Measuring urban dynamics in port-cities using an agent-based cellular automata land-use and transport interaction model

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Abstract

The urban environment is a complex system where general urban morphology patterns emerge from the local interactions of many agents. Examination on these interactions are crucial to enable successful transport and urban planning. While cellular automata (CA) models are suitable for modelling this self-organisation behaviour, measuring individual interactions from empirical data is still complicated due to their auto-correlation and to path-dependence in urban systems evolution. Due to this, manual methods are more often used in the calibration of urban land-use and transport interaction (LUTI) models based on CA, limiting the results to a few explored settlements. This paper therefore presents a method for applying the gradient-descent algorithm with momentum to calibrate an agent-based LUTI-CA model by representing the model as an optimisation problem. This process allowed efficient calibration for 46 port-related settlements and 10 non-port settlements across Great Britain, enabling cross-sectional analysis of whether observed relationships are unique to a study area due to its path-dependence, or if they have similarities with results from other study areas.

We found unique characteristics of urban dynamics separating port from non-port settlements in smaller urban systems, while the distinctions between the two groups were less prominent in larger settlements. However, there were variations in urban dynamics between larger settlements with respect to the effects of their services and manufacturing activities on other land-uses. The automated calibration of agent-based urban CA models in this paper enabled the quantification of these urban dynamics in multiple settlements, providing the ability to look beyond the uniqueness of individual case studies to find general patterns of interaction. This paper therefore provides improvement in the calibration of LUTI models based on CA and contributes to the better understanding of the dynamics between port and urban systems.

Keywords: cellular-automata, gradient-descent, LUTI-model calibration, port-urban dynamics

Introduction

The urban environment is a complex system characterised by self-organisation, where interactions of agents at the local scale result in the emergence of patterns at larger scales (Batty, 2007). Generalised insights into these individual interactions are critical in successful transport and land-use planning of urban settlements as they would allow planners to better predict the long-term outcomes of their plans. Urban models based on cellular automata (CA) are known to be capable of replicating this self-organisation behaviour (Batty, 1997). Most urban CA models simulate land-use evolution through transition rules with consideration of multiple factors representing the local interactions (Santé et al., 2010) and calibration of such models could be seen as a process to measure the effects of each factor.

However, most efforts in examining these interactions are limited to small numbers of urban settlements. The reason for this limitation is the prevalence of manual methods in calibrating land-use and transport interaction (LUTI) models based on CA which is due to the highly-correlated interactions between urban agents and the presence of path-dependence in the urban systems. Consequently, the interactions measured are often specific to urban dynamics of the few explored settlements as the presence of path-dependence prevents generalisation of results from one study area to other areas which may not share the same history.

To measure urban dynamics that can be generalised across a number of study areas, this research therefore adapted a CA-based LUTI model to enable automatic calibration using the gradient-descent algorithm. This model was then used to investigate the nature of urban dynamics in 46 port-based settlements and 10 non-port settlements of various sizes across Great Britain (Figure 1). Port and non-port dichotomy was used as an example to see if the presence of a port in the urban area creates distinct impacts on the urban dynamics. Settlements were then classified into groups depending on the similarity of their results and the characteristics of each group provided the generalised measurements of interactions driving the urban dynamics within the group.

Model structure and data requirements

This research used an urban CA model inspired by the state-of-the-art commercial urban CA model, Metronamica (RIKS, 2010), which predicts cell states based on their attractiveness to different types of land-use by considering (1) neighbourhood, (2) geographic, and (3) transport effects. Neighbourhood effects measured the impact of proximity to other activities while geographic effects measured physical suitability of land-use developments. Transport effects were subdivided into static effects representing the impact of proximity to transport infrastructure and dynamic effects representing the impact of accessibility to other activities. These effects were calculated for each cell, with the exception of dynamic transport which was calculated on the basis of transport analysis zones delineated from lower level super output areas (LSOAs). The model used regular hexagonal cells, as they have consistency advantages over square cells (Nugraha et al., 2020). Figure 2 provides an overview of the model spatial structure.

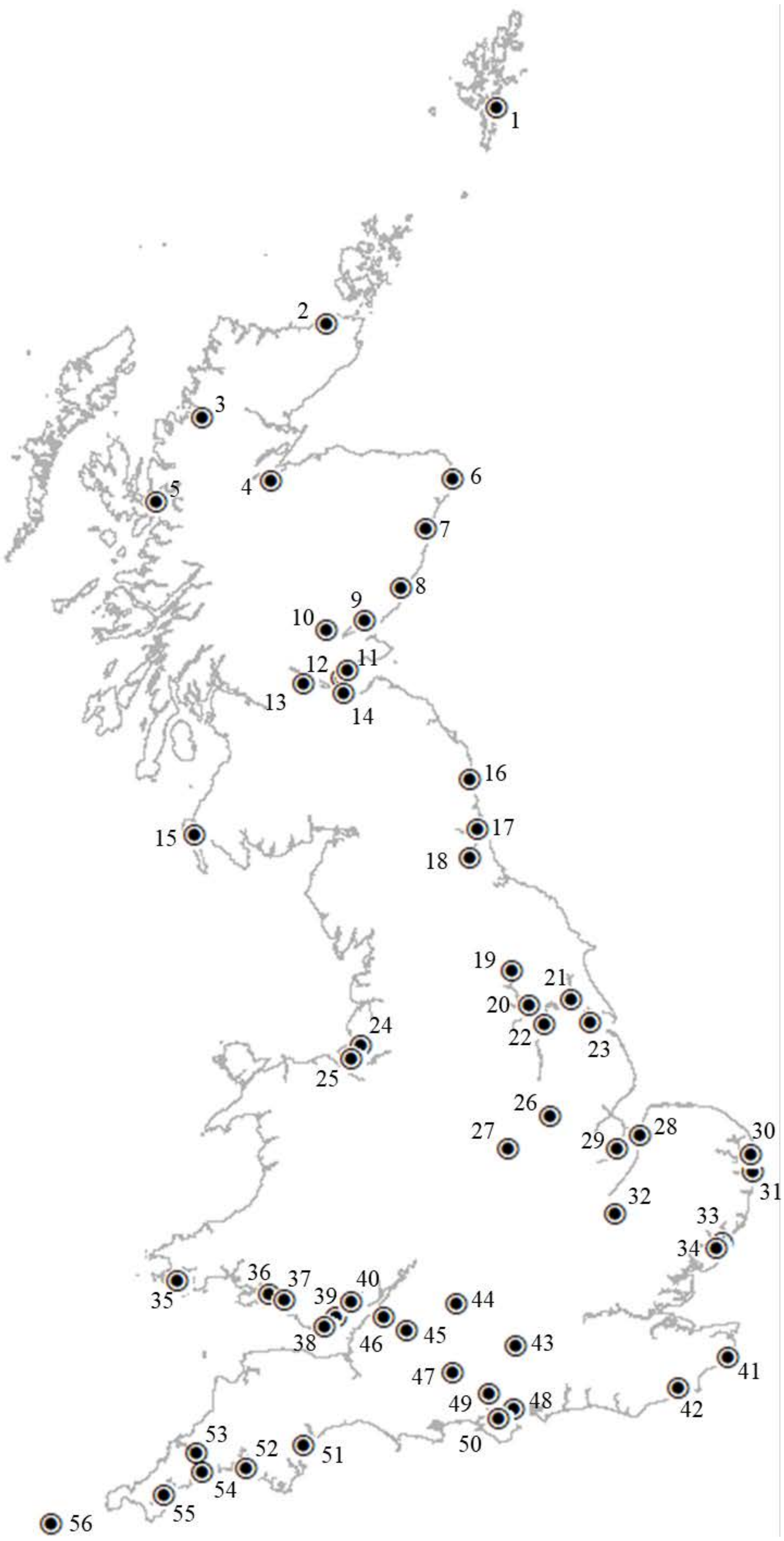
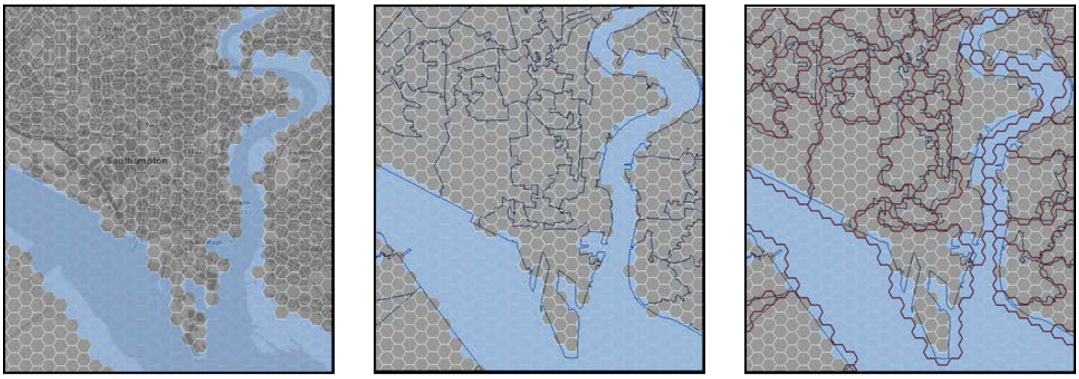


Figure 1. Map of study areas across Great Britain



(a)

Hexagons overlaid onto study area as the base of land use spatial unit (cells)

(b)

LSOA overlaid onto cells as the base for transport analysis zones

(c)

Assignment of cells into transport analysis zones

Figure 2. Representation of the model's spatial structure

Geographic suitability and proximities to transport infrastructure were calculated based on Ordnance Survey (OS) spatial datasets. For dynamic transport, journey times between zones were obtained using the OpenTripPlanner software as in Young (2016). The model used an agent-based approach to represent land-use as in Van Vliet and colleagues (2012), wherein cells are characterised by the levels of different activities they host rather than by categorical states representing their dominant land-use. This type of approach requires more information on land-use activities but represents varying activity densities and multi-use establishments better. Levels of land-use activities were obtained from the OS AddressBase® Plus dataset containing classed and geo-located addressable properties. These were then reclassified into 'housing', 'port', 'manufacturing', 'consumer-services', and 'business-services' which were the five land-use activities types used in this paper.

Model calibration using the gradient-descent algorithm

The gradient-descent algorithm is an optimisation technique that evaluates the fitness of an initial set of solutions $[\boldsymbol{x}]_{\mathbf{0}}$ through an objective function, $f([\boldsymbol{x}]_{\boldsymbol{t}})$. The algorithm then improves the solution by moving parameters in the direction of the steepest descent of the objective value. In order to calibrate the urban CA model using the gradient descent algorithm, the model was formulated as an optimisation problem using mostly differentiable functions as in Table 1.

The objective of the calibration process is to maximise the agreement of model predictions and the observed land-use distribution. As an optimisation problem this is represented as the minimisation of the sum of squared difference between the levels of observed, $Z_{v,j}$, and predicted, $Predicted_{v,j}$, land-use types, v, of all the cells, j, within the study area.

Table 1. Formulation of model into optimisation problem		
Objective function	$\min \sum_j \left(\frac{\left(Z_{v,j} - Predicted_{v,j}\right)^2}{Predicted_{v,j}} \right)$	(Eq.1)
where:		
Predicted values	$Predicted_{v,j} = \frac{P_{v,j}}{\sum_{j \mid j \epsilon SA} P_{v,j}} . Total_{v,SA}$	(Eq.2)
Cell potential	$P_{v,j} = G_{v,j} \,.\, T_{v,j} \,.\, N_{v,j}$	(Eq.3)
Geographic effect	$G_{v,j} = \prod_x B\left(F\left(C\left(\eta_{x,j}\right), \mu_{x,v}\right)\right)^{\omega_{x,v}}$	(Eq.4)
Consolidation function	$C(\theta) = c + (1 - 2c)\left(0.99\left(\frac{\theta - min_\theta}{max_\theta - min_\theta}\right) + 0.01\right)$	(Eq.5)
Shifting function	$F(\theta, \phi) = \left(1 - \left({}^1/_\phi\right)\theta\right)$	(Eq.6)
Bounding function	$B(\theta) = \frac{log\left(1 + e^{10\theta}\right)}{log\left(1 + e^{10}\right)}$	(Eq.7)
Transport effect	$T_{v,j} = ST_{v,j}{}^{\tau 1_v} \,.\, DT_{v,j}{}^{\tau 2_v}$	(Eq.8)
Static transport effect	$ST_{v,j} = \prod_y B\left(F\left(C\left(\rho_{y,j}\right), \nu_{y,v}\right)\right)^{\varphi_{y,v}}$	(Eq.9)
Cell to zone	$DT_{v,j} = DT_{v,jj} \quad for\; j \in jj$	(Eq.10)
Dynamic transport effect	$DT_{v,jj} = \sum_m \sum_u \sum_{ii} \left(\frac{\kappa_{u,v,m} . Total_{u,ii}}{\left(1 + ODTM_{jj,ii,m}\right)^{\partial_{u,v,m}}} \right)$	(Eq.11)
Neighbourhood effect	$N_{v,j} = S\left(\sum_u \sum_{i \mid i \in N(j)} \left(\left(Z_{u,i}\right)^{\lambda 1_{u,v}} .\; A_{u,v,i,j} - \left(Z_{u,i}\right)^{\lambda 2_{u,v}} .\; R_{u,v,i,j} \right)\right)$	(Eq.12)
Rectifier	$S(\theta) = log\left(1 + e^{\theta}\right) + 0.00001$	(Eq.13)
Masker	$Z_{u,i} = 0 \quad where \quad (u = v) \cap (i = j)$	(Eq.14)
Attraction effect	$A_{u,v,i,j} = \alpha_{A,\,u,v} - \frac{\alpha_{A,\,u,v}}{\left(1 + Exp\left(-\beta_{A,\,u,v} . \left(D_{i,j} - \gamma_{A,\,u,v}\right)\right)\right)}$	(Eq.15)
Repulsion effect	$R_{u,v,i,j} = \alpha_{R,\,u,v} - \frac{\alpha_{R,\,u,v}}{\left(1 + Exp\left(-\beta_{R,\,u,v} . \left(D_{i,j} - \gamma_{R,\,u,v}\right)\right)\right)}$	(Eq.16)

subject to the parameters:

$0 < \mu_{x,v} \leq 1$	$0 < \partial_{u,v,m} \leq 5$	$\lambda 1_{u,v} \geq 0$	$\lambda 2_{u,v} \geq 0$
$0 < \nu_{y,v} \leq 1$	$\kappa_{u,v,m} \geq 0$	$\alpha_{A,\,u,v} \geq 0$	$\alpha_{R,\,u,v} \geq 0$
$\omega_{x,v} \geq 0$	$\tau 1_v \geq 0$	$\beta_{A,\,u,v} \geq 0$	$\beta_{R,\,u,v} \geq 0$
$\varphi_{y,v} \geq 0$	$\tau 2_v \geq 0$	$0 \leq \gamma_{A,\,u,v} \leq 4$	$0 \leq \gamma_{R,\,u,v} \leq 4$

The gradient-descent algorithm is a local optimisation technique and is therefore prone to getting stuck on plateaus or local optima. Incorporation of momentum, a technique where parameters update considers gradients in previous iterations, was incorporated as it could help the algorithm overcome small hills and plateaus (Ruder, 2016). After some pilot runs and analyses to determine the algorithm's parameters, the optimisation process could be defined as a set of processes formulised in the equations in Table 2. Learning rate dictates the length of steps the algorithm takes at each iteration while momentum parameter dictates the rate of decay for the weights with which past gradients are considered. The number of iterations dictates the number of steps the algorithm takes.

Table 2. Formulation of the gradient descent algorithm with momentum

Objective function:	$\mathbf{min}\, f([\boldsymbol{x}]_{\boldsymbol{t}})$	(Eq.17)
Initial solution:	$[\boldsymbol{x}]_{\mathbf{0}} = \begin{bmatrix} x_1 \\ x_2 \\ \cdots \\ x_n \end{bmatrix}_{\mathbf{0}}$	
Gradient:	$[\boldsymbol{g}]_{\boldsymbol{t}} = \begin{bmatrix} \partial f([\boldsymbol{x}]_{\boldsymbol{t}})/\partial x_1 \\ \partial f([\boldsymbol{x}]_{\boldsymbol{t}})/\partial x_2 \\ \cdots \\ \partial f([\boldsymbol{x}]_{\boldsymbol{t}})/\partial x_n \end{bmatrix}_{\boldsymbol{t}}$	
Gradient with momentum:	$[\boldsymbol{v}]_{\boldsymbol{t}} = r[\boldsymbol{g}]_{\boldsymbol{t}} + p[\boldsymbol{v}]_{\boldsymbol{t-1}}$	
Updating solution:	$[\boldsymbol{x}]_{\boldsymbol{t}} = [\boldsymbol{x}]_{\boldsymbol{t-1}} - [\boldsymbol{v}]_{\boldsymbol{t}}$	
With the parameters used in the model:		
Learning rate:	$r = 10^{-6}$	
Momentum parameter:	$p = 10^{-1}$	
Number of iterations	$t_{max} = 2{,}000$	

Further, the algorithm was applied 20 times for each study area from randomised starting points so that it could cover more areas in the solution space. The algorithm as described in Table 2 successfully predicted land-use distribution in most study areas, but failed to make sensible predictions for a few relatively large study areas for housing (Plymouth), manufacturing (Bristol), or both (Aberdeen, and Swansea), and a few relatively small study areas for port (Amble, Burntisland, and Cowes). Figure 3 provides examples of predicted housing potentials highlighting the difference between successful and unsuccessful predictions. Visually, predictions for Birkenhead and Edinburgh follow the general pattern of the actual housing distribution while Plymouth's and Aberdeen's predictions follow the distance to waterfront and geographic slope respectively. These visual observations were accompanied by a simple numerical indicator, the Pearson's index (R) measuring the correlation between actual and predicted land-use distribution.

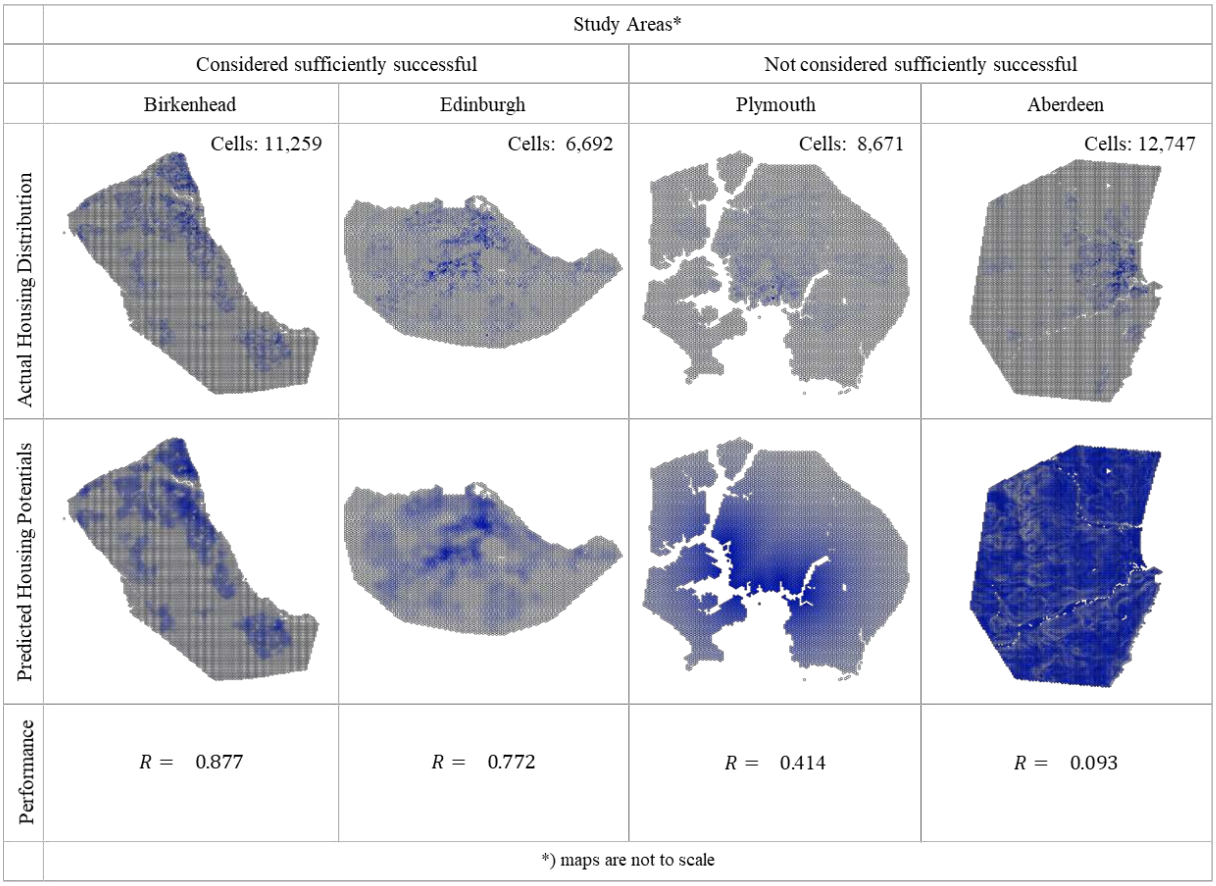


Figure 3. Examples of model calibration performance

To rectify this, the failed study areas were re-calibrated using a lower learning rate of 10^{-7}. At this learning rate, to enable equivalent search space potential coverage as the original run, the number of iterations should increase tenfold. However, this required more computational resources than were available to the researchers. Therefore, the number of iterations was kept at 2,000 but the process made use of informed starting points generated from the results of successful predictions in other settlements rather than randomised points. This second run is therefore referred to as the 'informed run'. Figure 4 presents comparisons of the results from the original and informed runs.

The process of generating the informed starting points consisted of clustering of study areas based on the calibration results. Cluster analysis could not be done directly on the parameters themselves as different combinations of parameters could lead to similar effects on cell potentials. Clustering was based instead on graphs formed by the calibrated parameters. This graph clustering technique took gauge points along one axis of a graph as clustering variables and each curve as one instance. After informed runs were applied, the same clustering technique was conducted to examine the final clusters formed by the study areas. The next section discusses the clusters and the nature of their urban dynamics.

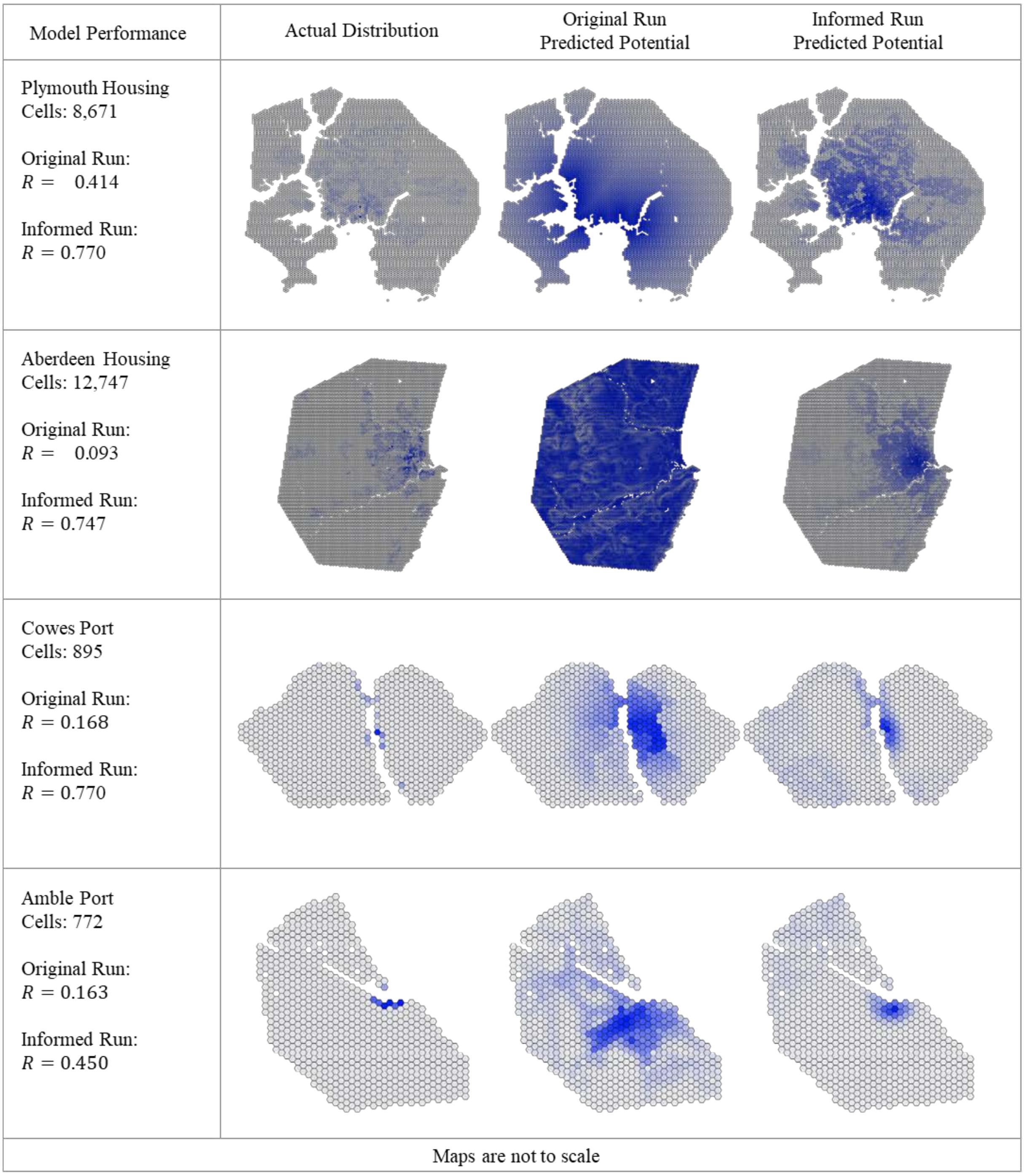


Figure 4 Comparison of the original and the informed calibration results

Urban dynamics in port-cities

Having successfully applied the methodology described in the previous section, this section examines the interactions between urban activities in port-cities which were quantified in the calibration process. The characteristics of some interactions were found to be similar across all study areas. Some examples of these were the neighbourhood effects of housing to port and consumer services activities, and of port to manufacturing. Figure 5 presents the generalised characteristics of these dynamics. The individual effects (dotted lines) were calculated by subtraction between the two logistic decay functions (attraction and repulsion) formed by the parameters α, β, and γ, and were scaled up to low (dot-dash lines), medium (dashed lines), and high (unbroken lines) levels using the scaling parameters λ1 and λ2 and the equations 12, 15, and 16 from Table 1.

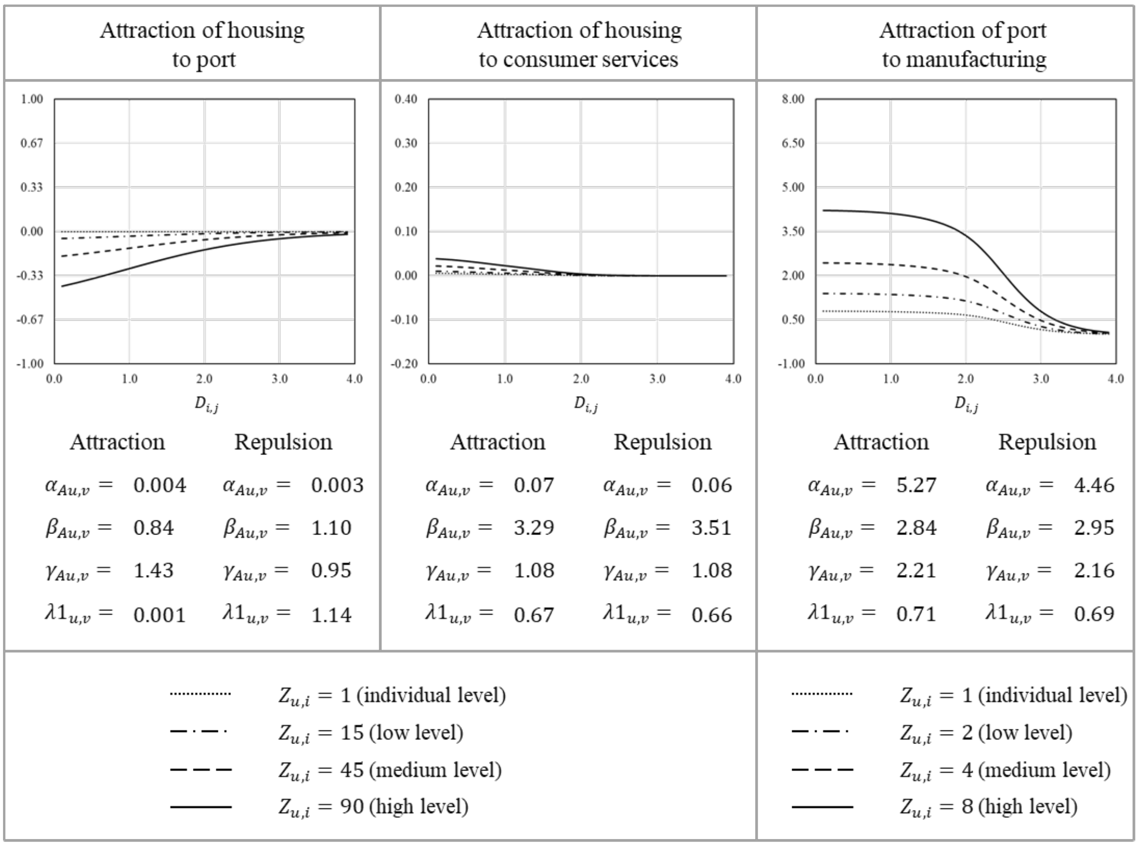


Figure 5 Examples of generalised urban dynamics across all settlements

The presence of housing initially exudes slight attraction to port but quickly become a repulsion as it grows in density. This supports the general observation in port-city literature (for example Hall, 2007) that port-urban connections in port-cities are initially strong but grow weaker or even antagonistic as the cities grow. Meanwhile, housing has a positive and increasing attraction on consumer-services (such as retail and restaurants) whose businesses rely on being accessible from residential areas. The effect of ports on manufacturing is also observed to be strongly positive, but this appears to be stable over longer distances. While the attraction of housing on consumer-services activities dissipates quickly as distance grows, manufacturing activities will tolerate being further from ports. This relativity might relate to the nature of flow within the two activities.

The characteristics of some interactions vary from one group of settlements to others. Figure 6 presents the 2-dimensional mapping of the proximity between the characteristics of interactions measured from the study areas. In general there were four groups and two outliers.

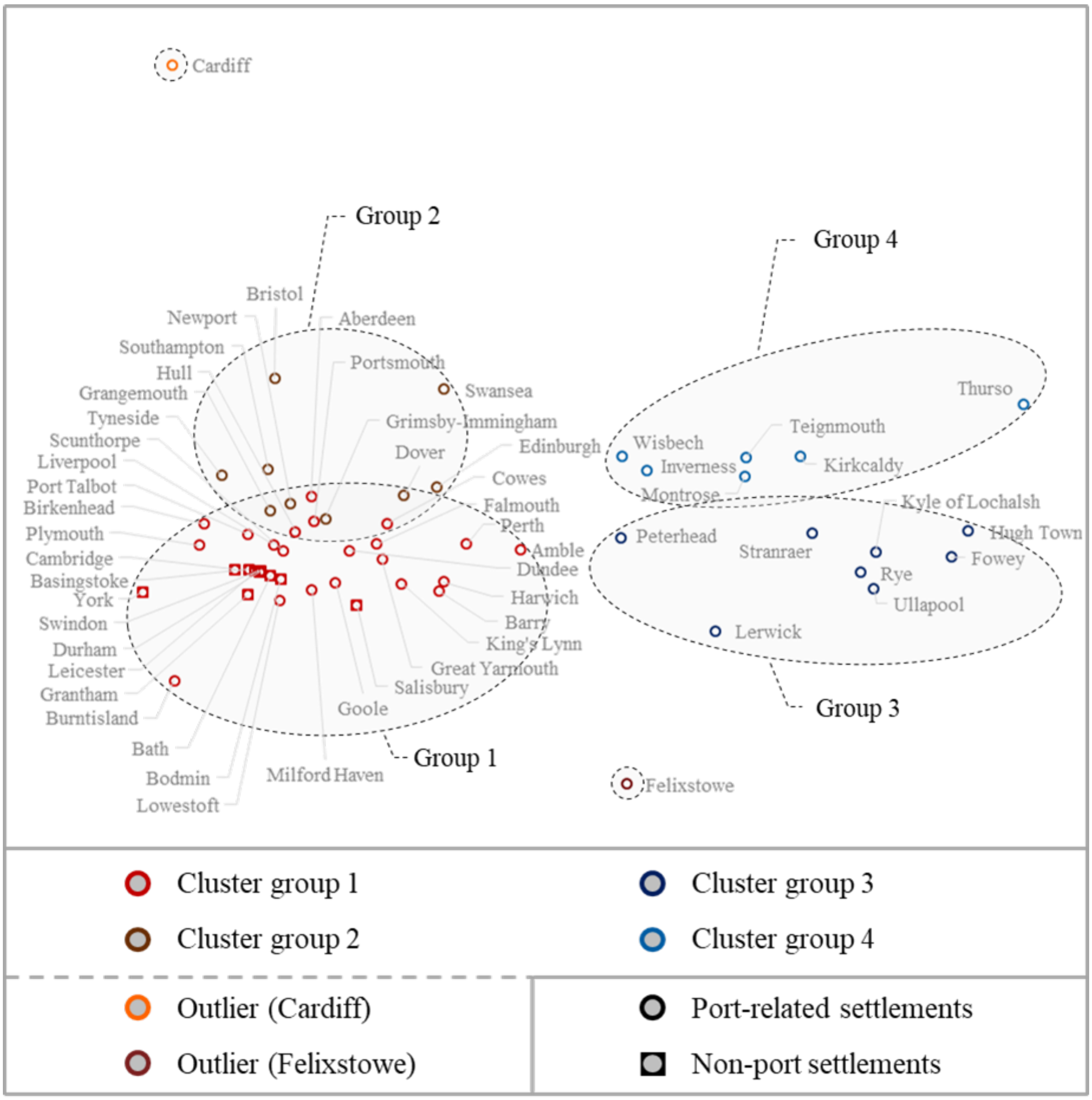


Figure 6 Proximity mapping of study areas

Groups 1 and 2 contain settlements where the effects of ports are relatively small. In fact, all non-port settlements are clustered into Group 1 while Group 2 consists of larger settlements whose economic activities may not rely too heavily on ports. In these groups attractions of ports' presences are small at individual levels and grows slightly (to business services), stagnates (to consumer services) or becomes negative (to housing) as port's activities intensify. Meanwhile in Groups 3 and 4, wherein smaller settlements cluster, ports seem to have generally positive impacts on these land-use activities. Figure 7 presents examples of urban dynamics comparisons between these groups. Again, these reflect stronger port-urban connections in smaller settlements, supporting findings in previous port-cities literature. These also indicate that the difference in urban dynamics between port and non-port settlements are more prominent in smaller settlements.

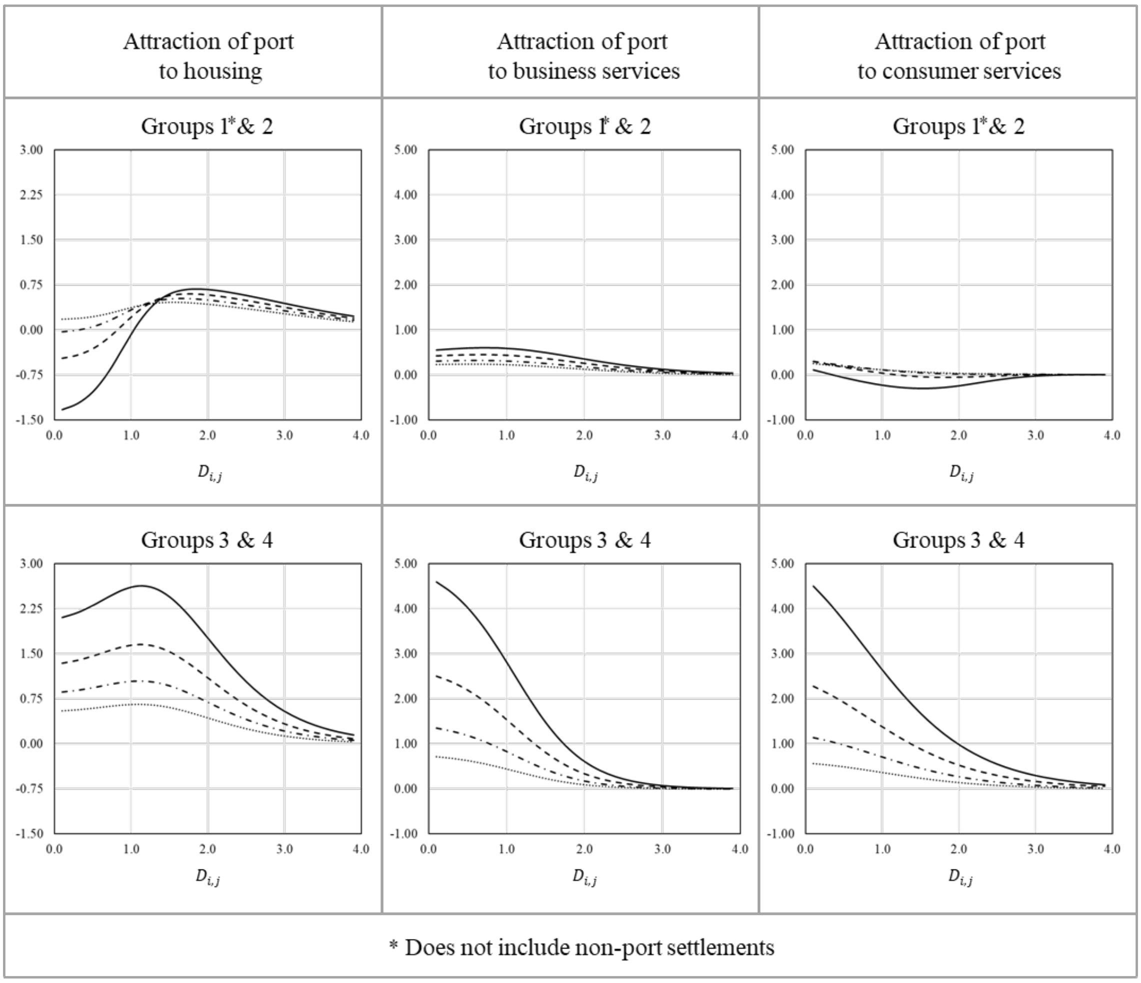


Figure 7 Examples of urban dynamics comparison between groups

The differences between Groups 1 and 2, as well as between 3 and 4, relates more to the effects of manufacturing and services rather than ports. For example, effects of consumer services on housing in Group 1 are higher than 2 while the reverse is true for the effects of manufacturing on housing. In Group 3, attractions of business services to housing development are stronger than in Group 4.

Cardiff and Felixstowe do not belong to any groups. Urban dynamics in Cardiff are closest to Group 2, but are unique as the relationship between port and services are weaker than settlements in Group 2. This might relate to the weaker maritime history in Cardiff where association of urban and port activities were never strong despite having prominent port activities during the Welsh coal boom in the late 18th century (Jenkins, 2007). The characteristics of urban interactions in Felixstowe are in the cross-over between Groups 1 and 3. Felixstowe's population and urban area size are closer to settlements in Group 1, but being the largest container port in the UK, its urban dynamics relating to port activities are similar to settlements in Group 3. Other major container ports, Southampton and Liverpool, are not grouped with Felixstowe as their non-port activities are likely to be more developed than Felixstowe and thus their effects have overshadowed the effects of ports.

Concluding remarks

This paper described a methodology enabling automatic calibration of LUTI models based on CA. Such methodology is an improvement to the current preferred calibration process relying heavily on manual processes. This consequently allowed calibration of multiple study areas efficiently which enabled cross-sectional analysis that can look beyond the presence of path-dependence in examining urban dynamics within an urban system. The methodology was then used to examine the urban dynamics of port-cities in Great Britain.

The penultimate section of this paper touched upon some of the main findings of this research. These findings supported the current view of port-cities literature that port-urban relationships are stronger in the initial development of port-urban systems but grow weaker and even antagonistic as the systems grow larger. These findings, however, went deeper in quantifying the urban dynamics within port-urban systems of various sizes and types (including non-port settlements). Such findings could enable transport and urban planners to better predict the long-term effects of their interventions. This paper therefore provided improvements in the calibration of LUTI models based on CA and contributed to the better understanding of the dynamics between port and urban systems.

Acknowledgements

This work was undertaken as part of PhD research funded by the Republic of Indonesia's Ministry of Finance through the Indonesia Endowment Fund for Education (Lembaga Pengelola Dana Pendidikan – LPDP) program.

This work made use of Ordnance Survey's AddressBase® Plus dataset, supplied in 2019, under the authorisation given in the Research Data Agreement document (Contract Number: 40133005). © Crown copyright and/or database right (2019) OS.

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