Random and spatially autocorrelated sensor noise effects on image classification

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Abstract— **One factor limiting the accuracy of land cover maps derived from classified, remotely-sensed imagery is the quality of the spectral data used in the classification process. Satellite data is routinely pre-processed to improve both its geometric and radiometric qualities. We implement a factorial design that assesses the individual and joint effects of simulated sensor noise on specific spectral bands and along continua of intensity and spatial configuration; an image with no added simulated noise is our control. Our focus is on the radiometric component of image quality, as we assume that for our single-image controlled experiment, the multispectral bands are all perfectly aligned and that topographic relief insignificantly affects the geometric properties of our data. For each simulated noisy image we produce a detailed land cover classification using identically-defined classification tree decisions and observe the spatial changes relative to the classification of the control image. We assess the classification accuracy between all noisy cases and the control using traditional error matrices and measures of overall thematic agreement. The objective is to perform a full sensitivity analysis that quantifies the effect of noisy data on image classification, both in terms of the aspatial class area tabulations and their spatial configurations. We link the classification differences with uncertainty metrics as a guide to improving the selection of classifiers and pre-processing techniques.**

Keywords: CART; random noise; autocorrelated noise; uncertainty; composition; configuration

I. Introduction

Accurate classification of multispectral satellite imagery requires data to have a high signal-to-noise ratio (SNR). Unfortunately, digital image acquisition is susceptible to 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) which can reduce the SNR. Both atmospheric corrections and systematic errors are reasonably well understood and widely corrected (Zhang et al., 1999; Liu and Morgan, 2006) and substantial efforts have been made to correct signal dependent noise (Rangayyan et al., 1998). The focus of this paper is not in the correction of signal-dependent noise per se but rather identifying the effect that such noise may have on the image classification process if it is not corrected. Ultimately, our goal is to investigate the stability of a fixed classification regime under widely varying simulated noise treatments.

When noise is present in data, the usual approach is to apply some form of filtering; several possibilities, within both the spatial and frequency domains, have been proposed for mitigating the effect of noise on classification accuracy. Generally applied to classified data in a post processing context, simple majority filtering improves class assignments due to the consideration of contextual spatial information (Wilson, 1992). Median filters (Gabbouj et al., 1992), weighted median filters (Ko and Lee, 1991), and adaptive centre weighted median filters (Lin, 2007) are also well documented in the literature. Kwang (1996) proposed an adaptive majority filter that considers the range of class distributions within a moving window before applying both a heterogeneity-based threshold and a maximum likelihood decision rule to assign an appropriate class to the filtered output layer. Hyperspectral data have received special attention where the filtering is performed on multidimensional data of the pre-classified bands (Letexier and Bourennane, 2008). In specific cases involving stationary periodic noise, reduction by filters applied to Fast Fourier Transformed (FFT) images have been successful, performing filtering operations within the frequency domain (Watson, 1993). Yildirim et al. (2008) provide a review of impulse detectors and their integration with various forms of median filtering before introducing their own fuzzy logic filter that preserves thin lines, edges, details, and texture from the input image.

While the literature is highly populated with studies entrenched in minimizing or removing the effects of noise, very little is ever said about quantifying the effect that such noise or errors have on the ability to accurately classify images. We test whether there are statistically significant effects altering the outcome of an image classification given increasing levels of spatially autocorrelated noise, increasing intensities of noise, and the interactions between these terms relative to the classification of a non-noisy image using a consistent set of classification rules. We perform all land cover classifications using a classification tree (CART) algorithm (van Aardt and Norris-Rogers, 2008).

II. Methods

A. *Study area and classificaiton*

Our study area was selected based on data constraints; we required an existing land cover classification layer in addition to the corresponding multi-spectral satellite channels used to perform the original image classification. We obtained a subset of a north-western Ontario land cover classification (Spectranalysis, 2005) along with the requisite red, green, blue, and near-infrared data channels from the IKONOS sensor. We selected a 1024×1024 pixel sub-scene from one of the available images that at 4 m spatial resolution represented an approximately 1678 ha area of boreal forest (Figure 1). The scene is centered at approximately 418054 m N, 5958262 m E (UTM, Zone 16) and contains aggregated land cover classes as defined by Table I (the proportions of land cover classes are almost equal). Further details of this dataset can be obtained from Perera et al. (2009) and Remmel and Perera (2010).

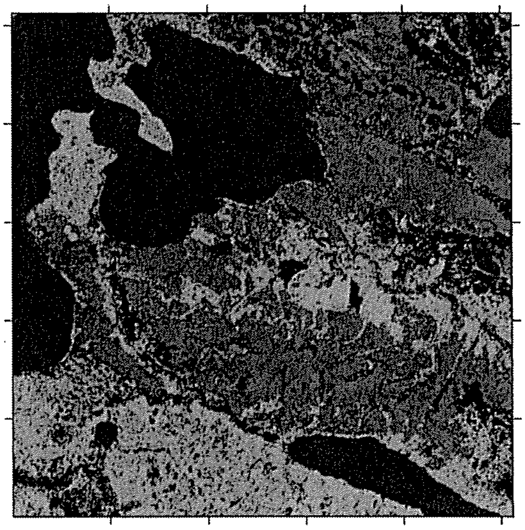

Figure 1. Classified map of the study area. Blue, green, brown, and black represent water, forest, burn, and non-forest respectively.

TABLE I. CLASSIFICATION LEGEND USED IN THIS STUDY

Class	Label
2	Burn
3	Forest
4	Non-Forest
5	Water

A set of classification rules was derived that would become consistently applied across all treatments of simulated noisy data, permitting us to compare the differences among alternative classification outputs, and attribute them to the effect of the noise. We developed a Classification Tree (*CT*) (Figure 2) with land cover class (*LC*) as the dependent variable and the blue (*B*), green (*G*), red (*R*), and near-infrared (*N*) bands as independent variables (c.f. Yang et al., 2002). Implementation was achieved using the tree function from the tree library (Ripley, 2009) in the open source statistical package R (R Development Core Team 2009):

$$CT < -tree(LC \sim B + G + R + N) \quad (1)$$

To assess the effect of noisy data, we simulated a series from random to spatially autocorrelated noise at increasing intensities (below); these noise layers were added to the existing near infrared band prior to re-running the CT classifier as developed using the 'clean' data above. In this preliminary study, the simulated noise was considered only as additive, manifested as positive speckle or impulse noise.

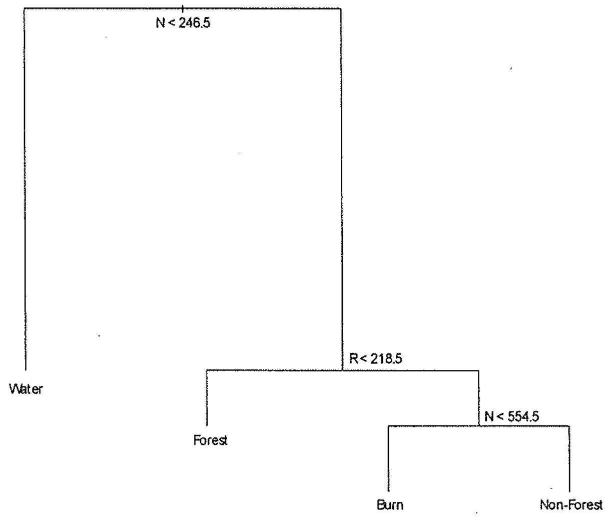

Figure 2. Classification Tree for category assignment

B. Noise simulation

We simulated a series of noise layers with identical extent and spatial resolution as our multispectral data (1024×1024 pixels at 4 m spatial resolution). The noise layers resulted in raster images with integer values ≥ 0, where simulation was achieved by the algorithm used in Remmel and Csillag (2003) using a conditionally autoregressive (CAR) model (Cressie, 1993) with parameters controlling the degree of spatial autocorrelation (Getis, 2007).

The isotropic spatial autocorrelation parameterizations produced noise fields ranging from random to highly spatially autocorrelated (analogous to Moran's I ranging from 0.0000 to 0.9999) along 11 equally spaced intervals. Specifics of how this model was parameterized are provided in the cited paper. Additionally, at each interval of spatial autocorrelation, 13 degrees of noise severity were produced by retaining increasingly greater proportions of the noise layer, by density slicing as threshold quantiles were varied from 1.00 through 0.94 to capture the positive tail of the distribution. All values below the specified quantile threshold were set to 0 (zero), indicating that there was no simulated noise at that pixel's location. The magnitudes of the simulated noise values were scaled between 0 and 200 (representing up to an almost 10% increase in a pixel's value; the component that we refer to as noise) and truncated to convert all numbers to positive integers. We produced 5 replicates at each of these 143 combinations, resulting in 715 noise layers.

The noise layers were coded with a two character code, the first character indicating the degree of spatial autocorrelation (A through K), the second its severity (M through Y) (Table II). These codes were followed by a digit indicating the replicate number and collectively were used to name the individual treatments. The same treatment codes are used to illustrate the results through the remainder of this paper.

TABLE II. TREATMENT CODES FOR SPATIAL AUTOCORRELATION AND INTENSITY VALUE MANIPULATIONS.

Intensity						
M	1.000	AM	...	FM	...	KM
⋮		⋮		⋮		⋮
S	0.970	AS	...	FS	...	KS
⋮		⋮		⋮		⋮
Y	0.940	AY	...	FY	...	KY
		0.0000000		0.1250000		0.2499999
		A	...	F	...	K

Spatial Autocorrelation Values (Isotropic)

Each individual treatment represented a unique combination of spatial autocorrelation and intensity, replicated five times. Examples of random and spatially autocorrelated noise layers are provided in Figure 3. Within each treatment (subscript, t), the simulated noise layer was added to the original near-infrared (N) band to produce a new noisy near-infrared band (nN_t) and would ultimately replace the original N band prior to being classified with the CT rules. Thus, 715 treatment-specific land cover (LC_t) maps were predicted from the original blue, green, and red bands in conjunction with the treatment-specific noisy near-infrared band:

$$LC_t \sim B + G + R + nN_t \tag{2}$$

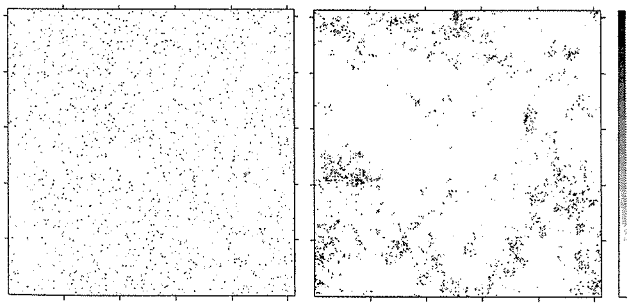

Figure 3. Sample noise layers (BW on the left and KW on the right). The scale ranges from 0 to 200, indicating the noise intensity.

C. Comparisons

To test whether noise has a significant effect on classification, we produced coincidence matrices between each treatment's classified result and the original classified map from Figure 1. From these coincidence matrices, acting as fully enumerated map comparisons (Remmel, 2009), we computed and compared measures of overall agreement, observing whether the increase in noise intensity or level of spatial autocorrelation had an effect on the classification.

III. RESULTS

Our results (Figure 4) indicate that increasing noise intensity resulted in an obvious and statistically significant decrease in the overall agreement with the original land cover map. We also observe that increasing positive spatial autocorrelation results in overall agreement values that have greater variability than for random treatments at identical intensity.

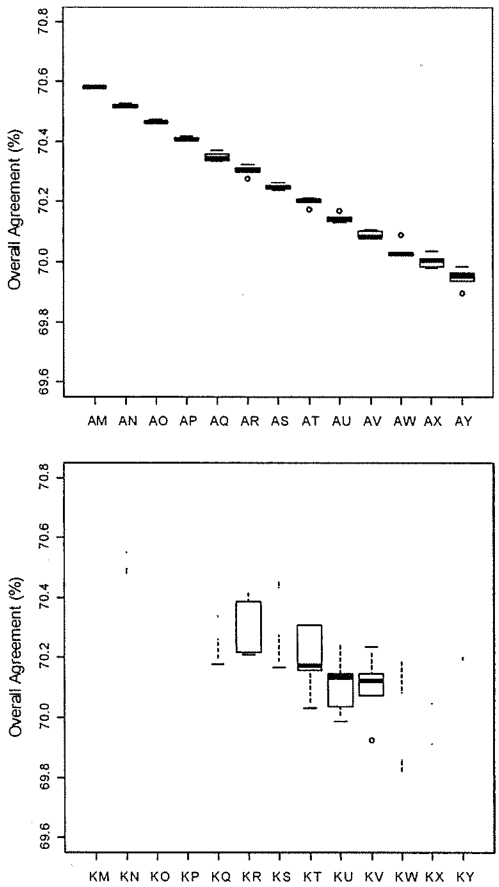

Figure 4. Summaries of overall agreement between classified maps of each treatment with the original land cover map. The upper panel represents the treatments where noise was spatially random (A) along a continuum of increasing intensity (M through Y). The lower panel represents the same intensity continuum, but for the treatment with the highest degree of spatially autocorrelated noise.

IV. DISCUSSION AND CONCLUSIONS

While considerable work has been conducted on the mitigation of noise effects on data and classification products, the absolute effect of noise is scarcely mentioned in the literature. Our simulation approach sought to explore the relationships among classification outputs and varying degrees of noise added to one band of the input data, of which we manipulated the intensity and degree of positive spatial autocorrelation. Our study employed a relatively simple land cover classification (4 classes), classifier (CART), and a CAR model to simulate the noise.

Our results overwhelmingly support the notion that noise acts to alter the classification results and that increased noise intensity leads to increasingly differing classification results. Furthermore, the inclusion of positive spatial autocorrelation increases the variability in the observed overall agreement decrease.

While our classification results changed significantly between treatments, they fluctuated within a relatively tight range. We attribute that to the tight controls on the study: 1) using a land cover classification with only four categories, 2) utilizing a relatively simple CT classifier, 3) implementing only additive noise, and 4), adding noise to only one band of the input data. Our intentions are to use the guiding results from this pilot project to scrutinize a much larger domain of variables, including the expansion to incorporate the four points above.

As expected, the water class was the most persistent given its distinct spectral character and thus represented the least quantity of conversion to other classes in the presence of noise. The spectrally diverse classes expressed significantly more variability and thus will benefit from further detailed investigations with higher thematic resolution.

Although the CART operates as a pixel-wise classifier, we note that the presence of spatial autocorrelation leads to more widely varying differences in the classification. This may seem counter-intuitive at first, as a set number of noisy pixels (regardless of their configuration) should only affect as many pixels. The difference is in the spatial autocorrelation itself, where high values of noise tend to cluster and thus can form regions where noise is applied at a higher level than in the randomly distributed treatments. Thus, we conclude that while all noise is potentially detrimental to classification (leading to differences from the true case), noise with increased intensity and higher levels of positive spatial autocorrelation are increasingly problematic.

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REFERENCES

Cressie, N.A.C. (1993). *Statistics for spatial data.* New York: John Wiley and Sons.

Gabbouj, M., Coyle, E.J., and N.C. Gallager. (1992). An overview of median and stack filtering. *Circuits, Systems, and Signal Processing.* 11 (1), 7–45.

Getis, A. (2007) Reflections on spatial autocorrelation. *Regional Science and Urban Economics.* 37 (4), 491-496.

Ko, S.J. and Y.H. Lee. (1991). Center weighted median filters and their applications to image enhancement. *IEEE Transactions on Circuits and Systems.* 38 (9), 984-993.

Kwang, E.K. (1996). Adaptive majoritiy filtering for contextual classification of remote sensing data. *International Journal of Remote Sensing.* 17 (5), 1083-1087.

Liu, J.G. and G.L.K. Morgan. (2006). FFT selective and adaptive filtering for removal of systematic noise in ETM plus imageodesy images. *IEEE Transactions on Geoscience and Remote Sensing.* 44 (12), 3716-3724.

R Development Core Team. (2009). *R: A language and environment for statistical computing. R Foundation for Statistical Computing,* Vienna, Austria. ISBN 3-900051-07-0, URL http://www.R-project.org.

Rangayyan, R.M., Ciuc, M., and F. Faghih. (1998). Adaptive-neighborhood filtering of images corrupted by signal-dependent noise. *Applied Optics.* 37 (20), 4477-4487.

Remmel, T.K. and F. Csillag. (2003). When are two landscape pattern indices significantly different? *Journal of Geographical Systems.* 5 (4), 331-351.

Remmel, T.K. (2009). Investigating global and local categorical map configuration comparisons based on coincidence matrices. *Geographical Analysis.* 41 (1), 113-126.

Ripley, B. (2009). *Tree: Classification and regression trees.* R package version 1.0-27. http://CRAN.R-project.org/package=tree

Song, C., Woodcock, C.E., Seto, K.C., Lenney, M.P., and S.A. Macomber. (2001). Classification and change detection using Landsat TM data: When and how to correct atmospheric effects? *Remote Sensing of Environment.* 75 (2), 230-244.

Spectranalysis. (2005). *IKONOS land cover classification for the assessment of forest burns.* Internal report prepared for the Forest Landscape Ecology Program, Ontario Forest Research Institute, Ontario Ministry of Natural Resources.

Watson, K. (1993). Processing remote sensing images using the 2-D FFT-noise reduction and other applications. *Geophysics.* 58 (6), 835-852.

Wilson, J.D. (1992). A comparison of procedures for classifying remotely-sensed data using simulated data sets. *International Journal of Remote Sensing.* 13 (2), 365-386.

Yang, C.C., Prasher, S.O., Enright, P. Madramootoo, C., Burgess, M., Goel, P.K., and I. Callum. (2003). Application of decision tree technology for image classification using remote sensing data. *Agricultural Systems.* 76 (3), 1101-1117.

Yildirim, M.T., Basturk, A., and M.E. Yueksel. (2008). Impulse noise removal from digital images by a detail-preserving filter based on type-2 fuzzy logic. *IEEE Transactions on Fuzzy Systems.* 16 (4), 920-928.

Zhang, M., Carder, K., Muller-Karger, F.E., Lee, Z., and D.B. Goldgof. (1999). Noise reduction and atmospheric correction for coastal applications of Landsat Thematic Mapper imagery. *Remote Sensing of Environment.* 70 (2), 167-180.