Crop Type Mapping with Multi-Temporal and Multi-Spatial Satellite Imagery
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Overview

We combine remote sensing imagery with deep learning algorithms to distinguish and map crop type from space.

Motivation: Over 800 million people in the world are undernourished and 85% of consumed food in the developing world comes from smallholder farms [1]. Having a better understanding of smallholder farms via crop type maps can provide unprecedented insight into food systems and food security. We tie this motivation into the UN's 2030 Sustainable Development Goals to contribute to goal three: zero hunger.

We focus in South Sudan and Ghana, Africa, where food security is of particular importance. We encounter challenges with sparse data labels, class imbalance, and high cloud cover.

模型架构

Convoluted Long Short Term Memory (C-LSTM) Cell:

\[\begin{align*}
\text{Self-Attention Version 1} & \\
\text{Self-Attention Version 2} &
\end{align*}\]

Data

Satellite Sources

- Sentinel-1 (S1) and Sentinel-2 (S2)
  - Spatial resolution: 10 m
  - Repeat Rate: 6-12 days
  - S-1 Spectral Bands:
    - VV, VH Polarization
  - S-2 Spectral Bands:
    - R, G, B, NIR, SWIR
  - Preprocessing: TGA, reflectance

- Planet
  - Spatial resolution: 3 m
  - Repeat Rate: 1-2 days
  - Spectral Bands: R, G, NIR
  - Preprocessing: filtered out images with >10% cloud cover; TGA

Ground Truth

- Ground-verified polygons with crop type label

Study Regions

- South Sudan, 2017
  - 4 classes: 28k pixels
  - Ghana, 2016
  - 17 classes: 233k pixels

Other Concepts

Method vs. State of the Art on Large Germany Data

Test Performance Confusion Matrix

Results in Smallholder Farms in Africa

- Ghana
  - Non-Model: 0.50
  - Model: 0.58
  - 0.50

- South Sudan
  - 0.70

- Germany
  - 0.60

Model

- Crop type
- Water
- Biomass
- Soil
- Rainfall
- Nitrogen
- Crop yield
- Meteorology
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Masked Model Predicts