Computers and Electronics in Agriculture 89 (2012) 51–61

Contents lists available at SciVerse ScienceDirect

Computers and Electronics in Agriculture

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

Combining explanatory crop models with geospatial data for regional analyses of crop yield using field-scale modeling units

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ARTICLE INFO

Article history:
Received 29 November 2011
Received in revised form 20 July 2012
Accepted 6 August 2012

Keywords:
Crop modeling
Geographic information systems
Spatial aggregation
Regional analysis
Sensitivity analysis
Land use change

ABSTRACT

Crop models are used to predict yield and resource requirements as well as to evaluate different climate or management scenarios at a specific site. However, problems involving land use or global climate change encompass larger, more diverse, spatial scales and would benefit from simulating over broader areas using high-resolution, spatially-distributed data. A geospatial interface was developed to combine the explanatory potato crop model SPUDSIM with the geographic information system (GIS) software ArcGIS using the scripting language Python. Multiple geospatial input data layers were incorporated, including weather, soil, management, and land use. Modeling units (MUs) were defined as homogeneous field-scale areas created by the intersection of the input layers. Crop production was simulated for each unique combination of climate, soil, and management for MUs classified as cropland. The outputs (crop yield, water use, and nitrogen uptake) were mapped to show the spatial distribution within each county and aggregated to the county-level over the region of interest. An example was provided for potato production in Maine and illustrates how potential crop yield varies spatially over the state. The geospatial crop model showed evidence of both spatial and temporal variability of crop yield at the county level. The interface was designed to be flexible and easy to apply to applications such as evaluating crop production capacity and response under different scenarios.

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1. Introduction

Numerous geospatial datasets have been developed that contain information about earth surface resources. Examples include the extensive network of weather stations in the National Climatic Data Center (NCDC), the high-resolution US soil profile database (SSURGO), and land use datasets such as the National Land Cover Database (NLCD) and the Cropland Data Layer (CDL). These datasets are publically available at a high resolution and national scale, however, they have varying formats, such as point vectors (e.g. NCDC), polygon vectors (e.g. SSURGO), and rasters (e.g. NLCD and CDL). Spatial datasets are commonly managed through the use of geographic information systems (GISs). The merger of computational models with geospatial databases through a GIS for regional-scale analysis has a history in the field of agriculture for many different applications. Examples include evaluating potential biofuel resources and transportation logistics (Resop et al., 2011), modeling soil conservation practices using the Water Erosion Prediction Project (WEPP) (Renschler, 2003), and simulating scenarios for watershed-scale water quality using the Soil and Water Assessment Tool (SWAT) (Di-Luzio et al., 2004; Sexton et al., 2011). The primary motivation for interfacing models with a GIS is to represent the spatial variability of natural phenomena. GIS interfaces also allow users to display model results geographically for improved visualization and decision making.

Crop production models have been developed for better understanding crop responses to environmental factors and management scenarios. They tend to be designed for site-specific simulations and best suited for analyses at individual fields (Hartkamp et al., 1999; Priya and Shibasaki, 2001). It is difficult to apply these models to larger extents, such as studying regional land use change and global climate change, due to the input data variability over space and time (Lal et al., 1993; Hansen and Jones, 2000). One example model, EPIC (Erosion–Productivity Impact Calculator), was developed for simulating the relationship between soil productivity and erosion (Williams et al., 1989); however, it has also been used to predict crop yield (Priya and Shibasaki, 2001; Tan and Shibasaki, 2003; Zhang et al., 2010). EPIC is empirically-based and uses a single equation to simulate the production of many crops (Steiner et al., 1987). While EPIC is frequently applied to higher-scale studies, the underlying assumption is that crop growth can be adequately simulated with a few empirically-derived parameters. An alternate approach is to use explanatory models that simulate process-level physiological responses of the

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0168-1699/$ - see front matter Published by Elsevier B.V.
http://dx.doi.org/10.1016/j.compag.2012.08.001

Table 1
Examples of geospatial crop model applications increasing in extent from field-scale to global-scale and ranging from fine resolution (meters) to coarse resolution (kilometers).

Extent[a]	Application	Resolution[b]	Reference
Field	Spatial variability	Vector	Engel et al. (1997)
Field	Precision farming	Vector	Irmak et al. (2001)
Field	Precision farming	Vector	Thorp et al. (2007)
Field	Precision farming	12-m	Han et al. (1995)
Field	Climate change	45-m	Thorp et al. (2008)
Subregional	Spatial variability	Vector	Carbone et al. (1996)
Subregional	Biofuel production	56-m	Zhang et al. (2010)
Subregional	Crop yield constraints	100-m	Lobell and Ortiz-Monasterio (2006)
Regional	Climate change	Vector	Guo et al. (2010)
Regional	Climate change	50-km	Mearns et al. (1999, 2001)
Regional	Climate change	50-km	Tsvetsinskaya et al. (2003)
Regional	Regional calibration	50-km	Xiong et al. (2008)
Regional	Climate change	50-km	Tao et al. (2009)
National	Spatial variability	Vector	Yun (2003)
National	Spatial aggregation	10-km	Olesen et al. (2000)
National	Spatial variability	10-km	Priya and Shibasaki (2001)
National	Climate change	50-km	Guereña et al. (2001)
National	Crop water stress	50-km	Challinor and Wheeler (2008)
Continental	Production potential	Vector	van Lanen et al. (1992)
Continental	Climate change	18-km	Jones and Thornton (2003)
Continental	Climate change	18-km	Thornton et al. (2009)
Continental	Crop yield forecasting	25-km	de Wit et al. (2010)
Continental	Crop yield forecasting	50-km	de Wit et al. (2005) and de Wit and van Diepen (2008)
Global	Climate change	Vector	Parry et al. (1999, 2004)
Global	Climate change	Vector	Lobell et al. (2008)
Global	Climate change	11-km	Tan and Shibasaki (2003)
Global	Water use productivity	50-km	Liu et al. (2007) and Liu (2009)

[a] The extent is the overall spatial scope of the project, increasing in approximate size.
[b] The resolution is the size of the modeling unit for raster-based methods.

plant to components of the soil–plant–atmosphere continuum. Such models, including the DSSAT suite (Decision Support System for Agrotechnology Transfer) (Jones et al., 2003), the APSIM suite (Agricultural Production Systems Simulator) (McCown et al., 1996), WOFOST (van Diepen et al., 1989), and SPUDSIM (Fleisher et al., 2010), are better suited to predict responses to conditions outside of which they were derived (Reddy and Reddy, 1998).

The interfacing of crop models with GISs for spatial analyses has been discussed in the literature for over a decade (Hartkamp et al., 1999; Hodson and White, 2010). Geospatial crop modeling has been implemented throughout the world at various scales for many different applications (see Table 1 for references). In general, these applications fall into two categories: (1) studying the effects of spatially-variable parameters on crop production; and, (2) predicting the effects of future global climate change on crop production. In spite of the quantity of research devoted to the subject, Hodson and White (2010) observed that the development of interfaces for geospatial crop modeling has been mostly limited to individuals (designed specifically for a particular application and region of interest) and as a result it has been difficult to establish a standard technique. Interfaces have been used for analyses at both a small extent (field or regional) with fine-resolution data (meter-scale) and a large extent (nationally or globally) with coarse-resolution data (kilometer-scale).

Small extent applications generally involve precision farming, such as studying the effect of soil and management practices on crop yield variability. Field-scale studies tend to use soil data measured at the research site and climate data from a nearby weather station. AEGIS is an interface developed by Engel et al. (1997) that combines DSSAT with ArcGIS, but is designed for older versions of ArcGIS and has not been updated for newer technologies. Users of AEGIS are restricted to the DSSAT interface for adding new soil or weather data, which can be difficult when working at the regional scale. Thorp et al. (2008) developed the interface Apollo, which also combines DSSAT with ArcGIS, for applications such as analyzing the effect of different soil profiles or management areas on crop production. Apollo assumes constant weather and cultivar data over the modeled area; however, it could be modified to account for additional spatial variability. Zhang et al. (2010) modeled bioenergy crop production and sustainability using high-resolution SSURGO data with the EPIC model, although the study was limited to only a few counties in Michigan. Small extent interfaces make good use of high-resolution spatial data; however, they lack the ability to model production trends at the regional-scale.

Large extent applications commonly concern expansive efforts to investigate the effects of climate change. Jones and Thornton (2003) used DSSAT to model corn production at 18-km (1/6°) resolution for South America and Africa and predict the effect of climate change in poorer regions. Liu (2009) applied EPIC to model multiple crops (wheat, corn, and rice) globally at 50-km (1/2°) resolution to evaluate crop water use productivity. The Crop Growth Monitoring System (CGMS) has been developed for predicting seasonal crop yield in Europe at the regional level using a “simulate first aggregate later” system; however, it relies on low-resolution soil and interpolated weather data (de Wit and van Diepen, 2008; de Wit et al., 2010). Due to the large extent, these studies are limited to coarse-resolution modeling units, typically on the order of many kilometers. While these studies can provide global trends of crop responses, they are unable to investigate the spatial variability and distribution of crop production within modeling units. Analyses with smaller, more regional, extents have been performed (Mearns et al., 1999; Tsvetsinskaya et al., 2003), but they also have been limited to coarse-resolution data.

Geospatial crop model interfaces have shown the importance of spatially-heterogeneous variables in influencing crop yield variability (Lobell and Ortiz-Monasterio, 2006); however, more work is needed to apply crop models to high-resolution data at the regional-scale. For this study, regional-scale is defined as an area the