A Geostatistical Framework For Accuracy Assessment Of Remotely Sensed Land-Cover Information

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Biography

Phaedon Kyriakidis is an Assistant Professor at the Department of Geography at the University of California Santa Barbara (UCSB) since 2001. He earned his Ph.D. from the Department of Geological and Environmental Sciences of Stanford University (USA) in 1999, with specialization in geostatistics. From 1999 to 2000, he was a Post-Doctoral Fellow at the Earth Sciences Division of Berkeley National Laboratory (USA), where he currently holds a Faculty Staff appointment. His research interests include the development of geostatistical methodologies for GIScience applications, stochastic environmental modeling, data fusion, and spatial accuracy assessment. He has published papers in Mathematical Geology, Atmospheric Environment, IJGIS, Environmental and Ecological Statistics, and other journals.

Jingxiong Zhang is a Post-Doctoral Researcher at the National Center for Geographic Information and Analysis (NCGIA) at UCSB. He earned his Ph.D. in Geography from the University of Edinburgh in 1997. He maintains interests in geospatial information science and engineering with a focus on uncertainty, integration of multi-source data, including those derived from photogrammetry and remote sensing. He is the author (with Michael Goodchild) of a recent monograph entitled: Uncertainty and Geographical Information, published by Taylor & Francis.

Introduction

Thematic data derived from remotely sensed imagery lie at the heart of a plethora of environmental models at local, regional, and global scales. Accurate thematic classifications are therefore becoming increasingly essential for realistic model predictions in many disciplines. Remotely sensed information and resulting classifications, however, are not error free, but carry the imprint of a suite of data acquisition, storage, transformation, and representation errors and uncertainties (Zhang and Goodchild, 2002). The increased interest in characterizing the accuracy of thematic classification has promoted the practice of computing and reporting a set of different, yet complementary, accuracy statistics all derived from the confusion matrix (Congalton, 1991; Stehman, 1997; Foody, 2002). Based on these accuracy statistics and their associated confidence intervals, users of remotely sensed imagery can evaluate the appropriateness of different maps for their particular application, and subsequently decide to retain a particular classification versus another.

Confidence intervals regarding accuracy statistics, however, are typically computed based on the assumption of random sampling. Although a few recent efforts have focused on the case of cluster sampling (Stehman, 1997; Edwards, et al. 1998), the spatial correlation of misclassification errors is not fully accounted for. Traditional design-based approaches relying on random sampling, which are by far the ones mostly used in remote sensing accuracy assessment, underestimate the standard error of accuracy statistics due precisely to the unaccounted effects of spatial correlation.

In this paper, we develop a geostatistical (model-based) framework for spatial accuracy assessment of land-cover classifications. The key component of the proposed framework is its ability to account for spatial or spatiotemporal correlation in observed classification errors, as well as to accommodate different data supports, without relying on probability-based sampling designs.

Proposed Approach

In the proposed approach, the indicators of correct and incorrect classification for each class are treated as a realization of a binary random set. The random set is partially specified by the proportion of correctly classified pixels, and their indicator covariance model that characterizes the spatial distribution of classification errors. Under this geostatistical framework, confidence intervals are derived for: (i) classification accuracy in each class, (ii) overall accuracy among all classes, and (iii) the kappa coefficient. These confidence intervals depend on the indicator covariance models, as well as on the geometric configuration of the validation pixels. In addition, no particular sampling design (e.g., random) is assumed.

We compare analytically-derived confidence intervals for the above accuracy statistics, with those resulting from stochastic simulation under non-random sampling designs. Given a set of validation pixels where both reference and classified labels are available, the simulation proceeds in the following steps: (i) several alternative simulated realizations of reference land cover classes are generated at the validation pixels using prescribed indicator covariance models; these realizations are conditioned on the training class labels available at the training pixels, and on a relationship between classified and reference labels, (ii) the classified class labels at the validation pixels are then compared to each realization of reference labels at the same pixels (it is also demonstrated that steps (i) and (ii) yield indicators of correct and incorrect classification that are spatially correlated), (iii) for each realization, a confusion matrix and its derived accuracy statistics are computed, (iv) the set of all simulated accuracy statistics, over all realizations of reference class labels at the validation pixels, constitutes the sampling distribution of these statistics, which in turn is linked to their standard errors for a given significance level. It is shown that the resulting confidence intervals derived from the above simulation procedure are closer to the ones derived from the proposed geostatistical framework than to those derived assuming classical design-based probability sampling.

We also address the issue of accuracy assessment based on data units that have different supports, e.g., pixels versus land parcels, within this geostatistical framework. We demonstrate that the spatial correlation of misclassification errors can be used to account for such different data supports. Finally, we address the issue of accuracy assessment in a change detection setting, by expanding the spatial correlation model to include the temporal dimension. In particular, the temporal dimension is accounted for by the cross-correlation between misclassification errors computed at two different times. Based on this spatiotemporal correlation model, confidence intervals for accuracy statistics pertaining to change detection are also derived within the proposed geostatistical framework.

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