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Maintaining the confidentiality of plot locations by exploiting the low sensitivity of forest structure models to different spectral extraction kernels

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The United States Forest Service Forest Inventory and Analysis (FIA) unit maintains a large national network of inventory plots. While the consistency and extent of this network make FIA data attractive for ecological modelling, the FIA is charged by statute not to publicly reveal inventory plot locations. However, use of FIA plot data by the remote sensing community often requires that plot measurements be matched with spatially correspondent values from spectral or geographic data layers. Extracting spatial data in a known way and associating it with plot information leaves open the possibility that a user might use extracted spatial characteristics and a moving window filter to directly infer the plot's location. Direct inference of plot location in this way would be impossible, however, if the original method of sampling the geographic data was unknown. Tests using five Landsat scenes covering a wide range of ecological types showed that varying the weights of pixels within approximately 50 m of the plot centre has little effect on the quality of subsequent models predicting basal area. This finding may support the development of automated extraction routines that vary (perhaps randomly) the geographic data extraction process and therefore increase the security of FIA plot locations.

1. Introduction

1.1 *Sharing spatially specific inventory data without revealing coordinates*

The United States Forest Service's Forest Inventory and Analysis (FIA) unit maintains an extensive network of systematically distributed forest inventory plots across the United States. This network supports federally mandated (McRoberts 2005) analysis of the status and trends of the nation's forests. FIA's plot data are also extensively used to train and validate remote sensing-based forest mapping (Gill *et al.* 2000, Schroeder *et al.* 2007, Zheng *et al.* 2007, Goward *et al.* 2008). A primary obstacle to the wider use of FIA data by the

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remote sensing community is a restriction, also federally mandated, that the exact location of the plots not be known by the public. This restriction serves to protect the privacy of forest owners, and, as is a concern with other strategic forest inventories, it also prevents differential management of stands known to contain sample plots.

Frequently, users want to model forest attributes collected on FIA plots as functions of any number of spatial predictor layers. Such predictor layers, for example satellite imagery or surfaces depicting ownership or climate, allow resulting models to be applied in the creation of forest attribute maps over large geographic areas. Because of plot security concerns, FIA has chartered a Spatial Data Services (SDS) team to provide, among other services, the link between spatial datasets and inventory information without revealing plot locations. Often, SDS accepts thematic or raster-based predictor layers from a user and extracts from those layers the values corresponding to FIA plot locations. The associated inventory and predictor data can then be used to both build and validate forest condition models without the user knowing exact plot locations.

Although extraction of spatial data associated with plot locations can be easily achieved through simple geographical information system (GIS) operations, SDS spends considerable time with each request to ensure that plots are not so unique with respect to the predictor data that their position on the map can be inferred. SDS could process orders more quickly if a method of predictor extraction was available that could significantly reduce the ability of a user to trace extracted predictor data back to a particular part of the landscape.

1.2 *A partial solution: variable pixel weighting*

This article considers the common case of raster-based predictor layers, such as Landsat satellite data, that have moderate spatial resolution. In such cases, where several pixels cover the area surveyed by an inventory plot (see figure 1), the possibility exists that a user might infer a plot's location by applying to the original predictor data a filter that mimics FIA's extraction routine. Figure 2 presents a simple example of a 3×3 extraction window, where the mean of the nine pixels nearest the plot centre is the spectral value delivered to the client for modelling. A user aware of this extraction routine could construct a moving window filter to simulate the extraction process, allowing all locations with the value extracted by SDS to be quickly highlighted. More complex extraction windows could also be mimicked. Simple probability theory dictates that with even strongly correlated 8-bit data (possible values 0–255, which is the low end of typical bit depth for this type of data) almost every possible plot location is likely to have a unique combination of predictor values in a typical six-band image.

The idea explored in this article is that the duplicative filtering illustrated in figure 2 might be largely avoidable if the spectral extraction routine was unknown to the user. One option for varying how spatial data are extracted is to vary how the pixels in the area of the plot are weighted. Figure 1 illustrates five variations of this idea. Each star within a particular weighting kernel represents a point at which the spatial data are sampled. All extracted values for each grid of points are averaged, meaning that pixels with more stars have a higher weight in the value extracted for the plot. If the number, density and orientation of points around each plot varied in an unknown way (perhaps at random within reasonable limits), it would be impossible to construct a duplicative filter that precisely identified possible plot locations. The pixel weighting strategies illustrated in figure 1 represent five out of an almost unlimited number of permutations of local plot weight configurations.

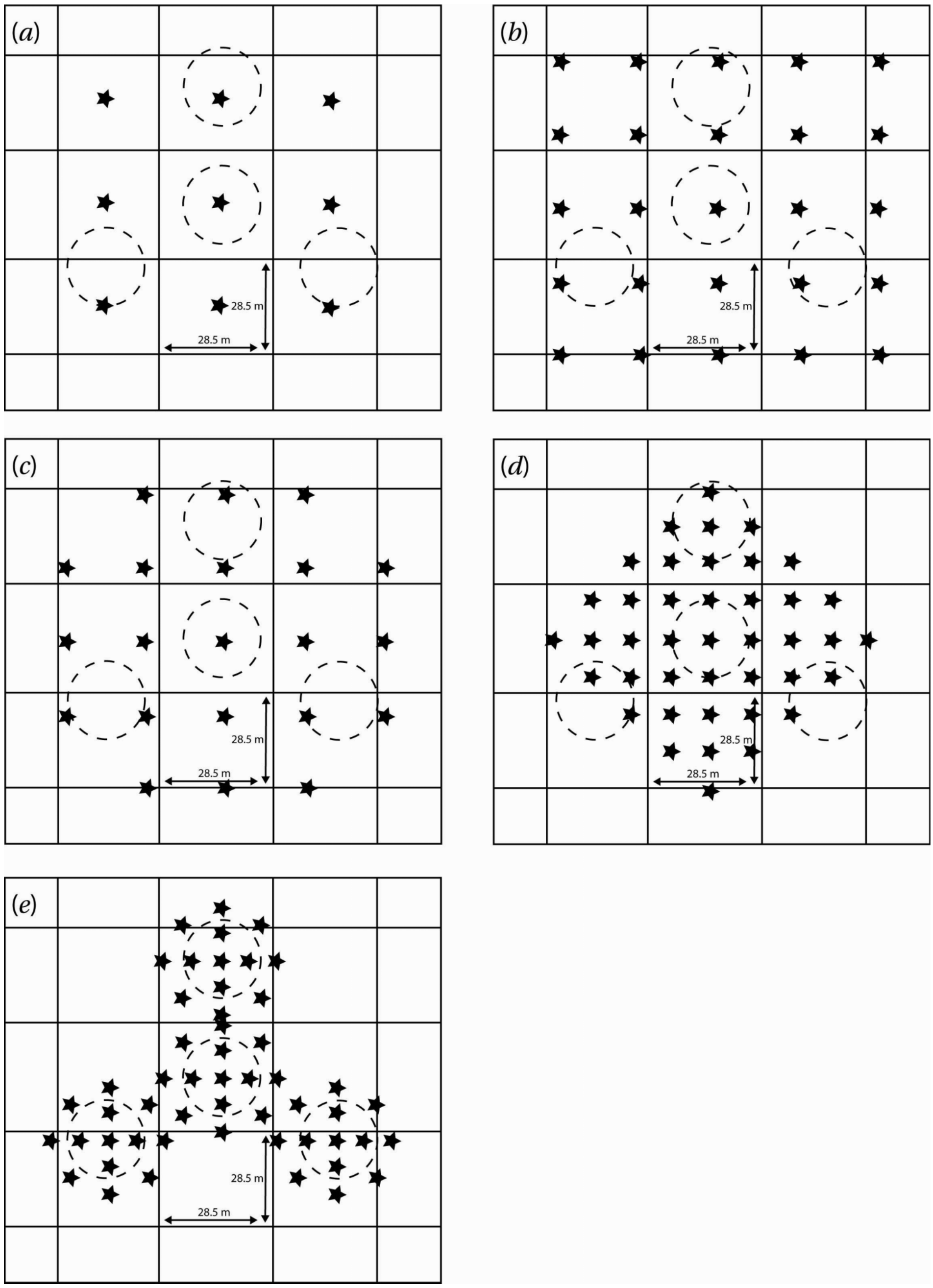

Figure 1. Spatial relationship between Forest Inventory and Analysis (FIA) plots (containing four 7.3 m-radius sub-plots, depicted with dashed-line circles) and Landsat-scale (28.5 m) pixels. The five extraction kernel methods used in this article and illustrated here include: (*a*) '3 × 3', (*b*) '5 × 5', (*c*) 'circle', (*d*) 'diamond' and (*e*) 'FIA'. Each star can be considered a 'vote' for the plot's spectral average, with pixels containing more stars having a greater weight in the extracted value.

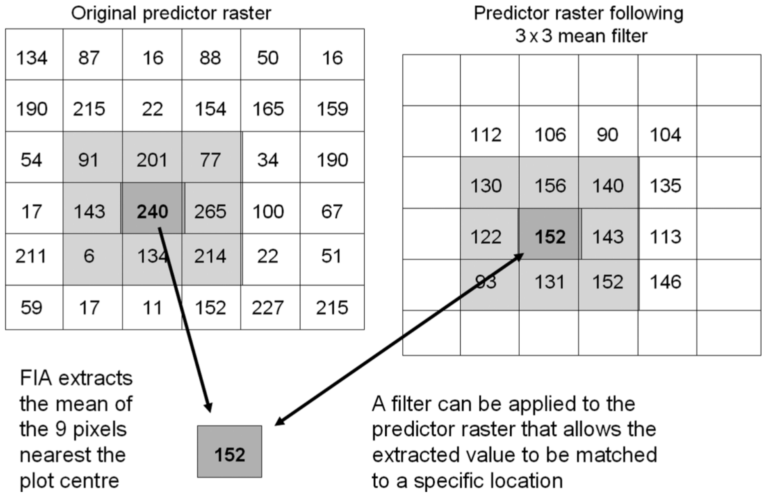

Figure 2. Illustration of how an extracted spectral value may be used to infer plot location if the extraction method is known. In this case, a 3×3 mean filter was used to duplicate the 3×3 extraction window. While the extracted value (152) corresponding to the plot centre (dark grey pixel) may match several potential locations within an image, the inclusion of this value in a vector of values extracted from the five other Landsat bands will dramatically narrow the field of potential plot locations.

While using this type of variable weighting kernel may prevent the type of location inference shown in figure 2, it would be useful only to the extent that extracted values have value for legitimate modelling purposes. We tested the five representative weighting kernels shown in figure 1 for their ability to support models of basal area. Significant differences in the quality of models resulting from the five weighting strategies would suggest that weighting of local pixels is an important variable, and that plot concealment through randomized extraction kernels would introduce new uncertainty to the modelling process. Insight from this investigation may be of use as SDS explores options for better supporting spatially explicit use of FIA data. More broadly, this test may inform researchers in their choice of an optimal extraction procedure; significant differences in model accuracy among pixel-weighting strategies would advocate for tailoring extraction kernels to the spatial properties of specific plot designs.

2. Materials and methods

2.1 *Study area*

Landsat imagery was acquired (table 1) for five ecologically diverse areas within the United States (figure 3). Two of those scenes (Worldwide Reference System 2, WRS-2, path/rows 45/29 in Oregon and 37/35 in Arizona) covered areas with relatively high topographic relief and coniferous forests. Scene 17/31 (in Pennsylvania and New York) covers primarily broadleaf forests with moderate topographic relief. The two other scenes (27/27 in Minnesota and 16/37 in South Carolina) are relatively flat and contain significant amounts of broadleaf, conifer and mixed stands. These areas are a subset of the national sample used by the North American Forest Dynamics Project (NAFD; Goward *et al.* 2008) to characterize national disturbance trends.

Table 1. Image and plot resource data for each study scene. Mean basal area was calculated from all available forested plots in each scene. Model root mean square error (RMSE) was derived from Random Forests predictions of basal area, averaged over all five extraction methods. 'Primary Forest Type' indicates whether within each scene there were significant numbers of plots labelled as coniferous (con), hardwood (hw), or mixed coniferous/hardwood (mixed) forest types.

WRS-2 path	WRS-2 row	US region	Image acquisition date	No. of plots available	Plot mean basal area ($m^2\ ha^{-1}$)	Model RMSE ($m^2\ ha^{-1}$)	Primary forest type
16	37	SE	19 July 2002	422	21.6	14.5	con, hw, mixed
17	31	NE	6 September 2000	385	24.3	10.3	hw
27	27	N	5 July 2001	961	17.4	8.4	hw, con
37	35	SW	9 July 2003	142	19.1	12.3	con
45	29	NW	18 August 2003	260	32.6	18.5	con

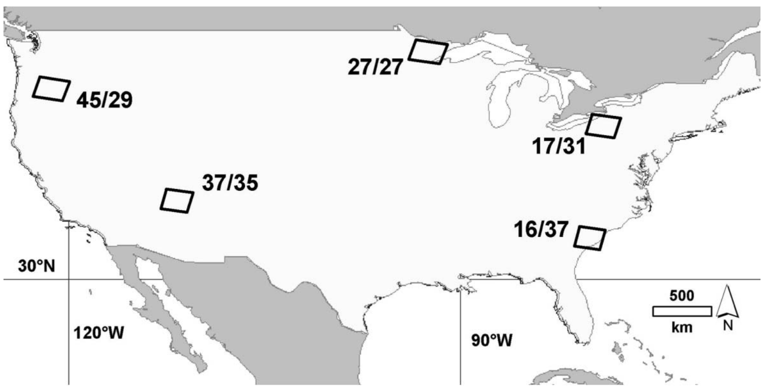

Figure 3. Locations of the five study areas within the United States. Path/row identities include: 16/37 (South Carolina), 17/31 (Pennsylvania, New York), 27/27 (Minnesota), 37/35 (Arizona) and 45/29 (Oregon).

2.2 *Assembly of spectral and plot data*

All imagery was acquired by the Landsat 5 TM (Thematic Mapper) sensor, except for the scene 27/27 image, which was acquired by the Landsat 7 ETM+ sensor (Enhanced Thematic Mapper Plus-scan line corrector – on). Radiometric conversion of bands 1–5 and 7 to surface reflectance was accomplished through the NASA Landsat Ecosystem Disturbance Adaptive Processing System Project (LEDAPS; Masek *et al.* 2006). These surface reflectance values were the spectral values tested in subsequent modelling. For the area covered by each Landsat frame, FIA plot-level measurements of basal area made within 2 years of image acquisition were assembled. FIA plot data may be freely downloaded (http://fia.fs.fed.us/, accessed February 2009), although for reasons stated above, the precision of geographic coordinates in publicly available data is deliberately degraded. Actual plot locations were used for this work. FIA measurement plots are comprised of four circular sub-plots, the orientation and dimensions of which in relation to 28.5-m pixels may be seen in figure 1.

Plots are distributed throughout the nation at a density of approximately one plot per 2430 ha. More detailed information about FIA sampling protocols is available elsewhere (Forest Inventory and Analysis 2008).

Basal area was chosen as a test variable because it is an important forest structure variable and because it can be well correlated with Landsat reflectance data. For example, Healey *et al.* (2006) found correlations between log-transformed basal area and simple spectral bands of the order of 0.5 to 0.6. Because FIA plots are sampled at different rates in different parts of the country, and because different scenes contain different areas of forest, the study areas contained varying numbers of FIA plots (table 1). Only plots falling completely within a forested condition were considered. Average basal area within the assembled plot data varied by study area, as detailed in table 1.

2.3 *Testing different pixel weighting configurations*

For each plot and each weighting kernel, lists were developed containing coordinates corresponding to the orientation of starred points shown in figure 1. The density and orientation of grid points around each plot varied by kernel, but each kernel sampled basically the same pixels surrounding the plot centre; no configuration had sample points greater than 50 m away from the plot centre. For each weighting scheme, the mean spectral values for each of the six Landsat reflectance bands were associated with FIA measurements of basal area. Sixty percent of the plots were randomly allocated to model building, and 40% were reserved as an independent test set.

Models for predicting basal area were made using Random Forests (Breiman 2001) with Landsat data extracted using each of the five pixel weighting strategies. Random Forest is a recursive, non-parametric, tree-based approach that is widely used in ecological modeling (e.g. Lawrence *et al.* 2006, Prasad *et al.* 2006, Cutler *et al.* 2007). This work was done with R statistical software (R Development Core Team 2008) using an implementation of Random Forests developed by Liaw and Wiener (2002) and adapted by Freeman and Frescino (2009). Each of the 25 test models (basal area in five regions predicted using Landsat data extracted five different ways) used 2000 trees created with random subsets of the test data. Although additional predictor variables such as elevation would normally be used as input for these models, only Landsat data were used in this comparison to simplify interpretation of any differences in predictive ability. Those differences were examined by performing repeated measures Analysis of Variance (ANOVA; Zar 1999) on three common diagnostics of prediction quality: root mean square error (RMSE), relative bias and variance ratio. Bias was how much higher or lower (by percentage) the mean prediction was than the mean test observation. Following Cohen *et al.* (2003), variance ratio was defined as the standard deviation of the predicted values divided by the standard deviation of observed values. This calculation will have a value above one if the variance of the predictions is higher than the variance of the test set, and a value below one if the variance of the predictions is lower than that of the test set. Using predictions for the independent test set, repeated measure ANOVA tested whether or not there were significant differences in the three prediction diagnostics among the five pixel weighting strategies over the five test sites.

3. Results

Diagnostics of model predictions showed relatively stable characteristics across the study scenes. RMSEs ranged from 40–70% of the mean plot value (table 1). Prediction bias was generally below 5% (positive), with the exception being scene 16/37 in South Carolina (figure 4(*b*)), in which predictions were negatively biased by 8–10%. Poor model performance in this scene was correlated to its diverse forest types (table 1); ancillary data related to species groups may have improved model performance. The variance of predictions in all scenes was significantly compressed relative to the

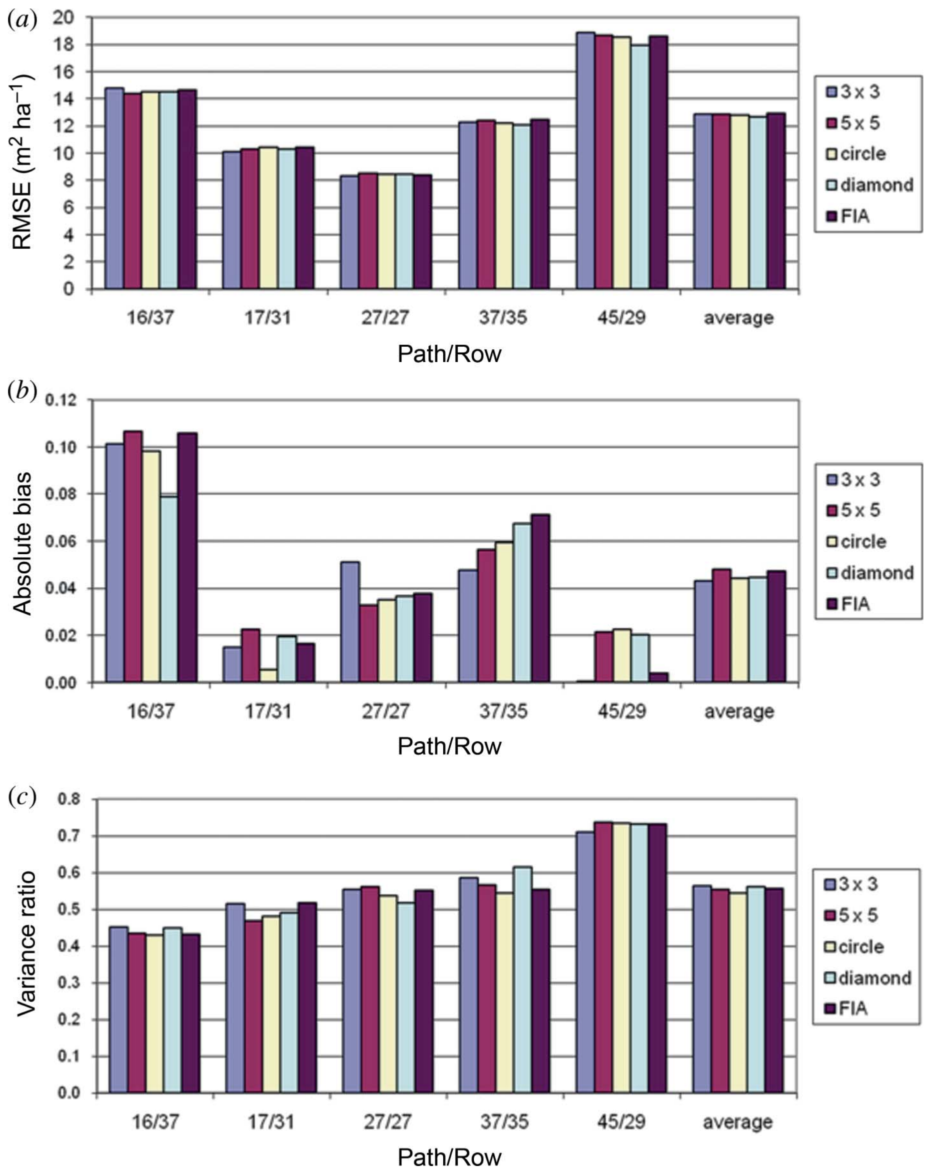

Figure 4. Diagnostics of models created using Landsat predictor data created with each of the five extraction kernels, including: (*a*) 3 × 3 pixel sample points, (*b*) 5 × 5, (*c*) circularly oriented sample points, (*d*) diamond-shaped, (*e*) and centred around the putative locations of the FIA sub-plots. Note that (*b*) shows the absolute value of the relative prediction biases. The mean bias values for 16/37 were actually negative; positive biases were seen in the other four scenes.

variance present in the test plots (figure 4(*c*)); this is a common phenomenon with ecological predictions derived from satellite data (Cohen *et al.* 2003).

Across the five study scenes, the five alternative pixel weighting strategies produced slightly different spectral values for each plot. The near-infrared band (Landsat B4) varied the least among weighting strategies (approximately 1% standard deviation of extracted values per plot) followed by the green (B2) and both shortwave infrared bands (B5 and B7; approximately 2%) and finally by the blue (B1) and red (B3) bands (3%). The models created using data extracted under the five tested approaches differed slightly in the predictions created for the independent test set (see figure 4). However, differences in the RMSE, bias and variance ratio of these predictions were not consistent over the five study areas, and repeated measures ANOVA suggested no significant differences among pixel weighting kernels in any of the three measures at the 0.10 confidence level.

4. Discussion

Across the five study regions, the configuration of the pixel extraction kernel had no significant effect on model error, bias or variance ratio. As might be expected, slightly different values were extracted using each method. However, differences in model characteristics were relatively small and were inconsistent from scene to scene. Considering the diversity of sample grid points used in the kernels that were tested, this suggests that models produced with moderate-resolution multispectral data are relatively insensitive to subtle alterations of the pixel extraction window.

Concerns about plot location aside, this finding downplays the importance of kernel selection in the image processing stage of model-building, at least with model variables and spectral data similar to those studied here. A straightforward 3×3 pixel extraction window (figure 1(*a*)) produced data with no more or less capacity to predict a basic measure of forest structure than data derived using pixel-weighting strategies designed to more closely reflect the geometry of the putative area measured by the FIA inventory (figure 1(*e*)). There are at least three factors that may explain why no difference was detected in the quality of models built using spectral values extracted in different ways. First, spatial autocorrelation of forest condition surely reduces the consequences of small changes in how spectral data are sampled. Keeping in mind that fairly homogenous stands can contain tens of thousands of Landsat pixels, relatively subtle changes in the extraction footprint may not result in significantly different modelling sets. Another factor minimizing the effect of variable pixel weighting is uncertainty related to the spatial correspondence between plot and image coordinates. Although orthorectified imagery was used in this experiment and plot coordinate accuracy is typically within approximately 10 m of the actual site (Hoppus and Lister 2007), errors in plot coordinates and image georeferencing may compound one another. The result may be a loss of spatial precision that may overcome any efforts to closely match an area of the image to the area sampled on the ground. Lastly, it must be acknowledged that the statistical relationship observed between Landsat reflectance and basal area was limited. RMSEs were typically over 40% of the mean basal area. Models producing more precise and accurate predictions, either because of different forest types, satellite data or modelling methodology may prove to be more sensitive to the method of spectral extraction.

One method of extracting spectral values not tested here would be to segment the imagery into coherent spectral objects and associate with each plot the characteristics of the surrounding object. This extraction method would conceal the location of the plot, at least within the image segment from which the spectral data were drawn. This approach has been successful with high spatial resolution imagery (e.g. Chubey *et al.* 2006), and may be particularly desirable when the mapping unit is the image segment rather than the image pixel. However, the usefulness of this extraction strategy in pixel-based modelling with moderate-resolution imagery is debatable, particularly in stands that are not extremely homogenous. Mäkelä and Pekkarinen (2001), working with Landsat data, found that expanding the extraction window beyond the approximately 3×3 pixel ($90\ \mathrm{m} \times 90\ \mathrm{m}$) area tested here resulted in a decline in the accuracy of subsequent models. This finding held even if image segments were used to ensure extraction of relatively uniform pixel populations. Image segments could theoretically be derived to capture only a small area around each plot, although such extraction windows would differ little from those studied here, and smaller segments would naturally have less value in obscuring plot location.

Another alternative for providing extracted data in a way that prevents inference of plot location would simply be to multiply each value by a random number near 1.0. Liknes *et al.* (2005) found that 'perturbing' extracted data in this way does indeed reduce the likelihood of tracing data back to a particular location, with greater randomness leading to greater uncertainty about plot location. Since removing spectral detail may result in a reduced ability to discriminate among forest conditions, it is desirable to add only enough 'noise' to maintain the possibility of multiple locations for each plot.

Like the approach of Liknes *et al.* (2005), the methods investigated here involve stochastic variation of pixel values. FIA could randomly vary pixel weights (five realizations of which were tested here) to add uncertainty to the relationship between a plot's location and any extracted spectral values. However, the level of this variation would be context-sensitive instead of uniform across an image (as was the approach of Liknes *et al.*). For plots in spectrally heterogeneous areas, differentially weighting local pixels should result in a greater range of returned spectral values than would occur in areas where spectral values have little local variation. This may be advantageous; the potential 'noise' added to spectral values is lower in homogenous forests and higher in locally variable forests where the reflectance of a single plot is more likely to be unique. Thus, more noise is added where it is needed. This is in no way, however, an optimization of the balance between the need to conceal plots and the need to retain spectral detail. Such optimization would be a worthwhile subject for future research. Rather, the approach studied here simply represents an easily implemented, locally sensitive means of perturbing extracted spectral data in a way that does not significantly degrade the quality of basic forest structure models.

5. Conclusions

For FIA, the demonstrated relative indifference of forest structure models to the extraction routine may provide a means to address an institutional challenge. In supporting the remote sensing community, FIA faces a balancing act between maintaining plot location confidentiality and trying not to remove too much of the spectral signal that ties the forest to satellite measurements. Indeed, it is the relationship between a location's reflectance and its forest cover that is at the heart of the modelling process. By randomly shifting the number and configuration of local spectral weighting points (five representative alternatives of which were tested here), FIA should be able to prevent the duplicative filtering that allows precise inference of a plot's location. At least for the type of moderate-resolution imagery studied here, subtle variations in pixel weights do not significantly affect the modelling process. Implementation of variable pixel weighting should therefore provide an automated extraction approach that addresses FIA concerns about plot confidentiality without compromising the value of the plot data in subsequent modelling applications.

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