Shipwreck Detection Using Semi-Automated Methods: Combining Machine Learning and Topographic Inference Approaches

Cal T. Pols
C.Pols@soton.ac.uk

PhD Student, Department of Archaeology
Leverhulme Trust Intelligent Oceans Scholar

Supervised By:
Prof. Fraser Sturt, Dr Crystal El Safadi, and Dr Antonia Marcu

1 Research Background

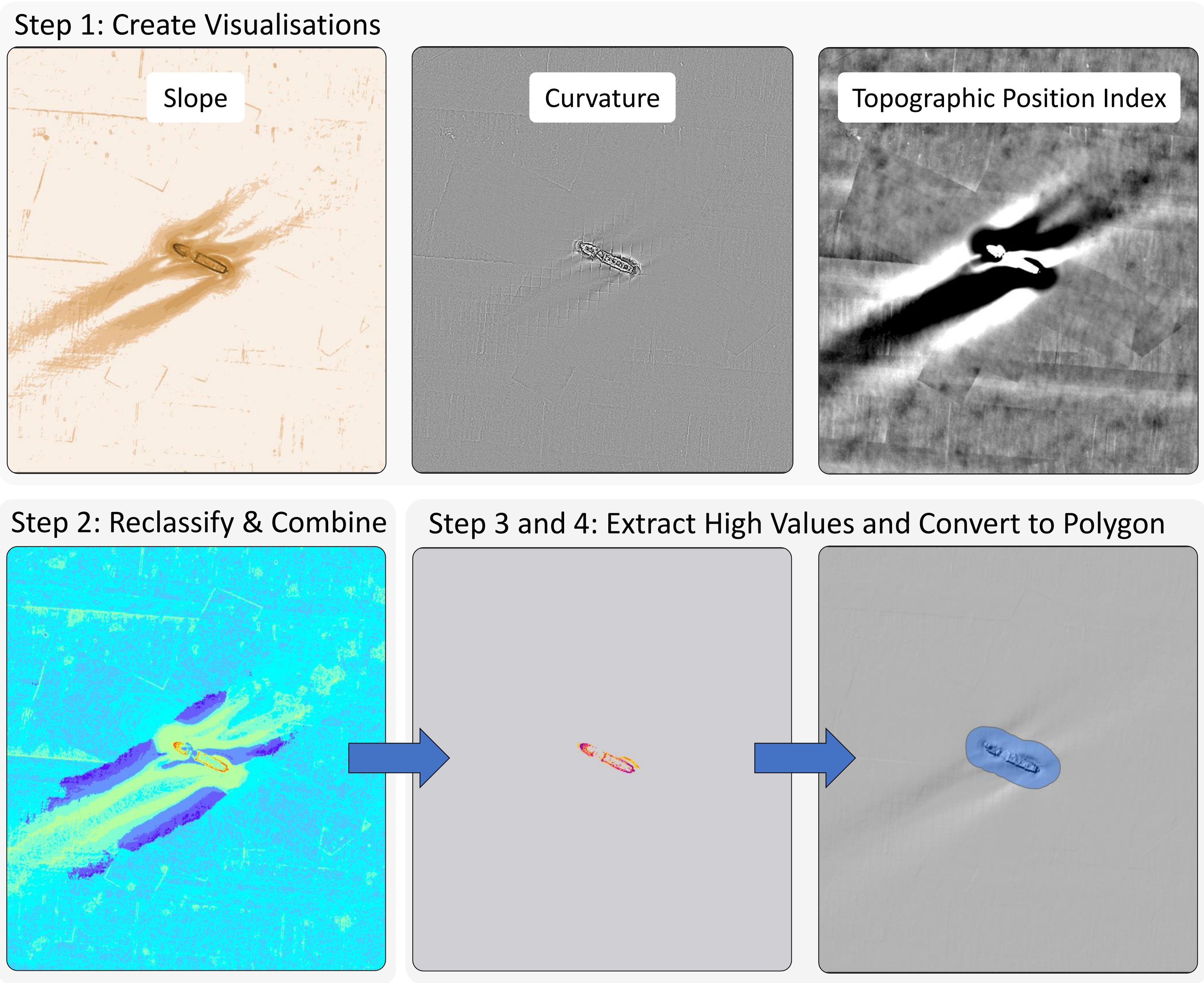
Shipwrecks constitute a significant amount of underwater archaeological sites that are likely to be increasingly discovered due to developments in autonomous marine survey methods and continued offshore development (Papageorgiou, 2018). Moreover, the increasing availability, spatial coverage, and resolution of marine remote sensing data is creating pressure on current archaeological workflows to identify potential underwater (Mayer *et al.,* 2018; Wölfl *et al.,* 2019). As a result, archaeological prospection studies are embracing semi-automated methods to identify archaeological sites and features in remote sensing imagery (Fiorucci *et al.,* 2020) including in underwater contexts (Character et al., 2021).

This research proposes a unique workflow that integrates two different semi-automated methods, raster-based extraction and machine learning, to identify shipwrecks in bathymetry data (seabed elevation) across large areas of the United Kingdom's continental shelf. All aspects of the geospatial analysis were completed using ArcGIS Pro software.

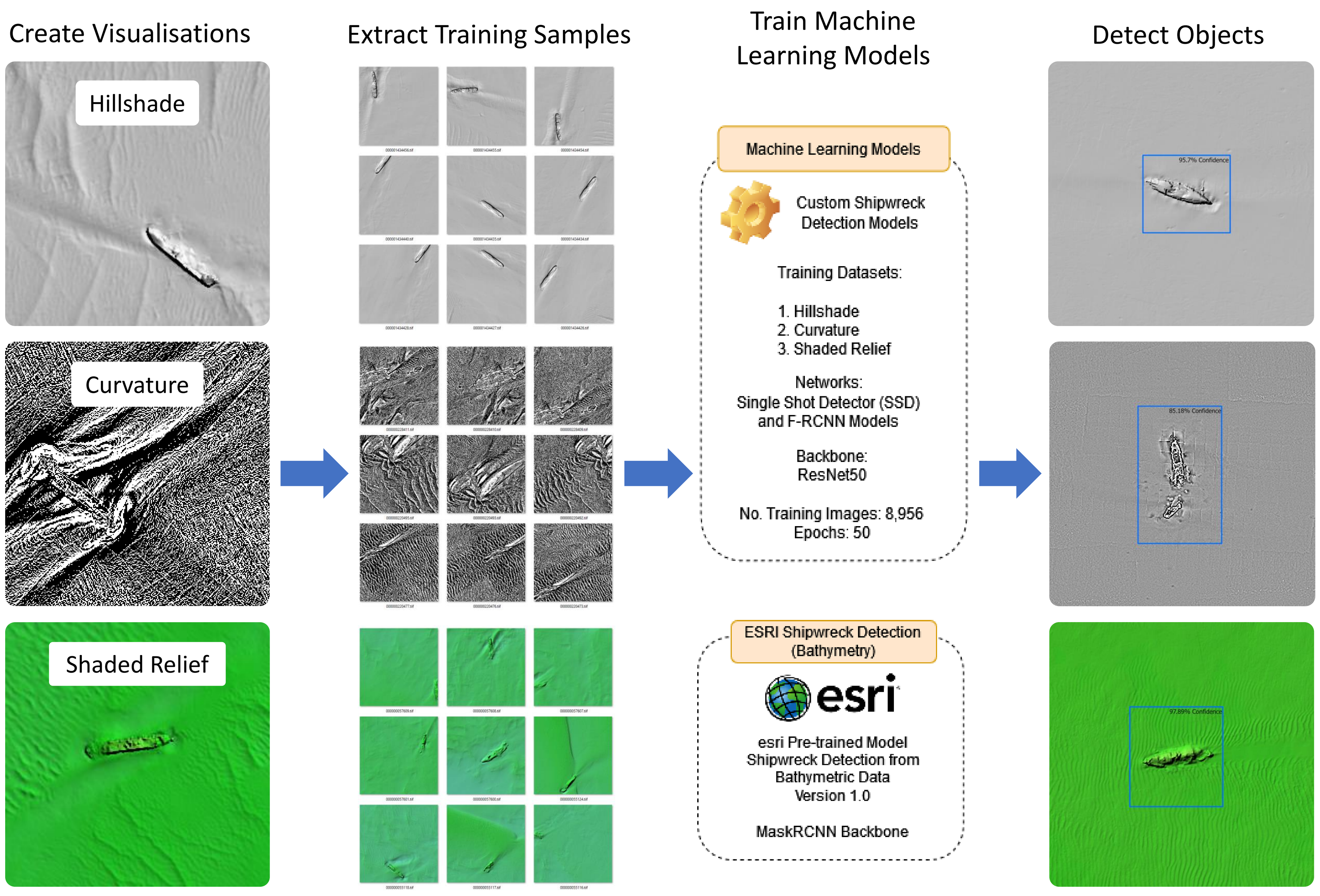
The first method (Raster Extraction) is a topographic inference approach which identifies shipwrecks based on their value signatures in different raster data visualisations. The results of this method are then used to filter the larger testing dataset for areas of high shipwreck potential, over which machine learning detection models are run.

The second method uses several machine learning algorithms trained to detect shipwrecks using different visualisations of bathymetry data. This includes a pre-trained detection model from ESRI (2021) as well as custom models created for this research. The performance of each method was evaluated against an existing shipwreck database (UKHO) and manual review.

2 Raster Extraction



3 Machine Learning



4 Results

Raster Extraction

	Accuracy 1: All Features (n=256)	Accuracy 2: Conspicuous Shipwrecks (n=107)
Recall	0.78	0.98
Precision	0.11	0.06
F1 Score	0.20	0.11

Machine Learning

	Hillshade		Curvature		Shaded Relief		ESRI
Accuracy 1: All Features (n = 197)							
	F-RCNN	SSD	F-RCNN*	SSD	F-RCNN	SSD	M-RCNN
Recall	0.70	0.20	0.47	0.73	0.75	0.73	0.55
Precision	0.13	0.01	0.45	0.47	0.20	0.42	0.24
F1 Score	0.22	0.02	0.46	0.57	0.32	0.53	0.33
Accuracy 2: Conspicuous Shipwrecks (n = 105)							
Recall	0.90	0.21	0.70	0.85	0.90	0.90	0.72
Precision	0.09	0.01	0.36	0.29	0.13	0.28	0.17
F1 Score	0.16	0.01	0.48	0.43	0.23	0.43	0.27

SSD = Single Shot Detector
F-RCNN = Faster Region CNN
M-RCNN = Mask Region CNN

Training Epochs = 50
Network Backbone: ResNet50
*Network Backbone: ResNet34

No. Training Images = 8,956
No. Training Shipwrecks:
Conspicuous/ Possible = 573/441

5 Discussion

Using an existing shipwreck database (UKHO), a total of 253 shipwreck anomalies were identified in the testing data across an area of around 900 km^2. These anomalies were split into two classes when evaluating the performance of each method; conspicuous (i.e. visually prominent) and 'possible' shipwrecks. This latter group was only able to be identified as wrecks using the UKHO database and typically were much smaller, less visually distinct features.

The Raster Extraction method was able to identify 78% of all anomalies in the testing area and performed particularly well on the conspicuous shipwreck class, with 98% being detected. This method had a low precision score (11%) but is still useful as a filtering step as it helps reduce the amount of data prior to further assessment using machine learning. The machine learning (ML) results have interesting variations across model networks and datasets. The best-performing ML model on all shipwreck features is an SSD trained on a curvature dataset, which identifies 73% of all features with 47% precision. The best ML model for identifying conspicuous wrecks is an SSD trained on a shaded relief (colourised hillshade) dataset which, despite a lower precision of 28%, detects 90% of these shipwrecks.

Overall, this research outlines a unique workflow combining both traditional (Raster Extraction) and new machine learning methods to overcome some of the challenges of semi-automated detection of archaeological features in large marine datasets.

References

Character, L., Ortiz JR, A., Beach, T. and Luzzadder-Beach, S. (2021) 'Archaeologic Machine Learning for Shipwreck Detection Using Lidar and Sonar', *Remote Sensing*, 13(9), p. 1759

ESRI (2021) Shipwreck Detection. Available at: https://www.arcgis.com/sharing/rest/content/items/28755e99bbde42508f22b957681a70e2

Fiorucci, M., Khoroshiltseva, M., Pontil, M., Traviglia, A., Del Bue, A. and James, S. (2020) 'Machine Learning for Cultural Heritage: A Survey', *Pattern Recognition Letters*, 133, pp. 102–108.

Mayer, L., Jakobsson, M., Allen, G., Dorschel, B., Falconer, R., Ferrini, V., Lamarche, G., Snaith, H. and Weatherall, P. (2018) 'The Nippon Foundation—GEBCO Seabed 2030 Project: The Quest to See the World's Oceans Completely Mapped by 2030', *Geosciences*, 8(2), p. 63.

Papageorgiou, M. (2018) 'Underwater cultural heritage facing maritime spatial planning: Legislative and technical issues', *Ocean & Coastal Management*, 165, pp. 195–202

Wölfl, A.-C., et al. (2019) 'Seafloor Mapping – The Challenge of a Truly Global Ocean Bathymetry', *Frontiers in Marine Science*, 6.

LEVERHULME TRUST

University of Southampton

SOUTHAMPTON MARINE & MARITIME INSTITUTE