Latin American Journal of Aquatic Research, 54(4): xxx-xxx, 2026
DOI: 10.3856/vol54-issue4-fulltext-3623

Research Article

A fuzzy logic approach for preliminary biological suitability assessment for aquaculture of two spiny lobster species

Evlin A. Ramírez-Félix[1], **Miguel Á. Cisneros-Mata**[2]
Enrique Villa-DiHarce[3] **& Juan Antonio García-Borbón**[4]
[1]Instituto Mexicano de Investigación en Pesca y Acuacultura Sustentables, Mazatlán, Sin., México
[2]Instituto Mexicano de Investigación en Pesca y Acuacultura Sustentables, Guaymas, Son., México
[3]Centro de Investigación en Matemáticas, Guanajuato, Gto., México
[4]Instituto Mexicano de Investigación en Pesca y Acuacultura Sustentables
La Paz, Baja California Sur, México
Corresponding author: Juan Antonio García-Borbón (antonio.borbon@imipas.gob.mx)

ABSTRACT. Selecting suitable species is a critical and complex decision in aquaculture development, requiring the integration of uncertain biological and economic variables. This study demonstrates the application of a Mamdani-type fuzzy inference system as a generalizable decision-support tool, using the farming suitability of two lobster species (*Panulirus inflatus* and *P. gracilis*) as a case study. The parameters considered were the growth performance index (phi prime), the abdominal-to-total weight ratio, the natural mortality rate (M), and mean fecundity. Gaussian membership functions were used for inputs and triangular for outputs, with 15 fuzzy rules. A Monte Carlo simulation estimated 95% uncertainty intervals. Based on the selected biological criteria, membership functions, and fuzzy rule base, *P. gracilis* obtained a higher preliminary suitability score than *P. inflatus*. The model proved robust to uncertainty, supporting its use as a flexible, adaptable framework for species selection in diverse aquaculture contexts under data-limited conditions. However, further validation under farming conditions is required before making definitive recommendations for aquaculture.

Keywords: farming suitability; fuzzy logic; aquaculture decision-making; lobster farming

INTRODUCTION

Traditional binary models (suitable/not suitable) often fail to capture the continuous and interrelated nature of biological and economic parameters in aquaculture. Fuzzy logic, introduced by Zadeh (1965), provides a mathematical framework for handling such imprecision and gradation, enabling nuanced decision-making under uncertainty. While fuzzy logic has been applied in aquaculture for environmental monitoring and control systems (Nagothu et al. 2025), this study fills that gap by presenting a fuzzy inference system designed to evaluate species viability, using two spiny lobster species as a case study, but with a framework readily transferable to other aquatic species.

Global production of aquatic resources has continued to grow, reaching a new high of 235 million tons in 2024, including both aquatic animals and algae, with aquaculture driving the growth. World aquaculture production reached a new record in 2024 at 142 million tons, with an estimated first-sale value of US$391 billion (FAO 2026). Sustainable aquaculture is essential to meet the growing demand for aquatic foods (FAO 2022). Notably, lobsters, along with shrimp, cod, and crabs, are the most imported aquatic products in China, accounting for 51% of the total value of its aquatic animal product imports in 2022. The primary target species for lobster fishing in the Mexican Pacific are the red spiny lobster (*Panulirus interruptus*), the green spiny lobster (*P. gracilis*), and the blue spiny

Associate Editor: Fernando Vega-Villasante

lobster (*P. inflatus*) (Sharma et al. 2025). Most of the catch is sourced from small-scale fisheries. The red lobster was excluded from this analysis to promote a potential increase in the production of less abundant lobsters (green and blue) in the Mexican Pacific, particularly in areas where this expansion would have social and economic benefits.

In Mexico, the spiny lobster market experienced strong growth due to high demand in cities such as Mexico City, Guadalajara, and Monterrey. Wild catches of spiny lobster (*Panulirus* spp.) in Mexico in 2022/2023 totaled just over 3,000 t, of which 2,204 t were exported, generating US$114 million in revenue and representing an essential source of income for small-scale coastal fishing communities. Given the increasing global demand for lobster, better management of fish stocks and growth in aquaculture production are necessary (Azra et al. 2022). Although lobster is a globally prized delicacy, its aquaculture is in its early stages. Given its high market value, significant efforts are underway to optimize live lobster production (FAO 2017).

Aquaculture is essential to meet the global demand for seafood; selecting suitable species involves evaluating complex biological factors, such as growth rates, mortality, and fecundity, which are often uncertain (FAO 2022). There are various criteria for evaluating an aquaculture project or program, such as infrastructure costs, farming costs at a particular size or weight, and payback time, among others. This paper aims to illustrate a process for evaluating biological selection criteria for suitability, particularly for the culture of two spiny lobster species, including growth rate, the abdominal/total weight ratio, natural mortality (M), and fecundity.

An important factor in deciding whether to cultivate a given lobster species is its feasibility, assessed based on biological traits and market demand. Decision matrices and statistical models are often used (Xu et al. 2009, Devi et al. 2020), but traditional approaches struggle with uncertainty and vague criteria. This study applies fuzzy logic to evaluate species viability under uncertain, incomplete, or contradictory data, enabling more rational decision-making in aquaculture.

Fuzzy logic has been effectively employed in aquaculture decision-making, including in adaptive systems that manage uncertain environmental and biological variables to support species viability and optimize production (Nagothu et al. 2025). This approach enables nuanced evaluations beyond binary thresholds, as demonstrated by fuzzy-based frameworks that integrate real-time data to support precise control and informed decision-making. The present study applies this methodology to biological suitability criteria.

To be considered feasible for aquaculture, a species must meet fundamental biological and technological requirements. These systems allow for the integration of both uncertainty and expert knowledge into decision-making processes. The study develops a Mamdani-type fuzzy inference system (FIS) to assess the suitability of *P. inflatus* and *P. gracilis*. The model integrates four input variables: 1) phi prime (growth performance index, ϕ'), used as a criterion for comparing interannual growth (Pauly & Munro 1984); 2) abdominal/total weight ratio, having to do with the edible portion of the species; 3) annual rate of M; and 4) mean fecundity.

Objective

Present a preliminary assessment of the suitability for farming purposes of *P. inflatus* and *P. gracilis* through a fuzzy inference system, based on available biological variables information. Suitability scores and their corresponding 95% uncertainty intervals are calculated, and membership functions are envisaged to support species selection for aquaculture.

MATERIALS AND METHODS

Software and hardware

The analysis was carried out in R 4.3.x using the FuzzyR package (Chen et al. 2020). Rtools 4.3 was used to compile the packages.

Fuzzy inference system (FIS)

A Mamdani-type FIS was designed (Pop et al. 2023) to calculate crisp (non-fuzzified) values of the response variable (farming feasibility) through defuzzification (Yager & Filev 1993) using the centroid method. Although the analysis is based on selected biological traits, it does not represent a complete aquaculture feasibility assessment. Other relevant factors include larval survival, seed availability, feed acceptance, disease resistance, tolerance to stocking density, production costs, market value, environmental impact, and regulatory constraints. The input parameter values included in this work (Table 1) and their rationale are defined as follows: growth performance index (phi prime). This index was proposed by Pauly & Munro (1984), who noted that the covariation between the instantaneous growth coefficient (*k*) and the asymptotic length (L_∞), ϕ'could be derived. The index is used to compare interannual growth of fish and invertebrates when their growth follows the von Bertalanffy model

Table 1. Input and output variables used in the fuzzy inference system.

Type	Variable	Range	Description
Input	Phi prime	[1.5, 3.7]	Growth performance
Input	Abdominal/total weight	[40, 60]	Percentage of abdominal biomass
Input	Mortality rate (M)	[0.08, 1.2]	Annual mortality rate
Input	Fecundity	[0, 1'500,000]	Number of eggs per female
Output	Suitability	[0, 100]	Percent suitability for cultivation

($\phi' = \log k + 2 \log L_\infty$), where *k* is the von Bertalanffy growth constant, and L_∞ is the species' asymptotic length. Is an index for comparing the growth performance of fish, measuring how efficiently food is converted into body biomass.

The abdominal-to-total weight ratio typically shows isometry, with limited phenotypic variability. When measured at the same ontogenetic stage (i.e. the adult stage), this ratio provides a value associated with economic and commercial yield (Émond et al. 2010).

M rate is a critical parameter in population dynamics models and stock assessments (Hoenig et al. 2025). It is not static and is likely to vary over time due to ecological and habitat conditions (Cao & Chen 2022). After reaching maturity, the mortality rate tends to stabilize, although it may increase again in older individuals due to senescence or increased vulnerability (Caddy 1996). For this study, a single representative value of M was considered. The rationale for using the M rate as an input variable in this study is as follows. M has been considered to reflect intrinsic or extrinsic factors (McCoy & Gillooly 2008). Intrinsic factors are life span, metabolic rate, and its two primary determinants: body size and temperature. Extrinsic factors, such as disease, predation, or accidents, can occur before a species reaches its maximum life span. The general agreement of the data with our model predictions is consistent with the hypothesis that mortality is under intrinsic control.

Fecundity refers to the number of offspring per brood, per breeding season, or across a female's lifetime (Pincheira-Donoso & Hunt 2015). In this study, fecundity data are drawn from sources that report the average number of offspring per brood in ovigerous females. Fecundity correlates with female body length or total weight (Goldstein et al. 2025).

Fuzzy membership functions

Input variables employed Gaussian membership functions (with mean and standard deviation σ), selected for their effectiveness in modeling smooth transitions within continuous biological parameters (Ross 2010). Parameter values for the input membership functions were sourced from published literature on the two lobster species. The standard deviations, however, were not derived from empirical distributions but were assigned heuristically (i.e. via an *ad-hoc* process). This approach is standard practice in fuzzy logic modeling when the goal is to create a transparent and interpretable system, and it is explicitly documented in standard references on the topic (Ross 2017). Arabshahi et al. (1993) recommend that, when empirical data on dispersion are unavailable, initial parameter selection should rely on designer judgment or heuristics before any adaptive tuning occurs. For the output variable (suitability), triangular membership functions were utilized due to their simplicity and ease of interpretation when representing fitness categories. The parameter values used in each of the three components of the membership functions are:

Phi prime: low ($\sigma = 0.15$, $\mu = 1.75$), medium ($\sigma = 0.20$, $\mu = 2.3$), high ($\sigma = 0.25$, $\mu = 3.15$).

Abdominal/total weight ratio: low ($\sigma = 1.0$, $\mu = 41.5$), medium ($\sigma = 2.0$, $\mu = 46.0$), high ($\sigma = 2.5$, $\mu = 54.5$).

M: low ($\sigma = 0.01$, $\mu = 0.095$), medium ($\sigma = 0.03$, $\mu = 0.18$), high ($\sigma = 0.20$, $\mu = 0.50$).

Fecundity: low ($\sigma = 30{,}000$, $\mu = 100{,}000$), medium ($\sigma = 80{,}000$, $\mu = 350{,}000$), high ($\sigma = 200{,}000$, $\mu = 900{,}000$).

Suitability: low (0, 20, 40), medium (30, 50, 70), high (60, 80, 100).

Gaussian membership functions were selected to represent continuous biological distributions because they can model gradual transitions. Triangular membership functions represent the output variable to facilitate the interpretation of discrete suitability categories (low, medium, and high) (Kosheleva et al. 2019).

Fuzzy rules

Fifteen fuzzy rules were established using the AND operator and unit weights. These rules were designed to capture logical biological relationships, with a focus on selecting combinations of reduced mortality, high fertility, and high growth performance index and abdominal/total weight. The rules are:

1) If the ϕ' and the abdominal/total weight ratio is high, M is low, and fecundity is high, then suitability is high. Justification: optimal biological conditions maximize cultivation suitability.

2) If the ϕ', the abdominal/total weight ratio, M and fecundity are medium, then suitability is medium. Justification: intermediate conditions produce moderate suitability.

3) If the ϕ', and the abdominal/total weight ratio is low, M is high, and fecundity is low, then suitability is low. Justification: unfavorable conditions make cultivation unadvisable.

4) If the ϕ', and the abdominal/total weight ratio is medium, M is low, and fecundity is high, then suitability is high. Justification: low mortality and high fecundity compensate for moderate growth performance.

5) If the ϕ', and the abdominal/total weight ratio is low, M is high, and fecundity is medium, then suitability is low. Justification: high mortality rates dominate, limiting cultivation options.

6) If the ϕ', and the abdominal/total weight ratio is high, M and fecundity is medium, then suitability is medium. Justification: high mortality reduces suitability.

7) If the $\phi'$is low, and the abdominal/total weight ratio is medium, M is high, and fecundity is low, then suitability is low. Justification: high mortality and low fecundity are limiting factors.

8) If the ϕ' is medium and the abdominal/total weight is high, M is low, and fecundity is medium, then suitability is high. Justification: low mortality and a high abdominal/total weight proportion favor cultivation.

9) If the ϕ' is low and the abdominal/total weight ratio is high, M is high, and fecundity is medium, then suitability is low. Justification: high mortality is a penalizing factor.

10) If the ϕ' is low, and the abdominal/total weight ratio is high, M is medium, and fecundity is medium, then suitability is medium. Justification: medium mortality produces moderate suitability.

11) If the ϕ' is low, and the abdominal/total weight ratio is high, M is medium, and fecundity is high, then suitability is high. Justification: high fecundity compensates for medium mortality.

12) If the ϕ' is medium and the abdominal/total weight is high, and M is medium, and fecundity is high, then suitability is high. Justification: high fecundity and abdominal/total weight proportion favor cultivation.

13) If the ϕ' is low, and the abdominal/total weight ratio is medium, M is medium, and fecundity is medium, then suitability is medium. Justification: intermediate conditions justify moderate suitability.

14) If the $\phi'$is medium, and the abdominal/total weight ratio is high, M is high, and fecundity is medium, then suitability is medium. Justification: high mortality is mitigated by abdominal/total weight ratio and fecundity.

15) If the ϕ' is medium, and the abdominal/total weight proportion is high, M is medium, and fecundity is medium, then suitability is medium. Justification: balanced conditions produce moderate suitability.

Overall justification: the rules cover key combinations, balancing the influence of the M rate (limiting factor) and fecundity, and the abdominal/total weight proportion (productivity), with ϕ'as a modifier.

Input data

P. inflatus: ϕ',= 2. Average of Juárez-Carrillo et al. (2006), Ramos-Santiago et al. (2020), Ramírez-Félix et al. (2024). Abdominal/total weight rate = 55%, M = 0.7 (Castro-Gutiérrez 2014, Ramírez-Félix et al. 2023). Fecundity = 410,000 (Gracia 1985).

P. gracilis: ϕ',= 1.8. Average of Cabrera-Mancilla & Gutiérrez-Zavala (2010), Ramos-Santiago et al. (2020), and Ramírez-Félix et al. (2023). Abdominal/total weight rate = 58%, M = 0.25 (Castro-Gutiérrez 2014). Fecundity = 568,000 (Pérez-González 2008).

In summary, during fuzzy logic, each input variable was assigned to a Gaussian membership function. In contrast, the output variable used a triangular membership function to define three fuzzy sets: low, medium, and high. Fuzzy rules were then designed and activated using the AND (minimum) operator to combine the outputs to yield a suitability value. By fuzzifying the input values with the Gaussian function, the degree of membership (low, medium, or high) was calculated for each input variable for both lobster species. Inference was implemented by activating the corresponding fuzzy rules. Defuzzification was then performed using the centroid method to compute the aggregated output, yielding an estimated suitability score (Fig. 1).

Uncertainty intervals for suitability

A Monte Carlo simulation was conducted with 10,000 iterations, using the mean and standard deviation of the Gaussian distributions for the input parameters. Simulated values were constrained within valid ranges (e.g. phi prime [1.5, 3.7]). The resulting intervals (e.g. *P. inflatus*: [26.5, 44.8]%; *P. gracilis*: [45.3, 68.3]%)

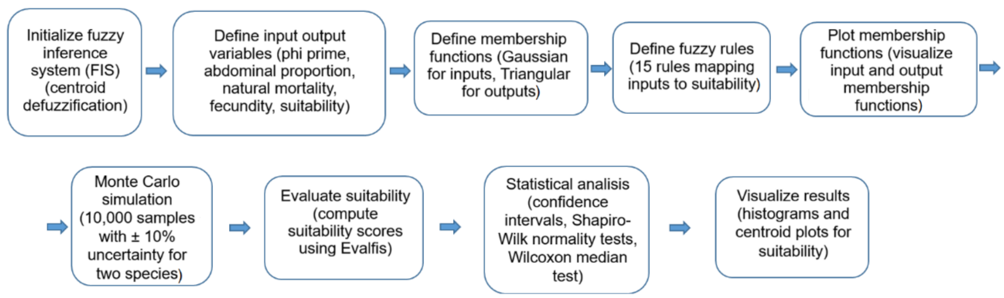

Figure 1. Fuzzy logic diagram for lobster species selection in aquaculture using Mamdani architecture.

should not be interpreted as conventional statistical confidence intervals in the frequentist sense (i.e. they do not represent a range that contains the true mean suitability with 95% probability in repeated sampling from a biological population). Rather, they are uncertainty intervals that reflect the propagation of the fuzziness inherent in the membership function definitions under the assumption that each input variable is normally distributed around its reported mean with a spread equal to the membership function's σ. This interpretation aligns with common practice in fuzzy-logic modeling when combined with Monte Carlo methods: the intervals quantify the sensitivity of the output to gradual transitions encoded by the Gaussian membership functions, not sampling error. For a true frequentist confidence interval, empirical standard deviations derived from repeated biological measurements would be required. The present intervals are therefore best described as fuzzy-propagated uncertainty ranges or membership-derived intervals rather than classical confidence intervals. Suitability was computed using the evalfis function, and 95% confidence intervals were derived from the 2.5 and 97.5% percentiles of the 10,000 random suitability values obtained for each lobster species.

Membership function visualization

The membership functions were visualized using FuzzyR's plotmf function, arranged in a 2×3 grid. Each plot illustrates the membership levels (low, medium, and high) against the corresponding variable values, with clearly labeled axes and categories.

Statistical analysis

Means, standard deviations, and ranges were computed for both the simulated input variables and the resulting suitability scores. Histograms of the suitability distributions were generated to assess variability and distribution characteristics.

To compare the farming suitability of the two lobster species based on the 10,000 simulated suitability values generated by the Monte Carlo procedure, a non-parametric statistical approach was employed. The Wilcoxon rank-sum test (also known as the Mann-Whitney U test) was selected for the following reasons: 1) normality assessment: Shapiro-Wilk tests performed on both simulated suitability distributions indicated significant deviations from normality (*P. inflatus*: W = 0.982, $P < 0.001$; *P. gracilis*: W = 0.976, $P < 0.001$), violating the normality assumption required for parametric tests such as the *t*-test, 2) ordinal interpretation: suitability scores, while numeric, are derived from a fuzzy inference system that produces values on an arbitrary 0-100 scale. The Wilcoxon test compares the relative ranking (median) of the two distributions rather than assuming equal intervals or specific distributional forms, and 3) robustness to outliers: the test is less sensitive to extreme values than parametric alternatives, which is advantageous given the bounded nature of suitability scores (0-100) and the presence of potential boundary effects.

The resulting *P*-value from the Wilcoxon test indicates the probability of observing the observed difference in median suitability between the two species (or a more extreme difference) if the null hypothesis -that the two distributions are identical- were true. A small *P*-value (here, $P < 2.2\times10^{-16}$) provides strong evidence against the null hypothesis, supporting the conclusion that the suitability distributions differ systematically between species. Crucially, the *P*-value should not be interpreted as the probability that one species is "better" than the other; rather, it provides evidence against the null hypothesis of equal distributions.

RESULTS

The model evaluated crisp suitability, generating average simulation results and 95% uncertainty intervals. The results are as follows:

P. inflatus. Mean suitability: 35.4%; 95% uncertainty interval: [26.5-44.8]%.

P. gracilis. Mean suitability: 54.3%; 95% uncertainty interval: [45.3-68.3]%.

P. gracilis showed a higher mean suitability score than *P. inflatus,* with a difference of 18.9%. Figure 2 shows the membership functions, confirming that the Gaussian membership functions for the inputs capture smooth transitions, and the triangular membership functions for suitability define clear categories.

Results of the Monte Carlo process to compute suitability values for both species are shown in Figure 3. The distribution of values for *P. inflatus* is narrower and centered at ca. 35%, while the distribution for *P. gracilis* is wider, with the mode centered at ca. 55%.

The non-parametric test, the Wilcoxon Rank-Sum test, for equality of medians indicated that the median farming suitability of *P. gracilis* is significantly greater than that of *P. inflatus* (W = 294,798; P = < 2.2e-16).

To exemplify the use of the method to obtain crisp suitability values, a graphical depiction of the calculation of the centroid for *P. gracilis* is shown (Fig. 4). Note that the input values used to generate this example were the original, while the fifteen rules were the same. The difference between the crisp value shown in the figure (53.56%) and the value provided above (54.3%) is because the former represents one realization of the crisp value. In contrast, the latter is the mean of 10,000 randomly generated crisp values.

DISCUSSION

The fuzzy logic approach applied here (input variables, membership functions, and rule sets) can be adapted to other species and farming contexts. It aligns with broader applications of fuzzy logic in aquaculture, such as water quality management (Sarala & Bhuvana 2025) and feeding optimization (Nagothu et al. 2025), underscoring its versatility as a decision-support tool.

The application of fuzzy logic can be an effective tool for decision-making and for identifying the most suitable species for farming. In this study, the criteria for selecting both lobster species were defined based on readily available information. While the approach provides a basic framework for evaluating species suitability, it can be adjusted. The criteria used in this study are relevant but reflect only a portion of the variables that could be included in the fuzzy system.

The higher suitability of *P. gracilis* was primarily driven by its lower natural mortality and greater fecundity. Nevertheless, several limitations should be acknowledged. First, the high mortality of *P. inflatus* dominates the fuzzy rules, triggering low-suitability outputs even when other inputs are favorable. Second, partial overlap of the 95% simulation intervals (up to 44.8% for *P. inflatus vs*. 45.3% for *P. gracilis*) indicates that ranking reversals are possible, although they occurred in only 1.2% of simulations. The current model relies on biological information from wild populations, excludes relevant economic and environmental variables, and assumes equal importance among input criteria. Future versions should incorporate factors such as water quality, disease resistance, stocking density, production costs, and market value, and assign weights that better reflect each variable's relative importance. Such refinements would improve model calibration, enhance predictive performance, and enable the framework to evolve as new biological and production data become available.

Because we assume that lobster cultivation is based on collecting early stages from the field, to enhance future assessments, additional factors should be incorporated, such as water quality, population density, disease resistance, production costs, market price per species, and environmental tolerance. These variables introduce layers of complexity that are usually characterized by uncertainty and subjectivity, conditions under which fuzzy logic proves particularly valuable. By integrating a broader range of ecological, economic, and biological parameters, decision-making processes can become more nuanced and adaptive, ultimately leading to more sustainable and context-sensitive strategies.

Incorporating new variables would enable a more comprehensive analysis, and, given their relevance, it would be advisable to assign them appropriate weights. Differentiating the weights of input variables would help prevent less significant factors from distorting the outcome, more accurately reflect each criterion's real impact, and support more informed decision-making. Furthermore, it would allow for a more finely tuned calibration of the fuzzy logic system. Additionally, this analysis can be updated as more evidence becomes available regarding the importance of each variable or in response to changes in environmental conditions.

Similar approaches have been successfully used in other sectors of aquaculture. For instance, fuzzy logic has been applied to monitor and optimize water quality

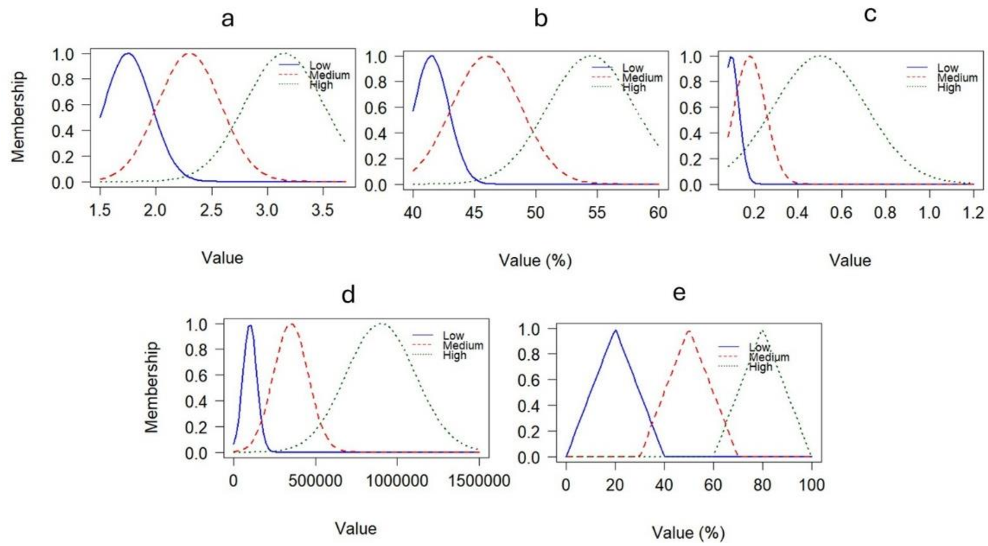

Figure 2. Membership functions of the fuzzy input variables: a) phi prime, b) abdominal proportion, c) natural mortality, d) fecundity, and the output variable, e) suitability.

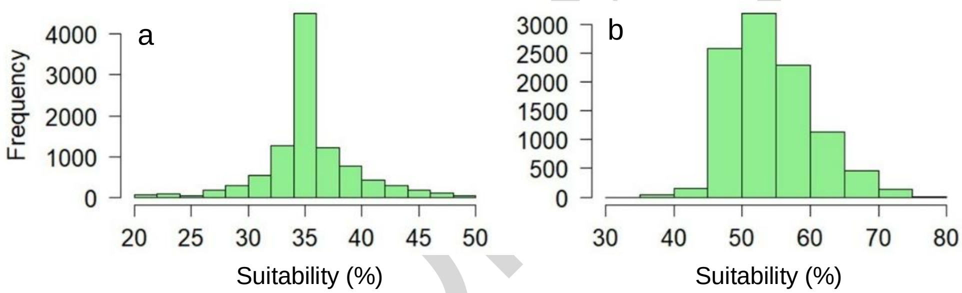

Figure 3. Frequency distribution of model-generated cultivation suitability scores for the two lobster species obtained from 10,000 Monte Carlo simulations. a) *P. inflatus*, b) *P. gracilis*. Suitability scores range from 0 to 100%, and each histogram reflects the propagation of uncertainty defined by the Gaussian membership function parameters (standard deviations) for each input variable.

parameters such as temperature, pH, dissolved oxygen, and salinity in fishponds, demonstrating high accuracy and adaptability in dynamic environments (Nagothu et al. 2025). Studies have also shown its effectiveness in controlling ammonia levels and predicting stress factors in aquatic species (Sarala & Bhuvana 2025).

In the context of fuzzy logic modeling, the precise definition of membership functions and the rules that relate input variables to output variables (Guzmán & Castaño 2006) integrate expert knowledge and experience as linguistic rules for decision-making (Mendoza-López et al. 2023). In this study, such expertise was expressed through 15 fuzzy rules combining logical postulates derived from experience along with information analysis, resulting in the conclusion that the species *P. gracilis* is the more suitable

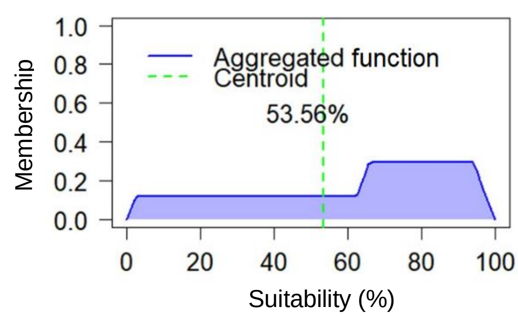

Figure 4. Exemplification of the estimate of a crisp value of suitability for *P. gracilis.*

option -a hypothesis confirmed through the applied methodology. The only logical operator used in the control rules was the minimum AND, resulting in a high fecundity requirement. Consequently, high suitability in most cases implies high fecundity (except in rule 8) and low mortality. Medium suitability was proposed with moderate fecundity and mortality levels (except for rule 14, which involves high mortality). Low suitability, on the other hand, is characterized by high mortality, at best moderate fecundity, and low growth.

This analysis used Monte Carlo simulations for calculating confidence intervals for farming suitability. The fact that the upper limit of suitability for *P. gracilis* is higher than that of *P. inflatus*, with slight overlap between the two, adds greater certainty and robustness to the results obtained, which is particularly relevant because, while fuzzy logic uses degrees of truth to represent imprecision and approximate reasoning (Zadeh 2008), Monte Carlo simulation allows for estimating uncertainty and computes the probability of different outcomes in the presence of random variables. In this case, those variables correspond to the input data for: phi prime, abdominal proportion, natural mortality, and fecundity.

The selection of *P. gracilis* as the better cultivation option is further supported by its commercial presence in Sinaloa (Pérez-González 2004, Ramírez-Félix et al. 2024), its higher specific fecundity relative to body size (Briones-Fourzán 2014), and its broad tolerance to diverse habitats including turbid areas near river mouths (Pérez-González et al. 1992, Pérez-González 2011). Additionally, *P. inflatus* exhibits a disproportionately large cephalothorax, whereas *P. gracilis* displays a more "balanced" ratio (Holthuis 1991). Briones-Fourzán & Lozano-Álvarez (2003) reported that *P. gracilis* has a weekly growth rate nearly twice that of *P. inflatus*. However, the fuzzy model uses the phi prime index (φ') rather than the short-term growth rate as the growth criterion. Phi prime integrates both K and L_∞ from the von Bertalanffy model ($\varphi' = \log K + 2 \log L_\infty$). This index was selected because (1) it captures long-term growth potential, (2) it is stable and comparable across species, and (3) available φ' values (*P. inflatus*: ~2.0; *P. gracilis*: ~1.8) show that *P. inflatus* reaches a larger asymptotic size, partially offsetting its slower weekly growth. Therefore, the model prioritizes integrated lifetime growth performance over short-term juvenile increments, which is more relevant for assessing long-term farming suitability. Furthermore, ovigerous females of *P. gracilis* reach slightly greater minimum and average lengths compared to those of *P. inflatus* (Weinborn 1977, Gracia 1985, Briones-Fourzán & Lozano-Álvarez 1992). Carapace length (CL), a key indicator of body size, is closely linked to physiological and ecological processes. In *Homarus americanus*, for example, males exhibit a greater CL than females (MacCormack & DeMont 2003). Trials under cultivation conditions could confirm the viability of *P. gracilis* in aquaculture.

Although lobster farming in Sinaloa still faces various challenges, fuzzy logic emerges as a powerful tool for addressing scenarios marked by uncertainty and ambiguity, optimizing the use of economic resources within a short timeframe. When combined with sensitivity analysis, it enables a deeper understanding of the system. Moreover, its integration with techniques and algorithms for solving complex problems -such as metaheuristics- could guide the identification of viable strategic pathways from the early stages of the process.

The fuzzy inference system presented can be adapted to diverse aquaculture species, enabling broader applications in selection processes where uncertainty prevails, as evidenced by fuzzy logic models that handle dynamic conditions and support sustainable management decisions (Nagothu et al. 2025). This flexibility enhances decision robustness across taxa, promoting adaptable strategies without rigid boundaries.

Several limitations merit consideration. First, input data derived from wild populations and culture conditions may alter key biological parameters. Second, the model lacks validation against empirical farming trials; suitability scores are relative indices, not absolute predictions. Third, the standard deviations of the Gaussian membership functions were assigned heuristically, and alternative choices could affect the outputs. Fourth, the 15 fuzzy rules are inherently subjective; different rule sets that emphasize alternative trade-offs could yield different rankings. Fifth, economic variables (feed costs, market prices) and environmental tolerances are omitted, limiting real-world applicability. Finally, the Monte Carlo intervals reflect the propagation of fuzziness rather than biological sampling variability and should not be interpreted as conventional confidence intervals. Future validation and model expansion are necessary before operational use in aquaculture decision-making.

This study considered four key biological variables, yet other factors, such as water-quality requirements, disease resistance, market-price volatility, and environmental impact, could further refine suitability assessments. Future implementations could incorporate these variables using weighted fuzzy rules or hybrid systems combining fuzzy logic with machine learning techniques (Cordón et al. 2004). Fuzzy models require calibration with empirical data, including pilot cultivation trials (Shahana et al. 2023, Haobijam et al. 2024) as part of the technical foundation, in line with standards of transparency and reproducibility, among others. Simulations must be contrasted with productive outcomes -such as growth and survival- obtained in real-world conditions, thereby ensuring the validity and applicability of the model. The use of genetic algorithms to automate the optimization of membership functions and rule sets could enhance model accuracy and adaptability across different taxa and regions.

CONCLUSION

This study demonstrates that a FIS combined with Monte Carlo uncertainty propagation provides a practical framework for comparing the suitability of lobster species for aquaculture under uncertain biological information. Within the evaluated conditions, *P. gracilis* consistently exhibited greater farming suitability than *P. inflatus*. Beyond the specific comparison presented here, the proposed framework offers a transparent and adaptable methodology that can be extended to incorporate additional biological, environmental, and economic criteria to support future aquaculture decision-making.

Credit author contribution

E.A. Ramírez-Félix: conceptualization, data curation, formal analysis, investigation, methodology, project administration, supervision, validation and visualization; M.Á. Cisneros-Mata: conceptualization, data curation, formal analysis, investigation, methodology, project administration, supervision, validation, visualization, writing original draft preparation, writing, review and editing; E. Villa-DiHarce: conceptualization, data curation, formal analysis, investigation, methodology and visualization; J.A. García-Borbón: conceptualization, formal analysis, investigation, methodology, visualization, writing, review and editing. All authors have read and accepted the published version of the manuscript.

Conflict of interest

The authors declare that they have no known competing financial or non-financial, professional, or personal conflicts that could have influenced the work reported in this paper.

ACKNOWLEDGMENTS

We thank Rick Brusca for his thoughtful comments on an early version of the manuscript, as well as two anonymous reviewers for their valuable suggestions, insightful comments, and the time they invested to improve the manuscript.

REFERENCES

Arabshahi, P., Marks, R.J. II, & Reed, R. 1993. Adaptation of fuzzy inferencing: A survey. In: Proceedings of the 1993 International Conference on Fuzzy Theory and Technology, Durham, pp. 1-5.

Azra, M.N., Jye, M.W., Van Doan, H., et al. 2022. Mapping of marine lobster research: A global outlook. Frontiers in Marine Science, 9: 976199. doi: 10.3389/fmars.2022.976199

Briones-Fourzán, P. 2014. Differences in life-history and ecological traits between co-occurring *Panulirus* spiny lobsters (Decapoda, Palinuridae). ZooKeys, 457: 289-311. doi: 10.3897/zookeys.457.6669

Briones-Fourzán, P. & Lozano-Álvarez, E. 1992. Aspects of the reproduction of *Panulirus inflatus* (Bouvier) and *P. gracilis* streets (Decapoda: Palinuridae) from the Pacific Coast of Mexico. Journal of Crustacean Biology, 12: 41-50. doi: 10.2307/1548717

Briones-Fourzán P. & Lozano-Álvarez, E. 2003. Factors affecting growth of the spiny lobsters *Panulirus gracilis* and *Panulirus inflatus* (Decapoda: Palinuridae) in Guerrero, Mexico. Revista de Biología Tropical, 51: 165-174.

Cabrera-Mancilla, E. & Gutiérrez-Zavala, R.M. 2010. Evaluación de la pesca de langosta (*Panulirus inflatus* y *P. gracilis*), en el Estado de Guerrero. Informe Final de Investigación 2009. SAGARPA/INP, Ciudad de México.

Caddy, J.F. 1996. Modelling natural mortality with age in short-lived invertebrate populations: definition of a strategy of gnomonic time division. Aquatic Living Resources, 9: 197-207.

Cao, J. & Chen, Y. 2022. Modeling time-varying natural mortality in size-structured assessment models. Fisheries Research, 250: 106290. doi: 10.1016/j.fishres.2022.106290

Castro-Gutiérrez, K.F. 2014. Variación interanual de la estructura y dinámica poblacional de las langostas *Panulirus inflatus* y *P. gracilis* (Decapoda: Palinuridae) en el sur de Sinaloa. M.Sc. Thesis, Universidad Autónoma de Sinaloa, Mazatlán.

Chen, C., Razak, T.R. & Garibaldi, J.M. 2020. FuzzyR: An extended fuzzy logic toolbox for the R programming language. IEEE International Conference on Fuzzy Systems (FUZZ-IEEE), Glasgow. doi: 10.1109/fuzz48607.2020.9177780

Cordón, O., Gomide, F., Herrera, F., et al. 2004. Ten years of genetic fuzzy systems: Current framework and new trends. Fuzzy Sets and Systems, 141: 5-31. doi: 10.1016/S0165-0114(03) 00111-8

Devi, S., Nayak, M.M. & Patnaik, S. 2020. Decision-making models and tools: a critical study. International Journal of Management and Decision Making, 19: 176. doi: 10.1504/ijmdm.2020.108204

Émond, K., Sainte-Marie, B. & Gendron, L. 2010. Relative growth, life-history phases, and sexual maturity of American lobster (*Homarus americanus*). Canadian Journal of Zoology, 88: 347-358. doi: 10.1139/Z10-008

Food and Agriculture Organization (FAO). 2017. The world lobster market. FAO, Rome.

Food and Agriculture Organization (FAO). 2022. The state of world fisheries and aquaculture 2022. Towards blue transformation. FAO, Rome. doi: 10.4060/cc 0461en

Food and Agriculture Organization (FAO). 2026. The state of world fisheries and aquaculture 2026. Blue transformation: turning vision into impact. FAO, Rome. doi. 10.4060/cd8357en

Goldstein, J.S., Gutzler B.C., Kough, A.S., et al. 2025. A review of American lobster (*Homarus americanus*) research since 2000. Reviews in Fisheries Science & Aquaculture, 34: 1-56. doi: 10.1080/23308249.2025. 2514440

Gracia, A.G. 1985. Variación estacional en la fecundidad de la langosta *Panulirus inflatus* (Bouvier, 1895) (Crustacea: Decapoda: Palinuridae). Ciencias Marinas, 11: 7-27.

Guzmán, D. & Castaño, V.M. 2006. La lógica difusa en ingeniería: principios, aplicaciones y futuro. Revista de Ciencia y Tecnología, 24: 2: 87-107.

Haobijam, B., Huang, Y.P., Chang, Y.S., et al. 2024. Transforming sustainable aquaculture: Synergizing fuzzy systems and deep learning innovations. International Journal of Fuzzy Systems, 26: 2536-2552. doi: 10.1007/s40815-024-01744-w

Hoenig, J.M., Hearn, W.S., Leigh, G.M., et al. 2025. Principles for estimating natural mortality rate. Fisheries Research, 281: 107195. doi: 10.1016/j. fishres.2024.107195

Holthuis, L.B. 1991. Marine lobsters of the world. An annotated and illustrated catalogue of species of interest to fisheries known to date. FAO Fisheries Synopsis, 125: 13.

Juárez-Carrillo, E., Ríos-Jara, E., López Uriarte, E., et al. 2006. Biología y pesca de la langosta azul *Panulirus inflatus* en la costa central de Jalisco, México. In: Jiménez-Quiroz, M.C. & Espino-Barr, E. (Eds.). Los recursos pesqueros y acuícolas de Jalisco, Colima y Michoacán. Instituto Nacional de la Pesca/SAGARPA, Ciudad de México, pp. 448-460.

Kosheleva, O., Kreinovich, V. & Nguyen, T.N. 2019. Why triangular membership functions are successfully used in F-transform applications: a global explanation to supplement the existing local ones. Axioms, 8: 95. doi: 10.3390/axioms8030095

MacCormack, T.J. & DeMont, M.E. 2003. Regional differences in allometric growth in Atlantic Canadian lobster (*Homarus americanus*). Journal of Crustacean Biology, 23: 258-64.

McCoy, M.W. & Gillooly, J.F. 2008. Predicting natural mortality rates of plants and animals. Ecology Letters, 11: 710-716. doi: 10.1111/j.1461-0248.2008.01190.x

Mendoza-López, R., Verduzco-Ramírez, J.A., Barrios-Hernández, C.J., et al. 2023. Modelo para determinar la calidad del agua en estanques acuícolas utilizando lógica difusa. Revista Electro, 45: 172-177.

Nagothu, S.K., Sri, P.B., Anitha, G., et al. 2025. Advancing aquaculture: fuzzy logic-based water quality monitoring and maintenance system for precision aquaculture. Aquaculture International, 33: 1-21. doi: 10.1007/s10499-024-01701-2

Pauly, D. & Munro, J.L. 1984. Once more on the comparison of growth in fish and invertebrates. Fishbyte, 2: 21.

Pérez-González, R. 2004. La pesca de langosta *Panulirus* spp. con redes agalleras en el sureste del Golfo de California, México: una pesquería multiespecífica. COASTFISH 2004. 1ª Conferencia de Pesquerías Costeras en América Latina y el Caribe. 4-8 Oct., pp. 65-78.

Pérez-González, R. 2008. Biología y pesquería de la langosta *Panulirus gracilis* Streets, 1871 en el sur de Sinaloa, México. Ph.D. Thesis, Universidad Nacional Autónoma de México, Ciudad de México.

Pérez-González, R. 2011. Catch composition of the spiny lobster *Panulirus gracilis* (Decapoda: Palinuridae) off the western coast of Mexico. Latin American Journal of Aquatic Research, 39: 225-235. doi: 10.3856/vol39-issue2-fulltext-4

Pérez-González, R., Flores-Campaña, L.M., Núñez-Pastén, A., et al. 1992. Algunos aspectos de la reproducción en *Panulirus inflatus* (Bouvier, 1895) y *P. gracilis* Streets, 1871 (Decapoda: Palinuridae) en el sureste del Golfo de California, México. Investigaciones Marinas CICIMAR, 7: 26-33.

Pincheira-Donoso, D. & Hunt, J. 2015. Fecundity selection theory: concepts and evidence. Biological Reviews, 9: 341-356. doi: 10.1111/brv.12232

Pop, M.D., Pescaru, D. & Micea, M.V. 2023. Mamdani *vs*. Takagi-Sugeno fuzzy inference systems in the calibration of continuous-time car-following models. Sensors, 23: 8791. doi: 10.3390/s23218791

Ramírez-Félix, E., Moreno-Borrego, V., Silva-Raygoza, J.H., et al. 2023. Estudio de las poblaciones de langosta y sus pesquerías en Sinaloa. Informe final. SADER, Ciudad de México.

Ramírez-Félix, E., Villa-Diharce, E.R., García-Borbón, J.A., et al. 2024. Life cycle and natural mortality rates of the blue spiny lobster (*Panulirus inflatus*). Journal of Shellfish Research, 43: 119-132. doi: 10.2983/035.043.0112

Ramos-Santiago, E., Labastida-Che, A., Oviedo-Piamonte, J.A., et al. 2020. Experimentación con trampas para la captura de langostas espinosas (*Panulirus* spp.) como arte de pesca alternativo en la costa de Oaxaca. Informe Final. IMIPAS/SADER/CRIAP, Ciudad de México.

Ross, T.J. 2010. Fuzzy logic with engineering applications. John Wiley & Sons, Hoboken. doi: 10.1002/9781119994374

Ross, T.J. 2017. Fuzzy logic with engineering applications. John Wiley & Sons, Ltd., Hoboken. doi: 10.1002/9781119994374.

Sarala, N. & Bhuvana, G. 2025. Fuzzy modeling control of water quality parameters in aquaculture. International Journal of Creative Research Thoughts, 13: f630-f639.

Received: March 5, 2026; Accepted: June 25, 2026

Shahana, G., Ezhilarasi, P. & Kannan, S.R. 2023. Adaptive neuro fuzzy data aggregation model for developing and planning for aquaculture farming practices. International Conference on Advances in Computing, Communication and Applied Informatics (ACCAI), Chennai, India, pp. 1-8. doi: 10.1109/ACCAI58221.2023.10200854.

Sharma, R., Barange, M., Agostini, V., et al. 2025. Review of the state of world marine fishery resources - 2025. FAO Fisheries and Aquaculture Technical Papers No. 721. Rome, FAO. doi: 10.4060/cd5538en

Weinborn, J.A. 1977. Estudio preliminar de la biología, ecología y semicultivo de los palinúridos de Zihuatanejo, Gro., México, *Panulirus gracilis* Streets y *Panulirus inflatus* (Bouvier) Anales del Centro de Ciencias del Mar y Limnología, 4: 27-78.

Xu, H., Hipel, K.W. & Kilgour, D.M. 2009. Matrix representation of solution concepts in multiple-decision-maker graph models. IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans, 39: 96-108. doi: 10.1109/TSMCA.2009.2007994

Yager, R.R. & Filev, D. 1993. On the issue of defuzzification and selection based on a fuzzy set. Fuzzy Sets and Systems, 55: 255-271. doi: 10.1016/0165-0114(93)90252-d

Zadeh, L.A. 1965. Fuzzy sets. Information and Control, 8: 338-353. doi: 10.2307/2272014

Zadeh, L.A. 2008. Is there a need for fuzzy logic? Information Sciences, 178: 2751-2779. doi: 10.1016/j.ins.2008.02.012