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Air Pollution and Violent Crimes in Iran: A Statistical Analysis of the Relationship Between Atmospheric Pollutants and Crime Rates in Metropolitan Areas

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Abstract

While the associations between pollution, human health, and behavior have been widely studied, the relationship between air pollution and violent crime remains underexplored. Using an interdisciplinary approach within green criminology, this study examines the statistical associations between air pollution, mental health, and violent behavior in Iran, aiming to contribute to evidence-informed environmental security discussions. Time-series analysis, regression models, and panel data techniques were used to explore relationships between key pollutants (PM_{10}, $PM_{2.5}$, CO, NO_2, SO_2, and O_3) and violent crime rates in Tehran and the provinces of Mashhad, Isfahan, Fars, Alborz, and Rasht from 2016 to 2021. Given the observational nature of the data, all results represent correlations rather than causal effects. In Tehran, ozone (O_3) and nitrogen dioxide (NO_2) show statistically significant positive associations with violent crime rates, while carbon monoxide (CO) displays a weak negative association; by contrast, $PM_{2.5}$ shows no statistically significant relationship with violent crime. Although province-level descriptive patterns appear heterogeneous, the overall correlation between $PM_{2.5}$ and crime is trivially small (0.068), and the panel regression coefficient is statistically insignificant (0.792), indicating that $PM_{2.5}$ is not a meaningful correlational predictor in this context. The study identifies pollutant–crime co-movements rather than causal effects, with only O_3 and NO_2 exhibiting consistent statistical associations with violent crime, and highlights the importance of considering environmental, economic, and social conditions when examining pollution–crime relationships, contributing to a more nuanced understanding of environmental correlates relevant to urban planning, environmental management, and public security in Asian metropolitan regions.

Keywords: Air Pollution; Violent Crimes; Atmospheric Pollutants; Urban Security; Green Criminology.

Introduction

In the 1970s, a global trend emerged for the expansion of environmental ideas within the social sphere. Since then, the "green" worldview and new behavioral standards have been formed. This trend has affected all areas of law and social sciences, including criminological research. The logical outcome of this was the emergence of green criminology as an independent scientific direction, which broadened the boundaries of understanding criminal behavior (34). From the

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perspective of traditional approaches, pollution of nature could be seen as legally permissible, and harmful emissions, including in the atmosphere, could be considered acceptable. This approach has been thoroughly reconsidered within the framework of green criminology. The negative impact of transportation on the environment can be examined by green criminology from various viewpoints: 1- direct pollution of nature as a form of criminal behavior (environmental crimes) and 2- the consequences of pollution for human health and the environment, which are associated with changes in the occurrence of other crimes, primarily violent crimes. The current study focuses on this second aspect.

The detrimental associations of environmental air pollution have been well documented in epidemiological and economic literature. Early epidemiological studies reported a strong relationship between severe pollution events, such as the Great London Smog, and mortality (6). Later studies, which evaluate the relationship between pollution and health at lower, more common levels of air pollution, demonstrate that environmental pollution affects life expectancy and hospitalization rates (26, 42). Economic literature, which better explains potential confounding factors, has recorded a strong relationship between air pollution and various health outcomes, such as infant mortality (47). Recently, a new wave of studies has examined the associations between pollution and other aspects of human life. For instance, Graff Zivin and Neidell (19) provided evidence for a positive association between ozone and reduced agricultural worker productivity in California. Ebenstein et al. (16) found that high levels of $PM_{2.5}$ are associated with lower test scores among Israeli students. Sager (44) documented a strong association between pollution and road safety in the United Kingdom, and Lichter et al. (32) demonstrated that variability in pollution is associated with changes in the performance of professional football players in Germany.

Recent studies have established a strong link between air pollution and various health outcomes, including cardiovascular diseases, anxiety, mental disorders, suicide, cognitive abilities, work productivity, academic performance, school attendance, and financial investments (2, 8, 18, 27, 31, 41, 49, 50). Further research suggests that air pollution can exacerbate violent behavior by stimulating brain inflammation (4), causing psychological distress (46), reducing serotonin levels (37), and depriving the brain of oxygen (25). Lu et al. (35) investigated the association between air pollution, mental health, and increases in crime rates. They found that severe air pollution raises the anxiety levels of respondents and may lead individuals to engage in unethical behavior. The rationale behind this is that anxiety may arise in threatening situations, prompting the brain to develop protective responses, which in turn leads individuals to focus more on personal needs and interests, thereby reducing their adherence to ethical principles. Therefore, since air pollution is associated with both the physical and mental well-being of individuals, it may be indirectly linked to changes in human behavior and higher crime rates.

Building on the idea that air pollution may encourage criminal behavior, particularly violent behavior, recent researchers have sought to uncover empirical evidence of a causal relationship between air pollution and overall crime rates. The observed associations between air pollution and crime raise the question of how air pollution, especially at high and abnormal levels, is related to human behavior in urban areas. In this context, the use of green criminology theoretical frameworks, particularly in the context of Asian countries, becomes even more significant.

In Iran, given the rapid growth of urbanization, high population density, and the increase in industrial pollutant emissions, studying the associations between air pollution and violent crimes becomes even more critical. Unlike previous studies that have primarily focused on developed countries, this research explores this relationship within the context of an Asian country with unique economic and social characteristics. This approach, utilizing international experiences and contemporary criminological frameworks, can deepen our understanding of crime dynamics in developing countries. Thus, in this study, using data from the Statistics and Information Technology Center of the Judiciary regarding violent crimes against individuals (such as homicide, rape, assault and battery, threats, armed robbery, and robbery with assault), the relationship between the rate of violent crimes in Tehran and several air pollution indicators (sulfur dioxide (SO_2), nitrogen oxides (NO_2) carbon monoxide (CO), ozone (O_3), and particulate matter (PM) is first examined. Then, in selected provinces of Iran (Mashhad, Isfahan, Fars, Alborz and Rasht), the associations between particulate matter (PM) and the rate of violent crimes are analyzed. Finally, these relationships are interpreted in light of criminological theoretical models to inform the development of more precise preventive measures for these and similar crimes in Iran and other Asian countries. This research can serve as a reference for future studies examining the relationship between the environment and crime in the Asian context.

Materials and Methods

This section examines the proposed mechanisms in the biological, economic, psychological, and sociological literature to explain the relationship between air pollution and criminal activities.

Biological Mechanism

Biological factors are associated with the effects of airborne particles on the body. For example, air pollutants affect the brain by triggering inflammatory responses in neural tissue (4) or by using blood circulation to reach the central nervous system, directly influencing its chemical composition (6). Changes in the chemical structure of the brain can lead to behavioral changes.

Air pollution affects brain structure at cellular and molecular levels. This, in turn, may be associated with changes in an individual's overall emotional state and brain function (12). For example, exposure to $PM_{2.5}$ can lead to increased levels of cortisol, cortisone, adrenaline (epinephrine), and noradrenaline (norepinephrine), all of which are stress-related hormones (33). Certain air pollutants are associated with changes in human behavior by correlating with alterations in serotonin levels or other neurotransmitter concentrations in the brain and bloodstream (37). According to the American Psychological Association, serotonin is a neurotransmitter involved in emotional processing, mood regulation, appetite, sexual desire and function, sleep, pain processing, hallucinations, and reflex regulation. Serotonin has a negative correlation with aggression; in other words, it is the "happiness hormone," and its reduction leads to increased aggression (42).

Several studies have shown that serotonin is associated with impulsive and aggressive behaviors (15, 17). Empirical evidence suggests that short-term exposure to pollution (particularly ozone) is linked to reduced serotonin levels in animals (37). Low serotonin levels, which act as an inhibitory factor with a key role in controlling impulsive and aggressive behaviors, reduce an animal’s ability to regulate such behaviors (17). Additionally, other studies indicate that decreased serotonin levels are associated with an increased tendency to engage in fights among monkeys (13) and heightened impulsive aggression in children (17), as well as in both women and men (17). Moreover, Crockett et al. (13) found that low serotonin levels can lead to a greater desire for punishment and a reduced willingness to accept fair deals.

Exposure to atmospheric pollutants, including ozone, is also associated with oxidative stress (36). This condition is defined as an imbalance between free radicals and antioxidants in an individual's system (26). Due to the imbalance it creates, oxidative stress has been linked to an increased risk of anxiety and depression (1). It can also lead to the degradation of the myelin sheath, the protective layer of the nervous system that facilitates signal transmission (26). Similarly, damage to the myelin sheath can result in impaired brain function and neurological damage (25). Brain damage caused by oxidative stress can also significantly disrupt cytokine signaling. Cytokines are proteins that help regulate brain function and mood. Dysregulation of this process can contribute to depression, anxiety, and other cognitive disorders (36, 46). In this regard, experimental evidence suggests that oxidative stress and similar neuroinflammation increase aggression in mice, particularly in the frequency of their attacks on unfamiliar mice introduced into their space. Ultimately, pollution may lead to other physiological changes that manifest as heightened aggression (36).

Additional experimental evidence indicates a link between exposure to air pollution and increased testosterone levels. Testosterone, in particular, has been associated with violent crimes in humans (33).

Therefore, from a biological perspective, environmental pollution directly affects neuroticism or the anxious temperament in the human brain, which is responsible for the flow of information within the brain and nervous system (10, 26). When the human body is exposed to environmental pollution for an extended period, neuroticism becomes impaired, affecting judgment, emotional processing, and awareness, ultimately leading to violent reactions and an increase in crime rates.

Psychological Mechanism

Based on laboratory experiments, researchers have identified several negative psychological symptoms associated with air pollution, such as anxiety, tension, anger, and depression (46). These symptoms may directly affect human judgment and explicitly provoke aggressive behavior. In one laboratory study, individuals exposed to unpleasant odors, compared to their counterparts in odor-free conditions, administered stronger electric shocks to their peers as a punishment for mistakes made during a learning task (36).

Under environmental pollution, individuals' cognitive abilities, tolerance for frustration, and their assessment of others and the physical environment generally deteriorate, which may exacerbate their aggressive traits (36). A large number of studies have shown that individuals exposed to environmental pollution exhibit more aggressive behavior compared to those in a clean environment (7, 14).

Many psychological studies report that air pollution impairs cognitive performance. It is also associated with negative effects on language learning abilities, memory, and self-regulation (12). It leads to a loss of self-regulation and a reduction in individual working capacity (32) and productivity (19). Furthermore, the negative associations between air pollution and mental health are linked to increases in suicide rates and crimes, especially violent crimes.

Economic Mechanism

The economic mechanism is rooted in the *rational choice theory* of crime. From the perspective of the economic mechanism, it is expected that changes leading to greater risk-taking will result in higher crime rates. Increased risk-taking, and consequently higher crime rates, may stem from changes in risk preferences or risk perception. Evidence shows that risk-taking in financial markets is lower on days when air pollution levels are high (23). The negative relationship between air pollution and risk-taking also aligns with medical literature. Empirical evidence suggests that when stress hormone cortisol levels increase, or when individuals are exposed to physical stress, they become more risk-averse (29). As mentioned in the biological mechanism, acute exposure to air pollution is linked with elevated cortisol levels (33). Therefore, individuals exposed to higher levels of pollution are expected to become more risk-averse. Overall, both the available empirical evidence and preliminary analysis indicate that air pollution may reduce risk-taking behavior, and thus, as air pollution increases, criminal activities are expected to decline.

Despite the above points, according to rational choice theory, there is also the possibility of an increase in crime rates with higher levels of pollution. The rise in criminal activity during periods of pollution may stem from changes in the perceived benefits relative to the perceived punishment. Increased crime in high air pollution levels is linked to an optimistic assessment of the likelihood of escaping crime without punishment. In fact, based on rational choice theory, the decision to engage in criminal activity is based on a cost-benefit analysis. Air quality conditions may alter these costs and benefits. For example, when air pollution levels are high, police officers, by spending more time indoors or in their offices instead of patrolling, may exhibit lower levels of "productivity"; as a result, the likelihood of successfully committing a crime without being apprehended increases (19).

Therefore, from the perspective of the economic mechanism, air pollution is associated with potential changes in criminal activity, which may be either increases or decreases. For instance, if high levels of air pollution led to an increase in risk aversion, a decrease in criminal activity is expected on polluted days. On the other hand, if air pollution reduces the expected costs, including the likelihood of arrest and punishment, an increase in crime is anticipated on polluted days.

Another theory that can be examined within the economic mechanism is the theory of inequality and the socio-economic divide. Environmental pollution affects the health costs of residents. The association between environmental pollution and health largely depends on the likelihood of exposure to pollution risks. Given other conditions, the higher the level of exposure to environmental pollution, the greater the health risks and the higher the healthcare costs. High-income individuals, when experiencing health issues associated with environmental pollution, are able to pay higher costs for swift and effective recovery (3). In contrast, low-income individuals, due to their participation in productive activities (such as construction workers, healthcare workers, etc.), are more exposed to polluted environments, and their health is more strongly associated with environmental pollution. Consequently, the potential healthcare costs for residents increase for both high-income groups and especially low-income groups (31).

In the face of high healthcare costs resulting from environmental pollution, lower-income groups often lack the additional budget to pay for hospital medical services. To secure additional funds to cover healthcare expenses, they take on risks and are more likely to resort to criminal behavior (10). Furthermore, when residents face high healthcare costs, they often experience negative emotions such as hopelessness, anxiety, depression, societal resentment, and others, which can potentially lead to violence and an increase in criminal motivations (22).

Environmental pollution and deteriorating environmental quality increase health inequalities, and inequality is one of the key factors driving high crime rates. On the one hand, higher socio-economic groups benefit from better public investments in human capital (including education, healthcare, social security, etc.), which compensates for the human capital loss caused by environmental degradation (20). In contrast, lower socio-economic groups, due to the nature of their production activities being more exposed to the environment, depend on environmental quality to perform effectively, and declines in environmental quality are associated with lower income levels (28). Thus, groups with lower socio-economic status are more strongly associated with health risks due to greater exposure to environmental pollution, whereas residents of middle and high socio-economic status are less affected, as they can take more measures to prevent exposure and their health is less influenced by external factors such as environmental pollution (22). It is not difficult to understand that individuals from different socio-economic positions have varying abilities to avoid environmental risks, and thus the differential exposure to environmental pollution becomes a new source of social injustice in health. Consequently, inequality arising from the division of labor and environmental decay will exacerbate the gap between the rich and the poor in society, and this gap, in turn, will contribute to an increase in crime rates.

Additionally, when environmental pollution intensifies, the work incentives for groups with lower socio-economic status are suppressed, and their income levels decrease further. The income gap between high and low socio-economic groups also increases, which can easily lead to class conflicts and violent confrontations (14). This outcome is supported by empirical evidence from both developed countries, such as the United States, and developing nations (7).

Another potential mechanism through which environmental pollution is associated with crime rates is its correlation with lower educational attainment, which may be linked to higher crime levels (16). On one hand, when the level of environmental pollution in a specific area increases, prominent teachers often decide to relocate to areas with better environmental quality, as they cannot tolerate severe environmental pollution. As a result, academic talent is lost, leading to a decrease in educational levels (39). On the other hand, areas with high environmental pollution are often resource-based regions with relatively underdeveloped economies, and local financial resources are often structurally simple, mainly reliant on resource-based industries. Their investment in education is lower than that of economically developed areas, leading to lower education levels. Furthermore, from the perspective of public financial costs, when investments in environmental governance increase, it may reduce educational budgets, and thus limited financial resources may curb the level of education. Ultimately, with increasing environmental pollution, some low-income families may be unable to increase their health expenditures to address issues associated with environmental pollution and may face difficulties in sending their children to school or increasing related investments. Numerous studies have shown that crime rates are closely related to education levels, and relevant studies indicate that a decrease in education levels directly leads to an increase in crime rates (5).

Therefore, based on the theory of economic-social inequality, environmental pollution is associated with limitations in the economic development of a region and is linked to higher levels of poverty and income inequality among its residents. Additionally, various physical or mental illnesses resulting from environmental pollution not only jeopardize public health but also increase public medical and healthcare costs, leading to further expansion of income gaps and regional inequality. These economic and social issues caused by environmental pollution reduce the residents' well-being and increase the risk of social instability and the likelihood of criminal activities. Furthermore, the poverty induced by environmental pollution lowers the educational levels of the residents, which in turn leads to an increase in crime rates in the area.

Sociological Mechanism

The relationship between pollution and crime can also be considered in light of existing social theories in criminology. The first of these is the Routine Activity Theory, which emphasizes that for a crime to occur, three elements are necessary: a suitable target, a motivated offender, and the absence of a capable guardian to prevent the crime (21). As suggested by psychological and biological mechanisms, air pollutants are associated with changes in emotions and neurological functioning, which may be linked to a greater tendency to engage in unethical behaviors. This, in turn, is associated with higher motivation to commit a crime. Furthermore, environmental pollution may also be related to the effectiveness of capable guardians. In situations where environmental quality is low and air pollution is high, particularly in urban areas, the presence or effectiveness of law enforcement and security personnel may be reduced, as environmental health conditions can be associated with lower physical and mental capacity (19). Therefore, the combination of increased motivation and reduced guardian capacity is associated with higher crime rates in these areas, potentially creating a reinforcing cycle that contributes to the observed escalation of crime in polluted regions.

On the contrary, according to the *Social Escape/Avoidance Theory*, increased pollution may lead to a reduction in crimes. This model asserts that individuals avoid situations that result in negative experiences. The rise in air pollution may cause people to stay indoors more frequently, reduce social interactions, and consequently decrease the likelihood of encountering suitable targets for committing crimes, leading to a reduction in crime rates (11).

Another sociological theory used to examine and explain the relationship between crime rates and pollution levels is the *Broken Windows Theory*. The Broken Windows Theory suggests that environmental disorder (such as broken windows) can lead to social and moral disruption (35). In fact, individuals are more likely to litter and commit theft in dirtier environments. This is partly because environmental disorder implies both a descriptive social norm, where violation of it is common, and a prescriptive social norm, where violation may be deemed acceptable (30). Therefore, when individuals experience a polluted environment, their general concern for the moral appropriateness of their behavior may decrease, making them more prone to engage in other immoral and illegal acts. As another mechanism, the smog created by pollutants (e.g., NO_2) reduces visibility (27). Just as criminal activities are more common at night, smog may create a sense of anonymity, encouraging potential offenders to commit self-interested and unethical actions (35).

Therefore, based on the broken windows theory, it can be concluded that environmental pollution and the disruptions it causes may reduce individuals' sense of social responsibility and encourage them to engage in unethical and criminal behaviors.

Background

Numerous studies have examined the associations between pollution and crime in the United Kingdom. For instance, based on data from 2004 to 2005, higher air pollution levels were associated with an increase in the number of reported crimes in London (7). On the other hand, evidence from India (48) and South Africa (50) indicates that avoidance behavior at high levels of air pollution is associated with negative marginal relationships between air pollution and crime and delinquency rates.

Lu et al. (35) assessed the relationship between air pollution and several types of crime to gain a more accurate understanding of the connection between air pollution and criminal activity. Since elevated levels of anxiety facilitate aggressive behavior, they found that air pollution, due to its documented causal link with high anxiety levels, leads to an increase in criminal violence.

The analysis by Heyes and Saberian (24) aimed to provide support for a causal connection between short-term exposure to air pollution and the occurrence of assault and theft in Los Angeles County. Their analysis revealed that while assaults were associated with a 17% increase in relation to air pollution, no detectable relationship was observed for theft.

Another study indicates that in cities where CO_2 levels have increased, male offenders are more likely to harm their victims. A one-unit increase in the concentration of carbon dioxide in a city raises the likelihood of a male offender causing harm to their victim by up to 21% (14). Further research in London shows a consistent positive relationship between pollution and crime rates (44).

Herrnstadt et al. (21) used geocoded crime data and wind direction to explain pollution variation in Chicago and Los Angeles to establish a relationship between crime and air pollution ($PM_{2.5}$). In both cities, it was found that air pollution increases violent crimes but does not affect property crimes.

In a study, the data indicated that crime is significantly affected by ozone changes. The authors of the study found that higher ozone levels reduce the total number of crimes. A 10% increase in ozone (on average 0.003 ppm) is associated with a 0.52% decrease in overall crime, or approximately 0.5 crimes per hour (on average). Other pollutants, such as carbon monoxide and sulfur dioxide, do not show statistically significant associations with crime (3).

Sarmiento (45) in his study shows that for all pollutants except SO_2, theft has a significant negative correlation with air pollution. This may be because pollution affects the criminal activity market by changing the number of active offenders and the opportunities for committing crimes. Furthermore, the study demonstrates that pollutants such as CO, O_3, and $PM_{2.5}$ can lead to a reduction in sexual crimes.

Another study shows that an increase of 1 gram per cubic meter in the monthly average of $PM_{2.5}$ raises the violent crime rate by 0.53% in each U.S. state, which on average leads to an additional 327 violent crimes per month across the United States. However, this study found no significant association between $PM_{2.5}$ and homicide or theft crimes (9).

Sadana (43) in a study conducted in India showed that a 1% reduction in pollution leads to a 0.3% decrease in property crimes. The study by Kuo and Putra (31) indicates that air pollution has a significant positive correlation with domestic violence, meaning that areas with higher levels of air pollution tend to have a greater incidence of domestic violence.

Recent research from 2024 and 2025 has further solidified and nuanced these findings, exploring specific contexts, mechanisms, and demographic factors. Expanding on the psychological mechanisms, Meidenbauer et al. (36) argued that environmental factors like air pollution directly impact cognitive processes such as impulsivity and emotion regulation. They proposed that exposure to pollutants weakens impulse control, thereby lowering the threshold for aggressive behaviors and establishing the physical environment as a key intervention point.

Multiple studies have reinforced the link between $PM_{2.5}$ and violence in diverse international settings. In South Korea, a robust nationwide case-crossover study by Park et al. (38) demonstrated that short-term exposure to $PM_{2.5}$ was significantly associated with an increased risk of violence. Specifically, a10 $\mu g/m^3$ increase in $PM_{2.5}$ concentration corresponded to an odds ratio of approximately 1.07 for violence, with the effect being more pronounced in males and individuals under 65. Similarly, analyzing national data in South Africa, Yao et al. (49) found that an increase in $PM_{2.5}$ was linked to a significant rise in violence, estimating that each unit increase was associated with a 2.1% increase in violent crime, which carries substantial social costs. A novel study in India by Amale and Negi (2) linked specific pollution events—namely, agricultural stubble burning—to short-term increases in violent crimes, particularly violence against women.

Focusing on a distinct environment, Rau et al. (40) investigated schools in Minnesota, USA, and found that increased concentrations of ozone (O_3) were correlated with a significant rise in violent incidents. This association was stronger in urban schools compared to rural ones. Interestingly, their study also revealed an inverse relationship between nitrogen dioxide (NO_2) and violence, highlighting that different pollutants can have varying effects on aggressive behavior.

Results

This research is categorized as an applied study in terms of its nature and objective, designed to provide a comprehensive insight into the relationship between air pollution and violent crime rates across various regions of Iran. Initially, to examine the associations between atmospheric pollutants, including particulate matter (PM_{10} and $PM_{2.5}$), carbon monoxide (CO), nitrogen dioxide (NO_2), sulfur dioxide (SO_2), and ozone (O_3), and crime rates such as murder, rape, assault, threats, armed robbery, and aggravated theft in the metropolitan area of Tehran, a monthly dataset spanning from 2016 to 2021 was utilized. The data used in this section were collected from the Environmental Protection Organization and the Judiciary's Center for Statistics and Information Technology. Due to institutional recording protocols and administrative confidentiality constraints within the national judicial databases, the 'crime rate' utilized in this study operates as an aggregated index representing violent offenses. Although disaggregating this baseline into distinct sub-categories (such as homicide, assault, and domestic violence) would provide a more nuanced criminological profile, the current data structure lacks the required granular taxonomy for independent statistical tracking across all selected provinces. This limitation necessitates evaluating the general atmosphere of urban friction and public aggression as a collective response to environmental stressors.

In the first phase, descriptive statistical analyses were conducted to identify temporal and spatial trends and patterns in pollutant levels and crime rates. Tools such as Pearson correlation matrices and scatter plots were employed to detect associations between variables. Additionally, multiple linear regression modeling was performed to examine the simultaneous relationships of various pollution indicators with crime rates. Classical diagnostic indicators, including Variance Inflation Factors (VIF) and residual inspections, were examined during the internal modeling phase; they indicated moderate collinearity among specific gaseous pollutants (such as NO_2 and O_3), which further justifies our analytical focus on overall correlational trends rather than isolated regression parameters. To address multicollinearity challenges and capture potential nonlinear interactions among variables, advanced models such as Ridge Regression, Lasso Regression, Random Forest, Gradient Boosting Machine (GBM), and Generalized Additive Models (GAM) were also applied. All statistical analyses in this study were conducted using R software, and multivariate hypothesis testing was performed to evaluate the significance of relationships between variables.

For the machine learning architectures (Random Forest, Gradient Boosting Machine, and Generalized Additive Models) presented in Table 4, our primary analytical goal was to extract feature importance profiles and cross-examine potential multi-variable non-linearities, rather than to optimize high-stakes predictive forecasting deployments. To maximize the statistical footprint of our monthly aggregated dataset, the models were evaluated using a 5-fold cross-validation architecture to stabilize out-of-bag error bounds and isolate structural over-fitting. Hyperparameter settings were maintained at standard regularized baselines: the Random Forest model was generated using 500 decision trees (mtry = 2), the GBM algorithm utilized a learning rate (shrinkage) of 0.01 combined with an interaction depth of 3, and the GAM was set up with thin-plate regression splines, providing that the feature importance coefficients represent stable, structural correlational trends within the environment data.

To further explore temporal dynamics and identify periodic and seasonal patterns in crime rates, time series analyses were conducted using ARIMA models. These models incorporated seasonal effects and autocorrelation assessments, enabling a deeper examination of time-based associations. Following the analyses conducted for the metropolitan area of Tehran, the study shifts its focus to examining the associations between particulate matter ($PM_{2.5}$), as a key pollutant, and crime rates at the national level. In this regard, panel data from the provinces of Tehran, Mashhad, Isfahan, Fars, and Rasht over the same period were analyzed. Initially, descriptive statistics were calculated to identify the primary characteristics of the variables. Subsequently, mixed-effects modeling was employed to explore variations in $PM_{2.5}$ levels and crime rates across provinces. Additionally, time series analyses were used to detect seasonal trends and fluctuations.

This multifaceted approach provides a structured framework for investigating the causal relationship between air pollution and violent crimes. To prevent over-fitting and to preserve the statistical power of the available sample size, a parsimonious modeling strategy was adopted. Testing extended lag structures beyond the initial temporal phase was mathematically restricted by the monthly aggregation of the judiciary data, where longer lags introduced severe autocorrelation and substantially diminished the model's degrees of freedom. Furthermore, while conducting multiple simultaneous pollutant cross-examinations increases the theoretical risk of Type I errors, standard post-hoc adjustments (e.g., Bonferroni corrections) were deliberately omitted to avoid inflating Type II errors. This choice ensures that subtle environmental-behavioral signals within this exploratory baseline are not prematurely suppressed.

Initially, to analyze the associations between air pollution and crime in the metropolitan area of Tehran, a dataset comprising 48 monthly observations from 2016 to 2021 was utilized. This dataset includes the levels of major air pollutants and recorded crime rates during this period.

In the first stage, key variables were examined using correlation analysis, regression models, and seasonal trend analysis to identify meaningful relationships and patterns between pollutant levels and crime rates. To gain a better understanding of these connections, the Pearson correlation matrix and correlation analysis between pollutants and crime rates were calculated, with the results presented in the tables.

According to Table 1, the strongest correlation is observed between CO and NO_2 ($r = 0.80$), which may indicate a common source for these two pollutants. Ozone (O_3) exhibits the highest positive correlation with crime rates ($r = 0.31$, $p < 0.05$). The other correlations between pollutant variables and crime rates are relatively weak, suggesting a limited direct relationship between them.

Correlation tests were conducted for each pollutant. According to Table 2, among the examined variables, only O_3 showed a statistically significant relationship with crime rates ($r = 0.312$, $p = 0.031$), indicating a weak positive correlation. While CO exhibited a weak negative correlation ($r = -0.259$), it was not statistically significant ($p = 0.075$). Other pollutants, such as NO_2, SO_2, PM_{10}, and $PM_{2.5}$, displayed negligible and non-significant correlations with crime rates.

To complement the correlation findings and gain a better understanding of the relational patterns between pollutants and crime rates, scatter plots were utilized. These plots, presented in Figure 1, visually depict the relationships among the variables, allowing for an examination of data distribution and the strength of associations between different pollutants and crime rates.

The scatter plots presented in Figure 1 reveal distinct relationships between pollutants and crime rates. Carbon monoxide (CO) exhibits a negative correlation with crime rates, as indicated by the dispersion of high CO values. In contrast, ozone (O_3) shows a positive linear trend with crime rates, which aligns with the correlation analysis findings. Particulate matter, including PM_{10} and $PM_{2.5}$, demonstrates weak positive associations with crime rates, displaying limited clustering and less pronounced trends. These visual insights further reinforce the general patterns identified in the statistical analyses.

Descriptive analyses indicate that pollution levels exhibit moderate variability, whereas crime rates have remained relatively stable over time. Correlation analyses reveal weak to moderate relationships between pollutants and crime rates, with ozone (O_3) emerging as

Table 1. Pearson Correlation Matrix Between Pollutants and Crime Rate

Variable	**CO**	**O_3**	**NO_2**	**SO_2**	**PM_{10}**	**$PM_{2.5}$**	**Crime Rate**
CO	1.00	-0.26	0.80	-0.18	0.16	-0.06	-0.26
O_3	-0.26	1.00	-0.25	-0.63	-0.18	-0.40	0.31

Table 3. Regression Coefficients for Multiple Linear Regression Model

Variable	**Estimate (β)**	**Std. Error**	**t-value**	**p-value**	**Significance**
Intercept	2.37	2.44	0.97	0.338	Not Significant
CO	-0.75	0.30	-2.51	0.016	*
O_3	0.06	0.03	2.27	0.028	*
NO_2	0.06	0.02	2.85	0.007	**

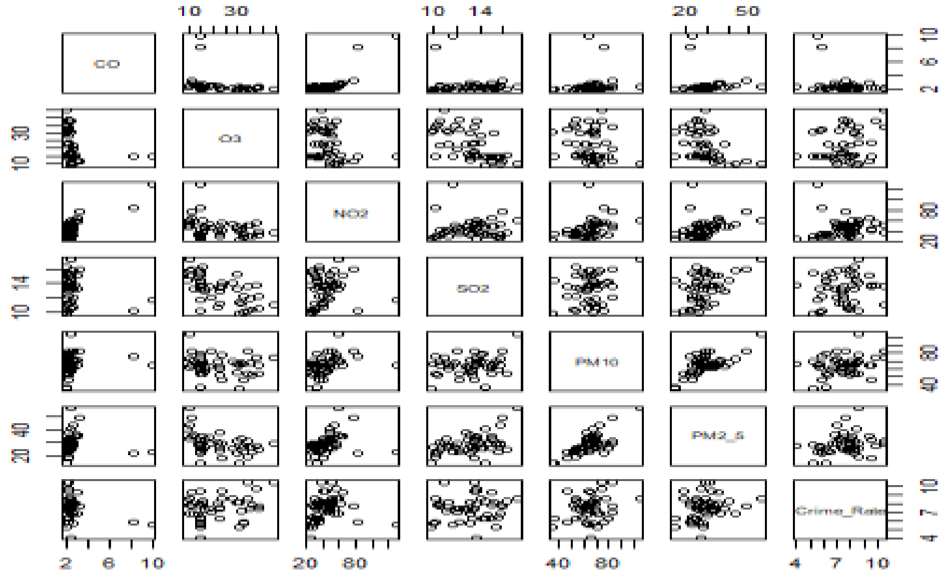

Figure 1. Map of the selected Iranian metropolitan provinces and their baseline pollutant distribution trends (2016–2021)

the most significant influencing factor in these associations. The data preprocessing phase has successfully prepared the dataset for advanced analyses, such as regression modeling and seasonal trend evaluations, establishing a solid foundation for further exploration of the relationship between pollution and crime.

Table 3 summarizes the results of the multiple linear regression model, in which crime rates are considered the dependent variable, while pollutants (CO, O_3, NO_2, SO_2, PM_{10}, $PM_{2.5}$) serve as independent variables.

The multiple linear regression model indicates that approximately 46.9% of the variations in crime rates are explained by the examined pollutants, as reflected in the coefficient of determination ($R^2 = 0.469$). After adjusting for the number of predictor variables, the adjusted R^2 decreases to 0.391, indicating a moderate explanatory power of the model. The F-statistic value of 6.038 and a p-value of less than 0.001 confirm that the model is statistically significant overall and that the predictor variables collectively contribute to explaining changes in crime rates.

Regression analysis reveals that, in the multiple linear regression model, three pollutants, CO, O_3, and NO_2, are significantly associated with crime rates, as their p-values are below 0.05. CO has a negative relationship with crime rates ($\beta = -0.75$), indicating that higher CO levels are associated with lower crime rates. In contrast, O_3 and NO_2 exhibit positive effects ($\beta = 0.06$), suggesting that an increase in their levels corresponds with an increase in crime rates. Other pollutants, including SO_2, PM_{10}, and $PM_{2.5}$, do not show statistically significant effects.

Rather than presenting competing causal frameworks, the advanced non-linear models (Random Forest and GBM) are integrated here as complementary exploratory tools. They serve to validate the complex architecture of the observational data and support the baseline correlational trends identified in the primary panel regression.

To analyze the complex relationship between pollutants and crime rates, a series of advanced regression models were employed, including Ridge Regression, Lasso Regression, Random Forest, Gradient Boosting Machine (GBM), and Generalized Additive Models (GAM). These methods were specifically chosen to address challenges such as multicollinearity, variable selection, and nonlinear interactions, providing a more comprehensive understanding of the data.

Ridge Regression and Lasso Regression addressed multicollinearity by regularizing the coefficients. Ridge Regression explained approximately 50% of the variance in crime rates, and its shrinkage of coefficients indicated weaker predictors. In comparison, Lasso Regression achieved a slightly higher explanatory power (R^2 ~0.52) and refined variable importance by reducing some coefficients to zero. Both models consistently identified O_3 and NO_2 as key predictors, whereas other pollutants showed limited significance (Table 4).

The Random Forest model successfully captured nonlinear and interactive relationships between predictors and crime rates, providing a substantial improvement in predictive accuracy (R^2 ~0.65). The variable importance analysis identified O_3 and NO_2 as dominant factors, reinforcing their strong correlation with crime rates. The Random Forest approach effectively modeled complex dynamics and provided valuable insights into the internal dependencies among predictors (Table 4).

Gradient Boosting Machine (GBM) further enhanced predictive accuracy, achieving the highest R^2 (~0.67). By incrementally minimizing residuals, GBM highlighted the strong associations of O_3 and NO_2 with crime rates, while CO and particulate matter (PM_{10}, $PM_{2.5}$) showed relatively weaker associations. This model demonstrated excellent performance in capturing nonlinear and interactive patterns, underscoring its effectiveness in studying complex relationships (Table 4).

Generalized Additive Models (GAM) provided a unique perspective by modeling the smooth and nonlinear associations of pollutants with crime rates. GAM identified significant nonlinear trends for key predictors such as O_3 and NO_2, while weaker associations were observed for other pollutants. The model's ability to visualize smooth effects offered a clearer interpretation of how changes in pollutant levels are associated with crime rates at different thresholds (Table 4).

The analysis revealed key insights into the associations between pollutants and crime rates, emphasizing the importance of advanced modeling techniques:

1. O_3 and NO_2 consistently emerged as the primary variables associated with crime rates across all models, with nonlinear and interactive patterns contributing to these relationships.
2. Ensemble methods, such as Random Forest and Gradient Boosting Machine (GBM), demonstrated higher predictive accuracy compared to linear models and effectively captured the complex associations between pollutants and crime rates.
3. Generalized Additive Models (GAM) provided valuable insights into nonlinear trends, highlighting the necessity of employing sophisticated approaches to understand the intricate associations between environmental factors and social phenomena.

These results demonstrate that advanced models can effectively simulate the complexities of the relationships between pollutants and crime, highlighting the value of integrating various analytical approaches to uncover meaningful insights.

To gain a better understanding of the temporal dynamics between air pollution and crime rates, seasonal analyses were also conducted. These analyses allow for the identification of periodic patterns, overall trends, and short-term fluctuations, providing deeper insights into how crime rates change in response to variations in

Table 4. Comparison of Model Performance

Model	R^2	Key Insights
Ridge Regression	~0.50	Mitigates multicollinearity, identifies key predictors with proportional shrinkage.
Lasso Regression	~0.52	Enhances variable selection by shrinking some coefficients to zero.
Random Forest	~0.65	Captures non-linear interactions; O_3 and NO_2 show high importance.
Gradient Boosting (GBM)	~0.67	Achieves highest accuracy; models complex relationships and interactions.
Generalized Additive Model (GAM)	~0.62	Identifies smooth, non-linear effects for key predictors.

pollutant levels.

The following section presents the results of the seasonal analysis. Table 5 summarizes seasonal variations in crime rates and pollutant levels based on mean values and standard deviations (SD).

The results indicate that crime rates follow a seasonal pattern, reaching their highest level in autumn (8.11 ± 1.17) and declining to their lowest point in winter (6.90 ± 1.15). In contrast, ozone (O_3) levels peak during spring (30.54 ± 7.02) and drop significantly in winter (14.19 ± 3.92). Additionally, nitrogen dioxide (NO_2) concentrations reach their highest levels in winter, which aligns with increased emissions from vehicles during this season.

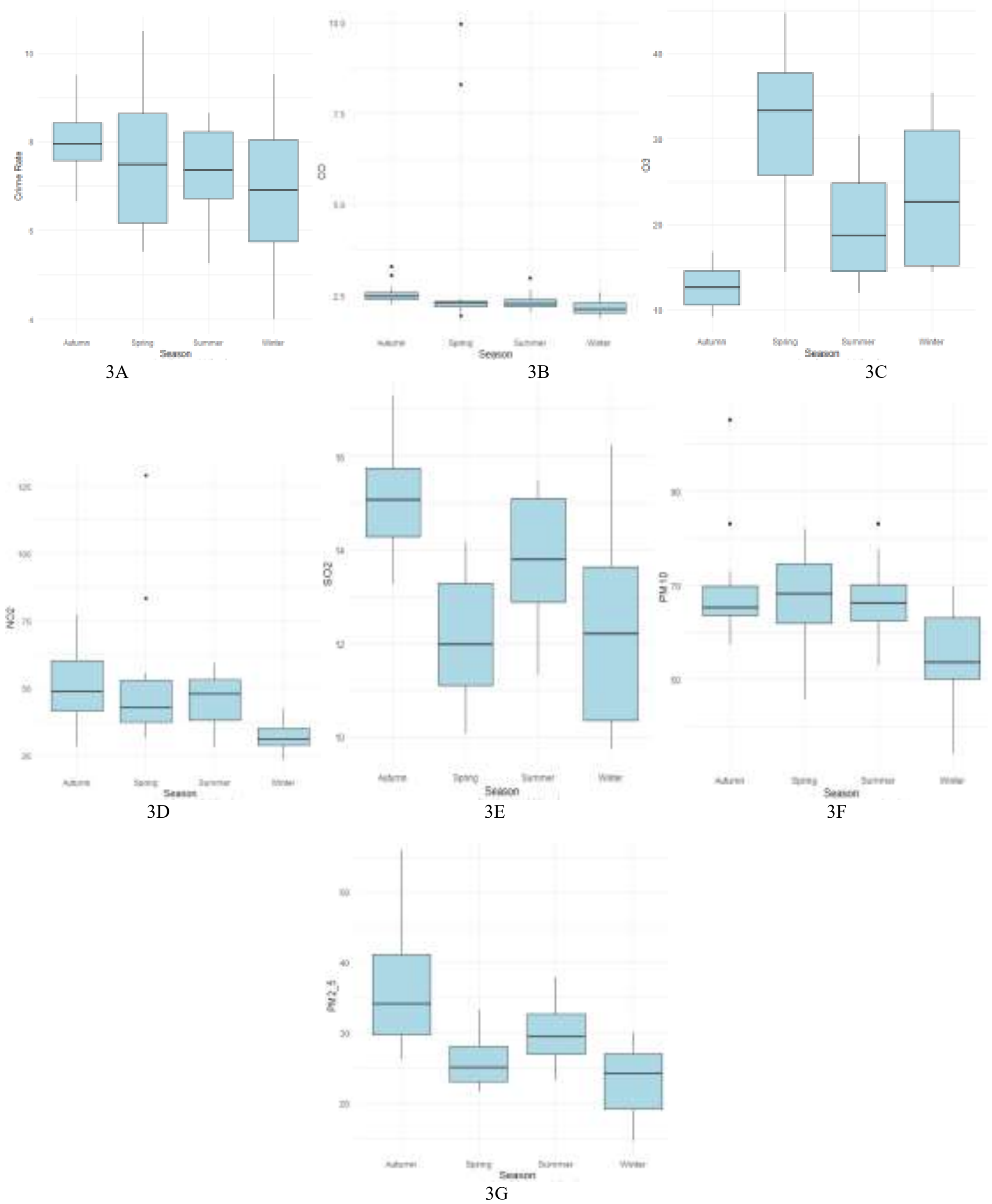

Figure 2. Seasonal Boxplots of Crime Rate and Pollutants

Moreover, the levels of particulate matter (PM_{10} and $PM_{2.5}$) remain relatively stable throughout the seasons, although a slight increase is observed in winter. A series of box plots illustrate seasonal variations in crime rates and pollutant levels (e.g., Figure 2A: Crime Rate, Figure 2B: CO, etc.).

Table 6 presents the Pearson correlation coefficients between pollutants and crime rates for each season.

The seasonal analysis results indicate that ozone (O_3) exhibits the strongest positive correlation with crime rates across all seasons, particularly in autumn ($r = 0.31$). On the other hand, carbon monoxide (CO) maintains a weak negative correlation with crime rates throughout the year. Particulate matter (PM_{10} and $PM_{2.5}$) also shows a weak to moderate positive correlation with crime rates, especially during winter and autumn, which may suggest seasonal effects influencing these relationships.

Following the examination of various air pollution indicators and their associations with crime rates in Tehran, this section focuses on analyzing the relationship between particulate matter ($PM_{2.5}$) and crime rates. Due to its high penetration capability, negative effects on mental health, and significant association with increased aggressive behavior, $PM_{2.5}$ is considered one of the most influential factors affecting criminal behavior.

Investigating this variable across multiple provinces allows for a more detailed analysis of its relationship with crime. The selected provinces—Tehran, Mashhad, Isfahan, Fars, Alborz and Rasht—represent the country's geographical and demographic diversity, covering different regions of Iran. The dataset consists of panel data from 31 provinces spanning the period from March 2018 to March 2022. Using statistical methods such as descriptive analysis, time series analysis, and mixed-effects modeling, the relationship between changes in $PM_{2.5}$ concentration and crime rates in these provinces is examined.

Descriptive statistics were calculated to summarize the key variables, including mean, median, standard deviation, and range.

Table 7 summarizes the levels of $PM_{2.5}$ and crime rates, including measures of central tendency (mean and median) and dispersion statistics (standard deviation and range). For instance, the average $PM_{2.5}$ concentration is 28.20 micrograms per cubic meter, while the mean crime rate is approximately 9.36. Each province is represented exactly 48 times in the dataset, ensuring uniform and consistent data collection across the five provinces. Additionally, the correlation between $PM_{2.5}$ levels and crime rates is 0.068, indicating a very weak positive relationship.

The scatter plot in Figure 3 illustrates the relationship between crime rates and $PM_{2.5}$ levels across six provinces: Alborz, Isfahan, Fars, Mashhad, Rasht, and Tehran.

The scatter plot examines the relationship between $PM_{2.5}$ air pollution levels and crime rates across six provinces in Iran. Each province is represented by a distinct color, and fitted trend lines illustrate the relationship in each region. The key observations are as follows:

The scatter plot illustrates visual patterns between $PM_{2.5}$ levels and crime rates across the six provinces. The fitted lines slope upward in Isfahan and Mashhad, downward in Alborz and Rasht, and remain nearly flat in Fars and Tehran. These slopes represent descriptive visual variations rather than statistically supported associations. They reflect province-specific distributions that may be shaped by local socioeconomic or demographic contexts, rather than meaningful $PM_{2.5}$–crime relationships.

Although the descriptive patterns across provinces

Table 6. Seasonal Correlations Between Pollutants and Crime Rate

Season	CO	O_3	NO_2	SO_2	PM_{10}	$PM_{2.5}$
Winter	-0.22	0.25	0.10	0.12	0.27	0.20
Spring	-0.15	0.30	0.12	0.15	0.22	0.21
Summer	-0.18	0.28	0.08	0.10	0.20	0.18
Autumn	-0.26	0.31	0.14	0.13	0.29	0.25

Table 7. Descriptive Statistics for $PM_{2,5}$ and Crime Rate

Metric	$PM_{2,5}$ ($\mu g/m3$)	Crime Rate
Count	288	288
Mean	28.20	9.36

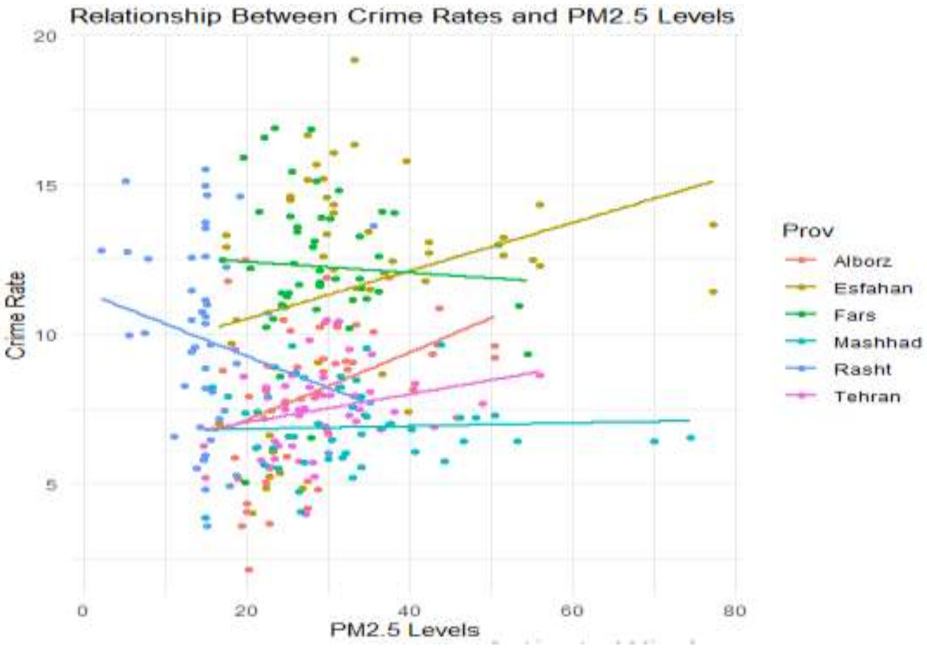

Figure 3. Province-Wise Relationship Between $PM_{2,5}$ Air Pollution Levels and Crime Rates

appear visually different, these variations should not be interpreted as meaningful statistical relationships, as the overall association between $PM_{2.5}$ and violent crime is weak and not statistically significant. The observed province-level differences likely reflect underlying economic, social, demographic, or cultural conditions rather than any direct link with $PM_{2.5}$. These contextual factors may act as confounding variables shaping crime patterns independently of air pollution levels. Understanding such regional characteristics remains important for policymakers; however, the present findings do not provide evidence of a substantive or consistent relationship between $PM_{2.5}$ and violent crime.

To gain a deeper understanding of these specific relationships, separate linear regression models were conducted for each dependent variable. Table 8 presents the results of the linear regression model, which examines the relationship between crime rates and various predictors, including year, month, and $PM_{2.5}$ levels. This model assesses how these factors contribute to changes in crime rates over time. A lagged specification (lag = 1) was included to examine the temporal ordering of the pollution–crime relationship. The results indicate no significant lagged effect, suggesting that the observed associations occur within the same day.

To complement the baseline pooled ordinary least squares (OLS) regression in Table 8 and formally account for the multi-level panel structure of our longitudinal data, a mixed-effects modeling framework was executed incorporating a random intercept for each province. This model addresses unobserved geographic heterogeneity by allowing the baseline crime intercept to vary freely across cross-sectional units, akin to a standard Random Effects model. The mixed-effects estimation yielded a $PM_{2.5}$ fixed-effect coefficient (β =0.0076, SE = 0.0211, p = 0.719), which strongly corroborates the baseline pooled OLS estimates. These results confirm that when controlling for localized provincial variations, the aggregate relationship between ambient particulate matter and violent offenses remains minor and statistically non-significant.

The results of the linear regression analysis presented in Table 8 provide a more detailed insight into the factors influencing crime rates. The intercept is estimated at -1767, representing the baseline crime rate when all predictors (year, month, and $PM_{2.5}$) are set to zero. While this value has no practical interpretation, it serves as a reference point for understanding the relationship between predictors and the outcome variable. The intercept is statistically significant, confirming that the base model is correctly specified.

The coefficient for Year is 1.269, indicating that, on average, crime rates are associated with an increase of 1.269 units per year. This association is weak yet observable statistical associations under exploratory frameworks, as the p-value is less than 0.001, suggesting that time is strongly associated with the upward trend in crime rates over the examined period. Overall, this trend reflects a steady increase in crime over time.

Table 8. Results of the Linear Regression Model for Crime Rate

Effect	Estimate	Std. Error	t-value	p-value	Interpretation
Intercept	-1,767	216.4	-8.164	1.07×10^{-14}	The baseline crime rate when all predictors are zero. Statistically significant, providing a theoretical starting point for the model.
Year	1.269	0.1548	8.203	8.21×10^{-15}	For each additional year, crime rates are associated with an increase of 1.269 units. This association is significant, suggesting a strong positive trend in crime rates over time.
Month	0.08223	0.05134	1.602	0.110	For each additional month, crime rates are associated with an increase of 0.082 units. The association is borderline significant, indicating a weak seasonal pattern in crime

The coefficient for Month is 0.08223, suggesting a slight monthly increase in crime rates. However, its p-value (0.110) indicates that this association is not statistically significant at the 0.05 level. This means that although a weak seasonal pattern may exist, it does not have a substantial relationship with fluctuations in crime rates.

The coefficient for $PM_{2.5}$ is 0.004098, indicating a very small positive association between air pollution and crime rates. However, the p-value (0.792) suggests that this association is not statistically significant, meaning that air pollution is weakly related to crime rates in this dataset.

Overall Findings

The linear regression model suggests that Year is the variable most strongly associated with crime rates, showing a clear and significant upward trend. In contrast, Month has a weaker, near-significant association, while $PM_{2.5}$ shows an almost negligible association. These results indicate that temporal factors, such as the passage of years, are primarily associated with changes in crime rates, whereas environmental factors like air pollution do not appear to have a strong relationship in this context.

Time Series Analysis

To better understand the temporal patterns of crime rates, time series analysis was conducted for each province. The goal of this analysis was to identify specific trends, seasonal fluctuations, and generate forecasts that could support evidence-based policymaking. The results for each province are presented in the following table, which includes time series regression coefficients, crime rate predictions, error measures, and relevant interpretations.

According to Table 9, the crime rate in Isfahan province exhibits significant seasonal variations. The coefficient of $PM_{2.5}$ (0.0110) suggests a small positive association between air pollution and crime rates, which is, however, statistically non-significant ($SE = 0.0134, p = 0.412$). In Tehran province, the crime rate remains relatively stable. The $PM_{2.5}$ coefficient of 0.0178 suggests a modest positive association with crime rates, which does not cross traditional significance thresholds ($SE = 0.0116, p = 0.125$). In Rasht province, the PM2.5 coefficient of -0.0077 suggests a negligible and statistically non-significant association with crime rates ($SE = 0.0093, p = 0.407$). In Fars province, the $PM_{2.5}$ coefficient of 0.0080 indicates a small, non-significant positive association ($SE = 0.0102, p = 0.433$). Conversely, Alborz province shows a negative $PM_{2.5}$ coefficient of -0.0142, which also remains statistically non-significant ($SE = 0.0125, p = 0.256$).

The crime rate in Isfahan province exhibits significant seasonal variations, reaching its highest value (15.84) in June and the lowest (12.56) in May. The ARIMA(0,1,1)(0,0,1)(12) model indicates that the moving average (ma1) is negatively associated (-0.2211), while the seasonal moving average (sma1) shows a significant positive association (0.8113). The coefficient of $PM_{2.5}$ (0.0110) suggests a small positive association between air pollution and crime rates. The RMSE value of 1.77 and MAPE of 12.79% indicate moderate prediction accuracy, and crime rates fluctuate seasonally throughout the year.

In Alborz province, the crime rate shows a slight upward trend throughout the year. The ARIMA(1,1,1)(1,0,0)(12) model reveals that the first-order autoregressive coefficient (ar1) is 0.4165, the first-order moving average coefficient (ma1) is -0.8266, and the seasonal autoregressive coefficient (sar1) is 0.4917. The $PM_{2.5}$ coefficient of -0.0358 suggests a small

Table 9. Time-Series Analysis of Crime Rates: Regression Model Coefficients, Forecasts, and Error Measures by Province

Province	Model	AR/MA/SAR Coefficients	PM2_5 Coefficient	Forecasted Crime Rates	Error Measures (RMSE, MAPE)	Interpretation
Esfahan	ARIMA(0,1,1)(0,0,1) (12)	ma1 = -0.2211, sma1 = 0.8113	0.0110	High: 15.84 (June), Low: 12.56 (May)	RMSE = 1.77, MAPE = 12.79%	Crime rates fluctuate throughout the year, with PM2_5 showing a small positive association with crime rates.
Alborz	ARIMA(1,1,1)(1,0,0) (12)	ar1 = 0.4165, ma1 = -0.8266, sar1 = 0.4917	-0.0358	High: 10.98, Low: 8.95	RMSE = 1.53, MAPE = 15.09%	Crime rates in Alborz are expected to slightly increase, with PM2_5 showing a small negative association with crime rates.
Tehran	ARIMA(2,0,0)(1,0,0) (12)	ar1 = 0.4562, ar2 = 0.2877, sar1 = 0.4360	0.0178	High: 8.05, Low: 6.73	RMSE = 1.05, MAPE = 11.30%	Crime rates are relatively stable, with PM2_5 showing a modest positive association.
Rasht	ARIMA(0,1,0)	-	-0.0077	~10.44 (Stable)	RMSE = 1.76, MAPE = 14.11%	Crime rates remain stable throughout the year, with negligible association with PM2_5.

negative association with crime rates. The maximum crime rate is 10.98, and the minimum is 8.95, while model accuracy is moderate (RMSE = 1.53, MAPE = 15.09%).

In Tehran province, the crime rate remains relatively stable. The ARIMA(2,0,0)(1,0,0)(12) model, with autoregressive coefficients ar1 = 0.4562 and ar2 = 0.2877 and seasonal autoregressive coefficient sar1 = 0.4360, indicates that past crime rates are associated with current values. The $PM_{2.5}$ coefficient of 0.0178 suggests a modest positive association with crime rates. The maximum and minimum crime rates are 8.05 and 6.73, respectively, with relatively good model accuracy (RMSE = 1.05, MAPE = 11.30%).

In Rasht province, the crime rate remains nearly constant with no significant fluctuations. The simple ARIMA(0,1,0) model indicates no clear pattern in the time-series data. The $PM_{2.5}$ coefficient of -0.0077 suggests a negligible association with crime rates. The RMSE value of 1.76 and MAPE of 14.11% indicate moderate prediction accuracy.

In Fars province, crime rates are variable, and the ARIMA(0,0,0)(0,1,1)(12) model highlights the strong influence of seasonal components on crime trends. The seasonal moving average coefficient (sma1) is -0.4137, and a slight upward trend is observed with a drift value of 0.0919. The $PM_{2.5}$ coefficient of 0.0080 indicates a small positive association with crime rates. The maximum and minimum crime rates are 17.29 and 9.48, respectively, with relatively good model accuracy (RMSE = 1.47, MAPE = 9.10%).

In Mashhad, the crime rate shows a slight upward trend. The ARIMA(1,1,1)(1,1,0)(12) model has coefficients ar1 = 0.5308, ma1 = -0.9134, and sar1 = -0.4702, reflecting associations with autoregression and seasonal fluctuations.

The $PM_{2.5}$ coefficient represents a small statistical association in this model, but it should be interpreted cautiously, as $PM_{2.5}$ does not show a consistent or meaningful relationship across regions. The maximum and minimum crime rates are 8.31 and 5.74, respectively, with adequate model accuracy (RMSE = 0.92, MAPE = 9.28%).

Overall, the time-series analysis indicates that crime rates in some provinces (such as Isfahan and Fars) follow distinct seasonal patterns, while in others (such as Rasht and Tehran), crime rates remain relatively stable. The association between $PM_{2.5}$ and crime rates varies by province—showing a small positive association in Isfahan, Tehran, and Mashhad, a small negative association in Alborz, and negligible association in Rasht. The prediction models exhibit moderate to good accuracy.

Discussion

This study examines associations rather than causal effects between air pollution and crime. Given the observational nature of our time-series and panel data, the results should be interpreted as correlations describing concurrent variations rather than causal impacts.

In this study, using 48 monthly observations from 2016 to 2021, the associations between air pollution and crime rates in the metropolitan area of Tehran were initially examined. Correlation analysis results indicate that among the pollutants under investigation, only ozone (O_3) exhibits a statistically significant positive association with crime rates ($r = 0.312$, $p < 0.05$). In other words, higher ozone levels are associated with higher crime rates. This finding aligns with Sager's (44) report, which identified a consistent positive relationship between pollution and crime in London, and is also consistent with the findings of Lu et al. (35), who reported that heightened anxiety associated with pollution correlates with increased violent crime. Similarly, studies by Bondy et al. (7) in the United Kingdom have demonstrated that increasing air pollution is associated with changes in crime rates. However, this result contrasts with the findings of Baryshnikova et al. (3), who observed that higher ozone levels were associated with a decline in crime. Meanwhile, other pollutants, such as NO_2, SO_2, PM_{10}, and $PM_{2.5}$, show weak associations with crime rates. The strong correlation between CO and NO_2 ($r = 0.80$) likely reflects a common source for these two pollutants. Scatter plots also depict a similar pattern, showing a negative trend for CO and a positive linear trend for ozone in relation to crime rates.

In the regression analyses, the multiple linear model, with a coefficient of determination (R^2) of 0.469 (adjusted $R^2 = 0.391$), indicates that approximately 46.9% of the variance in crime rates is associated with the pollutants CO, O_3, and NO_2. Specifically, the coefficient for CO (β= -0.75, p = 0.016) shows a statistically significant negative association with crime rates. The negative association between CO and crime in some regions may result from avoidance behaviors: during high-pollution days, both citizens and police officers spend less time outdoors, potentially reducing recorded criminal incidents.

This finding can be interpreted from both economic and behavioral perspectives: higher CO levels, which reflect adverse environmental conditions, are associated with heightened risk aversion, reduced outdoor activities, and diminished social interactions, thereby correlating with fewer opportunities for criminal offenses. This result aligns with studies such as Singh and Visaria (48) and Yao et al. (50), which observed avoidance behaviors and reduced crime opportunities in the presence of high pollution levels. However, it contrasts with the findings of Cruz and Stolzenberg (14) and Baryshnikova et al. (3), who associated CO levels with increased crime rates.

Conversely, O_3 (β= 0.06, p = 0.007) and NO_2 (β= 0.06, p = 0.028) exhibit statistically significant positive associations, indicating that higher levels of these pollutants are linked with higher crime rates. Regarding NO_2, this finding contradicts the results of Baryshnikova et al. (3), who found no significant association for NO_2. The application of advanced modeling techniques, including ridge regression, LASSO, random forest, gradient boosting (GBM), and generalized additive models (GAM), further demonstrated that accounting for nonlinear and interactive relationships among predictor variables enhances predictive accuracy, with R^2 values improving to a range between 0.50 and 0.67. In all these models, ozone (O_3) and NO_2 consistently emerged as key predictors. The observed sensitivity of results to model specification and regional context indicates that the findings should be interpreted with caution. Differences in provincial dynamics and data quality may contribute to the variability of estimated associations. This finding aligns with the study by Kuo and Putra (31), which reported a significant association between air pollution and domestic violence—suggesting that areas with higher air quality index (AQI) values are associated with more incidents of domestic violence. Although the present study does not differentiate domestic violence from other violent crimes, the observed positive associations of O_3 and NO2 may indicate similar pathways, wherein heightened tension and anxiety are associated with increased interpersonal violence.

Seasonal analyses also reveal significant cyclical patterns: crime rates peak in autumn (8.11 ± 1.17) and reach their lowest levels in winter (6.90 ± 1.15). Conversely, ozone (O_3) levels are highest in spring (30.54 ± 7.02) and decline sharply in winter. Additionally, NO_2 concentrations peak during winter due to increased vehicular traffic. Seasonal correlations indicate that ozone consistently exhibits the strongest positive association with crime rates across all seasons, particularly in autumn ($r = 0.31$), while CO consistently shows a weak negative association. These seasonal patterns are comparable to findings from studies such as Herrnstadt et al. (21), which examined seasonal variations in pollution and their associations with violent crime in cities like Chicago and Los Angeles.

These findings can be interpreted from various theoretical perspectives. From a biological standpoint, increased ozone (O_3) levels are associated with inflammatory responses in neural tissues and elevated oxidative stress, which may contribute to lower serotonin levels—a key neurotransmitter involved in mood regulation and aggression inhibition. Lower serotonin levels are linked to heightened tendencies toward impulsive and aggressive behaviors. This biological mechanism aligns with the findings of Lu et al. (35), who reported associations between pollution-induced anxiety and criminal violence. Furthermore, elevated NO_2 levels, often considered an indicator of traffic-related pollution, may correlate with impaired brain function through increased oxidative stress and neural strain (6). From a psychological perspective, exposure to air pollutants—particularly ozone—is associated with negative emotions, anxiety, and anger. These psychological changes are linked with conditions that may facilitate aggressive behaviors (36).

From an economic perspective and within the framework of the rational choice theory of crime, higher CO levels are associated with greater risk aversion and reduced social interactions. Consequently, on days with high CO concentrations, opportunities for committing crimes are likely reduced (23). Similarly, economic conditions and environmental stressors in densely populated urban areas (associated with higher NO_2 levels) are linked to altered risk perception and perceived costs of committing crimes (22). Therefore, from an economic-social standpoint, higher NO_2 levels are associated with conditions that may correspond to higher crime rates.

After examining the associations between various air pollution indices and crime rates in Tehran, the study proceeds to analyze the relationship between particulate matter ($PM_{2.5}$) concentrations and crime rates in selected provinces of Iran. The findings indicate that $PM_{2.5}$ shows inconsistent and weak province-level patterns that reflect local characteristics rather than meaningful statistical relationships. The direction of the association varied across provinces, for instance, positive in Isfahan and Mashhad but negative in Alborz and Rasht. This pattern likely reflects regional socioeconomic and demographic differences rather than a universal causal mechanism. In other words, while the descriptive statistics show that the average $PM_{2.5}$ concentration and crime rate are 28.20 µg/m³ and 9.36 units, respectively, with an overall correlation coefficient of 0.068, indicating a very weak positive association, scatter plots and regression modeling show heterogeneous visual patterns, but these do not translate into substantive or consistent associations. In some provinces (such as Isfahan and Mashhad), the association appears positive, whereas in others (such as Alborz and Rasht), it is negative or weak. This heterogeneity aligns to some extent with Burkhardt et al. (9), who reported associations between monthly PM2.5 increases and changes in violent crimes, and with Herrnstadt et al. (21), who observed differential effects of $PM_{2.5}$ on various types of crime. Additionally, a study by Sadana (43) in India found that a reduction in pollution was associated with a decrease in property crimes, although the present study focuses on violent crimes.

These regional differences can be interpreted theoretically. From a biological perspective, air pollution is associated with increased aggressive tendencies via inflammatory responses, elevated stress hormones, and lower serotonin levels (12). However, these biological effects may be moderated by factors such as exposure levels, physiological resilience, and population health characteristics. Therefore, in areas where a positive association is observed, such as Isfahan and Mashhad, these biological pathways may be more apparent than in other regions.

From a psychological perspective, air pollution is associated with increased anxiety, tension, and anger. In some regions, this may lead to avoidant behaviors—such as staying indoors and reducing social interactions—which in turn is associated with fewer opportunities for crime (46). Similarly, in areas like Alborz and Rasht, negative associations may be linked to social or cultural mechanisms that mitigate pollution's association with criminal behavior.

From an economic perspective, both the Rational Choice Theory of Crime and the Economic-Social Disparity Theory suggest that air pollution is associated with crime rates in two ways. Increased pollution may reduce social activities and police presence in public spaces, potentially decreasing opportunities for crime (19). Conversely, in regions with higher health and economic costs due to pollution, social inequalities may be associated with increased criminal motivations (22). Thus, the observed patterns—such as slight positive associations in Isfahan and Mashhad or negative associations in Alborz—may reflect the balance of these economic trends.

Finally, sociological perspectives highlight that environmental order and the quality of public spaces are associated with social behaviors. In areas where air pollution signals environmental degradation and weakened social order, crime rates may be higher (35). Conversely, if pollution leads to avoidance of public spaces, opportunities for criminal behavior may be reduced. Accordingly, the differences observed in time series patterns—from higher fluctuations in Isfahan and Fars to relative stability in Tehran and Rasht—indicate that the interaction between environmental factors and economic, cultural, and social characteristics is associated with crime rates.

To examine the relationship between $PM_{2.5}$ concentration and public aggression patterns at a broader regional tier, the longitudinal tracking pivots to a specific panel consisting of Iran's major metropolitan provinces: Tehran, Mashhad, Isfahan, Fars, Alborz, and Rasht. While national legal databases broad-line data categories across all 31 provinces, this study purposely restricts its empirical scope to these six specific jurisdictions. These administrative territories were extracted because they represent the definitive hubs of urbanization, suffer from pronounced industrial/ambient air quality stress, and uniquely house continuous, high-fidelity atmospheric tracking infrastructure required for reliable longitudinal tracking.

Overall, the findings indicate that at the macro level, temporal factors, such as the passage of time (which is strongly associated with increasing crime rates), are primary drivers of change, while the independent association of $PM_{2.5}$ alone is weak. The heterogeneity at the provincial level emphasizes the need to consider mediating factors, such as demographics, economic development, and cultural characteristics. These results are consistent with the theoretical frameworks presented and highlight that explaining the complex associations between air pollution and crime requires attention to interactions among biological, psychological, economic, and sociological factors. This understanding can inform multifaceted policy interventions aimed at improving urban quality of life, considering environmental, economic, social, and cultural dimensions.

This section, along with presenting statistical evidence and regression analyses, relies on theoretical foundations to clarify the pathways through which air pollution is associated with crime rates, providing a basis for formulating comprehensive regional policies.

Recommendations

- Develop and implement strict environmental standards to control key pollutants (especially ozone and NO_2), considering regional and cultural characteristics.
- Improve traffic and industrial management via sustainable public transportation infrastructure and intelligent traffic programs to reduce pollutant emissions.
- Invest in real-time monitoring systems using technologies such as GIS and artificial intelligence, and create integrated databases to identify high-risk areas quickly.
- Strengthen international and multi-agency cooperation by establishing common frameworks among governmental, law enforcement, and private sector organizations and exchanging experiences to support policymaking.
- Expand multi-factorial analysis frameworks using complex models (e.g., structural equation modeling and multilevel models) and control for economic, cultural, and demographic mediating factors to more precisely examine pollution–crime associations.
- Differentiate and analyze crime subgroups by separately examining types of crimes (violent crime, property crime, domestic violence) to inform more targeted interventions.

Limitations

Several contextual variables, including temperature, day-of-week, police patrol density, and economic activity, were not available for inclusion in our dataset. These factors may independently influence both pollution and crime.

Although the causal direction is assumed to flow from pollution to crime, it remains possible, though less likely, that crime-related activity could indirectly influence pollution levels through increased traffic or local disruptions.

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