Computers, Environment and Urban Systems 75 (2019) 229–243

Contents lists available at ScienceDirect

Computers, Environment and Urban Systems

journal homepage: www.elsevier.com/locate/ceus

A multi-scale urban integrated assessment framework for climate change studies: A flooding application

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ARTICLE INFO

Keywords:
Climate change
Cities
Urban planning
Land-use
Transport
Flooding

ABSTRACT

In order to assess the potential future impacts of climate change on urban areas, tools to assist decision-makers to understand future patterns of risk are required. This paper presents a modelling framework to allow the downscaling of national- and regional-scale population and employment projections to local scale land-use changes, providing scenarios of future socio-economic change. A coupled spatial interaction population model and cellular automata land development model produces future urbanisation maps based on planning policy scenarios. The framework is demonstrated on Greater London, UK, with a set of future population and land-use scenarios being tested against flood risk under climate change. The framework is developed in Python using open-source databases and is designed to be transferable to other cities worldwide.

1. Introduction

More than 50% of the world's population reside in cities, and this is expected to increase by a further 2.5 billion by 2050 (UN, 2014). Such spatially-focussed concentrations of population mean that cities will contribute significant greenhouse gas (GHG) emissions in the future above the current 70–80% of the global total (O'Meara, 1999; Rosenzweig, Solecki, Hammer, & Mehrotra, 2010). Urban areas, however, occupy less than 2% of the Earth's land surface (Balk, Pozzi, Yetman, Deichmann, & Nelson, 2005) and so the impact of cities on climate change far exceeds their proportional global spatial footprint. Population densities per square metre of between 100 and 1000 times those of rural areas (Hunt, Timoshkina, I, & Belcher, 2013) means that cities are also hot-spots of vulnerability and exposure to a differentially warming climate (Revi et al., 2014), with climate change impacts expected to be higher within urban areas (Stone, 2007). Even the most ambitious of mitigation policies may not significantly reduce the impact of climate change on cities in coming decades, so there is a need to develop long-term spatial plans and policies that address emissions reduction whilst moving towards robust adaptation to the impacts of climate change (Revi et al., 2014).

Studies have shown that urban forms and associated infrastructure can influence both climate change mitigation (Creutzig, 2014; Newman & Kenworthy, 1999; Sims et al., 2014) and adaptation efforts (Blankenstein & Kuttler, 2004; Dawson & Hall, 2006; Mavrogianni et al., 2011). To address these requires the development of robust spatial planning policies that address the impacts of climate change (Adger, Hughes, Folke, Carpenter, & Rockström, 2005; Bulkeley & Betsill, 2005; Dawson et al., 2011; Ford, Dawson, Blythe, & Barr, 2018). This in turn requires new analytical tools that allow planners to understand the complex spatial and temporal intersections between climate-related hazards, and the socio-economic components and actors defining the urban system (Ford et al., 2018). The IPCC Fifth Assessment report (Revi et al., 2014) identified that such tools need to be multi-scale so that understanding of the impacts of climate change can be undertaken from a systems perspective; from an entire city, down to impacts and adaptation options local scale. Moreover, the interconnected nature of modern cities and infrastructure means that impacts can often be felt in areas spatially-removed from hazard locations (Seto, Güneralp, & Hutyra, 2012), necessitating the ability to analyse and understand interactions between hazards, impacts and the socio-economic structure of cities.

Modelling efforts have attempted to capture these interactions in urban systems by examining individual sectors in turn. Many studies (such as Schreider, Smith, and Jakeman (2000)) have examined the effects of climate change on urban flooding impacts, demonstrating that changes to rainfall extremes will increase the magnitude and frequency of flood events. Hammond, Chen, Djordjević, Butler, and Mark (2015) examined methods for analysing flood risk in urban areas but future land-use and socio-economic changes were not included in the

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https://doi.org/10.1016/j.compenvurbsys.2019.02.005
Received 11 September 2018; Received in revised form 7 January 2019; Accepted 14 February 2019
Available online 28 February 2019
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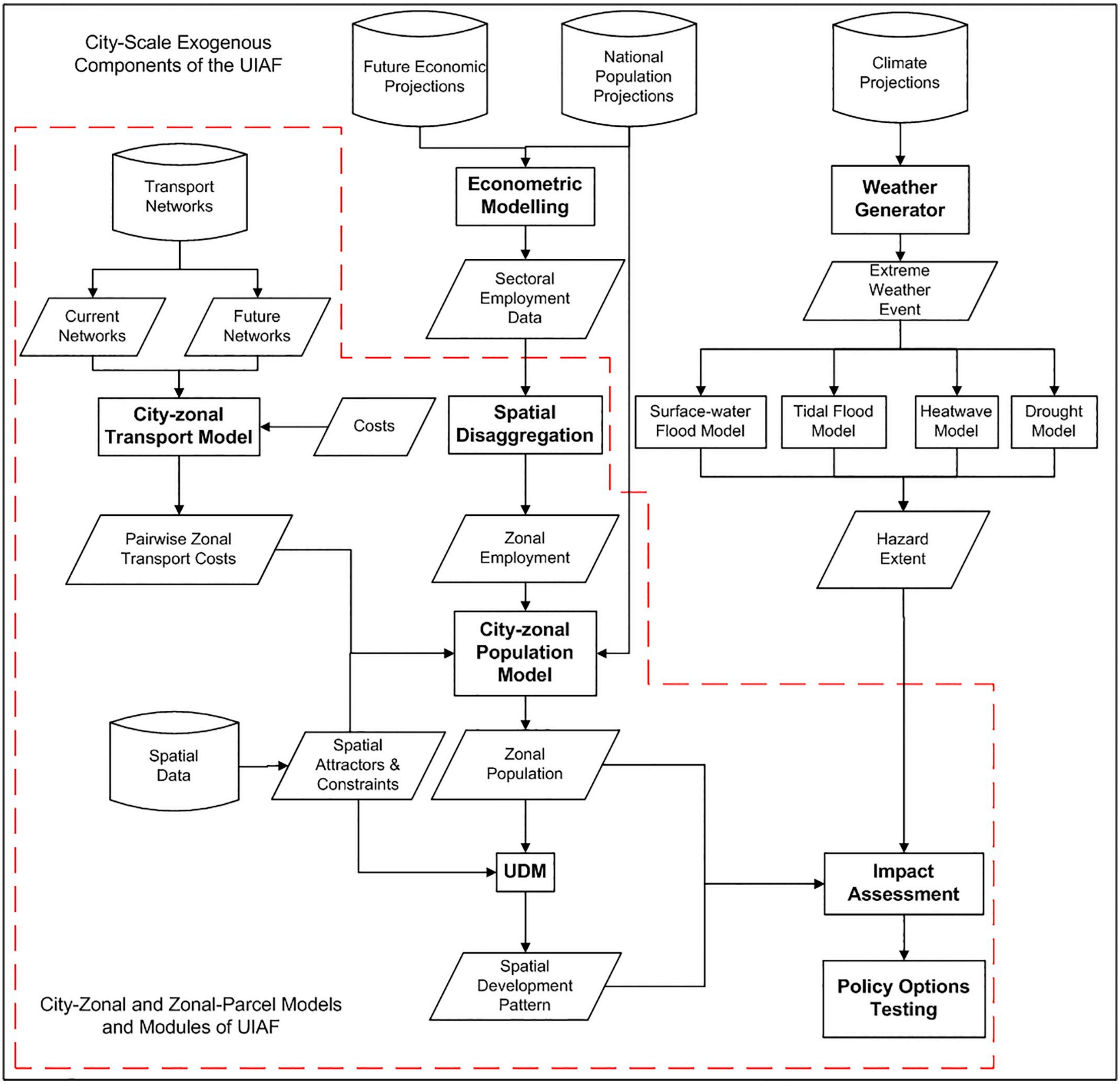

Fig. 1. The Urban Integrated Assessment Framework (UIAF).

approaches they reviewed. Miller and Hutchins (2017) stressed the need for models to understand "the impacts of urban densification and expansion [and] population distribution on urban flood risk and water quality". Hammond et al. also highlight the issue of impacts to infrastructure (particularly transport networks), a topic which has been addressed by a number of studies including Suarez, Anderson, Mahal, and Lakshmanan (2005) and Pregnolato, Ford, Wilkinson, and Dawson (2017).

This paper presents an Urban Integrated Assessment Framework (UIAF) designed to provide planners with a suite of integrated tools that allows a multi-scale analysis of the climate change impacts on cities and adaptation options that can be evaluated, alongside mitigation policies. The UIAF provides long-term simulations of climate impacts and economic, population and land-use change across an entire city. The modelling framework presented in this paper is intended to capture enough of the dynamics of urban processes to distinguish differences between scenarios in order to inform policy debate, visualising such differences and their implications for climate risk in an understandable way. The use of a framework of this type ensures that scenarios are plausible and driven by consistent sets of policies. We demonstrate the utility of this approach, and in particular its use of coupled transport, population and land-use models, to simulate future spatial development in Greater London, UK and test a number of spatial planning scenarios for adaptation to future flooding.

2. The Urban Integrated Assessment Framework

The UIAF comprises a suite of models and impact analysis modules that are coupled together to analyse how future global and national scenarios of climate and economic change could impact on cities (as shown in Fig. 1). The UIAF simulates urban activity and processes at multiple scales in order to analyse their spatial and temporal

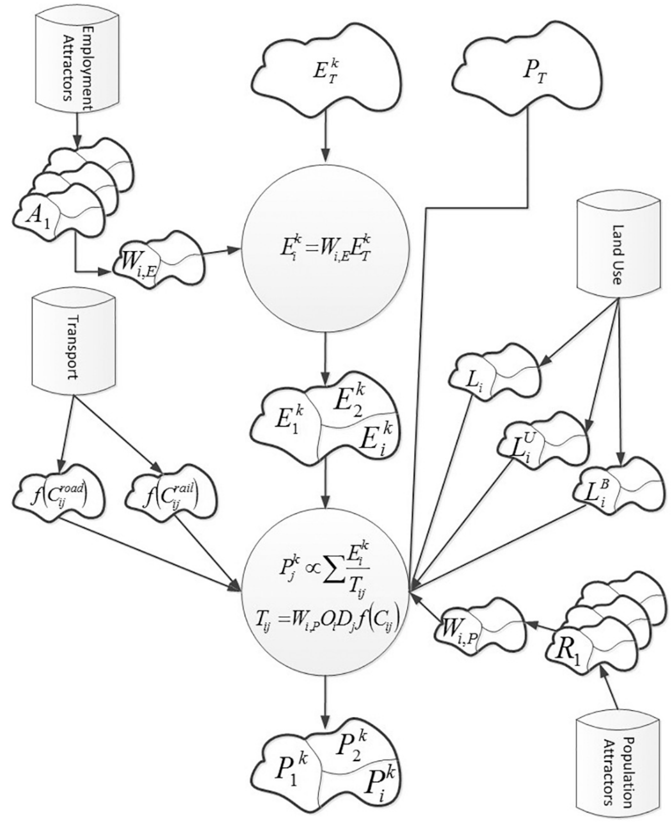

Fig. 2. City to city-zonal models used in the UIAF to derive zonal estimates of future population showing how total sectoral employment ($\boldsymbol{E_T}^{\boldsymbol{k}}$) and population ($\boldsymbol{P_T}$) are downscaled through sets of attractors ($\boldsymbol{W_{i,E}}$) and ($\boldsymbol{W_{i,P}}$), and total zonal available land ($\boldsymbol{L_i}$), unusable land per zone ($\boldsymbol{L_i}^{\boldsymbol{u}}$) and the amount of land assigned to 'basic industrial' economic activity per zone ($\boldsymbol{L_i}^{\boldsymbol{b}}$) to give zonal population ($\boldsymbol{P_i}^{\boldsymbol{k}}$) based on transport accessibility costs $\boldsymbol{f(C_{ij})}$.

intersection with future climate change hazards such as flooding, heat and, drought. Climate downscaling, taking model results from global models to local scale, is common in climate change impact analysis (Smid & Costa, 2018). The UIAF aims to provide similar downscaling of national and regional socio-economic projections to city-scale to enable the analysis of the coupled impacts of both climate change and socio-economic change.

The framework includes three hierarchical levels of representation; city, city-zonal and zonal-parcel. The city scale is represented by a suite of exogenous models that provide external global and national scenarios of climate and economic change. The city-zonal and zonal-parcel scale models allow these exogenous economic and climate predictions to be downscaled for analysis at finer spatial scales, either in administrative zones, spatial-parcels, or development sites (see Fig. 1). The city-zonal and zonal-parcel modelling provides the capacity to explore the effect of different planning and adaptation options available to policy makers across a range of spatial and temporal scales. Thus, the UIAF allows decision makers to explore a number of possible urban futures or adaptations with respect to global climate change and economic scenarios.

2.1. City-scale exogenous inputs to the UIAF

The UIAF requires two main global-scale exogenous inputs. The first is a projection of future socio-economic change for the city region under consideration in terms of aggregate change in total employment and total population. This total is taken as an input to the UIAF modelling components which distribute the aggregate values down to zonal scale. Such data is normally available from government organisations, such as the UK Office for National Statistics, for a number of future time periods. Econometric models can also be used to provide estimates of employment totals by economic sector (e.g. by SIC classification).

The second city-scale exogenous input is a set of climate projections for the area in which the city under analysis is located. Climate projections are available from a number of sources including the CMIP5 project outputs hosted by the IPCC Data Centre (Emori et al., 2016). Such data can be used at their native output resolution of up to 50 km to conduct climate impact studies of for urban areas as a whole (Guerreiro, Dawson, Kilsby, Lewis, & Ford, 2018). Often these are too coarse to resolve the full spatial variability within cities so require downscaling to a resolution that can be used for urban impact assessments. Such downscaling techniques for urban impact assessment applications are reviewed in Smid and Costa (2018).

2.2. UIAF city-zonal models

The city-zonal components of the UIAF comprise three spatial models and impact assessment modules to downscale the above socio-economic inputs to a finer spatial resolution to allow assessment of climate-related impacts. The city-zonal models provide simulations of the spatial distribution of future employment, population and related transport accessibility that are then used within the spatial impact assessment modules to evaluate the risk to future climate hazards and assess adaptation options at the city and city-zonal scale. Fig. 2 shows the detailed relationship between the three city-zonal scale models used in the UIAF.

2.2.1. City-zonal population model

City-zonal modelling starts with the estimation of employment (E_i^k) for zone *i* and sector *k* using a spatially-disaggregated model applied to the city-scale sectoral employment ($E_T{}^k$) generated by the econometric modelling (see Section 3). This is achieved by assigning a proportion of the total sectoral city employment ($E_T{}^k$) to a zone on the basis of its employment attractiveness ($W_{i,\ E}$). Usually employment attractiveness is represented by spatial database layers (as in Fig. 2) that can be used to build a suite of different employment development scenarios for multiple runs of the UIAF. For example, in the simplest case, employment may be assigned to a zone according to the current employment in the employment sector. However, it is possible to employ a set of attractors ($W_{i,\ E} = \{A_1, A_2, A_3, \cdots, A_n\}$) that express the attractiveness of a zone in terms of potential land available for development, employment transitions, transport infrastructure provision, and so on. These attractors reflect planning regulations for a given scenario (e.g. the importance of redeveloping brownfield sites), with weights reflecting the aggressiveness of the regulations implemented.

Future population (P_j) for zone *j* is simulated using a land-use transportation interaction (LUTI) model developed to generate 'what if' scenarios with respect to changing locations of employment and population and transportation infrastructure (Batty et al., 2013). This relatively simple model provides rapid predictions of zonal population, allowing a large number of different economic, infrastructure and population scenarios to be investigated with minimal parameterisation. More detailed urban simulation models such as UrbanSim, Delta, IRPUD, RSE, MUSSA, or TRANUS (Echenique, Grinevich, Hargreaves, & Zachariadis, 2013; Jin, Echenique, & Hargreaves, 2013; Martinez, 2018; Simmonds, Waddell, & Wegener, 2013) require very detailed parameterisation including, for example, information on household budgets and expenditure (Echenique et al., 2013). Equally, some more simple urban simulation models require less parameterisation (e.g. Cellular Automata (CA) models of urban growth (White, Uljee, & Engelen, 2012)) but only allow simulation of the patterns of development without links to zonal population. As such, the LUTI model approach adopted here offers an attractive analytically-robust approach to simulate zonal population with reduced complexity for rapid what-if scenario testing (Batty et al., 2013).

To obtain city-wide population (P_T) we employ the exogenous population projection for the city region, also used as input to econometric modelling to ensure consistency in the parameterisation of the exogenous economic model and the assignment of population using the LUTI structure (Batty, 2013). Other exogenous inputs to the LUTI model are represented in a similar manner to the employment attractors in the form of spatial database layers or fields (see Fig. 2). In particular, total zonal available land (L_i), unusable land per zone (L_i^u) and the amount of land assigned to 'basic industrial' economic activity per zone (L_i^b) (Batty, 2013; Batty et al., 2013) are obtained from various 'generic' digital map data-sets (see Section 3).

An iterative equilibrium solution to the population of each zone (P_j) is derived proportionally on the basis of the zonal employment and the trips that take place between a zone and all others. As in a number of other studies (), we have extended the standard trip calculation of the LUTI model to include a weight on zone attraction for households ($W_{i,P}$) which is expressed as a set of spatial layers/fields ($W_{i,P} = \{R_1, R_2, R_3, \cdots, R_m\}$) (see Fig. 2). This, in a manner similar to the economic spatial disaggregation, allows us to explore different zonal-level user defined scenarios and drivers of residential (population) development. Here the attractiveness of a zone is not altered by the exposure to climate hazards or the density of development, a recognised limitation of the current approach.

2.2.2. City-zonal transport model

The final city-zonal model employed in the UIAF is a transport model to characterise the spatial cost of accessibility ($f(C_{ij})$) between population and employment zones; information required for the trip calculation component of the LUTI model (see Fig. 2). This is achieved using a generalised cost model for each transport mode to give of C_{ij}, allowing investigation of how changes in transport planning and policy may influence the GHG emissions of a city, and the adaptation of cities to both direct and indirect impacts resulting from climate change hazards.

Calculation of the cost C_{ij} considers the connectivity for journeys between by road, bus, rail and light rail (e.g., metro and tram) transport modes (Ford, Barr, Dawson, & James, 2015). For each mode, we take into account the network distance, average travel speed, financial costs (e.g. petrol or ticket fare, zonal charges and/or congestion charges) and waiting times. This allows a comparison of the possible commuting choices between different modes to be undertaken; for example, the difference in cost between a slower but cheaper mode and a faster but more expensive one (Ortuzar & Willumsen, 2011; DfT, 2008;). The transport model estimates the generalised cost between all origins and destinations for a particular transport mode. The UIAF can characterise $f(C_{ij})$ as a single-mode generalised cost matrix (e.g., C_{road}, C_{rail}, C_{bus}or $C_{light-rail}$) or composite of all modes using the aggregate cost of travel method recommended by Ortuzar and Willumsen (2011).

2.3. UIAF zonal-parcel models

The output from the LUTI population model is, for each scenario and time period, an estimate of the total population P_j for each of the N zones that comprise a city or region. Depending on the particular type of impact analysis being conducted, these broad population values may need to be spatially disaggregated to understand the intra-zonal changes to land-use that may arise from this. In order to achieve this the UIAF zonal-parcel model called the Urban Development Model (UDM), has been developed to simulate the possible spatial pattern of housing development associated with the population prediction for each zone.

The UDM comprises a cell-based hybrid spatial Multi-Criteria Evaluation (MCE) model (Carver, 1991; Malczewski, 2006) and Cellular Automata model (CA) (Couclelis, 1985; Cecchini, 1996; Clarke et al., 1997; Wu and Webster, 1998; Engelen et al., 1999; Li and Yeh, 2000; Al-kheder, Wang, & Shan, 2008; Liu, 2008, White et al., 2012). Spatial MCE analysis is used to obtain a ranking of the suitability of development both intra-zonal and relative to the entire region under analysis. The CA model is then used to simulate the development of land for housing on the basis of this ranking.

UDM uses the set of R spatial attractors used within the LUTI model, along with their associated set of weights, $W_{i,\ P}$, to ensure that the suitability calculations are consistent with the attractors used in the population estimation. In addition to R, UDM can also employ a further set of attractors, R^{suit}, that characterise other 'local' influences that may drive the spatial pattern of housing development. Such attractors could include information on the performance of local schools, local accessibility (distance) to shops, services or transport hubs. Thus, UDM employs an augmented set of attractors R^+ ($R + R^{suit}$) which is used to derive a suitability surface S for a particular development scenario of interest for the entire study area (see Fig. 3.). This is achieved with the widely-used Linear Weighted MCE approach (Carver, 1991; Eastman, 1999; Malczewski, 2004; Mokrech et al., 2012). During this process a

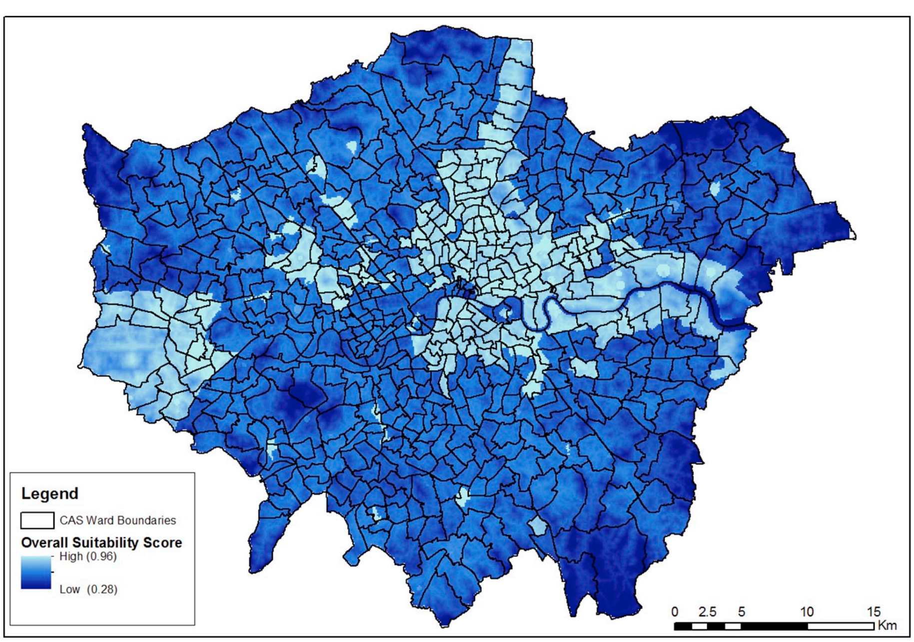

Fig. 3. An example of the combined MCE suitability raster used in UDM to simulate possible urban spatial residential development patterns resulting from population model outputs in London. In this case, high weights are given to areas targeted for development in the London Plan. Contains OS data © Crown copyright and database right (2018).

spatial field of constraints, $Con_{\{0,1\}}$ is created that denotes land that cannot be considered for urban development. As a minimum Con consists of spatial fields representing L^u and L^b. However, other spatial constraints can also be included such as protected sites and greenbelt restrictions.

In addition to the suitability surface S, the CA part of UDM requires a number of other inputs. The first of these is the total area of land to be developed in each zone which is derived on the basis of:

$$L_j^d = \Delta P_j / P_j^p \tag{1}$$

where for $\forall j \in N$ ΔP_j is the magnitude of population change ($P_j - P_j^{base}$) and P_j^p is either the current population density (P_j^{base}/L_j^{built} where $L_j^{built} = L_j^b + L_j^u$) or the desired population density per zone. In the case where P_j^p is set as the existing population density, this ensures that future development within a zone retains the spatial characteristics of the zone (i.e. high density residential areas will continue to contain high density housing whilst low density areas will not experience densification in the future). A further required input to the CA part of UDM is a spatial field (grid) of the land available for development, L_j^a. In the case of UDM, this is by default set to be $\neg Con$ (i.e., all land that does not form a constraint in the derivation of S). Finally, the area of cell size, c_{area}, employed in tesslating each zone for the grid-based inputs is required.

The initialisation of the CA urban development algorithm is processed by calculating and then ranking the mean suitability score for each zone $S_j^{\overline{x}}$ from S. Zones are then processed on the basis of descending $S_j^{\overline{x}}$. Iteration over the ranked zones is initiated by calculating S_j^{max} (the maximum suitability score of any cell in the zone j) and then calling the CA urban growth method UDMSPREAD (which we define formally in Listing 1).

In Listing 1, $c_{x,\,y}$ represents a cell within the zone j being processed, S^{Ω} are the suitability cells that fall within a neighbourhood of a cell, derived by applying a suitable neighbourhood function $f_n(c_{x,\,y})$; in the case of this study a Moore neighbourhood is employed. $adev$ is a accumulator variable that holds the current amount of land developed. The output of UDMSPREAD is the spatial field (grid) U^d that contains the cells that have been assigned as developed ($U^d = \left\{\begin{smallmatrix} 1 \text{ if developed} \\ 0 \text{ otherwise} \end{smallmatrix}\right.$). Fig. 4 schematically represents several iterations of UDMSPREAD showing how urban development will progress until the amount of land required for development is achieved.

One limitation of the approach adopted here is that the model does not allow for the phenomenon of urban sprawl, where cells can be spontaneously urbanised further away from existing development due to more suitable cells being held for land speculation. This limitation could be overcome by the introduction of more stochasticity in the UDM algorithm, something that will be addressed in further development of the UIAF.

3. A Greater London implementation

The Greater London Authority (GLA) covers an administrative area of 1579 km^2 with an estimated population in 2011 of 8.2 million (GLA, 2011), constituting approximately 15% of the population of England and Wales. Current population projections by the UK Office of National Statistics (ONS) forecast that the population of the GLA will increase to 10.9 million by 2039 (ONS, 2018). The GLA area is amongst the most at-risk urban conurbations in the UK to future climate change, being particularly vulnerable to water scarcity, heat waves, and future sea level rise leading to an increased risk of flood, water shortages, air quality problems, wind storms, and subsidence (London Climate Change Partnership, 2002; Evans et al., 2004; Environment Agency, 2007; London Climate Change Partnership, 2012; GLA, 2017). In the face of these pressures, the London Climate Change Partnership (LCCP) have investigated how climate change adaptation can be addressed along with spatial planning policies to help protect London and its inhabitants from the impacts of climate change (London Climate Change Partnership, 2002). As part of this process the UIAF has been used to investigate how different spatial planning and transport policies impact on the ability to reduce the exposure and risk of London's population to climate change hazards.

UDMSPREAD($S_j^{max}, c_{area}, L_j^d, L_j^a, S_j$)
$Stack := \emptyset$
$adev := 0$
$c_{x,y} \leftarrow S_j^{max}\{x,y\}$
DO
    $U^d \leftarrow \{c_{x,y}\}$
    $adev \leftarrow adev + c_{area}$
    $S^{\Omega} \leftarrow f_n(c_{x,y})$
    $\forall\, c_{x,y} \in S^{\Omega}$
        IF $c_{x,y} \notin Stack \wedge c_{x,y} \notin U^d \wedge c_{x,y} \in L_j^a$ **THEN** $Stack \leftarrow PUSH(c_{x,y})$
    $RANK(Stack, S_j)$
    $c_{x,y} \leftarrow POP(Stack)$
WHILE $adev < L_j^d \vee Stack \neq \emptyset$
RETURN U^d

S_j^{max}:	Maximum suitability score for zone j.
c_{area}:	Size of each cell within zone j.
L_j^d:	Total area of land to be developed in zone j.
L_j^a:	Land available for development in zone j.
S_j:	Suitability surface values for zone j.
$c_{x,y}$:	Current cell in zone j being processed.
$adev$:	Accumulator variable of the amount of land developed in zone j.
S^{Ω}:	The suitability cells that fall within a neighbourhood of $c_{x,y}$.
U^d:	Cells that have been assigned as developed in zone j.

Listing 1. Pseudo code listing of the CA urban development method applied to each zone to derive population drive urban development in UDM.

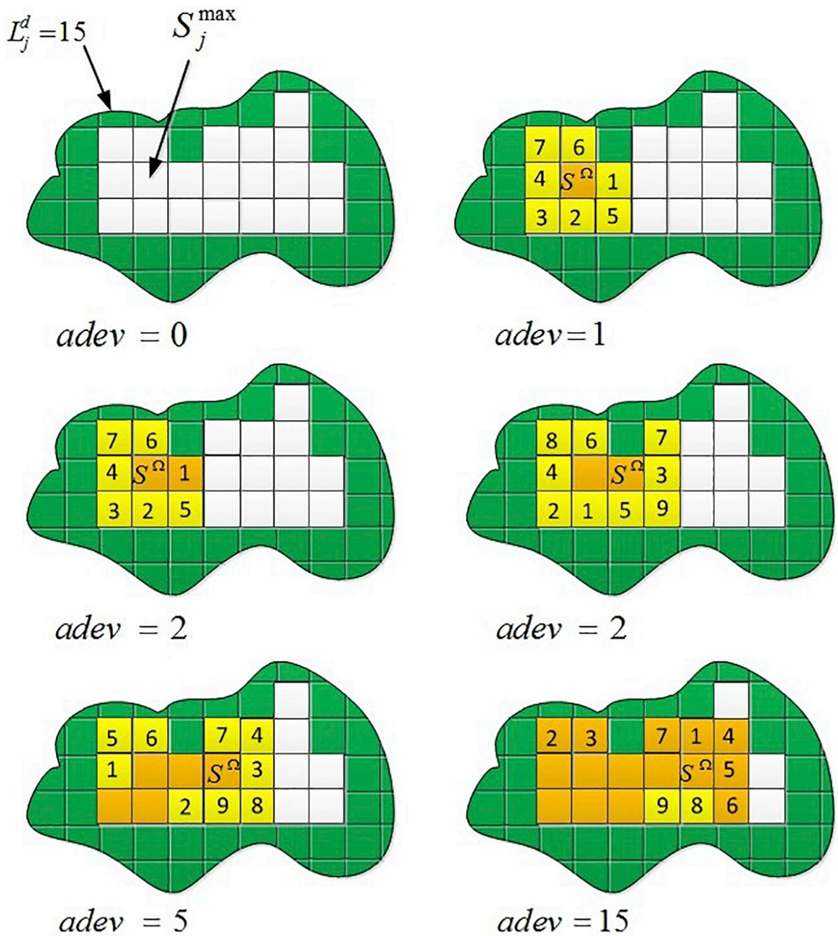

Fig. 4. Schematic showing several iterations of UDMSPREAD required to simulate urban development with the Urban Development Model (UDM). Green cells are outside of the current zone being simulated, white cells are undeveloped cells in the current zone, orange cells are those that have been developed in a previous iteration, and yellow cells are the cells currently under consideration for development. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

The sectoral economic employment predictions for the London case study, $E_T{}^k$, are provided by a Multisectoral Dynamic Model (known as MDM-E3). This model combines medium-term sectoral econometric models with input-output models to provide economic output projections using the Standard Industrial Classification (SIC), which themselves can be used to estimate long-term employment up to 2080 (Junankar, Lofsnaes, & Summerton, 2007). The MDM-E3 model is itself driven by the E3MG model, a global econometric model that produces, in the form of economic input/output tables, long-term economic forecasts to the year 2100 (Barker, Foxon, & Scrieciu, 2008). In the case of the UK, the MDM-E3 model provides predicted employment for 42 sectors at UK NUTS1 region scale.

One of the most significant hazards faced by London and its immediate region is the future flooding of the River Thames, which is expected to experience an increase in surge tide frequency due to projected changes in mean sea level of between 0.21 and 0.89 m by 2100 driven by climate change (Lowe et al., 2009). This would increase the risk of tidal flooding in London. The Thames tidal floodplain region encompasses an area of approximately 345 km^2, which contains 1.2 million people, nearly 500 schools and hospitals, 5540 ha of nationally- and internationally-designated sites of nature conservation importance (representing 16% of all land at risk of flooding), 2450 km of transport links (motorways, major roads and railways) and 516,000 properties, of which 476,000 are residential (GLA, 2017).

The exogenous spatial representation of potential future climate hazards are derived using climate projections to the year 2100 produced as part of the UK Climate Projections (UKCP09) programme. These projections provide a probability density function (PDF) of future climate for various greenhouse gas emission scenarios at a spatial scale of 25 km, which is too coarse for intra-city impact assessment and adaptation analysis (Tomlinson, McSweeney, Darch, & Kilsby, 2014). In order to address this, a 'spatial weather generator' is used to produce 1–5 km spatial fields of temporally correlated daily time-series projections of rainfall, temperature, humidity, wind and sunshine (Jenkins et al., 2014; Kilsby et al., 2007). These projections can be used to study hazards such as heatwaves, flooding from pluvial, fluvial and tidal sources, and drought (Fowler, Blenkinsop, & Tebaldi, 2007; Fowler & Wilby, 2007).

3.1. Studies of flood risk from the river Thames

In order to investigate how surge tides and flood flows in the River Thames and its estuary may change in the future, a flood risk model was employed that maps the spatial extent, depth, and duration of floods (Dawson et al., 2011; Dawson, Hall, Bates, & Nicholls, 2005). These results can be combined with the population and urban development aspects of the UIAF through depth-damage functions, which relate flood depth and duration to economic costs, to ascertain a value of economic damage (Dawson & Hall, 2006). In order to evaluate how different planning policies may change flood risk and the resulting economic damage by the year 2100, four land-use scenarios were developed. These were constructed from a portfolio of development incentives and constraints, alongside infrastructure improvements, and were simulated using the UIAF to predict their differing spatial patterns of population and land-development change.

The four scenarios comprised (i) a Baseline scenario where development continues to follow current trends exhibited in the London setting, (ii) an 'Eastern Axis' scenario that focuses development towards the east of the city in line with plans to develop the Thames Gateway area, (iii) a 'Centralisation' scenario that targets development towards central London, thus increasing the population where employment is traditionally highest and reducing GHG emissions from transport, and (iv) a 'Suburbanisation' scenario that disperses development from the centre of London towards the suburbs and satellite towns in order to reduce risk from future heatwaves (Walsh et al., 2011).

These spatial planning scenarios were underpinned by four transport infrastructure scenarios with similar storylines. The first, used in the Baseline scenario, involved the existing transport networks for the modes of road, rail, light-rail and bus. For the other three spatial planning scenarios new infrastructure development was included based on the T2025 report from Transport for London (TFL, 2006a), with two different levels of infrastructure investment including such projects as the Crossrail programme (Crossrail, 2014). These improvements, and others for other modes, were included in the network model by means of new links and stations to reflect the new routes or increased speeds on the existing lines (Ford et al., 2015).

3.2. UIAF spatial impact assessment parameterisation

3.2.1. Population and UDM model parameterisation

The model domain for this analysis is the GLA administrative area comprising 633 English Census Area Statistics (CAS) Wards. Climate impact assessment was undertaken for each of the future scenarios above allowing an estimation of the impact of planning policies on climate risk. A summary of the inputs for the London application of the UIAF is given in Table 1. All scenarios use a consistent employment prediction generated by the MDM-3 economic model for 2100, aggregated to five industrial sectors, namely: Primary industries; Retail; Construction; Finance; and Other services (e.g. public sector). Spatially-disaggregated employment values and population projections for 2100 used in the MDM-3 model run provided E_j^b (employment in 'basic economic' activity per zone) and P_T (future total population for London). The total employment across the model domain in 2100 is 6.15 million, whilst the total population varies by scenario (and thus land availability) but reaches a maximum of 10.5 million in line with government projections.

3.2.2. Transport generalised cost parameterisation

Each transport mode required its own detailed parameterisation including spatial representation of networks and attribution of these for travel distance, speed, and other generalised cost terms (see Ford et al., 2015). Certain terms in the calculation of generalised cost were kept constant for the four modes under investigation. In particular, the *VOT* (Value of Time) parameter (Mackie et al., 2009) was set to be the estimated average value of £5.04 for each hour of time (WebTAG, 2015). Table 2 outlines the data used to parameterise each transport mode. Further details of these scenarios can be found in Ford et al. (2015).

3.2.3. Software framework

The UIAF is implemented using a generic modelling framework designed to allow transferability, extensibility, flexibility, and transparency. A Python Model Interface (PMI) provides a standardised method of configuring and running models within the framework. In all models running under the PMI, a Python module which executes the model code is linked to database tables specifying model inputs, outputs and parameters. The database is built in the Postgres/PostGIS environment to ensure free and open-source capabilities for model users and developers. Models can be run individual via the PMI, or as a set of interlinked model groups (i.e. sequentially running the models shown in Fig. 1).

4. Results and discussion

4.1. City-scale land-use and urban development

Fig. 5 shows the London population results to 2100 for the four land use scenarios investigated, demonstrating how population distribution can be controlled by the City-zonal model to examine spatial patterns of future socio-economic change. For example, the Centralised scenario leads to a total 2100 population inside the London Congestion Charge zone of 710,017 people compared to 484,807 in the Suburban scenario and 548,820 in the Baseline, leading to a higher population density for central zones in the Centralised scenario. Similarly, the Eastern scenario leads to a total population in the Thames Gateway development area of 1,772,461 compared to a baseline population of 1,107,727, with residential development in this area driven by the attractors in Table 1.

These indicative scenarios demonstrate how spatial pattern of future population can vary greatly depending on the attractors and constraints used in planning decisions. The flexibility of the UIAF framework

Table 1
The four development scenarios used in the spatial impact models.

Scenario	Narrative	Attractors	Constraints
Baseline	Development patterns follow current trends with the London Plan being followed into the future, limited intervention in development decisions, and the current level of investment in transport infrastructure maintained.	Employment patterns increased pro-rata in existing locations, area attractors from the London Plan (Opportunity Areas, Metropolitan centres, Regeneration Areas, Areas for Intensification – see Fig. 4), transport investment following Transport for London future scenarios.	Current development (from Ordnance Survey Mastermap data), watercourses and lakes, environmental areas (e.g. nature reserves, greenspaces), floodplains.
Eastern	In order to revitalise the former dockland and industrial areas, significant investment in transport infrastructure and new employment is assigned to the east of London. This leads to new development occurring along the Thames estuary.	Employment focussed in areas accessible to the east of the London area, improvements in transport infrastructure in the corridor along the Thames estuary, additional attractors along the river and at the 2012 Olympic Games site.	Current development (from Ordnance Survey Mastermap data), watercourses and lakes, environmental areas (e.g. nature reserves, greenspaces), floodplains.
Centralised	In an effort to reduce CO2 emissions from transport (particularly commuting journeys), development is restricted outside the urban core of London (where most jobs are located) and new residential development is built at a much higher density than today.	Improvement to public transport frequency serving central London, increased attractors for development within the urban core, focussing of employment in central London.	Current development (from Ordnance Survey Mastermap data), watercourses and lakes, environmental areas (e.g. nature reserves, greenspaces), floodplains. Additional constraints placed on green land outside the urban core area.
Suburban	In order to improve the resilience of urban areas, new residential development is targeted outside the existing central area of London, with improved transport infrastructure allowing increased population in satellite towns and suburban areas.	Additional weighting for London Plan attractors (Opportunity Areas, Metropolitan centres, Regeneration Areas, Areas for Intensification – see Fig. 4) outside the urban core, improvement in transport accessibility between suburban areas.	Current development (from Ordnance Survey Mastermap data), watercourses and lakes, environmental areas (e.g. nature reserves, greenspaces), floodplains. Additional constraints places on green land within the urban core area.

Table 2
Transport scenarios used to drive population and development simulations.

Mode	Spatial Data	Generalised Cost Parameter Values	Future Scenarios
Road	Ordnance Survey Mastermap Integrated Transport Network (ITN)	Travel speed: *average speed from 2006 London Travel Report* (TFL, 2006b) *for three cordons in the city.*Distance: *computed from network data* Access time: *3* min Fuel costs: *computed from vector of a vector of vehicle mix and fuel efficiency and a vector of fuel prices (see*Ford et al., *2015, for full description)* Non-fuel operating costs: *computed using WebTAG equation* (ibid) Congestion charge: *£8 on routes entering or leaving the Congestion Charge zone* Vehicle occupancy: *1.16 people per trip for commuting in 2000 adjusted for the expected change of − 0.67% per year up to 2036* (WebTAG, 2015).	Low Investment: Thames Gateway Bridge added to network. High Investment: Silvertown Link Bridge added to network, national road user charging scheme assumed to add monetary cost to private car travel.
Rail	Ordnance Survey Meridian data, with all links assumed bi-directional and passenger-carrying.	Travel speed: *computed from average observed speeds for sections of railway line in the Greater London area (as timetabled)* Waiting time: *calculated as half the average service frequency at 7.5* min Fare: *average fare per km of 18p* (TFL, 2006b*)* Waiting disincentive: *2.6 times the in-vehicle travel time* (WebTAG, 2015) Walking weight: *1.6 times actual walking time*	Low Investment: improvements in train frequency and speeds reduces journey times across the rail network by 4.5%. High Investment: Crossrail 2 added to network.
Light rail	Ordnance Survey Meridian data, with all links assumed bi-directional and passenger-carrying.	Travel speed: *computed from average observed speeds for sections of light rail network (as timetabled)* Waiting time: *half the frequency of service or 3* min *across the network* Waiting weight: *as rail above* Fare: *as rail above* Walking weight: *1.6 times actual walking time*	Low Investment: DLR extensions added to network, Greenwich and East London transit systems included. High Investment: extensions to Tramlink and DLR extension to Dagenham Dock.
Bus	Transport for London data produced by Jacobs Consulting	Travel time: *included in dataset* Waiting time: *half the average frequency of service (assumed to be 7.5* min*)* Walking weight: *1.6 times actual walking time* Fare: *The 2006 London Travel Report* (TFL, 2006b) *found that over 85% of all journeys within London used an Oyster card for payment at a fixed cost of £1.00, which was used to set a fare price (equating to an additional cost in time of 12* min *per journey using VoT).*	Low Investment: 20% increase in bus supply (and thus frequency). High Investment: 40% increase in bus frequency.

allows experimentation with sets of spatial attractors and constraints, and the weights given to these, to explore potential spatial development patterns. Whilst the resultant scenarios may be considered ‘caricatures’ of future development, they can be used to explore upper and lower bounds of scenario space. Thus, such zonal maps can allow decision-makers to quickly visualise the potential impact of changes to planning policy or transport infrastructure across the urban area, and therefore consider the wider impacts on climate change mitigation and adaptation options (see below).

The population scenarios of Fig. 5 give future total population for each zone in the study area for the given scenario inputs. For some outputs from the UIAF, such as transport trip length and volume or energy usage, these aggregate totals for zonal units are sufficient (Harwatt, Tight, & Timms, 2011). However, where assessments require more detailed spatial indications of development location or population density, the totals are then passed to the UDM module for mapping of urban development. Fig. 6 shows the baseline UDM results for the four population scenarios investigated. As described above, the UDM uses a set of spatial attractors and constraints broadly consistent with the zonal totals employed by the City-zonal model. In Fig. 6, the attractors set out in Table 1 are used in spatial form to drive the patterns of development in UDM.

The UDM outputs allow the mapping of sub-zonal spatial patterns of potential development resulting from population outputs from the City-zonal model. This allows the estimation of the additional development land required to accommodate increases in population under each scenario, with, for example, increased development along the Thames estuary in the Eastern scenario and more development in outer London in the Suburban scenario. The total area of land developed in the Thames Gateway area in the Eastern scenario is 6756 ha, compared with 6022 ha in the Baseline scenario.

The population density of new development is, as mentioned above, assumed to remain at the observed level in each ward. Where more population is targeted to a zone by the LUTI model the population density may need to increase to accommodate the projected totals. Fig. 7 shows the required increases in population density in order to satisfy the future growth for each headline population scenario and the baseline UDM planning scenario. The largest increases for the Eastern scenario are visible along the river estuary, where population density increases to as much as 100 people/ha. The Centralised scenario focusses high density population in the centre of London, with population density in the urban core reaching similar values of over 100 people/ha. Conversely, the population density for new development in the Suburban scenario is reduced from between 20 and 50 people/ha in the Baseline scenario to under 10 people/ha. Such outputs highlight to policy-makers the decisions they are faced with: either relocating that population to another part of the city, or increasing the development density above existing levels in those areas. Each of these decisions will have concomitant effects on other aspects of urban function, such as risk from extreme weather events or energy use from transport.

4.2. Spatial impact assessment

The UDM output for each scenario was evaluated in terms of potential increase in flooding impacts from a flood risk model as outlined in Dawson et al. (2011). The flood outlines were spatially intersected with the UDM urban development outputs and the total amount of new development in the flood risk zones calculated. Table 3 summarises the increase in the area of new development in the zones, the mean new development population density, and the expected annual flood

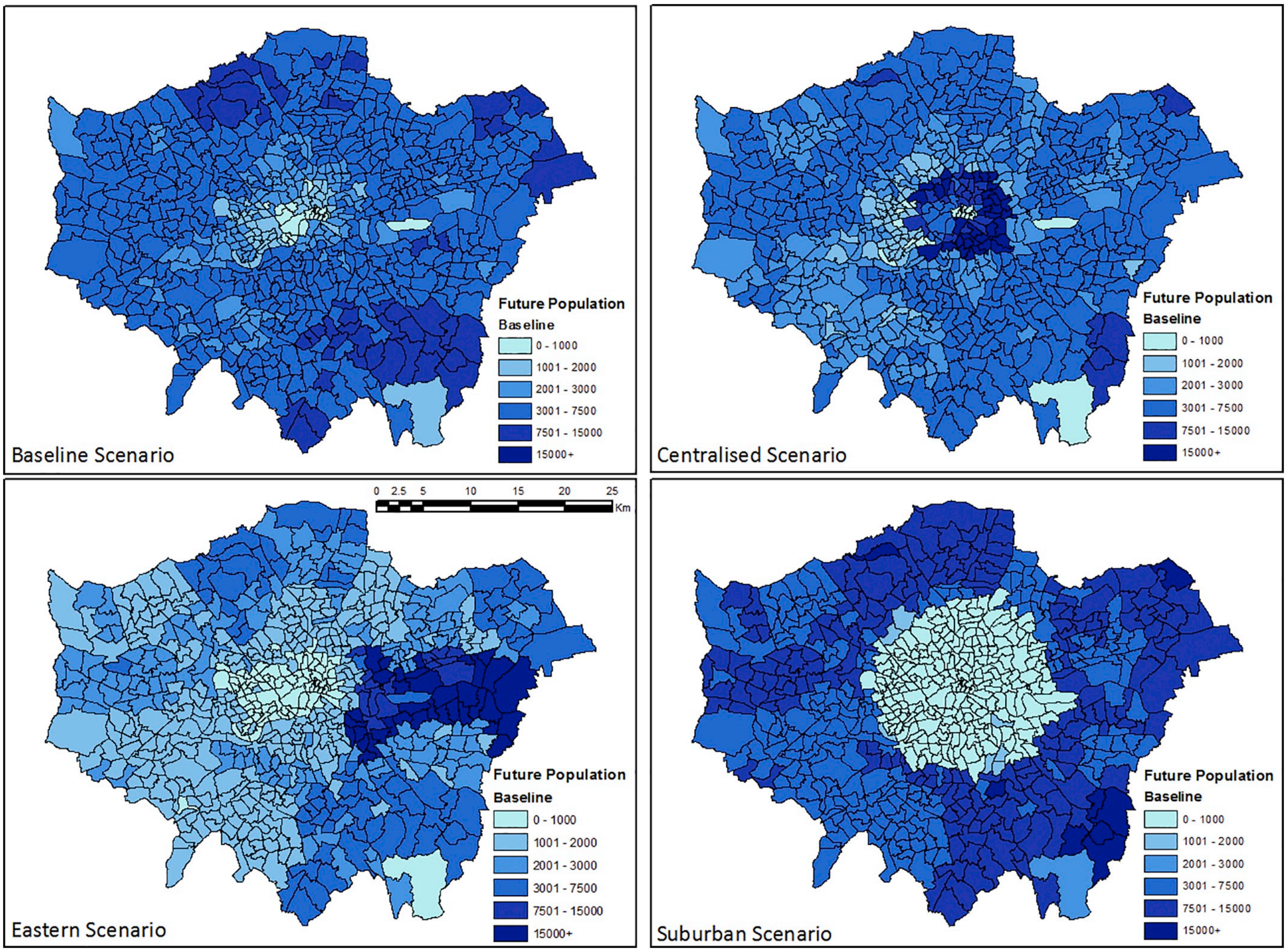

Fig. 5. Future (2100) population increase from 2005 figures in Greater London for each of the headline scenarios described Table 1. Contains OS data © Crown copyright and database right (2018).

damages for each scenario. The Baseline scenario would lead to an additional 1697 ha of development in flood-prone areas with a mean development density increase of 114 people/ha and an increase in expected annual damages of £47 million. The Eastern scenario sees the highest development in the flood area, with an additional 2530 ha of development and £89 million expected annual damages from current. The Centralised scenario sees a reduction in development in flood-prone areas but also leads to the highest density of population at 123 people/ha in new development as more people are targeted in the urban core where new land is scarce.

Having established the potential impacts of future development on exposure to climate hazards, the UDM can test spatial planning policies to reduce that exposure. The drivers and constraints of the Zonal-parcel model can be adjusted to preclude development from certain high-risk areas (such as flood zones) as a means of adaptation to future climate threats simply by adding further constraints to the inputs to the UDM. The integrated nature of the UIAF means that the trade-offs and implications of such local-scale policies can be examined in the context of city-scale plans, and feedbacks explored. Fig. 8 shows, for a small area of the Thames Estuary area, the result of a UDM run where development is not constrained, and the result for the same area where development is precluded in indicative flood extents. This scenario greatly reduces the possible development in this area and drives such development inland where possible, reducing the risk from flooding but adding to pressure for development.

The required population density in the areas which are developed increases dramatically under such a scenario, in some cases prohibiting any development at all within a ward. For example, in the South Hornchurch ward to the north-west of the image (in red) the development targeted in the flood area is reduced from 254 ha in the baseline planning scenario to 0 ha. In total, 2550 ha of floodplain development are simulated in the baseline planning scenario across London which must be accommodated elsewhere if this adaptation option is pursued.

To further test possible planning options in UDM, three alternative planning policies were simulated for the Eastern population scenario. The first policy (A) removes the greenbelt constraint around the edge of the London to allow more development away from the river. An attractor is still included to encourage future development along the river estuary to reflect the desirability of riverfront developments. The second alternative (B) is a policy to preclude any development in the floodplain but also keep the greenbelt restrictions in place. The final policy (C) retains the constraint on floodplain development but relaxes the greenbelt restriction to allow development around the edge of London.

Table 4 shows the results of these planning policies compared to the standard Eastern development scenario. In the case of Policy A, we obtain a minor reduction in the population density of new development due to the relaxing of the Greenbelt policy but see a large loss of green space around the edge of the city (an additional 3286 ha of development in Greenbelt land). Policy B leads to an increase in the mean

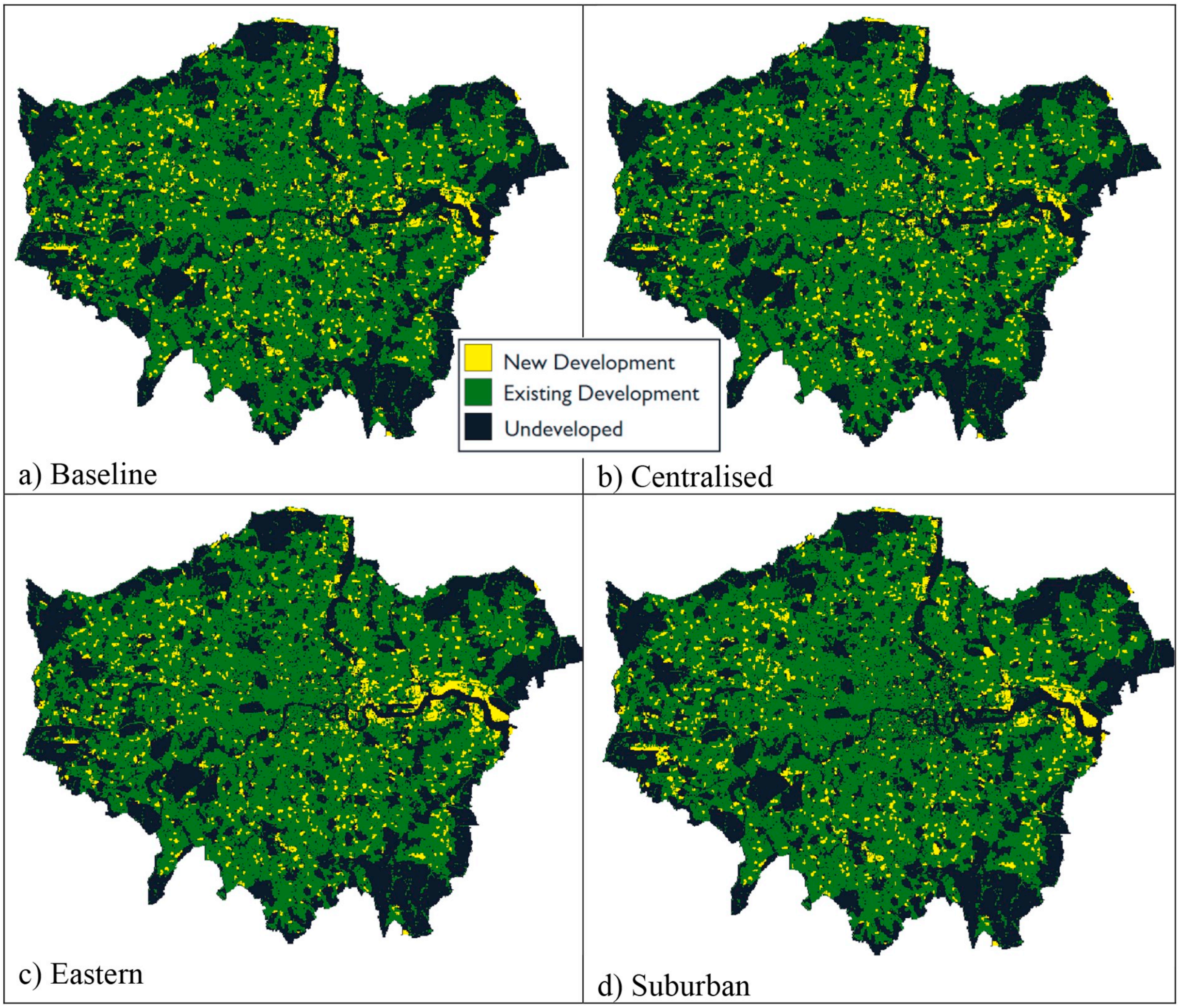

Fig. 6. UDM results for the four London population scenarios showing (top-left) Baseline population scenario, (top-right) Centralised scenario, (bottom-left) Eastern scenario, and (bottom-right) Suburban scenario. Contains OS data © Crown copyright and database right (2018). a) Baseline, b) Centralised, c) Eastern, d) Suburban.

population density in new development of 16 people/ha compared to present, particularly along the river where population increases in the Eastern scenario are focussed but where development land is now severely limited. Population density in flood-prone wards immediately adjacent to the River Thames is increased even further, with the current density of 98.10 people per hectare in these wards more than doubling to 203.28 people per hectare (compared to Manhattan's density of 188 people per hectare). Policy C leads to a large increase in greenbelt development compared to Policy A, with over 10,000 additional hectares lost to development from a total of almost 35,000 ha in the greenbelt, and a slightly higher density across development zones but no additional floodplain development.

These types of indicative statistics for each scenario allow an appreciation of the competing pressures facing decision-makers and the need to accept some consequences of a rising population in London: either land in the floodplain is used, Greenbelt land is used, or population density is increased (sometimes substantially). This highlights again the difficult decisions faced by policy-makers in the future, where the need to protect Greenbelt land must be balanced with the need to protect citizens from increased climate extremes.

Fig. 9, finally, shows the increased population density required for each of the planning options for the Eastern population scenario. It can be seen that the imposition of a floodplain constraint (bottom two images) increases the population density in the riverside wards, whilst the relaxation of the greenbelt restrictions (right-hand two images) reduces the population density around the perimeter of the Greater London area.

5. Conclusion

This paper has introduced a new approach to the integrated assessment of climate change impacts in cities using a modular spatial simulation framework. There is great spatial heterogeneity in the vulnerability of cities to climate change and the locations of biggest impacts. In order to understand future urban risks from climate change, it is vital to understand both climate change and land-use changes that may play out in cities. The framework demonstrated here shows that the downscaling of climate change impacts and socio-economic changes to a fine scale allows an understanding of the patterns of intra-urban vulnerability which arise from the combined effects of changes in the climate and urban policies.

Integration of spatial interaction modelling, cellular automata urban development simulation, and impact assessment provides a powerful framework for exploring the implications of different planning decisions and understanding the relative merits of different strategies. In London we showed that impacts of future flooding on the urban population can be ameliorated by land-use planning policies but that these policies come with trade-offs. Different spatial patterns, risks, conditions, and trade-offs exist in other cities, however, so the framework presented here has been developed in a generic way to allow

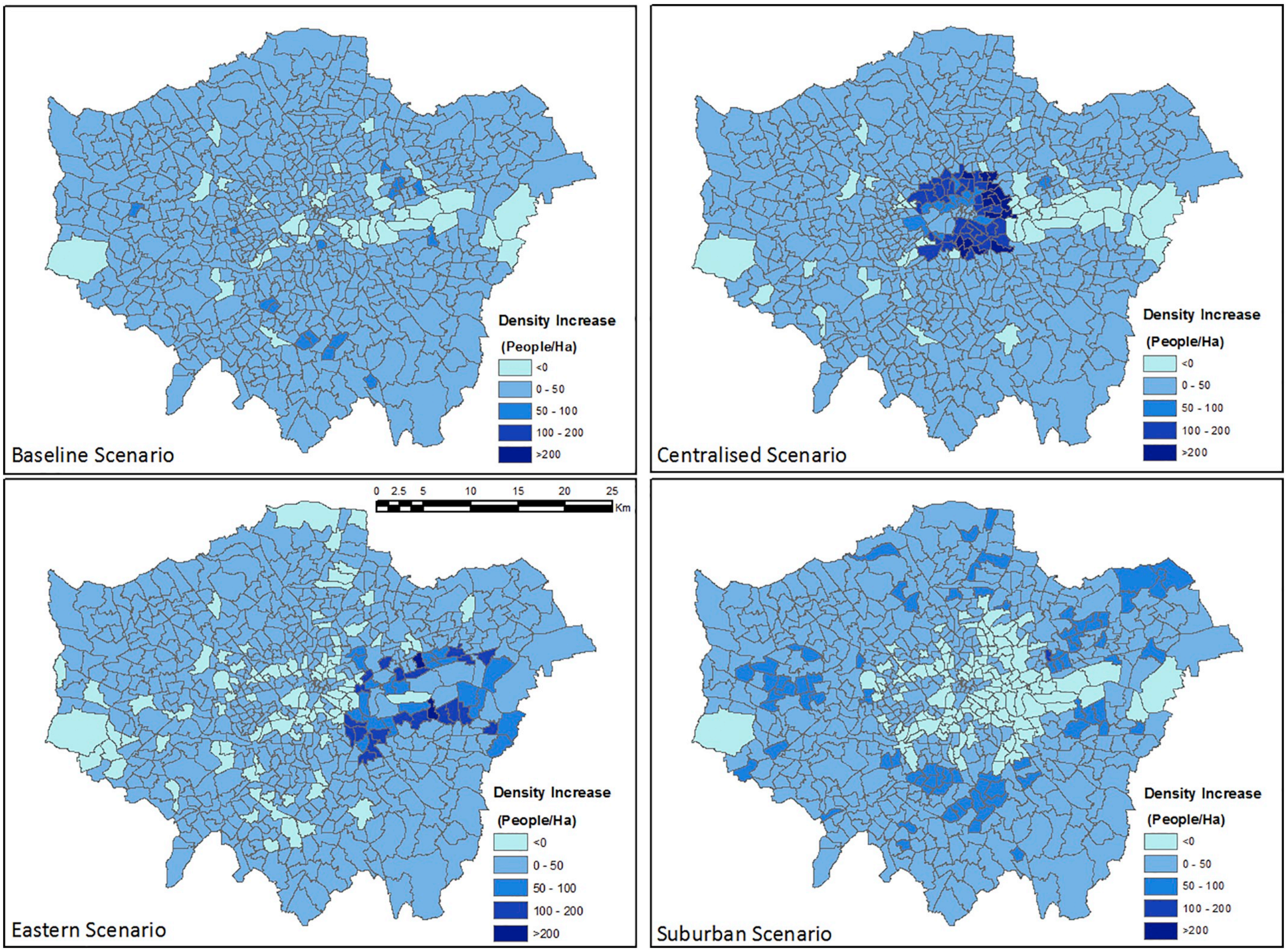

Fig. 7. Required population density increases from current ward averages in people per hectare in order to accommodate increased population in each of the LUTM scenarios (top-left: Baseline, top-right: Centralised, bottom-right: Suburban, bottom-left: Eastern). Contains OS data © Crown copyright and database right (2018).

Table 3
Increase in development in flood plain, plus population density of new development, for each scenario after UDM simulation.

Scenario	Area of development in flood plain	Population density in new development (mean)	Expected annual damages from flooding
Current	8419 ha	93.25 people/ha	£29 million
Baseline	10,131 ha	114.50 people/ha	£76 million
Eastern	10,964 ha	106.30 people/ha	£118 million
Centralised	9986 ha	123.10 people/ha	£72 million
Suburban	9937 ha	115.30 people/ha	£62 million

transferability to other cities worldwide. Predictions of the future are rarely accurate so the models developed in this paper intended to be used to structure informed debate and explore the potential impacts of options available to decision-makers, identifying preferred envelopes of future development. The framework therefore allows a downscaling of future global- or national-scale projections to local effects using consistent attractors and constraints and respecting physical limitations of land. As such, it is possible identify future modes of development which may mitigate future risk from climate change and therefore assist in the development of better planning policies to aid future adaptation strategies.

A number of the models used in the UIAF have been calibrated to past events. The MDM input-output model is part of a long tradition of such models developed by Cambridge Econometrics and in that sense have been validated in a policy environment and by replicating past data. The LUTI model is built at a cross section in time as are all such models. The CA Urban Development Model, although not validated for Greater London on past data, is based on plausible highly-constrained rules that reflect the quite tight constraints on the London land market and the way new development is approved or not by planning agencies.

In order to ensure this transferability and demonstrate the practical application of the modelling framework, a number of potential feedbacks and interactions in the modelling process have been omitted and simplified and a number of assumptions have been made. For example, the assumption that the attractiveness of a zone is defined at the beginning of the modelling process and remains constant throughout is unlikely to be the case in reality, given that attractiveness is related to land rent and likely to be dependent on development density, land-use patterns (see Silveira and Dentinho (2018)), flooding susceptibility, or other future climate risks. Other feedbacks, such as the impact of climate effects on the reliability, and thus attractiveness, of transport modes are also not included. These developments form the basis of ongoing further work to enhance the UIAF and the open-source nature of the framework will enable other researchers to assist in these efforts.

Future work could also include the expansion of the scenarios modelled using the UIAF to include other dimensions of urban socio-economic and infrastructure change. For example, new transport modes (such as shared mobility or autonomous vehicles) could have

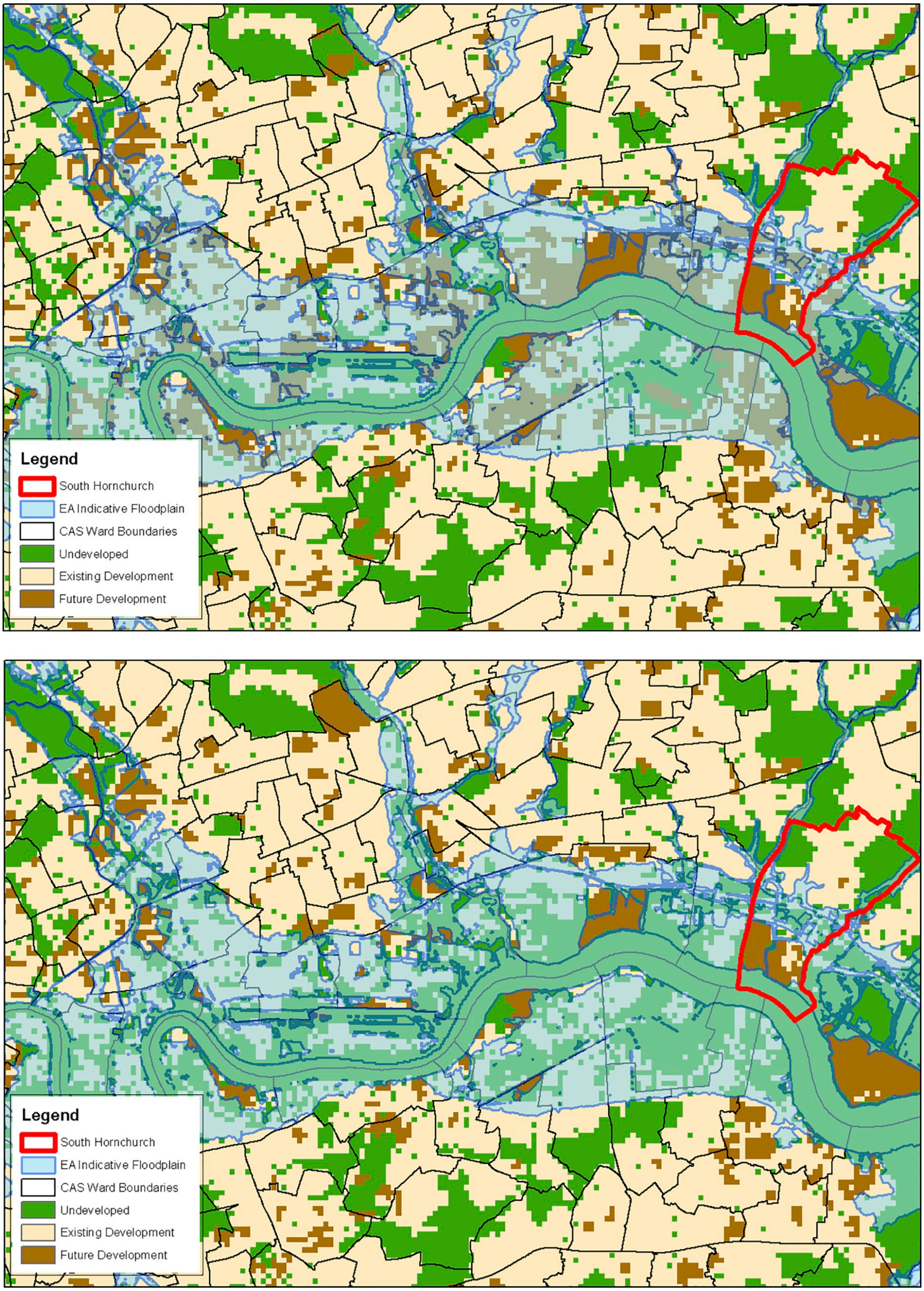

Fig. 8. A comparison of development patterns arising from UDM under a baseline scenario (top) and scenario where development is prohibited within the floodplain (bottom). Development can be seen, in some zones, to be displaced away from the river into other areas. The South Hornchurch ward is highlighted in red (to the right), showing development precluded from the blue indicative floodplain area. Table 4 shows the impact of such policies at city-scale. Contains OS data © Crown copyright and database right (2018). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 4
Development statistics for spatial planning options for Eastern population scenario.

Scenario	Area of development in flood plain	Area of development in greenbelt	Population density in new development (mean)	Development in South Hornchurch ward
Current	8419 ha	2955 ha	93.25 people/ha	299 ha
Eastern	10,964 ha	2955 ha	106.30 people/ha	452 ha
Eastern Policy A	10,601 ha	6241 ha	104.29 people/ha	492 ha
Eastern Policy B	8419 ha	2955 ha	109.60 people/ha	381 ha
Eastern Policy C	8419 ha	13,144 ha	107.62 people/ha	571 ha

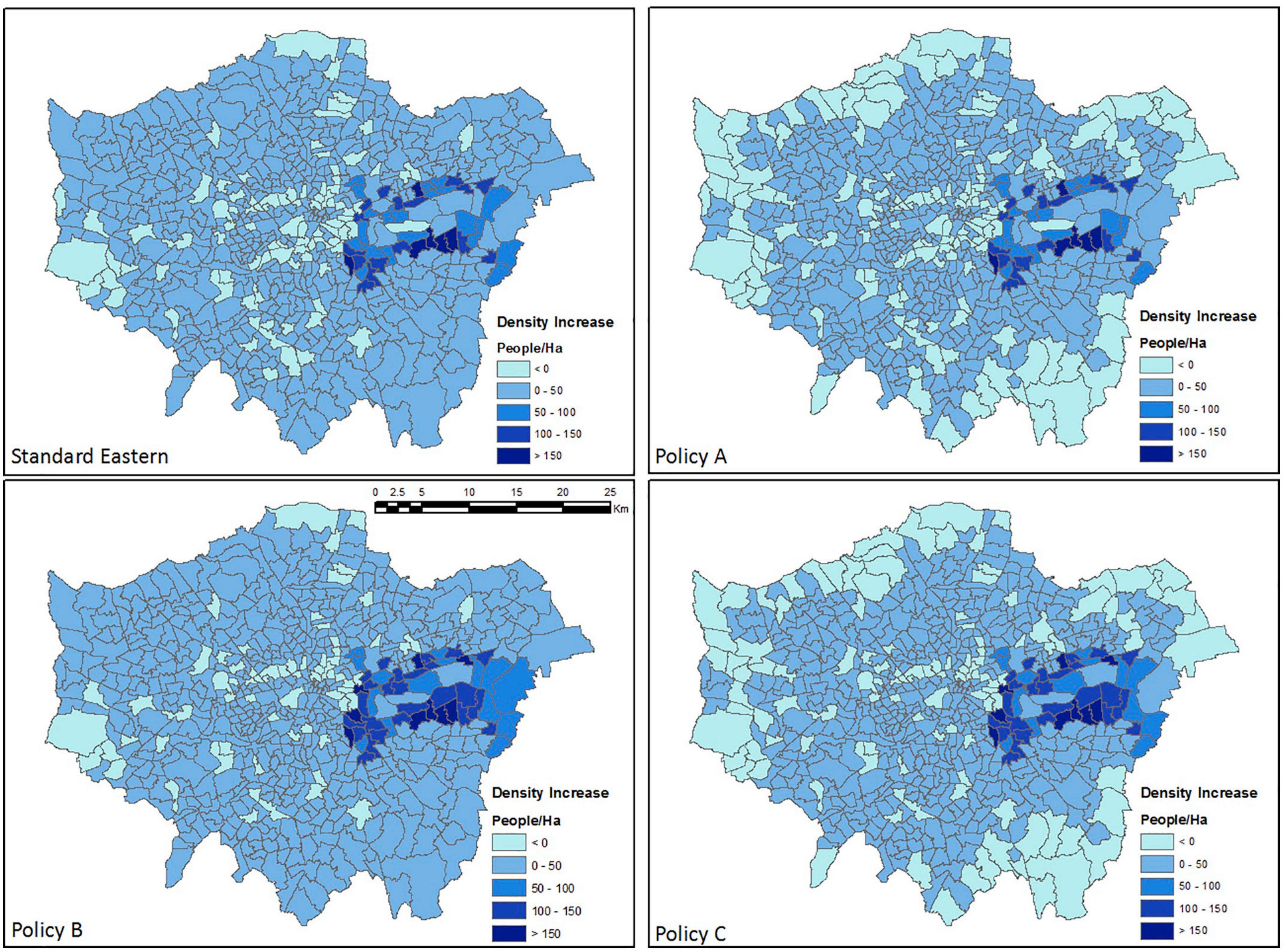

Fig. 9. Spatial population density increases from current in People/Hectare at ward level for Eastern population scenario and spatial planning Policies A to C as simulated in UDM. Contains OS data © Crown copyright and database right (2018).

considerable impacts on land-use patterns. Similarly, changes to behaviour, such as an increase in home-working or online shopping, will have impacts on location choice and travel demand, and therefore on exposure to climate hazards in the future. Active travel modes, namely walking and cycling, should also be included in the UIAF to ensure the trade-offs between adaptation and mitigation arising from modal shift are fully-understood. Ford et al. (2018) sets out these and other challenges faced by such modelling frameworks in more detail. Such simple models could also be employed in an optimisation framework (as described by Caparros-Midwood, Barr, & Dawson, 2015; Caparros-Midwood, Barr, & Dawson, 2017) to explore a large number potential development patterns and assess them against sustainability criteria such as flood risk.

As growing urban populations place pressure on cities to develop further (UN, 2018), undeveloped land in the floodplain or in previously protected green sites may need to be exploited (Fünfgeld, 2010) – trade-offs between issues such as living density, flood risk and loss of amenity, and broader sustainability are likely to increase (Bai et al., 2018). The UIAF is one approach to help cities reduce their exposure to future climate-related risks and has been developed using open-source tools to allow other researchers to adapt the models to their own city. The use of freely-available data, of the sort commonly available in many countries, will hopefully allow the uptake of such a framework to aid decision-makers to better understand the options available to them in response to a changing climate.

Acknowledgement

The authors would like to acknowledge the Tyndall Centre for Climate Change Research, UK and the Engineering and Physical Science Research Council, UK through the funded project – ARCADIA: Adaptation and Resilience in Cities: Analysis and Decision-making using Integrated Assessment (EP/G061254/2) for funding part of the work described here. Alistair Ford is supported by the ITRC-MISTRAL (Infrastructure Transitions Research Consortium; Multi-scale Infrastructure Systems Analytics) UK project grant (EP/N017064/1) and by funding from the European Community's Seventh Framework Programme under Grant Agreement No. 308497 (Project RAMSES). Additionally, Richard Dawson is funded by an Engineering and Physical Science Research Council, UK fellowship (EP/H003630/1)

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