

---

**Appendix 3 : Compliance with Point 10 of EPA request for additional information.  
Technical description of air quality model used Atmospheric Modelling  
ADVANCED GAUSSIAN PLUME MODEL**

---

**THE DEVELOPMENT OF AN ADVANCED GAUSSIAN PLUME AIR POLLUTION MODEL AIR****S. Durucan*****Imperial College of Science, Technology and Medicine, London, United Kingdom*****P.R. Johnston*****University of Milan, Milan, Italy******Abstract***

One of the commonest methods of air quality modelling is the Gaussian plume model, the strengths of which are: its relative simplicity; the fact that dispersion parameters can be estimated using readily obtainable surface meteorological observations; and that results obtained are often comparable to the results obtained by other more complex models. However, the Gaussian plume model has many limitations, not the least of these is that the dispersion parameters are estimated using generalized empirical methods. Recent research in atmospheric modelling has led to a better understanding of the physics of the atmospheric boundary layer and its influence on dispersion. Using these latest findings an advanced Gaussian plume model has been developed with the aim of providing improved air pollution predictions. This requires that the parameters of importance in dispersion, such as surface heat flux, surface friction, atmospheric stability, and the vertical boundary layer structure are introduced into the model.

Modularity at a higher level was achieved by the division of the model developed into a meteorological preprocessor and a dispersion model. Flexibility in the model input and output has been achieved by integrating the model with a Geographical Information System (GIS). As well as providing extended capabilities for model input and display, this also allows for the analysis of results directly or in combination with other forms of spatial data to model interacting environmental impacts of minerals extraction. The advanced model was evaluated using a well established validation kit which is comprised of data from three atmospheric dispersion field experiments. The results obtained have represented a considerable improvement in the air quality predictions made when compared to conventional Gaussian plume models.

***Introduction***

The dispersion of air pollutants primarily occurs within the atmospheric boundary layer. This boundary layer is the lowest layer of the atmosphere and is defined by interaction with the Earth's surface, responding to surface forcings with a time scale of about one hour or less<sup>1</sup>. Consequently, most modelling of air pollution dispersion is concerned with the study of the meteorology of this boundary layer.

The primary mechanism for dispersion in the boundary layer is turbulence. Combined with advection by the mean wind this results in a very efficient method for the transport and dispersion of air pollutants. However, the presence of turbulence presents considerable problems when it comes to modelling dispersion. Numerical methods for solving the complete set of equations that define boundary layer flow and turbulence, the Navier-Stokes equations, are both complex and computationally intensive.

Provided that certain assumptions are made about dispersion and advection in the boundary layer, the Gaussian plume model, which takes advantage of the fact that steady-state conditions can normally be assumed to exist in the boundary layer over an averaging period of one hour, can be used as a simpler alternative. The model assumes the advection transport of an air pollutant in the hourly mean wind direction combined with statistical descriptions of turbulent dispersion in the crosswind and vertical

directions. As the model name suggests, the dispersion distributions due to turbulence are Gaussian, the shape of which are functions of downwind distance. The parameters used in the model are defined using a minimum set of easily measurable meteorological observations. This is of particular importance when modelling air pollution from the minerals extraction industry, as operations are often located in remote areas. Using a Cartesian co-ordinate system the Gaussian plume model has the general form

$$\chi(x, y, z) = \frac{Q}{2\pi u \sigma_y \sigma_z} \exp\left[-0.5\left(\frac{y}{\sigma_y}\right)^2\right] \exp\left[-0.5\left(\frac{z-H}{\sigma_z}\right)^2\right] \quad (1)$$

where  $\chi$  is the concentration at a location  $(x, y, z)$ ,  $Q$  is the source emission rate,  $u$  is the average wind speed at the release height,  $H$  is the height of the plume centreline, which is the source release height for non-buoyant plumes, and  $\sigma_y$  and  $\sigma_z$  describe the Gaussian concentration distributions in the crosswind and vertical directions respectively, commonly termed the dispersion parameters. The  $x$  axis is taken as being in the wind direction, the  $y$  axis as the crosswind direction, and the  $z$  axis as the vertical; the origin is at ground level directly below the source release point.

The models currently used in practice typically use the empirical Pasquill-Gifford<sup>2</sup> method of atmospheric stability classification to define dispersion. The Pasquill-Gifford method uses an empirical scheme to define six stability categories ranging from unstable to stable. This classification is based on wind speed, cloud cover, time of day, and solar altitude to indirectly define the surface heat flux. These six stability categories are then used to define the stability. Although the Pasquill-Gifford method has the advantage of simplicity, the improved understanding of boundary layer physics has highlighted its deficiencies. These are: a) the use of stability categories introduces a stratification of atmospheric conditions, whereas in fact stability is a continuum; b) it is biased towards neutral conditions; c) it does not recognize the vertical structure of the boundary layer which can influence dispersion depending on the height of a release; and d) the vertical dispersion distribution in unstable conditions is now known to be non-Gaussian. These weaknesses in the model all lead to inaccurate definition of the dispersion, and have led to the Gaussian plume model performing poorly in application<sup>3,4</sup>. Predictions when compared to observations are often out by a factor of two or more. However, it is worth noting at this point that there is always a relatively large degree of uncertainty associated with all air pollution modelling because of the nature of the process.

The potential solutions to these weaknesses in the Gaussian plume model lie in applying the improvements that have been made in the understanding of the physics of the boundary layer. The starting point is the implementation of methods that define the fundamental parameters of the boundary layer, such as the surface heat flux and characteristic length and velocity scales. These can then be used to provide relationships that define the vertical structure of the boundary layer, stability, dispersion and vertical profiles of wind speed and temperature.

This paper describes the research that has been carried out to provide an effective and practical methodology for modelling air pollution from minerals extraction. An improved or advanced Gaussian plume model has been developed that provides a more accurate description of atmospheric dispersion in the boundary layer. During the development of the model the important criteria were considered to be:

- The model should reflect recent improvements in the theoretical understanding of the atmospheric boundary layer and should include the fundamental parameters that describe boundary layer meteorological conditions and dispersion. The emphasis in this area has been towards improving the basic principles of the model.
- The relative simplicity of the Gaussian plume model should be maintained, particularly the requirement that only a minimum set of meteorological observations be needed to define the parameters that characterize the dispersion and meteorological conditions.
- The model should be flexible and modular so that it can easily be updated as the understanding of the problem improves.
- Methods of input and output for the model should be clear and flexible, incorporating graphical presentation of the results to improve interpretation and environmental impact evaluation.

The last point is considered to be of importance as many of the Gaussian plume models currently in use are characterized by ungainly methods of input and output, with very little provision for the display of results.

### Theoretical Background

Related to the stability of the atmosphere mentioned in the introduction is the diurnal variation in the structure of the boundary layer. Normally during the daytime, incoming solar radiation heats the Earth's surface. This is then transferred to the atmosphere as a heat flux away from the surface. This generates convection within the boundary layer and can greatly enhance turbulence and dispersion, and the atmosphere is described as unstable. At night, the reverse process happens with heat transferred to the Earth's surface, and stable conditions generally exist. The simplest method for introducing the effect of this surface heat flux is to calculate the energy balance at the Earth's surface assuming an ideal surface with no heat or mass storage. The energy balance is then given by<sup>5</sup>

$$Q^* = Q_H + Q_E + Q_G \quad (2)$$

where  $Q^*$  is the net radiation,  $Q_H$  is the sensible heat flux,  $Q_E$  is the latent heat flux, and  $Q_G$  is the soil heat flux. Several simple parameterization schemes exist for the various components of the surface energy balance<sup>1,6</sup>.

Given this diurnal variation, our interest is in characteristic boundary layer parameters to define both the state of the atmosphere and the dispersion. The most important of these are:

a) The friction velocity,  $u_*$ , which is a measure of the surface momentum flux, or shear stress. The friction velocity can be determined from the logarithmic profile law for the wind, modified to account for atmospheric stability, so that<sup>7</sup>

$$u_* = k u \left[ \ln \left( \frac{z}{z_0} \right) - \psi_M \left( \frac{z}{L} \right) \right]^{-1} \quad (3)$$

where  $u$  is the wind speed measured at a reference height  $z$ ,  $\psi_M$  is a stability function,  $k = 0.4$  is von Kármán's constant, and  $z_0$  is the aerodynamic roughness length, the height at which the mean wind speed becomes zero. As can be seen, this relationship can also be used to define the vertical profile of the wind.

b) The Obukhov length (or Monin-Obukhov length),  $L$ , which is given by

$$L = - \frac{\rho c_p u_*^3 T}{kg Q_H} \quad (4)$$

where  $\rho$  is the density,  $c_p$  is the specific heat at constant pressure, and  $T$  is the temperature. The magnitude of the Obukhov length is a measure of the relative importance of buoyancy forces to shear forces. For stable conditions  $L > 0$ , for unstable conditions  $L < 0$ , and for neutral conditions  $L \rightarrow \infty$  as  $Q_H \rightarrow 0$ .

c) The convective velocity scale, a velocity scale of convection generated turbulence given by

$$w_* = \left( \frac{gh Q_H}{\rho c_p T} \right)^{1/3} \quad (5)$$

d) The height of the boundary layer. Methods for determining this height are dependant on atmospheric stability. In neutral conditions it can be found from<sup>8</sup>

$$h = c \frac{u_*}{f} \quad (6)$$

where  $c$  is an empirical constant  $f$  is the Coriolis parameter. In stable conditions the boundary layer height can be found using<sup>9</sup>

$$h = 0.37 \left( \frac{u_* L}{f} \right)^{1/2} \quad (7)$$

In the convective boundary layer the growth in the height of the boundary layer occurs in response to the continual supply of heat at the surface. As a consequence diagnostic equations have been found to be unsatisfactory for predicting the mixed layer height, and rate equations have to be used instead. The basic approach is to equate the heat supplied during the day to that absorbed<sup>1</sup>

$$\int_{t_0}^{t_1} \frac{Q_H}{\rho c_p} (t) dt = \int_{\theta_0}^{\theta_1} \theta_s d\theta \quad (8)$$

where  $\theta_s$  is the initial early morning potential temperature profile and  $Q_H / \rho c_p (t)$  is the surface heat flux from the initial time  $t_0$  to a time  $t_1$ . The exact details of various methods can be found elsewhere<sup>1,10,11</sup>.

There are three principle methods which are used for defining the dispersion<sup>12</sup>: a) surface layer similarity; b) convective scaling; and c) statistical theory analysis. The first two are forms of dimensional analysis which in part are also used in defining the previous characteristic boundary layer parameters. For example, using surface layer similarity theory it is argued that diffusion should be a function of the characteristic velocity scale  $u_*$  and the length scales  $z$  and  $L$ . Statistical theory analysis differs from the two forms of dimensional analysis by defining the dispersion as a function of either measured or estimated turbulent velocity fluctuations. However, the three methods are to some extent interrelated as, for example, the same scaling parameters used in the two forms of dimensional analysis are commonly used in statistical theory analysis in defining the turbulent velocity fluctuations.

There is a large number of formulae suggested in the literature<sup>12</sup> based on these three principle methods that can be used for defining the dispersion parameters, and it is not proposed to review them here. Given this wide array of possible formulae for the dispersion the choice of which to use remains to some extent the choice of the modeller, as there is no definitive best answer.

### **Model Development**

Based on the theory briefly outlined in the previous section, an advanced air pollution model has been developed. The model is broken down into two constituent parts, a meteorological preprocessor and a dispersion model. The meteorological preprocessor describes atmospheric conditions as a continuum in terms of characteristic boundary layer scaling parameters, derived using a minimum set of meteorological measurements. These characteristic scales are then used by the dispersion model for defining the dispersion and vertical profiles of parameters used in the advanced Gaussian plume model. The principle design criteria of the air pollution model were that it should be representative, modular, flexible and yet remain conceptually simple.

Generally, in an air pollution study the set of meteorological observations that are available for use is limited. Conventional Gaussian plume models using the Pasquill-Gifford dispersion scheme are capable of modelling air pollution using these limited measurements. This capability has been maintained for the advanced model so that the characteristic boundary layer parameters that describe the dispersion can be defined using the limited set of meteorological observations. For the meteorological preprocessor an absolute minimum required set of meteorological measurements was defined which for each modelling period are wind speed, wind direction, temperature and cloud cover. These are used to define the

parameters: a) surface heat flux,  $Q_H$ ; b) friction velocity,  $u_*$ ; c) Obukhov length,  $L$ ; d) convective velocity scale,  $w_*$ ; e) potential temperature scale,  $\theta_*$ ; and f) boundary layer height  $h$ . These boundary layer parameters are then used to define the dispersion and vertical profiles of wind speed and temperature in the dispersion model.

For dispersion, the atmospheric conditions have been classified into the stable, neutral and convective regions, with the boundaries between the regions defined by the characteristic length scales  $z$  (or  $H$ ),  $L$  and  $h$ . In the neutral and convective regions, a further distinction is made by the surface layer defined as  $z/h \leq 0.1$ , so that releases are classified as either surface releases for  $H/h \leq 0.1$ , or elevated releases for  $H/h > 0.1$ . In the stable and neutral regions the Gaussian distribution is used, with the dispersion parameters found from the turbulent wind fluctuations using a combination of statistical theory analysis and similarity scaling. If measured turbulent wind fluctuations are available at the source release height, these can be used instead. In convective conditions a Gaussian formulation is used for the lateral dispersion and also for vertical dispersion from surface releases at downwind close to the source, with the dispersion parameters determined using convective scaling. Given that interest is primarily in ground level concentrations, formulae for the dimensionless ground level crosswind-integrated concentration have been used to define vertical dispersion in all other conditions, which accounts for the non-Gaussian vertical distribution. The dispersion model also integrates into the dispersion calculations the standard approach<sup>13</sup> for dealing with plume buoyancy.

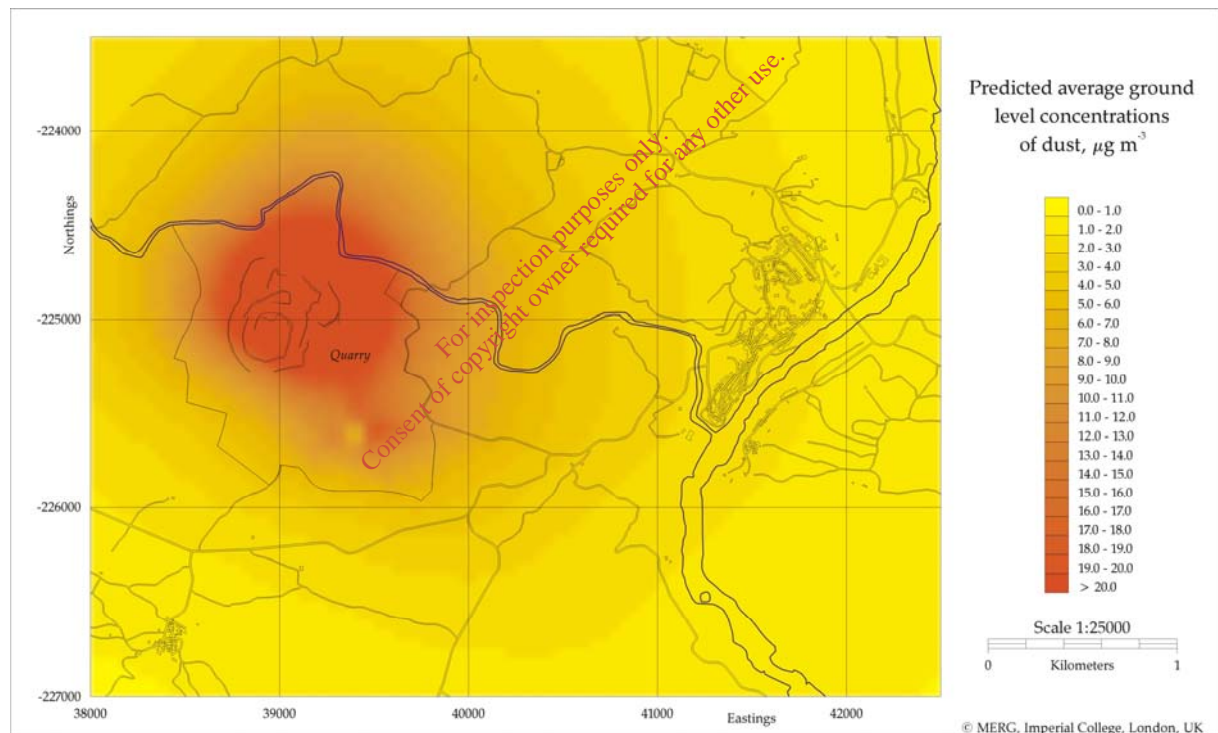


Fig. 1 : Air pollution model output: spatial representation of predicted dust concentrations in relation to other geographic and urban/rural features around a quarry.

The model has been coded in the object-oriented language C++ which allows a high degree of modularity in the program design. The importance of modularity in the model structure is that it allows the constituent model parts to be easily updated as improvements are made in the understanding of the dispersion, and this is an inherent feature of object-oriented programming. With object-oriented programming the problem domain is defined in terms of data types upon which distinct operations can be performed, resulting in a high degree of modularity. In this case, data types were meteorology, sources and receptors, on which distinct operations could be performed, either as an individual data type or in combination.

This modularity represents one form of flexibility in the design of a model. Another important area of flexibility in a model is in its input and output. Just as achieving a representative description of the dispersion is an important goal, equally important is the ability to interpret and analyze model parameters and results. At a practical level this includes the avoidance of ungainly methods of input and output. Whilst this does not affect the modelling ability of a particular air pollution model, it does enhance the possibility of sources of error in input and effects the interpretability of the end results. Flexibility in the model input and output has therefore been achieved by integrating the model with a GIS. As well as providing extended capabilities for model input and display, it also allows for the analysis of results directly or in combination with other forms of spatial data. This analysis is important as although the modelling of the physical process of atmospheric dispersion is an important part of understanding air pollution problems, equally important is the ability to interpret and analyze the results of the modelling. These results are of an inherently spatial nature, and interpretation and analysis will be in combination with other spatial data. This requirement is easily achieved through the integration of the model with a GIS. Fig. 1 demonstrates the enhanced model output display and analysis capability using the GIS.

### Model Validation

Model validation plays an important role in the development and the application of an air pollution model, by providing measures of the performance and capabilities of a model. This is achieved by comparison of various model parameters and predictions to the measured data of an evaluation scenario, and also possibly by reference to other models.

There are two basic methods used in the evaluation of air pollution models<sup>14</sup>: a) operational (or statistical) evaluation of a model in a particular application context using statistical performance measures, usually achieved with the comparison of observed to predicted concentration values; and b) diagnostic (or scientific) evaluation of the physics of a model, i.e. is the model giving good predictions for the right reasons. This should be carried out by assessment of the scientific basis of a model and by evaluation of the models parameters by reference to observations and predictions.

For operational evaluation there are six statistical measures in common usage<sup>14,15,16</sup>, as presented in Tab.

1. Here,  $\bar{C}_o$  is the mean of the observed concentrations  $C_o$ ,  $\bar{C}_p$  is the mean of the predicted concentrations  $C_p$ , and  $\sigma_{C_o}$  and  $\sigma_{C_p}$  are the standard deviations of the observed and predicted concentrations. In diagnostic evaluation several methods can be used: a) scientific judgment as to the validity of model physics; b) operational evaluation comparing observed to predicted concentrations; c) the comparison of predicted to observed model parameters, such as boundary layer height; and d) the comparison of the variation of model parameters to differences in concentrations. This last is usually carried out by plots that compare residuals, which are the difference or ratio between observed and predicted concentrations, to the variation in a model parameter. If there is a trend in the plot this may indicate an error in the model physics.

Tab. 1 : Statistical measures in common usage for operational evaluation

Name	Method	Description
Bias	$\text{BIAS} = \bar{C}_o - \bar{C}_p$	A measure of the variability of the differences between observed and predicted concentrations. Ideal value is 0.
Normalized mean square error	$\text{NMSE} = \frac{(\bar{C}_o - \bar{C}_p)^2}{\bar{C}_o \bar{C}_p}$	
Fractional bias	$\text{FB} = \frac{2(\bar{C}_o - \bar{C}_p)}{\bar{C}_o + \bar{C}_p}$	A measure of how well a model reproduces the mean of observed concentrations. The ideal value is 0 and it can range between -2 and +2, with $\pm 0.67$ representing

	$FS = \frac{2(\sigma_{C_o} - \sigma_{C_p})}{\sigma_{C_o} + \sigma_{C_p}}$	predictions within a factor of two of observations.
Fractional variance (scatter)	$r = \frac{(C_o - \bar{C}_o)(C_p - \bar{C}_p)}{\sigma_{C_o} \sigma_{C_p}}$	A measure of how well a model reproduces the spread of observed concentrations. The ideal value is 0 and it can range between -2 and +2, with $\pm 0.67$ representing predictions within a factor of two of observations.
Correlation coefficient		The value $r^2$ is the fraction of the variance resolved by the model, with a range of -1 to +1.
Fraction within a factor of two (FA2)	$0.5 \leq C_o/C_p \leq 2$	The fraction of predicted concentrations within a factor of two of observed concentrations, expressed as a percentage. The ideal value is 100%.

One of the major difficulties with air pollution model evaluation is that the uncertainty that exists in air pollution modelling is typically quite large<sup>14,16</sup>, a portion of which is essentially irreducible because of the nature of the process modelled. This uncertainty in an air pollution model is made up of three different elements<sup>16</sup>: a) uncertainty due to errors in the model physics; b) uncertainty due to errors in the data; and c) inherent uncertainty.

As part of the European Initiative on *Harmonization within Atmospheric Dispersion Modelling for Regulatory Purposes* a model validation kit has been prepared<sup>17</sup>. The purpose of the model validation kit was to provide a framework within which differing models could be directly compared using common data sets and standard model evaluation procedures. The model validation kit is comprised of data from three atmospheric dispersion field experiments, namely Kincaid, U.S.A., Copenhagen, Denmark and Lillestrøm, Norway. These validation data sets were used in assessing the performance of the advanced Gaussian model developed in this study. A brief outline of the results obtained from one of the field experiments, Kincaid, U.S.A., is presented here.

In order to facilitate comparison the Pasquill-Gifford based air pollution model ISC2 has also been applied to the field experiments. The ISC2 model is the US Environmental Protection Agency's (EPA) recommended regulatory model<sup>18</sup> for industrial sources of air pollution in both rural and urban conditions. The modelling options used were those recommended in the user's guide<sup>19</sup> for the conditions of the field experiments. It should also be noted that ISC2 has recently been updated to ISC3 by the US EPA. This has taken the form of some additions to its modelling capabilities, although the basics of the model have not changed.

### Kincaid field experiment

The Kincaid field experiment was carried out at the Kincaid power plant in Illinois during 1980-81, and is the most extensive of the three data sets. The area around the power plant is flat farmland with some lakes. The tracer used was SF<sub>6</sub>, released into a buoyant plume from a 187 m high stack. Monitoring stations were placed in arcs on a daily basis in accordance with the expected wind direction and the distance to the maximum ground level concentration. The concentrations compared were the maximum in each arc of monitoring stations, the arc-wise maxima, to the predicted plume centre-line concentration. Both observed and predicted concentrations were normalized by division by the emission rates.

A large number of variables were measured including boundary layer height and wind speed, wind direction and temperature at various heights up to 100 m. In accordance with the recommended guidelines<sup>17</sup> the observed boundary layer height was used as input for both models. Pasquill-Gifford stability categories for the ISC2 model were calculated using the standard method, and the meteorological preprocessor of the advanced model was used to calculate its input parameters.

The statistical analysis of the results from Kincaid for the two dispersion models is given in Tab. 2. The observed values of the statistical measures represent what a perfect model should achieve, although in practice no model could achieve these values because of the inherent uncertainty present in the diffusion process. Scatter and quantile plots of observed to predicted concentrations are shown in Fig. 2. The quantile plots are concentration values paired independently in time and space, i.e. highest to highest, second highest to second highest, etc.

Tab. 2 : Kincaid: Statistical measures of arcwise normalized concentration predictions compared to observations. Units are  $\text{s m}^{-3} \times 10^9$ .

Statistical measure	Observed values	Advanced model	ISC2
Mean	54.34	49.44	23.64
Standard deviation	40.31	48.29	30.21
Bias	0.00	4.90	30.69
NMSE	0.00	1.20	2.81
Correlation	1.000	0.191	-0.058
FA2	1.000	0.577	0.370
FB	0.000	0.094	0.787
FS	0.000	-0.180	0.286

From the examination of the statistical measures and the graphs of the results the following conclusions can be drawn:

- The comparison of the statistical measures between the models suggests that the advanced model has performed considerably better than the ISC2 model.
- As can be seen from the plots, the ISC2 model predicts a large number of zero concentrations when a non-zero concentration has been observed. This can be attributed to the “all or nothing” approach to plume penetration into the elevated stable layer above the boundary layer used in the model. This assumes that the ground level concentration is zero if the calculated effective height of the plume due to buoyancy is above the height of the boundary layer. However, this prediction of zero concentrations also occurs to a lesser extent for the advanced model, which may be an indication of problems with the partial plume penetration algorithm used in the model.
- These zero predictions have an influence on the statistical measures of the mean, bias and FB, suggesting underprediction by both of the models. However, examination of the quantile plots shows that the advanced model adequately match predictions to observations.
- The ISC2 consistently underpredicts concentrations.

Based on the statistical measures and the graphs of results, the advanced model has provided more accurate estimates of the concentration values for the Kincaid data set when compared to the ISC2 model.

The next stage in the evaluation is to ensure that these improvements in concentration predictions are attributable to improvements in the scientific basis of the advanced model compared to the ISC2 model. This was carried out using residual plots of the ratio  $C_p/C_o$  to the variation in a model parameter. Residual plots that use individual points can be difficult to interpret because of the variability in values of  $C_p/C_o$ . An alternative is to cluster the data and plot statistical values. As the ratio has been shown to follow a lognormal distribution<sup>14</sup>, each model parameter has been divided into approximately equal sized groups, and the geometric mean and uncertainty of  $C_p/C_o$  calculated for each group. The uncertainty was calculated as the 95% confidence limit of a lognormal distribution using the geometric standard deviation. The geometric standard deviation accounts for the inherent uncertainty in  $C_p/C_o$  and errors in the input meteorological measurements<sup>14</sup>.



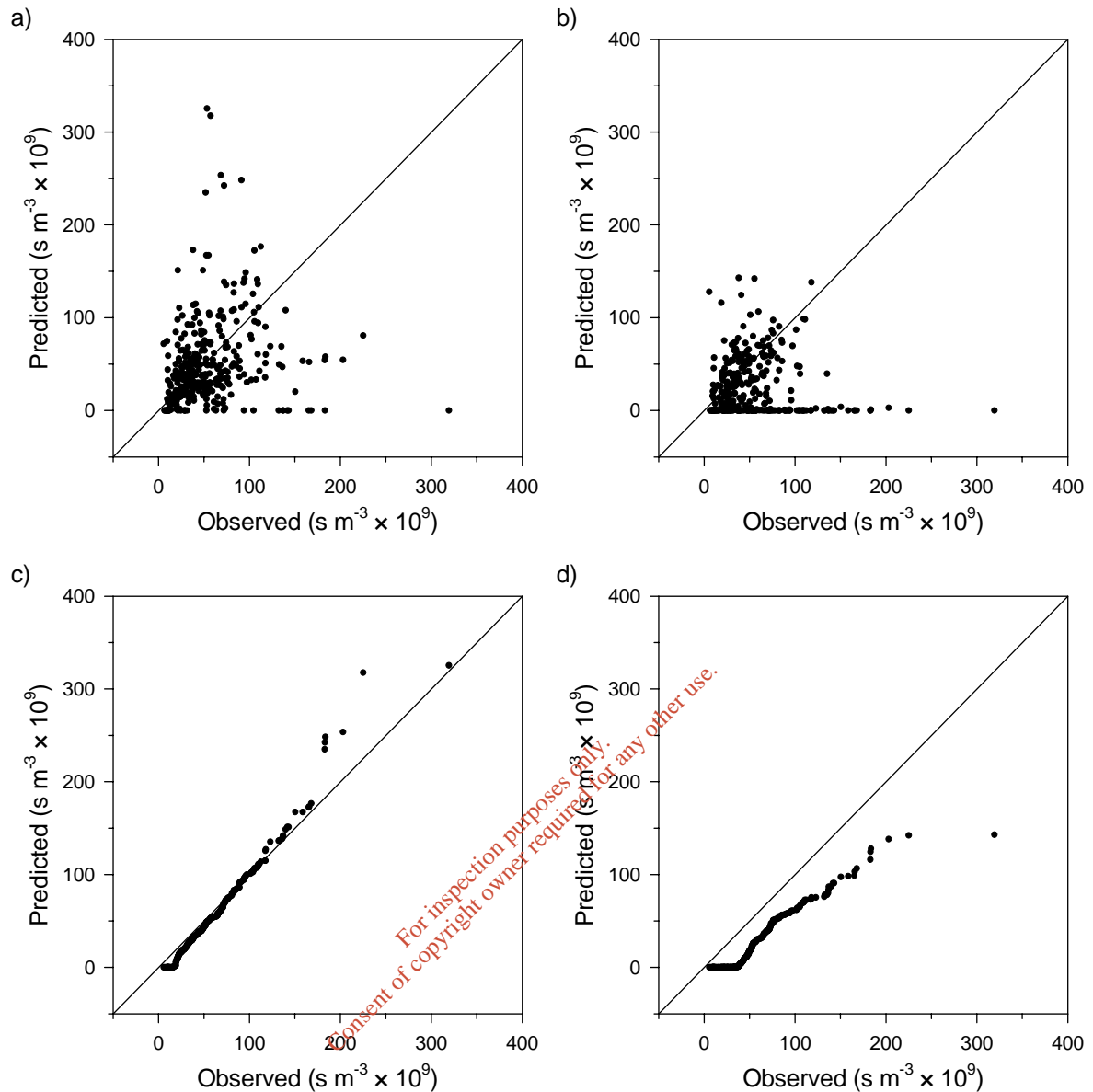


Fig. 2 : Kincaid: Plots of predicted to observed arcwise normalized concentrations where:  
 a) scatter plot, advanced model; b) scatter plot, ISC2; c) quantile plot, advanced model; and d) quantile plot, ISC2.

By way of illustration, residual plots using this approach for two model parameters, downwind distance from the source and boundary layer height, are shown in Fig. 3. Based on these plots alone the following points can be made:

- The ISC2 model has large underpredictions at distances closer than 10 km to the source, and the advanced model has a slight tendency towards underprediction. Given that Gaussian plume models are predominantly applied in ranges up to 10 km, any underpredictions in this range suggest serious deficiencies in a model.
- The advanced model overpredicts for the lower boundary layer heights. The ISC2 model has very erratic behaviour, with an overall tendency to underprediction.

Overall, the advanced model shows improved concentration predictions for the Kincaid data set, both in terms of operational and diagnostic evaluations. There are, however, possibly a few areas of weaknesses that have been highlighted, such as buoyant plume penetration of a capping stable inversion.

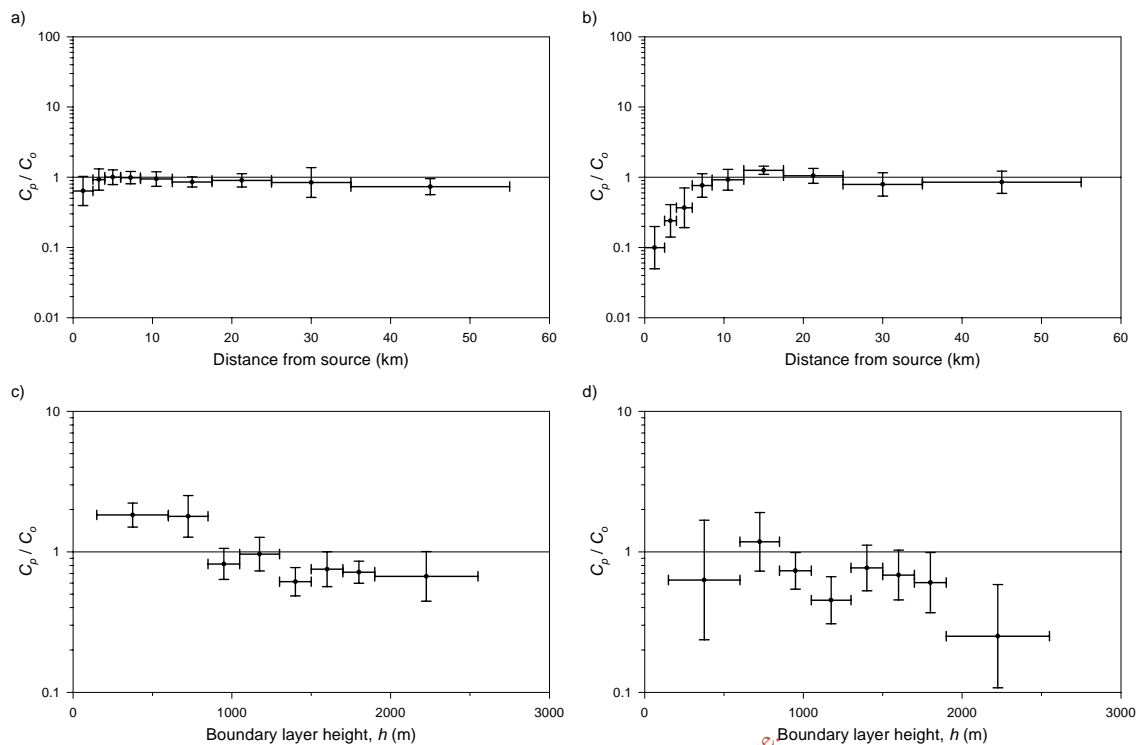


Fig. 3 : Kincaid: Residual plots of  $C_p/C_o$  against downwind distance from the source for where: a) downwind distance, advanced model; b) downwind distance, ISC2; c) boundary layer height, advanced model; and d) boundary layer height, ISC2.

### Conclusions

This paper has described the development of an advanced Gaussian plume air pollution model. The results obtained from the model evaluation suggest that the model developed represents a significant improvement over those air pollution models currently used in practice. A point of particular importance is that the improved results obtained from model evaluation arise from the use of a better physical characterization of the boundary layer and dispersion in the model.

The improvement in the results has also been achieved whilst retaining the relative simplicity of the meteorological input requirements of the model. This is of importance to the minerals extraction industry as operations are often located in remote areas where full scale meteorological monitoring campaigns will be impractical in terms of the cost and effort required. Overall, the advanced Gaussian plume model developed will improve the analysis of the environmental impacts of air pollution from minerals extraction, and should lead to a more effective means of quantifying and alleviating those impacts.

The other two criteria in developing the model have also been met. The first of these was flexible and modular design, which has been achieved by using an object-oriented programming environment. This allows the incremental design and update of individual model routines as the knowledge base of modelling improves. The second criteria was in model input and output, which was achieved by implemented the model within a GIS framework.

### References

1. R.B. STULL: *An Introduction to Boundary Layer Meteorology*, Kluwer Academic Publishers, Dordrecht, 1988.
2. F. PASQUILL: "The estimation of the dispersion of windborne material", *The Meteorological Magazine*, 1961, **90**, 33-49.
3. J.C. WEIL: "Updating applied diffusion models", *Journal of Climate and Applied Meteorology*, 1985, **24**, 1111-1130.
4. M.E. SMITH: "Review of the attributes and performance of 10 rural diffusion models", *Bulletin of the American Meteorological Society*, 1984, **65**, 554-558.
5. T.R. OKE: *Boundary Layer Climates (Second Edition)*, Methuen, London, 1987.
6. A.A.M. HOLTSLAG and A.P. VAN ULDEN: "A simple scheme for daytime estimates of the surface fluxes from routine weather data", *Journal of Climate and Applied Meteorology*, 1983, **22**, 517-529.
7. J.A. BUSINGER, J.C. WYNGAARD, Y. IZUMI and E.F. BRADLEY: "Flux-profile relationships in the atmospheric surface layer", *Journal of the Atmospheric Sciences*, 1971, **28**, 181-189.
8. A.K. BLACKADAR and H. TENNEKES: "Asymptotic similarity in neutral barotropic atmospheric boundary layers", *Journal of the Atmospheric Sciences*, 1968, **25**, 1015-1020.
9. F.T.M. NIEUWSTADT: "Some aspects of the turbulent stable boundary layer", *Boundary-Layer Meteorology*, 1984, **30**, 31-55.
10. D.J. CARSON: "The development of a dry inversion-capped convectively unstable boundary layer", *Quarterly Journal of the Royal Meteorological Society*, 1973, **99**, 450-467.
11. J.C. WEIL and R.P. BROWER: *Estimating Convective Boundary Layer Parameters for Diffusion Applications*. Report PPS-48, Environmental Center, Martin Marietta Corporation, Baltimore, MD, 1983.
12. G.A. BRIGGS: "Analysis of diffusion field experiments", *Lectures on Air Pollution Modelling*, A. Venkatram and J.C. Wyngaard, eds, American Meteorological Society, Boston, 1988.
13. G.A. BRIGGS: "Plume rise and buoyancy effects", *Atmospheric Science and Power Production*, D. Randerson, ed., US Department of Energy, DOE/TIC-27601, 1984.
14. J.C. WEIL, R.I. SYKES and A. VENKATRAM: "Evaluating air-quality models: Review and outlook", *Journal of Applied Meteorology*, 1992, **31**, 1121-1145.
15. W.M. COX and J.A. TIKVART: "A statistical procedure for determining the best performing air quality simulation model", *Atmospheric Environment*, 1990, **24A**, 2387-2395.
16. S.R. HANNA: "Air quality model evaluation and uncertainty", *Journal of the Air Pollution Control Association*, 1988, **38**, 406-412.
17. H.R. OLESEN: *Model Validation Kit for the Workshop on Operational Short-Range Atmospheric Dispersion Models for Environmental Impact Assessment in Europe*, Mol, November 21-24, National Environmental Research Institute, Denmark, 1994.
18. US EPA: *Guideline on Air Quality Models (Revised)*. EPA Pub. No. EPA-450/2-78-027R, US EPA, Research Triangle Park, NC, 1993c.
19. US EPA: *User's Guide for the Industrial Source Complex (ISC2) Dispersion Models, Vols 1, 2 and 3*, Pub. Nos EPA-450/4-92-008a-c, US EPA, Research Triangle Park, NC, 1992.