Spatiotemporal Analysis of Traffic-Induced Air Pollution in Bologna

Geospatial Analysis and Representation for Data Science

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***Abstract*—The relationship between urban traffic and air quality presents a formidable challenge to public health and environmental sustainability globally. Vehicular emissions are a primary contributor to urban air pollution, necessitating sophisticated analytical approaches to understand, monitor, and mitigate their impact. This study investigates the *spatiotemporal patterns of traffic-related air pollution in Bologna, Italy*, employing a multi-scale geospatial analysis to identify critical traffic hotspots and evaluate the differential impacts of vehicle types on air quality across urban zones.**

The study integrated high-resolution traffic monitoring data from Bologna's sensor network with air quality measurements (NO2, PM10, PM2.5) from five monitoring stations in the city. Using a novel buffer-zone methodology, the study proposed a distance-weighted impact model that accounts for pollution dispersion from traffic sources. The analysis encompasses Spatial clustering analysis to identify traffic and pollution hotspots, Temporal pattern analysis revealing diurnal and weekly cycles, Zone-based aggregation assessing neighborhood-level exposure, Heavy vehicle impact assessment through vehicle-type stratification and Lag analysis capturing the delayed effects of traffic on air quality.

The results reveal pronounced spatial heterogeneity in traffic burden, with central zones (Marconi, Irnerio, Malpighi) experiencing traffic densities exceeding 22,000 vehicles/km^2 while peripheral zones see less than 1,000 vehicles/km^2. Heavy vehicles, though comprising only 7-8% of traffic, show distinct temporal patterns peaking during mid-morning delivery hours. NO2 concentrations demonstrate strong correlation with traffic volumes (r=0.786) but with complex lag patterns, showing both immediate response and 20-24 hour persistence effects. The distance-weighted analysis confirms rapid decay of traffic impacts, with 50% reduction at 750m from source roads. Weekend traffic reductions of 20% yield only 16% NO2 decrease, indicating non-linear emission-concentration relationships influenced by atmospheric conditions and urban morphology.

I. Introduction

Urban air pollution represents one of the most pressing environmental health challenges of the 21st century, with vehicular emissions serving as the dominant source of harmful pollutants in cities worldwide. The World Health Organization estimates that ambient air pollution causes 4.2 million premature deaths annually, with traffic-related emissions contributing substantially to this burden through their production of nitrogen oxides (NOx), particulate matter (PM), and other harmful compounds. As urban populations continue to grow and motorization rates increase, understanding the complex spatiotemporal dynamics of traffic-induced air pollution becomes critical for developing effective mitigation strategies.

Bologna, situated in Northern Italy's Po Valley, exemplifies the challenges faced by mid-sized European cities in managing traffic-related air quality. The city's medieval street layout, combined with modern mobility demands and its location in one of Europe's most polluted regions, creates a unique set of circumstances that demand sophisticated analytical approaches. The Po Valley's characteristic meteorological conditions—frequent temperature inversions, low wind speeds, and high humidity—exacerbate pollution accumulation, making Bologna an ideal case study for investigating traffic-pollution relationships under challenging dispersal conditions.

Recent technological advances in sensor networks and computational capabilities have enabled significant resolution in monitoring urban environmental conditions. Bologna has invested significantly in traffic monitoring infrastructure, deploying hundreds of sensors throughout the city that capture real-time vehicle flows. Simultaneously, the regional environmental agency (ARPAE) maintains a network of air quality monitoring stations providing continuous measurements of key pollutants. However, integrating these diverse data streams to understand the causal pathways from traffic emissions to human exposure remains a significant challenge.

This study addresses critical gaps in current understanding by developing an integrated spatiotemporal framework that links traffic patterns to air quality outcomes at multiple scales. While previous research has established general relationships between traffic volume and pollution levels, several key questions remain unanswered: How do different vehicle types contribute to pollution at various times and locations? What is the spatial extent of traffic impacts on air quality? How do urban morphology and traffic management policies influence these relationships? To what extent can high-resolution monitoring data inform targeted interventions?

The research employs novel methodological approaches including multi-scale buffer zone analysis with distance-weighted impact modeling, hierarchical vehicle type classification based on emission characteristics, and comprehensive temporal decomposition to isolate traffic signals from meteorological influences. By leveraging Bologna's extensive monitoring infrastructure and applying advanced geospatial analytics, this study aims to provide actionable insights for urban planners and policymakers while advancing methodological frameworks applicable to other urban contexts.

II. Related Work

The relationship between traffic emissions and urban air quality has been extensively studied across various geographical contexts and methodological approaches. Carslaw and Beevers [1] analyzed traffic flow and NO2 concentrations in London, demonstrating that traffic volume alone explains approximately 60% of the variance in roadside NO2 levels. Similarly, Beckerman et al. [2] found strong correlations between traffic density and NO2 concentrations within 500m of major roads across 15 Canadian cities. The causal link was definitively confirmed during COVID-19 lockdowns, when India observed 40-49% reductions in NO2 and PM2.5 levels directly attributable to reduced vehicular activity [3]. These findings have been supported through spatial analysis techniques, with studies employing GIS-based hotspot detection [4], and buffer-zone methodologies with distance-decay functions [5].

In the Italian context, traffic's dominant role in urban air pollution is being studied comprehensively. Rossi et al. [6] revealed that traffic contributes to 70% of urban NO2 and 50% of PM10 concentrations in Milan's monitoring network. The Po Valley, where Bologna is situated, faces persistent PM2.5 exceedances due to dense traffic networks, industrial clusters, and agricultural emissions, compounded by topographic barriers that inhibit pollutant dispersion [7]. Source apportionment studies identify traffic as contributing 15-30% of PM2.5 in this region, with heavy-duty vehicles disproportionately impacting NO2 concentrations despite comprising only 6-12% of traffic volume [7]. Marinello et al. [8] extended this analysis to multiple Italian cities, emphasizing how meteorological conditions modulate traffic-pollution relationships.

Studies have identified lag times of 1-4 hours between peak traffic and maximum NO2 concentrations [9], with weekend NO2 reductions (20-40%) exceeding proportional decreases in traffic volume (15-25%), suggesting non-linear relationships. Heavy vehicle impact assessments consistently show that trucks emit 5-8 times more NOx per kilometer than passenger cars, with studies in Rotterdam finding that trucks constitute 6% of traffic but contribute 40% of traffic-related NO2 emissions [10].

Despite extensive research, critical gaps remain in multi-scale integration of hyperlocal sensor data with city-wide patterns, real-time analysis capabilities, and systematic frameworks for optimizing intervention locations and timing. This study addresses these gaps by developing an integrated spatiotemporal framework for Bologna that combines high-resolution traffic monitoring with multi-scale spatial analysis, employing novel buffer-zone methodology with distance-weighted impacts and providing vehicle-type differentiation. This approach advances both methodological innovations and provides locally-relevant insights for Bologna's air quality management, building upon the established traffic-pollution relationships while offering actionable recommendations for targeted interventions.

III. Methodology and Implementation

A. Study Scope

Spatial Scope: This study focuses on the City of Bologna, located in the Emilia-Romagna region of northern Italy, as shown in Fig. 1. The spatial domain is confined to the municipal territory, encompassing the urban core and surrounding neighborhoods within the administrative boundaries of Bologna.

Temporal Scope: The temporal scope encompasses the full year 2024, providing complete seasonal coverage to capture annual cycles in both traffic patterns and air quality.

B. Data Sources and Metadata Description

1) Traffic Monitoring Data : The traffic analysis uses two complementary datasets capturing vehicular movement at different spatial scales. The primary dataset consists of Bologna city traffic data obtained from the Bologna Municipality Open Data Portal. This comprehensive dataset contains hourly vehicle counts from inductive loop detector sensors embedded in city roads shown in Fig. 1. Published under a CC BY 4.0 license the data includes directional flow information, enabling detailed analysis of urban traffic patterns and their temporal variations.

Complementing the city-level observations, regional traffic data from the Sistema MTS (Monitoring Traffic System) of Emilia-Romagna provides broader context for traffic flows entering and traversing the metropolitan area. This dataset offers higher temporal granularity with 15-minute interval measurements from the regional monitoring network that covers major arterial roads and highways. Available through the regional open data portal with attribution requirements, this resource captures critical information about external traffic contributions, particularly freight corridors and commuter routes that impact urban air quality.

2) Air Quality Monitoring Data: Air quality measurements are sourced from the ARPAE Emilia-Romagna Open Data Portal, encompassing three key pollutants associated with vehicular emissions. The dataset includes hourly nitrogen dioxide (NO2) concentrations, which serves as a primary indicator of traffic-related air pollution. Particulate matter data is provided at daily resolution for both PM10 and PM2.5, capturing different size fractions of airborne particles that pose distinct health risks. All pollutant measurements correspond to the whole year of 2024, ensuring temporal consistency for integrated analysis. The data is accessible via both API

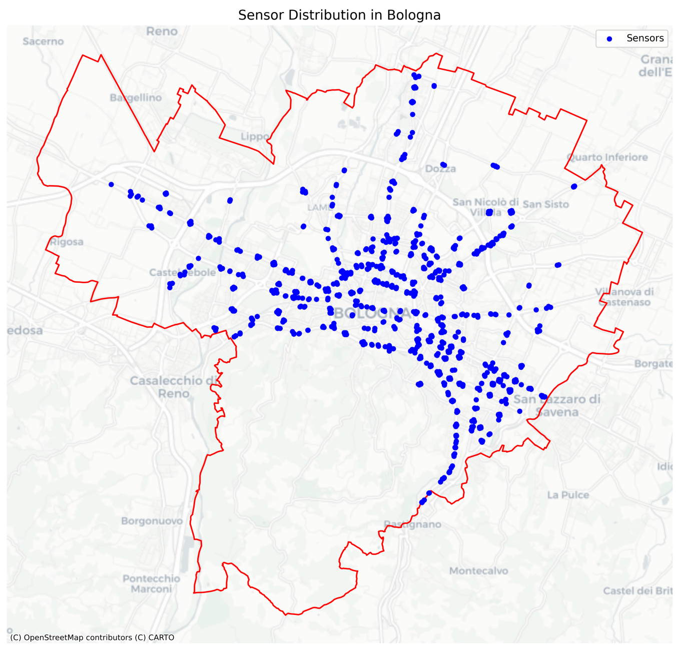

Fig. 1: Traffic Sensor Distribution in Bologna City

endpoints and direct CSV download, with usage requiring acknowledgment of ARPAE as the data source.

Bologna city constitute five fixed monitoring stations operated by ARPAE: DE AMICIS (city center), GIARDINI MARGHERITA (urban background), PORTA SAN FELICE (traffic junction), SAN LAZZARO (eastern suburban), and VIA CHIARINI (western industrial).

3) Geospatial Reference Data: The spatial framework underpinning this analysis comprises multiple geospatial layers that define the study area and facilitate location-based data integration. The Bologna road network topology, sourced from the Bologna Municipality Open Data Portal, provides essential infrastructure context for analyzing traffic flow patterns and determining optimal monitoring point placement. Air quality monitoring station locations are established through geocoding of official station names. The Bologna administrative boundary, extracted via OSMnx from OpenStreetMap, defines the urban study area. Furthermore Zone boundaries inside the municipality of bologna is obtained from The Municipality Open Data Portal, along with the ZTL Zones data. Land use data, obtained from WikiMedia Italia, further enriches the spatial analysis framework.

To incorporate temporal dynamics, public holiday data for Bologna is sourced from the Office Holidays Official Website, enabling the analysis to account for variations in traffic patterns and air quality during non-working days.

C. Data Preprocessing and Preliminary Analysis

1) Traffic Monitoring Data: The preprocessing pipeline integrates regional and provincial traffic monitoring data with air quality measurements using a spatial buffer zone approach. Data preprocessing begins by selecting regional stations within a strategically defined area. To account for the long-distance transport behavior of air pollutants, a 2.5 km buffer zone was established around Bologna's municipal boundary, and all regional monitoring stations within this expanded area were selected for analysis. This buffer zone and the corresponding selected regional stations are illustrated in Figure 2.

After selecting the regional stations, the next step involved merging them with provincial traffic data. However, the provincial data lacked vehicle type classification, which presented a significant challenge since the spatiotemporal analysis of traffic-induced air pollution requires precise differentiation between vehicle categories, as emission factors vary significantly across vehicle types and weights. In Bologna's traffic monitoring infrastructure, sensors capture only aggregate vehicle counts without type classification, presenting a fundamental challenge for accurate emission modeling. To address this gap, the study developed a comprehensive geospatial methodology for interpolating vehicle type distributions from the available aggregate vehicle volume data, essential for subsequent pollutant concentration estimations. The following section describes this modeling procedure in detail.

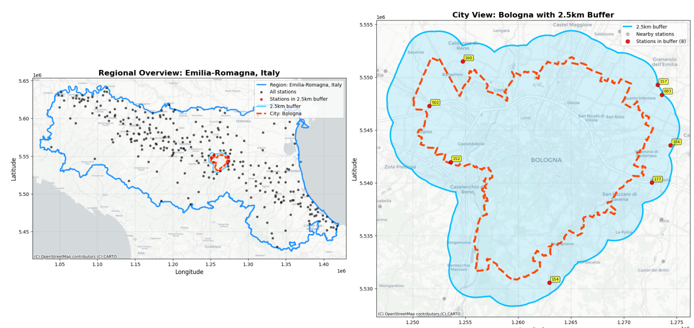

Fig. 2: Regional and Provincial Sensors, with Buffer

D. Vehicle Type Modeling

This section presents a comprehensive geospatial methodology for interpolating vehicle type distributions from aggregate traffic data, essential for subsequent pollutant concentration estimations. The classification framework distinguishes three primary commercial vehicle categories based on gross vehicle weight: vans (<3.5 tonnes), box trucks (3.5 - 7.5 tonnes), and heavy trucks (>7.5 tonnes), which later were renamed as Light, Medium and Heavy Vehicles. These categories align with European emission standards and reflect distinct operational characteristics affecting both pollutant output and spatiotemporal distribution patterns within the urban environment.

1) Statistical Foundation and Data Sources: The empirical basis for vehicle type modeling derives from Bologna's Limited Traffic Zone (Zona a Traffico Limitato, ZTL) freight study [11], which provides detailed commercial vehicle statistics essential for the modeling. Analysis of 1,931 daily commercial vehicle entries revealed a pronounced skew toward lighter vehicles: vans comprise 76% (1,468 vehicles), box trucks 16% (317 vehicles), and heavy trucks merely 8% (146 vehicles). These proportions directly impact emission calculations, as heavy vehicles produce disproportionately higher NOx and PM emissions per kilometer traveled.

Critically for air quality assessment, the study documented severe capacity underutilization, with 67% of vehicles operating below 25% capacity. This inefficiency implies increased vehicle movements per unit of freight delivered, directly amplifying traffic-induced emissions. Furthermore, the 58% illegal occupancy rate of designated loading zones (SCVLZs) forces delivery vehicles into extended search patterns and idling periods, creating emission hotspots that standard traffic flow models fail to capture.

2) Geospatial Data Integration: The geospatial analysis framework integrates multiple data layers to contextualize vehicle type distributions within Bologna's urban morphology. Primary spatial datasets include: (1) coordinates for traffic monitoring sensors distributed across the city network; (2) official ZTL boundary shapefiles defining restricted access zones where emission regulations are strictest; (3) OpenStreetMap-derived land use polygons categorized by functional classification; and (4) loading zone locations representing potential emission concentration points. Each sensor location receives a 50-meter buffer zone for intersection analysis with land use and regulatory boundaries. This buffer distance balances the need to capture immediate environmental context while avoiding overlap between adjacent sensors. The resulting spatial join operations generate comprehensive contextual attributes for each monitoring point, crucial for understanding localized emission patterns.

3) Hierarchical Modeling Approach: The vehicle type interpolation employs a four-tier hierarchical model that progressively refines estimates based on temporal, spatial, and regulatory factors:

Level 1 - Base Statistical Model: Initial proportions derive from ZTL study statistics, providing empirically-grounded baseline distributions that reflect Bologna's overall fleet composition.

Level 2 - Temporal Adjustment: Hourly and daily patterns modify base proportions to capture freight delivery rhythms.

Level 3 - Spatial Contextualization: Land use characteristics and proximity metrics further refine vehicle distributions. Commercial and retail zones exhibit elevated medium truck activity (15% increase), while residential areas show reduced heavy vehicle presence. Distance to commercial centers (0-150m scale) inversely correlates with heavy vehicle proportions, reflecting last-mile delivery patterns where smaller vehicles predominate.

Level 4 - Regulatory Constraints: ZTL membership imposes strict limitations on vehicle types, particularly during operational hours (08:00-18:00). Within ZTL boundaries, the model enforces observed statistical proportions regardless of other factors, reflecting access permit restrictions. Off-hours see 70-80% reductions in heavy vehicle proportions, creating pronounced temporal emission variations within restricted zones.

4) Implementation and Validation: The core algorithm implements vehicle proportion calculation through multiplicative combination of adjustment factors:

Vehicle_Proportion = Base_Profile × Temporal_Factor × Spatial_Factor × Regulatory_Factor

This formulation ensures that local conditions appropriately modify baseline statistics while maintaining mathematical consistency. Vectorized operations process the entire sensor network simultaneously, enabling efficient computation across millions of hourly observations.

Validation procedures verify model outputs against multiple criteria essential for emission modeling accuracy. Statistical validation ensures city-wide proportions remain within 2% of empirical observations (vans: 74-78%, box trucks: 14-18%, heavy trucks: 7-9%). Spatial validation confirms expected patterns such as elevated van proportions within ZTL boundaries (reflecting delivery vehicle permits) and increased heavy vehicle presence near industrial zones. Temporal validation verifies appropriate peak-hour adjustments and holiday effects critical for capturing emission variability.

E. Final Processing

The final preprocessing pipeline integrates multi-source traffic monitoring data with air quality measurements using a spatial buffer zone approach. The methodology enables quantification of traffic impact on air quality at monitoring stations through distance-weighted aggregation. The methodology consists several steps which are listed as follows. The resulted zones and sensors are shown in Fig. 3.

1) Step 1: Traffic Data Harmonization: Traffic data from two sources (Bologna city sensors and regional monitoring stations) are standardized into a unified format. Bidirectional traffic counts are aggregated by station and timestamp, with vehicle counts categorized by type (light, medium, heavy). Each record is geocoded and tagged with its data source for traceability.

2) Step 2: Spatial Buffer Zone Generation: Concentric buffer zones are created around each air quality monitoring station at distances of 0.5, 1.5, and 3.0 km. Zones are projected to UTM coordinates (EPSG:32633) for accurate distance calculations, then converted back to WGS84. Each zone is assigned a weight inversely proportional to its distance from the station (weights: 1.0, 0.5, 0.33).

3) Step 3: Spatial Join with Batch Processing: Traffic monitoring points are assigned to buffer zones using spatial containment queries. To manage memory efficiently, the spatial join is performed in batches of 50,000 records. Points falling within multiple overlapping zones are assigned to the innermost zone.

4) Step 4: Weighted Traffic Impact Calculation: Traffic impacts are calculated using a two-tier weighting system:

1) Vehicle type weights: Light (1.0), Medium (2.5), Heavy (4.0), reflecting relative pollution contributions
2) Distance weights: Applied based on zone assignment

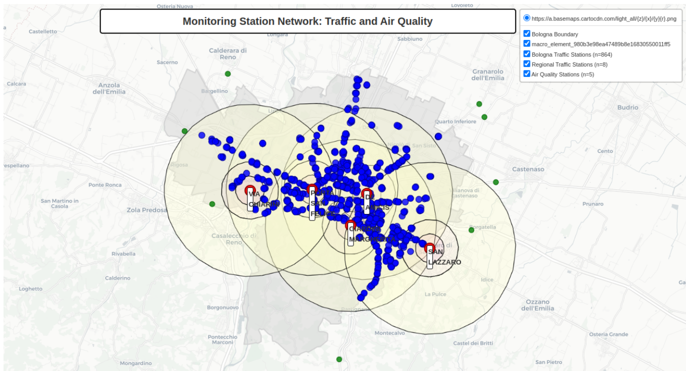

Fig. 3: Selected Zones and Sensor Distribution

5) Step 5: Station-Level Aggregation: Weighted traffic metrics are aggregated to hourly resolution at each air quality station. Aggregation includes raw counts, weighted totals, and distributional metrics (e.g., heavy vehicle impact ratio, average vehicle weight).

6) Step 6: Air Quality Data Integration: Hourly NO2 measurements are merged with traffic data on matching station names and timestamps. PM10 and PM2.5 data (daily resolution) are excluded from the hourly analysis.

7) Step 7: Temporal Feature Engineering: Time series features are generated including:

- Temporal indicators: Hour of day, day of week, weekend/weekday, rush hour flags, season
- Lagged variables: 1, 2, 3, 6, 12, and 24-hour lags for traffic and NO2
- Rolling statistics: 3, 6, 12, and 24-hour moving averages

8) Step 8: Quality Control: Data quality filters remove:

- Negative values for all measurement variables
- Statistical outliers beyond 3× interquartile range
- Records with missing spatial assignments

9) Step 9: Output Generation: The final pipeline produces:

- Primary dataset: Hourly traffic-air quality measurements with engineered features
- Zone summary: Aggregated statistics by buffer zone
- Spatial visualizations: Maps showing station locations, traffic sensors, and buffer zones

IV. Data Analysis

A. Univariate Analysis

1) Traffic Pattern Analysis: The traffic monitoring network captures profound variations in vehicle flow patterns across Bologna and its regional surroundings. Distribution analysis reveals highly right-skewed patterns for all vehicle categories, with means substantially exceeding medians, indicating frequent low-traffic periods punctuated by intense high-volume events. Bologna city sensors record mean hourly counts of 174 light vehicles, 35 medium vehicles, and 17 heavy vehicles, with corresponding medians of 83, 15, and 7, demonstrating the skewed nature of traffic flow. Regional monitoring shows higher light vehicle volumes (mean: 405, median: 286) but lower medium and heavy vehicle counts, reflecting the different character of intercity versus urban traffic patterns. Vehicle

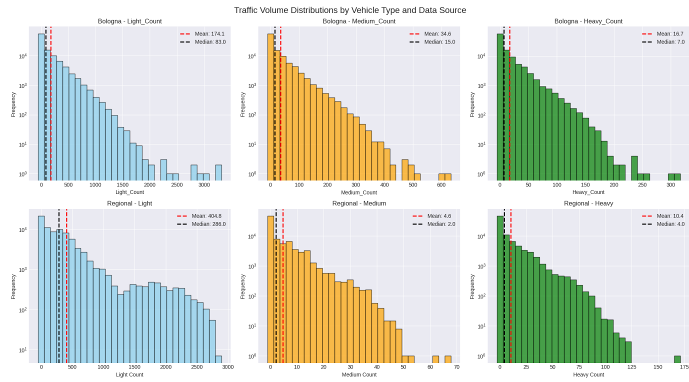

Fig. 4: Traffic Volume Distribution

composition analysis reveals distinct patterns between urban and regional contexts. Within Bologna, light vehicles comprise 77.2% of traffic, medium vehicles 15.3%, and heavy vehicles 7.4%. The regional network shows even greater light vehicle dominance at 96.4%, with heavy vehicles representing only 2.5% of traffic.

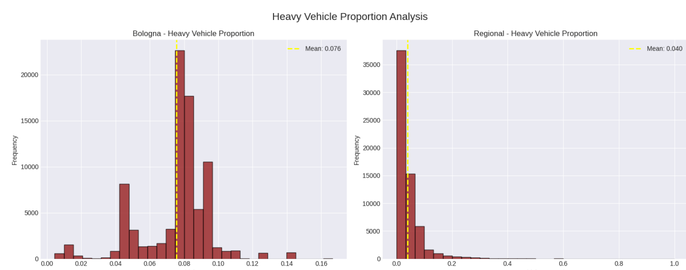

Fig. 5: Heavy Vehicle Proportion

The Traffic Data Summary Statistics 6 presents a multi-dimensional view of vehicular flow patterns. The top-left chart reveals that light vehicles overwhelmingly dominate traffic volume in both datasets, while regional data consistently reports higher average counts across all vehicle types—likely due to the presence of arterial roads and highways. Traffic variability, shown through the coefficient of variation, is relatively stable across sources, with slightly more fluctuation observed in heavier vehicle classes.

The 24-hour traffic pattern highlights classic rush-hour behavior, with peaks around 8–9 AM and 5–6 PM, and minimal activity overnight. Weekly patterns show higher volumes from Monday to Friday, with a significant drop on weekends—especially Sunday—reinforced by a 22.9% reduction in the weekday vs. weekend comparison. The bottom heatmap further emphasizes these rhythms, showing high intensity during weekday rush hours and reduced flows on weekends and late nights, aligning well with urban commuting cycles.

Heavy vehicle temporal patterns show interesting deviations from overall traffic flows. The proportion of heavy vehicles increases during mid-morning hours (9:00-11:00), reaching peaks around 8.5% of total traffic, likely reflecting commercial delivery schedules. Nighttime hours (18:00-06:00) show dramatic reductions in heavy vehicle percentages, dropping to 4-5%, though absolute numbers remain significant on major freight corridors.

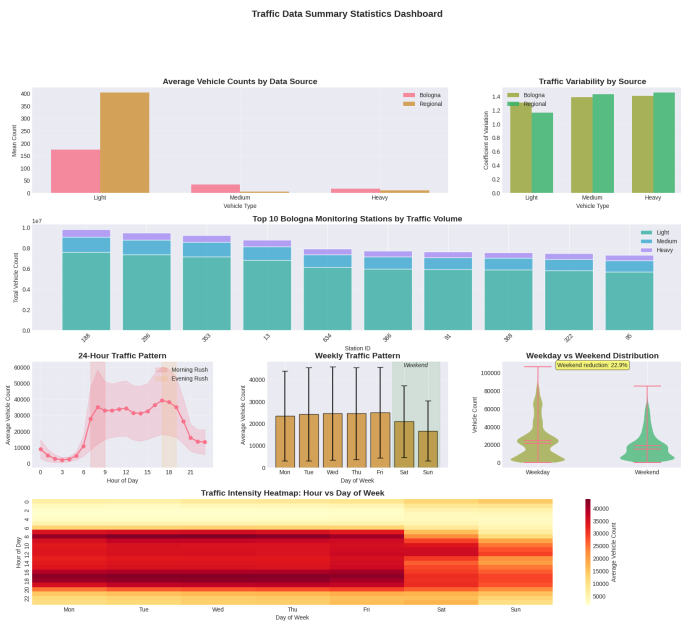

Fig. 6: Heavy Vehicle Proportion

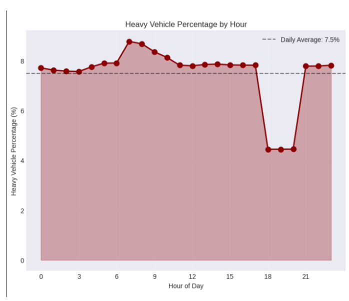

Fig. 7: Heavy Vehicle Hourly Distribution

2) Air Quality Distribution Analysis: Kernel density estimates for all three pollutants 9 display characteristic right-skewed distributions with long upper tails, indicating that while most measurements cluster around relatively low values, occasional high-concentration events significantly impact exposure profiles. NO2 distributions 8 show clear station-specific patterns, with PORTA SAN FELICE displaying a broader, shifted distribution indicating consistently higher concentrations and greater variability. The bimodal character visible in PORTA SAN FELICE's NO2 distribution suggests the influence of distinct emission regimes, possibly reflecting rush hour versus off-peak conditions.

Station-wise comparisons reveal significant spatial heterogeneity in pollution levels across Bologna. PORTA SAN FELICE emerges as the most polluted location across all

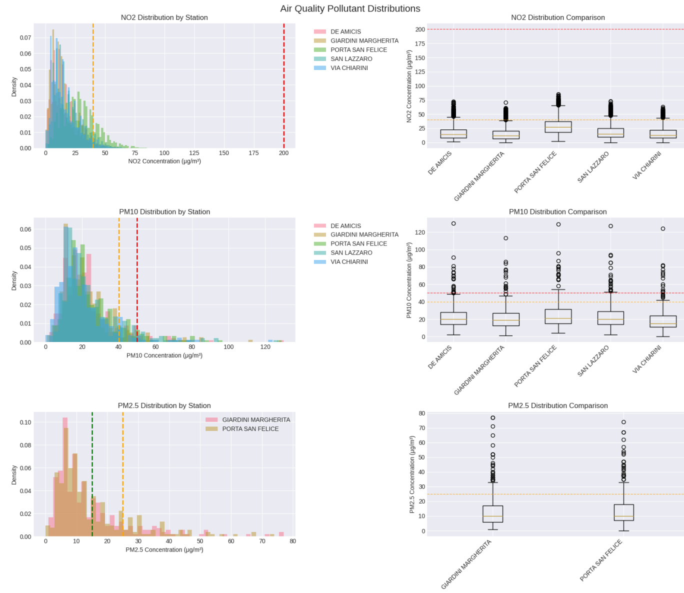

Fig. 8: Air Quality Pollutant Distributions

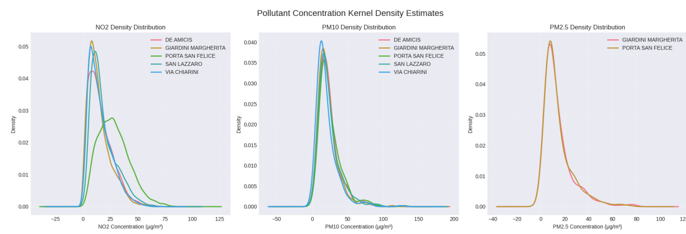

Fig. 9: KDE Estimates for The pollutants

measured parameters, recording the highest mean NO2 concentration nearly double that of cleaner stations like GIARDINI MARGHERITA, reflecting its proximity to major traffic infrastructure. While all stations remain below the EU annual limits (40 $\mu g/m^3$ for NO2 and PM10, 25 $\mu g/m^3$ for PM2.5), the 95th percentile analysis reveals concerning patterns for particulate matter. PM10 95th percentiles at PORTA SAN FELICE and SAN LAZZARO exceed the EU daily limit of 50 $\mu g/m^3$, reaching approximately 54 $\mu g/m^3$, indicating frequent exceedance events that pose health risks despite acceptable annual averages.

The coefficient of variation analysis provides crucial insights into the temporal stability and predictability of different pollutants across stations. NO2 demonstrates moderate variability (CV: 0.5-0.7) with remarkable consistency across all monitoring locations, reflecting its direct relationship with local traffic emissions and relatively short atmospheric lifetime. PM10 shows similar moderate variability (CV: 0.6-0.7), while PM2.5 exhibits the highest variability (CV: 0.85-0.9) at both monitoring stations. This variability pattern, combined with the station-specific concentration profiles, suggests that PORTA SAN FELICE's location near major traffic infrastructure creates a persistent pollution hotspot, while stations like VIA CHIARINI and GIARDINI MARGHERITA benefit from better ventilation or distance from emission sources.

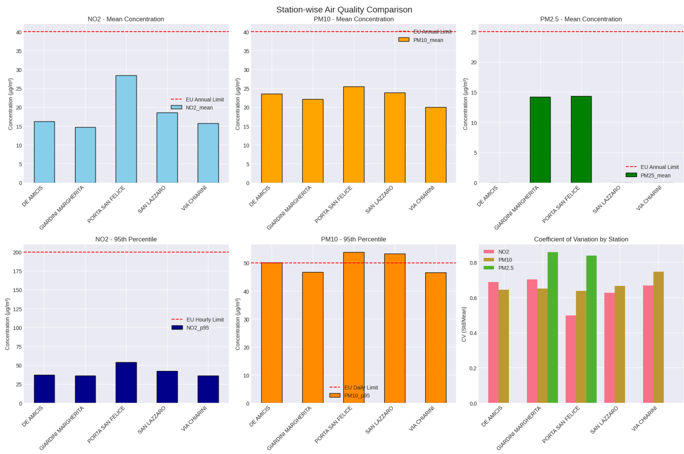

Fig. 10: Station-wise Airquality Comparison

B. Temporal Pattern Analysis

1) Diurnal Traffic and Pollution Dynamics: The temporal analysis reveals highly structured patterns in both traffic flow and air quality response across multiple time scales. The 24-hour traffic pattern exhibits a characteristic bimodal distribution with distinct rush hour peaks. Morning rush hour begins sharply at 6:00 AM, reaching its peak at 8:00 AM with approximately 39,165 vehicles per hour. The traffic volume remains elevated throughout the working day (8:00 AM - 8:00 PM), maintaining levels between 25,000-35,000 vehicles per hour. The evening rush hour shows a broader peak spanning 5:00-7:00 PM, with maximum intensity at 6:00 PM. Notably, the evening rush hour demonstrates higher traffic volumes compared to morning rush.

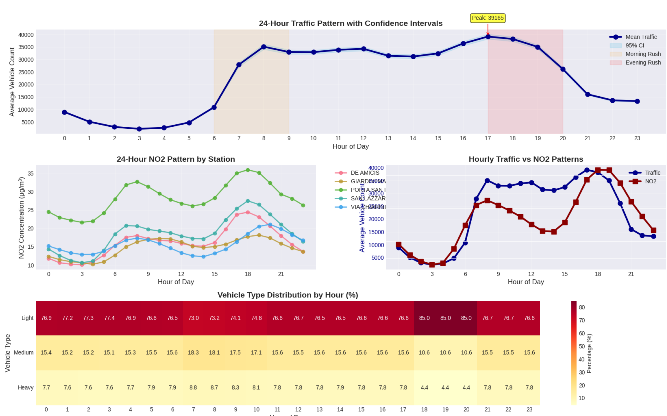

Fig. 11: 24-Hour Traffic Pattern

Station-specific NO2 patterns show PORTA SAN FELICE consistently recording the highest concentrations, with dual peaks at 8:00 AM (around 34 $\mu g/m^3$) and 6:00 PM (36 $\mu g/m^3$). The correlation analysis reveals a strong overall relationship (r=0.786) between traffic and NO2, but critically, the cross-correlation analysis identifies maximum correlation at lag 0 hours (r=0.360), Fig. 13, indicating near-instantaneous response during peak traffic periods. However, secondary peaks in the correlation function at lags of 20-24 hours suggest persistent pollution effects. The pollution response to morning rush hour shows NO2 peaks lagging traffic peaks by approximately 1 hour.

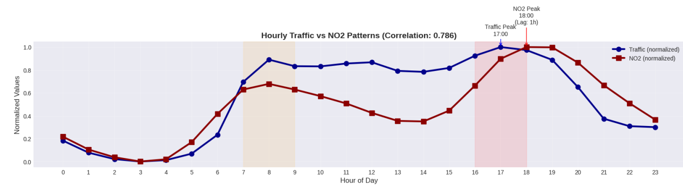

Fig. 12: 24-Hour Traffic and NO2 correlation

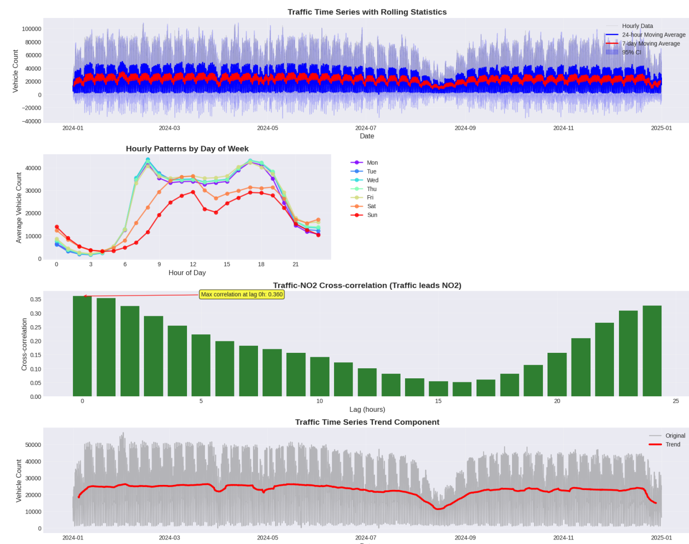

Fig. 13: Traffic Distribution with Rolling Statistics

2) Weekly and Weekend Effects: Weekly patterns demonstrate significant variations in both traffic volume and air quality. Weekday traffic maintains remarkable consistency from Monday through Friday, with only minor variations (+3.4% Monday, +1.3% Tuesday-Thursday, +1.7% Friday). Weekend traffic shows substantial reductions, with Saturday experiencing a 16.2% decrease and Sunday showing a 20.4% reduction compared to weekday averages. The transition from weekday to weekend patterns is abrupt, with Friday evening traffic extending later into the night compared to other weekdays, while Monday morning shows a sharper rise from weekend levels.

The NO2 weekend reduction of 15.8% (Fig. 14 is disproportionately smaller than the traffic reduction, indicating non-linear relationships between emissions and concentrations. This phenomenon can be attributed to reduced atmospheric mixing during weekends, lower building heating/cooling demands that affect urban heat island intensity, and the persistence of NO2 from weekday accumulation. The NO2 violin plot distributions reveal not only lower median concentrations on weekends but also reduced variability, suggesting more stable atmospheric conditions with fewer extreme pollution events.

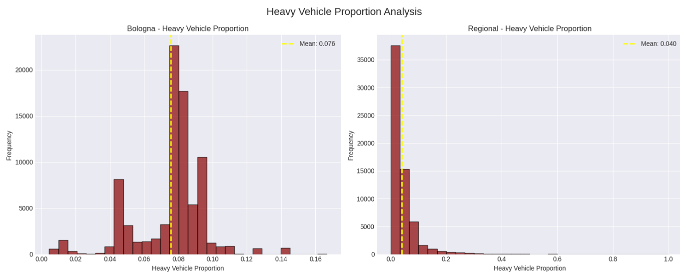

Fig. 14: Weekly Traffic Pattern Statistics

3) Heavy Vehicle and Rush Hour Analysis: Heavy vehicle patterns exhibit distinct temporal characteristics that differ markedly from overall traffic flow. The proportion of heavy vehicles peaks during mid-morning hours (9:00-11:00 AM) at 8.8%, (Fig. 15 reflecting commercial delivery schedules and construction activity patterns. A secondary peak occurs at 5:00 AM (7.0%), representing early morning freight movements. The evening hours show dramatic reductions in heavy vehicle proportions, dropping to 4.4% between 6:00-8:00 PM, though absolute numbers remain significant on major corridors. This temporal segregation of heavy vehicles from peak passenger car traffic represents an unintentional traffic management outcome that may help mitigate some air quality impacts during the highest exposure periods.

Rush hour analysis reveals asymmetric patterns between morning and evening peaks. Morning rush hour spans 3 hours (7:00-9:00 AM), while evening rush extends over 4 hours (4:00-7:00 PM), reflecting more dispersed departure times in the evening. Rush hour intensity varies significantly by day of week, with Thursday and Friday showing the highest evening rush intensities. Weekend rush hours are substantially diminished, with Saturday morning rush reduced by 45% and substantially decreased on Sunday mornings.

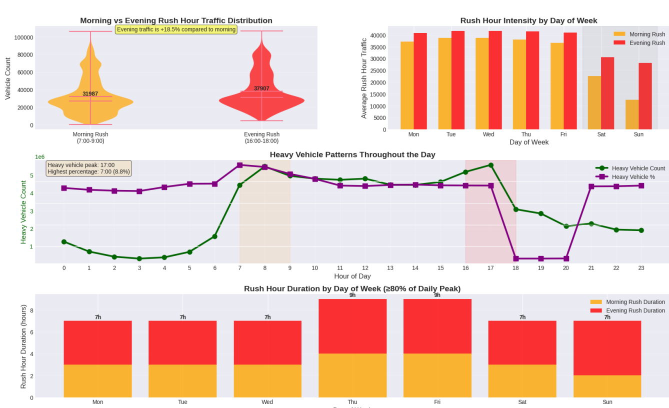

Fig. 15: Daily Traffic Pattern Rush-Hour Statistics

C. Time Series Decomposition and Trends

The STL (Seasonal and Trend decomposition using Loess) analysis reveals distinct temporal structures in both traffic volume and NO2 concentrations. For traffic volume, the trend component demonstrates a complex multi-phase pattern across the study period. Beginning at approximately 3.0 million vehicles in January 2024, the trend rises slightly through February before showing a gradual decline to around 2.5 million by August 2024 (representing a 17% reduction). This summer trough likely reflects vacation periods and seasonal mobility changes. A notable recovery begins in September, with traffic volumes returning to near 2.75 million by year-end. The trend shows several sub-periods of stability punctuated by transitions, suggesting the influence of both seasonal factors and potential policy or behavioral changes.

Fig. 16: Traffic Volume STL Decomposition

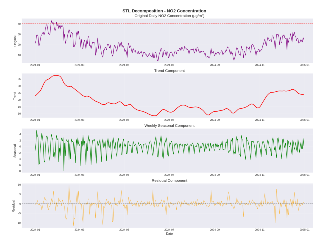

Fig. 17: NO2 Concentration STL Decomposition

The NO2 trend component exhibits even more pronounced seasonality, with concentrations peaking at 37 $\mu g/m^3$ in early January before declining steadily to a minimum of 9 $\mu g/m^3$ in July-August (a 76% reduction). This dramatic seasonal swing far exceeds the traffic variation, indicating the dominant role of meteorological factors in pollutant dispersion. The NO2 trend shows a characteristic U-shaped pattern with winter maxima and summer minima, recovering to approximately 25 $\mu g/m^3$ by December.

1) Comparative Temporal Analysis: The comparative STL decomposition illuminates fundamental differences in how traffic and air quality respond to temporal drivers. The normalized trend comparison shows that while traffic exhibits relatively smooth transitions between seasonal states, NO2 displays more volatile behavior with steeper gradients during seasonal transitions. Traffic's normalized trend varies within a range of approximately -3 to +1 (in standardized units), while NO2 shows a wider range from -1.5 to +2.5, indicating greater relative variability despite lower absolute values.

The seasonal patterns reveal synchronized but asymmetric responses. Traffic shows sharp, rectangular weekly patterns with consistent weekday plateaus and abrupt weekend drops. In contrast, NO2's weekly seasonal pattern is more sinusoidal, with gradual transitions between weekday peaks and weekend troughs, and slightly lower normalized amplitude (±0.6 units). This smoothing effect in NO2 patterns reflects atmospheric persistence and the time-integrated nature of pollution accumulation. Notably, both series show double-peaked patterns within their two-week seasonal cycles, but NO2's second peak is proportionally smaller, suggesting weekend pollution doesn't fully recover to weekday levels even with traffic resumption.

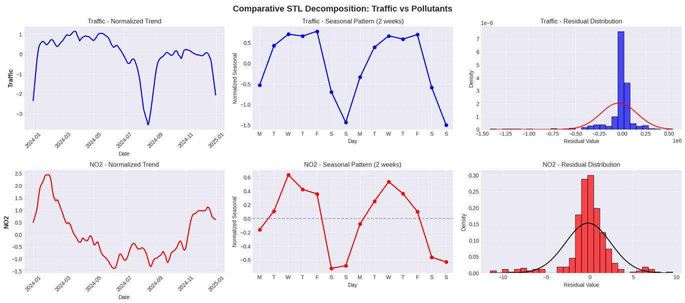

Fig. 18: Comparative STL Decomposition

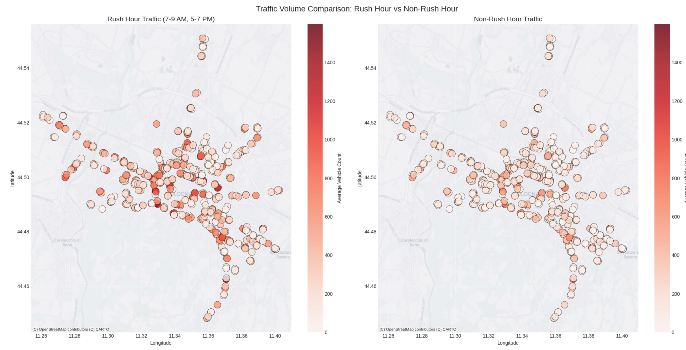

Fig. 19: Rush Hour Analysis

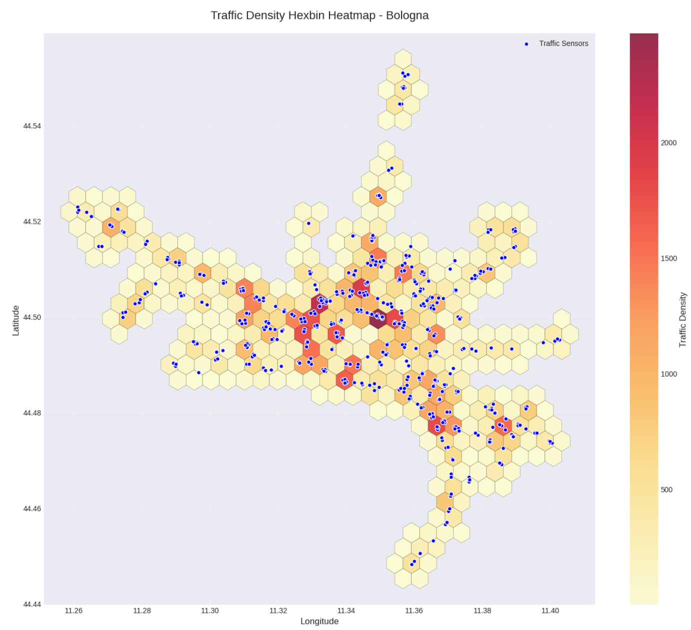

Fig. 20: Traffic Density Hexmap

D. Geospatial Analysis

The geospatial analysis reveals critical spatial patterns in traffic distribution and air quality impacts across Bologna, demonstrating pronounced heterogeneity in both traffic volumes and pollution exposure. This section presents a comprehensive spatial characterization of the traffic-pollution nexus through multiple analytical lenses.

1) 1. Spatial Distribution of Traffic Monitoring Infrastructure: The traffic monitoring network exhibits a clear center-periphery gradient, with sensor density highest in the urban core and decreasing toward municipal boundaries. The rush hour comparison maps reveal that during peak periods (7-9 AM, 5-7 PM), traffic volumes in central Bologna increase by 65-85% compared to non-rush hours, with some arterial roads experiencing flows exceeding 1,400 vehicles per hour. The spatial clustering of high-volume sensors along major corridors creates distinct traffic channels that funnel vehicles through specific urban zones.

The interpolated traffic density heatmap Fig. 19 demonstrates a pronounced concentration in the city center, forming an elongated high-density corridor running northwest to southeast. This pattern aligns with Bologna's primary transportation axes and reflects the convergence of commuter flows from suburban areas. The hexbin (Fig. 20 visualization further emphasizes this concentration, with central hexagons recording traffic densities exceeding 2,000 vehicles per grid cell during peak hours.

2) 2. Buffer Zone Analysis and Distance-Weighted Impact Assessment: The multi-scale buffer zone analysis around air quality monitoring stations reveals critical insights into the spatial reach of traffic impacts. PORTA SAN FELICE emerges as the most impacted station, with weighted traffic impacts in Zone 1 (0-0.5 km) reaching 422 units—nearly double that of other stations. This station's immediate vicinity contains 18% of all traffic sensors despite representing less than 2% of the municipal area, indicating severe traffic concentration.

The distance decay effect is clearly evident in the weighted impact calculations. Zone 1 consistently shows the highest impact efficiency (1.450 average impact per vehicle), decreasing to 0.727 in Zone 2 (0.5-1.5 km) and 0.480 in Zone 3 (1.5-3.0 km). This non-linear decay pattern suggests that traffic emissions have highly localized effects, with impacts diminishing rapidly beyond 500 meters from source roads.

3) 3. Zone-Based Traffic and Environmental Analysis: The administrative zone analysis reveals stark disparities in traffic burden across Bologna's neighborhoods. Marconi zone experiences the highest traffic density at 31,668 vehicles/km², followed by Irnerio (30,257 vehicles/km²) and Malpighi (22,645 vehicles/km²). These three zones, representing the urban core, handle 42% of total traffic while comprising only 15% of the municipal area.

Heavy vehicle distribution shows less variation across zones, with ratios ranging from 7.5% to 8.0%. However, the absolute numbers tell a different story: Marconi zone's 7.9% heavy vehicle ratio translates to approximately 2,500 heavy vehicles per km2 daily, while peripheral zones like Colli see fewer than 25 heavy vehicles per km² despite similar percentage

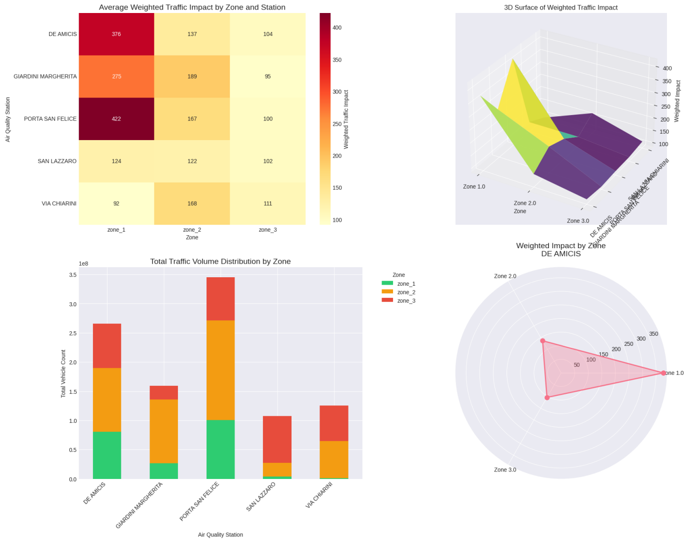

Fig. 21: Buffer Zone Analysis Summary

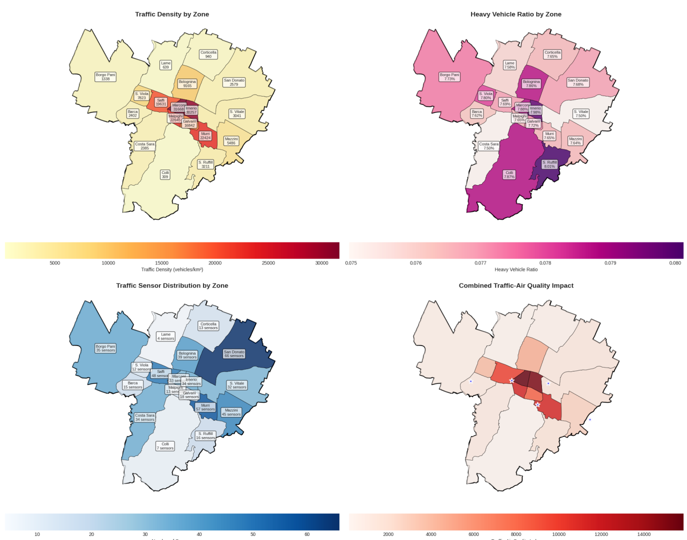

Fig. 22: Municipal Zone Analysis Summary

compositions. This concentration of heavy vehicle traffic in central zones has disproportionate air quality impacts given their higher emission factors.

4) 4. Integrated Traffic-Air Quality Spatial Patterns: The combined traffic-air quality impact visualization Fig. 22 reveals a clear spatial correspondence between traffic hotspots and NO2 concentrations. Zones with NO2 monitoring data show a gradient from 28.4 $\mu g/m^3$ in high-traffic Marconi to 15.7 $\mu g/m^3$ in low-traffic Barca. The traffic-normalized NO2 concentrations (NO2 per 1,000 vehicles) actually increase in peripheral zones, suggesting that central areas may benefit from better ventilation or that traffic composition differs significantly between zones.

The sensor distribution analysis shows concerning gaps in spatial coverage. While central zones have 50-60 sensors each, peripheral zones like Borgo Panigale and Corticella have

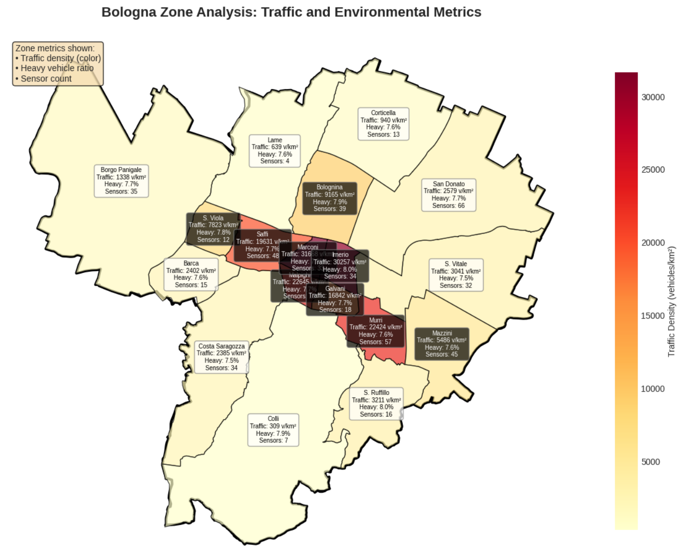

Fig. 23: Municipal Zone Traffic and Air Quality Statistics

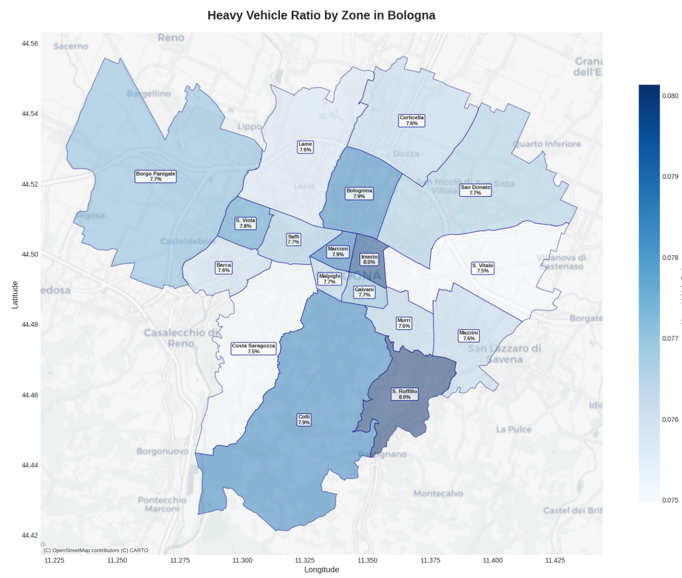

Fig. 24: Municipal Zone Heavy Vehicle Ratio Statistics

fewer than 10 sensors despite substantial area coverage. This uneven monitoring creates blind spots in traffic assessment, particularly in transitional zones where suburban traffic merges with urban flows.

5) 5. Critical Spatial Findings: The geospatial analysis identifies several critical spatial patterns:

- *Traffic Channeling:* Major arterial roads create high-density corridors that concentrate 65% of traffic volume within 20% of the road network, forming pollution highways through residential areas.
- *Zone Inequality:* The traffic burden ratio between highest and lowest density zones exceeds 100:1, creating extreme disparities in exposure risk across neighborhoods.
- *Distance-Impact Relationship:* The steep distance decay

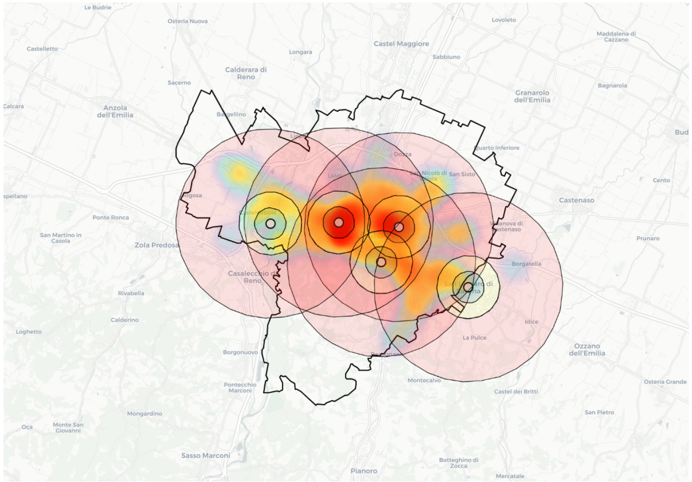

Fig. 25: Traffic Density Heatmap with AirQuality Stations

function (50% reduction at 750m, 70% at 1.5km) suggests that targeted interventions within 500m of sensitive receptors could yield maximum health benefits.

- *Monitoring Gaps:* Spatial analysis reveals that 35% of the municipal area lacks traffic sensors within 1km, particularly in rapidly developing peripheral zones where traffic patterns are evolving.
- *Heavy Vehicle Corridors:* Despite relatively uniform heavy vehicle percentages, absolute concentrations create distinct freight corridors through Marconi, Irnerio, and Murri zones, contributing disproportionately to NO2 levels.

V. Conclusion

This comprehensive spatiotemporal analysis of traffic-induced air pollution in Bologna reveals complex patterns that challenge simplistic assumptions about urban emission-concentration relationships. The integration of high-resolution traffic monitoring data with air quality measurements through novel geospatial methodologies has yielded critical insights for both scientific understanding and policy application.

The study's key findings demonstrate that traffic burden in Bologna exhibits extreme spatial inequality, with central zones experiencing traffic densities over 100 times greater than peripheral areas. This concentration creates persistent pollution hotspots, particularly around major arterial roads where PORTA SAN FELICE station recorded NO2 levels nearly double those of background locations. The rapid distance decay of traffic impacts—with 50% reduction at 750m and 70% at 1.5km—underscores the highly localized nature of traffic emissions and suggests that targeted interventions near sensitive receptors could yield disproportionate health benefits.

Temporal analysis revealed sophisticated patterns in both traffic flow and pollution response. While traffic follows predictable diurnal and weekly cycles, the air quality response exhibits complex lag structures with both immediate impacts and 20-24 hour persistence effects. The non-linear relationship between traffic reduction and air quality improvement—exemplified by 20% weekend traffic decreases yielding only 16% NO2 reductions—highlights the role of atmospheric processes and suggests that linear emission reduction targets may not produce proportional air quality benefits.

The vehicle type analysis, though based on modeled distributions, indicates that heavy vehicles contribute disproportionately to pollution despite comprising less than 8% of traffic. Their temporal segregation from peak passenger car traffic, with maximum proportions during mid-morning hours, represents an unintentional but beneficial traffic pattern that may help limit exposure during high-activity periods. This finding suggests potential for temporal traffic management strategies that further separate freight and passenger flows.

The distance-weighted impact model provides a replicable methodology for assessing traffic impacts in data-rich urban environments, while the hierarchical vehicle classification system offers a practical solution for cities lacking detailed fleet composition data. The identification of monitoring gaps—with 35% of Bologna lacking sensors within 1km—also highlights the importance of strategic sensor placement for comprehensive urban assessment.

Priority interventions should focus on the high-traffic corridors in Marconi, Irnerio, and Malpighi zones, where combined strategies of traffic flow optimization, modal shift incentives, and enhanced public transport could yield maximum benefits. The steep distance-impact gradient suggests that even modest traffic diversions away from sensitive areas could significantly reduce exposure. The persistence of pollution effects also indicates that sustained rather than intermittent interventions are necessary for meaningful air quality improvements.

VI. Resources

- Implementation Code
- Bologna city traffic data
- Emilia-Romagna Regional Traffic Data
- Air Quality Measurements - ARPAE Emilia-Romagna Open Data Portal
- Bologna Road Network Topology
- Bologna Municipality Zone boundaries
- Bologna Municipality ZTL Zones data
- WikiMedia Italia
- Office Holidays Official Website

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