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A multi-scale analysis of spatiotemporal variability and environmental influences on urban noise

Junhyeon Kweon, Sugie Lee *

Department of Urban Planning & Engineering, Hanyang University, Science & Technology Bld. 303-1, 222 Wangsimni-ro Seongdong-gu, Seoul 04763, Republic of Korea

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ABSTRACT

Urban noise has emerged as a critical environmental stressor affecting public health in densely populated cities. Most existing studies, however, rely on temporally aggregated approaches that obscure how noise-environment relationships vary across seasons and times of day, limiting analytical insight and spatial coverage.

This study presents an integrated spatiotemporal framework for urban noise analysis in Seoul, South Korea, using five years of continuous IoT sensor data from 762 monitoring locations. Temporal contexts were defined through Circular K-means clustering, yielding 28 season-by-time-of-day combinations, with meteorological effects explicitly controlled to isolate urban structural contributions. Independent ExtraTrees models were trained for each context and applied to unmeasured locations, with results aggregated to administrative units for neighborhood-scale exposure assessment.

Results reveal that noise-environment relationships are not temporally invariant — while road infrastructure consistently ranked as the primary predictor, its relative importance was systematically displaced by commercial activity indicators during evening hours and by topographic features during summer contexts, patterns that a temporally pooled model would fail to detect. Districts with similar mean noise levels exhibited substantially different temporal profiles, underscoring that location alone is insufficient to characterize noise burden. Spatial analysis identified significant neighborhood-scale clustering, with central areas exhibiting both higher exposure and greater temporal variability.

These findings demonstrate that context-stratified modeling reveals dimensions of urban noise dynamics that static approaches systematically obscure. The framework is transferable to other data-rich cities seeking evidence-based noise management.

1. Introduction

Noise was first discussed as a critical factor for managing environmental quality in human settlements at the 1972 United Nations Conference on the Human Environment (Berglund et al., 1999; United Nations, 1972). Since then, urban noise has been consistently identified as a significant environmental stressor, with documented adverse effects on public health (Berglund et al., 1999; Hahad et al., 2025). This recognition has prompted growing attention to noise pollution and spurred discussions on establishing noise standards and urban design strategies for healthier acoustic environments.

Urban noise levels have risen substantially with increasing population density and intensified human activities. While traffic remains a primary source, contemporary urban soundscapes reflect diverse contributors including commercial activities, industrial operations, and construction (González, 2012). Beyond source intensity, noise propagation and perception are shaped by the built environment: land use patterns, building configurations, street layouts, and landscape features all influence measured noise levels and resident exposure (Ragettli et al., 2016; Song et al., 2024; Van Renterghem et al., 2011). Topographic conditions, street-level visual characteristics, and other fine-grained urban attributes have further been shown to modulate both noise intensity and its perceptual dimensions (Huang et al., 2024; Zhao et al., 2023). Understanding these interactions requires analytical frameworks that capture both spatial heterogeneity and temporal variability in urban acoustic environments.

Recent advances in IoT sensor networks have created new opportunities for continuous, citywide noise monitoring. However, raw IoT sensor data often require careful quality control prior to analysis, as device malfunctions and transmission errors can introduce substantial

* Corresponding author.
E-mail addresses: legojun98@hanyang.ac.kr (J. Kweon), sugielee@hanyang.ac.kr (S. Lee).

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noise into the dataset (Krishnamurthi et al., 2020). Beyond data quality, existing studies largely rely on temporally aggregated measurements that may obscure meaningful variation across seasons and times of day, which has been shown to span several decibels within the same urban area (Munir et al., 2021; Tsai et al., 2009; Xu et al., 2022). Similarly, while machine learning methods have advanced noise prediction considerably (Wu & Wang, 2025; Zhang et al., 2026), most models treat predictor-noise relationships as temporally invariant, potentially misrepresenting the context-dependent dynamics of urban acoustic environments.

This study addresses these gaps through an integrated spatiotemporal framework for urban noise analysis in Seoul, South Korea. Three hypotheses guide the analysis. First, noise levels exhibit temporal heterogeneity across seasons and times of day, necessitating context-specific rather than aggregated modeling. Second, the relative importance of urban environmental predictors varies across temporal contexts, reflecting shifts in dominant noise sources and activity patterns. Third, noise exposure exhibits spatial clustering across administrative districts. Through this framework — combining IoT monitoring, temporally stratified machine learning, and spatial prediction — this study provides empirical evidence for developing context-specific noise management strategies in high-density urban environments.

2. Literature reviews

2.1. Noise in urban environments

Urban noise significantly affects quality of life and public health in cities worldwide. Outdoor noise levels exceeding recommended thresholds have been associated with a range of adverse health outcomes, including sleep disturbance, cardiovascular disease, and cognitive impairment, contributing to measurable losses in healthy life years (Berglund et al., 1999; Hahad et al., 2025; Münzel et al., 2014; Razai et al., 2025; Zhang et al., 2025), with levels above 73 dB considered environmental pollution requiring intervention (da Paz et al., 2018; World Health Organization, 1999).

Urban noise exhibits substantial spatial and temporal variability across cities. Road traffic remains a dominant source, but noise levels vary considerably across different land uses, with mixed-use districts often experiencing elevated and persistent noise from combined residential, commercial, and transportation activities (Tong & Kang, 2021; Wu & Wang, 2025). This spatial heterogeneity reflects the complex interplay of urban density, transportation networks, building configurations, and street morphology, necessitating fine-grained measurement approaches that capture neighborhood-scale variation.

Recent advances in IoT sensor technologies have transformed urban noise monitoring capabilities. IoT-based sensors enable continuous measurement at high spatial and temporal resolution, supporting noise regulation monitoring, problem area identification, and source classification (Abeßer et al., 2018; Mydlarz et al., 2017; Park & Baek, 2023; Peckens et al., 2018). However, raw IoT sensor data often requires careful quality control prior to analysis, as device malfunctions and transmission errors can compromise data integrity (Krishnamurthi et al., 2020). By positioning sensors proximate to residents' daily environments, these networks provide the foundation for evidence-based noise management strategies at citywide scale.

2.2. Factors influencing urban noise

In urban areas, road traffic is the primary source of noise, prompting extensive research on relationships between traffic volume, road characteristics, and measured noise levels (Kim et al., 2019; Morillas et al., 2018; Ryu et al., 2017). Land use patterns are critical determinants of noise distribution, with land use regression models demonstrating that different land use types produce distinct noise profiles that explain substantial spatial heterogeneity in exposure (Chang et al., 2019; Ragettli et al., 2016; Xu et al., 2022).

Beyond road network characteristics, the built environment exerts multifaceted influences on urban noise. Significant relationships have been identified between noise levels and urban form indicators including population density, building coverage, and floor area ratio (Tang & Wang, 2007; Wu & Wang, 2025; Zhang et al., 2026). Building morphology and street geometry further modify noise propagation: building arrangement, height variations, sky view factors, and vegetation coverage in street view all shape exposure patterns (Huang et al., 2024; Van Renterghem et al., 2011; Zhao et al., 2023). Topographic conditions constitute an additional modulating factor, as slope and elevation have been shown to attenuate or amplify sound depending on terrain configuration (Heimann, 2010; Li & Xie, 2021). These findings collectively demonstrate that urban noise results from complex interactions among transportation infrastructure, built form, and landscape characteristics.

Temporal variability in urban noise has received comparatively less attention. Noise levels have been shown to vary meaningfully across seasons and times of day within the same urban area (Tsai et al., 2009; Xu et al., 2022), yet most existing studies rely on temporally aggregated measurements — typically 24-h or daytime/nighttime averages — that may obscure context-specific noise dynamics. Meteorological conditions, including temperature and humidity, have also been identified as significant modulators of ambient noise levels through their effects on both sound propagation and human outdoor activity patterns (Munir et al., 2021; Van Renterghem et al., 2011).

Machine learning methods have recently gained prominence in urban noise analysis due to their ability to model complex nonlinear relationships (Wu & Wang, 2025; Zhang et al., 2026). Ensemble algorithms such as Random Forest, Gradient Boosting, and Extra Trees have demonstrated superior predictive performance compared to traditional linear models, effectively capturing nonlinear associations between diverse urban features and noise levels (Poblete et al., 2026; Wu & Wang, 2025).

2.3. Research gaps and objectives

Despite methodological advances in urban noise research, three critical gaps persist in literature. First, most studies employ temporally aggregated approaches — such as annual averages or broad daytime/nighttime distinctions — that obscure meaningful variation across seasons and times of day (Munir et al., 2021; Tsai et al., 2009; Xu et al., 2022). This aggregation risks masking peak exposure periods and misrepresenting the context-specific dynamics of noise-environment relationships, particularly given that meteorological conditions modulate noise levels across temporal contexts (Van Renterghem et al., 2011).

Second, citywide analyses incorporating diverse urban environmental variables remain limited. Many existing studies rely on a small number of monitoring points or low-cost sensors with constrained spatial coverage (Abeßer et al., 2018; Mydlarz et al., 2017; Peckens et al., 2018), and most focus predominantly on traffic-related predictors while neglecting the broader range of built environment, topographic, and activity-based factors that shape urban acoustic environments. Although land use regression models have advanced noise prediction, these efforts are typically confined to small study areas and a limited set of explanatory variables (Chang et al., 2019; Ragettli et al., 2016), leaving the relative contributions of diverse urban features across large metropolitan areas poorly understood.

Third, the translation of noise modeling into comprehensive spatial exposure assessment at administratively relevant scales remains underdeveloped. While machine learning models have improved predictive accuracy (Wu & Wang, 2025; Zhang et al., 2026), most studies focus on prediction performance rather than citywide exposure mapping or neighborhood-scale inequity analysis. The spatial distribution of noise burden across administrative districts — and its relationship to socioeconomic characteristics — has received limited systematic attention,

constraining the policy relevance of existing findings (Casey et al., 2017; Dale et al., 2015).

This study addresses these gaps through an integrated analytical framework applied to Seoul, South Korea. Specifically, we (1) characterize fine-grained spatiotemporal noise patterns using five years of continuous IoT sensor data from 762 monitoring locations, examining variations across seasonal and diurnal contexts; (2) develop temporally stratified machine learning models to capture context-dependent relationships between comprehensive urban environmental features and noise levels, with explicit meteorological control; and (3) generate citywide noise predictions for unmeasured locations and aggregate results to administrative units for indicative spatial exposure assessment. Together, these objectives address the temporal heterogeneity of urban noise exposure and demonstrate its implications for understanding urban environmental conditions across spatial and temporal contexts.

3. Methodology

This study follows a three-stage analytical framework, as illustrated in Fig. 1. First, temporal contexts are defined through Circular K-means clustering to enable time-stratified analysis of noise-environment relationships. Second, context-stratified machine learning models are trained and evaluated, with meteorological effects explicitly controlled to isolate urban structural contributions to noise exposure. Third, trained models are applied to virtual prediction points for citywide spatial prediction, with results aggregated to administrative units for neighborhood-scale exposure assessment. Each stage is described in the following sections.

3.1. Study area and data

Seoul, the capital of South Korea, is a megacity with a population of approximately 9.7 million within an area of 605 km^2, of which 61% constitutes urbanized land. Its high building density, extensive transportation infrastructure, and diverse land use patterns make it a suitable testbed for urban noise analysis. Noise levels in parts of the city have been reported to exceed WHO recommended thresholds (Kim et al., 2025; Lee et al., 2014).

This study utilizes the Smart Seoul Data of Things (S-DoT) network, an IoT-based environmental monitoring infrastructure comprising 1159 pole-mounted sensors deployed citywide since 2019. Sensors are installed at approximately 3–4 m height and record noise, temperature, humidity, and other parameters at hourly intervals (Park & Baek, 2023). Data are transmitted wirelessly and released weekly through the Seoul Open Data Plaza Portal. Each sensor is administratively labeled by the Seoul Metropolitan Government according to its surrounding environment — including residential area, commercial area, traditional market, industrial area, main street, and public facilities — to facilitate infrastructure management and reflect ambient conditions experienced by residents, rather than formal land use designations. While approximately 70% of sensors are labeled as residential, the S-DoT network was designed to provide broad spatial coverage across diverse urban environments, and sensor distribution should be interpreted accordingly.

The study period spans five years, from March 2021 to February 2025, capturing the earliest point at which all sensors in the network had reached full operational status. This extended temporal coverage facilitates stable aggregation of observations, minimizing the influence of sporadic missing values and short-term anomalies in estimating noise levels across temporal contexts. Noise levels, recorded as equivalent continuous sound pressure levels (Leq, dB) temperature (°C), and relative humidity (%) — parameters consistently recorded across all sensors throughout the study period — were used as the dependent variable and meteorological control variables, respectively.

Raw IoT sensor data may contain erroneous or missing records arising from device malfunctions and transmission errors, necessitating systematic quality control prior to analysis (Krishnamurthi et al., 2020). Sensors were excluded if noise measurements were missing for more than 50% of the study period ($n = 41$), or if more than 50% of recorded days showed no diurnal variation, indicating potential malfunction ($n = 232$). Sensors located within 100 m of another sensor were further reduced by retaining the one with fewer missing values ($n = 124$ removed). Quality control was based solely on noise measurements, as temperature and humidity gaps consistently coincided with noise data gaps. The final dataset comprised 762 spatially distributed sensors (Fig. 2).

3.2. Urban environmental features

Urban environmental features were constructed by extracting spatial variables within buffer zones around each sensor location, drawing on factors identified in prior literature as significant predictors of urban noise exposure (Ragettli et al., 2016; Wu & Wang, 2025; Xu et al., 2022). As summarized in Table 1, variables were organized into six categories: Land Use, Built Environment, Natural Environment and Topology,

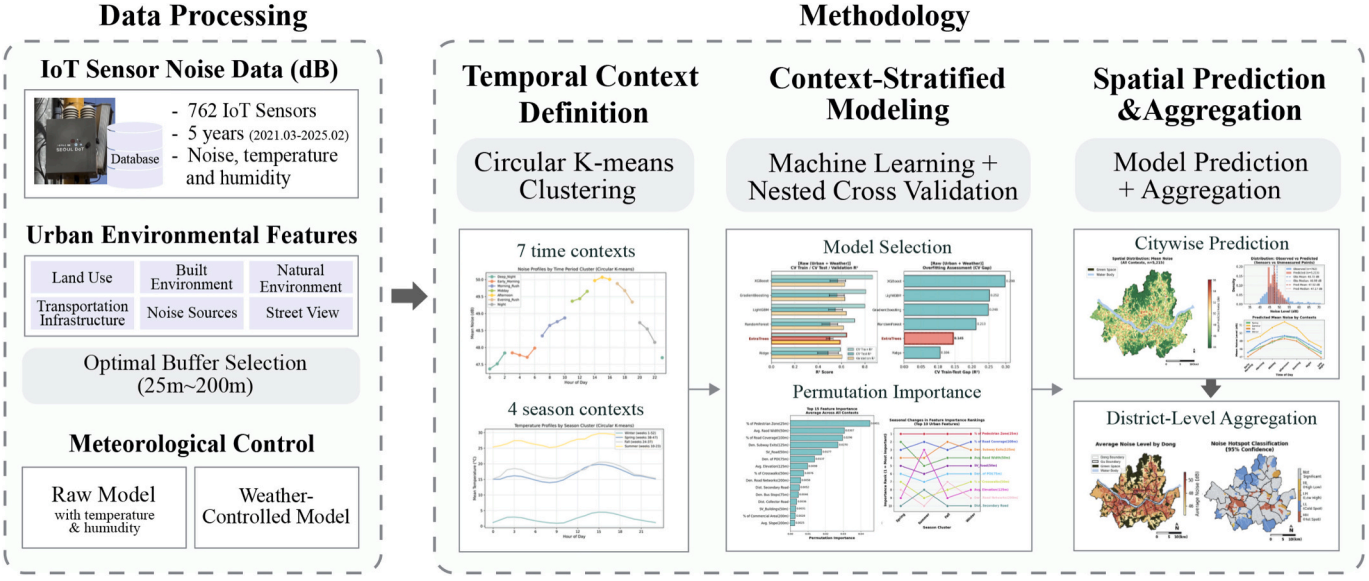

Fig. 1. Overall analytical framework of the study.

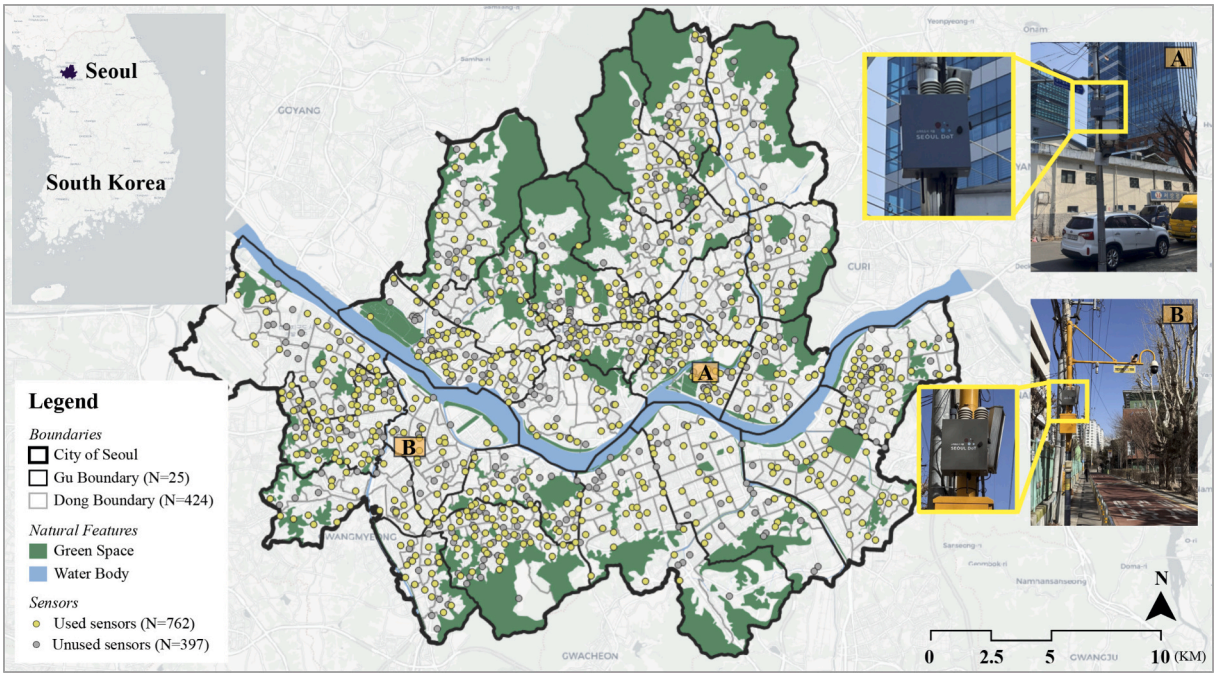

Fig. 2. Study area and sensor network in Seoul, South Korea. Note: Administrative boundaries sourced from Seoul Metropolitan Government. Natural features derived from national land cover data. Map lines delineate study areas and do not necessarily depict accepted national boundaries. Representative photographs of S-DoT sensors installed in urban street taken by authors (2026).

Transportation Infrastructure, Noise Sources, and Street View Elements.

Buffer size selection was addressed explicitly to avoid arbitrary spatial scale assumptions. Previous studies have applied buffers ranging from 25 m to 500 m, with larger buffers capturing broader environmental conditions at the risk of diluting localized noise variation (Zhang et al., 2026), while most significant predictors have been found to emerge within 150 m of the measurement point (Wu & Wang, 2025). Given that optimal buffer sizes vary across urban contexts and variables, this study constructed predictors at eight buffer distances from 25 m to 200 m at 25 m intervals, rather than relying on a single fixed scale. This approach addresses the Modifiable Areal Unit Problem (MAUP) by allowing the data to determine the most appropriate spatial resolution for each variable (Openshaw, 1984).

To identify the optimal buffer for each variable, buffer distances from 25 m to 200 m at 25 m intervals were evaluated against the sensor-level five-year noise mean using the absolute Pearson correlation coefficient. Prior studies have selected variable-specific buffer distances based on similar criteria, such as model R^2 (Wong et al., 2025) or strength of association between environmental variables and outcomes (Lechner et al., 2012). For each variable, the buffer distance yielding the highest absolute correlation with the sensor-level noise mean was selected as the optimal value. Criterion values across all candidate buffer distances and descriptive statistics for all urban environmental variables are provided in supplementary materials.

3.3. Temporal context definition

Temporal contexts were defined using Circular K-means clustering, an approach suited to cyclical data structures such as time-of-day and seasonal patterns. Unlike conventional K-means, Circular K-means operates on angular representations of cyclic variables, ensuring that temporal boundaries — midnight (0 h/24 h) — are treated as continuous rather than discrete transitions, thereby preserving the periodicity of the data (Charalampidis, 2005). Two clustering procedures were conducted: hourly noise observations were used to partition the 24-h cycle into time-of-day clusters, while mean temperature was used to delineate seasonal clusters. The optimal number of clusters for each dimension was determined by maximizing the silhouette coefficient. The combination of time-of-day and seasonal clusters yields a set of mutually exclusive temporal contexts, capturing a distinct spatiotemporal condition.

3.4. Context-stratified modeling

Six machine learning algorithms were evaluated: Ridge regression as a regularized linear model, and five tree-based ensemble methods — Random Forest, Gradient Boosting, XGBoost, LightGBM, and Extra Trees. Tree-based ensemble methods were prioritized because they can effectively capture nonlinear relationships and complex interactions among predictors without requiring assumptions of linearity or independence among explanatory variables (Breiman, 2001; Friedman, 2001). Model selection was conducted using nested cross-validation, with a 5-fold outer loop for performance estimation and a 3-fold inner loop with grid search for hyperparameter tuning (Cawley & Talbot, 2010). The dataset was split into a training set (80%, $n = 609$ sensors) and a held-out validation set (20%, $n = 153$ sensors) prior to cross-validation. The training set was used for all nested CV procedures, while the validation set was reserved for final model evaluation. R^2 served as the evaluation metric. Prior to context-level evaluation, all models were assessed on a sensor-level baseline specification in which the dependent variable was the overall five-year noise mean aggregated across all seasons and times of day, without temporal stratification. This baseline specification served as the reference for overall model performance evaluation and selection.

Two model specifications were estimated to isolate the contribution of urban environmental features. A Raw model incorporated both urban environmental and meteorological variables as predictors of observed noise levels. A Weather-Controlled model first removed meteorological effects via ordinary least squares regression, with the residuals used as the dependent variable and urban features as the sole predictors. This two-stage specification enables direct assessment of urban structural contributions to noise independent of meteorological variation. The final model was selected based on a criterion balancing predictive performance (CV Test R^2), generalizability (train-test gap), and cross-fold

Table 1
Description of urban environmental features.

Category	Name	Optimal Buffer	Description	Data Source
Land Use	Residential area coverage	200 m	Proportion of residential / commercial / business district area from in each buffer (%)	V-World
	Commercial area coverage	200 m		
	Business area coverage	75 m		
	Land use mix	125 m	Shannon diversity index of 4 land use types (Containing 3 types in above and 'others')	
Built Environment	Density of buildings	150 m	Proportion of building footprint area to total buffer area / mean height and maximum height of buildings within buffer (m)	
	Mean building height	125 m		
	Maximum building height	200 m		
Natural Environment & Topography	Green space ratio	25 m	Proportion of green space / water body within buffer (%)	
	Water body ratio	25 m		
	Mean slope	200 m	Mean terrain slope within buffer	
	Mean elevation	125 m	Mean elevation above sea level and its standard deviation within buffer	
	Elevation standard deviation	25 m		
Transportation Infrastructure	Road coverage ratio	100 m	Proportion of road surface area within buffer (%)	Seoul Open Data Portal
	Mean road width	50 m	Mean width (m) and density of road segments within buffer	
	Road networks density	150 m		
	Intersections density	150 m	Density of intersections within buffer	
	Distance to overground railway	N/A	Shortest distance to overground railway, and 4-level public roads (m) from the center point of buffer	
	Distance to arterial / secondary / collector / local roads	N/A		
Noise Sources	Pedestrian zone density	25 m	Density of pedestrian zone / crosswalks / public bike dock stations / bus stops and exits of subway stations within buffer	
	Crosswalks density	50 m		
	Bike docks density	125 m		
	Bus stops density	75 m		
	Subway exits density	125 m		
Street view elements	Point of interests (POI) density	75 m	Density of all points of interest (urban amenities and conveniences) within buffer	Kakao Map
	Sky coverage	125 m	Mean proportion of each urban element visible within street view images in the buffer area, derived from semantic segmentation using HRNetV2 + OCR, trained with Cityscapes dataset applied to Kakao Map street view imagery	
	Buildings coverage	50 m		
	Terrain coverage	150 m		
	Walls coverage	50 m		
	Road coverage	175 m		
	Sidewalk coverage	50 m		

Note: All data sources are publicly available from Seoul Open Data Portal (data.seoul.go.kr, operated by The Seoul Metropolitan Government), V-World (vworld.kr, operated by the Ministry of Land, Infrastructure and Transport, Republic of Korea) and Kakao Map (map.kakao.com, operated by the Kakao Corporation). All data were accessed and processed in 2025. In the following results, abbreviated variable names are used for brevity: % = proportion, Avg. = mean, Den. = density, Max. = maximum, and SV_ = mean proportion of each urban element in street view imagery.

consistency (standard deviation of fold-level R^2).

Feature importance was assessed using permutation importance (Breiman, 2001; Strobl et al., 2008), which measures the decrease in R^2 when each feature is randomly permuted on the held-out test set. Permutation importance was preferred over Gini-based importance for its robustness to correlated features and its direct grounding in out-of-sample predictive performance (Christoph, 2020). Importance scores were computed with 10 permutations per feature and analyzed both globally across all contexts and stratified by temporal context to examine variation in feature-noise relationships.

3.5. Spatial prediction and aggregation

To extend noise estimates beyond monitored locations, virtual prediction points were generated at 200 m intervals across Seoul — a spacing sufficient to ensure comprehensive citywide coverage while encompassing the full range of buffer distances used in variable construction. Points overlapping green space or water body areas were excluded. Urban environmental features were extracted at each point using the variable-specific optimal buffer distances identified in Table 1, maintaining methodological consistency with the sensor-level models. Predictions were generated independently for each temporal context, and the resulting point-level estimates were aggregated to Seoul's administrative 'Dong' districts to enable neighborhood-scale noise exposure assessment and spatial pattern analysis.

4. Results

4.1. Temporal context definition

Circular K-means clustering was applied to hourly noise observations and mean temperature records to define temporal contexts for noise aggregation. The optimal number of clusters was determined on the silhouette coefficient, yielding seven time-of-day clusters and four seasonal clusters, labeled according to their noise and temperature profiles (Fig. 3).

For time-of-day clustering, three clusters covered the late-night to early-morning period — Deep Night, Early Morning, and Morning Rush — each spanning approximately four hours, while the remaining four clusters covered roughly three-hour intervals. This asymmetry reflects finer-grained noise variation during daytime hours relative to the more gradual and uniform changes observed at night. For seasonal clustering, four clusters broadly corresponding to Spring, Summer, Fall, and Winter were identified, consistent with the pronounced temperature contrasts characteristic of the South Korean climate. The combination of seven time-of-day and four seasonal clusters yielded 28 temporal contexts serving as the analytical unit for all subsequent modeling and spatial prediction.

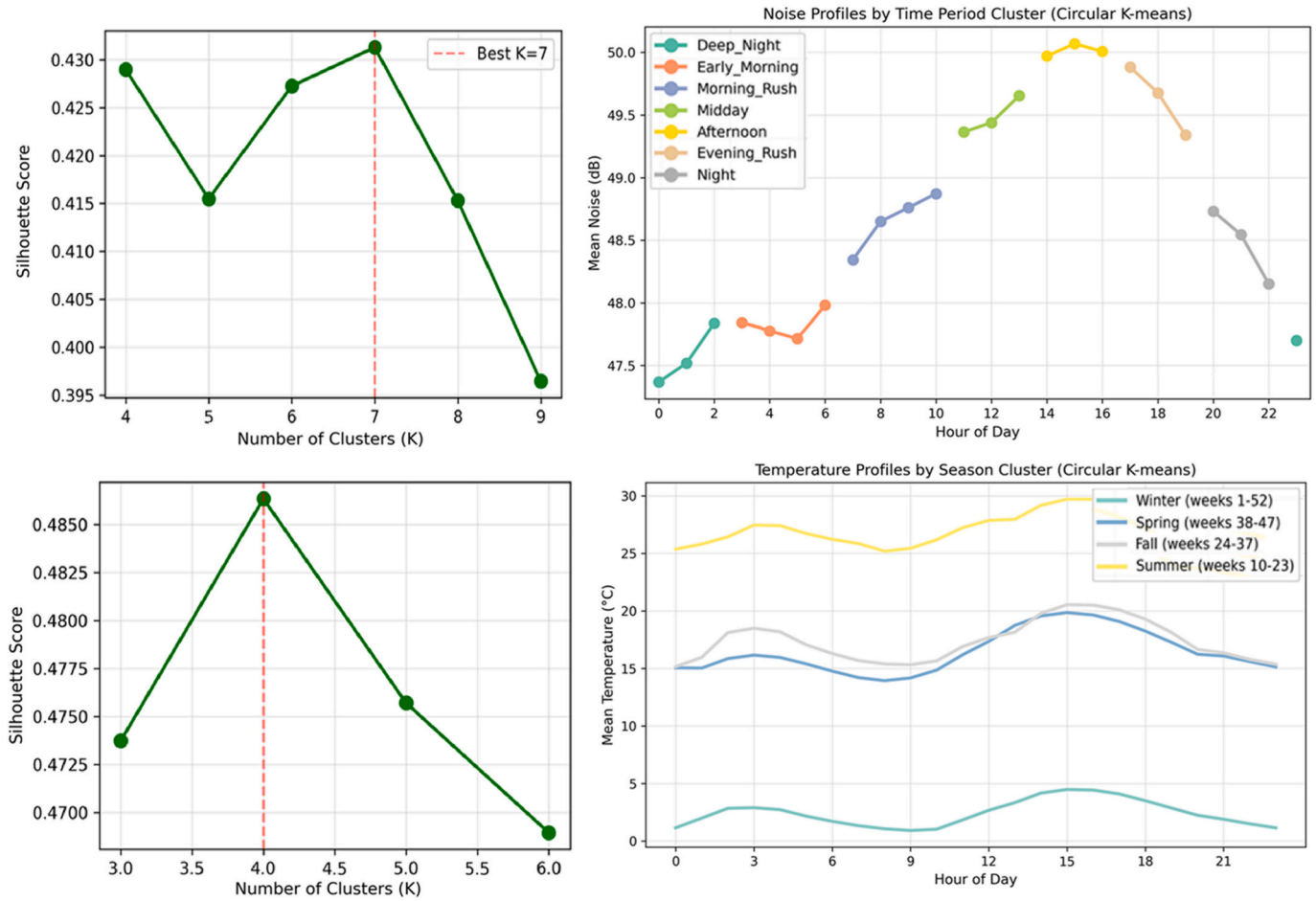

Fig. 3. Temporal context definition process by Circular K-means clustering. Note: (Top-left) Silhouette scores for time-of-day clustering (K = 4–9), with the optimal solution at K = 7 (Top-right). Mean noise profiles by time-of-day cluster, plotted against hour of day. (Bottom-left) Silhouette scores for seasonal clustering (K = 3–6), with the optimal solution at K = 4 (Bottom-right). Mean temperature profiles by seasonal cluster, plotted against hour of day.

4.2. Spatiotemporal noise characteristics

Table 2 presents summary statistics of noise levels across temporal contexts. The overall mean across all 762 sensors over the five-year period was 48.72 dB (SD = 7.05 dB). Diurnal variation spanned approximately 2.2 dB, with the Afternoon context recording the highest mean (50.02 dB) and Early Morning the lowest (47.83 dB). Seasonally, Summer showed the highest mean (49.68 dB) and Fall the lowest (48.07 dB), a difference of 1.6 dB.

Fig. 4 illustrates these patterns across all 28 contexts. Mean noise levels followed a consistent inverted-U trajectory across all seasons, peaking in the Afternoon and declining toward Late Night, with Summer consistently exceeding other seasons. Noise variability was highest during Afternoon and Evening periods (SD ≈ 7.2–7.3 dB) and lowest during Early Morning in Winter (SD = 6.5 dB), as shown in the heatmap. These patterns indicate meaningful spatiotemporal heterogeneity across temporal contexts, supporting the use of context-stratified modeling in subsequent analyses.

Table 2
Summary statistics of noise levels by temporal context.

Category	Context	Mean	S.D.	Min.	Max.
Overall	All data	48.72	7.05	26.41	101.78
Season	Spring (mean temp. 16.4 °C)	48.34	7.10	35.00	79.78
	Summer (mean temp. 27.2 °C)	49.68	7.04	26.41	101.78
	Fall (mean temp. 17.4 °C)	48.07	7.09	35.00	77.35
	Winter (mean temp. 2.4 °C)	48.59	6.88	35.00	78.06
Time of Day	Early Morning (3–6)	47.83	6.76	26.41	101.78
	Morning (7–10)	48.66	6.96	34.98	73.94
	Midday (11–13)	49.49	7.08	35.00	74.38
	Afternoon (14–16)	50.02	7.21	35.00	79.15
	Evening (17–19)	49.63	7.20	35.00	79.78
	Night (20–22)	48.48	7.08	35.00	75.31
	Late Night (23–2)	47.61	6.83	34.66	78.55

Note: Statistics computed from 762 sensors over 5-year period (2021–2025). SD = standard deviation.

4.3. Model performance and feature importance

Model performance was evaluated using nested cross-validation under two specifications: a Raw model incorporating urban environmental and meteorological variables, and a Weather-Controlled model in which meteorological effects were first removed via linear regression and the residuals served as the dependent variable. A preliminary regression of noise on temperature and humidity yielded a training R^2 of 0.406, indicating that meteorological variables alone explained approximately 41% of observed noise variance. The Weather-Controlled specification accordingly isolated urban structural contributions, with residuals exhibiting a mean near zero and a standard deviation of approximately 5.16–5.32 dB.

As shown in Fig. 5, ExtraTrees achieved a CV Test R^2 of 0.516 (Raw) and 0.224 (Weather-Controlled), with Validation R^2 of 0.608 and 0.335, respectively. While XGBoost and GradientBoosting recorded higher CV Test R^2 values under the Raw specification, both exhibited substantially larger train-test gaps (0.298 and 0.248), indicating overfitting risk.

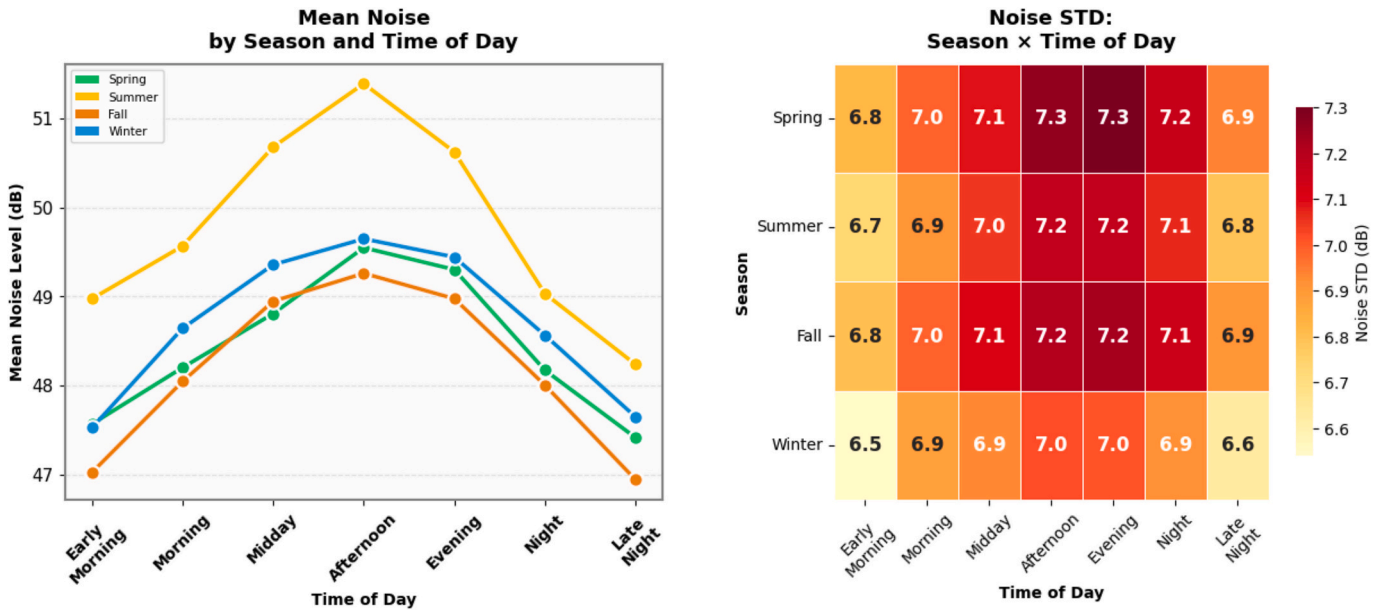

Fig. 4. Spatiotemporal noise patterns across 28 temporal contexts. Note: (Left) Mean noise levels by season and time-of-day cluster, averaged across 762 sensors. (Right) Noise standard deviation (SD) heatmap by season × time-of-day context.

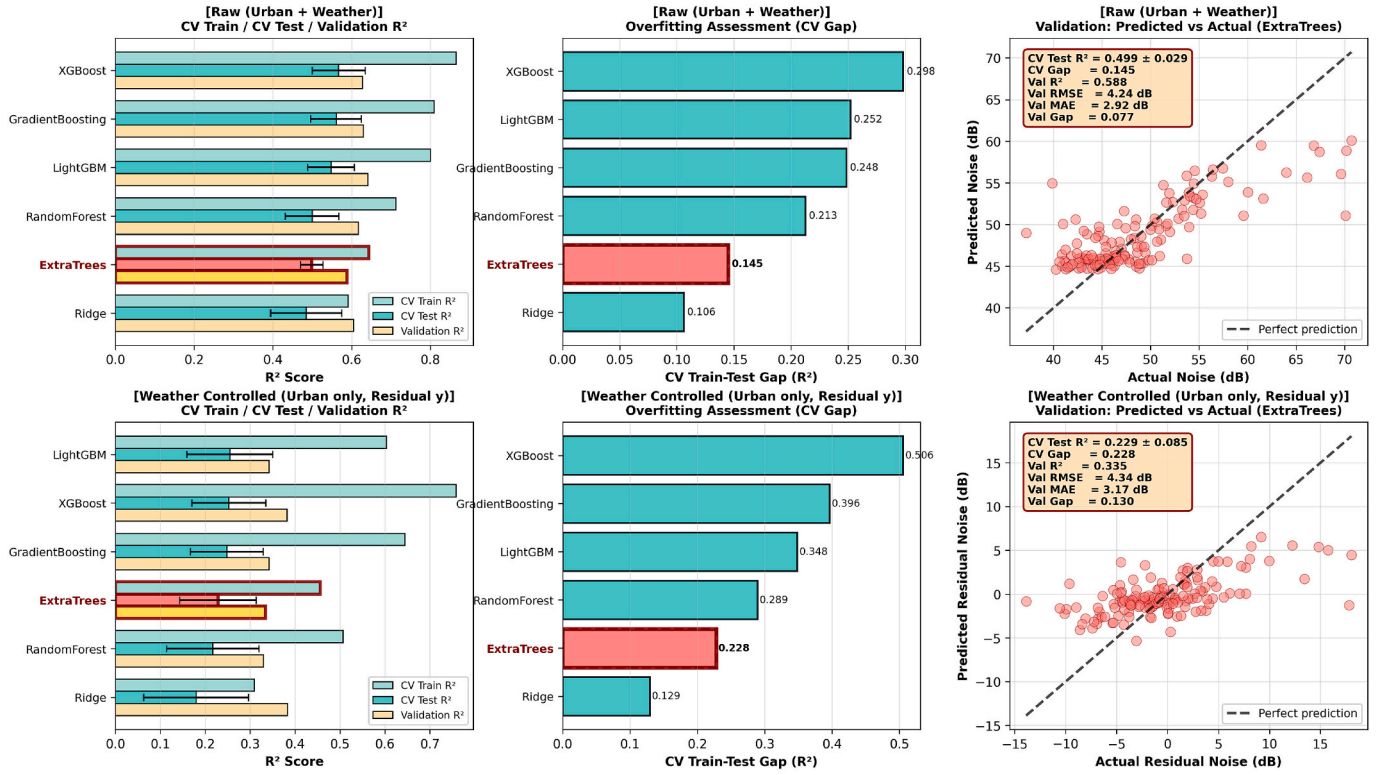

Fig. 5. Baseline model comparison under Raw and Weather-Controlled specifications. (Left) CV Train, CV Test, and Validation R^2 across models. (Center) CV train-test gap. (Right) Predicted vs. actual values for the selected ExtraTrees model on the held-out validation set.

ExtraTrees demonstrated the most favorable balance between predictive performance and generalizability, with the lowest fold-level standard deviation among tree-based models and CV gaps of 0.145 (Raw) and 0.228 (Controlled), supporting its selection as the final model. The randomized feature and split-point selection inherent to Extra Trees contributes to variance reduction and improved generalization relative to boosting (Geurts et al., 2006).

The ExtraTrees model was subsequently applied to each of the 28 temporal contexts under the Weather-Controlled specification (Fig. 6). Context-level Test R^2 ranged from 0.206 to 0.329, with nighttime contexts consistently yielding higher explanatory power than daytime periods, particularly Afternoon (mean $R^2 = 0.245$). Train-test gaps remained moderate across contexts (0.129–0.229). The decline in R^2 relative to the sensor-level baseline ($\Delta R^2 = -0.006$ to -0.129) reflects the inherent increase in within-context residual noise when stratifying by temporal period, rather than a deterioration in model quality.

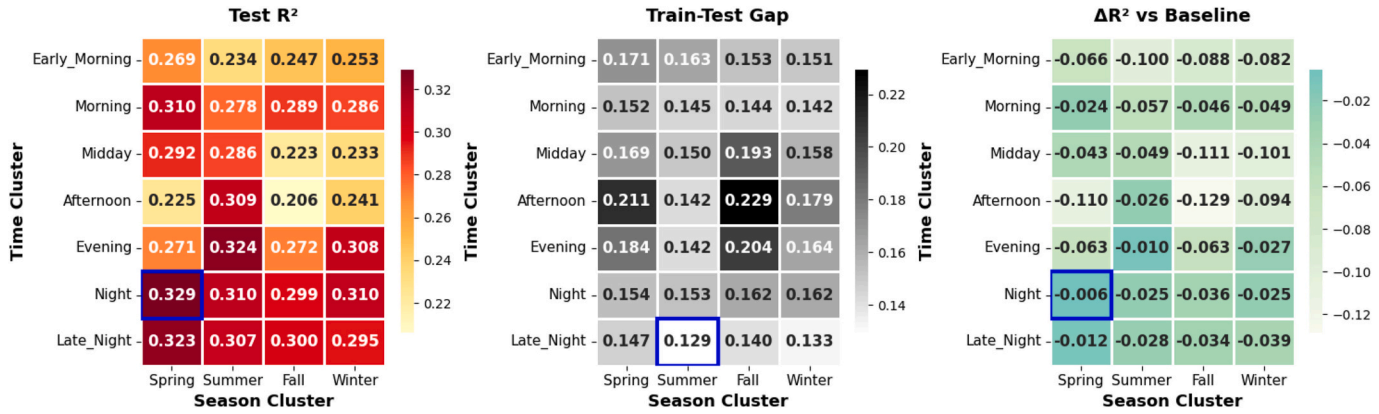

Fig. 6. Context-level model performance of the ExtraTrees model across 28 temporal contexts. Note: (Left) Test R^2. (Center) Train-test gap. (Right) ΔR^2 relative to the sensor-level baseline.

Permutation-based feature importance was computed for each of the 28 context-level models to identify urban environmental variables most predictive of weather-controlled noise residuals. Fig. 7 presents the top 15 features averaged across all contexts alongside those of the best-performing context (Spring Night, $R^2 = 0.329$).

Across all contexts, Pedestrian zone coverage (25 m) emerged as the most influential predictor (mean importance = 0.045), followed by mean road width (50 m, 0.031) and road coverage (100 m, 0.030). Subway exit density (125 m) and street view road coverage (50 m) also ranked consistently among the top five, suggesting that noise levels in Seoul are predominantly shaped by road infrastructure and pedestrian environment characteristics at fine spatial scales. Comparison with the Spring Night context reveals notable shifts: Road Width assumed the highest importance (0.071), surpassing pedestrian zone coverage (0.067), and several variables absent from the overall top list entered the top 15, indicating that the relative contribution of individual features varies meaningfully across temporal contexts.

Fig. 8 further illustrates this temporal heterogeneity in feature importance rankings. Seasonally, pedestrian zone coverage maintained the top rank across all four seasons, while road coverage and road width exhibited considerable rank fluctuation. Across time-of-day clusters, road coverage ranked first during daytime periods but was overtaken by pedestrian zone coverage at night, while POI density rose in importance during Evening and Night contexts, likely reflecting increased commercial activity during those hours. These patterns indicate that urban feature importance is context-dependent, varying meaningfully across both seasonal and diurnal dimensions.

4.4. Citywide noise prediction and spatial patterns

The spatial distribution of context-averaged predicted noise is shown in Fig. 9. Elevated noise was concentrated in the central urban core and along major transportation corridors, while peripheral and green space areas exhibited comparatively lower levels. The predicted mean across all points and contexts was 47.52 dB (median = 47.17 dB), closely approximating the sensor-observed mean of 48.72 dB, indicating reasonable spatial transferability of the models.

The distribution of predicted values was notably narrower than

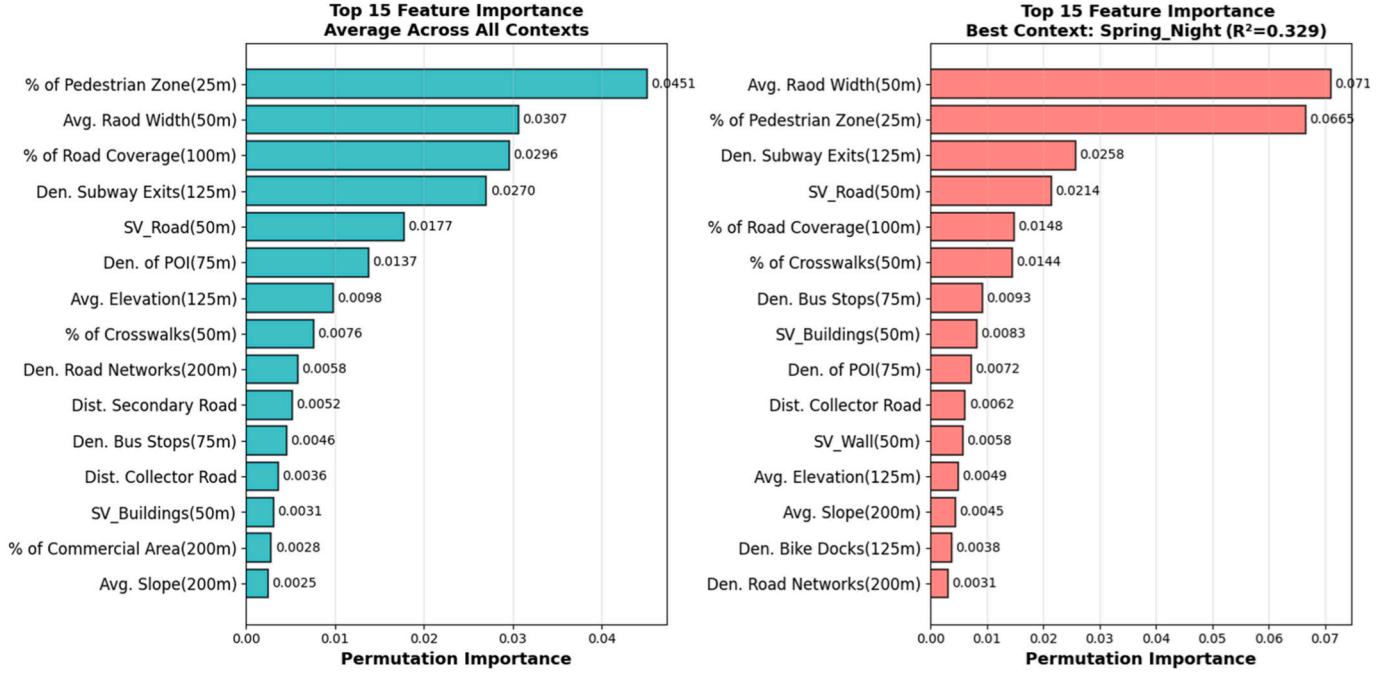

Fig. 7. Top 15 permutation feature importance scores. Note: (Left) Average importance across all 28 temporal contexts. (Right) Feature importance for the best-performing context (Spring_Night, $R^2 = 0.329$). Values represent the mean decrease in R^2 when each feature is randomly permuted on the held-out test set.

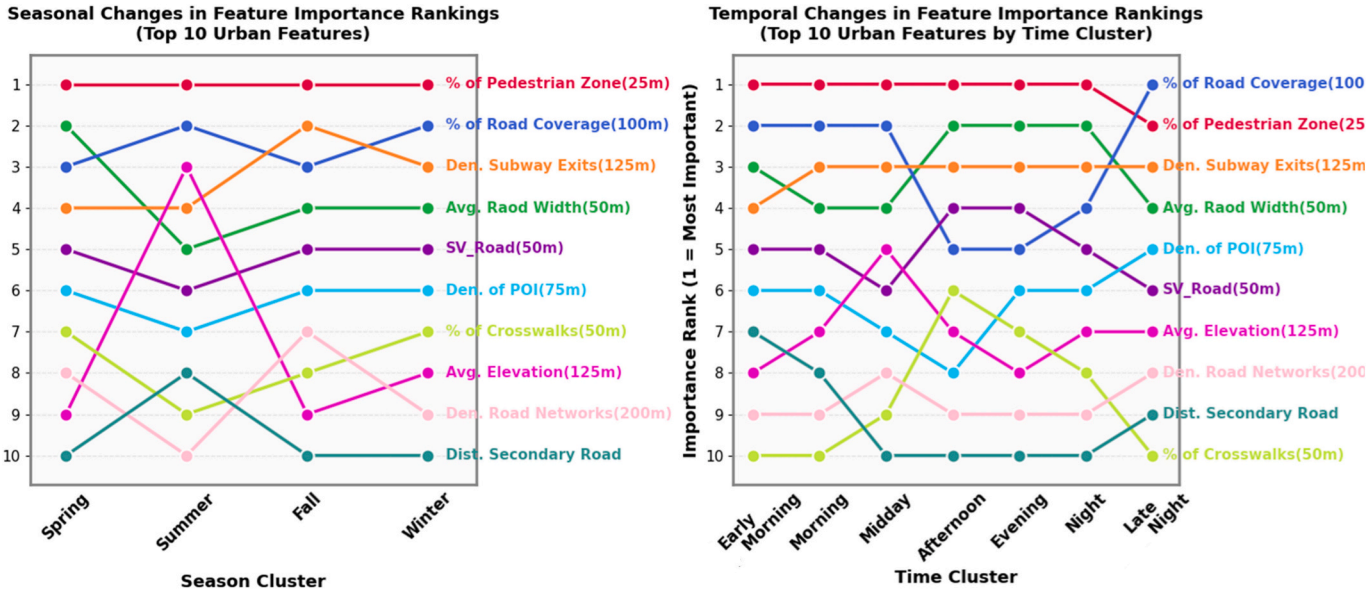

Fig. 8. Feature importance ranking dynamics across temporal contexts. Note: (Left) Seasonal variation in the rankings of the top 10 urban features. (Right) Time-of-day variation in feature importance rankings. Rank 1 indicates the most important feature within each context.

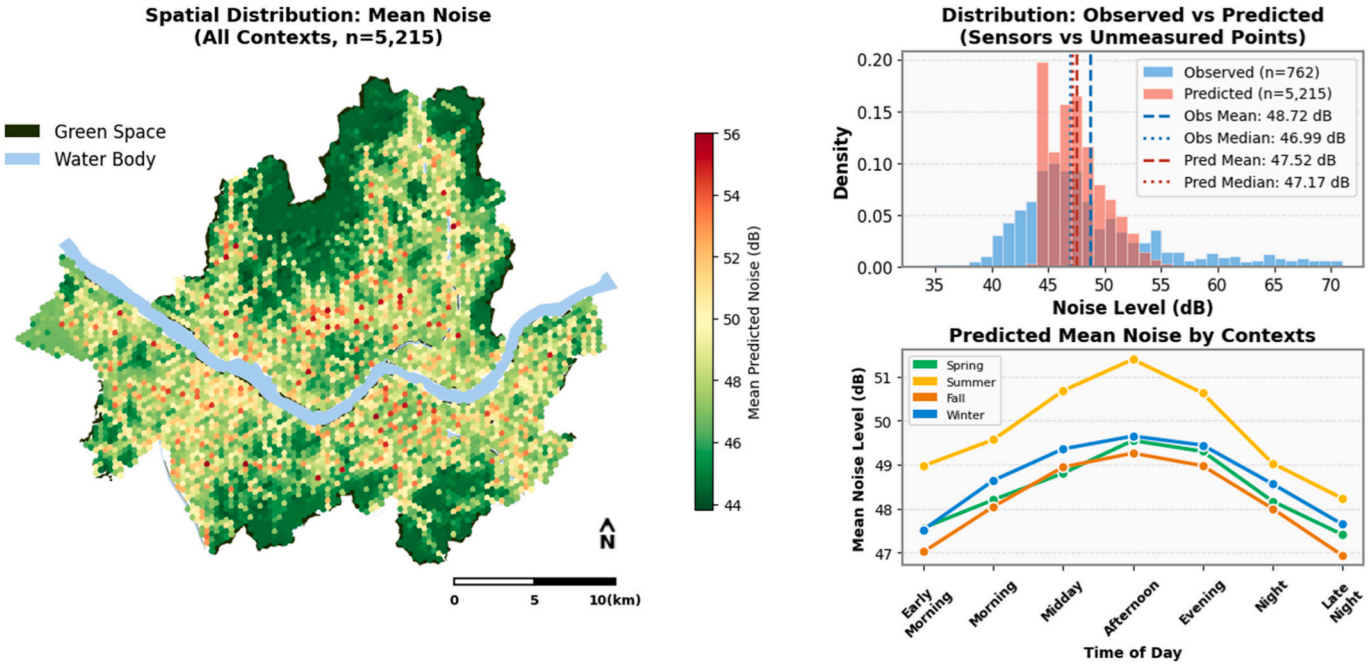

Fig. 9. Citywide noise predictions for unmeasured points. Note: (Left) Spatial distribution of context-averaged predicted noise levels. (Upper right) Distribution of predicted noise compared to sensor-observed values. (Lower right) Predicted mean noise by season and time-of-day context.

sensor observations (Fig. 9, upper right), reflecting the smoothing effect of spatial averaging and the absence of localized extreme events captured by individual sensors. Temporal patterns in predicted noise (Fig. 9, lower right) replicated sensor-observed trends: Summer consistently yielded the highest predicted levels, peaking during Afternoon (≈50.1 dB), while Fall produced the lowest. All seasons followed a consistent inverted-U diurnal trajectory, converging toward lower levels during Late Night.

Sensor coverage varied across dong district, ranging from 0 to 7 sensors per dong (386 of 424 dong contained at least one sensor). Accordingly, context-level predictions were aggregated to Seoul's 424 administrative dong districts to enable neighborhood-scale noise exposure assessment (Fig. 10). The dong-level mean predicted noise ranged from approximately 44 to 52 dB, with an overall mean of 48.01 dB (median = 48.05 dB), closely aligned with the sensor-level mean (Fig. 10, bottom left).

Spatially, elevated noise was concentrated in the central urban core and northern districts, while peripheral areas dominated by greenery exhibited comparatively lower levels (Fig. 10, top left). Temporal variability across time-of-day contexts (up to 3.5 dB) was more pronounced than seasonal variability (0.8–2.8 dB), suggesting that diurnal activity patterns exert a stronger influence on neighborhood-scale noise fluctuation than seasonal differences (Fig. 10, top center and right).

These spatiotemporal patterns collectively suggest that the acoustic

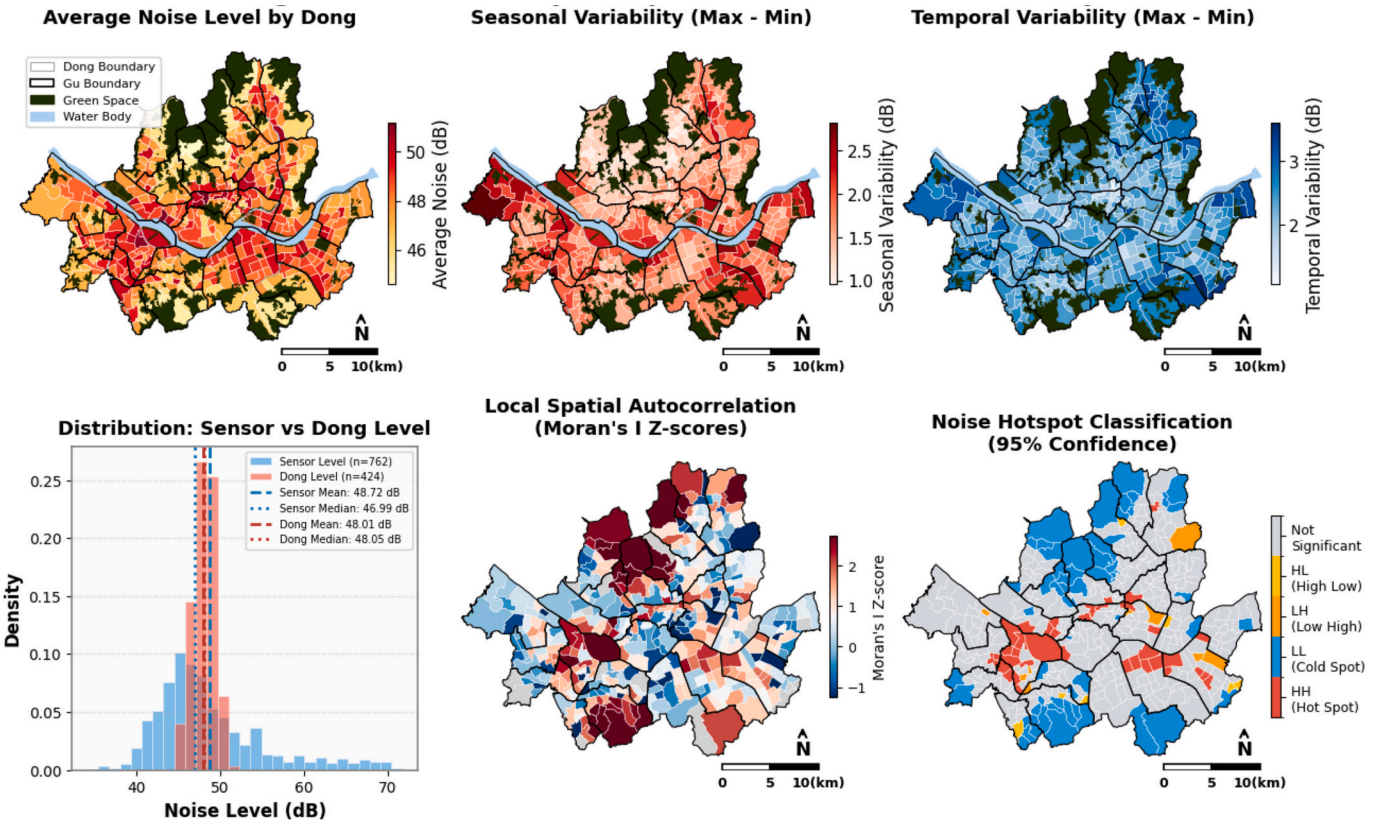

Fig. 10. Predicted noise exposure patterns across Seoul's 424 administrative districts. Note: (Top left) Context-averaged mean predicted noise. (Top center) Seasonal variability (max − min across four seasonal contexts). (Top right) Temporal variability (max − min across seven time-of-day contexts). (Bottom left) Distribution of predicted noise at sensor level versus dong level. (Bottom center) Local spatial autocorrelation based on Moran's I *Z*-scores. (Bottom right) Noise hotspot classification at 95% confidence level (HH = hotspot, LL = cold spot, HL/LH = spatial outliers).

character of a neighborhood cannot be adequately described by its mean noise level alone. Districts with similar average exposure may exhibit fundamentally different temporal profiles — with some experiencing pronounced diurnal fluctuation driven by commercial activity, and others maintaining relatively stable conditions across the day — highlighting the analytical value of context-stratified prediction over static mapping.

Spatial clustering analysis using contiguity-based weights indicated that noise exposure exhibits spatial autocorrelation at the dong level (Fig. 10, bottom center and right). High-High clusters were identified predominantly in central and northeastern districts, while Low-Low clusters appeared in peripheral, green-dominant areas. A limited number of spatial outliers were observed at transitional zones between high-density and residential areas, reflecting abrupt local contrasts in acoustic exposure.

5. Discussion

5.1. Temporal heterogeneity and context-stratified Modeling

Context-level Test R^2 ranged from 0.206 to 0.329 across temporal contexts, with Night and Late Night contexts consistently yielding higher explanatory power than daytime periods. Nighttime noise environments involve fewer concurrent noise-generating activities, rendering static urban structural features more dominant and predictable. Conversely, the Afternoon context — the noisiest on average — exhibited the lowest R^2, consistent with the complexity of peak-hour noise dynamics that static predictors cannot fully capture.

Temporal variability across time-of-day contexts was more pronounced than seasonal variability, with noise levels across seasons showing minimal differences within a given time-of-day context. This suggests that diurnal cycles constitute the primary axis of urban noise heterogeneity in Seoul, supporting the use of time-of-day stratification as the dominant analytical dimension (Xu et al., 2022).

The decline in R^2 from the sensor-level baseline (0.333) to context-level models (mean = 0.276) reflects a methodological consequence of temporal stratification rather than a deterioration in model quality. Aggregating observations across a narrower time window necessarily retains greater within-context residual variation that static urban features cannot explain. The cross-context variation in R^2 itself constitutes evidence of temporal heterogeneity in noise-environment relationships, reinforcing the analytical value of context-stratified modeling over a temporally pooled approach. This context-dependent variation in explanatory power suggests that a single pooled model would not only underperform but would systematically misrepresent the noise-environment relationship across different urban conditions. Critically, this context-dependent variation in explanatory power reveals that the relationship between urban environmental features and noise levels is not fixed — the same predictor can exhibit substantially different levels of influence depending on the temporal context in which it is evaluated, a pattern that temporally aggregated or static models would systematically obscure.

Given that diurnal cycles constitute the primary axis of acoustic variability, time-of-day differentiated regulations may be more effective than season-based approaches for noise management. Korean environmental legislation and Seoul's municipal noise regulations already employ a three-tier time-of-day structure — distinguishing daytime, morning/evening, and nighttime periods with differentiated permissible noise levels (Ministry of Environment, 2023) providing an institutional basis for context-sensitive noise governance. The findings of this study

offer empirical support for further refinement of such frameworks, demonstrating that noise-environment relationships and their urban determinants shift systematically across temporal contexts in ways that uniform standards cannot adequately address.

5.2. Weather control and urban feature effects

Meteorological variables alone explained approximately 41% of observed noise variance ($R^2 = 0.406$), consistent with prior evidence that temperature and humidity influence both sound propagation and human outdoor activity patterns (Munir et al., 2021; Tsai et al., 2009; Van Renterghem et al., 2011). Failure to account for these effects risks attributing meteorological variation to urban structural predictors, inflating apparent feature importance.

The Weather-Controlled specification yielded a CV Test R^2 of 0.224, compared to 0.516 under the Raw specification. While the reduction in explained variance is expected, the controlled model provides a more methodologically rigorous estimate of the independent contribution of urban environmental features. The retained explanatory power (R^2 = 0.224–0.333) indicates that urban structural characteristics exert a meaningful influence on noise levels even after meteorological effects are removed.

ExtraTrees was selected as the final model based on its superior generalizability. Despite marginally lower predictive performance than gradient boosting-based alternatives, ExtraTrees achieved the lowest train-test gap and fold-level standard deviation among tree-based methods. This stability is particularly relevant given the 28 independently trained context models, where inconsistent generalization would compromise the comparability of feature importance estimates across contexts.

5.3. Urban determinants of noise exposure

Pedestrian zone coverage (25 m), mean road width (50 m), and road coverage (100 m) emerged as the three most influential predictors across all temporal contexts, consistent with prior evidence identifying road network characteristics as primary determinants of ambient noise exposure (Chang et al., 2019; Wu & Wang, 2025; Xu et al., 2022). However, while road infrastructure maintained a stable overall ranking, the relative importance of individual predictors shifted meaningfully across seasons and times of day — a pattern of temporal instability that static or temporally pooled models would fail to detect — and would instead misattribute to a single dominant predictor structure that does not reflect the underlying complexity of urban noise dynamics.

Feature importance rankings varied meaningfully across contexts. Average elevation rose in importance during summer contexts, consistent with evidence that topographic conditions modulate noise propagation (Heimann, 2010; Li & Xie, 2021), while road coverage importance declined during Afternoon contexts, when the diversity of concurrent activities may reduce the relative explanatory power of any single predictor. POI density showed increased importance during Evening contexts, potentially reflecting heightened commercial activity during those hours (Song et al., 2024), though this interpretation warrants caution as the analysis does not directly measure activity intensity. Road infrastructure interventions remain effective across all temporal contexts, while commercial land use regulations and pedestrian environment improvements may be most impactful during Evening and Afternoon periods, respectively. This temporal specificity aligns with Seoul's ongoing efforts to manage nighttime commercial activity in high-density districts, where balancing pedestrian access and noise control during evening hours has become an active policy concern (Ministry of Environment, 2023). Collectively, these patterns are consistent with prior evidence that noise-environment relationships vary meaningfully with temporal and activity context (Wu & Wang, 2025; Zhang et al., 2026), suggesting that activity-sensitive noise mitigation strategies calibrated to specific temporal and spatial conditions would be more effective than static land use-based approaches.

5.4. Noise exposure and socioeconomic equity

As a supplementary analysis, Spearman correlation coefficients were computed between predicted dong-level noise indicators and selected socioeconomic and land use characteristics to examine correlational patterns in neighborhood-scale noise exposure (Fig. 11). Given the ecological nature of the analysis and the limited set of variables examined, findings reflect associations rather than causal relationships and should be interpreted as indicative rather than conclusive. All socioeconomic variables were derived from publicly available sources and aggregated to the dong level; variable definitions, units, and data sources are provided in supplementary material.

Floating population showed the strongest positive association with mean noise ($r = 0.583$, $p < 0.001$), reflecting the role of pedestrian activity intensity in shaping acoustic environments. Commercial area ratio was also positively associated ($r = 0.448$), while residential area ratio ($r = -0.348$) and elderly ratio ($r = -0.298$) showed negative associations. Mean income showed a positive association with noise exposure ($r = 0.242$), suggesting that higher-income district tend to experience greater noise — a pattern that may reflect the spatial concentration of high-income populations in Seoul's commercially active urban cores rather than a straightforward socioeconomic gradient. This contrasts with patterns reported in Western urban contexts, where lower-income areas tend to bear greater noise burden (Casey et al., 2017; Dale et al., 2015), though direct comparability is limited given the different urban and institutional contexts. For noise range, income ($r = 0.314$) and residential area ratio ($r = -0.290$) were the most notable correlates, while elderly ratio and floating population showed no significant association with temporal variability.

These patterns suggest that noise burden in Seoul is more closely tied to urban activity structure than to socioeconomic disadvantages per se. Nonetheless, elderly populations may face disproportionately severe noise exposure challenges due to their heightened physiological sensitivity, with evidence suggesting that areas with higher elderly ratios may exhibit non-linear noise-health relationships (Hayward & Helbich, 2024). This underscores the need for population-targeted noise management approaches that prioritize vulnerable groups regardless of absolute exposure levels, as noise policy should reflect demographic characteristics rather than decibel thresholds alone (Xie et al., 2025; Zhang et al., 2025). More rigorous causal analysis incorporating individual-level exposure data would be needed to draw firmer equity-related conclusions.

5.5. Limitations

Several limitations of this study should be acknowledged. First, the analysis relied solely on noise levels recorded by IoT sensors, without distinguishing noise by source type or capturing peak noise events. Prior research has employed more nuanced acoustic indicators including frequency-weighted levels, impulsive noise metrics, and soundscape indices to assess differential health impacts and perceptual responses (Chang et al., 2019; Ragettli et al., 2016; Song et al., 2024; Xu et al., 2022; Zhao et al., 2023). The inability to disaggregate noise by source type limits interpretation of feature importance findings, as the relative contributions of traffic, commercial, and other noise sources cannot be separately attributed.

Second, spatial dependence among prediction districts was not explicitly modeled, and residual spatial autocorrelation in model errors was not formally tested or addressed. The aggregation of point-level predictions to districts introduces scale sensitivity, and findings may vary under alternative spatial configurations. The smoothing effect of spatial averaging further results in underestimation of localized extreme values. Future validation efforts incorporating district-level ground truth measurements would help assess the reliability of aggregated

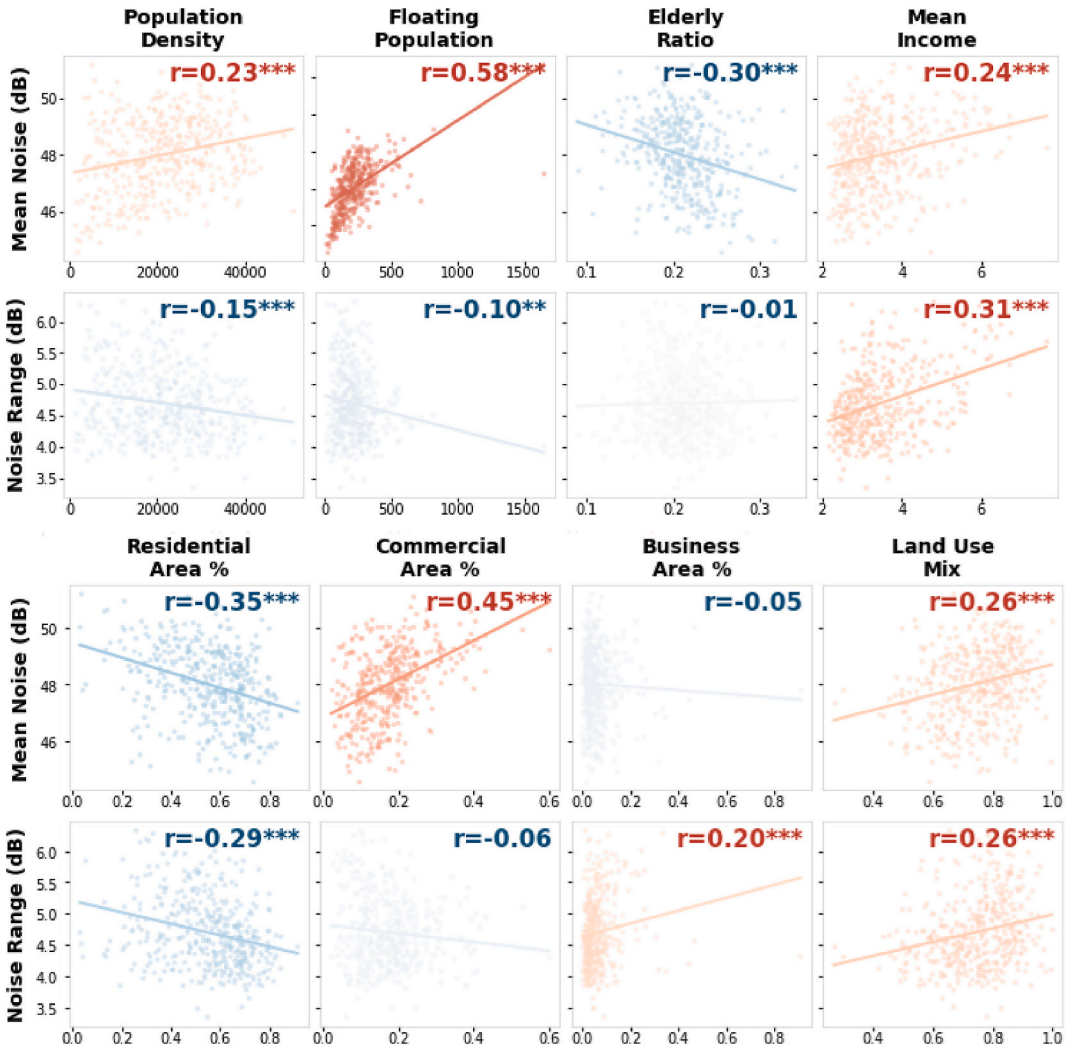

Fig. 11. Spearman correlations between dong-level socioeconomic indicators and predicted noise exposure. Note: Each panel shows a scatter plot with regression line; r values indicate Spearman correlation coefficients (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).

predictions at finer spatial scales.

Finally, all predictor variables were treated as temporally static. While urban structural features such as road networks, building morphology, and land use are inherently static in nature, urban noise environments are also shaped by dynamic factors such as traffic flow that have been identified as significant noise determinants in prior research. This reliance on static predictors is reflected in the moderate model explanatory power observed (Test $R^2 = 0.206–0.329$), as dynamic factors such as real-time traffic volume, pedestrian activity intensity, and event-driven noise sources were not incorporated. Feature importance analysis provides a useful summary of predictor contributions but offers limited insight into nonlinear interactions and direction of influence; more granular interpretation methods are needed to fully characterize the mechanisms underlying noise-environment relationships.

Future research could extend the current framework in several directions. First, integrating source-specific acoustic metrics would enrich the noise characterization beyond equivalent continuous levels, enabling more health-relevant exposure assessment. Second, incorporating time-varying predictors such as real-time traffic volume and mobile activity data, alongside more complex spatiotemporal modeling architectures, would address the limitations of static predictors and potentially improve explanatory power beyond the moderate levels observed here. Third, applying spatially explicit approaches alongside unit-level sensor validation in under-monitored areas, would improve the spatial reliability of predictions and formally address residual spatial autocorrelation. Finally, testing the framework across cities with diverse urban morphologies would establish the conditions under which the approach generalizes.

6. Conclusion

This study presented an integrated spatiotemporal framework for urban noise analysis, applied to Seoul using five years of continuous observations from a citywide IoT sensor network. The framework combines temporal context definition, weather-controlled machine learning, and spatial prediction to enable comprehensive noise exposure assessment at both citywide and neighborhood scales.

The three hypotheses guiding this study were substantiated by the results. First, urban noise exhibited significant temporal heterogeneity, with diurnal variation emerging as the dominant axis — confirming that temporally aggregated approaches would obscure meaningful variation in noise dynamics. Second, the relative importance of urban environmental predictors shifted systematically across temporal contexts: road infrastructure consistently dominated, while commercial activity indicators gained prominence during evening hours. Critically, these relationships are not temporally invariant in ways that static or pooled models cannot capture. Third, noise exposure exhibited systematic spatial clustering at the neighborhood scale: when sensor-level

predictions were aggregated to administrative dong units, high-noise concentrations emerged predominantly in central and commercially active areas of Seoul.

These findings carry practical implications for urban noise management. The demonstrated temporal heterogeneity suggests that effective noise governance may benefit from context-sensitive approaches that account for how noise dynamics shift across seasons and times of day, including time-of-day differentiated regulations, activity-sensitive strategies, and population-targeted considerations. The spatial prediction framework developed here may offer a useful basis for noise exposure monitoring and intervention planning in other high-density cities with comparable IoT infrastructure.

AI Statement

During the preparation of this work, the authors used Claude Sonnet 4.5 (Anthropic) for language editing, grammar correction, and improvement of sentence structure. After using this tool, the authors reviewed and edited the content as needed and took full responsibility for the content of the publication.

CRediT authorship contribution statement

Junhyeon Kweon: Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Sugie Lee:** Writing – review & editing, Supervision, Project administration.

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Declaration of competing interest

The authors declare no conflicts of interest.

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None.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.compenvurbsys.2026.102537.

Data availability

This study is based entirely on publicly available data. All data sources are cited in the manuscript; please refer to the main text for details.

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