Accuracy assessment for Fuzzy classification in Tripoli, Libya

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Abstract

Satellite imagery is a longstanding and effective resource for environmental analysis and monitoring at local, regional and global scales. Thematic map accuracy continues to be problematic; especially when Boolean representations are used as each image pixel is assumed to be pure and is classified to one and only one class. In reality the pixel may be mixed, containing many classes. This paper will describe the field work that was undertaken to validate the fuzzy change estimates arising from fuzzy set classification. The main objective of this paper to carry out a comparative study of different accuracy assessment measures to check the accuracy of fuzzy classified images. By using different models to determine the validation of soft classification, to check the accuracy of fuzzy classified images, complete information about the class proportions in each pixel are required to be known.

Fuzzy classifications may be useful as multiple class memberships are assigned. A membership function is defined for each class against the feature value (digital numbers) and membership values of a class to belong to a particular pixel are determined based on function definition. Quantifying classification accuracy is an important aspect of map production as it allows confidences to be attached to the classifications for their effective end use. Accuracy measures serve as the analysis of

errors, arising from the classification process due to complex interactions between the spatial structure of landscape, classification algorithms, land cover change and sensor resolutions.. Therefore, other accuracy measures may appropriately including the fuzziness in the classification outputs and/or reference (ground) data. These include . Measure of closeness distance, Euclidean Distance, fuzzy set operators, and fuzzy error matrix based measure. Generally, the confusion matrix compares ground observations for a given set of validation samples with the classification result.

From the results of accuracy indices for user defined and actual classification, it can be said that all of the measures methods can be used successfully to check the fuzzy accuracy of classification

1. Introduction

The study area is located in North West Libya (the capital city Tripoli and surrounding regions) and this area contains different types of land use and land cover. These include urban, forest; agriculture area .The extent of land patches is frequently small leading to a prevalence of mixed pixels. The study area is subject to rapid changes in land cover and land use due to increases in population, and human activity and requirements for, more urban land, and food production.

In generally the accuracy assessment is based on the accuracy or confusion matrix, which compares ground truth data with the equal classification for a given set of validation samples (Congaltion et al., 1999; Foody, 2002). The accuracy matrix enables the source of the most common evaluation criterions firstly overall accuracy, secondly producer accuracy, finally user accuracy. A detailed overview is given by (Foody 2002; Congaltion et al. 1999).

For the assessment of soft classifications in general, various suggestions have been made such as fuzzy error matrix, Entropy, cross Entropy and cross tabulation (Binaghi et al., 1999; Foody, 1995; Woodcock et al. (2000); Green et al., 2004; Lewis et al., 2001; Pontius et al., 2006; Townsend, 2000). The fuzzy error matrix Binaghi et al. (1999) is one of the most attractive approaches, as it represents a generalization (grounded on the fuzzy set theory) of the traditional confusion matrix. Specifically, for a cross-comparison to be consistent with the traditional confusion matrix, it is popular that the cross-comparison results in a diagonal matrix when a map is compared to itself, and that its marginal totals match the total of membership grades. More significantly, a cross comparison should convey readily interpretable information on the confusion between the classes. To date, the applicability of the fuzzy error matrix has been mostly concentrated on generating accuracy indices such as the overall accuracy, the user and producer accuracy, the kappa, and the conditional kappa coefficients (Binaghi et al., 1999; Okeke et al., 2006; Shabanov et al., 2005).

2. Field survey

The fuzzy land cover information have been generated from remotely sensed data (different fuzzy classification) identifies fuzzy memberships to five land cover classes (urban, vegetation, woody land, grazing land and bear area). There are five predicted fuzzy membership values for each pixel. I undertook some field work, recording the sub-pixel memberships at 210 locations. Each of the 210 pixels was sub-divided into 16 and the land cover recorded at each point. This gives me observed fuzzy memberships for the same five classes. In this paper we will compare the two sets of predicted and observed fuzzy memberships to determine some measure of fuzzy accuracy

3. Result and dissociation

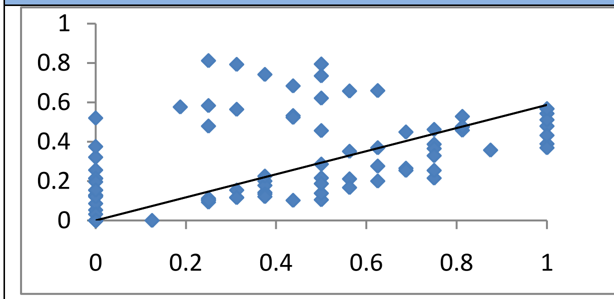
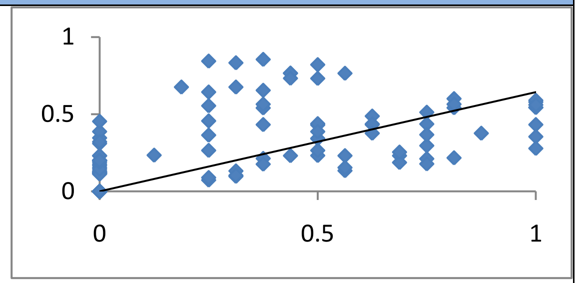
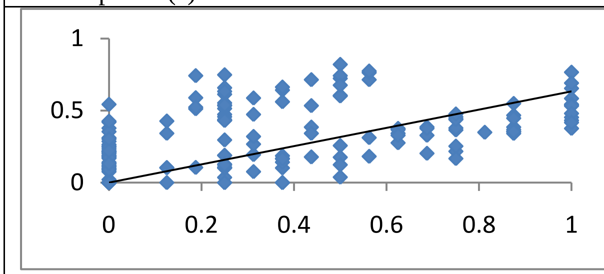
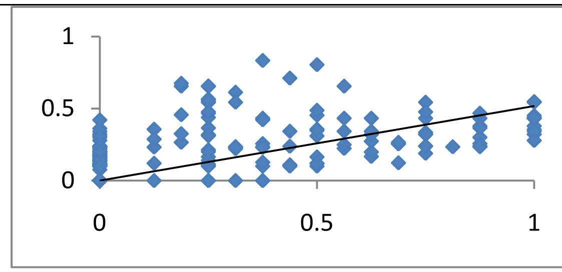
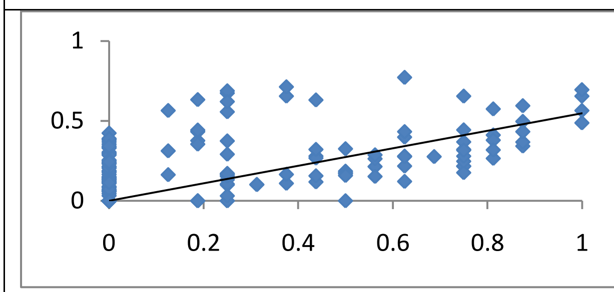
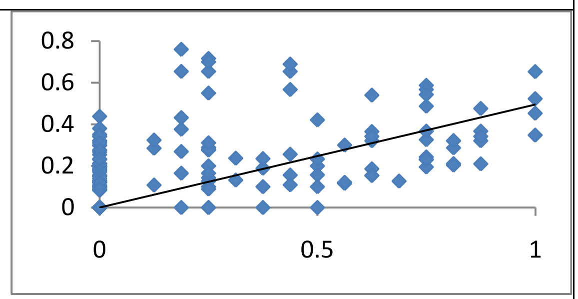
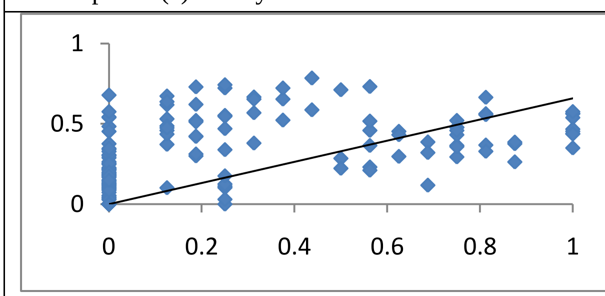
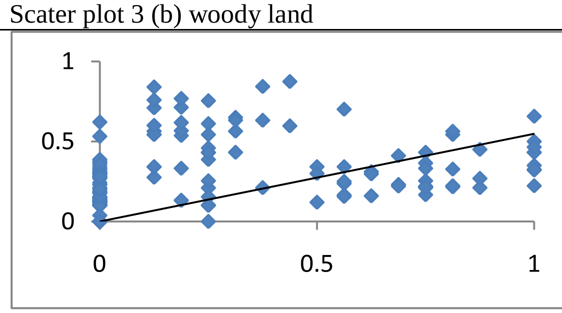
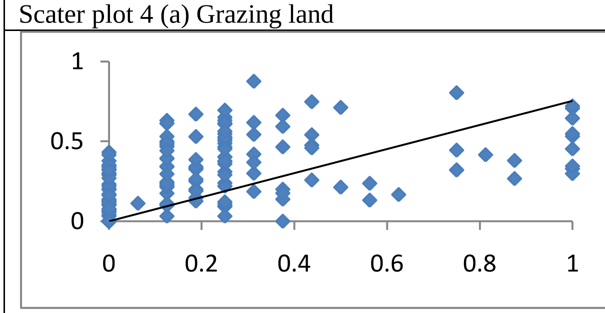
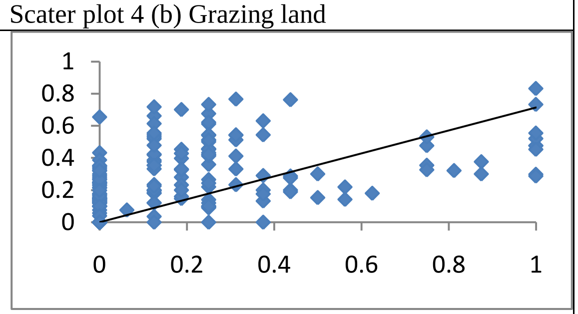
Membership of field points and classification points from fuzzy set classification	Membership of field points and classification points from fuzzy C-mean classification
 Scater plot 1 (a) urban	 Scater plot 1 (b) urban
 Scater plot 2 (a) Vegetation	 Scater plot 2 (b) vegetation
 Scater plot 3 (a) woody land	 Scater plot 3 (b) woody land
 Scater plot 4 (a) Grazing land	 Scater plot 4 (b) Grazing land
 Scater plot 5 (a) Bare area	 Scater plot 5 (b) Barea area

Table 1 Membership of field points and classification points

Generally these plots in table1show the degrees of membership of field points and classification points for all the classes, from the scatter plots there are many points scattered and there is a variation between the field points and classification points. The first column illustrates the field points and fuzzy set classification, the second column illustrates the field points and fuzzy C-mean, there is a bit difference between the two classification, these difference from training set which was taken it is not the same for both method. Generally the distribution of the points in both classifications is acceptable.

3. Regression

The regression was used to compare between the referenced data from the field and data from classification image. Table 2 illustrated regression statistics for multiple R and R^2 in the classes urban, vegetation, woody land, Grazing land and bare area, the result from fuzzy set classification and fuzzy C-mean, when the R and R^2 are high that means there are a good correlation and good classification. From the table we can see that the R^2 and multiple R is higher in fuzzy set compared with fuzzy C-mean in all the classes and the value of R and R^2 in the urban class is the highest in fuzzy set ($R=0.71725$, $R^2=0.51445$) and in fuzzy C-mean is ($R=0.69495$, $R^2=0.48295$), the lowest value of R and R^2 in the bare area class in fuzzy set is ($R= 0.56127$ and $R^2=0.31663$), and in fuzzy C-mean ($R=0.48901$, $R^2=0.23917$) this gives indication that the urban class more accurate than the others, the reason for that the bare area and vegetation classes were changing from time to time and from season to season.

Class	R fuzzy set	R C-mean	R^2fuzzy set	R^2 C-mean
Urban	0.71725	0.69495	0.51445	0.48295
Vegetation	0.62448	0.49900	0.38497	0.24987
Woody land	0.61410	0.51514	0.33712	0.26538
Grazing land	0.58384	0.44515	0.34087	0.22763
Bare area	0.56217	0.48901	0.31663	0.23917

Table 2 illustrated regression statistics for R^2 and multiple R for fuzzy set classification and fuzzy C-mean

4. Conclusion

Accuracy assessment of soft classifiers is still a big issue. This study studied methods to evaluate the performance of soft classifiers but they are sensitive to the use of a higher accurate proportion coverage of each informational class per pixel as a soft ground truth data which in practical situations is sometimes a bit difficult to obtained. It is needed to conduct further investigation on how we can assess soft classifiers taking into consideration the multiclass assignment problem and using soft ground truth data. Among these the Euclidean distance may be stated to be the best method since this measure takes into account the ambiguity and vagueness in the data, can be used for any probability distribution and provides a suitable accuracy index of classification also.

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