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Keywords	Noise mapping; uncertainty; urban variables; road traffic.
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Statistical attribution of errors in urban noise modeling

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Abstract

Due to the great variability of sound levels present in a city, static characterizations based on average values are falling out of favour. A distribution of differences analysis between the measured and calculated sound levels is conducted in this study to evaluate the accuracy of the noise model, and to analyse the different urbanistic and road traffic characteristics that influence their uncertainties. Results show that the noise model underestimates noise values in the road categories with the highest and lowest road traffic flows, specified as categories 1 and 5, respectively. Monitoring of vehicle speed in category 1 and use of an appropriate on-site measurement strategy could improve these estimates. Furthermore, a clear influence was observed of the number and percentage of heavy vehicles in overestimating noise values. Finally, the relationship of uncertainties with urban variables was studied as a possible alternative method of estimation. A multivariate model developed from urban variables recorded in different

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road categories, except for category 5, captured 70% of the variability of noise model uncertainty.

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1. Introduction

Noise pollution is an increasing environmental problem widely present in urban and natural environments [1]. A relationship between environmental noise and health effects has been shown in several studies [2]. Therefore, its evaluation, control, and reduction are among the major environmental health concerns for public authorities of developed countries.

To assess noise levels in cities, two different strategies are usually considered. In the first method, noise levels are measured in the streets *in situ*, and in the second, the noise is estimated using modelling methods implemented in specific software. Both strategies are included in the Environmental Noise Directive (END) [3]. Although modelling methods have great potential and are usually proposed for noise mapping, they must be complemented with *in situ* measurements to calibrate their estimates [4-5].

For direct-measurement methods, the END [3] indicates that the method 'may be defined on the basis of the definition of the indicator and the principles stated in ISO 1996-2: 1987 and ISO 1996-1: 1982'. The only sampling selection point strategy proposed in the ISO 1996-2 standard is the use of a grid [6-8]. The grid method has been commonly used in previous studies [9, 10]. Nevertheless, this method presents important drawbacks in urban environments with a high sound level variability or in the presence of large physical obstacles [11, 12]. Because this sound level spatial variability in urban environments is attributed mainly to road traffic, other *in situ* sampling strategies are commonly employed to consider the urban road type [13, 14] or to directly consider the traffic flow [15].

For noise calculation, adequate selection of the modelling method is very important because the estimates obtained may differ depending on the modelling method [16, 17]. For Member States having no national computation methods or those wishing to change their methods, the END established the French national computation method NMPB-Routes-96/XPS 31-133 as the recommended method for road traffic noise [3]. A new revision of the END states that all Member States should use a common noise assessment methodological framework beginning in 2019 [18].

The similarity between *in situ* noise measurement and noise values obtained from noise computational models indicates the suitability of these noise models. However, it is difficult to determine the point at which both noise levels can be considered as similar. In general, a maximum value of 3 dB as the difference between the calculated and measured noise levels is considered as a reference [19-23]. Independent of this reference value, investigating the possible reasons for these differences could be of interest. Possible causes are associated with model limitations, such as limitations in the modelling method and the use of only one noise source; limitations in the data introduced in the model, such as the type of vehicle flow, vehicle speed, vehicle type percentages, absorption coefficient of the elements of the model, absence of some details or elements in the model, and type of pavement; or even limitations in the calculation configuration of the model, such as the number of reflections, and the meteorological conditions. Some of the aforementioned possible factors can affect the difference, resulting in positive, negative or indistinct results. In any case, the sign of the difference (that is, whether the model overpredicts or underpredicts actual noise levels) must be considered as important information about its possible source.

Thus, one of the objectives of this study is to analyse the differences between measured and calculated sound values in 547 measurements conducted on different types of urban roads. The procedure used to analyse the positive, negative, absolute, and average differences between the measured and calculated sound values presented in this work is novel. This method can be used to evaluate the accuracy of fit of the modelling method and to analyse the possible source of these differences; therefore, it is a tool for analysing calculation models in future studies.

An additional aspect of the present study is that, apart from the functionality of streets as a communication path, the sampling point selection considers the variability of urban features such as street width, longitudinal profile, number of inhabitants, presence of crossings, presence of certain interest areas, and other factors. *A priori* knowledge in the analysis of different urban variables could help to improve the functionality of the streets, even for a researcher with no knowledge of a particular city. The influence of urban variables on street functionality implies relationships with both traffic and noise [14, 15]; thus, several studies have shown a significant relationship between urban features and noise levels [24-28]. Therefore, relationships could exist between urban variables and the uncertainty of computational acoustic models. Identifying and evaluating such relationships are also objectives of the present work.

2. Methods

2.1. Studied city

Located in southwestern Spain, the city of Cáceres has a population of about 95000, which increases to more than 110000 during the teaching period owing to an influx of tourists and students of the University of Extremadura. The urban development of the city has been influenced by a need to conserve older parts of the city centre (UNESCO World Heritage site) and by differences in altitude in among areas in the city. The transformation of some streets into pedestrian zones and the traffic restriction of other streets in the old parts of the city have benefited the acoustic environment [29, 30]. In recent years, construction of a ring road around the city has changed the traffic patterns, which has greatly reduced the number of vehicles passing through the city. This has in turn reduced the noise, particularly from heavy vehicles. Industrial activities are concentrated mainly in the outskirts of the city, although these activities are of minor relevance.

2.2. Sampling measurement

Sampling points were placed in various locations according to the role played by the different streets in connecting the different zones of the city, and the streets were assigned to one of five categories (Figure 1). The categories were defined following previous research in Cáceres [31].

At each sampling point, four 15-minute measurements were collected during the following time intervals in local time: 7–11 a.m., 11 a.m.–3 p.m., 3–7 p.m., and 7–11 p.m. The measurements were performed following ISO 1996-2 guidelines [7, 32]. Brüel & Kjaer 2250-L Class 1 sound-level meters and Brüel & Kjaer 4231 Class 1 calibrator were used. All of the measurements were conducted during the aforementioned time intervals on different working days of the week during 2013 and 2014.

The sound-level meter was located 1 m from the curb. The traffic flow was visually identified and classified during sampling as cars, heavy vehicles, and motorcycles. Other relevant information such as meteorological conditions, street dimensions, road surface type, and conservation of the road surface was also noted. Traffic was the major noise source registered in the measurements. When other short noise sources such as horns or sirens were detected, the measurements were paused or reinitiated.

2.3. Simulation results

A representation of the city for acoustic modelling purpose computer model of the city was built with Predictor v.9.12 commercial software. The final model of the city contained 949 roads, 7025 buildings, and 987 ground regions near 50000 height lines or height points and 600 elements of other objects such as Global Positioning System (GPS) points, barriers, and bridges. A three-dimensional (3D) version of the created model is shown in Figure 2. The following configuration options were assessed in the modelling:

- Computational model: XPS 31-133
- Number of reflections: 1
- Meteorological conditions: default values of Toolkit 17 of the ‘Good Practice Guide for Strategic Noise Mapping and the Production of Associated Data on Noise Exposure’ report [33]
- Building height: ground floor: 4 m; each additional floor: 3 m
- Absorption of buildings: reflecting
- Flow type: Constant flow

In total, 547 noise values were calculated in the described acoustical model to correspond with measurements where vehicles had passed during the measurement time. In each calculation, the receiver was placed in the same location as that in the *in situ* measurement by using photographs and geographic coordinates taken during the sampling. In addition, the vehicle flow and composition was the same as that measured during the sampling. The height of the receiver was the same as that of the sound-level meter, at 1.5 m.

2.4. Urban variables

All 142 streets in Cáceres that included a sampling point were characterised by 118 urban variables. The values of some of these variables were noted simultaneously during the sound measurements. Others were determined through geographic information system (GIS) [34] data or by revisiting the areas surrounding the sampling points. The registered urban variables were classified in the following groups:

1. Location of the street and demography: population and distance to the city centre, etc.
2. Urban land use: industrial, sports, leisure, cultural, green, shopping, administrative, educational, lodging, worship, and health areas, etc.
3. Street geometry: street length, street width, average building height, lane information, parked car, road profile, road slope, and road surface, etc.
4. Traffic and connectivity: traffic lights, pedestrian crossings, crossroads, U-turns, speed, communication nodes, etc.
5. Public and private transport: urban buses, taxis, parking areas, gasoline stations, interurban buses, urban waste collection points, etc.

2.5. Statistical methods

Firstly, descriptive or exploratory analysis was conducted with the uncertainties; that is, with the differences of the measured and calculated sound values [$L_{measurement}$ - L_{model} (dBA)]. Centralization, including averages and averages of absolute values, and dispersion, including standard deviation, were analysed. Information of the data distribution is presented in graphs such as box plots, scatter plot, and bar charts. This analysis of the distribution of the differences between the measured and calculated values considering both the sign and the magnitude of these values is one of the novelties of this study. This analysis could help to determine the origin of the uncertainties in the calculation models.

Secondly, inferential analyses were conducted to compare average values and related variables. The difference between measured and calculated sound values did not present significant differences with respect to a normal distribution ($p > 0.05$ according to the Kolmogorov–Smirnov test). Therefore, Student's T test was used to analyse whether the mean of the differences between the measured and calculated sound values differed from the zero value. Noise model estimates are more accurate when their uncertainties are close to zero. For the study of possible relationships between variables, bivariate and multivariate analyses were conducted. First, Pearson's correlation coefficient was used to analyse the bivariate relationships. The relationships among the difference in measured and calculated sound levels, vehicle flow and type, and urban variables were analysed. Then, stepwise multiple linear regression analysis was conducted between the differences in the measured and calculated sound levels and urban variables. For this analysis, only urban variables having a significant correlation with the difference between the measured and calculated sound levels were selected. Moreover, the direction selections of 'forward selection' and 'backward elimination' were used in the multiple regression analysis (stepwise regression). At each step of 'forward selection', an urban variable (independent variable) having smallest p-value for test F that was not present in the regression model was introduced; this p-value must be less than 0.05. At each step of 'backward elimination', urban variables having the highest p-value for test F that were present in the regression model were deleted. Only independent variables with a p-value less than 0.05 remained in the model. The method ended when no variable candidates could be included or eliminated. This method also avoids collinearity in the selection of independent variables. The resulting multiple linear regression models were validated for normality, homoscedasticity, and linearity according to the Shapiro–Wilk, Breusch–Pagan, and Ramsey Regression Equation Specification Error (RESET) tests, respectively, and their prediction capacities were analysed on the basis of new noise measurements.

3. Results and discussion

3.1. Accuracy of fit analysis of the city acoustical model

As preliminary verification, the accuracy of fit of the noise model was evaluated. For this verification, all of the sampling points in which vehicles passed through during the noise measurement were modelled. Thus, 547 different model calculations were conducted. As the first step for these calculations, the considered vehicle speed was the maximum allowed in the 'Good Practice Guide for Strategic Noise Mapping and the Production of Associated Data on Noise Exposure' report [33]. The differences between the modelled noise levels and the measured levels are summarised in Table 1 and are shown in Figure 3.

As shown in the figure, the differences between the measured and calculated noise levels presented a distribution similar to Gaussian with centre near the zero value. This hypothesis was verified by using the Kolmogorov–Smirnov test (p-value > 0.05). Negative values indicate that the calculated value is higher than measured one. As previously mentioned, some reasons for this behaviour can be attributed to the data introduced in the model, such as differences in actual and modelled speed and in the building absorption characteristics; to the model itself, such as inappropriate power data associated to the different noise sources; or to the technician, such as bad positioning of the receiver or generalization of vehicle flow. On the contrary, positive values imply that the calculated noise value is lower than the measured one. This could be attributed to the presence of sources other than traffic noise or to the same factors previously described such as erroneous data introduced in the model, bad positioning of receivers, and other factors. Errors caused by bad positioning of receivers in the acoustical model were avoided by calculating only those points in which a photograph of the sound-level meter was provided. In addition, an attempt was made to avoid the presence of other noise sources at the location of the sampling points during the measurement such that the sound-level meter was placed in an area in which no other important noise sources were present. Measurements that included significant noise sources other than vehicle traffic were reinitiated during the sampling or were not modelled. Some of the other possible influences will be discussed in this work. In Figure 4, a good relationship is shown between the logarithm of the traffic flow and the measured sound levels; indeed, the linear fit indicates that 85% of the sound level variability is explained by the traffic flow.

As shown in Figure 3, the distribution of the differences exhibited slight positive skewness. Thus, the average value found for the difference was 0.73 dBA. This value is statistically different from the zero value according to the T test, as shown in Table 1. The average values for each studied category are also presented in the table. Categories 1 and 5 present the highest average differences, with average values near 1 dB and those statistically different from zero according to the T test. On the contrary, categories 2, 3, and 4 presented average differences which were not statistically different from zero. Although the mentioned average in the difference between measured and calculated noise levels can give information on the accuracy of the model, is also important to evaluate its precision. As such, the average values of the absolute value of these differences are also shown in Table 1. In all categories, the average value was less than 3 dBA; similarly, the global average value was 2.43 dBA.

The average values of the absolute differences obtained were lower than those obtained in recent noise mapping studies [13]. In the present study, categories 1 and 5 have the highest values.

Considering the absolute values of the differences obtained in all categories and the aforementioned value of 3 dBA, 68% of the differences were less than this reference value. Similar percentages were obtained by Lisle [17]. Considering the various categories, category 5 had the lowest percentages of differences that were less than this reference value.

On the basis of these results, the errors of the noise model were in the range of values considered acceptable. The source of these errors was then analysed. To this end, the relationship of the errors with speed and type of vehicles, street category and urban features were studied. The identification of errors through the analysis of noise sources or urban characteristics will contribute to the reduction of errors in modelling.

3.2. Influence of vehicle speed

During the sampling, the estimated vehicle speed was annotated in the sampling file. This speed was usually higher than the street speed limit in categories 1 to 3, with average increments of 10–15 km/h, but was lower in categories 4 and 5, with average decrements of 5–10 km/h. To evaluate the effect of using estimated vehicle speed, the same analysis described in the previous section for the differences between measured values and calculated values was conducted for the estimated speed values.

As shown in Table 2, the average absolute differences in categories 1, 2, and 3 were lower than the averages shown in Table 1, which included the street speed limit. Thus, a larger number of differences that were less than the 3 dBA reference value were present. Category 1 presents the highest decrease in the uncertainty. Indeed, the average value of the difference between measured and calculated values was not significantly different from the zero value, as shown in Table 2. Nevertheless, the results were worst for categories 4 and 5.

These results indicate that more accurate characterization of the vehicle speed can reduce the underestimation observed in the model in the case of streets with higher traffic flows. However, the estimated speed is merely an estimation; the remainder of the analysis was conducted by using the posted speed limits of the streets.

3.3. Influence of vehicle type

Vehicle flow has a major influence on the measured noise levels, particularly when considering that the rest of noise sources have been avoided, as previously mentioned. Thus, a clear relationship between the measured noise levels and the logarithm of the vehicle flow is present, as shown in Figure 4. The Pearson correlation coefficient ($R = 0.92$) showed a very significant positive correlation between both variables ($p \leq 0.001$).

This study evaluated the influence of the number of vehicles and the differences between motorcycles and heavy and light vehicles as well as the percentages in the observed differences among measured and calculated noise levels considering all the differences, only positive differences, and only negative differences. As shown in Table 3, for all of the differences, only the number and percentage of heavy vehicles had a significant correlation with the differences between the measured and calculated values. Extraction of more information for this and other influences is important to analyse positive and negative differences individually.

Considering the negative differences in the first step, specifically those obtained when the simulated noise values were higher than the measured values, the sign and the significance of the correlation coefficient were analysed. A positive correlation coefficient indicates that an increase in the value of the variable (i.e. the number or percentage of each type of vehicle) produced a decrease in the difference between the measured and calculated noise values and vice versa (Figure 5). As shown in Table 3, only the number and percentage of heavy vehicles and the percentage of light vehicles showed significant correlation. The increase in both number and percentage of heavy vehicles implies an increase in the negative difference between measured and calculated noise values. An increase in the percentage of light vehicles implies a decrease in the negative difference between measured and calculated noise values. Because the percentage of light vehicles is complementary to the percentage of heavy values, both results are congruent. Therefore, the analysis results of the negative differences indicate that the overestimation differences of the model are related to the number and percentage of heavy vehicles.

Considering the positive differences in the second step, specifically those obtained when the simulated noise values were lower than the measured values, a positive correlation coefficient indicates that an increase in the value of the number or percentage of each type of vehicle resulted in an increase in the difference between the measured and calculated noise values (Figure 5) and vice versa. In this case, an increase in the type of vehicle resulted in a significant decrease in a positive difference between the measured and calculated values. Thus, the number of any type of vehicle tended to reduce the underestimation of the modelled noise level. The obtained correlation, although significant, was lower than that obtained for the negative differences. Indeed, when the differences were analysed without considering the sign of the difference ('all differences' column in Table 3), motorcycles and light vehicles did not show significant correlation.

Figure 6 shows the relationship of positive differences between the measured and calculated values and road traffic flow. The measurements with the lowest traffic flows presented the highest values of the studied difference and the highest variability. As the flow increased, the positive difference decreased, at R = -0.14 with $p \leq 0.01$. However, a deeper analysis of the figure reveals that a clear decrease in positive differences in the range of 0 to 500 vehicles, at R = -0.21 with $p \leq 0.001$. This occurred because no significant correlation was noted for values greater than 500 vehicles, at R = -0.08 with $p > 0.05$. Streets of categories 4 and 5 are mostly residential with low vehicle flows. With low vehicle speeds, and contribution of the motor effect on vehicle noise is generally lower than those of acceleration and braking. This can also explain the higher sound levels observed in the *in situ* measurements with respect to the calculated values.

3.4. Special case of category 5

Category 5 (the one with the lowest traffic density) had a higher dispersion of data with the highest standard deviation, as shown in Table 1, owing to the different characteristics of the mainly residential streets included. This high variability has been described in previous research [35]. Information of residential streets is scarce because traffic monitoring stations are generally located in streets with high traffic flows [36]. Indeed, some previous works modelled only streets with high traffic flows [23, 37, 38].

In this category, 62.5% of the difference between measured and calculated noise levels were positive, indicating that the noise model generally underestimated the noise level.

Figure 7 shows an in-depth analysis of the differences between the measured and calculated values in this category. A significant number of points showed high values of this difference (right side of the graphic) but with very small traffic flows (bottom of the graphic). This important bias towards positive values indicates that the assessment of noise in these ‘quiet’ streets can also be biased. Thus, the errors of the model for this category, showing the difference between measured or calculated noise levels, are compared in Table 4 with the standard deviation as an uncertainty index of the *in situ* measurement considering the number of vehicles passing during the 15 min of sampling. The *in situ* measurements appeared to result in be more precise noise levels when the number of vehicles was fewer than 10. The absolute difference between the measured and simulated values was clearly high when the number of vehicles was low. Therefore, an adequate *in situ* measurement strategy could be a good alternative to calculation models including residential streets with low vehicle flows.

3.5. Relationships between urban variables and model uncertainties

As previously mentioned, each studied street (those with sampling points) was characterised by 118 urban variables classified in the following groups: (1) location of the street and demography, (2) urban land use, (3) street geometry, (4) traffic and connectivity, and (5) public and private transport. In total, 122 points were used for the multivariable analysis, and 20 additional points were randomly extracted to test the obtained models. Although this extraction was random, the proportion of data of each category was maintained.

In the first step, the relationships were analysed between each urban variable, or independent variables, and the difference between the measured and calculated sound values, or dependent variables. In Table 5, only those variables with significant correlation to the dependent variable are shown. After this analysis, the 118 initial variables were reduced to 22, as shown the table, to study the multivariate models. These variables are related to the location of the street and the demography (V4–V6, V12), urban land use (V8–V10, V13, V17, V19, V20), street geometry (V1, V7, V14, V15), traffic and connectivity (V11, V18, V21, V22), and public and private transport (V2, V3, V16), or groups 1–5, respectively.

In the second step, stepwise multiple linear regression analysis was conducted with the urban variables (independent variables) with significant correlation, or those shown in Table 5. Considering the special characteristics of the streets of category 5, with low vehicle flow and possible influences of nearby sources, three different regression analyses were conducted: one with all of the differences of the study; one with differences only of categories 1, 2, 3, and 4; and, one with differences of category 5. The results of these three analyses are shown in Table 6. The three regression models shown in the table were validated for normality, homoscedasticity, and linearity.

Owing likely to the high variability of sound levels present in category 5, the differences between the measured and simulated noise values in this category predicted by urban features were worse than those predicted by other analyses. In this case, two independent variables, V1 and V8, were included in the model, and a correlation coefficient of 0.49 was obtained (Table 6). This correlation coefficient is the lowest of the three models. For categories 1 to 4, the obtained correlation coefficient was 0.84, indicating a high degree of explanation of the variability in the differences between the measured and calculated values with urban features. Finally, when all of the data were considered, the correlation coefficient obtained was influenced by the high number of data in category 5 owing to its large number of streets, and the correlation coefficient was 0.54.

Once the multiple regression models were validated (Table 6), they were tested with 20 additional points. As shown in Table 7, the average absolute values of the differences (bottom row) were similar to the residual standard errors obtained in multiple regression models (right column in Table 6). This indicates a high accuracy of fit in the obtained models.

Is important to note that the three multiple regression models analysed in this study had a negative constant, as shown in Table 6. Therefore, when the regression coefficient was negative, an increase in the independent variables led to an increase in the negative error (dependent variable) and vice versa.

As previously mentioned, the V1 and V8 urban variables were selected in the category 5 regression model. The number of directions of the road (V1) implied a decrease in the model error, or negative error. A road with many directions generally has a greater number of lanes and likely a larger traffic flow. Table 3 showed that an increase in the number of vehicles is related to a decrease in the positive differences. These positive differences occurred in a greater proportion in category 5 (Figures 6 and 7). The presence of a leisure area (discotheque), or V8, generated an increase in negative error. These activities may have influenced the presence of sources other than road traffic. It should be noted that these activities are generally nocturnal; the measurements for this study were conducted during the daytime, as mentioned. However, light trucks provide drinks, food, and other items to such places during the day. This implies an increase in the percentage of heavy vehicles related to the increase in negative error, as shown in Table 3. In this category, considering the low flow of vehicles, an increase in the number of heavy vehicles has a great influence on the percentage of heavy vehicles.

The urban variables selected for the multiple regression model obtained with data of categories 1 to 4 were V6, V10, V14, V18, V21, and V22. The higher speed observed in the streets of these categories than those in category 5, particularly in categories 1 to 3, implied lower differences between the measured and calculated values (Table 2). Therefore, an increase in the maximum speed of the street (V22) consistently led to a decrease in the negative difference. The same decrease in negative difference was observed in the number of crossroads providing access to the road (V21). The presence of crossroads indicates the proximity of other streets that may influence the sound level of the sampling point, thereby increasing the recorded sound level. This increase could be attributed to the effect of acceleration or deceleration of vehicles or underestimation of the noise of adjacent streets by the model. With regard to urban variables that influence the increase in negative differences, or those with a negative coefficient in Table 6, two variables are frequently present in the main streets of the city where a significant percentage of heavy vehicles is generally present: a U-shaped longitudinal profile, V14, and the number of pedestrian crossings per metre, V18. In the city of Cáceres, these pedestrian crossings are generally associated with traffic lights, which are usually present in the streets to provide an important function for communication between the different parts of the city. Two other urban variables that indicate increases in the negative studied differences are the presence of teaching buildings, V10, and the distance from the end of the street to the city centre, V6. Urban buses, or heavy vehicles, are usually employed by students to reach the teaching centres. Moreover, ring roads that have been created in Cáceres to divert part of the heavy traffic are located on the outskirts of the city. Therefore, the relationships among these two variables and heavy traffic indicates an increase in negative differences between the measured and calculated noise values.

Finally, urban variables V1, V2, V1, and V10 were included in the model considering all of the data. The positive influence of V1, or the decrease in negative differences between the measured and calculated values, was similar to that explained for results of the data only from category 5. It should be considered that 57% of the points sampled belong to category 5. The remaining independent variables contributed to increase in negative differences. V10 and V2 are directly related to the presence of two types of heavy vehicles: urban buses and garbage trucks. V11 was present only in main roads; therefore, this result is linked to the presence of heavy vehicles.

In light of the increasing development and access to GIS, models considering urban variables can be economic alternatives for estimating sound levels. Moreover, as the results of this study show, the regression models developed for categories 1-4 predictions captured 70% of the variability of the errors of the calculation models. This percentage is similar to that achieved by models that determine the sound levels from urban variables [26].

4. Conclusions

A road traffic noise model was developed for the city of Cáceres, and its predictions were compared with a large number of *in situ* measurements conducted on different types of urban roads. Analysis of the distribution of the differences between the measured and calculated sound levels was proposed in this study to evaluate the accuracy of fit of the noise model and to analyse the different urbanistic and road traffic characteristics that influence their uncertainties. Thus, this analysis strategy considered the variability of sound levels, which is important when developing noise maps.

The uncertainties in the noise model followed a normal distribution. Therefore, the mean value analysis lacked information on the precision of the noise models. Analyses of the negative, positive, and absolute errors of the noise models conducted with different types of urban roads made it possible to determine the following results.

- The noise models were underestimated in the categories with the highest traffic flow because the estimated speed of the vehicles was higher than the posted speed limits.
- A significant relationship was noted between negative errors in noise models (overestimation) and the percentage and number of heavy vehicles.

- Positive errors noted in noise models (underestimation) in residential streets with low traffic flow were higher than the standard deviation of *in situ* measurements. Appropriate *in situ* sampling strategies can therefore be an alternative to noise models for these roads types.

Urban variables can provide alternatives to determining the uncertainties in noise models given the relationship between urban variables and the functionality and flow of road traffic. The results of this study showed that 22 urban variables presented a significant correlation with respect to the uncertainties in the noise model. In addition, a multivariate regression model developed from urban variables representing land usage and other factors of the different road categories, except in category 5, captured 70% of the variability of the uncertainty in the noise models. Therefore, regression models developed specifically with urban variables in other cities could provide an alternative to the assessment of noise models and serve as a useful tool for urban managers and planners.

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Table Captions

Table 1. Analysis of differences between measured and calculated noise levels in each category.

Table 2. Analysis of differences between measured and calculated noise levels, calculated using estimated speed.

Table 3. Relationship of number and percentage of vehicles including light vehicles, heavy vehicles, and motorcycles and difference in measured and simulated noise levels.

Table 4. Average absolute difference between measured and calculated noise levels and standard deviation of *in situ* measurements for recorded values in category 5, with 1 to 10 vehicles during 15 min of sampling.

Table 5. Significant correlation among urban variables and the difference between measured and calculated noise levels.

Table 6. Table of regression coefficients, correlation coefficient, and standard error of the estimates of multiple regression models.

Table 7. Absolute estimation error of the multiple regression models.

Table 1

		Category				
	Overall	**1**	**2**	**3**	**4**	**5**
Number of sampling points	142	15	11	16	20	98
Number of pairs of data (simulated and measured)	547	60	44	64	80	299
Average value ± standard deviation	0.73 ± 3.10	1.37 ± 2.44	0.12 ± 2.59	-0.39 ± 2.96	0.19 ± 2.62	1.08 ± 3.33
Significance (T test)	≤0.001	≤0.001	>0.05	>0.05	>0.05	≤0.001
Average value ± standard deviation (absolute values)	2.43 ± 2.04	2.36 ± 1.48	1.79 ± 1.86	2.30 ± 1.88	2.09 ± 1.57	2.66 ± 2.28
Percent between 0 and 3 dB	67.82	70.00	81.82	67.19	72.50	64.21

Table 2

	Category					
	Overall	**1**	**2**	**3**	**4**	**5**
Number of pairs of data	547	60	44	64	80	299
Average value ± standard deviation	0.77 ± 3.19	-0.16 ± 2.48	-0.74 ± 2.47	-0.41 ± 2.76	0.34 ± 2.64	1.54 ± 3.41
Significance (T test)	≤0.001	>0.05	>0.05	>0.05	>0.05	≤0.001
Average value ± standard deviation (absolute values)	2.49 ± 2.13	2.05 ± 1.38	1.76 ± 1.87	2.03 ± 1.89	2.15 ± 1.56	2.88 ± 2.39
Percent between 0 and 3 dB	67.64	78.33	77.27	76.56	71.25	61.20

Table 3

R^a	All differences	Only negative differences	Only positive differences
Number of heavy vehicles	-0.18^{***}	-0.35^{***}	-0.15^{**}
Percent of heavy vehicles	-0.27^{***}	-0.47^{***}	$-0.11^{n.s.}$
Number of light vehicles	$-0.01^{n.s.}$	$0.01^{n.s.}$	-0.14^{**}
Percent of light vehicles	$-0.08^{n.s.}$	0.31^{***}	$0.01^{n.s.}$
Number of motorcycles	$-0.06^{n.s.}$	$-0.03^{n.s.}$	-0.13^{**}
Percent of motorcycles	$0.06^{n.s.}$	$0.04^{n.s.}$	$0.04^{n.s.}$

[a] Correlation coefficient (Pearson).
** Significant at $p \leq 0.01$.
*** Significant at $p \leq 0.001$.
$^{n.s.}$ Non-significant correlation ($p > 0.05$).

Table 4

Number of data	Number of vehicles	Average absolute difference between measured and simulated noise levels	Standard deviation of measurements
40	1	4.0	2.6
42	2	3.0	2.6
26	3	2.6	2.2
15	4	3.6	2.4
12	5	2.3	1.5
13	6	3.2	2.0
13	7	1.9	2.5
13	8	2.6	1.8
9	9	1.4	1.2
10	10	1.7	1.5

Table 5

Code	Variable	R Pearson	Significance
V1	Number of directions of the street	0.30	≤0.001
V2	Number of urban waste collecting points per kilometre	-0.29	≤0.01
V3	Number of urban waste collecting points	-0.20	≤0.05
V4	Distance from the start of the street to the city centre	0.27	≤0.01
V5	Distance from the middle of the street to the city centre	0.27	≤0.01
V6	Distance from the end of the street to the city centre	0.26	≤0.01
V7	Mean height of buildings (m)	-0.27	≤0.01
V8	Presence of discotheques	-0.21	≤0.05
V9	Presence of bars	-0.21	≤0.05
V10	Presence of teaching buildings	-0.22	≤0.05
V11	Number of street lights on the street	-0.23	≤0.05
V12	Number of inhabitants	-0.23	≤0.05
V13	Presence of administration buildings	-0.22	≤0.05
V14	Type-U street geometry	-0.22	≤0.05
V15	Number of angled parking places	-0.21	≤0.05
V16	Number of taxi stops	-0.21	≤0.05
V17	Presence of health centres	-0.21	≤0.05
V18	Number of pedestrian crossings per metre	-0.19	≤0.05
V19	Presence of gyms	-0.19	≤0.05
V20	Presence of sports centres	-0.19	≤0.05
V21	Number of crossroads that give access to the road	0.18	≤0.05
V22	Maximum speed for the street	0.18	≤0.05

Table 6

Model		Coefficients		T	Significance	R	Standard error of estimate
		B	Standard error				
All categories	(Constant)	-2.46	0.81	-3.04	≤0.01	0.54	2.20
	V1	2.40	0.47	5.15	≤0.001		
	V2	-0.19	0.05	-3.76	≤0.001		
	V11	-77.89	31.83	-2.45	≤0.05		
	V10	-2.11	0.90	-2.36	≤0.05		
Categories from 1 to 4	(Constant)	-1.43	2.12	-0.68	>0.05	0.84	1.40
	V14	-1.73	0.47	-3.69	≤0.01		
	V18	-164.15	29.36	-5.59	≤0.001		
	V10	-1.90	0.46	-4.17	≤0.001		
	V22	0.11	0.04	3.03	≤0.01		
	V21	0.20	0.06	3.30	≤0.01		
	V6	-0.81	0.37	-2.21	≤0.05		
Category 5	(Constant)	-1.87	1.02	-1.84	>0.05	0.49	2.38
	V1	1.92	0.59	3.22	≤0.01		
	V8	-3.18	1.25	-2.55	≤0.05		

Table 7

		Absolute estimation error (dBA)		
Category	**Point**	**All categories model**	**Categories 1–4 model**	**Category 5 model**
1	1	2.69	3.34	
1	2	4.76	2.06	
2	3	2.20	0.06	
3	4	0.79	1.40	
3	5	0.46	1.25	
3	6	5.00	2.59	
4	7	3.82	0.51	
4	8	2.80	2.29	
4	9	1.97	1.82	
4	10	0.63	0.21	
5	11	1.75		1.77
5	12	0.37		0.01
5	13	0.49		0.37
5	14	6.62		6.98
5	15	0.66		0.78
5	16	0.31		0.01
5	17	1.41		1.72
5	18	3.06		2.94
5	19	2.95		3.07
5	20	1.50		3.01
Average		2.21	1.55	2.07

Figure Captions

Figure 1. Street categories and locations of sampling points in the city of Cáceres.

Figure 2. 3D model of the city of Cáceres.

Figure 3. Distribution of differences between measured and simulated noise levels.

Figure 4. Relationship among measured noise levels and the logarithm of traffic flow (vehicles/h).

Figure 5. Interpretation of the correlation coefficient for positive and negative differences between measured and calculated noise values.

Figure 6. Relationship among positive differences between measured and calculated noise values and road traffic flow.

Figure 7. Scatter plot of the differences between measured and calculated values and the number of vehicles noted during the 15 min of sampling for points of category 5.

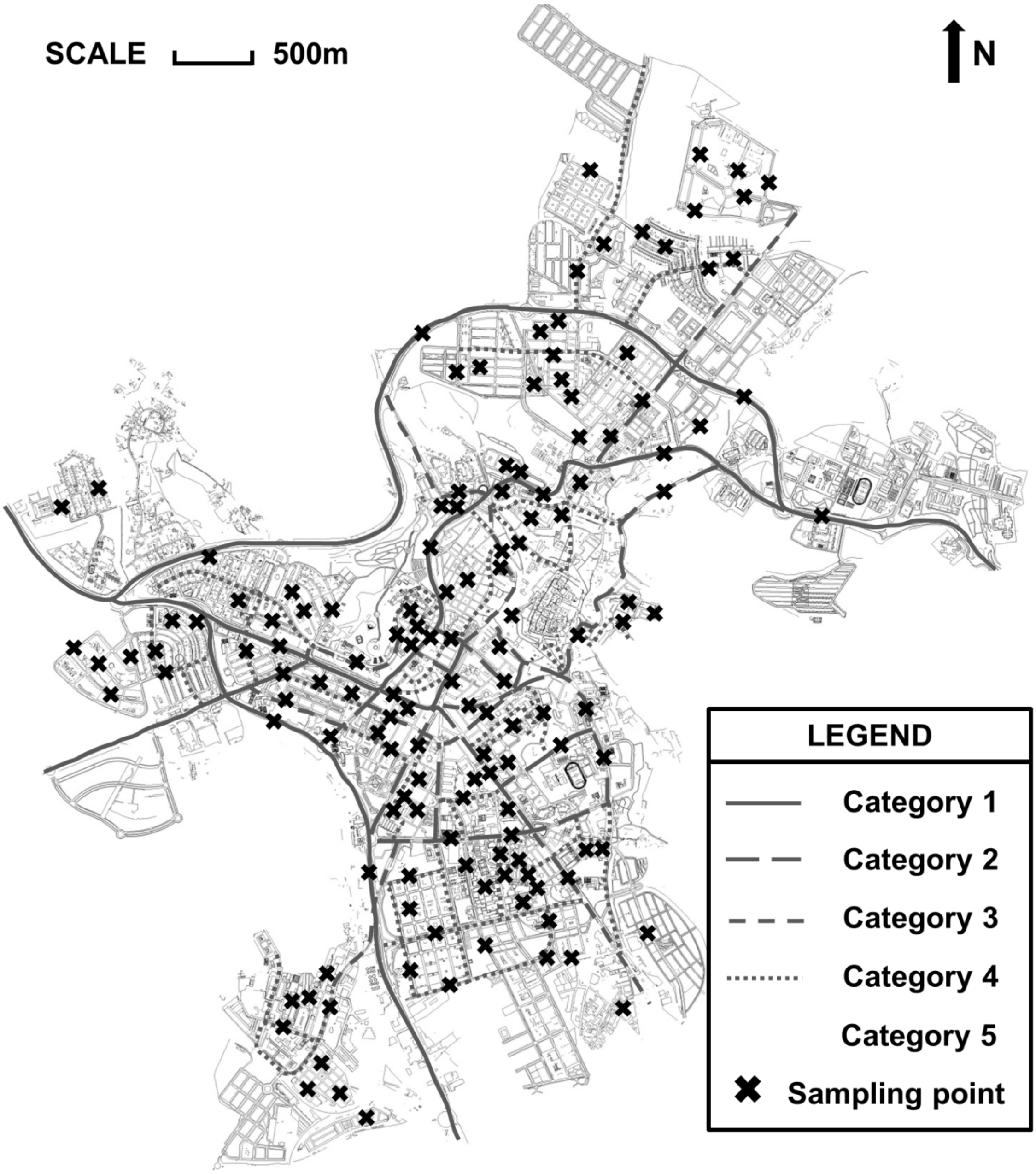

SCALE
500m
N
LEGEND
Category 1
Category 2
Category 3
Category 4
Category 5
Sampling point

Figure 1

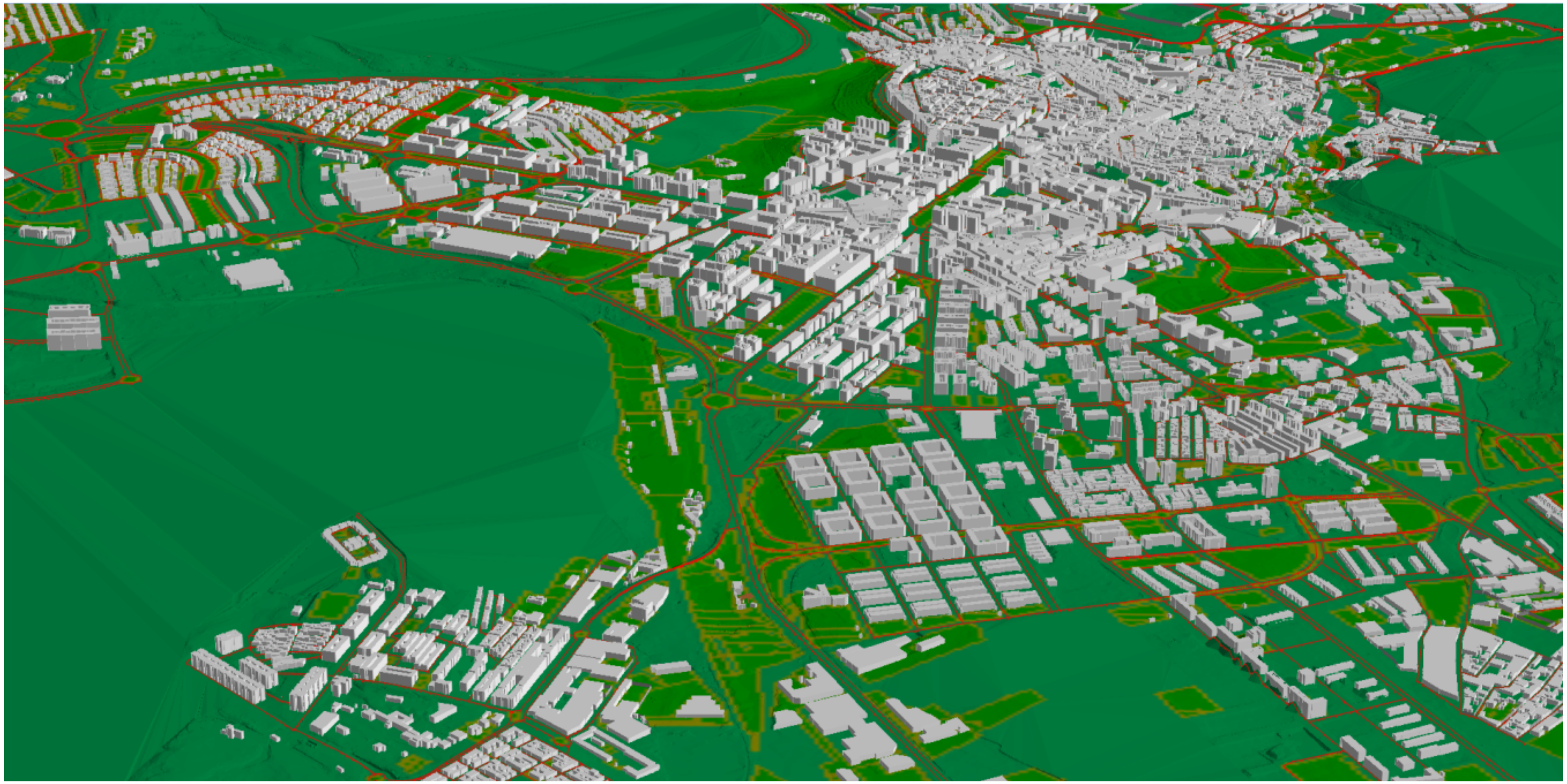


Figure 2

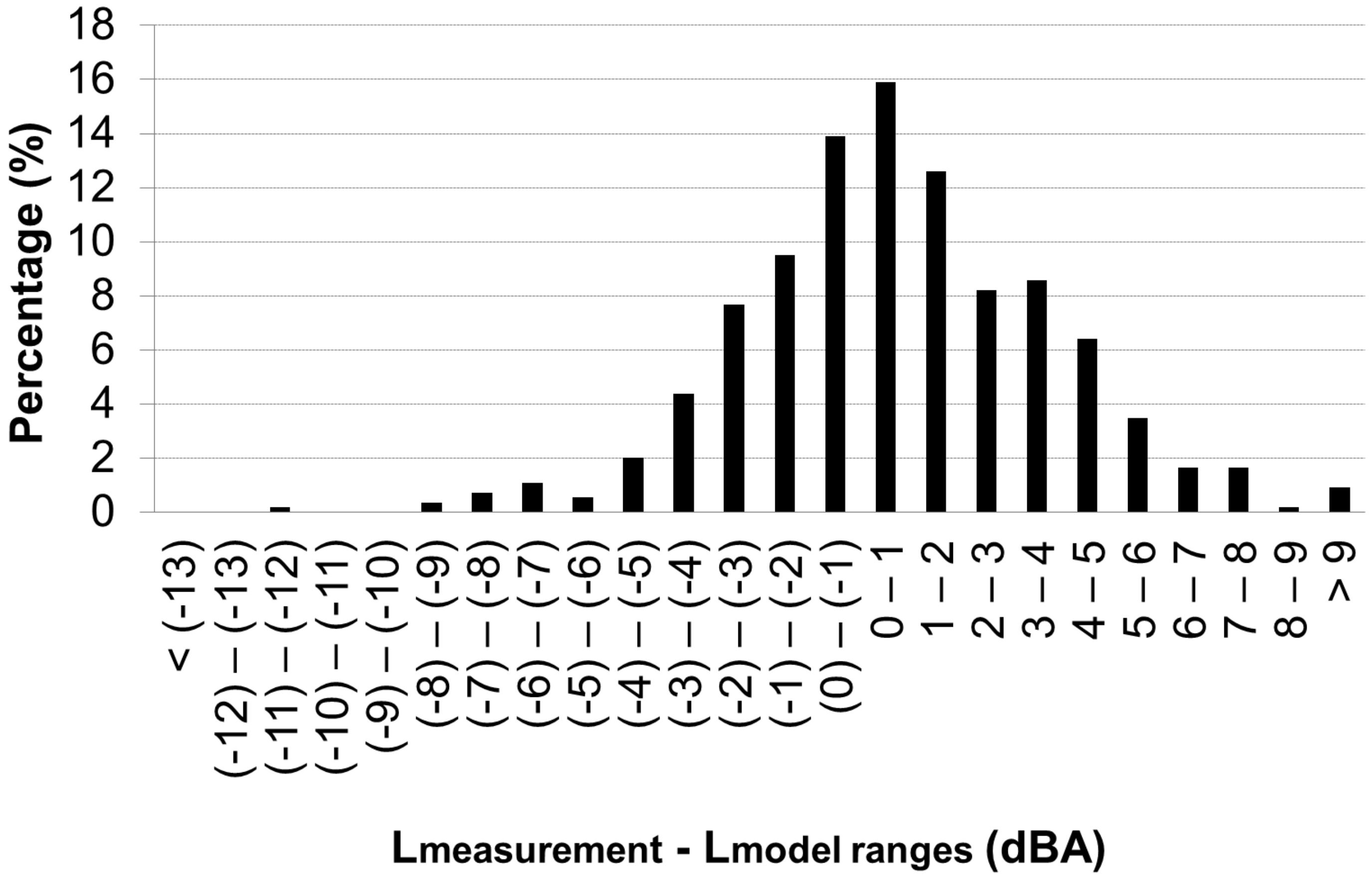
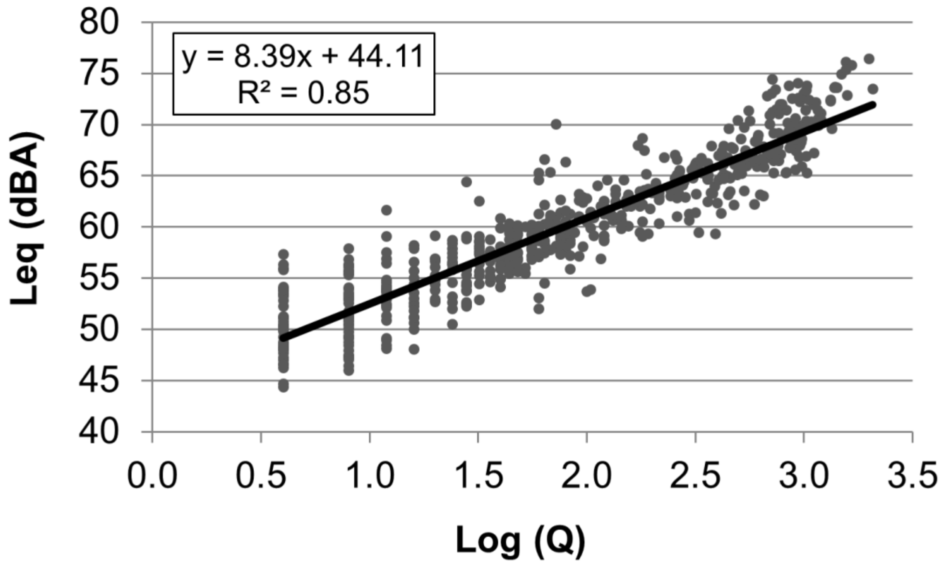

Percentage (%)
0
2
4
6
8
10
12
14
16
18
< (-13)
(-12) – (-13)
(-11) – (-12)
(-10) – (-11)
(-9) – (-10)
(-8) – (-9)
(-7) – (-8)
(-6) – (-7)
(-5) – (-6)
(-4) – (-5)
(-3) – (-4)
(-2) – (-3)
(-1) – (-2)
(0) – (-1)
0 – 1
1 – 2
2 – 3
3 – 4
4 – 5
5 – 6
6 – 7
7 – 8
8 – 9
> 9
Lmeasurement - Lmodel ranges (dBA)

Figure 3



y = 8.39x + 44.11
R² = 0.85
80
75
70
65
60
55
50
45
40
Leq (dBA)
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
Log (Q)

Figure 4

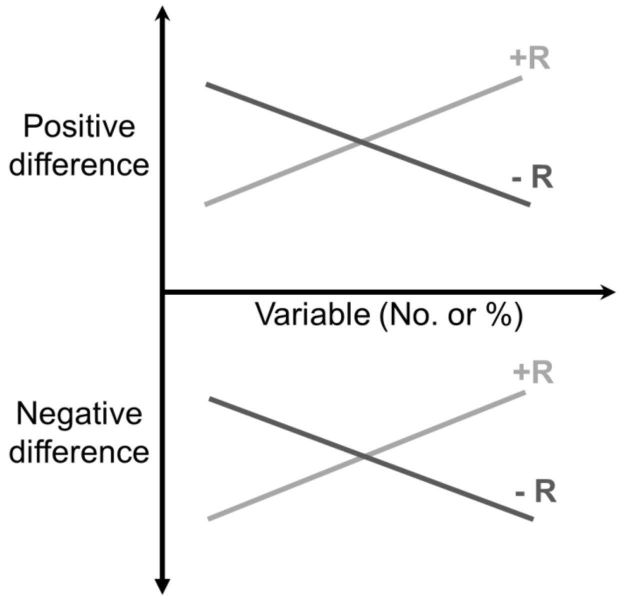
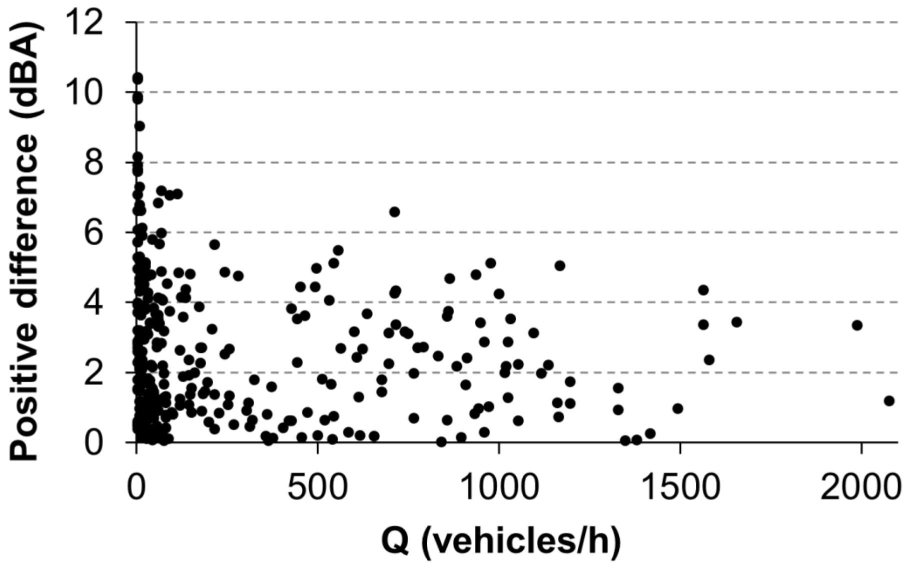
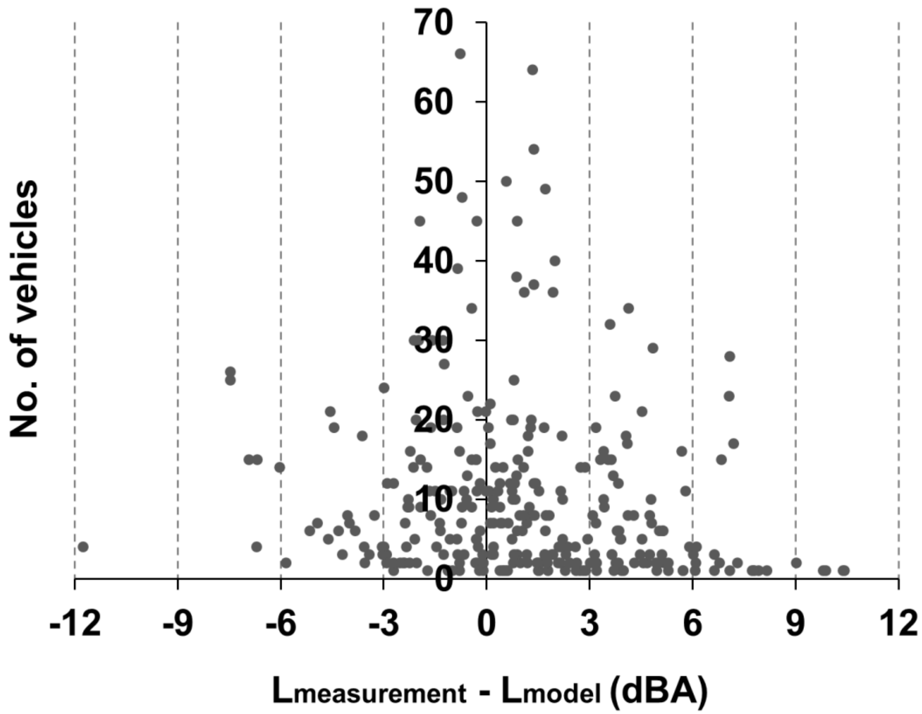

+R
Positive
difference
- R
Variable (No. or %)
+R
Negative
difference
- R

Figure 5



12
10
8
6
4
2
0
Positive difference (dBA)
0
500
1000
1500
2000
Q (vehicles/h)

Figure 6



No. of vehicles
70
60
50
40
30
20
10
0
-12
-9
-6
-3
0
3
6
9
12
Lmeasurement - Lmodel (dBA)

Figure 7