Mapping land use and land cover changes faster and at scale with deep learning on the cloud

Policymakers rely on Land Use and Land Cover (LULC) maps for evaluation and planning. They use these maps to plan climate-smart agriculture policy, improve housing resilience (to earthquakes or other natural disasters), and understand how to grow commerce in small communities. A number of institutions have created global land use maps from historic satellite imagery. However, these maps can be outdated and are often inaccurate, particularly in their representation of developing countries.

We worked with the European Space Agency (ESA) to develop a LULC deep learning workflow on the cloud that can ingest Sentinel-2 optical imagery for a large scale LULC change detection. Sentinel-2 has high temporal and spatial resolutions, is openly licensed, and can be freely downloaded from ESA or other service providers. The workflow aims to create automated, accurate, fast, scalable LULC maps to support decision making around natural resource management and urban resilience, especially in developing countries.

Our current workflow can be broken down into three steps:

1. Generating training data;
2. Training deep learning models on the cloud;
3. Predicting LULC over a new area of interest (AOI)

It's an end-to-end workflow that sits on top of two comprehensive tools, SentinelHub, and eo-learn, which seamlessly link earth observation data with machine learning libraries. It can take in the labeled LULC and associated AOI in shapefiles, set up a task to fetch cloud-free, time series imagery stacks within the defined time interval by the users. It will pair the satellite imagery tile with it's labeled LULC mask for the supervised deep learning model training on the cloud. On the deep learning model training side, we're using Dynamic UNet from Fast.ai. Users can swap-in a variety of models to be used as the UNet encoder. This allows users to quickly experiment and switch the models according to their task, AOI, diversity of data and desired LULC classes. Once a well-performing model is trained, it can be exported as a Tensorflow/Pytorch serving docker image to work with our cloud-based model inference pipeline, Chip n' Scale. The inference pipeline can automatically scale with the number of images to be processed.

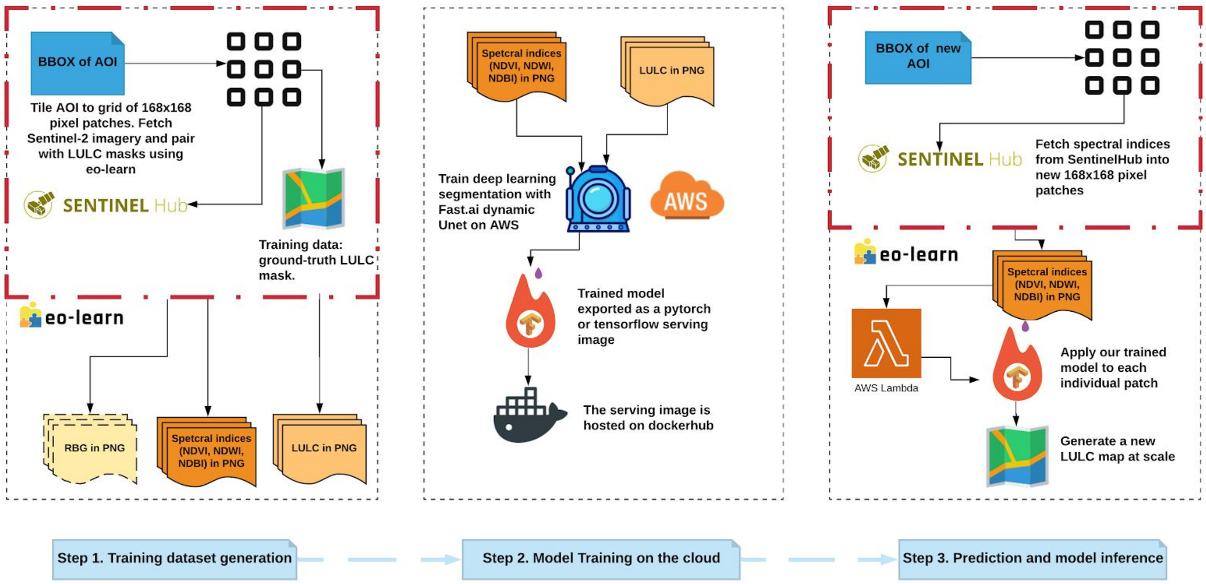

Figure 1. The deep learning pipeline that fetches and creates training data for LULC modeling on the cloud. It can be scaled up with our current open-sourced and cloud-based pipeline Chip n' Scale.

Figure 2. The pipeline fetches training data, Sentinel-2 optical imagery and labeled 10 classes LULC, for the AOI (in green) that covers 1296 km2 in Slovenia. A UNet using ResNet50 as the encoder was trained, and the model prediction was done over a new area (in red), and the LULC classification is shown on the right.

Land, forests, and water are intimately connected to how people live. Changes in land use are heavily influenced by human activities (e.g. agriculture, deforestation, human settlement expansion) and have been a great source of greenhouse gas emissions. Sustainable forest and land management practices vary from region to region, which means having flexible, scalable tools will be critical. With these tools, we can empower analysts, engineers, and decision-makers to see where contributions to climate-smart agricultural, forestry and urban resilience programs can be made. The pipeline will be open sourced in the next few weeks.