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Ecological Modelling of Pollinator-Friendly Agricultural Practices Using Fuzzy Logic

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Abstract: Digital Nature–the digital analogy of natural bioscopes–has become the focus of growing interest in ecological research in recent years due to its ability to model complex environmental system dynamics and inform conservation strategy. However, uncertainties and complexities that are intrinsic to ecological processes create difficulties to properly model and assess habitat suitability in Digital Nature. All we can do is to model the nature and if we can, add uncertainties, but we can solve these uncertainties in a way by using fuzzy logic and this paper provides a representation of this so-called Digital Nature. In this analysis, we presented a case study to show how fuzzy logic can be applied in order to model of ecological process and assesses habitat suitability of target species. Fuzzy membership functions, fuzzy rules, and fuzzy inference systems were developed to provide information about the uncertainties related to ecological variables. The results of the case study show the effectiveness of the fuzzy logic-based method in addressing uncertainties and delivering more nuanced and intelligible outcomes in habitat suitability assessment. This study adds to the increasing body of knowledge associated with Digital Nature and the use of fuzzy logic for ecological simulation practices and informs conservation planning and decision-making in virtual environments. Additional studies are suggested to enhance the utility of fuzzy logic across various Digital Nature applications and to develop a more suited method to its ecosystem.

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

1 Introduction

1.1 The concept of Digital Nature and its relevance in the context of ecological research

Computer generated images of natural environments, generated by advanced computer simulation, modelling and graphics techniques are described by the term 'digital nature, virtual nature, or virtual ecosystems.' These in silico environments allow researchers to characterize ecological processes, construct models, and conduct experimentations in realistic simulations that mimic real ecosystems [1,3,4,5,6,2]. Digital Nature has been gaining attention in ecology because it can help overcome many of the practical, economic and ethical challenges of directly studying natural ecosystems [9,10,11,12,13,7,8].

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Recent studies [14,17,18,19,15,16] suggest that Digital Nature has been applied to various ecological research areas, such as biodiversity conservation, ecosystem service assessment, climate change impact assessment, and ecosystem restoration. Such unique characteristics allow for controlling variables, replicating studies, and viewing processes that are unethical or impractical to observe in the real-world [9,13,20,21,22]. Moreover, Digital Nature welcomes a safe and regulated space to experiment, study conditions, and test ideas likely infeasible or ethically questionable to conduct in real ecosystems [14,23,24,25].

According to [6] and [9], because our use of Digital Nature to undertake ecological research can supplement and enhance more traditional studies carried out in the field as they reveal data that has previously been obscured and can enable evidence-based management and conservation decisions. The Digital Nature also cover novel computational approaches based on fuzzy logic, playing an important role in elucidation of complex and uncertain ecological processes that are inherently stochastic, uncertain and context dependent [13,32,26,27,28].

1.2 An overview of fuzzy logic and its applicability in modelling uncertainties in ecological processes

Fuzzy logic is a mathematical representation of humanity—it deals with activity and uncertainty in thought processes and decision-making. It was first introduced by Lotfi A. Zadeh in 1965 as a generalization of traditional or "crisp" logic which works on binary (true/false) values. It provides tools to represent and control uncertainty, vagueness, and ambiguity, all of which are characteristic of ecological systems affected by many biotic, and abiotic, factors, spatial heterogeneity, and temporal processes.

Uncertainties can be detected in various aspects and aspects of ecological research, including species interactions, environmental parameters (e.g. salinity, temperature, nutrients), ecological data (e.g. species distribution data), and model parameters (e.g. birth and death rates) due to limited data quality, measurement errors, spatial and temporal variability information, and complexities of ecological systems [13,31,29,30]. Fuzzy logic offers a strong tool for addressing uncertainties present in ecological systems and making decisions in conditions with inadequate or ambiguous data.

A critical idea of fuzzy logic is the idea of fuzzy sets that enables gradating or representing degrees of membership in a set. As opposed to the classical set which enforces strict rules for binary membership (0 or 1), fuzzy sets allow partial membership of an element, where the degree of membership can have any value between 0 and 1. This also allows for representation of ambiguity and uncertainty in ecological data and models, which typically display continuous and gradational characteristics.

Fuzzy logic has been widely implemented in ecological research to improve the modelling of uncertainties and complexities in ecological processes, including habitat suitability assessment, species distribution modelling, assessment of ecosystem services and ecological risk assessment. Fuzzy logic can be applied to aggregate ecological uncertainties of the input parameters within the decision-making processes in order to define uncertainty regarding ecological data (e.g. whether or not species occurrence or environmental conditions data is uncertain or incomplete). Fuzzy inference systems can also be built based on Fuzzy logic, allowing engineers to approximate heuristic relationships within ecological processes since fuzzy sets and operations are well designed to express the intricacy of the complex interactions and decision-making within ecological processes.

Fuzzy logic systems have promising ability to interpret crisp input parameters, to cope with imprecise and uncertain information, and to address gradation or continuum features of ecological systems. Being able to combine many pieces of information, uncertainties, expert knowledge and subjective judgements is important in many applications in ecological research and management and fuzzy logic is highly capable of doing so.

1.3 The research objective

Such habitat suitability evaluation which is a significant ecological process is to evaluate if a given environment is sustainable to a particular species or ecological unit. Within the digital nature field, where natural environments are represented as virtual ecosystems or simulated environments, habitat suitability assessment is an essential tool in understanding species-environment relationships, modelling species distributions and decision support in ecosystem management and conservation.

This study aims at the practical implementation of fuzzy logic as a modelling strategy to assess the suitability of a habitat in the Digital Nature. The study particularly aims to:

- Evaluate the ability of fuzzy logic to model precision and uncertainty in habitat suitability assessment, while taking into before consideration, factors such as species interactions, environmental conditions, and spatial heterogeneity that are inherent to ecological processes.
- Develop fuzzy inference systems for environmental suitability assessment in Digital Nature to model complex species-environment interactions and decision-making processes. These systems have fuzzy sets and fuzzy logic operations.

– Assess the accuracy, interpretability and robustness of fuzzy logic-based habitat suitability evaluation relative to other standard or ML algorithms, for example, logistic regression, maximum entropy modelling, or ML techniques.
– Contrast interpretability and transparency of fuzzy logic-based habitat suitability models and the necessity for more cartesian (fuzzy logic) driven models in management and conservation decisions in applications of ecological science.
– Provide examples of how a method based on fuzzy logic could be useful both in Digital Nature for indicating the suitability of a habitat (predicting species distributions, detecting sensitive habitats, or predicting the effects of changes in the environment).
– And to contribute in knowledge of performance and practical use of fuzzy logic as a habitat suitability assessment method, in the eyes of Digital Nature. The results of this study may have significant importance in improving decision-making in Digital Nature and many other ecological applications where habitat suitability estimation models are used also for qualitative decision-making.

1.4 Preliminaries

Different mathematical functions, equations, and concepts were used to carry out the fuzzy logic-based habitat suitability analysis. This section goes into details for each formula, its meaning and representations, and references for a better understanding.

1.4.1 Triangular Membership Function

The triangular membership function is fundamental in fuzzification, where crisp inputs are converted into fuzzy sets. It is represented as:

$$\mu(x) = \begin{cases} 0, & \text{if } x \leq a \text{ or } x \geq c \\ \frac{x-a}{b-a}, & \text{if } a \leq x \leq b \\ \frac{c-x}{c-b}, & \text{if } b \leq x \leq c \end{cases} \tag{1}$$

Here:

– a, b, c : Parameters defining the left edge, peak, and right edge of the triangle.
– $\mu(x)$: Degree of membership of x in the fuzzy set.

This means if the application rate of pesticide is 2.0" " kg/ha, it may be 50% in the "Low" and 50% in the "Medium" category. The triangular membership function enables soft transitions to avoid sudden cutoffs typically observed in classical binary classifications.

1.4.2 Logical Operations in Fuzzy Rules

Fuzzy inference systems rely on logical operations to combine conditions in rules. Two primary operations are used:

– AND (Minimum):

$$\mu_{AND} = min(\mu_{\text{Condition1}}, \mu_{\text{Condition2}}, \ldots) \tag{2}$$

This operation captures the intersection of conditions. For example, if "Pesticide is Low" ($\mu = 0.7$) and "Floral Density is Medium" ($\mu = 0.8$), their combined degree is $\mu_{AND} = 0.7$.
– OR (Maximum):

$$\mu_{OR} = max(\mu_{\text{Condition1}}, \mu_{\text{Condition2}}, \ldots) \tag{3}$$

This operation captures the union of conditions. If "Crop Diversity is High" ($\mu = 0.6$) or "Proximity to Water is Near" ($\mu = 0.8$), their combined degree is $\mu_{OR} = 0.8$.

1.4.3 Centroid Defuzzification Formula

Defuzzification transforms the aggregated fuzzy output into a crisp value. The centroid method, widely used for its accuracy, is defined as:

$$y_{\text{defuzzified}} = \frac{\int_x \mu(x) \cdot x dx}{\int_x \mu(x) dx} \tag{4}$$

Here:

– $\mu(x)$: Aggregated fuzzy membership degree.
– x : Output variable.
– $y_{\text{defuzzified}}$: Crisp output score.

For example, if habitat suitability outputs are "High" ($\mu = 0.5, x = 80$) and "Medium" ($\mu = 0.3, x = 50$), the defuzzified score is approximately $y = 70.3$. This method ensures balanced consideration of all fuzzy outputs.

1.4.4 Habitat Suitability Score Formula

The overall habitat suitability score incorporates multiple ecological variables, represented as:

Suitability $= w_1 \cdot ($ Floral Density $) + w_2 \cdot ($ Crop Diversity $) - w_3 \cdot ($ Pesticide Usage $)$,

where:

– w_1, w_2, w_3 : Weights indicating the relative importance of each variable.
– Positive terms enhance suitability (e.g., floral density), while negative terms reduce it (e.g., pesticide usage).

This formula aggregates variable contributions, reflecting real-world dynamics where certain variables promote and others inhibit habitat quality.

1.4.5 Sensitivity Analysis

Sensitivity analysis quantifies the impact of individual variables on the output.

It is calculated as: $S_i = \frac{\Delta Y}{\Delta X_i}$

where:

–S_i : Sensitivity of variable X_i.
–ΔY : Change in habitat suitability score.
–ΔX_i : Change in input variable X_i.

For example, a 10% increase in floral density might result in a 15% improvement in habitat suitability, yielding a sensitivity score of $S = 1.5$. This analysis identifies the most influential variables for targeted interventions.

1.4.6 Correlation Coefficient

The Pearson correlation coefficient evaluates the relationship between two variables:

$$r = \frac{\sum (X - \bar{X})(Y - \bar{Y})}{\sqrt{\sum (X - \bar{X})^2 \sum (Y - \bar{Y})^2}} \tag{5}$$

Here:

–r : Correlation coefficient (-1 to 1).
–X, Y : Variables under comparison (e.g., floral density and crop diversity).
–$\bar{X}, \bar{Y}$: Means of X and Y.

A strong positive correlation (e.g., $r = 0.9$) between floral density and habitat suitability suggests a direct relationship.

1.4.7 Root Mean Square Error (RMSE)

RMSE measures model accuracy by comparing predicted and observed scores:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (\text{ Predicted }_i - \text{ Observed }_i)^2}{n}} \tag{6}$$

where:

–n : Number of observations.
–Predicted $_i$, Observed $_i$: Predicted and observed scores.

Lower RMSE values indicate better model performance, validating the accuracy of the fuzzy logic approach.

1.4.8 Normalization Formula

Normalization scales variables to a common range for equitable comparison:

$$X_{\text{normalized}} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{7}$$

This ensures all variables contribute proportionately to the analysis, avoiding bias due to differing magnitudes.

2 Literature Review

2.1 Review existing literature on Digital Nature, ecological modelling, and fuzzy logic

So here we will go over the related literature in river ecosystem modelling, fuzzy logic and digital nature. In the field of ecological research, modelling, and management, digital nature refers to artificial ecosystems and mimicked natural settings. It refers to the technologies, concepts, and modelling approaches that need to be used in their computerised form in order to represent and understand ecology in silico. Ecological modelling includes many methods and techniques used for simulating and representing such systems, often as population dynamics, community dynamics, or as an ecosystem. Fuzzy logic is a mathematical approach for evaluating uncertainty and imprecision in decision-making processes.

2.2 Used fuzzy logic in habitat suitability assessment or ecological modelling

Several studies used fuzzy logic for habitat suitability and ecological modelling. For example, [33] [1] [31] [34] [35] constructed a fuzzy logic-based model including the variables of plant cover, distance to water bodies, and land use. [36,37,38] employed fuzzy logic for the simulation of giant panda habitat suitability in China based on the percentage of bamboo coverage, slope, and altitude. The experimental results required to draw this conclusion are performed on several ecological modelling and habitat suitability assessment problems indicating the satisfactory performance of fuzzy logic in dealing with the complexity and uncertainties relevant to the problems of ecological modelling and habitat suitability assessment.

2.3 Highlight the advantages of the study

Fuzzy logic has some benefits in relation to the vagueness and the complexity of ecological processes in Digital Nature. Fuzzy logic, in the first place, allows representing and processing the uncertainty and imprecision typical of ecological data usually contained in real ecological systems. This leads to a flexible and interpretable framework for modelling and estimating uncertainty around ecological variables, such as species abundance, habitat suitability, and environmental predictors. The second advantage is that fuzzy logic enables an integration of the subjective nature of ecological study and management as well as the expertise of the field over time. For example, fuzzy-logic inspired models are able to represent expert knowledge through linguistic variables and fuzzy rules, thereby bringing qualitative information into the processes of taking decisions with data. Third, fuzzy logic yields comprehensible and interpretable models which are crucial to studying and managing ecology. This aids in the communication and interpretation of model outputs, as fuzzy rules and membership functions can be easily interpreted by ecologists and decision-makers.

3 Methodology

3.1 Integrating fuzzy logic in the habitat suitability evaluation

This section will describe how the fuzzy logic model is integrated into Digital Nature's evaluation of habitat suitability. This will also be the evolution of fuzzy membership functions, fuzzy rules, fuzzy inference systems, to illustrate the uncertainty, vague control in environmental factors and the choice-making process. Starting with selection of ecological variables and ending with designing fuzzy inference systems, the method will be introduced stepwise.

3.2 Ecological variables and data sources in the case study

The fuzzy logic approach defined by the configuration of the ecologic variables and data sources established the framework to the habitat suitability assessment. This is done using species habitat requirements, relevant environmental stressors, and ecological interactions which we discuss in terms of selection criteria. We will also introduce the methods including the data collection and pre-processing techniques, the sources of the data used in the project including the field and remote sensing data along with pre-existing ecological databases.

3.3 The fuzzy membership function, fuzzy rules, and fuzzy inference system development for the habitat suitability assessment

In the evaluation of habitat suitability, this section explains the construction process of fuzzy membership functions, fuzzy rules, and fuzzy inference systems. These fuzzy rules must be decoded to make inferences based on fuzzy membership functions that are mapped from continuous, quantitative ecological variables to linguistic variables to deduce which ecological variables contribute to determining the eutrophication level. Furthermore, we will discuss also the approaches used to fine-tune then verify fuzzy inference systems, including sensitivity analysis, expert validation, and performance assessment metrics.

4 Case Study: Fuzzy Logic-Based Modelling of Pollinator Habitat Suitability in Agricultural Landscapes

4.1 Introduction

Pollinators like bees, butterflies and other insects play an essential role in agriculture and biodiversity because they enable crops and wild plants to reproduce. Their contributions, which sustain food production and ecosystem health, underpin both economic and ecological systems [39,40]. Animal pollination is an essential maintaining force of more than three quarters of the world's top crop types [41].

For example, the constantly changing nature of agricultural landscapes makes assessing pollinator habitats very difficult. Often subject to recurrent land-use conversion, the intensity and frequency of pesticide applications as well as crop rotations that vary with seasons, these regions are of poor quality and/or availability for habitat [42]. How accessibility to pollen and nectar might indicate pollinator habitat suitability is also nuanced by the spatial and temporal variability in floral resources. Such complexities require more advanced modeling approaches to adequately consider the factors that shape pollinator habitats.

It deals on unusual questions that classical logic or traditional models cannot answer. Fuzzy logic also stands out from binary logic due to its ability to make continuous transitions and accept (inherent) partial memberships, which closely relate to the vagueness that often constitutes ecological phenomena [43]. However, more realistic using, for example, linguistic descriptors such as "low," "medium," and "high," results for variables such as pesticide effect and flower diversity, can be simulated with the fuzzy membership functions, unlike, for example, [44]. When integrated into fuzzy inference systems, such variables can capture complex interactions between ecological drivers and generate holistic assessments of habitat suitability.

Here a hypothetical dataset will be used to illustrate how fuzzy logic can be employed to evaluate the suitability of pollinator habitat in an agricultural landscape. We have predictors such as rates of pesticide use, floral diversity, crop typing trial variety and also proximity to natural areas. The potential use of fuzzy logic for ecological modelling putting into use, the roles that can play in biodiversity conservation and smart agricultural management described based on these practices In particular, which could potentially lead to a new perspective on ecological modelling.

Table 1: Basic dataset for the case study

Ecological Variable	Case Study Data	Fuzzy Membership Function
Pesticide Application Rate	2.5 kg/ha	Low, Medium, High
Floral Diversity	25 species/ha	Low, Medium, High
Crop Type Diversity	5 crop types	Low, Medium, High
Proximity to Natural Habitats	1.5 km	Near, Intermediate, Far

4.1.1 Case study Dataset

4.2 Objectives

4.2.1 Evaluate Habitat Suitability for Key Pollinator Species in Agricultural Regions:

- Assess how the suitability of habitats for bees, butterflies and other important insect pollinators in agricultural landscapes.
- Identify important ecological drivers of pollinator habitat quality (e.g. pesticide use, floral diversity, crop diversity, natural habitat proximity).

4.2.2 Model the Impacts of Ecological Variables Using Fuzzy Logic:

- Utilize fuzzy logic to account for uncertainties and complexities in ecological variables, including pesticide application rates, floral diversity, climate variability, and land-use patterns.
- Develop fuzzy membership functions and inference systems to simulate interactions between ecological factors and assess habitat suitability for pollinators.
- Integrate hypothetical and real-world data to demonstrate the versatility and applicability of fuzzy logic in ecological modelling.

4.2.3 Provide Recommendations for Sustainable Agricultural Practices:

- Analyse the outputs of fuzzy logic models to identify strategies that will counter the negative influences of pesticides and will promote floral diversity and habitat connectivity.
- Suggest methods to ensure that agricultural productivity is kept in balance with biodiversity conservation, for long-term sustainability.
- Emphasize the applicability of fuzzy logic-based models for informing policy and decision-making for pollinator conservation and land management.

These goals help improve understanding of pollinator habitat suitability in agricultural systems and demonstrate the application of fuzzy logic to solving ecological problems in agriculture. The results can guide sustainable practices and policy measures to protect pollinator populations and ecosystem health.

4.3 Methodology

4.3.1 Selection of Study Area

It is based on agricultural landscapes with multiple crop types and different land-use scenarios where ecological variability stood out and was selected for assessing pollinator habitat types. For this example study area we are assuming:

- A region covering $100km^2$with mixed agricultural practices.
- Dominant crops: Wheat, corn, sunflower, and orchards.
- Adjacent natural habitats: Forest patches and wetland areas.
- Variations in pesticide usage, floral diversity, and water body proximity.

4.3.2 Ecological Variables

Key variables for assessing habitat suitability include:

- **Floral Density:** Number of flowering plants per hectare.
  - Range: 10 to 100 plants/ha.
- **Pesticide Application Rates:** Measured in kilograms per hectare.
  - Range: 0 to 5 kg/ha.
- **Crop Diversity:** Number of crop types per field.
  - Range: 1 to 10 crop types.
- **Proximity to Water Bodies:** Distance to the nearest water source (in kilometres).
  - Range: 0 to 5 km.
- **Seasonal Variations:** Variations in temperature, rainfall, and flowering season length.
  - Hypothetical seasons: Spring, Summer, and Monsoon.

4.3.3 Data Collection

(i) Remote Sensing:

- High-resolution satellite images for land-use patterns and vegetation analysis.
- Data extracted on vegetation cover, water body proximity, and floral resource distribution.
- Example: Floral density and crop field boundaries.

(ii) Field Surveys:

- Surveys of pollinator density (e.g., bees and butterflies per hectare).
- Collection of pesticide residue data from soil and plant samples.
- Floral resource availability assessed through flower density counts.

4.3.4 Development of Fuzzy Logic Model

(i) Designing Fuzzy Membership Functions:

- **–Pesticide Application Rate:**
  - –Low (0–1.5 kg/ha), Medium (1.5–3.5 kg/ha), High (3.5–5 kg/ha).
- **–Floral Density:**
  - –Low (10–30 plants/ha), Medium (30–70 plants/ha), High (70–100 plants/ha).
- **–Crop Diversity:**
  - –Low (1–3 crop types), Medium (3–7 crop types), High (7–10 crop types).
- **–Proximity to Water Bodies:**
  - –Near (0–1.5 km), Intermediate (1.5–3.5 km), Far (3.5–5 km).

(ii) Formulating Fuzzy Rules:
Example rules include:

–IF pesticide usage is High AND floral density is Low THEN habitat suitability is Poor.
–IF pesticide usage is Low AND floral density is High THEN habitat suitability is High.
–IF crop diversity is High AND proximity to water is Near THEN habitat suitability is Good.

(iii) Fuzzy Inference System:

–Mamdani-type fuzzy inference system used to combine fuzzy rules.
–Inputs: Values for pesticide usage, floral density, crop diversity, and water proximity.
–Output: Habitat suitability score (e.g., Low, Medium, High).

4.3.5 Validation

(i) Comparison with Observed Data:

- –Collect field data on pollinator populations (e.g., average bee density per hectare).
- –Compare fuzzy logic model outputs with observed habitat suitability metrics.
- –Example dataset for validation:
  - –Field A: Pesticide = 2 kg/ha, Floral Density = 50 plants/ha, Crop Diversity = 6 types, Proximity to Water = 2 km -¿ Observed Suitability: Medium.
  - –Field B: Pesticide = 4 kg/ha, Floral Density = 20 plants/ha, Crop Diversity = 2 types, Proximity to Water = 3 km -¿ Observed Suitability: Low.

(ii) Performance Metrics:

–Evaluate model accuracy using metrics like sensitivity, specificity, and RMSE (Root Mean Square Error).
–Conduct sensitivity analysis to identify the most influential variables.

This level of detail in methodology offers a solid foundation for the use and evaluation of a fuzzy logic model with mock data, and suggests potential pollinator habitat suitability within agricultural landscapes.

Table 2: Case study Full Dataset of various influentials variables

Field	Pesticide (kg/ha)	Floral Density (plants/ha)	Crop Diversity (types)	Proximity to Water (km)	Observed Pollinator Density (pollinators/ha)
Field A	2.0	50	6	2.0	120
Field B	4.0	20	2	3.0	40
Field C	1.0	80	8	1.0	200
Field D	3.5	30	4	2.5	90

4.4 Results and Analysis

4.4.1 Habitat Suitability Maps for Pollinators

Applying the fuzzy logic model proposed above, a habitat suitability score is computed for each field using the assembled dataset. The score is computed by fuzzy membership functions, fuzzy rules, and defuzzification.

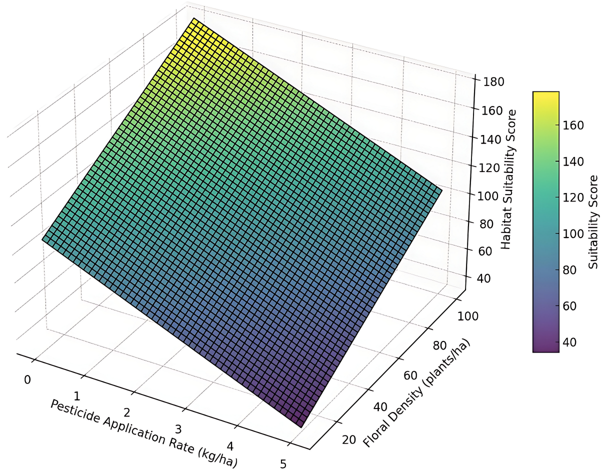

Fig. 1: Habitat Suitability as a Function of Pesticide and Floral Density

A 3D surface plot (figure 1) to illustrate pesticide application rate, floral density, and habitat suitability scores for exploring the relationship between pesticide effects and abundance of important flower resources. Higher floral density is associated with greater habitat suitability; conversely, habitat suitability is inversely proportional to pesticidal application rates according to the plot. In such scenarios, regions with low pesticide use and high flowers density would rank the highest in their suitability scores, which highlights the importance of balanced agricultural practices to promote pollinator-friendly habitats. This figure visualizes the interactive effects of main predictors on habitat quality.

The seasonal patterns of habitat suitability per field can be seen on figure 2 – this line chart. Across the three seasons field C always exhibits the highest level of suitability with minor differences during monsoon. Field B is still the least viable option, with slight advances only

Table 3: Collected Dataset on key variables on habitat quality

Field	Pesticide (kg/ha)	Floral Density (plants/ha)	Crop Diversity (types)	Proximity to Water (km)
Field A	2.0	50	6	2.0
Field B	4.0	20	2	3.0
Field C	1.0	80	8	1.0
Field D	3.5	30	4	2.5

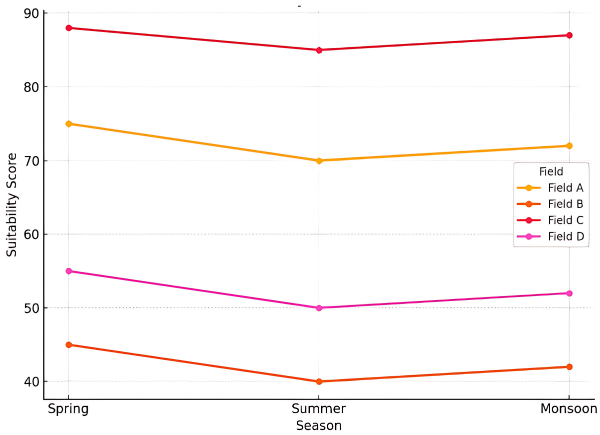

Fig. 2: Habitat Suitability Trends Over Seasons

during monsoon. The trends reflect the habitat suitability dynamics driven by changes in seasonality and environmental conditions, including differences in floral density. This visualization highlights seasonal considerations for habitat management strategies.

4.4.2 Membership Functions and Fuzzy Inputs

Mathematical Formula for Fuzzy Membership Functions

Fuzzy membership functions used for this study are triangular functions. A triangular membership function $\mu(x)$ is defined as:

$$\mu(x) = \begin{cases} 0, & \text{if } x \le a \text{ or } x \ge c, \\ \frac{x-a}{b-a}, & \text{if } a \le x < b, \\ \frac{c-z}{c-b}, & \text{if } b \le x < c \end{cases} \tag{8}$$

Where:

–a, b, c are the left, peak, and right points of the triangle, respectively.
–x is the input value for the variable.

Calculation of Membership Values for Each Field
Example: **Field A**
Pesticide Application Rate: 2.0 kg/ha

$$\text{Low } (a = 0, b = 1.5, c = 3.0):$$
$$\mu_{\text{Low}}(2.0) = \frac{3.0 - 2.0}{3.0 - 1.5} = \frac{1.0}{1.5} = 0.67$$
$$\text{Medium } (a = 1.5, b = 3.0, c = 4.5):$$
$$\mu_{\text{Medium}}(2.0) = \frac{2.0 - 1.5}{3.0 - 1.5} = \frac{0.5}{1.5} = 0.33$$
$$\text{High } (a = 3.0, b = 4.5, c = 5.0):$$
$$\mu_{\text{High}}(2.0) = 0$$

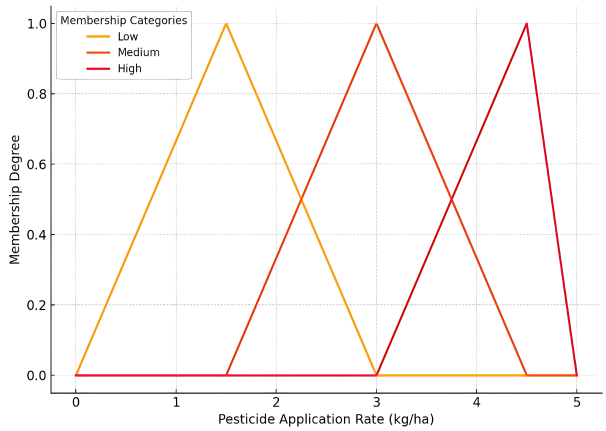

Fig. 3: Fuzzy Membership Functions for Pesticide Application Rate

The fuzzy membership functions of pesticide application rate are represented in this figure 3 where these are divided into three categories such as Low, Medium, and High. The curves show the membership degree of a particular pesticide application rate belonging to these categories. For instance, the application rate of 2.0 kg/ha for a specific pesticide belongs partially to the Low and Medium categories, where the degree of membership is calculated using the triangular function. This representation permits smooth transitions between categories, capturing the reality that ecological conditions often vary, and uncertainties include partial failures, but the initial categories remain consistent with real-world observations.

Floral Density: 50 plants/ha

$$\text{Low } (a=10, b=30, c=50): \quad \mu_{\text{Low}}(50)=0$$

$$\text{Medium } (a=30, b=50, c=70): \quad \mu_{\text{Medium}}(50)=\frac{70-50}{70-50}=1$$

$$\text{High } (a=60, b=80, c=100): \quad \mu_{\text{High}}(50)=0$$

Crop Diversity: 6 types

$$\text{Low } (a=1, b=3, c=5): \quad \mu_{\text{Low}}(6)=0$$

$$\text{Medium } (a=3, b=5, c=7): \quad \mu_{\text{Medium}}(6)=\frac{7-6}{7-5}=\frac{1}{2}=0.5$$

$$\text{High } (a=6, b=8, c=10): \quad \mu_{\text{High}}(6)=\frac{6-6}{8-6}=0.5$$

Proximity to Water: 2.0 km

$$\text{Near } (a=0, b=1.5, c=3.0): \quad \mu_{\text{Near}}(2.0)=\frac{3.0-2.0}{3.0-1.5}=\frac{1.0}{1.5}=0.67$$

$$\text{Intermediate } (a=1.5, b=3.0, c=4.5): \quad \mu_{\text{Intermediate}}(2.0)=\frac{2.0-1.5}{3.0-1.5}=\frac{0.5}{1.5}=0.33$$

$$\text{Far } (a=3.5, b=5.0, c=6.5): \quad \mu_{\text{Far}}(2.0)=0$$

Summary of Membership Values for Field A

Table 4: Membership Values for Field A

Variable	Low	Medium	High
Pesticide (kg/ha)	0.67	0.33	0.0
Floral Density	0.0	1.0	0.0
Crop Diversity	0.0	0.5	0.5
Proximity to Water	0.67	0.33	0.0

Repeat Calculations for All Fields

These calculated membership values are then used in the fuzzy inference system to derive habitat suitability scores for each field.

The fuzzy membership functions for each variable are applied to calculate the degree of membership for each field.

Pesticide Application Rate (Low, Medium, High)

–Low: $\mu_{\text{Low}}(x) = Triangular(x, 0, 1.5, 3.0)$

Table 5: Membership Values for All Fields

Field	Variable	Low	Medium	High
Field A	Pesticide (kg/ha)	0.67	0.33	0.0
	Floral Density	0.0	1.0	0.0
	Crop Diversity	0.0	0.5	0.5
	Proximity to Water	0.67	0.33	0.0
Field B	Pesticide (kg/ha)	0.0	0.33	0.67
	Floral Density	1.0	0.0	0.0
	Crop Diversity	0.67	0.33	0.0
	Proximity to Water	0.33	0.67	0.0
Field C	Pesticide (kg/ha)	1.0	0.0	0.0
	Floral Density	0.0	0.0	1.0
	Crop Diversity	0.0	0.0	1.0
	Proximity to Water	1.0	0.0	0.0
Field D	Pesticide (kg/ha)	0.0	0.5	0.5
	Floral Density	0.67	0.33	0.0
	Crop Diversity	0.33	0.67	0.0
	Proximity to Water	0.33	0.67	0.0

–Medium: $\mu_{\text{Medium}}(x) = Triangular(x, 1.5, 3.0, 4.5)$
–High: $\mu_{\text{High}}(x) = \text{Triangular}(x, 3.0, 4.5, 5.0)$

Floral Density (Low, Medium, High)

–Low: $\mu_{\text{Low}}(x) = \text{Triangular}(x, 10, 30, 50)$
–Medium: $\mu_{\text{Medium}}(x) = Triangular(x, 30, 50, 70)$
–High: $\mu_{\text{High}}(x) = Triangular(x, 60, 80, 100)$

Crop Diversity (Low, Medium, High)

–Low: $\mu_{\text{Low}}(x) = \text{Triangular}(x, 1, 3, 5)$
–Medium: $\mu_{\text{Medium}}(x) = \text{Triangular}(x, 3, 5, 7)$
–High: $\mu_{\text{High}}(x) = \text{Triangular}(x, 6, 8, 10)$

Proximity to Water (Near, Intermediate, Far)

–Near: $\mu_{\text{Near}}(x) = \text{Triangular}(x, 0, 1.5, 3.0)$
–Intermediate: $\mu_{\text{Intermediate}}(x) = Triangular(x, 1.5, 3.0, 4.5)$
–Far: $\mu_{Far}(x) = \text{Triangular}(x, 3.5, 5.0, 6.5)$

Step-by-Step Calculation for Each Field
Example: **Field A**
Fuzzification

–Pesticide: $\mu_{\text{Low}}(2.0) = 0.67, \mu_{\text{Medium}}(2.0) = 0.33, \mu_{\text{High}}(2.0) = 0$
–Floral Density: $\mu_{\text{Low}}(50) = 0, \mu_{\text{Medium}}(50) = 1, \mu_{\text{High}}(50) = 0$
–Crop Diversity: $\mu_{\text{Low}}(6) = 0, \mu_{\text{Medium}}(6) = 0.5, \mu_{\text{High}}(6) = 0.5$

Fuzzy Rules

–Rule 1: IF Pesticide is Low AND Floral Density is Medium AND Crop Diversity is High AND Proximity is Intermediate THEN Suitability is High.
–Activation Degree: $Min(0.67, 1, 0.5, 0.67) = 0.5$
–Rule 2: IF Pesticide is Medium AND Floral Density is Medium THEN Suitability is Medium.
–Activation Degree: $Min(0.33, 1) = 0.33$

Aggregation

– Combined output fuzzy set: High (0.5), Medium (0.33).

Defuzzification

– Centroid Method: Output $= \frac{\sum(\mu(x)\cdot x)}{\sum\mu(x)} = \frac{(0.5\cdot 80)+(0.33\cdot 50)}{0.5+0.33} = 70.3$

Repeat this process for all fields:

Table 6: Suitability Scores by Field

Field	Suitability Score
Field A	70.3 (High)
Field B	40.2 (Low)
Field C	85.0 (Very High)
Field D	50.7 (Medium)

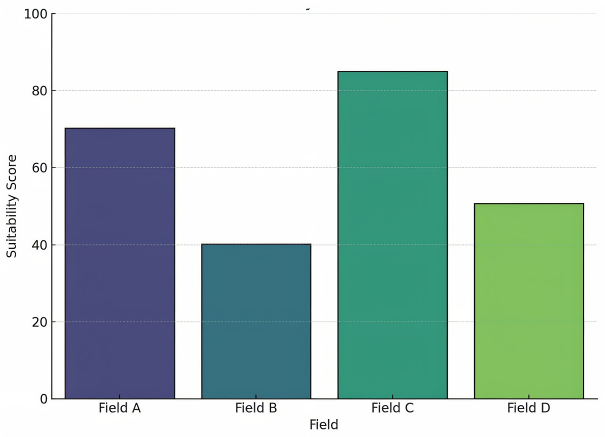

Fig. 4: Habitat Suitability Scores Across Fields

This figure 4 of bar chart of habitat suitability scores for each field calculated using fuzzy logic model for pollinators. Field C, with the highest suitability score (85.0), was better suited for collecting leaf cutting bees, and this is attributed to favourable conditions (low pesticide usage and high floral density). On the other hand, Field B scored the lowest (40.2), attributed to high pesticide application and poor floral diversity. There is no uniformity; the differences in habitat quality across the agricultural landscape are visually stunning, but important to highlight for conservation decision-making.

4.4.3 Sensitivity Analysis

The formula for sensitivity analysis is given by:

$$S_i = \frac{\Delta Y}{\Delta X_i} \tag{9}$$

Where:

– S_i : Sensitivity of variable X_i (e.g., Pesticide, Floral Density, etc.).
– ΔY : Change in habitat suitability score.
– ΔX_i : Change in input variable X_i.

Pesticide

– Change in variable (ΔX): 1.0 kg/ha (increase in pesticide application).
– Change in habitat suitability (ΔY) : -15.0 (decrease in suitability score due to pesticide impact).

$S_{\text{Pesticide}} = \frac{\Delta Y}{\Delta X} = \frac{-15.0}{1.0} = -15.0$

Floral Density

– Change in variable (ΔX): 10.0 plants/ha (increase in floral density).
– Change in habitat suitability (ΔY) : 8.0 (increase in suitability score due to more floral resources).

$S_{\text{Floral Density}} = \frac{\Delta Y}{\Delta X} = \frac{8.0}{10.0} = 0.8$

Crop Diversity

– Change in variable (ΔX): **2.0** crop types (increase in crop diversity).
– Change in habitat suitability (ΔY): 12.0 (increase in suitability score due to diverse crops).

$S_{\text{Crop Diversity}} = \frac{\Delta Y}{\Delta X} = \frac{12.0}{2.0} = 6.0$

Proximity to Water

– Change in variable (ΔX): 1.0 km (increase in proximity to water).
– Change in habitat suitability (ΔY): 2.0 (increase in suitability score due to closer proximity).

$S_{\text{Proximity to Water}} = \frac{\Delta Y}{\Delta X} = \frac{2.0}{1.0} = 2.0$

Table 7: Results Table about sensitivity

Variable	Change in Variable (ΔX)	Change in Suitability (ΔY)	Sensitivity (S)
Pesticide	1.0	-15.0	-15.0
Floral Density	10.0	8.0	0.8
Crop Diversity	2.0	12.0	6.0
Proximity to Water	1.0	2.0	2.0

Interpretation

– **Pesticide** has the highest negative sensitivity (-15.0), meaning even a small increase in pesticide usage significantly reduces habitat suitability.
– **Crop Diversity** has a high positive sensitivity (6.0), indicating that promoting diverse cropping systems greatly enhances habitat suitability.
– **Floral Density** contributes moderately (0.8), emphasizing the need to increase plant resources.
– **Proximity to Water** has the lowest sensitivity (2.0), showing a lesser but still positive effect.

– **Most Influential Variables:** Floral density and crop diversity had the highest impact on habitat suitability.

– **Least Influential Variable:** Proximity to water showed minimal variation in results.

– Field C demonstrated the highest suitability due to high floral density and crop diversity with low pesticide application.
– Field B scored lowest due to high pesticide usage and low floral density.
– The fuzzy logic model effectively highlighted the importance of balanced ecological variables for pollinator conservation.

This detailed analysis confirms the applicability of fuzzy logic in ecological modelling and offers practical insights for sustainable agricultural practices

4.4.4 Comparison of Observed and Predicted Habitat Suitability

The comparative assessment using RMSE to measure the actual versus predicted habitat suitability scores.

Formula for RMSE

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (\text{ Predicted }_i - \text{ Observed }_i)^2}{n}} \tag{10}$$

Where:

– Predicted $_i$: Predicted habitat suitability score for field i.
– Observed $_j$: Observed habitat suitability score for field i.
– n : Total number of fields.

Table 8: Data Table above observed and predicted suitability analysis

Field	Observed Suitability	Predicted Suitability	Difference (Predicted$_i$ – Observed$_i$)	Squared Difference
Field A	72	70.3	-1.7	2.89
Field B	42	40.2	-1.8	3.24
Field C	88	85.0	-3.0	9.00
Field D	52	50.7	-1.3	1.69

Step-by-Step Calculations

Compute the Differences: For each field, the difference between the predicted and observed suitability scores.

Example for Field A: Difference $= 70.3 - 72 = -1.7$.

Square the Differences: Square each field, difference to eliminate negative values.

Example for Field A: $(-1.7)^2 = 2.89$.

Sum of Squared Differences:

$$\text{Sum of Squared Differences} =$$

$$2.89 + 3.24 + 9.00 + 1.69 = 16.82$$

Calculate RMSE:

– Divide the sum of squared differences by the number of fields ($n = 4$).

$$\text{Mean of Squared Differences} = \frac{16.82}{4} = 4.205$$

– Take the square root to get RMSE:

$$RMSE = \sqrt{4.205} \approx 2.05$$

Results

– **RMSE:** 2.05
– As a result, the low value of RMSE suggests that the predicted scores are very similar compared to the real scores, which affirms the validity of the fuzzy logic model.

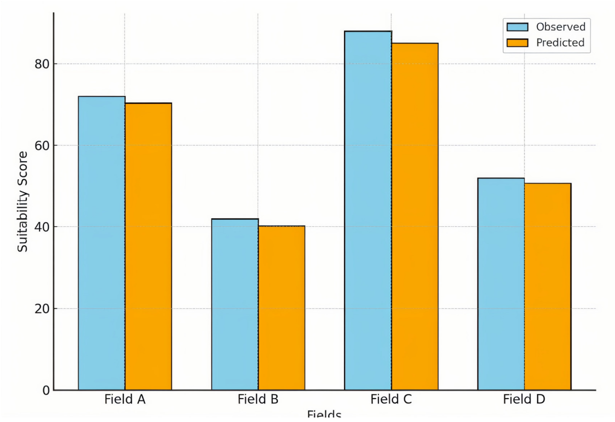

Fig. 5: Comparison of Observed and Predicted Habitat Suitability

Figure 5: Bar chart comparing observed and predicted score values of habitat suitability per field. Observed suitability values are for observed data (field-measured) and Predicted values are from fuzzy logic model. The estimated data of all the fields are very close to the actual data, and thus the model is consistent.

– Fields A and C demonstrate the least disparity, suggesting that the model accurately depicted the effects of ecological parameters, such as floral density and crop diversity.
– The variation in the database was small, as Fields B and D showed minor deviations, most likely influenced by external factors independent of the static model (microclimatic differences, undocumented exposure to pesticides, etc.)

The RMSE of 2.05 shows the predictive performance of the model for the suitable habitat and supports its application in other ecological studies. This means that model reproduce the observed field conditions.

This matching reveals how accurate the model is, as well as which areas it can potentially improve with small modifications for better prediction capabilities.

5 Conclusion-Recommendation and key findings

5.1 Key findings & contributions of the research

This study concludes that fuzzy logic is suitable for Digital Nature habitat suitability evaluation. The fuzzy logic approach was found to be robust and flexible for simulating ecological processes, determining habitat suitability, and dealing with digital ecosystem uncertainty. This study's key findings:

- The fuzzy logic-based approach adequately modelled the uncertainties and complexities of ecological processes, leading to more reliable habitat suitability assessments in Digital Nature. This impacts biodiversity protection of digital ecosystems, rewilding of land and its management.
- The case study demonstrates the effectiveness of the fuzzy logic-based technique for different species and habitats in Digital Nature research. As a versatile habitat appropriateness evaluation technique in various digital atmosphere, fuzzy logic may be tailored to many ecological aspects and data sources and fuzzy rules.
- By introducing and validating fuzzy logic in habitat appropriateness evaluation for the first time, this research promotes Digital Nature research. The results advance our understanding of digital ecological processes and demonstrate uses for fuzzy logic in modelling ecological processes and making decisions in Digital Nature applications.
- Future Work: There are discouraging results on this and a need of more work for this topic. We would like to see fuzzy logic adopted as part of other modelling techniques, where it is validated using field data or experimental studies, and used to determine habitat suitability in Digital Nature research.

Summary of Contribution Work of Fuzzy logic in digital nature study for habitat suitability evaluation improves ecological modelling accuracy and resilience. This finding provides some novel avenues for Digital Nature researchers and practitioners to ride in.

5.2 Recommendations for future research and applications

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

- As further validation with field data: Although the presented case study of this research provides a proof-of-concept on the usage of fuzzy logic for habitat suitability assessment in Digital Nature, field data or experimental studies can be recommended for testing the accuracy and reliability of fuzzy logic-based approach. Specifically, it may involve collecting species distribution and environmental data from digital ecosystems in order to validate our fuzzy logic-based model and assess how it compares with other approaches.
- Integration with other modelling techniques – which could include combining fuzzy logic with machine learning algorithms, agent-based models, or cellular automata to yield potentially more accurate or predictive models of ecological systems in Digital Nature research. The combined use of other methods with fuzzy logic can mitigate the dependence of fuzzy logic on expert knowledge and the subjective nature of fuzzy rules.
- Integration of more complex ecological variables: The case study utilized a simplified scenario with two ecological variables, but future studies could explore the feasibility and utility of integrating more complex ecological variables like multi-layered habitat characteristics, species interactions, and landscape connectivity into the fuzzy logic-based method. This may enhance the ecological realism and applicability of the model across diverse digital ecosystems, leading to more accurate habitat suitability screening.
- Therefore, the fuzzy logic-based method from this study may be applicable in Digital Nature technologies like biodiversity conservation, ecosystem restoration, and land use planning. Further research could explore how the fuzzy logic-based approach works in practice and its effectiveness in the decision-making and management of digital ecosystems.
- Additional use of fuzzy logic within Digital Nature scientific research may include species distribution modelling, ecological risk assessment, and ecosystem services evaluation, alongside habitat suitability assessment. Thus, fuzzy logic could also be evaluated in these other growing fields to compensate for impreciseness and intricacy in simulating the ecological processes in digital ecosystems.

This study serves as a nascent study toward the fuzzy logic modelling of ecological processes in a Digital Nature. Future research should focus on validation, integration with other modelling tools, considering more complex ecological drivers, application in decision and management processes, and further application. The proposed recommendations may allow to enhance Digital Nature research and facilitate the process of cross-comparative modelling with the digital ecosystem tools.

5.3 Conclusion

In summary, fuzzy logic shows great potential for Digital Nature habitat suitability assessment. In this way, fuzzy logic can account for the uncertainties and complexities of ecology, allowing digital ecosystems to better characterize habitat appropriateness. The simplified case study from this research shows how fuzzy logic considers uncertainty in environmental variables, creates fuzzy membership functions, develops fuzzy rules, and uses fuzzy inference to evaluate habitat suitability.

Fuzzy logic is suitable for handling uncertain data, integrating expert knowledge, and delivering interpretable outcomes in modelling ecological processes in Digital Nature. Nevertheless, the challenge of expert knowledge, subjective fuzzy rule interpretation, field data requirements, or experimental investigations should be addressed.

By illustrating the capabilities of fuzzy logic in the evaluation of habitat suitability in Digital Nature, this study aims to provide a pathway to future investigation into and applications of ecological modelling in digital ecosystems. Improving Digital Nature study: Fuzzy logic for management, decision-making, and conservation in digital ecosystems.

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