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A spatial explicit assessment of food security in Africa based on simulated crop production and distribution

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ABSTRACT

The continent of Africa has the highest prevalence of hunger and poverty in the world. In this paper, an Environmental Policy Integrated Climate (EPIC) model combined with a Crop Choice Decision Model (CCDM) is applied to simulate the production and spatial distribution of rice, wheat, millet, maize, sorghum and cassava in Africa from 1993 to 2012 converted into calories. From this, we calculate the size of the undernourished population according to the Average Dietary Energy Requirement index of the Food and Agriculture Organization of the United Nations (FAO) and study the trends experienced in different countries. The results show that (1) the distribution of different crops has a horizontal zonality from north to south; (2) although the distribution of different crops in Africa did not change significantly from 1993 to 2012, the total crop planting area declined, especially in the middle part of Africa; (3) the undernourished population has increased, while the proportion of undernourished people decreased; and (4) land tenure reform and international food aid has made a great contribution to improved food security in Africa. A GIS-based EPIC (GEPIC) model combined with a CCDM can enable the spatial explicit assessment of food security and the microscopic study of food security on large scale, providing more accurate decision-making information for policy makers.

1. Introduction

Food security, defined as people having “access to sufficient, safe and nutritious food which meets their dietary needs and food preferences for an active and healthy life” (FAO, 2013a), remains an elusive reality for much of the world’s population (Pirani and Arafat, 2016). It is the focus of a considerable amount of literature that has largely assessed food security at different spatial-temporal scales as a consequence of changes in global climate, world population, food policies and agricultural technology (Battisti and Naylor, 2009; Tao et al., 2009; Lobell et al., 2008).

Many studies have concentrated on the African continent because of the increase, in absolute numbers, of under-nourished people and its unstable and serious food problem, which is worse than any other region (Conceição et al., 2016; Devereux, 2012). According to FAO-food security indicators, approximately 22.9% of the Africa population suffered from undernutrition between 2010 and 2012, nearly double the world average (12.5%), and 28.9% did not have access to adequate food supplies (FAO, 2013b). Undernourishment results in increased rates of disease, increased mortality reduced labor productivity and restricts the economic growth of many African countries. It occurs when the dietary consumption of people is continuously below the average dietary energy requirement of enough food to maintain health and perform normal physical activities (Soriano and Garrido, 2016), and formally recognized by people’s anthropometric scores falling below a selected cut-off point (Nube, 2001). Low food production associated with population growth also means that Africa’s overall food production per capita is declining and starvation rates are increasing (Mbow et al., 2014).

In order to adapt food supplies to meet future challenges, researchers have developed tools to support the protection of cultivated land and associated policymaking. Models to simulate crop production and distribution are receiving increased attention (Rosenzweig et al., 2013). These are process-based models that simulate growth, development and yield of crops as a function of weather and soil conditions, crop management scenarios and

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genetic information (Fischer et al., 2005). Using hypothetical conditions, they predict the behavior of feedback-regulated ecosystems (White et al., 2011). However, process type models may fail when yield-decreasing factors are not included in the model (Nendel et al., 2013). Compared with process type models, statistical-based models have a reduced execution time and demand for input data, so may offer an alternative at least at a regional scale (Wenkel et al., 2013). However, the variations in input data may mean that the results generated by these models are insufficiently accurate, especially when applied in un-calibrated conditions (Asseng et al., 2013; Eitzinger et al., 2012).

Although these previous studies have provided important information relating to food security, and have even been used to support the implementation of policies for fighting the food crisis and eradicating poverty and hunger, they still have limitations. For example, most of the data used in these studies were obtained from statistical yearbooks rather than firsthand data. It is therefore hard to reveal the influence of soil, climate, topography and land use policies on food security directly. On the other hand, some of these studies evaluate food security by establishing index systems that may involve many subjective judgments, leaving them lacking in objectivity.

This paper attempts to overcome these limitations by an applying an Environmental Policy Integrated Climate (EPIC) model developed by the Geographic Information System (GIS) method to predict crop production levels. This model, selected for its robustness and availability of data, is combined with a Crop Choice Decision Model (CCDM) to simulate the production and distribution of six crops in Africa from 1993 to 2012 at the resolution of 30'. The available calories are calculated for each crop produced and the numbers of undernourished people in African countries estimated based on the minimum dietary energy requirement (MDER) index. From these data, recommendations are made to improve food security in Africa.

2. Methods and materials

2.1. GIS-based EPIC model

The United States Department of Agriculture Agricultural Research Service first developed the EPIC model in 1984. It enables the researcher to model changes in crop environment, such as plant and soil moisture and nutrients, which are the major production constraints in agricultural systems. One version of this system is a GIS-based agro-ecosystem model that combines EPIC with the GIS to form the GEPIC model. This can be used to simulate the spatial and temporal dynamics of the major processes of a soil–-crop–atmosphere-management system (Liu et al., 2007; Wu et al., 2011). “With the integration of GIS, EPIC can be extended to applications at the global or regional level” (Tan and Shibasaki, 2003). The general idea of the GEPIC model is expressed in Fig. 1. The EPIC model can simulate site-specific processes such as crop growth, the hydrological cycle, N cycle, C cycle, climate change etc. By integrating EPIC with a GIS, the GEPIC model treats each grid cell as a site and simulates the above processes for all predefined grid cells at any spatial resolution (Liu, 2009). A loose coupling approach is used to integrate EPIC with the GIS, which relies on the transfer of data files between the GIS and simulation models. With this approach, the GEPIC interface abstracts most of the required data from GIS raster maps and edits them to the EPIC-required data format before transfer to the EPIC model. The simulation results of the EPIC model are then transferred to the GEPIC interface to generate output maps (Liu, 2009).

2.2. The GEPIC model combined with the Crop Choice Decision Model

We apply the CCDM developed by Wu et al. (2007) to simulate the distribution. The probability that a crop i is chosen for cultivation can be stated as (Greene, 1997):

$$P_{\mathrm{i}} = \frac{e^{u_{\mathrm{i}}}}{\sum_{\mathrm{i}=1}^{N} e^{u_{\mathrm{i}}}} \tag{1}$$

where

$$u_{\mathrm{i}} = a_{\mathrm{i}} + \sum_{\mathrm{j}=1}^{M} b_{\mathrm{j}} x_{\mathrm{j}} \tag{2}$$

with $i = 1,2,3 \ldots, N$ representing the crop selected for simulation, P_i denotes the probability for crop i and u_i represents the utility of crop i in (1). In (2), a_i denotes a constant for crop i, and $j = 1,2,3 \ldots, M$ is the number of explanatory variables, x_j represents the explanatory variable and b_j is the coefficient to be estimated for the variable x_j (McFadden, 1973).

The framework in this study combines GIS data with the EPIC simulation model, as illustrated in Fig. 2. GIS inputs of raster maps and the database are transferred to text input files by an input data translation module, which then generate EPIC input files with the help of the UTIL (Universal Text Integration Language) provided with the EPIC model (Liu et al., 2007). Finally, the GIS software ArcGIS, is run in the EPIC model for each simulated grid cell and combines these with the CCDM outputs and generated GIS outputs, which are converted to text output files.

2.3. Data sources and processing

Soil data are obtained from the Harmonized World Soil Database (HWSD): including the depth, percentage of sand, percentage of organic carbon content, pH, silt and bulk density. HWSD is a 30-arc-second raster map database combined with the 1:5 000 000 scale FAO-UNESCO Soil Map of the World. However, it cannot be read by the GEPIC directly and therefore the 30-arc-second raster is converted into a 30-arc-minute map in which each grid shows the dominant soil type. Each soil type in the raster map has its own code in the database that contains detailed soil information (Huang et al., 2014).

Daily climate data are obtained from the National Climate Data Center Global daily summary. Dew point temperatures, mean wind speeds, precipitation and maximum and minimum temperatures are selected as the inputs for the GEPIC model with the daily date

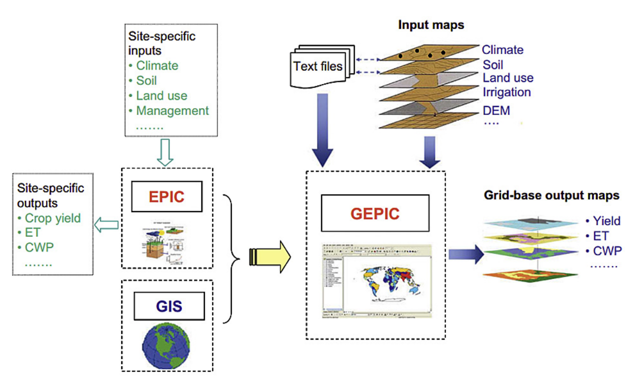

Fig. 1. Framework of the GEPIC model (Liu, 2009).