Hyperspectral image unmixing with LiDAR data-aided spatial regularization – Complementary results

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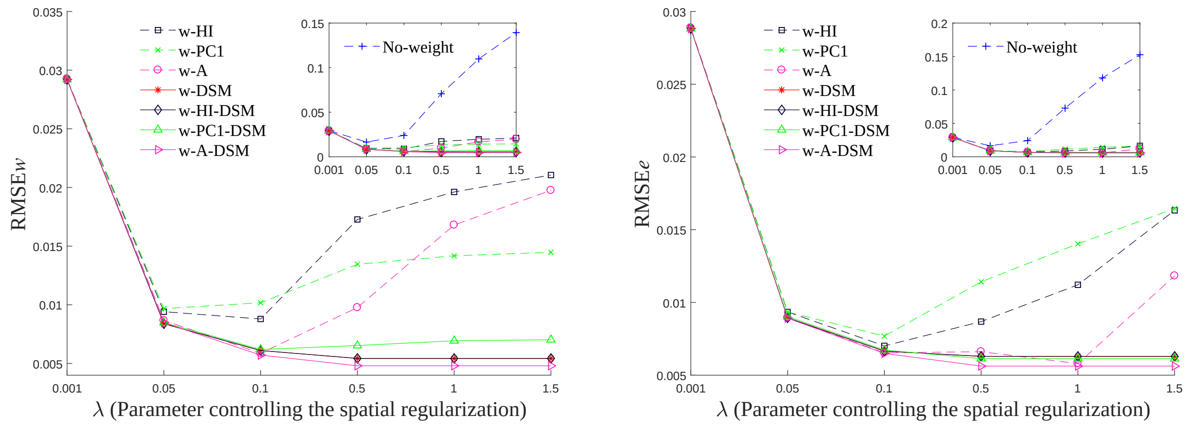
Abstract

This supplementary material provides additional results. Section I shows the results of SIM1 obtained from DSM with different amounts of noise. Section II shows the abundance maps of all classes.

I. Results of SIM1 derived from DSM with different amounts of SNRs

In SIM1, synthetic DSM was generated and used to test the methods. The amount of noise in the synthetic DSM could be controlled and artificially added when generating the synthetic DSM. The results derived from DSM of 50 dB were shown in the main paper. In this supplementary material, the results obtained from different amounts of noise (40 dB and 30 dB) were shown. RMSE_e and RMSE_w derived using DSM of different SNRs (40 dB and 30 dB) were shown in Fig. 1 and Fig. 2. As expected, RMSE increased when SNR was lower. When using noisy DSM with 30 dB, RMSE estimated by w-A produced smaller RMSE than the methods (w-DSM, w-HI, w-PC1-DSM, w-HI-DSM) in the range between 0.1 and 1. Each method that uses a combination of DSM and another guidance map improved abundance estimates, compared with the method that use only a single guidance map derived from hyperspectral imagery or abundance maps. This showed that the combination of DSM and other guidance maps could produce smaller RMSE than the use of only DSM when DSM was noisy. It was more difficult to extract edge information from noisy DSM. However, the methods that incorporated the combination of DSM and another

This report provides complementary results to the paper [1].



(a) (b)

Fig. 1: SIM1: Abundance estimation errors derived from DSM with 40 dB as functions of λ. (a) $\mathrm{RMSE_w}$ computed for the whole pixels. (b) $\mathrm{RMSE_e}$ computed for the pixels located in the edge areas.

guidance image for the weight estimation could produce more accurate, or comparable estimates of abundances compared with other methods that did not incorporate DSM.

The influence of σ on RMSE derived from DSM with different SNRs (40 dB and 30 dB) was shown and validated for each method (Fig. 3 and Fig. 4). The influence of σ on RMSE derived from DSM with 30 dB was different to those derived from DSM with 40 dB for the methods (Weight-PC1, w-PC1-DSM, w-HI-DSM and w-A-DSM). The main difference was that RMSE became larger when using a smaller value (10^{-5}) of σ. This showed that when DSM is noisy, the value of σ needs to be larger in order to prevent noise to be mistakenly considered as an edge.

II. Abundance maps of all endmember classes

In the main paper, the abundance maps of only tree and grass were shown. In this supplementary material, the abundance maps of all endmember classes were shown (Fig. 5). Abundances of road, buildings, soil were similar while abundances of tree and grass were different especially in the edge areas.

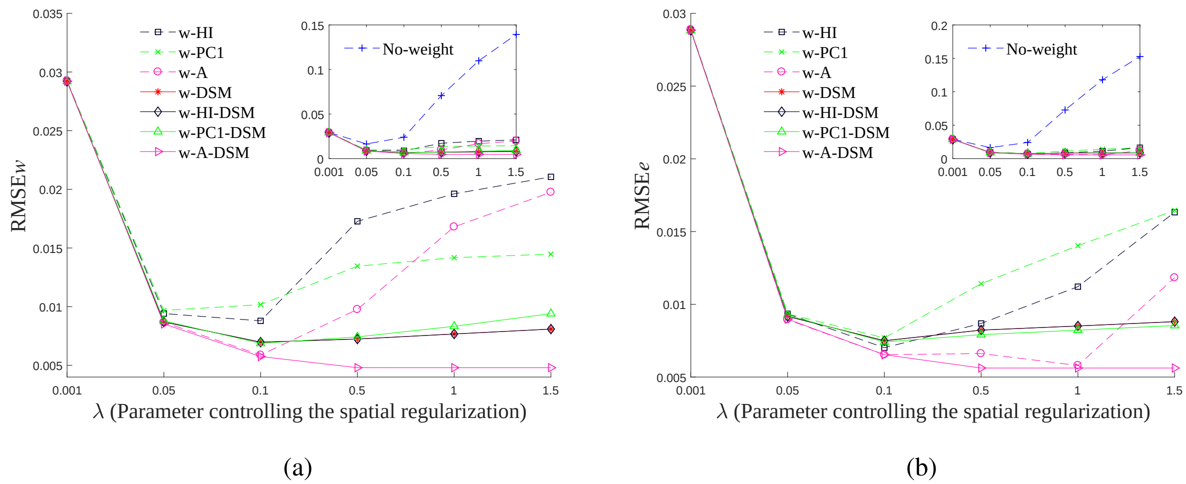


Fig. 2: SIM1: Abundance estimation errors derived from DSM with 30 dB as functions of λ. (a) $\mathrm{RMSE_w}$ computed for the whole pixels. (b) $\mathrm{RMSE_e}$ computed for the pixels located in the edge areas.

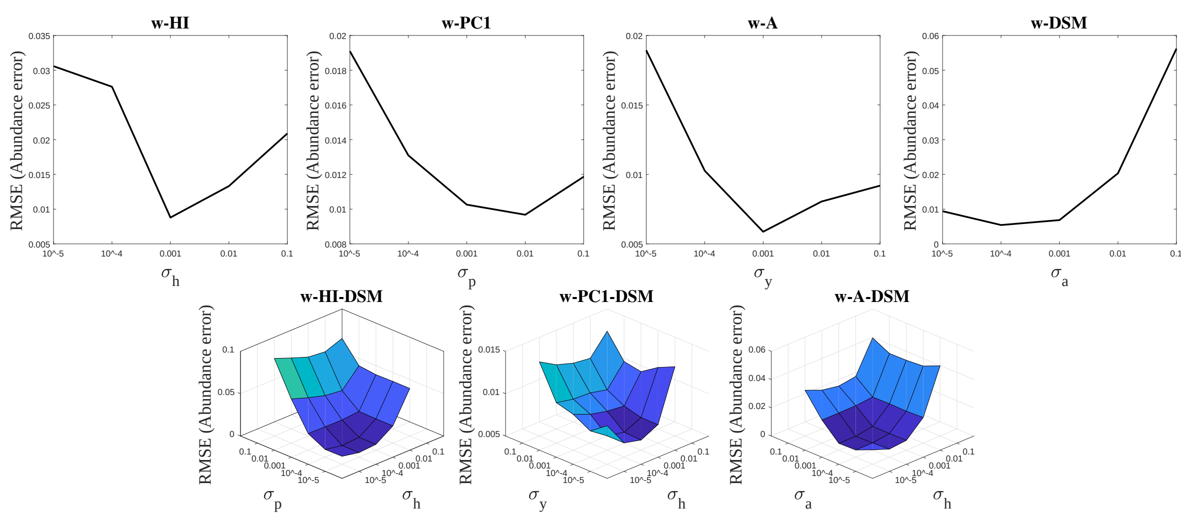


Fig. 3: SIM1: Influence of σ on the 7 methods in SIM1. DSM images (40 dB) were selected for w-DSM, w-PC1-DSM, w-HI-DSM and w-A-DSM. Abundance error (RMSE) as functions of λ

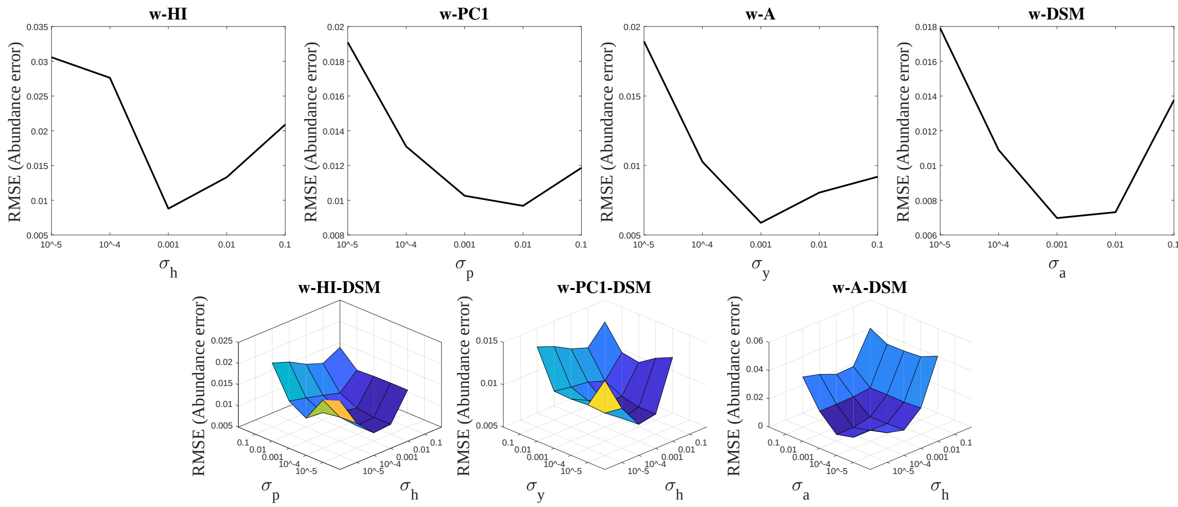


Fig. 4: SIM1: Influence of σ on the 7 methods in SIM1. DSM images (30 dB) were selected for w-DSM, w-PC1-DSM, w-HI-DSM and w-A-DSM. Abundance error (RMSE) as functions of λ

References

[1] T. Uezato, M. Fauvel, and N. Dobigeon, "Hyperspectral image unmixing with LiDAR data-aided spatial regularization," *arxiv*, submitted.

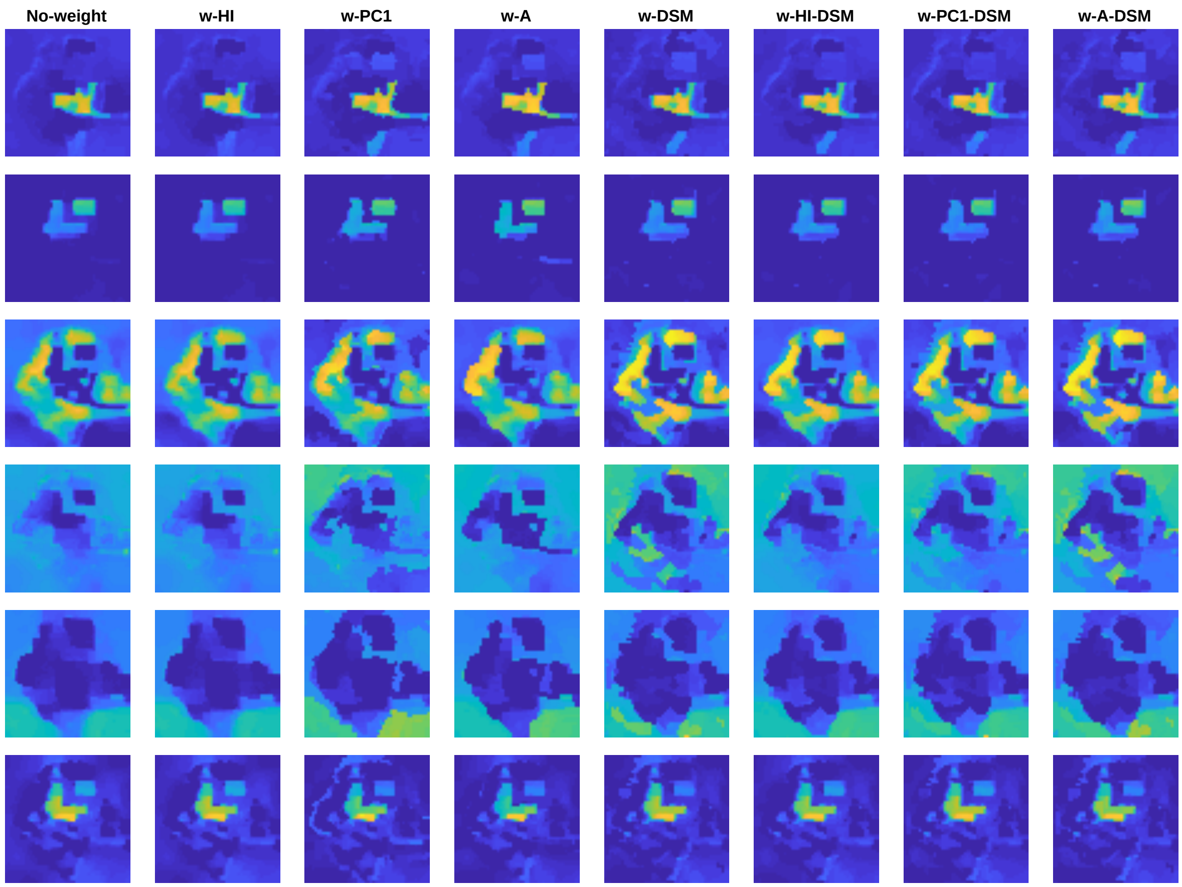


Fig. 5: Real image: abundances estimated for road (first row), building 1 (second row), tree (third row), grass (fourth row), soil (fifth row) and building 2 (sixth row).