Article:
Manley, E. and McNamee, D.C. (Accepted: 2026) Brain-inspired representations of urban space. International Journal of Geographical Information Science (IJGIS). ISSN: 1365-8816 (In Press)

https://doi.org/10.1080/13658816.2026.2660988

Brain-inspired representations of urban space

Ed Manley[a] and Daniel C. McNamee[b]

[a]School of Geography, University of Leeds, Leeds, United Kingdom
[b]Champalimaud Centre for the Unknown, Lisbon, Portugal

ARTICLE HISTORY
Compiled April 13, 2026

ABSTRACT

Geography and neuroscience share a core interest in understanding human behaviour in spatial environments. Yet, interdisciplinary collaboration is often limited by differences in methodology and epistemological assumptions. To help bridge this divide, we introduce a translational link between cognitive models of spatial processing in neuroscience and representations of geographic space. Building on long-standing theories that the brain predicts possible futures, the predictive map hypothesis suggests that locations in space are encoded according to their association with possible locations in the future. Here, we adapt a formal instantiation of this idea, the successor representation (SR), to urban space resulting in the geographic successor representation (gSR). We show that this cognitive model of geographic representation produces compelling unique features of urban space while remaining closely aligned with brain mechanisms of spatial processing. We outline several promising directions for extending this work, and propose that the gSR and its variants may provide spatial representations capable of supporting deeper integration between geographic and neuroscientific research.

KEYWORDS
spatial cognition, computational neuroscience, cognitive maps, spatial representation, street networks

1. Introduction

There is broad evidence that the structure of geographic space has a deep connection with human spatial behaviour (Golledge 1992, Coutrot *et al.* 2022). Urban design shapes how we mentally understand space, how we navigate through it, and even how we respond emotionally and physically within it (Hillier and Iida 2005, Hackman *et al.* 2019, Pykett *et al.* 2020). The structure of urban space has an influence on geographic phenomena, as movement choices give rise to the emergence of crowding, congestion, and other collective social dynamics (Batty 2007, Manley and Cheng 2010). With emerging technologies and new data collection methods, it is now possible to observe behaviour across real-world environments in far greater detail. This creates unprecedented opportunities to rigorously link geographic space, human behaviour, and sociospatial processes with ecological validity. Practically, such links could motivate new, and enhanced, designs of urban systems (Pappalardo *et al.* 2023).

CONTACT Ed Manley. Email: e.j.manley@leeds.ac.uk

Yet fully evidencing the impact of the space on spatial behaviour and, in turn, geographic phenomena requires a robust set of explanatory variables that quantitatively explain the precise influences of geographic form and structure on human navigators. For decades, geographers have relied upon Euclidean space and geometric features as an adequate representation of human-environment relationships. Several attempts have been made to challenge (Tobler 1976, Golledge and Hubert 1982) and propose alternatives (Cohn 1997, Tomko *et al.* 2007, Goodchild *et al.* 2007, Yuan 2024) to the Euclidean representation. The most widely used alternative to the Euclidean model of space is the 'spatial network', where feature associations and proximities are derived from topological connections (e.g. between road intersections) (Barthélemy 2011). Spatial networks have been employed in GIScience and other fields, yielding a set of measures suitable for spatial behavioural analysis, such as travel time (Salonen and Toivonen 2013). Measures of centrality (Crucitti *et al.* 2006) for example, which differentiate network features based on their location and connectivity, have shown associations with flows of pedestrians (Penn *et al.* 1998), commercial success of a shops (Porta *et al.* 2012), and the occurrence of crime (Summers and Johnson 2017). The definition of spatial networks from conventional geospatial data has had considerable coverage in the literature, yielding a variety of approaches, many of which are based on Euclidean distance measures (Porta *et al.* 2006, Jiang *et al.* 2008, Jiang and Jia 2011).

Despite advances in methods for quantitatively describing space, we still lack a fundamental grounding that connects these measures to the cognitive mechanisms underlying human behaviour. Without this grounding, targeted design interventions to improve particular conditions for the human urban experience often lack robust causal support. While existing experimental studies have provided some valuable conceptual and empirical measures (e.g. findings from (Dalton 2003) supports use of angular minimisation), they rarely establish direct links between environmental structure and the perceptual and cognitive navigational processes that guide everyday spatial behaviour. There is a growing suit of evidence directly linking brain function with geographic space. Coutrot and colleagues demonstrated how the street network structures experienced during childhood influenced future navigation abilities (Coutrot *et al.* 2022). This study identified the street network entropy of a city (Boeing 2018) as a determinant of navigation behaviour (while other network measures were shown not to have an effect), but it is significant that this factor was not originally developed with a link to human cognition. Findings from neuroscience have show how Euclidean distances alone are a poor predictor of geographic navigation behaviour, with evidence of non-Euclidean representation across several studies (Warren *et al.* 2017, Baumann and Mallot 2023, Peer *et al.* 2024). These findings have prompted interest in how non-Euclidean or graph-like models influence spatial navigation (Chrastil and Warren 2014). Of most significance to geographic analysis is a study of London Black Cab drivers, which showed how local transition entropy and the successor representation (SR) of the street network plays a role in route planning efficiency (Fernandez Velasco *et al.* 2025). The SR is particularly significant as it stands out as the only measure with an empirical and theoretical link to neural mechanisms relating to spatial cognition. In other studies, the SR is shown to replicate hippocampal place cell firing patterns, as a prediction of future movement, and can reproduce activation of grid cells (Stachenfeld *et al.* 2017). The SR has the potential to capture basic cognitive representations of geographic space that underpin other spatial cognitive processes.

Beyond its use in behavioural studies, the application of the SR to interpreting geographic space has not been explored, and therefore presents an opportunity for geographic analysis in enhancing the representation of cognition of space. The benefits are not only to geographers. The development of cognitive representations of space are of potential utility in interpreting behaviour in real-world spaces. Thus, constructing an SR for geographic space has the potential to enhance the ecological validity of research on environmental cognition across a range of real-world settings and disciplines.

This paper examines how the successor representation (SR) can be defined and applied within geographic space. We begin by reviewing conceptual parallels and methodological developments in GIScience and neuroscience, which have largely progressed in isolation. We then outline how SR, as a model of brain activity, yields concepts that can be translated into geographic space, and introduce a methodological framework for doing so – defining the geographic successor representation (gSR). Next, we present an initial implementation of this framework, and analyse the measures that emerge from it. We conclude by considering the broader value of the gSR approach for GIScience and identifying directions for future research.

2. Background

2.1. *Geography and neuroscience*

Geography and neuroscience both seek to understand how humans move through space. Although geographers may be more interested in the determinants and implications of spatial cognitive processing, while neuroscientists concentrate more on the neural circuitry that supports navigation (Moser *et al.* 2017), the two fields share a common conceptual terrain. Central to this overlap is the concept of the *cognitive map* (O'Keefe and Nadel 1978): the idea that space is represented within the brain, and that such spatial representations underpin human navigation and behaviour. Yet barriers to collaboration remain, reinforced by a lack of common methodology and representational conventions.

The concept of the cognitive map has been adopted within geography as a contrast to objective measures of space, reflecting the concept that geographic features, interpersonal variation and prior experience are inherent in shaping spatial behaviour. Several influential works have explored how geographic features, such as landmarks, areas (e.g. neighbourhoods), boundaries, and surfaces (e.g. topography), influence or are inherent to the cognitive map. Many studies have examined how cognitive maps are produced and encoded within this conceptual framework, incorporating questions of individual perception (investigated through diverse methodologies), language, and both individual and group differences (Ishikawa and Montello 2006). As large movement trajectory datasets have become available in recent years, further evidence regarding how these concepts shape human cognition has emerged (Bongiorno *et al.* 2021, Manley *et al.* 2015a). Where models of cognitive spatial representation do exist, these have tended to adapt concepts from spatial cognition into geographic features (Manley *et al.* 2015b, Filomena *et al.* 2020) or sought associations with spatial cognition after their inception (Penn 2003, Kim and Penn 2004). Research evolving from robotics has sought to construct topological representations of cognitive space, but without implementation in geographic models (Kuipers *et al.* 2003). Furthermore, these prior models make no formal connection with brain processes, and have tended to conflate low-level cognitive perception with higher-level inference and reasoning (e.g. travel times). There remains an opportunity to derive a robust methodology for representing cognitive maps that formalises a link to the brain, while enabling systematic integration with GIScience.

In neuroscience, the concept of the cognitive map has been more grounded in the brain structures that inform spatial cognition, primarily in the context of spatial navigation (Behrens *et al.* 2018). As a result, neuroscience has established a comprehensive model of brain circuitry supporting spatial navigation, primarily based on the hippocampal formation, which is proposed to encode cognitive maps (Witter *et al.* 2014). In particular, the hippocampus contains neurons tuned to specific spatial locations known as place cells (O'Keefe and Dostrovsky 1971), while neurons in the entorhinal cortex, monosynaptically connected to hippocampal neurons in a recurrent circuit, exhibit hexagonally organized firing fields across an environment (Moser *et al.* 2008). Place and grid cells, along with a variety of other cell types identified in the entorhinal-hippocampal loop, such as boundary cells (Solstad *et al.* 2008, O'Keefe and Burgess 1996) and goal-vector cells (Sarel *et al.* 2017), form a diverse set of spatial coding mechanisms in the brain that collectively represent a cognitive map of external space.

Despite the advances in the neuroscience of spatial cognition, there are relatively few ecologically valid studies in humans, providing evidence of their role in navigation in real-world geographies. Technological innovations, such as mobile EEG (Electroencephalography), support this transition (Stangl *et al.* 2023), but to date computational neuroscience models of spatial cognition have not been implemented in geographic contexts.

Despite similar interests, shared taxonomy, and potential translational benefits, effective collaboration between geography and neuroscience remains relatively scant. A point that has been highlighted by geographers several times in recent years. Montello (2009), Portugali (2018), Downs (2018) and Manley *et al.* (2021) highlight that geographers could benefit from closer collaboration with cognitive neuroscience, and better alignment with work on understanding brain structure and function. Schinazi *et al.* (2016), who also highlight the potential for collaboration but suggest presently there exists a "tenuous relationship at best", suggest geographers take the theory-driven approaches inherent to neuroscience to cognitive geographic problems. Pykett *et al.* (2020) reflected on the role neuroscience can play in broadening our understanding of factors such as urban wellbeing and stress, in the context of critical geographic approaches.

According to Wilson (2022), interdisciplinary collaboration requires a shared view of a system, a theory of how the system works, and the methods or models by which to represent that theory. In considering collaboration between neuroscientists and GIScientists, while the first two components may be established, both neuroscientists and GIScientists understand that humans act within geographic space influenced by a cognitive map, the third component has been lacking. Recent developments in both computational neuroscience and GIScience suggest that a pathway for interaction may be within reach.

Recent years have seen rapid advances in the theory, evidence, and models underpinning cognitive computation. In this context, a significant focus has resided upon modelling the cognitive map, and its role in structuring knowledge and encoding relationships between entities (Behrens *et al.* 2018, Burak and Fiete 2009, McNamee *et al.* 2021). It is increasingly recognised that the cognitive map has relevance in both spatial and non-spatial domains (Whittington *et al.* 2022), encoding structures of spatially associated features or abstract concepts (such as personal relationships) (Peer *et al.* 2021). These studies use reinforcement learning (RL) to model mechanisms for cognitive computations based on cognitive maps (Behrens *et al.* 2018). Reinforcement learning is the theory of how an agent learns to select actions in an environment in order to maximize the "reward" the agent receives (Sutton and Barto 2018). For example, the agent may receive reward by moving selecting actions to move to particular target environment positions. For example, a successful transition to a target spatial location would result in a positive reward. Remarkably, a growing suite of research has demonstrated how some RL models can predict patterns of human cognitive activity. Several RL models have presented evidence that links value estimation with neural activation during spatial navigation (Momennejad 2024, Behrens *et al.* 2018, Stachenfeld *et al.* 2017). Of particular significance has been the application of the successor representation (SR) methodology (Daw 2012) to predicting hippocampal activity. This approach has been shown to predict observed activation patterns of place and grid cells (Stachenfeld *et al.* 2017).

These findings have provided a formal computational link between cognitive maps and how the brain generates rational behaviour, with implications for various academic domains, including geography. Rather than considering maps as Euclidean (as originally proposed by Tolman (1948), and later by O'Keefe and Nadel (1978)), these RL models associate the map to a set of states (e.g. places, landmarks) and transition probabilities, linked through a graph-like structure. This principle is not only an artifact of an RL model, several studies point towards a graph-like structure to the cognitive map (or "cognitive graph") (Peer *et al.* 2021, Chrastil and Warren 2014), as an explanation of non-Euclidean navigation behaviour (Warren 2019). It is argued that Euclidean and non-Euclidean, graph-like structures may exist in parallel in the brain, serving different purposes (Peer *et al.* 2021). Now we have a much stronger link between the idea of the cognitive map, its underpinning neural structure, and how it can be modelled.

A significant challenge in developing RL relates to representation (Whittington *et al.* 2022). How we abstract states and transitions from real-world perception is inherent to how we model the cognitive map, and thus predict its role in shaping behaviour. Considerations of representation is not a new concern for GIScience (Yuan 2001, Goodchild *et al.* 2007), and there is an opportunity to consider how our existing models of space relate to the production of a cognitive map. To date, despite the extensive work on RL in the context of spatial navigation and cognitive maps, there has been no explicit linkage to geographic data. The production of a geographic model of cognitive space, based on RL, has significant potential to *a)* strengthen the use of perceived differences in distance and location arising from spatial cognition in GIScience, and *b)* produce avenues for collaboration between computational neuroscience and geography.

2.2. *Reinforcement learning and successor representation*

Reinforcement learning (RL) aims to characterize the process of learning how to select actions appropriately. This learning process takes place within a Markov Decision Process (MDP), which specifies the learning environment (i.e. the states $s \in S$, actions $a \in A$, and rewards $R(s, a)$) for an RL agent which receives input about the environment state and selects actions (Sutton and Barto 2018). A prominent class of RL algorithms, known as *value-based* reinforcement learning, aims to learn a value $V(s)$ for each state (s_0) that reflects the expected sum of rewards over future states (s_t):

$$V(s_0) = \mathbb{E}\Big[\sum_{t=0}^{\infty} \gamma^t R(s_t) | s_0 = s\Big]$$

where γ is a discount factor that downweights distal rewards. The transitions between states is controlled by a policy π, which, as the learning process progresses, is adjusted to increase the probability of the agent entering states with high estimated value.

Within the context of spatial learning, the design of the environment is an important consideration. The state within an MDP in a spatial context could represent a physical location, such as a landmark, place, street intersection, or even a vista (Yan *et al.* 2019). More abstractly, it could represent a status, such as 'available', 'vacant', or a vector of values representing a condition which may not be directly observable to the agent.

RL algorithms are conventionally divided into two classes, namely *model-free (MFRL)* and *model-based (MBRL)*, with distinct implications for the efficiency and flexibility of the resulting learning. Under MFRL, the agent moves through an environment, undertaking trial-and-error in learning the best combinations of states and actions that maximise reward. Within an MBRL setting, the agent learning is directed via an internal model of the environment, which enables a planning of action selection without actually exploring the environment physically (McNamee and Wolpert 2019). The MBRL agent effectively contains a map of the environment, which grants a degree of flexibility, since the agent can plan a novel route for a new goal. However, learning a model of a large environment is computationally costly. An MFRL on the other hand, does not build a map and is less flexible since it needs to adapt its policy based on experiences from environmental interactions whenever the task, or reward function, changes.

We suggest that the limits of both approaches have presented a barrier to the uptake of RL more widely within GIScience. MBRL requiring extensive calibration of the internal model in each new geographic setting. Each new context is different and learning must begin from scratch. This does not align with our understanding in geography, where we know that performance of one task (e.g. going to work) can support or enhance learning of how to do another task (e.g. finding a shop). Although, there is much research in RL agents on multi-task performance where algorithms are developed to improve performance transfer between tasks (Schaul *et al.* 2015). We also understand that some facets of behaviour are common across spatial contexts, including in previously unseen environments. On the other hand, MFRL does not construct any map-like model of space, which loosens the attachment to a specific environment. However, there are a limited number of applications that are context-free in geography. While applications in spatial environments are feasible (e.g. (Chen *et al.* 2019)), these are generally within constrained settings, and are not reflective of how humans undertake similar navigation tasks (e.g. in reference to internal or external maps).

The successor representation (SR) (Dayan 1993) provides an alternative approach to model-free and model-based reinforcement learning, with significant potential implications for geography. The SR encodes the structure of an environment in the form of future state occupancies. That is, the representation of a state s is a vector corresponding to the rate at which the agent will occupy all states in the future. Many of the tenets of geographic analysis are underpinned by principles of dependencies between current and associated locations. Spatial relations are shaped by characteristics such as proximity (Tobler 2004), attraction (Wilson 1971), and propensity to generate flows (Hillier and Iida 2005), among others, that are replicable across geographic contexts. The SR provides a structure that can embed spatial relations as a 'prior' within the RL value function, avoiding overspecifying a model for a location, such as with MBRL, or rejecting all notions of geography, as could be the case with MFRL.

This beneficial characteristic feature of the SR is evidenced by the decomposition of the value function V_π according to:

$$V_\pi(s) = \sum_s M_\pi(s, s')R(s') \tag{1}$$

where π is the policy, R is the reward function, and M_π (the SR) is the expected discounted occupancy of future states s' following the state s:

$$M_\pi(s, s') = \mathbb{E}_\pi\left[\sum_{t=0}^{\infty} \gamma^t \mathbb{I}(s_t = s')|s_0 = s\right]$$

where $\mathbb{I}(s_t = s') = 1$ if $s_t = s'$ else 0, at time t. M_π is a matrix with $|S|$ rows and $|S|$ columns where $|S|$ is the number of states. Thus, each row corresponds to an environment state, and the row vector is the expected number of times other states will be occupied in the future. The critical implication of this decomposition (Eqn. 1) is that, if the reward function is changed e.g. from R to R', corresponding to a change of agent goal or task, then the value function can be rapidly computed as the matrix-vector product $V'_\pi = M_\pi R'$. This endows SR-based RL (SRRL) with the flexibility to rapidly adapt to changes in the reward function. In contrast, MFRL agents would have to explore the environment in order to understand the new task R' while MBRL agents would have to use more laborious internal modeling algorithms (such as Q-DYNA) in order to update the value function to V'_π. While the SR can be computed analytically as $M_\pi := (I - \gamma T)^{-1}$, it can also be learned online through environmental interactions via temporal difference (TD) rules (Sutton and Barto 2018, Stachenfeld *et al.* 2017).

A body of literature has emerged in computational neuroscience that links the SR to neural activity in the brain during spatial navigation (Stachenfeld *et al.* 2017, Russek *et al.* 2017). The SR provides the basis for encoding both efficiency and flexibility in learning and decision-making as apparent in neural processing (Gershman 2018). The principle hypothesis is that the firing fields of grid cells and place cells, cell populations that are proposed to encode a spatial representation in the brain, are structured in a way that relates current position to future future. For example, the activity of place cells are known to be skewed in the direction that an animal is likely to travel (Mehta *et al.* 2000). Grid cell activity also gradually shifts over experience to positions that animals are likely to occupy. Therefore, rather than the cognitive map representing a static structure of locations, the proposal is that the map encodes potential future states, facilitating the navigator with a degree of foresight on where to go next (Boccara *et al.* 2019). The link between these future-oriented spatial representations in the brain and the SR is that the SR provides a formal predictive theory regarding how and why such neural receptive fields should be present relating current and future positions (Stachenfeld *et al.* 2017).

The SR may hold broader significance for geography beyond serving as a model for cognitive map formation. By encoding the associative structure between spaces, it enables the development of novel cost measures that capture shared use, accessibility, or connectivity. In this sense, the SR offers an alternative to conventional distance metrics—one grounded in the principles of cognitive neuroscience. This shared foundation provides a compelling basis for integrating geographic and neuroscientific approaches to spatial representation and behaviour.

3. Framework for the Geographic Successor Representation

The previous section evidences significant potential value in the construction of a GIScience methodology for successor representations. In integrating the SR methodology within geographic spaces, we can theoretically begin to construct geographic representations that reflect the neural activation patterns of humans navigating the space. Furthermore, the resulting measures arising from such a model have the potential to identify salient features of geographic space from geographic representation alone, similar to how network centrality measures imply importance (Crucitti *et al.* 2006, Porta *et al.* 2012). For the purpose of extending the SR methodology to geographic space, and in view of the potential geographic properties emerging from the model, we will refer to the geographic Successor Representation (gSR). There are several factors to consider and explore in the construction of the gSR. These relate to how to embed geographic spaces within the formal framework of Markov Decision Processes (MDP) and methodological concerns regarding the meaning and specification of reward functions and the selection of model parameters. This exploration of possible configurations of the gSR is not exhaustive, and aims to encourage further exploration in future work.

3.1. *States and Actions*

How should states $s \in S$ and actions $a \in A$ be defined in the geographic context? A summary of possible configurations is provided in Table 1, supported by previous geographic thinking on these structures (Golledge 1998).

The state is the basic unit from which the gSR is constructed. As such, while anchor points and landmarks may capture a richer description of likely cognitive activation in geographic space, our subjective definition of their importance pre-supposes their location. The gSR allows us to reconstruct hippocampal activation from basic spatial configuration, activation that may predict the locations of landmarks or semantically-important features. Indeed, such activation in locations invoked by urban form, may play a role in defining the semantic prominence (or aesthetic design) of a landmark. As such, it is clear that a gSR should be constructed on the most basic unit in geography. This unit could relate to a grid cell in raster space, as is often adopted in computational neuroscience, however there is little evidence that a grid cell has relevance to spatial movement decisions. Given the focus on larger scale conceptions of space (e.g. the perception of distance across a geographic region) that arise through movement and exploration, we propose these units to be intersections or road segments. Road network representations constrain possible transitions across space to those between intersections. This abstraction aligns with the objective of considering movement at the larger spatial scale, rather than at the scale of individual streets.

Actions reflect the possible transitions (or movements) between states, weighted according to a transition probability (encoded within the transition matrix T). Given the definition of a state as an intersection, an action would relate to the adjacent intersections, connected by road segments. In other words, this would arise in the *primal* topological representation of the road network (Porta *et al.* 2006). If we were to define a state as a road, an action would refer to a transition into an adjacent street (e.g. a turn). This is referred to as the *dual* topological representation of the road network (Porta *et al.* 2006).

In the context of geographic spatial navigation, the likelihood of transitioning between two states is determined by a distance-related cost imposed at an intersection,

Table 1. Features of state space and candidate GIS features for use in gSR, with supporting evidence of relevance and data availability measured in three categories (a: widely established data and methodology; b: partially established methodology or data; c: weakly established data or methodology).

Param.	**Feature**	**Description**	**Evidence**	**Avail.**
State S	Intersection	Decision point	Lynch (1960)	a
	Road	Salient or semantic object	Lynch (1960)	a
	Axial line	Visual or cognitive feature	Penn (2003), Turner (2007)	b
	Natural or named streets	Semantic or cognitive feature	Jiang and Claramunt (2004), Jiang *et al.* (2008)	b
	Landmarks	Landmark-based routing	Lynch (1960), Raubal and Winter (2002)	c
	Anchor points	Variety of personal features	Couclelis *et al.* (1987)	c
	Grid cell	Arbitrary segmentation of raster space	None	a
Action A	No weight	All actions equally probable	None	a
	Metric distance	Distance minimisation	Many	a
	Time	Time-based cost	Many	a
	Angular deviation	Turns away from current direction inhibited	Dalton (2003), Montello (1991)	a
	Target deviation	Turns away from target destination inhibited	Bongiorno *et al.* (2021)	b

and as such, the dual representation is adopted for the gSR. The simplest assumption would involve applying no variation in cost between subsequent states, in other words, assigning a cost of 1 to all transitions. This approach would neglect any variation between road and junction types, and therefore ignores evidence from prior studies that distance costs are are a product of neighbourhood design and structural characteristics (Manley *et al.* 2021). It is also reasonable to consider Euclidean distance costs at the scale of local transitions. Evidence suggests Euclidean distances are encoded within brain, and used to determine continuous movements in open spaces (Peer *et al.* 2021, 2024). Measures that capture angular deviation, either in relation to the road network or a perceived target location (e.g. a city centre), might better encode likely transitions between adjacent states, and are simple to compute. In all cases a transition probability can be constructed by:

$$p_{ij} = \Pr(X_{n+1} = j \mid X_n = i)$$

3.2. *Learning Rates and Transition Biases*

Future discount rates and transition biases (introduced through rewards) can also play an important role in the construction of the gSR, and provide pathways to incorporating behavioural determinants of spatial learning. Table 2 summarises some of the potential configurations of these parameters in construction of the gSR.

The discount rate (usually γ) determines how much distant states are discounted in estimating value. Higher values (e.g. $\gamma = 0.99$) impose lesser constraints on the value of distant states compared to low values. The discount rate can be useful in shaping the scale at which decisions are taken. As noted by Momennejad and Howard (2018), the discount rate can potentially be used to control the scale at which a decision is taken. When navigating across larger spaces, or, where we can expect to visit states quite far from an originating state then a high discount rate value would be imposed, reducing the discount on distant states. Under conditions where only immediate states are relevant, then a larger discount can be imposed corresponding to a lower discount parameter. To borrow an example from Momennejad and Howard (2018), where one is to consider where to buy lunch near one's office, we might impose a higher discount on distant states. But if we are considering a journey across town, we would more likely want to make use of all potential state relations to aid navigation, and thus impose a lower discount on distant states. Although theoretically feasible, there is an absence of empirical evidence linking discount rate to scale and task type, meaning its specific definition may be challenging. A similar concept to discount rate in GIScience is *distance decay*. Distance decay may be implemented as the decay exponent within a spatial interaction model, or in defining the kernel bandwidth within a Geographically Weighted Regression (GWR) model. While decay functions similarly integrate the value of distal states, they are not used in defining future transitions.

Transition biases can be imposed through introduction of rewards, as well as adjustments to transition costs and state saliency. In the context of the gSR, transition biases can be used to account for different characteristics of space, known to be important to movement or spatial cognition. This could include introducing rewards that naturally encourage learning that shape the gSR towards usually particular paths, such as fast, safe, or reliable routes. Biases could also theoretically relate to possible destinations in space (e.g. workplaces, points-of-interest), or sub-goals, bottlenecks (e.g. bridges), and landmarks, that are likely to feature during path planning. Setting the biases in these

Table 2. Other parameters of the gSR, with exemplar approaches and parameter ranges.

Parameter	Approach	Treatment
Discount rate γ	Low discounting of distant states, favours longer-distance navigation	∼0.95-0.99
	High discounting of distant states, favours short-distance navigation	∼0.5
Rewards R	No rewards assigned	None
	Destinations (e.g. points-of-interest, workplaces)	By importance
	Routes (e.g. motorways)	By reliability
	Bottlenecks and sub-goals	By structural character

contexts is feasible, and clearly adds behavioural realism, but there is limited empirical evidence to support their definition. As mentioned in 2.2, rewards (R) are decoupled from the computation of the SR, and used in the calculation of $V(s)$ (Eqn. 1). The exclusion of rewards allows the SR to be computed on the transition matrix, according to $M = (I - \gamma T)^{-1}$, as outlined in 2.2. This approach implicitly assumes that the SR is learnt through random walks across the state-space, where rewards are equally distributed. Within GIScience, transition biases are generally limited to edge weights applied to network models. These models are typically uniform (e.g. the same cost unit applied to each weight), and there is no systematic pathway for integrating sub-goals or rewards.

3.3. *Computation and Properties*

The computation of the gSR follows the approach outlined in 2.2, whereby the matrix M is computed from identity I and transition T matrices. This derivation is similar to that used elsewhere (e.g. Stachenfeld *et al.* (2017), Dayan (1993)), and is appropriate where the transition matrix is fully known. For the purposes of introducing the concept and the limitations of existing data explained above, we ignore rewards in the construction of the gSR in this instance. This means we generate a model that is essentially averaged for a population, although without a behaviourally realistic displacement of people and activities within the space. The gSR is therefore generated solely on the basis of the state-space we adopt and not any particular behaviour within the space. The implications of these design choices are discussed in more depth in the Discussion later.

There are several notable properties of the gSR. The matrix products of the gSR M contain the expected discounted occupancy rates for every future state s' from origin state s. This matrix yields four properties with potential value in GIScience:

- **The gSR (M)** We propose the gSR as a formal instantiation of a cognitive map of geographic space, directly related to neural activity underpinning spatial processing. This predictive form of the cognitive map provides a basis for predicting future movements (e.g. navigation choices). Further gSR variations based on environmental and behavioural biases can be used to explore interpersonal variation in map structure.

- **Activation intensity ($C(s)$)** Next we derive the spatial extent of $M(s)$ for all states (or network nodes), yielding a relative measure of the intensity of the activation to local areas. States with higher activation intensity are those with a heavily skewed distribution in its $M(s)$ vector. We define a threshold for capturing the intensity from s, based on density of highest $M(s, s')$ measures, selected according to a threshold τ_s. Formally, this measure can be defined as:

$$C(s) \;=\; \mu\Big(\mathrm{conv}\big(\{s' \in \mathcal{S} \;:\; M(s,s') \geq \tau(s)\}\big)\Big)\,, \tag{2}$$

  where μ represents a Lebesgue measure (e.g. area) of the state space M and τ_s is a definable threshold.
- **Predictive visitation ($M(s, s')$)** By capturing the future occupancy from one state to another, the gSR encodes a measure of future visitation likelihood from state s to state s'. The strength of the connection between two states in the SR is indicative of the cognitive association between them, and thus provides a measure of cognitive distance that can be contrasted against conventional distance indicators.
- **Predictive visitation inequality ($B(s) = \sum_{s'} M(s, s') - M(s', s)$)** For each distance component $M(s, s')$ there is an alternative $M(s', s)$, which provides an opportunity to consider asymmetries in state-state associations. This can be computed for each state-state pair or, as we propose, as a sum difference for each originating state to all other states. A negative $B(s)$ suggests a location with more expected visits from all other states, a positive $B(s)$ suggests a location with more expected visits elsewhere. We can view these as analogous to potential state-space bottlenecks, where many paths converge on a single state, potentially akin to commonly-known locations on the network. This property of the SR has not been explored in navigation contexts previously.

4. Implementation

4.1. *Case Studies and Data Sources*

In order to demonstrate the validity and potential of the gSR approach to GIScience, we present several case studies for London and Chicago. These cities were chosen to ensure diversity in street network entropy (Boeing 2018), an important factor in shaping navigation (Coutrot *et al.* 2022), geography, and city size.

Following the explanations outlined in the Methodology, the precise definition of the gSR methodology is outlined as follows. The dual graph form is adopted for the analysis, such that states ($s \in S$) relate to road segments and actions ($a \in A$) relate to transitions between roads (e.g., turns). Transition probabilities (T) are calculated on the basis of angular deviation between consecutive road segments. To be precise, for successive road states s_i and s_j, the probability of transition is defined as $T_{ij} = 180 - d_{ij} / \sum_{k \in K} 180 - d_{ik}$, where angular deviation d is taken to be in degrees, and K incorporates all potential next states from s_i, including s_j. For the reasons outlined above, we take a simple approach to defining discount rate and rewards. Discount rate is defined as $\gamma = 0.99$, which favours identifying links across large spatial scales. Rewards are left undefined for these case studies, and as such, the gSR M is computed from the transition matrix T as $M = (I - \gamma T)^{-1}$.

The production of the gSR according to the definitions above can be accomplished mainly through two open-source Python packages, *osmnx*, which uses OpenStreetMap data to construct street network graphs and simplify topologies, and *momepy*, which converts *osmnx* graphs into the dual form. The code used to develop the gSR has been made available on Dryad (see Code Availability Statement).

4.2. ***Properties of the gSR***

The gSR yields a matrix that maps the cognitive association between states, or locations in this context. Evidence from neuroscience suggests that a column of this matrix $M(s, s')$ replicates place cell activity at state s. The remainder of this section reviews various derived properties of the gSR, and considers the value of the representations in deriving relevant facets of urban form. As there is no equivalent measure against which cognitive association, or expected use, may be compared, the measures derived from the gSR are compared against spatial indicators that indicate structural connectivity or potential use. The similarities or discrepancies that arise against conventional measures can help indicate the relative novelty of the measure, and point to opportunities for wider utility.

4.2.1. Activation intensity

The gSR matrix M with entries $M(s, s')$ captures the relationship between a state s and all future possible states s', and thus, for each state s provides an indication of the spatial intensity of activation in relation to nearby successor states s'. The properties of the distribution of $M(s, :)$ may be informative as a measure of the structure of the city. For example, a state which relies on several others to enable access to the wider city (e.g. a dead end road, or tree-like structure) would result in a heavily skewed $M(s, :)$.

We can assess the intensity of the distribution of $M(s, :)$ according to the spatial density of the highest values. For this purpose, we set τ_s to take the top 1% of successor states s' from state s, according to values in $M(s, s')$. We then take the convex hull of this subset of states, and calculate its area. The total area of this convex hull is assigned to the originating state s to yield a measure of spatial intensity $C(s)$. The smaller the area, the more intense the peak in activation around that particular state. This measure of intensity is then mapped for each state, to yield a spatial distribution of state activation. The map of activation intensity for London and Chicago are shown Figure 1.

The figures exhibit considerable heterogeneity in spatial activation intensity, with several distinct regions of high intensity in both settings. The areas of higher intensity show a stronger relationship between local spaces and expected visits than elsewhere, and as such, appear to relate to higher local connectivity. Assessing the two contexts, we see a correlation between this gSR intensity measure and local commercial districts in London (e.g. Mayfair, Covent Garden, Bank) and Chicago (e.g. Fulton Market, River North).

There appears to be some association between higher intensity and road network density, so we take the Pearson (r) and Spearman (ρ) ranked correlations between intensity $C(s)$ and road network density, taken here as a count of other roads within a 250 metre radius. The correlation scores are r = -0.72 and ρ = -0.57 in London, and r = -0.30 and ρ = -0.06 in Chicago, evidencing only partial association between network density and intensity. This may be explained by the locations of lower intensity, which

(a) London (b) Chicago

Figure 1. Spatial distribution of activation intensity $C(s)$ in London and Chicago, based on the area of the convex hull covered by the top 1% of $M(s, s')$ values for each road state. Spatial intensity is higher for areas with more local connectivity and correlates with commercial districts for example.

tend to be associated with simpler geometries (e.g. highway and overpasses, bridges, roads through parks), being less well integrated with the wider road network structure. These areas are more strongly associated with environmental restrictions that support for longer distance movements.

4.2.2. Predictive visitation

The association between states captured in $M(s, s')$ can be considered a prediction of visitation from state s to state s'. On a neural basis, this measure can be considered analogous to the prediction of place cell activity, in that place cell firing predicts association with nearby, future locations (Stachenfeld *et al.* 2017). As such, it should be compared against other conventional geographic measures of proximity. In this case we consider four alternatives distances (d), three of these are calculated as pairwise optimal paths computing using Dijkstra's algorithm, based on metric distance, segment counts, and angular change, the fourth distance measure used is Euclidean distance. Pearson (r) and Spearman (ρ) ranked correlations are calculated between $M(s, s')$ and $d(s, s')$.

Across all node pairs, the correlation coefficients are as shown in Table 3. As one would expect, there is a strong ranked correlation between the distance measures and predicted visitation. The negative correlations are indicative of the fact that higher $M(s, s')$ measure, that is states that are afforded greater value, are related those that are closer within $d(s, s')$. That is to say that conventionally nearer features are more likely to visited from any given state. However, linear correlation measures suggest poor alignment in all instances, reflecting potentially different distributions of the distance measures. Results are consistent across both case study cities. Figure 2 shows these data for two sample states from both cities. The figures show a skewed distribution in gSR measures, signifying a strong bias towards local features relative to other distance measures. Relatively little variation in gSR values can be found at states more than around 1000 metres from the origin state. These distributions suggest that the gSR

Table 3. Correlations for all states between $M(s, s')$ and conventional distance measures

City	Distance measure	Pearson r	Spearman ρ
London	Topological metric distance	-0.41	-0.96
	Cumulative angular change	-0.45	-0.94
	Topological segment count	-0.45	-0.98
	Euclidean distance	-0.23	-0.23
Chicago	Topological metric distance	-0.49	-0.94
	Cumulative angular change	-0.51	-0.98
	Topological segment count	-0.56	-0.96
	Euclidean distance	-0.19	-0.27

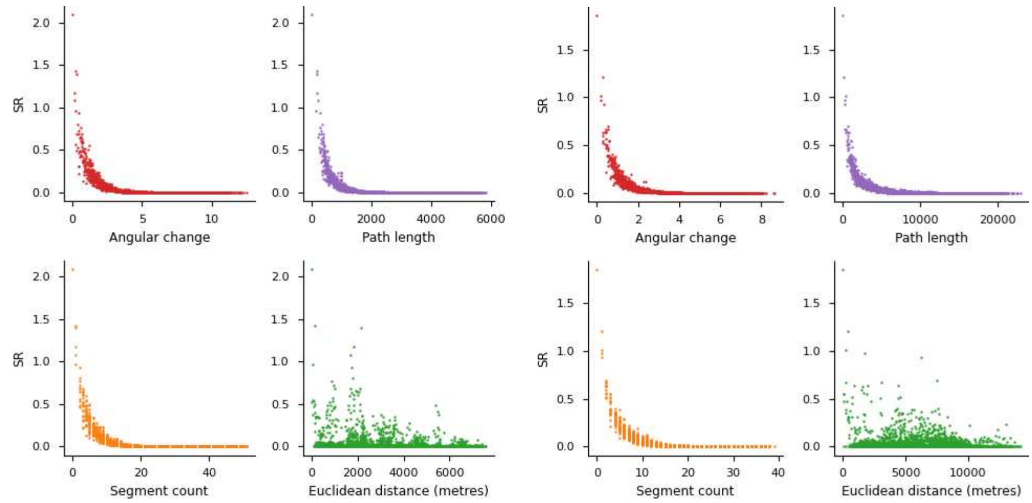
does track distance, but offers a notable alternative distance measure to convention, aligned to ranked distance along streets, but strongly biased by local context. While there remain several methodological and conceptual factors meaning this measure can not be yet proposed as a reliable estimate of any individual's place cell activation in geographic space, it does provides a theoretically grounded basis for producing distance estimates inspired by brain cell activation.

4.2.3. Predictive visitation inequality

While predictive visitation ($M(s, s')$) provides a measure of likely association based on the gSR, measures of inequalities in predictive visitation highlight areas of potential significance. Inequality, in this context, reflects an asymmetric visitation relationship between pairs of states, such that $M(s, s')$ is different from $M(s', s)$. Where this occurs consistently for a single state, or where there are more expected visits to one state than others, may be indicative of the relative importance of a feature. This indicator is termed $B(s)$ in the Methodology above.

The production of $B(s)$ for our case study cities is shown in Figures 3 and 4. The maps highlight several conventionally 'well-known' routes and locations in each city. River and rail bridges are highlighted in both contexts, as are major routes (e.g. Euston Road, Whitehall, and Regent's Street in London, North Ogden in Chicago) and intersections (e.g. Trafalgar Square, the Rotunda). These features appear to be where located features hold high local importance, due to the confluence of local movements, essentially forming 'bottlenecks' in the network. Several locations indicate lower prominence than may be expected based on their infrastructure. These include the I-90 and I-41 in Chicago, and Hyde Park Corner in London. While these locations are important from enabling longer distance movements, they maybe relatively less important for enabling local movements, especially considering the availability of alternative routes nearby. As such, while these infrastructure enable faster movement across the network, they present less of a bottleneck.

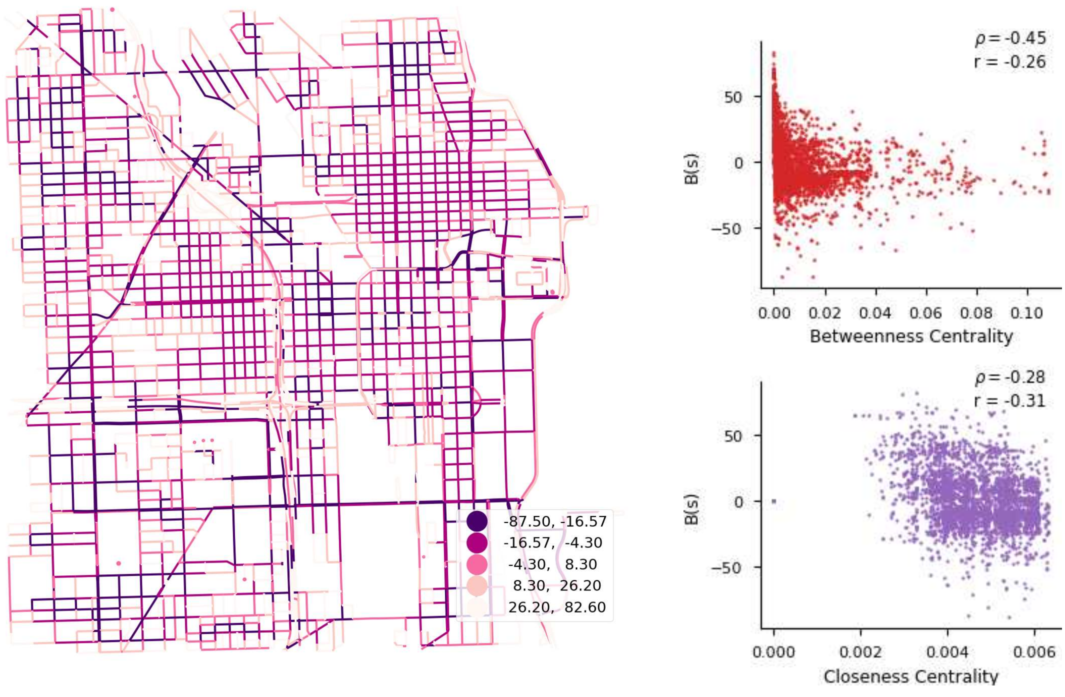
In the context of spatial network analysis, the most widely uses measures of prominence are centralities computed from the road network. Betweenness centrality has been shown to be associated with spaces of high flow, while closeness centrality is associated with points of proximity to the wider network. Both measures may be reasonably associated with features of particular salience. We compute centrality measures using the same road network used for the computing of the gSR, and the tests shows



(a) London (b) Chicago

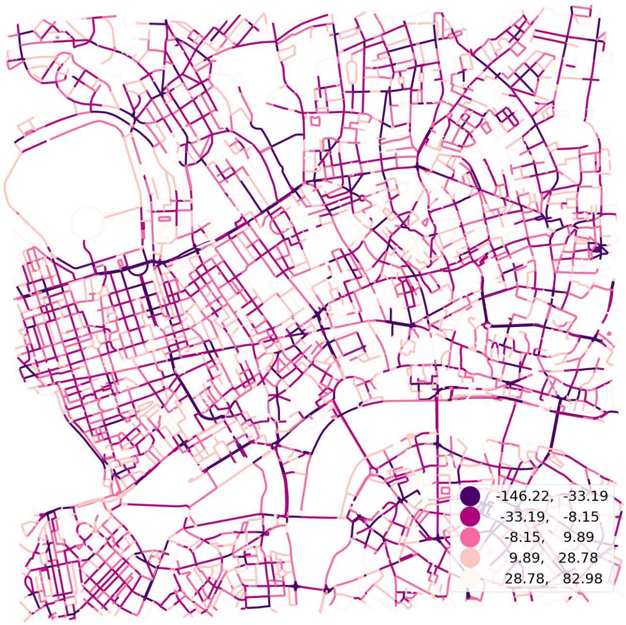
Figure 2. Correlations between $M(s, s')$ and conventional distance measures for a randomly chosen state in a) London and b) Chicago

.

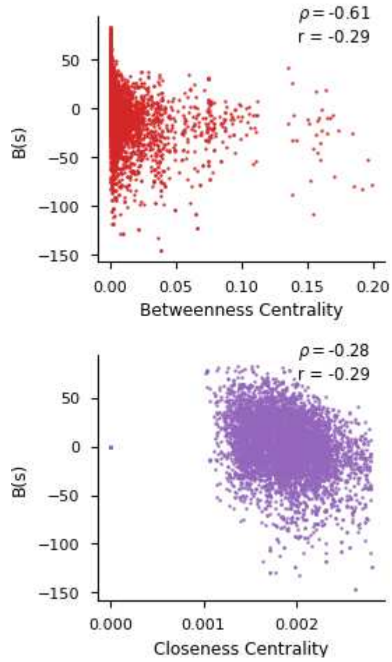


(a) (b)

Figure 3. a) Spatial distribution of bottleneck prediction measure $B(s)$ and b) relationship with betweenness and closeness centrality measures in Chicago (with Spearman ρ and Pearson r correlation coefficients).



(a)



(b)

Figure 4. a) Spatial distribution of bottleneck prediction measure $B(s)$ and b) relationship with betweenness and closeness centrality measures in London (with Spearman ρ and Pearson r correlation coefficients).

no clear association between the inequality measures $B(s)$ and centrality measures for either network in either city. In Chicago, shown in Figure 3, betweenness (ρ = -0.45, r = -0.26) and closeness centrality (ρ = -0.28, r = -0.31) suggest a noisy relationship with a small association between higher centrality and lower $B(s)$ measures. London, in Figure 4, shows a similar situation, with a slightly stronger relationship between those with lower $B(s)$ measures and higher betweenness centrality than seen in Chicago (Betweenness: ρ = -0.62, r = -0.29; closeness: ρ = -0.28, r = -0.29).

5. Discussion and Conclusions

It is evident that there remain considerable opportunities for collaboration between geography and neuroscience, and that a lack of shared representations remains a barrier to enhanced interaction. In this paper we have explored a potential remedy to this schism, in the form of the successor representation. The implementation of the geographic Successor Representation (gSR) makes conceptual and methodological contributions to GIScience. Conceptually, it introduces a framework for estimating neural responses to geographic space, building on a robust theoretical and empirical grounding developed within neuroscience. This alignment aims to broker pathways for new collaborations across domains. The paper has also outlined a methodological framework for the development of the gSR within GIScience, including the definitions and considerations required during its construction. Through two case studies, we have explored some of the initial properties of the gSR where constructed using a parsimonious definition, without reward or learning rate variations. There are indications from these case studies that the gSR produces representations and measures of the street network unlike those presently used within geographic analysis. The methodological contributions require considerably more exploration, and the framework proposed in this paper aims to enable that exploration by others.

Even the initial implementations of the gSR raise questions around the value of its properties to geographic analysis, beyond the scope for this paper. The gSR serves as a prediction of the perceived connectivity of places within a city given that its theoretic role in explaining the neural encoding of cognitive maps. The measures of *activation intensity* show how gSR activations vary in spatial extent and show association with particular areas of the road network. These measures suggest structures akin to city neighbourhoods, or associated with common land use, and require further exploration. *Predictive visitation* measures have similarities with conventional distance metrics, but important differences too, which emphasise the locally-skewed nature of cognition across urban space. The inequalities in predictive visitation expose another intriguing property, by highlighting areas of the city with theoretical salience or attractiveness. The locations highlighted by this measure align with some intuitively prominent settings, such as major routes, intersections, bridges, and activity sites, while other important sites are missing from this representation. Such findings raise questions about how far the gSR, constructed from the street network alone, can capture important features of the city.

This paper is intended to introduce the concept of the gSR with relative parsimony, and its potential role in geographic analysis. It is useful to reflect on its similarity with and differences from conventional geographic methods. The first clear analogue are conventional distance decay functions (including those based on inverse, exponential, kernel-based decay functions), where the gSR offers several clear deviations from current approaches. First, although the implementation in this paper introduces a simple cost matrix, the $M(s, s')$ itself may incorporate transition biases that skew linear associations between adjacent states (e.g. landmark or land-use effects, as mentioned in Section 3.2). Second, the value function $V(s)$ can incorporate the contribution of rewards, which may be allocated to encourage completion of specific tasks or sub-tasks, enabling descriptions of learning that better reflect real-world behaviours. The introduction of rewards at geographic points-of-interest, for example, would potentially better reflect the spatial biases in transitions between states, by virtue of goal-directed movement. Finally, the RL learning function itself need not necessarily take a deterministic or analytical form as implemented in this paper, as mentioned in Section 2.2 the value function can be constructed through Temporal Difference learning), enabling introduction of stochasticity and variations in learning. The characteristic provides an opportunity to explore how heterogeneity is encoded within the production of the gSR, through varied experience, spatial skill, and other relevant determinants, which can not be afforded through a simple distance decay function. The utility of the gSR framework in this context is potentially quite different - rather than predicting street network characteristics as produced in this paper, it enables the simulation of goal-directed navigation and route choice behaviour. A second strong analogue exists with spatial or topological networks, given the approach to gSR exploring within this paper. The structural definitions outlined in sections 3.1 and 3.2 focus on representations based on street networks, but the gSR is not dependent on a network-based state-space and may be constructed using other geographic features, neighbourhood associations or aesthetic similarities be incorporated by adding new state features, reducing weights between street network nodes, or adding rewards for movement within grouped areas of the network. Similarly, shifting the availability of actions and definitions of weights can shift assumptions from walking to driving, or other kinds of spatial behaviour.

While we have focused on construction using street networks, other features (such as landmark buildings, or hierarchies (Momennejad 2024)) may be incorporated within construction of the state space. Regardless of how the fundamental gSR is enhanced, the principle remains that spatial knowledge is structured around future likely movements between adjacent spaces. Future developments should seek to calibrate and validate models based on observations of human perception and behaviour.

The prospect for a theoretically grounded model of cognitive space in GIScience has been of interest to many over many years (Montello 2018), given the prospect of enhancing interdisciplinary collaboration across spatial cognition research, but its implications potentially span even wider. The gSR framework introduces two significant avenues of further research with the potential to catalyse such collaborations. First, the gSR itself, as evidenced in this paper, encodes representations of the environment of potential value for urban analytics. As measures such as betweenness and closeness centrality have shown, relatively simple models of environmental structure can be highly beneficial in explaining geographic and social phenomena. The introduction of the measures in this paper may provide similar areas for exploration, with underlying linkages to cognitive activation. Further work is needed in uncovering how the gSR can enhance descriptions of urban form and explanations of urban processes. Second, the approach provides a novel conception of spatial proximity and association. Several areas of GIScience rely on a null expectation of association, and often these assume Euclidean properties. While spatial networks offer a topological basis for association between features, there remain assumptions of distance uniformity, and no consideration of future states in state-to-state transitions. The gSR encodes both association between successive states (or locations) and future states, such that the relationship between objects is not assumed to be homogenous, and may be context or individual specific. It is notable that the measures of predictive visitation in our case studies demonstrate a relatively sharp distinction from conventional distance measures. This representation may provide a theoretically grounded model of space underlying human distance perception, with potential applications across spatial analysis and GeoAI. By extending the approach to incorporating heterogeneity in spatial learning, as afforded by the RL framework, it may be possible to also robustly represent variation in spatial perception and behaviour across populations. Future developments - which will require validation - may open up opportunities to measure the influence of spatial cognition beyond movement. This could include improving our measures of perceived access to job opportunities and retail destinations, or the role of spatial structure in reinforcing sentiment and reputations about place.

Acknowledgements

This research was supported by the Leverhulme Trust, the Champalimaud Foundation, and The Alan Turing Institute.

Disclosure Statement

The authors report there are no competing interests to declare.

Data and Code Availability Statement

The data and codes that support the findings of this study are available at the following link: `https://doi.org/10.5061/dryad.02v6wwqhs`.

Author Biographies

Ed Manley is a professor at the University of Leeds, where he studies the role of spatial cognition in shaping mobility and urban complexity. He contributed to the conceptualisation, methodology, analysis, and writing the paper.
Dan McNamee studied mathematics at Trinity College Dublin and did his PhD at Caltech in computation and neural systems. Currently, he is Principal Investigator at Champalimaud Research in Lisbon, Portugal. He contributed to the conceptualisation, methodology, and writing the paper.

References

Barthélemy, M., 2011. Spatial networks. *Physics Reports*, 499 (1), 1–101. Available from: `https://www.sciencedirect.com/science/article/pii/S037015731000308X`.

Batty, M., 2007. *Cities and Complexity: Understanding Cities with Cellular Automata, Agent-Based Models, and Fractals*. The MIT Press.

Baumann, T. and Mallot, H.A., 2023. Metric information in cognitive maps: Euclidean embedding of non-Euclidean environments. *PLOS Computational Biology*, 19 (12), e1011748. Available from: `https://journals.plos.org/ploscompbiol/article?id=10.1371/journal.pcbi.1011748`.

Behrens, T.E.J., *et al.*, 2018. What Is a Cognitive Map? Organizing Knowledge for Flexible Behavior. *Neuron*, 100 (2), 490–509. Publisher: Elsevier, Available from: `https://www.cell.com/neuron/abstract/S0896-6273(18)30856-0`.

Boccara, C.N., *et al.*, 2019. The entorhinal cognitive map is attracted to goals. *Science*, 363 (6434), 1443–1447. Publisher: American Association for the Advancement of Science, Available from: `https://www.science.org/doi/abs/10.1126/science.aav4837`.

Boeing, G., 2018. *Urban Spatial Order: Street Network Orientation, Configuration, and Entropy*. Rochester, NY: Social Science Research Network, SSRN Scholarly Paper ID 3224723. Available from: `https://papers.ssrn.com/abstract=3224723`.

Bongiorno, C., *et al.*, 2021. Vector-based pedestrian navigation in cities. *Nature Computational Science*, 1 (10), 678–685. Number: 10 Publisher: Nature Publishing Group, Available from: `https://www.nature.com/articles/s43588-021-00130-y`.

Burak, Y. and Fiete, I.R., 2009. Accurate Path Integration in Continuous Attractor Network Models of Grid Cells. *PLOS Computational Biology*, 5 (2), e1000291. Publisher: Public Library of Science, Available from: `https://journals.plos.org/ploscompbiol/article?id=10.1371/journal.pcbi.1000291`.

Chen, J., Yuan, B., and Tomizuka, M., 2019. Model-free Deep Reinforcement Learning for Urban Autonomous Driving. October. ArXiv:1904.09503 [cs], Available from: `http://arxiv.org/abs/1904.09503`.

Chrastil, E.R. and Warren, W.H., 2014. From Cognitive Maps to Cognitive Graphs. *PLOS ONE*, 9 (11), e112544. Publisher: Public Library of Science, Available from: `https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0112544`.

Cohn, A.G., 1997. Qualitative spatial representation and reasoning techniques. September. Springer, Berlin, Heidelberg, 1–30. Available from: `https://link.springer.com/chapter/10.1007/3540634932_1`.

Couclelis, H., *et al.*, 1987. Exploring the anchor-point hypothesis of spatial cognition. *Journal of Environmental Psychology*, 7 (2), 99–122. Available from: http://dx.doi.org/10.1016/S0272-4944(87)80020-8.

Coutrot, A., *et al.*, 2022. Entropy of city street networks linked to future spatial navigation ability. *Nature*, 604 (7904), 104–110. Publisher: Nature Publishing Group, Available from: https://www.nature.com/articles/s41586-022-04486-7.

Crucitti, P., Latora, V., and Porta, S., 2006. Centrality measures in spatial networks of urban streets. *Physical Review E*, 73 (3), 036125. Available from: https://link.aps.org/doi/10.1103/PhysRevE.73.036125.

Dalton, R., 2003. The secret is to follow your nose: route path selection and angularity. *Environment and Behavior*, 35 (1), 107–131. Number: 1 Publisher: SAGE, Available from: http://dx.doi.org/10.1177/0013916502238867.

Daw, N.D., 2012. Model-Based Reinforcement Learning as Cognitive Search: Neurocomputational Theories. Available from: https://direct.mit.edu/books/edited-volume/4000/chapter/166632/Model-Based-Reinforcement-Learning-as-Cognitive.

Dayan, P., 1993. Improving Generalization for Temporal Difference Learning: The Successor Representation. *Neural Computation*, 5 (4), 613–624. Conference Name: Neural Computation, Available from: https://ieeexplore.ieee.org/abstract/document/6795455.

Downs, R.M., 2018. The future of behavioral and cognitive geography: a coda. *In*: *Handbook of Behavioral and Cognitive Geography*. Edward Elgar Publishing Limited.

Fernandez Velasco, P., *et al.*, 2025. Expert navigators deploy rational complexity–based decision precaching for large-scale real-world planning. *Proceedings of the National Academy of Sciences*, 122 (4), e2407814122. Publisher: Proceedings of the National Academy of Sciences, Available from: https://www.pnas.org/doi/abs/10.1073/pnas.2407814122.

Filomena, G., Manley, E., and Verstegen, J.A., 2020. Perception of urban subdivisions in pedestrian movement simulation. *PLOS ONE*, 15 (12), e0244099. Publisher: Public Library of Science, Available from: https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0244099.

Gershman, S.J., 2018. The Successor Representation: Its Computational Logic and Neural Substrates. *The Journal of Neuroscience*, 38 (33), 7193–7200. Available from: https://www.jneurosci.org/lookup/doi/10.1523/JNEUROSCI.0151-18.2018.

Golledge, R.G., 1998. *Wayfinding behavior: Cognitive mapping and other spatial processes.* Johns Hopkins University Press.

Golledge, R.G. and Hubert, L.J., 1982. Some Comments on Non-Euclidean Mental Maps. *Environment and Planning A: Economy and Space*, 14 (1), 107–118. Publisher: SAGE Publications Ltd, Available from: https://doi.org/10.1068/a140107.

Golledge, R.G., 1992. Place recognition and wayfinding: Making sense of space. *Geoforum*, 23 (2), 199–214. Available from: https://www.sciencedirect.com/science/article/pii/001671859290017X.

Goodchild, M.F., Yuan, M., and Cova, T.J., 2007. Towards a general theory of geographic representation in GIS. *International Journal of Geographical Information Science*, 21 (3), 239–260. Publisher: Taylor & Francis _eprint: https://doi.org/10.1080/13658810600965271, Available from: https://doi.org/10.1080/13658810600965271.

Hackman, D.A., *et al.*, 2019. Neighborhood environments influence emotion and physiological reactivity. *Scientific Reports*, 9 (1), 9498. Publisher: Nature Publishing Group, Available from: https://www.nature.com/articles/s41598-019-45876-8.

Hillier, B. and Iida, S., 2005. Network and Psychological Effects in Urban Movement. *In*: A.G. Cohn and D.M. Mark, eds. *Spatial Information Theory*, Berlin, Heidelberg. Springer, 475–490.

Ishikawa, T. and Montello, D.R., 2006. Spatial knowledge acquisition from direct experience in the environment: Individual differences in the development of metric knowledge and the integration of separately learned places. *Cognitive Psychology*, 52 (2), 93–129. Available from: https://www.sciencedirect.com/science/article/pii/S0010028505000733.

Jiang, B., Zhao, S., and Yin, J., 2008. Self-organized natural roads for predicting traffic flow:

a sensitivity study. *Journal of statistical mechanics: Theory and experiment*, 2008 (07), P07008.

Jiang, B. and Claramunt, C., 2004. Topological Analysis of Urban Street Networks. *Environment and Planning B: Planning and Design*, 31 (1), 151–162. Available from: https://doi.org/10.1068/b306.

Jiang, B. and Jia, T., 2011. Agent-based simulation of human movement shaped by the underlying street structure. *International Journal of Geographical Information Science*, 25 (1), 51–64. Available from: http://dx.doi.org/10.1080/13658811003712864.

Kim, Y.O. and Penn, A., 2004. Linking the Spatial Syntax of Cognitive Maps to the Spatial Syntax of the Environment. *Environment & Behavior*, 36 (4), 483–504. Available from: http://eab.sagepub.com/cgi/doi/10.1177/0013916503261384http://discovery.ucl.ac.uk/278/1/kim-penn-2004-cognitivemaps-nonsageversion.pdf.

Kuipers, B., Tecuci, D., and Stankiewicz, B., 2003. The Skeleton In The Cognitive Map: A Computational and Empirical Exploration. *Environment & Behavior*, 35 (1), 81–106. Available from: http://eab.sagepub.com/content/35/1/81.abstract.

Lynch, K., 1960. *The image of the city.* vol. 1. MIT press.

Manley, E.J., Addison, J.D., and Cheng, T., 2015a. Shortest path or anchor-based route choice: a large-scale empirical analysis of minicab routing in London. *Journal of Transport Geography*, 43, 123–139. Available from: https://www.sciencedirect.com/science/article/pii/S0966692315000083.

Manley, E. and Cheng, T., 2010. Understanding Road Congestion as an Emergent Property of Traffic Networks. *Intrernational Multiconference on Complexity, Informatics and Cybernetics*, 1.

Manley, E., Filomena, G., and Mavros, P., 2021. A spatial model of cognitive distance in cities. *International Journal of Geographical Information Science*, 35 (11), 2316–2338. Available from: https://doi.org/10.1080/13658816.2021.1887488.

Manley, E., Orr, S., and Cheng, T., 2015b. A heuristic model of bounded route choice in urban areas. *Transportation Research Part C: Emerging Technologies*, 56, 195–209. Bibtex: MANLEY2015195, Available from: http://www.sciencedirect.com/science/article/pii/S0968090X15001059.

McNamee, D. and Wolpert, D.M., 2019. Internal Models in Biological Control. *Annual Review of Control, Robotics, and Autonomous Systems*, 2 (Volume 2, 2019), 339–364. Publisher: Annual Reviews, Available from: https://www.annualreviews.org/content/journals/10.1146/annurev-control-060117-105206.

McNamee, D.C., *et al.*, 2021. Flexible modulation of sequence generation in the entorhinal–hippocampal system. *Nature Neuroscience*, 24 (6), 851–862. Publisher: Nature Publishing Group, Available from: https://www.nature.com/articles/s41593-021-00831-7.

Mehta, M.R., Quirk, M.C., and Wilson, M.A., 2000. Experience-Dependent Asymmetric Shape of Hippocampal Receptive Fields. *Neuron*, 25 (3), 707–715. Publisher: Elsevier, Available from: https://www.cell.com/neuron/abstract/S0896-6273(00)81072-7.

Momennejad, I., 2024. Memory, Space, and Planning: Multiscale Predictive Representations. February. ArXiv:2401.09491 [cs], Available from: http://arxiv.org/abs/2401.09491.

Momennejad, I. and Howard, M.W., 2018. Predicting the Future with Multi-scale Successor Representations. October. Pages: 449470 Section: New Results, Available from: https://www.biorxiv.org/content/10.1101/449470v1.

Montello, D.R., 1991. Spatial Orientation and the Angularity of Urban Routes: A Field Study. *Environment and Behavior*, 23 (1), 47–69. Available from: http://eab.sagepub.com/content/23/1/47.short.

Montello, D.R., 2009. Cognitive Research in GIScience: Recent Achievements and Future Prospects. *Geography Compass*, 3 (5), 1824–1840. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1749-8198.2009.00273.x, Available from: https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1749-8198.2009.00273.x.

Montello, D.R., 2018. *Handbook of Behavioral and Cognitive Geography.* Edward Elgar Publishing. Google-Books-ID: 8ihWDwAAQBAJ.

Moser, E.I., Kropff, E., and Moser, M.B., 2008. Place cells, grid cells, and the brain's spatial representation system. *Annual Review of Neuroscience*, 31, 69–89.

Moser, E.I., Moser, M.B., and McNaughton, B.L., 2017. Spatial representation in the hippocampal formation: a history. *Nature Neuroscience*, 20 (11), 1448–1464. Publisher: Nature Publishing Group, Available from: https://www.nature.com/articles/nn.4653.

O'Keefe, J. and Dostrovsky, J., 1971. The hippocampus as a spatial map. Preliminary evidence from unit activity in the freely-moving rat. *Brain Research*, 34 (1), 171–175.

O'Keefe, J. and Burgess, N., 1996. Geometric determinants of the place fields of hippocampal neurons. *Nature*, 381 (6581), 425–428. Publisher: Nature Publishing Group, Available from: https://www.nature.com/articles/381425a0.

O'Keefe, J. and Nadel, L., 1978. *The Hippocampus as a Cognitive Map*. Oxford: Clarendon Press. Available from: http://www.getcited.org/pub/101782291.

Pappalardo, L., *et al.*, 2023. Future directions in human mobility science. *Nature Computational Science*, 3 (7), 588–600. Number: 7 Publisher: Nature Publishing Group, Available from: https://www.nature.com/articles/s43588-023-00469-4.

Peer, M., *et al.*, 2021. Structuring Knowledge with Cognitive Maps and Cognitive Graphs. *Trends in Cognitive Sciences*, 25 (1), 37–54. Available from: https://www.sciencedirect.com/science/article/pii/S1364661320302503.

Peer, M., Nadar, C., and Epstein, R.A., 2024. The format of the cognitive map depends on the structure of the environment. *Journal of Experimental Psychology: General*, 153 (1), 224–240.

Penn, A., 2003. Space Syntax and Spatial Cognition or Why the axial line? *Environment and Behavior*. Available from: http://en.cnki.com.cn/Article_en/CJFDTOTAL-SJZJ200511005.htmhttp://eab.sagepub.com/content/35/1/30.short.

Penn, A., *et al.*, 1998. Configurational modelling of urban movement networks. *Environment and Planning B: Planning and Design*, 25 (1), 59–84. Available from: http://www.envplan.com/abstract.cgi?id=b250059.

Porta, S., Crucitti, P., and Latora, V., 2006. The network analysis of urban streets: A dual approach. *Physica A: Statistical Mechanics and its Applications*, 369 (2), 853–866. Available from: https://www.sciencedirect.com/science/article/pii/S0378437106001282.

Porta, S., *et al.*, 2012. Street Centrality and the Location of Economic Activities in Barcelona. *Urban Studies*, 49 (7), 1471–1488. Publisher: SAGE Publications Ltd, Available from: https://doi.org/10.1177/0042098011422570.

Portugali, J., 2018. History and theoretical perspectives of behavioral and cognitive geography. *In*: *Handbook of Behavioral and Cognitive Geography*. Edward Elgar Publishing Limited.

Pykett, J., Osborne, T., and Resch, B., 2020. From Urban Stress to Neurourbanism: How Should We Research City Well-Being? *Annals of the American Association of Geographers*, 110 (6), 1936–1951. Publisher: Taylor & Francis _eprint: https://doi.org/10.1080/24694452.2020.1736982, Available from: https://doi.org/10.1080/24694452.2020.1736982.

Raubal, M. and Winter, S., 2002. Enriching wayfinding instructions with local landmarks. *Geographic information science*, 243–259. Available from: http://www.springerlink.com/index/vrg51hqe271wc9cl.pdf.

Russek, E.M., *et al.*, 2017. Predictive representations can link model-based reinforcement learning to model-free mechanisms. *PLOS Computational Biology*, 13 (9), e1005768. Publisher: Public Library of Science, Available from: https://journals.plos.org/ploscompbiol/article?id=10.1371/journal.pcbi.1005768.

Salonen, M. and Toivonen, T., 2013. Modelling travel time in urban networks: comparable measures for private car and public transport. *Journal of Transport Geography*, 31, 143–153. Available from: https://www.sciencedirect.com/science/article/pii/S096669231300121X.

Sarel, A., *et al.*, 2017. Vectorial representation of spatial goals in the hippocampus of bats. *Science*, 355 (6321), 176–180. Publisher: American Association for the Advancement of Science, Available from: https://www.science.org/doi/10.1126/science.aak9589.

Schaul, T., *et al.*, 2015. Universal Value Function Approximators. *In*: *Proceedings of the 32nd International Conference on Machine Learning*, June. PMLR, 1312–1320. ISSN: 1938-7228, Available from: https://proceedings.mlr.press/v37/schaul15.html.

Schinazi, V.R., Thrash, T., and Chebat, D.R., 2016. Spatial navigation by congenitally blind individuals. *WIREs Cognitive Science*, 7 (1), 37–58. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/wcs.1375, Available from: https://onlinelibrary.wiley.com/doi/abs/10.1002/wcs.1375.

Solstad, T., *et al.*, 2008. Representation of Geometric Borders in the Entorhinal Cortex. *Science*, 322 (5909), 1865–1868. Publisher: American Association for the Advancement of Science, Available from: https://www.science.org/doi/10.1126/science.1166466.

Stachenfeld, K.L., Botvinick, M.M., and Gershman, S.J., 2017. The hippocampus as a predictive map. *Nature Neuroscience*, 20 (11), 1643–1653. Number: 11 Publisher: Nature Publishing Group, Available from: https://www.nature.com/articles/nn.4650.

Stangl, M., Maoz, S.L., and Suthana, N., 2023. Mobile cognition: imaging the human brain in the 'real world'. *Nature Reviews Neuroscience*, 24 (6), 347–362. Publisher: Nature Publishing Group, Available from: https://www.nature.com/articles/s41583-023-00692-y.

Summers, L. and Johnson, S.D., 2017. Does the Configuration of the Street Network Influence Where Outdoor Serious Violence Takes Place? Using Space Syntax to Test Crime Pattern Theory. *Journal of Quantitative Criminology*, 33 (2), 397–420. Available from: https://doi.org/10.1007/s10940-016-9306-9.

Sutton, R.S. and Barto, A.G., 2018. *Reinforcement Learning, second edition: An Introduction*. MIT Press.

Tobler, W., 1976. The geometry of mental maps. *Spatial choice and spatial behavior*, 69–81. Available from: https://www.researchgate.net/profile/Waldo-Tobler/publication/242637096_The_Geometry_of_Mental_Maps/links/54a173830cf257a636036fae/The-Geometry-of-Mental-Maps.pdf.

Tobler, W., 2004. On the First Law of Geography: A Reply. *Annals of the Association of American Geographers*, 94 (2), 304–310. Publisher: Routledge _eprint: https://doi.org/10.1111/j.1467-8306.2004.09402009.x, Available from: https://doi.org/10.1111/j.1467-8306.2004.09402009.x.

Tolman, E., 1948. Cognitive maps in rats and men. *The Psychological Review*, 55 (4), 189–208. Available from: http://books.google.com/books?hl=en&lr=&id=dnwkmQ1fuUAC&oi=fnd&pg=PA27&dq=Cognitive+maps+in+rats+and+men&ots=xn15XCWZzQ&sig=B2Rb5e5rJdkMZuAy8UUXeNVP2UM.

Tomko, M., Winter, S., and Claramunt, C., 2007. Experiential hierarchies of streets. *Computers, Environment and Urban Systems*, 32 (1), 41–52. Available from: http://linkinghub.elsevier.com/retrieve/pii/S0198971507000221.

Turner, A., 2007. From axial to road-centre lines: a new representation for space syntax and a new model of route choice for transport network analysis. *Environment and Planning B: Planning and Design*, 34 (3), 539–555. Available from: http://www.envplan.com/abstract.cgi?id=b32067.

Warren, W.H., 2019. Non-Euclidean navigation. *Journal of Experimental Biology*, 222 (Suppl_1), jeb187971. Available from: https://doi.org/10.1242/jeb.187971.

Warren, W.H., *et al.*, 2017. Wormholes in virtual space: From cognitive maps to cognitive graphs. *Cognition*, 166, 152–163. Available from: https://www.sciencedirect.com/science/article/pii/S0010027717301373.

Whittington, J.C.R., *et al.*, 2022. How to build a cognitive map. *Nature Neuroscience*, 25 (10), 1257–1272. Publisher: Nature Publishing Group, Available from: https://www.nature.com/articles/s41593-022-01153-y.

Wilson, A., 1971. A family of spatial interaction models, and associated developments. *Environment and Planning*, 3 (January), 1–32. Available from: http://www.environment-and-planning.com/epa/fulltext/a03/a030001.pdf.

Wilson, A., 2022. *Being Interdisciplinary: Adventures in urban science and beyond*. UCL Press. Accepted: 2022-08-05T15:37:53Z, Available from: https://library.oapen.org/handle/

20.500.12657/57795.
Witter, M.P., *et al.*, 2014. Architecture of spatial circuits in the hippocampal region. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 369 (1635), 20120515. Publisher: Royal Society, Available from: https://royalsocietypublishing.org/doi/abs/10.1098/rstb.2012.0515.
Yan, B., *et al.*, 2019. A spatially explicit reinforcement learning model for geographic knowledge graph summarization. *Transactions in GIS*, 23 (3), 620–640. Available from: https://onlinelibrary.wiley.com/doi/abs/10.1111/tgis.12547.
Yuan, M., 2001. Representing Complex Geographic Phenomena in GIS. *Cartography and Geographic Information Science*, 28 (2), 83–96. Publisher: Taylor & Francis _eprint: https://doi.org/10.1559/152304001782173718, Available from: https://doi.org/10.1559/152304001782173718.
Yuan, M., 2024. Multiple representations in geospatial databases, the brain's spatial cells, and deep learning algorithms. *Cartography and Geographic Information Science*, 51 (5), 687–701. Publisher: Taylor & Francis _eprint: https://doi.org/10.1080/15230406.2023.2264758, Available from: https://doi.org/10.1080/15230406.2023.2264758.