate. These measured data can be used as a fundamental database to help develop air quality predictive models and evaluate model forecasting performance. Thus, data quality is of paramount importance. Heber et al. (2006) pointed out that more efforts should be made to maximize the confidence, credibility, and consistency of measured data for obtaining a high-quality database. In this study, the established principles of quality assurance and quality control were applied throughout the gas sample collection, and great emphasis was placed on data quality. However, the final data set still presented three main types of problems: general errors, outliers, and missing observations. General errors are wrongly recorded observations, probably due to calibration and other reasons, that could result in biased measurements. A 70% valid data policy (Heber et al., 2006) was used to calculate hourly, daily, and monthly averages to avoid these errors. Outliers are extreme observations that do not appear to be consistent with the rest of the data. Outliers arise for several reasons and can cause severe problems. Hoff et al. (2006) reported that the H_2S emissions measured during the independent slurry removal event would increase by an average of 62 times relative to the H_2S emission levels before the removal. Thus, air quality data during the slurry agitation process should be considered as outliers and removed from the database. Missing observations are due to a variety of reasons, such as lost samples, malfunctioning instruments and sensors, and challenging weather (lightning), to name a few. A majority of the missing air quality data in this research was missing not at random (MNAR). The best way to handle MNAR data is to develop a regression model to estimate missing values (Dunning and Freedman, 2008). In a word, initial data analysis must be applied to ensure database quality.

Another important issue for an air quality database is the sample representativeness and completeness. Representative and complete sample measurements should fully characterize long-term (at least one year) air emission profiles and corresponding emission factors since gas concentrations and emissions vary with time of day, season, building characteristics, ventilation rate, animal size and density, manure handling system, and weather conditions (Jacobson et al., 2005).

TYPICAL METEOROLOGICAL YEAR

Selecting appropriate representative meteorological data is vitally important to accurately predict indoor climate and long-term air quality levels. Normally, representative meteorological data consist of a multi-year and long-term average measured data series that represents a year of prevailing weather conditions for a specific location. It is noted that the use of typical climatic parameters instead of multiple-year data can reduce a great deal of time and computation in computer simulation and facilitate performance comparisons of different system types, configurations, and locations. Therefore, typical weather data have been extensively used for building energy simulation and solar energy analysis to assess the expected heating and cooling costs for the design of industrial and residential buildings. Currently, the most prevalent weather representations are test reference year (TRY), typical meteorological year (TMY3), and weather year for energy calculations (WYEC2). These data sets are used for different simulation purposes (Pedersen, 2007). TRY is suited to short-term energy predictions due to the representation of weather characteristics, while TMY3 and WYEC2 are most suitable for long-term energy estimations because the data represent long-term weather features. Yang et al. (2008) investigated the energy simulation results for office buildings in the five main climate zones of China and compared the results using TMY2 with those using multi-year data (1971-2000). They found that TMY2 was able to predict monthly load and energy use within 5.4% of the long-term mean. Based on these results, it was concluded that TMY3 data were an acceptable meteorological data set to be used for this current study.

TMY3 is composed of typical hourly meteorological values at a specific location over a long period of time (30 years). For each TMY3 dataset, 12 typical months are selected using statistics (Sandia method; NSRDB, 2008) determined by five important parameters: global radiation on a horizontal surface, direct normal radiation, dry bulb and dew point temperatures, and wind speed (NSRDB, 2008). These important parameters were chosen because solar radiation determines the heat gain, dry bulb temperature and wind speed determine heat loss by convection, and dew point temperature is an absolute measure of humidity, which determines latent energy. The 12 months judged to be most typical were picked by the Sandia approach to form a complete year. Due to adjacent TMY3 months from different years, linear interpolation was performed to smooth the gap for 6 h on each side of adjacent months. In each TMY3 month, mean values of the TMY3 elements are the closest to the averages of the elements for multiple years. Thus, TMY3 can represent long-term average climatic conditions.

AIR QUALITY MODEL

Modeling source air quality in a swine deep-pit building is a complicated dynamic system with many nonlinear governing relationships. Moreover, there still exist some circumstances of gaseous emissions that cannot be explained with our current limited scientific understanding (Sun et al., 2008). Therefore, a black-box modeling approach using artificial neural networks (ANN) would be a potential method for handling air quality predictions. Black-box models do not need detailed prior knowledge of the structure and different interactions that exist between important variables. Meanwhile, their learning abilities make the models adaptive to system changes. Recently, there has been an increasing number of applications of ANN models in the field of atmospheric pollution forecasting (Hooyberghs et al., 2005; Grivas and Chaloulakou, 2006; Sousa et al., 2007; Sun et al., 2008). The results show that ANN black-box models are able to learn nonlinear relationships with limited knowledge about the process structure.

Sun et al. (2008) employed backpropagation neural network (BPNN) and generalized regression neural network (GRNN) techniques to model gas and PM₁₀ concentrations and emissions generated and emitted from a swine deep-pit finishing building. Note that GRNN is a term used to represent the Nadaraya-Watson kernel regression used in artificial neural networks. The obtained BPNN and GRNN predictions were in good agreement with field measurements, with coefficient of determination (R^2) values between 81.2% and 99.5% and very low values of systemic performance indices. The good results indicated that ANN techniques were capable of accurately modeling source air quality within and from these livestock production facilities. Furthermore, it was found that the process of constructing, training, and simulating the BP network models was very complicated. The effective way of obtaining good BP modeling results was to use some trial-and-error methods and thoroughly understand the theory of backpropagation. Conversely, for the GRNN models, there was only one parameter (the smoothing factor) that needed to be adjusted experimentally. Additionally, the GRNN performance was not sensitive to randomly assigned initial values and the GRNN approach did not require an iterative training procedure, as in the backpropagation method. Other significant characteristics of the GRNN in comparison to the BPNN were the excellent approximation ability, fast training time, and exceptional stability during the prediction stage. Thus, it was recommended by Sun et al. (2008) that a GRNN be used for source air quality modeling.

In the current research, a GRNN model was developed to explore the complex and highly nonlinear relationships between air pollutants and many input variables on diurnal and seasonal NH₃, H₂S, and CO₂ levels and emissions. This developed air quality model was then used to forecast long-term gas concentrations and emissions from a typical swine deep-pit building associated with five significant input elements: outdoor temperature obtained from a specific year or the TMY3 data, a typical swine growth cycle, and ventilation rate and indoor air temperature predicted by the transient BTA model (Sun and Hoff, 2010). It is noted that in the mid-western U.S., it is common practice to store manure in deep concrete pits for one calendar year. This year-long slurry storage system is also a concentrated source of gas concentrations and emissions (Hoff et al., 2006). Therefore, in-house manure storage level was considered as an additional factor

representing the deep-pit system for the AQP model. The manure depth changes with swine production time, from 0.3 m (empty pit) to 2.1 m (full pit) throughout the year. The full and empty events generally occur before and after slurry removal, which is typically conducted once per year in the fall after harvest (i.e., October).

RESULTS AND DISCUSSION

A comparison was made between the predicted and actual gas concentrations and emissions in 2003 to evaluate the accuracy of the BTA-AQP model estimates. In addition, the simulated results using the TMY3 data set and a five-year

mean weather data set were compared to validate the assumption that the TMY3 could accurately represent long-term source air quality levels. Finally, overall prediction errors of the BTA-AQP model were analyzed, and future work is identified for improving the model.

BAT-AQP MODEL EVALUATION USING 2003 WEATHER DATA

Boxplots were used to provide graphical information on the median, spread, skewness, and potential outliers of the actual vs. predicted data sets. The primary purpose was to evaluate the data early, before conducting in-depth statistical analysis. Comparative boxplots of hourly actual vs. predicted

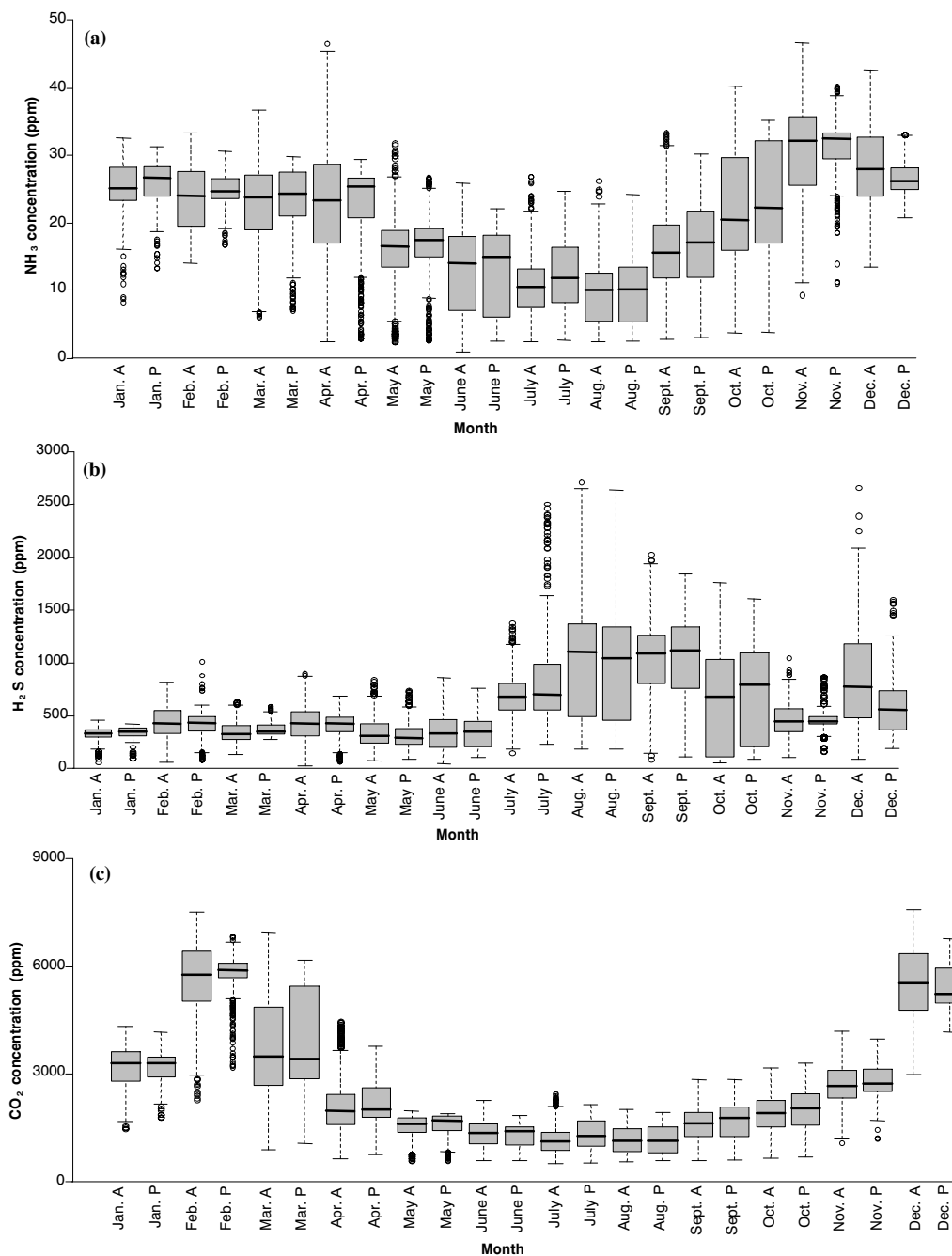


Figure 2. Actual vs. predicted hourly (a) NH₃, (b) H₂S, and (c) CO₂ concentrations in 2003 (A = actual, P = predicted, and circles = potential outliers).

NH₃, H₂S, and CO₂ concentrations for each month in 2003 are shown in figure 2. It was observed that the field-collected and predicted gas concentrations during the majority of the time had similar median, spread, and skewness, which indicated that these comparative data sets were generally distributed in a similar way, which is an indication of good model performance. However, significant differences between the two data sets in some months can be seen, e.g., gas (NH₃, H₂S, and CO₂) concentration predictions in December, NH₃ concentration predictions in April, H₂S concentration predictions in July, and CO₂ concentration predictions in February. The poor gas concentration predictions in December were probably due to two growth cycles appearing in the

same month, i.e., mature pigs (120 kg) were gradually shipped to market in early December and smaller pigs (~20 kg) entered at the end of December. During these times, air quality levels and indoor climate were highly influenced by the management of the swine barn and workers' involvement, which were not considered as a factor in the development of the BTA-AQP model. The poor NH₃ concentration predictions in April and CO₂ concentration predictions in February may be attributed to the relatively inaccurate ventilation rate estimations by the BTA model, which should be improved in future work (fig. 5). The poor H₂S concentration predictions in July could partially be explained by the fact that some important variables were excluded in the H₂S pre-

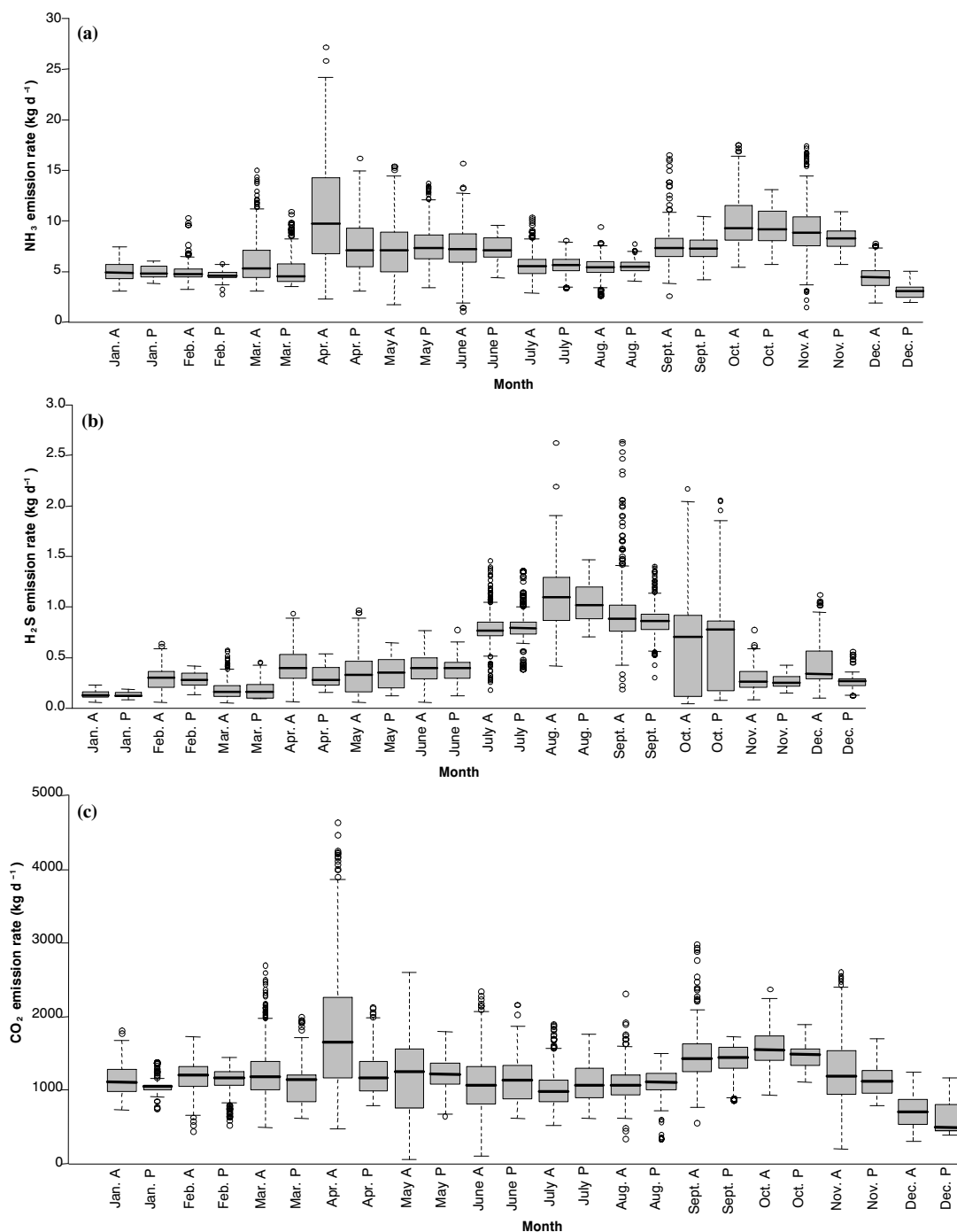


Figure 3. Actual vs. predicted hourly (a) NH₃, (b) H₂S, and (c) CO₂ emissions in 2003 (A = actual, P = predicted, and circles = potential outliers).

dictive model, such as manure characteristics and surface temperature. The manure temperature may be an important variable affecting H₂S release in hot weather. Moreover, in early July, some underestimated ventilation rates were observed at the beginning of a new swine growth cycle, resulting in a corresponding higher predicted H₂S concentration.

Comparative boxplots of hourly actual vs. predicted NH₃, H₂S, and CO₂ emissions for each month in 2003 are illustrated in figure 3. Overall, the median, spread, and skewness of the field-collected and predicted gas emissions were similar, except for February, April, and December. Again, the poor forecasting performances in February and April were mainly due to the fact that the relatively inaccurate ventilation rate predictions, in comparison to other monthly fitted values, led to greater error in gas emission calculation. For the poor predictions in December, the reason could be that the AQP model was not able to estimate gas concentrations resulting from barn management and pig activity, as previously outlined. Furthermore, it was found that the BTA-AQP model with an additional variable, in-house manure level, could largely improve H₂S prediction accuracy. When in-house manure level was incorporated into the model, the overall average absolute error (AE = 100% × |predicted - measured| / measured) dropped to 11% from an original 24% without manure depth considered. It should be noted that the data points that were outside the spread, as shown in figures 2 and 3, can be considered as potential outliers.

Table 1 summarizes the statistical performance of the BTA-AQP model for predicting hourly gas concentrations and emissions in 2003. The following statistical measures were employed to ensure the quality and reliability of the BTA-AQP model predictions. A more detailed description is given by Sun and Hoff (2010):

Mean absolute error:

$$MAE = \frac{1}{N} \sum_{i=1}^N |P_i - O_i| \quad (1)$$

Coefficient of mass residual:

$$CMR = \frac{\sum_{i=1}^N P_i - \sum_{i=1}^N O_i}{\sum_{i=1}^N O_i} \quad (2)$$

Index of agreement:

$$IoA = 1 - \frac{\sum_{i=1}^N (P_i - O_i)^2}{\sum_{i=1}^N (|O_i - \bar{O}| + |P_i - \bar{O}|)^2} \quad (3)$$

Nash-Sutcliffe model efficiency:

$$NSEF = \frac{\sum_{i=1}^N (O_i - \bar{O})^2 - \sum_{i=1}^N (P_i - O_i)^2}{\sum_{i=1}^N (O_i - \bar{O})^2} \quad (4)$$

where N is the total number of observations, P_i is the predicted value of the i th observation, O_i is the observed value of the i th observation, and \bar{O} is the mean of the observed values.

As shown in table 1, the annual predicted averages and standard deviations (SD) of the gas concentrations and emissions were in very good agreement with the actual measurements. For all the parameters, the MAE/SD ratios were less than 0.5, indicating that the BTA-AQP models' performance for the residual variations was very good. The CMR values approximated 0, meaning that there was no systematic under- or overprediction by the BTA-AQP model. The IoA values were close to 1, implying excellent agreement between the observed and predicted values. The NSEF values were greater than 0.5, indicating that the simulated data matched the measured data very well. Therefore, the BTA-AQP model was able to accurately predict indoor climate and gas concentrations and emissions from the monitored swine deep-pit building.

LONG-TERM NH₃, H₂S, AND CO₂ CONCENTRATIONS AND EMISSIONS

A comparison was made between the TMY3 data set and the long-term mean weather data and the corresponding air quality predicted by the BTA-AQP model in order to investigate how the air quality values using TMY3 data followed the actual long-term means (figs. 4 to 7). The long-term period selected for this study was 2004 to 2008 due to the availability of a complete on-line weather data set for the region near the monitored swine facility. Hourly predictions were made using on-site weather data for each year (2004 to 2008, inclusive), with the monthly average minimum and maximum predictions determined. The maximum and minimum designations were determined by month and not year, e.g., the predicted minimum in January and the predicted minimum in February could have occurred in different years. The Des Moines International Airport was chosen as the TMY3 site, which is about 100 km away from the swine facility used for field data collection, since it is the closest Class I site in the Iowa TMY3 data set. Class I stations are those with the lowest uncertainty in weather information. In addition to the predictions made with on-site weather data from 2004-2008 and the predictions using TMY3 weather data, the actual measured monthly averages from 2003 are given for completeness (figs. 4 to 7).

Figure 4 illustrates the relationships among the long-term mean (i.e., on-site five-year average data), the TMY3 gener-

Table 1. Statistical performance of the BTA-AQP models.

| Parameter | Actual ±SD | Predicted ±SD | MAE | CMR | IoA | NSEF |
|------------------|-------------------------------------|---------------|--------------|-------|--------|------|
| NH ₃ | Concentration (ppm) | 19.9 ±6.8 | 20.5 ±6.7 | 0.9 | 0.028 | 0.99 |
| | Emission rate (kg d ⁻¹) | 6.86 ±2.04 | 6.38 ±1.78 | 0.14 | 0.005 | 0.99 |
| H ₂ S | Concentration (ppb) | 553 ±260 | 560 ±254 | 57 | 0.013 | 0.97 |
| | Emission rate (kg d ⁻¹) | 0.473 ±0.295 | 0.463 ±0.295 | 0.056 | -0.022 | 0.98 |
| CO ₂ | Concentration (ppm) | 2636 ±1618 | 2674 ±1601 | 68 | 0.015 | 0.99 |
| | Emission rate (kg d ⁻¹) | 1226 ±280 | 1143 ±210 | 116 | -0.068 | 0.83 |

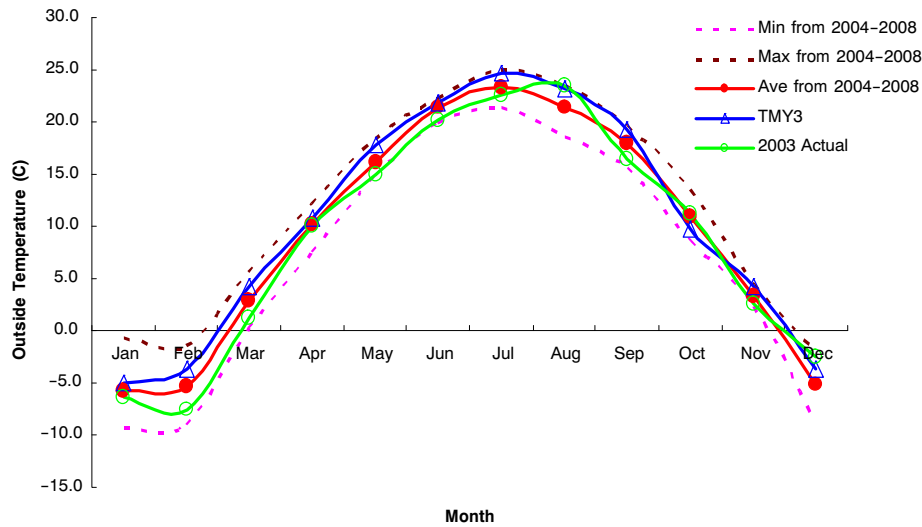


Figure 4. TMY3 vs. long-term means and 2003 field data for the outside temperature.

ated values, and 2003 field measurements for outside temperature. The minimum and maximum dashed lines represent the minimum and maximum ranges of the outside temperature during the selected five-year period (2004-2008). It was observed that the TMY3 data and 2003 field measurements fell within the min-max range, but some noticeable differences between the TMY3 and the long-term means were evident, especially in February, May, August, and December. The overall absolute error between those two data sets was 16.3% throughout the year. In addition, the differences between 2003 field data and the long-term means can be seen in February, March, August, and September.

Figures 5 and 6 summarize monthly ventilation rate and indoor temperature estimated by the BTA model (Sun and Hoff, 2010) using the TMY3 data set and the on-site 2004-2008 weather data, respectively. The 2003 field measurements and the minimum and maximum ranges of the predicted ventilation rate and indoor temperature during the selected five-year period are shown in figures 5 and 6 as well. The monthly ventilation rate predictions based on TMY3 data were higher than the long-term means during warm weather but closely matched the long-term means during

cold weather (fig. 5). This was probably caused by a discrepancy in outdoor temperatures between the TMY3 data set and the 2004-2008 weather data, i.e., a relatively higher outdoor temperature using TMY3 in the summer resulted in a higher estimated ventilation rate. Conversely, the predicted indoor temperatures were in good agreement with the long-term means (fig. 6). The overall absolute error was less than 2.0%. Furthermore, the 2003 field-measured ventilation rates fell into the ranges of min-max expect for January, February, and April, while for all 12 months of the year, the 2003 field indoor temperatures were slightly higher than TMY3 predictions and long-term means. These differences between the 2003 actual data and TMY3 predictions could be due to different outside weather conditions and the forecasting error of the BTA model.

The monthly air quality predictions using the TMY3 data were compared with the averaged results of the five-year period and the 2003 field measurements, as illustrated in figures 7, 8, and 9. It was found that: (1) the NH_3 , H_2S , and CO_2 concentrations and emissions obtained by the TMY3 data set and the long-term air quality means were between the minimum and maximum values of the five individual year

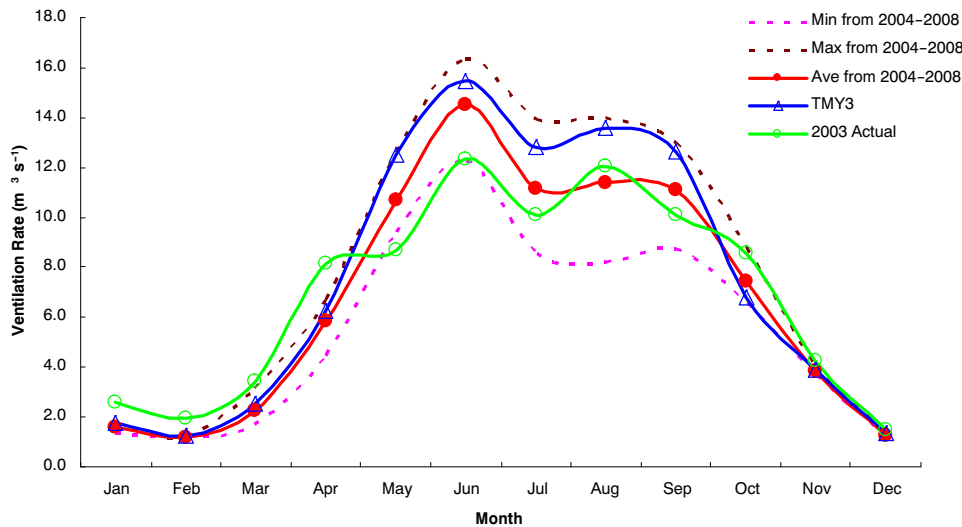


Figure 5. TMY3 predictions vs. long-term means and 2003 field data for the estimated ventilation rate.

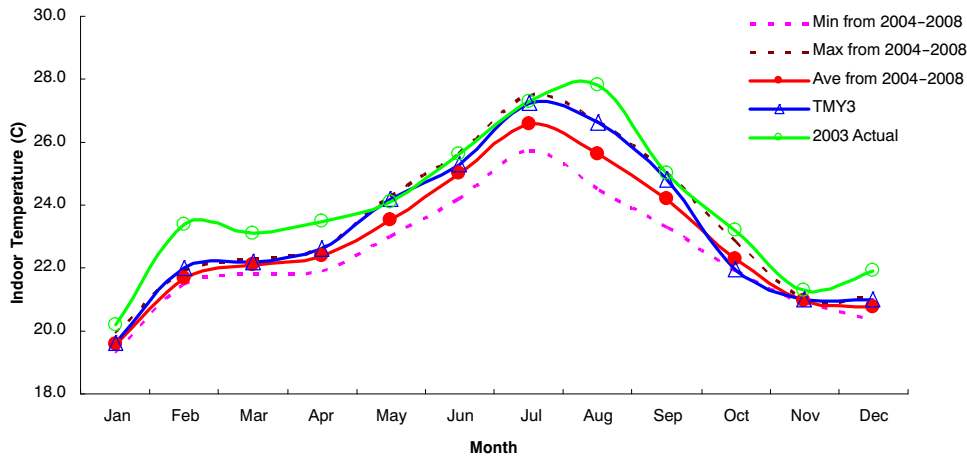


Figure 6. TMY3 predictions vs. long-term means and 2003 field data for the estimated indoor temperature.

simulations, e.g., each of the five predicted data sets used one year of weather data from 2004 to 2008; (2) the TMY3 predictions followed the long-term means well; and (3) although the majority of the 2003 field measurements were within the min-max ranges of the predictions using on-site 2004-2008 weather data, some distinct differences between the actual data and the TMY3 predictions can be observed in figures 7, 8, and 9 (e.g., NH_3 emissions in January and April; H_2S concentrations in December; H_2S emissions in April, July, and December; CO_2 concentrations in December; and CO_2 emissions in January, March and April). Again, these distinct dif-

ferences were mainly attributed to different outside weather conditions and the forecasting error of the BTA model.

It can be further seen that the TMY3 values were within 6.0%, 7.0%, and 5.1% of the mean weather year (2004-2008) annual total for the NH_3 , H_2S , and CO_2 concentrations, respectively, and within 2.1%, 3.5%, and 2.6% of the mean weather year (2004-2008) annual total for the NH_3 , H_2S , and CO_2 emissions, respectively. These good agreements between the TMY3 data set predictions and the long-term means indicate that TMY3 data can be used in performing accurate long-term simulations of source air quality.

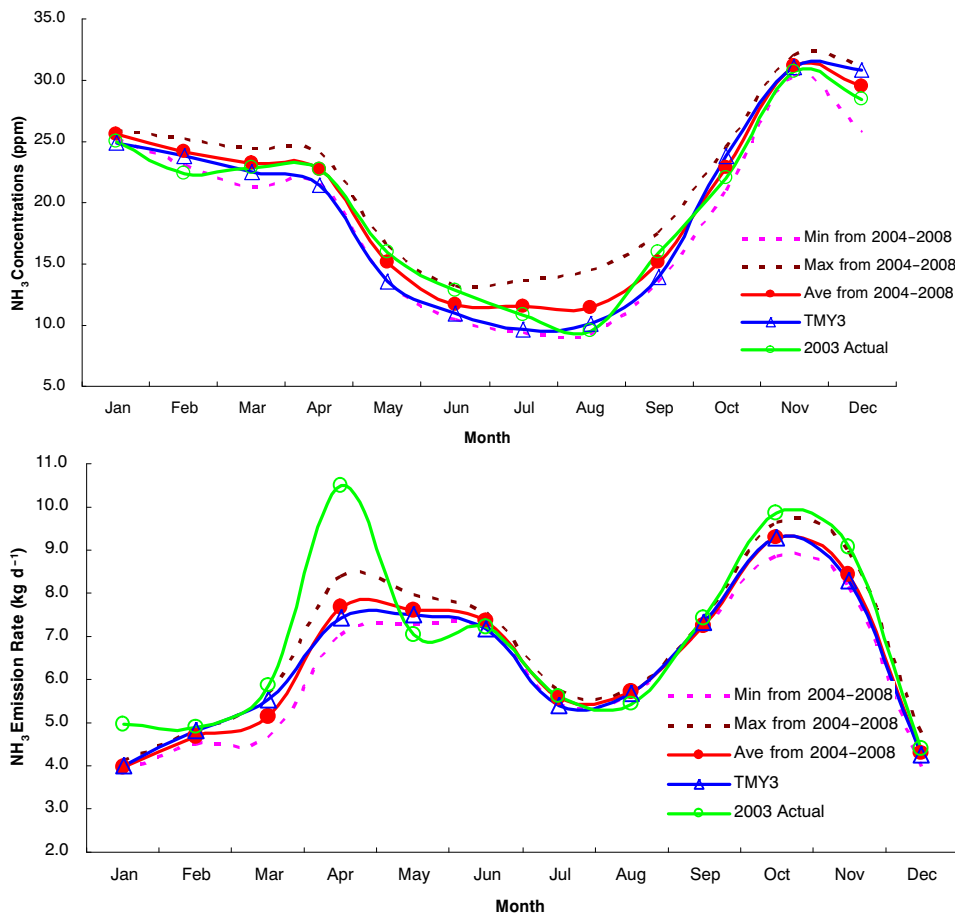


Figure 7. TMY3 predictions vs. long-term means and 2003 field data for monthly NH_3 concentrations and emission rates.

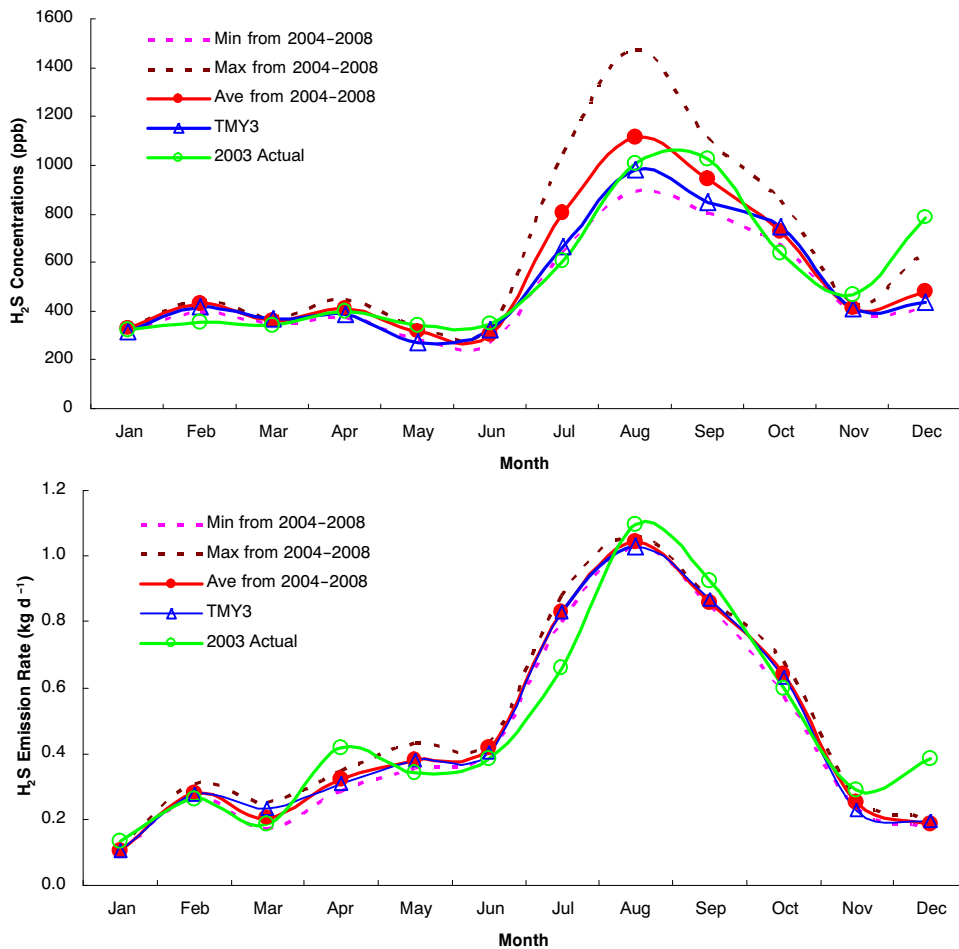


Figure 8. TMY3 predictions vs. long-term means and 2003 field data for monthly H₂S concentrations and emission rates.

Table 2 gives the absolute errors between annual averaged predictions using the TMY3 data and the predictions using a single year of weather data from 2004-2008. No major differences were observed between annual TMY3 predictions and any one single year. The minimum AE (2.0%) occurred with NH₃ emissions in 2004, while the maximum AE (11.1%) appeared in H₂S concentration in the same year, which suggests that annual gas concentrations and emissions can be obtained using a TMY3 data set instead of an individual year of weather data without resulting in large errors. These results show that a Class I TMY3 data set can be employed to evaluate annual air quality levels with an acceptable accuracy, especially for livestock producers and environment researchers who might not be able to acquire complete, Class I level local weather information near a particular animal facility. However, it should be noted that the TMY3 data are not appropriate to estimate peak values for a particulate period of time.

Table 2. Comparison of predicted air quality using TMY3 and a single year (ER = emission rate).

| Year | NH ₃ | | H ₂ S | | CO ₂ | |
|------|-----------------|--------|------------------|--------|-----------------|--------|
| | Conc. (%) | ER (%) | Conc. (%) | ER (%) | Conc. (%) | ER (%) |
| 2004 | 8.3 | 2.0 | 10.4 | 3.5 | 6.5 | 3.1 |
| 2005 | 6.5 | 4.0 | 7.1 | 6.0 | 5.4 | 4.2 |
| 2006 | 5.2 | 3.7 | 8.9 | 7.1 | 4.3 | 6.0 |
| 2007 | 5.6 | 2.2 | 7.3 | 4.7 | 5.5 | 3.5 |
| 2008 | 8.7 | 4.6 | 7.9 | 6.7 | 8.0 | 4.8 |

OVERALL MODEL ERROR ANALYSIS AND FUTURE WORK

The developed BTA-AQP model with TMY3 data can be used for accurately predicting indoor climate and long-term gas concentrations and emissions, but improvement in its accuracy should be made according to the following sources of error:

Uncertainties in Source Air Quality Data

Since the source air quality data are important to develop the BTA-AQP model and evaluate the model predictive performance, more efforts should be made to maximize the confidence, credibility, and consistency of the measured data.

Prediction Errors of the BTA Model

As the number of assumptions in a model increases, the accuracy and relevance of the model diminishes. For example, the swine heat production data used in this research were from ASABE Standards established decades ago. With improved genetics, feed management, and diets, swine heat production (HP) has changed. Brown-Brandl et al. (2004) reported that the lean percent increase of 1.55% in the last ten years has caused an increase in HP by approximately 15%. Future work is needed to collect new swine HP data from the latest literature.

Prediction Errors of the AQP Model

The accuracy of the artificial neural network AQP model depends on the completeness of the data set and availability of various model input factors that significantly affect source

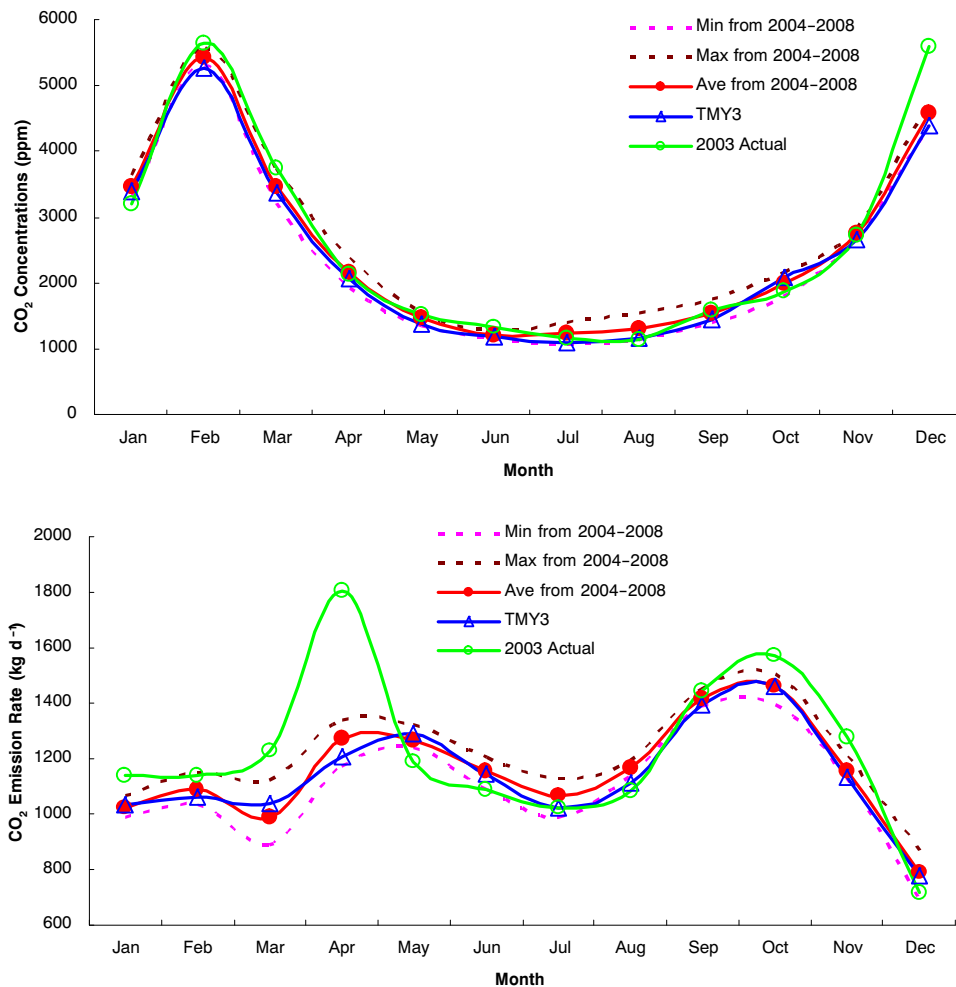


Figure 9. TMY3 predictions vs. long-term means and 2003 field data for monthly CO₂ concentrations and emission rates.

air quality. The complete emission profiles should cover all possible swine production stages for a long period of time. In this study, one-year source air quality data were used, which might not capture all of the relationships between gaseous concentrations and emissions and these input factors. More gas measurements are needed to expand the size of the data set. For the model input parameters, more important factors beyond indoor and outdoor temperatures, ventilation rate, swine growth cycle, and in-house manure storage level should be considered and incorporated into the model. Added variables such as feed nutrient content, management practices, and manure temperature might prove to be important input variables. When pigs grow, the amount and composition of the feed intake change, as do the amount and composition of the manure. Thus, the amount of gas generation tends to increase. However, sharp decreases in the amount of daily nitrogen excretion were found when diet formulation changes were implemented. This adjustment process alleviates the amount of nitrogen in the manure converted to ammonia and other gases. Swine management practices are also vital factors to determine air quality levels. Good management practices can maintain proper environmental requirements for the animals and decrease daily air emissions. Manure temperature might be a factor that may directly influence H₂S release.

Bias Error of TMY3 and its Limited Application

Uncertainty values exist in the meteorological elements of the TMY3 data set (NSRDB, 2008). Additionally, TMY3 data are suitable for simulating solar energy conversion systems and building systems, since each TMY3 month was selected according to five elements (global horizontal radiation, direct normal radiation, dry bulb and dew point temperatures, and wind speed) that are the most important for solar energy and building systems. No literature has shown that the TMY3 data are suited to air quality predictions as well. Therefore, further research may focus on the development of new TMY data that are determined to be more appropriate for air quality simulations.

SUMMARY AND CONCLUSIONS

The overarching goal of this study was to develop a building thermal analysis and air quality predictive (BTA-AQP) model to quantify indoor climate and long-term air quality (NH₃, H₂S, and CO₂ concentrations and emissions) from swine deep-pit buildings.

A comparison was made between the predicted and actual gas concentrations and emissions collected in 2003 in order to evaluate the accuracy of the BTA-AQP model estimates. It can be observed from the comparative boxplots that the median, spread, and skewness of the field-collected and pre-

dicted gas concentrations and emissions were similar. Poorer predictions in some of the months could be due to the relatively inaccurate ventilation rate predictions by the BTA model and the AQP model's inability in estimating gas concentrations resulting from barn management and pig activity. For all the predicted parameters, the MAE/SD ratios were less than 0.5, the CRM values approximated 0, the IoA values were close to 1, and the NSEF values were greater than 0.5. These good model performance ratings indicated that the BTA-AQP model was able to accurately predict indoor climate and gas concentrations and emissions from swine deep-pit buildings.

The monthly air quality values estimated by the BTA-AQP model using TMY3 data were compared with those using five-year on-site weather data. It was observed that the predictions using the TMY3 data followed the long-term mean patterns very well, which suggests that the TMY3 data can be used in performing accurate long-term simulations of source air quality. In addition, annual gas concentrations and emissions can be obtained using TMY3 data instead of an individual year weather data without resulting in large errors. These results demonstrate that a convenient approach to evaluate annual air quality levels within an acceptable accuracy is possible without long-term expensive on-site measurements. However, it should be noted that the TMY3 data are not appropriate to estimate peak values for a particulate period of time.

Improvement in the BTA-AQP model accuracy should be made according to four main sources of error: uncertainties in air quality data, prediction errors of the BTA model, prediction errors of the AQP model, and bias errors of the TMY3 data and its limited application.

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