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Heuristic cellular automaton model for simulating soil organic carbon under land use and climate change: A case study in eastern China

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A B S T R A C T

The concentration of soil organic carbon (SOC) is one of the most important soil properties, and its spatio-temporal variability greatly affects the global climate and agroecology. To investigate the effects of land use and climate change on SOC, a heuristic cellular automaton (HCA) model was proposed and applied to a plains area in eastern China with a high population density and rapid urbanization rate. The HCA model was designed to simulate the geographical variation in SOC dynamics over the long term (2080), and lateral carbon (C) migration is represented by revised neighbourhood variables at the macro scale. Three widely used soil mapping techniques were applied for comparison: multiple linear regression (MLR), support vector machine (SVM) and kriging with external drift (KED). The HCA model enhanced the accuracy of the predicted SOC by 15.27% over MLR, 12.31% over SVM and 10.98% over KED. Future land use maps were produced using legacy land use data and artificial neural network-based cellular automata (CA), and the simulation results showed the rapid urbanization of this area, where the percentage of cropland declined by 23.75% and that of village/urban areas increased by 22.90% from 2010 to 2080. The overall SOC concentrations are anticipated to increase by 2080 given the rising mean annual air temperature and mean annual precipitation. Our results also suggested that land use change clearly influenced the change in soil C, with village/urban areas exhibiting higher SOC than cropland. To provide stakeholders with accurate soil information, it is important to understand the comprehensive impacts of land use and climate change on soil evolution; this study illustrates the value of integrating pedogenetic information in soil C simulation models.

1. Introduction

Soil organic carbon (SOC) concentrations generally play a pivotal role in soil functioning. The diversiform tillage activities and continual changes in land use and climate promote soil evolution (Leifeld et al., 2005). SOC affects various physical and chemical processes in the soil, and its spatio-temporal pattern is characterized by heterogeneity and uncertainty (Dorji et al., 2014; Ye et al., 2016). Dynamic modelling of SOC change is necessary for the effective monitoring of SOC stocks and for agricultural management.

Understanding soil-forming factors is critical for the simulation of carbon (C) dynamics. The SOC allocation of primary components is altered by both macro- (e.g., climate change and topography) and micro-factors (e.g., microbial decomposition rates) (Jandl et al., 2014). Thus, organic matter is affected by multiple interacting environmental controls, although one factor might be dominant. The most important variables affecting these factors are typically identified based on case studies (Paz et al., 2016). In general, climate, land use and soil type act as the main controls of SOC in different landscapes (López-Ulloa et al., 2005; Li and Shao, 2014; Paz et al., 2016). Anthropogenic activities are accelerating the rate of land use change and play an important role in impacting soil evolution in terms of fertilization, deforestation, urbanization and so on (Gelaw et al., 2014; Xiong et al., 2014; Ross et al., 2016). These environmental variables can be parameterized in predictive models to enhance SOC stock estimation (Dorji et al., 2014; Jandl et al., 2014; Paz et al., 2016).

The spatial pattern of the SOC concentration can be discretely modelled as a regular grid-based map. This method, known as digital soil mapping (DSM), has been widely applied by pedologists, and it differs from mapping models assuming that soil variation is

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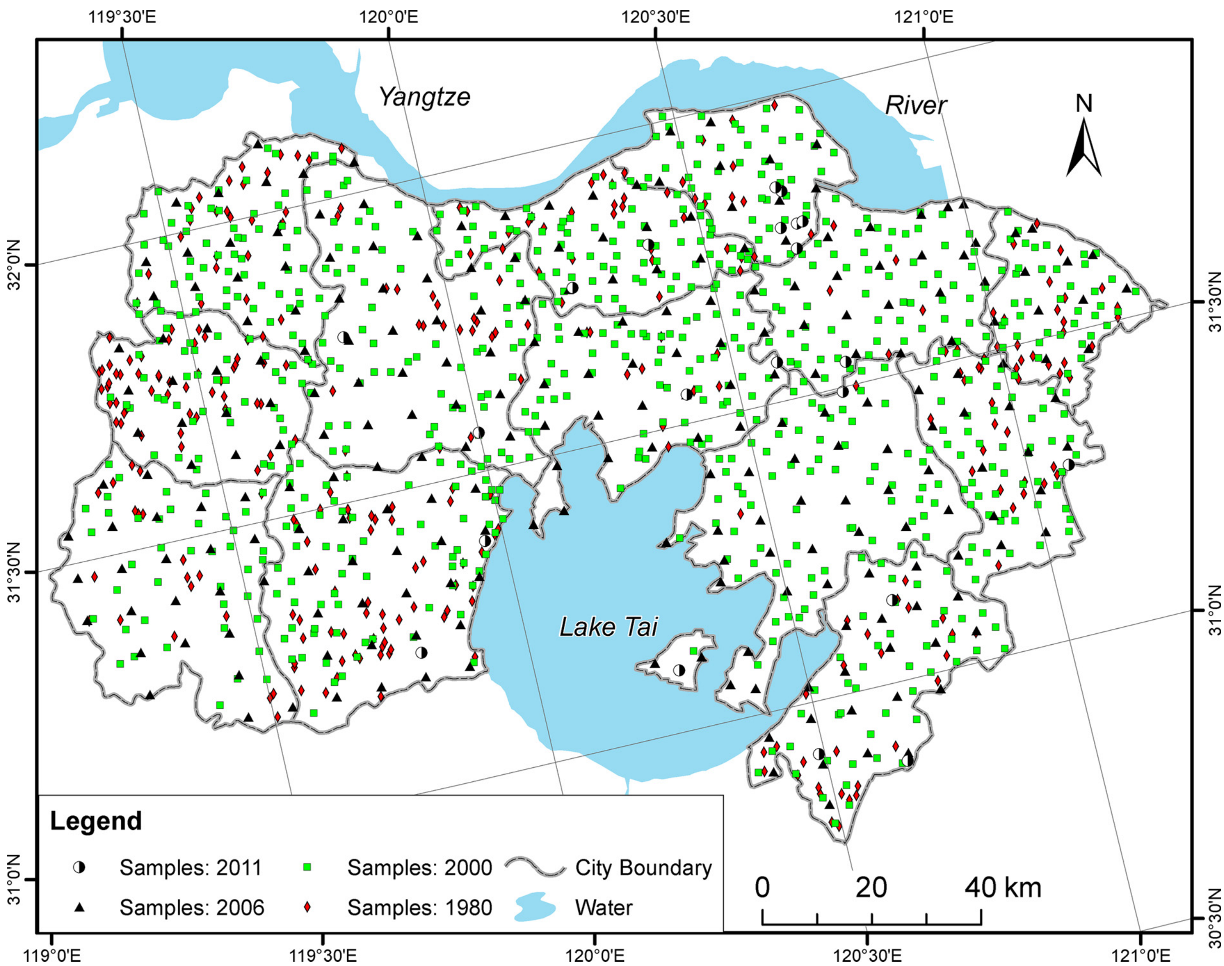

Fig. 1. Location of the study area.

homogeneous within a given landscape unit (Jandl et al., 2014). Numerous studies have attempted to identify the most important predictors (Bodaghabadi et al., 2011), compare predictive models (Grunwald, 2009) and summarize the regional changes in SOC stocks (Dorji et al., 2014). While considerable progress has also been achieved in spatio-temporal simulations (Jandl et al., 2014; Yigini and Panagos, 2016), shortcomings remain, particularly with respect to the spatial heterogeneity of SOC. For instance, due to the fragmented ownership of cropland in China, farms with an area of a few tenths of a hectare engage in variable cultivation practices (Song et al., 2016). Detailed soil information can be obtained only through costly field sampling, which hampers the production of up-to-date soil maps using DSM approaches. Furthermore, how to select the most useful predictors remains a challenge for model calibration, as models might be susceptible to noisy training data. In addition, given the same soil data and environmental predictors, the predictors selected based on stepwise methods (Kempen et al., 2011; Guo et al., 2015) or machine learning (Taghizadeh-Mehrjardi et al., 2016) might differ. This situation does not conform well to pedogenic theory, as some important predictors would be removed due to the low correlations between soil properties of interest and predictors, such as parent material, climate and terrain attributes. Various process-based and data-driven models have improved soil C simulations in the context of land use and climate change (Yu et al., 2013; Jandl et al., 2014; Zhang et al., 2016a; Muñoz-Rojas et al., 2017). However, few studies have quantified the effect of lateral C fluxes on SOC dynamics in terms of the transfer of dissolved organic C (DOC) and particulate organic C (POC) in paddy fields, soil erosion and other land surface processes, although these impacts are far from negligible (Parton et al., 1987; Almagro and Martínez-Mena, 2014; Wang et al., 2017; Wei et al., 2017). It may be plausible to use soil data sampled in different periods; however, in ecosystem modelling using complex functions, the requirement of numerous parameters might prohibit easy implementation, and ill-defined parameters will greatly bias simulation performance (Li et al., 2016a; Brilli et al., 2017).

Cellular automata (CA) models have been of interest in geographic modelling for over fifty years, including land use change simulations (Aburas et al., 2016), geomorphic process simulations (Fonstad, 2013), and seismicity descriptions (Jiménez, 2013), and these models show obvious advantages over empirical models and physically based models. CA models are composed of a regular grid of cells with several states that are affected by local interactions with neighbourhoods and are transformed according to a given rule. Therefore, CA models have been widely adopted to simulate limited states (Oku and Aihara, 2010; Basse et al., 2014). Furthermore, based on the paradigm of CA, macroscopic cellular automata (MCA) have been proposed to model infinite states through a discrete formulation, such as groundwater modelling (Ravazzani et al., 2011), ecohydrological dynamics modelling (Mendicino et al., 2015) or soil moisture modelling (Song et al., 2016). Compared with physically based equations, the transformation rules can be trained via machine learning techniques, and the goodness-of-fit of these models can be evaluated by quality indices (Wang and Li, 2011; Song et al., 2016). Regarding the source of C migration, SOC enrichment will greatly affect the redistribution process, and thus, calculating the neighbourhood state of SOC in terms of CA cells is promising to improve the simulation of soil C migration from the perspective of a "black box" by combining neighbourhood variables with prediction methods.

In this study, a heuristic cellular automaton (HCA) model was