Google Earth Engine Apps – a novel method for highlighting the role of Satellite-Derived Bathymetry (SDB) to non-specialists and citizens – a case study for Irish Bays

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Abstract

Coastal zones are constantly exposed to environmental and human pressures. Maintaining detailed, up-to-date information under such conditions requires efficient methodologies capable of capturing these dynamic changes. Satellite-derived bathymetry (SDB) offers notable advantages but requires suitable imagery, specialised algorithms, highly skilled personnel, and powerful computing infrastructure, especially for temporal analyses. These requirements can create barriers to access and limit the use of these techniques across different stakeholders. Cloud-based platforms have emerged as promising alternatives, providing accurate, rapid, cost-effective, and regularly updated analysis capabilities. In this context, this research aims to develop an automated image-ranking approach in Google Earth Engine (GEE) to identify and curate suitable Sentinel-2 and Landsat-8 imagery for shallow-water along the Irish coast; to develop an open-access GEE application that encourages a broader and non-specialist user base to derive bathymetric data from optical satellites using Lyzenga's 1978 log-linear model, and to produce materials for training and outreach. The app enables users to analyse a curated list of pre-ranked satellite images based on the best-performing R-squared (R^2) and Root Mean Square Error (RMSE) results. It provides SDB maps, validation plots, and metadata summarising information for five pilot bays: Dublin, Dungarvan, Portrane, Rosses, and Tramore. The findings confirm the pre-ranking strategy is effective, as it prioritises images with high correlation/low error, ensuring only the most appropriate are provided to the end-user for bathymetric modelling.

1. Introduction

Coastal regions are highly variable, with many impacts potentially magnified by climate change. Regularly updated, detailed seabed data, such as near-shore bathymetry, are essential for human well-being (Wölf et al., 2019), assessing geological hazards (Monteys et al., 2015) and tracking changes in seafloor (Barnard et al., 2019) to identify areas of significant sediment movement and short-term changes in seafloor bathymetry (Amal et al., 2019). Accurate bathymetric data are essential to protect the world's oceans (*30% - Target 3 of the Kunming-Montreal Global Biodiversity Framework*) and directly support *SDG 14 - Life Below Water*.

In Ireland, despite the optically complex coastal waters, promising SDB results have been obtained for depths of 10-15 m, with accuracies of ±0.5 to ±1 m (Monteys et al., 2015; Cahalane et al., 2019; Casal et al., 2020), generally from short-term research projects that lack temporal continuity. Access to the full optical Sentinel-2 (S2) and Landsat-8 (L8) catalogues provide unprecedented temporal coverage for this analysis and quality assessment. Temporal analysis of bathymetry is crucial for assessing and monitoring changes in seabed topography and water levels, and consequently in coastal areas. Understanding these changes is important not only for engineering, industry, and coastal ecosystem management (Duan et al., 2022) but also for assessing the resilience of coastal regions to climate change impacts (Caves and Johnsen, 2021).

New cloud platforms, such as Google Earth Engine (GEE), show promise for handling the data volumes required to improve this (Li et al., 2021), emerging as a promising alternative to overcome these obstacles, offering users a way to derive valuable insights from satellite data accurately, quickly, and cost-effectively by leveraging frequent image updates. GEE provides users with access to high-performance computing resources, enabling the processing of very large geospatial datasets (Gorelick et al., 2017). Earth Engine Apps (EEA) are designed as curated applications for specialist topics that help lower the barrier to entry for these cloud platforms and provide dynamic, shareable interfaces for both specialists and non-specialists to conduct analysis using the extensive multispectral satellite data catalogue and analytical capabilities. These EEAs can be shared via unique URLs generated upon publishing and, importantly, do not require a GEE account for viewing or interaction (Figure 1).

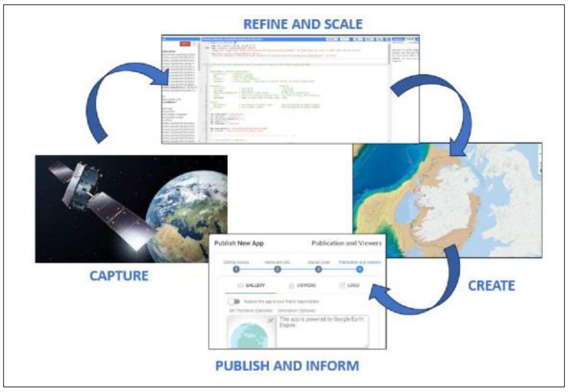

Figure 1. Outline of the research – proceeds through data processing, methodological refinement and scaling, creation of SDB data, and publishing the method via EEA.

Despite the demonstrated effectiveness of satellite data for bathymetric measurements, this type of analysis requires highly skilled personnel and extensive computing power, particularly for high-temporal-frequency change analysis. These requirements can create barriers to applicability and reuse, further limiting the adoption of this data by a broad range of stakeholders whereas the ability to develop EEAs within the GEE environment provides end users with easy access. It encourages untrained users to begin to explore the full image catalogue and produce customised bathymetry layers for a range of applications, including coastal change, habitat mapping, water quality, and training.

Several existing EEAs have already demonstrated the potential of cloud computing for coastal monitoring and SDB. For example, Kras et al. (2022) developed a SDB model app along the Dutch coast using Spearman's correlation to visualise temporal patterns and compare coastal elevations through overlaying multiple bathymetric layers, including features that allow quick examination of time-dependent changes with Video Map Tiles. Klein et al. (2023), as part of the Cassie-Core (Coastal Analyst System from the Space Imagery Engine) project, developed an Earth Engine web app that employs geospatial observation and forecasting solutions to monitor, mitigate, and adapt to the coastal zones. Other EEAs have focused on SAR imagery processing frameworks for locating, detecting, and tracking hydrocarbon slicks on the ocean surface caused by subsea oil and gas sources (Hernández-Hamón et al., 2023) and on the use of Remotely Piloted Aircraft Systems (RPAS) to manage shallow coral reef ecosystems using images by Zapata-Ramírez et al. (2023).

Although these previous studies have demonstrated the versatility of cloud-computing methods and GEE for coastal applications, none have provided an operational, open-access workflow specifically designed for the Irish coastal environment, nor have they included long-term national datasets for validation. Our key contribution is ensuring the app is accessible to non-specialists through a data pre-ranking process. These gaps highlight the need for a national-scale, user-friendly SDB platform that integrates international and Earth Observation (EO) missions, as well as Irish in-situ datasets. This research seeks to leverage established SDB collaborations and accelerate temporal analyses of long-term satellite data time series to derive bathymetry using cloud-based solutions that make large EO catalogues easily accessible. Importantly, it leverages data from the 2020 to 2024 Pilot Coastal Monitoring Survey Programme and the Integrated Mapping for the Sustainable Development of Ireland's Marine Resource programme (INFOMAR) as the primary source of bathymetric input and 'ground' truth for the models. Finally, the research promotes the democratisation of access to SDB products for a wide range of stakeholders, including the public, by developing an EEA that simplifies data access and analysis. Therefore, this research aims to achieve the following scientific objectives:

1. To develop an automated image ranking approach in GEE to identify and curate suitable Sentinel-2 and Landsat-8 imagery for shallow water SDB along the Irish coast.
2. To develop an open-access application in GEE to enable non-specialist users to generate bathymetric models from S2 and L8 imagery.
3. To promote training and outreach to a wide range of users and stakeholders, including integration into postgraduate teaching.

2. Materials and Methods

The app development workflow included study area definition and data collection; data preparation and preprocessing; selection of S2 and L8 imagery; image ranking and filtering; and final app development using the GEE environment and the EEA JavaScript API.

2.1 Study area

Eighteen Irish coastal monitoring sites were initially considered in this study: Ardmore, Ballyheigue, Cloughnahinchy, Doolin, Dublin, Dungarvan, Enniscrone, Liscannor, Moville, Portmarnock, Portrane, Rosses, Rosslare, Rossnowlagh, Sloden, Strandhill, Tramore and Youghal. These locations are part of Ireland's Coastal Monitoring Support Programme (CMSP) and represent coastal environments facing common management challenges, including coastal flooding, erosion, sediment transport, and dredging pressures. Five sites: Portrane, Dublin, Tramore, Dungarvan, and Rosses were selected as pilot locations for the initial development and testing phase of the app (see Table 1). The map displaying the distribution of the pilot bays along the Irish coast is presented in Figure 2, and the different water types expected.

Pilot Bays	Description
Portrane Rush	It is in Fingal, about 25 km north of Dublin City on Ireland's east coast, and consists of two sandy beaches, the long South Rush Beach and Burrow Beach, approximately 2 km long, with a fast-flowing channel of the Rogerstown Estuary. The site is known for ongoing coastal erosion and shoreline change (Monteys et al., 2025).
Dublin Bay	Located on Ireland's east coast, forms a C-shaped embayment with an approximately 10 km wide entrance. It is a meso-tidal estuary with an average tidal range of 2.75 m and an intertidal area of approximately 16 km² (Brooks et al., 2016) and represents a large urban coastal system influenced by significant anthropogenic pressures.
Tramore Bay	Located approximately 13 km south of Waterford City on Ireland's south-east coast. With a depth range of 0 to 30m, Tramore is characterised by a 4.8 km sandy strand backed by dunes, coastal defences, and a barrier-beach system of national and international conservation importance.
Dungarvan Bay	Situated in County Waterford along Ireland's south coast, this estuarine system has a depth range of 0 to 15 metres and features extensive intertidal habitats that support significant migratory and wintering waterbird populations (Crowe, 2005).
Rosses Point	Located in Sligo Bay along Ireland's north-west Atlantic coast, it is an exposed sandy coastal area influenced by wave conditions and active sediment transport, with a depth range of 0 to 14 metres.

Table 1. List of the five bays and a geographical description of each bay, including factors influencing water clarity.

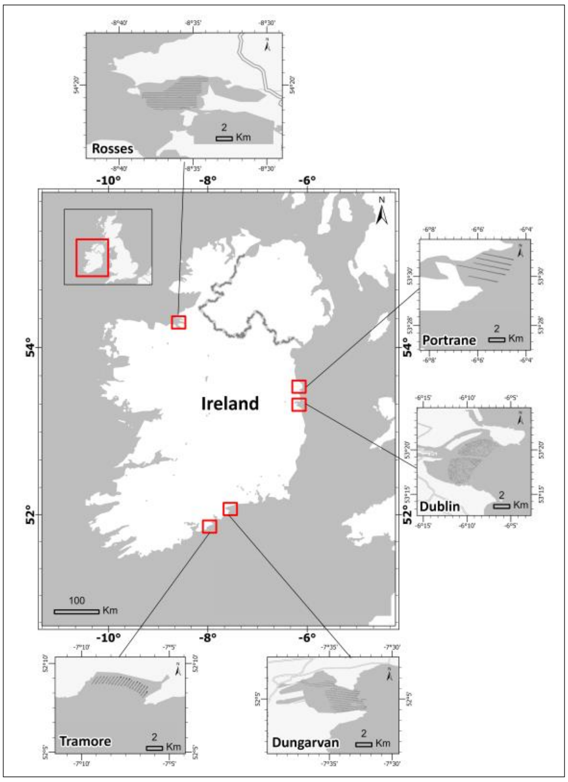

Figure 2. Study areas - highlighting the distribution of the five pilot bays along the Irish coastline (Portrane, Dublin (Irish Sea) Tramore, Dungarvan and Rosses (North Atlantic)).

2.2. Bathymetry Data Collection and Preprocessing

Bathymetric survey datasets collected between 2020 and 2024 were available for the five pilot sites. The surveys were carried out using a Norbit iWBMSe multibeam echosounder with 512 beams (0.9° × 1.9°) operating at 400 kHz. Additional bathymetric datasets were obtained from the INFOMAR programme for Portrane. These INFOMAR datasets were collected between 10 November and 3 December 2021 aboard the Research Vessel (RV) *Geo* operated by the Geological Survey of Ireland (GSI), using a multibeam echosounder. The Bathymetric data were validated to ensure compliance with the International Hydrographic Organisation (IHO) Order 1a standards.

A subset analysis was conducted in ArcGIS Pro 3.5.0 using a Python notebook to standardise the bathymetry datasets for all bays. Each dataset was limited to 2,000 points to ensure consistency, minimise bias from densely clustered points, and improve computational efficiency. About 70% of the bathymetry points were used for training, with the remaining 30% reserved for validation.

The post-processed bathymetric points were then imported into the GEE environment as assets and used to support the development and validation of SDB models. This involved importing the processed bathymetry points, defining points of interest (POIs) based on ranked images, and ensuring all datasets, such as satellite imagery collections and depth data, were properly configured for analysis and modelling.

2.3. Satellite Images

This study used the S2 and L8 datasets because they offer the leading public multispectral datasets at 10 m and 30 m resolutions, respectively, making them highly suitable for the SDB. S2 offers a five-day revisit cycle, with three satellites in the constellation (S2A, S2B, and S2C), although S2C was not used in this project due to the start date. Since Ireland lies approximately between 53° and 55° North, it experiences a two- to three-day revisit cycle for S2 due to orbital overlaps, with a 290 km swath width that covers larger areas and increases the chances of obtaining cloud-free images. In contrast, L8 has a 16-day revisit cycle and a swath width of 185 km, leading to less orbital overlap over Irish latitudes (Li and Roy, 2017).

We used geometrically corrected data from both satellites, available in the GEE catalogue as Level-1T (S2) top-of-atmosphere (TOA) reflectance images and Level-1C (L8) TOA reflectance tiles in the Worldwide Reference System (WRS-2) path/row coordinate system, these products were minimally processed and retain the original radiometric information while maintaining spatial alignment, making them suitable for generating SDB models.

2.4. Filtering and Ranking Satellite Images

When querying image collections in the GEE environment, standard spatial queries typically return hundreds of satellite images for any given coastal site. While this might be ideal for expert users who can interrogate the metadata, evaluate water-quality conditions by eye, and recognise sensor specific limitations, it is a barrier to broader application by non-specialist users, as identifying the most appropriate images requires domain-specific expertise.

From a technical perspective, filtering and ranking images in real time would degrade the application's performance for end users, despite the performance improvements a cloud platform offers. For this reason, instead of having the end user evaluate all images for the chosen year in the EEA, we propose a method in which high-quality satellite images are pre-selected. This ensures that users only access the pre-approved images, making the final application faster, incorporating domain expertise for the public, and supporting an efficient system across the pilot sites (Figure 3), which importantly will let a user see the value of SDB, not lose the enthusiasm faced with a selection of poor-quality scenes.

A JavaScript algorithm implementing the Lyzenga (1978) log-linear regression model was used to rank all S2 and L8 images based on their suitability for SDB. Although the literature presents many alternative approaches to measure SDB (Monteys et al., 2015; Cahalane et al., 2019; Casal et al., 2020; Monteys et al., 2025), including complex optimisation and machine learning (Sagawa et al., 2019), which require more intensive processing and larger training datasets, the Lyzenga model was selected because it offers a robust empirical method for exploring the relationship between reflectance and depth. For each candidate image, a regression model was fitted to the available multibeam bathymetry data, and image performance was evaluated using the coefficient of determination (R^2).

This enabled efficient filtering to support our research aims by retaining images with $R^2 \geq 0.7$ as suitable candidates. This threshold offers a reasonable balance by selecting images that display a strong relationship between reflectance and depth while maintaining sufficient scenes for multi-temporal analysis and aligns with previous studies in North Atlantic coastal waters by Casal et al. (2019) and Monteys et al. (2025). No additional filtering was necessary because the high correlation naturally excluded images affected by clouds or other conditions unsuitable for SDB, including turbidity, algae, cloud shadow or weeds.

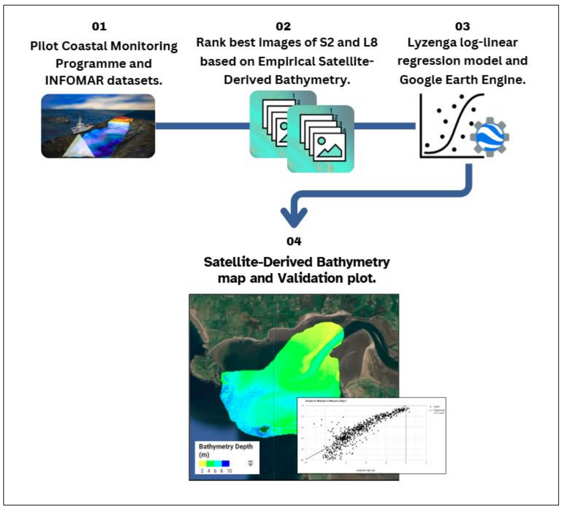

Figure 3. Key phases of app development include dataset acquisition, satellite imagery ranking based on empirical SDB, the Lyzenga regression model, outputs such as SDB maps, and the validation plot and metadata for users.

2.5. Empirical Satellite-Derived Bathymetry (SDB) Model

Empirical SDB methods typically rely on specific bands within the visible spectrum, mainly blue, green, and red (used as independent variables), together with a set of known in situ depths (the dependent variable). These inputs are used in simple or multiple linear regression models to estimate bathymetry across the study area.

Lyzenga's (1978) linear model was employed in this research. The model uses three visible bands corresponding to the blue, green, and red wavelengths (S2: B2 (490 nm), B3 (560 nm), B4 (665 nm); L8: SR_B2 (480 nm), SR_B3 (560 nm), SR_B4 (655 nm)). Lyzenga proposed a transformation to approximately linearise the relationship between the transformed reflectance values and water depth. This approach assumes a linear relationship between the log-transformed spectral bands and known depth through a multiple linear regression model:

$$z = h0 + \sum_{i=1}^{N} hiXi \tag{1}$$

where *h0* and *hi* = slope and coefficients derived using linear regression, respectively
N = the total number of bands used

According to Lyzenga (1978), X_i is defined as:

$$Xi = ln\,(\mathrm{Rw}\,(\lambda\mathrm{i}) \;-\; \mathrm{R\infty}\,(\lambda\mathrm{i})) \tag{2}$$

where R_w = the above-surface reflectance for a band λ_i, and R_∞ = the average deep-water reflectance used to approximate the background reflectance of optically deep water

2.6. SDB Model: App Development Workflow

The development of the bathymetric model for the application started with image selection. Only images that meet specific criteria, such as location, seasonal solar altitude (April to September), and less than 30% cloud cover, were chosen, as outlined in a previous study by Monteys et al. (2025).

The satellite images were then analysed using an empirical SDB model and validated against national datasets covering bathymetric depths from 0 to -10 metres (Figure 4). The top-performing images were saved as a GEE asset and incorporated into the app development environment, where the final model outputs included bathymetric maps, validation plots, and downloadable CSV files with metadata.

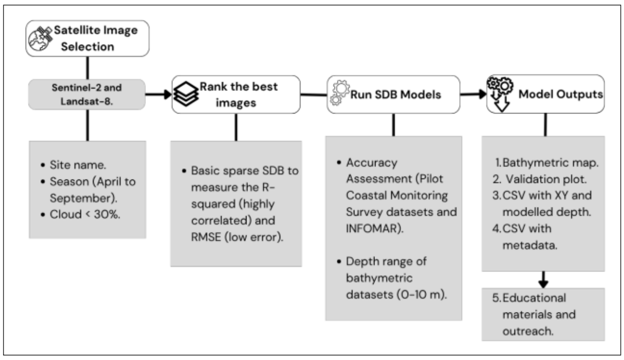

Figure 4. This workflow outlines the process for deriving the SDB from S2 and L8 for EEA development.

3. Results

3.1. The Earth Engine Application

The Earth Engine App developed during this research is publicly accessible[1] via a unique URL and requires no GEE account to operate. All the JavaScript code used for ranking and app development is available on GitHub[2].

The interface guides non-specialist users through a six-step workflow: selecting a pilot bay, choosing a year, and selecting a pre-ranked satellite image (Sentinel-2 or Landsat-8) from a dropdown menu. Clicking *"Run SDB Model"* runs the Lyzenga log-linear regression and renders the bathymetric output directly into the GEE map viewer, where users can click and interrogate any location to inspect the modelled depth at that point (Figure 5).
Samples of the bathymetric map and the validation scatterplot of modelled versus measured depth are displayed in Figure 6. After reviewing the outputs, users can also download the results as a CSV file containing x, y, and modelled depth coordinates, or export the validation plot as an SVG or PNG with accompanying cartographic symbols. A metadata summary reports the bay name, image identifier, year, model type, and RMSE.

[1] ee-bathymetryproject.projects.earthengine.app/view/satellite-derived-bathymetry-to-citizens-for-irish-bays
[2] github.com/bathy25/SDB_EarthEngineApp/tree/faca6df78b6004c56bd8e4164f122834619c6bdc/javascript-code

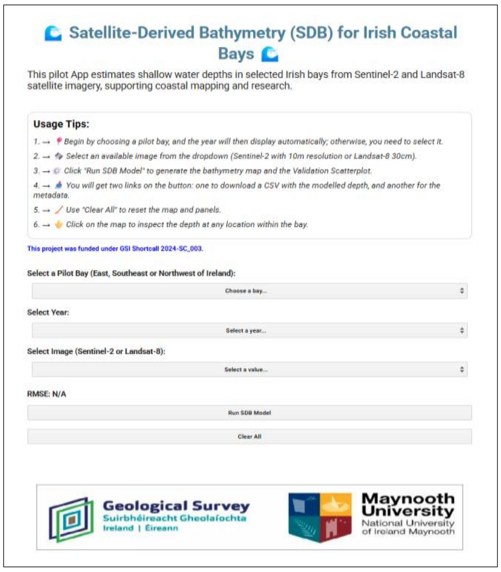

Figure 5. The app's User Interface (UI) shows a brief description, user guidance, interactive dropdowns for selecting the bay, year, and satellite image, and *'run'* and *'clear'* buttons.

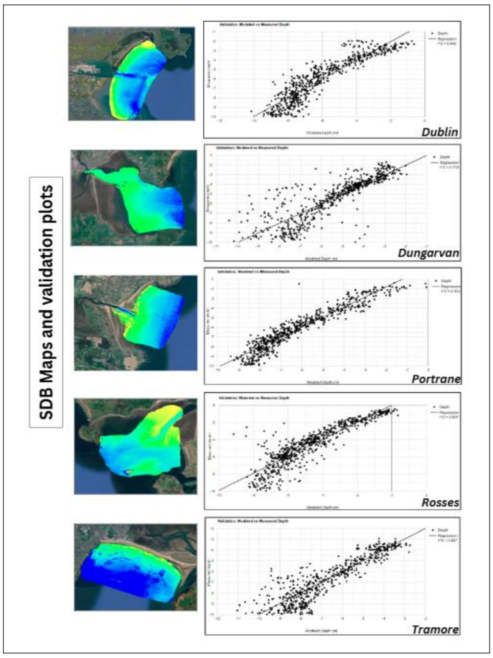

Figure 6. Sample SDB maps and validation plots for each bay are provided to users after running the SDB model in the EEA.

3.2. Bathymetric Model Performance

Model performance across the five pilot bays is summarised in Figures 7 and 8. R^2 values ranged from 0.71 to 0.90, reflecting moderate to high predictive accuracy across sites. Portrane Rush achieved the strongest performance (R^2=0.90, RMSE=0.68 m), while Dungarvan showed the greatest depth-prediction variability (R^2=0.71, RMSE=1.1 m), likely reflecting turbidity from estuarine regions and extensive intertidal habitats.

Dublin Bay, Rosses Point, and Tramore Bay returned results consistent with the optically complex conditions typical of Irish coastal waters. Across all five bays, modelled depths show a strong positive correlation with in-situ measurements, indicating that the Lyzenga log-linear model effectively captures spatial bathymetric patterns in the test areas. S2 generally performed better across the pilot bays, whereas L8 returned comparable results for most sites, with Dungarvan Bay being the only bay where it performed marginally better than S2. No L8 image passed the ranking threshold for Dublin Bay, where S2 remained the sole viable option for bathymetric modelling.

Overall, both sensors demonstrated the capability to capture shallow-water bathymetry across contrasting Irish coastal environments, with performance differences reflecting the diversity of conditions encountered. These results confirm the effectiveness of the pre-ranking strategy in ensuring that only the most suitable satellite images enter the modelling workflow and, importantly, contribute to the user-focused aspect of our design approach.

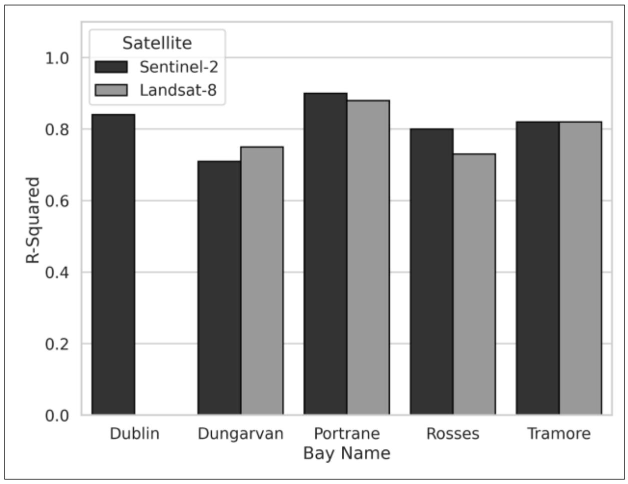

Figure 7. The chart above displays the R^2 values, which reflect the performance of the assessed satellites. S2 has only marginally better predictive performance, particularly in Portrane and Rosses. Although L8 surpasses S2 in Dungarvan and Tramore, Dublin data is unavailable because no suitable images were found during the ranking process.

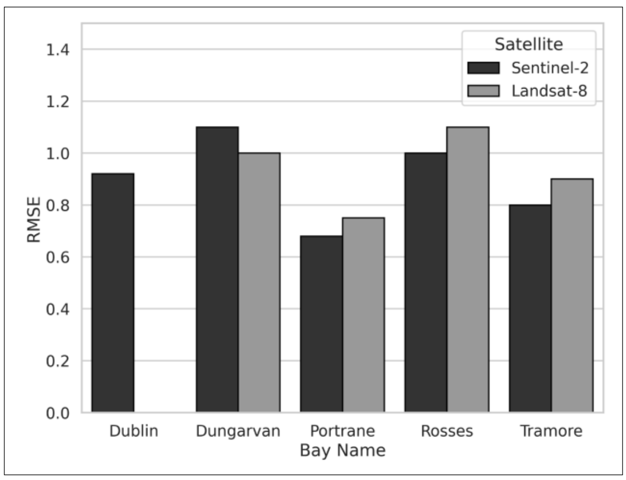

Figure 8. RMSE values for bathymetric models derived from S2 and L8 across the five bays. S2 showed lower RMSE across most bays. The RMSE value for Dublin Bay is missing for L8, as no suitable image was found for the ranked year.

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The plot in Figure 9 illustrates the performance results for the S2 and L8 sensors across the selected bays. S2 (black dots) display a stronger correlation between depth and reflectance. In contrast, L8 data points (grey crosses) are more dispersed, with a weaker fit and slightly higher errors, due to their coarser spatial resolution and broader spectral bands.

This indicates that, for these bays, L8 is influenced more by turbidity and atmospheric changes than S2. This emphasises the importance of the ranking process proposed in our study. The zone of best performance appears in the top-left corner, indicating the lowest error and highest accuracy.

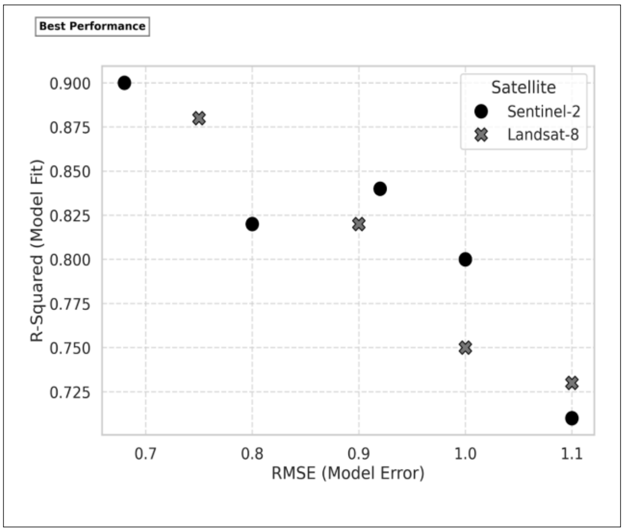

Figure 9. The plot assesses bathymetric model performance by displaying R-squared (model fit) and RMSE (model error) values for S2 and L8.

4. Discussion and Conclusion

This paper presents a cloud-based, open-access workflow for SDB tailored to typical Irish coastal conditions, with a focus on accessibility, capacity building, and scalability. The results demonstrate the method's effectiveness across a range of environmental settings, from the relatively clear waters of Portrane to the more turbid, estuarine conditions of Dungarvan, confirming that the pre-ranking strategy maintains reliable bathymetric outputs across contrasting coastal environments. Expanding the application to additional Irish coastal sites, including those supported by existing INFOMAR data, represents a natural next step.

The generally stronger performance of S2 relative to L8 across the pilot bays can be attributed to several factors. The greater availability of S2 imagery, a result of its shorter revisit cycle and wider swath, increases the likelihood of identifying suitable scenes that pass the ranking threshold, as demonstrated by the absence of any valid L8 image for Dublin Bay. The finer spatial resolution of S2 (10 m versus 30 m for L8) also provides greater detail in shallow coastal environments, where depth gradients can change rapidly over short distances. Differences in spectral band configuration and L8's greater sensitivity to turbidity and atmospheric effects are likely additional contributing factors, though their relative influence varies across sites. Optical satellite-based imagery imposes a fundamental depth limitation that varies with water clarity, ranging from just a few metres in turbid coastal environments to over 20 m in exceptionally clear waters (Dekker et al., 2011). For Irish coastal conditions, this effective depth range is precisely what this study demonstrates and will be further characterised as the growing database of SDB models is compiled. Other current limitations include the availability of suitable, good-quality optical imagery, the optical complexity of Irish coastal waters, and the constraints of empirical spectral modelling in representing radiative transfer processes in the water column (Lee et al., 1998).

The pre-ranking of imagery was performed outside the App to avoid runtime performance limitations. While this ensures efficiency and reliability, one limitation of this approach is that it restricts users to a fixed set of pre-selected images. A threshold will always be necessary to shield users from imagery with little or no SDB potential, and therefore, integrating a dynamic ranking approach directly within the EEA represents a natural future improvement.

This application is the first SDB tool designed to deliver only imagery-suitable outputs to encourage adoption by non-specialist users, significantly lowering the barrier to access and marking a first step toward a broader and more ambitious coastal monitoring vision. In practice, the application can support a broad range of uses, including ocean modelling, environmental monitoring, coastal protection, habitat mapping, marine spatial planning, ports and harbours, aquaculture, and conservation. In doing so, it helps democratise access to up-to-date seabed information, enhances the value of existing open data programmes such as Copernicus and INFOMAR, and ensures that coastal managers, local authorities, maritime agencies, environmental bodies, and ultimately the wider public stand to benefit as the tool matures.

Education and capacity building, through active engagement with universities, agencies, and the wider coastal community, are central to the long-term vision of this work, with the application already incorporated into postgraduate teaching and assessment, for example, at the Remote Sensing Master's programme at Maynooth University. Building on this foundation, geographical expansion of the application beyond its current pilot scope is envisaged. Future development will focus on incorporating additional variables and more advanced empirical approaches, such as those in Cahalane et al. (2019), Casal et al. (2020), and Monteys et al. (2025), including machine learning models, improving the robustness of the validation framework, and enriching outputs to allow users to tailor their exports. The growing temporal record of S2 and L8 imagery, now exceeding a decade, presents a compelling challenge for capturing and monitoring coastal change.

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5. References

Amal, R., Bergsma, E.W.J., Maisongrande, P., Melo de Almeida, L. P. (2019). *Wave-derived coastal bathymetry from satellite video imagery: A showcase with Pleiades persistent mode.* Remote Sensing of Environment, 231, 111263.

Barnard, P.L., Erikson, L.H., Foxgrover, A.C., Finzi Hart, J.A., Limber, P., O’Neill, A.C., van Ormondt, M., Vitousek, S., Nathan Wntood, N., Hayden, M., K., J., J. M. (2019). *Dynamic flood modelling is essential to assess the coastal impacts of climate change.* Nature 9, 4309.

Brooks, P.R., Nairn, R., Harris, M., Jeffrey, D., Crowe, T.P., (2016). *Dublin Port and Dublin Bay: reconnecting with nature and people.* Regional Studies in Marine Science.

Cahalane, C., Magee, A., Monteys, X., Casal, G., Hanafin, J., Harris, P. (2019). *A comparison of Landsat 8, RapidEye and Pleiades products for improving empirical predictions of satellite-derived bathymetry*. Remote Sensing of Environment, 233, 111414.

Casal, G., Harris, P., Monteys, X., Hedley, J., Cahalane, C., McCarthy, T. (2020). *Understanding satellite-derived bathymetry using Sentinel 2 imagery and spatial prediction models*. GIScience and remote sensing, 57:3, 271-286.

Casal, G., Monteys, X., Hedley, J., Harris, P., Cahalane, C., McCarthy, T. (2019). *Assessment of empirical algorithms for bathymetry extraction using Sentinel-2 data.* International Journal of Remote Sensing, 40 (8), 2855-2879.

Caves, E.M., Johnsen, S. (2021). *The sensory impacts of climate change: Bathymetric shifts and visually mediated interactions in aquatic species*. Proc. R. Soc. B 288.

Crowe, O. (2005). *Ireland’s Wetlands and their Waterbirds: status and distribution.* BirdWatch Ireland, Newcastle.

Dekker, A.G., Phinn, S.R., Anstee, J., Bissett, P., Brando, V.E., Casey, B., Fearns, P., Hedley, J., Klonowski, W., Lee, Z.P., Lynch, M., Lyons, M., Mobley, C., Roelfsema, C. (2011). *Intercomparison of shallow water bathymetry, hydro-optics, and benthos mapping techniques in Australian and Caribbean coastal environments.* Limnology and Oceanography: Methods, 9, 396–425.

Duan, Z., Chu, S., Cheng, L., Ji, C., Li, M., Shen, W. (2022). *Satellite-derived bathymetry using Landsat-8 and Sentinel-2A images: assessment of atmospheric correction algorithms and depth derivation models in shallow waters.* Opt. Express 30, 3238–3261.

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., Moore, R. (2017). *Google Earth Engine: Planetary-scale geospatial analysis for everyone.* Remote Sensing of Environment, 202, 18–27.

Hernández-Hamón, H., Ramírez, P. Z., Zaraza, M., & Micallef, A. (2023). *Google Earth Engine app using Sentinel 1 SAR and deep learning for ocean seep methane detection and monitoring*. Remote Sensing Applications: Society and Environment, 32, 101036.

Klein, A., Almeida, L., Gonçalves, R., Unas, P., Bughi, C. H., Tomasi, M. F., ... & Tallmann, J. (2023). *Coastal analyst system from space imagery engine (Cassie-Core): a cloud-based toolset for geoscientists.* In Coastal Sediments 2023: the Proceedings of the Coastal Sediments 2023 (pp. 1584–1596).

Kras, E., Luijendijk, A., Donchyts, G., Santinelli, G., Langemeijer, J., Gwee, R., & Rodenas, A. M. (2022). *Satellite-derived bathymetry for monitoring nearshore dynamics.* Coastal Engineering Proceedings, (37), 46–46.

Lee, Z.P., Carder, K.L., Mobley, C.D., Steward, R.G., Patch, J.S. (1998). *Hyperspectral remote sensing for shallow waters: A semianalytical model.* Applied Optics, 37(27), 6329–6338.

Li, J., Knapp, D.E., Lyons, M., Roelfsema, C., Phinn, S., Schill, S.R., Asner, G.P. (2021). *Automated Global Shallow Water Bathymetry Mapping Using Google Earth Engine.* Remote Sens., 13, 1469.

Li, J., & Roy, D. P. (2017). *A global analysis of Sentinel-2A, Sentinel-2B, and Landsat-8 data revisit intervals and implications for terrestrial monitoring*. Remote Sensing, *9*(9), 902.

Lyzenga, D.R. Passive remote sensing techniques for mapping water depth and bottom features. *Appl. Opt.* 1978, *17*, 379–383.
Monteys, X., Isler, T., Casal, G., & Gallagher, C. (2025). *Improving Satellite-Derived Bathymetry in Complex Coastal Environments: A Generalised Linear Model and Multi-Temporal Sentinel-2 Approach*. Remote Sensing, 17(23), 3834. https://doi.org/10.3390/rs17233834.

Monteys, X., Harris, P., Caloca, S., Cahalane, C. (2015). *Spatial Prediction of Coastal Bathymetry Based on Multispectral Imagery and Multibeam Data*. Remote Sensing, 7,13782-13806.

Monteys, X., Isler, T., Casal, G., & Gallagher, C. (2025). Improving Satellite-Derived Bathymetry in Complex Coastal Environments: A Generalised Linear Model and Multi-Temporal Sentinel-2 Approach. *Remote Sensing*, *17*(23), 3834.

Sagawa, T., Yamashita, Y., Okumura, T., & Yamanokuchi, T. (2019). *Satellite-derived bathymetry using machine learning and multi-temporal satellite images*. Remote Sensing, *11*(10), 1155.

Wölf, A.C., Snaith, H., Amirebrehimi, S., Devey, C.W., Dorschel, B., Ferrini, V., Huvenne, V.A.I., Jakobsson, M., Jencks, J., Johnston, G., Lamarche, G., Mayer, L., Millar, D., Pedersen, T.H., Picard, K., Reitz, A., Schmitt, T., Visbeck, M., Weatherall, P., Wigley, R. (2019). *Seafloor Mapping – The Challenge of a Truly Global Ocean Bathymetry.* Frontiers in Marine Science, 6.

Zapata-Ramírez, P. A., Hernández-Hamon, H., Fitzsimmons, C., Cano, M., García, J., Zuluaga, C. A., & Vásquez, R. E. (2023). *Development of a Google Earth Engine-based application for the management of shallow coral reefs using drone imagery.* Remote Sensing, 15(14), 3504.