BRIDGING DISPERSION MODELLING AND FIELD ODOUR OBSERVATIONS USING STATISTICAL REGRESSION FOR ODOUR IMPACT ASSESSMENT

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Abstract

In Victoria, the Guidance for Assessing Odour (EPA Publication 1883) provides a tiered framework for evaluating odour risk to surrounding land uses. For complex scenarios, it provides some guidance on incorporating atmospheric dispersion modelling alongside field odour surveillance data as part of a Level 3 assessment. However, while Publication 1883 identifies that modelled results should be correlated with field observations, no prescriptive methodology is provided for how this should be achieved. This paper presents a statistical framework developed to address this gap. Multiple rounds of field odour surveys were conducted at an industrial facility in Victoria following the principles outlines in EPA Publications 1881 and 1883. Observations were classified using an ordinal exposure risk scale aligned with the risk categories in Publication 1883. The facility was equipped with an onsite meteorological station. For each observation, site-specific meteorological conditions recorded at the time of the survey were used alongside nominal emission rates for identified sources as inputs to the AERMOD dispersion model. A dynamic peak-to-mean ratio, accounting for atmospheric stability and plume travel time, was applied to convert hourly model outputs to short-term peak concentrations matching the field observation averaging period. The adjusted modelled concentrations were then correlated with the observed exposure risk categories using ordinal logistic regression, which models the cumulative probability of falling within each ordered risk level as a function of predicted concentration. The resulting framework provides a defensible translation from dispersion model output to the ordinal risk categories of Publication 1883. Predicted concentrations from future scenarios can be converted into risk categories calibrated against ground-level odour observations, enabling forward-looking assessment of proposed operational changes, facility expansions or greenfield development. This paper demonstrates the practical application of the approach, particularly where no analogous facility exists and forward-looking assessment would otherwise not be possible.

Keywords: odour, dispersion modelling, ordinal logistic regression, peak-to-mean ratio.

1. Introduction

Odour remains one of the most common sources of environmental complaint in Victoria (CES, 2023). Assessing the impact of odour-emitting facilities on surrounding communities requires a framework that links emissions to the likelihood of adverse odour exposure at sensitive receptors. The Victorian EPA's Guidance for Assessing Odour (EPA Publication 1883) provides a tiered assessment framework for this purpose. At the highest tier, level 3 assessment can use tools for applicable scenarios: (i) Comparison with similar operations, (ii) Risk assessment using field odour surveillance data, (iii) complaint data analysis, (iv) Community surveys, and (v) dispersion modelling.

Atmospheric dispersion modelling for predicting odour concentration is not recommended to be used as the only evidence of impact assessment, modelled results are required to be validated against field odour surveillance data as the basis for complex assessments. However, where no analogous facility exists and proposed operational changes or expansions represent a novel scale of activity, dispersion modelling may offer the only realistic assessment option; comparative tools such as case study benchmarking or complaint data analysis are not applicable in the absence of an operating reference facility.

Publication 1883 identifies that modelled concentrations should be correlated with field observations to establish a relationship between predicted odour levels and observed community

experience. However, no prescriptive methodology is provided for how this correlation should be developed or validated. This represents a significant gap for practitioners tasked with demonstrating compliance or assessing the impact of proposed changes to operations.

The methodology approach uses ordinal logistic regression for the ordinal nature of the exposure risk categories defined in Publication 1883, and the non-linear relationship between modelled odour concentration and observed exposure risk, which linear regression cannot appropriately capture.

2. Methodology

2.1. Field odour surveys

Ten (10) rounds of field odour surveys were conducted at an industrial facility in Victoria following the principles specified in EPA Publications 1881 and 1883. Surveys were conducted under a range of meteorological conditions to capture the variability of odour dispersion across different atmospheric stability regimes and wind patterns. The surveys combined the transect method and the area surveillance method documented in EPA Publication 1881. Observers walked lines downwind of the source and sniffed for odour every at distances of

approximately 100, 250 or 500 m from the first transect. Where odour was detected, a five-minute observation was recorded. As the availability of land for surveying varies by direction and odour detection depends on conditions during each survey, the exact number of observation points and five minute surveys per round could not be predetermined.

Each observation was classified on field according to the intensity of odour observed (0) no odour, (1) subtle and (2) obvious. The odour exposure risk was then translated based on character, odour intensity and frequency of predicted odour over each observation period and fitted to the six-point scale (0 to 5) using Table 11 in EPA Publication 1883 (EPA Victoria 2022).

The inclusion of a zero category and instantaneous measurements, where observers traced the plume and did not detect odour, were considered important to capture locations for comparison to dispersion model predictions of non-zero concentrations, but where no odour is perceived, providing a lower bound for calibration. Both survey-driven frequency-rated observations (88 discrete observations) and instantaneous zero-detection (99 discrete points) observations were incorporated.

2.2. Dispersion modelling

The regulatory atmospheric dispersion model AERMOD was used to simulate odour concentrations at each observation location for the specific time period corresponding to each observation time. The facility was equipped with an onsite meteorological station providing continuous 5 minutes measurements of wind speed, wind direction, temperature, and other parameters. These data were processed through AERMET to generate the surface and profile meteorological files required by AERMOD, ensuring that the model inputs reflected actual site conditions during each observation period.

Nominal emission rates were assigned to the identified odour sources on site based on the aggregate character and frequency of odour observed across the ten survey rounds combined and kept constant for all model runs. No per-round iterative adjustment was adopted for emission rates. The model was configured to output one-hour average concentrations at the coordinates of each field observation point.

2.3. Peak-to-mean conversion

AERMOD produces concentrations averaged over one-hour periods. However, human odour perception responds to short-term concentration fluctuations on the order of seconds to minutes. The field odour observations were conducted over five-minute assessment periods. To bridge this temporal mismatch, a dynamic peak-to-mean ratio based on the principles of the Austrian Odour Dispersion Model (AODM) was applied (Piringer et al. 2015).

Unlike fixed peak factors, the AODM ratio is non-linear and varies with atmospheric stability class and downwind plume travel time, capturing the physical reality that unstable conditions produce intermittent plumes with sharp near-source peaks while stable conditions produce more coherent plumes with lower peak factors. Where multiple source groups are present at varying distances and emission rates, an emission and distance weighted effective peak factor is calculated to reflect the proportional contribution of each upwind source, and this was applied to the one-hour AERMOD output to produce an estimated peak concentration for each observation. The same peak-to-mean conversion was applied uniformly to both observation types, using each observation's own paired meteorological hour.

2.4. Statistical correlation using ordinal logistic regression

Having derived five-minute peak modelled concentrations paired with observed ordinal risk categories, a statistical method was required to establish the correlation. Standard linear regression demonstrated to be inappropriate due to the response variable (exposure risk rating 0 to 5) is ordinal rather than continuous. Binary classification would discard the ordered structure of the

categories. Ordinal logistic regression (OLR) was therefore selected as the most suitable method. The use of OLR was determined prior to the field campaign, based on a previous application of the approach to field survey data. The resulting sample size and its distribution across risk categories were therefore an outcome of standard field survey practice, not a target set in advance for statistical analysis.

Ordinal logistic regression, also known as the proportional odds model, models the cumulative probability of an observation falling at or below each risk level as a logistic function of the predicted concentration. The model estimates a single regression coefficient for the continuous predictor (modelled concentration) and a set of threshold values, termed cut-points or intercepts, that define the boundaries between adjacent risk categories (McCullagh 1980). For a given modelled concentration, the model produces a predicted probability distribution across all six risk levels from which the most probable category can be assigned.

A key assumption of the proportional odds model is that the effect of concentration on the odds of exceeding any given risk level is constant across all cut-points. This proportional odds assumption, also referred to as the parallel lines assumption, was tested using the Brant test (Brant 1990). A non-significant result ($p > 0.05$) confirms that the assumption holds and that a single model adequately describes the relationship across the full ordinal scale.

3. Application

3.1. Risk of odour exposure potential

The risk of odour exposure potential at each observation point was determined by reference to the "unwelcome" character of the detected odour, which reflects the nature of the emission source. The observed obvious or subtle odour frequency at which odour was detected at each measurement point was calculated as a percentage of the total observation time.

Following Tables 12 and 13 of EPA Publication 1883, the detected frequency was assigned to an appropriate frequency band based on the obvious or subtle character of the odour. Each frequency band corresponds to a risk of odour exposure potential category, consistent with the colour-coded scale in Tables 12 and 13 of EPA Publication 1883. A risk of odour exposure potential rating was assigned to each observation measurement point on this basis.

3.2. Empirical distribution of modelled concentrations

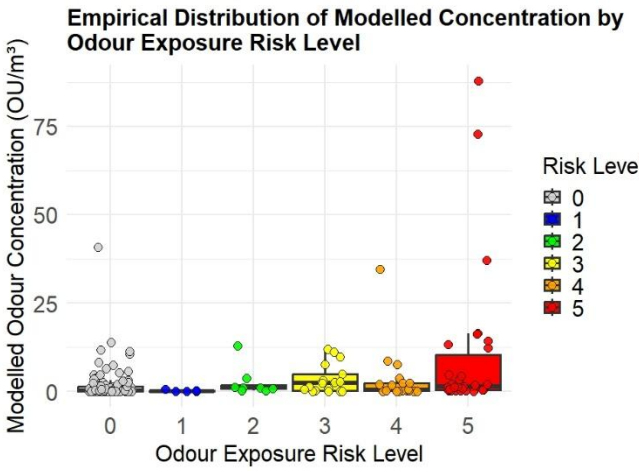
The overall statistical distribution of modelled concentrations for the observation points is summarised in Table 1. The distribution showed strongly right-skewed pattern, with the median considerably below the mean. The majority of observation points recorded low modelled concentrations, while a small number of near-source or strongly downwind locations produced substantially elevated values that extend the upper tail of the distribution.

Table 1: Overall statistical distribution of five-minute peak modelled odour concentrations (OU/m³) across all observation points (n = 187)

Risk	Count of risk level	Average Modelled concentration (OU/m3)	Maximum	Minimum	25th Percentile	Median (50th Percentile)	Q3 (75th percentile)
0	107	1.84	40.9	0.0028	0.05	0.28	1.45
1	5	0.23	0.66	0.003	0.1	0.11	0.25
2	8	2.66	12.8	0.272	0.71	1.04	1.83
3	17	3.51	11.8	0.0843	0.23	2.42	4.83
4	20	3.28	34.5	0.0473	0.16	0.48	2.36
5	30	9.94	87.9	0.0092	0.36	1.42	10.5
Overall	187	3.44	87.9	0.0028	0.1	0.49	2.47

The by-risk-level breakdown of modelled concentrations summarised in Table 1 and illustrated in Figure 1 shows a general escalating trend in modelled concentration evident from Risk 0 through to Risk 5, with Risk 5 clearly standing apart from all other categories. This is consistent with the expectation that higher modelled concentrations should correspond to higher observed risk levels. However, non-monotonicity is present at Risk Levels 1 to 4, where the median and average concentrations do not increase consistently between adjacent levels.

Figure 1: Empirical distribution of five-minute peak modelled odour concentration (OU/m³) by observed odour exposure risk level



This arises from the structure of the field classification itself. Observers record odour intensity on a three-level scale (no odour (0), subtle (1) and obvious (2)), which is then mapped to the six-point risk scale (0–5) via the frequency and character lookup in Tables 12 and 13 of Publication 1883. No-odour observations map directly to Risk 0, and obvious-intensity observations at even moderate frequency resolve to Risk 3 or above, so the intermediate risk levels are populated predominantly by subtle-intensity observations further differentiated by frequency. This concentrates the dataset at the extremes: Risk 0 (n = 107) and Risk 5 (n = 30), leaving Risk Levels 1 to 4 with substantially fewer observations (n = 5 to 20 per level). Descriptive statistics are inherently volatile at these sample sizes, and a simplistic percentile-banding approach would fail to produce monotonic thresholds. This does not undermine the statistical analysis: the proportional odds model estimates a single slope across the full ordinal scale without requiring stable means or medians within each category. Whitehead's (1993) effective sample size (ESS) was evaluated in R for the observed category distribution using the counts per risk level in Table 1, returning ESS = 150.8. The 187 paired observations therefore carry statistical information equivalent to approximately 151 observations of a continuous response.

Two benchmarks were considered against this figure. Peduzzi et al. (1996) found that for events-per-variable (EPV) values of 10 or greater, no major problems occurred in logistic regression estimation; the sparsest cumulative comparison in this model (Risk ≥ 5) contains 30 observations against a single predictor, satisfying this criterion.

Second, Harrell (2015) provides a benchmark for estimating a full set of probabilities reliably: 184 observations are needed for predicted probabilities to fall within 10 percentage points of their true values, at 95% confidence.

The ordinal logistic regression was investigated to address this directly by fitting a single smooth relationship across the full dataset, and override the noise introduced by small and unevenly distributed samples in intermediate risk categories.

3.3. Ordinal logistic regression model

The proportional odds model was fitted using the function in R environment, with five-minute peak modelled concentration as the single continuous predictor and observed risk level (0–5) as the ordered factor response. The model coefficient and intercepts reported in Tables 3 and 4 indicate:

- The regression coefficient (β = 0.069) is positive, confirming that as modelled odour concentration increases, the log-odds of being in a higher odour exposure risk category increase accordingly. For every one-unit increase in modelled concentration, the log-odds of moving to a higher risk level are estimated to increase by 0.069.
- The standard error of 0.024 is small relative to the coefficient, indicating a precise estimate.
- The Wald t-statistic of 2.86 and associated p-value of 0.0047 confirm statistical significance at the 1% level.
- The model is therefore appropriate for the full ordinal scale. The residual deviance of 472.9 and AIC of 484.9 are consistent with a well-fitted model given the dataset size and the inherent variability of field odour observations.

This indicates that the relationship between the dispersion model output and the observed odour exposure risk rating is statistically reliable, and that the model provides a valid basis for converting predicted concentrations into odour exposure risk categories consistent with EPA Publication 1883.

Table 4 provides the ordinal logistic regression model intercept values which are shown on Figure 2 (see Appendix).

The intercepts define the log-odds boundaries between adjacent risk categories and increase monotonically from 0|1 (0.487) through to 4|5 (1.945), confirming that the ordered structure of the model is internally consistent and that the risk categories are ordered along the concentration scale.

3.3.1. Brant Test

The Brant test was applied to assess whether the proportional odds assumption holds for the fitted model, that is, whether the effect of modelled concentration on the log-odds of exceeding any risk boundary is constant across all five cut-points. The omnibus p-value was 1.0, indicating no evidence of a violation. A p-value of 1.0 does not imply that the

model is a perfect predictor of risk level. With a single continuous predictor, the proportional odds assumption requires only that one coefficient remain constant across the ordinal scale, and the Brant test has limited power to detect departures in this setting, particularly given the sparse intermediate categories discussed in Section 3.2. The result confirms that the proportional odds assumption is tenable for this dataset and that the sample size is sufficient for the single-predictor model to satisfy the assumption. This interpretation is independently supported by the monotonically increasing intercepts (Table 4), which confirm that the ordered structure of the risk categories is preserved along the concentration scale.

3.4. Concentration banding

The predicted probability curves from the fitted model are presented in Figure 2. At zero modelled concentration, Risk 0 (no odour) has the highest predicted probability at approximately 0.60. As concentration increases, the probability of Risk 0 declines sharply and the probability of Risk 5 (very high exposure) rises steeply, becoming the dominant category at concentrations above approximately 30 OU/m³.

3.4.1. Transition point analysis

To objectively identify the concentration at which the predicted probability of one risk level surpasses another, transition points were calculated numerically from the fitted probability curves illustrated in Figure 2. For each pair of risk levels, the concentration at which their respective probability curves intersect was identified by detecting sign changes in the difference between the two curves across the modelled concentration range.

Only two statistically meaningful crossovers were identified. No crossover was detected between Risk 0 and Risk Levels 1, 2 or 3 at any concentration within the observed range.

The crossover between Risk 0 and Risk 5 at 17.6 OU/m³ represents the transition in the model where the concentration at which the probability of very high odour exposure first exceeds the probability of no odour detection. Above this threshold, Risk 5 becomes the dominant predicted outcome. The crossover between Risk 0 and Risk 4 at 30.9 OU/m³ marks the point at which high odour exposure also surpasses the declining Risk 0 probability curve.

Since the probability curves for Risk Levels 1 through 4 do not become the single most probable category at any concentration, the band boundaries cannot be derived from the points at which one curve overtakes another. Instead, the bands were derived from the cumulative predicted probabilities of the fitted model, consistent with the established proportional odds interpretation (Agresti 2010; McCullagh 1980). For each risk level j, the lower bound of that band was taken as the modelled concentration at which the cumulative probability of being at or above that level, $P(Y \geq j)$, first exceeds 0.5 — that is, the concentration at which an observation becomes more likely than not to fall at or above risk level j. This yields a set of monotonically increasing non-overlapping boundaries derived entirely from the model. The resulting band floors are 7.2, 8.8, 11.6, 18.2 and 28.4 OU/m³ for Risk Levels 1 to 5 respectively. The No odour band (Risk 0) is assigned to concentrations below the point at which any odour exposure first becomes more probable than not, with a pragmatic lower threshold of 1.0 OU/m³ applied consistent with common practice for negligible impact. The Very High threshold of 18.2 OU/m³ is independently corroborated by the Risk 0 / Risk 5 probability crossover at 17.6 OU/m³, where the probability of very high exposure first exceeds that of no odour, providing two convergent lines of evidence for this key boundary. It is acknowledged that the lower band floors sit higher in concentration than the bulk of the observed low-risk data. This is a direct consequence of the shallow regression coefficient, which indicates that modelled concentration is a statistically significant but relatively weak discriminator of risk level at low concentrations for this dataset. The bands therefore reflect the genuine predictive structure of the calibrated model rather than the raw empirical percentiles, which are themselves non-monotonic across the sparsely sampled intermediate categories. The calibrated concentration banding derived from this combined approach is presented in Table 5 (See Appendix).

4. Discussion

The framework presented in this paper addresses a methodological gap in Victorian regulatory guidance for odour assessment. While EPA Publication 1883 identifies the need to correlate dispersion modelling with field observations, the absence of a prescribed method has meant that practitioners have relied on ad hoc approaches of varying rigour.

A critical point of interpretation is that the concentration bands derived from this analysis are not intended as universal thresholds applicable to other facilities or assessments. They are not a general conversion table assigning odour concentrations to the risk categories of EPA Publication 1883, and they should not be applied as such. Rather, they represent a calibrated relationship between modelled concentrations and observed field outcomes that is specific to this facility, its emission sources, its meteorological setting, and the surveys conducted under those conditions. However, the approach presented in this paper can be readily applied to other locations where

odour modelling requires calibration against field odour surveys, providing a greater level of confidence in modelled odour impact assessments than has previously been possible. A uniform bias in the assumed emission rates is absorbed into the fitted regression coefficient, since it rescales the single continuous predictor linearly and does not affect the model's statistical significance.

The polarised distribution of observed risk levels in the calibration dataset, and the relatively abrupt concentration–risk relationship captured by the model, are consistent with a structural characteristic of EPA Publication 1883 itself. Risk Levels 1 and 2 remain accessible only through a narrow combination of inoffensive character, subtle intensity and the lowest predicted frequency. This structural feature biases outcomes toward the upper risk categories independently of the true magnitude of odour impact, and is an inherent consequence of mapping a three-parameter, coarsely discretised input space onto the six-point ordinal scale. It represents an area where the guidance could beneficially be refined to provide finer resolution at the lower end of the risk spectrum. The calibrated framework presented in this paper is constrained by this structure, and the uncertainty associated with the lower concentration bands is acknowledged accordingly.

5. Conclusions

This paper has presented a statistical framework, using ordinal logistic regression, for translating atmospheric dispersion model output into the ordinal odour exposure risk categories of EPA Publication 1883, calibrated against field odour observations at an industrial facility in Victoria. The fitted model was statistically significant, with no evidence found against the proportional odds assumption, though statistical power to detect a violation varied across risk-level boundaries due to the uneven distribution of observations.

As discussed in this paper, the resulting concentration bands are calibrated to this facility's emission sources, meteorological setting and survey conditions, and are not intended as universal thresholds or a general conversion between odour concentration and the risk categories of EPA Publication 1883. Their value lies in enabling forward-looking, evidence-based assessment of proposed operational changes, expansions or greenfield developments, particularly where no analogous operating facility exists to benchmark against.

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Appendix

Table 2: Observations per survey round

Round	5 min observations	Instantaneous observations
Round 01	14	12
Round 02	7	12
Round 03	6	12
Round 04	7	21
Round 05	10	6
Round 06	8	12
Round 07	6	6
Round 08	12	5
Round 09	6	5
Round 10	12	8
Total	88	99

Table 3: Ordinal logistic regression model coefficient

Parameter	Value (β)	Std. Error	t value	Pr(>|t|)
Modelled concentration	0.069	0.024	2.86	0.0047

Table 4: Ordinal logistic regression model intercepts (cut-points)

Intercept	Value	Std. Error	t value
0|1	0.487	0.163	2.995
1|2	0.603	0.165	3.659
2|3	0.795	0.169	4.694
3|4	1.247	0.185	6.728
4|5	1.945	0.225	8.635

Residual Deviance: 472.9

AIC: 484.9

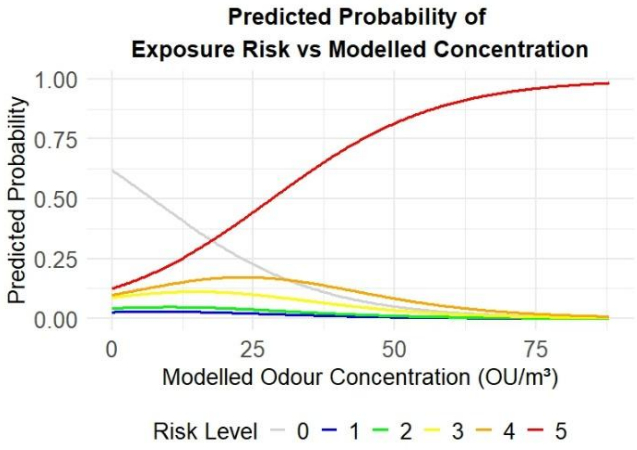


Figure 2: Predicted probability of each odour exposure risk level as a function of five-minute peak modelled concentration

Table 5: Calibrated concentration bands for odour exposure risk level classification

Risk	Category	Conc. Range (5-min, OU/m³)	Basis
0	No odour	< 1.0	Pragmatic threshold for no significant impact; below the concentration at which any odour exposure (Risk ≥ 1) becomes more probable than not.
1	Negligible	1.0 – 7.2	Upper bound is the concentration at which the probability of low odour (Risk ≥ 2) first exceeds 50%.
2	Low	7.2 – 8.8	Upper bound is the concentration at which the probability of moderate odour (Risk ≥ 3) first exceeds 50%.
3	Moderate	8.8 – 11.6	Upper bound is the concentration at which the probability of high odour (Risk ≥ 4) first exceeds 50%.
4	High	11.6 – 18	Upper bound is the concentration at which the probability of very high odour (Risk 5) first exceeds 50%.
5	Very high	≥ 18	Threshold at which the probability of very high odour (Risk 5) exceeds 50% and surpasses the probability of no odour. Corroborated by the Risk 0 / Risk 5 probability crossover at 17.6 OU/m³.