Mapping Irrigation with Fully Convolutional Neural Networks

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Bridging the Food-Energy-Water Nexus

Thomas Colligan, David Ketchum, Doug Brinkerhoff, Marco Maneta. University of Montana, Missoula, Montana

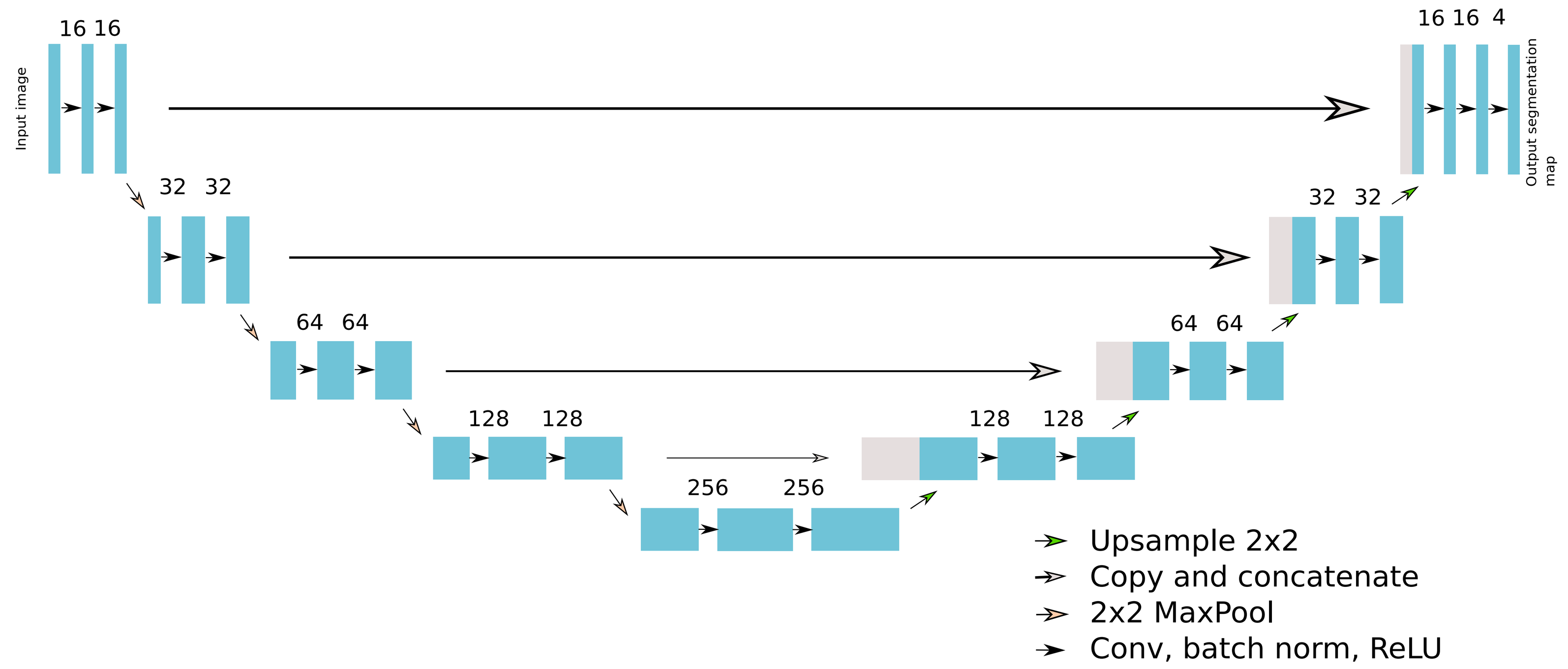
Abstract

Irrigation is responsible for approximately 70 percent of global freshwater withdrawal and accounts for 80-90 percent of consumptive water use in the United States. As global population grows, the need for irrigated cropland will only become more prevalent. Quantifying irrigated acreage will help inform responsible decisions about irrigation and provide insight into matters such as groundwater depletion and water stress. Here we describe a novel method of mapping irrigation in using convolutional neural networks. Using a general U-Net architecture we segment Landsat-8 images over Montana into 4 classes: irrigated, unirrigated, uncultivated, and fallow. Our method achieves a test set accuracy of 97% with a 1-score for the irrigated class of 0.91.

Introduction

Past approaches to mapping irrigation can roughly be classified into two categories: studies using Google Earth Engine (GEE) and studies using conventional neural networks. GEE is a cloud computing platform that is massively parallelized and has many remote sensing datasets preloaded. However, custom machine learning algorithms can't be used with GEE. Conventional neural networks have also been used to map irrigation with impressive results. Typically these models have been applied at smaller spatial scales because of the inherent computational requirements. Fully Convolutional Neural Networks combine the flexibility of a custom machine learning algorithm with speed, and are a novel approach to mapping irrigation.

Fully Convolutional Neural Networks



Neural network architecture used to map irrigation. Numbers indicate the number of convolutional filters applied in a layer. This design is commonly referred to as UNet. Activation maps from layers early in the network are concatenated with activations from later layers, allowing the network to combine high and low level representations of the input data.

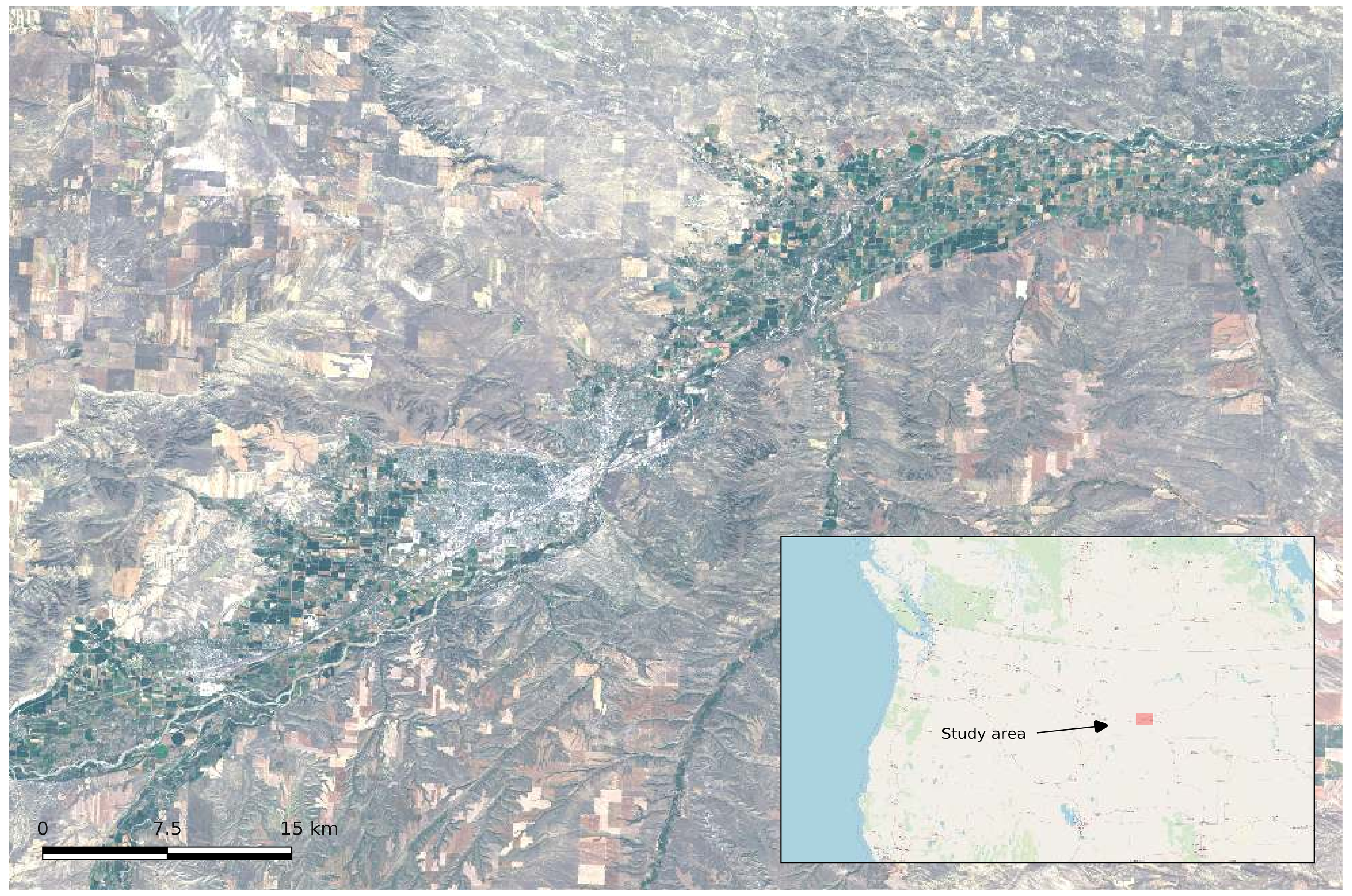
What are they?

- Functions that map an input image to an output image pixel by pixel. The input image is Landsat 8 bands concatenated with climate data and a digital elevation model, and the output image is a pixel-wise map of irrigation.

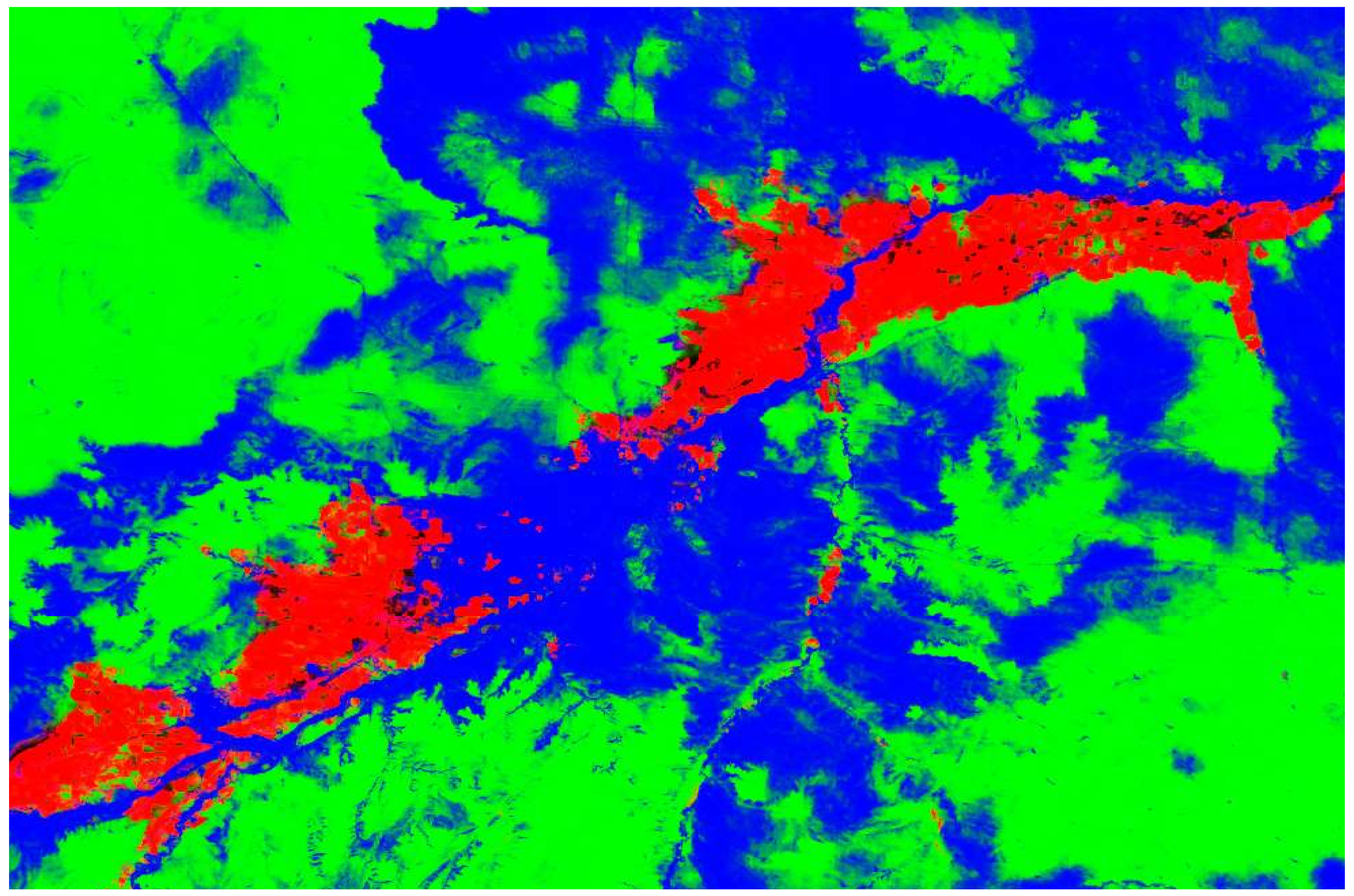
Why are they better than other neural networks for this task?

- They're *fast*, meaning irrigated maps can be produced on a large scale with limited computational resources.
- They excel at the task of semantic segmentation, which is fundamentally the same task as mapping irrigation.

Method



Above is Landsat 8 optical imagery of the Huntley irrigation district in southeast Montana from the summer of 2013. Below is the output of the neural network on the image above. Red indicates irrigation.



Input Data

Landsat 8 Level 1 products from three capture dates during a growing season, climate data, and digital elevation models. All rasters are stacked together to force the neural network to learn the time signals that are important for determining irrigation. No preprocessing is performed on the input data.

Results

Confusion matrix i, j: Predicted to be i, known to be j

	irrigated	unirrigated	uncultivated	fallow	precision
irrigated	104992	5366	3596	2375	90.25%
unirrigated	5944	8613056	97431	9165	98.71%
uncultivated	1855	189310	5243977	2689	96.44%
fallow	788	457	257	3048	66.99%
recall	92.44%	97.78%	98.11%	17.64%	

Cell i, j in the confusion matrix to above indicates the number of pixels the neural network predicted to be class i that are known to be class j. The last row and column of the matrix give the recall and precision of the model for each class, respectively.

Precision i: The percent of pixels the model predicted to be class i that are actually class i.
Recall i: The number of pixels the model predicted to be class i divided by the number of pixels that are class i in the dataset.

Future Directions

- Scale the model up to the western US
- Using the model to determine irrigated extent over time
- Comparing model outputs to agricultural census results
- Comparing model outputs to other irrigation mapping models

Author contact: thomas.colligan@umontana.edu

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