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RELATIVE IMPORTANCE OF ROAD TRAFFIC IN THE TEMPORAL STRUCTURE OF CITY NOISE

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ABSTRACT

The urban sound environment has a great variability over time and, at each instant, has a high complexity in its physical characteristics. This is a consequence of the multiple sound sources that may be present and the multiple circumstances that may occur and that will configure the characteristics of the sound environment of a street. In most city streets, road traffic represents the fundamental sound source, both in relative importance and in the variability of sound levels over time. A methodological proposal has recently been published which, by using a matrix variable, each value representing the proportion of traffic flow corresponding to one hour of the year, could explain the part of the annual variability of urban noise that is caused by road traffic. This proposal is analysed by comparing the results obtained from this variable at some point in the city with those obtained using the flows measured at the gauging stations close to the point where the noise levels are measured. As a result, in general, a higher coefficient of determination is obtained for the correlation of the sound levels measured at a given station in Madrid and the overall traffic flow variable than when correlating these same sound levels with traffic flows measured at the nearest stations.

Keywords: *monitoring network, road traffic noise, categorization method, urban traffic flow, noise pollution*

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1. INTRODUCTION

Urban environments are characterized by complex and dynamic sound environments, resulting from numerous interacting acoustic sources that fluctuate constantly over time. Among these sources, road traffic consistently emerges as the dominant contributor, significantly influencing both overall noise levels and their temporal variability within urban settings [1-3]. Given its prominence, managing road traffic noise has become crucial not only for urban planning and environmental policies but also for enhancing the quality of life and well-being of urban populations [4-8].

Previous studies have established clear associations between road traffic noise and adverse health outcomes, including cardiovascular diseases, disrupted sleep patterns, elevated stress levels, and general annoyance [9-12]. Such impacts underscore the importance of gaining detailed insights into the temporal distribution and intensity of traffic-generated noise. To achieve effective noise management, it is essential to quantify how fluctuations in vehicle flows across different temporal scales influence the acoustic characteristics of urban streets [13-17]. In this sense, the COVID-19 lockdown significantly improved air quality and reduced noise levels; however, noise still exceeded WHO guidelines, highlighting the need for increased public transport to transform urban mobility [18].

To study the noise distribution in a city in a fast and efficient way, the categorization method proposed by Barrigón Morillas et al. [19] can be followed, which has been analyzed in a wide variety of city typologies [20,21]. Yet, recent methodological advancements [22] propose the use of matrix-based variables, capturing hourly distribution of annual traffic flow, to represent the

temporal dynamics of road traffic comprehensively. This approach has the potential to simplify the analysis of traffic-induced noise variability by correlating traffic flow with urban noise measurements.
The objective of the present research is to evaluate this methodological approach by comparing the proposed traffic-flow matrix with empirical traffic data from established gauging stations located in proximity to urban noise monitoring sites. That is, this comparative analysis aims to determine which variable better explains the variability observed in sound levels recorded by a noise monitoring station in the city of Madrid: the mean hourly traffic flow ratio calculated globally for each hour of the year, the same yearly traffic flow ratio calculated for each street category, or the specific traffic flow values provided by traffic measurement stations closest to the sound level monitoring station.

2. METHODOLOGY

Madrid (Spain) has around 3.3 million inhabitants (6.8 million in the metropolitan area). To study vehicle flow variations, it maintains 60 traffic-monitoring stations, of which 54 operated properly in 2019. In addition, the city has a network of 31 class 1 noise level monitoring stations with microphones fixed approximately 4–6 m above the ground. Because the two networks serve different purposes, noise-level measurement devices are positioned separately from traffic-flow monitoring stations (Fig. 1). The flows of road traffic and sound levels recorded hourly throughout 2019 at the different monitoring stations were analysed in Barrigón Morillas et al. [22].

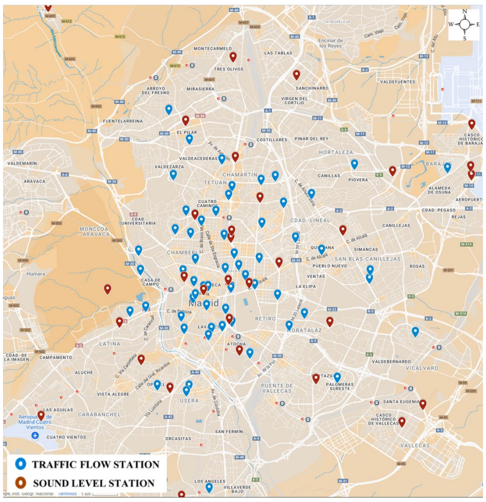

Figure 1. Monitoring stations of traffic-flow and sound-level distributed throughout Madrid.

Barrigón Morillas et al. [19] showed urban traffic flow exhibits consistent hourly patterns city-wide, enabling the use of a single metric —mean hourly flow ratio (MHFR)— to represent traffic variability. This metric allows accurate hourly analyses of traffic-related environmental variables throughout the entire city. Statistically significant relationships were found between the defined matrix variable (MHFR), used as an independent variable, and the sound levels recorded at each noise measurement station, considered as dependent variables. The sound level indicator used was $L_{Aeq,1h}$. The p-values obtained were less than 0.001 for all analysed cases. The explanatory power for noise level variability ranged from 16 % to 80 %.
Obtaining a single variable to define hourly traffic flow variability in the city is motivated by:

- The noise measurement stations have no associated traffic counting stations.
- Most city streets lack traffic counting stations.

Therefore, if the single matrix variable (MHFR) adequately predicts noise level variability in streets where validation is possible, it is expected that this variable can be applied to all city streets, or at least to those similar to the streets used to obtain it.
The usefulness of this variable to predict the sound level in a given area compared to using specific local traffic flow data or data from points with similar annual flow characteristics is going to be analyzed at the present study. So, this study compares the coefficient of determination (i.e., the proportion of variance in the dependent variable that is predicted by the statistical model) obtained through linear regression analysis. The independent variables considered are: (1) the global annual traffic flow variable (MHFR); (2) the annual traffic flow variable defined for stations located in streets belonging to the same category (as established in [19], identified as $MHFR_{Cn}$, with *n* ranging from 1 to 4, since there are no traffic flow monitoring stations in category 5 streets in Madrid); and (3) the local traffic flow measured by traffic flow monitoring stations in Madrid located near the sound level monitoring stations. The dependent variable is the sound level recorded at specific sound level monitoring stations in Madrid.
Nine noise measurement points throughout the city were selected. For only one of these points, the traffic counting stations are on the same street as the sound level measurement station but at relatively distant locations. The other points were chosen to reflect distinct traffic flow conditions, differing from each other and from the first selected point.

3. RESULTS

The nine sound-level measurement stations were analyzed using data from 23 (17 different) nearby traffic flow stations.

Sound-level station (SLS) 6 is located on Paseo de la Castellana, which has one traffic flow station (TFS 36) about 2.2 km to the north and another station (TFS 1) approximately 700 m to the south (Fig. 2).

Figure 2. Location, from top to bottom, of TFS36, TFS42, TFS12 and TFS1 (in blue) and SLS48 and SLS6 (in red).

Linear regression analyses of noise levels at SLS 6 against traffic flow data provided the following results: TFS 1 (p-value < 0.001, coefficient of determination [R^2] = 0.654), TFS 36 (p-value < 0.001, R^2 = 0.644). Considering two additional nearby stations, TFS 12 showed p-value < 0.001, R^2 = 0.495, and TFS 42 showed p-value < 0.001, R^2 = 0.629. These values are somewhat lower than those obtained using the MHFR variable, with R^2 = 0.678, p-value < 0.001. The difference between both values varies between 27 % (TFS 12) and 3.5 % (TFS 1). In the case of $MHFR_{C1}$, R^2 = 0.707, p-value < 0.001, the higher R^2 is obtained. In this case, the difference between both values varies between 30 % and 7.5 %.

For another nearby sound-level station (SLS 48), the following results were obtained: TFS 1 (p-value < 0.001, R^2 = 0.641), TFS 12 (p-value < 0.001, R^2 = 0.507), TFS 36 (p-value < 0.001, R^2 = 0.639), and TFS 42 (p-value < 0.001, R^2 = 0.622). In contrast, using the MHFR, results showed p-value < 0.001, R^2 = 0.671. The difference between both values varies between 24 % (TFS 12) and 4.5 % (TFS 1). In the case of $MHFR_{C1}$, R^2 = 0.697, p-value < 0.001. Again, this value is slightly higher than those obtained using nearby traffic flow stations (Tab. 1). In this case, the difference between both values varies between 28 % and 8 %.

Table 1. Coefficient of determination for the linear regression analysis for SLS6 and SLS48.

	SLS 6	SLS 48
TFS 1	0.654	0.641
TFS 12	0.495	0.507
TFS 36	0.644	0.639
TFS 42	0.629	0.622
MHFR	0.678	0.671
$MHFR_{Cn}$	0.707 (Cat. 1)	0.697 (Cat. 1)

These findings indicate that, in complex traffic environments with multiple streets simultaneously contributing noise sources to measurement stations, and possible variations in traffic flow due to construction work or lane repurposing, it appears preferable to use a general averaged traffic variability variable (MHFR) to predict noise-level variability, rather than relying on specific street traffic flow data, even from apparently similar streets and relatively close points.

Figs. 3 to 10 and Tabs. 2 to 9 present the location and the analysis results for the rest of sound-level stations studied. In all cases, p-values obtained were below 0.001.

In the next analyzed environment, there are three sound-level stations, SLS 26, SLS 27, and SLS 55, and only one traffic-flow station, TFS 58 (Fig. 3). Now, the MHFR variable explains a higher proportion of variation in the dependent variable than the traffic flow measured at the nearest station or $MHFR_{Cn}$ (Tab. 2). However, the difference between the explanation of each variable is lower than 2.5 %.

Figure 3. Location of TFS58 (in blue) and SLS26, SLS27 and SLS55 (in red).

Table 2. Coefficient of determination for the linear regression analysis for SLS26, SLS27 and SLS55.

	SLS 26	SLS 27	SLS 55
TFS 58	0.693	0.737	0.687
MHFR	0.710	0.753	0.694
$MHFR_{Cn}$	0.702 (Cat. 1)	0.745 (Cat. 4)	Without data (Cat. 5)

Now, in the next environment, there is only one sound-level station, SLS 10, but five traffic-flow stations, TFS 4, TFS 15, TFS 17 TFS 19, and TFS 40 (Fig. 4). Even in this case, where multiple traffic flow stations surround the sound-level station considered, the highest percentage of explained variation in noise level is provided by the global variable MHFR, better than $MHFR_{Cn}$. Although the difference is not large, the value obtained using MHFR remains higher. (Tab. 3), varying between 21 % (TFS 17) and 2.7 % (TFS 19).

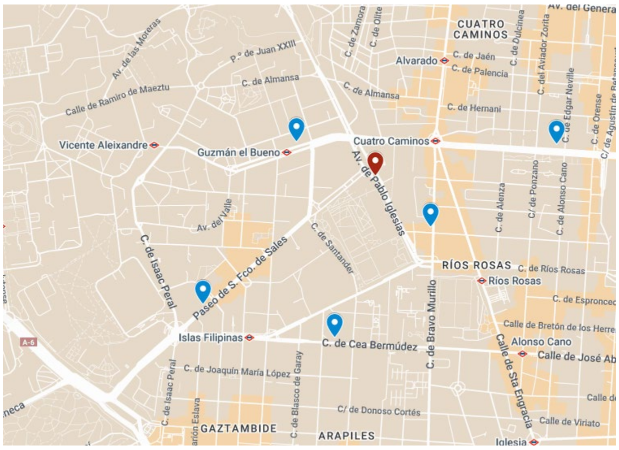

Figure 4. Location of TFS4, TFS15, TFS17 TFS19, and TFS40 (in blue) and SLS10 (in red).

Table 3. Coefficient of determination for the linear regression analysis for SLS10.

	SLS 10
TFS 4	0.653
TFS 15	0.587
TFS 17	0.534
TFS 19	0.659
TFS 40	0.582
MHFR	0.677
$MHFR_{Cn}$	0.669 (Cat. 2)

For the next environment, there were two traffic-flow stations, TFS 7 and TFS 43 and one sound-level station, SLS 19 (Fig. 6). However, TFS 7 provided anomalous data for 2019 and was therefore excluded. In this case, R^2 was higher for the local traffic flow instead of MHFR. Nevertheless, the difference between both values is lower that 5 % (Tab. 4).

Figure 5. Location of TFS7, and TFS43 (in blue) and SLS19 (in red).

Table 4. Coefficient of determination for the linear regression analysis for SLS19.

	SLS 19
TFS 43	0.720
MHFR	0.686
$MHFR_{Cn}$	Without data (Cat. 5)

For the next environment, there were six traffic-flow stations: TFS 26, TFS 8, TFS 25, TFS 35, TFS 34, and TFS 9 around one sound-level station: SLS 3 (Fig. 6). However, traffic-flow stations TFS 25, TFS 35, and TFS 34 provided anomalous data for 2019 and were therefore excluded from the analysis. In this case, also, R^2 was higher for the local traffic flow instead of MHFR. Nevertheless, the values for R^2 were the lower values for the studied environment, around 20 % of explanation or lower. In these cases, where traffic flow explains only a relatively small portion of noise-level variation, local traffic flow values appear to explain a greater percentage of the noise-level variation (Tab. 5), varying between 26 % (TFS 8) and 1.8 % (TFS 9).

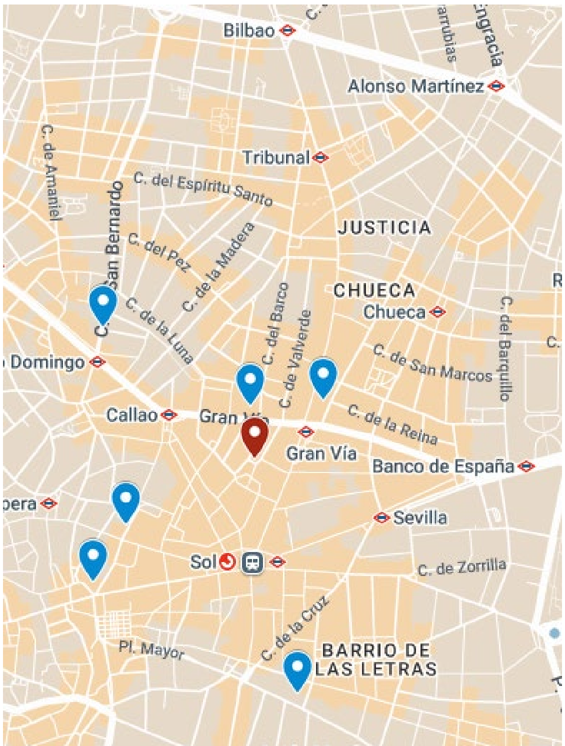

Figure 6. Location of traffic-flow stations: the top three, from left to right, and the bottom three, from top to bottom are TFS26, TFS8, TFS25, TFS35, TFS34, and TFS9 (in blue) and sound-level station SLS3 (in red).

Table 5. Coefficient of determination for the linear regression analysis for SLS3.

	SLS 3
TFS 8	0.220
TFS 9	0.166
TFS 26	0.195
MHFR	0.163
$MHFR_{Cn}$	Without data (Cat. 5)

For the last environment considered in this study, there were three traffic-flow stations: TFS 23, TFS 29, and TFS 5 around one sound-level station: SLS 2 (Fig. 7). Again, even with the three traffic flow stations surrounding the sound-level station, higher R^2 values are obtained using the global variable MHFR (varying the explanation between 12 % for

TFS 29 and 4.2 % for TFS 23) or $MHFR_{Cn}$ (varying the explanation between 16 % and 7.9 %) (Tab. 6).

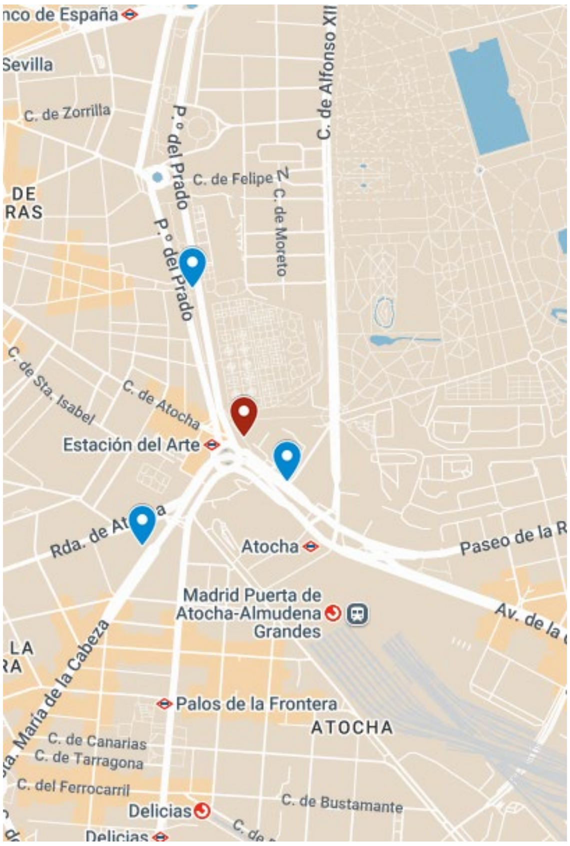

Figure 7. Location of traffic-flow stations: TFS23, TFS29, and TFS5 (in blue) and sound-level station SLS2 (in red).

Table 6. Coefficient of determination for the linear regression analysis for SLS2.

	SLS 2
TFS 5	0.565
TFS 23	0.596
TFS 29	0.545
MHFR	0.622
$MHFR_{Cn}$	0.647 (Cat. 2)

4. CONCLUSIONS

Nine sound-level stations in Madrid were analysed using linear regression to relate sound levels to traffic flow measured by designated stations. At SLS 2, the $MHFR_{Cn}$ variable explained noise-level variations better than correlations with any of the three closest traffic-flow stations. Similarly, for SLS 6 and SLS 48, $MHFR_{Cn}$ outperformed nearby traffic-flow stations. In the case of SLS 10, SLS 26, SLS 27 and SLS 55, the better explanation was for the global variable MHFR and for SLS 2, SLS 6 and SLS 48 MHFR offered a better explanation of the sound level variability than the local traffic flow stations. For SLS 3 and SLS 9, nearby stations provided better explanations than MHFR or $MHFR_{Cn}$. In the case of SLS 3, explanatory power was low in all scenarios, while at SLS 9, the explanatory difference between MHFR and the nearest station was less than 5 %.

These findings align with conclusions by Barrigón Morillas et al. [19], suggesting the global MHFR variable can support informed decision-making in urban traffic management, potentially reducing the population's exposure to noise pollution and other traffic-related pollutants varying hourly.

5. ACKNOWLEDGMENTS

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