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Between Space Syntax and Transportation Planning

Understanding the trade-offs between accuracy and complexity of Space Syntax and Transportation planning approaches to explain movement.

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ABSTRACT

Traditionally, explaining how and why people move has been the domain of transportation planning (TP). In general, TP models take into account the sociodemographic characteristics of the population and the utility of available destinations and modes of transport. As a result, these models provide accurate and detailed insights into the effect of planning decisions on the mobility pattern in a given area. However, these insights come at the cost of a large amount of data required to calibrate and run the TP models. An alternative approach proposed by Space Syntax scholars explains movement as a function of the configuration of urban form. This approach gained attention due to its simplicity and applicability in the context of developing countries or early design stages when much information required by the TP model is simply not available. Despite the apparent advantages of the Space Syntax approach, it is unclear what is the effect of its simplicity on the accuracy of the resulting movement model.
Thus, in this study, we investigate the trade-offs between the complexity and accuracy of the TP and Space Syntax models in the scope of empirical study in Weimar, Germany. Our results suggest that the Space Syntax model provides valuable insights into the overall movement pattern. However, its accuracy drops below the acceptable standards when evaluating the traffic flows at the most frequented locations. Here, the more complex TP models are required. If confirmed by future studies, these findings provide guiding principles for the movement model selection in the context of urban planning.

KEYWORDS

Transportation, Movement, Accuracy, Complexity, Modeling

1 INTRODUCTION

Understanding how people move is a key aspect of urban planning and policymaking. The discipline traditionally dealing with the issues related to mobility is transportation planning. To devise and evaluate plans, the transportation planning scholars deployed a multitude of models able to assess the impact of design decisions on where people go and how they get there. If the task at hand is to devise large-scale infrastructural decisions with high costs and long-term impact, transportation planners usually employ the macroscopic class of transportation models. These models do not reveal much about the choices and behaviour of individuals; however, they are able to explain and predict the movement pattern on an aggregated scale.

The four-step model is the standard approach in the macroscopic modelling of transport demand. It is based on the human activity approach to transportation modelling (Fox, 1995; Jones et al., 1983), revolving around the idea that the purpose of individual travel is not to reach a given location but to fulfil individual needs (e.g., hunger) by performing particular activities (e.g., visiting a restaurant). Additionally, it is assumed that people tend to maximize the utility of each trip and minimize its costs by choosing among different destinations, paths, and modes of transport.

The respective parts of the macroscopic transportation planning model (TPM) formalizing the above-mentioned concepts are 1) Trip generation, 2) Trip distribution, 3) Mode choice, and 4) Trip assignment. Without going into the details, the TPM combines the sociodemographic data with the distribution of economic activity and characteristics of the transportation infrastructure to estimate where people go and how they get there (Mcnally et al., 2000).

In addition to TPM, an alternative approach to understanding and explaining movement was proposed by Hillier and Hanson (1984) under the term Space Syntax. It encompasses a variety of theories and methods for the analysis of space and its effect on human behaviour.

The Space Syntax method revolves around graph theory – a field of mathematics specialized in quantifying configurational characteristics of relational systems. When it comes to explaining movement, the spatial graph used by Space Syntax scholars is based on lines of movement[1]s (i.e., graph nodes) and their relationships (i.e., graph edges). It is important to note that spatial graphs are routinely applied in the field of geography; however, what makes the Space Syntax approach unique is the definition of relationship (i.e., distance) between different locations. Instead of the commonly used metric or temporal distance, the Space Syntax model embraces two versions of cognitive distance. The early development came together with the topological distance and was later extended by angular distance (Dalton, 2001; Turner, 2001). The rationale behind the Space

[1] Space Syntax method employs several representations urban space such as visual axes (i.e. axial map), their segments (i.e. segment map) or street center lines.

Syntax model (SSM) is based on the assumption that, in general, people do not choose the metric shortest but cognitively easiest path when navigating through the urban environment.

The most important feature of the SSM is that this abstract model of urban form has the ability to explain how people move. As Penn, (2003) claimed, the Space Syntax approach can explain 60 to 80% of the variance in movement flows as an effect solely of the street network configuration. The simplicity of SSM is of great value in cases such as early design stages or planning in the context of developing countries when only limited information on sociodemographic characteristics of inhabitants and distribution of economic activities is available. Here, the "light-weight" SSM approach often provides the only feasible alternative to the "data-hungry" four-step TPM model.

Despite the apparent advantages of the SSM, it remains a topic of ongoing discussion how a model with no information about where people are and what they need provides any meaningful insights about how people move. Nevertheless, the strong association between the configurational measures provided by SSM and the distribution of movement flows has been repeatedly empirically confirmed throughout geographies, scales, and modes of transport (Hillier and Iida, 2005; Lerman et al., 2014; Turner and Dalton, 2005).

Hillier addressed the controversy surrounding the SSM in his seminal paper with the suggestive subtitle "why space syntax works, when it looks as though it shouldn't" (Hillier, 1999). He provides a theoretical argument saying that the distribution of people and activities follows the movement potential given by the urban form, and this "natural movement potential" is amplified by a feedback cycle between movement and activity distribution pattern. Consequently, since everything follows the urban form, no additional information is needed to explain the movement.

It is important to say that even though the argument is logically sound, it has never been empirically tested and as pointed out by Ratti and others (Pafka et al., 2020; Ratti, 2004), there might be many cases when it does not hold in the real world. This objection is well reflected in the Space Syntax literature, with authors finding highly varying fitness of the identical SSM approach when explaining movement at different locations. For instance, Schneider et al. found that SSM accounts for only 38% of explained variance in vehicular traffic in small German towns (Schneider et al., 2017), while Hillier was able to explain up to 77% of the variance in vehicular movement in the London's district of Clerkenwell (Hillier and Iida, 2005). In other words, in some cases, the movement is almost entirely the product of urban form, while in others, the urban form plays a much smaller role with other factors driving how people move. Thus, on the one hand, it is unquestioned that the SSM is a practical approach when explaining the effect of urban form on movement; on the other hand, it remains unclear what is the overall explanatory power of SSM.

1.1 Research Gap

It must be mentioned that the uncertainty about the explanatory power of SSM does not pose any conceptual difficulty for the Space Syntax scholars who treat SSM as a model of urban form with the ability to explain the movement, instead of a model of movement based on urban form (Hillier, 1999). However, we argue that this brings up significant difficulties in the practical application of SSM. Since it is impossible to assess the explanatory power of the SSM model when evaluating the impact of design decisions on future movement, it is difficult to base any decision on such a model. In other words, it is hard to say if and how a large effect suggested by the SSM is going to translate into reality.

This might suggest that the traditional TP approach might be preferred over the SSM when it comes to practical application. Nevertheless, as already pointed out, the major limitation of TPM is the demanding data acquisition and model calibration. As a result, there is no single best approach, but the SSM and TPM seem to have their individual trade-offs between explanatory power (i.e., accuracy) and model building costs. This is perfectly aligned with the much broader statement that models differ in their approaches depending on the modeler's purpose and resources (Minsky, 1968). The problem in the case of macroscopic movement modelling when it comes to SSM and TPM lies in our lack of knowledge about the costs-accuracy trade-offs of the individual models.

1.2 Research Question

To enhance our ability to choose the best model for a given purpose, we must know how the model costs (i.e., the data required to set up, calibrate and run the model) relate to the model performance (i.e., prediction accuracy or explanatory power of the model). Moreover, we do not only want to know how the fully specified TPM approach performs when compared to the SSM but also how it's individual parts contribute to the overall accuracy. For this purpose, we represent each part of the four-step TPM as a layer of information increasing the complexity of the movement model (i.e., increasing its costs) when compared with the SSM. In other words, we can imagine a series of models starting with SSM as the simplest model and ending with TPM as a fully specified and most complex model.

The resulting question is how the additional data and computation related to each subsequent model contributes to the model accuracy? The underlying research hypothesis is based on the assumption that as the model complexity increases, the accuracy will increase. However, the overall goal of this study is not only test the positive relationship between the model complexity and accuracy but to quantify the respective effects.

1.3 Limitations

In this study, we investigate the trade-offs between the complexity and accuracy of TPM and SSM approaches to explain the distribution of movement flows. We restrict our study to macroscopic modeling of individual vehicular traffic as this is the traditionally most widespread application of TPM. Nevertheless, the research methodology devised in this study can be readily applied to other modes of transport, such as cycling, walking, or public transport, as these are rapidly gaining importance in the context of urban mobility. This restriction effectively reduces the complexity of the study design as the “mode choice” step of the TPM can be ignored. Furthermore, we simplify the “trip assignment” step of TPM by assuming that in the given case study of Weimar, Germany, the road capacity does not play a significant role. In other words, there is no congestion affecting the path choice when undertaking a travel. This simplification is based on previous research and empirical evidence from Weimar and serves to simplify the testing procedure further. By doing this, we focus our study on quantifying the effect of the first two steps of the TPM approach - the trip generation and trip distribution on the model accuracy.

2 METHODS AND DATA

2.1 Study Design

We devise a series of empirically calibrated models explaining the individual vehicular traffic in the administrative boundaries of the city of Weimar, Germany. Each model represents a different level of complexity expressed by the first two steps of the four-step TPM approach (i.e., trip generation and trip distribution). If we render the information embedded in each step as a distinct dimension of model complexity, we arrive at a two-dimensional space (Figure 1a). For the sake of simplicity, we treat each axis of the complexity space as a discrete variable (i.e., it is either fully defined or not) which results in four different options for how to specify the traffic model (Figure 1b). At location [1,1], we have the fully specified model containing the information about a) how much traffic is generated and attracted by each location (i.e., trip generation) and b) how traffic is distributed between each origin and potential destination by considering the costs and utility of each trip.

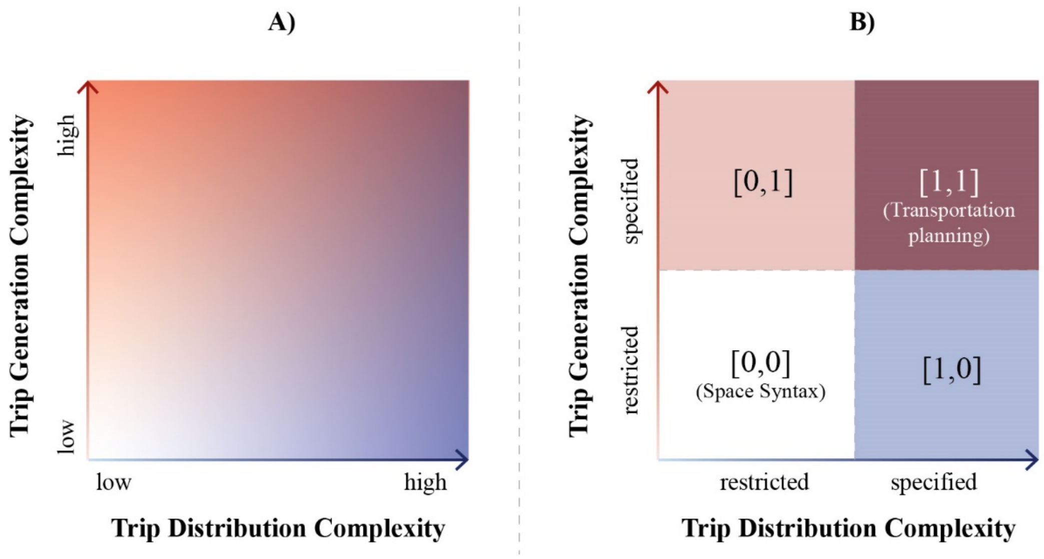

Figure 1: Movement model complexity represented in 2-dimensional space. A) continuous model complexity. B) Discretized model complexity.

The specificities of the calculation and required data are covered in the following section. The important thing to realize is that the fully specified model has the highest complexity as it carries the most information and is considered the base model. All remaining models systematically leave some portion of the fully specified model out, with the SSM at the location [0,0] (Figure 1b) being the simplest and most restricted model.

To quantify the effect of information included in each model on its accuracy, we measure the deviation of the movement flows predicted by the restricted models from the prediction of the base model – the fully specified model. The deviation from the fully specified model represents the loss of accuracy, which is to be attributed to the model restriction (i.e., the simplification achieved by leaving some information out). We want to note that one could also compare all four models to empirical traffic data if these are available. Nevertheless, due to the absence of empirical data on vehicular traffic, we treat the fully specified TPM as the ground truth and measure how restricted models with lower complexity deviate from it.

2.2 Model Definition

In the following, we define the two axes of model complexity in their specified as well as the restricted state. We start by introducing the TPM as a model specified on both axes and continue with the description of SSM as a completely restricted model. Finally, we introduce the remaining two models as different combinations of SSM and TPM.

Fully Specified Model

The standard approach of TPM is the four-step model which is described by Ortúzar Salar and Willumsen as: “The approach starts by considering a zoning and network system, and the collection and coding of planning, calibration and validation data. These data would include base-year levels for the population of different types in each zone of the study area as well as levels of economic activity, including employment, shopping space, educational and recreational facilities. These data are then used to estimate a model of the total number of trips generated and attracted by each zone of the study area (trip generation). The next step is the allocation of these trips to particular destinations, in other words, their distribution over space, thus producing a trip matrix. The following stage normally involves modelling the mode choice, which results in modal split, i.e., the allocation of trips in the matrix to different modes. Finally, the last stage in the classic model requires the assignment of the trips by each mode to their corresponding networks: typically private and public transport.” (Ortúzar Salar and Willumsen, 2011, p. 21)

Trip Generation - Specified

Lohse (2011, p.254) defines a general model for a specific production, meaning the number of trips starting in a zone, O_{ig} of trips based on sociodemographic homogenous groups (e.g., Working population with a car; pensioners; students) g and activity chains a with a specific mobility rate MR_a

$$O_{ig} = \sum_{a} MR_a * n_g$$

Which can then be summed up over all sociodemographic groups g to calculate the overall production of an origin O_i:

$$O_i = \sum_g O_{ig}$$

The calculation of the specific production can also be executed with more detail: For each sociodemographic group, a specific mobility rate for activities (e.g., going to work; shopping) or for an activity chain, describing a series of activities starting and finishing at home (e.g., home-work-shopping-home) can be used.

A similar calculation to the production can be developed on the attraction potential D of a destination j based on the generalized attraction rate AR_s of a structural property (e.g., number of workplaces; retail space) s and the value/size of the structural property x_s:

$$D_{js} = AR_s * x_s$$

Summed up overall structural properties s, the overall attraction D_j of a destination j is calculated:

$$D_j = \sum_s D_{js}$$

It has to be noted that the attraction potential is just a potential. It does not necessarily need to be fulfilled. A further discussion of the need to fulfill the potential can be found in (Lohse, 2011, pp.247-249).

Trip Distribution - Specified

The trip distribution describes the selection of destinations for trips. In general, these models all aim to resemble the decision of a homo oeconomicus, which makes their decision with the goal to maximize the utility (by reaching the best option with the least effort). The first models to resemble the trip distribution were based on an analogy with Newton's gravitational law and therefore called gravity models. According to Ortúzar Salar and Willumsen (2011, p.182), the resulting traffic T_{ij} can be calculated based on the population P of the zones i and j , the distance between the two zones d_{ij} and a factor α:

$$T_{ij} = \frac{\alpha * P_i * P_j}{d_{ij}^2}$$

The model was developed further, first by replacing the populations with the production and attraction values gained from trip generation and then by replacing the term d_{ij}^2 by a distance decay function $f(c_{ij})$. It represents the utility of destination as an inverse relationship between costs and distance, as depicted in Figure 2. Ortúzar Salar and Willumsen (2011) refer to this function as:" *'deterrence function' because it represents the disincentive to travel as distance (time) or cost increases."*. The resulting equation results to:

$$T_{ij} = \alpha * O_i * D_j * f(c_{ij})$$

The distance decay is traditionally expressed via the Logit function resulting in the following specification:

$$T_{ij} = \alpha * O_i * D_j * e^{\beta * U_{ij}}$$

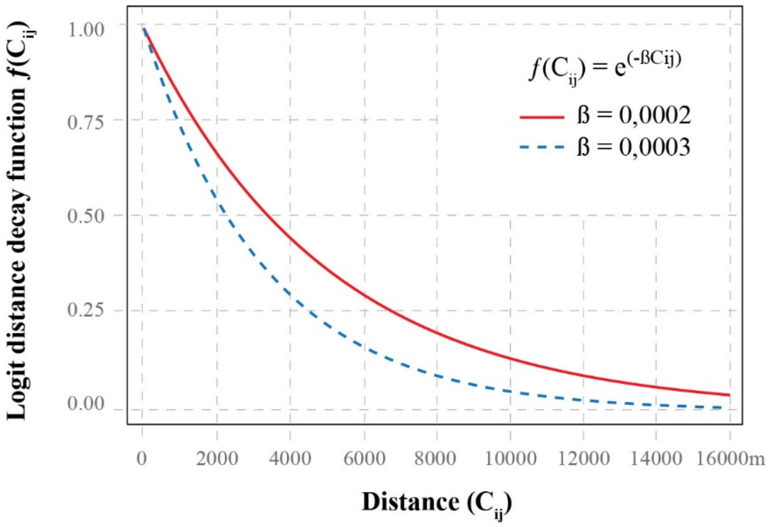

Figure 2: Logit distance decay function. Beta coefficient = 0.0002 (in m) was used in the specified distance decay function.

Fully Restricted Model

Coming to the completely restricted SSM approach, we argue that the betweenness measure of graph centrality (i.e., the "choice" in Space Syntax jargon) as a measure used by Space Syntax scholars to explain movement can also be interpreted as a restricted case of the TPM. The betweenness centrality was introduced by Freeman (1977) as an indicator of the importance of nodes in a social network and later adapted by geographers as a measure of flow in spatial graphs. "Considering all shortest paths in a network between all possible pairs of nodes, we can find out how often a node happens to be on the shortest path between two other nodes." (Nourian et al., 2015, p11).

$$BC_v = \sum_{i=0,\ j=0,\ i \neq j, d_{ij} < t}^{n} \sigma_{i,j}(v) \qquad \text{(X)}$$

The betweenness centrality can also be interpreted as a restricted case of TPM, assuming a) homogenous distribution of population throughout the network and b) that distance does not affect our choice of destination[2]. More specifically, the trip generation and trip distribution can be described as follows:

Trip Generation - Restricted

The SSM approach utilizes the unweighted betweenness centrality as described above. If interpreted in terms of the TPM, it does not differentiate between sociodemographic groups with various mobility rates and assume a homogenous population with equal distribution over space.

$$O_i = 1$$

[2] All destinations in given radius are treated as equally attractive.

Similarly, the attraction potential of all destinations is constant.

$$D_j = 1$$

Trip Distribution - Restricted

The betweenness centrality adopted by Space Syntax scholars is based on the cumulative accessibility measures. All destinations in a given distance radius are equally likely to be visited (Bhat et al., 2002). This representation of the distance decay function (see Figure 3) is the simplest approach to modelling the relationship between the distance and attractivity of the destination (Handy and Niemeier, 1997). Despite the ease of calculation and interpretation, cumulative accessibility has been often criticized for “the lack of a behavioral dimension and the incapability to model the differences in the perception of near and far opportunities, i.e., opportunities are equal regardless of their cost and desirability for users” (Cascetta et al., 2016). To represent the utility of the cumulative accessibility by means of the distance decay functions defined in the specified trip distribution, we restrict the beta coefficient of the logit distance decay function to zero. This is equivalent to betweenness centrality radius N (i.e., traveling from all nodes to all other nodes) and results in the following specification:

$$T_{ij} = \alpha * O_i * D_j$$

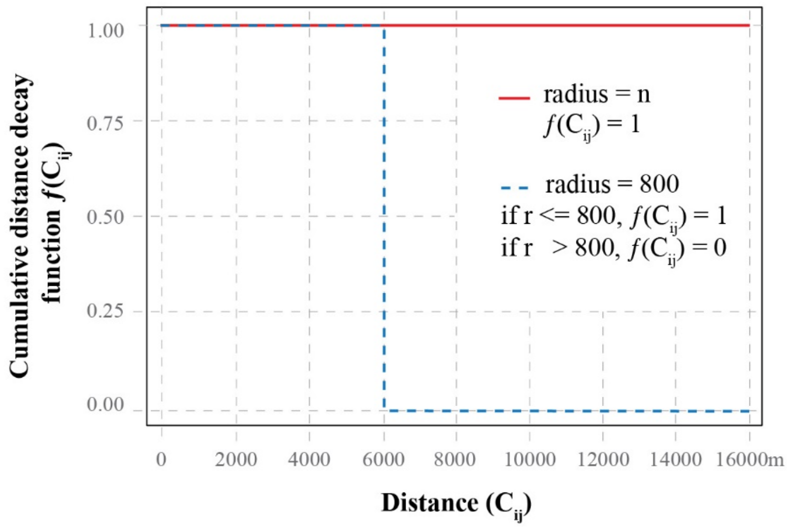

Figure 3: Cumulative distance decay function. Beta coefficient = 0 was used in the restricted distance decay function.

2.3 Model Overview

To summarize, we briefly present the specification of the four different movement models devised in this study. Each movement model is composed of the trip generation and trip distribution step. What makes them different is the complexity of each step as it can take the restricted (i.e., simple) form or specified form (i.e., more elaborated, more complex). Important to mention is the representation of the transportation system (TS), which can be thought of as the basis for any calculation in the individual steps of the movement models. In the TS, we specify the representation of a) of the street network geometry, b) the origins and destination of movement (i.e., traffic zones), and c) the distances. Traditionally, the TS is defined differently in TPM and SSM; however, to compare different models and quantify the effect of their complexity on the accuracy, they all must be based on the same underlying TS. Thus movement models employed in this study are based on a) network geometry represented as a simplified center-line map, b) origins and destination zones represented at each street segment, and c) the traditional metric representation of distance[3] augmented by cognitive distance[4] proposed by Turner (2001).

The resulting movement models are defined as follows:

- **M1** | Fully specified model (i.e., base model) with the trip generation and trip distribution steps defined in their complex form. This means that information on the distribution of sociodemographic characteristics of the population and economic activities is considered in the first step of the model. In the second step, the utility of each potential destination is taken into account.
- **M2** | Partially specified model with the trip generation step specified as in the TPM and trip distribution step is restricted as in SSM. Compared to the fully specified base model M1, the utility of all potential destinations is independent of their distance.
- **M3** | Partially specified model with the trip generation step restricted as in the SSM and trip distribution step specified as in TPM. Compared to the fully specified base model M1, the trip generation step assumes that the distribution of sociodemographic characteristics of the population and economic activities is equal throughout the whole network.
- **M4** | Restricted model with both the trip generation and drip distribution steps restricted as in the SSM. This model assumes equal distribution of population with homogenous travel demand. Furthermore, the distance of the potential destination does not affect its attractivity.

2.4 Data & Software Implementation

The empirical study was conducted in the administrative boundaries of Weimar - a historical, mid-size city located in the German state of Thuringia. The size of the city - 64855 inhabitants on 84,420 km^2 (Statistisches Jahruch, 2018) makes it possible to cover and analyze the city as a whole, which eliminates the 'edge effect' that can bias the partial analysis of larger urban systems (Gil, 2015).

The street network geometry of Weimar is represented as a street center-line map manually adjusted at the intersections to accommodate the requirements of the angular shortest path calculation as described by Krenz (2017). The resulting network consists of 4624 line segments.

[3] Metric distance is used in the trip distribution step to asses the utility of various destinations via the logit distance decay function.

[4] Angular distance is used to calculate the shortest paths between the origins and destinations of travel.

The specified trip generation and trip distribution steps are based on the City of Weimar's official traffic model[5]. The model consists of 113 traffic analysis zones (TAZ) representing the City of Weimar and some adjacent villages. The traffic zones are mapped on the underlying street segments, resulting in 4624 individual traffic zones.

The default calculation in the model consists of a tour-based approach with simultaneous trip distribution and mode choice. The demand model uses seven sociodemographic groups and six activities, which are combined into 36 activity chains. The trip generation uses specific mobility rates for each of the 107 combinations of sociodemographic group and activity chains (demand strata).

Table 1 - Sociodemographic groups used in the model.

AzuBi	Students in vocational education
EmP	Working population with a private car
EoP	Working population without a private car
NEmP	Non-working population with a private car
NEoP	Non-working population without a private car
Sch<18	Pupils
Sch>=18	Students in higher education

Table 2 - Activities used in the model.

A	Work
B	Vocational/higher Education
E	Shopping
P	Private Errands
S	School
W	Home

The trip distribution uses a logit function with a generalized impedance in the distance decay function. The mode choice uses a Logit function with the distance, travel time, and access and egress times as impedances in the distance decay function.

The modeling of trip generation, trip distribution, and mode choice was done in PTV VISUM 17, a program aimed at the modeling of macroscopic traffic flows. The angular shortest paths were calculated by the DeCodingSpaces plugin for Rhino3d/Grasshopper[6].

[5] The official traffic model for city of Weimar was created by traffic planning office Verkehr2000.

[6] For all computational analyses presented in this study, we used the version 2021.07 accessed and published in July 2021 from https://toolbox.decodingspaces.net/.

3 RESULTS

After calibrating and running the four traffic models, we normalize and visualize the resulting distribution of traffic flows (Figure 4). Due to different model specifications (e.g., population size, population demography, mobility rates), the resulting distributions are comparable only on a relative scale. For this purpose, we normalize the traffic models in such a way that we keep the overall traffic volume[7] constant across the individual models, as described by Bielik (2021).

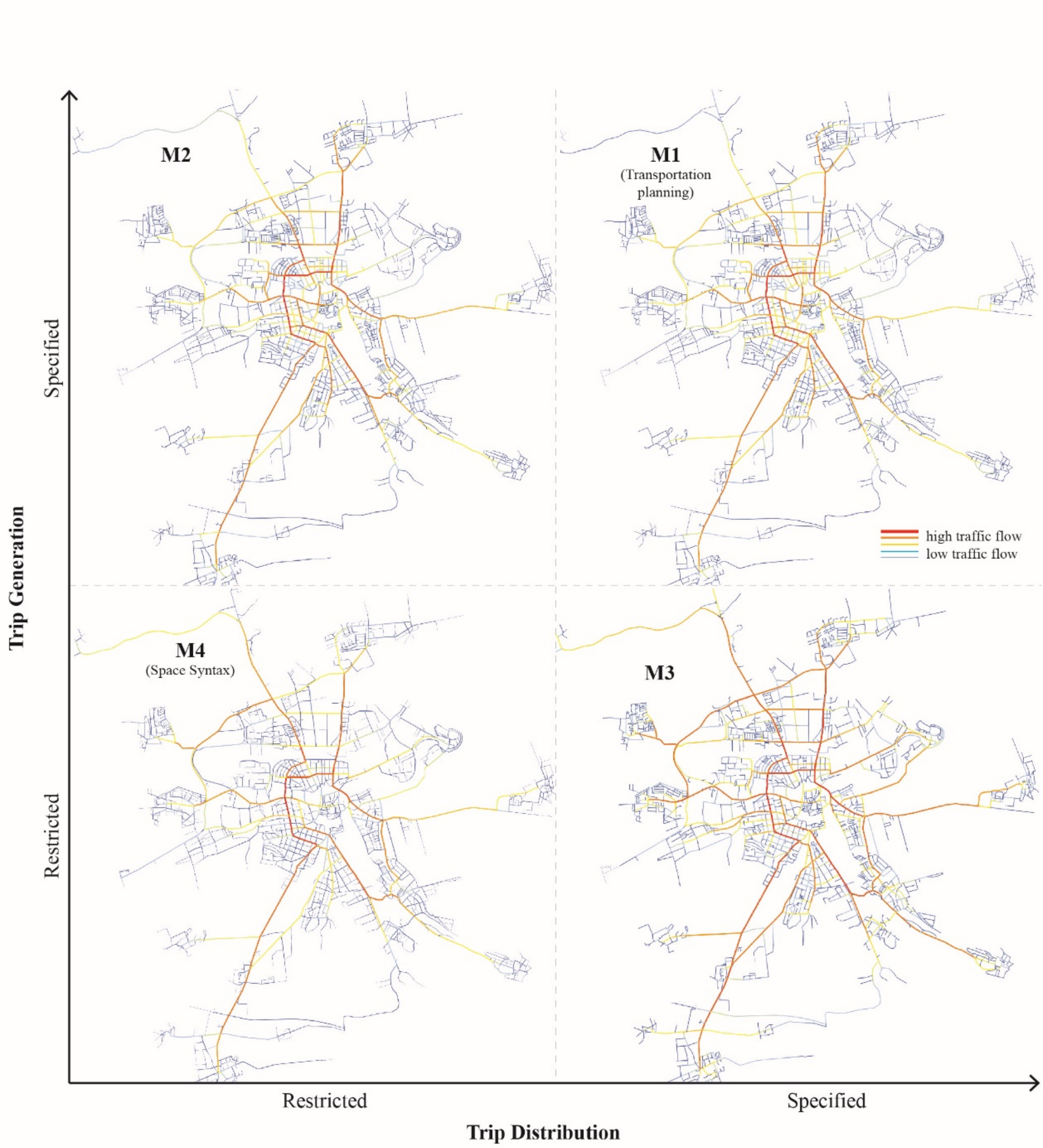

Figure 4: Distribution of log-transformed traffic flows calculated by fully specified M1 model (i.e., TPM), partially restricted M2 model, partially restricted M3 model and fully restricted M4 model (i.e., SSM).

We observe that all four models show closely related patterns of traffic flow. They all highlight a similar set of most frequented streets and streets with low vehicular traffic. The visual

[7] Traffic volume at given street segment represent the total number of vehicles driving through per given period of time. Relative traffic volume can be approximated by multiplying traffic frequency by the length of each street segment.

similarities between the models are reflected by their linear relationships captured by Pearson's correlation coefficient r. As presented in the hierarchically clustered correlation matrix (see Figure 5), we observe that all models are highly correlated and significant ($p < 0.05$), with r ranging between 0.937 and 0.998. Additionally, the matrix reveals two groups of linearly almost identical models, as also highlighted by the hierarchical clustering (Figure 5). The first group consists of models M1 and M2, while the second consists of M3 and M4. When comparing the two groups, the main difference lies in the definition of the trip generation step. In models M1 and M2, the distribution of sociodemographic characteristics of the population and economic activities is considered, while in models M3 and M4, it is ignored. Since the only difference between the models within the two groups is the specification of the trip distribution step, it seems that its effect on the model outcome is only minor.

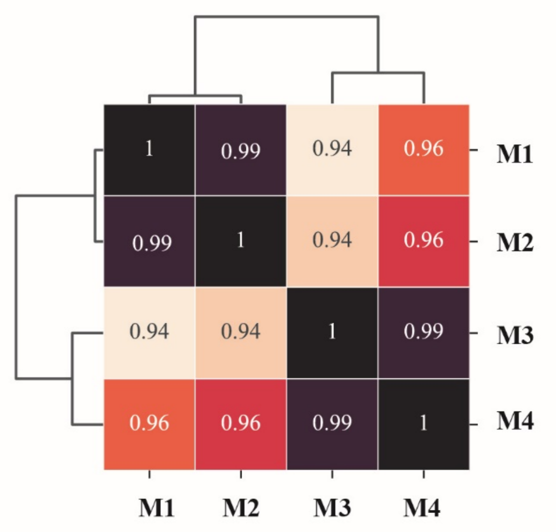

Figure 5: Hierarchically clustered Pearson's correlation matrix for models M1, M2, M3 and M4.

To quantify the effect of the model complexity on its accuracy, we compare the restricted models M2, M3, and M4 with the fully specified base model M1. We quantify the accuracy by calculating the linear fit between the restricted and base model (see Figure 6). In other words, we regress the fully specified model on the restricted model and derive the goodness of fit – r squared. This represents in a range from 0 to 1 how much variance does the restricted model share with the fully specified model. If they are completely identical (i.e., no loss of accuracy can be observed), we get $r^2 = 1$. At the other extreme, if they do not share any variance, we would observe $r^2 = 0$.

We found that model M2 shares 99,6% of the variance with the base model M1, as also visible from the scatterplot in Figure 6a. Since the only difference between M1 and M2 is the specification of the distance decay function in the trip distribution step, the results suggest that its effect is negligible. Coming to model M3, we see a drop in accuracy with 87,7% shared variance with the base model. Finally, we observe model M4 sharing 91,8% of the base model variance. This comes as unexpected as the M4 is the simplest model representing the SSM approach while the M3 is augmented by the distance decay function found in the TPM approach; however, M4 performs slightly better than the more complex M3.

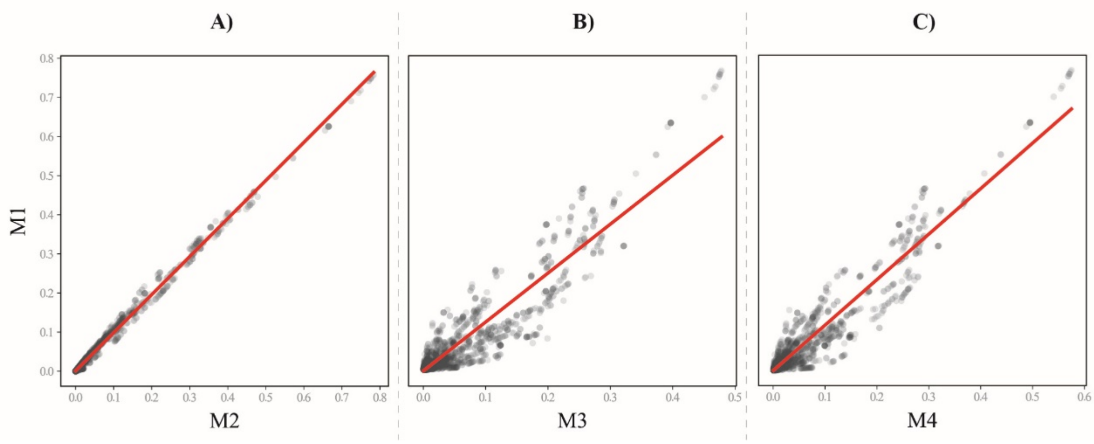

Figure 6: Scatterplot capturing the linear relationship between the reference model M1 (i.e., fully specified TPM) and a) partially restricted M2 model, b) partially restricted M3 model and c) fully restricted M4 model (i.e., SSM).

In addition to the linear regression method, we quantify the fitness of the restricted models M2, M3, and M4 via scalable quality value (SQV) - an established method used in the field of transportation planning. The SQV is a quality measure in which the deviation of observed and modelled values is analysed. The metric was developed and first described in (Friedrich et al. 2019), and the authors define it as:

$$g_{SQV} = \frac{1}{1 + \sqrt{\frac{(m-c)^2}{f * c}}}$$

Where m is the modeled value and c is the observed value. The factor f is a scaling factor for the magnitude of the values. The main conceptual difference between SQV and the r-squared derived from the linear regression is that SQV does not measure the linear fit between two variables but rather the deviation of two observations. This deviation is normalized to range from 0 to 1 and can be calculated for each street segment. Traditionally, SQV is calculated for a set of locations for which traffic counts exist. As the nature of the study does not allow for a comparison with real-world counting data, we treated the data from M1 as the observed data and the other models as calculated values. This would be possible to calculate for all network elements, but the results would be not very usable, as on some links, traffic load is very small and does not change much through the different modelling approaches. This would lead to very good SQV values, but those would not be very representative for the changes in the model. Therefore, we have decided to calculate the SQV values for twelve relevant locations in the street network where we expected to see changes in the traffic load. These locations (see Figure 7), where one would also set up counting locations, can be grouped into four groups: locations on main arterial roads (2,4,5,8,10), locations on the inner (1,3) or the outer (12) ring road and on important tangential connections (6,7,9,11).

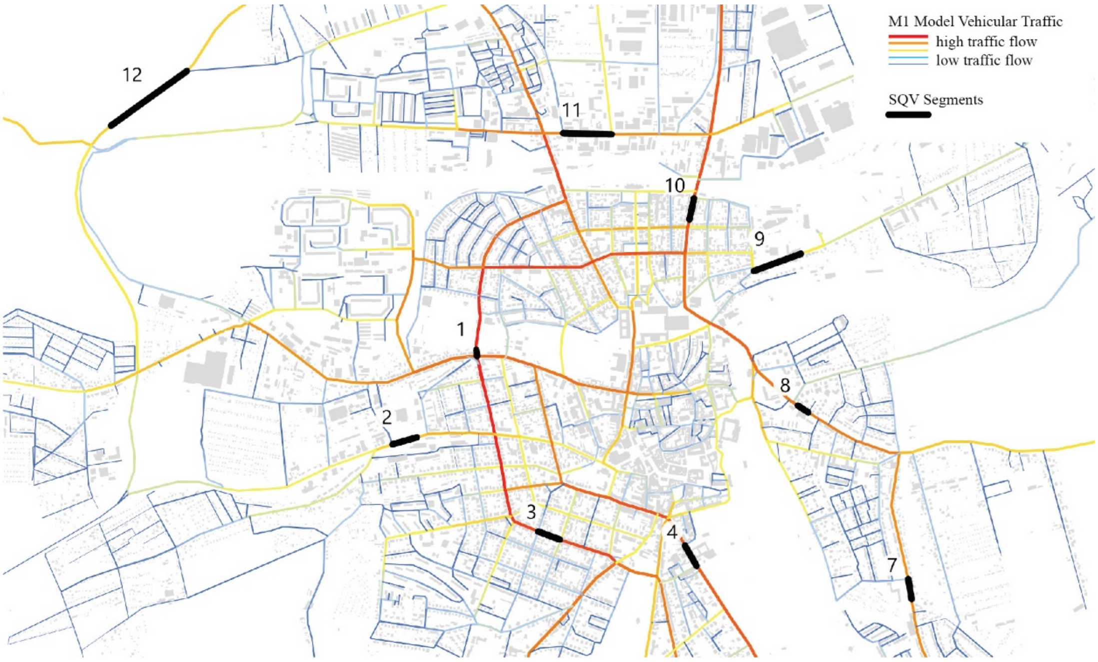

Figure 7: Location of segments chooses for the SQV test. The map is showing the traffic flows derived from the fully specified M1 model.

For the interpretation of the SQV we adopt the categories recommended by Friedrich et al. (2019). They suggest to interpret SQV > 0.9 as "very good match", SQV > 0.85 as "good match" and SQV > 0.8 as "acceptable match". We found high variation in the SQV statistics across the location and different models. The best mean SQV across all selected locations was measured for the M2 = 0.83, which is to be considered as an acceptable match. However, as displayed in Figure 8, the SQV varies a lot, with the minimum as low as 0.37 while the maximum reaches 0.99. The remaining two models M3 and M4 have similar mean SQV of 0.72 and 0.71. As such, the model M3 and M4 are deemed as unacceptable.

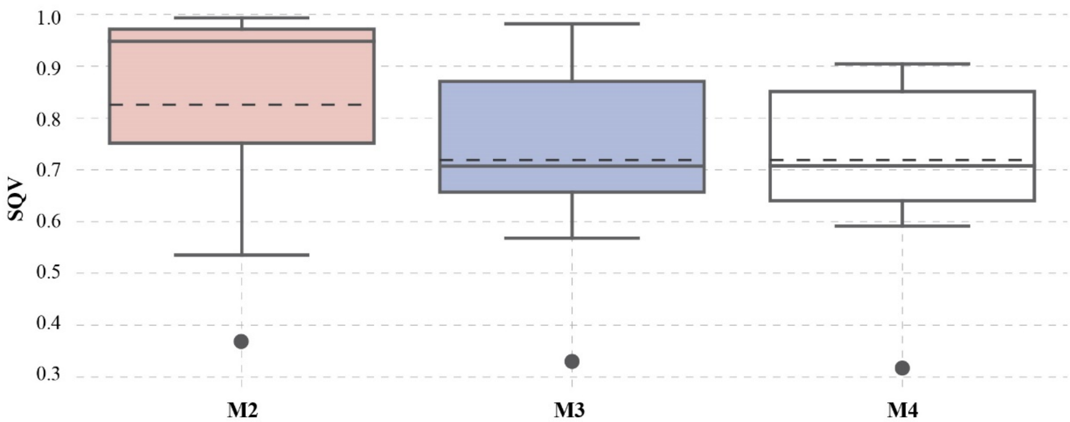

Figure 8: Box plot visualization of the SQV statistics for 12 selected street segments per model. Full line inside of the box represents median, dashed line represents mean.

4 DISCUSSION & CONCLUSIONS

In this study, we devised a series of models for individual vehicular traffic in the German city of Weimar to measure how the level of model complexity affects its accuracy. It is important to note that all results discussed in this paper are bound to one particular study area, and any generalization would require confirmation of our results in further studies.

With this in mind, we found that when it comes to modeling vehicular traffic, the specification of the sociodemographic characteristic of the population and the distribution of economic activities have a major impact on the model accuracy. When ignored, the resulting models were missing between 8,2% to 12,3% of the variance compared to the fully specified model. This means that the simplest SSM model provides high accuracy of 91,8% when looking at the city as a whole. As such, this underlines the value of the SSM in the context of limited resources or missing or information to calibrate and run the more complex TPM. Nevertheless, when looking only at the most frequented streets, the SSM accuracy drops below the acceptable standards set in transportation planning and needs to be replaced by a more complex movement model, including more detailed methods for route assignment.

Furthermore, we found that in the case of the individual vehicular traffic in Weimar, the specification of the distance decay function (i.e., effect of distance on the utility of the destination) does not play a significant role. In other words, all destinations can be considered equally attractive regardless of their distance. We run the Chi-Square Test for Independence comparing pairs of models differing only by the specification of the distance decay function and found that both can be considered as coming from the same distribution ($p < 0.05$). We argue that this might be the result of the relatively small size of Weimar's traffic system as the difference between the specified and restricted decay function grows with the trip size (see Figure 9). Nevertheless, the results of M2 show differences in the traffic load, especially on those links leading to places with a high attraction, but a great distance from the city center, thus highlighting the boundaries of the random trip distribution (i.e., restricted distance decay function) as discussed by Lohse (2011, p. 304) and Knepper (2021, p.80). Lohse sees potential for the application of the model until a city diameter of 6km, which in the case of Weimar fits for most locations (the mean distance between Weimar's traffic zones is 3,2 km), but is exceeded for some locations on the outer part of the town (see Figure 9).

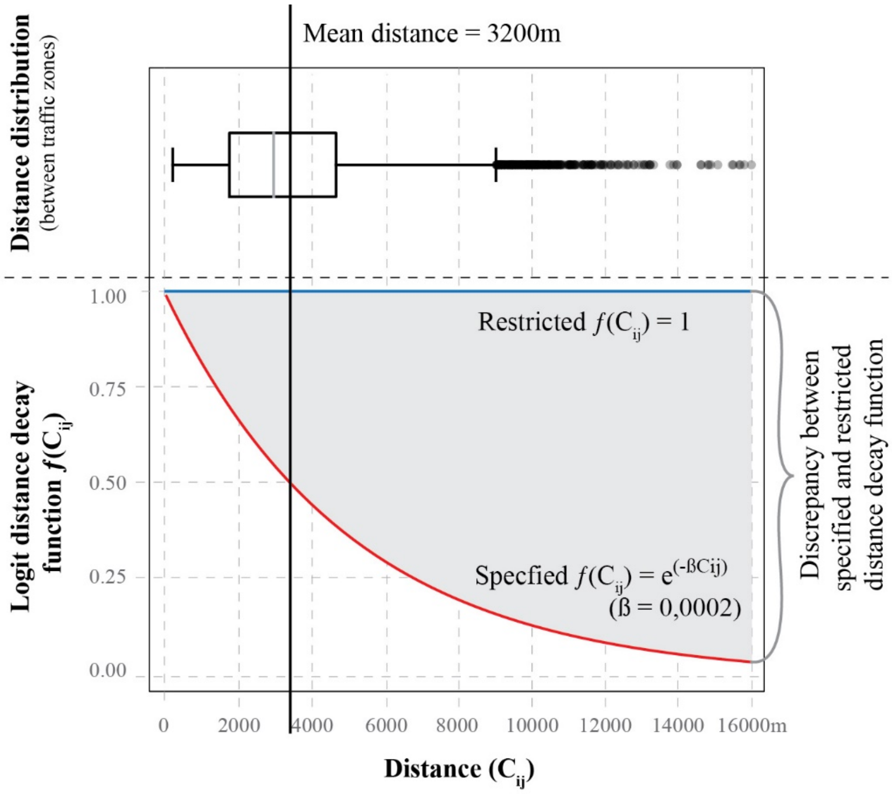

Figure 9: Lower part of the plot shows a comparison between the specified and restricted distance decay function in the Trip Distribution step. The upper part of the plot shows the distribution of distances between individual travel zones in Weimar.

After discussing the overall precision of individual models, we look at the spatial distribution of the error to understand their source and implications for planning. For this purpose, we represent the deviation of the restricted models from the fully specified model as regression residuals[8] and visualize them on the map (see Figure 10). The resulting Figure 10b, Figure 10c, and Figure 10d show the distribution of positive and negative residuals. The positive residuals represent locations where the model restriction leads to underestimating the traffic flow, while the negative residuals highlight locations where the restricted model expects more traffic than the fully specified model.

When comparing all three restricted models, we observe the largest residuals (i.e., model inaccuracy) in M3 and M4, while in M2, the deviation from the base model is almost negligible, as confirmed by the high accuracy of the M2 model. The residual distribution in M3 and M4 reveal a similar pattern of positive residuals in the city center and negative at the main radials at the outskirts. This pattern can be explained by the distribution of outgoing trips when considering the sociodemographic characteristic of the population and the distribution of economic activities. As shown in Figure 10a, the trip distribution is not equal as assumed in M3 and M4 but shows a

[8] Regression residuals are defined as the difference between observed and predicted values. In our case it is the difference between the fully specified model M1 and the values expected by the restricted models M2, M3 and M4.

higher concentration in the city center with a gradual fall-off towards the suburbs. The pattern is slightly disrupted by the presence of shopping malls.

This heterogeneous loading of the network is in turn, represented in the model errors. As a result, the restricted models M3 and M4 perform well in low-traffic residential areas; however, they systematically under and overestimate the traffic flow on the main arteries.

Figure 10a: Spatial distribution of the trip frequencies defined by the fully specified reference model M1. Figure 110b, c, d: Spatial distribution of model errors – residuals for b) M2 model, c) M3 model and d) M4 model. The amplitude of the error is expressed by the line thickness while the valence is defined by color (red = positive residuals, blue = negative residuals).

Consequently, the answer to the question about the optimal trade-off between model complexity and accuracy depends on the purpose of the model. The simplest M4 model (representing the Space Syntax approach) might be a great tool when understanding the overall movement structure or focusing on the residential low-traffic areas. However, when it comes to applications focused on planning high-traffic segments of the road network (e.g., designing road sections based on expected traffic load), the same model seems to be suffering from an unacceptable level of systematic bias. These findings underline the need for informed model selection in a real-life urban planning context with different projects requiring different models.

When it comes to model selection, we must also mention that the SSM and TPM do not only differ in their accuracy but also their interpretability. While the TPM provides as outcome a spatial distribution of traffic flow per time, the SSM is unitless. As a result, we know from SSM what is the expected relationship between frequency on two different streets (e.g., traffic frequency on street A is ten times more traffic than on street B), but we do not know how much it is in absolute terms. Thus, if the task is to design a street cross-section or allocate parking lots, the results of SSM might be difficult to interpret.

Finally, we want to emphasize that this paper offers a methodological blueprint for the study of the trade-offs between complexity and accuracy of movement models; however, more evidence is needed to apply our results in practice. For a further and more precise quantification of the trade-offs between different models, the study design for future studies needs to be extended and include comparisons on the level of the route assignment and a comparison with traffic loads observed in the real world.

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CONFLICTS OF INTEREST

The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

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