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# Exploring the role of spatial cognition in predicting urban traffic flow through agent-based modelling

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ABSTRACT

Urban systems are highly complex and non-linear in nature, defined by the behaviours and interactions of many individuals. Building on a wealth of new data and advanced simulation methods, conventional research into urban systems seeks to embrace this complexity, measuring and modelling cities with increasingly greater detail and reliability. The practice of transportation modelling, despite recent developments, lags behind these advances. This paper addresses the implications resulting from variations in model design, with a focus on the behaviour and cognition of drivers, demonstrating how different models of choice and experience significantly influence the distribution of traffic. It is demonstrated how conventional models of urban traffic have not fully incorporated many of the important findings from the cognitive science domain, instead often describing actions in terms of individual optimisation. We introduce exploratory agent-based modelling that incorporates representations of behaviour from a more cognitively rich perspective. Specifically, through these simulations, we identify how spatial cognition in respect to route selection and the inclusion of heterogeneity in spatial knowledge significantly impact the spatial extent and volume of traffic flow within a real-world setting. These initial results indicate that individual-level models of spatial cognition can potentially play an important role in predicting urban traffic flow, and that greater heed should be paid to these approaches going forward. The findings from this work hold important lessons in the development of models of transport systems and hold potential implications for policy.

## 1. Introduction

Cities are archetypal complex systems, combining dense mixtures of infrastructure, people and systems that together are capable of increasing productivity, reducing environmental impact and improving the health of its inhabitants (Glaeser, 2011). Understanding cities, and helping them to operate to their most efficient capabilities, represents one of the most pressing challenges of the 21st Century. While the emerging availability of new, rich datasets enable the improved explanation of cities, it can be argued that there remains a fundamental shortage in our ability to predict the future of cities. This situation is no truer than in transportation modelling (Cascetta et al., 2015). Many transportation modelling methods were born in a 'data poor' era, where detail around the heterogeneity and diversity of behaviour was unavailable. These models served cities well for some time, but continuing inefficiencies and the persistence of poorly planned infrastructure indicates that improvements are possible (Flyvbjerg et al., 2005; Bartholomew, 2007).

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Any modelling of cities – be it relating to transportation, housing, the economy, or crime – should build from a deep appreciation of their complexities. Urban systems are a product of the behaviour and interactions of many – sometimes millions – of autonomous individuals. Understanding how these actions coalesce and influence the formation of complex dynamic patterns is therefore vital in sustaining the prosperity of the urban centre. Recent years have seen a growing utilisation of practices and models relating to complexity theory in the explanation of urban systems. In employing this approach, it has been demonstrated how urban systems – rather than defining system behaviour through their physical structure alone – are in fact *defined by* the behaviour of their constituent entities (Batty, 2007). The whole system, in this sense, is 'greater than the sum of the parts' (Von Bertalanffy, 1972), and thus to understand a system one should endeavour to understand its individual components. Yet further than merely a static representation of a system, one should equally seek to identify how a system changes state. In this one must seek to identify how individuals interact with each other and with their wider environment in dynamics of both local and global scale. In many cases the origins of these patterns may be not clear and may demonstrate non-linearity in evolution. It is these dynamics that influence how we view and experience the system in space and time; these are the by-products of the existing organisation of and interaction between individuals.

Urban road traffic networks are a very strong example of this type of highly dynamic, non-linear and complex system. The process by which the system changes state in this way is strongly influenced by the actions of the individual and of the collective. The behaviours of travellers, and their fluctuation as a collective drives the evolution of congestion effects. Congestion is not simply a product of network engineering and hyper-demand, but is driven fundamentally by facets of human behaviour. The emergence of a *Science of Cities* (Batty, 2013), accompanied by new, rich sources of data and improved simulation methods opens up new opportunities for understanding the inherent complexity of traffic congestion. Today we are granted, more than ever before, significant potential to re-examine conventional assumptions around the fundamental bases of these systems.

This paper will argue the case that transportation modelling should better incorporate the facets of human cognition that contribute to the inherent complexity of transportation dynamics. In particular, we focus on behavioural elements of driver route selection and bounded knowledge of space, modelling these behaviours at the individual traveller level. Whereas, in recent years, there has been considerable advancement with respect to the context within which travel takes place (Arentze et al., 2000; Bowman and Ben-Akiva, 2001; Miller et al., 2005), the incorporation of elements of cognition and complex decision-making has been less well served. This shortfall is well highlighted by Portugali in *Complexity, Cognition and the City* (Portugali, 2011), where it is claimed that advances in cognition science have been 'ignored' within the wider domain of urban complexity theory, and that existing applications of these approaches remain insufficient (p. 103–104). There is a strong opportunity for developments in cognitive science to help to more comprehensively describe individual travel behaviour, and subsequently allow us to better model and explain the dynamics of the wider transport system.

This work will aim to address one further outstanding issue around whether more descriptive models of cognition are truly necessary in explaining complex systems. In opposing that described above, it could be argued that while cognitive models may appear more realistic in principle, the added value they offer to prediction system behaviour is negligible. This may be deemed particularly true within the context of urban traffic systems, where trip distributions are broadly constant and strict movement control mechanisms are in place. In this context, it may be argued that the interpretation of behaviour is less important than the engineering of the system itself. Through a series of simple, exploratory agent-based simulations, the paper seeks to address the verity of this argument.

In achieving these aims, we will first seek to identify the gap between representations of behaviour within conventional urban traffic models and research findings from within the cognitive science domain. The findings from this review are then incorporated into a simple agent-based model environment, with the aim of addressing the relatively influence that behavioural definition has on predicting traffic flows. The paper will conclude in addressing the most important findings from this study, highlighting some the wider lessons learnt through this work and identifying areas for further investigation.

## 2. Models of route choice in urban transportation

For over fifty years, the interpretation and representation of route choice and urban navigation has been an important research area in disciplines of both transportation modelling and cognitive science. Yet, as the literature reflects, there is a significant difference between the approaches taken by the respective disciplines in exploring this shared objective.

Transportation modelling, in respect to the movement of traffic on an urban road network, continues to be heavily influenced by the 'first principle of traffic equilibrium' laid out by Wardrop in 1952 (Wardrop, 1952). This principle states that on a road network loaded with traffic no single vehicle may improve their journey time through unilateral action. Underlying this principle, it is assumed that each driver has considered all of their route options, with a complete knowledge of the road network structure and prevailing flow conditions, and have subsequently selected their path of least journey time. This approach found favour, and has seen a range of approaches developed that conform to the general principle of user equilibrium. More advanced incarnations of this approach incorporate dynamic elements to traffic flow distribution (Merchant and Nemhauser, 1978), varying, stochastic distributions of perceived journey times (Bell, 1995), or flexible 'indifference' to journey times (Mahmassani and Chang, 1987), but rely on the same assumptions around a system-level traffic organisation. Importantly, with respect to transportation policy, equilibrium models are widely used, and are implemented within the most popular commercial tools for traffic flow simulation.

Simple intuition presents some notable challenges to the equilibrium paradigm. Equilibrium models make simplistic assumptions about the basis of individual route choice, assuming pure rationality in preference for the quickest path with little or no consideration for alternative route characteristics. They do not consider the influence of partial route knowledge, and how individuals may be restricted or bounded in their behaviour. Individuals are modelled homogeneously with any population variation only introduced through stochastic variables. These assumptions are not only simplistic within the context of urban complexity outlined earlier, but furthermore recent research have demonstrated that driver behaviours are far more complex. A variety of empirical analyses have been carried out in recent years, examining heterogeneity in route choices through the analysis of a growing set of observed routing datasets (Manley et al., 2015a; Zhu and Levinson, 2015; Lima et al., 2016; Li et al., 2016; Jayasinghe et al., 2016; Ciscal-Terry et al., 2016).

While traffic equilibrium models continue to be widely used in transportation decision-making across the world, research has moved more towards modelling route choice through random utility models as well as applications of prospect and regret theory (Ramos et al., 2014). These approaches allow the improved modelling of choice under uncertainty (Avineri and Bovy, 2008; Gao et al., 2010), information use (Ben-Elia and Shiftan, 2010), and the influence of perceived risk of delay (Sun et al., 2012). However, many of these approaches remain rooted to underlying assumptions of 'shortest path' routing behaviour through the methods used to define choice sets, and shown to poorly reflect observed choice (Bekhor et al., 2006; Kaplan and Prato, 2012; Manley et al., 2015a). Yet while these methods are clearly more behaviourally comprehensive than equilibrium approaches, limitations are rarely discussed directly in the literature (Nakayama et al., 2001; Kazagli et al., 2015). Only recently have researchers began to discussing the need to consider alternative decision-making methodologies, with a growing recognition that existing approaches are not wholly appropriate (Sun et al., 2016; Di and Liu, 2016). The aforementioned empirical analyses furthermore look set to cast new light on existing modelling assumptions.

The argument for revisiting the outstanding assumptions at the heart of transport modelling becomes more fervent when one considers the concurrent developments in spatial cognition research. In the context of this work we focus on two key research areas – the concept of the cognitive map, and the process of route selection. The existence of a cognitive map was described by Tolman in 1948 (Tolman, 1948), following multiple experiments involving both humans and animals. The map is essentially a mental model that individuals maintain of the world around them – it has been shown to be subjective to the individual, experiential, non-Euclidean and naturally incomplete. Further work has established that this representation is found within the hippocampus, with this part of the brain vital in orientation and navigation (O'Keefe and Nadel, 1978). One of the most important theoretical advances was carried out by Lynch in *Image of the City* (Lynch, 1960), where the author sought to identify elements of the city that are most salient in an individual's mind (or cognitive map). According to Lynch, the city is cognitively constructed of paths, edges (contrasts in urban structure), districts, nodes (intersections) and landmarks. Later work has generalised these classifications into route (road and path network), survey (image of environment) and landmark knowledge, a now widely accepted principle for spatial knowledge (Tversky, 1993; Montello, 1998). Barring a few notable examples (Hannes et al., 2012; Chorus and Timmermans, 2010; Kusumastuti et al., 2011; Manley, 2016) there have been few examples of the explicit application of cognitive maps to transportation modelling.

The cognitive map does not, of course, sit in isolation, it holds a functional purpose, namely to aid navigation. Recent work has made advances in identifying how different parts of this mental construction are used in route selection. It has been identified that people use personal landmarks (or anchors) for orientation (Golledge and Spector, 1978; Golledge et al., 1985; Passini, 1984) and employ a process of path integration to estimate routes through lesser known environments (McNaughton et al., 2006). Other work has outlined heuristics by which individuals choose a route, usually identifying a tendency to reduce the cognitive complexity of the route. This may be achieved by selecting a coarse region-based route towards the target to be executed step-wise (Wiener and Mallot, 2003; Wiener et al., 2009), or by reducing the number of decisions that need to be made on route, through selecting the straightest path (Conroy-Dalton, 2001) or by minimising the number of decision points (Wiener et al., 2004). The least angular routing approach is also prominent within architectural research into how individuals move through the urban environment (Turner, 2009). Determining which features of the cognitive map one utilises in route selection is influenced by the salience of the feature to the individual in relation to the nature of the routing task (Couclelis et al., 1987). It is thought that the salience of a feature, although subjective, is determined according to some feature hierarchy (Hirtle and Jonides, 1985; Winter et al., 2007). In this way, nearby, more salient features would therefore be favoured early into a route, for example, where a landmark-based heuristic is employed.

There are indications of transportation modellers beginning to explore some of the concepts emerging from spatial cognition research. In addressing the gap, Kaplan and Prato (2012) implemented a model with explicit measures of spatiotemporal constraints and cognitive capabilities. The modelling associated reduced time routes and increased turns with habit, familiarity, and spatial ability. Prato and colleagues elsewhere identify the role of landmarks within the routing mechanism (Prato et al., 2012), while other models have explicitly incorporated anchor points within the route choice model (Manley, et al., 2015b; Alizadeh, et al., 2017). Nevertheless, the subfield is developing, and there is presently an opportunity for exploratory testing of the potential impact of these approaches on traffic flow simulation.

It has been shown through this brief review of the literature that behavioural representations used in existing transport models fall some way from the research being carried out in cognitive science, and appear, in this context, to be unrealistic. There is clearly also a volume and strength to the findings developing in cognitive science that should not be disregarded where seeking to understand the dynamics unfolding within the urban environment. Despite the subjective and experiential nature of individual movement within the urban realm, there is a strong case for the better inclusion of these principles within new models of traffic flow. Yet despite these findings, the question raised earlier of the relative impact of behavioural definition in shaping macroscopic patterns remains. The follow sections of this paper employs agent-based simulation to quantitatively describe the impact that changes in models of driver behaviour have on resulting predictions of traffic flow.

## 3. From cognitive models to traffic flow distributions

In this following section, we seek to explore how the incorporation of driver cognition within a computational modelling environment can influence the prediction of traffic dynamics. This link from a model of individual cognition to macroscopic pattern prediction is achieved here through exploratory agent-based modelling (Batty, 2013). The models presented here are not concerned with reflecting real-world traffic, but rather demonstrating how individual-based decision rules impact on derived traffic flow distributions, and whether elements of spatial cognition are significant in redistributing flows.

Agent-based simulation is a technique for the investigation of relationships between the behaviour of individual entities and their influence in shaping system dynamics (Bonabeau, 2002). Entities represented with an agent-based model – be them people, organisations, animals or any other cohesive object – are modelled distinctly, being granted an autonomy that enables them to act and interact independently. By representing individuals distinctly, this approach enables the introduction of population-level heterogeneity. In capturing a large degree of the autonomy and heterogeneity existing within the system these approaches do not restrict modelled output to specific predefined ideas of how a system should evolve. Instead the result is built from the ground upwards, with the dynamics of the system emerging through the interactions of the constituent parts. Agent based simulation is an important tool in modelling complex systems, and thus this paradigm appears to provide a useful setting for modelling the relationship between models of driver cognition and resulting traffic flow distributions. Agent-based simulation has been applied in the simulation of a number of urban social phenomena, including transportation (see Bazzan and Klügl, 2014 or Chen and Cheng, 2010 for full reviews), land-use, housing, crowd movements and crime, to name a few.

Through the simple agent-based simulations presented below, we are able to explore variance in modelled behaviours resulting from a set of design scenarios. Within the controlled setting introduced here, these models will clarify the degree to which the inclusion of spatial cognition within the model can impact simulated traffic flow. The following sections describe the definition of driver cognition within the agent-based modelling framework, moving onto the execution of six case studies based within a real-world scenario.

### 3.1. *Modelling spatial cognition through agent-based simulation*

As was highlighted earlier, the movement of individuals in the city is heavily influenced by personal knowledge of urban space and a preference mechanism for traversing that space. It is therefore necessary for our agent-based model to investigate the influence of these specific behaviours on defining global patterns of movement. The models introduced here encapsulate simple representations of possible driver behaviours, aligned to significant sections of the spatial cognition literature. The following section describes the behaviours to be investigated in both conceptual and technical terms – in the first instance, those behaviours highlighted within the literature that will be implemented here, and second, how those behaviours are represented within the agent-based model.

Conceptually, the representation of driver cognition incorporates a number of the most important findings identified within the spatial cognition research domain. With respect to spatial knowledge, we look at the influence of limited and experiential knowledge (Tolman, 1948; O'Keefe and Nadel, 1978), with heterogeneity in this attribute across the population of drivers. Spatial knowledge, as described elsewhere in the literature (Montello, 1998), is attributed according to a *survey* representation of a local area in addition to a wider comprehension of the skeletal *route* network. In terms of individual route selection, this is investigated according to four previously highlighted preference mechanisms – least metric distance (Wardrop, 1952), least travel time (Golledge, 1995), least angular deviation (Turner, 2009) and turn minimisation (Conroy-Dalton, 2001) routing. Distance and travel time minimisation are widely used in traffic modelling, and have been identified as prominent stated preferences for route choice in surveys (Golledge, 1995). The least turn and least angularity routes offer a less cognitively complex approach, and so more in line with other findings (Turner, 2009; Conroy-Dalton, 2001), as they seek to reduce the number of decisions they have to make regarding turning. With these facets defined, each individual will select a route from their origin to their destination according to the limits of their distinct spatial knowledge, selecting the exact path according to their own preferences for route selection. The implementation of both heterogeneous spatial knowledge and route preference within a single agent-based simulation framework represents a novel research development.

#### 3.1.1. *Spatial knowledge*

An objective to investigate these elements of cognition is one part, how these are actually implemented within the modelling framework requires further definition. The assignment of the agent's spatial knowledge is, as described above, set either as partial and personal to that individual, or as complete – in which the case individual has a complete familiarity with the simulated environment. In the case of partial knowledge, spatial knowledge is distinguished according to survey and route familiarity. Survey or local knowledge is specified either as a 500-m or 1000-m radius circular buffer around the agent's origin and destination locations. These locations are then supplemented with additional route knowledge, this being the network of what might be considered the 'main roads' of the city, assigned according to transport authority definitions. An example of the resulting spatial knowledge representation is shown in Fig. 1 for London, where a 500-m radius has been selected. It is accepted that the partial definitions of route knowledge are somewhat simplistic. However, it is felt that they theoretically represent the broad relationship between an agent's experience of space and their knowledge of their environment. This approach is closer to the findings within the literature described earlier, and thus may be contrasted against the complete knowledge approach commonly used in conventional traffic models.


**Fig. 1.** Map showing limited spatial knowledge through limiting roads 'known' to an agent, for a given origin and destination in London, with 500-m radius local knowledge and skeletal representation of 'main roads'

#### *3.1.2. Route choice*

In selecting a route between their origin and destination, agents utilise their distinct spatial knowledge in addition to a route preference algorithm. Agents are assigned one of the route preference mechanisms mentioned above, namely either distance minimisation, travel time minimisation, least angular routing or least turn routing with distance minimisation. Each route is calculated using the Dijkstra shortest path algorithm at the start of each agent journey, across a road network limited by the agent's bounded spatial knowledge. The route attributes in each case are specified as follows:

- Distance: Calculated as the shortest metric distance across the road network between origin and destination.
- Travel Time: Free flow least travel time routes are calculated according to free-flow travel time, using data relating to the speed limit data on each road.
- Angular: Angular deviation is calculated between each straight-line segment on the road network, with a greater deviation between segments scoring more highly.
- Turns with Distance: A turn is recorded when the deviation between two segments is greater than 60°. In these cases, the metric distance between these segments (taken as the total of half of each segment length) is doubled. This weighting acts as a simple repellent against taking multiple turns along a minimal distance route.

The approaches adopted for these two latter methods, again while not necessarily fully explanatory of all driver cognition, represent a mechanism closer to findings identified in spatial cognition research, and thus make an interesting comparison against existing modelling approaches.

### *3.2. Case studies*

#### *3.2.1. Simulation environment*

The location of the case studies for this paper is an area of the road network in central London, United Kingdom. Datasets for the model are obtained from Transport for London, the transport authority for the city, including data relating to the road network, speed limits, link capacities and trip distributions. Road regulations are also incorporated into the simulated road network, to ensure that all selected paths are valid. The trip distribution matrix details journey volumes between 205 regions, for a 30-min period during an average weekday morning peak period. This matrix exceeds the bounds of the simulated environment to cover the whole London area, however the simulation incorporates only trips that begin or end within the simulation area. This is a simplification but will nevertheless provide a reasonable spread of routes within the simulation area. In line with the distribution data around 15,000 agents are generated within the simulation environment during this time period. The agent-based model was developed using Repast

Symphony, a Java-based modelling framework.

Driver agents are initially located within the modelled environment according to the trip distribution matrix. From their starting location, agents select a route towards their given destination according to the definition of their behaviour, as described above. Agents begin their journey at a time predetermined within the trip distribution matrix. In executing their journey, each road link the agent selects a counter is incremented, yielding a dataset detailing traffic flow across the simulated road network. Given the focus on flow distribution resulting from variation in the choice model, no interaction rules are incorporated into the simulation, and thus no delay computed. The simulation ends once all agents have completed their journeys.

The model is executed six times, with each case study testing the influence of a single element of driver cognition on shaping traffic flow distributions. These aspects of cognition – relating to route choice and spatial knowledge – are the only features to change between each scenario, with all additional elements of the environment maintained between each case study. With regard to the testing of the four route selection mechanisms, agents are granted a complete knowledge of the road network with only their preference alternating – between a least distance route, free flow least travel time route, least angular route and least turn route. Where spatial knowledge is tested, all agents select a least distance route, with the degree of spatial knowledge switched between 500-m and 1000-m radius survey knowledge of the origin and destination locations.

To highlight how the distribution of traffic shifts between case studies, all results are compared against the first test describing the traffic flow of least distance-complete knowledge agents (henceforth, the base case). This scenario was picked as the base case as it is a simple and widely used basis for modelling route choices in many contexts. The remaining scenarios describe the redistribution in traffic flow.

Differences between the base case and each scenario is analysed by calculating the mean and standard deviations in the differences in traffic flow simulated on each road segment. We can identify areas of the road network where traffic has been redistributed towards and away from between the base case and other scenarios. The full results for each scenario are presented in Fig. 2 A-F, in these diagrams stronger red colours indicate locations where traffic increases between the base and observed case (indicating a redistribution towards these routes from the base case), blue colours indicate where traffic has reduced between scenarios.

Data relating to the spread of simulated traffic across each scenario can also be extracted by road classification. Using the UK Department for Transport road classification scheme, the percentage of traffic flow utilising routes on each hierarchy of the network is extracted. These results describe the degree of variance in traffic flow generated by each form of the agent model definition. These results can be found in Table 1.

*3.2.2. Results*

The primary finding from these case studies is that they demonstrate how a simple change in the definition of driver agent cognition can significantly alter resulting traffic flow distribution. In each scenario, large shifts in traffic flow are observed, with all scenarios describing a greater than 2.5 standard deviation from the mean (in either direction, assuming a Poisson distribution). Importantly also, the spatial patterns of these redistributions alter across each scenario. This not only indicates a large cross-variation between each scenario, but also highlights how certain areas of the network become more favoured according to how the agents are defined. It is worth exploring this latter relationship in some further detail.

The free flow least travel time results demonstrates how, when defined in this way, there is a macroscopic-level increase in preference for routes in central London that have been engineered for higher free flow speeds. We observe an increase in A Road usage (generally limited to 30mph in this area), and reduction in the use of other roads (between 20 mph and 30 mph speed limit), compared to the least distance model. This is perhaps to be expected. What is surprising, however, is that this shift is not spatially homogenous, with a greater influence apparent in the western section of the case study area. This would suggest that the relative influence of higher speed routes is less significant in the east of central London, possibly influenced by the nature of the road network in those areas.

The least angular route model demonstrates a greater heterogeneity in the redistribution of traffic across the road network. In this case, however, longer, straighter sections of the roadway are apparently preferred, regardless of their engineering. In Table 1 we can see that roads classified as Minor are more heavily here used than in other models, to the detriment of travel time and distance minimisation. If one considers the findings from the literature review, the resulting route pattern can be considered to represent a cognitively less complex distribution than that produced by the least travel time agents.

Likewise, the least turn route model similarly describes an increase in the heterogeneity of the distribution of traffic, corresponding to an alternative spatial pattern that previously observed. Longer, straight routes are again generally preferred; however, the impact of the distance minimisation means that the overall shift in traffic is less severe than observed in the other scenarios. Again, this routing mechanism does represent, one can consider, a more cognitively simplistic approach to routing. This is demonstrated by a shift away from dense, more complex areas of the road network, as might be expected in reality.

The results from the introduction of limited spatial knowledge similarly demonstrate significant shifts in the distribution of traffic. These limitations applied to spatial knowledge, while not realistic in definition, demonstrate the impact of limiting the choices available to an individual. In the case of the 500-m radius representation, traffic is shown to shift strongly to major routes, as identified by route classifications in Table 1. There is a movement in traffic away from the more complex areas of the network and, as one might expected, towards those engineered for greater throughput of traffic and thus, theoretically, more likely to be known. The impact is lesser in the case of 1000-m radius spatial knowledge, however greater heterogeneity in the redistribution of traffic can be observed. The routes with a greater attraction for flow, in this case, appear to be a product of the locations of origins and destinations across the city. It is most notable that limitations on spatial cognition results in a higher concentration of traffic along major routes, relative to other models, demonstrating a potential relationship between bounded spatial knowledge and congestion formation.

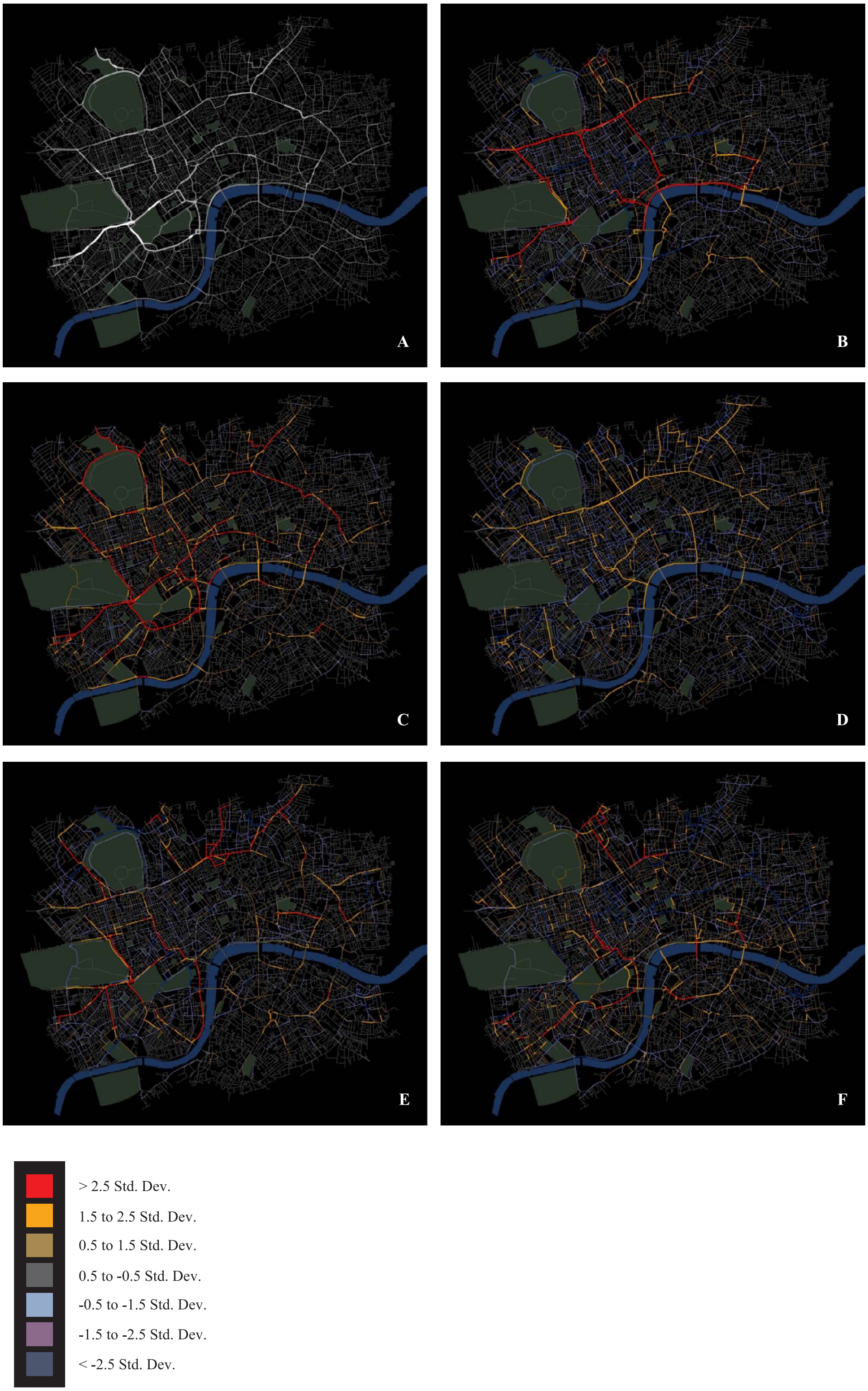


**Fig. 2.** Traffic flow maps for six case studies, agent behaviour defined as below: A: Least Distance, Complete Knowledge – Base Case, demonstrative of volume of traffic flow, with thicker, whiter lines indicating higher flow. B: Least Travel Time, Complete Knowledge. C: Least Angular, Complete Knowledge. D: Least Turns with Distance Minimisation, Complete Knowledge. E: Least Distance, 500-m Radius Survey Knowledge. F: Least Distance, 1000-m Radius Survey Knowledge. Key (left) shows colour scheme for standard deviation from the mean relative to differences from base case in scenarios B-F.

**Table 1**
Distributions of traffic flow across road hierarchy classifications, varying by the specification of agent spatial cognition.

| Agent definition | Percentage traffic flow | | | |
|---|---|---|---|---|
| | A roads | B roads | Local roads | Minor roads |
| *Complete spatial knowledge* | | | | |
| Least distance | 50.45 | 6.16 | 30.25 | 8.78 |
| Least travel time | 54.12 | 5.48 | 28.25 | 7.87 |
| Least angular deviation | 48.10 | 7.73 | 29.07 | 11.56 |
| Least turns with distance minimisation | 53.10 | 5.97 | 27.08 | 9.50 |
| *Bounded spatial knowledge with distance minimisation* | | | | |
| 500-m radius spatial knowledge | 57.04 | 5.46 | 26.38 | 7.25 |
| 1000-m radius spatial knowledge | 50.93 | 6.11 | 30.39 | 8.75 |

## 4. Discussion

Through exploratory agent-based simulation, we have demonstrated how the definition of the cognition of individuals as part of a complex system significantly alters the resulting global predictions of system behaviour. While the models are relatively simple, and do not fully capture the complexity of real-world conditions, they demonstrate how alternative models of driver cognition significantly influence emergent responses in traffic flow. The degree of spatial variation in traffic flow, within the context of fixed models in trip generation and distribution, demonstrates the importance of establishing strong fundamental representations of individual behaviour and bounded rationality when dealing with complex systems of this type. There are naturally different approaches towards modelling these behaviours, but this paper has shown how strongly such assumptions impact the development of simulated flows. These simulations, and emerging evidence elsewhere, presents a significant challenge to the status quo around the development and delivery of transport policy.

Addressing urban movement specifically, the results show a large deviation in traffic distributions where different underlying models of behaviour are considered. This aspect is demonstrated to be important in spite of the restrictions imposed by traffic engineering and restrictions. While no single model of behaviour can be deemed correct or incorrect at this stage, there is a clear argument for further investigation into the true nature of behaviour. The results offer a serious indication that the current underlying assumptions of behaviour that are pervasive within existing transport models be investigated in greater depth and urgency. While promising research is emerging, as outlined earlier, more can be done to question existing assumptions and methodologies. This is particularly true when considering the extensive collection of research coming out of the cognitive science domain. Our results indicate that it is no longer acceptable to simply assume that individuals minimise their journey distance or travel time. These assumptions have fundamental consequences around the transport policies generated through conventional methods.

This work has intentionally not sought to judge these models against real traffic flows. These simple models alone demonstrate a very important point with respect to the definition of models of complex systems. However, it is also clear from the literature survey that, specifically in regard to the experiential nature of spatial knowledge, a great deal of behavioural heterogeneity naturally exists within such systems. The representations of behaviour may not offer the complete solution, but are a step forward in achieving an improved result and demonstrate the viability of incorporating these behaviours in modelling traffic flow. As mentioned earlier, other work around cognitive route choice models and bounded spatial knowledge are beginning to emerge, but it is hoped that this work will expand into the future. Naturally, extensions of these simulations should account for the impact of temporally varying demand, traffic information, road-level congestion, the influence of anticipated delays, and use of navigation devices, in order to fully capture full heterogeneity in driver behaviour.

The results should raise questions for transportation modellers and policymakers. Emerging research, born through an availability of new data, is evidencing the complexity of travel behaviour, casting doubt onto conventional modelling approaches. While there is a security in traditional methods, the simulations presented here demonstrate how simple changes in modelling assumptions in relation to traveller behaviour heavily impacts the generation of traffic flow. In light of this and other research, along with the improved availability of behavioural data, modellers should be seeking to gain a better handle on the true extent of individual behaviour, that integrate natural levels of heterogeneity that better reflect the reality of the environment.

The simple simulations presented in this paper should not claim to represent an alternative approach to transportation modelling, nor call for the end of the use of conventional methods. However, in highlighting heterogeneity in behaviour caused by the representation of driver cognition, this work does suggest that transportation modellers be more mindful of the assumptions embedded in their methods. These findings, along with the wealth of developing research on human behaviour in urban areas, suggest that these principles should be more widely incorporated within transportation modelling. It is clear that future transport models, whether based on agent-based, discrete choice, or assignment approaches, should not remain satisfied with established assumptions of behaviour, and continue to seek better approaches to modelling the complete complexity of traveller behaviour.

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