Large-scale crop classification from satellite images

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1 Introduction

- Farmland inspection like validating cultivated crop types, detecting over-fertilization, and estimating the grass cutting frequency is a time-consuming, laborious and costly process today. Moreover, sending human inspectors on the ground leads to very sparse data in both time and spatial extent.
- It is thus important to develop automated systems that monitor crops based on remotely sensed imagery densely in space and time.
- In this project, we are currently working on crop type classification method from publicly available Sentinel-2 images.

Fig 1. Example of a crop field in Switzerland (source: blw.admin.ch).

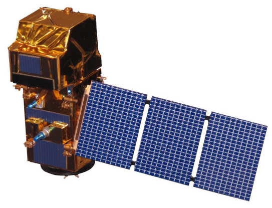

Fig 2. Sentinel-2 is an Earth observation mission from the EU Copernicus Programme that systematically acquires optical imagery at high spatial resolution over land and coastal waters.

2 Motivation & Method overview

- Most previous work uses physics-inspired models. They compute one or multiple vegetation-related indexes, form time series, and feed them to a classifier, e.g, a random forest. Such models capture only a limited part of the complex reflectance distribution of the vegetation and its evolution.
- We posit that this is one of the factors that limit their performance, and undermines their robustness against noise in the data, even when advanced pre-processing techniques are used.
- Our approach is based on deep learning, which has recently shown great success in prediction tasks, from both image data and time series (e.g. in speech processing). We use a recurrent multi-layer neural network to learn the complex spectral, spatial and temporal patterns that differentiate different crop types from raw data.
- Our model (see Fig. 3) is fed with a temporal sequence of images (X_i) and encodes both spectral and temporal information, from which it then predicts the likelihoods of different crop types. We do not do any pre-processing, rather we let the model learn to disregard uninformative and noisy data, such as clouds and cloud shadows.

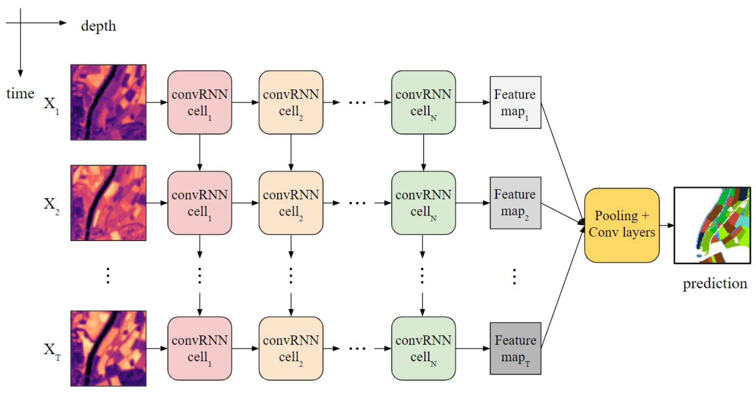

Fig 3. Illustration of our deep multi-layer convolutional recurrent neural network model.

3 Experiments

Setup: Initial experiments are done with data from Canton of Bern, Solothurn, Zug, and Schwyz. All the available Sentinel-2 data (10m and 20m resolution bands) in 2017 are used (which means a maximum of 83 timestamps). Patch sizes of 240m-by-240m (24-by-24 pixels images) are used as input to a model.

The dataset is divided into training (70%) and test (30%) splits. The model is trained with the training set and tested on the test set. For evaluation, we compute pixel-wise accuracy, and field-wise accuracy by applying consensus pooling within each crop field.

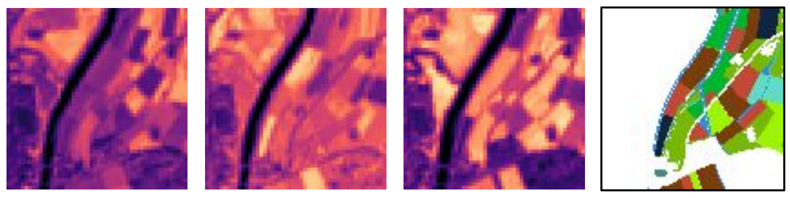

Fig 4. Example for input patches which belongs to different timestamps (first 3 images), and the corresponding ground-truth label map (Each color represents different crop type.).

Preliminary results: We achieve 78% pixel-wise amd 93% field-wise accuracies on the test set.

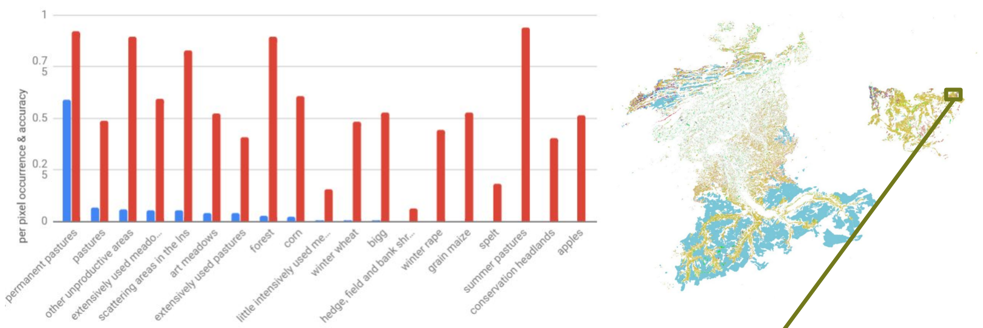

Fig 5. Class-wise performance. Blue and red bars show class occurrence frequencies and pixel-wise test accuracies, respectively.

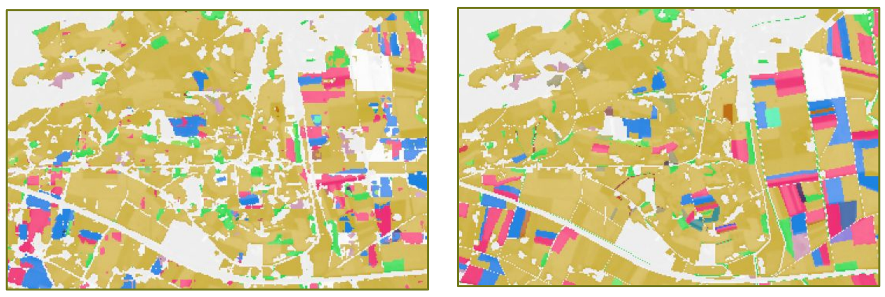

Fig 6. Qualitative results: Prediction (left), ground-truth (right). Each color represents different crop type.

4 Conclusion

In this project, we develop an intelligent system to automatically predict cultivated crop types in farmlands based on remotely sensed imagery.

- Our research leads to more economic and environmental sustainability in food systems by making time-consuming, laborious, and costly crop monitoring task fully-automatic and countrywide scalable.
- Since our research can be used for improving food sustainability, quality, and security it supports reaching SDGs of the UN Agenda 2030.

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