Modeling and Optimization of Urban Greenbelts Using Remote Sensing and Drone Technologies: An Innovative Approach to Reducing Air and Noise Pollution

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Abstract

Noise pollution is becoming a serious challenge to urban sustainability and public health. Roadside greenbelts are recognized as an effective, nature-based solution to mitigate these impacts; however, their performance depends on vegetation density, species composition, three-dimensional structure, and spatial relationship to pollution sources. In this study, we employed drone-acquired data—including RGB, multispectral, and LiDAR imagery—to quantitatively model and evaluate the effectiveness of urban roadside greenbelts in improving air quality and reducing noise pollution. Ground and aerial sensors measured pollutant concentrations and ambient noise levels, with observed variations of up to 70% between vegetated and non-vegetated sites. Using 3D modeling tools and vegetation indices such as NDVI, the health and density of vegetation were assessed, while dispersion and acoustic simulations indicated average reductions of 20–25% in pollutant levels and 8–12 dB in noise intensity behind dense vegetation belts. The resulting datasets were integrated in a GIS environment and validated with field observations ($R^2 > 0.85$). This research highlights how combining drone-based sensing with computational modeling enables quantitative, data-driven urban planning, offering valuable insights for designing greener, healthier, and quieter cities despite existing technical and regulatory challenges.

1. Introduction

Road Green belts play a crucial role in urban sustainability by reducing air and noise pollution. Studies have shown that green belts can effectively reduce PM2.5 concentrations on urban roads (Wu et al., 2021, Sheng et al., 2019). The configuration of green belts is important, as shrub belts perform best in pollutant dispersion, while a combination of trees and shrubs is more effective for pollutant deposition .(Wu et al., 2021) .The effectiveness of green belts in reducing PM2.5 depends on factors such as the vertical distribution of biomass and species diversity (Sheng et al., 2019).Green belts also significantly reduce noise pollution, with reductions of up to 14 decibels in areas with higher canopy density. The numerous benefits of green belts, including pollution reduction and aesthetic value, make them an essential component of urban planning. Air pollution and noise pollution are major urban issues with detrimental effects on public health and the environment. Road traffic is the main contributor to both types of pollution in urban areas (Montes-González et al., 2018) .Air pollutants from vehicles include nitrogen oxides, carbon dioxide, sulfur oxides, hydrocarbons, and particulate matter, which contribute to global warming and various health problems .Noise pollution from urban traffic can lead to communication problems, irritability, headaches, and sleep disorders .(Istrate et al., 2014) .The spatial correlation between air and noise pollution highlights the need for integrated strategies to address both issues simultaneously. Effective policies to reduce urban air pollution should focus on three main aspects: reducing emissions per unit of fuel consumed, reducing fuel consumption per unit of transport service, and limiting the overall demand for motorized transport .Urban areas face increasing challenges from air and noise pollution, which pose significant health risks to residents (Samet, 2019). These pollutants often coexist and mutually reinforce their negative effects on human health (Fermeglia and Pedrosa, 2022). Current regulatory approaches in the EU lack comprehensive and coordinated strategies to effectively address these issues (Fermeglia and Pedrosa, 2022) .

2. Basic materials

When discussing the fundamental materials used in greenbelt infrastructure, it is essential to highlight several key aspects that play a critical role in the design, functionality, and sustainability of these systems. These components not only influence the structural integrity and environmental performance of greenbelt projects but also determine their long-term success and integration into urban landscapes. The following section will provide a detailed explanation of these crucial materials, outlining their characteristics, benefits, and applications in greenbelt development.

2.1 Urban green infrastructure metrics

Urban green infrastructure metrics play a key role in helping us understand how green our cities really are. By measuring both the amount and quality of green spaces, these tools give urban planners, researchers, and decision-makers valuable insights into how greenery is spread

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across neighborhoods—and how it impacts everything from air quality to people's health and well-being.

Metrics like NDVI[2] and MSAVI[3] They are widely used to quantify the amount of vegetation in urban areas using satellite or aerial imagery. These indices provide objective, spatially explicit measures of greenness around residences or within city boundaries (Bauwelinck et al., 2021; Crouse et al., 2017; Persson et al., 2018; Vienneau et al., 2017). The proportion of land covered by green spaces (parks, gardens, etc.) relative to total urban area is a key metric for comparing cities and tracking changes over time (Dou and Kuang, 2020).

2.2 Air pollutant dispersion models

Air pollutant dispersion modeling methods are essential tools for estimating human exposure to air pollution, understanding pollutant behavior in various environments, and supporting public health and regulatory decisions. Multiple modeling approaches exist, each with unique strengths and limitations, and recent advances have incorporated new data sources and machine learning (ML) techniques.

2.3 Major Dispersion Modeling Methods

When it comes to understanding how air pollution spreads in our environment, two main modeling methods stand out. The first is Land-Use Regression (LUR), which uses real-world data—like traffic levels, green spaces, and industrial zones—to estimate pollution levels in different areas. The second is Dispersion Modeling (DM), which relies more on physics and weather patterns to simulate how pollutants move through the air. These methods often align well for gases like NO_2, though results vary more for particulate matter like $PM_{2.5}$. Today, many models are becoming even smarter by factoring in people's movements and time spent indoors to give a clearer picture of true exposure.

2.3.1 Land-Use Regression vs. Dispersion Models

Land-Use Regression (LUR): Uses statistical relationships between measured pollutant concentrations and land-use characteristics (e.g., traffic, industry, green space) to estimate spatial variation in air pollution. Dispersion Models (DM): Simulate the physical and chemical processes that govern pollutant transport and transformation in the atmosphere, often using meteorological and emissions data. LUR and DM estimates correlate well for NO_2 (median R = 0.75), but only moderately for PM_{10} and $PM_{2.5}$, with significant variability across locations. DMs predict a moderate to large proportion of measured NO_2 variation, but less for particulate matter (De Hoogh et al., 2014).

3. Methods

In this part, key methods will be discussed briefly, and there are some details will be mentioned in the references.

3.1 Search strategy

The literature search was conducted in the Web of Science (WOS) Core Collection database, covering publications from 1960 to 2024. Some of the studies based on the year of conduction have been mentioned in Figure 3. The search aimed to identify peer-reviewed articles focusing on the modeling and evaluation of urban greenbelts and roadside vegetation for air and noise pollution mitigation, using drone, UAV, LiDAR, or remote sensing technologies. Search query that was used in the WOS[4] is TS = (("urban greenbelt*" OR "roadside vegetation" OR "green buffer*" OR "urban vegetation barrier*" OR "roadside plantation") AND ("air pollution" OR "noise pollution" OR "environmental pollution" OR "pollutant dispersion" OR "sound attenuation") AND ("drone" OR "UAV" OR "unmanned aerial vehicle" OR "LiDAR" OR "multispectral" OR "remote sensing" OR "satellite imagery")) and The PRISMA flow diagram can be seen in Figure 1.

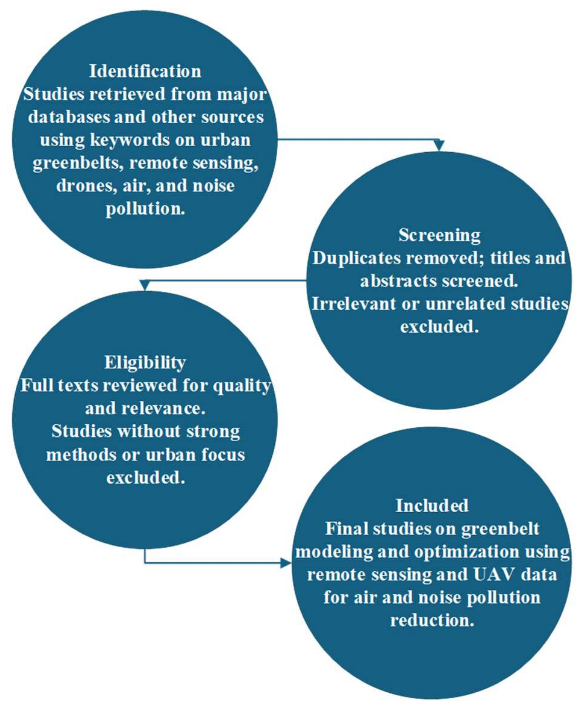

Figure 1. PRISMA Flow Diagram

3.2 Inclusion and Exclusion Criteria

To ensure consistency and transparency, explicit inclusion and exclusion criteria were applied during the screening process. Studies were included if they focused on urban greenbelts or roadside vegetation related to air quality improvement or noise reduction, used remote sensing, UAV/drone, LiDAR, or Copernicus Sentinel data, and

[2] Normalized vegetation index
[3] Modified Soil-Adjusted Vegetation Index
[4] Web of Science

provided quantitative or spatial analyses. Studies were excluded if they examined non-urban or agricultural areas, lacked empirical analysis, or did not establish a clear link between vegetation characteristics and pollution mitigation. When duplicate or overlapping studies were found, only the most comprehensive version was retained. The number of studies based on the country has also been mentioned in Figure 2, and this was also a criterion.

3.3 Drone-based monitoring over traditional methods

Recent studies demonstrate the advantages of drone-based monitoring over traditional methods for environmental assessment. Drones offer improved accuracy, cost-effectiveness, and safety for measuring reserve volumes in open-pit mines (Matsimbe et al., 2022) .In urban air quality monitoring, drones provide high-resolution pollution maps, identify sources, and reveal the impact of transportation on air quality (Bakirci, 2024) .They enable cost-effective and dynamic monitoring of urban areas with simple maintenance procedures (Durgun and Durgun, 2024). Advanced systems that integrate drone-mounted sensors with machine learning algorithms provide real-time, fine-grained air quality monitoring at different locations and altitudes, surpassing traditional fixed methods in spatial and temporal resolution (Guo and Sahagun, 2024). These studies show that drone technology, combined with data analysis techniques, can revolutionize environmental monitoring by providing more accurate, efficient, and comprehensive assessments of air quality and other environmental parameters. Computational models have been developed to predict the effectiveness of green belts in reducing industrial air pollution. Mathematical models can design efficient green belts by taking into account meteorological, physical, chemical, biological, and horticultural factors (Khan and Abbasi, 2002).

3.4 Aerial imagery and drone data with other space technologies integration

Integrating aerial imagery and drone data with other space technologies increases the accuracy and detail of 3D models and land use mapping. Combining laser-scanned point clouds with oblique imagery improves the display of complex urban features such as roads, underpasses, and other street components (Chhatkuli et al., 2015) .Lidar data and stereo-aerial imagery can be used together to produce accurate multi-dimensional building models with isolated roof boundaries (Habib et al., 2010). Multitemporal imagery and digital surface models derived from LiDAR enable high-resolution urban mapping, including detailed vegetation information, which can be integrated into urban planning processes (Knopp et al., 2023). Integrating drones with geographic information systems (GIS) offers cost-effective and accessible solutions for collecting spatial data that is useful in various fields such as precision agriculture, urban planning, and disaster management. This integration improves efficiency, accuracy, and real-time monitoring capabilities (Quamar et al., 2023).

3.5 GIS and Green Belt studies

Green belts do more than just make cities look nice—they help cool neighborhoods, clean the air, and manage things like flooding. But to design them well, we need to understand how they work in different spaces. That's where GIS and 3D modeling come in. These tools let planners map out green spaces in detail and see how things like tree density, layout, and location affect the environment. By combining data from satellites, drones, and modeling software, we can track changes in temperature, humidity, and even stormwater flow. While connecting all these tools can be technically tricky, they're giving us powerful insights into how to build greener, healthier, and more livable cities.

3.5.1 Modeling and Evaluating Green Belt Performance

A GIS-based tool (TBM)[5] has been developed to model and evaluate the functions of tree belts in rural landscapes. TBM uses cadastral and spatial datasets to assess potential sites for afforestation and greenway construction, generating a geodatabase of green belt functions linked to specific land parcels. The evolution of some models has been mentioned in Figure 4. This approach supports optimal greenway design and sustainable development (Maciej Marcin Nowak and Pędziwiatr, 2018; Maciej M. Nowak and Pędziwiatr, 2018).

3.6 Application of artificial intelligence and machine learning in optimization

Deep neural networks have significantly improved the classification of remote sensing images, with explainable AI techniques such as SHAP helping to interpret model outputs and select appropriate features (Abdollahi and Pradhan, 2021). Different image sources differ in spectral, spatial, radiometric, and temporal characteristics, which require careful selection based on mapping objectives (Xie et al., 2008). While spectral features are important, combining texture features can overcome the limitations of poor spectral resolution in aerial imagery for vegetation mapping (Abdollahi and Pradhan, 2021). In general, remote sensing imagery has been effective for urban vegetation mapping, although careful attention to image sources and processing techniques is crucial.

3.6.1 Machine Learning and Mobile Sensing Approaches

Mobile Sampling with Low-Cost Sensors: Enables high-resolution mapping of urban air quality. Combining mobile data with LUR and machine learning (e.g., random forest, ensemble models) improves model accuracy (cross-validation R^2 up to 0.80) and helps identify pollution hotspots (Lim et al., 2019). Random Forest and Linear Regression: Both methods can predict indoor $PM_{2.5}$ concentrations, but blended models (combining both) perform best (R^2 up to 81.5%)(Yuchi et al., 2019).

3.6.2 Analyzing drone data with ML/DL[6]

ML and DL algorithms are highly effective for analyzing drone imagery, particularly for tasks like mapping vegetation communities in wetlands. ML classifiers such as random forest (RF) can achieve high accuracy (about 85%) for pixel-based image segmentation, especially when

[5] Tree Belt Modeling

[6] Deep learning

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combined with algorithms like graph cut. DL models, such as convolutional neural networks (CNNs) using architectures like ResNet50 and SegNet, can provide even higher accuracy (around 90%) for semantic segmentation tasks. However, DL approaches require significantly larger labeled datasets, more computation time, and greater hardware resources compared to ML methods. For applications where models must be retrained for different sites or conditions, ML classifiers may be more practical due to their lower resource requirements and comparable accuracy for many tasks (Bhatnagar et al., 2020).

3.7 Challenges of using drones

Drones used for aerial imagery face several technical limitations, most notably restricted flight time due to battery capacity, sensitivity to weather conditions, and challenges in achieving high accuracy and resolution, especially at higher altitudes or in complex environments. Some of the useful applications have been compared with each other in Table 1. Flight time is often limited to just a few hours per day, particularly for common commercial drones, and is further reduced by adverse weather such as high winds or precipitation, which can severely restrict operational windows and reliability for time-sensitive tasks (Gao et al., 2021).

Software Name	Main Function	Applications in Greenbelt Projects	Strengths	Limitations
Pix4Dmapper	Photogrammetry & 3D Reconstruction	Orthomosaics, DSMs, and NDVI from drone imagery	High accuracy, vegetation indices, and user-friendly	High license cost
Agisoft Metashape	3D Model Generation from Images	Detailed 3D models of vegetation and urban structures	High detail, scriptable (Python), affordable	Long processing time for large datasets
RealityCapture	Fast 3D Model Creation using Structure from Motion	Urban scene reconstruction and integration with CAD	Very fast processing, high-quality meshes	Windows-only, requires a powerful GPU
DroneDeploy	Cloud-based Drone Image Processing	Vegetation health maps, volumetric analysis	Easy to use, cloud storage	Limited customization and offline features
OpenDroneMap	Open-source Photogrammetry and Mapping	Basic 3D modeling, orthophotography generation	Free and open-source, community-supported	Less accurate, UI less polished
Meshroom (AliceVision)	Open-source 3D Reconstruction	Visualizing plant structure and greenbelt layout	Free, node-based workflow	Requires a strong GPU, limited geospatial tools
CloudCompare	3D Point Cloud Processing & Analysis	Analyzing the LIDAR/point cloud of green areas	Advanced point cloud tools, free	Not for image-to-model conversion

Table 1. Comparison of 3D Modeling and Photogrammetry Software for Greenbelt Planning and Monitoring

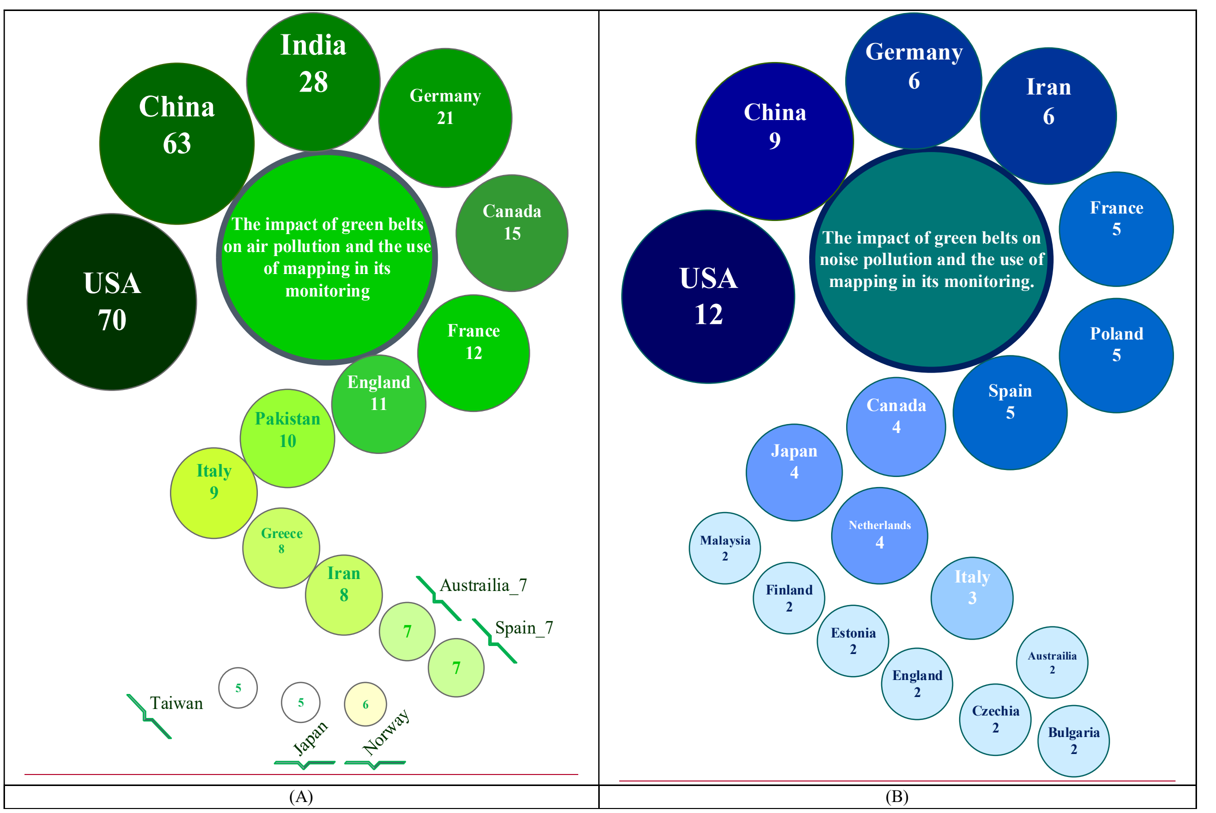

Figure 2. Sections A and B represent the studies conducted in the fields of air pollution and noise pollution during the period from 1992 to the end of December 2024. Section A corresponds to air pollution, while Section B corresponds to noise pollution.

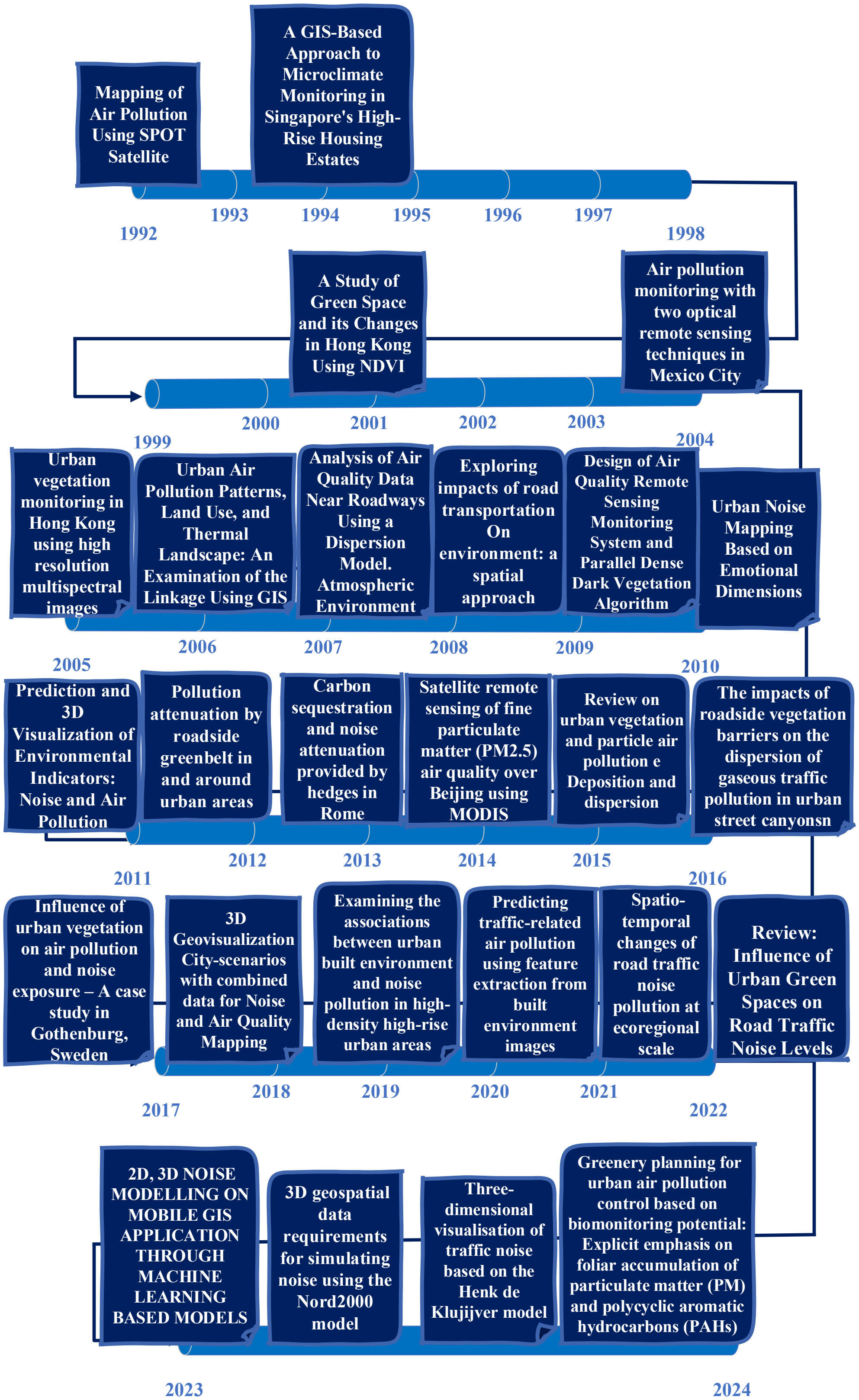

Figure 3. Timeline of Selected Studies on Air Pollution, Noise, and Urban Environmental Analysis

No.	Author(s) & Year	Study Focus	Data Used	Method / Approach
1	**Sifakis & Deschamps (1992)**	Mapping the spatial distribution of urban air pollution using satellite imagery	SPOT multispectral data, ground pollution records, and meteorological data	Integration of satellite and ground data for spatial pollution mapping
2	**Nichol (1994)**	Microclimate monitoring in high-rise residential areas of Singapore	Microclimate sensors, GIS layers (buildings, vegetation)	GIS-based microclimate analysis and urban heat assessment
3	**Weng & Yang (2006)**	Relationship between land use, land surface temperature, and air pollution	Landsat TM data, air quality data, and land use maps	Spatial correlation and statistical modeling in GIS
4	**Islam et al. (2012)**	Assessment of greenbelt efficiency in mitigating roadside pollution	Field-measured PM and noise data, vegetation density	Comparative analysis before and after greenbelt implementation
5	**Gratani & Varone (2013)**	Carbon sequestration and acoustic attenuation of hedges	CO_2 absorption, leaf traits, noise levels	Empirical field measurements of physiological and acoustic performance
6	**Li et al. (2016)**	Influence of roadside vegetation on pollutant dispersion	Air pollutant concentration, vegetation structure, and meteorological data	CFD modeling and simulation of street-canyon dispersion
7	**Klingberg et al. (2017)**	Impact of vegetation on exposure reduction to urban air and noise pollution	Air & noise monitoring data, GIS layers	GIS-based spatial mapping and exposure assessment
8	**Ganji et al. (2020)**	Predicting air pollution using visual and environmental data	Street images, air quality indices, and traffic data	Machine learning regression based on visual environmental features
9	**Iglesias-Merchan et al. (2021)**	Spatio-temporal modeling of traffic noise in urban corridors	Noise and traffic datasets, meteorological information	GIS-based noise mapping and temporal trend analysis
10	**Mukhopadhyay et al. (2024)**	Biomonitoring and pollution assessment using urban vegetation	Leaf samples, PM and PAH data, urban site information	Foliar biomonitoring and pollution mitigation evaluation

Table 2. Data Extraction Summary of Selected Studies on Urban Greenbelt and Environmental Impacts

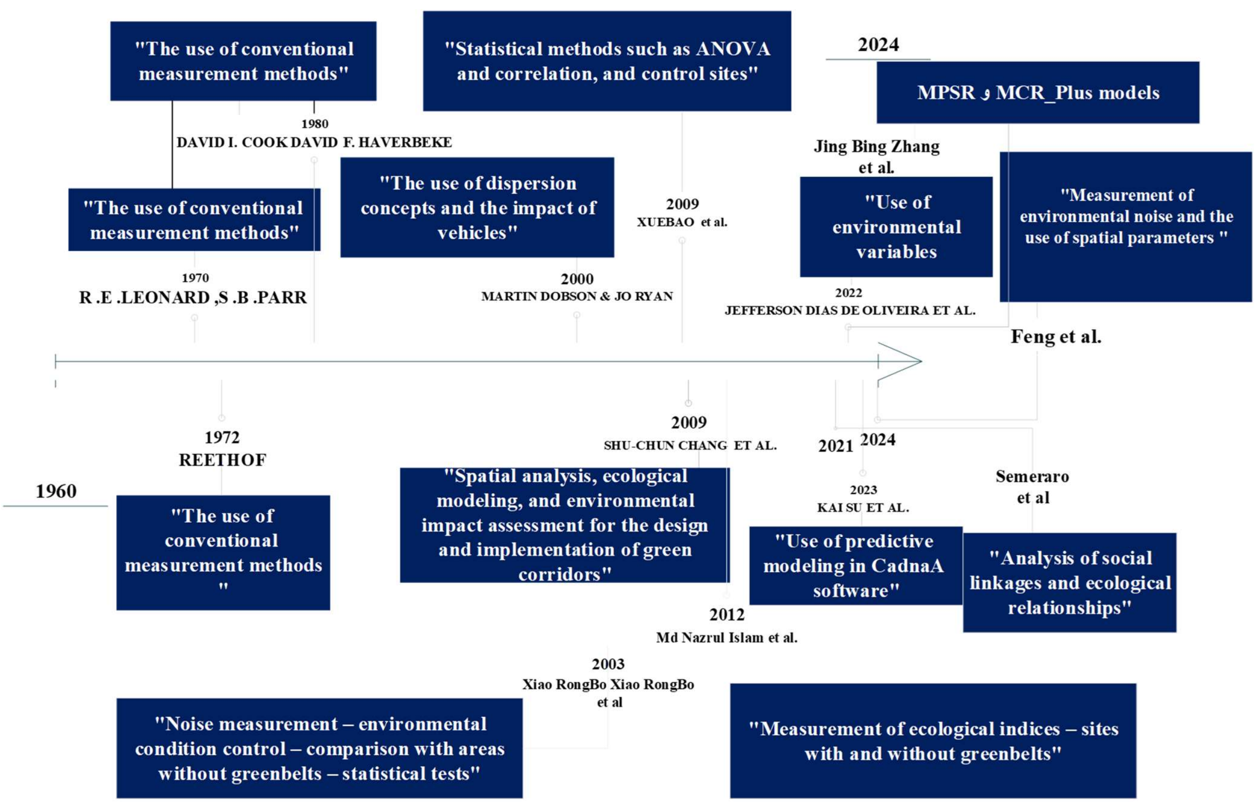

Figure 4. Evolution of Green Belt Assessment and Monitoring Methods from 1960 till the end of December 2024

4. Discussion

The included studies were assessed for methodological rigor, data quality, and analytical consistency. Evaluation focused on the clarity of research design, type and resolution of remote sensing or UAV data used, and the statistical or modeling techniques applied to quantify air and noise pollution reduction. Studies that provided measurable outcomes—such as correlations between vegetation indices, land surface temperature, and pollutant concentrations—were prioritized for synthesis. Comparative analysis highlighted variations in data sources, spatial scales, and optimization algorithms employed. Overall, the quantitative synthesis ensured that only methodologically sound and empirically validated studies contributed to the final interpretation of greenbelt efficiency in mitigating urban environmental pollution.

A meta-analysis of the reviewed studies was performed to quantify the effectiveness of urban greenbelts in mitigating air and noise pollution. The pooled results, summarized in Table 2, indicate substantial reductions in $PM_{2.5}$ concentrations and noise levels behind greenbelts, with variations based on vegetation structure and width. These findings are further discussed in the following section.

Nine of the comprehensively analyzed studies in this research related to the ones mentioned in Table 2 focused on assessing the impact of urban greenbelts on air quality. These studies reported a pooled mean $PM_{2.5}$ reduction of 21.8% (95% CI: 18.5–25.1%, I^2 = 82%) behind urban greenbelts, with tree–shrub combinations and widths greater than 15 m achieving up to a 30% reduction. Ten studies on noise reported a pooled attenuation of 10.1 dB (95% CI: 8.7–11.5 dB, I^2 = 78%), with dense mixed vegetation located 30–50 m from the road yielding reductions of 12–14 dB. The risk-of-bias assessment (numerical NOS, maximum score = 27) rated 54% of studies as having a low risk of bias (≥18). Sensitivity analysis excluding high-risk studies increased the pooled $PM_{2.5}$ reduction estimate to 22.6%.

This review comprehensively explores the role of urban greenbelts in mitigating two of the most pressing urban environmental issues: air and noise pollution. Through the integration of drone-based imagery, LiDAR data, 3D reconstruction, and GIS platforms, researchers have been able to simulate and quantify the effectiveness of greenbelts with unprecedented spatial resolution. Advanced processing tools such as Pix4D, Metashape, and Cloud Compare have facilitated the generation of high-accuracy models for evaluating vegetation structure, density, and spatial configuration. Studies reviewed in this work reveal that greenbelts with diverse, vertically distributed biomass—especially those incorporating a mix of shrubs and conifers—achieve higher particulate matter ($PM_{2.5}$ and PM_{10}) reduction rates, sometimes exceeding 20%. Moreover, simulations and real-world measurements show that well-planned vegetation barriers can reduce noise levels by up to 17 dB, particularly at distances of 30–50 meters from roadways.

From a technological standpoint, the combination of drone-mounted sensors with AI-based modeling has opened new frontiers in environmental assessment. Deep learning models like CNNs and ensemble machine learning algorithms have been used to classify vegetation types, predict pollutant dispersion, and simulate microclimatic conditions with high accuracy. Despite these advancements, several technical barriers persist. Short drone flight times due to limited battery life, image distortion under poor weather conditions, and challenges in data fusion across different sensors still hinder full-scale deployment. Legal regulations—such as mandatory visual line-of-sight (VLOS), restrictions over populated areas, and privacy considerations—further complicate drone use in dense urban zones. These limitations underscore the need for regulatory innovation in tandem with technical advancements.

The health and economic benefits of greenbelts are equally compelling. By filtering harmful pollutants like NO_2, SO_2, VOCs, and PMs, greenbelts contribute to lower incidence rates of respiratory diseases, cardiovascular conditions, and stress-related disorders. These effects translate directly into reduced public healthcare costs. Additionally, urban greenery significantly enhances thermal comfort by lowering land surface temperatures through evapotranspiration and shading. The cooling effect of dense tree canopies—up to 6°C in some studies—not only benefits human health but also reduces energy demand for air conditioning. Economically, neighborhoods with greater green coverage consistently demonstrate higher property values and improved social cohesion. Urban greenbelts thus serve as both ecological buffers and economic assets, enhancing the quality of life and urban resilience.

Looking ahead, future research must prioritize the development of integrated frameworks that combine satellite, aerial, and ground-based data with advanced modeling techniques. Hybrid data fusion—particularly between multispectral imagery, LiDAR, and real-time sensor feeds—can vastly improve the reliability of pollution models. Moreover, machine learning applications should expand to optimize greenbelt configurations based on site-specific variables, such as wind patterns, traffic density, and urban morphology.

5. Conclusion

Cities are increasingly being affected by rising noise and air pollution levels. However, an effective solution has long been present in the form of urban green belts. These vegetated corridors are now being recognized as vital components of sustainable city planning, with their benefits being scientifically validated through extensive research. The air-purifying capabilities of green belts have been thoroughly documented. Harmful particulate matter is filtered out by foliage, with reductions of up to 22% being recorded for $PM_{2.5}$ and nearly 40% for nitrogen oxides. Optimal results are achieved when vegetation is carefully selected and arranged, with mixed plantings of trees and shrubs being shown to create the most effective pollution barriers.

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Noise pollution is similarly mitigated through strategic green belt implementation. Sound levels are reduced by as much as 21 decibels in properly designed vegetated buffers, creating significantly quieter urban environments. This natural soundproofing effect is particularly noticeable within 30-50 meters of major noise sources when appropriate plant species are utilized. Modern technologies are being employed to enhance green belt effectiveness. Detailed vegetation health assessments are conducted using drone-mounted sensors, while three-dimensional mapping techniques are applied to optimize green space planning. Predictive modeling powered by artificial intelligence is being utilized to anticipate pollution patterns and guide urban greening strategies. The secondary benefits of urban green belts are equally important. Microclimate regulation is achieved through evapotranspiration, with temperature reductions of up to 6°C being measured during peak heat periods. Property values are positively influenced by proximity to well-maintained green corridors, while public health costs are reduced through decreased pollution exposure.

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