EJTIR

Issue 17(1), 2017
pp. 103 – 131
ISSN:1567 – 7141
tlo.tbm.tudelft.nl/ejtir

Scale effect in a LUTI model of Brussels: challenges for policy evaluation

Jonathan Jones[1]
Center for Operations Research and Econometrics, Université catholique de Louvain, Belgium

Dominique Peeters[2]
Center for Operations Research and Econometrics, Université catholique de Louvain, Belgium

Isabelle Thomas[3]
Center for Operations Research and Econometrics, Université catholique de Louvain, Belgium

The aim of this paper is to assess the reliability of policy evaluation based on Land Use and Transport Interactions models, relative to the choice of the Basic Spatial Units. An *UrbanSim* (+ *MATsim*) model applied to Brussels (Belgium) is used as the case study. The evolution of the study area over twenty years is forecasted for four levels of Basic Spatial Units and five scenarios (business-as-usual and four alternatives). Results show larger variations between Basic Spatial Units levels than across scenarios. These findings are valid for various sustainability indicators and for a simple cost-benefit analysis aiming at ranking the scenarios. The direction of the variations resulting from the implementation of the scenarios remains, however, the same for all Basic Spatial Units levels. Hence, the influence of the scale on policy evaluation based on Land Use and Transport Interactions models appears limited when it is only intended to compare scenarios, but it will have a crucial role when evaluations are based on absolute variations or threshold values.

Keywords: *Brussels, LUTI models, MAUP, Policy evaluation*

1 Introduction

Nowadays, many cities seek to implement transport and/or land-use policies for increasing their sustainability. Land Use and Transport Interactions models (hereafter LUTI) are a natural choice of assessment tool in this situation, thanks to their ability to forecast future urban pattern with and without the implementation of these policies (Rodrigue et al., 2013; for the type of policies that can be simulated by different LUTI models, see Geurs and van Wee, 2004; Hunt et al., 2005). Operational applications of LUTI models are, therefore, increasingly common (see Bartholomew, 2007; Thomas et al., 2015b, for reviews of US and European case studies).

In most of these applications of LUTI models, there is a lack of interest for spatial bias (Thomas et al., 2015a, Thomas et al., 2015b). The issues of spatial aggregation and of the Modifiable Areal Unit Problem (MAUP, see Openshaw, 1977; Openshaw and Taylor, 1979) has received a large attention in the geographic literature, but also in the field of transport modelling (e.g. Ding, 1998; Viegas et al.,

[1]A: Voie du Roman Pays 34, 1348 Louvain-La-Neuve, Belgium T: +32484967551 F: +3210474301 E: jonathan.jones@uclouvain.be
[2]A: Voie du Roman Pays 34, 1348 Louvain-La-Neuve, Belgium T: +3210474343 F: +3210474301 E: dominique.peeters@uclouvain.be
[3]A: Voie du Roman Pays 34, 1348 Louvain-La-Neuve, Belgium T: +3210472136 F: +3210474301 E: isabelle.thomas@uclouvain.be

2009; Connors and Watling, 2015). In particular, the Scale Effect, i.e. the fact that changes to the size of the Basic Spatial Units (noted BSU hereafter) will yield different results in statistical estimations (Briant et al., 2010)[4]. The scale effect is known to affect parameter estimates of econometric sub models within LUTIs (see e.g. Fotheringham and Wong, 1991; Arauzo-Carod and Manjon-Antolin, 2004; or Jones et al., 2015b). Nevertheless, it is almost never discussed in published papers or reports on LUTI models application (Jones, 2016). Hence, this paper aims to assess the sensitivity of LUTI models' outputs to the size of the BSU. It focuses on potential inconsistencies in policies evaluation. That is to say, can the implementation of one scenario be considered as profitable when the model is run for one size of BSU, but unprofitable for another one?

The empirical case study used here is the Brussels (Belgium). An *UrbanSim* model has been developed for four levels of BSUs. The model is run for a set of five land-use or transport scenarios (business-as-usual included; see section 3 for methodological details). The outputs for each BSU level are used to compute different sustainability indicators, and to perform a simple Cost-Benefit Analysis (CBA) of each scenario. The model system is thus considered here as a black box. To answer the research question, the variations of the indicators across scenarios are compared to those between BSU levels (for both their magnitude and direction). The CBA is used to assess if the ranking of each scenario varies from one BSU level to another.

The paper is organized as follows. Section 2 shortly reviews the methods used in conjunction with LUTI for policy evaluations. Data and methodology are detailed in section 3. Section 4 presents the results that are discussed in section 5. Section 6 concludes.

2 Policy evaluation using LUTI models

To select the indicators that will be used for comparing the scenarios, it is necessary to summarize how policy evaluation is performed in land use and transport planning, and the specificities of LUTI models. This evaluation usually relies on multi-criteria or cost-benefit analysis (Geurs and van Wee, 2004; van Wee, 2015). Both methods are widely described throughout the literature. The reader can refer to e.g. Ishizaka and Nemery (2013), Nijkamp and Blaas (1994) for the former one, and to Atkinson and Mourato (2006) or Boardman et al. (2006) for the latter. Nevertheless, different conceptual and technical challenges restrain the capabilities of LUTI models to perform policy evaluations.

The main criterion to evaluate a policy is often its sustainability. This notion is not exactly the same from economic (see e.g. Arrow et al., 2004) or geographic point-of-views (see e.g. Brown et al., 1987; Bulkeley and Betsill, 2005). In an urban/LUTI model perspective, the principal component is the influence of transport on environment (Geurs and van Wee, 2004; Rodrigue et al., 2013). The main conceptual challenge is thus to make this influence endogenous in the model. Car ownership and air pollution level, for instance, are rarely estimated (Wegener, 2004; Dowling et al., 2005; Hunt et al., 2005). Therefore, without additional methods or models, sustainability indicators estimated from the outputs of LUTI models are limited, and often rely on expert judgment (Geurs and van Wee, 2004).

Policy evaluation (i.e. the comparison between different scenarios) is, by definition, the last step of LUTI model projects. As noted by Wegener (2011), many operational applications have run out of time before reaching this stage due to unexpected practical difficulties. This is especially the case of micro-simulation LUTI models. Some other LUTI models (e.g. MARS, see Pfaffenbichler et al., 2008) are designed to be fast, but at the cost of a high spatial aggregation level.

Moreover, despite the large variety of detailed data required, one common and ancient (see Lee, 1973) criticism of LUTI models is that they produce only aggregated results. Again, sustainability

[4]Note that in this paper, the term scale effect will only be used to refer to that component of the MAUP, not to choice models.

indicators seem particularly prone to be available only at a meso- or study area level (Geurs and van Wee, 2004). Efthymiou et al. (2014) proposed multidimensional indicators to take advantage of the disaggregated nature (in space, time, and agents) of LUTI models. This approach has, however, not yet been used for policy evaluation.

Eventually, the main difficulty is the multidimensional nature of the sustainability, encompassing economic, social, and environmental components (Hély and Antoni, 2014; Proost et al., 2015). Aggregation can be done qualitatively, but a formal integration of these three pillars requires each indicator to be expressed in monetary units. For that purpose, Proost et al. (2015) have proposed a Social Welfare (SW) function that allows comparing the outcome of one scenario to those of the baseline. Its specification consists in a weighted sum of the utility of (a) the inhabitants, (b) the commuters, and (c) the rest of the world. The (d) local stock left to future generations is also included, together with (e) the cost of implementation of the scenario and (f) the generated income. Using the case studies of the EU-funded *SustainCity* project (Brussels, Paris, and Zürich) as examples, Proost et al. (2015) conclude, however, that the translation of this SW function from a theoretical formulation to a practical indicator is severely limited by data availability (see section 4).

To sum up, in operational applications, policy evaluation is often limited to a set of simple indicators (see Bartholomew et al., 2007 for review). Hence, the same approach will first be used in this paper. These simple indicators of the influence of the scenarios are assumed to have an equal weight here and will, therefore, be examined independently rather than in a multi-criteria analysis. In a second step, the SW level of each scenario will be computed, in order to rank them according to their profitability. The results of both the indicators and the CBA will be compared for the different BSU levels used here.

3 Data and methodology

3.1 Data

The empirical case study used in this paper is Brussels (Belgium). An *UrbanSim* model of the metropolitan area has been developed between 2009 and 2013, within the framework of the EU-funded project *SustainCity* (see Bierlaire et al., 2015). The database is re-used here while sub models, on the contrary, are re-estimated from scratch due to the change of the study area (see section 3.2). A detailed description of this model and of the database can be found in Cabrita et al. (2015). Note that Patterson and Bierlaire (2010) and Patterson et al. (2010) described earlier implementations of *UrbanSim* on Brussels. However, both works consist in prototype models, based on aggregated data, and have few common points with the model of Cabrita et al. (2015).

The study area used in the *SustainCity* project (or "*SustainCity* Area") raises several concerns (see Thomas et al., 2015a; Jones et al., 2015a), since it encompasses municipalities having few relationships with the CBD and/or that belong to the catchment area of another city (Figure 1b). Previous works (Jones et al., 2015b; Thomas et al., 2015a) have demonstrated that the extent and composition of the study area may influence the parameter estimates of the location choice's sub models within *UrbanSim* and the outcomes from the model.

For our case study, a more meaningful geographical delineation of Brussels is the Urban Region (or UR, see Van Hecke et al., 2009 and Figure 1a), to which we decided to reduce our study area. Note that this reduction is linked to the densely built nature of Belgium, and should not be seen as a general recommendation. In the case of a city isolated within rural areas, a large delineation may perform better than a small one. The UR has an extent of 1 526 km^2 and in 2001 (base year of the model) it accounted for 1.44 million inhabitants and 0.99 million jobs (see also Figure 3). Its core is composed of the 19 municipalities of the Brussels-Capital Region, hereafter noted BCR. For comparison, the "*SustainCity* area" reaches 5 169 km^2, representing 2.69 million of inhabitants and 1.45 million jobs.

Cabrita et al. (2015) uses Statistical wards as BSUs. These are the smallest areal units for which statistical data are available from the Belgian Directorate General Statistics and Economic Information

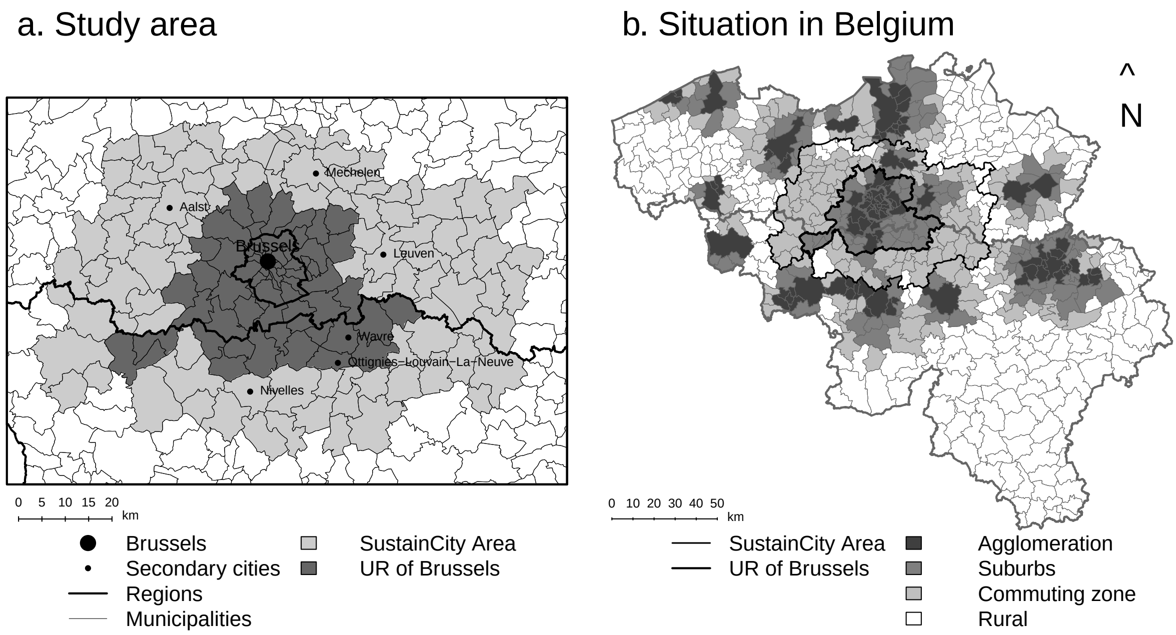

Figure 1. Urban Region of Brussels, relative to (a) the "SustainCity Area" and (b) to Belgium (typology of municipalities from Van Hecke et al., 2009)

(DGSIE). They can be aggregated into larger nested BSU levels: Sections, Former Municipalities, and Municipalities. They will all be used in the simulations. Table 1 summarizes their relative size. Note that these four BSU levels are perfectly nested into each other, meaning that there is no boundary overlap.

Table 1. General characteristics of the BSU (values for 2001)

		Surface (km^2)			**Inhabitants**		
BSU level	n	Min	Mean	Max	Min	Mean	Max
Statistical ward	2 074	0.01	0.74	13.70	0	694	4 608
Section	550	0.01	2.78	15.47	0	2 616	18 883
Former muni.	173	0.08	8.82	45.02	0	8 316	77 238
Municipalities	62	1.16	24.62	68.58	3 282	23 205	104 698

3.2 Methodology

The *UrbanSim* model is used to forecast the evolution of the Urban Region of Brussels. A detailed introduction to the model system can be found in Waddell (2000), Waddell et al. (2002), and Noth et al. (2003). Let us simply highlight that *UrbanSim* is a micro-simulation model with a disaggregated representation of agents (households, jobs, and buildings). It only simulates land-use and is thus interfaced here with the activity-based *MATsim* transport model (see Nagel et al., 2008), using the implementation developed by Nicolaï and Nagel (2015).

The base-year data in the model is 2001 (allowing the database to rely on the 2001 population census). Since forecasting the evolution of the city far into the future is not mandatory here, the simulation period is limited to 20 years (i.e. 20 iterations of *UrbanSim*). *MATsim* is run with an interval of five iterations, i.e. in 2001, 2006, 2011, and 2016. Calibration is performed after ten iterations (i.e. in 2011, year of the last existing population census). Simulations are performed independently for the four BSU levels. Moreover, five scenarios are defined, and it is assumed that they are implemented at the end of 2010. Note that the simultaneous implementation of different scenarios is not considered. Hence, we end up with 20 combinations BSU level and scenario. Note that within *UrbanSim* random sampling among existing agents (inducing a partially stochastic nature) performs the selection of new and relocating households or jobs. Hence, each combination of BSU level and scenario is simulated 10 times. In section 4, the indicators and the CBA are based on average values. Figure 5 summarizes the workflow of the paper.

To provide a reference to which the scenarios described hereafter can be compared, a business-as-usual situation is first defined. In this *Baseline*, the simulation period is uneventful. The only variations are the growth of the number of households and jobs. These forecasts come from the Belgian' Federal Planning Bureau and are detailed in Cabrita et al. (2015). For households, it is of about 1% per annum, from 743 487 in 2001 to 887 138 in 2020. Growth rates vary widely across employment sectors, from 9% (hotel/restaurant) to 59% (leisure activities). In absolute terms, the largest increases are observed for tertiary sector' jobs (+86 250), health (+44 766), and industrial activities (+32 320). Note that the variations of the number of agents over the simulation period are assumed to be equal for all scenarios.

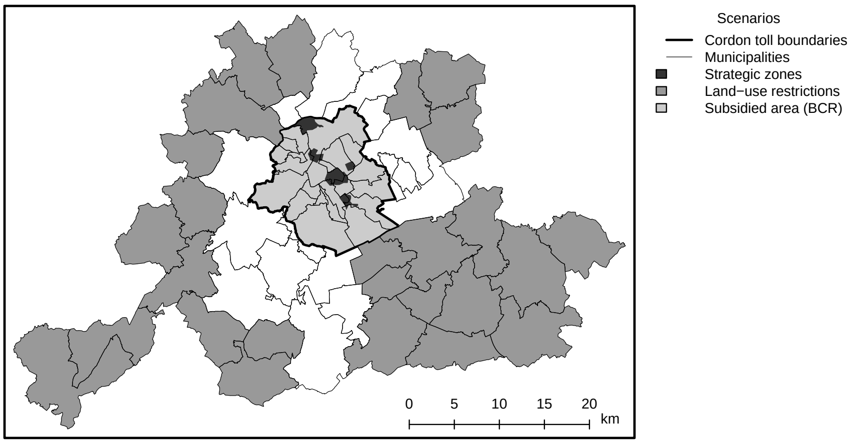

Figure 2. Implementation area of the scenarios

A *Cordon* toll scenario is then designed, to reduce the congestion problems to or within the BCR. Hence, the toll barriers are located at the intersection of the roads with the boundaries of the BCR (Figure 2). The fee is fixed to 5€, as in Cabrita et al. (2015), and has to be paid whatever the time of the day (this choice is the result of modelling constraints, see section 5). *MATsim* is used to simulate traffic and compute accessibilities in the study area, relying on an external configuration file defining the links of the road network affected, the type of congestion tax, the monetary value of the fee, and the period of time. For details see Cabrita et al. (2015) and Nicolaï and Nagel (2015). It is important, however, to mention that technical issues prevented us to implement mode choice in our model. Since it was not the main focus for the study, it was decided to continue without it. The implications of this shortcoming are discussed in sections 5.1 and 5.3.

The *Office* scenario builds on the 11 strategic zones defined by the BCR territorial development agency for future urban development (see ADT-ATO, 2015). A review of impact studies available from the ADT website indicates that new office spaces are planned for five of them (Figure 2), accounting for a total of about 440 000 square meters of floor space. We assume that these development projects take place at the level of the statistical wards and are later aggregated into larger BSU levels. The implementation of this scenario relies on the Scheduled Development Event Model (SDEM) within *UrbanSim* (see Gallay, 2010). Practically speaking, this sub model will increase the values of non-residential square meters[5] available in each zone by the required amount, in 2010.

Finally, the *Subsidy* and *Land-use* scenarios aim at reducing urban sprawl of households. For the first one, we assume that a fiscal incentive is allocated to households choosing to locate within the BCR. It accounts for an apparent decrease of real estate prices by 5%. The *Land-use* scenarios introduce stronger land-use planning regulations, decreasing the number of future residential units allowed in the suburbs of Brussels by 20%. Suburbs (see Figure 2) are defined here accordingly to Van Hecke et al. (2009). Both scenarios are implemented in *UrbanSim* by altering the average value per dwelling (*Subsidy*) or the residential units capacity (*Land-use*) within each zone, by means of the SDEM sub model.

The last step prior to running the simulations is to estimate the econometric sub models within *UrbanSim* (see Waddell et al., 2007; Sevcikova et al., 2011 for a complete description). They rely on regression analyses to forecast the evolution of real estate prices, and on Discrete Choice Models (DCM) for location choices of agents (households, jobs) and new real estate developments. The aim of this paper calls for a workflow where these sub models are estimated independently for all BSU levels (Figure 4). Hence, to ensure consistency and minimize potential selection bias, we rely on automatic variables selection procedures.

Update of real estate prices at the end of the iteration is performed in *UrbanSim* by a log-linear regression estimated by OLS. This specification was replicated in R and then calibrated by a backward procedure (iterative exclusion of independent variables whose *t*-test' significance level is higher than 0.05, starting by the least significant one). The main weakness of this approach, as shown in Table 7, is that several specifications are limited to fixed factors and/or to only one endogenous variable. Therefore, variations of population or jobs' densities will not influence these prices. Although this situation is unsatisfactory from a modelling point of view, we have decided to keep these specifications, to ensure consistency in the estimations.

Location choice sub models follow the framework proposed by McFadden (1978): a linear-in-parameters multinomial logit (MNL) model with random sampling of alternatives. Different sub models forecast the probability of a given building to be selected by new or relocating agents (households and jobs), or for real estate development project. Calibration is handled by estimating, within *UrbanSim*, ten specifications based on different combinations of the explanatory factors (Table 6). The specification having the lowest AIC value is selected. Note that for employment, estimations are only performed for non-home-based jobs. Given the lack of accurate data on home-based jobs, it has been decided to neutralize that part of the model system.

It should be noted that for Former municipalities and Municipalities, this procedure leads to frequent inclusion of non-significant variables (especially for employment, see Table 9). Hence, the AIC was perhaps not the best indicator (see e.g. Burnham and Anderson, 2002). However, the sub models have been estimated within *UrbanSim*, in which no other indicators were available for model comparison. To ensure the reproducibility of the results, it has been decided to stick to these specifications.

Endogenous variables (i.e. updated by *UrbanSim* during its iterations) are used as much as possible. Three constant variables are nevertheless considered to account for characteristics that cannot be forecasted by the model (Table 6). The following indicators account for agglomeration economies: Population density is defined as the number of inhabitants per square kilometre in each BSU. Job density (expressed in jobs per square km) is given first for the total jobs, then independently for each of the eight activities sectors (see Table 6). Accessibility factors are the Car Accessibility to Jobs, a logsum indicator estimated by *MATsim* (see Nicolaï and Nagel, 2012 for details), and the Euclidean distance (in meters) to the Brussels' CBD. This latter variable is measured between the centroid of the municipality of Brussels and the centroid of all other BSUs.

[5]Square meters are used here in place of square feet, see Cabrita et al. (2015)

Socio-economic amenities include the share of households within a BSU having a monthly income higher than 3 100 € or lower than 1 852 €. These categories come from the 2001 population census. In the households' location choice sub model (or HLCM), these variables are used as interaction term with a dummy variable equal to one if the household has a high income, and zero otherwise. The percentage of households within a BSU where (at least) one member has a university degree is also considered.

Other amenities are the House prices, the level of local taxes, and a Green amenities score. Available data on real estate prices are highly limited in Belgium. No transaction-level information is available, but only aggregated values (in euro per sq. meter) at the municipality level. Data for buildings other than houses are practically unusable, due to the many missing values induced by the small number of transactions. House prices serves thus as a proxy for other residential real estate types, and identical values are imputed to all BSUs belonging to the same municipality. Local taxes is an instrumental variable, included only into the real estate price' sub model (or REPM), to reduce potential endogeneity biases. Note that their level is limited to 9% of the federal taxes (i.e. if an household pays 10 000 €/year of taxes to the state, its municipality of residence can charge him a maximum of 900 € local taxes). The Green Amenities score is computed from the surface of each BSU covered by green areas (forest or agricultural land, data from the CORINE 2006 Land Cover Database) divided by the total surface.

Descriptive statistics of these variables at the level of the statistical wards are given in Table 6. For larger BSU levels, their value is computed by aggregating the database by sum or means. Note that in the econometric sub models, most of these explanatory factors are expressed logarithmically. Figure 3 shows their spatial distribution.

3.3 *Policy evaluation*

Simple indicators are first computed, for each BSU level and each scenario. Agents location choices are first considered, by computing the share of (1) households, (2) tertiary sector jobs, and (3) total jobs within the BCR at the end of the simulation period (i.e. 2020). At the study area level, the home-to-work (1) travel times and (2) distances are used, together with (3) green space consumption. By selecting these indicators, we attempt to cover different components of both the model systems and the sustainability issue. They also have the advantage of being direct outputs of either *UrbanSim* or *MATsim*. The variations in-between scenarios are later compared to those across BSU levels, to assess the sensitivity of the model to each component.

In the second step, a simple CBA is performed, by computing the Social Welfare (SW) level of each scenario (as proposed by Proost et al., 2015). The SW level, computed as in (1), has the advantage (compared to the simple indicators) of allowing ranking the scenarios.

$$SW = U + R - C \tag{1}$$

In equation (1), U is the final utility level at the case study level, R the direct revenues generated by the scenario, and C the implementation costs. This specification comes from Proost et al. (2015). Nevertheless, several simplifying assumptions are made: (a) the city is closed, meaning that the utility levels of commuters and the rest of the world are not taken into account. (b) The only time horizon considered is the end of the simulation period. (c) No assumptions are made on equity preferences. Therefore, an equal weight is imputed to all income classes. (d) The utility level U is computed as in equation (2).

$$U = INC - HC - TC \tag{2}$$

INC denotes the annual income. HC is the annual housing cost equal (as in Di Pasquale and Weathon, 1996) to the selling price times the interest rate (set here to 5%). TC is the annual transport cost, equal to the product of the commuting time with the number of working days per year

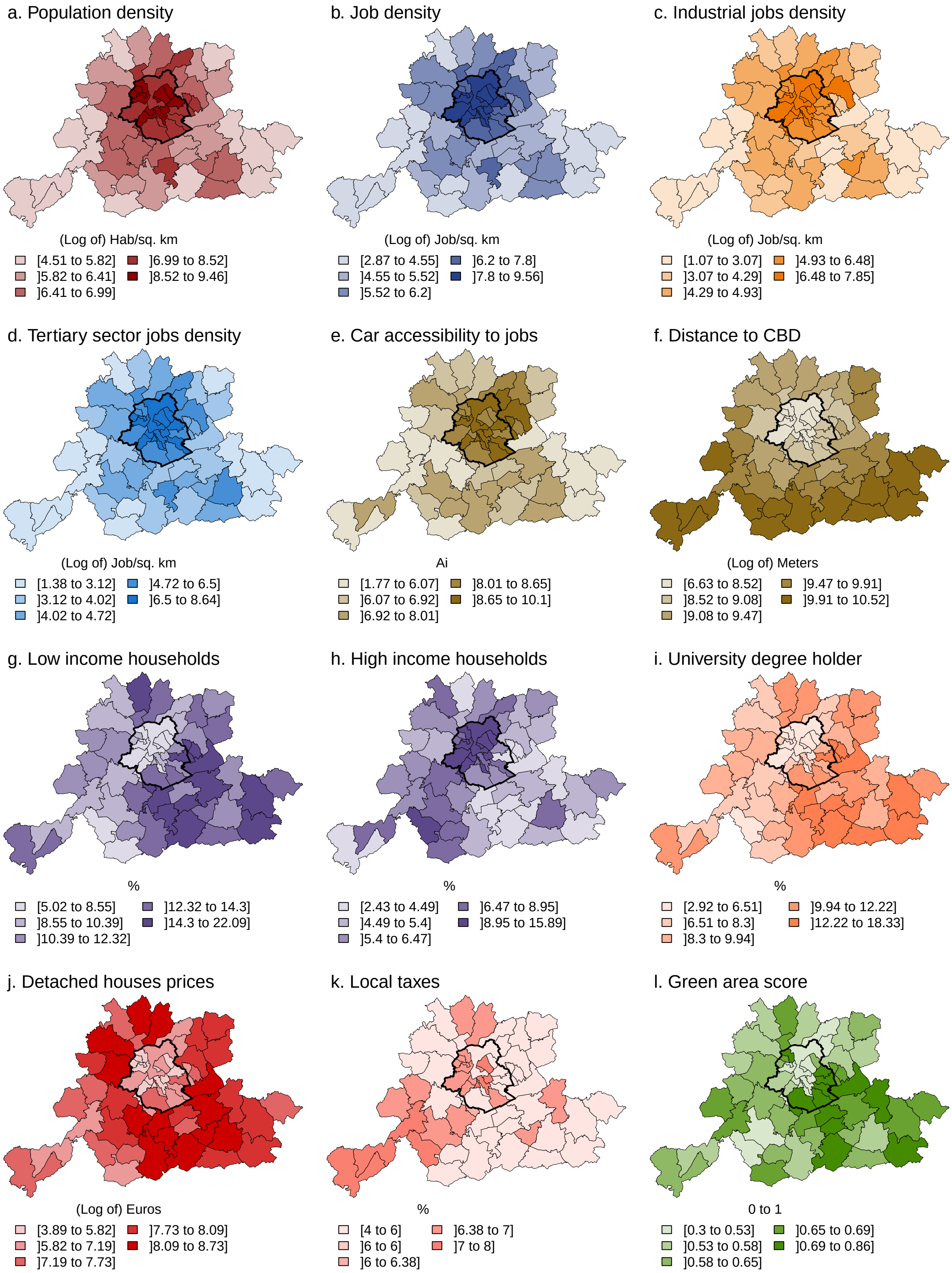

Figure 3. Spatial distribution of main variables (discretization: quantiles)

(220 here) and the value of time (0.15 €per minutes). All components of U are thus expressed in Euros. We follow here the specification and parameters' values of Proost et al. (2015). Housing and transport costs are endogenous to the model system. Evolution of incomes, on the contrary, is not modelled. The earnings of each household are thus constant over the simulation period. Cost and

revenues of the scenarios are estimated based on the literature. Since only rough estimates were found (see section 4.4), we preferred to rely here on the "post-hoc" policy evaluation described above, rather than on a continuous approach such as the Net Present Value, in order to reduce the number of assumptions that have to be made.

4 Results

4.1 Econometric sub models

Table 7 presents the parameter estimates of the real estate prices' sub model. For houses, all parameters have the expected sign. The adjusted R^2 increase from small to large BSU levels, while the number of significant variables decreases. The decreasing number of observation may constitute an explanation of these variations. The goodness-of-fit is lower for flats, but parameter estimates remains mostly of the expected sign.

For the households' location choice sub model, the best specification (using the AIC criterion) is identical for the four BSU levels, and corresponds to the inclusion of all explanatory factors (although the goodness-of-fit remains low). In the case of employment, the goodness-of-fit is generally high, but the specifications vary more widely between BSU levels. Parameter estimates are of the expected sign in most cases for both households (Table 8) and jobs (Table 9).

Note that sub models forecasting the location of future residential and non-residential developments have been constrained to a single specification, due to the lack of data on developers behaviour. For residential buildings, it involves the (log of) population density, Euclidean distance to the CBD, housing prices, and the car accessibility to jobs. The specification for non-residential buildings relies on the (log of) population density, job density, house prices, and on the car accessibility to jobs. Both parameter estimates have the expected sign and further details are, therefore, not included.

Parameter estimates of both regression and DCM are known to be sensitive to the scale effect of the MAUP (i.e. to a change of the size of the BSU). As expected, such variations are also observed here. The variations of parameter estimates will, however, not be further discussed since we focus here on changes in the outputs of *UrbanSim*. We refer to Fotheringham and Wong (1991), Arauzo-Carod and Manjon-Antolin (2004), and Jones et al. (2015b) for work dedicated to the MAUP.

4.2 Calibration of the Baseline scenario

Assessing the performance of the model for all BSU levels is necessary before comparing scenarios. Cabrita et al. (2015) recognize that the goodness of fit of their model is quite limited, due to shortcomings in data availability. An accurate model is, however, less crucial here (since we do not intend to use it for actual forecasts) than a model that performs similarly for all BSU levels. In that situation, it can indeed be assumed that eventual variations between BSU levels observed in 2020 will be linked with the scale effect, rather than noises due to a varying goodness-of-fit of the model.

In *UrbanSim*, as in other LUTI models, the calibration procedure consists in comparing the situation forecasted by the model with the observed reality on a given time step (Wegener and Fürst, 1999; Bonnel et al., 2014). Observed data come here from the 2011 population census (see DGSIE, 2015). The correspondence between the predicted (from the *Baseline* scenario) population densities in 2011 and this reference is given in Table 2. Note that the location of the jobs was not available, constraining to limit the calibration to households.

Table 2 shows, as expected, a limited absolute performance of the model. The population growth was underestimated during the development of the model, leading to a predicted number of inhabitants of 1 766 947 in 2011 (for all BSU levels) versus 1 906 258 according to the census. Figure 4 show that for all BSU levels the model underestimate the future population in the BCR and secondary urban centres, and overestimates it in rural areas. The spatial auto-correlation, however, is not significant (Table 2). On both Figure 4 and Table 2, extreme values seem more frequent for small BSUs (especially in the negative). This was expected, since in small areal units (some of them

Table 2. Calibration of the model (observed data from the 2011 population census; * = significant for $\alpha \leq 0.001$)**

	Indicator				
	(Obs. - Pred. inhab. km^2)/ (Obs. inhab. km^2) In %			Obs. versus pred. inhab/km^2	
BSU level	10% Quantile	Median	90% Quantile	Pearson's ρ	Moran's I
Statistical wards	-57.08	9.74	39.27	0.91***	-0.001
Sections	-42.66	8.71	28.63	0.95***	-0.004
Former Muni.	-6.35	18.23	36.82	0.98***	-0.007
Municipalities	3.02	15.25	23.93	0.99***	0.003

less than one square km, see Table 1) a limited variation of the absolute population may lead to large differences of densities. Nevertheless, the variation range of the indicators is similar for all BSU levels (especially Pearson's ρ). Overall, the performance of the model appears thus similar at all BSU levels.

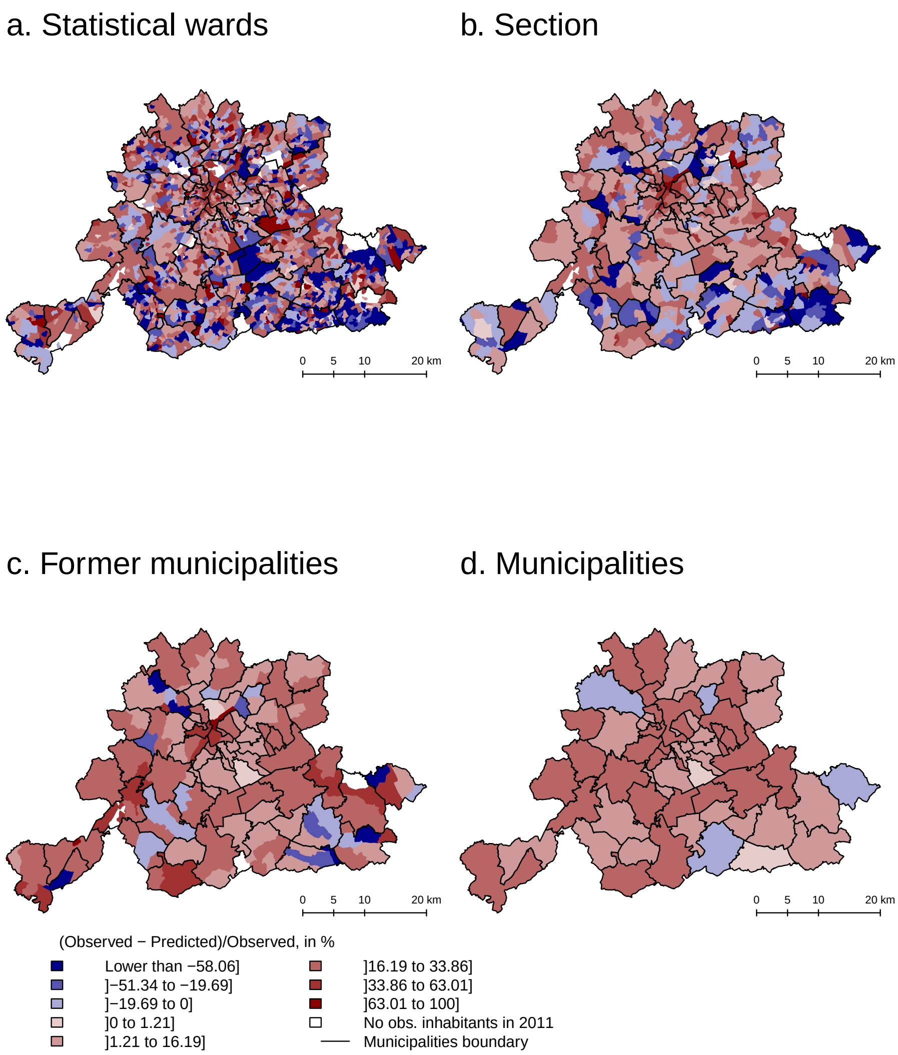

Figure 4. Variations of population density between 2011 population census and the Baseline scenario, through BSU levels (inhabitants per sq. km)

Table 3. Share of agents within the Brussels-Capital Region (average value over the 10 runs in 2020 in %; between brackets: inter-runs standard deviation)

		Scenario				
Indicator	**BSU**	*Baseline*	*Cordon*	*Office*	*Subsidy*	*Land-use*
Households	Stat. ward	51.23 (0.06)	51.23 (0.05)	51.26 (0.06)	51.24 (0.06)	51.24 (0.06)
	Sections	51.07 (0.02)	51.07 (0.00)	51.05 (0.01)	51.08 (0.01)	51.08 (0.02)
	Former muni.	54.96 (0.08)	54.98 (0.08)	54.91 (0.06)	54.93 (0.07)	54.93 (0.07)
	Municipalities	54.84 (0.02)	54.84 (0.02)	54.85 (0.02)	54.85 (0.02)	54.85 (0.03)
Tertiary jobs	Stat. ward	72.34 (0.04)	72.33 (0.03)	72.35 (0.04)	72.31 (0.06)	72.33 (0.04)
	Sections	72.34 (0.02)	72.33 (0.03)	72.28 (0.04)	72.30 (0.04)	72.32 (0.05)
	Former muni.	72.34 (0.05)	72.32 (0.03)	72.36 (0.07)	72.36 (0.04)	72.35 (0.05)
	Municipalities	72.35 (0.06)	72.32 (0.03)	72.32 (0.03)	72.33 (0.05)	72.30 (0.03)
Total jobs	Stat. ward	69.12 (0.03)	69.13 (0.01)	69.12 (0.02)	69.13 (0.02)	69.11 (0.01)
	Sections	69.15 (0.02)	69.12 (0.02)	69.11 (0.01)	69.13 (0.02)	69.12 (0.02)
	Former muni.	69.49 (0.03)	69.49 (0.01)	69.49 (0.02)	69.50 (0.02)	69.50 (0.01)
	Municipalities	69.49) (0.02)	69.48 (0.02)	69.46 (0.02)	69.50 (0.02)	69.48 (0.03)

4.3 Indicators of location choices, transport, and land-use

Outputs of the model are presented, for each combination of BSU level and scenario, in Table 3 (final share of agents located within the BCR) and 4 (transport and land-use indicators at the scale of the study area). In both tables, the rows show the differences observed between scenarios at one particular BSU level, while the columns give the variations across these geographic scales for a given scenario. Let us recall that our objective is assessing whether the scale effect can induce bias in policy evaluation. If larger differences appear in columns (i.e. across BSU levels) than in rows (between scenarios), then the answer will be yes.

Table 3 presents results for the Brussels-Capital Region. Note that the boundaries of all BSU levels perfectly match those of the BCR. Therefore, differences observed here are due to the model, not to any boundary effect. For households, variations are systematically larger between BSU levels (in columns) than across scenarios (in rows), by one order of magnitude (i.e. across scenarios, differences are only observed at for the second decimal digit; while between BSU it is at the first decimal digit). Two groups of BSU levels appear: ″small″ (Statistical wards and Sections) and ″large″ (Former Municipalities and Municipalities). Intra-group differences are limited (but still larger than across scenarios), while a large gap is observed between ″small″ and ″large″ BSU levels. For tertiary sector′ jobs (services), no differences are observed on Table 3, either between BSU levels or across scenarios. For all jobs, the gap observed between Sections and Former municipalities (in columns) is larger than the differences across scenarios (rows). Inside the group of ″small″ BSU levels, however, the differences in columns are as limited as across scenarios (in rows). The same is true for the ″large″ BSU levels.

Table 4. Transport and land consumption indicators (median value over the 10 runs in 2020 in %; between brackets: inter-runs standard deviation)

Indicator	BSU	Scenario *Baseline*	*Cordon*	*Office*	*Subsidy*	*Land-use*
Travel time (minute)	Stat. ward	38.35 (0.52)	39.97 (0.50)	37.96 (0.22)	38.20 (0.39)	37.98 (0.19)
	Sections	38.44 (0.20)	39.86 (0.28)	38.43 (0.21)	38.39 (0.24)	38.23 (0.16)
	Former muni.	38.24 (0.19)	39.29 (0.24)	38.36 (0.29)	38.27 (0.36)	38.50 (0.33)
	Municipalities	42.84 (0.81)	44.54 (1.13)	41.65 (0.21)	43.73 (0.56)	42.09 (0.34)
Travel distance (km)	Stat. ward	19.24 (0.03)	19.20 (0.03)	19.18 (0.03)	19.21 (0.03)	19.19 (0.02)
	Sections	19.09 (0.03)	19.06 (0.04)	19.11 (0.01)	19.12 (0.01)	19.1 (0.01)
	Former muni.	19.53 (0.05)	19.50 (0.03)	19.52 (0.02)	19.53 (0.05)	19.52 (0.02)
	Municipalities	19.20 (0.01)	19.18 (0.02)	19.2 (0.02)	19.23 (0.02)	19.2 (0.01)
Resid. area (%)	Stat. ward	23.99 (0.01)	23.99 (0.02)	23.96 (0.02)	23.99 (0.01)	23.99 (0.01)
	Sections	45.20 (0.05)	45.19 (0.08)	45.20 (0.07)	45.21 (0.07)	45.18 (0.06)
	Former muni.	40.53 (0.04)	40.54 (0.03)	40.55 (0.05)	40.55 (0.05)	40.55 (0.03)
	Municipalities	41.92 (0.04)	41.89 (0.02)	41.93 (0.01)	41.92 (0.01)	41.93 (0.04)

This contrast between the "small" and "large" BSU levels does not hold on Table 4. Variations of the commuting distance are very limited for both BSU levels and scenarios. Given this stability, no or few variations were expected for the commuting time. Table 4 shows that from Statistical wards to Former municipalities, values are indeed close to each other. Nevertheless, commuting time for Municipalities are 3 to 4 minutes larger than those estimated for other BSU levels (columns), for reasons that will be addressed in section 5. Finally, the share of surface occupied by green areas is stable across scenarios (rows). Larger variations are observed between BSU levels (in columns), in particular for the Sections compared to other BSU levels.

The standard deviation allows assessing the inter-runs variations. We did not report the results of the *t*-tests on Tables 3 and 4 for clarity purpose. However, across scenarios, significant differences are only observed for the commuting time, between the *Cordon* scenario and the other ones. Through BSU levels, significant differences mainly appear on Table 3 between the "small" and "large" groups of BSU, for households and all jobs, as well as on commuting time (Table 4) between Municipalities and other BSU levels.

4.4 Cost-benefit analysis

Table 5 gives the results of the CBA. Housing and transport costs are computed from simulation results, while the income level is constant. Estimates of the implementation cost of the scenarios, and of the direct revenues, are extrapolated from the literature. Since the scenarios are fictive (even if inspired from actual projects), the accuracy of the cost and revenues is limited, and they should be seen as an order of magnitude rather than exact values.

Efficiency and/or equity of cordon congestion taxes have been assessed in numerous theoretical works, but survey of real-world applications are much scarcer. Anas and Lindsey (2011) estimate the implementation costs in London (256 million € for toll area of 22 km^2), Stockholm (206 mil. € for 30 km^2), and Milan (7 mil. € for 8 km^2). Geographical and technical differences make, however, difficult to deduce generic values from these examples. In London, the perimeter of the tolled area is 21 km, leading to a cost of 12 million €/km. In Stockholm, it is of 6.8 million €/km (perimeter of 30 km), but the insular nature of the city strongly reduces the number of access points. Annual operation costs (including maintenance and investments) are far from being negligible. Anas and Lindsey (2011) estimate them to 245 (London), 31 (Stockholm), and 15 (Milan) million €. For Stockholm, Eliasson (2009) attributes the lower operating costs (compared to Oslo) to the use of a more automated system (note that a large amount of the operation cost was devoted to call centres and to provision for complaints or legal action). Hence, we have assumed an implementation cost of 10 millions €/km for the BCR which gives a total for the *Cordon* scenario of about 700 million €. In the absence of reliable figure for Belgium, operating cost had been set to 100 million €/year (value derived from those for Stockholm, see Eliasson, 2009). The total cost (implementation + operation) is thus equal to 1.7 billion € (0.7 + 0.1 times the number of years of operation, i.e. 10) and is independent from the BSU level. The revenues will be computed using the predicted number of commuters from outside the BCR, which may vary from one BSU level to another, times the cordon fee (5€), the number of working days per year (220), and the number of years (10). Since *UrbanSim* assumes a closed city (i.e. that there is no commuting coming from outside the study area), the balance between these revenues and the additional transport costs for the residents will be zero.

Information about construction costs of offices in Belgium is extremely partial. Based on two recent projects (EUROPA building, 55 000 sq. meter for 240 million €, see EC, 2015; and the new NATO HQ, 250 000 sq. meter for 1.1 billion €, see NATO, 2014), they can be estimated between 4 000 and 4 300 €/m^2 in the BCR. These two examples are, however, "high-end" buildings. Their requirements (prestige, security features) are not commonly found in basic office space. The construction cost for flats in the BCR was of 2 670 €/m^2 in 2011 (Knight Frank, 2012). Hence, a rough estimation of the *Office* scenario implementation cost would be of 1 to 1.6 billion € (assuming a price per sq. meter ranging from 2 500 to 4 000 €). This estimate is independent from the BSU level. Data on office space rents are more complete, at least for the BCR (from 165 to 285€/m^2/year in 2012 depending on the location, see CBRE, 2012). We can thus estimate the annual revenues taken from the implementation of the *Office* scenario to 81 millions € (for a 100% occupation rate), a value that is also independent from the BSU level. Assuming no inflation and the maximal estimated cost, the amortization period would be of 19 years, which seems conceivable. Furthermore, a public ownership is assumed for these new office spaces. If these developments' projects were to take place, it is most likely that they will be organized in a public-private partnership, an option that has not been considered here.

Uncertainties are lower for residential scenarios. In 2010, the cost of the *Subsidy* scenario would have been about 160 millions € (12 276 residential real estate transactions in the BCR, for a total price of 3.1 billion €; data from DGSIE, 2015). Its total cost over 2010 - 2020 is computed from simulation results, using the number of relocating households and the residential units price at their new location. Both factors are endogenous to the model system, and will thus vary through BSU levels, explaining the different values given in Table 5. The *Land-use* scenario only requires modifications in the land-use scheme by various public administrations. Its implementation cost can thus be considered as null.

On the short term, direct revenues of both *Subsidy* and *Land-use* scenarios are limited to variations in the stock of local taxes collected, which are defined by the municipalities and are thus, here, independent from the BSU level. Observed taxes (Figure 3) vary only slightly within the study area. To simplify, the direct revenues taken from the *Subsidy* and *Land-use* scenarios will thus be considered equal to zero.

Table 5. Cost-benefits analysis (average values over the 10 runs, in billion €; INC = income level; HC = housing cost; TC = transport cost; U = utility level; C = implementation cost of the scenario; R = direct revenues; SW = social welfare; Rank = rank of the scenario; note that the inter-run' variations does not affect the ranking)

		Scenario				
BSU		*Baseline*	*Cordon*	*Office*	*Subsidy*	*Land-use*
Stat. ward	INC	21.39	21.39	21.39	21.39	21.39
	HC	4.91	4.91	4.91	4.91	4.91
	TC	0.21	2.35	0.19	0.21	0.19
	U	16.27	14.13	16.29	16.27	16.29
	C	0	1.70	15.5 to 16.1	1.48	0
	R	0	2.12	0.80	0	0
	SW	16.27	14.55	15.5 to 16.1	14.79	16.29
	Rank	2	5	3	4	1
Sections	INC	21.39	21.38	21.39	21.39	21.39
	HC	4.89	4.90	4.89	4.89	4.89
	TC	0.21	2.21	0.20	0.20	0.19
	U	16.29	14.27	16.30	16.30	16.31
	C	0	1.70	15.5 to 16.1	1.44	0
	R	0	1.98	0.80	0	0
	SW	16.29	14.55	15.5 to 16.1	14.86	16.31
	Rank	2	5	3	4	1
Former muni.	INC	19.15	19.16	19.15	19.15	19.16
	HC	3.14	3.14	3.14	3.14	3.14
	TC	0.22	1.96	0.21	0.22	0.21
	U	15.78	14.47	15.80	15.79	15.81
	C	0	1.70	15.5 to 16.1	1.38	0
	R	0	2.11	0.80	0	0
	SW	15.78	14.06	15 to 15.6	14.41	15.81
	Rank	2	5	3	4	1
Municipalities	INC	19.17	19.17	19.16	19.17	19.16
	HC	2.78	2.78	2.77	2.78	2.77
	TC	0.65	2.56	0.58	0.65	0.60
	U	15.74	13.83	15.60	15.73	15.79
	C	0	1.70	15.5 to 16.1	1.37	0
	R	0	1.88	0.80	0	0
	SW	15.74	14.01	15 to 15.6	14.37	15.79
	Rank	2	5	3	4	1

5 Discussion

5.1 Consistency and limitation

The sensitivity of the outputs of a LUTI model to the size of the BSU has, to our knowledge, never been assessed in the scientific literature. Nevertheless, several components of the present paper can be related to previous findings. First, the sensitivity of parameter estimates on the size of the BSU is a known issue. As indicated in section 1, it is referred as the Scale Effect in the literature on the MAUP (Fotheringham and Rogerson, 2009; Briant et al., 2010). Variations observed here in parameter estimates are consistent with those found in works dedicated to the MAUP (see, in particular, Jones et al., 2015b). Secondly, Wegener (2011) explores stochastic variations (i.e. inter-run variations) due to changes in the ratio of the number of choices (i.e. agents who relocate) on the number of alternatives (i.e. BSU). His results show that stochastic variations decrease when this ratio increase. Since the number of agents is fixed here, inter-runs standard deviation should decrease from small to large BSU levels (reduction of the number of alternatives), which is indeed the case, especially for households (Table 3).

Thirdly, the low response of the model system to the scenarios is consistent with previous applications of LUTI models in Europe (see, e.g, de Palma et al., 2008 for Paris; or the MOEBIUS project for Luxembourg; see Lord and Gerber, 2013). The *Cordon* scenario in Cabrita et al. (2015), who uses the same model system than in this paper, is similar to the one implemented here. The observed relocation of agents is negligible in both cases, and the influence on commuting time and distances is also limited. On the contrary, the Densification scenario of Cabrita et al. (2015) leads to a large relocation of households towards the BCR (+8.5% compared to the baseline). It is, however, based on the very strong assumption that new residential units are constructed within the BCR at the rate of 2% of the total dwellings stock per annum, for five consecutive years. The changes implemented are, therefore, far larger than for our *Subsidy* and *Land-use* scenarios. Overall, the results appear thus consistent with previous works. Modelling choices and various constraints in data availability or the model system lead, nevertheless, to weaknesses that should be addressed.

Modal share of car and public transport would have been an interesting indicator to assess the sustainability of the scenarios. Technical issues prevented us to implement it in our model, which should have only a limited influence on the *Baseline*, *Office*, *Subsidy*, and *Land-use* scenarios but important one for the *Cordon* (see section 5.3). For this scenario, the workaround was to apply the congestion fee for the entire day, rather than for the morning peak hour only. To avoid the fee, households must thus either relocate inside the BCR, or select a job located outside of it. Both processes that have a reaction time far longer than a change in travel behaviour (see Wegener et al., 1986; Simmonds et al., 2013). Therefore constraining the low effects observed for the *Cordon* scenario. In any work requiring actual forecasts, enabling the mode choice is obviously more important than the scale effect for the proper assessment of a cordon toll scenario.

One could also argue that scenarios implementing larger deviations from the initial conditions would have triggered a larger response of the model system (as in Cabrita et al., 2015). This has not been attempted, since it would have contradicted the purpose of this work, in which variations induced by the scenarios are used as references to assess the sensitivity of a LUTI model to the Scale Effect. A more theoretically sound criticism is that a longer simulation period would have allowed slower urban processes, such as land-use changes (see Wegener et al., 1986; Simmonds et al., 2013) to take place. *UrbanSim*, however, is a path-dependent model: the utility function of agents, defined by the specifications of the location choice sub models, is fixed over the simulation period. Changes should thus start as soon as the scenarios are implemented, and continue until the development constraints are reached. Note that in *UrbanSim*, these development constraints account for the maximal non-residential floor space and number of residential units per building, defined using land use planning regulations. In our case study, only a limited number of zones, located within the BCR, reach this maximal level during the simulation period. Hence, if no variations are visible after 10 years, it is unlikely that they would occur after twenty or more.

5.2 *First and second order scale sensitivity*

The case study and the model used here have been selected thanks to their availability. However, the main interest is not to focus on Brussels, but to highlight general results of the sensitivity of LUTI models to scale. Variations observed in the location choices of agents (Table 3) appear to be linked with the spatial structure of their perceived utility-level. Figure 3 shows that households are less concentrated in the BCR than tertiary sector jobs. A monocentric structure seems thus to have a lower sensitivity to the scale effect than a polycentric one. This result is quite straightforward, since a large centre will always stand out from its neighbourhood, whatever the aggregation level, while small centres may be diluted for large BSU levels (see also Jones et al., 2015b). Variations in the distribution of agents can be seen as a first order scale's sensitivity of LUTI models. They are induced by the influence of the MAUP on econometric methods, specifically here the sensitivity of DCM to the size of the areal units that constitute their choice set (see Arauzo-Carod and Manjon-Antolin, 2004; Jones et al., 2015b).

A second order scale's sensitivity is observed in Table 4. These indicators are derived from agents' location choices, but their computations require additional parameters that are themselves sensitive to the BSU level. Let's consider the commuting times: *MATsim* uses as origins and destinations the centroid of the zone. For large BSU levels, a high number of agents are therefore concentrated on the same location. Yet, assuming that all agents within a zone are located on its centroid is usually a too strong hypothesis (see e.g. Goodchild and Gopal, 1989) and *MATsim* thus allows randomly distributing them in a buffer centred on each centroid. The width of this buffer was set here as the radius of a circle whose area is equal to the median area of each BSU level (from Statistical wards to Municipalities: 320, 790, 1 450, and 2 715 meters).

Such correction is needed to avoid local congestion effects that would otherwise arise from the concentration of a large number of agents in a small number of origins or destinations (note that the road network used is strictly identical at all BSU levels). Our approach appears to work properly for the three smallest BSU levels. On the contrary, the width of the buffer seems insufficient for the Municipalities, which shows that a process valid for one geographical scale may lead to peculiarities when applied at another scale. This issue can be related to the ecological fallacy problem (Robinson, 1950). Note that we did not try to adapt the agents' assignment methodology from one scale to another, since the aim of this work is precisely to assess whether an identical model may yield different results when applied to different BSU levels.

A related issue often found in operational applications of LUTI models (see Bartholomew, 2007; Jones, 2016) is the difference in the areal units used by the transport and land use side of the model. For instance, the transport model may operate with custom traffic analysis zones, while the land use side relies on census track. In such case, the indicators produced by the transport model will have to be spatially aggregated or disaggregated before feeding the land use model, which always raise technical difficulties (see e.g. Goodchild and Gopal, 1989).

The fraction of the area that is residential constitutes a second example of the challenges linked to spatial aggregation methods. This indicator depends on the average per BSU level of the median area of a residential plot. For detached houses and from Statistical wards to Municipalities, it is of 716, 982, 1 098, and 1 039 square meters. For Sections, the average plot size is far larger than those of Statistical wards, which explains the greater values observed in Table 4. While for "large" BSU levels, the increase in the median plot size is more than compensated by the relocation observed towards the BCR, where plot size are smaller.

5.3 *Ranking of the scenarios*

The social welfare level (Table 5) changes through BSU levels due to variations of the inputs (location of agents, real estate prices). The scenarios' ranking are, however, not affected. Let us note that the lower social welfare observed here for the *Cordon* scenario is due to the absence of mode choice: the agents only suffer the additional costs (toll) of its implementation, without receiving any benefits such as reduced congestion. With mode choice enabled, the social welfare level of this scenario would be higher. Hence, its ranking is the product of methodological shortcomings rather than of any general property of the cordon toll policy itself.

Nevertheless, the CBA provides consistent results through scale. Reasons are that the scenarios are either implemented at the building level (*Office*) or following the border of the municipalities (*Cordon*, *Subsidy*, *Land-use*). It was a natural choice here, since the municipalities are the only BSU level to have an administrative power. The sensitivity of the results to scale remains, however, an open question for scenarios with a more complex spatial footprint. Nevertheless, the CBA relies on aggregate values at the study area level, and large differences are observed in the balance (revenue minus cost) of the scenarios. Therefore, it seems unlikely that, for other case studies and/scenarios, major changes in the ranking of the scenarios would occur through scales.

5.4 Recommendations for operational applications of LUTI models

The results presented here raise several concerns for operational applications of LUTI models. Let us first note that DCMs are used in almost all state-of-the-art LUTI models (see Wegener, 2004; Simmonds et al., 2013). Therefore, the sensitivity to scale observed for *UrbanSim* is likely to be present in other models, even if variations in magnitude remain an open question. It is also probable that other case studies will show a significant level of sensitivity to scale, linked to the initial spatial distribution of agents. Polycentric patterns (i.e. households here) appear more influenced by the size of the BSU than monocentric one (services). A careful exploratory spatial data analysis should help to assess the potential magnitude of spatial biases. These findings also confirm that a good knowledge of the study area is vital for LUTI model projects (Nguyen-Luong, 2008).

One can argue that a model developed at the parcel level can be considered unbiased. However, recent applications of such purely disaggregated model have encountered similar, or even worse, development' difficulties than zone-based LUTI models (see e.g. Lord and Gerber, 2013; Schirmer et al., 2015). Given the aforementioned stochastic variations issue (Wegener, 2011), and the considerable data requirement of a parcel-level model, it is likely that more aggregated LUTI models will remain the most commons applications in a foreseeable future. In any case, it was impossible to add that geographical scale on the analysis presented throughout this paper, essentially due to a lack of data for our case study (see also Cabrita et al, 2015). Nevertheless, we encourage future works to study these potential differences between parcels and zones.

The main finding is that the sensitivity to the size of the BSU varies from one output of the model system to another. It is unclear if primary (i.e. the final location of agents) or secondary (e.g. travel times) indicators should be preferred. LUTI models have long been criticized for producing only the kind of aggregated results that the former one constitutes (Lee, 1973). The meaning of the latter may, however, be obfuscated by their computation that requires additional parameters varying with the BSU level. Yet, they highlight an additional dimension of the urban realities. Indicators at the agents' level (as in the CBA) would allow taking advantage of the disaggregated nature of micro-simulation model. However, as long as the LUTI model is not based purely on individual observations and agents, the spatial bias will persist. And it is unclear if an evolution towards more disaggregation is a desirable path for LUTI models, due to stochastic variations and longer computation times (see Wegener, 2011), but also constraints on data availability (see Thomas et al., 2015a).

The research question of this paper was: can the scale effect bias policy evaluation? Our results suggest that it depends on the indicator used. If policy makers require predictions threshold values (e.g. that the commuting time should decrease by 10%), then the answer is yes. Nevertheless, the direction of the variations between scenarios is identical through BSU levels. For instance, when the implementation of the scenario increases the value of one indicator, an increase happens at all BSU levels, even if the magnitude of this increase varies (the only example where statistically significant differences are observed being the increase of travel time between the *Baseline* and *Cordon* scenarios, see Table 4). This is also true for the ranking of the scenarios according to their SW level (Table 5). Hence, when the model system is used as a simplified reality, to compare options, then the size of the BSU does not seem to be an issue. This result can be related to the discussion between explanative versus predictive models (Shmueli, 2010).

Unhopefully, to our knowledge, LUTI model results often favour actual predictions (see Badoe and Miller, 2000; Bartholomew, 2007; Handy, 2008). Generalizing policy evaluation methods based on a consistent, multi-dimensional, economic framework (e.g. Hély and Antoni, 2015; Proost et al., 2015) may reduce the risk of wrongheadedness due to the Scale Effect. They do not, however, solve the fundamental problem that LUTI models themselves (and particularly their econometric components) are sensitive to spatial bias (see Jones et al., 2015b; Thomas et al., 2015a; Thomas et al., 2015b), for which no easy or straightforward solution exists. We would like to urge here (following Nguyen-Luong, 2008) that a good knowledge of the study area is vital to select the adequate BSU level, according to data availability constraint and the spatial structure of the city.

6 Conclusion

This paper proposes a sensitivity analysis of a LUTI models output to the size of the areal units used by the model. Using an empirical case study (Brussels, Belgium) and four BSU levels, the results show that variations with scale are generally larger than those between scenarios. A polycentric structure appears more sensitive than a mono centric one, but variations of the results are not monotonous with the BSU level and thus cannot be easily generalized. The main reason is that econometric methods in LUTI models are sensitive to the scale effect of the MAUP, confirming previous works by Jones et al. (2015b). These results have important implications for policy evaluations based on LUTI models. Actual predictions are likely to be biased by the BSU chosen for the model, especially if separated indicators are used rather than a unified economic framework (cost - benefit analysis). On the contrary, when the model is used as a simplified reality to compare scenarios, the results are consistent through scales. Together with Thomas et al (2015a) and Thomas et al (2015b), these findings call for a better awareness of potential spatial bias in operational applications of LUTI models. Space may bias LUTI models and, therefore, space matters in their operational applications.

Acknowledgments

The authors would like to thanks all the persons involved in the development of the Brussels case study within the EU-funded (FP7) *SustainCity* project, as well as three anonymous reviewers for their useful comments on a previous version of this paper.

References

ADT-ATO (2015). Zones stratgiques. URL: http://www.adt-ato.brussels/fr/zones-strat%C3%A9giques, accessed 29 oct. 2015.

Anas, A. and Lindsey, R. (2011). Reducing urban road transportation externalities: road pricing in theory and practice. Review of Environmental Economics and Policy, 5(1), 66-88.

Arauzo-Carod, J.M. and Manjn-Antoln, M. (2004). Firm size and geographical aggregation: an empirical appraisal in industrial location. Small Business Economics, 22(3-4), 299-312.

Arrow, K., Dasgupta, P., Goulder, L., Daily, G., Elhrlich, P., Heal, G., Levin, S., Mailer, K.G., Schneider, S., Starrett, D., and Walker, B. (2004). Are we consuming too much? Journal of economics perspectives, 18(3), 147-172.

Atkinson, G., and Mourato, S. (2006). Cost-benefit analysis and the environment: recent developments. OCDE.

Badoe, D., and Miller, E. (2000). Transportation-land-use interaction: empirical findings in North America and their implications for modelling. Transportation Research Part D, 5, 235-263.

Bartholomew, K. (2007). Land use-transportation scenario planning: promise and reality. Transportation, 34, 397-412.

Bierlaire, M., de Palma, A., Hurtubia, R., and Waddell, P. (eds). Integrated transport and land use modelling for sustainable cities, EPFL Press, Lausanne.

Boardman, A., Greenberg, D., Vining, A., and Weimer, D. (2006). Cost-benefits analysis: concepts and practice. Prenctice Hall, New Jersey.

Bonnel, P., Coulombel, N., Prados, E., Sturm, P., Arnaud, E., Boittin, C., Bouzouina, L., Delgado, J.C., Capelle, T., Delon, J., Gilquin, L., Hilaire, V., De Lapparent, M., Nguyen-Luong, D., Nicolas, J-P., Saujot, M., Tschirhard, A., and Vidard, A. (2014). A survey on the calibration and validation of integrated land use and transportation models. Paper presented at the symposium Towards integrated modelling of urban systems, Oct 2014, Lyon, France. URL : https://hal.inria.fr/hal-01093254

Briant, A., Combes, P-P., and Lafourcade, M. (2010). Dots to boxes: do the size and shape of spatial units jeopardize economic geography estimations. Journal of Urban Economics, 67(3), 287-302.

Brown, B.J., Hanson, M.E., Liverman, D.M., and Merideth, R.W. (1987). Global sustainability: toward definition. Environmental management, 11(6), 713-719.

Bulkeley, H., and Betsill, M. (2005). Rethinking sustainable cities: multilevel governance and the urban politics of climate change. Environmental politics, 14(1), 42-63.

Burnham, K.P., and Anderson, D.R. (2002). Model selection and multimodel inference : a practical information-theoretic approach. Springer, New York.

Cabrita, I., Gayda, S., Hurtubia, R., Efthymiou, D., Thomas, I., Peeters, D., Jones, J., Cotteels, C., Nagel, K., Nicolai, T., and Rder, D. (2015). Integrated land use and transport microsimulation for Brussels. In Bierlaire, M., de Palma, A., Hurtubia, R., and Waddell, P. (eds) Integrated transport and land use modelling for sustainable cities. EPFL Press, Lausanne.

CBRE (2012). Brussels Office MarketView. URL: http://www.cbre.be/be_en/research/be_enResearch%20%20Content/BrusselsOfficeMarketView_Q42012.pdf, accessed 29 oct. 2015.

Connors, R.D., and Watling, D.P. (2015). Assessing the demand vulnerability of equilibrium traffic networks via network aggregation. Network Spatial Economics, 15, 367-395.

de Palma, A., Motamedi, K., Nguyen-Luong, D., Ouaras, H., and Picard, N. (2008). SIMAURIF: the whole calibration and application to the north tangential railways project. URL: http://www.ekf.vsb.cz/export/sites/ekf/projekty/cs/weby/esf-0116/databaze-prispevku/clanky_ERSA_2008/135.pdf, accessed 30 oct. 2015.

Ding, C. (1998). The GIS-based human-interactive TAZ design algorithm: examining the impacts of data aggregation on transportation-planning analysis. Environment and Planning B: Planning and Design, 25, 601-616.

Di Pasquale, D., and Wheaton, W.C. (1996). Urban economics and real estate markets. Prenctice Hall, New Jersey.

Dowling, R.G. (2005). Predicting air quality effects of traffic-flow improvements: final report and users guide. Transportation Research Board National Research.

Efthymiou, D., Farooq, B., Bierlaire, M., and Antoniou, C. (2014). Multidimensional indicators analysis for transport policy evaluations. Transport Research Record, Journal of the Transportation Research Board, 2430, 83-94.

European Council (EC) Council of the European Union (2015). Council buildings. URL: http://www.consilium.europa.eu/en/contact/address/council-buildings/, accessed 30 oct. 2015.

Eliasson, J. (2009). A cost-benefits analysis of the Stockholm congestion charging systems. Transportation Research Part A: Policy and Practice, 43(4), 468-480.

Eliasson, J., Hultkrantz, L., Nerhagen, L., Rosqvist, L.S. (2009). The Stockholm congestion-charging trial 2006: overview and effects. Transportation Research Part A: Policy and Practice, 43(4), 240-250.

Fotheringham, A.S. and Wong, D.W. (1991). The modifiable areal unit problem in multivariate statistical analysis. Environment and planning A, 23(7), 1025-1044.

Fotheringham, A.S., and Rogerson, A. (2009). The SAGE handbook of spatial analysis. SAGE Publications Ltd, London, England.

Gallay, O. (2010). Starting with UrbanSim: on the creation of an introductory project. URL: http://infoscience.epfl.ch/record/152471/files/Gallay_UrbanSim_2010.pdf.

Geurs, K.T., and van Wee, B. (2004). Land-use/Transport interaction models as tools for sustainability impact assessment of transport investments: review and research perspectives. European journal of transport infrastructure research, 4(3), 333-355.

Goodchild, M., and Gopal, S. (1989). The accuracy of spatial databases. Taylor and Francis, London.

Handy, S. (2008). Regional transportation planning in the US: An examination of changes in technical aspects of the planning process in response to changing goals. Transport Policy, 15, 113-126.

Hély, V., and Antoni, J-P. (2014). A theoretical approach to combine sustainability indicators for decision making in planning issues. Paper presented at the 12th International Conference on Design Decision Systems in Architecture and Urban Planning, Eindhoven.

Ishizaka, A., and Nemery, P. (2013). Multi-criteria decision analysis: methods and software. John Wiley and Sons, Ltd.

Jones, J., Peeters, D., and Thomas, I. (2015a). Is cities delineations a prerequisite for urban modelling? The example of land prices determinants in Brussels. Cybergeo: revue europenne de gographie. URL: http://cybergeo.revues.org/26899.

Jones, J., Thomas, I., and Peeters, D. (2015b). Forecasting employment location choices by Discrete Choice Models: A sensitivity analysis to scale and implications for LUTI models. REGION, 2(1), 67-93.

Jones, J. (2016). Spatial bias in LUTI models. Doctoral dissertation, Presse Universitaire de Louvain, Belgique.

Knight Frank (2012). Brussels residential reports new builds. URL: http://content.knightfrank.com/research/464/documents/en/2012-1018.pdf, accessed 30 oct. 2015.

Lee, D. (1973). Requiem for Large-Scales model. Journal of the American Planning Association, 39(3), 163-178.

Lord, S. and Gerber, P. (2013). Immigration, dynamiques socio-conomiques territoriales et mouvements rsidentiels. Quelles perspectives pour les rsidents du Luxembourg ? Annales de gographie, 690, 175199. URL: www.cairn.info/revue-annales-de-geographie-2013-2-page-175.htm.

McFadden, D. (1978). Modelling the choice of residential location. In Karlqvist, A., Lundqvist, L., Snickars, F., and Weibull, J. (eds) Spatial interactions theory and planning models, North Holland, Amsterdam.

Nagel, K., Grether, D., Beuck, U., Chen, Y., Riser, M., and Axhausen, K. (2008). Multi-agent transport simulations and economic evaluation. Journal of economic and statistics, 228(2+3), 173-194.

NATO (2014). New NATO Headquarters. URL: http://www.nato.int/cps/en/natohq/topics_49287.htm, accessed 29 oct. 2015.

Nguyen-Luong, D. (2008). An integrated land use-transport model for the Paris Region (SIMAURIF): Ten lessons learned after four years of development. URL: http://web.mit.edu/11.521/proj08/readings/D_Mes_documentsDNLpredit3ERSA_2008article_SIMAURIF_10_lessons.pdf, accessed 30 oct. 2015.

Nicolaï, T., and Nagel, K. (2015). Investigating accessibility indicators for feedback from a travel to a land use model. SustainCity working paper. URL: http://www.sustaincity.org/publications, accessed 3 feb. 2016.

Nicolaï, T., and Nagel, K. (2015). Integration of agent-based transport and land use models. In Bierlaire, M., de Palma, A., Hurtubia, R., and Waddell, P. (eds) Integrated transport and land use modelling for sustainable cities. EPFL Press, Lausanne.

Nijkamp, P., and Blaas, E. (1994). Impact assessment and evaluation in transportation planning. Kluwer academic publisher, Dordrecht, The Netherlands.

Noth, M., Borning, A., and Waddell, P. (2003). An extensible modular architecture for simulating urban development, transportation and environmental impact. Computer, Environment and Urban Systems, 27, 181-203.

Openshaw, S. (1977). A geographical solution to scale and aggregation problems in region-building, partitioning, and spatial modeling. Transactions of the Institute of British Geographers, 2, 459-472.

Openshaw, S., and Taylor, P.J. (1979). A million or so correlation coefficients: three experiments on the modifiable areal unit problem. In Wrigley, N. (ed.) Statistical applications in the social sciences. Plon.

Patterson, Z., and Bierlaire, M. (2010). Development of prototypes UrbanSim models. Environment and Planning Part B, 37(2), 344-366.

Patterson, Z., Kryvobokov, M., Marchal, F., and Bierlaire, M. (2010). Disaggregate models with aggregate data: Two UrbanSim applications. Journal of Transport and Land-Use, 3(2), 5-37.

Pfaffenbichler, P., Emberger, G., and Shepherd, S. (2008). The integrated dynamic land use and transport model MARS. Networks and Spatial Economics, 8(2-3), 183-200

Proost, S., Van der Loo, S., Antoniou, C., and Efthymiou, D. (2015). Indicators of sustainable development for microsimulation models. In Bierlaire, M., de Palma, A., Hurtubia, R., and Waddell, P. (eds) Integrated transport and land use modelling for sustainable cities, EPFL Press, Lausanne.

Rodrigue, J.P., Comtois, C., and Slack, B. (2013). The geography of transport systems. Routledge, New York.

Schirmer, P., Zollig Renner, C., Mlcer, K., and Axhausen, K. (2015). Land use and transport microsimulation in the canton of Zurich using UrbanSim. In Bierlaire, M., de Palma, A., Hurtubia, R., and Waddell, P. (eds) Integrated transport and land use modelling for sustainable cities, EPFL Press, Lausanne.

Sevcikova, A., Raftery, A.E., and Waddell, P. (2011). Uncertain benefits: application to a Bayesian melding to the Alaskan way viaduc in Seattle. Transportation Research Part A: Policy and Practice, 45, 540-553.

Shmueli, G. (2010). To explain or to predict. Statistical sciences, 25(3), 289-310.

Simmonds, D., Waddell, P., and Wegener, M. (2013). Equilibrium versus dynamics in urban modelling. Environment and Planning B: Planning and Design, 40, 1051-1070

Thomas, I., Cotteels, C., Jones, J. and Peeters, D. (2013). Revisiting the Extension of the Brussels Urban Agglomeration: New Methods, New Data New Results? Belgeo [online], 1-2. URL: http://belgeo.revues.org/6074.

Thomas, I., Cotteels, C., Jones, J., Pholo Bala, A., and Peeters, D. (2015a). Spatial challenges in the estimation of LUTI models: some lessons from the sustaincity project. In Bierlaire, M., de Palma, A., Hurtubia, R., and Waddell, P. (eds) Integrated transport and land use modelling for sustainable cities. EPFL Press, Lausanne.

Thomas, I., Gerber, P., Jones, J., and Caruso, G. (2015b). On the delineation of cities in applied land use and transportation interaction (LUTI) models in Europe: a geographers viewpoint. Paper presented at the XIII NECTAR International Conference, Ann Harbor (USA), 14 june 2015.

Van Hecke, E., Halleux, J-M., Decroly, J-M., and Mérenne-Schoumaker, B. (2009). Noyaux dhabitats et rgions urbaines dans une Belgique urbanise. Monographie de lenqute socio-conomique gnrale 2001. Bruxelles. URL: http://statbel.fgov.be/fr/modules/publications/statistiques/enquetes_et_methodologie/monographies_de_l_enquete_socio-economique_2001.jsp.

van Wee, B. (2015). Towards a new generation of land-use transport interactions models: a viewpoint. Journal of Transport and Land-Use, 8(3), 1-10.

Viegas, J.M., Martinez, L.M., and Silva, E.A. (2009). Effects of the modifiable areal unit problem on the delineation of traffic analysis zones. Environment and Planning B: Planning and Design, 36(4), 625-643.

Waddell, P. (2000). A behavioural simulation model for metropolitan policy analysis and planning: residential location and housing market components of UrbanSim. Environment and planning B: planning and design, 27, 247-263.

Waddell, P. (2002). Urbansim: modelling urban development for land use, transportation and environmental planning. Journal of american planning association, 68(3), 297-314.

Waddell, P., Borning, A., Noth, M., Freier, N., Becke, M., Ulfarsson, G. (2003). Microsimulation of urban development and location choices: design and implementation of urbansim. Networks and spatial economics, 3(1), 43-67.

Waddel, P., Ulfarsson, G., Franklin, J., and Lobb, J. (2007). Incorporating land use in metropolitan transportation planning. Transportation research part A, 41, 382-410.

Wegener, M., Gnad, F., and Vannahme, M. (1986). The time scale of urban change. In Hutchinson, B., Batty, M. (eds) Advances in Urban Systems Modelling. North Holland, Amsterdam.

Wegener, M., and Fürst, F. (1999). Land-use transport interactions: state of the art. Technical Report, Institute of Spatial Planning, Dortmund.

Wegener, M. (2004). Overview of land-use transport models. In Hensher, A., and Button, K. (eds) Transport geography and spatial systems. Pergamon/Elsevier science, Kindlington, United Kingdom.

Wegener, M. (2011). From macro to micro: how much micro is too much? Transport Reviews, 31(2), 161-177.

Appendix

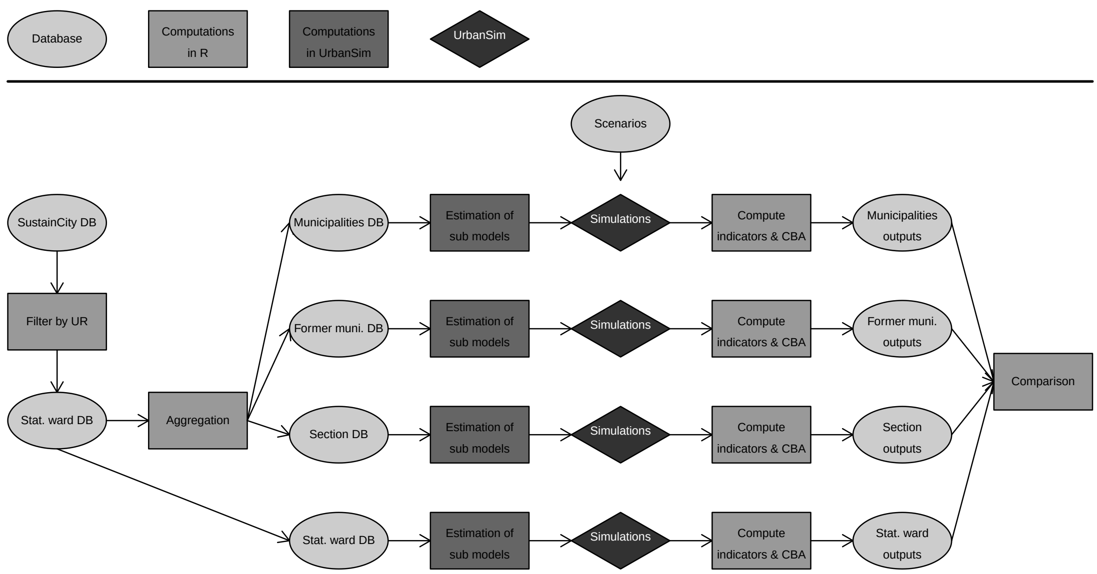

Figure 5. Workflow of the analyses

Table 6. Variables of the econometric sub models (descriptive statistics at the statistical ward level; SD = standard deviation)

Amenities	Variable	Type	Level	Units	REPM	ELCM	HLCM	Descriptive statistics Min	Mean	Max	SD
Agglomeration	(Log of) Pop. Density	Endogenous	Zones	Inhab/km2	Yes	Yes	Yes	0	8.16	10.75	1.52
	(Log of) Job Density (total)	Endogenous	Zones	Job/km2	Yes	Yes		0	7.75	11.26	1.97
	- Industrial activities	″	″	″		″	Yes	0	8.03	12.22	1.67
	- *Office*	″	″	″		″		0	8.84	13.7	1.58
	- Retail	″	″	″		″		0	7.28	11.84	1.34
	- Hotel/restaurant/bar	″	″	″		″		0	7.11	13.17	1.49
	- Gov and Public sector	″	″	″		″		0	8.63	14.12	1.71
	- Education	″	″	″		″		0	6.99	11.25	1.3
	- Health	″	″	″		″		0	7.08	11.76	1.29
	- Leisure activities	″	″	″		″		0	6.22	11.03	1.25
Accessibility	Car Accessibility to Jobs	*MATsim*	Zones	Logsum	Yes	Yes	Yes	-3.72	7.41	11.25	2.22
	(Log of) Dist. to CBD	Fixed	Zones	Meters	Yes	Yes	Yes	4.54	9.44	10.61	0.84
Socio-economic	High income Households	Endogenous	Zones	%		Yes	Yes * high inc. hh	0	11.33	100	8.53
	Low income Households	Endogenous	Zones	%			Yes * high inc. Hh	0	6.64	100	5.97
	HH with univ. degree holder	Endogenous	Zones	%		Yes		0	9.01	100	7.27
Local	(Log of) Houses prices	Endogenous	Municipalities	1 000 €	Dependant	Yes	Yes * hh inc. level	11.37	11.68	11.92	0.1
	Housing taxes	Fixed	Municipalities	%	Yes			4	6.25	8	0.78
	Green Amenities score	Fixed	Zones	0 to 1	Yes		Yes	0	0.6	1	0.18

Table 7. Parameter estimates of the Real Estate Price sub model (between bracket: standard deviation; significativity level: * = $\alpha \leq 0.05$, ** = $\alpha \leq 0.01$; * = $\alpha \leq 0.001$)**

Building type	Variable	Statistical ward	Section	Former municipalities	Municipalities
Houses	Constant	11.38*** (0.09)	11.59*** (0.04)	11.61*** (0.07)	11.17*** (0.12)
	(Log of) Pop. density (hab/km2)		0.011*** (0.003)	0.014** (0.005)	0.052*** (0.007)
	(Log of) Job density (jobs/km2)				
	Car Access. to Jobs (logsum)	0.010*** (0.002)	0.004* (0.002)		
	(Log of) Dist. to CBD (meters)	0.034*** (0.006)			
	Housing taxes (%)	-0.088*** (0.005)	-0.043*** (0.004)	-0.052*** (0.007)	-0.03** (0.01)
	Green Amenities score (0 to 1)	0.28*** (0.02)	0.27*** (0.02)	0.32*** (0.06)	0.59*** (0.09)
	Adjusted R-square n	0.18 2 074	0.35 550	0.39 173	0.54 62
Flats	Constant	11.73*** (0.04)	11.74*** (0.07)	11.04*** (0.29)	11.50*** (0.26)
	(Log of) Pop. density (hab/km2)				
	(Log of) Jobs density (jobs/km2)				
	Car Access. to Jobs (logsum)	0.006*** (0.001)			
	(Log of) Dist. to CBD (meters)	-0.007* (0.003)		0.05* (0.02)	
	Housing taxes (%)	-0.038*** (0.002)	-0.081*** (0.009)	-0.08*** (0.01)	-0.07* (0.03)
	Green Amenities score (0 to 1)	0.21*** (0.01)	0.30*** (0.05)	0.33** (0.12)	0.66** (0.22)
	Adjusted R-square n	0.3 2 074	0.16 550	0.21 173	0.23 62

Table 8. Parameter estimates of the Households' Location Choice sub model (between bracket: standard deviation; significativity level: * = $\alpha \leq 0.05$, ** = $\alpha \leq 0.01$; * = $\alpha \leq 0.001$)**

Amenities	Variable	Statistical ward	Section	Former municipalities	Municipalities
Agglomeration	(Log of) Pop. Density (hab/km2)	0.09*** (0.01)	0.13*** (0.01)	0.82*** (0.02)	-0.19*** (0.02)
	(Log of) Job Density (job/km2)	-0.11*** (0.02)	-0.03** (0.01)	0.08*** (0.01)	0.56*** (0.02)
Accessibility	Car Accessibility to Jobs (logsum)	0.045*** (0.006)	0.103*** (0.007)	0.048*** (0.009)	0.002 (0.01)
	(Log of) Dist. to CBD (meters)	-0.32*** (0.01)	-0.33*** (0.01)	0.43*** (0.02)	0.38*** (0.03)
Socio-economic	% high inc. HH x high inc. HH (%)	0.32*** (0.02)	0.26*** (0.02)	0.39*** (0.03)	0.41*** (0.04)
	% low inc. HH x low inc. HH (%)	0.086*** (0.007)	0.084*** (0.008)	0.07*** (0.01)	0.06*** (0.01)
Local	(Log of) Houses prices (%)	-1.58*** (0.04)	-1.90*** (0.05)	-1.61*** (0.05)	-2.003*** (0.05)
	x high income HH	0.52** (0.15)	0.75*** (0.16)	0.71*** (0.18)	0.55** (0.17)
	x low income HH	-0.65*** (0.16)	-0.75*** (0.17)	-0.82*** (0.21)	-0.87*** (0.18)
	Green Amenities score (0 to 1)	0.14*** (0.02)	0.07** (0.02)	0.31*** (0.02)	0.11*** (0.02)
	Adj. LL Index AIC	0.07 56 620	0.13 53 440	0.22 47 400	0.11 54 800

Table 9. Parameter estimates of the Employment' Location Choice sub model (between bracket: standard deviation; significativity level: * = $\alpha \leq 0.05$, ** = $\alpha \leq 0.01$; * = $\alpha \leq 0.001$)**

Sector	Variable	Statistical ward	Section	Former municipalities	Municipalities
Industrial Activities	(Log of) Pop. Density (hab/km2)	-0.117*** (0.007)	-0.26*** (0.02)	0.05 (0.03)	-1.09*** (0.05)
(Obs = 222 009)	(Log of) Job Density (job/km2)	-0.69*** (0.02)	-0.41*** (0.04)	-0.09 (0.05)	0.73*** (0.08)
	(Log of) sector job density (job/km2)	1.19*** (0.02)	1.04*** (0.04)	0.88*** (0.04)	0.63*** (0.05)
	Car Accessibility to Jobs (logsum)	0.161*** (0.005)	0.08*** (0.02)	0.02 (0.02)	-0.05 (0.03)
	(Log of) Dist. to CBD (meters)	-0.16*** (0.01)	-0.21*** (0.04)		0.16 (0.09)
	% High income HH (%)	-0.022*** (0.002)	-0.04** (0.01)		-0.007 (0.04)
	% HH with univ. Degree (%)	-0.123*** (0.005)	-0.05 (0.03)	0.07* (0.03)	-0.04 (0.1)
	(Log of) Houses prices (€)	6.65e-05*** (1.03e-05)	9.8e-05** (3.6e-05)	0.0001* (4.7e-05)	8.2e-05 (5.3e-05)
	Adj. LL Index AIC	0.19 121 500	0.27 11 130	0.26 11 250	0.15 12 910
Office (Obs = 280 873)	(Log of) Pop. Density (hab/km2)	-0.132*** (0.009)	-0.21*** (0.02)	0.03 (0.03)	-1.48*** (0.04)
	(Log of) Job Density (job/km2)	-0.72*** (0.02)	-0.53*** (0.05)		0.62*** (0.12)
	(Log of) sector job density (job/km2)	1.25*** (0.03)	1.03*** (0.04)	0.74*** (0.02)	1.09*** (0.11)
	Car Accessibility to Jobs (logsum)	0.349*** (0.004)	0.16** (0.02)	0.04 (0.02)	-0.13*** (0.03)
	(Log of) Dist. to CBD (meters)	-0.611*** (0.008)	-0.46*** (0.003)		0.52*** (0.08)
	% High income HH (%)	0.002 (0.002)	-0.04*** (0.01)		-9e-04 (0.04)
	% HH with univ. Degree (%)	-0.083*** (0.004)	0.07* (0.03)		0.02 (0.11)
	(Log of) Houses prices (€)	0.0001*** (8e-06)	1e-05 (3.2e-05)	0.0002*** (2.7e-05)	-0.0001* (4.7e-05)
	Adj. LL Index AIC	0.22 149 100	0.3 13 200	0.34 12 510	0.24 14 530

... Continued from previous table

Sector	**Variable**	**Statistical ward**	**Section**	**Former municipalities**	**Municipalities**
Retail (Obs = 59 321)	(Log of) Pop. Density (hab/km2)	-0.17*** (0.02)	-0.28*** (0.06)		-1.17*** (0.12)
	(Log of) Job Density (job/km2)	-0.34*** (0.04)	-0.23*** (0.06)	-0.31*** (0.07)	0.44*** (0.09)
	(Log of) sector job density (job/km2)	1.02*** (0.05)	0.98*** (0.07)	1.03*** (0.09)	1.02*** (0.12)
	Car Accessibility to Jobs (logsum)	0.177*** (0.009)	0.15*** (0.04)	0.09 (0.05)	-0.02 (0.01)
	(Log of) Dist. to CBD (meters)		-0.11 (0.07)		
	% High income HH (%)		-0.01 (0.03)	0.007 (0.05)	
	% HH with univ. Degree (%)	-0.059*** (0.008)	-0.05 (0.09)	0.02 (0.14)	0.01 (0.01)
	(Log of) Houses prices (€)	-0.0001*** (1.7e-05)	-6.2e-05 (6.6e-05)	6.9e-05 (7.8e-05)	3.3e-05 (8.6e-05)
	Adj. LL Index AIC	0.11 36 060	0.18 3 290	0.22 3 089	0.09 3 630
Hotel, Restaurant, Bar (Obs = 35 039)	(Log of) Pop. Density (hab/km2)	-0.07** (0.02)	-0.09 (0.07)	-0.04 (0.11)	-1.52*** (0.12)
	(Log of) Job Density (job/km2)	-0.29*** (0.04)	-0.30** (0.09)	0.06 (0.14)	1.31*** (0.24)
	(Log of) sector job density (job/km2)	1.01*** (0.05)	0.86*** (0.09)	0.78*** (0.11)	0.46* (0.18)
	Car Accessibility to Jobs (logsum)	0.16*** (0.01)	0.22*** (0.05)	0.07 (0.07)	-0.13 (0.11)
	(Log of) Dist. to CBD (meters)	-0.71*** (0.02)	-0.44*** (0.08)	0.16 (0.16)	
	% High income HH (%)	-0.001 (0.006)	-0.007 (0.03)	-0.02 (0.07)	
	% HH with univ. Degree (%)	0.03 (0.01)	0.01 (0.11)	0.08 (0.2)	0.22* (0.11)
	(Log of) Houses prices (€)	5.3e-05 (2.7e-05)	-5.8e-05 (9.6e-05)	0.0002* (1e-04)	-6.03e-05) (1e-04)
	Adj. LL Index AIC	0.19 19 080	0.29 1 689	0.33 1 642	0.23 1 831

... Continued from previous table

Sector	Variable	Statistical ward	Section	Former municipalities	Municipalities
Government & Public Service	(Log of) Pop. Density (hab/km2)	-0.04** (0.01)	-0.17*** (0.04)		-1.59*** (0.06)
(Obs = 169 822)	(Log of) Job Density (job/km2)	-0.65*** (0.03)	-0.51*** (0.06)	-0.18* (0.07)	0.97*** (0.13)
	(Log of) sector job density (job/km2)	1.22*** (0.03)	1.01*** (0.04)	0.98*** (0.04)	0.79*** (0.06)
	Car Accessibility to Jobs (logsum)	0.336*** (0.005)	0.36*** (0.02)	0.07* (0.03)	-0.04 (0.05)
	(Log of) Dist. to CBD (meters)	-0.75*** (0.01)		0.31*** (0.07)	0.46*** (0.11)
	% High income HH (%)	0.010*** (0.002)			-0.08 (0.06)
	% HH with univ. Degree (%)	-0.056*** (0.006)	-0.13*** (0.02)		0.36* (0.14)
	(Log of) Houses prices (€)	1.4e-05 (1.4e-05)	-0.0002*** (4.9e-05)		-0.0002*** (7.5e-05)
	Adj. LL Index AIC	0.27 84 010	0.38 7 093	0.49 5 809	0.39 6 902
Education (Obs = 57 953)	(Log of) Pop. Density (hab/km2)	-0.12*** (0.03)	-0.20** (0.06)	-0.12 (0.08)	-1.51*** (0.09)
	(Log of) Job Density (job/km2)	-0.72*** (0.07)	-0.26*** (0.07)	-0.28** (0.08)	
	(Log of) sector job density (job/km2)	1.50*** (0.08)	0.85*** (0.06)	1.12*** (0.08)	1.47*** (0.07)
	Car Accessibility to Jobs (logsum)	0.21*** (0.01)	0.27*** (0.04)	0.02 (0.05)	0.007 (0.07)
	(Log of) Dist. to CBD (meters)	-0.14*** (0.02)			
	% High income HH (%)	0.007 (0.004)			
	% HH with univ. Degree (%)	-0.03* (0.01)	0.08** (0.03)	-0.01 (0.05)	
	(Log of) Houses prices (€)	4.5e-05* (1.7e-05)	-0.0002*** (6.8e-05)	0.0002** (8e-05)	-0.0001* (5.4e-05)
	Adj. LL Index AIC	0.12 34 520	0.24 2 961	0.33 2 685	0.22 3 060

... Continued from previous table

Sector	Variable	Statistical ward	Section	Former municipalities	Municipalities
Health (Obs = 76 850)	(Log of) Pop. Density (hab/km2)	-0.20*** (0.02)	-0.21*** (0.04)		-1.54*** (0.1)
	(Log of) Job Density (job/km2)	-0.56*** (0.04)	-0.31*** (0.06)	-0.13 (0.07)	0.47*** (0.09)
	(Log of) sector job density (job/km2)	1.35*** (0.05)	0.96*** (0.05)	1.02*** (0.06)	1.05*** (0.08)
	Car Accessibility to Jobs (logsum)	0.051*** (0.008)	0.18*** (0.03)	0.12* (0.05)	0.03 (0.06)
	(Log of) Dist. to CBD (meters)	-0.44*** (0.02)		0.48*** (0.1)	
	% High income HH (%)	-0.012** (0.003)			
	% HH with univ. Degree (%)	0.003 (0.01)	-0.05 (0.03)		-0.04 (0.05)
	(Log of) Houses prices (€)	0.0002*** (1.5e-05)	-8.7e-05 (5.6e-05)		7.31e-05 (7.8e-05)
	Adj. LL Index AIC	0.12 46 250	0.32 3 626	0.34 3 404	0.16 4 346
Leisures activities (Obs = 26 326)	(Log of) Pop. Density (hab/km2)	-0.009 (0.033)			-1.61*** (0.16)
	(Log of) Job Density (job/km2)	-0.30*** (0.04)	-0.42*** (0.05)		0.11 (0.22)
	(Log of) sector job density (job/km2)	1.02*** (0.05)	0.96*** (0.07)	1.25*** (0.08)	1.45*** (0.12)
	Car Accessibility to Jobs (logsum)	0.11*** (0.01)	0.12* (0.06)		0.08 (0.14)
	(Log of) Dist. to CBD (meters)	-0.64*** (0.03)	-0.33** (0.11)	0.77*** (0.18)	
	% High income HH (%)	-0.024*** (0.005)			
	% HH with univ. Degree (%)	0.008 (0.009)			-0.02 (0.12)
	(Log of) Houses prices (€)	0.0001*** (3.2e-05)		1e-04 (1e-04)	1e-04 (1e-04)
	Adj. LL Index AIC	0.27 13 010	0.34 1 196	0.47 917	0.3 1 190