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A GWR analysis of land cover accuracy

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Abstract

In remote sensing the confusion matrix is the most common way of expressing the accuracy of land cover data. Reference land cover data are compared with data for the same locations classified from remotely sensed images in a cross-tabulation. The confusion matrix has been criticised for not containing information relating the spatial distribution of classification errors. This paper describes the use of Geographically Weighted Regression (GWR) to model the spatial variations in the accuracy of both Boolean and fuzzy land cover classes. The confusion matrix is extended to include maps of the spatial variation in the correspondences between class pairs and to describe the spatial non-stationarity of accuracy measures. The results are discussed and suggestions for methodological developments for describing the spatial accuracy of thematic data are outlined.
Keywords: remote sensing, accuracy, confusion matrix, Geographically Weighted Regression, spatial variation.

1 Introduction

Assessing map accuracy in some objective manner is fundamental to most land cover mapping projects [1]. The accepted paradigm for doing this is through comparison with some alternative data in order to generate measures of accuracy which describe the 'correctness' of a map or classification [1]. Accuracy descriptions can help the user decide between land cover datasets, especially where there is a choice between different thematic data [2], and to determine the limitations of using the data for the user's intended application.

The most common approach for assessing land cover accuracy is to compare the classified land cover with alternative but spatially and temporally coincident data, which is considered to be of higher accuracy. The resulting cross tabulation of predicted against observed is commonly known as the confusion matrix and it supports a number of error reporting measures can be generated [3] [4].

Two major drawbacks with reporting error summaries using the confusion matrix have been identified [5]:

- Confusion matrices are aspatial and do not describe the spatial distribution of errors;
- Overall accuracy measures may be inappropriate for particular sub-regions.

This paper describes the use of Geographically Weighted Regression (GWR) [6] [7] to analyse the variation in the relationship between the 'observed' and the 'predicted' land cover measures. GWR is used to describe the varying spatial relationship between observed and predicted land cover classes using both Boolean and fuzzy class assignments. This research addresses two important issues:

- The need for a better understanding of non-stationarity in the spatial discontinuous in error measures [5];
- The need for maps of the spatial variation in classification error [1].

In so doing it seeks to develop spatially distributed measures of accuracy and to present a method for so doing from the standard data collected as part of a standard land cover validation exercise: comparison with an alternative, but assumed to be more accurate dataset collected through field survey or form higher resolution imagery.

2 Background

The confusion matrix and statistics that can be generated from it are described in [4]. Its use has been questioned by a number of different authors and extensions to the confusion matrix have been proposed. One of the key issues relates to the use of Boolean classifications in confusion matrices. Within the remote sensing community it is increasingly recognised that soft classifications such as fuzzy sets may provide a more representative model of the world by accommodating some of the uncertainty associated with the pixel [8]. In fuzzy classifications pixels can have partial memberships of different classes and the assumption of crisp membership embedded in the confusion matrix may be inappropriate for the assessment of accuracy. A number of extensions have been proposed by different authors [9 - 14].

A second problem with the confusion matrix is that is does not deal with geographic space very well. It neither allows the spatial distribution of errors to be described or reported, however. These have been found to be autocorrelated in many studies over a long period of time [15 – 19]. A few analyses have examined the variability or non-stationarity of the distribution of errors using Getis and Ord statistic [20] and kriging [21].

3 Methods

3.1 Data and Study area

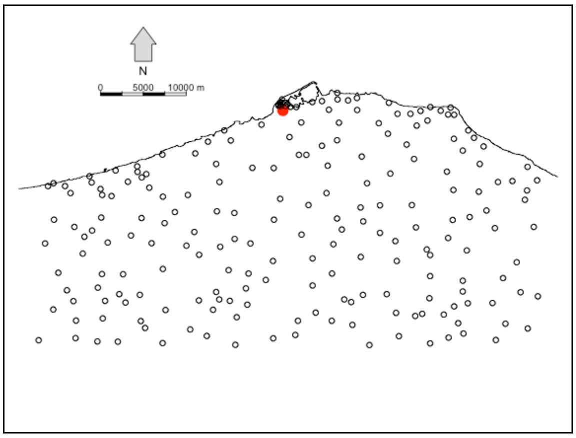
The area of the present study is located in the North Western part of Libya in the northern part of the Jifara Plain. Satellite imagery from the Système Pour l'Observation de la Terre 5 sensor from 2009 was resampled to 30m and was classified into 6 classes (Urban, Woodland, Vegetation, Grazing land, Bare areas and Water bodies). This was done in 2 ways using the same training data:

1. a standard Boolean classification using a maximum likelihood classifier;

2. a fuzzy classification using the Fuzzy c-Means [22].

A validation dataset was collected by field survey. Data were collected at 210 sample locations in 21 blocks of approximately 100km2 and 10 locations in each block were selected randomly. At each sample location the land cover at 16 points in a 4 x 4 grid within a 30m x 30m area, was recorded. Precise sub-pixel locations were established using differential GPS. Thus, sampling points were identified using a stratified random scheme. The data for each sub-pixel location were used to generate fuzzy memberships to each class and a Boolean class for each pixel using the most common class. The reference data points and their location are shown in Figure 1.

Figure 1: The study area in Libya, around the port of Tripoli (red circle at the most northern point), and the location of the 210 reference data sites.



3.2 Geographical Analysis

A GWR analysis was used to analyse the spatial variations in the relationship between the field data and the results of the two classifiers. GWR allows for the possibility that relationships vary over geographical space to be tested by allowing regression coefficients to vary with location. GWR has the following form:

$$y_i = b_0(u_i,v_i) + b_1(u_i,v_i)x_{1i} + b_2(u_i,v_i)x_{2i} + \varepsilon_i \quad (1)$$

where y_i is the independent variable to be predicted, x_{1i} and x_{2i} are the explanatory variables, ε_i is a random Gaussian error term with mean zero variance σ^2 and the coefficient for each of the explanatory variables is assumed to vary across the two-dimensional geographical space defined by the coordinates (u, v). Thus the coefficients in GWR can be considered as functions of these coordinates, rather than single-valued variables.

In contrast to global models where processes are assumed to be stationary (i.e. location independent), these local models are spatial disaggregations of global models, the results of which are location-specific. The template of GWR is similar to an ordinary regression model – the model is a linear regression model – but the coefficients are allowed to vary geographically using a kernel function. A moving window computes a local regression analysis at each location – points that are further away from the specific location under consideration contribute less to the solution Then a weighted regression is carried out where the weight associated with each location (*ui,vi*) is some decreasing function of di, the distance from the centre of the window to (*ui,vi*) Because GWR estimates regression coefficients locally using spatially dependent weights, under the assumption that the effect of the predictor variables on the dependent variable will vary continuously over space, it is an approach that addresses spatial non-stationarity.

All of the statistical analysis and mapping was implemented in R version 2.13.2, the open source statistical software http://cran.r-project.org/.

4 Results

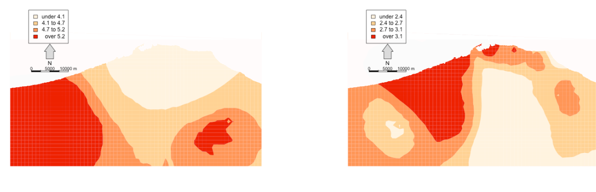
4.1 GWR analysis of Boolean accuracy

A geographically weighted logistic regression was used to explore the spatial variation in the relationship between observed and predicted Boolean data. The comparisons for the Boolean Urban and Grazing land classes are shown in Table 1, with the minimum, median, maximum and 1st and 3rd quartiles for all derived coefficients of the regression are reported together with the global value and the inter-quartile range (IQR). The results show 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 variation in the coefficients in the study area – high ones indicate that the coefficients vary spatially and the global figure approximates to an ordinary linear regression model. The data shows that there is considerable spatial variation in the relationship between predicted and observed Urban and Grazing land classes. Figure 2 maps the spatial variation.

Table 1: Summary of the coefficients of the relationships between the observed Boolean validation data and the predicted 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	2.371	2.692	3.059	2.478	**0.688**
Bare	3.939	3.987	4.033	3.974	0.094

Figure 2: The spatial distribution of the GWR coefficients of observed Boolean land cover for two classes, Urban and Grazing land, as predicted by the predicted Boolean classes.



Urban Grazing land

4.2 GWR analysis of fuzzy accuracy

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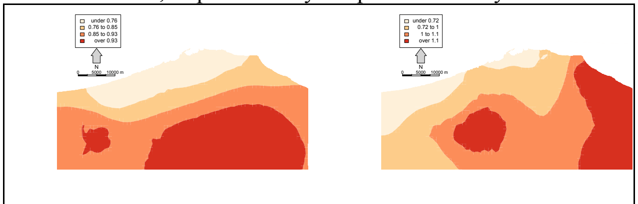
GWR was also used to analyse the spatial variation in the relationships between the reference data and the fuzzy classification. The coefficients from the GWR pair-wise models are summarised in Table 2. Spatial variation is evident in the relationships between the predicted memberships to Vegetation and Woodland classes with the observations made in the field. The maps in Figure 2 illustrate the spatial variation.

Table 4: Summary of the coefficients of the relationships between the observed validation data and the predicted data classified from remotely sensed imagery.

Class	1stQu	Median	3rdQu	Global	IQR
Urban	0.988	1.037	1.070	1.048	0.083
Vegetation	0.755	0.854	0.932	0.855	**0.177**
Woodland	0.716	1.002	1.002	0.930	**0.286**
Grazing	0.757	0.774	0.781	0.758	0.024
Bare	0.645	0.655	0.659	0.650	0.015

Figure 2: The spatial distribution of the GWR coefficients of observed Boolean land cover for two classes, Vegetation and Woodland, as predicted by the predicted fuzzy classes.



Vegetation Woodland

5 Discussion

Despite books and conferences describing 'spatial accuracy' originating from within the remote sensing community explicit methods for describing the spatial distribution of thematic data accuracy have not been widely reported. In part this situation may be driven by a lack of demand for spatially more informative descriptions of error and accuracy (remote sensing researchers implicitly assess the quality of the data they use in their analyses) but also because of a lack of methodological advances in this field. Some have argued that for analyses of remotely sensed data to be useful, probabilistic measures are needed to generate robust inferences about land cover distributions. Other research has proposed the use of nearest neighbor techniques with forest inventory data [24].

Other research ahs explored the use of GWR in a remote sensing context. This includes analysis of the relationship between normalized difference vegetation index (NDVI) and rainfall [24]. Other work has used GWR examine the relationships between net primary production and a range of environmental variables [25]. They noted that GWR made better predictions than ordinary least squares regression due to the spatial autocorrelation of the features under observation. Foody [26] explicitly presented an approach based on GWR to derive local estimates of thematic classification accuracy and surfaces of accuracy were computed from confusion matrices at regular points in the study area.

The results of using GWR to model error spatial non-stationarity suggests a number of discussion points: the current use of the confusion matrix, possible extensions to the confusion matrix, the subjectivity of comparing one set of data collected in one particular way with data collected in another and the extension of spatially explicit methods into change analysis.

The mapped outputs of the GWR analysis of Boolean data and the geographically weighted analysis of fuzzy memberships indicate the spatial variation in the extent to which the observed classes in the field were predicted by the remote sensing analysis. The outputs of the Boolean analysis describe the spatial variation in the probability of correctly identifying observed field values, given the predicted data. The outputs of the fuzzy geographically weighted analysis of the difference between the observed and predicted fuzzy memberships provide spatially distributed measure of fuzzy prediction accuracy. Figures 3 and 4 show broadly similar patterns for Boolean and Fuzzy accuracy for the class of Urban and of Grazing Land, but with subtle local differences in each case, reflecting the different classification approaches.

The geographically weighted approach in this paper a kernel Foody [26] but with a number of critical differences. This research was developed on a much smaller sampel (210 data points not 1000 as in [26]). An extension to this research would be to spatially distributed measures of the probabilities from the coefficients of correctly identifying the (Boolean) presence or absence of each class in the field, given the data classified from the remotely sensed imagery. Similalry spatially distributed measures of fuzzy prediction accuracy could be generated. These would be driven by differences in the denominators: in the GWR the accuracy coefficients at any given location reflect the proportion of validation locations under the kernel and not the total in the entire study area, as in a confusion matrix. Thus the generated inthsi paper can be calculated from standard validation data with little cost [26].

The use of Geographically Weighted Regression as a statistical method for analysing local land cover validation data shows that spatially explicit measures of accuracy. Such mappings could accompany land cover data as metadata [27], similar to visualisations in soil mapping, and if decisions are to be made on the basis of the results of analysing thematic spatial data, then some system for communicating the spatial distribution of possible uncertainties will be of benefit.

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