https://doi.org/10.48047/AFJBS.6.13.2024. 1802-1815

African Journal of Biological Sciences

Environmental Impact Assessment of Agricultural Practices and Biological Scaling Using Fuzzy Logic and Mathematical Modeling

M. Clement Joe Anand[1*], A. P. Pushpalatha[2], Shweta S. Salunkhe[3], Dipti Thakur[4], Amir Barhoi[5], S. Karthik[6]

[1] Department of Mathematics, Mount Carmel College (Autonomous), Bengaluru - 560052, Karnataka, India. Corresponding author e-mail: arjoemi@gmail.com

[2] Department of Mathematics, Velammal College of Engineering and Technology, Madurai- 625009, Tamil Nadu, India. e-mail: app@vcet.ac.in

[3] Department of Electronics and Telecommunication Engineering, Bharati Vidyapeeth's College of Engineering for Women, Katraj, Dhankawadi, Pune-411043, Maharashtra, India. e-mail: shweta.salunkhe@bharatividyapeeth.edu

[4] School of Studies in Mathematics, Pt. Ravishankar Shukla University, Raipur- 492010, Chhattisgarh, India. e-mail: dipti.thakur15@gmail.com

[5] Department of Mathematics, Duliajan College, Assam – 786602, India. e-mail: barhoiamir@gmail.com

[6] Department of Mathematics, Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Avadi, Chennai- 600062, Tamil Nadu, India. e-mail: karthik.kaka123@gmail.com

Article History

Volume 6, Issue 13, 2024

Received: 18June 2024

Accepted: 02July 2024

doi:***10.48047/AFJBS.6.13.2024.*** 1802-1815

Abstract

Environmental impact assessment is the need of the hour as it plays a pivotal role in promoting environmental sustainability and biological balance. This study demands a robust modelling framework to address diverse factors associated with agricultural activities and their complex relation patterns influencing sustainable development. This research work applies the Fuzzy Cognitive Mapping approach to make intensive studies on the factors subjected to the domains of agriculture, biological scaling, and environmental sustainability. Fuzzy logic and the cognitive mapping technique are competent in handling both the uncertainty and non-linearity in interrelation impacts between the factors of the study. The model developed in this work considers critical environmental factors derived from various input data sources. The modelling results demonstrate the efficacy of Fuzzy Cognitive Mapping in making environmental impact assessments of agricultural practices considering the factors of biological scaling. The insights from this research will facilitate agriculturalists and policymakers to enhance agricultural productivity by mitigating the environmental impacts and paving the way for sustainable development.

Keywords: Fuzzy Cognitive Maps (FCM), Environmental Impact Assessment (EIA), Sustainable Development, Agriculture.

1. Introduction

The agricultural activities are significant for the global population to sustain and they support the rural economic growth by contributing to resource management. Innovations and advanced techniques are applied in farming to enhance agricultural yield. The productivity is increased by employing rigorous farming methods. However, implementing intensive farming causes environmental degradation such as soil deprivation, water contamination, biodiversity loss, and high emissions of greenhouses. The extensive utility of fertilizers also contributes to the ecological imbalance. Agriculturalists of the modern age are promoting contemporary agricultural practices to optimize profit with minimum investments within a short period. Though profit earnings are considered to be the advantages of these farming methods, the environmental impacts are the major consequences of exercising such practices. The extent of negative environmental effects of agricultural practices is estimated using the tool of environmental impact assessment (EIA). This tool serves as a means of evaluating the adverse environmental effects to develop a suitable framework for ensuring environmental sustainability. In general, EIA considers several aspects of agricultural practices and ecological systems with biological scaling in making estimations of the environmental impacts. The conventional methods of EIA fall short in handling the complexity of the factors and uncertainties in their relationships. This unveils the need to develop a mathematical model with fuzzy logic to make an intense study of the factors related to the impact assessment. Fuzzy-based mathematical models are competent in dealing with uncertainties and imprecise information.

Fuzzy Cognitive Maps (FCM) are viable decision tools applied in investigating the interrelationship between the factors of the problem. FCMs are basically graphical structures that are more like directed graphs depicting both the factors and their relationship as nodes and edges respectively. The edge weights assume values between the ranges from -1 to 1 i.e. [-1,1]. The edge weights assume the value 1 if there is a positive impact between the factors, -1 if there exist negative impacts, and 0 if no impacts exist. These FCM structures are more robust and potent in handling complex patterns of relationships. FCM-based modelling is widely applied to different decision-making areas irrespective of the nature of the domain discipline. The FCM model developed in this work encompasses the techniques of biological scaling for making precise assessments after studying the inter-association impacts between the factors. The inclusion of biological scaling provides opportunities for considering different ecosystems in the study and also facilitates making suitable adjustments for modelling. Incorporating the aspects of biological scaling adds another layer of accuracy to the environmental assessment impact in this model. Fuzzy Cognitive Mapping is considered to be the most apt option in examining the factors of the study. FCMs are more accommodative and flexible as they engages intuitions from different perspectives. This decision framework begins with the identification of crucial study factors focusing especially on environmental aspects influenced by agricultural activities. The intervention of the experts and the stakeholders is highly demanded in graphing the FCM architecture based on the ecological data. Mathematical modelling of the factors and their relationships are determined with FCM techniques. The linguistic representation of the associational impacts is determined using fuzzy logic and triangular fuzzy numbers are applied in quantification of these linguistic representations. On simulating the FCM model with various scenarios, the resultants of agricultural impacts shall be determined. By employing this model, the decision-makers shall formulate suitable measures to mitigate the environmental challenges.

The primary objectives of this research work are

- Development of a more comprehensive FCM model considering factors affiliated with the environmental impact assessment of the agricultural activities embracing biological scaling.
- Determination of the inter-associational impacts between the factors to outline the mitigating measures for handling environmental disarray caused by intensive farming practices

The contents of the paper are structured into the following segments. Section 2 presents the related works. Section 3 sketches the modalities of developing fuzzy cognitive frameworks. The section develops an FCM model to examine the inter-associational impacts. Section 4 discusses the outcomes of the model and makes inferences from the model results. The last section concludes the work with impending directions based on this research work.

2. State of Art of Work

This section exhibits the applications of FCM in the context of agriculture, promoting farming practices, and environmental sustainability. The existing research gaps are also identified and the specific contributions made in this work are also highlighted. Fuzzy Cognitive Maps (FCM) stem from cognitive map structures developed by Axelrod [1]. Kosko [2] discussed cognitive structure with fuzzy logic and unveiled the conceptualization of FCM. These fuzzy graphical structures are widely applied in social contexts and later extended to different domains of decision-making to consider core factors and their relationships in modelling. Some of the noteworthy contributions of FCM in agriculture and related components are presented in this section. Markinos et al [3] described the utility of FCMs in demonstrating precision agriculture for fostering farming practices. Papageorgiou et al [4,5] applied the soft computing techniques of FCM to build a relation between the parameters of cotton crop production and employed FCM in making predictions on cotton yield. Kontogianni et al [6] applied FCM as a decision support system in handling the risks of the marine environment. Ceccato [7] studied the implications of participatory FCM in environmental assessments. Kang et al [8] developed a more comprehensive decision model to evaluate environmental management systems and industrial perspectives. Peng et al [9] focused on the applications of the steady states obtained using FCM models in studying the three-rivers ecosystem. Pourreza et al [10] discussed the opportunities of improving the environmental improvement in energy sectors with FCM structures. Vimala [11] developed an integrated FCM model with advanced graphical features to make an analysis of organic agriculture with the comprehension of complex systems. Ortega et al [12] constructed FCM models to promote environmentally sustainable practices in the background of water quality management systems. Mourhir et al [13] explored the advantages of the FCM model in precision farming and its potential impacts on environmental sustainability. Jayashree et al [14] determined the competency of the FCM model in precision farming by applying it to a specific instance of coconut yield management. The effects of smart farming are articulated by Mohamed [15] with agent-based modeling and dynamic FCM models.

Bahri et al [16] initiated the development of a hybrid model combining FCM approaches with multi-agent systems to promote sustainable agriculture. Kokkinos et al [17] presented the FCM modelling framework to mitigate the carbon emission encompassing circular economy and energy transition. Poomagal et al [18] developed a prediction-based FCM model to determine the dangerous impacts of agricultural practices on the environment. Yarahmandi et al [19] described the evaluating efficacy of the FCM model in making environmental assessments. Alomia et al [20] applied FCMs to study various farming systems and livestock management from the perspectives of the stakeholders. Sivakamasundari and Smitha [21,22] studied the impacts of pesticide usage in agriculture using an intuitionistic fuzzy-based FCM model. Papageorgiou et al [23] aggregated FCM models to explore different dimensions of agriculture. Mourhir [24] presented a recent review of the potential of FCM models in environmental management and various types of fuzzy parameters were discussed [25-48]. The literature above showcases CFM models' potential to serve as decision tools in enhancing operational efficiency primarily in risk assessments, performance evaluation, and predictions. The framework of FCM models is highly competent, robust, and flexible to accommodate complex and dynamic decision systems. Leveraging FCM models in decision-making facilitates policymakers to devise suitable strategies for agricultural development. However, this section spots a few research gaps as follows,

- FCM modelling on environmental impact assessment with a holistic perspective is not initiated
- Comprehensive outlook of the factors adhering to biological scaling are not subjected to the FCM model to the best of our knowledge, only a few significant factors from the model's components are taken into account of the earlier framed models.

This has motivated the authors to design a more comprehensive FCM model to identify the consequential impacts of agricultural practices that are obstructing and enhancing the sustainability of the environment together with biological scaling.

3. FCM Framework

This section presents the procedure of a fuzzy cognitive map in constructing a model to make investigations on the inter-associational impacts between the factors. The framework is presented in Fig.1.

Step 1: Concept Definition

In general, building an FCM model begins with the definition of concepts or the factors subjected to the nature of the decision-making problem. In the context of making assessments on the environmental impacts of agricultural practices and biological scaling few significant environmental parameters are considered.

Step 2: Construction of Connection Matrix

A connection matrix W is formulated reflecting the inter-associational impacts between the concepts say Ci and Cj. The elements of the matrix say wij indicates the associational impacts or the relational impacts between the concepts. The values of wij in general assume values between the interval range [-1,1]. However, in this case, the linguistic connection matrix is framed.

Step 3: Fuzzification of the Matrix

The linguistic variables are quantified using triangular fuzzy numbers of the form (l,m,n), and the respective numerical quantification is given for the linguistic representations.

Step 4: Initialization of the State Vector

The initial state vector is $A^{(0)}$ is defined in such a way the values represent the levels of each of the concepts.

$A^{(0)} = [\, a_1^{(0)}, a_2^{(0)}, \ldots a_n^{(0)}]$, where n is the number of concepts.

Step 5: Updation of the State Vector

The state vector is updated by passing on to the connection matrix and using the FCM rule

$A^{(t+1)} = f\,(A^{(t)} \times W)$ ----------------------- (1)

Where f is the sigmoid function of the form $f(x) = \frac{1}{1+e^{x}}$

Step 6: Determination of Fixed Point

The above step is repeated until the fixed point is determined. The iterative approach is followed and the procedure is truncated if the convergence is attained.

Fig. 1 FCM Framework

M. Clement Joe Anand /Afr.J.Bio.Sc. 6(13)(2024).1802-1815

4. FCM Modelling of the Factors Contributing to the Decision Problem

This section develops an FCM model by considering the factors from various perspectives. The factors that are considered in general are presented in Fig. 2

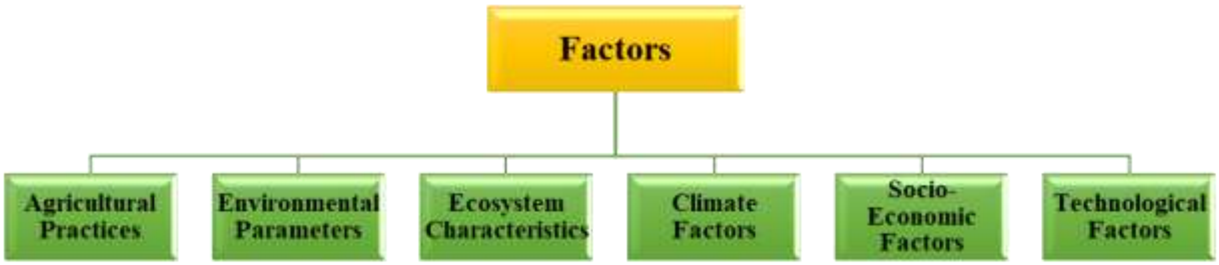

Fig. 2 Core Factors of FCM

The concepts that are subjected to each of the factors are presented in Fig. 3

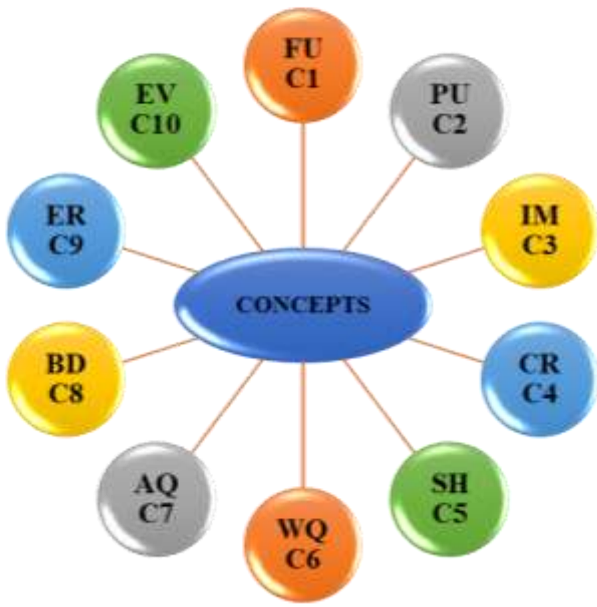

Fig. 3 Core Concepts of FCM

The description of the concepts considered in this FCM framework is presented in Table 1. The factors considered for the study are more pertinent to agricultural practices and environmental impacts. The factors in the biological systems are carefully chosen with scaling effects and the interconnections are represented using fuzzy logic.

Table 1 Description of the Concepts

Concepts	Description
C1: Fertilizer Usage (FU)	Utility of fertilizers in agriculture influencing soil fertility and crop productivity
C2: Pesticide Usage (PU)	Utility of the pesticides to mitigate the effects of the pests
C3: Irrigation Methods (IM)	Watering of the crops to promote crop health
C4: Crop Rotation (CR)	Variation in crop cultivation to enrich soil health

C5: Soil Health (SH)	Quality of the soil supporting crop cultivation
C6: Water Quality (WQ)	Composition of water affected by agricultural activities
C7: Air Quality (AQ)	Emission of pollutants caused by agricultural activities
C8: Biodiversity (BD)	Variation of species in agricultural settings
C9: Ecosystem Resilience (ER)	Potency of the ecosystem to withstand and recover from environmental challenges
C10: Ecosystem Viability (EV)	Profitability from agricultural activities

Based on the expert's opinion and ecological data, the connection matrix W with linguistic variables is formulated as in Table 2. The factors in the biological systems are carefully chosen with scaling effects and the interconnections are represented using fuzzy logic. The construction of the connection matrix explicates the impacts between the factors assuring holistic and robust assessments.

Table 2 Linguistic Connection Matrix

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
C1	NI	MPI	WPI	NI	SNI	MNI	WNI	WNI	NI	WPI
C2	MPI	NI	WPI	NI	MNI	SNI	MNI	WNI	NI	WPI
C3	WPI	WPI	NI	WPI	WPI	MNI	WNI	WNI	NI	MPI
C4	NI	NI	WPI	NI	MPI	WPI	WPI	MPI	MPI	MPI
C5	SNI	MNI	WPI	MPI	NI	SPI	MPI	MPI	MPI	WPI
C6	MNI	SNI	MNI	WPI	SPI	NI	MPI	MPI	MPI	MPI
C7	WNI	MNI	WNI	WPI	MPI	MPI	NI	WPI	MPI	WPI
C8	WNI	WNI	WNI	MPI	MPI	MPI	WPI	NI	MPI	WPI
C9	NI	NI	NI	MPI	MPI	MPI	MPI	MPI	NI	MPI
C10	WPI	WPI	MPI	MPI	WPI	MPI	WPI	WPI	MPI	NI

The description of the linguistic variable and its equivalent numerical quantification is made using triangular fuzzy numbers and is presented in Table 3.

Table 3 Representation and Quantification of Linguistic Variables

Linguistic Variable	**Notation**	**Triangular Fuzzy Number Quantification (l,m,n)**	**Defuzzified Value** $\frac{(l+m+n)}{3}$
Strong Positive Influence	SPI	(0.7,1,1)	0.9
Moderate Positive Influence	MPI	(0.4,0.7,1)	0.7
Weak Positive Influence	WPI	(0.1,0.4,0.7)	0.4
No Influence	NI	(-0.1,0,0.1)	0
Weak Negative Influence	WNI	(-0.7,-0.4,-0.1)	-0.4
Moderate Negative Influence	MNI	(-1,-0.7,-0.4)	-0.7
Strong Negative Influence	SNI	(-1,-1,-0.7)	-0.9

M. Clement Joe Anand /Afr.J.Bio.Sc. 6(13)(2024).1802-1815

The FCM graphical representation is presented in Fig.4. The figure is a directed graph representation with nodes representing the concepts and the edges the relationship between the concepts with edge weights as defuzzified values. The graphical depiction has ten nodes.

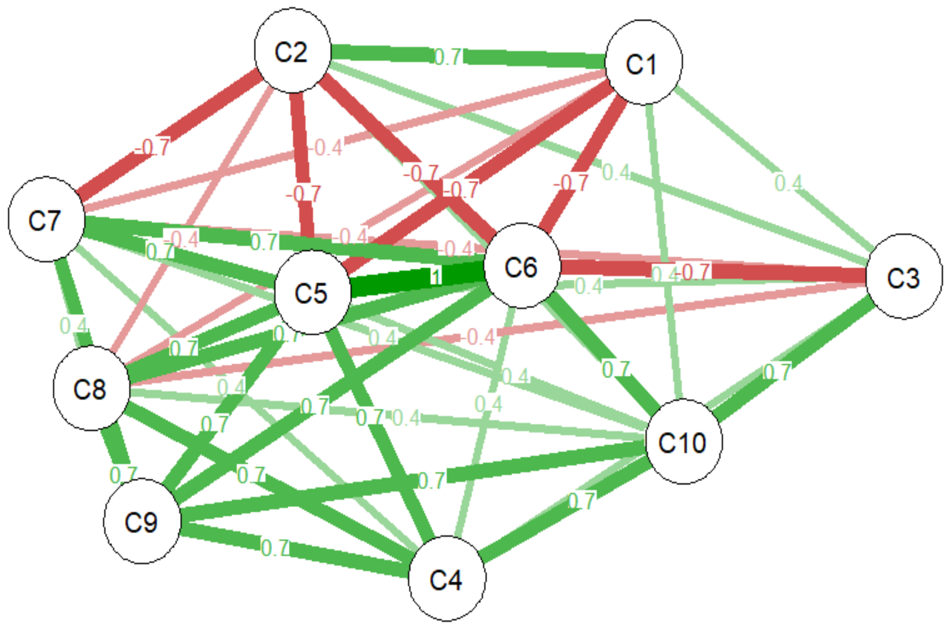

Fig. 4 FCM Architecture

The modified connection matrix is presented in Table 4 using the defuzzification mentioned in Table 3.

Table 4 Modified Connection Matrix

	C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**	**C10**
C1	0	0.7	0.4	0	-0.9	-0.7	-0.4	-0.4	0	0.4
C2	0.7	0	0.4	0	-0.7	-0.9	-0.7	-0.4	0	0.4
C3	0.4	0.4	0	0.4	0.4	-0.7	-0.4	-0.4	0	0.7
C4	0	0	0.4	0	0.7	0.4	0.4	0.7	0.7	0.7
C5	-0.9	-0.7	0.4	0.7	0	0.9	0.7	0.7	0.7	0.4
C6	-0.7	-0.9	-0.7	0.4	0.9	0	0.7	0.7	0.7	0.7
C7	-0.4	-0.7	-0.4	0.4	0.7	0.7	0	0.4	0.7	0.4
C8	-0.4	-0.4	-0.4	0.7	0.7	0.7	0.4	0	0.7	0.4
C9	0	0	0	0.7	0.7	0.7	0.7	0.7	0	0.7
C10	0.4	0.4	0.7	0.7	0.4	0.7	0.4	0.4	0.7	0

By performing the FCM modelling using Python the following convergence plot is determined and presented as Fig. 5

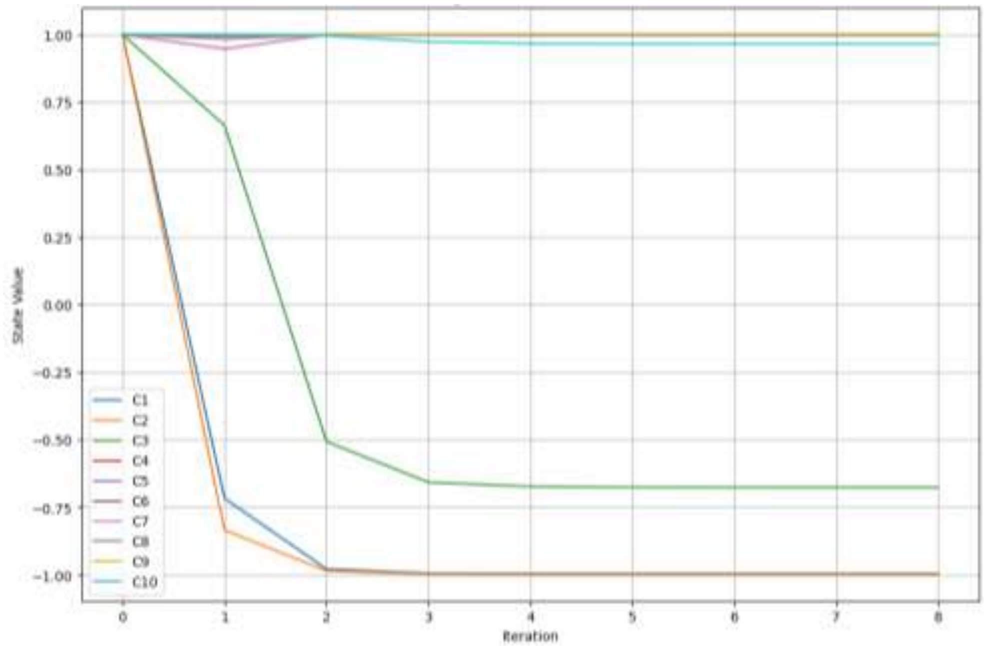

Fig. 5 Convergence of FCM State Values

Using Python, the final state vector obtained is

[-0.99487224, -0.99717321, -0.67594209, 0.99731111, 0.99995976, 0.99999074, 0.99981761, 0.99981762, 0.99952635, 0.96592959]. This vector represents the influences of the concepts concerning agricultural practices and biological scaling.

5. Results and Discussion

The inferences from the final state vector are presented in Table 5.

Table 5 Inference from the State Values

Concepts	State Values	Inferences
C1: Fertilizer Usage (FU)	-0.995	Reduction of fertilizer utility is critical in balancing the ecosystem
C2: Pesticide Usage (PU)	-0.997	Minimizing pesticide usage contributes to ecological balance
C3: Irrigation Methods (IM)	-0.675	Irrigation methods shall be customized based on the requirements
C4: Crop Rotation (CR)	0.997	Crop rotations are beneficial to the ecosystem
C5: Soil Health (SH)	0.999	Soil health is significant for a sustainable ecosystem
C6: Water Quality (WQ)	0.999	The maximum values indicate the significance of maintaining quality standards
C7: Air Quality (AQ)	0.999	Good air quality is crucial for sustaining the

		ecosystem
C8: Biodiversity (BD)	0.999	Underscores the significance of conserving the species
C9: Ecosystem Resilience	0.999	Contributes to a maximum of sustaining ecosystem
C10: Ecosystem Viability	0.962	Favours robust ecosystem

From Table 5 above, it is very evident that a well-composed and sustainable ecosystem is achieved by reducing the utility of both fertilizers and pesticides. On the other hand, enhancing crop rotation practices, ensuring soil, water, and air quality, and preserving biodiversity are more significant. The higher values of ecosystem resilience and viability contribute to a sustainable ecosystem. The final values of the concepts are depicted in Fig.6

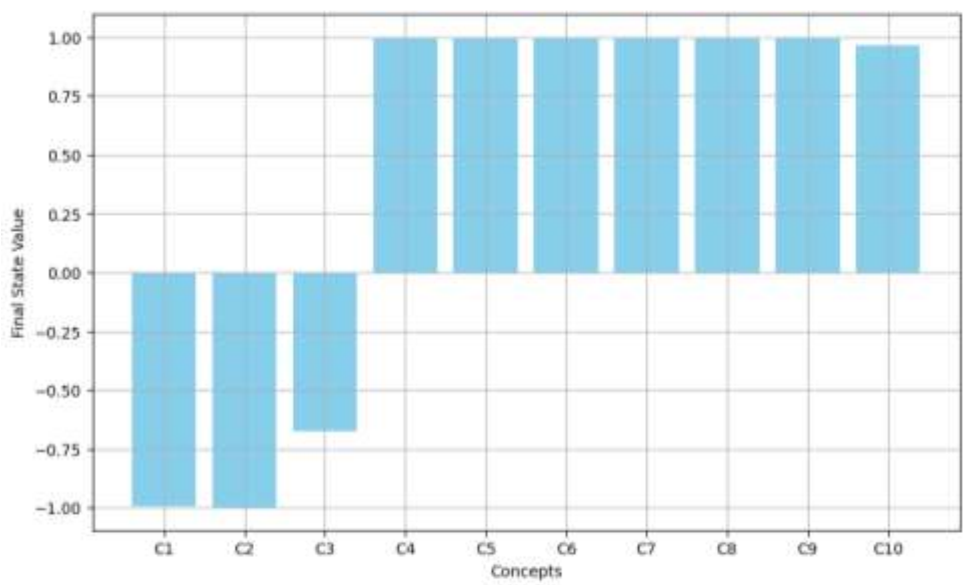

Fig. 6 Final State Values of the Concepts

In Fig 6, the concepts C1, C2, and C3 assume negative values indicating that these concepts have to be minimized in the context of environmental sustainability. On the other hand, the other concepts have to be maximized. The progression of the state vector over iterations is presented as heatmaps in Fig. 7 with different colours representing the state values.

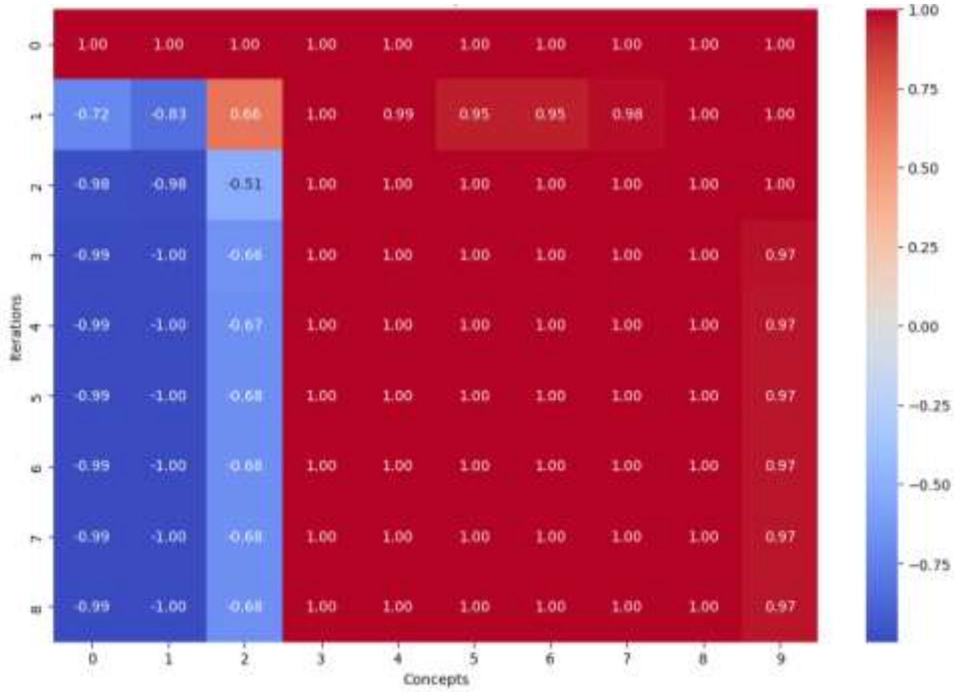

Fig. 7 State Vector Heatmap Over Iterations

From the above results, the factors contributing to the environmental impact assessments caused by agricultural practices and biological scaling are well examined and their interrelation impacts are studied.

6. Conclusion

This research work demonstrates the efficiency of fuzzy cognitive maps in evaluating and visualizing the inter-associations between agricultural practices and their environmental impacts. The fixed point obtained using FCM modelling indicates the concepts contributing to ecological imbalance. The other aspects contributing to environmental sustainability are also determined from the final vector. The graphical visualizations of FCM facilitate acquiring several insights into the dynamics of the model proposed in this research work. The proposed model promotes ecosystem resilience and viability and assists in making decisions on agricultural enhancement by embedding it into the framework of environmental impact assessments. This research work shall be extended with different versions of fuzzy representations.

References

[1] Axelrod, R. (Ed.). (2015). Structure of decision: The cognitive maps of political elites. Princeton University Press.

[2] Kosko, B. (1993). Adaptive inference in fuzzy knowledge networks. In Readings in fuzzy sets for intelligent systems (pp. 888-891). Morgan Kaufmann.

[3] Markinos, A., Papageorgiou, E., Stylios, C., & Gemtos, T. (2007). Introducing Fuzzy Cognitive Maps for decision making in precision agriculture. In Precision agriculture'07 (pp. 223-231). Wageningen Academic.

[4] Papageorgiou, E. I., Markinos, A. T., & Gemtos, T. A. (2010). Soft computing technique of fuzzy cognitive maps to connect yield defining parameters with yield in cotton crop production in central Greece as a basis

for a decision support system for precision agriculture application. Fuzzy cognitive maps: Advances in theory, methodologies, tools and applications, 325-362.

[5] Papageorgiou, E. I., Markinos, A. T., & Gemtos, T. A. (2011). Fuzzy cognitive map-based approach for predicting yield in cotton crop production as a basis for decision support system in precision agriculture application. Applied Soft Computing, 11(4), 3643-3657.

[6] Kontogianni, A., Papageorgiou, E., Salomatina, L., Skourtos, M., & Zanou, B. (2012). Risks for the Black Sea marine environment as perceived by Ukrainian stakeholders: A fuzzy cognitive mapping application. Ocean & coastal management, 62, 34-42.

[7] Ceccato, L. (2012). Third Essay: Using participatory Fuzzy Cognitive Maps for structuring the Environmental Flow Assessment process in the Lower Paraguaçu Basin. Three Essays on participatory processes and Integrated Water Resource Management in developing countries, 60.

[8] Kang, J., Zhang, J., & Gao, J. (2016). Improving performance evaluation of health, safety and environment management system by combining fuzzy cognitive maps and relative degree analysis. Safety science, 87, 92-100.

[9] Peng, Z., Wu, L., & Chen, Z. Research on Steady States of Fuzzy Cognitive Map and its Application in Three-Rivers Ecosystem. Sustainability. 8, 40 (2016).

[10] Pourreza, P., Saberi, M., Azadeh, A., Chang, E., & Hussain, O. (2018). Health, safety, environment and ergonomic improvement in energy sector using an integrated fuzzy cognitive map–Bayesian network model. International Journal of Fuzzy Systems, 20, 1346-1356.

[11] Vimala, K. (2018). Application of Graph Theory in Fuzzy Cognitive Mapping: Analysing organic agriculture. J. Sci, 11(4), 222-224.

[12] Ortega, R. G., Vázquez, M. L., Sganderla Figueiredo, J. A., & Guijarro-Rodriguez, A. (2018). Sinos river basin social-environmental prospective assessment of water quality management using fuzzy cognitive maps and neutrosophic AHP-TOPSIS. Neutrosophic Sets and Systems, 23(1), 13.

[13] Mourhir, A., Papageorgiou, E. I., Kokkinos, K., & Rachidi, T. (2017). Exploring precision farming scenarios using fuzzy cognitive maps. Sustainability, 9(7), 1241.

[14] Jayashree, L. S., Palakkal, N., Papageorgiou, E. I., & Papageorgiou, K. (2015). Application of fuzzy cognitive maps in precision agriculture: a case study on coconut yield management of southern India's Malabar region. Neural Computing and Applications, 26, 1963-1978.

[15] Mohamed, D. (2020). Smart Farming Decision Support Using Agent-Based Modeling and Dynamic Fuzzy Cognitive Maps.

[16] Bahri, O., Mourhir, A., & Papageorgiou, E. I. (2020). Integrating fuzzy cognitive maps and multi-agent systems for sustainable agriculture. Euro-Mediterranean Journal for Environmental Integration, 5, 1-10.

[17] Kokkinos, K., Karayannis, V., & Moustakas, K. (2020). Circular bio-economy via energy transition supported by Fuzzy Cognitive Map modeling towards sustainable low-carbon environment. Science of the Total Environment, 721, 137754.

[18] Poomagal, S., Sujatha, R., Kumar, P. S., & Vo, D. V. N. (2021). A fuzzy cognitive map approach to predict the hazardous effects of malathion to environment (air, water and soil). Chemosphere, 263, 127926.

[19] Yarahmadi, R., & Soleimani-Alyar, S. (2021). The performance analysis of health, safety, environment, and energy integrated management system (hsee-ims) using fuzzy cognitive mapping method. Proceedings on Engineering, 3(4), 441-452.

[20] Alomia‐ Hinojosa, V., Groot, J. C., Andersson, J. A., Speelman, E. N., McDonald, A. J., & Tittonell, P. (2023). Assessing farmer perceptions on livestock intensification and associated trade‐ offs using fuzzy cognitive maps; a study in mixed farming systems in the mid‐ hills of Nepal. Systems Research and Behavioral Science, 40(1), 146-158.

[21] Sivakamasundari, K., & Smitha, M. V. Analysis on the Causes for Using Endosulfan in Agriculture by Induced Fuzzy Cognitive Maps (IFCM).

[22] Sivakamasundari, K., & Smitha, M. (2014). Identifying the Cause of Using Endosulfan in Agriculture by Induced Fuzzy Cognitive Maps (IFCMs) Approach. International journal of science and research, 3, 2151-2155.

[23] Papageorgiou, K., Papageorgiou, E., Mourhir, A., & Stamoulis, G. (2019). Exploring OWA Operators for Aggregating Fuzzy Cognitive Maps Constructed by Experts/Stakeholders in Agriculture.

[24] Mourhir, A. (2021). Scoping review of the potentials of fuzzy cognitive maps as a modeling approach for integrated environmental assessment and management. Environmental Modelling & Software, 135, 104891.

[25] Varalakshmi. A., Kumar. S.S., Shanmugapriya. M. M., Mohanapriya. G., M. Clement Joe Anand: Markers location monitoring on images from an infrared camera using optimal fuzzy inference system. International Journal of Fuzzy Systems, 2022.

[26] Miriam. M. R., Martin. N., and M. Clement Joe Anand: Inventory model promoting smart production system with zero defects. International Journal of Applied and Computational Mathematics, vol. 9(4), 2023.

[27] Bharatraj. J., M. Clement Joe Anand: Power harmonic weighted aggregation operator on single-valued trapezoidal neutrosophic numbers and interval-valued neutrosophic sets. In Fuzzy Multi-criteria Decision-Making Using Neutrosophic Sets, Springer International Publishing, pp. 45–62, 2019.

[28] M. Clement Joe Anand, and Bharatraj. J.: Gaussian qualitative trigonometric functions in a fuzzy circle. Advances in Fuzzy Systems, pp. 1–9, 2018.

[29] M. Clement Joe Anand and Bharatraj. J.: Interval-valued neutrosophic numbers with WASPAS. In Fuzzy Multi-criteria Decision-Making Using Neutrosophic Sets, Springer International Publishing, pp. 435–453, 2019.

[30] Justin Raj. P., Prabhu. V. V., Krishnakumar. V., M. Clement Joe Anand: Solar Powered Charging -of Fuzzy Logic Controller (FLC) Strategy with Battery Management System (BMS) Method Used for Electric Vehicle (EV). International Journal of Fuzzy Systems, 25, 2876-2888 (2023).

[31] A. Victor. Devadoss, M. Clement Joe Anand, A. Felix.: A CETD matrix approach to analyze the dimensions of the personality of the person. 2014 International Conference on Computational Science and Computational Intelligence, (2014)

[32] M. Clement Joe Anand and J. Bharatraj.: Theory of Triangular Fuzzy Number. Proceedings of NCATM - 2017, 80–83 (2017).

[33] Manshath, A., Kungumaraj, E., Lathanayagam, E., M. Clement Joe Anand, Martin, N., Muniyandy, E., Indrakumar. S.: Neutrosophic Integrals by Reduction Formula and Partial Fraction Methods for Indefinite Integrals. International Journal of Neutrosophic Science, ISSN: 2690-6805, 23(1), 08-16 (2024).

[34] M. Clement Joe Anand, Bharatraj, J.: Interval-valued neutrosophic numbers with WASPAS. In Fuzzy Multi-criteria Decision-Making Using Neutrosophic Sets, Springer International Publishing, pp. 435–453, 2019.

[35] S. Sudha, Nivetha, M., M. Clement Joe Anand, Palanimani, P.G., Thirunamakkani, T., Ranjitha, B.: MACBETH-MAIRCA Plithogenic Decision-Making on Feasible Strategies of Extended Producer's Responsibility towards Environmental Sustainability. International Journal of Neutrosophic Science, 22(2), 114-130 (2023).

[36] S. K. Prabha, M. Clement Joe Anand, V. Vidhya, G. Nagarajan, U. Saikia, Nivetha Martin, M. S. Kumari, M. Tiwari, "Sorting Out Interval Valued Neutrosophic Fuzzy Shortest Cycle Route Problem by Reduced Matrix Method", International Journal of Neutrosophic Science, Volume 23, Issue 2, PP: 91-103, 2024.

[37] E. Kungumaraj, E. Lathanayagam, Utpal Saikia, M. Clement Joe Anand, Sakshi Taaresh Khanna, Nivetha Martin, Mohit Tiwari, Seyyed Ahmad Edalatpanah, "Neutrosophic Topological Vector Spaces and its Properties", International Journal of Neutrosophic Science, Volume 23, Issue 2, PP: 63-76, 2024.

[38] M. Clement Joe Anand, C. B. Moorthy, S. Sivamani, S. Indrakumar, K. Kalaiarasi, A. Barhoi, "Fuzzy intelligence inventory decision optimization model of sustainability and green technologies for mixed uncertainties of carbon emission," In: 2023 International Conference on Information Management (ICIM), IEEE, 2023. https://ieeexplore.ieee.org/document/10145085

[39] K. Rajesh, Sharmila Rathod, Jyoti Kundale, Nilesh Rathod, M. Clement Joe Anand, Utpal Saikia, Mohit Tiwari, Nivetha Martin, "A Study on Interval Valued Temporal Neutrosophic Fuzzy Sets", International Journal of Neutrosophic Science, Vol. 23, Issue 1, PP: 341-349, 2024. https://doi.org/10.54216/IJNS.230129

[40] A. Manshath, E. Kungumaraj, E. Lathanayagam, M. Clement Joe Anand, Nivetha Martin, Elangovan Muniyandy, S. Indrakumar, "Neutrosophic Integrals by Reduction Formula and Partial Fraction Methods for Indefinite Integrals", International Journal of Neutrosophic Science, ISSN: 2690-6805, Vol. 23, Issue 1, pp. 08-16, 2024. https://doi.org/10.54216/IJNS.230101

[41] M. Clement Joe Anand, C. B. Moorthy, S. Sivamani, S. Indrakumar, K. Kalaiarasi, A. Barhoi, "Fuzzy intelligence inventory decision optimization model of sustainability and green technologies for mixed uncertainties of carbon emission," In: 2023 International Conference on Information Management (ICIM), IEEE, 2023. https://ieeexplore.ieee.org/document/10145085

[42] M. Clement Joe Anand, N. Martin, A. Clementking, S. Rani, S. S. Priyadharshini, S. Siva, “Decision making on optimal selection of advertising agencies using machine learning,” In 2023 International Conference on Information Management (ICIM), IEEE, 2023. https://ieeexplore.ieee.org/document/10145172

[43] C.T. Nagaraj, M. Clement Joe Anand, S. Sujitha Priyadharshini, P. Aparna, “GCNXG: Detecting Fraudulent Activities in Financial Networks: A Graph Analytics and Machine Learning Fusion”, International Conference on Renewable Energy, Green Computing, and Sustainable Development, Part of the book series: Communication in Computer and Information Science (CCIS, Vol 2081). pp. 17-32. https://link.springer.com/chapter/10.1007/978-3-031-58607-1_2

[44] Prabha, S.K., M. Clement Joe Anand, Vidhya, V., Nagarajan, G., Saikia, U., Martin, N., Kumari, M.S., Tiwari, M.: Sorting Out Interval Valued Neutrosophic Fuzzy Shortest Cycle Route Problem by Reduced Matrix Method. International Journal of Neutrosophic Science, 23(2), 91-103 (2024).

[45] M. Clement Joe Anand, S. Sujitha Priyadharshini, N. Martin, M. E. Anand, B. Poorani, S. K. Mohiddin, “Decision Trees in the Selection of Electric Vehicles Based on Various Parameters”, In 2023 First International Conference on Cyber-Physical Systems, Power Electronics and Electric Vehicles (ICPEEV). https://ieeexplore.ieee.org/document/10391877

[46] Rajesh, K., Rathod, S., Kundale, J., Rathod, N., M. Clement Joe Anand, Saikia, U., Tiwari, M., Martin, N.: A Study on Interval Valued Temporal Neutrosophic Fuzzy Sets. International Journal of Neutrosophic Science, 23(1), 341-349 (2024).

[47] M. Clement Joe Anand, K. Kalaiarasi, N. Martin, B. Ranjitha, S. S. Dharshini, M. Tiwari, “Fuzzy C-Means Clustering with MAIRCA-MCDM Method in Classifying Feasible Logistic Suppliers of Electrical Products”, In 2023 First International Conference on Cyber-Physical Systems, Power Electronics and Electric Vehicles (ICPEEV), https://ieeexplore.ieee.org/document/10391835

[48] Kungumaraj, E., Lathanayagam, E., Saikia, U., M. Clement Joe Anand, Khanna, S.T., Martin, N., Tiwari, M., Edalatpanah, S. A.: Neutrosophic Topological Vector Spaces and its Properties. International Journal of Neutrosophic Science, 23(2), 63-76 (2024)