### Using Machine Learning to Efficiently Deliver CMECS Compliant Benthic Habitat Maps

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# Mapping physical and biological seafloor conditions with Sediment Profile and Plan View Imaging (SPI-PV)

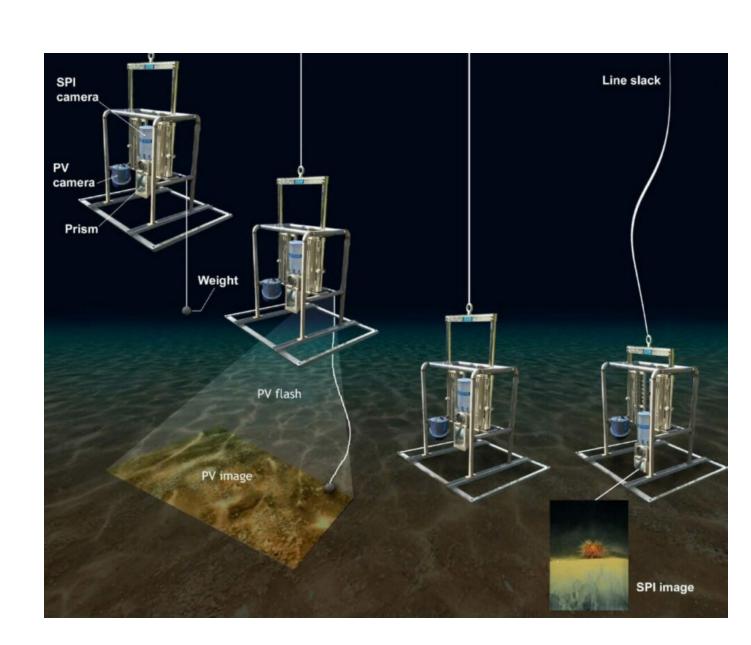
SPI-PV technology is a well-established survey method for mapping physical and biological seafloor conditions. It is being used to map seafloor habitats at many offshore wind energy sites.

#### How does it work?

The SPI-PV camera rapidly collects paired sediment profile (SPI) and plan view images at high densities. The plan view image provides a top-down landscape image while the SPI image provides a cross section of the upper sediment column. The PV image is used for classifying substrates and epifauna, while the SPI image is used for grain size analysis and the identification of infauna and biogenic structures in the sediment, allowing the development of detailed substrate and seabed biota maps.



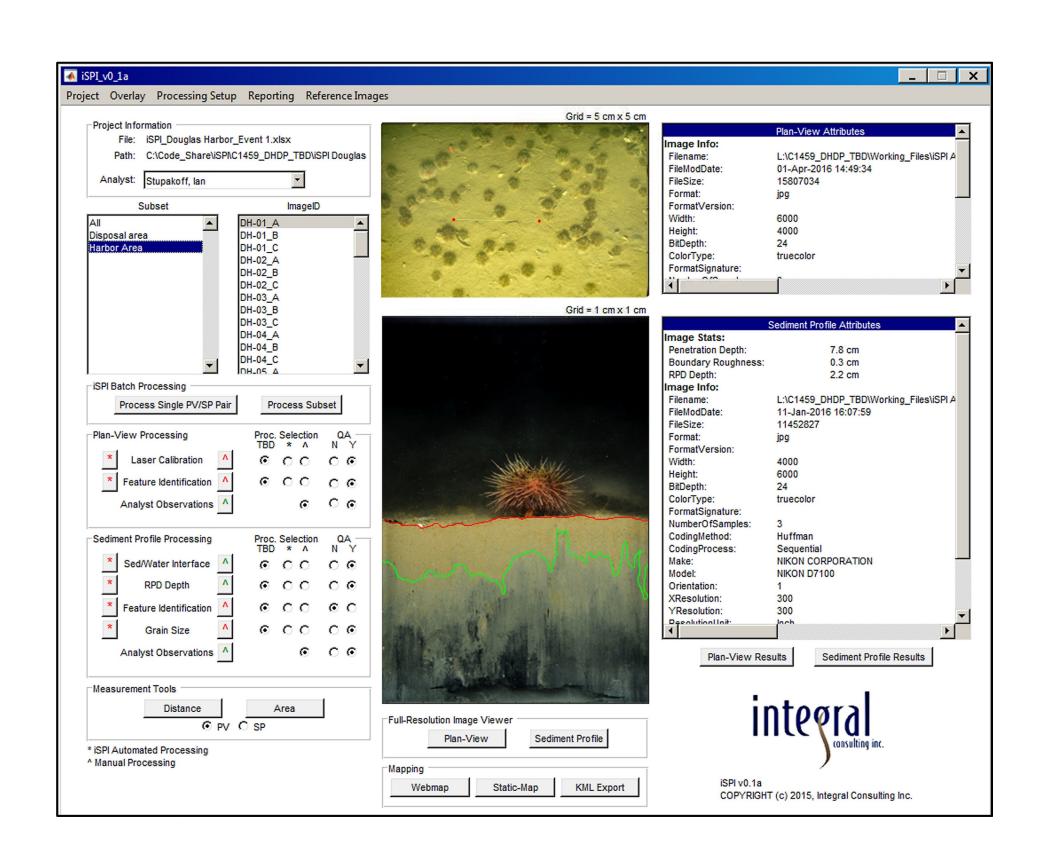
Representative plan view (left) and sediment profile (right) images



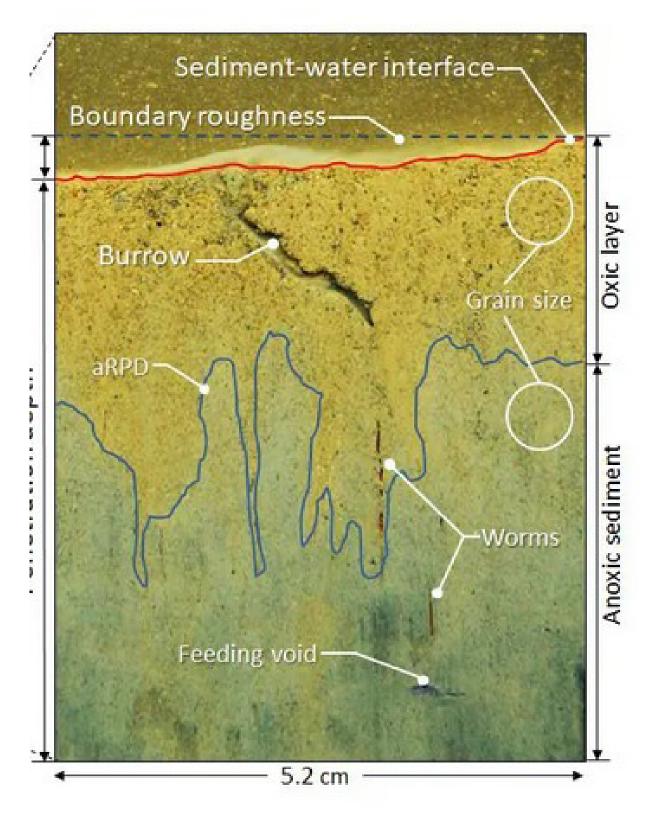
SPI–PV system deployment

### Using machine learning to analyze SPI-PV images

Using Integral's **iSPI** application, machine learning algorithms automatically determine grain sizes and sediment—water interface (SWI) in SPI images. This supervised automation approach reduces image analysis time and the opportunity for bias/user error, resulting in standardized and repeatable data sets across image analysts. **However, while this workflow is efficient for SPI images, iSPI is not optimized for plan view images.** 



Interface of our integrated image analysis platform, iSPI

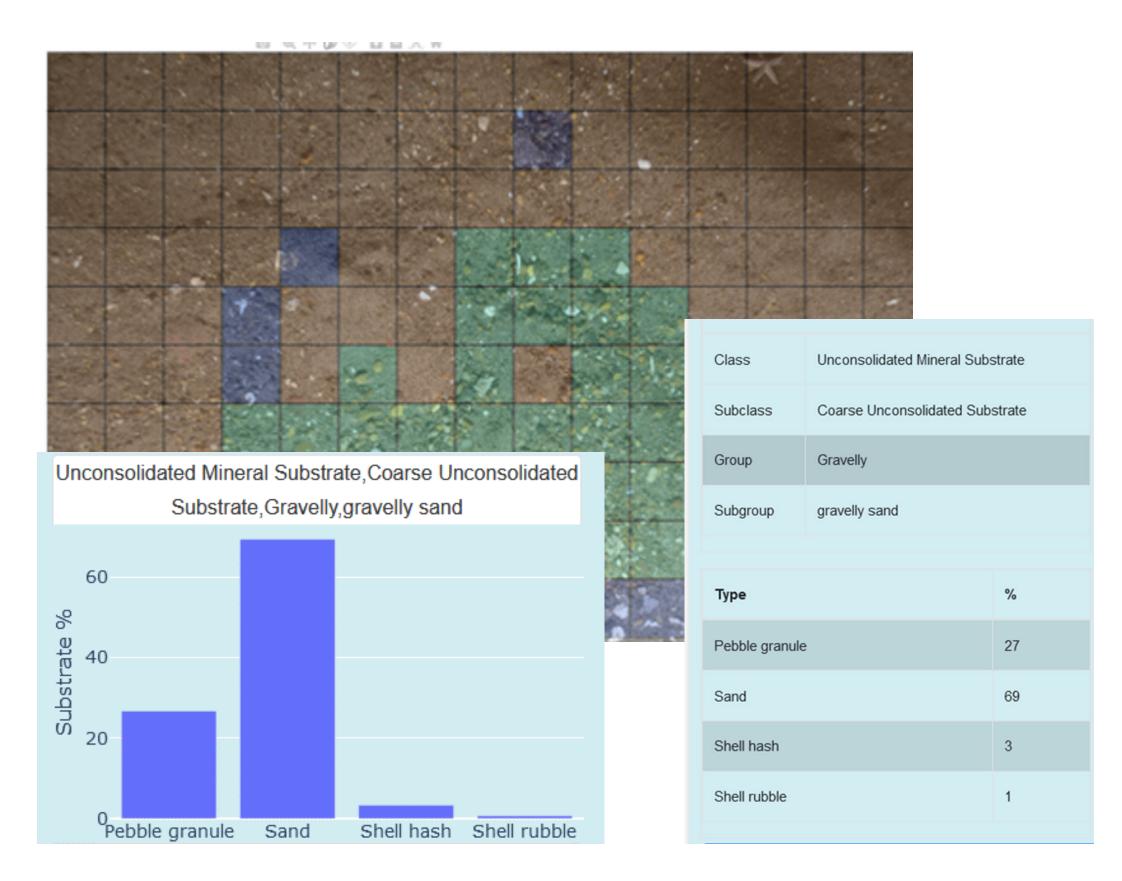


Annotated SPI image showing physical, geochemical, and biogenic features

### New application capabilities

### Annotation of substrate coverage in PV images

- Plan view images are annotated with a standard-sized grid for substrate type and automatically classified into CMECS\* compliant substrate designations (class, subclass, group, subgroup).
- The analyst quickly defines the sediment texture in each cell.
- Substrate percentages are automatically calculated, standardizing results across analysts and providing a more quantitative approach to CMECS substrate classification.



New application interface for annotating substrate on PV images—grids of gravel are green and grids of sand are orange

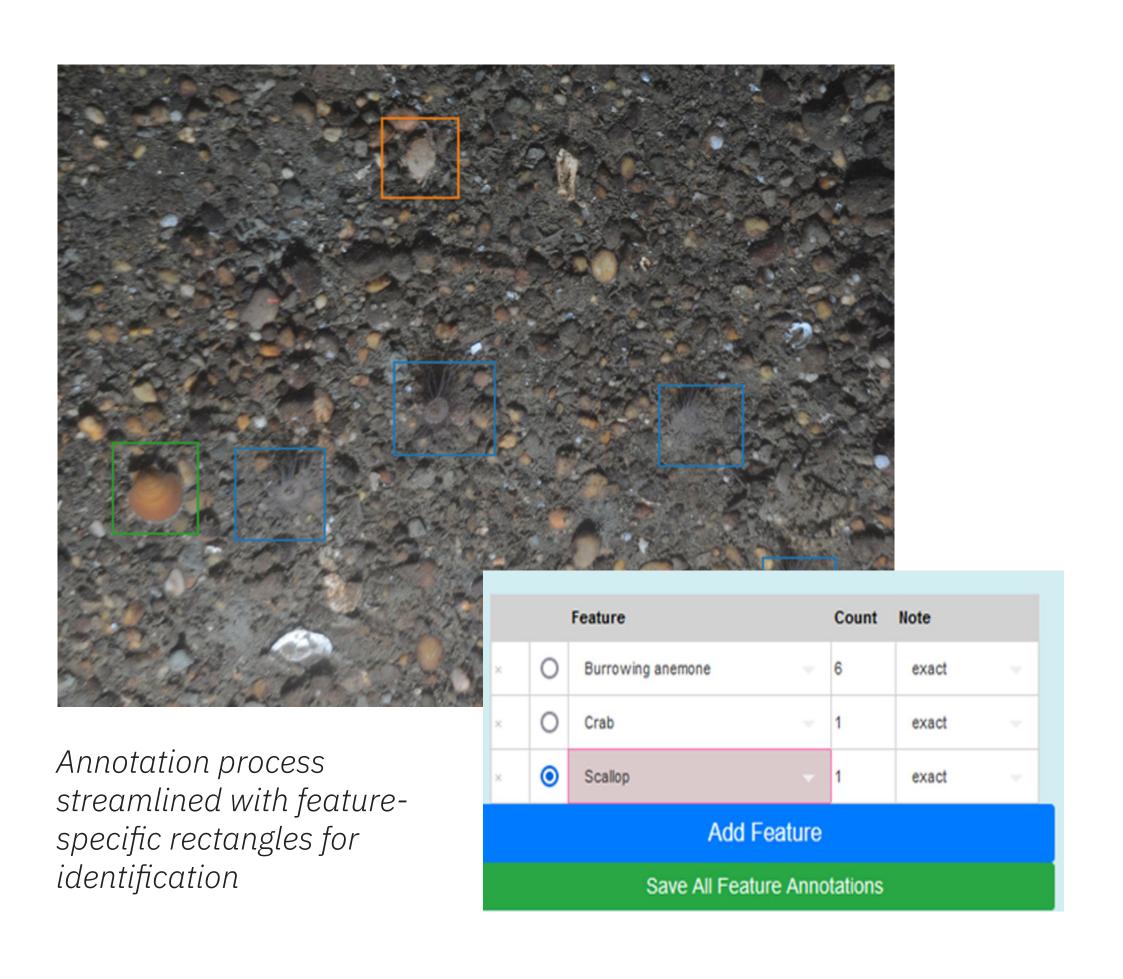
## Applying machine learning in our new application

#### In progress

- Integrating auto-SWI and auto-grain size analysis into new app.
- Fully automating substrate classification and feature identification for PV images.
- Applying Faster R-CNN\*, previously used for feature identification on SPI, to PV feature analysis as well.
- Generating robust training sets for an object so the machine learning algorithm can find, classify, and count features of interest. This will allow for quick and accurate benthic epifauna identification and substrate classification, even with an untrained eye.

#### Feature identification

• Benthic features such as egg cases and epifauna are very quickly identified.



Each square of classified substrate and identified features are introduced as individual data points. This boosts the number of training points, adding robustness to a training set for our neural networks.

## Improving accuracy, efficiency, and accessibility

- The substrate classifications derived from the images are being used to ground-truth multibeam and backscatter data for seafloor habitat mapping.
- Use of Python for application development allows for better technical support because it is open source.
- Rapid advances in neural networks and machine learning enable us to create a more accurate and trustworthy tool with potential to provide real-time CMECS and sensitive habitat classifications at sea.



