Illuminating illegal fishing through satellite imagery and vessel tracking systems

Problem statement

Fisheries play a vital role in global food security and the livelihoods and well-being of coastal populations worldwide. They provide more than 3 billion people with a principal source of protein, and up to 10% of the global population relies on fisheries for their livelihoods[1]. Thus, fisheries and fish products are essential in the fight against hunger and poverty, and enhanced efforts towards healthy fisheries are a key component of the world's sustainability agenda over the next decade. However, **each year, more than 20% of catch is lost to illegal, unreported and unregulated (IUU) fishing[2], threatening communities' food security and livelihoods and robbing governments of US $26–50 billion per year[3]**. The unreported and unregulated elements of IUU fishing, from both industrial and small-scale fleets, jeopardize effective setting of catch limits, leading to overfishing and depletion of natural resources for all[4]. IUU fishing also has been linked to organized crime and human rights violations, such as drug smuggling, human trafficking and slavery[5]. To secure the environmental and social sustainability of crucial marine resources, we need new tools that can illuminate pathways for action to reduce IUU fishing and its impact at local and global scales.

While several approaches currently are being applied to understand IUU fishing patterns, each has biases and limitations, inhibiting the development of effective management and policy interventions. Most research focuses on a widely available Automated Information System (AIS) dataset to track fishing vessels at sea and make inferences about their activities[6]. However, AIS can be turned off intentionally and its signal reception drops significantly in crowded areas, such as in high-traffic fishing grounds and near ports – potential key hubs of illegal activity[7]. Vessel Monitoring Systems (VMS) within national waters can bridge some of those gaps, but transmit less frequently than AIS and are often not publicly available. VMS is also typically only required for vessels >12 m, and AIS for vessels >15–21 m, missing most small-scale fleets, which globally contribute two-thirds of fish for human consumption[8].

Research ideas

We propose to develop an innovative AI-based algorithm using computer vision to automatically analyze satellite imagery, detect fishing vessels, and integrate AIS and VMS data to address key gaps in the understanding of IUU fishing, particularly near ports and coastal areas where industrial vessels' AIS signals drop and small-scale fleets are predominant. Inferring vessel activities from satellite imagery and vessel tracking systems can provide new insights into fishing activities and compensate for weaknesses in different data types. We will focus on three knowledge gaps that are critical to actions and policies for sustainable fisheries: 1) understanding the spatial and temporal dynamics of vessels at ports; 2) illuminating "dark vessels" that are not transmitting AIS or VMS signals; and 3) assessing the extent and activity of small-scale fleets.

We propose to focus on Peru as a case study because it has one of the largest fisheries in the world (10% of the global catch), as well as having small-scale fleets that employ 25% of the fisheries sector[9]. In 2017, Peru ratified the Port State Measures Agreement, a UN agreement that mandates port controls to prevent IUU vessels from landing their catch. However, many vessels use unofficial landing sites and private docks to escape detection. Furthermore, Peru's fisheries law provides limited management of small-scale fisheries, despite their critical role in providing food for vulnerable groups. Together, these management challenges make Peru a compelling focus for our work. At the same time, Peru is one of the few countries with available AIS and VMS data that includes tracking for some of the small-scale fleets. This level of data availability will support development of algorithms to detect vessels in satellite imagery and address key knowledge gaps.

Developing effective fisheries management requires an understanding of vessel dynamics at port, where catches are landed, and at sea,where fishing activities take place. **Within ports**, we will investigate overall usage patterns and how they are affected by events such as the implementation of port state measures. **On the water**, our analysis will help illuminate key parts of the "dark fleet", including illegal fishing. Under the Peruvian fisheries law, fishing activities are zoned by distance from shore, with a nearshore zone being reserved for small-scale fleets using manual gears. However, "dark" vessels without AIS/VMS are operating illegally there. Our proposed AI-based approach aims to illuminate these vessels. Our work can provide key insights into developing more effective fisheries management by identifying how many vessels are fishing in a given nearshore area and highlighting how much fishing effort is missed by traditional monitoring approaches. Results can feed directly into ongoing work by Stanford's Center for Ocean Solutions (COS) to make the case for greater port stewardship as well as concerted action by coastal nations to close their waters to IUU fishing.

Problem solving approach

AI offers an opportunity to enable analysis of satellite imagery at a scale and level of detail not feasible through human manual inspection. This summer, we piloted an AI-driven approach to describe the spatial and temporal patterns of vessels from satellite images. **We developed a tool to automatically analyze Planet's 3-m resolution optical daily satellite imagery and identifies shipping vessels using computer vision**. The tool was built on a deep neural network with ResNet-50 and Mask RCNN, trained on over 15,000 satellite images of vessels that are publicly available. The tool was integrated into a streamlined pipeline that fetches satellite images from Planet, reformats and reshapes images, applies an AI-based interpretation of satellite imagery, and generates a table that summarizes vessel positions and sizes in the area of interest. We applied our pipeline to an area at the port of Chimbote, Peru, and successfully described spatial patterns of vessels' location, including small-scale fleets (<15 m) without AIS/VMS.

To improve the accuracy and expand the scope and scale of our work, we will: (1) create our own training dataset that includes small-scale fleets and fishing activities, (2) improve the AI-based satellite imagery analysis to attain scale-invariant performance, (3) develop a statistical method to characterize spatial and temporal patterns, and (4) verify the findings using high-resolution satellite imagery. The new training dataset would capture features of interest, including: vessel directions based on their wakes; multiple small vessels tied together in the port for potential in-port transshipments or catch transfers; and arc-shaped wakes created by purse seiners illegally operating near coastal areas. Currently, the performance of our AI-based satellite imagery analysis depends on the size of the area of interest. We will address this issue by developing a new filter in the pipeline. Further, we will explore the possibility of improving performance by incorporating a temporal order to the images, which has not been used in current vessel detection algorithms[10]. Because individual vessel detection may be challenging at the resolution and time-scales at which images are collected, we will focus on describing spatial and temporal patterns in vessels using spatial statistics and time-series analysis. We will validate our analyses from 50-cm high resolution satellite images from Planet, which are commercially available.

We propose to combine vessel detection data with available AIS and VMS data to paint a comprehensive picture of fleet dynamics, including dark fleets. Through data fusion, we can link vessels identified in satellite imagery with AIS and VMS data, to gain additional information on vessel flag, gear type and other characteristics that will help us understand vessel behavior both at sea and at port, and potential illegal activities. We will also elucidate key gaps in currently available data and priorities for future research. Finally, we will identify what strategies, such as broader sharing of VMS data or use of super high-resolution images, have the greatest potential for improving transparency and addressing IUU fishing.

Team

Our project will be co-led by **Fiorenza Micheli** (Professor of Marine Science, Co-director of COS), **Jim Leape** (Senior Fellow at Woods Institute for the Environment, Co-director of COS), **Serena Yeung** (Assistant Professor of Biomedical Data Science), **Trevor Hastie** (Professor of Statistics), **Elizabeth Selig** (Deputy Director of COS), **Colette Wabnitz** (Research Associate at COS), and **Shinnosuke Nakayama** (Data Research Scientist at COS). The interdisciplinary team encompasses ocean management, fisheries, computer vision, AI, and statistical expertise necessary to undertake our ambitious project.

Budget

We request a total of $75K. Salary and fringe: $38.6K – a data scientist (15%) and one research assistant (15 hours per week over 10 weeks each quarter and 40 hours per week over 10 weeks during summer quarter); Consultant agreement: $500 – in-country expert on Peruvian fisheries; Computing/Miscellaneous: $35.9k – computing costs and high resolution imagery.

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