Classification of Intertidal Flat Surfaces by Means of Deep Learning

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1. Introduction

The intertidal zone is the coastal area, where the ocean meets the land within the tidal range. The intertidal flats can provide crucial ecological services, as well as the commercial and recreational functions. In recent years, the intertidal zone has been exposed to anthropogenic threats, which makes it necessary to realize the intertidal cover classification and continuous monitoring.

With the fast development of Synthetic Aperture Radar (SAR) sensors, multi-band and multi-polarization SAR data has been applied for the classification of the intertidal zone in some research. Compared with pre-defined features using traditional machine learning, the features from data-driven deep learning models prove to be more robust, which offers promise for building new data-driven models for sediments and habitats classification on intertidal flats in SAR images. However, there is still very little research reported on this task through literature search.

2. Objective and methodology

We propose a Texture-Enhanced UNet-based Network (**TE-UNet**) for intertidal sediments and habitats classification using multi-band multi-polarization SAR images.

Main innovative points: multi-band; multi-polarization; texture-enhanced; fine-grained classification.

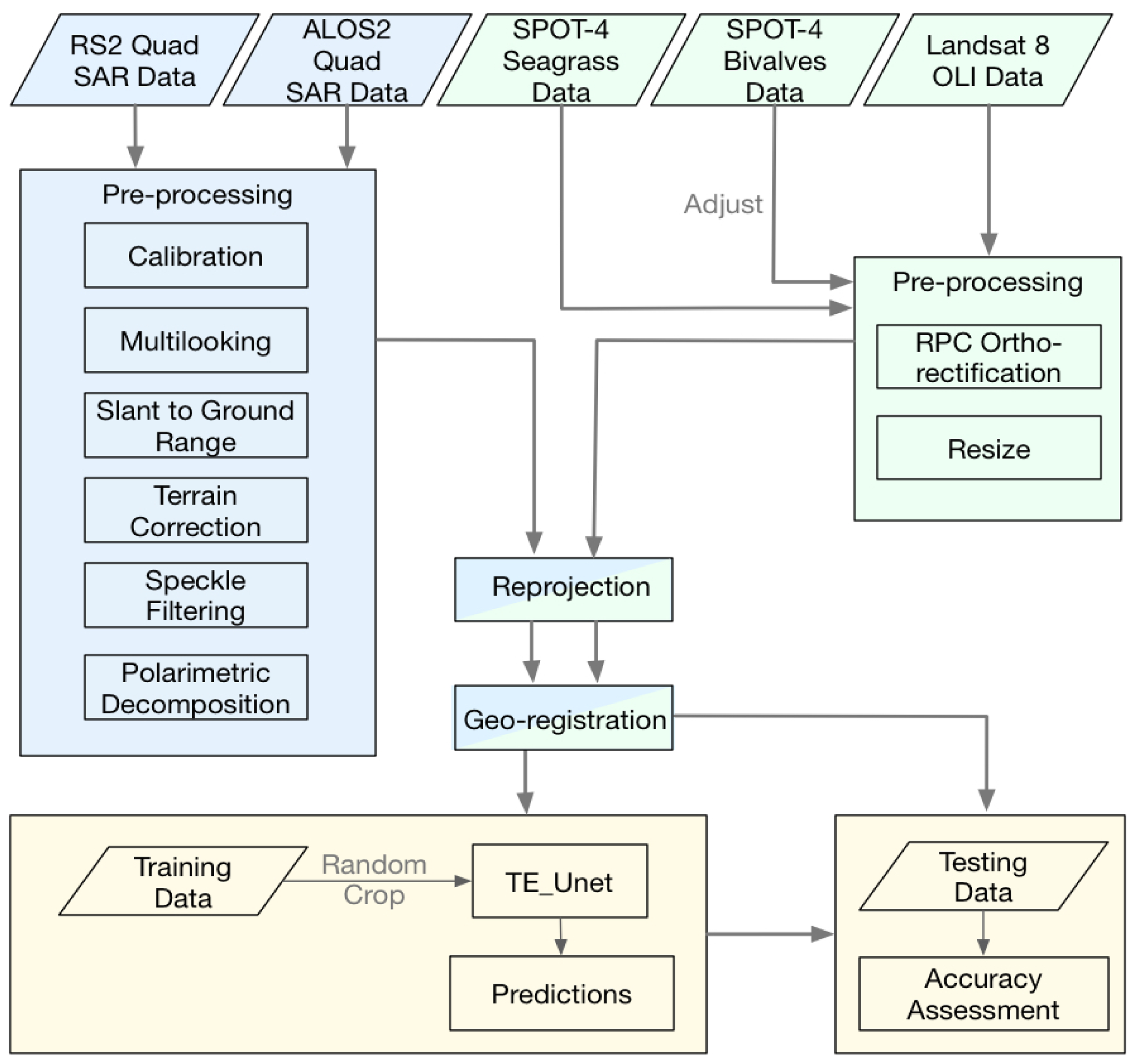

Fig. 1. Processing diagram for the TE-UNet.

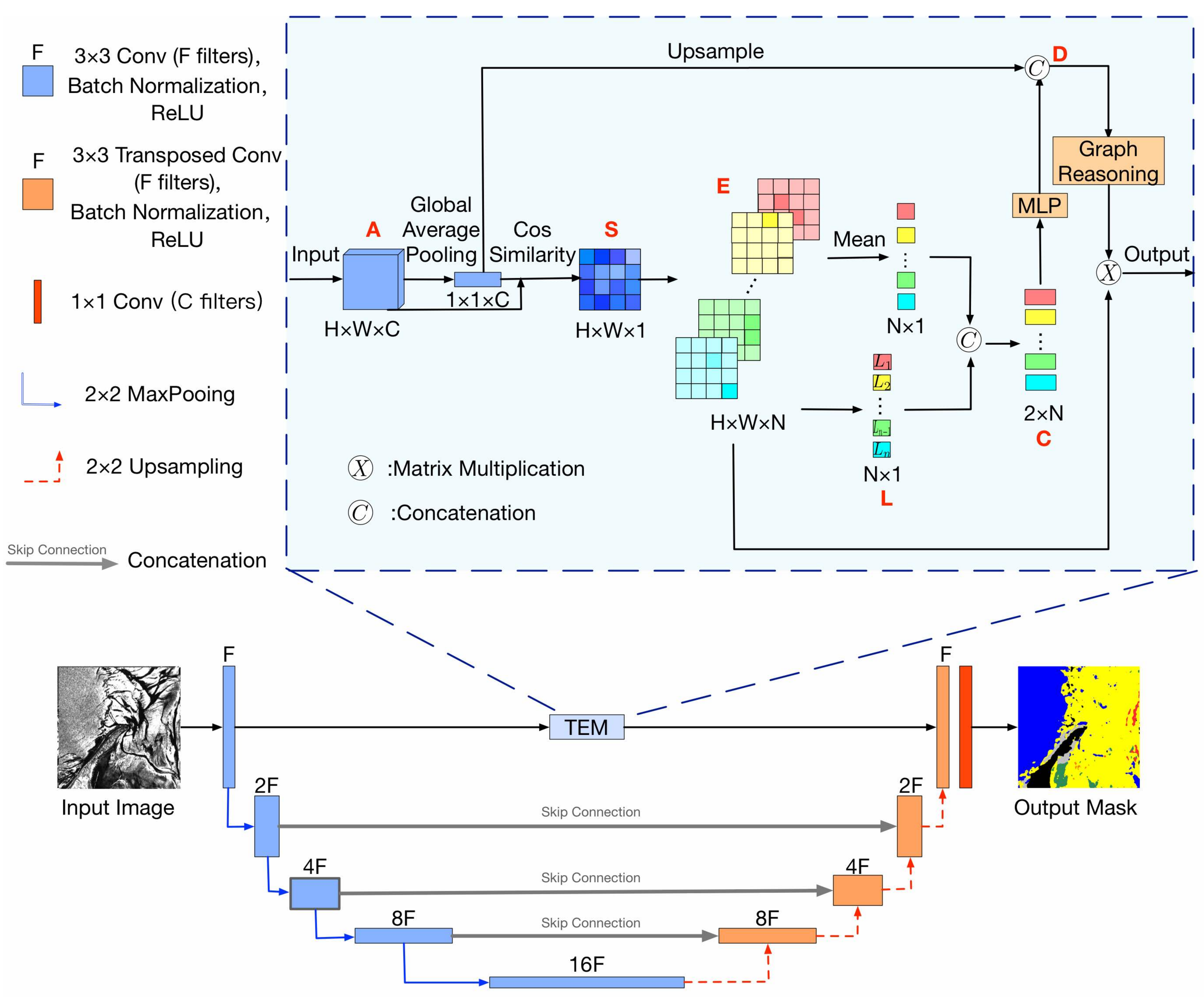

Fig. 2. Illustration of the overall architecture of TE-UNet.

3. Results

Tab.1. Comparing quantitative results of different instance segmentation models

Model	F1(%)							mF1(%)	mIoU(%)	AA(%)	OA(%)
	land	Seagrass	Bivalves	Beach	Water	Sediments	Thin Coverage				
DeeplabV3 Plus[1]	**97.49**	18.09	0.28	3.37	79.73	**78.74**	0.00	39.67	34.02	40.21	**84.25**
UNet[2]	96.39	13.83	3.18	15.09	79.65	77.23	**3.09**	41.21	34.41	42.87	83.04
HR-SARNet[3]	96.31	18.39	**10.05**	3.99	78.91	78.32	0.00	40.85	34.27	41.80	83.14
TL-FCN[4]	95.82	9.05	9.30	16.08	**80.17**	77.25	0.00	41.09	34.31	42.52	83.01
TE-UNet	97.11	**18.87**	2.30	**18.49**	79.63	77.75	1.49	**42.23**	**35.43**	**43.69**	83.95

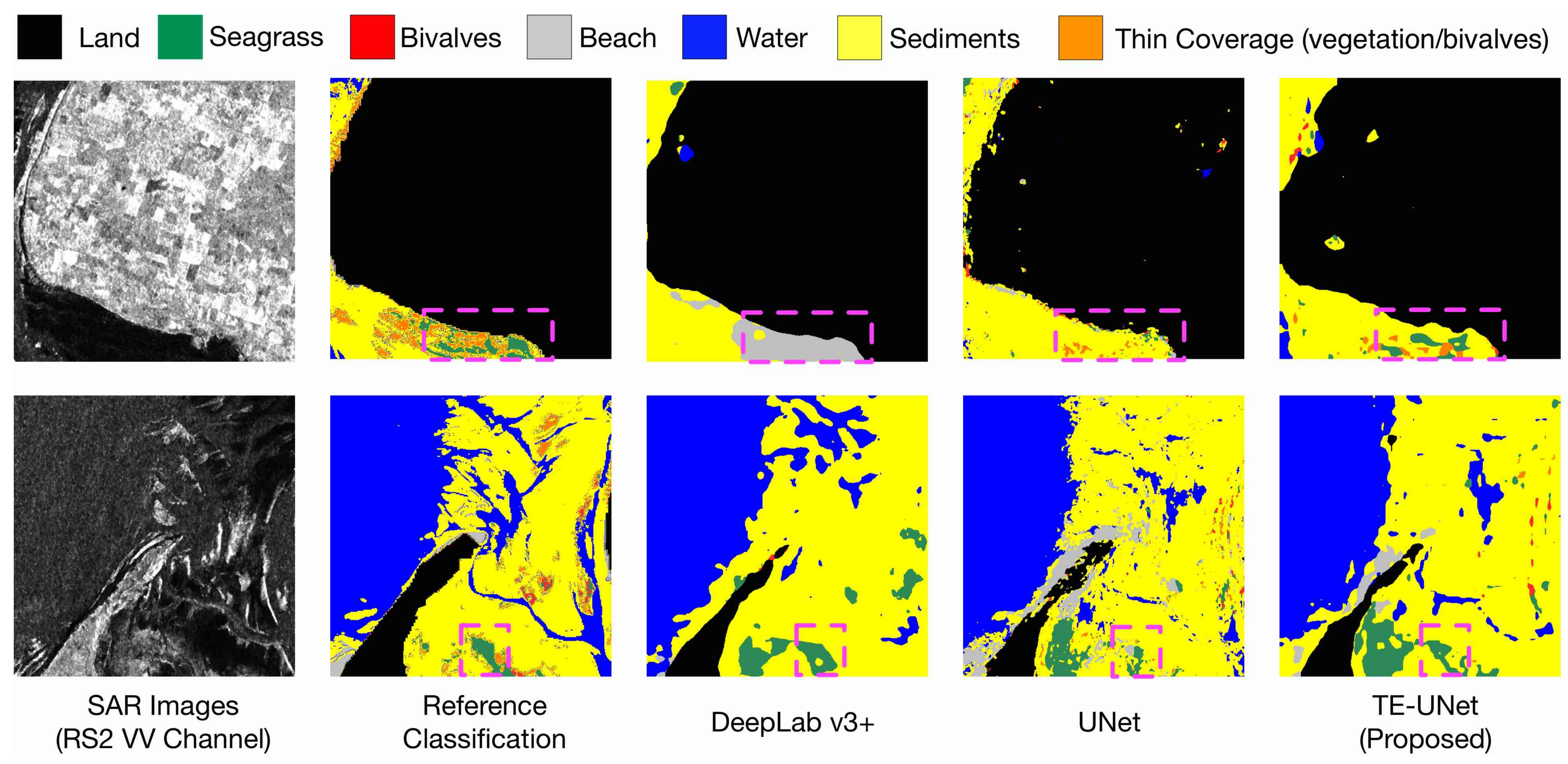

Fig. 3. Comparison of segmented maps obtained by different models.

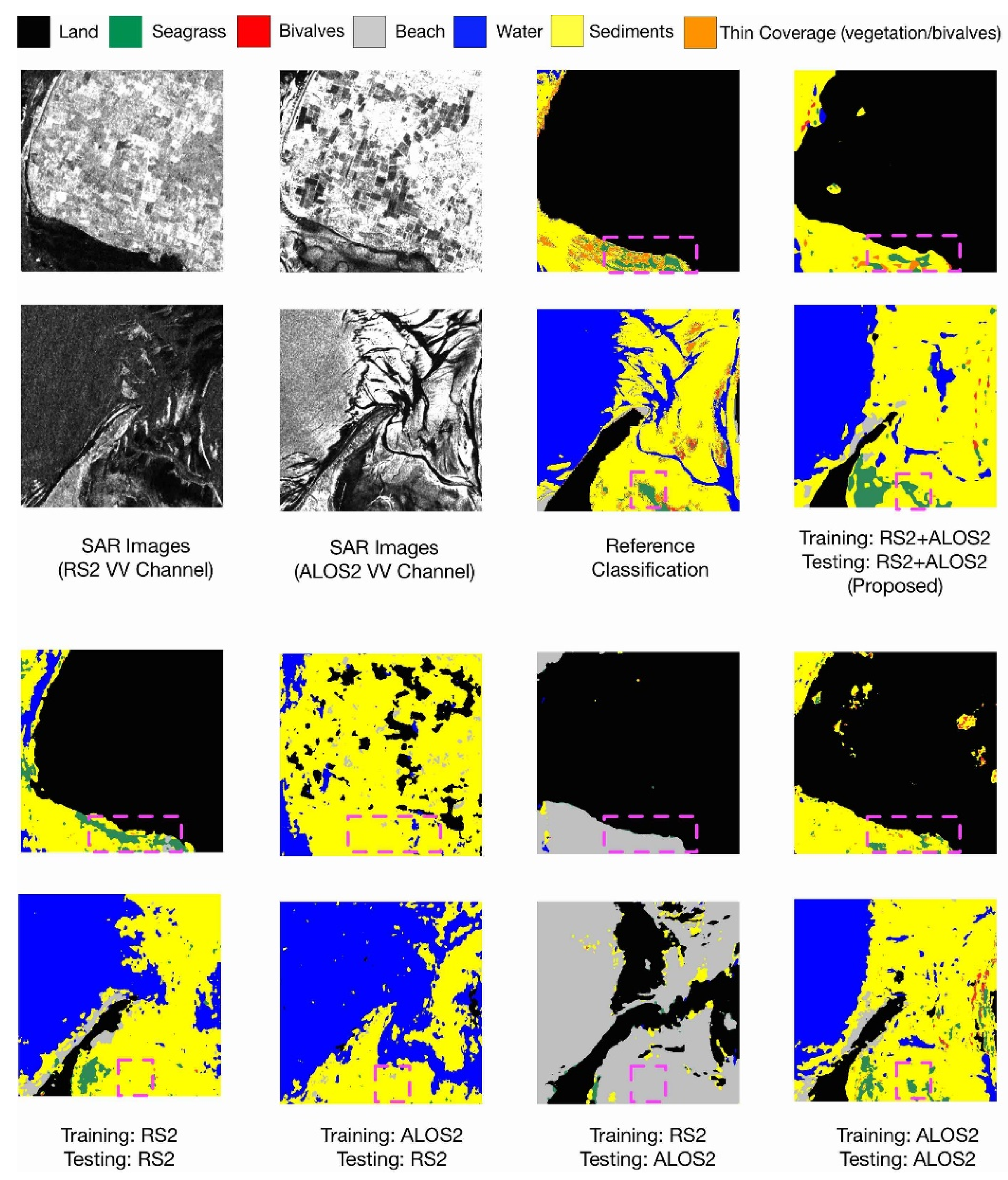

Fig. 4. Comparison of segmented maps of different train and test dataset inputs.

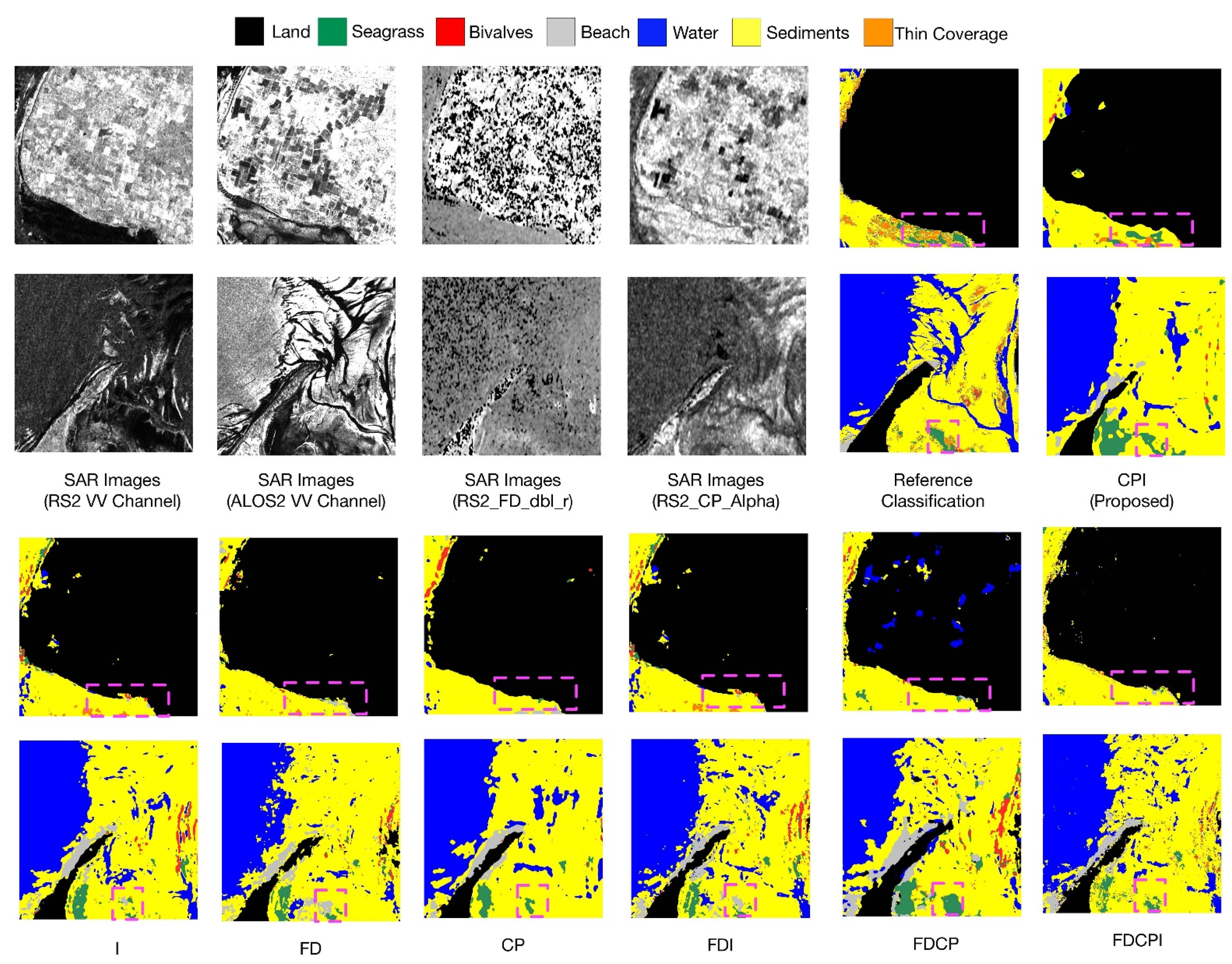

Fig. 5. Comparison of segmented maps obtained by different input channels.

4. Conclusions & Discussions

- Further improvements of texture enhancement
- Proper fusion mechanisms for multi-band and multi-polarization SAR data
- More polarimetric decomposition components

References

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