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Assessing uncertainty in landuse/landcover classification using remote sensing images

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Land-use/land-cover (LULC) classification using remote sensing images have been widely applied for earth surface monitoring, environmental change detection, water resources management, etc. All supervised classification methods require using a set of training data to establish class-assignment rules for pixels of unknown classes. A confusion matrix (or error matrix) which summarizes classification results of the training data or an independent set of reference data is then used to assess the classification accuracies of individual classes. However, classification accuracies of the training or reference data presented in the confusion matrix are estimates of the true and unknown classification accuracies of the population, i.e. all pixels of individual LULC classes. The class-assignment rules are derived from training data which are samples of individual classes, thus classification accuracies are inherently associated with uncertainties, i.e. sample variability would cause the uncertainty of classification accuracy. Besides, the ratio between sample sizes of difference classes could affect the classification accuracy. Conventional way of evaluating the LULC classification results is to choose an independent set of reference data and use the decision rules established by the training dataset for reference data LULC classification, and then examine the reference-data-based confusion matrix. We argue that such practices have limited capability in providing meaningful assessments since different reference datasets can yield significantly different accuracies in the reference-data-based confusion matrix. In this study, we investigated the uncertainty in classification accuracies (including the producer's, user's and overall accuracies) by using a bootstrap resampling approach. Unlike most LULC classifications, the proposed approach can provide 95% confidence intervals for class-specific classification accuracies. We also showed the theoretical basis and demonstrated that the conventional reference-data-based confusion matrix has very limited capability in assessing LULC classification results. Therefore, we conclude that LULC classification results should be evaluated by assessing the uncertainty of training-data-based confusion matrix and confidence intervals of class-specific classification accuracies can be provided by using the proposed bootstrap resampling approach.