2011

Simulation of Impacts of Different Animal Management Practices and Geographic Area on Long-Term Air Quality

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Abstract

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Keywords

Air quality, Animal management practices, Geographic areas, Livestock, Simulated impacts

Disciplines

Agriculture | Bioresource and Agricultural Engineering

Comments

This article is from *Transactions of the ASABE* 54, no. 4 (2011): 1465–1477.

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G. Sun, S. J. Hoff

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Source airborne pollutants within and from livestock production facilities are affected by barn characteristics, outdoor weather conditions, indoor climate, diurnal and seasonal effects, animal growth cycles, in-house storage levels, and barn management. Studying the impacts of these factors on air quality is very important for helping environmental researchers and animal producers understand the parameters influencing livestock air quality so that they might make wise decisions regarding the selection and implementation of odor and gas mitigation techniques.

Most recent studies have investigated the effects of several parameters, such as sampling sites, time of day, season, ambient air temperature, building ventilation rate, flooring systems, and pen hygiene on the odor and gas concentrations and emissions (OGCERs) for various animal facilities (Aarnink et al., 1995; Groot Koerkamp et al., 1998; Zhu et al., 1999; Ni et al., 2002; Gay et al., 2003; Jacobson et al., 2005; Guo et al., 2006; Hoff et al., 2006; Banhazi et al., 2008a, 2008b; Seedorf et al., 1998; Sun et al., 2008b, 2010c). However, few have explored how animal management practices (e.g., the thermal insulation characteristic of an animal building, barn setpoint temperature scheme, and animal production schedule) and geographic factors impact long-term source air quality. It is reasonable to hypothesize that enforcing different animal management policies may be a simple, inexpensive, and effective abatement strategy to reduce airborne pollution, although no evidence to support or refute this hypothesis was found in the literature.

Absence of evidence in the literature might be attributed to several factors. Firstly, testing the hypothesis is almost impossible in the field since actual animal buildings are not currently configured as laboratory testing rooms to allow changes to barn operational parameters for a period of time (e.g., from a couple of months to a year). Secondly, a laboratory testing room is inappropriate for use in hypothesis validation because it misses complexities in the real environment of animal buildings. Thirdly, conducting direct and long-term airborne contaminant measurements in different geographic areas is not practical due to complex experiment design, expensive monitoring system requirements, and high personal and management overhead.

On the contrary, the use of air quality predictive models could facilitate this type of hypothesis testing far more rapidly and economically than field or lab experiment methods. Therefore, the objectives of this research were to: (1) apply a validated building thermal analysis and air quality predictive model (BTA-AQP; Sun and Hoff, 2010a, 2010b) to different animal management practices and geographic area scenarios, (2) compare the corresponding air quality profiles with those under normal barn management conditions, and (3) assess the simulated impacts of the new scenarios on long-term air quality (ammonia, hydrogen sulfide, and carbon dioxide concentrations and emissions).

Submitted for review in November 2010 as manuscript number SE 8936; approved for publication by the Structures & Environment Division of ASABE in May 2011.

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  ISSN 2151-0032

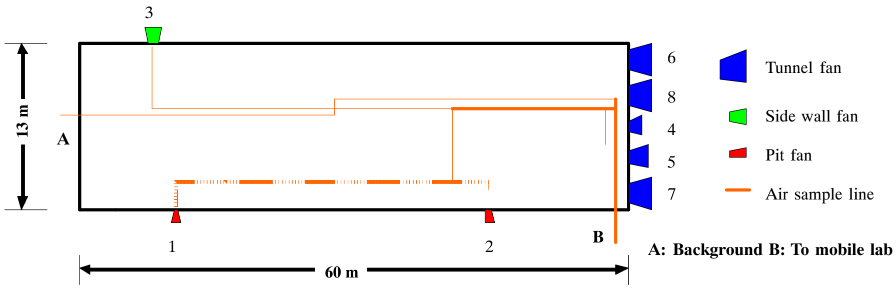


Figure 1. Layout of typical deep-pit swine finishing building.

Table 1. Statistical performance of the BTA-AQP model.[a]

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	0.97
NH_3 emission rate (kg d^{-1})	6.86 ±2.04	6.38 ±1.78	0.14	0.005	0.99	0.99
H_2S concentration (ppb)	553 ±260	560 ±254	57	0.013	0.97	0.88
H_2S emission rate (kg d^{-1})	0.473 ±0.295	0.463 ±0.295	0.056	-0.022	0.98	0.93
CO_2 concentration (ppm)	2636 ±1618	2674 ±1601	68	0.015	0.99	0.99
CO_2 emission rate (kg d^{-1})	1226 ±280	1143 ±210	116	-0.068	0.83	0.52

[a] MAE = mean absolute error, CMR = coefficient of mass residual, IoA = index of agreement, and NSEF = Nash-Sutcliffe model efficiency.

Materials and Methods

Typical Deep-Pit Swine Building Description

A mechanically ventilated deep-pit (2.4 m) swine finishing building, located in central Iowa, was modeled for this study. As shown in figure 1, this swine building was 60 m long and 13 m wide, designed to house 960 finishing pigs from ~20 to 120 kg. During cold-to-mild seasons, pit fans 1 and 2, sidewall fan 3, and tunnel fans 4 and 5 (fig. 1) combined with a series of ten rectangular center-ceiling inlets were used to distribute fresh air and remove moisture, odors, and aerosols within the building (Hoff et al., 2009). In warm and hot weather, all the fans (except sidewall fan 3) and an adjustable curtain at the opposing end wall were used to maintain a suitable indoor environment. The building shown in figure 1 was the basis for all field data collected and used for model validation, a topic covered in previously published literature (Sun and Hoff, 2010a).

BTA-AQP Model Description

The building thermal analysis and air quality predictive (BTA-AQP) model developed by Sun and Hoff (2010a, 2010b) was utilized in this research to predict source air quality from swine deep-pit buildings with different animal management practices and geographic area scenarios.

The BTA model is capable of acquiring the transient behavior of ventilation rate and indoor air temperature according to the thermophysical properties of a typical swine deep-pit building, setpoint temperature scheme, fan staging scheme, transient outside temperature, and the heat fluxes from pigs and supplemental heaters. The obtained ventilation rate and resulting indoor air temperature combined with animal growth cycle, in-house manure storage level, and outdoor weather data were fed into the AQP model (Sun et al., 2008a) to calculate hourly ammonia, hydrogen sulfide, and carbon dioxide concentrations and emission rates. The good model performance ratings and the graphical interpretations presented by Sun and Hoff (2010a, 2010b) indicate that the BTA-AQP model is able of accurately predicting indoor climate and air quality for a swine deep-pit building. Table 1 shows the good statistical performance of the BTA-AQP model.

To better compare air quality results among different scenarios, a typical meteorological year (TMY3) database (NSRDB, 2008) was used instead of the single weather year data used for the field measurements that were ultimately used to develop the BTA-AQP model. TMY3 consists of a multi-year, long-term (30 years) average measured data series that represents a year of prevailing weather conditions for a specific location. The Des Moines (DSM) International Airport was selected as the TMY3 site in this research for the normal barn management scenario. This TMY3 site is about 100 km away from the swine facility used for field data collection and was the closest Class I site (a Class I site has the lowest uncertainty in weather information) in the Iowa TMY3 dataset. Dallas TMY3 weather data were employed to compute long-term air quality in Texas, which was used to test the geographic area (GA) factor in this research.

Accuracy Evaluation of Simulated Results

Due to lack of field measurements, evaluating the accuracy of model simulations under different scenarios is a challenge to model users. Regarding the ANN (artificial neural network) based AQP model (Sun et al., 2008a), two important aspects, including proper model training methods and a high-quality training dataset, might be specially considered during the model development in order to gain reliable predicted values. In other words, these two aspects would have the model outputs approximate target values given new data that are not in the training set. Proper model training methods were presented in detail by Sun et al. (2008a), e.g., how to determine optimum values for the number of model layers and neurons, type of activation functions and training algorithms, learning rates, momentum, and smoothing factors. High-quality training datasets should possess three essential traits: a sufficiently large sample number, a representative subset, and complete information related to the target (Haykin, 1999).

The sufficient number of training samples for a given size neural network can be computed from the following:

$$N >= \log(n/(1-a)) * w/(1-a) \quad (1)$$

where

N = number of training samples

n = number of neurons in the network

a = desired accuracy on the test set

w = number of weights for the network.

In this research, n, a, and w were equal to 45, 90%, and 225, respectively (i.e., four inputs, 45 hidden neurons, and one output; thus, according to the network architecture, the number of weights is equal to 4*45 + 45*1 = 225). Thus, the minimum required sufficient number of training samples would be 5970. This study used a total of 7330 samples as the training dataset, which indicates that the AQP model contained sufficient information pertaining to livestock air quality. Furthermore, these training samples characterized nearly all cases of hourly air emission profiles and corresponding emission factors throughout the year and presented typical variation patterns of air emissions and emission factors under different weather conditions, such as cold, mild, and warm weather. Meanwhile, the collected training data covered a wide range of outside temperatures, from as low as -24°C to as high as 36°C, and included two complete animal growth cycles. One cycle was from early February 2003, when small pigs (~20 kg) entered the room, to the end of June 2003, when the larger pigs (~120 kg) were shipped to market. The other cycle was from the middle of July 2003 (~20 kg) to early December 2003 (~120 kg). Pigs of different ages experiencing cold-mild-warm seasons resulted in a range of setpoint temperatures, fan staging schemes, and animal heat fluxes and supplemental heaters and thus influenced the indoor climate (e.g., ventilation rate and inside temperature) and gas concentrations and emissions. In general, these cases expanded the representative samples in the training dataset and provided a solid basis for model generalization.

In addition to proper model training methods and a high-quality training dataset, another aspect of good model generalization is that a neural network performs best when using testing data that are within the range of the training dataset. In other words, to ensure the accuracy of the predictions, the cases from a new scenario should resemble the known training data to a large extent. If the new testing data falls within the range of the training samples or are more or less surrounded by neighboring training cases, then the values predicted by the AQP model are trustworthy. However, if the new cases fall far outside the range of the training data, then the predictions are scarcely reliable.

With the help of graphical presentations, a 3-D scatterplot (fig. 2) illustrates the relationship between the Dallas site GA scenario and the training dataset to demonstrate whether the Dallas results simulated by the AQP model are dependable and therefore acceptable. The Dallas site data were selected as an example because the difference between the Dallas cases and the training dataset was the largest among all the scenarios investigated in this research. It should also be pointed out that the air quality dataset has a five-dimensional input space, so it obviously could not be represented in a 3-D plot. This problem was solved using principle component analysis (PCA; Sun et al. 2008c), which is able to reduce the data dimensionality and transform a number of correlated variables into a smaller number of uncorrelated variables. After performing the PCA, the five-dimensional input space had five principle components (PC1 to PC5) based on five input variables (ventilation rate, indoor air temperature, animal growth cycle, in-house manure storage level, and outdoor temperature). Each PC, which was a linear combination of the five original variables, represented a significant variance of the whole dataset. The PCA results revealed that the fourth and fifth principle components (PC4 and PC5) were responsible for only about 3.76% and 5.44% of the total variance, respectively, and were certainly negligible factors. The first three PCs (PC1 to PC3) were able to explain more than 90% of the total variance, which suggested that the air quality data could be adequately described using the first three PCs (PC1 to PC3 in fig. 2) instead of the five original features.

As can be seen from the different viewing angles in figure 2, a majority of the data from the GA scenario (Dallas, Tex.) fell into the range of the training data, and some cases were encircled by nearby training samples. Only a few of the Dallas site data were far removed from the training cases. To avoid the viewing illusion that these two datasets looked closer than actual, the Bhattacharyya distance (B-distance) was employed to measure the similarity of their statistical distributions and determine the relative closeness of the two sample sets (Bhattacharyya, 1943). The closer the B-distance is to 0, the more similar the two datasets become. The Bhattacharyya distance coefficient was equal to 0.1643 and indicated that the Dallas site data and the training samples seemed to overlap. Thus, it can be concluded that the new cases from the Dallas site scenario could bear much resem-

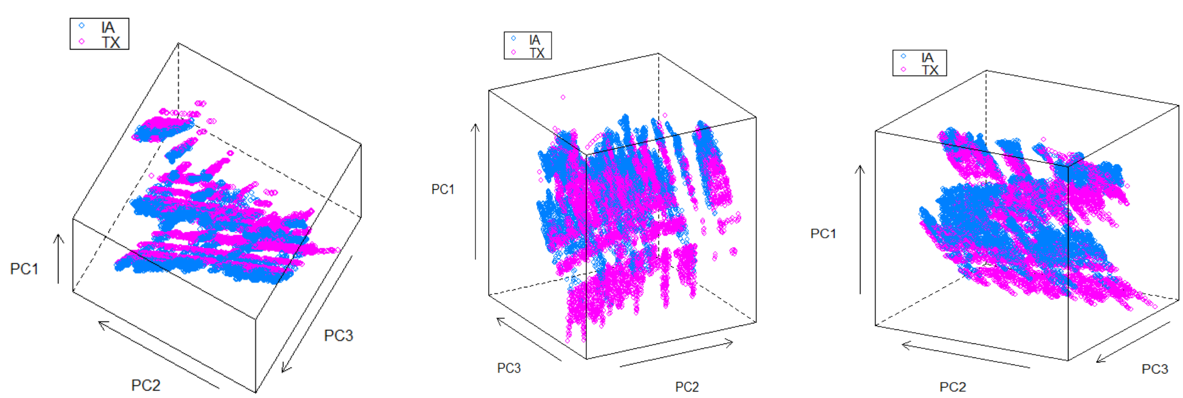


Figure 2. 3-D scatterplots of Dallas site cases vs. the training dataset from different viewing angles (IA = training data sampled in Iowa; TX = new cases predicted by the BTA model at Dallas site, Texas).

blance to the training data, and the corresponding predictions by the AQP model would be reliable. Likewise, the new cases from the other scenarios (BHLF, SPT, APS) resembled the training data as well.

Animal Management Practices and Geographic Area Scenarios

Different animal management practices and geographic area scenarios were tested to evaluate their possible effects on long-term air quality. In total, 24 air quality predictions (six NH_3, H_2S, and CO_2 concentration and emission simulations per scenario) were made by the BTA-AQP model using four new scenarios: building heat loss factor (BHLF), barn setpoint temperature (SPT), animal production schedule (APS), and geographic area (GA). The BHLF scenario assumed a 50% decline of the current BHLF value, which means that the typical deep-pit swine grower/finisher building was on average double-insulated. The barn SPT scenario decreased the originally tested setpoint temperature scheme by an average of 28.7% throughout the swine growth phase. The APS scenario would lead to a new animal growth cycle starting in mild weather instead of a warm or cold climate as was the case for the actual field measurements. For the GA scenario, Dallas, Texas, was selected as a new sampling site, representing a significant change in annual outdoor weather conditions from central Iowa. Conducting different animal management practices and finding an optimal BHLF, barn setpoint temperature, and animal production schedule may be a simple, inexpensive, and effective abatement strategy to reduce air pollution.

Table 2. Mean annual air quality simulations using different management practice and geographic area scenarios.

Statistic[a]	Scenario[b] DSM	BHLF	SPT	APS	GA
NH_3 concentration (ppm)					
Mean	19.5	19.4	19.0	20.5	13.7
SD	9.1	9.0	11.1	10.3	9.1
%	--	-0.3%	-2.4%	5.2%	-29.7%
NH_3 emission rate (kg d^{-1})					
Mean	6.65	6.66	7.08	6.21	6.93
SD	2.52	2.60	4.07	2.01	2.44
%	--	0.2%	6.5%	-6.6%	4.2%
H_2S concentration (ppb)					
Mean	519	510	370	534	424
SD	368	364	271	524	330
%	--	-1.7%	-28.6%	3.1%	-18.3%
H_2S emission rate (kg d^{-1})					
Mean	0.469	0.475	0.419	0.403	0.530
SD	0.346	0.347	0.360	0.306	0.411
%	--	1.3%	-10.7%	-14.2%	12.8%
CO_2 concentration (ppm)					
Mean	2334	2341	2084	2282	1696
SD	1335	1345	1084	1061	1124
%	--	0.3%	-10.7%	-2.2%	-27.3%
CO_2 emission rate (kg d^{-1})					
Mean	1176	1194	1217	1084	1159
SD	360	366	698	332	375
%	--	1.5%	3.5%	-7.8%	-1.5%

[a] SD = standard deviation, and % = the percentage difference between Des Moines and the different scenarios.

[b] DSM, BHLF, SPT, APS, and GA indicate average annual air quality in Des Moines (control) and air quality changed by different building heat loss factor, setpoint temperature, animal production schedule, and geographic area (Dallas), respectively.

Results and Discussion

Table 2 summarizes the mean annual simulated air quality values for the four scenarios. The Des Moines (DSM) scenario (a typical swine deep-pit building located in Des Moines under normal barn management conditions) was considered the control against which the other scenarios were compared. Side-by-side box plots were constructed to visually compare the sample distributions of the new scenarios with the DSM scenario. These boxplots provide a comparison of the location, spread, and shape of the distributions by showing the relative positions of the medians, the interquartile ranges (indicated by the heights of the boxes), the relative lengths of the whiskers, and the presence of outliers (at the ends of the whiskers). Table 2 and the associated boxplots for each scenario are discussed in the following sections. It should be understood that the results given are speculative and require field-collected data in an on-farm setting that could be adjusted according to the scenarios being suggested.

BHLF Scenario

The total building heat loss factor for the deep-pit swine building in Iowa monitored for this research was 965 W per °C (Sun and Hoff, 2010a). The BHLF scenario used half of that value, i.e., 482 W per °C, to test this scenario. This new BHLF would decrease energy loss through the building and thus affect inside room temperature as a function of ventilation rate and fan staging, all of which are modeled with the BTA model and are thus interrelated.

From table 2, the percentage difference in mean annual air quality data between the BHLF scenario and DSM scenario, calculated by (BHLF value - DSM value)/(DSM value), was very slight, within ±1.5%. This can be also verified in figure 3. The comparative boxplots of hourly gas predictions for each scenario show nearly the same median, spread, and skewness throughout the year, which suggests that these two datasets were generally distributed in the same way. Thus, the BHLF scenario had a negligible effect on the source long-term air quality ($p > 0.05$).

Barn SPT Scenario

Different setpoint temperature curves used in animal buildings would result in changes in the indoor climate during the animal production period, possibly affecting air quality parameters. Figure 4 shows two different SPT curves: one was the SPT curve used in the field study (DSM scenario), and the other was a new SPT curve, which decreased the current SPT by an average of 28.7% throughout the growth cycle (4°C to 6°C temperature setting reduction).

As shown in table 2, the SPT scenario reduced mean annual gas concentrations by -2.4% to -28.6% in comparison to the DSM scenario. It can also be seen that the largest decrease in gas concentrations was for H_2S (-28.6% reduction). This large reduction was probably due to a much higher ventilation rate as a result of the lowered setpoint temperature, especially during hot weather. Hence, increasing the ventilation rate would be a significant way to expedite the air exchange rate and substantially lower the indoor H_2S level. However, despite a large reduction in H_2S concentrations, the mean

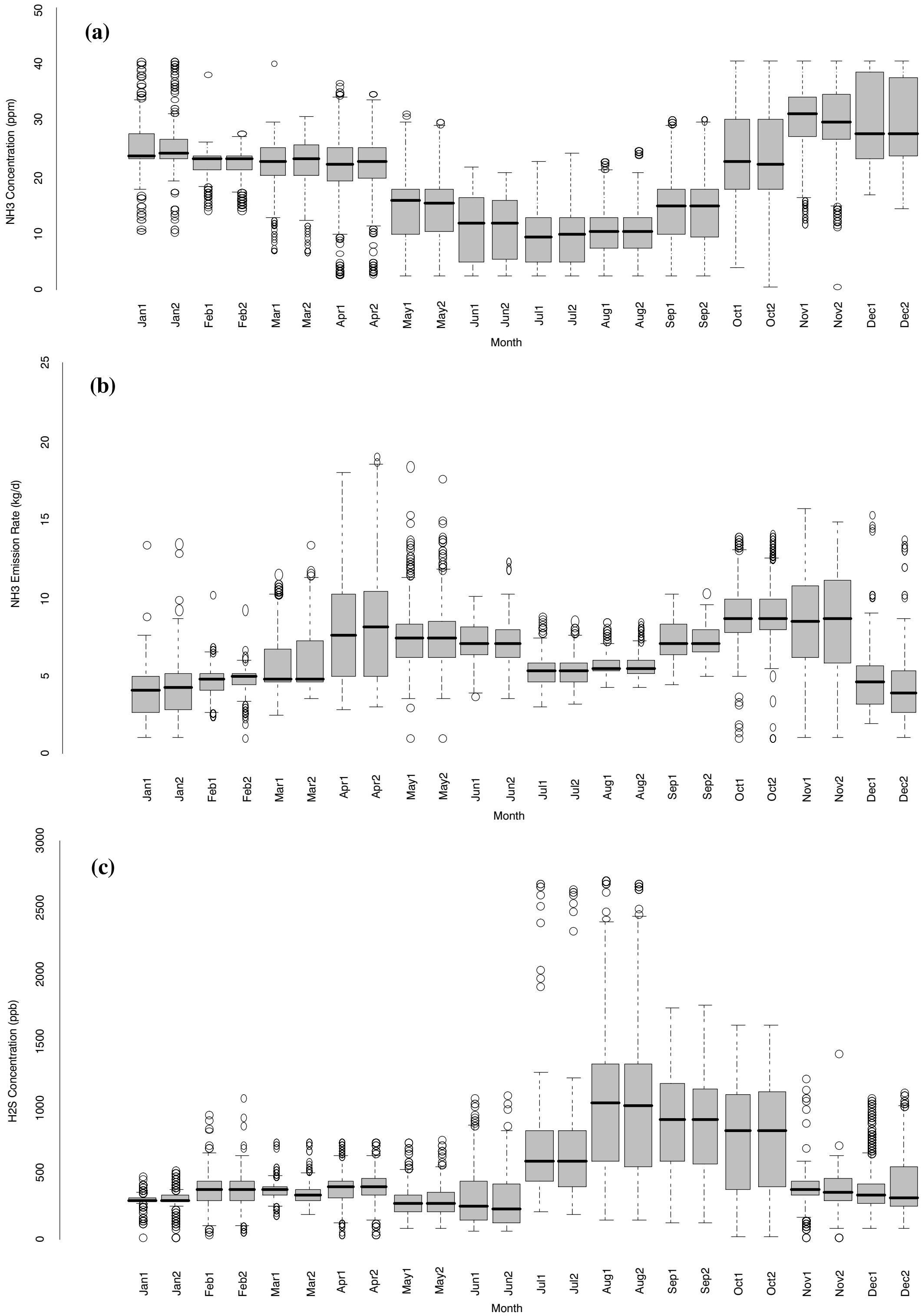


Figure 3. Long-term hourly NH_3, H_2S, and CO_2 concentrations (a, c, e) and emissions (b, d, f) for the DSM and BHLF scenarios (1 = DSM scenario, 2 = BHLF scenario, and circles = potential outliers) (cont'd).

annual NH_3 and CO_2 concentrations did not follow this reduction pattern. Contrarily, their mean annual emissions increased slightly, since the emission rate is the product of gas concentration and ventilation rate and there is an inverse relationship between them.

Figure 5 shows the long-term hourly NH_3, H_2S, and CO_2 concentrations and emissions over 12 months for the SPT and DSM scenarios. Compared with the DSM scenario for each month, the SPT scenario shows a decreasing trend in the magnitudes of location (as measured by the median) of the gas concentration distributions throughout the year, except for January, February, March, and April. Additionally, the observed shapes of these concentration distributions during April to September appeared to be right-skewed, with either long right tails or outside values on the right tail. The lower locations and right-skewed shapes indicate that the majority

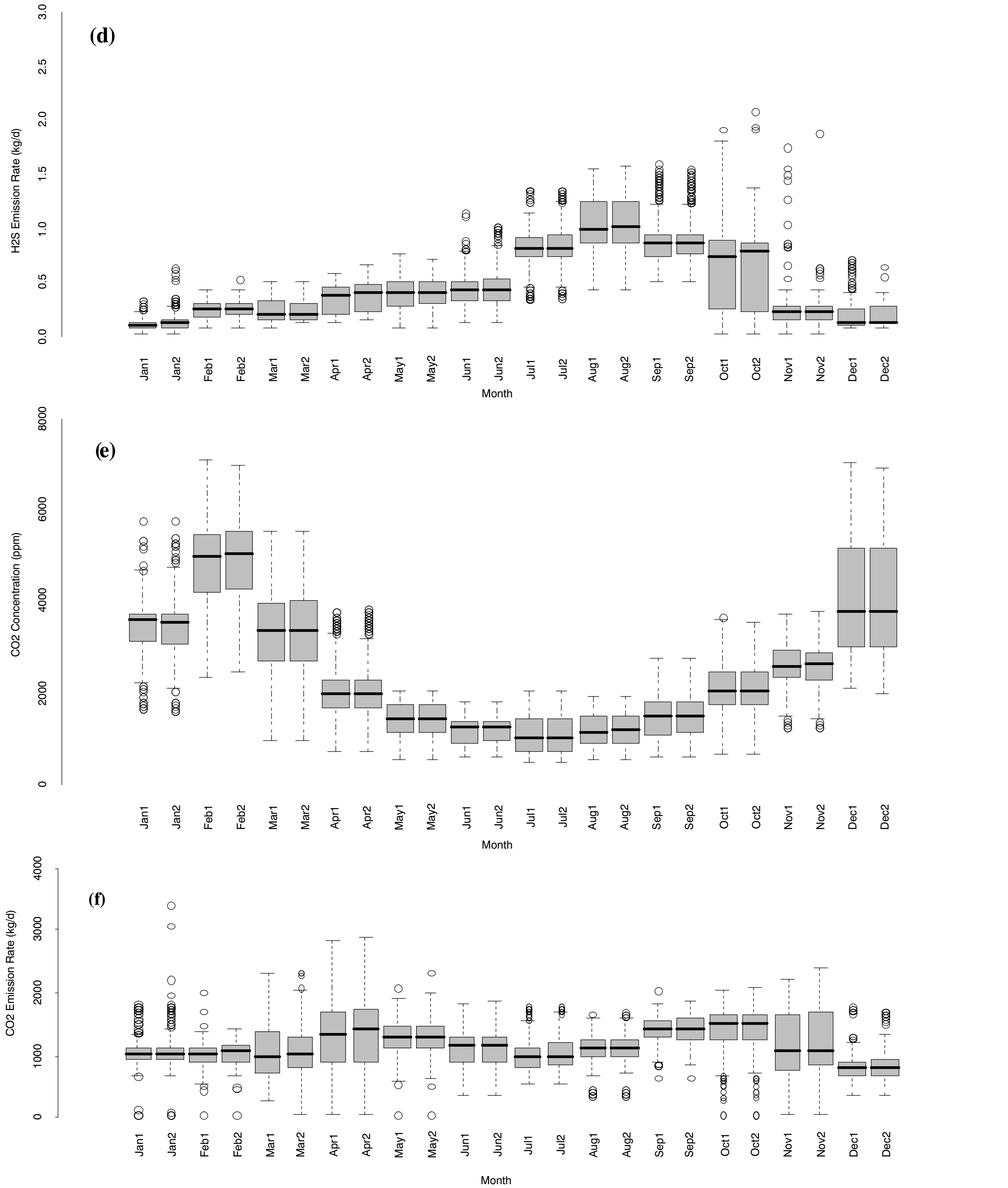


Figure 3 (cont'd). Long-term hourly NH_3, H_2S, and CO_2 concentrations (a, c, e) and emissions (b, d, f) for the DSM and BHLF scenarios (1 = DSM scenario, 2 = BHLF scenario, and circles = potential outliers).

of the predicted gas concentration data were highly concentrated in the very low range, and only few high values fell into the upper range, i.e., the SPT scenario was capable of reducing indoor gas levels during most times under warm weather due to higher ventilation rates. Meanwhile, the corresponding gas emissions did not increase significantly. Thus, the current barn setpoint temperature curves might be adjusted by setting a few degrees lower in warm season in order to reduce the risk of relatively high gas concentrations (especially H_2S concentrations) inside the building and protect the health of workers and animals.

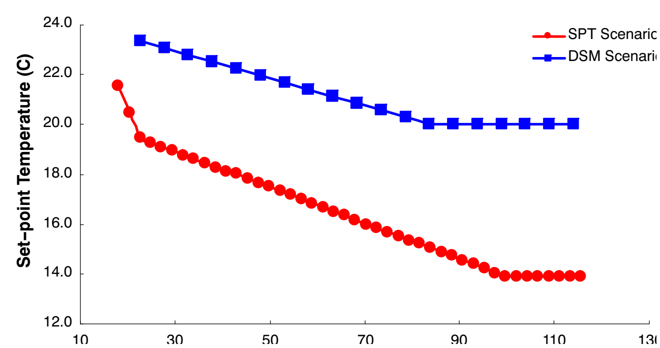


Figure 4. Setpoint temperature curves with the SPT and DSM scenarios.

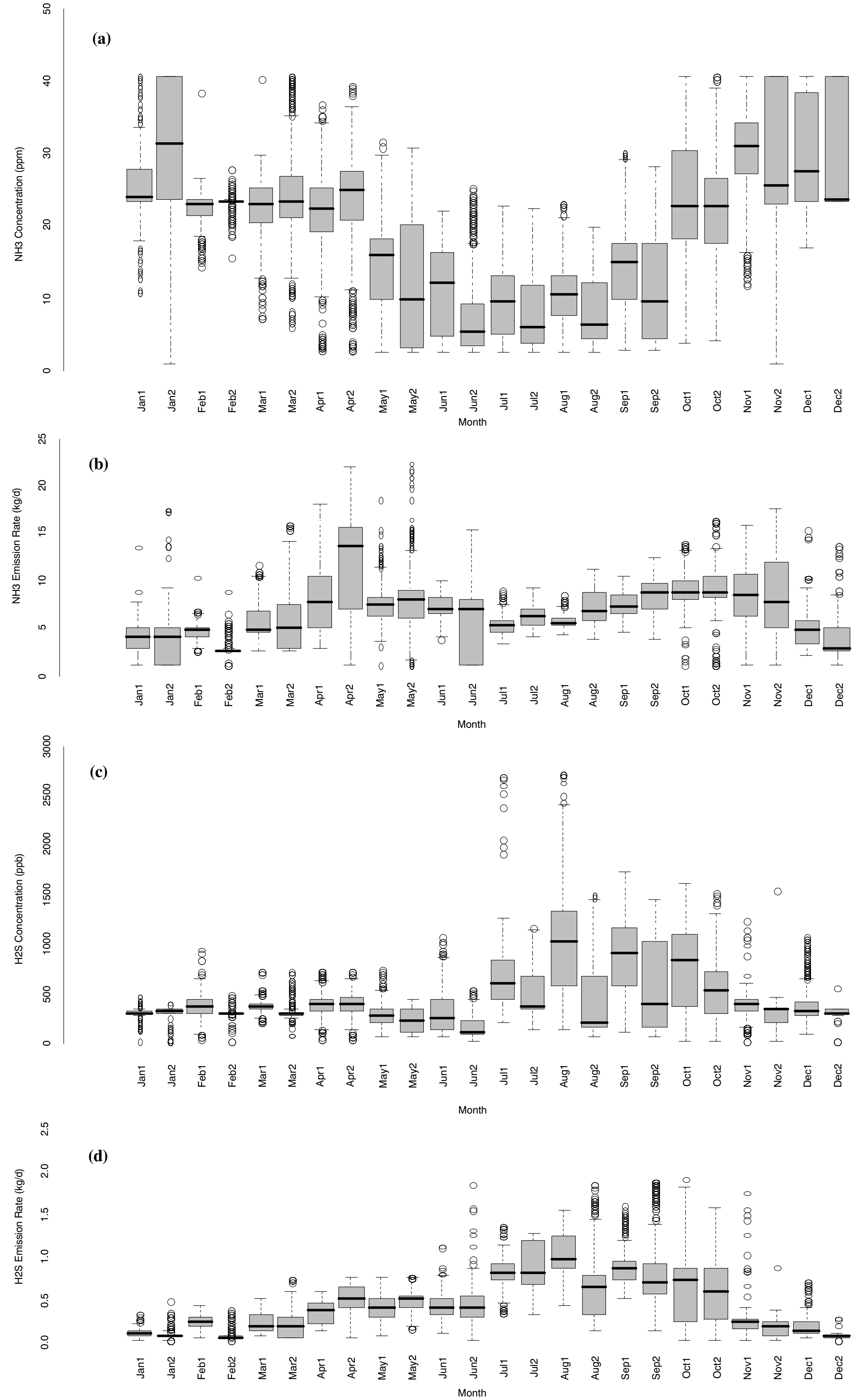


Figure 5. Long-term hourly NH_3, H_2S, and CO_2 concentrations (a, c, e) and emissions (b, d, f) for the DSM and SPT scenarios (1 = DSM scenario, 2 = SPT scenario, and circles = potential outliers) (cont'd).

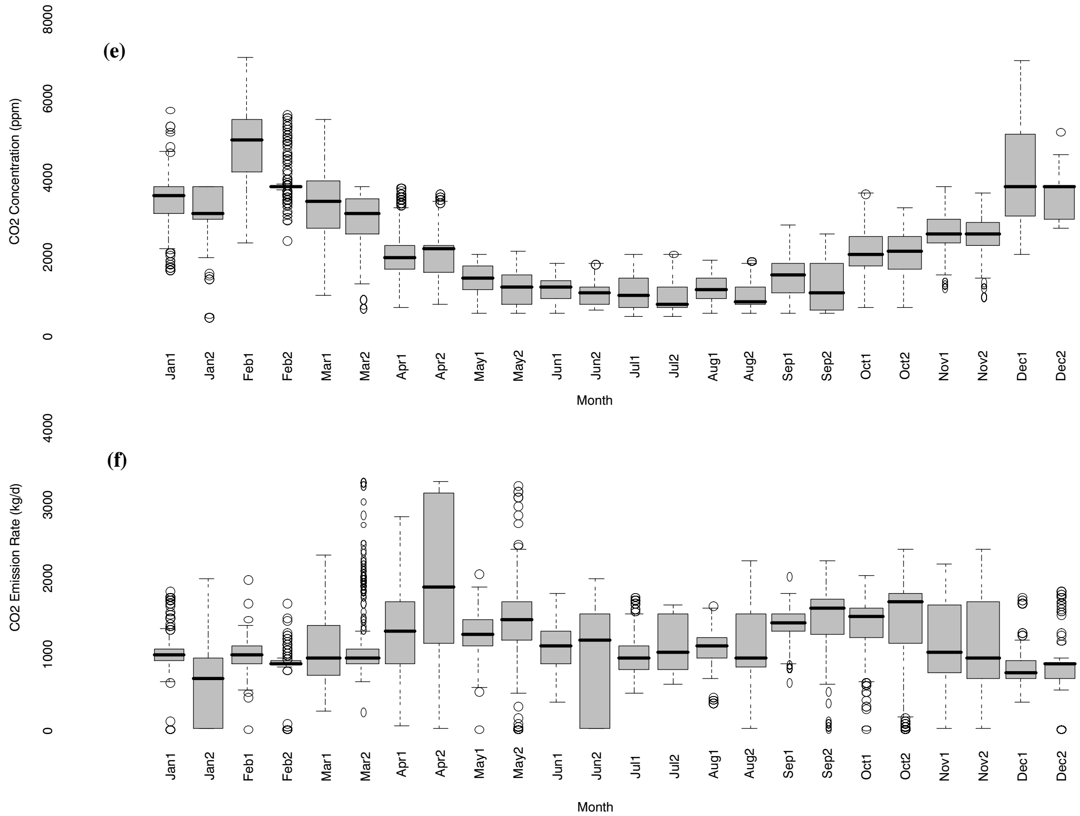


Figure 5 (cont'd). Long-term hourly NH_3, H_2S, and CO_2 concentrations (a, c, e) and emissions (b, d, f) for the DSM and SPT scenarios (1 = DSM scenario, 2 = SPT scenario, and circles = potential outliers).

APS Scenario

For grower-finisher swine production operations, animal growth cycle indicates the growth period as pigs mature from approximately 20 to 120 kg inside the building. Typically, one complete animal growth cycle for grower-finisher pigs is about 140 days or 4.5 months, and thus there are 2+ growth cycles in a year. These two growth cycles started either in the winter or in the summer during field measurements. Pig weight determined the indoor setpoint temperature, and different SPT settings during different seasons would conceivably impact diurnal and seasonal air quality. To study the effect of animal production schedule on long-term air quality, a new swine production timetable was established and used in this research. The starting date of this new timetable was on the first day of April.

The percentage difference between the APS and DSM scenarios ranged from -2.2% to 5.2% for the mean annual gas concentrations and from -6.6% to -14.2% for the mean annual gas emissions (table 2). The simulated results revealed that the new animal production schedule had no significant effect on gas concentrations ($p > 0.05$) but could cause a moderate decrease in gas emissions. The ventilation rate variation resulting from the new schedule might account for this emission reduction.

As shown in the boxplots in figure 6, the observed APS distributions of gas concentrations had different locations, spreads, and shapes compared with those of the DSM scenario. For example, the median of the APS NH_3 concentration in February was larger than that of the DSM distribution. This may be due to two reasons: one was that the larger pigs used for the APS scenario (87 to 105 kg per pig) produced more gas and manure waste than the smaller pigs (20 to 38 kg per pig) in the DSM scenario; the other was that to maintain the setpoint temperature during cold weather, a similar minimum ventilation rate was supplied for both scenarios. Hence, more gas accumulation inside the barn for the APS scenario resulted in much higher indoor NH_3 concentrations, while in July the APS scenario showed an obvious pattern, i.e., low locations and a right-skewed shape with heavy tail, for all gas concentrations. The possible explanation might be the lower setpoint temperature and the corresponding higher ventilation rate caused by the larger pigs during that time in the APS scenario. It can be further seen that, for all gas emissions, most APS emission distributions appeared to be similar to the DSM scenario distributions throughout the year, expect for July, September, and October. Again, the emission rate is a function of gas concentration and ventilation rate, and there is an inverse relationship between them.

GA Scenario

Different regions in the U.S. have different temperature, relative humidity, wind speed and direction, rainfall frequency and intensity, solar energy, and barometric pressure. These climatic factors might significantly influence gas concentrations and emissions if the rates of gaseous emissions were measured in different areas of the country (e.g., northern, midwestern, and southern). In this research, Dallas was used as a representative southern site to study the effect of a warmer geographic area on long-term livestock air quality.

Mean annual simulated NH_3, H_2S, and CO_2 concentrations decreased by -29.7%, -18.3%, and -27.3%, respectively, in comparison to those in Des Moines (table 2). The relatively high temperature and large ventilation rates in Dallas most likely accounted for this large reduction in gas con-

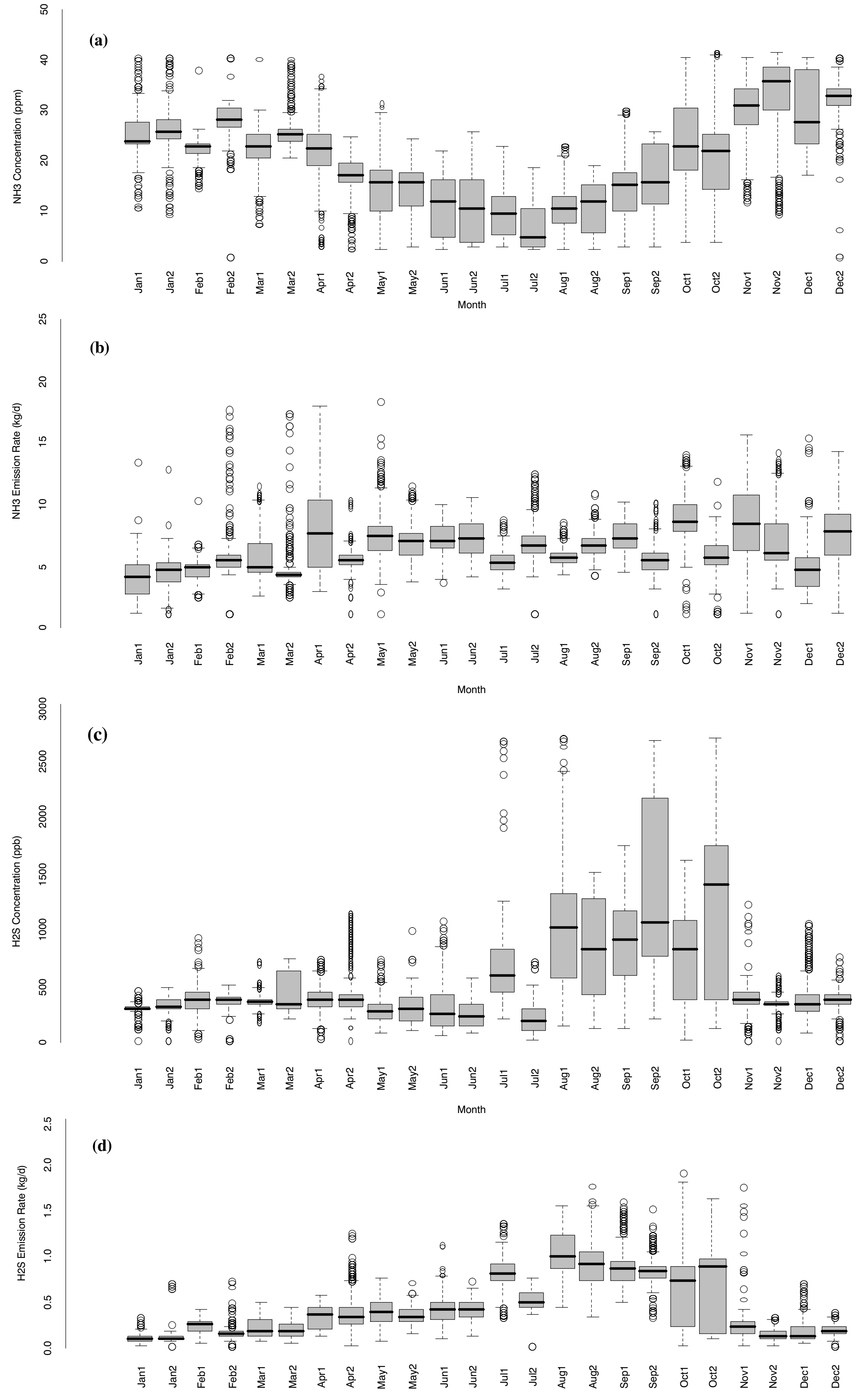
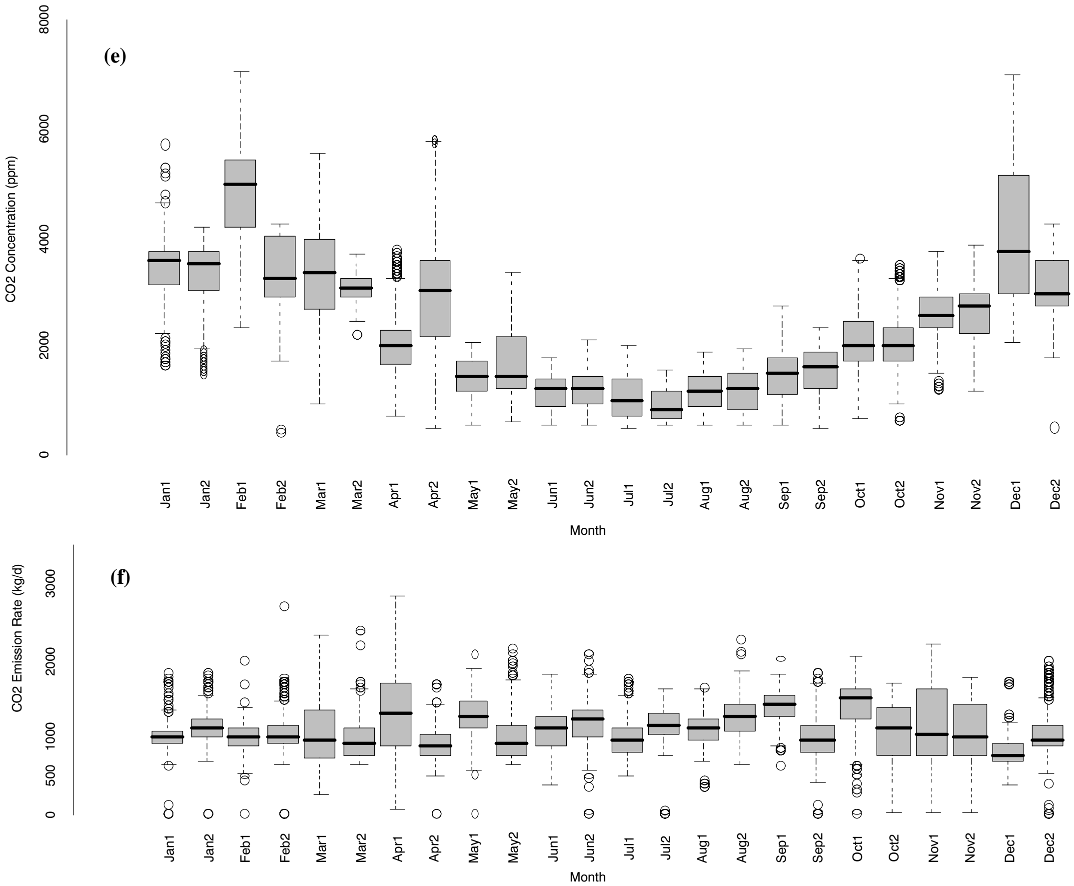


Figure 6. Long-term hourly NH_3, H_2S, and CO_2 concentrations (a, c, e) and emissions (b, d, f) for the DSM and APS scenarios (1 = DSM scenario, 2 = APS scenario, and circles =potential outliers) (cont'd).



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centrations. However, due to the inverse relationship of gas concentrations and ventilation rate, the estimations of gas emissions did not present a similar pattern. The BTA-AQP model predicted only -4.2%, -12.8%, and 1.5% declines in the NH_3, H_2S, and CO_2 emissions, respectively.

From figure 7, it is clear that the medians of the Dallas gas concentration distributions during a majority of the time were much lower than those of the DSM scenario, and their distributions were markedly shifted to the right of the locations, thus showing that most of the Dallas gas concentrations were regarded as very low values compared with the DSM distributions. For example, average monthly DSM NH_3 concentrations during the summer (June to September) were two times higher than the mean of the Dallas levels. Although there appeared to be a big difference between the DSM and Dallas scenarios for the gas concentration distributions, the boxplots of the gas emissions over 12 months look very similar. This could be explained by the gas concentrations varying inversely with the ventilation rate and ambient temperature. Therefore, it may be concluded that, for swine deep-pit barns with similar building characteristics and management practices, a different geographic area had a large impact on indoor gas concentrations but very little effect on mean annual gas emissions.

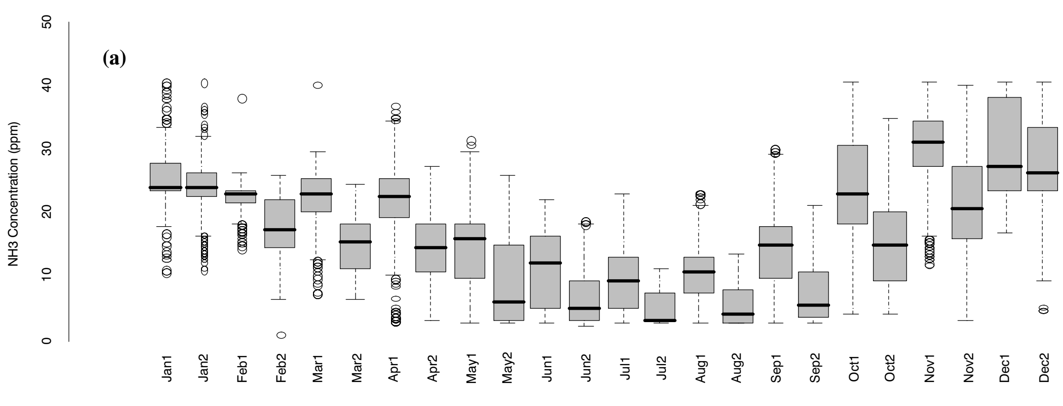

Figure 7. Long-term hourly NH_3, H_2S, and CO_2 concentrations (a, c, e) and emissions (b, d, f) for the DSM and Dallas scenarios (1 = DSM scenario, 2 = Dallas scenario, circles = potential outliers) (cont'd).

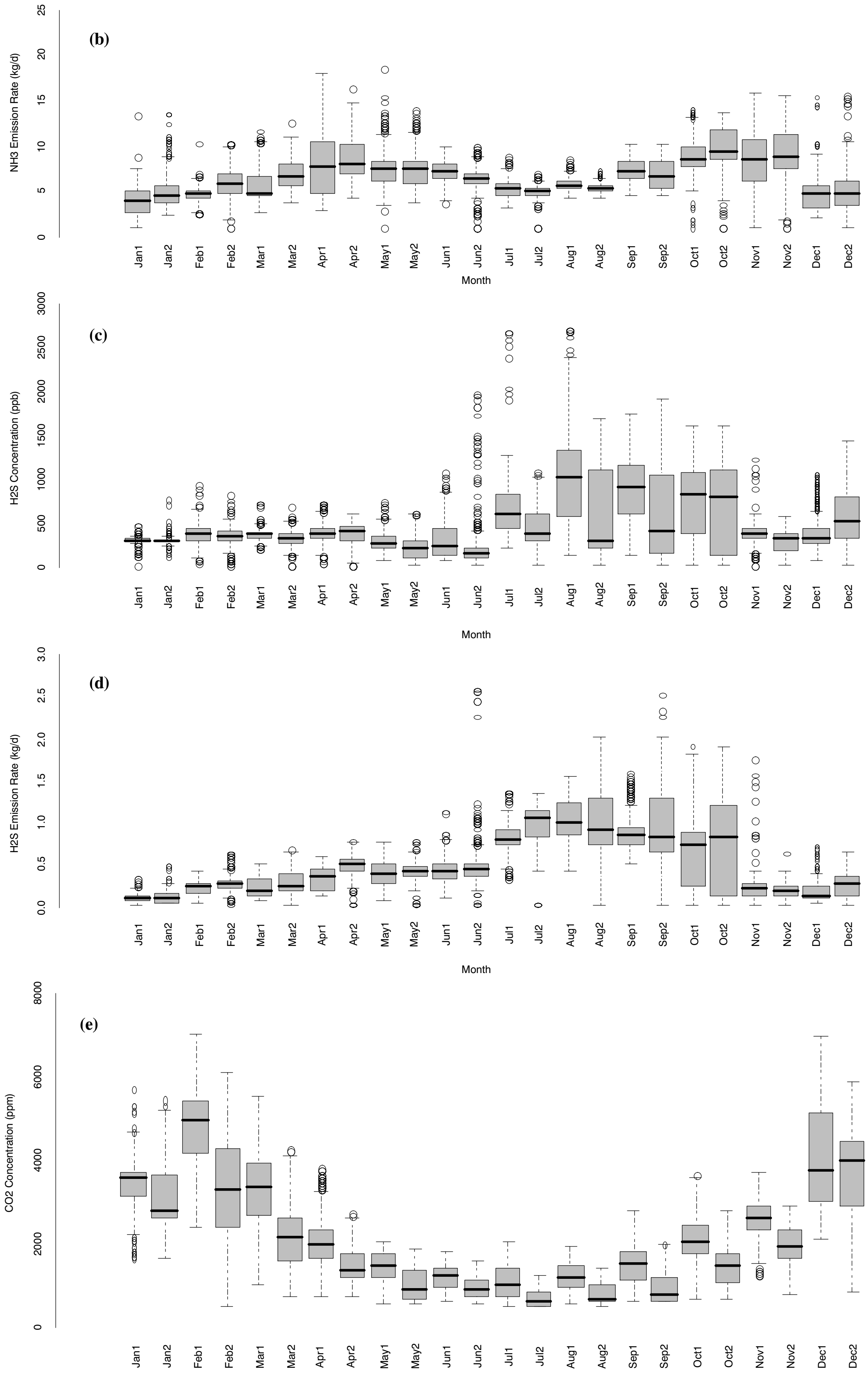

Figure 7 (cont'd). Long-term hourly NH_3, H_2S, and CO_2 concentrations (a, c, e) and emissions (b, d, f) for the DSM and Dallas scenarios (1 = DSM scenario, 2 = Dallas scenario, circles = potential outliers) (cont'd).

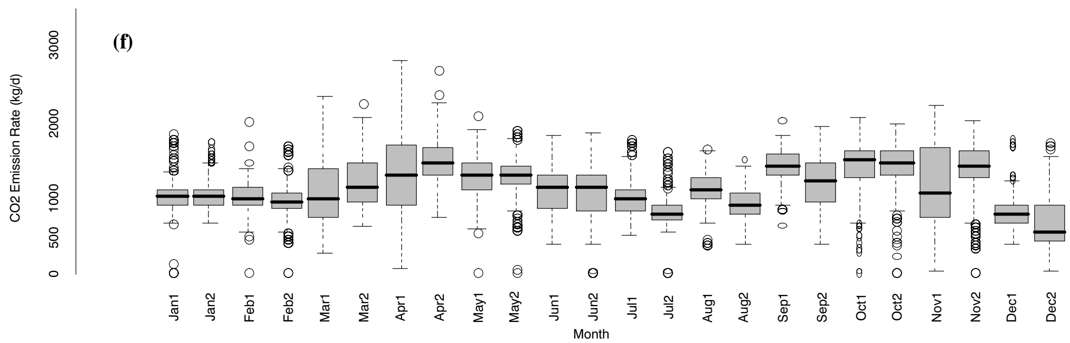

Figure 7 (cont'd). Long-term hourly NH_3, H_2S, and CO_2 concentrations (a, c, e) and emissions (b, d, f) for the DSM and Dallas scenarios (1 = DSM scenario, 2 = Dallas scenario, circles = potential outliers).

Summary and Conclusions

Studying the impacts of various important factors on air quality is vital for helping animal producers and environmental researchers understand the parameters that influence livestock air quality so that they might make wise decisions regarding the selection and implementation of gas/odor mitigation techniques. So far, few researchers have evaluated the possible effects of different animal management and geographic area factors on long-term source air quality because it is a complex and difficult task in the field.

In this research, a total of 24 air quality predictions (six NH_3, H_2S, and CO_2 concentration and emission simulations per scenario) were made by our validated BTA-AQP model using four new scenarios: building heat loss factor (BHLF), barn setpoint temperature (SPT), animal production schedule (APS), and geographic area (GA). The specific conclusions are:

- The BHLF scenario used a 50% decline of current BHLF value (965 W per °C), which had no effect on the source air quality.
- The SPT scenario (decreased current setpoint temperature by an average of 28.7% throughout the growth cycle) was capable of reducing indoor gas levels during most of the time under warm weather due to higher required ventilation rates. The corresponding gas emissions did not increase substantially. Hence, the current barn setpoint temperature curves might be adjusted lower in warm seasons in order to reduce the risk of relatively high gas concentrations (especially H_2S concentrations) in the building and protect the health of workers and animals.
- The new animal production schedule, which started pigs in the barn in mild weather (April 1), had no significant effect on mean annual gas concentrations but could cause a moderate decrease in mean annual gas emissions.
- Different geographic areas can have a large impact on indoor gas concentrations and ventilation rate but very little effect on mean annual gas emissions since the emission rate is a function of gas concentration and ventilation rate and there is an inverse relationship between them.

It should be noted that the simulated results are speculative. Although a great deal of effort has been made to guarantee the accuracy of the predicted values, some of the results of the scenarios are still incompletely understood. However, these outcomes could enrich our present knowledge in order to be prepared for future research.

Acknowledgements

The authors wish to acknowledge the USDA-IFAFS funding program for providing the funds required to collect the field data used in this research project, and the USDA Special Grants funding program for providing the funds for this specific research project. Their support is very much appreciated.

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