Comparing Forest/Nonforest Classifications of Landsat TM Imagery for Stratifying FIA Estimates of Forest Land Area

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Abstract.—Landsat Thematic Mapper (TM) satellite imagery and Forest Inventory and Analysis (FIA) plot data were used to construct forest/nonforest maps of Mapping Zone 41, National Land Cover Dataset 2000 (NLCD 2000). Stratification approaches resulting from Maximum Likelihood, Fuzzy Convolution, Logistic Regression, and k-Nearest Neighbors classification/prediction methods were superior to an unstratified, simple random sampling approach for producing stratum weights used to lower the variance of estimates of FIA mean proportion forest land. The stratification approaches were comparable to one another.

Each of the Forest Inventory and Analysis (FIA) units of the U.S. Department of Agriculture is required to report estimates of forest land area for their respective regions every 5 years. These estimates are obtained by multiplying total area inventoried by the mean proportion forest land estimated from forest inventory field plots. Forest land, as defined by FIA, includes commercial timberland; some pastured land with trees; forest plantations; unproductive forest land; and reserved, noncommercial forest land. Additional criteria for FIA forest land include 10 percent minimum stocking (5 percent canopy cover for several western woodland types where stocking cannot be determined), minimum area of 0.405 ha (1 acre), and minimum continuous canopy width of 36.58 m (120 ft) (USDA 2002). National FIA precision standards limit the allowable error for estimates of forest land area. Due to natural variability among plots and budgetary constraints, sample sizes sufficient to satisfy national FIA precision standards are seldom achieved. To meet these standards, a stratified estimation approach is used to reduce errors of estimates.

Traditionally, FIA has interpreted a set of aerial photo plots to obtain stratum weights (Phase 1). A subset of Phase 1 plots was measured in the field (Phase 2). This double sampling approach produced estimates that attained national precision standards for forest area (Hansen 1990). However, stratification based on aerial photography has some limitations: It is labor intensive and subjective; photos are expensive and cumbersome to transfer, handle and store, the interpretation is prone to bias when field plots are interpreted differently than nonfield plots; and the photos can be of variable quality and timeliness (McRoberts *et al.* 2002a).

To overcome these limitations, FIA is developing methods of satellite image classification for creating Phase 1 strata. Image pixels within an area of interest are divided into homogeneous classes, based on predictions of land cover. These classes form strata for stratified estimation of Phase 2 data. Stratified estimation can yield increases in precision, even when within-stratum sampling intensities are independent of stratification (McRoberts *et al.* 2002a). Advantages of using satellite imagery for stratification include the following: the resulting coverage is "border-to-border," not a sample of the analysis area; stratum weights are obtained easily from pixel counts; Phase 2 plots are assigned objectively to strata using a geographic information system (GIS); and satellite image stratification can be much cheaper and faster than photo-based stratification. The question is, How precise are estimates based on these stratifications—do they satisfy allowable error standards?

The North Central Research Station (NCRS) FIA program (NC-FIA) measures plots every 5 years across 11 States in the upper Midwest and Great Plains. A stratification based on Landsat-5 Thematic Mapper (TM) or Landsat-7 Enhanced Thematic Mapper Plus (ETM+) imagery will require processing of approximately 125 scenes in the NC-FIA region. Thus, a need exists for rapid processing of TM imagery for creation of Phase 1 strata used in stratified estimation.

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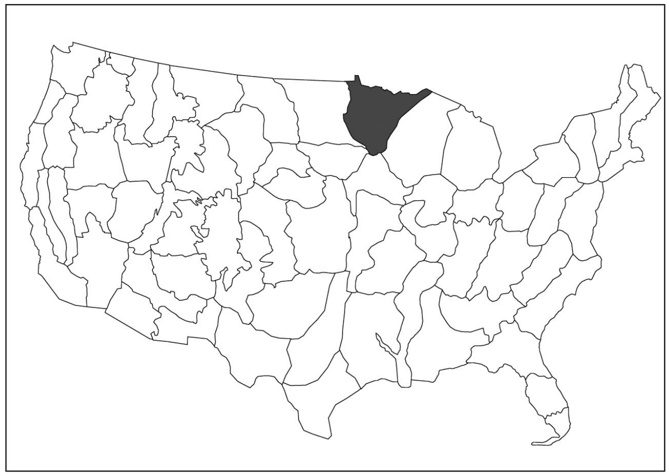
The Multi-Resolution Land Characterization (MRLC) consortium of the U.S. Geological Survey has mosaicked Landsat TM and ETM+ imagery into regional mapping zones. These National Land Cover Dataset 2000 (NLCD 2000) mapping zone image data allow for more efficient image classification than when individual TM scenes are used (Homer and Gallant 2001).

The objective of our study was to compare stratifications produced from classifications of an NLCD 2000 mapping zone data set using four approaches: (1) maximum likelihood supervised classification, (2) maximum likelihood fuzzy convolution classification, (3) a classification using a logistic regression modeling approach, and (4) a classification using a non-parametric, k-Nearest Neighbors (k-NN) approach.

Figure 1.—*NLCD 2000 Mapping Zones and the Zone 41 study area (gray).*



Study Area

The study was conducted within NLCD 2000 Mapping Zone 41, hereafter referred to as Zone 41. This zone encompasses 181,000 square kilometers in portions of eastern Minnesota, northwestern Wisconsin, and northwestern Michigan (fig. 1). The area is characterized by prairie agriculture, a diverse mixture of forest land including both coniferous and deciduous species, and a portion of Lake Superior.

Data

Satellite Imagery

Satellite data for Zone 41 are from TM and ETM+ images (fig. 2). This set of images has the following attributes: (1) 30 m x 30 m pixels from bands 1-5 and band 7; (2) absolute radiance units scaled to 8 bits; (3) processing to level 10: radiometrically corrected, using satellite model and platform/ephemeris information, rectified using ground control points and digital elevation model terrain correction, and resampled, using cubic convolution with resulting root mean square error less than 8.5 m; and (4) geo-referencing to USGS Albers Equal Area projection, NAD83. Image data include optical band values and tasseled cap transformations for three seasons: spring, leaf-on (summer) and leaf-off (late fall / early winter). Kauth and Thomas (1976) introduced the "tasseled cap" transformation of Landsat Multispectral Scanner (MSS) imagery as an easily visualized, three-dimensional construct of the most important phenomena of crop development. Key forest attributes, e.g., species, age, and structure also may be revealed by the transformation (Cohen *et al.* 1995). Crist and Cicone (1984) modified the tasseled cap transformation for TM imagery. Images resulting from the transformation collectively explain about 97 percent of spectral variance within a scene while reducing six original TM bands to three components: brightness, greenness, and wetness.

Figure 2.—*NLCD 2000 Mapping Zone 41, leaf-on, true color image; TM/ETM+ bands 1 (blue), 2 (green), and 3 (red).*

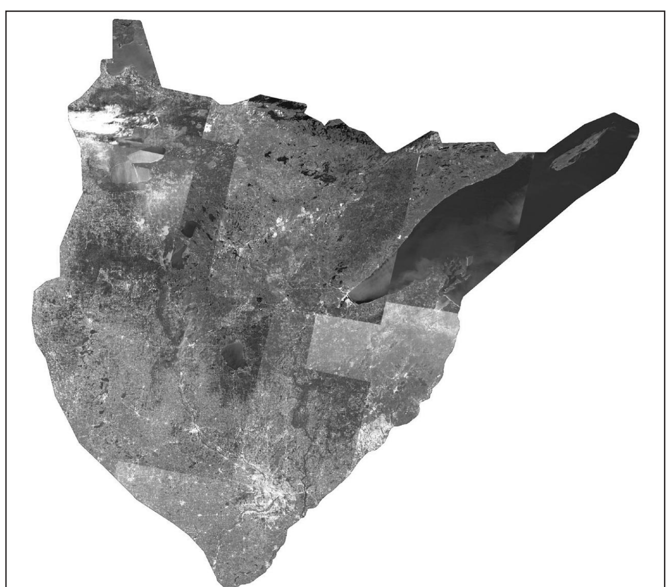
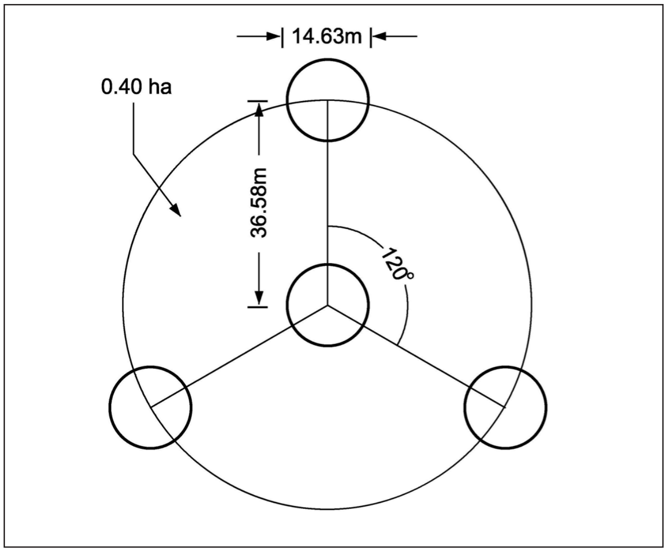


Figure 3.—*FIA Phase 2 plot design.*



FIA Plot Data

Under the FIA program's annual inventory system, field plots are established in permanent locations using a systematic sampling design with each plot representing 2,403 ha (McRoberts 1999). Approximately 20 percent of the plots in each State are measured annually. Locations of forested or previously forested plots are captured using global positioning system (GPS) receivers. Locations of nonforested plots are determined using digitization methods.

Each field plot consists of four 7.31-m (24-ft)-radius circular subplots, configured as a central subplot and three peripheral subplots with centers separated by 36.58 m (120 ft) at azimuths of 0°, 120°, and 240° from the center of the central subplot (fig. 3).

Observations obtained by field crews include the proportions of subplot areas that satisfy specific land use conditions. Plot-wise proportions of forest and nonforest land are determined by computing the mean proportions of these two land uses across the four subplots. Measurements from 5,939 plots associated with cloud-free areas of Zone 41 satellite imagery were used in this study: 5,242 from Minnesota (years 1999–2001) and 697 from Wisconsin (years 2000–2001). Of the measured plots, 2,439 were completely forested, 94 were partially forested, and 3,406 were nonforested.

Methods

Mapping

Seven stratification maps were produced using variations of two classification methods and two prediction methods: (1) maximum likelihood (ML), (2) fuzzy convolution (Fuzz), (3) logistic regression modeling (Log) and (4) k-Nearest Neighbors (k-NN), respectively. Names of stratification approaches incorporate notation for the classification or prediction method (e.g., ML), the number of input training classes for the two classification methods, and the presence or absence of edge strata (table 1).

ML

ML classifications were produced using training data from the following tasseled cap images: spring brightness, spring greenness, spring wetness, leaf-on greenness, and leaf-off brightness.

Table 1.—*Approaches for producing stratified estimates of mean proportion forest land, NLCD 2000 Mapping Zone 41; Nonforest (NF), Nonforest Edge (NFE), Forest (F), Forest Edge (FE), Terrestrial Nonforest (TNF), and Water (W) strata*

Stratification approach	Classification/ prediction method	Inputs	Strata					
			NF	NFE	F	FE	TNF	W
ML2Edge	ML	Nonforest, forest	X	X	X	X		
ML3	ML	Nonforest, forest, water			X		X	X
ML3Edge	ML	Nonforest, forest, water	X	X	X	X		
Fuzz3	Fuzz	ML3, distance			X		X	X
Fuzz3Edge	Fuzz	ML3, distance	X	X	X	X		
LogEdge	Log	Proportion forest land use	X	X	X	X		
k-NNEdge	k-NN	Proportion forest land use	X	X	X	X		

These image layers were selected to correspond with those identified as the "best" bands for k-NN analysis (see below). Chen and Stow (2002) recommend using single pixels for training because pixels that are contiguous or close together may exhibit spatial autocorrelation. If training data are collected from autocorrelated pixels, the variance of this training data tends to be reduced. This may produce biased training signatures that are less representative. Therefore, we used single pixels associated only with central subplots, which are spatially separated from pixels associated with central subplots of other plots.

Based on proportion forest land use, each subplot was categorized as nonforest (< 0.25) or forest (≥ 0.25) before performing the image classifications. The 0.25 minimum threshold for proportion forest land is comparable to the definition of forest land currently used for the Natural Resources Conservation Service (NRCS) Natural Resources Inventory (NRI) (Lessard *et al.* 2003) and is approximately equivalent to FIA's requirement of 10 percent minimum stocking. In comparison, the NLCD definition of forest is land that has 20 percent or more forest cover (tree crown cover or crown closure); Anderson *et al.* (1976) define forest land as having 10 percent or more tree-crown density (crown closure percentage).

Nonforest and forest class signature files were created by appending individual spectral signatures from image pixels associated with each plot location. Due to the cumbersome nature and long processing time associated with nearly 6,000 individual signatures (1 pixel for each central subplot), a guided clustering technique was used (Bauer *et al.* 1994, Lillesand *et al.* 1998). Using this approach, two ISODATA unsupervised classifications were performed, one for pixels associated with central subplots defined as nonforest and one for pixels associated with central forested subplots. Parameters for both ISODATA classifications were as follows: classes = 5, iterations = 20, convergence threshold = 0.98. The resulting five signatures each for nonforest and forest were subsequently merged into one signature for each of the two classes. A classification based on these two signatures was used to produce the ML2Edge stratification.

Merging the five nonforest signatures into a single signature resulted in a bimodal distribution of tasseled cap data—a violation of the requirement for normal data distribution when performing a maximum likelihood classification. Therefore, ISODATA classes 1 and 2 and ISODATA classes 3, 4, and 5 were merged into two normally distributed signatures, characteristic of water and terrestrial nonforest, respectively. Water, terrestrial nonforest, and forest signatures were used to complete a supervised classification using the ML parametric rule and a fuzzy classification option. Output consisted of the three best classes per pixel with a corresponding distance image. Layer one of the fuzzy classification output represents the most likely class for each pixel and was used to produce the ML3 stratification. Following classification, water and terrestrial nonforest pixels were recoded as a single nonforest class, resulting in a classification used for the ML3Edge stratification. ML3Edge is comparable to ML2Edge, but the classification used for ML3Edge conforms to the requirement for using normally distributed data in ML analyses.

Fuzz

Fuzzy convolution is a technique that creates a classification layer by "…calculating the total weighted inverse distance of classes in a window of pixels and assigning the center pixel the class with the largest total inverse distance summed over the entire set of fuzzy classification layers" (Pouncey *et al.* 1999). Whereas classes with higher distance values may change to a neighboring value, classes with a very small distance value will remain unchanged. The result is a context-based classification with reduced speckle. The Fuzz3 stratification was produced using the ML3 fuzzy classification and distance layers described above. The distance neighborhood weighting was calculated within a 3-by-3 window with the central pixel weighted by 1.0, four vertical/horizontal pixels weighted by 0.646, and four diagonal pixels weighted by 0.500. Following classification, water and terrestrial nonforest classes were merged into a single nonforest class. This nonforest class, along with the Fuzz3 forest class was used to produce the Fuzz3Edge stratification.

Log

A logistic regression model with mathematical properties that restrict predictions in the interval [0,1] was selected to accommodate forest land proportions, which also are constrained to the interval [0,1]. McRoberts and Liknes (2002) describe this approach for estimating proportion forest land. In this approach, all four subplots associated with each plot were used.

In brief, a three-step process was used to select spectral bands for inclusion in models. First, the data were transformed to permit use of a linear model, which accelerated the computer processing speed for selecting optimal image band combinations. Second, simple linear regression models were fit to the transformed observations. Third, Logistic models using the five best combinations of bands with smallest Root Mean-Square Error (RMSE) were fit to the forest land proportion observations using weighted nonlinear regression where the weights reflected the correlations among observations of subplots within the same plot. The model using the band combination and the corresponding parameter estimates obtained from the nonlinear analyses was used to create a map of forest land proportion predictions by calculating a prediction for each pixel. Each of the five best Log models contained three spectral bands. The best combination of bands identified for the Log approach were leaf-off near infrared (TM band 4), leaf-off normalized difference vegetation index (NDVI), and leaf-on NDVI. Continuous estimates of proportion forest cover were divided into forest and nonforest land cover strata using the same definitions as for ML, described above.

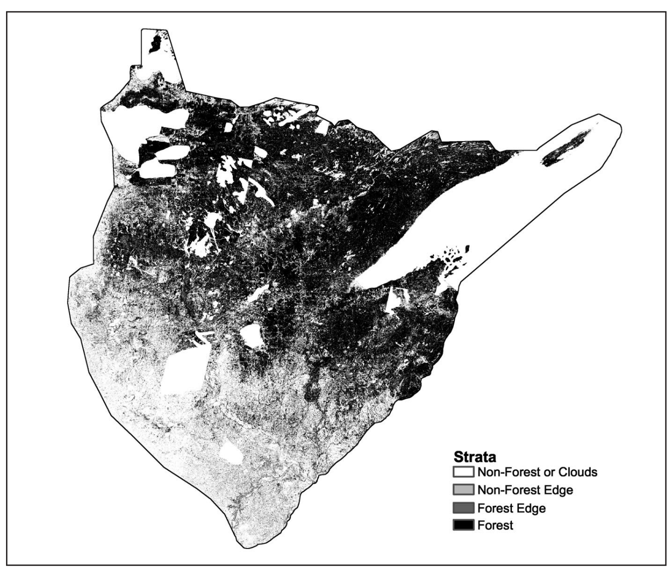
k-NN

The k-Nearest Neighbors technique is a nonparametric approach for predicting values of point variables. Similarity is based on a covariate space between the point and other points with observed values of the variable. McRoberts *et al*. (2002b) describe the k-NN methodology used in this study to create continuous estimates of forest cover. The observed values are the forest cover proportions for each FIA subplot. The forest cover prediction for each pixel is based on the average proportion forest cover of the k subplots with corresponding pixel spectral values nearest to that of the pixel in question. Unweighted Euclidean distance was used to identify those k-neighbors nearest in spectral space. The value of k was based on the number that minimized RMSE for each combination of spectral bands. The leaving-one-out method was used to obtain RMSE of forest land proportion. The five combinations of spectral bands with smallest resulting RMSE were used to predict proportion forest cover for each image pixel. The five best k-NN calibrations had three to five bands. The best calibration contained five bands (tasseled cap: spring brightness, spring greenness, spring wetness, leaf-on greenness, leaf-off brightness) and had a value of k=24. Continuous estimates of proportion forest cover were divided into forest and nonforest land cover strata using the same definitions as for ML and Log, described above.

Classifications based on ML, Fuzz, Log, and k-NN methods were processed further using clump and eliminate functions (Pouncey *et al.* 1999) to remove isolated single pixels and groups of pixels of one class when their contiguous area was smaller than < 0.405 ha (FIA definition of 1-acre minimum area).

Hansen and Wendt (2000) and McRoberts *et al.* (2002a) reported that the efficiency of stratifications was improved when separating edge strata from forest and nonforest strata at forest/nonforest boundaries. Therefore, before performing stratified estimation, image pixels were processed to subdivide both forest and nonforest classes into interior and edge classes. Pixels of either forest or nonforest class that are within a 2-pixel distance (60 m horizontal/vertical distance, 85 m diagonal distance) from a forest/nonforest boundary are labeled as edge pixels. All other pixels are considered non-edge and retain their original designation as forest or nonforest. This procedure resulted in the following classes representing four strata: nonforest, nonforest edge, forest, and forest edge (fig. 4). Edge pixels were not identified for ML3 or Fuzz3 stratification approaches (table 1).

Figure 4.—*ML3Edge stratification: nonforest, nonforest edge, forest, and forest edge strata.*



Stratified Estimation

Stratified estimates of mean plot forest land proportion, $\overline{P}$, and estimated variance, $\hat{Var}\left(\overline{P}\right)$,, are calculated using formulae for stratified analysis (Cochran 1977):

$$\overline{P} = \sum_{h=1}^{L} w_h \overline{P}_h \quad (1)$$

and

$$\hat{Var}(\overline{P}) = \sum_{h=1}^{L} w_h^2 \frac{\hat{\sigma}_h^2}{n_h} \quad (2)$$

where h = 1,…,L denotes stratum; w_h is the h[th] stratum weight; $\overline{P}_h$ is the mean forest land proportion for plots assigned to the h[th] stratum; n_h is the number of plots assigned to the h[th] stratum; and $\hat{\sigma}_h^2$ is the within-stratum variance for the h[th] stratum. Variance estimates obtained using (2) ignore the slight effects due to finite population correction factors and to variable, rather than fixed, numbers of plots per stratum.

Stratum weights were determined as the proportions of pixels assigned to strata. Each FIA plot was assigned to one stratum. We avoided the mathematical complexity associated with spatial correlation among four subplots by assigning plots, rather than subplots, to strata. For this study, only the pixels associated with central subplot locations (plot centers) were used for assigning strata to plots.

Comparisons

Estimates of mean forest land proportion and the standard error of the mean were calculated assuming simple random sampling (SRS) for comparison purposes. Stratified analyses were conducted using either three or four strata, as defined in table 1. For the Log and k-NN analyses, stratifications from only the single best models (based on the smallest standard error of mean proportion forest land) were used (McRoberts 2002).

Results

Zone 41 estimates of mean proportion forest land were similar among all stratified approaches and were slightly smaller than the SRS estimate. Standard errors (SEs) of these estimates were noticeably smaller for the stratified approaches than for the SRS unstratified approach. For ML classifications, replacing bimodally distributed spectral signatures with signatures of normal distribution did not change estimates or standard errors of estimates. Standard errors based on stratifications with four strata were indistinguishable for ML, Fuzz, and Log approaches, and were slightly larger for the k-NN approach. Standard errors were slightly smaller when using stratifications with four strata (nonforest, nonforest edge, forest, and forest edge) than when using stratifications with three strata (water, terrestrial nonforest, and forest) for both ML and Fuzz approaches (table 2).

Discussion

Zone 41 stratifications derived from image classifications are useful for reducing standard errors of mean proportion forest land estimates. None of the stratification approaches is superior to the others, but all are superior to the unstratified SRS

Table 2.—*Simple random sampling and stratified estimation of mean proportion forest land, NLCD 2000 Mapping Zone 41*

Estimate	Stratification approach	Mean proportion forest land	Standard error
Unstratified	SRS	0.41	0.0061
Stratified	ML2Edge	.37	.0038
Stratified	ML3	.38	.0040
Stratified	ML3Edge	.38	.0038
Stratified	Fuzz3	.38	.0039
Stratified	Fuzz3Edge	.38	.0038
Stratified	LogEdge	.38	.0038
Stratified	k-NNEdge	.38	.0039

approach. A vegetation index (NDVI) and a tasseled cap transformation were more useful than TM/ETM+ optical band data for the k-NN and Log approaches, respectively.

In two related studies, both within Zone 41, standard errors of estimates from the Log approach were smaller than for ML and larger than for k-NN approaches in a less heavily forested area in central Minnesota (Nelson *et al.* 2002) but smaller than for the k-NN approach in a more heavily forested area in northeastern Minnesota (McRoberts 2002).

The ML, Fuzz, Log, and k-NN approaches all require acquisition and processing of satellite imagery. A visual comparison revealed the Fuzz approach produced smoothed variants of ML classifications, as expected. Although ML and Fuzz approaches are available as standard components of image processing software, Log and k-NN approaches are less accessible. A tool currently being developed to allow k-NN processing directly from ERDAS Imagine software will allow more widespread use of k-NN for processing satellite imagery. Although the k-NN technique is conceptually easy to implement, careful attention must be paid to its calibration to achieve optimal results. In addition, several precautions should be observed when using the k-NN technique (McRoberts *et al.* 2002b).

More work is needed to determine the optimal threshold for producing stratifications from continuous estimates of proportion forest (e.g., Log and k-NN estimates). Rather than producing a binary stratification (nonforest vs. forest) a stratification with multiple strata could be tested, e.g., 0.0 – 0.2, 0.2 – 0.4, 0.4 – 0.6, 0.6 – 0.8, and 0.8 – 1.0 proportion forest land. Since the estimate of proportion forest land follows a continuum, could we stratify along a comparable continuum? Multiple iterations of stratified estimation could be run, selecting those thresholds where SE's are minimized. If FIA policy requires a nonforest/forest stratification, the above methods could provide a benchmark of potential SEs to gauge performance of nonforest/forest stratification methods.

Zone 41 Landsat TM and ETM+ imagery consists of three seasonal mosaics of adjacent, semi-overlapping scenes from 1999-2001. Spring, leaf-on, and leaf-off imagery include scenes from early March through early May, early June through early August, and mid October through mid November, respectively. When producing zonal mosaics, MRLC gave precedence to selecting overlapping portions of scenes to those dates with least cloud cover. Despite these and other image processing steps employed by MRLC, some cloud cover and scene-related radiometric variability is evident within each seasonal mosaic (fig. 2). The classification/estimation of any portion of an NLCD 2000 mapping zone (e.g., individual TM/ETM+ scene) depends upon the selection of plots and their associated pixels. Future study could compare classifications of individual scenes using only the pixels associated with plots in that scene with their corresponding areas subset from classifications of zonal mosaics using pixels associated with plots distributed throughout the zone. When conducting stratified analyses requiring complete coverage of an area (assigning every pixel to a stratum for determining stratum weights), additional image processing of zonal mosaics may be required to eliminate cloud cover.

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