Mapping on-farm irrigation systems in southern Idaho

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Extended Abstract

Irrigation withdraws the largest share of freshwater resources in the United States (0.45 of 1.06 billion m3 per day in 2015) (Dieter et al. 2018) but vast amounts of water diverted for irrigation are not efficiently used for agricultural production. This is because many factors including the method of irrigation influence irrigation efficiency. At the farm level, the type of irrigation used has a profound influence on irrigation water efficiency. Irrigation systems used in the United States can be broadly categorized into 3 three groups: surface irrigation, sprinkler irrigation and drip / microirrigation. In surface irrigation systems (e.g. furrow irrigation and flood irrigation), water is delivered to crops by gravity-fed overland flow of water. Sprinkler irrigation involves the transport and delivery of water to whole fields using pressurized systems and nozzles. Microirrigation (e.g. surface or subsurface drip irrigation) allows water to be delivered directly to individual plants or plant roots using drip nozzles. Surface irrigation and sprinkler systems are the most common forms or irrigation in the United States, collectively accounting for 93% of all irrigated areas. Sprinkler irrigation is more water efficient than surface irrigation leading to strong federal and state incentives for the former irrigation method compared to the latter. Watershed scale monitoring in the Pacific Northwest has shown appreciable water savings and water quality improvements as previously furrow irrigated fields were converted to sprinkler irrigation (Bjorneberg et al. 2015).

Maps of irrigation methods used across the agricultural landscape are needed for assessment and planning purposes. For example, the US Geological Survey (USGS) regularly reports estimates of water use in the U.S. (e.g., Dieter et al. 2018) including total acreage by irrigation method but lacks accurate tools to systematically map these irrigation methods. Past relevant mapping efforts have been limited to mapping irrigated areas irrespective of the type of irrigation used (e.g., Bazzi et al. 2020; Pageot et al. 2020; Xie et al. 2019) or to the detection of only one type of irrigation method (often the center pivot irrigation method) (e.g., de Albuquerque et al. 2020; Saraiva et al. 2020; Tang et al. 2021; Zhang et al. 2018). Advances in Machine Learning (ML) and Computer Vision combined with the availability of satellite data provide unique opportunities to develop tools that accurately classify the different irrigation methods used across the landscape.

The aim of this study was to develop a ML-based methodology to map irrigation methods across irrigated areas. The developed method was based on the U-Net architecture, a type of fully convolutional neural network to predict irrigation methods. The developed model uses surface reflectance data from Landsat 5 and 8 bands reduced to U-Net model input images for each prediction year. The U-Net model was trained on the Utah Water Related Land Use (WRLU) dataset collected by the Utah Division of Water Resources as part of the state water plan. This dataset is available from years 2003 to 2021. The dataset contains many important water-related attributes collected at the field scale across the State, including irrigation methods classified as sprinkler or flood irrigation, dry crop, sub-irrigated, drip, and none.

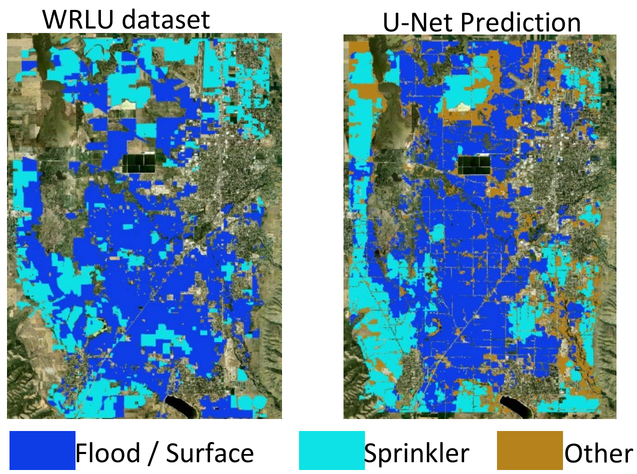

Figure 1 Irrigation methods prediction for year 2003 using the trained U-Net model for agricultural areas near Logan, UT

Preliminary results show that the trained U-Net model on the WRLU data had an overall accuracy of 77%, precisions of 77% in each of the Flood, Sprinkler and Other irrigation classes and recall values of 70%, 78% and 84% respectively. Predicted maps of Flood vs. Sprinklers pixels were in general agreement with observed spatial patterns of irrigation methods across agricultural areas of Utah (e.g., Figure 1). Future steps include the evaluation and refinement of the developed U-Net model to predict irrigation methods beyond the spatial extent of the training dataset. With this tool, historical and current irrigation methods map can be developed for major irrigated areas of the northwestern U.S.

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