Space-borne super-resolution remote sensing technology for detecting, mapping, and classifying Halophila stipulacea subtidal small-leaved tropical seagrass meadows

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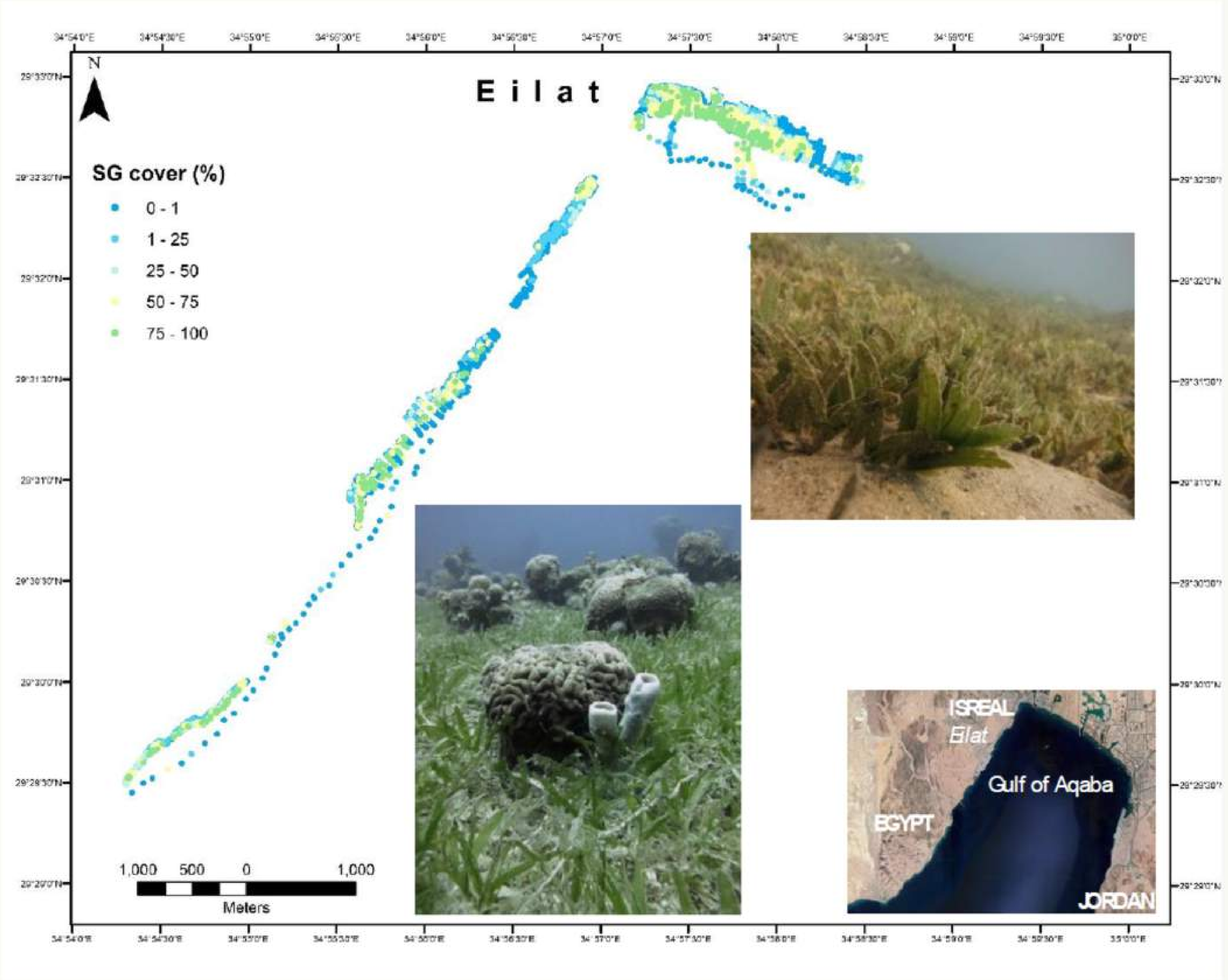


INTRODUCTION

Seagrass meadows are complex marine habitats that provide important ecosystem functions including carbon storage, water filtration, and coastal protection as noted by Duarte et al. (2005). Out of these, the small leaved tropical seagrass, Halophila stipulacea, found in the northern Gulf of Aqaba is especially important for the biodiversity and ecosystem integrity (Winters et al., change, 2017). anthropogenic However, activities subtidal and seagrass occasional communities flash are floods under (Al-Rousan threat et from al., climate 2011).

The management and assessment of these subaqueous vegetation communities is complicated by the fact that they are underwater, sparse, and covered by water which hampers the application of conventional remote sensing strategies (Brook et al., 2022). New remote sensing data such as VENµS and Sentinel-2 high-resolution satellite imagery, along with advanced machine learning approaches, have the potential to help in overcoming these challenges (Coffer et al., 2020; Traganos et al., 2018).

METHODOLOGY

Study Area

The study focused on three locations in the northern Gulf of Aqaba: North Beach, Katzaa Beach, and Taba Beach. These sites were chosen for their ecological importance and varying exposure to flash floods, enabling a comprehensive analysis of seagrass dynamics under different environmental conditions.

Data Sources

Two satellite datasets were utilized: VENµS, with a 5 m spatial resolution, 11 spectral bands, and a 2-day revisit, and Sentinel-2, with a 10 m resolution and indices such as NDWI, CDOM, MCARI and Chlorophyll index. Ground truth data were collected via snorkeling and drop-camera surveys at depths of 2–50 meters to validate the satellite observations.

Pre-Processing

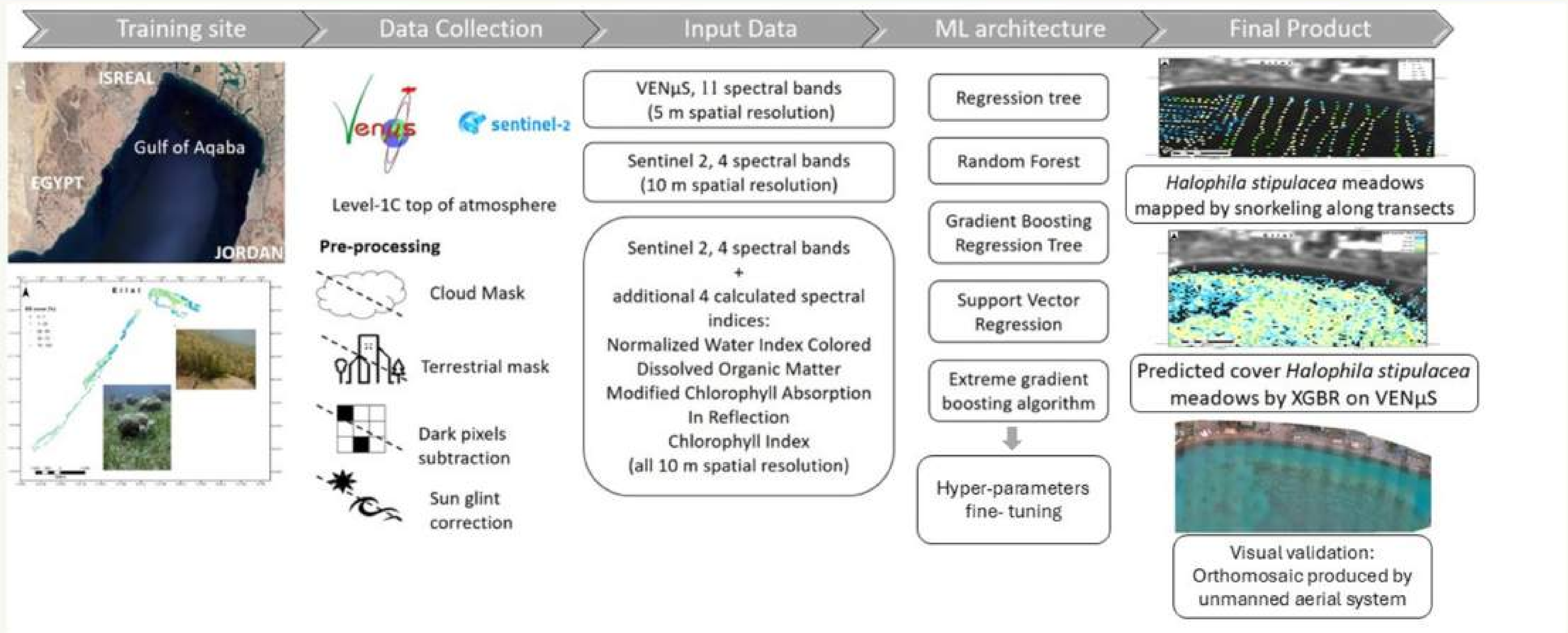
Pre-processing included sun-glint correction to minimize surface reflection, atmospheric correction using the Sen2Cor processor, and super-resolution processing of VENµS imagery to enhance its spatial detail for accurate classification of seagrass meadows.

Machine Learning Models

Five machine learning models were applied: Regression Tree (RT), Random Forest (RF), Gradient Boosting Regression Tree (GBRT), Support Vector Regression (SVR), and Extreme Gradient Boosting Regression (XGBR). XGBR, tuned with a learning rate of 0.05, max_depth = 6, and 200 estimators, achieved the highest accuracy (R^2 = 0.97; RMSE = 0.21).

Testing and Validation

Models were trained on 80% of the data and tested on 20%. Validation with ground truth data demonstrated XGBR's superior performance, particularly in handling low-density vegetation and underwater noise, making it the most robust for submerged habitat mapping.



RESULTS

Best Model Performance

The Extreme Gradient Boosting Regression (XGBR) model outperformed other algorithms, achieving R^2 = 0.97 and RMSE = 0.21. Its robust performance effectively handled low-density vegetation and underwater noise.

ML algorithm	R^2 Training (70%)	R^2 Testing (30%)	RMSE (SG%)
RT	0.8230	0.7668	2.9055
RF	0.7925	0.7264	3.1712
ensemble GBRT	0.8750	0.8466	2.1051
SVR	0.9080	0.8887	1.5193
ensemble XGBR	**0.9890**	**0.9718**	0.2124

Feature Importance

The most important variables for predicting seagrass cover (%) in the XGBR model were wavelengths in the green spectrum (491.9 nm, 555 nm) with F-scores of 78% and 38%, followed by blue spectrum wavelengths (446.9 nm, 423.9 nm). Near-infrared wavelengths contributed minimally to the predictions.

Performance at Depths

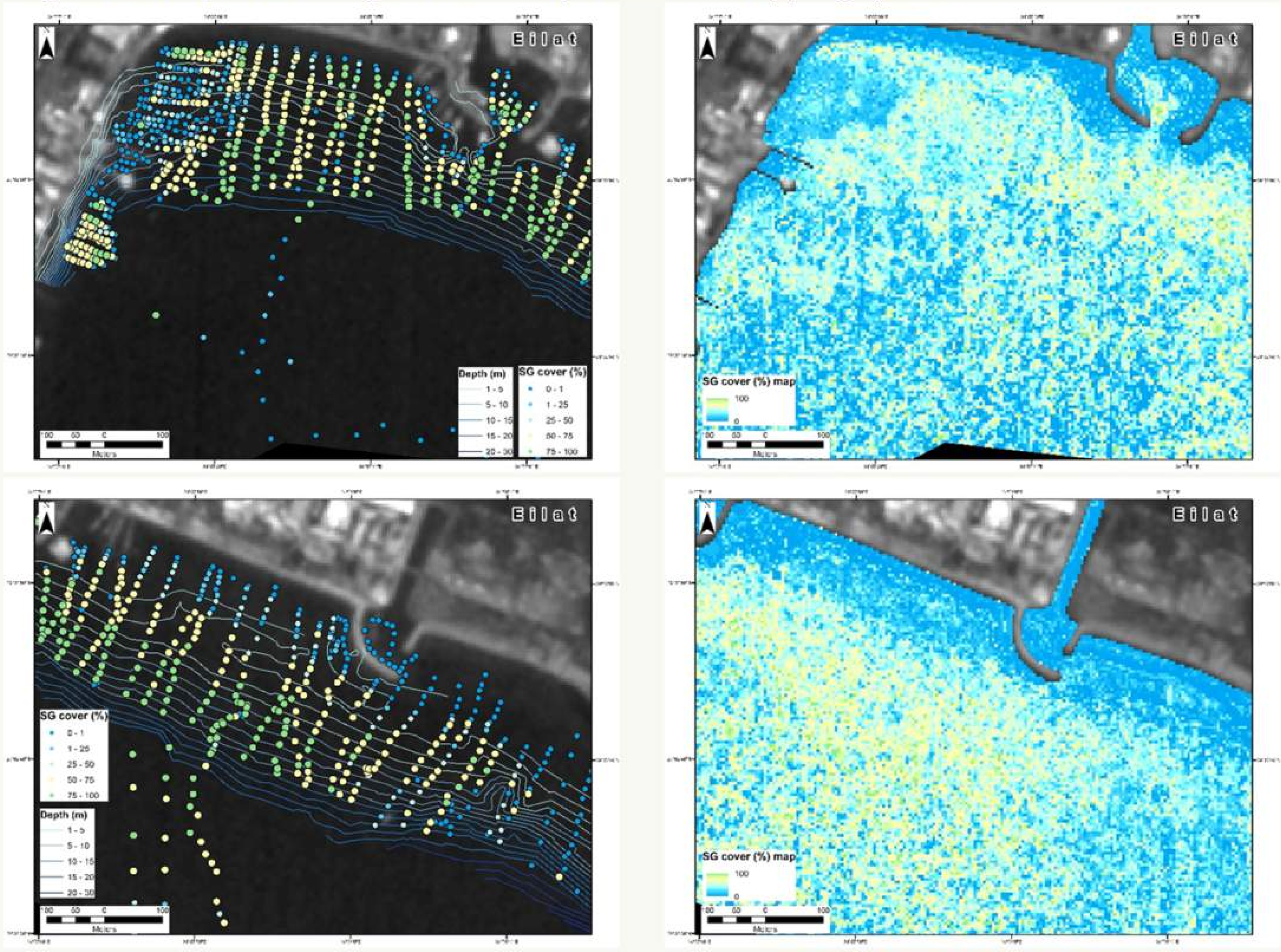
The XGBR model maintained an RMSE <0.3 for depths up to 15 m but showed decreased accuracy in deeper waters (>25 m) due to limited data availability

Seagrass Cover Categories

The XGBR model performed consistently across four seagrass cover categories (low: <25%, mid: 25–50%, high: 50–75%, very high: >75%), with minimal variation in RMSE values

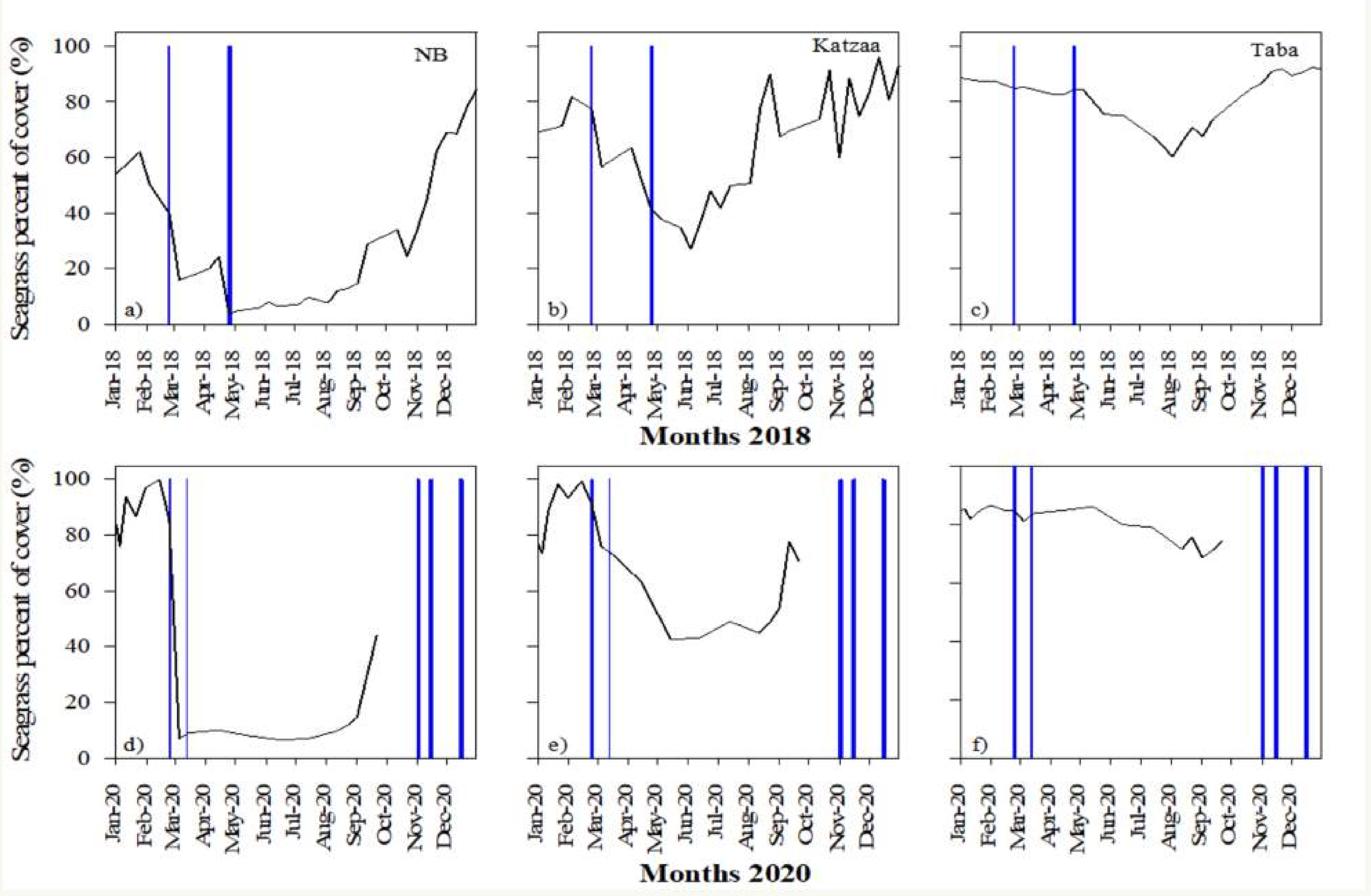
Spatial Accuracy

demonstrates the close alignment between in-situ measurements and the XGBR-predicted seagrass cover, showcasing the model's precision in mapping spatial distributions.



Impact of Flash Floods

Flash floods greatly affected seagrass cover (SC%) from 2018 to 2020. After the 2018 flood, North Beach's cover dropped from 40% to 10%, fast with Taba sluggish Beach recovery. Katzaa Beach was moderately inundated during recovery, although not regularly. Blue lines show floods and black lines show SC changes.



CONCLUSION

The use of VENµS imagery along with the XGBR model was very efficient in predicting the distribution and cover 0.97. of There Halophila are stipulacea still with issues an with R^2 the of ability to identify sparse vegetation and depths of more than 20 meters. Flash flood was a major cause of severe loss of seagrass which exposed the vulnerability of the ecosystem. Further research should seek to improve the detection of seagrass in deep water and also consider other stressors in the environment for the purpose of conservation.

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