Proceeding of the 10th International Symposium on Spatial Accuracy Assessment in Natural Resources and Environmental Sciences

Florianopolis-SC, Brazil, July 10-13, 2012.

Geographically weighted methods for examining the spatial variation in land cover accuracy

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Abstract

The confusion matrix is used to describe land cover accuracy. It describes correspondence between alternative sources of land cover information and is a standard technique in remote sensing. BUT the confusion matrix is aspatial – it provides no information about the spatial distribution of accuracy. And, despite much work suggesting methods for describing the spatial variation of accuracy (Foody, 2002; 2005), these have not been adopted by the remote sensing community. This paper demonstrates how geographically weighted approaches can be used to analyse the spatial relationships between land cover data classified from remotely sensed data and data collected in the field, for both Boolean and Fuzzy classifications. These approaches each use a moving window or kernel to compute local accuracy measures, whose size is specified dynamically, and are 'geographically weighted' because the kernel allows for the fact that the more distant observations may be of less local relevance and their influence is weighted accordingly. Fuzzy and Boolean maps of the spatial distribution of accuracy were generated. This research demonstrates that data collected as part of a standard remote sensing validation exercise can be used to derive measures of accuracy that vary spatially and suggests that there is potential to move land cover validation from the aspatial to spatially explicit reporting of accuracy.

Keywords: confusion matrix, geographically weighted regression, spatial variation of accuracy, fuzzy difference

1. Introduction

Assessing map accuracy is fundamental to most land cover mapping projects (Foody, 2002; Strahler *et al*., 2006). In remote sensing, the conventional method for doing this is by comparing the land cover classified from remotely sensed data with some alternative, but spatially and temporally coincident, data in correspondence or confusion matrix. The data land cover 'predicted' by remote sensing analyses compared against some 'observed' reference data and the resulting cross tabulation allows a number of accuracy reporting measures to be generated (Congalton, 1991; Congalton and Green, 1999).

The paradigm of the confusion matrix has been criticised: it provides no information about the spatial distribution of error and the global accuracy measures derived from it may be not describe actual error rates for local sub-regions, where local error rates may be much larger or smaller than the global measures (McGuire and Fisher, 2001).

The dangers of treating the confusion matrix as anything other than a summary measure of accuracy, (that is - it is inappropriate for any operational use or geo-statistical inference), are highlighted by a number of research from a long time ago: Campbell (1981) found that misclassified pixels tended to be clustered, Congalton (1988) that that the spatial pattern of errors in remotely sensed data are influenced by topography and other landscape properties, Steele *et al.* (1998) used kriging interpolate map error and McGuire and Fisher (2001) use of Monte Carlo analyses to model the spatial distribution of data errors. Thus errors in remotely sensed (Chen and Wei, 2009; Gonzalez *et al.*, 2010).

Geographically Weighted Regression (GWR) (Fotheringham *et al.*, 2002; Brunsdon *et al.*, 1996) allows for the possibility that relationships vary over geographical space to be tested by allowing regression coefficient estimates to vary with location. A 'geographically weighted' approach is one that uses a moving window or kernel and a Geographically Weighted Regression is one that computes local estimates of the regression coefficients at each location. This is in constrats to ordinary linear regression which implicitly assumes spatial stationarity of any relationships identified - ie that the relationships between the variables remain constant over geographical space. However, many processes, trends and patterns in the real world ARE clustered spatially – that is relationships (or patterns) that apply in one areas does not always apply in another. GWR provides a method to model such spatial non-stationarity by allowing coefficients to vary over geographic space.

This research applies geographically analyses to explore the spatial variation in in Fuzzy and Boolean land cover measures colledcted in the field and from a remote sensing analysis. It extends the work of Foody (2005) who presented an approach based on GWR but who did this to compute confusion matrices at regular intervals in his study area. This research extends the use of GWR in remote sensing analyses to accuracy assessment and addresses two long-standing gaps in the analysis and communication of accuracy and error in thematic land cover data: geographically weighted methods are used to model the spatial variation in the relationships between observed and predicted land cover classes, and, it uses gegraphicallyweigted methods to determine the spatial non-stationarity of error and to visualise classification error variations.

2. Methods

2.1. Study Area, Data and Pre-processing

The area of the present study is located in the North Western part of Libya in the northern part of the Jifara Plain, around Tripoli. SPOT 5 satellite imagery sensor from 2009 was resampled to 30m x 30m and was classified into 5 classes: Urban, Woodland, Vegetation, Grazing Land and Bare areas. A supervised Boolean classification was preformed using the maximum likelihood classifier and a Fuzzy classification from the Fuzzy *c*-Means were generated, as implemented in the in Idrisi the *Maxlike* and *Fuzclass* modules respectively. Both classifications were generated using the same training data.

A validation dataset was collected by field survey at 210 spatially stratified random locations. At each location the Boolean land cover and the Fuzzy land cover were recorded. The Fuzzy data were collected in the following way: land cover at 16 points in a 4 x 4 grid within a 30m x 30m area was recorded and the sub-pixel measures of land cover composition were combined over each pixel to generate Fuzzy memberships at each location.

2.2. Spatial Analysis

The approach was to logistically regress the observed Boolean class (dependent variable) on the predicted Boolean class (independent variable). This was carried out for each class.

The *logit* function is defined by:

$$logit(Q) = \frac{exp(Q)}{1 + exp(Q)} \tag{1}$$

The logistic geographically weighted regressions were calculated as follows:

$$pr(y_i = 1) = \text{logit}(b_{0(u_i,v_i)} + b_1 x_{1(u_i,v_i)}) \tag{2}$$

where y_i is observed Boolean class, x_{1i} is the predicted Boolean class, and the coefficient estimates for the explanatory variable are assumed to vary across the two-dimensional geographical space defined by the coordinates (u, v). A moving window calculates a local weighted regression analysis at each location with points that are further away from the specific location under consideration contributing less to the solution. Equation (2) returns the probabilities of correctly identifying the observed Boolean field values from the predicted Boolean class, generating a Portmanteau measure of accuracy – i.e. considering both specificity and sensitivity.

For the Fuzzy analysis, a geographically weighted Difference approach was taken using the absolute difference between the two Fuzzy memberships:

The geographically weighted fuzzy difference were calculated as follows:

$$D_{(u,v)} = 1 - \text{abs}(\text{y}_{(u,v)} - x_{(u,v)}) \tag{5}$$

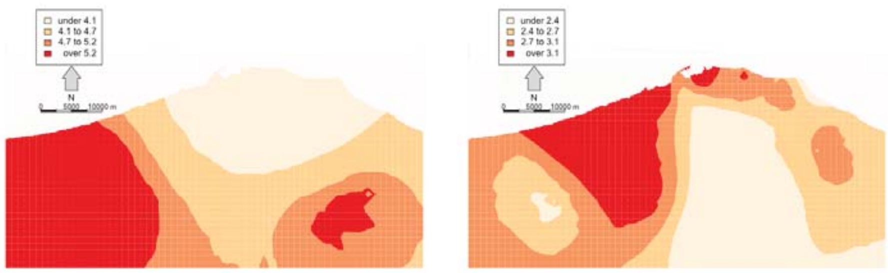
All of the statistical analysis and mapping were implemented in R version 2.14.1, the open source statistical software http://cran.r-project.org, using the *spgwr* library was used to perform the geographically weighted analyses. The data and code developed for this analysis will be provided to interested researchers on request.

3. Results

A geographically weighted logistic regression was used to explore the spatial variation in the relationship between observed and predicted Boolean data. The results for the diagonal comparisons of the same Boolean classes are shown in Table 1, where the 1st and 3rd quartiles for all derived coefficients of the regression are reported together with the median and global values and the inter-quartile range (IQR). These show two things: the extent to which the observed reference data (so called 'ground truth') are inferred by the predicted data (from satellite imagery), and the variation in GWR models. The IQR gives an indication of the overall spatial variation in the coefficients in the study area – high ones indicate variation and the global figure approximates to an ordinary linear regression model. Table 1 shows that there is considerable spatial variation in the relationship between predicted and observed Urban and Grazing land classes. The mappings in Figure 1 illustrate these variations.

Table 1: Summary of the coefficients of the relationships between the observed Boolean validation data and the modelled Boolean data classified from remotely sensed imagery.

Class	1stQu.	Median	3rdQu.	Global	IQR
Urban	4.079	4.659	5.197	4.458	**1.118**
Vegetation	2.207	2.235	2.263	2.235	0.056
Woodland	2.137	2.196	2.239	2.176	0.102
Grazing land	2.371	2.692	3.059	2.478	**0.688**
Bare	3.939	3.987	4.033	3.974	0.094



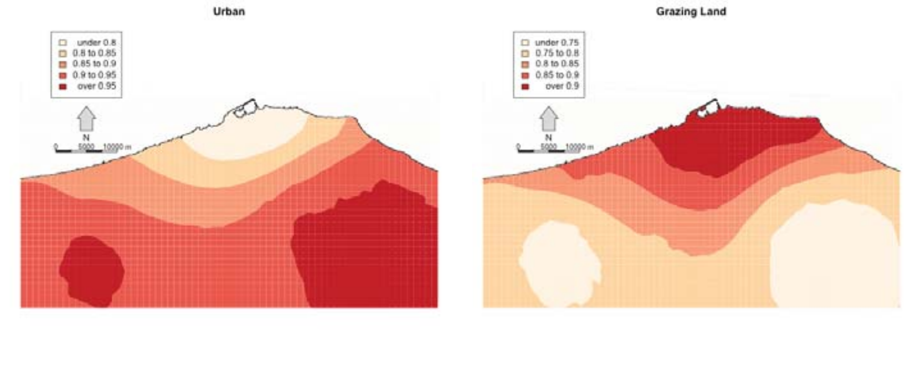
Urban Grazing land

Figure 1: Examples of the spatial distribution of the GWR coefficients of observed Boolean land cover for two classes, Urban and Grazing land, as predicted by the modelled Boolean classes.

The Fuzzy analysis proceeded in a similar way and identified the same 2 classes as having the greatest variations. The geographically weighted difference identified the spatial variation in the extent to which Fuzzy land cover classes observed in the field were predicted by the Fuzzy classes derived from remote sensing. The results are summarised in Table 2 and in Figure 2 for the classes of Urban and Grazing Land with the highest IQRs.

Table 2: Summary of the variation of the differences between observed and predicted Fuzzy classes.

Class	1stQu.	Median	3rdQu.	Global	IQR
Bare	0.842	0.841	0.84	0.841	0.002
Grazing Land	0.863	0.808	0.763	0.822	**0.100**
Urban	0.943	0.911	0.859	0.89	**0.084**
Vegetation	0.821	0.808	0.797	0.809	0.024
Woodland	0.837	0.837	0.836	0.836	0.001



Urban Grazing Land

Figure 2: The spatial distribution of the accuracy of the Fuzzy land cover for Urban and Grazing Land.

4. Discussion

This research develops spatially distributed measures of accuracy and per class reliability using a geographically weighted approach for both Boolean and Fuzzy classifications. The Boolean analysis modelled the spatial variation in the extent to which the observed classes in the field were predicted by the remote sensing analysis and the Fuzzy analysis modelled the geographically weighted difference providing a spatially distributed measure of Fuzzy prediction accuracy. Figures 1 and 2 show broadly similar patterns.

A cursory review of the literature reveals that geographically explicit (ie local) analyses of the *spatial accuracy* remote sensed data products have not been widely reported, despite research papers, monographs, edited volumes and even conferences (!) of this name originating from within the remote sensing community. The lack of spatially explicit methods and paradigms for reporting error and accuracy is counterintuitive to many of the recent developments in spatial statistical analysis and to geographical analysis as a discipline - witness spatially static protocols for data quality metadata for OGC, ISO and Dublin Core standards.

The aim of this paper was to show that it is possible to develop spatially explicit, local statistical analyses of the variation in error and accuracy from data collected as part of standard remote sensing validation exercise. The methods presented in this paper indicate the opportunities for a methodological shift in remote sensing validation: from the static to the dynamic.

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