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Spatial accuracy measures of soft classification in land cover

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Abstract

Accuracy of land cover maps is important for map users. The soft classification of land cover has been developed for avoiding mixed pixel problem, however the proportional map is traditionally assessed only by a global measure, such as R-squared and root mean square error (RMSE), lacking local information of accuracy. We developed a way of local measures of accuracy employed by a geographically weighted (GW) model. GW-Rsquared and GW-RMSE are locally assessed a soft classification map of urban agglomeration as a case study. Lower accuracies are found at the edge of urban boundary surrounding the core of the urban area and such local information is valuable for a deeper understanding of spatial accuracy.

1. Introduction

Land cover maps are important for those who are interested in climate change, biodiversity and anthropogenic impacts on terrestrial environments and the accuracy of the map is an important consideration. Traditionally land cover maps classified as categorized classes (hard classification) are assessed by building a confusion matrix that compares predicted and observed classes, with predicted classes derived from the classification and observed classes from independent validation data. Measures of user, producer and overall accuracy and kappa index are calculated from the matrix. The reliability of land cover data classified using continuous measures such as fuzzy set memberships (soft classification) is frequently assessed using measures such as R-squared and root mean square error (RMSE) (Chen *et al.* 2010; Tsutsumida *et al.* 2016; Yuan *et al.* 2008). However these measures only provide global measures of reliability and accuracy, and they do not take spatial configuration into account. Local assessments would be valuable for a deeper understanding of spatial accuracy.

2. Background

Spatial accuracy assessments for hard classification of land use and land cover have been considered by some previous studies (Foody 2005; Pontius *et al.* 2011). In particular, geographically weighted (GW) logistic regression model have recently been developed (Comber *et al.* 2012; Comber 2013). These generate local confusion matrices at discrete location in the study area and generate spatially distributed estimates (surfaces) of user, producer and overall accuracy. However, little work has focused on spatially distributed accuracy measures for soft classifications. In this study we develop the spatial accuracy measures of soft classification by determining R-squared and RMSE locally. A GW model is applied to develop such measures spatially.

3. Materials

A map of fractional impervious surface area (ISA) in Jakarta metropolitan areas, the biggest urban agglomeration in Indonesia, in 2012 was used in this study (Figure 1). This map was one of annual ISA maps inferred by a random forest regression over space and time during the period 2001-2013 produced by Tsutsumida *et al.* (2016). The ISA rate was documented in this map in the range of 0-100% according to the result of the random forest regression. Randomly distributed independent 401 validation samples constructed by the visual inspection of very high resolution satellite images in Google Earth were used for the accuracy assessment. The global R-squared and %RMSE were 0.557 and 20.18, respectively.

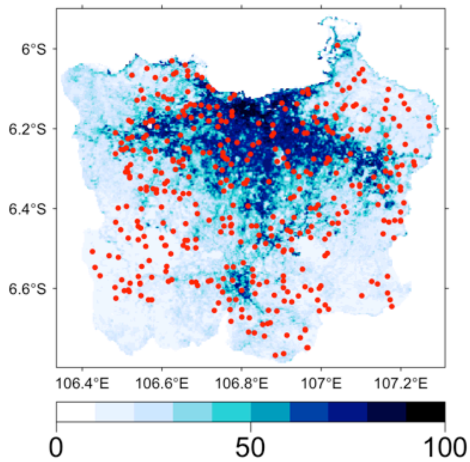

Figure1. Estimated proportion of impervious surface areas and validation samples in the study area.

4. Methodology

4.1 Geographically weighted accuracy measures

In this study, R-squared and %RMSE were considered and incorporated into geographically weighted models. GW-Rsquared can be explained using GW-mean as follows:

GW-Rsquared: $$Rsq_{(x_i,y_i)} = 1 - \frac{\sum_{j=1}^{n} \omega_{ij}\left(y_j - x_j\right)^2}{\sum_{j=1}^{n} \omega_{ij}\left(x_j - m(x_i)\right)^2}, \quad (1)$$

here $m(x_i)$ is GW-mean explained as

GW-mean: $$m(x_i) = \frac{\sum_{j=1}^{n} \omega_{ij} x_j}{\sum_{j=1}^{n} \omega_{ij}}, \quad (2)$$

x_i and y_i are is observed and predicted value at any location i, respectively, and ω_{ij} accords to a kernel function.

GW-RMSE can be written as:

GW-RMSE: $$rmse_{(x_i,y_i)} = \frac{\sqrt{\sum_{j=1}^{n} \omega_{ij}\left(y_j - x_j\right)^2}}{\sum_{j=1}^{n} \omega_{ij}}, \quad (3)$$

4.2 Bandwidth selection

The kernel type and bandwidth should be determined before implementation of any GW model. A kernel is selected from one of a number of distance functions such as Gaussian, exponential, box-car, bi-square, or tri-cube. The bi-square has widely used due to its simplicity (Harris *et al.* 2014). The kernel gives null weights when the distance of observation is greater than b. The weight decreases as the distance of observation point from the centre of the kernel increases until this distance corresponds to b (Gollini *et al.* 2013). The distance b can be specified either as a fixed distance or a fixed number of considered data in a kernel. As the validation samples are distributed randomly and irregularly, an adaptive kernel specifying a fixed number of data points was used in this study. While approaches have been developed for automated bandwidth selection with GWmodel and other GWR implementations, procedures for determination of bandwidth optimality for other models such as GW-Rsquared and GW-RMSE, are lacking. Thus, this analysis tested several adaptive kernels with sizes of 5, 10, 15, and 20% of the data points. The results of using 10% of validation samples are shown here because local variations were described well.

5. Results and Discussions

The generation of spatial accuracy surfaces describing the spatial distribution of GW-Rsquared and GW-RMSE are shown in Figure 2. The classification can be regarded as being more reliable in areas where higher values of GW-Rsquared or lower values of GW-RMSE exist. High accuracy was suggested both in the northern-west part of the study area, however the local estimations of accuracy in these locations may be due to the lack of validation data compared to other locations. Lower local accuracies were found at the urban boundary surrounding the core of the urban area by GW-RMSE. This is a complex urban frontier between urban/non-urban areas where it is difficult to estimate impervious surface cover proportions.

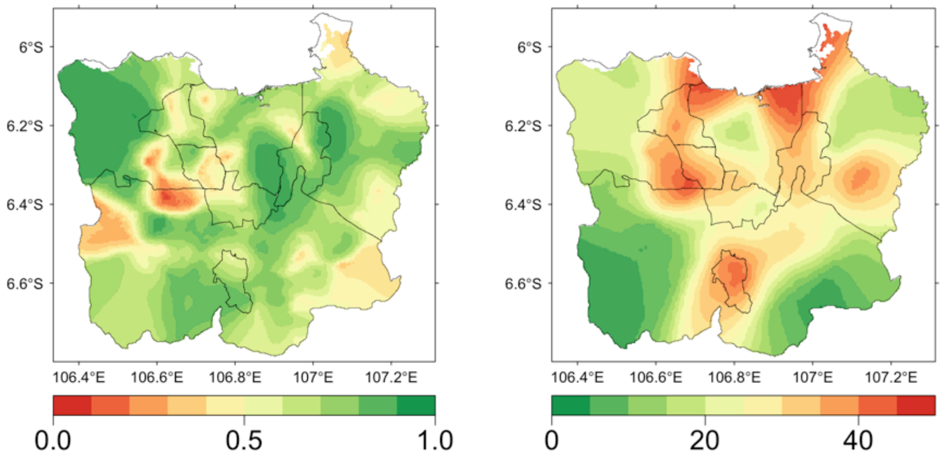

Figure 2. Spatial accuracy measures of proportional impervious surface map estimated by GW-Rsquared (left) and GW-RMSE (right).

6. Conclusions

The extension of global accuracy measures into spatial ones is beneficial to understanding where land cover soft classification maps are accurate or not. In this case study, lower accuracies were found on the urban frontier. Such findings have not identified before. Other measures often used for the assessment of soft classification such as mean absolute error will developed in future work for the general use of accuracy assessments to be more informative.

Acknowledgements

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