Selecting high resolution sample images for land cover studies. Part 2: Application to estimating land cover composition

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Abstract

We tested the effectiveness of the Purposive Selection Algorithm (PSA, described in the companion first paper) to accurately estimate land cover composition over a large area. The knowledge of land cover distribution over large areas is increasingly more important for numerous scientific and policy purposes. Unless a complete detailed map is necessary, a sampling approach is the best strategy for determining the relative proportions of individual cover types because of its cost-effectiveness and speed of application. With coarse resolution land cover maps at continental or global scales increasingly becoming available, the possibility arises of using such maps synergistically with a sample of high resolution satellite coverage. The goal of such synergy would be to obtain accurate estimates of land cover composition over large areas as well as the knowledge of local spatial distribution. We evaluated PSA performance for sample selection over a 136,432 km^2 area (domain) in the BOREAS Region of Saskatchewan and Manitoba, Canada. Two maps were prepared for the domain, one based on NOAA Advanced Very High Resolution Radiometer (AVHRR, 1 km pixels) and one on LANDSAT Thematic Mapper (TM, 30 m). After dividing the area into 134 tiles, a PSA sample was selected using the AVHRR tiles. A random sample was also selected for comparison. The domain AVHRR cover type fractions were then corrected using TM maps for the selected tiles, following the method of Walsh and Burk (1993). The land cover composition obtained through the combined 'domain AVHRR/sample TM' data was then compared with the domain TM coverage. We found that PSA provided a representative sample to correct the AVHRR map, particularly for small sample sizes. Compared to the random selection, PSA yielded more accurate results at all tested sampling fractions (up to 30% of all tiles). With a PSA sample of 7% (18%), the average absolute difference per class between the correct and the estimated fraction was 0.058% (0.043%). For the same sample fractions, the average relative error per class was 16.1% (9.8%) for PSA and 24.5% (18.7%) for random selection. The difference between PSA and random selections was significant at the 0.001 probability level. It is concluded that the PSA strategy is an effective way to combine coarse and fine resolution satellite data to obtain expedient and cost-effective land cover information over large areas. An important benefit of the synergistic combination of the two maps is knowledge of land cover distribution at the landscape level. This is because the coarse resolution map provides the overall distribution patterns across the domain, while the fine resolution map supplies the average composition of the coarse resolution pixels in each cover type. Thus, each coarse pixel can be statistically divided into the component high resolution classes.

Introduction

Land cover is a critical biophysical parameter that determines the functioning of terrestrial ecosystems in biogeochemical cycling, in hydrological processes, and in the interaction between the surface and the atmosphere. It is therefore of strong interest in scientific studies aimed at improved understanding of the dynamics of terrestrial processes, at all scales from site to globe. Land cover is also a key input into land use and management decisions. Thus, its extraction from satellite remote sensing data has been the focus of many studies using a variety of data sources and methods. While initially these utilized high spatial resolution data sources such as aerial photography (Colwell, 1960) and later Landsat and similar data, recently considerable attention has been given to data at coarser resolutions, 1-8 km (e.g., Townshend, 1994). This trend reflects the growing importance of land cover for environmental studies at various spatial scales.

Ideally, land cover information should be available in great spatial detail, with high temporal frequency, and over large areas. These requirements lead to an excessive demand for the acquisition, processing and analysis of satellite data, which has heretofore been impossible and only recently have proposals been made to advance in this direction (e.g., Ahern et al., 1998). Over large areas, the use of coarse to medium resolution data has been favoured as a more practical solution, and it will remain the preferred method for monitoring seasonal and interannual dynamics. However, data with a resolution of 10^2-10^3 metres generally consist of mixed pixels, and maps derived from these often contain mixed classes. It is therefore important to know the composition of these classes. Such information can be obtained by using a sample of high resolution data. For this characterization to be accurate and effective it is important to select the sample appropriately.

In a companion paper (Cihlar et. al., 1998) we have described an algorithm for selecting a sample of tiles to represent the entire region of interest (domain). Here we test the effectiveness of the method to characterize land cover composition over a larger area, using domain coverage of 1 km resolution data and selecting a sample of tiles to be covered with high resolution (30 metres) data. As in the companion paper, the effectiveness is evaluated by using domain coverage with 30 m data.

Data and methodology

The study was carried out within the BOREAS Region located in Saskatchewan and Manitoba, Canada. Two maps of land cover were prepared from Advanced Very High Resolution Radiometer (AVHRR; 1 km pixels) and Landsat Thematic Mapper (TM, 30 m pixels) data, respectively. The AVHRR map was produced for the entire Canadian landmass from AVHRR data representing mean growing season conditions for 1995 (Cihlar and Beaubien, 1998). The images to be classified were obtained by processing data for the entire growing season and then computing mean values for AVHRR channel 1, 2 and NDVI. The TM map utilized six TM images approximately covering the transect between Prince Albert, Saskatchewan and Thompson, Manitoba (Table 1). Both classifications employed a similar classification legend, differing only to the extent necessary to accommodate the differences in spatial resolution (Table 2). The enhancement - classification methodology (ECM; Beaubien et al., 1999) was used to separately produce each map. Detailed information on the maps is given by Cihlar and Beaubien (1998) for AVHRR and Beaubien et al. (1999) for TM.

For this study, the area corresponding to the TM map (‘domain’) was cut out of the AVHRR map of Canada. This AVHRR mapped area was spatially registered to the TM image mosaic and resampled to 30 m pixels using the nearest neighbour algorithm. The rectangle bounding the domain was divided into 225 tiles (15 rows x 15 columns), each 1550 x 940 (30m) pixels in size. Of the 225 tiles, 134 contained some land cover and were retained for analysis. For each AVHRR tile as well as the entire area, the land cover composition was computed. The Purposive Selection Algorithm (PSA, Cihlar et al., 1998) was then applied to the 134 AVHRR tiles, using land cover composition as the only basis for selection. Briefly, at each iteration (i.e., when selecting the next tile) PSA seeks to identify the subset of tiles for which land cover composition is closest to that of the AVHRR domain; the difference is quantified using Euclidean distance ED between the domain and the ensemble of the selected tiles. Thus, the tile added at each iteration is that which brings the land cover composition of the sample closer to that of the domain than any other candidate tile. To allow combining TM and AVHRR estimates (see below) the first tile was selected to be (i) the closest to the domain and (ii) among tiles which contained all land cover types. To assess PSA effectiveness, a random sample was also selected among the 134 AVHRR tiles and used in subsequent computations.

Numerous studies have previously been carried out on the combined use of coarse and fine resolution data (Mayaux and Lambin,1995, 1997; Moody, 1998; Moody and Woodcock, 1996;

Walsh and Burke, 1993). In most cases, these studies deal with two land classes, and seek to maximize the accuracy of one class of interest (e.g., total forested area). In this case, we are interested in the area of all cover types. Walsh and Burk (1993) have described the appropriate theoretical framework. The basic relationship is:

$$\hat{p}_i = \sum_{j=1}^{k} \frac{(f_j + n_{.j})}{N} * \frac{n_{ij}}{n_{.j}}, \qquad (1)$$

where

$\hat{p}_i$ = vector of estimated proportions of the individual cover types;

n = number of units in the reference sample (i.e., TM pixels);

N = combined number of units in the reference and classification data set (i.e., the sum of AVHRR-based and TM pixels, both with 30 m pixels);

f = column vector of number of $(N-n)$ units in each class (i.e., the number of AVHRR-based pixels for each cover type);

i = subscript for reference data set (TM-based, rows);

j = subscript for classified data set (AVHRR-based, columns);

k = number of cover types;

. = sum over all i's.

The asymptotic variance of this estimator is (Walsh and Burk, 1993):

$$\text{var}\left(\hat{p}_i\right) = [p_i(1-p_i)(1-K_i)/n] + [p_i(1-p_i)K_i/N], \qquad (2)$$

$$K_i = \frac{p_i\left(\sum_{j=1}^{k} q_{ij}^2 / (p_i - 1)\right)}{1-p_i},$$

$$q_{ij}^2 = (f_j + n_{.j})n_{ij} / (n_{.j} N p_i),$$

where:

q_{ij} = misclassification probability;

p_i = vector of actual cover type proportions.

Eq.1 thus provides an estimate of the fraction of each land cover type for the domain based on the combination of the AVHRR domain map and the selected TM tiles.

Several parameters have been defined below to assess the accuracy and consistency of the samples. These parameters compare absolute (i.e., the total area is 100%) and relative (each class is 100%) accuracies; weighted (all pixels are equally important) and non-weighted (all classes are equally important) accuracies; direct identification (omission and commission errors matter) and total area estimates (only the total class area is important). The various perspectives are needed for a comprehensive assessment of the merits of the sampling strategies.

For the analysis discussed below we assumed that the TM domain map is 100% correct. Although not true (Beaubien et al., 1999) this assumption is inconsequential to the stated objective of assessing whether fine resolution map statistics can be obtained with the aid of a coarse resolution map.

Results and discussion

Area estimation accuracy

Figure 1 shows the area by class for the AVHRR and TM domain maps. Four classes are large, the remaining ones do not exceed 10% of the domain each. The absolute difference between the two maps, i.e. the AVHRR error, varied between +5 and -5% (Figure 1), a significant amount considering the size of the classes.

As more PSA-selected TM tiles were included in the calibration set the differences between calibrated AVHRR land-cover estimates and the corresponding TM based estimates diminished, at first rapidly and then at a declining rate. However, it can temporarily increase depending on the land cover composition of the added tiles. Figure 2 shows three parameters used to measure the trend: diagonal accuracy (*DiAc*), area accuracy (*AA*), and weighted absolute difference (*WAD*):

$$DiAc = \frac{\sum_{i=1}^{n} NP_{i,i,AVHRR,u,s}}{\sum_{i=1}^{n} NP_{i,TM,s}}, \qquad (3)$$

$$AA = \sum_{i=1}^{n} f_{i,TM,d} * \frac{NP_{i,AVHRR,d,c}}{NP_{i,TM,d}}, \quad (4)$$

$$WAD = \sum_{i=1}^{n} f_{i,TM,d} * | f_{i,AVHRR,d,c} - f_{i,TM,d} |, \quad (5)$$

$$f_i = \frac{NP_i}{\sum_{j=1}^{n} NP_{i,j}},$$

where *NP* is the number of pixels; *n* is the number of cover types; *i* and *j* refer to cover type; and subscripts TM, AVHRR, *d*, *s*, *u* and *c* refer respectively to: TM map, AVHRR map, domain, selected tiles, uncorrected values, and corrected values based on selected tiles. $NP_{i,i,AVHRR}$ is the number of pixels in class *i* (TM) identified as class *i* by AVHRR in the selected tiles.

The direct identification accuracy of the AVHRR data (i.e., the diagonal entries in the confusion matrix) was relatively low (~30-40%, Figure 2), principally because of the mixed-cover nature of the AVHRR pixels although lack of spectral differentiation could also be important in some cases. It did not change appreciably as more tiles were selected, confirming the heterogeneity of land cover in the mapped domain. The overall area accuracy *AA* (weighted by the class size, Eq. 4) is low for two tiles but converges fairly rapidly on the TM domain as the number of tiles increases. This is also evident from the weighted absolute difference between the corrected AVHRR and TM estimates which decreased as the number of selected tiles grew from 2 (1.5% sample) to 10 (7.5%), then less rapidly to 24 18%) and 40 (30%) tiles.

Figure 3 shows scattergrams for the true (TM) and estimated (Eq.1) domain class fractions with an increasing number of tiles *s*. The r^2 increased rapidly from *s*=0 (Figure 3a) to 2, temporarily decreased to *s*=5, and after *s*=24 the increase was minimal. The fluctuations for *s*=5 (for *s*=10) are due to two large classes (one medium class) which were not well represented in the tiles selected at that point (Figure 3b, 3c). With more tiles, the representation evidently stabilized and further increases were monotonic, even though diminishing. Figure 3 illustrates the effectiveness of combining few well-selected TM tiles with the AVHRR data, most of the scatter having disappeared by *s*=5 (Figure 3b). Figure 4 shows the absolute difference between true and estimated fractions for the minimum (*s*=2) as well as other selections. Note that many of the deviations for *s*=2 were smaller than for *s*=5 and consistently stabilized after *s*=10. This indicates that although the correction may be excellent for very few tiles, such result can occur only if these are representative of the domain. In general, robustness is achieved by selecting more tiles. PSA provides an indication of when this may occur, from a plot of WAD against the number of tiles selected (Cihlar et al., 1998).

Purposive and random sample selection

The performance of PSA and random selection is compared in Figure 5 by using a relative class *i* accuracy measure *RCA* after *s* selected tiles:

$$RCA_{i,s} = \frac{f_{i,AVHRR,c}}{f_{i,TM,d}}. \qquad (6)$$

Several consistent trends can be observed. First, the relative accuracy of forested classes (1-9, Figure 5a, 5c) was more consistent and converged to the TM domain value more effectively than for others, most likely because these were ubiquitous classes (Figure 1) and thus better represented in the selected tiles. Second, the convergence from the original AVHRR land cover composition to the true (TM) composition was more rapid for PSA than for randomly selected tiles. The random selection performance was worse for both groups but more so for the smaller classes. For example, with 24 tiles the range in *RCA* (highest minus lowest) was 35% (Figure 5a) and 37% (5b) for forest and nonforest classes, respectively; the comparable values for random selection were 71% (5c) and 98% (5d). Third, the PSA convergence was relatively rapid initially but also more erratic, obviously in response to the representation of individual classes in the added tiles. A comparison of Figure 5b and 5d shows that while the random selection improved the representation of the small classes gradually and fairly monotonically, PSA resulted in a more erratic initial trend, even though the differences from the true values were always lower than for random selection. This is because PSA preferably selected to represent the larger classes first, and only later did the smaller ones become relatively more important. Figure 5 also shows that after 10-24 tiles (i.e., about 10-20% sample), the $RCA_{i,s}$ for all classes was within about 20% of the true value and further improvements in exactly matching the value of each class were only gradual. This is consistent with results of Cihlar et al. (1998) for a smaller area.

Figure 6 shows two overall accuracy measures for the corrected land cover fractions, *WAD* (Eq. 5) and relative difference *RD*:

$$RD_s = \frac{1}{n}\sum_{i=1}^{n}\frac{NP_{i,TM,d} - NP_{i,AVHRR,c,d}}{NP_{i,TM,d}}. \qquad (7)$$

PSA-based estimates were consistently closer to the true values than those based on random selection, in both absolute and relative terms. The absolute difference decreased from about 0.2% per class to <0.05% with a 20% sample. *WAD* ratio ranged from 130 to 218% (Figure 6a), indicating that for the same number of tiles PSA provided a substantially better estimate than random selection. The relative difference *RD* (Figure 6b) decreased more gradually but consistently as sample size increased. The difference between *WAD* (6a) and *RD* (6b) reflects the impact of small classes. Since large classes have relatively more weight in WAD (Eq. 5), this parameter increases more rapidly initially than RD where the absolute class size is not important (Eq. 7). PSA thus not only performed better for a given sample size but its effectiveness was higher in the correction of small classes, with *RD* ratio ranging from 1.52 to 2.06 for $s<40$. - It should be noted that the asymptotic variance (Walsh and Burk, 1993) of the class area estimates was very low in all classes because of the large number of pixels, below $6\text{x}10^{-8}$ for PSA and $5\text{x}10^{-8}$ for random selection. As expected, the variance decreased as more tiles were added. In all cases, however, the value was very small, mainly as a result of the large number of pixels included in the sample. Also, the difference between the two selection strategies was negligible.

To evaluate the effect of random sample selection, we used a Student's t. Ten selections of tiles were made using a random number generator, and the resulting WAD values were compared against PSA (Steel and Torrie, 1960). For all sample sizes tested (up to 130), the t value ranged from 5.6 to 9.3. These are all significant at 0.001 probability level (4.78).

The above analysis was based on the premise that the same classification scheme is used for both data types (Table 2). This may not always be possible, especially when the classes are mixed at coarse resolution but resolved at fine resolution. Although the above statistical procedure [Eq. 1,2] cannot be employed, the PSA sample can nevertheless be used effectively in this case. Once the sample is selected, the composition is computed simply as the average for the high resolution sample. Figure 7 shows WAD values computed using Eq. 5 but after replacing the AVHRR domain component by the TM sample. The same TM sample was used as above, i.e. selected based on the AVHRR-derived map. The performance of PSA was at least twice as good as for the random selection for all the sample fractions tested. This is because the PSA sample always strives to approximate the mean composition of land cover for the entire domain.

Comments

Three strategies are possible for accurately estimating land cover composition from remotely sensed data: a) a complete coverage of the domain of interest by high resolution remote sensing data, b) a sample of fine resolution data, and c) a combination of coarse and fine resolution data. The first approach is mandatory when site-specific information is required for the entire domain of interest. However, when only area statistics are needed, this strategy is expensive and unnecessary, besides stretching the present data acquisition and analysis capabilities to the limit (although improvements in these aspects are forthcoming). The second approach would normally employ a sample of the high resolution coverage, selected through random sampling or possibly stratified sampling if an independent information is available to base the stratification on; this approach is represented by the random selection case in this study. The third approach, represented by PSA, aims to make optimum use of the coarse resolution data in making the selection of the high resolution sample. The justification underlying this selection is the knowledge of the pattern of distribution of individual classes, even though the detailed area distribution of each class throughout the domain is not known. The selection is thus not random but is guided by the residual difference between the cover type composition of the domain and the sample selected so far. Case c) may be thought of as a form of sampling which is proportional to the difference between the domain and sample land cover fractions.

The above results show the consistently better choice of sample tiles by PSA compared to random selection. This confirms that the coarse resolution land cover map provides information which may be effectively employed to select an efficient and effective sample, thus optimizing the use of the available resources. The PSA effectiveness is due to the sample being selected to represent the entire domain. Conceptually, this corresponds to unequal probability sampling in which the selection should be made as nearly as possible proportional to the values of the variable in the population (Stuart, 1976).

The effectiveness of PSA will depend on the heterogeneity of land cover distribution within the domain. If the domain of interest is homogenous with respect to land cover composition then selecting a tile would be as effective as selecting any other tile and a random selection would be as useful as a directed selection (but no more so). This is because the Euclidean distance ED between the domain and individual tiles would be the same. The PSA effectiveness thus depends on the degree to which the composition of individual tiles differs from that of the domain, absolutely as well as relatively.

The methodology as employed above requires that the classification legends for coarse and fine resolution data be identical. This may not always be possible, especially as the difference between the spatial resolutions at the two mapping scales increases. It is, however, generally possible to have compatible classifications through hierarchically nested subdivisions of the basic categories. The two can then be made compatible by grouping the more detailed classes upward. Where the two classification legends cannot be reconciled PSA selection can still be used and the cover type composition then computed from the fine resolution sample alone. This is still preferable since, as shown in Figure 3, the PSA sample represents the domain very well. While this simpler approach allows estimation of cover composition of the domain, it does not permit to compute the variance of the class proportion estimates using e.g. the method of Walsh and Burk (1993). However, this may not be an important drawback since the variances are rather small in this type of application.

PSA assumes that the coarse resolution map represents the actual distribution of land cover. This should be true for a good map but it is possible that classes occurring in small patches will be underrepresented or even not shown in the coarse resolution mapping legend. In that case, there is a possibility that these classes may be incorrectly estimated using the PSA sample. Two factors mitigate against this. First, the above results show that even a small sample of a cover type leads to a large improvement in the estimate; in fact, the largest improvements occur with the initial tiles (Figure 5,6). Second, small or infrequent cover types are very likely to be spatially related to one or more of the larger ones (simply because the large classes are more widespread) and thus selected implicitly. It should be noted that in this study small classes were not missed, even though they represented as little as 0.6% of the area (Figure 1). The random selection strategy would eventually find a sample of small cover types but without some ancillary information there is no basis for determining the number of samples that would have to be collected; the difficulty in obtaining such information is self-evident as it presupposes knowledge of the distribution of land cover at fine resolution.

The above combination of the coarse and fine resolution data is based on the premise that land cover can be mapped adequately with high resolution data such as the TM. Since errors in the fine resolution map translate directly into errors in the combined product this is a firm requirement, and it highlights the critical importance of developing and using high performance classification methods as well as robust procedures to compensate for inadequacies of spectral information available in high resolution satellite images.

After the integration of the coarse and fine resolution maps, detailed data sets of land cover distribution can be produced. Most coarse resolution pixels are a mixture of cover types, as also evident from the low *DiAc* values (Figure 3a). However, the combination with fine resolution data allows quantification of the composition of each coarse resolution class, and thus also an average composition of each coarse resolution pixels. This is because each coarse pixel can be expressed in terms of fractions of the individual high resolution map classes. Such a mapping product will be fully adequate for most modelling tasks carried out over large areas. In such applications, a model can be run separately for each cover type fraction of the coarse pixel provided that the soil and topographic differences within the pixel are not significant.

Since the fractional composition of each coarse pixel will be applied uniformly to the entire class it is important that these coarse pixel classes each have a similar a mix of cover types across the mapped domain. However, it is not necessary that each coarse resolution pixel belong to only one land cover category. Thus, with accurate data at the fine resolution, the low direct identification accuracy of the coarse resolution data (*DiAc*, Figure 2,3a) loses significance.

In this study, the tile size was a compromise between a) making tiles as close as possible to actual high resolution satellite images and b) having many tiles inside the domain, thus making the selection challenging. In practice, the tiles would be dictated by the size of the high resolution images, for example a full frame Landsat image. Given the speed of processing there is no particular advantage in selecting subsets of high resolution images once full scenes are acquired. The situation will be different if high resolution satellite data can be readily obtained for any area. Then the choice of a tile size would best be done through PSA tests with various hypothetical tile sizes for the domain of interest, to obtain an optimum compromise between the number of tiles and the tile size.

It should be noted that PSA makes it possible to select an optimum sample for particular cover types, e.g. forests only. In this case, one can simply combine the remaining classes with the background and then apply PSA in the standard manner. It is also possible to optimize the selection in response to other considerations, e.g. when accurate estimates are needed for specific administrative units such as provinces, or ecological regions such as biomes or ecozones. These possibilities are explored in our current research.

Conclusions

In this paper, we have assessed the effectiveness of PSA for estimating land cover composition over an area of 136,432 km^2 located in the BOREAS Region of Saskatchewan and Manitoba, Canada. The method of Walsh and Burk (1993) was employed to statistically combine the composition information provided as a wall-to-wall coverage by AVHRR and a sample based on TM data. The results were compared with those from a randomly selected sample of TM tiles.

We found definitive and consistent differences in the performance of the two selection procedures. The PSA-selected tiles resulted in a more rapid convergence on the true land cover fractions. For a given number of tiles, the PSA-based class fraction estimates were closer to the true values than those based on randomly selected tiles. The effectiveness of the PSA selection continued or increased as more tiles were added, at least for samples of ≤30%. For a PSA sample of about 7% (a sample of 18%), the average absolute difference between the true and estimated class fractions was 0.058% (0.043%); the corresponding values for a randomly selected sample were 0.126% and 0.056%. The differences were also marked in comparing relative class accuracies, with PSA being 1.5 to 2.1 times more effective in reducing the estimation error. Overall, the difference between PSA and random selections was significant at the 0.001 probability level.

By taking full advantage of the knowledge of land cover patterns provided by coarse resolution data PSA enables the selection of an optimum sample of high resolution images for precise area estimation. Since the procedure effectively defines the composition of each coarse resolution class, it makes it possible to (statistically) divide each coarse pixel into fractions of the fine resolution classes. It thus provides a very useful tool for land characterization over large areas where the precise location of all land cover patches (i.e., complete high resolution coverage) is not required.

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Table 1. Landsat TM images used for the land cover classification

Path/Row	Date (YY/MM)
33/21	92/06/06
34/21	92/08/06
35/21	91/08/11
35/22	91/08/11
36/22	96/07/30
37/22	91/08/09

Table 2. Classification legends for AVHRR and TM data

1. High density needleleaf forest
2. Medium density needleleaf forest
3. Low density needleleaf forest
4. Deciduous broadleaf forest
5. Mixed needleleaf forest
6. Mixed intermediate forest
7. Mixed broadleaf forest
8. Burns with low green vegetation cover
9. Burns with green vegetation cover
10. Wetland/shrubland
11. Barren land
12. High biomass cropland
13. Medium biomass cropland
14. Low biomass cropland
15. Water

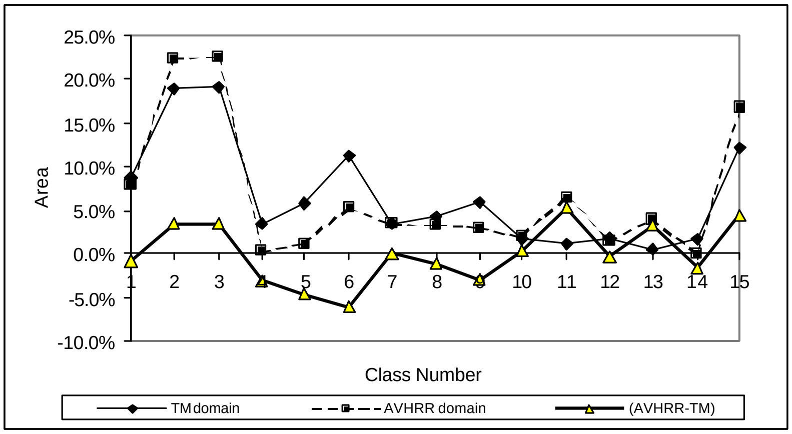

Figure 1. Land cover class fractions for the area as mapped using AVHRR (1 km) and TM (30 m) data.

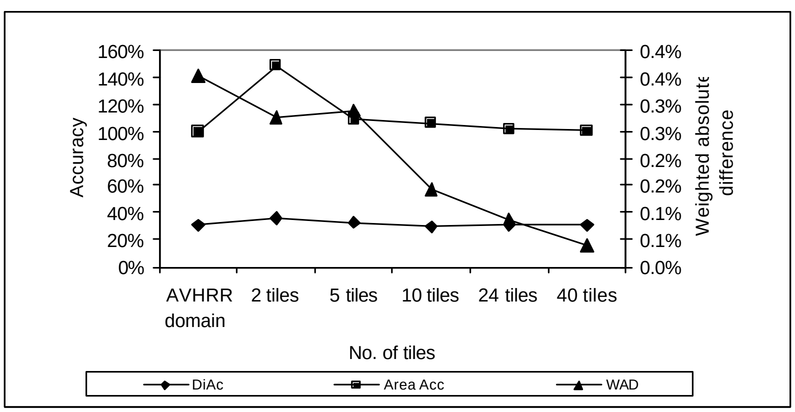

Figure 2. The effect of increasing the number of tiles selected using PSA. *DiAc*, *AA*, and *WAD* are average diagonal accuracy of the confusion matrix, average area accuracy and the average absolute difference between the corrected AVHRR and the true (TM) class fractions.

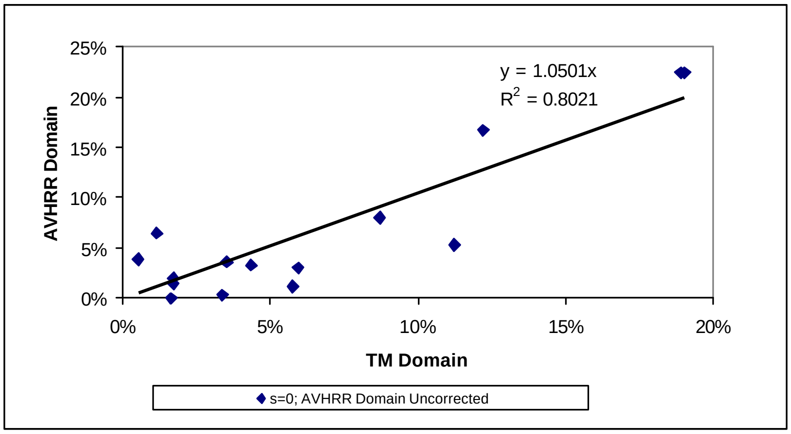

Figure 3a

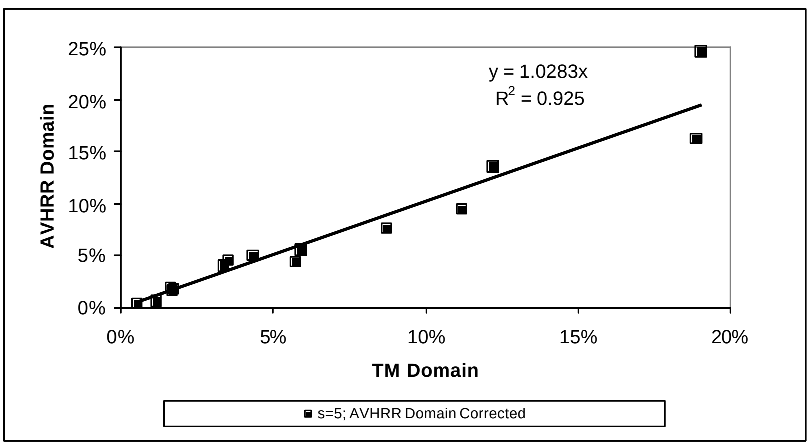

Figure 3b

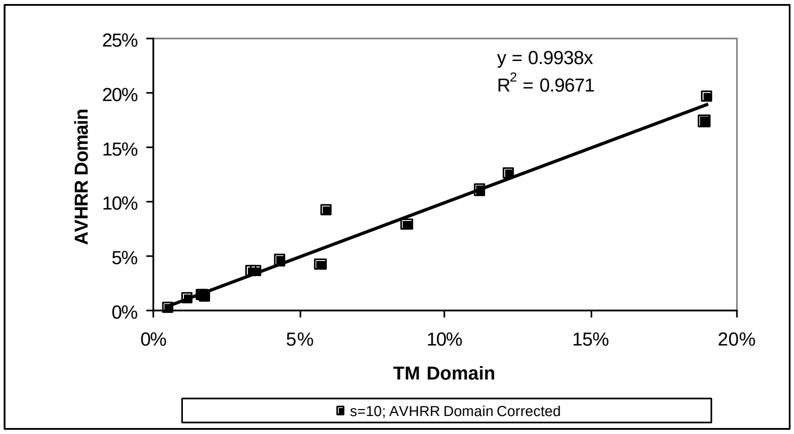

Figure 3c

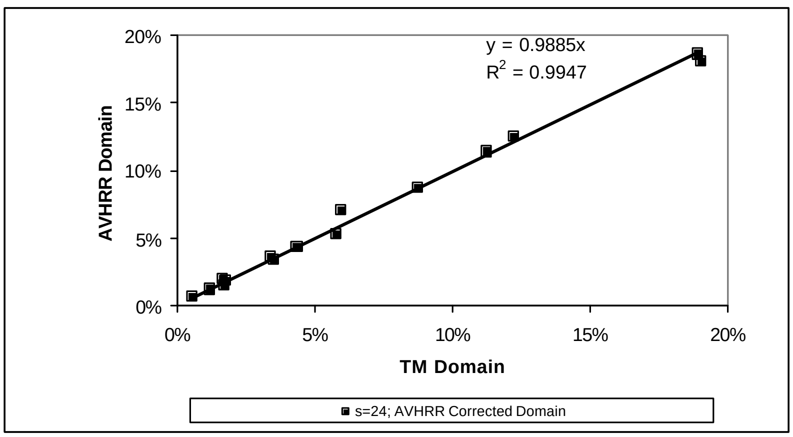

Figure 3d

Figure 3. True (TM, x) vs. estimated (AVHRR - y) fractions of land cover types. Figure 3a: uncorrected AVHRR estimates; 3b: corrected AVHRR estimates based on 10 tiles; 3c corrected AVHRR estimates based on 24 tiles; 3d: corrected AVHRR estimates based on 40 tiles.

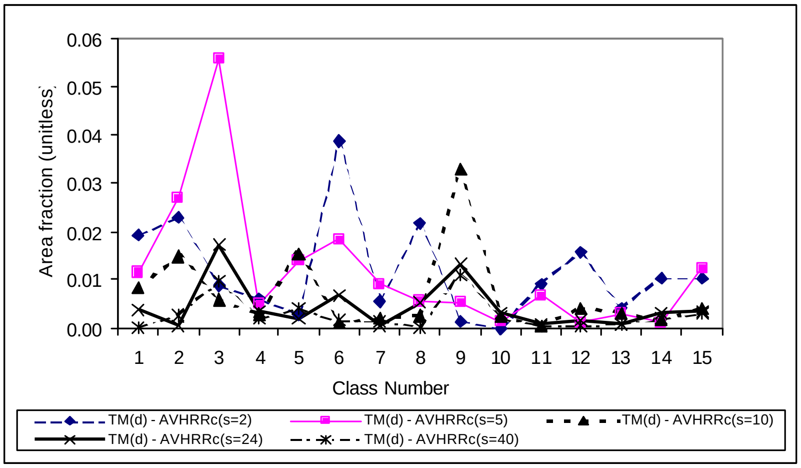

Figure 4. Absolute difference between corrected AVHRR and true (TM) class fractions for various PSA sample sizes.

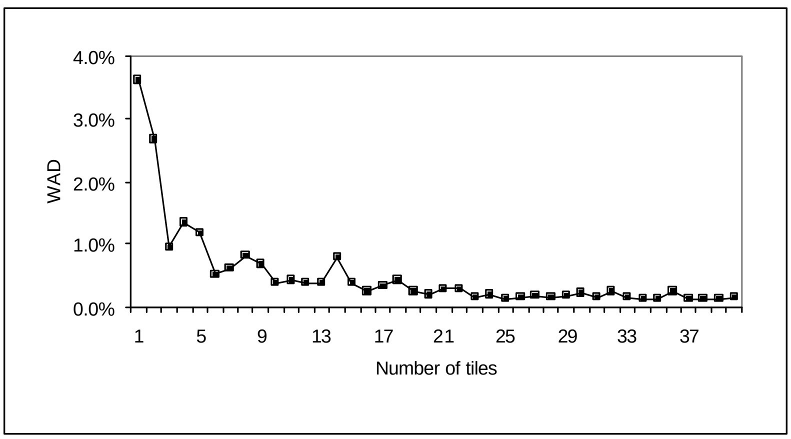

Figure 5. Relative class accuracy of corrected AVHRR data for two selection strategies and two groups of cover types, compared to TM domain values. Figure 5a: PSA, forest; 5b: PSA, nonforest; 5c: random selection, forest; 5d: random selection, nonforest.

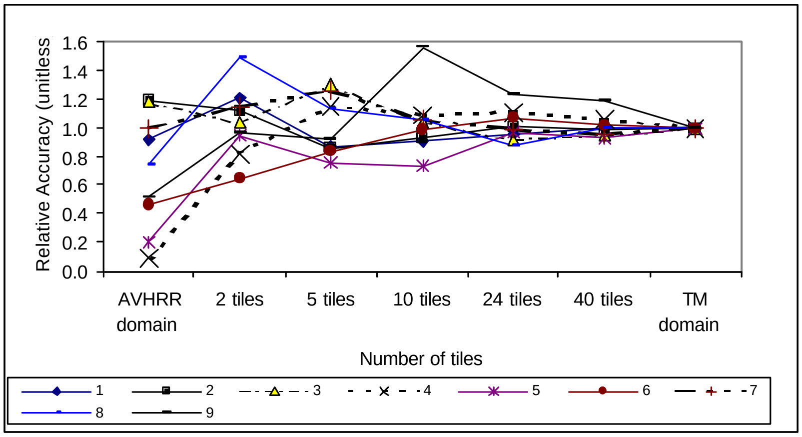

Figure 6a

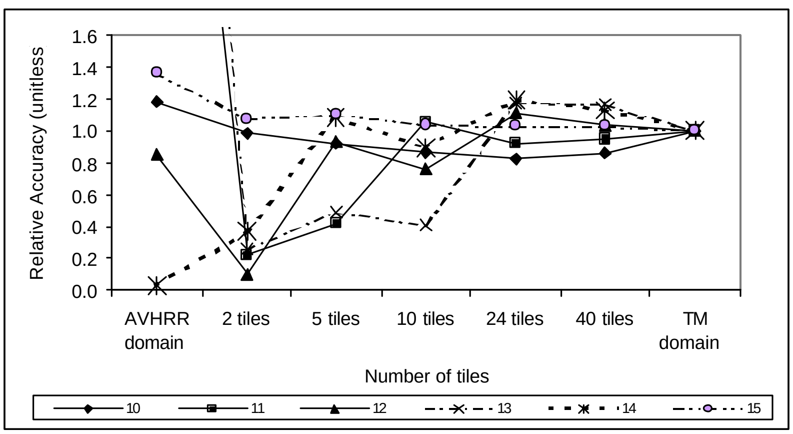

Figure 6b

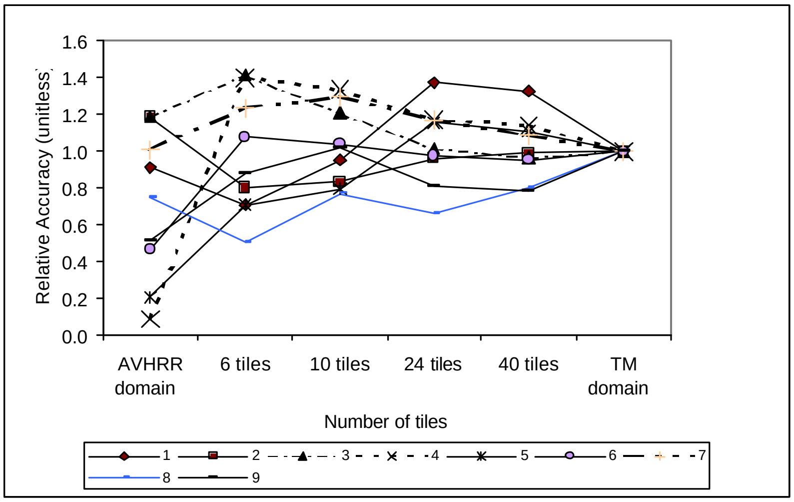

Figure 6c

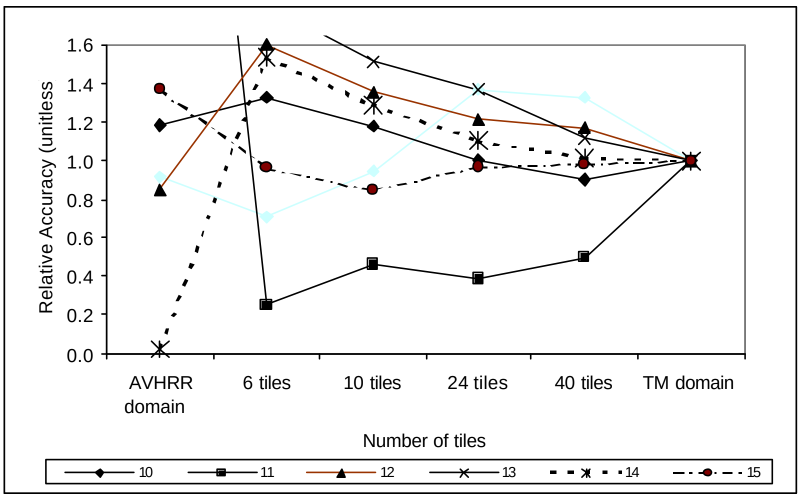

Figure 6d

Figure 6. Absolute and relative effectiveness of the random and PSA selections. See text for discussion.

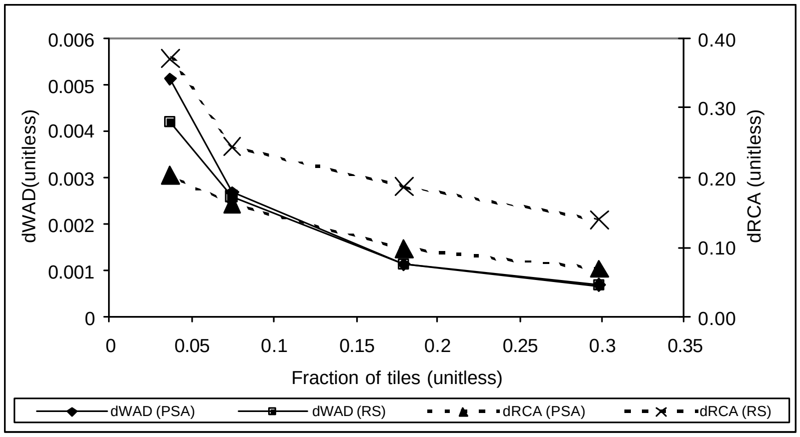

Figure 7. Weighted area difference *WAD* between the TM sample only and the TM domain, selected with PSA or through random selection.