Unravelling the dynamics behind the urban morphology of port-cities using a LUTI model based on cellular automata

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Abstract

The urban morphology is a complex system characterised by self-organisation where interactions of multiple agents produce emerging patterns on the urban form. Additional complexities in port cities arise from the port-urban relationship which could either benefit or cause tensions for each other. Most urban cellular automata (CA) models simulate land-use evolution through transition rules with consideration of multiple factors representing the local interactions. Calibration of such models could be seen as a process to measure the effect of each factor. Due to the complexity of the calibration process of urban land use and transport interaction (LUTI) models based on CA, manual methods are often preferred. This, however, limits the insights on urban interactions to a few explored settlements and in turn prevents applications for planning in other port-urban contexts. This paper, therefore, seeks to address three main points. First, the paper demonstrates an improved methods for the calibration of LUTI models based on CA. Second, using the aforementioned method, the paper contributes to a better understanding of the dynamics between port and urban system by quantifying generalizable interactions between urban agents from a wide range of port-urban settlements. Finally, this paper illustrates how the use of these interactions in a simulation model can allow long-term impact predictions of planning interventions.

These were done by formulating an urban CA-LUTI model in a structure akin to a neural network model to enable automatic calibration using an application of the gradient-descent algorithm. The model was then used to quantify the dynamics between geographic, land-use, and transport factors in 46 port-based and 10 non-port settlements across Great Britain, thus enabling cross-sectional analysis. Some interactions were found to be generalizable across all settlements, such as the effect of proximity to port on manufacturing activities. Meanwhile, other interactions were observed to vary between settlements. In order to examine the nature of these variations, cluster analysis of the study areas was conducted on the basis of the calibrated interactions. This produced two main groups, one of which was populated by non-port settlements and relatively larger port settlements and the second consisted of smaller port settlements. In the first group, the attractions of ports to other urban land-use activities were either small or negative, while these effects were more positive in settlements in the second group. Overall, the findings of the research are consistent with existing evidence in the port-cities literature but go further in quantifying the interaction between urban agents within port-urban systems of various sizes and types. These quantified interactions will enable planners to better predict the longer-term consequences of their interventions.

1. Introduction

The urban morphology is a complex system characterised by self-organisation where interactions of multiple agents produce emerging patterns on the urban form (Batty, 2007). In port cities, this is made more complex by the port-urban interactions which could be mutually beneficial in some parts and antagonistic in other parts, especially as port-urban systems grow in size (Hall and Jacobs, 2012). The successes of both port and urban developments in port cities are linked through the spatial organisation (land-use) and spatial interaction (transport) between the different functions in the cities (Merk, 2013). Indeed, tensions between port and urban functions often materialise in the forms of transport (congestion) and land use (space limitations and competitions) problems (Ducruet and Lee, 2006). In order to plan successful long-term interventions, transport and urban planners working in the context of port cities must therefore have a better understanding of the dynamics between different factors within the port-urban system. Generalised insights into these individual interactions are therefore 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.

Cellular automata (CA) models are often used for modelling urban land-use due to their capability in replicating self-organisation behaviour (Batty, 1997; Batty, 2007). Most urban CA models simulate land-use evolution through transition rules with consideration of multiple factors representing the local interactions (Santé et al., 2010). Calibration of such models could be seen as a process to measure the effect of each factor. However, measuring these individual effects from empirical data is complicated due to their autocorrelation and to the effects of specific events occurring in their history (known as path-dependence) on their urban forms (Van Vliet et al, 2013). Due to these complications, manual methods are prevalent in the calibration of urban land-use and transport interaction (LUTI) models based on CA (Aljoufie et al., 2013). This limits the insights into urban interactions to a few explored settlements. 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.

This is even more problematic when the variability between port cities is considered. Ducruet and Lee (2006) proposed a framework with 9 categories of port cities depending on the balance of their centrality and their intermediacy. These are concepts used to describe characteristics of transportation hubs (Fleming and Hayuth, 1994) which were contextualised as the intensity of their urban (centrality) and port (intermediacy) activities compared to the rest of the regions. Beyond this framework, there could be variations in the spatial organisations between urban and port functions. Hoyle (2000) proposed that western port cities often began with both functions being in proximity to each other but the link between them become weaker as the two functions grow. However, other port cities may follow the East Asian spatial growth model (Lee et al., 2008) where strong links between port and city are maintained as the functions grow, or the Middle Eastern model (Akhavan, 2017), where the development of one of the functions lags behind the other function. Furthermore, the effect of ports on the urban areas would also vary depending on the nature of the traffic carried which would have different impacts on the urban economy through the industry interlinkage (Yochum and Agarwal, 1988; Kwak et al., 2005). Due to these variabilities of port city systems, it is important for port cities studies to expand beyond specific case studies and put more effort into testing the applicability of port city evolutionary models in the more generalised context of port cities (Ng et al., 2014). In particular, in the context of port cities' urban form there is a need to examine the contributions of geographic conditions, transport access and proximity to other land uses to the potentials of urban areas in attracting certain types of land use activities within different port city settings.

The aims of this paper are therefore; to introduce an effective automated calibration method of urban CA-LUTI models, to quantify the interactions between urban agents over a wide range of port settlements, and to illustrate how these interactions can be used in a simulation model to predict long-term impacts of planning interventions. The next section describes a representation of an urban CA-LUTI model in a structure akin to a neural network model to enable an automatic calibration process described in the third section. The fourth section discusses the quantified land use interactions as results of the model calibration and the penultimate section illustrates the use of these quantified interactions in predicting the long-term impacts of planning scenarios. The final section sets out some conclusions.

2. Agent-based Urban Cellular Automata Model

CA models are spatially explicit land use models utilising a lattice of regular and uniformly sized cells to represent geographic location (Van Vliet et al., 2012). They simulate the states of cells as the result of their own states and the states of their neighbouring cells through a set of transition rules (Batty, 1997). Previous work (Nugraha et al., 2020) has shown that urban CA models with hexagonal cells have consistency advantages over those with square cells. Therefore, the model in this paper is made up of regular hexagonal cells with each cell having an area size of 22,500 m^2, which is below the maximum recommended size for urban CA models according to Samat (2006). As mentioned, while urban CA models are capable of representing self-organisation behaviour (Batty, 1997) by simulating individual interactions, calibrating these individual effects from empirical data is complicated due to their autocorrelation (Van Vliet et al, 2013). The neural network research field has developed automated calibration approaches for identifying patterns in large data, so it seems beneficial to marry a neural network approach and the calibration of urban CA models.

The approach starts with a model loosely based on Metronamica (RIKS, 2010), which uses cell-potential-based transition rules to simulate cell states (Santé et al., 2010). Rather than employing a fully cell-based approach where cells have categorical states, the model uses a multi-agent approach (as in Van Vliet et al., 2012) where each cell contains information on the levels of different land uses activities co-existing within it. In this agent-based model, the agents are defined as individual unit of activities found in port-city systems, classified into five main representations; 'residential' (such as houses and flats), 'port' (such as harbour and terminal facilities), 'manufacturing' (such as industrial complexes), 'consumer-services' (such as restaurants and shops), and 'business-services' (such as offices). The calibration process therefore measures the interactions between these agents, as well as the way these agents react to geographic and transport conditions, which resulted in their locational decision within the urban system.

In this way, the model explicitly represents multi-purpose developments and developments at varying density levels. More importantly, however, the near-continuous cell states of this approach allow an easier adoption of the gradient descent algorithm, which deals with continuous solution space. The potentials of these cells in attracting certain types of developments are calculated from neighbourhood, geographic, and transport effects. Neighbourhood effect represents the way agents react to the effect of proximity to other land use activities while geographic effect represents the physical suitability of land for certain types of developments. Transport effect is measured by both the proximity to transport infrastructure (static transport effect) and the level of ease other land use activities can be accessed from the cells (dynamic transport effect). With the exception of dynamic transport, these effects are calculated for each cell. Dynamic transport effect is calculated from the amount of activities that can be reached from cells and the amount of time it takes to reach them. The latter is simulated using a 4-stage transport model and the use of cells as spatial unit in this case would require more computational resources than what are available to the research. Therefore, transport analysis zones are used as the spatial unit for dynamic transport calculation. Analysis zones have a disadvantage over cells that their sizes are often based on the importance of area with smaller zones representing more important areas (usually denser areas in urban context). Consequently, when used in simulation over long period, such may be necessary to understand evolution in urban forms, the use of analysis zones may provide artificial barriers for previously vacant areas to develop into dense urban centres or sub-centres. To compensate this, an element of dynamism is introduced to the analysis zones using the framework described by Nugraha and colleagues (2018), where analysis zones are decomposed into smaller zones when they hit certain density thresholds.

To enable the use of gradient descent algorithm, model calibration is represented as an optimisation problem with an objective function that minimises the disagreement between actual land use distribution and the predicted cell potentials. Cell potentials are, in turn, calculated from a network of differentiable functions. The gradient descent algorithm uses partial differentiations of the objective function with regards to calibrated parameters to update solutions towards an optima. Table 1 presents the mathematical model with annotations of the intermediate calculation. Meanwhile, Table 2 presents the glossary for model data inputs not defined in Table 1. The calibration process determines the values of the parameters at the bottom of Table 1.

Table 1. Formulation of model into optimization problem	
Objective function	$\boldsymbol{min}\sum_j\left(\frac{\left(Z_{v,j}-Predicted_{v,j}\right)^2}{Predicted_{v,j}}\right)$
where:	
Predicted values	$Predicted_{v,j} = \frac{P_{v,j}}{\sum_{j\mid j\epsilon SA} P_{v,j}}.Total_{v,SA}$
Cell potential	$P_{v,j} = G_{v,j}\,.\,T_{v,j}\,.\,N_{v,j}$
Geographic effect	$G_{v,j} = \prod_x B\left(F\left(C(\eta_{x,j}),\mu_{x,v}\right)\right)^{\omega_{x,v}}$
Projection function	$C(\theta) = c + (1-2c)\left(0.98\left(\frac{\theta - min_\theta}{max_\theta - min_\theta}\right)+0.01\right)$
Shifting function	$F(\theta,\phi) = \left(1-\left({}^1\!/_\phi\right)(1-\theta)\right)$
Bounding function	$B(\theta) = \frac{log\left(1+e^{10\theta}\right)}{log\left(1+e^{10}\right)}$
Transport effect	$T_{v,j} = ST_{v,j}\,.DT_{v,j}$
Static transport effect	$ST_{v,j} = \prod_y B\left(F\left(C(\rho_{y,j}),\upsilon_{y,v}\right)\right)^{\varphi_{y,v}}$
Cell to zone	$DT_{v,j} = DT_{v,jj} \quad for\, j \in jj$
Dynamic transport effect	$DT_{v,jj} = \sum_m\sum_u\sum_{ii}\left(\frac{\kappa_{u,v,m}.Total_{u,ii}}{\left(1+ODTM_{jj,ii,m}\right)^{\partial_{u,v,m}}}\right)$
Neighbourhood effect	$N_{v,j} = S\left(\sum_u\sum_{i\mid i\in N(j)}\left(\left(Z_{u,i}\right)^{\lambda_{A,u,v}}.\ A_{u,v,i,j} - \left(Z_{u,i}\right)^{\lambda_{R\,u,v}}.\ R_{u,v,i,j}\right)\right)$
Rectifier	$S(\theta) = log\left(1+e^\theta\right)+0.00001$
Masker	$Z_{u,i} = 0 \quad where \quad (u=v)\cap(i=j)$
Attraction effect	$A_{u,v,i,j} = \alpha_{A,\,u,v} - \frac{\alpha_{A,\,u,v}}{\left(1+Exp\left(-\beta_{A,\,u,v}.\left(D_{i,j}-\gamma_{A,\,u,v}\right)\right)\right)}$
Repulsion effect	$R_{u,v,i,j} = \alpha_{R,\,u,v} - \frac{\alpha_{R,\,u,v}}{\left(1+Exp\left(-\beta_{R,\,u,v}.\left(D_{i,j}-\gamma_{R,\,u,v}\right)\right)\right)}$
subject to the calibrated parameters:	
Geographic parameters	$0<\mu_{x,v}\leq 1\,,\ \omega_{x,v}\geq 0$
Static transport parameters	$0<\upsilon_{y,v}\leq 1\,,\ \varphi_{y,v}\geq 0$
Dynamic transport parameters	$\kappa_{u,v,m}\geq 0\,,\ \partial_{u,v,m}\geq 0$
Neighbourhood effect parameters	$\alpha_{A,\,u,v}\geq 0\,,\ \beta_{A,\,u,v}\geq 0\,,\ \gamma_{A,\,u,v}\geq 0\,,\ \lambda_{A,\,u,v}\geq 0$ $\alpha_{R,\,u,v}\geq 0\,,\ \beta_{R,\,u,v}\geq 0\,,\ \gamma_{R,\,u,v}\geq 0\,,\ \lambda_{R,\,u,v}\geq 0$

Table 2. Model inputs glossary	
$Z_{v,j}$	Observed land use activity v in cell j
$Total_{v,SA}$	Total amount of activity v in study area SA or within the zone ii
$\eta_{x,j}$	Suitability of geographic factor x for development in cell j
$\rho_{y,j}$	Distance to transport infrastructure y from cell j
$ODTM_{jj,ii,m}$	Journey time from origin zone ii to destination zone jj using mode m
$D_{i,j}$	Distance between cells i and j

The effect of a geographic feature x on a land use activity v is quantified by $\mu_{x,v}$, regulating the range of $\eta_{x,j}$ values within which the effect is most sensitive, and $\omega_{x,v}$, regulating how sensitive the land use is to the change in geographic feature. The same mathematical structure applies in static transport with the parameters $\upsilon_{y,v}$ and $\varphi_{y,v}$ regulating the effect of $\rho_{y,j}$. The effect of accessibility to a land use activity u, measured by journey time on a specific mode of transport m, on cell's attractiveness to land use activity v is regulated by $\kappa_{u,v,m}$ scaling attractiveness linearly to the intensity of land use activity u at the destination, and $\partial_{u,v,m}$ which decreases attractiveness log-linearly as access time increases. The neighbourhood effect is the most complex interaction regulated by the most variables. An individual neighbourhood interaction between two land use activities is governed by two main constituents, attraction and repulsion. Each is in turn governed by the parameters $\alpha_{u,v}$ representing the general potency of the effect, $\beta_{u,v}$ representing how sensitive that potency changes with distance, $\gamma_{u,v}$ representing the potency at immediate distance, and $\lambda_{u,v}$ representing how quickly that potency grows as the neighbour's presence intensify.

3. Measurement of Urban Dynamics

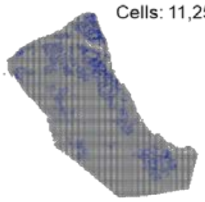
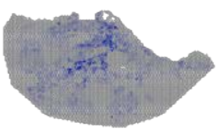
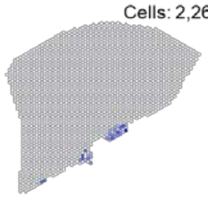
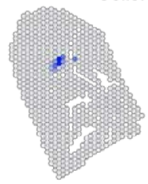
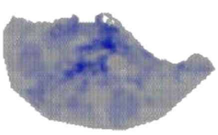
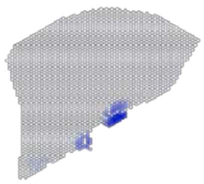
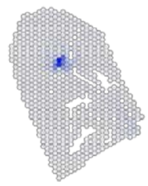
In order to measure urban dynamics of port cities, the model described in the previous section was calibrated for 46 settlements with ports of various sizes across Great Britain and an additional 10 non-port settlements as comparison. The population and area sizes of these study areas range from a settlement with a population of 650 over an area of 1 km^2 (Kyle of Lochalsh) to one with over 1.5 million population with a 563 km^2 area (Tyneside metropolitan area). Note, however, that these selections excluded larger settlements such as Greater London due to computational resources limitations. As mentioned, these study areas also included settlements without ports such as Swindon and Salisbury as well as settlements where port activity has ceased such as York (a major port during the Viking era). Types of ports included highly containerised port such as Felixstowe, non-container freight ports such as Grimsby and Immingham, mainly passenger ports such as Harwich, fishing ports such as Peterhead, and those with mixed traffic such as Dover (ferry passenger and non-containerised freight) and Southampton (cruise passenger and containerised freight). These study areas also vary in terms of their form of waterfront from coastal settlements such as Dover and Peterhead, estuarial such as Southampton and Fowey, inland such as Wisbech (with port) and Grantham (without port), and also smaller island settlements such as Hugh Town, Lerwick, and Cowes. The general patterns of urban dynamics are uncovered by comparing results from calibrations of these study areas.

Land use data for these settlements were sourced from Ordnance Survey's AddressBase® Plus dataset containing classed and geo-located addressable properties. Data on geographic suitability and locations of transport infrastructures were also obtained from Ordnance Survey while origin-destination journey time matrices for dynamic transport calculation were obtained using the OpenTripPlanner software as in Young (2016). Calibration for each study area was done by minimising the disagreement between actual and predicted land use distributions using an adaptation of the gradient descent algorithm with momentum and multiple start points. Table 3 summarises the mathematical functions involved in the gradient descent algorithm with momentum (see Ruder, 2016 for a more detailed discussion).

Table 3. The gradient descent algorithm with momentum	
Objective function to optimise	$\boldsymbol{min}\, f([x]_t)$
Solution at iteration t	$[x]_t = [x_1 \quad x_2 \quad \cdots \quad x_n]_t$
Gradient at $[\boldsymbol{x}]_t$	$[g]_t = \left[\frac{\partial f([x]_t)}{x_1} \quad \frac{\partial f([x]_t)}{x_2} \quad \cdots \quad \frac{\partial f([x]_t)}{x_n}\right]_t$
Solution update at iteration t	$[v]_t = r[g]_t + p[v]_{t-1}$, $\quad$ $where\ 0 < p < 1$
Solution at iteration t+1	$[x]_{t+1} = [x]_t - [v]_t$

The parameter r is the learning rate dictating the length of steps taken at every solution update. The momentum factor, p, dictates the weight with which updates in the previous iterations are considered in current iteration. Each calibration started from 20 randomised initial solutions and the best solution at the end of the 2,000th iteration was used as the final solution. After conducting a pilot study, a learning rate of 10^{-6} and a momentum factor of 0.1 were used in model calibrations. For a small number of study areas, a finer calibration with a learning rate of 10^{-7} starting from informed solution points was necessary as the model diverged at the higher learning rate. Table 4 shows some example comparisons between actual and predicted distributions of land uses activities.

Table 4. Comparisons of model predictions with actual distributions

	Study Areas*			
	Birkenhead's Housing	Edinburgh's Housing	Dover's Port	Rye's Consumer Services
Actual Distribution	Cells: 11,259 	Cells: 6,692 	Cells: 2,262 	Cells: 715 
Predicted Distribution				
	Prediction performance – Pearson's correlation index			
	$R = 0.877$	$R = 0.772$	$R = 0.622$	$R = 0.901$
	*) maps are not to scale			

Cluster analysis of the study areas identifies whether urban dynamics measured from some study areas are similar enough that they can be generalised into groups. The calibration approach has been effective in untangling urban form into the individual interactions, which describes how an average unit of land use development react to individual factors (e.g. neighbourhood reaction to each type of land use activities, each geographic suitability factors). These individual factors, in theory, could be decomposed even further to the effect of individual parameters. The calibration approach described in this paper stops short of untangling these individual parameters' effect. Such endeavour would require a more microscopic analysis likely consisting mainly of stated preference approach asking individual urban agents how they would react in a series of hypothetical situations. While such microscopic examination might contribute to theoretical study of urban system, it does not improve the model's practical use in planning and requires much more effort, especially considering the number of study areas.

In other words, the calibration approach in this paper by examining locational revealed preference of agents in the urban form is not sensitive to the noise around the exact values of individual parameters effect. It is, however, sensitive to the individual interactions which are the combined effect of the constituent parameters. Therefore, curves formed by the individual parameters for each study area better describe these individual interactions than the individual parameters' values. Cluster analysis is therefore conducted using the graph clustering method. The graph clustering method aims to group similar curves together by taking gauge points along an axis. Curves are clustered based on their scores across the clustering variables. In the examples given in Figure 1, the 2nd and 3rd curves are more similar and therefore more likely to be clustered into the same group than the curve in the 1st instance. Clusters are formed using principal component analysis to extract curve(s) that are linearly uncorrelated to one another. Each of these principal component represents unique group of urban dynamics.

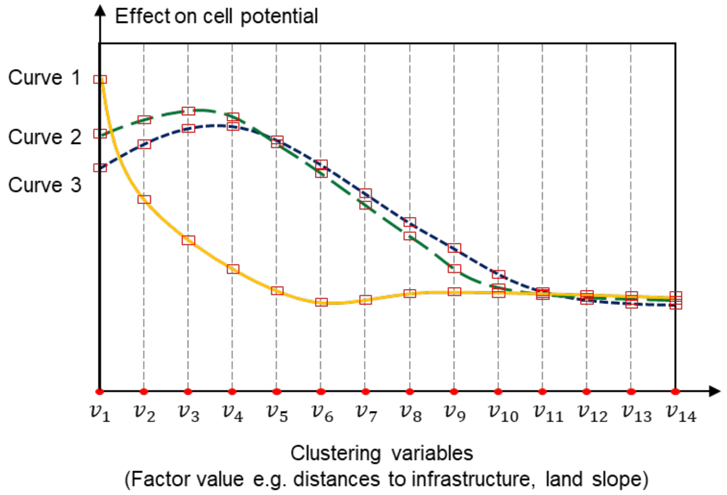


Figure 1. Illustration of the graph clustering method

4. Analysis of Land Use Interactions in Port Cities

This section describes the calibration results starting with neighbourhood effect. Cluster analysis discovered two main groups of port cities in the study areas which differed especially in their interactions between their urban and port activities. These main groups could be further subdivided into two subgroups. The distinctions between the subgroups were attributed more to the effects of manufacturing and services activities. Additionally, Cardiff and Felixstowe were singled out as outliers. Figure 2 describes the overall hierarchy of these clusters.

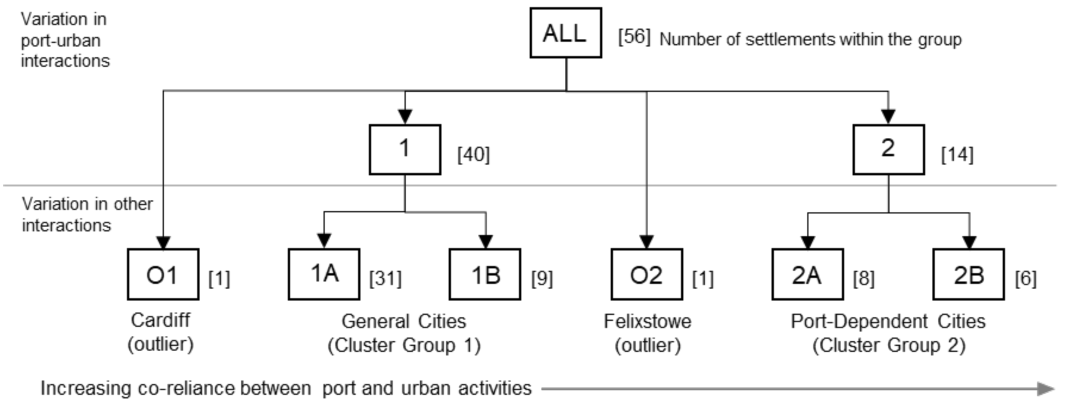
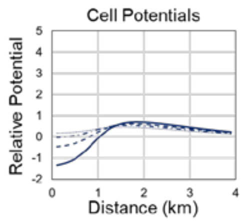
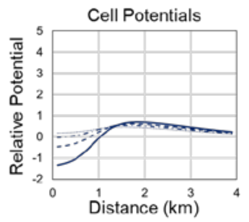
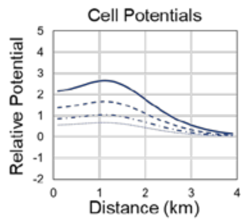
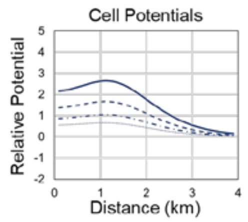
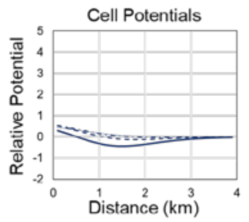
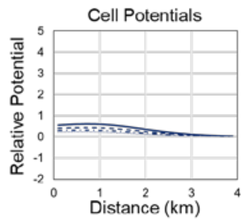
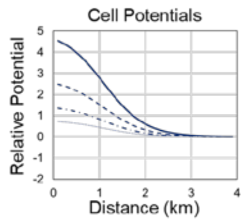
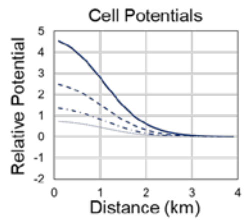
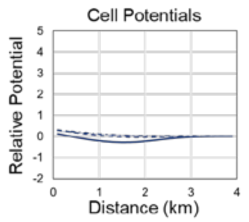
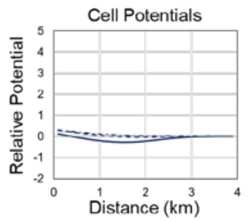
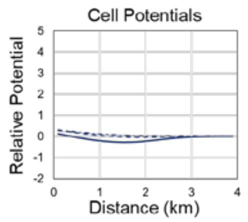
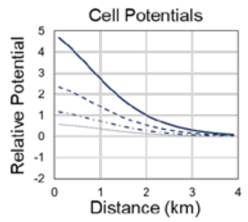


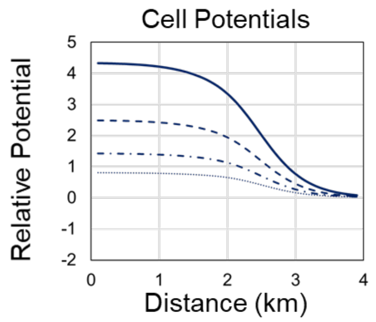
Figure 2. Clusters hierarchy from variations in neighbourhood effects

Most settlements fell into the first group, “General Cities”, which was populated by non-port settlements and relatively larger port settlements. Meanwhile, the second group, “Port-Dependent Cities” consisted of smaller port settlements. In the first group, the attractions of ports to other urban land-use activities were either small or negative, while these effects were more positive in settlements in the second group. This supports the general observation of port-city literature where port-urban connections are strong initially when a system is relatively small but grow weaker or even antagonistic as the port city becomes more developed (Hall and Jacobs, 2012). Additionally, this indicated that the presence of ports was a distinguishing factor in the urban dynamics of small settlements, while less prominent differences were observed between the urban dynamics of port and non-port settlements in larger study areas. Felixstowe appeared to show similar port-urban interactions as port dependent cities, but had some elements of general cities’ behaviours such as the weaker relationships between port and consumer services activities. Meanwhile Cardiff showed an even weaker port-urban connection than general cities. Table 5 presents some examples of port-urban interactions within the main clusters.

Table 5. Examples port-urban interactions observed in the main clusters

Cardiff	*General cities*	*Felixstowe*	*Port-dependent cities*
The effect of proximity to ports on housing			
			
The effect of proximity to ports on business services			
			
The effect of proximity to ports on consumer services			
			
individual level — low level — medium level — high level			

In the mainstream subgroup, 1A, the biggest subgroup with 31 out of 56 settlements and containing all non-port settlements, the net effects of manufacturing on housing are negative in small distances and positive around a distance of about 2km. In the 9 settlements grouped as 1B, while the peak attraction occurred at about the same distance, housing developments are not repulsed by being too close to manufacturing activities. This was more typical of the urban dynamics between manufacturing and housing in smaller settlements in the second group. Meanwhile, the attraction of retail establishments on housing is stronger in subgroup 1A than in 1B. The subgroups of the second group, 2A and 2B, were more similarly sized at 8 and 6 settlements. In settlements in subgroup 2A, which were of relatively larger sizes than subgroup 2B, self-agglomeration behaviour of services activities was more prevalent, mimicking the behaviour of services activities in group 1. Some interactions, however, were found to be similar across all study areas including the effects of port on manufacturing as shown in Figure 3. Finally, Figure 4 summarises neighbourhood interactions observed in the model calibration. These star diagrams indicate the overall nature of interactions using green line and plus symbol (+) to represent attraction and red line and backslash symbol (\) for repulsion. Unbroken lines indicate interactions that are sensitive to distance while dashed lines indicate those that are not. The width of the lines indicates the strength of these interactions.



Combination option of Calibrated Parameters

Attraction		Repulsion	
$\alpha_{Au,v} =$	5.27	$\alpha_{Ru,v} =$	4.46
$\beta_{Au,v} =$	2.84	$\beta_{Ru,v} =$	2.95
$\gamma_{Au,v} =$	2.21	$\gamma_{Ru,v} =$	2.16
$\lambda_{A\,u,v} =$	0.71	$\lambda_{R\,u,v} =$	0.69

individual level — low level — medium level — high level

Figure 3. The effect of proximity to ports on manufacturing

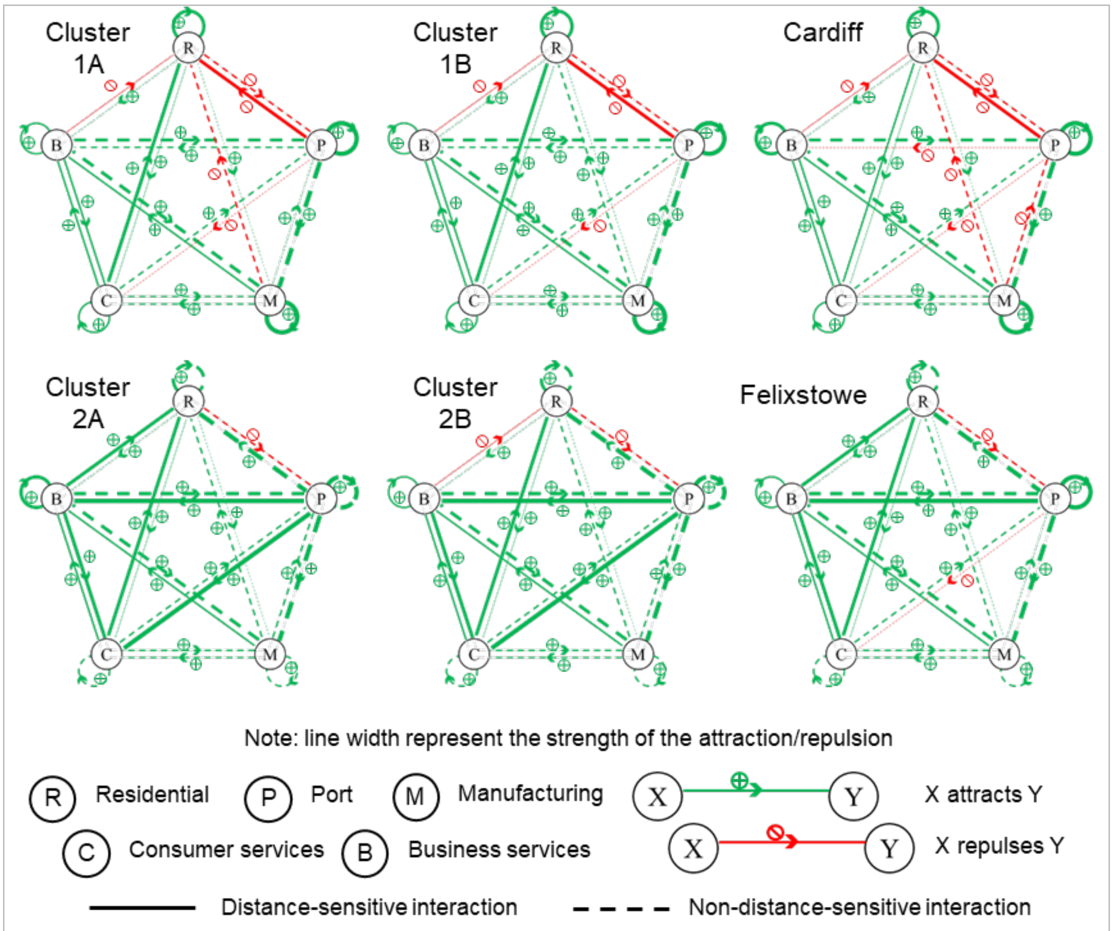


Figure 4. Summary of urban interactions in the settlements observed

Moving on to transport and geographic effects, these were generally found to be similar across the study areas. One of the key findings was that employment activities benefit from access to housing developments although the neighbourhood effects of housing on other land uses were found to be generally weak. Consequently, areas with high levels of employment activities were generally accessible (due to sensitivity to transport effect), but not necessarily nearby (due to insensitivity to neighbourhood effect), from residential areas. Further, access to rail connection was found to have a stronger attraction effect on employment activities rather than housing developments. An exception to this was on smaller and more compact settlements where housing developments cluster more closely to rail stations. This is shown in Figure 5 with the dashed line being more sensitive to distance than the unbroken line.

Calibrated Parameters			
		ν	φ
Residential		0.718	0.365
Residential*		0.550	1.432
Port		0.481	0.835
Manufacturing		0.817	1.544
Consumer Services		1.000	2.451
Business Services		1.000	1.948

*applies to compact cities
with rail station within their urban area

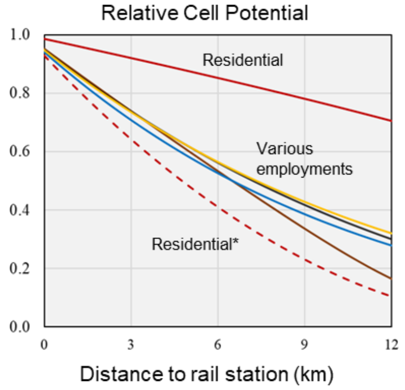


Figure 5. The effect of proximity to rail station on cell potentials

5. Predicting Policy Impacts in Port City

This section briefly discusses the benefits of the quantifications of urban dynamics by demonstrating their use to assist planning in a real port development policy in Southampton. The Associated British Port (ABP), Port of Southampton's operator, has been planning to turn Dibden Bay, a site on the western bank of River Test opposite the current port site, into a container terminal. However, these plans have been rejected due to the detrimental impacts of such development on the environment. A simulation LUTI model has used the urban dynamics described in the previous section to predict long-term land use and transport impacts of different policy options. Some of the model's results are presented in Figure 6.

Promotion policy predictably resulted in the rise of port development in Dibden Bay. However, this would also trigger housing developments around the site. This is due to the attraction of access to port employment in Dibden Bay, but noticeably this occurred at some distance away rather than immediately next to the port as proximity to port is not necessarily attractive for housing. Mainly, this resulted in housing densification in existing sub-centres north (Marchwood) and south (Hythe) of Dibden Bay, but they also sprawl to green site enveloping Dibden Bay. While this may alleviate housing needs near the city centre, there could be additional loss of green spaces nearby Dibden Bay. Promotion policy also resulted in the current port site nearby the city centre being overtaken by retail (not pictured) and residential development. This indicated a similar trend that Liverpool has seen in the historic docks and indeed would be continuing an existing trend in Southampton.

The transport sub-component of the model, based on the traditional 4-stage transport model, also detected some changes in traffic conditions between the two policies. By promoting port development in Dibden Bay, city centre traffic was alleviated by the removal of port traffic away from the city, but this was replaced by currently suppressed urban traffic, resulted only in minor reduction of traffic around the city centre. This meant that additional measures to promote public transport and non-motorised transport would be required to lock-in the traffic benefits of the port's migration to Dibden Bay. Additionally, transport infrastructure connecting the new port site to the rest of the region would likely need improvement to handle the increased demand. The model therefore could contribute to the policy decision-making process.

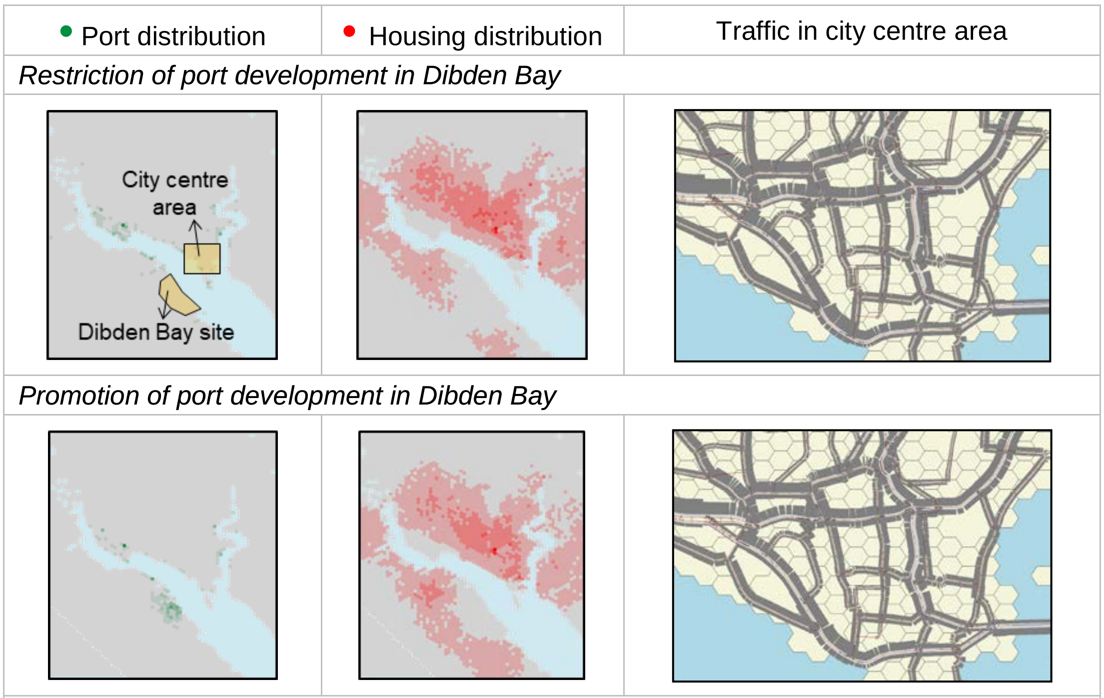


Figure 6. Simulations of long-term development policy impact in Southampton

6. Conclusions

This paper has presented an automated calibration approach to calibrate an urban CA model, thus allowing quantification of urban dynamics in the general context of port cities, as opposed to case specific examinations currently dominating the field (Ng et al., 2014). Overall, the findings of the research are consistent with existing evidence in the port-cities literature but go further in quantifying the interaction between urban agents within port-urban systems of various sizes and types. In this regard, the majority of the study areas were classified into the general cities clusters while port-dependent cities consisted mainly of smaller ports within a relatively small settlements. This supports Hall and Jacobs' (2012) observations that in the system where both port and urban components are small, the urban economy rely heavily on activities directly related to the port. When the system grows, however, this reliance seems to weaken. This was true even when the urban growth is driven by the port such as in Dover. This is because as ports grow, they induce the growth of interlinked industries (Kwak et al., 2005) which may not be directly related to port activities such as retail and leisure to accommodate the needs of ports' labour. These less impactful activities, in turn, become more attractive for housing and other forms of urban development rather than the port, thus weakening the port-urban interactions in terms of wider urban form.

This paper therefore demonstrates improved methods for the calibration of LUTI models based on CA which provide insights into the behaviours of individual interactions between urban agents. Such findings provide important insights for future research by contributing to a better understanding of the dynamics between port and urban agents within a port city system. These are also invaluable for the transport and urban planning of port-cities as they enable planners to better predict the longer-term consequences of their interventions.

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