Downwind Odor Predictions from Four Swine Finishing Barns Using CALPUFF

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Abstract. A collaborative research effort by several institutions is investigating odor emissions from swine production facilities, and the impacts of those emissions on farm neighbours. Trained human receptors were used to measure the downwind odor concentrations from four tunnel ventilated swine barns near Story City, Iowa. Twenty-six measurement events were conducted between June and November 2004 and modeled using a specially coded short time-step version of CALPUFF to predict short time step durations. Source emission measurements and extensive meteorological data were collected along with ambient olfactometry analysis using the Nasal Ranger™ device (St. Croix Sensory, St. Paul MN). Approximately 64% of measured odor generally falls within the range of modeled values. Analysis of measured odor concentration and corresponding meteorology indicate that maximum ambient odor impacts occur with lower ambient temperature during non-turbulent conditions. Analysis of the data set did not yield a strong relationship directly (R²=0.33), but a regression analysis indicated that the modified CALPUFF model yielded a slope or scaling factor of 0.99, indicating overall a good relationship between model and observed. However, when the data is tested with the Spearman’s rank correlation coefficient an r_s of 0.17 was calculated, indicating a poor rank correlation and was not significant (p ≤ 0.05). Statistical analysis is inconclusive as to whether the results have bias, but indicate large error in the results. Given that there were no scaling or peak to mean ratio adjustments to the model predictions, the results are very promising for predicting odors using CALPUFF.

Keywords. CALPUFF, Odor modeling, field olfactometry, Nasal Ranger™ device

Introduction

Odor issues from livestock and poultry production facilities have become a limiting factor in the viability and growth of the agricultural sector in the United States. Many times odor issues generate nuisance complaints and are responsible for excessively conservative and arbitrary separation distances and setbacks in state regulations or local zoning regulations and comprehensive plans. Odor and gas dispersion of livestock facilities is a complicated process that depends on many factors, such as the production system, stocking density, season, localized weather patterns, terrain, and receptor locations relative to production areas. The National Research Council (NRC, 2003) suggested that one of the two major ways to deal with the effects of airborne emissions from animal feeding operations was to replace the current emission factor approach with process-based modelling. Methods and tools are needed to assist in describing the odor impact from new and existing facilities to the neighboring community in the United States. Such methods and processes would be valuable to the livestock and poultry industry and rural communities to aid in the siting of new facilities and the expansion of current production sites. Such a process would also be useful in the advancement and adoption of control and mitigation strategies, for which there is little justification or credit given for such technology in the siting process.

Currently there are several models being used in the United States to evaluate odor impact. Researchers at the University of Minnesota, have used INPUFF-2, a US EPA Gaussian puff model (Peterson and Lavdas,
1986)(Bee-Line Software co, Asheville, NC) to model odors in the development of OFFSET (Odor From Feedlots Separation Estimation Tool) (Jacobsen et. al, 2003). The University of Nebraska-Lincoln is using a Gaussian dispersion model, AERMOD (AMS/ EPA Regulatory Model) which was a model developed in a joint effort by the American Meteorological Society and the US EPA, the replacement to ISC3 (Industrial Source Complex), to develop the Odor Footprint Tool (OFT) (Koppolu et. al, 2004, Schulte et. al, 2004).

Lastly, Iowa State University is developing its own model, called CAM (Community Assessment Model) for predicting odor dispersions in a community (Hoff and Bundy, 2003)

DATA AND METHODOLOGY

Field Odor Measurements

Four locations downwind of the plume were selected by the principal investigators, the configuration was either a diamond pattern or transect along the centerline of the plume. At each location, duplicate measurements were taken using the following instruments or techniques. Hydrogen sulfide using a Jerome meter, olfactometry using 10 L tedlar bags for analysis at one of the Universities olfactometry labs, field intensity assessment technique based on an n-butanol standard, field olfactometry using the Nasal Ranger, and a limited number of Mask Scentometry assessments, using a device developed by Henry and Sheffield (Sheffield, et. al, 2004, Henry, 2004).

Assessments were taken for a period of 15 minutes by all of the techniques. For olfactometry, samples were drawn in over a 2-4 minute period at the start of the period and then again at the 7.5 minute mark, so the samples could be averaged for the period. Nasal Ranger assessments were taken twice during the 15 minute period. Nasal Ranger assessments were performed by operating the instrument at a high dilution to threshold value and decreasing (with a blank between each setting) until odor was detected. The assessor then reversed two steps (a blank and the previous dilution), then forward again to confirm the reading. This technique was performed at the start of the 15 minute run period and then again at the 7.5 minute mark (halfway). The average of both assessments were reported for the period.

All assessors recorded measurements on respective individual data sheets. A lead researcher synchronized his watch with the weather station clock so measurements would correspond to modeled data. The lead researcher would then start all of the assessors and people responsible for sampling at the same time.

Dispersion Modeling with CALPUFF

Plume dispersion modelling has undergone significant refinement in recent years. Steady state Gaussian plume air dispersion models such as ISC3, which formed the basis of air dispersion modelling, are now being replaced by a new generation of models, most notably the USEPA's CALPUFF. These new models incorporate many additional algorithms simulating influences which are ignored by the steady state Gaussian models but which are known to significantly impact plume dispersion.

The USEPA regulatory model, CALPUFF, overcomes the main limitations of the Gaussian models. It is a multi-layer, multi-species non-steady state puff dispersion model that can simulate the effects of time and space varying meteorological conditions on pollutant transport, transformation and removal (Scire et al., 2000). The model contains algorithms for near-source effects such as building downwash, partial plume penetration, sub-grid scale interactions as well as longer-range effects such as pollutant removal, chemical transformation, vertical wind shear and coastal interaction effects. The model employs dispersion equations based on a Gaussian distribution of pollutants across the puff and takes into account the complex arrangement of emissions from point, area, volume, and line sources.

These models generally depend on high definition meteorological data for best performance. The averaging times for the odor observations must be matched by the model’s temporal resolution. Normally, CALPUFF calculates hourly average concentrations based on hourly average meteorological data. However, PAE has coded a short time-step version of CALPUFF to deal with situations such as this. (Since this work, a new version of CALPUFF that permits sub-hour timesteps has been released.) The time-step has been reduced to 1 minute, which provides very good resolution. This short-step version of the model is available for the quasi-three dimensional mode operating with measured turbulence parameters.

CALPUFF requires the following input data:

- Meteorological data;
- Emission data;
- Facility layout and dimensions; and
- Receptor information.

Meteorological Data

For this project, extensive meteorological data were collected from the following two weather stations:
- A 10 meter tower measuring temperature, relative humidity, wind direction and speed (cup), and net solar radiation over a one-minute interval. The location of tower is adjacent to the barns (Figure 1).
- A 3.8 meter tower measuring wind speed and direction (sonic), turbulence (\(\sigma_u\), \(\sigma_v\) and \(\sigma_w\)), temperature, and derived variables such as heat flux, friction velocity (\(u^*\)), roughness length (\(z_0\)), and temperature scale (\(T^*\)) over a one-minute interval. The meteorological station is located approximately 80 m (260') to the northeast of barn 4 (Figure 1).

Facility Layout and Dimensions
- A schematic of the facility layout is presented in Figure 1. It consists of four swine barns, approximately 58 m (190') in length and 14 m (46') in width. Internal temperature and air quality conditions are maintained by a combination of ventilation modes:
  - Pit fans - air is drawn through vents located on the sidewalls down both sides of the shed and expelled from two fans located on the south side of each barn. The total flow rate of these fans is approximately 7,000m3/hour.
  - Tunnel fans - air is primarily drawn through large inlet openings located on the western side of the shed at the end opposite the fans at a total flow rate of between 98,000 m3/hour and 15,000 m3/hour. Each barn has five fans located on the eastern side.

A ten-meter meteorological tower was located 5 meters off the tunnel fan plane and between barns 2 and a second meteorological tower, called a 2-meter tower, (actual height was 3.8 meters high) was located approximately 80 m to the northeast of barn 4.

![Figure 1. Farm layout showing location of swine barns, center of pit fans (e.g. B4PW), center of tunnel fans (e.g. B1T) and meteorological stations during sessions 1 & 2 and 3.](image)

Emissions Data
- Emissions were developed at the time of the field assessments (and modelling periods) from a well-instrumented deep-pit swine finisher in Story County, Iowa. The facility is located in flat agricultural terrain. Each barn is 13.7 m wide by 61 meters long, with 19.8 meters between buildings. Each barn houses 950 head of finishing pigs. A mobile emission laboratory was deployed to record emissions data for another research experiment concurrently (USDA, 2001). The middle two barns were instrumented by the mobile laboratory. Exhaust air was collected from the fans during the events in duplicates (one at the beginning of the session the other at the 7.5 minute mark during the 15 minute assessment event), The sample bags were transported to either the University of Minnesota or University of Iowa olfactometry lab within 24 hours of the event and analysed for dilution to threshold using a venturi-type dynamic dilution olfactometer (AC’SCENT®International Olfactometer, St. Croix Sensory, Inc. Stillwater, MN). Odor detection threshold, defined as the concentration that the panelist first detects a difference in the air sampled compared to two clean samples, was measured in accordance with ASTM standard E679-91 using trained panellists.
Emissions from tunnel- or pit-ventilated swine barns are directed horizontally, with no significant vertical component. Even small temperature differentials, as small as 1-2°C, may have a significant effect on near-field ground level concentrations (Ormerod et al. 2003). Therefore, any plume rise occurs as a result of thermal buoyancy of the emissions, with no plume rise component due to vertical momentum. To deal with the effects of the buoyancy for this study, the horizontally-directed fans have been modelled as four pseudo-point sources to negate mechanically-generated plume rise whilst maintaining the thermal mass of the plume. To achieve this, efflux velocity was set at the recommended value of 0.01 m/s (e.g. NCDENR, 2003; NDEQ, 2001; NMAQB, 2003).

Analysis of the temperature differences between two barns and the 4 meter tower (ambient) confirm this observation, with barn temperatures up to 1°C warmer than corresponding ambient temperatures during the summer project measurement. Even modest plume rise can give rise to difficulties in validating models if this is not taken into account. The issue applies most particularly to the near-field region.

Receptor Information

The modelling domain consists of uniformly spaced receptor points 50 m apart over an area of approximately 30 ha (74 acres), centered on the swine barns. In addition to the gridded receptors, discrete receptors coinciding with the measurement locations were selected for each event modelled. General experience with model validation shows that time-space matching of modelled and observed results can exhibit relatively low correlations, even with good quality emissions and meteorological data. This is an inevitable result of random atmospheric turbulence and the use of models to predict ‘ensemble’ averages. In other words, for a given set of meteorological inputs to a model, a range of actual concentrations could be expected even though the model provides a fixed value. In the current case, the good temporal resolution of the meteorological data will assist in reducing scatter, but we would still expect some predictions to be more than a factor of 2 outside observed values. In recognition of the random turbulence effects, it is better to predict concentrations in a small region around the target receptor. Taking account of model predictions at near grid points (if suitably spaced) can considerably improve the validation. Consequently a small grid of model receptor points was set up around each actual observation point.

Results and Discussion

Results were analyzed for each measurement individually (D’Abreton, 2007), where modeled predictions were compared to the observed measurements taken by the field surveyors. The data is shown in Figure 3.
Figure 3. Modeled Predictions (Average over time period) versus Observed (Nasal Ranger™)

**Direct Comparison and Rank Order**

A plot of all data averaged for the time period for model predictions and observations is shown in Figure 3. The 1:1 line is also shown in this figure, and it is apparent that CALPUFF under predicts odor concentrations observed by the field assessors during the same time periods. When regression is performed, with the intercept forced through zero, a slope of 0.98 is produced with an R squared of 0.32, indicating that there may not be a need to adjust model predictions. This suggests that the data, while there is considerable scatter, overall the CALPUFF predictions and Nasal Ranger measurements are comparable.

Spearman’s rank correlation coefficient ($r_s$) is a nonparametric test that can be used to compare the consistency of a model’s prediction to high observations when they are high, and low observations when they are low. This test uses the differences of the ranks to ascertain correlation and an ideal value is close to 1 (range -1 to 1). When this dataset was analyzed, an $r_s$ of 0.17 was calculated, indicating a poor rank correlation and was not significant ($p \leq 0.05$).
Figure 4 Relationship between wind speed (upper left), standard deviation of vertical wind speed (upper right), 1/L (lower left), mean $\Delta T$ (lower right) and observed odor concentration

**Measured Odor Concentration vs. Meteorology**

A comparison of measured odor concentration against a number of corresponding meteorological variables is shown in Figure 4. Higher predicted odor appears related to stronger wind speed. The Monin–Obukhov stability length (1/L) between -0.01 and 0 suggests that a neutral to slightly unstable atmosphere results in elevated ground-level odor. Conversely, there does not seem to be a clearly defined correlation between $\sigma_w$ and odor concentrations. There appears to be an inverse relationship between odor concentration and the average difference in temperatures between the north and south barns with the mean ambient temperature (denoted by $\Delta T$). This suggests that when the temperature in the barns is close to ambient temperature (minimal thermal buoyancy in the plume) downwind ambient odor concentrations are higher.

**Ratio of Measured Odor Concentration and Emission Rates vs. Meteorology**

A comparison of the measured odor concentration divided by the emission rate (rate of dilution) against a number of corresponding meteorological variables is shown in Figure 5. Temperature shows an inverse exponential relationship, with a lower dilution factor with warmer temperatures. The relationship between dilution factor and $\sigma_w$ indicates a similar relationship. These findings suggest that the odor plume from the swine barns are less diluted under colder, low turbulent flow. Neutral to a slightly unstable atmosphere results in higher odor concentration and emission rates ratio. There is no clear relationship between $\Delta T$ and the ratio of odor concentrations and emission rates.

**Bias and Error**

Fractional Bias and Model Bias are commonly used to compare model predictions with observations Wilmott (1981) and Pielke (1984). The Fractional Bias test is symmetrical and bounded by the values between 2 and -2. A value of zero indicates no bias. For model bias, an ideal value is zero, which indicates no bias. Normalized Mean Square Error and Root Mean Square Error are commonly used to judge performance of model predictions, with ideal values being those nearest zero.

Figure 5 Relationship between temperature (upper left), standard deviation of vertical wind speed (upper right), 1/L (lower left), mean $\Delta T$ (lower right) and ratio of observed odor concentrations and emission rates.
Table 2. Model Performance Statistics

<table>
<thead>
<tr>
<th>Metric</th>
<th>Value</th>
<th>Note</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean of Observed</td>
<td>12.2</td>
<td></td>
</tr>
<tr>
<td>Mean of Modeled</td>
<td>6.4</td>
<td></td>
</tr>
<tr>
<td>Standard Deviation of Observed</td>
<td>12.2</td>
<td></td>
</tr>
<tr>
<td>Standard Deviation of Modeled</td>
<td>7.7</td>
<td></td>
</tr>
<tr>
<td>Model Bias (MB)</td>
<td>5.9</td>
<td>Ideal value is 0</td>
</tr>
<tr>
<td>Fractional Bias (FB)</td>
<td>0.63</td>
<td>Ideal value is between 0.67 and 2</td>
</tr>
<tr>
<td>Normalized Mean Square Error</td>
<td>2.6</td>
<td>Ideal value is 0</td>
</tr>
<tr>
<td>Root Mean Square Error</td>
<td>1.6</td>
<td>Ideal value is 0</td>
</tr>
</tbody>
</table>

The performance statistics from Table 2 show model bias is not ideal, however fractional bias is very close to ideal. NMSE and RMSE are also appear to be far from ideal, suggesting that there is considerable error in the data set.

Another analysis was conducted that evaluated how often the average observation from the Nasal Ranger™ was within the range of the model prediction, given that there were 15 model predictions for every 2 assessments. For example, for receptor D, the field assessor’s both reported an average DT of 2.9 (average from two assessments of a 0 DT and a 7 DT), the model predicted an average 0.5 OU, but the predictions ranged from 0 OU to 3.1 OU. While the model did not accurately predict the concentration of 2.9 OU, it was within the range of predictions over the sampling period. It is important to understand that the model is predicting the average concentration, while the assessor is only assessing short time periods during the sampling period. In this instance, the average concentration was within the range of the model predictions and this was the case 64% of the time. This may be due to temporal differences in between when assessments are made and model predictions. In this analysis, no peak to mean ratio adjustments, were incorporated into the model predictions. It is interesting to note that the peak to mean ratio’s (max/mean) of the model predictions and the observations (Nasal Ranger) were 2.6 and 2.2 respectively.

Conclusions

Downwind odor concentrations from four tunnel ventilated swine barns were measured by trained human receptors during twenty-six measurement events between June and November 2004. Typically, 6-8 measurement events were conducted in a two-day period. Receptors were located at distances between 50 meters and 950 meters downwind. Source emission measurements and extensive meteorological data were collected along with the field odor concentration measurements. In this study, modelling of the measurement events at specific receptor locations was compared to field odor measurements at the same locations.

A modified version of the US EPA regulatory model, CALPUFF, was used to calculate short-term concentrations based on 1-minute average meteorological data. This short-step version of the model was used in a quasi-three dimensional mode operating with measured turbulence parameters from a single meteorological station. This application is deemed appropriate in near-field applications, when spatial variability in the meteorological field is not significant. In this study horizontally-directed fans have been modelled as four pseudo-point sources to negate mechanically-generated plume rise whilst maintaining the thermal mass of the plume.

The model results have been compared to field odor measurements. Approximately 64% of measured odor generally falls within the range of modeled values. A number of observations, however, exceed modelled values. This may be due to the uncertainty in the key inputs (emission rates, winds, mixing heights and stability); uncertainty in locating the observation point relative to the plume centerline, which is mainly a function of uncertainty in mean wind direction, or temporal differences in the met data and plume tracking. This can be highly significant in areas where the model predicts strong gradients in ground level concentration.

Analysis of measured odor concentration and corresponding meteorology indicate that maximum ambient odor impacts occur with lower ambient temperature during non-turbulent conditions.

Analysis of the data set did not yield a strong relationship directly ($R^2=0.33$), and a regression analysis indicated that the modified CALPUFF model yielded a slope or scaling factor of 0.99. However, when the data is tested with the Spearman’s rank correlation coefficient an $r_s$ of 0.17 was calculated, indicating a poor rank correlation and was not significant ($p>0.05$).

Finally, model and fractional bias are contradictory, one suggesting good agreement and the other indicating poor agreement. NMSE and RMSE tests indicated substantial error in the ability of the model to predict odor concentrations. These results are consistent with other modelling studies which show relatively poor performance in predicting specific short-term events, i.e., large scatter in time- and space-paired
results, but good performance in predicting the basic statistics of ground level concentration over the longer term. Further analysis of this dataset is on-going.

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References