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Analysis of the Relationship between the Characteristics of the Areas of Influence of Bus Stops and the Decrease in Ridership during COVID-19 Lockdowns

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Abstract: This study aimed to investigate the relationship between the characteristics of the areas of influence of bus stops and the decrease in ridership during COVID-19 lockdowns and subsequent initial reopening processes. A novel GIS methodology was developed to determine these characteristics from a large amount of data with high spatial detail and accurately assign them to individual bus stops. After processing the data, several multiple linear regression models were developed to determine the variables related to different activities and changes in mobility during lockdown that may explain the variation in demand owing to the COVID-19 pandemic. The characteristics related to population and land use were also studied. The proposed methodology can be used to improve transit planning during exceptional situations, by strengthening public transport in areas with a predictably higher transit demand, instead of uniformly decreasing the availability of public transport services, promoting sustainable mobility. The efficiency of the proposed methodology was shown by performing a case study that analysed the variation in bus demand in A Coruña, Spain. The areas with the highest sustained demand were those with low inhabitant incomes, a high population density, and significant proportions of land use dedicated to hospitals, offices, or supermarkets.

Keywords: COVID-19; GIS; bus stop patronage; transit planning; urban mobility; land use

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1. Introduction

The COVID-19 pandemic has led to a significant decrease in the use of public transport, which is an essential pillar of sustainable mobility. This decrease has not been homogeneous across city areas and population groups, and has varied with the restrictions enforced by local governments during different periods of the pandemic. This study attempts to analyse the variables that explain these variations. Although the characteristics of the surrounding areas of bus stops may help explain these differences, the lack of available data could complicate the analysis. Geographic information system (GIS) methodologies are extremely useful, permitting accurate spatial allocation of population data and land use characteristics, and are employed to solve the data problem herein. The methodology proposed in this study may help in determining the transit supply required during similar pandemic periods to bolster the available transit services in zones and neighbourhoods with high potential demand. The proposed methodology is applied to a case study of the city of A Coruña, which is located in the Galicia region of Spain.

1.1. Context and Literature Review

COVID-19, which is caused by SARS-CoV-2, is believed to have emerged in Wuhan, People's Republic of China, in December 2019. COVID-19 was declared a pandemic on

11 March 2020 owing to the alarming levels of the spread and severity of the disease [1]. Europe became the epicentre of the pandemic, and severe outbreaks led to the enforcement of a nationwide lockdown in Spain on 15 March. In the following months, several countries imposed unprecedented travel and social restrictions in an effort to control and limit the spread of COVID-19 [2,3]. These limitations had a considerable impact in several fields. Many researchers have studied its economic and psychological effects [4–7] as well as its positive effect on the pollution emissions decrease [8,9].

These limitations also led to significant decreases in the demand for public transport worldwide. Munawar et al. [10] examined the impact of the COVID-19 pandemic on the transport sector using Google and Apple mobility trends and data from Moovit and official Australian government websites. Owing to the government-imposed travel restrictions in early April 2020, Australian public transport usage was 80% lower than that of pre-COVID-19. Despite the relaxation of the imposed restrictions and a lower number of infections, people remained uncomfortable with using public transport. Orro et al. [9] studied urban mobility during lockdown, the reopening process, and the new normal period in A Coruña. The results revealed that bus demand during the lockdown was 8–16% of that during the same period in 2017–2019. During the new normal period after the restrictions were lifted, bus use was only about 60% of that during the previous years. This study only considered normal working days, with data obtained from smart card use, automatic vehicle location, and bus stop boarding. The impact of the COVID-19 lockdown on urban mobility was also studied in the city of Santander, Spain, using data from the public transport intelligent transport system (ITS), traffic counters, videos from traffic control cameras, and environmental sensors [11]. The results revealed that the number of public transport passengers decreased by 93%.

Liu et al. [12] analysed the dimensions of this unprecedented reduction in public transport demand in the United States and attempted to explain the variations in the impact of the pandemic on different communities and social groups based on social factors. Transit demand data were obtained from a transit mobile phone app that provides real-time public transit data and trip planning. The results of their study demonstrated that populations with a higher proportion of African Americans, Hispanics, women, people over 45 years old, essential workers, and those making several Google searches for information relating to COVID-19 were more likely to maintain higher levels of minimal demand during the pandemic.

Mobility in the United States during the COVID-19 pandemic was also examined by Kim and Kwan [13], who considered two different disease waves. In particular, they analysed the relationship between social, political, spatial, and policy factors with the variations in mobility demand. County-level mobility data were obtained from mobile phone signals. The results revealed that people with lower incomes were more likely to continue travelling via public transport, as most of them were essential workers who continued working during the pandemic. Moreover, the results reflected that an individual's response to the COVID-19 pandemic was strongly related to their political inclinations. The influence of U.S. political partisanship on the response to COVID-19 measures was also studied by Allcott et al. [14], Grossman et al. [15], and Hart et al. [16]. Habib et al. [17] analysed travel behaviour during a four-month-long full lockdown in the Greater Toronto Area in Canada through individual surveys. Age, income, gender, household size, and household car ownership were shown to have a significant influence on activity and travel adjustments.

Socioeconomic conditions have been shown to be the decisive factors in the response of an individual to lockdown measures [18–20], as well as in terms of the effect of the pandemic on a particular population [21,22]. Dueñas et al. [23] studied the relationship between socioeconomic conditions and mobility patterns during the COVID-19 pandemic. Their results revealed that compared to pre-lockdown mobility, the decrease in mobility during lockdown in Bogotá, Colombia, was lower in communities with worse socioeconomic conditions (higher levels of poverty, informal work, lower socioeconomic strata). The areas with the highest level of poverty had a 24% higher mobility flow than those with the lowest levels of poverty. The city was divided into six strata, based on the income levels of the residents, from low to high. Before the lockdown, the mobility flows of the lowest socioeconomic strata (SES) were 35% lower than those of the highest SES. However, after the lockdown, the lowest SES flows were 54% higher than those of the highest SES. The socioeconomic data were primarily obtained from geolocated census data.

Hu and Chen [24] analysed the decline in transit ridership in Chicago owing to COVID-19. Their results revealed that smaller passenger declines are present in regions with more transportation, utility sectors, and jobs in trade. On the other hand, boardings decreased more in regions with higher educated and white individuals, higher incomes, and regions with more commercial lands. In addition, the highest reduction in bus trips during the COVID-19 pandemic in Korea also took place in wealthier neighbourhoods, according to Kim et al. [25]. In that research, the relationship between bus usage and land use (residential, office/commercial, public, and industrial, among others) and land price was studied.

Currie et al. [26] performed a multiple-regression analysis of selected Australian, North American, and European ridership data to determine the best explanatory variables that affect mobility. This method can be applied to determine significant socioeconomic variables related to mobility flow, as well as to determine explanatory variables that could attract mobility flows, such as the location of hospitals or supermarkets. For this reason, this methodology will be applied in our research to analyse the relationship between different factors and mobility during the COVID-19 lockdowns. Other authors have also analysed the variations in patronage following a similar methodology in situations prior to COVID-19 [27,28].

1.2. Objectives and Contributions

This paper faces two main objectives. The first one is to develop a methodology to quantify the characteristics of bus stops' surroundings that may influence transit use during a period of activity restrictions. This methodology should specify the process to use detailed georeferenced public data in order to make it applicable in different cities without specific field-data gathering. The second objective is to develop a model to explain the variability of boarding decreases among bus stops and to forecast this decrease under similar future situations.

To analyse the relationship between the decrease in bus patronage during the pandemic and the characteristics of the stops' surroundings, this study will take into consideration both land use and socioeconomic data nearby each bus stop. Despite all the published research about the COVID-19 and the reductions in transit mobility that it has entailed, the relationship between the magnitude of this reduction and the characteristics of the surroundings of the bus stops has not been studied in detail yet. This study fills that gap in the literature.

The variation of bus ridership during the COVID-19 lockdown and the first reopening phase will be studied in A Coruña in comparison with the same periods of pre-pandemic average data from years 2017–2019. A set of regression models will be developed for each of the periods in which different mobility restrictions were imposed.

1.3. COVID-19 Spread and Lockdown Regulations in Spain and Galicia

Spain first imposed a severe lockdown on 15 March 2020 [29]. The measures imposed by the Spanish government to contain the spread of COVID-19 and the subsequent reopening processes in Spain and Galicia are described in Table 1.

Table 1. Lockdown and reopening processes in Spain and Galicia.

Date	Stage of the Pandemic and Measures Imposed	Source
13 March 2020	Spanish President announced the declaration of a "State of Alarm".	[30]
15 March 2020	First lockdown was established in Spain: mobility restrictions were imposed (except for travel for work, buying essential goods, and a few other activities); non-essential establishments were forced to close; and in-person classes were suspended for students. The "State of Alarm" was initially imposed for 15 days from 14 March 2020 and was subsequently sequentially extended until 20 June 2020.	[31–35]
28 March 2020	A severer lockdown was imposed until 9 April 2020, during which only essential workers were allowed to travel.	[36]
9 April 2020	Restrictions return to those of the initial lockdown (15–27 March).	[36]
28 April 2020	A total of four phases, from Phase 0 to Phase 3, were announced by the Spanish Government to gradually return to the "new normal", by lifting various lockdown restrictions. Each Spanish region could independently advance their reopening phase.	[37]
4 May 2020	Galicia entered Phase 0. Retail trade centres and professional services with areas of less than 400 m^2 could be opened. Take-away restaurants, hair and beauty salons, opticians, dentists, and some other establishments were also reopened.	[38]
11 May 2020	Galicia entered Phase 1. Outdoor individual sports and walks were allowed at specific hours. The terraces in bars could be opened with a maximum capacity of 50%.	[39]
25 May 2020	Galicia entered Phase 2. Bars and restaurants could open indoor areas, ensuring a minimum distance of 2 m between tables. Shopping centres could reopen with limitations. People were allowed to perform in-person work, but remote work was recommended.	[40]
8 June 2020	Galicia entered Phase 3. Designated time slots for outdoor individual sports and walks were removed. The terraces in bars could open with a maximum capacity of 75%. Stores could have a capacity of 50%. Nightclubs and nightlife establishments remained closed.	[41,42]
9 June 2020	All seats on transit vehicles and boats could be occupied in Galicia.	[43]
15 June 2020	Galicia reached the "new normal" phase (first Spanish region to do so). Face masks were still mandatory. Mobility restrictions were removed.	[44]
20 June 2020	End of the "State of Alarm" in Spain. Subsequent outbreaks of COVID-19 in Spain have led to the application of various regulations and even a second and third state of alarm, but none were more restrictive than the first severe lockdown.	[45,46]

During the lockdown, activities such as in-person education, non-essential retail, hospitality business, sport, or leisure activities were suspended. Travel was permitted only to purchase essentials (food, pharmacy), receive medical attention, attend work, and other force majeure situations [29]. Considering public transit, from 15 March 2020, the national supply of public railway, air, sea, and road services was reduced by at least 50%, except for commuter trains and regional and municipal transport, which were regulated by local policies. Between 28 March 2020 and 9 April 2020, a severer lockdown was established in Spain, and non-essential workers were forced to stay at home. From 9 April 2020, a phase similar to the previous lockdown was established, which was followed by four additional phases to gradually return to the "new normal". This first period of closure and reopening is analysed in this study, as it includes the most restrictive periods. Therefore, this study focuses on the period of February–June 2020, inclusive of both months.

2. Data Processing and Spatial Analysis

The municipality of A Coruña, located in northwest Spain, extends across an area of 37.69 km^2 and has a population of 247,604 [47]. The unemployment rate in 2020 was 12.2%, with an occupancy rate of 46.3% for the same period [48]. The services sector provided employment to 91.7% and 86.3% of all employees in 2019 and 2020, respectively [48].

A report on mobility in A Coruña [49] revealed that 38.0% of all mobility was on foot (mainly shopping and leisure travel), 41.1% was by conventional cars, and 11.8% was by urban buses. Furthermore, the report stated that public transit use was more prevalent when travelling for study, business affairs, and medical reasons. A total of 22 regular urban bus lines form the bus network in the city [50]. In addition, a special night service operates only on weekends, and a special university service exists as well. The number of bus stops in the city is approximately 470; however, this value changes every year. Some of these stops are only operational during summer or if bus routes are temporarily deviated.

2.1. Selection of Bus Stops and Time Periods

The bus stops in A Coruña were studied and screened to compare bus patronage during different periods in 2017–2020. The daily number of passengers boarding at each stop was analysed to determine anomalous values owing to work, repairs, sporting or social events, and other peculiar situations that could affect bus routes and patronage. The abnormal daily data due to external factors were removed to ensure that they did not bias the model results.

The daily bus boardings data for 2017–2020 were obtained from the Transit Management System of Compañía de Tranvías de La Coruña, the company that provides the bus service. The Transit Management System records the bus stop arrival time, number of passengers boarding at each bus stop for each expedition, type of ticket, and payment method. Only the normal working days (NWDs) are considered herein, which excludes weekends and bank holidays. Therefore, only normal days from Monday to Friday are considered in this study. Short school holidays were not considered either. The purpose of eliminating these data is to avoid the effect of demand fluctuations on non-working or non-school days. The special university bus lines are also excluded because they were suspended during the COVID-19 lockdown.

The influence of COVID-19 on bus ridership in A Coruña was studied, and the passenger boarding variations in the following phases were examined, considering the equivalent NWDs in 2017–2019:

- February (normal situation)
- 1–12 March (normal situation, but influenced by information about the pandemic in Italy and certain Spanish regions)
- 13–14 March (state of alarm announced, first teaching activity restrictions)
- 15–27 March (lockdown)
- 28 March–9 April (severer lockdown)
- 10 April–3 May (lockdown)
- 4–10 May (Phase 0)
- 11–24 May (Phase 1)
- 25 May–7 June (Phase 2)
- 8–14 June (Phase 3)
- 15–30 June (new normal)

To compare the passenger boarding data during these periods in 2020 to previous years, the average passenger boarding data during 2017, 2018, and 2019 were calculated for each bus stop and period, considering only NWDs. The dependent variable (hereinafter referred to as sustained demand) was obtained by dividing the average number of passengers boarding in 2020 by that of 2017, 2018, and 2019 for each corresponding period. Consequently, the dependent variables corresponding to each of the 11 periods were calculated as a percentage that represents the proportion of passengers who continued to use the bus service during 2020 compared to previous years.

As the variable is a percentage of change in short comparison periods, it is relevant that the values can provide an adequate measure of the variation in patronage owing to the pandemic. For this reason, it was necessary to remove from the database the stops with few boardings (percentage can present high variations for little changes in ridership) or with a high variability in patronage during these years, which cannot provide a stable baseline for comparison. For NWDs, the mean and standard deviation of the daily number of passengers boarding at each bus stop were calculated from a total of 151,063 data points from 2017 to 2019. The coefficient of variation (CV) of each bus stop was obtained by dividing the standard deviation by the daily average number of passengers. A maximum CV of 0.4 was used to determine whether a given bus stop was included in the study. If the CV of a bus stop was above 0.4 in 2017, 2018, or 2019, it was studied individually to identify the causes of the variation and to determine whether it should be selected or rejected. If the CV was above 0.4 in all three years, the stop was rejected. Any bus stops that were only operational in 2020, or those that were operational in 2017–2019, but not in 2020, were rejected. After this data refinement, 341 bus stops were selected from the total of 470 bus stops present in A Coruña.

In addition, a minimum average limit of 100 daily passengers boarding at a given bus stop was established for the period 28 March–9 April (severer lockdown) in 2017–2019. Accordingly, a total of 161 bus stops were finally selected for the subsequent analyses. The locations of these stops are shown in Figure 1 along with the urban bus lines and the population density per census section in A Coruña.

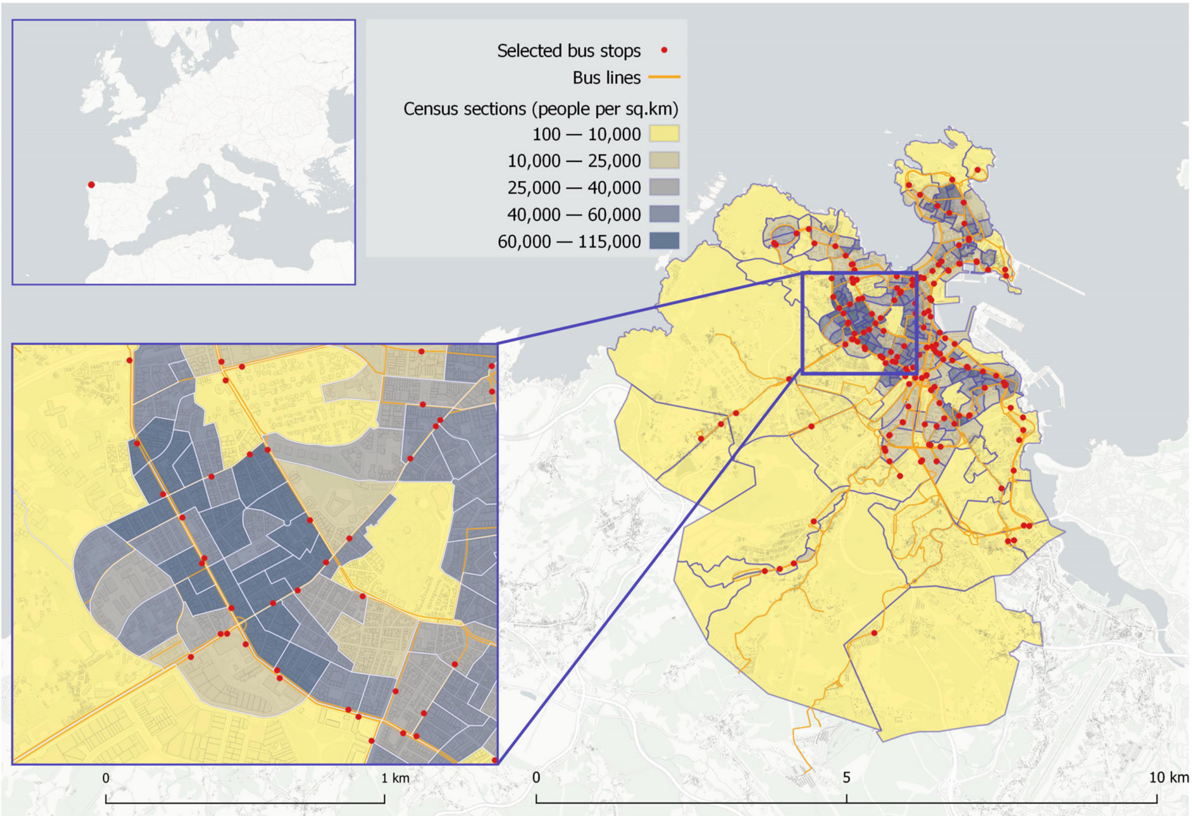

Figure 1. Selected bus stops, bus lines, and population density per census section in A Coruña.

Figure 2 shows, for the periods considered, the number of stops in each interval of sustained demand. In addition, the histogram for each period is represented (with blue bars) in order to compare the distributions among them. At the bottom, descriptive statistics are also presented for each period. Although the absolute values of the variability are similar to those of the previous period (February and 1–12 March), the CV increased significantly during the pandemic. Before the initial lockdown (February 2020), the passenger demand was between 70% and 140% of that of previous years (2017–2019), except for exceptional cases. The mean was 111%, the standard variation was 18%, and the CV was 0.17. In contrast, during the severer lockdown, the demand was between 2% and 34% of that of previous years, with a mean of 10%, a lower standard variation of 5%, and a significantly higher CV of 0.49. Notably, during this period, some stops had a sustained demand that was 15 times higher than that at other stops. During the consecutive phases of the reopening process, the sustained demand increased steadily, and the CV decreased.

% sustained demand		Number of stops and histogram										
%2020 vs 2017–2019		February	1–12 March	13–14 March	Lockdown	Severer Lockdown	Lockdown	Phase 0	Phase 1	Phase 2	Phase 3	New Normal
5%		1	2	2	3	13	6	3	2	0	0	0
>5%	10%	0	0	0	35	74	62	21	2	0	0	0
>10%	15%	0	0	0	68	50	48	59	10	0	0	0
>15%	20%	0	0	0	30	16	27	42	35	2	0	0
>20%	25%	0	0	2	14	5	12	17	45	4	0	0
>25%	30%	0	0	2	4	2	5	12	38	20	4	1
>30%	35%	0	0	2	4	1	0	5	15	33	5	1
>35%	40%	0	1	8	1	0	1	1	8	43	18	4
>40%	45%	0	0	16	0	0	0	0	4	31	23	12
>45%	50%	0	0	26	1	0	0	1	1	10	51	17
>50%	55%	0	0	22	0	0	0	0	1	8	31	40
>55%	60%	0	0	25	0	0	0	0	0	6	14	42
>60%	65%	0	0	25	0	0	0	0	0	1	10	21
>65%	70%	0	0	11	0	0	0	0	0	2	1	12
>70%	75%	2	1	9	0	0	0	0	0	1	3	5
>75%	80%	2	3	4	0	0	0	0	0	0	0	3
>80%	85%	1	2	3	0	0	0	0	0	0	1	1
>85%	90%	3	10	2	0	0	0	0	0	0	0	1
>90%	95%	3	16	1	1	0	0	0	0	0	0	1
>95%	100%	8	29	1	0	0	0	0	0	0	0	0
>100%	105%	26	29	0	0	0	0	0	0	0	0	0
>105%	110%	36	23	0	0	0	0	0	0	0	0	0
>110%	115%	30	20	0	0	0	0	0	0	0	0	0
>115%	120%	21	11	0	0	0	0	0	0	0	0	0
>120%	130%	19	10	0	0	0	0	0	0	0	0	0
>130%	140%	6	1	0	0	0	0	0	0	0	0	0
>140%		3	3	0	0	0	0	0	0	0	0	0
Mean		111%	103%	55%	15%	10%	13%	16%	24%	38%	48%	56%
s.d.		18%	19%	14%	9%	5%	6%	7%	8%	9%	9%	9%
CV		0.17	0.18	0.26	0.61	0.49	0.47	0.43	0.32	0.24	0.19	0.17

Figure 2. Number of stops and histogram per period and percentage of boardings in 2020 compared to 2017–2019.

The most representative phase of this analysis is the severer lockdown phase (28 March–9 April 2020), as the bus patronage during this period represents the number of people who had an actual need to use the bus service despite the harshest restrictions in Spain and indicates the places that most passengers travelled to.

2.2. Data Sources and Variable Description

This study aims to explain the variation in the proportion of passengers who continued to use bus services in A Coruña during the selected periods based on the socioeconomic data of the nearby residents and the mixture and intensity of land use around each bus stop. The socioeconomic data—the average income per inhabitant and census section (2017), and the population per census section (2019)—were obtained from the website of the Instituto Nacional de Estadística [47]. Considering the variables that represent land use, the surface data were acquired from the cartographic viewer of the cadastral electronic website [51]. The land use data considered in the model are: surfaces used for educational purposes (including school, high school, university, and official non-university studies), supermarkets, offices, hospitals, hospitality businesses (including hotels, hostels, restaurants, and bars), and non-essential stores. Non-essential stores refer to the shops that were not considered essential by the public authorities during the COVID-19 lockdown and remained closed.

2.3. GIS Data Processing

The aim of the GIS process is to obtain a highly accurate characterisation of the surroundings of each bus stop. A detailed spatial analysis was developed to obtain representative values of each variable for each of the preselected 161 bus stops (Figure 1). The area of influence of a bus stop extends to a radius of 300 m from its location. This value is commonly used in other related studies [52,53].

Municipalities in Spain are subdivided into zones named census sections. In this paper, the population variable was obtained from these census sections. In total, 189 census sections were studied herein (Figure 1), with an average population of 1341.14 inhabitants and a maximum of 2793 inhabitants. The average area of the urban census sections was 59,219.07 m^2. However, the average area of the census sections located further away from the city centre, which are associated with rural areas, was 3,505,046.52 m^2, and the lowest population in these sections was 691 inhabitants. Therefore, the population densities varied substantially between different census sections. The population in a given census section was assigned to each dwelling and building in each zone, using the methodology described in the subsequent paragraphs, to better determine the actual location of the inhabitants. A geographic information system (GIS) software was used for this purpose.

Building data were obtained from the cartographic viewer of the cadastral electronic website [51]. The building layer includes information about the number of dwellings in the attribute table. This layer was processed in GIS, correcting building geometries and converting building information from an area to a point format to avoid generating errors in the buildings located between census sections. The building layer was screened, such that buildings with at least one dwelling were retained, and non-residential buildings were discarded.

Subsequently, the number of dwellings in each census section were added. The population per dwelling ratio of each section was calculated by dividing the total population by the total number of dwellings in each census section. This ratio was assigned to each building and multiplied by the number of dwellings to estimate the total number of inhabitants in each building. This procedure is schematically described in the flowchart shown in Figure 3. The buildings with dwellings and the number of inhabitants in a three-census-section intersection zone are shown in Figure 4.

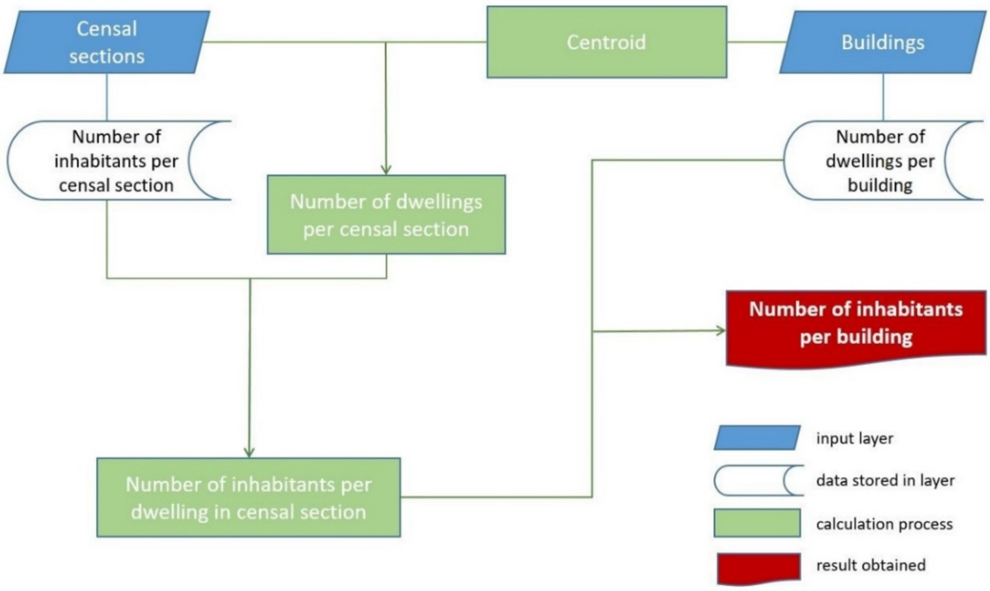

Figure 3. Flowchart of the procedure for estimating the number of inhabitants per building from data based on census sections.

Figure 4. Number of inhabitants per building in an intersection zone with three census sections.

The total number of inhabitants in the area of influence of each bus stop was determined by creating a 300 m buffer zone around each stop in GIS and adding the number of inhabitants in the buildings inside the buffer zone, as shown in Figure 5. This value represents the potential ridership for home-based bus trips from the area. The population density in each area of influence was calculated by dividing the number of inhabitants in each area of influence by the surface area of the buffer zone (282,743.34 m^2). Finally, the density of bus stops within each area of influence was determined to consider the distribution of passengers across multiple stops in the same buffer zone. The number of stops without any incident and with more than five daily passengers boarding in 2017–2019 was obtained for each area. The density was calculated by dividing the population density in the area by the number of stops.

The average income per inhabitant (obtained per census section) was also assigned to each building. The total income per building was acquired by multiplying the average income per inhabitant by the number of inhabitants per building. The total average income of each building within the buffer zone was added and divided by the total number of inhabitants in the area of influence to obtain the total average income per inhabitant in the area. Through this procedure, the different income characteristics of the census sections around each stop can be adequately considered in the analysis.

The land use variables reflect the trip attraction attributes of each area and were analysed in detail to associate them with the area of influence of each bus stop. The georeferenced information obtained from the cadastral data and other sources includes the land uses and their corresponding surface area in m^2 for each building. Relevant work of data refinement and integration was needed. A total of 281,631 records related to more than 200 land uses in A Coruña were verified, screened, and classified into 50 types. The areas under neighbouring municipalities were analysed, as long as they are included within the area of influence of the bus network. Various land uses were selected based on their relationship with the activities that were restricted during the different periods considered herein and their statistical significance during the severer lockdown period. Finally, seven land uses were chosen: educational facilities, non-essential stores, supermarkets, offices, hospitals, and hospitality businesses.

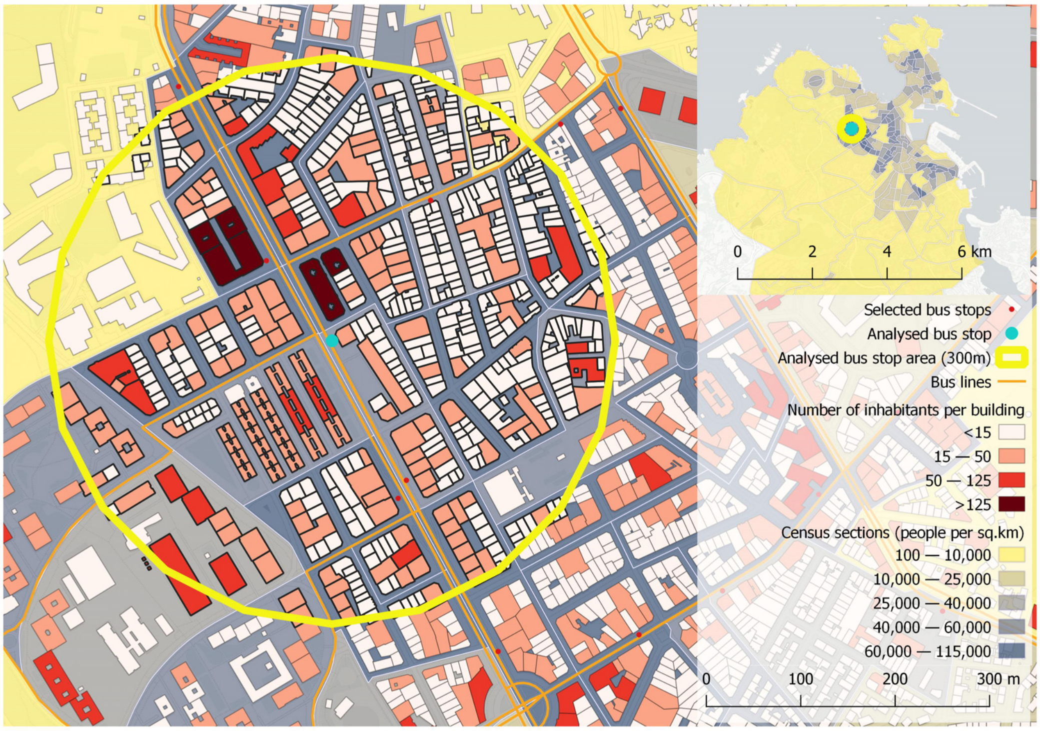

Figure 5. Buildings included in the area of influence of the selected bus stop.

The dependent variable of the model, namely, the sustained demand during a given period, is dimensionless. Therefore, a transformation of the surfaces related to each land use was considered to better characterise the area surrounding each bus stop. First, the total surface area occupied by each of the selected land uses was calculated for the buffer zone of every bus stop. Second, each of these surfaces was divided by the total non-residential built surface area within the corresponding buffer zone to obtain the ratios that are used as independent variables.

The independent variables considered in the study are presented in Table 2.

Table 2. Description of the independent variables considered in the analysis.

Abbreviation	Definition of the Variables	Mean	SD
Pop_dens_stop (1000 inh/km^2/bus stop)	Population density (thousands of inhabitants (inh) per square kilometre) per bus stop inside the area of influence of each stop.	2.9512	1.6254
Ave_income_inh (1000 €/inh)	Average income in thousands of EUR per inhabitant.	14.2676	3.5671
Surf_Educat	Ratio of non-residential built surface occupied by educational facilities.	0.0152	0.0179
Surf_non_ess	Ratio of non-residential built surface occupied by non-essential stores.	0.0486	0.0301
Surf_superm	Ratio of non-residential built surface occupied by supermarkets.	0.0079	0.0114
Surf_office	Ratio of non-residential built surface occupied by offices.	0.0368	0.0325
Surf_hospit	Ratio of non-residential built surface occupied by hospitals.	0.0126	0.0076
Surf_hos_buss	Ratio of non-residential built surface occupied by hospitality businesses.	0.0119	0.0655

3. Modelling and Discussion

A multiple linear regression (MLR) model was developed for each period, as described in Section 2. The independent variables of the model are listed in Table 2, and the dependent variable (that we will refer to as sustained demand) is the ratio of bus demand during the selected periods in 2020 to the average bus demand in previous years (2017, 2018, and 2019) during the equivalent NWD periods. Table 3 presents the results of the MLR for the period 28 March–9 April (severer lockdown). All the independent variables were found to be significant, with a confidence level of 95%. Keeping the rest of the variables unaltered, an increase of 0.1 in the ratio of the non-residential built surface occupied by supermarkets increases the sustained demand by approximately 0.09. In contrast, without any change in the rest of the variables, an increase of 0.1 in the ratio of the non-residential built surface occupied by educational institutions decreases the sustained demand by around −0.05. Considering the standardised coefficients (SC) of the severer lockdown period, the ratio of the non-residential built surface occupied by hospitals had the highest positive influence on sustained demand, whereas the population density per bus stop had the least positive influence. The ratio of the non-residential built surface occupied by non-essential stores and the average income per inhabitant had the highest negative influence on sustained demand. This can be attributed to the ability of inhabitants with higher income levels to work remotely or to choose private transport for travel.

Table 3. Regression results for severer lockdown.

Period: Severer Lockdown (28 March–9 April)				
Dependent Variable: Ratio of Bus Demand in 2020 to 2017–2019 Mean				
		Coefficient	**Standard Error**	**SC**
Const		0.1529 *	0.019	
Pop_dens_stop		0.0057 *	0.002	0.1802 *
Ave_income_inh		−0.0032 *	0.001	−0.2215 *
Surf_Educat		−0.5318 *	0.198	−0.1860 *
Surf_non_ess		−0.4496 *	0.128	−0.2638 *
Surf_superm		0.8972 *	0.309	0.1999 *
Surf_office		0.3893 *	0.161	0.2470 *
Surf_hos_buss		−1.1703 *	0.522	−0.1730 *
Surf_hospit		0.3284 *	0.059	0.4194 *
N	161			
R2	0.359			
Adjusted R2	0.325			

* Coefficients are significant at the 95% level.

The parameter values of the independent variables analysed during each period are listed in Table 4. The cells highlighted with an asterisk, located in the upper row of each variable, represent the significant variables with a confidence level of 95%. The lower row shows the standardised coefficients of each variable. Although there was already a noticeable variability of sustained demand between stops for the period 1 February–12 March in 2020 compared to 2017–2019 (Figure 2), no variable was statistically significant before the declaration of the state of alarm. Therefore, this variability cannot be explained by the variables considered herein. In contrast, all variables were found to be significant during the severer lockdown. As the restrictions were relaxed and progressed through the phases to return to the new normal, most of the independent variables were no longer significant.

Table 4. MLR parameter results during each period. Standardised coefficients are presented in the lower row for each variable.

Period	**February**	**1–12 March**	**13–14 March**	**Lockdown (15–27 March)**	**Severer Lockdown (28 March–9 April)**	**Lockdown (10 April–3 May)**	**Phase 0 (4–10 May)**	**Phase 1 (11–24 May)**	**Phase 2 (25 May–7 June)**	**Phase 3 (8–14 June)**	**New Normal (15–30 June)**
Variable (Coef/SC)								**Reopening Process**			
Const	1.0962 *	1.0834 *	0.6672 *	0.2331 *	0.1529 *	0.1837 *	0.2028 *	0.2635 *	0.4717 *	0.5167 *	0.5765 *
Pop_dens_stop	0.0036 0.0321	−0.0075 −0.0656	0.0066 0.0579	0.0047 0.0850	0.0057 * 0.1802 *	0.0078 * 0.2150 *	0.0092 * 0.2141 *	0.0143 * 0.2984 *	0.0048 0.0846	0.0073 0.1309	0.0071 0.1218
Ave_income_inh	−0.0006 −0.0111	−0.0005 −0.0104	−0.0113 * −0.2156 *	−0.0053 * −0.2128 *	−0.0032 * −0.2215 *	−0.0046 * −0.2818 *	−0.0036 −0.1833	−0.0040 −0.1839	−0.0062 * −0.2399 *	−0.0025 −0.0989	−0.0014 −0.0512
Surf_Educat	0.3597 0.0350	−0.2973 −0.0286	−1.4459 * −0.1392 *	−0.9668 * −0.1940 *	−0.5318 * −0.1860 *	−0.6001 * −0.1833 *	−0.7261 * −0.1859 *	−0.8008 * −0.1840 *	−1.3195 * −0.2560 *	−1.0310 * −0.2053 *	−0.8294 −0.1572
Surf_non_ess	−0.5641 −0.0920	−0.6375 −0.1030	−0.1592 −0.0257	−0.6339 * −0.2135 *	−0.4496 * −0.2638 *	−0.4898 * −0.2510 *	−0.6372 * −0.2738 *	−0.7989 * −0.3080 *	0.0861 0.0280	0.1440 0.0481	−0.1034 −0.0329
Surf_superm	0.8353 0.0518	0.9113 0.0559	1.4214 0.0872	1.2946 * 0.1655 *	0.8972 * 0.1999 *	1.0646 * 0.2072 *	1.5885 * 0.2592 *	1.0982 * 0.1608 *	0.6605 0.0816	0.3130 0.0397	0.9035 0.1091
Surf_office	−0.2832 −0.0500	−0.0191 −0.0033	0.7006 0.1224	0.6318 * 0.2301 *	0.3893 * 0.2470 *	0.4028 * 0.2233 *	0.2738 0.1272	0.4540 0.1893	−0.0692 −0.0244	−0.3177 −0.1148	−0.1762 −0.0606
Surf_hos_buss	2.4039 0.0988	0.0088 0.0004	1.0065 0.0410	−1.3742 −0.1166	−1.1703 * −0.1730 *	−0.7288 −0.0941	−0.0851 −0.0092	1.2395 0.1204	−0.1763 −0.0145	−0.3118 −0.0262	−0.1325 −0.0106
Surf_hospit	0.2780 0.0987	0.1788 0.0629	0.2838 0.0998	0.4868 * 0.3568 *	0.3284 * 0.4194 *	0.3350 * 0.3737 *	0.2815 * 0.2632 *	0.2558 * 0.2147 *	0.2040 0.1446	0.1994 0.1450	0.1308 0.0905
R-squared	0.0275	0.0249	0.1117	0.2544	0.3592	0.3226	0.2539	0.2104	0.1730	0.1308	0.0767
Adj. R-squared	−0.0236	−0.0264	0.0649	0.2152	0.3255	0.2869	0.2146	0.1688	0.1295	0.0850	0.0281
Standard Error	0.1865	0.1887	0.1370	0.0791	0.0421	0.0496	0.0620	0.0711	0.0862	0.0861	0.0933

* Coefficients are significant at the 95% level.

Restrictive measures were first announced on 13 and 14 March, and schools, high schools, and universities were closed. Consequently, the ratio of the non-residential built surface occupied by educational institutions was significant and negative from then until Phase 3. Remote education measures continued until the end of the school year in June.

From the announcement of the first restrictions on 13 and 14 March, and during all the phases of the lockdown, the average income per inhabitant had a significant negative effect on sustained demand. This negative influence remained intact during all the reopening phases, although it was only 95% significant during Phase 2. In contrast, population density per bus stop had a positive effect on sustained demand. Although this was not significant during the first phase of the lockdown and after Phase 2 of the reopening process, it remained positive throughout.

During lockdown, as well as during Phases 0 and 1, the ratio of the non-residential built surface occupied by supermarkets had a positive influence on sustained demand, whereas that occupied by non-essential stores had a negative influence. The ratio of surface occupied by hospitals had a positive influence on sustained demand throughout the lockdown and reopening phases (it was not significant at 95% from Phase 2 onwards).

The ratio of the non-residential built surface occupied by hospitality businesses was not significant during any periods, except during the severer lockdown. During the severer lockdown, hospitality businesses had a higher negative coefficient (in absolute values).

The results obtained during each period for the ratio of the non-residential built surface occupied by offices were remarkable. From 13 March until Phase 1, this parameter had a positive influence on sustained demand. However, it had a negative influence during the previous and subsequent periods, although it was not significant. This change in influence can be explained by the in-person workers, who were a high proportion of the few passengers who continued to use the bus service from 13 March until Phase 1. As the reopening phases progressed and the bus demand increased [9], the weight on patronage of the in-person workers was diluted, as was the case during February and early March.

To ensure that the correlation between the variables does not jeopardise the robustness of the model, a variance inflation factor (VIF) was calculated herein. According to most recent studies [54], the correlation between variables is a problem if the VIF is higher than 5. The VIF values of the variables analysed were less than 2.5, indicating that there are no multicollinearity problems in the MLR.

Figure 6 depicts the variables (Table 2) that had a positive influence on the sustained demand. A colour scale from yellow to dark blue was used to show the lowest to highest values of these variables for the areas of influence of the 161 bus stops. As the variables were calculated for a 300 m buffer zone around each bus stop, some of the buffer zones overlap, and the average of the intersected values was calculated for each 25 m $\times$ 25 m zone. The bus stops shown in Figure 6 correspond to the 50 stops with the most extreme values and coincide with those that had a sustained demand of less than 6.16% (magenta dot) and those with a sustained demand of more than 14.9% (green dot) during the severer lockdown. For example, considering hospitals, the figure denotes that in an area of influence with a high ratio of the non-residential built surface occupied by hospitals, the sustained demand of the corresponding bus stop was high. This is particularly noticeable in the southeast area of the city, which has hospitals with a high capacity and good customer service. Similarly, the figure illustrates how some of the stops that had the highest sustained demand were surrounded by zones that had a high ratio of the non-residential built surface occupied by supermarkets. However, in general, as the effects of different land uses overlap, the sustained demand cannot be explained by only considering one variable.

Figure 7 depicts the variables that had a negative influence on the sustained demand, based on the same selection criteria. Considering hospitality businesses, the zones with the highest proportion of this land use coincided with most of the stops with the lowest sustained demand, as leisure activities were suspended during the severer lockdown. The closure of educational institutions is also reflected by the lack of sustained demand in areas with a high ratio of educational facilities.

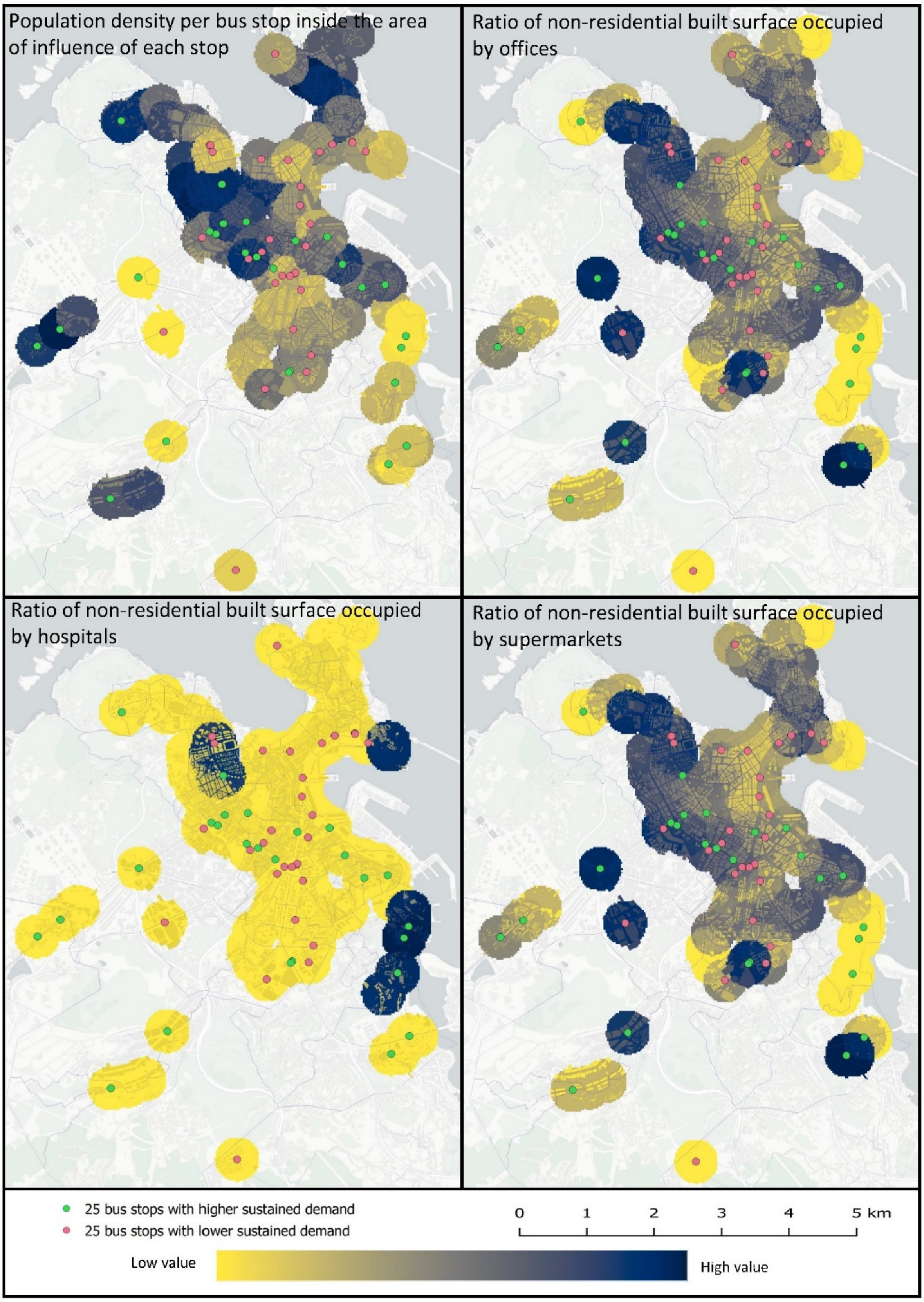

Figure 6. Variables with a positive influence on sustained demand during the severer lockdown and the 25 bus stops with the highest and lowest sustained demand.

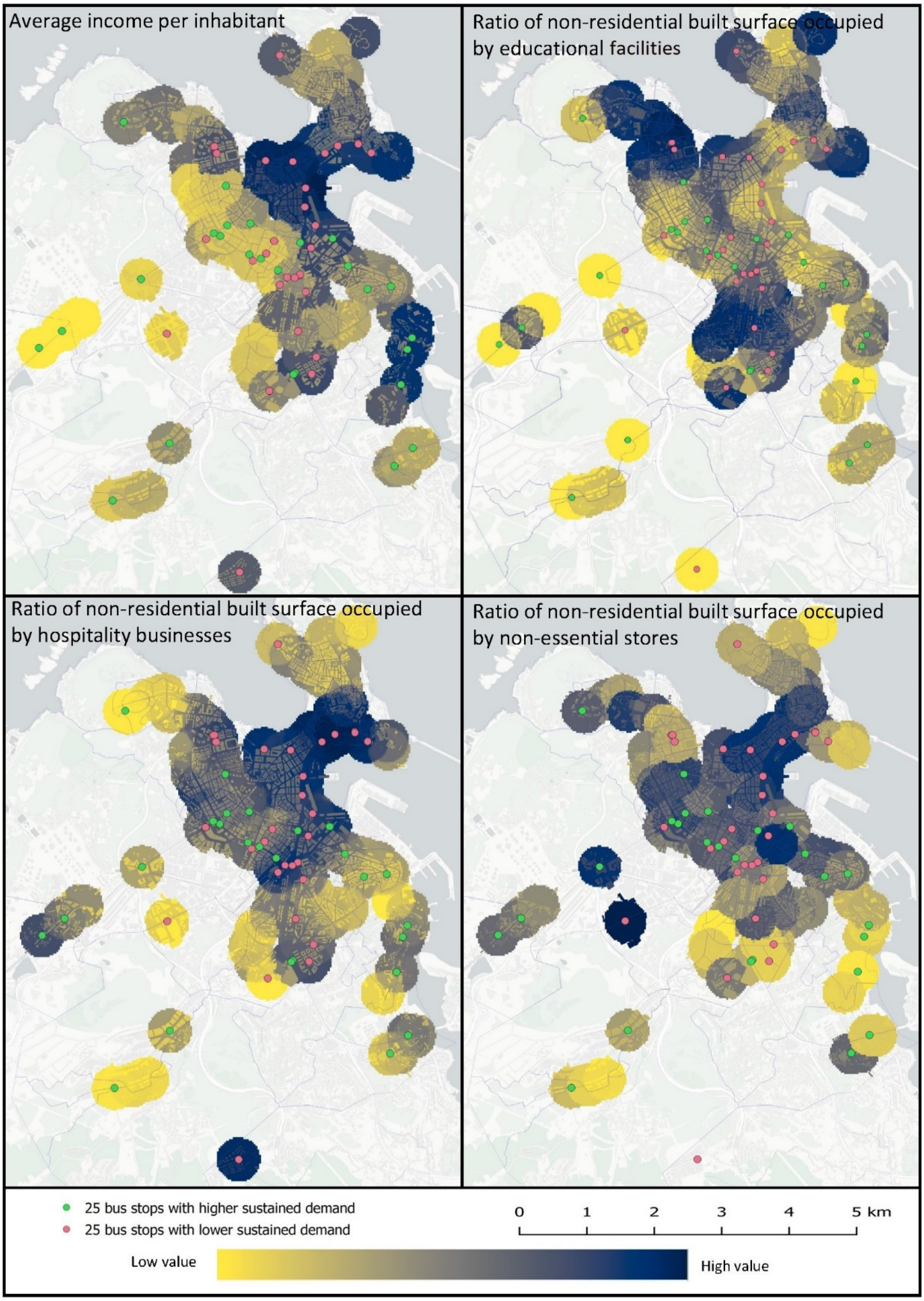

Figure 7. Variables with a negative influence on sustained demand during the severer lockdown and the 25 bus stops with the highest and lowest sustained demand.

4. Conclusions

The measures imposed during the COVID-19 pandemic did not affect all levels of society in the same way. Low-income populations are generally associated with essential labour sectors (supermarkets, bakeries, warehouses, distribution, etc.), wherein remote work is not an option. Crucially, this section of the population faces greater difficulty in choosing an alternative to public transport. The decrease in the supply and frequency of public transport services during lockdown, which was associated with a significant decrease in demand, has been assumed to be practically homogeneous, without considering additional factors, such as the characteristics of various areas and populations.

As it is vital to guarantee the provision of essential services during crises, we propose a novel methodology herein that can be applied to public transport planning during pandemics, to reinforce public transport in areas with the highest demand. This research faced the challenge of objectively and accurately quantifying the characteristics of bus stops' surroundings by processing public data. The proposed methodology to achieve this goal uses a combination of a large amount of highly detailed and georeferenced data on socioeconomic characteristics and land use. These data were processed using GIS to accurately distribute them across the study area.

The decrease in transit use due to the pandemic was not homogeneous throughout the different zones of each city and the diverse periods of restrictions. Therefore, it is relevant to shed light on the possible reasons for this variability. For this purpose, a set of regression models was proposed to analyse the variables associated with a higher sustained demand during the lockdown and reopening process. These models can be used to determine the areas that require a higher level of transit availability, even during exceptional periods.

As the COVID-19 pandemic is still underway with new variants of SARS-CoV-2 emerging, this study can be used to establish strategies to enhance public transport in areas with the greatest need by replicating the proposed methodology. It can serve as an invaluable tool for reassessing transit planning and strengthening transit services in areas with more demand, instead of enforcing a uniform reduction in the supply of public transit services.

A case study was conducted to demonstrate the efficiency of the proposed methodology. The explanatory variables were all found to be statistically significant during the severer lockdown (the period with the most restrictive measures), despite having no statistical significance pre-lockdown. Therefore, the variability of sustained demand before the announcement of the state of alarm cannot be explained by the variables considered in the analysis. Notably, the independent variables can explain the variations in demand during the pandemic, as they are related to changes in activities and mobility during the COVID-19 lockdown. The results indicate that public transport services can be guaranteed by paying special attention to areas with a high population density per bus stop, low income per inhabitant, and high ratios of land use dedicated to supermarkets, offices, or medical centres.

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