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Simulating the co-emergence of urban spatial structure and commute patterns in an African metropolis: A geospatial agent-based model

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ABSTRACT

Urban spatial structure and mobility patterns co-evolve. A fundamental process that underpins the emergent structure of cities and commuting patterns is location choice with respect to housing and employment. Consequently, location choice models constitute important sub-components of land use-and-transport-interaction (LUTI) and urban growth models. This paper documents the development and application of the Metropolitan Location and Mobility Patterns Simulator (METLOMP-SIM). METLOMP-SIM is a geospatial agent-based model that simulates how urban structure and travel patterns co-emerge, as a function of the location decisions of heterogeneous households and individuals within a spatially-explicit urban context. After specifying a generic conceptual model that identifies the model's structure, entities and agents' decision-making framework, METLOMP-SIM is implemented using the Kumasi Metropolis in Ghana, Sub-Saharan Africa as case study. Overall, the implemented model demonstrates that the encoded micro-scale behaviour of households and individuals are able to mimic some macro-scale residential and job location patterns, and patterns of home-work trip flows that closely match patterns in the case study metropolis. The current model represents property and job market dynamics in both their 'formal' and 'informal' manifestations, making it potentially relevant to dynamic, agent-based LUTI model development and applications in Sub-Saharan African cities.

1. Introduction

The spatial distribution of land use activities and patterns of spatial interaction in cities co-evolve (Batty, 2013). Various urban development and property market processes underpin the distribution of land use activities observed in different urban contexts. One of such fundamental processes that is common across all cities is the location decisions of various actors in the urban property and employment markets. Individuals, households, property developers, businesses and the public sector make location decisions, which, ultimately, determine the spatial distribution of activities such as the place of residence, employment and ancillary amenities in the city. The land use patterns that emerge from the aforementioned location decisions reflect the distribution of various urban opportunities, which in turn, generate the need for travel (Batty, 2013; Wegner, 2004).

In view of the above, research on the linked responses between the urban land use system and the transportation system has long focused on understanding, representing and simulating the long-term urban location choice behaviours of individuals, households and firms (Pagliara et al., 2010). This stems from the basic understanding that the ability to comprehend and model these long-term choices would improve our understanding of the structural conditions shaping daily mobility patterns and travel behaviours, as well as inform travel demand forecasting and management strategies (Pinjari et al., 2011; Habib et al., 2011). To this end, the field of Land Use and Transport Interaction (LUTI) modelling has become an established domain of interdisciplinary research, bringing together the traditionally separate fields of spatial development planning and transportation planning.

Over the past six decades, significant efforts have gone into the development of several state-of-the-art LUTI models (see e.g. Wegener, 2004; Iacono et al., 2008; Acheampong & Silva, 2015; Moeckel et al., 2018). LUTI models have evolved in terms of their underlying theories, assumptions and modelling techniques. The earliest generation of models adopt aggregate modelling methodologies, which are grounded in classical urban micro-economics theories (e.g. Alonso, 1964; Wingo, 1961) and entropy-based spatial interaction assumptions (Lowry, 1964; Wilson, 1970). In recent years, there has been a transition from these aggregate approaches to disaggregate modelling paradigms such as

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Agent-Based Modelling (ABM). The disaggregate turn in modelling has been motivated, among other things, by the need to improve the behavioural realism in urban models (Acheampong & Silva, 2015; Batty, 2013).

ABM, being a bottom-up computational paradigm has opened up new possibilities to create, analyse and experiment with simulation models composed of autonomous, purposive agents that interact with each other and their environment (Lippe et al., 2019; Heppenstall et al., 2016; Crooks et al., 2018; Railsback & Grimm, 2011). In recent years, a new generation of disaggregate models of urban location choice employing the ABM paradigm have been developed (see e.g. Babakan & Taleai, 2015; Matthews, Gilbert, Roach, Polhill, & Gotts, 2007; Bao et al., 2020; Huang et al., 2014; Marini, Chokani, & Abhari, 2019; Murray-Rust et al., 2013; Ravulaparthy et al., 2017; Zhuge & Shao, 2019). Marini, Gawlikowska, et al. (2019), focusing on immigration and residential development, simulate the co-evolution of household population growth and urban development in the Swiss agglomeration of Lausanne. Others have also focused on the location behaviour of firms and how that determines demand and development of office buildings. For example, in the 'Selfsim' model developed by Zhuge and Shao (2019), they simulate how firms and office buildings co-evolve, by modelling important processes, including firm birth, growth, relocation and closure, and how this affect the demand and development of office buildings.

ABM models of residential location choice, which is the focus of this paper, share a number of common attributes. They represent heterogeneous decision-makers that are differentiated based on a number of socio-demographic factors. However, as we will elaborate shortly **in section 2**, these models differ in terms of realism, as a result of the ways they represent spatial attributes as objects of agents' choice; the extent to which supply and demand-side processes underpin price formation and evolution (see e.g. Ettema, 2011; Filatova et al., 2011; Hosseinali et al., 2013; Murray-Rust et al., 2013) and whether or not they integratively model residential and job location choices (Waddell et al., 2007; Yang et al., 2013).

Context does have significant influence on the representation of the aforementioned processes in disaggregate urban models. A survey of the literature, however, shows that, most operational LUTI models as well as new generation of ABM-based location choice models have been developed with conditions, assumptions and processes in cities in developed countries in the Global North in mind (Acheampong & Silva, 2015; Agyemang & Silva, 2019). For example, most of the existing models operate on assumptions of formal property markets, implying that they are limited in terms of their potential applications in cities in different regions such as Africa, where such interactions occur in both 'formal' and 'informal' property markets (Acheampong, 2017).

This paper documents the development and application of an agent-based model of urban location choice and travel patterns. The model, hereafter, referred to as the Metropolitan Location and Mobility Patterns Simulator (METLOMP-SIM), simulates how the residential and job location choice outcomes of heterogeneous households and individuals, co-emerge with mobility patterns. The empirical context for the current model is the Kumasi Metropolis, the second largest, and rapidly urbanizing, metropolitan area in Ghana, with an estimated resident population of over two million (see Asabere et al., 2020). METLOMP-SIM is spatially explicit, capturing the unique attributes of location and spatial goods. The model also represents the dynamics of the urban property markets, involving bilateral transactions and competition among agents. Most importantly, METLOMP-SIM has been developed with the prevailing realities of 'formal' and 'informal' property and job markets, as they pertain to most Sub-Saharan African cities in mind.The unique 'informal' aspects represented in the model are the rent-free housing sector—a non-market housing arrangement in traditional compound housing common in urban West Africa, that is linked to extended family relations; abstraction of the self-build incremental housing development practices (see e.g Amoako and Boamah, 2017) that is largely responsible for the supply side of the rental and ownership sectors; and representation of both home-based and out-of-home employment in the informal economy. These characteristics of the property and jobs markets and how they have been incorporated in the model are elaborated in **supp appendix 1, section 3.2.**

The main contributions of this paper are as follows. Firstly, by explicitly modelling both residential and job location choices, the paper demonstrates the output capability of the resulting model, including generation of commute flows based on the emergent home-work patterns—a capability that is absent in ABMs of location choice that do not integrate these two important choice processes underpinning the emergent spatial structures. Secondly, by integrating relevant 'formal' and 'informal' property and employment market processes, the current paper offers new insights and assumptions beyond those underlying existing urban models that have been developed mainly on the assumptions and logics of formal property markets in the Global North. To this end, the paper provides empirically-grounded heuristics and decisions rules that could ultimately inform the development of operational LUTI models in contexts where these property and employment market processes are evident. Finally, the paper also demonstrates a systematic process of combining 'parameter sweeping' and categorical calibration experiments to identify 'best-fit' parameter values, as well as accounting for stochastic variations in outputs of interest that is inherent in complex agent-based models. In doing so, the paper offers useful methodological insights to the development and calibration of complex urban simulation models.

The rest of the paper is organized as follows. In the next section, a review of the literature on the state-of-the-art in agent-based urban location choice models is presented. In **section 3**, the model framework, showing the overall structure and implementation of METLOMP-SIM is presented. The model calibration and parameter sweeping experiments are described in **section 4,** followed by presentation and analysis of the simulation results in **section 5**. The main findings and their implications are discussed in **section 6**, followed by concluding remarks in **section 7**.

2. *State-of-the-art: agent-based models of urban location choice*

A wide range of urban models has been developed to simulate different urban phenomena. In the field of integrated land use and transport studies, several operational LUTI models such as UrbanSim (Waddell et al., 2010), PECAS (Hunt et al., 2008) and ILUMASS (Moeckel et al., 2002) have been developed using micro-simulation techniques. In recent years, ABMs are being developed to simulate a wide range of socio-spatial and ecological processes (e.g. Bao et al., 2020; Bithell & Brasington, 2009; Dragićević & Hatch, 2018; Filatova et al., 2011; Liu & Silva, 2015; Brown & Robinson, 2006; Marini, Chokani, & Abhari, 2019; Omer, 2005; Ge, Polhill, & Craig, 2018; Tilahun & Levinson, 2013; Wahyudi et al., 2019). One of these processes is urban location choice—a fundamental process that underpins the emergent structure of cities and thus, forms a critical component of LUTI and urban growth models.

ABMs of urban location choice typically use a combination of empirical insights, heuristics and principles from theories such as random-utility, access-space-trade-off, complexity theory, bounded rationality and decision making under uncertainty to simulate residential location choice (Batty, 2007; Filatova et al., 2011; Rasouli & Timmermans, 2014). In these models, realism depends on the level of detail captured with respect to agent heterogeneity; the types and attributes of discrete choice alternatives represented; and representation of property market processes such as bilateral transactions and competition among agents (Ettema, 2011; Huang et al., 2016; Parker & Filatova, 2008).

In ABMs of residential location choice, agent classes may be differentiated based on income (Hosseinali et al., 2013; Lemoy et al., 2010), life-cycle-stages (e.g. Haase et al., 2010) or a combination of the two criteria. For example, MobiSim—an individual-based model of residential choice developed by Tannier and Colleagues (2016), represent some 72 types of households differentiated based on different combinations of variables including income, age and household composition.

However, some models do not explicitly simulate bilateral property market transactions and associated competition involving bidding, counter-bidding and price formation (e.g. Hosseinali et al., 2013; Murray-Rust et al., 2013; Robinson & Brown, 2009). These categories of models often consider the supply side of the property market as exogenous and therefore do not represent the micro-economic decision--making interactions of agents that result in price formation and different market power scenarios. In the model developed by Hosseinali and Colleagues (2013), for example, the only form of market competition captured is when some cells (i.e. land parcels) are simultaneously chosen for development by more than one household agent. Competition outcomes for any given land in their model, therefore, do not arise from market interactions among household agents expressing willingness to pay and subsequently engaging in a bidding process, based on the asked and take prices evolving from those transactions. As previous researchers in this domain have noted, the lack of bilateral market transaction and competition in these models makes it difficult to gain insights into the underlying economic forces driving land development decisions (Ettema, 2011; Filatova et al., 2009; Magliocca et al., 2011).

Other ABMs of urban location choice have sought to explicitly incorporate market processes involving bidding between buyers and sellers and price formation outcomes (e.g. Magliocca et al., 2011; Ettema, 2011; Parker & Filatova, 2008). In Ettema's (2011) model of residential relocation, for example, house prices emerge through bilateral transactions between buyers and sellers. Transactions are constrained by agents' budgets, housing preferences and their perceptions of market conditions. In CHALSM (Magliocca et al., 2011) a bilateral transaction framework links developers' rent expectations in the housing market to their bid price in the land market, and use adaptive expectations of future prices and market conditions to compare the utility of present and potential future transactions. While these models have improved the way property markets are represented, they rely mainly on assumptions of formal property markets, thereby limiting their relevance to other contexts where informal market processes also underline location choice outcomes.

Furthermore, most of the existing models focus on unique parcels of land as the only discrete alternatives of households' choice decisions (e.g. Filatova et al., 2011; Haase et al., 2010; Hosseinali et al., 2013; Jjumba and Dragićević; 2012; Robinson & Brown, 2009). A handful of residential location choice models represent dwellings as discrete choice alternatives. Ettema (2011), in his model, define dwellings as spatially fixed agents. However, the model does not specify the distinguishing characteristics of dwellings such as type, size and type of tenancy it is meant for (i.e. whether for rent or for owner-occupation). Apart from not being spatially explicit, another limitation of Ettema's model is that it simulates a market of relocating households given a fixed dwelling stock and focusing on households only wanting to buy or sell residential properties. Moreover, in the model developed by Magliocca et al. (2011), they distinguish between eighteen different types of houses: house types are defined by lot and house size (i.e. small, medium and large house) without providing detailed categorization into typology (i.e. whether flats, semi-detached or detached dwelling units) and their attributes (e.g. number of bedrooms).

Last but not least, in most of these models, the traditional assumption of exogenously determined employment centre (in the case of monocentric models) or centres (in the case of polycentric models) is maintained without necessarily simulating the job search processes of individuals as part of the residential location choice process. The reverse assumption is held the model ABODE—Agent-Based Model of Origin and Destination Estimation (Tilahun & Levinson, 2013) in which they explicitly simulate job search and marching processes arising from the interaction between firms and individual job seekers. ABODE, however, does not explicitly simulate the housing location choice process.

This paper presents the development of an integrated geospatial and agent-based model of location choice and travel-to-work flows (i.e. METLOMP-SIM), that builds on the latest advances and insights from these previous research.

3. Methodology—model framework specification

3.1. Overview and purpose of the model

METLOMP-SIM is a disaggregate model to simulate how urban spatial structure and mobility patterns co-evolve, as a function of heterogeneous households and individuals making residential location, employment location and travel decisions. The model's generic framework comprises six interrelated sub-components (Fig. 1). A comprehensive description of the model's entities, simulation environment, sub-models and the encoded procedures and heuristics is provided as supplementary material, using the ODD protocol—Overview, Design concepts, and Details (**see Supp appendix 1**).

Moreover, as a facsimile (i.e. empirical) model, it draws on two foundational empirical works on residential and job location choice behaviour (see Acheampong, 2018, Acheampong, 2017) and home-work travel patterns and mode choice (see Acheampong, 2020) conducted in the Kumasi Metropolis (Ghana), which will be referred to later in the relevant sections of the paper and/or the accompanying supplementary material.

3.2. Model implementation

3.2.1. Case study area, input data and model initialization

METLOMP-SIM is implemented in the open-source ABM software Netlogo (Wilensky, 1999). The model initializes with inputting several layers of geospatial data from the Kumasi Metropolitan Area (KMA)—the case study metropolis (**see supp appendix 1, section 3.1**) to characterise the spatial environment for the simulation. This spatial input datasets are summarised in Table 1. All together, the attributes characterising the spatial environment of METLOMP-SIM are of two broad categories namely, attributes characterising location at cell/land parcel level and attributes characterising dwelling units. A conceptual illustration of the model's spatial environment is presented in Fig. 2. Moreover, at initialization, a series of encoded procedures classifies the heterogeneous household and individual agents according to the relevant socio-demographic characteristics, as documented in the ODD Protocol (**supp appendix 1, section 1.2).**

3.2.3. Sub-models and encoded agents' decision making rules and heuristics

METLOMP-SIM has three sub-models, namely (a) residential location choice sub-model (b) job location sub-model and (c) travel choice sub-model. In the **residential location choice sub-model,** purposive household agents use a hybrid utility and heuristics framework to accomplish the task of choosing a suitable place of residence. The utility at any location for a household is a function of attributes formalized as:

$$\mathrm{U}^{\mathbf{o}}_{(\mathbf{x},\ \mathbf{y})} = \mathbf{U}_{\mathrm{Z}},\ \boldsymbol{\chi}^{\mathbf{D}},\ \mathbf{P}^{\mathbf{x}}_{\mathbf{ij}},\ \mathbf{P}^{\mathbf{x}}_{\mathbf{amty}} \quad (1)$$

Where:

$\mathrm{U}^{\mathbf{o}}_{(\mathbf{x},\ \mathbf{y})}$ denotes utility of a location;
$\mathbf{U}_{\mathrm{Z}}$ denotes urban zone of the location (x, y)
$(\boldsymbol{\chi}^{\mathbf{D}})$ denotes the attributes of the dwelling at location (x, y)
$\mathbf{P}^{\mathbf{x}}_{ij}$ denotes distance between employment location (*i*) and residential location (*j*)
P^{x}_{amty} denotes proximity of dwelling to amenities (e.g. school, shopping, terminals)

Equation (1) therefore shows all the locational factors at the dwelling and wider urban environment levels that are considered by a household

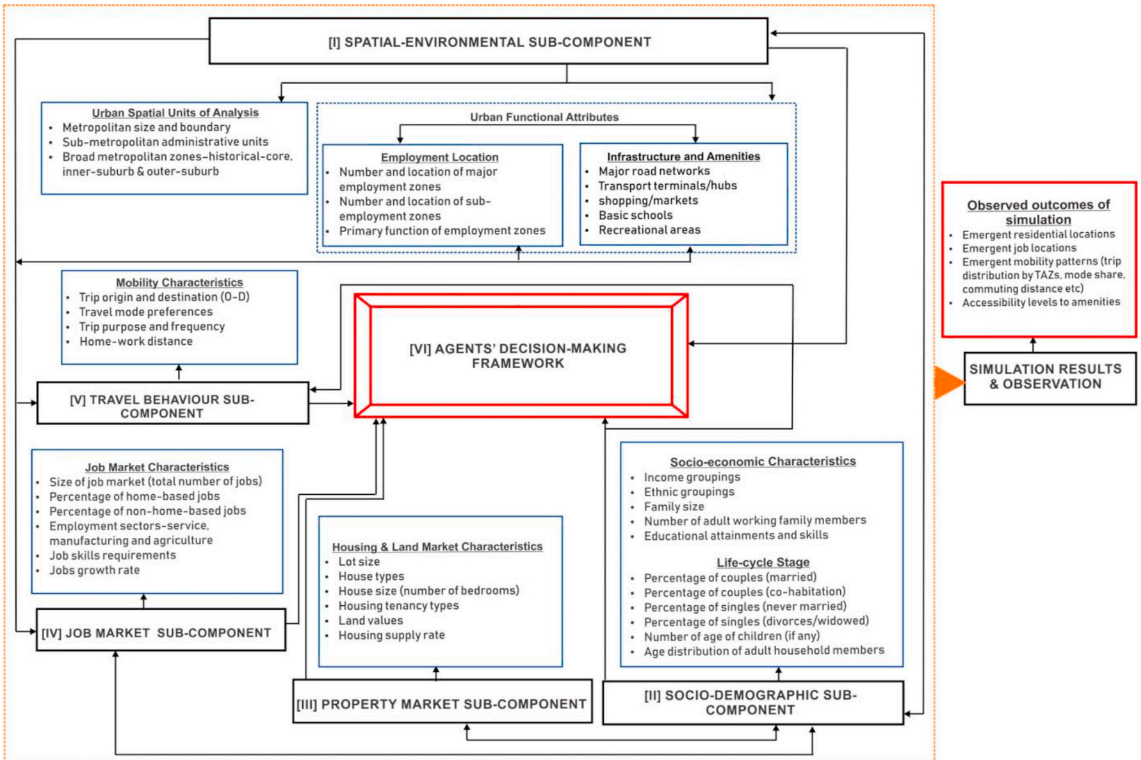

Fig. 1. Structure of the conceptual model behind METLOMP-SIM.

Table 1
Summary of input spatial datasets for the case study implementation of METLOMP-SIM.

GIS datasets	Description of layer
Metropolitan boundary	Polygon: Vector data of the administrative boundary of Kumasi Metropolitan Area (KMA) covering a total area of 212 km^2
Sub-metropolitan units' boundary	Polygon: Vector data of the 9 sub-metropolitan divisions within the KMA.
Urban-zone divisions	Polygon: Vector data of three broad urban-zones defined within the KMA—Historical core (22 km^2) Inner-suburb (38.7 km^2) and Outer-suburb (145 km^2)
TAZ System	Polygon: Vector data of the 29-internal micro and 6-macro TAZs of the KMA
Primary road-network (public transport service routes)	Polyline: Vector data showing the major road system in the KMA
Location of public transport stations	Point: Vector data showing the spatial distribution of public transport stations in the KMA
Location of primary schools	Point: Vector data showing the spatial distribution of primary schools in the KMA
Location of local shopping/market centres	Point: Vector data showing the spatial distribution of major shopping/market centres in the KMA
Housing/dwelling units	Point: Vector data of the spatial location of sampled housing/dwelling units in the metropolis.
Major employment zones	Polygon: Vector data showing the spatial locations of the main employment zones within the metropolis
Nature-reserves and no-go areas (development constraints)	Polygon: Vector data of restricted development areas extracted from the metropolitan land use map.

in deciding a place of residence. The case study metropolis is divided into three broad zones ($\mathbf{U_Z}$), namely the historical-core, inner-suburban and outer-suburban zones, based on historical urban growth data (see Acheampong, 2018). The households can perceive this spatial information under some specified constraints. The amenity proximity parameter in equation (1) (P^x_{amty}) is also encoded as a utility function (equation (2)), with which a household agent evaluates potential locations in searching for a suitable place of residence:

$$U^0_{\mathbf{HA(x,y)}} = \prod_{\mathbf{i=1}}^{\mathbf{n}} [\mathcal{Z}\mathbf{i}(\mathbf{x},\mathbf{y})]^{\alpha\mathbf{iHA}} \tag{2}$$

Where:

$U^0_{\mathbf{HA(x,y)}}$ denotes the utility of location (x, y) for household HA, in terms of distance-based accessibility to available amenities
αiHA denotes preference weight the household *HA* places on factor *i*
$\mathcal{Z}$i(x, y) denotes the value of factor *i* at location (x, y)
n denotes the number of factors evaluated

Thus, the utility function in equation (2) provides the framework to combine and weight the factors that the household agents evaluate to decide a suitable place of residence. The utility function implies that there are a given number of locational factors or opportunities (e.g. shopping, roads and schools) for which there are values we term *proximity index*, calculated as the Euclidian distance-based accessibility between a dwelling unit and each of the locational factors. The proximity indices are normalized between zero and one while the preference weights across all the proximity factors evaluated by the household are constrained to the sum of one.

For each of the locational factors, a household has *amenity proximity preference value (APPV),* which is a range of distance-based accessibility levels they are willing to tolerate and *amenity preference weights* (APW), which ranks their preferred accessibility levels to the available amenities in order of importance. The preference weights were derived from the household survey. The APPV values were derived based on the current accessibility levels of households of different socio-economic groups in the case study area. The empirically derived APPV and APW values for the different households represented in the model are indicated in supp

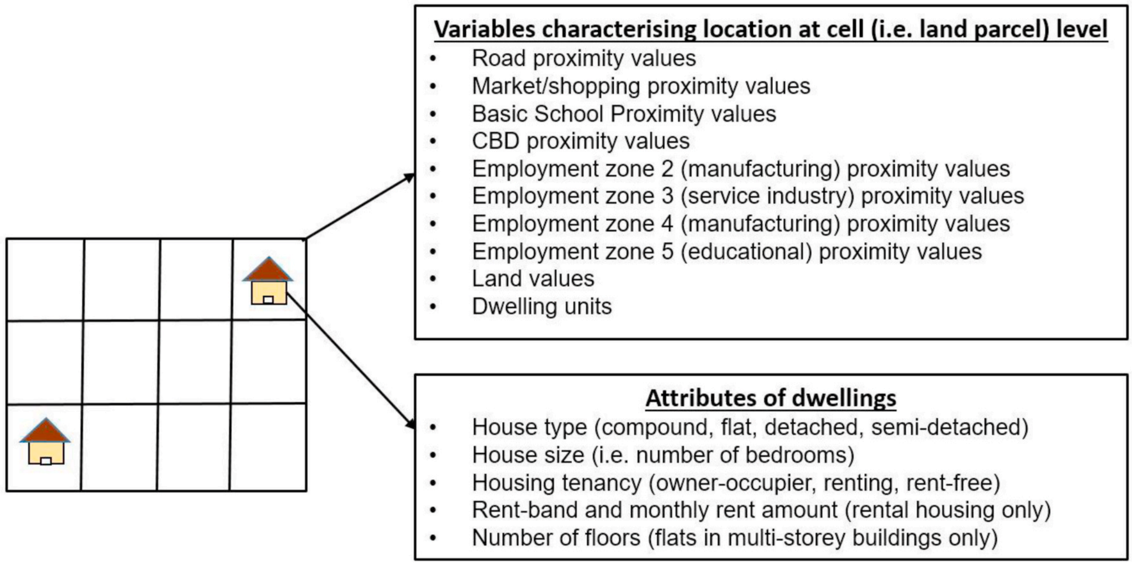

Fig. 2. Attributes defining METLOMP-SIM's spatial environment at model initialization.

appendix Fig. 6. The general principle implemented here is that low-income households have shorter tolerable distance to amenities compared to high-income households.

Using the households' proximity preference levels and their weights, the *expected utility* for each households, based on their income-group, is first calculated using equation (2). This results in each household having an overall *expected utility* value that ranges between 0 and 1 at the onset of the residential search process. For example, a given household in the model could have an expected utility value of 0.1–0.3, depending on their empirically derived preference weights. The utility that can be realized at any location is also calculated, based on the accessibility information embedded in the model's spatial environment, using equation (2). With these two pieces of information, a household during the residential search process, looks for potential residential locations where they can realise a utility value that is equal to or greater than their expected utility. Households evaluate location alternatives for APW, APPV and preferred housing using the satisficing strategy— a search strategy by which households stop at the alternative that meets their preferences regardless of the number of alternatives that have been evaluated previously from the pool of randomly selected locations.

The residential location search process is implemented in seven sequential tasks, which includes household agents probabilistically choosing among three urban-zones (i.e. historical-core, inner-suburb and outer-suburb); forming a bid price; and engaging in bilateral transaction and competition with other household agents in the property market. The encoded choice probabilities are derived from the results of a discrete multi-nominal logistic regression analysis of residential location choice in the case study area (see Acheampong, 2018). A detailed description of the encoded choice processes is presented in supp appendix 1, **section 3.2** and supp Fig 6.

In the **job location choice sub-model,** adult individual agents realise employment search and job location objectives. The job location choice follows sequentially from the residential location choice process outlined above. Job location outcomes in METLOMP-SIM is a function of:

$$\mathbf{J_l = E_n,\ E_{jv}, .P^x_{ij},\ S_m} \quad (3)$$

Where;

J_l denotes job location of an individual worker within a household;
E_n denotes number and location of employment opportunities available;
E_{jv} denotes the availability of vacant jobs at the employment locations
P^x_{ij} denotes the distance separation between potential employment and residential locations; and
S_m denotes the skills match between the available vacant jobs and the job seeker

The encoded job location search procedures, involve prospective job seekers deciding a potential suitable job location among the five major employment zones to seek employment, based on job availability and jobs skills match. The ODD protocol details the employment search process and outcomes implemented in METLOMP-SIM **(see supp appendix 1, section 3.2** and supp Fig 7).

In the **travel choice sub-model,** individual workers choose their work travel mode, as a function of their demographic characteristics, work location type, home-work distance separation and available travel mode options. Exactly how these processes are implemented is explained in detail by the ODD protocol provided as supplementary material **(see supp appendix 1, section 3.2** and supp Fig 8).

4. Parameter sweeping and calibration experiments

4.1. Initial calibration and determination of minimum model runs

METLOMP-SIM is calibrated using the categorical method of searching for parameter values that produce outputs of interest within a range of plausible values, based on the observational data. This method was considered appropriate over calibration towards a single best-fit value, mainly because of the complexity and the underlying stochasticity of ABMs such as METLOMP-SIM (see Thiele et al., 2014).

Outputs of interest and their corresponding expected output ranges (i.e. calibration criteria) of the simulation are identified in the second and third columns of Table 2, based on the observational datasets. The main parameters that are calibrated during the simulation are outlined in Table 3, under the various sub-models and choice processes implemented in the model. There are four main parameters— Urban zone choice probabilities, WTP for housing, employment choice probabilities and travel mode choice probabilities–disaggregated into sub-parameters under each sub-model.

The model's parameters were first dimensioned with estimates obtained from the observational datasets, labelled in Table 3 as the 'empirical-values'. With these initial parameter settings, simulation

Table 2
Model simulation results based on different initializing household population sizes.

Sub-model	Outputs of interest	Expected output Range/calibration criteria	Initializing household population and simulated results						
			1000	5000	10000	15000	20000	25000	30000
	Total simulated residential households	–	1507	8407	17026	26683	36039	45147	58217
Residential location	Households occupying compound housing	40–54%	51%	51%	48%	44%	48%	43%	43%
	Households occupying detached housing	5–15%	15%	11%	9%	8%	8%	9%	8%
	Households occupying semi-detached housing	9–15%	7%	6%	12%	8%	9%	8%	9%
	Households occupying flat	20–40%	27%	32%	31%	39%	35%	39%	40%
	Renting households	40–50%	23%	21%	21%	20%	22%	22%	40%
	Owner-occupier households	20–30%	51%	46%	55%	53%	47%	44%	30%
	Rent-free households	25–35%	26%	33%	24%	27%	31%	34%	30%
	Historical-core zone of residence	25–30%	62%	55%	51%	45%	43%	42%	28%
	Inner-suburban zone of residence	40–50%	25%	24%	23%	27%	27%	27%	41%
	Outer-suburban zone of residence	30–40%	13%	21%	26%	28%	31%	31%	31%
	Average distance of home to shopping/ market	100–2084m	1467.74	1495.91	1563.69	1640.74	1614.58	1514.53	1821.41
	Average distance of home to school (households with children)	100–853m	562.69	626.03	566.69	634.58	687.04	606.13	613.14
	Average distance of home to transport terminal	100–3432m	1644.30	1924.06	1693.41	1737.36	1831.46	1964.94	2349.81
	Average distance of home to major roads	100–554m	359.14	471.42	432.86	390.01	433.58	446.52	448.89
	Total simulated workers	–	2417	12099	22312	34639	44456	55186	63733
Job location	Total non-home-based employment locations	60–70%	58%	61%	62%	60%	61%	61%	62%
	Total home-based employment locations	30–40%	42%	39%	38%	40%	39%	39%	38%
	CBD employment locations	40–50%	44%	41%	43%	41%	42%	43%	42%
	Zone2 employment locations	5–12%	7%	12%	10%	11%	11%	11%	11%
	Zone3 employment locations	30–40%	40%	37%	36%	36%	36%	34%	36%
	Zone4 employment locations	2–5%	3%	5%	4%	5%	4%	4%	4%
	Zone5 employment locations	5–7%	7%	6%	7%	7%	7%	7%	7%
	Average home-employment location distance (non-home-based jobs)	100–5000m	4579.80	5020.29	4927.21	4874.55	4930.63	5186.30	5025.96
Home-work distribution (TAZs)	Total work-trip origin TAZ-301	2–5%	1%	2%	1%	1%	1%	1%	2%
	Total work-trip origin TAZ-302	10–20%	13%	13%	13%	12%	13%	16%	14%
	Total work-trip origin TAZ-303	15–25%	20%	18%	14%	14%	14%	26%	18%
	Total work-trip origin TAZ-304	17–30%	33%	29%	28%	42%	37%	27%	29%
	Total work-trip origin TAZ-305	15–25%	21%	20%	16%	15%	26%	20%	23%
	Total work-trip origin TAZ-306	11–15%	11%	19%	28%	16%	8%	11%	14%
	Total work-trip destination TAZ-301 + TAZ-302	30–50%	29%	27%	31%	27%	30%	33%	29%
	Total work-trip destination TAZ-303	10–20%	14%	12%	10%	9%	9%	16%	12%
	Total work-trip destination TAZ-304	20–30%	38%	34%	33%	43%	39%	32%	34%
	Total work-trip destination TAZ-305	12–20%	15%	18%	14%	14%	21%	17%	19%
	Total work-trip destination TAZ-306	5–10%	6%	10%	15%	8%	3%	3%	6%
Mode choice	Motorized transport use	60–70%	58%	61%	62%	60%	61%	61%	62%
	Non-motorized transport use (walking)	30–40%	41%	39%	37%	40%	39%	38%	38%
	Private-car ownership and use	15–25%	26%	22%	21%	22%	22%	22%	21%
	Public transport	79–90%	75%	78%	79%	78%	78%	79%	79%
	Public transport (Trotro/mini-bus) use	80–90%	87%	88%	89%	88%	89%	88%	88%
	Public transport (taxi) use	7–15%	13%	12%	11%	12%	12%	12%	12%

Notes: The values under the observational data column are those obtained from the detailed survey data collected specifically for this research in 2015. In addition to the survey, two large-scale datasets from the population and housing census for the years 2000 and 2010 and were used. Thus, the upper and lower limits of the calibration criteria/expected output range were chosen using these three datasets as the guide.

experiments to determine the minimum number of simulation runs were conducted.

The ***Co-efficient of Variation (CV)*** metric—the ratio of the standard deviation to the mean of each of the model's output of interest—was computed for each output of interest across the multiple model runs. Computing this metric helps to determine the minimum number of repetitions where the CV values of the simulation outputs stabilize and remain the same (see Lee et al., 2012; Thiele et al., 2014), thereby accounting for the effect of stochastic variations in the model's outputs of interest. Based on the co-efficient of variation analysis, we found that a minimum run of 45 repetitions per simulation is required was required for the results to converge and to consider the stochastic effects in the model and to reduce uncertainty resulting from variations in output of interest. In practice, what this means is that the results of the model are averaged across the 45 runs, with each run comprising 15 iterations.

4.2. *Parameter sweeping experiments and simulation results*

Parameter sweeping experiments were conducted to fine-tune the parameter settings of the model. This involved a systematic process of using Netlogo's BehaviorSpace tool to explore all possible values of the parameters of interests and their combinations (see Supp appendix 2). The combinations of model parameters that produced simulated results that fall within the calibration criteria were then retained as the 'best-fit'[1] parameter values (see Table 3).

Changes in parameter values under the job choice and residential choice sub-models can be observed, following the parameter sweeping experiments (Table 3). The observed differences were particularly

[1] 'best-fit' is used here to imply the combination of parameter values that were eventually selected to generate the simulation results presented in this paper.

Table 3
Model parameter settings before and after parameter sweeping experiments.

Sub-models and choice processes	Parameter name	Parameter Value Settings	
		Empirical-values	Best-fit-values
Residential choice: Urban zone choice probabilities ***(Range: 0–1)***	Core/suburban choice probability: urban-poor	0.38	0.28
	Inner-suburban/outer-suburban choice probability: urban-poor	0.65	0.65
	Core/suburban choice probability: low-income	0.38	0.28
	Inner-suburban/outer-suburban choice probability: low-income	0.65	0.65
	Core/suburban choice probability: lower-middle-income	0.29	0.19
	Inner-suburban/outer-suburban choice probability: lower-middle-income	0.55	0.55
	Core/suburban choice probability: upper-middle-income	0.22	0.12
	Inner-suburban/outer-suburban choice probability: upper-middle-income	0.51	0.55
	Core/suburban choice probability: high-income	0.17	0.10
	Inner-suburban/outer-suburban choice probability: high-income	0.63	0.63
	Core/suburban choice probability: rich	0.17	0.10
	Inner-suburban/outer-suburban choice probability: rich	0.63	0.63
Residential choice: WTP for housing in rental market (% of monthly income) ***(Range: 0–100)***	WTP Low-income (lower-half)	11%	11%
	WTP Low-income (upper-half)	15%	15%
	WTP Lower-middle income (lower-half)	10%	10%
	WTP Lower-middle income (upper-half)	12%	12%
	WTP Upper-middle income (lower half)	32%	32%
	WTP Upper-middle income (upper-half)	55%	55%
	WTP High income (lower-half)	20%	20%
	WTP High income (upper-half)	31%	31%
	WTP Rich (lower-half)	50%	50%
	WTP Rich (upper-half)	60%	60%
Job choice: Home-based employment choice probability ***(Range: 0–1)***	Home-based employment choice probability: low-skilled at historical-core zone	0.31	0.10
	Home-base employment choice probability: low-skilled at inner-suburban zone	0.23	0.05
	Home-base employment choice probability: low-skilled at outer-suburban zone	0.30	0.05
	Home-base employment choice probability: intermediate-skilled at historical-core zone	0.38	0.05
	Home-base employment choice probability: intermediate-skilled at inner-suburban zone	0.25	0.02
	Home-base employment choice probability: intermediate-skilled at outer-suburban zone	0.31	0.02
	Home-base employment choice probability: high-skilled at historical-core zone	0.32	0.02
	Home-base employment choice probability: high-skilled at inner-suburban zone	0.23	0.01
	Home-base employment choice probability: high-skilled at outer-suburban zone	0.26	0.01
Travel choice: Motorized travel mode choice (private car vs public transport) ***(Range: 0–1)***	Private car ownership probability: urban poor	0.01	0.01
	Private car ownership probability: low-income	0.01	0.01
	Private car ownership probability: lower-middle-income	0.08	0.08
	Private car ownership probability: upper-middle income	0.25	0.25
	Private car ownership probability: high income	0.57	0.57
	Private car ownership probability: rich	0.78	0.78
Travel choice: Public transport mode choice (mini-bus/Trotro vs taxi) ***(Range: 0–1)***	Mini-bus/Trotro choice probability: urban poor	0.91	0.91
	Mini-bus/Trotro choice probability: low-income	0.88	0.88
	Mini-bus/Trotro choice probability: lower-middle-income	0.91	0.91
	Mini-bus/Trotro choice probability: upper-middle income	0.88	0.88
	Mini-bus/Trotro choice probability: high income	0.79	0.79
	Mini-bus/Trotro choice probability: rich	0.64	0.64

significant for parameter values under the job choice sub-model, suggesting that the model is sensitive to parameters in this sub-model. After carefully checking the encoded rules and heuristics through various unit testing experiments (see Cioffi-Revilla, 2014), a possible source of the changes in parameter values could be related directly to limitations of the cross-sectional survey data on which the 'empirical-values' are based.

Moreover, to explore the 'computational limits' of the current model, additional simulations were implemented, whereby the model was initialized with different starting household populations from 1,000, and increased systematically in an interval of 5,000 up to 30,000, at which point the simulation slowed down significantly. For each starting population, the model was run 45 times, with 15 iterations/time-steps making a full run. Each iteration/time step mimics one year in the real-world. Table 2 shows the aggregated results for each output of interest under their respective starting populations. Results of the final simulation, which was initialized with 30,000 households (see Table 2, column 10) are elaborated further in **section 5**.

5. Simulation results

5.1. Emergent residential location patterns

Initializing the simulation with 30,000 households, a total of 63,608 households were generated at the end of the simulation. Thus, on the average, new households were formed endogenously from the starting population at a rate of 5.14% per annum. A total of 58,217 households, representing 92% of the total household population generated in the model, successfully implemented their residential location choice objectives at the end of the simulation. Fig. 3 shows the distribution of simulated household residential locations (i.e. dwellings) at selected iterations of the simulation.

In addition to the broad residential location patterns shown in Fig. 3, the model's observed dynamic behaviour during the simulations are summarised in Fig. 4 and explained as follows.

The model's dynamic behaviour shows a trend whereby there is an initial spike in the total housing stock (Fig. 4b) and the proportion of households realising residential locations (Fig. 4a), but this slows down over subsequent time-steps. A careful examination of this trend revealed that at the start of the simulation where fewer households enters the model to begin their location search, a relatively higher proportion of that population are able to realise their preferred residential locations. This is because there are relatively fewer bilateral transactions and overall level of market competition among household agents is less fierce at these initial stages. In addition, at these initial iterations, house rents and land prices have not yet increased from their initial values set when the model initializes. This means that rent/prices are well within the WTP of the household agents even when some of them attempt to benefit from the surplus of transactions by initially lowering their WTP. However, as the case is in the real-world, as population increases, the number of household agents active in the property market also increases, while the housing supply slows down (Fig. 4b), thereby intensifying the number of transactions and the level of competition for the available housing. House rents and land prices also evolve. As the simulation advances towards the last iteration (Fig. 4a), the residential search tends to be concentrated in the outer-suburban zone where more land becomes available for would-be owner-occupiers who ultimately become concentrated in this zone. This means that the opportunity for these households to meet their preferred residential locations increases, resulting in relatively more households successfully realising their residential locations, based on their expected utilities. The interplay of these cumulative property market dynamics and outcomes therefore explain the trend whereby the rate of households realising their residential locations increases initially, slows down and rises slightly as the simulation progresses towards the 15th iteration.

A further breakdown of the emergent residential locations according to the income-groups of households and their tenancy arrangements is presented in Fig. 5. Most of the simulated households (41%) found residential locations in the inner-suburban locations of the metropolis compared to those in the historical-core (28%) and outer-suburb zone (31%). The proportion of high-income households increases from historical-core (13%) to inner suburban (29%) and outer-suburban locations (43%), while low- and middle-income household are concentrated in the historical-core zone of the metropolis (Fig. 5a). A larger proportion of households (43%) realized their residential locations in compound housing (43%). In terms of simulated tenancies, rent-free tenancy arrangement dominates in the historical-core zone (73%), while home-ownership and renting are particularly pronounced in the inner-suburban and outer-suburban zones (Fig. 5b). The aforementioned simulated residential locations patterns are broadly consistent with patterns in the case study area, based on the observational data.

Moreover, simulated households distance-based accessibility to amenities are compared by income-groups, using a radar chat (Fig. 6).

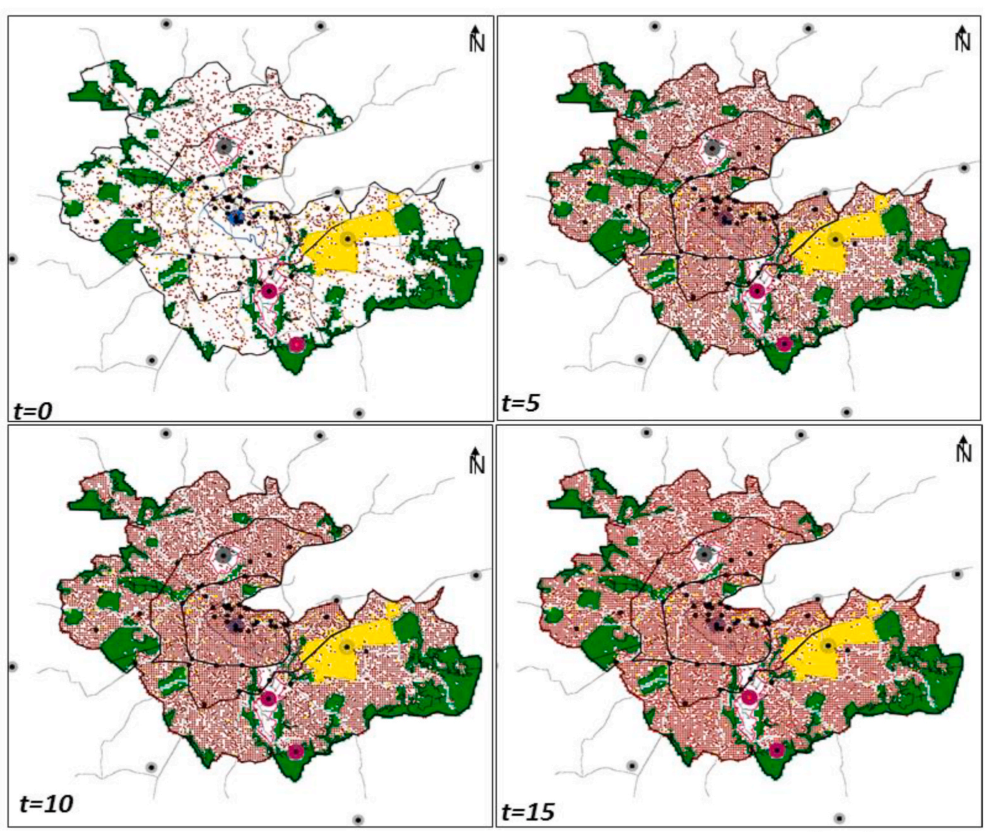

Fig. 3. Distribution of the location of simulated household's dwellings at the beginning, 5th, 10th and 15th iterations of the simulation. Note: household dwellings are shown in brown. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

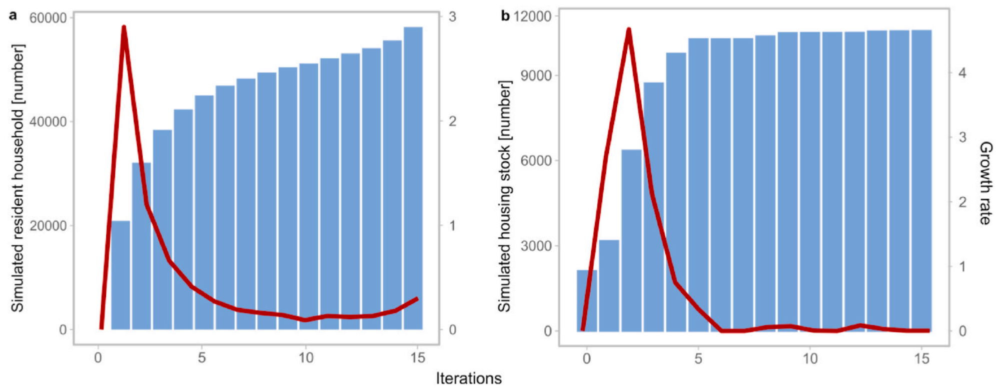

Fig. 4. Simulated residential household population and dwelling units.

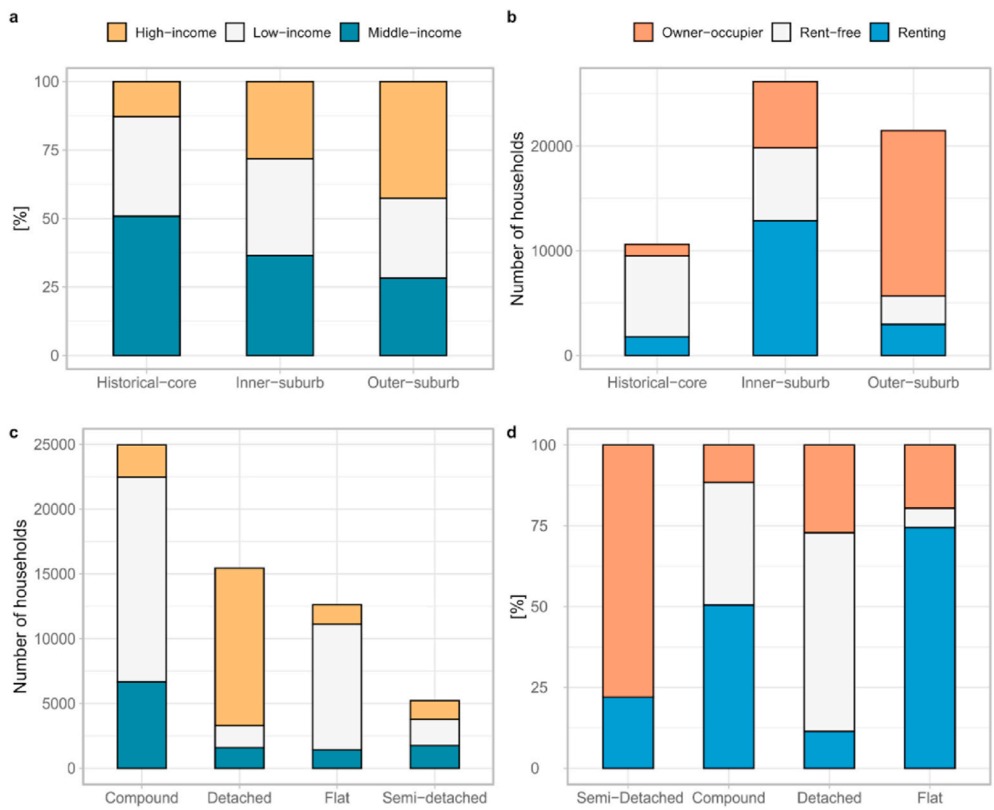

Fig. 5. Distribution of simulated (a) households across urban zones (b) tenancies of households across urban zones (c) housing tenancies across different income-groups and (d) housing tenancies across different housing types.

We can immediately observe that overall, consistent with their encoded preferences, households of lower income-groups achieved residence relatively closer to the available essential amenities. The 'rich' household group also achieved higher proximity to the available amenities. The main explanation is that having the highest income levels and therefore competitive advantage in the property market in terms of WTP, the 'rich' households are able to realise their location choice in relation to the available amenities with very limited competition. That said, it is also important to mention that their accessibility levels, while relatively lower in terms of distance to amenities, are not significantly different from the other household agents for each of the four amenities represented in the model.

5.2. Emergent property market dynamics

The emergent property prices in the rental market at the end of the simulation, differentiated by dwelling type, size and urban-zone is are provided in appendix 3, supp Table 1. The house rent formation and evolution patterns resulting from the encoded market transaction rules are illustrated in Figs. 9–11, supp appendix 3, for detached dwellings (Fig. 9), semi-detached dwellings (Fig. 10), and flats (Fig. 11). A notable trend whereby rent amount is high initially, but falls over time, was observed in Figs. 9f and 11f. The observed systematic fall in the rent of these properties is a direct result of the internal price adjustment and learning mechanisms implemented in the model, by which a property that remains unlet after being evaluated by the households several times, decreases its ask rent to increase the chance of being let. Moreover, in Fig. 10f, it can be observed that house rent for >5-bedroom house in the inner-suburban zone spiked around the 7th iteration. From the perspective of overall model behaviour, this stems partly from the fact that at this time-period, the search for housing intensified in the suburban locations of the metropolis. The resulting competitive bidding

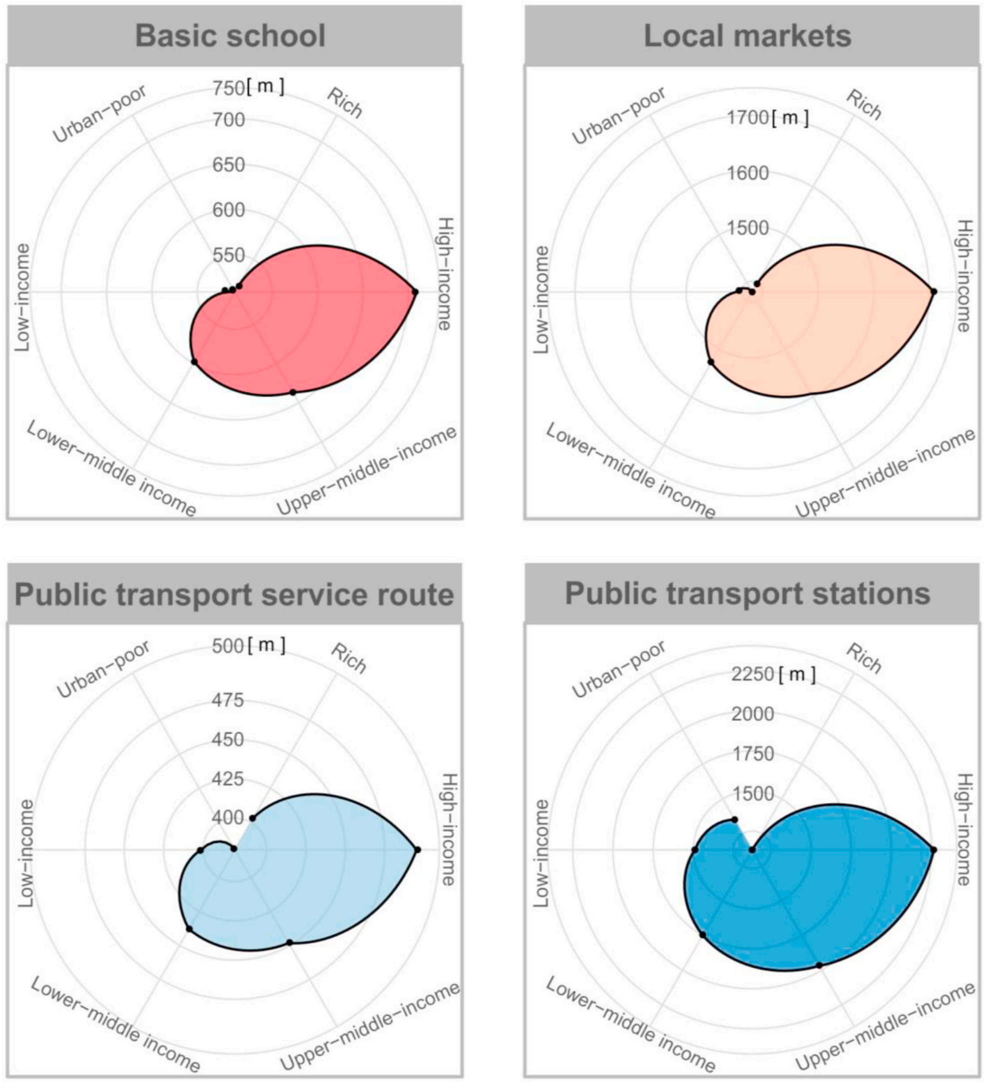

Fig. 6. Simulated distance-based accessibility to amenities by households. Proximity to basic schools is calculated for households with children only.

behaviour by households seeking residence in the inner-suburban zone is reflected in the spike in rent.

Furthermore, supp appendix 3, Fig. 12a shows emergent land prices at the end of the simulation, presented in discrete rings of 1 km radius from the centre of the cases study metropolis. Overall, the results show that the highest land prices per acre emerged in areas located within 5 km km radius from the CBD. As expected, land prices tend to fall beyond the 6th km radius, which are areas in the outer-suburban zone of the metropolis. The evolution of the land price within each of the 10 discrete concentric zones, across the model's iterations is shown in supp appendix 3, Fig. 12b.

5.3. Emergent employment location patterns

The job locations of 63,733 individual workers from the settled household were simulated. Out of this total, 23,995 (38%) individual workers had home-based employment locations while the remaining 39,739 workers (62%) had non-home-based job locations (see Table 2). The spatial distributions of individuals' simulated employment locations are shown according to urban-zones for home-based workers (Fig. 7a) and according to the five major employment zones within the metropolis (Fig. 7b). As expected, a disproportionately larger share of all home-based employment (71%) generated by the simulation are in the historical-core, followed by the inner-suburban-zone (24%) and outer suburban zone (5%). On the average, all non-home-based workers lived some 5.03 km from their job locations. The emergent home-work distance separations also appear to respond to the encoded work distance minimization objective among individuals from households of different income-groups: low-income and urban-poor workers have relatively shorter average home-work distance (i.e. 4.5 km) compared to high-income workers with an average of 6.1 km.

5.4. Emergent travel-to-work flows and mode choice

Simulated home-work trip production and attraction patterns are presented, using the six macro Traffic Analysis Zone (TAZs) in the case study area as the spatial units of analysis. The results show that the model is able to reproduce home-work mobility patterns that strongly reflect the functional structure of the target metropolitan system. The contributions of TAZs to total trip origins and destinations in percentage terms have been summarised in Table 2. A summary visualization of the simulated home-work trip exchanges among the macro-TAZ in the study area is presented in Fig. 11. As broadly expected based on the observational data, a significant proportion of work trips begin and end in the

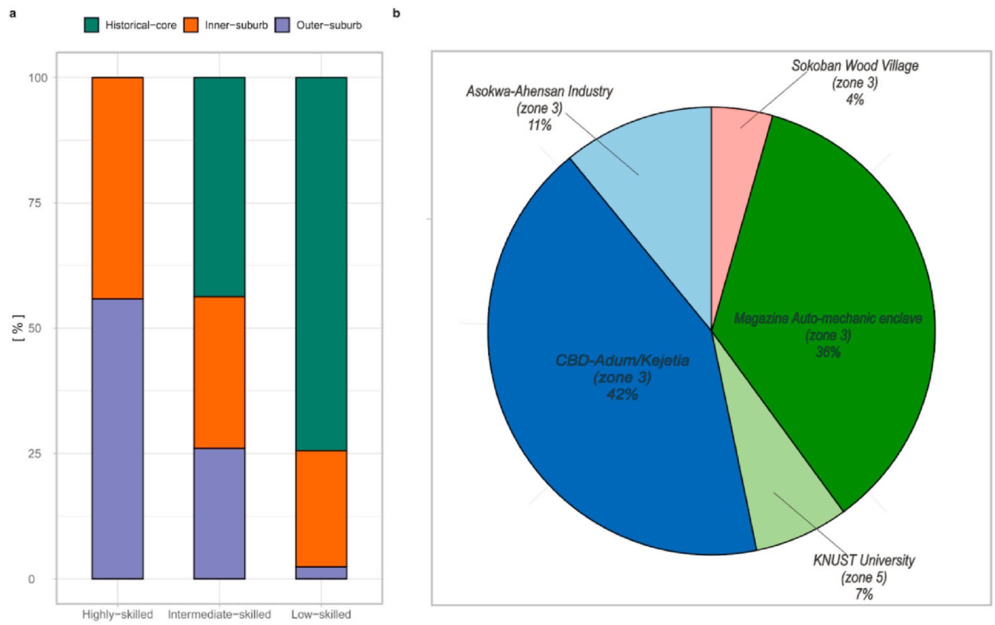

Fig. 7. Distribution of employment locations among (a) home-based workers (b) non-home-based workers.

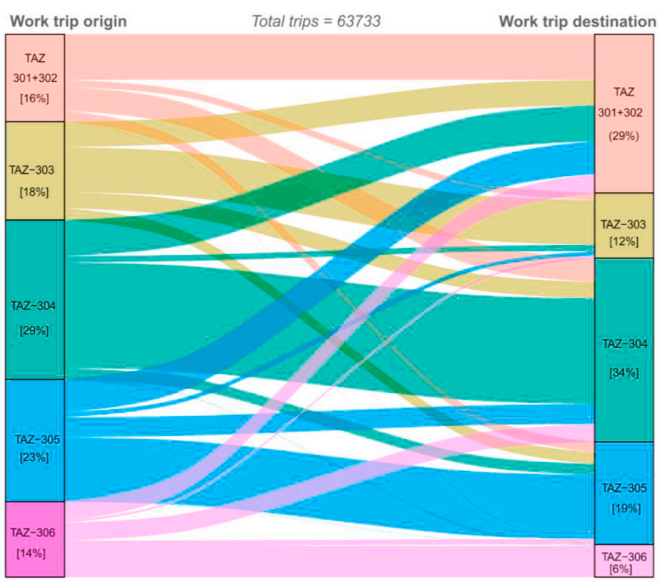

Fig. 8. Distribution of total work trips of each origin TAZ among the destination TAZs.

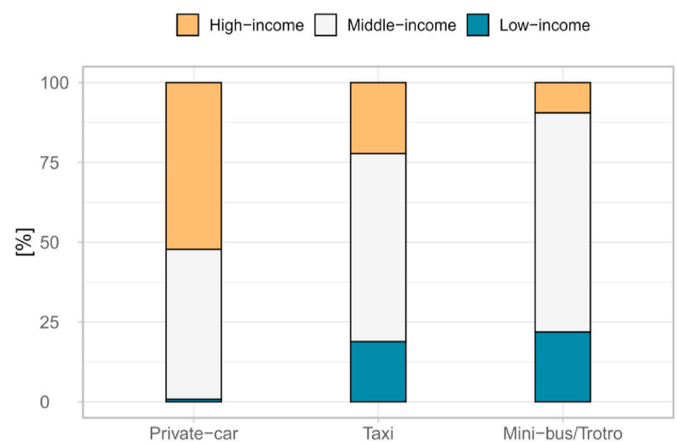

Fig. 9. Simulated work travel mode choice among workers of different income-groups.

same TAZ (Fig. 8). Simulated travel-to-work mode share also reflect the observational data as summarised in Table 2. The simulated travel mode choice for the private car and public transport alternatives (i.e. taxi and minibus/trotro), among workers of different income-groupings is presented in Fig. 9.

6. Discussion and implications

This paper has presented the initial development of METLOMP-SIM—an agent-based model of the co-evolution of spatial structure and commute flows. Building on efforts in previous works (e.g. Ettema, 2011; Murray-Rust et al., 2013; Parker and Filatova, 2009), this work was driven by the need to improve realism in agent-based models of urban location choice, by specifying the full range of spatial goods and location-defining attributes. The model also represents unique characteristics of 'informal' and 'formal' property and job market dynamics that are common in developing countries. Moreover, in a bid to enhance METLOMP-SIM's output capabilities in being able to generate trip flows, the model explicitly simulates both residential and job location choice processes.

The procedures and decision rules implemented in METLOMP-SIM are able to mimic some macro-scale urban location and spatial interaction patterns, which closely match patterns in the case study area. Through the simulation, we show how housing and land supply mechanisms interplay with the process of competitive bidding and market transactions by households and individuals seeking to maximize their residential location utilities, to shape market dynamics and residential location outcomes over time. The simulations reveal a number of fundamental insights about property markets, whereby at the onset where there are fewer people seeking housing, more households are able to realise their housing need at their preferred locations in the urban area. However, population increase and associated increase in housing/land demand and prices result in not all households being able to meet their housing need at preferred locations in the urban area.

Moreover, the residential and employment location outcomes replicated in this model are based on revealed preferences, which reflect overall accessibility and welfare maximization expectations of different household-agents in the real-world, as encoded in the choice modelling framework. As reflected in the utility function underlying location choice, when households are able to realise their preferred residential location choice, even under sub-optimal conditions, they do so realising access to jobs and amenities. For example, the majority of low-income households are able to maximize their overall utility in the historical-core areas where housing is relatively cheaper to rent or available rent-free through the family housing sector. At these locations, they are also able to have access to markets for both out-of-home and home-based employment, which ultimately results in the emergence of the informal economy, as it exists in the case study area. Furthermore, the housing-job location outcomes of households interact with their socio-economic characteristics to shape their travel choices. For example, those who find residence in the historical-core area are more likely to choose non-motorized forms of transport and public transport because they live closer to their jobs. On the contrary, suburban residential location and associated out-of-home employment locations change the emergent commute flows in terms of housing-job distance separation and travel mode use, with motorized transport in general and car use in particular becoming higher.

In terms of practical relevance, the model presented in this paper provides a key insight by demonstrating how the co-evolving land use patterns and transportation infrastructure shape differential jobs and amenities accessibility outcomes for different groups of households in the case study area. This insight could be useful for integrated land use and transport planning and policy. A key goal of integrated land use and transport planning is to provide equitable accessibility to different groups. To this end, the encoded preferences and accessibility-based expected utilities could be relevant to integrated land use and transport planning. The modelling and simulations presented in this paper offer useful insights about the range of factors that combine to shape the location preferences for heterogeneous households and individuals in the study area. These insights could inform policy measures that seeks to achieve desirable housing-job balance as reflected in the expected utilities of the different households in meeting their residential location choice objectives. The empirically-derived *amenity proximity preference values* (APPV) and amenity *preference weights* (APW) used to calibrate the utility framework underpinning residential location decisions in the model, effectively represent accessibility expectations of the different households in the real-world. These could therefore be useful in evaluating possible differential accessibility of policies such as the provision of roads, schools, markets and transportation terminals.

Finally, as demonstrated at the onset of this paper, microscopic urban location choice and transport models that are sensitive to the unique contexts of developing countries, especially urban areas in Sub-Saharan Africa are rear. For any modelling framework to be relevant to these contexts, it has to reflect the unique urban contexts and the related formal and informal property and employment market processes. By focusing on Kumasi, Ghana as the empirical context, and abstracting, modelling and replicating 'formal' and 'informal' employment and property market processes that are fundamental to the emergence of urban spatial structure, METLOMPSIM provides a useful framework of heuristics and decision rules that could be relevant to other urban areas in the sub-Saharan African context. For example, we know that in urban West Africa, living rent-free in the compound housing sector is common, especially among low-income households. This non-market housing sector constitutes one of the key components of METLOPMSIM that is explicitly modelled and simulated for the first time. The abstracted rules and heuristics would therefore be useful in extending the current model or developing new models in the other urban areas on the continent where these fundamental market processes are evident.

7. Conclusion and future work

This paper has presented the development of an ABM of the co-evolution of spatial structure and commute flows in the Kumasi Metropolis in Ghana, West Africa. While the current model is work in progress from the point of view of fundamental research, the goals is to ultimately develop an operational LUTI model that could be applied to different urban contexts, especially cities in Sub-Saharan Africa. To this end, the current model is being developed further by incorporating other commuting-related choices for different activities within the framework of activity-based modelling. Future work on the model is also focusing on the inclusion of other important urban processes and outcomes, such as the formation and growth of informal settlements and slums; modelling and simulating the incremental housing development process; and representing social processes, including upward social mobility and the role of social networks in job and property market outcomes. The biggest challenge so far in this endeavour has been the limited availability of large-scale urban data at the appropriate spatial and temporal resolutions to calibrate and validate the simulation results. To this end, additional empirical and modelling work are being conducted to curate disaggregate time-series data that could be employed to verify and validate the simulation results in a robust manner.

Model and data availability statement

In addition to the supplementary appendices, the data and model codes that support the findings of this study are available from the corresponding author, upon request.

Author credit statement

Ransford A. Acheampong: Conceptualization, Methodology, Investigation, Formal analysis, Writing - Original Draft, Writing - Review & Editing, Data curation.

Stephen Boahen Asabere: Visualization, Formal analysis, Writing - Review & Editing.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.habitatint.2021.102343.

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