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A land-use transport-interaction framework for large scale strategic urban modeling

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ABSTRACT

We introduce a family of land use transportation interaction (LUTI) models which enable future employment, population and flows or trips between these activities to be explained and predicted. We begin by focusing on the generic spatial interaction model, noting the ways in which its components reflect demand and supply at different locations measured in terms of employment and working population. This suggests an equilibrium structure which is our starting point in developing a simplified version of the model which we extend to deal with four different activity sectors – housing, retail activities, schools, and health facilities. We use this generic structure to develop four related versions of the generic LUTI model equations for residential populations, retailing, education and hospitals which are all driven by employment in terms of where people live and work. This constitutes our integrated framework that we use in calibrating, that is fine-tuning the model to three urban areas (cities) in Europe: to Oxford and its county, Turin and its region, and Athens in its hinterland of Attica reflecting population volumes from 700,000, 1.7 million and 3.8 million persons respectively. In each case, we use the models to predict the impact of different scenarios – new housing developments in Oxfordshire, new universities and metro lines in Turin, and economic development in the Athens region. We describe the details of these scenarios in Supplementary Information (SI) which shows the versatility of using the models to examine such impacts and we conclude with directions for improving the various models and nesting them at different scales within the land use-transport planning process.

1. Introduction

Global urbanisation is continuing apace with an ever-increasing proportion of world population living in cities. This now stands at 56% with more than 75% of Europeans now living in urban areas (Statista, 2021). The world's urban population is projected to increase to 68% by 2050 (United Nations Department of Economic and Social Affairs, 2018) and by the end of this century, almost everyone will be living in cities of one size or another. The wider urban environment, particularly in Europe, reveals that its cities are becoming ever more complex systems of interconnected and interdependent infrastructures, and to address this complexity, there is an increasing need to urgently develop relatively simple digital simulation models as support tools to inform decision-making, particularly when cities grow to more than 1 million persons. In this paper, we will introduce a class of Land-Use Transport-Interaction (LUTI) models that can be constructed in modular fashion. These LUTI models will be adapted to different sectors of the urban system which are integrated through movements between work, retail centres, schools, and hospitals defined with respect to their spatial patterns of demand and supply.

The impetus for the development of these models is that they are needed as an integral part of the H2020 HARMONY[1] transport modeling project funded by the European Commission. HARMONY is a tool box of digital models to support metropolitan area authorities in their strategic, tactical, and operational urban and transport planning. It is designed as a Model Suite (MS) that combines spatial and multimodal transport planning tools where the modes with respect to the LUTI models are based on road, bus and railway networks. HARMONY is structured

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[1] HARMONY is the acronym for 'Holistic Approach for Providing spatial & transport planning tools and evidence to Metropolitan and regional authorities to lead a sustainable transition to a New mobility era', see https://harmony-h2020.eu.

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across three different levels:

- Strategic (long-term) demographic land use transport models, the subject of this paper.
- Tactical (medium-term) individual (agent-based) and freight load-based models.
- Operational (short-term) multimodal network models in highly disaggregate form (Kamargianni et al., 2021).

The LUTI models are part of the strategic planning toolbox and are being applied in three pilot areas: Oxfordshire (UK), the Turin Functional Urban Area (FUA) (Italy), and Attica (i.e. the Athens metropolitan area) (Greece). In developing the model, we will illustrate applications to these three regions, but the model is sufficiently flexible and accessible so that agencies in many large cities would be able to assemble the data for adapting the model to their own area, easily designing and running a model from the code which we are making widely accessible on various public repositories such as GitHub.

The LUTI model here is based on a long line of models that first emerged during the 1960s in the United States (Jin, Echenique, Wegener, & Batty, 2023). These kinds of model have evolved in that they have become more and more detailed in terms of their land use and activity types, larger in terms of the degree of spatial resolution as reflected in the number of their zones, and faster in terms of our abilities to run such models interactively. Many of these models have developed at ever finer spatial scales, embracing agent-based and microsimulation although the complexity of such structures, has meant that the focus in LUTI models has been mainly on their integration with models associated with other sectors of the urban system, rather than their disaggregation. There is a fairly long tradition of LUTI models which have been developed in the UK, and more recently those that have been developed at UCL have been large scale desktop models that run extremely fast but in standalone fashion. SIMULACRA (Batty et al., 2013) is a model for Greater London and the outer metropolitan area which predicts the location of employment, services and housing while DyME is a spatial epidemiological model for the UK developed during the pandemic by a group including ourselves at the Alan Turing Institute based on four related spatial interaction models which link population to places and activities where they might get infected (Spooner et al., 2021). The other model that is instrumental in the construction of the HARMONY LUTI model is a web-based version of both SIMULACRA and DyME (without the epidemiological component) called QUANT that is designed to cover all areas of the UK at fine spatial scale (Middle Layer Super Output Areas) (Batty & Milton, 2021). In this sense, the model to be presented here is somewhat different from the largest scale land use transport models such as ILUTE, PECAS, UrbanSim, and LonLUTI which are complex models that are usually developed for one-off applications as part of an agency's longer term planning focus (see Lopes, Grangeiro Loureiro, & Van Wee, 2019 and Miller, 2018).

In Italy, LUTI models have been developed for Naples (Hunt, 1994), Venice (Lautso et al., 2004), and Reggio Calabria (Malavenda, Musolino, Rindone, & Vitetta, 2020) using software already developed for similar models built by MEPLAN (Echenique, Grinevich, Hargreaves, & Zachariadis, 2013) and the PROPOLIS project (Lautso et al., 2004). Because a rich combination of infrastructure projects such as a new university, a new hospital, a new metro line and new regional government HQ to be constructed by 2030, the city of Turin was chosen to implement a standalone digital model based on the ideas presented here to assess the impact of these changes. In Greece, although important transport infrastructure projects have been implemented in the last 40 years (e.g. the Athens Metro System, Attiki Odos in Athens, Thessaloniki's Outer Street, etc.), LUTI models do not appear to have been used in Greek cities, the only exception being an application to the city of Thessaloniki by Pozoukidou (2014), but no significant results have been generated yet due to poor data quality. However here, in collaboration with OASA (Attica's transport authority who runs the Athens Mass Transit System), we have applied the LUTI framework to the metropolitan area of Athens (the Attica region) to evaluate a major significant land use change – the re-purposing of the former Elliniko Airport to an Experience Centre and Business District to be completed by 2045 (designed by Foster and Partners Ltd et al., 2016).

There is a long tradition of using spatial interaction as the core of LUTI models from the first efforts to develop transport, then land use models in the early 1960s (Lowry, 1964; Voorhees, 1955). These however have been fairly inaccessible to analysts and policymakers due to the fact that their size, data, mathematical structure and programming requirements have often outstripped the expertise available to continually adapt them to ill-defined policy contexts (Dennett, 2018). In the earliest days, such models were largely in the domain of the model-builders rather than policy makers and this limited their usefulness. The family of such models was first articulated formally by Wilson (1971), but many variants have been developed (see for example Birkin & Clarke, 1991; O'Kelly, 1986; Yano, Nakaya, & Ishikawa, 2000) with retailing as well as transport modeling the main focus of their application (Huff, 1964). Mixtures of constraints on their form have been proposed which integrate models in the fourfold activity framework (Batty, 1976; Batty & Mackie, 1972) while different formulations of the way activities are attracted to one another (Fotheringham, 1983) and how different travel cost constraints are able to be incorporated (Cordey-Hayes & Wilson, 1971) have been widely exploited. Applications to migration movement over much longer time periods have also been developed using similar models which range from commuting (Harland & Stillwell, 2010), and internal local migration (Raymer, Bonaguidi, & Valentini, 2006) to international migration and trade (Dennett & Wilson, 2013).

These models provide highly suitable tools for examining the cause-effect connections between transport and land use (Gavanas, Pozoukidou, & Verani, 2016). Simultaneously, they provide answers to policy-related questions about large-scale spatial developments, such as land use changes and infrastructure developments (van Wee, 2015). The key contribution of LUTI models to policy making consists in assessing trends in residence choices, predicting land use and mobility patterns and calculating the long-term impact of transport and land use policies (Department for Transport, 2014). LUTI models help evaluate transport policies, providing statistical analyses and quantitative results assessment of outcomes (Pozoukidou, 2014). Such models are prescient in that their results do not provide conclusive answers for specific plans, but can be utilised to assess and contrast multiple solutions to any problem. Essentially they provide frameworks to explore the problem. For example, they can be widely used to develop strategic plans for multimodal urban transport systems, such as Sustainable Urban Transport Plans (SUTPs) and Sustainable Urban Mobility Plans (SUMPs) (European Commission, 2007), which is one of the key objectives of the HARMONY project. In both SUTPs and SUMPs, LUTI models constitute key tools for developing alternatives, helping stakeholders better understand the impact of measures and policies proposed within strategic plans (Wefering et al., 2014).

In the rest of this paper, we will begin with a presentation of the theory of spatial interaction which lies at the heart of how LUTI models connect land use activities to transportation. We articulate spatial interaction as the flow from locations where an activity is supplied, to locations where that activity is demanded. We define the activity as working population, where it is supplied at their place of residence and where it is demanded at their place of work. In this sense, if the system were in complete balance, everyone would live and work in the same places but in fact, for a variety of reasons ranging from physical constraints and behavioural preferences, this is unlikely. In fact, the situation we observe is one where demand and supply are balanced but not in the same locations. This balanced spatial interaction is what we observe at any point in time but to generalise this to enable activity to be predicted in different locations, we can relax the demand and supply constraints. This framework then enables us to introduce the suite of spatial interaction models that determine the way the LUTI model is constructed.

After outlining the model and showing how it can be disaggregated for different modal networks (road, rail and bus), we discuss how we operationalise the model in software. Our focus is on exploring the differences due to varying data requirements and different scenario tests that each of these model applications are able to illustrate. Even though the models are identical in structure, as soon as we apply them to different situations, data differences make each application unique. Comparisons can be tricky, as first noted some 40 years ago in the International Study Group on Land Use Transportation Interaction models (ISGLUTI) (Webster, Bly, & Paulley, 1988). We will then conclude this comparison with a discussion of various differences between the models, pointing the reader to subsequent applications of these models as part of the overall HARMONY Suite. The detailed outcomes from the various scenarios are included as Supplementary Information (SI).

2. Interaction and equilibrium

The generic framework for LUTI models begins with activities such as employment or population which are determined by their demand and supply at different locations. Demand and supply can be construed in different ways but in the context of the models to be developed here, the linkage between them is in terms of spatial interaction or flow. A typical example might be the demand for employment in location i which we can define as O_i and the supply of that employment defined as D_j. The relationship, linkage, interaction or flow between demand and supply is thus defined as T_{ij}. To fix ideas, we might think of employment at location i as the volume of activity which the population demands for work while population at location j is the volume of activity supplied to places where the population wishes to live. If demand and supply were balanced, then people would live and work in the same place, that is $O_i = D_i$ but this is unlikely because of a multitude of factors ranging from differential preferences and market imperfections to competitive differences associated with alternative activities. However in any city system, demand is a function of supply and vice versa, that is $D_j = f(O_1, O_2, O_{31}, \ldots, O_n)$ and $O_i = g(D_1, D_2, D_{31}, \ldots, D_n)$ and this implies that we need to balance this relationship using suitable models which predict supply from demand and demand from supply. This relationship has largely been glossed over in LUTI models apart from in some MEPLAN models (Lautso et al., 2004), but we have the flexibility to invoke it through overall iteration of the model framework.

Our generic model is based on the gravitational hypothesis which we write as

$$T_{ij} \propto f_i(O_i) g_j(D_j) h(c_{ij}) \tag{1}$$

where T_{ij} is the flow between i and j, $f_i(O_i)$ is some function of the demand at i, $g_j(D_j)$ is some function of the supply at j, and c_{ij} is a measure of how the travel cost or distance between i and j moderates the flow. From this type of model, the total demand for work at i and supply of working population (living) at j is defined as the summations of the flows from all locations of supply to demand and all locations of demand to supply. That is,

$$\sum_j T_{ij} = O_i = f_i(O_i) \sum_j g_j(D_j)\ h(c_{ij}) \tag{2}$$

$$\sum_i T_{ij} = D_j = g_j(D_j) \sum_i f_i(O_i)\ h(c_{ij}) \tag{3}$$

This model can be estimated in its equilibrium form from

$$f_i(O_i) = O_i \Big/ \sum_j g_j(D_j) h(c_{ij}) \tag{4}$$

$$g_j(D_j) = D_j \Big/ \sum_i f_i(O_i) h(c_{ij}) \tag{5}$$

where we can iterate on these equations starting with, say $g_j(D_j) = 1, \forall_j$ in Eq. (4). We then substitute $f_i(O_i)$ from (4) into (5), continuing the iteration with a new value of $g_j(D_j)$ from (5) into (4) until the equilibrium demand and supply relations in Eqs. (2) and (3) are solved. In fact, the functional relations $f_i(O_i)$ and $g_j(D_j)$ can be simplified to $f_i(O_i) = A_i O_i$ and $g_j(D_j) = B_j D_j$ and then Eqs. (4) and (5) can be written in more familiar form as:

$$A_i = 1 \Big/ \sum_j B_j D_j h(c_{ij}) \tag{6}$$

$$B_j = 1 \Big/ \sum_i A_i O_i h(c_{ij}) \tag{7}$$

This is equivalent to the doubly constrained interaction models used in the four stage transport planning process (Wilson, 1971). We can also scale the measures of demand and supply to reflect agglomeration economies as $f_i(O_i) = A_i O_i^{\alpha}$ and $g_j(D_j) = B_j D_j^{\beta}$ if this is deemed appropriate.

These equilibrium relations only generate a model that predicts trip movements as the location of employment demand and working population supply are fixed, constrained to be met in the model in Eq. (1) and subsequent variants in Eqs. (2) to (7). In fact, the variant which we will develop here is based on the assumption that we know the demand for the activity O_i but the supply is to be predicted by the model. We formulate this model as

$$T_{ij} = A_i O_i D_j exp(-\lambda c_{ij}) = O_i \frac{D_j exp(-\lambda c_{ij})}{\sum_j D_j exp(-\lambda c_{ij})} \tag{8}$$

where we now define the trip cost function as a negative exponential exp $(-\lambda\ c_{ij})$. Demand is fixed from $\sum_j T_{ij} = O_i$ and supply $D_j^{'}$ is elastic, and predictable from

$$\sum_i T_{ij} = D_j^{'} = D_J \sum_i A_i O_i exp(-\lambda c_{ij}). \tag{9}$$

The model in Eqs. (8) and (9) can be complemented by using another model to predict the supply which might be a model of land development that relates to the demand from O_i. We have constructed such a model and this predicts the supply of land development L_j as some measure of a series of independent spatial variables X_j^z that relate to the suitability of land for development defined as

$$L_j = \vartheta + \gamma^1 X_j^1 + \gamma^2 X_j^2 + \gamma^3 X_j^3 + \ldots + \gamma^m X_j^m = \vartheta + \sum_{z=1}^{z=m} \gamma^m X_j^m \tag{10}$$

where ϑ and γ^m are the weights determined from the fit of this linear equation to land development L_j. The amount of land development can be used for the attractor variable in Eq. (8) as $T_{ij} = A_i O_i L_j exp(-\lambda c_{ij})$ where the predicted supply is $D_j^{'}$. If the predicted supply $D_j^{'}$ is different from the observed L_j, then this could generate an iterative sequence where the weights on land development could be adjusted to ensure that the model would ultimately meet the observed capacity. We will not present this model here, but it has been applied to our case studies and it will be reported in a later paper (Lopane et al., 2022).

3. Model methodologies

3.1. The mathematical structure

The core of the generalised LUTI model that we will present here is based on the generic gravitational Eq. (1), or more specifically (8), where we relax the constraint on supply but ensure that the constraints on demand are fixed. Demand is defined as O_i which is activity at location i linked to its supply D_j in location j by the flows or trips T_{ij} from i to j. This variant in the family of the spatial interaction models is called singly-constrained (Wilson, 1971) where the constraint on demand is met as

$$\sum_j T_{ij} = O_i \tag{11}$$

and from which the predicted supply $D_j^{'}$ is

$$\sum_i T_{ij} = D_j^{'} \tag{12}$$

The model form that we use from Eq. (6) is $T_{ij} = A_i O_i D_j exp(-\lambda c_{ij})$ where we define the balancing factor A_i to ensure that the origin constraint in Eq. (11) is

$$A_i = \left[\sum_j D_j exp(-\lambda c_{ij})\right]^{-1} \tag{13}$$

Now this model assumes a single network for travel, but in our applications we have data on at least 3 modes $k = 1, 2, 3$ which are road, rail and bus with cost matrices $\{c_{ij}^k\}$. Assuming the modes compete with one another for patronage – for different proportions of the origin activity, then we can generalise the model in Eq. (8) to

$$T_{ij}^k = A_i O_i D_j exp\left(-\lambda^k c_{ij}^k\right) \tag{14}$$

where

$$\sum_j \sum_k T_{ij}^k = A_i O_i \sum_j \sum_k D_j exp\left(-\lambda^k c_{ij}^k\right) = O_i \tag{15}$$

and the balancing factor is now

$$A_i = \left[\sum_j \sum_k D_j exp\left(-\lambda^k c_{ij}^k\right)\right]^{-1} \tag{16}$$

If we examine the ratio of trips by any mode to all trips, that is

$$\frac{T_{ij}^k}{\sum_k T_{ij}^k} = \frac{exp\left(-\lambda^k c_{ij}^k\right)}{\sum_k exp\left(-\lambda^k c_{ij}^k\right)} \tag{17}$$

then the locations of demand and supply O_i and D_j do not have any relationship to the modal split that in this model depends entirely on the relative costs of travel for different modes.

The spatial interaction model in Eq. (8) is a modular model that can be applied to several activities or sectors $s = 1, 2, 3, \ldots, S$. Thus we may write it as

$$T_{ij}^{sk} = A_i^s O_i^s D_j^s exp\left(-\lambda^{sk} c_{ij}^{sk}\right) \tag{18}$$

where the balancing factor is defined so that $\sum_j \sum_k T_{ij}^{sk} = O_i^s$ and the predicted supply as $\sum_i \sum_k T_{ij}^{sk} = D_j^{s'}$. Now there are S such models and they can be run separately, or they can be linked through their demand and supply origins and destination variables. In fact, there may well be interactions between demand and supply in different sectors s and z defined as T_{ij}^{szk} and this can lead to an iteration to secure an overall equilibrium. For example, we might have one model predicting T_{ij}^{szk} which provides a prediction for $D_j^{z'}$ and if $D_j^{z'}$ then becomes a demand variable for the s sector, where $O_i^{s'} = D_j^{z'}$ an iterative sequence can begin, which in principle is likely to converge where demand and supply are in balance. This extension which links a series of singly-constrained models together has not been invoked here but the fact that the modules are generically the same, makes it a simple matter to relate them in a manner that enables such an iterative sequence to invoked.

The LUTI model we have built consists of four spatial interaction sub-models which are defined and then applied in each case study, depending on data availability which we detail in the next main section. This has never been done in this form before and this innovation is only possible because data is available for these four activity sectors in a form that makes it possible to calibrate their interaction functions from flow data. We specify these sub-models using the following origin and destination variables and their equivalent flows which represent trips or journeys between activities linking demand to supply. These are the:

- journey to work (w) defined by daily commutes from work to home which we define as T_{ij}^{wk}
- journey to retail centres (r) defined by retailing trips from population at residences to retail centres as T_{ij}^{rk}
- journey to schools (e) defined by the educational population at residences travelling to schools as T_{ij}^{ek}, and
- journey to hospitals (h) defined by patients moving from residences to clinics and hospitals as T_{ij}^{hk}.

The structure in Eq. (18) is used for each of these origin constrained sub-models, the first of which simulates trips T_{ij}^{wk}, from workplaces (origins) i to households (destinations) j by transport mode k. Three modes of transport are used for Oxfordshire and Turin (car: k=1, bus: k=2, rail: k=3) and two for Athens (public transport: k=1; and private transport: k=2). In the journey to work model, the variable at the origin i is employment O_i^w and the attractor at the destination j is household floorspace D_j^w (measured in terms of the number of residences). In fact, we have shown that working population is the generic attractor in Eq. (18), but all these variables depend on data availability. We do not have specific networks for each of the four models so c_{ij}^k is the travel time from i to j by transport mode k (expressed in minutes) and this is used for the modes in all four sectors. This is because although the relevant flows or trips use different networks at the physical network layer level, we do not have data on particular travel costs for different sectors by mode. We define all the relevant variables for the four models in Table 1 and when we come to specify the actual applications below, we will details these issues further with respect to the flow data.

While each singly-constrained sub-model has a different definition of attraction, the cost matrices (c_{ij}^k) are based on the origin-destination trips associated with different transportation networks (according to the different modes of transport for each case study). While in the w sub-model, the cost and trip matrices are symmetric in terms of zones, that is $n\ x\ n$ where n is the total number of zones, which is the same set for origins and destinations; for the other sub-models the matrices contain the full set of n zones of the model as origins, but a different set of zonal locations as destinations (i.e. retail centres, schools, and hospitals) and this results in an asymmetrical order of $n\ x\ m$ matrices where m varies according to the sub-model. In these models, the travel costs are defined as travel time with all the c_{ij}^k matrices calculated in minutes.

According to the approach developed in the QUANT model (Batty & Milton, 2021), intra-zonal travel times are determined using two metrics: the average journey distance for each zone and the average speed. The average journey distance is divided by the average speed for each mode of transportation to determine the average intra-zonal travel time. The radius of a circle with an area equal to half of the zonal area is used to calculate the average journey distance. For each zone n by mode of transport k, the intra-zonal travel time (C_i^k) is calculated as follows:

$$C_i^k = \sqrt{\frac{A_n}{2\pi}}\ \frac{1}{sp^k} \tag{19}$$

Table 1
The structure of the LUTI sub-models.

Sub-model type	Predicted flows T_{ij}^{wk}	Origin activity O_i^z	Destination activity D_j^z	Attraction parameter L_j^z	Case study
Journey to Work (w)	T_{ij}^{wk}	E_i employment	P_j working population	residential floorspace	Oxfordshire, Turin, Athens
Journey to Retail (r)	T_{ji}^{rk}	P_i residential population	r_j retail sales	retail floorspace	Oxfordshire
Journey to Schools (e)	T_{ji}^{ek}	e_i students	s_j schools	schools' capacity	Oxfordshire, Turin
Journey to Hospitals (h)	T_{ji}^{hk}	P_i residential population	h_j hospitals	Number of beds	Oxfordshire, Turin

where A_n is the area of the zone n, and $\bar{sp}^k$ is the average speed for the mode of transport k.

We must make one final point before we begin to apply these models. The core model is the Journey to Work which predicts the amount and location of the working population which resides in the destination zones j. The other three sub-models take population-related inputs, namely retailing trips from population at residences, educational population at residences, and patients moving from residences to clinics and hospitals and allocates these to retail centres, schools, and clinics and hospitals. We could define these variables as functions of population P_j, that is define $r_j = \sigma(P_j)$, $s_j = \varsigma(P_j)$ and $h_j = \tau(P_j)$. If we were to do so, then we could define the numbers of those shopping, partaking in education, and using hospitals as generating in turn categories of employment that would then provide new inputs to the Journey to Work model. New predicted values of employment, based on these three sectors, would thus be defined as $E_i = K(\sigma(P_i)) + L(\varsigma(P_j)) + M(\tau(P_j)) + E_i(other)$. We do not need to establish the definite form here for these links from employment to population and then back to employment via retailing, education, and health care have not been used this way to ensure equilibrium in the models so far. But this does indicate the direction in which these kinds of models can be further developed, as was implied as far back as the original model developed by Lowry (1964) for Pittsburgh.

It is worth noting that as the model is modular with respect to the use of spatial interaction models, various versions of these can easily be substituted for the models defined here. For example, intervening opportunities models might be more useful for retailing and the journey to work while variants such as the radiation model (Masucci, Serras, Johansson, & Batty, 2013) could be used. Changing the level of detail to individual travel behaviour, discrete choice models could also be applied but this would then take the model into the agent behaviour realm and would massively add to the time taken to run the overall model. This is of course for the future but it does indicate that there are several obvious innovations to these kinds of model apart from our focus on making these LUTI models work rapidly in relatively data scarce environments (such as emerging and rapidly developing metropolitan areas in the Global South).

3.2. *Software implementation*

The mathematical framework presented above is built and run in Python (Van Rossum & Drake, 2009), mainly using libraries based on Pandas (Mckinney, 2010), NumPy (Harris et al., 2020), Pickle (Van Rossum, 2020) and Geojson (Butler et al., 2016). The main source for the Python code is from the RAMP project (Rapid Assistance in Modeling the Pandemic, The Royal Society, 2020) as published in the DyME model (Spooner et al., 2021) which in turn was taken from the QUANT model (Batty & Milton, 2021; http://quant.casa.ucl.ac.uk/quant2/).

In the repository, the config.py module is a configuration module containing two dictionaries: inputs and outputs. Each dictionary has the names of input and output variables as keys and file paths as arguments. The main.py module contains the base model and the formulation of the different scenarios for each case study. The journey to work model equations are defined in the quantlhmodel.py module, which is built around the standard singly-constrained model defined by Wilson (1971) whose first formal application was the retail model developed by Lakshmanan and Hansen (1965). Accordingly, the journey to retail sub-model is defined in the quantretailmodel.py module, the journey to school sub-model in quantschoolsmodel.py and the journey to hospitals sub-model in the quanthospitalsmodel.py.

LUTI models are usually calibrated via some form of nonlinear optimisation or regression (Batty & Mackie, 1972; Oshan, 2016). In this model, the calibration of the parameter value (β^k for the Journey to Work) is achieved from a nonlinear regression of the value of the travel cost parameter β^k against different values of the mean trip length C^k calculated on either real (Oxfordshire) or modelled (Turin) flow data (according to availability) which represents the average trip length for each transport mode for Oxfordshire and Turin. Due to the lack of observed data in Athens case study, the mean trip calibration values were set to 37 min for private transport according to Numbeo (2021) and to 47 min for public transport according to Moovit (2021). In short, the calibration method is equivalent to a fine-tuning or dimensioning of the model to the real data. It simply reproduces various statistics of the trip frequency distributions, namely the mean trip length with other statistics being used to judge the validation of the model further. Strictly speaking this is a not a full validation of the model although it is equivalent to solving the maximum likelihood equations (Batty & Mackie, 1972). Once the code has run, the values of the optimal predicted C^k and the calibrated β^k are generated, while the flows T_{ij}^k of commuters and the flow probabilities are exported in a csv format. Simultaneously, for the journey to work model, job and housing accessibility maps are produced as well as shape files to represent the flows mapped as additional output. The four sub-models are calibrated in this standard fashion, and there are many kinds of visualisation that the model package can generate once the user has produced an optimal calibration to the observed data.

The structure of the Python code as summarised here is shown in the methodology flow chart in Fig. 1 which indicates how the modules are sequenced.

4. The three city case studies

The three case studies relate to the expertise and location of the partners who came together to form the HARMONY Consortium. LUTI models tend to be built for urban populations of at least 500,000 and a key criterion was to choose a very small number cities in the EU but with quite a wide representative range of city sizes. In this way, the various models in the HARMONY suite could be best adapted to urbanisation in the EU while at the same time taking account of the inevitable differences in data between the various case studies. The three applications to Oxford and its county, Turin and its Functional Urban Area (FUA), and Athens within the wider Attica region reflect a range of population sizes from nearly 700,000 in Oxfordshire, nearly 1.8 million in Turin, and 3.8 million in Athens. This range is consistent with the notion that the size and density of these cities is such that they would reflect key agglomeration economies as well as being focal points for economic growth within their wider regions.

There three cities are also very different in their composition and role in the urban hierarchy. Oxfordshire is essentially a peri-urban, low density, prosperous rural commuter belt to Greater London centred on a

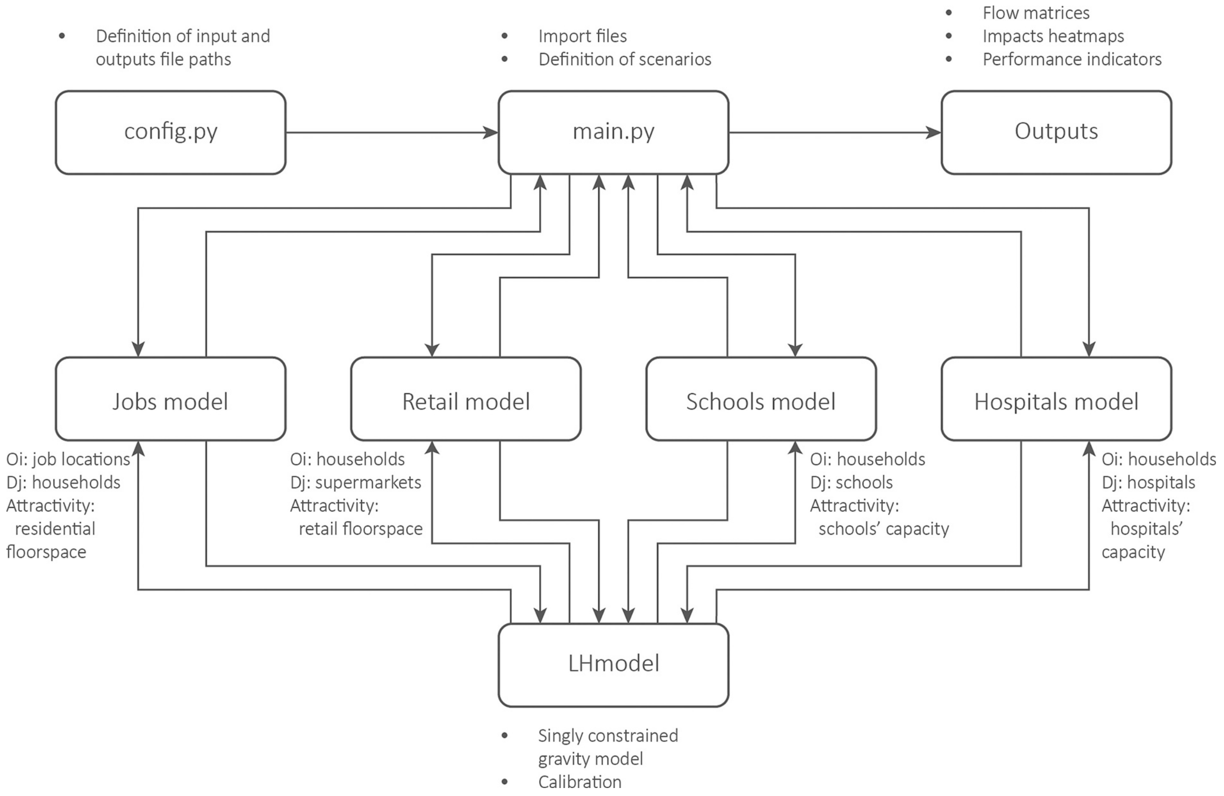

Fig. 1. The methodology flowchart: the structure of the Python code.

medieval town. In this sense, it is representative of many parts of southern Britain outside the biggest cities. Turin goes back to Roman times and is a relatively well defined local capital of the Piedmont region in North-western Italy. It is also relatively prosperous. Athens of course is a world city, a national capital of a very highly centralised country and it dominates its nation state. These three cities have very different transport systems and thus their scenarios for future growth also differ as do their densities of population and employment. This is reflected in the various scenarios we test in the applications that follow and in the material reproduced in the Supplementary Information.

We will deal with each of these applications beginning with the most complex of the models, but the most simplest of cities, that in Oxfordshire, then the simplest model (due to limits on data) but the most complex city, that of Athens, and finally to Turin, somewhere between the first two, where there is higher data quality and availability with respect to Athens (e.g. available location and capacity information on education and health facilities), and the city is more self-contained than the other two. In each case, we will begin with a little more detail about each city, then outline the scenarios to be tested. We have relegated our discussion of the impacts that these scenarios show to Supplementary Information (SI) which enables readers more familiar with each case study to explore more detail in model outcomes. We should stress however that we do not deal here with the detailed calibration of the models which is very standard. But suffice it to say that we consider the goodness-of-fit of each model to be acceptable and our focus in this paper is indicative as to what kinds of urban development scenarios can be tested at three different scales.

4.1. Oxfordshire: Oxford and its county

Oxfordshire is a semi-rural English county whose area is some 2600 km^2 located some 60 kms northwest of London. It comprises five district councils[2] and although rural, it is sufficiently close to Greater London to be within its commuting field and as such, it might be classed as peri-urban. The case study area is divided in 86 Middle Layer Super Output Area (MSOAs) zones which is one of the Census geographies in the UK Population Census. Of the 700,000 population, about one quarter or 180,000 live within the Oxford city boundary.

As should be quite clear from the brief history of these models implied above, LUTI models can evaluate the impact of significant changes in land-use and transportation, either as one-off developments at different scales or from a continuing stream of policy measures relating to land use and transport. In Oxfordshire, the provision of new housing is a key local and national objective, and a new housing development plan foresees the building of over 33,000 new dwellings by 2031. Based on the 2011 Census Population and on population projections for subsequent years provided by the HARMONY Demographic Forecasting model (which in turn is based on the microsimulation model SPENSER (Lomax & Smith, 2020), two different scenarios were developed, one for the reference year (2019) and one for the projection year (2030). These are:

- *New Housing Development at 2019*: Oxfordshire divided into its 86 zones (MSOAs) is used for the calibration using employment from HARMONY Regional Economy model which we sketch in a related paper (Lopane et al., 2022). This scenario is based on the number of dwellings and travel times from the 2019 Journey to Work sub-model, population, supermarket floorspace and travel times from

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[2] Oxford City Council, Cherwell, South Oxfordshire, Vale of White Horse, and West Oxfordshire.

the 2019 Journey to Retail model, population data for primary and secondary pupils, schools' capacity, and travel times from the 2019 Journey to Schools model, and population data, hospital floorspace and travel times from the 2019 Journey to Hospitals sub-model.

- *New Housing Development to 2030*: this scenario defines the Journey to Work sub-model where the number of jobs and the travel times remain the same as the 2019 data, while the number of dwellings has been increased by 33,263 dwellings in total from 2019 to 2031. For the Journey to Retail sub-model, the square metres of supermarket floorspace and the travel times remain the same, while the population has been increased by 79,831. For the Journey to Schools school sub-model, each educational level (primary, secondary) of the school's population has been increased proportionately by 2030, but the travel times and the schools' capacity do not change. For the Journey to Hospitals sub-model, the square metres of hospital floorspace and the travel times also remain the same, while the population has been increased.

4.2. Athens and Attica

Athens is a capital city with the world's third largest and Europe's first port in terms of passenger numbers (Weng, 2014). The wider Attica region which is dominated by Athens has an area of approximately 462 km^2 with some 3.8 million citizens (from the 2011 Population Census) excluding nearby islands and other regional units. Attica consists of 66 municipalities with an average population density of about 7 residents/km^2 (Hellenic Statistical Authority, 2011). About 25% of the population live in Athens city centre, where there is also an equivalently high percentage (30%) of jobs (Milakis, Vlastos, & Barbopoulos, 2008). In this application, Attica is split in a system of 1265 zones defined by the Athens Urban Transport Organization (OASA) and these are compatible with other HARMONY models. However, although its spatial units or zones are a little smaller in average population size from those in Oxford and Turin, the city is very much bigger than the other two and in size it is approaching mega-city status. The total daily journeys (all sectors and modes) in Attica are some 8 million with 50% of them undertaken by private vehicles, 40% by public transport and the remaining 10% by walking or cycling. According to the Athens Urban Transport Organisation (2009), 40% of daily journeys are to and from work, 12% for shopping, 9% for leisure, 15% for personal reasons, 6% for education and 7% for social reasons.

The LUTI model for Athens is geared to evaluating the impact of one of the most important land use changes in Greece during the last decade: the renovation of the former airport in Elliniko. The regeneration of Elliniko is of utmost importance not only for Athens but also for the whole of Greece, as it will contain the largest park in Europe, one of the largest coastal parks in the world and it is estimated that it will attract more than one million extra tourists each year (Lamda Development, 2019). The project began in 2020 and will be implemented in 3 phases: Phase– 1A (Years: 1–5) 2021–2025 and 1B (Years: 6–10) 2026–2030; Phase 2 (Years: 11–15) 2031–2035, and Phase 3 (Years: 16–25) 2036–2045. Employment in the area is expected to increase by 25,000 by the mid-2030s. In the following years, with the gradual conclusion of construction activities, but with the simultaneous increase of business activities in full operation, the number of jobs maintained in the area on an annual basis is estimated to be about 21,000. After the end of construction of the Metropolitan pole, about 90,000 jobs generated from this project will have been planned for 2045 in the Attica region.

For these reasons, three scenarios have been defined based on the three construction phases of the project. The first scenario describes the distribution of flows of the journeys to work in 2019, the second scenario concerns predictions for the year 2030 (by which time 25,000 new jobs will have been created, many of which will be temporary) and the third scenario concerns the year 2045, when the project will be completed, and 90,000 permanent jobs will have been created.

The methodology in Fig. 1 is simplified for the Athens model as only the Journey to Work sector is modelled. As Table 1 implies, this particular application of the model lacks information on three other sectors – retail, schools and hospitals. As the framework is flexible, however, if and when information becomes available for these sectors, the LUTI model is easily extensible. It has thus been adapted to test the impacts of the three scenarios in following project phases.

- *The Attica Region Scenario 2019*: based on 1265 zones in the Attica region, the model is run using employment data provided by the HARMONY Regional Economy model, households floorspace data from 2011, and travel times from 2016, the most recently available data.
- *The Elliniko Scenario 2030*: in the four zones where the project is being developed, 2000 jobs are added. Then, the model is run using the calibrated parameters λ^z for the base year model (2019).
- *The Elliniko Scenario 2045*: in the zones of the Elliniko project, the number of jobs is increased to 90,000. Simultaneously the floor space of the new households will take some 291,000 ha, which are added to the respective zones of the model through the attractor variables D_j. Afterwards, the process is the same as in the Elliniko Scenario 2030.

4.3. Turin and its functional urban area

The Turin Functional Urban Area (FUA) includes the municipality of Turin and 87 other municipalities within the province of Turin while the total population of the FUA is about 1,75 million persons (as of 2018) of whom about 870,000 live in the Municipality of Turin. Within the FUA, the Municipalities are split in 270 zones to match the transport model zoning systems of the other HARMONY models.

The LUTI model for Turin assesses the impact of both land use and transportation infrastructure changes which are covered by a series of comprehensive urban plans. According to the Sustainable Urban Mobility Plan for Turin (Città Metropolitana di Torino, 2021) in 2030 a new hospital called "Città della Salute" (City of Health) will be built, and will replace part of the current hospital system in Molinette area. The hospital "Casa di Cura Villa di Salute" in Trofarello will be expanded, while four hospitals (Azienda Ospendaliera O.I.R.M.S. Sant' Anna, Ospedale Molinette, Ospedale Maggiore and Ospedale Santa Croce) will close. Moreover, the universities of Unito – Facoltà Agraria e Veterinaria, and the Politecnico Lingotto will expand further to host more students. Additionally, the administrative centre of the Piedmont Region will be transferred to the Lingotto area by constructing a landmark skyscraper ("Palazzo della Regione") which aims to concentrate the main sectors of the administration in a single location, leading to a strengthening centrality of the area given more than 1000 additional employees.

Regarding changes in the transportation system, a new tram line (line 12) will be added to the existing tram network while tram lines 3, 4 and 10 will be extended. A new automated metro line (line 2) will connect the municipalities of San Mauro in the north-east and Orbassano in the south-west. Based on the above descriptions and the methodology in Fig. 1 which has been used to develop the LUTI model, the two scenarios for Turin case study are defined as follows:

1) *Turin 2019*

- The Turin FUA is divided in 270 zones and the model uses employment data from the HARMONY Regional Economy Model, household floorspace data and travel times from 2019 (Journey to Work model)
- Population projections are provided by the HARMONY Demographic Forecasting model for each educational level, schools' capacity and travel times from 2019 (Journey to Schools model) and population data from the HARMONY Demographic Forecasting model, and the number of beds per hospital and travel times from 2019 (Journey to Hospitals model).

2) *New Land Use and Infrastructure Development 2030*

- The Journey to Work model adds nearly 8000 new jobs in 2030 due to the new administrative centre of the Metropolitan City of Turin with changing travel times due to new metro and tram lines in 2030, while household floorspace data remain unchanged.
- The Journey to Schools model is built for each educational level (primary, middle, high school, and university) consistent with the population changes in 2030 as well as travel times. The schools' capacity only changes for universities, where the capacity of Politecnico Lingotto is extended from 5000 to 7500 students and the capacity of Facoltà Agraria e Veterinaria from 5000 to 10,000 students.
- The Journey to Hospitals model decreases the number of hospitals from 50 to 47 as in 2030, four hospitals will close and a new one will open. For this reason, the numbers of beds at hospital "Casa di Cura Villa di Salute" will extend from 170 to 404 and the planned new hospital "Città della Salute" will be added with 1040 new beds. The population and travel times also change accordingly in 2030.

5. Discussion: evaluating LUTI models in HARMONY

5.1. Accuracy of the calibrations

The three models are calibrated using standard practice by ensuring that the friction of distance parameters λ^{zk} are chosen to reproduce the relevant means of the observed trip lengths in the appropriate gravity models. Once this has been done for all relevant sectors and modes, an analysis of the predicted trip frequencies can be made and compared against those observed at the baseline. Key indicators that validate how well the model is calibrated is the percentage of the population that uses car, bus and rail and we will deal with these in turn for each case study application. Here we use data on all trips from various travel surveys but as it is not possible to disaggregate these trips by sector, we make comparisons only with the journey to work.

In Oxfordshire, the model reveals that 52.5% travelled by car, 17.8% by bus and 29.7% by rail in 2019, while in 2030 car commuting drops slightly to 52.2%, but bus and rail increase to 17.9% and 29.9% accordingly. These are only marginal changes. However, statistics from Oxford City Council (2014) show that 66% of commuters were travelling by car, 10% by bus, 3% by train and 21% on foot or bicycle in 2011. The discrepancy in the results for all the modes of transport and especially for rail can be explained by the fact that the model does not include walking and cycling as transportation modes, but these networks are currently being added (to the QUANT model) and this will result in a huge improvement in the predictive capability of this kind of LUTI model.

In Turin, the results indicate that 42.8% of commuters used car in 2019 while 15.6% used bus and 41.5% rail. In 2030, 41.9% use car, 15.4% bus and 42.7% rail, again fairly marginal changes. According to statistics from the EMTA Barometer EMTA (2022) which are based on 2019 data, 39% travelled by car, 14% by bus, 10% by rail and 37% by bike or on foot. The results of the model match with statistics in terms of car and bus, but not for rail. This discrepancy is again due to the limitations of the model from excluding cycling and walking as a means of transport.

From the results of the Athens model, we observe that 54.5% of the population use private transport and 45.5% public. In fact, based on Kepaptsoglou et al. (2015), 50% of trips are done by private vehicle, 40% by public transport and the remaining 10% by walking or cycling. Since this model does not consider walk or bicycle as modes of transport, the fact that the additional 4.5% in private and 5.5% in public transport resulting from the calibrated model suggests that these trips relate to other means of transport. Even if these inferences were not the case, the results of the Athens model reflect the observed situation to an acceptable degree of approximation.

5.2. Aggregate and disaggregate models: data limitations

The basic problem with developing the same model for different applications is that the degree of detail that is available with respect to data is highly variable and this makes strict comparisons between different case studies highly problematic. For example, the Oxfordshire and Turin examples use three modes of transport while Athens has only two. As we have highly aggregated trip frequencies, these are not directly comparable and as the average population sizes of zones in the three examples ranges from some 3000 in Athens to 8000 in Oxfordshire, the errors induced by aggregations from lower to upper levels, although unknown, could be significant. In the case of sectors, retailing, education, and health care are likely to differ in their actual definition between Oxfordshire and Turin, making comparisons more problematic.

The HARMONY suite of models ranges from aggregate LUTI, demographic and regional economic models to disaggregate travel demand models and models for active travel and although the implication is that there should be a strict causal chain of aggregation from the individual and household to aggregates of population and employment many orders of magnitude greater, this chain is impossible to unravel. In fact, when building generic models for the range of urban areas that require LUTI models, data is taken from very diverse sources and usually it is not possible to get access to the most disaggregate forms of data due to limits on confidentiality. Moreover, a considerable quantity of data needs to be synthesized from diverse sources and missing data needs to be estimated. All of this compounds comparisons and obfuscates the development of consistent data bases for LUTI and other models in the HARMONY Model Suite.

5.3. Transferability and scalability

One of the greatest advantages of the LUTI framework we have presented is that it can be applied to different metropolitan areas, but also at different scales (e.g. metropolitan, regional and national level). We have not illustrated our work elsewhere on our UK national model QUANT, but models can be nested within one another and in this sense, spatial variations that pertain to different scales can be consistently explained and predicted. This is possible as, regardless of the country, much of the data needed (employment, population, flows from origins to destinations in different sectors and on different modes, etc.) are available mainly in csv or xls format which are easily imported into Python code, and therefore relatively easy to manage. Provided we have commensurate data availability, the framework is flexible enough to be adapted to different case studies (in countries other than the UK, Greece, or Italy). Different scales and resolutions only imply larger data volumes (and consequentially longer run times) as the framework does not embody radically different constraints at different scales, resolutions, or regions.

A relevant point regarding the transferability and applicability of the LUTI framework to data poor contexts, is that the lack of flows observations in Athens did not prevent the application of the model (further details in Section 5.4); this would currently be the case for many cities of the Global South, where an estimation of the average journey to work trip length (either through secondary data, surveys or testing of different assumptions) could suffice for the calibration of the β^k parameter, and consequently the generation of results to support data-driven policy-making in urban and transport planning.

5.4. Refining the LUTI models

A limitation of the Athens model is that observations concerning the travel time from zone to zone are largely absent and any related observed data cannot be used to calibrate the model using conventional spatial interaction techniques. Instead, the model relies on statistics from measurements generated by Numbeo (2021) and Moovit (2021) from which we have set the average travel time or trip length at 37 min for private and 47 min for public transportation. This is far from an ideal way to calibrate LUTI models as a calibration against observed origin and destination flows provides much more accurate results; however, it also demonstrates the flexibility of such models in absence of default input data. Rules of thumb such as this are much easier to invoke in calibrating such aggregate models despite the need exercise caution in their definition.

Another limitation of the journey to work model is that it uses the household floorspace as an attractor, but it does not take into account economic factors such as rental prices. Although the developed model is a complete tool that can be used directly, the aforementioned limitations also constitute a good starting point for future implementation of the proposed methodology which we can summarise as follows:

- Including more scenarios, such as those based on 1) the prediction of flows in case of teleworking during a pandemic such as COVID-19, 2) the assessment of the impact of the construction of a new metro line in Athens by 2029, 3) an evaluation of the impact of land use changes that will occur from the 2021 implementation of the Athens Regulatory Plan, or 4) neighbourhood regeneration in Turin.
- Using an alternative approach: instead of travel time, travel (monetary) costs can be used or included directly as travel costs c_{ij}. More modes of transport could also be considered in the model. For instance, these could be divided into: car, motorcycle, bus, railway, subway, tram, bicycle, walk and ferry. However, such data includes considerable detail and are difficult to collect. However, an urgent priority would be to include walking and cycling as modes of transport in the considered case studies.
- Instead of using the floorspace as an attractor, a more advanced version of the models could include rental prices in each zone multiplied with the area of residential floorspace as an attractor. A more sophisticated way of defining a more complete attractor was developed for a retail agglomeration model by Piovani, Zachariadis, and Batty (2017) and this could be easily added to the LUTI model, subject to data availability.

6. Conclusions

As the HARMONY LUTI model is embedded in a wider suite of programs dealing with the entire land use and transport planning process, there are substantial opportunities to adapt the framework to many specific features of particular applications. Other models which focus more on location than spatial interaction and more on economic than physical land development processes could be used at the same level as the LUTI models, but much depends on data and in particular, economic data other than employment is difficult to guarantee. However, there are many improvements that can be made to the models presented here and the limitations that have been identified serve to emphasise that models such as these will always remain as indicative tools that inform the debate about future land use and transport scenarios, rather than providing clear and steadfast predictions for what the urban future holds.

A key focus of the LUTI model that we have developed here is its relative simplicity with respect to its data requirements which in turn are reflected in the fact that it is an aggregate demo-economic structure operating at a relatively coarse spatial scale. In fact, arguably these kinds of models are far more applicable to real planning problems than their much bigger and more data hungry equivalents. Throughout the history of this field, there has been a quest to produce bigger, more disaggregate models at ever finer spatial scales. But the tide is turning. There is now much more recognition that cities reveal almost infinite complexity and the idea that we should aim to capture as much of this as possible tends to fly in the face of the fact that parsimony is essential in understanding complex systems and in thinking about their future. Simplicity therefore is to be valued and as Einstein (2010) once said: "Everything should be made as simple as possible, but not simpler". This must be the mantra for improving these models further.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.compenvurbsys.2023.102007.

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