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A Narrative Summary of Air Pollution Awareness: The Recent Modeling Implications

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About 91% of the world's population are living in places where ambient air pollution exceeds the limits set by the World Health Organization (WHO). Given 4.2 and 3.8 million people die due to exposure to ambient and indoor air pollution, respectively. So, lack of effective measures toward airborne emissions leads to sacrificing lives on a daily basis [1]. The impact of air pollution on the environment and humans has been already extensively discussed and many countries were successful in raising the public awareness about its deleterious consequences. However, the statistics show that air pollution exposure increased the death rates[2-5]. The most famous example of air pollution and its effects occurred in 1952; "London smog", coined from "smoke" and "fog" [6]. Another example of a famous air pollution abatement is the United States after enacting the first federal air pollution legislation in 1955 and later in 1970, which led to the establishment of Environmental Protection Agency (EPA) [6].

However, many developing countries has sacrificed air pollution for economic growth, including Iran [7]. Given the extensive contributions made to understand the dynamics and health impacts of indoor and ambient air pollution on the environment and humans [8-12], brighter prospects are not far-fetched. To this end, effective policies should be adopted in the developing countries, similar to the developed countries, to reduce ambient airborne emissions from mobile as well as industrial sources [12]. In the developing countries, the threat of air pollution often emerges in the winter, when atmospheric entrapment, diesel- and mazut-burning power plants, emissions, and the demand for thermal energy concur; an exacerbated scenario is very likely.

In urban areas, air pollution is impacted by human activities rather than natural sources of air pollution. Furthermore, limited human activities often decrease indoor and outdoor air pollution, as the current COVID-19 pandemic reduced the air pollution [13-15]. Accordingly, Berman and Ebisu [16] found that COVID-19 pandemic declined NO_2 emissions by 25.5% as well as $PM_{2.5}$ pollution in the United States. Although the COVID-19 lockdowns are considered as the main factor in air pollution decline [17], they led to higher traffic congestion in urban areas due to the limited use of public transportation [18]. Human beings have developed many strategies after COVID-19 lockdowns to promote the use of remote working and efficiency of traffic restrictions on air pollution, which reduced the carbon footprint imposed on the environment. However, these remote and online activities may not fully-satisfy the demand to decrease carbon footprint. Obringer, Rachunok, Maia-Silva, Arbabzadeh, Nateghi, and Madani [19] suggested that the standard range of carbon footprint of 1 GB was from 28 to 63 g CO_2. The novel implications of air pollution modeling using machine learning algorithms have attracted attention and proved applicable for air pollution dispersion. Rezaali, Fouladi-Fard, Mojarad, Sorooshian, Mahdinia, and Mirzaei [12] implemented a random forest model to estimate the spatio-temporal distributions of benzene, toluene, ethylbenzene, and xylene (BTEX). Zhang, Fu, and Tian [20] adopted a deep learning approach to estimate air pollution using the images captured by mobile devices. Machine learning methods can also improve the accuracy of traditional techniques, such as land-use regression. Lautenschlager, Becker, Kobs, Steininger, Davidson, Krause, and Hotho [21] proposed a machine learning approach for optimizing and facilitating the widely-used land-use regression. Therefore, application of machine learning algorithms can pave the way for future mitigation of air pollution as well as public awareness of pollution levels.

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