Optimizing PlanetScope-Based Satellite-Derived Bathymetry: A Single-Band Approach with 3D Spatial and Statistical Filtering

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Abstract : *Satellite-Derived Bathymetry (SDB) is an efficient method for mapping shallow water depths, particularly in large tropical areas that are difficult to survey using conventional techniques. This study optimises the single-band approach on PlanetScope imagery by integrating statistical filtering with 3D geospatial interpolation to improve accuracy and reduce prediction errors. Of the three spectral channels used (red, green, blue), the green band provided the best initial performance (R^2 = 0.211; RMSE = 2.080 m) and was selected for the basis predictive model advanced. Bathymetry reference data from Single Beam Echosounder System (SBES) surveys, reduced to Mean Sea Level (MSL), were used as reference data for model calibration and validation, with 30 points as controls. Optimisation involved applying Cloth Simulation Filtering (CSF) to the estimated depth point cloud, followed by spatial interpolation using Kriging, Inverse Distance Weighting (IDW), Spline, and Natural Neighbour methods. The results show that the combination of CSF and IDW provides the best performance with an increase in the correlation value of 0.462 (from R = 0.211 to R = 0.673), an increase in determination R^2 of 0.251, and a decrease in RMSE to 1.619 m. Additionally, using a smaller cloth resolution resulted in a more accurate model, indicating the high sensitivity of the CSF parameter to the quality of the final results. This study demonstrates that the integration of statistical filtering and geospatial interpolation can significantly improve the performance of single-band SDB method, offering an accurate and cost-effective solution for large-scale bathymetry mapping with improved accuracy.*

Keywords: Satellite-Derived Bathymetry (SDB), PlanetScope, Statistical Filtering, 3D Geospatial Filtering, Bathymetry Accuracy

1. Introduction

Bathymetric data has an important contribution in various marine and coastal studies, such as navigation safety, habitat mapping, coastal zone management, and climate change studies (Calder & Mayer, 2003; IHO, 2022). Accurate and up-to-date information on ocean depths is needed to support development planning and coastal ecosystem conservation activities. Hydrographic surveys using conventional methods such as single beam and multibeam echosounders are considered the standard for obtaining bathymetric data. Although they have high accuracy, these methods are costly, time-intensive, and often limited to specific areas, such as shallow waters and hard- to-access tropical regions.

As an alternative, satellite-based remote sensing is developing significantly and can support bathymetric mapping, known as Satellite-Derived Bathymetry (SDB). The principle is based on the utilisation of light penetration into the water column, where the intensity of surface reflectance is correlated with depth (Stumpf et al., 2003). This approach offers broader spatial coverage, relatively low costs, and high data acquisition frequency. Previous studies have shown that SDB can produce fairly accurate depth estimates, even though its accuracy is still affected by water conditions, image quality, and the processing techniques used (Sagawa et al., 2019).

PlanetScope, as a satellite imagery provider with high spatial resolution and daily recording frequency, has high potential in supporting the implementation of SDB. However, the main challenge is to select the optimal spectral channel and the correct processing steps to minimise depth estimation errors. In general, satellite image-based bathymetry research uses the ratio of bands or a combination of multiple spectral channels, such as the ratio between the blue and green bands, to enhance the relationship between reflectance and water depth. Although this multiband approach is popular, it is difficult to evaluate the specific contribution of each spectral channel to the accuracy of depth estimation. In this case, the single-band approach is essential because it allows for direct evaluation of the sensitivity of single channel (Stumpf et al., 2003; Thomas et al., 2021).

Based on this background, this study focuses on optimising the single-band approach in bathymetric estimation using PlanetScope imagery. Optimisation is carried out by applying the Cloth Simulation Filter (CSF) to reduce noise and separate surface data from more representative depth information. This research is expected to make a contribution in the development of a simpler yet reliable SDB method, which can be applied more widely in tropical coastal areas with limited access to conventional bathymetric surveys.

2. Literature Review

Several research studies have been conducted to evaluate the potential of Satellite-Derived Bathymetry (SDB) in mapping shallow ocean depths. This method uses the mathematical relationship between the spectral reflectance of satellite images and water depth. One of the early models was introduced by Lyzenga in the late 1970s, which was then further developed by Stumpf et al. (2003) through logarithmic transformation of reflectance as a more stable empirical approach. To the current day, SDB continues to be used on various satellite sensors ranging from Landsat, Sentinel-2, PlanetScope, to WorldView, with results depending on water optical conditions and the processing techniques used (Evagorou et al., 2025; Sagawa et al., 2019).

PlanetScope is one of the sensors with potential to support SDB due to its high spatial resolution (3-5 metres) and daily temporal coverage. Several studies have reported that the green channel is more stable in water column penetration than other bands, so it was selected in the single-band regression approach. Studies by Traganos & Reinartz (2018) and Sagawa et al. (2019) show that although this approach is potential, the accuracy results obtained are often still low, with small coefficient of determination (R^2) values and relatively large Root Mean Square Error (RMSE). Moreover, external factors such as water turbidity, surface ripples, and seabed substrate heterogeneity often cause noise that affects the quality of depth estimation.

Based on the standards of the International Hydrographic Organisation (IHO, 2022), the accuracy of bathymetric surveys is determined according to specific categories, where the vertical error tolerance values become increasingly stringent for higher-order surveys. Many simple regression-based SDB results are unable to reach these standards, requiring optimisation strategies both in the pre-processing and post-modelling stages. Research in tropical regions indicates that the optical complexity of the water, such as high suspended sediment content and substrate variation, create a substantial challenge in upgrading the quality of satellite-based bathymetric models (Sagawa et al., 2019; Thomas et al., 2021).

Many researches have developed optimisation approaches to reduce these limitations, one of them is through the application of filtering methods on depth estimation data. Cloth Simulation Filter (CSF), which was previously used in LiDAR data processing, has proven to be effective in separating ground points from noise in point clouds, so it can improve the quality of elevation models (Zhang et al., 2016). The application of CSF to SDB results provides an opportunity to reduce the influence of spectral noise caused by foam, turbidity, and reflectance anomalies. The advantages of CSF over other filtering methods are its simple parameters, flexibility of application, and its ability to preserve the actual basic morphological shape (Lee et al., 2025).

Other than filtering, geospatial interpolation also has an important contribution in developing a more representative bathymetric model. Interpolation methods such as Inverse Distance Weighting (IDW), Kriging, Spline, and Natural Neighbour are mostly used to produce a smooth depth surface from SDB estimation point data. Research by Li et al. (2021) shows that the choice of interpolation method has a significant effect on the final accuracy of the model, especially in complex seabed morphology areas (Evagorou et al., 2025). The integration of CSF-based filtering with three-dimensional spatial interpolation has the potential to improve estimation performance and enhance the spatial distribution of the resulting depth.

Based on a literature review, previous research has been exploring Satellite-Derived Bathymetry (SDB) methods using various satellite sensors and modelling algorithms. However, studies related to the integration of the single-band regression approach with Cloth Simulation Filter (CSF)-based filtering techniques and spatial interpolation have not been widely conducted. This confirms the existence of a relevant research gap, especially for tropical and narrow areas with shallow water conditions such as Baron Beach, Yogyakarta, which is the study location in this research. Therefore, this research focuses on developing a PlanetScope-based SDB optimisation method through a combination of single-band regression, CSF statistical filtering, and spatial interpolation to generate more accurate, reliable, and applicable bathymetry estimates in shallow tropical coastal areas.

3. Methodology

3.1. Study Area

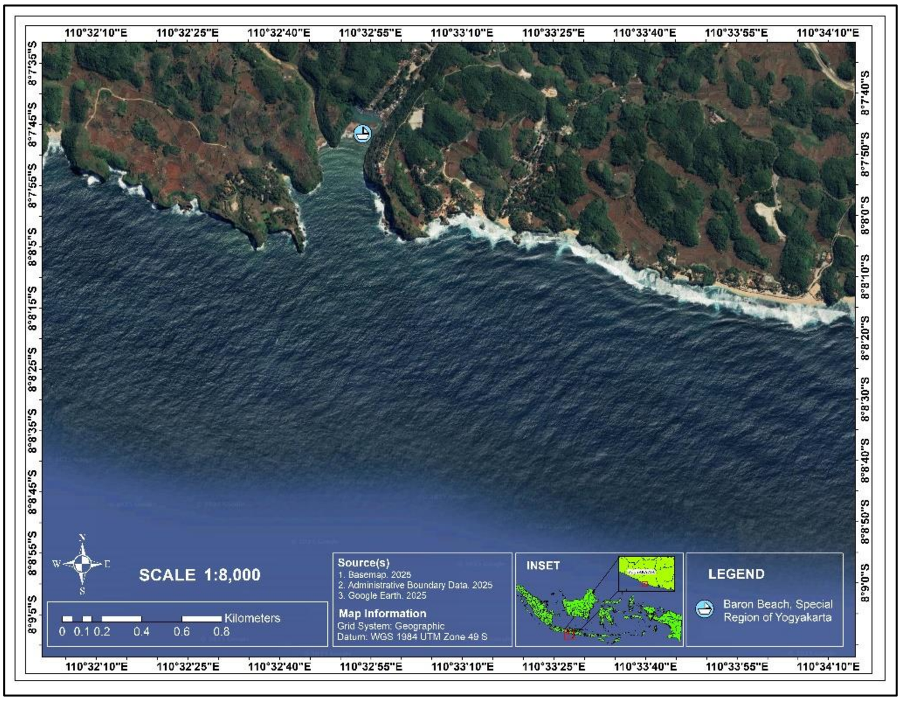

Figure 1: Map of The Study Area.

This research was located at the Baron Beach waters, Gunungkidul Regency, Special Region of Yogyakarta (110°32'–110°33' E and 8°9'–8°10' S). Baron Beach (Figure 1) is a marine tourism area managed by the Gunungkidul Regency Government and has shallow tropical waters with an average depth of <30 m. The seabed conditions at Baron Beach are dominated by sandy substrates and volcanic rocks, making it representative for the assessment of the Satellite-Derived Bathymetry (SDB) method in areas with limited space.

The high activity levels of tourism and fisheries in this area increase the urgency for the availability of accurate and efficient bathymetric data.

3.2. Data

The data used in this study includes:

1. PlanetScope satellite imagery with a spatial resolution of 3-5 metres, used as the main input for depth estimation through a single-band regression approach.
2. Reference bathymetric data from ground surveys using a Single Beam Echosounder System (SBES), reduced to Mean Sea Level (MSL) datum for model calibration and validation.
3. Tidal data used for vertical correction, to ensure consistency of depth data with MSL datum.

3.3. Processing Workflow

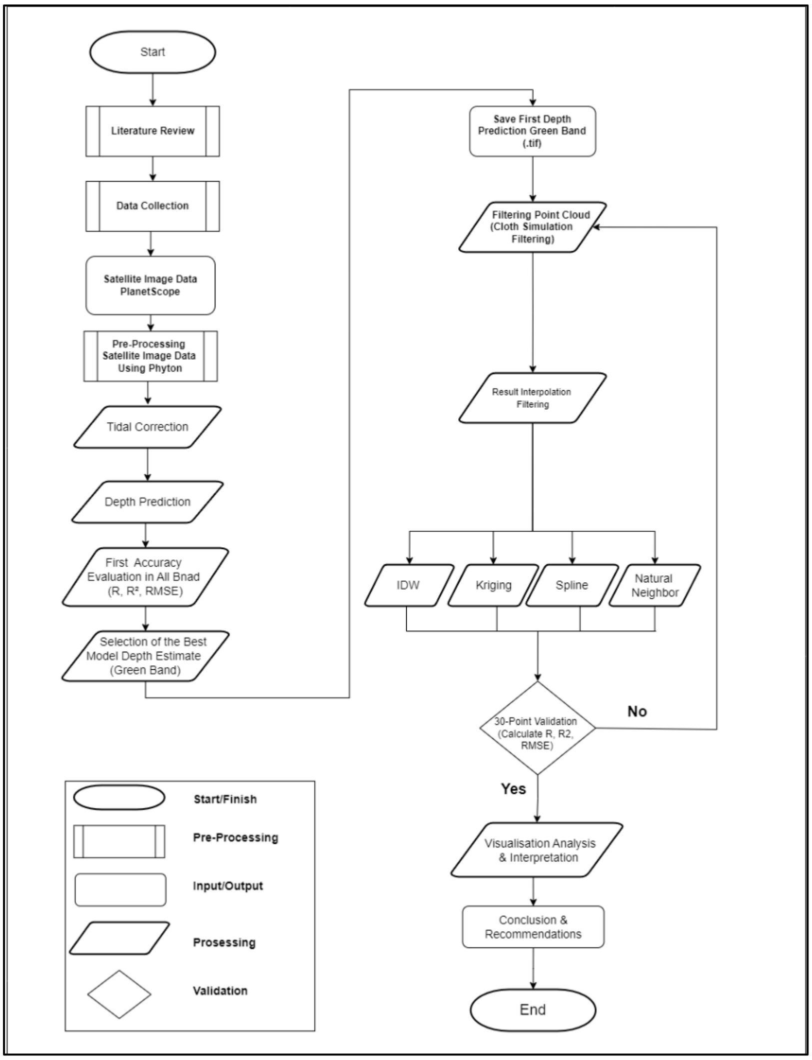

Figure 2: The Workflow of Research.

The overall workflow of this study is illustrated in the research flowchart (Figure 2). The process begins with pre-processing of PlanetScope imagery, which includes radiometric correction, conversion to top-of-atmosphere (TOA) reflectance, and masking of land and water areas using the Normalised Difference Water Index (NDWI). A tidal correction was then applied to standardise the depth predictions to the Mean Sea Level (MSL) datum. The next stage is bathymetric modelling using a single-band regression approach on the red, green, and blue spectral channels. An initial accuracy test was conducted to assess the performance of each channel against reference bathymetric data, and the green channel was selected as the optimal predictor for further optimisation.

Optimisation was carried out by applying the Cloth Simulation Filter (CSF) to the depth prediction outputs in point cloud format. This filtering step was designed to minimise noise caused by factors such as surface ripples, water turbidity, and substrate heterogeneity, while retaining the true bathymetric signal. The filtered outputs were then interpolated into continuous bathymetric surfaces using four geospatial interpolation methods, i.e. Inverse Distance Weighting (IDW), Kriging, Spline, and Natural Neighbour. These methods were selected to evaluate different spatial modelling approaches, ranging from distance-based weighting (IDW), spatial autocorrelation (Kriging), smooth curve approximation (Spline), to neighbour-based estimation (Natural Neighbour).

Finally, the interpolated bathymetric models were subjected to an accuracy validation using independent control points. The results of this validation were then analysed to identify the best-performing method and provide insights into the optimisation of the single-band SDB approach using PlanetScope imagery.

3.4. Validation

The accuracy of the interpolated bathymetric models was validated using 30 SBES reference points that were not included in the calibration stage. Validation was conducted by calculating the Root Mean Square Error (RMSE) and the coefficient of determination (R^2). The RMSE was calculated to quantify the average deviation between the estimated depths from satellite imagery and the in-situ SBES measurements, using formula:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(At-Ft)^2}{n}} \qquad (1)$$

Where:

Ft = Measured depth from SBES survey,

At = Estimated depth from satellite-derived bathymetry.

N = Number of validation points.

The coefficient of determination (R^2) was used to evaluate the proportion of variance in SBES-measured depths that could be explained by the satellite-derived estimates.

Validation was carried out to identify the best-performing spectral band of PlanetScope imagery based on the lowest RMSE and the highest R^2 values. The band with the best performance was then used for the final depth estimation, which was subsequently optimised and visualised in bathymetric maps. Furthermore, the results were compared with the accuracy standards defined by the International Hydrographic Organisation (IHO, 2022) to determine their suitability for shallow-water bathymetric mapping

4. Results and Discussion

4.1. Initial Model Performance

Initial modelling results using a single-band regression approach show that the green channel performs best compared to the red and blue channels. The depth map resulting from the green channel regression (Figure 3) shows a depth distribution of up to -40.11 metres, but with low accuracy when compared to SBES reference data. The initial validation yielded values of correlation (R) of 0.44, coefficient of determination (R^2) of 0.21, and Root Mean Square Error (RMSE) of 2.27 m. These values are relatively low according to the International Hydrographic Organisation (IHO, 2020) standards for first-order bathymetric surveys, so advanced optimisation is required.

The weakness of this initial model was generally the presence of reflectance noise due to turbidity, surface ripples, and substrate heterogeneity at Baron Beach. The optical complexity of tropical waters meant that the relationship between depth and reflectance was not always linear, making it difficult to achieve optimal results with simple regression.

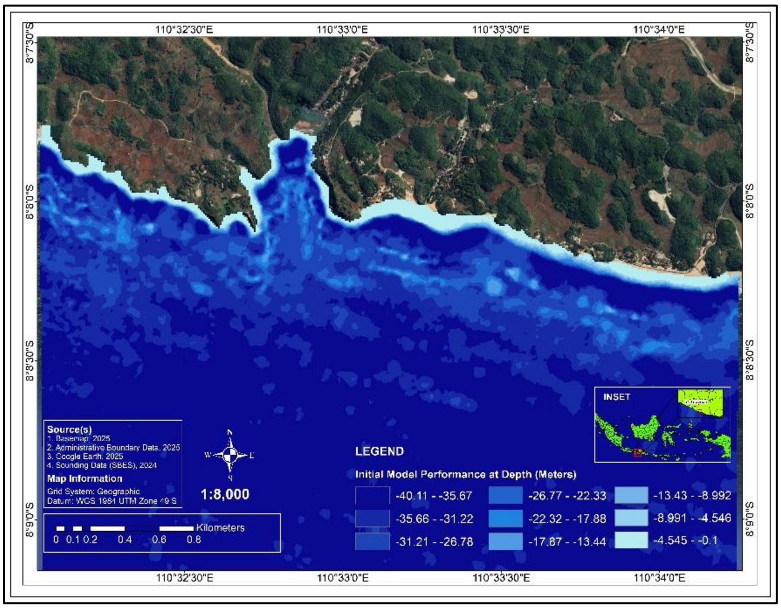

Figure 3: Bathymetric Map Resulting from Green Interpolation of Initial Data.

4.2. Optimisation with Cloth Simulation Filter (CSF)

Cloth Simulation Filter (CSF) was applied to enhance the results, on the point cloud of the green channel regression (Figure 4). CSF was effective in separating the seabed points from noise, resulting in a more representative point cloud. These results became the basis for spatial interpolation.

The advantage of CSF lies in its ability to smooth data without losing key morphological characteristics. Cloth resolution settings have been shown to affect filtering quality, with small resolutions providing better detail, while large resolutions tend to smooth excessively. This filtering is therefore a crucial step in reducing initial errors before interpolation is performed.

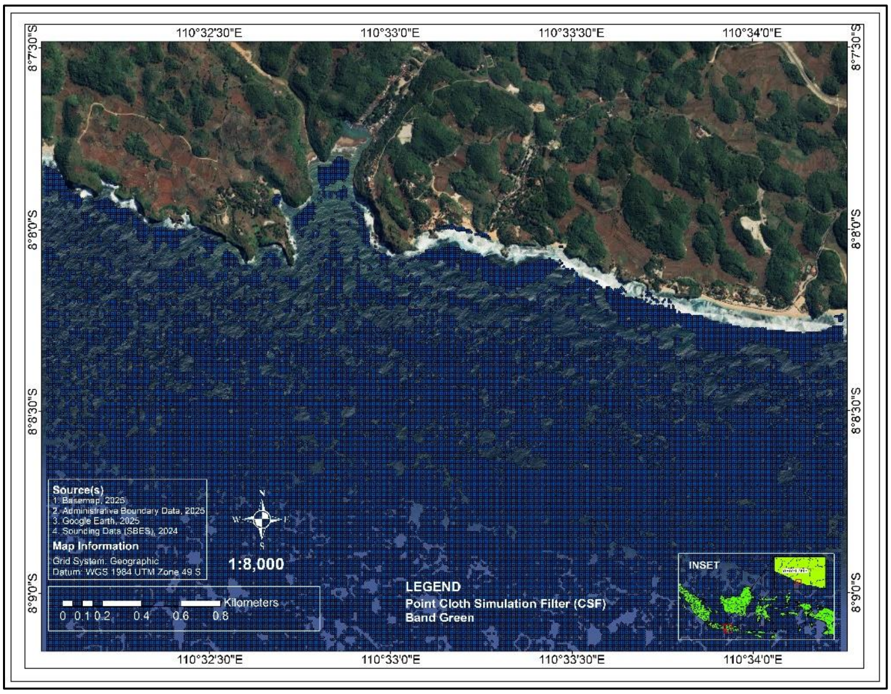

Figure 4. Point Cloth Simulation Filter (CSF) Band Green

4.3. Interpolation Results from CSF-Filtered Data

A. CSF + IDW Interpolation

The interpolation results using the CSF + Inverse Distance Weighting (IDW) method are shown in Figure 5. The resulting depth distribution pattern appears smooth and consistent with the SBES reference data. The transition from shallow to deep waters appears gradual. IDW proved to be effective because it emphasises the contribution of the nearest points, which is in line with the dense distribution of SBES data on Baron Beach.

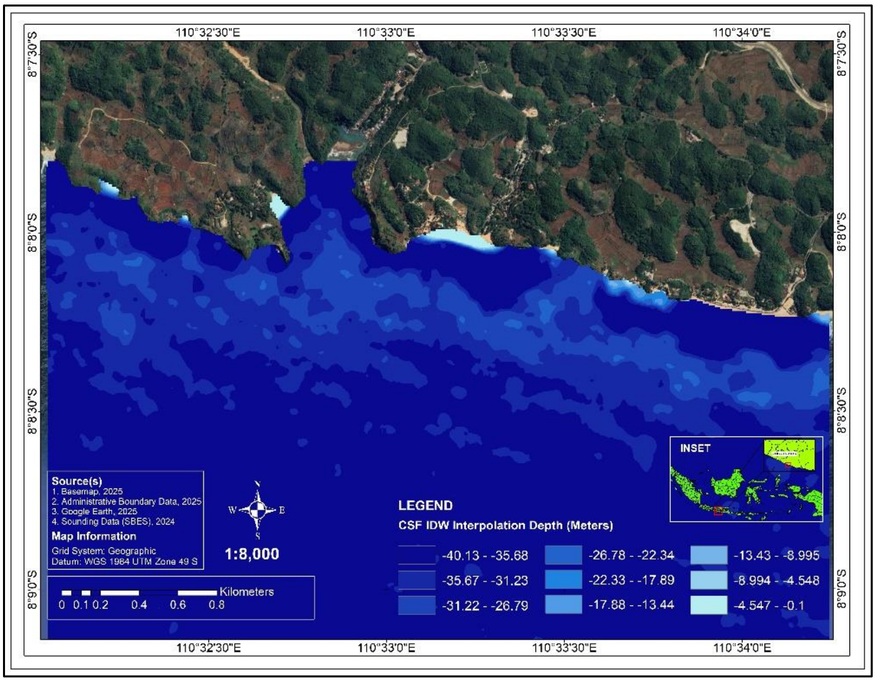

Figure 5: Bathymetric Map Resulting from IDW Interpolation of CSF-filtered Data.

B. CSF + Kriging Interpolation

Interpolation using the CSF + Kriging method produces a map as shown in Figure 6. Kriging shows more complex details in areas with high point density. However, its weakness appears in areas with sparse data distribution, where the pattern appears unrealistic. This shows that Kriging is highly dependent on uniform data distribution for optimal results.

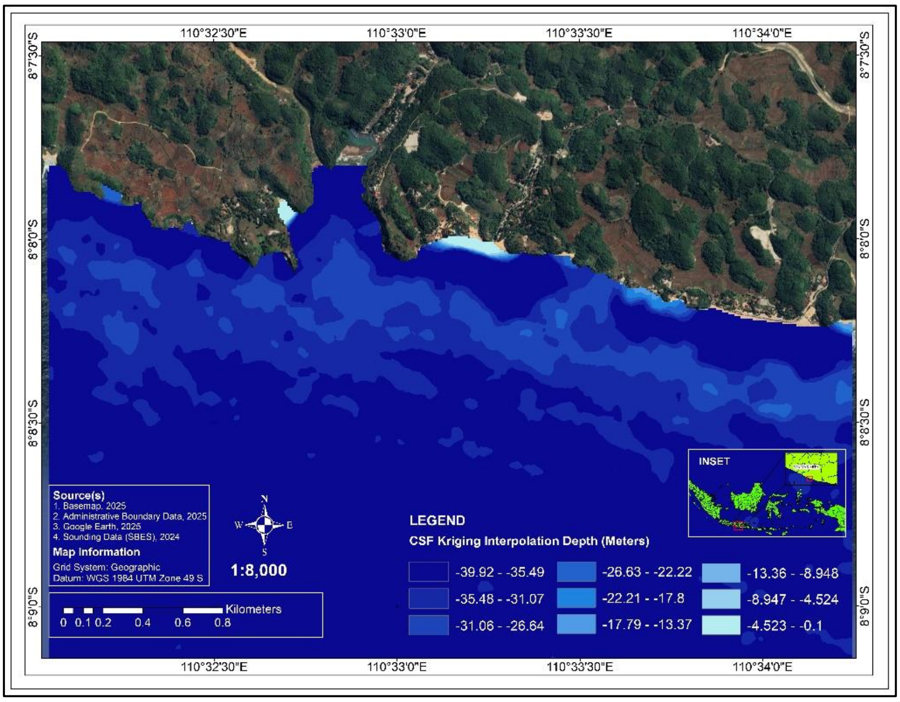

Figure 6: Bathymetric Map Resulting from Kriging Interpolation of CSF-filtered Data.

C. CSF + Natural Neighbour Interpolation

The interpolation results using the CSF + Natural Neighbour method are shown in Figure 7. This method produces a stable map, with moderate depth distribution without causing significant artefacts. However, its weakness is that it is less responsive to local variations. The depth contours appear flatter than IDW and Kriging, so that the details of the seabed morphology are not fully represented.

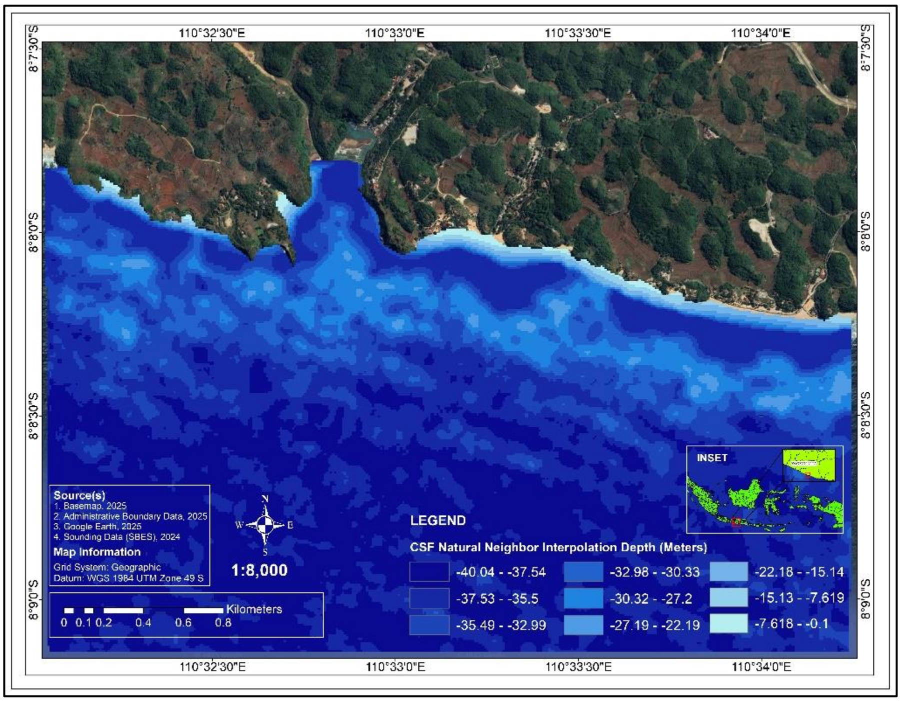

Figure 7: Bathymetric Map Resulting from NN Interpolation of CSF-filtered Data.

D. CSF + Spline Interpolation

Interpolation using the CSF + Spline method is shown in Figure 8. The result is a very smooth depth surface, but it tends to be over-smoothed. Depth variations are reduced, making the seabed contours appear flatter. Although this method is useful for general visualisation, the results are less suitable when the research objective is to detect details of seabed morphology changes.

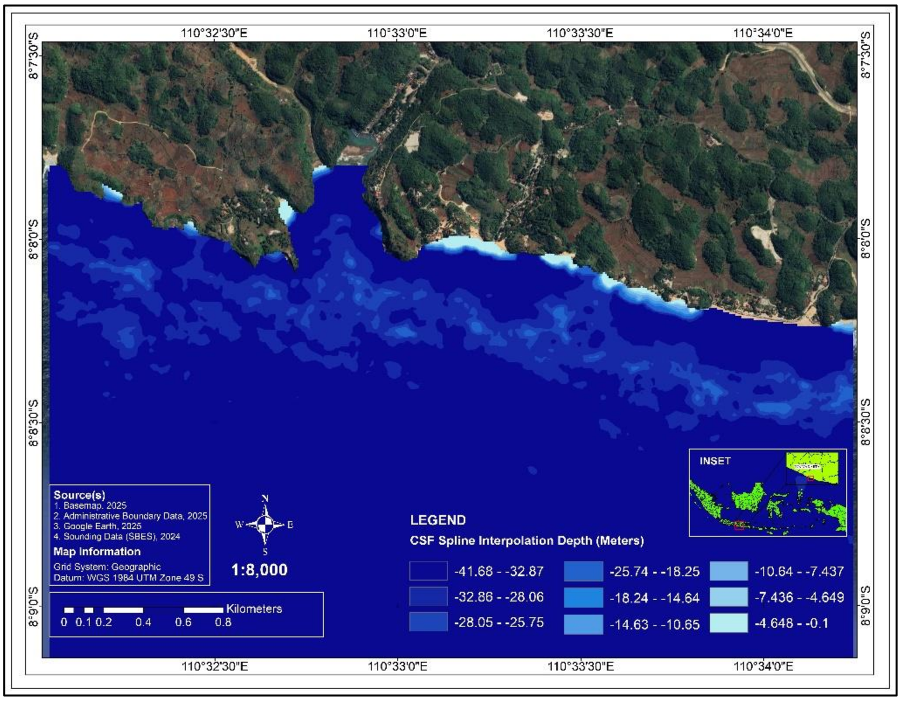

Figure 8: Bathymetric Map Resulting from Spline Interpolation of CSF-filtered Data.

4.4. Statistical Comparison

The statistical test results reinforce the differences between interpolation methods (Table 1). The combination of CSF + IDW provided the best performance with values of R = 0.673, R^2 = 0.462, and RMSE = 1.619 m. Compared to the initial model, the increase in R^2 of 0.251 and the decrease in RMSE of 0.461 m indicate that optimisation with CSF and IDW interpolation effectively improves the accuracy of the model.

Table 1: Statistical Performance of Initial and Optimised Models

Model	R	R^2	RMSE (m)
Initial Green Band	0.460	0.211	2.080
CSF + IDW	0.673	0.453	1.619
CSF + Kriging	0.670	0.449	1.626
CSF + Natural Neighbour	0.642	0.412	1.674
CSF + Spline	0.669	0.448	1.625

The results of the statistical comparison between the initial model (Green Band Regression) and the optimised results using a combination of CSF + interpolation are shown in Table 1. The initial model only produced a correlation value (R) of 0.460, a coefficient of determination (R^2) of 0.211, and a Root Mean Square Error (RMSE) of 2.080 m. These values indicate that only about 21.1% of the depth variation can be explained by the model, while the rest is error or the influence of external factors. The RMSE exceeding 2 metres also indicates a significant deviation compared to the SBES reference data.

After optimisation, there was a significant increase in accuracy. The combination of CSF + IDW produced an R value of 0.673, an R^2 of 0.453, and an RMSE of 1.619 m. This means that this model is able to explain around 45.3% of the depth variation with a lower error than the initial model. The CSF + Kriging method produced results close to IDW with an R^2 value of 0.449 and an RMSE of 1.626 m. Meanwhile, the Natural Neighbour and Spline methods produced R^2 values of 0.412 and 0.448, respectively, with slightly higher RMSE values of 1.674 and 1.625 m.

The statistical results thus reinforce that IDW is the best interpolation method for processing CSF filtering results at Baron Beach. The improvement in RMSE of 0.461 m compared to the initial model shows that the filtering stage plays a major role in reducing errors. The increase in R^2 of 0.242 also shows that the integration of CSF with spatial interpolation is more representative in explaining the variation in shallow water depth.

4.5 Integrated Discussion

In general, this study shows that the integration of single-band regression, CSF filtering, and spatial interpolation can improve the quality of bathymetric estimates from PlanetScope images. CSF filtering is key to reducing reflectance noise, so that interpolation produces a more realistic surface.

Of the four interpolation methods, IDW proved to be the most suitable for SBES data at Baron Beach, where the distribution was relatively dense. Kriging produced good detail, but its sensitivity to uneven point distribution was a weakness. Natural Neighbour was more stable but less detailed, while Spline smoothed the data too much, reducing local variation. When compared with the International Hydrographic Organisation (IHO, 2022) standard, the best results (CSF + IDW with RMSE 1.619 m) are still in Category 1. This means that this model is suitable for medium to regional scale coastal mapping, but does not yet meet the high accuracy standards (Special Order) required for navigation of major shipping lanes. Even so, the improvement in accuracy from the initial model to the optimised results shows the high potential of this method as an alternative solution in tropical regions with limited access to conventional surveys.

Conclusion and Recommendation

This research shows that single-band PlanetScope based Satellite-Derived Bathymetry (SDB) optimisation can be improved through the application of Cloth Simulation Filtering (CSF) and spatial interpolation. The initial Green Band regression model has low accuracy ($R^2 = 0.211$; RMSE = 2.080 m), but after optimisation, the best results were achieved with a combination of CSF + IDW ($R^2 = 0.453$; RMSE = 1.619 m). These results are at the IHO Order 1 standard and are suitable for tropical coastal mapping with greater efficiency in terms of time and cost compared to conventional surveys.

Recommendations for the next research are to test the integration of a multi-band approach, the use of machine learning algorithms, and the application of this method in other tropical coastal locations to test the consistency and transferability of the results.

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