Object Based Image Classification and Analysis for Remote Sensing

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Abstract: *Remote sensing is the process of detecting and monitoring the physical characteristics of an area by measuring its reflected and emitted radiation at a distance. In this paper, we have shown object-based image analysis on ARD data obtained from Landsat satellite and applying NDVI, zonal statistics, classification, segmentation, change detection.*

Keywords: Classification, Remote-sensing, change-detection

I. INTRODUCTION

Environmental monitoring requirements, conservation goals, spatial planning enforcement, or ecosystem-oriented natural resources management, to name just a few drivers, lend considerable urgency to the development of operational solutions that can extract tangible information from remote sensing data. The 'work horses' of satellite data generation, such as the Landsat and SPOT satellites or the ASTER and MODIS instruments, have become important in global and regional studies of biodiversity, nature conservation, food security, deforestation impact, desertification monitoring, and other application fields.[1]

U.S. Landsat Analysis Ready Data (ARD) are pre-packaged and pre-processed bundles of Landsat data products that make the Landsat archive more accessible and easier to analyze and reduce the amount of time users spend on data processing for time-series analysis.[2]

1.1 NDVI

The NDVI is a dimensionless index that describes the difference between visible and near-infrared reflectance of vegetation cover and can be used to estimate the density of green on an area of land. The NDVI is computed as the difference between near-infrared (NIR) and red (RED) reflectance divided by their sum.

$$NDVI_i = \frac{(NIR - RED)}{NIR + RED}$$

$NDVI_i$ represents smoothed NDVI (sNDVI) observed at time step i and their ratio yields a measure of photosynthetic activity within values between − 1 and 1. Low NDVI values indicate moisture-stressed vegetation and higher values indicate a higher density of green vegetation. It is also used for drought monitoring and famine early warning.[3]
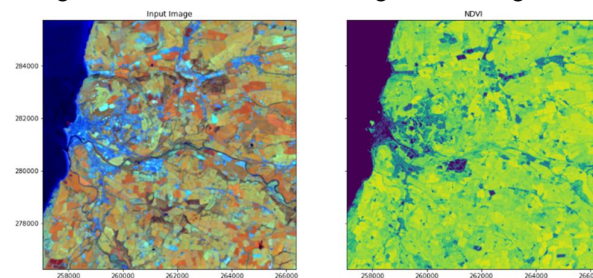

Figure 1: Input image and final output after NDVI processing

1.2 .Zonal Statistics

Populating various vector formats (points and polygons) from raster images for looking at fallow, growing and cropping cycles in agricultural/rice paddies in Vietnam, using radar imagery. Radar data is measured in backscatter where high values are associated with high structure (vegetation) and low values are associated with low structure (non_vegetated/water/bare).

1.3 Classification

Based on the idea that different feature types on the earth's surface have a different spectral reflectance and remittance properties, their recognition is carried out through the classification process. In a broad sense, image classification is defined as the process of categorizing all pixels in an image or raw remotely sensed satellite data to obtain a given set of labels or land cover themes.[4]
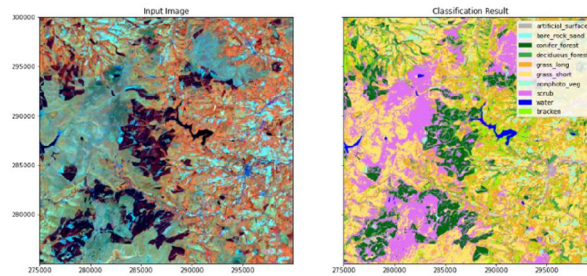

Figure 2: Per-pixel machine learning classification

1.4 Segmentation

Segmentation means the grouping of neighbouring pixels intoregions (or segments) based on similarity criteria (digital number, texture). Image objects in remotely sensed imagery areoften homogenous and can be delineated by segmentation. Thus, the number of elements as a basis for a following imageclassification is enormously reduced. The quality of classification is directly affected by segmentation quality. Hencequality assessment of segmentation is in the focus of this evaluation of different presently available segmentation software[5].
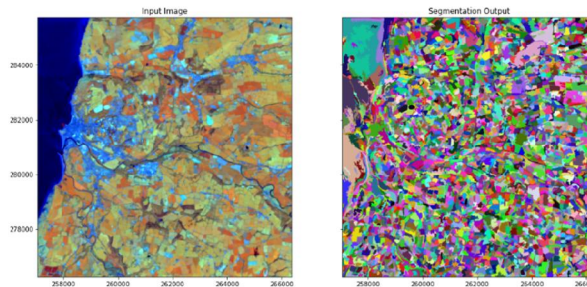

Figure 3: Shepherd et-al, image segmentation result

1.5 Change Detection

Remote sensing change detection is a process for determining and evaluating differences in a variety of surface phenomena over time. Detecting, describing, and understanding changes in the physical and biological processes that regulate the earth system is of considerable interest for ecologists and resource managers today. Detecting land use change, range condition, desertification, changes in forest cover, regional evapotranspiration differences, soil moisture condition, and other physical and biological processes allows for the documentation of the spectral and temporal changes that are occurring within ecosystems. Change detection studies recognize that the bioticand abiotic components of the biosphere are linked and that human impacts on the earth now approach the global scale of biosphere processes (Hobbs, ed.1990). Thus, change in any one of several components in the biosphere may potentially influence the other components.[6]

II. RELATED WORK

In this section we will focus on the related work that has been done previously by several researchers who have developed various applications based on OBIA in remote sensing. In an article by M.V.K Sivkumar and Donald e Hinsman, Agricultural planning and use of agricultural technologies need applications of agricultural meteorology. Satellite remote sensing technology is increasingly gaining recognition as an important source of agrometeorological data as it can complement well the traditional methods agrometeorological data collection. Agrometeorologists all over the world are now able to take advantage of a wealth of observational data, product and services flowing from specially equipped and highly sophisticated environmental observation satellites. In addition, Geographic Information Systems (GIS) technology is becoming an essential tool for combining various map and satellite information sources in models that simulate the interactions of complex natural systems. The Commission for Agricultural Meteorology of WMO has been active in remote sensing and GISapplications in agrometeorology. The paper provides a brief overview of the satellite remote sensing and GIS Applications in agricultural meteorology along with a description of the WMO Satellite Activities Programme. The promotion of new specialised software should make the applications of the various devices easier, bearing in mind the possible combination of several types of inputs such as data coming from standard networks, radar and satellites, meteorological and climatological models, digital cartography, and crop models based on the scientific acquisition of the last twenty years[7].

Another paper by Aishwarya Gupta, Ayush Shroff, Aman Saxena on Monitoring Mangrove Forest Cover Changes Using Remote Sensing and GIS Data with Machine Learning Techniques studied that change in green cover of mangrove in parts of Sundarbans region using machine learning techniques with the help of remote sensing and GIS. It compares the result of various algorithms to detect change in forest cover such as rule-based techniques and learning based techniques. Monitoring of mangrove forest decline has become an urgent need for our country. As lack of mangroves will result into depletion of the plant population which will result into increasing the carbon dioxide level in the environment which will lead to ozone depletion, pollution etc. and the ecosystem will collapse. In this paper image classification technique has shown drastic changes than earlier used decision learning and support vector machine algorithms.[8]

Major study by Andreas Bernhard Brink*, Hugh Douglas Eva monitored 25 years of land cover change dynamics in Africa their study examines the changes in sub-Saharan's natural land cover resources for a 25-yearperiod. We assess these changes in four broad land cover classes – forests, natural non-forest vegetation, agriculture, and barren – by using high spatial resolution Earth observing satellites. Two sets of sample images, one 'historical' targeted in 1975 and a second 'recent' targeted at the year 2000, have been selected through a stratified random sampling technique over the study area, targeting a sampling rate of 1% in each of the strata. The results, presented at eco-region level and aggregated at sub-Saharan level, show a 57% increase in agriculture area at the expense of natural vegetation which has itself decreased by 21% over the period, with nearly 5 million hectares forest and non-forest natural vegetation lost per year. The impacts of these changes on the environment on one site and on the socio-economy on the other site are discussed and possible pressures on human wellbeing are highlighted.[9]

III. RESULTS

We have outputted testing and training accuracies and here is a comparison of all the classification results.

Table 1: Comparison Of accuracies

	test	train
refl_knn	0.990637	0.988983
linnorm_knn	0.990637	0.989831
sdnorm_svm	0.986891	0.991525
refl_svm	0.986891	0.989266
linnorm_svm	0.983146	0.989548
linnorm_et	0.983146	1.000000
refl_et	0.983146	1.000000
refl_rf	0.981273	1.000000
linnorm_rf	0.981273	1.000000

sdnorm_et	0.981273	1.000000
sdnorm_knn	0.981273	0.987288
refl_gbt	0.979401	1.000000
linnorm_gbt	0.977528	1.000000
sdnorm_rf	0.975655	1.000000
sdnorm_gbt	0.973783	1.000000
refl_nn	0.960674	0.958475
sdnorm_nn	0.958801	0.947175
linnorm_nn	0.953184	0.962147
linnorm_ml	0.911985	0.917514
refl_ml	0.129213	0.106215
sdnorm_ml	0.129213	0.106215

As we can see that the training and testing scores look identical with highest higher scores for almost all classifiers. However, when visualization is done there is a large difference seen in the results

IV. CONCLUSION

Geo-spatial data and machine learning together create vast suite of opportunities for analysis of different kinds of terrains without physically collecting data. Assessing land-cover change in forested areas is straightforward and easily implementable with image subtraction. Among (Gaussian Maximum Likelihood, Support Vector Machines, Random Forests, Extra Tress, Gradient Boosted Trees, Neural Network, K Nearest Neighbour) K Nearest Neighbour provided results with the highest accuracy.

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