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Opinion

Environmental Justice and the Use of Artificial Intelligence in Urban Air Pollution Monitoring

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Abstract: The main aims of urban air pollution monitoring are to optimize the interaction between humanity and nature, to combine and integrate environmental databases, and to develop sustainable approaches to the production and the organization of the urban environment. One of the main applications of urban air pollution monitoring is for exposure assessment and public health studies. Artificial intelligence (AI) and machine learning (ML) approaches can be used to build air pollution models to predict pollutant concentrations and assess environmental and health risks. Air pollution data can be uploaded into AI/ML models to estimate different exposure levels within different communities. The correlation between exposure estimates and public health surveys is important for assessing health risks. These aspects are critical when it concerns environmental injustice. Computational approaches should efficiently manage, visualize, and integrate large datasets. Effective data integration and management are a key to the successful application of computational intelligence approaches in ecology. In this paper, we consider some of these constraints and discuss possible ways to overcome current problems and environmental injustice. The most successful global approach is the development of the smart city; however, such an approach can only increase environmental injustice as not all the regions have access to AI/ML technologies. It is challenging to develop successful regional projects for the analysis of environmental data in the current complicated operating conditions, as well as taking into account the time, computing power, and constraints in the context of environmental injustice.

Keywords: environmental injustice; air pollution monitoring; artificial intelligence (AI); air pollution modelling; smart city

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1. Introduction

Currently, 7.9 billion people live on the Earth; the population of the planet is constantly growing, and, according to some forecasts, by 2050 it will increase by two billion people, even taking into account the low birth rate. The world is characterized by urbanization and the population is rapidly relocating from rural areas to cities. According to some forecasts, in about 30 years, 70% of people will live in an urban environment [1].

Despite the economic growth in cities and significant efforts to introduce green initiatives and a comfortable urban environment, most modern cities are becoming more people-unfriendly, while urban ecosystems face various problems, including air [2,3], water [4], and soil [5,6] pollution; excess incidences of infection diseases due to the high population density [7]; a higher risk of developing mental illness compared to rural areas [8]; the limited access of poor people to high-quality and nutritious food, which results in health problems [9]. In addition to these problems, excess noise levels [10,11] is also critical due to the annually growing number of motor vehicles and other sources, which often lead to increased levels of stress and irritability [12]. Industrial and metropolitan cities are characterized by an unaesthetic urban environment due to the lack of greenery or low plant biodiversity [13] essential in the urban environment [14–16], general grayness, the accumulation and drabness of buildings [17] causing moral discomfort, and aggression because of overcrowding. Against the background of these problems, many cities of the world have begun to develop the concept of smart cities [18], which, among other things, widely uses artificial intelligence (AI) and machine learning (ML) [19,20].

The problems of environmental injustice [21] or environmental inequality have become pressing. This is exacerbated in cities due to different levels of wealth and economic development. It is well-known that, within modern megacities, there are more and less prosperous locations. The richer the location, the better the access to air pollution monitoring systems and the higher the level of health care.

The term *air pollution monitoring* requires specification with the use of AI/ML methods. If we are dealing with classical environmental monitoring, we mean air quality monitoring using stationary networks. They usually include several instruments continuously measuring different pollutants. However, due to the widespread use of AL/ML, when the data can be inserted into models to estimate pollution exposure and its source distribution, the term air pollution monitoring has broadened. In this case models can be both statistical, based only on monitoring data from stationary networks, or dynamic, based on emission monitoring data from pollution sources (point, linear, or area).

Smart city solutions are implemented worldwide, an increasing number of internet of things (IoT) devices are being deployed in urban infrastructure, including for air quality monitoring. More and more cities implement AI technologies to solve their air pollution problems.

The purpose of this paper is to consider environmental justice in air quality monitoring in a smart city, and the problems associated with the use of AI to predict air conditions. Environmental justice issues will be addressed both globally and regionally.

2. Environmental Justice at the Global Level

We consider global air monitoring and the use of AI within the global-used concept of smart city. In practice, smart cities are often praised as a means of transforming urban areas into modern cities [22], thus contributing to the achievement of sustainable development goals and environmental justice. However, although smart technologies use technological innovation, digital technologies are neither beneficial to society nor solve the pressing problems in the city, such as crime, drugs, and homelessness. The emerging smart city reproduces actual and implied urban inequalities; rich residential areas and new economy spaces become "smart". but most of the city is left behind [23].

Moreover, it is obvious globally that environmental inequality will only grow with the introduction of smart cities. Whereas smart cities are based on breakthrough technologies, it is evident that countries fenced off from such technologies will turn into labor force and resource appendages over the coming decades, and the world will become more unequal. Thus, by 2050, one part of humanity will live in high-tech smart cities, while the other part will live in environmentally unfavorable conditions.

This divide can also be seen in other contexts. During the COVID-19 pandemic some countries were fenced off from medical technologies and had no local vaccines. Such countries naturally faced higher infection rates. Many low- and middle-income countries experienced severe vaccine shortages. By the end of 2021, a little less than 9% of people in Africa were vaccinated against COVID-19 [24], which could eventually extend the pandemic due to the emergence of mutations and their global spread from Africa [25]. There is also the pressing problem of the acceptance and readiness to obtain the vaccines among the population [26]. Similarly, African countries are more prone to the incidence of other diseases due to their poorly developed medical systems. The situation is aggravated because the continent is isolated from the technologies of developed countries. Poliomyelitis seriously affected the continent, and it took them about 30 years to control it [27].

The fencing off of countries also occurs for other reasons; economic sanctions, which are applied more often during interstate conflicts, also restrict countries from new technologies. For example, sanctions and economic barriers can stop entire countries from accessing semiconductor technologies, which are crucial for the technological progress. The problem of the global openness of scientific data and developments is obviously becoming more acute. The question arises as to whether technologies belong to one hegemon or result from fundamental research of the all of humanity and whether it is fair to impose economic restrictions and sanctions, thereby increasing the gap and injustice within and between countries. The role played by the interaction of the international scientific community should be clearly understood.

3. Environmental Justice at the Local Level

A pressing problem of modern cities is polluted air. Monitoring air conditions and the use of AI for predicting air quality are trends annually gaining momentum due to the development of smart cities. However, there are sharp contradictions in the context of environmental justice both at the local and the global level.

3.1. Air Pollution Monitoring Problems

3.1.1. Limitations of Different Air Pollution Monitoring Technologies with Stationary Networks

There is an environmental justice issue associated with the organization of the continuous monitoring of air pollution at ground stations in low- and middle-income locations [28]. This has led to the formation of complex and not always well interconnected monitoring systems. Community-based monitoring networks were formed in different locations, when people bought inexpensive portable sensors for ground-based measurements, and their motivation varied from self-actualization and obtaining their own benefit, to a desire to benefit society [29]. Besides ground-based measurements, community-based monitoring and advanced networks use data from remote sensing satellites.

Examples of such international projects are the Windy project [30], which uses Earth remote sensing satellites [31], and the QAir project [32]. Each of these technologies can be useful for public health research and the distribution of clinically relevant information to the population. Note, however, that there is an issue of distrust in interpreting monitoring data and assessing risks to the population [33].

The problem concerns the scientific validity of the obtained data. The point is that we should study where the data comes from, the paths they might have taken, the effectiveness of the collection mechanisms, and the sensors themselves (expected battery life, harsh conditions, data gaps, etc.). Monitoring networks based on cheap sensors have been developed in many cities; however, the problem of the reliability of the data obtained from cheap sensors is also questionable. Pollutants are measured using a wide range of gas sensors, as well as $PM_{2.5}$ and PM_{10} sensors, which need to be pre-calibrated and re-calibrated. Such sensors generally have internal and external errors associated with their operating mechanism, the environment, the location area, and the model [34]. $PM_{2.5}$ and PM_{10} are difficult to measure, so several main groups of measurement technologies are used. Common reference instruments include research-grade instruments (e.g., scanning mobility particle sizer (SMPS), aerodynamic particle sizer (APS), and GRIMM dust monitor), and portable instruments (e.g., TSI SidePak and TSI PTrak). Moreover, the World Health Organization recommends using a gravimetric method for measuring $PM_{2.5}$ and PM_{10} [35] based on the collection and laboratory weighing of particles, which is time and resource consuming. This method naturally has limitations in online applications. Currently, there are analyzers based on a Quartz Crystal Microbalance (QCM) [36], which is a thin layer of quartz crystal less than 1 mm thick. Gold films deposited on both sides of the quartz layer serve as electrodes, through which oscillations pass with a frequency typical of quartz. The microbalance elements are mounted on impactor plates. Aerosol particles deposited on them lead to a drop in the oscillation frequency proportional to the mass of the deposited particles. The surfaces of the elements can be easily cleaned and reused.

Another example is the online monitoring of atmospheric formaldehyde. Laboratories usually perform monitoring by sampling and analysis using liquid chromatography. The number of sensors for measuring HCHO is limited [37], and there are no cheap, accurate, and sensitive HCHO sensors which can determine low concentrations of formaldehyde with sufficient accuracy.

3.1.2. Do We Measure What We Really Need to?

First, one should clearly understand that the assessment of air condition by the concentrations of standardized pollutants cannot fully establish the degree of danger to human health and the environment. For example, the main problem of $PM_{2.5}$ and PM_{10} particles is not only their concentration in the atmospheric air, but also their composition of various toxicants, including polyaromatic hydrogens, heavy metals, etc. Previous studies proved the presence and concentration of such heavy metals as As, Cr, Co, Cd, Ni, and Pb in $PM_{2.5}$ and PM_{10}, which increase the risk of cancers [38,39]. In theory, chronic exposure to these particles can cause gastrointestinal disorders in the form of dysbacteriosis, affect our nervous system, cause respiratory diseases, and lead to impaired glucose metabolism and other negative cell changes [40,41].

It is not enough to monitor the concentration of $PM_{2.5}$ and PM_{10} now. The amounts of metalloids and other substances included in $PM_{2.5}$ is also of great importance. Sampling of pathogenic bioaerosols will become important in the future, which is an important topic in connection with the COVID-19 pandemic and monkeypox. A related problem is the need to create new sensors. Perhaps one of the solutions will be quantum sensors, which can provide high sensitivity and accuracy for measuring key information in quantum or classical physical systems [42,43]. Recent achievements in quantum technologies helped to reach a new level in measuring the parameters of the studied systems. While toxicants in PM cannot be measured, it is necessary to monitor PM by all the technologically available methods.

3.1.3. Security and State/Commercial Secrets

In this situation, we face military and commercial injustice, as well as the dilemma of whether such data can be military or commercial secrets. First, pollutants, together with air currents, can spread over great distances, reaching other regions within a country and crossing international borders. Therefore, one cannot assure that the data on substances in the atmosphere will remain secret. Second, when it comes to the impact on human health, correct and accurate information should be reported in order to protect the population.

3.2. Issues Related to Air Pollution Modeling Using AL/ML

In the previous section we considered the reliability of data obtained with stationary networks. Now we consider the issues of air pollution monitoring in terms of modeling and extend this to pollutant emission at point (e.g., emissions at plant stacks), linear (e.g., highways) and area (e.g., landfills, parking lots) sources, the calculation of pollutant concentrations, and the assessment of the reliability of data from stationary networks. It should be noted that we define point source pollution as any contaminant that enters the environment from an easily identified and confined place. Examples include smokestacks or discharge pipes. Linear pollution sources are associated with traffic among various air pollution sources in cities. Area sources consist of lots of smaller pollution sources that are not significant by themselves but when considered as a group can be.

3.2.1. Accuracy of Input Data

There are the problems of data reliability. If monitoring data do not meet reliability requirements, the input data for the model might initially have errors. Then the model or method itself will not predict accurately. In the case of emission sources, this inaccuracy is mainly related to the category of the source, for example, emission intensity and the composition of pollutants. In such a case, the input data on emissions or meteorological conditions may be ambiguous or incorrect due to measurement or estimation errors [44]. Data on emissions from large industrial sources and small sources such as vehicles are generally used to model air quality. Data from large sources are usually relatively precise;

however, in some cases they can be questionable. Emissions from small sources are more ambiguous due to the variation and range of different emissions. According to some data, the ambiguity of the input data for various pollutants from point sources ranges from ±15% to ±40%, area sources from ±40% to ±50%, and linear sources from ±30% to ±50% [45].

3.2.2. Validity of Other Input Data Underlying the Model

There are methods for calculating vehicle emission forecasts, which are based on AI recognizing vehicles from a video camera. This technology can estimate in real time the emissions from motor transport in a transport flow by using motion vectors as input data [46,47]. An example of corrupting data on the emissions from different types of vehicles is the story of Volkswagen, the German motor vehicle manufacturer, which in 2007 introduced a new diesel engine labeled "clean diesel" as a marketing ploy in the US and Europe. However, in 2015, the US Environmental Protection Agency discovered that special software was installed illegally to obtain fake results of vehicle emissions [48,49]. According to some reports, in 2018, BMW similarly falsified its emissions statistics, while positioning itself as an innocent party in this incident [48]. Questions about the data reliability from global automobile companies naturally arise, since the story of Volkswagen is probably not unique. Some authors note that the accuracy of measuring meteorological parameters (temperature, wind speed, pressure) exceeds the accuracy of measuring concentrations of pollutants and emissions, when models become more sensitive to meteorological data than to variations in emissions. Notably, the Western COPERT model for estimating emissions from road transport has weaknesses like its analogs in other countries. The model is based on the calculation of statistical data on the emission source at the national level. However, it cannot accurately show the true emission situation, since it first needs to take into account the type of terrain, differences in the types and models of vehicles from different manufacturers, and the fuel used in the vehicle.

The use of remote sensing methods on roads has shown that real emissions do not coincide with the model data and change even for one country or one city depending on the conditions [50,51]. This proves the above weaknesses of the models for calculating mobile sources on roads, which take into account only a small part of the data needed to correctly estimate vehicular emissions.

3.2.3. Black Box Models and Other Artificial Intelligence Models

AI methods are often black-box models [52] operating on the basis of a certain input for entering information and an output for displaying the results, where the system operating processes remain unknown even to the developers. Such models work under constant conditions, and the modern world and environment tend to change; hence the question arises whether it is fair to use these methods. If you trust a black-box model, you also trust the entire database, from which the model itself is built directly using an algorithm that combines variables [53]. White-box models often use a large range of parameters, which can eventually help to detect various patterns and heterogeneities; however, the high dimensionality of big data creates problems, such as measurement errors or spurious correlations, which can eventually lead to incorrect statistical and scientific conclusions [54]. In other words, the more factors the model takes into account, the more it explains, but the more errors it can accumulate [55]. AI has proved to be an extremely useful tool for research and the analysis of large-scale data [56], since the main goals of big data include predicting future observations and obtaining insights into the relationship of the studied object.

There is also the problem of trust in AI [33,57]. As AI methods are not widely understood, the problem of trust arises due to misunderstanding. Explaining automated decision making to users can reduce uncertainty (although no comprehensive study has been carried out on this subject). However, given the complexity of ML models, attempts to explain them may even increase uncertainty. It can also lead to a certain level of forced credibility such as "trust us because we can explain it ourselves (even if you cannot understand our explanation)". Thus, building confidence in AI remains an open research challenge.

3.3. Is Monitoring and Predicting Necessary at All?

3.3.1. To What Extent Are the Economic Costs Legitimate?

Methods of monitoring of air quality are quite expensive. Perhaps a more efficient option is to allocate funds to improve or purchase new gas cleaned "dry" system or a "wet" system; at the same time, it requires a full consideration of all factors, such as deciding what gas clean-up system would be used. The saved funds may be also allocated to the development of other air protection technologies. The effect of the renovation of the urban environment in gas and air purification could avoid the need for online monitoring, since due to competent and adequate changes in gas purification equipment, atmospheric emissions of pollutants could be reduced significantly. However, there is a different view: developing emission control technologies is important, and effective air quality monitoring is still critical at this time for, for example, reporting unexpected pollution events, source distribution, exposure assessment, refining existing models, and studying secondary pollutants (ozone and $PM_{2.5}$).

3.3.2. Going Around in Circles (Costs of Public Monitoring Systems)

States establish standards and controls for air quality and monitoring according to state-approved methodologies. The question arises about the reliability and credibility of such highly inflexible systems. Perhaps it is worth expanding the horizon in terms of the methodologies used and, after an appropriate analysis, choose the most suitable, rather than short-term, options. The state policy does not guarantee that no exceptions were made for economically significant enterprises in the form of changes in one-time maximum concentrations, etc.

3.3.3. Substitution of Concepts

We need a balance of public control and proper and honest state control to avoid a sense of impunity, especially for such economically significant enterprises that are the main sources of pollution. We should put a priority on assessing the state of the environment where people live and avoid the situation when "the driver is more important than the passengers". Concepts are often substituted under these conditions. We need a balance of sustainable development and environmental justice. We need open discussions, not stonewalling. The biggest substitution of concepts is that a smart city is not about sensors and AI, since they are only tools of the smart city. A smart city is a city with smart solutions for the comfort of the people who live there.

4. Conclusions

AI and ML approaches have proven to be extremely useful tools for the large-scale analysis of air monitoring data. No matter how useful they are, implementing AI and ML methods is a complicated task. Several warnings, weaknesses, and nuances should be taken into account (and in many cases circumvented) to provide appropriate solutions and to avoid the formation of environmental injustice and take full advantage of these emerging paradigms.

We are convinced that the development and implementation of smart city approaches in terms of robust statistical and computational algorithms supported by optimized data collection, storage, management, and analysis platforms, as well as properly integrated software solutions supported by a strong ethical policy consistent with respect for privacy, confidentiality, and individuality, are an ambitious but achievable goal. By combining modern computational and learning methods with best data collection and management practices, we can follow up on the promise of AI/ML in environmental air quality monitoring and avoid exacerbating the issue of environmental injustice.

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