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GIS and Transport Modeling—Strengthening the Spatial Perspective

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Abstract: The movement and transport of people and goods is spatial by its very nature. Thus, geospatial fundamentals of transport systems need to be adequately considered in transport models. Until recently, this was not always the case. Instead, transport research and geography evolved widely independently in domain silos. However, driven by recent conceptual, methodological and technical developments, the need for an integrated approach is obvious. This paper attempts to outline the potential of Geographical Information Systems (GIS) for transport modeling. We identify three fields of transport modeling where the spatial perspective can significantly contribute to a more efficient modeling process and more reliable model results, namely, geospatial data, disaggregated transport models and the role of geo-visualization. For these three fields, available findings from various domains are compiled, before open aspects are formulated as research directions, with exemplary research questions. The overall aim of this paper is to strengthen the spatial perspective in transport modeling and to call for a further integration of GIS in the domain of transport modeling.

Keywords: GIS; transport research; data; transport models; geo-visualization

1. Introduction

Transport is a function of moving objects (e.g., people or goods) in the two dimensions of physical time and space. Although the spatial nature of mobility is obvious, it is often neglected in transport modeling. Since the early years of Geographical Information Systems (GIS), the geospatial community has a strong affiliation to mobility and transport research. Hägerstrand's concept of space-time paths [1], for example, provides the conceptual foundation of the activity-based modeling paradigm, which is currently the preferred modeling approach in many models [2]. The computational and analytical application of Hägerstrand's space-time paths within a GIS [3] can be regarded as a cornerstone in the domain of Transport Geography and GIS for Transport (GIS-T), respectively. The contribution of GIS to transport research subsequently grew during the 1990s, as conceptual papers by Waters [4], Miller [5], Thill [6] and Goodchild [7] at the turn to the 21st century clearly indicate. At the same time, geography and GIS remained a niche topic within traditional transport modeling. In the first editions of the standard textbook by Ortúzar and Willumsen [8], to name just one prominent example, GIS is covered only marginally. Spatial characteristics and relations are highly abstracted in standard transport modeling frameworks, while GIS was primarily used as tool for data preparation and, to a lesser degree, for visualization [9].

Since the beginning of the 21st century, things have changed fundamentally. At least three major innovation paths can be identified. First, ICT (Information and Communication Technologies) has not only changed the way people and goods are moved, but also what we know about this mobility. Within a couple of years the situation has flipped from data scarcity to a deluge of sensors and data streams [10]; second, policy is forced to move from the paradigm of an expanding infrastructure to smarter traffic management. Thus, it is necessary to actively manage traffic demand and supply and to activate unused potentials, such as public transit, active mobility, sharing schemes or smart logistics. The required Intelligent Transportation Systems (ITS) rely on accurate data and well-performing communication, management and analysis components, each with a distinct spatial notion [11,12]; third, within the transport modeling community, a paradigmatic shift from aggregated models, with the Four-Step Model (FSM) as the most prominent example (see McNally [13] for an overview), to activity-based and micro-scale models, can be observed. Associated with this shift, the relevance of the geographical space has become widely acknowledged [2,14].

With regard to the growing integration of geospatial functionalities and transport modeling, this paper focuses on three key aspects which the authors regard as relevant to both: the GIS and transport research community, namely, data for transport models, disaggregated models, and the role of (geo-) visualization. Each of these topics is dealt with from an explicit spatial perspective.

The paper is structured as follows: after a brief, general overview of the current contribution of GIS to transport modeling, the three aspects mentioned above are treated in detail. For each topic, the status-quo is described from a spatial perspective. Subsequently, issues as yet unresolved are raised and compiled into key research directions. A concluding section wraps up the major findings.

2. GIS and Transport Modeling: A Brief Overview

GIS and transport research have always been interrelated. Thus, it is hard to ultimately decide whether transport modeling is an application domain of GIS or spatial capabilities are incorporated in transport models. Examples exist in both domains and current transport modeling software products increasingly provide integrated GIS capabilities.

GIS are capable environments for the capturing, management, analysis and visualization of spatial data. They allow for an integration of various data sources into a scalable, dynamic and adaptable geospatial framework (see Figure 1). Through models, simulations and analyses, each with an explicit consideration of the spatial nature of transport, new information can be generated. Besides, GIS also facilitates information visualization which serves as a communication platform with feedback loops to the data integration and the settings of models, simulations and analyses.

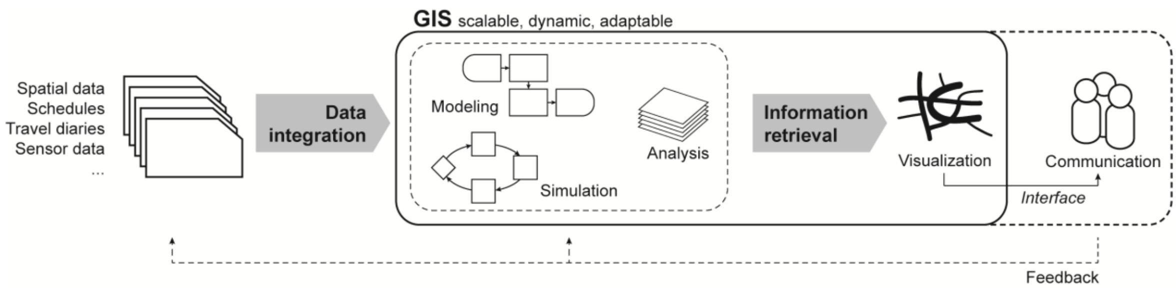

Figure 1. Capabilities of a GIS environment for transport modeling: "GIS (. . .) as the ultimate information integration technology" [6] (p. 4).

2.1. Spatial Characteristics and Relationships

In a standard aggregated transport model, GI systems have been primarily employed for data processing, the delineation of traffic analysis zones (TAZ) and the visualization of model results. TAZ form the spatial reference for demand-based transport models, where the numbers of trips from, to and through these zones are estimated. For these estimations, various socio-demographic, economical and structural data are related to each other in a regression analysis and fed to the model, which then calculates travel demands based on trip production and trip attraction for each TAZ. Spatial dependencies, as well as variations within and spatial relationships between TAZ, are widely ignored at this stage. In the next step of the FSM, the generated trips are distributed over the whole study area. This is usually done in origin-destination (OD) matrices, which exhibit only very abstract spatial information. Using physical models (such as gravity models), the generated trips are distributed according to the OD matrix [8]. The shortcomings of simplistic approaches in demand modeling have been discussed extensively, both conceptually [15] and methodologically [16]. From a geospatial perspective, at least three implications, which we discuss in the following paragraphs, are relevant for any, but especially for aggregated, demand models: scaling and zoning, spatial dependencies, and spatial heterogeneity (see Figure 2).

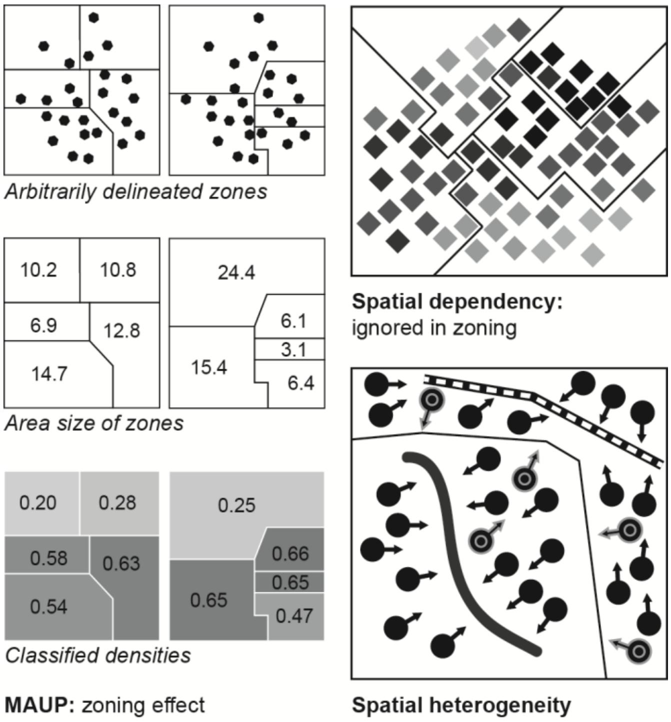

Figure 2. MAUP (Modifiable Areal Unit Problem), spatial dependency and spatial heterogeneity as relevant spatial implications in transport modeling.

In the case of the FSM, traffic analysis zones play a central role: once delineated, they cannot be altered unless the model parametrization starts from scratch. Associated with the delineation of the zones, is the Modifiable Areal Unit Problem (MAUP). In short, the MAUP describes the effect of scale (spatial aggregation level) and spatial zoning on model or analysis results [17]. The MAUP has been widely acknowledged, for example, in regional statistics [18] or public health [19], both domains that use more or less arbitrarily defined spatial reference units, such as administrative boundaries. Miller [5] and Viegas *et al.* [20] extensively discussed the implications of MAUP for transport modeling and describe the potential contributions of GIS in dealing with it. If raw data are available, GIS can be used to assess the effect of scaling and zoning and to delineate optimized TAZ. Scaling and zoning effects, in a wider sense, are not only relevant in demand-based models, but in virtually all kinds of transport models. Wallentin and Loidl [21], for example, demonstrated the effect of different spatial delineations of the study area on the outcome of an agent-based bicycle traffic simulation for Salzburg.

Usually, TAZ or other spatial entities are characterized independently from each other, based on various input variables. In doing so, the spatial association or dependency (see Páez and Scott [22] for an overview) between these entities is largely ignored. In contrast to most statistical routines, which require independent samples, geospatial analyses account for the function of similarity and spatial proximity, commonly referred to as the "First Law of Geography" [23]. With regard to transport modeling, it can be assumed, for example, that the similarity of mobility behaviors depends on the spatial proximity of the respective agents and their origins and destinations [24]. On the other hand, spatial clustering of origins and destinations affects travel demand. Bolduc *et al.* [25] were probably one of the first authors who pointed to the effect of spatial autocorrelation on OD flow matrices. Geospatial analysis methods help to determine the degree of spatial dependency [26] and to account for it properly in consecutive modeling and analysis steps.

The concept of spatial heterogeneity is tightly related to spatial dependency. While it can be assumed that many spatial processes are linearly related on a macroscale, this does not necessarily hold true on a microscale level. Here the influence of location, or the function of proximity, can vary over space (non-stationary). Disregarding the effect of spatial heterogeneity might lead to biased model parametrization or misleading interpretation of analysis results [22]. In order to deal with spatial heterogeneity, several techniques have been developed and implemented in GIS applications, such as the Geographically Weighted Regression Analysis (GWR) by Brunsdon *et al.* [27], that can be used for determining and weighting parameters of transport models.

2.2. Examples for Geospatial Transport Modeling Approaches

Miller and Shaw [12] made a compelling case for geospatial analyses as integrated elements of transport models in order to enhance the possibilities of applications and the quality of predictions. The effect of incorporating spatial statistics and analysis into a traditional demand model was, among others, impressively demonstrated by Lopes *et al.* [28], although the final application is restricted to a mono-modal, static traffic model. To our knowledge, there are currently only a very few examples where multi-modal transport models with a high degree of spatial and temporal flexibility have been set up. Chen *et al.* [29] proposed an object-oriented concept for a GIS-T data model that allows for changing attributes of transport objects. Although a certain degree of dynamics can be represented in this frame work, real-time input data were not implemented. Greulich *et al.* [30] suggested a flexible framework for an agent-based model (ABM), where agents can reschedule their trip when unexpected events occur. Besides computational limitations of the ABM, the availability of suitable data has been a bottleneck; both factors might lose their relevance in the near future. The difficulty of incorporating (real-time) data from various sources was demonstrated by Nantes *et al.* [31]. They integrated data from loop detectors and data with a detailed temporal and spatial resolution from GPS and Bluetooth sensors into a real-time traffic prediction model for a very small section of an urban road network.

Irrespective of the modeling paradigm, multi- and inter-modality remains a severe challenge in current transport models. Whereas vehicular traffic can be represented in demand models, bicycle and pedestrian traffic is hardly adequately captured. Thus, Dobler and Lämmel [32] developed a model framework that facilitates a combination of macro-scaled demand models with micro-scaled, force-based and agent-based models, where the latter is meant to represent active modes of transport. With such an approach, the geospatial bias in demand models for multiple modes can be, at least to a certain degree, overcome. Without geospatial scalability, the MAUP becomes evident for multi-modal demand models: TAZ, which might be appropriate for motorized traffic (with a bigger range) is hardly able to adequately capture the typical range of bicycle or pedestrian traffic at the same time. This is a major conceptual reason why many demand models simplify the mode choice and consider only one transport mode [13] or restrict themselves to very similar variations of one transport mode (e.g., different modes of public transit [33]). The difficulties of highly aggregated transport models to efficiently represent multi-modality are at least partly due to the abstract representation (e.g., connected centroids of TAZ in an OD matrix) or neglect of space. In contrast, the linear road or infrastructure space is represented as a georeferenced graph within a GIS [34]. This representation in a one-dimensional node-edge data model, together with associated attributes, allows for real-flow models of various modes, which can be run independently and subsequently projected onto the common spatial reference. Moreover a geospatial, graph-based data model allows for scalability, multiple levels of abstraction and model granularity, as well as for a combination of static and dynamic system elements [29], which are all necessary components of "intelligent", multi- and inter-modal transport models.

In the last two decades, there was a shift from aggregated, regional-scale transport models to simulations on the disaggregated or individual level. This has been made possible by a tremendous increase of computational power and a significant improvement of data availability. Tightly connected to this conceptual change and the advancements in the ICT sector—which facilitated the data deluge—the role of GIS has become more important. Disaggregated models require much more geospatial intelligence than aggregated transport models [12]. Thus, the understanding of transport systems—including infrastructure, vehicles and people—as complex systems in space and time and mobility behavior on an individual basis, can be significantly enhanced by GIS [2].

3. Geospatial Data for Transport Models

Although geospatial data are ultimately important for any transport model, they are rarely addressed in the transport modeling literature explicitly. In most publications and textbooks, data are regarded as given, ignoring the huge effect of data quality, scale, timeliness, or aggregation level on the validity of models and robustness of results. McNally and Rindt [16] stated that, "In the field of transport research, nothing is more valuable yet simultaneously more limiting to validation of theory and models than data" (p. 63). Considering this issue, the current status will be critically reflected before research directions concerning the geospatial data for transport models are formulated.

3.1. Current Status

Transport models crucially depend on adequate input data. Thus, the type of data defines the suitability for different models and purposes. Additionally, the heterogeneity of data formats is a barrier for the integration of different data sources. To prepare the ground for the subsequent research directions, four major types of data and their respective implication for transport models are briefly described in the following paragraphs. Subsequently, we discuss the relevant data formats and current attempts for standardization. Finally, issues concerning geospatial data models and data quality are brought up.

3.1.1. (Geospatial) Data Types

Up to now most transport models rely exclusively on static data. These are datasets that are generated at a certain point in time for a specific purpose. Examples are road network graphs, travel diaries, census, or land use data, *etc*. The amount of available, static data varies depending on the analysis area. Open (Government) Data and crowd-sourced spatial data, with OpenStreetMap as the most prominent example, facilitate many transport-related geospatial analyses. In the United States, socio-demographic data are largely available, whereas the situation is less liberal in most parts of Europe. The same holds true for timetables of public transit, but with a greater variation of availability between cities and regions. Mainly for privacy reasons, address-specific data are treated restrictively almost everywhere. Thus, statistical data on the individual or household level are related to blocks, census districts, or regular grids as the spatial reference unit. In the European Union, the publication of authoritative transport data currently gains momentum due to the INSPIRE (Infrastructure for Spatial Information in the European Community) and PSI (Public Sector Information) directives, which push authorities to publish their data in a freely accessible manner [35]. The latter aspect is expected to result in a more positive ratio between data availability and accessibility.

Although dynamic, mobility-related data are generated in a yet unknown volume, they are generally less accessible than static data. This can be explained by at least two factors. First, most sensor data are generated in closed, often proprietary systems. Outside the operation environment they are hardly ever accessible, except for specific research purposes (see Liu *et al.* [36], Castro *et al.* [37]

or Calabrese *et al.* [38] as examples). Second, privacy concerns and regulations impede the publication of personal sensor data independently from their existence and availability. The situation is different for geo-coded, social media data, which potentially serve as proxy for collective mobility and can often be accessed via Application Programming Interfaces (APIs). Independently of the data source, dynamic data can be divided into two categories: mobile sensors, where the movement in space and time is sensed, and fixed sensors, which constantly measure a certain phenomenon.

Smart city developments with an abundance of inter-connected sensors provide enormous amounts of data, often referred to as "big data" [39]. Many data sets in this context are highly relevant for transport research, as they sense the flows of people and goods in space via operating systems [40], mobile phone network [41], Bluetooth [42], or social media [43]. These data sets are conceptually different from sampled data, which have usually been used in transport models so far. Instead of representative samples from which the population and its characteristics are estimated, big data potentially allows for considering the full (sensed) population. Since sampled data, such as travel diaries, have drawbacks (including small sample size, limitations in temporal and spatial scale, or a low update frequency, to name a few), data from pervasive systems are regarded as a promising alternative [38,44].However, besides technical challenges in modeling and linking data from these sources [45], conceptual and ethical questions still remain unanswered [46].

In contrast to collected static and dynamic data, derived data are not necessarily directly captured, but estimated based on samples and/or timelines. Simulated, interpolated and extrapolated data usually exhibit a large degree of variability, depending on data processing algorithms. Thus, it is of crucial importance for the interpretation of model results to know their processing history (applied algorithms) in case these data are used as input variables. In transport models, derived data are, for example, used to predict future OD flow matrices or for population parameters based on samples [8].

3.1.2. Transport Data Formats and Standards

The variety of data types is directly reflected by the abundance of data formats for transport-related data. Although several industry and *de jure* standards exist, a significant amount of data is still captured and managed in closed formats. Thus, these standards are obstructive for interoperability and harmonization, two key aspects for transport models and Intelligent Transport Systems (ITS). For infrastructure-related, spatial data (e.g., a digital road network graph), national standards, at the least, exist in many countries. Beyond that, international directives for metadata standards ensure a certain degree of interoperability for these data. Besides these efforts for the standardization of authoritative data, open, crowd-sourced data are increasingly relevant. OpenStreetMap has established itself as an integration platform for all kinds of static data and is already successfully employed in transport models [47]. Based on its popular routing portal, Google has pushed a standard for static and real-time public transit (PT) information. Although more and more PT operators provide their data following the General Transport Feed Specification (GTFS) [48], the availability and quality still leaves room for improvement [49]. In contrast to standardization efforts in the PT sector, or for infrastructure data, especially dynamic data are hardly ever standardized. Thus, they suffer from a significant lack of interoperability. Floating Car Data (FCD), for example, are still sensed within closed systems. Floating car fleets are established for research purposes [50–52], but mainly for proprietary services of private data and navigation providers (TomTom (Amsterdam, Netherlands), INRIX (Kirkland, WA, USA) and others).

3.1.3. Data Models, Scale and Resolution

Due to the conceptual shift from aggregated trip-based to disaggregated activity- and agent-based transport models, the complexity of data which needs to be stored and managed for transport models has significantly increased. Thus, GIS-T data models are required to adapt to the complexity of spatially, temporarily and attributively interrelated and dynamic data. Shaw and Wang [53] proposed a relational database with stringent normalization routines in order to prevent redundancies. In contrast to the relational database, Chen *et al.* [29] preferred an object-oriented data model, where topological and semantic relations allow for a combination of static and dynamic objects. Independently from the fundamental conceptual design, spatial data models for GIS-T applications in transport models need to be adapted accordingly to the respective requirements. For dynamic, predictive transport models, a static data representation in a GIS is not sufficient. Instead, a performant GIS must be built upon data models that support dynamic data from various sources in order to serve as an integrated environment [12].

Geospatial data are always captured at a specific scale. As a consequence, the data cannot be adequately used in models and analysis routines on a finer scale. Similarly, the level of aggregation defines the resolution of any operation based on these data. The impact of scale and level of aggregation is often ignored in transport models. Associated with the spatial scale and the level of aggregation, are the MAUP, discussed in the previous section, and the ecological fallacy [54], each with direct, negative effects on the outcome of any model. Besides a common lack of awareness for spatial data issues, data availability problems and the cost of data capturing are reasons for the utilization of unsuitable data. In order to support experts who integrate several, heterogeneous datasets, information tools for the data quality and fitness of use have been developed [55], but, to our knowledge, they have not been specified for transport models in particular. Besides the heterogeneity of data itself, transport modeling furthermore needs to master the semantic variability in a multi-disciplinary environment. As the spatial and attributive heterogeneity of data is a major bottleneck in transport modeling, Liang *et al.* [56] suggested the development of ontologies for a cross-domain employment of datasets.

Since data errors directly affect any GIS-T application [6], research on the interdependency of data characteristics and transport models is required from several perspectives. At the core of the questions raised in the following section, is the challenge to find or sense the optimal data for a given model context at reasonable costs.

3.2. Research Directions

As outlined in the previous section, there is comparably little, explicit research done on geospatial data for transport models and the questions raised here might not cover the entire range of necessary research. However, the following research directions are regarded as relevant for the GIS-T as well as for the transport modeling community.

3.2.1. Data Availability, Accessibility and Privacy Concerns

For a long time, data availability was the bottleneck in any transport-related research and application, especially in Europe. This has been constantly changing over the last years. Driven by legislative initiatives and new web-based distribution channels, an increasing number of data sets, which are relevant for transport modeling (road network, address, or traffic state data, *etc.*), have become accessible, although national and regional differences still exist.

Further research has to be conducted on how additional data, which are of great importance for transport modeling, can be made accessible while addressing privacy concerns. This holds especially true for socio-demographic, statistical data and movement data. In both cases, the data do exist for operation and administrative purposes, but are withheld due to privacy concerns. There are strong arguments for keeping strict data policy laws, as long as no political and technical guidelines and regulations exist for the utilization of such data. Rossi *et al.* [57] demonstrated how sensitive GPS trajectories are in terms of privacy, while de Montjoye *et al.* [58] proved that even coarsened movement data provide information about individuals. Oksanen *et al.* [59], therefore, proposed a method to preserve privacy in mobility hotspot maps.

While legal regulations for privacy, property rights and related issues exist for authoritative data and mobility data, which are generated for operational purposes (e.g., mobile phone network), the situation is less clear and subject to debates (data ownership, definition of public *versus* private sphere, *etc.*) in the Web 2.0 context [60,61]. Nevertheless, the potential of Web 2.0 data for mobility research is huge. Krumm *et al.* [62], for example, developed analysis routines to reconstruct and predict mobility from Twitter data. It is thus necessary, not only in the context of transport modeling, to define legal, but also ethical, rules for the utilization of Web 2.0 data, especially since the consciousness for privacy implications is very weak among users [63].

3.2.2. Data Quality, Fitness of Use, Metadata and Standardization

Currently, too little attention is paid to the quality and fitness of use of data in transport models. The impact on the model output is huge, but hardly ever discussed explicitly. Hence, we argue for the development of quality assessment tools for transport data and a specification for the transport model domain of the approach proposed by Devillers *et al.* [55]. The urgent need for an explicit consideration of data quality stems from the increasing availability of crowd-sourced data and the heterogeneity of data sources in general.

Many data sets which are employed in transport models lack a sound description. Consequently, it often happens that data from different points of time with a different resolution and acquisition scale are combined without any further processing steps. Research should thus be conducted on how to consider metadata (data describing data) in transport models. This is especially relevant for derived data, where the processing history is crucial for the interpretation of the data.

Tightly related to the issue of metadata are standardized data formats and interfaces. As noted above, standards for several data types do exist (such as the GTFS for public transit data), but many data are still sensed and managed in closed, proprietary environments. The question of data accessibility depends, thus, not only on privacy issues (see previous section), but also on interoperability. Consequently, the development and application of standards should be put on the agenda of researchers and practitioners.

3.2.3. Data Models for Dynamic Environments

Most GIS-T applications and transport models rely on either relational or object-oriented databases. Both approaches are suitable for a range of applications, especially as long as static data are employed. The requirements for data models are different in a dynamic environment. The current research challenge is to design data models that are flexible and able to handle huge data amounts from various sources, with different formats and resolutions, while ensuring high performance in analysis and visualization tasks [12]. Another, though not new, issue is the adequate consideration of time in geospatial databases.

3.2.4. Data Characteristics and Spatial Pitfalls

The impact of data on model validity and reliability as well as on the possible representations is obvious. Still, spatial data are frequently used in non-spatial models, without considering the spatial characteristics of the input data. The effect of subsequent spatial biases needs to be investigated and assessed systematically. Research is also necessary with regard to the scale and aggregation level (resolution) of the data and the model, respectively.

Routines for determining spatial and spatio-temporal characteristics of data, such as autocorrelation, are well established for static data [26,64,65]. Thus, it is possible to assess and account for the spatial influence on models accordingly. Similar measures for highly dynamic, spatio-temporal data are less common. Further research is required on how spatial dependencies in dynamic data sets can be assessed and the model routines accordingly adapted. Similarly, spatially enhanced transport models must account for the aggregation and scale level of dynamic data. Flexible aggregation and disaggregation routines have to be developed for dynamic data sets in order to feed and calibrate transport models adequately.

3.2.5. Cost of Data Acquisition and Impact on Model Results

With the current deluge of data on the one hand, and the increasing performance of disaggregated transport models on the other hand, uncountable variations of model parametrization and analysis became available. Nonetheless, it is not yet clear to which degree the validity and reliability of the model results have increased due to these new opportunities. Thus, we propose to investigate the relation between the amount of input data, as well as the effort (or cost) of data acquisition and the quality of the model results. Results will inform further research and of course budget allocation for transport modeling.

4. GIS and Disaggregated Transport Models

The spatial distance between everyday activities—such as working, shopping and recreation—has considerably increased over the last decades, with direct effects on individual daily travel routines. Modern urban utopias, with strictly separated functional zones (see for instance Anthony [66] for a reflection on Le Corbusier's urban utopias), have been built upon this necessity and ability to travel. These utopias are illustrative examples of the fundamental understanding of travelling in disaggregated transport models, where mobility results from participation in activities that are spatially separated. Hence a prime function of transport is to connect activities at different locations. Whereas aggregated transport models, such as the FSM, focus on the number of trips between traffic analysis zones, disaggregated transport models represent single trips according to individual activity chains and travel preferences. The flows that emerge from disaggregated models, thus, are a synopsis of the structure of geographic space and individual travel behavior. The trend towards disaggregated models is mainly driven by the urge to adequately address heterogeneous and complex mobility patterns.

The following section provides an overview of the main approaches to disaggregated transport modeling, followed by research directions related to spatial aspects.

4.1. Current Status

Transport models represent the spatial dimension at various levels of disaggregation. At the one end, there are trip-based models, such as the FSM, that operate at a long-term and highly aggregated level [8]. For parameterization of trip-based models, widely available census data can be used and the models are reasonably efficient in terms of computing power. Therefore, they have long been a pragmatic approach to support infrastructure planning [67]. Typical application examples are the design of higher order street networks or public transport facilities. The level of spatial aggregation into travel analysis zones is high, and has proven sufficient for this purpose [68].

At the other end of the level of disaggregation, are individual based approaches, such as activity-based models, microsimulations and agent-based models. Activity-based models aim for a more adequate representation of human social behavior [2,14,67]. This approach simulates individual sequences of behavior (also called "daily patterns"), assuming that households or other social structures strongly influence travel behavior [68]. Daily activity patterns organize single trips into more complex tours. Conceptually, activity-based models can still be based on aggregated spatial units. However, recent models tend to use micro-zones that represent greater spatial detail, such as census blocks or even individual parcels [69]. Behavioral realism in activity-based models is often associated with the spatially disaggregated approach of microsimulation.

Microsimulation refers to the simulation of individuals sampled from aggregate attribute distributions and, thus, are in the spirit of traditional statistical models [70]. As single persons are represented explicitly in a microsimulation model, their individual choices and activities can be tracked and combined logically over the course of a simulation. Therefore, microsimulation allows for the development of more sophisticated traffic models based on probabilistic choices. Probabilistic sampling introduces some degree of randomness, so that microsimulation models are stochastic in contrast to deterministic trip-based models.

Agent-based models, finally, are rooted in complexity theory. Agents are "intelligent" individuals that are aware of their local context. Unlike individuals in microsimulation that act in accordance to an aggregate probability distribution, agents in ABMs act according to rules in response to their local environment, to their neighboring agents and potentially also to their past experiences. The added value of the spatial dimension as an integrating framework can, thus, fully unfold in ABMs. Exemplary applications include the effect of road pricing schemes on congestion patterns [71], optimization of traffic signals timing [72], vehicular communication [73], context-aware route choices [74,75], or the mechanism underlying the safety in numbers phenomenon [76]. On the downside of agent-based approaches is the high computational cost [77–79], so that the extent of modelled areas, typically, was limited to street crossings, individual city districts or abstract road networks. Only recently, ABMs have become capable of representing larger areas such as entire commuting regions around cities [21,80].

In practice, differences between the three approaches to disaggregate transport modelling are blurred; ABM and microsimulation are sometimes used synonymously and many models are combinations thereof. Generally, the application of disaggregated transport models is still limited by data availability and accessibility, as well as processing power. However, the frontier is currently being pushed forward at a high pace. A plethora of frameworks to support disaggregated modelling for traffic planning and management purposes in large real-world networks have been developed, with foci mainly on demand generation or flow analysis. Examples of such modelling frameworks include TAPAS [81], MATSIM [82], SUMO [73], ALBATROSS [83], TRANSIMS [84], VISSIM [85], TransCAD [86] and SACSIM [87]. Further, multi-purpose agent-based simulation tools with more flexible functionalities, such as NetLogo [88] or Repast [89], have been used in transport research to explore emergent traffic phenomena, mainly on a conceptual level [76,90,91].

From a geographic perspective, the shift towards disaggregated models in general and ABMs in particular, reflects a trend in transport geography that started from static maps, developed further to dynamic routing and navigation, to finally incorporate the behavior of discrete entities [7]. Spatial microsimulation has become a mainstream approach for incorporating the geographic dimension into dynamic transport models. However, if the specific purpose of a model was to represent spatial heterogeneity and to explore its effect on emergent traffic phenomena, microsimulation would need to define aggregate probabilities for each specific spatial arrangement on the local scale. In such cases it is more efficient to use context-specific rules of ABMs [92,93]. Even if the properties of all agents were the same, explicit representation of spatial heterogeneity would result in the emergence of distinct traffic patterns.

Within a given spatial and temporal structure, transport systems emerge from human behavior and their interactions [69]. While behavior can be encoded in activity-based microsimulation, representation of interaction and adaptive behavior in response to interaction between agents is specific to ABMs; it cannot be represented with probability-based microsimulation. An added value of representing adaptive behavior is offered by the integration of game theory. Game theory, in general, deals with models on how rational travelers react to the behavior of others, that is, either in a cooperative or a selfish manner [94,95]. Applied to spatial transport models, game theory can lead to the emergence of unexpected flow patterns. Examples include a number of paradoxes, in which selfish behavior of individuals lead to unexpected latencies in the traffic network that counteract the intention of certain infrastructure measures (e.g., [96]). However, Scholz [97] showed that simulation models with adaptive, learning agents result in different spatio-temporal movement patterns than strictly selfish agents.

A major challenge that disaggregated transport models face is losing generality for the sake of realism and connected issues of model validation [98,99]. Liu *et al.* [100] pointed at a mismatch in the granularity and abundance of simulation outcomes *versus* traffic count data, which has usually been used for external validation. Therefore, they suggested using real-time and spatially disaggregated mobile phone data for validation. A promising validation strategy for ABMs is pattern-oriented modeling, which has been developed in the domain of ecology to evaluate structural model validity [101]. This approach defines a set of patterns for different attributes and at different scale levels that a model needs to reproduce simultaneously to prove structural validity. Transferred to mobility research pattern-oriented modelling, it could prove useful for the validation of agent-based transport models [21]. However, Batty and Torrens [70] demonstrated that ABMs rely upon countless assumptions and, thus, exhibit a vast number of degrees of freedom, which makes it conceptually impossible to fully validate such models against data. To address related epistemological questions, Millington *et al.* [102] argued for using additional approaches to model validation and communication based on narratives.

4.2. Research Directions

The leading question that should guide research from a spatial perspective is what the explicit representation of spatial heterogeneity in transport models has to offer for advancing our understanding of transport systems and human mobility behavior. To fully exploit the geographical dimension in transport models, further research should be directed towards the fields of emergence, adaptation and validation.

4.2.1. Emergent Phenomena from Spatial Heterogeneity

The use of spatially disaggregated transport models builds on the assumption that explicit consideration of disaggregated space critically affects outcomes on an aggregated level. Stanilov [103] provided a general overview of the role of space in ABMs, related to four main aspects: issues of scale, space as the interaction component, space as the attribute of agents and the environment, and the role of space in communication and validation. Further research should be directed towards a systematic analysis of these aspects in the field of spatial transport models, specifically with respect to potential particularities due to the representation of network space.

4.2.2. Emergent Phenomena from Adaptive Behavior

Activity-based models have brought along a change of focus from land-use driven demand models to models that are governed by human behavior. Agent-based approaches have further added the capability of agents to interact, learn and adapt their behavior according to their prior experiences and local contexts. However, until recently, respective ABMs have been largely restricted to abstract spatial representations. This limitation was not least due to scarcity of adequate data, which allows for a description of human behavior. Today, data on individual human mobility is increasingly accessible through social networks and distributed real-time sensor networks. Additionally, mobility data from social media networks are linked to several social dimensions that might serve as indicators for mobility behavior (interests, socio-economic status, living conditions *etc.*). Further research should thus address the integration of adaptive behavior, facilitated by these newly available data sources. Exploration of theory-based concepts as, for example, game theory, should then be evaluated in real-world contexts, which can be expected to yield further important insights into transport systems.

4.2.3. Limited by Complexity? New Views on Validation

In recent years, static and highly aggregated models have been complemented and are increasingly superseded by disaggregated, agent-based models. The implication of this trend is not least the embracement of the complexity and uncertainty that is inherent in these models. Further research should address the implications of the conceptual restrictions that stem from this high level of complexity. Possible research directions can borrow from novel approaches to ABM validation that have been suggested in other domains, such as pattern-oriented modeling in ecology or the narrative approach in the spatial system sciences.

5. The Role of (Geo-) Visualization in Transport Modeling

For a long time, the role of geo-visualization in transport modeling was restricted to the cartographic presentation of final results [9]. Driven by two complementing lines of development, this has started to change in recent years. Firstly, through the advent of interactive (geo-) visualization environments, the rise of Visual Analytics [104,105] and the availability of massive data sets, geo-visualization has become increasingly popular beyond the core domains of geography and cartography [106]. Secondly, the growing relevance of geo-visualization in transport modeling can be attributed to the paradigm shift from highly aggregated to disaggregated modeling approaches, which put a stronger focus on the heterogeneity and inter-dependences of mobility behavior and result in detailed information on individual activity patterns. In this context geo-visualizations are more than visual presentations of final model results, but powerful tools that "stimulate visual thinking about geospatial patterns, relationships and trends" [107] (p. 391). Nevertheless, the potential of (geo-) visualization in transport modeling has not yet been fully employed. Up to now, only a small number of examples are available that make use of (geo-) visualization techniques in order to explore input data and constituting model elements, to validate model results, or to communicate dynamic content [11,108,109]. However, the implementation of available geo-visualization methods and technologies in transport modeling and the development of domain-specific applications are regarded as promising for the whole domain of GIS-T and transport research. Therefore, we collect (geo-) visualization concepts for transport models and present case studies that employ different features and visualization platforms. As with the preceding two sections, we wrap up with research directions.

5.1. Current Status

Although disaggregated transport models are data intensive and an abundance of sensors feed these models with data, (geo-) visualization techniques are hardly ever employed as an interface to this data deluge and the transport models built upon it. Thus, modelers are missing opportunities, for instance, to visually screen and validate input data and subsequently explore model elements, simulation states, or the evolution of final model results. Visualization concepts rooting in space–time geography are available for transport data [110–114], but they are not directly integrated in transport modeling workflows yet. On a more basic level, general design principles from cartography and information visualization can be applied to transport data in order to make the data accessible. Before we provide an overview of existing (geo-) visualization concepts and design principles for transport data and models, we set the stage and briefly turn to the general framework for the visualization of transport data and models.

5.1.1. General Framework for the Visualization of Transport Data and Models

Applying (geo-) visualization concepts to transport data and models requires consideration of a wide range of different aspects, which, in turn influence the choice of appropriate designs and visualization environments. On the most basic level, this means that it is necessary to decide on what should be visualized, for whom, and for which purpose. Extending these fundamental questions defines the general framework for the visualization of transport data. Figure 3 summarizes the dimensions that need to be considered in our context and which are, of course, highly interdependent.

The type of data at hand is of primary interest, as it affects all successive decisions. In the transport modeling domain, the following data types are relevant: point data (e.g., activity locations, public transport stops), line features (e.g., trajectories, aggregated traffic flows), polygon data (e.g., population density in census districts, traffic analysis zones), matrix-based data (e.g., OD matrices, timetables) and descriptive data (e.g., socio-economic data, cultural preferences, mobility habits).

Whereas various types of visualizations have been widely employed to communicate results of transport models [9], the use of visualizations as an interface for the modeling process is not yet established in the transport modeling domain. Here, recent paradigmatic developments in the geography and cartography domain towards Geovisual Analytics [115–118] provide new conceptual as well as methodological frameworks and tools for visualizations supporting the modeling process in transport research. Thus, a new target audience of visualizations, namely, the model developer and domain experts that interact with the model, can be identified and needs to be considered accordingly.

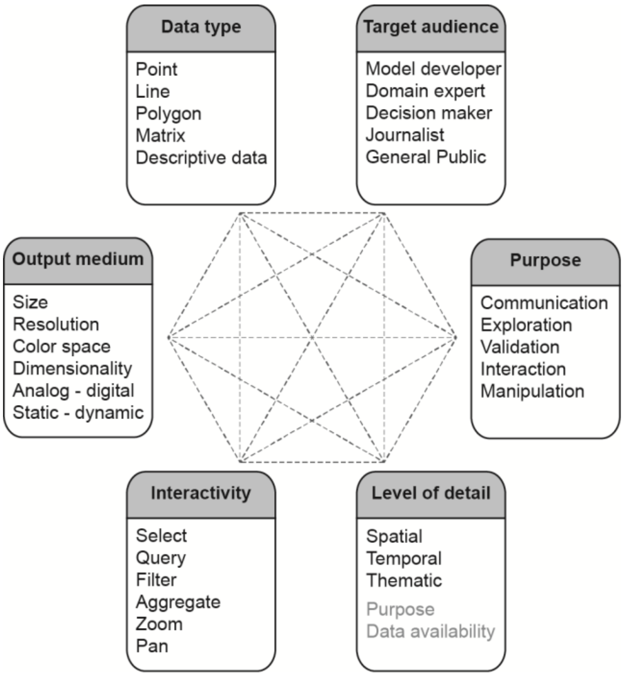

Figure 3. Interdependent dimensions that are relevant for the choice of appropriate (geo-) visualizations of transport data.

Tightly related to the audience that is to be addressed, the purpose of the visualization directly affects the design of the visualization environment. For the process of transport modeling, we regard data exploration, model building (data integration), calibration (interaction and manipulation), validation, and the communication of processes and results as relevant purposes. There are only a few examples in literature where visualization techniques are employed to interact with the data and the model, respectively: Andrienko and Andrienko [104] established a Visual Analytics platform for pattern detection in massive trajectory data. Picozzi *et al.* [119] presented a visual interface for the exploration of a real-world transport system. Cyganski *et al.* [109] used mapping techniques in a transport modeling environment for the sake of validation and communication. The latter example is one of the few where geo-visualization and transport modeling are fused in an integrated environment.

The desired level of detail is closely related to the type of information that is to be visualized (purpose) and is limited by the characteristics of the available data. Applicable aggregation approaches include spatial, temporal and thematic aggregations. Potential levels of detail range, for example, from individual GPS tracks or precisely positioned, individual agents to aggregated flows between TAZs. In cases where primarily dynamics over time are visually conveyed, the spatial reference can be partly or entirely omitted.

Visualizations in a digital environment allow for a wide range of interactive features. Here, the benefit of geo-visualization as an integrated part of the modeling process can be fully exploited. Frihida *et al.* [108], for instance, presented an object-oriented GIS prototype to extract and dynamically visualize individual space–time paths from tabular activity chains. Chen *et al.* [120] pushed this concept further and provided a GIS-based, interactive exploration environment for activity diaries. Again, examples for visual interaction with transport data from the GIS and Visual Analytics communities are numerous, but they are rarely transferred and integrated into transport modeling environments.

The output medium decides on the options for a (geo-) visual representation of data and model processes. Digital and interactive media are most relevant when visual interfaces are employed in transport modeling.

5.1.2. Geo-Visualization Concepts for Transport Data and Models

Since transport data and models are characteristically dynamic, visualization concepts have to acknowledge the temporal dimension adequately. In geo-visualization, dynamic phenomena are commonly represented either by map symbols (arrows, labels), small multiples, or animations [121,122]. These concepts are complemented by interactive elements and by extending the planar representation with an additional dimension, resulting in 2.5D (extrusion of 2D representation) or 3D visualizations. Table 1 provides an overview of visualization concepts for transport data, demonstrated with selected use cases. For a more extensive overview, we refer to Chen *et al.* [123].

As demonstrated in several studies cited in Table 1, interactive environments facilitate the exploration of spatio-temporal transport data on various levels of aggregation and through different visualization types (spatial and non-spatial). Geo-visualization concepts on a high level of generalization are necessary to provide an overview of the whole study area and the entire time period. Prominent examples of the visualization of overall activity in an area include heatmaps and space–time density and flow maps. The latter, together with vector fields, enables analysts to visualize directionality and flow volumes simultaneously. On an intermediate level of detail, geo-visualization concepts are used to focus on a certain area, time interval, or topic. Relations between selected origins and destinations, mobility patterns of a given day, or trip characteristics of a certain mode of transport can be visualized with greater detail compared to an overall perspective. Geo-visualization concepts for the most detailed level become increasingly important in the context of disaggregated transport models and microsimulations (see e.g., Guo *et al.* [124]). Building upon concepts from time geography [1], the role of geographical information systems in the visualization of highly detailed data is widely anticipated in literature [2].

Table 1. Visualization concepts for selected use cases.

Level of Detail	Use Case	2D Visualization	3D Visualization	Animated	Literature
Low	Overall activity/density	Heatmap Point density map	Surface map (2.5D; density as z dimension) Space-time density (time as z dimension)	Evolving map	[125,126]
	Main movements: direction and volume	Vector fields	3D vector fields	Evolving vector fields	[127]
	Clustered flows	Mobility graph	Mobility prism		[128,129]
	OD relations: direction and volume	Flow map (volume as line width)	Extruded flow map	Evolving flow map	[122,130–132]
	Network graph: flow volume	Mapped network (volume as line width)	Extruded network map	Evolving network map	[133]
	Microsimulation for intersections	Mapped trajectories	Extruded map symbol	Animation of queue buildup	[124]
	Individual trajectories	Path	Space–time path	Animated path	[134,135]
High	Accessibility	Isochrones Potential path area	Space–time prism Potential path space	Evolving isochrones	[3,136,137]

5.1.3. Efficient Geo-Visualization Features

The range of geo-visual tools and functionality is large and well established in the domains of information visualization, cartography and GIScience [106]. For the visualization of transport data and models, the following features can be regarded as essential: overview, drill down, filter and query, avoidance of occlusion (e.g., through clustering), comparison, animation and print or report functionalities.

To provide users with the necessary spatial, temporal and thematic context information, overview features should provide a generalized, global view of the data. Depending on the map purpose and the addressed user group, base maps and overlays help frame the data and put them into a spatial and thematic context. To control the level of detail that is displayed, drill down, filter and query features allow the user to advance from a generalized overview to more detailed views [123]. Besides a reduction of complexity through filtering, intelligent clustering algorithms [128] and dynamic insets [138] are being developed to avoid visual occlusion and overload. In order to facilitate a better understanding of changes, for example, through variable model parameters or between time intervals, it is essential to provide suitable comparison tools. Similarly, animation features, which are typically implemented in GIS software (e.g., QGIS Time Manager [139]), facilitate the exploration of change over time. Primarily for the purpose of communicating and sharing results, geo-visualization frameworks should provide access to print, report and export features. Standardized exchange formats, such as SVG for vector graphics, and interfaces, are preferable in this context.

While all these features are already implemented in independent, specific software packages, a direct integration into transport modeling environments is still lacking in most cases. Thus, it is cumbersome to dynamically interact with transport data and models through a visual interface during the entire modeling process. Disaggregated transport models are usually built upon large data sets, which can hardly ever be completely overseen in advance, and ABMs exhibit a large degree of freedom anyway. Here, concepts from Geovisual Analytics with deductive elements, a high number of iterations and immediate visual response would help to explore the data, test hypothesis and gain spontaneous insights (see Keim *et al.* [117] on the Visual Analytics process).

5.2. Research Direction

The body of literature on geo-visualization is huge and constantly growing. Thus, it can be stated that concepts, methodologies and tools are available and established. However, we see, so far, unused potentials for geo-visualization in the transport modeling domain. As we have argued, Geovisual Analytics [115] promote visualizations, not only as presentation or communication media, but also as a dynamic, interactive interface for data and models. While appealing visualizations, which are intended to serve as eye-catchers, do have their place in transport modeling, the integration of tools to visually extract patterns, dynamics and interdependencies for modeling processes is still in its infancy. In this context, we see the following—yet not all-encompassing—research directions.

5.2.1. Development of Geo-Visualization Guidelines

Visualization and animation techniques have enabled users to develop a large variety of geo-visual representations. Recent papers (e.g., [109,123,124,128]) address the problem of finding adequate types of (geo-) visual representations that facilitate an intuitive interaction with extensive, complex data sets and models. We expect that in the near future transport modeling, GIS and Geovisual Analytics will be integrated much tighter than they are today. In light of this development, we call for research on guidelines for the identification and implementation of adequate geo-visualization concepts and tools into transport modeling environments, considering the dimensions summarized in Figure 3.

5.2.2. Trade-off between Visual Accessibility and Level of Detail

With the increasing availability of highly detailed data, it is necessary to address the question of an appropriate level of detail with greater vigor. The trade-off between visual accessibility and level of detail needs to be investigated for different data sources and model scales. However, this question is not only relevant from a geo-visualization perspective, but affects transport models as such. Thus, further research needs to determine the benefit of highly detailed over aggregated data for the model results and the corresponding geo-visual interface. In the latter context, research should be directed towards intelligent aggregation and clustering algorithms with regard to computational power and response time.

5.2.3. Communicating Model and Process Dynamics

As models and derived visualizations are often used for decision making, it is vital to correctly communicate the uncertainties inherent in input data, the sensitivity of the model dynamics and the variance of model results. Especially in scenario analysis—a major field of application for transport modeling—analysts often have to deal with a variety of assumptions and predictions whose implications and interdependencies are not obvious at first sight. Sources of uncertainty include, for example, variance in population forecasts, sensitivity due to estimated parameter specifications, or fairly unpredictable behavior adaption of road users over time. These influential factors often lead to a range of prospective scenarios rather than a single definite forecast. Ultimately, this raises the research question of how to handle the extent and impact of uncertainty at the different levels of transport model visualizations. It particular, it is necessary to understand how planners and decision makers can be enabled to come to informed decisions under these circumstances.

5.2.4. The Right Tool for the Job

Spatial data cannot only be dealt with in traditional GIS software. Standard transport modeling software suites provide growing geospatial functionalities (e.g., network editing). Additionally, programming and scripting languages increasingly allow for spatial analysis and geo-visualization functionalities through spatial libraries. In this context, Java (Processing), Python, R, and Javascript (D3) are to be named due to their popularity. While current GIS packages in combination with spatial databases are well suited to deal with data complexity, they usually do not provide adequate rendering performance to visually interact with big amounts of transport data efficiently. Hence, future research and development is needed to combine geospatial functionalities with transport modeling, while providing an efficient, interactive, visual interface for data exploration, manipulation, analysis and visualization.

6. Conclusions

We have argued that the relevance of geospatial information for transport modeling is significant, but not yet adequately considered in most cases. In this context, we have pointed to three fundamental, spatial issues that inevitably influence any transport model result, namely the MAUP, spatial dependencies and spatial heterogeneity. As we have outlined, these characteristics can be adequately captured and considered with GIS. Additionally, the role of geospatial information in transport models will be necessarily further strengthened. This is mainly due to fundamental shifts in the transport modeling domain: from data scarcity to a data deluge, from expanding infrastructure to smart management, and from aggregated to disaggregated models.

Taking all these aspects together, we have presented a strong case for the integration of geospatial information into transport models. We identified three fields in the context of transport modeling, where we regard the spatial perspective as essential and see substantial research gaps: (1) the current status of geospatial data usage for transport models; (2) the spatial implications of disaggregated transport models; and (3) geo-visualization. The research directions, with exemplary research questions, which we have formulated for the respective fields, focus on spatially relevant aspects and contribute to the research agenda for interdisciplinary future work at the intersection of GIS and transport modeling. As it became obvious at several points, the spatial dimension is not isolated from the temporal and human dimensions. Consequently, we call for additional studies that investigate the impact of temporal and human dimensions on transport models, before a consolidated, holistic framework for transport modeling can be developed.

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Abbreviations

The following abbreviations are used in this manuscript (in alphabetical order):

ABM	Agent-Based Model
API	Application Programming Interfaces
FCD	Floating Car Data
FSM	Four-Step Model
GIS	Geographical Information Systems
GIScience	Geographical Information Science
GIS-T	GIS for Transport
GPS	Global Positioning System
GTFS	General Transport Feed Specification
GWR	Geographically Weighted Regression Analysis
ICT	Information and Communications Technology
INSPIRE	Infrastructure for Spatial Information in the European Community
ITS	Intelligent Transportation Systems
MAUP	Modifiable Areal Unit Problem
OD	Origin-Destination
PSI	Public Sector Information (Directive 2003/98/EC)
TAZ	Traffic Analysis Zone

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