

COMMON ANALYSIS METHODS FOR GASEOUS AND SOLID CONTAMINANTS EMITTED FROM DIFFERENT POLLUTION SOURCES: A REVIEW PAPER

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(Received 20 January, 2022; Accepted 21 March, 2022)

ABSTRACT

Cement is widely used for building construction and infrastructural purposes. In the last thirteen years, this product's global annual production has increased by 78 percent, to 4,200 Mtpa. However, cement factories have been found to be harmful to air quality, plantations, and houses. Dust emission occurs through all the stages of cement production, such as storage, frying, packing, and even in the transportation stage. Cement factories cause environmental contamination worldwide, including in developed countries facing problems related to managing and controlling pollution, and also enforcing stringent legislation to prevent it. By reviewing different studies concerning cement plant emissions, we observed that various mathematical and statistical models have been applied to analyse and determine the effect of these emissions on the environment. Our study is focused on these analytical and statistical methods for analysing gaseous pollutant and particulate matter emissions from various pollution sources, especially cement plants. Identifying the elements of emissions and the development stages of other authors' analysis methods allowed us to conduct the most precise report possible. Our study also depicts the determinants of these strategies and their advantages, limitations, and implementation variables. The findings of these other studies were discussed, and it was discovered that the output differed depending on the technique used. The frameworks utilised ranged from using a single model to two or more models, in order to compare or combine them. GIS was used as an additional tool to improve the model's functionality in several studies. Some authors used programming languages such as Python and R to make their models more realistic.

KEY WORDS : Air pollution, Gases, Particulate matter, GIS

INTRODUCTION

Air pollution kills 3.7 million people prematurely annually, according to the World Health Organization (WHO) (World Health Organization., 2016). Particulate matter (PM), which is among the substances comprising air pollution, is deemed to be the most dangerous in some studies (EEA, 2013; Krzyzanowski *et al.*, 2005; Sharma *et al.*, 2018). PM can lead to several health problems, including asthma, bronchitis, heart disease, and lung cancer

(Anderson and Thundiyil, 2012; Massey *et al.*, 2016). People all over the world are worried about air pollution due to its negative effect on public health and well-being. Air pollution-related illnesses have been recorded in many instances, including shortness of breath, sore throat, chest discolouration, nausea, asthma, bronchitis, and lung cancer. Air pollution is known to damage plants, wildlife, forests, and natural ecosystems, in addition to its adverse effects on health. Furthermore, metal, leather, rubber, and fabrics can suffer from cracking,

soiling, rust, and degradation (Boubel *et al.*, 1994).

Size and chemical composition are essential influent parameters in PM's potential to be unsafe (Harrison and Yin, 2000). Particles vary in size from micrometres to nanometres; PM_{10} (particulate matter with a diameter of less than 10 μm) can penetrate the respiratory system and reach the lungs. The coarser particles, i.e. those with a diameter of 10–2.5 μm ($PM_{10-2.5}$), reside in the upper respiratory tract, whilst the finer particles, i.e., those with a diameter of less than 2.5 μm ($PM_{2.5}$), move directly to the lungs and are capable of entering the bloodstream. (Sánchez-Soberón *et al.*, 2015). However, irregular, intermittent air pollution sources can cause the acute health risk used in dispersion modelling to be overstated, with respect to the improbable occurrence of emissions under the most severe weather conditions (Balter and Faminskaya, 2017).

WHO estimates that about 800,000 fatalities worldwide occur annually as a result of respiratory and cardiovascular diseases, as well as air pollution-related lung cancer (Zarandi *et al.*, 2015). Over the last few decades, extensive research has been conducted on long-term human exposure to nonlethal air pollution and the impact of emissions on regional and international atmospheric cycles. The pollutants that have earned special recognition include PM, ozone (O_3), total suspended particulates (TSP), nitrogen dioxide, sulphur dioxide, carbon monoxide, and lead, among others (Kirk and Othmer, 2007).

The cement industry's power usage is estimated to account for 2% of global energy use, with cement production accounting for 5% of global CO_2 emissions (Worrell *et al.*, 2001). Mineral dust contains elevated amounts of certain metals that are thought to be toxic to plants, wildlife, and humans (Dubey and Bhopal, 2013). It has been estimated that one kilogram of cement produced in Egypt produces approximately 0.07 kilograms of atmospheric dust (Hindy *et al.*, 1990).

Pollutant sources at manufacturing plants are mainly categorised into two categories: (1) point sources, which are piles exiting at manufacturing plants; and (2) volume sources, which are spaces within production facilities from which pollutants usually depart via controlled outlets (Abu-Allaban and Abu-Qdais, 2011). The primary sources of global pollution emitted from cement manufacturing are gas and dust. The specific pollutants found in the gas are SO_2 , NO_2 , and CO; they can be classified under raw mill and kiln stack exit point source

emissions. The specific pollutants found in the dust include TSP, PM_{10} , and $PM_{2.5}$; they are emitted from the clinker cooler and exit locations of cement mill stacks as point sources, and also from outlets through dust control devices as volume sources (Al Smadi *et al.*, 2009). By polluting the climate and posing health risks, the cement industry causes great environmental instability. Cement processing requires extensive use of natural raw materials and resources, resulting in atmospheric and soil emissions. The ability to control the cement manufacturing process and the degree of emissions can be a rewarding career (Madsen and Thyregod, 2004).

This review paper presents the most common methods for estimating, predicting, and analysing air pollution. Furthermore, we have recognised the strengths and weaknesses of each model based on the literature review. Moreover, this study focuses on methods that utilised industrial sources of pollution, especially cement plants, rather than urban, traffic, or other sources.

The production of cement

The cement production summary distinguishes three basic production steps (Figure 1) (Hendriks *et al.*, 2003).

1. Mixing/homogenising, grinding, and preheating (drying) provides the raw meal.
2. Burning the raw meal forms cement clinker in the kiln, i.e., raw meal components react at high temperatures (900–1500 °C) in the precalciner and rotary kiln to produce cement clinker.
3. Clinkers are melted and combined with contaminants, i.e., the clinker is ground with additives after cooling.

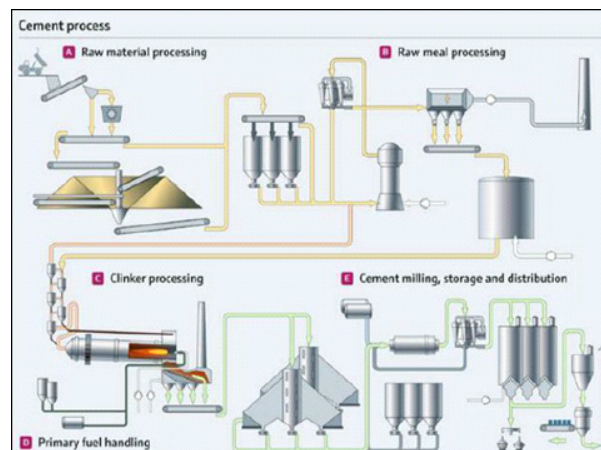


Fig. 1. Cement process plan (Devi, 2018).

Cement industry emissions

Cement manufacturing is a massive operation that necessitates a large amount of energy and resources, including raw materials, thermal fuels, and electrical power (Devi, 2018). The major environmental effects of cement production can be classed as follows.

Gases and volatile organic compounds

Typical pollutants emitted into the air from the manufacture of cement include NO_x , SO_2 , CO , CO_2 , H_2S , volatile organic compounds (VOCs), dioxins, furans, and particulates (Mishra and Siddiqui, 2014). It is possible to divide these major contaminants into two categories: gaseous and particulate. The combustion of fuel produces gaseous pollutants such as nitrogen oxides, sulphur oxides, carbon oxides, hydrogen sulphide, and volatile organic compounds. Quarrying is a source of PM in the form of dust and carbon particles, generated by fracking, blasting, transport, cement mills, petrol preparation, packing, road sweeping, and stacks (Al Smadi *et al.*, 2009), (Asuoha and Osu, 2015), (Hesham *et al.*, 2012).

The amount of emissions generated is typically influenced by several factors, including oxygen, nitrogen, and combustion temperatures. The alkaline cement is replaced by reacting with sulphur dioxide and some nitrogen oxide (Devi, 2018).

VOCs are released directly into the air due to evaporation or some form of volatilisation. Further sources include stored petrol, solvents, and other raw compounds, and also some industrial processes. Failure to burn various fuels is also a significant source of VOC emissions into the atmosphere (Zimwara *et al.*, 2012).

Dust

The cement industry is a significant emitter of mineral dust, with rotary kilns, raw mills, clinker coolers, and cement mills being the primary sources of dust pollution in the cement manufacturing process (Uliasz-Bocheńczyk, 2019).

Noise

Another consequence of the cement industry is noise pollution. The stone crushers, frames, furnaces, cement transport systems, compressor chambers, and other machine operating sites generate significant levels of noise. In fact, in the cement industry, noise is a safety issue; long-term noise sensitivity can result in hearing loss (Arachchige, 2019).

Bad smell

A foul smell usually occurs during the chemical and discharge processes due to not cleaning before emissions are generated. However, the extensive washing required to prevent odour is challenging in factories where production machinery isn't properly maintained, with odorous ambient gases leaking into the atmosphere (Danish Environmental Protection Agency, 2002).

Air pollution models

To accurately estimate the air pollution index (API), precise modelling of air pollution is required. The probability density function (PDF) selected to reflect the observed air pollution data is used to assess air quality (Al-Dhurafi *et al.*, 2018).

Dispersion models

The Gaussian plume model

Several decades have passed since atmospheric dispersion models were established to describe spontaneous and volatile substances thrown into the air. The Gaussian plume model is commonly employed for simplicity; this type of plume is produced by a point source with persistent unidirectional wind emission. These simplifications allow analytical solutions to be obtained by adding minor variations to the model to make it more realistic, such as incorporating particular vertical velocity variations due to atmospheric strata.

Gaussian plume models have the fastest response time to new information. The model employs a single formula for each data point, which significantly outweighs the additional computational cost of turbulence. The duration of the model may be reduced, particularly in real-time and near real-time support applications (Brusca *et al.*, 2016).

The Gaussian diffusion model was developed to help manage manufacturing operations and air pollution control under various circumstances, and also confront dangerous air pollution crises (Tang *et al.*, 2020).

There are several different forms of pollution sources: a point, a volume, an area, an open pit, and a line. In general, Gaussian models can be used with more than one source by employing the superposition theorem. The Gaussian plume can be described as follows. First, a Cartesian orthogonal reference system is assumed, with the origin

referring to the position of the pollution source and the x-axis oriented perpendicular to the wind direction. The y-axis is perpendicular to the x-axis and horizontal, while the z-axis is vertical and reflects the height above the earth's surface (Brusca *et al.*, 2016).

Goudarzi *et al.* (2017) and Fakinle *et al.* (2018) detailed the equations for the basic formulation of deciding the ground level concentration, as given by the Gaussian model (GM) in a downwind direction expressed by Equations 1 and 2:

$$x = \frac{Q}{2\pi u_s \delta_y \delta_z} \left\{ \exp \left[-0.5 \left(\frac{x_r - h_e}{\delta_z^2} \right)^2 \right] + \exp \left[-0.5 \left(\frac{x_r + h_e}{\delta_z^2} \right)^2 \right] + A \right\} \quad (1)$$

$$A = \sum_{N=1}^N \left[\exp \left(\frac{-0.5(x_r - h_e - 2Nz_l)^2}{\delta_z^2} \right) + \exp \left(\frac{-0.5(x_r - h_e - 2Nz_l)^2}{\delta_z^2} \right) + \exp \left(\frac{-0.5(x_r - h_e - 2Nz_l)^2}{\delta_z^2} \right) + \exp \left(\frac{-0.5(x_r - h_e - 2Nz_l)^2}{\delta_z^2} \right) \right] \quad (2)$$

where x is concentration in the downwind direction ($\mu\text{g}\cdot\text{m}^{-3}$); Q is rate of pollutant emission ($\text{g}\cdot\text{s}^{-1}$), u_s is the wind speed in the stack ($\text{m}\cdot\text{s}^{-1}$); δ_y and δ_z are the standard deviations of lateral and vertical dispersion (m), respectively; vertical scattering (m); z_r and z_i are the receptor height above ground level and the mixing height (m), respectively; and h_e is the height of the central plume (m).

The different measures to approximate CO concentrations in the downwind direction using wind speed are employed in Equations 3–11. Using Equation 3 as a reference, the air velocity at 10 m above ground level is converted into wind speed in the stack nozzle.

above ground level is converted into wind speed in the stack nozzle.

$$u = u_0 \left(\frac{H_s}{Z_0} \right)^n$$

where u and u_0 are the wind speed ($\text{m}\cdot\text{s}^{-1}$), H_s is the stack height (m), Z_0 is the reference height (m), and n is an exponent of the wind profile.

Furthermore, to calculate the initial buoyancy flux (F_b), Equation 4 is used:

$$F_b = \frac{W_0 R_0^2 g}{T_{p0} (T_{p0} - T_{a0})} \quad (4)$$

where W_0 is the initial gas flow velocity, R_0 is the stack radius, T_{p0} the temperature of the initial plume, and T_{a0} is the ambient temperature at stack height.

Moreover, the temperature is required to calculate the buoyant plume rise (dh), given by Equation 5 at stack high wind speeds:

$$dh = 38.71 \frac{F_b^{0.6}}{u_s} \quad (5)$$

Equation 5 received a buoyant increase of $55 \text{ m}^4\cdot\text{s}^{-3}$ in the Pasquill stability classes A–D; in this analysis, the F_b volume was calculated to be less than this figure.

The final plume rise (dh) in a stable atmosphere for classes E and F is given by Equation 6:

$$dh = 2.6 \left(\frac{F_b}{u_s} \right)^{\frac{1}{3}} \quad (6)$$

Stack height (h_s) plus plume rise (dh) equals the final effective height of the plume (H) in metres, given by Equation (7):

$$H = h_s + dh \quad (7)$$

For the rural process, Equations 8–10 (roughly in line with the Pasquill–Gifford curves) have been used to compute δ_y and δ_z :

$$\delta_y = 465.11628(x) \tan(TH) \quad (8)$$

$$\delta_z = ax^b \quad (9)$$

$$TH = 0.017452393[-\ln(x)] \quad (10)$$

where parameter x is the downwind distance. The values of a , b , c , and d were calculated using Pasquill stability classes.

Meteorological data and stacking factors

Meteorological information from either surface weather observation stations close to the cement factory or meteorological websites is required to evaluate the environmental impact assessment. The data and information required are listed as follows (Goudarzi *et al.*, 2017):

1. Wind speed and direction, for drawing seasonal wind roses
2. Carbon monoxide samples, obtained from stacks in the cement plant
3. The temperature of gas flow
4. Exit gas velocity
5. The stack height for Electro and Kiln filters
6. The inner diameter of the stack, used for modelling dispersion

A.J. (2013) depended on Lodge (1995), and Rao (2006) classified and derived the average wind speed as illustrated in Table 1 below:

Limitations of the Gaussian plume model

Several experiments have been performed to understand the limitations of Gaussian air pollution estimation approaches due to their susceptibility to inputs and questionable precision (Beychok, 1979), and also their limited predictive capability (Carrascal *et al.*, 1993). The Pasquill–Gifford stability

Table 1. The Pasquill-Gifford stability classification based on wind speed values.

Wind speed (m.s ⁻¹) (at z=10m)	Day – time insolation			Night – time cloud cover	
	Strong	Moderate	Slight	>4/8 Cloud	<3/8 Cloud
< 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

Where, A: Highly unstable, B: somewhat unstable, C: mildly unstable. E: Somewhat stable, F: stable

classification framework, which only considers the temperature gradient, is used for most Gaussian models. Other systems involve meteorological parameters, such as wind speed and direction, cosmic rays, gradients of accessible heat, etc. when categorising stability (Lapse Rate, Pasquill–Gifford, Turner, -, and Richardson Number). Moreover, plume rise formulas other than the Briggs equations were examined for their appropriateness within existing environmental conditions. As a result, a general kind of model is expected to combine various stability classification systems and plume rise configurations to deliver the best combination that balances the shortcomings of the Gaussian plume model with enhanced predictive capability (Awasthi *et al.*, 2006).

Plume models use steady-state approximations, which may not account for the time it takes for the pollutant to reach the receptor; this is a severe limitation of particle simulation dispersion models. (Holmes and Morawska, 2006).

There are many models associated with the Gaussian model, such as AERMOD, HIWAY-2, CALINE-4, CAR-FMI, OSPM, AEROPOL, UK-ADMS, SCREEN3, and CALPUFF (Holmes and Morawska, 2006).

AERMOD

The AERMOD model is AERMIC's scheme, including moist PM and gaseous deposition and source or plume depletion. The AERMOD model can be used in both rural and city settings, on flat and diverse land, ground and raised releases, and multiple outlets. Every effort was made to prevent discontinuities in model formulation, where significant differences in measured concentrations result from minor adjustments in parameters. This method was formulated to be physically practical and easy to execute. AERMOD does not require the definition of complex terrain regimes (WANG Hai-chao, JIAO Wen-ling, 2010).

Given the height of the surface (Z_0), the wind direction, and the temperature, AERMOD only needs a single surface wind speed calculation (calculated between Z_0 and 100 m). The flow of data in AERMOD calculates the convective mix's height during the day (Kalhor and Bajoghli, 2017). AERMOD can replace the ISC3 platform by operating using National Weather Service (NWS) data of a type that is readily available to stations. The parameters used by the meteorological guide inside AERMOD produce profiles of the meteorological variables required. Vertical depths of all available meteorological measurements are used to measure the wind level, wind direction, humidity, temperature, and temperature gradients (Atabi and Nouri, 2016). AERMET's key objective is the measurement of maximum layer parameters for use in AERMOD.

Nonetheless, if a cloud obscures two vertical temperature measures (typically at 2 and 10 metres) and a solar radiation measurement (e.g., from the on-site monitoring program), they are replaced. AERMOD is programmed to operate on the bare minimum of observed weather parameters. To construct similarity profiles of corresponding PBL parameters, ground features (surface area, roughness, Bowen ratio, and albedo) are also required. Besides that, AERMET considers all meteorological measurements concerning AERMOD (Uncertain and Hoffnagle, 2018).

A detailed explanation of the basic AERMOD dispersion model formula is given below. A dispersion model's actual implementation, such as AERMOD, can be demonstrated by developing a simple model for estimating concentrations at ground level linked to ground release, as shown in Figure 2.

Assuming the toxin release rate is Q (g.s⁻¹) for convenience, it is suggested the pollutant blends well around the plume's cross-sectional region, both horizontally and vertically. The height (h) multiplied

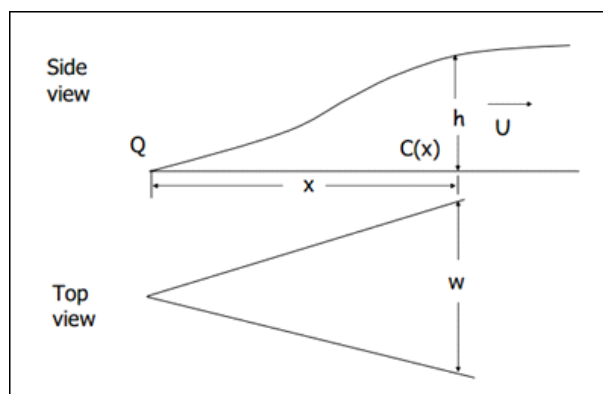


Fig. 2. Template of surface-release plume dispersion (Venkatram and Modeling, 2008)

by the width (w) equals the cross-sectional area on a line (x) from the source. The substance which moves through this region is then given by $C(x)hwu$, where u is held constant over the plume height. If we assume that the field does not absorb any material, then the emission rate (Q) must be equivalent to the material transfer through the plume cross section at any distance. The following concentration expression is introduced as a result of this $C(x)$:

$$C(x) = \frac{Q}{Uhw} \quad \dots (11)$$

Although this is a highly simplified real-world model, it contains the basic aspects of regulatory dispersion models. Equation 1 multiplied by a constant provided the basis for Pasquill's proposed dispersion scheme in 1961. How can we determine the height and width of a plume when the concentration is not consistent across the plume's cross section? Observations reveal that the average

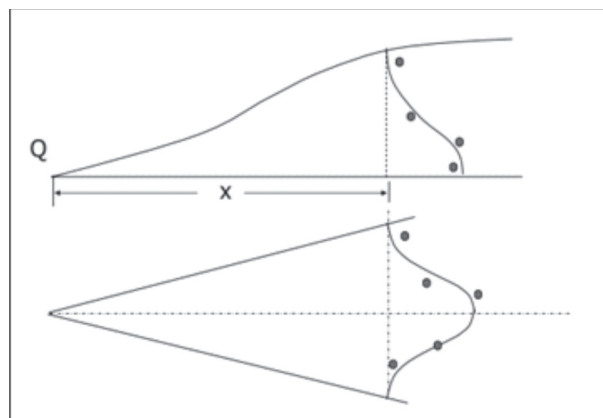


Fig. 3. Concentration levels at any height are describable Regarding Gaussian distributions formed by the bell. True calculations can be significantly deviating from straight curves (Venkatram & Modeling, 2008)

time concentration has roughly Gaussian distributions both horizontally and vertically, as seen in Figure 3.

The distribution of concentration, $C(x, y, z)$, can be represented for any height by

$$C(x, y, z) = C(x, 0, 0) \exp\left(-\frac{y^2}{2\sigma_y^2}\right) \exp\left(-\frac{z^2}{2\sigma_z^2}\right) \quad \dots (12)$$

where y is the distance from the plume's centreline, as shown in Figure 3 as a dotted line; σ_y is the standard deviation of the Gaussian horizontal distribution; z is the height from the ground; and σ_z is the standard deviation of the Gaussian vertical distribution.

The plume's horizontal and vertical spreads are respectively compared to the distribution's standard deviations, σ_y and σ_z . Remember that individual concentration measurements can differ significantly from the formula's smooth curve (Venkatram and Modeling, 2008).

Some notes regarding the emission process are as follows:

1. When the stack pollution concentration is below the acceptable level, long-term exposure will pollute the atmosphere and endanger people's health (Jayadipraja *et al.*, 2016).
2. It is not common practice to use the full hourly time series of estimated concentrations in ISC / AERMOD; employing the series in its entirety induces randomness and accumulates in the desired direction (Avaliani *et al.*, 2016).
3. These cement plants provided the data for estimating the emission factor, as did bibliographical research on comparable cement plants and the AP-42 guidelines. The most important information for calculating TSP pollution factors from these cement plants involves stacks; every cement plant has four active stacks to regulate emissions: the main kiln, the clinker cooler, the cement mill, and the raw mill, as well as bag filters (Abril *et al.*, 2016).
4. Concentrations of released dust vary significantly during the cement manufacturing process, especially for fugitive sources, based on the local sources' quality and other considerations such as topography and overall climate conditions. Moreover, emitting events differ over time, and the information is always incomplete (Abril *et al.*, 2016).
5. Gaussian ground level concentrations can be assessed in a specific study region within a non-

uniform Descartes receptor network at a defined radius in kilometres from the sources (Amoatey *et al.*, 2019).

6. The calibration equations previously mentioned could be used to change measured PM values. (Adeniran and Aremu, 2018). The WolfPack® Compact Field System tracked all gaseous pollutants. Urban air control devices. It is embedded with a WinCE® operating system running Gray Wolf's WolfSense® 2009 application software to view, register, and monitor critical parameters (Adetayo *et al.*, 2019).

Meteorological and topographical measurements

The AERMET model incorporates climate data such as wind speed and distance, temperature, cloud cover, and also surface data, including albedo, surface roughness, and Bowen ratio (Jayadipraja *et al.*, 2016; Cimorelli *et al.*, 2005).

To compute a representative terrain impact height, also referred to as terrain height, AERMAP uses grid elevation data. The AERMAP terrain data can be extracted from GTOPO30 (Seangkiatituth *et al.*, 2011). AERMAP also supports topographic grid data taken from digital elevation models (DEMs) and receptor locations counted from mean sea level (MSL) (Jayadipraja *et al.*, 2016; Cimorelli *et al.*, 2005).

Validation of model results

Validation is based on comparing the modelled performance and actual information (Paegelow, M., and Olmedo, 2008). Mean, standard deviation, fractional bias (FB), geometric mean bias (MG), geometric variance (VG), index of agreement (IOA), the factor of two (FAC2), and the normalised mean square error (NMSE) are statistical performance measurements used to evaluate dispersion models (Kumar *et al.*, 2006). Concentration should be statistically analysed because it is a random variable (Sykes, 1989). Furthermore, Kumar *et al.* (2006) suggested that in order to be applicable, every model should satisfy specific criteria. Time-series graphs of predicted and modelled TSP levels of concentration at both monitoring locations were given by Abril *et al.* (2016). Although the typical values sometimes did not match, average model values displayed similar trends to those found, and this was mirrored in the implementation of validity indices. It is critical to pay attention to the challenges of obtaining adequate PM validation results, taking into account the sources of emission number, the

operation diversity of these sources (the majority of which are fugitive), and the uncertainties arising from the methodology of calculating emission factors.

Using statistical metrics, Amoatey *et al.* (2019) assessed the accuracies and reliability of the estimated daily SO₂ and NO₂ levels of CALPUFF and AERMOD with field concentrations. The five statistical metrics used to verify model performance according to USEPA guidelines included FB, NMSE, IOA, MG (Amoatey *et al.*, 2019), as seen in Equations 13–17:

$$FB = \frac{2(\bar{C}_O - \bar{C}_P)}{\bar{C}_O + \bar{C}_P} \quad (13)$$

$$NMSE = \frac{(\bar{C}_O - \bar{C}_P)^2}{\bar{C}_O \bar{C}_P} \quad (14)$$

$$IOA = 1 - \frac{\sum (C_P - \bar{C}_O)^2}{\sum (C_P - \bar{C}_O) \bar{C}_O \bar{C}_P} \quad (15)$$

$$MG = e(\ln \bar{C}_O - \ln \bar{C}_P) \quad (16)$$

$$VG = e^{[(\ln \bar{C}_O - \ln \bar{C}_P)^2]} \quad (17)$$

The expected and monitored CP and CO, respectively, represent mean concentration values. The dimensionless value FB is utilised to test data sets with C values ranging from +2 to “2. Positive and negative FB values reflect under-predictions and over-predictions, respectively (Chang and Hanna, 2004). Also, the NMSE equation computes the variance and dispersion between modelled and calculated data. Consequently, a complete model has FB and NMSE values equal to zero (Lee *et al.*, 2014). Similarly, IOA is used to allocate a score of 0–1 for model accuracy. In an ideal world, IOA would be greater than 0 and less than 1. However, an IOA value of 0.5 is considered powerful (Sciences, 2015). FB and NMSE are adaptive methods for calculating and modelling data sets with a narrow range of values. MG and VG are well suited for log transformation-based data set normalisation. MG and VG values are consistent across data sets, and a great model will incorporate them (Amoatey *et al.*, 2019).

HIWAY-2 and CALINE-4

HIWAY-2 and CALINE-4 are the principal representative models of the road diffusion process. The HIWAY-2 model categorises atmospheric

stability into three classes (unstable, neutral, and stable) and considers the mechanical turbulence's impact during the diffusion process on atmospheric stability. The CALINE-4 model splits the highway into many parts of the route, which can be used to measure the distribution and variance of pollutants in the 500 m range on both sides of the highway and then to predict the pollutant emission concentration on the highway (Quan *et al.*, 2018).

CAR-FMI

The CAR-FMI model (Contaminants in the Air from a Road, Finnish Meteorological Institute) is a Gaussian Plume model based on Luhar and Patil's equations. In this model, the hourly concentrations of CO, NO, NO₂, NO_x, and PM_{2.5} in automobiles are measured. Scaling the boundary layer describes atmospheric equilibrium. CAR-FMI, like other Gaussian models, has limited applicability to low wind conditions (Holmes and Morawska, 2006).

OSPM

The Operational Street Pollution Model (OSPM) is a functional, quick, and effective model of street pollution developed in Denmark that is now widely used around the world. In this model, the concentrations of engine exhaust emitted by road vehicles are measured by employing a plume model for direct contribution and a box model for street contaminant diffusion (Kakosimos *et al.*, 2010).

AEROPOL

Tartu's air pollution modelling work began in the mid-1990s, leading to the development of the AEROPOL model.

The core features of AEROPOL 2.0 are as follows:

- Gaussian dispersion is included—the dry and wet fluxes, as well as concentrations, are measured.
- It contains dispersion parameters that depend on height and building effects.
- It considers both PM and gaseous pollutants.
- It considers point, line, and area sources of pollution.
- Its estimates are feasible for various meteorological conditions, time series, or temperature distributions.
- Modern Windows versions are available on PC.

Line sources include roads, which are shaped as segmented lines. Area sources include suburban traffic and domestic heating. Gridding is used for line and area sources, and every grid cell (usually

50–100 m) is viewed as a point source.

The AEROPOL model incorporates the following data:

- Stack data (coordinates, height, diameter, velocity and temperature of the gas, source pressure (g·s⁻¹));
- Geometric data (buildings and obstacles);
- Admixture data (deposition velocity and washout coefficients (for gases), particle density and diameter);
- Meteorological data (wind speed and direction, temperature, cloudiness, date and time (dispersion parameters are calculated using Pasquill stability classes) (Kimmel and Kaasik, 2003).

UK-ADMS

The Atmospheric Dispersion Modelling System (ADMS) is a dispersion model which simulates bouncy, straightforwardly energetic particles and gasses in the atmosphere (Carruthers *et al.*, 1994). In its met pre-processor, the model can predict boundary layer structures (Bachtar and Davies, 2018). The model uses a regular, unstable, and neutral Gaussian distribution (Holmes and Morawska, 2006). ADMS was developed by the UK government and industry consortium (Field *et al.*, 2001).

SCREEN3

The Industrial Source Complex Dispersion Model (ISC3) is sampled in SCREEN3 (Gang-jun *et al.*, 2007). The SCREEN3 model utilises a Gaussian plume model that considers source-related factors and meteorological factors (Zhong *et al.*, 2011). In this model, it is assumed that the pollutant has no chemical reactions and that the feather during transport from the source does not work for other deletion methods, such as water or dry disposal (Brode, 1995).

CALPUFF

The California Puff Model (CALPUFF) was created by the California Air Science Board, funded by the Sigma Research Corporation. For case-by-case usage in various landscape and wind situations, CALPUFF is a receptor model recommended by the U.S. EPA (Scire *et al.*, 2000). CALPUFF is a Lagrangian dispersion model, which is multi-layer, multi-species, and non-state. For isolated "puffs" released from models, dispersion is simulated. When dispersion, transfer, and elimination are

measured, the puffs are monitored before the modelling domain is eliminated (USEPA, 2004). A puff model opens emissions regularly (Silverman *et al.*, 2007). CALPUFF was developed to model spaces 10–100 km from a source (Jittra *et al.*, 2015).

Box models

The box is the most essential mechanism for dispersion models, whereby the airshed is represented by a particular box or atmosphere volume. In these models, air contaminants in the box are spread uniformly and theory is used to estimate average levels of pollutants in the box. Nevertheless, while helpful, these models' capacity to predict air contaminant dispersal through an airshed is minimal since it assuming a homogenous distribution of pollutants does not accurately reflect reality (Oliveri Conti *et al.*, 2017).

Lagrangian models

Lagrangian particle dispersion models (LPDMs) can adapt approaches for simulating atmospheric gas, aerosol distribution, and turbulent mixing (Pisso *et al.*, 2019). The Numerical Atmospheric-dispersion Modelling Environment (NAME) is an example of a Lagrangian model (Jones *et al.*, 2007). Since the topography in a power plant's immediate surroundings is typically quite complex, LPDMs help to analyse pollutant flow, mainly using concentrations from the power plant's immediate environment (Park *et al.*, 2016).

On the other hand, Lagrangian puff models are non-state, which implies that the model's input parameters change over time. Lagrangian models are frequently used to quantify the near-instantaneous impacts of a small number of high-resolution sources. In general, Lagrangian models are more stable but also more complex than Gaussian models. Many Lagrangian models are associated with gas and particle chemistry (Oliveri Conti *et al.*, 2017).

Computational fluid dynamic models

Computational fluid dynamic (CFD) models are used to predict wind and turbulence in a given setting and the transport and dispersal pollutants. They have become the community's preferred air quality model for understanding complex flow and the resulting dispersion behaviour. CFD models provide information about flow patterns that would be difficult or expensive to analyse using conventional experimental techniques. CFD models

predict fluid flows in a qualitative and/or quantitative manner using mathematical formulas (partial differential equations), numerical techniques (discretisation and solutions), and software (solvers, pre-processing, and post-processing).

Given identical inputs, different CFD models demonstrate great agreement in the overall wind flow field but substantial variations in speed and turbulence. The discrepancy in wind tunnel information could be due to the various models' closing mechanisms (Gidhagen and Johansson, 2004).

Spatial methods-based GIS

To enhance inventory accuracy and allow data management, a systematised emission inventory needs to be developed. The geographic information system (GIS) has sufficient storage capabilities, manipulating and processing digital data and delivering it to models appropriately. In the late 1980s, GIS was first widely used in transportation research (Thill, 2000). However, it wasn't until the late 1990s that GIS was applied to modelling and managing air quality (Dalvi *et al.*, 2006).

The spatial correspondence between air quality and disease statistics in the affected region can be reflected by GIS. The visualisation of information from various points of view categorises and reclassifies the information based on class breaks. In particular, GIS should investigate the following (Yerramilli *et al.*, 2011):

- The relative spatial phenomenon of pollutant distribution in terms of position, extent, and time;
- The spatial scale and rate of pollutant dispersion below the impact zone at every geographical point;
- The socioeconomic characteristics of the populations impacted by these pollutants.

Interpolation methods

Inverse distance weight (IDW), ordinary kriging (OK), and universal kriging (UK) are normal interpolation processes utilised to estimate air pollutant concentrations (Xu *et al.*, 2019). GIS spatial interpolation technologies can interpolate successive air emission amounts based on distinct point values (Zou *et al.*, 2010). Lawal and Asimiea (2017) used the Gaussian plume model following the geostatistical technique (empirical Bayesian kriging (EBK) to estimate the potential spatial distribution of fugitive dust emitted from the Obajana Cement Plant in Nigeria.

Bhattacharjee and Chen (2020) used the kriging interpolation method to create a more accurate spatial prediction for OCO_2 concentration measurements. According to the author, prior research has demonstrated that geostatistical interpolators, mainly multiple variants of kriging, are the most commonly used techniques for producing a full mapping of sparsely sampled data. Nonetheless, there is variation caused by many factors, such as the predictor smoothing factor, the available observed/sampled positions, and the category of auxiliary information. Geostatistical spatial interpolation and simulation techniques can produce raster grid-cell-based maps of soil pollutants and use spatial analysis to investigate differences in heavy metal emissions. Soil pollution maps allow for the separation of an area's natural baseline levels from anomalous increased levels due to human activity, as well as the identification of areas of polluted topsoil that require remedial action (Suh, 2017).

Spatial proximity models

Spatial proximity models are used based on the hypothesis that the emission source's spatial proximity is a proxy for exposure in the healthy human environment to establish associations between air environment and health consequences (Gupta, 2018).

When the intensity of spatial monitoring stations is limited, GIS-based proximity models are among the essential tools for evaluating air pollution exposure (Zou *et al.*, 2016). On the other hand, proximity models have some issues, including the fact that greater exposure is associated with smaller distances between receptors and sources of pollution. If the distance between a receptor and its nearest pollution source falls under a predetermined threshold, the receptor will assesses exposure levels in a "binary end mode" (Zou *et al.*, 2009).

The spatial proximity method includes the transition of parameters from adjacent catchments to the unmanned catchment; since environment and catchment conditions can have similar spatial variations, catchments near each other are expected to behave similarly. This approach, being dependent on the density of the gas basin network, is intuitively attractive. Note that many improvements have been suggested for this procedure, such as reverse weighting of the donor catchments and the correction of the model's parameter values (Oudin *et al.*, 2008).

Python formulation and implementation

Land use regression (LUR) models can be employed to calculate maps of air pollution concentration and as a predictor component that is available as a separate raster disk. A script that is dependent on the degree of pollution can yield dangerous results. LUR model calculations are shown in raster Python (Schmitz *et al.*, 2019).

This is a novel, data-driven statistical approach, wherein dominant PM_1 species driver patterns and total PM_1 concentrations are analysed and evaluated. To clarify measured speciated and total PM_1 , a machine learning model is used with meteorological concentrations from SIRTASupersite, southwest Paris. The mathematical model simulates daily fluctuations in particle concentrations and interprets and quantifies atmospheric processes that cause relatively high episodes in various seasons using a SHAP-value method (Stirnberg *et al.*, 2020).

Since ArcGIS does not support universal kriging (UK) with randomly selected patterns, in UK, the variables employed are the predictor variables chosen for the final LUR model standard in Python and R, which are both displayed in ArcMap GIS. UK is believed to have an exponential correlation form, with the average and variogram parameters adjusted to maximum probability (Ma *et al.*, 2019).

Land use regression models

LUR models are critical for accounting for air pollution fluctuations in cities. Since they connect readily accessible land use characteristics and pollutant calculations, LUR models are an excellent option for these conventional approaches. Similarly to the other methods of measuring air emissions mentioned above, LUR models require pollutant samples obtained at sampling sites to select independent variables; however, they are less data-intensive (Gupta *et al.*, 2018). In recent years, too much emphasis has been placed on this form of understanding city air dynamics by incorporating it into other types of algorithms to improve prediction accuracy (Rahman *et al.*, 2017).

The GIS-based regression mapping approach employed in their analysis provides an effective technique for generating maps of traffic-related contaminants like NO_2 . These maps reliably estimate emission levels correctly at un-sampled sites. Nevertheless, as with any analytical strategy, regression mapping has some drawbacks; for

instance, it potentially suffers from being case- and area-specific. When models are created exclusively through trial and error, a statistical optimisation process is particularly true. As the results for Amsterdam in this analysis suggest, the regression equations used cannot be true outside of that particular field of study. Nevertheless, when regression models are based on a basic underlying theory, as is the case in Prague and Huddersfield, the models can be more generalised (Briggs *et al.*, 1997).

Based on previous conclusions, it is clear that the performance of the LUR models in different locations are considerably different because of the unique features of each site, the variability of impacts on pollutants examined for the predictor variables, and the choice of LUR models (Rahman *et al.*, 2017).

Hybrid models

Owing to the shortcomings of individual methods, multiple authors have opted to use the predictive validity of two or more air pollution models together. Lau *et al.* (2019) incorporated a wide range of models for air quality, such as the AERMOD and CMAQ diffusion models, using the leading meteorological Weather Research and Forecasting (WRF) model and benefitting from the advantages of a hybrid air quality model, which produces a more effective analysis of the required distribution of primary and secondary pollutants, as well as many other environmental data. Beckerman *et al.* (2013) developed a hybrid solution that combines two models: a LUR model selected by machine learning technology and LUR space-time residuals (BME) for LUR interpolation to measure PM smaller than 2.5 metres in the air. It can be inferred that combining the Support Vector Machine (SVM) and Partial Least Squares (PLS) in an urban environment provides a more convenient solution to time series forecasting for estimating Tehran's hourly and periodic atmospheric emissions (Yeganeh *et al.*, 2012).

Additional models

Given different criteria, accuracy, and available data, there are several other methods to measure the air pollution emitted from line, point, and area sources such as transportation and urban, industrial, and service areas. Examples of such models include the following: photochemical models (evaluating the efficacy of air pollution control policies provides

valuable methods for regulatory research and demonstration) (Oliveri Conti *et al.*, 2017), the WRF model (a numerical weather prediction method of the future for atmospheric science and operational forecasting) (Karl *et al.*, 2015), and receptor models (receptor models play an essential role to identify specific pollutant sources and evaluate each source's quantitative contributions related to environmental data) (Yang *et al.*, 2013).

DISCUSSION

The previous sections show that studies dealing with pollution from industrial regions are typically divided into two main parts: (1) managing these pollutants and providing solutions to reduce them, and (2) analysing the impact of pollutants on health and land cover spatially or statistically. This study discusses the spatial and statistical analysis of pollutants using the methods and models mentioned previously in the methods section. The results of the methods used differ according to the type of analysis method. Some are not intended to be fit for purpose unless combined with secondary methods to give a spatial analysis that serves the study's objective. The spatial analysis represents the final important product through which it is possible to know the number of pollutant concentrations affecting the study area. As for the statistical analysis, its results can demonstrate the existence of risks without a spatial dimension. Table 3 summarises the studies of modelling the dust and gaseous pollutants emitted from different sources.

AERMOD

Assael and Kakosimo (2011) examined the impact of industrial PM emissions in the region of Thessaloniki, Greece. The results were checked by the available monitoring stations and achieved improved agreement. A comparison between AERMOD's estimated PM₁₀ concentrations and those observed by the monitoring station showed fair agreement, according to the measured validation metrics such as FB = 0.17 (less than 0.3), MG = 1.17 (between 0.7 and 1.3) and VG = 1.07 (less than 1.6).

In an environmental risk analysis, the 12-receptor AERMOD model was implemented by Seangkiatiyuth *et al.* (2011) to assess the release of nitrogen dioxide (NO₂) from a cement complex. On the one hand, the results demonstrated a difference between AERMOD's simulations for the dry season

and the wet season. The overall results from measuring and simulating NO₂ concentrations showed that the NO₂ concentration limit set by Thailand's National Ambient Air Quality Standards (NAAQS) was not exceeded. However, the AERMOD program was restricted to predicting air pollutants at a distance of 5 km from the reference point, especially in the wet season. AERMOD is a dispersion model without a reaction module, so NO₂ deposition reactions occur in wet and dry conditions.

Two models can be implemented in a comparative manner; for instance, Jittra *et al.* (2015) used two models (AERMOD and CALPUFF) in the Thailand industrial region of Maptaphut, to evaluate their success in forecasting NO₂ and SO₂. Data from 292 point sources in the field of research were collected. These measured data from 10 receptor sites were compared with the modelled findings. The researchers concluded that for both the NO₂ and SO₂ predictions, AERMOD produced more accurate results than CALPUFF. As far as the highest values are concerned, the highest total concentration study results show that AERMOD is more effective than CALPUFF to forecast the highest concentration. The results represented by Q-Q statistical plots and a tabular view, and the final comparison between AERMOD, CALPUFF, and site observations are shown in Figure 4 and Table 2 below.

Topographic influence can be taken into account in these procedures. Jayadipraja *et al.* (2016) used AERMOD to simulate SO₂ and NO₂ dispersion and measure the field of view of dispersion for PT Semen Tonasa in three districts in Indonesia. The highest hourly average and highest annual average of SO₂ and NO₂ values are based on meteorological

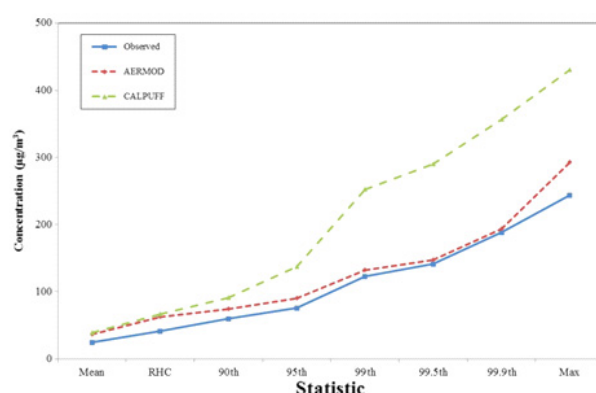


Fig. 4. Predicted and observed SO₂ statistics (mean, RHC, percentile statistic, and maximum) for all sites (Jittra *et al.*, 2015)

and topographical data (SRTM30 satellite imagery) and analysis using AERMOD. Also, the authors noted that the west-to-east wind has a more significant impact because it does not run into any obstacles. Additionally, the wind is obstructed by the mountains' altitude diffusing the wind's force from the east. The average wind speed is 4.25 m.s⁻¹, with minimal variation.

Balter and Faminskaya (2017) identified a Monte Carlo algorithm for controlling the intermittent, erratic source emission timeline to obtain realistic estimates of the expected maximum hourly concentrations and the subsequent acute non-carcinogenic risk. Despite its comprehensiveness, this algorithm was only applicable to the AERMOD simulation of air pollutant dispersion, which is very general and could cope with pollution from other habitats and other types of intermittent activity types. This study considered the risks caused by unreliable and intermittent sources of air pollution.

Table 2. Nitrogen dioxide and statistics of concentrations of sulfur dioxide performance assessment

Nitrogen dioxide concentration for all stations									
Monitoring site	No. of samples	Mean	Standard deviation	r ²	RMSE	IOA	fb	fs	RHC
Observed	78800	39.8	82.01	-	-	-	-	-	63.91
AERMOD	78800	41.0	30.97	0.99	5.35	0.99	- 0.03	0.90	64.99
CALPUFF	78800	40.2	40.97	0.99	15.50	0.99	- 0.01	- 0.66	69.64
Nitrogen dioxide concentration for all stations									
Observed	50831	24.5	97.03	-	-	-	-	-	41.47
AERMOD	50831	36.8	29.10	0.98	13.88	0.99	- 0.40	1.07	62.67
CALPUFF	50831	38.6	49.14	0.98	27.24	0.97	- 0.44	0.65	66.93

Where, r²: correlation coefficient, IOA: agreement index, fb: fractional bias, fs: fractional variance and RHC: robust highest

From previous studies' debates [98, 99], the authors thought that this was a significant problem, but maybe not a critical one, since the examples given in these documents aimed at complying with short-term air quality requirements that were statistically based on continuous sources. However, the researchers' experiments with plants grown from intermittent sources indicate that it may be otherwise. The acute non-carcinogenic risk was critical in most risk management programs for the factory exclusion zone and the adjacent built-up areas. The feasibility of having an exclusion zone that omitted these areas largely depended on whether the significant sources' unusual presence had been taken into consideration.

Atabi and Nouri (2016) contrasted the predicted and observed atmospheric NO_2 concentrations in the fourth gas refinery in Asaluyeh. Land observations from nine gas refinery monitoring sites were included in the evaluation data, using receptors. The researchers concluded that all values calculated by statistical criteria demonstrated excellent modelling, and the predicted NO_2 concentrations agreed well with the measured evidence. In this simulation, all of the fourth gas refinery stacks were deemed to be the only sources of NO_2 pollution. This is the main reason for the slight variation in the results of the predicted and field measurements.

In this work, nine receptors were used to collect the field data, but this number of receptors is considered very small and causes weakness in evaluating the model's performance compared to the four stacks of the refinery. It should be noted here that the validity of the field measurements and the spatial distribution in the maps are understandable.

Amoatey *et al.* (2019) calculated possible impacts on communities and the atmosphere by estimating SO_2 and NO_2 concentrations in the refinery's immediate area. The findings showed that three metrics agreed with AERMOD, but four disagreed with CALPUFF. According to AERMOD, the levels of contaminants were within appropriate limits. Pollutants were measured over three seasons, each with different meteorological conditions. The concentrations differed slightly between the hot, dry wind and sea breeze but were substantial across the whole area. While there were many limitations to this project, AERMOD can reliably measure future health risks in the Tema area and the surrounding towns. This investigation could help solve the public health problem of pollution and pave the way for epidemiological studies within the city limits. Table 3 shows the acceptability of the AERMOD and CALPUFF models based on statistical indices such as FB, VG, NMSE, IOA, MG.

Adetayo *et al.* (2019) measured ambient air quality and used air pollution dispersion simulations to assess air quality at a major cement plant in Ibese, Ogun State, Nigeria. PM and gaseous pollutants ($\text{PM}_{2.5}$, PM_{10} , TSP, SO_2 , NO_2 , CO, and VOCs) were tested using 14 portable samplers and AERMOD. According to the findings, the SO_2 emissions cap from all fence points was maintained for 1 hour. The 1-hour NO_x levels met the cap in all regions, whereas the 24-hour CO and VOC levels were just under the limit. After 24 hours, the SO_2 and NO_x concentrations in specific locations exceeded their thresholds. Nevertheless, for the 1-hour NO_x emission levels, PM and gaseous pollutants from all point sources were below their local areas' limits. More systemic experiments should be conducted to investigate the emission and

Table 3. Validation of AERMOD and CALPUFF models with statistical indices

SO_2					
Model	FB	NMSE	IOA	MG	VG
CALPUFF	0.41	0.39	0.73	3.85	1.01
AERMOD	0.38	0.43	0.83	1.43	2.04
NO_2					
Model	FB	NMSE	IOA	MG	VG
CALPUFF	0.36	1.34	0.36	3.45	2.61
AERMOD	0.52	0.62	0.87	1.64	1.04

The values shaded in green indicate the agreement

dynamics of NO₂ from this cement plant complex.

Gaussian Plume Model

Awasthi *et al.* (2006) built a general Gaussian plume model using Java and Visual Basic programming tools. The model had some limits, which are described as follows: the formula did not account for inversion, wet deposition, or terrain heterogeneity; GPD was evaluated by matching it to one analytic solution; the error from the numerical method was nil. The field experiments were conducted at four receptor locations around the Dadri power plant. The IOA value for all falsities was 0.471–0.519 (the equation to use is $d = 0.522$). The receptor at Khangora (R3) had significant inter- and intra-quantile variance, but its Q-Q plots indicated a firm agreement for all possible concentrations. However, checking the model against one dataset does not entirely validate the model.

Farhadi *et al.* (2017) utilised two models to assess cement dispersion in Doroud, Iran. The central dispersion of NO_x was to the southern plant. The concentrations for the C (slightly unstable) and D (neutral) stability classes were the greatest and smallest, respectively. The results from SCREEN3 and the Gaussian model corresponded close to the source; the estimated NO_x concentrations were above the NAAQ limits. This tells us that residents in the area will be affected by the nearby NO_x pollution from the cement factory. People and activities should not be situated closer than 650 m to the factory. The procedures suggested by the cement industry to measure emissions had worked. Both models provided valuable information for NO_x dispersion for predictive use; therefore, applying dispersion models should be encouraged. The outcomes of this study are not represented spatially; the statistical charts are limited by the distance from the source; and the author did not mention the impact of pollutants on land cover classes such as plantation, water, and soil.

Lawal and Asimiea (2017) examined the spatial distribution of fugitive dust (FD) emissions from the Obajana Cement Plant using the Gaussian plume model with interpolation techniques (EBK). The FD distribution across the study may have exceeded 15 g·m⁻¹. Due to conservative assumptions, it was clear that two atmospheric conditions increased the risk of instability. Additionally, there was a high degree of FD exposure in the Harman period. When not all of the information is required, evaluating the effect a proposed pollution source or factory has on an

area is done rapidly. It is possible to inform decision-makers about the uncertainty in the model results by creating probability maps. Based on the data and expectations, it seems that the Federal Ministry of Environment (FMEnv) guidelines may need to be updated. Even after considering the forecast and standard error, FD was still elevated in large sample regions. It was also clear that high FD was not restricted to the immediate vicinity. In light of the possible human health implications, efforts should be made to review the FMEnv guidelines.

They employed EBK as an additional tool for simulation, and applied the semivariogram to find expected semivariogram values and thus estimated priors, so weights, after which the Bayes' rule was applied to find the Bayes' posterior.

Goudarzi *et al.* (2017) examined the distribution of carbon monoxide (CO) from the stacks of a cement plant in Doroud. This study found that the most common direction for CO dispersion was southwest. Spring and fall were expected to have the highest and lowest maximum concentrations, respectively. However, the overall CO concentrations did not exceed NAAQS across the different seasons, so CO has no effect on human health in this region.

To obtain solid and improved predictive atmospheric studies, these findings highlight the importance of validating the operating dispersion model results with measured data; however, the authors did not work on the validity of the model used in their study. Figure 5 illustrates the concentration of CO over four seasons with a maximum distance of 4 km from the source, which considers a limited distance in order to cover the urban areas around the plant.

De Marco (2018) identified and analysed the environmental dispersion of fine particles from the same cement plant in Doroud, Iran, using SCREEN3 and the Gaussian plume model. There was significant agreement between the measured and modelled findings, indicating that both models can be utilised to forecast PM concentrations downwind of a source, especially in regions far from the source of pollution, as seen in Figure 6. Even though the study demonstrates good validation of pollution results with in situ observations, the spatial representation is weak compared with statistical outcomes.

A.J. (2013) developed a comprehensive dispersion model to calculate the PM concentration at every downwind distance from the cement

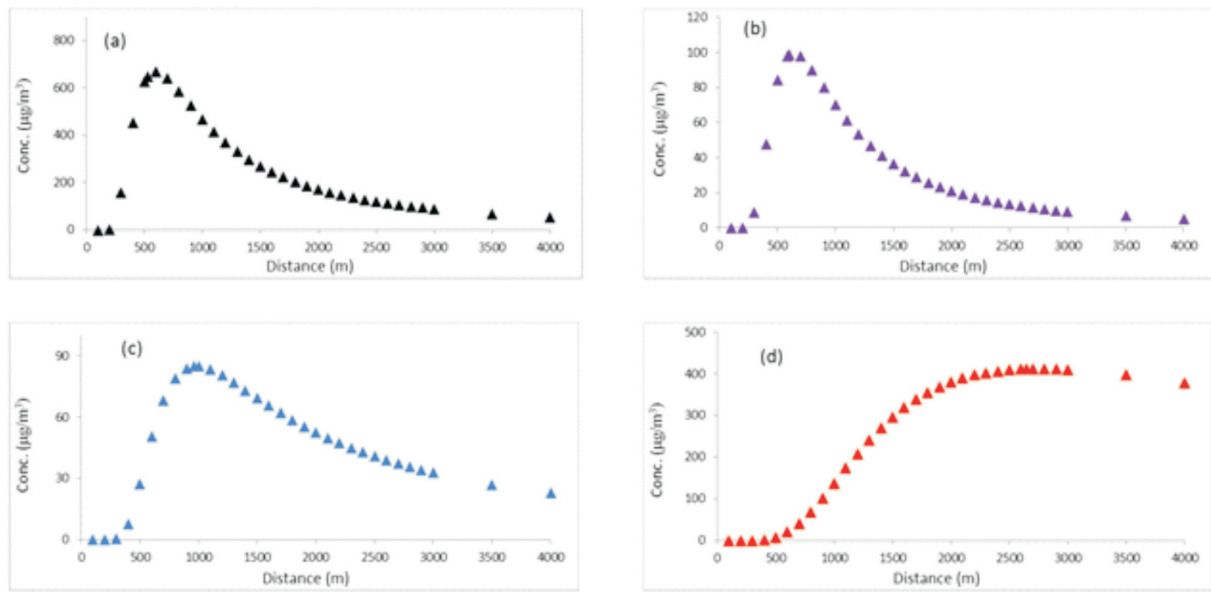


Fig. 5. CO dispersion at various distances from the cement plant during the (a) spring season, (b) summer season, (c) fall season, and (d) winter season (Goudarzi *et al.*, 2017)

factory stack, according to the Gaussian distribution equation.

Even though the statistical analysis showed promising results for the Gaussian model within a specified distance (100–200 m), where the conformity was at least 94% for all stacks, this can be attributed to additional emissions close to the emission sources in question, such as the parking lot, the homogenisation section, and the mixing storage. However, due to terrain variation, sedimentation, erosion, and the interception of trees and buildings in the region, the results for distances greater than 200 metres were poor. Additionally, all site measurements were taken within 5 km of the cement plant's stacks, as seen in Figure 7.

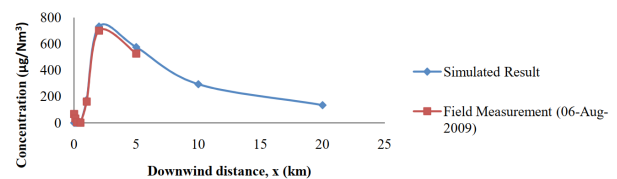


Fig. 7. For Stack 1, the field and simulated data are plotted against the downwind distance (A.J., 2013)

Hybrid models

Bougoudis *et al.* (2016) developed and applied a hybrid method, namely Easy Hybrid Forecasting (EHF), to predict air pollution without using sensor measurements or data from expensive software. Furthermore, the use of this model is flexible and

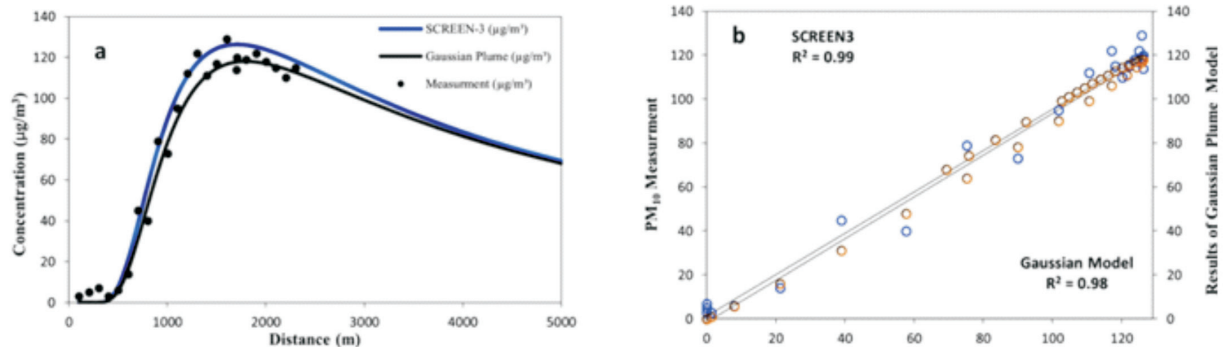


Fig. 6. (a) Comparing simulated daily PM_{10} concentrations by the SCREEN3 and Gaussian plume models, and (b) Spearman r^2 values (A.J., 2013).

accessible for observers. In this model, machine learning and computer languages such as Java and Python are key. The study was applied to four stations in Attica Prison, United States. The data included five gases: CO, NO, NO₂, O₃, and SO₂. The researchers used four unsupervised learning algorithms: SOM, Neural Gas ANN, Fuzzy C-means, and a SOM algorithm. For each of the algorithms, the most harmful pollutant values were used. Then, they compiled all of the data from the extreme clusters into four datasets, one for each algorithm. Although the researchers used several machine learning techniques, there was no spatial representation of the risk of pollution on the land cover, and the number of stations was minimal for a relatively small region.

A selection tool (the Partial Least Square (PLS) method) and predictor (the Support Vector Machine (SVM) model) were used as a hybrid model and compared with the SVM model by Yeganeh *et al.* (2012) to measure the CO concentration in Tehran, Iran. According to the analysis, the hybrid model outperformed the SVM model in CO concentration forecasting while using the same input parameters. Moreover, as opposed to SVM preparation and grid scan, the deployment of PLS for size reduction saved time. Even though PLS has consequences for both the daily and hourly prediction models' effectiveness, the PLS effectiveness for the daily estimation of CO concentration was better than the hourly estimation technique. In this study, the robustness of combining two models as a hybrid over the use of a single model was confirmed, but once again, the study did not present a risk map to represent the effect of CO concentration spatially.

Lai *et al.* (2019) merged various air quality models, including a diffusion model (AERMOD)

and a grid model (CMAQ), to model air quality for the source apportionment of PM_{2.5} in Taichung City, Taiwan. The hybrid model provided a comprehensive evaluation of the distribution of primary pollutants, secondary pollutants, and other environmental information. In comparison to monitoring station results, the hybrid model outperformed simple CMAQ simulation. This analysis selected two major delicate PM_{2.5} events to evaluate the hybrid model's effectiveness, in order to examine the effect of traffic and the coal-fired Taichung Power Plant on PM_{2.5} in the Taichung area.

According to the authors, although the hybrid model works better, there are some shortcomings in the new hybrid model's identification of primary and secondary pollutants. Furthermore, the modelled concentrations are meant to be solved in order to enhance the modular architecture.

Liu *et al.* (2019) designed a new hybrid model called EWT-MAEGA-NARX, which was formed by merging two models: the EWT, MAEGA, and NARX neural networks. The model was used to forecast four pollutants (PM_{2.5}, SO₂, NO₂, and CO) in Beijing, China, in order to verify the model. This study compared five selected models: VMD-MAEGA-NARX, EWTMAEGA-SVM, MAEGA-NARX, EWT-NARX, and EWT-ARIMA-NARX. The hybrid model demonstrated greater accuracy than the rest models, determined through the statistical calculation of errors (mean absolute error (MAE), mean absolute percentage error (MAPE), and root mean square error (RMSE)). In this study, the outcomes are restricted to calculations and statistical charts, without spatial distribution maps.

Mohebbi (2006) simulated and predicted PM₁₀ in Kerman Cement Factory, United States, using three models: the Eulerian model, the Gaussian plume

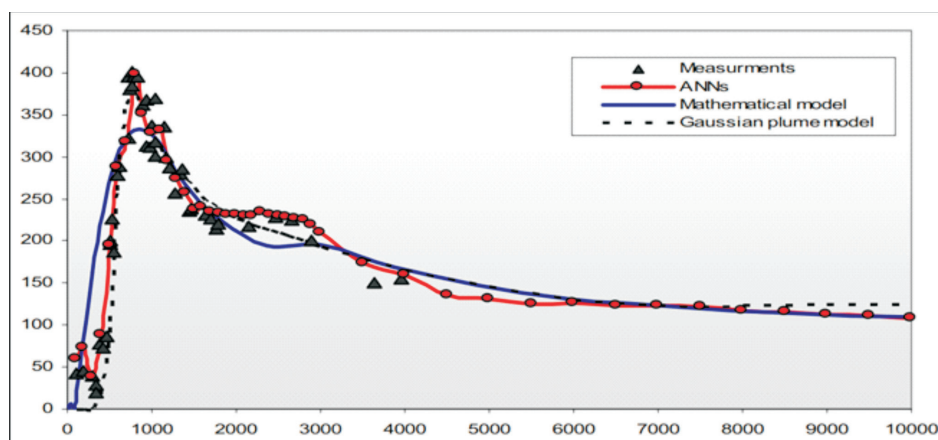


Fig. 8. Measured data vs. results of three utilized models (Mohebbi A, 2006)

model, and an artificial neural network. The outputs of the models were compared to data that had been collected. The results of the Eulerian model, the Gaussian plume model and the artificial neural network had Average Absolute Percent Deviation (AAPD) values of 25.53%, 15.38%, and 5.91%, respectively, as shown in Figure 8 below (the x-axis represents the distance in metres and the y-axis represents the concentration of PM_{10} in $mg \cdot m^{-3}$).

Al-Dhurafi *et al.* (2018) proposed three approaches for modelling API qualities in Klang, Malaysia: traditional models, API structure models, and descriptive status models. According to the results, the API structure models are better for the classification and estimation of API. The suggested hybrid model is a superior, versatile type that is utilised in a variety of fields. The API data was represented well by the hybrid model as well. It could also be combined with other modules to estimate Klang API data for other regions and towns. The study was limited to comparing the approaches used with API without generating risk or forecast maps to determine pollution.

Carotenuto *et al.* (2018) employed two methods to analyse the intensity of CO_2 emissions from an industrial point source in Biganos, France. The first one was a mass balance method based on aircraft observed data, and the second was a dispersion simulation approach incorporating the CALMET diagnostic meteorological model and the CALPUFF puff dispersion model. The CALMET/CALPUFF model chain was run using WRF-modelled outputs from ECMWF reanalysis, WRF-modelled outputs from CFSR reanalysis, and local in situ measurements. The two methods compared had advantages and disadvantages, making an integrated system especially appealing. According to the development parameters, this method needs to be regularly updated in pace with the rapid development of airplanes and sensors.

Land use regression

LUR models were developed by Rahman *et al.* (2017) to estimate the concentrations of NO_2 and NO_x in the Brisbane Metropolitan Area (BMA), Australia, from 2009 to 2012. With leave-one-out cross-validation R^2 values of 3–49% and 2–51%, the final models described 64% and 70% of spatial variation for NO_2 and NO_x , respectively. Distance from a major road or industrial area is a specific predictor for NO_2 and NO_x levels, implying that road traffic and industrial emissions play a

significant role. The innovative modelling technique used in this study can also be applied to other cities. Despite the advantages of the model used, there are some limitations, including the number of field-measured sites being limited to 31 sites, and just one season of monitoring was performed at the short-term sites.

Ma *et al.* (2020) developed the PyLUR for LUR modelling and emission mapping. Using the Python platform-based GDAL/OGR library, it can create a LUR model and efficiently produce pollutant concentration maps. PyLUR's innovations and benefits include the ability to model more kinds of possible predictor variables; an automated regression modelling module; the ability to manage accurate GIS data and perform fine-resolution predictions easily and stably; and the fact that it is open-sourced, with the source code being accessible to researchers interested in LUR modelling or programming using GDAL/OGR. PyLUR's drawback is the lack of an advanced interface, such as that of RLUR. This can be resolved by doing separate GIS data exploration and displaying the output concentration maps in commercial GIS applications. PyLUR is currently available as PyLUR 1.0. The authors are working on a user-friendly PyLUR GUI and will update it soon to PyLUR 2.0.

GIS tools

Wang and Huang (2014) used trend analysis methods to estimate the potential effects of pollutant emissions from point sources in Saskatchewan, Canada. The first method used was trend analysis, to show how the total number of point sources and their spatial distribution has changed over time. The second method used was IDW, to produce interpolation surfaces for the significant air contaminants emitted by industrial sources. The trend analysis showed that the overall number of facilities has been growing explosively, and most of the new facilities are in southern Saskatchewan, where most of the province's total population resides. Correspondingly, the findings from IDW showed that most emission hot spots are in the country's southern part. The methods used can estimate the pollution from new industrial projects built according to pre-determined requirements. Furthermore, the outcomes can assist with selecting a site and resident migration if necessary. Although IDW interpolation performs well for points that are uniformly distributed, it is less effective for outliers; data clusters that are unevenly distributed can

introduce errors (Azpurua and dos Ramos, 2010).

Another GIS analysis was carried out by Teggi *et al.* (2018), who designed a new GIS-based Gaussian model named CAREA. Programmed using Python language, this model forecasts field concentrations and surface dry deposition fluxes from complex area sources. In particular situations, this model offers an some advantages over AERMOD and other similar models.

In the CAREA model, the amount of time can be accommodated, and large numbers of sources and receptors are possible, in contrast to AERMOD. A limitation of CAREA is that it only offers ground values; in general, it is only applicable to relatively simple terrain types and, unlike AERMOD, does not include pollution from stacks, lengths, open-pit, or wet deposition.

Ali *et al.* (2018) also used the IDW interpolation method to evaluate the concentration of PM_{10} over Kirkuk, Iraq. This study showed that significant fumes, solid particulates, and considerable vehicle emissions have been generated due to excessive amounts of these places. IDW perfectly represented the PM_{10} projected map. The PM_{10} emission level was appropriate for Iraq's proposed NAAQS, but not for WHO's guidelines.

Samad *et al.* (2020) investigated the air quality in a large cement factory's vicinity by looking for PM in the air. The results were assessed statistically using SEM photographs and spatially using GIS. It was found out that the average PM_{10} and $PM_{2.5}$ levels were considerably more significant than those permitted by the air quality standards established by numerous regulatory agencies. This statement is supported by the similarity between the SEM representations of particles captured in the analysis tool and those found in tree leaves and cement particles. The use of GIS to construct a visual view of the PM concentration distribution made it simpler to illustrate the study's hypotheses, even to a layperson. The spatial analysis interpolation approach was IDW combined with Quantum GIS.

Torres *et al.* (2020) used Python software to generate figures and plots of NO_2 concentration outcomes. Ma *et al.* (2020) described a LUR modelling and pollution visualisation software called PyLUR that uses Python-based GDAL/OGR libraries and can create a LUR model and produce efficient maps of pollutants concentration. Motyka *et al.* (2020) examined the air quality model SYMOS 97 in comparison to the biomonitoring survey findings and vice versa; this model is also based on Python

language programming.

Wyrwa (2015) used the δ ESA model to evaluate the concentration of $PM_{2.5}$. This model includes three components: TIMES-PL (an energy-economic model), Polyphemus (an air quality modelling system), and MAEH (a new module for environmental and health assessment). Polyphemus is based on the C++, FORTRAN 77, and Python programming languages.

CONCLUSION

This study explores the methods and models used for analysing pollutants generated from sources of emissions (e.g., factories, urbanisation, and transport), how they function, and their limitations. The emphasis was on analytical models from factory sources, especially cement plants, as they negatively affected them. We found the following through a review of previous research:

1. Some researchers only used one statistical model for pollutant dispersion.
2. In other studies, two or three models were used independently and compared with site measurements, thereby determining which model is optimal.
3. Furthermore, the combination of two models (i.e., a hybrid model) has been used by several researchers to obtain a new model that provides better performance.
4. Moreover, several studies have used GIS as an additional tool to the model used, in order to support findings and analytical methods, such as interpolation, buffers, etc.
5. The final approach is to use languages such as Python and RNN to program the models, in order to provide GIS with a new tool that adds a qualitative analysis of the risks of air and land cover pollution.

The most effective model or system for measuring and estimating air pollution is one whose findings are very close to those obtained from field measurements. Furthermore, to validate the actual test model, it is preferable to take several samples at distances ranging from the source's nearest location to more remote areas. Furthermore, taking field measurements over more extended periods yields better results. Furthermore, classifying areas near the source into different forms of land cover can help demonstrate the effect of pollution on human health, plants, soil, and water bodies.

Table 3. Common spatial and statistical methods of air pollution analysis

Objective	Data	Method	Source
Estimate the carbon monoxide (CO) delivery from Doroud cement industry stacks	In situ measurements of CO, parameters (stack, model, and receptors), and Meteorological	Gaussian Plume Model	(Goudarzi <i>et al.</i> , 2017)
Distinguish and analyze fine particle dispersion in the environment from a cement plant stack in Doroud (Iran)	In situ measurements of PM ₁₀ and Meteorological data	SCREEN3 software and Gaussian plume model	(De Marco, 2018)
Evaluate air pollution (PM ₁₀ , NO ₂ , and O ₃) on cardiovascular mortality in Kermanshah, Iran, between 2014 and 2015.	Air quality data, Meteorological, and epidemiological parameters	The Air Quality Health Impact Assessment (AirQ2.2.3 model)	(Khaniabadi <i>et al.</i> , 2017)
Utilizing outdoor air quality control and air pollution dispersion simulation to measure the air quality at a major cement plant in the Nigerian city of Ibesse, Ogun State.	SO ₂ , NO, NO ₂ , CO, and VOCs site observations, all sources of pollutant emission in cement plant, and meteorological data.	AERMOD Model	(Adetayo <i>et al.</i> , 2019)
Examine the effect of a cement factory on the atmosphere around the air forensically.	Terrain, Meteorological, and in situ PM observations	Spatial analyst using GIS	(Abdul Samad <i>et al.</i> , 2020)
Display a new model of GIS-based Gaussian model for complex source areas named CAREA Model	Polygons for source areas, source emission rates, receptors, meteorology, concentrations, and deposition fluxes	CAREA Model and is coded by Python language	(Teggi <i>et al.</i> , 2018)
Present a scheme for predicting PM _{2.5} concentrations using RNN and LSTM in Taiwan	Pollutants and meteorology data	Recurrent Neural Network (RNN) and Long Short-Term Memory networks (LSTM)	(Tsai <i>et al.</i> , 2018)
Generate concentration maps for air pollutants	Pollutants monitoring in the site and variables of possible predictor	LUR Model and PyLUR software mapping of pollution	(Ma <i>et al.</i> , 2020)
Observe the concentration of PM daily and nightly and compare between them over Bihar City, India	In situ observations of PM ₁ , PM _{2.5} , and PM ₁₀	Statistical Charts	(Jena <i>et al.</i> , 2020)

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