Database description.

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Abstract

Satellite images coupled with Machine Learning provide a unique solution to tackle challenges that would otherwise seem unapproachable. Problems like sustainable development, autonomous agriculture, and urban planning require sight from the sky to become more efficiently addressed. The dataset presented in this report is focused not only on the delivery of land cover, but that of spectral bands analysis that only satellites capable of capturing infrared light can capture. *Index terms*— satellite imagery, Sentinel2 imagery, fertile land, Ground truth masks, earth engine.

1 Data Set

Images were queried from the earth engine API from Google[1], and further processed by the geemap library[2]. The ee (earth engine) primary methods used for image export are .getThumbURL; for png and jpg format, and a custom method that changes the GEO_TIFF extension to TIF extension. Since both methods return one image each, the geemap library integrates the .stratifiedSample method that allocates random points on the region of interest (ROI)— one image per point with x and y coordinates. Additionally, to automatize the process with more agility, 25 processes were used for parallel processing. Geempap library also provides an interactive map to deine a ROI with, and extract the coordinates in question. (A feature not available in Python3 with ee). The parameters of the images from the database generator script are shown in figure 1.

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```
params = {
    'count': 10,  # How many image chips to export
    'buffer': 1000,  # The buffer distance (m) around each point
    'scale': 100,  # The scale to do stratified sampling
    'seed': 1,  # A randomization seed to use for subsampling.
    'dimensions': '256x256',  # The dimension of each image chip
    'format': "png",  # The output image format, can be png, jpg, ZIPPED_GEO_TIFF, GEO_TIFF, NPY
    'prefix': 'tile',  # The filename prefix
    'processes': 25,  # How many processes to used for parallel processing
    'out_dir': './YES',  # The output directory. Default to the current working directly
}
```

Figure 1:

The semantic difference between the images is given by the infrared light-wave reflection; a phenomenon that results in a variety of shades of green where the more bright the more healthy vegetation or crops are. On the other hand, poor reflection results in absorption of red light, and thus the image indicates poor or almost to none vegetation present.

2 Land Cover Classification

The classification train dataset contains 100 images of the 'fertile' class, and 100 images of the 'non fertile' class (examples are shown below) of size of 256 x 256 pixels, with added test/validation sets, each with 30/30 images further split into the two classes (corresponding to a split of 70%15%15%). All images contain RGB data with a pixel resolution of 6.77 cm and each tile is equivalent to 100 m^2. Some example land cover class label 'fertile' (right) and 'non fertile'(left) images are shown below.

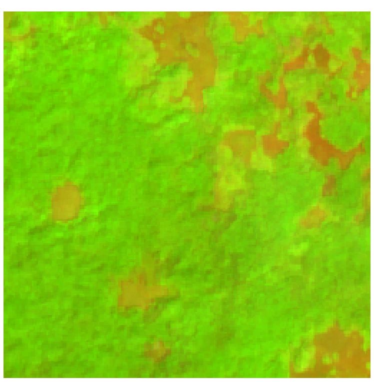


Figure 2: fertile

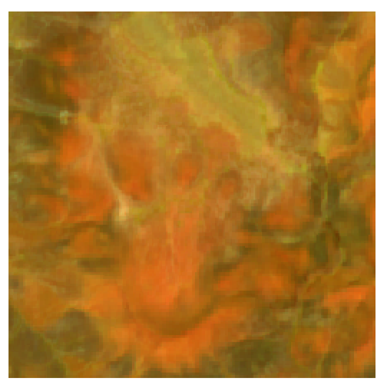


Figure 3: non fertile

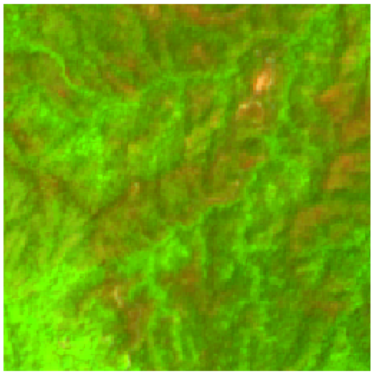


Figure 4: fertile

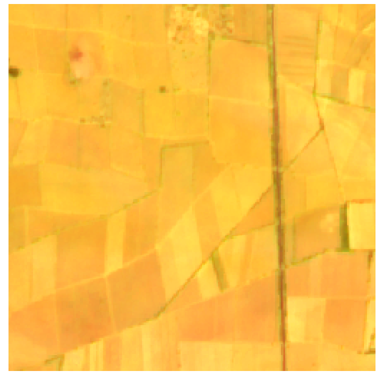


Figure 5: non fertile

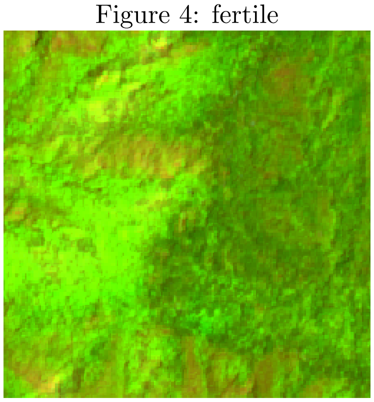


Figure 6: fertile

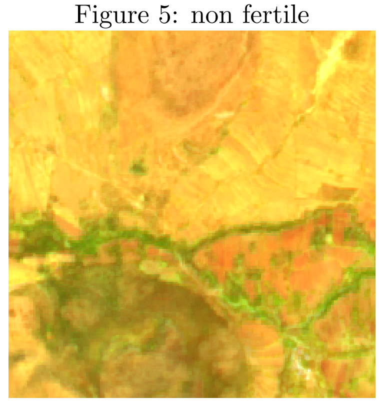


Figure 7: non fertile

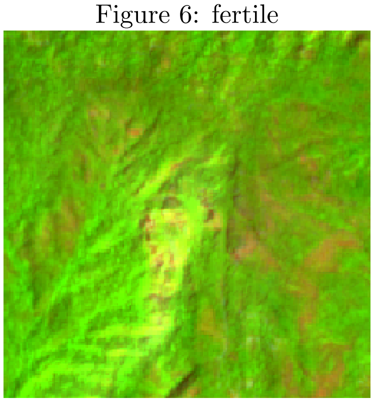


Figure 8: fertile

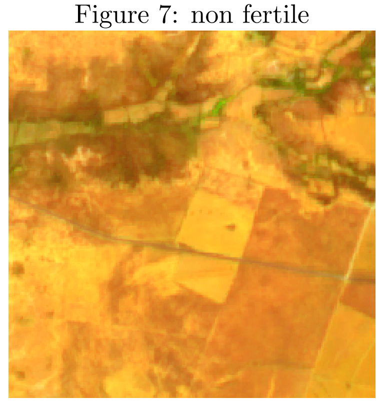
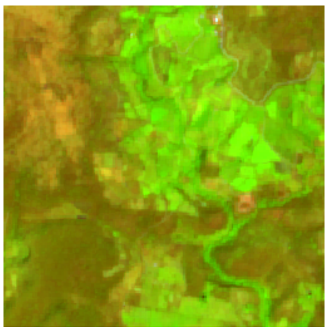
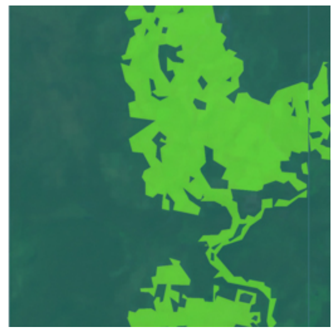
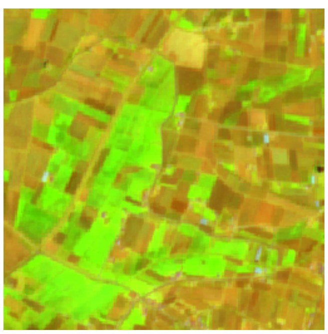


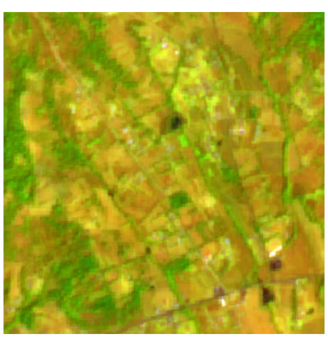
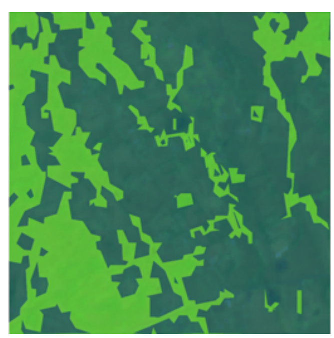
Figure 9: non fertile

3 Fertile land detection

The data set for image segmentation contains 100 images (available in png and tif format) with more or less equal distribution of fertile and non fertile land, and 100 additional images of their corresponding jpg groundtruth masks (a list of light green polygons). All images contain RGB data with a pixel resolution of 6.77 cm and each tile is equivalent to 100 m^2. Some example land cover class label (right) and corresponding original image(left) pairs are shown below.



4 Conclusions

The goal of this report lies in the belief that this dataset will become a valuable benchmark in satellite image understanding, enabling more collaborative interdisciplinary research in the area, that can be fairly compared and contrasted using this benchmark, leading to new exciting developments at the intersection of computer vision, machine learning, remote sensing, and geosciences.

References

[1] Wu, Q., (2020). geemap: A Python package for interactive mapping with Google Earth Engine. The Journal of Open Source Software, 5(51), 2305. https://doi.org/10.21105/joss.02305

[2] Google Earth Engine. https://earthengine.google.com/