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GIS-Based Spatial Analysis and Python Transcript for Predicting Traffic Noise Pollution Over Kirkuk City, Iraq

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Abstract

As traffic increases in Kirkuk, Iraq, noise pollution has become a pressing issue, particularly on the major road, Baghdad Road in Kirkuk City, which connects densely populated areas. This study aims to assess traffic noise levels along Baghdad Road, addressing challenges such as time-intensive measurements, the selection of appropriate mapping methods, and the integration of geographic and noise data. It also presents an innovative combination of GIS and Python scripting to model and predict traffic noise pollution in Kirkuk City, Iraq, offering a replicable method for urban areas with limited noise monitoring. Noise levels were measured using a digital sound level meter, with sampling points spaced 500–750 meters apart along entry and exit roads. Maximum noise levels (Max) were recorded during peak traffic hours (8:00–10:00 AM and 5:00–7:00 PM). The highest recorded noise level was 92.15 dB at site K-B.R4 in the morning, while the lowest was 74.2 dB at site K-B.R13 in the evening. Temporal variations were notable, particularly on Fridays, a local holiday, with noise levels ranging from 92.1 dB to 75.5 dB. Spatial analysis revealed that K-B.R4 was the most congested area, while K-B.R13 was the least. The RLS 90 model, implemented in Python, was used to create noise maps via spatial analysis and interpolation in ArcGIS Pro 3.0.2. The model's spatial approach achieved higher accuracy and classification precision than other methods. These findings emphasise the importance of considering temporal and spatial factors in noise studies, offering valuable insights for environmental monitoring, urban planning, and noise management.

1. Introduction

Road traffic noise is considered one of the major sources of noise pollution in urban environments, contributing up to 80% of noise levels [1], [2]. Motor vehicle emissions are a major source of pollution, which has been associated with numerous health issues, including tinnitus, impaired cognitive function, poor sleep, cardiovascular diseases, and more [3]. As a result, traffic noise control has emerged as an important part of urban health management strategies [4], [5]. There is engine noise, exhaust noise, tyre noise, and air disturbance noise, with the last being affected by the vehicle type, speed, road surface pattern, traffic density, and other features [6].

A high volume of traffic and vehicle speed also produce a high level of noise; the types of vehicles and the road surface further increase the noise level. The remaining environmental weather factors also play an important role in the dispersion and reduction of noise, namely, terrain, vegetation, and noise barriers [7].

The impacts of traffic noise on health are in the long run, especially for children and the elderly. Therefore, there is a need to regulate noise pollution in urban areas [8], [9]. Forecasting and management of noise exposure in urban contexts are challenging owing to the spatiotemporal distribution of traffic noise [10]. Acoustic mapping also plays an important role in sound management in towns and cities, while field studies remain the conventional method for acquiring traffic noise measurements [11]. However, achieving accurate noise mapping requires more complex interference patterns and spatial data analysis, as well as specifying factors such as road networks, traffic flow, and land-use patterns [12], [13]. Environmental noise mapping refers to the utilisation of GIS, spatial statistics, and signal processing to develop maps that locate the most noise-impacted communities to guide planning for noise reduction efforts [14].

Extensive research has focused on analysing several approaches to quantifying and predicting traffic noise in structural environments. For example, Zambon et al. [15] categorised vehicles by speed and then used these categories to construct noise spectra, while Ovenden et al. [16] and Sakieh et al. [17] evaluated the effects of green areas and noise forms. These works provide significant knowledge on the relationship between city characteristics and noise transfer. Last of all, dynamic modelling of traffic noise using GPS, as 3D noise maps have exhibited higher traffic noise predictions in cities across different countries [18]. The application of GIS-based modelling has become an essential approach for analysing and managing environmental noise in urban areas [19]. The RLS 90 model has been widely used to predict traffic noise by incorporating factors such as traffic characteristics, climatic conditions, and infrastructure changes [20]–[22]. Consequently, GIS modelling tools provide an effective framework for assessing, planning, and regulating urban noise pollution

Traffic noise mapping employs other methods of spatial interpolation or prediction, including inverse distance weighting (IDW) of noise-level measurements to estimate noise levels in unassessed regions [23], [24]. Other relevant factors include noise diffusion, which encompasses road surface characteristics, vehicle characteristics, geographical terrain, vegetation, and built-up areas. These indicate that, for accurate outcomes in noise propagation models, the calculation must include all of these factors [20], [25]. Static and dynamic noise maps based on field data and GIS could identify areas of high noise to analyse noise sources, reduce noise, and design the city [26]. The integration of RLS 90 with ArcGIS Pro and Python scripting enables extensive spatial analysis of traffic noise intensity distributions across geographic space. Therefore, helps in decision-making to control the noise in urban areas [20].

Effective noise management is critical in developing cities like Kirkuk, Iraq, where heavy traffic and outdated vehicles exacerbate noise, and it is beginning to pose a significant threat. This is compounded by the absence of integrated noise control measures, high traffic density, and aged vehicles. This study aims to utilise GIS-based noise mapping, combining the RLS 90 model with ArcGIS Pro 3.0.2 and Python scripting to evaluate the extent of traffic noise on Baghdad Road in Kirkuk City. A critical innovation, characterised by the inclusion of Python code to automate data processing and spatial prediction, enables high-resolution noise maps for both temporal periods (morning and evening) and daily (Tuesday, Thursday, Friday, and Saturday). Thus, by supporting the identification of noise hotspots in cities, it aims to advance urban planning and public health initiatives. The approach highlights a pragmatic spatial analysis to meet the need for noise assessment and management amid rising traffic noise pollution in Kirkuk.

2. Materials and Methods

2.1 Study Area

Kirkuk City, located 250 km north of Baghdad (E: 445,744.63, N: 3,535,902.33), lies in the Kirkuk Governorate, within the Tigris-Euphrates River Basin [27]. The city's terrain includes low-altitude hills, plains, and valleys, influencing noise pollution and traffic emissions. Fig. 1 illustrates the geographical location and urban extent of Kirkuk City. Kirkuk's elevation ranges from 350 to 500 meters above sea level, with the Khasa and Al-Adhaim rivers flowing through the area [28], [29]. Kirkuk has experienced rapid urbanisation, with a population of 1,075,000. The city faces environmental challenges, exacerbated by its semi-arid climate. Industrial zones, including cement plants and refineries, contribute significantly to noise and air pollution [30], [31]. The Kirkuk-Baghdad Highway and other major roads experience heavy traffic, leading to elevated noise and emissions. Rush-hour congestion and vehicle exhaust fumes are major sources of pollution, posing health risks, as highlighted by the WHO [28].

2.2 Data Collection

Data for this study were collected through extensive field surveys utilising various data sources to ensure comprehensive coverage of traffic and noise pollution levels in Kirkuk. Traffic volume data were gathered from transportation departments using automatic traffic counters and classifiers strategically placed along Baghdad Road. These stations provided accurate traffic patterns across the road's length.

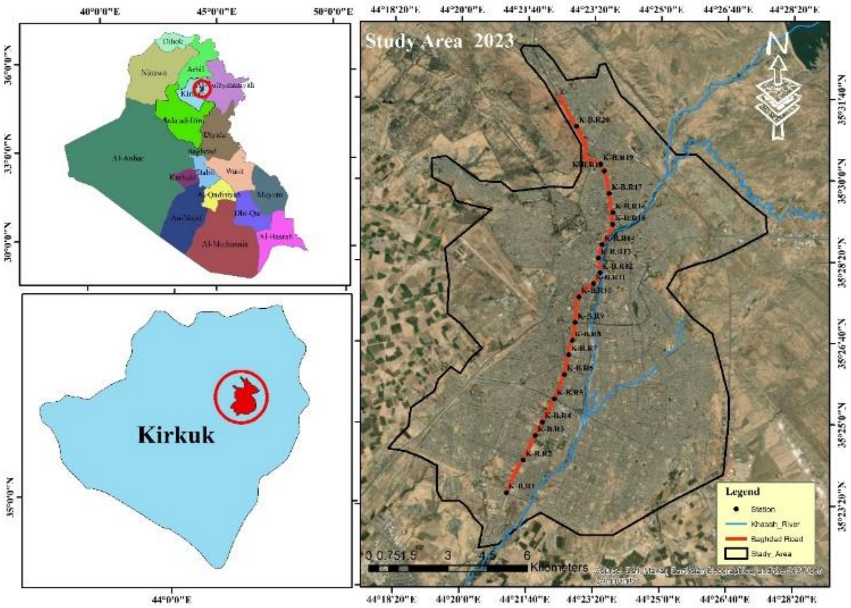

Fig. 1 *Location of Kirkuk City within the Kirkuk Governorate, Iraq*

Noise measurements were taken using UNI-T UT353 decibel meters, which can measure sound levels from 30 to 130 dB. These measurements were performed at carefully selected points along the road, including intersections and high-traffic zones, to ensure a representative sample of the area's noise conditions across different times of day.

The study used Python in ArcGIS Pro 3.0.2 to perform spatial analysis and interpolation of traffic noise data using the RLS 90 noise model. This approach has been applied for the first time in Kirkuk; it provides better refinement of noise maps and time-space integration. Using the RLS 90 model, noise intensity from traffic impacts was assessed and mapped to identify areas with high noise exposure and to provide a general sense of noise levels during peak traffic conditions, contributing to the planning and management of noise reduction.

Road locations, land use, and distances to sensitive receptors such as residential areas and schools were obtained from the GIS database. These spatial factors were essential to classifying the various types of environmental noise pollution within the study area.

The study was centred on Baghdad Road in Kirkuk, a busy road with heavy daytime traffic due to the city's dense population. Data were collected along 16.93 km of this road, with observations taken at 500-750 m intervals to capture fluctuations in noise levels. It reduced interference from brief, loud sounds produced by cars, motorcycles, and other sources, and provided a better representation of overall traffic sound. The data was then classified and finally analysed graphically to determine the distribution of noise along the road. According to Ali & Albayati [28], the noise level in Kirkuk ranged from 60 to 80 dB. The data collected in the present study also ranged within a similar level. The gathered information, when visualised by using GIS, helps in understanding noise pollution data and planning the development of Kirkuk city. Fig. 2 represents the approach of collecting information on Baghdad Road and is illustrated in the graph of the collected Noise Maximum.

2.3 Data Processing

These analyses involved developing Python scripts to properly analyse the collected data and perform spatial statistics. These scripts are web-reliant on strong libraries such as Pandas for data processing, NumPy for numerical processing, and Matplotlib for advanced statistical visualisations.

Furthermore, ArcGIS Pro was used to support complex spatial analysis, including field estimation and spatial data analysis, and to prepare the noise pollution maps. The opportunity to employ IDW interpolation methods in ArcGIS Pro, along with the available toolbox for interpolating noise data and producing useful noise prediction surfaces, was available. This approach enabled understanding of the spatial distribution of noise pollution in the study area, which could be important for environmental quality assessment, even in urban planning schemes.

The data was compiled in Python to ensure that the analysis of noise pollution along the Baghdad Road in Kirkuk would be conducted using the appropriate method: spatial analysis in ArcGIS Pro. Not only was it useful then for fine-tuning the various analyses that went into the final work, but it can also serve as a guideline for formulating these strategies to minimise noise pollution in our cities.

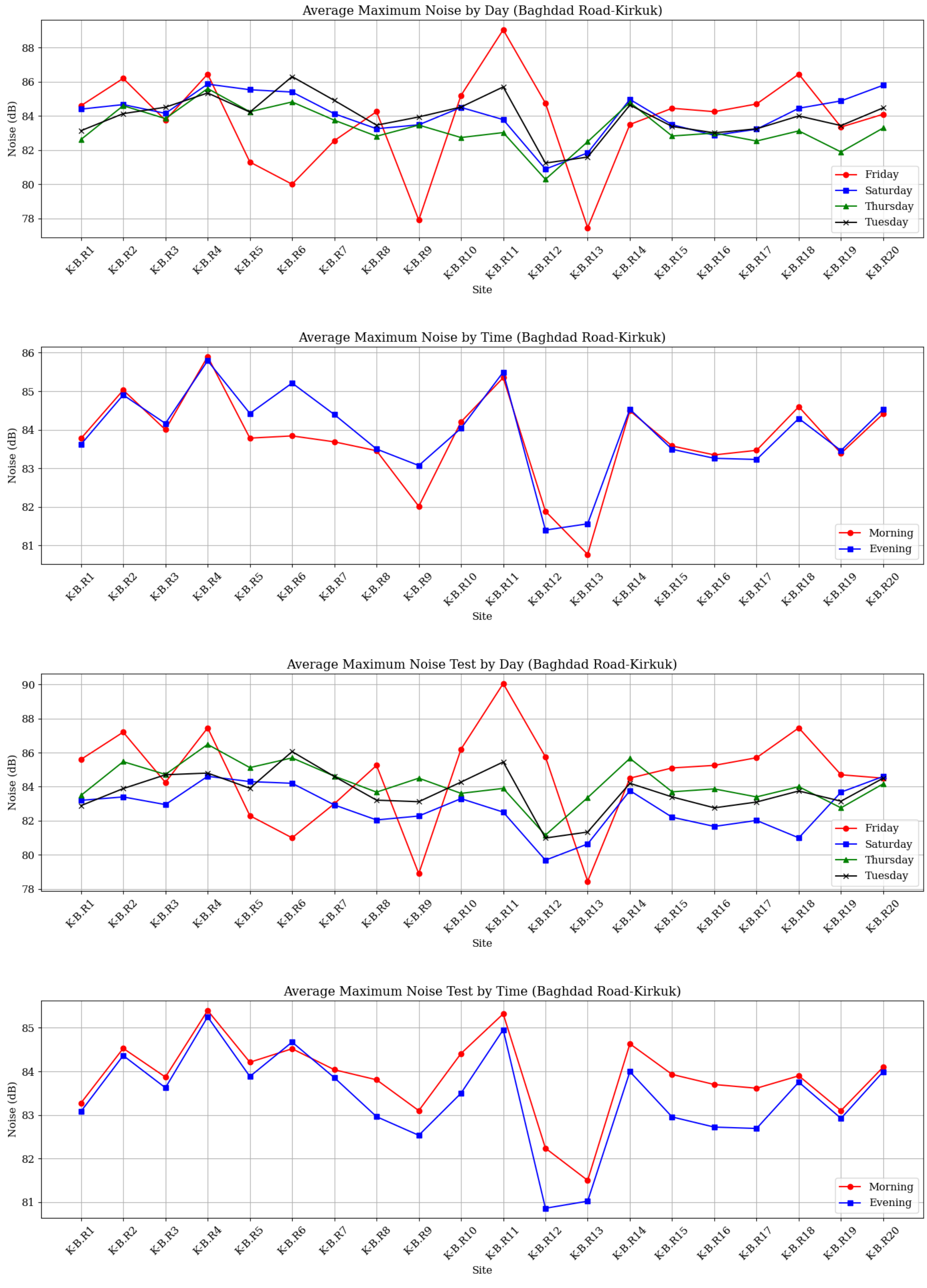

Fig. 2 *Graph of collected maximum noise levels measured by day and time, and test results by day and time*

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In this study, data analysis was performed using Python scripts integrated with ArcGIS Pro for geospatial statistical analysis and noise pollution mapping. Python libraries such as Pandas and NumPy were employed for data processing, and Matplotlib was used for statistical visualisation. ArcGIS Pro supported complex spatial analyses, such as field estimation and noise map generation. It was possible to use methods such as IDW interpolation to generate noise prediction surfaces to assess the dispersion of pollution within the study area, and to plan the city layout.

2.4 Model Development

The noise prediction model was established from advanced spatial statistical methods and optimisation algorithms. Preliminary descriptive characterisation identified zones of elevated noise exposure, accounting for proximity to roads, activity types, and altitude. These analyses helped determine the effects of environmental factors on the distribution of noise along Baghdad Road.

Traffic congestion levels, vehicle type, road conditions, and speed were used to predict noise using the RLS90 model in ArcGIS and Python. Some of the advantages included eliminating manual noise estimation in the input and output of data and results, as well as efficient data input and visualisation of results. The integration of the exposure model enhanced the analysis of road noise exposure to avoid, mitigate, or reduce its effects, including the use of noise barriers [32], [33].

To evaluate the model's performance, cross-validation was used to compare predicted noise levels with actual measurements at specific validation sites along Baghdad Road. This helped develop and validate the model's efficiency in operating under real-world conditions. Table 1 to Table 3 present statistical analyses of the noise survey and show noise levels across different days and times.

The application of an integrated approach to model development and validation offers a robust noise prediction system for Baghdad Road, allowing planners, developers, and engineers to gain a deeper understanding of the noise pollution challenges facing Kirkuk, enabling long-term control and reduction in future urban development.

Table 1 *Descriptive statistics of noise measurements along the main road in Kirkuk City*

Measurement location	Noise value (dB)	Mean	Standard Deviation	Minimum value(dB)	Maximum value(dB)
K-B.R1	Max	83.53	3.10	78.15	89.20
K-B.R2	Max	84.69	4.05	78.60	92.61
K-B.R3	Max	84.83	3.14	80.65	91.10
K-B.R4	Max	85.98	3.99	79.00	92.90
K-B.R5	Max	84.71	4.31	76.40	91.00
K-B.R6	Max	86.73	7.80	75.20	110.00
K-B.R7	Max	85.34	5.82	77.90	101.90
K-B.R8	Max	83.99	4.20	75.70	92.30
K-B.R9	Max	84.92	8.54	75.00	105.60
K-B.R10	Max	84.98	6.36	76.60	102.20
K-B.R11	Max	86.06	6.63	76.20	102.00
K-B.R12	Max	81.98	5.21	74.00	89.20
K-B.R13	Max	82.16	5.54	74.00	92.80
K-B.R14	Max	85.22	5.41	76.30	98.10
K-B.R15	Max	83.94	4.37	75.85	90.80
K-B.R16	Max	83.52	4.29	76.65	92.50
K-B.R17	Max	83.69	4.07	76.25	89.40
K-B.R18	Max	84.50	4.86	74.50	93.50
K-B.R19	Max	83.62	3.74	72.20	87.21
K-B.R20	Max	84.79	3.41	76.70	90.00

Table 2 *Descriptive statistics for noise levels by day on main roads in Kirkuk City*

Measurement date	Noise value (dB)	Mean	Standard Deviation	Minimum value(dB)	Maximum value(dB)
Friday	Max	83.71	2.81	77.45	89.05
Saturday	Max	84.08	1.28	80.89	85.87
Thursday	Max	83.29	1.19	80.29	85.61
Tuesday	Max	83.96	1.23	81.24	86.31

Table 3 *Descriptive statistics for noise levels by time on main roads in Kirkuk City*

Measurement data by time	Noise value dB	Mean	Standard Deviation	Minimum value(dB)	Maximum value(dB)
Morning	Max	83.75	1.18	80.77	85.90
Evening	Max	83.92	1.13	81.40	85.79

In addition, to assess the noise levels of the measured and predicted data against regulatory standards, Table 4 summarises the maximum allowable noise levels by location [34], [35]. It assesses legal noise-management requirements against existing noise-level regulations to determine the model's accuracy in estimating noise impacts along Baghdad Road.

Table 4 *Standards for maximum noise levels based on location categories [36]*

location	Maximum Acceptable Noise Level (dB)
Residential areas	55-65 dB
Commercial areas	60-70 dB
Industrial areas	70-80 dB
Highways	65-75 dB

2.5 Traffic Noise Dispersion Modelling (RLS 90)

The RLS90 traffic noise model is described as an upgrade over the original RLS81 in the Guidelines for Noise Protection on Streets. RLS90 is an efficient model for calculating the noise rating level of road traffic [37]. The average hourly traffic flow, broken down into motorcyclists, heavy, and light vehicles, as well as the average speed for each category, the size, geometry, and type of the road, and any man-made or natural impediments, must all be fed into the model [38]. Road characteristics, including width, curvature, and type, as well as natural or artificial barriers, influence model accuracy [39]. RLS90 also incorporates factors like vegetation, barriers, air absorption, reflections, and diffraction effects in noise transmission [40].

This model can estimate noise attenuation from barriers and assess the reflectivity of roadside screens, enabling precise evaluations of noise levels and mitigation strategies. These capabilities make RLS90 a valuable tool for noise management and urban planning in urban and suburban areas. This is one of the few models in the addiction literature that can assess a parking lot's sound emissions. An average level, L_{me}^{25} measured at a distance of 25 meters from the centre of the road lane, serves as the starting point for the calculation. The variables *L-me*-25 are dependent on the quantity of vehicles per hour (Q) and the proportion of heavy trucks (P) (weight > 2.8 tons) in an idealised setting (i.e., 100 km/h, road gradient <5%, and specific road surface) [40], [41]. Analytically, L_{me}^{25} is given by:

$$L_{me}^{25} = 37.3 + 10\lg\left[M(1 + 0.0082P)\right] \tag{1}$$

$$L_M = L_{me}^{25} + D_s + D_{rs} + D_g + D_e + D_{d_{air}} + D_{g_{atom}} + D_{t_{build}} + 10\lg\left(\frac{d_0}{D_0}\right)^{1+\beta} + 10\lg\left[\frac{\psi_a(\varphi_1,\varphi_2)}{\pi}\right] \tag{2}$$

The correction values for road surface conditions at different speed limits (dBA) are presented in Table 5, offering crucial insights into how road surface conditions affect noise levels across different speeds [32]. This table serves as a fundamental reference for understanding the impact of road surfaces on noise emissions.

Table 5 *The road surface condition correction values under different speed limits (dB) [42]*.

Surface Type	30 km/h	40 km/h	≥ 50 km/h
Smooth or concrete asphalt	0	0	0
Concrete	1.0	1.5	2.0
Smooth surface	3.0	2.5	3.0
Other	3.0	4.5	6.0

The RLS90 model for noise prediction involves creating anticipation noise models based on various parameters, which are then used to generate maps evaluating noise pollution in the study area. Noise exposure, especially in populated areas, is now considered environmentally unacceptable. Fig. 3 illustrates the procedure for traffic noise modelling using the RLS90 model, which combines multiple data sources to predict noise levels and visualise the results.

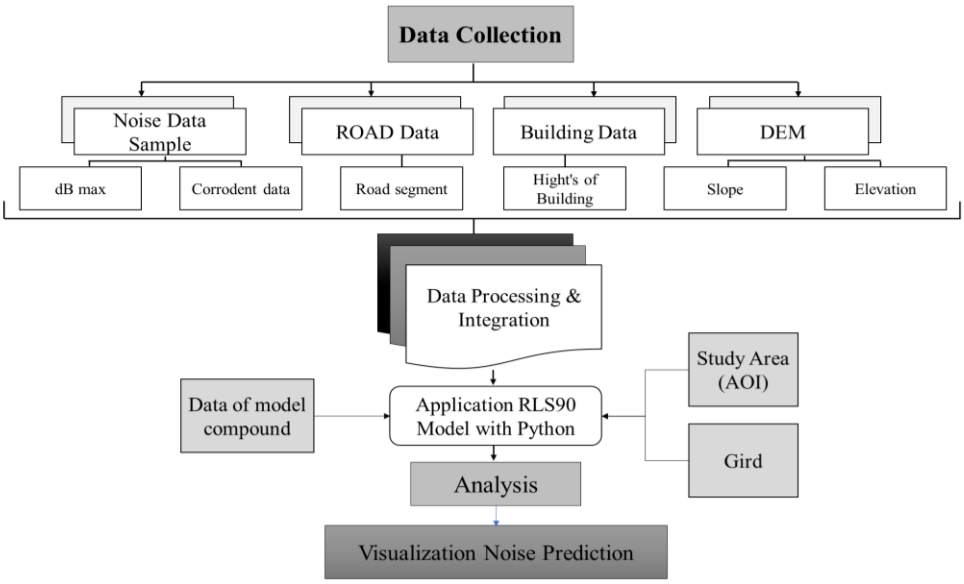

Fig. 3 *Scenarios for evaluating interpolation methods, RLS90 modelling and noise prediction*

The methodology also involves gathering noise data from various areas, as well as other characteristics such as traffic intensity, vehicle types, road types, and surface materials. Corresponding coordinate values are measured for each noise sample collected and referenced to the study area. Extra information, like road slope, vertical profile changes, and characteristics of buildings, including heights, construction material, and structure of the building, is also considered to determine how noise travels.

It is then used as input to the RLS90 dataset, which includes other parameters, such as noise values associated with road type, vehicle speed, and building absorption coefficients. The model uses additional functions, such as inverse distance weighted, to enrich data quality. The distribution of noise in the study area is characterised by a concentration of loud areas near roads and intersections, as well as sensitive facilities such as schools and hospitals. The noise maps are 2D, showing noise contours, gradients, and fluctuations resulting from elevation differences. By integrating data and applying the RLS90 model, noise patterns are identified, enabling urban planners and policymakers to address noise pollution effectively and improve urban livability.

3. Results and Discussion

3.1 Noise Spatial Distribution Resultant Maps

The maps were generated from geospatial analysis with the RLS90 noise model in Python. While the validation process was based on regression analysis. Maps depicting the spatial distribution of noise pollution across Kirkuk City were generated using ArcGIS Pro. These maps highlight areas with high noise pollution concentrations, providing valuable insights into the geographical patterns of noise pollution within the city. The spatial distribution of noise in the resultant maps is shown in Fig. 4.

The resulting maps demonstrate the extent of noise distribution within a given region of Kirkuk City. The study spanned two months and involved data collection from 20 locations along Kirkuk Baghdad Road. Using the RLS90 model implemented in ArcGIS Pro to analyse noise levels across different periods, the days are Friday, Saturday, Thursday, and Tuesday, and the times are morning and evening. This approach enabled understanding of fluctuations in noise levels over the day and across various temporal segments. Every period offered conceptual assumptions about statistics.

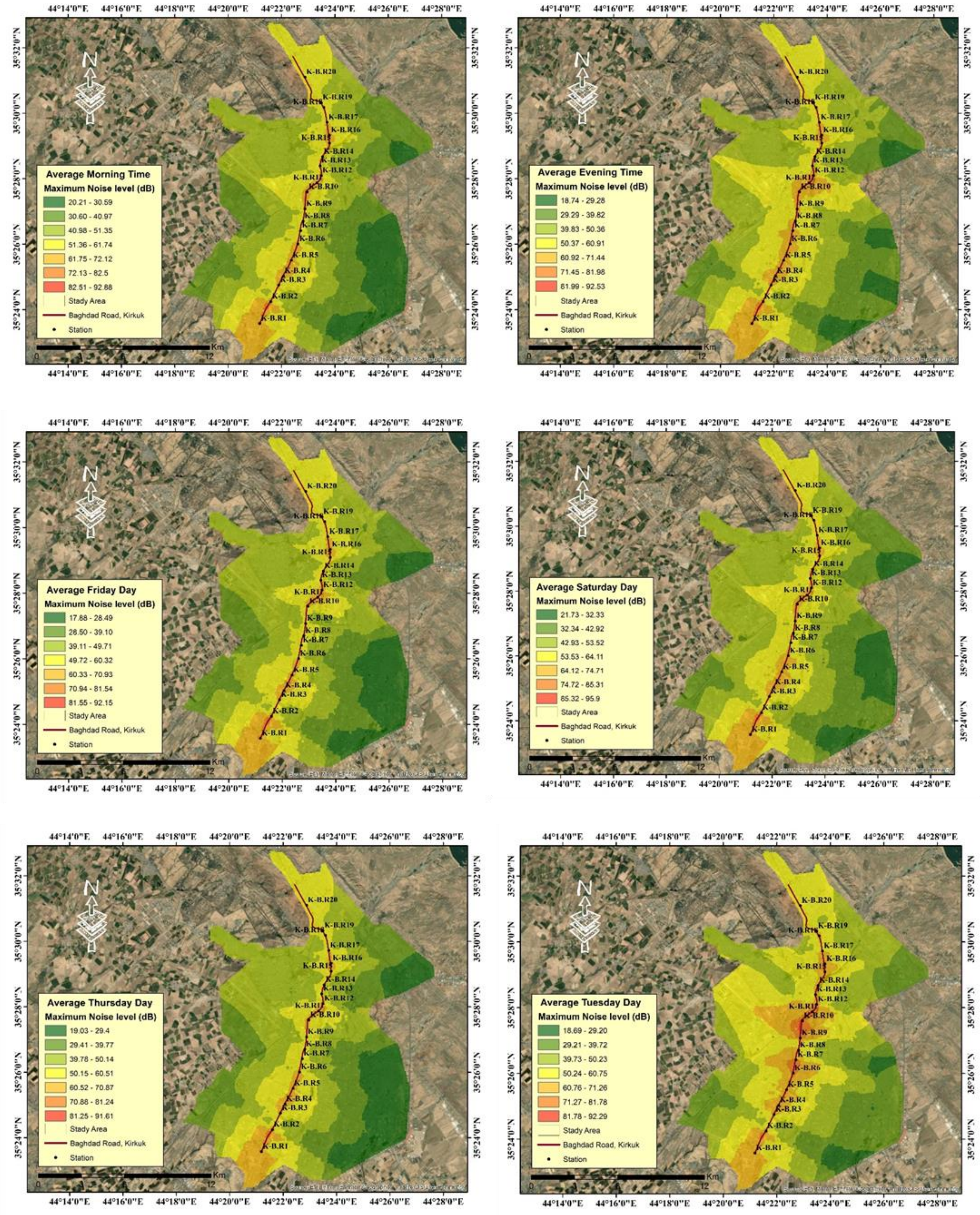

Fig. 4 *Noise spatial distribution resultant maps*

Analysis of Friday's data revealed a standard deviation of 3.65. The highest recorded noise level reached 92.1dB at location K-B.R11, while the lowest, 75.5dB, occurred at K-B.R9. The mean noise level across all locations was calculated as 83.96 dB. In contrast, Saturday exhibited a narrower distribution with a standard deviation of 1.07. The maximum noise level recorded was 85.62dB at K-B.R4, with a minimum of 81.22dB at K-B.R12, and a mean of 83.9545dB, indicating relatively stable conditions compared to other days. Thursday's data displayed a standard deviation of 3.59, similar to Friday's, with a peak noise level of 92dB at K-B.R14 and a trough of 77.5dB at K-B.R12. The mean noise level on Thursday was slightly higher at 84.859dB than on Friday.

Data from Tuesday showed a standard deviation of 1.28, implying relatively low variability. The highest noise level recorded was 91.675 dB at K-B.R6, with a minimum of 86.808dB at K-B.R12 and a mean of 89.53125 dB, potentially reflecting different environmental conditions or operational factors. During the evening, the maximum noise level was recorded at K-B.R4 The highest value of 92.12dB to a minimum of 74.2dB at K-B.R13. As seen, the extent of variation in the mean noise level was above average at 84.664dB, while the standard deviation in the morning session was moderate, with the variation between the maximum and minimum being 92.15dB and 75.82dB at K-B. R4 and K-B.R13, respectively. The overall mean noise for this period was calculated to be 84.820, which is in line with reports for the morning hour.

These results show the differences in environmental factors between days and times, thus emphasising the importance of temporal analysis when studying spatial data. Creating the RLS90 model in Python was useful. It enabled effective exposure of the identified loopholes in environmental monitoring and subsequent decision-making [43]. Furthermore, in addition to traffic, this study analysed standard, maximum, and minimum noise values.

In other words, the present study emphasises that experimental data, including both mean values and standard deviations, are essential for describing experimental outcomes. Higher mean values may indicate stable or favourable performance conditions, while larger variability suggests the need for further investigation into the sources of dispersion. Additional analyses, such as bivariate and multiple correlation coefficients and sensitivity analysis, can help clarify the relationships among variables and the nature of the observed measurements. Such analyses are important for refining experimental procedures, improving repeatability, and guiding the design of future studies.

3.2 Noise Model Performance and Validations

The developed noise prediction model gave promising results when predicting noise levels in Kirkuk City. The evaluation matrix's coefficient of determination (R^2) suggests a high level of correlation between the predicted and measured noise levels. Spatial variability in noise pollution was incorporated into the model, yielding good estimates of noise levels across different locations in the study area. In sum, the applications of the prediction model were beneficial for analysing and controlling noise pollution levels in the city.

The collected data were then analysed statistically to establish relationships among traffic flow, land-use factors, and noise pollution levels. Quantitative characteristics of noise pollution included mean noise levels, standard deviations, and variances across city areas.

The analysis of R^2 values across days of the week and times of day provides valuable insights into the regression model's performance and identifies potential areas for improvement. Comparing actual (Friday: 0.9110, Saturday: 0.9150, Thursday: 0.9013, Tuesday: 0.9017, Morning: 0.9078, Evening: 0.9049) and treated datasets (Friday: 0.9005, Saturday: 0.9075, Thursday: 0.9030, Tuesday: 0.9000, Morning: 0.9099, Evening: 0.9049), the R^2 values consistently demonstrate a strong fit of the model to the data, mostly exceeding 0.90. This indicates that a significant portion of the variance in the dependent variable is effectively explained by the independent variables across various temporal dimensions.

Specifically, slight reductions in R^2 values were observed for Friday (from 0.9110 to 0.9005) and Saturday (from 0.9150 to 0.9075) after treatment, suggesting a minor decrease in the model's ability to explain variability on these days. Conversely, Thursday's R^2 value improved slightly from 0.9013 to 0.9030, indicating enhanced model fit. Similarly, Tuesday showed a negligible decrease from 0.9017 to 0.9000, suggesting minimal impact from the treatment.

Additionally, R^2 values for Morning raised slightly, from 0.9078 to 0.9099. After treatment, indicating that the morning traffic has a positive impact on the explanation of the model. Specifically, the evening R^2 values for both groups did not change, indicating that Stability in the value remained unchanged at 0.9049 for actual and treated datasets, showing that the model fit did not deteriorate during the evening period despite the application of treatment.

The impact of temporal factors and the type of data also underscore the regression model's sensitivity to the given analysis. Potential procedures that may be employed to counter the observed reductions on Friday and Saturday include, first, optimising the model parameters and, second, using alternative regression analyses. Conversely, if Thursday and Morning indicate optimisation of data preprocessing or the modelling approach, this improves the achievable predictive accuracy.

The stability of R^2 values stressing Tuesday and Evening suggests a highly reliable methodological model for these temporal settings, which in turn can determine high predictive accuracy. Overall, this research provides meaningful findings on the applicability of regression analysis across time frames and underscores the need for effective model assessment in various circumstances. Understanding variability in R^2 values across days of the week and times of day enables researchers and practitioners to refine modelling strategies, thereby improving the reliability and effectiveness of predictive models across various domains. The model's performance validation is shown in Fig. 5, while model validation by test measurements is shown in Fig. 6.

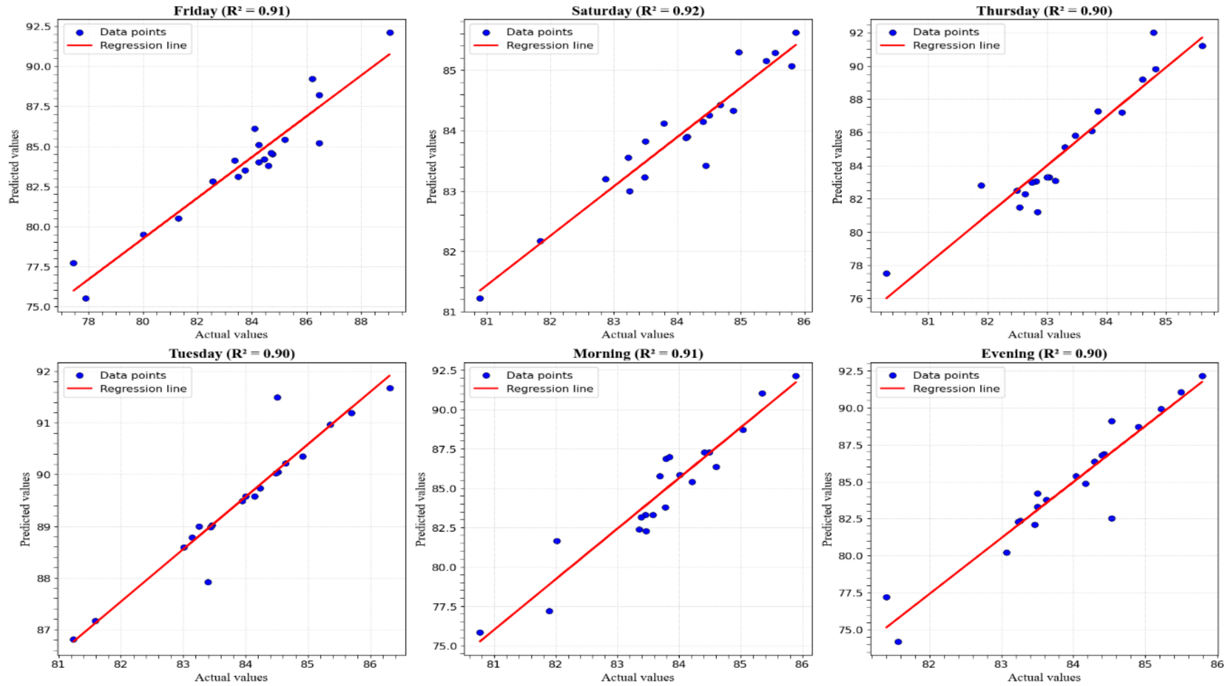

Fig. 5 *Model performance validation by actual data*

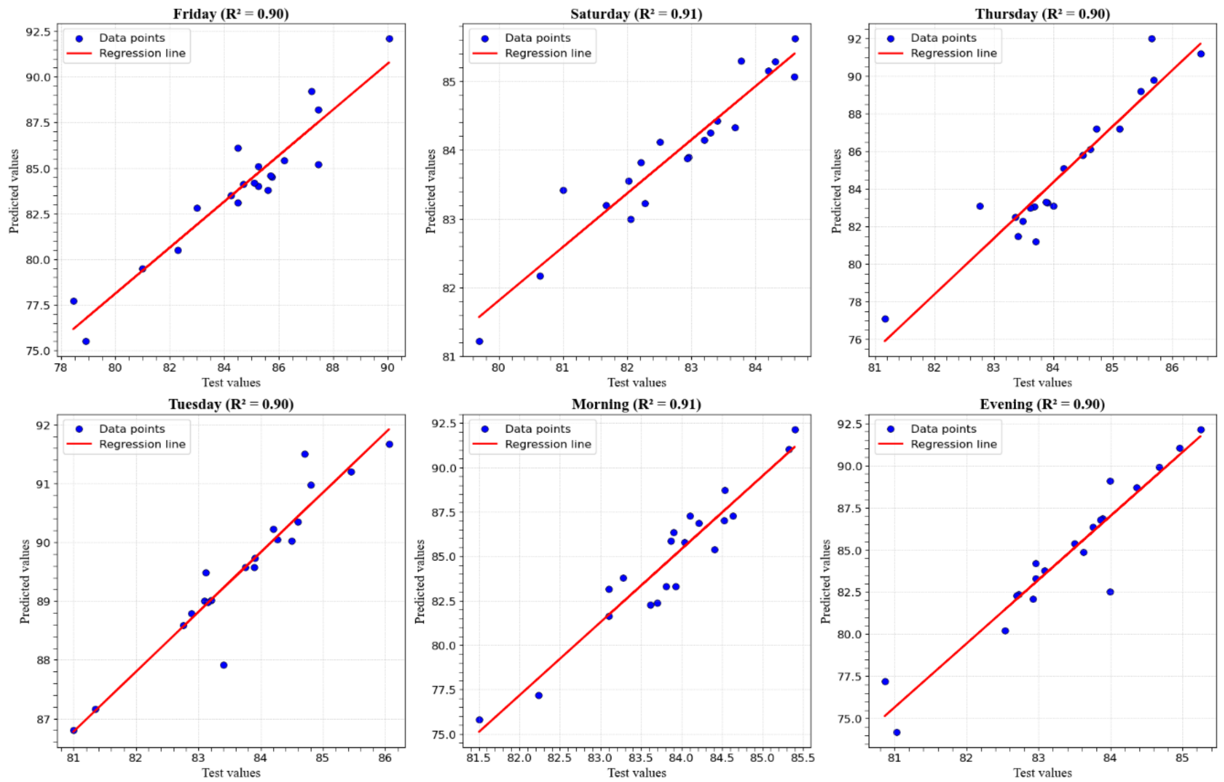

Fig. 6 *Model validation by test data*

This study highlights significant temporal variations in noise levels, underscoring the need to account for temporal dynamics in analyses of spatial noise distribution. Peak traffic times (8:00-10:00 AM and 5:00-7:00 PM) saw the highest noise levels, with a maximum of 92.15 dB at site K-B.R4 in the morning and a minimum of 74.2 dB

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at site K-B.R13 in the evening. Friday's noise ranged from 92.1 dB to 75.5 dB, identifying K-B.R4 as the most crowded and K-B.R13 as the least crowded on Baghdad Road, particularly on Fridays.

The general range of traffic noise levels in the study area is 17-93 dB, with considerable variation; even the upper limit of this range exceeds most general noise pollution levels, particularly in relation to its probable effects on human health and the quality of the discipline. Lower Bound (17 dB): This level is slightly above the normal volume level and would not, in general, be considered a problem. Upper Bound (93 dB): It's very high and can be equated to sound pollution – the noise one can experience when living close to a highway, during construction work, or using some industrial machinery. According to the World Health Organisation (WHO) guidelines, for outdoor residential areas, the noise level during the daytime must not be more than to achieve this level of sound intensity limits will have to be put in place, particularly on noise that is disruptive to daily activities such as conversation and resting, which should not exceed 55dB.

Any exposure to noise above 85 dB for longer periods will cause hearing loss. According to WHO guidelines, noise levels above 70 dB are considered dangerous for any duration of exposure. EPA (U.S) recommendation: Health effects start where noise reaches and exceeds 70 dB for long times. The EPA also recommends levels below those mentioned for areas near schools, hospitals, and residential districts. Exposure Limits by Occupation: Any noise exposure exceeding 85 dB is considered high and requires adequate protection during continuous exposure. This may explain the greater variability in noise levels, which range from 17 to 93 dB.

This raises the possibility that other efforts to minimise noise, such as barriers, traffic regulation, or changes to zones, could be helpful, particularly in areas close to car traffic. Our findings align with previous studies on traffic-related noise pollution but offer localised insights specific to Kirkuk City. It is important for identifying specific measures, such as noise walls or changes in traffic patterns, and for integrating noise into the planning of our cities to enhance citizens' well-being.

The study also provides an orientation on refined data processing and statistical analysis [44]-[46]. The more common approaches to implementing the assessment involve conventional methods that primarily rely on manual data sorting, which is cumbersome, time-consuming, and error-prone. In this sense, automation with scripts involves not only speed but also near-perfect reproducibility and intrinsic accuracy.

The features in ArcGIS Pro support a range of complex spatial analysis techniques, such as Inverse Distance Weighting (IDW) interpolation. This method provides detailed prediction surfaces that could show the extent of noise pollution across the region.

Compared with simpler methods or static noise mapping, IDW and similar spatial interpolations in ArcGIS Pro enable more accurate predictions of how noise levels change across regions. This is particularly significant for evaluating environmental quality and land use, as noise dispersion patterns clearly affect population well-being.

Using the RLS90 traffic noise model raises concerns about updating the predictive models, as RLS90 is superior to the previous RLS81 model. This choice makes the study more consistent with current best practices in ageing for traffic noise modelling compared to other studies that may use less efficient or older models.

However, the present studies often lack this combined approach and instead rely on a single technique, either GIS or statistical analysis. The analyses obtained here could serve as a roadmap for designing noise control strategies, whether through changes to road structures or the use of noise walls.

More research should be carried out, with other features, such as industrial activities and public events, considered, and Longitudinal studies should be conducted to analyse changes or trends in noise pollution. Mapping the relationships among noise pollution, air quality, and the availability of green space may help in understanding the state of the subject's environmental health in urban areas.

By addressing these limitations and expanding research areas, future studies can enhance strategies for managing urban noise pollution, promoting sustainable urban development and improving quality of life in cities.

4. Conclusion

This study provides a detailed analysis of traffic-related noise pollution in Kirkuk City, focusing on the main entry and exit roads that serve residential, commercial, service, industrial, public, and recreational areas. According to the Iraqi Noise Control Law of 2015, noise levels in these areas should not exceed 50–70 dB during the daytime and 40–65 dB at night. However, our findings show that actual noise levels often surpass limits.

The RLS90 model demonstrated significant flexibility and ease of use in initialising and modifying the semi-variogram model, proving effective for surface interpolation and spatial analysis of noise. This study developed the RLS90 model in Python and integrated it into ArcGIS Pro. Based on the results, the RLS90 model provided accurate estimates and was far superior to the IDW method across both measurement periods. Due to the plugin's extensibility, users can freely modify the code, for example, by changing the colour gradient of the map indicator based on the noise level. The study on the spatial patterns of traffic noise in Kirkuk City helped us recognise areas of danger and susceptibility in its distribution. Noise pollution from traffic hazards affects people's health through physiological and psychological stress and impaired cognition.

The main purpose of reducing traffic noise pollution is to promote a healthier environment for people living in cities, so one can consider specific strategies such as sound barriers and traffic-calming measures. Noise should be a factor in land use and development, used to manage the arrangement of cities to make them less noisy. Also, raising awareness, educating residents, and engaging them in the community enables them to fight noise pollution. approaches to exploit environmentally sustainable transport may help alter behaviour and advocate for noise-mitigating measures. Our study contributes to the body of knowledge on traffic noise pollution in Kirkuk City by offering recommendations for effective decision-making and policy formulation. Further studies in this area should continue to track noise pollution levels and analyse their interactions with other environmental characteristics, including air quality and the availability of green spaces, to formulate more effective interventions to improve people's quality of life and the environmental sustainability of urban centres.

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Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript.

Author Contribution

The authors confirm their contributions to the paper as follows: ***Study conception and design****: Mohammed Hashim Ameen, Mastura Azmi;* ***Data collection****: Mohammed Hashim Ameen;* ***Analysis and interpretation of results****: Mohammed Hashim Ameen;* ***Draft manuscript preparation****: Mohammed Hashim Ameen, Mastura Azmi. All authors reviewed the results and approved the final version of the manuscript. The author confirms sole responsibility for the following: study conception and design, data collection, analysis and interpretation of results, and manuscript preparation.*

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