Popular Summary

FOREST BIOMASS MAPPING FROM LIDAR AND RADAR SYNERGIES

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Lidar and Radar sensors use transmitted and received electromagnetic radiation to measure forest canopies. The combined use of lidar and radar instruments to measure forest structure attributes such as height and biomass at global scales is being considered for a future Earth Observation satellite missions. Large footprint lidar makes a direct measurement of the distance of canopy scattering elements (i.e., leaves, branches, ground) within the illuminated area and can yield accurate information about the vertical profile of the canopy within these lidar. Synthetic Aperture Radar (SAR) is known to sense the forest canopy volume, especially at longer radar wavelengths and provides image data. Methods for biomass mapping by a combination of lidar sampling and radar mapping need to be developed since neither can do the whole job individually.

In this study, several issues were investigated using aircraft borne lidar and SAR data over Howland, Maine, USA. We used a stepwise regression technique and selected the lidar derived height indices rh50 and rh75 of the Laser Vegetation Imaging Sensor (LVIS) data for predicting field measured biomass with a R^2 of 0.71 and RMSE of 31.33 Mg/ha. The above-ground biomass map generated from this regression model was considered to represent the true biomass of the area and used as a reference map since no better biomass map exists for the area. Random samples were taken from the biomass map and the correlation between the sampled biomass and co-located SAR signature was analyzed. The best models obtained through these analyses were used to extend the biomass estimates from lidar samples into all forested areas in the study area, which mimics a procedure that could be used for the future DESDYnI Mission. It was found that depending on the type of SAR data used (i.e,.quad-pol or dual-pol) the SAR data can predict the lidar biomass samples with R^2 of 0.63-0.71, RMSE of 32.0-28.2 Mg/ha up to biomass levels of 200-250 Mg/ha. The mean biomass of the study area calculated from the biomass maps generated by lidar- SAR synergy was within 10% of the reference biomass map derived from LVIS data. The results from this study are preliminary, but do show the potential of the combined use of lidar samples and radar imagery for forest biomass mapping. Various issues regarding lidar/radar data synergies for biomass mapping are discussed in the paper.

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Abstract

The use of lidar and radar instruments to measure forest structure attributes such as height and biomass at global scales is being considered for a future Earth Observation satellite mission, DESDynI (Deformation, Ecosystem Structure, and Dynamics of Ice). Large footprint lidar makes a direct measurement of the heights of scatterers in the illuminated footprint and can yield accurate information about the vertical profile of the canopy within lidar footprint samples. Synthetic Aperture Radar (SAR) is known to sense the canopy volume, especially at longer wavelengths and provides image data. Methods for biomass mapping by a combination of lidar sampling and radar mapping need to be developed.

In this study, several issues in this respect were investigated using aircraft borne lidar and SAR data in Howland, Maine, USA. The stepwise regression selected the height indices rh50 and rh75 of the Laser Vegetation Imaging Sensor (LVIS) data for predicting field measured biomass with a R^2 of 0.71 and RMSE of 31.33 Mg/ha. The above-ground biomass map generated from this regression model was considered to represent the true biomass of the area and used as a reference map since no better biomass map exists for the area. Random samples were taken from the biomass map and the correlation between the sampled biomass and co-located SAR signature was studied. The best models were used to extend the biomass from lidar samples into all forested areas in the study area, which mimics a procedure that could be used for the future DESDYnI Mission. It was found that depending on the data types used (quad-pol or dual-pol) the SAR data can predict the lidar biomass samples with R^2 of 0.63-0.71, RMSE of 32.0-28.2 Mg/ha up to biomass levels of 200-250 Mg/ha. The mean biomass of the study area calculated from the biomass maps generated by lidar- SAR synergy was within 10% of the reference biomass map derived from LVIS data. The results from this study are preliminary, but do show the potential of the combined use of lidar samples and radar imagery for forest biomass mapping. Various issues regarding lidar/radar data synergies for biomass mapping are discussed in the paper.

Keywords: Forest biomass, DESDynI Mission, lidar waveform, LVIS, SRTM, PALSAR, InSAR, SRTM

1. Introduction

Above-ground biomass can not be directly measured by any sensor from space. Land cover stratification combined with ground sampling is the traditional method to inventory the biomass of a region. Remote sensing data are playing increasingly important roles in forest biomass estimation. For example, biomass data from field measurements (e.g., FIA – Forest Inventory and Analysis plots) (Blackard, J. A., et al. 2008) and lidar (GLAS – Geoscience Laser Altimeter System) (Baccini, A., et al. 2008; Nelson et al., 2009) and image data from LANDSAT, MODIS have been used together to perform regional biomass mapping.

Large-footprint lidar systems (Blair et al., 1999) have been developed to provide high-resolution, geo-located measurements of vegetation vertical structure and ground elevations beneath dense canopies. Over the past decade, several airborne and space-borne large-footprint lidar systems have been used to make measurements of vegetation. The lidar waveform signature from large-footprint lidar instrument, such as the Scanning Lidar Imager of Canopies by Echo Recovery (SLICER) (Harding et al., 1995, 1998) and the Laser Vegetation Imaging Sensor (LVIS) (Blair et al., 1999) has been successfully used to estimate the tree height and forest above-ground biomass (Lefsky et al., 1999a, b; Dubayah and Drake, 2000; Hofton et al., 2002; Drake et al., 2002, 2003, Sun et al., 2008). The relationship between forest carbon storage and the vertical structure from lidar waveform is relatively unexplored. Further studies on the data properties, (e.g. the effects of multiple scattering and ground slope on lidar signatures) are needed to verify and improve the retrieval algorithms. One major limitation of current spaceborne lidar systems (i.e., ICESat GLAS) is the lack of imaging capabilities and the fact that they provide sparse sampling information on the forest structure.

Radar, because of its penetration capability and sensitivity to water content in vegetation, is sensitive to the forest spatial structure and standing biomass. Radar data (both polarimetric and interferometric) have been used for forest biomass estimation (Ranson and Sun, 1996, Ranson et al., 1995, 1997a,b; Kasischke et al., 1995; Dobson et al., 1992, 1995; Le Toan et al., 1992; Kurvonen et al., 1999; Saatchi et al., 2007) and canopy height estimation (Hagberg et al, 1995; Treuhaft et al., 1996, 2004; Askne et al, 1997; Kobayashi et al, 2000; Kellndorfer et al., 2004; Simard, M., et al. 2006, 2008). These applications require ground sampling data for both training and validation purposes.

The signature from these two kinds of sensors bears commonality due to the biophysical and ecological nature of vegetation communities. The vertical distribution of the reflective surfaces revealed by lidar data implies the overall structure supporting the leaf distribution. The relative importance of microwave backscattering from various tree components (e.g. leaves, branches, trunks) depends on the vertical, as well as horizontal distributions of these components. Reflectance from vegetation canopy is controlled by canopy structure as well as the biochemical

composition of the canopy foliage. The use of lidar and radar instruments to measure forest structure attributes such as height and biomass are being considered for future Earth Observation satellite missions. The first such mission to be flown within the next decade is called DESDynI, a combined lidar and radar mission designed to address scientific questions in terrestrial ecosystem structure as well as solid earth and ice dynamics (http://desdyni.jpl.nasa.gov/, Donnellan et al., 2008). In anticipation of this mission, methods for biomass mapping by combining lidar samples and radar imagery need to be investigated.

Data fusion or synergy is required in remote sensing applications, especially for complex tasks such as mapping of forest structural parameters (Patenaude et al. 2005). Synergistic use of various data and approaches has been applied in various studies. For example, Anderson et al. (2008) used waveform lidar with hyperspectral imagery to estimate three common forest measurements - basal area, above-ground biomass and quadratic mean stem diameter in a northern temperate mixed conifer and deciduous forest. Results suggested that the integrated data sets of hyperspectral and waveform lidar provide improved outcomes over use of either data set alone in evaluating common forest metrics. Using Shuttle Radar Topographic Mission (SRTM) and ICESat/GLAS data, Simard et al. (2008) conducted 3D mapping of mangrove forests. Walker et al. (2007) developed the first-ever high-resolution map of canopy heights for the conterminous U. S. using an empirical InSAR-optical fusion approach. In two investigations of radar-lidar synergy, in a North Carolina pine forest (Nelson et al. 2007) and a wildlife habitat analysis (Hyde et al. 2006), authors found that there was little to be gained or only marginal improvement by adding radar data to lidar data. However, the current satellite lidar technology only samples the earth's surface, whereas radar has the mapping capability required for continuous global biomass mapping. For example Kellndorfer et al, 2010 combined ICESat GLAS, SRTM INSAR and Landsat imagery to make large area estimates of above ground woody biomass and Lefsky (2010) used MODIS and ICESat lidar data together to produce a global map of forest heights. The ecosystem structure component in the DESDynI mission is to measure 3D structure of forests by taking advantage of the spatial continuity of SAR and the direct measurements from lidar samples (Donnellan et al. 2008). This presents a special case for lidar and radar data fusion for mapping forest biomass and other structural parameters globally.

In this study, some issues of combined use of lidar and radar were investigated using data acquired near Howland, Maine, USA. The potential information on biomass from a lidar waveform and the required lidar samples for reliable biomass estimation were studied using field data. The best prediction model was used to generate a reference biomass map from the Laser Vegetation Imaging Sensor (LVIS) data. Random samples were then taken from the biomass map and the correlation between biomass and SAR signature was studied. Proper models were used to extend the biomass

126 from lidar samples into all forested areas in the study area. The new biomass map was compared with the reference

127 biomass map derived from LVIS data. The results of the combined use of lidar samples and radar imagery for forest

128 biomass mapping are presented. Biomass mapping was also performed using field data and SAR data to show that the

129 biomass maps from lidar sample and SAR data were better. Various issues in the lidar/radar data fusion for regional

130 biomass mapping are also discussed in this paper.

131 **2. Study site and data**

132 *2.1. Site description and field data*

133 The test site for this project is the mixed hardwood and softwood forest of the Northern Experimental Forest (NEF),

134 Howland, Maine (45°15'N, 68°45'W). This site, about 10 Km by 10 Km in size, is used for interdisciplinary forest

135 research and experimental forestry practices. The natural stands in this northern hardwood - boreal transitional forest

136 consist of hemlock-spruce-fir, aspen-birch, and hemlock-hardwood mixtures. Topographically, the region varies from

137 flat to gently rolling, with a maximum elevation change of less than 135 m within the study area. Due to the region's

138 glacial history, soil drainage classes within a small area may vary widely, from excessively drained to poorly drained.

139 Consequently, an elaborate patchwork of forest communities has developed, supporting exceptional diversity in forest

140 structure (Ranson and Sun, 1994). While a significant part of forests were preserved for research purposes, various

141 forest management and harvesting practices have changed the forest structure. Fig. 1 is a false color ASTER image of

142 July 22, 2002 (15m pixel resolution) showing different types of forests in the study area.

143

144   <Fig. 1>

145

146 A stem map (the larger rectangle in Fig. 1), identifying location, diameter at breast height (dbh) and species for every

147 tree with a dbh greater than 3 cm in a 200 m by 150 m area, was collected in 1989 and again in 2003. This data set will

148 be referred to as stem map data in this paper. This data set served well for model simulation and data analyses in

149 previous studies (Ranson et al., 1997b; Kimes et al., 1997). A metal label was attached to every tree in 1989 to aid

150 identification and re-measurement in 2003. The 2003 dataset includes those trees with dbh greater than 3 cm in 2003

151 that were not measured in 1989. The canopy biomass can be calculated using dbh from allometric equations listed in

152 Young et al (1980). The corners of the stem map were located using a Trimble differential GPS instrument with an

153 accuracy of less than 1 meter. Fig. 2 shows locations of trees and the LVIS footprints (circles) within the stem map. A

154 total of 112 footprints were completely inside the stem map.

155 Twenty sites (Fig. 1 and Table 1) across the study area were sampled in October, 2003 for biomass and other forest

156 parameters. In each site three to four plots with radius of 4 or 7 m were arranged in the center, and 30 m north, south-

157 west, south-east from the center. The dbh for every tree with a dbh > 3cm, and the height, crown length and width of 8

158 trees in each plot were measured. These sites represent a range of forest structures and biomass levels. The locations of

159 the 2003 sampling sites were determined using a backpack borne Garmin V GPS Unit including a Garmin V Personal

160 Navigator and a MBX-3S Differential Beacon Receiver with known accuracy up to 1 meter, 95% of the time in good

161 receiving conditions. The major parameters of these sampled forest sites were listed in Table 1.

162

163 <Fig. 2>   <Table 1>

164

165 *2.2. LVIS data*

166 NASA's Laser Vegetation Imaging Sensor (LVIS) is an airborne laser altimeter system designed, developed and

167 operated by the Laser Remote Sensing Laboratory, Goddard Space Flight Center (GSFC) (Blair et al., 1999). The LVIS

168 system measures the intensity of backscatter returns within 30 cm intervals and the time delay (or traveled distance by

169 laser beam) through the forest canopy. These recorded signals form a vertical profile or lidar waveform of the lidar

170 footprint, which is a direct measurement of the forest structure. In the summer of 2003, LVIS obtained waveform data

171 for forested sites in New England, generating the most detailed forest structural data sets currently available for these

172 regions. The LVIS data used in this study were acquired on July 26, 2003 and processed at GSFC (B. Blair, M. A.

173 Hofton, and D. L. Rabine. 2006; http://lvis.gsfc.nasa.gov). LVIS Ground Elevation (LGE) data were used, which

174 include location (latitude/longitude), surface elevation, and the heights (relative to surface) where 25%, 50%, 75% and

175 100% of the waveform energy occur. These quartile heights are referred as rh25, rh50, rh75 and rh100 to represent the

176 relative heights in this study. ENVI's gridding function, which uses Delaunay triangulation of a planar set of points, was

177 used to grid the LVIS LGE data to 15m ASTER base images. Fig. 3-A is a false color image showing the rh50 (R),

178 rh100 (G), and rh25 (B) from LVIS data.

179 The quartile heights are direct measurements of the vertical profile of canopy components. Waveform measures are a

180 function of the complex and variable 3-D structure of canopy components and their spectral properties, as well as the

4

181 spectral properties of the ground/litter. The rh25 and rh50 are lower for the selectively cut areas as seen in Fig. 3-A. In

182 the area around the stem map in Fig. 3-A (the solid red rectangle) all three relative height indices are high so it appears

183 white in the false color image.   This corresponds to a forest area without disturbances. When the trees were partially cut

184 (the patch of forest across the road to the east of the stem map), the relative lidar signature returned from tree crowns

185 was reduced and that from the ground surface increased resulting in the lower values of rh25 and rh50, so the false color

186 of the selectively cut area in Fig. 3-A does not appear white but green. Fig. 3-B depicts the centers of LVIS footprints

187 overlaid on the 15m ASTER image, showing that there were more than 20 footprints in a window of 5x5 15m pixels.

188

189   <Fig. 3>

190

191 *2.3. SAR and LANDSAT images*

192 PALSAR images from the Japanese Aerospace Exploration Agency (JAXA) Advanced Land Observing System used in

193 this study are listed in Table 2. Data were ordered as Level 1.1 data. The spatial resolution of the single-look image is

194 3.556 m and 9.369 m in azimuth and range directions, respectively. As a Level 1.1 product, the data were

195 radiometrically calibrated and in complex format. The data in Table 2 form two pairs of InSAR data, and were

196 processed using ROI_PAC software (Repeat Orbit Interferometry PACkage, http://www.roipac.org/) to create coherence

197 data. SRTM data were downloaded from the USGS site (http://srtm.usgs.gov/), and the height of the scattering phase

198 center was derived from the SRTM DEM minus the surface elevation measured with LVIS. Fig. 4 shows false colour

199 images of SAR data.

200

201   <Table 2>   <Fig. 4>

202

203 While the forest area surrounding the stem map has been preserved for scientific studies, the rest of the forests in the

204 study area have been actively managed. The logging methods were changed from clear-cut in the 1980s, to strip-cuts in

205 the 1990s and to select-cuts (shelter wood cuts) after 2000. Since the data used in this study were from different years of

206 2000, 2003 and 2007, the logged areas during this period need to be identified. Three LANDSAT ETM+ data acquired

5

on July, 2, 2000, September 10, 2003 and July 22, 2007 were used to map the changed areas, so they could be omitted for this study.

3. Method

3.1. Image Data Processing

Rasterized LVIS height indices data, SAR data, and the phase center height from SRTM and LVIS DEM data were all co-registered with the 15m ASTER base images. LVIS indices and SAR data were extracted from the co-registered images using windows with various sizes (1x1, 3x3, 5x5) corresponding to various scales (15m, 45m, 75m), respectively.

Definiens Developer 7.0 (Baatz et al., 2004), which allows for the automatic and optimal delineation of local homogenous regions, was used to perform a segmentation of ETM+ images. The polygon segments formed were classified to create a change mask. Fig. 5-A shows the polygon segments overlaid on the 2007 ETM+ images, and Fig. 5-B shows the changed areas identified from the classification of the polygons segments. A mask (Fig. 5-C) was generated to exclude these changed areas and non-forest areas in further analyses. The non-forest areas were identified using rh50 <= 0 since the waveform from an ideal bare surface would have rh50 = 0.

<Fig. 5>

3.2. Biomass estimation from LVIS data

3.2.1. Correlations of forest biomass with lidar waveform indices

The height indices (relative to the ground surface) rh25, rh50, rh75 and rh100 were extracted from LVIS LGE data for each of the LVIS footprints within stem map (Fig. 2). Trees within a diameter of the footprint size of 20m were used to derive the biomass for each footprint, and step-wise regression was performed to select the best prediction model. The correlation was low probably due to the errors in lidar footprint locations and field-measured tree positions

Aggregation of both biomass measurements and the LVIS indices into a larger unit will reduce measurement uncertainty. The suitable aggregation scale was investigated by randomly sampling the stem map using different pixel sizes. In Fig. 3-B, the square pixels are 15m pixels from ASTER data. A window with 2x2, 3x3, and 5x5 pixels will form pixels with sizes of 30m, 45m and 75m. It can be seen that in most cases, there will be several lidar footprints in one of the 30-75m pixels. The

6

234   biomass prediction models at pixel sizes of 15m, 45m and 75m were examined. Thirty points were randomly selected

235   within the stem map, such that a pixel with size of 15m, 45m and 75m was entirely within the stem map. The biomass of

236   these points was calculated from the stem map data using the pixel sizes. The remote sensing data were extracted at

237   these points with a window size of 1, 3 and 5 from co-registered LVIS and SAR data. The stepwise regression function

238   from S-plus (S-Plus, 2010) was used to find the best biomass prediction model. The suitable pixel size for biomass

239   mapping was determined from the analyses.

240   3.2.2. Prediction model and biomass mapping from LVIS data

241   The 2003 field samples covered forest sites with very different structures. It was found that when the data were extracted

242   from a 3x3 15m window, the correlations between LVIS height indices and biomass were low. The window size was

243   increased to 5x5 pixels for extracting LVIS and SAR data for the sites sampled in field. The stem map was divided into

244   twelve 50m by 50m sub-plots and the total above-ground biomass of these sub-plots was calculated. The biomass of

245   these sub-plots was (Mg/Ha): 115.3, 119.4, 136.1, 143.8, 149.8, 166.7, 170.9, 175.5, 193.9, 206.5, 209.6, and 210.2.

246   These biomass data were used to develop models to generate biomass from LVIS and SAR data. The stepwise

247   regression was used to pick the best LVIS variables for biomass estimation. An above-ground biomass map from LVIS

248   data was generated using the regression model.

249   *3.3. Forest biomass mapping using field samples and SAR data*

250   The data from SAR include ALOS PALSAR polarimetric data (PLR mode) from two dates (April 16 and June 1, 2007),

251   and dual-pol (HH and HV) images (FSD mode) from two dates (July 10 and August 25, 2007). These PALSAR data

252   were ordered as L1.1, and form two pairs of InSAR data. The data were radiometrically calibrated by JAXA and in

253   complex form (I + jQ). The equation, Normalized Radar Cross Section (NRCS) (dB) = $10*log10(<I^2+Q^2>) + CF$ -

254   32.0, where CF= -83.0, provided by JAXA (https://auig.eoc.jaxa.jp/auigs/en/doc/an/20090109en_3.html) was used to

255   convert the complex data to NRCS. The complex coherence (Gaveau et al., 2003) between dual-pol data from July 10

256   and August 25, 2007 was relatively high, so the coherence was used as a variable for biomass estimation. The ratio of

257   HV to HH was calculated for each of these PALSAR data. For the polarimetric data, the total power (HH+VV+2HV)

258   was also calculated and used as the independent variables. SRTM elevation data represent the elevation of the scattering

259   phase center over the vegetated areas. By subtracting the surface elevation from LVIS data from the SRTM elevation,

260   the height (from the ground surface to the scattering center within the canopy) can be obtained. This height was used as

261   a variable in the regression analyses.

The stepwise regression was used to find the best regression models for biomass estimation when the dependent variable is the field biomass and the independent variables include 1) PALSAR PLR data with and without SRTM phase center height, 2) dual-pol PALSAR data with and without SRTM phase center height, and 3) both PLR and dual-pol PALSAR data with and without SRTM phase center height. The best regression models were used to generate biomass maps from SAR data.

3.4. Extending LVIS biomass samples using SAR data

3.4.1. Mapping biomass using LVIS samples and SAR data

The biomass map from LVIS data was treated as a reference biomass map. The purpose of the study was to investigate the possibility of generating a comparable biomass map using limited samples from LVIS-derived biomass and the SAR imagery. One hundred samples were randomly selected from the areas not masked out by the mask image (Fig. 5-C). The LVIS-derived biomass and SAR signatures at each point were extracted using a 5x5 window. This data set includes the following variables: LVIS derived biomass, srtm-lvis_ht, HH, HV, VH, VV intensity, the total power of two polarimetric SAR images, HH, HV intensities of two dual-pol SAR images, coherence of HH polarization of dual-pol images, and he HV to HH ratio for all SAR images.

The stepwise regression was used to find the best SAR variables for biomass estimation. The regression models were then applied to the same area mapped by LVIS data.

3.4.2. Model performance and error assessments

For each biomass estimation equation, the root mean square error (RMSE) was calculated as SQRT(SUM((Bpred-Bref)^2/n). The mean, variance and correlation of the estimated biomass map were calculated and compared.

Re-sampling techniques, such as bootstrapping and jackknifing (Efron, 1981) can provide estimates of the standard error, confidence intervals, and distributions for any statistic without the normality distribution assumption. The lidar sampled biomass was randomly picked in the forested area that was not disturbed during the period of 2000-2007. Bootstrapping was used to investigate the stability or reliability of the prediction models.

4. Results

4.1. Biomass mapping from LVIS data

4.1.1. Correlations of forest biomass with lidar waveform indices

When the waveform indices from 112 LVIS footprints within the stem map were used to predict forest biomass for the 20 m footprints, the step-wise regression selected all energy quartiles from LVIS LGE data. The relation between the biomass calculated from the forest stem map data and that predicted by the lidar waveform indices was

$$B = 17.0\text{-}10.3\ rh25+23.0\ rh50\text{-}22.4\ rh75+13.7\ rh100 \qquad (1)$$

with Multiple R-Squared: 0.315, RSE: 21.1 Mg/ha, F-statistic: 12.17 on 4 and 106 degrees of freedom, and a p-value of 3.543e-008.

To investigate the regression relations at different spatial scale, thirty points were randomly selected within the stem map, such that a pixel with size of 15m, 45m and 75m was entirely within the stem map. The biomass of these points was calculated from the stem map data and the LVIS height indices were extracted at these points with a window size of 1x1, 3x3 and 5x5 from co-registered imagery data. The results from the stepwise regression show that when the pixel size increased from 15 to 45 and 75 meters, the R^2 increased from 0.171 to 0.496 and then to 0.725. Because of the small size of the stem map, when the pixel size increases, there will be much overlap between sampling points. The range of the biomass also decreases. The increases of R^2 here may not entirely result from the increase of the pixel size. Nevertheless, the increased averaging reduced the variance of the data caused by the spatial sampling and geo-location mis-matching between lidar footprint and tree locations. The 75m pixel size was used in the following procedures for biomass mapping.

4.1.2. Prediction model and biomass mapping from LVIS data

The best regression equation from stepwise regression using field biomass and LVIS height indices was

$$B = \text{-}1.717 - 6.208\ rh50 + 8.625\ rh75 \qquad (2)$$

With a residual standard error (RSE) of 32.91 Mg/ha, Multiple R^2 of 0.70, F-statistic of 34.08 on 2 and 29 degrees of freedom, and a p-value of 2.43e-08. The relationship between field and predicted biomass shown in Fig. 6 was

$$B_{pred} = 48.5276 + 0.7015\ B_{field} \qquad (3)$$

with $R^2 = 0.70$, and the RSE of 27.10 Mg/ha. The RMSE calculated from SQRT(SUM((Bpred – Btot)^2)/32) was 31.33 Mg/ha. Fig. 7 is the above-ground biomass map from LVIS data using the equation (2). The model was applied to the entire image, but all the biomass statistics, and the comparisons between different biomass maps were performed on the pixels defined by the mask image (Fig. 5-C).

315   \<Fig. 6> \<Fig. 7>

316

317 *4.2. Biomass mapping using field biomass data and SAR data*

318 Stepwise regression was used to find the best variables and models for various combinations of the variables from SAR

319 data. Polarimetric and dual-pol data were treated as two groups of data and stepwise regression was applied separately.

320 Table 3 shows the variables selected by stepwise regression, and the RSE, R^2, and p-values of these models. It can be

321 seen from these models that the height of scattering phase center (srtm-lvis_ht) is an important variable, but couldn't

322 predict biomass alone. The coherence of L-band HH data is not a very sensitive variable for biomass estimation. The

323 regression models from 3 and 7 in Table 3 were used to generate the biomass map of the study area. The regression

324 relation between predicted from model 3 and the reference biomass is:

325       $B_{pred} = 38.2452 + 0.7019\, B_{ref}$ (4)

326 with $R^2 = 0.7019$, and the RSE of 24.32 Mg/ha. The RMSE is 28.73 Mg/ha. The biomass map from model 3 is shown in

327 Fig. 8. Comparing with Fig. 7, the biomass is obviously high, and spatial distribution pattern is vague.

328

329   \<Table 3> \<Fig. 8>

330

331 *4.3. Extending LVIS biomass samples using SAR data*

332 The biomass map shown in Fig. 7 was treated as a reference map. One hundred points were randomly picked from the

333 map shown in Fig. 7. The stepwise regression was used to find the best regression models. Table 4 is a list of these

334 models from stepwise regression when different independent variables were used. The stepwise regression selected

335 different variables from those shown in Table 3. Though the R^2 in Table 4 are lower than those in Table 3, the RSE and

336 p-value are also lower, because of larger number of data points. Fig. 9 shows the comparison of predicted biomass using

337 SAR data with the reference biomass using the model 7 in Table 4. The regression relation between predicted and

338 reference biomass is:

339       $B_{pred} = 38.8803 + 0.7126\, B_{ref}$ (5)

340 with $R^2 = 0.71$, and the RSE of 24.06 Mg/ha. The RMSE is 28.21 Mg/ha. Fig. 10 is the biomass map predicted using

341 this model.

342

343   <Table 4>   <Fig. 9> <Fig. 10>

344

345 *4.4. Model performance and error assessments*

346 Equations 3-5 showed that the regression models for biomass estimation from LVIS-field, SAR-field and SAR-LVIS

347 have similar RMSE and R^2. But by applying these models on LVIS or SAR data, the resulting biomass maps are quite

348 different. Table 5 shows the statistics of these biomass maps and the correlations of these maps with the reference maps

349 from LVIS-field data. Fig. 11 shows the histograms of above-ground biomass in the areas not masked out by Fig. 5-C.

350 First we can see that the two biomass maps from SAR-field are very similar, as are the three biomass maps from LVIS-

351 SAR models. The average biomass from SAR-field models was too high. Stem map is a preserved mature stand with an

352 average above-ground biomass of about 170 Mg/ha. The average biomass of the stem map extracted from the biomass

353 maps using the models listed in Table 5 were 161.6, 200.5, 206.7, 141.3, 159.8 and 173.7 Mg/ha, respectively. Large

354 parts of the forest areas in the study area have been harvested since 1980. The biomass level from Field-LVIS and all

355 LVIS-SAR models is closer to reality (Table 5). The LVIS-SAR models gave similar mean biomass as the Field-LVIS

356 model. The high correlation of these maps with the Field-LVIS map indicates similar spatial distribution patterns as well.

357 The combined RMSE of the two-step models shown in Equations 3 and 5 will be sqrt(31.33^2 + 28.21^2) = 42.16

358 Mg/ha.

359

360   <Fig. 11>   <Table 5>   <Table 6>

361

362 The statistics from bootstrapping of the coefficients of the regression model LVIS-SAR-ALL (Table 5) are shown in

363 Table 6. The means are very close to the observed values and the distributions of these coefficients were close to normal

364 (graphs not shown here).

365 **5. Discussion**

366 *5.1. Forest parameters retrieval at lidar footprint scale*

367 The biomass within a lidar footprint was calculated from trees with trunks inside the footprint. The lidar waveform is the

368 result of reflectance from the tree crowns and the ground surface within the lidar beam while the major biomass is from

369 tree trunks. While a trunk may be inside a footprint, a portion of its crown may fall outside. Similarly, the crown of a

370 nearby tree outside the footprint may be partially illuminated by the lidar beam. This mis-matching will reduce the

371 correlation between the biomass calculated for lidar footprints and the lidar waveform indices. The effect depends on the

372 forest spatial structure and the spatial scales at which the forest parameters are to be estimated. At flat areas, the bigger

373 footprint size will have less edge effect. The direct measurements of lidar waveform are the vertical profile of reflectors

374 within the footprint. It is directly related to the tree or canopy height information, but is not direct measurements of the

375 biomass. The correlation between biomass and lidar waveform indices may depend on the species and spatial structure

376 of forests. To define and determine the biomass in a footprint requires clear understanding of the relations between lidar

377 waveform, crown structure and the biomass of forest stands.

378 *5.2. Aggregation of data into various spatial scales*

379 No matter what models (multivariable regressions, regression trees, neural networks, etc.) are used to retrieve forest

380 physical parameters from lidar waveform indices, several factors will always cause errors, as long as the model is

381 statistical in nature. In addition to the fact mentioned above, the spatial heterogeneity of the canopy determined in part

382 by its successional stage, natural and anthropogenic disturbances, and local terrain will cause more error from

383 uncertainties. These include 1) the uncertainties in field data; 2) the uncertainties in waveform indices, and 3) the mis-

384 matching between locations of field sampling and lidar footprints. Aggregating the data and increasing the samples

385 reduce the uncertainties and improve accuracy. A window of 5 by 5 15m pixels (75m spacing) was used in this study.

386 Because of the discrepancy in data acquisition dates, and inadequate field sampling data, this issue has not been fully

387 explored in this study.

388 *5.3. Forest biomass information in SAR data*

389 This study shows that no single channel of SAR data provides enough information for biomass retrieval, so multiple

390 channels from multiple polarizations, bands and operation modes, and temporal acquisitions were needed. The height of

391 the scattering phase center at C-band from SRTM DEM – LVIS surface elevation was an important variable in this

392 study. Polarimetric SAR interferometry (Pol-InSAR) data has been used to estimate forest height (Cloude and Papathanassiou,

393 2003) and then were subsequently converted to forest biomass through forest height-biomass relation (Mette, Papathanassiou and

394 Hajnsek, 2004; Caicoya et al., 2010). The DESDynI mission will provide temporal L-band InSAR data. The height of

395 scattering phase center at L band derived from these data if surface DEM is available, and the temporal coherence data

396 may play the similar rule in the biomass estimation. The preference of polarizations of SAR data is not very clear in this

397   study probably because of the flat terrain of the study area. When terrain slope exists, the effects of terrain on co-

398   polarization signature will be more significant, so cross-polarization should not be excluded from future missions.

399   *5.4. Comparability of lidar and SAR data for forest biomass estimation*

400   The regression models developed using randomly selected LVIS-derived biomass samples and SAR data can generate

401   biomass maps comparable to the biomass map from LVIS data at 75m pixel spacing. The multi-channel SAR data can

402   explain more than 70% (R^2 in Table 4) of the variation of the biomass information contained in the LVIS data. It was

403   found that if the SAR data were used to predict rh50 and rh75, the best regression models selected by stepwise

404   regression had R^2 of 0.7699 and 0.767 (Equations and plots not shown in the paper). The results from this study show

405   that the SAR data can be used to extend the forest biomass samples at lidar footprints to entire area covered by SAR

406   data. The mean biomass from Field-LVIS model and LVIS-SAR models are very close. The differences were 4.6%,

407   4.5% and 7.1% for the three models shown in Table 5. The spatial correlations between the LVIS-SAR biomass maps

408   and the Field-LVIS map were high: 0.78, 0.78 and 0.8.

409   *5.5. Differences of the biomass maps derived from lidar and SAR data using field data*

410   The biomass map generated from Field-LVIS model is closer to the mean biomass in the study area than the biomass

411   map generated from Field-SAR model. Theoretically, if both LVIS and SAR data can be used to predict biomass, they

412   should give similar results. The only reason for this departure is the inadequate samples of the field biomass for

413   developing the SAR model: it doesn't cover the proper range of forest structures. In this study the number of samples of

414   field data is only 1/3 of the random samples, the Field-SAR model can not produce the similar biomass maps generated

415   from the LVIS biomass samples and the SAR model.

416   It is also important to note that the PALSAR data were acquired in 2007 and SRTM data was acquired in 2000 while

417   both the field data and the LVIS data were collected in 2003. Even though the areas with significant changes were

418   excluded in the analyses, the natural changes, such as tree growth and mortality were not considered in the study. In our

419   future studies, data collected at the same time and at various scales will be used to further investigate the issue. This

420   will provide the basis for future analysis.

421   *5.6. Errors in the biomass maps from one step (Lidar only) and two steps (lidar sample and SAR data)*

422   The RMSE of the Field-LVIS prediction model was 31.33 Mg/ha. This can be improved with more field samples, using

423   more indices from lidar waveform, and more waveform samples by more aggregation. One of the major tasks in

424   algorithm development for the future DESDynI Mission is improving biomass estimation from the lidar waveform data.

The RMSE of the best LVIS-SAR prediction model (7 in Table 4) was 28.21 Mg/ha. The combined RMSE of the two-step models will be 42.16 Mg/ha. It can be seen from Fig. 9 that the error is relatively even across the entire range (0-250 Mg/ha) of the biomass, which indicates that the "saturation" may not be a huge problem when multiple SAR variables were used. The accuracy of biomass prediction from lidar waveforms should be lower when the biomass is low or trees are shorter, because in these cases the return from vegetation canopy will merge with those from the ground surface. The signature from canopy was hidden in the ground peak, and the index which is most sensitive to biomass (e.g. rh50) is near zero (very close to the ground peak) and is easily affected by the shape of the ground peak. This may need to be addressed when the two-step method is used in the future.

5.7. Comparison of histograms of the biomass maps

Fig. 11 shows that the histogram of Field-LVIS biomass map has two modes. The biomass maps from the LVIS-SAR models have similar means to the Field-LVIS map, but show only little evidence of a bimodal distribution in their histograms. The lower mode of the histogram is around 18-35 Mg/ha, and was from clear cut areas and some other low biomass areas. When the canopy height and biomass are low, the signature from canopy and ground surface will overlap in the lidar waveform, which may cause the uncertainty in biomass estimation from lidar waveform data. This issue may need to be carefully investigated in future studies. The SAR-derived biomass map gave surprisingly high values. This needs to be further investigated, probably by additional field observations.

6. Concluding remarks

The purpose of this study was to prove the concept of combined use of lidar-samples and radar-imagery for biomass mapping. The model relating lidar indices to measured biomass explained 71% of the variation at the aggregated 75m pixel resolution. We used the map of biomass values generated from this model as the reference for this study. The results showed that by selecting 100 samples randomly from the reference map and using these samples to develop a prediction model from SAR data, the model can produce a new biomass map which has similar biomass levels and spatial biomass distributions. There is no obvious biomass "saturation" up to 250 Mg/ha, the limit of our measured field data.

Previously, various studies in SAR biomass estimation have been conducted using field measurements of biomass. The consensus is that both polarimetric and interferometric SAR data can be used to estimate forest biomass up to a certain level, depending on radar wavelength. Multiple channels of SAR data from multi-polarization, temporal, interferometric SAR data and transformations of these data can provide adequate information to extend the biomass information at lidar footprints across entire radar images. How to fully use the information and avoid over fitting will be a future research

14

topic. The height of the scattering phase center in the C band derived from SRTM data was an important variable in biomass estimation.

This work represents a preliminary analysis of possible methods that can be used to combine lidar derived biomass (sampled) with SAR image data to provide detailed maps of accurate biomass. The future DESDYnI mission is expected to rely on data and methods similar to that used here. Of course acquisition of SAR and Lidar data sets at nearly the same time, such as envisioned for DESDYnI should improve the results. New airborne contemporaneous NASA UAVSAR and LVIS data are becoming available along with supporting field measurements. The techniques described herein and other methods can be tested with these data sets.

Acknowledgments

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587

588   Figure Captions
589
590   Fig. 1. Study site near Howland, Maine: The red rectangle is the location of the stem map. Yellow circles are the field

591   sampled sites in October 2003.

592   Fig. 2. Stem map – Dark dots are locations of trees and the circles represent the LVIS footprints. 112 footprints were

593   completely inside the stem map.

594   Fig. 3. A) Gridded LVIS rh50 (Red), rh100 (Green), and rh25 (Blue), solid red rectangle is the stem map used in this

595   study. The greenish area across the road to the east of the stem map is an area with selective cutting. The top canopy

596   height remains unchanged, but the density of trees was reduced as shown on ASTER images. B) Centers of LVIS

597   footprints overlaid on the 15m ASTER image, showing the sampling density of LVIS data in the region.

598   Fig. 4. ALOS PALSAR data: A) polarimetric data acquired on April 16, 2007: Lhh (red), Lhv (green), Lvv (blue) and

599   B) Dual-pol data acquired on July 10, 2007 and SRTM phase center data in 2000: Lhh (red), Lhv (green), phase center

600   height (blue). The phase center height was the difference between SRTM DEM and the ground surface elevation from

601   LVIS data.

602   Fig. 5. (A) Polygons from the multi-resolution segmentation of the Landsat ETM+ scenes (7/2/2000, 9/10/2003, and

603   7/22/2007) (processed in Definiens Developer 7.0) overlaid on the ETM+ image of 7/22/2007; (B) Map of changed

604   areas produced from segmentation and classification: green areas – areas that changed between 2003 and 2000; red

605   areas – areas that changed between 2003 and 2007. (C) The mask used in this study. Forest areas disturbed during 2000 – 2007

606   and the non-forest areas were masked out.

607   Fig. 6. Predicted biomass vs. field measurements (stars): the biomass prediction model was developed from field

608   sampled forest sites and 12 sub-plots within the stem map 1. Bpred = -1.717 +6.208 * rh50 + 8.625 * rh75, R^2=0.71,

609   P-value = 2.4e-08.   The "fit" line: Bpred = 48.53 + 0.71 Bfield, r2 = 0.71, RSE=27.1 Mg/Ha. RMSE calculated from

610   SQRT(SUM((Bpred – Bfield)^2)/32) is 31.33 Mg/ha. The lines "LCL" and "UCL" are the lower and upper 95%

611   confidence lines.

612   Fig. 7. Biomass map using LVIS height indices from the regression model developed using field biomass data. The

613   mask shown in Fig. 5-C was used in extraction of image data for developing regression model, and for comparisons of

614   the biomass mapping results. Nevertheless, the prediction models were applied to entire images that are shown in this

615   and following images.

616 Fig. 8. Biomass map from SRTM phase center height and PALSAR data using regression model developed from field

617 biomass data. Comparing with the biomass in Fig. 7, the biomass level is much higher, and the spatial pattern of biomass

618 distribution is not very clear.

619 Fig. 9. Biomass predicted by SAR vs. the reference biomass mapped by LVIS data: one hundred random samples were

620 selected in forested area. The line is 1:1 line. Prediction model: B = -87.599 + 12.878 * srtm.lvis + 4.799 * X10900totp

621 + 12.343 * X10900hv2hh + 10.172 * X20890hv2hh -8.509 * X20900VV + 9.226 * X20890HH. The prediction results

622 (line "Fit"): Bsar = 36.8803 + 0.7126 Blvis, R^2=0.71, RSE=24.06 Mg/ha, p-value is 0, RMSE= 28.21 Mg/ha. "LCL" and

623 "UCL" are the lower ad upper 95% confidence lines.

624 Fig. 10. Biomass map from SRTM phase center height and PALSAR data developed from regression model using

625 random biomass samples from LVIS-derived reference map

626 Fig. 11. Histograms of the biomass maps: The mask image of Fig. 5-C excluded about 16.5% pixels from these images.

627 These six histograms correspond to the six images listed in Table 5. The SAR 1 and 2 biomass maps have significant

628 higher mean biomass than the reference biomass map from LVIS data.

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630

631 Table 1. Field sample sites in Howland, Maine in 2003: MaxDBH – maximum DBH; Maxht – maximum of tree height;
632 DBH_ht – height weighted by Square of DBH; cfb_ratio – percentage of biomass from conifer trees; m_biom – mean
633 biomass averaged over sampling sites.

634

Site	MaxDBH	Maxht	DBH_ht	cfb_ratio	m_biom
	(cm)	(m)	(m)	(%)	(Kg/m2)
5	28.3	12.9	11.5	100	7.22
7	15.6	17.41	12.27	0	10.37
8	16.5	17.91	12.65	0	10.64
10	10.55	13.91	6.47	60	6.06
15	25.9	21.94	14.46	73.8	16.93
24	32.3	23.92	20.82	6	10.03
25	18.1	13.66	10.5	92.2	13.85
27	27.7	22.55	19.79	4.4	24.88
30	41.8	20.44	18.37	100	28.56
33	20.6	19.9	13.17	42.7	18.99
36	30	21.37	17.2	41.3	21.11
38	17.1	13.2	11.5	100	27.10
39	16.1	12.71	11.48	100	4.05
40N	34.2	18.81	17.16	100	22.26
40	39.0	19.87	18.6	100	19.55
41	33.9	22.01	19.21	41.9	21.35
42	27.5	17.04	14.59	30.2	15.15
43	32.3	18.35	15.5	98.8	11.46
46	38.6	19.79	15.41	100	16.96
48	34.9	19.45	15.75	96.3	14.00

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636 Table 2. ALOS PALSAR data used in the study: all data were acquired around 3am with ascending orbits. The numbers
637 in bold were use to identify the data variables in this paper. PLR – polarimetric mode; FBD – Dual-pol (HH and HV)
638 mode.

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Image Name	Date	Sensor Mode	Angle
ALPSRP0652**10900**	4/16/2007	PLR	21.5
ALPSRP0719**20900**	6/1/2007	PLR	21.5
ALPSRP0776**10890**	7/10/2007	FBD	34.3
ALPSRP0843**20890**	8/25/2007	FBD	34.3

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650 Table 3. Regression models generated from stepwise regression using various POLSAR variables and the field plots.
651 Adding more SAR variables will further increase the multiple R-square and reduce the Residual Standard Error. Model
652 3 and 5 were used to generate biomass maps from SAR imagery data. RMSE was calculated by SQRT(SUM((Bpred –
653 Bfield)^2)/N) and N is the number of field sites
654
655

Model	Variables	Selected Var.	RSE (Mg/ha)	Mult. R2	p-value	RMSE
1	HH, HV, VH, VV from 4/16/07 and 6/1/07	HV,VH of 4/16/07; VH of 6/1/07	52.01	0.28	0.025	
2	Add total power, HV/HH ratio to 1	VH of 4/16/07, VV, HH, totP and HV/HH of 6/1/07	48.7	0.41	0.012	
3	Add srtm-lvis_ht to the variables in 2	VH, HV/HH of 4/16/07 VV, HH, totP and HV/HH of 6/1/07; srtm-lvis_ht	35.75	0.71	0.00003606	30.96
4	Dual-pol HH and HV, HV/HH, HH coherence from two dates in 2007	HH, HV, HV/HH of 8/25/07 Coherence of the two HH images	54.6	0.24	0.112	
5	Add srtm-lvis_ht to variables in 4	Srtm-lvis_ht	51.99	0.23	0.005528	
6	All SAR data (combine variables in 2 and 4)	HH of 8/25/07, HV/HH of 4/16/07 and VV, HH, totP of 6/1/07	46.52	0.51	0.004335	
7	Add srtm-lvis_ht to 6	HH of 8/25/07, VH, HV/HH of 4/16/07, VV, HH, totP, HV/HH of 6/1/07 and srtm-lvis_ht	33.92	0.75	0.0002362	28.76

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659 Table 4. Regression models generated from stepwise regression using various POLSAR variables and 100 random
660 samples. Model 3, 5 and 7 were used to generate biomass maps from SAR imagery data. RMSE was calculated by
661 SQRT(SUM((Bpred – Bfield)^2)/100).
662

Model	Variables	Selected Var.	RSE (Mg/ha)	Mult. R2	p-value	RMSE
1	HH, HV, VH, VV from 4/16/07 and 6/1/07	HV,VV of 4/16/07; VV, HV, HH of 6/1/07	43.6	0.36	6.294e-8	
2	Add total power, HV/HH ratio to 1	HV, HV/HH, totP of 4/16/07, VV, totP of 6/1/07	40.96	0.43	2.35e-10	
3	Add srtm-lvis_ht to the variables in 2	totP, HV/HH of 4/16/07 VV, totP of 6/1/07; srtm-lvis_ht	29.64	0.70	0.0	28.73
4	Dual-pol HH and HV, HV/HH, HH coherence from two dates in 2007	HVof 7/10/07, HH, HVHH of 8/25/07 Coherence of the two HH images	44.26	0.32	2.223e-07	
5	Add srtm-lvis_ht to variables in 4	Srtm-lvis_ht HV/HH, HH of 8/25/07	32.66	0.63	0.0	32.00
6	All SAR data (combine variables 2 and 4)	HH, HV/HH of 8/25/07, HV, VV, totP, HV/HH of 4/16/07 and VV, totP of 6/1/07	39.19	0.50	1.56e-10	
7	Add srtm-lvis_ht to 6	HH, HV/HH of 8/25/07, totP, HV/HH of 4/16/07 and VV of 6/1/07 and srtm-lvis_ht	29.26	0.71	0.0	28.21

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Table 5. Statistics of biomass maps from different data and methods: 1) Field-LVIS –from LVIS height indices and field data; 2) Field-SAR-PLR – from two PALSAR PLR data and field data; 3) FIELD-SAR-ALL – from the PALSAR PLR data, two dual-pol PALSAR data and field data; 4) LVIS-SAR-PLR and 5) LVIS-SAR-ALL – similar to 2 and 3, 100 randomly selected samples from Field-LVIS were used instead of the field data. 6) LVIS-DualSAR from 100 samples and dual-pol PALSAR data only. The height of the scattering center derived from SRTM and LVIS DEMs was always used in the regression models. The 'Corr' is the spatial correlation between these biomass images.

Models	Min	Max	Mean	Stdev	Corr
Field-LVIS	5.6	285.78	**126.82**	57.31	1.00
Field-SAR-PLR	1.15	979.58	200.61	52.63	0.59
Field-SAR-ALL	2.86	1095.39	200.53	55.20	0.54
LVIS-SAR-PLR	1.11	318.67	**120.97**	46.93	0.78
LVIS-SAR-ALL	1.12	321.75	**121.13**	47.31	0.78
LVIS-DualSAR	0.86	272.18	**117.8**	44.87	0.80

Table 6. Statistics from Bootstrap of the regression coefficients of model LVIS-SAR-PLR in Table 5. One thousand re-samples were used in the process. The Mean is very close to Observed for all coefficients of the model.

Coefficients of	Observed	Bias	Mean	SE
(Intercept)	-8.7599	0.4305406	-8.3294	7.3988
srtm.lvis	1.2878	-0.0031205	1.2847	0.1375
X20890HH	0.9226	-0.0126622	0.9099	0.3886
X20890hv2hh	1.0172	0.0006902	1.0179	0.3510
X10900totp	0.4799	0.0186490	0.4985	0.2836
X10900hv2hh	1.2343	0.0292449	1.2635	0.2700
X20900VV	-0.8509	0.0180304	-0.8329	0.3407