Many volcanic fields can be found along the East African Rift (EAR), an active divergent plate boundary. Marsabit (2.32°N, 37.97°E) and Nyamiben Hills (0.42°N, 37.96°E) are located on the eastern shoulder of the Kenyan Rift, part of the eastern branch of the EAR (Fig. 1). Both volcanic fields formed in the late Pleistocene and Holocene and both are host to hundreds of pyroclastic cones and maar craters. Previous research has established that trends of linear arrays and the morphology of extrusive volcanic features can reflect the locations of subsurface feeder dikes, which are often not visible at the surface (Paulsen and Wilson, 2010; Murhead et al., 2015). Analysis of dike orientations can supply valuable information regarding regional tectonic stress and the locations of pre-existing lithospheric structures. Manually mapping extrusive volcanic features can be time consuming and subjective.

You Only Look Once version 2 (YOLOv2) is an object detection system developed in 2017 by Joseph Redmon and Ali Farhadi. Here we present our results in the use of this machine learning algorithm to identify extrusive volcanic features in Marsabit and Nyamiben Hills. We use training data from Marsabit to identify features in both Marsabit and Nyamiben Hills to assess the usefulness of YOLOv2 to aid in the mapping and analysis of these features.

Object Detection Algorithms
Object detection refers to the identification of one or more objects in an image by outlining the target with a bounding box. A training dataset is a series of annotated images with bounding boxes identifying the objects within (Fig. 4). ANNs mimic human neural networks. Thousands of interconnected processing nodes work together to neurons, organized into layers. The individual processing nodes in the first layer “examine” an image without the annotated bounding boxes. As information passes through the layers of the network, it loses much of its semantic meaning. YOLOv2 divides the training images into a grid and examines each grid square individually. Hidden layers are also structured to perform operations akin to filtering in traditional computer vision, and its output layer contains predictions for the label and bounding box of the features in the image. The last step is a loss calculation where predictions are compared to the provided bounding boxes. Weights are then adjusted—correct predictions have more weight than incorrect predictions.

The whole process, called an epoch, is then repeated. The training process adjusts the weights in the neural network to become better at detecting the visual patterns in the image that identify the objects. Finally, a validation dataset is fed to the trained ANN to assess accuracy.

Identification of Extrusive Volcanic Features with YOLOv2

Introduction

Nyamiben Hills: A comparison between YOLOv2 identified features and manually identified features reveal some discrepancies. Fig. 2A is a validation image with green bounding boxes around the YOLOv2 identified features. When the bounding boxes are overlaid on manually mapped features (Fig. 2B), it becomes apparent that some boxes contain up to three pyroclastic cones. This location has a total of 71 cones.

Results

Marsabit: A comparison between manually mapped volcanic features in Google Earth Pro (Fig. 3A) compared to YOLOv2 identified features from the training and validation dataset (Fig. 3B). There are many errors of commission, particularly in the desert regions to the west and the lava fields in the southeast. Maar craters are more easily identified than cones. The wide variety in cone morphology may explain errors of omission.

Error Analysis & Conclusions

Accuracy is measured two ways: by loss function (Fig. 5) and an informal errors analysis for Marsabit. The loss function graph measures how well YOLOv2 performs over epochs. Predictions for training data tend to be better than validation data—this may be a result of the greater number of training data (173 images) over validation data (50 images). The loss function graph indicates that accuracy in prediction grows over epochs.

An informal error analysis is performed by comparing 30 randomly chosen previously mapped features on Marsabit to Figure 3B, which contains all YOLOv2 identified features. Interestingly, all maar craters but one were identified correctly. Out of the 30 randomly selected features, 14 were within YOLOv2 predicted bounding boxes, indicating a success rate of 46.7%. There are also many errors of commission, especially in the desert to the west, where 31 false positives are identified.

In conclusion, this technique is not overly successful in the identification of extrusive volcanic features. Marsabit is an ideal location for areas with prominent basaltic lava flows. The presence of lava flows in the Turkana basin, such as Hurri Hills, Dilo-Durkana, and Mega, could provide enough data to make YOLOv2 a more efficient predictor.

Methods

• Landsat 8 OLI/TIRS imagery of Marsabit and Nyamiben Hills is obtained from EarthExplorer
• Preprocessing is performed in IDRISI TerrSet 2020. Two footprints cover Marsabit; they are mosaicked and subset. A multiplicative merge of bands 4, 5, 6, and 8 (red, NIR, SWIR, and panchromatic) covering wavelengths between 0.64-0.89, 0.89-0.88, 1.57-1.65, and 0.50-0.68 μm is performed to create a false color composition with a resolution of 15 meters.
• The false color composition of Marsabit is “sliced” into 512x512 pixel squares using Spectral Python
• A training dataset is created from 173 images of extrusive volcanic features and maar craters are identified and annotated in labelling. This creates two files: a PNG image and an XML file in PASCAL VOC to denote bounding box locations.
• A validation dataset is created from 7 images of Marsabit and 3 images of Nyamiben Hills.
• An open source Jupyter Notebook (YOLOv2-Tensorflow-2.0, created by GitHub user jmpaj) is modified and run for 100 epochs.

Figure 1. (A) Map of the East African Rift. Red lines indicate major faults, dashed blue lines indicate the extent of thermal domes. Adapted from Murel et al., 2015. (B) Marsabit and Nyamiben Hills in the context of southern Ethiopia and northern Kenya.

Figure 2. (A) A validation image from Nyamiben Hills. (B) The same feature with manually identified features, created in AVGS Pro with shaded relief.

Figure 3. (A) A true color composition of Marsabit created in Google Earth Pro. Blue polygons outline extrusive volcanic features manually mapped in a previous project. (B) A false color composition of Marsabit created from the training and validation dataset with bounding boxes around objects identified by YOLOv2. The 180 “shores” created by spectral Python have been stitched together to create the composition.

Figure 4. An image from the Marsabit training dataset.

Figure 5. Log loss function graph, which plots the change in log-loss (cost function) over epochs. The lower the log-loss (cost function), the more accurate the prediction.

Figure 6. A true color composition of Marsabit created in Google Earth Pro. Blue polygons outline extrusive volcanic features manually mapped in a previous project. (B) A false color composition of Marsabit created from the training and validation dataset with bounding boxes around objects identified by YOLOv2. The 180 “shores” created by spectral Python have been stitched together to create the composition.