# BUDEM: An urban growth simulation model using CA for Beijing metropolitan area

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**ABSTRACT**

It is in great need of identifying the future urban form of Beijing, which faces challenges of rapid growth in urban development projects implemented in Beijing. We develop Beijing Urban Developing Model (BUDEM in short) to support urban planning and corresponding policies evaluation. BUDEM is the spatio-temporal dynamic model for simulating urban growth in Beijing metropolitan area, using cellular automata (CA) and Multi-agent system (MAS) approaches. In this phase, the computer simulation using CA in Beijing metropolitan area is conducted, which attempts to provide a premise of urban activities including different kinds of urban development projects for industrial plants, shopping facilities, houses. In the paper, concept model of BUDEM is introduced, which is established basing on prevalent urban growth theories. The method integrating logistic regression and MonoLoop is used to retrieve weights in the transition rule by MCE. After model sensibility analysis, we apply BUDEM into three aspects of urban planning practices: (1) Identifying urban growth mechanism in various historical phases since 1986; (2) Identifying urban growth policies needed to implement desired urban form, namely planned urban form; (3) Simulating urban growth scenarios of 2049 in different policies.

**Keywords:** cellular automata, policy simulation, urban growth simulation, logistic regression, BUDEM, MonoLoop, desired urban form

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## 1. INTRODUCTION

In the background of the boom of domestic macro-economy and Olympic economy, it is in great need of identifying the future urban form, including post-Olympic games (2009), the end year of urban master planning (2020), and the 100 anniversary of the foundation as P. R. China's capital (2049). Furthermore, it is essential to forecast the long-term urban form to support the next round of urban planning. At the same while, in some of major metropolitan area, such as London metropolitan area, San Francisco bay, California area, comprehensive urban models have been developed to simulate urban systems. Yet, it is still vacant for Beijing, even for main cities in whole China. Hence, we develop Beijing Urban Developing Model (BUDEM in short) to support urban planning and corresponding policies evaluation. BUDEM is the spatio-temporal dynamic model for simulating urban growth in Beijing metropolitan area, using cellular automata (CA) and Multi-agent system (MAS) approaches. BUDEM is developed for the municipal government and planning committee of Beijing metropolitan area with an area of 16410 $km^2$, and its spatial resolution is 500m. In this phase, the computer simulation using CA in Beijing metropolitan area is conducted, which is attempting to provide a premise of urban activities including different kinds of urban development projects for industrial plants, shopping facilities, houses, etc.

Regarding urban model, which is initiated in the early years of twentieth century, has experienced structural model, static model and dynamic model phases. Traditional urban models, basing on differential equations or quasi dynamic, usually simulate urban system in macro level, and are lack of reflecting the dynamic, self-organizing, emerging characters of urban system in some degree. With the developing of GIS and complex science, the urban model, based on artificial life or discrete dynamics, is the hot point in researches. In recent years, it is prevailing to simulate urban growth by means of CA, which is based on self-organizing theory, and is different from system dynamic model. It is composed by a series of basic rules, instead of strictly defined physics equations or functions. Besides, discrete is the key character for the time, space and status in CA. CA is adapted to simulate the emergence, self-organizing and chaos phenomenon in the urban system.

Nowadays, CA is a practical tool to simulate urban growth, which is also one main field for its application. Tober(1970) initially simulates urban expansion of five lake region of America. Couclelis(1985, 1988, 1989, 1997) claims that it is possible for CA with simple rules to generate complex urban forms in a virtual city, and it shows the great potential of CA to be able to be applied in urban growth field. White and Engelen(1993) attempt to apply CA in urban planning, and White and Engelen(1997) simulate the land use pattern of Cincinnati of America. Clark and Gaydos(1998) establish SLEUTH model, and apply it to simulate long-term urban growth of San Francisco bay area and Washington-Baltimore area of America, which is the earlier practice for CA to simulate for real cities. Besides, Batty(1991, 1994, 1996, 1997, 1998, and 1999) conducts abundant researches on fractal and CA to study urban formation and expansion phenomenon. Xie(1994) simulates the land use change of Buffalo of America. Wu(1998a, 1998b, and 2002) employs MCE to found the status transition rule of CA, and apply it in the urban expansion simulation of Guangzhou, China.

Regarding domestic relevant applications of CA, Li and Yeh explore various intelligent methods to retrieve transition rule of CA, bring forward constrain CA model to simulate sustainable urban form of Pearl River Delta, and develop uncertainty analysis of CA (Li and YEH, 1998, 2000, 2002, and 2004; YEH and Li, 2001, 2002, and 2006). In brief, other academicians separately employ CA to simulate urban growth of Haikou city (Wu and Zhao, 2002)), Wuhan main city (Luo, 2005), Fuzhou city (Li, 2005), Xian city (Guo *et al*, 2004), Northern China (He *et al*, 2006), Partial Beijing metropolitan area (Shen *et al*, 2007).

In summary, there are many applications on simulating urban growth using CA, and in China, CA is also employed to predicting urban growth in some cities. However, it is not reported that simulating urban growth of Beijing metropolitan area using CA. BUDEM, as an urban form simulating platform, is tightly developed for Beijing urban planning practice, and is a tempting practice of CA for urban planning application of a maga-city. Firstly, with respect to model establishing method, logistic regression and MonoLoop are integrated to retrieve transition rule of CA, which is also one innovative method to realize desired urban form. Secondly, with respect to spatial factors considered in BUDEM, comprehensive environmental constraining, urban planning condition are adopted to reflect the Chinese urban developing characters. Finally, regarding model application, we obtain historical urban growth mechanisms since 1986 via logistic regression, advance the urban growth policies needed to achieve planned urban form of 2020, and predict urban form of 2049 with different policies sets.

## 2. MODEL ESTABLISHING

### 2.1 Spatial factors selection

The urban growth researches in macro level, which do not consider urban spatial distribution, regard the urban system as one whole entity, and the drivers for urban growth consist of population changing, SciTech varying, economy increasing, political structure, etc (Stern, 1992). However, the paper prefers the self-organizing process research inner urban system. It is clear in classical urban land use model that urban developing is influenced by location and geographic conditions. Alonso (1964) points out in the single center urban location theory that the distance to urban center is the principal factor on urban land use structure. The optimum land type will change with the distance to urban center, because of the change of the accessibility and transportation cost. In addition, Doxiadis, who found human settlement science, concludes that distance to present urban center, to main road, to natural landscape are the main forces for human settlement (WU, 2001). In addition, Hedonic model provides clearer framework, which considers that commodity price is determined by the total utility of different properties, and price differs from the number and composition of commodity’s properties (Lancaster, 1966). For example, Butler (1982) holds the point that residential price is affected by three types of factors, location, architecture structure and neighborhood, and its price reflects the total preferences by the consumer. Urban developing is quite familiar with residential price, and its probability is the reflection of relevant parameters of the lot or block by developer. Hence, we choose spatial variables in CA as shown in table 1, referring the theory of Hedonic and considering the acquiring possibility of corresponding data.

Table 1. Spatial variables in CA

| Type | Name | Value | Description | Data |
|---|---|---|---|---|
| SELF-STATUS | *isrural* | 0，1 | Whether is rural built-up | LANDUSE, LANDi |

| Type | Name | Value | Description | Data |
|---|---|---|---|---|
| | *isagri* | 0，1 | Whether is agriculture land | LANDUSE |
| LOCATION | *d_tam* | >=0 | Minimum distance to Tian’anmen square | LOCATION |
| | *d_vcity* | >=0 | Minimum distance to VIP new city | |
| | *d_city* | >=0 | Minimum distance to new city | |
| | *d_vtown* | >=0 | Minimum distance to VIP town | |
| | *d_town* | >=0 | Minimum distance to town | |
| | *d_river* | >=0 | Minimum distance to river | |
| | *d_road* | >=0 | Minimum distance to road | |
| | *d_bdtown* | >=0 | Minimum distance to town boundaries | BOUNDARY |
| GOVERNMENT | *planning* | 0, 1 | Whether planned as urban built-up | PLANNING |
| | *con_f* | 0, 1 | Whether in forbidden zone | CONSTRAIN |
| | *landresource* | 1-8 (integer) | Land classification for agricultural suitability | LANDRESOURCE |
| NEIGHBOR | *neighbor* | 0-0.125 | Developing intensity in neighborhood | LANDi |

Note: Data LANDi is the generated land use layer when CA iterating

### 2.2 Concept model

The premises of BUDEM establishing are as followed. Firstly, urban is a complex self-adaptive system, and bottom-to-up method is available to simulate urban growth. Secondly, urban growth forces can be classified into promoting type and restraining type. Meanwhile, they can be divided into market driving and government inducting types. Thirdly, the historical developing rule is also fit for the future one with the same developing trend. Finally, various urban growth scenarios can be generated with some modification basing on baseline predicting scenario.

With the above premises, Concept model of BUDEM using CA is established (Shown in formula 1). CA lattices are Beijing metropolitan area, with an area of 16410 km$^2$, which is adjustable according to the simulating purpose. Cell size of CA is 500m*500m with the shape of square, and totally 65628 cells is contained in the whole lattices. Cell states of CA is 1 or 0, while 1 stands for urban built-up land, and 0 stands for non urban built-up land. Multi-criteria evaluation (MCE in short) is applied as transition rule of CA, and 3*3 Moore is used as CA neighborhood with 8 adjacent cells. Regarding discrete time of CA, we use the total number of urban built-up cells to link the relationship between it and the real time.

$$
\begin{aligned}
V_{i,j}^{\,t+1} &= f\left\{V_{i,j}^{\,t}, Global, Local\right\} \\
&= \left\{V_{i,j}^{\,t}, LOCATION, GOVERNMENT, NEIGHBOR\right\} \\
&= f\left\{\begin{array}{l}
V_{i,j}^{\,t}, isrural_{i,j}, isagri_{i,j} \\
d\_tam_{i,j}, d\_vcity_{i,j}, d\_city_{i,j}, d\_vtown_{i,j}, d\_town_{i,j}, \\
d\_river_{i,j}, r\_road_{i,j}, d\_bdtown_{i,j}, \\
planning_{i,j}, con\_f_{i,j}, landresource_{i,j}, \\
neighbor^{t}{}_{i,j}
\end{array}\right\}
\end{aligned} \tag{1}
$$

$V_{i,j}^{\,t}$ is the cell status at ij of time t

$V_{i,j}^{\,t+1}$ is of the cell status at ij of time t+1

$f$ is the transition rule

On the whole, the cell status in each iteration is influenced by self status variables of last iteration, global variables and local variable as listed in table 1. Self status variables include *isrural* and *isagri*, reflecting the just cell’s status in last iteration. With respect to global variables, location type and government type variables are included, which keep static among all iterations. Variable *neighbor* is the only local variable in CA, and it keeps changing when iterating. In BUDEM, the transition from urban non built-up to urban built-up is simulated, while the reversed process is not considered, and the urban redevelopment is also not reflected.

Besides CA model, we develop Macro-restraining sub-model (MSM in short) as the other part of BUDEM. MSM, using urban developing serial data as described in “Data” section, is capable of predicting the total amount of urban built-up of each future year. The total amount is the core parameter for controlling the number of CA iterations, namely the time point of model terminating. In addition, it can calculate the corresponding real time (Year) for each step of model simulating.

Urban Economists adopt regression method, such as logistic regression, multi-logit model, etc., to calculate the urban developing probability, and it is proved to be one reasonable method to identify the relationship between land use change and locational characters. However, the self-organizing process of land development is not considered. Spontaneous growth and self-organizing growth integrated in BUDEM using CA is its leading merit to simulating urban growth.

### 2.3 Status transition rule

Transition rule, as the core of CA, has been being the hot point in the field of CA research. Various methods to retrieve transition rule are developed, such as MCE, grey theory, principal component analysis (PCA), artificial neural network (ANN), genetic algorithm, rough sets, case-based reasoning, etc. MCE is implemented to establish the CA status transition rule in the paper.

On one hand, Landis(1994, 1995, 1998a, 1999b) develops CUF and CUF-2 to predict urban form, which is the typical application of MCE in urban growth modeling field. CUF and CUF-2 use DLU (Developing land use unit) as the basic modeling unit, instead of cell of CA. Regarding simulating urban growth using CA with MCE, Wu (2002) brings forward the transition rules as shown in formula 2.

$$P_c^t = P_g * con(s_{ij}^t = suitable) * \Omega_{i,j}^t \tag{2}$$

In the above formula, $P_g$ is the urban growth suitability, namely global probability, calibrated by MCE method, $\Omega$ is the neighborhood effect, *con* is the environmental restraining effect, and $P_c^t$ stands for joint probability. Wu(1998a, 1998b) adopts AHP method to obtain the weights of spatial variables in MCE, and Wu(2002) avails logistic regression to retrieve the weights basing historical developing data. Wu finds one essential and convenient method, namely MCE, as applicable CA transition rule, yet the means of acquiring weights for spatial variables in MCE is concerned by us. AHP method is lack of repeating and also over subjective, and it is impossible to identify the historical urban developing trend. With respect to the latter method for obtaining MCE weights, neighborhood and environmental effects are separately multiplied to $P_g$, instead of being included in the logistic regression procedure. As a result, the logistic regression does not include all the relevant factors. Therefore the weights via regression can’t entirely explain the urban growth developing trend in some history phase.

On the other hand, Clark and Gaydos(1998) put forward rigorous calibration method. In the method, firstly, generate simulating result with different parameter sets (Nested loops). Secondly, match each simulated result with observed form, and calculate the matching indexes (the r-squared fit between the actual and predicted number of Urban pixels, Edges in the images, Separate clusters and A modified Lee-Sallee shape index). Finally, the parameter set with best matching index is then employed to predict urban form in future. Five parameters are considered in Clark’s model, and respectively 6, 6, 6, 5, 7 values for each parameter are tested. Consequently, 7560 parameter sets are generated and used to calibrate, and it takes 252 hours for the rigorous calibration process. If the number of parameters increased, the calibrating time cost will go up exponentially. With regard to BUDEM, there are 14 parameters in it. Supposing that every parameter has 6 values for testing and the same time cost for every iterating, the total calibrating time cost will probably be 298189 years, not to speak of the limitation of only 6 choices for each parameter. In spite that Clark and Gaydos’ method can identify the most possible parameter set for model simulating, the time cost for such an intensive computing will not be acceptable even calibrated by the most advanced workstation.

We integrate the methods of Wu(2002) and Clark and Gaydos(1998), with each advantage, to retrieve the weights in MCE formatted transition rule of BUDEM (Shown in formula 3). In BUDEM, all the spatial variables, except *neighbor*, are included in the logistic regression equation, and the corresponding coefficients, namely weights $w^{1-13}$ in MCE, can be obtained. In the regression, dependent variable is 1 or 0, since that the land use changing status is either “Developed” or “Undeveloped”. Independent variables in regression are 13 spatial variables (all except neighbor). Dependent variable is acquired by algebra operation on LANDUSE datum of start year and end year. Basing sample tool in ESRI ArcGIS, dependant variable and independent variables for logistic regression are sampled into a table, and then is analyzed in SPSS environment to obtain $w^{1-13}$ in form of coefficients.

$$
\begin{aligned}
& s_{ij}{}^{t} = \beta_0 + \beta_1 * isrural_{ij} + \beta_2 * isagri_{ij} \\
& + \beta_3 * d\_tam_{ij} + \beta_4 * d\_vcity_{ij} + \beta_5 * d\_city_{ij} + \beta_6 * d\_vtown_{ij} + \beta_7 * d\_town_{ij} \\
& + \beta_8 * d\_river_{ij} + \beta_9 * r\_road_{ij} + \beta_{10} * d\_bdtown_{ij} \\
& + \beta_{11} * planning_{ij} + \beta_{12} * con\_f_{ij} + \beta_{13} * landresource_{ij} \\
& + \beta_{14} * neighbor^{t}{}_{ij} \\
& p_g{}^{t} = \frac{1}{1 + e^{-s_{ij}{}^{t}}} \\
& p_{ij}{}^{t} = \exp\left[\alpha\left(\frac{p_g{}^{t}}{p_g{}^{t}{}_{\max}} - 1\right) * RI_{ij}{}^{t}\right] \\
& \qquad RI_{ij}{}^{t} = 1 + \left(\gamma_{ij}{}^{t} - 0.5\right)/k \\
& if\ \ p_{ij}{}^{t} > p_{threshold}\ then\, V_{ij}{}^{t+1} = 1
\end{aligned} \tag{3}
$$

After that, the weigh for variable neighbor ($wN^*$) can be calibrated out, by using sole parameter looping method (MonoLoop), instead of looping all parameters' weights like Clark and Gaydos. Various *wN* values are calibrated to find $wN^*$ with the best matching index while keeping obtained $w^{1\text{-}13}$ constant. Then, $wN^*$ retrieved accomplishing with $w^{1\text{-}13}$ are inputted in the transition rule to simulate urban growth form. *Goodness-of-fit* (accuracy of point to point comparing, *G* in short) is selected to assess the matching degree between simulated and observed urban forms, and its maximum value in theory is 100%. For one thing, our method combining logistic regression and MonoLoop can reduce model calibrating time greatly. For another thing, the method is able to identify historical urban growth trend.

In the formula 3, $s_{ij}{}^t$ stands for developing suitability, $\beta$ stands for coefficients in logistic regression, $p_g{}^t$ stands for initial transition probability, $p_g{}^t{}_{max}$ is the max value of $p_g{}^t$ in iteration *t*, $p_{ij}{}^t$ stands for final transition probability, $p_{threshold}$ stands for urban growth threshold, *RI* stands for random item, $\gamma$ stands for random value varying from 0 to 1, *k* stands for random index, used to regulate *RI*, and $\alpha$ stands for dispersion parameter ranging from 1 to 10, indicating the rigid level for developing. The bigger $\alpha$ is, the stricter the developing control is, namely, the smaller developing probability with the same suitability. Hence, the parameter $\alpha$ has a great impact on the simulated urban form.

Moreover, random item (*RI*) is included in transition rule to denote the developing out of the explanation of selected spatial variables, such as leapfrog type developing. With introducing *RI* into the transition rule, the simulated result will be more practicable. Constant threshold ($p_{threshold}$) is applied, instead of static or random one, which can guarantee the same developing standard for urban develop in different phases. Meanwhile, variables *isagri* and *isrural* stand for the transition from agriculture land and rural built-up, which is concerned by Beijing municipal government.

### 2.4 Data

We classify spatial data in BUDEM into seven types, LANDUSE, PLANNING, CONSTRAIN, LANDRESOURCE, LOCATION, BOUNDARY, as well as UrbanInfoSeries. All spatial data are converted into ESRI single band GRID format, with the same coordinate and projection system.

(1) LANDUSE: as the most complete data ever since the foundation of China, the time points of them cover the years of 1947, 1964, 1976, 1981, 1986, 1991, 1996, 2001 and 2006, in which, data of year 1947 is digitalized from relief map, data of year 1964 is interpreted from DISP aerial image, data of year 1976 and year 1981 are interpreted from MSS images, and others are interpreted from TM images. LANDUSE is classified into six land use types, urban built-up area, rural built-up area, agriculture area, forest area and vacant area. Variable *landuse* is retrieved from LANDUSE data, and it is valued 1 for urban built-up area, and 0 for other area.

(2) PLANNING: five times urban master plans for Beijing metropolitan area were conducted, and currently it covers the years of 1958, 1973, 1982, 1993 and 2004, which is classified into urban built-up area and non urban built-up area (Beijing urban planning committee et al, 2006). Variable *planning* is retrieved from PLANNING.

(3) CONSTRAIN: it reflects the urban developing constraining degree, and is generated by 110 spatial layers of natural resources protection and hazard prevention according to current laws, legislations, and standards of China. CONSTRAIN

is zoned into three types, forbidden built-up area, constraining built-up area and suitable built-up area. Variable *con_f* stands for forbidden built-up area.

(4) LANDRESOURCE: it stands for the suitability of agriculture land use, which is classed into eight types ranging from 1 to 8, showing the suitability in turn (Beijing planning commission, 1988). Variable *landresource* is obtained from LANDRESOURCE with the same value.

(5) LOCATION: it stands for the location condition, including the minimum distance to urban or town centers of different administrative levels, to road (*d_road*) and to river (*d_river*). Location type spatial variables are retrieved from LOCATION using Distance/Straight Line command in ESRI ArcGIS.

(6) BOUNDARY: it consists of administrative, ring road, eco-zoning, as well as watershed boundaries, and different transition rules in various areas are available with the data (not conducted in the paper). Variable *d_bdtown* is retrieved from the data.

(7) UrbanInfoSeries: population, resources, environment, economy and society data is included in UrbanInfoSeries, which favors the Macro-restraining sub-model (Beijing statistic bureau, 1999).

# 3. SENSIBILITY ANALYSIS

Urban system is an open system, which is disturbed by complex natural factors and artificial factors. Therefore, the model for simulate urban system contains uncertainty in its structure and parameters, and it is necessary to analyze the sensibility of the model to estimate the influencing of model structure and parameters on its simulation result. Generally, there are two kinds of methods for sensibility analysis, one is analyzing the sensibility of parameters to status and objective, and the other is analyzing the sensibility of status to objective. We choose the first one as the sensibility analysis method, and emphasizes on the influences of status transition rule to simulating status variables and objective.

In BUDEM, the adjustable parameters are $w^{1\text{-}14}$, $\alpha$, $k$ and $p_{threshold}$. Definition of the base parameter set (BPS in short) is the premise for sensibility analysis. In the base parameter set, $w^{1\text{-}14}$ are the same with BEIJING2020, $\alpha$=3, $k$=20, $p_{threshold}$=0.99, and the iteration number is set to be 10, that is to say that the model will terminate at the end of iteration 10. The influence on the simulating result by adjusting various single parameter can be calculated by simulating with changed parameter set. We select five indicators to describe the influence, including $x$ (the number of cells with changed status), *AveSij* (average of $s_{ij}$ in all lattices), *AvePg* (average of $p_g$ in all lattices), *AvePij* (average of $p_{ij}$ in all lattices), and $G$. The sensibility analyzing procedures are listed as below:

(1) Simulate with BPS, acquire the simulating result of iteration 10, and calculate each indicator's value $W_i(BPS)$, where $i$=1-5, standing for the ID of indicators.

(2) Replace parameter $j$ in BPS with multiplying by 0.8 while holding other parameters constant in BPS, and get indicator $i$'s value $W_i(BPS_j*0.8)$, where $j$=1-17, standing for the ID of parameters.

(3) Calculate the sensibility of parameter $j$ to indicator $i$: $U_{ij}$=abs[$W_i(BPS_j*0.8)$ / $W_i(BPS)$-1], where "abs" stands for the absolute value. The result of sensibility analysis is shown in table 2.

Table 2. Result of sensibility analysis

| Parameter Name | *U(x)* | *U(AveS)* | *U(AvePg)* | *U(AvePij)* | *U(G)* | *U(SUM)* |
|---|---|---|---|---|---|---|
| $\alpha$ | 0.018 | 0.000 | 0.005 | 0.321 | 0.003 | 0.347 |
| $k$ | 0.001 | 0.000 | 0.000 | 0.001 | 0.000 | 0.002 |
| $p_{threshold}$ | 0.171 | 0.004 | 0.088 | 0.031 | 0.013 | 0.308 |
| $w^{isrural}$ | 0.006 | 0.004 | 0.013 | 0.001 | 0.001 | 0.024 |
| $w^{isagri}$ | 0.088 | 0.031 | 0.103 | 0.030 | 0.012 | 0.265 |
| $w^{d\_tam}$ | 0.040 | 0.108 | 0.138 | 0.095 | 0.005 | 0.385 |
| $w^{d\_vcity}$ | 0.005 | 0.022 | 0.029 | 0.022 | 0.001 | 0.078 |
| $w^{d\_city}$ | 0.033 | 0.047 | 0.075 | 0.052 | 0.004 | 0.212 |
| $w^{d\_vtown}$ | 0.054 | 0.067 | 0.163 | 0.141 | 0.007 | 0.433 |
| $w^{d\_town}$ | 0.018 | 0.017 | 0.042 | 0.030 | 0.002 | 0.110 |

| Parameter Name | *U(x)* | *U(AveS)* | *U(AvePg)* | *U(AvePij)* | *U(G)* | *U(SUM)* |
|---|---|---|---|---|---|---|
| $w^{d\_river}$ | 0.023 | 0.031 | 0.049 | 0.036 | 0.003 | 0.141 |
| $w^{d\_road}$ | 0.004 | 0.041 | 0.019 | 0.013 | 0.001 | 0.078 |
| $w^{d\_bdtown}$ | 0.005 | 0.006 | 0.008 | 0.006 | 0.001 | 0.026 |
| $w^{planning}$ | 0.146 | 0.019 | 0.210 | 0.166 | 0.020 | 0.562 |
| $w^{con\_f}$ | 0.002 | 0.002 | 0.003 | 0.002 | 0.000 | 0.009 |
| $w^{landresource}$ | 0.005 | 0.007 | 0.010 | 0.008 | 0.001 | 0.031 |
| $w^{neighbor}$ | 0.013 | 0.011 | 0.112 | 0.100 | 0.002 | 0.238 |
| ***U(SUM)*** | 0.633 | 0.418 | 1.068 | 1.055 | 0.076 | |

From table 2, the weight of *planning* is most sensitive, and then is the weight of *d_vtown*, while k is lest sensitive. Regarding indicators, *AvePg* is most sensitive, while *G* is lest sensitive. On one hand, with respect to indicator *x*, $p_{threshold}$ is most sensitive, and then is the weight of *planning*. On the other hand, with respect to indicator *G*, *planning* is most sensitive, and then is $p_{threshold}$. In summary, sensibility analysis is the base of model calibration and application, and the model calibrating rule can be identified via such work.

In addition, to better understand the input and output relationship, it is essential to track the status changing trend with iteration number. We select *dx/dt*, *d(AvePij)/dt* and *dG/dt* as indicators for status of the model, store the relevant data in database for iteration 1 to 100, plot and analyze it. Pages limited, the details are not prescribed here.

# 4. MODEL APPLICATION IN BEIJING

## 4.1 Historical analysis

Urban growth rules in different historical phases can be acquired by logistic regression, including 1947-1964, 1964-1976, 1976-1981, 1981-1986, 1986-1991, 1991-1996, 1996-2001, and 2001-2006. In logistic regression, variables *d_tam*, *d_vcity*, *d_city*, *d_vtown*, *d_town*, *d_bdtown*, *landresource*, and *con_f* do not change in different phases; yet, variables *planning*, *d_road*, *isrural*, *isagri* and dependent variable vary from historical phases. In addition, variable *neighbor* is not considered in logistic regression. Through the process, it is available to compare urban growth mechanisms of various phases. Regression result of 2001-2006 is listed in table 3, and the accuracy of regression is acceptable 88.5%. As is shown in table 3, the coefficient of *d_river* is the biggest one, and accordingly the developing probability will decrease 0.024%, if the minimum distance to river increases by 1 meter. Regarding *d_road*, it is positive correlated to the developing probability, and it is clear that the urban growth along roads in this phase is not evident. Besides, the developing probability of the cell located in the forbidden built-up zone is lower by 65.9% than that of others area, and the cell in planned built-up area has a developing probability of 36.7% higher than that of non planned area.

Table 3. Variables in the equation of logistic regression of 2001-2006

| | | B | S.E. | Wald | df | Sig. | Exp(B) |
|---|---|---|---|---|---|---|---|
| Step 1[a] | d_tam | -.000042 | .000 | 68.054 | 1 | .000 | 1.000 |
| | d_vcity | -.000018 | .000 | 10.018 | 1 | .002 | 1.000 |
| | d_city | -.000032 | .000 | 26.877 | 1 | .000 | 1.000 |
| | d_vtown | -.000019 | .000 | 3.829 | 1 | .050 | 1.000 |
| | d_town | -.000036 | .000 | 4.590 | 1 | .032 | 1.000 |
| | d_river | -.000224 | .000 | 41.815 | 1 | .000 | 1.000 |
| | d_bdtown | -.000057 | .000 | .434 | 1 | .510 | 1.000 |
| | con_f | -1.076304 | .143 | 56.624 | 1 | .000 | .341 |
| | landresource | -.023686 | .040 | .347 | 1 | .556 | .977 |
| | isrural | 3.284309 | .321 | 104.865 | 1 | .000 | 26.691 |
| | isagri | 4.376267 | .157 | 781.214 | 1 | .000 | 79.541 |
| | d_road2001 | .000061 | .000 | .310 | 1 | .578 | 1.000 |
| | planning2004 | .312422 | .139 | 5.043 | 1 | .025 | 1.367 |

The coefficients of logistic regression in different historical phases are shown in table 4 (LANDUSE data before 1986 is under processing. Therefore, corresponding logistic regressions are not conducted to data.). Comparing the dominant factors in different phase, it is clear that the urban growth mechanism differs from each other in a great degree; in addition, market and government role also vary in different phases. In 2001-2006, riverside developing is notable, and then is the central city, while road along type is not notable. In 1996-2001, road along developing is notable, and then is new city, while areas around town grow in a low speed. In 1991-1996 and 1986-1991, road along developing is notable.

Comparing the variation of factors in different phases, according to the table 4, with regard to $w^{planning}$, it keeps positive, and reaches its maximum value in 1986-1991. In others phases, it does not changes greatly. We can see that in the first several years of social market economy, urban planning played a leading role in urban growth. However, with the introduction of market mechanism into China, its role is being partially replaced by market factors. Regarding $w^{con\_f}$, it remains negative, and its absolute value continually increases, which means that its role for urban growth control is increasing, and the strengthen for ecological space protection and hazard prevention is also going up. Additional, $w^{landresource}$ keeps positive with its absolute value declining, and it shows that the protection intensity for more cultivating suitable area is descending. Moreover, $w^{d\_bdtown}$ is positive before 1996, and is negative after that. It can be concluded that the restricting action by administrative boundary is gradually fading in Beijing.

Table 4. Coefficients of logistic regression in different historical phases

| variable | *B(2001-2006)* | *B(1996-2001)* | *B(1991-1996)* | *B(1986-1991)* |
|---|---|---|---|---|
| $w^{d\_tam}$ | -0.000042 | -0.000049 | -0.000054 | -0.000012 |
| $w^{d\_vcity}$ | -0.000018 | -0.000032 | 0.000003 | -0.000047 |
| $w^{d\_city}$ | -0.000032 | -0.000094 | -0.000034 | -0.000028 |
| $w^{d\_vtown}$ | -0.000019 | -0.000029 | -0.000018 | -0.000014 |
| $w^{d\_town}$ | -0.000036 | 0.000129 | 0.000023 | -0.000021 |
| $w^{d\_river}$ | -0.000224 | -0.000078 | -0.000066 | -0.000021 |
| $w^{d\_road}$ | 0.000061 | -0.000734 | -0.000365 | -0.001232 |
| $w^{d\_bdtown}$ | -0.000057 | -0.000463 | 0.000001 | 0.000182 |
| $w^{planning}$ | 0.312422 | 0.459742 | 0.416635 | 1.302933 |
| $w^{con\_f}$ | -1.076304 | -0.613198 | -0.449983 | -1.274498 |
| $w^{landresource}$ | -0.023686 | -0.140539 | -0.131834 | -0.350835 |
| $w^{isrural}$ | 3.284309 | -3.774535 | -3.949259 | -5.534083 |
| $w^{isagri}$ | 4.376267 | 3.279759 | 1.802018 | -0.156322 |

### 4.2 BEIJING2020

In 2004, State Department of China approved Beijing master planning (2004-2020). How to realize the planned urban form (represented by Data PLANNING2004), and what the possible urban form will be in years from now to 2020, concern the Beijing municipal planning committee and even Beijing municipal government. Regarding the issue of simulating desired urban form, it is impossible to retrieve best parameter set via methods of differential equation or optimum theory, since CA model is one completely non-linear method. Moreover, in above paragraphs, it is discussed for nest-loop method failing to avail it. Here we employ the integrating logistic regression and MonoLoop method, as described in “Model Establishing” section, to retrieve corresponding parameter set to establish the transition rule for desired urban form (BEIJING2020).

To begin with, logistic regression is conducted. The dependent variable is calibrated via algebra operation on PLANNING2004 and LANDUSE2006, and then $w^{1-13}$ can be obtained by means of logistic regression (regression result as shown in table 5, accuracy of regression is as high as 96.8%). From the below table, the significance of each independent variable is at the acceptable level.

Table 5. Variables in the equation of logistic regression in 2006-2020

| | | B | S.E. | Wald | df | Sig. | Exp(B) |
|---|---|---|---|---|---|---|---|
| Step 1[a] | isrural | 6.88621 | .311 | 489.806 | 1 | .000 | 978.683 |
| | isagri | 6.97187 | .212 | 1081.601 | 1 | .000 | 1066.213 |
| | d_tam | -.00010 | .000 | 351.190 | 1 | .000 | 1.000 |
| | d_vcity | -.00003 | .000 | 22.971 | 1 | .000 | 1.000 |
| | d_city | -.00010 | .000 | 242.798 | 1 | .000 | 1.000 |
| | d_vtown | -.00028 | .000 | 512.563 | 1 | .000 | 1.000 |
| | d_town | -.00011 | .000 | 46.814 | 1 | .000 | 1.000 |
| | d_river | -.00052 | .000 | 162.656 | 1 | .000 | .999 |
| | d_road | .00096 | .000 | 110.505 | 1 | .000 | 1.001 |
| | d_bdtown | -.00027 | .000 | 10.079 | 1 | .001 | 1.000 |
| | planning | 8.77071 | .270 | 1055.034 | 1 | .000 | 6442.743 |
| | con_f | -.20097 | .138 | 2.111 | 1 | .146 | .818 |
| | landresource | -.09355 | .039 | 5.850 | 1 | .016 | .911 |

After logistic regression, MonoLoop procedure is followed. We attempts 27 values for *wN*, and it costs 21.5h for 2997 iterations totally. The relationship between *G* and *wN* is shown in figure 1. In the figure, *G* keeps steadily being around 97.6% when *wN* ranges from 0 to 5, *G* decreases sharply to 93.0% when wN is within 5 and 35, and *G* rises when *wN* is bigger than 35. Moreover, if *wN* is bigger than 35, the number of developed cells in the first iteration is too much (that is to say that the neighborhood action is too big), even exceeds the total number of destined built-up cells, to fulfill the simulation. Therefore, we choose $wN^*$ as 4.59808 to simulate BEIJING2020, and correspondingly, *G* will be around 97.6%, which is near the ideal maximum value 98.9% (Regarding the ideal maximum value, in the planning scheme of PLANNING2004, the number of urban built-up cells is 9376, while in the observed urban form of LANDUSE2006, the number of urban built-up cells is 5297. Through overlay analysis on PLANNING2004 and LANDUSE2006, 712 cells are the observed urban built-up out of planned form. Hence, the ideally maximum of *G* should be equal to (65628-712)/65628=98.92%).

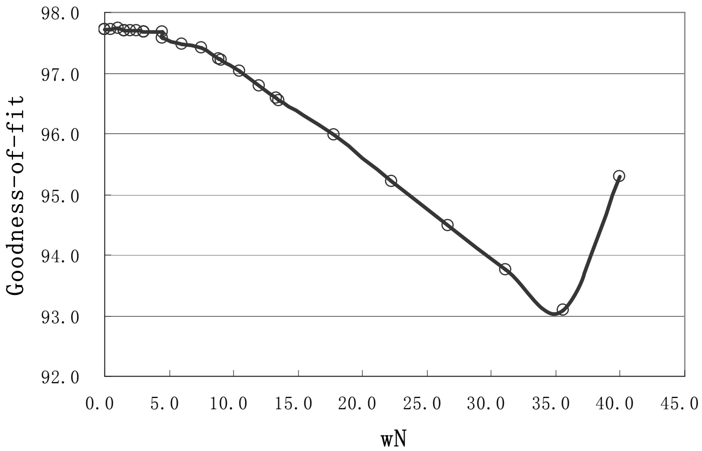


Fig. 1. *dG/dt* of MonoLoop procedure in BEIJING2020

Weights $w^{1\text{-}13}$ obtained by logistic regression and $wN^*$ calibrated by MonoLoop are simultaneously inputted into the established transition rule, and then urban form of BEIJING2020 is simulated with 208 iterations and 6297s' time cost. Simulated urban form is shown in figure 2, with 10104 developed cells. It is evident that the simulated urban form and planned one is greatly consistent. The simulated urban form of 2020, together with that of various phases from now to 2020, can be consulted by urban planning department as pre-awareness or references for regulate corresponding policies.

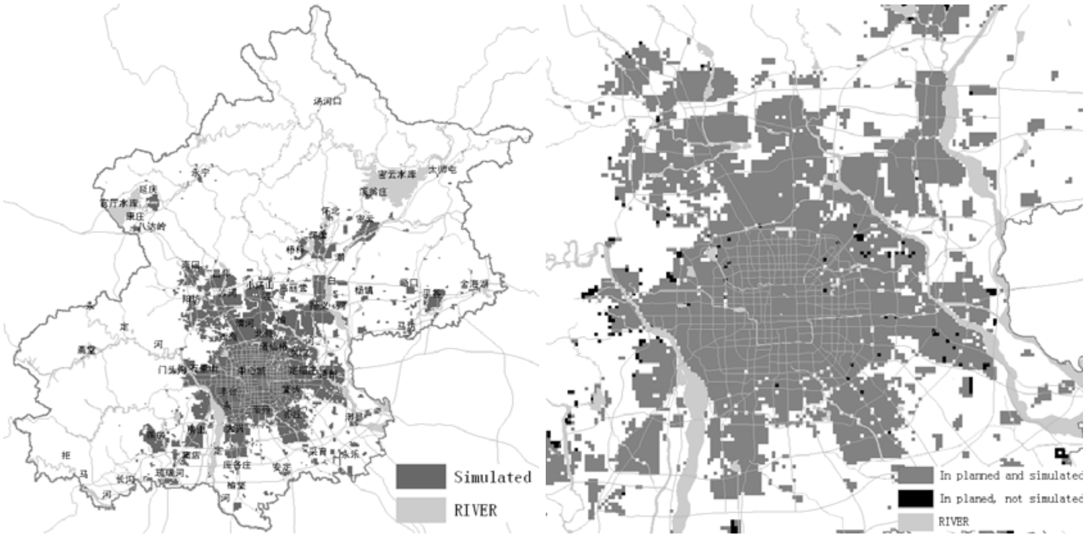


Fig. 2. Simulated urban form of BEIJING2020 (Left) and its comparative image with planned form in Beijing central metropolitan area (Right)

*G* values during the simulation process of BEIJING2020 are plotted in figure 3, and it shows that the maximum *G* appears at the iteration of 117 (*G*=97.75%), instead of at the last iteration 208 (*G*=97.57%) as presumed. With MRM, iteration 117 corresponds to year 2019. It illustrates that the real realization year of this round of urban planning is 2019, in contrast with 2020. Therefore, it is necessary and timely for Beijing municipal planning committee to carry out the new round of urban planning in 2019, and we should also prepare for the new urban planning in far advance, such as 2015.

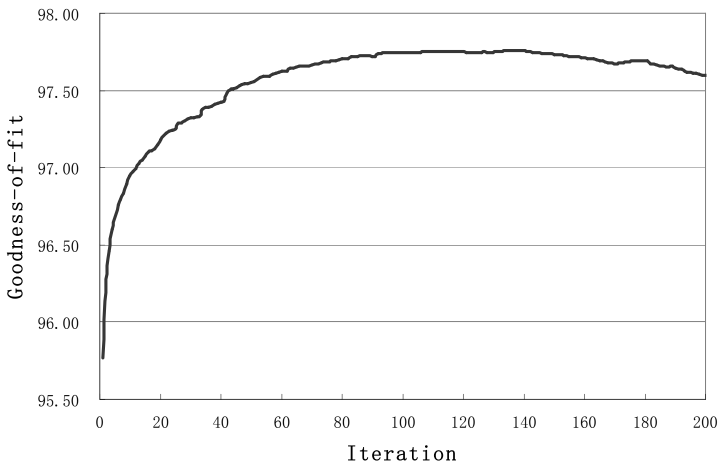


Fig. 3. *dG/dt* of BEIJING2020 simulation

Accordingly, the urban growth policies to achieve planned urban form can be identified, via comparing the logistic regression coefficients of BEIJING2020 with those of some historical phase. Through contrasting the present policies and achieved policies, we can recognize whether they are consistent, if not, corresponding regulating is available to be bring out by BUDEM. For instance comparing with the coefficients of 2001-2006, to realize the planned urban form, we should strengthen the intensity of urban planning implementing, emphasize urban growth along the main road, and increase the constructing actions at VIP towns. Moreover, the protection degree for forbidden built-up area does not need be enhanced. In particular, BUDEM is capable to generate other urban forms in 2020 via adjusting the obtained policies for BEIJING2020, to testify various spatial developing policies advanced by the government.

In contrast with generous CA model for urban growth, point to point comparing validation of CA is conducted during MonoLoop process in the above simulation, and the accuracy for point to point comparing validation is 97.6%. The *G* is one key constraining condition in MonoLoop of BUDEM, which guarantees the highest model accuracy on point to point comparing. Hence, it shows one of the merits of BUDEM with MonoLoop method. There are many kinds of methods for CA model validation, such as fractal indexes, spatial structure indexes, etc. Besides point to point comparing method, we adopt Moran I index (the degree of spatial autocorrelation) to validate the simulated result of BEIJING2020. The Moran I is equal to 0.12 (*Z* Score = 31.1) for planned urban form, and is equal to 0.16 (*Z* Score = 43.6) for simulated one. It is clear that not only simulated but also planned urban form is comparatively concentrated (It is one character for the planned urban form conducted by planners instead of natural growth), while simulated urban form is more congregated than planned one.

### 4.3 BEIJING2049

As is known, year 2020 is the end of this round of urban master planning drafted by Beijing municipal planning committee, while year 2049 is the 100 anniversary for Beijing as the capital of P. R. China. To prepare for the next round of urban planning of Beijing, it is necessary to predict the urban form from 2020 to 2049, especially 2049. The prediction is divided into two aspects, one is to forecast the total amount of urban built-up area, and the other is to distribute the forecasted total amount of built-up into different space.

It will be more accuracy to forecast Beijing urban form of 2049 basing on the planned urban form of 2020 than basing on the observed urban form of 2006, in condition of the higher probability for BEIJING2020 to realize. In China, land developing is controlled by government by means of urban planning in great degree, and urban planning form can explain most of urban developing activities, which are mostly located in planned as urban built-up area. Therefore, it is reasonable to forecast long-term urban growth using planed urban form of some middle year, which is possible to reduce the uncertainty of long-term forecasting. However, in some leading western countries, land property is greatly charged by private owners, and the urban developing is less controlled by government than by planning department of China. Hence, we forecast urban form of 2049 with the premise of the implementation of BEIJING2020 planned form.

Formula 4 is used to forecast the total amount of urban built-up of Beijing metropolitan area. As shown in the formula, $a$=2344km$^2$ (Total urban built-up area planned in year 2020), $b$=30km$^2$/a, $c$=2020, $x$ stands for the year number to forecast, and $y$ stands for the forecasting result of urban built-up (km$^2$). Regarding $d$ as increasing parameter, it is used to adjust the urban built-up increasing velocity.

$$y = a + b * (x - c)^d \tag{4}$$

After forecasting the total urban built-up area, CA is used to simulate its distribution. In the established transition rule, the value of weight stands for the intensity of corresponding urban growth policy (Valued as 0 denoting that the just policy is not considered). Furthermore, spatial variable itself also stands for urban growth polity, for example, the spatial distribution of *con_f* stands for the extent of protected zone, which is also a policy. Thus, it is possible to simulate different urban growth scenarios for Beijing 2049 by BUDEM by means of adjusting the weights or the variables' spatial distribution, such as urban sprawl scenario, grape-cluster scenario, sustainable scenario, center city promoting scenario, town promoting scenario, riverside promoting scenario, roadside promoting scenario, agriculture protecting scenario, rural built-up controlling scenario, etc. Moron I index, agricultural land encroachment, forbidden built-up area encroachment, rural built-up area covered are available to assess different scenarios and identify the implementing effect of scenarios. Pages limited, we only propose the urban growth scenario with the same trend of BEIJING2020 here (d=1), and the parameter set is the same with that of BEIJING2020. The simulated result is shown in figure 4, from which we can see that urban growth in 2049 engrosses partial forbidden area, and urban sprawl phenomenon also appears. Thus, it is necessary to adjust the urban growth policies from 2020 to 2049, and re-simulate to generate a more sustainable urban form, avoiding such phenomenon.

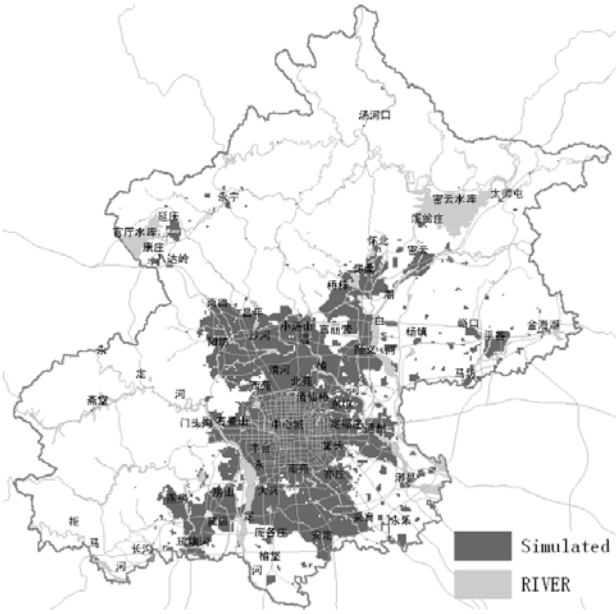


Fig. 4. Simulated urban form of BEIJING2049

## 5. CONCLUSION

This paper mainly discusses the calibration of CA urban growth simulation model in Beijing metropolitan area in order to find a solution of simulating possible urban form of Beijing in the future. We develop BUDEM as the urban growth simulation platform with sufficiently relevant database, identify the urban growth mechanism of different historical phases, and conduct model sensibility analysis to better understand BUDEM itself, which is also one key work for model calibration and application. In BEIJING2020 section, we propose the method integrating logistic regression and MonoLoop to retrieve the transition rule for desired form. In addition, through comparing the weights obtained and historical ones, the realization policies for urban planning form can be given out. We also attempt to predict urban form in 2049, and BUDEM is capable to simulate different scenarios by various policies sets. CA has been proved as one applicable tool for urban planning issues, and it has played an important role in the practice work, since the urban form confirmation is one core content in urban planning.

As the further work of this phase, we plan to apply BUDEM in amounts of urban planning management and workout practices by means of simulating urban growth. Meanwhile, it is considered to add simulate urban density and competing land use transition functions to apply BUDEM in block scale. For our further research of the second stage of BUDEM, MAS employing discrete choice model will be added into current BUDEM in order to simulate urban agents of different activities based on different scenarios of urban policy.

*Note: the simulated form of Beijing metropolitan area is the primary output of BUDEM, which is the authors' self view instead of BICP.*

# APPENDIX: DATA DESCRIPTIVE STATISTICS TABLE

| Variable | N | Minimum | Maximum | Mean | Std. Deviation |
|---|---|---|---|---|---|
| *d_tam* | 65628 | 0 | 129711 | 57737.08 | 26952.19 |
| *d_vcity* | 65628 | 0 | 102504 | 46545.37 | 23392.81 |
| *d_city* | 65628 | 0 | 78824 | 24801.90 | 14730.19 |
| *d_vtown* | 65628 | 0 | 36530 | 13255.02 | 6968.38 |
| *d_town* | 65628 | 0 | 42005 | 8286.05 | 5298.70 |
| *d_river* | 65628 | 0 | 14230 | 3212.68 | 2416.59 |
| *d_bdtown* | 65628 | 0 | 7762 | 1239.24 | 1173.94 |
| *d_road1986* | 65628 | 0 | 29681 | 2514.47 | 3675.36 |

| Variable | N | Minimum | Maximum | Mean | Std. Deviation |
|---|---|---|---|---|---|
| *d_road1991* | 65628 | 0 | 29954 | 2390.63 | 3577.05 |
| *d_road1996* | 65628 | 0 | 29820 | 2341.07 | 3635.95 |
| *d_road2001* | 65628 | 0 | 24000 | 1925.85 | 2494.29 |
| *d_road2006* | 65628 | 0 | 29820 | 2306.49 | 3613.74 |
| *landuse1986* | 65628 | 1 | 6 | 4.32 | 1.02 |
| *landuse1991* | 65628 | 1 | 6 | 4.31 | 1.03 |
| *landuse1996* | 65628 | 1 | 6 | 4.27 | 1.10 |
| *landuse2001* | 65628 | 1 | 6 | 4.24 | 1.14 |
| *landuse2006* | 65628 | 1 | 6 | 4.19 | 1.20 |
| *planning1958* | 65628 | 0 | 1 | 4.28E-02 | .20 |
| *planning1973* | 65628 | 0 | 1 | 5.00E-02 | .22 |
| *planning1982* | 65628 | 0 | 1 | 2.77E-02 | .16 |
| *planning1992* | 65628 | 0 | 1 | 5.16E-02 | .22 |
| *planning2004* | 65628 | 0 | 1 | .14 | .35 |
| *con_f* | 65628 | 0 | 1 | .44 | .50 |
| *landresource* | 65628 | 1 | 8 | 3.92 | 1.66 |
| Valid N (listwise) | 65628 | | | | |

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