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Optimization and Application of Integrated Land Use and Transportation Model in Small- and Medium-Sized Cities in China

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Abstract: Integrated land use and transportation models are helpful when policy, planning, or environment impacts are being evaluated, but the strengths and limitations in these models must be optimized. To optimize the ITLUP (Integrated Transportation and Land-Use Planning) model and apply it in small- and medium-sized cities in China, this study considered the constraints of land use intensity and introduced two critical indicators (the maximum number of households and maximum employment) to characterize the land capacity and improve the practicality of the model. Then, Monte Carlo simulation analysis was used to analyze the uncertainty factors using the coefficient of variation (C.V) and standardized regression coefficient (SRC). The results suggest that the maximum future employment and households may exceed the land limit and must be adjusted to a new zone, and the model operation simulation was closer to the actual situation of small- and medium-sized cities. The C.V value of the model output showed the increasing trend of the uncertainty of the model output variable over time, especially affected by DRAM model parameters, traffic demand forecasting model parameters and the peak hourly flow ratio. Such findings are meaningful for policymakers, planners, and others when the ITLUP model is used to anticipate the zonal employment and household allocation and to further explore the interaction between land use and transportation.

Keywords: small- and medium-sized cities; integrated land use and transport; ITLUP model; optimization; maximum number of households; maximum employment

1. Introduction

China is now in a rapid development period of motorization and urbanization, and green, smart, safe and sustainable urban development is an inevitable trend. Land is the carrier of all human production and life; its structure, mode and dynamic changes affect the operation of the entire city. Land carrying capacity, land use intensification, and land structure complexity are all issues that need to be considered in city planning around land usage. Transportation is the skeleton of urban operation and also profoundly affects the cities' sustainable development. The integration of land use and transportation development is the focus of urban planners.

The interaction between land use patterns and travel behaviors has been recognized for decades in the literature [1]. The general relationship between transportation and land-use may be defined in terms of three primary components: economic activity (i.e., employment), demographic activity and transportation facilities [2]. Understanding the interactions and mechanisms is of great significance to build well-organized urban space organizations and alleviate urban transport problems. ITLUMs (Integrated Transport-Land Use Models) enable analysts to anticipate the system response to new policies, preference functions, economic conditions and other scenarios.

Several ITLUMs have been applied to date and are publicly available in practice [3–12]. Lowry's Model of Metropolis is the first attempt to implement an urban land use traffic feedback cycle in the operating model, which is the basis for most subsequent research and has stimulated many increasingly complex modeling methods [3]. Putman found that nonlinear mathematical programming formulations of a combined model of the location, trip-making, and trip assignment can effectively avoid model convergence problem [13,14]. The MEPLAN framework was most applicable in situations where consistent land use and transport predictions and evaluations are required due to its various strengths, especially where there are relatively few observed data points [15]. Kockelman et al. explored a random-utility-based multiregional IO (RUBMRIO) model based on spatial IO theories and applied it in Texas, which provides a valuable set of relationships and can be used to predict the trade flows, location choices/production levels, and relative market prices [16]. SLEUTH (Slope, Land Use, Excluded, Urban, Transportation and Hillshade model) is a computational simulation model that uses adaptive cellular automata to simulate the way cities grow and change their surrounding land uses, while the analysis process usually lack combination with the local city development characteristics [10,17,18]. However, based on the demographic, policy, economic and market changes, the strengths and limitations of these models are present in the context of data requirements, model calibration, result presentation, etc. [19–23]. In addition, the spatial resolution of present models is still too coarse to model neighborhood scale policies and effects [24].

ITLUP (Integrated Transportation and Land-Use Planning) and UrbanSIM (Urban Simulation Model) are two typical procedures to explore the relationship between transportation and land use [25,26] and have been widely used in practice [27]. These two land use models were compared based on data requirements, calibration, and result presentation [1]. The results show that the highly aggregate data required for ITLUP (which seeks to simulate the development of individual parcels and the decisions of individual households and firms [9]) are relatively easy to gather, whereas the disaggregate data required for UrbanSim may take months or even a few years to refine to an acceptable level of reliability [1,24] and are more extensive [28]. The Bayesian Melding calibration method under development by the UrbanSim team provides great convenience to users, who otherwise must rely on statistical software and have expert knowledge of the estimation process. However, it requires two or more years of data, which implies that full calibration may not be possible. The data required for the ITLUP model calibration are more readily available. There are numerous options to present the results for UrbanSim, whereas the ITLUP model is very limited in its presentation capabilities. In general, ITLUP is a simple model with less flexibility, and UrbanSim is a complex model with more flexibility. The data required for ITLUP are easier and less expensive to gather than that for UrbanSim.

There are great differences in the status quo of land use and transportation development in China's big as well as small- and medium-sized cities. At the same time, there are many restrictions on the development of small- and medium-sized cities (here, this usually refers to counties, which are the third part of the administrative division of China; there are 2876 counties in China in 2018) in China. In view of the limitations (fewer available statistical data) of small- and medium-sized cities in China that may exist in the rapid urbanization process and Duthie's comparison results of ITLUP and UrbanSim in data requirements and model calibration, this study selected the ITLUP model to analyze the relationship between land use and transportation systems. Moreover, from the perspective of functional positioning and sustainable development of small- and medium-sized cities in China, it is not necessary to carry out high-intensity urban land development. Therefore, this study regarded environmental capacity as an important factor in the planning of land use in small- and medium-sized cities and introduced two indicators (maximum number of households and maximum employment) to improve the practicality. In addition, considering the dynamics and complexity of urban planning and traffic planning, policy may have changes over time, which in turn affects the input variables and has an uncertain effect on the output of the model. Thus, this study explored the uncertainty of input variables and parameters. The above forms the main component of Section 2, which is followed by a description of the results, a discussion, and the conclusion.

2. Methods and Data

Compared with big cities, the level of land intensification in small- and medium-sized cities in China is generally low. Furthermore, the transportation system in small- and medium-sized cities in China has several main characteristics: usually lower per capita road area (not always); insufficient public transportation system in route scale, density and operating kilometers; lack of consistency between urban land use and transportation systems; and disjointed or semi-detached land use planning and traffic planning [27].

Considering the traffic development situation and the difficulty in obtaining enough data in small- and medium-sized cities in China, and comprehensive consideration of model data, calibration methods and prediction results, we chose the ITLUP model for research. The ITLUP model mainly includes a land use model and a traffic demand forecast model. The land use model consists of EMPAL (Employment Allocation Model) and DRAM (Disaggregate Residential Allocation Model) [29]. The ITLUP model provides an interactive feedback mechanism for EMPAL, DRAM and traffic demand forecast model.

2.1. Components of the ITLUP Model

2.1.1. Land Use Model and Its Application

(1) EMPAL

EMPAL (Employment Allocation Model) is applied to predict the future zonal distribution of employment. Its formulation includes two parts: the zonal employment growth of a specific zone and the employment attracted from other zones. The formulation is shown in Equation (1):

$$E_{j,t} = \left(\frac{e^{\delta}}{1+e^{\delta}}\right)r_t^h \sum_i H_{i,t-1}\left[\frac{W_{j,t-1}e^{\beta_p c_{ji,t}^p + \beta_{op} c_{ji,t}^{op}}}{\sum_k W_{k,t-1}e^{\beta_p c_{ki,t} + \beta_{op} c_{ki,t}}}\right] + \left(\frac{1}{1+e^{\delta}}\right)r_t^e E_{j,t-1} \tag{1}$$

where the term on the left side of the plus sign denotes the employment attracted to zone j in time period t; the term on the right side of the plus sign refers to the employment growth of zone j in time period t; $E_{j,t}$ is the future distribution of employment in zone j in time period t; $H_{i,t-1}$ is the zonal households of all types in zone i in the previous time period $t-1$; $W_{j,t-1}$ is the zonal employment attraction function in the previous time period $t-1$; $c_{ji,t}^p$ is the peak travel time from zone j to zone i in time period t; $c_{ji,t}^{op}$ is the off-peak travel time from zone j to zone i in time period $t-1$; r_t^h is the ratio of total employment in time period t to total number of households in previous time period $t-1$ of the entire area; r_t^e is the ratio of total employment in time period t to total employment in previous time period $t-1$ of the entire area; and δ, β_p, and β_{op} are empirical parameters.

The zonal employment attraction function $W_{j,t-1}$ is expressed as Equation (2):

$$W_{j,t-1} = \left(E_{j,t-1}\right)^{\delta_1} \times \left(L_j\right)^{\delta_2} \tag{2}$$

where is area of zone L_j; and δ_1 and δ_2 are empirical parameters.

Due to the characteristics (e.g., mainly labor-intensive urban industry and relatively low proportion of the service industry and its land use) of the small- and medium-sized cities in China, this study divided jobs into three types: basic, commercial and service employment.

(2) DRAM

DRAM (Disaggregate Residential Allocation Model) is applied to predict the future zonal distribution of households and formulated as shown in Equation (3):

$$\hat{N}_{i,t} = \sum_j E_{j,t} r_t \left[\frac{W_{i,t} e^{\beta_p c^p_{ij,t} + \beta_{op} c^{op}_{ij,t}}}{\sum_k W_{k,t} e^{\beta_p c^p_{kj,t} + \beta_{op} c^{op}_{kj,t}}} \right] \tag{3}$$

where the part in the bracket denotes the zonal household attraction; $\hat{N}_{i,t}$ is the household forecast of zone i in time period t; $W_{i,t}$ is the zonal household attraction function in time period t; and r_t is the ratio of total household to total employment in time period t of the entire area.

The zonal household attraction function $W_{i,t}$ is expressed in Equation (4):

$$W_{i,t} = (L_{i,t})^{\theta \prod_{k=1}^{n} \left(1 + \frac{N^k_{i,t}}{\sum_{k=1}^{n} N^k_{i,t}}\right)^{\gamma_k}} \tag{4}$$

where $L_{i,t}$ is the area of zone i in time period t; and θ and γ_k are empirical parameters.

This study divided the households into three types according to their annual income: low, medium and high income.

2.1.2. Travel Demand Model and Its Application

Travel demand forecasting in the ITLUP model is based on the traditional four-step model:

(1) Trip generation analysis: Estimate the number of trips that a person or vehicle makes in a particular location (usually a zone). It is assumed that the trip production is a linear function of the number of households, and the trip attraction is linear with employments.
(2) Double-constraint gravity model: Predict trip distribution [29].
(3) Multinomial Logit Model: Predict the sharing rate of different traffic modes. Then, the trip distribution is multiplied with the sharing rate to obtain the trip distribution of different traffic modes. The distribution of peak/off-peak travel hours is calculated according to the trip distribution rates of peak/off-peak travel hours.
(4) SUE (Stochastic User-Optimized Equilibrium) in TransCAD: Assign the trips of peak travel hours and off-peak hours in the road network [29]. The travel time estimation is based on the BPR function, and the road network is mainly divided into three types.

2.2. Optimization Method of the ITLUP Model

Through careful analysis and research on the ITLUP model, it can be found that the model has certain limitations: (1) the model does not consider land use intensity constraints, it allocates employment and families to the area even if they do not have enough capacity; (2) the EMPAL and DRAM models are applied sequentially, ignoring the interaction between employment and household; and (3) the ITLUP model does not consider the impact of land prices and commodity trade on employment and household distribution. This limitation will have a greater impact on the application of the model in large cities, while the impact is small in small- and medium-sized cities in China [22]. Therefore, for small- and medium-sized cities, the limitations are mainly reflected in the lack of consideration of urban land capacity. Thus, this study introduced two indicators to illustrate the environmental capacity: maximum number of households and maximum employment.

(1) Maximum number of households

The maximum number of households is the number of households (assume average three persons per household) in a residential area when the residential land per capita reaches the minimum acceptable range. It is formulated as Equation (5):

$$H_i^{\max} = \frac{1}{3} \times \frac{R_i}{R_{aver}^{\min}} \tag{5}$$

where $H_i^{\max}$ is the maximum number of households that zone i can accommodate; R_i is the total area of zonal residential land; and $R_{aver}^{\min}$ is the minimum acceptable residential land per capita.

(2)　Maximum employment

Employment can be divided into basic, commercial and service employment. We analyzed the maximum employment quantity.

The zonal maximum employment on industrial land is the number of employees when the per capita land area reaches the minimum value. It is expressed as Equation (6):

$$B_i^{\max} = \frac{I_i}{I_{aver}^{\min}} \tag{6}$$

where $B_i^{\max}$ is the zonal maximum basic employment; I_i is the total industrial land area in zone i; and $I_{aver}^{\min}$ is the minimum industrial land per capita.

The population of different public facilities consists of two parts: employment and customers. Thus, the zonal maximum employment is equal to the population (when the per capita land area is minimal) multiplied by the ratio of employment to trip attraction. The maximum commercial and service employment are expressed as Equations (7) and (8), respectively:

$$C_i^{\max} = \frac{C_i}{C_{aver}^{\min}} r_i^c \tag{7}$$

where $C_i^{\max}$ is the zonal maximum commercial employment; C_i is the total commercial land area in zone i; $C_{aver}^{\min}$ is the minimum commercial land per capita (it can be defined by Urban public facilities planning norms GB50442-2008); and r_i^c is the ratio of the commercial employment to trip attraction of each zone.

$$S_i^{\max} = \sum_{z=1}^{3} \frac{O_{iz} \times r_{iz}}{O_{aver}^{z\,\min}} \tag{8}$$

where $S_i^{\max}$ is the zonal maximum of other service employment; O_{iz} is the total land area of type z in zone i (z = 1, 2, 3, where 1 indicates administrative land, 2 indicates medical land, and 3 indicates education land); $O_{aver}^{Z\min}$ is the minimum land area per capita of type z; and r_{iz} is the ratio of type-z employment to trip attraction in zone i.

By studying the application and optimization methods of the ITLUP model, the basic frame of the improved ITLUP model is shown in Figure 1.
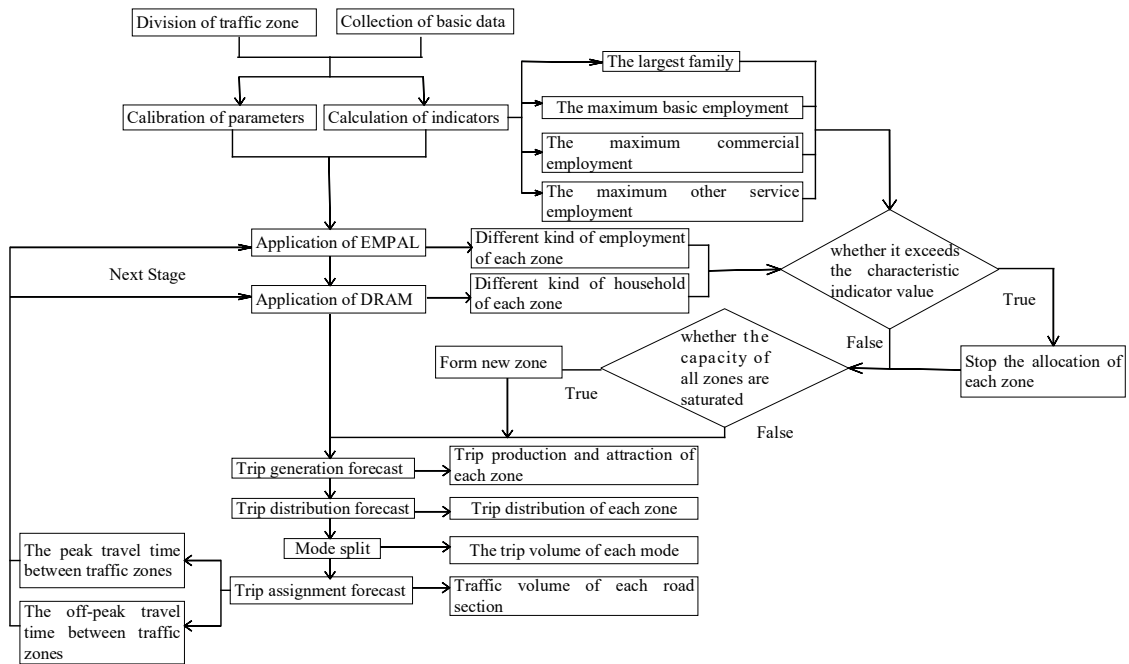
Figure 1. Application process of the improved ITLUP model in small- and medium-sized cities.

2.3. Uncertainty Analysis of the ITLUP Model

2.3.1. Quantitative Method of Uncertainty Factors of the ITLUP Model

(1)   Determining the probability distribution of the input variables and parameters

According to the empirical and historical data and considering the input variables and parameter characteristics of the ITLUP model, we selected the suitable probability distribution for the input variables and parameters. In each part of the prediction model, many variables can only change in the nonnegative range. To avoid the negative number in the process of generating random numbers, we used the lognormal distributions to represent the input variables and parameters [30]. We chose the multivariate log-normal distribution to represent the probability distribution of the input variables and parameters of the ITLUP model.

The log-normal distribution probability density function is shown with location parameter μ_{Int} and shape parameter σ_{Int} as follows:

$$f(t) = \frac{1}{\sqrt{2\pi}\sigma_{Int}} \exp\left[-\frac{1}{2}\left(\frac{Int - \mu_{Int}}{\sigma_{Int}}\right)^2\right] \tag{9}$$

where μ_{Int} is the mean value of the location parameter after the logarithm, which is called the logarithmic mean; and σ_{Int} is the shape after the logarithm of the probability density curve, which is called the logarithmic standard deviation.

The coefficient of variation (C.V) is formulated as Equation (10):

$$C.V = \frac{\sqrt{D((t)}}{E(t)} = \frac{\sqrt{\left(e^{\sigma_{Int}^2} - 1\right)\exp\left(2\mu_{Int} + \sigma_{Int}^2\right)}}{\exp\left(\mu_{Int} + \frac{1}{2}\sigma_{Int}^2\right)} = \sqrt{e^{\sigma_{Int}^2} - 1} \tag{10}$$

(2)   Determining the C.V of the input variables and parameters

The C.V was chosen as the expression variable for the uncertainty of the input variables and parameters. In general, the C.V of some input variables cannot be directly determined. According to the study of Kockelman and related scholars [31], the C.V of an input value is assumed to be 0.3. Thus,

we could calculate their standard deviation by multiplying the mean model inputs by the coefficient of variation.

(3)   Simulation analysis

The simulation analysis was conducted by @Risk (Monte Carlo simulation software). Monte Carlo simulation software can directly generate random samples according to the probability distribution of input variables and the parameters. It can also calculate the output value and distribution of the model in the random samples.

2.3.2. Uncertainty Analysis Method of the ITLUP Model

The multivariate sensitivity analysis method was used to analyze the uncertainty of the ITLUP model. Based on the linear regression of the input and output, the effect of the model input variables and parameters on the uncertainty of the output variables was analyzed.

(1)   Multiple linear regression analysis

Multiple linear regression analysis is a statistical analysis that studies the interrelationship between a dependent variable and multiple independent variables. It assumes that there are P independent variables (X_1, X_2, ... , X_P,) and one dependent variable Y. The linear regression function of these variables is shown as Equation (11):

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_p x_p + \varepsilon \tag{11}$$

where $\beta_0, \beta_1, \ldots , \beta_p$ are regression coefficients; and ε is the error term of the mormal distribution N $(0, \sigma^2)$.

In the uncertainty analysis of the model, a specific output variable can be set as a dependent variable, and the input variables and parameters can be set as independent variables. Then, it combines with Monte Carlo method to calculate the distribution results. The estimated value of the regression coefficients ($\beta_0, \beta_1, \ldots , \beta_p$) can be obtained using the SPSS software.

(2)   Regression coefficient significance test

Using the SPSS software to test the significance of the regression coefficient, the T value and corresponding P value of β_j can be obtained. If P is less than the significant level α (generally 0.05), it implies that β_j is not equal to zero. In other words, the corresponding variable x_j significantly affects the model output variables. If P is greater than 0.05, the corresponding variable x_j will not affect the model output.

(3)   Sensitivity analysis

After performing the linear regression analysis and significance test on the input variables for the output variables, we calculated the standardized regression coefficients (SRC_i) using Equation (12):

$$SRC_i = \frac{\beta_i \times \sigma_i}{\sigma_y} \tag{12}$$

where SRC_i is the standardized regression coefficient; β_i is a regression coefficient; σ_i is the standard deviation of the independent variable; and σ_y is the standard deviation of the dependent variable.

2.4. Data Acquisition

This study considered the main urban area of Huangling County (in Shaanxi province, China) as an example to run the whole optimization method. Referring to the document of "Huangling County Urban Comprehensive Traffic Planning 2014–2030", the main urban area was divided into nine traffic zones, where Zones 1–7 are the inner zones, and Zones 8 and 9 are the external zones. The population of the main urban area is 35,892. Current zonal land use data, zonal number of household and employment, households type due to household income, employment type, peak and off-peak travel time between zones, travel time and travel expenses of various modes of transportation, annual average growth rate of employment and population were needed to operate this model.

The current zonal land use data of each internal traffic zone are shown in Table 1. The current employment and household distribution are shown in Table 2.

Table 1. Current status of the classified land area of each zone (10,000 m^2).

Zone	Residential Land	Commercial Land	Administrative Land	Medical & Health Land	Education Land
1	6.11	0.75	0	0	0
2	4.25	1.30	0	0	0
3	8.62	3.11	0	0	0
4	17.19	0	0	0	0
5	8.71	2.48	0	0	0.92
6	8.07	4.66	1.91	1.31	1.25
7	7.51	0	0	0	0

Table 2. Current status of the classified households and employment in the zone.

Zone	Commercial Employment	Other Service Employment	Low-Income Family	Medium-Income Family	High-Income Family
1	307	0	151	333	121
2	553	0	105	231	84
3	1439	0	213	469	171
4	0	0	425	935	340
5	1149	234	215	474	172
6	2073	5242	200	439	160
7	0	0	186	409	149

Note: According to the household income, the households were divided into three types: low income (annual income less than ¥30,000), medium income (annual income ¥30,000–70,000) and high income (annual income above ¥70,000).

3. Results and Discussion

3.1. Prediction Results of the Model

Based on the survey data and Equations (5)–(8), the maximum allowable number of households and employment in each zone were calculated, and the results are shown in Tables A1 and A2 (see Appendix A).

The model parameters were calibrated by the data from 2012 and 2014. Assuming that the input C.V was 0.3, the predicted results of all types of employment were obtained. The results are shown in Appendix A.

The prediction results show that, under the effect of the model input and parameter uncertainty, the maximum employment and households in the main urban areas of Huangling County will exceed the land capacity limit index by 2030. The main results are as follows: (1) The whole maximum employment of the largest commercial employment and other services in the main urban areas exceed the land bearing limit (17,980 = 9026 + 8954), which is expected to reach 2967 (1489 + 1478).; (2) The maximum employment of other services exceeds the land bearing limit (8954), which is expected to reach 1478 (see Table A1 in Appendix A). (3) The maximum number of households exceeds the land limit (9782), which is expected to reach 1873 (see Table A2 in Appendix A). (4) The C.V value of the commercial and other service employment (excluding the other service employment in Zone 6) and the number of households in each zone increase compared with the input coefficient variation coefficient (0.3). Therefore, according to the established optimization model, Huangling County must build a new Zone 10 to satisfy the demand growth of the city in terms of population and employment.

As shown in Table A3 in Appendix A, the maximum traffic volume on all roads during peak hours reaches 90% of capacity. In addition, the V/C ratio during peak travel time is 0.9–1.0. Thus, the LOS of the road is E, indicating that the traffic flow is in an unstable state and will result in significant

time delays. Therefore, in the follow-up urban planning work, a series of adjustments to the urban space layout and road traffic conditions is necessary. For instance, from the perspective of green transportation and sustainable development, planners can consider optimizing land use mix, urban residential space design, and traffic structure to improve accessibility and reduce carbon emissions.

3.2. Prediction Results of Uncertainty Analysis

The multivariate sensitivity analysis was used to analyze the effect of the input changes on the uncertainty of the output, and the standardized regression coefficients were calculated. The statistical distribution of the optimized employment and household after Monte Carlo simulation is shown in Figure 2. The results of the sensitivity analysis are shown in Tables A4 and A5 in Appendix B.
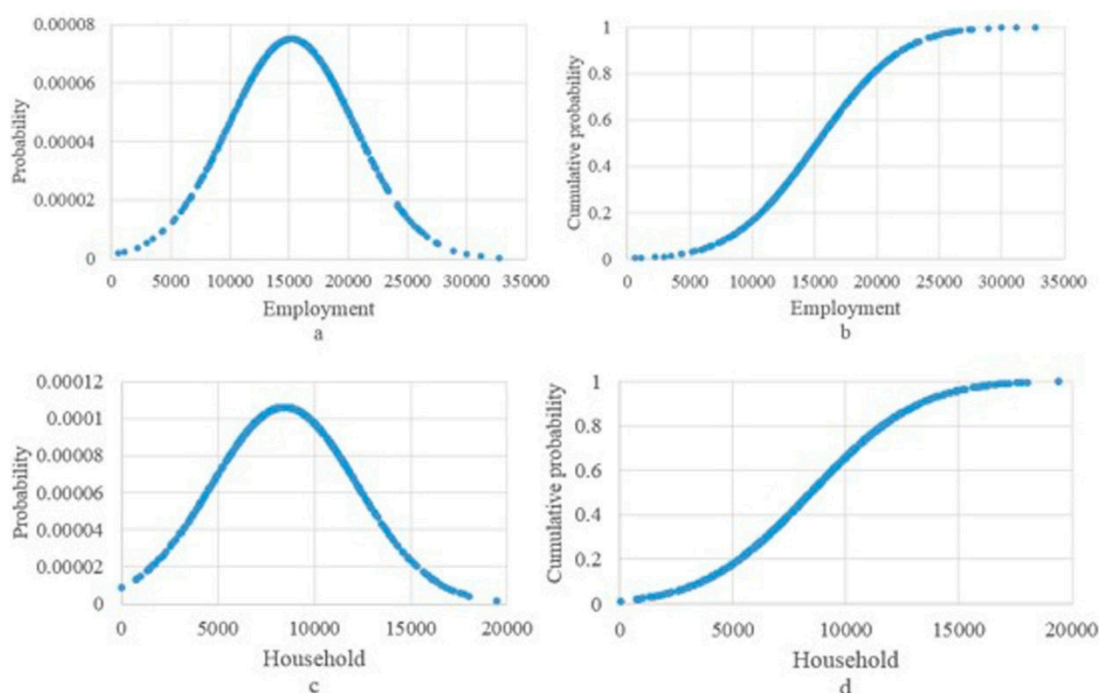

Figure 2. Optimized statistical distribution of employment (**a**, **b**) and household (**c**, **d**).

The sensitivity analysis results show three points. (1) The input with a large impact on the uncertainty of urban employment included the DRAM model parameters. The most influential factors were γ_3^M (SRC = 3.112), γ_2^H (SRC = 0.753), and β_P^H (SRC = 0.387). In other words, when the level of uncertainty in the input parameters of the DRAM model decreased, the level of uncertainty in the forecast of urban employment also decreased. (2) The input with a large impact on the uncertainty of the household volume included the traffic demand forecasting model parameters, where the most influential factors were b_2^M (SRC = 0.159) and β_1 (SRC = 0.191). In other words, when the level of uncertainty in the parameters of the traffic demand forecasting model decreased, the uncertainty of the model prediction of the household volume also decreased. (3) The uncertainty of the peak hour flow of various roads was mainly affected by the peak hourly flow ratio μ. The SRC (0.211) of arterial road μ was the largest, which indicated that it greatly affected the uncertainty of the arterial road flow. The off-peak hour flows were mainly affected by r_p (SRC = 0.231/0.221/0.227), c_1^c and traffic demand parameters c_1^c (SRC = 0.179/0.172/0.177) and β_{link}^k (K = 1/2/3, corresponding SRC$_1$ = 0.199, SRC$_2$ = 0.190, SRC$_3$ = 0.196). In other words, the uncertainty of the predicted value of the peak hourly flow of each type of road decreased with the decrease in uncertainty of the peak hour flow rate. The uncertainty of the forecast of the off-peak hour flow decreased when the uncertainties of the average population growth rate (r_p) and traffic demand parameters decreased (c_1^c and β_{link}^k).

3.3. Analysis of the Uncertainty Propagation Over Time

The C.V of the output was used to study the evolution of the model uncertainty with time. The variation trend of C.V over time is shown in Figure 3.
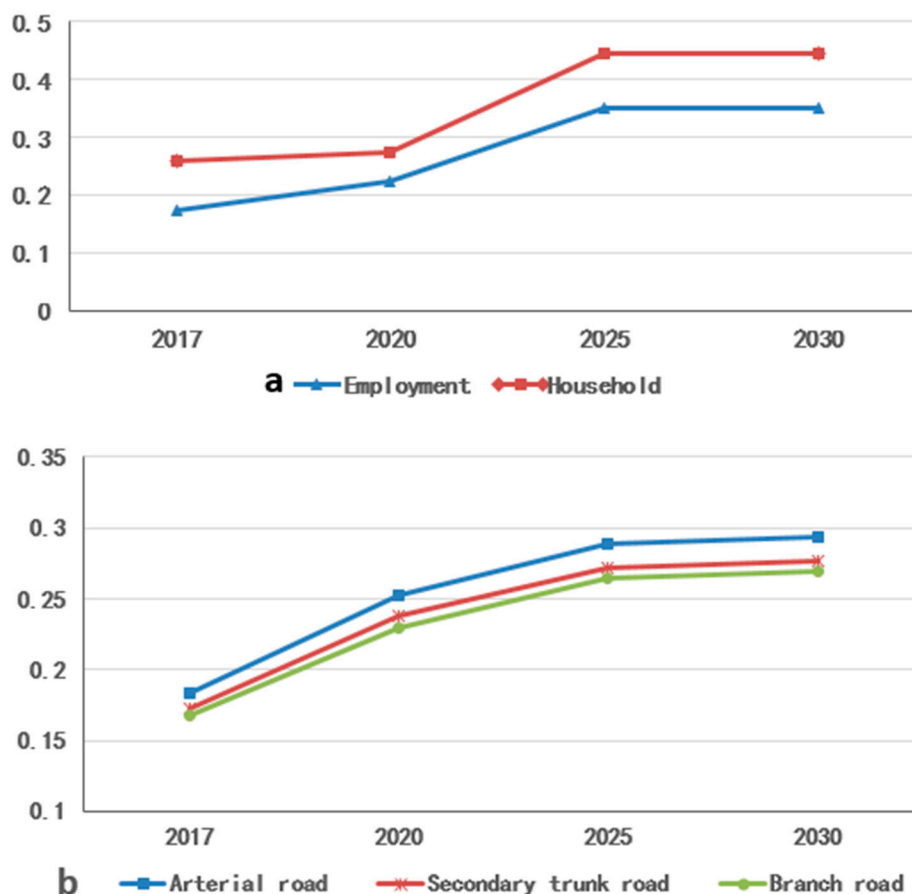

Figure 3. Time-varying trend chart in the main urban area: (**a**) total employment and household; and (**b**) peak period road V/C ratio.

The C.V of the output variables of the model gradually increased with time. For 2030, the uncertainty levels of employment and households were 35% and 44.5%, respectively. In the future planning process, urban planners should pay more attention to the layout structure of residential areas and pay attention to the flexibility of medium and long-term residential design. The uncertainty levels of the traffic V/C ratios at various road peak times were: arterial road was 29.4%, secondary trunk road was 27.7%, and branch road was 26.9%. Thus, decision makers should pay attention to the balance of different grades of road layout when planning traffic.

4. Conclusions

Based on the characteristics of land use and transportation systems in small- and medium-sized cities, this study selected the ITLUP model as the method and studied its application. By analyzing the limitations of the ITLUP model in application and the development characteristics of small- and medium-sized cities, we introduced two indicators: maximum number of households and maximum employment, to optimize the ITLUP model. Then, by analyzing the sources of uncertainty, the meanings of the model input variables and parameter uncertainties and their effect on the model were expounded. The analysis method of uncertainty of the ITLUP model was established. The effects of the model input variables and parameter changes on the uncertainty of output and evolution of the uncertainty of model predictions over time were studied. The results show that:

(1) Through the introduction of two characteristic indicators, the traditional ITLUP model was optimized for employment and family allocation, and the model operation simulation was closer to the actual situation of small- and medium-sized cities. The prediction results show that the county needs to build a new zone to satisfy the demand growth of the city when zonal land capacity is considered. Thus, it is important to coordinate the relationship between urban development and resource and environment carrying capacity. Planners may analyze the future urban land use development based on the forecast results, and carry out effective resource allocation to provide reference for land structure optimization, green traffic and environmental protection.

(2) The uncertainty of the model output variable gradually increased with time (The C.V value of the model output shows the increasing trend over time). Therefore, when using this model to predict the development of small- and medium-sized cities, it is necessary to ensure the accuracy of these variables, which are DRAM model parameters, traffic demand forecasting model parameters and the peak hourly flow ratio (see Section 3.2). At the same time, the model had great uncertainty for long-term planning, and the prediction for short- and medium-term was more accurate.

The findings of this study emphasize the importance of ITLUMs in the study of integration development of Land use and transportation [12,32,33]. In general, by considering land use restrictions, the introduction of maximum number of households and maximum employment can effectively alleviate the inconsistency between the construction of transportation systems and the pace of urban economic development in the urban development process. Using the optimized model, urban planners can leave a buffer for the short- and medium-term urban construction by measuring the maximum land use restrictions, which can effectively avoid the traffic congestion caused by land tension in future urban developments. This study enriches the practical application in small- and medium-sized cities in China and illustrates the applicability of the ITLUP model, which takes land carrying capacity into account in small- and medium-sized cities. It can also be a reference for future development.

However, the limitations in this study should be recognized. First, the example in the study did not consider the mode of public transportation. The ITLUP model should be applied to the development forecast of other small- and medium-sized cities, and the effect of public transportation development trend and model uncertainty on it should be applied to make the application of the model more extensive. Second, the two characteristic indicators for model optimization were mainly calculated based on the corresponding specifications, but different cities have different land use situations, and their values may vary. Therefore, it is necessary to further analyze and research in conjunction with the actual situation of specific cities to determine the value of the characteristic indicators. Third, in the uncertainty analysis of the model, to reflect the model input variables and parameter changes, their coefficient of variation was set. However, this is relatively simplistic, and might not be accurate. Therefore, it is necessary to further study the value of the coefficient of variation to more accurately represent the uncertainty of the model input.

Appendix A Prediction Results of the Optimized ITLUP Model

Table A1. Zonal distribution of employment in 2030.

Zone	Type	Min	Mean Value	Max	Standard Deviation	5% Quantile Value	95% Quantile Value	C.V
1	C	344	426	*502*	167	361	480	0.393
2	C	618	764	*904*	242	648	862	0.316
3	C	1611	1994	*2353*	810	1692	2250	0.406
5	C	1286	1591	*1878*	667	1350	1795	0.419
	S	263	325	*383*	123	276	367	0.379
6	C	2316	2866	*3389*	943	2432	3233	0.329
	S	5858	7249	*8571*	2157	6151	8178	0.298
Total		12,289	15,207	*17,980*	5323	12,903	17,156	0.350
10	C	1014	1254	1489	468	1064	1415	0.373
	S	1006	1245	1478	422	1056	1404	0.339

NOTE: C, Commercial; S, Service. Total (17,980) = Total C (9026) + Total S (8954). The bold values, the maximum allowable number of employment in each zone.

Table A2. Zonal distribution of households in 2030.

Zone	Minimum Value	Mean Value	Maximal Value	Standard Deviation	5% Quantile Value	95% Quantile Value	C.V
1	692	857	*989*	408	727	967	0.476
2	480	594	*687*	227	504	670	0.383
3	976	1207	*1395*	594	1024	1362	0.492
4	1942	2403	*2781*	994	2039	2711	0.414
5	986	1220	*1409*	619	1035	1376	0.507
6	912	1128	*1306*	449	957	1273	0.398
7	850	1052	*1215*	485	893	1187	0.461
Total	6830	8452	*9782*	3761	7171	9534	0.445
10	1275	1578	1873	705	1339	1780	0.447

NOTE: The bold values, the maximum allowable number of households in each zone.

Table A3. Distribution of the road V/C ratio in the main urban area in 2030.

Time	Type	Min	Mean	Max	Standard Deviation	5% Quantile Value	95% Quantile Value	C.V
Peak travel time	1	0.68	0.84	1.00	0.24	0.71	0.95	0.289
	2	0.64	0.79	0.94	0.22	0.67	0.89	0.272
	3	0.62	0.77	0.91	0.20	0.65	0.87	0.264
Off-peak travel time	1	0.37	0.46	0.55	0.14	0.39	0.52	0.294
	2	0.35	0.44	0.52	0.12	0.37	0.49	0.277
	3	0.34	0.42	0.50	0.11	0.36	0.48	0.269

NOTE: 1, Arterial road; 2, Secondary trunk road; 3, Branch road.

Appendix B Prediction Results of Uncertainty Analysis

Table A4. Results of the sensitivity analysis of employment and household.

Input Variable	Total Employment SRC	p	Total Family SRC	p	Input Variable	Total Employment SRC	p	Total Family SRC	p
β_p^C	−0.285	0.001	-	-	γ_3^H	−0.766	0.001	-	-
δ_1^C	0.224	0.013	-	-	β_p^H	0.387	0.038	-	-
β_{op}^S	-	-	−0.167	0.046	b_2^M	-	-	0.159	0.028
γ_1^M	−3.326	0.000	-	-	c_1^C	0.212	0.001	-	-
γ_2^M	0.212	0.026	-	-	α_1	-	-	−0.221	0.025
γ_3^M	3.112	0.000	-	-	β_1	-	-	0.191	0.045
θ^H	0.242	0.025	-	-	α_2	-	-	−0.249	0.012
γ_2^H	0.753	0.001	-	-	α^2	0.158	0.021	-	-

NOTE: C, Commercial; S, Service; M, Medium; H, High; c_1^C, α_1, β_1, α_2 and α^2 are the traffic demand forecasting parameters.

Table A5. Results of the sensitivity analysis of all types of road V/C ratio.

Input Variable	Arterial Road Peak Travel Time SRC	p	Arterial Road Off-Peak Travel Time SRC	p	Secondary Trunk Road Peak Travel Time SRC	p	Secondary Trunk Road Off-Peak Travel Time SRC	p	Branch Road Peak Travel Time SRC	p	Branch Road Off-Peak Travel Time SRC	p
r_E	-	-	0.138	0.049	-	-	0.132	0.050	-	-	0.136	0.048
r_P	-	-	0.231	0.001	-	-	0.221	0.001	-	-	0.227	0.001
c_1^C	-	-	0.179	0.013	-	-	0.172	0.012	-	-	0.177	0.014
μ	0.211	0.000	-	-	0.202	0.000	-	-	0.208	0.000	-	-
β_{link}^1	-	-	0.199	0.006	-	-	-	-	-	-	-	-
β_{link}^2	-	-	-	-	-	-	0.190	0.008	-	-	-	-
β_{link}^3	-	-	-	-	-	-	-	-	-	-	0.196	0.009

NOTE: C, Commercial; r_E is the average employment growth rate; r_P is the average population growth rate; μ is the peak hourly flow ratio; β_{link}^1, β_{link}^2 and β_{link}^3 are the traffic demand forecasting parameters.

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