APPLICATION OF VARIOUS DISPERSION COEFFICIENTS TO INVESTIGATE THE SENSITIVITY OF OFFSITE CONSEQUENCES

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ABSTRACT

In the event of a nuclear power plant accident, the release of radioactive materials into the atmosphere is likely to spread over a wide area, making the atmosphere the primary medium for human exposure. Therefore, it is essential to assess the dispersion of radioactive material for conducting an offsite consequence analysis. Most offsite consequence analysis codes utilize the Gaussian plume model for atmospheric dispersion analysis. The dispersion coefficient is a critical factor that determines the vertical and horizontal concentration distribution in the downwind direction of the Gaussian plume model. A majority of dispersion coefficients are calculated based on the Pasquill-Gifford curve, which was developed for flat terrain, and various fitting equations have been proposed to utilize it effectively. In this study, several dispersion coefficients, including Tadmor-Gur, Eimutis-Konicek, Briggs, Martin, and Seinfeld, were investigated and applied to offsite consequence analyses. Radiological Consequence Analysis Program (RCAP) developed by Korea Atomic Energy Research Institute (KAERI) and MELCOR Accident Consequence Code System (MACCS) developed by Sandia National Laboratories (SNL) were employed to perform offsite consequence analyses. Subsequently, the influence of the dispersion coefficient on the offsite consequences was analyzed. The results of this study highlight how the selection of dispersion coefficients in Gaussian plume models can affect offsite consequences. The insights gained from this study are expected to contribute to future Level 3 probabilistic safety assessments (PSAs) and emergency planning zone (EPZ) assessments.

Keywords: Atmospheric dispersion, Dispersion coefficient, Offsite consequence analysis, Level 3 PSA

I. INTRODUCTION

PSA (Probabilistic Safety Assessment) has continued to evolve as an effective and systematic tool for identifying and evaluating risks associated with nuclear facilities. It is generally categorized into three levels according to the protective boundaries of a nuclear power plant: Level 1 evaluates core damage frequency, Level 2 addresses containment failure and radioactive release, and Level 3 assesses the radiological impact on the environment and the public. Among them, Level 3 PSA aims to quantify the consequences of radioactive materials released into the environment, particularly through atmospheric dispersion and deposition, and its resulting impact on surrounding populations and ecosystems. In recent years, the significance of Level 3 PSA has become increasingly prominent due to growing societal concern and enhanced regulatory demands.

In the event of a nuclear accident, the atmosphere serves as the primary pathway through which radioactive materials can exert the most significant short-term impact on the environment and the public. Accordingly, atmospheric dispersion models are employed to quantitatively evaluate the transport and dispersion behavior of released radionuclides. These models are used to predict the atmospheric concentration distribution of the released radioactive material and the resulting radiation dose. Among such models, the Gaussian plume model is one of the most widely adopted, which assumes that the concentration of released contaminants follows a Gaussian distribution in both the horizontal and vertical directions relative to the plume centerline.

In this process, the dispersion coefficient is a key parameter in quantifying the extent of plume spread in the atmosphere, directly influencing the accuracy of concentration distribution and dose prediction. Dispersion coefficients are typically derived from Pasquill-Gifford (P-G) fitting curves [1] based on the results of the Prairie Grass experiment [2], and a variety of empirical fitting expressions have been proposed to put them into numerical form. They are expressed in various equation forms depending on the differences in experimental conditions and the range of meteorological factors considered in each model. The selection of dispersion coefficient models can result in considerable variations in prediction outcomes depending on atmospheric stability conditions, particularly affecting the spatial characteristics of plume dispersion and the subsequent offsite consequence assessment. Therefore, the choice of dispersion coefficient model should be considered as a factor directly related to the reliability and quantitative validity of offsite impact predictions, and a more careful and systematic approach is required.

This study compares the characteristics of five dispersion coefficient models—Tadmor-Gur, Eimutis-Konicek, Briggs, Martin, and Seinfeld—and conducts offsite impact assessments using the Radiological Consequence Analysis Program (RCAP) and the MELCOR Accident Consequence Code System (MACCS) to quantitatively evaluate the differences among the models. The results provide a quantitative understanding of the sensitivity of the choice of dispersion coefficient model to the results of the offsite impact assessment, and contribute to the development of model selection criteria for conducting more reliable Level 3 PSAs in the future.

II. METHODOLOGY

II.A. Atmospheric Dispersion Modeling using Gaussian Plume Approach

In this study, the Gaussian plume model was employed to evaluate the atmospheric dispersion of radioactive materials released during a nuclear accident. This model defines the spatial concentration distribution of the plume based on the standard deviations of the Gaussian distribution in the horizontal (σ_y) and vertical (σ_z) directions. The dispersion of the plume occurs in all directions due to atmospheric turbulence, with vertical dispersion being particularly influenced by surface roughness and thermal structures of the atmosphere, such as inversion layers. In contrast, horizontal dispersion is less constrained and is further enhanced by plume meandering along the centerline. Dispersion in the downwind direction is generally negligible due to the significantly lower turbulence velocity compared to the mean wind speed. Owing to its simplicity and computational efficiency, the Gaussian plume model is widely used to simulate the dispersion of radioactive materials in the atmosphere following reactor accidents. When the plume dispersion is not constrained by surface contact or inversion layers, the concentration distribution is defined by the Gaussian plume equation introduced by Turner [3].

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

In Equation 1, χ denotes the time-integrated atmospheric concentration, Q represents the emission rate of the pollutant from the source, and h is the effective release height. The coordinates x, y, and z refer to the downwind, crosswind, and vertical distances, respectively. σ_y and σ_z represent the standard deviations of the concentration distribution in the crosswind and vertical directions. The parameter u denotes the mean wind speed at the effective release height.

II.B. Atmospheric Dispersion Parameters

II.B.1. Atmospheric Stability

To apply the Gaussian plume model for evaluating atmospheric dispersion, it is first necessary to determine the atmospheric stability of the environment under consideration. Atmospheric stability is typically classified based on meteorological observation data, using empirical schemes proposed by Pasquill and Gifford [4]. The classification criteria for stability categories are presented in Table I, which are established by comprehensively considering meteorological parameters such as wind speed, solar radiation, and cloud cover. Since the dispersion characteristics of a plume vary significantly depending on the atmospheric stability class, the corresponding dispersion coefficients also exhibit marked differences across stability conditions.

Table I. Pasquill-Gifford Atmospheric Stability

Wind speed (m/s)	Day time – Solar Radiation			Night time – Cloud cover	
	Strong	Moderate	Slight	Cloudy	Clear
< 2	A	A-B	B	-	-
2 – 3	A-B	B	C	E	F
3 – 5	B	B-C	C	D	E

5 – 6	C	C-D	D	D	D
> 6	C	D	D	D	D

A: Very unstable / B: Moderately unstable / C: Slightly unstable / D: Neutral / E: Slightly stable / F: Stable

II.B.2. Dispersion Coefficient

In this study, a total of five dispersion coefficient models were employed for analysis. Dispersion coefficients are calculated based on the determined atmospheric stability and are classified into horizontal dispersion coefficients σ_y and vertical dispersion coefficients σ_z. One of the most representative atmospheric dispersion experiments, the Prairie Grass experiment, was conducted in 1956 in O'Neill, Nebraska, USA. This experiment demonstrated that the dispersion behavior within a range of approximately 1 km could be predicted by considering meteorological parameters such as atmospheric stability and wind direction variability. Based on the results of this experiment, Pasquill and Gifford established curves representing horizontal and vertical dispersion coefficients according to atmospheric stability, which have since served as a reference standard for various dispersion models (Fig. 1).

Among the models considered, the Tadmor-Gur and Briggs models are empirical formulations that differ from the conventional Pasquill-Gifford (P-G) curve-based models, yet are widely applied both domestically and internationally as representative dispersion coefficient models. The remaining models are derived by fitting empirical equations to the P-G curves, mathematically expressing the dispersion characteristics associated with each stability class. The equations for each dispersion coefficient model, along with the major meteorological parameters considered, are summarized in Table II.

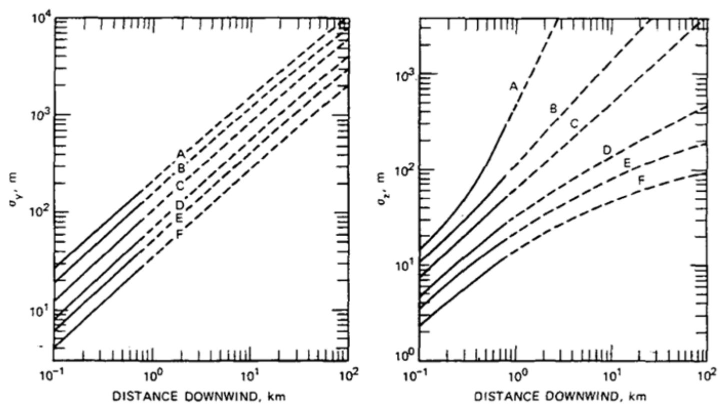


Figure 1. Pasquill-Gifford (PG) Curves [5]

Table II. Dispersion Coefficient Models

Model	Equation	Meteorological Factors
Tadmor-Gur (1969)	$\sigma_y = ax^b, \sigma_z = cx^d$	Distance (x), Stability Class (A-F)
Eimutis-Konicek (1972)	$\sigma_y = Ax^{0.9031}\ (A = k_1\sigma_\theta^2 + k_2\sigma_\theta + k_3)$ $\sigma_z = cx^d + f$	Distance (x), azimuthal wind direction fluctuations (σ_θ), lapse rate (ΔT)
Briggs (1973)	$\sigma_y = Ax(1 + 0.001x)^{-1/2}$ $\sigma_z = Bx(1 + Cx)^D$	Distance (x), Stability Class (A-F)
Martin (1976)	$\sigma_y = ax^{0.894},\ \sigma_z = cx^d + f$	Distance (x), Stability Class (A-F)
Seinfeld (2006)	$\sigma_y = R_y x^{r_y},\ \sigma_y = \exp\,[I_y + J_y \ln x + K_y(\ln x)^2]$ $\sigma_z = \exp\,[I_z + J_z \ln x + K_z(\ln x)^2]$	Distance (x), Stability Class (A-F)

The Tadmor-Gur dispersion coefficient [6] is developed based on the results of the Prairie Grass field experiment. Previous studies proposed dispersion coefficient equations in the form of a power law. Fuquay et al. [7] experimentally demonstrated that the horizontal dispersion coefficient σ_y is proportional to $(\sigma_\theta \bar{u})t^p$, while Smith and Singer [8][9] expressed dispersion as a power-law relationship in the form of $\sigma = ax^p$. Tadmor and Gur applied this $\sigma = ax^p$ formulation separately for each atmospheric stability class (A–F), reporting good agreement between the fitted expressions and the graphic curves presented by Gifford.

The Eimutis-Konicek dispersion coefficient [10] defined continuous expressions for both horizontal and vertical dispersion coefficients (σ_y and σ_z) as functions of downwind distance (x) and meteorological parameters such as the standard deviation of wind direction fluctuations (σ_θ) and lapse rate (ΔT). The horizontal dispersion coefficient is primarily influenced by distance and wind direction fluctuations, while the vertical dispersion coefficient also incorporates the effects of lapse rate. In this model, σ_y is based on the Tadmor-Gur model [6], with further refinement through regression analysis using the standard deviation of wind direction fluctuations. σ_z is derived from a piecewise function structure originally proposed by Martin [11].

The Briggs dispersion coefficient [12] integrated the Pasquill, BNL (Brookhaven National Laboratory), and TVA (Tennessee Valley Authority) curves based on observations up to 10 km downwind and applies theoretical concepts related to the asymptotic limits of the formulas to develop a set of empirical equations. According to this model, the initial plume spread under all atmospheric stability conditions is proportional to the downwind distance (x), and at long distances, the horizontal dispersion coefficient σ_y follows a $x^{1/2}$ dependence, consistent with the Fickian and Taylor theories of diffusion.

The Martin dispersion coefficient [13] is introduced to improve upon the mathematical limitations of Turner's formulation. While Turner modeled σ_y as a curved function based on experimental data, it was argued that if σ_y truly follows a power-law relationship with distance (x), it should appear as a straight line on a log–log plot. Accordingly, Martin removed the constant term in the σ_y equation to ensure that the transformed function remains linear when plotted on a logarithmic scale.

The Seinfeld dispersion coefficient [14] is formulated using an exponential equation with three parameters, derived from PG curves. The coefficient expresses the vertical dispersion coefficient σ_z as a function of $\ln(x)$, enabling a more refined representation of distance dependence. The coefficient is based on a collection of experimental data from multiple studies, including Gifford (1976), Weber (1976), AMS Workshop (1977), Doran et al. (1978), Sedefian and Bennett (1980), and Hanna et al. (1982). The applicability of the empirical expression is limited to downwind distances of up to 10 km, with a corresponding formulation also available for σ_y.

II.C. Offsite consequence Assessment Tools

II.C.1. RCAP code

RCAP (Radiological Consequence Analysis Program) [15] is a computational tool developed by the Korea Atomic Energy Research Institute (KAERI) to probabilistically assess the radiological impact on surrounding areas in the event of a radioactive release from a nuclear facility. The program is designed to model the atmospheric dispersion and transport of released radionuclides, as well as their deposition onto the ground surface, enabling quantitative evaluation of both short-term consequences and long-term environmental and health effects. RCAP employs the Gaussian plume model as its physical model.

II.C.2. MACCS code

MACCS (MELCOR Accident Consequence Code System) [16] is an analytical code developed by Sandia National Laboratories (SNL) to probabilistically estimate the offsite consequences of potential severe accidents at nuclear power plants. The code allows for the modeling of hypothetical radioactive release scenarios and is designed to comprehensively evaluate their impacts on human health and the economy. It incorporates a wide range of factors, including atmospheric dispersion and transport, wet and dry deposition, environmental transfer, protective action strategies, radiation dose assessment, health effects, and economic damages. Although MACCS is configured to accommodate both the Gaussian plume model and the HYSPLIT model as selectable physical models, this study adopts the Gaussian plume model as the default within MACCS to ensure consistency in the comparative analysis between the two codes.

III. RESULTS AND DISCUSSION

III.A. Dispersion Coefficients by Atmospheric Stability Class

This study conducted a comparative analysis of five previously introduced dispersion coefficient models under six atmospheric stability classes and downwind distances up to 30 km, which corresponds to the maximum boundary of the Urgent Protective Action Planning Zone (UPZ) [17]. The key findings can be summarized in two main points. First, the differences in dispersion coefficients among models tend to increase with distance. Second, the model exhibiting the highest or lowest dispersion performance varied depending on the atmospheric stability condition. The corresponding results are presented in Fig. 2.

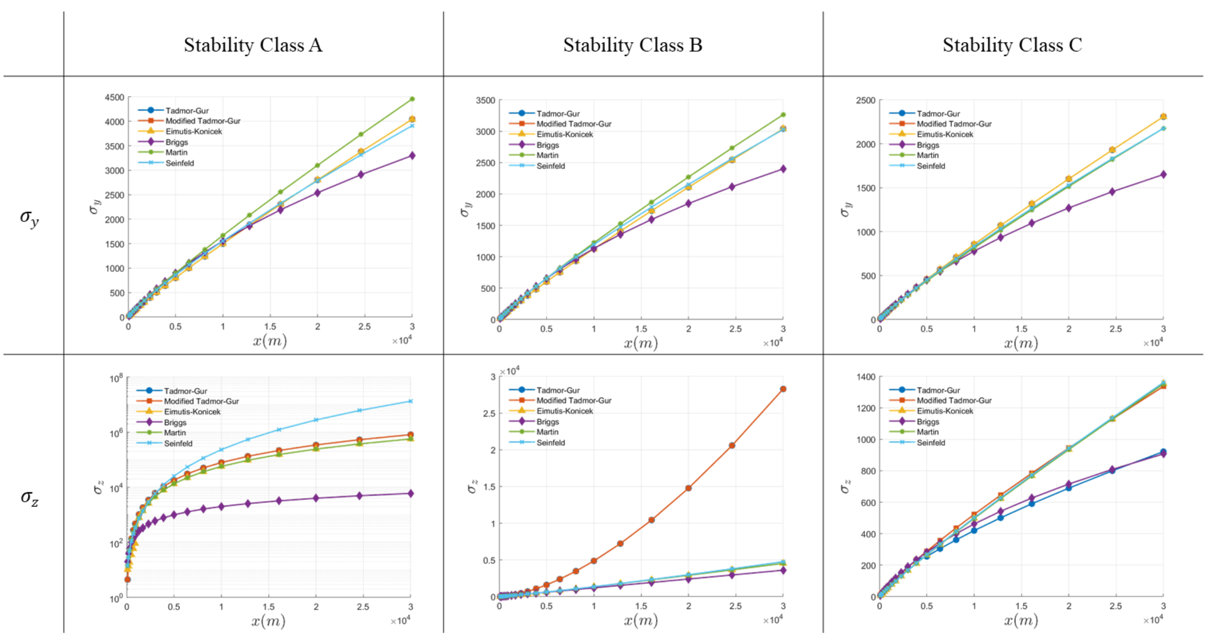
Under unstable atmospheric conditions (Stability Classes A, B, and C), the Briggs model consistently produced the lowest values for both horizontal and vertical dispersion coefficients. For horizontal dispersion, the Martin, Tadmor-Gur, and Modified Tadmor-Gur models generally yielded higher values; however, excluding the Briggs model, most models exhibited similar patterns and magnitudes. In contrast, vertical dispersion coefficients showed more pronounced variation, with the Seinfeld and Tadmor-Gur–based models displaying significantly higher values compared to others.

Under neutral atmospheric conditions (Stability Class D), the Briggs model again produced the lowest horizontal dispersion coefficients, while the Tadmor-Gur–based models yielded the highest. In contrast, vertical dispersion coefficients exhibited similar patterns and magnitudes across all models, indicating minimal differences among them.

Under stable atmospheric conditions (Stability Classes E and F), the Briggs model produced the lowest coefficients in both horizontal and vertical directions. The Eimutis-Konicek, Tadmor-Gur, and Modified Tadmor-Gur models yielded the highest horizontal dispersion coefficients, while the Modified Tadmor-Gur model resulted in the highest vertical dispersion coefficients.

As previously mentioned, the Eimutis-Konicek model adopts the dispersion coefficients of the Tadmor-Gur model in the horizontal direction and those of the Martin model in the vertical direction. Consequently, its results are largely overlapped by these models and are not clearly distinguishable in the plots.

Subsequently, an analysis was conducted for four atmospheric stability classes, excluding the extreme conditions represented by classes A and F among the six standard categories. For each of the four stability classes, the two models with the greatest difference in dispersion coefficients were identified, and their ratios were averaged to assess overall divergence. The results indicated that, at a distance of 5 km, the horizontal dispersion coefficient showed a marginal difference of approximately 0.99 times, while the vertical dispersion coefficient differed by about 1.4 times. At 30 km, the horizontal dispersion coefficient exhibited a difference of approximately 1.35 times, and the vertical dispersion coefficient showed a pronounced variation of up to 3 times.



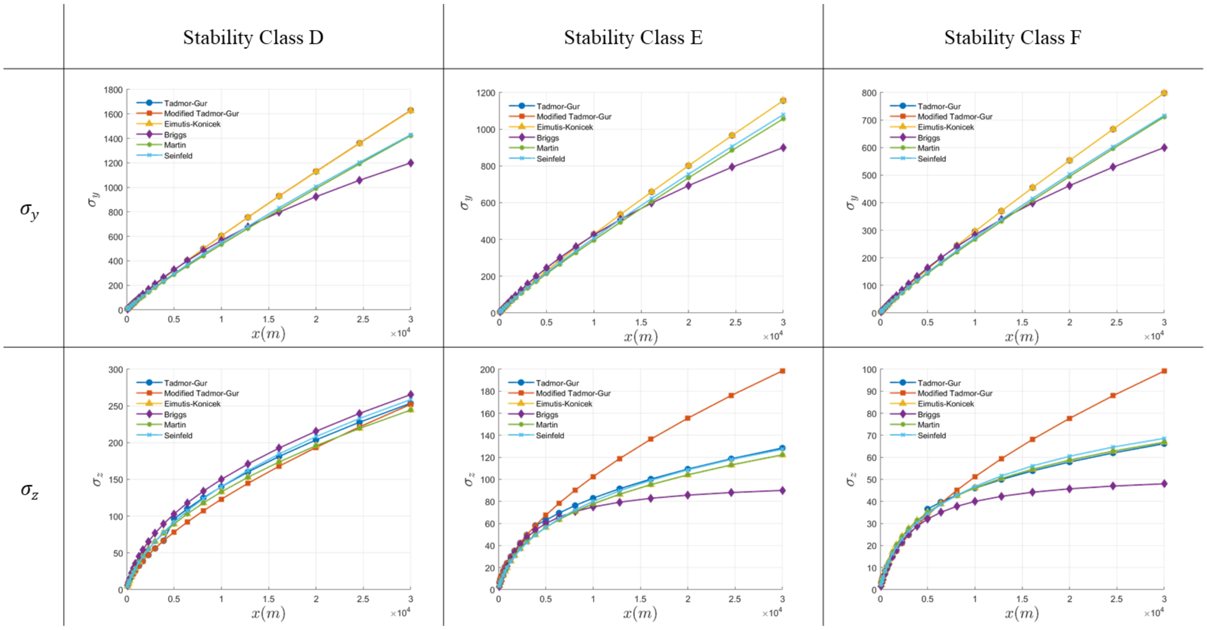


Figure 2. Distributions of Horizontal (σ_y) and Vertical (σ_z) Dispersion Coefficients by Stability Class for Each Model

III.B. Offsite Impact Assessment using RCAP and MACCS

In this study, a comparative analysis was conducted to evaluate the impact of different dispersion coefficient models using the RCAP and MACCS codes, based on a reference site located on flat terrain in Korea. All input conditions were kept identical across simulations, except for the choice of dispersion coefficient model. A total of six dispersion models were considered. The analysis focused on two output indicators that directly reflect the impact of the selected dispersion model: ground-level dilution and mean peak dose.

The wind speed was set to 2.1 m/s, based on the national average observed over the 20-year period from 2004 to 2024 [18], and six atmospheric stability classes (A to F) were considered. Receptors were placed at 20 downwind distances ranging from 0.1 km to 30 km, and in 16 azimuthal directions. Among these, two key assessment points were selected: 5 km, corresponding to the maximum boundary of the Precautionary Action Zone (PAZ), and 30 km, corresponding to the maximum boundary of the Urgent Protective Action Planning Zone (UPZ) [17].

Figure 3 presents a comparison of ground-level dilution predictions across distances for each dispersion coefficient model, using both RCAP and MACCS. In this analysis, the ground-level dilution was based on the calculated values for Cs-137, selected as a representative radionuclide. Under unstable (A, B, C) and neutral (D) atmospheric conditions, the differences between models remained relatively small; however, under stable conditions (E, F), the predicted concentrations varied more significantly depending on the dispersion model applied. In addition, regardless of the stability class, the Briggs model consistently predicted the highest concentrations as the distance approached 30 km.

Table III provides a quantitative comparison of model predictions under Stability Class E, where the largest differences among models were observed at both 5 km and 30 km. At both distances, the maximum and minimum predicting models were the same for RCAP and MACCS, and the magnitude of difference between the two codes was also comparable. At 5 km, the Martin model produced the highest predicted concentration, while the Modified Tadmor-Gur model produced the lowest, with a difference of up to 1.26 times. At 30 km, the Briggs model yielded the highest value, whereas the Modified Tadmor-Gur model yielded the lowest, resulting in a maximum difference of 2.65 times.

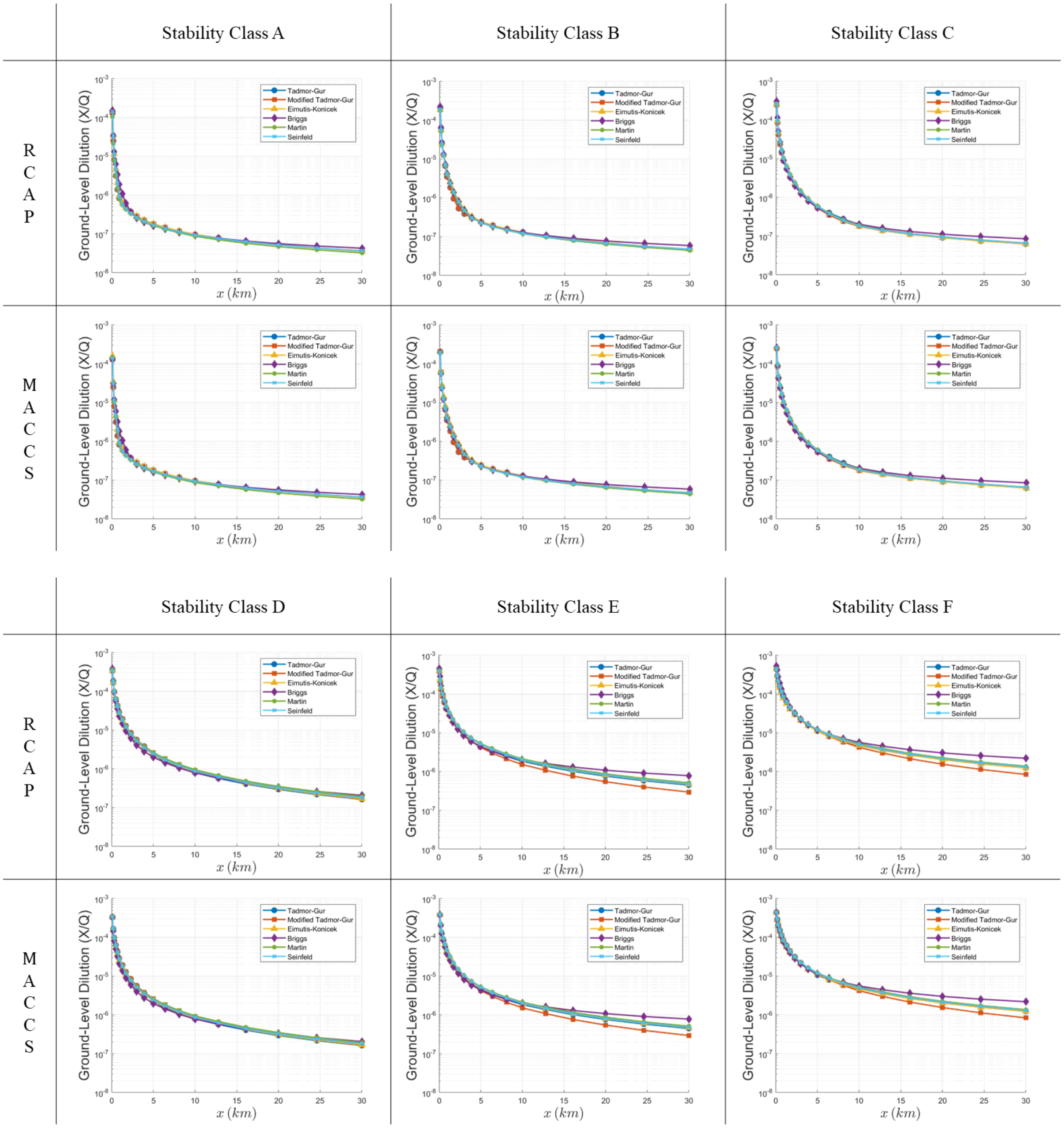


Figure 3. Comparison of Ground-Level Dilution Predictions by Dispersion Coefficient Models under Different Atmospheric Stability Conditions (RCAP & MACCS)

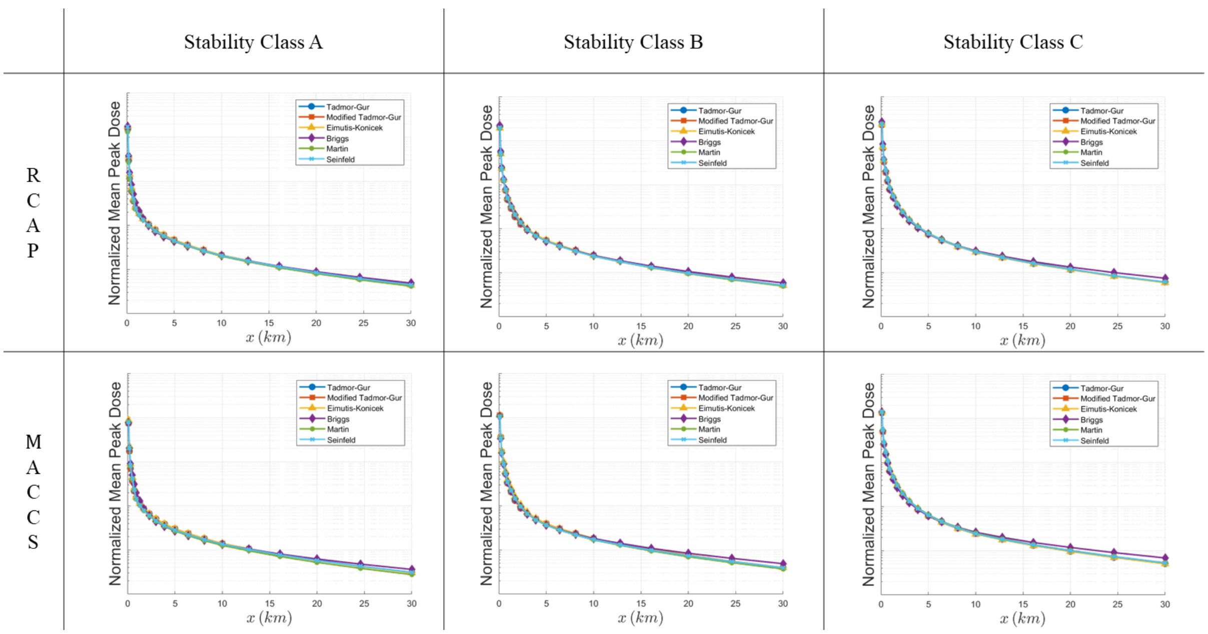
Table III. Quantitative Comparison of Ground-Level Dilution Predictions at 5 km and 30 km under Stability Class E Using RCAP and MACCS

Ground-Level Dilution (sec/m^3)	**Distance**	**T-G**	**Modified T-G**	**E-K**	**Briggs**	**Martin**	**Seinfeld**
RCAP	**5km**	4.46E-06	4.27E-06↓	5.03E-06	4.44E-06	5.39E-06↑	5.22E-06

	30km	4.48E-07	2.95E-07↓	4.71E-07	7.84E-07↑	5.14E-07	4.83E-07
MACCS	**5km**	4.49E-06	4.26E-06↓	4.98E-06	4.36E-06	5.34E-06↑	5.19E-06
	30km	4.48E-07	2.95E-07↓	4.70E-07	7.81E-07↑	5.12E-07	4.81E-07

Figure 4 compares the predicted mean peak dose across distances for each dispersion coefficient model using RCAP and MACCS. The mean peak dose results are based on the effective whole-body dose equivalent, a representative radiological dose metric. Consistent with the ground-level dilution results presented in Figure 3, the differences among models were relatively small under unstable (A, B, C) and neutral (D) atmospheric conditions, but became more pronounced under stable conditions (E, F). Regardless of stability class, a consistent trend was observed in which the Briggs model predicted the highest mean peak dose as the distance approached 30 km.

Table IV provides a quantitative comparison of mean peak dose predictions at 5 km and 30 km under stability class F, where the differences among models were most evident. The values were normalized to the maximum predicted dose at the 5 km distance to facilitate relative comparison across models. At both distances, RCAP and MACCS showed consistent trends, with the same models producing the maximum and minimum predicted doses. At 5 km, the Martin model yielded the highest dose prediction, while the Tadmor-Gur model produced the lowest, resulting in a maximum difference of 1.12 times. At 30 km, the Briggs model predicted the highest dose, and the Modified Tadmor-Gur model the lowest, with a maximum difference of 1.77 times.



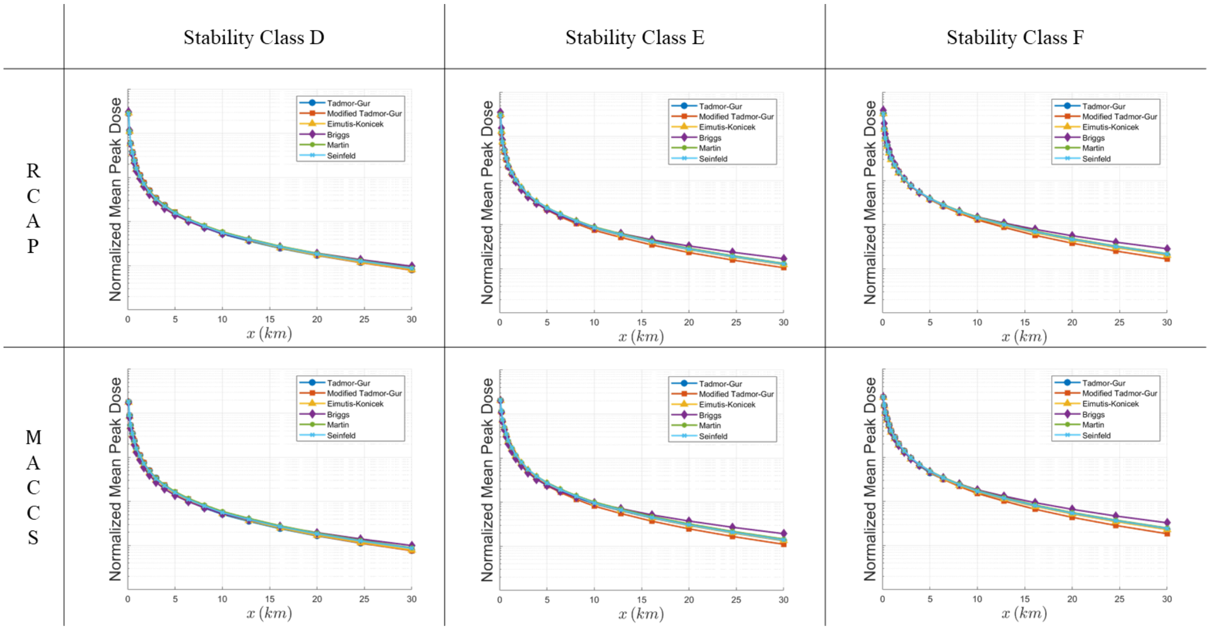


Figure 4. Comparison of Normalized Mean Peak Dose Predictions by Dispersion Coefficient Models under Different Atmospheric Stability Conditions (RCAP & MACCS)

Table IV. Quantitative Comparison of Normalized Mean Peak Dose Predictions at 5 km and 30 km under Stability Class F Using RCAP and MACCS

Normalized Mean Peak Dose	Distance	T-G	Modified T-G	E-K	Briggs	Martin	Seinfeld
RCAP	5km	7.51E-01↓	7.61E-01	7.63E-01	7.81E-01	8.10E-01↑	7.98E-01
	30km	4.11E-02	3.36E-02↓	4.11E-02	5.79E-02↑	4.47E-02	4.37E-02
MACCS	5km	8.95E-01↓	9.31E-01	9.35E-01	9.60E-01	1.00E+00↑	9.84E-01
	30km	4.66E-02	3.74E-02↓	4.66E-02	6.64E-02↑	5.06E-02	4.92E-02

The observed tendency for greater variation among dispersion coefficient models in ground-level dilution and mean peak dose under more stable atmospheric conditions can be attributed to the suppression of vertical and horizontal turbulent diffusion in Stability Classes E and F. Under such conditions, atmospheric dispersion becomes more limited, causing the predicted ground-level dilutions and mean peak doses to respond more sensitively to the structural form and model-specific differences of the dispersion coefficients.

IV. CONCLUSION

This study conducted a comparative analysis of dispersion coefficient models under varying atmospheric stability conditions and quantitatively assessed the extent to which the choice of model influences offsite consequence assessment results. It was observed that even under identical distances and atmospheric conditions, significant differences exist in the predicted horizontal and vertical dispersion coefficients depending on the selected model. These differences tended to become more pronounced as the distance from the release point increased.

The offsite consequence assessment results using RCAP and MACCS showed overall consistent trends. For both ground-level dilution and mean peak dose, greater discrepancies among dispersion models were observed under more stable atmospheric conditions. Notably, the largest differences at both 5 km and 30 km occurred under Stability Classes E and F, suggesting that dispersion under such conditions is more sensitive to the structural forms and assumptions of the dispersion models.

At 5 km, both indicators showed that the Martin model predicted the highest values. In contrast, the lowest values were predicted by the Modified Tadmor-Gur model for ground-level dilution and by the Tadmor-Gur model for mean peak dose. The corresponding differences between the highest and lowest values were up to 1.26 times and 1.12 times, respectively. At 30 km, both ground-level dilution and mean peak dose were highest with the Briggs model and lowest with the Modified Tadmor-Gur model, showing maximum differences of up to 2.65 times and 1.77 times, respectively.

These findings highlight that even with identical input conditions, the choice of dispersion coefficient model can lead to meaningful differences in predicted results. This effect becomes more pronounced under stable atmospheric conditions or at longer distances from the source. Consequently, the selection of a dispersion model introduces a notable source of uncertainty in offsite consequence assessments, particularly in evaluations that consider long-range distances such as the UPZ. To ensure more reliable risk assessments, it is therefore essential to perform prior sensitivity analyses on dispersion coefficient models and adopt a systematic approach to selecting the most appropriate model based on the specific purpose and environmental conditions of the assessment.

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