Can. J. Remote Sensing, Vol. 33, No. 3, pp. 214–225, 2007

Physically based inversion modeling for unsupervised cluster labeling, independent forest classification, and LAI estimation using MFM–5-Scale

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Abstract. Unsupervised clustering is important for regional- to national-scale forest inventories where supervised training data are impractical or unavailable. However, labeling clusters in terms of land-cover classes can be labour intensive and problematic, and clustering and related methods do not provide biophysical–structural information (BSI). Canopy reflectance models such as 5-Scale are powerful forest remote sensing tools; however, 5-Scale can only be run in forward mode and is not invertible to obtain the required forest information. This problem was solved using multiple-forward-mode (MFM) coupled with 5-Scale to enable MFM–5-Scale inversion of land cover and BSI using a look-up table (MFM–LUT) approach that matches satellite image reflectance values with modeled reflectance values that have associated land cover and BSI, such as density, leaf area index (LAI), and crown dimensions, as well as subpixel-scale component fractions. MFM requires no training data or a priori BSI and can optionally be stratified (generalized) by species, structural, hierarchical, mixed forest, and other class definitions. In this paper, MFM–5-Scale was used with Landsat thematic mapper (TM) imagery at the Boreal Ecosystem–Atmosphere Study (BOREAS) southern study area (SSA) modeling subarea (MSA) in Saskatchewan, Canada. MFM–5-Scale was used to label unsupervised cluster sets (n = 17 and 97) from a previous land-cover classification by progressive generalization (CPG), with the best results obtained from independent, stand-alone MFM classification (87%, 76%, and 71% for the three hierarchies of 16 forest type, species, and density classes) validated against the provincial (SERM) forest inventory map and also compared with a standard maximum likelihood (ML) classification. Further, MFM–5-Scale estimated LAI at 24 BOREAS plots within ±0.57 LAI compared with ground-based tracing radiation and architecture of canopies (TRAC) LAI validation data. BSI is not provided by CPG clustering or ML. Based on this and other studies, we conclude that MFM provides an inversion modeling context for sophisticated forest radiative transfer models to retrieve a higher level of land cover and BSI, with detailed LUTs providing a rich set of forest information suitable for query, analysis, and follow-on simulation studies. These methods can augment existing regional- to national-scale remote sensing based inventories by providing a robust cluster labeling and BSI capability or can provide stand-alone capabilities over a variety of applications and scales.

Résumé. La technique de regroupement non dirigé est importante pour les inventaires forestiers à l'échelle régionale et nationale où les données d'entraînement dirigées ne sont pas pratiques ou non disponibles. Cependant, l'étiquetage des regroupements en termes de classes de couvert peut être onéreux en temps et problématique, sans compter que la technique de regroupement ainsi que les méthodes connexes ne fournissent pas d'information biophysique–structurale (BSI). Les modèles de réflectance du couvert, tel que le modèle 5-Scale, sont des outils puissants de télédétection des forêts, quoique le modèle 5-Scale ne puisse tourner qu'en mode avant et ne soit pas inversible pour obtenir l'information nécessaire sur la forêt. Cette situation a été résolue en utilisant le mode MFM (multiple forward mode), couplé avec le modèle 5-Scale, pour permettre l'inversion MFM–5-Scale du couvert et de l'information BSI en utilisant une approche basée sur la table de

Received 13 February 2007. Accepted 24 April 2007. Published on the *Canadian Journal of Remote Sensing* Web site at http://pubs.nrc-cnrc.gc.ca/cjrs on 24 July 2007.

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visualisation (MFM–LUT) qui établit une correspondance entre la réflectance de l'image au satellite et les valeurs de la réflectance modélisée associant le couvert et les informations BSI telles que la densité, l'indice LAI et les dimensions des couronnes de même que les composantes des fractions à l'échelle du sous-pixel. Le modèle MFM ne requiert aucune donnée d'entraînement ni d'information BSI a priori et peut, de façon optionnelle, être stratifié (généralisé) en fonction des espèces, de la structure, de la hiérarchie, des forêts mixtes et des autres définitions de classes. Dans cet article, le modèle MFM–5-Scale a été utilisé avec des images TM de Landsat de la sous-zone de modélisation (MSA) de la zone d'étude sud (SSA) du projet BOREAS (« Boreal Ecosystem–Atmosphere Study »), en Saskatchewan, au Canada. Le modèle MFM–5-Scale a été utilisé pour étiqueter des ensembles de regroupements non dirigés (n = 17 et 97) provenant d'une classification CPG (« classification by progressive generalization ») préalable du couvert. Les meilleurs résultats ont été obtenus à partir d'une classification MFM indépendante et autonome (87 %, 76 %, 71 % pour les trois hiérarchies de seize classes de types de forêts, d'espèces et de densité), validée par rapport à la carte provinciale d'inventaire forestier (SERM) et comparée également avec une classification standard par maximum de vraisemblance (MV). De plus, les estimations de LAI dérivées du modèle MFM–5-Scale sur vingt-quatre parcelles BOREAS à l'intérieur de ±0.57 de LAI étaient comparables aux données de validation TRAC LAI au sol. Les informations BSI ne sont pas fournies par le regroupement CPG ou la classification utilisant le MV. Basé sur cette étude ainsi que sur d'autres études, nous concluons que la classification MFM constitue un contexte de modélisation de l'inversion permettant aux modèles de transfert radiatif sophistiqués de la forêt d'extraire un niveau plus élevé d'information sur le couvert et les caractéristiques biophysiques–structurales, les tables de visualisation (LUT) apportant un ensemble riche en informations sur la forêt utilisable pour les études de requêtes, d'analyse et de simulations subséquentes. Ces méthodes peuvent complémenter les inventaires existants à l'échelle régionale ou nationale basés sur la télédétection en fournissant une capacité robuste d'étiquetage des regroupements et d'information biophysique-structurale, ou encore fournir des capacités autonomes pour une variété d'applications et d'échelles.
[Traduit par la Rédaction]

Introduction

Physical models of radiative transfer and canopy reflectance from forest stands provide a powerful tool for airborne and satellite image analysis for obtaining detailed forest information (Hall et al., 1995; Strahler, 1997; Schowengerdt and O'Neill, 1999; Chen et al., 2000a; Chen and Leblanc, 2001; Asner et al., 2003; Gamon et al., 2004). These models provide the critical linkage between remotely sensed spectral response and the dimension, geometry, composition, density, and spectral properties of forest canopies and stands. This provides a physical basis to image analysis and represents a higher level of information extraction compared to more traditional statistical–empirical approaches that are based primarily in the spectral domain and therefore are limited in scope. As a result, the introduction of an explicit physical–structural basis to remote sensing image analysis using canopy reflectance models is potentially of greater and more direct interest to forest management, inventory, and environmental monitoring. Further, it can augment existing unsupervised land-cover products that often characterize large-area regional- to national-scale studies (Cihlar, 2000; Cihlar and Jansen, 2001; Chen et al., 2002; Franklin and Wulder, 2002; Cihlar et al., 2003; Wulder et al., 2003).

Geometric optical canopy reflectance models can generally be used in either forward or inverse mode. In forward mode, the model produces as output a modeled pixel reflectance value in each spectral band, with some models also producing associated scene component fractions. Forward-mode inputs typically include physical and spectral descriptors of forest stands (e.g., canopy dimension, density, and end-member reflectances) and the view and illumination geometry. When run in inversion mode, the model produces canopy physical descriptors as output, based on the inputs of satellite image pixel values, end-member spectra, and view and illumination geometry.

Although these different types of model usage provide very useful and diverse information, they are not without limitations. Forward mode requires exact inputs (or estimates) of forest structural information; however, these may be difficult to obtain with confidence in terms of measurement practice (i.e., accuracy) and the spatial variability of forest stands. It is inappropriate to assume that a single value for a given forest attribute is representative for large areas, regions, or national-scale studies. For inversion mode usage, a major issue is that some models cannot be inverted, particularly ones with greater complexity, yet that level of complexity is often required for more sophisticated, current-day applications and (or) complex landscapes. Further, inversion models are often computationally very demanding with rather slow, iterative, non-exact, or in some cases no solutions produced.

Look-up table (LUT) inversion provides an alternative and practical approach that overcomes central issues with traditional inversion methods (Kimes et al., 2000; Weiss et al., 2000; Combal et al., 2002). In this paper, multiple-forward-mode (MFM) is presented as a different model-based LUT approach for using physical models such as 5-Scale. MFM eliminates the need for exact model inputs in forward mode while still achieving the goals of deriving forest biophysical–structural information (BSI) as in model inversion. Land-cover and BSI output are unified in one algorithm with a physical basis, unlike most other approaches that are decoupled and empirical. MFM is also well suited for multi-temporal applications because it models explicitly the effect of illumination changes due to different solar zenith angles (SZA) and azimuth angles of images acquired on different years, seasons, and dates (Peddle et al., 2003a). In mountainous regions, MFM provides direct access to explicit and variable surface geometry available in some models. It enables different class structures, including rigorous dynamic mixed forest specification, and, since no training or other data are required, MFM is particularly well suited for use in large, sparse areas such as Canada, where input data may be limited or nonexistent. The latter point is of particular interest since MFM can be used without any inputs (i.e., completely blind usage) whereby a simple two-stage iterative modeling approach is used to identify valid structural ranges for analysis.

MFM modeling was first developed by Peddle (1999) and has since been used in Canada by the Canada Centre for Remote Sensing, Canadian Forest Service, Canadian Model Forests, Alberta Ingenuity Centre for Water Research, and in the USA by the National Aeronautics and Space Administration (NASA) moderate-resolution imaging spectroradiometer (MODIS) Science Team and the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) as part of the NASA contribution to the North American Carbon Program (Cihlar et al., 2002a; NACP, 2005). In these and other projects, MFM has been used successfully in a variety of applications (land cover, biomass, stand and crown volume, stem density, height, LAI, topographic correction and validation, structural change detection and damage assessment, crown closure, forest fires, and water–hydrology applications) in different locations and ecosystems in Canada (six different provinces from coast to coast, Newfoundland to British Columbia) and the USA (MODIS and LEDAPS validation sites) using different canopy reflectance models coupled with MFM (e.g., GOMS, GORT, 4-Scale, 5-Scale) and with a variety of airborne and satellite remote sensing systems (e.g., SPOT, Landsat TM – Landsat enhanced thematic mapper (ETM), MODIS, IKONOS, airborne multispectral video (MSV), compact airborne spectrographic imager (casi)) as described in Peddle et al. (2003a; 2003b; 2003c; 2004; 2005), Soenen et al. (2005; 2007a; 2007b), and Pilger et al. (2003), with broader perspectives on MFM provided in Cihlar et al. (2003) and Gamon et al. (2004).

This study builds on positive results from a different MFM–5-Scale study (Peddle et al., 2004) that involved a multitemporal mosaic of seven Landsat TM scenes over the entire BOREAS region (southern study area (SSA), northern study area (NSA), and the SSA–NSA transect), with validation expressed as agreement between independent MFM classifications and an existing satellite-based enhancement–classification method (ECM) (Beaubien et al., 1999) product and field data. In this paper, the focus is instead on (*i*) unsupervised cluster labeling as a new MFM land-cover application; (*ii*) consideration of hierarchical class structures; and (*iii*) use of an independent forestry inventory map as a different source of validation, together with follow-on BSI retrieval. Accordingly, the MFM approach is described and then evaluated for three analytical objectives: (*i*) labeling unsupervised clusters produced at two levels of precision, (*ii*) generating independent MFM land-cover classifications (i.e., separate from unsupervised clustering) for comparison with MFM cluster labeling and standard maximum likelihood (ML) classification, and (*iii*) BSI retrieval of LAI to show additional capabilities of MFM beyond classification.

Canopy reflectance modeling

5-Scale model

The 5-Scale model (Leblanc and Chen, 2000) is the merging of 4-Scale (Chen and Leblanc, 1997) and leaf incorporating biochemistry exhibiting reflectance and transmittance yields (LIBERTY) (Dawson et al., 1998). 4-Scale is a geometric–optical radiative transfer model of forest structure at four scales of canopy architecture, namely tree groups, crowns, branches, and shoots. The fifth and most detailed scale at the leaf level is provided by the LIBERTY radiative transfer model, which simulates the reflectance and transmittance of individual leaves or leaf stacks. Tree crowns are modeled as discrete geometrical objects using cones and cylinders for coniferous species and spheroids for deciduous species. A non-random spatial distribution (Neyman 1939) is used to simulate the patchiness of forest stands, with crown size decreased for large clusters of trees. The simulation of light competition is further enhanced using a repulsion effect to eliminate vertical overlap of crowns. Within-crown branch architecture is defined using a single inclination angle (Leblanc et al. 1999). A geometrical multiple scattering scheme with imbedded view factors is used to compute the reflectivities (Chen and Leblanc, 2001).

Multiple-forward-mode (MFM) modeling: MFM–5-Scale

The MFM approach represents a way to achieve the objectives of inversion modeling but without the need for an explicit inversion model. It works by multiple application of standard forward-mode modeling concepts. In forward mode, the user must provide input values specifying a number of physical descriptors of forest canopy dimension and form and other physical, spectral, and scene-specific inputs. The model computes a corresponding output pixel value based on these physical inputs and the spectral component measurements. In MFM, the model is run multiple times in forward mode over a range of possible physical canopy parameters and other model inputs, with each model run representing one of n possible combinations of these different input parameters. Results are stored in an MFM–5-Scale look-up table (MFM–LUT) consisting of a maximum of n entries. An optional prescreening procedure can eliminate MFM input structural combinations that could not occur in nature, based on known BSI or species properties. For example, given that all possible combinations of the structural input variables are processed in sequence to produce a modeled reflectance output that is stored in the MFM–LUT, there may be some structural combinations in the MFM–LUT that could be eliminated a priori based on general or specific forest information for a given area (e.g., in a mature forest with areas of disturbance from logging, insect defoliation, fire, etc., very high stand densities would be associated with younger areas of regeneration, so structural combinations such as very high stand density with maximum trunk and crown heights would not be plausible and thus could be removed from the MFM–LUT; similarly, characteristic height to width ratios can be used to exclude MFM–LUT entries that violate established criteria). These prescreening capabilities are optional and designed to provide the user with an ability to utilize a priori information to advantage, if available. It is important, however, to emphasize that no prescreening is required in MFM and that, in fact (as described later in the paper), the MFM approach is designed to also work in conditions where absolutely nothing is known about a forest (i.e., "completely blind" mode). One of the fundamental design criteria of MFM was to facilitate improved forest information retrieval in situations ranging from minimal (or zero) to extensive supporting information. This is consistent with the diversity of information available in different countries, regions (e.g., remote–urban forests), and applications (small research test plots to broad expanses of forests with no inventory or other information).

A key advantage of MFM is that specific physical dimension and form inputs are not required; instead, only a range of values and a model increment must be entered. For example, instead of specifying pixel or stand-specific values for crown dimension or tree height for a particular forest species, the user need only specify a range of values. The set of MFM–5-Scale input and output parameters is shown in **Table 1**, together with a listing of those which may be varied within a specified range in MFM (additional optional parameters are also available in 5-Scale). This range may be broad, extending to theoretical minima and maxima if required or desired, or it may be small if a focused analysis is of interest. When dealing with larger or more diverse areas, a range of values is more representative compared with specifying individual canopy descriptors in standard forward mode which invariably are based on mean values from field samples or inventories but may not properly represent individual occurrences, and certainly are not representative over larger regions or at national scales.

In situations where little or no a priori information exists, a two-stage MFM process can be used to produce an initial MFM–LUT based on larger model ranges and coarser increment values to first identify the general range of appropriate physical model inputs that produce reflectance values similar to those of the remote sensing image. In this way, MFM can be used when nothing is known about a given area (i.e., fully blind use). The output is used to identify smaller, more focused input ranges where matches occurred, for which a more detailed MFM analysis with finer increments is used to produce the final MFM–LUT. These MFM–LUTs contain reflectance values with associated physical–structural information, scene fractions, and view and illumination geometry retained from the inputs that created the forward-modeled reflectance value. All of this information is stored in the MFM–LUT as a digital library of rich forest information for subsequent query, search, retrieval, and analysis. This MFM–LUT can serve as a stand-alone tool for detailed model simulation studies, or the MFM reflectance values can be matched with satellite image reflectance to provide land-cover and BSI over small or large areas.

Matching modeled and satellite reflectance

Once the MFM–LUT has been created, it can be used for direct BSI retrieval and (or), if land cover is required, MFM classification is invoked by stratifying the LUT according to class definitions (e.g., by land cover based on species end-members, physical descriptors, or both). A given satellite pixel is then associated with one of those classes by matching the input multispectral satellite image reflectance value with the corresponding reflectance values produced by the model. This can be based on exact match criteria using the reflectance equality method (REQ), with options to specify more advanced thresholding methods such as root mean square error (RMSE) to determine the closest matching modeled reflectance values based on the nearest spectral distance (NSD) and by assessing spectral distance with respect to a spectral range domain (SRD), as described in full by Soenen et al. (2007b). These methods are also designed to capture any reflectance variability or error inherent to the sensor, processing, and modeling elements. They also provide tools to specify criteria for heterogeneous and (or) hierarchical forest properties of interest, such as mixed forest classes, or multiscale assessments. Once this matching process is achieved, the corresponding physical inputs to the 5-Scale model which gave rise to this reflectance value in the MFM–LUT are extracted (see **Table 1B**). This is the essence of the MFM–5-Scale inversion. Satellite image values are input to MFM in the same way as with any inversion model, with land cover and physical canopy dimension information provided as output.

In determining matches between satellite reflectance values and those generated by the model and stored in the MFM–LUT, there may be no direct matches, one match, or multiple matches. The correspondence between measured and modeled reflectance is in part a function of MFM increment step precision within input ranges, as well as any uncertainties, errors, and differences in precision of the canopy reflectance model and remote sensing instrument measurements (e.g., radiometric resolution, sensor noise, model assumptions, and abstraction) and any issues with image corrections or other postprocessing functions (e.g., atmospheric correction and reflectance calibration). Methods to deal with multiple matches are described fully in Soenen et al. (2007b) and therefore are only summarized briefly here.

Matching is dealt with sequentially based on proximity criteria developed in spectral space populated by MFM spectral outputs and satellite image values. If there is one unique match, the algorithm uses that MFM–LUT entry as the basis for BSI and land-cover retrieval. Regarding multiple matches, in some situations these represent final output, in that it is sometimes acceptable or desired to provide ranges of output. For example, some carbon–water–energy models are based on model input ranges; indeed, over larger areas, preserving multiple matches may be more representative of reality both in terms of model precision and the spatial variability over larger regions. However, if a unique solution is required, this is handled using distribution analyses of multiple solution sets involving

Table 1. Primary MFM–5-Scale model inputs and outputs.

(A) MFM inputs and outputs

Term	MFM input	MFM output
Pixel size, B	√[a]	√
Density, D	√[b]	√
Trunk height, H_a	√[b]	√
Crown height, H_{bc}	√[b]	√
Crown radius, r	√[b]	√
Leaf area index, LAI	√[b]	√
Solar zenith angle, SZA	√[a]	√
View angle, VZA	√[a]	√
Canopy end-member reflectance, ρ_c (per species; by λ)	√[a]	√[c]
Background end-member reflectance, ρ_b (by λ)	√[a]	—
Modeled reflectance, ρ_T (by λ)	—	√[d]
Canopy fraction, C	—	√
Background fraction, B	—	√
Shadow fraction, S	—	√

(B) Example model input, MFM–LUT output, and image data (one entry shown for each)

MFM model input[e]	B	D	H_a	H_{bc}	r	LAI	SZA	VZA	ρ_c	ρ_b				
MFM–LUT output	B	D	H_a	H_{bc}	r	LAI	SZA	VZA	ρ_c	ρ_b	ρ_T	C	B	S
Satellite image reflectance											ρ_r			

Note: MFM–LUT analysis involves matching remotely sensed pixel reflectance (ρ_r by λ) with modeled reflectance values (ρ_T by λ). MFM outputs contain the land-cover class label (based on species of canopy end-member ρ_s) and the associated biophysical–structural information.

[a]Inputs kept constant here but could be varied.

[b]Inputs varied within a specified or automatic range in this study.

[c]Species identification (used for land-cover class).

[d]Modeled reflectance (for matching).

[e]User-specified or automatically generated ranges for some or all inputs; exact values not required.

summary statistics and spatial context (Soenen et al., 2007b). The first phase of this uses statistical measures of central tendency and variance to describe the distribution of matching reflectance values, with median-based processing optimal for dampening any outlier affects. This can optionally be supplemented based on nearest-neighbour value retrievals with a spatial threshold tolerance limiting case, with an additional option to incorporate ancillary information (e.g., elevation, slope, aspect from a digital elevation model) to further constrain matches to both reflectance and ancillary conditions if desired and available. These methods are described in full by Soenen et al. (2007b).

If there are no matches (and this assumes the front-end prescreening test for appropriate model inputs was passed), then a spectral space proximity thresholding algorithm is invoked whereby the nearest matches are (*i*) assessed as a unique class, (*ii*) treated as mixed forest (with dynamic, pixel-specific outputs), or (*iii*) assigned as a nonforest pixel. These thresholds can be generated automatically or defined by the user. This results in a more rigorous, detailed, and explicit description of mixed forest (and other) classes. Unlike typical mixed forest classes, in MFM these are not constrained by arbitrary, broad definitions, and they also have associated BSI retrievals yet require no input, training, or a priori class data or definitions. If desired, however, these can still be grouped into classes through simple MFM–LUT postprocessing, if more generalized output is preferred or required for compatibility with existing map classes or other products.

Study area and datasets

Study area and satellite imagery

The study was set within the BOREAS region (Sellers et al., 1997) in Saskatchewan and Manitoba, Canada, with a focus on the SSA modeling subarea (MSA) in Saskatchewan for which appropriate land-cover and biophysical validation information was available (Newcomer et al., 2000). The MSA is centred at 53.93°N, 104.84°W and covers 1487 km^2 of boreal forest terrain comprised primarily of black spruce, jack pine, and aspen, with occurrences of mixed forests, fen, nonproductive–disturbed land, and water. A Landsat-5 TM satellite image acquired over the BOREAS SSA on 30 July 1996 was atmospherically corrected and converted to reflectance by Newcomer et al. (2000) with reference to a 1994 BOREAS Landsat TM scene for compatibility with field-based red and near-infrared (NIR) end-member reflectance values (Hall et al., 1997). Therefore, Landsat TM bands 3 (red) and 4 (NIR) were used in this study; however, we note the following: (*i*) MFM can process any number of bands (e.g., hyperspectral); (*ii*) although commonly used reflectance data are not required in MFM as long as the end-member spectra and image data are in common (e.g., raw digital numbers, image end-member DNs, calibrated radiance, or other units); (*iii*) end-member spectra can be varied using a range and increment, as with any other MFM input; and (*iv*) in addition to field measurement, end-member spectra can be obtained in a variety of ways (e.g., spectral libraries, image end-members, canopy reflectance models; see Peddle et al. (1999) where field, image, and modeled end-members were used), but these other options were not explored in this study.

Land-cover validation data

Land-cover information for SSA MSA from independent forest inventory maps was used for validation and accuracy assessment of all classifications in this study. These forest inventory maps were produced in vector format by the Inventory Unit of the Saskatchewan Environment and Resource Management (SERM) Forestry Branch as maps interpreted from 1 : 12 500 scale aerial photography acquired prior to 1989. These data were processed and gridded to a 30 m raster format by Newcomer et al. (2000). All validation data used in this study (including the SERM data) are available in the public domain online from the BOREAS Information System (see Newcomer et al., 2000). The major classes from these raster SERM maps were used in this study, including black spruce, jack pine, and aspen species for which end-member spectral model inputs were available, as well as mixed forest classes. The SERM map was used to establish three sets of classes within a hierarchical class structure at three different levels of precision with respect to class descriptions (**Table 2**). The three levels are (1) forest cover (conifer, deciduous, mixed), (2) 10 cover–density classes, and (3) 16 species–density classes. Levels 2 and 3 included four density strata in all cases except mixed classes (two density strata) as defined in the SERM inventory map, with forest cover and species classes designated based on >80% composition. The classification analyses in this study were based on a sample of over 3×10^5 pixels in the SSA MSA, with pixels corresponding to classes such as roads, water, crops, and other forest species excluded. Although these SERM data are independent and considered to be a reasonable representation of land-cover and density information (Newcomer et al., 2000), issues such as possible human photointerpretation bias and timing (assessing 1996 satellite imagery against aerial photography acquired prior to 1989) may introduce external error leading to underestimation of actual land-cover accuracy as reported here.

Although the focus of this work is MFM cluster labeling and MFM independent classifications, it was also useful to place these in context through comparison with a conventional classification approach. Accordingly, a supervised ML classification was performed with training and test data obtained from the SERM map (for larger areas, this typically would not be possible). A stratified random sample of independent, mutually exclusive training and test pixels was derived from the SERM map (10% per class) with a ratio of 70% to 30% used for separating training and test data, respectively, with the latter used to estimate ML accuracy for comparison with that of the various MFM products.

Table 2. Hierarchical class structure based on SERM forest inventory map classes.

Class	Forest type or species	Density (%)
Level 1		
1	Conifer	
2	Deciduous	
3	Mixed forest	
Level 2		
1	Coniferous (>80%)	10–30
2	Coniferous (>80%)	30–55
3	Coniferous (>80%)	55–80
4	Coniferous (>80%)	>80
5	Deciduous (>80%)	10–30
6	Deciduous (>80%)	30–55
7	Deciduous (>80%)	55–80
8	Deciduous (>80%)	>80
9	Mixed forest	>55
10	Mixed forest	<55
Level 3		
1	Black spruce (>80%)	10–30
2	Black spruce (>80%)	30–55
3	Black spruce (>80%)	55–80
4	Black spruce (>80%)	>80
5	Jack pine (>80%)	10–30
6	Jack pine (>80%)	30–55
7	Jack pine (>80%)	55–80
8	Jack pine (>80%)	>80
9	Aspen (>80%)	10–30
10	Aspen (>80%)	30–55
11	Aspen (>80%)	55–80
12	Aspen (>80%)	>80
13	Mixed coniferous forest (spruce and pine 50%–80%)	>55
14	Mixed coniferous forest (spruce and pine 50%–80%)	<55
15	Mixed deciduous forest (aspen 50%–80%)	>55
16	Mixed deciduous forest (aspen 50%–80%)	<55

Unsupervised clustering

In the cluster labeling component of this study, two unsupervised cluster sets were produced from the 1996 Landsat TM image using the classification by progressive generalization (CPG) method (Cihlar et al., 1998). CPG involves initial image enhancement, quantization, and filtering; the identification of a larger number of spectral combinations that serve as seed clusters; assigning input pixels to seed clusters based on minimum Euclidean distance; and progressive grouping of clusters based on spectral and spatial proximity (Cihlar et al., 1998). Two levels of cluster grouping were applied, resulting in sets of 17 and 97 clusters. This was done to test the MFM–5-Scale cluster labeling process for different levels of cluster groupings.

All image and map products (TM image, raster SERM map, and the various classifications) were geometrically coregistered using 25 spatially distributed ground-control points input to a nearest neighbour resampling algorithm, with an RMSE of 3 m tolerated for the 30 m grid.

Field LAI validation data

LAI field validation data were obtained for the SSA MSA area for 24 plots (15 jack pine, 9 black spruce) from the BOREAS CD-ROM set. These data are also available from the Earth Observing System Data and Information System (EOSDIS) Distributed Archive Center (DAC) (Newcomer et al., 2000). There were no aspen plots with available LAI data within this area. The ground-based LAI data were collected by BOREAS project RSS-07 (Chen et al., 2000b) using a tracing radiation and architecture of canopies (TRAC) instrument (Chen and Cihlar 1995; 1996) that accounts for canopy gap fraction and gap size distribution (clumping index). All plots had associated global positioning system (GPS) positions from which they were located in the TM image.

Analysis and results

MFM–LUT production

MFM–5-Scale was used to produce one MFM–LUT for use with the unsupervised CPG cluster labeling analyses and the independent MFM classifications. In each case, all three levels in the hierarchical class structure were classified (**Table 2**). Level 2 is of most interest, since conifer species discrimination (introduced at level 3) is less critical for ecological process and carbon models and can also be more difficult in some cases because of spectral similarity of pine and spruce stands for the Landsat bands used here. However, all three levels were classified by stratifying the MFM–LUT according to each set of class definitions to test the ability of CPG clusters and MFM–5-Scale for various levels of species and density discrimination.

The MFM–5-Scale model inputs used in this study are shown in **Table 3** and are based on a 30 m Landsat TM pixel. Physical–structural input ranges and model increments were specified with reference to BOREAS forest data (Halliwell and Apps, 1997; Newcomer et al., 2000) and chosen to ensure comprehensive coverage for all species considered (LUT size: $n = 7 \times 10^6$), although this is not a requirement. MFM does not need any training data or do any iterative learning, nor does it require any SERM data on input. Other inputs were held constant for MFM–5-Scale model runs and included spectral end-member component reflectance values (from Hall et al., 1997), the solar position at the time of Landsat TM image acquisition (17:00 GMT), and the satellite sensor view angle (nadir). Each model execution in MFM was specific to a species as defined by the given end-member set.

Table 3. MFM–5-Scale model input ranges and increment steps.

Model input	Min.	Max.	Step
Trunk height, H_a (m)	1	10	0.5
Crown height, H_{bc} (m)	1	10	0.5
Crown radius, r (m)	0.50	10.00	0.25
Density, D (%)	0	100	10
LAI	0.25	10.00	0.25

Cluster labeling and classification results

Cluster labeling

In unsupervised image classification, cluster labeling is the most labour intensive step (Cihlar et al., 2003). Through the development of advanced radiative transfer models and approaches such as MFM–5-Scale, it is possible to use model outputs to label unsupervised spectral clusters efficiently and objectively. This was achieved in MFM–5-Scale by computing measures of central tendency for each cluster and using those measures as the search criteria to locate appropriate modeled reflectance values. Two unsupervised cluster sets from CPG were labeled: a 97 cluster set, and a 17 cluster set (MFM-CGP-97 and MFM-CGP-17, respectively). The TM reflectance values that made up each cluster were extracted from the image, from which mean, median, mode, standard deviation, and range were computed for each cluster. **Figure 1** shows the distribution of clusters in spectral space for the 17 cluster set, where the centre and radius of each cluster were determined as the mean and one standard deviation, respectively, and plotted as spectral ellipses. Some of the clusters appear to be closely grouped, with the remaining clusters more spectrally distinct. The mean reflectance value in each band for each cluster was used as the search key for identifying matching MFM–LUT reflectance values. The corresponding land-cover class for that MFM–LUT entry as defined by the species end-member set used on MFM input was identified and applied at each of the three levels in the classification hierarchy, with all associated physical–structural parameters for that entry also assigned to that cluster. The TM image spectral and MFM–5-Scale modeled physical attributes for each cluster were compiled for the entire 97 and 17 cluster sets. The end result was a set of attributes for each cluster that contain not only the land-cover label (over different levels in the hierarchy), but also a full set of physical canopy and stand descriptors together with scene fractions, which themselves can be useful descriptors or predictors of forest structural–biophysical parameters (Peddle et al., 1999).

MFM cluster labeling classification results

The classification accuracies obtained at each hierarchical level are shown in **Table 4**, expressed as percent agreement

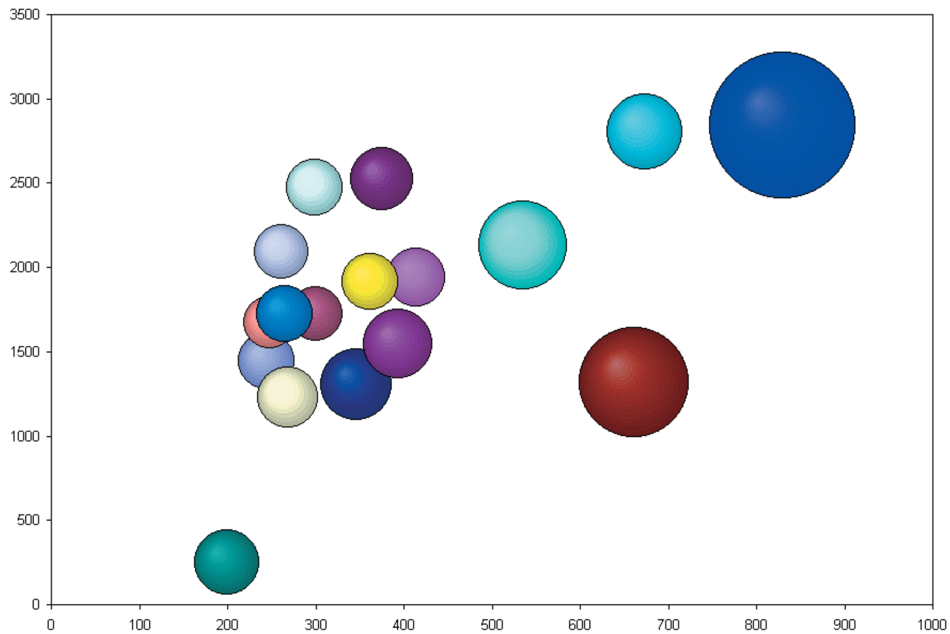

Figure 1. Red (x axis) versus near infrared (y axis) plot illustrating the relative position and spectral extent of 17 clusters in spectral space.

Table 4. Classification accuracies for MFM–5-Scale analysis of 17 clusters (MFM-CPG-17), 97 clusters (MFM-CPG-97), independent MFM–5-Scale (MFM–IND), and separate maximum likelihood (ML) classifications, expressed as percent agreement with SERM forest inventory map data processed to three levels of hierarchical classes (see **Table 2**).

Level	No. of classes	MFM-CPG-17 (%)	MFM-CPG-97 (%)	MFM–IND (%)	ML (%)
1	3	87	87	87	82
2	10	69	68	76	73
3	16	60	61	71	71

with the SERM inventory map. The results from MFM-CPG-17 (17 cluster set) and MFM-CPG-97 (97 cluster set) were similar within each level, with maximum accuracies of 87%, 69%, and 61% obtained for levels 1, 2, and 3, respectively. The MFM–5-Scale labeling results were constrained by any errors that exist in the original cluster sets. For example, a pixel assigned to a given cluster that has a different land cover from that of other pixels in the same cluster will nonetheless contribute to the statistics which define that cluster and are used to determine the search criteria in the MFM–LUT used as the basis for cluster labeling. As a result, given the ability to label individual clusters using MFM, the rationale and need for merging clusters a priori may be substantially reduced, since merging may introduce unwanted error and generalization into cluster–class associations. Cluster merging is often a focal point of unsupervised classification labeling; however, this step can be avoided in MFM, and in fact it may be preferable not to perform merging at all. Instead, a larger number of smaller clusters can be processed using MFM–5-Scale and subsequently merged based on matching class labels (i.e., postclassification, if desired). This avoids excessive merging at the clustering stage, and the resulting overgeneralization and additional error. In this study, the 97 cluster results were essentially equivalent to the merged 17 cluster results, suggesting that the merging performed prior to MFM–5-Scale labeling was appropriate and not overgeneralized. However, the overall levels of agreement with the SERM inventory map for the level 2 and level 3 products were somewhat lower (60%–69%), suggesting the degree of land-cover separation provided by both sets of clusters was not optimal.

Independent MFM–5-Scale classifications

Although the MFM–5-Scale approach was originally pursued as a method for unsupervised cluster labeling in this study, we also used it as a stand-alone, independent approach for full classification. The main difference between the unsupervised cluster labeling and the independent MFM–5-Scale classifications is that the latter approach is performed in an unconstrained, per-pixel environment in which individual pixels are classified independently, whereas the cluster labeling process is necessarily constrained by each cluster group (a "per-cluster" approach). The same MFM–LUT that was used with the unsupervised cluster labeling was also used for the independent MFM–5-Scale classifications.

The MFM–5-Scale independent (MFM–IND) classifications yielded the highest accuracy of all methods tested at each hierarchical level (**Table 4**), except for level 1 (MFM–IND and both MFM–CPG results were 87%) and level 3 (MFM–IND and ML were 71%). For the level 2 case, the overall accuracy obtained was 76% for 10 classes defined by forest type and density, followed by ML (73%) and the two cluster approaches. In the 16 class level 3 classification, the MFM–IND accuracy (71%) was 10% higher than the best unsupervised cluster accuracy. These results, particularly the level 2 product, are regarded as acceptable and significant for this application of MFM–5-Scale.

The full contingency matrix for the MFM–IND level 2 product (**Table 5**) shows individual class accuracies were consistently good, with eight of 10 classes ≤70% and three classes ≥90%. Further, classification error was confined primarily to within coniferous or deciduous forest types and was usually manifested as errors with adjacent density classes, thus the error severity was generally low. It is possible that some of these nonsevere errors were due to the SERM forest inventory map. That map was produced by subjective interpretation of aerial photography and thus may have some internal error or inconsistencies. Further, the aerial photographs were acquired prior to 1989 and over different years, thus there was a minimum of 8 years difference from the 1996 satellite image. During the intervening periods, normal forest growth and changes in forest density may change some stands to the next higher density class by 1996, which would then be shown incorrectly as classification error in **Tables 4** and **5** (i.e., SERM map outdated; MFM correct). More substantive post-1989 changes such as disturbance by fire, logging, defoliation, or other activities would show up (incorrectly) as more severe errors in this analysis of 1996 imagery with respect to the earlier SERM map.

BSI retrieval: MFM LAI results

LAI is one of the direct outputs from MFM–5-Scale and was tested using Landsat TM image pixel reflectance values at field-validated BOREAS plots. The LAI associated with LUT entries whose reflectance matched satellite image pixels was the basis for BSI retrieval, with multiple matches resolved by average LAI. These LAI values were produced completely independent of any field information or land-cover reference. As a result, the full set of field LAI was available for validation purposes (i.e., no field LAI data were required or input to MFM). For larger areas (e.g., Chen et al., 2002; Cihlar et al., 2002b) and with sparse or no field validation, MFM can still produce LAI and other BSI, since no training or other field inputs are needed.

The MFM LAI retrieval results (**Table 6**) show the range, average, and standard deviation of LAI from MFM and ground-measured TRAC LAI and summary statistics from the differences (absolute value) by plot. The results for all SSA MSA plots (n = 24) and by species (jack pine, black spruce) indicated that the MFM LAI values covered a greater LAI range than that of the measured values. The smallest and largest differences between measured and modeled LAI for all plots were ΔLAI = ±0.07 and ±0.97, with an average difference of ΔLAI = ±0.57. The largest error by species was ΔLAI = ±0.97 for jack pine (n = 15) and ΔLAI = ±0.68 for black spruce (n = 9), with closest correspondences of ΔLAI = ±0.20 and ±0.07, respectively. This is considered to be a good set of results for these two conifer species, given the reasonable sample size and high quality of independently field measured LAI that spans a reasonable range of LAI values (TRAC LAI: 2.17–5.33).

Conclusion

Multiple-forward-mode (MFM) provides an inversion modeling context for the powerful but non-invertible 5-Scale

Table 5. Contingency matrix showing MFM classification accuracy for 10 classes at level 2 (see **Table 2**).

Class	Class 1	2	3	4	5	6	7	8	9	10
1	**70**	0	0	0	0	0	0	12	0	0
2	20	**96**	4	0	0	0	0	0	0	2
3	0	0	**90**	15	0	0	0	0	0	0
4	0	0	0	**69**	0	0	0	0	14	0
5	2	4	6	6	**78**	5	5	3	0	1
6	0	0	0	0	12	**70**	0	0	0	1
7	0	0	0	0	6	24	**65**	0	0	0
8	0	0	0	0	0	1	30	**77**	2	0
9	0	0	0	10	0	0	0	8	**74**	5
10	8	0	0	0	4	0	0	0	10	**91**
Total	100	100	100	100	100	100	100	100	100	100

Note: All entries expressed as percent agreement with SERM forest inventory map. Diagonal entries represent individual class accuracy (shown in bold), and columns total 100%. Overall accuracy is 76%. Classes 1–4, conifer density; classes 5–8, deciduous density; classes 9–10, mixed forest (see **Table 2** for detailed class description).

Table 6. MFM LAI retrieval results and BOREAS project RSS-07 ground-based LAI (TRAC) data for jack pine, black spruce, and all SSA MSA plots.

	TRAC LAI	MFM-5-Scale LAI	LAI difference (per plot)
All SSA MSA (n = 24)			
Min.	2.17	0.63	0.07
Max.	5.33	5.94	0.97
Avg.	3.47	2.95	**0.57**
SD	0.93	1.90	0.25
Jack pine (n = 15)			
Min.	2.17	0.63	0.20
Max.	3.54	4.56	0.97
Avg.	2.85	2.00	**0.67**
SD	0.36	1.44	0.24
Black spruce (n = 9)			
Min.	3.67	2.64	0.07
Max.	5.33	5.94	0.68
Avg.	4.51	4.54	**0.42**
SD	0.58	1.49	0.20

Note: Absolute values of differences shown by plot, with mean difference shown in bold. n, number of plots; SD, standard deviation.

canopy reflectance model. MFM–5-Scale was tested for two unsupervised cluster labeling products and an independent MFM classification for three sets of hierarchical land-cover classes and compared to standard maximum likelihood (ML) classification. The independent MFM–5-Scale was additionally used for biophysical–structural information (BSI) retrieval of leaf area index (LAI).

MFM has a number of important advantages over other classification and modeling strategies:

(1) MFM eliminates the need for exact model input parameters such as canopy structural dimensions, since only a range and model increment are needed. These are easily obtained, are insensitive to error, are more appropriate and spatially representative over large areas, and can be generated automatically if no information is available (i.e., completely “blind” usage) using a simple two-stage procedure. The appropriate values are instead selected through the MFM per-pixel matching process. The blind usage capability is a key advance of potential interest to programs at the large-area, regional, and national levels.

(2) MFM provides extensive physically based information on canopy dimension and forest structure, in addition to land-cover labels. Information such as subpixel-scale fractions is also provided, which is useful in predicting biophysical variables.

(3) No training data are required for input to MFM.

(4) For classes with limited validation data, there is no need to divide a sample into training and test sets, and thus all available data can be used for validation and any sample size constraints are eased.

(5) MFM creates an inversion model capability for models that cannot be used in regular inverse mode. Also, MFM is compatible with any forward mode radiative transfer model, thus enhancing their utility.

(6) MFM is less complex in terms of both computational efficiency and mathematical approximation for dealing with inversion problems because of the rapid speed of individual forward-mode runs and efficient database search technology.

(7) MFM–LUTs provide a rich library of forest information as a basis for mapping, query assessment, or analysing spectral–biophysical relationships (e.g., model simulation, intercomparisons, statistical or graphical evaluations).

(8) In terms of land-cover classification, the approach is flexible and amenable to different class structures and definitions (including multiple and hierarchical class structures) without requiring additional model runs (the existing MFM–LUT is simply restratified). Mixed forest classes can be dynamically described without needing any a priori class definition.

(9) Models such as GOMS (Li and Strahler, 1992) include terrain information (e.g., slope, aspect) and have considerable utility for both montane forest and other mountain applications and for topographic correction (Soenen et al., 2007a; 2005; Peddle et al., 2003a).

MFM–5-Scale yielded good results in this BOREAS study in terms of land-cover classification accuracy, with additional biophysical–structural information (BSI) provided. A capability was shown for effective MFM labeling of existing unsupervised clusters generated separately from MFM. The MFM independent classification provided the best results over three hierarchical class structures compared with cluster labeling and ML. MFM is well suited for satellite image mosaics encompassing different dates and seasons, variable solar zenith, and view angles and from different sensors and spectral bands. MFM may thus have potential to augment regional- to national-level programs for mapping land cover (e.g., Cihlar et al., 2003; Wulder et al., 2003), LAI (e.g., Chen et al., 2002; Cihlar et al., 2002a; 2002b) and other forest attributes (e.g., provincial–territorial inventories, National Forest Inventory (NFI)), or as a stand-alone, primary processing engine (e.g., MODIS Science Team, LEDAPS).

Acknowledgements

We gratefully acknowledge the Forestry Branch of Saskatchewan Environment and Resource Management for providing digital forest inventory maps to the BOREAS project. Members of the BOREAS staff are thanked for processing these maps into the raster data products used here and for providing other data and support. Rasim Latifovic, Gunar Fedosejevs, and Goran Pavlic, Canada Centre for Remote Sensing, are thanked for assistance with data preprocessing. Dr. Peddle gratefully acknowledges support and collaboration from the Natural Sciences and Engineering Research Council of Canada (NSERC), Alberta Ingenuity Centre for Water Research (AICWR), Prairie Adaptation Research Collaborative (PARC), Water Institute for Semiarid Ecosystems (WISE), NASA Goddard Space Flight Centre and University of Maryland, Natural Resources Canada (NRCan), Alberta Research Excellence Grants, Western Canada Research Grid (WestGrid/NETERA) computing resources, and University of Lethbridge.

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