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LAND COVER CLASSIFICATION: SOME NEW TECHNIQUES, NEW SOURCE DATA

David A. Hastings[1] and Ryutaro Tateishi[2]

(1)World Data Center - A, Boulder Centers
National Oceanic and Atmospheric Administration
National Geophysical Data Center
325 Broadway, Boulder CO 80303, USA
Email: dah@ngdc.noaa.gov

(2)Center for Environmental Remote Sensing, Chiba University
1-33 Yayou-cho Inage-ku, Chiba 263, JAPAN
Email: tateishi@rsirc.cr.chiba-u.ac.jp

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ABSTRACT

Land cover classifications have advanced from using single Landsat Multispectral Scanner scenes to using "full resolution" AVHRR time series. Three current approaches to global land cover study with AVHRR involve (1) compiled climatologies from AVHRR data at 16-km nominal latitude-longitude gridding, (2) over 16 years of 8-km nominal Goode's projection gridding in the NOAA/NASA Pathfinder collection, and (3) a short time-series of 1-km nominal Goode's projection gridding by the U. S. Geological Survey and others. Despite such progress, the link between imagery-based classifications and ground observations remains somewhat weak, and not always logical to the field scientist. This paper discusses several processes that may potentially improve global land cover classifications.

1   BACKGROUND

Reliable global land cover information is necessary for global change studies and global/continental land use management and planning. In order to meet such needs, a global four-minute gridded land cover data set was produced using global 8-km 10-day composite AVHRR NDVI data from the NOAA/NASA Pathfinder project, for the year 1990 (Wen and Tateishi, 1997). For this project, a new land cover classification with hierarchical structure was proposed. A ground-truth data base was prepared at the same 4-km gridding. The classification scheme incorporated ground truth data, an extended ground truth model, and a binary decision tree method.

During the reporting of this project at an ISPRS workshop during the 18th Asian Conference on Remote Sensing, we had a chance to reflect on the current state of land cover classification processes, and of possible improvements. This paper summarizes combined thoughts of Hastings (1997) and Tateishi (in Wen and Tateishi, 1997).

2   INTRODUCTION

Land cover classification techniques have undergone several advances in the last few years, particularly for large areas. Early efforts used single unmosaicked Landsat Multispectral Scanner scenes (about 185 x 185 km areas maximum per scene). These offered a 80 m ground field of view (GFOV) (about 225 m ground resolution), but suffered from recording the "almost always anomalous" conditions of a single instant in time, not-very-synoptic view of a macro-scale ecosystem, and certain spectral limitations.

The Landsat Thematic Mapper offered a 30 m GFOV (about 80 m resolution) with greater spectral sophistication than MSS. Specialists noted that the reduced scale of pixel mixing significantly improved the statistical "accuracy" of supervised and unsupervised classifications. Nevertheless, single scenes were still used, limiting the classification to a single instant in time and an area under 200 x 200 km.

SPOT offered yet higher spatial resolution (20 m GFOV, about 55 m resolution) for multispectral data, but only three non-optimized spectral channels, small viewing area, high price, and copyright restrictions. Perhaps because of the latter considerations, SPOT is rarely used for multispectral land surface classifications.

More recently, one school of thought has investigated the challenges of national- to global-scale land surface classifications. These use the Advanced Very High Resolution Radiometer (AVHRR; http://www.ngdc.noaa.gov/seg/globsys/avhrr.shtml), operating since 1978 on the U. S. National Oceanic and Atmospheric Administration's Polar Orbiting Environmental Satellites. AVHRR was designed for:

(1) daily global coverage,
(2) rigorous mathematical georeferencing rather than previous, less precise control-point and rubber sheeting methods,
(3) time-series analysis,
(4) visible, reflected and on-board calibrated thermal spectral channels.

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Land cover efforts begun by Tateishi and Kajiwara (1991) and by Loveland et al (1991) computed the Normalized Difference Vegetation Index (Tarpley and others, 1984; Tateishi and others, 1991; Hastings and Kineman, 1993) for several AVHRR scenes representing as much seasonal variability as possible. Unsupervised cluster analyses were run, producing a large number of clusters (sometimes as many clusters as the program could produce). The clusters were then assessed manually (sometimes with limited digital correlation with other data such as elevation) to produce the land cover classification.

These techniques introduced the advantage of multi-date input imagery, which improved the discrimination of land cover types with differing seasonal characteristics. As the availability of better AVHRR NDVI time series improves, this method should result in increasingly better land cover classifications.

However, we are still challenged by several systematic deficiencies in the land cover classification process:

1. NDVI has been shown to be most valuable for land cover assessment when the NDVI is relatively high. However, in most parts of the world at any one time, NDVI is relatively low. Land cover is comprised of more things than merely vigorously growing vegetation. Dry areas, areas out of growing season, bare soil, etc. tend to have low NDVI. How to find and incorporate more sophisticated indicators of the land surface than just NDVI?

2. How to select the AVHRR (NDVI and perhaps other indicators) data set most appropriate for land cover studies? How to produce improved data for such studies? How to better reduce noise in the AVHRR mosaics? Can noise be turned into signal, to actually enhance the land cover classification process?

3. How to optimize the classification process?

These topics will be discussed below.

3   ADDING SPECTRAL SOPHISTICATION

The current model of correcting AVHRR Channels 1 and 2, then computing Normalized Difference Vegetation Index (NDVI) is recognized as valuable primarily for areas with high NDVI values. Considering that most of the Earth's surface is relatively dry, or has vegetation that is relatively inactive for at least part of the year, this is less than ideal. In addition, some areas with high vegetative activity may have low computed NDVI caused by cloud contamination. Adding information from AVHRR's two thermal channels (such as the computed Precipitable Water Index [PWI]) complements NDVI. When higher spectral sophistication becomes available with regional/global coverage, such sophistication can be expected to improve regional/global land cover classifications. PWI is currently available on a just-released dataset (Gutman and others, 1997), and may be computed from

calibrated AVHRR thermal infrared data contained in other collections of AVHRR imagery (Gutman and others, 1995). The NOAA/NASA Pathfinder 8-km global AVHRR Land Dataset, for example, contains calibrated thermal channel data potentially amenable for computing PWI at 8 km gridding.

4   Selecting Source Data for Land Cover Assessments

Tateishi and Kajiwara (1991) performed their work on reprocessed NOAA Global Vegetation Index (Kidwell, 1994) data. These have the advantage of long time series (1982 to present). However, the data are uncalibrated, which akters the data's record of environmental variability.

The NOAA/NASA Pathfinder AVHRR 8-km land data set, which includes (http://www.gsfc.nasa.gov/ CAMPAIGN_DOCS/FTP_SITE/readmes/pal.html) AVHRR channel data and NDVI, was designed to include numerous corrections to improve the data for land surface studies. The time series runs from 1981 to the present. The calibrated thermal data (channels 4 and 5) offer promise for computing PWI data, to add spectral sophistication in an enhanced land cover classification scheme. In addition, the long time series offers possibilities for computing temporal standard deviations, which may add to a classification scheme. However, the data are projected and stored in the Goode's Interrupted Homolosine Projection (http://www.ngdc.noaa.gov/seg/globsys/acrscla1.shtml# select), which is inconvenient for data storage, and also for use in most analytical software. The data must usually be reprojected to be used with other data in a GIS. When the Pathfinder program's own reprojection software is used, the "interruptions" in the Goode's projection do not go away; small interruptions remain in the data (http://www.ngdc.noaa.gov/seg/ globsys/acrsclon.shtml). In short, either the Pathfinder data are incorrectly projected, or the supplied software misregisters the data. Misregistrations go beyond this problem; Taiwan, for example, appears about 15 km to the west of its proper location. Wen and Tateishi found as much as 3 grid-cell misregistrations in the Pathfinder data, which they attempted to correct by rubber sheeting. Hastings used the Pathfinder project's reprojection software, and found that data reprojected to latitude-longitude "projection" in this manner were many (hundreds of) grid cells misregistered toward the poles (where grid cells are narrow), with a tendency toward lower longitudinal misregistration (in increasingly wider grid cells) toward the equator. Latitudinal misregistration was less pronounced. Thus the Pathfinder 8-km data provide a desirable time series, but need additional georeferencing before use.

The Pathfinder 1 km AVHRR data set (http://edcwww.cr.usgs.gov/landdaac/1KM/ikmhomepag e.html) is too new to have a long time series of data. In addition, it is in a similar version of the Goode's Interrupted Homolosine Projection, so georeferencing must be confirmed. However, this project holds promise for the future.

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The Gutman et al (1997) data set may be worth using, at least until higher-resolution alternatives become more mature. The Gutman et al (1997) data were used by Hastings (1997) to develop a prototype hierarchical land cover map.

5   CONVERTING SPECTRAL NOISE TO ENVIRONMENTAL SIGNAL

Variations between years in parameters like NDVI may reflect climatic variations, such as different dates of onset of a monsoon. Other variations may reflect embedded cloud contamination. We cannot yet remove all cloud contamination. However, can we turn this to our advantage?

Time series standard deviations of NDVI and PWI can be computed and used in developong a land cover model. Can such temporal standard deviations be considered as enhancements of information relevant to land cover classifications? We think that the answer might be "yes," as temporal variability of NDVI and PWI correlate with temporal variability of insolation and climate, and probably to the land surface's short-term response to climate.

6   REFINING THE CLUSTERING TECHNIQUES

Under current tradition, the analyst provides a multi-temporal NDVI data base to a clustering algorithm, then asks that algorithm to provide "many" clusters. Experiments by several groups, including Wen and Tateishi (1997) and Hastings (1997) suggested that it is worth building hierarchical sets of clusters, starting with a very simple differentiation of classes. In the example of Wen and Tateishi (1997) the legend was developed hierarchically, and is seven layers deep. The Wen and Tateishi hierarchy aimed for broad compatibility with the International Geosphere-Biosphere Programme Data and Information System's (IGBP-DIS') classification scheme, and with a spatial database of field observations developed for Asia and Oceania. The unsupervised clusters were compared with the ground truth database to help assign classes. Outside Asia and Oceanic, existing thematic maps were used to help assign classes.

In Hastings' (1997) case, the actual clustering was developed hierarchically. In this example, the analyst instructs the cluster algorithm to provide two classes, then three, etc. S/he analyzes the de-facto patterns of clusters, and also analyzes the spatial pattern-of-change when the algorithm adds another class. Attempting to relate these patterns with in-situ observations offers insights into setting hierarchies, and into developing classes within hierarchies.

Hierarchy levels:

1. For example, in one experiment, the first hierarchy might begin with desert and non-desert areas. (In Hastings' (1997) case history, this was the case. This was not the result of pre-judgement by Hastings; but the result of the clustering process on the given database.)

2. The second level of hierarchies in this model might be within deserts, and separately within non-desert areas.

2B. The hierarchy under "deserts" appeared to fall mostly into rock and soil reflectance properties, so was largely a pedological/geological differentiation. However, features such as irrigated agriculture and oases also appeared within desert areas. (Whether these are considered "desert" terranes depends on one's sense of a desert, and of one's minimum mapping unit).

2B.The hierarchy under "non-deserts" appeared to fall mostly into temporal patterns of greenness. Vegetation with seasonal leaf cover, grasslands, and northern vs. southern hemispheric patterns were included in these classes.

This experiment was performed globally (between 75 degrees North latitude and 55 degrees South latitude), using the Gutman et al (1997) data. The following 48 data files were entered into an unsupervised cluster classification scheme:

1.   Twelve monthly (5-year mean) climatological NDVI values,
2.   Twelve monthly (5-year mean) climatological PWI values,
3.   Twelve monthly standard deviations of NDVI, and
4.   Twelve monthly standard deviations of PWI.

PWI is based on the hypothesis that thermal infrared signals are absorbed by atmospheric water vapor, and that this absorption varies by IR wavelength. Thus the two AVHRR channels should show differential absorption where atmospheric water vapor exists. The process is described in greater detail by Gutman et al (1995).

The clustering algorithm is first told to offer only two classes. Then three, four, etc. Each result was studied, to help the analyst to understand how the additional class is created spatially. In addition, the analyst may discover that the two-class clustering makes sense, where some other number of classes makes no sense. The analyst soon discovers that certain clustering results make no sense when compared with in-situ observations of the landscape. These results are discussed by Hastings (1977) and at http://www.ngdc.noaa.gov/seg/globsys/acrscla2.shtml# refine).

Testing of such techniques with skeptics of remote sensing techniques may provide further guidelines toward developing workable classification schemes.

7   ADDING OTHER DATA

Several scientists have proposed that adding topography, temperature, precipitation, and other data may be useful in future. This project supports such a concept. However, investigations (which have concentrated on temperature, precipitation, and

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topography) are even more in their infancy than those treating the clustering process only on various compilations of satellite imagery.

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