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Original Article

Modelling the spatial distribution of the yellowfin tuna, *Thunnus Albacares* in the Persian Gulf using a fuzzy rule-based classification

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Abstract: Yellowfin tuna, *Thunnus albacares,* are the most important ecological and economic fishes in the Persian Gulf. In recent decades, their populations have faced overfishing, environmental problems and climate change. In this study, using some environmental variables affecting the habitat of tuna fish, i.e. sea surface temperature at night and day, reflection of 645 nm wavelength as a water turbidity, angstrom view of aerosol 443 to 965 nm, aerosol optic thickness at 869 nm, organic and inorganic particle carbon, photosynthetic active radiation, absorption by phytoplankton at 443 nm and chlorophyll-*a* concentration from 2002 to 2018, on the spatial distribution of yellow-fin tuna has been modelled by fuzzy rule-based classification. Over the years, the variables had different degrees of importance in the models. There was a great variation in the spatial distribution of the species from year to year.

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Introduction

Aquatics are the largest natural wealth of the Persian Gulf, if we do not consider oil reserves in this region. In fact, fisheries is the most widespread profession in the area and the economy of the region is dependent on the Persian Gulf ecosystem after oil (Alavian Petroody et al., 2013). The tuna fish population, as the commercially important species, has declined in the Persian Gulf (Sadeghi, 2001). Overfishing (Worm et al., 2009), climate change (Cheung et al., 2008; Klein et al., 2017; Cheung and Oyinlola, 2018) and pollution (Moran et al., 2011) are amongst the factors that decreased their stocks especially in closed and semi-closed ecosystems.

Management of aquatic resources needs information about behaviour of species and environmental factors affecting distribution of aquatics such as temperature (Guillen et al., 2014), salinity, turbidity (Pekcan-Hekim., 2007), sea surface temperature and chlorophyll-*a* (Putri et al., 2018). Often, comprehensive information is needed for management purposes. Thus, access to such information is possible through satellite remotely-sensed data (Chassot et al., 2011). This information helps to make predictive models to forecast future status of species. Such models are beneficial in assessing the vulnerability of endangered species (Miguel and Santos, 2000; Amiri et al., 2017).

There are many numerical ways to predict the future status of ecosystems, including time series (Coro et al., 2016; Amiri et al., 2018), neural networks (Kim et al., 2012) and fuzzy logic (Nishidaa et al., 2007). Among them, nonlinear methods can deal with uncertainty problems. What distinguishes fuzzy logic from other predictive methods is the knowledge of human experts that can be set in some rules to solve complex real-world problems (Riza et al., 2015).

This study investigated the distribution pattern of the yellowfin tuna, *Thunnus albacares*, in the Persian Gulf using a fuzzy rule-based classification. This species is pelagic, distributing in tropical and subtropical seas except the Mediterranean Sea. It feeds on fishes, crustaceans and squids. Its maximum length and weight reach to 150 cm and 200 kg, respectively (Eagderi et al., 2019). Yellowfin tuna is an ecologically and commercially important species and

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Table 1. The importance of each environmental parameter in the studied years. Refer to the text for the abbreviated terms of the table. No model was made in 2017 and 2018 due to the lack of enough data.

	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	mean
PIC	16.04	0	40.1	83.37	0	0	0.24	9.486	30.3947	4.9333	7.031	0.7931	96.546	72.287	12.24	24.89740667
r645	0	72.176	0	59.45	77.37	34.1932	24.933	82.219	97.3244	10.0628	81.017	42.8922	2.857	100	0	45.63297333
poc	16.568	11.45	17.884	0	16.51	20.0841	26.511	40.95	16.4405	0	37.196	1.2974	89.894	33.292	79.79	27.19113333
SSTD	51.971	26.93	22.774	100	49.48	82.6564	100	80.236	3.1329	4.3196	59.415	18.6374	5.892	3.617	66.2	45.01742
SSTN	47.422	14.73	25.682	19.35	43.65	63.2712	79.718	100	0	100	64.238	21.8098	0	0	54.41	42.2854
PAR	100	100	100	68.52	100	100	75.842	88.895	31.2473	64.777	79.988	100	22.288	26.671	55.74	74.26455333
Chl	26.59	24.066	24.405	22.41	15.83	16.6738	22.936	48.548	26.8063	0.1347	33.719	0	76.685	77.928	63.13	31.99078667
Phy	9.952	26.789	47.205	27.66	34.5	22.4875	26.584	57.277	0.1412	0.9107	24.102	9.4786	98.682	62.906	100	36.57833333
a869	39.731	5.471	2.224	58.69	15.73	0.6543	0	0	100	26.5269	0	12.9175	9.676	63.029	22.35	23.79998
a443	35.1	12.477	30.949	89.76	37.3	14.1703	6.592	28.521	53.3986	15.0026	100	7.4689	100	81.545	64.77	45.13696

one of the near-threatened species in the Persian Gulf and the world (Eagderi et al., 2019).

Materials and Methods

Data sets: The coordinates of the presence points of yellowfin tuna were downloaded from the GBIF site (Global Biodiversity Information Facility, 2017). The environmental data of all oceans were obtained from the website of the Modis project (modis.gsfc.nasa.gov) of NASA. The environmental data were reflection in 645 nm (r645, sr^{-1}) as a surrogate of turbidity (Chen et al., 2007), angstrom view of aerosol (965-443 nm, a443), aerosol optics thickness in 869 nm (a869), organic and inorganic carbon particles (PIC, POC, mol m^{-3}), photosynthetically active radiation (PAR, Einstein m^{-2} day^{-1}), the absorption of light by phytoplankton in 443 nm (Phy, m^{-1}), sea surface temperature at day and night (SSTD, SSTN, °C) and chlorophyll-*a* concentration (Chl, mg m^3). The annually-averaged data was in network common data form (.nc) format. Data were transformed to raster format using the package raster in R3.5.1 and were stacked.

Statistical analysis: We used Ishibuchi's method based on hybridization of GCCL and Pittsburgh (Riza et al., 2015) to model effects of environmental parameters on the presence or absence of yellowfin tuna. All fuzzy methods were performed using the package frbs in R. To avoid overfitting, a Monte Carlo cross-validation was used (Kuhn and Johnson, 2013). Seventy five percent of the data were randomly selected as the training data and the rest as the testing data. The selected 75% of the training data was used for modelling for 25 times. The performance of the model was examined using the area underneath of the ROC chart, accuracy and the Cohen's Kappa statistic (Kuhn and Johnson, 2013). The importance of each environmental factor, as a predictor in the model, was examined using the function varImp() of the package caret in R. To examine the relationship between independent variables, a Pearson's correlation coefficient was used. The plots and the maps were drawn using the dismo packages in R3.5.1.

Results

The average of the importance of different environmental parameters during 2002-2018 indicated that among the 10 variables, PAR was the most important factor influencing the presence of this species. At the second and third degrees, water turbidity and angstrom view of aerosol were the important factors influencing the distribution of yellowfin tuna (Table 1).

PAR was the most important factor in prediction of spatial distribution of yellowfin tuna in 2002, 2003, 2004, 2006 and 2007 (Table 1). The maximum correlation among the independent variables were belonged to those of PAR and sea surface temperature at night. In 2013, PAR was also the most important predictor in the model with the highest correlation was found between PAR and SSTD.

In the years 2005 and 2008, SSTD was of the highest importance in the model. The greatest correlation was found between SSTD and PIC, and

Table 2. The performance of the fuzzy model in 2002-2018.

Year	Accuracy	Kappa	Year	Accuracy	Kappa
2002	0.9438	0.8875	2010	0.9208	0.8417
2003	0.9609	0.9216	2011	0.9692	0.9366
2004	0.9732	0.9464	2012	0.9655	0.931
2005	0.8235	0.6483	2013	0.9568	0.9139
2006	0.9723	0.9444	2014	1	1
2007	0.9938	0.9876	2015	0.8000	0
2008	0.9885	0.977	2016	0.8571	0
2009	0.9733	0.9467	2017	-	-

Table 3. The parameters used in the model. The data source of the all parameters was modis.gsfc.nasa.gov. Temporal resolution of the data was annual with a 9-km spatial footprint.

Environmental variables	Abbre.	Unit
Reflection is 645 nm	r645	sr^{-1}
Sea surface temperature at day	SSTD	°C
Sea surface temperature at night	SSTN	°C
Angstrom view of aerosol 443-965nm	a443	nm
Aerosol optics thickness in 869nm	a869	nm
Particles Organic carbon	POC	mol/m^3
Particles inorganic carbon	PIC	mol/m^3
Photosynthesis active radiation	PAR	$Einstein/m^2/day$
Absorption of light by phytoplankton in 443nm	Phy	m^{-1}
Chlorophyll-a Concentration	Chl	mg/m^3

between SSTN and aerosol optics thickness in 869 nm in those years, respectively.

In 2009 and 2011, the SSTN the most important predictor of the model. In those years, the greatest correlations were found between SSTN and POC, and between SSTN and PAR, respectively. In 2010, a869 was of the highest importance in the model. The greatest correlation was found between POC and Phy.

In 2012 and 2014, a443 was of the highest importance in the model, and a869 had the highest correlation with turbidity. In 2015, water turbidity was the most important parameter of the model with the greatest correlation was found between POC and PAR. In 2016, Phy had the highest importance in model.

The most probable presence of tuna fish in the Persian Gulf was found in 2010, 2014, 2015 and 2016. No model was made for the Persian Gulf in 2017 and 2018 due to lack of enough data (Table 1 and Fig.1). The Kappa's statistic in most years was >0.8 and in one case (2005) was <0.8. The Kappa's statistic was zero in 2015 and 2016 (Table 1). Accuracy was >0.8 in all studied years (Table 2).

The fuzzy logic model predicted high variation in probability of presence of *T. albacares*. No clear trend was discernable in spatial distribution of the species over time. From 2000 to 2010, the middle part of the Persian Gulf had the highest probability of presence of this species. After 2014, an increase in probability of presence of yellowfin tuna was found in the region with all parts of the Persian Gulf was predicted have to highly probable of presence of this species.

Discussions

Fishes are poikilothermic animals and their life history follow the variation of several environmental parameters controlling their biology including seasonal migration and presence in any given place (Gunarso, 1985). Environmental parameters interact to each other causing positive or negative synergistic effects that are finally being reflected in behaviour (Rezagholinejad et al., 2016). The present study, predicted spatial distribution of an economically important fish in the Persian Gulf using the distributional data of the species in other parts of the world.

The present study found great variation in the probability of presence of yellowfin tuna. Although

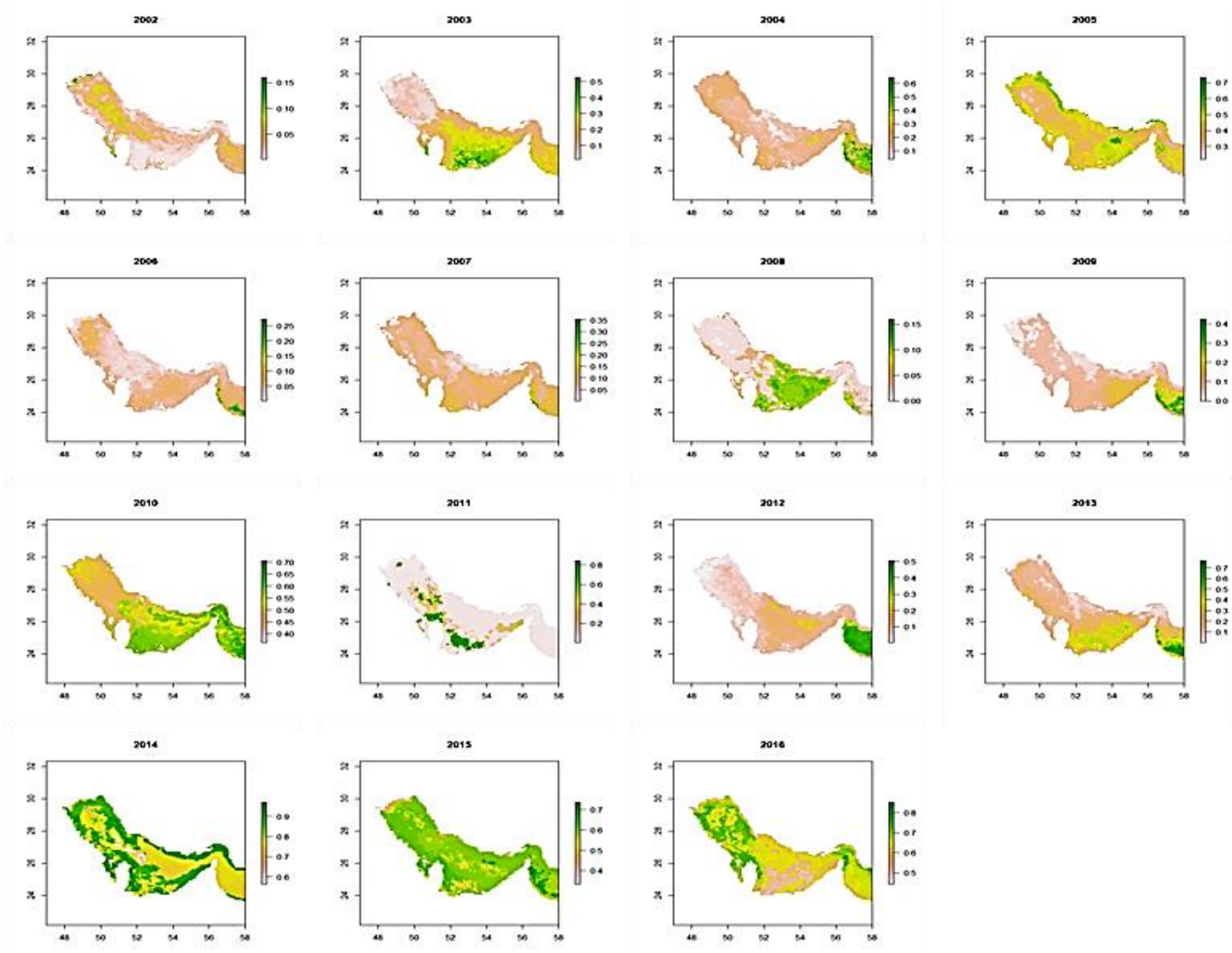

Figure 1. The predicted probability of presence of yellowfin tuna in the Persian Gulf in 2002-2018.

the middle area of the Persian Gulf were predicted to had the greatest probability of presence before 2010, an increase was found in the area of the Gulf that had a high probability of presence of this species after 2010. In later years, aerosol and turbidity were the environmental parameters that had the greatest importance in the models. This may suggest that those parameters may have had correlation with dust storm and enrichment of the Persian Gulf with the minerals carried by the storm (Poorbagher and Eagderi, 2017).

In years 2003, 2004, 2006, 2007 and 2013, PAR had a high correlation with sea surface temperature at day and night indicating its increasing effect on the sea surface temperature. A study shows that there is an inverse relationship between sea surface temperature and chlorophyll-*a* (Nurdina et al., 2013). Therefore, this may explain decrease or limited presence of this fish in the Persian Gulf.

Our study (Nishidaa et al., 2007) indicated that fuzzy rule-based modelling can successfully predict spatial distribution of species where the dependent variable is binary. There are many fuzzy rule-based models that are implemented in R. The package frbs provides various method that enable modelling both categorical and continuous data.

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