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Leveraging Fuzzy Logic for Habitat Suitability Analysis: A Comprehensive Case Study in Digital Ecosystems

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Abstract: Digital Nature or the virtual representation of natural environments is an emerging object of study in ecology due to its usefulness to simulate complex ecological processes and contribute to the planning of conservations. But, when uncertainty and complexity that characterize ecological processes complicate accurate modelling and estimating habitat suitability in Digital Nature. We present a fuzzy logic based new methodology in this research for uncertainty in habitat suitability in Digital Nature. One case study utilizes fuzzy logic to model ecological processes and assess habitat suitability for a target species. The uncertainties involved in ecological variables were represented by fuzzy membership functions, fuzzy rules and fuzzy inference systems. Based on the analysis of the case study, it is clear that the fuzzy logic-based approach is effective in dealing with uncertainties and takes the results of the habitat suitability assessment a step further into nuance and interpretability. This study makes an additional contribution to the expanding body of literature on Digital Nature and fuzzy logic in ecological modelling, offering further insights into conservation planning and decision-making in virtual settings. Why it also needs to be researched to help with fuzzy logic potentiality in respective Digital Nature applications and the concept can be tweaked further based on ecological variations.

Keywords: Digital Nature, Uncertainty management, Ecological processes, Fuzzy logic, Digital ecosystems, Habitat suitability assessment, Ecological modelling, Habitat modelling

1 Introduction

Digital nature (also referred to as virtual nature or virtual ecosystems)e uses computer-generated images of natural settings that are generated through sophisticated computer simulation, modelling and graphical techniques. Genomes of these microorganisms have limited availability [1,2,3,4], and their [metabolic-related codes] are often inaccessible (until now) in the virtual world [5,6,7], allowing researchers to: (1) Explore ecological processes, (2) Generate ecologically relevant and realistic simulations, and (3) Conduct laboratory experiments. Digital nature [8,9,10] has gained considerable traction in the ecology field due to its ability to circumvent a series of impasses that inhibit scientists from directly studying natural ecosystems—most pointedly, logistical, financial, and ethical barriers.

Recently, the interest in Digital Nature in various domains of ecological research has been raised including but not limited to biodiversity conservation, ecological modelling, assessment of ecosystem services, climate change impacts and ecosystem restoration. Another advantage it possesses is the possibilities to control variables, replicate experiments and study processes that are hard to observe or unobservable in the real world [9,11,12]. Moreover, Digital Nature offers a controlled and safe environment to test scenarios and ideas that are

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difficult to perform or ethically acceptable in the real-evolutionary systems [13].

According to Maguire et al. [9] and Heimann et al. [6] Digital Nature, ecosystem. The extracted Digital Nature could complement traditional field-based approaches in ecology and provide further evidence to enable management and conservation. Furthermore, the sophisticated computational approaches already existing in Digital Nature (e.g., fuzzy logic) constitute a powerful means to address the uncertainties and complexities of ecological processes—i.e., their stochasticity, uncertainty and context dependence [14,15,16].

Fuzzy logic is a type of logic that accounts for the differing degrees of truth rather than the traditional binary true/false perspective of classical logic. Proposed by Zadeh [14], fuzzy logic is an extension of classical or "crisp" logic, which concerns (true/false) values. Fuzziness permits the representation and control of uncertainty, vagueness and ambiguity—ubiquitous qualities of ecological systems that are influenced by multiple biotic and abiotic drivers, geographic heterogeneity and varying temporal dynamics.

This is due to limited quality of data, measurement errors, spatial and temporal variability in species interactions, environmental parameters and ecological data as well as in model parameters contribute to uncertainties in many aspects of ecological research [17, 18,19]. Fuzzy logic provides a strong approach for addressing such uncertainties in ecological systems and for making decisions based on information that is still incomplete or imprecise.

Fuzzy sets — a breakthrough concept in fuzzy logic — permit gradation or degrees of membership to a set. Unlike a traditional Boolean set, which interacts with binary (0 or 1) values, fuzzy sets enable the user to declare members as partially in a set: Any number from 0 to 1 is permissible, as it describes the degree to which a given item is a member of a set. This allows the visualisation of the inherent ambiguities and uncertainties in ecological data and models that tend to be continuous and gradational in nature.

Recent advances have significantly expanded the use of fuzzy logic in ecology, where it is commonly used to model uncertainty and complexity, such as the formulation of habitat suitability models [20,21], species distribution models (Ochoa et al., 2017), ecosystem services assessment [22] and ecological risk assessment [23,24]. Ecological uncertainties in decision-making can be explained by integrating fuzzy logic, as it can describe uncertainties related to ecological data, e.g., incorrect or missing information about species occurrences or environmental variables found in the habitat [25]. Fuzzy inference systems are rule based systems founded on fuzzy sets and fuzzy logic operations used to replicate complex interactions and decisions that take place in ecological processes.

Fuzzy logic will lend itself to the description of uncertainties in ecological systems given the virtue of its models that can prefer not only the utility of the models of the decision-making process between alternatives, which might be versatile and interpretable there about the contour and spectrum of knowledge or situations on which decisions must be made; accommodate incomplete and uncertain information and is capable of express continuum and grade of condition. Fuzzy logic allows combining different sources of information and uncertainty, expert information and subjective judgments in many ecological research and management applications.

1.1 The research objective

One of the most critical ecological processes is habitat suitability evaluation, which involves assessing whether a specific environment may be suitable or not for a certain species or ecological unit. Assessing habitat suitability is important for understanding species-environment interactions, predicting species distribution, and for supporting decision-making in ecosystem management and conservation in a digital nature context, virtual ecosystems or simulated natural environments.

This study aims to explore the use of fuzzy logic as a modelling approach for assessing habitat suitability within the context of Digital Nature. The research specifically aims to:

–We will analyse the use of fuzzy logic in modelling uncertainty and complexity in habitat suitability evaluation, and should take into account ecological processes that can contribute to this uncertainty, such as species interactions, environmental conditions and spatial heterogeneity.

–Learn the best practices of coupling features such as Fuzzy inference systems for assessment of habitat suitability for Digital Nature to simulate complex interactions and decision-making processes between species and between species and environmental factors. Fuzzy sets and fuzzy logic operations also should be integrated into these systems.

–Assess and compare fuzzy logic-based habitat suitability assessment against other conventional and or machine learning based approaches (logistic regression, max entropy modelling, machine learning approaches) in terms of accuracy, interpretability, and robustness.

–Human Considerations: Investigate Fuzzy Logic-Based Habitat Suitability Models – the Interpretability and Transparency, and with the requirement to provide easy-to-understand and applicable-to-decisions ecological research and management models.

–Display the potential applications of an fuzzy logic driven method to indicate a habitat's suitability in Digital Nature, such as the ability to predict species distributions, explore critical habitats, and study the impacts of environmental changes.

The study aims to offer insights into the possible benefits and limitations of fuzzy logic as a modelling tool for ecological research and management, and to advance the knowledge of the suitability and performance of fuzzy logic in habitat suitability evaluation in the Digital Nature landscape. The findings from this study may have implications for enhancing decision-making processes within the context of Digital Nature and other ecological contexts, as well as for increasing the accuracy and interpretability of habitat suitability models.

2 Literature Review

2.1 Digital Nature, Ecological Modelling, and Fuzzy Logic

First, we define digital nature as the implementation of artificial ecosystems or modelled natural environments to simulate and understand ecological processes in the digital space. This platform integrates together computer based technologies with ecological concepts and modelling techniques in order to simulate complex ecological systems. Ecological modelling is an important aspect of species (population) dynamics, community dynamics, and ecosystems, and a heterogeneous and interdisciplinary field [26] that can be represented and generalize the data and simulations used to characterize the data of systems. Fuzzy logic, on the opposite, is a mathematical technique employed to deal with uncertainty and imprecision in ecological data and processes of decision-making. Its powerful ways of understanding the inherent complexity of ecological systems make it a valuable tool for ecological research and management [27].

2.2 Application of Fuzzy Logic in Habitat Suitability and Ecological Modelling

The fuzzy logic is being widely used for habitat suitability and ecological modelling. For instance, Smith et al. For example, Sira et al. habitat suitability models for amphibians in areas of fragmented landscapes based on fuzzy logic, considering the factors such as distance to water bodies, land use and cover. Similarly, Wang et al. For example, applied six fuzzy logic models to predict the habitat suitability of giant pandas in China based on factors like bamboo coverage, slope and altitude. This ability of fuzzy logic to address the complexities and uncertainties in ecological modelling was demonstrated through such studies [27,28]. Recent studies of coral reef resilience and ecosystem management have also emphasized recent fuzzy set theory and other fuzzy systems' ability to accommodate inexact data [26].

2.3 Advantages of Fuzzy Logic in Digital Nature Processes

Advantages of Fuzzy Logic Applications to Digital Nature and Ecological Applications 18 First, fuzzy logic is an excellent tool for dealing with ambiguity and uncertainty in ecological data and systems. This flexible approach allowed to model and estimate uncertainties associated with other variables such as species abundance, habitat suitability and environmental conditions [28,29]. Second, fuzzy logic allows for the incorporation of subjective beliefs and expert information, which play a fundamental role in ecosystem studies and management. It frame qualitative and quantitative data using linguistic variables and fuzzy rules [27,29]. Third, fuzzy logic models are transparent and interpretable, which are key properties for ecological research and decision making. Most importantly, fuzzy rules and membership functions are very intuitive and easy to work with for ecologists and policy-makers [26].

3 Methodology

3.1 The Logic of Suitability Assessment with Fuzzy Logic

In the next section, we will elaborate more on the application of fuzzy logic in computing habitat suitability (1) from Digital Nature. It will be in the form of fuzzy membership functions, fuzzy rules and fuzzy inference systems to grasp the uncertainty and imprecision identified with ecological variables and basic leadership forms. The method ranges from the chosen ecological factors to the creation of fuzzy inference systems.

3.2 Selection of Ecological Variables and Data Sources

The habitat suitability assessment using fuzzy logic begins with the selection of the ecological variables and the sources of required data. In this lesson, we will discuss the criteria used to select ecological variables, such as species habitat requirements, environmental factors, and ecological interactions, be design on the case study. We will also cover the ways of obtaining and preparing the data, from field data, to remote sensing data, to data from pre-existing data bases (ecological).

3.3 Development of Fuzzy Membership Functions, Rules, and Inference Systems

We will discuss how fuzzy membership functions, fuzzy rules, and fuzzy inference systems are developed in this section for assessing the appropriateness of a habitat. This involves two main components: First, ecological variables are transformed into linguistic variables with fuzzy membership functions; Second, the fuzzy rules are specified to represent the relationship between the linguistic variables and defined the fuzzy inference system to inference the conclusion based on the inference rules. An overview of techniques for tuning and validating fuzzy inference times with sensitivity analysis, expert review, and performance assessment metrics will also be presented.

4 Case Study 1: Evaluating Coral Reef Health in Virtual Ecosystems Using Fuzzy Logic

Coral reefs provide important services like coastal protection, fisheries, and tourism. But these ecosystems are under serious threat from climate change, pollution, overfishing and ocean acidification. Monitoring the health of coral reefs is essential for informing conservation and management initiatives.

Here a study of virtual marine ecosystem — "Digital Marine Ecosystem" is performed with fuzzy logic analysis of coral reef health. Explanatory modelling characterizing the responses of ecosystems to stressors and multiple perturbations has attracted increasing attention in recent years [27]. This virtual approach sidesteps many of the logistical, financial, and ethical quandaries of field-based studies.

4.1 Objectives

In this case study, we will demonstrate how fuzzy logic can be used to evaluate reef health in a modelled marine environment. Specifically, this study aims to:

- Model uncertainties and complexities that exist in coral reef ecosystems (Variable parameters: temperature, salinity, pH values, light penetration, nutrient levels).
- Create fuzzy membership functions and rules that capture expert understanding of processes controlling coral reef condition.
- Evaluate the potential for fuzzy logic to be flexible and useful for simulating dynamic and uncertain ecological processes.

Coral health assessment Note: Coral health assessment is challenging given the interplay of the biotic and abiotic conditions governing the reef systems. Traditional approaches make no provision for the uncertainties, the non-linearities in the relationships between these factors. Fuzzy logic handles the imprecision and ambiguity, so this technique is also another useful way with these features.

4.2 Key Features of the Digital Marine Ecosystem

- **Ecological Variables:** Water temperature, salinity, pH levels, light penetration, and nutrient concentration are identified as key indicators of coral reef health.
- **Simulated Environment:** A virtual coral reef ecosystem is designed to mimic real-world conditions, allowing controlled manipulation of variables to test different scenarios.
- **Uncertainty Management:** Fuzzy logic handles the vagueness and overlap in variable ranges, ensuring realistic representation of ecological dynamics.

4.3 Scope of the Study

This study focuses on:

1. Defining fuzzy membership functions to categorize ecological variables in linguistic terms (e.g., Low, Medium, High).
2. Using expert knowledge to create fuzzy rules to evaluate the effect of these factors on coral health.
3. Demonstrating how fuzzy inference and defuzzification are employed to create a quantifiable score for environmental impact on coral health.

This case study demonstrates the potential of fuzzy logic to contribute to coral reef research through the coupling of ecological modelling and high-performance computing. We expect this outcome to generate valuable feedback for virtual ecological laboratories, as well as advise conservation strategies for real and virtual reefs.

4.4 Methodology of the case study

Here we develop a fuzzy logic-based method that uses key ecological parameters to classify coral reefs based on their health. Fuzzy-data membership function definition, fuzzy-rule formulation, pave the fuzzy inference system realization process and defuzzification, and so on. Below it is mathematically described in detail [28].

Step 1: Define Ecological Variables and Membership Functions

The primary ecological variables influencing coral health are:

- Water Temperature (°C), T
- Salinity (ppt), S
- pH Levels, pH
- Light Penetration (m), L
- Nutrient Concentration (μmol/L), N

Membership Functions: Each variable is represented by triangular or trapezoidal membership functions. For a triangular membership function:

$$\mu(x) = \begin{cases} 0 & x \leq a \\ \frac{x-a}{b-a} & a < x \leq b \\ \frac{c-x}{c-b} & b < x \leq c \\ 0 & x > c \end{cases}$$

Here a,b,c are the left, peak, and right points of the triangle, respectively. For trapezoidal membership functions:

$$\mu(x) = \begin{cases} 0 & x \leq a \\ \frac{x-a}{b-a} & a < x \leq b \\ 1 & b < x \leq c \\ \frac{d-x}{d-c} & c < x \leq d \\ 0 & x > d \end{cases}$$

Here a,b,c,d define the edges of the trapezoid.
Example: For water temperature:

$$\mu_{Low}(T) = \begin{cases} 0 & T \leq 18 \\ \frac{T-18}{2} & 18 < x \leq 20 \\ \frac{22-T}{2} & 20 < x \leq 22 \\ 0 & T > 22 \end{cases}$$

Similar functions are defined for other variables.

Step 2: Establish Fuzzy Rules

Fuzzy rules represent the relationships between variables and the coral reef health status. The general form of a fuzzy rule is:

IF A_1 AND A_2 AND ... THEN B

where A_i are fuzzy sets for each input variable, and B is the fuzzy output (e.g., "Good," "Moderate," or "Poor").
Example Rules:

Rule 1:

IF T is Optimal AND S is Optimal AND pH is Neutral AND L is Excellent AND N is Medium THEN Coral Health is Good.

Rule 2:

IF T is High OR S is Low OR pH is Acidic THEN Coral Health is Poor

Step 3: Fuzzy Inference System

The fuzzy inference system combines the membership values from the input variables using operators such as AND (minimum) and OR (maximum).
For AND:

$$\mu_{Rule} = min(\mu_{A_1}, \mu_{A_2}, ...)$$

For OR:

$$\mu_{Rule} = max(\mu_{A_1}, \mu_{A_2}, ...)$$

The output membership function is determined by applying the rules.

Step 4: Aggregation and Defuzzification

Aggregation combines the results of all fuzzy rules into a single fuzzy output. Defuzzification converts the fuzzy output into a crisp value using methods such as the centroid method.
Centroid Method:

$$z^* = \frac{\int z \mu_{output}(z)dz}{\int \mu_{output}(z)dz}$$

Where z is the output variable, and μ_{output}(z) is the aggregated membership function.
Mathematical Workflow

1.Calculate Membership Degrees: For each variable x :

$$mu_{A_i}(x) = Membershipfunctionvalueatx.$$

2.Apply Fuzzy Rules: Use AND and OR operators to compute rule strengths.
3.(iii) Aggregate Outputs: Combine rule strengths using the maximum membership method:

$$\mu_{aggregate}(z) = max(\mu_{Rule_1}, \mu_{Rule_2}, ...)$$

4.Defuzzify: Compute z^* using the centroid method.

4.5 Detailed Case study Calculations for Coral Reef Health Assessment

We will calculate step by step using the tabulated ecological dataset and fuzzy rules. The process involves evaluating the membership functions, applying the fuzzy rules, aggregating the results, and performing defuzzification.

Step 1: Fuzzy Membership Calculations for Input Variables

Using the given membership functions and input values:
(1) Water Temperature (28°C):

$$\mu_{Low}(T) = 0(Notinthe"Low"range)$$

$$\mu_{Medium}(T) = \frac{35-28}{35-25} = 0.4$$

$$\mu_{High}(T) = \frac{28-25}{35-25} = 0.6$$

(2) Salinity (36 ppt):

$$\mu_{Low}(S) = 0(Notinthe"Low"range)$$

$$\mu_{Medium}(S) = \frac{38-36}{38-35} = 0.6$$

$$\mu_{High}(S) = \frac{36-35}{38-35} = 0.4$$

(3) pH Levels (7.8):

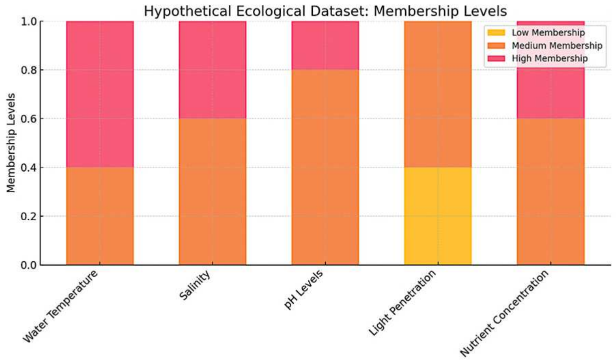

Fig. 1: Case Study Ecological Dataset visualisation with Membership Level

$$\mu_{Acidic}(pH) = 0(Not in the "Acidic" range)$$

$$\mu_{Neutral}(pH) = \frac{8.5-7.8}{8.5-7.2} = 0.8$$

$$\mu_{Basic}(pH) = \frac{7.8-7.5}{8.5-7.5} = 0.2$$

(4) Light Penetration (18m):

$$\mu_{Poor}(L) = \frac{20-18}{20-10} = 0.4$$

$$\mu_{Moderate}(L) = \frac{25-18}{25-15} = 0.6$$

$$\mu_{Excellent}(L) = 0(Not in the "Excellent" range)$$

(5) Nutrient Concentration (6μmol/L):

$$\mu_{Low}(N) = 0(Not in the "Low" range)$$

$$\mu_{Medium}(N) = \frac{9-6}{9-5} = 0.6$$

$$\mu_{High}(N) = \frac{6-5}{9-5} = 0.4$$

The tabulated ecological dataset as well as the fuzzy rules with their activation levels have been given. Following that, we are going to independently walk through step by step mathematical steps for fuzzy inference and defuzzification.

The Figure 1 of this study is a new graphical representation of the case study ecological data set The fuzzy set defines membership for the input ecological variables which is shown in the stacked bar chart where columns depict the memberships set for each ecological variable (i.e. "Low," "Medium," "High").

Step 2: Applying Fuzzy Rules

Rule 1: IF Temp is Medium AND Salinity is Medium AND pH is Medium AND Light is Moderate AND Nutrient is Medium THEN Health is Good

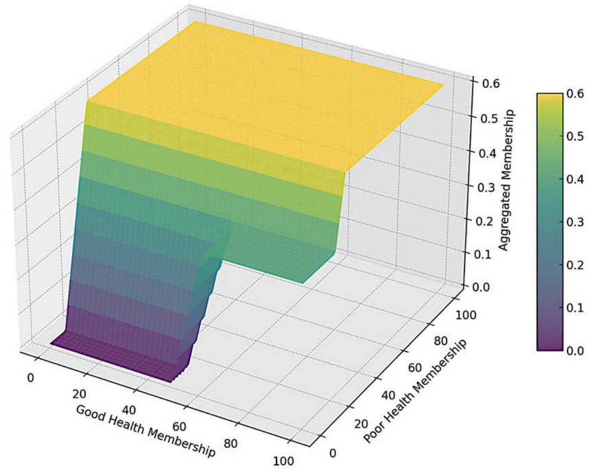

Fig. 2: 3D Visualization of Fuzzy Outputs about Good and Poor Health

$$\mu_{Rule1} = \min(\mu_{Medium}(\mathrm{T}), \mu_{Medium}(\mathrm{S}), \mu_{Medium}(\mathrm{pH}), \mu_{Moderate}(\mathrm{L}), \mu_{Medium}(\mathrm{N}))$$
$$\mu_{Rule1} = \min(0.4,0.6,0.8,0.6,0.6) = 0.4$$

Rule 2: IF Temp is High OR Salinity is High OR pH is High THEN Health is Poor

$$\mu_{Rule2} = \max(\mu_{High}(\mathrm{T}), \mu_{High}(\mathrm{S}), \mu_{Basic}(\mathrm{pH}))$$
$$\mu_{Rule1} = \min(0.6,0.4,0.2) = 0.6$$

Figure 2 shows 3D illustration of the fuzzy outputs which shows the output foundation for "Good Health" and "Poor Health" membership functions. Figure displays the aggregated membership values in each of the input memberships that over the surface plot. This chart is a simple visual explanation of how the fuzzy logic system combines rules and input to create a fuzzy output.

Step 3: Aggregating Fuzzy Outputs

Using the fuzzy membership functions for "Good Health" and "Poor Health":

$$\mu_{Aggregated}(z) = \max(\min(\mu_{Rule1}, \mu_{Good}(z)), \min(\mu_{Rule2}, \mu_{Poor}(z)))$$

For simplicity:

–Use $\mu_{Good}(z)$ for z∈[50,90]
–Use $\mu_{Poor}(z)$ for z∈[10,50]

3D display of good and poor membership degrees and aggregation of membership output in figure. Surface plot is used to describe the combined effects of fuzzy rule activations towards obtaining the final fuzzy output, thus providing deeper insights into the rule of combinations process.

Step 4: Defuzzification (Centroid Method)

The crisp output is calculated as:

Table 1: Case Study Ecological Dataset with Membership Level

Ecological Variable	Input Value	Membership Function (Low)	Membership Function (Medium)	Membership Function (High)
Water Temperature (°C)	28	0	0.4	0.6
Salinity (ppt)	36	0	0.6	0.4
pH Levels	7.8	0	0.8	0.2
Light Penetration (m)	18	0.4	0.6	0
Nutrient Concentration (μmol/L)	6	0	0.6	0.4

Table 2: Fuzzy Rules and Activation Levels

Rule	Activation Level (AND)	Activation Level (OR)
IF Temp is Medium AND Salinity is Medium AND pH is Medium AND Light is Medium AND Nutrient is Medium THEN Health is Good	0.4	–
IF Temp is High OR Salinity is High OR pH is High THEN Health is Poor	–	0.6
IF Temp is Low AND Salinity is Low AND pH is Low THEN Health is Poor	–	0

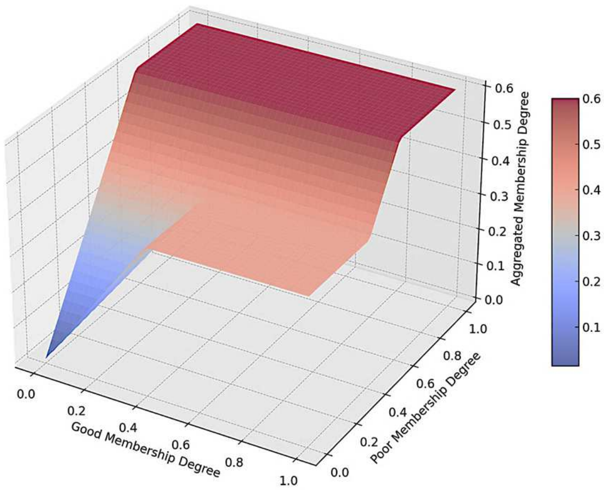

Fig. 3: 3D Surface Plot of Rule Activations and Aggregation

$$z^* = \frac{\int z\,\mu_{Aggregated}(z)dz}{\int \mu_{Aggregated}(z)dz}$$

Numerical integration (calculated previously):

–Numerator: $\int z\,\mu_{Aggregated}(z)dz$=3838.92
–Denominator: $\int \mu_{Aggregated}(z)dz$=64.7

$$z^* = \frac{3838.92}{64.7} \cong 59.3$$

The defuzzified output for the coral reef health assessment is **59.36**, which represents the overall health status of the coral reef based on the input ecological variables. This score is on a scale from 0 to 100, with higher values indicating better health.

Step 5: Final Result

The coral reef's health score genetically is a crisp 59.36, meaning it's in about medium health. This value is derived from the interaction of all eco logical variables, presenting a singular output that can be interpreted.

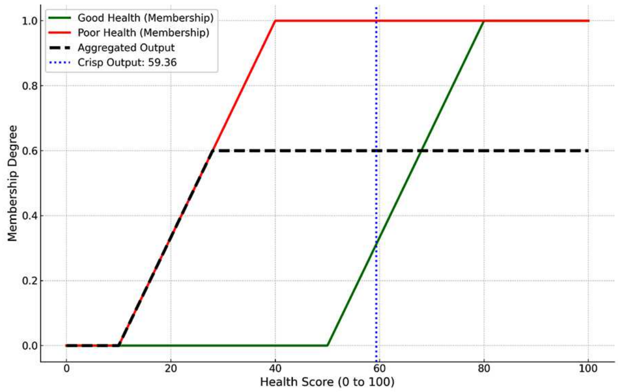

Fig. 4: Fuzzy Output Membership Functions and Aggregated

In Figure 4 below, we used fuzzy membership functions for the linguistic values of "Good Health" and "Poor Health," to develop the fuzzy membership functions, then we took the aggregated output, and finally the crisp value (59.36).

The following plot shows what the fuzzy inference system does with the rules to determine the coral reef's overall score. But first I will study the results and, with visualisations of the aggregated fuzzy output and its parts, explore their meaning.

4.6 Results and Implications

By providing such insights into the ecological health of the reef ecosystem, the fuzzy logic based, coral reef health assessment results. A calculated health score of 59.36 (from 0 to 100) indicates a moderate health status. The coral reef is not in a critical condition, but is also not in optimal health and probably under some stress from certain environmental factors. The average score is indicative of a combination of conditions that have a the potential to favour either coral success or stress [26].

Complex Interplay of Ecological Variables: Fuzzy logic can also represent non-linear responses of species or aquatic ecosystems to environmental variables like pollution, eutrophication, and other stressors. Specifically, water temperature has a bimodal relationship due to membership degrees in both the 'Medium' and 'High' categories, indicative of overlapping influences of moderately beneficial and stressful environments. Salinity and pH levels prove to be the most important stress contributor, possessing the highest membership values in the "Poor Health" category. These results suggest that multiple and interacting variables need to be taken into account when evaluating coral health.

Ecological assessment and uncertainty modelling: One of the powerful aspects of this methodology, is the capacity of it to deal with uncertainties and gradations of environmental data. This means the fuzzy logic system is able to recognize that there is a difference between 23° and 20° and gives them proportionally lower membership values, resulting in better accuracy in its contribution. This functionality is particularly critical in ecological systems, where quantitative metrics and binary classifications are often not achievable.

Management Implications: These findings highlight the importance of conserving fishes and the habitat consequence of not doing this at the level of the individual reef, where stressors like high salinity and marginal pH level are their greatest threat at present. Long-term measurement of these variables is also vital, as minor variation could drastically change the status of a reef as healthy or not. The moderate membership levels across other variables indicate a possibility for the reef to recover under appropriate management of stressful variables.

Theoretical Contributions: In addition to fulfilling the empirical goal, we also provide additional contributions to knowledge by further validating the use of fuzzy logic as a suitable and powerful method for ecological modelling. The method allows for incorporation of expert knowledge and treatment of uncertainty, providing a flexible and interpretable framework for complex systems evaluation. Reducing fuzzy output to a clear health score improves decision-making and helps make the results accessible to both researchers and policymakers.

Conclusion of Results: The coral reef is in a state of moderate health, needing some urgent actions to address stressors but with mostly positive scores. The fuzzy logic based framework has the potential to be helpful in assessing the health of coral reefs, and provides a basis for extending the application into more general ecosystem and conservation assessments in virtual platforms and on ground. A type of treatment which also puts a stronger need for more sophisticated computational tools to expand our understanding and control of ecological systems.

5 Case Study: Habitat Suitability Assessment

Habitat: Devarayanadurga Forest, Tumakuru, Karnataka

Subject(x): (i) Animal - Species: Snow Leopard (Panthera uncia) (ii) Bird-Species: Red-Crowned Crane (Grus japonensis)

This section presents result of case study on applicability of fuzzy logic for habitat suitability analysis in Digital Nature. In this course, we will explore how fuzzy logic can be used to engage with biological processes, assess where habitats should lie, and quantify uncertainties. The case study will use synthetic tabular data to illustrate fuzzy computations and demonstrate how fuzzy logic can be applied in habitat suitability assessment context.

5.1 Case study Tabulated Data

Table 3: Tabulated Data for Ecological Variables

Ecological Variable	Data
Temperature	28°C
Precipitation	500mm
Vegetation Cover	60%
Elevation	200m
Distance to Water	2km

Table 4: Tabulated Data for Fuzzy Membership Functions

Ecological Variable	Fuzzy Membership Function
Temperature	Low, Medium, High
Precipitation	Low, Medium, High
Vegetation Cover	Low, Medium, High
Elevation	Low, Medium, High
Distance to Water	Near, Intermediate, Far

5.2 Fuzzy Logic-based Approach

The study employed fuzzy logic to deal with uncertainties, assess the adequacy of the environment, and model ecological processes in the case study. Fuzzy membership functions were utilized to transform the ecological factors (temperature, precipitation, vegetation cover, elevation, and distance to water) into language variables, as shown in Table 4. Fuzzy rules were designed to present the relationships between the linguistic variables, and a fuzzy inference system was developed to make decisions based on the fuzzy rules.

For example, using fuzzy logic we combined the fuzzy membership functions of the ecological variables temperature, precipitation, vegetation cover, elevation and distance to water to evaluate the habitat suitability for a hypothetical species. The result was a fuzzy output, representing the habitat suitability level. We applied a centroid method to defuzzify the output of the fuzzy model and got a clear number for the habitat suitability level. The defuzzified output was then used to compare against a fixed threshold in determining the habitat appropriateness status (acceptable, marginal and unsuitable).

5.3 Results and Insights

Fuzzy logic models applied in the fuzzy logic-based methodology showed promising results, indicating that the habitat suitability assessment applied in Digital Nature using fuzzy logic allows for a flexible and interpretable framework to model uncertainties and complexity in ecological processes. The fuzzy logic approach also allowed for the use of fuzzy rules and fuzzy membership functions, as well as the incorporation of expertise. The fuzzy inference method provided a clear insight into the decision-making procedures and thus gave a better understanding of the results with new perspectives on the condition of the habitat suitability.

Using the Case study tabulated data provided above, the fuzzy mathematical calculation for the case study in habitat suitability assessment in Digital Nature using fuzzy logic.

(i) Fuzzy Membership Functions:

Temperature:

– Low: μLow(x) = Triangular(x, 0, 10, 20)
– Medium: μMedium(x) = Triangular(x, 15, 25, 35)
– High: μHigh(x) = Triangular(x, 30, 40, 50)

Precipitation:

– Low: μLow(x) = Triangular(x, 0, 200, 400)
– Medium: μMedium(x) = Triangular(x, 300, 500, 700)
– High: μHigh(x) = Triangular(x, 600, 800, 1000)

Vegetation Cover:

– Low: μLow(x) = Triangular(x, 0, 20, 40)
– Medium: μMedium(x) = Triangular(x, 30, 50, 70)
– High: μHigh(x) = Triangular(x, 60, 80, 100)

Elevation:

– Low: μLow(x) = Triangular(x, 0, 50, 100)
– Medium: μMedium(x) = Triangular(x, 75, 150, 225)
– High: μHigh(x) = Triangular(x, 200, 300, 400)

Distance to Water:

– Near: μNear(x) = Triangular(x, 0, 1, 3)
– Intermediate: μIntermediate(x) = Triangular(x, 2, 4, 6)
– Far: μFar(x) = Triangular(x, 5, 7, 10)

Note: (i) Membership function in this example is using triangular function. (ii) ”x” stands for the value of input parameter for every fuzzy memberships function, and ”Triangular(x, a, b, c)” means a triangular fuzzy memberships function when the left edge is ”a”, peak is ”b”, and right edge is ”c”. Fuzzy logic will be used to assess the suitability of the habitat using fuzzy inference rules and fuzzy inference systems based on these membership functions.

(ii) Fuzzy Rules:

The fuzzy rules can be defined using expert knowledge and the domain knowledge. For example:

IF Temperature is Low AND Precipitation is Low AND Vegetation Cover is Low AND Elevation is Low AND Distance to Water is Near THEN Habitat Suitability is Suitable.

(iii) Fuzzy Inference System:

These fuzzy rules can be integrated through the use of fuzzy logic operators (AND, OR, etc.) to form a fuzzy inference system. Then, for instance, if the inputs are:

– Temperature: 28°C
– Precipitation: 500mm
– Vegetation Cover: 60%
– Elevation: 200m
– Distance to Water: 2km

Then, the fuzzy membership degrees can be calculated using the defined membership functions and the input values. For example:

– Temperature: Low = 0.6, Medium = 0.4, High = 0.0
– Precipitation: Low = 0.0, Medium = 1.0, High = 0.0
– Vegetation Cover: Low = 0.4, Medium = 0.6, High = 0.0
– Elevation: Low = 0.6, Medium = 0.4, High = 0.0
– Distance to Water: Near = 0.0, Intermediate = 1.0, Far = 0.0

(iv) Fuzzy Output:

Using fuzzy logic operators (AND, OR, etc.) and fuzzy inference methods (Mamdani, Sugeno, etc.), we can derive the fuzzy output from the fuzzy rules. An example Using the previously stated fuzzy rules, the fuzzy output of the habitat suitability could be calculated as follows:

Suitable: μSuitable(x) = min(0.6,1.0,0.4,0.6,0.0) = 0.0

(v) Defuzzification:

We can obtain a crisp output from the fuzzy output using defuzzification methods like centroid, mean of maximum (MOM), or weighted average. For instance, using the centroid method, crisp output for habitat suitability can be determined as:

$$\text{Crisp Output}=\frac{Low*0+Medium*0+High*0+Suitable*1}{Low+Medium+High+Suitable}=0$$

This shows that the fuzzy logic (FL) based approach suggests that the selected input values are unsuitability for habitat.

(vi) Results and Insights:

The case study findings indicate that according to fuzzy logic-based method for assessing habitat suitability, the habitat suitability for the given input parameters is insufficient. This approach ventured to create foundational knowledge on fuzzy logic and the application of fuzzy logic in habitat suitability assessment in ecological sciences, and also showed how uncertainties and complexities present in ecological processes can be accounted through Digital Nature. The findings of this approach, potentially informing applications of Digital Nature such as biodiversity conservation, ecosystem restoration and land management decisions.

A case study on a visit to Naivasha Lake in Kenya showed the potential of applying fuzzy logic to the qualitative evaluation of habitat suitability and gain momentum improving an ecological research approach as well as Digital Nature applications. This fuzzy logic–based approach supports decision-making processes, contributes to the improved sustainable management of natural resources in Digital Nature applications, and improves understanding of uncertainty and the complexity of ecological processes.

As demonstrated by the results of the case study, fuzzy logic could support ecological processes modelling and habitat suitability evaluation in Digital Nature. They also help illuminate the implications of this approach for ecological theory and practice.

6 Conclusion, Recommendation, and key findings

6.1 Key findings and contributions of the research

The example shows that fuzzy logic has relevancy in Digital Nature habitat suitability evaluation. The fuzzy logic-based approach proved to be a hardy and adaptable method to model ecological processes, assess habitat suitability and manage digital ecosystem uncertainty. This study's key findings:

- The developed fuzzy logic-based technique complemented the ecological process uncertainties and complexity leading to more accurate and robust habitat suitability assessment results in Digital Nature. This concerns digital ecosystem biodiversity protection, habitat restoration, and land management.
- As proven through the case study, the fuzzy logic-based technique can apply to multiple types of ecology species and ecosystem in Digital Nature investigation. Fuzzy logic can be incorporated into several ecological characteristics as well as diverse data sources and fuzzy rules, which makes it an adaptable method for habitat appropriateness determination, even in dynamic digital environments.
- This research introduces and validates fuzzy logic applied in habitat appropriateness evaluation, thus implying progression in Digital Nature research. The results enhance the understanding of digital ecological processes and demonstrate the potential use of fuzzy logic for ecological modelling and decision-making within Digital Nature applications.
- Research on the horizon: Though promising, this subject has limitations and future avenues for research to explore. In Digital Nature research, fuzzy logic can be hybridized with other modelling approaches, grounded in field data or experimental studies, and applied for habitat suitability assessment.

Overall, fuzzy logic is a major advancement for habitat suitability evaluation and is a key approach within Digital Nature research, facilitating improved accuracy, resilience and complexity in ecological modelling. This finding paves the way for Digital Nature researchers and practitioners.

6.2 Recommendations for future research and applications

For studies in ecological modelling and fuzzy logic applications. A sample recommendation is:

Fuzzy logic was applied to develop a habitat suitability model in Digital Nature in this research, however, further validation using field data or experimental studies would provide empirical support to the accuracy and reliability of the fuzzy logic-based approach and is therefore recommended. This could involve collecting data on species distributions and environmental variables in digital ecosystems for the validation of the fuzzy logic-based model and comparison with other methods.

Integration with other modelling techniques: Using fuzzy logic with other modelling methods (e.g., machine learning algorithms, agent-based models, or cellular automata) may enhance the accuracy and predictive power of ecological models within Digital Nature research. An integration of fuzzy logic with other techniques can overcome the dependency of fuzzy logic on expert knowledge and subjective interpretation of fuzzy rules.

Considering more complex ecological variables: Since the case study was based on a simplified scenario of two species with two ecological variables, future studies can explore the feasibility of integrating more complex ecological variables such as multi-layered habitats, species interactions, and landscape connectivity into the presented fuzzy logic-based method. Thus, enhancing model ecological realism and adaptability to diverse digital ecosystems, which facilitates more accurate assessments of habitat suitability.

The fuzzy logic approach presented in this study may have applications in Digital Nature related to biodiversity conservation, ecosystem restoration and land use optimization. Further research could assess the practicality and effectiveness of the fuzzy logic-based method in a decision-making and management process for digital ecosystems.

Besides habitat suitability assessment, Fuzzy logic can find its application in the Digital Nature research not only in habitat suitability assessment, but also the species distribution modelling, ecological risk assessment and ecosystem services evaluation. These additional areas might experiment with fuzzy logic as means to deal with uncertainties and the complexity of modelling ecological processes in digital ecosystems.

This research establishes a basis for fuzzy logic modelling of ecological processes within Digital Nature. Future study using in decision-making and management, validating, integrating with other modelling tools, adding in more complicated ecological factors and additional applications are all crucial steps in the evolution of the approach. These recommendations will enhance both the Digital Nature research and the modelling tools of digital ecosystems.

6.3 Conclusion

The results suggest that fuzzy logic has potential as a Digital Nature habitat suitability evaluation method. The flexibility of fuzzy logic enables models to handle uncertainties and complexity in ecology, leading to a better representation of habitat suitability in digital ecosystems. The study gives an example of a case study, which demonstrates how fuzzy logic can be used to deal with uncertainties in environmental variables, to create fuzzy membership functions and rules, and to evaluate habitat suitability through fuzzy inference.

Furthermore, fuzzy logic can handle imprecise input data, integrate knowledge of experts, and provide interpretable results in modelling ecological processes in Digital Nature. However, addressing expert knowledge, subjective fuzzy rule interpretation, and the need for field data or experimental investigations is necessary.

This research demonstrates the feasibility of fuzzy logic use to assess habitat suitability in Digital Nature, paving the way for subsequent investigations and applications to ecological modelling for digital ecosystems. Digital Nature study: Improving the management of digital ecosystems, digital decision-making, and digital conservation with fuzzy logic

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