SmartPass

An Innovative Approach to Measure Fishing Effort Using Smart Cameras and Machine Learning

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Introduction

Marine recreational fisheries across the United States provide significant social and economic value to communities around the nation. Furthermore, recreational harvest of many species matches or exceeds commercial harvest, yet commercial fisheries are monitored much more closely. Sustainable management of recreational fisheries depends, in part, on robust catch data, and improvements are needed to modernize data collection systems and increase efficiency. Here we present learnings from initial research and development of an innovative fisheries monitoring approach called “SmartPass,” which leverages shore-based cameras and machine learning[1] to provide fishery managers with near real-time estimates of marine recreational fishing effort. We also document the current capabilities of a SmartPass approach and outline future opportunities to inspire collaboration across the public and private marketplace to stimulate an ecosystem of innovation at the intersection of fisheries management, technology and conservation.

[1] machine learning – “the process by which a computer is able to improve its own performance (as in analyzing image files) by continuously incorporating new data into an existing statistical model” (Merriam-Webster)

Background

Given the importance of recreational fisheries to our nation, there is a strong need to improve fisheries data collection to ensure the sustainability of shared fish stocks and ultimately maximize fishing opportunities and societal benefits.

In 2017, it is estimated that approximately 8.6 million saltwater anglers took 202 million fishing trips generating $73.8 billion in sales impacts, $41.5 billion in value-added impacts, $24.7 billion in income impacts and supported 487,000 U.S. jobs (National Marine Fisheries Service, 2018). Despite the significant size of this fishing sector in the United States, there are still concerns about the uncertainty of total catch estimates in many recreational fisheries around the nation (The National Academies of Sciences, Engineering, and Medicine, 2017). Given the importance of recreational fisheries to our nation, there is a clear need to improve fisheries data collection to ensure the sustainability of shared fish stocks and ultimately maximize fishing opportunities and societal benefits. While data collection is challenging in any fishery, it is especially so in the marine recreational sector due to the wide spatial and temporal dispersion of fishing effort (Brownscombe et al., 2019). Fishery managers around the nation face the tremendous task of managing a limited natural resource, while attempting to generate maximum public value. These managers must make decisions tied to complex ecological and political systems, often with limited and highly constrained budgets. Management uncertainty within recreational fisheries can further complicate decision-making and is made up of two primary sources: untimely data (e.g., characterized by a significant time-lag between when the harvest occurs and when the data are available for decision-making) and inaccurate quantification of the true catch. These sources of uncertainty can lead to increased risk of over-harvesting (which impacts all fishery sectors) or more restrictive recreational harvest limits (NOAA Fisheries, 2011). Solutions are clearly needed to reduce management uncertainty and improve the science available for decision-making without exceeding fishery managers' budgets.

To address these challenges, we can look toward technological advancements such as machine learning that have been applied across numerous other fields of study to help "do more with less." The most tractable way to increase the timeliness, availability and certainty of fisheries management data within static budgets is to leverage the continual development of technologies that can help augment data collection, streamline workflows and automate the time-consuming data analytics and data management tasks. Capitalizing on the efficiencies to be gained from evolving data capture and data analysis methodologies will help the skilled staff of fishery management agencies to effectively achieve management goals and maximize the public value of recreational fisheries.

The Current Landscape of Data Collection

Fundamental to sustainable fisheries management is an accurate assessment of the total catch, which allows managers to monitor if the resource is being over- or under-harvested with respect to sustainable limits. However, the current methods for collecting this data, described in more detail below, are resource-intensive and in many cases lack the level of accuracy needed for effective management. Measuring total catch with significant accuracy becomes increasingly complex and costly in large, heterogeneous recreational fisheries. Thus, managers commonly estimate *catch rate* and *fishing effort* to calculate total catch. (Fig. 1).

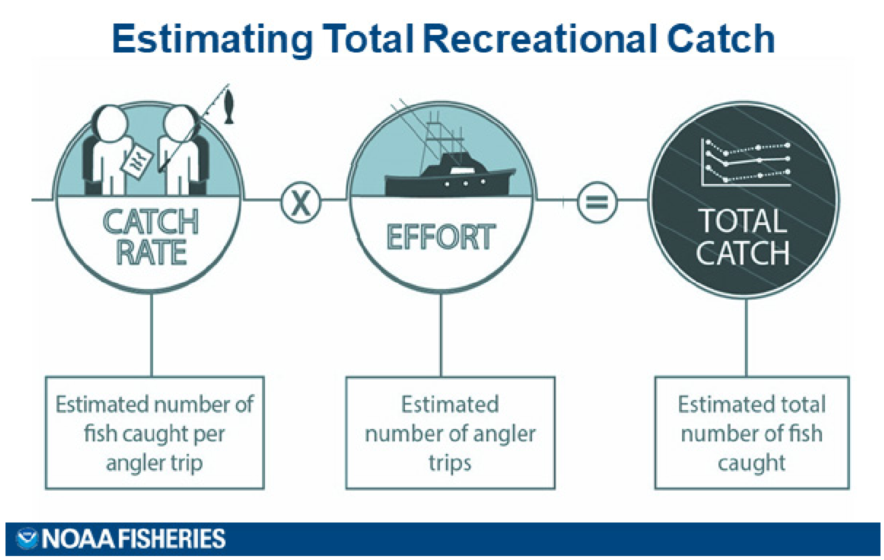

Figure 1. Basic estimation of total catch in recreational fisheries using catch rate and effort. (Source: NOAA Fisheries)

Catch rate is usually estimated by surveys administered by dockside samplers and/or by electronic angler self-reporting via mobile applications and websites. Many advances have been made over the past decade to estimate catch rate more accurately using mobile apps and state/federal surveys (via mail, phone and email). Angler self-reporting through mobile apps has provided one pathway to improving the accuracy of catch rate estimates but has encountered broad challenges tied to angler participation, sources of bias, integration with ongoing fisheries programs and meeting data-quality standards (Venturelli et al., 2017).

Fishing effort is typically estimated by mail, phone and/or email surveys to sample the general population, often supplemented with information from fishing license sales. The temporal variability, geographical spread and sheer size of most marine recreational fishing fleets render accurate effort accounting particularly challenging. As with any data collection based on sampling a population, higher variability across spatial and temporal scales introduces additional sources of error. For example, “pulse” fisheries – in which effort rapidly increases and decreases – and other “rare event” fisheries such as those pursuing highly migratory species experience high variability of effort and make it difficult for managers to produce precise catch estimates (The National Academies of Sciences, Engineering, and Medicine, 2017). These challenges, however, have given rise to innovative solutions.

To improve the timeliness and accuracy of local data collection, some recreational fishery managers have used shore-based observers to estimate effort at ocean egress points, especially during short fishing seasons and pulse fisheries. Florida’s Fish and Wildlife Conservation Commission (FWC) has employed this methodology in the South Atlantic region during recreational red snapper seasons (Sauls et al., 2017). Additionally, the Oregon Department of Fish and Wildlife (ODFW) started to use shore-based observers in 1979 with the added advantage that it provided a daily estimate of effort by the end of each day, which was much timelier than telephone based surveys that were in use by the National Marine Fisheries Service (NMFS) surveys at that time (Ames and Schindler, 2009). While these methods have improved key aspects of data collection for each of those fisheries, they also incur an opportunity cost in that the highly trained staff are not able to simultaneously provide other services and functions that they might otherwise be able to fulfill while serving as shore-based observers.

Direct enumeration of fishing effort is not typically sustainable for a year-round approach within the realities of finite budgets and staffing availability. Furthermore, there are examples from the Gulf of Mexico, South Atlantic and Mid-Atlantic fishery management regions where disparate data collection methods to estimate effort (i.e., simultaneously administered state-run surveys and the Federal Effort Survey run by NOAA Fisheries) lead to disputes among fishing sectors and state and federal fishery managers, generating mistrust in data collection and management decisions. Such disputes can lead to decision-making gridlock and if unresolved, much like other uncertainties in fisheries data, can lead to either over-harvesting or overly cautious and restrictive harvest limits. In these cases of disparate data collection methods, additional methodologies to cross-reference effort estimates would be particularly valuable.

An Opportunity

Given the current capabilities of digital video cameras and image analysis methodologies, opportunity is ripe to harness and adapt these capabilities to improve fisheries data collection. To bring these innovative opportunities to fisheries, technology providers and non-governmental organizations (NGOs) can offer support to constrained management agencies to explore, pilot, adapt and refine new technologies and methodologies. Over the past two years, Environmental Defense Fund (EDF) has been working with multiple partners and stakeholders to develop a broad concept under which shore-based cameras could be coupled with image analysis automation techniques to augment and complement marine recreational fishing effort estimates.

Given the current capabilities of digital video cameras and image analysis methodologies, opportunity is ripe to harness and adapt these capabilities to improve fisheries data collection.

Recent studies demonstrating multiple ways in which shore-based cameras can improve our understanding of recreational fisheries, including estimation of effort (Greenberg & Godin, 2015; Hartman et al., 2019; Keller et al., 2016; Powers & Anson, 2016; Schindler et al., 2015,Van Poorten, 2015), inspired a small number of technology providers and NGOs, including EDF, to explore augmenting or fully automating the effort estimation process by pairing cameras with machine learning. Research has shown that even along vast coastlines where a prohibitive number of cameras would be required to capture a majority of access points, pairing creel surveys with cameras can fill in spatial and temporal gaps between more costly, broader reaching approaches like panel surveys (in which a select panel of anglers is interviewed regularly across multiple data-collection periods), aerial access surveys (which use observers or cameras to collect fishing effort estimates from the air), and diary or logbook surveys (in which anglers record their effort and/or catch over a specific time period) (Hartill et al., 2020). It has also been shown that cameras can enhance understanding of temporal and spatial patterns of fishing effort thereby helping to refine creel survey and sampling design, improving cost effectiveness (Smallwood et al., 2012; Edwards and Schindler, 2017). Thus, the timing was right to take a shore-based camera approach to the next level, working to streamline and evolve the data workflow to optimize efficiency, cost-effectiveness and public value.

The first step in this endeavor was to connect with two technology providers, Teem Fish Monitoring and SnapIT, who began pioneering the integration of data collected by shore-based camera with machine learning processes in 2018 to monitor recreational fishing effort in Kitimat, British Columbia, a location where the recreational fishery monitoring program did not change with the significant population and fishery growth over 20 years. The team developed a camera system paired with machine learning to convert the footage of the primary boat launch into still images of vessels, greatly reducing the time for reviewers to enumerate the total number of recreational fishing vessels accessing the fishery. Ultimately, human observers reviewed 100% of the footage and provided the resulting information to local stakeholders for use in co-management of the fishery (personal communication, Amanda Barney, Teem Fish Monitoring). As technologies continue to advance and the cost of hardware continues to decrease, the opportunities are immense to similarly support evolution of fisheries data collection across the globe. With this vision in mind, the concept for a SmartPass framework was born and EDF began connecting with additional technology providers and others to expand the piloting potential.

What is SmartPass?

Working with collaborators, including Teem Fish Monitoring, SnapIT and CVision AI, EDF has been piloting the SmartPass concept since 2019, which is proving to be a promising approach for measuring marine recreational fisheries effort through the use of shore-based camera systems coupled with image recognition and machine learning. SmartPass consists of a camera system(s) with a control box (computer) that captures, records and stores video of vessels moving through a coastal bottleneck such as a "pass", river mouth or harbor, such as in Fig. 2. The data are then uploaded to a cloud-based review platform to observe and annotate (either by humans, machines or a combination of both), and a machine learning pipeline uses a suite of algorithms to perform key analytical functions such as object detection, object tracking from frame to frame and object classification. These machine learning components help to automate image review for enumeration of marine recreational fishing boats. The technology protects the privacy of individual vessels by simply classifying each as an unnamed object that is broadly classified as recreational or commercial to enable the enumeration of different vessel types traveling through the pass over a specified time series. In an initial proof of concept test of SmartPass in collaboration with Teem Fish Monitoring and SnapIT in the Gulf of Mexico, we were able to detect fishing vessels with 90% accuracy. This technology can be used to count, in near real-time and year-round, during all daylight hours (without obscuration from heavy fog or other weather), the number of recreational fishing vessels leaving a port or coastal pass. Thus, digital cameras paired with machine learning offer an opportunity to expand the scope of shore-based effort monitoring, both spatially and temporally.

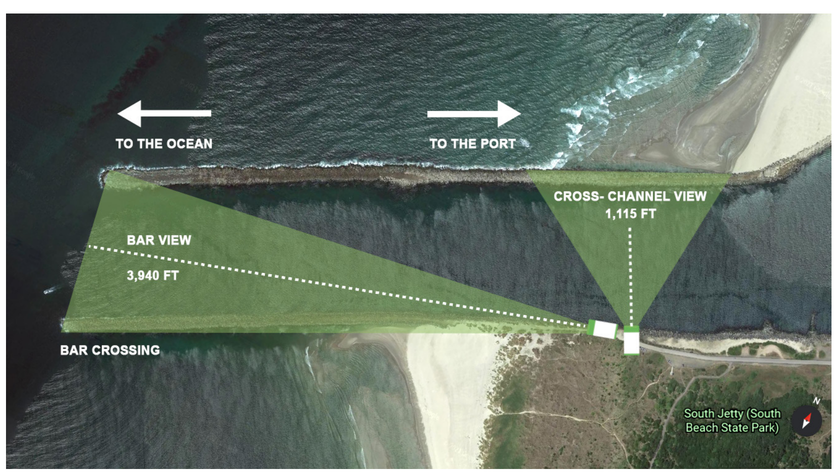

Figure 2. Diagram of the SmartPass setup in Newport, OR using one camera for the "cross-channel view" and one for the "bar view."

The SmartPass algorithm pipeline consists of three major components: vessel detection, vessel tracking and vessel classification. The detector is the function that identifies a vessel in a frame (Fig. 3). The tracker then connects tracks of individual vessels from one frame to the next and ultimately determines whether a count is made for a vessel entering or exiting the area. The classifier makes a preliminary determination of the type of vessel (e.g., recreational vs. commercial). Developing each of these components includes a human-assisted training and review element of key performance metrics before moving on to the next phase (Fig. 4). For example, during the training of the object detector, a human reviewer drew a digital box around each vessel in a series of videos to identify the presence of the target. With each new training image, the machine learning algorithm began to "learn" or identify characteristics and patterns in the image data to begin predicting targets in new datasets, therefore improving with each training dataset. The accuracy of the predictive algorithm was measured against a dataset with a known number of targets and if the algorithm did not meet an accuracy threshold, the steps were repeated. This general process of using labeled, known datasets to train the algorithm to detect and analyze data within unknown datasets was the basis for developing each of the SmartPass components.

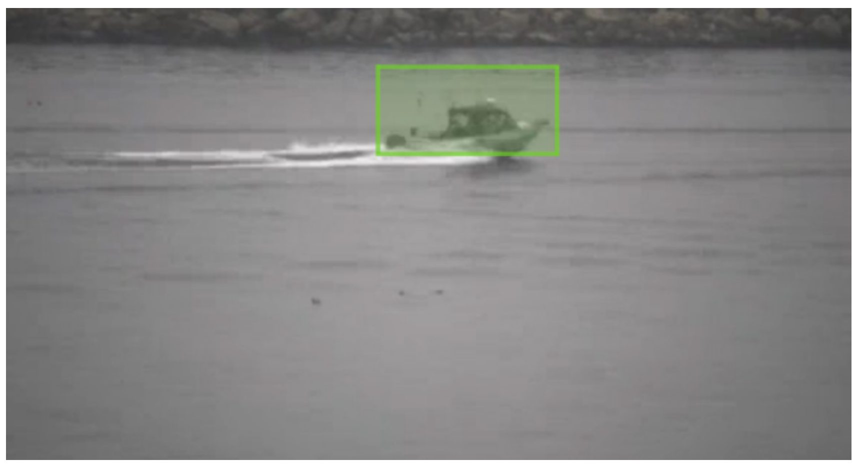

Figure 3. Recreational fishing vessel detected by the algorithm.

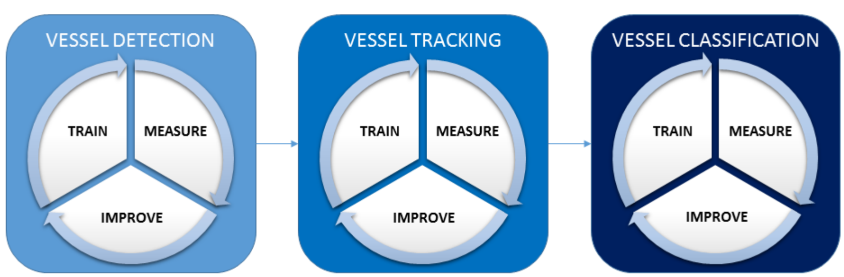

Figure 4. High level overview of the algorithm pipeline.

Where is the SmartPass Framework Most Applicable?

Given the current capabilities of digital video cameras and image analysis methodologies, opportunity is ripe to harness and adapt these capabilities to improve fisheries data collection.

The SmartPass framework was developed for application in coastal fisheries. Given the current technical specifications of affordable digital cameras that are well-suited for use in the SmartPass framework, the best candidate sites generally include smaller coastal passes, ports and harbors where vessels must move through a navigable waterway that is less than 365 m wide. The cameras currently deployed in pilot projects can identify and classify vessels up to approximately 365 m (~1200 ft or 4 football fields) from the lens. Current applications of SmartPass also require a steady power supply for video recording and reliable cellular connection for system health checks. In areas where the primary coastal pass is greater than 365 m, the total effort can still be quantified by employing more camera installations at the ports, marinas and smaller passes further inland that provide access to the primary coastal pass of interest. The use of cameras to generate recreational effort estimates works best in geographic settings with a small number of well-defined coastal passes. Camera-based monitoring can also be used to fill specific data gaps in geographies with numerous coastal access points and/or large passes when directly paired with methodologies such as dockside, telephone or mail surveys (Hartill et al., 2020).

Throughout research and piloting of the core SmartPass concept, EDF interviewed nearly two dozen subject matter experts – representing a range of state and federal management agencies and the technology provider community – to identify qualitative characteristics of potential SmartPass sites. These interviews also aimed to better illuminate how a SmartPass approach could address monitoring needs in select recreational fisheries. Experts largely agreed that the most promising sites would: 1) already have skilled staff and structures in place to run an existing monitoring and data collection program, and 2) have staff who are interested in exploring new technologies to support their work. Key success factors include collaboration among open-minded partners from both the fisheries management and technology provider communities, and clear definition of how SmartPass will directly integrate with existing data collection programs. Experts also shared that the successful rollout of newer technologies tends to be smoothest at sites where some modernization efforts such as electronic monitoring and reporting are already underway.

Foundational to the SmartPass concept is the understanding that the specific enabling hardware and software configurations continue to evolve rapidly, and there is a broad range of solutions for specific limiting factors already available at specific price points. For example, an optical range greater than the current 365 m can be obtained with a higher class of lenses and sensors for a higher price point. Solar panels or wind turbines can provide reliable power to remote locations, and a range of transmission methodologies such as cellular, satellite or private broadband networks can facilitate data transfer. In the foreseeable future, portions of the algorithm pipeline could be moved from the cloud directly onto the recording stack (i.e., the camera and computer in the video shack) allowing for the recorder to only save video segments with vessel activity, greatly reducing data storage needs and moving towards feasibility of cellular-based data transfer. Ultimately, continued rapid development of technology will reduce costs while enhancing capabilities, allowing the hardware and machine learning tools to evolve in ways that support more robust and well-informed fisheries management. It bears emphasizing that these tools are not designed to replace human staff but rather to make some discrete aspects of their jobs more efficient, thereby allowing them more time to focus on other priorities such as administering dockside surveys or collecting other data essential to fisheries management.

Case Study

OREGON, USA

The most robust, on-going pilot of the SmartPass concept is in the state of Oregon, in partnership with the Oregon Department of Fish and Wildlife (ODFW) and the technology provider CVision AI. ODFW has been a pioneering state fishery agency in the use of cameras to bolster estimates of marine recreational fishing effort, a methodology that started with shore-based observers. The timeliness and accuracy of data afforded by shore-based observers was a crucial development in successfully managing their highly regulated and economically important fisheries such as coho and Chinook salmon and Pacific halibut. However, this methodology did not monitor fishing effort throughout the entire day and relied on estimated fishing effort during the unmonitored hours. Thus, ODFW sought to evolve their data collection paradigm in 2007 by testing the use of cameras together with human video reviewers to increase monitoring hours and potentially decrease costs. They found that video monitoring could increase observer coverage to roughly all daylight hours, decrease reliance on estimates, and reduce costs of estimating recreational fishing effort by more than 60% annually when compared with the previous methods (Ames and Schindler, 2009). ODFW has since fully transitioned to this methodology at nine of the eleven major ocean passes in the state.

ODFW's methodology using shore-based cameras provided an important foundation of existing infrastructure, hardware and institutional knowledge upon which to build a SmartPass pilot. Throughout the pilot, the team has followed a "build-measure-learn" process to produce a rapidly prototyped product that can be quickly developed, tested and systematically improved. The first step in this process was working through the idea phase with ODFW and CVision AI to understand ODFW's current effort estimation methodologies, identify pain points where efficiencies could be made, and map out pathways to incorporate advanced techniques into fisheries management. In many ways this initial phase was the most important because it helped ODFW and CVision AI envision a minimum viable product that could augment ODFW's existing process without taking years to build and test.

The team selected two of the busiest recreational fishing ports to pilot the SmartPass concept. Both SmartPass digital camera systems were installed during the summer of 2020 at locations that already had ODFW's analog video cameras, enabling direct comparison of the methodologies, and were mounted on a long pole to elevate the camera's viewpoint. Each system also leveraged an existing cinder block "video-shack" to house the computer and keep the equipment secure, and a steady power supply. Each two-camera system (Fig. 5) cost approximately $7,500 for the hardware and build out; additional costs included monthly fees for data storage and algorithm processing on the cloud. At one site, agency staff swapped out the data storage USB every two weeks and uploaded the data to a cloud-based server via computers at the nearest ODFW office. The other site was connected to WiFi and therefore data transfer to the cloud could be scheduled for any frequency based on the needs of ODFW, which in this case was weekly.

Figure 5. Example of two-camera system. Each imaging sensor was rated for operating temperatures between 0 and 45 degrees Celsius, with a storage temperature between -30 and 60 degrees Celsius, and was powered via Ethernet which allows for the sensor to be deployed 100 meters away from the recording computer without any extenders. Each sensor and associated optics were installed in a waterproof housing which protected against dust and sand; these protections were critical, given the damp, cold weather that dominates the Oregon coast for much of the year.

The installations were performed by one EDF staff and one ODFW staff with only remote assistance from CVision AI. This importantly demonstrated that the hardware needed to support a SmartPass framework can be easily installed by customers without the logistics and costs from installations performed by the tech provider. The simplicity of the installation was a key driver of success during all the social disruption of COVID-19 and an important factor for managers to consider with adoption of any new technology.

Using the rapid prototyping process, the team developed a fully functional review platform designed to improve the efficiency of video review. The review platform included a detection algorithm to detect vessels and a classifier algorithm to classify vessels as recreational or commercial. The team trained and developed these algorithms using video from the Newport installation recorded in August 2020. A significant portion of the recorded video was impacted by moderate to heavy fog, during which the algorithms struggled to detect and classify vessels with high confidence. A fog detection algorithm identified periods of moderate to heavy fog, which helped reduce these spurious vessel counts by more than 90%. However, the team determined that in the initial phase of the pilot, enumeration and classification of vessels using these algorithms should be limited to days with no fog or light fog, which was approximately 75% of the reviewed hours in August. Staff at CVision AI reviewed this portion of the video, manually counting 1,758 examples of vessels moving through the cross-channel view in Newport. The detection algorithm was then tested against this video dataset (Table 1). From the 1,758 examples of vessels, ODFW staff reviewed and classified 1,340 vessel images as recreational or commercial. A random sample of 90% of this data set was used to train the classifier algorithm and the remaining 10% was used to generate performance metrics for the classifier algorithm (Table 2).

Table 1 Results from the performance evaluation of the detection algorithm

Number of Vessels Entering Port		Number of Vessels Exiting Port	
Human estimate	1015	Human estimate	743
Algorithm estimate	1059	Algorithm estimate	777
Absolute error	44	Absolute error	34
Average error	0.043	Average error	0.046

Table 2 Results from the performance evaluation of the classifier algorithm

Number of Recreational Vessels		Number of Commercial Vessels	
Human estimate	15	Human estimate	119
Algorithm estimate	14	Algorithm estimate	118
Absolute error	1	Absolute error	1
Average error	0.067	Average error	0.008

Throughout this first year of the pilot, the team of collaborators successfully conceptualized, built, installed and tested the three major components of the system: the recording hardware, the review platform (Fig. 6) and the machine learning analysis pipeline. The next phase of work will focus on addressing user feedback to prioritize and improve specific capabilities of these systems, including refinement of the algorithms to enumerate vessels that enter the ocean by crossing through the bar view, as well as a step-by-step comparison of the SmartPass approach versus the existing methodology. We will also perform an analysis of one-time and recurring costs associated with applying this range of solutions to estimate a cost recovery time frame. All elements of this system have been designed to be modular and easily scaled such that they can be customized to fit a broad range of data collection needs and budgets.

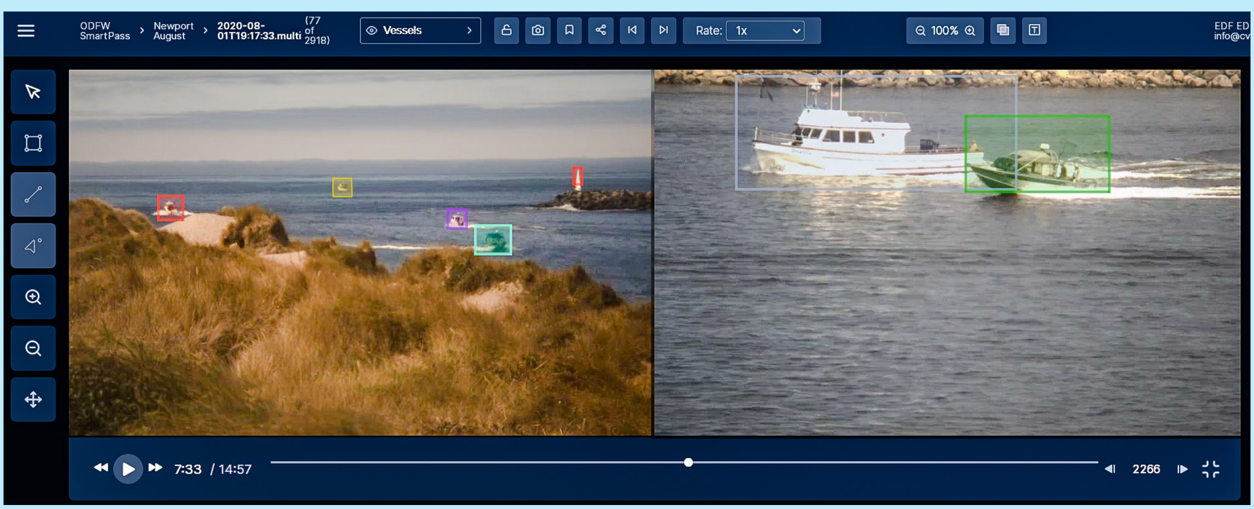

Figure 6. Snapshot of the review platform designed for the Oregon pilot. Shown here is the pass at Newport, OR with the bar view on the left and the cross-channel view on the right, and bounding boxes around the detected fishing vessels.

Looking Forward

There is immense potential to improve estimations of fishing effort in fisheries around the globe – not only for recreational fisheries but also for commercial and small-scale fisheries with similar data needs.

Given the modular and customizable nature of the SmartPass approach, there is immense potential to improve estimations of fishing effort in fisheries around the globe – not only for recreational fisheries but also for commercial and small-scale fisheries with similar data needs. To this end, EDF is working with additional partners to test the utility and applicability of the SmartPass concept across different technology providers, countries and fishing sectors. For example, a pilot study is ongoing in Indonesia's blue swimming crab fishery (Fig. 7). This commercial fishery comprises many small-scale fishing vessels that exert a high level of effort distributed widely throughout the Indonesian archipelago. Due to the absence of dockside survey methodologies, this pilot incorporates a mobile catch reporting application to collect estimates of catch per vessel into the SmartPass system to improve total catch estimates for a single port in the Lampung province. Design and implementation successes in Indonesia are building upon successes and learnings in Oregon, and vice versa, helping to advance this field as a whole. In turn, more accurate and timely data support robust management and can help to foster improved sustainability, food security, resilience to disturbances (e.g., climate change, pandemics, etc.), and sustained livelihoods of small-scale and recreational fishers globally.

There is a wide variety of ways in which a SmartPass approach could further support fisheries management that are yet to be explored. In particular, the technology can help managers develop a more resolute understanding of fishing patterns – such as fishers' typical depart/return times, seasonal patterns, responses to weather changes and characteristics of pulse fisheries – in order to better tailor dockside surveys and on the water monitoring and enforcement. Managers' ability to observe these changes in near real-time can allow for immediate adjustments to monitoring and enforcement activity. With some improvements to the machine learning and/or use of detectable charter permits/decals, SmartPass could also be used to effectively generate and/or validate charter fishing effort estimates. There may also be public interest in the technology. Live footage of an ocean pass could provide the public, including anglers and other recreational boaters, the current weather and boat traffic conditions helping to improve safety at sea.

Figure 7. Snapshot from the SmartPass pilot in Lampung Province, Indonesia.

Challenges and Opportunities

A meaningful pilot program must include thoughtful co-design with relevant agencies to ensure the new technology will be appropriately integrated with existing management.

While technology is rapidly advancing and providing new opportunities to augment management capabilities in effective and cost-efficient ways, there are some barriers that slow or prevent the testing, implementation and uptake of such technologies. Often these barriers can be addressed through purposeful, participatory design and implementation. As with any camera-based monitoring system overlooking public spaces, it is important to address and mitigate privacy concerns among fishing communities. However, there is also an acknowledgement among stakeholders that passive approaches like camera systems can provide fishers a relief from other, seemingly more cumbersome forms of data collection such as telephone and mail surveys. To address privacy concerns before full implementation, there needs to be adequate consideration, planning and outreach about the specific data collected, how the data will be protected, and how the data will be used. For example, ODFW conducted extensive planning and outreach with stakeholders during the initial stages of implementing the use of shore-based cameras. A meaningful pilot program must include thoughtful co-design with relevant agencies to ensure the new technology will be appropriately integrated with existing management. It is important to develop a clear pathway to scale at the agency level with adherence to specific protocols and data standards both locally and across fisheries management jurisdictions. The process should also include normalization or "calibration" of historic data to make direct comparisons to the new technology-supported data streams. As pilots begin to move out of the proof of concept phase, it is also important to lay the framework for regional and/or national collaboration; otherwise, pilots can end up as stovepipes, or singular efforts that do not connect to a broader management system.

Funding remains a consistent concern raised by most stakeholders with respect to modernizing fisheries data collection, and the costs associated with staff time are often perceived to be a larger hurdle than the cost of the technology itself. Most local, state and federal capacities are already stretched thin with the existing responsibilities. Therefore, the need to harness tools that can help staff perform their duties more efficiently is high; however, so is the activation energy required to transition to newer tools or methodologies. To overcome this barrier and drive innovation, it will help to open the marketplace from the vendor perspective to achieve better economies of scale. One approach to this could be in broadening the potential applications of SmartPass technology as discussed above. Capitalizing on opportunities to build public-private partnerships will help to spread the risk of development costs across a broader base of support rather than leaving the onus entirely on individual emerging technology companies or state and federal agencies. Another approach that broadens the development burden is through the establishment of governmental grants – such as the existing Small Business Innovation Research (SBIR) and Small Business Technology Transfer (STTR) programs, as well as the National Fish and Wildlife Federation Electronic Monitoring and Reporting Grant and the Saltonstall-Kennedy Grant – or other appropriations mechanisms made through federal and state legislatures.

Conclusions

With any research and development endeavor, testing new applications requires time and resources. The initial design and testing phase is one in which the NGO community can help to successfully catalyze development by providing funding and person-power for the initial engineering requirements as long as there are willing partners on the fisheries management side, to provide the testing grounds and institutional knowledge, and on the technology provider side, to customize applications for the needs of fisheries. NGOs can also help by serving as a neutral facilitator between tech providers and fishery managers and by supporting state/national policies that encourage innovation. Active collaboration from fishery managers is crucial to identify where engineered solutions are needed and how they could be incorporated into management. Similarly, camera systems, review platforms and machine learning already exist in various forms in other fields and these technologies are not themselves novel; however, their coupled application in recreational fisheries is emerging and requires the collaboration of technologists to successfully adapt effectively and efficiently.

Overall, we see real potential for the SmartPass framework to serve fisheries management and augment the public value gained from recreational and small-scale fisheries. There are ample opportunities for scaling and to continue developing additional capabilities within the framework. The time is right for more entities to begin testing the framework themselves, and as new organizations engage, EDF, ODFW and CVision AI welcome the opportunity to share lessons learned. Additionally, the algorithm that CVision AI developed for the Indonesia and Oregon pilots is open source and freely accessible. Relationship building in areas of opportunity across the public and private sector will be critical to foster development of a growing market that drives innovation and capable partners in scaling. Lastly, all stakeholders operating in this space, including managers, tech providers, fishers, NGOs and funders should understand that acting to remove key barriers to technological solutions will help stimulate an ecosystem of innovation across all fisheries. Ultimately this collective effort will help deliver improved management, healthy ecosystems and resilient fishing communities.

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