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Connection between the Spatial Characteristics of the Road and Railway Networks and the Air Pollution (PM10) in Urban–Rural Fringe Zones

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Abstract: Atmospheric particulate matter (PM10) is one of the most important pollutants for human health, and road transport could be a major anthropogenic source of it. Several research studies have shown the impact of roads on the air quality in urban areas, but the relationship between road and rail networks and ambient PM10 concentrations has not been well studied, especially in suburban and rural landscapes. In this study, we examined the link between the spatial characteristics of each road type (motorway, primary road, secondary road, and railway) and the annual average PM10 concentration. We used the European 2931 air quality (AQ) station dataset, which is classified into urban, suburban, and rural landscapes. Our results show that in urban and rural landscapes, the spatial characteristics (the density of the road network and its distance from the AQ monitoring points) have a significant statistical relationship with PM10 concentrations. According to our findings from AQ monitoring sites within the urban landscape, there is a significant negative relationship between the annual average PM10 concentration and the density of the railway network. This result can be explained by the driving wind generated by railway trains (mainly electric trains). Among the road network types, all road types in the urban landscape, only motorways in the suburban landscape, and only residential roads in the rural landscape have a significant positive statistical relationship with the PM10 values at the AQ monitoring points. Our results show that in the suburban zones, which represent the rural–urban fringe, motorways have a strong influence on PM-related air pollution. In the suburban areas, the speed of vehicles changes frequently near motorways and intersections, so higher traffic-related PM10 emission levels can be expected in these areas. The findings of this study can be used to decrease transportation-related environmental conflicts related to the air quality in urban, urban–rural fringe, and rural (agricultural) landscapes.

Keywords: Spearman's correlation coefficient; road; rail; urban fringe; rural; landscape; PM10; sustainable development

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1. Introduction

Urbanization is transforming rural landscapes around the world and causing many environmental problems. Transportation-related environmental conflicts, mainly related to air quality, occur not only in cities but also in suburban areas and rural (agricultural) landscapes [1]. Particulate matter (PM) pollution, to which road traffic is the main contributor, has recently become a major global public health problem [2]. PM10 is one of the pollutants in the atmosphere that not only causes respiratory diseases but also impairs visibility and affects the climate at the local, meso, and macro level [3]. Although the sources of anthropogenic PM emissions are different in urban, suburban, and rural landscapes, road traffic is a major contributor to particulate matter in all landscape types. Air pollution levels are higher near traffic junctions, especially during congestion [4]. The traffic intensity, local traffic composition, vehicle movement characteristics (e.g., speed and acceleration), road gradient have a significant impact on PM10 emissions [5,6]. Regarding the fact that the increase in air pollution in connection with road traffic is highly dependent on the road traffic volume, the Annual Average Daily Traffic (AADT) could be an effective factor for air pollution analysis [7]. Another relevant reference unit for road traffic analysis is the daily or the average daily traffic, which is the ratio between the total volume and the duration (in days) of the analysis. The road traffic volume distribution during particular hours on working days usually shows certain patterns on specific types of roads [8]. When the design speeds are different, the traffic volume values corresponding to different design speeds are different [9].

In addition to the vehicle traffic characteristics mentioned above, the spatial structure of the transportation infrastructure network, density, and distances to environmental receptors (air quality monitoring stations) can also have a significant impact on the measured PM10 immission. The spatial characteristics of the road and rail network (e.g., the density of the road and rail network and the distance of air quality (AQ) monitoring stations from the nearest road or railway) can have a significant influence on the PM10 concentration levels measured at AQ monitoring sites [10–16]. Some authors [17] suggest that the impact of the rail network on PM concentrations should be investigated. The density of the road and rail network and the distance can be used as proxies for the degree of exposure to traffic pollution in cases where direct measurement of pollutant levels is not possible [18–20]. The impact of the transportation infrastructure on the air quality (PM10 concentration) can depend significantly on the type of road (primary road, secondary road, motorway, etc.) [18,21]. Some studies have evaluated the PM10-increasing effect of the transportation infrastructure related to, e.g., the construction of new motorways [22,23]. Studies on real-time air quality monitoring and the modelling of traffic-related pollutant emissions [24–26] also highlight the importance of the effect of road density (RD) on AQ estimations [24,27–29].

According to our hypothesis, the relationship between the spatial structure of the transportation infrastructure network (the road and rail network) and the PM10 concentration in the air differs significantly between rural, urban, and urban fringe (suburban) landscapes. To verify this hypothesis, we investigated the dependence of PM10 emission values at AQ monitoring points in rural, suburban, and urban landscapes on the type (primary road, secondary road, residential road, link road, motorway, and railway) and distance of the transport network. The aim of our study was to answer the following questions based on the available data on the annual average PM10 concentration on the European scale (a total of 2931 AQ monitoring stations):

- How does the relationship between the spatial structure of the road network and the PM10 air quality change within rural, suburban, and urban landscapes?
- What types of transportation networks (road or railway networks) are sources of PM10 pollution in rural, suburban, and urban landscapes?
- How does the relationship between the density of each type of road (as a source of pollution) and the PM10 immissions?
- Measured at AQ monitoring points change at different distances (buffer zones) from the measurement points?
- What is the relationship between PM10 levels at AQ monitoring points and the distance of these monitoring points from the road and rail networks in rural, suburban, and urban landscapes?

The aim of this study is to provide landscape planners and decision-makers with useful information for developing strategies to manage the air quality in urban, suburban, and rural landscapes. The relationship between spatial markers of roads and railways and PM10 immission can provide important information for land-use planning around roads, as it can be used to define the minimum distances within which environmentally sensitive land uses (residential or recreational zones, hospitals, kindergartens, etc.) are not allowed or are allowed only in certain cases. The remainder of this paper is organized as follows.

In Section 2, we present a systematic review of the previous scientific literature related to our study. In Section 3.1, we introduce the study area. We describe the datasets and methodologies applied in the statistical data analysis used to determine the relationship between spatial characteristics of different road types, railway networks, and annual PM10 concentrations in Section 3.2. In Section 4, we present the relationship between road and rail networks and PM10 immissions within circles of different radii measured from the AQ measurement points. In Sections 5 and 6, we compare our results with the international literature, highlighting new results and similarities and differences between our work and publications by other authors.

2. Review of the Scientific Literature

Many studies have investigated the driving forces of air pollution (in particular, particulate matter) in order to support research on the impact of high PM concentrations on health. Lenschow et al. [30] demonstrated that around half of the observed elevation in PM10 concentration at the roadside above the urban background could be attributed to the resuspension of road dust particles. Thorpe and Harrison [31] investigated sources and properties of non-exhaust particulate matter from road traffic. Querol et al. [32] supplied quantitative data on the regional background, the city background, and the local traffic background to the mean annual levels of PM10. Their results showed that along-range transport processes and winter traffic peculiarities contributed to the increase in PM10 levels. Marinella [22] assessed the impact of PM10 on air quality during road construction and operation phases. The author found that 85% of the PM10 produced during construction is due to storage, transit on unpaved roads, and crushing. Rossi et al. [14] evaluated the effect of road traffic on air pollution using experimental evidence from the COVID-19 lockdown. Correlation analyses and multivariate linear regression models were applied to non-rainy days in 2020, 2018, and 2017 but no evidence of a relationship between road traffic and PM10 was found. Phillips et al. [33] applied a national analysis to the spatial extent of road pollution in Britain. They demonstrated that the highest levels of road pollution are localized around the busiest roads. Rodríguez et al. [34] compared PM10 and PM2.5 source contributions at rural, urban, and industrial sites during PM episodes in eastern Spain. Mineral dust concentrations at the urban and industrial sites were higher than those at the rural site because of the urban road dust and the ceramic production contributions, respectively. At the urban site, the vehicle exhaust product was the main contributor to PM10 emissions.

Karagulian et al. [35] reviewed and analyzed the available source apportionment studies on particulate matter in urban areas. Traffic was found to be one important contributor to the ambient PM in cities. To reduce air pollution in cities and the substantial disease burden it causes, solutions to sustainably reduce the PM from traffic, industrial activities, and biomass combustion should urgently be sought. Reizer et al. [36] identified the drivers of the high particulate matter concentrations observed in several urban areas in Poland. Industrial point sources had the largest share (70–80%) in PM10 levels on days with the maximum PM pollution, while residential/traffic sources determined the air quality in the early stages of PM episodes. Wang et al. [37] evaluated changes in air quality related to the control of COVID-19 in China. They concluded that the improvement in the air quality was most likely due to the reduction in emissions from the transportation and secondary industrial sectors. Yuchi et al. [38] found an association between road proximity and the incidence of Parkinson's disease, Alzheimer's disease, and multiple sclerosis. Gualtieri et al. [39] assessed the importance of road traffic, residential heating, and meteorological conditions as major drivers of urban PM10 concentrations during critical air pollution episodes in the city of Florence (Italy) during the winter season. Gehrig et al. [40] determined the contribution of railway traffic to local PM10 concentrations in Switzerland. The railway-induced contribution to the ambient PM concentration decreased rapidly as the distance from the tracks increased. At 120 m, this contribution dropped to only 25% of the contribution observed at a distance of 10 m. Chen et al. [41] found that the operation of a high-speed rail network can reduce haze pollution by 17% on average.

3. Material and Methods

3.1. Study Area

We used the European road network dataset from GEOFABRIK, which includes data from the Open Street Map project and the rail network dataset of all European countries. Based on the Euro-Global Map, we used the annual PM10 emission datasets of 2931 AQ stations based on the Airbase (the European AQ database) reported by the European Environment Agency in 2018 [42]. The PM10 emission data used in our study were also categorized by the European Environment Agency (EEA) based on the type of air pollutant source and the location (the landscape type) of the monitoring station. Based on the predominant pollutant source, the EEA distinguishes three groups of AQ monitoring points: industrial, traffic, and background stations (where the source of PM10 is unclear) [43]. In addition, this dataset groups AQ stations by surrounding landscape type and land use and separates AQ monitoring points into urban, suburban, and rural landscape types (Figure 1).

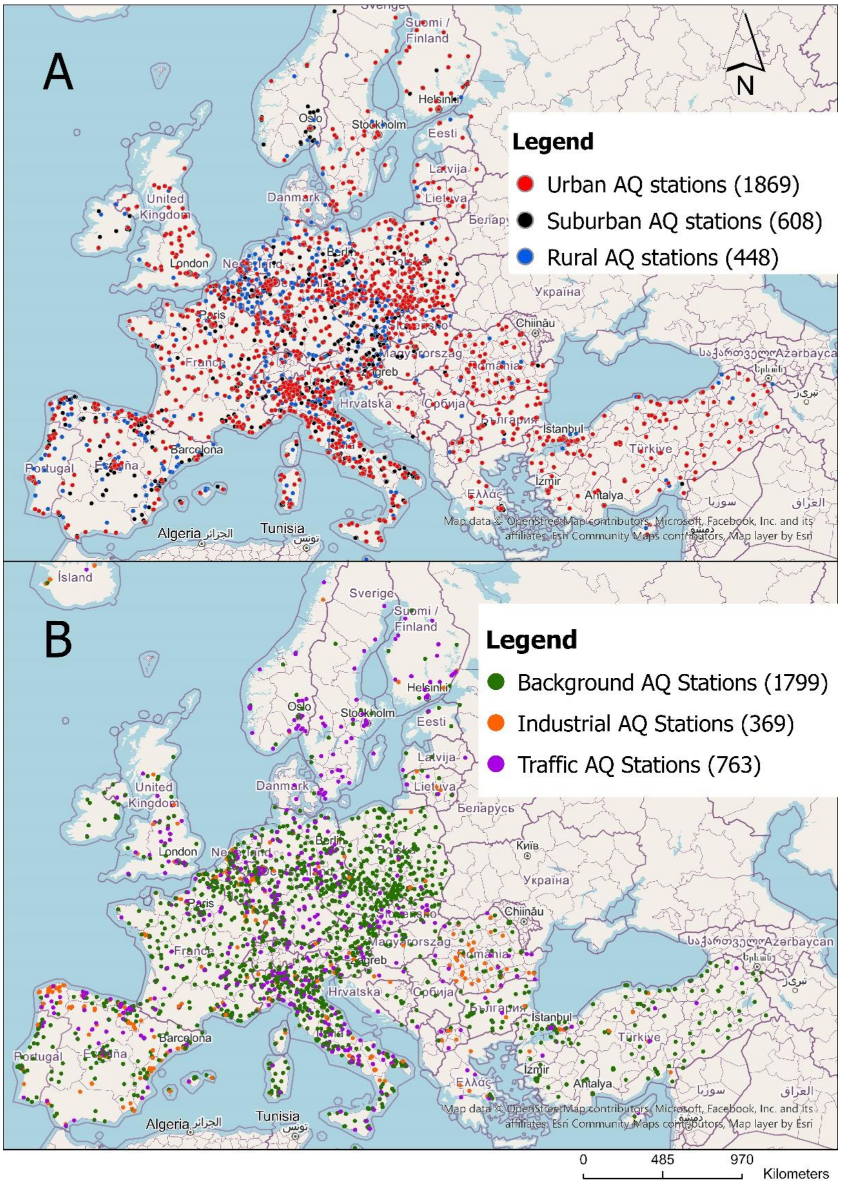

Figure 1. Study area. (**A**) Distribution of air quality (AQ) monitoring stations based on the landscape types and (**B**) distribution of AQ stations based on the main sources of PM10 emissions.

3.2. Spatial Analysis and Statistical Methods

Using Arc Map 10.6.1, QGIS 3.18, and ArcGIS Pro, we created buffer zones with radii of 250, 500, 1000, 1500, 2000, 2500, and 3000 m around each AQ monitoring station to conduct the spatial analyses (Figure 2). The average density (Km/Km^2) of road and rail networks was calculated within all buffer zones (circles with a radius of 250, 500, 1000, 1500, 2000, 2500, and 3000 m) of monitoring stations to examine the relationships between the mean annual PM10 concentrations at AQ monitoring stations in urban, suburban, and rural landscapes. Using the ArcGIS 10.6.1 software, each buffer zone around each AQ monitoring station was merged with digital maps displaying the spatial characteristics of the various classes of roads and the rail network. Within each buffer zone, the average density of each type of studied road and rail network (km/km^2) was computed.

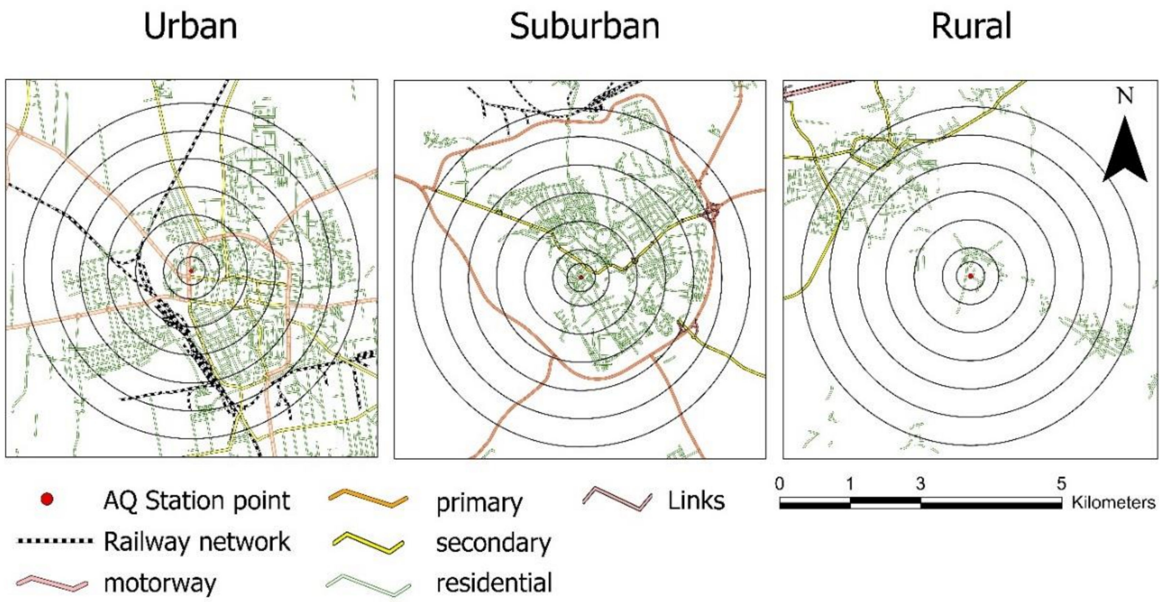

Figure 2. The typical spatial characteristics of the road and railway network surrounding an AQ monitoring station situated in urban, suburban, and rural landscapes.

For preliminary statistical analyses of the density of the transportation infrastructure (the road and railway network) and PM10 data pairs, we employed the Descriptive Statistics function (Figure 3) and the Shapiro–Wilk normality test in the IMB SPSS Statistics software, version 28.0.0. The Shapiro–Wilk normality test results show that the distribution of road types in each buffer zone surrounding the AQ monitoring stations is not normal (Table 1).

Table 1. Distribution characteristics of the aggregated groups of data pairs according to the landscape types inside the 3000 m buffer zones of AQ stations.

Variables	Urban Landscape			Suburban Landscape			Rural Landscape		
	Mean	SD	*N*	Mean	SD	*N*	Mean	SD	*N*
PM10 Quality	21.17 μg/m^3	5.39 μg/m^3	3427	20.15 μg/m^3	5.34 μg/m^3	1037	17.16 μg/m^3	5.52 μg/m^3	401
Road Density	5.16 km/km^2	0.001 km/km^2	3427	3.06 km/km^2	5.85 km/km^2	1037	1.20 km/km^2	2.15 km/km^2	401
Rail Density	0.009 km/km^2	0.019 km/km^2	1420	2.59 km/km^2	1.44 km/km^2	463	2.08 km/km^2	1.02 km/km^2	163

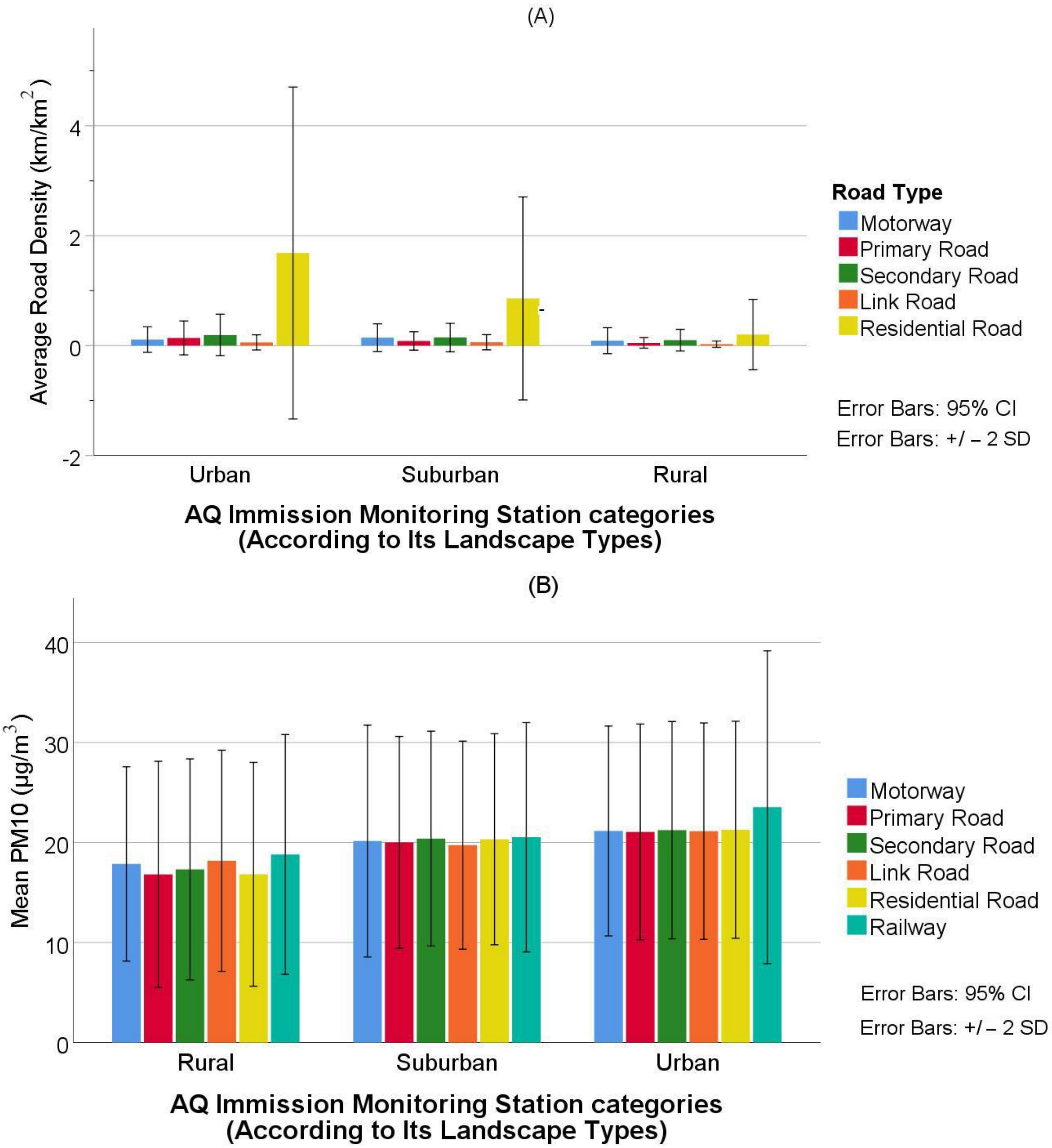

Figure 3. Clustered bar means of (**A**) the average road density (km/km^2) and (**B**) the annual mean PM10 levels (µg/m^3) by road type in urban, suburban, and rural landscapes.

To analyze the statistical relationship between PM10 immission levels and the spatial characteristics of the road and rail network, Spearman's correlation coefficient was calculated using the IMB SPSS Statistics software since the variables we studied did not have a normal distribution [44]. An analysis of the relationship between the density of the road and rail network and the PM10 values measured at AQ measurement points was performed for each Open Street Map road type (Table 2).

Table 2. Road classification according to the Open Street Map (OSM) legend description [45].

Road Types	Description
Motorway	Restricted-access major divided highway, normally with two or more running lanes plus an emergency hard shoulder. Equivalent to the Freeway or Autobahn. 50–130 km/h.
Primary	The link roads (slip roads/ramps) lead to/from a motorway from/to a motorway or lower-class highway. Normally with the same motorway restrictions. 30–90 km/h.
Secondary	The next most important roads in a country's system. Often link larger towns. 30–90 km/h.
Residential	These roads are primarily lined with and serve as access to housing. 10–70 km/h.
Road Link	Motorway links, primary links, secondary links, link roads (slip roads/ramps) leading to/from a motorway, primary or secondary roads from/to another road or a lower-class highway. 20–60 km/h.

In contrast, the transport infrastructure was classified into only two major categories (road and rail), and the type of road (primary, secondary, residential, etc.) was not considered in this analysis of the statistical relationship between the distance of roads and railroads from AQ measurement points and the PM10 values measured there. When attempting to understand the results at the European level, the size of the analyzed datasets demands special consideration [29]. Since Pearson's correlation requires at least 25 data pairs (as the sample size), we ignored datasets with fewer than 25 data pairs inside the buffer zones surrounding the AQ monitoring sites in order to achieve more reliable statistical results [30].

Using Spearman's rank correlation coefficient, relationships between PM10 immissions detected at AQ monitoring sites and their distance from the closest road and rail network were also examined. However, in this study, the PM10 values at AQ monitoring points were considered only once, for each of the buffer zones to which they belonged based on their distance from the nearest road or rail network. For example, if the nearest railway to an AQ point was 2480 m away, the annual average PM10 value measured there was considered only for the 2000–2500 m buffer zone. The annual average PM10 values of the AQ stations that were classified as belonging to a buffer zone based on their proximity to the road or railway infrastructure were compared inside each buffer zone with their distances from the nearest road or railway lines.

AQ measurement points are grouped by the European Environment Agency (EEA) according to two criteria. First, the points are grouped by the sort of landscape that surrounds them (rural, suburban, or urban). Second, the points are grouped according to the primary source of pollution (industrial, traffic, or background). In our research, we also divided the AQ monitoring sites into the categories used by the EEA classification nomenclature. Therefore, we were able to distinguish nine small PM10 immission data groups from AQ stations (Figure 4). According to the type of PM10 source, the EEA AQ database distinguishes between AQ monitoring points in areas where the source of air pollution is industrial or traffic-related and those where there is no clear source of air pollution, that is, where the source of air pollution cannot be identified based on the type of PM10 source.

In addition, the PM10 and traffic infrastructure data pairs were also examined by creating larger (aggregated) data groups according to the dominant landscape type (the main land use) surrounding the AQ monitoring point (urban, suburban, or rural) and according to the dominant PM10 pollutant source in the vicinity of the AQ monitoring points (Figure 5). The data analysis described above was performed for each road type and railway in the buffer zones of each group of AQ monitoring stations, and these groups were aggregated according to the landscape type (rural, suburban, or urban) and pollutant source type (industrial, transport, or background).

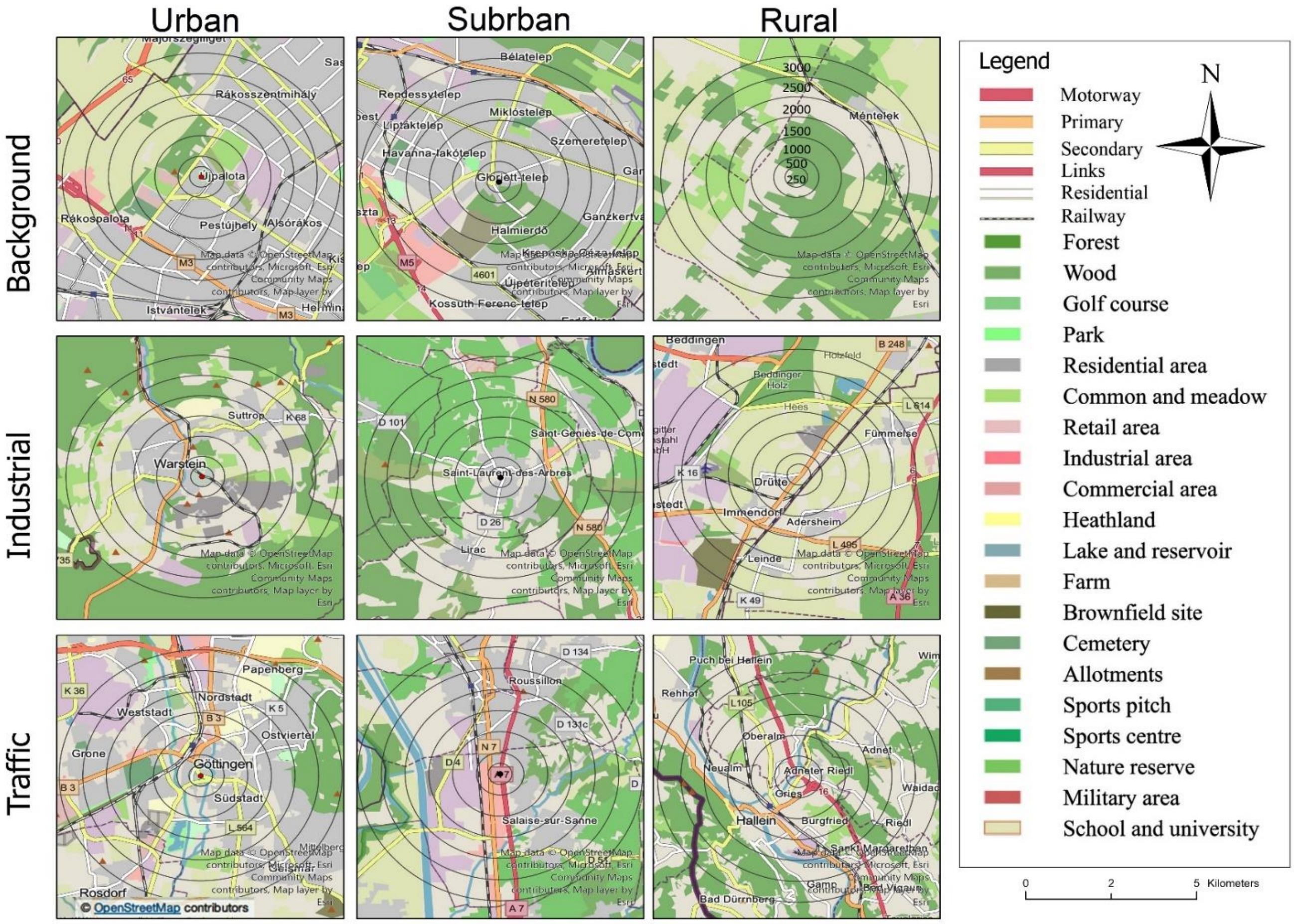

Figure 4. The main landscape categories of the AQ monitoring points and the spatial distribution of the main road types and railway networks in the different buffer zones (based on the OSM legend [46]).

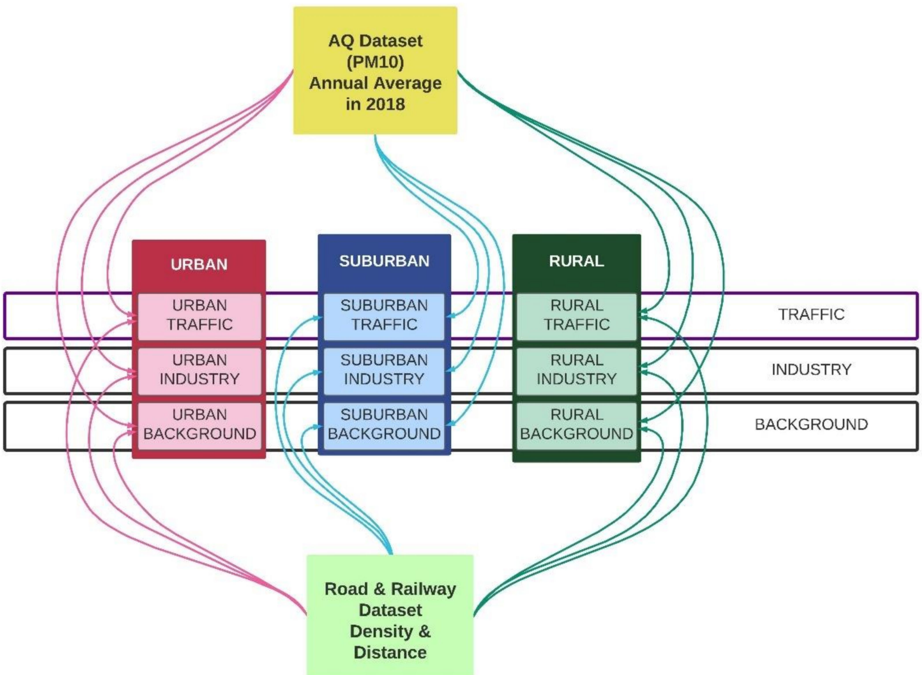

Figure 5. The small and aggregated data groups of the compared data pairs: PM10 immission, and the spatial structure of the road and railway network (distance and density).

4. Results

Regarding the connection between annual mean PM10 concentration and road and railway density in urban, suburban, and rural landscapes for AQ monitoring stations located in the urban landscape where the source of air pollution could not be clearly identified, the density of the link road network within each buffer zone (up to 3000 m from the AQ monitoring point) shows a significant positive relationship with PM10 immission values. Additionally, a positive significant correlation between the density of the motorway network and the PM10 concentrations obtained at the monitoring stations for the buffer zones at greater distances (0–2500 m and 0–3000 m) from the stations where the source of air pollution was not evident was discovered. For AQ measurement points where the source of air pollution was related to transportation or industrial processes or where the source of air pollution was not immediately apparent, the density of primary roads within the 0–1000 m buffer zone of the AQ monitoring stations also has a significant positive correlation with PM10 levels.

The density of secondary roads and detected PM10 concentrations in buffer zones more than 1000 m from AQ monitoring points also have statistically significant positive and negative correlations. A significant positive correlation between road density and yearly mean PM10 concentration was found in most data groups at monitoring stations where there were no clear sources of air pollution. In other cases, however, we identified a surprisingly significant negative correlation between primary road density and mean annual PM10 concentration. For instance, this is the case in the 0–2500 m and 0–3000 m buffer zones around AQ monitoring points where industry is the main source of air pollution and where there is no dominating source of air pollution, respectively (Table 3).

Table 3. Spearman's rank correlation coefficient results between road density (RD) and PM10 concentration inside different data pairs grouped based on road types and the main PM sources in urban landscapes (small data groups).

Urban Landscape															
	Link Road			**Motorway**			**Primary Road**			**Residential Road**			**Secondary Road**		
Buffer Zones	**Background**	**Traffic**	**Industry**	**Background**	**Traffic**	**Industry**	**Background**	**Traffic**	**Industry**	**Background**	**Traffic**	**Industry**	**Background**	**Traffic**	**Industry**
0–250 m	**0.261** *	−0.108		0.198	−0.37		**0.315** **	0.104	−0.049	**0.426** **	**0.122** **	**0.262** *	0.082	−0.033	0.026
0–500 m	**0.148** *	0.009	−0.181	0.192	0.01		**0.147** **	0.87	0.142	**0.458** **	**0.148** **	**0.346** **	**0.116** **	0.011	0.104
0–1000 m	**0.175** **	0.066	−0.03	0.057	0.06		**0.218** **	**0.130** *	**0.400** **	**0.521** **	**0.116** **	**0.469** **	**0.341** **	0.025	**0.354** **
0–1500 m	**0.143** *	0.013	−0.027	0.179	0.189		−0.04	0.099	−0.319	−0.089	0.027	**−0.472** **	−0.034	**0.163** **	−0.327
0–2000 m	**0.128** **	0.003	−0.035	0.088	0.096		**0.092** *	**0.090** *	**0.256** *	**0.227** **	0.065	**0.244** *	**0.126** **	0.024	**0.298** **
0–2500 m	**0.144** **	0.04	−0.196	**0.254** **	**0.188** *	0.037	**−0.111** *	0.066	−0.186	**−0.120** *	−0.02	**−0.379** *	−0.037	**0.143** **	**−0.396** *
0–3000 m	**0.166** **	0.089	−0.144	**0.206** **	0.116	0.034	0.088	0.057	−0.203	**0.124** **	−0.004	−0.268	−0.028	**0.147** **	**−0.409** **

Positive correlation is significant at the 0.05 level (2-tailed). Positive correlation is significant at the 0.01 level (2-tailed). The number of data pairs is less than 25. Negative correlation is significant at the 0.05 level (2-tailed). Negative correlation is significant at the 0.01 level (2-tailed). *: correlation is significant at the 0.05 level (2-tailed). **: correlation is significant at the 0.01 level (2-tailed).

The density of primary and secondary highways had the biggest impact on PM10 levels at AQ monitoring stations in suburban areas. Only at AQ monitoring sites where no significant air pollution sources were identified did motorway and secondary road densities significantly positively correlate with PM10 values. Surprisingly, there were significant negative correlations between PM10 values at AQ monitoring points in suburban areas and secondary road densities within the 0–1500 m buffer zone for AQ monitoring points with industry-related air pollution and within the 0–2000 m buffer zone for areas with traffic pollution (Table 4).

Table 4. Spearman's rank correlation coefficient results between road density and PM10 concentration inside different data pairs grouped based on road types and the main PM sources in suburban landscapes (small data groups).

Suburban Landscape															
	Link Road			Motorway			Primary Road			Residential Road			Secondary Road		
Buffer Zones	Background	Traffic	Industry	Background	Traffic	Industry	Background	Traffic	Industry	Background	Traffic	Industry	Background	Traffic	Industry
0–250 m	−0.034						0.193	−0.133		0.053	−0.228	−0.063	**0.230 ***	−0.109	−0.192
0–500 m	0.092			**0.427 ****			0.052	−0.336	0.057	0.005	−0.241	−0.043	0.056	−0.152	0.123
0–1000 m	0.119	−0.283	0.151	**0.340 ****	0.024		−0.002	−0.258	0.263	−0.014	−0.159	−0.1	−0.081	−0.251	−0.016
0–1500 m	0.103	−0.283	0.085	**0.325 ***	0.024		0.072	−0.258	−0.092	−0.007	0.404	−0.155	0.159	−0.251	**−0.290 ***
0–2000 m	0.005	−0.299	0.204	**0.261 ****	0.061	0.207	0.026	−0.19	0.028	−0.039	−0.129	0.058	−0.016	**−0.284 ***	−0.132
0–2500 m	−0.061	−0.299	0.179	**0.278 ***	0.061	0.235	0.033	−0.19	−0.033	−0.06	0.319	−0.103	**0.165 ***	−0.234	−0.22
0–3000 m	0.006	−0.299	0.168	**0.271 ***	0.061	0.015	0.029	−0.19	0.056	−0.079	0.318	−0.137	**0.159 ***	0.264	−0.165

Positive correlation is significant at the 0.05 level (2-tailed). Positive correlation is significant at the 0.01 level (2-tailed). The number of data pairs is less than 25. Negative correlation is significant at the 0.05 level (2-tailed).*: correlation is significant at the 0.05 level (2-tailed). **: correlation is significant at the 0.01 level (2-tailed).

Analysis of small numbers of data pairs in rural (agricultural) areas frequently produced inconclusive results. In rural areas where the sources of air pollutants could not be easily identified, there is a statistically significant positive correlation between the density of secondary roads and the network of residential roads and the PM10 readings at AQ monitoring stations. Only at distances of 0–2000 m from AQ points in background zones (where the dominant source of PM10 is unclear) and at distances of 0–150 m from AQ stations (where industry is the dominant source of PM10) does the density of secondary roads demonstrate a significant positive correlation with the PM10 values (Table 5).

Table 5. Spearman's rank correlation coefficients between road density and PM10 concentration inside different data pairs grouped based on road types and the main PM sources in rural landscapes (small data groups).

Rural Landscape															
	Link Road			Motorway			Primary Road			Residential Road			Secondary Road		
Buffer Zones	Background	Traffic	Industry	Background	Traffic	Industry	Background	Traffic	Industry	Background	Traffic	Industry	Background	Traffic	Industry
0–250 m										0.078					
0–500 m							0.238			**0.204 ***			−0.078		
0–1000 m	0.126						0.116			**0.227 ****			0.07		
0–1500 m	0.203						0.024			**0.340 ****			0.192		**0.516 ****
0–2000 m	0.015			0.176			0.176			**0.264 ****			**0.277 ****		
0–2500 m	−0.232			0.089			−0.133			**0.252 ****			0.192		
0–3000 m	−0.209			−0.117			−0.167			**0.221 ****			0.195		

Positive correlation is significant at the 0.05 level (2-tailed). Positive correlation is significant at the 0.01 level (2-tailed). The number of data pairs is less than 25. *: correlation is significant at the 0.05 level (2-tailed). **: correlation is significant at the 0.01 level (2-tailed).

Data analysis by landscape type offers comparable findings to data analysis based on smaller sets of data (separated by major PM sources). The yearly average PM10 concentrations observed at AQ monitoring stations in the urban environment indicate a significant positive association with the spatial density of motorways, primary roads, and residential roads. The buffer zones between 0 and 1500 m from the AQ monitoring points have the most significant correlation between the density of the network of residential roads and the annual average PM10 values. The results of the analysis of small groups of data from this landscape type are identical to the data aggregated by the suburban landscape type, which emphasizes the particular significance of the spatial density of residential roads to PM10 pollution inside the rural–urban fringe zones.

Conversely to the analyses of the small data groups, secondary road density does not significantly correlate with the PM10 immissions in the aggregated datasets of the suburban landscape category. Residential and secondary roads exhibit a substantial positive connection with annual mean ambient PM10 concentrations in rural areas. Residential road density generally had the greatest influence on PM10 levels in both urban and rural areas (Table 6).

Table 6. Spearman's rank correlation coefficient results between road density and PM10 concentration based on the small groups of data pairs.

	Urban Landscape					Suburban Landscape					Rural Landscape				
Buffer Zones	**Links**	**Motorway**	**Primary**	**Residential**	**Secondary**	**Links**	**Motorway**	**Primary**	**Residential**	**Secondary**	**Links**	**Motorway**	**Primary**	**Residential**	**Secondary**
250 m	0.103	0.048	**0.217** **	**0.309** **	0.027	0.122	0.138	0.011	−0.004	0.077				0.132	−0.27
500 m	0.077	0.073	**0.119** *	**0.344** **	**0.076** *	0.161	**0.353** **	−0.048	−0.034	0.029			0.247	**0.179** *	0.003
1000 m	**0.125** **	0.069	**0.188** **	**0.386** **	**0.224** **	0.046	**0.283** **	0.002	−0.057	−0.101	0.171	0.23	0.046	**0.219** **	0.082
1500 m	0.062	**0.189** **	0.012	−0.011	0.034	0.00	**0.304** **	0.069	−0.034	0.036	0.175	0.232	0.111	**0.309** **	0.207
2000 m	**0.066** *	0.07	**0.088** **	**0.166** **	**0.090** **	−0.05	**0.232** **	−0.016	−0.045	−0.084	0.031	0.232	0.077	**0.239** **	**0.277** **
2500 m	0.052	**0.194** **	−0.045	−0.048	0.012	−0.06	**0.218** *	0.044	−0.068	0.08	−0.328	0.248	−0.019	**0.247** **	0.153
3000 m	**0.098** *	**0.138** **	−0.03	−0.047	0.012	0.037	**0.214** *	0.037	−0.084	0.086	−0.222	−0.207	−0.057	**0.242** **	0.167

Positive correlation is significant at the 0.05 level (2-tailed). Positive correlation is significant at the 0.01 level (2-tailed). The number of data pairs is less than 25. *: correlation is significant at the 0.05 level (2-tailed). **: correlation is significant at the 0.01 level (2-tailed).

In most of these cases for the three analyzed landscape types (urban, suburban, and rural), a significant negative statistical relationship between rail network density and annual average PM10 values was found. Similar to the case with the road network, the density of the rail network near background AQ monitoring points (where the source of PM10 was unknown) and AQ monitoring sites with industrial air pollution exhibit the strongest statistical correlation with PM10 values in the majority of cases (Table 7). Only zones between 0 and 1000 m from AQ monitoring points with industrial air pollution and zones between 0 and 2500 m from traffic areas show a significant positive correlation between annual PM10 levels and rail network density. In the majority of cases, the density of the rail network had a significant negative correlation with annual PM10 values (Table 8).

The analysis of the extensive dataset in combination with the three types of landscapes revealed a strong negative connection between the mean annual ambient PM10 pollution level and the density of the rail network, but only for the urban landscape (Table 9).

Table 7. Spearman's rank correlation coefficient between road density, railway density, and PM10 concentration based on large groups of data pairs aggregated according to the surrounding landscapes and dominant PM sources.

Buffer Zones	Aggregated Group—Railway Network			Aggregated Group—Road Network		
	Urban	Suburban	Rural	Background	Traffic	Industry
0–250 m	−0.02	0.087		**−0.190 ****	−0.017	−0.072
0–500 m	**−0.091 ***	−0.024	−0.034	**−0.220 ****	−0.018	−0.077
0–1000 m	−0.054	−0.039	−0.055	**−0.245 ****	−0.016	−0.056
0–1500 m	**−0.056 ***	−0.045	−0.16	**−0.262 ****	−0.019	**−0.151 ***
0–2000 m	−0.009	−0.027	−0.025	**−0.276 ****	−0.018	**−0.152 ***
0–2500 m	**−0.216 ****	−0.029	0.012	**−0.284 ****	−0.018	**−0.170 ****
0–3000 m	**−0.288 ****	−0.044	0.044	**−0.327 ****	−0.018	**−0.187 ****

Negative correlation is significant at the 0.05 level (2-tailed). Negative correlation is significant at the 0.01 level (2-tailed). The number of data pairs is less than 25. *: correlation is significant at the 0.05 level (2-tailed). **: correlation is significant at the 0.01 level (2-tailed).

Table 8. Spearman's rank correlation coefficient results between railway density and PM10 concentration in large groups of data pairs aggregated according to the dominant PM sources.

	Urban Landscape			Suburban Landscape			Rural Landscape		
Buffer Zones	Background	Traffic	Industry	Background	Traffic	Industry	Background	Traffic	Industry
0–250 m	−0.152	0.089	0.137	0.045	−0.089	0.132			
0–500 m	**−0.245 ****	0.016	0.185	−0.085	−0.216	0.302	−0.034		
0–1000 m	**−0.163 ****	0.023	**0.331 ****	−0.124	0.038	0.146	−0.055		
0–1500 m	−0.071	−0.036	−0.094	−0.079	−0.077	0.125	−0.16		−0.126
0–2000 m	−0.005	0.014	**−0.073 ***	−0.077	−0.032	0.178	−0.025		−0.348
0–2500 m	**−0.406 ****	**0.085 ***	**−0.272 ****	−0.079	0.061	0.11	0.012		−0.146
0–3000 m	**−0.424 ****	0.07	**−0.226 ****	−0.108	0.093	0.102	0.044		−0.112

Positive correlation is significant at the 0.05 level (2-tailed). Positive correlation is significant at the 0.01 level (2-tailed). The number of data pairs is less than 25. Negative correlation is significant at the 0.05 level (2-tailed). Negative correlation is significant at the 0.01 level (2-tailed). *: correlation is significant at the 0.05 level (2-tailed). **: correlation is significant at the 0.01 level (2-tailed).

Table 9. Spearman's rank correlation coefficient between rail density and PM10 concentration in large groups of data pairs aggregated according to the surrounding landscapes.

Buffer Zones	Aggregated Data Group (Traffic + Industry + Background)		
	Urban Landscape	Suburban Landscape	Rural Landscape
0–250 m	−0.02	0.087	
0–500 m	**−0.091 ***	−0.024	−0.034
0–1000 m	−0.054	−0.039	−0.055
0–1500 m	**−0.056 ***	−0.045	−0.16
0–2000 m	−0.009	−0.027	−0.025

Table 9. *Cont.*

Buffer Zones	Aggregated Data Group (Traffic + Industry + Background)		
	Urban Landscape	Suburban Landscape	Rural Landscape
0–2500 m	**−0.216 ****	−0.029	0.012
0–3000 m	**−0.288 ****	−0.044	0.044

The number of data pairs is less than 25. Negative correlation is significant at the 0.05 level (2-tailed). Negative correlation is significant at the 0.01 level (2-tailed). *: correlation is significant at the 0.05 level (2-tailed). **: correlation is significant at the 0.01 level (2-tailed).

The Connection between the Distance to the Road and Railway Network and PM10 in Urban, Suburban, and Rural Landscapes

For AQ monitoring points with industrial air pollution sources or where the type of air pollution source could not be determined, there was a significant negative relationship between the annual mean PM10 concentrations at the monitoring points and the distance from the nearest road to the points. This means that the closer the road is in terms of Euclidean distance, the higher the annual PM10 immission values are at AQ monitoring points in rural areas. (Table 8). Only the urban AQ monitoring sites without a clearly identifiable source of air pollution nearby display a significant negative connection between their PM10 concentrations and their distance from the closest road. In contrast, we found a significant negative correlation in rural areas where the source of air pollution is unknown (in buffer zones > 500 m) or is industry (in buffer zones > 1500 m) (Table 10).

Table 10. Spearman's rank correlation coefficient between the distance of AQ measurement points to roads and PM10 concentration in large groups of data pairs aggregated according to the dominant PM sources.

Buffer Zones	Background			Traffic			Industry		
	Urban	Suburban	Rural	Urban	Suburban	Rural	Urban	Suburban	Rural
0–250 m	**−0.198 ****	−0.05	−0.162	−0.046	0.199		−0.133	0.072	−0.067
250–500 m	**−0.205 ****	−0.075	−0.125	−0.045	0.216		−0.157	0.112	−0.067
500–1000 m	**−0.209 ****	−0.006	**−0.199 ****	−0.042	0.228		−0.178	0.12	0.177
1000–1500 m	**−0.209 ****	0.003	**−0.232 ****	−0.042	0.21		−0.178	0.085	−0.256
1500–2000 m	**−0.209 ****	0.003	**−0.231 ****	−0.042	0.21		−0.16	0.085	**−0.298 ***
2000–2500 m	**−0.209 ****	0.003	**−0.236 ****	−0.042	0.21		−0.175	0.085	**−0.337 ***
2500–3000 m	**−0.208 ****	0.003	**−0.218 ****	−0.042	0.21		−0.175	0.085	**−0.403 ****

The number of data pairs is less than 25. Negative correlation is significant at the 0.05 level (2-tailed). Negative correlation is significant at the 0.01 level (2-tailed). *: correlation is significant at the 0.05 level (2-tailed). **: correlation is significant at the 0.01 level (2-tailed).

The datasets aggregated by pollutant source type also show that, in each of the buffer zones of these AQ monitoring points with no identifiable pollutant source, there is a strongly significant negative relationship between PM10 exposure and the distance of the monitoring point from the nearest road (Table 11).

The analysis of the distance of the rail network from the AQ measurement points shows a statistically significant positive relationship with the AQ values only for AQ monitoring points located in an urban area and for which no specific pollutant source can be identified (Table 12). This is true for both the group of AQ monitoring points aggregated by the main PM sources and for the group of AQ monitoring points clustered by the main landscape types (Table 13).

Table 11. Spearman's rank correlation coefficient between the distance of AQ measurement points to roads and PM10 concentration in large groups of data pairs aggregated according to the dominant PM sources.

Buffer Zones	Aggregated Data Group		
	Background	Traffic	Industry
0–250 m	**−0.190 ** **	−0.017	−0.072
250–500 m	**−0.220 ** **	−0.018	−0.077
500–1000 m	**−0.245 ** **	−0.016	−0.056
1000–1500 m	**−0.262 ** **	−0.019	**−0.151 * **
1500–2000 m	**−0.276 ** **	−0.018	**−0.152 * **
2000–2500 m	**−0.284 ** **	−0.018	**−0.170 ** **
2500–3000 m	**−0.327 ** **	−0.018	**−0.187 ** **

Negative correlation is significant at the 0.05 level (2-tailed). Negative correlation is significant at the 0.01 level (2-tailed). *: correlation is significant at the 0.05 level (2-tailed). **: correlation is significant at the 0.01 level (2-tailed).

Table 12. Spearman's rank correlation coefficient between the distance of AQ measurement points to railways and PM10 concentration in large groups of data pairs aggregated according to the surrounding landscapes.

Buffer Zones	Background			Traffic			Industry		
	Urban	Suburban	Rural	Urban	Suburban	Rural	Urban	Suburban	Rural
0–250 m	−0.029	−0.141		−0.025			0.072		
250–500 m	0.031	−0.005	−0.038	−0.009	0.141		−0.026	−0.223	
500–1000 m	0.073	0.119	0.108	0.007	−0.132		0.003	−0.113	
1000–1500 m	**0.125 ** **	0.108	0.137	0.012	0.012		0.01	0.017	
1500–2000 m	**0.102 ** **	0.074	0.008	0.008	0.016		−0.054	−0.002	0.075
2000–2500 m	**0.112 ** **	0.052	0.074	0.018	0.013		−0.77	−0.067	0.012
2500–3000 m	**0.125 ** **	0.076	0.008	0.022	0.014		−0.128	−0.038	0.103

Positive correlation is significant at the 0.01 level (2-tailed). The number of data pairs is less than 25.
**: correlation is significant at the 0.01 level (2-tailed).

Table 13. Spearman's rank correlation coefficient between the distance of AQ measurement points to railways and PM10 concentration in large groups of data pairs aggregated according to the main PM sources.

Buffer Zones	Aggregated Data Group		
	Background	Traffic	Industry
0–250 m	−0.036	−0.072	−0.01
250–500 m	0.02	−0.023	−0.127
500–1000 m	**0.089 * **	−0.003	−0.058
1000–1500 m	**0.116 ** **	0.021	0.02
1500–2000 m	**0.080 ** **	0.019	−0.031

Table 13. *Cont.*

Buffer Zones	Aggregated Data Group		
	Background	Traffic	Industry
2000–2500 m	**0.074 ***	0.025	−0.093
2500–3000 m	**0.071 ***	0.028	−0.09

Positive correlation is significant at the 0.05 level (2-tailed). Positive correlation is significant at the 0.01 level (2-tailed). *: correlation is significant at the 0.05 level (2-tailed). **: correlation is significant at the 0.01 level (2-tailed).

5. Discussion

According to our results, in the case of the AQ monitoring points located in urban landscapes, we found a significant positive correlation between PM10 level and the density of all types of roads in most of the studied buffer zones surrounding the AQ monitoring points. Other studies confirm that the density of the road network has a positive correlation with PM10 concentrations in urban landscapes [11,47]. The authors concluded that when the road density (RD) is low, the development of road traffic contributes to the reduction in the PM concentration, which is compatible with our findings. In the rural and urban landscapes, residential roads had the highest significant positive correlations with the annual average PM10 values in 2018. This means that the denser the residential roads, the higher the air pollution levels in these landscapes. Although Ren et al. [32] mentioned that the highest degree of tyre wear occurs on busy (urban and rural) main roads and motorways, several studies have shown a relationship between PM-exposure-related disease in local residents and the proximity of residential roads [10,33–38]. This can be explained by the fact that speed limits are more frequently imposed on residential roads. Drivers have to decelerate and accelerate more often than on other types of roads (e.g., motorways). In residential areas, the high population density results in more traffic and a higher number of traffic stops; therefore, the air pollution (PM10) from traffic is high in both urban and rural landscapes with high densities of residential roads [48–50]. Gualtieri et al. [39] suggest that this may also be due to other major sources of emissions, such as residential heating, close to residential roads. The results of Wang et al. [37] highlight the importance of emissions from the residential sector to wintertime pollution in northern China, and they showed that this source of pollution must be taken into account when developing pollution mitigation plans. In addition, the high risk of an increase in the PM10 concentration in urban and rural areas should be considered to be a main issue in road construction in these areas [51,52].

In suburban landscapes, only motorway density showed a strongly significant positive relationship with PM10 concentration. In these suburban, i.e., urban–rural fringe zones, road type is of particular importance to air quality because motorways are connected to the metropolitan transport network and drivers must frequently change speed, which increases the PM10 pollution from traffic [6,53]. In these urban–rural fringe areas, the high number of commuters also leads to high PM10 concentrations from road traffic and is the reason for the relationship between highway density and PM10 emission level [54].

For urban and suburban landscapes, the density of some road types (especially in buffer zones at a distance from AQ points) showed a surprising negative correlation with PM10 concentration. There may be several reasons for this result. It is possible that where the source of PM10 pollution has been well identified (e.g., an industrial area near the AQ point), secondary winds generated by vehicles in transport corridors may produce lower PM10 concentrations in areas with a high road network density. Another possible explanation for the significant negative relationships for AQ points where industrial pollutants have been measured is that the effect of the density of the road network on the PM10 concentration is offset by the presence of an industrial pollutant near the measurement point. In this case, the apparent (pseudo-)correlation may be due to the fact that the PM10 immission depends values depend much more on the types and sizes of industrial estates within a radius of 2500 or 3000 m around the AQ point than on the density of the road network [55].

Due to the results of the datasets aggregated based on the main landscape types, the most significant correlation between the density of each road type and PM10 values was found for urban AQ monitoring points. In cities, the areas of monitoring points within the buffer zone with a 1000 m radius show the highest significant correlation with PM10 values, suggesting that the density of all road types within these areas has a significant impact on AQ. In similar study, Xu et al. [20] set five buffer zones with radii of 0.5, 1, 2, 3, and 4 km in Wuhan, China. The road length within the 2 km buffer zone around the site showed the highest average correlation with the concentrations of PM10; however, they did not consider the land use type and the types of roads.

The density of the rail network correlated with PM10 values only in the urban landscape, but the sign of the correlation was negative, i.e., urban areas with a high rail network density have lower PM10 concentrations. This finding cannot be explained by some literature results [17,40,56]. For example, Jaffe et al. [17] assumed that the increase in PM2.5 due to the trains is linearly and positively related to the total train traffic in urban areas. Their study was based on an observation period of one month at only two locations adjacent to rail lines. They also calculated the PM concentration depending on the train type. Gehrig et al. [40] assessed the contribution of railway traffic to local PM10 concentrations in Switzerland and concluded that railway lines indeed emit PM10, leading to small but measurable increases in ambient PM10 concentrations in the immediate vicinity of the tracks. As the above studies focused on diesel locomotives and railcars, our result can be explained by the fact that most European traffic consists of electric locomotives and high standards [17,40,57], the introduction of electric vehicles offers the potential for reductions in all road-traffic-related emissions [58,59], and the driving wind generated by trains has a cleansing effect on the air quality near railway lines, resulting in lower PM10 concentrations compared with other areas. Our research results are consistent with empirical results that indicate that the operation of a high-speed rail network can reduce haze pollution and PM10 concentrations [41].

The air-purifying effect of the driving wind can also be confirmed by the fact that the average distances of AQ measurement points from the nearest railway network show a significant negative correlation with PM10 values, i.e., the further away from the railway the station measuring PM10 immissions is, the lower the annual average PM10 values measured there are. Interestingly, this correlation is only valid at longer distances from AQ measurement points (buffer zones with a radius of more than 1500 m). The reason why the air-cleaning effect of the density and distance of the rail network is not detectable near the AQ measuring stations can be explained by the high proportion of urban air pollutants from other sources (industry, residential buildings, road networks), which means that the wind-tunnel effect from the movement of the rail carriages does not cause statistically detectable changes in PM10 concentrations.

According to the results of the datasets aggregated based on the main PM sources (traffic, industry, and background), the most significant and highest Spearman's rank correlation coefficient was found for the AQ monitoring points characterized as belonging to the background category, where there is no dominant PM10 source. This indicates that the effects of spatial characteristics of the road network on AQ are most pronounced in these areas, as other factors affecting AQ (e.g., land use type [20,60], meteorological characteristics such as annual wind speed [6,14,61], soil type, and traffic volume [19]) are not as dominant as in other areas.

Industrial areas tend to have much higher densities of rail networks than other areas and, therefore, showed a significant and positive but non-realistic or pseudo-correlation between rail network density and PM10 levels. For the same reason, the significant negative correlation between the residential and secondary road types and PM10 values within certain buffer zones of AQ monitoring stations measuring industrial pollution can also be considered a pseudo-correlation. Another reason why the PM10 values at AQ monitoring stations measuring industrial pollution show a significant negative correlation with the density of certain road types within some buffer zones is the air-cleaning effect of vehicle-generated driving winds. Surprisingly, at the AQ monitoring points where most of the air pollution was caused by traffic, there was no significant positive correlation between RD and PM10 values within the buffer zones closer to the monitoring point, except for residential roads. This finding is in contrast with the results of Wang et al. and Minguillón et al. [62,63], who suggested that the possible sources of PM10 are traffic and industrial activities. On the other hand, Rossi et al. [14] reported no evidence of a relationship between traffic and PM10 in their study.

As expected, we found a significant negative correlation between the distance to the nearest road and PM10 exposure in urban background areas, which is consistent with the research results of Hart et al. [64], while the opposite relationship was observed for the distance to the nearest rail network. This means that a greater distance to the road network and a smaller distance to the railway lead to a lower PM10 concentration for all types of landscapes (rural, suburban, and urban).

According to the results of the analysis of the distance to the nearest road and rail network, the associations between PM10 and the road and rail network in the case of the urban landscape are significant only in the case of the background source (i.e., where the source of PM10 is unclear). This is a similar result to those of other authors. For instance, it was reported in Lenschow et al. [30] that the PM10 concentration near busy streets is about 40% higher than that in the urban background environment, where the source of air pollution is unclear. In our study, we demonstrated the effect of motorways on increases in PM10 concentrations in the suburban landscape, which is mentioned by [12].

The distance of the AQ measurement points from the nearest railway line showed no significant correlation with the AQ values in the case of the closer buffer zones (0–250, 250–500, and 500–1000 m), while in the other buffer zones inside of the urban landscapes, the distance of the railway lines had a significant statistical correlation with the PM10 values. This means that the air-cleaning effect of railway lines is detectable in the closer areas, but in buffer zones with a larger radius, the distance of the railway network has a significant cleaning effect on the ambient PM10.

In the suburban landscape, we discovered a significant correlation between the spatial characteristics of the road and rail network and the measured PM10 immission values only in the case of the background areas, where the source of PM10 is unclear. The fact that the effect of the distance from roads on PM10 pollution could not be detected at the AQ stations where the source of pollution (industry or traffic) is precisely known suggests that other factors, such as land use, climate [61,65], topography, and soil characteristics, have a greater influence on PM10 concentration levels. This implies that future studies investigating the causes of PM10 pollution will require the inclusion of multiple datasets, such as land use type, annual wind speed, soil type, and topography datasets, and the use of multivariate models as a method of analysis may provide new insights into the problem [2,19,66–69].

6. Conclusions

In this study, we addressed different types of roads (motorways, primary roads, secondary roads, link roads, and residential roads) and railway density and annual PM10 concentration reports at the European scale in 2018. Our results show that as the road density increases, the PM10 concentration increases in urban and rural landscapes. The annual mean PM10 concentrations observed at AQ measurement stations in urban landscapes showed a positive and significant relationship with the spatial density of motorways, primary roads, and residential roads. In the case of agricultural landscapes, the density of residential roads showed a strongly significant positive correlation with almost all buffer zones surrounding AQ monitoring points where the source of PM10 pollution is not well defined. This may correspond to the fact that residential areas are more likely to have speed limits set or that a higher residential population leads to more daily traffic, transportation stops, buildings, and air pollution (PM10) in both urban and rural landscapes.

In suburban landscapes (urban–rural fringe zones), motorways were detected to be the most effective road types, but only in areas where the source of PM10 pollution is unclear. The density of the rail network had a significant negative correlation with annual PM10 values in all landscape types. We found that the PM10-reducing effect of the rail network in urban areas varied according to the distance; the greater the distance from roads, the lower the PM10 pollution in urban and rural landscapes with no dominant source of PM. This suggests that fewer roads (especially motorways) and more rail networks in suburban landscapes should be used to create a sustainable transportation network in the urban–rural fringe areas most affected by air pollution. The findings of this study may help environmental managers, road designers, landscape planners, and decision-makers to reduce PM10 emissions and make the construction and operation of road networks more environmentally sustainable. According to the results of the dataset aggregated based on the main PM sources, the most significant and highest Spearman's rank correlation coefficient was found at the AQ measurement points classified as background areas where no dominant PM10 source is present. This means that other factors, such as land use type, meteorological characteristics, soil type, and traffic volume, affect the PM10 concentration level at AQ station points.

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