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Quantifying Landscape Pattern and Fragmentation: A Transect Analysis Approach in Alberta

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ABSTRACT

Land use and land cover change represents one of the main driving forces on biodiversity world-wide. Although the international community currently recognises its impacts over biodiversity, hydrology and biochemical cycles, the impact at the landscape level of these extraction forces is less understood when the concept of land use intensification is taken into consideration. In many cases, the interpretation of changes on landscape structure processes relies on the use of common landscape fragmentation metrics. In this research project, a new class division index and percolation model has been developed to study Land Use and Land Cover Change impacts on forested and agricultural landscapes. This model is proving to be fundamental to understanding the cumulative effects of oil and gas exploration at the landscape level. Key findings of this project indicate that common landscape metrics and image classification techniques may be failing in terms of quantifying the impact of linear features.

ACKNOWLEDGEMENT

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INTRODUCTION

The scientific community recognizes that the impacts of land-use and land-cover change (LUCC) on global environmental change are reaching proportions similar to those from global warming. One of the major ongoing LUCC processes is deforestation, and the paramount impact thereof is biodiversity loss. The relationship between land use intensity and the maintenance of biodiversity is not well characterised, but has important implications not only for the future of life on the planet, but also for the delivery of ecosystem service benefits to society. The intensification of land use is expected to continue with pressures to double global food production over the period 1990 - 2020, with seven-fold increases needed in some regions. The overall goal of this project is to contribute to a better understanding of the relationship between land use intensification/land cover change and biodiversity losses in Canada. Our research project recognises that these losses take place at multiple levels (landscape, ecosystem, species, and genes), spatial scales (local to regional), and dimensions (biophysical drivers, proximal causes and social/human drivers).

The main objective of this research project was to develop methodologies and tools, using remote sensing and Geographic Information systems, that permit the integration of LUCC processes and environmental changes into decision making and strategies in the context of conservation biology and sustainable forest management at the regional/sub-regional level. The project is organised around the following questions:

i. What is the relationship between the levels of agricultural intensification, forestry, oil/gas extraction, and biodiversity in countryside landscapes?

ii. What is the impact on linear features at the landscape level?

iii. How can GIS and remote sensing help to design practical measures in the area of ecosystem restoration, enhancing the capacity of countryside habitats to sustain biodiversity and ecosystems services while under increasing pressure from human activities?

These questions will be addressed through a transect analysis in Alberta (Figure 1 and 2, Appendix A). A Northeast-Southwest transect was selected to incorporate existing projects where biodiversity data sets are available. We will use 8 sites: *three NCE sites, three sites from TROLS, a site at Calling Lake, and a final site in the agricultural area at the Meanook Biological Station.* These sites differ in land use intensity and type, and we will relate patterns of avian diversity and species richness to landscape disturbance, intensity, land use/cover change and overall forest cover.

Figure 1: Distribution of Sites in Province of Alberta

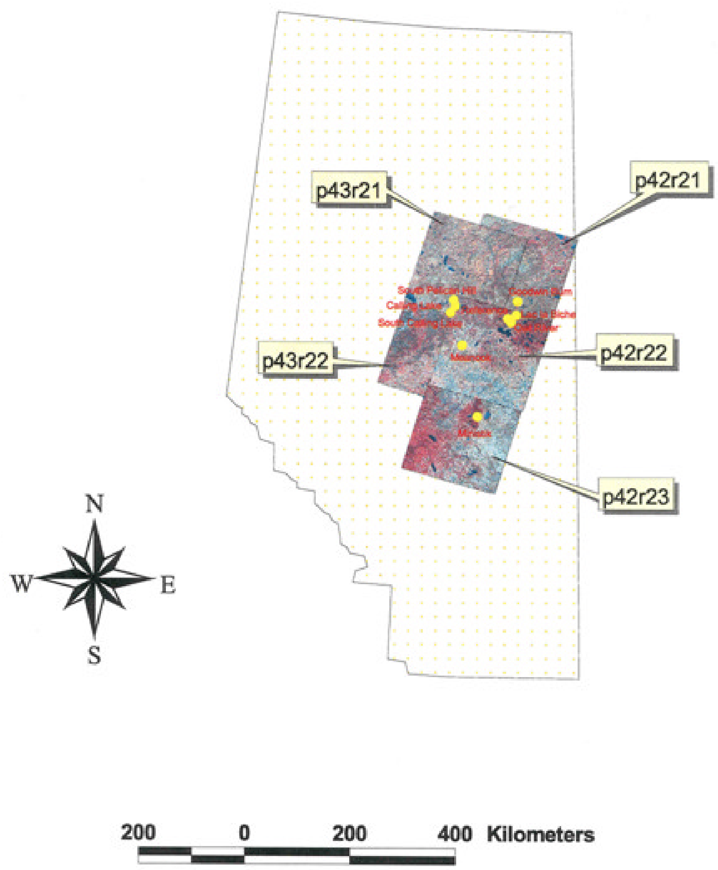
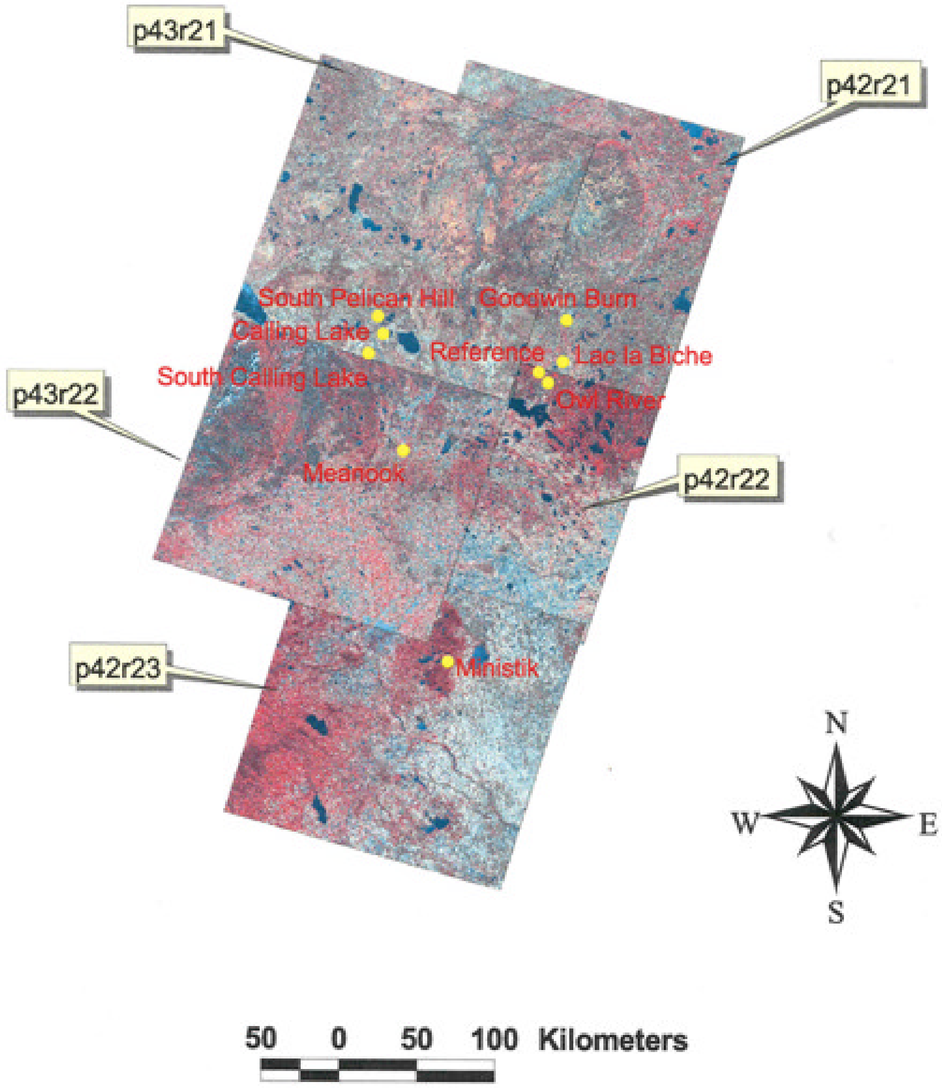


Figure 2: Distribution of Sites over Landsat-5 Satellite Scenes



SUMMARY OF DATA ANALYSIS

Materials

A total of 4 Landsat Thematic Mapper 5 satellite scenes (28.5 m resolution and 7 spectral bands) were used in this project. These images were provided by Alberta Environment. Additional information on the images used in this study can be found at (http://eosl.eas.ualberta.ca). All images were orthorectified to UTM zone 11, and the average mean square error (MSE) was 0.2 pixels.

Satellite Image Processing

The classification of the sites in this project was performed using an "Hierarchical Method" (Figure 2), in which groups of spectrally similar classes were removed from the image one at a time based on their distinguishing characteristics with respect to less distinct classes. One of the problems with automated classification arises when certain classes are spectrally indistinguishable. In this case the analyst must either accept substantial error in the form of mistaken classes, or spend a substantial amount of time modifying the computer's results after a rigorous quality control session. The Hierarchical Method requires constant attention from the analyst throughout the classification process, using personal experience to separate classes at the end of each step in the hierarchy.

The first step in the Hierarchical Method is to prepare the imagery. For this study, band 6 was removed from the images since it is low resolution and would not add any extra information to the process. The image is then ready to begin classification. Since the first step is to remove the most distinct features (roads, settlements, burns, water bodies, rivers and streams, and any clouds and their shadows), a 45 class isodata unsupervised classification was run with a class convergence of 0.98. Once complete, the analyst can easily isolate clouds, shadows, and hydrographic features. Urban features, burns, and smaller creeks and streams were identified with a rasterized version of digitized base features received from the provincial government.

The second most distinguishable set of features includes forest cut blocks and agricultural cropland and pasture. Since these features (especially cut blocks) are difficult to discern spectrally from urban features on occasion, the first group of classes is used to mask the image. The masked image is used for the second step while the classes in the first step (that is, the mask) are held back for reassembly at the final step (see Process 1 in diagram). The masked image is classified using the same unsupervised method as in the first step. This time the analyst uses the classification to identify the cut blocks and agricultural land, setting out to delineate them as precisely as possible on-screen and lumping them into their own classes. In the process of this study it was found that any more than about forty-five classes simply added too much confusion to the signature set from classification, while less did not separate the features enough to help identify them prior to delineation.

Again, the product of the second step (cut blocks and agricultural features) is used to mask the image from which it was extracted. This leaves the analyst with an image containing no more anthropogenic features, hydrography or burns. Of the remaining classes the next most distinguishable feature is deciduous forests. These forests stand out well in a 432 band combination as a bright red feature, and are thus easily detected in another forty-five class unsupervised classification. Once the signature sets are collected and labeled as deciduous, another mask is performed leaving only the most difficult classes to be grouped. Note that the analyst does not make the call on whether these deciduous forests are open or closed. Ancillary data collected in the field will be used to make that distinction later in the process.

For the final classification it was originally intended to run a supervised classification using the signatures from points collected during the ground-truthing stage of the project. Unfortunately this still did not lend a significant enough difference between some of the major classes, primarily certain wetland features and conifer stands, but also many mixed woods and conifer forests. As a result the method was altered to perform a final unsupervised classification, this time with sixty-five classes. Using a tactic similar to that in the third step, the analyst can then tag each of the classes with a label most closely approximating what experience dictates the class to be.

After these labels have been applied, the analyst uses the ground-truthed points to cross-reference with the chosen classes and assign a true value to each of the sixty-five categories.

Classes with no intersecting field data are assigned a value based on the analyst's initial expectations as well as through comparison to surrounding classes. The same method is used on the deciduous mask to apply labels to the varying deciduous classes.

Once all classes have been assigned a label, the four masks are ready to be reassembled into a final classified image. Pixel values are standardized so that a simple raster addition may be applied without adding classes together. The final image is colour coded and printed at a large scale on transparent paper for overlay on a print of the original image. A second analyst uses these prints to quality control the classification, denoting regions that need further cleaning, and returns it to the primary analyst for re-examination. This last step of quality control is done every time a change is made and continues until both analysts are satisfied with the product. Accuracy assessment follows after the classification has been completed, so as not to influence the analysts during their task.

Geographic Information Systems (GIS)

This phase, the integration of spatial and non-spatial information, was critical to achieving the project's goals. Since the conservation potential of many species may rest on preserving or enhancing aspects of countryside landscapes, GIS and remote sensing will play a key role in the definition and delineation of such areas. Classified satellite images weere processed at two levels: a) considering linear features produced by oil and gas exploration and b) without considering these linear features.

The following landscape metrics were calculated using FRAGSTATS (McGarigal and Marks 1995.): mean patch area, mean patch standard deviation, number of patches, total edge, mean patch edge, mean fractal dimension, and mean shape index. In addition the following landscape fragmentation statistics were implemented (De-Camino-Beck and Sanchez-Azofeifa 2001).

The spatial block entropy H^b, a metric useful in determining the organization or randomness of a landscape, is calculated as follows:

$$H^b = \frac{1}{b} \sum_i p_i \log p_i \qquad 1$$

where p_i is the probability of configuration i in the landscape, and b is the block size. Higher values of H^b mean a higher degree of randomness in the landscape (all the possible configurations of blocks b on the landscape have the same occurring probability). This type of metric is widely used in the description of CA configurations (Wolfram1983, 1984).

Landscape division (Jaeger 2000) is the probability of the animal placed in the landscape not belonging to the same patch. It is calculated as:

$$D = 1 - \sum_{i}^{n} \left(\frac{a_i}{A} \right)^2 \qquad 2$$

where a_i is the area of patch i, and A is the total landscape area. When D approaches 1 the landscape is highly divided.

Class division (De-Camino-Beck & Sanchez 2001) is similar, but A is the class area instead of the total landscape area. As class division approaches 1, the class is highly divided. That is, the total mass of the class is segmented into a high number of patches. As class division approaches 0, the class is distributed in a single large patch.

Percolation was measured by simulating flow throughout each landscape using the following CA rule: Let Z^2 be the landscape. In the percolation rule, a site a can be in any of 3 states: 0 (empty), 1 (occupied) or 2 (percolated). If a = 1, and there is at least one site in the neighborhood in state 2, then a changes to 2. In any other case, the site stays the same. The percolation simulation was applied to each of the artificial landscapes, starting with all sites at the top of the landscape in state 2, and it was iterated until an equilibrium condition was reached, where the density of sites in state 2, stayed the same from one generation to the other. We applied the percolation simulation using the 4N and 8N neighborhoods (figure 2) to estimate the p_c (p_c^4 and p_c^8 respectively) under both neighboring rules. The probability of percolating cluster p_s is then calculated:

$$p_s \approx \frac{r_2}{r_1} \qquad 3$$

where r_2 and r_1 are the density of sites in state 2 and 1, respectively

Based on Hutt & Neff (2001) measures of CA homogeneity, we applied these measures in the classified satellite imagery. CA homogeneity is a special case of a two-dimensional correlation, that focuses in neighborhood interaction. Let I be a 2-dimensional n x m (n,m ε N) image. The analysis CA rule for every site (or pixel) a ε I is:

$$a_{ij} \rightarrow \frac{1}{|N_{ij}|} \sum_{b \in N_{ij}} \Theta(a_{ij}, b) \qquad 4$$

In this mapping, $|N_{ij}|$ is the number of sites in the neighborhood N of site i,j. The function T is defined depending on the state space. If the state space S is a set of qualitative information, i.e. S={*forest*, *non-forest*} in classified images, then T is defined:

$$\Theta(a,b) = \begin{cases} 1, a = b \\ 0, a \neq b \end{cases}$$

The overall CA homogeneity H[I] of an image is then defined:

$$H[\mathrm{I}] = \frac{1}{nm} \sum_{ij} \frac{1}{|N_{ij}|} \sum_{b \in N_{ij}} \Theta(a_{ij}, b) \qquad 5$$

Where m and n are the dimensions of the image.

RESULTS

A complete description of the results can be found in De-Camino-Beck & Sanchez-Azofeifa (2001). The following are key highlights of our research project:

- Our comparison between landscapes using percolation and class division indexes indicate that most forestry modified landscapes still hold percolation values above the theoretical percolation value of 0.59.

- When linear features are considered across all landscapes a significant increase in fragmentation metrics is observed. In many cases, key indicators such as the number of islands, increases more than 50% (Figure 3).

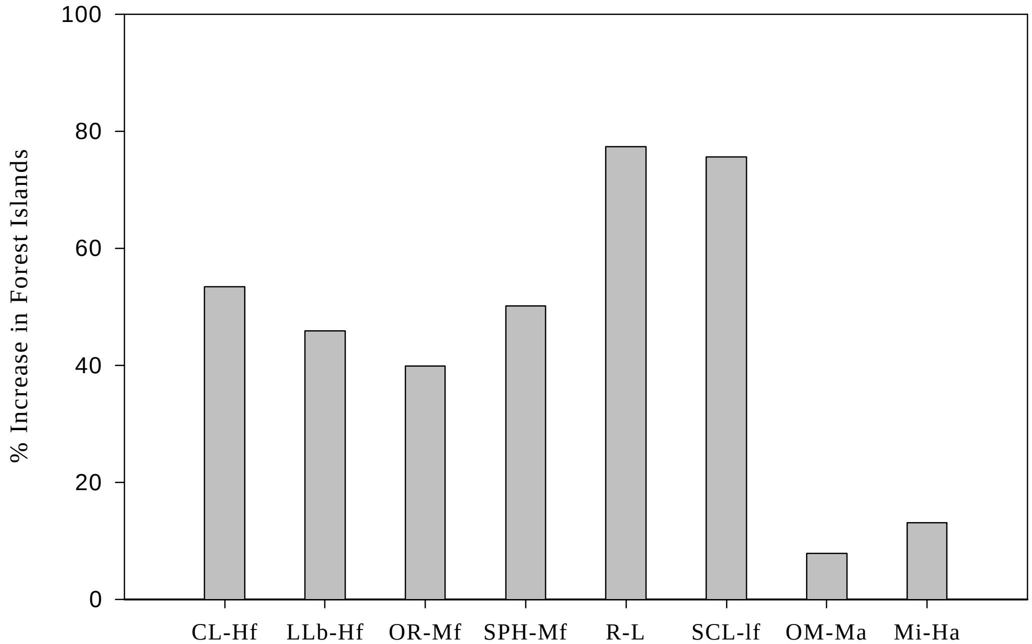


Figure 3: Increase in forest islands as a result of integrating linear features into the landscape structure analysis for the following sites: Calling Lake (High Forestry, CL-Hf), Lac La Biche (High Forestry, LLB-Hf), Owl River (Moderate Forestry, OR-Mf), South Pelican Hills (Moderate Forestry, SPH-Mf), Reference (No impact, R-L), South Calling Lake (Low Forestry, SCL, Lf), Owl Meanook (Moderate Agriculture, Ma) and Ministik (High Agriculture, Mi-Ha).

- The Ministick region shows one of the highest class division (0.97), a low probability of percolation (0.536), and therefore a low forest density. This landscape, representative of highly intensified agricultural regions, suggests that most agricultural landscapes are highly fragmented with little possibility of restoration. The homogeneity value for this region is also the lowest, as compared to the other sites. This low value is related to the high fragmentation of forest. It is also interesting that the entropy value is the lowest (the highest organization level), the reason for this is due to the effect of linear features.

- The South Pelican Hills show the lowest class division. This site has a high percolation probability, although this site has only 52% of forest cover. We consider that the effect of linear features and logging has not affected key landscape metrics such as percolation and class division.
- The highest homogeneity value occurs in the South Calling Lake site. The high homogeneity indicates that the forest consists of large continuous patches. This result is confirmed with the high percolation probability. The class division is low, but not the lowest;. a consequence of the natural segmentation of wetlands and rivers.
- Owl river, also shows a low class division. It is not the lowest, because there is a main road that divides the landscape in two sections.
- The reference site has the highest forest density, but a medium class division. This division is explained mainly by the segmentation of the landscape by three main roads. However, the percolation probability is high, hence the site has a high connectivity.

RECOMMENDATIONS FOR MANAGEMENT

Figure 4 shows a theoretical model developed to characterise the impact of fragmentation and the expansion of linear features at the landscape level. The percolation/class division model can be used as a tool for fast landscape characterisation, as well as new approach to evaluate the potential level of energy that a landscape may need in order to achieve a level of organisation that can allow for connectivity across the landscape. Additionally, the percolation/class division model can be considered a new approach to accounting for the cumulative impacts of oil and gas exploration on the boreal landscape. Additionally, the model is a potential tool for linking to current biodiversity data bases, and looking at the relationship between biodiversity richness and landscape structure.

Figure 4 shows the application of this concept to the study sites in Alberta. Our analysis indicates that if linear features are not considered in the landscape structure analysis, most landscapes, with the exception of highly fragmented agricultural areas, are in regions that may not be considered fragmented. When linear features are considered in the analysis, the impact on fragmentation is evident. This model has the potential to supply key information to biologists and land managers interested in evaluating not only the impact of land use changes such as logging, but also to start looking at the impacts of oil and gas exploration on the boreal landscape.

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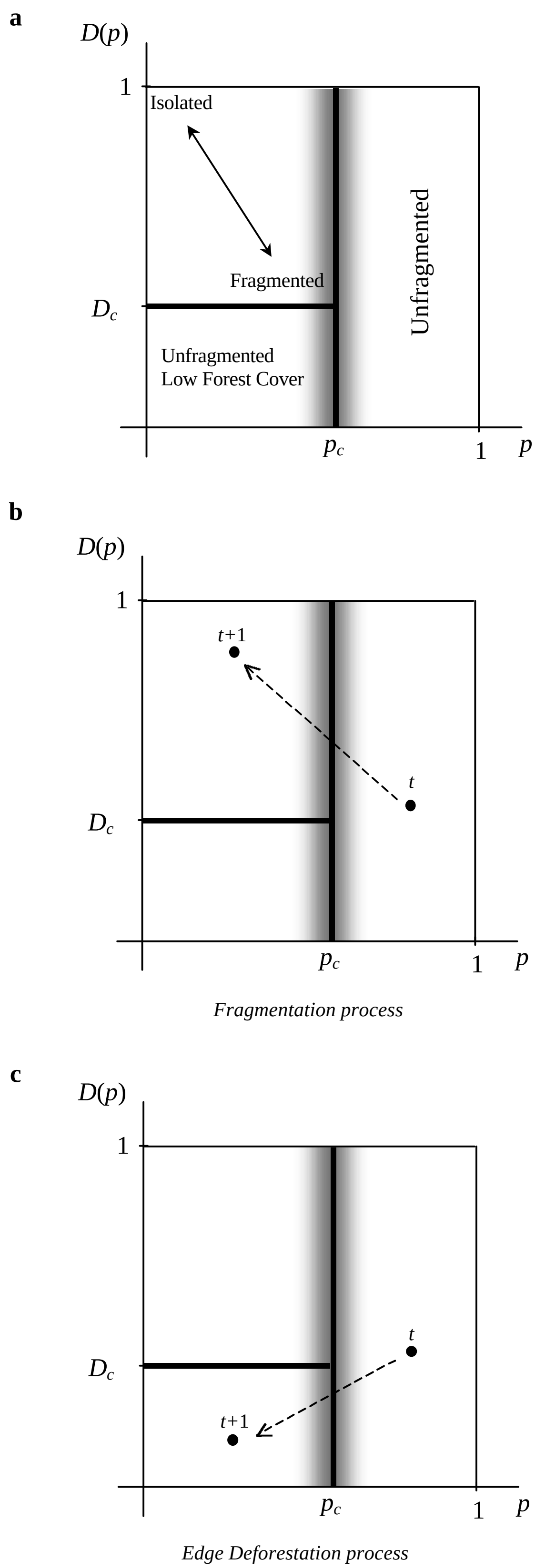

Figure 4. Conceptual model to establish fragmentation based on percolation threshold (p_c) and landscape division ($D(p)$).Changes in occupation density (p) and D over time could mean: b)decrease in p due to fragmentation process, c) decrease in p with frontal deforestation (After De-Camino-Beck and Sanchez-Azofeifa 2001)

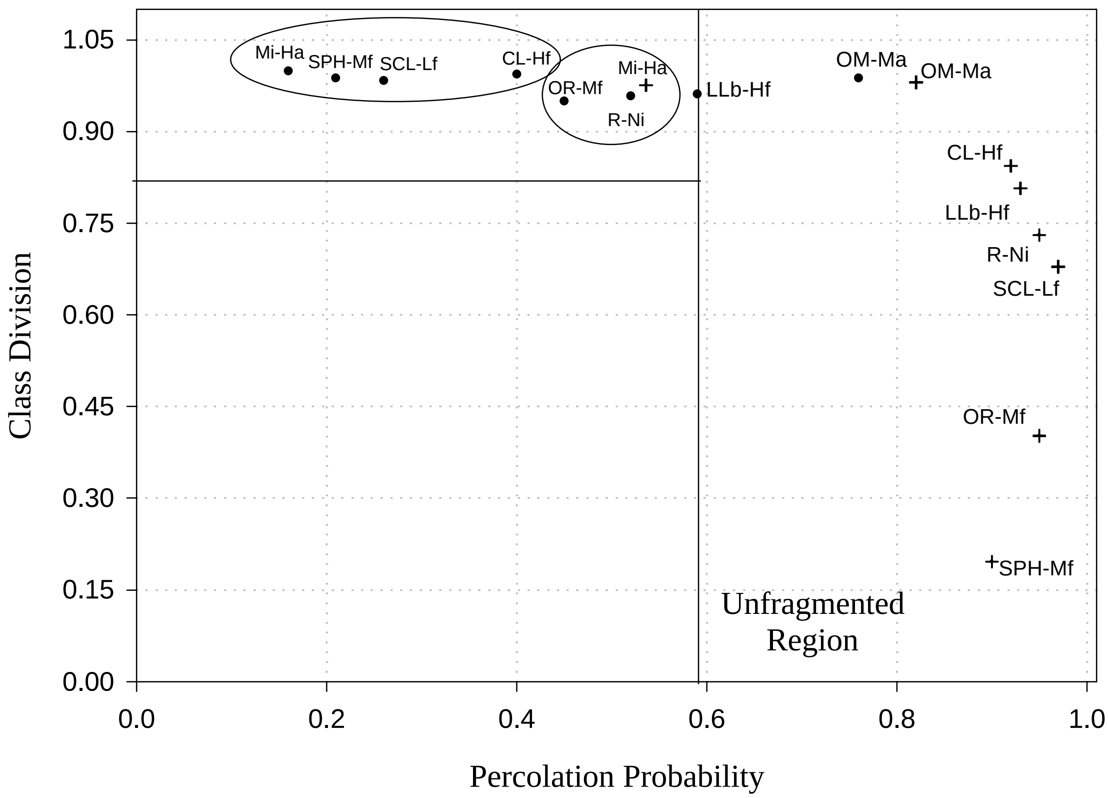

Figure 5. Landscape characterization as a function of landscape division and percolation probability for the selected study areas. Dots represent areas considering linear features and crosses represent sites without considering linear features. Sites such as Ministick (MI-Ha), South Pelican Hill (SPH-Mf), South Calling Lake (SCL-Lf), and Calling Lake (CL-Hf) present a high level of division and percolation once linear features are considered in the analysis.