INTEGRATION OF LIDAR AND LANDSAT ETM+ DATA

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ABSTRACT

Lidar data provide accurate measurements of forest canopy structure in the vertical plane however current lidar sensors have limited coverage in the horizontal plane. Landsat data provide extensive coverage of generalized forest structural classes in the horizontal plane but are relatively insensitive to variation in forest canopy height. It would therefore be desirable to integrate lidar and Landsat data to improve the measurement, mapping, and monitoring of forest structural attributes. We tested five aspatial and spatial methods for predicting canopy height, as measured by an airborne lidar system (Aeroscan), from Landsat ETM+ data: regression, kriging, cokriging, and kriging and cokriging of regression residuals. Our 200 km^2 study area in western Oregon encompassed Oregon State University's McDonald-Dunn Research Forest, which is broadly representative of the age and structural classes common in the region. We sampled our continuous lidar coverage in eight systematic patterns to determine which lidar sampling strategy would optimize lidar-Landsat integration: transects sampled at 2000, 1000, 500 and 250 m frequencies, and points sampled at these same spatial frequencies. The aspatial regression model results, regardless of sampling strategy, preserved actual vegetation pattern, but underestimated taller canopies and overestimated shorter canopies. The spatial models, kriging and cokriging, produced less biased results than regression but poorly reproduced vegetation pattern. The integrated models that kriged or cokriged regression residuals were preferable to either the aspatial or spatial models alone, because they preserved the vegetation pattern like regression yet improved estimation accuracies above those predicted from the regression models alone. We concluded that in our study landscape, an integrated modeling strategy is most suitable for estimating and mapping canopy height at locations unsampled by lidar, and that a 250 m point sampling strategy would be more useful for lidar-Landsat ETM+ integration than sparser transect sampling strategies planned for satellite missions.

1. INTRODUCTION

Lidar data provide detailed information on forest canopy structure in the vertical plane but over a limited spatial extent (Lefsky et al., in press). Landsat data provide useful structural information in the horizontal plane (Cohen and Spies, 1992) but are relatively insensitive to canopy height. Lidar-Landsat ETM+ integration is therefore a very logical goal to pursue. No remote sensing instrument is suited for all applications, and there have been several calls for improving the applicability of remotely sensed data through multisensor integration. Most multisensor integration studies published up to this point have involved Landsat imagery (e.g. Oleson et al., 1995; Asner et al., 1997) but none have integrated Landsat imagery with lidar data.

Lidar-Landsat ETM+ integration has immediate relevance due to the anticipated launches of the Ice, Cloud, and Land Elevation Satellite (ICESat) and Vegetation Canopy Lidar (VCL) satellite missions. The global sampling of the earth's forests, as VCL should provide, will be a huge boon for forest resource assessments. For example, the VCL mission has potential to greatly narrow the uncertainty surrounding estimates of global C pools. Discontinuous lidar data will need to be integrated with continuous optical imagery to produce comprehensive maps that have practical value to forest ecologists and forest resource managers (Lefsky et al., 1999c). Given the continued demand for Landsat imagery, the growing supply of imagery from Landsat 7, and the recent decommissioning of Landsats 4 and 5 (and thus any further TM or MSS data), ETM+ imagery from Landsat 7 is a logical choice for integrating with lidar sample data.

In this study, our first objective was to estimate canopy height at locations unsampled by lidar, based on the statistical and geostatistical relationships between the lidar and Landsat ETM+ data at the lidar sample locations. We used the most basic data from lidar (maximum canopy height) and Landsat ETM+ (raw band values) and tested widely used, straightforward empirical estimation methods: ordinary least squares regression, ordinary kriging, and ordinary cokriging.

Prior research has shown that landscape pattern varies principally as a function of the areal size of individual stands in the heavily managed forests of western Oregon, or at a typical scale of 250-500 m (Cohen et al., 1990; Milne and Cohen, 1999). Thus, we hypothesized that VCL may undersample the landscape relative to the spatial scale at which most canopy variation occurs in western Oregon forests, and in perhaps most other forested regions. Our second (yet equally important) objective was to determine what spatial sampling design would optimize the integration of lidar and Landsat ETM+ data for accurate mapping.

2. BACKGROUND

2.1 Lidar

Lidar (LIght Detection and Ranging) is an active remote sensing technology like radar but operating in the visible or near-infrared region of the electromagnetic spectrum. Lidar at its most basic level is a laser altimeter that determines the distance from the instrument to the physical surface by measuring the time elapsed between a laser pulse emission and its reflected return signal. This time interval multiplied by the speed of light measures twice the distance to the target; dividing this measurement by two can thus provide a measure of surface elevation (Bachman, 1979). Processing of the return signal may identify multiple pulses and returns. As a result, trees, buildings, and other objects are apparent in the lidar signal, permitting accurate calculation of their heights (Nelson et al., 1984). Studies using coincident field data have indicated that lidar data can provide non-asymptotic estimates of structural attributes such as basal area, biomass, stand volume (Nilsson, 1996; Nelson et al., 1997; Lefsky et al., 1999a,b; Means et al., 1999, 2000), and leaf area index (LAI) (Lefsky et al., 1999b), even in high-biomass forests. Lidar allows extraordinary differentiation between young, mature, and old-growth stand structure that is currently unrivaled by any other remote sensing technology (Lefsky et al., 1999b; Weishampel et al., 2000).

Lidar instruments can be divided into two general categories: discrete return and waveform sampling (Lefsky et al., in press). They are distinguished in part by the size of the laser illumination area, or footprint, which typically is smaller with discrete-return systems (0.25-1 m) than with waveform-sampling systems (10-100 m). Waveform-sampling systems compensate for their coarser horizontal resolution with finer vertical resolution, providing sub-meter vertical profiles, while discrete-return systems record only 1-5 returns per laser footprint. Discrete-return systems are more suited for supplying the demand for accurate, high-resolution topographic maps and digital terrain models, and are therefore becoming widely available in the commercial sector (Lefsky et al., in press). The most advanced vegetation application of waveform-sampling lidar data to date has been the development of a canopy volume profile in high-biomass forests, which provides a more direct measure of physical canopy structure than any other remote sensing technology so far (Lefsky et al., 1999b).

VCL is a spaceborne, waveform-sampling lidar system that will inventory canopy height and structure between ±68° latitude for an estimated 2 years. VCL footprints will be approximately 25 m in diameter and arrayed in single file along transects. Originally, VCL was designed to acquire along 3 parallel transects spaced at 2 km intervals. More recently, this spacing was broadened to 4 km (http://essp.gsfc.nasa.gov/vcl). The ground track of the VCL satellite will be randomly placed on the Earth's surface; the juxtaposition of the ascending and descending orbital paths will form a web of transects sampling the Earth's surface (Dubayah et al., 1997).

ICESat is a spaceborne, waveform-sampling lidar system that will measure and monitor ice-sheet topography as well as cloud and atmospheric properties. Like VCL, it will acquire data in the near-infrared region at 1064 nm, but ICESat will also acquire data in the visible green region at 532 nm (http://ltpwww.gsfc.nasa.gov/eib/glas.html). It has a 70 m footprint that will likely prove too large for measuring tree heights in areas with steep slopes. However the 175 m spacing of the lidar point samples could be better for integrating with passive optical imagery.

2.2 Landsat ETM+

Landsat imagery is the most common satellite data source used in terrestrial ecology. This is in large part due to its widespread availability and unrivaled length of record (since 1972), but also because the grain, extent, and multispectral features make Landsat suitable for a variety of environmental applications at landscape-regional scales. Landsat spectral data are typically related to vegetation structural attributes via spectral vegetation indices (SVIs). Ecologically relevant structural attributes such as LAI have been estimated from SVIs of croplands (e.g. Wiegand et al., 1979; Asrar et al., 1984), grasslands (e.g. Friedl et al., 1994), shrublands (e.g. Law and Waring, 1994), and forests (e.g. Chen and Cihlar, 1996; Fassnacht et al., 1997; Turner et al. 1999). Sensitivity of SVIs to variation in LAI or biomass generally declines, however, as foliar densities increase between ecosystems (e.g. Turner et al., 1999). The greater structural complexity of forests requires, not surprisingly, more complex image processing techniques. For instance, Cohen and Spies (1992) used all 6 Landsat radiance bands, rather than just the red and near-infrared bands as with most SVIs. Other notable yet more complicated approaches to enhancing the extraction of canopy structure information from Landsat imagery include using multi-temporal TM data to capture variable illumination conditions (Lefsky et al., 2001) and spectral mixture analysis to quantify canopy shadows (e.g. Adams et al., 1995; Peddle et al., 1999). The new ETM+ instrument on board Landsat 7 features enhanced radiometric resolution over its TM predecessor, which should aid all of the empirical methods just described. Yet there are fundamental limitations to the utility of passive optical sensors for characterizing vertical forest canopy structure, which will probably make them perpetually inferior to lidar for this task (Lefsky et al., 2001).

2.3 Estimation methods

All of the estimation methods we employed are empirical and were chosen for their broad use and general applicability: ordinary least squares regression (OLS), ordinary kriging (OK), and ordinary cokriging (OCK). The literature documents many variations on these aspatial (e.g. Curran and Hay, 1986) and spatial (e.g. Journal and Rossi, 1989; Stein and Corsten, 1991; Pan et al., 1993; Knotters et al., 1995) estimation methods. We deemed it less useful to conduct an exhaustive study of them all than to concentrate on the three methods just named because they broadly represent the basic empirical estimation techniques.

3. METHODS

3.1 Study Area

The 200 km^2 study area features Oregon State University's McDonald-Dunn Research Forest in the eastern foothills of the Coast Range in western Oregon. The area has elevations ranging from 58-650 m. Most of the area is coniferous forest dominated by *Pseudotsuga menziesii* and co-dominated by *Tsuga heterophylla*, but hardwood stands featuring *Acer macrophyllum* and *Quercus garryana* also are common. Stands span the full range of successional stages: young, intermediate, mature, and old-growth, and three management themes: even-aged, two-storied, and uneven-aged (http://www.cof.orst.edu/resfor/mcdonald/purpose.sht).

3.2 Image Processing

Small-footprint lidar data were acquired from an airborne platform (Aeroscan, Spencer B. Gross, Inc., Portland, OR) in January 2000. The Aeroscan instrument records 5 vertical returns within small footprints having an average diameter of 60 cm and geolocated in real time using an on-board, differential global positioning system to an accuracy of 75 cm (horizontal) and 30 cm (vertical). North-south paths were flown to provide continuous lidar coverage of the entire area. Maximum canopy height values were calculated for each footprint as the difference between the first (canopy top) and last (ground) returns using waveform processing algorithms developed in IDL (Research Systems Inc., Boulder, CO) by coauthor Lefsky. Maximum height values in each footprint were then aggregated into 25 x 25 m bins to produce a maximum canopy height image of 25 m spatial resolution. Every pixel was assigned a maximum canopy height value from a population of 10-764 lidar footprints, with a median of 26 footprints per pixel.

A Landsat ETM+ image (USGS-EROS Data Center, Sioux Falls, SD) acquired on 7 September 1999 was coregistered to a 1988 base image using 90 tie points selected through an automated spatial covariance procedure (Kennedy and Cohen, in review). Georegistration was performed in Imagine (ERDAS, Cambridge, U.K.) using a first-order polynomial function with nearest neighbor radiometric resampling, with a root mean square error of ± 14.3 m.

3.3 Sampling strategies

Possession of an actual height image across a large area allowed us to sample across a range of spatial frequencies. We simulated not only the original VCL sampling interval (2000 m) but also doubled the sampling frequency three times to 1000, 500 and 250 m; we sampled not only along transects (as VCL) but also in point patterns (as ICESat) at these same 4 spatial frequencies, or the intersections of the mentioned transects. The total of 8 height datasets were sampled in ERDAS Imagine.

3.4 Estimation methods

The histogram of the maximum canopy height data exhibited a strong positive skew. We therefore normalized each of the 8 height datasets with a square root transformation (SQRTHT) prior to applying any of the estimation methods; afterwards, all estimated SQRTHT values were backtransformed (squared) before comparing to measured height values.

3.4.1 Aspatial. The SQRTHT sample data were regressed on the raw ETM+ bands 1-7, as well as the Universal Transverse Mercator (UTM) X and Y locations, using stepwise multiple linear regression. Variables were assigned only if they added significantly to the model ($\alpha = 0.05$).

3.4.2 Spatial. The SQRTHT sample data were normal-score transformed prior to modeling. This non-linear, ranked transformation normalizes the data to produce a standard Gaussian cumulative distribution function with mean equal to zero and variance equal to one (Deutsch and Journel, 1998). After modeling, the estimates were backtransformed to the original SQRTHT data distribution; the estimates at the sample locations were an exact reproduction of the original SQRTHT sample data.

Ordinary kriging and ordinary cokriging operations were performed using algorithms in GSLIB (Statios, San Francisco, CA). We modeled the sample semivariograms by nesting nugget estimates with two exponential models. Only a model semivariogram for the primary variable was needed for ordinary kriging. For cokriging, a model semivariogram was also required for the secondary variable, along with a cross semivariogram modeling the spatial cross correlation between the primary and secondary variables. The ETM+ panchromatic band was the logical choice to serve as a secondary variable for cokriging, since this band has the highest resolution (15 m) among the ETM+ bands and therefore the highest spatial information content. The secondary data were also normal-score transformed before modeling. We were careful to observe the positive definiteness constraint on the linear model of coregionalization while developing the 3 semivariogram models required for each cokriging operation (Isaaks and Srivastava, 1989; Goovaerts, 1997).

3.4.3 Integrated. Residuals from the OLS regression models were exported from IDL as ASCII files and imported into GSLIB for kriging/cokriging. The same rules and procedures were followed for modeling the residuals as for modeling the SQRTHT data.

3.5 Validation. A comprehensive image of lidar-measured height values allowed exhaustive validation of the 5 estimation methods and 8 sampling strategies tested. To ensure comparability, the same validation points were used to evaluate all estimation methods and sampling strategies. Two sets of validation points were systematically selected to compare measured and estimated height values using Pearson's correlation statistic. One set of validation points was designed to assess the height estimates for the study area as a whole, with no regard to distance from sample locations; the other set was designed to assess the height estimates as a function of distance from sample locations.

Histograms, scatterplots, and graphs of measured versus estimated height values were graphically compared, and correlation coefficients were calculated in IDL. Estimated height and estimation error images were mapped in Arc/Info GRID (ESRI, Redlands, CA). Moran's Coefficient (I) calculations for spatial autocorrelation in the model residuals were performed using S-PLUS (Insightful, Seattle, WA) functions developed by Dr. Robin Reich (Colorado State University, Fort Collins, CO). The significance test to evaluate each I statistic assumed normality in 700 residual values sampled from the population of errors. The theory underlying Moran's I statistic can be pursued more thoroughly in Moran (1948) and Cliff and Ord (1981).

4. RESULTS

4.1 Empirical models

Separate stepwise multiple regression models were developed for the 8 sampling strategies tested. In every case, ETM+ band 7 was the first variable selected. All 9 independent variables contributed significantly, and were therefore included, in the 4 transect cases. The number of variables included in the point models decreased as sample data volume decreased, with only one variable selected in the lower extreme case (2000 m point strategy).

For the spatial and integrated models, unique semivariogram models of the height and height residual datasets were generated for all 8 of the sampling strategies tested. The range and sill parameters, and the shape of the semivariograms, were very similar among the 8 height datasets, and among the 8 height residual datasets. Nugget variance increased in the cases of the relatively sparse 1000 and 2000 m point samples. For cokriging, each of the 8 sampling strategies also required unique model semivariograms of the secondary data semivariograms and the respective cross semivariograms. As with the primary datasets, the range and sill parameters and semivariogram shapes were consistent amongst all 8 sample datasets, and nugget variance was again greater in the 1000 and 2000 m point samples. There was less spatial autocorrelation to exploit in the residual data than in the SQRTHT data. Similarly, the spatial cross correlation between the primary and secondary data was considerable with regard to the SQRTHT datasets, but relatively low with regard to the residual datasets. Very tight model fits were achieved for all of the primary, secondary, and cross semivariograms by nesting a nugget value and two exponential models.

4.2 Estimation accuracy

4.2.1 Global. Histograms of the full populations of estimated height values were used to evaluate global accuracy. Deviations in the estimated height histograms away from the measured height histograms were a good indicator of estimation biases at various heights. These biases were most pronounced in all of the regression results, and in the kriging/cokriging results based on sparse point samples (1000 or 2000 m). Biases in the estimates from the integrated methods were relatively minor, and decreased as sampling frequency increased. Correlations between measured and estimated heights were always better using the integrated models than using either the regression or spatial models alone. Cokriging produced slightly higher correlations than kriging. Correlations also were higher with the transect samples than with the point samples at each spatial sampling frequency.

Scatterplots of measured vs. estimated height values were also generated to compare the 5 models and 8 sampling strategies tested. Deviations in the slope of the fitted trendlines away from the 1:1 line helped show that the regression models suffered the most from underestimating the taller heights while overestimating the shorter heights. These deviations corresponded closely with the deviations in the estimated height histograms from the measured height histogram. Furthermore, correlations between measured and estimated height values in the scatterplots agreed well with the correlations calculated from the global height estimates. It is thus safe to conclude that the 700 points in these scatterplots were highly representative of the full population of height estimates, and their errors.

4.2.2 Local. Local estimation accuracy was also assessed according to Pearson's correlation statistic. Accuracy decreased as the distance from sample locations increased. The spatial models were more accurate than the regression models below distances of approximately 200 m from the sample locations. The integrated models preserved the accuracy of the regression estimates beyond this distance to the nearest sample. A sampling interval of 250 m ensured that all estimates were <180 m from the nearest sample, which improved estimation accuracies of the spatial and integrated models above those of regression, at all locations.

4.3 Mapping. Regression-based maps were virtually indistinguishable regardless of the sampling strategy or number of variables included. In dramatic contrast, the sampling strategy caused obvious artifacts in the kriging or cokriging maps that were most pronounced at the sparser sampling frequencies. These artifacts were however greatly attenuated in the maps produced from the integrated models. The kriging and cokriging maps were virtually indistinguishable when the same primary data were modeled.

Maps of estimation errors were produced by subtracting the actual height map from the estimated height maps. Overall, every model underestimated canopy height, although the estimation bias was an order of magnitude greater for the regression models than for any of the spatial or integrated models. The standard deviation of the estimation errors for the spatial and integrated models decreased as the spatial sampling frequency increased.

Spatial patterns in the error maps for the spatial and integrated models became less apparent as sampling density increased, while sampling density had no effect on error patterns for the aspatial regression models. Moran's I statistic was useful for quantifying the significance of the spatial autocorrelation remaining in the height estimation errors for all models. All regression models, and all models derived from the two sparser point sample datasets (2000 and 1000 m), failed to remove the spatial dependence from the residuals. The spatial models applied to the 2000 m transect sample dataset also left significant spatial autocorrelation in the residual variance, although the integrated models did not. All other models successfully accounted for spatial autocorrelation in the sample data.

5. DISCUSSION

5.1 Ordinary Least Squares Regression

The high similarity among all regression estimates of height indicates the insensitivity of the regression models to sample size, sample pattern, sampling frequency, or number of ETM+ bands selected. Regression suffered the worst from a consistent estimation bias, overestimating shorter stands while underestimating taller stands. On the other hand, regression did preserve the spatial pattern of stands across the study landscape.

We included the UTMX and UTMY location variables in the regression models as an easy way to account for a potential geographic trend across our study area, following the approach of Metzger (1997). Yet most of the height data variance explainable with regression was explained by ETM+ band 7 alone. The location variables (particularly UTMY) were selected by some of the stepwise regression models but only for those sampling strategies with a high data volume. In these cases, the addition of the location variables and other ETM+ bands as explanatory variables carried statistical significance but probably lacks biological significance.

Regression models of canopy height from future VCL-Landsat ETM+ integration will likely be less accurate than in this study. We developed a multiple regression model for estimating canopy height in southern Washington at the Wind River Canopy Crane Research Area (Hudak, unpublished), an area with canopy structure and composition very similar to the McDonald-Dunn Research Forest. The regression model was developed from a 1995 Landsat TM scene (bands 1-7, plus UTMX and UTMY locations) and lidar data acquired in 1995 by the SLICER instrument, a waveform-sampling lidar system more similar to VCL than the discrete-return Aeroscan lidar used in this study. The correlation between measured and estimated height values at Wind River was substantially less ($r = 0.57$) than at McDonald-Dunn ($r = 0.76$). Whether height estimates after adding a kriged/cokriged VCL residual surface to the regression surface will also be less accurate remains to be seen, but should not comprise the utility of our integrated modeling approach.

5.2 Ordinary Kriging/Cokriging

In stark contrast to regression, height estimates from the spatial methods were only slightly biased, but were highly sensitive to sampling frequency and pattern, which produced spatial discontinuities in the resulting maps. These discontinuities were visually distracting when the modeled variable (canopy height in this case) was undersampled relative to the spatial frequency at which it actually varies; the semivariograms indicate that the range of spatial autocorrelation in canopy height is no more than 500 m in this landscape. Beyond 500 m from the nearest sample, the semivariograms carried little or no weight in the estimation; this produced the smoothing effect visible especially in the 2000 and 1000 m kriged/cokriged maps. At sampling intervals of 500 or 250 m, all estimates were at or below the range of spatial autocorrelation for this landscape, so little smoothing occurred.

Stein and Corsten (1991) found that kriging/cokriging estimates differ only slightly from each other, and that the advantage of cokriging is greater when a highly correlated secondary variable is sampled intensely. We found cokriging slightly more advantageous than kriging at all sampling frequencies, perhaps because canopy height and the ETM+ panchromatic band were only weakly correlated (r = -0.43).

Journel and Rossi (1989) showed how ordinary kriging or cokriging is capable of modeling a trend component in interpolation situations, which is confirmed in our study by the lack of any visible trend or anisotropy in the error maps from the spatial models. Ordinary kriging or cokriging is advisable only in interpolation situations such as in this study; in extrapolation situations, it may be better to use universal kriging (Journel and Rossi, 1989; Stein and Corsten, 1991) or ordinary kriging with an external drift (Berterretche, 2001). In cases where anisotropy exists in the landscape, anisotropic kriging models having a directional component can be employed. Goovaerts (1997) thoroughly presents the many kriging/cokriging procedures available.

5.3 Integrated Method

Most of the bias in the regression estimates was eliminated in the integrated models, where the regression residuals were subsequently kriged and added back to the regression surface. We found the advantage of cokriging over kriging to be greater with the height residuals than with the height values. Perhaps because the regression models explain such a large proportion of the total variation in canopy height ($r^2 = 0.58$), the height residuals may correspond more closely than the height values to the fine-scale structural features in the panchromatic image.

The integrated methods proved superior because they preserved the spatial pattern in canopy height, like the regression models, while also improving global and local estimation accuracy, like the spatial models. They have no apparent disadvantage relative to aspatial or spatial methods alone.

The estimation methods applied to lidar canopy height data in this analysis are applicable to field data, as has already been demonstrated by Atkinson (1992, 1994). The samples need not be situated along a systematic grid; the methods are as applicable to random or subjective sampling strategies, as long as the samples represent the population in both statistical and geographical space.

5.4 Alternative Modeling Techniques

For estimation, inverse regression models (Curran and Hay, 1986) should be considered when the explanatory variables are dependent on the variable of interest. Surface radiance is influenced by canopy height, however Landsat imagery is much more sensitive to the spectral properties of the surface materials than to their height. Another criticism of standard regression is that it accounts for errors in only the explanatory variables (Landsat bands 1-7) and assumes a lack of measurement error in the independent variable (lidar height). All remotely sensed data including lidar are subject to several sources of error: irradiance variation, sensor calibration, sensor radiometric resolution, sensor drift, signal digitization, atmospheric attenuation, and atmospheric path radiance. An alternative approach that accounts for errors in both the independent and dependent variables is reduced major axis (RMA) regression (Curran and Hay 1986). Regardless of the regression method selected, we argue against using regression models alone to estimate canopy height. Our regression equations were useful for explaining a large proportion of the total variance in canopy height due to high covariance with measured radiance, but not due to any functional relationship. As stated in our objectives, we considered it most useful to present the most commonly used techniques for this paper, and OLS regression is clearly the standard empirical modeling tool.

For mapping, conditional simulation can be a good alternative to the estimation methods presented here (Dungan, 1998, 1999). Conditional simulation “conditions” stochastic predictions of the modeled variable within the spatial range of the sample data, as defined by the same semivariogram model used for kriging. Although locally inaccurate, conditional simulation preserves the global accuracy and spatial pattern of the data modeled. These qualities can be important for some applications, such as modeling variables as input for ecological process models. For example, Berterretche (2001) simulated LAI values across a boreal forest, for the purpose of informing a spatial model of net primary production (NPP). A single eddy flux tower centered at the site predicted NPP from a continuous stream of trace gas, light, temperature, and humidity measurements (Running et al., 1999). LAI is the key structural parameter driving NPP, yet one of the largest sources of uncertainty for modeling NPP at the ecosystem level. Conditional simulation provided multiple realizations (maps) of LAI, each map having a pattern of LAI values similar to remotely sensed indices of canopy structure (Berterretche, 2001). This set of maps provided a probability distribution of LAI predictions for every pixel (except those “conditional” locations where LAI was measured in the field, where the field value was preserved). Such multiple realizations of LAI provide a spatial measure of uncertainty, which could prove important for assessing the sensitivity of ecosystem NPP to spatial variation in LAI.

A sensitivity analysis was not possible with the single map realizations created in this study, but neither was it necessary. We ran conditional stochastic simulations of canopy height, and height residuals, from our 8 sample datasets. In every case, local accuracy was markedly lower than for any of the estimation methods we tested. Since local accuracy was important for our objectives, while multiple realizations were not, we pursued simulation methods no further for this paper. The decision of which estimation or simulation methods to use for modeling LAI, height, or any other variable ultimately depends on user objectives.

5.5 Sampling Strategy

Traditionally, most remote sensors have afforded analysts with a certain luxury by sampling the entire population within the extent of coverage. This has precluded any need to apply spatial interpolation strategies such as kriging, yet imagery is full of underexploited spatial information. A number of studies have demonstrated the value of geostatistical analysis tools such as semivariograms (e.g. Curran, 1988; Glass et al., 1988; Woodcock et al., 1988;

Cohen et al., 1990; Hudak and Wessman, 1998). As remote sensing technology has advanced towards increasing spectral, spatial, and temporal resolution, data processing and storage technologies have kept pace, enabling the continued availability of comprehensive data even as those data volumes have exponentially increased. While these trends may very well continue, it is instructive and useful to consider the applicability of remote sampling instruments such as ICESat and VCL.

We found that a 2000 m transect sampling strategy simulating the original VCL sampling design is not optimal for vegetation mapping of dense coniferous forests. The more recent, 4000 m transect sampling design of VCL would be even more problematic, at least in western Oregon where forest structure predominantly varies at the scale of individual stands with spatial frequencies of <500 m (Cohen et al., 1990). Better maps of canopy height could be achieved with less lidar data if a 250 m point sampling strategy were used. This reduced data volume would alleviate data transmission, storage, and processing loads. Processing time is proportional to data volume when running geostatistical models in particular. Whether or not a point sampling strategy could be feasibly designed into the next lidar satellite for vegetation applications is an engineering issue and beyond the scope of this paper, but the point sampling design of ICESat suggests that this technology already exists. Future lidar missions designated for vegetation inventories should be designed by engineers and vegetation ecologists who have given due consideration to application of the data.

6. CONCLUSION

Integration of lidar and Landsat ETM+ data using straightforward empirical modeling procedures can be used to improve the utility of both datasets for forestry applications. Our integrated technique of ordinary cokriging of the height residuals from an OLS regression model proved the best integration method for estimating and mapping canopy height. We encourage the use of our integrated modeling approach in a variety of ecosystems once lidar sample data become readily available. Results strongly support our hypothesis that the VCL satellite will undersample the highly managed forest landscapes of western Oregon and probably many other regions. Future lidar satellites for vegetation mapping in this region should sample points at spatial intervals of 250 m or less. This would ensure that every estimate is no more than 180 m from the nearest sample while also keeping the sample data volume to a manageable level and therefore maximizing the efficiency of our integrated modeling approach. An equitable distribution of sample data is critical for lidar-Landsat ETM+ integration.

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