

# Assessing land clearing potential in the Canadian agriculture–forestry interface with a multi-attribute frontier approach



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## ABSTRACT

The pattern of forest land clearing in a region can be viewed as a gauge of sustainable (or unsustainable) use of agricultural and forest resources. In this study we examine the geographical distribution of land clearing potential in the Canadian agriculture–forestry interface and propose a new landscape-scale indicator that quantifies this potential. We consider the possibility that forested land will be cleared for agriculture as a trade-off between the land's capacity to support agriculture and its comparative value if it remains forested. However, this trade-off is complicated by the land's susceptibility to fragmentation (and subsequent conversion), which derives from the local pattern of forest, agriculture and other land cover types. We find the locations in the agriculture–forestry interface with the highest land clearing potential by delineating nested multi-attribute frontiers in the dimensions of the land's agricultural capacity, its estimated forest productivity and its fragmentation potential. The multi-attribute frontier concept addresses our lack of knowledge about the relative importance of these multiple drivers of land conversion by objectively combining them into a single-dimensional land clearing pressure metric in a geographical setting. Overall, our approach provides a simple yet informative indicator which reveals the geographical stratification of land clearing pressures across large regions. In general, the spatial delineation of areas with high land clearing potential agrees well with recent evidence of land clearing and deforestation events in Canada.

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## 1. Introduction

Land clearing (deforestation) is part of the process of converting forested areas to other land uses. Forests and shrublands have historically been seen as a potential source of agricultural land (Ramankutty and Foley, 1999). In many parts of the world,

conversion of forested lands to agriculture is one of the key processes in modern landscape dynamics (Foley et al., 2005; Green et al., 2005; Millennium Ecosystem Assessment, 2005). The potential of forest land to be cleared for agriculture can be seen as a gauge of the degree of sustainable (or unsustainable) use of forested landscapes.

In Canada, deforestation is caused mainly by the conversion of forested lands to agriculture, but also by industrial and urban development, mining and road building (NRCAN, 2011). The rate of deforestation in Canada has declined over the last decade (NRCAN, 2011) with the annual rate dropping from over 64,000 ha yr<sup>-1</sup> in 1990 to approximately 44,800 ha yr<sup>-1</sup> in 2009. Historically, the land area cleared for agriculture and pasture has constituted the largest portion of the annual deforestation footprint, accounting for 65% of total area cleared (41,900 ha) in 1990 and 43% (19,100 ha) in 2009.

Land clearing is a significant source of greenhouse gas (GHG) emissions (Fitzsimmons et al., 2004; Gibbons and Lindenmayer,

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2007; Environment Canada, 2012). In 2010, land clearing activities in Canada resulted in net greenhouse gas (GHG) emissions of 14.8 million tonnes of carbon dioxide equivalent (Environment Canada, 2012). In the long run, land clearing reduces the resilience of ecosystems (Bennett, 1999; Walker and Salt, 2006), leads to an irreversible gradual loss of natural habitats (Cogger et al., 2003) and diminishes the capacity of ecosystems to sustain plant productivity (Green et al., 2005; Millennium Ecosystem Assessment, 2005; Wentworth Group of Concerned Scientists, 2003).

While numerous negative impacts of land clearing have been recognized (Foley et al., 2005; Green et al., 2005), estimating the potential of forested land to be cleared is difficult. Estimating economic triggers that cause land to be converted to agriculture is particularly challenging because landowners' decisions to clear forested woodlots often include subjective motivations which cannot be described in terms of conventional cost-benefit calculations. Landowners often show reluctance when considering projects that involve long-term allocation of land and reveal preferences for short-term projects, which give them more managerial flexibility (Korhonen et al., 2002; Blanco and Forner, 2000), and thus tend to move into activities with short production cycles such as agriculture (Parks, 1995; Parks and Hardie, 1995). Factors that are often omitted in conventional cost-benefit calculations include potential irreversibility in land use change and future uncertain costs associated with maintaining long-term projects versus more certain benefits of short-term projects (Pindyck, 1995). The issue of estimating land clearing potential becomes especially important in forecasting nationwide economic production scenarios in the agricultural and forestry sectors (Horner et al., 1992) because conversions between agricultural production and forestry usually mean long-term land use commitments. The latter aspect has been recognized as a significant concern for many landowners (Stevenson, 2003a,b) and could have serious implications for agricultural and forest sector production capacities.

### 1.1. Estimating the land clearing potential based on land's productivity capacity

Several methodologies have been proposed to quantify land clearing pressures at large geographical scales. One method evaluates risks of habitat degradation and land cover change by analyzing the historical dynamics of forest fragmentation and changes in key landscape mosaic types (Riitters et al., 2009a,b; Riitters and Coulston, 2005; Wickham et al., 2010). Other methods employ statistical and spatial regression techniques for estimating land use change potential (Hobson et al., 2002; Aguiar et al., 2007) by linking historical land use change data acquired from satellite imagery to econometric information (Nelson and Hellerstein, 1995; Vance and Geoghegan, 2002; De Pinto and Nelson, 2007), or by applying various discrete choice models (Fleming, 2004). Other common approaches estimate potential costs associated with the loss of environmental services provided by forest lands after clearing (Barbier, 2007) or future costs of associated greenhouse gas emissions (Kindermann et al., 2008). Some studies have framed the land clearing problem in terms of finding the optimal time to switch away from an existing land use policy (Irwin and Bockstael, 2001; Vance and Geoghegan, 2002).

Many of the aforementioned modelling approaches require considerable amounts of spatially referenced econometric data. This information may not be available for large, sparsely populated regions, such as vast portions of the agriculture–forestry interface in sub-boreal Canada. In such situations, broad-scale assessments based on land's production capacity can be used to limit the geographical extent of future data gathering efforts to areas with high land clearing potential. Fortunately, the information required to assess production capacity at a broad scale can be found in standard

land surveys and forest inventories, which – unlike detailed econometric data – are generally available for large, sparsely populated regions.

In this study, we develop a new landscape-scale indicator that evaluates the potential for forested areas to be cleared for agriculture as a trade-off between the areas' capacity to support agricultural production and their productivity if they were to remain forested. Notably, this is not always a straightforward trade-off, since some forested areas may be predisposed towards conversion due to a pattern of expected (or ongoing) landscape fragmentation. Our assessment is focused on forested areas in the Canadian agriculture–forestry interface, a 36-million ha transition zone between semi-boreal forests and the major areas of agricultural production in Canada (Fig. 1). We divide the entire area of the Canadian agriculture–forestry interface into small land parcels (250 m × 250 m map cells) and analyze each parcel in the dimensions of its capacity to support (1) agricultural or (2) forest biomass production, as well as (3) its fragmentation potential, which describes the likelihood of forest conversion based on local land cover pattern. We then approach the estimation of land clearing potential as a multi-criteria ordering problem and find the parcels with the highest clearing pressures via delineation of nested multi-attribute frontiers in the three aforementioned criteria dimensions.

## 2. Methods

### 2.1. Multi-attribute frontier (MAF) concept

Integration of multiple data sources into a single-dimensional metric is often accomplished via multi-criteria decision analysis (MCDA). MCDA involves a variety of approaches, such as listing multiple lines of evidence (King and Richardson, 2003), indexing (Feron et al., 2004), scoring (McDonald et al., 2007) or other statistical methods (Landis, 2003; Linkov et al., 2009). Generally, these methods help determine a preference order among a number of available options (or scenarios) in a multi-dimensional criteria space based on various types of information obtained from a multitude of data sources (Janssen, 1992; Lahdelma et al., 2000; Linkov et al., 2006; Yatsalo et al., 2007).

The assignment of weights to individual criteria is one of the simplest and most popular methods in the MCDA toolset (Linkov et al., 2009, 2011). Linear weighted averaging (LWA) represents one of the most common weighting methods (Steele et al., 2009). For example, when constructing a map composed of  $j$  land parcels (or map cells), the criteria – in our case, the capacity of a parcel to support (1) agriculture or (2) forest vegetation as well as its (3) fragmentation potential – may be standardized to scores that are then combined by weighted averaging into a continuous metric:

$$R_j = \sum_{k=1}^K Z_{jk} w_k \quad (1)$$

where  $Z_{jk}$  is the normalized value of criterion  $k$  for element  $j$ , which falls within a common numeric interval,  $[Z_{\min}, Z_{\max}]$ ,  $w_k$  is the normalized weight for criterion  $k$  and  $K$  is the size of the criteria space ( $K=3$  in our case). Ideally, the weighting coefficients  $w_k$  are estimated using exogenous information about their relative importance. However, such knowledge is often incomplete or unavailable and the weights are instead determined through the subjective assessments of experts. Several approaches have been proposed to reduce the biases of experts in this context, such as constructed (Keeney and Raiffa, 1976) or triangulatory (Florin et al., 2001; Morgan et al., 2000) rankings, treatment of experts' beliefs as distributions and their subsequent rankings via stochastic dominance criteria (Andrews et al., 2004; Hadar and Russel, 1969; Levy

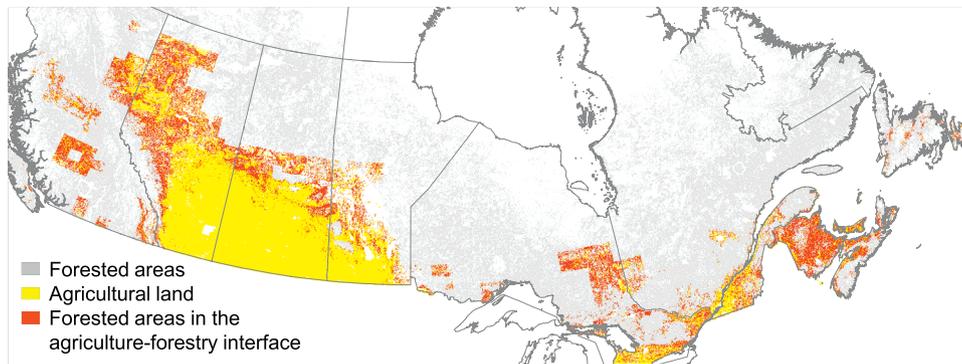
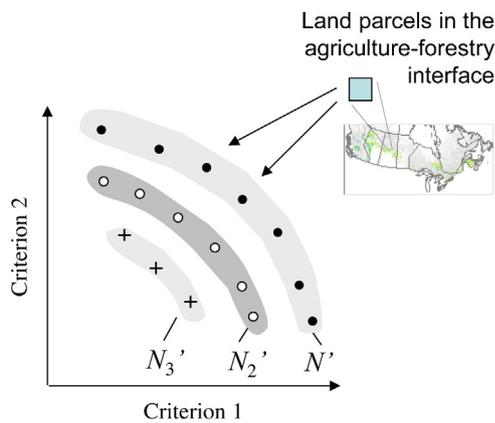


Fig. 1. Map of the Canadian agriculture–forestry interface.



Nested multi-attribute frontiers (MAFs):

- - Non-dominated subset  $N'$  (dominates sets  $N_2'$  and  $N_3'$ )
- ⊙ -  $N_2'$  (dominates  $N_3'$ , dominated by  $N'$ )
- + -  $N_3'$  (dominated by  $N'$  and  $N_2'$ )

Fig. 2. The concept of nested multi-attribute frontiers (MAF).

and Wiener, 1998), or using fuzzy aggregation rules (Jiang and Eastman, 2000; Yager, 1988). Nevertheless, none of these modifications truly eliminate the subjectivity of weights estimated from incomplete knowledge about the individual criteria, their relative importance or interactions.

In this paper we present an alternative technique for aggregating land production capacities and land use fragmentation potential in a single-dimensional indicator metric. The technique does not require specification of criteria weights. Instead, it employs the concept of finding nested multi-attribute frontiers in dimensions of the individual criteria  $Z_{jk}$  (Eq. (1)). Although we use three criteria dimensions in our study, Fig. 2 illustrates the multi-attribute frontier concept using a simpler, two-dimensional example. Assuming that an area of interest consists of  $N$  individual land parcels (map cells), each parcel  $j$  ( $j \in 1, \dots, N$ ) can be represented as a point in the criteria space. The points form a  $K$ -dimensional cloud,  $\mathfrak{N}$ , where the position of each point in the cloud is defined by the point's values for the individual criteria  $k$ . If the criteria dimensions are oriented so the combinations of their largest values denote the highest land clearing potential, then the outer convex boundary of the point cloud  $\mathfrak{N}$  (i.e., outer layer  $N'$  in Fig. 2) represents the combinations of the points with the highest possible land clearing potential in the area of interest. This convex boundary represents a multi-attribute frontier of the  $K$ -dimensional point set  $\mathfrak{N}$ . For a set of

$N$  points in a  $K$ -dimensional criteria space, the multi-attribute efficient frontier is outlined by the subset of the total population,  $N'$ , that is non-dominated by the rest of the population (i.e., the points in frontiers  $N_2'$  and  $N_3'$ , Fig. 2). Dominance (or non-dominance) between points is determined according to a simple rule: a point  $S_1$  dominates another point  $S_0$  when

$$S_{1k} \geq S_{0k} \forall k = 1, \dots, K \text{ and } S_{1k} > S_{0k} \text{ for some } k. \quad (2)$$

In the context of a geographical area of interest, the points on the multi-attribute frontier correspond to land parcels with the most “extreme” combinations of agricultural productivity potential, forest productivity potential and fragmentation potential; in short, no other points (i.e., parcels) in the full set have combinations with higher expected land clearing potential than those on the outer frontier (Fig. 2). Procedurally, we assign all points on the outer frontier an integrated land clearing pressure rank of 1. These points are then removed temporarily from the set and a new multi-attribute frontier is constructed. The points along this second frontier are assigned a rank of 2, removed temporarily from the set and so on until all points are assigned a land clearing pressure rank. There is no need to provide prior estimates of weights for the criteria since the land clearing pressure ranks are drawn from a partial order of elements in the multi-attribute criteria space (Fig. 2).

The delineation of nested multi-attribute frontiers is a sequential process, which we conducted in two directions. First, we adopted a “descending” ranking approach where we began the delineation of nested multi-attribute frontiers from the parcels (map cells) with the highest land clearing potential (generally, parcels with the highest agricultural capacity, lowest forest productivity and highest fragmentation potential). We also adopted an “ascending” approach where we inverted the criteria values and began delineation of the nested frontiers from the parcels with the lowest land clearing potential and ultimately outlined the areas of highest clearing potential through step-by-step elimination of the lower-rank locations.

Prior to ranking, we assigned unique identifiers to each parcel (map cell) and then converted them to points in our  $K$ -dimensional criteria space. After completing the delineation of nested multi-attribute frontiers, we used the points' identifiers to map the frontier ranks back to geographical space (Fig. 3). To compare different scenario realizations, we rescaled the ordinal land clearing pressure ranks to a [0;1] range, such that values close to 1 denoted the highest land clearing potential and the ranks of the lowest frontiers were close to 0. Conceptually, the analysis is based on the multi-attribute map aggregation technique described in Yemshanov et al. (2013).

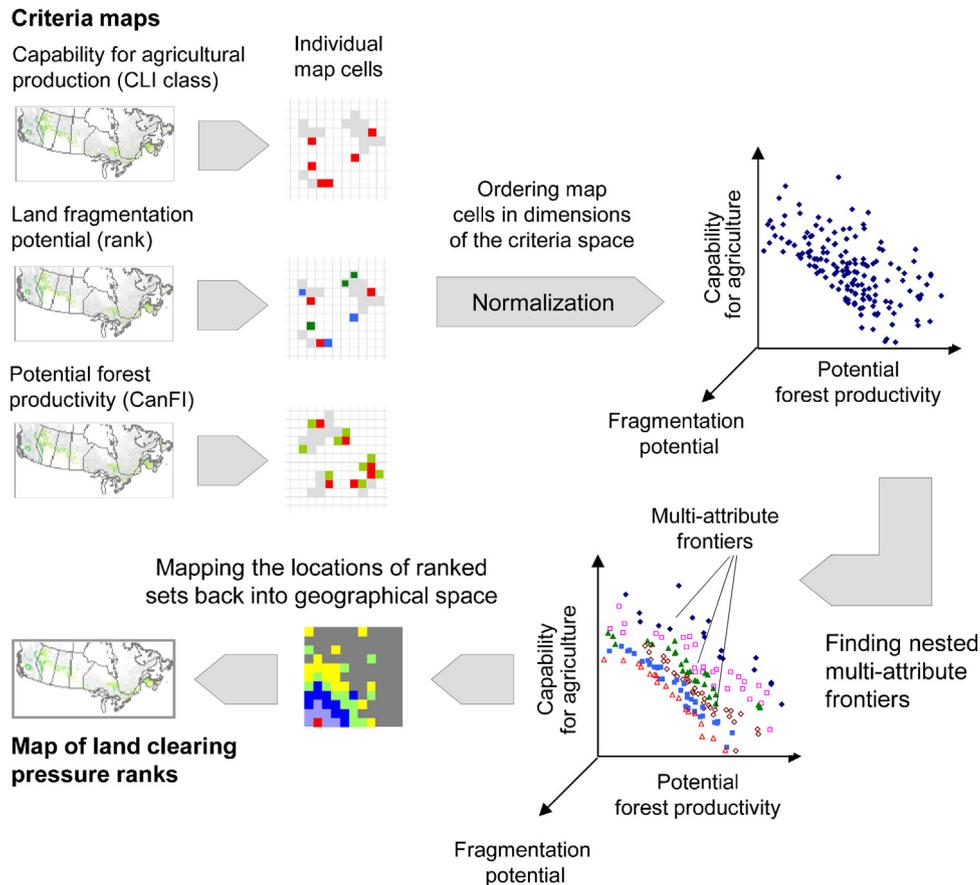


Fig. 3. Analysis summary.

### 3. Data

The Canadian agriculture–forestry interface encompasses a wide transition zone between non-forested areas, such as the Prairie ecozone in western Canada and major agricultural production regions in eastern Canada, and adjacent forest-dominated areas (Fig. 1). We focused on forested lands in this zone with sufficient climatic conditions to support agriculture, which could thus potentially be converted. To do this study we needed geographical information about the land’s capacity for agricultural production, forest productivity potential and land use fragmentation potential. We used the Canadian Land Inventory database (AAFC, 2010) to depict the capability of land to support agricultural production. Recent forest biomass estimates from Canada’s National Forest Inventory (CanFI, Gillis, 2001; Gillis et al., 2010) fused with medium-resolution forest land cover classification data (Yemshanov et al., 2012) were used to derive probabilistic estimates of forest productivity. We also used a tri-polar model similar to that described in Riitters et al. (2009a,b) to develop a map of fragmentation potential.

#### 3.1. Geospatial estimates of agricultural capacity

We used the Canadian Land Inventory database (CLI) to estimate the capacity of currently forested land to support agricultural production. We used CLI “Level I” (1:250,000 scale) data, which provided digitized information from existing land inventories and were based on significant research and development efforts undertaken by The National Archives of Canada, Statistics Canada and Agriculture and Agri-Food Canada (AAFC, 2010).

In the CLI database, land capacity to support agricultural production is represented by CLI land capability class. Class 1 includes high-productivity lands that generate the highest crop yields and could be considered prime locations for agricultural production. Classes 2–3 delineate medium-productivity lands and classes 4–6 depict low-productivity, marginal lands that are probably best used for pasture. The CLI data are stored as GIS polygons linked to attribute tables that document the occurrence percentages of each land capability class within the polygons. Since our analysis was carried out in a raster map setting (i.e., the landscape was divided into a rectangular grid of 250 m × 250 m map cells), we applied a spatial algorithm to allocate the expected values of CLI land classes to the map cells within each CLI polygon. We used the polygons’ occurrence percentages for each CLI class to generate probabilistic estimates of agricultural capacity via Monte Carlo simulations (Appendix S1, Fig. 1). Using the occurrence percentages for each CLI class we generated a vector of probabilities that a given map cell belonged to a particular CLI class. This vector was then used to assign a CLI class to the cell via randomized Monte Carlo draws. For each map cell, the final CLI classification depicted the land’s expected potential to support agriculture, with the lowest value (1) representing the most productive lands and values above 6 denoting marginal lands unsuitable for agriculture.

#### 3.2. Geographical estimates of forest productivity

In Canada, quantitative information about forests is compiled as part of the national forest inventory (CanFI), which is an aggregation of provincial and territorial forest management stand inventories and reconnaissance-level observations (Gillis, 2001; Gillis et al., 2010). The stand-level inventory data provided by provincial and

territorial management agencies are converted to a national classification scheme and then reported at the ‘map sheet’ level. Map sheets are roughly rectangular or simple polygonal shapes that are approximately 100 km<sup>2</sup> in extent, or sometimes larger depending on the province in which they are located.

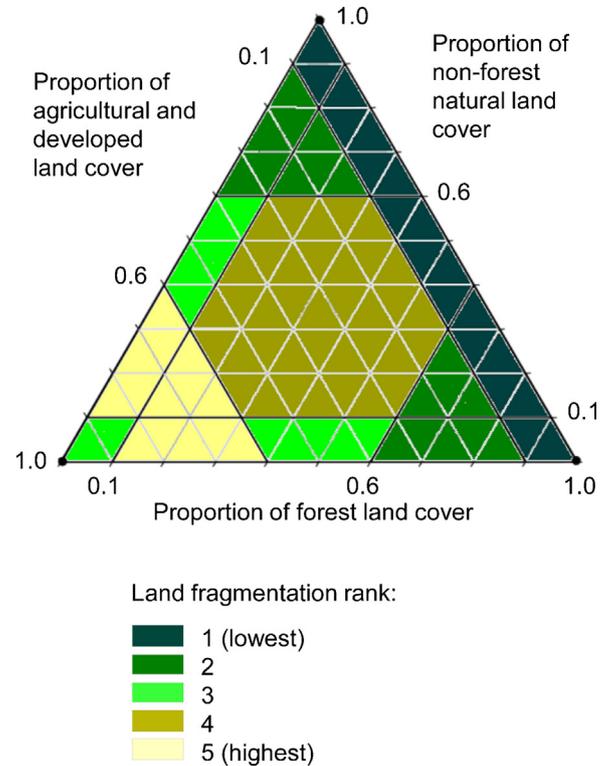
Finer-scale spatial details on forest productivity and tree species composition are typically obtained through air photo interpretation (OMNR, 1998). Like the stand-level inventories, these data are managed by provincial resource management agencies across Canada, and form a large part of the data aggregated in CanFI. However, inter-provincial differences in spatial data structure and proprietary issues make the generation of a seamless, high-resolution national forest productivity database challenging. A second source of fine-scale forest resource information is classified multi-spectral Landsat TM satellite imagery (Polson et al., 1989). Such imagery was used in the Canadian Forest Service Earth Observation for Sustainable Development of Forests (EOSD) initiative to generate a map of general forest types and land use change patterns for Canada (Wulder and Nelson, 2003; Leckie et al., 2002). The EOSD coverage was based on image classification techniques that are consistent across large spatial scales (Wulder, 2000; Wulder et al., 2003, 2008) and delineates three basic forest vegetation types: mixedwood, coniferous, and broadleaf-dominated forests (Wulder and Nelson, 2003).

We linked the CanFI data and the EOSD product using a spatial allocation technique described in Yemshanov et al. (2012). The method distributes map-sheet-level forest composition information from the CanFI database records to the appropriate forest cover classes in the EOSD map via the following basic steps. First, estimates of area occupied by different forest tree species and forest age groups are converted into probabilistic measures of relative occurrence for each CanFI record describing a given map sheet. Next, we apply a Monte Carlo randomization technique using these measures of relative occurrence to distribute the data stored in a given CanFI record across the EOSD coverage, resulting in a randomized distribution of the CanFI records across forested EOSD map cells. The final stage adjusted the allocation of CanFI records by calculating the probability of a given CanFI record belonging to a particular forest cover class (i.e., hardwood, mixedwood and softwood) identified in the EOSD classification and used these values to adjust the CanFI record’s relative occurrence in the map sheet, to ensure that the estimates of biomass and species composition in the final product match data from the CanFI records (Yemshanov et al., 2012).

This allocation process allowed us to build a geospatial coverage consisting of randomized predictions of forest productivity (i.e., biomass) at the level of generalized conifer and hardwood tree species groups. For our study, we aggregated these broad species groups and generated 100 independent realizations of the geospatial coverage to calculate an average forest biomass productivity value for each map cell (Appendix S1, Fig. 2).

### 3.3. Land fragmentation potential

We adapted a landscape mosaic model described in Riitters et al. (2009a,b) to develop a map of land fragmentation potential for the Canadian agriculture/forestry interface. The landscape mosaic model classifies landscape context according to land-cover composition in a neighborhood and is sensitive to composition, diversity and dominance of particular land cover classes. To highlight interface zones arising from relatively intensive agricultural and anthropogenic land uses, we defined the landscape mosaic classes in terms of agricultural, developed, forest and other ‘natural’ (i.e., not agricultural, developed or forest) land cover types. The model is implemented by classifying the landscape (i.e., a geographical neighborhood defined by a fixed-area square window)



**Fig. 4.** Tripolar model of fragmentation potential based on the landscape proportions of three major land cover classes: (1) agriculture + developed, (2) forest and (3) non-forest natural land cover.

surrounding each pixel of land cover, and mapping the landscape mosaic at the pixel level. The classification scheme can be depicted as a tri-polar (ternary) chart (Fig. 4), similar to the ‘soil triangle’ (e.g., Gee and Bauder, 1986), which classifies soil texture based on the proportions of sand, silt, and clay in a soil sample. In the landscape mosaic model, the proportions of three generalized land-cover types (i.e., agriculture + developed, forest and other natural) replaced the proportions of soil components along the three axes, and the classes referred to the landscape mosaic instead of soil texture. We used the threshold values from Riitters et al. (2009a,b) of 0%, 10%, 60%, and 100% along each axis to identify general land fragmentation ranks. The selected threshold values distinguished between landscape mosaics on the basis of the presence (0%), substantial presence (10%), dominance (60%), and exclusivity (100%) of the three generalized land-cover types (Riitters et al., 2009a,b).

We used land cover maps based on 30-m resolution multi-spectral Landsat satellite images, which were used in the Canadian Forest Service EOSD initiative (Leckie et al., 2002; Wulder and Nelson, 2003). We condensed the original EOSD land cover classes into our three generalized land-cover types. We then placed a 250 m × 250 m window (corresponding to the resolution of our other spatial datasets) around each pixel on the land-cover map, evaluated the land-cover composition within that window and mapped the corresponding landscape mosaic at the location of the focal pixel. We repeated this procedure for all pixels on the land-cover map.

Mapping the landscape mosaic as a contextual measure at the pixel level offers multiple ways to aggregate the land cover composition information. Since the focus of our study was on the agriculture–forestry interface, our choice of land fragmentation ranks was stratified into five distinct groups with respect to the abundance of forest and agricultural land cover classes (Fig. 4). We assigned the highest land fragmentation potential to landscape mosaics that contained more than 60% agricultural and developed

land, unless the forest or other natural cover types were also rare (<10%). The second-highest fragmentation risk rank was assigned to landscapes that presented a generally “inter-mixed” matrix where none of the three land-cover types was dominant, again excepting the case where the forest and other natural cover types were rare (i.e., less than 10%); landscape mosaics in this latter category received the third-highest rank. Landscape mosaics with forest cover above 90% were assigned the lowest rank, while the rest of the study area (where the percentage of forest cover varied between 60 and 90% and the proportion of agricultural land was below 30%) was assigned the second lowest fragmentation risk rank (Fig. 4). The rankings (including the sites where the forest and natural cover types are below 10%) are consistent with Riitters et al. (2009b) analysis of forest change using the tripolar model.

## 4. Results

### 4.1. Exploratory geospatial data analysis

Fig. 5 depicts land clearing potential ranks for a portion of western Canada (the figure only shows the map based on the descending ranking approach because the descending and ascending rankings yielded similar broad-scale allocations of high- and low-risk areas). The maps show several general trends in the geographical distribution of the land clearing potential ranks. Parcels with high land clearing potential were commonly found close to regions of major agricultural production with large quantities of high-quality (i.e., CLI class 1) agricultural land. In addition, several high-risk hotspots were identified in smaller agricultural regions in the northern boreal zone, such as the Peace River region in Alberta. Forested areas in the boreal and semi-boreal zones received relatively low land clearing pressure ranks. Proximity to urban areas moderately increased land clearing potential, but this could be due to the higher proportion of agricultural land that often surrounds urban centres.

The maps also show relatively high land clearing potential for very small forested areas surrounded by large areas of agricultural production (Fig. 5). The incorporation of the land fragmentation criterion helped discriminate these areas from the forested patches that demarcate natural features, such as riparian zones in the Prairies and southern Ontario. The latter elements are rarely affected by clearing because of environmental regulations and, furthermore, their generally low capacity to support agricultural production (for which they received low land clearing rank values). The ranking results support previous assessments for the Canadian Prairies (Fitzsimmons, 2002, 2003) and the U.S. (Kress et al., 1996) that reported a negative relationship between the size of forest patches and the local deforestation rates. Small forest patches surrounded by agricultural lands may have soil properties approaching the quality of the neighboring agricultural fields, but will rarely be cleared. With respect to our rankings, this aspect was addressed in the map of fragmentation potential, where areas with scarce forest cover were assigned moderate land clearing ranks (i.e., rank 3, the lowest left corner of the triangle in Fig. 4). Note that we did not assess how well the land clearing rank may correlate with the proportions of large- or small-size patches in a landscape, so we did not expect a perfect correlation between the land clearing rank values and the patch size distribution. This aspect would require incorporating additional criteria to characterize the patch size composition in a landscape and was considered beyond the scope of the current study.

### 4.2. Land clearing ranks in dimensions of land capacity for agriculture and forestry

Fig. 6 depicts broad classes of land clearing ranks in the dimensions of land's capacity to support agriculture (a CLI class) versus

**Table 1**  
Total area under risk of clearing versus land clearing rank threshold.

Forested area under risk of clearing (ha)	Land clearing pressure rank threshold <sup>a</sup>	
	Descending ranking	Ascending ranking
5000	0.99	0.948
20,000	0.981	0.916
50,000	0.971	0.893
100,000	0.957	0.868
500,000	0.897	0.790
1 million	0.855	0.734

<sup>a</sup> Minimum land clearing pressure rank value that corresponds to the area footprint specified in the first lefthand column.

forest vegetation (a merchantable stand biomass volume equivalent). We depict the third criterion (land fragmentation potential) by presenting separate two-dimensional plots for low, moderate and high levels of fragmentation potential. As expected, the areas with the greatest clearing pressures are typically sites where the risk of fragmentation is high. Notably, the set of areas with the highest land clearing potential (the lower left corner in the graphs in Fig. 6) includes a number of areas with “no data” values. This suggests that many forested lands with a combination of high capacity for agriculture and low forest productivity have been already converted to agriculture or other uses.

The descending and ascending ranking scenarios have notable differences. The descending ranking scenario reveals two distinct groups of high-risk locations (Fig. 6a, callouts I and II). Group I includes land parcels that have both extremely low forest productivity and a very high capacity to support agriculture. The second group (Fig. 6a, II) includes sites that have an extreme productivity value in at least one dimension (i.e., near-zero forest productivity potential or the highest capacity for agriculture). The ascending ranking scheme does not include the second group (Fig. 6b, callout I). The omission of this group can be explained by the nature of the ascending ranking, where the delineation of nested multi-attribute frontiers starts from parcels with the lowest land clearing pressure and identifies the areas of highest clearing pressure via successive elimination of parcels with lower pressure ranks. In short, the ascending and descending rankings start the delineation of multi-attribute frontiers from opposite sides of the multi-criteria point cloud. As a result, the boundaries between broad land clearing classes are concave in the descending ranking (Fig. 6a) and convex in the ascending ranking scheme (Fig. 6b). In the ascending ranking scheme, a parcel can be expected to have the highest land clearing potential only if all three criteria – highest capability for agriculture, lowest capability for forestry and highest land fragmentation potential – have extreme values. The descending ranking scheme adds the assumption that parcels with extreme values in any one of the three criteria could also be cleared. Since the descending scenario assigns high clearing pressure ranks to a larger area, it follows that many land parcels with lower risk of being cleared under the ascending scenario have comparatively higher ranks under the descending scenario.

### 4.3. Estimates of land area under clearing pressure

Table 1 lists the rank threshold values, under both the ascending and descending scenarios, which correspond to a given footprint of forested area designated at risk of being cleared. As Table 1 suggests, the land clearing ranks drop more rapidly with smaller area footprints and then decline less rapidly as the area footprint increases over 100,000 ha. This behavior indicates selective delineation of the highest rank values.

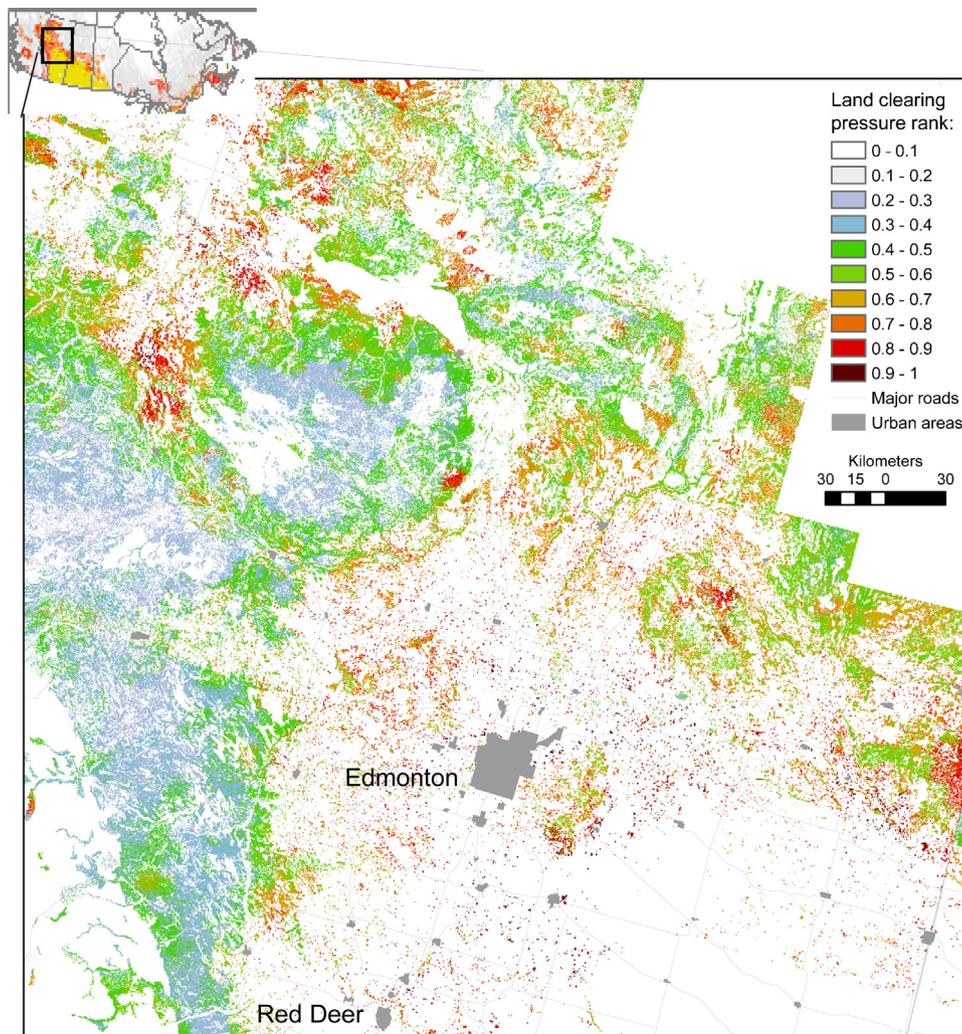


Fig. 5. Map of land clearing potential ranks in Western Canada (the descending ranking scenario is shown).

Table 2

Area percentages (%) under different land footprints by province.

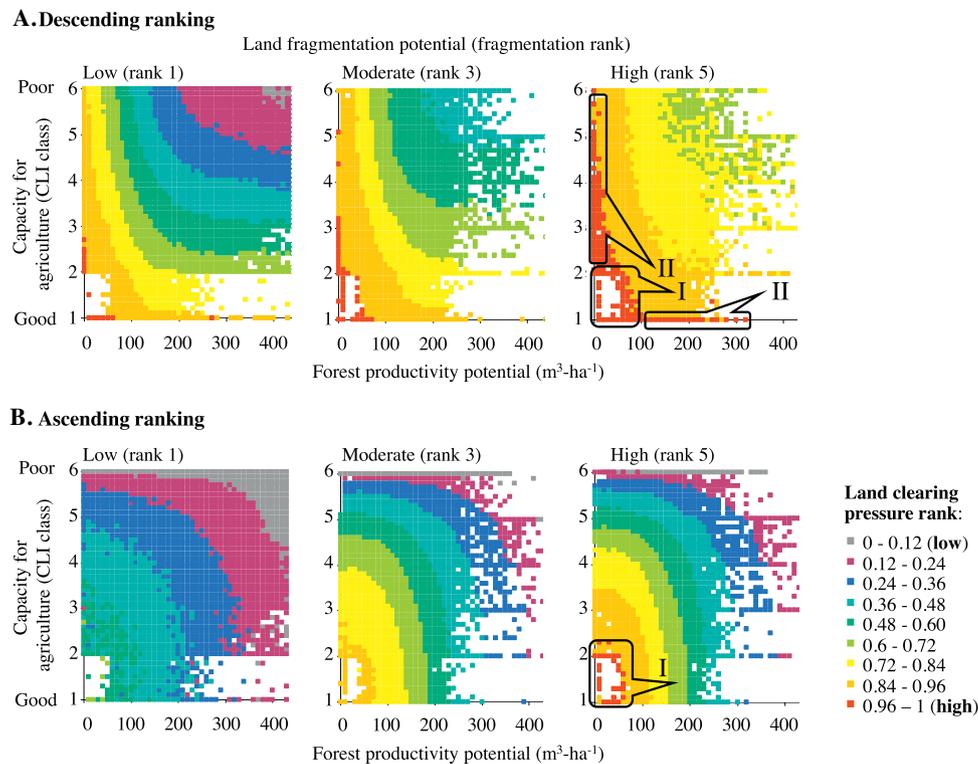
Forested area under risk of clearing <sup>a</sup> (ha)	Provinces									
	ON <sup>b</sup>	QC	AB	BC	MB	NB	NF	SK	PE	NS
	A. Ascending ranking									
5000	7.2	4.2	25.7	0.8	2.8	–	–	56.6	–	2.8
20,000	18.8	7.4	34.5	0.6	3.1	0.3	–	23.8	–	11.5
50,000	23.3	9.4	29.0	1.1	6.2	1.6	0.1	15.3	–	14.0
100,000	26.9	9.5	27.3	0.3	5.9	3.7	0.1	10.4	–	15.8
500,000	25.0	10.3	21.7	0.7	2.1	10.9	0.2	13.3	0.6	15.2
1 million	23	13.2	21.2	0.6	2	10.7	0.4	12.6	0.5	15.8
	B. Descending ranking									
5000	47.7	0.8	31.5	4.0	0.5	–	–	15.0	–	0.5
20,000	63.9	1.6	21.3	0.4	0.9	0.1	0.03	10.8	–	1.0
50,000	46.1	3.1	26.0	0.5	1.1	2.0	0.1	17.0	–	4.3
100,000	58.8	3.3	20.4	0.4	1.8	0.6	0.2	12.0	–	2.6
500,000	32.5	10.4	25.4	2.2	4	3	0.5	15	0.9	6.1
1 million	18.5	11.9	28.6	6.0	6.0	5.5	0.8	12.9	0.2	9.5

<sup>a</sup> The land area with the highest clearing pressure ranks.

<sup>b</sup> Canadian provinces: ON – Ontario; QC – Quebec; AB – Alberta; BC – British Columbia; MB – Manitoba; NB – New Brunswick; NF – Newfoundland and Labrador; SK – Saskatchewan; PE – Prince Edwards Island; NS – Nova Scotia.

The inter-provincial distributions of land area under different area footprints are provided in Table 2. The table shows notable differences in the provincial allocations of high-risk areas under the ascending and descending ranking scenarios. For example, for the 5000 ha of forested land in the interface zone with the highest

risk of being cleared, either 25.7% (ascending) or 31.5% (descending) of that land is allocated in Alberta, 0.8 or 4.0% in British Columbia, 7.2 or 47.7% in Ontario and 15 or 56.6% in Saskatchewan. Thus, for the ascending scenario, more than half of land area in the 5000-ha footprint was allocated in Saskatchewan, while nearly half of



**Fig. 6.** Land clearing pressure ranks in dimensions of land's capacity for agricultural production and forest productivity. Graphs represent the cross-sections of the three-dimensional criteria cloud at fragmentation rank levels 1 (low), 3 (moderate) and 5 (high). A – descending ranking; B – ascending ranking.

the area was allocated to Ontario under the descending scenario (Table 2). However, as the land area footprint increases the allocation of land among the provinces becomes more even between the two ranking scenarios. Despite being large in terms of total land area, British Columbia and Newfoundland and Labrador had relatively low percentages of forested land under high risk of being cleared (Table 2), which is a result of the relatively low proportion of agriculture–forestry interface in these provinces.

## 5. Discussion

The land clearing indicator presented in this study helps prioritize areas of concern where conversion from forest to agriculture may be driven by considerations of the land's productivity and land cover pattern composition. The approach aggregates production capacities and complex landscape patterns in a single-dimensional metric using a multi-attribute frontier approach. This metric can be applied not only for research purposes but also for decision-making and policy development (Bertollo, 1998; Girardin et al., 1999).

Our results suggest that most land parcels with high risk of being cleared are allocated to woodlots bordering major regions of agricultural production in Canada or to areas with good road access (see Fig. 6). This result is consistent with historical evidence of land clearing activities in Canada (Fitzsimmons, 2002; Fitzsimmons et al., 2004; Hobson et al., 2002). We believe this assessment represents a good starting point in those situations when knowledge about social and economic drivers of land use change is poor or lacking. Land cover maps, geographical land surveys and forest inventories are the only consistent sources of data for large, sparsely populated rural regions such as northern Ontario and the Canadian Prairies. In these situations, our methodology provides a simple yet tractable way of using these data to find the geographical hotspots where the land clearing potential could be high. These estimates could then guide further efforts to gather

econometric information which, in turn, could help better understand economic and social aspects of land clearing dynamics in these regions. The approach is generic and can be applied in other regions of the world where econometric data on social and economic drivers of land conversion are lacking but estimates of land production capacity and landscape fragmentation potential based on remote sensing data are available.

### 5.1. Differences between the ascending and descending ranking scenarios

The ascending and descending ranking schemes show notable differences between the rank values. In general, the descending ranking scheme assigns higher rank values to larger amounts of map elements (i.e., map cells) than the ascending scheme. This difference can be explained by the delineation of an extra group of land parcels in the descending scenario that have extreme values in at least one criteria dimension (Fig. 6, callout II). Differences in rank values between the ascending and descending scenarios appear to be consistent and increase slightly with the area footprint. This is a result of the sequential delineation of nested multi-attribute frontiers that define the rank values. Differences in rank values start to increase linearly once the area footprint exceeds approximately 80,000 ha. This indicates that major differences between the descending and ascending schemes occur in the delineation of the highest-risk sites. In practical terms, the ascending and descending ranking schemes can be viewed as implementations of optimistic and pessimistic strategies for assessing land clearing potential. The ascending scheme assigns the highest ranks to the parcels that have a combination of extreme values in all criteria, so it represents a somewhat optimistic perception of the land clearing process (when land clearing is only triggered if all three criteria reach extreme values). The extra areas allocated in the descending ranking scheme (Fig. 6, callout II) can be interpreted as a pessimistic scenario that adds the assumption that some landowners' decisions to convert

forested parcels to agriculture may simply be driven by consideration of whether agricultural or forest production is more like to yield the greatest return, regardless of the parcels' current forested status or land fragmentation potential.

## 5.2. Insights for environmental decision-making and future work

Despite our limited understanding of forest land clearing pressures in the Canadian agriculture–forestry interface, it is a nationally relevant issue, so the ability to generate consistent, spatially referenced criteria and indicators of these pressures based on limited data is essential. The technique described in this paper offers a strategy for developing a meaningful indicator despite scarce knowledge about the relative importance of key biophysical and socio-economic drivers of land clearing. Instead of relying on arbitrary weights or the judgments of experts, the MAF technique objectively combines these drivers into a single-dimensional assessment metric that ranks every location in an area of interest.

On a formal basis, the rank values delineated with the MAF technique are derived from a partial order of elements in each criterion set (Fig. 2), and are therefore reasonably stable in the face of moderate errors in the criteria values. Essentially, it takes a higher degree of variation in the criteria values to change the dominance relations (i.e., the relative rankings) between elements in a set than to change their actual values. Although experts can generally identify the critical land conversion factors, they are rarely able to determine the precise threshold values in these factors where clearing of forested woodlots becomes highly probable. Notably, the MAF approach bypasses this issue of thresholds, and instead exploits the fact that each criterion in a multi-dimensional space can be ordered along a “high–low” relative gradient, making it straightforward to delineate nested multi-attribute frontiers in the criteria space.

By aggregating this set of nested frontiers, the MAF technique describes the multi-dimensional criteria space by a single rank score. However, the final rank values of the elements (e.g., map locations) within that criteria space are ordinal values. While ordinal values can be used in many practical situations, in cases when distinct criteria sets are represented in the same measurement frame (e.g., cost estimates for different aspects of land use versus mapped values of environmental benefits), a numeric multi-criteria score could be a useful metric because it enables the comparison of the criteria sets. This can be achieved via application of a portfolio-based approach.

In financial asset allocation, portfolio optimization typically considers tradable investment assets whose past market performance is used to estimate their net return values as well as the degree of uncertainty in those returns (Salo et al., 2011). In our case, individual elements of a multi-attribute set (i.e., individual spatial locations) can be seen as individual portfolios, while the criteria that describe the set can be considered analogous to different financial asset types (cf. Keisler and Linkov, 2010). Each location (i.e., a portfolio) can be characterized by the criteria values in the same way that financial portfolios are characterized by their proportions of these different asset types. In turn, the assessment of land clearing potential can be envisioned as an attempt to identify the most “efficient” portfolios (i.e., the locations with the greatest expected risk of land clearing) in terms of criteria that represent the locations' productivity and fragmentation potential (Keisler and Linkov, 2010). Conceptually, this task is similar to how a financial analyst might delineate an efficient frontier of portfolios with the combinations of financial assets that provide the best returns (Elton et al., 2010). It also resembles how portfolio analysis is used in other disciplines, for instance to evaluate the reliability of large-scale engineering projects (Aerts et al., 2008; Skaf, 1999; Zhou et al., 2012) or to assess multi-factor environmental and public health risks (Galligan and Marsh, 1988; Prattley et al., 2007). The

subsequent calculation of a single numeric multi-criteria score (rather than an ordinal score) involves a two-stage portfolio allocation process. In the land clearing context, the first stage is as just described: identifying the elements (i.e., the map locations) in a multi-criteria set with combinations of the criteria values that represent the highest risk of land clearing (i.e., the elements, or locations, that fall along the “efficient frontier”). The next allocation stage finds the distance in multi-criteria space between each element of the set and the nearest element of the efficient frontier and translates it into a numeric score. This could be an interesting topic for future work.

Application of a portfolio-based approach could potentially help address another limitation of the MAF technique, which is its poor capacity to delineate multi-attribute frontiers when there are very many criteria dimensions. Portfolio allocation techniques based on optimization algorithms (such as discussed in Keisler and Linkov, 2010) provide means of finding efficient portfolio frontiers for high-dimensional sets. Moreover, portfolio-based techniques offer a way to account for various decision-making preferences, such as a desired degree of portfolio diversification or the minimization of uncertainty (Elton et al., 2010; Keisler and Linkov, 2010; Maillard et al., 2010; Michaud, 1989; Zhou et al., 2012). To further support decision-making, portfolio allocation could also be embedded interactively into multi-criteria assessment methods (Argyris et al., 2011). For example, the process of selecting efficient portfolios could be adjusted iteratively according to elicited information about decision-makers' preferences with respect to the individual criteria values (Argyris et al., 2011). Incorporation of interactive preference selection could broaden the traditional decision-making process to include alternative assessments that may better agree with both the decision-makers' preferences and real-world constraints.

In geographical applications, such as the study presented above, the MAF-based land clearing ranks provide the opportunity to incorporate an area-based indicator of land clearing pressures into forest- and agricultural sector-based economic models. Sector-based models such as the partial equilibrium Canadian Regional Agriculture Model (CRAM, AAFC, 1993; Horner et al., 1992; Webber and Graham, 1986) could make use of this type of information to enhance their ability to model land conversion between different sectors. Sector-based models typically require information about the areas potentially susceptible to land conversion. The maps of land clearing pressures presented in this study rank all map locations (map cells) in the Canadian agriculture–forestry according to their level of clearing risk, thereby providing the technical means to assess the land clearing potential for specific regional delineations (such as Canadian provinces, Canadian Census divisions or agricultural regions) that are regularly used in sector-based economic models. Sector-based models (such as CRAM) can then use regional summary curves to track future costs of land conversion to agriculture. This could improve the performance of sector-based models and provide a more realistic portrayal of economic scenarios that introduce land clearing pressures.

## 6. Conclusions

Canada is considered a ‘forest nation’, with the forest sector traditionally representing a large portion of the economy, so the prospect of forest land clearing raises serious social and political concerns. While the current levels of land clearing in Canada remain low, future land use forecasts under climate change scenarios project a gradual decrease in forested area and an increase in areas under cropland or pasture (Darwin et al., 1995; van Kooten and Arthur, 1997). This necessitates the development of landscape-level indicators that could help identify the geographical areas

where conversion of forested lands to agriculture is most likely. The approach presented here assesses the potential of forested lands to be cleared for agriculture as a trade-off between the land's capacity to support either agricultural production or forest vegetation, as influenced by the land's susceptibility to fragmentation and eventual conversion. The results can be used to help enhance sector-based economic assessments in agriculture and forestry. The final map of land clearing pressures incorporates land fragmentation patterns, spatial features of the Canadian Land Inventory, as well as geographical variations in forest productivity as ascertained from CanFI inventory estimates. We anticipate a substantial demand for these products, particularly as inputs to sector-based partial equilibrium economic models which can make use of spatial projections of land clearing information in the assessment of future economic and climate scenarios.

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## Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at <http://dx.doi.org/10.1016/j.ecolind.2015.02.019>.

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