Crop Area Management Based on Fuzzy Analysis of Historical Sensor Readings Combined Within a Unified IoT Platform

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Abstract: - The network-centric approach to building control systems using wireless technologies has shown its effectiveness in practice. Currently, active research is underway in the field of implementing a network-centric approach to improve the management of business entities. A network-centric control system is a distributed control system in which its main components are integrated into a single information space. The purpose of this research is to develop proposals for building a network-centric model for managing geographically distributed crop areas based on a digital IoT-platform, which represents a universal info-communication environment. The features of network-centric control using fuzzy modeling systems that provide analytical support for decision-making under uncertainty are considered. As an example, it is considered a method of fuzzy modeling and forecasting of segments of averaged sensor readings from web-devices, which can provide information support for predictive and prescriptive analytical solutions. Proposed solutions can be used not only in the field of precision agriculture, but also to build a digital network-centric management platform for any business entity.

Key-Words: - Crop area management, network-centric control, IoT platform, sensor readings, fuzzy set, fuzzy time series, forecasting.

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1 Introduction

Crop area management system includes sources and consumers of information, telecommunications facilities, as well as a center for processing input data and preparing information for users. A network-centric management system based on a unified IoT information platform embodies the idea of creating "Smart Agriculture", which is a high-tech set of solutions that allows for maximum automation of specialized agricultural sectors, as a result of which agricultural production becomes profitable and economically beneficial. A huge layer of hidden and useful information is concentrated in the form of data that, through IoT technology, has become possible to obtain from the operating web-devices of agricultural enterprises. Crops, soil, irrigation devices, agricultural equipment and web-devices that monitor climate conditions, including temperature and ground humidity, can accumulate, send and process data, creating invisible images ready to be used to make preventive, tactical and strategic decisions.

Sensors of connected web-devices permanently collect data in a dedicated environment necessary to solve planned problems. At certain intervals, this data is transmitted to an integrated information IoT-platform using wireless technologies such as Wi-Fi, Bluetooth, Zigbee, LoRa, cellular networks (Nb-IoT, LTE, etc.), providing energy-efficient long-range networks actions, or by connecting directly to the Internet via Ethernet. The choice of connection means depends on the scope of application of a particular web-device within the framework of the IoT-based remote monitoring system.

2 Crop Area Management System

Figure 1 shows the structure of a network-centric management system (NCMS) for geographically distributed crop areas, built on the basis of the unified information IoT-platform, which receives data from sensors from web-devices located directly on controlled cultivation areas, and the results of multispectral analysis of data from multi-copters in the form of vegetation maps.

The correctness of the closure of individual circuits of the proposed NCMS is determined by the sufficient set of tools that provide the required adequacy of information support in the process of collecting, storing and processing sensor readings from web-devices and multispectral data from remote monitoring of the current state of the crop area, carried out by multi-copters in real time. The organization of each level of control involves the use of the unique set of built-in knowledge compilation models, information support, description of the microclimate in a dedicated environment, etc. Taking into account the latest advances in the field of artificial intelligence and related scientific disciplines [1], the tools for compiling knowledge in solving management problems can and should be subjected to significant revision. Its main essence lies in a radical change in the point of view on the role and place of modern intelligent technologies in the organization of hierarchical management of complex dynamic objects.

The main goal of this study is to develop the tool for processing sensor data to provide information support for making agricultural decisions based on the identified patterns in the fuzzy paradigm.

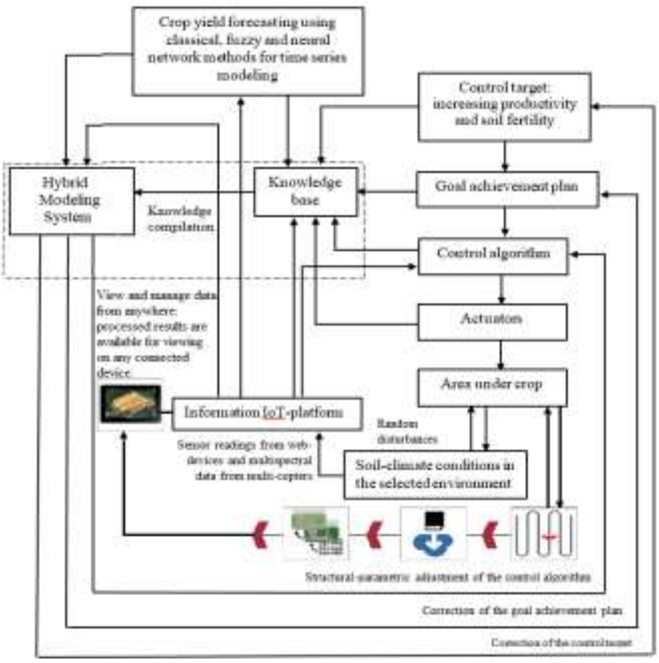

Fig. 1: Generalized structure of a crop area management system using IoT and unmanned technologies

3 Fuzzy Predictive Model Based on Humidity Sensor Readings

Figure 2 shows the time series reflecting the dynamics of changes in ground humidity on the specified sown area. Using this example, it is necessary to develop a methodology for constructing adequate predictive models of time series that reflect the dynamics of changes in data received in the form of sensory signals from web-devices that monitor the state of vegetation and climatic conditions, which have a significant impact on the yield of the crop being grown.

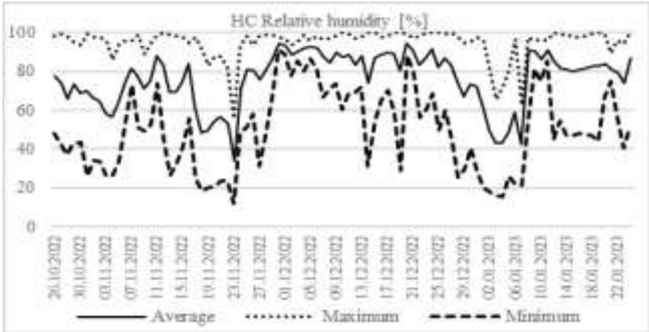

Fig. 2: Time series "Ground humidity"

Recent advances in solving forecasting and decision-making problems have been achieved mainly through the use of neural-fuzzy data processing technologies. Over the past decades, impressive results have been obtained in the field of forecasting volatile time series using fuzzy methods for analyzing historical data, [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17].

The object of our study is the "Ground humidity" time series, covering the set of historical data for the period from 26.10.2022 to 24.01.2023 inclusive (Figure 2). Because the ground humidity indicator is established by the usual arithmetic averaging of sensor readings from several sections of the crop area, each of its values $x(t)$ at time t will be considered as weakly structured historical data, which can be interpreted in the form of a fuzzy set (FS) A_k (k = 1÷n), characterized by the following tuple:

$$\{x(t) / \mu_{Ak}[x(t)]\},\ \mu_{Ak}[x(t)] \to [0, 1] \quad (1)$$

where $\mu_{Ak}(\cdot)$ is the membership function of the fuzzy set A_k. In this case, the fuzzy set A_k is the evaluation concept and is used as a qualitative criterion for assessing sensor readings. For each specific time series, the number of qualitative assessment criteria is set step by step as follows, [13].

Step 1. Sorting the sensor readings $x_t = x(t)$ (t=1÷91) into the ascending sequence $\{x_{p(i)}\}$, where p is a permutation that sorts the humidity readings in ascending order: $x_{p(i+1)} \geq x_{p(i)}$. Hereinafter, sensor readings at a given time should be understood as averaging sensor readings from several sections of the crop area.

Step 2. Calculation of the average value based on the totality of all pairwise distances $d_i = |x_{p(i)}-x_{p(i+1)}|$ between any two consecutive values $x_{p(t)}$ and $x_{p(t+1)}$ according to:

$$AD = \frac{1}{n-1}\sum_{i=1}^{n-1} | x_{p(i)} - x_{p(i+1)} | \qquad (2)$$

and standard deviation according to the formula

$$\sigma_{AD} = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n-1}(d_i - AD)^2} \qquad (3)$$

Step 3. Elimination of anomalies – outliers that need to be removed. The values of pairwise distances that do not satisfy the following condition are subject to emission:

$$AD-\sigma_{AD} \leq d_i \leq AD+\sigma_{AD} \qquad (4)$$

Step 4. After re-calculating the average value AD over the set of pairwise distances remaining after the release of anomalous values, the corresponding number of qualitative assessment criteria (m) is calculated using the formula:

$$m = [D_2\text{-}D_1\text{-}AD]/[2\cdot AD] \qquad (5)$$

where $D_1 = D_{\min}\text{-}AD$; $D_2 = D_{\max}+AD$; $D_{\min}$ and $D_{\max}$ are the minimum and maximum values in the humidity sensor readings, respectively.

Applying formulas (2) and (3) to sets of humidity sensor readings (n = 91), we obtained the average value AD = 0.67 and the standard deviation σ_{AD} = 1.14, respectively. By discarding d_i that do not satisfy condition (4) or, more specifically, the condition

$$-0.47 = 0.67\text{-}1.14 \leq d_i \leq 0.67+1.14 = 1.81$$

using formula (2), the final value of the average value for the totality of the remaining pairwise distances d_i was obtained: AD = 0.40. Then, according to [13], the segment $D = [D_1, D_2]$ is selected as a universal set covering the range of humidity sensor readings, where $D_1 = D_{\min}\text{-}AD$ = 34.02-0.40 = 33.62, $D_2 = D_{\max}+AD$ = 94.60+0.40 = 95. Then, according to (5), the acceptable number of criteria for assessing the humidity sensor readings is: m = [95-33.62-0.40]/[2·0.40] = 75.72 ≈ 76.

Now that the number of criteria for the qualitative assessment of ground humidity sensor readings has been established, it's time to determine their fuzzy formalisms, that is, their descriptions in terms of fuzzy sets. To do this, it is necessary to decide on the choice of a suitable membership function.

One of such functions is the symmetric trapezoidal membership function, which in the context of the problem under consideration is given in the following form:

$$\mu_{A_k}(x) = \begin{cases} 0, & x < a_{k1} \\ \dfrac{x - a_{k1}}{a_{k2} - a_{k1}}, & a_{k1} \leq x \leq a_{k2}, \\ 1, & a_{k2} \leq x \leq a_{k3}, \\ \dfrac{a_{k4} - x}{a_{k4} - a_{k3}}, & a_{k3} \leq x \leq a_{k4}, \\ 0, & x > a_{k4}, \end{cases} \qquad (6)$$

where $a_{k2} - a_{k1} = a_{k3} - a_{k2} = a_{k4} - a_{k3}$; k = 1÷m. Starting from (6), to describe the readings of ground humidity sensors in the form of fuzzy subsets of the universe $D = [D_1, D_2]$ = [33.62, 95], the appropriate 76 symmetric trapezoidal membership functions are identified (Figure 3), the parameters of which are summarized in Table 1.

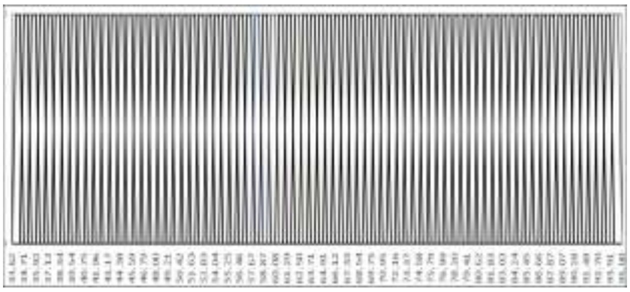

Fig. 3: Trapezoidal membership functions

Fuzzification of historical data of the "Ground humidity" time series is carried out according to the principle, [13]: the sensor reading is described by the fuzzy set to which it belongs to the greatest degree. When the sensor reading belongs to the interval $[a_{k2}, a_{k3}]$ (projection of the upper base of the k-th trapezoid onto the x-axis, see (10)), it is relatively easy to find its fuzzy analog. For example, the sensor reading x_{13} = 81.71 for the date 07.11.2022 is described by the fuzzy set A_{60} (Table 1), because it belongs to the interval [81.42, 81.83]. In other cases, additional calculations are required. In particular, for the sensor reading x_{11} = 64.19 for date 05.11.2022 we have: μ_{A39}(64.19) = 0.2023 and μ_{A38}(64.19) = 0.7977 (Figure 4). Therefore, A_{38} is chosen as the fuzzy analog.

Table 1. Fuzzy Sets as Criteria for Assessing Sensor Readings

Fuzzy set	Trapezoidal membership function parameters			
	a_{k1}	a_{k2}	a_{k3}	a_{k4}
A_1	33.62	33.91	34.31	34.71
A_2	34.31	34.71	35.12	35.52
A_3	35.12	35.52	35.92	36.32
A_4	35.92	36.32	36.73	37.13
A_5	36.73	37.13	37.53	37.93
A_6	37.53	37.93	38.34	38.74
A_7	38.34	38.74	39.14	39.54
………………				
A_{38}	63.30	63.71	64.11	64.51
A_{39}	64.11	64.51	64.91	65.32
………………				
A_{70}	89.07	89.48	89.88	90.28
A_{71}	89.88	90.28	90.69	91.09
A_{72}	90.69	91.09	91.49	91.89
A_{73}	91.49	91.89	92.30	92.70
A_{74}	92.30	92.70	93.10	93.50
A_{75}	93.10	93.50	93.91	94.31
A_{76}	93.91	94.31	94.71	95.00

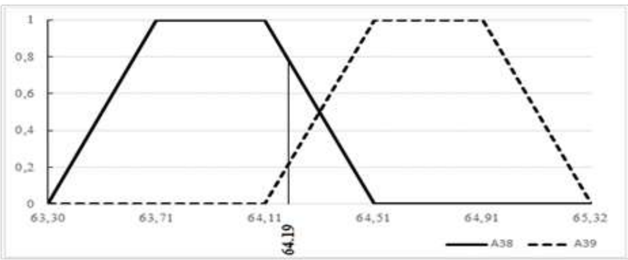

Fig. 4: Evaluation criteria in the form of fuzzy sets A_{38} and A_{39}

Thus, guided by the principle proposed in [13], the fuzzy analog of the "Ground humidity" time series was constructed and summarized in Table 2.

The next step in constructing the predictive model is to identify internal connections that determine cause-effect relationships between sensor readings throughout the entire observation period. Depending on the number of prerequisites in the fuzzy relation of the form "If <...>, then <...>", internal relationships are divided into groups of 1st, 2nd, and high-orders. Internal relationships (or fuzzy relations) of the 1st order are grouped according to the principle: if the fuzzy set A_t is connected with A_p and A_s, then the 1st order group is localized relative to it: $A_t \Rightarrow A_p$, A_s. For example, the fuzzy set A_{29} is connected with the fuzzy sets A_{25} и A_{38}, then the 1st order group $A_{29} \Rightarrow A_{25}$, A_{38} is localized relative to it (Table 3, Group G_{29}). The breakdowns by groups of internal relationships of the 1st and 2nd order are presented in Table 3 and Table 4, respectively.

Table 2. Fuzzy Time Series "Ground Humidity"

Date	x_t	Data	FS	Date	x_t	Data	FS
26.10.2022	x_1	77.67	A_{55}	11.12.2022	x_{47}	88.62	A_{69}
27.10.2022	x_2	73.90	A_{50}	12.12.2022	x_{48}	83.09	A_{62}
28.10.2022	x_3	65.97	A_{41}	13.12.2022	x_{49}	88.14	A_{68}
29.10.2022	x_4	73.42	A_{50}	14.12.2022	x_{50}	73.79	A_{50}
30.10.2022	x_5	68.91	A_{44}	15.12.2022	x_{51}	87.02	A_{67}
31.10.2022	x_6	70.01	A_{46}	16.12.2022	x_{52}	88.62	A_{69}
01.11.2022	x_7	66.53	A_{41}	17.12.2022	x_{53}	89.75	A_{70}
02.11.2022	x_8	64.66	A_{39}	18.12.2022	x_{54}	89.23	A_{69}
03.11.2022	x_9	58.38	A_{31}	19.12.2022	x_{55}	80.50	A_{59}
04.11.2022	x_{10}	56.76	A_{29}	20.12.2022	x_{56}	94.60	A_{76}
05.11.2022	x_{11}	64.19	A_{38}	21.12.2022	x_{57}	90.73	A_{71}
06.11.2022	x_{12}	73.83	A_{50}	22.12.2022	x_{58}	83.48	A_{62}
07.11.2022	x_{13}	81.71	A_{60}	23.12.2022	x_{59}	87.07	A_{67}
08.11.2022	x_{14}	77.55	A_{55}	24.12.2022	x_{60}	91.48	A_{72}
09.11.2022	x_{15}	71.04	A_{47}	25.12.2022	x_{61}	82.08	A_{61}
10.11.2022	x_{16}	74.92	A_{52}	26.12.2022	x_{62}	86.69	A_{66}
11.11.2022	x_{17}	87.83	A_{68}	27.12.2022	x_{63}	83.60	A_{62}
12.11.2022	x_{18}	83.09	A_{62}	28.12.2022	x_{64}	74.86	A_{52}
13.11.2022	x_{19}	69.22	A_{45}	29.12.2022	x_{65}	66.79	A_{42}
14.11.2022	x_{20}	69.26	A_{45}	30.12.2022	x_{66}	73.19	A_{50}
15.11.2022	x_{21}	74.44	A_{51}	31.12.2022	x_{67}	72.24	A_{69}
16.11.2022	x_{22}	83.68	A_{63}	01.01.2023	x_{68}	62.00	A_{62}
17.11.2022	x_{23}	61.18	A_{35}	02.01.2023	x_{69}	49.43	A_{68}
18.11.2022	x_{24}	48.49	A_{19}	03.01.2023	x_{70}	43.34	A_{12}
19.11.2022	x_{25}	49.53	A_{20}	04.01.2023	x_{71}	42.91	A_{12}
20.11.2022	x_{26}	54.39	A_{26}	05.01.2023	x_{72}	48.47	A_{19}
21.11.2022	x_{27}	56.31	A_{29}	06.01.2023	x_{73}	59.03	A_{32}
22.11.2022	x_{28}	53.11	A_{25}	07.01.2023	x_{74}	42.49	A_{11}
23.11.2022	x_{29}	34.02	A_1	08.01.2023	x_{75}	90.67	A_{71}
24.11.2022	x_{30}	71.01	A_{47}	09.01.2023	x_{76}	90.46	A_{71}
25.11.2022	x_{31}	81.06	A_{59}	10.01.2023	x_{77}	86.47	A_{66}
26.11.2022	x_{32}	80.30	A_{58}	11.01.2023	x_{78}	91.18	A_{72}
27.11.2022	x_{33}	75.55	A_{52}	12.01.2023	x_{79}	85.03	A_{64}
28.11.2022	x_{34}	81.04	A_{59}	13.01.2023	x_{80}	81.73	A_{60}
29.11.2022	x_{35}	86.75	A_{66}	14.01.2023	x_{81}	81.13	A_{59}
30.11.2022	x_{36}	94.60	A_{76}	15.01.2023	x_{82}	79.92	A_{58}
01.12.2022	x_{37}	93.21	A_{74}	16.01.2023	x_{83}	81.19	A_{59}
02.12.2022	x_{38}	88.62	A_{69}	17.01.2023	x_{84}	81.59	A_{60}
03.12.2022	x_{39}	90.42	A_{71}	18.01.2023	x_{85}	82.55	A_{61}
04.12.2022	x_{40}	91.97	A_{73}	19.01.2023	x_{86}	82.78	A_{61}
05.12.2022	x_{41}	92.45	A_{73}	20.01.2023	x_{87}	83.78	A_{63}
06.12.2022	x_{42}	92.02	A_{73}	21.01.2023	x_{88}	80.82	A_{59}
07.12.2022	x_{43}	87.17	A_{67}	22.01.2023	x_{89}	79.05	A_{57}
08.12.2022	x_{44}	84.37	A_{63}	23.01.2023	x_{90}	73.93	A_{50}
09.12.2022	x_{45}	89.83	A_{70}	24.01.2023	x_{91}	86.75	A_{66}
10.12.2022	x_{46}	87.42	A_{67}				

The 1st order internal relationship between the sensor readings x_t and x_{t+1} can be interpreted as the fuzzy implication

"If x_t is A_k, then x_{t+1} is A_p",

where t = 1÷91; k, p = 1÷76. In particular, the internal 1st order relationship $A_{11} \Rightarrow A_{71}$ (Table 3, G_2) between the readings x_{74}(42.49) and x_{75}(90.67) (Table 2) is interpreted as "If x_{74} is A_{11}, then x_{75} is A_{71}". If the internal relationship of the 1st order is represented in the form $A_k \Rightarrow A_{p1}, \ldots, A_{pr}$, where k, p_1, $p_2,\ldots, p_s$ = 1÷76, then in the form of the fuzzy implication it looks like this: "If x_t is A_k, then x_{t+1} is

A_p or x_{i+1} is A_r or x_{i+1} is A_s". In particular, the 1st order internal relationship $A_{52}\Rightarrow A_{42}$, A_{59}, A_{68} between sensor readings x_{64}(74.86) and x_{65}(66.79), x_{33}(75.55) and x_{35}(81.04), x_{16}(74.92) and x_{17}(87.83) (Table 2), interpreted as:

"If x_t is A_{52}, then x_{t+1} is A_{42} or x_{t+1} is A_{59} or x_{t+1} is A_{68}".

Accordingly, the 2nd order fuzzy relation, for example, A_{47}, $A_{59}\Rightarrow A_{58}$ can be interpreted as the fuzzy implication: "If x_t is A_{47} and x_t is A_{59}, then x_{t+1} is A_{58}", or relationship A_{59}, $A_{58}\Rightarrow A_{52}$, A_{59} can be interpreted as the fuzzy implication:

"If x_t is A_{59} and x_t is A_{58}, then x_{t+1} is A_{52} or x_{t+1} is A_{59}"

Table 3. Groups of Internal Relationships of the 1st Order

Group	Relation	Group	Relation
G_1	$A_1\Rightarrow A_{47}$	G_{16}	$A_{44}\Rightarrow A_{46}$
G_2	$A_{11}\Rightarrow A_{71}$	…	………………………..
G_3	$A_{12}\Rightarrow A_{12}$, A_{19}	G_{31}	$A_{64}\Rightarrow A_{60}$
G_4	$A_{19}\Rightarrow A_{20}$, A_{32}	G_{32}	$A_{65}\Rightarrow\varnothing$
G_5	$A_{20}\Rightarrow A_{26}$	G_{33}	$A_{66}\Rightarrow A_{62}$, A_{72}, A_{76}
G_6	$A_{25}\Rightarrow A_1$	G_{34}	$A_{67}\Rightarrow A_{63}$, A_{69}, A_{72}
G_7	$A_{26}\Rightarrow A_{29}$	G_{35}	$A_{68}\Rightarrow A_{12}$, A_{50}, A_{62}
G_8	$A_{29}\Rightarrow A_{25}$, A_{38}	G_{36}	$A_{69}\Rightarrow A_{59}$, A_{62}, A_{70}, A_{71}
G_9	$A_{31}\Rightarrow A_{29}$	G_{37}	$A_{70}\Rightarrow A_{67}$, A_{69}
G_{10}	$A_{32}\Rightarrow A_{11}$	G_{38}	$A_{71}\Rightarrow A_{62}$, A_{66}, A_{71}, A_{73}
G_{11}	$A_{35}\Rightarrow A_{19}$	G_{39}	$A_{72}\Rightarrow A_{61}$, A_{64}
G_{12}	$A_{38}\Rightarrow A_{50}$	G_{40}	$A_{73}\Rightarrow A_{67}$, A_{73}
G_{13}	$A_{39}\Rightarrow A_{31}$	G_{41}	$A_{74}\Rightarrow A_{69}$
G_{14}	$A_{41}\Rightarrow A_{39}$, A_{50}	G_{42}	$A_{75}\Rightarrow\varnothing$
G_{15}	$A_{42}\Rightarrow A_{50}$	G_{43}	$A_{76}\Rightarrow A_{71}$, A_{74}

Table 4. Groups of Internal Relationships of the 2nd Order

Group	Relation	Group	Relation
G_1	A_{55}, $A_{50}\Rightarrow A_{41}$	G_{16}	A_{52}, $A_{68}\Rightarrow A_{62}$
G_2	A_{50}, $A_{41}\Rightarrow A_{50}$	…	………………………..
G_3	A_{41}, $A_{50}\Rightarrow A_{44}$	G_{47}	A_{62}, $A_{68}\Rightarrow A_{12}$, A_{50}
G_4	A_{50}, $A_{44}\Rightarrow A_{46}$	…	………………………..
G_5	A_{44}, $A_{46}\Rightarrow A_{41}$	G_{75}	A_{72}, $A_{64}\Rightarrow A_{60}$
G_6	A_{46}, $A_{41}\Rightarrow A_{39}$	G_{76}	A_{64}, $A_{60}\Rightarrow A_{59}$
G_7	A_{41}, $A_{39}\Rightarrow A_{31}$	G_{77}	A_{60}, $A_{59}\Rightarrow A_{58}$
G_8	A_{39}, $A_{31}\Rightarrow A_{29}$	G_{78}	A_{58}, $A_{59}\Rightarrow A_{60}$
G_9	A_{31}, $A_{29}\Rightarrow A_{38}$	G_{79}	A_{59}, $A_{60}\Rightarrow A_{61}$
G_{10}	A_{29}, $A_{38}\Rightarrow A_{50}$	G_{80}	A_{60}, $A_{61}\Rightarrow A_{61}$
G_{11}	A_{38}, $A_{50}\Rightarrow A_{60}$	G_{81}	A_{61}, $A_{61}\Rightarrow A_{63}$
G_{12}	A_{50}, $A_{60}\Rightarrow A_{55}$	G_{82}	A_{61}, $A_{63}\Rightarrow A_{59}$
G_{13}	A_{60}, $A_{55}\Rightarrow A_{47}$	G_{83}	A_{63}, $A_{59}\Rightarrow A_{57}$
G_{14}	A_{55}, $A_{47}\Rightarrow A_{52}$	G_{84}	A_{59}, $A_{57}\Rightarrow A_{50}$
G_{15}	A_{47}, $A_{52}\Rightarrow A_{68}$	G_{85}	A_{57}, $A_{50}\Rightarrow A_{66}$

4 "Ground Humidity" Fuzzy Time Series Forecasting

Various rules are applied to determine fuzzy predictions and defuzzify them [8], [9]. As applied to our task, the essence of some of them is as follows. If the sensor reading x_t is described by the fuzzy set A_j, which within the totality of time series data forms only one internal relationship of the 1st order, for example, in the form of the fuzzy relation $A_j\Rightarrow A_k$, then the prediction for the next (t+1)-th period is the fuzzy set A_k. In the case when there is a group of relationships, for example, $A_j\Rightarrow A_{k1}$, A_{k2}, …, A_{kp}, then the union $A_{k1}\cup A_{k2}\cup\ldots\cup A_{kp}$ is the fuzzy predict for the (t+1)-th period. To defuzzify fuzzy predicts, the following two rules can be applied.

Rule 1. In the case of a fuzzy relation of the form $A_i\Rightarrow A_j$, where A_i is the fuzzy analog of the sensor reading on the i-th day, the predict in nominal terms for the next (t+1)-th day is the abscissa of the middle of the upper base of the trapezoid, reflecting the fuzzy set A_j. Indeed, this is confirmed by the defuzzification rule of the fuzzy set A, which is implemented according to the following formula

$$F(A)=\frac{1}{\alpha_{\max}}\int_0^{\alpha_{\max}} M(A_\alpha)d\alpha \qquad (7)$$

where $A_\alpha=\{u|\mu_A(u)\geq\alpha,\ u\in U\}$ is the α-level sets ($\alpha\in[0, 1]$); $M(A_\alpha)$ is powers of the corresponding α-level sets, calculated by the formula $M(A_\alpha)=\frac{1}{n}\sum_{k=1}^{n}u_k$, $u_k\in A_\alpha$.

In particular, for the fuzzy set (Table 2) A_{71}= {0/89.88, 1/90.28, 1/90.69, 0/91.09}, which is the predict in the conjunction $A_{11}\Rightarrow A_{71}$, for $0<\alpha<1$ we have:

$$\Delta\alpha = 1,\ A_{71,\alpha} = \{89.88,\ 91.09\},$$
$$M(A_{71,\alpha}) = (89.88+91.09)/2 = 90.485.$$

Then, according to (7), the prediction in nominal terms is:

$$F(A_{10})=\int_0^1 M(A_{71\alpha})d\alpha \approx M(A_{71\alpha})\cdot\Delta\alpha = 90.485\cdot 1 = \\ = 90.485.$$

Rule 2. In the case of the fuzzy relation $A_t\Rightarrow A_j$, A_i, A_p, where A_t is the fuzzy analog of the sensor reading for the t-th day, the crisp prediction for the next (t+1)-th day is calculated as the arithmetic mean of the abscissa of the midpoints of the upper bases of the trapezoids, corresponding to the fuzzy sets A_j, A_i and A_p, [2], [3]. In particular, according to the internal relationship $A_{68}\Rightarrow A_{12}$, A_{50}, A_{62} the predicts for the dates 12.11.2022, 14.12.2022 and 03.01.2023 are calculated as follows (Table 2):

$$\frac{\frac{42.77+43.17}{2}+\frac{73.37+73.77}{2}+\frac{83.03+83.44}{2}}{3}=66.59\,.$$

Thus, the predictions obtained using Rules 1 and 2 for the 1st and 2nd order predictive models are summarized in Table 5 and Table 6 in Appendix. The corresponding geometric interpretations of the forecasting results are presented in Figure 5.

At the end of Table 5 and Table 6 (Appendix), the values of statistical criteria for assessing the adequacy of predictive models are presented, [18]: MSE (Mean Squared Error), MAPE (Mean Absolute Percentage Error) and MPE (Mean Percentage Error), which are calculated using the corresponding formulas:

$$\text{MSE} = \frac{1}{m}\sum_{t=1}^{m}(F_t - R_t)^2 \ ,$$

$$\text{MAPE} = \frac{1}{m}\sum_{t=1}^{m}\frac{|F_t - R_t|}{R_t}\times 100\% \ ,$$

$$\text{MPE} = \frac{1}{m}\sum_{t=1}^{m}\frac{F_t - R_t}{R_t}\times 100\% \ ,$$

where m is the length of the time series; R_t is the actual indicator of the ground humidity at the t-th moment of observation; F_t is the predict of R_t.

When interpreting these metrics, their characteristics should be taken into account. For example, MSE being one of the most common metrics of forecast errors, allows to evaluate the accuracy of the forecast in absolute units of measurement, while MPE and MAPE show the deviation as a percentage. In particular, MAPE can be useful for comparing the forecast accuracy of different models processing different ranges of data.

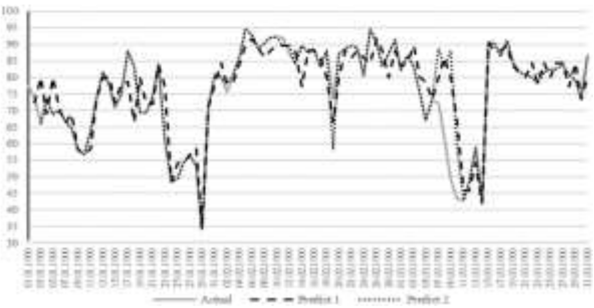

Fig. 5: Time series predictive models of 1st and 2nd orders

As can be seen from Table 5 and Table 6 in Appendix, the MSE indicators for the 1st and 2nd order predictive models are equal to MSE_1 = 49.16 and MSE_2 = 30.52, respectively. According to the MAPE criterion, which demonstrates the percentage of the forecast error in comparison with the actual values of the time series, the identified errors MAPE_1 = 6.44% and MAPE_2 = 2.53% also demonstrate the preference of the 1st and 2nd order predictive models over the exponential smoothing model, for which MAPE = 9.18%. According to the MPE indicator, which is a more informative criterion for assessing the adequacy of the forecasting model, acceptable "biases" of these predictive models were obtained as MPE_1 = -2.03% and MPE_2 = -1.68%, which does not exceed the normative 5%-th threshold to the left of zero.

5 Conclusion

In the process of implementing IoT technology, unique challenges arise that entail the use of signals from multiple web-devices in real-time. To solve them, it is necessary to develop new methods for processing signals and information. The result presented in the article is only one minor fragment in the general methodology for processing sensory signals carried out as part of the application of IoT technology in precision agriculture. This or similar methodology has the potential to enable an intelligent IoT platform despite being overshadowed by other aspects of IoT technology such as communications architecture, sensor technologies, and power management. The approach proposed in this paper is capable of supporting predictive and prescriptive analytical decisions by linking previously collected data from smart sensors, equipment, and other agricultural assets. This approach facilitates the creation of tools for monitoring the current state of crops and controlling the growing environment and is aimed at increasing the yield of the crop as a whole. By anticipating undesirable situations, one can permanently maintain a high level of care for the crop area.

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APPENDIX

Table 5. 1st Order Time Series Predictive Model

Date	Data	FS	Fuzzy output	Predict
26.10.2022	77.67	A_{55}	-	-
27.10.2022	73.90	A_{50}	$A_{47} \cup A_{50}$	72.36
28.10.2022	65.97	A_{41}	$A_{41} \cup A_{44} \cup A_{60} \cup A_{66} \cup A_{67} \cup A_{69}$	79.88
29.10.2022	73.42	A_{50}	$A_{39} \cup A_{50}$	69.14
30.10.2022	68.91	A_{44}	$A_{41} \cup A_{44} \cup A_{60} \cup A_{66}\ A_{67} \cup A_{69}$	79.88
31.10.2022	70.01	A_{46}	A_{46}	70.35
01.11.2022	66.53	A_{41}	A_{41}	66.32
02.11.2022	64.66	A_{39}	$A_{39} \cup A_{50}$	69.14
03.11.2022	58.38	A_{31}	A_{31}	58.27
04.11.2022	56.76	A_{29}	A_{29}	56.66
05.11.2022	64.19	A_{38}	$A_{25} \cup A_{38}$	58.67
06.11.2022	73.83	A_{50}	A_{50}	73.57
07.11.2022	81.71	A_{60}	$A_{41} \cup A_{44} \cup A_{60} \cup A_{66} \cup A_{67} \cup A_{69}$	79.88
08.11.2022	77.55	A_{55}	$A_{55} \cup A_{59} \cup A_{61}$	80.28
09.11.2022	71.04	A_{47}	$A_{47} \cup A_{50}$	72.36
10.11.2022	74.92	A_{52}	$A_{52} \cup A_{59}$	78.00
11.11.2022	87.83	A_{68}	$A_{42} \cup A_{59} \cup A_{68}$	78.67
12.11.2022	83.09	A_{62}	$A_{12} \cup A_{50} \cup A_{62}$	66.59
13.11.2022	69.22	A_{45}	$A_{45} \cup A_{52} \cup A_{67} \cup A_{68}$	80.01
14.11.2022	69.26	A_{45}	$A_{45} \cup A_{51}$	71.96
15.11.2022	74.44	A_{51}	$A_{45} \cup A_{51}$	71.96
16.11.2022	83.68	A_{63}	A_{63}	84.04
17.11.2022	61.18	A_{35}	$A_{35} \cup A_{59} \cup A_{70}$	77.33
18.11.2022	48.49	A_{19}	A_{19}	48.61
19.11.2022	49.53	A_{20}	$A_{20} \cup A_{32}$	54.24
20.11.2022	54.39	A_{26}	A_{26}	54.24
21.11.2022	56.31	A_{29}	A_{29}	56.66
22.11.2022	53.11	A_{25}	$A_{25} \cup A_{38}$	58.67
23.11.2022	34.02	A_{1}	A_{1}	34.11
24.11.2022	71.01	A_{47}	A_{47}	71.16
25.11.2022	81.06	A_{59}	$A_{52} \cup A_{59}$	78.00
26.11.2022	80.30	A_{58}	$A_{57} \cup A_{58} \cup A_{60} \cup A_{66} \cup A_{76}$	84.36
27.11.2022	75.55	A_{52}	$A_{52} \cup A_{59}$	78.00
28.11.2022	81.04	A_{59}	$A_{42} \cup A_{59} \cup A_{68}$	78.67
29.11.2022	86.75	A_{66}	$A_{57} \cup A_{58} \cup A_{60} \cup A_{66} \cup A_{76}$	84.36
30.11.2022	94.60	A_{76}	$A_{62} \cup A_{72} \cup A_{76}$	89.68
01.12.2022	93.21	A_{74}	$A_{71} \cup A_{74}$	91.69
02.12.2022	88.62	A_{69}	A_{69}	88.87
03.12.2022	90.42	A_{71}	$A_{59} \cup A_{62} \cup A_{70} \cup A_{71}$	86.05
04.12.2022	91.97	A_{73}	$A_{62} \cup A_{66} \cup A_{71} \cup A_{73}$	88.07
05.12.2022	92.45	A_{73}	$A_{67} \cup A_{73}$	89.68
06.12.2022	92.02	A_{73}	$A_{67} \cup A_{73}$	89.68
07.12.2022	87.17	A_{67}	$A_{67} \cup A_{73}$	89.68
08.12.2022	84.37	A_{63}	$A_{63} \cup A_{69} \cup A_{72}$	88.07
09.12.2022	89.83	A_{70}	$A_{35} \cup A_{59} \cup A_{70}$	77.33
10.12.2022	87.42	A_{67}	$A_{67} \cup A_{69}$	88.07
11.12.2022	88.62	A_{69}	$A_{63} \cup A_{69} \cup A_{72}$	88.07
12.12.2022	83.09	A_{62}	$A_{59} \cup A_{62} \cup A_{70} \cup A_{71}$	86.05
13.12.2022	88.14	A_{68}	$A_{45} \cup A_{52} \cup A_{67} \cup A_{68}$	80.01
14.12.2022	73.79	A_{50}	$A_{12} \cup A_{50} \cup A_{62}$	66.59
15.12.2022	87.02	A_{67}	$A_{41} \cup A_{44} \cup A_{60} \cup A_{66} \cup A_{67} \cup A_{69}$	79.88
16.12.2022	88.62	A_{69}	$A_{63} \cup A_{69} \cup A_{72}$	88.07
17.12.2022	89.75	A_{70}	$A_{59} \cup A_{62} \cup A_{70} \cup A_{71}$	86.05
18.12.2022	89.23	A_{69}	$A_{67} \cup A_{69}$	88.07
19.12.2022	80.50	A_{59}	$A_{59} \cup A_{62} \cup A_{70} \cup A_{71}$	86.05
20.12.2022	94.60	A_{76}	$A_{57} \cup A_{58} \cup A_{60} \cup A_{66} \cup A_{76}$	84.36

Date	Data	FS	Fuzzy output	Predict
21.12.2022	90.73	A_{71}	$A_{71} \cup A_{74}$	91.69
22.12.2022	83.48	A_{62}	$A_{62} \cup A_{66} \cup A_{71} \cup A_{73}$	88.07
23.12.2022	87.07	A_{67}	$A_{45} \cup A_{52} \cup A_{67} \cup A_{68}$	80.01
24.12.2022	91.48	A_{72}	$A_{63} \cup A_{69} \cup A_{72}$	88.07
25.12.2022	82.08	A_{61}	$A_{61} \cup A_{64}$	83.64
26.12.2022	86.69	A_{66}	$A_{61} \cup A_{63} \cup A_{66}$	84.31
27.12.2022	83.60	A_{62}	$A_{62} \cup A_{72} \cup A_{76}$	89.68
28.12.2022	74.86	A_{52}	$A_{45} \cup A_{52} \cup A_{67} \cup A_{68}$	80.01
29.12.2022	66.79	A_{42}	$A_{42} \cup A_{59} \cup A_{68}$	78.67
30.12.2022	73.19	A_{50}	A_{50}	73.57
31.12.2022	72.24	A_{69}	$A_{41}\cup A_{44}\cup A_{60}\cup A_{66}\cup A_{67}\cup A_{69}$	79.88
01.01.2023	62.00	A_{62}	$A_{59} \cup A_{62} \cup A_{70} \cup A_{71}$	86.05
02.01.2023	49.43	A_{68}	$A_{45} \cup A_{52} \cup A_{67} \cup A_{68}$	80.01
03.01.2023	43.34	A_{12}	$A_{12} \cup A_{50} \cup A_{62}$	66.59
04.01.2023	42.91	A_{12}	$A_{12} \cup A_{19}$	45.79
05.01.2023	48.47	A_{19}	$A_{12} \cup A_{19}$	45.79
06.01.2023	59.03	A_{32}	$A_{20} \cup A_{32}$	54.24
07.01.2023	42.49	A_{11}	A_{11}	42.16
08.01.2023	90.67	A_{71}	A_{71}	90.48
09.01.2023	90.46	A_{71}	$A_{62} \cup A_{66} \cup A_{71} \cup A_{73}$	88.07
10.01.2023	86.47	A_{66}	$A_{62} \cup A_{66} \cup A_{71} \cup A_{73}$	88.07
11.01.2023	91.18	A_{72}	$A_{62} \cup A_{72} \cup A_{76}$	89.68
12.01.2023	85.03	A_{64}	$A_{61} \cup A_{64}$	83.64
13.01.2023	81.73	A_{60}	A_{60}	81.63
14.01.2023	81.13	A_{59}	$A_{55} \cup A_{59} \cup A_{61}$	80.28
15.01.2023	79.92	A_{58}	$A_{57} \cup A_{58} \cup A_{60} \cup A_{66} \cup A_{76}$	84.36
16.01.2023	81.19	A_{59}	$A_{52} \cup A_{59}$	78.00
17.01.2023	81.59	A_{60}	$A_{57} \cup A_{58} \cup A_{60} \cup A_{66} \cup A_{76}$	84.36
18.01.2023	82.55	A_{61}	$A_{55} \cup A_{59} \cup A_{61}$	80.28
19.01.2023	82.78	A_{61}	$A_{61} \cup A_{63} \cup A_{66}$	84.31
20.01.2023	83.78	A_{63}	$A_{61} \cup A_{63} \cup A_{66}$	84.31
21.01.2023	80.82	A_{59}	$A_{35} \cup A_{59} \cup A_{70}$	77.33
22.01.2023	79.05	A_{57}	$A_{57} \cup A_{58} \cup A_{60} \cup A_{66} \cup A_{76}$	84.36
23.01.2023	73.93	A_{50}	A_{50}	73.57
24.01.2023	86.75	A_{66}	$A_{41}\cup A_{44}\cup A_{60}\cup A_{66}\cup A_{67}\cup A_{69}$	79.88
MSE_1				49.16
$MAPE_1$				6.44
MPE_1				-2.03

Table 6. 2nd Order Time Series Predictive Model

Date	Data	FS	Fuzzy output	Predict
26.10.2022	77.67	A_{55}	-	-
27.10.2022	73.90	A_{50}	-	-
28.10.2022	65.97	A_{41}	A_{41}	66.32
29.10.2022	73.42	A_{50}	A_{50}	73.57
30.10.2022	68.91	A_{44}	A_{44}	68.74
31.10.2022	70.01	A_{46}	A_{46}	70.35
01.11.2022	66.53	A_{41}	A_{41}	66.32
02.11.2022	64.66	A_{39}	A_{39}	64.71
03.11.2022	58.38	A_{31}	A_{31}	58.27
04.11.2022	56.76	A_{29}	A_{29}	56.66
05.11.2022	64.19	A_{38}	A_{38}	63.91
06.11.2022	73.83	A_{50}	A_{50}	73.57
07.11.2022	81.71	A_{60}	A_{60}	81.63
08.11.2022	77.55	A_{55}	A_{55}	77.60
09.11.2022	71.04	A_{47}	A_{47}	71.16
10.11.2022	74.92	A_{52}	A_{52}	75.18
11.11.2022	87.83	A_{68}	A_{68}	88.07
12.11.2022	83.09	A_{62}	A_{62}	83.24
13.11.2022	69.22	A_{45}	A_{45}	69.54
14.11.2022	69.26	A_{45}	A_{45}	69.54

Date	Data	FS	Fuzzy output	Predict
15.11.2022	74.44	A_{51}	A_{51}	74.38
16.11.2022	83.68	A_{63}	A_{63}	84.04
17.11.2022	61.18	A_{35}	A_{35}	61.49
18.11.2022	48.49	A_{19}	A_{19}	48.61
19.11.2022	49.53	A_{20}	A_{20}	49.41
20.11.2022	54.39	A_{26}	A_{26}	54.24
21.11.2022	56.31	A_{29}	A_{29}	56.66
22.11.2022	53.11	A_{25}	A_{25}	53.44
23.11.2022	34.02	A_{1}	A_{1}	34.11
24.11.2022	71.01	A_{47}	A_{47}	71.16
25.11.2022	81.06	A_{59}	A_{59}	80.82
26.11.2022	80.30	A_{58}	A_{58}	80.01
27.11.2022	75.55	A_{52}	$A_{52} \cup A_{59}$	78.00
28.11.2022	81.04	A_{59}	A_{59}	80.82
29.11.2022	86.75	A_{66}	A_{66}	86.46
30.11.2022	94.60	A_{76}	A_{76}	94.51
01.12.2022	93.21	A_{74}	A_{74}	92.90
02.12.2022	88.62	A_{69}	A_{69}	88.87
03.12.2022	90.42	A_{71}	A_{71}	90.48
04.12.2022	91.97	A_{73}	A_{73}	92.10
05.12.2022	92.45	A_{73}	A_{73}	92.10
06.12.2022	92.02	A_{73}	$A_{73} \cup A_{67}$	89.68
07.12.2022	87.17	A_{67}	$A_{73} \cup A_{67}$	89.68
08.12.2022	84.37	A_{63}	A_{63}	84.04
09.12.2022	89.83	A_{70}	A_{70}	89.68
10.12.2022	87.42	A_{67}	A_{67}	87.26
11.12.2022	88.62	A_{69}	A_{69}	88.87
12.12.2022	83.09	A_{62}	A_{62}	83.24
13.12.2022	88.14	A_{68}	A_{68}	88.07
14.12.2022	73.79	A_{50}	$A_{12} \cup A_{50}$	58.27
15.12.2022	87.02	A_{67}	A_{67}	87.26
16.12.2022	88.62	A_{69}	A_{69}	88.87
17.12.2022	89.75	A_{70}	A_{70}	89.68
18.12.2022	89.23	A_{69}	A_{69}	88.87
19.12.2022	80.50	A_{59}	A_{59}	80.82
20.12.2022	94.60	A_{76}	A_{76}	94.51
21.12.2022	90.73	A_{71}	A_{71}	90.48
22.12.2022	83.48	A_{62}	A_{62}	83.24
23.12.2022	87.07	A_{67}	A_{67}	87.26
24.12.2022	91.48	A_{72}	A_{72}	91.29
25.12.2022	82.08	A_{61}	A_{61}	82.43
26.12.2022	86.69	A_{66}	A_{66}	86.46
27.12.2022	83.60	A_{62}	A_{62}	83.24
28.12.2022	74.86	A_{52}	A_{52}	75.18
29.12.2022	66.79	A_{42}	A_{42}	67.13
30.12.2022	73.19	A_{50}	A_{50}	73.57
31.12.2022	72.24	A_{69}	A_{69}	88.87
01.01.2023	62.00	A_{62}	A_{62}	83.24
02.01.2023	49.43	A_{68}	A_{68}	88.07
03.01.2023	43.34	A_{12}	$A_{12} \cup A_{50}$	58.27
04.01.2023	42.91	A_{12}	A_{12}	42.97
05.01.2023	48.47	A_{19}	A_{19}	48.61
06.01.2023	59.03	A_{32}	A_{32}	59.08
07.01.2023	42.49	A_{11}	A_{11}	42.16
08.01.2023	90.67	A_{71}	A_{71}	90.48
09.01.2023	90.46	A_{71}	A_{71}	90.48
10.01.2023	86.47	A_{66}	A_{66}	86.46
11.01.2023	91.18	A_{72}	A_{72}	91.29
12.01.2023	85.03	A_{64}	A_{64}	84.85
13.01.2023	81.73	A_{60}	A_{60}	81.63
14.01.2023	81.13	A_{59}	A_{59}	80.82
15.01.2023	79.92	A_{58}	A_{58}	80.01
16.01.2023	81.19	A_{59}	$A_{52} \cup A_{59}$	78.00

Date	Data	FS	Fuzzy output	Predict
17.01.2023	81.59	A_{60}	A_{60}	81.63
18.01.2023	82.55	A_{61}	A_{61}	82.43
19.01.2023	82.78	A_{61}	A_{61}	82.43
20.01.2023	83.78	A_{63}	A_{63}	84.04
21.01.2023	80.82	A_{59}	A_{59}	80.82
22.01.2023	79.05	A_{57}	A_{57}	79.21
23.01.2023	73.93	A_{50}	A_{50}	73.57
24.01.2023	86.75	A_{66}	A_{66}	86.46
MSE_2				30.52
$MAPE_2$				2.53
MPE_2				-1.68

Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

The authors equally contributed in the present research, at all stages from the formulation of the problem to the final findings and solution.

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Conflict of Interest

The authors have no conflicts of interest to declare.