Water Storage Retrieval using Remote Sensing and in situ Bathymetric Data

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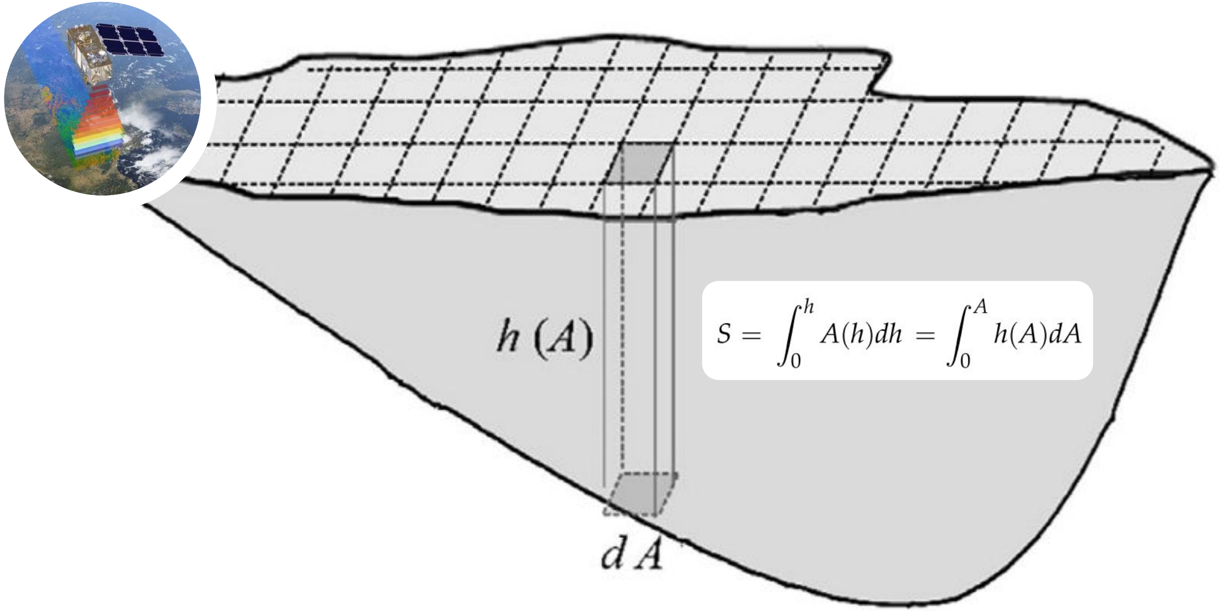
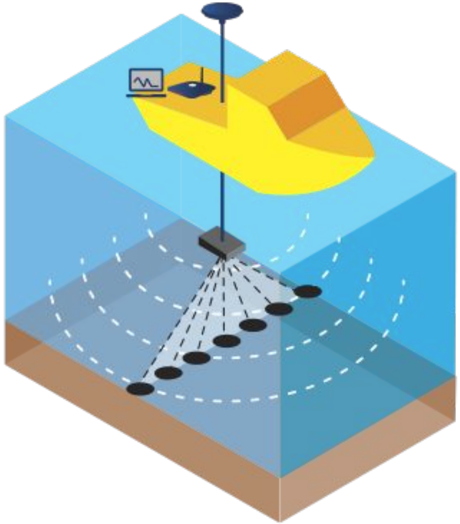
Parameter-surface based bathymetry



$$S = \int_0^h A(h)dh = \int_0^A h(A)dA$$

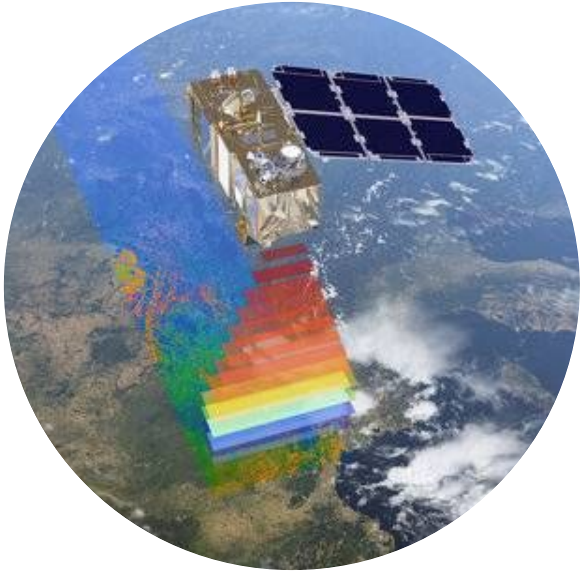
$$S = \sum_{i=1}^{n} S_i = \alpha \sum_{i=1}^{n} h_i$$

Data



ecohydros
ecología avanzada del agua

Bathymetry



esa

Google Earth Engine

Sentinel-2

Methodology

1

Phase I: Automatic Water Classification *(unsupervised)*

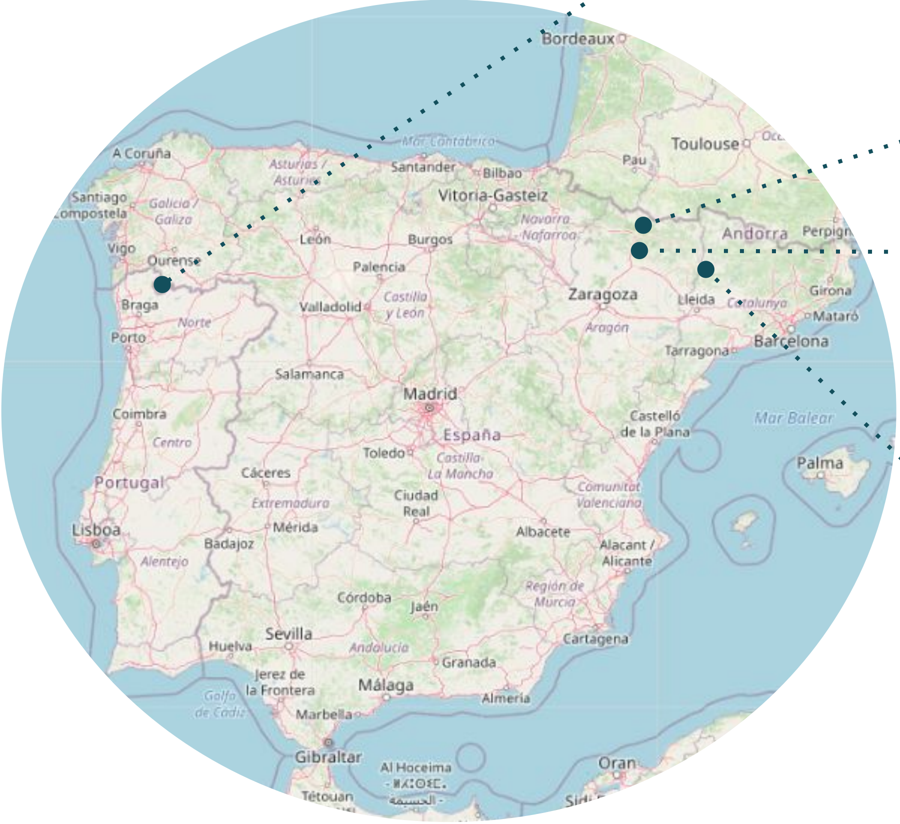
2

Phase II: Satellite-derived Bathymetry *(supervised)*

3

Phase III: Water Storage Retrieval *(union of phases I and II)*

Study Cases: Reservoirs



Alto-Lindoso | 379 hm^3
Power Generation

Bubal | 63 hm^3
Power Generation
Fishing

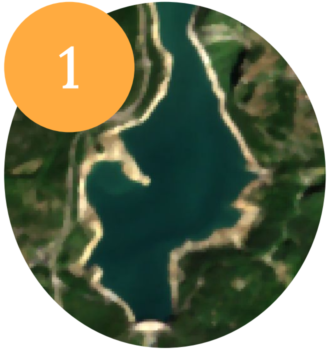
Grado | 400 hm^3
Consumption
Power Generation
Irrigation

Canelles | 679 hm^3
Power Generation
Fishing
Irrigation
Navigation

1 Automatic water classification

1

Automatic water classification



Preprocessing

10 m bands | Blue (B2), Green (B3), Red (B4), NIR (B8)

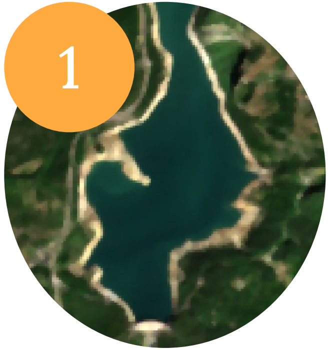
Clouds/Shadows masking

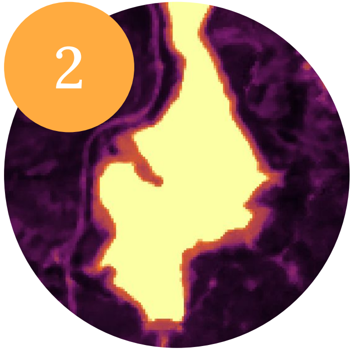
3x3 median low-pass filter

Median per pixel (> 1 image)

1

Automatic water classification





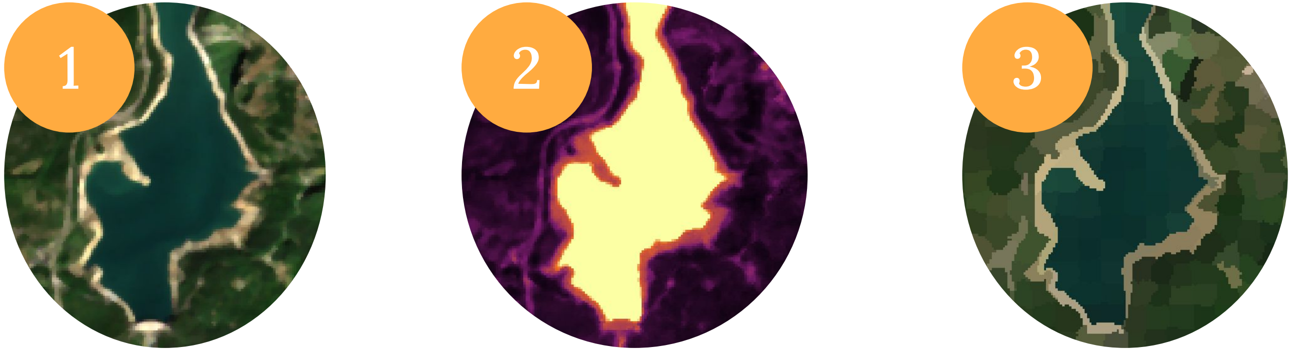
NDWI (Normalized Difference Water Index)

Green (B3) - NIR (B8) / Green (B3) + NIR (B8)

Google Earth Engine

1

Automatic water classification



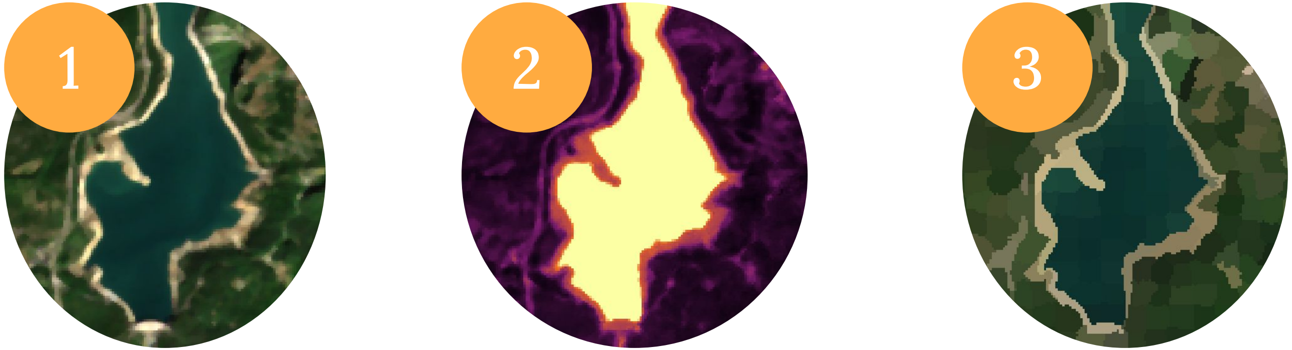
GEOBIA (Geographic Object-Based Image Analysis)
SNIC (Simple Non-Iterative Clustering)
Seed based superpixels

Inputs
B2, B3, B4, B8, NDWI

Google Earth Engine

1

Automatic water classification



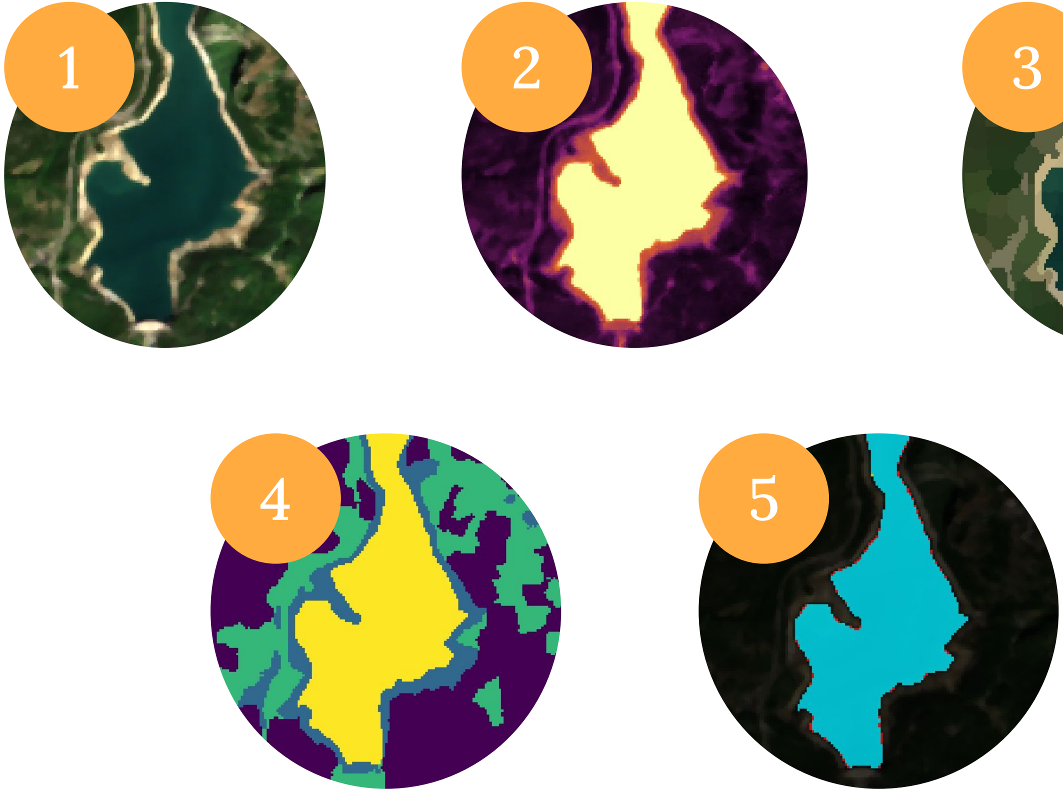
k-means
Superpixels' clustering

Inputs
B2, B3, B4, B8, NDWI

Google Earth Engine

1

Automatic water classification



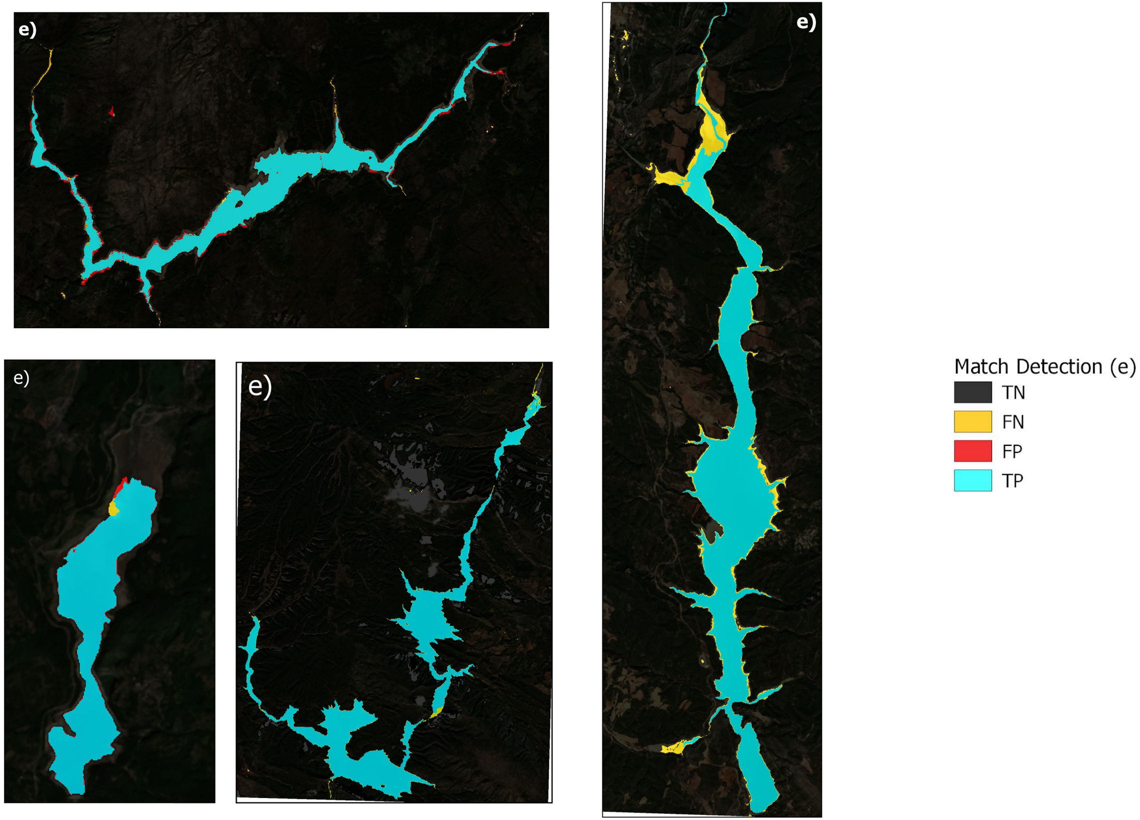
Water Superpixels

Cluster with the highest NDWI value

Google Earth Engine

1

Best model: **Reservoirs**



2 Satellite-derived bathymetry

2

Satellite-derived bathymetry

IDW (Inverse Distance Weighting)

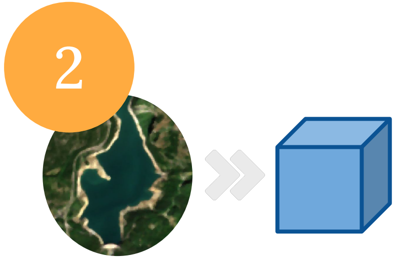
Bathymetric data + shoreline data interpolation

Interpolated bathymetry = ***Target feature***

Google Earth Engine

2

Satellite-derived bathymetry



Data transformation

10 m bands to table: pixels to rows

Predictor features (15 features)

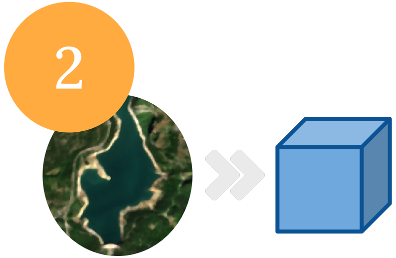
10 m bands | B2, B3, B4, B8

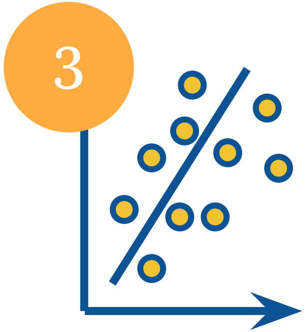
Cumulative cost | Distance to shoreline

Lyzenga Transform | LT2, LT3, LT4, LT8

Ratio Transform | RT23, RT24, RT28, RT34, RT38, RT48

Satellite-derived bathymetry





Bathymetry estimation

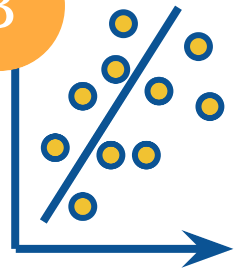
Linear Regression (LR)
Random Forest (RF)
Gradient Boosting (GB)

Samples| 372,833
Training | 354,191 (95%)
Test | 18,642 (5%)

2

Bathymetry estimation: **Training RMSE**

3

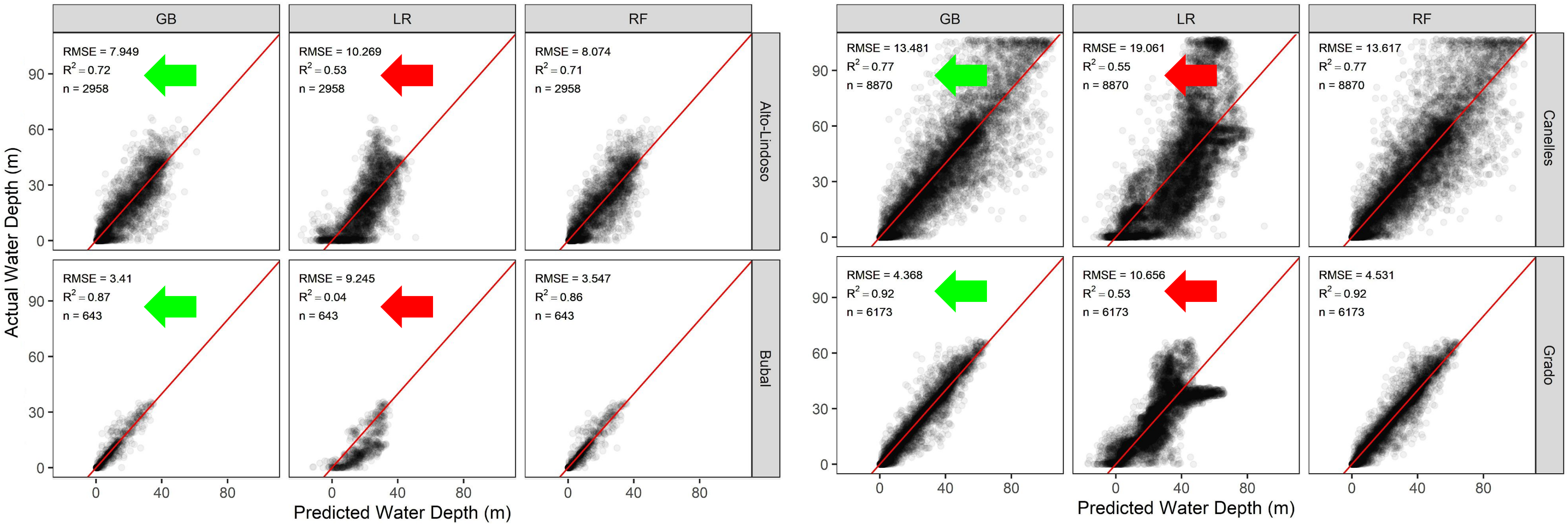


Random Forest | 10.717 ± 1.664 *m*

Gradient Boosting | 10.591 ± 1.671 *m*

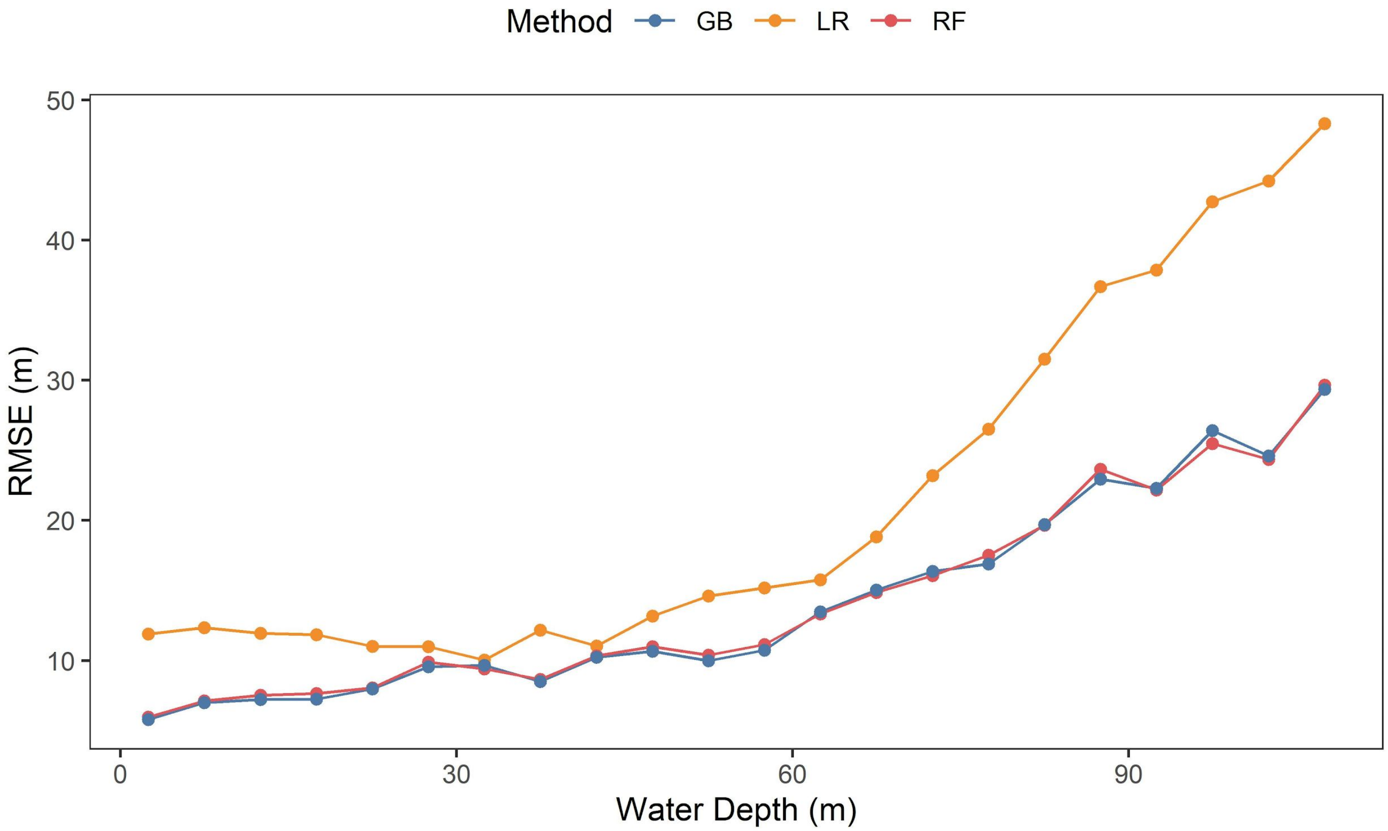
Linear Regression | 14.810 ± 1.294 *m*

Results: Test



2

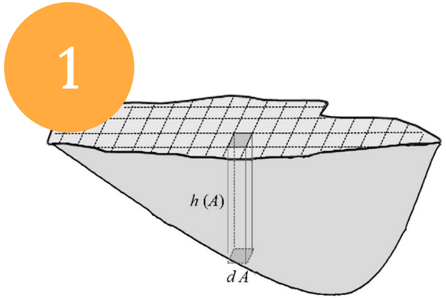
Error variation due to water depth



3 Total water storage retrieval

3

Total water storage retrieval



Total water storage retrieval
Water mask prediction for reservoir
Water depth prediction for reservoir
Estimation through surface-parameter method

Total water storage retrieval

		LR		RF		GB	
Reservoir	S (hm³)	$\hat{S}$ (hm³)	ε (hm³)	$\hat{S}$ (hm³)	ε (hm³)	$\hat{S}$ (hm³)	ε (hm³)
Alto-Lindoso	111.934	114.946	3.012	113.359	1.425	113.701	1.767
Bubal	13.626	22.184	8.558	13.676	0.050	13.821	0.196
Canelles	678.025	663.126	-14.899	673.421	-4.604	671.747	-6.278
Grado	316.147	312.277	-3.870	313.206	-2.941	313.415	-2.733

Conclusions

1

Water mask | GEOBIA + *k*-means | B2, B3, B4, B8, NDWI
Best model (Sentinel-2) | G = squared | S = 10 px | K = 4
Errors near the shoreline | *Low water depth regions*

2

Bathymetry estimation | GB > RF > LR | Cumulative cost
Error increases with water depth | *absorption and dispersion*
Future work | CNN

3

Water storage retrieval | GEOBIA + *k*-means + Ensembles
Error increases (underestimation) with water depth | (< 4 hm^3)

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