# IrrNet: Spatio-Temporal Segmentation guided Classification for Irrigation Mapping

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## 1. Problem Overview

Irrigation systems can vary widely in scale, from small-scale subsistence farming to large commercial agriculture (see Fig. 1). The heterogeneity in irrigation practices and systems across different regions adds to the complexity of mapping (see Fig. 1). **Distinguishing between irrigated and non-irrigated** areas is challenging due to the spectral characteristics of various irrigation systems and practices across different regions, further complicating the task of mapping different types of irrigation. For example, rainfed agriculture is prevalent in the Midwest, Southeast, and parts of the Northeast U.S., while irrigation is common in arid Western and Southwestern states. Rainfed farming can result in highly variable patterns of cultivation. Farmers may practice rainfed agriculture in some fields while irrigating others, leading to a complex mosaic of irrigated and non-irrigated areas within the same region.

Currently, there is no established method for accurately mapping different irrigation techniques in areas where various methods are used simultaneously. While there has been significant progress in using machine learning and deep learning for agriculture-related tasks, the specific challenge of mapping irrigation practices when different types are used in the same field has not been thoroughly explored. Although some efforts have been made to distinguish irrigated areas from non-irrigated ones, these approaches often overlook the importance of considering changes over time.

### 1.1. Hypothesis of the Research

*Our hypothesis in this proposal is as follows:*

- *develop a deep learning system for irrigation mapping using publicly available remote sensing data as input enhancing the robustness of the segmentation classifier, while also improving its interpretability.*
- *strengthen the model's ability to generalize effectively, particularly in regions where data availability is low,*
- *analyze the significance of different bands within the satellite images, determine the optimal data volume required, and explore additional features that can be incorporated into the training process.*

## 2. Background and Literature Review

Current irrigation mapping products provide spatial data without detailing irrigation methods [18, 20]. While remote sensing has been utilized to map irrigated fields, especially in areas of mixed agriculture [1], distinguishing between irrigation types remains challenging due to landscape complexity and subtle practice variations. Computer vision and machine learning have made strides in identifying specific systems like center pivots [7, 19, 21], but the broader task of irrigation mapping demands nuanced analysis.

Instance segmentation is critical in this context, predicting instance-specific masks and classes [2, 6, 9, 13, 16, 23]. These methods harness various features, from prototype masks to orientation maps, to facilitate real-time analysis. Meanwhile, semantic segmentation works at the pixel level to classify image parts, with innovations aiming for speed without sacrificing accuracy [12, 24, 26].

Recent studies have targeted joint semantic and instance segmentation, aiming for comprehensive image understanding [3, 8, 10, 11, 14, 15, 17, 22]. Techniques like UPSNet, FPSNet, PanopticDeepLab, and LPSNet advance efficient segmentation by generating semantic masks and identifying instances [3, 7, 10, 11, 25]. Concurrently, methods like PanopticFCN and MaskFormer predict masks for all scene elements [4, 5, 14]. The evolution of these techniques represents the progress toward real-time, detailed understanding of diverse agricultural landscapes.

## 3. Problem Formulation

The problem of comprehensive irrigation mapping involves two main tasks: irrigated and non-irrigated field segmentation, and specific irrigation method classification. Let $X$ represent the input satellite image. The goal is to obtain a binary segmentation mask $M_{seg}$ that indicates the spatial boundaries of agricultural fields focusing on whether a field

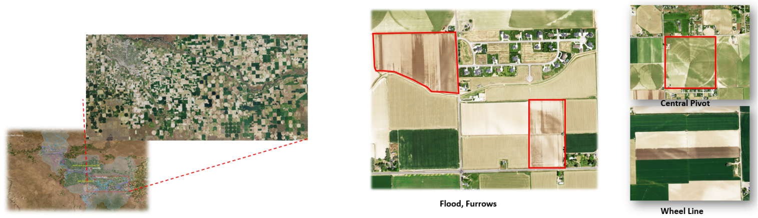


Figure 1. Example Satellite image from Utah region (Left Most). Different irrigation type forming different pattern in the field. (Right)

Table 1. Results of the evaluation of the ensemble of trained U-Net models in test areas near the Utah towns of Elwood, Logan, Richmond, Sutherland, and in the Twin Falls Canal Company (TFCC) irrigation project in southern Idaho. Performance metrics are overall accuracy (A), precision (P), recall (R), and F1-score (F1) calculated from pixel-to-pixel comparisons between predicted and observed irrigation methods. Precision, recall, and F1 are reported for each irrigation class labeled as F for surface/flood irrigation, S for sprinkler irrigation, and O for other types of irrigation.

| **Area** | **Accuracy** | **Precision** | | | **Recall** | | | **F1** | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **A** | **F** | **S** | **O** | **F** | **S** | **O** | **F** | **S** | **O** |
| Elwood | 0.79 | 0.84 | 0.49 | - | 0.76 | 0.53 | 0.50 | 0.88 | 0.51 | 0.60 |
| Logan | 0.59 | 0.61 | 0.48 | - | 0.65 | 0.39 | 0.41 | 0.71 | 0.43 | 0.50 |
| Richmond | 0.59 | 0.20 | 0.85 | - | 0.73 | 0.63 | 0.60 | 0.30 | 0.70 | 0.63 |
| Sutherland | 0.74 | 0.91 | 0.10 | - | 0.46 | 0.77 | 0.69 | 0.83 | 0.17 | 0.51 |
| TFCC | 0.70 | 0.60 | 0.72 | - | 0.83 | 0.54 | 0.85 | 0.57 | 0.78 | 0.63 |

is irrigated ($I_{irr}$) or not ($I_{non-irr}$) based on visual cues in the image. Lastlty, for irrigated fields, the model must do pixel wise classification on the specific irrigation method ($I_{method}$) being used. This is conditional on the irrigation status being classified as irrigated. To optimize the model for these tasks, a multi-task learning approach is employed.

The comprehensive irrigation mapping model employs a multi-task learning approach, utilizing a combined loss function defined as:

$$L_{total} = \alpha \cdot L_{seg} + \beta \cdot L_{spec\_irr}$$

where $L_{seg}$ and $L_{spec\_irr}$ represent the losses for field segmentation and specific irrigation method classification, respectively.

- $L_{seg}$ is typically calculated using binary cross-entropy or dice loss to differentiate between irrigated and non-irrigated fields.
- $L_{spec\_irr}$ is implemented using categorical cross-entropy to classify the specific irrigation method within irrigated fields.

The hyperparameters $\alpha$ and $\beta$ are used to balance the importance of each task during the training process, ensuring both segmentation accuracy and classification precision.

## 4. Preliminary Results

Results of the performance evaluation by region are summarized in Table 1. Accuracy values in most test regions were consistent with the 0.78 overall accuracy of the model

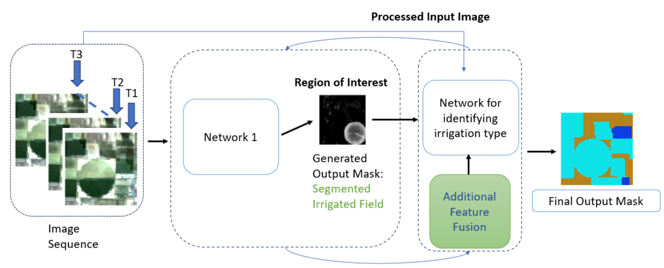


Figure 2. A demo overview of the model

(Table II). Accuracy was the highest in the Elwood region (0.79) and lowest in the Logan (0.59) and Richmond (0.59) regions. Figures 6 and 7 show that many of the S irrigated areas in the Logan and Richmond quadrangles were incorrectly predicted as F. Many of the mismatches occur in areas where small areas of one irrigation class appear within large blocks of another class, suggesting that the U-Net models were not highly sensitive to small individual fields but relied on broad spatial patterns to accurately recognize irrigation methods. The coarse resolution of the Landsat bands (30 m for RGB and SWIR and 60 m for the thermal band) likely limits the ability of small spatial features to be accurately capture by the U-Net models. Improvements may be possible with the use of higher resolution satellite products such as Sentinel 2. The Sutherland region was dominated by flood irrigation which was adequately predicted (P = 0.91).

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