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# Urban ecological footprint prediction based on the Markov chain

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ABSTRACT

Long-term observation of the urban ecological footprint will present useful knowledge of anthropogenic impact on and sustainable solutions for cities. This paper proposed a new framework to predict dynamic change and intrinsic structure of urban ecological footprint with the Markov chain. The system dynamic model based on Markov chain was then established for estimating Beijing's footprint during the period of 2001–2020. The results showed that Beijing's footprint kept stable in the long term due to steady consumption pattern and environmental mitigation policy. The footprint intensity has been decreasing constantly due to the expanding population against the stable total footprint. Energy consumption was found to be the major contributor to Beijing's footprint. Sensitivity analysis was also presented by testing the population and economic growth under five scenarios. This work may provide insights into the land metabolism mechanism and guidance for urban planning.



## 1. Introduction

City is one of the basic units of human society, which is organized and sustained by circulating materials and energy flows (Lu and Chen, 2014). These input and output flows are key drivers of urban production and consumption activities that give rise to the strained conflict between the increasing demands and tighten carrying capacity for the urban area (Chen and Chen, 2015). For this sake, maintaining the balance between urban development and environmental sustainability requires better understanding of both socio-economic demands and natural capital to support the related resource utilization and absorb the wastes (Hubacek et al., 2009).

Ecological footprint shows the total area of bioproductive land and water kept requiring by a given population to meet their demands, and to accumulate and dispose all of the waste (Rees and Wackernagel, 1996), which may provide a feasible benchmark to measure both consumption level and carrying capacity to reflect the anthropogenic impacts on nature. There are currently two main branches of footprint studies. One is based on the input–output table to convert monetary flows into the material and energy flows in a given economy and account for the embodied resource use along the supply chains (Ferng, 2001; Lenzen and Murray, 2001; McDonald and Patterson, 2004; Wiedmann et al., 2006; Chen et al., 2013; Turner et al., 2007; Li et al., 2015). However, money-based input–output table can hardly describe the real resource consumptions within an economy. Data accessibility also remains the barrier to combine input–output analysis with ecological footprint analysis. Hence, using consumption data to capture the actual material and energy use based on local consumption census is more feasible for ecological footprint analysis (Luck et al., 2001; Wackernagel et al., 2006). Different tools such as material flow analysis have also been incorporated into the footprint framework to provide explicit basic information for material footprint metrics (Haberl et al., 2001; Monfreda et al., 2004; van Vunuen and Bouwman, 2005; Wackernagel et al., 2006; Chen et al., 2007). The modified ecological footprint analysis based on thermodynamics also composes a twig of footprint studies (e.g., Chen and Chen, 2006, 2007; Pereira and Ortega, 2012; Shao et al., 2013).

So far, some researchers have investigated the ecological footprint based on local consumption census at urban level. Barrett et al. (2002) incorporated the material flow analysis into the urban footprint analysis to indicate the ecological pressures on York. Muniz and Galindo (2005) and Muniz et al. (2013) recognized the footprint drivers of urban transport and households in the Barcelona metropolitan region. Moore et al. (2013) developed an urban metabolism-based footprint framework to measure the resource

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utilization in Vancouver metropolitan region via tracking diverse material flows. Geng et al. (2014) compared the ecological pressures of Shenyang and Kawasaki by urban footprint analysis. However, although the static footprint accounting has been explored extensively, the studies of the developing trends and major driving forces of urban ecological footprint (UEF), which can meet the basic requirement of urban planning and systematic regulation, are still very few. To address this issue, dynamic predictions of urban ecological footprint have aroused increasing attentions, which is particularly significant for documenting the natural capital used by human beings (Wackernagel et al., 2004a, 2004b). Although scenario analysis, regression analysis and system dynamics model concerning multiple socioeconomic factors (e.g., economic growth, urbanization rate, population dynamics, consumption patterns, technical improvements, etc.) have been conducted (Hubacek et al., 2009; Jin et al., 2009; Li et al., 2010), more efforts are still needed to explore the transforming mechanism and influencing factors of the UEF variations in the long run.

The Markov chain is a powerful tool to represent a system transforming from one state to another during a concerned period (Anderson and Goodman, 1957; Balzter, 2000). It has been proved as a feasible approach to describe the inner transitions among all footprint categories (i.e., cropland, pasture, forest, etc.), thus facilitating our cognitions of why and how the UEF changes. The Markov chain has been widely applied to predicting the dynamics of both natural and artificial systems, especially the observation of land use and landscape change at multi-levels (Lopez et al., 2001; Weng, 2002; Guan et al., 2011; Kamusoko et al., 2009; Strigul et al., 2012; Ma et al., 2012). Being expressed with virtual land area as well as six regular categories, UEF and its intrinsic transitions can be quantified by integration of Markov chain.

In this context, we propose a Markov chain-based dynamic model to predict the trends of UEF and investigate the interactions among footprint categories. In the following, Section 2 develops a framework for the UEF accounting and prediction in combination with the traditional footprint accounting, Markov chain, and system dynamics. Section 3 proposes an UEF prediction system dynamics model with three sub-models for Beijing during 2001–2020. Section 4 then analyzes the main modeling results of total footprint and intensity changes and intrinsic structure transitions as well among six footprint categories of Beijing. Finally, Section 5 discusses the main conclusions, limitations and further improvements of this work.

## 2. Material and methods

### 2.1. Urban ecological footprint

The ecological footprint answers the question of how much biocapacity is required and consumed by a given population or human activity (Kitzes and Wackernagel, 2009). Bioproductive lands (i.e. cropland, pasture, forest, built-up land, fishery, and fossil energy land) are the most concentrated footprint categories, composing the total ecological footprint (TEF) for a given system (e.g. a city).

Within the administrative boundary of the case city, a basic framework is proposed to provide brief guidance of the UEF accounting (see Fig. 1). Each category of urban footprint is the product of the land area and equivalence factor (Wackernagel et al., 2004b; Monfreda et al., 2004):

$$EF_i = A_i \times ef_i = \sum_n \frac{C_{in}}{y_{in}} \times ef_i \tag{1}$$

where $i$ represents the different categories of UEF, including cropland, pasture, forest, fishery, energy land and build-up land; $ef_i$ is the equivalence factor of each footprint category, indicating the global average potential productivity of a city related to the world average potential productivity of all footprint categories; and $A_i$ is the requiring area during the average global productivity of the $i$-th type of land, which is based on the local consumption data of the case city ($C_{in}$) and should be standardized by the average global yield ($y_{in}$). All of the consumption data were collected from the urban census, and the global yield data were extracted from the Food and Agriculture Organization database (available from the website: http://faostat.fao.org/site/291/default.aspx). Thus, TEF of the case city is the sum of six footprint categories:

$$TEF = \sum_{i=1}^{6} EF_i \tag{2}$$

### 2.2. Markov chain

The Markov chain is the core to unveil more details of the intrinsic transitions of the UEF categories and thus to explain the mechanism of footprint dynamics. Some hypothesis should be set firstly to ensure the feasibility of incorporating this tool into the footprints predictions as follows. 1) All of the urban footprint categories can be transferred into the others. For instance, croplands can be converted into the forests or pastures in China due to some agricultural policies. But for the transition of UEF, it should be considered as the reflection of various consuming patterns and lifestyles, since both of them can great change the structure of UEF (e.g., the cropland transferring to pastures means more meats, milks, eggs are consumed than crops). 2) Time homogeneity, i.e., the probability distribution of next state only depends on current state and is independent of the preceded events. 3) The average transfer state of UEF is relatively stable along the concerned time series, which can be characterized as the transferring pattern of the city.

Based on these hypotheses, the transferring state vector matrix $\boldsymbol{S} = [p_i(j)]$ can be established, where $p_i(j)$ shows the percentage of the $i$-th footprint category occupied in the $j$-th year:

$$p_i(j) = \frac{EF_i(j)}{TEF(j)} \tag{3}$$

When $j = 0$, $p_i(0)$ shows the data in the base year (the first year in the dataset). Then, the previous-year matrix $\boldsymbol{X_{pr}}$ and the post-year matrix $\boldsymbol{X_{po}}$ are divided to extract the transferring pattern of UEF:

$$X_{pr} = \begin{bmatrix} p_1(0) & p_2(0) & \dots & p_6(0) \\ p_1(1) & p_2(1) & \dots & p_6(1) \\ \vdots & \vdots & \dots & \vdots \\ p_1(m-1) & p_2(m-1) & \dots & p_6(m-1) \end{bmatrix} \tag{4}$$

$$X_{po} = \begin{bmatrix} p_1(1) & p_2(1) & \dots & p_6(1) \\ p_1(2) & p_2(2) & \dots & p_6(2) \\ \vdots & \vdots & \dots & \vdots \\ p_1(m) & p_2(m) & \dots & p_6(m) \end{bmatrix} \tag{5}$$

The multiple regression analysis and least square estimation for the state vector matrix $\boldsymbol{S}$ should be done to get the Markov transfer probability matrix $\boldsymbol{P}$, and thus to reflect the intrinsic transition pattern of UEF:

$$P = Y^{-1} M \tag{6}$$

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