RESEARCH ARTICLE | MAY 06 2024

Fuzzy logic model of assessment soil salinatization FREE

Dilnoz Muhamediyeva ; Abdurashid Samijonov; Shakhzodbek Bakhtiyorov; Kamal Alimbaev

AIP Conf. Proc. 3147, 040008 (2024)
https://doi.org/10.1063/5.0210432

Fuzzy Logic Model of Assessment Soil Salinatization

Dilnoz Muhamediyeva[1, a)], Abdurashid Samijonov[2, b)], Shakhzodbek Bakhtiyorov[2], Kamal Alimbaev[2]

[1]*"Tashkent Institute of Irrigation and Agricultural Mechanization Engineers" National Research University, Tashkent, Uzbekistan*
[2]*Tashkent University of Information Technologies named after Muhammad al-Khwarizmi, Tashkent, Uzbekistan*
[a)] *Corresponding author: dilnoz134@rambler.ru*
[b)]*an_samijonov@mail.ru*

Abstract. The article discusses the construction of a fuzzy logic model for assessing soil population. The developed model for assessing soil salinity, based on the Mamdani fuzzy logic apparatus, represents a significant step in solving the problem of classifying and assessing the degree of soil salinity. Fuzzy logic allows for uncertainty and fuzziness in data and rules to be taken into account, which is especially important in areas where precise numerical values can be difficult to determine. The model works with linguistic data, such as "low" or "medium" salinity, which makes the results more visual and understandable for users. The "black box" characterization of the model makes it easy to interpret results without the need for deep mathematical knowledge, making it accessible to a wide range of users. The model's flexibility and adaptability allow rules and inputs to be quickly changed to adapt to different situations and conditions. It is important to note that the model not only provides qualitative estimates, but also allows you to obtain quantitative results in a fuzzy form, which enriches the information and increases the accuracy of the conclusions. The use of fuzzy set theory provides a scientific basis for the model, making it more consistent and reliable. These advantages make the Mamdani fuzzy logic model a powerful tool for estimating soil salinity. It can be useful in various fields, including agriculture, ecology and land management, where the analysis and recording of soil salinity is important for decision-making and improving the quality of land resources.
Keywords. Assessment, fuzzy set theory, mamdani logic model, membership function, soil salinization.

INTRODUCTION

Assessing soil salinity in the Republic of Uzbekistan is important given current agricultural activities and the use of irrigated land, which constitute a small part of the country's total area (9.7%). Soil salinity is a serious problem as it can lead to reduced yields and deterioration of soil quality.

To increase biomass productivity and maintain soil fertility, it is necessary to systematically assess salinity levels. It is important to account for and replenish nutrients in the soil that may be lost due to salinization and exploitation of agricultural crops. This is important for maintaining the sustainability of agriculture and ensuring food security in the country.

Therefore, it is necessary to carry out measures to control and manage soil quality in Uzbekistan, taking into account the limited available irrigated land and its role in agriculture [1].

Assessing soil salinity to improve biomass productivity and replenish soil nutrients for crop production is relevant and critical for sustainable agriculture and food security. Soil salinity can significantly reduce crop yields because salt can increase the osmotic pressure in the soil, making it difficult for plants to get water and nutrients. This leads to reduced growth and yield. Assessing salinity levels allows agricultural workers to take soil management measures, such as optimizing irrigation, using salt-tolerant crop varieties, and implementing soil salt management techniques. Replenishing nutrients in the soil is necessary to maintain fertility and yield levels. If nutrients are carried away by plants at harvest and not returned to the soil, this can lead to poor soil quality and reduced future yields. Given limited land resources in Uzbekistan and the need to ensure food security, effective soil management becomes critical to

International Scientific and Practical Conference on Actual Problems of Mathematical Modeling and Information Technology
AIP Conf. Proc. 3147, 040008-1–040008-8; https://doi.org/10.1063/5.0210432
Published under an exclusive license by AIP Publishing. 978-0-7354-4927-5/$30.00

increasing agricultural yields and productivity. Soil salinity assessment and soil nutrient replenishment are key aspects of sustainable agriculture and food security in resource-limited settings [2].

The use of soil salinity classification when assessing their suitability is important and makes it possible to more accurately take into account the salt tolerance of plants when planning agricultural activities [3]. This classification helps determine which crops can be grown successfully on certain areas of land, given the level of salinity in the soil. Salt Tolerant Soils have low salinity levels and can support the cultivation of a wide range of crops without significant salt stress problems. A variety of crops such as grains, vegetables and fruits can be grown here. Moderately saline soils have salinity levels that can negatively impact some crops. It is important to select salt-tolerant plant varieties for growing in such areas or to use irrigation and drainage methods to reduce salt stress. Saline soils have high levels of salinity and may be unsuitable for growing most crops. However, in such areas you can try to grow salt-tolerant crops, such as some types of salt-loving plants [4].

Problems that professionals face when solving classification problems include the following aspects:

Lack of up-to-date, real-time information: Effective classification requires access to up-to-date data. The lack of such real-time information can hinder the classification process, especially in the case of tasks involving rapidly changing environments, such as medical diagnostics or financial analytics [5].

Lack of documented information databases and automated decision support systems: The presence of documented information and automated decision support systems can significantly simplify the classification process. The absence of such a system can lead to the need for manual analysis and decision-making, which requires a lot of time and effort.

Lack of knowledge bases and rule bases: Classification often requires the use of knowledge and rules that can be formulated based on experience and expert opinion. Lack of access to such knowledge bases and rules can limit automation and classification accuracy [6].

Lack of integrated software systems: In some cases, classification tasks may require the integration of different software systems and tools. The lack of such integration can complicate the classification process and reduce its efficiency.

Solving these problems may require the development and implementation of specialized information systems, automated algorithms and machine learning methods, as well as providing access to up-to-date data and knowledge bases. This will make the classification process more efficient and accurate, which in turn can lead to improved decision making in a variety of fields, including medicine, finance, science and industry [7].

Using soil salinity classification allows agricultural specialists to optimize the use of land resources, select appropriate soil and crop management methods, and minimize the negative impact of salinity on crop yields and productivity. It is an important tool for ensuring sustainable and efficient agriculture in conditions where soil salinity can be a serious problem [2,8-11].

METHODS

We consider the problem of assessing soil salinity, which is described by the Mamdani fuzzy logic model:

$$\bigcup_{p=1}^{k_j}\left(\bigcap_{i=1}^{n} x_i = a_{i,jp} - c \;\; weight \; w_{jp}\right) \rightarrow y = d_j$$

Here: $a_{i,jp}$ - term in conjunction string ($jp = \overline{1,k_j}$).

Using Mamdani fuzzy logic model to estimate soil salinity is a common and effective method [12]. This model allows for uncertainty and fuzziness in data to be taken into account when estimating soil salinity. Here's how to consider applying the Mamdani model to the problem of estimating soil salinity:

Input Variables: To assess soil salinity, various input variables can be used, such as the level of soil electrical conductivity, salt content in the soil sample, climatic factors, etc. These variables can be represented in the form of fuzzy sets, for example, “low”, “medium” " and "high" level of electrical conductivity.

Output Variable: The output variable in the Mamdani model can represent the degree of soil salinity, such as “low”, “medium” and “high” salinity levels.

An algorithm has been developed for the task of assessing soil salinity.

1 – creating a selection: Incoming (X_j, r_j), $j = \overline{1,M}$, selection - generating experimental data, in which $X_j = (x_{j,1}, x_{j,2}, ..., x_{j,n})$ - j – the incoming vector in the string and r_j - value of its output vector, respectively. When getting a selection, the data in it can consist of integers, floating point numbers, real numbers, and values in linguistic form. All values of the resulting sample are normalized to a certain common range.

2 - normalization: In this case, the incoming sample and the r vectors corresponding to it are normalized to the interval $[0,1]$.

$$u_i^k = l\frac{x_i^k - x^{\min}}{x^{\max} - x^{\min}},$$

$$u^k = l\frac{r^k - r^{\min}}{r^{\max} - r^{\min}}.$$

Here $x^{\min}, x^{\max}$ - X is the maximum and minimum elements of the input data matrix, $r^{\min}, r^{\max}$ - are the maximum and minimum elements of the output vector r.

3 – facification: Normalized u_i^k and u^k based on the data, the fuzzification process is carried out using the relevance function. In this case, a bell-shaped function was obtained intuitively (based on intuition) as a function of relevance. In many cases, it is the problems solved using the bell-shaped relevance function that have the highest level of accuracy and performance.

$$\mu^j(u_i^k) = \exp\left(-\frac{1}{2}\left(\frac{u_i^k - c_j}{\sigma_j}\right)^2\right),$$

$$\mu^j(u^k) = \exp\left(-\frac{1}{2}\left(\frac{u^k - c_j}{\sigma_j}\right)^2\right),$$

$$j = 0,1,2,...,l.$$

Here c_j and σ_j parameters of the function are calculated and they are adjusted using neural networks in the next stages of the algorithm.

4 – maximization: according to the results of fazification, an appropriate maximization operation is performed:

$$\mu^*(u_i^k) = \max_j \mu^j(u_i^k),$$

$$\mu^*(u^k) = \max_j \mu^j(u^k).$$

5 - evaluation of the conclusion: In this process, the execution of the conclusions based on the maximized data and rules is evaluated:

$$SP^k = \mu^*(u_1^k)\cdot\mu^*(u_2^k)\times...\times\mu^*(u_n^k)\cdot\mu^*(u^k).$$

Here k ($k = \overline{1,M}$) – rule number. In the next stages of the algorithm, the process of normalization of the obtained rule base is carried out again.

6 – normalization: The obtained rule base is normalized to the interval $[0,1]$:

$$\eta^k = l\frac{SP^k - SP^{\min}}{SP^{\max} - SP^{\min}}.$$

7 – fuzzification: The normalized rule base is fuzzified with the appropriate relevance function:

$$\mu^j(\eta^k) = \frac{1}{1+\dfrac{(\eta_k - c_j)}{\sigma_j}}.$$

8. Necessary rules: Experts and agronomists can determine the necessary rules for estimating salinity based on input variables. For example, "if the electrical conductivity level is high and the salt content in the soil is high, then the degree of salinity is high."

9. Use of linguistic variables: An important part of Mamdani's model is the definition of linguistic variables that describe the fuzzy sets and rules used for estimation. These variables and rules can be formulated based on the knowledge of experts in the field of soil science.

10. Aggregation and output: Mamdani model aggregates the rules and outputs a fuzzy output representing the degree of soil salinity based on the input data and rules.

11. Defuzzification: Defuzzification is used to convert the fuzzy output into a specific numerical value that can be used to estimate the degree of soil salinity.

12.Validation and Tuning: The Mamdani model can be tuned and validated using available soil salinity data to ensure its accuracy and reliability.

This is a general method for applying the Mamdani fuzzy logic model to the problem of soil salinity estimation. It allows you to take into account uncertainty and fuzziness in data, which is especially important in problems associated with natural and agricultural systems.

RESULTS

A Mamdani fuzzy logic model for assessing soil salinity was constructed.

$$\text{If}\left(x_1 = \frac{\sum_{j=1}^{q}\mu(a_{11}^j)a_{11}^j}{\sum_{j=1}^{q}\mu(a_{11}^j)} \wedge x_2 = \frac{\sum_{j=1}^{q}\mu(a_{12}^j)a_{12}^j}{\sum_{j=1}^{q}\mu(a_{12}^j)} \wedge \ldots \wedge x_8 = \frac{\sum_{j=1}^{q}\mu(a_{18}^j)a_{18}^j}{\sum_{j=1}^{q}\mu(a_{18}^j)} \right)$$

Then $y =$ Non-saline soils,

$$\text{If}\left(x_1 = \frac{\sum_{j=1}^{q}\mu(a_{21}^j)a_{21}^j}{\sum_{j=1}^{q}\mu(a_{21}^j)} \wedge x_2 = \frac{\sum_{j=1}^{q}\mu(a_{22}^j)a_{22}^j}{\sum_{j=1}^{q}\mu(a_{22}^j)} \wedge \ldots \wedge x_8 = \frac{\sum_{j=1}^{q}\mu(a_{28}^j)a_{28}^j}{\sum_{j=1}^{q}\mu(a_{28}^j)} \right)$$

Then $y =$ The degree of soil salinity is weak,

$$\text{If}\left(x_1 = \frac{\sum_{j=1}^{q}\mu(a_{31}^j)a_{31}^j}{\sum_{j=1}^{q}\mu(a_{31}^j)} \wedge x_2 = \frac{\sum_{j=1}^{q}\mu(a_{32}^j)a_{32}^j}{\sum_{j=1}^{q}\mu(a_{32}^j)} \wedge \ldots \wedge x_8 = \frac{\sum_{j=1}^{q}\mu(a_{38}^j)a_{38}^j}{\sum_{j=1}^{q}\mu(a_{38}^j)} \right)$$

Then $y =$ The degree of soil salinity is average,

$$\text{If}\left(x_1 = \frac{\sum_{j=1}^{q}\mu(a_{41}^j)a_{41}^j}{\sum_{j=1}^{q}\mu(a_{41}^j)} \wedge x_2 = \frac{\sum_{j=1}^{q}\mu(a_{42}^j)a_{42}^j}{\sum_{j=1}^{q}\mu(a_{42}^j)} \wedge \ldots \wedge x_8 = \frac{\sum_{j=1}^{q}\mu(a_{48}^j)a_{48}^j}{\sum_{j=1}^{q}\mu(a_{48}^j)} \right)$$

Then $y =$ The degree of soil salinity is strong,

$$\text{If}\left(x_1 = \frac{\sum_{j=1}^{q}\mu(a_{51}^j)a_{51}^j}{\sum_{j=1}^{q}\mu(a_{51}^j)} \wedge x_2 = \frac{\sum_{j=1}^{q}\mu(a_{52}^j)a_{52}^j}{\sum_{j=1}^{q}\mu(a_{52}^j)} \wedge \ldots \wedge x_8 = \frac{\sum_{j=1}^{q}\mu(a_{58}^j)a_{58}^j}{\sum_{j=1}^{q}\mu(a_{58}^j)} \right)$$

Then $y =$ The degree of soil salinity is very strong.

Here:

x_1 - neutral salinity acidity indicator;

x_2 - total amount of salts during chloride, sulfate-chloride salinity; soils by ion ratio, mmol(eq)/100 g soil;

x_3- total amount of salts during chloride-sulfate salinization of soils according to the ratio of ions, mmol (equiv)/100 g of soil;

x_4 - total amount of salts during sulfate salinization of soils according to the ratio of ions, mmol (equiv)/100 g of soil;

x_5 - indicator of acidity of alkaline salinity;

x_6 - the total amount of salts during soda and soda-chloride salinization of soils according to the ratio of ions, mmol (equiv)/100 g of soil;

x_7 - total amount of salts during sulfate-soda and soda-sulfate salinization of soils according to the ratio of ions, mmol (equiv)/100 g of soil;

x_8 - the total amount of salts during sulfate-chloride-carbonate salinization of soils according to the ratio of ions, mmol (equiv)/100 g of soil.

Here:

$$\mu(a_{11}^j)=\begin{cases}1, & a_{11}\le 8.5,\\ \left([1+(a_{11}-8.5)]^2\right)^{-1}, & a_{11}>8.5.\end{cases}\qquad \mu(a_{12}^j)=\begin{cases}1, & a_{12}\le 0.1,\\ \left[1+\dfrac{(a_{12}-0.1)^2}{0.001}\right]^{-1}, & a_{12}>0.1.\end{cases}$$

$$\mu(a_{13}^j)=\begin{cases}1, & a_{13}\le 0.2,\\ \left[1+\dfrac{(a_{12}-0.2)^2}{0.004}\right]^{-1}, & a_{13}>0.2.\end{cases}\qquad \mu(a_{14}^j)=\begin{cases}1, & a_{14}\le 0.3,\\ \left[1+\dfrac{(a_{12}-0.3)^2}{0.009}\right]^{-1}, & a_{14}>0.3.\end{cases}$$

$$\mu(a_{15}^j)=\begin{cases}\left[1+\dfrac{(a_{15}-8.5)^{-1}}{0.9}\right]^{-1}, & a_{15}\ge 8.5,\\ 0, & a_{15}<8.5.\end{cases}\qquad \mu(a_{16}^j)=\begin{cases}1, & a_{16}\le 0.1,\\ \left[1+\dfrac{(a_{16}-0.1)^2}{0.001}\right]^{-1}, & a_{16}>0.1.\end{cases}$$

$$\mu(a_{17}^j)=\begin{cases}1, & a_{17}\le 0.15,\\ \left[1+\dfrac{(a_{17}-0.15)^2}{0.002}\right]^{-1}, & a_{17}>0.15.\end{cases}\qquad \mu(a_{18}^j)=\begin{cases}1, & a_{18}\le 0.2,\\ \left[1+\dfrac{(a_{18}-0.2)^2}{0.004}\right]^{-1}, & a_{18}>0.2.\end{cases}$$

$$\mu(a_{21}^j)=\begin{cases}1, & a_{21}\le 8.5,\\ \left([1+(a_{21}-8.5)]^2\right)^{-1}, & a_{21}>8.5.\end{cases}\qquad \mu(a_{22}^j)=\left[1+\frac{(a_{22}-0.15)^2}{0.002}\right]^{-1}.$$

$$\mu(a_{23}^j)=\left[1+\frac{(a_{23}-0.3)^2}{0.009}\right]^{-1}.\qquad \mu(a_{24}^j)=\left[1+\frac{(a_{24}-0.4)^2}{0.015}\right]^{-1}.$$

$$\mu(a_{25}^j)=\begin{cases}\left[1+\dfrac{(a_{25}-8.5)^{-1}}{0.9}\right]^{-1}, & a_{25}\ge 8.5,\\ 0, & a_{25}<8.5.\end{cases}\qquad \mu(a_{26}^j)=\left[1+\frac{(a_{26}-0.15)^2}{0.002}\right]^{-1}.$$

$$\mu(a_{27}^j)=\left[1+\frac{(a_{27}-0.2)^2}{0.004}\right]^{-1}.\qquad \mu(a_{28}^j)=\left[1+\frac{(a_{28}-0.3)^2}{0.009}\right]^{-1}.$$

$$\mu(a_{31}^j)=\begin{cases}1, & a_{31}\le 8.5,\\ \left([1+(a_{31}-8.5)]^2\right)^{-1}, & a_{31}>8.5.\end{cases}\qquad \mu(a_{32}^j)=\left[1+\frac{(a_{32}-0.3)^2}{0.009}\right]^{-1}.$$

$$\mu(a_{33}^j)=\left[1+\frac{(a_{33}-0.5)^2}{0.035}\right]^{-1}.\qquad \mu(a_{34}^j)=\left[1+\frac{(a_{34}-0.7)^2}{0.05}\right]^{-1}.$$

$$\mu(a_{35}^j)=\begin{cases}\left[1+\dfrac{(a_{35}-8.5)^{-1}}{0.9}\right]^{-1}, & a_{35}\ge 8.5,\\ 0, & a_{35}<8.5.\end{cases}\qquad \mu(a_{36}^j)=\left[1+\frac{(a_{36}-0.25)^2}{0.008}\right]^{-1}.$$

$$\mu(a_{37}^j)=\left[1+\frac{(a_{37}-0.32)^2}{0.009}\right]^{-1}.\qquad \mu(a_{38}^j)=\left[1+\frac{(a_{38}-0.45)^2}{0.018}\right]^{-1}.$$

$$\mu(a_{41}^j)=\begin{cases}1, & a_{41}\le 8.5,\\ \left([1+(a_{41}-8.5)]^2\right)^{-1}, & a_{41}>8.5.\end{cases}\qquad \mu(a_{42}^j)=\left[1+\frac{(a_{42}-0.6)^2}{0.04}\right]^{-1}.$$

$$\mu(a_{43}^j)=\left[1+\frac{(a_{43}-0.8)^2}{0.07}\right]^{-1}. \qquad \mu(a_{44}^j)=\left[1+\frac{(a_{44}-0.115)^2}{0.09}\right]^{-1}.$$

$$\mu(a_{45}^j)=\begin{cases}\left[1+\frac{(a_{45}-8.5)^{-1}}{0.9}\right]^{-1}, & a_{45}\ge 8.5,\\ 0, & a_{45}<8.5.\end{cases} \qquad \mu(a_{46}^j)=\left[1+\frac{(a_{46}-0.4)^2}{0.02}\right]^{-1}.$$

$$\mu(a_{47}^j)=\left[1+\frac{(a_{47}-0.5)^2}{0.03}\right]^{-1}. \qquad \mu(a_{48}^j)=\left[1+\frac{(a_{48}-0)^2}{0.001}\right]^{-1}.$$

$$\mu(a_{51}^j)=\begin{cases}1, & a_{51}\le 8.5,\\ \left([1+(a_{51}-8.5)]^2\right)^{-1}, & a_{51}>8.5.\end{cases} \qquad \mu(a_{52}^j)=\begin{cases}\left[1+\frac{(a_{52}-0.8)^{-1}}{10}\right]^{-1}, & a_{52}\ge 0.8,\\ 0, & a_{52}<0.8.\end{cases}$$

$$\mu(a_{53}^j)=\begin{cases}\left[1+\frac{(a_{53}-1)^{-1}}{10}\right]^{-1}, & a_{53}\ge 1,\\ 0, & a_{53}<1.\end{cases} \qquad \mu(a_{54}^j)=\begin{cases}\left[1+\frac{(a_{54}-1.5)^{-1}}{12}\right]^{-1}, & a_{54}\ge 1.5,\\ 0, & a_{54}<1.5.\end{cases}$$

$$\mu(a_{55}^j)=\begin{cases}\left[1+\frac{(a_{55}-8.5)^{-1}}{0.9}\right]^{-1}, & a_{55}\ge 8.5,\\ 0, & a_{55}<8.5.\end{cases} \qquad \mu(a_{56}^j)=\begin{cases}\left[1+\frac{(a_{56}-0.5)^{-1}}{7}\right]^{-1}, & a_{56}\ge 0.5,\\ 0, & a_{56}<0.5.\end{cases}$$

$$\mu(a_{57}^j)=\begin{cases}\left[1+\frac{(a_{57}-0.6)^{-1}}{7}\right]^{-1}, & a_{57}\ge 0.6,\\ 0, & a_{57}<0.6.\end{cases} \qquad \mu(a_{58}^j)=\left[1+\frac{(a_{58}-0)^2}{0.001}\right]^{-1}.$$

The results of classification using the Mamdani fuzzy logic model were obtained and a comparative analysis was carried out.

TABLE 1. Accuracy of results calculated using Mamdani neuro-fuzzy model (%)

№	Value of σ	Number of terms 3	5	7	9
1	0.10	91.54	92.64	92.52	96.32
2	0.20	92.45	92.52	92.44	96.31
3	0.30	90.56	92.44	92.54	96.29
4	0.40	88.47	92.54	92.34	96.21
5	0.50	86.49	92.34	92.32	96.19
6	0.60	86.45	92.32	92.31	95.55
7	0.70	86.47	92.31	92.29	95.57
8	0.80	86.65	92.29	92.21	95.32
9	0.90	86.77	92.27	92.19	95.31
10	1.00	86.94	92.11	90.55	95.73
		95.75	95.74	95.57	96.77

According to forecast data, the area of saline lands will change in the period from 2022 to 2025. Here are the forecast indicators:

In 2022, the area of saline lands is expected to be 1,884 thousand hectares.

In 2025, the area of saline lands is projected to decrease and amount to 1,810 thousand hectares.

These data can be useful for developing strategies and interventions to manage and combat soil salinity, as well as predicting potential impacts on agriculture and the environment.

CONCLUSION

The developed model for assessing soil salinity using the Mamdani fuzzy logic apparatus represents a significant step towards an effective solution to the problem of assessing and classifying the degree of soil salinity. Fuzzy logic allows for fuzziness in data and rules to be taken into account, which is especially useful in problems where precise numerical values may be difficult to determine. This allows the model to work with linguistic data, such as “low” or “medium” salinity, which is more visual and understandable to humans. Characterizing the model's operation as a "black box" means that users can understand and interpret its output without the need to know complex mathematical or statistical techniques. This increases the accessibility and suitability of the model for a wide range of users. Fuzzy systems allow rules and inputs to the model to be easily manipulated and changed. This allows you to quickly adapt the model to different situations and conditions. Despite the fact that the model works with linguistic data, it allows obtaining quantitative estimates in a fuzzy form. This allows you to obtain more accurate and informative results than just qualitative estimates. The use of fuzzy set theory provides a mathematical basis for the model, which makes it more harmonious and scientifically sound. These advantages make the Mamdani fuzzy logic model an excellent tool for assessing and classifying the degree of soil salinity.It can be useful in various fields such as agriculture, ecology and land management, where soil salinity needs to be taken into account and analyzed for decision making. Soil salinization can negatively affect agriculture and the environment. The development of assessment models makes it possible to effectively manage land resources and minimize the negative consequences of salinization. Building fuzzy models and checking their correctness and adequacy is important to ensure the accuracy and reliability of the results. This allows you to trust the models and make informed decisions based on them. Integration of the developed models with standard algorithms and programs makes them more accessible and convenient for use in various fields, including agriculture, ecology and geology. The development and use of fuzzy models contributes to scientific research in the field of soil salinity by promoting better understanding and prediction of this phenomenon. Thus, the development of a fuzzy logic model for assessing soil salinity with automation of the formation of fuzzy rules, checking their correctness and integration with programs is a current direction and allows solving important problems in various areas related to soil salinization.

REFERENCES

1. Turdaliev Zh.M., Mansurov Sh.S., Akhmedov A.U., Abdurakhmonov N.Yu. Salinity of soils and groundwater in the Fergana Valley // Scientific review. Biological Sciences. – 2019. – No. 2. – P. 10-15;
2. Chen G. et al. A new approach to classification based on association rule mining. Decis. Support Syst. 2006; 42:674-689.
3. Muhamediyeva D.T., Raxmonova M.R. Application of a genetic algorithm for solving problems of optimization of placement and rotation of crops in cotton crops // Proc. SPIE 12564, 2nd International Conference on Computer Applications for Management and Sustainable Development of Production and Industry (CMSD-II-2022), 125640K (5 January 2023). 2022, Dushanbe, Tajikistan.
4. Egamberdiev N., Mukhamedieva D. and Khasanov U. Presentation of preferences in multi-criterional tasks of decision-making // IOP Conf. Series: Journal of Physics: Conference Series 1441 (2020) 012137. DOI: https://doi.org/10.1088/1742-6596/1441/1/012137
5. Han Y., Lam W., Ling C.X. Customized classification learning based on query projections, Information Sciences 177 (2007) 3557–3573.
6. Mamdani E. H., Efstathion H. J. Higher -order logics for handling uncertainty in expert systems. “Int. J. Man - Mach. Stud.”, 1985. -№ 3, -p. 243-259.
7. Muhamediyeva D.T. Aproaches to the Construction of Fuzzy Models of Intellectual Analysis of the State of the Low-Formalized Processes //2019 International Conference on Information Science and Communications Technologies (ICISCT), Tashkent, Uzbekistan, 2019, pp. 1-5.
8. Muhamediyeva D.T. Building and training a fuzzy neural model of data mining tasks // IOP Conf. Series:Journal of Physics: Conference Series, 2182 (2022) 012024. DOI https://doi.org/10.1088/1742-6596/2182/1/012024
9. Zagidullin B.I., Nagaev I.A., Zagidullin N.Sh., Zagidullin Sh.Z. A neural network model for the diagnosis of myocardial infarction. // Russian Journal of Cardiology. 2012; (6): 51-54.
10. Zaychenko Yu. The Fuzzy Group Method of Data Handling and Its Application for Economical Processes forecasting // Scientific Inquiry. -Vol. 7. -No 1, June, 2006. -p. 83-98.

11. Rotshtein A. P. Fuzzy multicriteria selection of alternatives: the worst case method // Izv. RAS. Theory and control systems. 2009. - No. 3. - P. 51-55
12. Rutkovskaya D., Pilinsky M., Rutkovsky L. Neural networks, genetic algorithms and fuzzy systems: Translation from Polish. I.D. Rudinsky. -M.: Hotline-Telecom, 2004. -452 p.