Course 2.1: Data-centric Explainable Machine Learning for Land Cover Mapping

1.1 Introduction

We have observed significant advancements in land cover classification during the past decades due to the availability of Earth Observation (EO) data and the rapid development of machine learning algorithms. To date, there is a proliferation of advanced machine learning models that are highly predictive. Many remote sensing researchers and analysts use a model-centric approach that focuses on improving machine learning algorithms and overall accuracy. Although improving machine learning algorithms is good, limited and imbalanced training data impede machine learning models. In many cases, remote sensing researchers rarely communicate information on the quality of training data and their impact on model performance. Furthermore, most advanced machine learning models are opaque and difficult to interpret and explain.

Recently, it has become more critical than ever to understand and explain how machine learning models work since researchers use them to solve important land use and climate change challenges. As a result, experts have called the machine learning community to embrace a data-centric explainable machine learning approach. This approach focuses on improving the quality of training data and explaining how the models work. To improve the accuracy of machine learning models, remote sensing researchers and analysts should acquire high-quality training data, perform pre-processing, train the models and apply explainable machine learning techniques in an iterative process of model development.

Researchers have recently developed methods to address the complexity and explainability of machine learning models (Roscher et al. 2019, Apley and Zhu 2020). In addition, there have been calls to incorporate transparency and accountability in machine learning models. As a result, many researchers are working hard to develop explainable and interpretable machine learning models (Molnar 2019, Biecek and Burzykowski 2020). Explainable machine learning is difficult to define. In this course, explainable machine learning refers to the extent to which the underlying mechanism of a machine learning model can be explained (Biecek and Burzykowski 2020). That is, explainable machine learning models allow us (humans) to explain what the model learned and how it made predictions (post-hoc). Note this is different from interpretable machine learning (e.g., linear and logistic regression models), which refers to the extent to which a cause and effect are observed within a model (Molnar 2019).

1.2 Test site

We will use Gweru -a small city in Zimbabwe - as a test site. Gweru is located about 285 km south of Harare metropolitan area. The elevation in the test site varies from about 1,300 m and 1,500 m. The hottest month is October, while July is the coldest (Kamusoko et al. 2021). The average temperature range from 21 °C in July to 30 °C in October. The rainy season is from November to March, and the annual rainfall is about 684 mm. The population increased significantly from 38,480 in 1969 to 158,233 in 2012 (ZimStats 2012). Gweru is centrally located between Harare and Bulawayo and is an important transport hub. The city provides mining and commercial agriculture services in the surrounding areas. Gweru also produces ferrochromium, textiles, dairy foods, footwear, and building materials.

1.3 Data

1.3.1 Satellite imagery

In this course, we will use seasonal Sentinel-1 (S-1) and Sentinel-2 (S-2) data compiled from Google Earth Engine (Gorelick et al. 2017) to map land cover. The seasonal S-1 data consist of mean and median rainy season S-1, mean and median post-rainy season S-1, and mean and median dry season S-1 composites (Table 1). We will use mean and median seasonal S-1 data because the imagery shows lower speckle than single-date imagery. Therefore, we will not perform speckle reduction, which generally reduces spatial resolution. The seasonal S-2 data comprises median rainy season S-2, median post-rainy season S-2, and median dry season S-2 composites (Table 2). The rainy season is between January and March, the post-rainy is between April and June, and the dry season is between July and October in the test site.

Table 1. Specifications of Sentinel-1 data

Polarization	**Incidence Angle**	**Pixel Size (m x m)**	**Orbit Properties**
VV	36 - 40	10	Ascending
VH	36 - 40	10	Ascending

Table 2. Spectral bands for the Sentinel-2 sensors

Sentinel-2 bands	**Sentinel-2A**	**Sentinel-2B**	**Spatial resolution (m)**
	Central wavelength (nm)	**Central wavelength (nm)**	
Band 1 - Coastal aerosol	442.7	442.2	60
Band 2 - Blue	492.4	492.1	10
Band 3 - Green	559.8	559.0	10
Band 4 - Red	664.6	664.9	10
Band 5 - VRE 1	704.1	703.8	20
Band 6 - VRE 2	740.5	739.1	20
Band 7 - VRE 3	782.8	779.7	20
Band 8 - NIR	832.8	832.9	10
Band 8A - Narrow NIR	864.7	864.0	20
Band 9 -Water vapor	945.1	943.2	60
Band 10 -SWIR (Cirrus)	1,373.5	1,376.9	60
Band 11 -SWIR 1	1,613.7	1,610.4	20
Band 12 - SWIR 2	2,202.4	2,185.7	20

Note: VRE - vegetation red edge; NIR - Near-infrared; and SWIR - short-wave infrared bands

1.3.2 Reference data for land cover classification

Remote sensing analysts digitized reference data for the test site from very high-resolution imagery available from Google Earth™ and ESRI Satellite. The remote sensing analysts made a lot of effort to prepare reliable and accurate reference data. However, reference data were compiled from different sources. Therefore, it is inevitable that some errors are found within the reference data. The reference data is still beneficial since the remote sensing analysts carefully interpreted and checked some locations, especially peri-urban areas.

In this course, the focus is on mapping land cover. Table 3 shows the target land cover classes based on the author's a priori knowledge of the test site. We will use six land cover classes in this course: (1) built-up; (2) bare areas; (3) cropland; (4) grass/ open areas; (5) woodlands; and (6) water.

Table 3. Land cover classification scheme

Land Cover	**Description**
Built-up (BU)	Residential, commercial, services, industrial, transportation, communication, utilities, and construction sites.
Bare areas (BA)	Bare sparsely vegetated area with >60% soil background. Includes sand and gravel mining pits, rock outcrops.
Cropland (Cr)	Cultivated land or cropland under preparation, fallow cropland, and cropland under irrigation.
Woodlands (Wd)	Woodlands, riverine vegetation, shrub, and bush.
Grass/ open areas (Gr)	Grass cover, open grass areas, golf courses, and parks.
Water (Wt)	Rivers, reservoirs, and lakes.

References

Apley DW, Zhu J (2020) Visualizing the effects of predictor variables in black box supervised learning models. J. Roy. Stat. Soc. B 82 (4), 1059-1086. https://doi.org/10.1111/rssb.123777

Biecek P, Burzykowski T (2020) Explanatory Model Analysis: Explore, Explain, and Examine Predictive Models. With examples in R and Python. https://ema.drwhy.ai/preface.html

Gorelick N, Hancher M, Dixon M, Ilyushchenko S, Thau D, Moore R (2017) Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote. Sens. Environ. 202*, 18–27, doi:10.1016/j.rse.2017.06.031

Kamusoko C, Kamusoko OW, Chikati Enos, and Gamba J (2021) Mapping Urban and Peri-Urban Land Cover in Zimbabwe: Challenges and Opportunities. Geomatics 1, 114-147. https://doi.org/10.3390/geomatics1010009

Molnar C (2019) Interpretable Machine Learning - A Guide for Making Black Box Models Explainable. https://christophm.github.io/interpretable-ml-book/ Accessed 20 July 2021

Roscher R, Bohn B, Duarte MF, Garcke J (2019) Explainable machine learning for scientific insights and discoveries arXiv: 1905.08883

ZimStats (Zimbabwe National Statistics Agency) (2012) Census 2012: preliminary report. Harare, Zimbabwe