Mapping the spatial distribution of urban traffic congestion: methodological exploration using web based services

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Abstract. Sustainable transport systems are a necessary requirement to achieve efficient economic performance, enhance urban quality of life and diminish environmental costs. Congestion, a negative externality of mobility, is responsible for urban pollution, inefficiency and has adverse effects over individuals facing this problem. For these reasons, transport and city planning agencies have developed interests in defining and measuring transportation congestion. Although, different definitions and metrics have been used, congestion measurements are found aggregated at a city level or for particular road segments. This study proposes a methodology that produces information from a web traffic service to map traffic congestion within an urban area. The method is simple and generalizable enough to be adopted in different urban areas. This paper presents the analysis of four European cities (Amsertdam, Glasgow, Goteborg and Lisbon) and show that the conclusions are consistent with the results obtained from internationally recognized organizations such as INRIX and TomTom.

1. Introduction

In 2015, global leaders agreed to work towards the 2030 Agenda for Sustainable Development. A total of 18 Sustainable Development Goals (SDGs) were identified as the blueprint for development. The importance of transport to achieve these goals can be direct or indirect, and transportation related indicators are found in eight of these goals (direct: 3.6, 7.3, 9.1, 11.2 & 12.c and indirect: 2.3, 3.9, 6.1, 11.6, 12.3, 13.1 & 13.2) (Booth, Hanmer, and Lovell 2000; UN-Habitat, UNEP, and SLoCaT 2015). Sustainable transport systems are acknowledged to be necessary pre-conditions to enhance socio-economic opportunities, diminish environmental costs and improve road safety conditions (Jennings 2016).

By 2030, United Nations projected that urban areas will host 60% of global population, within cities over 80% of the total wealth is being produced (McKinsey Global Institute 2011; UN 2018) and the positive externalities associated with urbanity have been extensible registered. Cities are successful because at their core, places of intense human interactions, allowing people to connect easily (Glaeser 2011). Consequently, the success of cities cannot be explained without the fundamental role of mobility (Diakaki, Kotsialos, and Wang 2003). However, as cities become more attractive, population density increases and a set of negative externalities such as pollution, crime and congestion erode the benefits of urban life (Eurostat 2016; United Nations 2016; Jones and Hervik 1992; Glaeser 2011; Stempfel et al. 2016). Nevertheless, traffic congestion is a major urban problem (Downs 1992) because it affects cities' core ability to connect people to other people which is a crucial factor for social and economic development (Falcocchio and Levinson 2015).

In the last century, cities all over the world have been facing a constant increase in the demand for transportation services, resulting in severe traffic congestion. The future does not look promising, nothing indicates that the situation will get any better. A survey to transportation professionals in Bertini (2005) shows that almost 80% believe that congestion problems has worsen. If nothing is done, as a result of congestion travel time, energy consumption and environmental cost will continue rising if (Bull 2004; Diakaki, Kotsialos, and Wang 2003). According to conservative estimates the benefits of increasing the travel speed of private cars by 1 km/h and public transport by 0.5 km/h are worth 0.1% of the Gross Domestic Product (GDP) (Thomson 2000).

There is an extensive amount of research that has been quantifying the negative impacts of traffic congestion, the European Commission (2001) alert that Europe might lose economic competitiveness if no actions are taken to address the problem. The external costs of road traffic were estimated to increase by 80 billion EUR (1% of the EU GDP). In a similar note, Cervero (1998), The Texas A&M Transportation Institute (2019), and Lomax, Turner, and Shunk (1997) argues that these social costs are equal to 2-3% of GDP and Schrank, Lomax, and Eisele (2011) arrives to similar conclusions for the U.S.

In a more comprehensive attempt, Bilbao-ubillos (2008) decomposes the costs of congestion into eight categories and provide a detailed methodological tool to quantify the total welfare loss and Choi, Coughlin, and Ambrosio (2013) show demonstrate for the U.S. that commuting time have a negative effect in the well-being. Finally, under congested scenarios drivers levels of stress and aggression tend to rise, increasing the probability of unsafe driving (Hennessy and Wiesenthal 1999).

Significant amount of resources are allocated to understand and measure traffic within cities, decrease in technological costs and fast adoption of mobile devices introduce the possibility of collecting, analyzing and modelling traffic congestion on a wider and more precise scale that in the past (Rempe, Huber, and Bogenberger 2016). In the past 10 years new information sources and techniques were explored. Cameras and sensors can provide accurate measurements, but only specific road segments are evaluated and the cost of maintaining these devices is high. Alternative methods to collect data at large scale and lower cost is needed(Panita Pongpaibool, Tangamchit, and Noodwong 2007; S. Wang et al. 2015; Pattara-atikom, P. Pongpaibool, and Thajchayapong 2006).

The aim of this research is to provide a methodology to measure how congestion is distributed across an urban area. The map of congestion can provide useful information to local authorities and planners since more dis-aggregated spatial information will be provided.

2. Theoretical Background

2.1. What is congestion

The definition of congestion in transportation facilities has evolved over the years (Falcocchio and Levinson 2015) and there is no universal accepted definition for the problem. According to Lomax, Turner, and Shunk (1997), different actors are interested in understanding different aspects of the problem traffic congestion; hence depending on the what the objective of the study is, different definitions can be adopted, impacting in what metrics are being used and what information is needed to be collected (Aftabuzzaman 2007). In fact, Bertini (2005) shows that in practice the definition of congestion is a contested arena, with no clear predominance of one over the other. Time, speed, volume of vehicles, level of service (LOS) and cycle failure are among the most used components to define congestion.

In some cases the definition of congestion is confused with the consequences it produces.

Aftabuzzaman (2007), proposes to categorize the definitions in 3 groups: (i) demand capacity related, (ii) delay-travel time related, and (iii) cost related. But in the second and third cases, congestion is defined by its outputs and this is found conceptually inaccurate.

Traffic engineers would define congestion as a situation (without a negative connotation) produced when the amount of infrastructure users exceeds it's capacity. The overuse of the infrastructure results in a set of side effects (Diakaki, Kotsialos, and Wang 2003). According to Falcocchio and Levinson (2015), to be helpful in congestion management decisions, the definition should be based on a comparison of "actual travel times" with "expected travel times" for peak hour and off-peak conditions.

This idea is rejected by Downs (1992) and Joe Cortright and CEOs (2010), arguing that estimation strategies based on *'inescapable'* travel decisions are misleading. The *'hypothetical alternative of "congestion-free" travel during peak hours is an unattainable myth'* and *'comparing that illusory alternative with what happens and declaring the time difference "wasted" is a misleading exercise.'*. The debate still continues (Hamad and Kikuchi 2002).

Modern definitions include the idea of acceptable waiting or travel times. Although, still there is no clean-cut definition about what congestion is what is not, this definition introduces flexibility and allows the problem to be adjusted depending on different local contexts (Downs 1992; Falcocchio and Levinson 2015) Finally, Stopher (2006) and Skabardonis, Varaiya, and Petty (2003) makes a distention between two types of congestion, based on what created the time delay anomaly. Non-recurring congestion are those delays produced by a random event such as an accidents, concerts or vehicle breakdowns, whereas recurring congestion makes reference to those delays that occur at the same place and time, usually on working days.

This study, as most of the research and policy issues are concern with the later form and as time related measurements will be further explored.

2.2. Metrics and maps

The definition of how traffic congestion is defined have direct impact over how it will be measured. For instance, if congestion is defined as a travelling below normally accepted values, because of high density of traffic flow, then a threshold of what the *normally accepted* travel speed is needed. Lomax, Turner, and Shunk (1997) suggests that any congestion measure should show clarity and simplicity, describe the magnitude, allow comparison, includes time and must be related to congestion relief. Using this list of attributes, a variety of congestion measurements were evaluated suggesting that different uses demand different measurements (Aftabuzzaman 2007; Lomax, Turner, and Shunk 1997). Among the different measurements evaluated to describe congestion, the ones related to the supply side or infrastructure, were left behind. The objective here was to describe what places are affected by congestion, not to assess traffic conditions in different parts of the road network.

A family of indicators were calculated in absolute values such as the **delay rate**, which consisted in the difference between actual travel time and a free-flow situation or accepted time. Also, relative metrics can be generated using the same information. For instance, taking the **delay rate** relative to the accepted travel rate generates the **delay ratio or travel time index (tti)**. After processing the information, the results are shown in tables that rank different cities, this could be use with traffic counts, but planning and transportation agencies would need more information to generate effective traffic congestion reduction policies. After the extensive review done here, almost no maps of cities were showing how congestion was spatially distributed. To design better transportation policies, information about, origin, destination and motive of travel are needed. Furthermore, from the reports showing the ranking of cities it would be virtually impossible to know which citizens are facing this problem.

3. Methodology

At its core the methodology described in this section details a process of collecting and processing data from an internet service that provides traffic estimations and routing optimization. This section provides a detailed description of the steps followed to spatially capture how congestion is distributed across the city. As a general overview, the process can be divide into 5 main stages: (i) the study area is defined and subdivided, (ii) a list of trips is created, then (iii) travel information is extracted and (vi) the information captured is processed, analysed and (v) the indices are calculated.

3.1. Defining study area

In order to understand how congestion is distributed across an urban area, the first step is to select the urban area of interest. Then a decision regarding the boundaries of the area must be taken. Once this is settled, the area must be divided into different regions. For this purpose different already geographical representations could be used, using existing division will allow to later relate different socio-economic or environmental characteristics with travel information. Goteborg area could be divided using a regular grid, neighbourhoods, or other institutional maps could be useful, such as census tracks. After the urban area is subdivided, the center of each polygon is extracted as a latitude and longitude coordinate (centroids).

3.2. Creating a synthetic Origin-Destiny matrix

The centroids extracted from the first step are now considered to be the starting point (or destination) of a trip and making pair permutations among the set of points creates a list of trips from one point to the other; then from a second point to all others and so forth. Taking n as the number of zones, this process creates a total of of n*(n-1) routes. For instance, is the area to be studied contains 3 areas (A, B & C), the OD matrix will consider the following routes: (i) A to B, (ii) A to C, (iii) B to A, (iv) B to C, (v) C to A & (vi) C to B.

3.3. Capturing travel data

As seen in the previous section, one of the manifestations of congestion is to experience longer travel times. To determine the level of congestion a benchmark scenario needs to be used for comparison. Then it would be needed to define a *congested* and *non-congested* situations. For instance a morning rush hour can be taken as a a *congested* moment and a late nigh (3AM) moment can be used a the *non-congested*. Because Google Distance Matrix will be used, future dates need to be considered. This implies specifying not only the time, but also a date, a month and the year. Thus, it is important to take into consideration holidays and which weekday will be used for the analysis. Fridays might be less busy days than Wednesdays or December and July show less activity than October (in the northern hemisphere countries). After specifying these moments, the list of all origins and destination is used jointly. A request for each trip at the *congested and non-congested* moments is executed. The API requests an origin, a destination, a time and a travel mode. As a result, the generated response (json file) contains information of the addresses, the length of the path taken and the travel time. The data set containing all the trips from all possible destinations to all possible destinations for the two scenarios is stored for later processing.

3.4. Processing and analyzing information

The data obtained is then reviewed to check if the process finished successfully and if for all the trips the details were generated. In some cases, the centroid might be positioned in a places that is impossible to access by car: in an extreme situation a lake or the ocean. If this is the case, the point is then removed from the analysis. Then basic descriptive statistics for the trips length and time are reported. If in presence of outliers, special consideration must be taken.

After scrutinizing the data the distribution of travel times is observed by plotting histograms and scatters of distance against travel time are drawn to enrich the analysis.

3.5. Calculating the metrics and visualizing

Once the data set is consolidated, two congestion metrics are calculated: (i) the time difference in minutes between the *congested and non-congested* scenarios and (ii) travel time index (tti) which is the ratio between the *congested and non-congested.*

Finally, taking the mean values, the results are aggregated by each origin and the results are joined to the original polygons that were used at the beginning of this process.

In order to obtain values at the level of the whole metropolitan area, an extra step can be taken. By taking the average values of the entire data set, the travel time difference and tti are calculated.

The method presented here uses the Distance Matrix API form Google Inc. to retrieve data but a similar exercise could be done with other services such as HERE or TOMTOM. Furthermore, given the quantity and nature the methodology that will be described above, was coded and executed using R in Rstudio and the functions written can be found in GitHub.

4. Test case

To demonstrate how the method could be used in practice, four European cities where selected as a proof of concept.In this opportunity, as a proof of concept the 1km2 population grid from the EuroStat (GEOSTAT 2011) was used. Amsterdam, Glasgow, Goteborg and Lisbon were selected and from their historical centre a buffer zone was used to delimit the *city* boundary. The geographic coordinates of the centroid of each 1km2 square were used to create the list of all possible routes.

From this list of origins a synthetic Origin-Destiny matrix was created to retrieve data for a *congested* and *non-congested* moments. Thursday, October 15, 2020 8:30:00 AM was chosen as a *congested* moment and Wednesday, July 15, 2020 3:30:00 AM, as a *non-congested.*

4.1. Data retrieved

The process generates information for a total n*(n-1) routes (n being the number of zones). For instance, Lisbon is divided into 119 squares and the number of possible routes is 119*118 = 14,042 (then 28,084 travels were estimated). Amsterdam has 131 zones, Glasgow 136 and Goteborg 123 (17,030, 18,360 and 15,006 routes respectively). A summary of the descriptive statistics for the time in minutes can be found in Table 1.

	Congested scenario (mins)	Routes	Mean	S.D.	Min	Max
1	Amsterdam	17,023	20.26	6.86	0.65	48.57
2	Glasgow	18,355	23.08	8.68	1.42	56.88
3	Goteborg	14,997	18.01	6.82	1.37	57.97
4	Lisbon	14,043	28.16	11.70	1.37	84.63
	Non-Congested scenario	Routes	Mean	S.D.	Min	Max
1	Amsterdam	17,023	11.70	3.71	0.52	24.90
2	Glasgow	18,355	11.93	3.99	0.83	24.85
3	Goteborg	14,997	13.09	5.29	1.10	49.18
4	Lisbon	14,043	12.82	5.77	0.77	46.90

Table 1: Descriptive Statistics of travel times by city

The amount of route information retrieved is consistent with the amount of zones in the city and as expected, the *congested* situation on average takes longer time. Formally an independent-samples t-test was conducted to compare the travel times under a *congested* and *non-congested* situations. For each city, the time difference was found statistically significant with a confidence level of 99%.

[Jorge Gil: I would include the maps and charts for Goteborg in this section: grid with distance, scatter with two colours, density histogram, boxplot. the left part of slide 3

5. Results

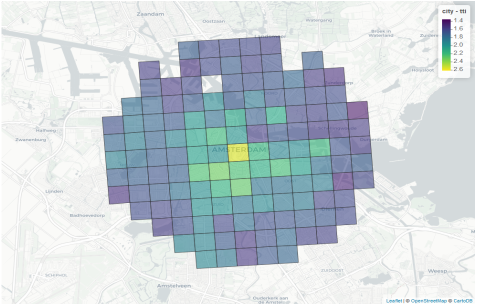
After capturing, processing and aggregating the data obtained from the API, table 2 on page 6 contains the descriptive statistics for time difference and TTI. In this case, the number of observations corresponds to the number of zones in the map and each zone holds the mean of all the trips departed from that origin. The results show that the methodology successfully captured diversity between cities. For instance, in Lisbon the average time difference is of 15.3 mins, with a maximum of 21.6 mins, meanwhile in Goteborg on average delays are of 4.9 mins with a maximum of 8 mins.

	Time Difference (mins)	Zones	Mean	S.D.	Min	Max
1	Amsterdam	131	8.57	2.39	5.38	19.03
2	Glasgow	136	11.15	1.88	7.66	15.64
3	Goteborg	123	4.92	0.99	3.22	8.06
4	Lisbon	119	15.34	2.67	9.74	21.57
	TTI	Zones	Mean	S.D.	Min	Max
1	Amsterdam	131	1.74	0.23	1.36	2.61
2	Glasgow	136	1.94	0.14	1.60	2.31
3	Goteborg	123	1.38	0.09	1.21	1.69
4	Lisbon	119	2.21	0.16	1.70	2.57

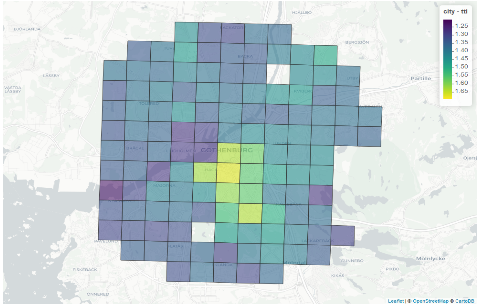
Table 2: Aggregated descriptive statistics by zones

Although, the table above reveals relevant insights about these cities, local authorities or planners would not know which places or who is being affected by traffic congestion. Therefore, in figure 1 the TTI for each city was mapped. By looking at these maps several conclusions about where and how bad congestion is across the city. For instance, in all four cities, although the historical centre is the nearest point to all other destinations, when congestion is taken into account, these places face the highest TTI. This indicates that in a *non-congested* situation, the city centre is highly accessible but when *congested*, the advantage of being central gets eroded.

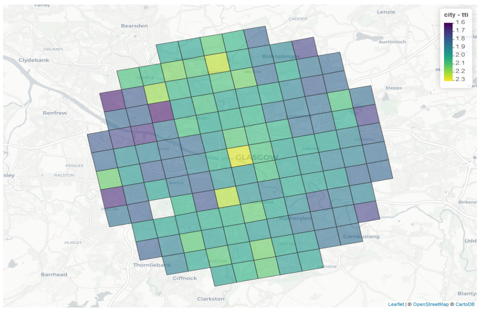
These maps also show that the methodology presented in this study was able to capture differences across cities successfully. In Goteborg, the historical city centre gets mainly congested, meanwhile the other parts of the city remain with similar levels of congestion. In Lisbon, traffic congestion is more scattered across the city, presenting islands of low congestion (where the CBD and commercial areas have moved to).



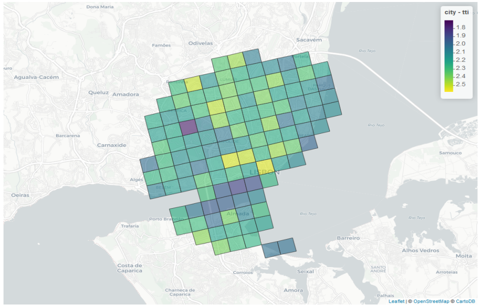
(a) Amsterdam



(c) Goteborg

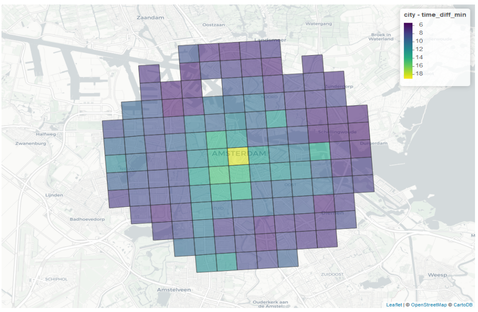


(b) Glasgow

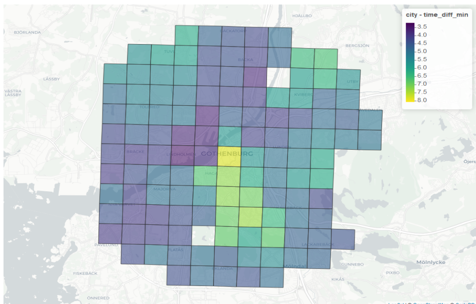


(d) Lisbon

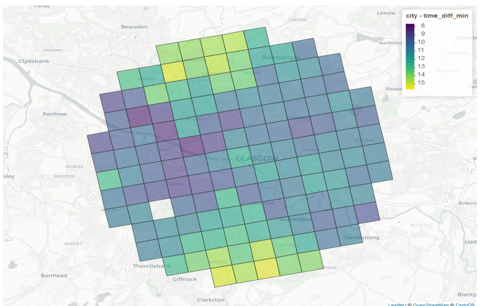
Figure 1: Images extracted from results



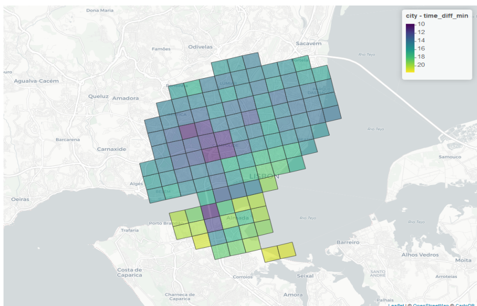
(a) Amsterdam



(c) Goteborg



(b) Glasgow



(d) Lisbon

Figure 2: Images extracted from results

6. Discussion

The methodology presented in this paper exploits a new data source to provide spatial insights about traffic congestion in different cities. The information generated allows planning and transport agencies to reconstruct some of the most popular indexes discussed in the theoretical background section.

In order to determine the validity of the methodology presented here, the aggregated results by city were compared against the results published by two internationally recognized companies which offer transportation solutions. With different business models, INRIX, HERE and TomTom in the last years started to offer transportation insights as a service. Historically, INRIX has been consulted to provide he levels of congestion in several countries in the OECD and U.S. transport agencies (Eurostat 2016; The Texas A&M Transportation Institute 2019), but given the increase in the amount of devices embedded with GPS, other businesses have found them self in a position of exploiting these new data sources. Nowadays, they all offer transportation consulting services. Inrix (2018) and Tom Tom (2018) publish results on traffic congestion and rank cities according to different criteria. For instance INRIX reports the amount of hours lost in congestion, the cost per driver, travel time and speed whereas TOMTOM shows a congestion percentage. Although, is difficult to compare across these indicators, if the ranking of cities is taken into account the methodology presented here, along with TomTom and INRIX, position Goteborg as the least congested, followed by Amsterdam, Glasgow and finally Lisbon. It is relevant to highlight that, INRIX and TomTom provide more detailed information for each city, but no maps are found and the spatial distribution of the problem remains unknown.

This process was not conceived to show congestion levels at street level, but to identity areas which area affected by this phenomena. Transport or planning practitioners interested in getting traditional information about levels of service, will not find answers by applying this methodology.

Traffic congestion deteriorate different domains of urban life and as a consequence the focus on the problem varies across disciplines. *'Throughout the world, traffic congestion reduces the core benefit of cities: the ability to connect with other people easily'* (Glaeser 2011), so it becomes crucial to understand who suffers from congestion the most and what parts of the city are more vulnerable to the problem. Therefore looking at the congestion level of street segments is useful for traffic planning, but insufficient to solve broader issues.

The maps of congestion produced as a result of applying this methodology establish the relationship between a population living in an area and the level of congestion faced.

When dealing with city planing, it is difficult to understand how an urban intervention or policy affects the rest of the city.This approach can be iterated over time, to see how transport congestion evolves over time and evaluate to what extent certain policies are being effective in changing traffic congestion patterns.

6.1. Limitations and future work

The methodology presented in this study relays primarily in Google's web service and this fact is a drawback as users of the API have no control over the service standards, usability or costs. For instance, the type request performed during this study had a cost of 10 U$D/1000 requests, considering a grid of 100 cells, will generate 9,900 travel routes and to estimate congestion a total of 19,800 requests will be needed. This process will involve a cost of 198 U$D and almost to hours to complete. Consequently, before considering expanding the study to cover more cities, take into consideration extensive metropolitan areas or repeating the process for different moments, budget constraints must be taken into consideration.

The results presented here, took the EuroStat population 1km2 grid cell to retrieve traffic information. Certainly, this decision was arbitrary and the shape/size of these areas can be subject of debate. Although, to map the historical city center this representation is to big, it make sense for planning and data purchase became affordable.

The zones used for the analysis can be easily interchanged with other geographical representations, allowing the process to be enriched in several dimensions. Census tracks with socio-economic information could be used to refine the method, the amount of cars or age groups could help to better understand to what degree this citizens are affected and to explore whether there is a relation between car use and congestion levels. Moreover, an origin and destination survey with geographical zones can be used used in the study to weight the different desire lines of travel. Depending on the characteristics of each data source, this methodology can be expanded and refined in different manners.

The results presented here, do not necessarily imply that *'more congested'* places are demanding for solutions from public administration, but attention. *'Traffic problems'* can be the result of poor infrastructure, an excess of demand or a combination of both. The method only reflects time delays faced by private commuting and in some cases, such as in city centres, this can be a desirable tool to demotivate car use.

Google API also offers estimations for public transport, that can be used provide a more comprehensive estimation of how congestion by different transport modes.

Finally, this work presented an alternative of how synthetic data can be used to provide new insights. The method only uses a dull origin and destination matrix with modelled traffic information. Traditional data sources such as population census or travel survey could be combined to update or generate richer data sets. In this case, the population grid was used because it would eventually allow to weight the results obtained and give relative importance to different zones based on population. Travel surveys, with information about time, commuting modes, car type and specific origins and destinations could be used to feed this methodology to model precisely how much GHGs are being emitted and bench-marked under *non-congested scenarios.*

7. Conclusion

The study presented a methodological approach to study the how traffic congestion is spatially distributed within an urban area. Generating a synthetic Origin-Destiny matrix, the method uses an online routing service to estimate different travel routes. The methodology provides a non-expensive, generalizable and systematic to estimate congestion in different parts of a city. The data retrieved can be mapped, thus used by city planners and transportation agencies. The aggregation of the data provide conclusions that are consistent with internationally recognized institutions such as INRIX and TomTom.

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