Fuzzy cognitive modeling of agricultural land productivity in the context of food security

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Abstract. The article deals with the problems of fuzzy cognitive modeling and evaluation of the productivity of reclaimed soils, taking into account the combination of natural-climatic, soil and environmental factors. To construct a fuzzy model, the parameters to be modeled were the coefficient of bioclimatic productivity with a range of variation of 0.5-1.5, and the yield of grain crops, which varied within 10...45 dt/ha for different natural and climatic zones. The theoretical basis for the development of a model of land productivity is the theory of fuzzy inference based on the fuzzy-multiple approach. The main stages of fuzzy modeling using the Mamdani algorithm in interactive mode are presented. An algorithmic representation of the dependence of the integral indicator of the productivity of agricultural land on the value of the yield of grain crops, and the coefficient of bioclimatic productivity is obtained. The constructed fuzzy model allows to obtain estimates of the generalized indicator of agricultural land productivity based on the yield values for the range of values of the bioclimatic coefficient. The constructed model can be used as a part of a system for predicting the level of food security.

1. Introduction

Solving the problem of food security requires reliable numerical estimates of the main components that determine it: production, consumption, stocks, and imports. Therefore, to assess the potential opportunities for agricultural production, it is important to obtain reliable estimates of agricultural land productivity in order to rationally plan the development of agricultural production, preserve soil fertility, and prevent degradation processes [1]. This is possible with the application of methods of mathematical modeling and optimization [2].

Mathematical modeling of agricultural land productivity requires taking into account hundreds of parameters of various physical nature, including soil (type, chemical composition, structure and density of addition), natural and climatic (heat and moisture availability, wind map), reclamation state (humus layer, hydrology, salinity), environmental, etc. [3]. To eliminate the problem of the "curse of dimensionality", which characterizes a fairly strict multi-factor mathematical description of agricultural land productivity, it is possible to use methods of fuzzy-multiple modeling [4, 5].

Traditional approaches to mathematical modeling based on the construction of statistical multi-factor regression models, additive or multiplicative convolutions, or classical neural networks [6, 7], they also require explicit consideration of the significant dimension of the models. This led to the choice of a fuzzy-multiple approach for modeling the productivity of agricultural land in the cultivation of agricultural crops.
Fuzzy approaches are more effective when there is incomplete or insufficient certainty of information about the studied natural and anthropogenic system. It is interesting to use cognitive approaches based on the construction of cognitive maps that allow structuring and generalizing expert information obtained on the basis of empirical descriptions of modeled processes [8, 9].

2. Materials and methods
The initial data for modeling were the yields of various crops and coefficients of bioclimatic productivity for various natural zones of the Lower Volga region. The data of Sazhin et al. [6] that characterize long-term indicators that determine the productivity of agricultural land in arid conditions, on the example of the Volgograd region, are presented in Table 1.

To construct a fuzzy model, the coefficient of bioclimatic productivity with a range of variation of 0.5-1.5, and the yield of grain crops, which varied within 10...45 dt/ha for various natural and climatic zones, were taken as modeled parameters (Table 1).

The theoretical basis for developing a model of land productivity is the fuzzy inference theory based on the fuzzy-multiple approach. Modeling included the construction of the membership function for the selected basic indicators, the formation of a database of logical inference rules using the values of linguistic variables, and subsequent defuzzification [10].

Table 1. Long-term indicators of agricultural land productivity in arid conditions of the Volgograd region.

| Natural zone                          | Coefficient of bioclimatic productivity | Yield, centners per hectare |
|--------------------------------------|----------------------------------------|----------------------------|
|                                      |                                        | winter wheat | spring-wheat | barley | corn |
| Steppe chernozem soils               | 1.24                                   | 42.1         | 21.7         | 25.7   | 40.0 |
| Dry steppe of dark chestnut soils    | 1.08                                   | 36.0         | 16.5         | 22.0   | 35.0 |
| Dry-steppe chestnut soils. Right bank| 1.03                                   | 31.1         | 14.5         | 20.1   | 30.0 |
| Dry-steppe chestnut soils. Left bank | 0.93                                   | 25.0         | 14.0         | 20.1   | -    |
| Semi-desert light chestnut soils     | 0.90                                   | 23.0         | -            | 13.1   | -    |

The mathematical-oriented environment of the MATLAB application software package, which includes a number of computer modeling tools, was chosen as the modeling software platform for building the developed model. For software implementation of the developed fuzzy model, the fuzzy Logic Toolbox module of the MATLAB package was used, which has a wide range of fuzzy modeling tools [11].

3. Results and discussion
In the course of research, a fuzzy computer model was developed for assessing the productivity of agricultural land, designed to assess and rank risks, taking into account both linguistic qualitative and quantitative factors. The software implementation of the developed model allows the use of various software systems focused on computer mathematical modeling.

The General structure of the developed model in the notation of the fuzzy Logic Toolbox module of the MATLAB package is shown in Figure 1.
The implementation of fuzzy logical inference directly based on the developed model was carried out through the following stages.

**Stage 1. Fuzzification**

Fuzzification, which is a definition of fuzziness using a certain membership function (MF) for term sets of input and output variables based on their linguistic definitions:

- $x_1$ is a "Yield" variable of the linguistic type;
- $x_2$ is a variable "Coefficient of bioclimatic productivity" of the linguistic type;
- $y$ is the linguistic variable "Normalized productivity level".

The generated term set for both the input linguistic variable $x_1$ and the output $y$ includes three linguistic terms $T = \{\text{Low (H)}, \text{Medium (C)}, \text{High (B)}\}$, which characterize the low, medium, and high levels of these variables, respectively. For the input linguistic variable $x_2$, the term set is bounded by two terms $T = \{\text{Low (H)}, \text{High (B)}\}$, which characterize the low and high levels of values of these variables, respectively. The view of graphs of selected MFs for term sets of input linguistic variables is shown in Figure 2.

The variable $x_1$ is characterized by continuous bell-shaped dependencies, and $x_2$-piecewise linear. To defuzzify the output linguistic variable $y$ ("Normalized level of agricultural land productivity"), the term set consists of three terms: Low land productivity (LOW); Average land productivity (MIDDLE); and High productivity (HI). Piecewise linear MFs of the output variable $y$ are shown in Figure 2.

**Stage 2. Creating a database of inference rules**

A database of fuzzy inference rules is formed for the developed model. In the Mamdani algorithm, the rule base is defined as a structure with two inputs and one output (Figure 3).

The fuzzy inference rules implemented by the model are written in equation systems of the form:

\[ \text{"IF } X = a, \text{ then } Y = b", \]
\[ \text{"IF } X = c, \text{ then } Y = d", \]

Figure 1. The structure of fuzzy model using Fuzzy Logic Toolbox module of MATLAB.

Figure 2. Accessories functions: a - for the input variable $x_1$; b - for the input variable $x_2$. 
The generated "rule Base" reflects logically justified relationships between the input linguistic variables $x_i$ and output $y$, where in our case $i = 1, 2$. The rule Base is built by analysts together with experts based on general theoretical ideas about the regularities of the formation of agricultural land productivity and ensures the functioning of the fuzzy logical inference mechanism. A fragment of the formulated base rules for fuzzy inference to ensure fuzzy logical inference is presented in Table 2.

Table 2. Fragment of the fuzzy production rules database.

| The Antecedent | The Consequent |
|----------------|----------------|
| $x_1 = \text{Low} \lor x_2 = \text{Low}$ | $y = \text{LOW}$ |
| $x_1 = \text{Medium}$ | $y = \text{MIDDLE}$ |
| $x_1 = \text{High} \lor x_2 = \text{High}$ | $y = \text{HI}$ |

Each of the rules of the generated database, presented in table 1, is entered into the created fuzzy output system in the "Rule Editor" window of the fuzzy Logic Toolbox module of the MATLAB package.

Stage 3. Defasification

Defasification is the process of determining the numerical values of an output variable based on its linguistic values obtained by applying production rules. The fuzzy inference system developed in the Fuzzy Logic Toolbox environment makes it possible to obtain a numerical estimate of the simulated normalized productivity of agricultural land at the defasification stage.

Productivity modeling using the developed fuzzy model is performed as follows. In the window of graphical output by using the interface Rule Viewer of Fuzzy Logic Toolbox module the original values $x_1$ and $x_2$ of the simulated input parameters are entered (Figure 4). For example, if the value yields of 27.5 centners/ha the value of the linguistic variable $x_1$ corresponds to the term Average (A). The value of the "Coefficient of bioclimatic productivity" $x_2 = 0.856$ corresponds to the value of the linguistic variable $x_2$ that corresponds to the term Low (L).

For the entered numeric values $x_1$ and $x_2$, logical rules 1 and 2 of Table 1 are activated. The resulting value of the normalized output variable $y$ is 0.39.
Figure 4. Parameters input window for fuzzy modeling of agricultural land productivity.

Figure 5 shows the nature of the simulated dependence of the normalized indicator of agricultural land productivity on the value of grain yield, constructed with a fixed value of the coefficient of bioclimatic productivity $x_2 = 1.10$.

Figure 5. Visualization of changes in the generalized indicator of agricultural land productivity: a - dependence of land productivity on the value of grain yield; b – view of the three-dimensional surface of the response of agricultural land productivity.

Note that the pronounced non-linearity of the dependence (2), which is not explicitly known in advance, is determined by the set of production rules (1) of the developed fuzzy inference system.

$$y = f(x_1, x_2).$$

The developed fuzzy output system, implemented on a PC in the Fuzzy Logic Toolbox environment of the MATLAB software package, has extensive adaptation capabilities.
4. Conclusion
The fuzzy output system allows to vary the values of input indicators and their range of changes, the type and numerical parameters of membership functions. In addition, one can adjust the composition of the database of product rules set by analysts together with experts. As the research continues, it is planned to increase the number of input indicators and, accordingly, the hyperspace dimension of the response surface corresponding to the simulated indicator of agricultural field productivity.

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