GIS in Water Resource Project Update

Edward Park

Objective

The ultimate goal of Geographic Information System (GIS) is to model our world. However, the modeling process is too complicated and requires elaborateness that we should not rely entirely on computer. At this time, I will do the accuracy assessment of classification of raster pixels which is usually done by computer by comparing hand digitized reference image and look into how it varies depending on spatial resolution of the image by using spatial autocorrelation analysis.

Title

Application of spatial autocorrelation analysis in determining optimal classification method and detecting land cover change from remotely sensed data

STUDYAREA

- Fluvial region around Lake Travis, Austin TX (approximately 2km*1.5km)

DATA SOURCE

- Scene

2009 Landsat 7 ETM+ Images from USGS
LE70270392009032EDC00
LE70270392009064EDC00

- Reference data

· 2009 Aerial Photograph from Capcog (capcog.org) and Trinis (trinis.org)

- · TOP0809_50cm_3097_33_4_CIR_01062008 (natural color)
- · TOP0809_50cm_3097_33_4_NC_01062008 (color infrared)
- MANSFIELD_DAM (29 mrsid files stitched)
- · Field Visit with GPS
- · Other reference data

• Land-cover map, vegetation cover map, hydrograph map, Google earth (for oblique view), daily water level data of Lake Travis from 2009

PROCEDURE

- Three major analysis will be introduced in this research using spatial autocorrelation: 1) analysis of error produced based on different types of classification method, 2) monthly change detection using spatial autocorrelation, 3) changing pattern of error depending on spatial resolution.

- First, I will do hand digitizing for the aerial photograph and classify to 5 land-cover types: c₁, c₂, c₃, c₄, c₅ based on spectral value (i.e. c₁ is a class with the lowest spectral values and c₅ with the highest which are water and road respectively). Several methods of classification will be used including maximum likelihood, ISODATA, nearest neighbor and etc., for Landsat scene and will be overlaid with the hand digitized reference image to produce difference images. Different values of 0, 1, 2, 3, and 4 depending on the degree of disagreement will be assigned to each of the pixels in difference image in a white (0) to grey color scale (1, 2, 3, 4)¹. Spatial autocorrelation will be performed within grey and black pixels in difference images in various distances to determine the most suitable classification method. For some of the sites that I'm not sure with the land-cover type, I will visit and see exactly what is there at the site.
- Once the optimal classification type is determined then multi-temporal (monthly) change detection based on spatial autocorrelation analysis will be performed between two different dated Landsat imageries. Difference image will be produced using the same method which is by using degree of disagreement to quantify the result. Through this process measuring the amount and quality of changing is possible.
- Last part of my study would analyzing the relationship between spatial resolution and the accuracy of automatic classification using spatial autocorrelation. The effect of level of spatial resolution to the map using spatial auto correlation has been performed (Chou, 1991); however, how the spatial resolution affect the difference image based on various classification method has not been done yet even though this is highly inferable. So at this time, I will quantify the effect of resolution in difference image using spatial autocorrelation.

¹ Difference Table

Color scheme below will be assigned to the corresponding pixel. For example, if C_2 is classified as C_4 then 3 will be assigned to the corresponding pixel in difference image.

ETM+ Reference	C_1	C ₂	C ₃	C_4	C ₅
C_1	0	1	2	3	4
C ₂	1	0	1	2	3
C ₃	2	1	0	1	2
C ₄	3	2	1	0	1
C ₅	4	3	2	1	0

REFERENCE

Bruzzone, L. (2000). Automatic analysis of the difference image for unsupervised change detection. IEEE transactions on geosciences and remote sensing, 38 (3).

Chou, Y. H. (1991). Map resolution and spatial autocorrelation. Geographical analysis, 23 (3).

Dormann, C., McPherson, J. M., Araujo, M. B., Bivand, R., Bolliger, J., Carl, G., Davies, R. G., Hirzel, A., Jetz, W., Kissling, D., Kuhn, I., Ohlemuller, R., Peres-Neto, P. R., Reineking, B., Schroder, B., Schurr, F., and Wilson, R. (2007). Methods to account for spatial autocorrelation in the analysis of species distributional data: a review. Ecography, 30, 609-628.

Henebry, G. M. (1993). Detecting change in grasslands using measures of spatial dependence with Landsat TM data. Remote sensing of environment, 46, 223-234.

Legendre, P. (1993). Spatial autocorrelation: trouble or new paradigm? Ecology, 74 (6), 1659-1673.

Monroe, D., Southworth, J., and Tucker, C. M. (2001). The dynamics of land-cover change in western Honduras: Spatial autocorrelation and temporal variation. AAEA annual meeting.

Overmars, K. P., de Koning, G. H., and Veldkamp, A. (2003). Spatial autocorrelation in multi-scale land use models. Ecological modeling, 164, 257-270.

Qi, Y., and Wu, J. (1996). Effects of changing spatial resolution on the results of landscape pattern analysis using spatial autocorrelation indices. Landscape ecology, 11 (1), 39-49.

Rees, W. G. (2000). The accuracy of digital elevation models interpolated to higher resolutions. International journal of remote sensing, 21 (1), 7-20.

Russel, G. C. (1988). Using spatial autocorrelation analysis to explore the errors in maps generated from remotely sensed data. Photogrammetric Engineering and Remote Sensing, 54 (5), 587-592.

Verbyla, D. L., and Hammond, T. O. (1995). Conservative bias in classification accuracy assessment due to pixel-by-pixel comparison of classified images with reference grids. International journal of remote sensing, 16 (3), 581-587.

As Project proceeds, more data and techniques will be added.