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Quantifying downed coarse woody material and residual forest basal area following retention harvesting in northeast Minnesota using Landsat sensor data

Wolter, PT
Department of Natural Resource Ecology and Management, Iowa State University, 339 Science Hall II, 2310 Pammel Drive, Ames, IA, 50011, USA
ptwolter@iastate.edu
515.294.7312

Hilgemann, LA
Virgin Islands Department of Agriculture, RR1 Box 10345, Kingshill, VI 00850, USA
louishilgemann@gmail.com
340.778.0997 ext. 240

White, MA
The Nature Conservancy, Minnesota, North and South Dakota, 394 Lake Avenue South, Duluth, MN, 55802, USA
mark_white@TNC.org
218.727.6119

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Abstract

Retention harvesting shows great promise for restoring and maintaining forest structural and compositional diversity. However, economical, comprehensive monitoring is needed to advance understanding of the effectiveness of these management strategies through time. We investigate multi-temporal winter Landsat sensor data (capturing snow ground cover at 7.6 cm and 106.7 cm depths) as a tool for discriminating between and providing regional estimates of both residual forest basal area (BA) and downed coarse woody material (DCWM) volume following retention harvesting in Minnesota, USA. Measurements from 34 ground plots were used with Landsat predictor variables to estimate these two biophysical forest parameters. According to similar studies, results for DCWM volume estimation are considered adequate, with an $R^2_{adj} = 0.54$ and absolute RMSE ($RMSE_a$) = 19.02 m$^3$ ha$^{-1}$. Residual forest BA estimates were similar: total BA $R^2_{adj} = 0.55$ ($RMSE_a$ = 1.85 m$^2$ ha$^{-1}$), hardwood BA $R^2_{adj} = 0.67$ ($RMSE_a$ = 1.23 m$^2$ ha$^{-1}$), and conifer BA $R^2_{adj} = 0.52$ ($RMSE_a$ = 0.94 m$^2$ ha$^{-1}$). Use of winter Landsat imagery was key to quantifying these important forest biophysical parameters – a tool which carries the potential to transform our understanding of the impact of human and natural disturbance regimes on northern forest ecosystems.
1. INTRODUCTION

The simplification of forest structure and composition resulting from intensive management is a global phenomenon (Puettmann et al. 2009). Disturbances from industrial forestry are drastically different from natural disturbance regimes (Lindenmayer and Franklin 2002). These intensive management activities threaten biodiversity and key ecosystem services such as clean water, erosion control, pest control, pollination, carbon storage, as well as local ecosystem resilience and stability. All of these services are a byproduct of natural processes linked to healthy forest systems with rich structural and compositional diversity (Franklin et al. 2007). Given this, forest management and conservation agencies are faced with important decisions on how to best manage forest lands by balancing human commodity needs while also promoting restoration of essential ecosystem services degraded by past forest management strategies (Franklin 2003). Hence, interest exists in silvicultural systems that emulate natural disturbance and increase biological diversity, structural complexity, and spatial heterogeneity in managed forests (Drever et al. 2006, Franklin et al. 2002).

Ecology and forestry have always been intrinsically linked (Toumey 1929). However, the more recent use of the term “ecological forestry” refers specifically to burgeoning silvicultural practices that aim to preserve or promote residual stand structure that more closely resembles natural disturbance. Examples include group selection with variable opening sizes; irregular shelterwood harvests; irregular multi-cohort harvests; and, in all, the deliberate retention of larger diameter living trees, snags (standing dead trees), and downed coarse woody material (DCWM) to promote forests that more closely resemble historically diverse structural and compositional conditions (Hanson et al. 2012). Decaying wood is of particular importance for fire fuels modeling (Seielstad and Queen 2003) and biodiversity in the world’s forests (Woodall et al. 2009); especially boreal forests, since many rare and specialized species are dependent on DCWM (Pesonen et al. 2008). Since the introduction of ecological forestry over twenty-five years ago, the core principle of preserving “biological legacies“ on the landscape has gained wide
attention as a tool for achieving structural complexity goals (Lindenmayer et al. 2012) and, hence, promoting and strengthening both ecosystem resilience and adaptive capacity to climate change (D’Amato et al. 2011, Franklin et al. 2007).

In practice, key elements of structural complexity (influenced by management) should be monitored at multiple spatial scales through time in order to gauge effectiveness in achieving structural goals (White et al. 2017, D’Amato et al. 2011). Unfortunately, ground-based monitoring efforts are rarely implemented due to cost (Pesonen et al. 2008), and those that do exist, such as the U.S. Forest Service’s national Forest Inventory and Analysis (FIA) database, are often collected at spatial sampling intensities (e.g., one plot per 2428 hectares) that preclude usefulness as a monitoring tool at finer spatial scales (see Woodall and Monleon 2008). Due to these information gaps, land management agencies and organizations have been working to develop and implement monitoring systems for assessing disturbance impacts on forest complexity. The Minnesota DNR’s Wildlife and Ecological Services divisions are developing field sampling approaches to monitor forest conditions over time and assess impacts of forest harvest on wildlife habitat indicators including basal area and DCWM (MN DNR, 2017, LCCMR 2016). The Nature Conservancy uses a field sampling system to measure key elements of forest complexity including residual basal area and DCWM on all restoration sites in northern Minnesota (> 300 sites, > 4,000 ha). Landsat time series at 5-year intervals are used to track moderate to high severity disturbances, patch sizes, and cover types for larger landscapes (104-106 ha) (TNC 2017, White et al. 2017). However, for key variables such as residual basal area and DCWM, these efforts capture only a small fraction of forest conditions in northern Minnesota.

Bridging these information gaps will facilitate greater understanding of the effectiveness of applied silvicultural treatments, especially our ability to identify and adapt management strategies in a timely manner to more closely meet short- and long-term goals (Lindenmayer et al. 2012, Pesonen et al. 2008). Hence, satellite-based assistance in providing spatially explicit estimates of the biological
legacies following harvesting treatments is a logical next step (Pesonen et al. 2008). Periodic satellite monitoring as stands develop will also satisfy a growing need for long-term, spatially explicit examination of the impacts of late-successional restoration treatments on the structural and compositional development of northern, second-growth forests (D’Amato et al. 2015), while also facilitating a deeper understanding of plant-wildlife responses to residual biological legacy prescriptions, forest disturbance, and carbon and nutrient cycling dynamics (Pastor and Naiman 1992).

Progress has been made in mapping standing and DCWM volume using lidar data (Pesonen et al. 2008), but a more readily available and economical remote sensing data source would be preferred. Because the Landsat series of satellite sensors provide a rich source of free image data (1972-present) with frequent revisit times (currently 16 days), moderate spatial resolution (30 m), meticulous preprocessing (Schmidt et al. 2013), and a commitment exists (e.g., Landsat 9) to ensure future data continuity (Irons et al. 2012), it follows that these sensor data should be considered for their ability to be used as a monitoring tool to track, quantify, and assess ecological forestry management objectives before accessing any of the suite of high spatial resolution commercial satellite sensor data (e.g., WorldView, Quickbird or GeoEye, IKONOS). While commercial satellite sensor spatial resolutions are desirable, these data are extremely expensive to acquire, especially new acquisitions (e.g., $23-$29 per km², http://www.landinfo.com/satellite-imagery-pricing.html), and have small swath sizes (e.g., Quickbird, 16.5 km) compared to Landsat (185 km), which preclude affordable, repeated, regional mapping efforts. With that said, once the Landsat 9 sensor is launched in 2020 (planned 8-day staggered orbit with Landsat 8), the probability of acquiring cloud-free imagery will increase substantially, further increasing the utility of these data (https://landsat.gsfc.nasa.gov/landsat-9/). The reader should note that the new Multispectral Instrument (MSI) sensors aboard the European Space Agency’s Sentinel-2A and 2B satellites –not available at the time of our study— are a viable alternative for regional mapping.
efforts, as these data are also freely available, have a large swath size (290 km), 5-10 day repeat cycle, and high spatial resolution (10, 20, and 60 m).

Authors have hinted, logically, that the spatial resolution of conventional satellite remote sensing data (e.g., Landsat) would limit methodologies for quantifying smaller components of DCWM, but quantitative evidence was not provided (Pesonen et al. 2008). Hence, the goals of our study include examining whether Landsat imagery can be used to quantify 1) DCWM volumes and 2) residual live and standing dead basal area (hereafter simply referred to as residual BA) following variable retention harvest treatments in mixed hardwood and conifer forest ecosystems of northern Minnesota (Figure 1) with sufficient precision to enable long-term, regional monitoring efforts. With respect to DCWM, we hypothesize that satellite images capturing varying depths of snow accumulation (e.g., 5 to 100+ cm) through the course of one winter season can be leveraged to allow multi-spectral discrimination of DCWM volume from standing forest biomass. Due to the 30-meter spatial resolution of the Landsat sensors, however, we further hypothesized that only the larger diameter components (≥ 10 cm) of overall DCWM volume —along with associated shadow structures—would be most visible (see Pesonen et al. 2008) and, hence, yield the strongest calibrations between satellite and ground data. A key assumption in these hypotheses was that the spectral contributions from standing, residual trees under different snow depths would be more-or-less static compared to the changing spectral contributions from DCWM components as they are gradually covered by snow accumulation. Hence, we hypothesized under our second objective that if, indeed, the deepest snow cover levels (i.e., 100+ cm) completely concealed DCWM that it should be possible using these Landsat sensor data to spectrally distinguish sparse residual forest BA following silvicultural treatments with little to no confusion with horizontal DCWM components.

Previous studies, under substantially higher forest BA conditions (e.g., > 20 m² ha⁻¹) than those following silvicultural treatments, have shown that winter satellite imagery with snow ground cover...
produced stronger predictors of forest basal area than similar imagery from other seasons (Wolter et al. 2008, Wolter et al. 2012). The key advantage of snow, as discussed above, is that it effectively covers small branches and leaf litter, soil, rock and other material on the forest floor that would otherwise confound the spectral signatures of standing forest trees (Wolter et al. 2008). In doing so, snow ground cover provides a bright, spectrally homogenous surface upon which dark contrasting shadows of standing tree structures are accentuated. Justification for relating tree shadows to forest BA, biomass, or volume is logical since tree diameter is strongly related to aboveground biomass (Jenkins et al. 2003). Hence, it stands to reason that the two-dimensional representation of this biomass—shadows on snow—would also be related to a diameter-specific quantity such as BA. With regard to Landsat, previous studies have provided strong empirical evidence to support this relationship (Wolter et al. 2012).

To our knowledge, though, this is the first study to attempt calibration of both DCWM volume and residual forest BA models using multi-temporal winter satellite sensor data. We use a robust, recursive statistical approach to automatically identify a salient subset of Landsat-based predictors to facilitate modeling DCWM volume and residual forest BA. We then report the degree to which these Landsat-based estimation models explain observed variance in DCWM volume and residual forest BA. Hence, we address two salient questions. First, can difference in snow depth be used as a vehicle to enable simultaneous, satellite-based estimation and mapping of DCWM volume and standing residual forest BA? Secondly, can Landsat satellite sensor data be used in boreal and sub-boreal forests as an economical substitute to ground-based monitoring to track and assess regional ecological forestry management benchmarks and goals?

2. METHODS

2.1 Study site

The test study site is approximately 490 ha (1,212 ac) within the Manitou Landscape located in Lake County in northeast Minnesota, USA (Figure 1). This area lies within the North Shore Highlands...
subsection of the Minnesota Ecological Classification System, a band which parallels the shore of Lake Superior 32 to 40 km inland. Elevation ranges from 200 to 700 m across this gently rolling landscape punctuated with some steep areas and bedrock outcroppings (Heinselman 1973). The study site lies within the Cabin Lake Till Plain where soils range from moderately well-drained to well-drained loams of silt and sand. Lake Superior moderates the local climate throughout the year, resulting in cool, moist conditions in the spring and summer and warmer conditions in the fall and winter relative to inland areas (Baker et al. 1985). The overall continental climate has a mean growing season length of 104-168 frost-free days, mean annual temperature of 4.7°C, and mean annual precipitation of 77.5 cm. Average annual snow accumulations is 150.4 cm (1971–2000, Midwest Regional Climate Center, http://mcc.sws.uiuc.edu).

This study site lies within a complex mosaic of forest and wetland communities (Heinselman 1973). Since European settlement, extensive logging and intense slash fires have resulted in unnatural simplification and homogenization of forest structure and composition (Schulte et al. 2007). This has shifted the landscape from later successional forests dominated by conifers such as white spruce (Picea glauca), white pine (Pinus strobus) and northern white-cedar (Thuja occidentalis) to an early successional landscape dominated by sprouting, shade intolerant hardwoods, mainly quaking aspen (Populus tremuloides) and paper birch (Betula papyrifera) (Schulte et al. 2007). Upland forests are now composed of northern mesic mixed species, including various mixtures of quaking aspen, paper birch, balsam fir (Abies balsamea), white spruce, white pine, and northern white-cedar (Heinselman 1973). Northern hardwood patches occur on loamy uplands composed of sugar maple (Acer saccharum), yellow birch (B. allegheniensis), and northern white-cedar within the boreal conifer-hardwood matrix (White and Host 2000). While stand replacing fire was a major disturbance agent in the past (Heinselman 1973), large crown fires in this region are now far less common. However, large-scale
defoliation by spruce budworm was and continues to be a significant disturbance agent to stands of balsam fir and spruce in this region (Robert et al. 2012).

In response to regional forest homogenization (Schulte et al. 2007, White and Host 2008) a collaborative landscape group composed of public agencies and private landowners developed harvest prescriptions designed to restore compositional and structural variability within this 490 ha patch (Cornett and White 2013). Long-term (> 100 years) project objectives include a large late-successional forest patch dominated by long-lived conifers such as white pine, white spruce and northern white-cedar with high structural diversity including standing dead and DCWM. Silvicultural prescriptions were based on moderate severity natural disturbances typically occurring in this region (40-70 percent canopy removal) (MN DNR 2003). From 2010 to 2013 288 ha were harvested using seed tree and shelterwood based prescriptions (Figure 2). The shelterwood treatment (123 ha) resulted in a 65 % reduction in forest BA ($m^2$ ha$^{-1}$) while the seed tree harvest (165 ha) yielded a 76 % reduction in BA. Post-harvest activity included planting of white pine, white spruce, and northern white-cedar at total densities of 1000 tree/ha.

2.2 Field data

*In situ* measurement of residual forest structures (BA and DCWM) was conducted between 5 June and 14 August 2014 within 34 randomly established ground plot locations following variable retention harvest treatments (Figure 2). Ground plots were generated using the “Create Random Points” function in ArcMap 10.1, and located using a WAAS-enabled GPS receiver (Garmin GPSMAP 62stc; 2drms ≤ 3 m). Each ground plot consisted of a total of five subplots: one located at plot center (subplot 1) and four arranged orthogonally 30 m from plot center (Figure 3). The initial azimuth from subplot 1 to subplot 2 was determined randomly and dictated placement the remaining subplots around plot center (Figure 3). Landsat images for a given footprint are coregistered automatically as part of the U.S. Geological Survey (USGS) Data Processing and Archive System (DPAS) stream with specified pixel-to-
ground circular error to be less than 0.4 pixels (Irons et al. 2012). Our ground plots are designed to represent an area larger than a Landsat pixel (ca. 42 x 42 m for DCWM and up to 60 x 60 for BA measurements) to account for 12-15 meter pixel registration errors. For BA, measurements are spatially pooled and converted to an average area per hectare. Similarly, DCWM is scaled to an average volume per square meter. Hence, when plot locations are used to extract pixel values, even if image-to-ground registration is imperfect, ground data will remain representative of reflectance from that offset pixel (see Wolter et al. 2008, Wolter et al. 2009).

At each subplot, residual BA by species (live and standing dead) was collected using a metric basal area factor one prism where plot radius varies according to the bole diameter of each tree (Grosenbaugh 1952). Diameter at breast height (DBH, 1.37 m above ground) was measured for each tree in the subplot. Bole diameters (cm) by species were recorded for all residual live and standing dead trees. In a few instances standing dead trees had no bark and were simply recorded as either dead hardwood or conifer. The tree height datum for each plot was based on the average clinometer measurements of two representative live tree heights per plot. Heights of all standing dead trees (snags) were also measured. Residual forest BA data (m^2 ha^{-1}) collected at the five subplots were pooled (by species, hardwoods, conifers, and total BA) and averaged to provide one set of dependent variable values for each full plot.

The DCWM was sampled along two orthogonal 60 m transects and four 15 m transects between each subplot, totaling 180 m at each plot (Figure 3). While some suspect that use of relatively short transect lengths (<100 m, Harmon and Sexton 1996) may limit the ability to fully capture spatial variation in DCWM volume (D’Amato et al. 2008, S. Fraver (personal communication, 2017)), others claim that many shorter transects provided more reliable estimates of DCWM volume (Waddell 2002). Howard and Ward (1972) found that the amount of coarse wood was highly variable in harvested areas and that a small number of long transects did not adequately capture this variation. Based on their
conclusions, we added the four 15 m transects described above between the outer subplots to both avoid
over-sampling near plot center (D. Mladenoff (personal communication, 2008)) and facilitate spatial
integration with 30 m Landsat pixels (Wolter et al. 2008).

During DCWM sampling, only those logs and branches encountered along transect intersections
(Brown 1974) that were greater than five cm in diameter were measured. While 7.5 to 10 cm is a
common minimum diameter range in DCWM assessments (Woodall et al. 2009), we chose a five cm
minimum due to the abundance of DCWM below 7.5 cm throughout the study site. Measurement of
DCWM diameter (cm) and height above ground (cm) were performed only when transects crossed the
center or central axis of the log (Brown 1974). If the transect crossed the same piece of DCWM more
than once, then measurements were made at each intercept (Brown 1974). Total DCWM volume for
each plot was estimated using the following formula according to VanWagner (1968), where $V$ is wood
volume ($m^3$ ha$^{-1}$), $d$ is DCWM diameter (m), and $L$ is overall transect length (m):

$$V = \left( \frac{\pi^2}{8L} \right) \sum \frac{d^2}{B} \cdot \frac{10,000 \, m^2}{ha}.$$  

In line-intersect sampling theory, length ($L$) is considered to be one long sampling line at each plot
(Hazard and Pickford 1986). While multiple DCWM transects were used at each plot in this study, the
total transect length ($L$) remains as the combined length of all transects (Waddell 2002). Hence, volume
calculations are considered both independent of individual DCWM element length and size of the
sampled area (VanWagner 1968).

It is important to note that there are three main sources of error in the Brown (1974) DCWM
sampling method that involve basic assumptions about log shape, log orientation relative to local
topography, and height of log relative to ground surface. First, reliance on just one diameter
measurement at the point of intersection to calculate volume assumes that log shape is cylindrical (no
taper) and that the point of intersection represents the midpoint (VanWagner 1968). The DCWM
encountered in this study was logging residue composed of logs and sticks that were generally both
cylindrical and straight. Second, DCWM elements are assumed to be randomly oriented throughout a
sample area with a Poisson distribution (Waddell 2002). This orientation assumption is violated (biased
sample) if logging residue is positioned primarily in one direction. Potential orientation bias in sampling
can be avoided by using two or more transects extending out from a common point at different angles
(Van Wagner 1968). Therefore, we sampled DCWM along six transect lines in four different directions
(Figure 3) to reduce orientation bias in our samples (Waddell 2002). The final sampling assumption of
Brown (1974) is that all DCWM elements are parallel to the ground. Even though Van Wagner (1968)
found that the DCWM-ground separation angle can vary substantially before a serious error will occur
in the volume estimate, the DCWM elements encountered in this study were generally horizontal, with
only minor angular separations from the ground. A comprehensive accounting of downed DCWM
decay class, such as that described by Maser et al. (1979), was not performed in this study – only a few
logs showing the most decay were noted (i.e., class 5).

To prepare for tests of ground-to-satellite model calibration sensitivity, estimates of DCWM
volume were calculated based on three different minimum diameter limits (≥ 5 cm, ≥ 7.5 cm and ≥ 10
cm), which we will refer to henceforth as classes. These DCWM volume classes were further stratified
into two height classes based on measured suspension heights of individual DCWM elements above the
ground at the point where diameters were measured (< 8 cm and ≥ 8 cm), for a total of six volume
classes. The height-based volume classes were specifically designed to distinguish between DCWM
volumes based on logs that were partially embedded in the soil from those that were not, as the former
volumes may potentially be obscured from the satellite sensor’s view under relatively light snow cover.
As such, the 8-cm height threshold was determined based on modeled snow accumulation (source
provided below) during the first two Landsat overpass dates early in the winter season (Table 1).

Creating a set of DCWM volume response variables that specifically excluded near-ground DCWM
volumes facilitated a more pragmatic approach to understanding results of model sensitivity tests during
the ground-to-satellite calibration phase.

2.3 Predictor variables and model calibration

We used three Landsat-8 Operational Land Imager (OLI) scenes for this study acquired during
the winter season following summer 2014 ground data collection. These Landsat-8 sensor data included
November (N), December (D), and March (M) dates (Table 1). We assumed no changes in DCWM or
BA occurred between ground data collection and image acquisition.

These images were downloaded from the USGS Earth Resources Observation and Science
84 coordinates. These Landsat-8 OLI sensor data are made available as precision-orthorectified, surface
reflectance image products. Modeled snow depth conditions on the days of sensor overpass (Table 1)
were similarly light for the N and D dates (7.6 cm), and relatively deep on the M date (106.7 cm).
Modeled snow depth data were acquired from the Minnesota Climatology Working Group archive
(source: [http://climate.umn.edu/doc/snowmap.htm](http://climate.umn.edu/doc/snowmap.htm)).

In addition to the Landsat-8 OLI reflective bands for each image date (OLI 1–7), we derived
several spectral indices to be used as candidate predictor variables for estimating DCWM and residual
BA. These indices included the normalized difference vegetation index (NDVI, Rouse et al. 1974),
shortwave infrared-based (SWIR, OLI6 [1.560–1.660 µm] and OLI7 [2.100–2.300 µm]) indices
(moisture stress index, MSI, Rock et al. 1986; normalized difference snow index, NDSI, Dozier 1989;
shortwave infrared to visible ratio, SVR, Wolter et al. 2008), and a modified version of SVR, SVR6,
which is computed as OLI6 divided by the sum of the three visible bands. SWIR-based indices were
included in these analyses because formulations using SWIR wavelength intervals are known to be
sensitive to forest BA (Horler and Ahern 1986, Wolter et al. 2008), and have been used to study forest
structural parameters, particularly forest density and tree size (Cohen and Spies 1992, Hansen et al.
When compared to visible wavelengths, near-infrared (NIR, 0.845–0.885 µm) and SWIR regions of the electromagnetic spectrum experience relatively minor water vapor and Rayleigh scattering effects (Larsen and Stamnes 2005, Liang et al. 2002). Disproportionate diffuse irradiance (Dubayah 1994) in the visible region of the electromagnetic spectrum accounts for partial illumination of geometric tree shadows, which lowers contrast sensitivity between the fully illuminated and shaded forest floor (Wolter et al. 2012). Indices composed of NIR, SWIR, or contrasts between these and visible wavelengths enable the clearest possible contrast between sunlit and shaded forest floor signatures (Wolter et al. 2012) and other structures casting shadows on the forest floor, such as DCWM. We included normalized difference shortwave infrared (OLI5) to green (0.525–0.600 µm) ratio (ND53) in these analyses for this reason. Visible wavelength intervals, especially red (e.g., OLI4: 0.630–0.680 µm), are known to be responsive to vegetation biomass (Roy and Ravan 1996) and other structural properties (Turner et al. 1999). Coniferous forest reflectance in the visible region varies inversely with biomass parameters such as basal area (Franklin 1986). The normalized difference visible red to green ratio, ND43 ([red-green]/[red+green]), was tested as a visible band index that may exhibit wavelength-specific variation in snow reflectance saturation that varies with forest structure (BA and DCWM, see Dozier 1989).

Caution should always be exercised when using winter Landsat sensor data in northern latitudes in areas with complex or dissected terrain due to the effect of low sun angle illumination (Wolter et al. 2008). While terrain within the study area is gentle, we decided to included shaded relief images, generated using a 30-m digital elevation model (DEM, source: http://ned.usgs.gov/) and the Landsat solar ephemeris from Table 1, to account for potential effect of local terrain on geometric shadows (i.e., hard shadows) or differences between sun-lit and hard-shaded surfaces (Wolter and Townsend 2011).

Finally, we generated change predictor variables to capture DCWM spectral differences between the low (N) and high (D, M) snow depth dates; for example, March minus December shaded relief difference.
(DIFFSHD_MD), March to December SWIR (OLI6) difference (DIFF6_MD), NDVI difference for March and November (DIFFNDVI_MN), etc.

Two separate sets of model calibrations were performed between ground-measured variables (BA and six cases of DCWM volume) and the candidate satellite variables to test our hypotheses: one set using just the high snow depth image predictors and the second set using the full complement of image predictors from both high and low snow depth dates. In each case, residual forest BA and all DCWM volume variables were modeled using iterative exclusion partial least-squares (xPLS, Wolter et al. 2012) regression. The first set of model calibrations used just the high snow accumulation image predictors from March (M), while the second set of models used both the high and low snow accumulation image predictors as well as the respective image difference variables. Each calibration case was initiated using the respective full suite of candidate image predictor variables; 15 for high snow accumulation and 30 for the combination of high and low snow accumulation.

Use of the partial least squares (PLS) regression approach is appropriate in cases where independent or dependent regression variables are highly collinear (Geladi and Kowalski 1986), as is often the case with satellite sensor data (Wolter et al. 2008). After xPLS decomposition of the dependent and independent regression data blocks into uncorrelated latent structures, the routine automatically removes predictor variables that display low or no variation with respect to the block of dependent ground variables without compromising predictive precision (Wolter et al. 2008, Wolter et al. 2012). In doing so, the xPLS model calibration approach avoids both model over fitting and multicollinearity issues among highly correlated predictors (Carrascal et al. 2009, Wold et al. 2009). For detailed discussions of PLS and xPLS, see Wold et al. (2009), Carrascal et al. (2009), and Wolter et al. (2012).

Because PLS regression is known to be sensitive to the presence of outliers (Rousseeuw and Leory 2003), we evaluated the ground response variables prior to xPLS calibration steps using the
Shapiro-Wilk test to identify potential outliers and deviations from normality (Thode 2002), which is recommended when observation sample size is less than 50 (Elliott and Woodward 2007). The Shapiro-Wilk test assumes a null hypothesis that the data come from a normal distribution. Thus, a p-value less than or equal to 0.05 suggests that data are not normally distributed, and a p-value greater than 0.05 indicates data that are normally distributed. Prior to model calibrations, all dependent ground variables were natural log transformed to achieve normality (Pesonen et al. 2008) and then back transformed following model development. Two reliability metrics were used to determine the accuracy of predictions. Absolute root mean squared error (RMSE\(_a\)) is calculated as:

\[
RMSE_a = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}}, \tag{2}
\]

where \(n\) is the number of sample plots, \(y_i\) is the observed value, and \(\hat{y}_i\) is the associated estimate. The relative RMSE (RMSE\(_r\)) value was calculated by dividing the RMSE\(_a\) by the mean and also the range of the observed values.

3. RESULTS

3.1 Plot data

Post-treatment total residual forest BA was low throughout all ground plots (mean 6.89 m\(^2\) ha\(^{-1}\), range 2.80-14.60 m\(^2\) ha\(^{-1}\)). Mean hardwood and conifer residual BA were 4.61 m\(^2\) ha\(^{-1}\) (range 1.40-10.40 m\(^2\) ha\(^{-1}\)) and 2.1 m\(^2\) ha\(^{-1}\) (range 0.2-5.2 m\(^2\) ha\(^{-1}\)), respectively. Average respective volumes for the \(\geq 5\) cm, \(\geq 7.5\) cm, and \(\geq 10\) cm DCWM diameter classes were 67.8 m\(^3\) ha\(^{-1}\) (range 24.0-144.6 m\(^3\) ha\(^{-1}\)); 62.9 m\(^3\) ha\(^{-1}\) (range 22.6-132.5 m\(^3\) ha\(^{-1}\)); and 55.2 m\(^3\) ha\(^{-1}\) (range 12.0-127.0 m\(^3\) ha\(^{-1}\)). For DCWM logs \(\geq 8\) cm above the forest floor, average volumes in the \(\geq 5\) cm, \(\geq 7.5\) cm, and \(\geq 10\) cm diameter classes were 26.9 m\(^3\) ha\(^{-1}\) (range 4.8-73.5 m\(^3\) ha\(^{-1}\)); 22.6 m\(^3\) ha\(^{-1}\) (range 4.2-72.0 m\(^3\) ha\(^{-1}\)); and 22.1 m\(^3\) ha\(^{-1}\) (range 3.8 – 72.0 m\(^3\) ha\(^{-1}\)), respectively. Statistics for these ground dependent variables are provided in Table 2.

3.2 Model development
Calibrations between image predictor variables and transformed DCWM volume for three DCWM diameter classes (≥ 5 cm, ≥ 7.5 and, ≥ 10 cm), without height above ground distance limits, resulted in respective adjusted multiple correlation coefficients ($R^2_{\text{adj}}$) of 0.43 (RMSE$_a$ 22.70 m$^3$ ha$^{-1}$: 33.5% of mean, 15.7% of range); 0.54 (RMSE$_a$ 19.02 m$^3$ ha$^{-1}$: 30.3% of mean, 14.4% of range); and 0.52 (RMSE$_a$ 18.05 m$^3$ ha$^{-1}$: 32.7% of mean, 14.2% of range). Repeating calibrations using only DCWM logs that were above the threshold height limit (≥ 8 cm) resulted in a viable model for only the largest DCWM log diameter class: $R^2_{\text{adj}}$ 0.53 and RMSE$_a$ 10.49 m$^3$ ha$^{-1}$ (49.7% of mean, 14.6% of range) (Table 3).

In each of the successful DCWM volume calibration cases discussed above, cross-date shaded relief and cross-date snow-depth difference image variables from March-November (MN) and March-December (MD) were selected exclusively by xPLS regression over all other date-wise bands, date-wise indices, and terrain variables. For these DCWM volume models, the predictor variable reduction percentages from initial to final models ranged from 73.3 to 86.7%, where there were 30 predictor variables in the initial candidate pool (Table 4). Similar DCWM volume calibrations were attempted using satellite-based and terrain predictor variables solely from the high snow depth date (March, 100+ cm), but none of these calibration attempts arrived at viable solutions.

Conversely, the strongest model calibrations between image predictors and both residual total forest BA and hardwood BA (Table 3) were characterized by exclusive use of the March high snow depth image predictor variables (Table 4) for these respective models: $R^2_{\text{adj}}$ 0.55 (RMSE$_a$ 1.85 m$^2$ ha$^{-1}$: 26.9% of mean, 12.7% of measure range) and 0.67 (RMSE$_a$ 1.23 m$^2$ ha$^{-1}$: 26.7% of mean, 11.8% of range). These results represents substantial increases in $R^2_{\text{adj}}$ (14.5% and 53.7%) and RMSE$_a$ (8.0% and 34.6%) over their combined, low-high snow, multi-date calibration counterparts. Conifer BA calibration with an $R^2_{\text{adj}}$ 0.49 (RMSE$_a$ 1.00 m$^2$ ha$^{-1}$: 48.8% of mean, 18.1% of range) was somewhat better (5.8% increase in $R^2_{\text{adj}}$ and 6% reduction in RMSE$_a$) when one image predictor variable from the
November (low snow) image date was included with two image variables from the March (high snow) date. None of these residual standing forest BA model calibrations made use of shaded relief variables (Table 4).

Strongest models in each category (DCWM volume, total BA, hardwood BA, and conifer BA) were defined as those having the best combination of low RMSE\(_a\), low cross-validated predicted residual sum of squares (PRESS), high \(R^2_{adj}\), and low number of predictor variables. For example, while the DCWM volume model that specifies only DCWM logs ≥ 10 cm diameter and ≥ 8 cm height above the ground has a superior RMSE\(_a\) (10.5 vs. 19.0 m\(^3\) ha\(^{-1}\)) and comparable \(R^2_{adj}\) values compared to the other DCWM volume models, this model is twice as complex in terms of the number of predictor variables required and has the highest PRESS value (Table 3). Plots of the predicted versus observed dependent variable values for the strongest models are shown in Figure 4. Regression results for these models (Table 3) show hardwood BA as retaining the highest number of predictor variables (8), followed by DCWM ≥ 7.5 cm diameter volume (4), conifer BA (4), and total BA (3). March-December shaded relief difference (DIFFSHD_MD), March-November SWIR6 difference (DIFF6_MN), and March-December SWIR5 difference (DIFF5_MD) were retained in all DCWM models. The strongest models for each of the dependent variables were used to map these attributes throughout the study area (Figure 5).

4. DISCUSSION

4.1 Mapping post-harvest residual forest structures

This research addresses the question of whether 30-meter Landsat-8 satellite sensor data can be used in boreal and sub-boreal forests of North America as a viable substitute for extant, costly ground-based monitoring efforts to track and assess ecological forestry management benchmarks and goals at landscape and regional scales. Specifically, can Landsat sensor data be used to (1) quantify and track
residual DCWM volume (m$^3$ ha$^{-1}$) and (2) reliably detect sparse, residual standing forest BA (m$^2$ ha$^{-1}$) –
in this case, residual BA ranging from ca. 2.8 to 14.6 m$^2$ ha$^{-1}$ (Avg. 6.89 m$^2$ ha$^{-1}$, Table 2)?

Landsat sensor data have been used in a similar capacity to map forest BA in this region under
substantially higher BA (e.g., 15-40 m$^2$ ha$^{-1}$, Wolter et al. 2008). Moreover, combinations of summer
and winter Landsat data have been used to accurately discriminate and quantify the relative abundance
of standing dead trees ($R^2_{adj}$=0.83, RMSE$_a$=9.1%) from total forest BA ($R^2_{adj}$=0.86, RMSE$_a$=2.95 m$^2$ ha$^{-1}$)
(Wolter et al. 2014). However, research involving either discrimination of DCWM volume or
biomass from standing forest elements using remote sensing technologies (e.g., Pesonen et al. 2008) is
rare, especially in the Great Lakes region of North America. Van Aardt et al. (2011) used an airborne
lidar system with a 1.4 m footprint (four returns per pulse and over five hits per m$^2$) in oak dominant
forests of central Appalachia, Kentucky, USA to model 10-hour (0.64-2.54 cm DIA) and 100-hour
(2.54-7.62 cm DIA) DCWM fuel loads. Their DCWM volume models had $R^2_{adj}$ values between 0.77-
0.99, although only ranges of $R^2_{adj}$ and RMSE$_a$ values were reported. In a data fusion study, Huang et
al. (2009) combined ground measurements with data from two National Aeronautics and Space
Administration/Jet Propulsion Laboratory (NASA/JPL) sensors – optical Airborne Visible/Infrared
Imaging Spectrometer (AVIRIS) and Airborne Synthetic Aperture Radar data (AirSAR) — to calibrate
models for estimating both total coarse woody material quantity (standing dead plus DCWM in tons ha$^{-1}$)
and quality (proportion of standing dead to total dead wood) in post-fire conifer dominated stands in
Yellowstone National Park following the 1988 wildfires. In both cases (dead wood quantity and quality)
results were moderate at best, with the quantity calibration yielding $R^2 = 0.54$ (RMSE$_a$ 29.1 tons ha$^{-1}$)
and an overall quality classification accuracy of 40.3% among five standing dead to total dead wood
proportion classes: $\geq$ 40%; 15-40%; 7-15%; 3-7%; and $\leq$ 3%. While direct accuracy comparisons
between Huang et al. (2009) and our estimates of standing BA (m$^2$ ha$^{-1}$) and DCWM volume (m$^3$ ha$^{-1}$)
are certainly not appropriate, their study serves to underscore the difficulty in achieving even moderate
levels of accuracy when estimating dead wood biophysical parameters using remote sensing data,
especially distinguishing DCWM from residual standing forest (live or dead). What is particularly
notable about the Huang et al. (2009) study is the high quality of remote sensing data they used (see Lou

In our research, we gauge the usefulness of winter Landsat sensor data (Table 1) for
discriminating between—and mapping—sparse, residual forest BA (live + dead) and DCWM volume in
northern Minnesota following retention harvesting treatments using a novel approach, which we
summarize below.

4.2 Residual Forest BA

The typical low tree densities (i.e., BA) following application of retention harvesting practices
presents unique mapping challenges when using satellite-based imaging sensors. Under substantially
higher stand densities (e.g., BA 15-40 m² ha⁻¹), many authors have successfully calibrated models for
estimating BA using imaging satellite sensor data (Wolter et al. 2009), lidar sensor data (Hawbaker et al.
2009), and combinations of both technologies (Hudak et al. 2005). Typical levels of error among
estimates of forest BA (measured by RMSEa) have ranged from 2.79 m² ha⁻¹ (Wolter et al. 2012) to 7.18
m² ha⁻¹ (Franco-Lopez et al. 2001). While the former study included some forest areas that contained
comparably low BA (minimum 2.4 m² ha⁻¹), they were not exclusively low BA forests as were the post-
harvest stands in this study.

Interestingly, in classifying thematic BA ranges (0-10, >10-20, >20-30, and >30 m² ha⁻¹) in
northern Minnesota using a k-nearest neighbors approach, Franco-Lopez et al. (2001) found agreement
accuracies with ground truth data were consistently highest (commission error = 56-66%, omission error
= 42-54%) for the lowest BA range class (0-10 m² ha⁻¹). This seems reasonable for a classification
result as the lowest BA range class, which includes zero BA, may artificially boost accuracy for that
class if there is a disproportionate abundance of non-forest in a study area. In other studies where actual
continuous estimates of forest BA were modeled and mapped, a lower BA threshold of 15 m$^2$ ha$^{-1}$ was imposed to exclude low BA ground plots prior to model calibration procedures with Landsat data. This was done in an effort to exclude plots where forest was not the dominant, reflective signal (Wolter et al. 2008).

In this study, the remedy used for normalizing the confounding spectral effects of non-forest targets was to take advantage of snow cover with sufficient depth to completely cover ground targets (Wolter et al. 2012), in this case downed DCWM. Having Landsat imagery collected under both high and low snow cover conditions (Table 1) facilitated further validation of this general technique (see Wolter et al. 2012, Wolter et al. 2014). For total forest BA and hardwood BA, superior calibrations with ground data were achieved using the high snow cover (H), single-date, Landsat reflectance data ($R^2_{\text{adj}}$ 0.55 vs. 0.67, respectively) compared to calibrations that made use of the multi-date, high and low snow depth (HL) image combination (Table 3). The conifer BA models, on the other hand, showed a puzzling weak, opposite result, which we suspect may be linked to a combination of (1) very low conifer BA (2.05 m$^2$ ha$^{-1}$ on average) compared to hardwoods (Table 2) and, more importantly, (2) a disproportionately higher ground shadow area contribution from conifer canopies (winter leaf-on) compared to the typical hardwood canopy, given the same tree height. Furthermore, we suspect the more discrete conifer shadow size may show greater inter-species variability compared to lesser, diffuse canopy shadows produced by leaf-off hardwoods in winter (e.g., pine, spruce, cedar versus maple, birch, aspen), which Landsat is likely sensitive to. However, we have no specific quantitative evidence to support such conjecture at this time.

In any event, both the conifer BA and total BA calibration results show stronger deviation from unity with ground data than that of the hardwood BA results (Figure 4), where regression slopes, in each case, are less than one. Because of this, and because these models are independent of each other, the mapped results for total BA shows lower BA values than that depicted by the hardwood BA map in...
some areas (Figure 5). In retrospect, with regard to calibration and mapping, it may be preferable in the future to model these dependent variables simultaneously using xPLS regression so that a common set of image predictors would be used to build all maps, which may help resolve some of the mapping bias disparities depicted in Figure 5. Alternatively, total and hardwood BA could be modeled exclusively and simultaneously, then, to map conifer BA, one could simply subtract hardwood BA from total BA to arrive at a conifer BA solution.

Overall, however, BA mapping under these sparse, post-harvest, forest conditions using Landsat sensor data were surprisingly good and compared favorably with studies under substantially higher BA levels (Wolter et al. 2008). Potential certainly exists, via use of higher spatial resolution satellite sensors, to build upon these results (e.g., Wolter et al. 2009). Nevertheless, success of this approach for regional mapping efforts will depend primarily on two factors: 1) availability of cloud-free imagery and 2) sufficient snowfall to cover DCWM. Regarding the former, Landsat has an unprecedented legacy of archived data and there is a strong commitment from NASA and the U.S. Geological Survey to advance Earth system science via continuation of these sensor data into the future (Irons et al. 2012), which, with eight-day repeat coverage by 2020 (i.e., offset 16-day orbital cycles between Landsat 8 and 9), makes these satellite sensor data especially attractive for long-term monitoring efforts. On the other hand, lack of consistent or sufficient snow depth across larger regions could limit this approach to lesser landscape scales, but this has not yet been attempted. In any event, detailed, historical snow depth records provide helpful insight into the probability of receiving sufficient snow coverage in any one year (e.g., http://climate.umn.edu/doc/snowmap.htm).

4.3 DCWM Detection

The use of multi-temporal winter imagery, capturing dates with contrasting low and high snow depth levels (7.6 and 106.7 cm, respectively), was key to distinguishing DCWM from the standing residual forest structures. This was evidenced by the fact that cross-date image difference predictor
variables were retained exclusively by all attempts to develop estimation models during the xPLS (Wolter et al. 2012) automatic calibration and variable selection process (Table 4).

Given the 30-meter spatial resolution of the Landsat-8 sensor, however, we were somewhat surprised that it was the intermediate DCWM diameter class (≥ 7.5 cm DIA, ≥ 0.0 cm HT above ground), and not the largest diameter class, that yielded the strongest model calibrations between Landsat and ground data (Table 3). Our initial large diameter class assumption was based, in part, on the results of past forest structure research involving use of laser altimetry (Seielstad and Queen 2003). Hence, we assumed that the size-shadow geometry from the largest DCWM diameter class, which accounted for 81.3% of the total average DCWM volume measured (Table 2), would likely produce the most distinct multi-spectral signature at 30-meter spatial resolution.

Interestingly, while it appears that there was better ground-to-satellite agreement among DCWM models upon lowering the DCWM diameter class threshold from ≥ 10 cm to ≥ 7.5 cm (representing an increase in average DCWM volume by ca. 14%), a similar positive calibration response did not occur when the diameter threshold was further lowered, by an equal increment, to ≥ 5 cm (additional volume increase of ca. 8%, Table 3). In fact, an opposite response occurred, as $R^2_{adj}$ dropped by 10% (based on 0-100 range) and RMSE$_a$ increase by 3.68 m$^3$ ha$^{-1}$ (Table 3). This begs the question of whether DCWM volume (4.98 m$^3$ ha$^{-1}$) within this smaller diameter class range (5-7.5 cm) was largely concealed by the ca. 7.6 cm of snow cover during the 2014 Landsat overpasses on the November and December dates -- assuming DCWM logs and sticks were in contact with, and parallel to, the ground. This seems plausible since 53.6% of the measured DCWM volume between the low and intermediate diameter class thresholds was below 8 cm above ground. Moreover, if logs were parallel to the ground but slightly elevated, wind events occurring between the snowfall and imaging dates could have blown off any snow piled on top of these smaller diameter DCWM logs, effectively removing these key shadow structures.

However, we have no in situ evidence to support such conjecture. For larger diameter DCWM logs,
even if heaped snow was removed by intervening wind events, the DCWM, itself, would cast the characteristic shadow structures, especially at low sun elevation angles (Table 1).

Globally, among countries that measure DCWM in their forest inventories (Woodall et al. 2009), there are similar proportions of countries that use 7-7.5 cm versus 10 cm as lower diameter limits to measure downed DCWM. Here, we included the ≥ 5 cm diameter threshold to calculate DCWM volume for two reasons: due to the abundance of DCWM between 5-7.5 cm in diameter on our study plots (4.98 m³ha⁻¹, Table 2) and to gauge the sensitivity/utility of the Landsat sensor data for DCWM mapping purposes. It has been pointed out that the choice of 7.6 cm lower DCWM diameter threshold is reflective of legacy with the 3-inch English measurement unit commonly used for differentiating between fine and heavy fuels in fire behavior models (Woodall et al. 2009). Some countries, however, specify much lower diameter limits (e.g., 1.5-2 cm), but, generally, ground measurement efficiency and relatively small contributions to total DCWM volume favors use of larger diameter thresholds (Woodall et al. 2009).

In this study, 60.4%, 56.5%, and 50.25% of the DCWM volume above the 5, 7.5, and 10 cm minimum diameter classes, respectively, resided within the 0-8 cm height range above ground (Table 2). Proportions of DCWM volume in diameter ranges below 10 cm, but found in height zones greater than eight centimeters above ground, were slight (e.g., DCWM volume in DIA range 5-7.5 cm = 2.3%) compared to overall DCWM volumes measured (Table 2). Hence, it is clear why the two smaller diameter class DCWM volume model calibrations for heights above 8 cm failed (Table 3).

While the ca. 7.5 cm lower diameter threshold for DCWM measurement is common worldwide, the authors have not found satellite remote sensing cited as the cause or justification for this threshold choice. Interestingly, our results show that this lower threshold of 7.5 cm may also represent the approximate optimal detection limit for these 30-meter, 16-bit, Landsat-8 sensor data used in this research following the approach discussed above. According to Pesonen et al. (2008), the plot-level
accuracy resulting from our best DCWM volume calibration (RMSE\(_r\) = 30.3 %, RMSE\(_a\) = 19.02 m\(^3\)ha\(^{-1}\)), subsequently used to map estimates of DCWM volume across our study area (Figure 5), may be considered “adequate” and is “reliable” for preliminary, regional mapping. These authors used lidar data in eastern Finland to predict plot-level DCWM volume and achieved RMSE\(_r\) values of 51.60% (RMSE\(_a\) = 14.09 m\(^3\)ha\(^{-1}\)), which compare favorably to results of this study (Table 3).

4.4 Implications and future work

Landsat sensor data, and now Sentinel-2 sensor data, provide the most economical source of data to date for initiating consistent, long-term, landscape-scale monitoring efforts for tracking residual forest structures in areas where variable retention harvests are gaining greater appeal across multiple stakeholders and agencies (Briedis et al. 2011). There is no doubt that advancements in airborne lidar systems, and methods to process these data, are rapidly reshaping all fields engaged in Earth system science and monitoring (Harpold et al. 2015). However, at present, while lidar data or data from other airborne sensors have produced comparable or better estimates of DCWM, the current repeat frequency of wall-to-wall coverage for these raw datasets is sporadic at best, or not available at all. For example, the current wall-to-wall lidar coverage for Minnesota (collected at one pulse per m\(^2\)) was initiated in 2006 and took six years to complete. Initial planning for the next complete lidar coverage for Minnesota is now underway (ca. 15 pulses per m\(^2\)) and will require an approximate six-year (2017-2023) collection window (T. Kaebisch (personal communication, 2017), MN Department of Natural Resources, Resource Assessment, Grand Rapids, MN). These lidar data collection intervals and lags may be satisfactory for many forest mapping needs, but for other purposes it may be necessary to produce regional forest biophysical parameter estimates at more frequent intervals. Landsat-8’s 16-day repeat cycle and improved spectral and radiometric resolutions over its predecessors (Irons et al. 2012) ensures that these sensors will continue to be valuable assets for regional forest monitoring needs.
As described earlier, the treatment areas in this study consisted of residual forests with low BA (Table 2), which begs the question of whether this DCWM detection strategy would be possible for mature, continuous canopy forests of much higher BA (e.g., 25–45 m² ha⁻¹). In Wolter et al. (2012), winter Landsat sensor data were used to estimate and map substantially higher hardwood forest BA with high precision (R²_adj=0.90, RMSEₐ=2.79 m² ha⁻¹). These same winter satellite data were later combined with summer (leaf-on) Landsat data to estimate the relative abundance of standing dead BA (R²_adj=0.83, RMSEₐ=9.1%) (Wolter et al. 2014). Hence, given the appropriate sets of ground and winter satellite data (i.e. low and high snow depths), we suspect estimation of DCWM under fully stocked hardwood forest conditions would yield results comparable to this study. However, the proportion of coniferous species in a given pixel will affect this outcome, as conifer canopies remain relatively opaque to the Landsat sensor in all seasons, with the exception of eastern larch (Larix laricina) – a deciduous conifer.

Theoretically, L-band SAR data, such as the Phased Array L-band Synthetic Aperture Radar (PALSAR-2) launched by the Japan Aerospace Exploration Agency (JAXA) aboard the ALSO-2 platform in 2014, could be used to afford a better look through conifer canopy cover to the forest floor, as certain elements of forest canopies, including foliage and smaller branches, are relatively invisible at L-band wavelengths (Cartus et al. 2012, Pulliainen et al. 1999). Use of winter L-band SAR data may provide additional benefits over other seasons since much of the confounding backscatter variability due to wet soil (Askne and Santoro 2005) and DCWM moisture content may be reduced under frozen conditions (Wolter and Townsend 2011). Hence, further research is needed to (1) gauge the effectiveness of the DCWM estimation technique presented in this paper under varying levels of conifer cover and (2) test combinations of winter Landsat and L-band SAR data for DCWM estimation and mapping under predominantly coniferous forest conditions.

In any event, the importance of DCWM in forest ecosystems cannot be overstated. Presence of DCWM in advanced stages of decay serves as a critical seedbed for the germination and regeneration of...
long-lived forest tree species such as yellow birch and northern white-cedar (Cornett et al. 2001). These two species were once dominant forest components in many areas of northern Minnesota but have declined since European settlement due to a variety of pressures (Bolton and D’Amato 2011).

Currently, DCWM biomass in managed forests in this region is significantly lower compared with unmanaged stands (Duvall and Grigal 1999). The DCWM volume modeling and mapping performed in this study may be applied to larger regions to support a wide swath of research needs, which will provide needed direction for landscape-scale studies focused on regeneration of these increasingly rare forest species. For example, retention harvesting activities produce disturbance patterns that vary in abundance, size, and distribution compared to natural disturbances (wind, fire, insects etc.). It follows that these ground-to-satellite calibration methods to quantify DCWM and BA could easily be applied to forests following natural disturbance events that are known to alter standing BA and generate substantial volumes of DCWM, including large wildfires (Cooley et al. 2016), blow down (Woodall and Nagel 2007), and insect and disease outbreaks (MacLean and Ostaff 1989).

Finally, while distinguishing between DCWM and residual standing forest biomass following harvest treatments is the centerpiece of this research, future efforts of this nature should include detailed measurements of DCWM decay stage to enable volume adjustments (Fraver et al. 2013) and, perhaps more important, facilitate potential remote sensing-based decay class detection and mapping studies. Detection of DCWM decay class via satellite or airborne sensor data would be an extremely difficult task, especially for Landsat. Much would depend on (1) detecting DCWM moisture content, which is known to vary by species and decay class (Fraver et al. 2013) and (2) density and type of overstory biomass, which is linked to soil moisture variability (Kasischke et al. 2011). However, multi-polarization, multi-frequency SAR sensor data (e.g., AIRSAR) may provide the best possible solution for remote detection of attributes associated with DCWM decay classes under forest canopies.

Theoretically, the dielectric properties of different ground targets, including forest species (Salas et al.
(1994), could be leveraged to distinguish moisture differences among decayed wood classes. In addition to factors listed above, distinguishing backscatter returns linked to soil moisture differences (Kasischke et al. 2011) from DCWM moisture status—all compounded by changing climatic conditions—would be a monumental challenge. Nevertheless, SAR-based DCWM decay class detection hypotheses should certainly be the target of future investigations, as there are numerous remaining knowledge gaps (e.g., wildlife, fuel/ fire ecology, carbon, structure, nutrient cycling, etc.) in our understanding of DCWM ecology that need to be answered, especially at multiple scales (Woodall and Monleon 2008).

5. CONCLUSIONS

Based on our results, we conclude that Landsat sensor data can be used to provide adequate, preliminary estimates and maps of residual standing and downed forest structures following variable retention harvests in mixed hardwood and conifer forests of the North American Great Lakes Region to support and shape regional forest management decisions and goals. The novel use of winter Landsat imagery—with low and high snow depths—was determined to be key for successful discrimination between these two forest biomass pools. Our results have significant implications because estimates of DCWM and BA following treatments (Klockow et al. 2013) are needed to further understand the impacts of late-successional restoration treatments on the structural and compositional development of second-growth northern hardwoods (D’Amato et al. 2015), boreal and sub-boreal forest (Niemela 1999), as well as the myriad of flora and fauna that depend on them. However, it remains unclear whether methodologies to estimate DCWM volume using Landsat sensor data alone will perform as well under mixed or pure conifer forest conditions. In such cases, use of additional remote sensing data to augment these methodologies, including multi-frequency, multi-polarization SAR sensor data, may be necessary.

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Figure 3. Ground plot design showing five variable radius BA subplots, four of which are arranged orthogonally 30 m from plot center. Measurements of DCWM were collected along the two 60 m subplot axes and along the four outer 15 m transects for a total transect length of 180 m (adapted from Wolter et al. 2009).
Figure 4. Cross-validated model results showing natural log (ln) transformed dependent ground variables (residual forest basal area [BA] and downed coarse woody material volume [DCWM]) plotted against predictions of these respective variables based on calibrations with Landsat satellite sensor data. Absolute root mean squared error (RMSE) values are given in their original, respective units. Shaded area represents the 95% confidence limits, dotted lines are the 95% prediction limits, and a 1:1 line is shown for convenience.

418x337mm (96 x 96 DPI)
Figure 5. Model extrapolations at 30-meter spatial resolution throughout the northern Minnesota treatment areas for the respective estimates of residual forest basal area (BA) and downed coarse woody material (DCWM) volume.
<table>
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<tr>
<th>Image date</th>
<th>Image code</th>
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<th>Solar azimuth</th>
<th>Snow depth (cm)</th>
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<td>Total BA</td>
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<td>2.80</td>
<td>14.60</td>
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<tr>
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<td>DCWM ≥ 5 cm DIA &amp; HT ≥ 8 cm</td>
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<td>DCWM ≥ 7.5 cm DIA &amp; HT ≥ 8 cm</td>
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<td>21.12</td>
<td>3.78</td>
<td>71.96</td>
<td>16.17</td>
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<table>
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<th>DCWM DIA &amp; HT Ranges (cm)</th>
<th>DCWM Vol.</th>
<th>% of Total</th>
<th>% of DIA Class</th>
<th>% of HT Class</th>
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<tr>
<td>DIA ≥ 10 &amp; HT ≥ 8</td>
<td>21.12</td>
<td>31.1%</td>
<td>78.6%</td>
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</table>

<p>| DIA ≥ 5 &amp; 0 ≤ HT &lt; 8     | 40.98     | 60.4%      | 60.4%          |                |
| DIA ≥ 7.5 &amp; 0 ≤ HT &lt; 8   | 38.31     | 56.5%      | 60.9%          |                |
| DIA ≥ 10 &amp; 0 ≤ HT &lt; 8    | 34.04     | 50.2%      | 61.7%          |                |</p>
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<th>$R^2$</th>
<th>RMSE$_a$</th>
<th>RMSE$_r$</th>
<th>PRESS</th>
<th>p-val</th>
<th>$B_0$</th>
<th>$B_1$</th>
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<th>Vars$_f$</th>
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<td>0.43</td>
<td>0.45</td>
<td>22.7</td>
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<td>6</td>
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<td><strong>0.55</strong></td>
<td><strong>19.02</strong></td>
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<td><strong>1.8</strong></td>
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<td>DIA ≥ 5 cm, HT ≥ 8 cm</td>
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<td>30</td>
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<tr>
<td>DIA ≥ 7.5 cm, HT ≥ 8 cm</td>
<td>29</td>
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<tr>
<td>DIA ≥ 10 cm, HT ≥ 8 cm</td>
<td>34</td>
<td>0.53</td>
<td>0.54</td>
<td>10.49</td>
<td>0.497</td>
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<td>0.5</td>
<td>30</td>
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</tr>
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**BA variables**

| Total BA (H)                      | 33 | 0.55       | 0.56 | 1.85     | 0.269    | 0.72  | <0.001 | 0.8   | 0.6   | 15       | 2        |
| Total BA (LH)                     | 33 | 0.47       | 0.49 | 2.01     | 0.292    | 0.76  | <0.001 | 1     | 0.5   | 30       | 3        |
| **Hardwood BA (H)**               | 34 | **0.67**   | **0.68** | **1.23** | **0.267** | **0.72** | **<0.001** | **0.5** | **0.7** | **15**   | **8**     |
| Hardwood BA (LH)                  | 34 | 0.31       | 0.33 | 1.88     | 0.408    | 0.73  | <0.001 | 1     | 0.3   | 30       | 8        |
| Conifer BA (H)                    | 34 | 0.49       | 0.5  | 1        | 0.488    | 0.83  | <0.001 | 0.5   | 0.5   | 15       | 3        |
| **Conifer BA (LH)**               | 34 | **0.52**   | **0.54** | **0.94** | **0.459** | **0.73** | **<0.001** | **0.1** | **0.1** | **30**   | **3**     |

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<th>Dependent Variable</th>
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