**Land change in Guam from 2006 to 2022**

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**Introduction**

Studying land change is an essential form of research for land conservation. This type of research is significant for small islands like Guam, which are environmentally fragile areas that are difficult to restore if the environment is overly damaged. Land conservation is necessary because irrational land development can lead to soil erosion, which can damage the local environment. Focusing on past land changes will allow us to better predict and plan for future land use. Our study will use GEE, R, TerrSet, and ArcGIS Pro to analyze local data. We will compare Guam in 2006, 2014, and 2022 and analyze the land change in Guam now by comparing maps.

**Study Area**

The study area for this analysis is Guam. Guam is an unincorporated territory of the United States in the western Pacific Ocean. It has an area of 540 square kilometers and a population of 168,801. In Oceania, Guam is the largest and southernmost of the Mariana Islands and the largest island in Micronesia. The majority of the population resides on the coral limestone plateau in the north, with political and economic activity concentrated in the central and northern regions. The rugged geography of the south has a largely limited settlement in the rural coastal areas. Guam has a tropical rainforest climate with generally hot and humid weather throughout the year and slight seasonal temperature variations. Guam has severe natural ecological problems, including the receipt of anthropogenic and natural influences, and because of its location and size, Guam is particularly sensitive to climate change. Guam exploits its natural resources for economic benefit based on the ocean.

**Object**

1, Classify Guam land uses to study the land change in Guam.

2, Combine these variables into a classification model using TerrSet and ArcGIS Pro.

3. test the model, variables, and variable cross-correlation using TerrSet's multilayer perceptron neural network image classifier.

4. look at the manually classified maps compared to TerrSet's map classification and analyze the map comparison.

This study aimed to build a map of Guam using TerrSet's multilayer perceptron neural network image classifier. Few research articles focus on land change in Guam, so we would like to use this study to learn more about land change in Guam. Our results from this study will be used to inform land planning and land conservation and to develop effective strategies for protecting Guam's ecosystem and sustainable development.

**Methodology**

For methods, we first downloaded the Guam land use land cover maps in 2006 and 2014 from the U.S. Department of Agriculture (USDA), which are shapefiles with polygon data. At the same time, Sentinel 2 images in 2022 of Guam were also collected from the Google Earth Engine (GEE).

Initially, seven classes (barren land, agriculture, forest, grassland, urban, water, and wetland) were chosen for reclassifying the land use maps (2006 and 2014), and we reclassified them in R because that is more efficient than operating in ArcGIS pro. After that, the dissolve function in ArcGIS pro was implemented to the reclassified shapefile images so that it would be helpful when converting them into vector data in TerrSet.

In TerrSet, to make maps comparable, the images (land change maps in 2006 and 2014 and the Sentinel 2 images) should keep spatial parameters, such as the coordinate system and the pixel size, the same. Therefore, several functions, PROJECT, INITIAL, and RASTERVECTOR, were applied step by step to make it work.

The next step is to classify the Sentinel 2 images. When digitizing the training sites, we found the agriculture area is small and hard to distinguish it from grassland or forest, so as the wetland. Thus, we reclass the classes into five types, barren land, forest, grassland, urban, and water, to improve the accuracy of the classification result. Two classification methods, Maximum Likelihood (MaxLike) and Multiple Layer Perceptron (MLP) were conducted for classification.

The final step is to make a map comparison in 2006, 2014, and 2022.

**Result**

The supervised classification results of MaxLike and MLP are similar, but the MaxLike has many Non-data pixels so we chose MLP classification map as our final output. Plus, when scrutinized carefully, we also found the result of MLP should be more accurate than MaxLike.

From the cross-tabulation, we had an overview of each land use type in these 3 years. In 2006, the proportion of barren land, forest, grassland, urban, and water is 0.93%, 45.45%, 23.39%, 30.02%, and 0.21% respectively.In 2014, the proportion has changed to 2.01% of barren land, 56.26% of forest, 20.21% of grassland, 20.46% of urban, and 0.56% of water.And in 2022, the proportion of each class is 7.09% of barren land, 41.65% of forest, 42.93% of grassland, 7.87% of urban, and 0.46% of water;

The map shows a clear decrease in commercial land use and urbanized areas, which has been converted to forest or pasture. Forests still continue to decrease however the grasslands increases. This could be due to incorrectly increasing data due to different classification methods of the classifier, or it could be due to the increased protection of grassland due to new environmental policies.

**Discussion and conclusion**

MLP and MaxLike methods allow a more apparent separation of urban land from non-urban land (e.g., vegetation), thereby improving classification accuracy. This facilitates a more accurate understanding of urban expansion and the occurrence of land conservation. We found a significant improvement in bare land and grassland compared to 2006 and 2014 data.

Also, with increased environmental protection awareness by local governments, there are now many initiatives to protect, restore, and enhance targeted native limestone forests, canyon forests, and savanna habitats. These are all initiatives that will benefit Guam's ecosystem restoration. Yet Guam continues to have serious environmental problems, including poaching by locals and cutting down trees. Some news reports from Guam state that despite Guam's humid climate, many forest fires occur each year, so it is reasonable to suspect that most of these wildfires are caused by humans. Therefore, we attribute the increase in wilderness and grassland to the revegetation of damaged land and areas that were originally forested after the wildfires. At the same time, we acknowledge that our classification method needs to be more precise, leading to inaccurate classifications and resulting in less detailed subsequent analyses. This is because the training data were not selected sufficiently to facilitate the computation of the model. And since we are identifying feature information from images, it may be difficult for us to find the correct location because we are not familiar with the local environment.

**Reference**

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