Environmental Modelling & Software 46 (2013) 44–49

Contents lists available at SciVerse ScienceDirect

Environmental Modelling & Software

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

Dynamic fuzzy models in agroecosystem modeling

Ralf Wieland*, Wilfried Mirschel, Claas Nendel, Xenia Specka

Leibniz-Centre for Agricultural Landscape Research, Institute of Landscape Systems Analysis, Eberswalder Str. 84, 15374 Muencheberg, Germany

ARTICLE INFO

Article history:
Received 21 September 2012
Received in revised form
15 February 2013
Accepted 16 February 2013
Available online 29 March 2013

Keywords:
Fuzzy modeling
Agro-ecosystem modeling
Climate change
SAMT

ABSTRACT

A new concept of dynamic fuzzy models used to estimate yield of agricultural crops (demonstrated for winter wheat) under the terms of climate change is introduced. Results of this fuzzy approach were compared to simulation results of MONICA, a traditional deterministic agro-ecosystem model, and YIELDSTAT, a statistics-based yield estimation model, for the federal state of Thuringia, Germany. The pros and cons of the fuzzy approach are discussed in terms of modeling effort, accuracy, calculation speed and maintenance. Some enhancements, including ensemble simulation using different experts models, are discussed. The main aim of this paper is to prove the concept of the dynamic fuzzy approach.

1. Introduction

Yield estimation is a central issue for crop modeling to analyze the impact of climate change on agricultural production over the next 50 years and the consequences for global food security (Olesen et al., 2011; Pearson et al., 2008; Bae et al., 2011). In order to estimate yields for Germany, well-known agro-ecosystem models such as CERES (Langensiepen et al., 2008) were adapted for parts of Germany. The Agricultural Production and Externalities Simulator (APES) model (Therond et al., 2011) was developed for impact assessment in Europe. Another model in this class is MONICA (Nendel et al., 2010) which is used as a benchmark for the new modeling approach based on dynamic fuzzy modeling in this paper. The pros and cons of using a deterministic ecosystem model under different spatial resolutions are discussed in Nendel et al. (submitted for publication). MONICA is a point-based model that includes all relevant processes in the plant, soil and water compartments in order to investigate behavior at the field scale. All of these deterministic models have in common that they consist of modules which again are deterministic models for different topical compartments, such as the water, plant, or soil compartment. Each module is controlled by a set of parameters, which were derived from detailed field or laboratory experiments. Parameterization of such sophisticated simulation models (Specka et al., submitted for publication) is a difficult procedure. To prepare MONICA for the simulation of new crops for energy plant production, parameterization requires a sensitivity analysis (Varella et al., 2010; Nossent et al., 2011; Janssen, 2012) to determine the most relevant parameters, which are then optimized in a second step (Wu and Liu, 2012). MONICA has more than 150 parameters, of which a considerably large set is used to fine-tune soil and plant simulations. Most of the deterministic models have a similar number of parameters. It goes without saying that uncertainties in parameters lead to uncertainties in the simulation result. Poor simulation results necessitate the adaptation of parameters if the model is used in different regions or for different crops. One advantage of these models, however, is that they can also be used to simultaneously calculate important system variables such as nitrogen leaching and soil organic matter dynamics; they are not merely restricted to yield estimation. Their numerous state variables can be analyzed to gain more insight of how the system works and reacts on external impacts.

Another issue at stake is the scale-related availability of information which is discussed in Hansen and Jones (2000). MONICA was adapted to the regional scale, which means it must cope with a lack of detailed data to control MONICA at this scale. For example, soil profiles used by MONICA are not available in such a high resolution in regional data maps. To overcome these restrictions, we set out to build a model that relies only on the set of input data at the regional scale. This well-known problem leads to the recommendation of finding a different modeling approach, discussed in Liu (2009). When it comes to yield estimation, models should be used without parameter adaptation or with as little information as possible. This can be achieved following principles (i, ii, iii):

* Corresponding author.
E-mail address: rweiland@zalf.de (R. Wieland).

1364-8152/$ – see front matter © 2013 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.envsoft.2013.02.006

(i) Keep it simple and stupid (KISS principle).
(ii) Reduce the number of parameters to a minimum.
(iii) Be general: generic model for different crops.

Models can be simplified using expert knowledge, as discussed in Krueger et al. (2012). Expert knowledge is often implemented using fuzzy models. How a fuzzy model can be used to estimate yield is shown in Wieland et al. (2011), for example. Fuzzy rules can be trained to enhance the accuracy of such an approach. As an alternative to fuzzy modeling, a Bayesian approach is discussed by Chen and Pollino (2012), leading to a model resembling a fuzzy approach. However, it does not have the flexibility and power of a rule-based fuzzy model (Samarasinghe and Strickert, 2013). It should be noted that neural networks and, nowadays, support vector machines can also be used to estimate yield (Wieland et al., 2010).

An alternative approach based on statistics and expert knowledge is the YIELDSTAT model (Mirschel et al., 2011). This model has been used in large-scale simulations in Germany, e.g. for Thuringia (Mirschel et al., 2012) and Saxony (Mirschel et al., 2010). What all these models have in common is that they are more or less static models that are not responsive to daily weather, daily plant growth, and so on. YIELDSTAT, for example, uses the climate water balance (climate water balance = sum of precipitation − potential evapotranspiration) for different periods of the growing season. To overcome this restriction, fuzzy models should be part of a dynamic process. In industrial process control, fuzzy controllers are used as part of a closed loop (Nagi et al., 2013; Gao et al., 2012) to control nonlinear processes. To follow this idea, fuzzy models should be part of a dynamic modeling approach. A step midway between a static and a dynamic model is given in Lauzon and Lence (2008). In the next section, a new method using fuzzy models as the main part of a dynamic modeling approach is introduced. The aim of the model development is to generate a simple, fast and accurate crop model to estimate yield under the terms of climate change.

The new model, "YIELDFUZZY", should react to climate change, which generally means higher temperatures and a change in precipitation distribution within the vegetation period, as well as a higher atmospheric CO_2 content. The model should therefore be sensitive to such changes. Although the investigation region is a federal state of Germany, namely the Free State of Thuringia, the model should also function for nearby states such as Saxony and Brandenburg without having to be recalibrated. In these regions, water availability is the most restrictive parameter for yield. For this reason, the model development should start with a "soil–water–plant" model, to which other parts (heat stress, CO_2, management, etc.) can be added as required.

2. Method

The method part of this paper consists of four subsections. In the first subsection, the principle of dynamic fuzzy modeling is introduced. In the second subsection, the approach is applied to the dynamic fuzzy models modules and its implementation is explained. In the third subsection, a description is given of the parameter optimization of fuzzy models. The fourth subsection provides a short introduction to the model implementation and the basic software used.

2.1. Development principle of the fuzzy approach

Fig. 1 shows how the model is implemented.
The model consists of the following components:

(i) "Plant water need": calculates water demand according to the development stage of the plant (Plant) and potential evapotranspiration ET_{pot}.
(ii) "Plant growth": calculates the development stage of the plant (Plant) depending on daily temperature (T) and water supply (Water supply) from the "Soil water storage".

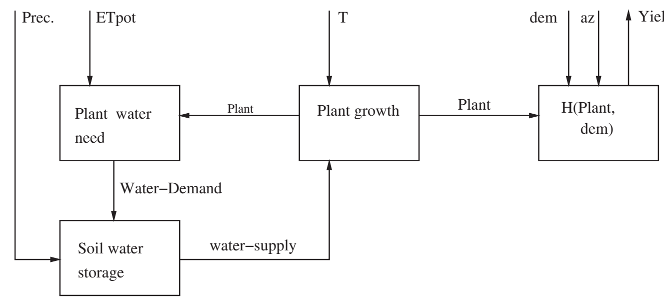

Fig. 1. Dynamic fuzzy approach of the crop model.

(iii) "Soil water storage": calculates the water supply from the soil according to daily precipitation and the plants water demand (Water demand).
(iv) "The scaling model H" used to adapt the model to specific soil (*dem* − elevation, *az* − soil quality index) and management properties will be explained later.

The "Plant growth" model has the variable "Plant" and "Soil water storage" has the variable θ to represent the states of plant development and water storage, respectively. In a traditional modeling approach, models implement approximations of a differential equation such as the following, often used for growth modeling:

$$\frac{dP(t)}{dt} = K \times P(t)^k \times (B - P(t)^w). \quad (1)$$

This equation is a variant of the famous "Evolon" (Peschel et al., 1984). In this equation, parameter $\{K, k, B, w\}$ must be fitted according to measured data. Modelers have to cope with a number of difficulties:

(i) Expensive data collection,
(ii) Nonlinear parameter fitting,
(iii) Parameter interpretation and adaptation.

On the other hand, modelers often have the experience and know-how to describe the model in principle, for example using fuzzy rules. The idea is to replace the nonlinear right-hand side of the differential equation with a fuzzy model:

$$\frac{dP(t)}{dt} = Fuzzy(T, SW, P) \quad (2)$$

and to solve it using a trapeze rule (KISS principle):

$$P(t+1) = P(t) + Fuzzy(T, SW, P) \quad (3)$$

($SW = 1.0 - supply/demand$, $P = Plant$).[1] The trapeze rule is used as a simple solver for differential equations according to the KISS principle.

2.2. Fuzzy models for crop growth modeling

To explain fuzzy models, we must focus on the plant growth and soil water storage models, which are the most interesting ones. Plant growth models have to implement a "sigmoid growth" function, which is standard for plant growth. This means that a plant starts out as a small plant with a slow growth rate and gradually develops to the "main growth" stage. During the main growth stage, the plant has a high growth rate and the plant develops well. At the end of the main growth stage, the growth rate decreases and the plant proceeds to the ripeness stage. Temperature (T) and water stress (SW) are control parameters. State variable P is part of the fuzzy model. To ensure a sigmoid growth of the plant, the fuzzy model should approximate a bell shaped function.[2] The fuzzy library of SAMT (Wieland et al., 2006) used allows only triangular and trapezoid membership functions (or "left open" and "right open") for inputs and singletons as outputs. Fig. 2 shows how to approximate a bell-shaped function using triangular membership functions:

The idea is to divide the input "plant" into small parts at the beginning and end of the region and into large overlapping parts in the middle. For example, if the state variable P has reached a value of 0.3, then it belongs to the classes medium small (ms) and medium (m) with $\mu_{ms}(P) \approx 0.6$ and $\mu_m(P) \approx 0.4$. Together with the interpolation of the output (which are singletons), a good approximation of a bell-shaped function can be achieved. The rule set is fairly simple compared to the membership functions, as exemplified by a number of rules in Table 1:

[1] Here we use water stress SW instead of water supply for convenience.
[2] An integral over a bell-shaped function is a sigmoid function.