A GIS-based Approach for Modeling the Spatial and Temporal Development of Night-time Lights

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1 Introduction

One of the few directly observable indicators of human activity in spatially explicit form are night-time satellite imagery data. Nocturnal lighting can be regarded as one of the defining features of concentrated human activity, such as flaring of natural gas in oil fields (CROFT, 1973), fishing fleets, or urban settlements (FOSTER, 1983; GALLO ET AL., 1995; ELVIDGE ET AL., 1997a). Consequently, extent and brightness of nocturnal lighting correlate highly with indicators of city size and socio-economic activities such as GDP, and energy and electricity use (WELCH, 1980; GRÜBLER AND NAKICENOVIC, 1990; GALLO ET AL.; 1995; ELVIDGE ET AL., 1997b).

In this paper we report on a GIS-based approach for simulating night-time lights as spatially explicit indicator of socio-economic activities for China. With continued demographic and economic growth, China is projected to become the world's largest regional economy within the next two to three decades (NAKICENOVIC ET AL., 1998). Longer-term scenarios suggest that China's economy may even expand by up to a factor 100 towards the end of the 21st century (NAKICENOVIC ET AL., 2000). Corresponding scenarios of possible future spatial distributions of economic activity and resulting energy use and environmental impacts are hence an important input for transport and energy infrastructure planning, as well as environmental impact assessments.

The GIS approach presented links night satellite imagery data of visible, near-infrared light with other spatially explicit data on topography, infrastructure availability and well as demographics. These data set are used in a stochastic gravity model of spatial interactions to simulate geographic patterns of growth in nocturnal lighting. The simulation results can serve as a proxy for emerging spatial patterns of socio-economic activity and energy use useful for infrastructure planning and energy demand and supply analysis.

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2 Material & Methods

2.1. Input Data

The ***night-time visible lights*** data were obtained from the US Air Force Defense Meteorological Satellite Program (DMSP) Operational Linescan System (OLS) digital data set developed by the US National Oceanic and Atmospheric Administration's National Geophysical Data Center. (ELVIDGE ET AL., 1999). The data are composites of cloud-free visible band observations made by the DMSP-OLS in the years 1995/1996. Further data processing assures sufficient cloud-free observations and elimination of ephemeral lights that arise from fires and lightning. The spatial resolution of this data set is 0.1 geographic degrees.

Topographical data (DEM and derived data of landscape slopes) are based on the Global Land One-km Base Elevation–Project (GLOBE; HASTINGS ET AL., 1998; http://www.ngdc.noaa.gov/seg/topo/globe.shtml). To match the night-time lights data resolution these maps were rescaled to a cell-size of 0.1 degrees.

Data on ***transport infrastructure networks*** (road and railways) were obtained from the Center for International Earth Science Information Network (CIESIN, http://sedac.ciesin.org/china/). To create a suitable grid based format out of this vector information density maps were calculated.

Data on the spatial distribution of ***population densities*** are also taken from CIESIN (TOBLER ET AL., 1995; http://www.ciesin.org/datasets/gpw/globldem.doc.html).

A map of ***China's political borders*** (ArcWorld, ESRI 1999) was used to clip all above mentioned input data sets.

2.2 Modeling approach

For the work presented here ESRI ArcView 3.1 GIS and the MapModels extension (RIEDL & KALASEK, 1998; RIEDL, 1999), a flowchart based modeling-tool allowing iterative simulations, were used.

The MapModel for night-time light development is illustrated in Fig. 1. The model's key feature is to calculate the probability for changes in night-time light intensity within each cell at a given time *t*. This probability is determined by two influencing factors:

- environmental conditions (altitude, slope, road-, railway-, population density)
- the cell's present internal status and the status of surrounding cells in a defined radius

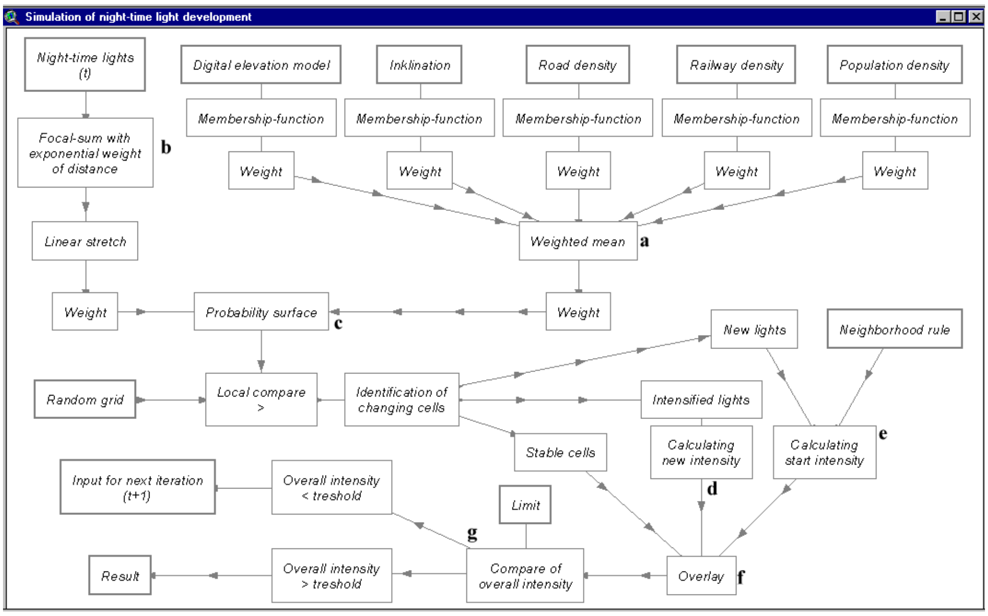

Fig. 1: MapModel to simulate the spatial and temporal development of night-time lights.

To implement the first modeling step for each parameter a simple probability surface was calculated by using fuzzy membership-functions (ZADEH, 1987). The weighted mean was computed to combine these surfaces (Fig. 1a).

The second modeling step is based on the gravity model of spatial interactions (ISARD ET AL., 1979; GAILE & WILLMOTT, 1984; for a general formulation see eq. 1). This concept describes the intensity *I* of interactions between two objects *i* and *j*. This intensity depends on the mass (*M*) of the objects and the distance (*d*) between them. α, β and δ are parameters generally estimated empirically:

$$I_{ij} = \alpha \frac{M_i^{\beta_i} M_j^{\beta_j}}{d_{ij}^{\delta}} \qquad (1)$$

This concept is implemented into the GIS environment by application of cellular automata techniques. Cellular automata can be characterized by following features (WEIMAR 1998):

- They consist of a regular discrete lattice of cells.
- The evolution takes place in discrete time steps.
- Each cell is characterized by a state taken from a finite set of states.
- Each cell evolves according to the same rule which depends only on the state of the cell and a finite number of neighboring cells.

- The neighborhood relation is local and uniform.

TAKEYAMA & COUCLELIS (1997) demonstrated the suitability of a combination of cellular automata with GIS by adaptation of the Map-Algebra formalism of TOMLIN (1990). Especially local and focal functions are useful to simulate the spatial and temporal development of cells. In this study we use a focal-sum operator to determine the night-time light dependent probability of a intensity change within a cell (Fig. 1b): the higher the sum of the surrounding values the higher the probability. The focal-sum has an annular design and exponential weights for each annulus to ensure that more distant cells have less influence on a target cell. The number of annuli and their sizes and weights, respectively, can be chosen freely.

This focal-sum is combined with the “environmental probability surface” mentioned above to a final probability surface (Fig. 1c). Resulting values are compared with a random value to identify those cells changing their status. In a next step the model distinguishes between new lights (cells that have zero values and change their status) and intensified lights (changing cells that have already a light value).
To calculate the amount of the increase of intensified lights (Fig. 1d) different functions can be applied (e.g. exponential, logistic or power).
For calculation of new light cells a distance-dependent fraction of the maximum value in a given radius is determined. Furthermore a neighborhood-rule is applied to ensure, that new cells can only appear when at least one cell in a defined neighborhood shows light already (Fig. 1e).
Afterwards the generated layers are summed up with non changing cells to a new intermediate result (Fig. 1f). The overall intensity of this intermediate result is compared with a predefined limit to decide, whether the final result is reached or the respective layer serves as input for the next iteration (Fig. 1g).

3 Results

The results of one simulation are shown in Figure 2. It displays the initial stage (Fig. 2a), an increase of the total light sum by a factor 5 (Fig. 2b), 10 (Fig. 2c) and by a factor 40 (Fig. 2d) respectively. As expected the greatest increase is located in the eastern parts of China, especially the regions around Beijing, Shanghai and Honk Kong. By way of contrast the growth in the western areas is far less.

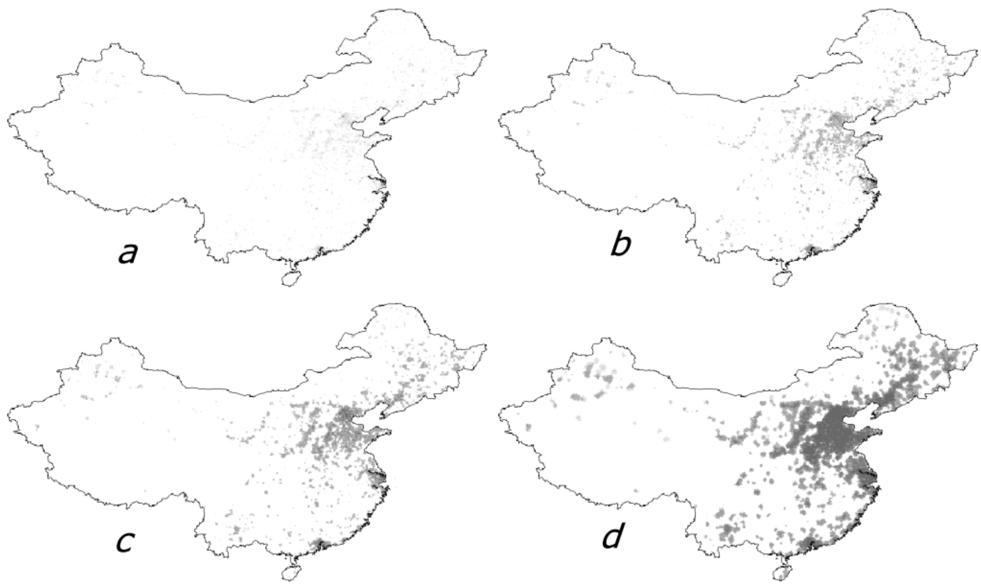

Fig. 2: Results showing the development of night-time lights in China. a: initial (1995/1996) state, b: total increase by factor 5, c: total increase by factor 10 d: total increase by factor 40.

4 Conclusions & Outlook

The presented work is an attempt to apply GIS tools for dynamic simulations of spatially explicit indicators of human activity. In particular, we show that satellite based measurements of night-time lights can be used as proxy indicator to simulate future patterns of economic activities and to derive scenarios of future developments of human settlements and energy demand densities. We conclude this feasibility study in an affirmative manner. First it was possible to obtain sufficient data for a developing economy such as China as well as to integrate the heterogeneous and dispersed data sets into an operable GIS. Secondly, it proved feasible to apply GIS tools in developing a stochastic gravity model of spatial interactions and to perform dynamic simulations. This constitutes a significant improvement of the state of art that has to date largely relied on linear scaling techniques. The first results obtained are thus encouraging, but evidently much further work is needed. The formulation and dynamic behavior of our model need further extensive testing. Above all, time series of night-time lights are required to calibrate the model's parameters and to validate its dynamic behavior. Nonetheless we believe that the preliminary results obtained indicate a new avenue forward in the modeling of indicators of human activity in a spatially explicit manner and to provide improved techniques to support urban planning, infrastructure investments as well as energy demand and supply decisions.

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