Leveraging Deep Learning to Improve Satellite Data based Crop Yield Estimation using UAS Data as Side Information.

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Introduction: A recent upsurge in Unmanned Aircraft Systems (UAS) development largely contributed to implementing High Throughput Phenotype for precision agriculture applications (Singh and Frazier, 2018). However, the scale of the experiment is limited by the aerial coverage of the UAS. On the contrary, satellite remote sensing data are widely utilized for crop yield estimation over a large area, though the coarser spatial resolution is still a concern for many precision agriculture applications. There is a knowledge gap combining UAS and satellite data for crop yield estimation. This research explores how UAS derived information can be provided as side information to improve satellite-based crop yield prediction.

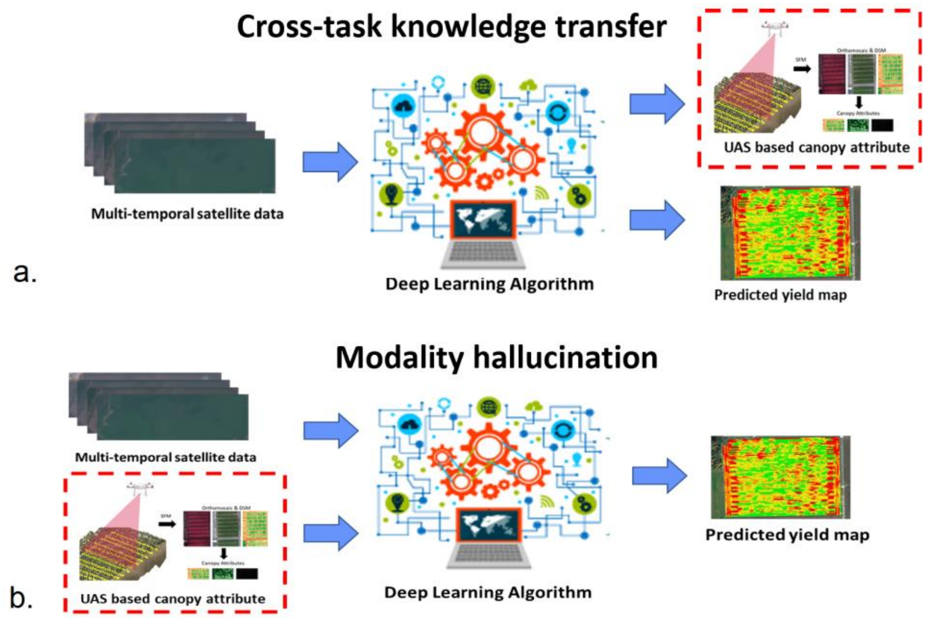

Figure 1. Process flow of the deep learning methodology with UAS derived canopy attributes used as a side information.

Methodology: As this research aims to predict the yield over a larger area even at the locations where UAS data were not collected, UAS derived canopy attributes can only be utilized as side information at the time of training the multi-temporal satellite-based yield prediction model. The proposed methodology demonstrated two ways to include UAS derived canopy attributes as side information to the satellite-based crop yield prediction model. The first approach is based on cross-task knowledge transfer, where UAS derived information was used as one of the outputs along with the yield (Figure 1 a). This approach utilizes transfer learning and domain adaptation which learns to share information from one task to another (Wang et al., 2018). Initial training is performed to predict UAS-based canopy attributes using satellite data. Later, intermediate features learned from this task were utilized to improve the yield prediction model. The second approach is based on modality hallucination (Hoffman et al. 2016), where during the training time, satellite and UAS data are combined to improve the yield prediction (Figure 1 b). Moreover, another channel called "hallucination network" was introduced to mimic the UAS data network while taking satellite data as input. With successful hallucination training, it replaced the UAS based data network at the test time.

Results: The deep models considered in this study were: the baseline model, which utilized only the satellite data, along with cross-task knowledge transfer and hallucination models, which utilized UAS data as side information along with satellite data. The baseline model successfully identified relevant features from multi-temporal satellite data for yield estimation (test R^2 of 0.71). However, the test result over the independent test site was not encouraging (R^2 of 0.56). Hallucination and cross-task knowledge transfer models outperformed baseline model (test R^2 of 0.78 and 0.8 respectively). Additionally, test results over the independent test site were also superior (R^2 of 0.68 and 0.69 respectively). This study explored deep learning based methodologies to incorporate additional information, in the form of UAS derived canopy attributes, to improve the multi-temporal satellite-only yield estimation model. Future direction in this work would include incorporating multi-year, multi-location data along with additional domain adaptation techniques.

FOR FURTHER READING:

Singh, K.K., Frazier, A.E., 2018. A meta-analysis and review of unmanned aircraft system (UAS) imagery for terrestrial applications. International journal of remote sensing 39, 5078-5098.
Wang, A.X., Tran, C., Desai, N….Ermon, S., 2018. Deep transfer learning for crop yield prediction with remote sensing data, Proceedings of the 1st ACM SIGCAS Conference on Computing and Sustainable Societies, pp. 1-5.
Hoffman, J., Gupta, S., Darrell, T., 2016. Learning with side information through modality hallucination, Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 826-834.