Habitat International 69 (2017) 104–113

Contents lists available at ScienceDirect

Habitat International

journal homepage: www.elsevier.com/locate/habitatint

The dynamics of public safety in cities: A case study of Shanghai from 2010 to 2025

Danlin Yu [a], [*], Chuanglin Fang [b], [**]

[a] Earth and Environmental Studies, Montclair State University, Montclair, NJ 07043, United States
[b] Department of Urban Development, Institute of Geographical Science and Natural Resources Research, Chinese Academy of Sciences, Beijing, China

ARTICLE INFO

Article history:
Received 27 May 2017
Received in revised form
24 July 2017
Accepted 18 September 2017
Available online 28 September 2017

Keywords:
Public safety
System dynamics
Grey system simulation
Prediction
Shanghai

ABSTRACT

Cities in China are facing increasing challenges. Urban public safety concerns including urban crime, urban livability and urban disasters start to attract governmental, academic as well as public attention. Applying a system dynamics modeling scheme, this research investigates and attempts to simulate the public safety dynamics of Shanghai with a set of collected indicators that describes Shanghai's infrastructure and development, population, crime, livability and disaster during the past decade (2000–2009). The feedback loops are constructed based on exploratory data mining through regular statistical analyses and grey system simulation. The analytical results suggest Shanghai's public safety is increasing due to a high level of urban socioeconomic development, which provides a foundation for urban public safety. In the meantime, factors that 'expend' such foundation (crimes and disasters) increased at a relatively lower level. Dynamic simulation on Shanghai's public safety suggests that the city could still enjoy its continuous improvement of public safety providing the city continues to develop like in the past decade, which might not be the case in the long run. A few scenarios are presented by altering a few critical variables to demonstrate potential public safety dynamics of Shanghai in the next 15 years.

1. Introduction

Urban spaces are highly concentrated locations for people, wealth, information, and built environments. Not to mention cities are also the most important spaces in the lives of humankind. The UN has forecasted that over half of the world's population will live in cities by the year of 2020. This has happened in the industrialized nations in Western Europe, North America and Japan. The newly developed economies especially that of China, catch up with this trend rapidly.

Urbanization in China has now exceeded slightly over 50% (Fang & Yu, 2016). Understanding cities' vulnerability towards a variety of common threats, such as urban crimes, urban fire disaster, urban traffic incidents, urban environmental pollution, etc., would be of utmost importance for not only the cities' governments and planners, but also the urban dwellers, business owners, insurance underwriters, and potential investors as well (Blokland & Nast, 2014; Van & Van, 2015; Yu, Fang, Xue, & Yin, 2013). Studies on urban vulnerability at the city-scale have seen growing interests in the past decades (Borden, Schmidtlein, Emrich, Piegorsch, & Cutter, 2007; Ceccato & Lukyte, 2011; Cutter, Boruff, & Shirley, 2003; Piegorsch, Cutter, & Hardisty, 2007). Scholars attempt to establish a series of relationships between the possibility of various disasters' occurrence and a variety of the cities' social, economic, physical and environmental characteristics via statistical approaches (Blokland & Nast, 2014; Piegorsch el al., 2007). Such studies provide quite useful understanding at a national/regional scale for policy makers to have a general view that will indicate which cities are prone to certain disasters. Within a city, however, such studies offer limited information regarding how vulnerable the city is against various urban threats, why so and what the future will be.

Apparently, there exists a gap in urban vulnerability study that focuses specifically on individual cities. The complexity nature of cities might be one of the reasons why there is such a gap. On the other hand, however, the cities' complexity seems to be a nice target for modeling schemes that treat cities as non-linear, high order and complex systems. Modeling techniques such as system dynamics (Forrester, 2007), cellular automata/agent based modeling (Batty & Xie, 1999; Beall, Parnell, & Albertyn, 2015; Yin, 2013) are well developed to model the dynamics of cities from a

---

[*] Corresponding author.
[**] Corresponding author.

E-mail addresses: yud@mail.montclair.edu (D. Yu), fangcl@igsnrr.ac.cn (C. Fang).

https://doi.org/10.1016/j.habitatint.2017.09.007

variety of perspectives (Haghshenas, Vaziri, & Gholamialam, 2015; Xue & Luo, 2015). For instance, scholars have applied such modeling techniques to understand the process and dynamics of urban water management (Che et al., 2009; Chu, Chang, Lin, Wang, & Chen, 2010; Qi & Chang, 2011; Tidwell, Passell, Conrad, & Thomas, 2004; Winz, Brierley, & Trowsdale, 2009), urban sustainability (Duran-Encalada & Paucar-Caceres, 2009; Jin, Xu, & Yang, 2009; Kopfmuller, Lehn, Nuissl, Krellenberg, & Heinrichs, 2009; Levine, Hughes, Mather, & Yanarella, 2008; Wigle, 2014; Xue & Luo, 2015), urban land use/land cover changes (Haghani, Lee, & Byun, 2003a; Haghani, Lee, & Byun, 2003b; He et al., 2005; Li & He, 2008), urban sprawl (Han, Hayashi, Cao, & Imura, 2009; Liu et al., 2010a), and urban solid waste management (Dyson & Chang, 2005; Kollikkathara, Feng, & Yu, 2010) and urban traffic safety (Goh & Love, 2012; Haghshenas et al., 2015). The booming applications of such system thinking techniques to investigate urban problems indicate a relative consensus in the urban study community that the complex cities need to be studied via theories and methods that treat complexity internally.

Urban public safety is a relatively newly emerged concern in the trajectory of urban development. The tragic events of September 11, 2001 in New York City, and the ever-increasing concentration of people, traffic, wealth, and decision-centers (such as transnational corporation headquarters) within the cities render urban public safety a primary concern in today's urban development. Studies specifically designed to address public safety issues within individual cities, however, often concentrated on specific issues, most notably urban traffic and relevant studies (Delucchi & Kurani, 2014; Haghshenas et al., 2015). On the other hand, while applied to human/social systems such as cities, the system dynamic modeling schemes mentioned above often suffer from relative rigidity when relationships between different variables have to be determined confirmatively from the data (Yu, Mao, & Gao, 2003), which could potentially limit the model's applicability. This is especially true when the data contain relatively short temporal series and some data items are quite sporadically recorded or fluctuate drastically, which is often the case in human/social systems. A grey system time series simulating technique (Deng, 2002; Liu, Dang, Fang, & Xie, 2010b) has been promoted to introduce flexibility when attempting to derive regularity from temporally recorded data. Coupling grey system simulation with system dynamic simulation has been applied in regional sustainability studies (Mao & Yu, 2001a; Mao & Yu, 2001b; Yu et al., 2003), and proves to provide more reasonable simulation results.

To this regard, the current study attempts to adopt a system thinking strategy, coupling with grey system simulation technique, to study the dynamics of urban public safety in Shanghai, one of the largest and most developed cities in China. Following the introduction section, we'll briefly introduce the theories of system thinking and techniques of system dynamic modeling and grey system simulation. This is then followed by establishing a feedback loop diagram of urban public safety based on Shanghai's data from 2000 to 2009. A detailed narration of some primary system relationships identification will be provided to present the model structure. Evaluation of the model and a near and intermediate prediction based on the model are presented in the fourth section. An urban public safety index (UPSI) as promoted in (Yu et al., 2013) is then calculated to provide a basis for discussion of Shanghai's urban public safety in the near and intermediate future. We conclude our study in the fifth section.

2. Theories of system dynamics and grey system

2.1. System thinking and system dynamic modeling scheme

When system thinking strategy was first introduced more than half a century ago (Forrester, 2007), it has embraced both welcome and criticism from scholars who are interested in understanding the complex internal of systems. System dynamic modeling scheme has been regarded as an effective means to create a "laboratory-like" environment for complex systems, especially human/social systems that are either very difficult or impossible to put into a controlled environment like physical, chemical, mechanical or other close systems (Yu et al., 2003). In addition, system dynamic modeling scheme can be (and often is) used to answer "what-if" scenario questions (Han et al., 2009).

The essence of system thinking strategy is to treat a complex system as an *integrated*, feedback loop connected collection of system components. Each component is related with other components via complex relationships that can hardly be expressed in a linear and clearly predictable manner. Yet among limited, specific components, simpler relationships can be identified (via observing the co-variation of variables) and model structure based upon. The system dynamics strategy hence attempts to dissect the complex system into a variety of relatively simpler relationships among specific components (a top-down approach), and then connects them together (via feedback loops) to create a simulative system attempting to mimic the real system's behavior. The feedback loops are often constructed beforehand to reflect the modeler's understanding of the system and altered later based on data analysis. The actual relationships among specific components are usually identified via statistical, numerical or other methods with historical data (temporal series data). Specifically, three steps are essential for system thinking and system dynamic modeling:

The first step is system analysis (or dissection). Any system can be dissected based on the scholar's understanding of the system and research purposes. In our study, we dissect the urban system into four specific sub-systems based on our concern on urban public safety, i.e., urban development, urban crime and instability, urban housing and livability, and urban disasters (Yu & Yin, 2011; Yu et al., 2013). The sub-systems will then be analyzed and further dissected to be a series of individual stock, rate and auxiliary variables (termed indicators in our study) that reflect the different aspects of the sub-system. Stock variables are indicators that accumulate/deplete over time via certain rate. Rates are often depending on time and/or other auxiliary. Auxiliary variables, on the other hand, are indicators influenced by other auxiliary and/or stock variables. Determination of stock, rate and auxiliary variables is usually based on data analysis. In this step, feedback loops among individual indicators will be established to mimic the possible linkage in the real system.

The second step is system components integration. After system analysis and the establishment of feedback loop structure, the model is then composed of individual indicators, and first order feedback relationships among them. Such feedback relationships can be represented via a series of equations composed of stock, rate and auxiliary variables (Hannon & Ruth, 2001; Yu et al., 2003). Facilitated by a system thinking software package, STELLA$^{®}$ (ISEE, 2011), we could collectively express these equations as:

$$
\begin{aligned}
&S_{i(t+1)} = S_{i(t)} + R_{i(t)}dt \quad (i\in[1,\cdots,n]) \\
&R_{i(t)} = f\left(A_{j(t)}, S_{k(t)}, t\right) \quad (j,k\in\{indicators\ related\ with\ ith\ stock\ changing\ rate\} \\
&A_{j(t)} = g(A_{l(t)}, S_{k(t)}, t) \quad (l,k\in\{indicators\ related\ with\ jth\ auxilliary\ indicator\}
\end{aligned}
\tag{1}
$$