Impacts of sensor noise on land cover classifications: sensitivity analysis using simulated noise

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Abstract

Land cover maps are typically derived through classification of remotely-sensed data, usually relying on a multispectral set of views from satellite-borne sensors. A number of corrections can be applied to improve the geometric and radiometric quality of the data. We have been assessing the importance of radiometric quality using a factorial design to assess the impacts of various levels of sensor noise, and spatial autocorrelation of that noise on classified land cover maps. We compare simulated noise-affected maps to a control with no noise addition. The objective is a sensitivity analysis to quantify the effects of noisy data on image classification, both on the overall accuracy statistics and the spatial configurations of error maps. We have tested a series of noise models, and our first results show that most classifications are relatively robust except in conditions of noise with high spatial autocorrelation. We are continuing to refine our noise models to better represent typical combinations of sensor and atmospheric conditions.

Background and Relevance

Accurate land cover maps from classified multispectral images require high signal-to-noise ratios, which are affected by signal-dependent noise (Rangayyan *et al*., 1998), atmospheric influences (Song *et al*., 2001), and systematic sensor errors, such as striping (Pan and Chang, 1992; Torres and Infante, 2001). Much work has gone into attempts to understand and correct for these sources of noise, but there is very little research on quantifying the impact of these potential errors on classification of the data into land cover categories. Therefore, we aimed to study the stability of common classification regimes in the presence of a range of likely noise treatments. Initial experiments using this approach (Remmel and Mitchell, 2010) employed regression trees for the classification and only 4 classes, and found very little difference between treatments, likely due to the high thematic aggregation. We have moved to more detailed classes, and are examining alternative error models. This presentation demonstrates the first findings from this process. The full results of this analysis will guide methods selection for further land cover products, and justifications of the effort used to correct imagery for given applications.

Methods and Data

We selected a boreal forest study site in north-western Ontario, centred around 418054 m N, 5958262 m E UTM zone 16. The choice was based on access to an existing land-cover classification along with the multi-spectral IKONOS imagery used to develop the classified map (Remmel and Perera 2009). We used a 1024x1024 pixel sub-scene for our work, which at 4m spatial resolution results in a 1678 ha area of boreal forest for our analysis. Land cover classes in the original product were distributed between Bedrock, Complete Burn, Partial Burn, Dense Conifer, Sparse Conifer, Alder Shrub Woodland and Low Shrub, Wetland, and Water.

Using training sites based on the original classification, we developed new classified maps, using supervised maximum-likelihood (ML) and sequential maximum *a posteriori* (SMAP) approaches. Mimicking the process used to produce the original map, we classified based on the IKONOS input bands (blue, green, red, near infra-red and panchromatic), plus a texture image based on the panchromatic band, targeting the same classes listed above. This lead to new versions of the land cover map, used as the reference data for the rest of the study. The purpose of the re-classification was to provide class signatures that could be used for all further classifications with noisy data.

Noise was generated across a spectrum of intensity and spatial autocorrelation using an isotropic conditionally autoregressive model (Cressie, 1993, algorithm presented in Remmel and Csillag, 2003). Outputs from the model were divided into seven categories of intensity, and autocorrelation corresponding to Moran's I ranging from 0 to 0.99999. The modelled noise was thresholded so that our treatments were based on frequency of pixels with noise, rather than the absolute levels. In other words, low noise images had a few relatively high noise values, whereas high noise images had greater frequency of noise pixels, covering a wider distribution of intensity.

The resulting images were scaled to correspond to between 1% and 6% error in each original band, and added to the original multi-spectral bands (blue, green, red and near-infrared, but not panchromatic) across 30 replicates, to provide 1470 alternative input images across the 49 treatments. New classified maps were generated for each realization, using the training generated above. Map comparisons were made using contingency tables and distributions of overall agreement were analyzed.

Results

In the absence of spatial autocorrelation, overall agreement dropped small but statistically significant amounts with increasing frequency of noisy pixels (Figure 1). Agreements were consistently higher using SMAP classification: overall agreements under increasing noise went from over 89% to about 87% agreement using SMAP, and from about 82.5% to 79% agreement using ML.

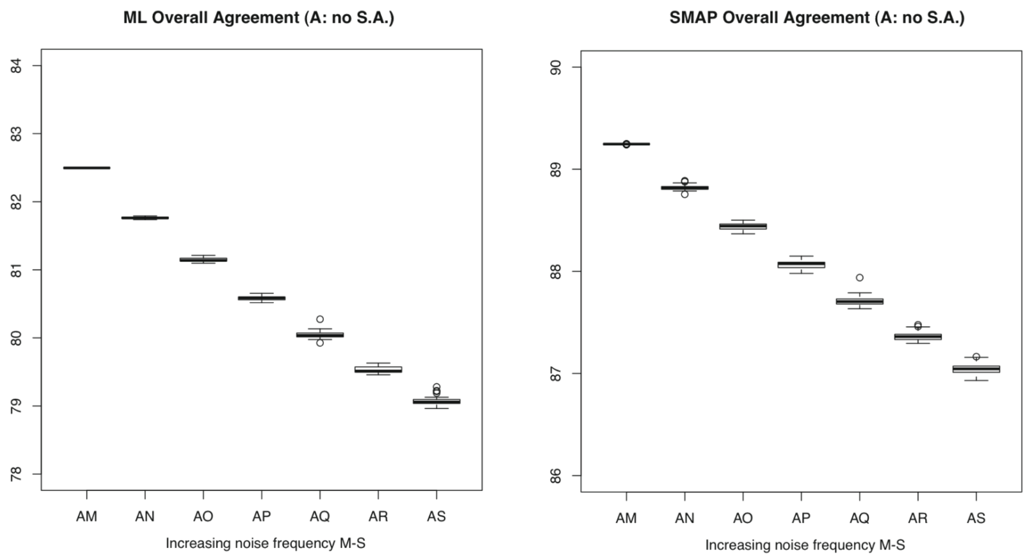

Figure 1 – Impact of noise frequency (treatment codes AM increasing through AS on the x-axis) on overall agreements between treatment land cover map and reference map with no spatial autocorrelation (treatment code A) in the error models.

Increasing spatial autocorrelation of noise increased the variance of agreement between realizations, overwhelming the effect of noise frequency at higher levels of autocorrelation. These results are summarized in Figures 2 and 3.

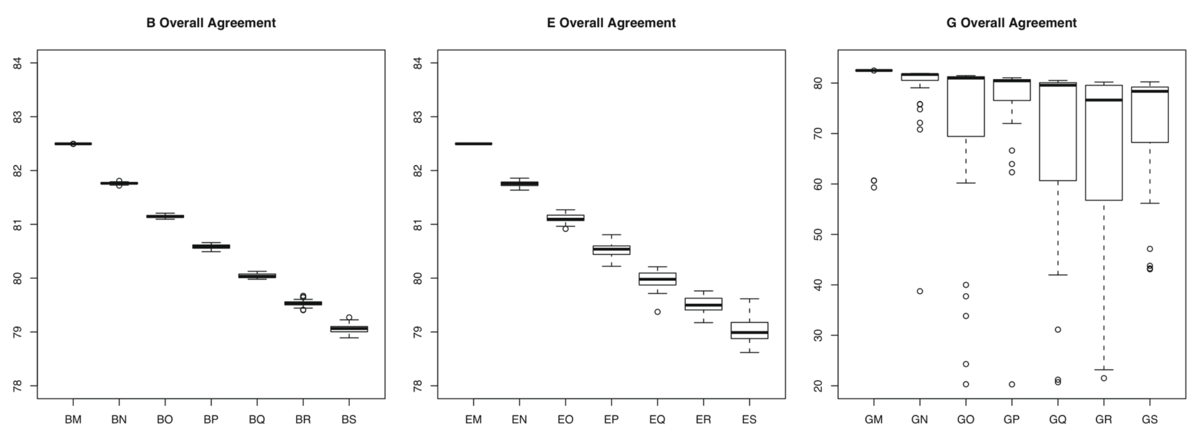

Figure 2 – Impact of noise frequency (x-axis treatment codes xM through xS, where x is the spatial autocorrelation treatment) on overall agreement between reference maps and error treatments with low (B), medium (E), and high (G) spatial autocorrelation, using maximum likelihood (**ML**) classifications. Note change in overall agreement (y) axis range in the right-most graph.

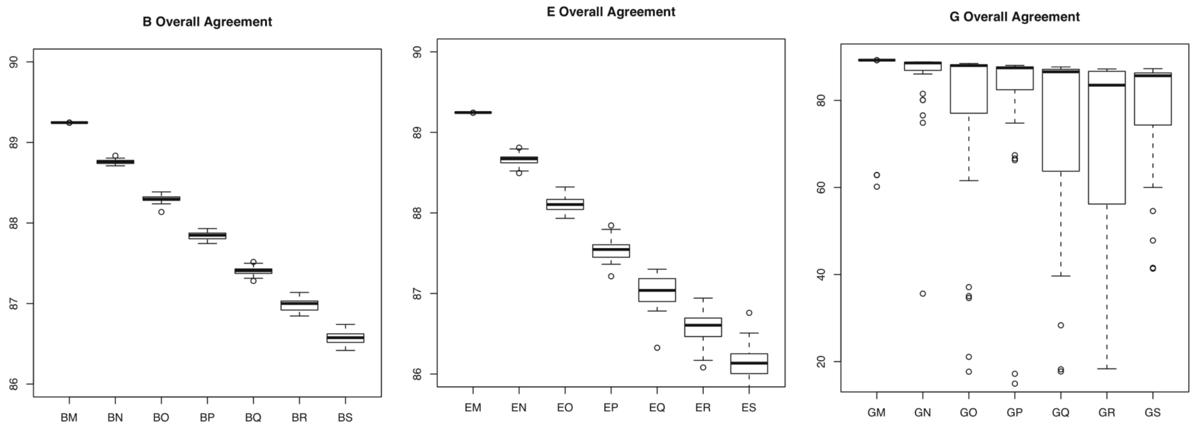

Figure 3 – Impact of noise frequency (x-axis treatment codes xM through xS, where x is the spatial autocorrelation treatment) on overall agreement between reference maps and error treatments with low (B), medium (E), and high (G) spatial autocorrelation, using sequential maximum *a posteriori* (**SMAP**) classifications. Note change in overall agreement (y) axis range in the right-most graph.

Conclusions

As expected, at low levels of noise, the likelihood-based classification methods are fairly resistant to misclassification, even with classes that have high possibility of confusion. The SMAP classification algorithm performed better than maximum likelihood in all cases, remaining higher than the 85% agreement threshold commonly used in classification error assessments, in all but the highest spatial autocorrelation error treatment. At the highest levels of spatial autocorrelation of errors, classification accuracy dropped dramatically, likely due to threshold effects in the relationship between the error-infused multi-spectral bands and the texture of the unaffected panchromatic band.

We continue to research error properties of actual remote sensing platforms, and are working on new noise models with multiplicative rather than additive noise, and based on sensor characteristics rather than arbitrary distributions. We will combine these findings with results from atmospheric correction research to create the desired sensitivity analyses.

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