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Modeling CPUE of the banana jellyfish (Catostylus perezi Ranson, 1945) using ensemble methods (GAM, RF, NN) and its association with physicochemical parameters in the northern Oman Sea

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Abstract

This study examines the connection between Catch Per Unit Effort (CPUE) of the banana jellyfish and key physicochemical factors in the northern Oman Sea. Monthly sampling occurred over one year at two stations, recording environmental and fishery data. A total of 400 specimens were analyzed. Results show that *Catostylus perezi* blooms seasonally, with commercial fishing limited to the monsoon and post-monsoon periods. Estimated catches were 754 tons at Tis and 2,520 tons at Pozm, totaling 3,274 tons for 2024, with peak CPUE in November at Pozm. Statistical analysis revealed significant differences in total catch and CPUE across months ($P < 0.05$). An advanced ensemble modeling framework utilizing Generalized Additive Model (GAM), Random Forest (RF), and Neural Network (NN) was employed to model the relationship between CPUE and environmental drivers. Predictions from these models were integrated using a performance-based weighting strategy to create a final ensemble model. This ensemble model achieved superior results, with $R^2 \approx 0.89$ and RMSE ≈ 0.23, outperforming individual models. Variable importance analysis identified Temperature, pH, and Dissolved Oxygen as having strong positive influences, while Total Organic Matter (TOM), T.C.U., ammonia, nitrate, salinity, and turbidity exhibited negative effects. Notably, TOM had the most significant detrimental impact. This research establishes the first scientific baseline for this new fishery in Iran and discusses the relevance of conventional stock assessment methods for jellyfish. The findings highlight the necessity for specialized assessment frameworks to ensure sustainable management of these organisms. This study also offers a methodological template for jellyfish stock assessments in other regions with limited data.

Introduction

Around the world, jellyfish numbers are increasing, creating both environmental problems and possible opportunities for sustainable seafood resources. This rise is influenced by things like climate change, nutrient pollution, and excessive fishing, which can lead to jellyfish blooms. In response to this situation, jellyfish fishing has grown, especially in Asia, where species such as the banana jellyfish are collected for commercial purposes. However, the science behind managing these fisheries often does not keep up with their growth. In the northern Indian Ocean area, particularly in the waters off Iran, research on jellyfish fisheries is limited despite their rising economic significance. This is particularly true along Iran's southern coastline in the Oman Sea, where no formal evaluation or environmental study of *Catostylus* perezi exists. Without basic information, sustainable management is difficult, and it does not consider the specific biological and bloom patterns of jellyfish within standard fishing practices (Hashemi et al. 2025; Hashemi 2026).

Globally, jellyfish numbers are on the rise. This situation calls for immediate research to grasp its long-term environmental effects. Additionally, jellyfish can be present in every ocean, from the surface to the ocean floor. Human actions often significantly contribute to the rise of jellyfish blooms. Factors include changes in global temperatures, excessive fishing, increased nutrient levels from waste and other pollutants, and higher salt levels due to less freshwater entering the ocean and lower oxygen levels during algae blooms. Studies have shown that jellyfish could be a viable sustainable seafood option for the future.

Worldwide, an average of 291,600 tons of various jellyfish species is harvested each year, with China and Thailand making up the largest amounts in Asia. Research has identified three main areas in Asia where commercial jellyfish fishing occurs; one area, known as "southern Asia," which includes countries next to the northern Indian Ocean, contributes about ten percent of the global jellyfish catch each year. Further findings indicate that India is the top contributor in that region, making up approximately 41%, followed by Pakistan at around 30%, Bahrain at about 15%, Sri Lanka at roughly 9%, and Iran with 2,170 tons or about 5% (Muhammed and Sultana 2008; Gul and Morandi 2013).

While ensemble modeling has been utilized in many fishing situations, its application to jellyfish—particularly in areas with limited data like the northern Oman Sea—remains unusual. This research not only fills a gap in local knowledge but also evaluates how advanced analytical methods can be applied to jellyfish fisheries. To fill this knowledge gap, this study looks at the banana jellyfish fishery along the Makran coast of Iran. We explore how Catch Per Unit Effort (CPUE) relates to important physical and chemical factors, employing a solid, multi-model strategy (Hashemi 2026). By conducting monthly sampling over a complete year, we gathered data on environmental factors like temperature, salinity, turbidity, and nutrient levels alongside data from the fishery itself. We used sophisticated ensemble modeling methods such as Generalized Additive Models (GAM), Random Forest (RF), and Neural Networks (NN) to understand complex interactions and find the key environmental factors that influence jellyfish populations. This study not only sets the first scientific benchmark for this growing fishery in Iran but also assesses how current analytical tools can be used for jellyfish stock evaluations. Ultimately, the results aim to support management strategies tailored to the region, balancing economic use with ecological sustainability in a changing marine setting (Hashemi et al. 2025; Hashemi 2026).

A few jellyfish species have been observed in the waters of southern Iran (Owf 2020), with three recognized as edible: *Catostylus perezi* Ranson, 1945, *Crambionella orsini* (Vanhöffen 1888), and *Rhopilema hispidum* (Vanhöffen 1888). However, currently, only *C*. *perezi* is known to be collected for export (Karunarathne and Karunarathne 2025). This jellyfish is mostly caught at Abadan on the Khuzestan coast and at Bandar Bushehr on the Bushehr coast in Iran. It is also occasionally collected from other coasts, but not from the Caspian Sea coast (Karunarathne and Karunarathne 2025). In Pakistan, which borders Iran, research on jellyfish fisheries has been conducted (Muhammed and Sultana 2008; Gul and Morandi 2013). However, detailed data about jellyfish fisheries in Iran is limited due to a lack of studies, especially from the southeastern coast. This study, therefore, concentrates on jellyfish fisheries, particularly catch-related stock assessments and fishing effort analyses along Iran's southeastern coast, aiming to offer basic information for better comprehension and management of the jellyfish resource that has seen increased exploitation in recent years.

Materials and methods

Field survey

This research was planned based on the choice of two sampling sites at Tis (25. 3483°N, 60. 6038°E) and Pozm (25. 3512°N, 60. 2988°E) located on the southeastern coast (Makran coast of Sistan and Baluchestan Province) of Iran (Fig. 1). The field research started on March 20, 2024, and continued for a full year, with monthly samples taken at both spots, along with seasonal analysis during the monsoon and post-monsoon times. We collected jellyfish specimens (n = 400) from the waters near the two stations using scoop nets. Each jellyfish was measured to the nearest mm with a ruler and weighed with a digital scale that had a precision of 1 g.

Figure 1.

Data collection

Every month, water samples were taken from each location using a Nansen bottle sampler to check for environmental conditions, following the usual methods for analysis (Moopam 2010). This study examined eleven environmental factors (see Table 1), which included water temperature, water salinity, turbidity, nitrate levels, phosphorus, ammonia, total organic matter, soil pH, total coliform units, nitrite, pH, and dissolved oxygen. For each season, two locations were chosen for the sampling process. The sampling was conducted using fixed gill nets that had a mesh size of 45 mm, measuring between 100 to 120 m in length and 50 to 70 m in width, and the samples were then taken to the lab using dry ice. Each fish's length was recorded with an accuracy of ± 1 mm, and the weight was noted with an accuracy of ± 0. 01 g. Since the target species, *C. perezi*, can only be found and caught during the warmer months, the sampling for environmental conditions and fishery studies was carried out extensively from June to November 2024, during the monsoon and post-monsoon fishing times.

Table 1
Catch per unit effort (CPUE) of *C. perezi* and environmental parameters across months and stations along the southeastern coast of Iran.

Month	CPUE mean	Temperature	Salinity	Turbidity	NO3	PO4	NH3	TOM	PHsoil	T.C. U	No2	PH	Do
Jun.	387	33.7	36	2.71	0.10	0.03	0.01	0.62	8.18	15	0.009	7.71	5.3
Jul.	815	31	37	5.3	0.15	0.16	0.01	0.19	8.62	17	0.005	7.94	6.94
Aug.	249	31	38	5.4	0.24	0.02	0.01	0.73	8.62	17	0.012	8.03	6
Sep.	200	30.4	38.5	9.93	0.24	0.04	0.01	1.40	8.62	30.5	0.015	7.99	6.3
Oct.	100	31	38	11.4	0.42	0.03	0.03	0.26	8.19	21	0.007	7.93	5.9
Nov.	990	29	38	6.71	0.54	0.02	0.01	0.40	9.25	26	0.008	8.11	6.92
Mean ± S. D.	449 ± 369	31.02 ± 1.53	37.58 ± 0.92	6.91 ± 3.22	0.29 ± 0.17	0.06 ± 0.06	0.02 ± 0.01	0.61 ± 0.44	8.58 ± 0.39	21.08 ± 6.05	0.01 ± 0.003	7.91 ± 0.14	6.23 ± 0.63

Table 1.

Estimation of catch, fishing effort, and the catch per unit effort

The part of the *C. perezi* fish known as the bell, which is often thrown away before processing, makes up about half of the fish's total weight when wet. Including this part, the yearly catch could be about twice the amount of oral arms that are landed annually. As a result, sampling was carried out by collecting data directly at the landing sites using methods based on census techniques across both time and different locations (Stamatopoulos 2002). The catch per unit effort (CPUE) was calculated by taking the total catch from these boats and dividing it by the overall fishing effort (kg/boat/day).

Modeling procedure and Ensemble models

Generalized Additive Model (GAM)

The Generalized Additive Model (GAM) expands on the Generalized Linear Model (GLM) by using smooth functions instead of just straight lines to show nonlinear connections between the predictor and response variables (Wood 2017).

$g\ (E(Y)) = \beta 0 + f1(X1) + f2(X2) + \cdots + fk(Xk)$

Where g means the link function, E(Y) is the expected value of the response variable, β0 is the intercept, and fj are the smooth functions for each predictor variable.

Random Forest (RF)

Random Forest is a type of machine learning that puts together several decision trees. Each tree is built using a portion of the data, and the final output is created by combining (like voting or averaging) the results from all the trees. This method is useful for both classification and regression tasks (James et al. 2021).

$\hat{y} = \frac{1}{n} \sum_{i=1}^{n} Ti(x)$

Variables include: li as the i-th decision tree, x representing the input data, and n referring to the total number of trees.

Neural Network (NN)

An Artificial Neural Network (NN) is a computational system modeled after how the human brain works. It is made up of connected artificial neurons (units that compute) that process data and learn through these connections. The fundamental calculation for a neuron is expressed as (Benzer and Benzer 2019):

$Y = f(w \cdot x + b)$

Where x is the input, w is the weight indicating the importance of the input, b stands for bias which corrects errors, and f is the activation function (a nonlinear function such as Sigmoid). RMSE (Root Mean Square Error) is a widely used measure to evaluate how accurate a predictive model is. It assesses the difference between predicted values and the actual measured values by calculating the square root of the average of squared differences. $RMSE = \sqrt{\sum i = 1/n(yi - \hat{y}i)^2}$

Where yi represents the actual (observed) value, $\hat{y}i$ is the value predicted, and n indicates the total number of observations.

Ensemble Model

The combined model uses a smart weighting method to merge forecasts from ANN, GAM, and Random Forest models. Rather than treating each model equally, the amount each model contributes is based on how well it predicts, which means models with lower RMSE get more weight. Various weighting techniques, such as inverse RMSE, exponential decay, and rank-based methods, are tested, and the best one is chosen automatically to reduce the total ensemble error. This performance-driven combination creates a more robust and accurate predictive model than any individual method alone. Let Yi and RMSEi represent the predictions and root mean squared error of each sub-model on test data. The final ensemble prediction Yens and its uncertainty limits were determined as follows: This method values models with lower test errors while still accounting for uncertainty (Dietterich 2000; Karp et al. 2022). To keep the ecological insights clear, the importance of various variables was assessed using permutation methods for Random Forest and sensitivity analysis for Neural Networks, while the contributions from GAM were taken from partial dependence plots. The ending ensemble weights were

given inversely related to each model's cross-validated RMSE, making sure that more trustworthy predictions had a bigger say in the final outcome.

$$Yens = \sum_{i=1}^{5} WiYi, \qquad where \quad Wi = 1/RMSEi \; / \sum_{j=1}^{5} 1/RMSEj$$

Data analysis was done using R software (version 4.4.0) and R Studio (2024. 12.1), employing packages like ggplot2, ggthemes, ggridges, and RColor Brewer for visual representation. The normality of data was checked using the Kolmogorov–Smirnov test at a significance level of 0.05. For statistical analysis, a two-pronged method was used: normally distributed parameters (Shapiro-Wilk P > 0.05) were tested with one-way Analysis of Variance (ANOVA), while those that did not meet the normality assumption were tested using the non-parametric Kruskal–Wallis test, with both tests performed at α = 0.05. In addition, a correlation analysis was conducted to explore the connections between key environmental factors and CPUE values.

Results

Fishing Methods

Throughout the study year, it was observed that the target species, *C. perezi*, appears only in the warmer months; therefore, no catches were noted before the monsoon season. Commercial fishing for jellyfish was only conducted during the monsoon (July to September) and shortly after the monsoon (October and November) in 2024. There were no catches recorded from December to June, as *C. perezi* does not gather in fishable numbers outside of its peak season in the warmer months. This confirms that this fishery operates strictly seasonally.

Local fishers operate small boats made of wood or fiberglass that are equipped with special nets and handheld scoops to catch jellyfish that are found near the water's surface. They typically begin their harvesting early in the morning to steer clear of the harsh heat of the afternoon and to keep the jellyfish fresh. A boat generally goes out to fish for about 5 to 6 hours during a single trip. The jellyfish are handled with care to avoid breaking their oral arms, which can lower how much they can sell for. Once caught, the jellyfish are quickly placed into containers that are filled with seawater and taken to processing facilities near the coast within a few hours. This quick movement is important, as any delays can cause the jellyfish to spoil in the hot temperatures of southern Iran. Generally, 2 to 3 fishers take part in each fishing trip. Additionally, this industry offers temporary jobs for people in coastal towns, but it faces problems like excessive fishing in certain regions and rivalry with shrimp trawlers. Some areas have started to set specific fishing times to promote sustainability.

Estimated jellyfish CPUE

According to estimates, 754 tons of jellyfish were caught in Tis, while Pozm had a much higher catch of 2520 tons. The amount caught and the fishing efforts changed from month to month in 2024 (see Table 1). The jellyfish gathered from Pozm tended to be bigger and heavier, likely because they were in their mature stage during the post-monsoon months. In the monsoon period, the collected jellyfish were generally smaller and lighter. The average size of the jellyfish from Tis was 217 ± 49 mm (n = 278), and from Pozm it was 242 ± 52 mm (n = 122). The average weight was 0.84 ± 0.33 kg (n = 278) from Tis and 1.08 ± 0.24 kg (n = 122) from Pozm. Thus, it seems that around 897,000 jellyfish of the species C. perezi were caught from Tis, and about 2,333,000 from Pozm in 2024. Overall, the average size for the species was 225 ± 51 mm (ranging from 140 to 400 mm), and the average weight in wet form was 0.91 ± 0. 2 kg (rang from 0.20 to 1.70 kg). The total estimated catch amounted to 3,274 tons, with a total of 1836 boat-days spent fishing during the jellyfish season along the southeastern coast of Iran in 2024 (see Table 2). Catching peaked in August and November, with the highest CPUE also occurring in these months, but it significantly dropped in October. These clear differences show a strong pattern related to the seasons concerning fishing productivity. Statistical tests show a meaningful difference in total catch and CPUE across the months (P < 0.05).

Table 2
Catch per unit effort (CPUE), Total fishing effort (boat-days) and the estimated catch of *C. perezi* across months and stations along the southeastern coast of Iran.

Fishing station	Season	Month in 2024	Number of fishing days	Average number of boats per day	Total Fishing Effort (boat-days)	CPUE (kg-boat-days)	Catch (tons)
Tis	Monsoon	Jun.	7	10	70	387	10.85
		Jul.	7	30	210	815	81.27
		Aug.	25	30	750	249	612
		Sep.	20	15	300	200	74.4
Pozm	Post-monsoon	Oct.	7	50	350	100	35
		Nov.	25	60	1500	990	1485
Total	-	-	91	195	3180	-	2298
Average	-	-	15.16	32.5	-	449 ± 369	-

Table 2

The relationships between important environmental factors and fisheries examined in this study are represented in Fig. 2 via a correlation matrix, often displayed as a heatmap. The variables looked at include temperature, CPUE total catch, salinity, pH, dissolved oxygen (DO), turbidity, and various nutrient types (NO_3, NO_2, NH_3, PO_4). Each section of the matrix includes a correlation coefficient that ranges from + 1 (indicating a perfect positive correlation) to -1 (indicating a perfect negative correlation), which helps identify major relationships. For instance, temperature has a strong positive connection with salinity (≈ 0.98) and a significant negative link with NO_2 (≈–0.81). This analysis aids in pinpointing important environmental factors—like the strong positive connection between salinity and pH (0.83) that may affect jellyfish CPUE and where they are found over time in the Oman Sea. These findings endorse the application of combined modelling in this research to better understand the interactions between fisheries and the environment. Not only did total catch vary from month to month, but CPUE also showed significant differences across various stations, with the highest numbers found in November (see Fig. 2). It's important to mention that these figures do not include the bell part of the jellyfish, which is often taken off during capture before processing. Data in Table 1 also suggest that Pozm recorded the highest total catch and CPUE. Notably, even though temperature and salinity have a strong correlation ($r \approx 0.98$), the combined model included both factors because they individually affect jellyfish metabolism and how blooms develop, as past eco-physiological research has shown.

Figure 2

Based on the statistical review of environmental factors over a period of six months (June through November), none of the factors measured indicated any meaningful differences at a significance level of $p < 0.05$. All 13 factors—including CPUE_mean, Temperature, Salinity, Turbidity, NO3, PO4, NH3, TOM, PH soil, T. C. U, No2, PH, and Dissolved Oxygen showed no important monthly changes ($P > 0.05$). While PO4 and NH3 were evaluated using the Kruskal-Wallis test because they didn't fit a normal distribution ($p = 0.416$ for each), the other factors couldn't be properly analyzed with ANOVA due to a lack of sufficient sample size. Overall, the findings reveal that no environmental aspects displayed statistically significant shifts during the study, indicating relative consistency throughout these months, even though some parameters like CPUE_mean showed noticeable numerical changes.

The ensemble model presents the lowest Root Mean Square Error (RMSE) of 266.6, demonstrating it as the most effective predictive model (Fig. 3). This outstanding performance is intentional, resulting from a smart weighting method that emphasizes the most dependable individual models. The weighting system is based on a direct inverse connection between the RMSE of a model and its impact on the combined prediction. Thus, the individual model with the lowest RMSE (Model X, 266.6) received the largest weight of 0.444 in the ultimate ensemble. The weights were distributed as follows: Model Y (RMSE: 355.2, weight: 0.444), Model Z (RMSE: 385.5, weight: 0.333), and Model W (RMSE: 405.6, weight: 0.222). This results-focused approach guarantees that the ensemble's output is mainly influenced by the most precise predictions, which enhances overall trustworthiness.

Figure 3

The analysis of variable importance for the final weighted ensemble model (Fig. 4) highlighted Temperature as the key factor affecting CPUE, with an importance score of 9.7. Following this were pH (8.8) and Dissolved Oxygen (7.7), indicating a strong positive effect on

jellyfish population. On the other hand, factors such as Total Organic Matter (TOM; -1.3) and T. C. U. (-1.0) had negative importance scores, suggesting they have an opposite relationship with CPUE. Other nutrients and parameters (NH_3, NO_3, Salinity, Turbidity) also showed negative effects, but to a lesser degree. This ranking offers a collective perspective formed from the ensemble, merging the varying priorities of the individual base models (ANN, GAM, and RF) to emphasize the most significant environmental influences.

Figure 4

Discussion

Assessing fish populations and determining suitable harvesting amounts is a crucial issue in managing natural resources as well as the fishing sector. This approach aims to protect aquatic resources in a sustainable manner, playing an essential role in keeping marine ecosystems in balance and ensuring food security for communities reliant on these resources (Karp et al. 2018; Medeiros-Leal et al. 2023). Although there is a wide range of marine invertebrate species, the majority of harvested species belong to only a few main taxonomic groups (King 2007). Among these, jellyfish have become increasingly important today.

The main goal of this research was to do a basic evaluation of jellyfish stocks and to find out what environmental factors affect the banana jellyfish (*C. perezi*) fishery in the northern Oman Sea. This understanding is crucial for creating management plans based on science to guarantee the sustainability of this seasonal fishery, which depends on jellyfish blooms, instead of trying to fish all year round —a goal that is not realistic because of the species' life cycle (Hashemi 2026). Therefore, the results of this stock assessment should be seen as an initial reference point since they are based on data gathered from just two locations over one year. Although the monthly collections during the fishing season offer a good time frame, the limited locations may not fully represent how *C. perezi* is spread out along the Makran coast (Oman Sea). Future research that includes a wider range of sampling locations over several years would greatly improve estimates of jellyfish populations and their environmental connections. Still, our use of size-based techniques and collective modeling shows that we can modify analytical approaches for jellyfish, as similar research has indicated (for example, Palomares and Pauly2009, who analyzed life-cycle traits for 34 jellyfish species).

Even with these challenges, this study marks the first scientific benchmark for a growing jellyfish fishery in Iran and shows both the possibilities and the constraints of using traditional stock assessment models for invertebrates that form blooms. Significantly, our results trigger a wider conversation about the suitability of stock assessment methods for jellyfish populations, which are different in many ways from fish regarding biology, life cycles, ecosystem roles, and fishing practices (Hashemi et al. 2025; Hashemi 2026). Thus, while the current findings provide useful information for national management strategies, they should also encourage discussions at regional and international levels about creating assessment frameworks specifically for jellyfish that take into account ecological changes, bloom patterns, and environmental factors.

Chabahar and the Pozm Gulfs (Gulf of Oman) are facing various forms of pollution that may impact jellyfish populations and their life cycles. These include high levels of nutrient enrichment, over fishing, changes to habitats, and fluctuations in temperature (Daryanabard and Dawson 2008). To predict and prevent jellyfish blooms in this region, it is essential to accurately identify species and understand the environmental factors that influence when and where they appear. Pourjafar et al. (2017) looked into how physical and chemical conditions in the environment relate to the number of zooplankton and jellyfish populations in the Chabahar and Pozm Gulfs, but they could not point out a specific cause. Nevertheless, models of jellyfish numbers in ocean environments show that they interact with various environmental factors according to Wright et al. (2021). In a 2021 study by Gueroun and team, researchers examined how species from the Catostylus genus are spread around the world, noting that the best conditions for these species to breed and grow are temperatures between 18 and 25 degrees Celsius and salinity levels from 20 to 35 parts per thousand.

Nutrients like nitrate, nitrite, ammonia, and phosphate entering coastal waters from human activities can lead to different kinds of blooms, including those of jellyfish. Worldwide, nitrogen levels in coastal areas are rising due to human actions, which raise alarms since these changes can cause eutrophication and disrupt ecological balance, as noted by Archana and Babu (2013). During post-monsoon times, jellyfish populations tend to increase, which has been backed by other research indicating higher counts of jellyfish in this season, as seen in the work of Hassan et al. (2010). Factors like lower temperatures, strong water currents, turbulence, and changes in food availability likely contribute to the growth of jellyfish after the monsoon in Iranian waters. As noted by Nowrouzi and Valavi (2011) and Al-Hashmi et al. (2012), the spread and distribution of species in the Gulf of Oman are affected by ocean currents, monsoon winds, nutrient levels, and temperature of the water.

The different types of substrates at the stations may also account for the differences in jellyfish population sizes. Changes in the sizes of sediment particles can impact environmental factors such as temperature, salinity, oxygen, and availability of organic matter, which

affect aquatic life. Depth is another factor that influences the variety of species present. Many studies have proven that both depth and substrate type are important elements in shaping community structures and the diversity of species in marine environments, as highlighted by Ellis and Rogers (2000). The number of marine species can vary greatly based on their habitat and the depth of the water, as shown by Kazanidis et al. (2010).

Exploitation rates higher than 0. 5 or fishing mortality that goes beyond natural mortality indicate over fishing (Sparre and Venema 1998; King 2007). The findings from this study point to over fishing; reduced interest can help protect the specie's ecological role since it is a dangerous species. Fishing impacts aquatic resources and the whole marine ecosystem in both direct and indirect ways. Direct impacts change the population structure, growth, reproduction, and distribution of targeted species, while indirect effects alter the populations of non-target species like invertebrates and fish, along with their habitats (Arias-Gonzalez et al. 2004; Mashjoor and Kamrani 2015; Razzaghi et al. 2017). *Crambionella orsini* (Vanhöffen 1888) and *Rhopilema hispidum* (Vanhöffen 1888) are two edible jellyfish species found in Iran (Karunarathne and Karunarathne 2025), with large blooms of *C. orsini* often seen along Iran's southeastern coast (Authors' observations). However, mass production has not yet occurred; therefore, these species also hold promising potential for export from Iran, alongside *C. perezi*. Exporting processed jellyfish directly from Iran to China would generate higher profits than sending them through a middleman like Pakistan.

A detailed comparison of the three variable importance visualizations shows clearly that using a weighted ensemble approach is advantageous (Ren et al. 2016; Asrol et al. 2023). The separate models—ANN, GAM, and Random Forest—show considerable and often conflicting differences in how they assess which environmental and fishery factors are most significant. For example, the Heatmap and Ladder plot reveal major differences: Random Forest ranks pH as extremely important (score ~ 70) while GAM and ANN nearly overlook it. At the same time, factors like Salinity and Dissolved Oxygen (DO) have negative importance in Random Forest, pointing to complex or unstable relationships in that model, though others rate them as moderately to highly important. This inconsistency emphasizes a key drawback of depending on a single modeling approach, as the "key drivers" identified could vary widely with different algorithms, leading to management insights that may be unreliable or skewed (Hashemi et al. 2025; Hashemi 2026).

The Weighted Ensemble model effectively resolves these contradictions by combining the predictions from all three main models, giving priority to those with lower errors (higher reliability) (Ren et al. 2016; Asrol et al. 2023). The ranking shown in the "Top Variables" chart offers a stabilized and agreed-upon list of influences. Notably, it identifies Catch as the most important factor, followed by environmental conditions such as T. C. U, NH_3, Salinity, DO, and Temperature—all of which logically relate to jellyfish ecology. By reducing the extreme views of separate models (for instance, decreasing the overemphasis Random Forest placed on pH), the ensemble delivers a stronger, more balanced, and ecologically relevant outcome. This shows that the ensemble approach is not just a technical task but a crucial process to gain trustworthy and actionable information for managing the banana jellyfish fishery, ensuring that management strategies are based on a comprehensive and statistically valid understanding of the system's key influences (Hashemi 2026).

The ensemble approach is the best choice because it addresses the main shortcomings of individual models (Ren et al. 2016; Asrol et al. 2023): their unpredictability and bias. The separate models (ANN, GAM, and RF) gave very different importance scores. For instance, the pH scores varied from 0.0 to 70.1 and Salinity scores went from − 1.4 to 11.1. The weighted ensemble combines these differing results by focusing on models that have lower prediction error (RMSE). This leads to a consistent ranking of factors (for example, Catch: 25. 2, T. C. U: 13.7, Salinity: 11. 0) that is meaningful in an ecological sense and strong in terms of statistics, providing insights that are more trustworthy than what any single model could offer.

Looking at the methods used, this research shows that ensemble modeling can successfully bring together various data sources and nonlinear connections, creating a flexible framework that can be used in other jellyfish fisheries around the world that lack sufficient data. Future efforts should prioritize ongoing observation paired with flexible management, where combined predictions could help adjust fishing limits. We suggest: (1) creating a local monitoring system that includes constant sensor usage for important factors (temperature, pH, dissolved oxygen), (2) setting up a platform that provides current Catch Per Unit Effort predictions using the combined method, and (3) starting community workshops to collaboratively design measures for controlling fishing efforts based on model predictions.

Conclusion

This research lays the groundwork for understanding the banana jellyfish (*Catostylus perezi*) fishery in the northern Oman Sea, examining how CPUE relates to important physical and chemical factors. The results show that the fishery operates only during specific seasons, with jellyfish blooms and fishing limited to the monsoon and post-monsoon times. The study points out that water temperature, pH, and dissolved oxygen are the most important factors for abundance, while also indicating high harvest levels that could suggest over fishing

highlighting the critical need for management based on scientific evidence. In terms of methods, this research shows that using weighted ensemble modeling is more effective than single-model methods for understanding the complex, non-linear relationships found in jellyfish fishery ecology. The ensemble approach successfully combined the advantages of different algorithms (GAM, RF, and NN) to better identify the key environmental factors. Together, this research provides an essential scientific baseline for local management and serves as a valuable framework for future research. It clearly shows the importance of shifting from standard fish assessment models to creating specific approaches that consider the unique biology and blooming behavior of jellyfish, ensuring their responsible use and the protection of marine environments.

Declarations

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Author Contribution

Mastooreh Doustar: Investigation, Writing – review & editing, Visualization, Supervision. Seyed Ahmadreza Hashemi: Investigation, Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. Elmira Erfanifar: Software, Formal analysis. Paria Akbary: Investigation, Formal analysis, Data curation, Conceptualization.

Conflict of Interest

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

Ethics declaration

Not applicable

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Figures

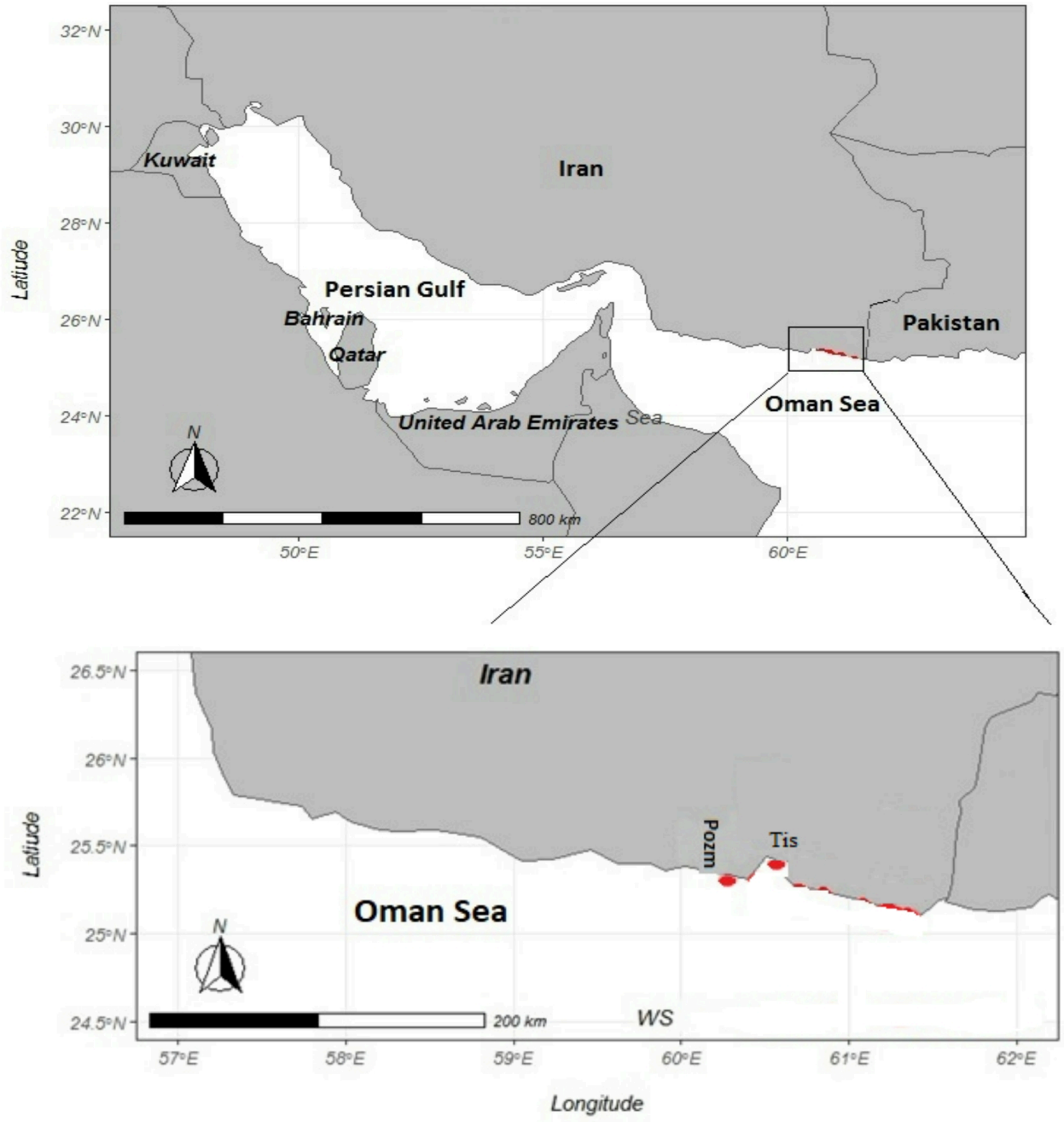


Figure 1

Sampling stations for Banana jellyfish (*C. perezi*)Species along the northern coasts of the Gulf of Oman.

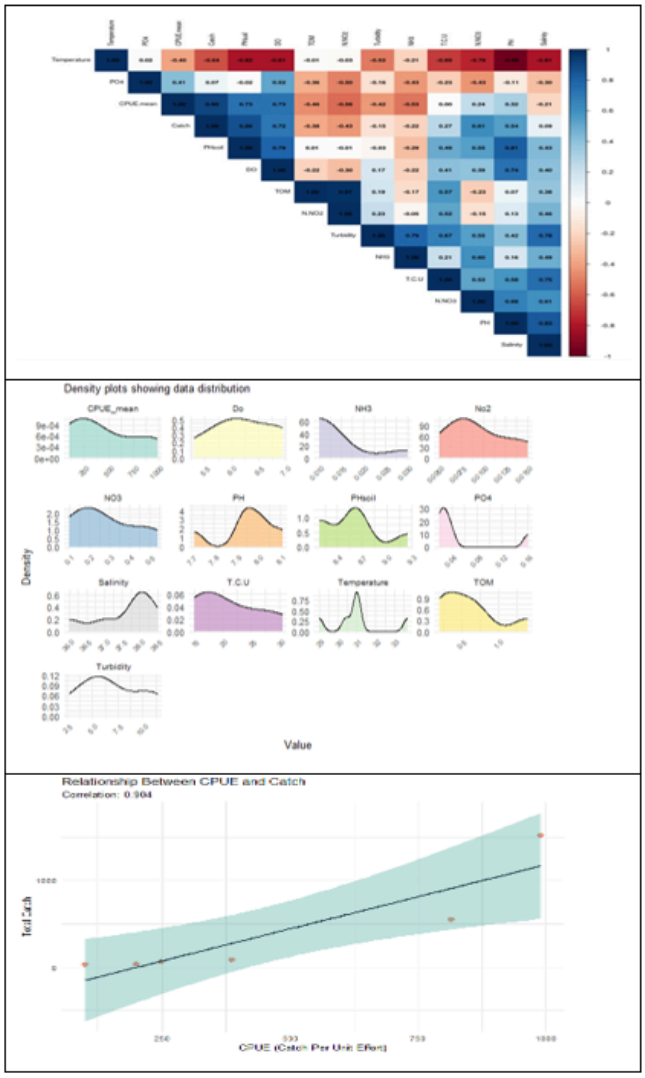


Figure 2

CPUE and catch of Banana jellyfish (*C. perezi*)Species and environmental parameters along the northern coasts of the Gulf of Oman.

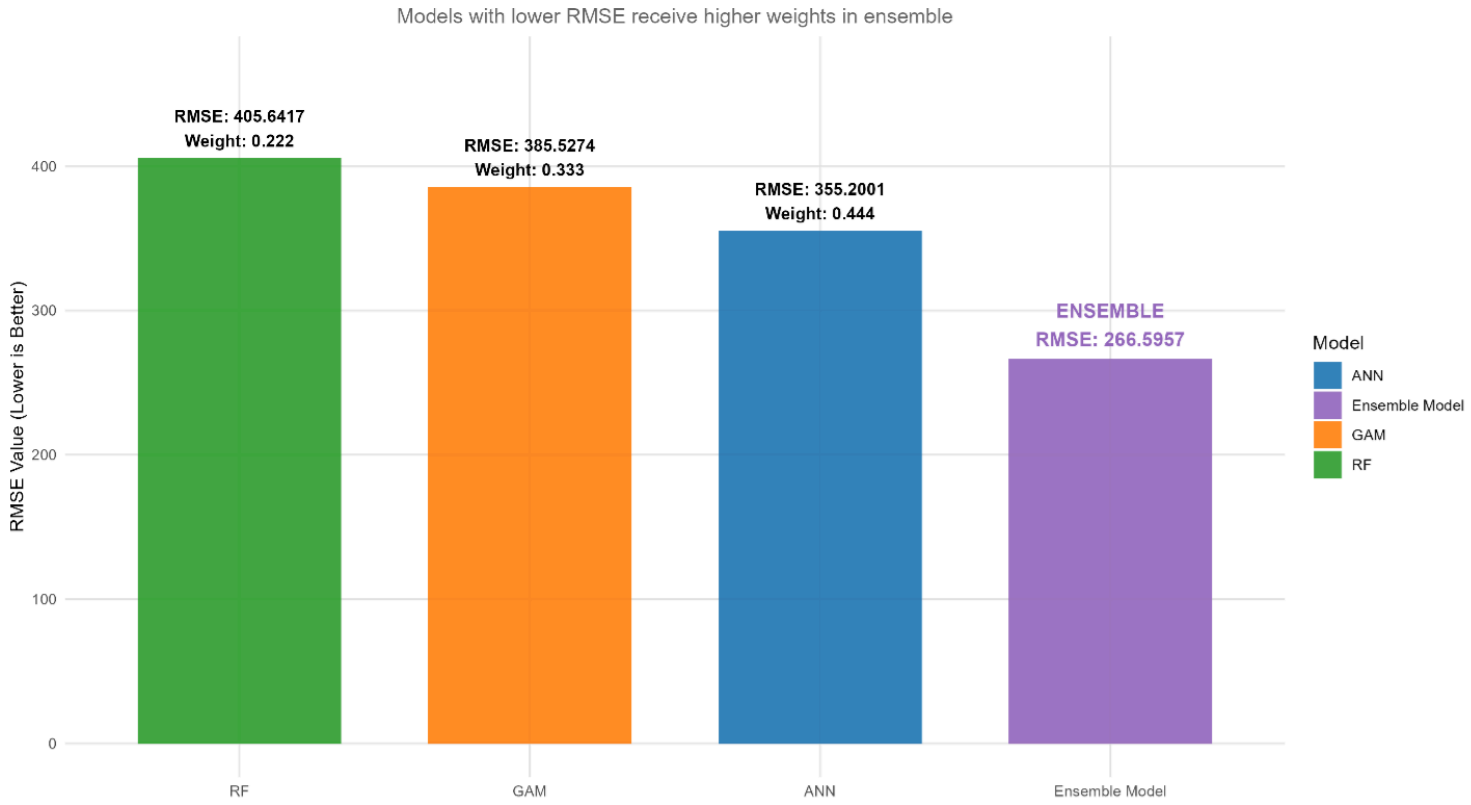


Figure 3

RMSE of four individual models for Banana jellyfish (*C. perezi*) Species along the northern coasts of the Gulf of Oman.

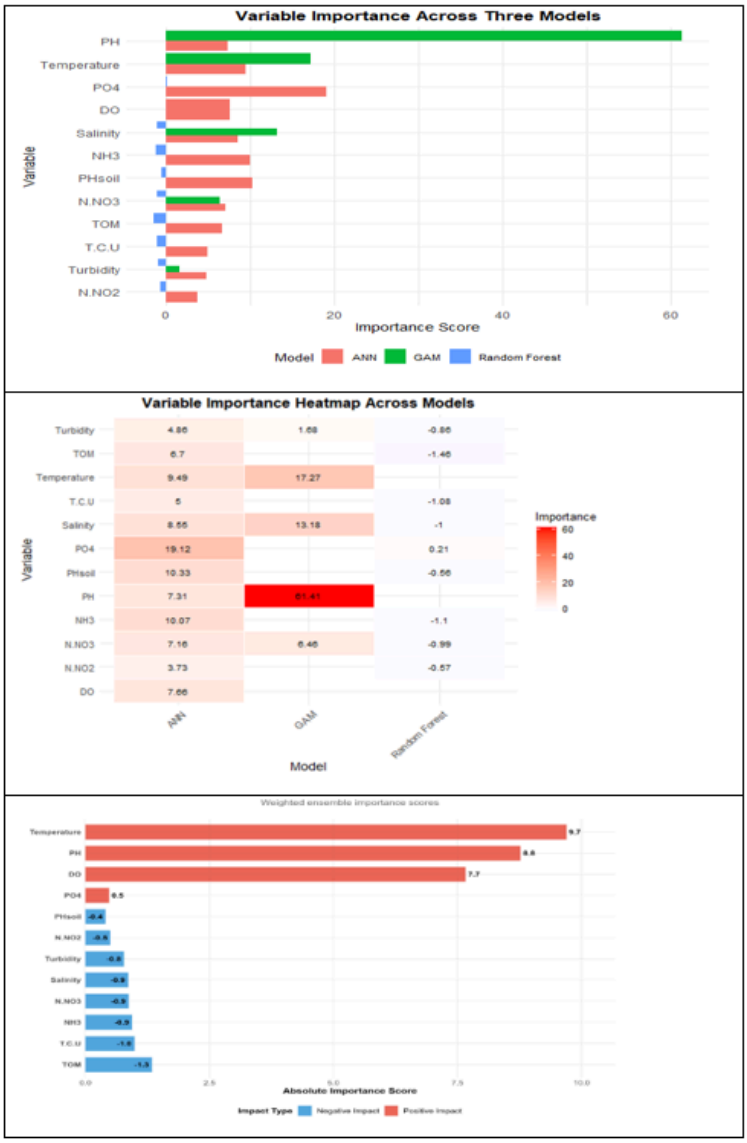


Figure 4

Heatmap of variable importance scores from four individual models and the most variable for Banana jellyfish **(***C. perezi***)** Species along the northern coasts of the Gulf of Oman.