REPLY TO SWARTZ ET AL.: Challenges and opportunities for identifying forced labor using satellite-based fishing vessel monitoring

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We appreciate Swartz et al. (1) for highlighting several key considerations for interpreting our results (2). While we discuss many of these in our paper, we are grateful to further highlight our work's strengths, limitations, and future opportunities.

A major challenge with understanding fisheries labor abuses is a lack of data. Automatic identification system (AIS) is only used by a subset of the global fishing fleet. However, AIS is valuable for monitoring certain types of fishing vessels, especially those that are large (~52 to 85% carry AIS) (3) and those fishing on the high seas (~80% carry AIS) (4). Mandating AIS and unique identifiers on fishing vessels and publishing vessel registries would facilitate more inclusive AIS-based analyses (5).

Data on fisheries labor conditions are also limited. We spent over 1 y identifying public reports of forced labor onboard specific fishing vessels ("positives"). We also tried to identify a public list of specific fishing vessels free of forced labor ("negatives") but were unable to, and therefore we were compelled to use positive-unlabeled learning. We assessed model performance using 10-fold cross-validation, an appropriate technique for small datasets (6) that uses resampling to train and validate multiple models using multiple training and separate validation data subsets. We estimated an average recall of 92%, the fraction of known positives correctly classified as positive (2). We used the term "high risk" for vessels classified as positive by the model for being above the threshold that maximizes a modified F1 score (7). While we cannot infer probability using this approach, it theoretically minimizes false positives and false negatives and equally weights the practical risks associated with both error types (7). Publishing information from forced labor vessel sanctions (5) (positives) and information from vessel inspections that identify either forced labor (positives) or decent working conditions (negatives) would increase training and testing data and facilitate more accurate analyses.

Our analysis focused on prediction not causation. We did not estimate what causes forced labor but predicted whether vessels have forced labor using observable vessel features. While unpacking correlations between features would be critical in causal inference, understanding these correlations is less important for prediction. Nevertheless, we removed highly correlated model features during data preprocessing (2), which reduces model complexity while increasing feature importance interpretability (8). Moving forward, new research on causal relationships is critical, as are interventions that address causal drivers.

When using predictive models, there is a risk that spurious or biased trends in the training data could lead to unjustified actions with serious human consequences (9). We recognize this ethical concern and stress the importance of further validation and evaluation of potential biases using new data. Nonetheless, predictive models can inform decisions within an otherwise opaque decision-making landscape (10). The path forward should include a suite of forced labor detection methods alongside interventions that address underlying drivers, reform labor policy, promote social responsibility in seafood production, and support victims. While we acknowledge the limitations of our approach, it lays the foundation for new opportunities to improve fisher working conditions.

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The authors declare no competing interest.

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