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Testing microsimulation uncertainty of the parcel-based space development module of the Baltimore PECAS Demo Model

Wanle Wang
Wuhan University of Technology &
Civil Aviation University of China
wlwang@whut.edu.cn

Ming Zhong (Corresponding author)
Wuhan University of Technology
mzhong@whut.edu.cn

Yiming Zhang
Wuhan University of Technology
578116605@qq.com

Yaqiu Li
Wuhan University of Technology
993786889@qq.com

Xiaofeng Ma
Wuhan University of Technology
maxiaofeng@whut.edu.cn

John Douglas Hunt
Wuhan University of Technology
University of Calgary
jdhunt@ucalgary.ca

John Edward Abraham
HBA Specto Incorporated
jea@hbaspecto.com

Abstract: A precise and stable microsimulation space development module is fundamental for supporting various policy decision-making exercises related to land development. This paper studies the dynamics or uncertainty of outputs of the parcel-based space development module of an integrated land-use and transport forecasting model—the Baltimore PECAS Demo Model. It is tested with two sub-studies: (1) running the model three times over the entire planning window from 2000 to 2030; and (2) running the model 30 times just one year ahead from 2000 to 2001. The outputs obtained are used to analyze such dynamics or uncertainty. Study results from the first sub-study show that, in general, the system is stable and consistent over runs and time, as supported by a set of paired t-tests. However, the coefficient of variation (COV) measuring the variation of estimated space quantity by category over four cross-section years indicates that the differences among runs are increasing over time through the planning window. The COV test over the second sub-study indicates the estimated space quantity is stable for most of the zones, except for a small portion of zones with a small space quantity.

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1 Introduction

Integrated land-use transport models (ILUTMs) are used to forecast future land-use and transport conditions based on a large amount of input data, thus providing a comprehensive representation regarding how the two interact with each other and their impacts on the society in general. Recently, there is a trend that the land-use transport modelling is moving away from the traditional aggregate, equilibrium and mathematical-equation-based approach to a more detailed, disaggregate, non-equilibrium and microsimulation-based one. The growth of information technology has offered unprecedented amount of data that are required for sustaining this trend, which encourages the development of ILUTMs with higher spatial, temporal and socioeconomic resolutions.

In particular, as the parcel database is readily available in the cities of some countries, an increasing number of ILUTMs with a better spatial resolution, e.g., using cells or parcels rather than medium-size land-use zones, have been developed, such as the UrbanSim and PECAS (the Production, Exchange and Consumption Allocation System) (Waddell, 2002; Hunt & Abraham, 2003). In general, the parcel-based ILUTMs are developed over many iterations to achieve a better representation of space development in the modelling area. For example, the PECAS model, which is drawn largely from the MEPLAN and TRANUS model, has been further enhanced in its space development module through microsimulation to represent the space with parcels and to reduce forecasting errors due to spatial aggregation used in the previous models. However, many issues could arise during the model development process, including data availability, computing capacity, model calibration and microsimulation errors. Meanwhile, if the outputs of the ILUTMs are misleading or inaccurate, it will result in uninformed decision-makings. Literature has suggested that microsimulation could impede the convergence of a model or result in a large oscillation in simulated results (Hunt et al., 2008).

Although existing studies (Clay & Johnston, 2005; Clay & Johnston, 2006; Pradhan & Kockelman, 2002; Krishnamurthy & Kockelman, 2003) have looked into the uncertainties in the forecasts of ILUTMs, none of them has investigated the impact of uncertainty related to microsimulation on the forecasting accuracy of these models over time and space, in particular, that related to their space development (SD) components. The purpose of this paper is to study the outputs dynamics or uncertainty of the space development microsimulation of an ILUTM—the Baltimore PECAS Demo model. In order to produce a rich output dataset for further investigating the forecasting uncertainty of its SD module, two sub-studies are carried out with the Baltimore PECAS Demo model: (1) running the full PECAS model three times over the entire planning window from Year 2000 to 2030; and (2) running the model 30 times just one year ahead from Year 2000 to 2001. A set of methods, including paired t-tests and COV (coefficient of variation), is used to measure the uncertainties of the SD module. Study results clearly suggest that, except for those zones with the space of a small quantity, the SD module of the Baltimore PECAS Demo model offers highly consistent forecasts over time and the model scenarios.

This paper is structured as follows: Section 2 provides related literature review; then an overview of the framework of Baltimore PECAS Demo model is presented in Section 3; in Section 4, the study methods, including the experimental setup, used to analyze the stability of Baltimore PECAS Demo model are described; the test results are reported in Section 5; finally, Section 6 summarizes the main conclusions and outlines our future research.

2 Literature review

The microsimulation method was first introduced in social science applications by Orcutt (1961), followed by a wide range of uses in the land use and transport field. For example, Hagerstrand (1968) used the microsimulation method to develop a spatial diffusion model; Chapin and Weiss (1968), Kreibich

(1979), Clarke and Holm (1987), Kain and Apgar (1985) also applied such method to simulate urban development, transport behavior, demographic and household dynamics, and housing choice, respectively. Clarke (1996) introduced an analytical framework to simulate the flexibility of individuals' behavior, which uses data from various sources (including income, health, education and welfare) to develop a more specific model. Nakamura, Hayashi and Miyamoto (1983) developed a land-use transport model (CALUTAS) for the Tokyo Metropolitan Area based on grids of 1 square kilometers. Later, Miyamoto, Vichiensan, Sugiki, and Kitazume (2007) integrated a land-use model—the RURBAN model with an existing transport model for Sapporo. In the study, the size of zone ranges from 10,000 square meters in the center of the city (8,025 zones) to 1,000,000 in the suburbs. With its land-use component based on the land-use parts of the existing IRPUD model, the ILUMASS model (the Integrated Land-Use Modelling and Transportation System Simulation) was developed completely by microsimulation (Moeckel, Spiekermann, & Schurmann, 2003). All the land-use changes and traffic flows are modelled at the level of individuals. Among the widely known ILUTMs such as the 20 urban models listed up in (Wegener, 2004), when considering space development, the UrbanSim, ILUTE (the Integrated Land Use, Transportation, Environment modelling system), MUSSA and PECAS tend to apply microsimulation at a smaller spatial unit (e.g., parcels) than other ILUTMs that use aggregated space development sub-models at the zonal level. Waddell (1998) firstly presented the structure of the UrbanSim model, which includes the interactions between urban development over time and space with individual choices and actions. The author also indicated the priorities for future research are increasing the resolution of location based on the grid measurement of spatial context and developing the microsimulation implementation of the location. Miller and Salvini (2001) presented the architecture of the Integrated Land Use, Transportation, Environment (ILUTE) system, exploring the possibility of a fully microsimulation modelling framework. Hunt and Abraham (2003) designed the PECAS framework to simulate the spatial economic systems with the land development at the parcel level, which is seen as a step forward for an improved land-use transport interaction model with a high spatial resolution. Zhong, Hunt, and Abraham (2007) developed a province-wide PECAS model for Alberta, Canada for the provincial government to make more informed economic, land use and transportation infrastructure decisions. Hunt et al. (2008) developed a PECAS Demo model to simulate the evolution of Baltimore. The Baltimore PECAS Demo model can simulate space development and land-use evolution at a very fine spatial scale (e.g., parcel). Their results showed that the "microsimulation error" of the space development module could be large, resulted from the relatively small number of occurrences of certain transitions at the level of individual parcels. In order to reduce the microsimulation error, a process called "pseudo parceling" was used to create smaller parcels and a smaller "dampening factor" of 0.25 was applied, which is found to significantly influence the convergence of the progress for transition. Miller (2018) argued that though integrated urban microsimulation models are not yet commonplace, they are needed in order to model successfully the complexities of the urban systems and their behavior.

Waddell (2009) agreed with Wegener (2009) in that integrated microsimulation models are likely to be unstable and suffer from excessive stochasticity. He also stated that uncertainty in models should be taken seriously. Rodier and Johnston (2002) conducted a sensitivity analysis of population, employment, fuel price and income projections using a travel demand and emissions models of Sacramento, USA. The results of their study showed that compared to the household income and fuel prices, population and employment projections are significant sources of uncertainty to the region's travel demand model. Zhao and Kockelman (2002) investigated the stability of transport demand model outputs by quantifying the variability in model inputs, such as zonal socioeconomic data and trip generation rates. They found that uncertainty is likely to compound itself over a series of models. Rasouli and Timmermans (2012, 2013) studied and reviewed the uncertainty in forecasts of origin–destination (OD) matrices using advanced activity-based demand. In order to reduce the uncertainty of the origin–destination matrices estimated using historical OD demand and observed traffic counts, Talebian and Shafahi (2015) applied fuzzy rules and the fuzzy C-mean clustering approach which shows a robust performance for a real transportation network. Petrik, Moura, and Silva (2014) showed that the variation of road capacity has a larger impact on the uncertainty related to assigned link volumes of the four-step model than the parameters of volume–delay function.

Studies have also been conducted on error propagation in land-use transport models, such as in the UrbanSim model presented by Pradhan and Kockelman (2002), and DRAM-EMPAL by Krishnamurthy and Kockelman (2003). The two studies found that model structure is significant in determining how the error propagates across model years. Pradhan and Kockelman (2002) concluded that the four most important sources of uncertainty are "natural uncertainty, uncertainty in model design and structure, data uncertainty and calibration error, and uncertainty in socioeconomic projections and other model inputs." Clay and Johnston (2005, 2006) tested the impact of uncertainty on model's outputs by varying three inputs (exogenous production, commercial trip generation rates, and perceived out-of-pocket cost of driving a Single Occupant Vehicle) and one parameter (the concentration parameter) in the MEPLAN model. Their studies concluded that the uncertainty from the commercial trip generation rates has the largest impact on model outputs, rather than the growth rate of population and employment found in previous studies. It is obvious that the above-mentioned previous work demonstrated that the outputs of different modelling frameworks are differently affected by variations in inputs and parameters.

Duthie, Voruganti, Kockelman, and Waller (2010) studied how decision making would change based on recognition of the uncertainty. They found that the ranking of improvement projects may indeed be different if uncertainty is considered relative to treating all parameters and data as deterministic. Wang and Kockelman (2018) compared the strengths and weaknesses of three methods for uncertainty propagation in transportation and land-use models: Local Sensitivity Analysis with Interaction (LSAI), Monte Carlo (MC) methods, and Bayesian Melding (BM) method.

In sum, the uncertainty within the inputs and outputs of integrated land-use and transport models are inevitable, because it is a natural component of the decision-making process and the behavior of socioeconomic activities. However, none of the studies to date has investigated the impact of uncertainty resulting from the microsimulation of their space development components on the forecasting accuracy over time and space. Therefore, the purpose of this study is to analyze such an impact using a fully integrated microsimulation land-use and transport forecasting model—the Baltimore PECAS Demo model.

3 Study model and data

3.1 An introduction to the PECAS framework

The PECAS, one of the popular ILUTMs, is used in this study. It stands for Production, Exchange, and Consumption Allocation System (PECAS). The PECAS model relies on random utility and discrete choice theory to simulate a large spatial economic system. Drawn from the previous MEPLAN and TRANUS model, the PECAS model reduces data-dependency and provides several theoretical enhancements compared to previous models (Hunt & Abraham, 2003).

The PECAS includes two basic modules that are linked together by the Transport Model and the Economic Demographic Aggregate Forecasting Model. The first module is the Activity Allocation module (AA module), which represents how activities locate within the space provided by developers and how these activities interact with each other at a given point in time. The AA module allocates the flows of commodities from the production location zone to the exchange location zone and from the exchange location zone to the consumption location zone and finds the corresponding set of prices at the exchange location zone that clears all markets. The other module is the Space Development module (SD module), which represents the actions of developers in the provision of space where activities can locate. This developed space is typically floor space of various types and is called "space" in the PECAS framework.

The PECAS Activity Allocation module is an aggregate representation based on spatially disaggregated forms of extended make and use input–output table. Based on random utility theory, it uses a "utility function" to describe the attractiveness of each option. The PECAS Space Development module, based on a set of logit allocation models, gives the quantities of space (including land and floor space) in each category in each land-use zone or parcel developed in the period from one point in time to the next.

The Transport Model represents the transport system connecting locations, including at a minimum a transport network, the transport demands that load onto this network (as a result of the economic interactions represented in the AA module) and the congested times and costs for interactions between locations arising with the loading of these demands.

The Economic Demographic Aggregate Forecasting Model is used to develop aggregate economic forecasts for the study area being modelled.

The four modules listed above are linked together as a system working through time in a series of discrete, fixed steps from one point in time to the next. AA module and SD module run at a one-year step, while the Transport Model runs less often considering the transportation conditions change relatively slowly and saving computation time. The study area is usually organized into a set of traffic analysis zones (TAZs). The land in each TAZ is further partitioned into parcels corresponding to cadastral legal parcels or portions of legal parcels (Abraham, Gordon, & Hunt, 2005).

See Hunt and Abraham (2003) and Abraham et al. (2005) for more detailed descriptions of the theoretical formulation and calibration methods of the PECAS model.

3.2 Baltimore PECAS Demo model—the model tested

The uncertainty of estimated space quantities from the SD module over time and space is analyzed based on the forecasting results of the Baltimore PECAS Demo model. It is acknowledged that the Baltimore Council generously allowed their model to be used for demonstration purposes without official endorsement. This model considers more than 20 activities, 30+ commodities and 10 transport modes. Its space demand module is developed based on the smallest land development unit —the legal parcel. The study area of the Baltimore PECAS Demo model covers the Baltimore Metropolitan Council area. The area has been divided into 185 land-use zones (LUZ) and 1,151 traffic analysis zones (TAZs), as shown in Fig.1(a). Fig.1(b) demonstrates the road network and built up areas of the City of Baltimore in December 2000 (see top left corner for the time stamp). In this paper, the TAZ is used as the spatial unit for analyzing the stability of the space development (SD) module of the Baltimore PECAS Demo model.

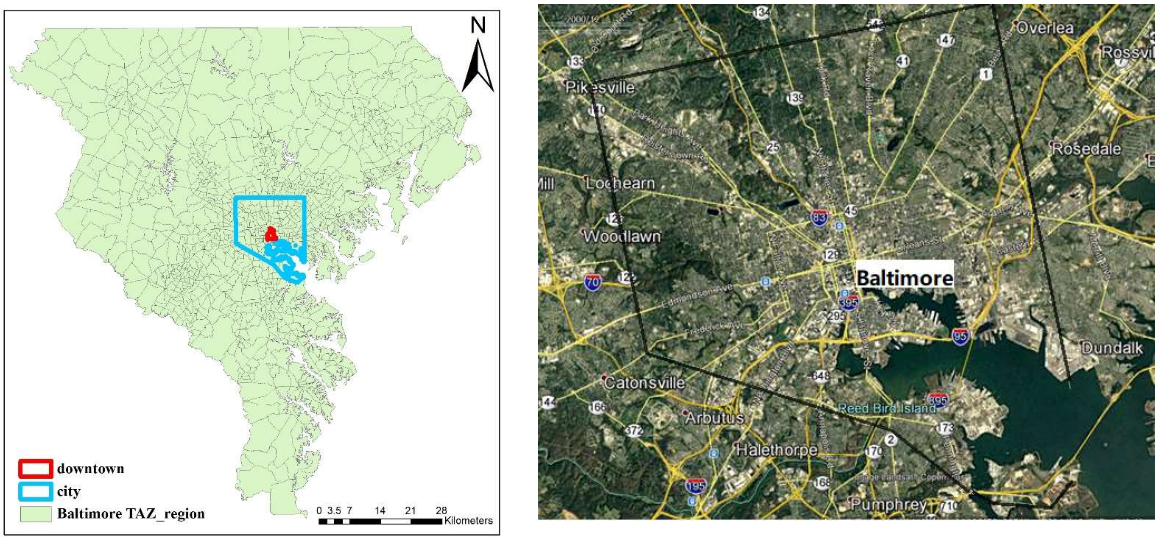

Figure 1. The city of Baltimore
(a) The city of Baltimore with TAZs
(b) The city of Baltimore from Google Earth in 2000

The SD module of the Baltimore PECAS Demo model is developed based on parcel-by-parcel microsimulation, which covers 2.17 million parcels in the base year of 2000. Fig. 2 shows the population density and population (a), and employment density and employments (b) of the City of Baltimore with 1,151 transport analysis zones used in the PECAS Demo model. The height of the zones represents the magnitude of population or employment in each zone, the higher the height, the larger the corresponding population or employment. Besides, the zones with red color located in the central area represents a higher density than the green ones, meaning that there is less land for the population and employment in the downtown of Baltimore, compared to suburban areas. The PECAS Demo model uses a road network consisting of 30,745 links, 10,978 nodes and 1,151 centroids. The average values of road capacity, speed, volume–delay functions and other attributes are provided by the Baltimore Metropolitan Council for 21 road types included in the network.

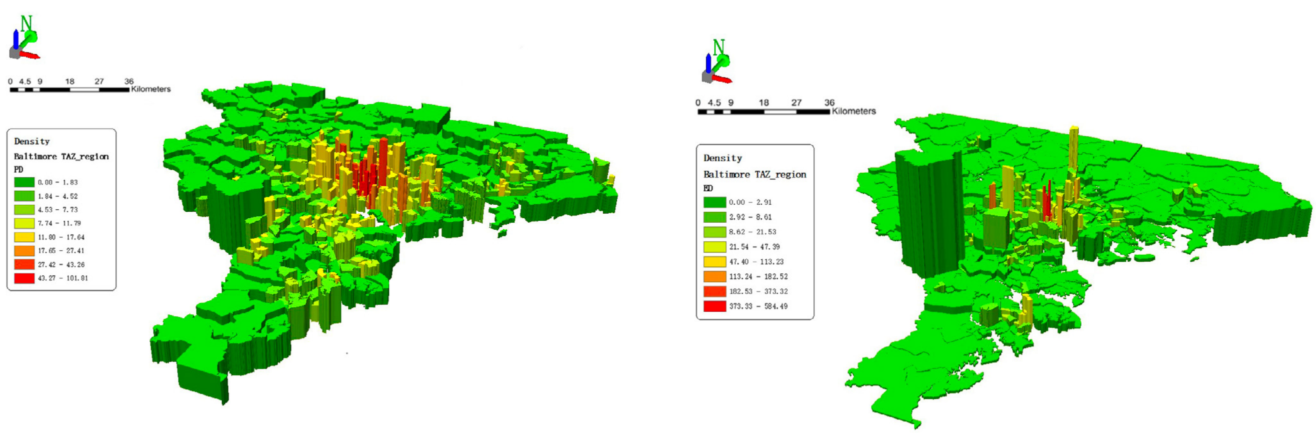

Figure 2. Population and employments of the 1,151 zones in 2000
(a) Population density and population of the 1,151 zones for the base year 2000 (b) Employment density and employments of the 1,151 zones for the base year 2000

After the integration of 2.17 million parcels, input–output tables, population and employment data, transportation network and other data into PECAS run scripts, the Demo model was fine-tuned and fully calibrated. The Space Development module of the PECAS Demo model gives the aggregate quantities of space in each category in each TAZ for each year, including six space types: commercial space, industrial space, low-density residential space, medium-density residential space, high-density residential space and other developed space. Commercial space includes retail and wholesale services areas, while industrial space includes the manufacturing and industrial parks. The three levels of residential space are distinguished by their density: low, medium or high (e.g., the dwelling units per unit area). Table 1 shows the summary statistics including the total quantity and percentage of the base year data for each type across the 1,151 TAZs used in the PECAS Demo model. It is obvious that the low-density residential space developed prevails all the other categories, followed by the commercial and industrial space. The amounts of the medium and high-density residential space in the region are fairly low (both less than 5% of the total). The other developed space takes about 10% of the total.

Table 1. Summary statistics of the base year space quantity (by category)

Space category	Quantities of 1,151 zones (km²)	Percentage of quantities
Commercial space	34.59	11.93%
Industrial space	33.06	11.41%
Low-density residential space	176.10	60.76%
Medium-density residential space	12.74	4.40%
High-density residential space	6.17	2.13%
Other developed space	27.18	9.38%

Fig. 3 describes the prevailed low-density residential space proportional to the total quantity of each TAZ in the Baltimore region of the year 2000. As we can see, low-density residential space takes more than 50% of the total developed space (all built space except for "Agricultural") in most TAZs of the City of Baltimore, especially in the peripheral zones. Low-density residential space takes a quite lower proportion in those TAZs near the downtown of Baltimore, which is in the middle of Baltimore close to the harbor (inside the green box shown). This can be observed in most cities in North America.

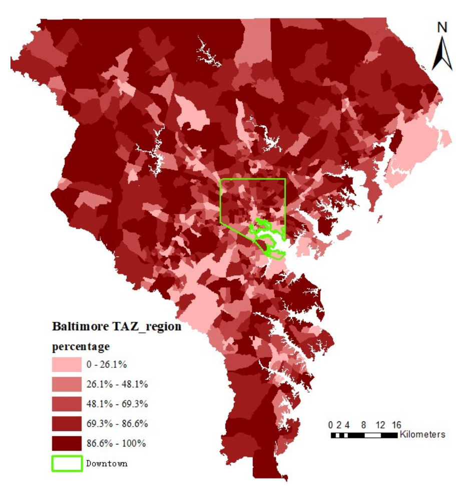

Figure 3. The percentage of low-density residential space over TAZs in the Baltimore region in 2000

4 Methodologies

Two sub-studies are conducted to study the forecast uncertainty of the SD module of the PECAS Demo model. Regarding the first sub-study, the Baltimore PECAS Demo model is run three times from the base year 2000 to 2030 with the same input datasets and model parameters. Each run is, in turn, defined as Scenario A (SA), Scenario B (SB), and Scenario C (SC). The second sub-study is running the Demo model thirty times from 2000 to 2001.

Paired t-tests and the coefficient of variation (COV) are used to evaluate the stability of the space quantity (by category) estimated by the Baltimore PECAS Demo model. Paired t-tests are a form of blocking with respect to the independence of membership in the two groups being compared (Student, 1908). Considering the space development activity within each TAZ is independent to each other among different runs, paired t-tests are used to analyze the difference between the space quantity (by category) estimated from the first sub-study in scenarios A, B and C, where the model is repeatedly run for three times with the same base-year input data.

The COV (coefficient of variation), which is also known as relative standard deviation, is defined as the ratio of the standard deviation to the mean (Everitt & Skrondal, 1998). It is used in the first sub-study to study the variation distribution for estimated space quantity over four cross-section years (2005, 2010, 2020 and 2030) across the scenarios A, B, and C, and in the second sub-study the uncertainty of the estimated space quantity (again by category) for running the model 30 times with only one-year step from Year 2000 to 2001. The detailed procedure related to the two sub-studies are presented below.

4.1 Sub-study 1: Analysis on scenarios A, B and C

4.1.1 T-tests between scenarios A, B, and C

Due to the fact that the estimated space quantity of each of 1,151 TAZ is independent to each other across the scenarios A, B and C, paired t-tests are used to test the hypothesis that there is no significant difference between the space quantity estimated from each scenario. The hypothesis of paired t-test is that the difference between two statistics variables is zero based on a two-sample location test method. As a form of blocking, the paired t-test has a great power to reduce the effects of confounding factors, when noise factors are independent of membership in the two groups being compared (Student, 1908). In this study, the paired t-test is applied to the following three matched pairs: SA vs. SB, SA vs. SC and SB vs. SC, for each of the six space types. The estimated space quantities from the scenarios A, B and C are paired based on TAZ ID and then subtract from each other to develop the three test data sets. Eq. (1) is used to test whether the difference between a pair is zero:

$$t = \left(\bar{x}_1 - \bar{x}_2\right) \Big/ \sqrt{S_1^2/n + S_2^2/n} \tag{1}$$

Where S_1^2 and S_2^2 represent the unbiased estimators of the variance of each paired group, $\bar{x}_1$ and $\bar{x}_2$ represent the average of the paired scenarios for the estimated space quantity (for a given category) respectively. When the difference between the estimated space quantities from a given pair of model scenarios is close to 0, we can infer that there is no significant difference between the two scenarios and therefore, the model's forecasts are quite consistent. The numerator of the Eq. (1) stands for the standard error of the difference between the two means. The variable n in the denominator is the number of samples in each group, representing 1,151 TAZs for all t-tests carried out in this study. Therefore, the degree of freedom for all of the t-tests is 1,150.

Once the t-tests are finished, the related statistics, t value and p value, are presented. If the calculated p value is below the threshold (0.05 is chosen in this paper) of statistical significance, the hypothesis that there is no significant difference between the estimated space quantity from the paired scenarios should be rejected.

4.1.2 COV analysis for the scenarios A, B and C

The coefficient of variation (COV), which shows the variability in relation to the mean of the sample, is defined as the ratio of the standard deviation σ to the mean μ (Everitt & Skrondal, 1998) as shown in Eq. (2):

$$\mathrm{cov} = \sigma / \mu \tag{2}$$

The COV method is used to evaluate the stability of the forecasts from the three 30-year runs (scenarios A, B and C). The estimated space quantity (by category) for each zone and each year from each of the three scenarios is used to calculate a COV. An advantage of the COV method used in this study is that the actual value of the COV is independent of the zone size or space quantity for the comparison between different samples.

4.2 Sub-study 2: COV Analysis on 30-time one-year runs

In this study, the COV method is also used to evaluate the stability of the forecasts from the 30 times of one-year run from Year 2000 to 2001. The estimated space quantity (by category) from the 30-time one-year runs are used to calculate the COVs. As the COVs can only take the measurements on non-negative values, it can be very efficient to test the stability of the forecasted space quantity from 30 runs for each zone.

5 Study results and discussion

5.1 Results from sub-study 1: Analysis on scenarios A, B and C

5.1.1 Summary statistics of the outputs of scenarios A, B and C

The space development module of the PECAS Baltimore Demo model shows a fully forecasted spatial allocation of the space developed. After three runs of the Baltimore PECAS Demo model from the base year 2000 to 2030 (Scenario A, Scenario B, and Scenario C), all forecasted quantities of the six space categories for all zones are provided. In this study, all of six space categories are analyzed, including commercial, industrial, low-density residential, medium-density residential, high-density residential and other developed space. Table 2 describes the estimated spatial allocation of the year 2030 in quantity by six categories under the SA, SB and SC, and the percentage of corresponding increase compared with the base year 2000. A very similar percentage of increase can be found in the estimated space quantities of the year 2030 in SA, SB, and SC, when compared to the base year 2000, which indicates a high stability of the forecasts of the parcel-based PECAS Demo model. Under certain government policies which may limit the development of high-density residential space, Table 2 shows the least increase of this category with a rate of about 0.5% over the 30-year period. However, with the gradual growth of population and household, more residential space is necessary, resulting in a maximum increase of about 26.7% under the SA, SB and SC for the medium-density residential space, compared to the base year 2000.

Table 2. Space quantity of 1,151 zones in 2030 in SA, SB, and SC compared to base year 2000, and the percentage of increase

Space category (km^2)	Quantities in Base year	Quantities in 2030 Under Scenario SA	Percentage of increase	Quantities in 2030 Under Scenario SB	Percentage of increase	Quantities in 2030 Under Scenario SC	Percentage of increase
Commercial space	34.59	41.30	19.39%	41.21	19.14%	41.37	19.60%
Industrial space	33.06	40.13	21.39%	40.08	21.23%	40.10	21.28%
Low-density residential space	176.10	198.30	12.61%	198.26	12.59%	198.45	12.69%
Medium-density residential space	12.74	16.15	26.79%	16.14	26.66%	16.15	26.73%
High-density residential space	6.17	6.21	0.65%	6.20	0.53%	6.20	0.41%
Other developed space	27.18	28.27	3.99%	28.28	4.04%	28.24	3.88%

It can be seen from Table 2 that none of the floor space types listed has a compound growth rate exceeding 1% over the study period and most of them are much slower. The reason for such a slow growth rate was tracked through the modelling process by looking into the growth rate of socioeconomic activities considered within the Baltimore PECAS Demo model (shown in Fig. 4). It can be seen from the figure below that these activities show quite flat curves (Fig. 4(a)) and low growth rates (around or less than 1% over 30-year period, Fig. 4(b)), which clearly explains why corresponding space development is slow.

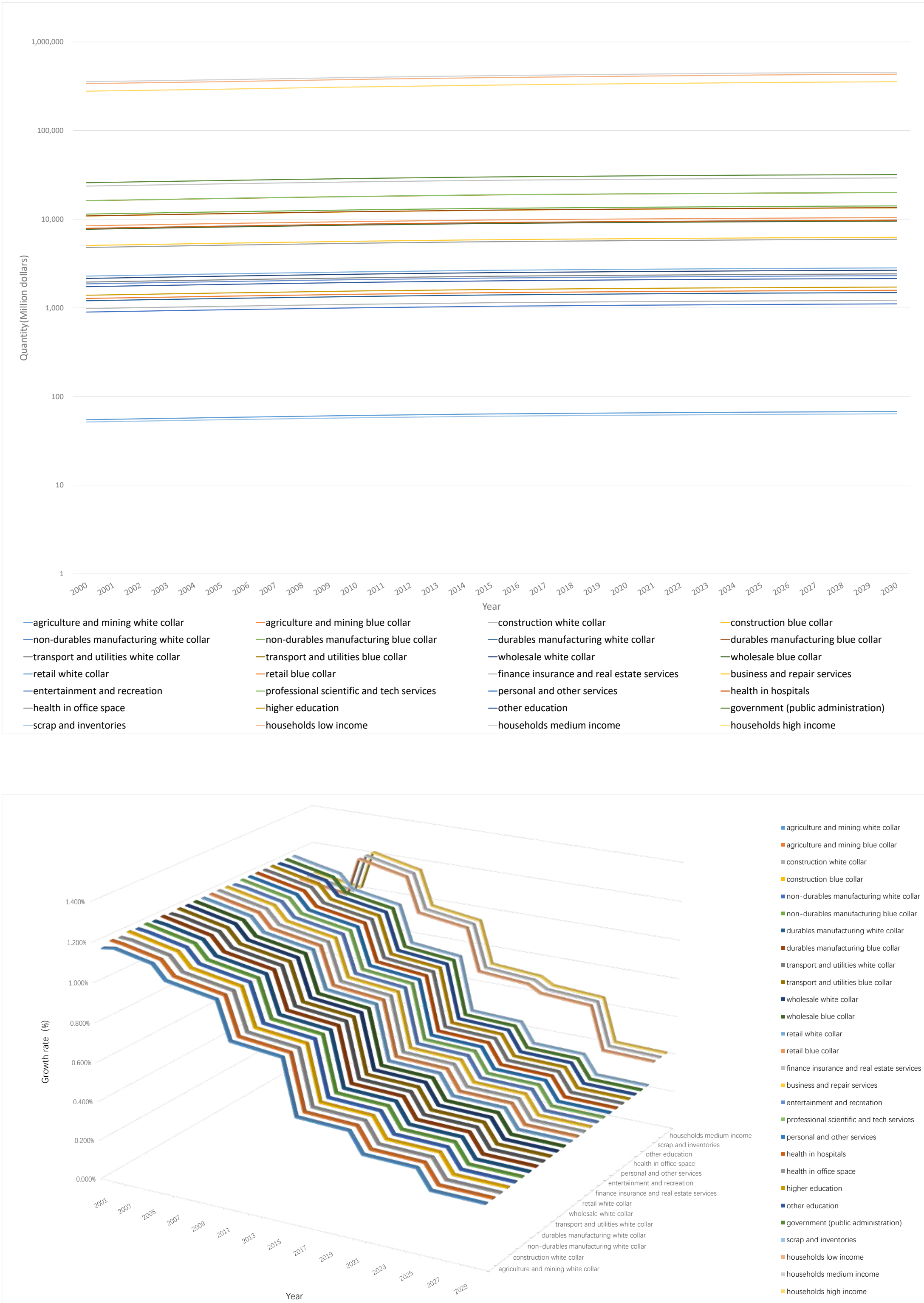

Figure 4. The forecasted activity totals and growth rates over 2000 – 2030 from the Baltimore PECAS Demo
(a) The forecasted totals of the socioeconomic activities over 2000 – 2030 from the Baltimore PECAS Demo
(b) The growth rates of the socioeconomic activities over 2000 – 2030 from the Baltimore PECAS Demo

The descriptive statistics of the total space quantities of the 1,151 TAZs by six categories in each year from the year 2000 to 2030 for Scenario A is shown in Fig. 5, where the x-axis represents the years considered, the y-axis the space quantities in square kilometers. It is obvious that the quantities of the low-density residential space are much larger than the others, which takes 60.76 percent of the total quantities of the six space categories in the base year 2000. The low-density residential space also shows the steepest slope, indicating the highest increase in quantity among all of the six categories, whereas the slope of the curves for the other five categories are flat and thus implying a relatively low increase rate. On the other hand, the "tiny" increase rate of the high-density residential space over 30-year period is very interesting, as this may indicate the local culture and space consumption behavior prefers low-density to high-density residential space. For most categories, the total space quantity keeps increasing over time, except for the commercial space. The sharp increase of commercial space in the year 2001, is found to result from several large development over the zones surrounding the downtown, such as zone 655, 654 and 656. Possible reasons for the decreasing trend after the year 2001 could be that (1) the metropolitan zoning or other policies may restrict such development or (2) the attractiveness of commercial space is decreasing due to certain reasons, when compared to the other categories. It should be noted that zoning regulations basically just tell what type of space is allowed or not allowed to develop in a parcel or a zoning unit. Developers still have the "freedom" to choose to develop a given type of space, which is allowed by the zoning, on a given parcel or a set of parcels, in order to maximize their profit gains. In this kind of "game playing," the resulting space development pattern is largely driven by the other policies or environmental variables (e.g., subsidy/stimulus plan or crime/pollution level).

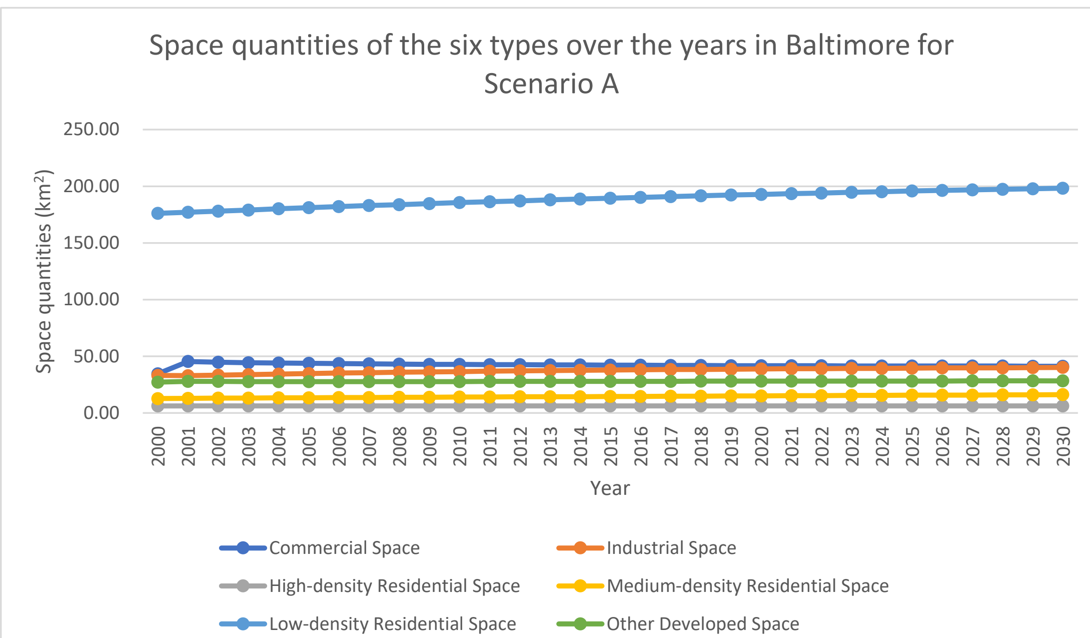

Figure 5. Total space quantities of six categories in Baltimore over 2000 to 2030 for Scenario A

5.1.2 Paired t-tests between the outputs of scenarios A, B and C

In order to test the stability of model's estimates of space quantity over 30-year between different runs, paired t-tests are applied to the estimated space quantity (by category) for 1,151 TAZs in the year 2030 to check if the estimated quantities by the PECAS Demo model across the Baltimore region over the three model scenarios (SA, SB and SC) are statistically different. The test results are shown in Table 3.

According to the assumption made in the paired t-tests, there is a significant difference between the paired space quantities with a P-value less than 0.05, which is calculated by subtracting estimated space quantity from a given pair of model scenarios (for the same space category and same zone). As shown in Table 3, the paired t-test results of SA vs. SB, SA vs. SC, SB vs. SC are not significantly different regarding the commercial space, industrial space, medium-density residential space, high-density residential space and other developed space. However, for the low-density residential space category, there is significant difference between SA and SC and between SB and SC. A detailed analysis indicates that only 2.9% zones show a large APD (absolute percentage difference, higher than 10%), which consistently have a zero or a very small quantity of the low-density residential space under one of the three scenarios (SA, SB or SC). Due to this, the APDs calculated tend to be consistently large. Therefore, it can be concluded that, except for the mentioned reason, in general, the PECAS simulation results are very much similar to each other, and the system is fairly stable and consistent over runs and times.

Table 3. Paired-samples t-tests for each space category in 2030

Space category (m^2)	Mean	Std. D.	Std. E.	t	df	P-value
Commercial Space						
SA vs. SB	75.19	4948.42	1455.79	0.516	1150	0.606
SA vs. SC	-63.89	4172.88	123.00	-0.519	1150	0.604
SB vs. SC	-139.08	5242.17	154.52	-0.9	1150	0.368
Industrial Space						
SA vs. SB	46.84	1865.99	55.00	0.852	1150	0.395
SA vs. SC	30.50	1768.37	52.12	0.585	1150	0.559
SB vs. SC	-16.34	1525.28	44.96	-0.363	1150	0.716
Low-density Residential Space						
SA vs. SB	29.63	2176.89	64.17	0.462	1150	0.644
SA vs. SC	-133.02	2148.67	63.33	-2.100	1150	0.036
SB vs. SC	-162.65	2311.21	68.12	-2.388	1150	0.017
Medium-density Residential Space						
SA vs. SB	14.78	915.71	26.99	0.548	1150	0.584
SA vs. SC	6.69	925.87	27.29	0.245	1150	0.806
SB vs. SC	-8.09	864.93	25.49	-0.317	1150	0.751
High-density Residential Space						
SA vs. SB	5.99	332.84	9.81	0.611	1150	0.541
SA vs. SC	13.09	567.38	16.72	0.783	1150	0.434
SB vs. SC	7.10	513.48	15.13	0.469	1150	0.639
Other Developed Space						
SA vs. SB	-10.73	2675.40	78.86	-0.136	1150	0.892
SA vs. SC	26.65	2335.58	68.84	0.387	1150	0.699
SB vs. SC	37.38	2126.03	62.67	0.596	1150	0.551

5.1.3 The COV distribution between the scenarios A, B and C

In this section, the stability of the PECAS Demo model across the years in the planning window is tested with the COV method. With the outputs from the spatial development module over the three scenarios (SA, SB, and SC), the summary statistics of the COVs based on the estimated quantity of the six space categories over 1,151 TAZs are calculated. However, due to limited space, only the COVs of commercial space is shown in Fig. 6, and only the description of COVs of commercial space and low-density residential space is presented in Table 4. It is clear that there is an increasing trend in mean, median and interquartile range of the COV values of commercial space from 1,151 TAZs over the planning window (only the results for Year 2005, 2010, 2020, and 2030 are presented) as shown in Fig. 6, which indicates that larger COV values tend to be more frequent and therefore the uncertainty of the estimation increases. Table 4 shows the summary statistics of the COVs for 1,151 zones for both the commercial and the low-density residential space. It can be seen that the COV values increase over the planning window, supported by the increasing mean, median and interquartile range over time, which in turn indicates that larger COV values tend to be more frequent and therefore the uncertainty of the estimation increases. In addition, a decreasing trend in the Skewness and Kurtosis values is found. Skewness is the indicator of the probability distribution of the COVs around its mean (skew to the right or left), while Kurtosis describes the shape (peaking) of a probability distribution of COVs. The decreasing trend of the Skewness indicates that the distribution of COV values tend to be less skewed over the planning window. On the other hand, the Kurtosis values implies that the distribution of COV values becomes more flat over time. The opposite trend of the standard deviation value of the COV values for the commercial and low-density residential space is interesting, as the one for the former is increasing over time, but that for the latter is decreasing. These values indicate that, as the time goes, the development of the commercial space is getting less homogeneously distributed over the region, whereas the development of the low-density residential space is getting more homogeneous. Although there is an increasing trend of COVs across the three scenarios, the PECAS SD module is, in general, stable based on the small COV values over the years.

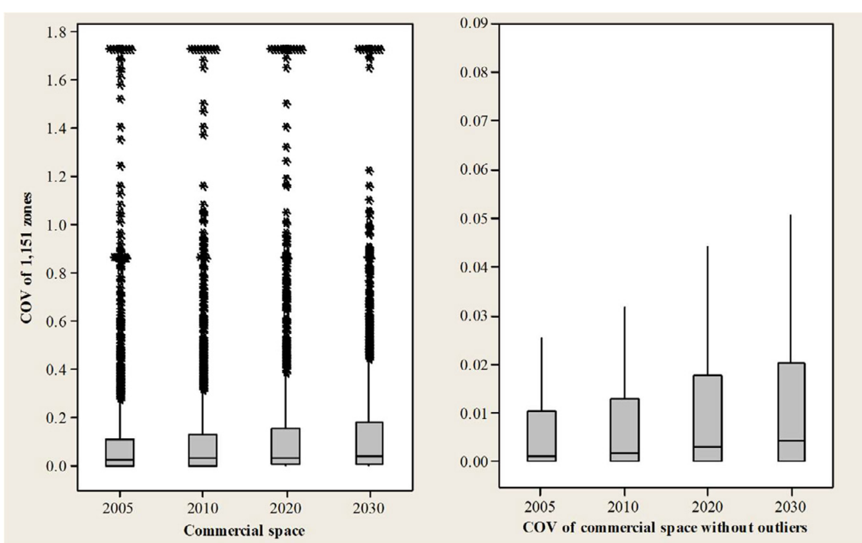

Figure 6. COVs of the 1,151 zones for commercial space and commercial space without outliers over the years

Table 4. Summary statistics of the COVs for 1,151 zones for commercial space and low-density residential space over the years

	Commercial space				Low-density residential space			
	2005	**2010**	**2020**	**2030**	**2005**	**2010**	**2020**	**2030**
Mean	0.027	0.031	0.039	0.043	0.018	0.018	0.019	0.021
Median	0.002	0.004	0.006	0.007	0.003	0.004	0.005	0.005
SDV	0.108	0.108	0.133	0.122	0.128	0.109	0.105	0.092
Minimum	0	0	0	0	0	0	0	0
Maximum	1.732	1.732	1.732	1.732	1.732	1.732	1.732	1.732
Interquartile range	0.017	0.021	0.029	0.034	0. 008	0.015	0.023	0. 024
Skewness	10.312	9.566	9.892	7.453	13.389	12.931	12.496	10.946
Kurtosis	132.494	117.776	95.658	77.428	206.335	185.851	175.050	130.994
Extremes	124 (≥0.044)	149 (≥0.053)	128 (≥0.074)	138 (≥0.086)	122 (≥0.047)	105 (≥0.056)	88 (≥0.07)	79 (≥0.077

5.2 Results from sub-study 2: The COV Analysis on 30-time one-year runs

In this study, the Baltimore PECAS Demo is run thirty times from the year 2000 to 2001 to test the simulation stability of its SD module across runs. For each space category, the COVs in the 1,151 TAZs are analyzed independently (due to the limited space here, only the COVs of commercial space and industrial space are presented in Fig. 7). Study results show that, for most zones, the COV values are very close to 0 for most space categories. The largest COVs are found for the industrial space and medium-density residential space, about 3.45 and 3.94 respectively. A close examination indicates that, because the size of several zones is large and only a small quantity of the two space categories exist in the base year, any incremental changes result in large COV values. It can be seen from Fig. 7(a) that those zones surrounding the downtown of the City of Baltimore show higher COV values for the commercial space, meaning that there is a higher uncertainty in the decision-making process of development of the commercial space in those areas than the others. On the other hand, the analysis related to the industry space shows the opposite trend, where the outer zones tend to have higher COV values, as shown in Fig. 7(b).

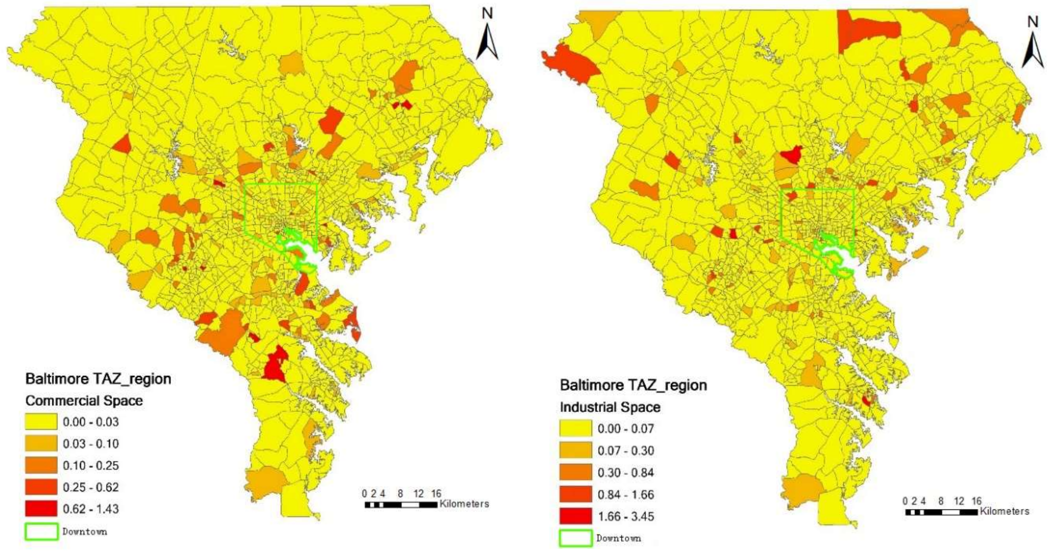

Figure 7. COV values distribution for estimated quantity of Commercial Space and Industrial Space over 30 one-year runs
(a) Commercial Space
(b) Industrial Space

Summary statistics for all the space categories available in Zone 659 across 30 one-year (2000-2001) runs is given in Table 5. There is no high-density residential space in this zone because of zoning regulations. According to Table 5, low-density residential space and industrial space show the highest quantities in 2001, followed by the other developed space, commercial space, and medium-density residential space. The same pattern can also be seen in the range and standard deviation of the space categories, except for the medium-density residential space. The COV value for the medium-density residential space is as high as 58%, while that for the other space categories are all less than 2%. Table 5 clearly shows that the quantity of the medium-density residential space is very small, on average is only around 100 square meters over 30 runs. In all the 30 runs from the year 2000 to 2001, the SD module estimated that no medium-density space would be developed in 15 runs, but with some estimated quantities for the rest 15 runs. Within the estimated quantities from the 15 runs, most of them are very small, only the corresponding quantity from the 27th run shows a great deviation. Except for this reason, the parcel-based Baltimore PECAS Demo model shows a high-degree of stability across runs in general.

Table 5. Summary statistics for the year 2001 for Zone 659 (by category)

	Commercial Space	Industrial Space	Low-density Residential Space	Medium-density Residential Space	Other Developed Space	Grand Total
Mean (m²)	1769.87	29644.10	270600.61	96.44	3570.76	3260050.29
Range(m²)	88.39	2282.26	3073.56	195.33	112.79	4667.21
Range as the percentage of Average	4.99%	7.70%	1.14%	202.54%	3.16%	0.02%
Std. D. (m²)	19.81	589.62	745.46	55.75	25.55	1024.61
COV	1.12%	1.99%	0.27%	57.81%	0.72%	0.03%

6 Conclusions and recommendations

This paper studies the stability of the microsimulation-based space development module, using a simplified fully integrated land-use and transport forecasting model—the Baltimore PECAS Demo model. Testing the stability or uncertainty of its space/land microsimulation component is important for evaluating the accuracy or "effectiveness" of the microsimulation approach and further enhancements of other components. The parcel-based Baltimore PECAS Demo is run many times in the two sub-studies to provide a rich output dataset from its space development module.

According to the results of the first sub-study, in general, the Baltimore PECAS Demo results in very stable, micro-simulated space quantities, except for a small number of TAZs with very low quantity of a certain type of space. However, the differences among runs are increasing over the planning window for all the space categories considered. In the second sub-study, our results show a very low percentage of the difference between each runs for the commercial space, industrial space, low-density residential space, medium-density residential space, and other developed space, except for a small proportion of industrial space and medium-density residential space of a few zones. In addition, it appears that the spatial distributions of those zones with a high COV value are largely correlated with their corresponding activities. Higher uncertainty is accompanied by more complex economic behavior. And in some zones, higher uncertainty is also found due to the small quantity of certain type of space in the base year.

In summary, the stability test of the parcel-based Baltimore PECAS Demo model generally shows a high forecasting reliability. As we can see, even though the zoning can constrain the space development on parcels, developers still have the "freedom" to develop, e.g., what type (e.g., commercial vs. residential) to develop, on which parcels (e.g., where to develop, among all those parcels allowed to develop the type of space that developers would like to develop) and develop how much (in what density). It is found that, except for a small number of cases, the forecasts are highly consistent and stable over time and space, which means that the simulated developers' decisions, behavior (what type of space to develop, where to develop and in what density) and space patterns show a very small variation over different model runs. This fact indicates that, even though the developers do have the "freedom" to develop in a "free" real estate market similar to that of the City of Baltimore, their behavior and resulting space development patterns are pretty much consistent to each other over different simulation runs. Therefore, it can be concluded that the developers simulated are very likely to be "reasonable decision makers," under the assumption that their space development behavior has been well modelled with the observed data and a high goodness-of-the-fit (Hunt et al., 2008). The study results of this paper provide insights about the uncertainty introduced by the micro-simulated space development module used in the Baltimore PECAS Demo model, which is shown to be very small and statistical insignificant in most cases, with only a few exceptions at those TAZs with a very small amount of existing space. Future work could investigate those exceptional cases by either reducing the simulation size (by time step or spatial unit) or changing the parameters (e.g., dampening factors) of microsimulation.

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