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Land use change monitoring in Maryland using a probabilistic sample and rapid photointerpretation

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ABSTRACT

The U.S. state of Maryland needs to monitor land use change in order to address land management objectives. This paper presents a change detection method that, through automation and standard geographic information system (GIS) techniques, facilitates the estimation of landscape change via photointerpretation. Using the protocols developed, we show a net loss of forest land, with losses due primarily to urban development and most gains in forest land coming from agricultural land conversions. This study indicates that about 75,000 photo plots would be needed to estimate land use change in Maryland at the county-level, assuming a uniform sampling intensity and a maximum desired county-level sampling error of 20 percent, with an estimated time requirement of 125 h. The protocol we present for designing, planning and conducting a photointerpretation-based land use change procedure can be used by other regions and is well suited for land use change monitoring, assuming that analysis of opportunity costs suggests that existing or new remotely sensed imagery classifications do not meet user needs.

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Introduction

Several recent studies have predicted that urban expansion will continue to be a significant factor affecting forests in many areas of the United States (Stein et al., 2005). For example, Nowak and Walton (2005) predicted that urban land in the United States would nearly triple from 2000 to 2050. Stewart, Radeloff, Hammer, and Hawbaker (2007) documented the current status of forests on the urban fringe, and highlighted potential impacts that continued urban expansion might have on them. Ecological impacts of urban expansion vary, but are generally related to loss of forest or other vegetative cover and increased edge habitat. Increases in edge habitat have been shown to affect populations of forest interior-dwelling species and affect other ecological processes associated with forest patches (Forman, 1995). Loss of forest cover also leads to loss of soil by both wind (Whicker, Pinder, & Breshears, 2008) and water (Rice & Lewis, 1991). The loss of topsoil has the potential to not only lower the productivity of agriculture crops and forest ecosystems, but also to impact aquatic ecosystems through sedimentation, nutrient enrichment, and other factors (Faulkner, 2004).

Data from the U.S. National Resources Inventory (NRI) indicate that more than 40,000 km^2 of forest land in the U.S. state of Maryland were lost to developed land uses between 1982 and 1997 (U.S. Department of Agriculture, 2000). Nowak and Walton (2005) predicted that the percent of forest land in urban areas in Maryland would more than double to 37 percent by 2050. For these reasons, Maryland resource agencies are interested in assessing and monitoring land use change. Of particular concern are the potential impacts of forest change dynamics on the ecologically-sensitive Chesapeake Bay, the watershed that occupies a large portion of the state (Claggett, Jantz, Goetz, & Bisland, 2004; Sprague, Burke, Claggett, & Todd, 2006). The Maryland legislature has adopted legislation (Maryland House Bill 706) that requires "no net loss of forest" by 2020, defined as at least 40% of the state having tree cover. The state must thus implement an affordable, repeatable, detailed assessment of "tree cover" on a periodic basis.

Estimation of forest loss with remotely-sensed data is generally done in three ways: direct observation of the attribute of interest with design-based estimation (e.g., Nowak & Greenfield, 2012), model-assisted estimation (also a design-based approach, e.g., McRoberts, 2010), or model-based estimation (e.g., Stahl et al., 2011). Gregoire (1998) describes the theory behind the use of

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remote sensing images in either a design-based or model-based approach. Generating estimates by creating summaries of pixels most closely resembles a model-based approach to estimation; this is what is typically done when products based on remote sensing are summarized in a geographic information system (GIS).

Olofsson, Foody, Stehman, and Woodcock (2013) point out that traditional remote sensing accuracy assessment methods are often flawed. Furthermore, a significant challenge with the pixel-summary approach to error reporting is that estimators are not necessarily unbiased (Thompson, 2012) and it can be complicated computationally to generate estimates of their variance (e.g., McRoberts, 2010). Probabilistic or design-based sampling, on the other hand, can be used with or without remotely-sensed information, and relies on traditional sampling theory from which to derive inferences (Thompson, 2012). One primary advantage of the direct observation approach with traditional probabilistic sampling is that the estimators can easily be calculated in a spreadsheet using well-understood, common procedures. Furthermore, practitioners and policy makers are very familiar with error indices that are commonly reported like confidence intervals and margins of error. Map-based estimates, on the other hand, require more complicated approaches like Bayesian inference (e.g., Finley, Banerjee, Ek, & McRoberts, 2008) and a reliance on either user-generated or pre-existing land cover products.

The National Land Cover Data (NLCD) (Fry et al., 2011) is a good example of a pre-existing land cover product that is commonly used for resource assessments. The NLCD is a 30×30-m pixel-based dataset created by automated classification of Landsat imagery. It is comprised of per-pixel estimates of percent canopy cover, land cover class for 2006, and change in land cover class between 2001 and 2006. Pre-existing image products like NLCD are not suitable for all applications, however. For example remote sensing-based products do not always provide information that meets user needs. In the case of the USDA Forest Service's Forest Inventory and Analysis Unit (FIA), which is responsible for generating national estimates of forest area dynamics, the definition of "forest" includes areas with ten percent tree cover that are at least 0.4 ha in size and greater than 37 m at their narrowest point (U.S. Department of Agriculture, Forest Service, 2012). Since Landsat pixels are 30-m squares, there is no combination of Landsat pixels that corresponds precisely with this definition. Raciti, Hutyra, Rao, and Finzi (2012) similarly found that differing definitions of "urban" can lead to very different estimates of carbon sequestration when calculated with remotely sensed data.

There are also contextual variables that are included in land cover or use definitions – the FIA forest land use definition, for example, is modified by the presence or absence of structures and roads. Along the same lines, most image classification processes can't incorporate landscape context into decisions – for example, a human observer's identification of cows in a grassland can help identify it as pasture, whereas this information is not available on a satellite image.

Another problem associated with using remote sensing products for resource assessments is simple classification inaccuracy – the model used to generate estimates does not consistently perform well across the landscape. For example, Nowak and Greenfield (2010) found that there were large discrepancies between known tree cover classifications and those contained in the NLCD, due mainly to poor performance of classifiers in heterogeneous areas and definitional differences. They thus chose to perform their own nation-wide photointerpretation-based estimation of tree and impervious cover using their own definitions and in a way that met their accuracy criteria (Nowak & Greenfield, 2012). Hansen et al. (2013) found that accuracy of a global 30-m land cover change product varied by climate zone and vegetation type, leading to both over- and underestimation of some change categories in certain ecosystems. Zheng, Heath, and Ducey (2012) also came to the conclusion that the inappropriate use of remote sensing for carbon quantification can lead to overestimates if fine-scale forest loss that is not detectable in the remote sensing product is not considered. Claggett, Irani, and Thompson (2013) determined that estimates of anthropogenic land cover classes from Landsat classifications were approximately 50% lower than those from more authoritative sources, probably due to some of the same resolution and radiometric limitations identified in Jones and Jarnagin (2009).

While many of these problems can be mitigated by creating new classifications with multitemporal, high resolution imagery, LiDAR and object-based image analysis procedures, creation of these more advanced products can require high levels of skill, specialized software, and significant hardware investments – something many resource agencies can't afford to maintain. These agencies thus often rely on pre-existing imagery products for resource monitoring, and would benefit from an alternative.

An example of the direct observation approach is field-based monitoring of land use change. FIA conducts a field-based, continuous, national forest inventory of the U.S. using standardized methods. FIA is national in scope, and uses standardized variable definitions and a standard timetable. However, by design, the plot and sample designs and variable definitions are not easy to change, making it difficult to adapt to novel monitoring requirements or new classification systems. Furthermore, the intensity of the FIA sample may not be sufficient to provide precise estimates of the area of forest conversion to other land use classes if it is a rare occurrence.

Another example of direct observation is photointerpretation (PI) from high resolution aerial imagery. Modern methods for conducting PI (e.g., computer-aided PI (Pithon, Jubelin, Guitet, & Gond, 2013)) exist, but suffer from some of the aforementioned problems. Ocular PI, on the other hand, has been found to be cost-effective and accurate when conducting large area resource assessments (e.g., Mena, Ormazabal, Morales, Santelices, & Gajardo, 2011; Nowak & Greenfield, 2012). Recent examples include Riva-Murray, Riemann, Murdoch, Fischer, and Brightbill (2010) and Ecke, Magnusson, and Hornfeldt (2013), both of whom conducted a large area PI to assess landscape fragmentation patterns. Canada uses PI as one of the foundations of its national forest inventory (Magnussen & Russo, 2012). The US Forest Service's FIA program has used and currently uses PI in different ways at the local, regional, and national scales (Bechtold & Patterson, 2005, 85 pp.). The primary advantages of ocular PI are that the technology is generally accessible to resource agencies that use GIS, it is easily teachable, land use or cover classes can be chosen to meet detailed user needs, and imagery is often served freely over the Internet and updated frequently, at least in the United States.

To address the challenges associated with using model-based or ground plot-based estimation of landscape change, we created a flexible, inexpensive procedure to supplement FIA land use change estimates using ocular observations on high resolution aerial photography. The objective of the study was to conduct an assessment of land use change in Maryland using methods that could serve to meet Maryland's needs for a repeatable, detailed, probabilistic sampling-based protocol for assessment of forest cover. A goal was to develop a method that could be implemented by resource agencies that might not have a large budget, nor possess the institutional knowledge to perform advanced satellite remote sensing analyses, nor be willing to accept some of the aforementioned challenges of satellite image classification. Additionally, we wanted to obtain information that was compatible with the FIA data and useful to federal and state resource agencies in Maryland.

Methods

Plot design

To estimate land use change using a sample-based approach, we first had to develop a plot design. We decided the plot would consist of at least one subplot made up of a single point at which a PI-based land use category would be assigned. From past experience, we determined that this type of plot is most amenable to rapid PI using FIA land use definitions (USDA Forest Service, 2012). The NLCD land cover change product (Homer et al., 2007) was used as a guide to help determine the optimal subplot count and configuration and to assess various subplot arrangements. The NLCD change product is a pixel-based geographic information system (GIS) dataset in which each 30-m × 30-m pixel is assigned a land cover change category based on comparisons of satellite imagery from circa 1990 and circa 2000. Although not PI-based, the NLCD data were used because they are the only spatially explicit and consistent land change data source that we could use to calibrate our PI study. Focusing on forest loss, we first recoded the NLCD change product such that each pixel was labeled forest loss (1) or other (0). We then randomly generated 100 plots for each county in Maryland, with each plot consisting of an array of 25 subplots arranged in a square grid with 100-m spacing between subplots (Fig. 1).

These plots were used to repeatedly sample the NLCD change product-derived forest loss data using different numbers of subplots per plot. The state-level sampling errors for estimates of forest loss were determined for 10 randomly-selected configurations of subplots for each subplot count category up to 10 subplots. With results for each combination of subplot count and configuration, we calculated the total cost to achieve an acceptable level of precision, which we defined to be a sampling error of 20 percent of the county estimate of mean proportion forest loss. We calculated the sample size and cost using the following equations:

$$n_{\text{required}} = \left(\left(t_{\alpha,n-1} * CV\right)/E\right)^2 \tag{1}$$

and

$$\text{Cost} = a\left(n_{\text{required}}\right) + i * b\left(n_{\text{required}}\right) \tag{2}$$

where n_{required} = the count of plots (sample size) required to reach the desired precision, $t_{\alpha,\,n-1}$ = the critical value of the t distribution associated with a sample size of n at the $1-\alpha$ confidence interval, CV = the coefficient of variation, E = the desired precision expressed as the desired proportion of the mean that the confidence interval will represent – in this case, 0.2, i = the number of subplots in the design, a = the cost in time required for the photointerpreter to switch between plots – in this case, 1 s, and b = the time required to complete a single subplot – in this case, 6 s.

Using the results of the NLCD-based plot design experiment as a guide, we chose the plot design for the PI study. Subplots were arranged on the corners of a 500-m × 500-m square. This was the greatest practical separation distance given the constraints of the photo image resolution and size of the image on the interpreter's screen.

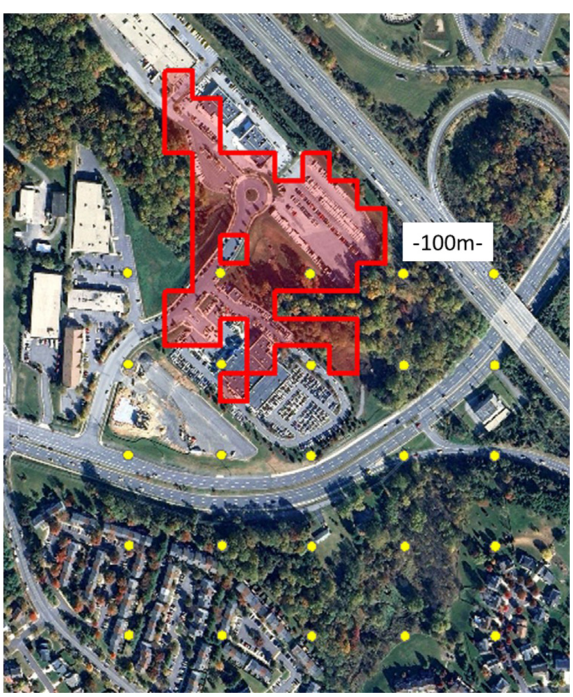

Fig. 1. The 25-subplot plot used to sample the NLCD change product. When subplots (small, yellow dots) intersected the NLCD change category labeled forest loss (red, shaded area), they were counted, and the proportion of subplots counted in this manner was assigned to the plot for purposes of estimating mean proportion of forest loss. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Sample design and PI methods

As a first step in determining the sample design, we defined the population as the land area of the state of Maryland, which is located on the east coast in the mid-Atlantic region of the United States. Since one of our goals was to conduct an assessment that is complementary to the FIA inventory, we chose a spatially balanced sample design that we treat like a random sample using the same principles as those employed by the FIA program and described in Bechtold and Patterson (2005, 85 pp.). Generally, for a given number of plots, a spatially balanced sample provides a more efficient, spatially uniform characterization of an area than a random sample (Cochran, 1977), due to the potential of plot clumping from strictly random designs. FIA assumes that spatial periodicity does not exist in the attributes it measures, making analyses using simple random sampling or post stratified estimators feasible.

To choose the sample, we established a spatially balanced plot network consisting of 5000 randomly selected plots across Maryland using a fractal-based tessellation approach described by Lister and Scott (2009). This method is analogous to that used by FIA to spatially balance the sample using a hexagonal tessellation, but is superior because it does not require decision rules that could potentially over- or under sample edges where partial hexagons occur (Lister & Scott, 2009). These data were then used to reevaluate the number of plots needed for acceptably-precise county-level estimates of land use change in Maryland, using Eqs. (1) and (2), only with the PI data instead of the NLCD change product data.

Land use category was assessed at two points in time (1998 and 2007) on each subplot by interpreting digital aerial imagery. The 1998 imagery consisted of panchromatic, leaf-on, 2-m-pixel resolution, digital orthophoto quadrangles (DOQs) from a state-level imagery dataset stored locally in an ArcGIS raster catalogue. The later date imagery consisted of color infrared, leaf-on, 1-m-pixel resolution, digital imagery from the National Agriculture Imagery Program (NAIP) collected for Maryland in 2007 and served over the Internet using a Web-mapping service (WMS). We assumed that the difference in grain size (pixel resolution) was irrelevant because both 1- and 2-m-pixels yield nearly identical information at the scale at which the aerial imagery we used was displayed. Furthermore, human interpreters are able to use context and logic while toggling between the two dates of imagery to make up for any grain size-related difficulties in classification.

Land use categories used were based on an aggregation of more detailed FIA definitions (USDA Forest Service, 2012), and included Forest, Agriculture, Developed, and Other Nonforest. A single interpreter was trained and conducted all PI for this study. As a quality assurance procedure, the interpreter flagged plots that were difficult to interpret or where she lacked confidence in her land use change decision. Each of these plots was checked by a more experienced interpreter and in some cases with auxiliary spatial data. Because we were primarily interested in studying forest cover change, each of the 322 subplots that were labeled as forest change was reclassified by a more experienced photointerpreter. A subset of 100 points was also randomly selected and blind checked (reinterpreted) to determine the repeatability of the PI methods.

To increase PI efficiency, an automation method was developed whereby an ArcGIS tool was used to extract a subset of imagery from the raster catalogue and the WMS to areas encompassing and slightly beyond the extent of the footprint of each plot. In other words, "snapshots" of imagery at a scale of 1:4000 were generated, with each image centered on the plot and containing sufficient detail for the interpreter to assess land use change. The two sets (1998 and 2007) of 5000 images were stored locally, and displayed using a Microsoft Access form. The form was designed to minimize the number of mouse clicks, wait time for images to load, and data entry time.

Data from the 5000 plots were used to estimate the area of land within each land use change class and its associated precision using a simple random sample estimator (Zar, 1999). Using the same points, the NLCD forest change imagery was sampled to assess its accuracy. In addition, Eqn. (1) was used to calculate the number of plots (and subplots) required to achieve acceptable precision for estimates of forest cover loss, given a more realistic, optimized PI procedure and plot and sample design. Similar calculations could be performed if other landscape attributes were of interest.

Results and discussion

Plot design results

Fig. 2 presents results of our evaluation of how various combinations of subplot counts and configurations affect sampling error, based on estimates of forest loss from the NLCD change product. As subplot count increased, large improvements in precision were observed until the subplot count reached 5 and then the rate of improvement was less pronounced. In other words, the change in the precision level after 5 subplots was not large enough to warrant the additional cost and time to add additional subplots into the final design. For plots with 3 and 4 subplots, we also graphed the average sampling error for those plots where the distance between subplots was maximized. In the best arrangements, subplots were located at the extremes of the subplot grid, where the intersubplot distances were maximized. One would expect this to be the case – subplots located farther apart are more likely to acquire different information about the landscape, making plot level summaries closer to the sample mean and thus lowering the variance of the overall estimate.

We conducted our cost analysis based on these results, using costs associated with between 1 and 5 subplots. With the cost function we chose (Eqn. (2)), we determined that 3 subplots would be the optimal subplot count (Fig. 3). However, for our PI pilot study, we decided to use a 4-subplot design so as not to limit analysis opportunities.

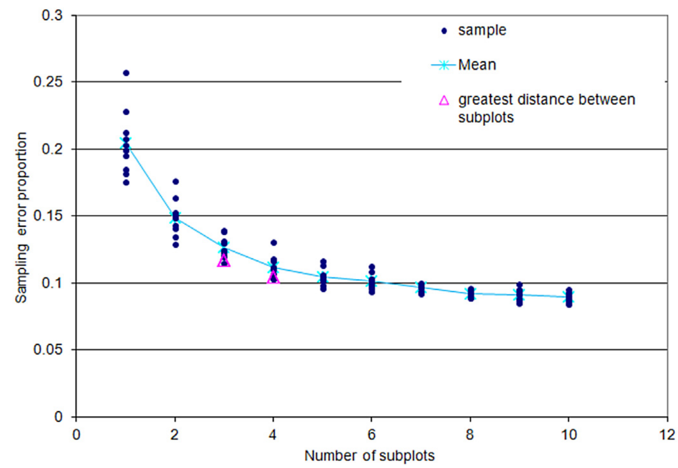

Fig. 2. The relationship between subplot count (various configurations) and sampling error of forest area loss from sampling the NLCD change product.

Quality assurance and control

Quality assurance and control were addressed using a combination of standard methods and project-specific techniques. We were primarily interested in presenting reliable information on forest change and therefore employed methods to limit errors of commission (indicating forest change where there was none) and omission (indicating no change where there was forest change). Classification discrepancies often occur as a result of attempts to classify ambiguous areas, which would be difficult to classify either on the ground or with photos (suggesting that a redefinition of classes should be considered). To mitigate this concern, we used a concept similar to the NLCD 2001 accuracy assessment's reference data confidence rating (Wickham, Stehman, Fry, Smith, & Homer, 2010), where the interpreter flagged certain plots as difficult to classify and in need of closer examination.

Errors of commission and omission were minimized by having a second interpreter re-assess all flagged plots where the original land use class determination was challenging or ambiguous. Errors of commission were further evaluated by having a second interpreter re-assess each of the points that the first interpreter classified as forest gain or loss. Of the 322 subplots that exhibited forest change, 302 were classified the same by both interpreters. Of the 100 random points chosen for the blind check, 96 were classified the same by both interpreters. The combination of the blind check and the reinterpretation of subplots with forest change served as a

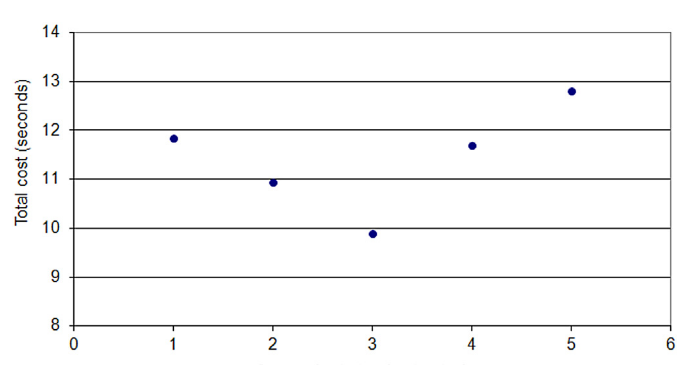

Fig. 3. The relationship between cost and count of subplots. The optimal count was the point at which the cost was minimized.

project-specific quality assurance protocol that would be reasonable for resource managers using this technique to implement.

We chose not to conduct a ground plot-based accuracy assessment because we assumed that photo classifications served as an adequate representation of ground truth. Wickham et al. (2010) state that the NLCD 2001 accuracy assessment procedure also used only photo reference samples. We agree with their assertion that using ground reference data would increase costs, but that future research should explore using a double sampling approach using photos and plots to estimate accuracy.

Land use change results

We analyzed our land use change data assuming a simple random sample design, because, like the FIA program, we assumed that there was no spatial periodicity in land cover change in Maryland (Cochran, 1977) and were interested in an efficient, convenient sample selection procedure. We thus chose to ignore any effects that the spatially balanced, quasi systematic sample might have on sampling errors.

Land use change results from the PI pilot study show an estimated net loss of 113 km^2 of forest land in Maryland from 1998 to 2007, which averages to be more than 12 km^2 per year (Fig. 4). The gross forest loss (267 km^2) was primarily due to conversion to development, accounting for 91 percent of the total forest loss. Most forest gains were from agriculture (91 percent). The loss of forest land to development is an expected result, as Maryland experienced increases in population and housing densities during this period.

The comparison of the NLCD cover change product with the PI indicates a low producer's accuracy: of the 210 subplots that were labeled as forest loss by the PI, only 13 showed the corresponding tree cover loss category on the NLCD product. Of the 123 subplots that showed forest gain from the PI, only one showed NLCD forest gain. For consumer's accuracy, results were similar: of the 231 PI points that showed tree cover loss from NLCD, only 13 showed forest loss from the PI, and of the 74 that showed NLCD gain, only one showed gain from the PI. Visual inspection of misclassified areas indicates that discrepancies arise from either the lack of correspondence between the dates of the NLCD and the PI imagery, definitional differences (tree cover vs. forest), or classification error in the NLCD. Although there was a poor agreement between the NLCD change product and our definition of forest change, we feel that the approach we used to calibrate our plot design is valid not only because our finding of the optimality of large subplot separation distances agrees with those of other studies (e.g., Kleinn, Morales, & Ramírez, 2001), but also, the average patch size of tree cover loss on the NLCD product in Maryland is 0.6 ha, which is plausible based on visual inspection of the imagery. Our conclusion on this matter is that the PI specialists in our study were able to more accurately and with more discriminatory power identify the cover change classes of interest than would have been achieved by naively using the NLCD tree cover change product to assess forest change.

Fig. 5 shows the distribution of forest loss in Maryland between 1998 and 2007. There is a high proportion of forest loss plots in the growing suburbs of Baltimore and Washington D.C., areas that have experienced the greatest pressure from urban expansion. For example, the highest proportion of forest loss plots is found in Prince George's County, which borders Washington D.C. From 2000 through 2007 more than 22,000 new housing units were approved for construction, making this one of the fastest growing counties in the state (Maryland Department of Planning, 2007).

The estimates of proportion of land in each land use change class from this study are similar to those from the FIA data (Fig. 6). These FIA data are based on land use calls made in the field from 954 plots visited in 1999 and revisited from 2004 to 2008. Since we are adopting a similar (spatially balanced) sample design and assumptions similar to those adopted by the FIA program (equal probability of selection of each plot), we interpret the greater precision of the pilot study estimate as an improvement over that from the FIA sample. Although every effort was made to standardize the class definitions and classification accuracy of the PI with those of the FIA ground sample, there may be differences in classification accuracy between the two methods. The added advantage of easily, inexpensively adding more PI plots to the sample and thus gaining precision for estimates of rare events may offset negative effects of small decreases in accuracy from using PI. It should be noted that if analysts are not confident in their ability to accurately characterize the land cover classes of interest from PI, they should collect information on ground plots in order to assess PI accuracy and bias.

Our pilot study's approach also offers the additional benefit of flexibility—it provides a framework with which to efficiently conduct multi-scale assessments. For example, based on results from the pilot study, a second project was conducted in which 3465 additional plots were located in Prince George's county, Maryland where finer-scale land use dynamics were assessed (Lister & Lister, 2006). Finally, the efficient methodology we developed will allow for not only spatial intensification, but also temporal intensification. Each time new NAIP or other resource imagery comes

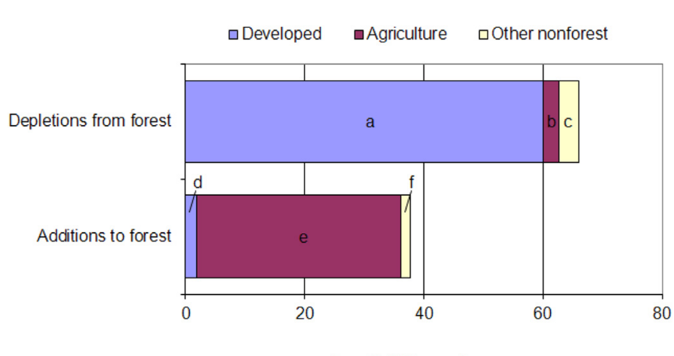

Fig. 4. Estimates of total areas of different land use change categories. Sampling errors are as follows: a: 8%; b: 35%; c: 32%; d: 33%; e: 10%; f: 45%.

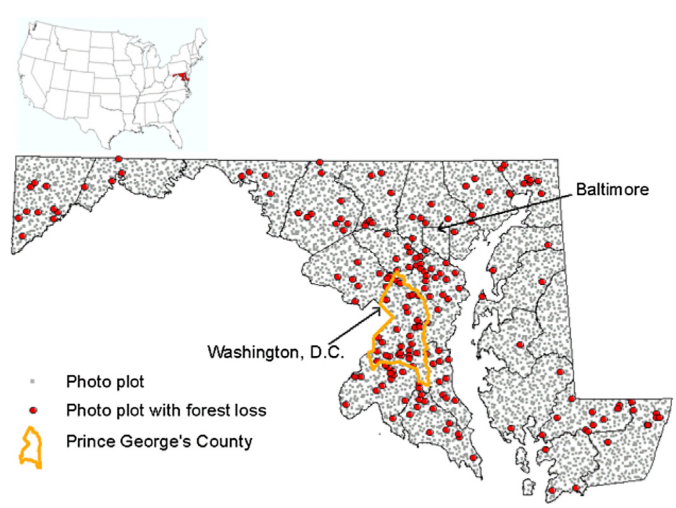

Fig. 5. Distribution of land use plots highlighting plots showing forest loss, 1998–2007, Maryland.

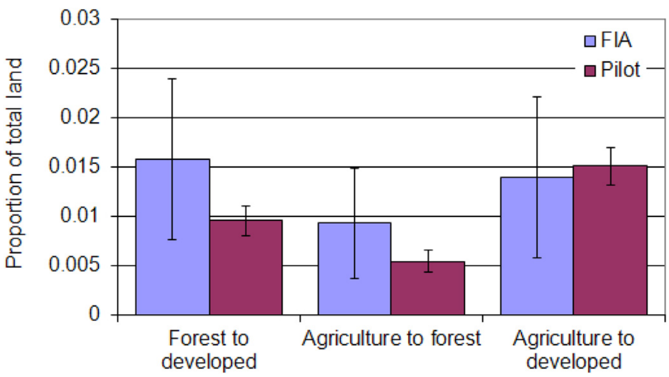

Fig. 6. Comparison of FIA (1999–2008) and pilot study (1998–2007) mean land use change categories, Maryland. Error bars represent 95 percent confidence intervals.

available, a new change assessment can be conducted using the same plots and exact same classification rules. FIA data, on the other hand, is tied to a 5-year remeasurement cycle, and the sample is unlikely to be temporally intensified in the future.

Reevaluation of study design using study results

During this study, we made improvements in PI methodology that substantially lowered the cost (in terms of time) involved in switching between photos and entering data. As our initial estimate of one second spent switching between photos neared zero (using our rapid PI tool), the time associated with doing a single plot of 4 subplots was not substantially different from doing 4 single-subplot plots. We therefore determined that the optimal plot design for future work would be a single subplot design.

Using results from the pilot study, we reevaluated the number of plots that would be necessary to estimate land use change at the county level in Maryland with our definition of acceptable precision – having a sampling error no more than 20 percent of the county-level estimate at a 95 percent confidence level. Due to differences in the amount of land cover change we observed in each county, the plot density needed (calculated from Eqn. (1)) for acceptably precise county-level estimates ranged from one plot per 11 ha in counties where change was rare to one per 135 ha in counties where change was more common. The counties where we would expect the greatest amount of forest land change based on housing starts data (Maryland Department of Planning, 2007) would be sufficiently sampled with a plot intensity of one plot per 37 ha. If we used this as a starting point on which to base a uniform sample of the entire state, we estimated that 75,000 plots would be needed in Maryland for acceptably precise county-level estimates of land use change in the counties of most interest to planners. Results from the study show that, on average, 10 points can be photointerpreted per minute, thus to complete the PI work for the whole state, this translates to approximately 125 h of work using our PI protocols. Future work should involve investigation of the use of bootstrap variance estimators, which have the potential to offer significant cost savings by requiring fewer plots in some situations (Efron, 1982). Similarly, different stratification approaches could target areas having higher risk for deforestation or more ecological importance with more plots.

Conclusions

Land managers must decide how the combination of their information requirements, budget, available remote sensing and GIS skills, and presence of existing data will affect design choices in landscape assessment projects. Opportunity costs should be considered – new or existing satellite imagery classifications have some advantages over ground- or PI-based approaches, but they might not meet user needs in a cost-effective way, especially if needs include complex classification systems that require knowledge of land cover context to apply. PI-based approaches can offer several advantages, including low interpreter skill and technology requirements, more flexibility and feasibility in meeting class definition requirements using ocular classification, the ability to use sampling theory to both design the inventory (determine required sample sizes for a given precision requirement) and interpret results (calculate sampling errors and other related indices), and the repeatability of methods and definitions through time as new aerial imagery acquisitions occur. One concern with the approach is that when large numbers of points are interpreted, quality could suffer. We highly recommend a rigorous focus on quality assurance and training of interpreters to mitigate this potential problem. The state of Maryland should consider a PI-based monitoring approach like that presented here to meet their land use monitoring needs.

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