Physica A 392 (2013) 5065–5073

Contents lists available at ScienceDirect

Physica A

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

Land cover change using an energy transition paradigm in a statistical mechanics approach

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ARTICLE INFO

Article history:
Received 11 June 2010
Available online 20 April 2013

Keywords:
Maxwell–Boltzmann statistics
Bose–Einstein statistics
Spatial
Urban planning
Land cover
Energy levels

ABSTRACT

This paper explores a statistical mechanics approach as a means to better understand specific land cover changes on a continental scale. Integrated assessment models are used to calculate the impact of anthropogenic emissions via the coupling of technoeconomic and earth/atmospheric system models and they have often overlooked or oversimplified the evolution of land cover change. Different time scales and the uncertainties inherent in long term projections of land cover make their coupling to integrated assessment models difficult. The mainstream approach to land cover modelling is rule-based methodology and this necessarily implies that decision mechanisms are often removed from the physical geospatial realities, therefore a number of questions remain: How much of the predictive power of land cover change can be linked to the physical situation as opposed to social and policy realities? Can land cover change be understood using a statistical approach that includes only economic drivers and the availability of resources? In this paper, we use an energy transition paradigm as a means to predict this change. A cost function is applied to developed land covers for urban and agricultural areas. The counting of area is addressed using specific examples of a Pólya process involving Maxwell–Boltzmann and Bose–Einstein statistics. We apply an iterative counting method and compare the simulated statistics with fractional land cover data with a multi-national database. An energy level paradigm is used as a basis in a flow model for land cover change. The model is compared with tabulated land cover change in Europe for the period 1990–2000. The model post-predicts changes for each nation. When strong extraneous factors are absent, the model shows promise in reproducing data and can provide a means to test hypothesis for the standard rules-based algorithms.

1. Introduction

From the 1970s urban planners have attempted to draw connections between urban modelling schemes and mathematical or physical distributions associated with land use planning. Some early approaches have used the concept of entropy as a means to study land cover (LC) change for non-impervious areas; some of the metrics in these studies have included landscape composition, patchiness, and density. The work by Brotchie and Lesse [1–3], for example, explored the underlying principle of entropy as the driving force behind land use change. Entropy metrics have also been applied in meaningful comparisons between cities with differing geographic dimensions [4] and have been employed in urban economic models using spatial patterns and their self-organization properties of complex forms [5–8].

Current LC approaches, including cellular automata (CA), incorporating rules-based strategies. These planning models are generally guided by a complex set of human decision processes and rules concerning development constraints such as

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http://dx.doi.org/10.1016/j.physa.2013.04.016

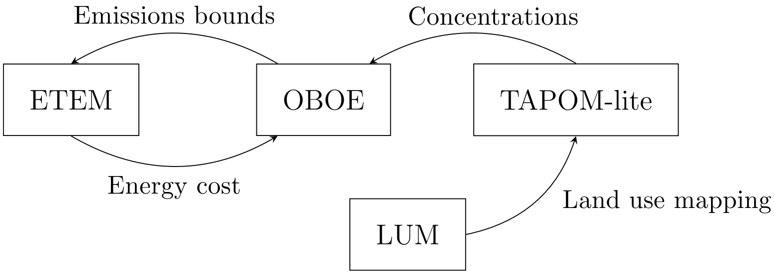

Fig. 1. The Luxembourg Energy Air Quality LEAQ model with the LUM extension.
Source: Adapted from Ref. [20].

zoning laws, land availability, economic viability, supply and demand considerations [9] as well as driving forces such as population growth [10]. Some of the more important techniques and the well established rules-based algorithms of CA can be found here [11,12].

In this paper, we model LC change according to a simple energy transition paradigm. Intuition has led us to approach the underlying statistics using Maxwell–Boltzmann (MB) statistics [13]. Basic counting statistics are scare in the literature of land cover dynamics, yet in some examples, Pólya Urn Model (PUM) processes [14] have been applied to similar counting exercises although in other fields (e.g. arthropod distributions on plants, [15]). The 'indistinguishability' of patterns of insect on plants and subsequent observations have shown that Bose–Einstein (BE) statistics [16,17], although not intuitive are, in fact, appropriate. In other unexpected areas, BE statistics are found in economic analyses [18] and in city size distributions [19]. The results of these studies and the 'indistinguishability' of similar LCs, in terms of unit area counts, suggest that a comparative counting study for LC is desirable. The statistical properties of land use transition explored here are therefore post-predictions, or prediction for the past using more remote past information. We consider only permutable land in the calculation, or land that can potentially change (e.g. forest land transforming to agricultural or urban areas). Though we consider unlikely situations where urban areas can transforming to agricultural areas, we do not consider a transformation to natural areas (LC3X–LC5X, Section 3).

The model, given in Section 2, provides the context and structure of the approach. Section 3 discusses the input LC areas used by the model. A rational for counting fractional LC is given in Section 4. A transition model is given in Section 5, followed by a discussion and conclusion in Section 6.

2. An energy–air quality–land use integrated assessment model

A driving motivation for LC models is the need for reliable projection of emission points by infrastructure and energy technologies; these are used as input to modern integrated assessment (IA) models. The long term projection of LC is required for accurate spatial emissions as input to the IA. The Luxembourg Energy Air Quality model (LEAQ) [20] is an IA model designed around a large-scale systems analytic method [21]. The model is used to assess air quality policies in urban regions and simultaneously evaluate energy technologies using an Energy-Technology-Environmental-Model (ETEM) [22]. The ETEM model, a partial equilibrium energy infrastructure expansion model, is coupled to an efficient air quality model TAPOM-Lite [23] via an Oracle Base Optimization Engine (OBOE) [24]. TAPOM-Lite simulates the levels of nitrous oxide $NO_2 + NO = NO_X$, volatile organic compounds, VOC and the secondary ozone O_3. The O_3 concentrations are simulated using the slow creation and elimination mechanisms for the gas. The coupled approach was develop to search for optimal (lowest cost) technology solutions to assist urban planners in predicting NO_X and O_3 levels and to determine if they will meet local air quality limits. An optimal (lowest cost) technological solution satisfying air quality constraints is found using convex optimization in a constrained system coupled approach. In this context, the LC projection methodology needs to be crafted in such a way that the decision parameters associated with the LC model represent convex functionals. The entire approach has been conceptually developed with a land use map (LUM) extension that would allow for optimization in this framework, Fig. 1. The next section describes the theoretical framework for LC conversion.

3. A land cover data

Land cover transition data have been made available from the Europe Statistical Bureau (EUROSTAT) [25] and the European Environmental Agency [26]. Land covers are listed according to the CORINE database and definition set. A list of 15 different LCs are given in Table 1 and the general country land area and GDP statistics for 1990 and 2000 are given in Table 2. GDP levels are determined from a 1990 benchmark using in terms of 1990 international dollars purchasing power parities (PPP) definition from Maddison [27,28]. The fraction of LCs for 22 countries is given in Table 3 and along with the spread of data, is shown in Fig. 2. The sampling size for the histogram is limited to the number of countries and this is reflected in the large data errors.