Mapping spatial distribution of particulate matter using Kriging and Inverse Distance Weighting at supersites of megacity Delhi

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Abstract

Anthropogenic airborne particulates are among the major contributors to urban air pollution and pose a significant health risk. Particulate matter has emerged as a serious pollution threat in India, specifically to the capital—New Delhi. The objective of this study is to map PM_{2.5} profile using two widely used spatial interpolation techniques (Kriging and IDW) by predicting their concentrations at distinct unmonitored locations. The implemented methodology has a wide-scope utility in the field of air pollution; especially in Low-Middle Income Countries where setting up new monitoring stations include financial/logistical/location problems. The generated maps can help in policy formulation and decision making by providing aid in PM_{2.5} visualisation of spatial and temporal variability. First phase of study involves prediction of concentrations at two sites (reinforcing the need for sustainable development of the city) using concentrations for 2015-2017. In the second phase, pollutant mixing ratios were obtained for four winter months between Nov-2017 to Feb-2018 at 17 monitoring stations. In this phase, predictions were made for 11 supersites (zones of important land-use). The average error of Kriging and IDW (taking both phases) was ~22% and 24%, respectively. The magnitude of change in the daily concentration was relatively negligible and annual trend can be identified.

Keywords: Spatial interpolation, Discrete predictions, Ordinary kriging (OK), Inverse distance weighted (IDW), Prediction accuracy, ASAP-Delhi project

Research highlights

- Application of interpolation techniques can improve the quality of air pollution mapping
- Two interpolation techniques were applied to predict concentrations at discrete sites in Delhi
- Particulate matter (PM_{2.5}) mapping for city of Delhi
- Cross-validation process and the percentage errors estimate the reliability of predictions
- Combination of these techniques with other tools and the data source is suggested

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Introduction

The impact of air pollution on human health in both developed and developing nations are significant (Chung et al., 2011; Kanada et al., 2013; Fotourehchi, 2016). Episodes of spikes in air pollution concentrations have increased in frequency over the last decade (Shukla et al., 2017; Cohen et al., 2017). Each year about 800,000 deaths and around 4.6 million lost life-years are caused by air pollution (WHO 2016). It has attracted attention from the Supreme Court of India (Rosencranz and Jackson, 2003), non-governmental organizations (Greenstone and Hanna, 2014) and numerous policymakers (Kandlikar and Ramachandran, 2000). In India, the prime air pollution monitoring agency is the Central Pollution Control Board (CPCB), which monitors air pollution through 731 nation-wide monitoring stations (CPCB, 2018). Delhi lacks significant natural water bodies, which intensifies the effect of PM_{2.5} among other pollutants and contributes to medical complications in various age groups. As per the latest policy of the Delhi government is the epitome of the integrated approach to smart cities, and its integrated systems need to function efficiently to ensure long lasting quality life for the city and the inhabitants (Silva et al., 2018).

Particulate matter (PM) is the net sum of all particles suspended in the air (Heal et al., 2012). The focus of this work remains on PM_{2.5}, which is referred to PM that has an aerodynamic diameter of $\leq 2.5 \mu\text{m}$ (Kumar et al., 2018). Air pollution from onsite burning of agricultural crop residue is one of the many causes of environmental hazard observed in northern India (Awasthi et al., 2011). Considerable significance is held by the phenomenon of the Asian Brown Cloud, and its multifarious impacts. It affects agriculture, health and climate change on both regional and global scale (Srinivasan and Gadgil, 2002). In cities such as Delhi, air pollution is attracting the attention from the administrators and policy makers, which has opened the way for a higher-level tactical approach to mitigate these problems (Kumar et al., 2017). The unavoidable migration towards the urban area gives way to analysing its effect on the natural resources and infrastructural capabilities of the cities (Silva and Mendes, 2012). Recent studies point out that vehicular particulate emissions have exhibited a decreasing trend in the last decade. But the overall particulate matter concentration has seen a consistent rise, adding to the significance of better inventory creation for it (Nagpure et al., 2016). A similar study in the Delhi region targeting particulate matter gives us the synergic interaction of various sources and what challenges interventions might face (Kumar et al., 2017). Accuracy did not depend of the nature of site, but adding constraints such as maximum values and daily variation to them can certainly provide presentable results. Physical characteristics of site data such as

geography and concentration variation would be relevant if the factors such as wind speed, temperature dependence of particulate matter and topographical variations would be considered. Since the sites were not spread over a huge geographical area, these factors would not cause significant variation in the results.

The difference in accuracy is due to the value of the PM_{2.5} concentrations, and not due to nature of the land use of the sites. In another work, the health impacts of air pollution have been studied in various megacities of India, including Delhi, indicating how hospital visits are correlated with an increase in pollutant concentration (Kumar et al., 2013). PM_{2.5} estimations were achieved using two interpolation techniques: Kriging, which is a function of statistical stationarity; and Inverse distance weightage (IDW) that is a function of the distance of separation amongst the sites. In the field of marine pollution, Kriging regression models are used to create surface maps for biological contamination and its spreading. Currently spatial interpolation techniques are being used to obtain predicted surfaces for air pollutant concentration also, to obtain reliable high-resolution predictive concentration values for major pollutants.

Data collection and generation is highly desirable to estimate/predict the required pollutant (Bonzar et al., 1993). Moreover, high demand for urban air quality estimation models, which help in calculating pollutant concentration at a desired discrete location is present (Hurley et al., 2005). Local geography and the various meteorological factors such as wind speed, pressure, temperature, precipitation in the control volume enclosed by the atmospheric boundary layer, have a contrasting effect on pollutant estimation (Baklanov et al., 2010). Nevertheless, it is not possible to consider the synergic effect of all such factors during physical modelling. Hence, pollutant data across India from Nation-wide Ambient Air Quality Monitoring Network (NAAQM) program is relied upon. Moreover, the dispersion of these pollutants, rather randomly in the lower layer of the atmosphere also introduces a varying degree of uncertainty (Mallet and Sportisse, 2008). The spatial and temporal distribution of the pollutants can be estimated using multiple basic laws of physical sciences such as equations of mass, energy, momentum conservation; but in addition to gas laws and thermodynamic parameters, one requires multiple boundary conditions at each grid boundary. In recent studies, kriging based regression model has been used to quantify the radioactive soil contamination.

Kriging based techniques have been used in structural analyses, specifically to analyse Timoshenko beams where conventional polynomial interpolation was usually used (Wong et

al., 2018). Monte Carlo Techniques combined with Kriging have used for Reliability Analysis of Mechanical System Models. It has helped to overcome specific drawbacks of using small failure probabilities (Lelièvre et al., 2018). In a recent study in Central Italy, Kriging based regression model was used to quantify the geogenic radon potential and subsequent exposure risk from the contaminated soil (Giustini et al., 2019). Ordinary Kriging, Regression Kriging and Co-Kriging were used to map potentially toxic metal concentrations in Southern China (Xu et al., 2019). In another recent study, Kriging regression models were used in estimating the surface contamination of biological origin (Rossi et al., 2017)

Metrological parameters such as wind speed are profoundly affected by the terrain of a site and these methods have also been previously modelled in various studies using unadorned methods such as IDW (Palomino and Martin, 1995). Earlier studies with spatial interpolation have observed significantly smaller errors when there are limited topographical variations across the study area. It has been seen during the assessment of parameters such as ambient temperature with spatial interpolation that, in case of mountainous region – the yielded errors are large in magnitude when compared to plain or rolling terrain (Kumari et al., 2016; Chung and Yun, 2004). Delhi has a complex terrain in terms of land use but has a fairly flat surface geographically, and hence the probability of predictions with large errors is modest.

Although among the two discussed methods, IDW is *simpler* as compared to Kriging, yet some studies observed it to outperform the latter (Vorapracha, et al., 2015). The satisfactory results obtained in the present study can form the basis of further evolution by hybrid algorithms such as random forest or neural networks to improve accuracy and reliability (Wu et al., 2018; Qi et al., 2018). These techniques can also be combined with data from low-cost sensors to improve monitoring networks worldwide (Dünnebeil, et al., 2017), and to explore application of Gaussian framework on Kriging in Delhi region as applied in other Asian locations (Park, 2016).

Even in the latest research works on the prediction of pollutant concentrations using geospatial techniques, there are few shortcomings. We observe a lack of comprehensive analysis of cross-validation and the need to increase the scale to obtain higher resolution predictions. Some of the relevant works are summarized in Table 1. The specific use of these techniques is not done in Delhi, where the geographical distance between sites was small yet monitoring gaps existed. The use of these techniques overrules the need for other boundary conditions apart from the geographical coordinates and measured concentrations. In order to fill these monitoring gaps,

the objective of this work is to obtain reliable predictions of important, yet unmonitored sites. The quality and the interrelation of the considered datasets played an important role in determining the accuracy and the efficiency of predictions. However, considering the scope of the study and future applicability, the results are encouraging. IDW and kriging used in this study can target three major challenges: (i) proxy PM_{2.5} developments in case of insufficient ambient air quality measurements station; (ii) imputation of inconsistent information on daily PM_{2.5} concentration; and (iii) identification of high and low PM_{2.5} hotspots and episodes.

Table 1 here

Study Area

Delhi, the capital of India, is a second most populated city of India, narrowly surpassing Mumbai (World population review, 2019) in the north of the country. New Delhi is one of the urban districts of Delhi and the seat of all three branches of Government. There has been rapid urbanization and a corresponding increase in traffic and energy consumption. Moreover, there has been growing evidence that ambient PM_{2.5} levels of are observed to be highest in Delhi (Shukla et al., 2018; Gupta et al., 2007), and the concentrations have even touched 999 µg/m³ in the worst months (Mukherjee et al., 2018). The vehicle count has exhibited a surge in the last decade which leads to an increased vehicular density. This contributes to higher pollutant concentrations apart from other problems (Panwar et al., 2018). Considering the significance this city holds in terms of the economic, cultural and industrial growth along with being the international gateway to the world, it is crucial to ascertain the sustainability of the city in terms of infrastructure and the massive population it resides.

The temperature of the city rises to as high as 45°C, in the summer months of April to June, whereas it falls to the lowest of 8 °C in the winter months of December to January. The annual average temperature is 25±7 °C for the study duration of 2015 to 2017. The monitoring stations and target locations (where predictions for PM_{2.5} are made) are shown in Figure 1. Location coordinates are superimposed on a shape-file of Delhi in ArcGIS (version 10.2).

Figure 1 here

Majority of the monitoring stations are maintained by the Central Pollution Control Board (CPCB), Delhi Pollution Control Committee (DPCC) and the Indian Institute of Tropical Metrology (IITM), Pune. Monitoring data is accessible to both public/institutional bodies and

individuals. However, there is a lack of a comprehensive network of monitoring stations, which are sometimes not practical to maintain.

Site Selection and Characteristics

Among 36 monitoring stations located within Delhi, only 17 monitored PM_{2.5} concentrations for the study period of January 2015 to December 2016 and November 2017 to February 2018. This highlights the need to use modelling-based prediction techniques to get dependable concentration estimates for these and other sites. Traffic and industrial hotspots, dense residential areas and other areas of maximum exposure were considered in ascertaining the target locations (Yedla and Shrestha, 2003). The residential zones listed face the huge magnitude of traffic flow daily. Hence PM_{2.5} becomes a significant cause of concern (Pandey et al., 2005). Institutional areas, which are away from the industrial areas, though devoid of most pollutants, still have large exposure to PM_{2.5} (Brunekreef and Forsberg, 2005). These sites are listed in table 2, along with the characteristics.

The sites under study lie in Delhi, which is a major hotspot of industrial and economic significance for the country and holds a prominent place globally as well (Desai and Vanneman, 2018). Although, the methods are simple, they provide a reliable estimate of PM_{2.5} concentrations at few target sites of significant importance, where instrumental monitoring is not feasible due to logistic or financial constraints. The city under study is host to a large population which is residing in relatively smaller area, contributing to high population density. Air pollution, especially particulate matter is threatening the sustainability of the city and posing a potential hazard to the significant population size. Working in synergy with other contributors, robust input about the estimate of this perilous pollutant, can ascertain the sustainability of the city and adjoining satellite towns (Bikkina et al., 2019).

Delhi exhibits a mixed land use pattern, making the traffic density higher and increasing the exposure to synergic air pollutants (Kumar et al., 2015). PM_{2.5} has a high potential to affect the people living in areas shared by various other types of land use (Mohan et al., 2011)

Table 2 here

The scope of the study is not expanded to monitoring sites of NCR, due to possible error formation from long-range extrapolation. The distance between monitoring sites of Delhi and locations of NCR is very high as compared to the inter-site distance inside Delhi itself. The identified monitoring stations undertake 24-hour monitoring in 3 batches of 8-hours samples for PM_{2.5}. Due care is taken to ensure that the standard guidelines are followed while monitoring and data inventory as CPCB is the authority to ascertain the guidelines. Additionally, the data were screened for any discrepancies of negative or zero concentrations along with certain unexplained spikes in the concentration, attributing them to monitoring errors.

PM_{2.5} concentrations are adopted from above-mentioned monitoring stations for two-phase durations: 24 months' data from 4 sites, and 4 months' data from 17 sites. Some data discrepancies have been observed, as noted in Table 2. The highest PM_{2.5} concentrations among adopted 24-month data are documented at Anand Vihar monitoring station in January 2016 (i.e. 329 µg/m³), whereas the lowest value (28 µg/m³) is recorded at Mandir Marg for the month of July 2016. The time series of PM_{2.5} datasets from January 2015 till December 2016 is presented in Figure 2. Furthermore, Figure 3 shows the recorded levels of PM_{2.5} from November 2017 till February 2018 under three site categories.

Figure 2 here

For the 4 months' data, the peak is observed at Anand Vihar, during the month of November 2017 (i.e. 330 µg/m³). On the other hand, the lowest value is exhibited by Lodhi Road at 90 µg/m³ for the month of February 2018.

Figure 3 here

Interpolation and Cross-Validation

A better database of pollutant data can be compiled if a spatial point estimation process is developed, although, there exists no best method to interpolate any data set. Some criteria to

choose among the available methods could be the accuracy level required, characteristics of the data available and the computer/human resources at disposal (Lin et al., 2002).

Current work applies two spatial interpolation techniques: Kriging, which is a stochastic method; and Inverse Distance Weighting (IDW), which is a deterministic interpolation method. Apart from the statistical and deterministic techniques, LUR and dispersion modelling are also used extensively to make air pollution predictions. Both of the modelling techniques have already been researched on both local and regional scales. Another interpolation technique available in ArcGIS is a spline function. It was not used for the study as it is better for datasets which exhibit mild variability, but we observe high seasonal variability in PM_{2.5} concentrations. Since different techniques yield different variations for the same data set, multiple methods need to be studied with regarding their surface analysis. Kriging is a geostatistical process, which defines a correlation (semivariogram) among the sample points; it is used to model the spatial variation in the pollutant concentration. Application of the methods for Delhi PM_{2.5} concentrations have been carried out due to two reasons. Firstly, it is a variable which is spatially distributed and secondly, it appears to be correlated across well-defined geographical regions (Jerrett et al., 2005). Base data for geospatial analysis is the monthly average data, obtained from 24-hour daily averages for PM_{2.5} from NAAQMs stations in Delhi. These stations provide hourly, 8 hourly and 24 hourly averages of various air pollutants along with values of temperatures and other meteorological parameters. The 24-hour average of PM_{2.5} at the stations were obtained from the stations and converted to monthly averages after filtering out zero and negative values attributed to measurement and instrumentation error.

We used a tool “geostatistical analyst” in ArcGIS to analyse spatially varying data inventory and generation of the two-dimensional surface using measured data while employing advanced statistical techniques. Spatial interpolation provides us with the best representation for a surface and helps in predicting the required values of unmonitored sampling points to create a comprehensible surface (Johnston et al., 2003). Spatio-temporal analysis of the pollutant helps to make informed policy changes and to concentrate mitigation efforts at critical locations which can be identified (Boiné et al., 2018)

Inverse Distance Weighting

IDW interpolation explicitly works on the assumption that things which are closer to each other are more alike than those which are farther apart. Greater weight will be assigned to the points

which are closest to the target location, and hence the allocated weights change as an inverse function of ' p^{th} power of distance', where power function (p) is a positive real number. Greater values of p grant greater influence on values which are closest to the point to be interpolated. The parameter prediction for the target location is a summation of the product of 'allotted weights' and 'measured values' for all sites. After reviewing numerous literature, p is taken to be 2 for the current study.

Kriging – Ordinary

Kriging offers some advantages over other interpolation techniques. It interpolates using weights independent of the data, hence practically, the weights after the first estimation can be used for all data sets. Also, it is an 'exact' interpolator i.e., estimate at any observational point is the observation itself (Zimmerman and Homer, 1991).

Kriging has a smoothening effect on the result where it overestimates the higher values and underestimates the lower values. Since the data has a smooth trend with lesser daily fluctuations, this was not a cause of concern in the study.

The necessary steps to predict with Kriging are uncovering the rule for getting the dependence and making estimations. The most significant contribution of Kriging based dependence estimation is the effect of 'statistical stationarity' in few cases of predicting values. Some data sets are observed to be random to the extent of contributing to a situation, in which the prediction methodology fails to establish any correlation to carry out dependable estimation. This is termed as a condition of 'pure nugget effect' which was observed in the months of June, July and December of 2015, and February to June of 2016. One month's variogram, where estimation failed because of pure nugget effect, is shown in Figure 4(b).

Other prediction techniques fail to identify this situation and lead to highly inaccurate estimations. Variograms and covariance functions are created to predict the required relationship called the statistical dependence (and called spatial autocorrelation). A sample variogram for the month of December 2017 is shown in Figure 4(a).

Statistical Stationarity and the Nugget Effect

Statistical Stationarity considers the total set of observed data points as a single variable series. Additionally, a system of repetition must be realized to develop any kind of deduction procedures; and if not present, created. Nugget effect refers to the discontinuity towards the origin of the semivariogram. This discontinuity is reported to be caused by measurement errors and micro-variability in the spatial phenomenon being considered (Howarth, 1978). In the current study, due to the ‘absence’ of statistical stationarity in the data set, ‘pure nugget effect’ was observed. Kriging failed in predicting the required values for June, July and December of 2015, and February to June of 2016. One month’s variogram, where Kriging failed because of pure nugget effect, is shown in Figure 4(b).

Figure 4 here

Cross-validation of concentration measured at monitoring sites

For cross-validation, recorded $PM_{2.5}$ concentrations from 3 monitoring stations are used to predict the value at the 4th site. This is then compared with the measured value at the 4th site, to obtain a percentage error. These errors give an estimate as to how well has the semivariogram been fitted over the plotted data points, and how dependable the predictions will be. Figures 5(a) and 5(b) represent the error between measured and predicted values at 4 monitoring sites (for 24-month $PM_{2.5}$ data) and 17 monitoring sites (for 4-month $PM_{2.5}$ data), respectively.

$PM_{2.5}$ concentrations have been mapped and estimated using Kriging and IDW techniques in multiple studies (Xie et al., 2017) and they are authentic prediction techniques as per credible references (Wu et al., 2018). Whereas, superior modelling development requires extensive work on the development which would reduce the scale of the current study and divert the purpose of the study towards a development-centric modelling criteria (de Hoogh et al., 2018). The major goal of the study had been to provide a comprehensive, ready-to-use mapped and predictive estimate of $PM_{2.5}$ blanket over the city. Inclusion of various metrological factors along with 3D building information and land use analysis would further require feasibility studies, which can be an interesting study area for research in future, although, for the immediate requirement of $PM_{2.5}$ estimates at indispensable sites of Delhi, this holds less relevance as the land use and topography is homogeneous (Ahmad et al., 2016)

Figure 5 here

Results and Discussions

Predictions based on 2-year data

Predictions were made at two locations: IIT Delhi campus and Central Park, Connaught Place using PM_{2.5} concentration data for each month from the period January 2015 to December 2016 from 4 monitoring stations (Anand Vihar, Punjabi Bagh, Mandir Marg and R K Puram). Both IDW and Kriging predictions were archived for the two locations, and the predicted concentrations are plotted against each other as shown in Figure 6.

Figure 6 here

The predictions at IIT Delhi showed a peak (274 $\mu\text{g}/\text{m}^3$) in November 2016 using the IDW technique. On the other hand, the lowest value (41 $\mu\text{g}/\text{m}^3$) is exhibited during August 2016 at using the same technique. Moreover, the peak prediction for Connaught Place is noted to be 271 $\mu\text{g}/\text{m}^3$ during November 2016 using Kriging, while the lowest value (31 $\mu\text{g}/\text{m}^3$) is exhibited for July 2016 at Connaught Place using the IDW technique.

Predictions based on 4 months' data

Figure 7 here

Figure 7 shows the predictions using four-month PM_{2.5} data from multiple monitoring stations. The IDW technique on the 4-months data for Residential and Institutional prediction locations showed the peak (305 $\mu\text{g}/\text{m}^3$) in November 2017 (i.e. at Rithala) as opposed to lowest values (114 $\mu\text{g}/\text{m}^3$) for the month of February 2018 at Shahdara. When it was used for Industrial, Transport and Commercial prediction locations, the peak (216 $\mu\text{g}/\text{m}^3$) is again observed in November 2017 (i.e. at Peeragarhi) while the lowest value (116 $\mu\text{g}/\text{m}^3$) is exhibited in February 2018 at ISBT Kashmere Gate.

When the Kriging technique was used for PM_{2.5} prediction using the 4 months' data for Residential and Institutional prediction locations, the peak (267 $\mu\text{g}/\text{m}^3$) is observed in November 2017 i.e. at Rithala. On the other hand, the lowest value (116 $\mu\text{g}/\text{m}^3$) is exhibited for the month of February 2018 at Shahdara. When it was used for Industrial, Transport and Commercial prediction locations, the peak (263 $\mu\text{g}/\text{m}^3$ at Peeragarhi) are again observed in November 2017 while the lowest value (122 $\mu\text{g}/\text{m}^3$) is exhibited for the month of January 2018 at, at AIIMS. The process of cross-validation is available in the geostatistical analyst of ArcGIS. The effectiveness of the fitted semivariogram is the measure of how accurate the predictions would be. The plotted percentage errors in Figures 5a,b show how well the semivariogram had fit. It also gives an estimate of how dependable the predicted values using these semivariogram would be.

Predicted surfaces

Figure 8 here

Figure 8a shows the predicted surfaces for the first phase i.e. November 2017 to February 2018 and in figures 8 (b) and 8 (c) for January 2015 to December 2016. The trend observed in the predicted value is like the trend observed in the monitored values, apart from the variation in magnitude.

Kriging exhibits failure for the months of June, July and December for 2015 and February to June for the year of 2016. IDW proves to be effective in predicting the values for these months. IDW is more efficient in identifying pollution hotspots from the mapped prediction surfaces. Kriging tends to have a 'smoothing' effect. But Kriging is more effective in predictions when the number of input points are higher and spatial orientation is important. This is noted in phase II of the study when PM_{2.5} data from 17 monitoring stations were used. Similar effects have been observed in a study of Arsenic contaminated soil samples (Qiao et al., 2018). For applications related to health impact assessments, the use of hybrid methods that combine air quality model outputs with observational data is suggested to obtain effective results. A large-scale study has been conducted in the Atlanta region of Georgia which compares various techniques and explore the said hybrid models (Yu et al., 2018). In a case when multiple pollutants are selected, for instance, PM₁₀ and PM_{2.5}, Kriging seems to perform better with

PM₁₀ and IDW is more suitable for PM_{2.5}. A recent study (Lin et al., 2018) conducted in Shanghai, China, reported similar results. Other studies have established that increasing the geographical area under consideration causes the predicted values to be unreliable as the distance between monitored sites and target sites increases, leading to uncertainties. The uncertainties are pertaining to inaccuracies in predictions as percentage error in cross-validation increase significantly. Considering one of the recent studies (Xu et al., 2019), the error analysis of predicted results indicates that as the distance increases, reliability reduces. Recently, Qiao et al (2018) compared Ordinary kriging with IDW while studying soil pollution in China and identified better prediction accuracy for IDW. Like this study, other techniques (Kriging based) were used where Ordinary Kriging failed to predict maximum and minimum concentrations.

As per the extensive study of the past researches on PM_{2.5} using Kriging and IDW, the variation in error percentage is subject to the geographical location of the site and their relative position with respect to each other and with the target location at which the value needs to be estimated. Larger grid sizes and therefore larger effective distances between sites of concern leads to higher errors in predictions (Alexeeff et al., 2015). Higher resolution studies cause the effective distance between sites and the variation in concentrations to reduce leading to more accurate predictions (Hu et al., 2019)

Another recent study in Madrid, Spain (Gómez-Losada et al., 2019) observed the effect of Urban Heat Island on the predicted pollutant values. Delhi is also known to be affected by the same phenomenon and hence the higher percentage errors in predictions for the summer months can be attributed to this. Additionally, the effect of wind speed on the predicted values has been studied in the Kocaeli region of Turkey (Erener et al., 2018). Adding the effect of wind speed to future studies would give better results. PM_{2.5} also affects the indoor air quality in places which are densely populated and residential zones are located closer to traffic and highways (Martins and da Graça 2018). Modelling techniques have been used to predict the effect of outdoor air quality on the indoor air quality highlighting the effect (Karri et al., 2018).

Prediction of pollutant concentration using Kriging and IDW techniques has acceptable dependability and the future scope of combining it with other spatial interpolation techniques is vast. If metrological and physical influences can be combined with the raw prediction results from Kriging and IDW, the reliability of the predictions shall increase manifold. These

techniques can be applied without the boundary conditions of having a grid which makes them versatile and usable for cases where the monitoring sites are scattered.

Improved interpolation techniques beyond simple Kriging and IDW have been developed as Probability Kriging, Disjunctive Kriging and Empirical Bayesian Kriging which are used for other applications, apart from air pollution prediction. Moreover, hybrid techniques have been developed which incorporates spatial interpolation technique (Kriging) and regression analysis that can produce a detailed prediction map with improved accuracy and prediction dependability (Yao et al., 2013). Yet, combining the two spatial interpolation techniques would require reprogramming of the techniques, validation of which can be studied through future studies. Therefore, apart from their aid to interpret results, combining them into a hybrid technique is beyond the scope of the current study, but can certainly make an interesting area of interest for future research.

There is a possibility of reducing the temporal scale of the study to daily and even hourly concentrations by integrated advanced computer programming. Further work towards ascertaining the statistical stationarity of the data without going through the Kriging process could provide an added advantage. This would lead to realising that the method has failed for the data set at hand at the semivariogram stage only. In turn, if the datasets were to be segregated while using other prediction techniques such as IDW (if required), both man hours and computational power can be reduced.

Figure 8 here

PM_{2.5} mapping methods used in this study can act as a baseline for various hotspots within the city, which are growing at an appreciable rate in terms of the population of people and road vehicles as well as the need for the total energy (Shukla et al., 2018; Kumar et al., 2013; Gulia et al., 2017) The mapped pollutant profile of concentrations can ensure that the policy changes and future town planning provisions are in accordance with the goal of mitigating the pollutant concentrations (Chowdhury et al., 2019).

Summary and Conclusions

PM_{2.5} is the major contributors to the health, transport and infrastructural challenges faced by the city. The study has utilised monitored concentrations of PM_{2.5} at various monitoring stations across the city of Delhi to predict corresponding values at other sites of interest in the city. We used two methods of interpolation: a deterministic technique namely Inverse Distance

Weighting and a statistical method namely Kriging. Cross-validation analysis concluded that 24-month PM_{2.5} concentrations exhibit errors of the magnitude as 19% and 17% for 2015, and 27% and 26% for 2016, for IDW and Kriging, respectively. Additionally, in phase II, when 17 monitoring stations were included in the study by using 4-month data (November 2017 to February 2018). PM_{2.5} concentrations predictions yielded an average error percentage of 23% by both IDW and Kriging individually. Thus, it is challenging to conclude one of the two methods better, although, for the gaps, where Kriging fails to interpolate due to the absence of data stationarity, IDW fills in well.

Within the scope of this work, there was no procedure to ascertain the verification of statistical stationarity, hence some of the results from the Kriging technique are omitted. The prediction, in this case, results in constant value over the whole of the predicted surface. Kriging is unable to interpolate data that is not statistically stationary. To ascertain the statistical stationarity of the data beforehand is a tedious process which is itself an emerging research topic and requires extensive use of high-level computing tools. The formulated PM_{2.5} thematic maps can eventually provide a basis for efficient actions to control air pollution and further handle various societal and technological challenges.

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Table 1: Review of past studies on spatiotemporal analysis-based air pollutant prediction.

Location	Target pollutant/ parameters	Study focus	Major findings	Remarks	Reference
China	PM _{2.5} and NO ₂	Regression-based improvement	Universal Kriging best	First high-resolution LUR models produced	Xu et al. (2018)
Beijing, China	PM _{2.5}	Comparison: STK and Kriging	Fitting error of Bilonick smallest	Critical areas in the north of the study area.	Lin et al. (2018)
Western Europe	PM _{2.5} , NO ₂ , O ₃ and BC	100m x 100m Hybrid models	Improved robustness	Kriging improves the quality of LUR	De Hoogh et al. (2008)
Spain	Wind and temperature	AMDAR improved	Models significant in predictions	Kriging proved reliable	Dalmau et al. (2017)
Morocco	(CH ₄), (CO ₂) and (N ₂ O)	Prediction using HPC	Data processing system used	IASI instruments used	Albert et al. (2014)
Los Angeles, CA, USA.	NO _x	LUR and Kriging evaluated	Kriging steadily outperformed	Ordinary Kriging is a kind of Universal Kriging	Mercer et al. (2011)
Tehran, Iran	PM ₁₀	Genetic algorithms (GAs)	GAs reduce the estimated error significantly	Kriging potent as a prediction technique	Shad et al. (2009)
Rome, Italy	NO ₂	Land-use regression	Land-use regression give well-fitting curves	Emission data did not bring variation in R ²	Rosenlud et al. (2008)
Hamilton, Canada	NO ₂	Models reviewed	Hybrid class of models appeared most suited	Statistical interpolation is most practical	Hoek et al. (2008)

Table 2. Characteristics of monitoring stations and target locations

Characteristic Site Name	Location (Longitude, Latitude)	Monitoring site/ Target Location	Land Use/ Major Activity
Anand Vihar *	28.650278N, 77.302778E	Monitoring Site	Transport
RK Puram*	28.56611N1, 77.176667E	Monitoring Site	Residential
Punjabi Bagh*	28.661944N, 77.124167E	Monitoring Site	Residential
Mandir Marg*,†	28.634167N, 77.200556E	Monitoring Site	Commercial
Aya Nagar	28.468881N, 77.127188E	Monitoring Site	Residential
Burari Crossing	28.728343N, 77.197495E	Monitoring Site	Residential
CRRM Mathura Road	28.551003N, 77.273836E	Monitoring Site	Institutional
DTU	28.749981N, 77.117236E	Monitoring Site	Institutional
IGI T3	28.554927N, 77.0844E	Monitoring Site	Transport
IHBAS, Dilshad Garden	28.68115N, 77.304583E	Monitoring Site	Institutional
ITO	28.627521N, 77.243774E	Monitoring Site	Commercial
Lodhi Road	28.59246N, 77.236729E	Monitoring Site	Commercial
NSIT, Dwarka	28.609088N, 77.03465E	Monitoring Site	Institutional
North Campus ^π	28.687613N, 77.21023E	Monitoring Site	Institutional
PUSA	28.63432N, 77.170913E	Monitoring Site	Institutional
Shadi Pur	28.652533N, 77.155121E	Monitoring Site	Commercial
Siri Fort	28.54991N, 77.219907E	Monitoring Site	Residential
Mukarba Chowk	28.734917N, 77.15579E	Target Location	Industrial
ISBT Kashmere Gate	28.669133N, 77.232001E	Target Location	Transport
Peeragarhi	28.67974N, 77.092688E	Target Location	Transport

AIIMS	28.567116N, 77.210046E	Target Location	Industrial
Geeta Colony	28.653868N, 77.271231E	Target Location	Residential
Shahdara	28.698056N, 77.290423E	Target Location	Residential
Shalimar Bagh	28.716447N, 77.154089E	Target Location	Residential
Connaught Place^a	28.63281N, 77.219421E	Target Location	Commercial
IIT Delhi^a	28.545042N, 77.192465E	Target Location	Institutional
Tilak Nagar	28.63858N, 77.084849E	Target Location	Residential
Rithala	28.718362N, 77.105188E	Target Location	Residential

**Additional 4 months data apart from 24 months data is taken for these sites*

^π No data available for November 2017 from this monitoring site

^a No Kriging-based predictions are obtained for these sites for June 2015; July 2015; December 2015 and February 2016 to June 2016

[†] No data available for August 2016 for this site

Figure 1. Monitoring stations and target locations. The distance between two prominent sites (Punjabi Bagh and RK Puram) is marked for a scale reference.

Figure 2. 24-Month time series of PM_{2.5} concentrations from 4 monitoring stations

Figure 3. 4 Months monitored data for (a) Residential, (b) Transport and Commercial and (c) Institutional Land Use Monitoring sites.

Figure 4 **(a)** Semivariogram exhibiting curve fit through covariance between concentration values of PM_{2.5} for December 2017. **(b)**. Pure Nugget Effect observed for June 2015 exhibiting failure of Kriging method.

Figure 5 (a) Percentage error between the measured and predicted value at 4 monitoring sites for 24-month $PM_{2.5}$ data (b) Percentage error between measured and predicted value at 17 monitoring sites for 4-month $PM_{2.5}$ data

Figure 6 Predicted PM_{2.5} Concentrations at IIT Delhi and Connaught Place using (a) IDW and (b) Kriging

Figure 7 Predictions for (a) residential and institutional locations (Kriging), (b) for Industrial, Transport and Commercial locations (IDW), (c) residential and institutional locations (Kriging) and (d) residential and institutional locations (IDW), between November 2017 and February 2018

Figure 8 (a; upper panel): Predicted surfaces using (i) IDW and (ii) Kriging for November 2017 to February 2018; (b; middle panel) IDW Predicted surfaces January 2015 to December 2016 at IIT Delhi campus and Connaught Place; (c; lower panel): Kriging Predicted surfaces January 2015 to December 2016 at IIT Delhi campus and Connaught Place