Fish Modeling and Deep Learning for the Lakshadweep Islands

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Introduction. Of the several ocean-related activities, fisheries is a major industry in the coastal states of India, employing millions of people and contributing to 1.1% of GDP and 5.3% of agricultural GDP. Globally, the Indian fishing industry is the third largest in the world. The total marine fish production is around 3 billion metric tons. Indian waters contain about 2,500 species of finfishes and shellfishes. Among these, there are about 65 commercially important species or groups. In 2004, 52% of these commercially important groups were pelagic and midwater species. In 2006, over 600,000 metric tons of fish were exported, to some 90 countries, earning over $1.8 billion [3]. Increased demand for fish, coupled with unsustainable fishing practices lead to over-exploitation and fast depletion of fish stocks. Coastal fisheries and aquaculture stocks often thrive on very specific water conditions. Building capabilities for coastal ecosystem forecasting will help ensuring and managing the survival and reproduction of healthy stock. Without sustainable fisheries management and conservation practices in place, the bounty of the ocean will not last much longer.

We first compile a comprehensive literature survey to review the status of fish modeling in the coastal oceans. Then, focusing on the Lakshadweep islands in India, where the main fishery is tuna, we complete a series of data-driven ocean-ecosystem simulations and analyses, using fish catch data [4] and our modeling capabilities [1, 9, 2]. We utilize the new capabilities of our MSEA\textsc{s} primitive equation ocean-ecosystem modeling system [6, 8, 5] to capture the complex oceanic phenomenon in the region of interest, and a tuna fish model based on SEAPO\textsc{dym} [7]. We also complete sensitivity analysis based on a Finite-Volume Framework [10]. Our modeling software can provide coastal ecosystem predictions for fisheries management, allowing sustainable management of fish stocks as well as identification of probable fish location. Such modeling efforts could help improve practices from a standpoint of sustainability and efficiency.

Fish Modeling Methodology. We use the spatial ecosystem and population dynamics model (SEAPO-DYM), which is based on Advection-Diffusion-Reaction (ADR) formulation that focuses on tuna spatial population dynamics [7]. It couples low-trophic-level (LTL) and high-trophic-level (HTL) biological models. The MSEA\textsc{s} primitive equation model is run coupled with a LTL biogeochemical model, to provide estimates of physical state variables such as, velocity fields ($\mathbf{u}$), temperature field ($T$), etc.; and primary production ($P$) estimates. The primary production acts as a source for the forage ($F$), after taking into account the recruitment time and mortality, given by source, $S = \frac{1}{\lambda}P \exp^{-m_r T_r}$, where $\lambda$ is the mortality, $T_r$ is the recruitment time, and $m_r$ is a loss coefficient. Thus, forage is governed by,

$$\frac{\partial F}{\partial t} + \nabla.(\mathbf{u}F) - \frac{1}{Pe} \nabla^2 F = -\lambda F + S \tag{1}$$

Tuna tends to favor certain temperature ranges and high food concentration. Thus habitat index, given by $I = g(F)\phi(T - T_o)$, acts as a spatial field which defines the favorability of location for fishes. Gradients of the habitat index could help define the movement of the fishes, which is captured by defining effective advection velocities, $A_x = u + \chi \frac{\partial I}{\partial x}$ and $A_y = v + \chi \frac{\partial I}{\partial y}$. The population density ($P_{den}$) of tuna is again governed by an ADR equation with the effective advection,

$$\frac{\partial P_{den}}{\partial t} + \nabla.(A P_{den}) - \nabla.(D \nabla P_{den})F = -Z(I)P_{den} + R \tag{2}$$

where $D$ is the diffusion coefficient, $Z(I)$ is a habitat index dependent mortality coefficient, and $R$ is growth rate. When combined with data and deep learning, this model is capable of forecasting tuna concentration.

Data-driven modeling and learning for the Lakshadweep Islands. We learn from fish catch data for four islands, Agatti, Kadmat, Kavaratti and Minicoy, in the Lakshadweep archipelago. The data was collected over a span of four years between January 2014 to 2018 under the community-based fisheries monitoring program of the Dakshin Foundation in India. The fish catch data has various features such as date stamp, total time and fuel, fish catch, etc., which can be used to compute catch-per-unit-effort (CPUE). We focus on the month of March, 2015, and relate the changes in fish availability with oceanic processes. For example, we show in Fig. 1 that the change in CPUE value is related to upwelling and downwelling processes near the islands. We also use the fish model and deep learning to describe the tuna concentration around the islands.
Figure 1: Change in CPUE value for the islands of Agatti and Minicoy for 15th March, 2015, and the corresponding oceanic processes simulated using the MSEAS PE model.

**Conclusion.** This work will provide a comprehensive view of the current state-of-the-art in fish modeling. We will also analyse the changes in fish concentration from the collected data, by comparing it with the oceanic processes happening at the same time. We will use the implemented fish model to do further reanalysis of tuna concentration around the Lakshadweep islands in India.

**References**


