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* **Corresponding Author:**

a_sahebgharani@iut.ac.ir

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The Effect of COVID-19 Pandemic on Emitted PM_{2.5} in Urban Road Networks: Using Loop Data and Kriging Method for Passenger Cars in the Central Part of the City of Lodz

Marta Borowska-Stefańska ¹, Michał Kowalski ¹, Paulina Kurzyk¹,
Alireza Sahebgharani^{2*}, Szymon Wiśniewski¹

¹Institute of the Built Environment and Spatial Policy, Faculty of Geographical Sciences,
University of Lodz, 90-142 Lodz, Poland

²Department of Transportation Engineering, Isfahan University of Technology, Isfahan 84156-
83111, Iran

ABSTRACT

In this paper, the effect of the COVID-19 pandemic on the emission of PM_{2.5} generated by passenger cars is investigated. First, traffic data collected from the inductive loop sensors is analyzed. Second, the traffic flow for the whole network system is estimated using an isometric transformed network and the Euclidean space, and the representative one is selected. Then, an emission model is presented for measuring the level of PM_{2.5} emissions by the passenger cars, and the integration process is given. Finally, the model is implemented on the central part of the city of Lodz, and the value of emissions before and after the COVID-19 pandemic is measured. Finally, the outputs and the process of the model calibration are depicted. Results show that before the pandemic, PM_{2.5} pollution was highly concentrated in the center and peripheral parts of the area under consideration, and it would gradually drop outside rush hours and grow at peak hours. After the lockdown, the pollution load throughout the whole area, and across its central parts in particular, decreased dramatically. Outputs also illustrate that restrictions not only lower the car-induced PM_{2.5} but also have a significant effect on the impact zones, areas affected by the pollutants. Another finding is that although the COVID-19 outbreak clearly poses a serious threat to life and health, it has had an exceptionally positive impact on the natural environment, becoming an unconventional mechanism for its restoration.

Keywords: COVID-19 pandemic, Transportation emission, Inductive loop data, Kriging method, Traffic flow

1 INTRODUCTION

Air pollution can be generated by different sources (e.g., fireplaces and human activities), among them, vehicles are considered as the main outdoor source of pollution in the urban settlements where combustion and consumption of fuels cause deterioration of both health and air quality (Agudelo-Castañeda *et al.*, 2013; Gualtieri *et al.*, 2015; de Fatima Andrade *et al.*, 2017; de Almeida Albuquerque *et al.*, 2018).

Several pieces of research can be found in the literature that attempted to analyze the linkage between road traffic and air pollution (Abdul-Wahab and Fadlallah, 2014; Borge *et al.*, 2018; Charabi *et al.*, 2018; Izquierdo *et al.*, 2020; Shahbazi and Hosseini, 2020). For example, Shahbazi *et al.* (2017) indicated that traffic flow has a significant contribution to the air pollution of mega-cities, and mentioned that considering traffic restricted zones can have positive impacts on the air pollution reduction. Guttikunda *et al.* (2019) reported that transportation is the major source of pollution

in the Bengaluru region. Pinto *et al.* (2020) modeled dispersion of the pollutions produced by the traffic flows and stated that air pollution is associated with vehicular movement in Belo Horizonte city in Brazil. It should be noted that although these studies depicted the connection between air pollution and vehicular movement, analyzing pollution emission of the traffic is problematic because of some reasons. First, as the recorded data in the urban environments are related to many sources (e.g., power plants and residential activities) (Duque *et al.*, 2016; Pan *et al.*, 2016), recognizing the share and distribution of pollutions emitted from the traffic can be difficult. Second, pollution generated by traffic flows in each link of a street network cannot be distinguished from monitoring stations directly because of the distance between the stations and the network segments (Pasquier and André, 2017; Rossi *et al.*, 2020). Third, due to the delays that might be occurred in the data collection process, temporal records are associated with lags which add more complexity to the vehicular pollution emission analysis (Shi *et al.*, 2018; Rossi *et al.*, 2020). Nevertheless, regarding the fact that models provide helpful tools to estimate pollution concentration and dispersion (Holnicki *et al.*, 2016; Khan and Hassan, 2020), vehicular emissions have been computed in various studies (Jenkins *et al.*, 1970; Clougherty *et al.*, 2008; Elangasinghe *et al.*, 2014; Perez-Martinez and Miranda, 2015; Pan *et al.*, 2016; Shi *et al.*, 2018; Qu *et al.*, 2019). These studies calculated the vehicular emissions by focusing on the flow data collected for a subset of links (e.g., a certain road or highway) in a network. However, the effect of flow distribution in the entire network was not included in the modeling framework.

On March 11, 2020, the COVID-19 pandemic was announced by the World Health Organization (WHO) (WHO, 2020). Countries have taken various actions to control and confront this infectious disease such as: staying at home and keeping social distancing (Şahin, 2020). Furthermore, many regions imposed lockdown and movement restrictions as one of the most effective measures for minimizing the risk of virus contractions (Le *et al.*, 2021). Execution of the lockdown policy not only has had implications for curbing the pandemic but also highly impacted the transportation system worldwide (Ranjbari *et al.*, 2021), and consequently, improvement of the air quality in different parts of the world (Gautam, 2020; Chen *et al.*, 2021).

Aside from the city and regional scale studies which considered the effect of lockdowns on the pollution emitted by the transportation system (Gualtieri *et al.*, 2020; Şahin, 2020; Wang *et al.*, 2020a; Chen *et al.*, 2021; Le *et al.*, 2021), some research has been done at the intra-urban level. Xiang *et al.* (2020) conducted research to examine the impacts of the COVID-19 responses on traffic-related air pollution utilizing flow data collected by the loop sensors for several links in the street network along with the pollution data gathered from a roadside monitoring station. Rossi *et al.* (2020) carried out a study to evaluate the effect of the traffic on air pollution before and after the COVID-19 lockdown using data of two traffic detectors and two closest monitoring systems. Ravina *et al.* (2021) analyzed the dispersion of traffic-induced pollution during the lockdown period based on the traffic data obtained from 31 sensors. These pieces of research mainly applied the data recorded by the detectors and monitoring stations for a set of places without considering the distribution of vehicles in the street network, which is critical for air pollution analysis at the intra-urban scale (Gualtieri *et al.*, 2020). This way, it can be inferred that flow of each link in a street network acts as a source of pollution.

Basically, traffic data can be acquired by origin-destination survey, traffic modeling software, and traffic data prediction. The latter one combined with smart data (e.g., loop sensors and real-time location-based data) is an alternative and low-cost approach to the survey and commercial software application and can provide satisfactory inputs for vehicular emission analysis (Fu *et al.*, 2017; Pinto *et al.*, 2020). Spatiotemporal flow prediction can be implemented by the utilization of spatial analysis tools, namely, Kriging interpolations (Selby and Kockelman, 2011; Yang *et al.*, 2018), Thiessen polygons (Gómez *et al.*, 2018), geographical regressions (Song *et al.*, 2018), spatial autoregressive models (Sun *et al.*, 2018), and neural networks (Fu *et al.*, 2017). Considering the potentials of the traffic prediction and spatial analysis tools for the vehicular emission analysis, recently, Pinto *et al.* (2020) applied spatial analysis interpolation in a Euclidian space together with an air pollution model to analyze emissions and air pollution reduction strategies. However, it should be noted that the predictive spatial models are sensitive to the distance of entities scattered in the environment, and for variables such as traffic flow, network-based distances can be calculated as well as the Euclidian ones. This way, alongside the latter, the network-based distances need to be computed to check which one is more representative for the application of spatial analysis techniques.

Therefore, based on the above-mentioned literature, it can be indicated that evaluating the effect of lockdown policy execution on traffic-related emissions by considering traffic flows in the entire links of a street network is an important research area. Notwithstanding the existing research dealing with the issue of analyzing transportation system pollutions before and after the lockdowns, there is still a gap in the body of knowledge to assess the traffic-based emissions while taking the flow of each link of a street network into account. Since spatial analysis techniques provide useful, efficient, and low-cost tools for the estimation of flows in the space, this study aims at analyzing the effect of lockdowns imposed on the city of Lodz, the most congested urbanized area in Poland (TomTom, 2021), by computing flow of each link in its street network. In addition, due to the potential and availability of the smart data in the city of Lodz, the evaluation can be carried out at the hourly temporal resolution by testing both Euclidian and network-based spaces that have not been studied in the previous air pollution analysis research (e.g., Pinto *et al.* (2020)).

The rest of this article is organized as follows. First, the study area and the data used for analysis are described. Second, traffic flow estimation and emission models along with the pollutant under consideration are explained and justified. Third, outputs of the models together with the research limitations are given and discussed, and finally, conclusions are drawn.

2 MATERIALS AND METHODS

In this part of the article, firstly, study area and data used for the analysis purposes are described. Then, two main components of the assessment framework (i.e., flow and emission models) are explained. Finally, the integrated structure applied for producing the results is represented.

2.1 Case Study and Data

Even though the research area discussed in the paper constitutes merely 13% of the administrative territory of Lodz, it is home to over 42% of the city's population, which, according to the Polish Central Statistical Office, amounted to 672,185 as of 31/12/2020. The analyzed area lies in the city's central part, within the inner ring road, and encompasses the Urban Core Zone with adjacent neighborhoods. The spatio-functional (inner and outer) borders of the area are roads that form the city's major transport arteries (fast traffic trunk roads). As shown by Borowska-Stefańska *et al.* (2019), these roads are exposed to the highest traffic load. Since the local network consists primarily (almost 90%) of low-class roads: other, local, and service, numerous issues are reported there, including extreme traffic load and congestion.

The current spatial development of Lodz, a former industrial city, is strongly conditioned by its history and cultural layering, which is particularly true of the selected study area, namely the city center in its broadest sense. Within the boundaries of this area, there is the greatest number of stately residential and factory buildings as well as regularly and most fully developed quarters (Dankowska, 2016). Due to its location, the researched area boasts high development density (amounting to 25.91% of the city's total built-up area) and a large number of business entities (including retail units and shopping centers, which constitute 60.91% and 33.33% of all city's facilities of this type respectively). In consequence, the area is exposed to extensive use that causes many urbanistic and environmental issues, e.g., air pollution (Fig. 1). It is therefore not only the area with the highest population density in the city, but it is also characterized by a high density of urban functions, both local and metropolitan, including trade, services, administration, but also recreation or culture. Therefore, the study of air quality in this area is particularly important.

The sub-system of private car transport plays a crucial role in the structure of transport in Lodz, which, according to the 2020 TomTom Traffic Index (TomTom, 2021), was the most congested city in Poland. Movement of the vehicles in Lodz can be obtained from the local Intelligent Transport System (ITS). Under the formal definition of ITS in the Polish Act on Public Roads, it is a system uses information and communication technologies not only in the field of road transport, covering infrastructure, vehicles and its users, but also in the field of traffic management as well as for interfaces with other modes of transport. In accordance with the information of the General Directorate for National Roads and Motorways in Poland (GDDKiA), Intelligent Transport System solutions are used to achieve specific benefits (e.g., improved travel safety, reduced travel times, more efficient use of the transport network) regardless of the spatial scale covered by the system.

Fig. 1. (A) Location of the researched area against spatial differentiation of population density and the city's road network, (B) types of built-up areas, and (C) distribution of retail facilities and average daily traffic of vehicles in 2019.

For ITS to function effectively, the road network is equipped with certain devices. Examples include measurement sensors, cameras, weather stations, variable message signs, communication networks.

Based on the ITS data, the average number of vehicles for the study area amounted to almost 76% of the city's total number of vehicles. As a result of this private car use, transport-related issues escalate, especially in the central part of Lodz, where the highest transport-induced air pollution is recorded. The 2020 report compiled by the Regional Department of Environment Monitoring (RDEM) in Lodz shows that excessive $PM_{2.5}$ concentrations stem, inter alia, from transport emissions, which is particularly noticeable along highly congested roads (including those in the city center). The analysis of the average annual $PM_{2.5}$ intensity [$\mu g\ m^{-3}$] between 2015 and 2019 reveals that all three air quality monitoring stations in Lodz (two of which are located within the researched area – Legionow 1 and Gdanska 16) recorded results slightly exceeding the acceptable standards of health protection recommended by the WHO. The highest readings were recorded in 2017, at the station on Legionow Street (located almost in the very center of the analyzed

area), where the average value of $PM_{2.5}$ concentration in this study is $32.5 [\mu g m^{-3}]$. In 2019, the intensity dropped by nearly 10 p.p. to $22.5 [\mu g m^{-3}]$ (RDEM in Lodz 2020). However, the guideline value of $PM_{2.5}$ concentration should not exceed $5 \mu g m^{-3}$ on an annual average basis (WHO, 2021).

Since most pollution is caused by linear emissions, it is also worth analyzing the city's private cars. According to the Polish Central Statistical Office in 2019, the majority of passenger cars registered in Lodz had an engine with a displacement ranging from 1,400 to 1,999 cc and a gross vehicle weight between 1,400 and 1,649 kg. As for commercial vehicles, over half were LCVs with a maximum payload of 999 kg. Another vital aspect for the analysis of air quality and transport-related pollution is vehicle age and fuel type used. Unfortunately, the Polish Central Statistical Office shows no specific data on the actual number of vehicles in the city, only information on the vehicles registered there. The available data shows that in 2019, the majority of vehicles registered in Lodz were between 16 and 20 years old, and that more than a half (53.2%) ran on petrol.

Information on traffic volumes throughout the road network was retrieved from the Regional Traffic Control System in Lodz, a derivative of the SCATS (Sydney Coordinated Adaptive Traffic System). SCATS monitors traffic within the network, controls traffic lights on the basis of traffic volumes and congestion, and, following specifically determined criteria, imposes a control and coordination strategy to manage neighboring intersections. Traffic density and load – input data indispensable for SCATS – are measured by detectors (inductive loops) installed a short distance ahead of the limit line (Li *et al.*, 2014) on each lane. On the basis of this data it is possible to capture traffic volumes within the network (Kowalski and Wiśniewski, 2017) and their directional structure (Borowska-Stefańska *et al.*, 2021b), which is particularly valuable for both macro- (Hueper *et al.*, 2009) and intermediate-scale analyzes (Bieker *et al.*, 2015; Borowska-Stefańska *et al.*, 2021a). The aforementioned detectors (inductive-loop traffic detectors) are a solution that is most commonly applied to measure road traffic parameters, since they offer good performance regardless of weather conditions (Gajda *et al.*, 2001). They utilize the phenomenon of eddy currents, i.e., a change in the magnetic field is caused by a metal object and this data is then registered (Burnos *et al.*, 2011). Despite their advantages, detectors cannot be claimed to be completely faultless and error-free, which may result in inaccurate measurements of the number of vehicles (Li *et al.*, 2014). Therefore, results must be verified – all extreme values and those predefined by the system as erroneous must be removed. SCATS data does not provide information on trip motivators, starting points and destinations that road users have in mind, it only presents the load of the network that reflects the journeys made by users at a given time. In consequence, SCATS-based studies are of a general, holistic nature – they analyze all trips without specifying individual dimensions of the traffic. However, there are attempts in the scientific literature to use these data to explore traffic issues in greater depth. An example of this is the modelling of movement using detector data with SUMO using the DFROUTER tool, which was used to generate the O-D matrix (Zambrano *et al.*, 2016).

The data used in our study was retrieved from the SCATS system and contains measurements conducted at 15-minute intervals by each detector located prior to the limit line on lanes for cars (no tram traffic included) within the researched area for a period of two separate months (March 2019 and March 2020). All duplicated measurements from sensors installed ahead of the limit line were ignored. The said detectors amount to 100% of this type within the analyzed area and 78.2% of all such sensors in Lodz (Fig. 2). Next, the data was aggregated to hourly measurements, with the average value for each hour calculated for each day of the week. In consequence, it was then possible (owing to detailed detector geolocation) to further aggregate the data. At this stage, any measurements incompatible on a year-to-year basis (e.g., due to modernization of the transport network or expansion of the SCATS system) were eradicated. As a result, a database was created. The database contained spatial information on the location of measurements within the transport network and average number of vehicles recorded within the network at individual hours for each day of the week in March 2019 and March 2020.

2.2 Flow Estimation Model

Reviewing the literature shows that several methods have been used in the previous studies for estimation of the traffic flow in the road networks (e.g., neural networks (Fu *et al.*, 2017), Thiessen polygons (Gómez *et al.*, 2018), spatial autoregressive moving average (Sun *et al.*, 2018),

Fig. 2. Distribution of inductive loops in the researched area and its immediate vicinity.

geographically weighted regression (Song *et al.*, 2018), and Kriging models (Selby and Kockelman, 2011; Selby and Kockelman, 2013; Shen and Hadi, 2013; Shamo *et al.*, 2015; Yang *et al.*, 2018; Pinto *et al.*, 2020)). Studies depicted that accuracy of Kriging methods taking multiple adapted weight parameters and correlated errors into account is more satisfactory for flow estimation

than the regression models which regard single parameter and treat errors as white noise (Van Beers and Kleijnen, 2004). Neural networks and Thiessen polygons also have some shortcomings. The former neglects error distribution and parameter stability (Fu *et al.*, 2017), and the latter allocates the same flow values to the segments in a polygon (Gómez *et al.*, 2018). In addition, regression-based techniques lack casual relationships and require a great amount of input data that increases analysis costs considerably (Khan *et al.*, 2018). However, Kriging models are suitable and reasonable choices for traffic-related applications (Zou *et al.*, 2012) because they are compatible with limited observations (Aultman-Hall and Du, 2006) and reliable for analyzing spatial data (Wang and Kockelman, 2009).

It should be noted that the above-mentioned predictive models cannot completely replace the real traffic counting procedure. But, they have a great potential to reduce data collection cost and time and to assist analysts to conduct their studies by providing representative flows for the networks (Pinto *et al.*, 2020) when real values are not available. Regarding the advantages of Kriging methods over the other predictive ones for spatial analysis and their acceptable results for modeling street networks (Kim *et al.*, 2016; Klatko *et al.*, 2017; Pinto *et al.*, 2020; Shukla *et al.*, 2020), this model is described in the next part of the text.

Kriging is a distance-dependent method in which the model outputs rely on the way the environmental distances are represented throughout the process. Mainly two distance types are considered for representation of the networks in the Kriging process, which are, Euclidean and network-based distances. Although some pieces of research indicated that network-based distances performed better than the Euclidean ones (Zou *et al.*, 2012), some other works found that using network-based distances had no significant impacts on improving the results compared to the Euclidean forms (Selby and Kockelman, 2011). This way, it can be said that the accuracy of the methods for modeling the road networks might be varied case by case, and to decide which one is more suitable for a study area, experimental and validation analysis is required. Also, it should be noted that there is a wide range of Kriging methods for estimating spatial phenomena from Simple, Ordinary, and Universal to Bayesian models. To select among these algorithms, autocorrelation and trend of the spatial data should be examined. Based on these features, the Kriging method compatible with the structure of the spatial data in a certain area can be identified. To do so, first, the related network to the study area is created through the below process proposed by Zou *et al.* (2012), and the flow values are assigned to the points in the transformed space.

- a) Midpoint of each link in the study area is created. It is assumed that each midpoint is the source of flow in the street network, which is an acceptable assumption in geographical sciences and used by the previous works (Selby and Kockelman, 2013; Pinto *et al.*, 2020).
- b) Network-based distance of the midpoints along with the inductive loops is measured using Network Analysis Tool and OD cost matrix in the ArcGIS environment.
- c) All points are transformed to the isometric space which results in new coordinates of the points keeping distances computed in Step a. For performing the transformation process, firstly, network-based distances are mapped into a high-dimensional subspace through Eq. (1) where d_{ij} is the network distance between points i and j .

$$b_{ij} = \frac{1}{2} \left(-d_{ij}^2 + \frac{1}{n} \sum_{j=1}^n d_{ij}^2 + \frac{1}{n} \sum_{i=1}^n d_{ij}^2 - \frac{1}{n^2} \sum_{i=1}^n \sum_{j=1}^n d_{ij}^2 \right) \quad (1)$$

Secondly, eigenvalues of matrix $B = \{b_{ij}\}_{n \times n}$ denoted by $\lambda_1 \geq \lambda_2 \geq \dots \lambda_n$ is generated, and the k greatest values represented by $\lambda_1 \geq \lambda_2 \geq \dots \lambda_k > 0$ are selected, and their normalized eigenvectors are computed $\Gamma = (e_1, e_2, \dots, e_k)$. Thirdly, new coordinates in the k -dimensional subspace is calculated by $\Gamma \sqrt{\Lambda}$ where $\Lambda = \text{diag}(\lambda_1, \lambda_2, \dots, \lambda_k)$. This step is executed in MATLAB environment.

- d) Accuracy of the constructed network in the previous step depends on the choice of parameter k . Therefore, the validity of the transformed coordinates needs to be assessed. Two metrics can be regarded for validity analysis. First, the ratio of the sum of the first k eigenvalues to the sum of the entire eigenvalues $K = \sum_{i=1}^k \lambda_i / \sum_{i=1}^n |\lambda_i|$ is obtained, and the

value of this proportion is calculated for different values of k (Mardia *et al.*, 1979). At a certain point, value of K does not improve significantly, and the optimum k can be found. Second, to evaluate the fitting quality, *STRESS* indicator introduced by (Kruskal and Wish, 1978) is quantified (Eq. (2)). This indicator has three cut-off points (i.e., 2.5%, 5%, and 10%). If *STRESS* is greater than 0 and smaller than or equal to 2.5%, the quality of the fitting is very good. If *STRESS* is greater than 2.5% and smaller than or equal to 5%, the fitting is good. If *STRESS* is greater than 5% and smaller than or equal to 10%, the fitting is fair. Otherwise, the fitting quality is bad.

$$STRESS = \sqrt{\frac{\sum_i \sum_j (d_{ij}^{obs} - d_{ij}^{est})^2}{\sum_i \sum_j (d_{ij}^{est})^2}} \quad (2)$$

- e) If the transformation process is valid, existing flow values will be joined to the points generated in Step d, and these new features will be considered for further analysis.

Second, having the distribution of points in the Euclidian and Network-based spaces, the spatial structure of data is checked in terms of autocorrelation and trend. Autocorrelation can be analyzed by measuring Moran's I , and this index can be statistically tested to examine whether the calculated value is significant. Moran's I is computed through Eq. (3), where I is Moran's I , n is the number of spatial units in a study area, w_{ij} is spatial weight of point i and j , $\bar{X}$ is the mean of spatial values, and x_i and x_j are values of point i and j , respectively. I varies between -1 and $+1$, and the more the value of I is closer to $+1$, the more the data is autocorrelated and has the clustered pattern. The null hypothesis for testing Moran's I indicates the lack of autocorrelation, and the alternative hypothesis states the existence of autocorrelation. If p -value is very small (i.e., smaller than 0.05 for confidence interval 0.95 or smaller than 0.1 for confidence interval 0.90), the existence of autocorrelation is confirmed, which means that the null hypothesis will be rejected and the alternative one will be accepted.

$$I = \frac{n \sum_{i=1}^n \sum_{j=1}^n (w_{ij} \times (x_i - \bar{X}) \times (x_j - \bar{X}))}{\left(\sum_{i=1}^n \sum_{j=1}^n w_{ij} \right) \times \left(\sum_{i=1}^n (x_i - \bar{X})^2 \right)} \quad (3)$$

Trend is a systematic change in data across an area and can be detected by drawing the trend graph that depicts the analytical pattern of the variation in a given dataset. After determining the proper Kriging method for the Euclidean and Network-based spaces, cross-validation is applied to identify which space representation performs better for simulation of the study area with a smaller amount of errors since there is a trade-off between the computational burden and accuracy level for each type of the space representations. For instance, the computational burden of the Network-based representation is much greater than Euclidean one, but it does not guarantee whether the Network-based predictions are meaningfully better than the Euclidean model. Thereby, implementing cross-validation is a necessary task before running the entire method and obtaining the ultimate outputs. Application of these tests together with the calibration and application processes are explained in Section 3.

2.3 Emission Model

There are different approaches for modeling emissions having traffic flows in the networks. For example, Liu *et al.* (2019) developed a model based on travel distance and emission variables for measuring the level of pollution dispersed by taxis in Hangzhou, China. Wang *et al.* (2020b) proposed an equation incorporating travel time, and emission and penetration rates in the dispersion calculation process. Fu *et al.* (2020) elaborated an emission model on the ground of computational fluid dynamics concepts working at the fine scales. Phillips *et al.* (2021) applied pollution source strength across the road types, background parameters, and dispersion patterns as the main factors and combined them using decay functions.

To select a general modeling structure along with supporting notion and spatial resolution of

the emission model, three factors need to be considered. The first factor is data availability, the second is modeling purpose(s), and the third is the expected usage of the results. Regarding existing data in the study area (described in Section 2.1) and the aim of this paper which is to analyze the general pattern of the pollution dispersion, an equation that concentrates on the main transportation-related variables is delineated for the passenger cars. This equation inspired by frameworks offered by Pinto *et al.* (2020) and Ntziachristos and Samaras (2020) is represented below, where PCE_i^j is the emission value of pollutant j generated by passenger cars along link i in the network, V_i is the flow in link i , L_i is the length of link i , and P_j is the amount of emitted pollutant j per length (i.e., kilometer).

$$PCE_i^j = V_i \times L_i \times P_j \quad (4)$$

Different pollutants have been taken into account in the existing literature (i.e., NO and NO₂ (Ferreira *et al.*, 2000), CO and CO₂ (MacNaughton *et al.*, 2014), O₃ (Bell, 2006), BC (Wang and Kockelman, 2009), BS (Brunekreef *et al.*, 2009), SO₂ (Son *et al.*, 2010), UFP (Zwack *et al.*, 2011; Kingham *et al.*, 2013), and VOC (Bigazzi and Figliozzi, 2015)). Among them, fine particulate matter (PM_{2.5}) is a pollutant that brings diverse and adverse health outcomes to people living in human settlements (Kheirbek *et al.*, 2016). This pollutant has a more destructive effect on the human respiratory system than the gaseous composites like CO₂ and NO₂ (Miri *et al.*, 2016). In addition, reports showed that PM_{2.5} causes 3.5 million of deaths from lung cancer and more than 220 thousand from cardio-vascular diseases annually (Hao *et al.*, 2012; Krishnan *et al.*, 2012). Additionally, the importance of evaluating this pollutant emitted from transportation systems has been explicitly emphasized by the previous studies (e.g., Zuurbier *et al.* (2010); Apte *et al.* (2011); Quiros *et al.* (2013); Weichenthal *et al.* (2015)). Thus, PM_{2.5} is regarded as the contributing pollutant in the emission model. It should be noted that so long as the required data be available and the modeling process be valid, the application of the given framework will not be limited to PM_{2.5}, and it can be utilized for assessing other pollutant types spatially and temporally. Another point is that P_j can be disaggregated based on several factors such as vehicle type, fuel type, vehicle weight, local observations, and so on. But, when only aggregated and low-resolution data be at hand, small-scale emission rates cannot be directly used in the calculations. One way to address this issue is to consider the conditions of a certain study area and to define a logical scenario compatible with the available data. A plausible scenario that provides perspectives for planning and has been followed by several studies (e.g., Iqbal *et al.* (2020)) is to model higher concentration values called the worst-case scenario. In this scenario, measurements are conducted based on the highest level of pollution generation rate. As large and heavy vehicles are banned to enter the study area and noting the fact that the dominant transportation mode is passenger car (about 88%) with petrol fuel (about 60%), considering the PM_{2.5} emission rate equal to 0.0022 g km⁻¹ would be admissible for the worst-case scenario according to (Ntziachristos and Samaras, 2020).

2.4 Integration of Flow and Emission Models

After developing both flow and emission models, the outputs can be obtained through an integrated structure illustrated in Fig. 3. First, traffic flow for each link in the network is estimated using a proper method identified by comparing and analyzing Kriging methods and data structures in the Euclidean and isometric transformed spaces. Second, based on parameters such as characteristics of the study area, and the existing data and literature, the emission model containing the flow factor is articulated. Third, outputs of the first and second steps are combined and emission generated along each link in the network is measured. Fourth, to produce the spatiotemporal pattern of pollution dispersion, the emission surface is interpolated through Kriging method utilized by other studies (e.g., Kumar *et al.* (2020); Pinto *et al.* (2020)).

3 RESULTS AND DISCUSSION

3.1 Network Representation and Kriging Model Selection

For creating the isometric transformed network, the method represented in Section 2.2 was

Fig. 3. Integration framework of flow and emission models.

applied to the points with the collected data. As the choice of dimensionality is the key component in the network construction, parameter K was measured for different values of dimensions denoted by k . Fig. 4 depicts that K had a sharp rise from dimensions 1 to 2 but its growing tendency slowed down for the higher dimensions. Furthermore, comparing semi-variograms for the dimensions did not show significant improvement by the increase in the number of dimensions.

To show the accuracy of the generated spaces, *STRESS* indicator was calculated through Eq. (2). For $k = 2$, *STRESS* value was 0.0036 that confirmed a very good fitting result. Putting all of these outputs together, it could be concluded that the increase in the dimensionality parameter which imposes more computational burden, did not lead to better results in the study area. This way, $k = 2$ is an acceptable choice for the development of the transformed space, and this value is used in other steps of the analysis.

Fig. 4. K value plotted versus dimensionality values.

Table 1. t-test results for RMSE and ASE values in the transformed and Euclidean spaces in March 2019 and 2020.

	t-value	Sig (2-tailed)
RMSE 2019	−0.017	0.987
RMSE 2020	−0.057	0.955
ASE 2019	0.518	0.607
ASE 2020	1.452	0.153

After creating the transformed space and having the Euclidean space, the trend and autocorrelation in the spatial data were checked for these configurations based on the collected data. Figs. S1 and S2 (given in Supplemental material) display the trend of spatial data in the transformed and Euclidean spaces in March 2019 (before pandemic) and 2020 (after pandemic), respectively. These diagrams confirm the existence of the trend in the hourly spatial data in both spaces and time spans.

Table S1 (given in Supplemental material) illustrates autocorrelation in the spatial data in the transformed and Euclidean spaces. This table, which includes Moran's I along with the results of the statistical significance analysis, shows that there is autocorrelation in the hourly spatial data in both spaces in March 2019 and 2020. Owing to the trend and stationarity in the spatial data structure, Universal Kriging with exponential function which is analytically able to present underlying patterns of stationary data with trends better than the other common Kriging models was utilized for the flow estimation. But, as the results can be acquired from the transformed and Euclidean spaces, before estimating flows for the entire network and constructing the ultimate transformed space that is computationally complex, the application of either space should be decided.

To do so, cross-validation was implemented on the gathered data in both spaces, and Root Mean Square Error (RMSE) together with Average Standard Error (ASE) were computed for the results. For evaluating meaningfulness of the statistical difference between the error values and the impact of the transformed space on the reduction of the modeling errors compared to the Euclidean one, t-test was performed on the obtained RMSEs and ASEs for March 2019 and 2020 separately. Table 1 shows the results and implies that the difference between the errors is not significant. Thus, considering the computational difficulty of calculations in the transformed space along with the experiments which confirmed that isometric transformation did not lead to lower errors in the study area, the Euclidean space was executed for further estimations.

3.2 PM_{2.5} Emission Estimation and Distribution Analysis

After flow calculation, emission along each link was calculated through Eq. (4), and the spatiotemporal distribution of PM_{2.5} across the study area was generated using Kriging method regarding trend and stationarity in the pollution data structure at hourly intervals in March 2019 and 2020. Fig. 5 portrays the hourly distribution of the normalized pollution values emitted in the study area. It shows that the level of emissions before and after the COVID-19 pandemic was considerably different and carrying out the restrictions had a substantial impact on the traffic flow generated by the passenger cars and consequently on the production of the emissions.

Fig. 6 depicts the spatial and temporal patterns of dispersion in four representative and distinctive examples (i.e., peak and off-peak times) before and after the pandemic. It can be seen that before the pandemic, pollution was highly concentrated around the edge and in the heart of the city. The level of concentration gradually went down after the peak hours and went up when the time moved toward such time slots. This effect could be explained by considering the condition that before lockdown, people tend to access facilities in the study area, and in the absence of the restrictive policies, generated flows spilled inward and outward of the area under consideration. After introducing bans and prohibitions including activity and travel limitations, the load of pollution became substantially lower all over the study area specifically in the central parts. Furthermore, several scattered pollution hotspots could still be identified around the boundary of the central area of the city of Lodz. However, the intensity of these places and their impact area were not as high as the states before the pandemic in March 2020. The reason is that after

Fig. 5. Normalized hourly pollution distribution in Mach 2019 (blue line) and 2020 (red line).

Fig. 6. Spatial pollution emission in March 2019 and 2020 (normalized values). The first set of plots (a1–a8) illustrates dispersion surface in the study area, and the second (b1–b8) shows dispersion at the street level.

implementation of the lockdown measures, some activities were closed and movement between different places was faced with difficulties. Therefore, traffic generation was decreased, and owing to the movement barriers, the volume of attracted and produced flows fell down. Consequently, emission values were reduced and impact areas affected by the pollutants became smaller. Besides, it could be said that despite the pollution and flow reduction in March 2020 compared to March 2019, due to the importance of doing some necessary activities or working in sectors delivering critical services even in the lockdown period, usage of the passenger cars was continued.

Moreover, apart from the general dispersion pattern described above, the pollution density of some spots was the same before and after the pandemic. These places are mainly located in the east and north-west part of the study area (Fig. 7). This way, such locations could be regarded as the high prioritized zones for preparing spatial policies such as land-use rearrangement or traffic pricing programs. Thus, another potential that can be taken for the application of the outputs in practice is the creation of pollution risk and intervention maps that could assist policy- and decision-makers in the establishment of future development strategies.

Fig. 7. Interventions zones. Hotspots (marked by the red circles) have been extracted from the representative pollution distribution maps by finding common locations with the highest pollution levels.

3.3 Research Limitations and Future Works

The first limitation of the model elaborated in this article is that although the applied method incorporates temporal dimension, it is static and does not represent dynamics underlying the pollution emission phenomenon. For example, in the utilized model, dispersion of the pollutants is modeled at a point in time, and the circulation of traffic flow inside and outside of the area under consideration is not taken into account between the pre-determined time steps (e.g., only dispersion at 00:00 and 01:00 is obtained but states in the middle of these times are not calculated). Although disregarding dynamic movement might deviate the results, outputs are still plausible following the previous studies (e.g., Pinto *et al.* (2020)) and the compatibility of the results with the general body of knowledge of the geographical analysis.

The second limitation is related to the factors affecting pollution dispersion. For more realistic outputs, variables such as wind direction, street channel, velocity, and acceleration can be considered in the modeling structure. However, to treat these factors, high-resolution data and more complex processes are required. Albeit the utilized framework in this article is admissible and supported by the existing literature (e.g., Kumar *et al.* (2020); Ntziachristos and Samaras (2020); Pinto *et al.* (2020)) and the available data, putting the indicated constructs in the modeling structure can be pursued by the future studies.

The third restriction pertains to the travel modes other than the passenger cars. Generally, in the transportation networks, different vehicles with different characteristics (e.g., mass, size, fuel consumption, and so forth) are involved, which can affect the amount of pollution generation. Although this item has not had a great impact on the study area represented in this research (as stated in Section 2.3), extending the proposed model to other modes can be regarded for future works.

Further to the above-mentioned limitations, other extensions can be taken into account for future studies. First, this article only examined the emission of PM_{2.5}. Therefore, the application of the model for finding the dispersion pattern of the other pollutants can be followed by another research. Also, in addition to the analysis and experiments presented in this article and the points brought up by the relevant studies (e.g., Wang and Kockelman (2009); Selby and Kockelman (2011); Selby and Kockelman (2013); Pinto *et al.* (2020)) which justify using spatial analysis techniques for the flow and emission estimation, in the case of data availability, testing other predictive

methods (e.g., meteorological and remote sensing ones) and comparing their outputs with the Kriging model can be regarded as another noteworthy extension to this research.

4 CONCLUSIONS

The purpose of the article was to determine (using Lodz as an example) the impact of the COVID-19 pandemic on PM_{2.5} emissions for urban transport networks. Data from inductive loops and the Kriging method were applied to accomplish the research objective. The impact (assessed by amounts of pollution) was determined exclusively on the basis of data on the numbers of passenger cars within the road network. The conducted analysis showed that the traffic restrictions introduced during the COVID-19 pandemic contributed to the improvement of air quality in Lodz.

Numerous studies have shown that air pollution is strictly correlated with transport, and PM_{2.5} emissions especially pose a particularly dire threat to life and health, primarily in populous urban areas. Levels of pollutant emissions before and during the pandemic fluctuated greatly. Prior to the pandemic, PM_{2.5} pollution was highly concentrated in the center and peripheral parts of the analyzed area. It would gradually drop outside rush hours and grow at peak hours. Upon the lockdown (including traffic restrictions due to the COVID-19 pandemic), the pollution load throughout the whole area, and across its central parts in particular, decreased dramatically. Not only did the restrictions lower the amount of car-induced PM_{2.5} emissions, but they also made the impact zones noticeably smaller. Therefore, the study clearly shows that restrictions in car use can play a crucial role in the reduction of air pollution in large cities, which, additionally, would help accomplish objectives of sustainable development. Although the outbreak of the COVID-19 pandemic clearly poses a serious threat to life and health, it has had an exceptionally positive impact on the natural environment, becoming an unconventional mechanism for its restoration. The implementation of pandemic-related traffic restrictions has made it possible to conduct a peculiar 'experiment' to assess the impact of changes in travel behavior on air pollutant emissions – an important issue not only in the analyzed city (Lodz), but many other large agglomerations with densely populated and highly developed city centers facing transport-related problems.

All actions taken to restore the natural environment are vital not only for us at this time, but, above all, for future generations. Importantly, the analyses described in this paper offer a practical dimension – for instance, the results and the model itself can be used to create pollution maps, which may be extremely useful for decision-makers responsible for transport policies wishing to follow the principles of sustainable development. What is more, those studies that have assessed air pollution and its decrease following the introduced car use restrictions will be very important in determining the durability of the effect once the COVID-19 pandemic restrictions are lifted fully. The results will enable the formulation of new guidelines and recommendations for transport policies (especially in urban areas) compiled to accomplish objectives of sustainable development, including improvement of air quality in cities. A new transport policy on traffic would help create low-emission zones in metropolises, which is essential in densely populated urban areas (which in Lodz refers, in particular, to the city center). Research of this kind also facilitates a better understanding of the impact car traffic restrictions have on air quality.

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SUPPLEMENTARY MATERIAL

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