Spectral variability related to forest inventory polygons stored within a GIS[1]

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Abstract

The union of geographical information systems (GIS) with remotely sensed data provides opportunities to update GIS attributes. The ability to update GIS polygons with regional scale remotely sensed data, such as Landsat TM, is limited by the distribution of variance of the spectral content both within and between the GIS polygons.

In this study, we address the distribution of spectral values in relation to forest inventory polygon information to benchmark the strength of the relationships between forest inventory information and image spectral response. Following the investigation of the distribution of variance we undertake to predict polygon labels from co-registered Landsat TM data.

Management units selected to represent softwood and hardwoods are identified correctly in approximately 64% and 72% of the possible cases respectively; whereas, the management unit selected to represent mixed woods was identified correctly in 15% of possible instances. When considering the results within the context of a polygon, filtering is possible to indicate the most likely class. Both the investigation of the polygon variance structure and the polygon classification indicate that given a sub-optimal variance structure a cohort classification approach is preferred over a per pixel classification.

Introduction

The synergy between remote sensing and GIS data is logical due to the nature of the data present with each information source. Remote sensing provides spatially explicit measurement of phenomena, while geographic information is produced through the analysis of measurements or other geographic data (Davis and Simonett, 1991). To best integrate remotely sensed measurement and geographic information, issues such as data transformations, scale dependence, and computational environments need to be addressed (Davis, et al., 1991). The ability to combine remotely sensed and GIS data has enabled the generation of new data based upon characteristics unique to each data source (He, et al., 1998).

Forest inventories in Canada are normally updated incrementally within an approximately ten-year cycle (Gillis and Leckie, 1993). As the inventory is updated incrementally, the forest inventory information is often not all of the same vintage. A means to update the forest inventory data to a common date is therefore desirable. We propose to use remotely sensed information to update the forest management units. Forest inventory polygons stored in a geographic information system (GIS) are normally created from digitization of manually interpreted air photographs (Gillis and Leckie, 1993). The criteria to delineate the forest management unit areas are the presence of homogeneity of characteristics such as species

assemblages, density class, crown closure, and development stage. The forest management unit information stored in the GIS is based on a complex series of conditions.

Satellite remotely sensed imagery can collect up-to-date information on forest conditions over large areas. Yet, the ability of regional-scale remotely sensed data, such as the 30 metre spatial resolution Landsat TM sensor, to capture the same suite of characteristics is limited. As a result, the relationship between forest stands as represented by GIS data and remotely sensed data are difficult to calibrate. Further, the location of boundaries between stands are often placed in subtle regions of transition between forest stands. An inability of forest polygons to properly represent the dynamic forest characteristics is argued by Holmgren and Thuresson (1997) who propose the dynamic allocation of management units. The presence of pixel variability within GIS polygons which are assumed to be homogenous cover-types has been noted in previous research (Franklin, et al., 1997). These results are further related though an investigation of image spatial dependence in reference to forest management units illustrating that forest inventory classes vary in relation to natural spectral classes (Wulder and Boots, 1998). Wang and Hall (1996) present the need for fuzzy boundaries between polygons as an acknowledgement of the nature of the transition across polygon boundaries.

The alternative to characterizing forest management units with spectral information is to rebuild the management unit according to remotely sensed estimates of the land cover attributes, such as height, density, and species. Before such an approach is viable, the methods for land cover attribute estimation with remotely sensed data require additional research to improve accuracy. The goal of this study is to investigate the use of remotely sensed data to characterize the spectral variability found within forest management polygons. An investigation of the spectral values found within and between identically typed forest management polygons will indicate the reliability of remotely sensed data in identifying critical attributes in a consistent manner.

Methods

Study Area
The 872,498-ha study area is located in south central New Brunswick, Canada, with approximate bounding coordinates 45 51 00N 66 35 16W (upper left) and 45 36 17N 64 53 53W (lower right). The study area is comprised of two provincial forest management regions located in the Acadian forest region and is composed of a variety of broadleaf deciduous and coniferous species and includes a wide range of forest conditions (Rowe, 1977); and with stand ages range from regeneration to old growth, resulting in a range of forest types, crown closures, stand densities, tree species, and LAI values. The Acadian forest region is characterized by a wide variety of forest species. Coniferous tree species are predominantly jack pine (*Pinus banksiana*), white spruce (*Picea glauca*), balsam fir (*Abies balsamea*), and red spruce (*Picea rubens*). The predominant deciduous species are red maple (*Acer rubrum*) and white birch (*Betula papyrifira*), with stands also including beech (*Fagus grandifolia*), striped maple (*Acer pensylvanicum*), trembling aspen (*Populus tremuloides*), long tooth aspen (*Populus grandidentata*), and sugar maple (*Acer saccharum*) (Wulder, et al., 1998).

Data Base Development and Data Fusion

Forest Inventory GIS Data
The forest inventory data is composed of 90 different forest management units, of which approximately 38 indicate forest vegetation, each containing a variety of classes. The forest inventory GIS data base is made up of 125,380 polygons resulting in a digital file size of approximately 171 megabytes. The study area is composed of two provincial forest management units, roughly of equal size, with inventories current to 1993 and 1994, respectively.

Landsat TM Image data
The Landsat TM image data utilized in this study was collected July 31, 1995, at 14:05:07 local time, resulting in a sun elevation of 51.41° and a sun azimuth of 124°. The imagery cropped to represent the

study area is composed of 5300 pixels by 3800 lines, resulting in an file size of approximately 1,600 megabytes including additional necessary layers of information.

The imagery was geocorrected to the UTM projection utilizing 72 ground control points to allow for co-registration of the satellite data to the same co-ordinate system as the GIS data. A root mean square error of 0.45 pixels and 0.34 lines was achieved using a 2nd order polynomial model and selecting ground control points from NTS 1:50,000 scale map sheets. A 30 x 30 metre pixel size was maintained for the image data.

Principal components analysis was applied to the six non-thermal Landsat TM image channels to explore the potential of a reduction in dimensionality of the data. The principal components analysis suggested the Landsat TM channels 3, 4, and 5, respectively representing visible, near infrared, and short wave infrared spectral regions. The use of Landsat TM 3, 4, and 5 is similar to findings of Horler and Ahern (1986), and is supported in the theory of Imhoff and Campbell (1978).

Fusion of Vector Inventory Data with Raster Image Data
GIS polygons were rasterized based upon the procedure published by Wulder (1998) and merged with the co-registered Landsat TM imagery pixel by pixel. The polygon identification number (PID), a unique code assigned to each polygon in a GIS, was used to link each pixel to the inventory attributes for the polygon in which the pixel resided. Computation of spectral statistics for a polygon is henceforth straightforward. These computations could be done using specifically developed code on the exported raster data (Wulder, 1998) or, as in this study, the exported data may be analyzed using statistical software (Stata, 1997).

When converting data from vector to raster formats some original detail is lost (Piwowar, *et al.*, 1990). The conversion of continuous vectors to discontinuous raster values results in the potential for the inclusion of non-representative spectral values around the borders of a polygon (Congalton, 1997). To reduce this problem, a one-pixel buffer was created around each rasterized polygon and this buffer was excluded from the analysis. A Hotelling's *T*-squared test (Kendall, et al., 1983) on the spectral contents of buffered versus non-buffered polygon contents indicated, at a 95% level of confidence, that in approximately 54% of the polygons the spectral contents of the buffered region differ from the non-buffered region.

Data Processing
Of the 90 forest management unit designations, approximately 38 indicate forest vegetation, each of which is composed of a variety of potential combinations of classes. To allow for a detailed investigation a representative sub-sample is required for analysis. As a result, a range of forest types are desired to capture the variability within the study region. The three cover-types of softwood, hardwood, and mixed wood, may be represented through inclusion of Balsam fir-spruce (BFSP), Intolerant hardwood – Tolerant hardwood (IHTH), and Balsam fir-Intolerant hardwood (BFIH). These three forest management types represent 953, 1781, and 1596 polygons, respectively, comprising 12% of the forest cover polygons within the study region. Polygons with less than 10 pixels are not included in the analysis as they were considered too small to give reliable estimates of the within-polygon variance of spectral values. Further, we required that each polygon selected for comparison not only have the same forest management unit label but that it is composed of similar attributes, such as an equal number of species classes, density classes, development classes, and crown closures.

The retained data records (pixels) contained the following variables: PID, forest management unit label, leading species code, density code, development class, crown closure category, and all Landsat TM 3, 4, and 5 digital numbers. To avoid repetition the data analysis portion of the methodology is described as a component of the following results and discussion.

The prediction of polygon labels from the digital numbers found within the polygons is undertaken using discriminant analysis (Davis, 1986) with separate estimates of the variance-covariance matrices and equal prior probabilities. From the entire set of BFSP, BFIH, and IHTH polygons available, 75 of each were randomly selected and removed to for independent validation. The resulting discriminant functions were used to predict for each pixel in the validation set the most likely forest management unit label. An error matrix is generated to assess the accuracy of the pixel-level forest management unit predictions. The

interpretation of the error matrix follows the methods and nomenclature suggested by Janssen and van der Wel (1994).

Results and Discussion

To update forest polygon labels with remotely sensed data, the remotely sensed data within a particular forest management unit must be consistent enough to allow accurate labeling. Further, the spectral differences between the labels must also be distinct to allow differentiation. Therefore, the success of the update depends critically on the ratio of spectral variance within and between polygons with unique labels.

Polygon Spectral Contents

As suggested by the principal components analysis, Landsat TM 3, 4, and 5 are considered in this analysis. Observation of the summary statistics of the digital numbers found within the selected polygons indicates some general trends. Landsat TM 3 appears to be of insufficient spectral range to allow for an effective differentiation between cover-types. The Landsat TM 4 and 5 spectral contents of the polygons appear to have unique distributional characteristics, both in terms of wavelength and cover-type. Further analysis, such as an analysis of variance, is required to assess if the variance structure of the spectral values is pursuant to an effective discrimination and typing of polygons.

Variance of the Digital Numbers within and between Polygons

If the spectral values found within a particular forest management unit type are not consistent prediction of unit type from digital numbers will be problematic. As an illustration of the within polygon spectral variability, histograms of the digital numbers found within each forest management unit, as exemplified by Figure 1. The histograms illustrate, for each forest management unit, the distribution of digital numbers as measured and as modeled to a normal distribution. The curves to represent the normal distributions are modeled from the mean and standard deviation measured for each channel within the management unit. The range of the TM 3 values for each forest management unit are small, also with a departure from normality indicated. The distribution of values for TM 4 and 5 more closely resemble the normal distributions. The regions of overlap of digital numbers within each forest management unit are also evident in the histograms. The regions of overlap are where the digital numbers measured may indicate more than one possible class.

To graphically illustrate the variance by spectral channel, between identically labeled polygons within each forest management unit, histograms are generated and presented in Figure 2 as an example. The histograms illustrate, for each Landsat TM channel, the distribution of digital numbers as measured and as modeled to a normal distribution, for each forest management unit. The curves to represent the normal distributions are modeled from the mean and standard deviation measured for each channel within the management unit. The TM 3 digital numbers are found to overlap, indicating that TM 3 is a poor channel for discrimination between forest management units. The regions of overlap occur where the digital numbers measured may indicate more than one possible class. Landsat TM 4 and 5 (see Figure 2 as an example) illustrate a larger range of digital numbers and the variability of the distributions for each forest management unit. While the distributions of TM 4 and 5 digital numbers found within the forest management units vary in form, the ranges tend to overlap. As a result, inclusion of the distribution characteristics of the digital numbers within a particular forest management unit is desirable to improve the ability to discriminate between classes.

As illustrated with the histograms, overlap of spectral values between and within forest management units is present. Yet, a successful TM-based discrimination of polygons with different labels requires the ability to differentiate between types with spectral values. We propose to use a signal to noise ratio (SNR) of polygon spectral variability to gauge our ability to classify polygons to forest management unit types. The *signal* is the variance between forest management units, and the *noise* is the variance found among and within identically labeled forest management unit polygons. Low SNR values indicate poor repeatability; whereas, high SNR values indicate the presence of useful spectral information within and between polygons. A significant spectral difference between polygons with identical labels would, with everything else being equal, jeopardize discrimination. An analysis of variance and estimation of the among and

within polygon variance of identically typed polygons will enable us to gauge the potential for an effective discrimination/classification procedure.

SNR is in essence a measure of repeatability, commonly used in quantitative genetics (Falconer, 1983). When we classify pixels within a polygon we are essentially taking repeat measures of an object (polygon). Within the context of the repeated measures the noise variance component of the signal to noise ratio declines at a rate in proportion to the sample size (number of pixels). In other words, our ability to correctly classify a polygon increases with the number of pixels. A similar argument applies at the forest management unit level where a large number of identically labeled polygons improves the rate of correctly classified polygons, as the between-polygon noise decreases as we increase the number of polygons measured. SNR consists of three components, the variance between distinct forest management units (σ^2_{unit}), the variance among polygons of the same unit ($\sigma^2_{poly/unit}$), and the within-polygon variance (σ^2_w). Mathematically SNR of the variance components is computed, for a given combination of polygons and pixels, as:

$$SNR_{n\_polygons,\ n\_pixels} = \sigma^2_{unit} / (\sigma^2_{unit} + (\sigma^2_{poly/unit} / n\_polygons) + (\sigma^2_w / (n\_polygons * n\_pixels))).$$

Where, $n\_polygons$ is the number of polygons, and n_pixels is the number of pixels. It is thus clear that the signal to noise ratio of the variance components, and with it our ability to correctly classify a polygon, improves as we increase the number of measurements of polygons and pixels.

When the $SNR_{n\_polygons,\ n\_pixels}$ is computed for each spectral channel, based upon the variance encountered over the entire data set, the following results are found, TM 3 = 0.01; TM 4 = 0.14; TM 5 = 0.19. The low repeatability value generated for TM 3 indicates a lack of variability between digital numbers found between identically labeled polygons. The $SNR_{n\_polygons,\ n\_pixels}$ values for TM 4 and 5 indicate an improvement in the ability to characterize the forest management units with the digital numbers found within the polygons. In contrast to consideration of the variance over the entire data set, the distribution of the variance may be considered at particular instances or as a continuum. In Figures 3a-c we present a continuum, by spectral channel, of the repeatability as a function of number of pixels and polygons in a forest strata of identically labeled polygons. Evident in the figures is the relationship between the number of pixels and polygons to the ability to characterize the spectral characteristics of a forest management unit. Increasing the number of measured pixels beyond ≈5 results in little improvement of $SNR_{n\_polygons,\ n\_pixels}$. Alternately, classifying a large number of polygons results in a sizable increase to the $SNR_{n\_polygons,\ n\_pixels}$. The increase to the initial $SNR_{n\_polygons,\ n\_pixels}$ allows for better overall variance characterization. As a result, an efficient update strategy is to classify 5 to 10 randomly selected pixels per polygon rather than a complete classification with little added gain in the classification results. These results relate the spatially autocorrelated nature of neighbouring pixels, where increasing the sample size has little explanatory effect, as the pixels within polygons are not independent observations (Cliff and Ord, 1981). For a discussion of the spatially autocorrelated nature of remotely sensed data see Wulder and Boots (1998).

Prediction of Polygon Labels on a Per Pixel Basis

In Table 1 we present the per pixel results of predicting forest management unit labels from the spectral values found within the polygon boundaries. The producers accuracy, as a function of omission, illustrates the highest accuracy for the hardwood vegetation cover (72%), followed by softwoods (64%), with mixed wood accuracy much lower (15%). The forest management units composed of an individual vegetation type (i.e. softwood: BFSP, hardwood: IHTH) are predicted with greater frequency than management units composed of multiple vegetation types (i.e. mixed wood: BFIH). However, the commission error indicates that there may be a predisposition towards particular classes, with the commission error following the same pattern as the omission error. Further, the commission relates that as a function of the total number of pixels placed in a particular class approximately half are falsely indicated. The high commission error indicates that, based upon the training data available, the classifier is limited in the ability to mathematically discriminate between the classes.

The discriminant analysis was undertaken aspatially. Consideration of the results spatially may allow for further insights to the results. Processing of the predicted classes with a majority (mode) filter, to provide a single label for the polygon is undertaken. The results demonstrate that it may not be necessary to correctly predict the forest management unit class for each pixel. If a majority of the pixels within a particular polygon are sufficiently characterized by the digital numbers, the polygon once filtered may have the

correct class predicted. Our SNR analysis points to the same results, as repeated measures on a single object (polygon) improves our chance of correct classification.

When predicting the polygon labels from the majority filtered results over the entire data set, the producers accuracy increases for the homogeneous units (BFSP, 68%; IHTH, 75%) but decreases, contrary to expectations, for the heterogeneous unit (BFIH, 7%) (Table 2). (However, alternate methods of predicting the object class may yield different results. An alternate approach may be to pool the posterior probabilities computed for each pixel within the polygon.) High commission errors are also present reinforcing the trend indicated on the per pixel accuracy assessment. The users accuracy results (all around 50%) indicate that a polygon is as likely to be classified incorrectly as classified correctly. The producers accuracy results indicate that certain forest management units may be updated or validated based upon remotely sensed data given access to *a priori* information. The users accuracy results indicate that caution should be exercised when providing labels to forest management units, with remotely sensed input, to polygons with no *a priori* label information.

Conclusions

In this study, we addressed the distribution of remotely sensed spectral values in relation to forest inventory polygon information to benchmark the strength of the relationships between forest inventory information and image spectral response. To assess the potential to use remotely sensed data to label forest management classes the spectral variability, both within and between forest cover classes, was investigated.

Initially we presented the distribution of the spectral characteristics which can be expected for Landsat TM 3, 4, and 5 within the forest management units relating softwood, hardwood, and mixed wood cover-types. Computation of repeatability ($SNR_{n\_polygons,\ n\_pixels}$) as an indication of forest management unit variance by image channel indicates the need for a wide distribution of sample pixels by forest management unit polygon. Insight to the statistical relationship is presented by overlaying the histograms for each management unit by image channel. The overlap that is evident indicates several spectral regions where multispectral classification may prove problematic.

The utility of the polygon data as training data for the estimation of unknown polygons or the update of dated inventory data is indicated in this study. The generation of discriminant functions for the estimation of classes from the digital numbers found within the forest management polygons allows for use of the polygons to set a context for classification. Estimation of classes for pixels within a defined region allows for filtering of the results. A majority filtering of the classes estimated from the discriminant analysis allows prediction of the most likely class based upon the classification results. This research indicates that when faced with a sub-optimal variance structure, as indicated by an initial investigation of variance component signal to noise, a pixel-by-pixel classification is likely inferior to a cohort classification approach.

Acknowledgements

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Tables and Figures
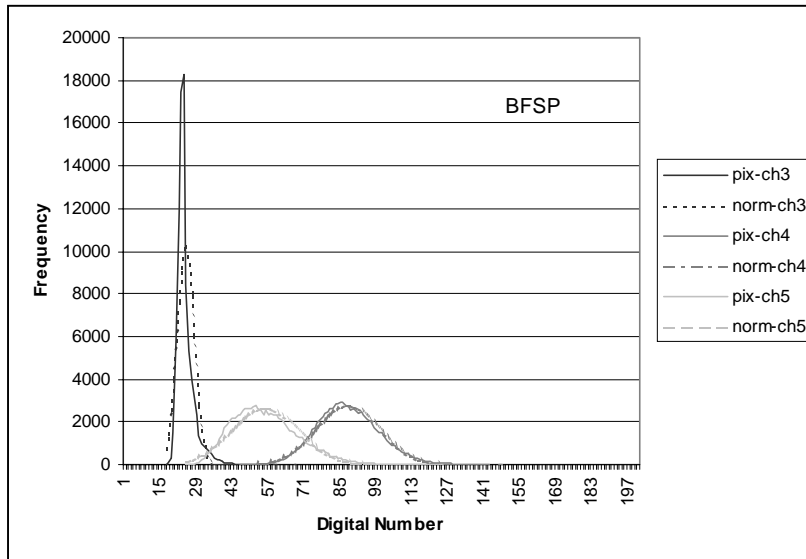
Figure 1. Histograms of digital numbers found within identically labeled polygons of softwood stands (BFSP) for TM channels 3, 4, and 5. Compared for each channel are the measured (pix) histogram distributions for each channel with a normal distribution (norm), input with the mean and standard deviation measured for the channel, within the management unit.
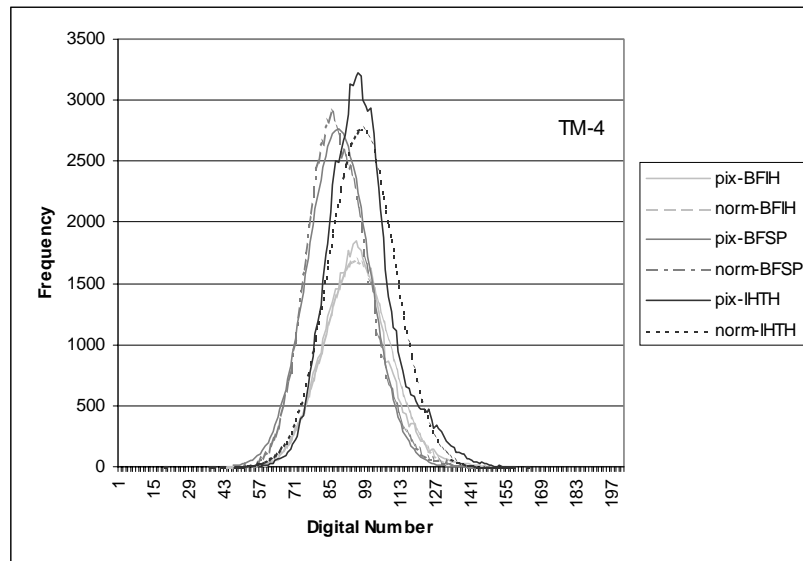
Figure 2. Histograms of digital numbers found within each forest management unit for Landsat TM channel 4. Compared for each channel are the measured (pix) histogram distributions for each channel with a normal distribution (norm), input with the mean and standard deviation measured for the channel, within each management unit.
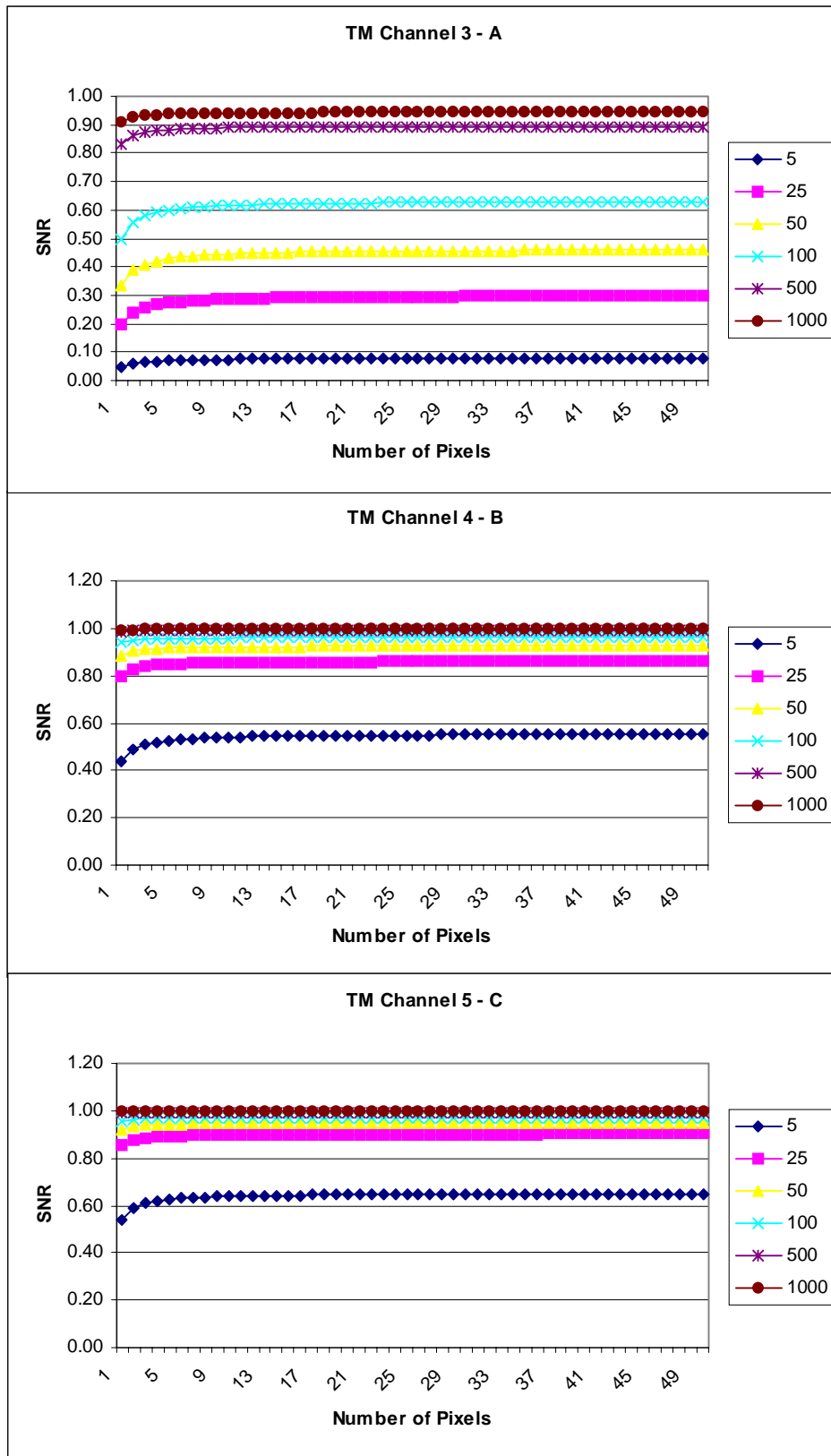
Figures 3 a-c. $SNR_{n\_polygons,\ n\_pixels}$ **as a function of numbers of pixels and polygons. Legend indicates number of polygons.**

Table 1. Confusion matrix illustrating the ability to predict forest management unit label from individual pixels within forest inventory defined management units. (225 polygons, 75 polygons of each select forest management unit, polygons with minimum of 10 pixels, total n = 20893 pixels)

		Predicted							**Accuracy**			
		BFIH		BFSP		IHTH		Row Total	Omission		Producers
		Count	%	Count	%	Count	%	Count	Count	%	%
Actual	BFIH	**1013**	**(14.8)**	2313	(3.7)	3540	(51.6)	6866	5853	(85.2)	**14.8**
	BFSP	681	(10.2)	**4244**	**(63.5)**	1756	(26.3)	6681	2437	(36.5)	**63.5**
	IHTH	475	(6.5)	1589	(21.6)	**5282**	**(71.9)**	7346	2064	(28.1)	**71.9**
	Col. Total	2169		8146		10578		20893			
Accuracy	Commission	1156	(16.7)	3902	(55.3)	5296	(77.8)				
	Users		**47.0**		**53.5**		**48.0**				

Table 2. Confusion matrix illustrating the frequency that forest management units (actual) are selected from the majority filter dictated (predicted) polygon labels. (75 polygons of each select forest management unit, polygons with minimum of 10 pixels, total n = 225 polygons)

		Predicted							**Accuracy**			
		BFIH		BFSP		IHTH		Row Total	Omission		Producers
		Count	%	Count	%	Count	%	Count	Count	%	%
Actual	BFIH	**5**	**(7)**	24	(32)	46	(61)	75	70	(93)	**7**
	BFSP	4	(5)	**51**	**(68)**	20	(27)	75	24	(32)	**68**
	IHTH	3	(4)	16	(21)	**56**	**(75)**	75	19	(25)	**75**
	Col. Total	12		91		122		225			
Accuracy	Commission	7	(9)	40	(53)	66	(88)				
	Users		**42**		**56**		**46**				