3rd Edition

Data Research meetup by MagIC

Improving nearshore bathymetry mapping through spatially adaptive machine learning

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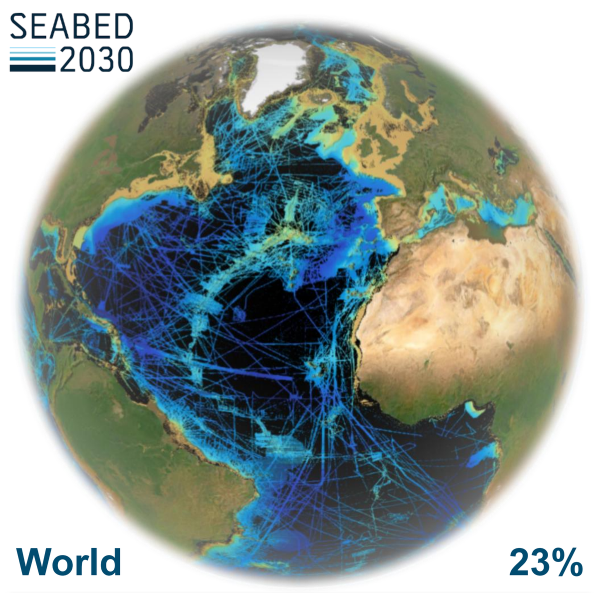
1 INTRODUCTION

➥ **Bathymetry** plays a pivotal role in **ocean science** and **blue economy** applications.

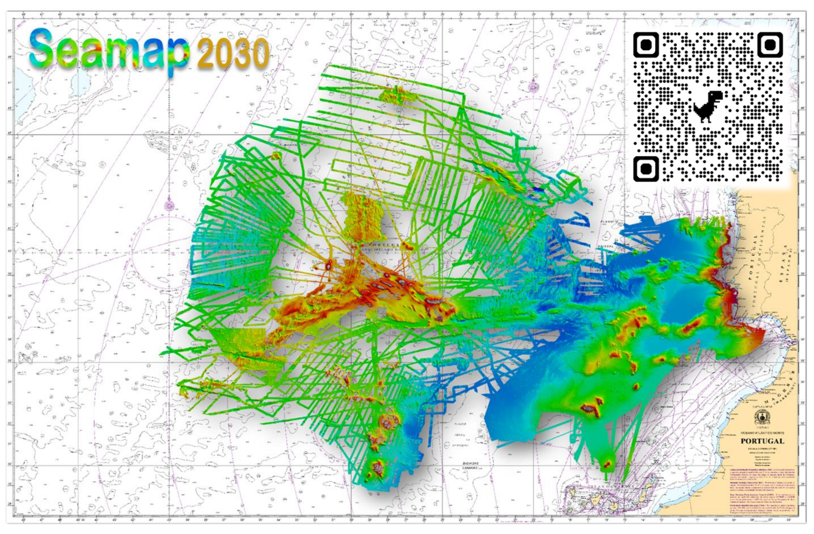
- 40% **World population** lives near the **coast**
- 80% **Global trade** transported by **sea**
- 99% **Communications** by **submarine** cables

➥ What is the current state of **seafloor mapping**?



World 23%

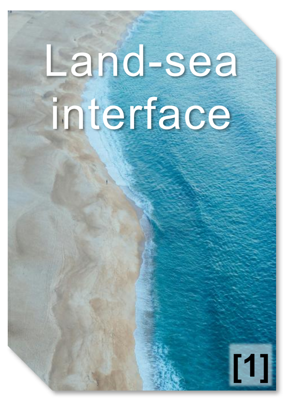
https://seabed2030.org/



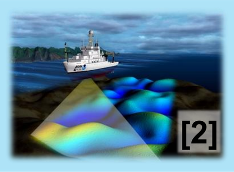
Portugal 66%

https://geomar.hidrografico.pt/

➥ The **land-sea interface** remains significantly **under-surveyed**.



In situ observations:
- Adverse sea conditions;
- Low efficiency.

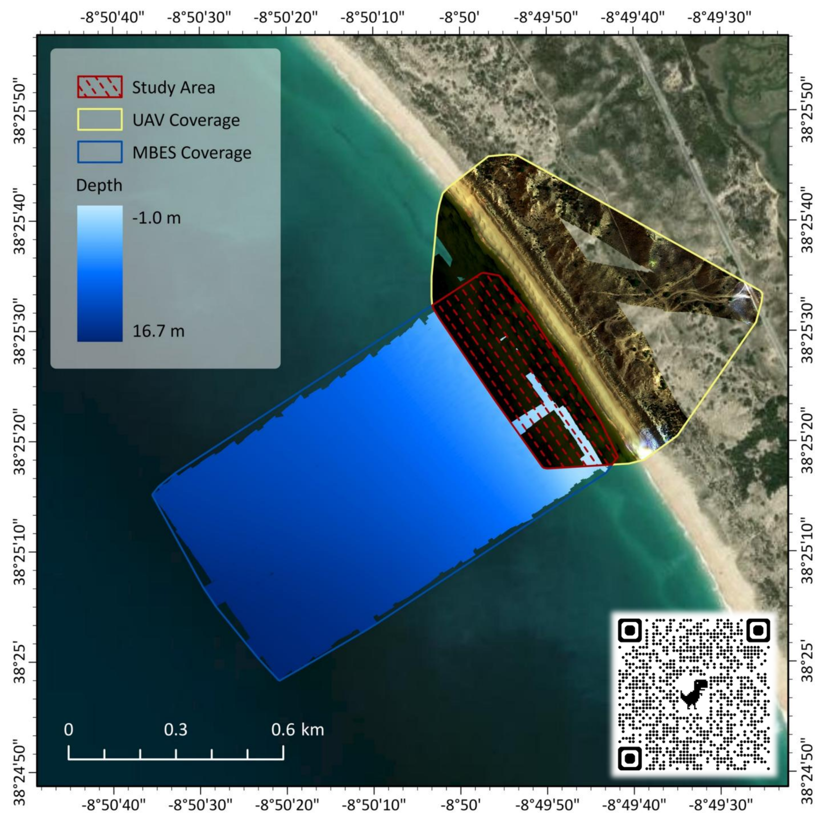


Remote sensing:
- LiDAR (expensive);
- Satellite (low resolution).

Unmanned Aerial Vehicle (UAV):
- Efficient and flexible;
- High spatial resolution;
- Optically derived bathymetry;
- Statistical/empirical approach;
- Machine learning (ML) techniques: GRF [4] and RF.

2 MATERIALS & METHODS

➥ **Study area:**



➥ **Data collection:**

Surface Survey Vessel
Multibeam Echosounder (MBES)

Unmanned Aerial Vehicle
Multispectral Camera

➥ **Methods:**

Data Acquisition → **Data Processing** → **ESDA** → **Model Development** → **Model Evaluation**

Data Acquisition
- *In situ* – MBES (0.25 m)
  Depth (target variable)
- Remote sensing – UAV (0.15 m)
  Multispectral bands (input features)
  (blue, green, red, red edge, near-infrared)

Data Processing
- Resampling
  1 660 412 data points (0.25 m)
  33 883 data points (1.75 m)

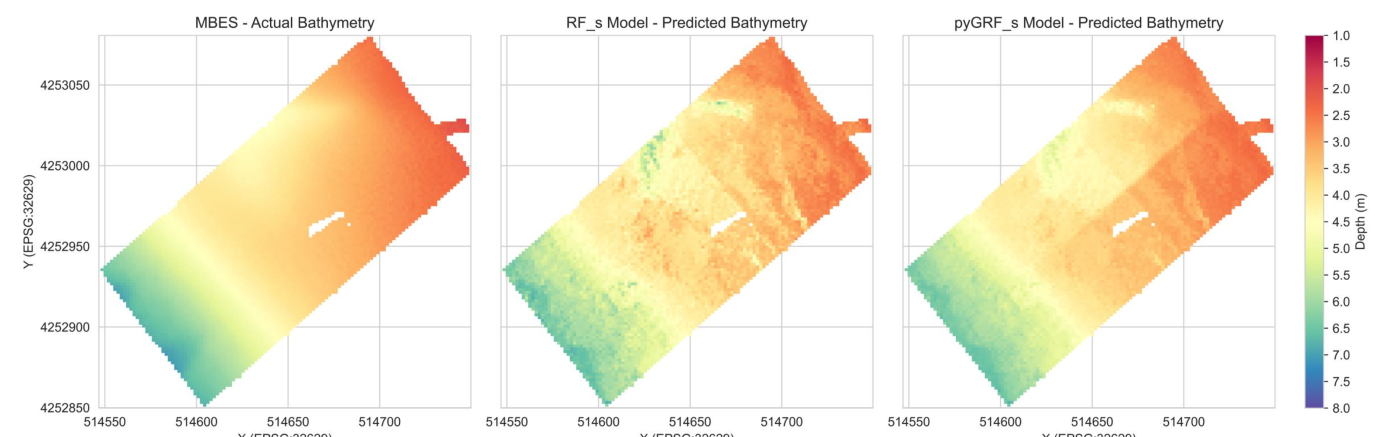
ESDA
- Global and spatial distribution
- Global correlation
  Pearson's (r) / Chatterjee's (ξ)
- Local bivariate relationships

Model Development
- RF / pyGRF (random split) – Baseline
- RF / pyGRF (geospatial split) – Evaluation
- Incremental spatial autocorrelation
- Geographically weighted regression
- Grid search

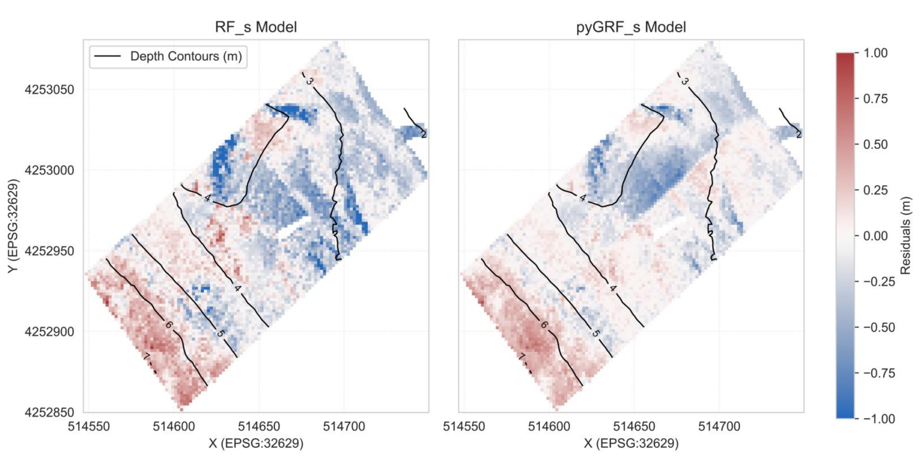
Model Evaluation
- Global metrics (MAE, MAPE, RMSE, R^2)
- Scatter plots (actual/predicted depth, residuals)
- Global and spatial distribution (residuals)
- Global and local feature importance
- Local R^2

3 RESULTS & DISCUSSION

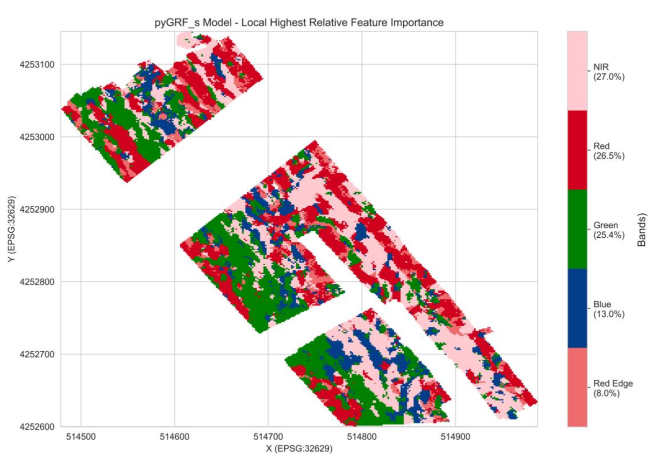
➥ **pyGRF** [5] improved all global metrics (MAE, MAPE, RMSE, R^2).



➥ Change of **residuals** sign (≈ 5 m depth).



➥ **Local** feature importance.



4 CONCLUSION

➥ **Contributions:**

- **Demonstrating** that Geographical Random Forest (GRF) improves **accuracy and interpretability** over a conventional Random Forest (RF) by capturing **spatially varying reflectance-depth relationships**;
- **Mapping** spatial variations in **feature importance** that remain hidden in global models:
  - **Red band**, globally the most influential predictor;
  - **Near-infrared band (NIR)**, locally dominant in shallow areas;
  - **Green band**, most relevant in the depth range with highest accuracy;
- **Identifying** a practical **optical depth limit** of approximately **5 m** for the study area, supported by multiple spatial diagnostics;
- **Providing** a **reproducible**, **spatially explicit** modelling **framework** suitable for broader application in coastal bathymetry.

➥ **Limitations:**

- Higher **computational cost**;
- Possible **prediction discontinuities** from spatial weighting.

➥ **Future work:**

- Extend the study to **other coastal regions** (e.g., cross-site testing, regional variability);
- Compare other **geospatial machine learning** models (e.g., XGBoost).

5 REFERENCES

[1] Photo by Sebastian Jacobsen on Unsplash (2024).

[2] Collecting Multibeam Sonar Data, NOAA's National Ocean Service (2009).

[3] Photo by SpaceX on Unsplash (2016).

[4] Georganos, S., Grippa, T., Niang Gadiaga, A., Linard, C., Lennert, M., Vanhuysse, S., Mboga, N., Wolff, E., & Kalogirou, S. (2021). Geographical random forests: a spatial extension of the random forest algorithm to address spatial heterogeneity in remote sensing and population modelling. *Geocarto International*, *36*(2), 121–136. https://doi.org/10.1080/10106049.2019.1595177.

[5] Sun, K., Zhou, R. Z., Kim, J., & Hu, Y. (2024). PyGRF: An Improved Python Geographical Random Forest Model and Case Studies in Public Health and Natural Disasters. Transactions in GIS. https://doi.org/10.1111/tgis.13248.

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