Classification of landslides in LANDSAT images: A neural network implementation
GEO-391
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Introduction
Mass wasting along hill slopes, or landslides, pose a significant danger to both local residents and their economies. The ability to predict landslide prone areas is essential as governments need statistical data to drive decisions regarding resources for engineering projects that will avert costly damages. In many landslide prone regions, heavy rainfall is often the major cause, and thus determining the probability of having a landslide given a certain amount of rainfall in landslide prone locations is important for hazard mapping. Heavy rainfall events saturate the subsurface quickly, which reduces the internal strength of the soil/sediment. When strength weakens below a certain threshold, either the cohesion or internal friction of the sediment, the material will begin to fail causing a landslide.

The land – ocean margin of the Big Sur region in California is an ideal place for landslides to occur with steep banks, dry and porous soil, highly variable vegetation cover, and significant rainfall events followed by periods of prolonged drought (Warrick et al., 2019). The geologic structure of this region is the result of transpression within the Gregorio-Hosgri fault system which has uplifted a combination of granitic, metamorphic, and sedimentary marine rocks creating a margin with highly variable bedrock strengths making it particularly prone to landslides (Warrick et al., 2019). Thus, the landslide chosen for this case study was the May 20th, 2017 Mud Creek landslide in the central Big Sur region of California (Figure 1).

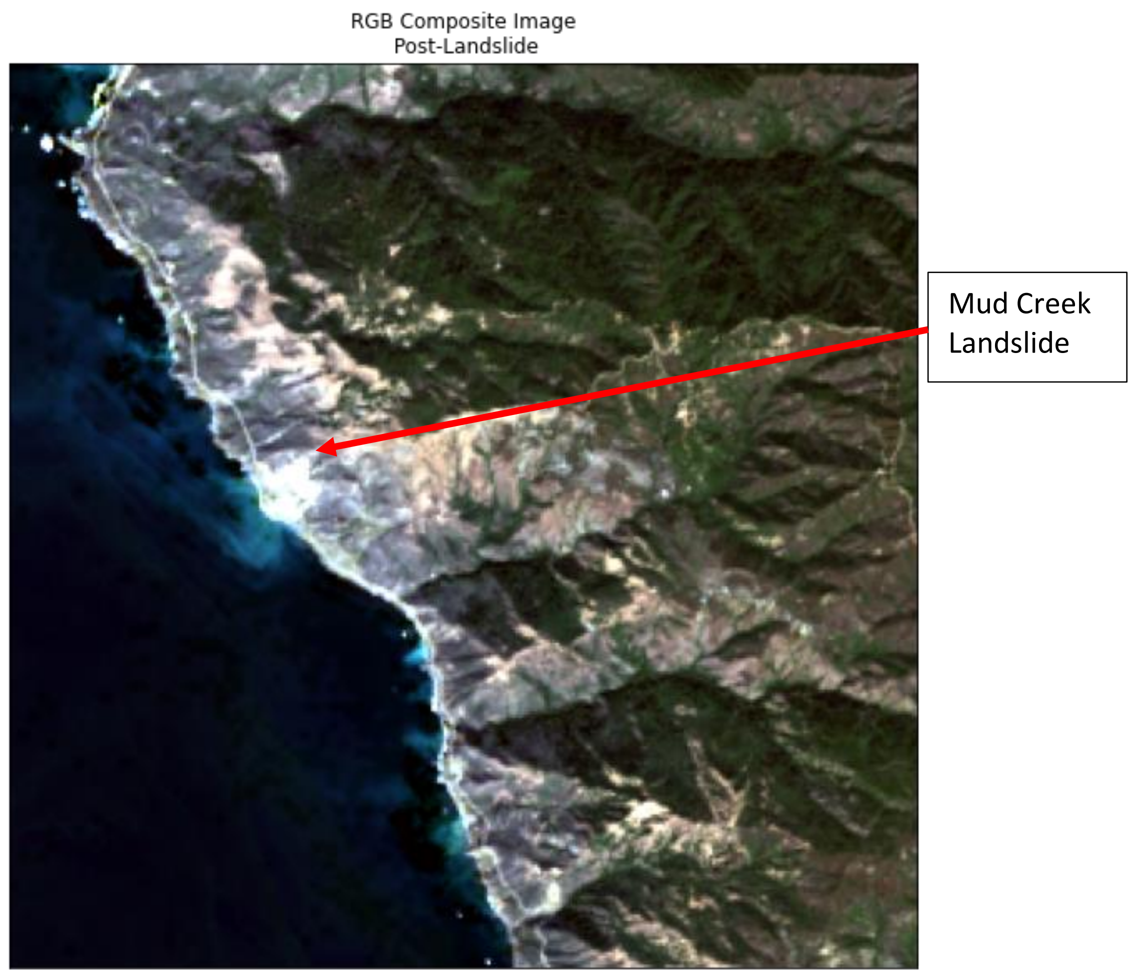

Figure 1: Mud Creek Landslide in the Big Sur region of California imaged from red, green and blue bands of the LANDSAT 8 satellite. This image was collected on 09/27/2017.

Landslide identification plays a key role in hazard mapping for locations within the Big Sur region, and other landslide prone locations in general. Numerous techniques have been employed for semi-automated landslide detection, such as pixel-based methods, object-oriented methods, and the use of digital terrain model (DTM) (Wang et al., 2021). Recently, machine learning approaches have been used to classify terrain and map historic landslides. Such approaches include the use of artificial neural networks and support vector machines to produce landslide inventories (Wang et al., 2021). The aim of this project was to develop a method which utilized a similar machine learning approach to extract and classify landslides from freely available LANDSAT data. This task was accomplished with a combination of geospatial and machine learning python libraries and the QGIS software.

Methods

Data selection

The LANDSAT data for the Mud Creek landslide was downloaded from the earth explorer section of the USGS website. An image from September 27th, 2017 was obtained from the LANDSAT 8 ARD package, which was used for ground truth creation. While the dataset contained 11 bands, only bands 1-7 were used as an input into the neural network. Bands 1-7 consist of the data for coastal aerosols, blues, greens, reds, near infrared (NIR), shortwave infrared (SWIR1), and SWIR2 respectively, all with a resolution of 30m. The last 4 bands, which were not used in the analysis, were the panchromatic band (band 8), the cloud observation band (band 9 – cirrus) and thermal observation bands (band 10 and 11).

Python libraries and ground truth generation in QGIS
Since the only available LANDSAT images for this region were significantly larger than the area of interest, they needed to be clipped and stacked. The python libraries used for this task included geopandas, rioxarray, earthpy, and shapely respectively. These were implemented to reduce the spatial dimensions of all the image bands to a rectangle 8.7 km by 8.73 km. Next, to obtain a ground truth data set for the classification algorithm, the clipped dataset was imported into QGIS, where the ground cover was classified (Figure 2).

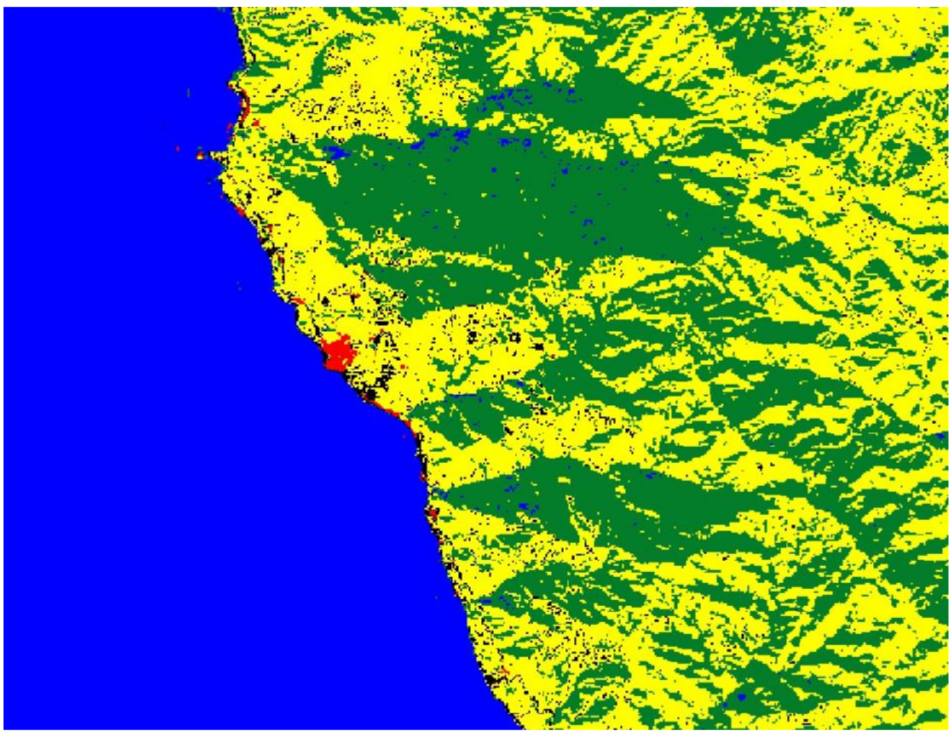

Figure 2: Ground truth classification for the study region. The colors represent the classifications, where 1 (blue) is water, 2 (green) is vegetation, 3 (yellow) is bare ground, 4 (red) is the landslide, and 5 (black) is other.

The ground truth classification generated values per pixel of 1-5, representing water, vegetation, bare ground, landslide, and other respectively. These data would become the labels that would be fed into the neural network. Because the landslide area is small relative to the total image size, the percentage of pixels occupied by the landslide is very small compared to the percentage of pixels classified as water, vegetation, and bare ground (Figure 3).

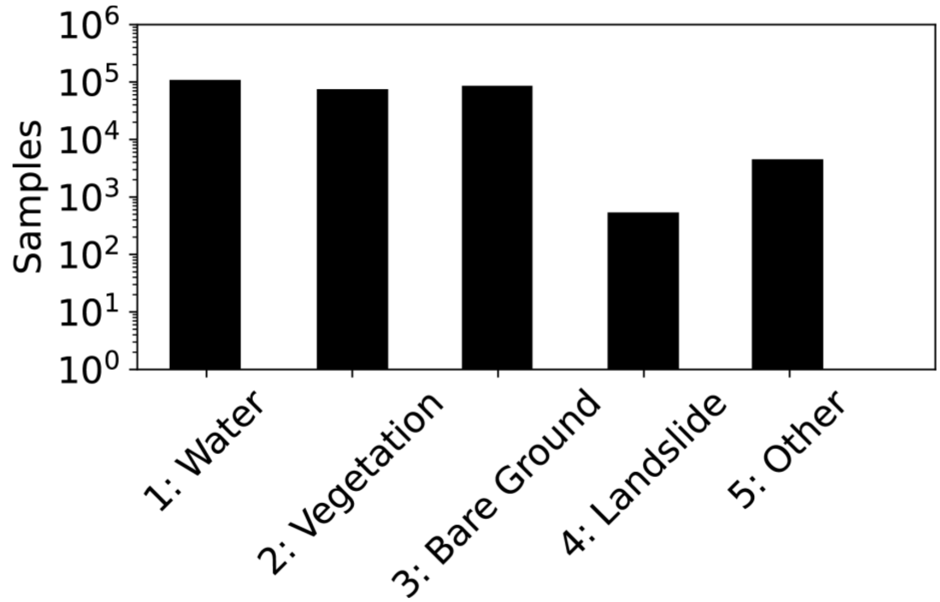

Figure 3: Histogram showing the uneven distribution of labels within the ground truth image.

A Neural Network approach to classification

A multilayered neural network is the computer application of a mathematical construct where inputs are passed through an activation function defined by the user and then to the loss function which is minimized. The network architecture for this project is shown in Figure 4.

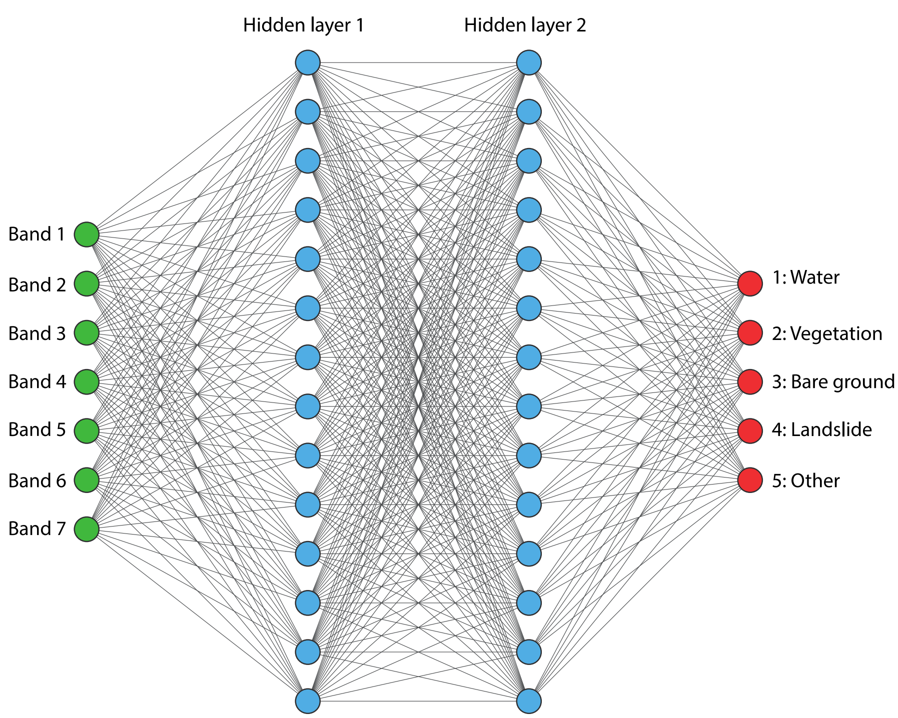

Figure 4**:** The neural network architecture used in this project consists of the inputs of the 7 bands (green), which are transferred to two hidden layers, each consisting of 14 nodes (blue). Finally, the output is passed to the output layer consisting of 5 nodes, one for each label (red).

The inputs for this neural network were the seven bands from the LANDSAT image described above, while the outputs are the values defined by the ground truth classifications done in QGIS. The initial shape of the input image was (7, 472, 575), where the first value is the dimension (number of bands), the second value is height, and the third value is the width in pixels. Similarly, the shape of the ground truth image was (472, 575), which is the same height and width as the input image shown in Figure 5. To apply this to a neural network, the input image was reshaped such that each column contained all pixel values from a single band and each row represented a single value (Figure 5). This produced an input array with a shape of (271400, 7). Similarly, the labels were reshaped to a 1-D array with a shape of (271400, 1). Prior to input into the neural network, all values in the input array were normalized by the maximum value of all pixels, 255.

The loss function chosen for this neural network was the categorical cross entropy loss function because the labels are not binary. However, because this loss function was used, the labels needed to be encoded, which meant converting the 1-D array of integer values (1, 2, 3, 4, and 5) to arrays (i.e. [1,0,0,0,0] for a value of 1, [0,1,0,0,0] for a value of 2 etc.). This encoding was accomplished using sklearns OneHotEncoder and produced an array of shape (271400,5). Finally, the optimizer chosen for this project was ADAM and the default learning rate of 0.001 appeared to work best.

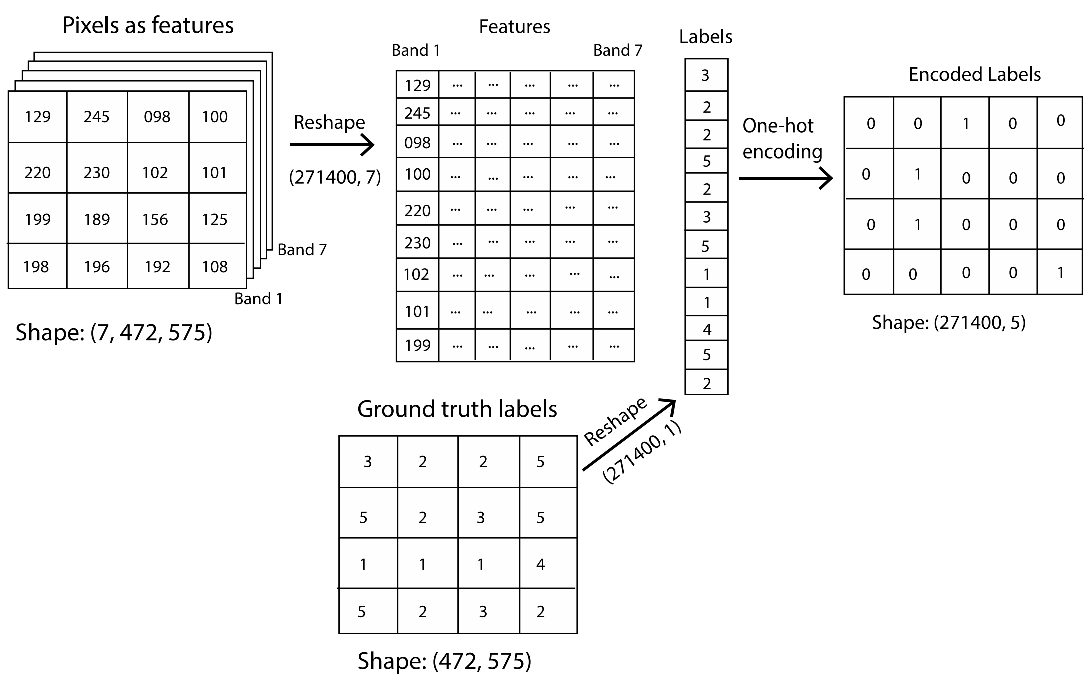

Figure 5*:* Preprocessing of the initial image from a 3-dimensional array to a 2-dimensional array, and processing of the ground truth from a 2-dimensional array to a 1-dimensional array. Finally, the 1-D ground truth array was encoded to become a (271400, 5) array, where 5 represents the number of labels.

Results

The metric I chose to maximize for this project was the F-1 score. This was because there a large bias towards pixels classified as water, vegetation, and bare ground in the image (Figure 3). Here, the metric accuracy, which provides the ratio of correct observation to total observations, would likely be artificially high and not representative of how well the landslides were classified because of the uneven class distribution (Figure 3). In contrast, the weighted average in the F-1 score will provide a more reliable metric for how well all the classes were classified.

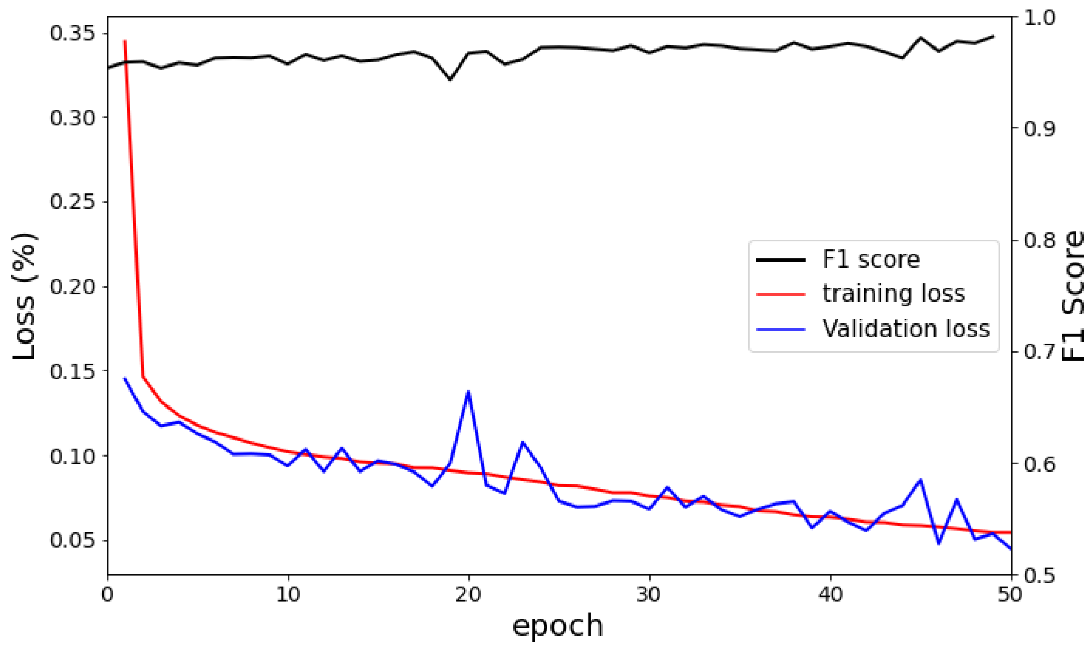

Figure 6: Training loss, validation loss, and F1-score for 50 epochs of the neural network.

Surprisingly, the F-1 score started very high at 0.953 and improved to 0.985 over 50 epochs (Figure 6). As the model improved, the training loss and validation loss decreased from 0.35 to 0.072 and from 0.15 to 0.065 respectively. It is interesting to note that there appears to be a negative correlation between the validation loss and the F-1 score, for instance, the increase in loss at epoch 20 corresponds to a decrease in the F-1 score for that epoch. However, this direct correlation does not appear in the training loss values.

A confusion matrix was generated to visually represent how well each label was classified (Figure 7). As expected, the water, vegetation, and bare ground were, for the most part, classified correctly with very few pixels being misclassified. In comparison, the landslide pixels were generally classified correctly, with only 18% being miss classified as bare ground. This suggests that the model did a reasonable job correctly distinguishing between the landslide surface and bare ground. The only label that the model struggled to classify was other. The other label consisted of manmade terrain, which in this image only consists of roads.

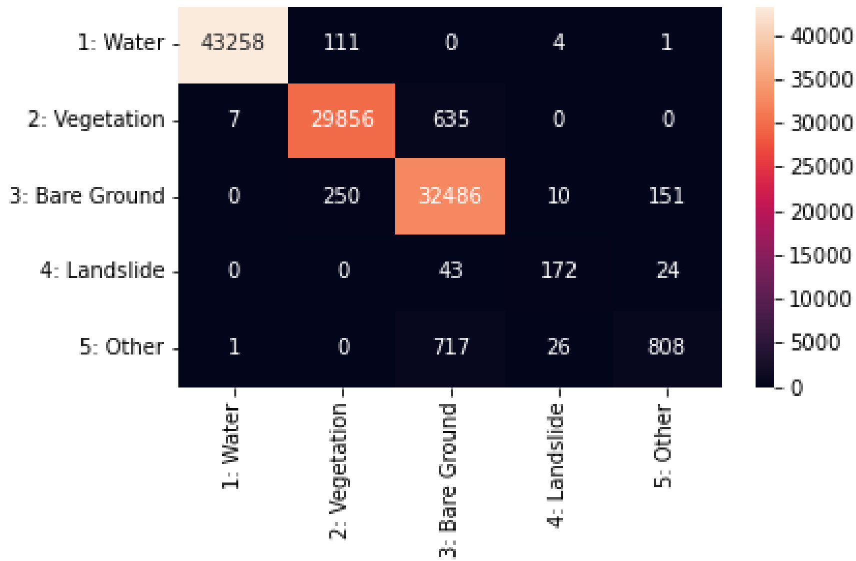

Figure 7: Confusion matrix for the test data. Generally, the model correctly classified the water, vegetation, bare ground, and landslide pixels. However, the model struggled to correctly classify pixels labeled other, general mistaking them as bare ground.

Conclusion

The final prediction made by the neural network produced an image (figure 8) very similar to the initial ground truth.

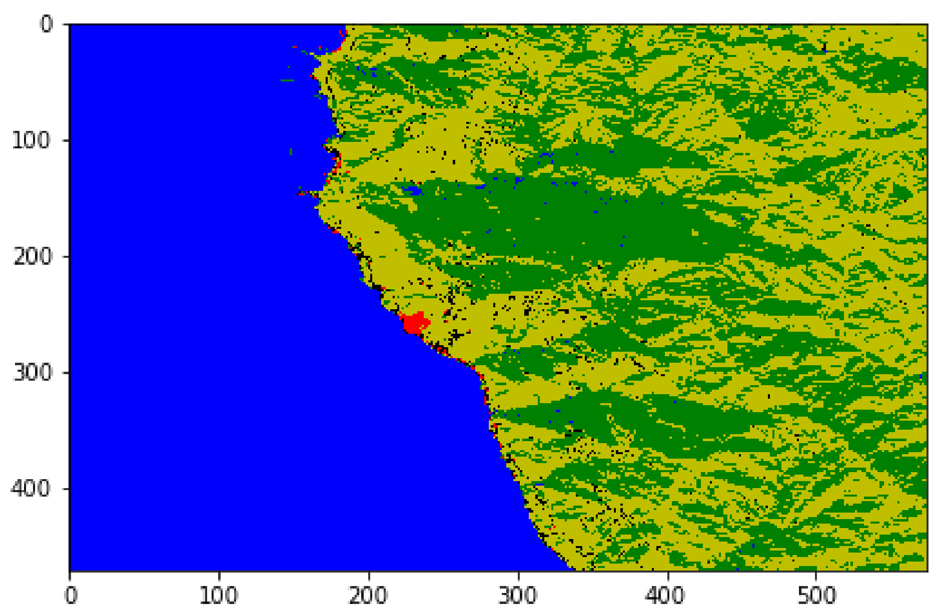

Figure 8: Final prediction showing the result of the model on classifying the test data.

There are some slight improvements such as fewer pixels incorrectly classified as landslide pixels and the model removed some of the vegetation which was misclassified as water (water pixels in the mountains). Overall, the model did a reasonable job classifying the landslide and next steps would be to test this model on a landslide from a different region. However, a major limitation for testing this model is the that the landslide would need to occur at an ocean-land margin for the classes to be correctly applied to the land surface.

References

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Warrick, J. A., Ritchie, A. C., Schmidt, K. M., Reid, M. E., & Logan, J. (2019). Characterizing the catastrophic 2017 Mud Creek landslide, California, using repeat structure-from-motion (SfM) photogrammetry. *Landslides*, *16*(February), 1201–1219. https://doi.org/10.1007/s10346-019-01160-4

Data

LANDSAT-8 image (LC08-CU-002010-2017927-20210503-02-SR) courtesy of the US-Geological Survey. Accessed: 11/8/2021 from https://earthexplorer.usgs.gov/