ANTHROPOGENIC ACTIVITIES CONTRIBUTE TO CHANGES IN FOREST COVER IN THE SHALE OIL AND GAS REGION OF NORTHEASTERN BRITISH COLUMBIA

by

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General abstract

The boreal forest ecosystems have been changing due to varying levels of anthropogenic land use processes such as logging, oil and gas activities, and agriculture. However, the cumulative impacts of these processes are likely to lead to a lasting degradation of the boreal forest ecosystem; and thus, contributing to environmental change. In this study, methods from Landscape Ecology, GIS, and remote sensing were used to process Landsat images and spatial data for shale gas infrastructure. These datasets and methods were used for measuring and assessing the forest change pattern in a study area in northeastern British Columbia (BC). The results of the study show that gross loss (5.98%) of coniferous forest cover in the timber harvest land base (THLB) is higher than the rate of gross loss (3.22%) of the coniferous forest cover in the area outside the THLB. However, the rate of net loss in coniferous forest cover is smaller in the THLB than that of outside the THLB (net loss THLB=0.6%; net loss non-THLB=1.7%). These dynamics in forest cover suggest that it is more likely for forest cover to regenerate much faster in the THLB than outside the THLB. The quantity of forest cover loss (0.163%) from shale oil and gas well pads development is more than the amount of forest loss from shale oil and gas access roads (0.017%) and pipeline development (0.057%). A higher amount of forest fragmentation is associated with periods and locations that have a high amount of anthropogenic-induced land classes in the landscape. These results of the study could serve as the information for modelling land change and fragmentation in the future. The finding from this study could assist land managers in the allocation of land uses across space as well as the formulation of effective and efficient policy frameworks and management initiatives.

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CHAPTER ONE

General introduction, theoretical background, and literature review

1.1 General background to the study

Most forest fragmentation and forest loss literature have shown that there are consequences of habitat fragmentation on biodiversity and ecological processes (Pardini, Nichols, & Püttker, 2017; Haddad et al., 2015). These consequences include increased predation and reduction in species habitat and diversity (Harper et al., 2015; Kunkel & Pletscher, 2000). According to Haddad et al. (2015), the majority of the forest fragments remaining on the earth's surface are, on average, less than 10 ha per patch size and at least half of the world's forest is within 500 m of the forest edge. Additionally, Hansen et al. (2013) have shown that the extent of the earth's forests is shrinking, and this has led to the reduction of up to a third of the world's forests. The rate at which the state of forest ecosystems is deteriorating intensifies the need for measures to regulate land uses and improve the efforts of reforestation and conservation.

In British Columbia, several anthropogenic activities (e.g., timber harvesting, agriculture, shale oil and gas activities, and mining) could potentially lead to forest cover loss and fragmentation (Goddard, 2009). Previous studies have shown that about 71% of industrial footprints are within the caribou range of northeastern BC (Goddard, 2009), and this is likely to increase the cumulative impacts of anthropogenic activities in the boreal forest (Suzuki & Parker, 2019). For instance, in the Kiskatinaw watershed, Paul (2013) has indicated that the increase in shale gas drilling and timber harvesting is profoundly impacting the land use dynamics but admits that the signature of the intensified natural gas development is narrowly displayed in land cover maps. This admission affirms that shale oil and gas features are less likely to be captured in the 30 m by 30 m spatial resolution Landsat images. Consequently, shale oil and gas features, and other anthropogenic disturbances that are finer than the spatial resolution of the Landsat images are likely to be excluded from land change analysis.

Furthermore, a reconnaissance survey conducted in northeastern BC in September 2017 revealed the extent of agricultural (mainly, pasture, grasses, and herbs) land as well as the oil and gas patches on agricultural land. These anthropogenic activities are occurring on lands that are surrounded by tracts of forest and that there is a likelihood that these anthropogenic activity locations were once covered by forest. However, little is known about the broader scale forest change from these anthropogenic activities apart from the watershed level analysis mentioned above. Also, there is inadequate information on how the medium resolution Landsat images can be used to identify the quantity and patterns of forest change from human activity-specific disturbances that have finer spatial resolution than the Landsat images.

This study applies landscape metrics and methods from GIS and remote sensing to assess forest cover change and fragmentation. Information from this forest change assessment could aid land managers in determining the cumulative impacts of human-induced land cover classes and the likelihood of forest cover regeneration. Also, the study offers a GIS and remote sensing-based approach for assessing the amount of land change by integrating Landsat images with spatial data from a high-resolution aerial image, an approach that could be applied elsewhere to measure recent changes in the landcover from anthropogenic activities (e.g., surface mining). The study has four interrelated research objectives, and these are to (i) measure the general forest change pattern from the competing anthropogenic land uses in northeastern BC; (ii) measure the forest change pattern from shale oil and gas infrastructure development in northeastern BC; (iii) compare and contrast forest change patterns from well pads, pipelines, and access roads in northeastern BC; and (iv) compare and contrast forest change pattern from shale oil and gas infrastructure in the four shale gas plays in northeastern BC.

The first objective provides a general assessment of the patterns of forest change with an emphasis on how the land use processes could contribute to the forest change pattern; it provides land managers with the information for further field studies about the causes of forest change. The second objective assesses the cumulative forest change from shale oil and gas infrastructure development and provides information for land managers in determining the additional land change that could be accommodated sustainably by the boreal forest ecosystem of the study area. The third objective provides information about the type of shale oil and gas infrastructure contributing to the largest amount of forest change, and this could aid land managers in the allocation of land for future land uses. The final objective provides an assessment of the forest cover change in the four shale gas plays and provides a context for land managers about the need to find a balance between socio-economic aspirations and conservation objectives. Thus, finding this balance ensures that setting conservation priorities do not result in a lack of opportunity to develop resources for socio-economic development.

Apart from filling a knowledge gap, this study provides a spatial model (up to date spatial information) for forest policymakers for effective and efficient forest management decisions. The study provides a relevant context for understanding the vital land dynamics; policymakers could decide whether there is a need for more stringent measures to protect forest resources. Also, the study contributes to the ongoing monitoring of forest resources in Canada, specifically British Columbia.

1.2 Theoretical background: landscape mosaic model

With the landscape mosaic model, the landscape is considered to be an area made up of assemblages of diverse patch types. The perspective of the landscape mosaic model is directly opposite to the school of thought that considers the landscape as an area that can be categorized simply into discrete patches. From the perspective of the landscape mosaic model, the landscape of the study area is viewed as an area made up of patches, and that focal patches are bounded by other patch types of different or similar characteristics (e.g., size and shape) (McGarigal, Cushman, & Ene, 2012).

The landscape dynamics in the study area are viewed as a process of interest where different agents and factors are likely to contribute to the differences and similarities in the characteristics of the patches. The characteristics of patches in the landscape are influenced by the extent of anthropogenic and natural disturbances and, thus, determine the spatial arrangement (pattern) and composition of the patches (Turner, 1989). For instance, connectivity in the forest landscape is determined by the amount of aggregation in the forest patches. Whereas the results of forest loss and fragmentation analysis in this study do not target any organism, it is likely that the ease of movement by the organisms in the landscape is inferred from the connectivity between focal patches and the amount of resistance posed by the intervening disturbances. However, based on evidence from other study locations and the results of the study, there are discussions about the implications of the forest cover loss and fragmentation on the boreal woodland caribou.

In the study area, the amount of patch aggregation is likely to be determined by the number of linear corridors and the quantity of forest cover cleared for oil and gas well pads, agriculture, and human settlement development. For instance, according to Goddard (2009), in northeastern BC, where shale oil and gas activities and agriculture are taking place, the increase in the linear corridors (roads and pipelines) is likely to increase and ease wolves' access to the caribou habitats. Similarly, the increase in oil and gas well pads increases the rate of caribou avoidance at the forest edges and areas that used to be caribou habitats.

To better understand the dynamics of anthropogenic impacts, land use-specific impacts should be measured to determine the need for conservation measures in landscapes. For example, in British Columbia, Alaback, Nowacki, and Saunders (2017) have indicated that the rate of timber harvesting over the past several decades significantly contrasts anthropogenic disturbances with natural patterns of disturbances. Hence, the conceptual and practical understanding of the intervening disturbances is necessary for maintaining naturally occurring patterns for ecological resilience in the landscape in this era of climate change and other stresses from anthropogenic activities (Alaback et al., 2017).

1.3 Effects of spatial scale on forest cover loss and fragmentation analysis

The scale effects in geospatial analysis account for both forest cover loss and fragmentation in terms of extent and grain size (Turner et al., 1989 cited in McGarigal et al., 2012). The extent, in this case, refers to the size of the study area (a nested landscape) selected to represent the overall landscape for analysis and drawing conclusions. The extent of the study area is likely to affect the results of the analysis in terms of how well the selected area is representative of the whole area. For instance, patch continuity or aggregation could be lower for a selected area, but the inclusion of a larger area for analysis is likely to yield a different result if the patch outside a study boundary is maximally aggregated. It would be relevant for a larger area extent to be used for drawing conclusions about the landscape. However, this effort is limited by the availability of data, inaccessibility to remote locations for ground-truthing, and possibly inadequate geospatial science functionalities. For example, during the reconnaissance survey of the study area at the preliminary stage of this study, many locations could not be accessed due to the remoteness and inadequacy of resources to survey a more extensive area for many weeks.

To detect features (phenomena) and disturbances in the landscape is a function of their grain sizes in satellite images. Thus, the grain sizes influence human ability and software (program) functionality in detecting and measuring changes in the landscape (Gao et al., 2017; Zhang et al., 2017; McGarigal et al., 2012). The grain unit is the size of the individual observations depending on how a system structures the observation or phenomenon. For instance, a system that records or captures individual units at 10 m by 10 m spatial scale structures the units under observation and records the observation at 10 m by 10 m resolution (Turner et al., 1989 cited in McGarigal et al., 2012).

With respect to this study, a Landsat image of 30 m by 30 m spatial resolution captures the objects or phenomena in the images to a 30 m by 30 m resolution. Thus, some observations may not be captured if the sizes of the observations are finer than the resolution at which the Landsat captures its images. For instance, a footprint of road or pipeline infrastructure, which is 15 m width, is likely not to be fairly represented in the Landsat image. Similarly, naturally occurring linear features (e.g., rivers and streams) that are finer than 30 m by 30 m resolution are likely not to be fully captured in a Landsat image. As such, the quantities of land cover classes in the medium spatial resolution Landsat images are likely to be underestimated.

The scale related problem is likely to influence the change analysis conducted in northeastern BC. For example, an area which was a forest class in 1975 but later in 1995 changed into a footprint of access road infrastructure is still recorded undisturbed forest cover instead of measuring forest cover loss in this area. Moreover, this area could measure forest patch continuity instead of recognizing the impact of the linear feature as an intervening disturbance, which is likely to disaggregate a continuous patch. This example is typical of an area with disturbances that are not extensive enough to be captured in the medium (30 m by 30 m) spatial resolution Landsat images.

In this study, the forest change analysis in the second chapter of this dissertation is likely to be affected by the spatial scale of the images used because it involves a general change analysis. Uncaptured disturbances and phenomena (pipelines, roads, seismic lines, and human settlements) would underestimate the quantity of developed land in the study area. However, the approach used in quantifying feature-induced forest change in chapters 3, 4, and 5 mitigates the impacts from the spatial scale of the Landsat images. Mitigating the scale effect was done by integrating spatial data from high-resolution images with the Landsat images, and hence, the actual sizes of the spatial data from high-resolution images are more likely to be represented in the Landsat images.

1.4 Organization of the dissertation

This dissertation is organized into six interrelated chapters. Chapter one consists of a general introduction, theoretical background, and a critical review of literature on the measurement of forest cover loss and fragmentation. Chapters two, three, four, and five are based on the four objectives of the study. Chapter six presents a summary of the major findings, limitations, and conclusions of the study. Whereas chapters two to five of this study may be related in terms of study methods or approaches, each of the chapters focuses on a unique aspect of forest change. Also, each chapter provides unique insights into land use and forest cover dynamics in the study area. Chapter two characterizes forest change patterns from 1985-2000 and 2000-2015 in northeastern BC, taking into consideration forest transition to and from other land categories (e.g., croplands/pasture, developed land, and barren land) as well as the amount of forest fragmentation. The third chapter assesses the cumulative quantity of forest change (loss and fragmentation) contributed by shale oil and gas infrastructure development (access roads, well pads, and pipelines). The relative impacts of shale gas infrastructure development on the forest landscape were assessed in the fourth chapter. The fifth chapter investigates the differences and similarities in forest change resulting from shale gas infrastructure in BC's shale gas plays (Montney, Liard, Cordova, and the Horn River Basin). Shale gas plays are shale formations made up of similar geological and geographic properties and contain a significate quantity of natural gas (Geoscience News and Information, 2017). In BC, these shale gas plays are also the oil and gas management areas designated by the BC Oil and Gas Commission.

1.5 Literature Review

1.5.1 Forest cover change and fragmentation: conservation and land management perspective

Understanding the complexities involved in assessing forest habitat fragmentation requires new guidelines to assist managers in improving, restoring, and maintaining the ecological function of the forest ecosystem (Carranza, Hoyos, Frate, Acosta, & Cabido, 2015). For instance, if a forest landscape records smaller patch sizes, then the role of fragmentation in contributing to a change in biodiversity is due to forest loss alone (Carranza et al., 2015). It is when there are decreasing patch sizes and increasing isolation between patches that forest fragmentation contributing to a change in biodiversity is attributed to both forest loss and changes in the spatial pattern of forest patches. However, if forest amount remains the same over time, a change in spatial pattern and configuration does not contribute to any change in species survival or biodiversity (Gavish, Ziv, & Rosenzweig, 2012 as cited in Carranza et al., 2015). Such information would be of help to forest managers about what to expect when there are changes in the forest cover, forest patch configuration, and the sizes of forest patches in the forest ecosystem.

The world's forest has declined in size from 4.1 billion ha to under 4 billion ha indicating a decrease of 3.1% (FAO, 2015). The global forest growth has, however, slowed down by more than 50 percent between 1990 and 2000 and then 2010 and 2015 (FAO, 2015). Globally, forests are shrinking in size and quality due to natural and human factors, and this has resulted in a reduction of up to a third of the world's forest (Hansen et al., 2013). In spite of the need to satisfy human needs, biodiversity conservation is important for a variety of reasons. The most important is the conservation of forest biodiversity due to empirical evidence of forest habitat loss in many regions of the world (Hansen et al., 2013; Smith et al., 1993; Roman et al., 2001). Biodiversity must be conserved and should be a priority due to the values attached to it. Roman et al. (2001) have identified two perspectives from which the values of the forest ecosystems should be viewed. The first is to look at it from the anthropocentric or human-centred perspective, which advises that the biodiversity on the earth must be valued for its benefits to humans. The second perspective is to look at it from the ecocentric or ecological viewpoint, and this is premised on the notion that ecosystems have an intrinsic value. From this perspective, the ecosystem and its biodiversity must be conserved not only for human use but also for the ecosystems' use.

While it is important to establish policies to regulate the activities leading to forest fragmentation, scientific information about the current state of the forest is needed. Scientific information about whether or not forest cover and habitats are being gained or lost over time is important for sound decision making. The way scientists conceptualize and measure forest fragmentation is an important step towards giving accurate measurements and information. In addition, determining the factors which contribute to forest fragmentation is relevant to provide information about what phenomena are contributing to more fragmentation in the forest cover.

1.5.2 Late to early conceptualizations of forest loss and fragmentation

Despite decades of deliberations on the science of forest fragmentation in conservation and management, there is no universal definition of what forest habitat fragmentation should be. The limitation of non-universality is partly due to complacency and satisfaction on the part of the scientific community, which has made it possible for every researcher to give any operational conceptualization of forest fragmentation (McGarigal, Cushman, & Regan, 2005).

Many researchers, especially landscape ecologists, biologists, and conservation ecologists at different points in time, have conceptualized the fragmentation of forest habitat from different perspectives. According to McGarigal et al. (2005), these differences in perspectives are dependent on how the focal habitat is perceived and represented in relation to other landscape elements, and whether the landscape structure is viewed as relatively static (unchanging) or dynamic (constantly changing). Saunders et al. (1991) have conceptualized forest fragmentation as the process where large and contiguous areas of similar native forest vegetation types break up into smaller units separated by other vegetation types and mostly close to locations where human activities are taking place. Davidson (1998) also conceptualized fragmentation as a process-outcome phenomenon. According to Davidson (1998), forest fragmentation is the breaking up of continuous habitats resulting in many changes in the landscape that can be quantified or measured: reduced area of habitats, increased edge, reduced interior area, increased the isolation of patches, increased number of patches and decreased average patch size.

The Forest habitat fragmentation process involves three major phases (Andrén & Delin, 1994). These are a pure loss of habitat, reduction in patch size, increasing spatial distance (isolation) between fragments. Haila's (1999) conceptualization of forest fragmentation corroborates Andren and Delin's (1994) conceptualization of what forest fragmentation is. According to Haila (1999), forest fragmentation is a process consisting of decreased patch size and increased isolation between forest patches. The conceptualization of forest fragmentation in this sense appears the same as Davidson (1998), stated above, as it included forest habitat loss, reduced patch size, and also the isolation of patches. Forest fragmentation, as conceptualized by most researchers, includes forest habitat loss and reduced patch size, an indication that such conceptualization takes into account some elements of forest cover loss.

Bennett and Saunders (2010) have conceptualized forest fragmentation as the 'breaking apart' of continuous forest habitats into distinct pieces. Three interconnected processes take place: shrinking of the total amount of the original vegetation (vegetation loss), the subdivision of the remaining vegetation into fragments, remnants or patches (habitat fragmentation), and intrusion into vegetation by new land uses (Bennett & Saunders, 2010). The conceptualization by Bennett and Saunders (2010) also indicates that there is an element of deforestation or forest loss in looking at the components of fragmentation and that as the vegetation cover gets fragmented, the process also leads to a loss of vegetation cover. Conceptualization of forest fragmentation by Fahrig (2002) differs from one by Bennett and Saunders (2010). Fahrig (2002) has argued that habitat amount alone is not adequate to answer the question of fragmentation, but also there is the need to consider the configuration of the forest patches and the nature of the intervening matrix. Fahrig (2003), in a further study on fragmentation, argued that forest loss and forest fragmentation should be studied differently under two different research goals. When the issue of forest habitat loss is considered, fragmentation (breaking apart of forest habitat) should then be calculated separately (Fahrig, 2003 as cited in Jackson and Fahrig, 2013).

According to McGarigal and McComb (1999), forest habitat fragmentation is a landscape-level process in which a specific habitat is progressively subdivided into smaller, geometrically altered, and more isolated fragments as a result of both natural processes and human activities. The process involves a change in landscape composition, structure, and function at many scales and occurs on a backdrop of a natural patch mosaic created by changing landforms and natural disturbances (McGarigal and McComb, 1999). There is an element of forest habitat loss in the conceptualization of forest fragmentation by McGarigal and McComb (1999). According to McGarigal, Cushman, Neel, and Ene, (2002), the term 'fragmentation' is used to refer specifically to the progressive subdivision of habitat blocks into fragments. Although forest habitat loss is most of the time associated with fragmentation, they are two different phenomena and should be distinguished (McGarigal et al., 2002). The idea of differentiating between forest habitat loss and fragmentation has been explicitly indicated by Fahrig (2003).

Even though Reddy et al. (2015) used Number of Patches, Mean Patch Size, Edge Density, and Largest Patch Index to account for the pattern and configuration of the forest, as an indication of forest fragmentation, a clear distinction was not made between forest cover loss and forest fragmentation based on the earlier conceptualizations. Percentage of forest cover can also be considered as one of the indicators of forest fragmentation (Reddy et al., 2015), a dissenting conceptualization of forest fragmentation to that of Fahrig (2003), which seeks to distinguish between forest habitat or cover loss from fragmentation.

Problems emanate from the conceptualizations of forest fragmentation as the definitions and explanations about it are not clearer and universal (Fahrig, 2003). Lack of tendency to separate processes leading to fragmentation creates a false impression that fragmentation estimates cannot be generalized. According to Fahrig (2003), however, generalization can be made when the aspects of fragmentation are explicitly defined, and all other aspects are held constant.

In sum, forest fragmentation has been conceptualized by two schools of thought, which have taken sides as far as the universality of the concept is concerned. While one school thinks of it as breaking up of the forest habitat blocks into several fragments which in turn affects the structure, shape, pattern of patches and habitat size; another school of thought conceptualizes it as breaking up of large forest habitats into smaller fragments and states clearly that forest habitat loss should not be part of fragmentation and that each of the phenomena should be treated differently.

1.5.3 Conceptualizing forest fragmentation from a post-positivist point of view

From a post-positivist perspective, it is believed that scientists embed some value orientations unconsciously, and that observation is influenced by the observer's theoretical perspective and knowledge background (Miller, 2000; Wildemuth, 1993). From this perspective, methods are seen to be imperfect, and that human imperfections do not allow the researchers or philosophers to know realities perfectly. These tendencies have given rise to many methods and truths about a single phenomenon (Moon & Blackman, 2014). A critical look at the conceptualizations of forest fragmentation brings to fore the many truths and ideas held by different researchers about what forest fragmentation should be. A possible explanation for this has been given using the post-positivist framework, which allows the production of many explanations and truths about a particular concept or phenomenon. The concept of forest fragmentation is made up of many accepted conceptualizations and definitions, and much effort has not been put in place leaping towards a universality. The many definitions and conceptualizations of the concept of forest fragmentation give credence to the fact that there is no perfect direction to go and hence extend to the methods used in measuring it. Relating the post-positivist approach to conceptualizing forest fragmentation means accepting the imperfections about the knowledge base and understanding of the concept and also accepting the parallel conceptualizations as truths about the concept. The literature about the concept shows that there is difficulty conceptualizing a perfect universal reality about forest fragmentation and that many alternative ways of conceptualizing forest fragmentation exist, all accepted and true.

The parallel conceptualizations of forest fragmentation lead many researchers to use different approaches to arrive at the truth, and this demonstrates the applicability of the post-positivists' framework to the conceptualizations of forest fragmentation. With human reasoning and intuition, the way to approach and measure forest fragmentation stems from the way researchers conceive forest fragmentation. That is, the relative nature of understanding of the concept should not be ignored in critically analyzing how forest fragmentation is conceptualized. Even though Fahrig (2003) has proposed studying some aspects previously considered as part of forest fragmentation separately, there is the recognition of the arguments presented by other researchers in their approach to the truth about the concept. In this case, the realities about the concept of forest fragmentation differ from one researcher to another and would change or get revised based on the personal experiences of researchers at a given point in time, at a given location and space.

Is there any possibility of a move towards a single universal conceptualization in the future? The move towards a universal conceptualization would help to avoid the conceptual confusion about forest fragmentation and make generalizations easier without objections and criticism. Human understanding and consensus between scientists would help to achieve this feat in the conceptualization of forest fragmentation. The likelihood of achieving universality would evolve from changes in human understanding about the concept of forest fragmentation and the capacity to reconstruct the realities about forest fragmentation into a single universal reality in the future. The conceptualizations about forest fragmentation looked universal during the twentieth century as compared to the twenty-first century, indicating a change or a shift over time and that a shift further is expected in the future. In the twentieth century, researchers conceptualized forest fragmentation as loss of forest, changes in shape, pattern, configuration and isolation between patches of forest. However, the twenty-first century saw a shift in position and understanding by many researchers trying to consider forest loss and deforestation differently from changes in shape, pattern, configuration and isolation between patches of forest. The shift can also be defined as a paradigm shift in the worldview and the shared understanding of the concept of forest fragmentation.

Even though the concept of forest fragmentation is understood by many researchers to be more about measuring the spatial pattern, configuration or spatial arrangement of forest cover across the forest landscape, change in the pattern and connectivity of forest patches cannot occur without some loss of forest cover (Kupfer, 2006). This emphasizes the conceptual confusion associated with what is to be measured when studying forest fragmentation. The plurality in conceptualization allows researchers to conceptualize forest fragmentation in ways that suit their research activities. This explanation supports what Wildemuth (1993) terms as a post-positivist research approach, whereby pluralism gives room for researchers to select methods, approaches, and ideas based on research questions being addressed.

1.5.5 Measuring forest fragmentation

1.5.5.1 Metrics and programs for measurements

Despite the increased use of spatial analysis in forest landscape fragmentation, researchers in this field of study have not reached consensus on how to measure and which metrics to use in measurement and interpretation (Davidson, 1998). It is not reasonable to use a single metric, or even a few metrics, to measure fragmentation in the landscape due to the number and variety of components of the landscape structure affected by fragmentation (McGarigal et al., 2005). The illusion of a single process of fragmentation of forest has led to the misconception that one measure of fragmentation is equal to another (Fahrig, 2003).

A multivariate approach is relevant for measuring fragmentation even though there is always a lack of theoretical understanding (McGarigal et al., 2005). McGarigal and Marks (1995) have identified some metrics and a combination of them to make a meaningful explanation of fragmented landscapes. Classification of metrics into categories is not straightforward for measuring fragmentation, but rather identifying such metrics has practical utility, because it ensures that a comprehensive suite of metrics is selected for a particular study (McGarigal & Marks, 1995). It is important to note that the specific metrics included in the list by McGarigal and Marks (1995) do not represent a comprehensive list of useful fragmentation metrics and do not necessarily include the 'best' metrics as considered from anyone's perspective. This shows the non-universal nature of the metrics used in calculating landscape fragmentation, as Davidson (1998) has noted.

1.5.5.2 Creating secondary metrics and combining programs

Kim, Song, and Lee (2013) have characterized forest fragmentation using landscape metrics (e.g., forest patch size, forest patch shape, and density of forest patches). The modification or normalization of existing primary metrics to create a surrogate of measures or units is due to the increase in complexity of the forest patch shape. The combination of area-weighted mean shape indices, area-weighted mean, patch fractal dimensions, edge densities, and mean patch sizes are used to measure such complexities (Kim et al., 2013). It is, however, important to note that there is no such universal method for determining which metrics to normalize. The non-universality in the normalization process is demonstrated in a different study by Wang, Hamann, and Cumming (2012), who computed landscape-level fragmentation using rasterized 30m resolution land cover data. The normalized total core area, normalized mean nearest neighbour distance, and normalized mean shape index were calculated by dividing raw metric measurements, the total core area (TCA), mean nearest neighbour distance (MNN) and mean shape index (MSI) by a theoretical maximum and then further scaling to values ranging from 0 to 1. Since there are no specified ways of normalizing the primary metrics, the reason for normalizing is influenced by the choice of the researchers. The same reason influences the choice of metrics to be normalized. This predisposition leads different researchers to come out with different forms of knowledge about a phenomenon.

Whereas the choice of using a particular set of metrics depends on the purpose of the study and how meaningful the metrics are, Carranza et al. (2015) selected a set of metrics because it has been empirically proven to be good and widely suggested for fragmentation analysis and also deemed adequate for sample-based estimations of landscape pattern. One would ask if such a reason for use would aid a shift in the future towards universality in terms of which metrics to use in measuring forest fragmentation. Continuous tests of metrics to determine which metrics are more meaningful to use is one of the ways to come up with a common ground and establish universality in measuring forest fragmentation.

Plurality in the measurement of forest fragmentation is seen not only in the use of different metrics within one program or software but also across programs and software. Tang, Bu, Yang, Zhang, and Chang (2012) used the area-weighted centroid method, the area-weighted mean patch fractal dimension (AWMPFD), and core area percentage of the landscape (CPL), to give an estimate of the spatial movement and spatial fragmentation process of forest cover. Such measures or units are within the same program. Other measures of forest fragmentation have cut across programs and metrics. ArcInfo GIS, Fragstat 3.3 and Matlab 7.10 have been used by Reddy, Sreelekshmi, Jha, and Dadhwal (2013) to measure forest fragmentation by combining several landscape metrics within each of the three programs. The extent of fragmentation of forest class is well measured by using patch density and size metrics (Reddy et al., 2013). The measurement of forest fragmentation gets more complex and robust due to the type of questions researchers ask in as well as how complex they perceive the landscape pattern to be.

1.5.5.3 Measurements and metrics from ontological and epistemological perspectives

The ontological perspective refers to the perspective from which reality is viewed or perceived. On the other hand, the epistemological perspective is the viewpoint from which knowledge about reality is gained or created (Petty, Thomson & Stew, 2012; Moon & Blackman, 2014). The ontological and epistemological position of researchers influences what to measure in terms of forest fragmentation and which metrics to use. The pluralities in the measurements and concepts used depend on the philosophical viewpoint held by the researchers on what constitutes forest fragmentation. Such pluralities are an indication that the concept of forest fragmentation is not made up of only one reality. That is, in relation to the relativist ontological point of view, the realities about forest fragmentation are many in terms of which metrics to use and that each researcher is capable of creating his or her version of the realities. The measurement of forest fragmentation and the metrics used are related to the ontological position, which is what researchers think should be measured and how they understand forest fragmentation as a phenomenon of being. The kind of knowledge to create, the kind of questions to ask, and all the knowledge claims are influenced by the epistemological position of the researcher (Moon & Black, 2014), and this also certainly affect the measurement and concept of forest fragmentation.

Depending on the kind of knowledge the researcher would want to create about forest fragmentation, the researcher chooses to either measure the spatial pattern and configuration or the patch sizes and amount of the patch class in a landscape. Wang, Blanchet, and Koper (2014) have opined that one of the reasons for using particular metrics is biological rationales and the option to use statistically robust metrics that are appropriate for achieving each study objective. The measurement or the metrics used depend on the aspect of forest fragmentation a researcher is looking to measure (Fahrig, 2003). For instance, a researcher who thinks the measurement of forest fragmentation should include both loss and pattern or configuration uses metrics that measure the percentage of landscape containing forest cover or Total Class Area (TCA) and then add other isolation and connectivity metrics. The reasons that are given by Wang et al. (2014) and Fahrig (2003) strongly demonstrate the relative positions each of them holds in determining which metrics to be used in measuring forest fragmentation.

1.6 Driving forces of forest cover change and fragmentation

Empirical research has indicated the various ways in which the plural causes of forest fragmentation are manifested. However, most of the studies have thrown more light on the nature of human activities. Human activities in the forest habitat reduce natural habitats of species of plants and animals to distinct fragmented patches (Gavish et al., 2012). Land development has been identified as one of the main driving forces of the fragmentation of forest habitat (Kim et al., 2013). Protected areas still show some degree of human activities pertaining to the process of forest fragmentation and transformation, and therefore interactive management practices are needed (Armenteras et al., 2003).

Wade et al. (2003) have emphasized on the various reasons for the increasing forest fragmentation. Forests may be fragmented by several activities or events, such as road construction, logging, conversion to agriculture, and thus, the fragmentation problem is either anthropogenic or natural (Hansen et al., 2010; Wade et al., 2003; Newman, McLaren, & Wilson, 2014). As the spatial demand for infrastructure development increases, the competition for land for all other anthropogenic land uses also increases (Damarad & Bekker, 2003).

According to Wade et al. (2003), globally, except the boreal and temperate conifer forest biomes, human-induced fragmentation is typically at least three times more prevalent than natural fragmentation. Total fragmentation in the boreal forest of North America is almost 23%, and it is practically due to natural fragmentation, low level of human-induced fragmentation, protection or remediation measures (Hansen et al., 2013; Kurz et al., 2008; Wade et al., 2003). Kurz et al. (2008) further argue that climate change is a contributing factor as far as the extent and severity of the outbreak of forest fire and diseases are concerned. Large scale fragmentation of native vegetation is a discernible result of human land-use throughout the world (Bennett & Saunders, 2010). From the Atlantic Forests of South America to the tropical forests of Southeast Asia, and in other regions of the world, much of the old-growth forest vegetation are in the form of fragments due to the expansion of land for food production, housing for human beings and other agricultural activities (Bennett & Saunders, 2010).

Apart from classifying the contributing factors of forest cover loss and fragmentation into natural and anthropogenic, further classification has been done by Geist and Lambin (2002).

Forest cover change and fragmentation have both underlying and proximate causes (Geist and Lambin, 2002). Proximate causes involve all human activities or immediate actions at the local level, such as agricultural expansion, extractive activities, infrastructure expansion, and other factors, including biophysical such as climate.

On the other hand, underlying causes include all fundamental social and economic processes, which include human population dynamics or agricultural policies that underpin the proximate causes. Such fundamental socioeconomic processes operate either at the local, national or global levels (Geist and Lambin, 2002). Within the extractive industry, shale gas drilling is a major human activity found to be contributing to forest fragmentation. Shale gas well pads are found to be one of the main driving forces associated with forest fragmentation, and it is noted to have an impact more than any other phenomena associated with the shale gas activities (Soeder et al., 2014 as cited in Abrahams et al., 2015). Landscape ecologists have found the need to consider roads and pipelines as it is believed to cut through the forest and disrupt the connectedness and intactness of the forest habitat (Abrahams et al., 2015; Drohan, Brittingham, Bishop, & Yoder, 2012).

1.6.1 Shale oil and gas activity-induced forest cover loss and fragmentation

Many studies have taken place in the areas of forest cover change and fragmentation in many parts of the world, including in the United States (US). One of the recent studies which looks at fragmentations in the forest with special reference to road density is one done by Heilman et al. (2002). Geographic Information Systems, remote sensing and analytical software were used by Heilman et al. (2002) to assess forest fragmentation levels. Even though such research was conducted in North America, it only concentrated on the US and did not also look at how fast-emerging shale gas drilling is contributing to the process of fragmentation. It is therefore relevant to investigate forest fragmentation taking into account the roads, shale gas pipelines, and shale gas wells pads in BC as shale gas wells in northeastern BC alone have increased to 23,933 since the early 1970s (Adams, 2014).

Shale gas well pads are found to be one of the main driving forces associated with forest fragmentation, and it is noted to have greater impacts than any other phenomena associated with the shale gas activities (Soeder et al., 2014 as cited in Abrahams et al., 2015). Landscape ecologists have found the need to consider roads and pipelines as it is believed to tend to cut through the forest cover and disrupt the connectedness and intactness of the forest habitat (Abrahams et al., 2015). Research which enquires into the effects of roads and pipelines on the forest resources is, therefore, necessary to quantify the level of fragmentation in the BC forest as current research is lacking. Thus, this study assesses the impacts of each of these phenomena in terms of forest fragmentation.

Drohan et al. (2012), in their assessment of the early trends in forest fragmentation due to Shale gas drilling, establishes the harm this socioeconomic activity is causing despite the economic benefits the State of Pennsylvania is getting from it. The province of British Columbia might also be reaping economic benefits from it, but the government and other stakeholders need to have access to fair and unbiased knowledge and more information about the cost associated with it. Drohan et al. (2012) give estimates of forest cover in the Susquehanna River basin, which is most developed, as 885 pads (26% in core forest). As of 2011, looking at the total number of development permits given to shale gas drillers, more forests would be lost in Pennsylvania (Drohan et al., 2012). Such forecasting would be needed about the BC forest, and that is what the proposed study intends to achieve and increase our knowledge about how some human activities are disturbing the forest.

CHAPTER TWO

Measuring forest change and forest land use dynamics in northeastern British Columbia: implications for forest management

Abstract

Boreal forest loss and fragmentation have implications for the diversity of animals that depend on large tracts of unfragmented forest cover. Boreal forests also are a very important component of the carbon cycle and their loss and fragmentation lead to the release of carbon dioxide into the atmosphere. However, boreal forests are under threat of degradation from anthropogenic processes such as logging, agriculture, human settlement development, as well as oil and gas development. Thus, land managers need up to date empirical information for the management of forest and allocation of anthropogenic land uses to achieve both short and long-term socio-ecological objectives. Using northeastern British Columbia (BC) as a case study, this chapter of the dissertation assesses forest cover change and fragmentation with an emphasis on how competing anthropogenic land uses are increasing at the expense of the dominant (coniferous) forest cover in the boreal forest zone. Landsat images from 1985, 2000, and 2015 were classified using the Random Forests (RF) classification algorithm. The study finds that for the 30 years (1985-2015) an annual net loss of 2.3 % (gain: 6.9%, loss: 9.2%) has occurred in the coniferous forest cover. Additionally, the timber harvest land base's (THLB) share of the coniferous forest gross gain and loss are higher than that of the area outside the THLB. Nonetheless, the net loss of coniferous forest in the non-THLB is higher than that of the THLB, suggesting that forest cover regrowth rate is higher in the THLB than the non-THLB. Furthermore, the study finds that the period with a lower amount of fragmentation has a smaller amount of coniferous forest cover loss and vice versa. The study outcome shows that coniferous forest cover is more likely to recover

from barren land, important information that would facilitate the modelling of future land use and forest change. Most importantly, land managers could use knowledge from this study as ancillary information in assessing the potential cumulative impacts of anthropogenic land uses in the boreal forest. In conclusion, this study suggests that the rate of forest recovery from anthropogenic-induced land categories is likely to account for the amount of forest fragmentation.

Keywords: land use processes; forest fragmentation; intensity analysis; Timber Harvest Land Base; northeastern British Columbia

2.1 Introduction

Forest ecosystems provide high levels of social, economic, and ecological services. For instance, forests store carbon through carbon sequestration, and hence aid in climate change mitigation (Naidoo et al., 2009). However, recent studies have shown that forest cover has been declining and is becoming increasingly fragmented in many regions of the world. For example, Birdsey and Pan (2015) report that, globally, old-growth forest cover has decreased by 3% since 1990. Likewise, Hansen et al. (2013) report that, worldwide, forest cover loss is a more common phenomenon than forest gain. Extensive clearing of forest for wildfire, logging, agriculture expansion, pasture production, and urbanisation are the main factors contributing to forest loss (Song et al., 2018; Hansen, Stehman, & Potapov, 2010). Quantifying these changes is the primary task of landscape monitoring programs (Kienast et al., 2015). Equally important is the ability to attribute observed changes in forest cover to specific sources of anthropogenic disturbances (Turner et al. 1993). Such information will allow land-use planners to understand better the factors driving the ecological patterns observed at the landscape level and adjust planning strategies accordingly.

The boreal forests of the world make up about one-third of the world's forest cover, and it covers 16.6 million km^2. Moreover, the boreal forests are the northernmost forests of the world stretching between latitudes of 50 to 70° N, located in Alaska, Canada, Russia, and the Scandinavian countries (Global Institute of Sustainable Forestry, 2020). In Canada, boreal forests form about 6 million km^2 (equivalent to 58% of Canada's land area) (Berkes & Davidson-Hunt, 2006). The northeastern portion of the province of British Columbia (BC), Canada, lies within a boreal forest ecosystem that is composed mainly of conifer-dominated stands. As such, wildfires and forest diseases are two of the main natural factors that contribute to forest change in the area as it is occurring in other parts of the boreal zone (e.g., Central Manitoba, Siberia, and Russia) (see Lyons, 2015; Chen, Loboda, Krylov, & Potapov, 2016; Potapov, Turubanova, & Hansen, 2011). However, over the past several decades, anthropogenic activities including oil and gas drilling, timber harvesting, agriculture, and human settlement development have had an increasing impact on the boreal forest (Clason et al., 2014; Potapov et al., 2011; Alfaro et al., 2010; Axelson et al., 2010).

Due to the high rate of disturbances in the forests, there is an increasing concern regarding the long-term sustainability of anthropogenic activities in the boreal zone. In the European boreal zone, for instance, a reduction in forest habitats from natural and anthropogenic disturbances affects the survivability of wildlife (the mainly reindeer or caribou) (Sandström et al., 2016; Kumpula, Kurkilahti, Helle, & Colpaert, 2014). Similarly, in northeastern BC, the impacts of anthropogenic land use include loss and fragmentation in the early winter boreal woodland caribou habitat (Goddard, 2009). The boreal woodland caribou requires large intact, contiguous, and undisturbed forest cover patches of suitable habitat for survival while avoiding areas cleared for anthropogenic activities (NRCan, 2019; Badiou et al., 2011). Moreover, these woodland boreal caribous are listed as threatened under the federal *Species at Risk Act*, 2002 (Badiou et al., 2011; Government of Canada, 2019), and the significant decline in the boreal woodland caribou is primarily due to the loss and fragmentation of their boreal forest habitat (Badiou et al., 2011; Polfus, Hebblewhite, & Heinemeyer, 2011). At a broader scale, Kuuluvainen and Gauthier (2018) note that in areas of the boreal forest with active forest utilization (e.g., logging, oil and gas exploration, and agriculture), there is an increasing trend in the frequency of young, managed forests at a cost to old-growth forests. Therefore, more extensive conservation measures, especially in the old-growth forest and critical boreal woodland caribou habitats, may be required.

Previous studies from many parts of the boreal forest zones (e.g. European Russian, Sweden and Norway) have found changes in the boreal forest cover from both natural and anthropogenic disturbances (see e.g., in Norstedt, Axelsson, Laudon, & Östlund, 2020; Potapov et al., 2011; Östlund, Ericsson, Zackrisson, & Andersson, 2003). Similarly, in BC and Alberta, studies have shown that boreal forests have changed significantly due to diseases and insects (Stralberg et al., 2018; Axelson et al., 2018) and wildfires (Mustaphi & Pisaric, 2018; Rickbeil et al., 2017; Gauthier et al., 2015). Paul, Li, Wheate, and Li (2018) projected future land change at a watershed level in Dawson Creek, BC. Other studies have integrated Landsat images with lidar plots to map forest structures and canopies in the boreal forest area (e.g., Matasci et al., 2018; Zald et al., 2016; Ahmed et al., 2015). These studies recorded more forest losses than gains (revegetation). However, these previous studies in the boreal zone have focused mostly on other disturbances (insects, diseases, forest fires, and geomorphic disturbances), and a few studies have focused on anthropogenic disturbances (e.g., Linke, & McDermid, 2012; Franklin, Lavigne, Wulder, & Stenhouse, 2002). Also, little is known about the land use and forest cover change dynamics in the THLB and non-THLB of the boreal zone. Thus, there is insufficient information on the role of anthropogenic influences on forest loss at the macro scale in the boreal forest. The study fills this gap by expanding the micro-level studies (such as in Paul et al., 2018) to a larger scale and assess how the competing anthropogenic land uses within the boreal forests are contributing to forest change using a study area in northeastern BC as a case study location. Even though this study uses northeastern BC as a case study, the relevance of the findings is applicable to the other boreal zones. For instance, the northeastern BC and conifer-dominated Russian boreal biomes share similar land use and land cover change dynamics (see Goddard, 2009; Potapov et al., 2011) and hence, it is likely that findings from a land change study in the boreal zone of northeastern BC could be relevant and applicable in land management in other conifer-dominated boreal forest zones.

The objective of this study is to assess forest cover change and fragmentation within an area of northeastern BC, where anthropogenic land uses have increased in recent years. Thus, this study hypothesizes that the dominant forest class is more likely to convert to other land cover classes, especially the barren land. This study focused on the coniferous forest cover since it is the dominant forest type and the main forest cover type that supports the caribou population in the study area (Environment Canada, 2011), although there are other forest cover types measured in this study. However, over time, deciduous forest land mostly converts to coniferous forest land and hence, the area of land occupied by the coniferous forest was once dominated by deciduous forest cover. The study further shows how the forest cover has changed in the timber harvest land base (THLB) of the study area. This study relies on GIS, remote sensing, and landscape metrics, a combination of tools that present a potential for monitoring broader changes in the landscape, for assessing forest change (LeClerc & Wiersma, 2017). Previous studies have used pixel and object-based classification algorithms to classify Landsat images (see examples in Lyons, 2015; Paul et al., 2018; Johnson et al., 2003). With the aim of improving land use-land cover classification accuracy, Random Forests (RF), a machine learning classification algorithm was used to map land classes and assess forest cover change and fragmentation in the study area. This study is relevant because it presents forest cover change and fragmentation and their implications for land degradation and land management. Based on the findings from this study, there is a further discussion about the need to conserve land for the survivability of the wildlife species, such as the boreal woodland caribou.

2.2 Materials and methods

2.2.1 Study area description

The study area is in the geographical northeast of British Columbia (see Figure 2.1) and found in the boreal forest zone of Canada. The study area map was delineated to cover all the locations in northeastern BC, where shale oil and gas activities, timber harvesting, human settlement development, and agriculture activities are the main land uses. The size of the study area is 10,320,800 ha (103,208 km^2) and falls within the BC Timber Supply Area (TSA) of Dawson Creek, Fort Nelson, and Fort St. John. Therefore, the study area is part of the area in BC, where 70 million m^3 of timber are harvested annually (Environmental Reporting BC, 2018). The study area has THLB. The THLB refers to 'an estimate of the land where timber harvesting is considered both acceptable and economically feasible, given the objectives for all relevant forest values, existing timber quality, market values and applicable technology' (FLNRORD, 2019). The size of the THLB changes from time to time, and consequently, there is the need to measure forest cover change and fragmentation at different times to ensure effective sustainable forest and land use management. Out of the 10,320,800 ha (103,208 km^2) study area size, 2,492,644 ha

(24926.44 km^2) of land is demarcated as the THLB. The area of timber harvested land (cutblocks) in the study area is 441,121 ha out of the total of 9,151,483 ha in BC (based on spatial data acquired from the BC government data catalogue) as at 2015.

The study area is within Spruce-Willow-Birch (SWB), Sub-Boreal Pine-Spruce (SBPS), Mountain Hemlock (MH), and Alpine Tundra (AT) Biogeoclimatic Ecosystem Classifications (BEC) zones. The SWB has an average annual temperature of -1.0°C. The SBPS zone is in the rain shadow of the Rocky Mountains. The mean annual temperature and precipitation of the SBPS are 1.5°C and 411 mm, respectively. In the MH, the average rainfall is between 3500 mm and 2000 mm. The average annual temperature ranges from 5°C to 1.4°C. The AT has a mean annual temperature of -1.9 °C. In the warmest month, the AT is less than 10°C, and precipitation ranges from 700 mm-3000 mm. The long-term dynamics of these weather conditions are likely to affect forest growth and hence, the quantity of forest cover (Natural Resources Canada, 2017). There are three major cities within the area, namely Dawson Creek, Fort St. John, and Fort Nelson (see Figure 2.1).

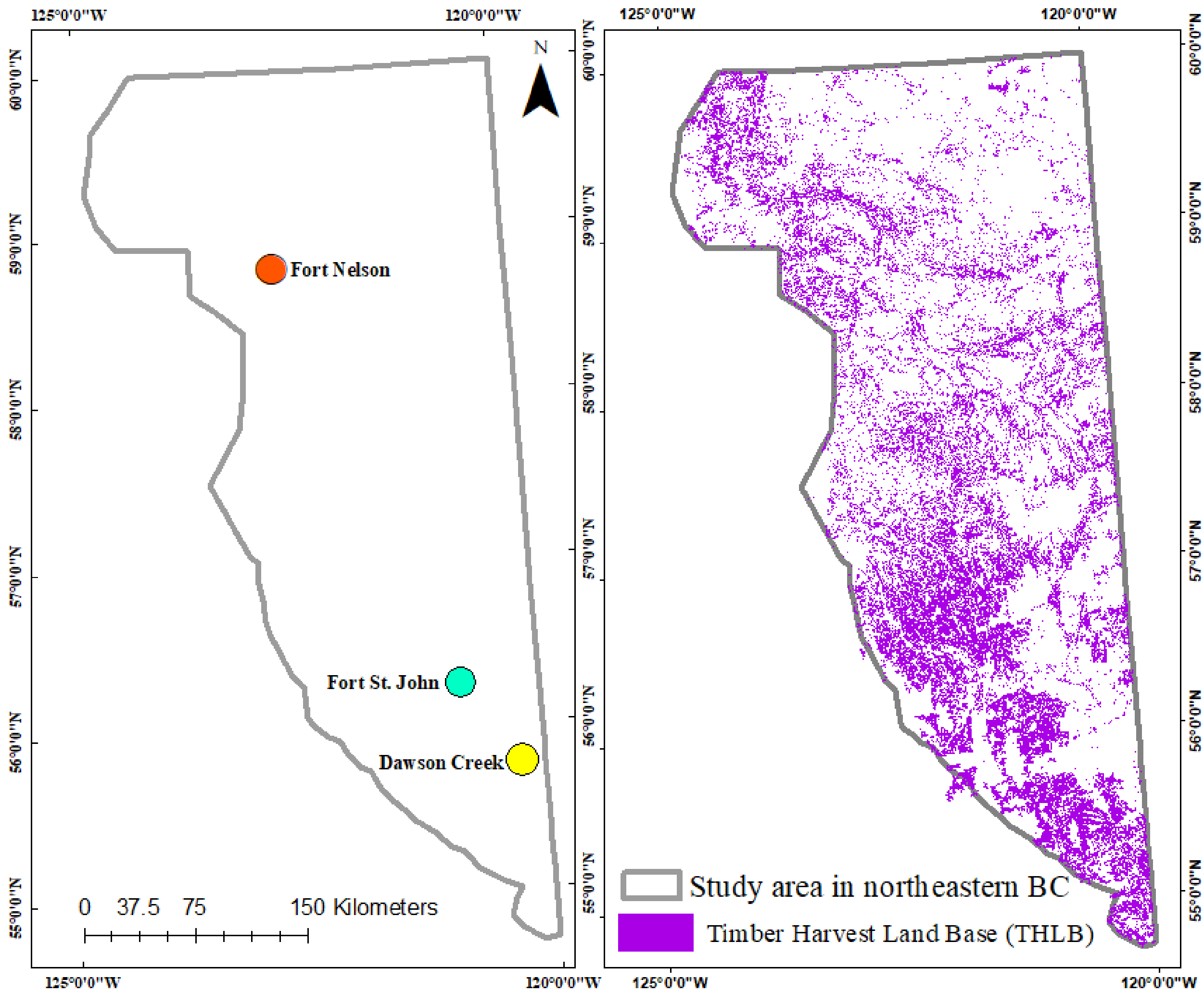

Figure 2.1 Map showing the study area, three major cities, and part of the BC's timber harvest land base in the study area (projected coordinate: NAD_1983_BC_Environment_Albers)

2.2.3 Data

Surface reflectance Landsat images acquired from the United States Geological Survey (USGS) for 1985, 2000, and 2015 were used in this study. The Landsat images of 1985 and 2000 were from Thematic Mapper (TM5), and that of 2015 were from Operational Land Imager/Thermal InfraRed Sensor (OLI/TIRS 8). A total of 33 (11 images for each of the selected years) multi-date Landsat images acquired between June 1 and August 31 of 1985, 2000, and 2015 were composited and used in this study. The images were selected from these years and months based on the availability of quality Landsat images and the time of acquisition to reduce seasonal variation and phenological differences in vegetation growth in the years selected for the analysis. These images were used to map two periods (1985-2000 and 2000-2015) of forest cover change and forest fragmentation. The lack of data free from snow limits land change analysis that focuses on many points in time and thus, conclusions drawn from this analysis are based on the available data. Analysis from many years would likely provide more insights into land dynamics.

Ancillary images (high-resolution images between 1 and 1.5m spatial resolution) were acquired from Google Earth Pro and used in this study. Additionally, Environmental Systems Research Institute (ESRI) DigitalGlobe basemap images (at 0.5m spatial resolution) were used to assist in the identification of land classes during the Landsat image classification process. Tilahun and Teferie (2015) and Cha and Park (2007) have demonstrated the usefulness of Google Earth images for classification accuracy assessment.

Based on the good practices recommendations for sampling (see Olofsson et al., 2014), a stratified sampling method was used to randomly select 473 ground truth samples from the original Landsat images between two periods (1985-2000 and 2000-2015). The stratification for sampling was based on change area and no-change area (see examples in Franklin et al., 2015; Ridd & Liu, 1998). Through image differencing (Ridd & Liu, 1998), the change and no-change area strata were identified in the original Landsat images to obtain the ground truth samples. Image differencing 'process simply subtracts one digital image, pixel-by-pixel, from another, to generate a third image composed of the numerical differences between the pairs of pixels' (Ridd & Liu, 1998, p. 96). One hundred and twenty-one ground truth samples were selected from the change area, and 352 ground truth samples were selected from the no-change area. The sample sizes were chosen based on the sizes of the two strata.

2.2.4 Data processing, Landsat image classification, and analysis

Composites of the images from TM 5 and OLI/TIRS 8 Landsat data were created to produce cloud- and haze-free images using the best-available-pixels approach (White et al., 2014; Franklin et al**.**, 2015). With this approach, best pixel candidates were selected based on nearness to clouds, cloud shadow, cloud opacity, type of sensor, and day of the year. In this study, the target day of the year for the candidate pixels is July 1, 1985, 2000, and 2015. However, land cover pixels from images collected 30 days before July 1 or 60 days after July 1 were also considered for selection for use in the Landsat image classification, and thus these pixels were considered for use in this study because of their temporal span.

Based on the spatial resolution of the Landsat images and mapping program functionality, the study area was classified into one of seven land categories (water, coniferous forest, deciduous forest, mixed forest, barren land, agricultural land, and developed land) (see details in Table 2.1). The classes were identified through visual inspection of the Landsat images (Olofsson et al., 2014; Stroppiana et al., 2012), high-resolution images, and topographic maps of the study area. The RF classification algorithm (Breiman, 2001) was used to map land classes from the Landsat images. RF is a nonparametric machine learning classifier that can accommodate nonlinear and non-normal relationships and capable of automatically accounting for interaction among predictors. The RF algorithm was utilized in the land classification process because of its robustness in dealing with circumstances that traditional classifiers are unable to handle (Liaw, & Wiener, 2002). The RF is a classification approach that uses ensembles of classification trees (Breiman, 2001). Each of the constructed trees is made up of a selected and permuted subset of randomized subsets of predictor variables. In this study, the default number (500) of trees was used in the classification process because Breiman and Cutler (2007) and Cutler et al. (2007) have shown that values greater the 500 have an insignificant influence on the classification outcome. The predicted classes were combined from all the trees based on majority votes to create the final land cover classes. Temporal filtering was applied to remediate illogical land transitions (see e.g., in conversion from developed land to forest) (Sexton, Urban, Donohue, & Song, 2013). Whereas RF machine learning classification has been proven efficient on many occasions, there are some limitations. For example, as strong as RF is, it is considered a low bias, high variance model. As decision trees are subject to overfitting, RF uses a 'majority rule' bagging to resample over and over and averaging out how the models are overfitting. Consequently, RF is more likely to overestimate low values and underestimate high values (Horning, 2010).

Table 2.1 Land categories and their components

Land use/land cover class	**Components**
Water	Permanent and intermittent lakes, rivers, streams, and creeks
Coniferous forest	Evergreen forest cover made up of pine, spruce, fir, hemlock, and western redcedar trees
Deciduous forest	Broadleaf trees, mostly trembling aspen and black cottonwood trees.
Mixed forest	It is a mix of different categories of forest cover, including evergreen and broadleaf trees; it is not made up of any predominant category of forest trees.
Barren land	Bare land, rocks, and gravel pits.
Agricultural land	Cropland, hay/pasture, grasslands, and herbs.
Developed land	Low and high-intensity residential, commercial, industrial, and transportation land uses and land cover

2.2.4.1 Change detection and intensity analysis

A multi-date change detection technique was used to determine land cover conversions. Through a visual interpretation of the classified Landsat images, the original Landsat images, and the high-resolution images, the change area and the no-change area were identified in the classified Landsat images (e.g., in Franklin et al., 2015). The ground truth sample of points acquired from the differenced images (showing change area and the no-change area) was compared to the change area and no-change area identified in the classified Landsat images. This process aided in determining the accuracy of the change area in the classified Landsat image. The accuracy of the amount of land change was assessed based on Olofsson et al. (2014), which considers both the total amount of selected ground truth samples and the proportion of change area and no-change area strata in determining the accuracy of the land change measured in this study. The margin of error in the ground-truth sampling was computed at a 95% confidence interval.

Intensity analysis (Aldwaik & Pontius, 2012), a quantitative framework, was used to compute the statistics for forest change in 1985-2000 and 2000-2015. It calculates the changes in the land cover at three levels (interval, category, and transition) from a general to a more elaborate analysis (see intensity analysis equations and notations defined below). Land change changes and transitions calculated from the intensity analysis framework are shown in percentages (%). Equation 1 shows the annual intensity of change, while equation 2 shows uniform annual change or uniform intensity at interval level analysis. According to Aldwaik and Pontius (2012), the uniform intensity 'gives one uniform rate for the entire temporal extent of the study, which would exist if the pattern of change were perfectly stationary in terms of rate of overall change' (p. 107).

At the interval level, if the amount of change is below the uniform intensity, then the change is slow; if the change (S_t) is above the uniform intensity *(U)*, then the change is fast.

$$S_t = \frac{\left\{\sum_{j=1}^{J}\left[\left(\sum_{i=1}^{J} Ctij\right) - Ctij\right]\right\} / \left[\sum_{j=1}^{J}\left(\sum_{i=1}^{J} Ctij\right)\right]}{Yt+1-Yt} \times 100\% \quad (1)$$

$$U = \frac{\sum_{t=1}^{T-1}\left\{\sum_{j=1}^{J}\left[\left(\sum_{i=1}^{J} Ctij\right) - Ctij\right]\right\} / \left[\sum_{j=1}^{J}\left(\sum_{i=1}^{J} Ctij\right)\right]}{YT-Y1} \times 100\% \quad (2)$$

Equations 3 and 4 show how the annual losses and gains were calculated. Equation 1 further calculates a value for uniform intensity for time interval t for the category level analysis. Therefore, equation 1 connects the interval level analysis to the category level analysis. If values of G_{tj} (*annual gains*) were equal for all j, then they would be equal to S_t (*annual change for time intensity*). Similarly, if values of L_{ti} (*annual losses*) were equal for all i, then they would be equal to S_t. The change values are compared to S_t (*from equation 1*) to interpret the annual losses or gains. For each category, if the loss or gain is below the uniform intensity S_t then the loss or gain is dormant (e.g., dormant loss or dormant gain). Conversely, if the gain or loss in a land category is above the uniform intensity S_t, then the loss or gain is active (e.g., active loss or active gain).

$$G_{tj} = \frac{\left[\left(\sum_{i=1}^{J} Ctij\right) - Ctij\right] / (Yt+1-Yt)}{\sum_{i=1}^{J} Ctij} \times 100\% \quad (3)$$

$$L_{ti} = \frac{\left[\left(\sum_{j=1}^{J} Ctij\right) - Ctij\right] / (Yt+1-Yt)}{\sum_{i=1}^{J} Ctij} \times 100\% \quad (4)$$

Equation 5 shows the transition 'TO' a category from other categories at transition level analysis. Equation 6 shows the uniform intensity of transition to a category n. If the quantity of land transitions from any of the other categories to n is below a uniform intensity W_{tn}, then n avoids that particular category. If the quantity of land transition from a particular category to n is above the uniform intensity, then that category is targeted by n.

$$R_{tin} = \frac{Ctin/(Yt+1-Yt)}{\sum_{i=1}^{J} \text{Ctij}} \times 100\% \tag{5}$$

$$W_{tn} = \frac{\left[\left(\sum_{i=1}^{J} Ctin\right) - Ctnn\right] / (Yt+1-Yt)}{\sum_{j=1}^{J} \left[\left(\sum_{i=1}^{J} \text{Ctij}\right) - Ctnj\right]} \times 100\% \tag{6}$$

Equation 7 shows transition intensity 'FROM' *m* to other categories, and 8 calculates the value for the uniform intensity at transition level. If the quantity of land transition (Q_{tmj}) from *m* to a category is below a uniform intensity V_{tm}, then category *m* is avoided. If the quantity of land transition from *m* is above the uniform intensity, then the category *m* is targeted.

$$Q_{tmj} = \frac{Ctmj/(Yt+1-Yt)}{\sum_{i=1}^{J} \text{Ctij}} \times 100\% \tag{7}$$

$$V_{tm} = \frac{\left[\left(\sum_{i=1}^{J} Ctmj\right) - Ctmm\right] / (Yt+1-Yt)}{\sum_{j=1}^{J} \left[\left(\sum_{i=1}^{J} \text{Ctij}\right) - Ctim\right]} \times 100\% \tag{8}$$

J number of categories;

i index for a category at the initial time point for a particular time interval;

j index for a category at the final time point for a particular time interval;

m index for the losing category in the transition of interest; a losing category is the land class which reduces in size as other classes increase in size.

n index for the gaining category in the transition of interest; a gaining category is the land class which increases in size as other classes reduce in size.

T number of time points;

t index for the initial time point of the interval *[Yt, Yt+1]*, where t ranges from *1 to T-1;*

Y_t year at time point *t*;

C_{tij} number of pixels that transition from category *i* at time *Yt* to category *j* at time *Yt+1*;

S_t annual intensity of change for time interval *[Yt, Yt+1]*;

U value of uniform annual change/intensity for time-intensity analysis;

G_{tj} annual intensity of gross gain of category j for time interval *[Yt, Yt+1]*;

L_{ti} annual intensity of gross loss of category i for time interval *[Yt, Yt+1]*;

R_{tin} annual intensity of transition from category i to category n during the time interval *[Yt, Yt+1]* where $i \neq n$;

W_{tn} value of the uniform intensity of transition to category n from all non-n categories at time Y_t during the time interval *[Yt, Yt+1]*;

Q_{tmj} annual intensity of transition from category m to category j during the time interval *[Yt, Yt+1]* where $j \neq m$;

V_{tm} value of the uniform intensity of transition from category m to all non-m categories at time *Yt+1* during the time interval *[Yt, Yt+1]*.

3.2.5 Fragmentation analysis

Version 4.2 of FRAGSTATS metrics (McGarigal et al., 2012) was used to perform the forest fragmentation analysis in this study. Both composition and pattern metrics were used for the fragmentation analysis to reduce redundancy in selecting the number and types of metrics (Coops et al., 2010). Class metrics, namely, the number of patches, mean patch size, coefficient of variation of patch size, mean shape index, the coefficient of variation of shape index, and aggregation index, were used in this study (refer to the description in Table 2.2).

The FRAGSTATS metrics selected for the fragmentation analysis were complemented with the core, edge, perforated, and patch forest measurements (see Table 2.3) from the Landscape Fragmentation Tool (LFT) based on an analysis by Vogt et al. (2007). A combination of metrics from FRAGSTATS and LFT gives meaningful analysis and interpretations (MaClean & Congnalton, 2010). For the classified Landsat image to support conclusions on land change, users need an accuracy of 85% or more for reliability purposes (Bhatta, 2013; Lillesand et al., 2014). In this study, because forest fragmentation analysis involved the use of classified Landsat images, there was the need to classify the images accurately for the reliability of the results. However, the spatial resolution (30m) of the Landsat images is likely to underestimate the actual size of some disturbances (e.g., roads) that are likely to contribute to a substantial amount of forest fragmentation.

Table 2.2 Descriptions of FRAGSTATS Metrics

Metrics	**Description**
Number of patches (NP)	NP is the total number of patches in each class. An increasing number of patches means an increasing fragmentation. However, other metrics are used in conjunction with the NP.
Mean Patch Size (Area_MN)	Area_MN refers to the average patch size in each class (measured in hectares). An increasing Area_MN shows an increasing amount of fragmentation.
Patch size coefficient of variation (Area_CV)	Area_CV measures relative variability about the mean (that is, variability as a percentage of the mean), not absolute variability. The higher the Area_CV, the higher the variability in the patch sizes and too much variability means an increasing amount of fragmentation.
Mean shape index (Shape_MN)	The shape index measures the complexity of patch shape compared to a standard shape (square) of the same size. The value is 1 when the patch is square and increases without limit as patch shape becomes more irregular (complex).
Coefficient of variation of forest patch shape Index (Shape_CV)	Shape_CV is variability in the patch shape expressed as a percentage of the mean shape index. A higher Area_CV means higher variability in the patch shape; patches become irregularly shaped as compared to square-shaped when Area CV is higher.
Aggregation index (AI)	AI measures patch aggregation. AI equals 0 when the focal patch type is maximally disaggregated and equals 100 when the patch type is maximally aggregated into a single, compact patch.

These metrics measure the patch composition and pattern of forest patches in the landscape. The information in the table is from McGarigal et al. (2012).

Table 2.3 Descriptions of categories of fragmentation

Category of fragmentation	Description
Patch Forest (PF)	PF is a fragment of completely degraded forest (does not contain any core forest pixel) by the "edge effect*." A higher PF means a higher level of fragmentation and forest degradation.
Edge Forest (EF)	EF occurs within the "edge effect" zone along the outside edge of a non-patch tract. A higher EF means an increasing amount of fragmentation.
Core Forest (CF)	CF occurs outside of the "edge effect" zone, and thus it is not degraded by fragmentation. A higher CF means a lower amount of fragmentation.
Perforated Forest (PPF)	PPF occurs within the "edge effect" zone along the edge of a clearing in a non-patch tract. A higher PFF means a higher amount of fragmentation.

* For general purposes analysis, an edge width of 100m was used in this study (see Laurance et al., 2018; Drohan et al., 2012). The edge effect area is a distance of 100m between the core forest and the non-forest beyond which competing land uses could degrade the forest.

2.3 Results

2.3.1 Interval level analysis: total percentage change between time points and accuracy

The amount of change in the land cover in the two periods is shown in Figure 2.2. In both the overall study area and the THLB, the observed change is higher between 2000 and 2015 as compared to that of between 1985-2000. The change observed in Figure 2.2 is the total percentage change (including losses and gains) from which all the changes measured at category and transition levels were derived. The average accuracy of the observed change area in the two periods is approximately 95% (see Appendix 1 Tables I and II for details of the full classification accuracy assessment results).

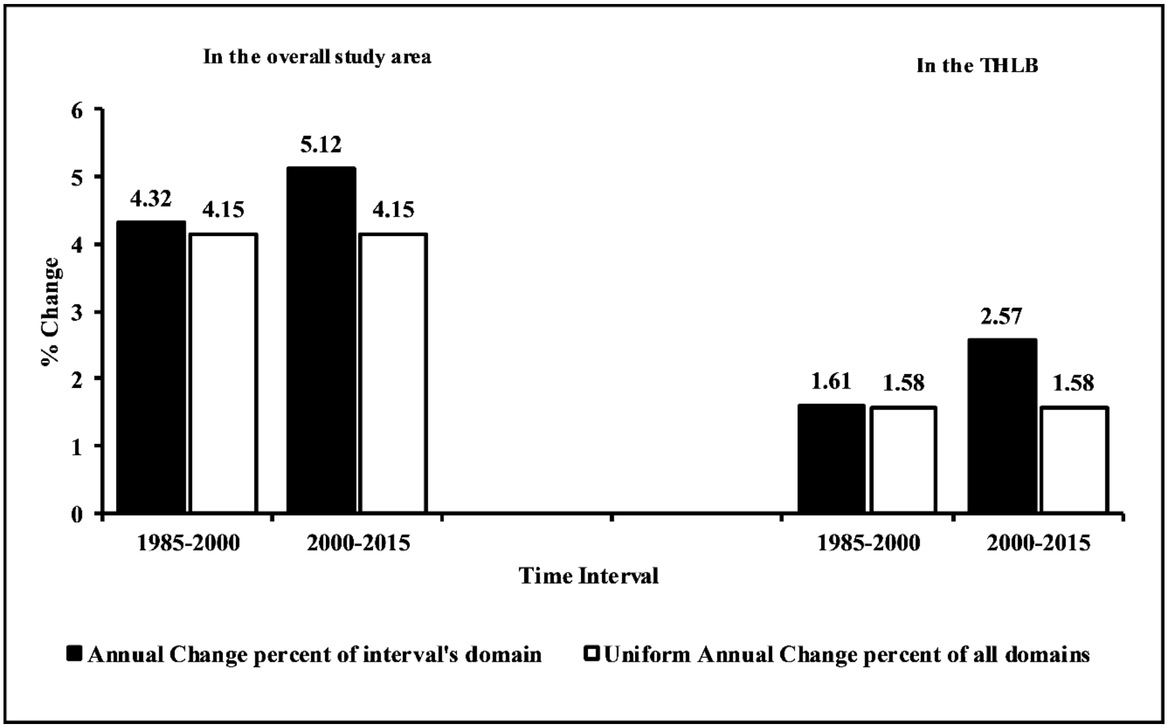

Figure 2.2 Percentage change in the land cover in the whole study area and timber harvest land base (THLB)

2.3.2 Category level analysis: forest cover gains and losses

Across the two periods, the losses in all the forest cover types exceeded the gains. For instance, between 2000 and 2015, a 4.9% loss and a 4.2% gain of coniferous forest cover were recorded in the study area. However, the net loss in the coniferous forest cover is higher (1.6%) between 1985 and 2000 as compared to the net loss (0.7%) between 2000 and 2015. In the THLB, forest cover loss is more than the gain, and this applies to the losses in all the forest cover types between 1985 and 2000. Most of the forest cover losses and gains in the study area occurred in the THLB (Figures 2.3 and 2.4). For example, 2.9% out of the 4.3% coniferous forest cover loss in the whole study area, occurred in the THLB between 1985 and 2000. Also, between 2000 and 2015, 3.08% out of the 4.9% of the coniferous forest cover loss occurred in the THLB. Similarly, between 1985 and 2000, 2.4% out of 2.7% of forest cover gain in the study area occurred in the

THLB. Figure 2.5 shows the land classes in the study area, and Figure 2.6 shows details of land classes and how these classes have changed over time in an area near Fort St. John, BC.

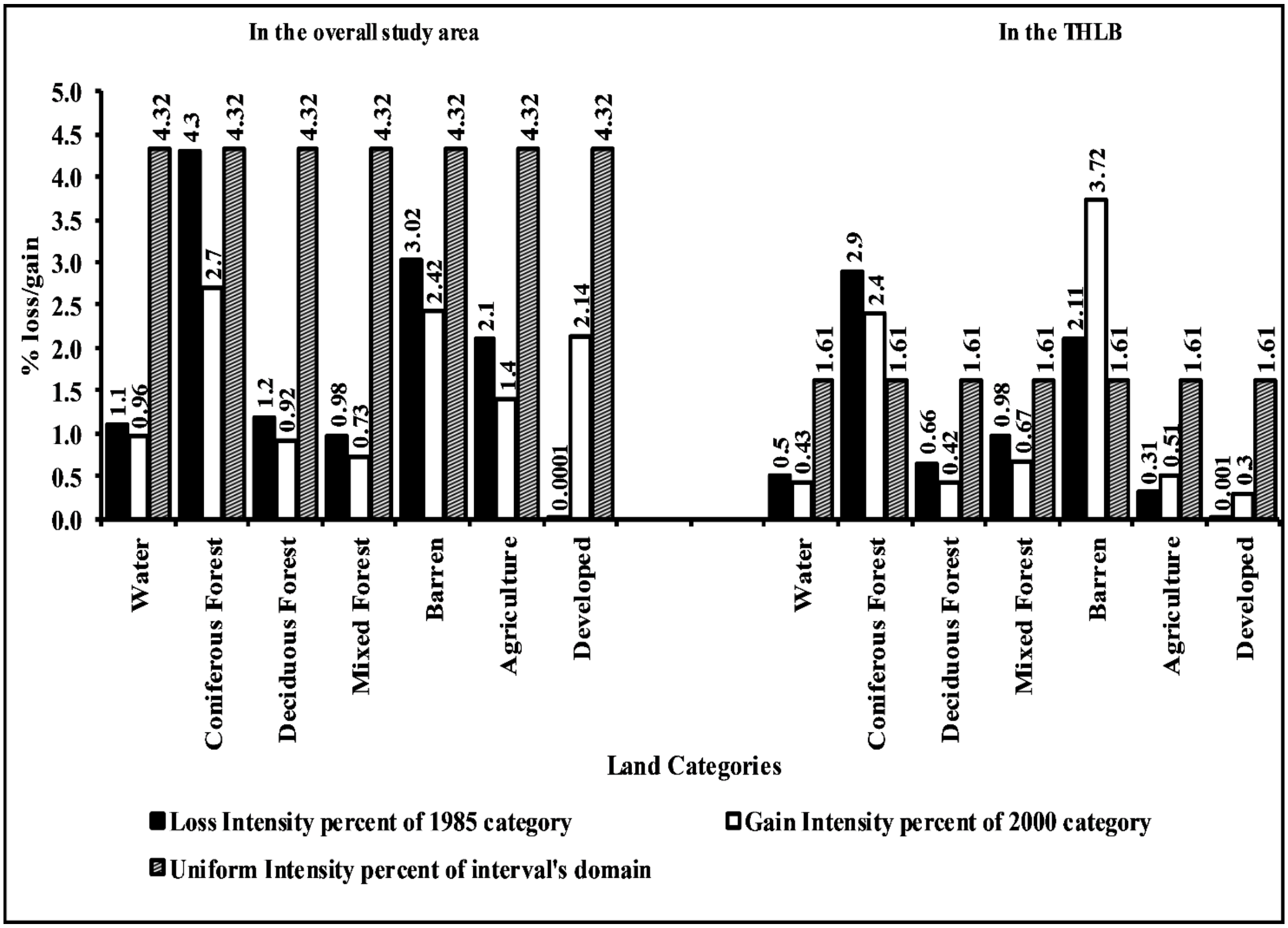

Figure 2.3 Gains and losses in forest cover types in the study area and timber harvest land base (THLB), 1985-2000

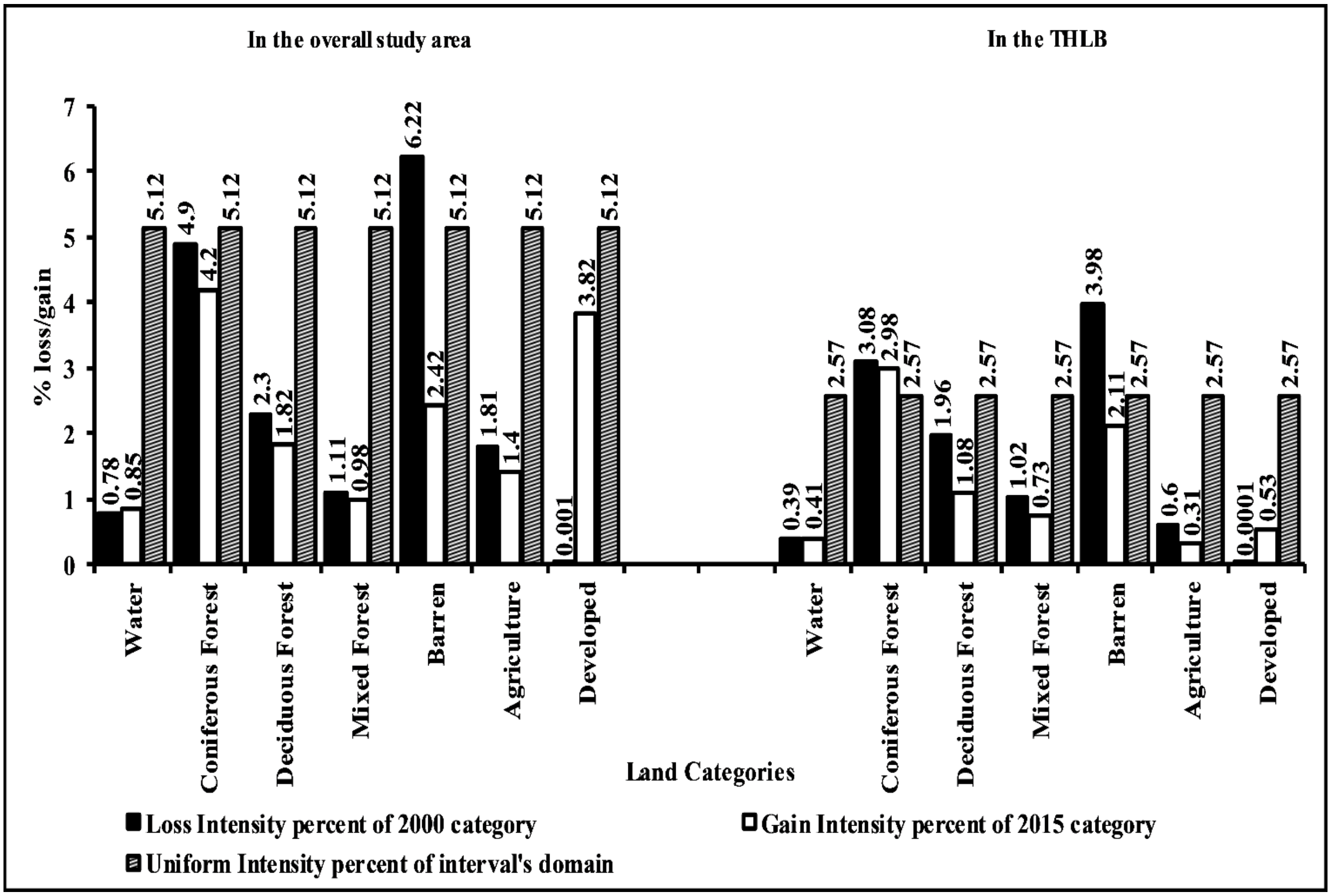

Figure 2.4 Gains and losses in forest cover types in the study area and timber harvest land base (THLB), 2000-2015

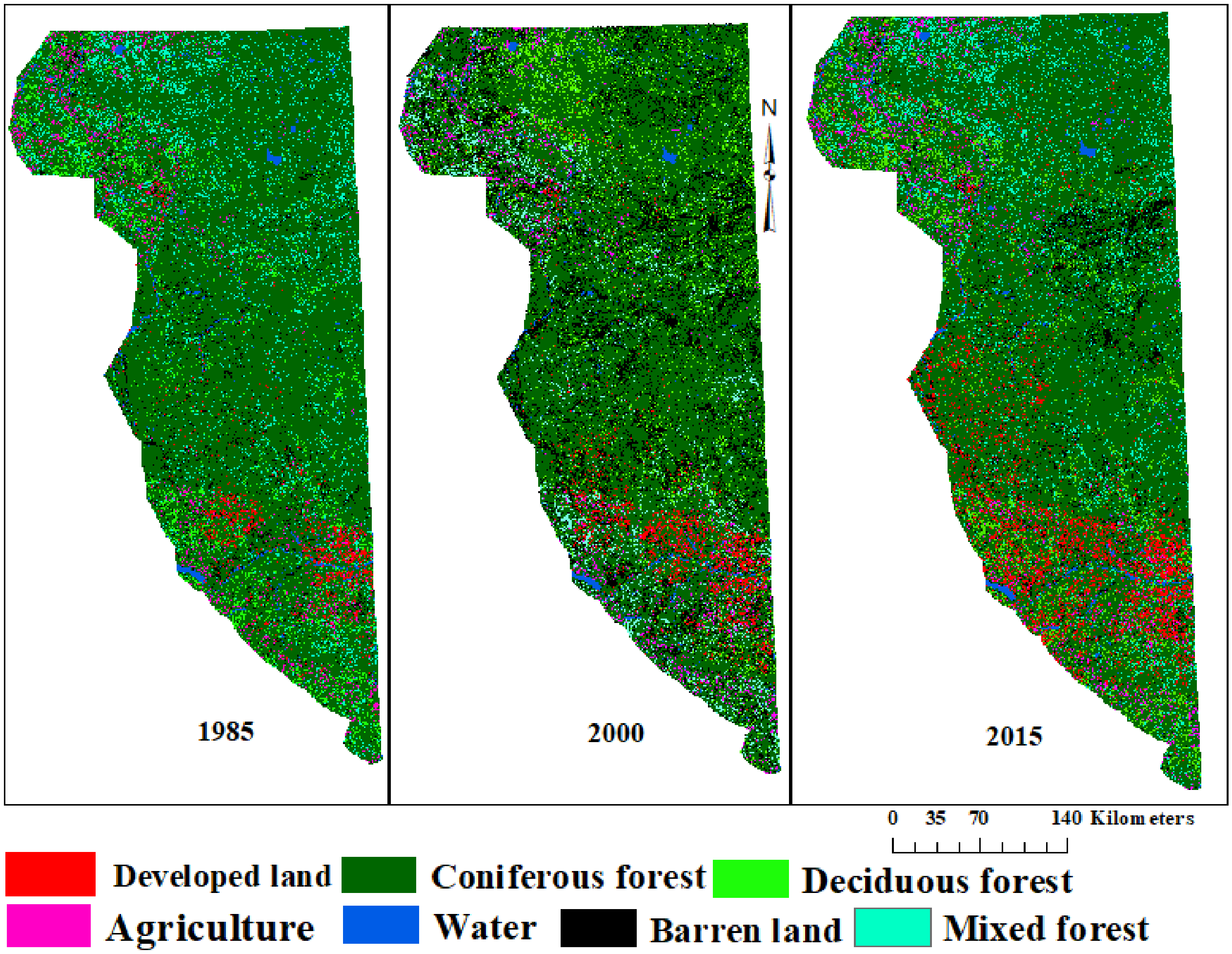

Figure 2.5 Classes of land use/land cover in the study area, 1985, 2000, and 2015

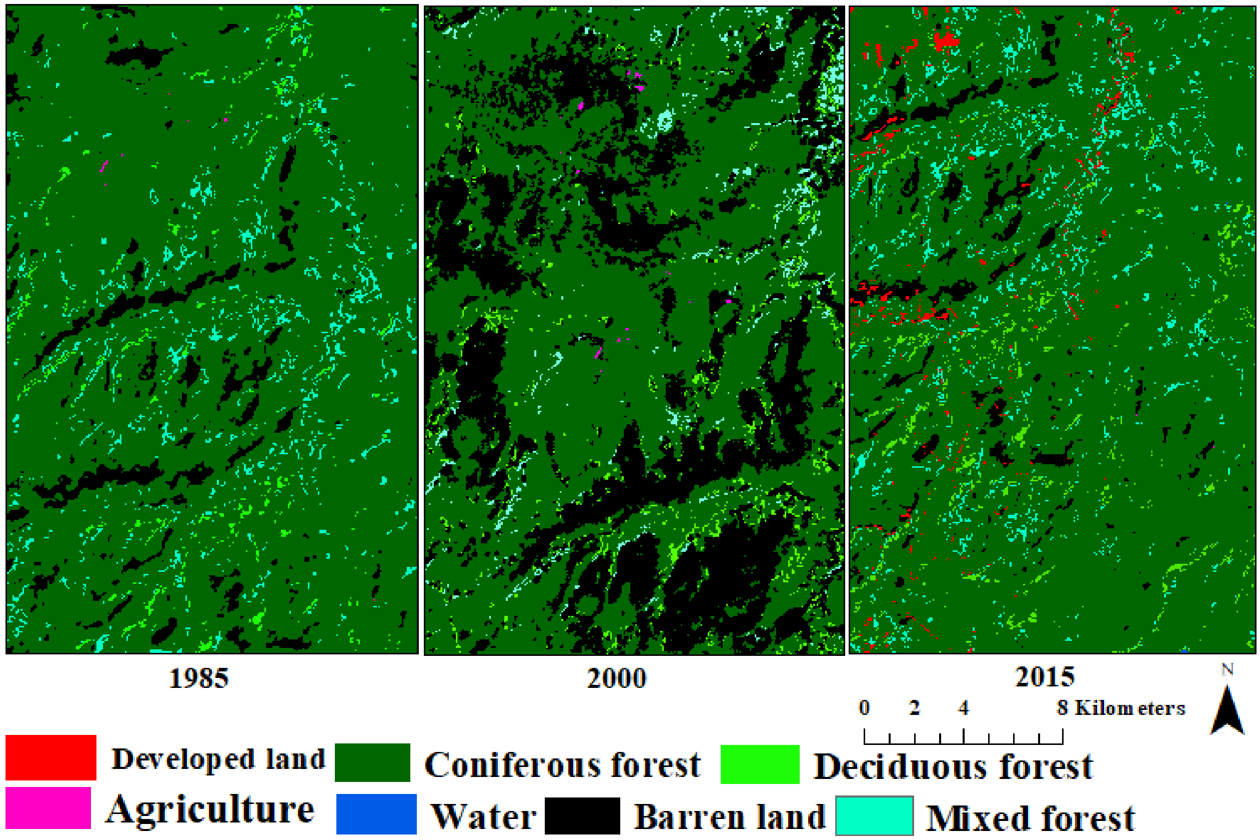

Figure 2.6 Zoomed-in land classes in the study area: an area near the city of Fort St. John, BC (centred around 57°18'24.30"N, 121°35'30.72"W), 1985-2015

2.3.3 Transition level analysis: conversion 'FROM' and 'TO' coniferous forest

In the study area, the dominant forest type, coniferous forest, converted mostly to barren land between 1985 and 2000 (Figure 2.7). Also, in the study area, most of the conversions (2.1% out of 3.6%) to barren land occurred in the THLB between 1985 and 2000. Between 1985 and 2000, other land classes converted to coniferous forest cover, especially the barren land. The barren land in the THLB is the main source of land for the growth of the coniferous forest (Figure 2.8).

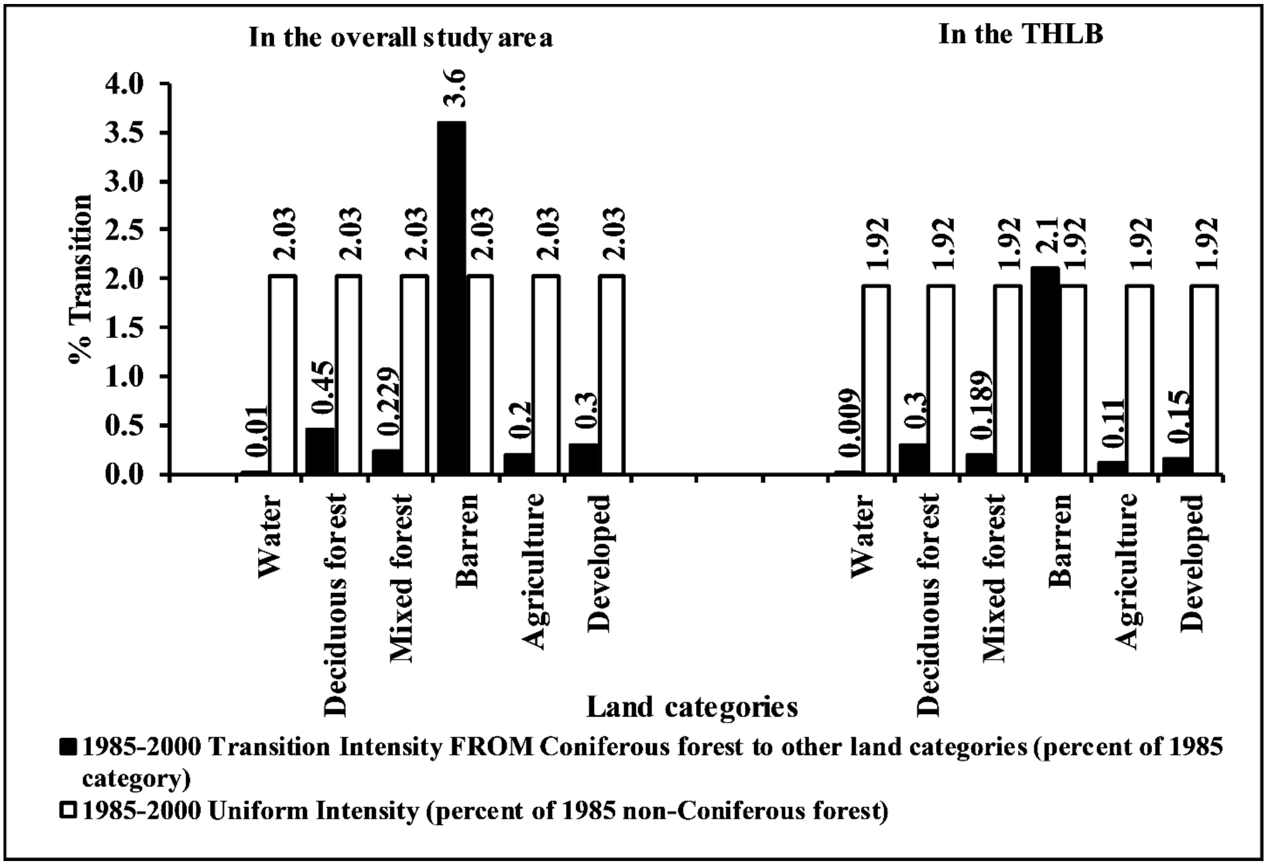

Figure 2.7 Transition FROM coniferous forest to other land categories in the study area and timber harvest land base (THLB), 1985-2000

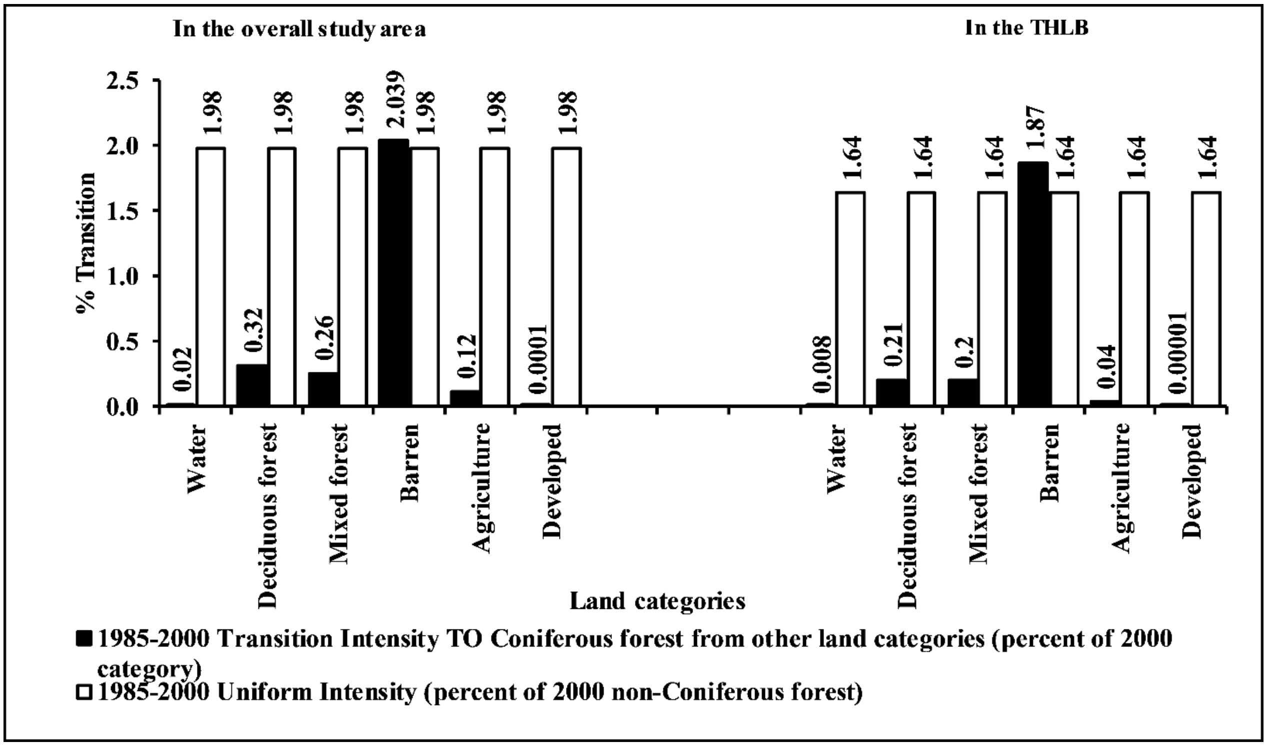

Figure 2.8 Transition TO coniferous forest from other land categories in the study area and timber harvest land base (THLB), 1985-2000

The transition pattern of the coniferous forest cover to other land cover types between 2000 and 2015 is similar to that of between 1985 and 2000. The results of the transition analysis show that coniferous forests mostly converted to barren land between 2000 and 2015 (Figure 2.9). Also, 2.38% out of the total of 3.08%, which converted to barren land, occurred in the THLB of the study area. In the study area, between 2000 and 2015, the major land class that converted to coniferous forest cover is the barren land (3.4%) (Figure 2.10).

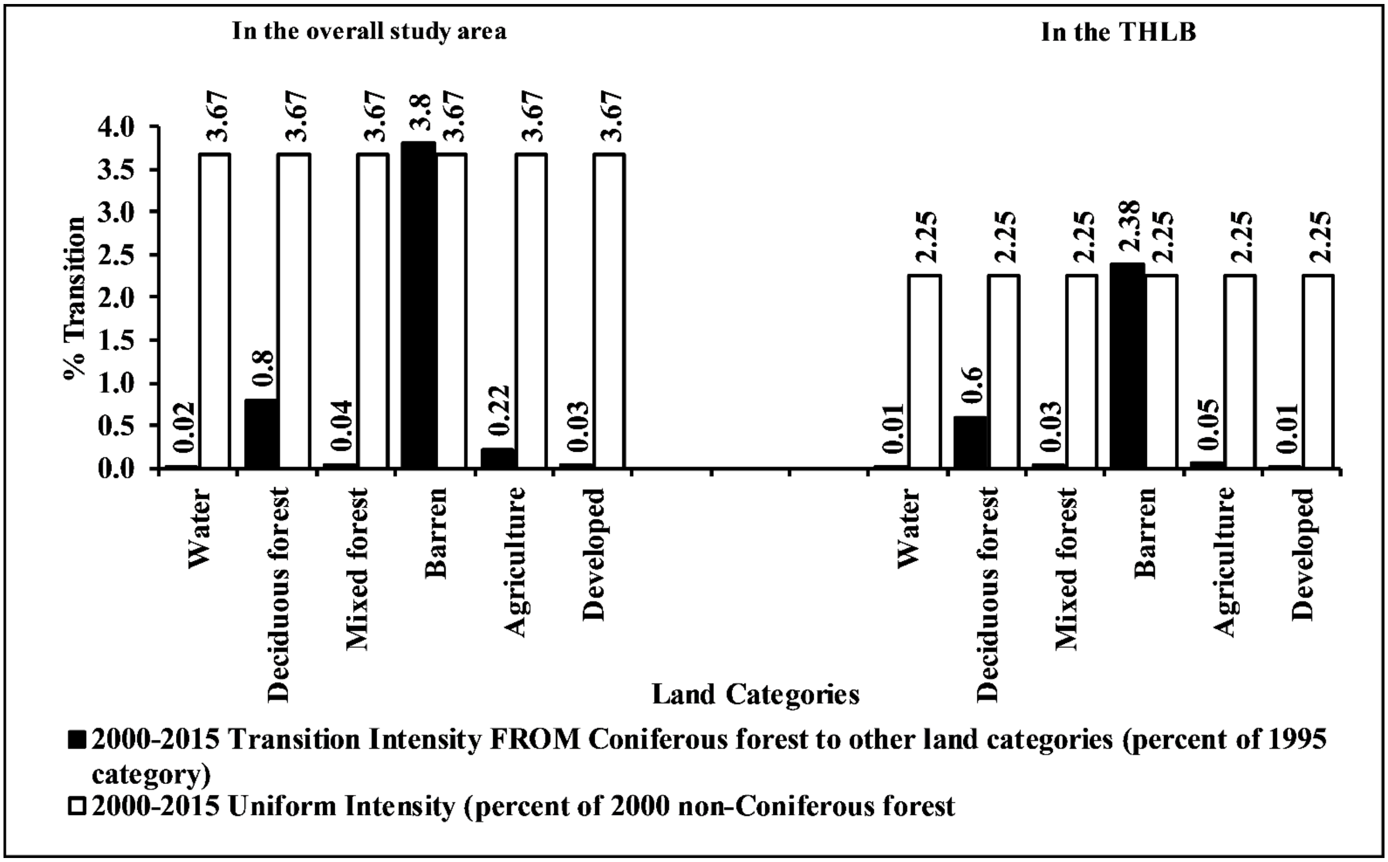

Figure 2.9 Transition FROM coniferous forest to other land categories in the study area and timber harvest land base (THLB), 2000-2015

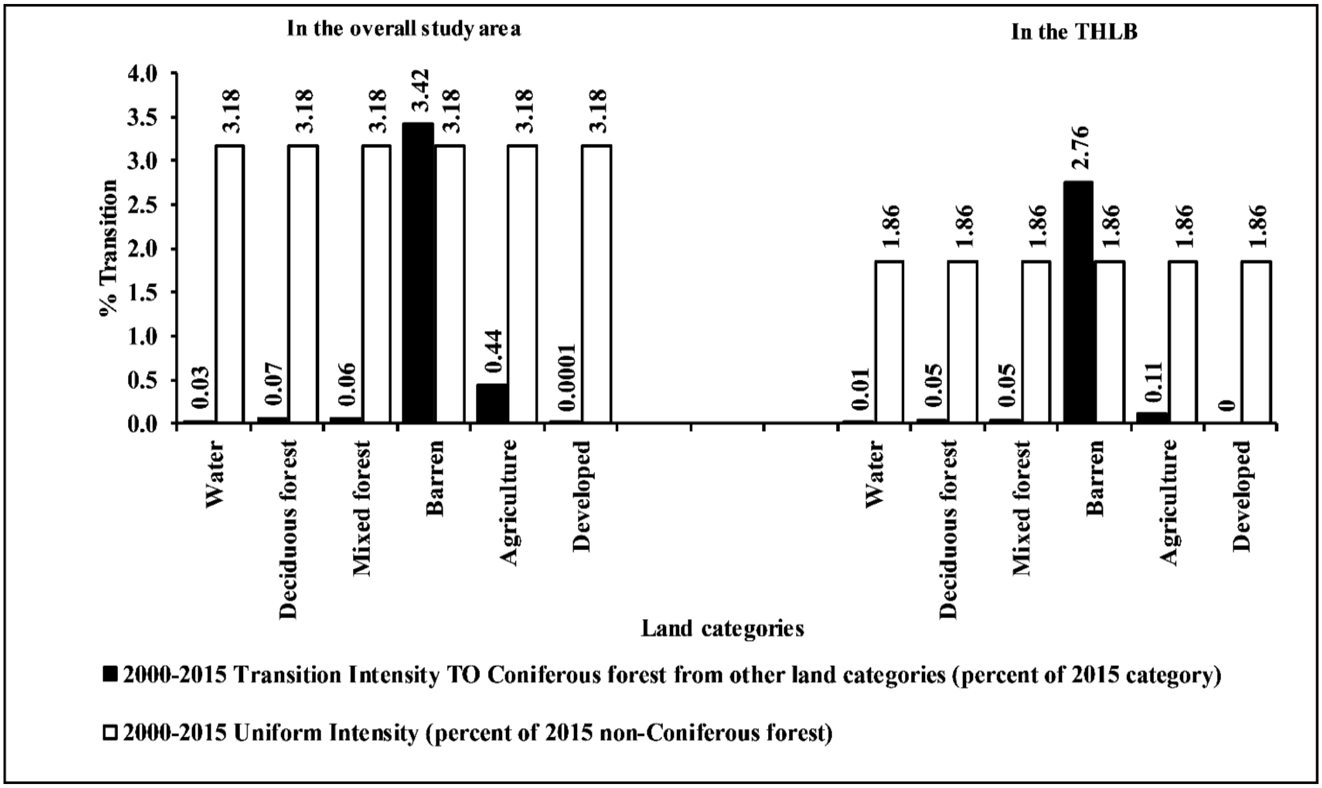

Figure 2.10 Transition TO coniferous forest to other land categories in the study area and timber harvest land base (THLB), 2000-2015

2.3.4 Forest fragmentation analysis

In all the time points (1985, 2000, and 2015), the core forest has been the largest amount of forest fragmentation category in the coniferous forest. However, the 1985 coniferous forest cover has the largest core forest as compared to that of 2000 and 2015 (Figure 2.11). The highest amount of perforated forest was recorded in the 2015 coniferous forest cover. The patch forest is the smallest amount of category of coniferous forest fragmentation in the study area in northeastern BC (see Figure 2.11). Also, the largest amount of change (reduction) was recorded in the core forest, as compared to that of edge forest, patch forest, and perforated forest, and this mainly occurred in the period between 1985 and 2000 (see Figure 2.12). Edge forest increased between 1985 and 2000 but decreased marginally by 0.88% between 2000 and 2015. Patch forest increased by 0.37% between 1985 and 2000

The number of coniferous forest patches increased by 81218 between 1985 and 2000 but reduced by 10418 between 2000 and 2015. Mean patch shape (A_MN) increased between 1985 and 2000 but reduced between 2000 and 2015 (see Table 2.4). Patch sizes were more variable between 1985 and 2000 than between 2000 and 2015; the variability in patch size (A_CV) reduced between 2000 and 2015. Similarly, the complexity (deviation from a regular square-shape) in the patch shape increased more between 1985 and 2000 than between 2000 and 2015 (see S_MN in Table 2.4). Also, the variation in the patch shape increased more between 1985 and 2000 than between 2000 and 2015 (see S_CV in Table 2.4). Whereas the cohesion between patches reduced between 1985 and 2000, it increased between 2000 and 2015 (see AI in Table 2.4).

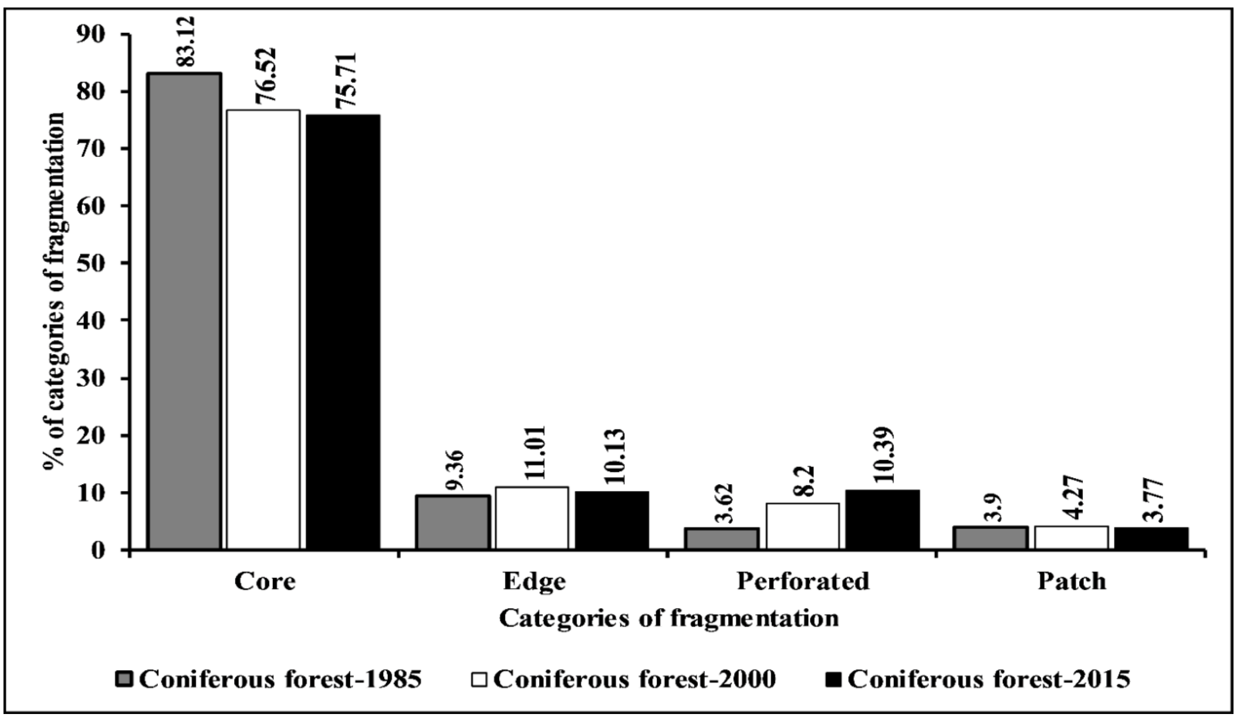

Figure 2.11 Percentage of categories and amount of forest fragmentation

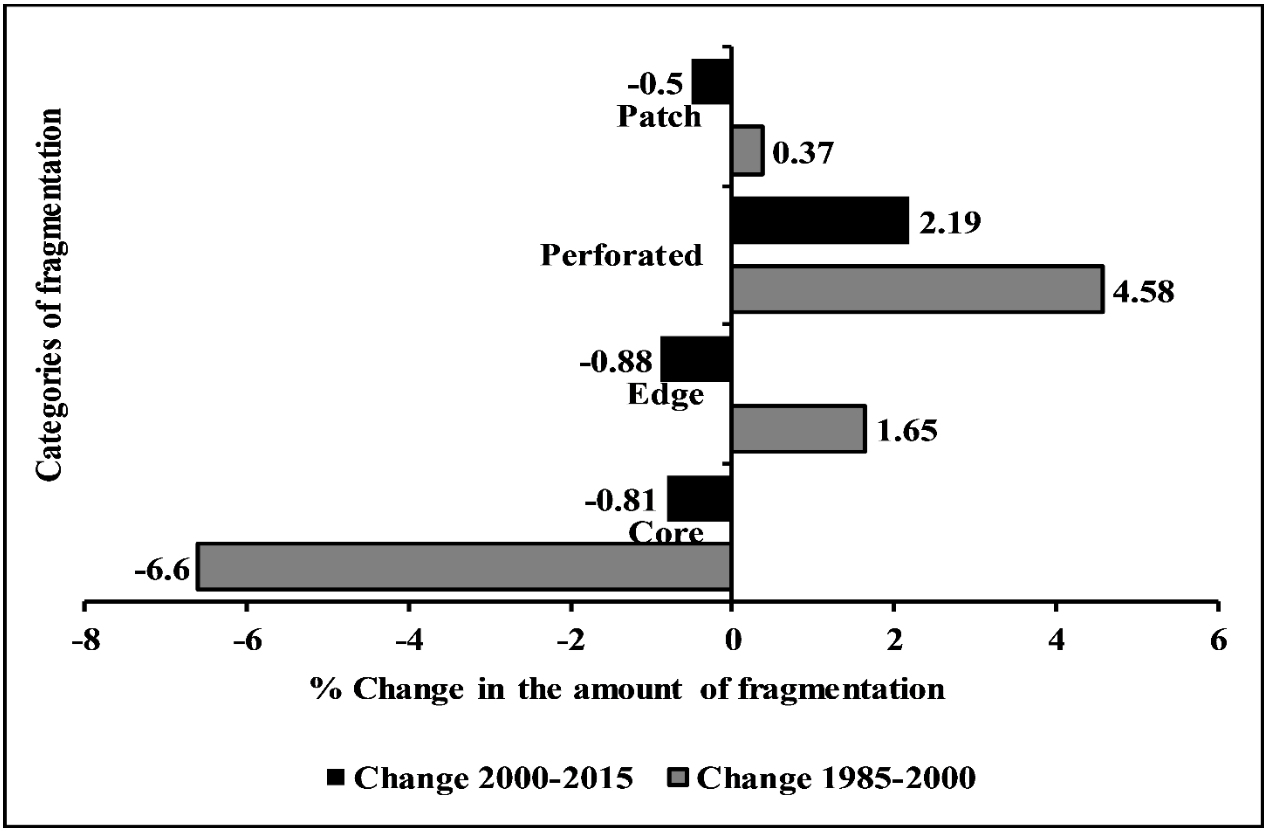

Figure 2.12 Percentage change in the amount of forest fragmentation

Table 2.4 Composition and configuration of coniferous forest cover patches

	Class Metrics++					
Class of Land	NP	A_MN	A_CV	S_MN	S_CV	AI
Coniferous forest-1985	31762	251.12	12986.32	1.16	124.36	96.13
Coniferous forest-2000	112980	77.21	25691.98	1.35	88.12	93.25
Coniferous forest-2015	102562	89.53	17964.12	1.37	86.1	95.22
Change (1985-2000)	81218	-173.91	12705.66	0.19	-36.24	-2.88
Change (2000-2015)	-10418	12.32	-7727.86	0.02	-2.02	1.97

++ NP- the number of forest patches, A_MN- the size of forest patches, A_CV- size coefficient of variation, S_MN- mean shape index, S_CV- shape index coefficient of variation, and AI- aggregation index.

2.4 Discussion

2.4.1 Forest cover losses, gains, and transitions

The accuracy of the land change area measured in this study is high. However, in a related study in BC, Paul et al. (2018) achieved a 90.45% classification accuracy in their watershed level analysis. Hansen et al. (2013) achieved a classification accuracy of approximately 99.5% using a decision tree classification algorithm to map global forest cover. Similarly, White et al. (2017) used Landsat images to produce a land cover change map of Canada and followed the accuracy assessment approach recommended by Olofsson et al. (2014). The accuracy of the change map was 89% (see White et al., 2017), which is less than the accuracy level achieved in this study which also followed the approach by Oloffson et al. (2014). Nonetheless, the accuracy assessment approaches and the land classification algorithms used differ among these studies. For instance, following Olofsson et al. (2014), the accuracy levels of the land classes or the land change area are determined by the randomness of the selected ground truth samples, the representativeness of the ground truth samples in relation to the land change area or the areas of the land classes, and the weight assigned to the less dominant land classes as compared to the larger land classes.

The findings from the change analysis in this study (refer to Figures 2.3 and 2.4) suggest there are net losses in the coniferous forest cover in the study area and the THLB. Whereas the change analyses from the two periods follow the same trend in terms of change and transition from barren land to coniferous forest and from coniferous forest to barren land, changes in the size of the THLB in previous years are likely to impact the results. Thus, future studies can focus on keeping track of the current size of the THLB and subsequent changes that may occur in the future. The THLB's share of the coniferous forest cover loss (gross) is higher than that of the non-THLB. However, the net loss of coniferous forest cover in the non-THLB is higher than that of the THLB. This suggests that it is more likely for the coniferous forest cover in the THLB to regenerate after forest cover loss as compared to that of the non-THLB. The pattern of gains and losses (net losses) in the forest cover might be due to the differences between the intensity of the factors contributing to the losses and gains in the THLB and non-THLB. This assertion is very likely to be the case in the study area because, in BC, about 80% of the timber harvested land is regenerated by planting; the rest of the harvested land is regrown through natural regeneration (FLNRORD, 2017). Thus, there is still the likelihood of net losses of forests, and this depends on the rate at which forest cover regenerates naturally to recover the remaining 20% harvested land that was not planted after the timber harvesting.

The results (net forest loss in the two periods) of this study is consistent with study findings from the European Russian and Swedish boreal forest where the forest stands are conifer-dominated and timber harvesting is a major land use activity (Nordberg, Angelstam, Elbakidze, & Axelsson, 2013). Potapov et al. (2011), for instance, reported that intensive gross forest cover loss due to forest felling (timber harvesting) have been recorded near the Russian–Finland frontier (Leningradskaya Obl and Karelia Rp) (Potapov et al., 2011). Thus, the previous findings and the results from the northeastern BC area have implications for global forest cover change. According to Hansen et al. (2013), because of slower regrowth dynamics of the forest cover, the ratio of boreal forest loss to gain is high (2.1 for >50% of tree cover). Whereas some forest areas have recorded net gains in forest cover, many locations such as in the boreal forests have recorded net losses (see Hansen et al., 2013), and consequently leading to net losses in the global forest cover. The similarity in the forest cover change trend between the global forest change analysis and the change analysis from northeastern BC suggests that northeastern BC is one of the areas contributing to the forest loss globally.

The three major timber supply areas in the study area have had their allowable annual cuts increased by 48.8%, 16.5%, and 70% in Dawson Creek, Fort St. John, and Fort Nelson, respectively, since 1989 (Government of British Columbia, 2019). However, the annual volume of timber harvest increased and peaked at 90 million cubic metres in 1987 but has reduced to 77 million cubic metres since then (Environmental Reporting BC, 2018). The vegetation resource inventory (VRI) data from the BC data catalogue show that the quantity of cutblocks in the study area increased by approximately 11% and 61% in 1985-2000 and 2000-2015, respectively (see Appendix 1 Table III). These are higher than the BC-wide increase (1985-2000= 6.601% and 2000-2015= 21.046%) in the quantity of cutblocks within the same time points. The replanting of harvested forest also peaked between 2005 and 2015 (FLNRORD, 2017). These dynamics of forest land use are likely to account for the pattern of forest change recorded in the forest cover, considering the period of increase and decrease in the harvest volume, the periods of increase in cutblocks, and the quantity of forest loss measured in the THLB and study area-wide.

Annual net loss of 1.6% and 0.7% were recorded in the coniferous forest cover in 1985-2000 and 2000-2015, respectively. However, in the Kiskatinaw River watershed of northeastern BC, Paul et al. (2018) recorded a net loss of approximately 5% in the coniferous and mixed forests but recorded a 5% net gain in the deciduous forest. The difference in the amount of forest change between the finding from our study and that of Paul et al. (2018) suggests that even though both studies focused on the boreal forest, the intensity of forest change depends on the location and differences in change factors (e.g., the quantity of human-induced land use types) (Arroyo-Rodríguez et al., 2017).

The barren land, which is mostly bare soil (and a few outcrops of rocks) is likely to be as a result of timber harvesting since about 95% of the barren land intersects with the spatial data for the harvested cutblocks. The higher rate at which barren land grew into coniferous forest cover in the two-time periods in the study area (mostly in the THLB) confirms this assertion about the components of the barren land. In BC, since October 1987, timber licensees are required to reforest harvested areas (FLNRORD, 2017), and this legislation could account for the higher rate of forest regeneration from the barren land in 1985-2000 and 2000-2015. However, the results suggest that the rate of recovery from the barren land is higher between 2000 and 2015 than that of between 1985-2000.

2.4.2 Forest fragmentation and pattern of change in forest patches

The core forest, edge forest, perforations, degraded patches, aggregation index, shape index, and patch size variation metrics show a varied amount of forest fragmentation in 1985-2000 and 2000-2015. The results from the fragmentation analysis suggest two forms of coincidence. The first one is during the period (1985-2000) of higher net coniferous forest loss and higher amount of coniferous forest fragmentation, and the second is the period of lesser net loss in the coniferous forest and a lower amount of fragmentation. However, the amount of forest fragmentation measured in this study is likely to be due to natural fragmentation (e.g., fragmentation from wetlands). The pattern of coniferous forest fragmentation suggests that forest fragmentation is likely to be higher when there is a higher amount of forest cover loss. The higher rate of forest recovery from barren land and the lesser amount of the coniferous forest fragmentation during the second period suggests that the recovery of forest cover from degradation is likely to reduce the amount of forest fragmentation. Spatial data for the timber harvest cutblocks show that the number of cutblocks increased between 2000 and 2015, contrary to the lesser amount of net forest loss measured at the same time as compared to between 1985 and 2000. However, the lesser amount of net forest loss measured between 1985 and 2000 is likely to be due to the government policy in 1987 which requires replanting of 80% of the harvested forest. Replanting of forest on harvested land reached its peak between 2005 and 2015 (FLNRORD, 2017) and that is, within the same period in which a lesser amount of net forest loss was recorded. Newmark et al. (2017) have found that increasing the rate of forest regeneration would increase contiguous patches and enhance wildlife species persistence. In northeastern BC, increasing the forest recovery from the barren land is, therefore, likely to reduce the likelihood of wildlife (e.g., caribou) habitat degradation. For instance, increasing the BC government planting programs to cover most of the barren lands would increase the regrowth of degraded forest habitats. In BC, extending the 'forest for tomorrow program' (Government of British Columbia, 2008) to cover most of the barren land in the boreal forest zone would be necessary. Also, increasing the replanting target from 80% to 90% of harvested lands would likely increase the rate at which degraded forest cover is regenerated.

The findings from the fragmentation analysis are related to a study by Soverel et al. (2010), which reported the amount of fragmentation in the national parks of Canada. The similarity between the amount of fragmentation measured in northeastern BC and that of the national parks of Canada is the observation that a higher amount of human induced-land classes are found in locations and time points that have an increased rate of forest fragmentation. The study results from northeastern BC and that of Soverel et al. (2010) show a similar trend of fragmentation and anthropogenic influence, and both studies do not establish causal relationships. In southeastern BC, D'eon and Glenn (2005) have predicted that forest cover could be more fragmented as timber harvesting increases. Timber harvesting is a significant activity in the study area, which is likely to partly account for the amount of fragmentation measured in this study. Other activities that account for the amount of fragmentation in the study area are the increasing shale gas drilling, access roads, and pipeline right of ways (Goddard, 2009).

2.4.3 Ecological implications and significance of the results for forest ecosystem management

The study findings (a reduction in core forest, an increase in the edge, and an increase in patch degradation) suggest deteriorating ecological integrity, especially between 1985 and 2000. For instance, animal communities are likely to reduce in terms of species richness as some forest-depended wildlife species require extensive tracts of forest for survival and reproduction (Ranius, Mestre, Bouget, & Schroeder, 2017; Baynes et al., 2016). In Alberta, Sorensen et al. (2008) have hypothesized that the boreal caribou population is unsustainable if industrial footprints are within more than 61% of the caribou range. BC's industrial footprint exceeds the threshold of 61%. Hence, about 75% of the boreal woodland caribou range is already fragmented, especially the core forest, which supports the boreal woodland caribou (Goddard, 2009). These impacts of forest fragmentation found in Alberta and the results of this study suggest to forest managers that there is the need to maintain extensive tracts of forest for the already endangered boreal woodland caribou and make further efforts to protect the degraded caribou habitats. According to Hebblewhite (2017), the increasing edge effects and the reduction in patch sizes would degrade caribou habitats and increase primary prey activities. In northeastern BC, the coniferous forest edge reduced (by 0.88%) between 2000 and 2015 but not as much as it increased (by 1.65%) between 1985 and 2000. The difference between the rate of increase and decrease in the forest edge suggests that even though edge effects are reducing between 2000 and 2015, the rate of reduction is at a slower pace as compared to the rate of increase between 1985 and 2000, and hence, recovery of caribou habitats from degradation is likely to be prolonged. Van Rensen et al. (2015), for instance, have found that disturbances from linear corridors (seismic cutlines) are likely to take about 60 years. However, these seismic cutlines are examples of oil and gas footprints that degrade the woodland caribou habitats and expose the woodland caribou to predation (Dabros, Pyper, and Castilla, 2018). Also, forestry activities such as logging are likely to lead to temporary loss of caribou habitats (Franklin, Macdonald, & Nielsen, 2019; Smith, Ficht, Hobson, Sorensen, & Hervieux, 2000)

The findings from this study could be integrated into managing the cumulative effects of anthropogenic land uses. For instance, in assessing cumulative effects in the old-growth forest in BC, land managers determine whether the number of anthropogenic disturbances falls within a limit based on a legal order (FLNRORD, 2017). However, this study could add to this assessment strategy by demonstrating the likelihood of forest recovery from these possible incursions. The information from this study can complement the information from free-growing surveys of harvested blocks and other surveys that are used in BC. Based on the study findings, land managers would be able to identify the land transition between forest and barren land in the boreal forest zones. That is, these findings from the study are useful to land managers. First, the findings provide information about the differences in coniferous forest cover loss and gain and the amount of fragmentation between time points. Second, these findings inform the land manager about the differences forest cover change in the THLB and outside the THLB and the need to ensure the protection of caribou habitats amid the timber harvesting activities. With these results, land managers could undertake forest cover monitoring, which transcends reporting only the quantity of anthropogenic incursions. Thus, land managers would be able to generate a land management model that fully takes into consideration both disturbances and recovery dynamics in the boreal forest zones.

2.5 Conclusion

This study assessed forest change with an emphasis on how competing land uses are contributing to forest loss and fragmentation. The study finds that between 1985 and 2015, there has been a 2.3% net loss in the coniferous forest in the study area and a 0.6% net loss of the coniferous forest cover in the THLB. Also, the study finds that coniferous forest gain and loss occurred mostly in the THLB of the study area. However, the net loss of the coniferous forest cover in the non-THLB is higher than that of the THLB. Based on these findings, the study concludes that forest cover recovery from natural and anthropogenic processes is higher in the THLB than that of the area outside the THLB. This information is important for sustainable land management because land managers can determine which measures to incorporate to prevent forest degradation in the area outside the THLB and improve the rate of forest cover regeneration in the boreal forest zone.

Based on the amount of forest fragmentation measured and its coincidence with the periods of high and low rate of coniferous forest gain/loss and periods of lower and higher rate of forest cover recovery, this study concludes that land managers could reduce forest fragmentation by maintaining a larger quantity of forest cover as well as facilitating recovery of forest from anthropogenic activities (e.g., timber harvesting). Anthropogenic-induced barren land could occur because of timber harvesting, abandoning oil and gas well sites and old roads, and agriculture activities. Further studies could focus on investigating the type of anthropogenic-induced barren land that transitions into forest cover using higher-resolution land cover data. Such studies are likely to detect the details of the anthropogenic-induced barren land in the study area and present a detailed measurement of the coniferous forest fragmentation due to the details in the high-resolution land cover data. Also, the use of high-resolution images could reveal other disturbances (e.g. windthrow, insects and diseases) that were likely to be masked in this study because of the resolution of the Landsat images used.

Appendix 1 Supplemental information

A1 Table I Accuracy assessment of change area and no-change area between 1985 and 2000

		Reference data				
	Area of land	**Change area**	**No-change area**	**Total ground samples**	**User's Accuracy (%)**	**Commission Error (%)**
Predicted	**Change area**	0.050	0.002	0.052	96.774	3.226
	No-change area	0.047	0.901	0.948	95.023	4.977
	Total	0.098	0.902	1		
	Producer's accuracy (%)	51.641	99.814	**Overall accuracy:** 95.114%		
	Omission error (%)	48.359	0.186	**Margin of Error (ME)[§]:** ±2.811%		

§ The ME was calculated based on a critical value of 1.96, and it shows how the ground truth samples for change area and no-change area are representative of the sizes of the two strata and total sample (473) in determining the overall accuracy. Cell entries are expressed as the estimated area proportion of the cells of the error matrix. The margin of error estimate is presented with a 95% confidence interval.

A1 Table II Accuracy assessment of change area and no-change area between 2000 and 2015

	Reference data					
	Area of land	**Change area**	**No-change area**	**Total ground samples**	**User's Accuracy**	**Commission Error**
Predicted	**Change area**	0.049	0.003	0.052	93.561	6.439
	No-change area	0.047	0.901	0.948	95.023	4.977
	Total	0.096	0.904	1		
	Producer's accuracy (%)	50.812	99.629		Overall accuracy: 94.956%	
	Omission error (%)	49.188	0.371		Margin of Error (ME)[§]: ±3.021%	

§ The ME was calculated based on a critical value of 1.96, and it shows how the ground truth samples for change area and no-change area are representative of the sizes of the two strata and total sample (473) in determining the overall accuracy. Cell entries are expressed as the estimated area proportion of the cells of the error matrix. The margin of error estimate is presented with a 95% confidence interval.

A1 Table III Quantity of timber harvested land (cutblocks) in the study area and British Columbia-wide

Year	Quantity (Ha) of harvested land (cutblocks) in the study area*	Quantity (Ha) of harvested land (cutblocks) BC-wide	Study area share of the total cutblocks (%)
1985	8353	187768	4.449
2000	9278	200162	4.635
2015	14914	242288.172	6.155
% change (1985-2000)	11.074	6.601	(4.635-4.449) 0.187
% change (2000-2015)	60.746	21.046	(6.155-4.635) 1.520

***** Quantity of harvested land was retrieved from the BC data catalogue (Vegetation Resource Inventory (VRI) spatial data). The author computed the percentages and percentage change in the quantities of cutblocks.

CHAPTER THREE

Measuring forest change patterns from shale oil and gas land use dynamics in northeastern British Columbia, 1975 to 2017

Abstract

Information about forest cover change patterns from shale oil and gas (SOG) activities could improve our understanding of the land use-land cover change nexus, aid in predicting future forest changes, and prompt the need for more mitigation measures in reducing impacts from the activities. However, little is known about forest cover change patterns from shale gas infrastructure development in northeastern British Columbia (BC). This chapter of the dissertation assesses forest cover change from the impacts of SOG infrastructure development using a geospatial approach. The study finds that the forest cover has reduced by 0.234% between 1975 and 2017, but forest cover change (-0.182%) between 1995 and 2017 was faster compared to that of the two decades before 1995. The faster change coincides with the period of SOG boom in BC. Between time points and locations, a larger amount of forest fragmentation was measured in the land cover for the year and location with larger quantities of human-induced land classes. The differences in the quantity of human-induced land cover types between time points and locations could account for the differences in the amount of fragmentation. The findings of this study suggest that time and quantity of forest change could be theoretically-relevant variables when predicting forest change. However, most importantly, the increase or decrease in the magnitude of change agents, processes, and factors such as SOG infrastructure construction and the boom and bust in SOG activities are the viable and key explanatory variables to consider.

Keywords: shale oil and gas; human-induced land cover; forest cover fragmentation; spatiotemporal forest change; landscape metrics; remote sensing of forest

3.1 Introduction

Forest loss and fragmentation are global environmental issues, and over the past few decades, forest ecosystems have been changed by humans because of the increasing demand for food, fibre, freshwater, and energy (Song et al., 2016). Canada's boreal forest is changing due to anthropogenic land uses (forestry, agriculture, shale oil and gas (SOG) drilling, transportation, and human settlement development) and wildfire events (Hansen et al., 2013). However, since 1995, SOG drilling has been one of the fastest-growing anthropogenic activities contributing to forest change in northeastern British Columbia (Adams et al., 2016). The recent growth in SOG activities is the direct result of improvement in technology (e.g., application of horizontal drilling and hydraulic fracturing) and changing socio-economic factors (Soeder et al., 2014; Rahm, 2011). According to Rivard et al. (2014), the first shale gas production in Canada was in northeastern BC, with more shale gas well pads being constructed in British Columbia than any other province in Canada.

SOG industrial activities have both socio-economic benefits and biophysical impacts. For instance, in the US, shale gas production forms a significant portion of the total natural gas produced annually (Baihly et al., 2010), and generates a substantial amount of revenue for local, state, and federal governments (Considine, Watson, Entler, & Sparks, 2009). Through oil and gas supply to overseas markets, the western provinces of Canada continue to maximize revenue (Hebblewhite, 2017). Despite these benefits, SOG development pose threats to the environment including the decline and fragmentation of fauna habitats (Wilbert, Thomson, & Culver, 2008; Dyer, O'Neill, Wasel, & Boutin, 2001; Dyer, O'neill, Wasel, & Boutin, 2002; Braun, Oedekoven, & Aldridge, 2002). For example, linear corridors (roads and pipelines) increase the ease of travel for the wolves and as such alter the wolf-caribou relationships (Hebblewhite, 2017; Latham,

Latham, Boyce, & Boutin, 2011; Goddard, 2009; Sorensen et al., 2008; Nellemann & Cameron, 1998). Other primary concerns are that reclaiming a piece of land from SOG activities takes a long time, and the cleared forest land may not regrow after decommissioning of SOG activities (Hebblewhite, 2017; Van Rensen, Nielsen, White, Vinge, & Lieffers, 2015). Van Rensen et al. (2015) have shown that footprints of seismic lines could last for as much as 60 years. The long-term land recovery from SOG land degradation is, therefore, likely to affect the rate at which degraded habitats recover to support fauna. These prompt the need for measuring the quantity of forest change and fragmentation in the forests which serve as habitats for the fauna.

Previous studies have found that shale gas activities contribute to changes in agricultural land cover more than any other land category (see Donnelly et al., 2017; Preston & Kim, 2016, Drohan et al., 2012). In Pennsylvania (PA), Drohan et al. (2012) assessed the early impacts of shale gas activities on the forests and measured a significant amount of fragmentation in the core forest. Racicot et al. (2014) predicted a less than 1% forest cover loss in the potential shale gas development areas in Quebec. In BC, most of the studies related to SOG development focus on water quality assessment (Mason, Muehlenbachs, & Olmstead, 2015; Rivard, 2014). There have been studies that model and predict the impacts of decreasing habitats and an increasing SOG infrastructure on fauna (Johnson, Ehlers, & Seip, 2015; Nellemann & Cameron, 1998). Nellemann and Cameron (1998) for instance did not consider how much the infrastructure has reduced and fragmented the forest cover over the past years. Thus, in BC, the impacts of SOG infrastructure on forest cover are not well understood. In this chapter, the main objective is to measure the impacts of SOG pipeline right of ways, access roads, and well pads on the forest cover in northeastern BC using GIS, remote sensing, and landscape metrics. This study contributes to the shale gas-land change literature with empirical evidence from a study area in northeastern BC. Findings from this study could guide land managers in the allocation of shale gas infrastructures on different land cover classes in the future.

The inability to identify features finer than 30m by 30m spatial resolution poses a challenge in using Landsat images to measure impacts from shale gas features. Whereas there are higher chances of identifying new well pads with medium spatial resolution images (Wasson & Franklin, 2018), old well sites and finer resolution features such as access roads, pipelines, and seismic lines are not likely to be detected in the Landsat images. Consequently, some shale gas features are likely to be excluded from this forest change analysis. However, this limitation is likely to be mitigated by extracting spatial data for SOG infrastructure from high-resolution aerial photos and integrating with the Landsat images for feature-change analysis (see examples in Donnelly, 2018; Donnelly et al., 2017; Abrahams et al., 2011). Previous studies have used classified images from the National Land Cover Data (NLCD) for measuring land changes from shale gas drilling, and often only considered one baseline or pre-shale gas development year, often the year after shale gas activities started booming (see examples in Donnelly, 2018; Donnelly et al., 2017; Abrahams et al., 2015; Drohan et al., 2012). This study considers two baseline years for analysis using Landsat images, high-resolution aerial photos, and spatial data of SOG infrastructure to provide insights into the forest change pattern before and after the SOG boom. The integration of spatial data from high-resolution images and Landsat images for analyzing forest change could be applicable in locations where classified national land cover data are not available to provide insight into the land changes that occurred before and after the boom in SOG activities.

3.2 Materials and methods

3.2.1 Study area profile

This study was conducted in the geographical northeast of British Columbia (Figure 3.1). It was delineated to incorporate all locations in the northeastern BC where shale oil and gas activities are taking place. Since the early 1950s, petroleum exploration and development have been prominent in the area (Natural Resources Canada, 2017). More than 18,000 SOG wells have been drilled to date. The study area lies within Spruce-Willow-Birch (SWB), Sub-Boreal Pine-Spruce (SBPS), Mountain Hemlock (MH), and Alpine Tundra (AT) Biogeoclimatic Ecosystem Classifications (BEC) zones. The study area is in the boreal forest, and it is dominated by trembling aspen, black cottonwood, spruces, and lodgepole pine. The area, therefore, provides habitats for wildlife (e.g., moose, caribou, elk, stone sheep, mountain goats, black bear, grizzly bear and grey wolves). SOG activities are, therefore, likely to disrupt the habitats of these diverse wildlife_populations if SOG developers target the forest ecosystem. Figure 3.1 shows the study area in northeastern BC, including a 'treatment area' and a 'control area'. Both the treatment and control areas are 103,208 km^2 (10,320,800 ha). Both the control area and the treatment area are found within the boreal forest zone, and both locations have forest cover (see the map of the boreal forest in Brandt, 2009). However, the control area has more surficial geology present as compared to the treatment area. This difference in the control area and the treatment area in terms of geophysical and physiographic characteristics is likely to influence the differences in the amount of forest fragmentation.

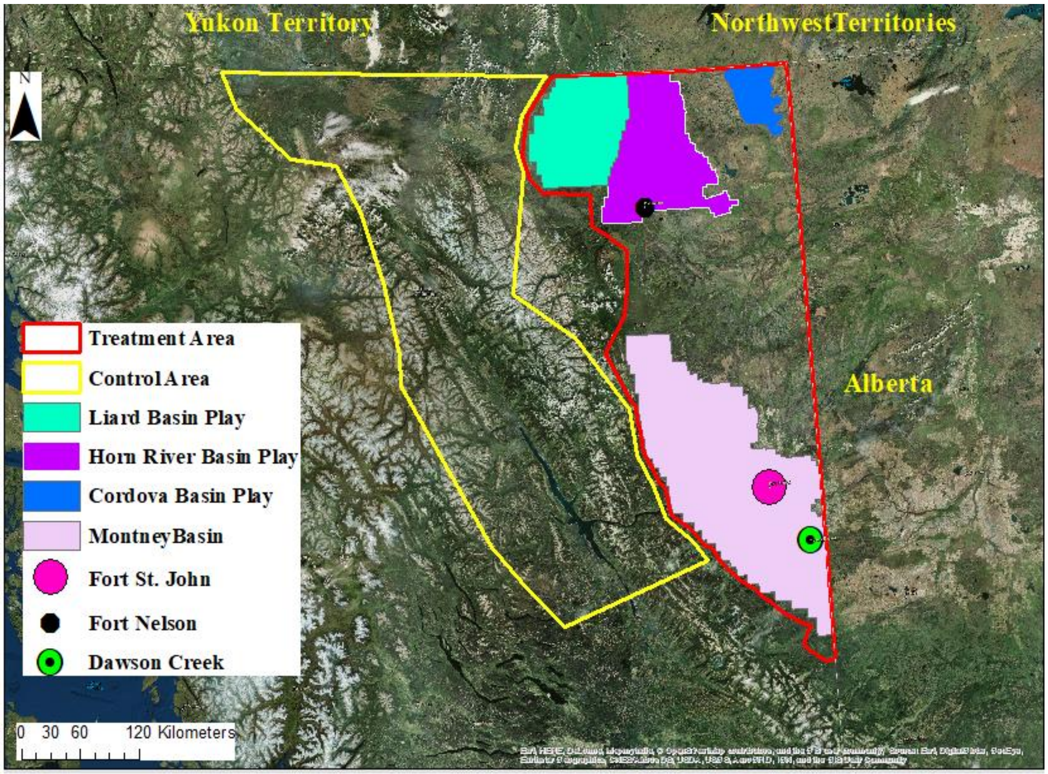

Figure 3.1 The study area and its surroundings.
Inside the red boundary (‘treatment’ area), there are both natural and anthropogenic (including shale gas land use) disturbances. Inside the yellow boundary (‘control’ area) are both anthropogenic and natural disturbances but without shale gas disturbances. The Montney, Liard, Cordova, and Horn Basin shale gas plays are the BC Oil and Gas Commission's management areas, and these are within the treatment area. Fort St. John, Dawson Creek and Fort Nelson are the major cities found in the treatment area.

3.2.2 Data types and sources

Surface reflectance Landsat images from 1975 (Multispectral Scanner (MSS) 5), and 1995 (Thematic Mapper (TM 5)) were used as base year datasets (pre-shale gas development images) for measuring changes between time points. Landsat images from 2017 (Operational Land Imager/Thermal Infrared Sensor (OLI/TIRS 8)) were used for making a comparison between the treatment area and the control area. The 1975 land cover data was chosen as a base year data because 85 percent of the wells were drilled in the years following this year (1975) (Adams et al., 2016). The 1995 Landsat image was used in this study to assess the differences in land change before and after the boom in shale gas activities in the mid-1990s. The 2017 OLI/TIRS images were used for comparison between the control area and treatment area because, as of December 2017, the SOG industry had constructed most well pads, pipelines, and other infrastructure. The imagery utilized was acquired between May-June of the years considered in this study and can be readily obtained from the US Geological Survey (see https://glovis.usgs.gov).

Additionally, high-resolution aerial photographs acquired from Google Earth Pro (1-1.5m spatial resolution) and ESRI DigitalGlobe (0.5m spatial resolution) were used in this study. These images aided in identifying the different land cover types in the Landsat images and as references for ground truth information. Google Earth images are suitable for accuracy assessment of classified land cover images (Dorais & Cardille, 2011) and were a relevant source of ground truth information in this study. Other spatial data used in the study are footprints of access roads, shale gas well pads, and shale gas pipeline right of ways (Figures 3.2 and 3.3). The spatial data for SOG well pads, pipelines, and roads were acquired from the British Columbia Oil and Gas Commission (BCOGC). The SOG data selected from the BCOGC database include all data for infrastructure approved and constructed between 1975 and 2017. Based on the good sampling practice recommendations (Olofsson et al., 2014), the stratified random sampling design was used to select 500 ground truths for each year randomly. For the 1995 image, the samples were chosen from 1995 high-resolution aerial photos, while a 2017 high-resolution aerial image was used to sample ground reference data for the 2017 data. For the 1975 classified image, random samples were from the original 1975 Landsat image for accuracy assessment.

Figure 3.2 Examples of shale oil and gas infrastructures from southern Dawson Creek in BC (centred around 55°35'28.60"N, 120°14'3.12"W)

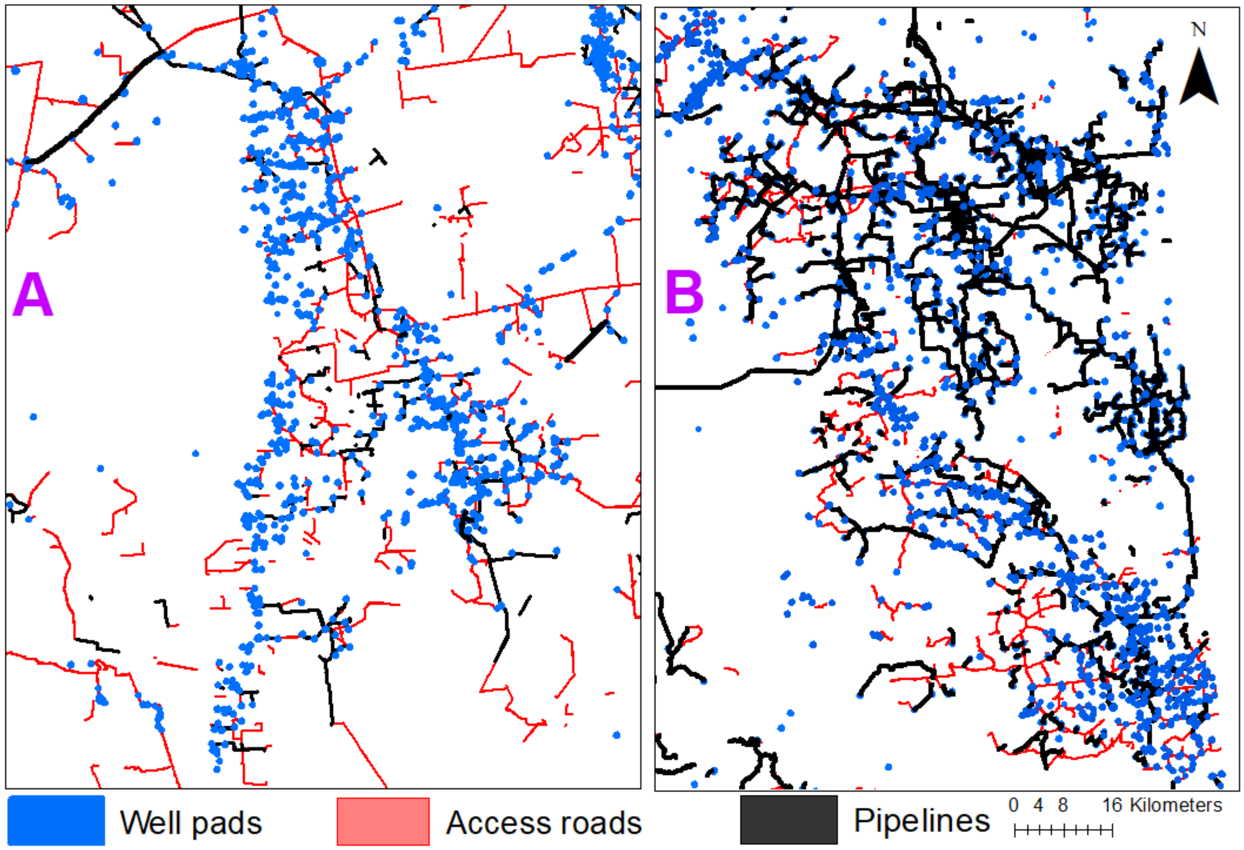

Figure 3.3 Shale oil and gas infrastructure (footprints) used in the feature-change analysis. Layer ‘A’ shows shale oil and gas infrastructure in the northern portion of the treatment area (centred around 59°26'5.98"N, 122°10'7.99"W). Layer ‘B’ shows shale oil and gas infrastructure in the southern portion of the study area (centred around 56°19'28.45"N, 120°37'17.10"W).

3.2.3 Image classification and accuracy assessment

Images from Landsat Multispectral Scanner (MSS 5), Landsat Thematic Mapper (TM 5), and Landsat Operational Land Imager/Thermal Infrared Sensor (OLI/TIRS 8) were composited to represent land cover conditions of 1975, 1995, and 2017, respectively. Following the best available pixels (BAP) approach, the images were composited to produce cloud and haze-free images (Franklin et al., 2015). A unified classification approach that combines unsupervised and supervised classification algorithms was used to classify each of the four images into five categories (water, forest, agricultural land, developed land, and barren land). The forest land category consists of trees including deciduous, evergreen, and mixed forest. Water is made up of perennial and permanent rivers, lakes, ponds, creeks, and streams. The barren land class includes bare ground, sand, gravels, and rock outcroppings. The agricultural land is made up of pasture, grasses, and herbs. Developed land consists of residential, commercial, transportation, and industrial land uses. These classes were identified based on visual inspection of the Landsat and high-resolution ancillary images (Stroppiana et al., 2012), and guidelines of image classification as proposed by (Anderson, 1976).

The K-means unsupervised classification algorithm was used to classify each of the Landsat images into 55 classes. A signature file was generated from the unsupervised classification process. A dendrogram (Environmental Systems Research Institute, 2016) was used to examine the relationship between land class identities in the signature file. The signature file was edited to reassign and re-group land cover pixels that could form new land classes. At the signature file editing stage, different classes of land assigned due to pixel reflectance similarities were reassigned to form appropriate classes. The signature file was updated and used as training data to perform a supervised classification using the Maximum Likelihood Classification (MLC) algorithm. Similar classification approaches that combine two or more algorithms have been used in a few studies and have proven very effective in image classification (e.g., Alphan, Doygun, & Unlukaplan, 2009; Kuemmerle, Radeloff, Perzanowski, & Hostert, 2006). However, an example of this classification approach has not been applied in a boreal forest environment to classify Landsat images.

The accuracy levels of the classified Landsat images were assessed using the ground truth points mentioned above. The good practices recommendation approach on accuracy assessment (Olofsson et al., 2014) was adopted to assess the accuracy of the classified Landsat images by taking into consideration the proportional area of the land classes, the number of ground truth samples, and the correctly predicted land cover pixels. The representativeness of the ground truth samples (in relation to the proportion of land classes) was assessed at a 95% confidence interval.

3.2.4 Aerial photograph interpretation and digitizing of shale gas features

Different methods have been used to acquire the spatial features representing SOG infrastructure. Donnelly et al. (2017) for instance, have extracted these features from high-resolution aerial images for a comparative study between Carroll County, Ohio and Washington County, Pennsylvania. Another method is by buffering centerlines and points which represent all the shale gas infrastructure to meet the actual sizes of the features on the ground (e.g., Langlois, Drohan & Brittingham, 2017; Drohan et al. 2012; Abrahams et al., 2015). The buffer distance is determined based on the actual sizes of the features (well pads, roads, pipelines) at the location under study (Johnson, Gagnolet, Ralls, & Stevens, 2011). For example, spatial data of road centerlines in northeastern BC could be buffered up to a specified width to represent the actual sizes of road width on the ground. However, buffering all points (representing well pads) or all centerlines (representing roads) with the same buffer distance or size means treating the features (well pads or roads) as if they are of the same sizes on the ground. There is a likelihood that these features would be overestimated or underestimated since the features are not of the same size or dimension.

For this study, there were challenges in identifying the access roads constructed purposely for SOG industrial activities. Because the footprint of the pipelines was not showing up clearly in the high-resolution images, there were challenges in differentiating them from the footprints of other linear features. Because of these complications, data for the shale gas features (well pads, pipelines and roads) from the BCOGC became an option for use in the study. Nonetheless, comparing the data from the BCOGC to the high-resolution aerial image from northeastern BC showed that not all well pads, pipelines, and roads are captured in the BCOGC's data. The spatial datasets representing the SOG infrastructure were overlaid on the high-resolution aerial imagery to ensure datasets from the BCOGC are up to date. Missing features were digitized from the high-resolution aerial image and added to the datasets acquired from the BCOGC (see Table 3.1 for the quantity of BCOGC's SOG data & the digitized data). Updating spatial datasets from the BCOGC is a step to reduce systematic biases that are likely to underestimate the quantity of shale gas infrastructure and their footprints on the landscape.

Table 3.1 Quantity of shale oil and gas infrastructure footprints used in the feature-change analysis

Shale oil and gas infrastructure/feature	Quantity* (ha) from BCOGC	Quantity* (ha) hand-digitized	Total Quantity (ha) on the landscape
Well pads	15,563.13	3,800.39	19,363.52
Access roads	1,796.21	238.37	2,034.58
Pipelines	2,155.36	610.79	2,766.15

***** quantity of shale oil and gas features used in the feature-change analysis also refers to the area of land or quantity of land occupied by the features. Note: BCOGC is the British Columbia Oil and Gas Commission.

3.2.5 Feature-change mapping: applying shale gas features to the categorical maps

The shale gas features were converted to raster layers and overlaid on the mapped classes. The classified images were resampled to 10m by 10m spatial resolution to capture the shale gas features appropriately. Different spatial resolutions (mainly 20 m by 20 m, 15 m by 15 m, and 10 m by 10 m) were tested. However, the 10 m by 10 m captures the fine spatial resolution (10 m by 10 m) SOG features in the classified land cover better than the other spatial resolutions tested. The omission of this step could affect the rate at which the SOG features impact the land cover as well as the spatial pattern and configuration of the end product of integrating the classified images with the shale gas features. Improper alignment between the shale gas features and the classified land cover image is likely to result in a wrong re-categorization of land, and thus, result in overestimation or underestimation of the actual impacts of SOG features on the landscape.

The raster layer of SOG features was applied to the classified images to produce feature-change land cover datasets. Based on an 'if-else' conditional analysis, the quantity of change in each of the land categories in the classified 1975 and 1995 Landsat images was evaluated. The 'if-else' conditional statement performs a cell by cell evaluation and reassigns cell values based on whether cells are evaluated as true or false. The statement is such that due to the construction of shale oil and gas infrastructure, the land cover categories have reduced to a developed land category. In the conditional analysis, if the cell value is evaluated as true, the land categories assume a value from the raster layer of shale gas features.

As part of the conditional analysis, if the conditional statement is evaluated as false, the forest and all the non-forest categories remain the same. First, any part of the forest land class found underneath the shale gas features is re-categorized into developed land. Second, in a situation where non-forest categories are underneath the raster layer of shale gas features, those non-forest categories were re-categorized into developed land. For example, if barren land is underneath the raster layer of shale gas features, the raster layer of shale gas features would affect the barren land category and, thus, convert that part of the barren land to developed land. Lastly, if the developed land category finds itself underneath the shale gas features, the developed land category would remain unchanged. The land cover images representing the land cover condition of 1975 and 1995 were compared to the land cover images representing the land cover conditions after shale gas features had been constructed. This comparison is parallel to comparing a landscape with fewer or no shale gas features to the same landscape with up to date or more shale gas features.

The approach to evaluating the cumulative land change from SOG infrastructure construction is likely to measure the amount of change in the whole landscape with a higher certainty. However, there is a limitation of slightly overestimating the change amount on a land class basis. That is, there is a possibility of slightly overestimating the size of the non-forest category or the portion of forest cover that changed into a developed land category when the SOG features are applied to the 1975 classified image. Between 1975 and 2017, land changes are likely to occur from disturbances other than that of shale gas features in the 1975 forest cover. The other disturbances could convert forest into other land cover categories. Disturbed areas that existed before the construction of the SOG infrastructure cannot be included in the analysis. Hence, those disturbances in the forest could be misattributed to the SOG features. Applying the shale gas raster layer to the 1975 forest cover data and converting some forest pixels into a developed land category means the shale gas features were constructed at locations where there were no disturbances in the forest cover before the construction of the features. For example, if there was a disturbance in the forest cover from agriculture in 1984, and a shale gas feature is constructed in the agricultural land in 2016, applying spatial data of SOG features from 2017 to a 1975 forest cover and attributing all changes to the features could be misleading. The calculated forest changes, however, would exclude the earlier disturbances in the forest contributed by the agricultural activities. It was, therefore, relevant to apply the shale gas features onto different land cover datasets at different points in time and discuss the observed differences in the changes that would occur. For this reason, the SOG features were applied to the 1995 classified Landsat image as well to compare with the change in the 1975 classified Landsat image.

3.2.6 Feature-change forest fragmentation analysis

After the feature-change datasets were produced from the classified land cover and the shale gas features, FRAGSTATS class metrics (McGarigal et al., 2012) were used to calculate the amount of fragmentation. The metrics used were mean patch size, the coefficient of variation of patch size, number of patches, mean shape index, the coefficient of variation of shape index, and aggregation index. The selected metrics are a combination of first and second-order metrics. Second-order metrics provide more useful information than first-order metrics (e.g., the number of patches, mean patch size) (Leitão, Miller, Ahern, & McGarigal, 2012). The use of second-order metrics is widely accepted and makes room for comparison between phenomena with different characteristics. For instance, using the coefficient of variation of selected metrics is relevant when comparing landscapes or classes with different mean patch sizes. Leitão et al. (2012) have posited that measuring variabilities are useful because using only the average statistics could be misleading. The occurrence of uneven distribution of values and the occurrence of extreme values (for example, very low values and very high values) are some of the limitations associated with using average measurements. The GIS-based Landscape Fragmentation Tool (LFT) (Vogt et al., 2007) was used to calculate the categories of fragmentation in the forest cover before and after the construction of the shale gas features. Descriptions of the metrics and categories of fragmentation are found in Tables 3.2 and 3.3, respectively.

The amount of forest fragmentation in the land cover of 1975 was compared to that of 'after 1975'. The land cover of 1995 was compared to that of 'after 1995'. The 'after 1975' land cover is the feature-change land cover made up of the 1975 classified Landsat image and the raster layer of shale gas features generated through the 'if-else' conditional analysis. The 'after 1995' dataset is the feature-change land cover made up of the 1995 classified Landsat image and the raster layer of SOG features. Also, a comparison between the treatment area and control area was made to establish the differences in the land cover composition and the amount of forest fragmentation.

Table 3.2 FRAGSTATS class metrics and their descriptions

Metrics*	**Description**
Number of patches (NP)	The total number of patches in each class.
Mean Patch Size (Area_MN)	Average patch size in each class measured in hectares.
Patch size coefficient of variation (AREA_CV)	It measures relative variability about the mean (that is, variability as a percentage of the mean), not absolute variability. A low value means less variability in patch sizes and vice versa.
Mean shape index (Shape_MN)	The shape index measures the complexity of patch shape compared to a standard shape (square) of the same size. The value is 1 when the patch is square and increases without limit as patch shape becomes more irregular.
Coefficient of variation of forest patch shape Index (Shape_CV)	Shape_CV is variability (standard deviation) in the patch shape expressed as a percentage of the mean shape index. A low value means less variability in the patch shape and vice versa.
Aggregation index (AI)	AI measures aggregation. AI equals 0 when the focal patch type is maximally disaggregated and equals 100 when the patch type is maximally aggregated into a single, compact patch.

The information in the table is from McGarigal et al. (2012). * Metrics were calculated using an edge width of 100m (which indicates the distance over which shale gas infrastructure and other land uses could degrade the forests) was used for the fragmentation analysis (Laurance et al., 2018; Laurance et al., 1998).

Table 3.3 Descriptions of categories of fragmentation

Category of Fragmentation	Description
Patch forest (PF)	They are fragments that are completely degraded (i.e., without forest pixels) by the "edge effect*." A low-value PF means a low amount of fragmentation and vice versa.
Edge forest (EF)	EF occurs within the "edge effect" zone along the outside edge of a non-patch tract. A low-value PF means a low amount of fragmentation and vice versa.
Core forest (CF)	CF occurs outside of the "edge effect" zone, and so it is not degraded by fragmentation. A high-value CF means a low amount of fragmentation and vice versa.
Perforated forest (PFF)	This category occurs within the "edge effect" zone along the edge of a small clearing in a non-patch tract. A low-value PFF means a low amount of fragmentation.

***** An edge width of 100 m (which indicates the distance over which shale gas infrastructure and other land uses are likely to degrade the forests) was used for the fragmentation analysis. The edge effect zone is within the 100 m width (Laurance et al., 2018; Drohan et al., 2012; Laurance et al., 1998).

3.3 Results

3.3.1 Changes in land categories from shale oil and gas infrastructure, 1975-2017 and 1995-2017

As compared to the water, agricultural land and barren land, the forest category received more impacts from SOG infrastructure development. However, the decrease in the forest cover in 1995-2017 (0.182%) is less than that of 1975-2017 (0.234%) (Table 3.4). The landscape of the study area in northeastern BC was altered by SOG infrastructure more in 1975-2017 than in 1995-2017 (see Figure 3.6), but the difference (0.02%) in the quantity of overall land change in these two periods is minimal. Figures 3.4 and 3.5 show the mapped land cover classes in the study area.

The accuracy levels measured from the classified Landsat images are 96.62% and 94.47%, respectively for the 1975 and 1995 classified images used in the 'if-else' conditional analysis. The classification accuracies for the 2017 classified images for the control and treatment areas are 92.56% and 96.53%, respectively. The average margin of error measured for the sampled ground truths in proportion to the areas of land classes is ±4.56%. The details of the accuracy assessment results for all classified images are in Appendix 2 Table I-IV.

Table 3.4 Categories of land and percentage of change, after 1975 and after 1995.

	After 1975 (1975-2017)		
Category	**% of category before OG**	**% of category after OG**	**% change in category after OG**
Water	2.641	2.636	-0.005
Forest	88.797	88.563	-0.234
Barren	0.903	0.882	-0.021
Agriculture	6.688	6.685	-0.003
Developed	0.971	1.234	0.263
	After 1995 (1995-2017)		
Category	**% of category before OG**	**% of category after OG**	**% change in category after OG**
Water	1.06535	1.06533	-0.00002
Forest	77.263	77.081	-0.182
Barren	5.876	5.847	-0.029
Agriculture	12.838	12.813	-0.025
Developed	2.958	3.193	0.235

The percentage of land category after the construction of shale oil and gas (OG) features is the quantity of land that persisted after OG activities, up to 2017. The percentage change in the category also represents the amount of land that transitioned into developed land.

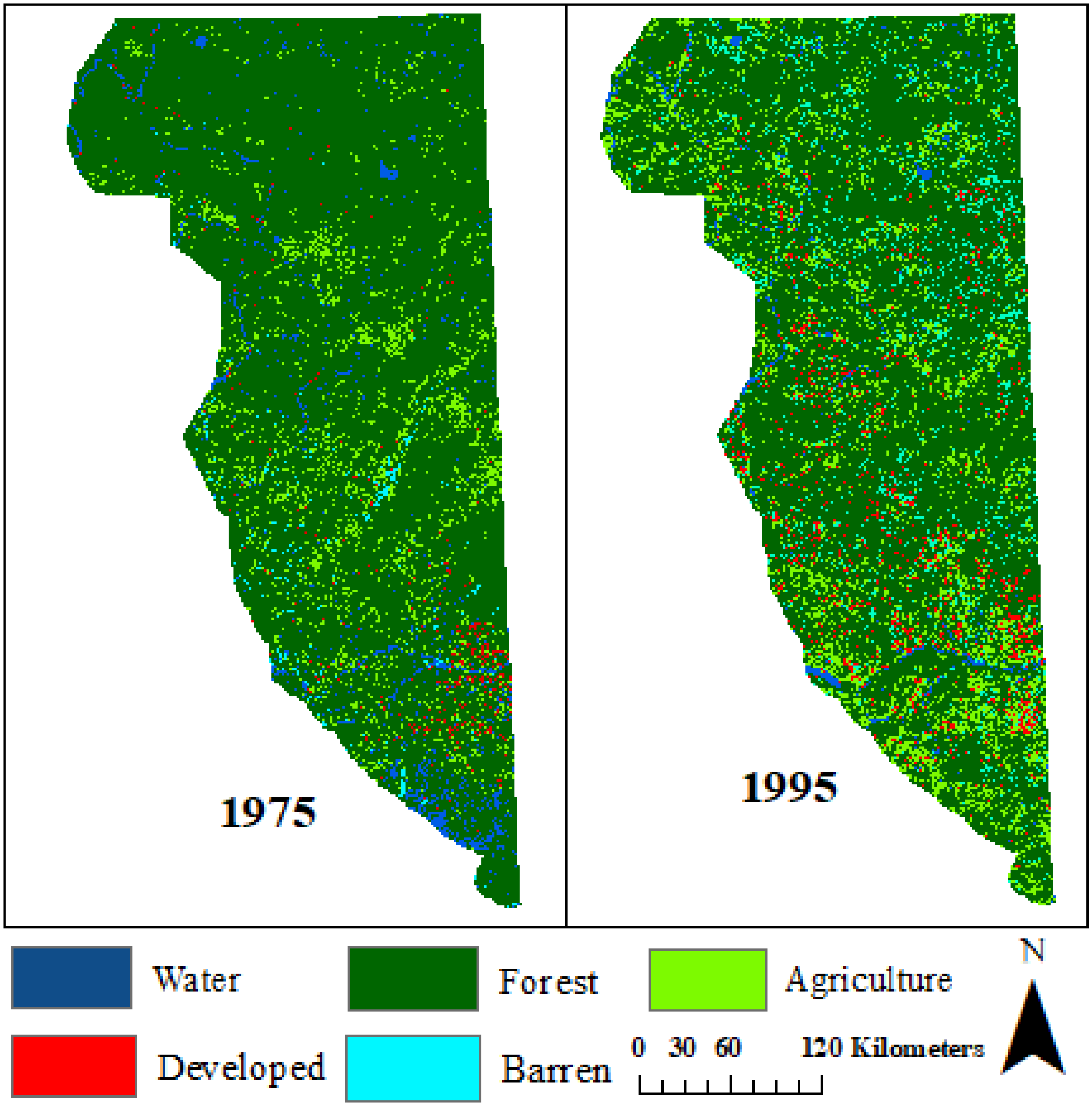

Figure 3.4 Land cover and land use classes (from the Landsat images) in the study area in 1975 and 1995

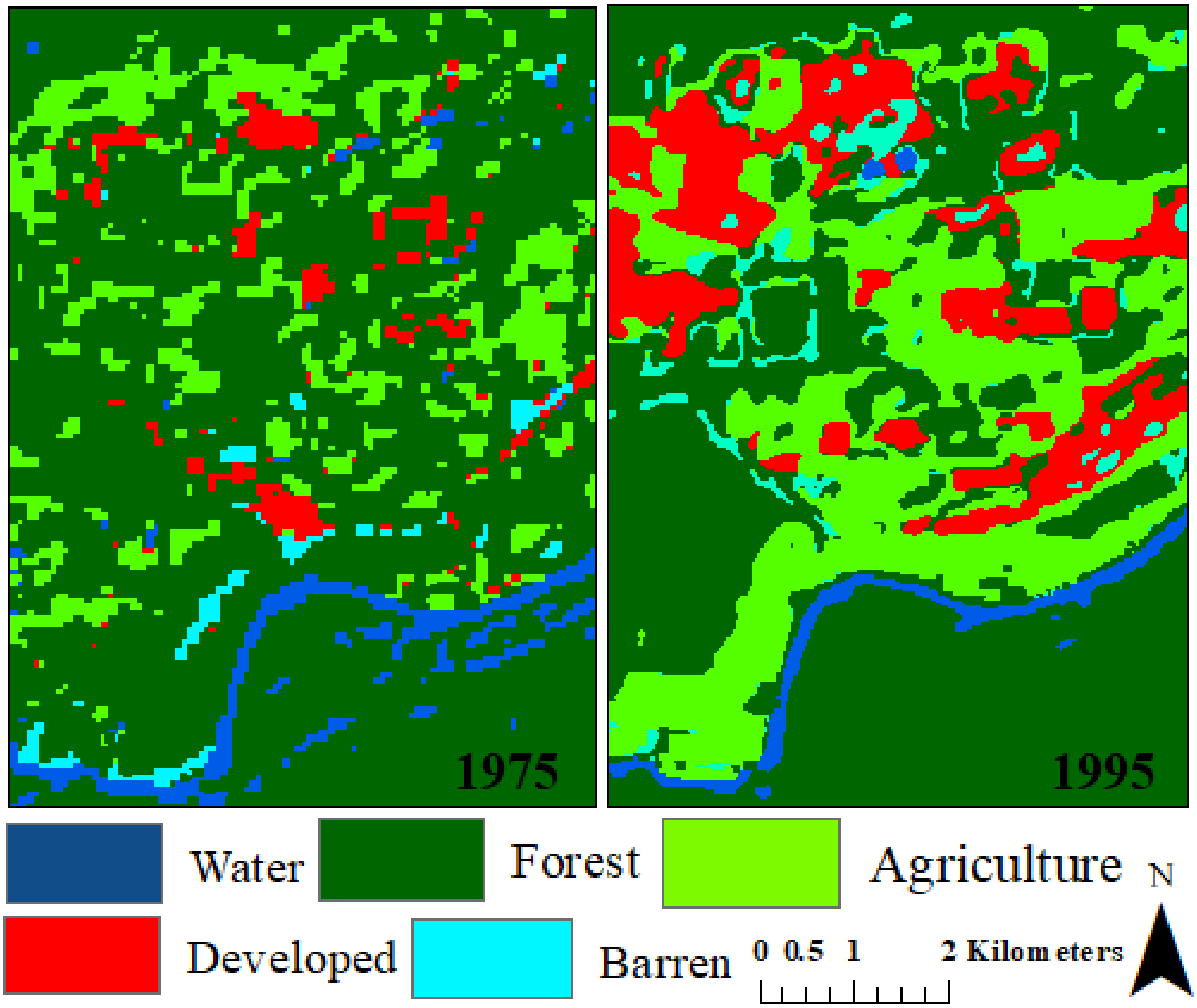

Figure 3.5 Zoomed in: a portion of the 1975 and 1995 classified Landsat images for the study area at a location in Chetwynd, BC (centred around 55°39'23.00"N, 121°42'34.35"W).

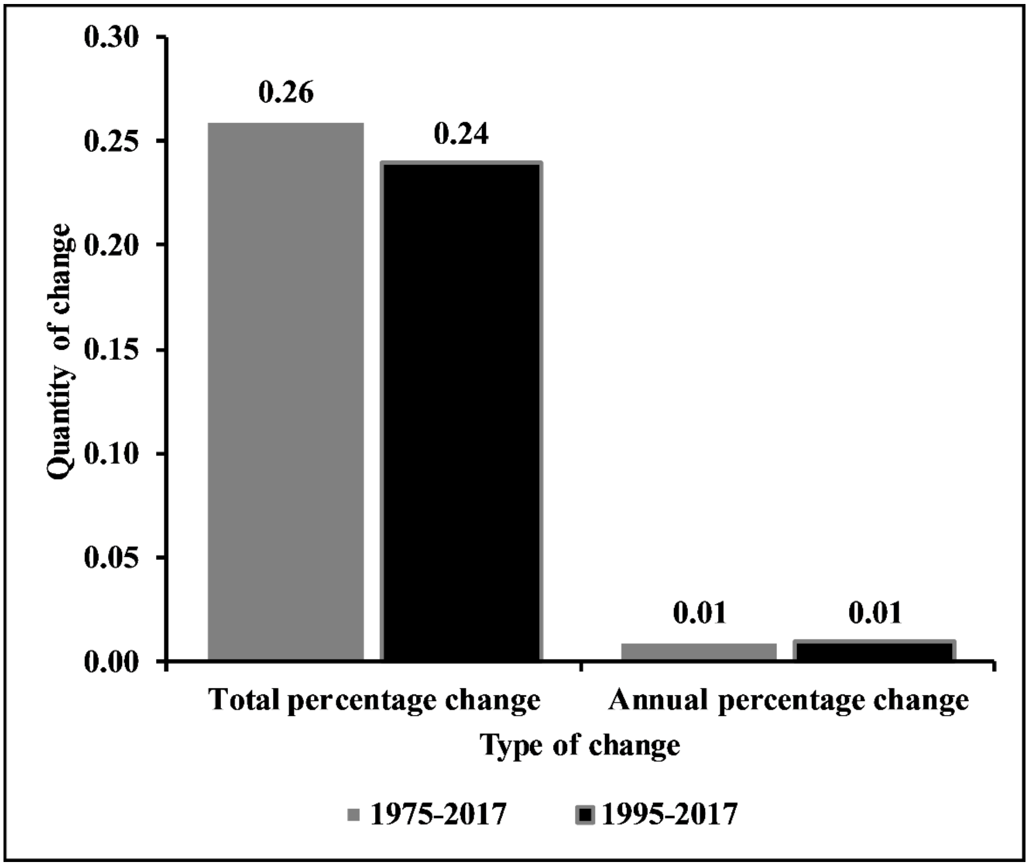

Figure 3.6 Overall change in the landscape after the shale oil and gas infrastructure development. This change represents the total amount of other land categories that reduced to developed land category.

3.3.2 Categories of fragmentation, composition, and pattern of forest patches after SOG infrastructure

The core forest reduced more during 1975-2017 than in 1995-2017 (see Table 3.5). Even though the period between 1995 and 2017 is shorter than that of between 1975 and 2017, the amount of forest fragmentation from the SOG infrastructure development in these two periods is similar. The higher intensity of forest fragmentation in 1995-2017 is apparent in the increased edge forest, perforations, and the degraded patches (see Table 3.5).

The patches of forest increased more in 1995-2017 than in 1975-2017 (see Table 3.6). The size of patches, however, reduced more in 1975-2017 than in 1995-2017 due to the creation of

SOG features. The sizes of the forest patches are more uniform in 1975-2017 than in 1995-2017. The forest patches in 1995-2017 are close to being square-shaped than the forest patches in 1975-2017. Forest patches are more aggregated in 1975-2017 than in 1995-2017 (see Table 3.6).

Table 3.5 Percentage of categories of forest fragmentation, 1975-2017 and 1995-2017.

Category of fragmentation	**% Category in 1975**	**% Category after 1975**	**% Change in category**
patch	0.696	0.704	0.008 (an increase)
edge	8.170	8.242	0.072 (an increase)
perforated	15.078	15.645	0.567 (an increase)
core	76.055	75.408	-0.647 (a decrease)
Category of fragmentation	**% Category in 1995**	**% Category after 1995**	**% Change in category**
patch	2.214	2.231	0.017 (an increase)
edge	14.372	14.473	0.101 (an increase)
perforated	15.254	15.662	0.408 (an increase)
core	68.160	67.634	-0.526 (a decrease)

Table 3.6 Forest landscape composition and configuration, 1975-2017 (before and after shale OG infrastructure construction)

	Metrics*					
Year/After OG	**NP**	**Area_MN**	**Area_CV**	**Shape_MN**	**Shape_CV**	**AI**
1975	33499	262.9516	14151.216	1.1418	133.9686	94.196
After 1975	33663	260.9536	14181.856	1.1425	136.1108	94.0519
Change after 1975	164	-1.998	30.64	0.0007	2.1422	-0.1441
1995	61989	120.3203	21295.5869	1.2085	125.1083	91.1644
After 1995	62351	119.3213	21356.493	1.209	126.264	91.0411
Change after 1995	362	-0.999	60.9061	0.0005	1.1557	-0.1233

* NP= the number of forest patches, Area_MN= mean patch size, Area_CV= coefficient of variation of mean patch size, Shape_MN= mean shape index, Shape_CV= coefficient of variation of the mean shape index, and AI= aggregation index.

3.3.3 Characteristics of forest cover patches at SOG area and non-SOG area

Figure 3.6 shows the proportions of land categories in the treatment and control areas. The treatment area has a larger quantity of forest cover than the control area. Also, the treatment area has a large portion of land cover classes that depict human activities (developed land and agricultural land). The differences in the proportion of human-induced land cover classes in the two study areas are in Figure 3.7, and Figure 3.8 is a visual representation of the land classes in the control and treatment areas.

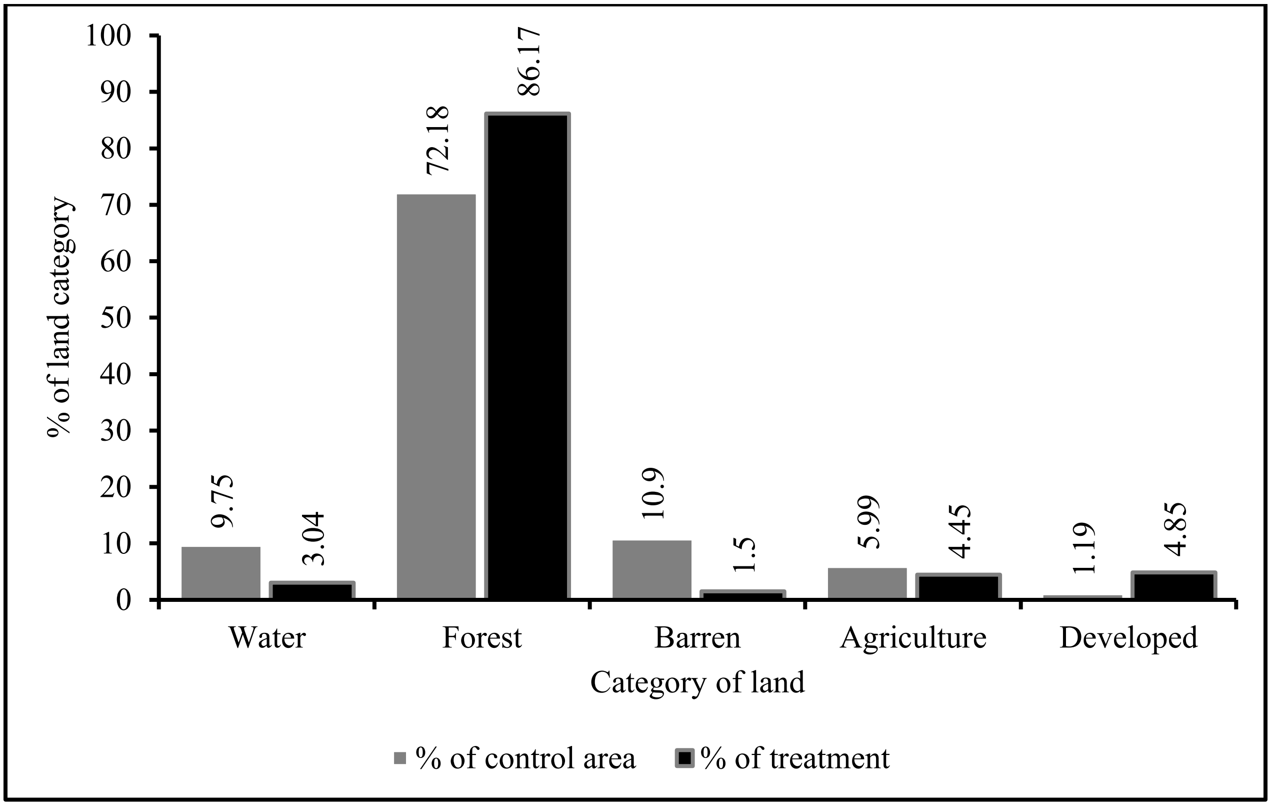

Figure 3.7 Quantity of forest cover in the control area and treatment area.
Figure 3.7 shows the forest cover compositions of the treatment area and the control area. Other land cover classes are also displayed to show how the amount of forest cover compares with the amount of other land cover classes.

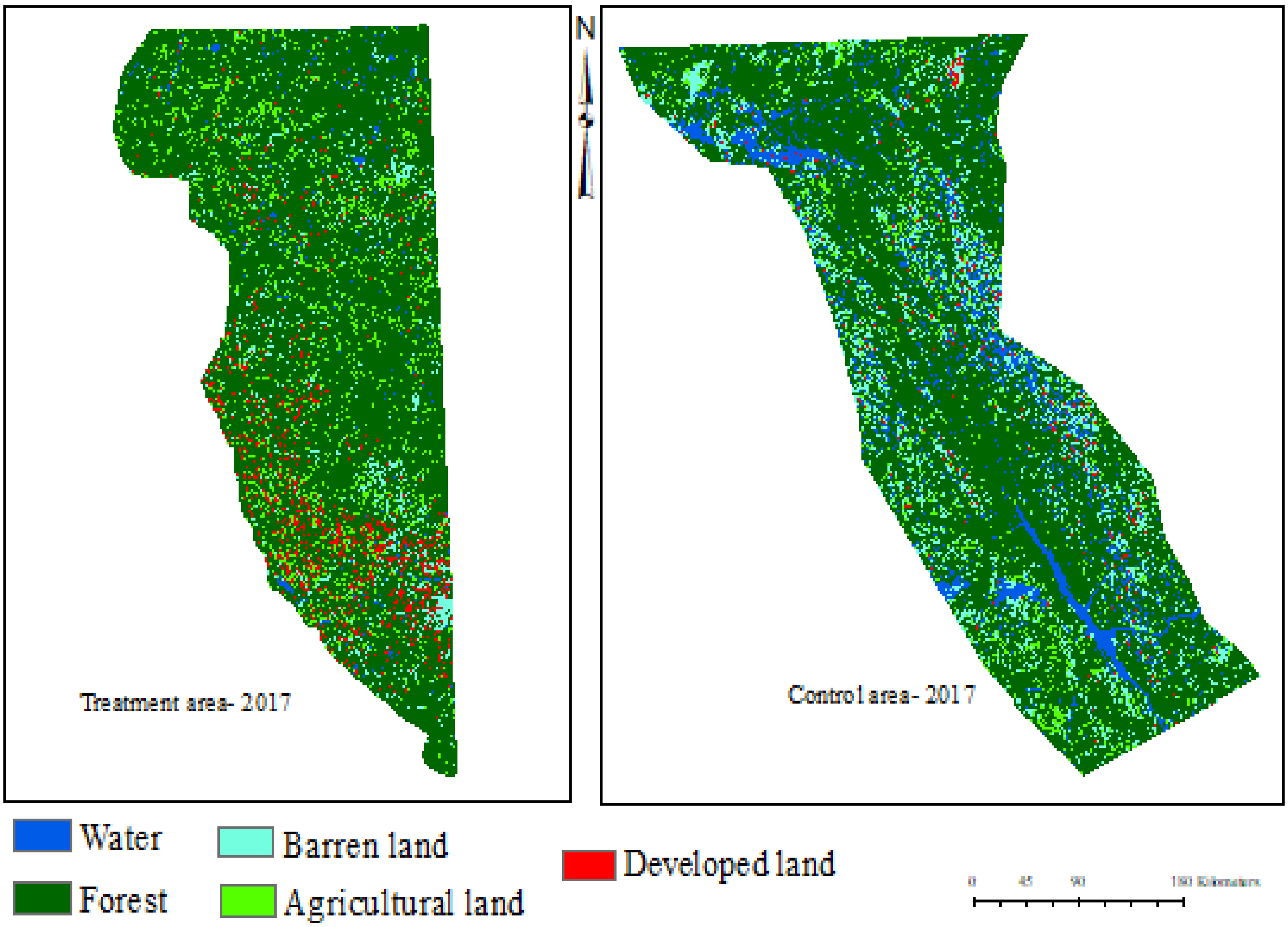

Figure 3.8 Mapped land classes in the control area and treatment area, 2017

The forest landscapes of the treatment area and control area exhibit distinctive characteristics regarding patch composition and pattern. Even though the forest cover in the treatment area is larger than that of the control area, the forest cover in the control area has more aggregated patches (see AI in Table 3.7). The coefficient of variation in the patch sizes shows the patch sizes are more similar in the control area than in the treatment area. Also, the coefficient of variation in the shape index shows more near-square shaped patches in the control area than in the treatment area (Table 3.7). The larger degraded patches of 1.8%, larger perforations and a smaller core area of the treatment area point out that the control area is less fragmented than the treatment area (Table 3.8). As of December 2017, the quantity of SOG infrastructure was mostly in the perforated and the core forest categories (see Table 3.9).

Table 3.7 Composition and configuration of forest patches in the treatment and control areas

				Metrics*		
Area	**NP**	**Area_MN**	**Area_CV**	**Shape_MN**	**Shape_CV**	**AI**
Control	33750	221.55	16815.10	1.27	93.64	94.97
Treatment	57065	145.84	23234.91	1.17	137.78	91.71

* NP- the number of forest patches, Area_MN- mean patch size, Area_CV- coefficient of variation of mean patch size, Shape_MN- mean shape index, Shape_CV- coefficient of variation of the mean shape index, and AI- aggregation index.

Table 3.8 Categories of fragmentation in the control and treatment areas in 2017

Category of fragmentation	% of the control area	% of treatment
Patch	0.97	1.8
Edge	11.39	8.5
Perforated	6.6	20.24
Core	81.03	69.47

Table 3.9 Quantity of shale oil and gas features in the treatment area as of 2017

Category of fragmentation	Quantity (ha) of OG features found on forest land	% of OG features found on forest land
Patch	498.96	4.53
Edge	1532.52	13.92
Perforated	5188.68	47.12
Core	3790.44	34.42

3.4 Discussion

3.4.1 Shale oil and gas feature-induced forest change

This study finds that the amount of forest change measured after 1975 is more than that of after 1995. However, the similarity in the quantity of forest cover change from SOG infrastructure development in the two periods suggests the following. First, it is less likely that there were more disturbances contributed by other land change agents that have been attributed to the shale gas features in 1975-2017. Second, the amount of reduction in the forest cover after 1995 implies there has been a faster change in 1995-2017 than in 1975-1995. Between 1975 and 2017 is forty-two years, and the average change (reduction) in the forest cover per year is computed as 0.006% (0.234/42 years). Conversely, between 1995 and 2017 the average change (reduction) in the forest cover per year is calculated as 0.008 (0.182/22 years). This pattern of change in the forest cover following SOG infrastructure construction suggests that in the two decades after 1995, the forest cover received more impacts than the two decades before 1995.

The reduction in forest cover and the increase in land use (agricultural land and developed land) between 1975 and 1995 could improve our understanding of dynamics of land use decision making and its effects on the biophysical characteristics of the land. As noted, the change in the quantity of the forest cover resulting from SOG features was higher in 1975-2017 than that of between 1995 and 2017. However, between 1995 and 2017 agricultural land increased and received more impacts from the SOG infrastructure development. Hence, after 1995, the rate of reduction in the non-forest land categories increased. This pattern of change suggests that as the non-forest land increases, some impacts from the construction of SOG features could be diverted towards it (the non-forest land). Specifically, in the study area, the results further suggest that at the time of the faster change in the landscape, it is likely that agricultural land received more impacts than before, especially when the quantity of agricultural land becomes larger than that of the previous years.

The intensity of SOG development could explain the differences in forest cover reduction before and after 1995. The effort wielded towards developing unconventional SOG increased during the mid-1990s (Natural Resources Canada, 2017). According to Natural Resources Canada (2017), with the horizontal drilling technology, a significant unconventional tight gas was identified and developed successfully in the mid-1990s in northeastern BC. Mason et al. (2015) have hypothesized that due to the use of horizontal drilling, the impacts of SOG on lands are expected to be lesser because developers could drill more wells on a well pad without the need to construct additional well pads that could alter the landscape. However, in northeastern BC, it is at this period (from 1995-2017) of increased horizontal drilling that SOG infrastructure development has impacted more on the forest cover in the two decades after 1995. It is likely that new SOG infrastructure was constructed in the forests of the study area during this period, and this is likely to lead to forest cover loss in the years after the mid-1990 in northeastern BC.

The findings from northeastern BC are inconsistent with results from land change studies in other parts of North America. For instance, Drohan et al. (2012) found that more shale gas features are in the agricultural land (45-62%) than in the forest land (38-54%) in Pennsylvania. The difference between the outcome of this study and that of Drohan et al. (2012) is that whereas this study from northeastern BC measures the actual land change contributed by shale gas features, the study from Pennsylvania calculates the percentage of features found in each of the land cover classes. However, more agricultural land would likely be converted as compared to forest land in PA since more of the features are found in the agricultural land than in the forest land. At an early stage of development in the Williston Basin, USA, shale gas development converted a larger quantity of agricultural land (49.5%) than forest cover (0.4%) (Preston & Kim, 2016). There are no studies in the Western Canadian boreal that are directly related to this study in northeastern BC to which these results can be compared; and thus the study compares results with other findings from Pennsylvania, Williston Basin, and other studies from the United States even though the ecological zones in these locations are different from that of northeastern BC. However, the basis of comparison between the studies from the United States and northeastern BC is the fact that these locations are undertaking shale oil and gas activities, and these activities have profound impacts on different land cover types.

The quantity of forest land and other non-forest categories at the initial time point of 1975 is likely to account for the higher impacts on the forest land as compared to that of the non-forest categories in the study area. The information in Table 3.4 shows that when the size of agricultural land increased after 1995, the impacts of shale gas activities on agricultural land also increased. In the Williston basin shale gas region, the quantity of agricultural land is almost equal to the quantity of forest land; wheat fields alone account for about 25% of the total land surface in the Williston basin (Preston & Kim, 2016). It is therefore reasonable that there were more impacts on the agricultural land than on the forest land in the Williston Basin. Similar to the shale gas region in the Williston Basin, Pennsylvania's SOG fields have 24% of its land as agricultural land (Drohan at al., 2012). Hence, land managers are likely to have options to avoid the construction of SOG infrastructure on the forest land to a greater extent and instead develop the SOG infrastructure on the agricultural land. In this study in northeastern BC, at the base years, agricultural land constituted 7% (1975) and 12% (1995) of the landscape whereas the forest cover formed 88% (1975) and 77% (1995). These land cover compositions might not present more options for decision-makers than to grant shale gas development permits on the forest land, especially when the SOG bearing rocks are underneath the forest cover. Most of the SOG infrastructure development avoid forest cover to some extent, and the rate of change or conversion in the forest cover is 0.23% in northeastern BC. Nonetheless, even though the SOG infrastructure development in the northeastern BC targets forest instead of agricultural land, they avoid the forest landscape better than in other locations such as the Williston Basin, where forest cover has reduced by 0.4% (see Preston & Kim, 2016).

Another difference between northeastern BC and the eastern USA in terms of oil and gas production and landscape impacts lies in the time the shale gas activities became more active in the two regions. According to Natural Resources Canada (2017), shale gas industrial activities in northeastern BC became more active in the mid-1990s. Studies from eastern North America show that the boom in shale gas industrial activities is recent but has contributed to a sudden change in land cover composition. Most of the land change studies, therefore, use pre-shale gas development land cover data acquired in the early 2000s (see for example Donnelly, 2018; Langlois et al., 2017; Donnelly et al., 2017; Preston & Kim, 2016; Abrahams et al., 2015; Drohan et al., 2012). At the booming stage (in the early 2000s) of SOG development, a considerable quantity of the forest cover might have already converted into agriculture or other land categories. These forest conversions from the previous land use are likely to explain why the shale gas industrial activities target other land categories instead of the forest cover in locations such as in Ohio and Pennsylvania. The faster change measured after 1995 in northeastern BC can, therefore, be compared to that of the eastern United States due to the similarities in the rapidity of the change following the boom in shale gas activities. The results from previous studies in the United States when compared to the findings from this study improve our understanding of the characteristics of past and recent land changes and how these are related to the boom in unconventional shale gas activities. These findings on land change could form a theoretical basis for modelling, simulating, or projecting forest change patterns from SOG infrastructure construction at a point in time.

3.4.2 Shale oil and gas feature-induced forest fragmentation

The results from the forest fragmentation analysis suggest that the boreal forests in the study area have been fragmented as a result of the oil and gas activities, and from an ecological point of view, the amount of fragmentation is likely to affect the boreal woodland caribou habitats. Fragmentation of the study area in northeastern BC's forest landscape was more pronounced in the core forest category in 1975-2017 than in 1995-2017. However, the difference in the quantity of core forest change is minimal when comparing between the two periods, an indication that the forests have been fragmented more in the two decades after 1995. Even though the core forest was affected more than the other categories of fragmentation, ecologically significant degradation (e.g., the increase in the edge and degraded patches) also occurred after 1995. The creation of forest edges is identified as a secondary form of fragmentation of the forest landscape (Abrahams et al., 2015). That is, the increase in edge forest occurs after there has been a primary fragmentation (reduction in core forest patches). The core forest has been the primary target for SOG infrastructure development as the past, and current research findings show. A simulation of forest change from SOG impacts in the St. Lawrence lowlands near Quebec City predicted a more than 39% reduction in the core forest (Racicot et al., 2014). The study by Racicot et al. (2014) did not measure the actual impacts, and hence, the actual impacts have to be measured in the future. However, the impacts measured in PA and northeastern BC show that this prediction is likely to be accurate regarding the core forest fragmentation. The quantity of land change could be dependent on factors such as the local decision making about the land and the boom or bust in SOG activities.

The impacts from the construction of SOG infrastructure in northeastern BC and its associated forest fragmentation are consistent with the pattern of land change in Pennsylvania as shown by Drohan et al. (2012). In both Pennsylvania and northeastern BC, shale gas infrastructure development has mostly occurred in the core forest. In Pennsylvania, 26% of the shale gas features (well pads) are found in the core forest. However, the methodological differences in the research from Pennsylvania and northeastern BC have led to the differences in the perspectives from which forest fragmentation has been reported. Whereas Drohan et al. (2012) reported the proportion of features found in each of the fragmentation categories, this study from northeastern reports the proportion of change in categories from the construction of the shale gas features.

Forest landscape fragmentation dynamics have also been assessed in this study by considering the differences in forest cover and patch composition and configuration between the shale gas field and a non-shale gas area. The treatment area which had a larger quantity of forest turned out to be the most fragmented as compared to the non-shale gas activity (control) area. However, the other categories of land use and land cover could explain these differences in the amount of fragmentation and composition of forest cover between the two areas. In the treatment area, anthropogenic activities such as agriculture, road construction, shale gas hydraulic fracturing have taken place on a larger scale. This land characteristic is especially true in the areas around Fort St. John and Dawson Creek.

The control area has biophysical characteristics that are different from the treatment area. Most importantly, the control area has a smaller agricultural land size, fewer road footprints, and a larger quantity of barren land (mostly outcrop of rocks). Previous studies have shown that landscapes with more footprints of human activities such as agriculture and road construction are likely to be more fragmented, characterized by a larger quantity of edge forest, smaller patch sizes, and discontinuous patches (Croissant & Munroe, 2016; Carranza et al., 2015; Chaplin-Kramer et al., 2015; Cattarino, McAlpine & Rhodes, 2014; Newman, McLaren, & Wilson, 2014; Bélanger & Grenier, 2002). The treatment area in this study exhibits such characteristics of forest fragmentation. The Fayetteville shale region in the United States, similar to the northeastern BC, has more edge forest in the gas field where road construction and other developments have increased as compared to locations off the gas field (Moran et al., 2015). The data in Tables 3.7 and 2.8 show that as at 2017, 20% of the forest cover was perforated, and in the same year, 47% of the shale gas features were found in the perforated portion of the treatment area. These land characteristics and composition of shale gas features suggest that the SOG infrastructure partly contributed to these perforations in the forest landscape. Also, the 34% (see Table 3.8) of shale gas features found in the core forest of the treatment area is a potential for further fragmentation of the forest cover.

3.4.3 Implications for forest land management

The findings of this study are relevant for forest resource management as well as managing the impacts of SOG development on the environment. The results show that more of the SOG wells are within the core forest area of the shale gas region. The results could be used as ancillary information by forest managers for determining the future allocation of well pads, access roads, and pipeline right of ways. The core forest forms a significant part of the habitats for the already endangered caribou species (Goddard, 2009). Land managers could prevent broader forest cover change and core forest fragmentation by reducing the quantity of the infrastructure in the forest, and this is possible currently due to advances in the technology for horizontal drilling. Empirical evidence from Ohio and Pennsylvania shows that shale gas infrastructure is likely to cut through forests to disrupt connectedness of forest habitat, reduce core forest and increase the forest edge (Donnelly et al., 2017; Abrahams et al., 2015; Drohan et al., 2012). In Alberta, Sorensen et al. (2008) have modelled the impacts of linear features and suggested the reduction in industrial footprints in the boreal caribou habitats. In BC, the industrial footprints are within 71% of the caribou range (Goddard, 2009), and the fact that most of the SOG infrastructure has impacted the core forest, increasing the shale gas industrial footprint is likely to increase access roads and most importantly well pad sites. These are likely to increase caribou habitat loss and exposure of caribou to predation. As the industrial footprints increase in the habitats, the ability of the caribou to distant themselves from the linear corridors reduces, and this, in essence, increases the likelihood of predation (Ritchie & George, 2012; Goddard, 2009).

The results from this study are also particularly relevant for managing cumulative effects (the actual and potential impacts of human activities) in the environment. For instance, in BC, land managers assess the human impacts in the old-growth forest by measuring the number of disturbances. The quantity of forest change measured in this study provides information for the forest managers in determining the count of human incursions that could be accommodated without disrupting the forest ecosystem. Land managers would be able to ascertain the quantity of additional forest loss and fragmentation (apart from the quantity measured in this study), which are deemed ecologically sustainable. In northeastern BC where forest land is more extensive than any other land category, shale gas industrial activities would likely take place in the forest, especially during periods of oil and gas boom. The quantity of forest cover reduction and fragmentation after 1995 could be relevant information for land management purposes. For instance, the amount of change measured in this study and its coincidence with the shale gas boom connote to land managers that the period of an economic boom in the oil and gas industry is a period to measure significant impacts from the shale gas features. Hence, during such a period, land managers could make efforts to increase unconventional shale gas industrial activities on non-forest land categories.

The reduction in forest cover, the increase in human-induced land categories, and the larger amount of fragmentation after 1995 are essential information for land managers to link proximate or direct forest change factors to forest change patterns in the study area. Also, the quantity of change measured in this study and its coincidence with the mid-1990 boom in shale gas activities make room for land managers to link underlying or indirect change factors to the forest change patterns. The findings from the control and treatment areas show there is a need for forest land managers to protect the areas with no SOG infrastructure while improving efforts towards land reclamation after decommissioning of SOG activities. As suggested by Klaiber et al. (2017), more wells could be added to the already constructed well pads to reduce the construction of new well pads. Developing new well pads is likely to lead to the clearance of the forest cover. Effective land management practices to protect areas with no SOG infrastructure could involve the enforcement of full utilization of the advantage of horizontal drilling of wells which includes the drilling of up to eight wells on a single well pad.

3.5 Conclusion

This study investigated the dynamics of shale gas land uses and forest cover change between time points and locations using GIS, remote sensing, and metrics from landscape ecology. In so doing, the study provides insight into the characteristics of forest change in the period of SOG activity boom, before and after 1995. The study finds the quantity of forest cover that reduced after 1975 and after 1995 are larger than the losses in the other land categories. The reduction in the forest cover between 1975 and 2017 is similar to the proportion of reduction between 1995 and 2017. This similarity suggests a faster forest change in 1995-2017 than that of the twenty years before 1995. The time of the faster change shows that the change coincides with the technological improvement in hydraulic fracturing and the boom in unconventional SOG activities after 1995. Based on the quantity of forest change measured in 1995-2017, this study concludes that it is likely to experience more changes in the forest cover whenever there is a boom in the SOG industry. Hence, a study that intends to model future forest cover changes from SOG infrastructure development could consider a change variable representing the boom in SOG activities.

The quantity of forest that lost was mainly from the core forest, and so this study concludes that the shale gas activities are likely to threaten caribou habitats in northeastern BC. In comparing between locations (control and treatment areas), a larger quantity of forest on the landscape did not mean a lower level of forest fragmentation. With this finding, the study concludes that the level of fragmentation in the forest cover transcends the quantity of forest cover. Instead, the differences in the anthropogenic and natural factors, processes, or agents of change are likely to shape and ascribe a level of integrity to forest ecosystems. Between locations and time points, the quantity of forest cover could be very large yet more fragmented. The results suggest that researchers modelling future land or forest fragmentation from SOG activities should be more interested in factors, processes, and agents of change instead of the time factor and the quantity of forest. Furthermore, based on the findings, it is suggested that the increase or decrease in agricultural land, human-induced barren land and developed land in the forest could be some of the crucial factors to consider when projecting future forest fragmentation in settings which has biophysical characteristics such as in the study area in northeastern BC.

The higher level of accuracy in the Landsat image classification and the use of multiple sources of data for generating spatial data for the SOG infrastructure facilitated the reliable assessment of forest change from shale gas activities. Future comparative study of the impacts contributed by shale gas and agriculture activities in the forest cover of northeastern BC is recommended. The reconnaissance survey in the study area in northeastern BC, as well as visualizing the land cover from high-resolution aerial images showed a larger agricultural footprint than the footprints from SOG infrastructure development. Hence, this study hypothesizes that it is likely agricultural activities would contribute more to forest change than the SOG infrastructure footprints.

Appendix 2 Supplemental information

A2 Table I Error matrix of estimated area proportions for the 2017 control area Landsat image based on 500 ground truth samples.

		Reference Data							
	Class	**Water**	**Forest**	**Barren**	**Agriculture**	**Developed**	**Total**	**User's accuracy (%)**	**Commission errors (%)**
Classified Image	Water	0.086	0	0.006	0.005	0	0.097	87.912	12.088
	Forest	0.023	0.675	0.006	0.012	0.006	0.722	93.496	6.504
	barren	0	0.004	0.100	0.003	0.003	0.109	91.765	8.235
	Agriculture	0.0004	0.002	0.001	0.055	0.001	0.060	92.500	7.500
	Developed	0	0.0012	0.0001	0.0004	0.010	0.012	81.481	18.519
	Total	0.110	0.682	0.113	0.075	0.019	1		
	Producer's accuracy (%)	78.138	98.907	88.156	73.369	50.725	Overall Accuracy= 92.560%		
	Omission errors (%)	21.862	1.093	11.844	26.631	49.275	Margin of Error (ME)*= ± 4.441%		

*The ME was calculated based on a 95% confidence interval (critical value= 1.96), and it shows how the ground truth samples for each of the land classes are representative of the areas of the land classes and total sample (500) in determining the overall accuracy. Cell entries presented are the estimated area proportion of the cells of the error matrix.

A2 Table II Error matrix of estimated area proportions for the 2017 treatment area Landsat image based on 500 ground truth samples

	Class	Water	Forest	Barren	Agriculture	Developed	Total	User's accuracy	Commission errors (%)
		Reference Data							
Classified Image	Water	0.029	0	0.002	0	0	0.030	94.286	5.714
	Forest	0.007	0.840	0	0.007	0.007	0.862	97.521	2.479
	barren	0	0.0004	0.014	0.0003	0.0003	0.0150	92.553	7.447
	Agriculture	0	0.001	0.0004	0.042	0.001	0.044	95.238	4.762
	Developed	0	0.006	0	0.002	0.040072	0.048	82.667	17.333
	Total	0.036	0.848	0.016	0.052	0.048	1		
	Producer's accuracy (%)	80.107	99.082	86.505	81.877	82.864	Overall Accuracy= 96.526%		
	Omission errors (%)	19.893	0.9184	13.495	18.123	17.136	Margin of Error (ME)*= ± 4.515%		

*The ME was calculated based on a 95% confidence interval (critical value= 1.96), and it shows how the ground truth samples for each of the land classes are representative of the areas of the land classes and total sample (500) in determining the overall accuracy. Cell entries presented are the estimated area proportion of the cells of the error matrix.

A2 Table III Error matrix of estimated area proportions for the 1975 treatment area Landsat image with 500 ground truth samples

		Reference Data							
	Class	**Water**	**Forest**	**Barren**	**Agriculture**	**Developed**	**Total**	**User's accuracy (%)**	**Commission errors (%)**
Classified image	Water	0.026	0	0.001	0	0	0.027	97.701	2.299
	Forest	0.007	0.861	0	0.007	0.007	0.881	97.692	2.308
	barren	0	0.0002	0.009	0.0002	0.0001	0.009	93.333	6.667
	Agriculture	0	0.004	0.0009	0.061	0	0.067	92.249	7.751
	Developed	0	0	0	0.0003	0.009	0.010	97.000	3.000
	Total	0.033	0.865	0.0109	0.069	0.016	1		
	Producer's accuracy (%)	79.320	99.480	84.886	89.361	57.691	Overall Accuracy		96.623%
	Omission errors (%)	20.680	0.520	15.114	10.639	42.309	Margin of Error (ME)*		± 4.624%

*The ME was calculated based on a 95% confidence interval (critical value= 1.96), and it shows how the ground truth samples for each of the land classes are representative of the areas of the land classes and total sample (500) in determining the overall accuracy. Cell entries are expressed as the estimated area proportion of the cells of the error matrix.

A2 Table IV Error matrix of estimated area proportions for the treatment area 1995 classified Landsat image with 500 ground truth samples

	Reference Data								
	Class	**Water**	**Forest**	**Barren**	**Agriculture**	**Developed**	**Total**	**User's accuracy (%)**	**Commission errors (%)**
Classified Image	Water	0.009	0.0001	0.0001	0	0	0.010	97.403	2.597
	Forest	0	0.731	0.014	0.023	0.005	0.773	94.567	5.390
	barren	0	0.002	0.054	0.002	0	0.057	93.939	6.061
	Agriculture	0	0.006	0.001	0.119	0.002	0.128	92.381	7.619
	Developed	0	0	0	0	0.029	0.029	100	0
	Total	0.010	0.739	0.069	0.143	0.036	1		
	Producer's accuracy (%)	100	98.922	77.845	82.656	80.362	Overall Accuracy= 94.470%		
	Omission errors (%)	0.000	1.078	22.155	17.344	19.638	Margin of Error (ME)*= ±4.649%		

*The ME was calculated based on a 95% confidence interval (critical value= 1.96), and it shows how the ground truth samples for each of the land classes are representative of the areas of the land classes and total sample (500) in determining the overall accuracy. Cell entries are expressed as the estimated area proportion of the cells of the error matrix.

CHAPTER FOUR

Quantifying the relative forest change from shale oil and gas well pads, pipelines and access roads in northeastern British Columbia: implications for policy and land development

Abstract

One of the principles of landscape ecology predicts that linear features (e.g., footprints of pipeline and access road) would contribute to more significant primary changes in the forest landscape than any other feature. While studies from some locations confirm this hypothesis, the quantity and pattern of forest change contributed by shale oil and gas (SOG) pipelines, well pads, and access roads in northeastern British Columbia (BC) are not well-known and understood. However, information about the relative forest change from these infrastructure types is necessary for policy amendment aimed at protecting the boreal forest resources (e.g., woodland caribou). Landscape metrics and methods from remote sensing and geographic information systems (GIS) were used to measure, compare, and contrast forest change from SOG well pads, pipelines, and access roads. The study finds that the quantity of forest cover loss (0.163%) contributed by well pads is more than that of pipelines (0.057%) and roads (0.017%). Even though well pads cover a surface area approximately three times larger than that of pipelines, this study finds that the amount of forest cover changes from the well pads and pipelines are similar. Furthermore, the study finds that whereas well pads contribute to a reduction in the core forest, pipelines contribute to an increase in the edge forest. The findings from this study suggest that policies and efforts towards reducing forest change from SOG infrastructure in northeastern BC should be directed toward the well pads and to a greater extent, the pipelines which are likely to contribute to a more significant change if more of them are constructed in the future.

Keywords: remote sensing of forest; GIS-based 'if-else' analysis; location-specific land use decisions; forest cover loss; forest fragmentation; landscape metrics

4.1 Introduction

The shale oil and gas (SOG) industry has thrived in recent years due to the improvement in extraction technologies. For instance, the combined use of horizontal drilling and slick water stimulation has improved the efficiency of SOG drilling (Langlois et al., 2017; Prpich et al., 2016; Lampe & Stolz, 2015; Moran et al., 2015; Soeder et al., 2014; Slonecker et al., 2012). The increase in global and national demand for oil and gas is also another essential factor for the recent increase in SOG drilling (Langlois et al., 2017; Brown, 2015). Hence, the exploitation of SOG resources is influenced by a combination of factors and not limited to only technology. In recent years, there has been an increase in anthropogenic land use practices in northeastern British Columbia (BC), especially the rise in the SOG activities which have increased the industrial footprints in the boreal forest (Goddard, 2009).

SOG development involves the construction of shale gas infrastructure including well pads, pipelines, access roads, processing plants, and storage facilities. Constructing these facilities reduces the quantity of forest cover and consequently are likely to affect the spatial pattern of forest patches (Drohan et al., 2012). Forest changes may be permanent, and that forest area-sensitive species of fauna are likely to be endangered (Shen, 2015). Changes in the spatial pattern of patches and forest cover affect the survivability, migration, and dispersal of fauna species such as the grizzly bear and the boreal woodland caribou (Tole, 2006). In northeastern BC, the increase in linear corridors and the industrial footprints in the boreal forests is likely to reduce the survivability of the already endangered caribou (Goddard, 2009). It is therefore relevant to measure the amount and pattern of forest change contributed by both the linear corridors (roads and pipelines) and well pads which contribute significantly to the industrial footprint in the northeastern BC. Insights from measuring the quantity of forest change from each of these SOG-specific infrastructure types could be used to inform SOG land use policy, wildlife management, and environmental protection.

One of the principles of landscape ecology predicts that linear features (e.g., gathering line or pipeline corridors) would contribute significantly to forest fragmentation because these features disrupt the connectedness and intactness of forest cover (Abrahams et al., 2015; Racicot et al., 2014; Drohan et al., 2012). Similar to the principle of landscape ecology, Racicot et al. (2014) assert that comparatively, a pipeline network would have a more significant footprint on the land cover as compared to the impacts from access roads. However, it has been theorized that the clearance of forest to construct well pads leads to loss of forest cover as well as altering the spatial pattern of the forest patches (Klaiber et al., 2017; Soeder et al., 2014 cited in Abrahams et al., 2015). Previous studies have projected that the land change from oil and gas development would be more than a double of the impacts from residential and urban development in the near future (Trainor et al., 2016). This land change projection could, however, be determined by the quantity of land used for the SOG activities (e.g., the construction of well pads, roads, pipelines, and other facilities).

According to Moran et al. (2015), a fully developed well pad in the Fayetteville shale gas region in Arkansas occupies on average a 2.5 ha of forest land and likely to disturb an additional 0.5 ha of forest. However, in Pennsylvania (PA), Drohan and Brittingham (2012) have estimated that each well pad requires the clearing of about 2.6 ha of forest. These differences in the sizes of well pads indicate that every jurisdiction has its well pad sizes. Researchers who assess the impacts of SOG infrastructure find it more convenient to consider well pads than pipelines and access roads in their analysis (Langlois et al., 2017). The current literature indicates that pipelines and access roads are omitted from many analyses (Langlois et al., 2017; Drohan et al., 2012). Many factors, including insufficient spatial data for pipelines and access roads and the time-consuming hand digitizing limit the inclusion of these shale gas infrastructure in many studies. Therefore, studies are likely to underestimate pipelines and access roads due to how data on these features are obtained (Langlois et al., 2017; Klaiber et al., 2017, Drohan et al., 2012).

In Canada, studies which show how land uses are contributing to landscape change range from studies about national parks and protected areas (e.g., in Carlson, Browne, & Callaghan, 2019; Soverel et al., 2010; Fraser et al., 2009; Young et al., 2006) to studies on abandoned mining areas (e.g., in LeClerc & Wiersma, 2017). Moreover, research that describes how each of the major SOG infrastructure types is changing the forest landscape is lacking. However, a few studies in the western Canadian boreal forest have modelled and predicted that there would be a significant impact on the caribou habitat following an increase in the industrial footprints (Goddard, 2009; Sorensen et al., 2008). A study from northeastern BC which measures forest change from SOG industrial activities could, therefore, improve the accuracy of prediction by explicitly indicating which of the infrastructure contributes more to forest cover losses and fragmentation. The impacts of linear SOG features have generally been understudied, and hence, particularly in northeastern BC, little is known about how each of the SOG features (pipelines, roads and, well pads) are impacting the forest cover. However, SOG wells in northeastern BC have increased by about 85% since the early 1970s (Adams, 2014). It is likely that access roads and pipelines would increase as more shale gas wells are constructed. These linear features, in terms of forest fragmentation, will have an effect on forests in the form of increased edge effect, potential reshaping of core forest into less compact patches, etc(see Drohan et al., 2012). The effect of edge (on forest obligates, for example) is well established (see Drohan et al., 2012). The objective of this study is to measure and interpret forest change resulting from selected SOG infrastructure using ecologically meaningful landscape metrics and methods from remote sensing and geographic information systems (GIS). Thus, this study addresses the question of how the impacts from well pad footprints compare and contrast with that of pipelines and access roads. The land use policy and land management implications of the change have also been discussed in this chapter.

Limitations such as the small size of land change features (e.g., access roads) found in medium resolution Landsat images, make it challenging to visualize and measure the impacts of minor but ecologically significant anthropogenic activities. Despite these limitations, efforts are being made to measure the SOG impacts successfully (see example in Drohan et al., 2012; Donnelly et al., 2017). Remote sensing methods, landscape metrics, and a GIS-based 'if-else' conditional analysis were used to evaluate retrospective forest change using Landsat image and spatial data for SOG infrastructure. Knowing about the SOG features that contribute the largest proportion of forest change is essential for decision making and planning the allocation of the infrastructure across space on different land categories. This evidence-based study conveys the need to regulate further the spread of specific SOG infrastructure types. The findings from this study provide a forest change model, important spatial information about the forest and SOG infrastructure development that would guide conservation and rehabilitation plans for northeastern BC and beyond.

4.2 Materials and Methods

4.2.1 Description of the study area

The study was conducted in the geographical northeast of British Columbia, an area where the land is shared between land uses such as timber harvesting, shale oil and gas activities, human settlement development and agriculture (Carlson et al., 2019; Goddard, 2009). The size of the study area is 103,208 sq. Km (10,320,800 ha). The study area is within the ecologically sensitive boreal forest zone where there are different species of plants and animals. SOG activities and other industrial footprints in the boreal forest could, therefore, be detrimental to different species of animals and their habitats. The study area is within the Boreal White and Black Spruce (BWBS) biogeoclimatic zone of BC. Within the BWBS zone are frigid winters and short growing seasons. The annual precipitation is between 330 and 570mm, and the mean annual temperature is between -2.9 and 2^0C (Meidinger & Pojar, 1991). These climatic factors are likely to affect plant growth within the study area in northeastern BC. Figure 4.1 shows the location of the study area and three major cities within the study area.

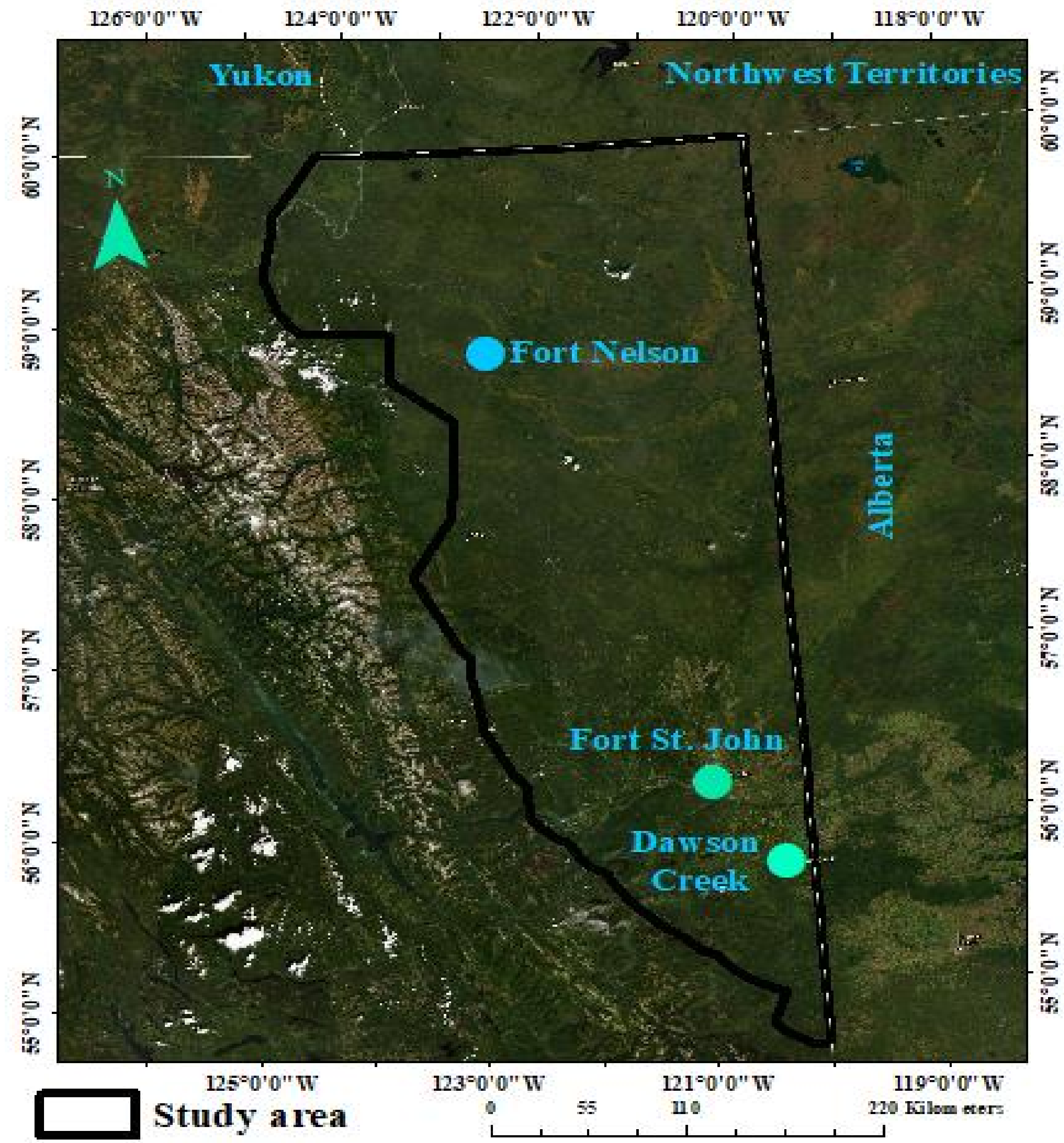

Figure 4.1 Map of the study area in northeastern BC. Fort St. John, Fort Nelson, and Dawson Creek are the three major cities in the study area.

4.2.2 Data

Landsat Multi-Spectral Scanner (MSS 5) images were acquired from the US Geological Survey archive and used in this study. The selected Landsat images used in this study are from the surface reflectance tier 1 collection and acquired by the US Geological Survey between April 1975 and June 1975. Landsat images (30 m by 30 m or 60 m by 60 m resolution) are not likely to capture SOG infrastructure (Wasson & Franklin, 2018), and thus not likely to sufficiently measure land change from SOG infrastructure development. This is a major limitation when measuring land change using Landsat images. For instance, the linear features (e.g., roads and pipelines) of less than 5 m width are less likely to be captured in a 60 m by 60 m medium-resolution Landsat images. To reduce the influence of this limitation on the analysis, this study integrated Landsat images with SOG data from high resolution aerial photos and draw signatures of infrastructure footprints in the Landsat images.

The multi-date Landsat images used in this study were used to create a composite image to represent the land cover condition of 1975. The images were composited using the best-available-pixel approach to get rid of the cloudy and hazy atmospheric attenuations (White et al., 2014). With this approach, the best pixels of the Landsat images were selected based on the type of sensor, day of year, nearness to clouds, and nearness to cloud shadow. The target day of the year is May 1. However, pixels of Landsat images were also selected 30 days before or after the targeted day of the year. Selecting 1975 land cover condition as a pre-SOG development was because more than 85% of the shale gas wells were drilled in years after 1975. Previous studies selected pre-SOG data from years that follow after the SOG boom (e.g. in Drohan et al., 2012; Donnelly et al., 2017). However, in the study area in northeastern BC, SOG activities were in existence before the boom in the mid-1990s, and hence measuring landscape change from these activities could also include the years before and after the boom. A high resolution (1-1.5m) aerial photo acquired from Google Earth Pro was used in this study. GIS-based vector data of SOG infrastructure, including the footprints of pipelines right of ways, access roads, and well pads were used in this study. The SOG spatial data (format: shapefile feature class; coordinate system: NAD_1983_BC_Environmental Albers) were downloaded from the British Columbia Oil and Gas Commission's (BCOGC) database. Only the shale oil and gas well pads, pipeline right of ways, and access road data within the northeastern BC area were included in this study.

The SOG spatial data from BCOGC's database indicated that not all the permitted infrastructure had been constructed on the landscape in the study area in northeastern BC as at December 2017. Therefore, in this study, only the constructed SOG features were used in the feature-change analysis. However, a visual inspection of the data from the BCOGC database and a high-resolution aerial image showed that there is a data gap and that not all constructed SOG well pads, pipelines, and access roads on the landscape in the study area have been added to the database. The data from the BCOGC were updated using digitized spatial data from the high-resolution aerial photos acquired from Google Earth Pro. Updating the SOG spatial data was done to ensure that the quantity of SOG infrastructure and its impacts on the landscape are not underestimated. From the updated spatial data, as at December 2017, constructed pipelines covered 2,766.15 ha of the study area. Well pads and access roads covered 19,363.52 ha and 2,034.58 ha of the study area, respectively. The spatial extents of these datasets show that more well pads have been constructed than roads and pipelines. However, these exclude the SOG infrastructure that could not be identified in the high-resolution aerial photo used in updating the datasets acquired from the BCOGC.

Five hundred ground truth samples were selected from the original 1975 Landsat image using a stratified sampling procedure, and these samples were used as reference data for accuracy assessment of classified Landsat image. The Landsat image was stratified based on the land classes identified in the image. The number of samples selected for each stratum and used for the accuracy assessment of the classified Landsat image depends on the size of the land classes. This sampling procedure was used to select the ground truth samples based on the good practices sampling recommendations (see Olofsson et al., 2014).

4.2.3 Landsat image classification

The USGS had radiometrically and geometrically corrected the tier 1 surface reflectance Landsat data used in this study. Hence, there was no further processing of the image apart from the standard radiometric and geometric processing done by the USGS. The Landsat image was classified into five land categories (water, forest, barren, agriculture, and developed land). Mapping the themes of land cover attributes are typically from a remote sensing and image classification method (Foody, 2002). In this study, a unified approach of unsupervised (K-means) (Cissell, Delgado, Sweetman, & Steinberg, 2018; Ragettli, Herberz, & Siegfried, 2018) and supervised (maximum likelihood classification (SMLC)) was used in classifying the Landsat image. According to Asmala (2012), the Maximum Likelihood Classification is a supervised classification algorithm based on the Bayes theorem. SMLC makes use of a discriminant function to assign pixels to the class with the highest likelihood. Pixels in the image are assigned to the classes with the highest likelihood or labelled as unclassified if the probability values are all below a threshold set by the user (Lillesand, Kiefer, & Chipman, 2014).

In this study, the unsupervised classification algorithm was used as a first step to classify the Landsat image into 55 classes. A signature file was generated from the unsupervised classification. The signature file from the unsupervised classification was edited to merge pixels of land cover that could form the same land categories. During the editing and merging stage, a dendrogram (see an example in Filchev & Roumenina, 2012) was used to examine the similarities and differences between the classes of land cover. With the aid of visual inspection of the original

Landsat image, information from the built dendrogram, and author's knowledge of the study area, the 55 land classes were merged and reduced to five. The land class identities were modified during the merging, and at this stage, the signature file was updated. The supervised classification algorithm was then applied to classify the land cover image using the updated signature file as training data. This classification approach made it possible to reassign some pixels of land cover to appropriate land classes with the aid of the original 1975 land cover image. Thus, the classification approach used reduced the impact of grouping pixels of the land cover into land classes based typically on the spectral characteristics of the Landsat image.

The details of the final five classes generated are as follows. The water class is made up of intermittent and permanent streams, rivers, creeks, lakes, and ponds. The forest land category includes the vegetated cover of mixed, evergreen, and deciduous forests. The barren land is made up of bare land and rock outcrops. The agriculture land class includes pasture, grasslands, and herbs. The developed land category is made up of residential, commercial, industrial, and transportation land uses and land covers. The classified Landsat image was assessed for accuracy using the 500 geographically ground truths (reference) points randomly collected from the original 1975 Landsat image. Accuracy assessment of the classified Landsat image was based on Olofsson et al. (2014) good accuracy assessment practices recommendation, which takes into consideration the number of ground truth samples selected in proportion to the area of land classes. Such an approach to accuracy assessment provides a mechanism to ensure that the rare classes are also accurately classified, and samples taken for accuracy assessment are representative of all classes of land and their sizes.

4.2.4 Determining shale oil and gas feature-changes in the land cover

In this study, measuring feature induced forest change from SOG infrastructure development was done in three interrelated steps. First, the shale gas features which were initially in vector formats were converted to raster data (newly created raster data of SOG features). This step was undertaken to ensure compatibility between the classified 1975 Landsat image and the spatial data for SOG infrastructure for the land change analysis. Second, the classified 1975 Landsat image was resampled from 60 m by 60 m to 10 m by 10 m resolution using the nearest neighbour resampling method (Shlien, 1979; Dwyer et al., 2018). The snap raster function in ArcGIS was used to resolve pixel mismatch between the classified Landsat image and the raster layers of SOG features. The resampling was done to ensure the shale gas features (finer in spatial resolution) are well represented in the 1975 classified land cover image. Also, this step is a means of possibly reducing systematic underestimation of the quantity of SOG features and their impacts on the landscape, especially with the linear features. However, the resampling process presents a unique limitation which is likely to reduce the data quality for further analysis. Moreover, the reduction in the data quality from the resampling process is likely to influence the feature-change analysis results as well as the landscape fragmentation analysis.

The third step calculates how much change has occurred in land cover using the raster layers of SOG pipelines, well pads, and access roads. The newly created raster features of SOG well pads, roads, and pipelines were used to update the classified 1975 Landsat image to reflect the amount of land cover change contributed by each of the features. Updating the classified raster data with the shale gas features was done using a GIS-based ‘if-else' conditional analysis. In this analysis, a conditional statement was evaluated as true or false to determine whether there has been a landscape change from the SOG infrastructure development. If the statement is evaluated as true, the classified Landsat image would assume a pixel value equivalent to developed land, and that, a class of land (forest, barren, water, agriculture, and developed land) in the landscape would change. Conversely, if the statement is evaluated as false, the value of the land classes in the classified Landsat image would remain unchanged. For instance, if the raster layer of SOG access roads overlay on the classified Landsat image, portions of the land classes (e.g., forest cover) in the classified image underneath the road layer would convert to industrial developed land. If the raster layer of access road overlays the agriculture land category, that part of the agriculture land would convert to industrial developed land. Consequently, the developed land class would increase in size if there has been a change in any of the other land classes to industrial developed land due to the construction of well pads, pipelines or access roads.

This approach was used to evaluate the feature-induced land change in the 1975 classified Landsat image using the three raster layers of SOG features. In using the 1975 land cover as a pre-SOG development data, the total land change in the overall landscape from each of the three SOG features is estimated with high accuracy. However, there could be a slight overestimation of the impacts of the SOG infrastructural footprints when considering the impacts of the infrastructure based on land cover types that are likely to be affected in the landscape. For example, the period between 1975 and 2017 is long enough for the forest class of 1975 to be converted for other land uses before SOG development. Thus, updating the 1975 land cover with any of the three raster layers of SOG features would mean that there were no disturbances in the forest land before the construction of the infrastructure between 1975 and 2017. The resultant land cover datasets after the feature-change evaluations are as follows. These are (i) composite raster data of roads and classified Landsat image; (ii) composite raster data of pipelines and classified Landsat image; and (iii) composite raster data of well pads and classified Landsat image. Once the updated datasets of classified Landsat image and each of the SOG features were derived, statistics on the datasets about the quantity of various land classes (including the forest cover) were calculated to determine how each of the features has contributed to changes in the forest cover. The amount of land change contributed by each of the SOG features were determined by comparing the statistics on the originally classified 1975 Landsat image to the statistics on datasets made up of the classified Landsat image and each of the shale oil and gas infrastructure (features).

4.2.5 Shale oil and gas feature-change forest fragmentation analysis

A combination of metrics was used to measure the amount of fragmentation contributed by each of the three shale gas features. That is, fragmentation results from processed/updated Landsat image (made up of classified Landsat image, pipelines, access roads, and well pads) were compared with the fragmentation results from the baseline data (pre-SOG image/classified 1975 Landsat image). In this study, the metrics used are the ones generated from FRAGSTATS, developed by McGarigal and Marks (1995) and McGarigal et al. (2012). FRAGSTATS was developed to quantify landscape structure and determine levels of fragmentation occurring in the landscape.

FRAGSTATS class metrics, namely, the number of patches, mean patch size, the coefficient of variation of patch size, mean shape index, the coefficient of variation of forest patch shape, and aggregation index were used in the study. According to McGarigal et al. (2012), class metrics are calculated for every patch type or class in the landscape to report the level of fragmentation. The number of metrics to use in a study or analysis depends on the user's discretion. However, a meaningful number of them must be used (McGarigal et al., 2002). In this study, the number and types of metrics used in measuring forest fragmentation reflect the measurement of both the composition and configuration of forest patches. The GIS-based landscape fragmentation tool (LFT) was used to categorize the forest into the core, edge, perforated and degraded patch (see Vogt et al., 2007). Descriptions of the categories of forest fragmentation from the LFT is found in Table 4.2. The resulting class output file from the FRAGSTATS is made up of a row (observation vector) for every class of land and columns (fields) representing specific metrics. The descriptions of the FRAGSTATS metrics used in this study are in Table 4.1.

Table 4.1 FRAGSTATS metrics and their descriptions

Metrics	Description
Number of patches (NP)	The total number of patches in a class. The NP increases as patches get disintegrated. However, this measure must be buttressed with other metrics.
Mean Patch Size (MPS)	Average patch size in a class measured in hectares (ha).
Patch size coefficient of variation (AREA_CV)	It measures relative variability about the mean (that is, variability as a percentage of the mean), not absolute variability. Area_CV is zero if all the patch sizes are identical, and it is more than zero as patch sizes get dissimilar.
Mean shape index (SI_MN)	The shape index measures the complexity of patch shape compared to a standard shape (square) of the same size. The value is 1 when the patch is square and increases without limit as patch shape becomes more irregular.
The coefficient of variation of forest patch shape Index (SI_CV)	The SI_CV is variability (standard deviation) in the patch shape expressed as a percentage of the mean shape index.
Aggregation index (AI)	AI measures aggregation. AI equals 0 when the focal patch type is maximally disaggregated and equals 100 when the patch type is maximally aggregated into a single, compact patch.

The information in the table is from McGarigal et al. (2012).

Table 4.2 Categories of forest fragmentation

Category of fragmentation	Description
Patch forest (PF)	PF are small fragments that are completely degraded by the "edge effect*." This category does not contain any forest pixels. The increase in the PF is a signal that there has been an increase in the amount of fragmentation.
Edge forest (EF)	EF occurs within the "edge effect" zone along the outside edge of a non-patch tract. The increase in the edge forest means there is an increase in the amount of fragmentation.
Core forest (CF)	CF occurs outside of the "edge effect" zone, and that it is not degraded by fragmentation. Mostly, it is made up of only forest pixels. A decrease in the CF amounts to an increase in the amount of fragmentation.
Perforated forest (PFF)	PFF occurs within the "edge effect" zone along the edge of a small clearing in a non-patch tract. The increase in the amount of PFF means an increase in the amount of fragmentation.

*Edge effect zone is a distance of 100 meters from the non-forest area and beyond this distance, SOG features and anthropogenic land uses are likely to degrade the forest cover. The 100m distance was selected for general purposes (see an example in Drohan et al., 2012).

4.3 Results

4.3.1 Forest cover change from shale oil and gas infrastructural development

The details of the agreement and disagreement between the classified Landsat image and the ground truth data are summarised in an error matrix table (see appendix 3 Table I). The appendix Table I shows that the accuracy of the classified image is high (96.623%), and the 500 ground truths are representative of the areas of land classes in the study area considering the low margin of error of ± 4.624%. Figure 4.2 shows the mapped land classes in the study area in northeastern BC. The three types of SOG infrastructure development has had relative impacts on the forest and the whole landscape. The results from the geospatial data analysis show that as compared to the access roads and pipelines, SOG well pads have contributed to more forest cover loss. Among the three types of SOG infrastructure, pipelines and roads have contributed the lesser (-0.0568%) and least (-0.0169%) reduction in the forest cover, respectively (See Tables 4.3 and 4.4). However, the SOG well pads, roads, and pipelines have also impacted on other land categories (e.g., agriculture and barren land) but not as much as they have impacted on the forest cover (Tables 4.3 and 4.4). Figure 4.3 shows that well pads infrastructure development has contributed more landscape conversion (to industrially developed land) than pipelines and access road development in the study area.

Table 4.3 Categories of land cover/land use before and after shale oil and gas features

Category	**% of the category before SOG features**	**% of the category after SOG well pads**	**% of the category after SOG pipelines**	**% of the category after SOG roads**
Water	3.2701	3.2665	3.2692	3.2698
Forest	85.3927	85.2297	85.3359	85.3758
Barren	1.0295	1.0273	1.0289	1.0293
Agriculture	9.0988	9.0846	9.0930	9.0973
Developed	1.2089	1.3919	1.2730	1.2278

Note: SOG is shale oil and gas. The proportion of land categories after shale oil and gas infrastructure also represents the persistence of the land cover class.

Table 4.4 Relative proportions of forest cover loss contributed by the shale oil and gas well pads, pipelines and roads

Category	**% change after SOG well pads**	**% change after SOG pipelines**	**% change after SOG roads**
Water	-0.0036	-0.0009	-0.0003
Forest	-0.1630	-0.0568	-0.0169
Barren	-0.0022	-0.0006	-0.0002
Agriculture	-0.0142	-0.0058	-0.0015
Developed	0.1830	0.0641	0.0189

Note: SOG is shale oil and gas. The percentage change in the land categories after shale oil and gas infrastructure construction also represents the proportion of land that transitioned into industrial developed land.

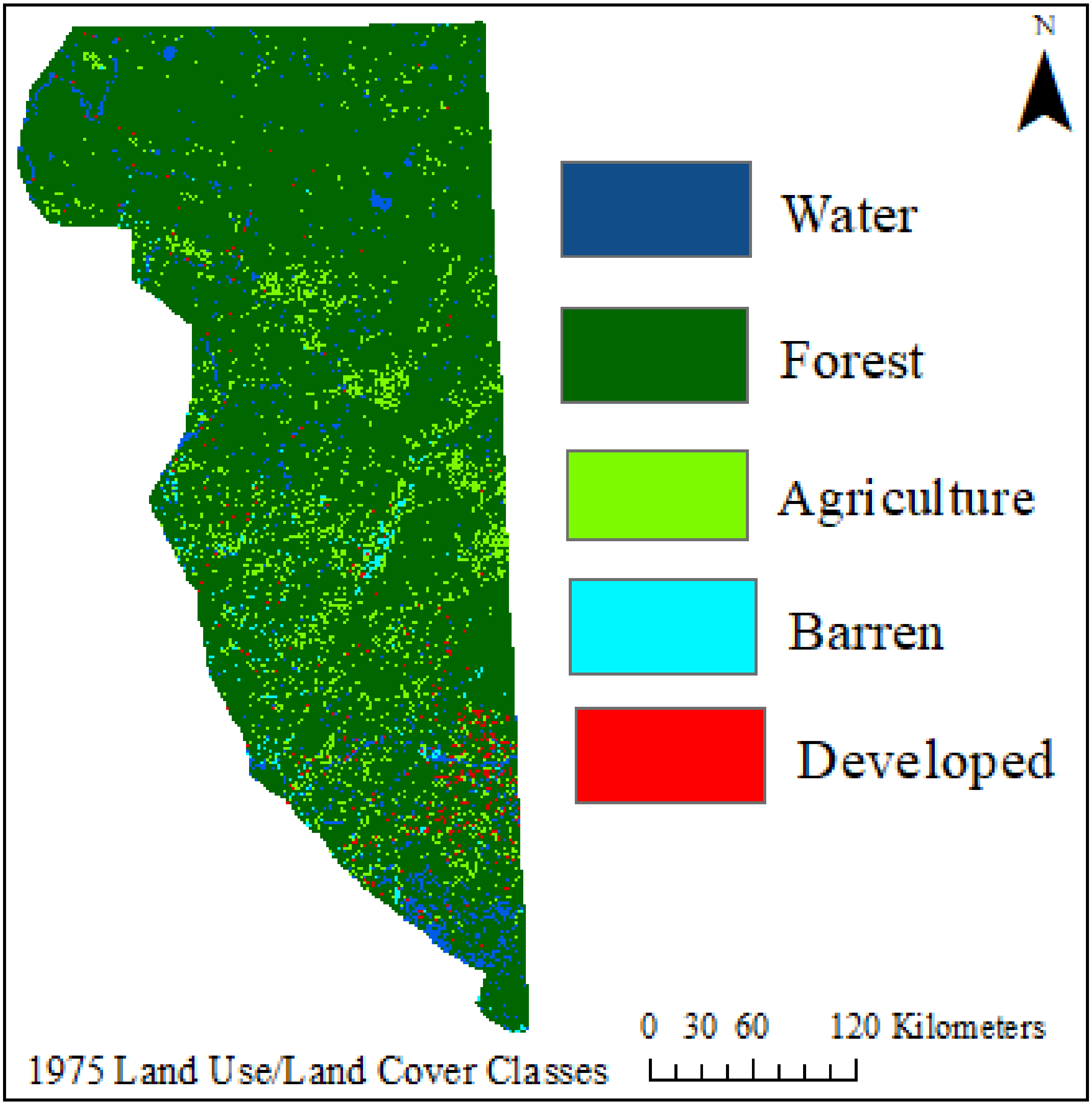

Figure 4.2 Mapped land classes (1975) of the study area in northeastern BC

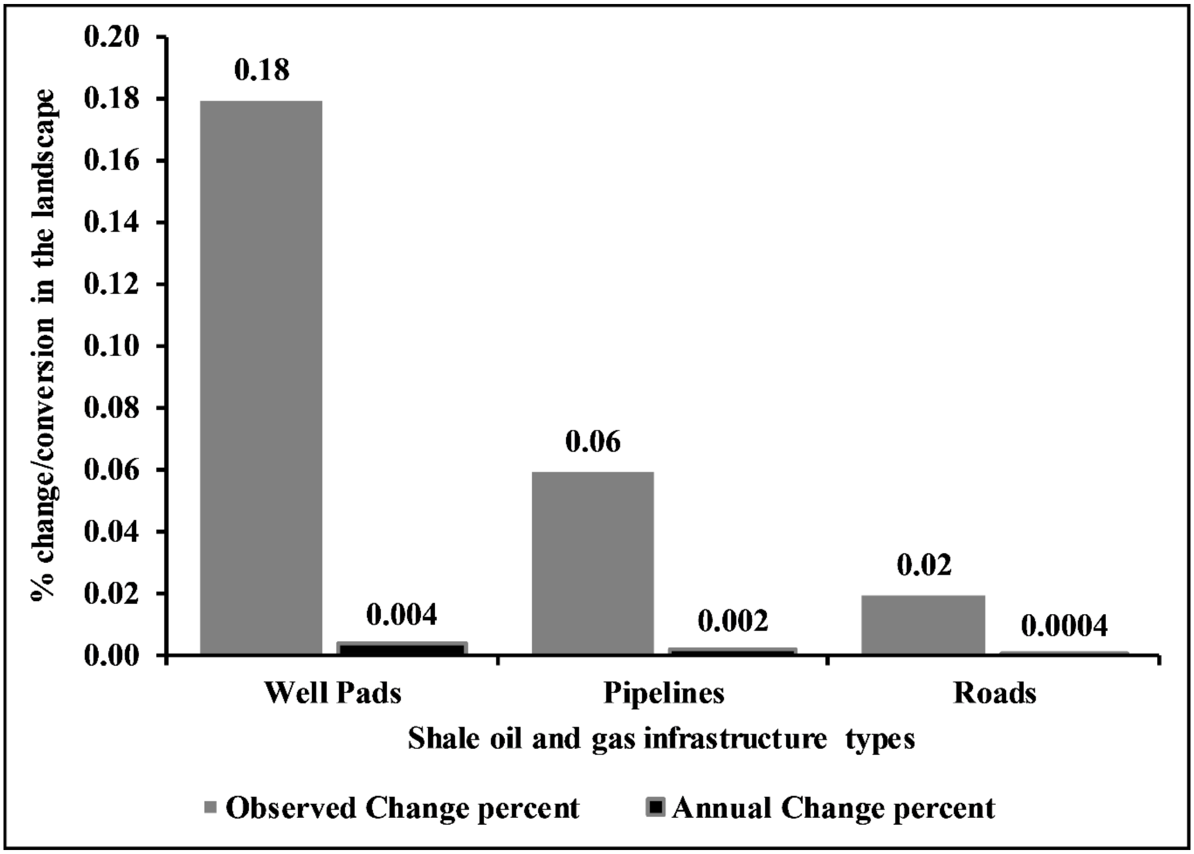

Figure 4.3 Observed relative change in the landscape contributed by shale oil and gas infrastructure.
The change in the overall landscape from shale oil and gas infrastructure development is how much the landscape has converted to industrially developed land.

4.3.2 Relative shale oil and gas infrastructure-induced forest fragmentation

The results from Table 4.5 show that the core forest has remained almost the same size throughout the years that follow after 1975. Even with this result, the amount of core forest loss contributed by the well pads is more than that of other SOG features. Pipelines also increased the edge forest and created more degraded patches (the patch category) more than well pads and roads (see Tables 4.5 and 4.6).

From the results, the number of patches increased after 1975 when most of the well pads, pipelines, and access roads have been constructed. However, there are variabilities regarding the amount of fragmentation from the construction of the pipelines, access roads, and well pads. As compared to the roads and pipelines, well pads contributed more to the increase in the number of forest patches (Table 4.7). Also, among the three infrastructure types, the well pads reduced the regularly square-shaped patches to complex-shaped patches (see Shape_CV), increased patch size complexities (see Area_CV), and reduced patch aggregation (see AI) more than the roads and pipelines (see Table 4.7). Comparatively, the SOG pipelines contributed to the forest fragmentation process by reducing the forest patch sizes more than any other infrastructure (see Table 4.7).

Table 4.5 Proportions of categories of forest fragmentation before and after shale oil and gas features

Category	% of categories before shale oil and gas	% after Pipelines	% after well pads	% after Roads
Patch	0.1107	0.1113	0.11094	0.11093
Perforated	1.4734	1.4719	1.4738	1.4732
Edge	8.2281	8.2311	8.2308	8.2286
Core	90.1877	90.1856	90.1845	90.1873

Table 4.6 Relative impacts of change in categories of forest fragmentation attributed to shale oil and gas features

Category	% change after pipelines	% change after well pads	% change after roads
Patch	0.0006	0.0002	0.0002
Perforated	-0.0015	0.0004	-0.0003
Edge	0.0030	0.0026	0.0004
Core	-0.0021	-0.0032	-0.0003

Table 4.7 Composition and configuration of forest patches after shale oil and gas features

Year/After OG	NP	A_MN	Metrics* A_CV	S_MN	S_CV	AI
1975	33499	262.9516	14151.216	1.1418	133.9686	94.196
After Well Pad	33581	261.8136	14165.0416	1.1421	134.9245	94.1136
Δ after well pad	**82**	**-1.138**	**13.8256**	**0.0003**	**0.9559**	**-0.0824**
After pipelines	33558	262.3149	14162.872	1.1421	134.3128	94.1449
Δ after pipelines	**59**	**-0.6367**	**11.656**	**0.0003**	**0.3442**	**-0.0511**
After roads	33512	262.7981	14154.1878	1.1419	133.5836	94.1808
Δ after roads	**13**	**-0.1535**	**2.9718**	**0.0001**	**-0.385**	**-0.0152**

(Note **Δ**= change) * NP- the number of forest patches, Area_MN- mean patch size, Area_CV- coefficient of variation of mean patch size, Shape_MN- mean shape index, Shape_CV- coefficient of variation of the mean shape index, and AI- aggregation index.

4.4 Discussion

4.4.1 Shale oil and gas feature-induced forest cover loss and fragmentation

The findings from the study area in northeastern BC suggest that there are variabilities in the changes contributed by SOG well pads, pipelines, and access roads in the various land categories. The results suggest that forest cover received more impacts from well pads and that among the SOG features, the well pads contributed to about two-thirds of the reduction in the quantity of forest cover measured in the forest landscape of the study area in northeastern BC. The quantity of forest change from SOG well pads is expected because the well pads cover the largest portion of the landscape as compared to the pipelines and access roads. Also, it is likely that well pads occur mostly in the forest and hence, a larger quantity of forest cover is degraded before these well pads are constructed. In comparing the linear features (roads and pipelines), the findings from this study show that pipelines have contributed to more changes in the landscape than access roads constructed in northeastern BC. The quantity of forest cover loss from these two linear features corroborates the assertion by Racicot et al. (2014) that pipelines will leave more physical footprints on the landscape than access roads. Furthermore, the land use dynamics and the forest change pattern in the study area suggest that the impervious and semi-pervious surfaces brought about by constructing SOG well pads are mostly found on the forest land. As such, it is unlikely that well pads construction and agricultural activities will compete for space (land) in northeastern BC as recorded in Pennsylvania, North Dakota, and Ohio where the well pads have mostly converted croplands/pasture fields to developed land (Drohan et al., 2012; Donnelly et al., 2017, Preston & Kim, 2016).

As indicated earlier in this chapter, constructed pipelines, well pads, and access roads cover 2,766.15 ha, 19,363.52 ha, and 2,034.58 ha of the study area, respectively. That is, there are more well pads in the landscape than the linear features, and hence the quantity of land area covered by the SOG features corresponds to the proportion of forest cover loss. However, comparably, the surface area of land covered by the well pads constructed is about 7-8 times the surface areas of the constructed roads and pipelines, but the percentage change in the forest cover contributed by the well pads is only about five times the proportion of change contributed by each of the two other infrastructure types (pipelines and roads). Even though there have been lesser quantities of pipelines and roads than the well pads in the landscape, the quantity of forest cover change from the pipelines and roads are still similar to that of well pads. For instance, all things being equal, if pipelines were to cover up to 19,363.52 ha of the surface area of the landscape, they would likely contribute to a reduction of about 0.35% in the forest cover because with the 2,766.15 ha of pipelines on the landscape, the forest cover reduced by 0.057%.

The similarities in the amount of land change from the various infrastructure suggest that if most of the permitted pipelines in northeastern BC are constructed, it is likely that they would contribute more forest cover losses. The forest cover change pattern, however, shows that the impacts of SOG pipelines in northeastern BC could contribute to more reduction in the forest cover than in Carroll County, Ohio and Washington County, Pennsylvania where forest cover has reduced by 0.226% and 0.267%, respectively, due to pipeline installations (Donnelly et al., 2017). Similarly, well pads have contributed to a reduction in the forest cover by 0.024 and 0.025% respectively in Carroll and Washington Counties (Donnelly et al., 2017). The forest cover reduction due to well pads development measured in Washington and Carrol Counties are, therefore, less than that of the study area in northeastern BC. The differences in the amount of forest change in northeastern BC, Washington County and Carrol County is likely to be because of the differences in the approaches used in measuring the changes contributed by the SOG well pads, pipelines, and access roads. Whereas Donnelly et al. (2017) measured the areas covered with the features and disturbances around the features separately, this study in northeastern BC measured the change contributed by the SOG features as the amount of area covered by the SOG features in addition to the disturbances (area cleared and covered with gravel) around the features.

The impact of SOG well pads on the forest cover resonates in the amount of forest fragmentation in the study area in northeastern BC. While most of the indicators or measures of fragmentation used in this study point to the well pads as the features with the largest footprint on the forest cover, pipelines still had some notable contribution to make, and it is more noticeable in contributing to ecologically significant forest fragmentation. For instance, the edge forest increased more from the impacts of SOG pipelines than the well pads and access roads. Also, the increase in patch forest from the construction of pipelines is more than the increase in patch forest due to the construction of well pads and access roads. As SOG well pads reduced the core forest, it is expected that it would create more edges and degraded fragments. Instead, it is the pipelines that created the edges and degraded patches of forest.

The long-standing principle in landscape ecology which hypothesizes that significant primary impacts will occur in the forest due to the construction of linear features in landscapes (Soeder et al., 2014) is incongruent with the results from this study. While results from other studies conform to this assertion, the findings in this study show otherwise. However, the similarity between well pads and pipelines in the amount of change contributed suggests that pipelines could contribute more forest change when most of the permitted pipelines are constructed in the future. In Ohio and Pennsylvania, SOG pipelines are found to be contributing to more forest cover loss and fragmentation than the well pads and roads (Langlois et al., 2017; Donnelly et al., 2017; Abrahams et al., 2015). The first and most likely reason for the differences between the findings from this study in northeastern BC and previous studies is the quantity of SOG features found on the surface area of the various landscapes. Locations such as Ohio and Pennsylvania have more pipelines and roads constructed than well pads, but in northeastern BC, it is otherwise. Thus, it is reasonable to measure more impacts from the linear features than the well pads in Pennsylvania. In northeastern BC where fewer pipelines and roads have been constructed, their impacts on the forest landscape are minimal. According to Donnelly et al. (2017), the primary infrastructure (well pads) could be constructed at an earlier stage of SOG development, but the secondary infrastructure construction could be delayed for a while. Conclusions on the impacts of various shale gas features on forests should, therefore, make reference to the quantity of the SOG features especially when it is unlikely to trace the footprints of all the features and include them in the feature change analysis. Moreover, the differences in the sizes of the SOG well pads are likely to be one of the reasons why there are differences in the quantity of forest cover loss in northeastern BC and other SOG activity locations. For instance, the size of a typical SOG well pad ranges between 1.2 ha and 2.8 ha in Pennsylvania. However, in northeastern BC, the size ranges between 2.02 ha and 34 ha. The larger sizes of the well pads in northeastern BC would likely contribute to a larger change in the forest cover than in other locations.

Within landscapes where forest cover is more extensive as compared to other land classes, SOG developers may not be able to avoid the forest cover to a greater extent, and well pad sizes would likely contribute to more forest loss and fragmentation. For instance, in the Marcellus shale gas play, before SOG development in 2005, about 84 percent of the landscape was made up of forest cover (Langlois et al., 2017) and in such a situation, SOG developers have fewer options of land categories to develop. Similarly, in the pre-SOG Landsat image used in this study, about 85% of the landscape is made up of forest, which suggests that in the period after 1975, SOG developers have fewer options in developing on other land categories apart from the forest. Thus, the onus is, however, on the regulatory agency or institution to determine the amount of forest that can sustainably be used for SOG infrastructure development.

The differences in decision making regarding the construction of well pads is also another essential factor likely to determine the quantity of infrastructure types on the landscape and the amount of forest cover loss. This decision-making process about land use is likely to determine either pipelines/well pads are constructed on lands that are already in use (such as agricultural land to bring about land use change) or to use lands that are in their more natural state (such as the forest). While location-specific decisions play a role in the siting of well pads in the SOG regions, the site where these shale resources are found may influence where to site the well pads and whether the forest cover will be altered. For instance, when shale rocks are found underneath forest resources, it is more likely that parts of the forest cover would be cleared or degraded by the SOG developers.

4.4.2 Implications for policy and forest ecosystem management

The rate at which the shale gas well pads and pipelines have reduced forest cover and contributed to core forest fragmentation could increase if all the permitted infrastructure types are constructed on the landscape of the study area. The current operation of the SOG industry in the study area which includes creating more well pads and constructing fewer roads and pipelines show the industry could still operate in the future without necessarily constructing more pipelines and roads. Policies and regulations to reduce impacts could be geared towards an assessment of the quantity of roads and pipelines which can sustain a particular quantity of well pads to ensure continuous operation of the SOG industry and at the same time protect the forest ecosystem. In the northeastern BC, SOG land use policy could determine a framework of infrastructure that shows a threshold of the number of well pads and the corresponding linear features above which operation of the SOG industry is deemed socio-ecologically unsustainable. Such a framework could be adjustable to increase the quantity of infrastructure constructed depending on the quantity of land reclaimed from decommissioned SOG well pad sites at different points in time. This practice would reduce the impacts from secondary infrastructure (such as roads and pipelines) and ensure reliable land reclamation measures and sustainable operations of the SOG industry socially, economically, and ecologically.

This study has shown that well pads and pipelines are the main features changing the forest cover, contributing more to fragmentation primarily by increasing the edge and reducing the core forest. These have ecological implications for the forest ecosystem of the study area. For instance, with an increase in the edge forest, there is a likely increase in the quantity of invasive species. Also, as the edge increases, forest growth declines with distance from the interior forest to the edge in response to heat stress during the growing season (Reinmann & Hutyra, 2017).

These forest fragmentation impacts suggest that as the edge forest increases, the ability of the forest ecosystem to grow and store more biomass could diminish. The findings from this study inform land managers about the rate at which further increase in the quantity of pipelines and well pads could impact the forest cover. The results from the study area in northeastern BC suggest that a further increase in both the well pads and pipelines is likely to expose the already endangered caribou species in the boreal forest. For instance, new pipelines would bring about an increase in the edge forest and create more routes for predators to access caribou habitats. Again, increasing the quantity of well pads (which would thus reduce core forest) would reduce the size of caribou habitats and increase caribou exposure to predators.

The BCOGC has a policy for land restoration after SOG activities have been decommissioned. With this policy, the BCOGC has established an endowment (through taxing the SOG companies), and this helps SOG companies to set funds aside for the reclamation of orphan sites Government of British Columbia, 2008- Oil and Gas Activities Act). Also, in covering land restoration costs, landowners can be compensated from the fund for loss of land use due to the failure by an operator of SOG to restore the land surface to standards as required by regulation. However, these funds do not guarantee the restoration of the degraded forest or agricultural land to its original form. Furthermore, these funds do not pay for the ecological destruction following the SOG activities. The BCOGC acknowledges it takes a long time for the forest and other land cover types to fully recover through reclamation and natural regrowth (BCOGC, 2015). The question which remains unanswered is whether having funds available gives positive results to restoration efforts. Since the well pads, pipelines, and access roads could leave lasting footprints in the forest cover, land managers should also put in more effort to find a viable solution to the changes in the biophysical characteristics of the land. One of the ways to ensure that lands are not degraded is to find a more sustainable way of operating through a policy that would reduce the operations of SOG activities on land cover types of ecological importance. In British Columbia, for instance, the delineation of the core forest area and minimizing the activities of the SOG industry in the core forest would be relevant because well pads and pipelines have reduced the core forest more and created more forest edges.

The experience from Pennsylvania shows the decommissioned SOG well sites are not easily reclaimed as envisioned. The effort towards the restoration of orphan well sites is becoming a facade in many of the SOG regions due to the low success rate. In Pennsylvania, as at 2012, only 16 percent of the well sites had been reclaimed partially because these well sites are made up of highly impervious surfaces which are difficult to clear after decommissioning (Drohan & Brittingham, 2012). The slower restoration progress is an issue of concern in Pennsylvania although the well pads are not the main features contributing to the significant land change. Moreover, it has been asserted that SOG well pad reclamation which involves the planting of grass, herbaceous plants, hardwood, and conifers may be limited by poor soil (Drohan & Brittingham, 2012). This challenge implies that the first step towards reclamation is the restoration of degraded soil at the well sites to facilitate plant growth. The experience from Pennsylvania and the results from this study (which show well pad construction has contributed more forest loss and fragmentation) suggest the need for a more sustainable way of siting these well pads. SOG land use policies in northeastern BC could include mandatory enhancement of soil fertility at SOG well sites since SOG well pads are the primary infrastructure contributing to forest cover loss among the three infrastructure types considered in this study.

Currently, there are no known unique methods for enhancing the restoration of SOG well pad sites, and as such, the implementation of measures by the BCOGC to reduce the construction of this infrastructure would be necessary. However, the current policy guidance manages the rate of SOG industrial incursion in the old forest and riparian areas (BCOGC, 2014a as cited in Wilson, 2016) and this does not include the protection of wildlife and habitat values (Wilson, 2016). Wilson (2016) has suggested a SOG land use policy made up of a mix of on-site mitigation measures (which would reduce the industrial influence) and implementation of management buffer (which would limit SOG activities) for protecting critical ecological resources. Nonetheless, in northeastern BC, the implementation of such a policy could present different forms of cost to the SOG industry and the national and local economies. For instance, on-site management such as enhancement of soil fertility for land reclamation could be costly to the SOG companies. Also, excessive restrictions on SOG development could suppress local and national economic gains (e.g., job creation and revenue generation). In the case of Pennsylvania, Abrahams et al. (2015) have suggested that regulatory measures seeking to minimize the land use impact of shale gas drilling on core forest should be targeted at pipelines routing practices, and this is because the SOG pipelines are the main features contributing to the loss and fragmentation of the forest cover. In northeastern BC, the findings from this study inform land managers that policies and efforts towards regulating SOG infrastructure should target well pads and to some extent, the pipelines, because of their contributions to decrease in the core forest and increase in the edge forest, respectively.

4.5 Conclusion

This study compared and contrasted the impacts of the SOG pipelines, well pads, and roads on the forest cover in northeastern BC. The results show that in comparing the three SOG infrastructure types, well pads have contributed more to the reduction in the forest cover, increased disaggregation in the forest patches, and increased the unevenness in the sizes and shape of patches. Well pads have contributed to the reduction in the core forest more than the SOG roads and pipelines. The results from this study are based on the available spatial datasets of constructed pipelines, well pads, and access roads acquired from BCOGC and updated using data from a high-resolution aerial photo. The study attained a high level of Landsat image classification accuracy, and with the aid of the data from BCOGC and high-resolution aerial images, most of the SOG features were digitized and included in the analysis. The method used in evaluating SOG feature -induced forest change is likely to be applicable in measuring land change at locations where recent changes in the landscape have occurred due to extractive activities.

Based on the results, this study concludes that even though the linear features covered lesser surface area of the study area in northeastern BC, the amount of change in the forest cover contributed by these linear features are similar to that of the well pads that cover the largest surface area. This study concludes that the amount of fragmentation contributed by each of the features is similar, despite the vast differences in the land surface area covered separately by well pads, pipelines, and access roads. Also, this study concludes that the fact that SOG well pads have reduced the core forest cover does not make them the only primary features to target if there is a need to minimize the impacts of SOG infrastructure. Pipeline footprints are equally compromising the integrity of the forest cover of northeastern BC and contribute to a significant form of forest fragmentation by increasing the edge forest.

Based on the results of this study and that of other locations discussed in this study, this study concludes that the impacts of SOG development on forest cover are location-specific phenomena. Every location has a distinct pattern of change in forest cover and that the amount of forest loss and fragmentation is likely to be determined by land use decisions, site of the shale resources (i.e., whether it is in the forest or on the agricultural land) and the quantity of SOG infrastructure. Therefore, efforts to model future forest change from SOG infrastructure could use site-specific characteristics.

Appendix 3 Supplemental information

A3 Table I Error matrix of estimated area proportions for the 1975 treatment area Landsat image with 500 ground-truth reference samples

	Reference Data								
Classified image	**Class**	**Water**	**Forest**	**Barren**	**Agriculture**	**Developed**	**Total**	**User's accuracy (%)**	**Commission errors (%)**
	Water	0.026	0	0.001	0	0	0.027	97.701	2.299
	Forest	0.007	0.861	0	0.007	0.007	0.881	97.692	2.308
	barren	0	0.0002	0.009	0.0002	0.0001	0.009	93.333	6.667
	Agriculture	0	0.004	0.0009	0.061	0	0.067	92.249	7.751
	Developed	0	0	0	0.0003	0.009	0.010	97.000	3.000
	Total	0.033	0.865	0.0109	0.069	0.016	1		
	Producer's accuracy (%)	79.320	99.480	84.886	89.361	57.691	Overall Accuracy		96.623%
	Omission errors (%)	20.680	0.520	15.114	10.639	42.309	Margin of Error (ME)*		± 4.624%

*The ME was calculated based on a 95% confidence interval (critical value= 1.96), and it shows how the ground truth samples for each of the land classes are representative of the areas of the land classes and total sample (500) in determining the overall accuracy. Cell entries are expressed as the estimated area proportion of the cells of the error matrix.

CHAPTER FIVE

Quantifying forest change pattern from shale oil and gas infrastructure development in the British Columbia's shale gas plays

Abstract

Understanding the interconnection between land use processes (e.g., oil and gas land uses) and the patterns of land change (e.g., forest cover loss and fragmentation) is yet to be achieved fully. Land change researchers have posited that the insufficient understanding is not due to lack of effort but rather the difficulty in the task of seeking understanding, theoretically and practically. This study combines a geospatial approach, metrics from landscape ecology, and statistical methods to compare and contrast forest change from shale oil and gas (SOG) infrastructure development in the four shale gas plays in British Columbia (BC). The study finds that cumulatively, between 1975 and 2017, the Montney, Horn, Liard, and Cordova basins have lost 0.36%, 0.25%, 0.14%, and 0.30% of forest cover, respectively, due to the construction of shale oil and gas infrastructure. The study also finds that the shale gas plays with the largest quantity of forest cover loss from shale oil and gas infrastructure construction have the highest amount of forest fragmentation and vice versa. Both parametric t-test and non-parametric Wilcoxon signed rank tests performed on samples of forest patches showed that the forest changes from SOG infrastructure development in the shale gas plays are statistically significant. The results, however, suggest that differences in the intensity of forest cover change from shale gas land use is likely to create different ecologically significant forest fragmentation patterns. The study provides land managers with a context for understanding the land use intensities and forest change pattern which is relevant for sustainable land management in the shale gas plays of British Columbia.

Keywords: Shale gas land uses; land use processes; land change pattern; forest fragmentation; landscape metrics; northeastern British Columbia

5.1 Introduction

Anthropogenic activities in the boreal forest have intensified over the past few decades. Notably, in the northeastern BC boreal forest, agriculture, forestry, and oil and gas activities are the dominant land uses transforming the landscape (Wilson & DeMars, 2015; Johnson & Miyanishi, 2012). However, shale oil and gas (SOG) production have grown over the past few years due to the advancement in technology for the drilling and completion of extraction wells, and it has increased the industrial footprints in the northeastern BC's landscape (Erdozain et al., 2018; Copeland., Pocewicz, & Kiesecker, 2011). Thus, ecological zones and industrial footprints overlap in northeastern BC (Willow, 2016). The technological advancement is demonstrated in the shift from vertical drilling to horizontal drilling and introduction of hydraulic fracturing, which has brought about large-scale commercial gas production (Vengosh et al., 2014; Sutton et al., 2010). Exploration of greater depths and the rise in the prices of oil and gas are other factors that account for the increase in the exploration and extraction of natural gas (Brasier et al., 2011). However, there are ecological implications for the recent SOG sprawl (Brittingham et al., 2014; Braun & Hanus, 2005).

Studies from different SOG activity locations have reported some of the impacts of SOG development, and these impacts range from socio-economic to biophysical (Jalbert, Willow, Casagrande, & Paladino, 2017). In the United States, SOG developers drill several tens of thousands of wells each year, and this has led to self-sufficiency in the production of gas. Among the other economic benefits, SOG production generates revenue for local and national economies (Considine, Watson, Entler & Sparks, 2009; Barth, 2013; Christopherson & Rightor, 2012) and creates job opportunities (Braun & Hanus, 2005; Kinnaman, 2011; Christopherson & Rightor, 2012; Thomas et al., 2017). The recent increase in the exploitation of shale resources has increased the unconventional gas share of the total amount of energy produced in countries where SOG production has become a significant economic activity (Baihly, Altman, Malpani, & Luo 2010; Stephenson, 2016).

Whereas the socio-economic impacts of SOG activities are practically known and understood, the biophysical impacts are still not fully known as fewer aspects of the biophysical impacts are reported (Muehlenbachs et al., 2012; Jaspal et al., 2014). In the United States and Canada, the focus of the biophysical studies has been on water quality (Lutz, Lewis & Doyle, 2013; Rahm et al., 2013; Vidic et al., 2013). A few of the biophysical studies have focused on forest change (see example in Drohan et al., 2012; Grushecky & Wang, 2012; Abrahams et al., 2015; Racicot et al., 2014; Klaiber et al., 2017; Donnelly et al., 2017) with most of these studies taking place in the United States. In the Province of British Columbia, the focus of the biophysical studies has been on baseline water quality (Rivard et al., 2014). Information on how shale gas development is changing the composition and pattern of the forest is inadequate in British Columbia, especially in the northeastern part of the province where the Montney, Horn, Liard, and Cordova shale gas plays are found. However, these shale gas plays are within the boreal forest area, an ecologically sensitive area that serves as a habitat for different species of animals. The main objective of this study is to quantify and assess forest cover loss and fragmentation from SOG infrastructure development in the four shale gas plays in northeastern BC. The study also addresses the implications of the amount of forest cover loss and fragmentation for land management and planning for future SOG land uses.

Similar to comparing and contrasting the performance (production efficiency) in different shale gas plays (Sutton et al., 2010), comparing and contrasting between shale gas plays in terms of the pattern and quantity of forest change would be essential for land management and planning for a balance between energy resource extraction and forest conservation objectives. However, comparison among shale gas plays could be a difficult task since they have different sizes as well as the intensities of production and land uses. Also, these SOG infrastructure would likely be more in locations where the SOG plays are fully developed than at locations that are still under development. There is a possibility that plays that are fully developed would experience more forest change than the ones that are yet to be fully developed. Nonetheless, an overlooked but most important condition is that there could be more infrastructures constructed in a fully developed shale gas play, but local and national level land management or policy decisions are likely to prevent forest cover degradation. In BC, oil and gas land use decisions are taken by crown agencies (e.g., the BC Oil and Gas Commission and the BC Ministry of Environment) as about 95% of the land base is owned by the BC government. For instance, the BC Ministry of Environment ensures that impacts of oil and gas land use are reduced in areas where there are boreal caribou population and habitats (British Columbia Oil and Gas Commission (BCOGC), 2018).

Methods from geographic information science (GIS), remote sensing (RS) and Landscape Ecology provide a meaningful way of measuring the changes in the forest landscape before and after shale gas infrastructures are constructed. With these methods, it is possible to quantify the amount of change in the landscape contributed by anthropogenic activities (Nagendra, Munroe, & Southworth, 2004; Armenteras, Gast, & Villareal, 2003). This study uses landscape metrics and techniques from GIS and RS to process Landsat images and SOG spatial data for measuring and assessing the differences and similarities in forest loss and fragmentation in the world-class shale gas plays of British Columbia. Furthermore, the study discusses the implications of the results for land management

5.2 Materials and methods

5.2.1 Description of the shale gas plays (study locations)

The study was conducted in the four world-class shale gas plays in northeastern British Columbia. A shale gas play is an area made up of oil and gas-charged sedimentary rock system where oil and gas drilling take place. In BC, the shale gas plays are also designated as the British Columbia Oil and Gas Commission's management areas. These plays where the study took place, are Horn River Basin, the Cordova Embayment, the Liard Basin, and the Montney play trend (See Figure 5.1). The Montney is the largest and most productive shale gas play. It stretches from the border between British Columbia and Alberta near Dawson Creek, extending 200 kilometres north-west to the BC Rocky Mountain foothills. The second largest and second most productive shale gas play in BC is the Horn River Basin. It stretches from south of Fort Nelson and north to the border of British Columbia and Yukon. As compared to the Montney and Horn, the Liard Basin and Cordova Embayment, are still in early development. The Liard Basin and Cordova Embayment are found west and east, respectively, of the Horn River Basin. These plays are also found at the edge of the British Columbia-Yukon border (Natural Resources Canada, 2016).

British Columbia's part of the basin of western Canadian sedimentary is primarily a gas-charged system. Conventional gas exploration and production have been in existence since the 1950s. However, unconventional gas became a recognized resource when large-scale exploration and production began in the mid-1990s with the use of horizontal drilling in the Devonian carbonates of the Jean Marie formation (Natural Resources Canada, 2016). The shale gas plays are in the boreal forest area, and hence most of the shale gas activities are taking place in the Boreal forest in British Columbia. British Columbia's boreal zone covers 32 million hectares (approximately 79 million acres). Accounting for about six percent of Canada's boreal forest, it forms an essential part of British Columbia's diverse and complex ecosystem network (Forestry Innovation Investment, 2017). Table 5.1 shows the amount of area covered by shale oil and gas activities in 2013 and 2014.

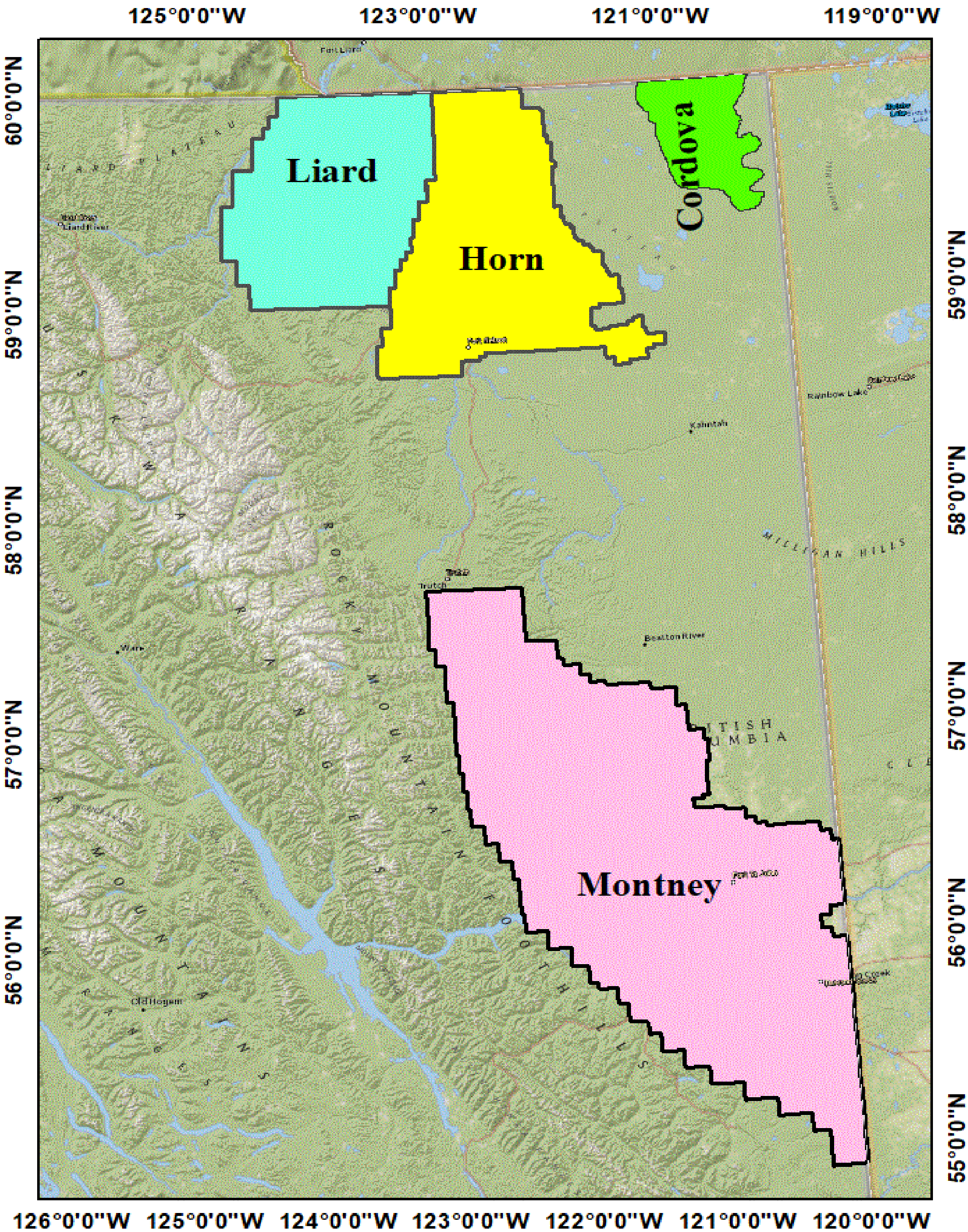

Figure 5.1 Map showing the four shale gas plays in northeastern British Columbia

Table 5.1 Land surface area for all shale oil and gas activities in each of the shale gas plays in northeastern BC (from the BC Oil and Gas Commission, 2014)

Shale formation/play	Total land area* (ha) for SOG activities	% of surface area*- 2013	% of surface area*- 2014	% change in surface area* for SOG activities
Horn River Basin	34670	3.18	3.03	-0.15
Liard Basin	12150	1.28	1.3	-0.02
Cordova Embayment	7492	3.08	2.79	-0.29
Montney Play Trend	110961	4.08	3.72	0.36

*The land surface area for shale oil and gas activities include areas covered with roads, pipelines, retention ponds, well pads and other facilities constructed for shale oil and gas industrial purposes.

5.2.2 Data types and sources

Different sets of geospatial data were used in this study. Surface reflectance images from Landsat Multispectral Scanner (MSS 5) were downloaded from the United States Geological Survey (USGS), composited, and classified for land change analysis. With the aid of the best-available-pixels approach (see White et al., 2014), images from 1975 were composited to represent 1975 land cover conditions for the feature change analysis. With this approach, the best land cover pixels were selected based on the day of the year, the sensor type, and nearness to clouds, cloud shadow and haze. The target pixels were from May 1, 1975. However, candidate pixels to be populated to generate Landsat image for the land classification were also selected from the MSS images acquired 30 days earlier than May 1 or 30 days after May 1, 1975. This image selection approach was used to generate a cloud- and haze-free 1975 image. The reason for selecting the 1975 Landsat image to represent the pre-SOG development land condition is that most of the shale gas wells (more than 85%) were constructed after 1975 (Adams, Janicki, & Balogun, 2016). The 1975 Landsat image is, therefore, the baseline data for measuring the cumulative landscape change from SOG infrastructure construction between 1975 and 2017. The study relied on the United States Geological Survey (USGS) for all the Landsat images used in this study.

The spatial data for roads, well pads, and pipelines footprints were collected from the BCOGC. High-resolution images from Google Earth Pro were used in this study. SOG features (access roads, well pads, and pipelines) were digitized (in vector format) from Google Earth Pro and used in this study. SOG features used were up to date spatial information of SOG infrastructure for the shale gas plays as at 2017. Shapefiles of the four study locations were also used in this study. These shapefiles were acquired from the BCOGC database.

Using stratified random sampling, 500 ground truth samples were selected from the original 1975 Landsat image for accuracy assessment of classified Landsat image. The stratification was based on the observed land classes in the Landsat image. The ground truth points were selected taking into consideration the sizes of land classes, especially the rare land classes (e.g., water). This class size consideration was to ensure that the samples of ground truth points collected are representative of all land classes identified in the Landsat image.

5.2.3 Classification of Landsat image

The images were classified into one of the following five land classes using an approach that integrates remote sensing and GIS techniques and reduces the effects of pixel reflectance in determining the classes of land cover. The land classes include water, forest, agriculture, barren, and developed land. To ensure accuracy in the land cover classification process and make use of the advantages of both semi-automated and automated classification algorithms, a hybrid classification approach (see a similar approach in Paolini et al., 2006) was used to classify the 1975 Landsat image into land categories. This hybrid approach makes use of both supervised and unsupervised classification algorithms to produce a classified land cover image. Firstly, the K-means unsupervised classification algorithm was used to classify the Landsat image into 55 land classes. A signature file was generated from the unsupervised classification and used for further classification. With the aid of a GIS-based dendrogram, the relationships between the land classes in the signature file were examined to determine the classes which could potentially merge to form a land class. The original 1975 Landsat image was examined visually to validate the relationships between the land classes shown by the built dendrogram. At this stage, the land classes were merged and reduced to 5 by changing the class identities in the signature file. The signature file was remapped to show the updated five land categories. By using the Maximum Likelihood Supervised Classification (MLSC) algorithm, further classification was performed using the updated signature file as training data.

Based on visual inspection, information from the built dendrogram, spectral separability, and merging of classes of land cover, five land classes were finally generated using guidelines from the classification system by Anderson (1976). The details of each of the classes of land are as follows. The forest land includes vegetated tree plants of deciduous, semi-deciduous, and mixed forest. The agriculture class is made up of hay/pasture, grasslands, and herbs. The barren land category consists of bare land and outcrop of rocks. The developed land class is made up of residential, commercial, industrial, and transportation land uses, including all impervious and semi-pervious surfaces. The water class consists of intermittent and permanent lakes, rivers, ponds, streams, and creeks.

The accuracy of the mapped land classes was assessed using the 500 ground truth samples selected from the original 1975 Landsat image. The accuracy assessment was done based on Olofsson et al. (2014), which takes into account the number of samples selected for each of the land classes proportionate to the sizes of the land classes. The use of this method of accuracy assessment ensured that the ground truth samples are selected from all land classes and fairly represented in determining the overall accuracy of the Landsat image classification. The margin of error for the selected samples of ground truths were calculated to determine the representativeness of the samples for the given sizes of the land classes. Shapefiles of the four shale gas plays were used as regions of interest to clip out the four study locations from the classified Landsat image. This step was performed to acquire separate classified Landsat images for each of the four shale gas plays.

5.2.4 Shale oil and gas feature-induced land change

In determining the locations and amount of land change from SOG infrastructure development, these steps were followed. Firstly, SOG features from BCOGC were visually inspected on the landscape of the four study location by overlaying all the SOG features on the high-resolution aerial image to ensure that (i) the SOG features exist on the landscape (ii) the sizes of the features match with the ones found in the high-resolution aerial image. The reason for undertaking this process was to exclude features that do not exist in the high-resolution image but found in the BCOGC's data and add features that are missing from the BCOGC's data but found in the high-resolution image. At a scale ranging between 1:2500 and 1:3000, missing SOG spatial datasets were hand-digitized from the high-resolution image. Also, SOG features from the BCOGC that did not meet the size of the features in the high-resolution image were reconstructed through hand-digitizing. This process ensured that the impacts of the features are not overestimated or underestimated.

Secondly, the SOG features (in vector formats) were converted to raster format to match the format of the classified Landsat image. To ensure that the SOG features are well represented and aligned with the classified Landsat image, the image was resampled to a spatial resolution of

10 m by 10 m. This process was also to ensure that the likelihood of higher underestimation or overestimation of the spatial data for the shale gas infrastructures would reduce and hence, its actual impacts on the land cover could be measured. Thus, systematic biases in assessing land change from the SOG features are likely to reduce.

In the next step, the spatial data for the SOG features were applied to the classified 1975 Landsat image through an ‘if-else’ analysis. In this analysis, areas (pixels of land cover) in 1975 that that were previously of particular land cover characteristics (e.g., forest, barren, agriculture, water) would change to industrial developed land if there has been a disturbance in the landscape from any of the SOG features (infrastructure). If this statement is evaluated as true, land cover types (forest, barren, agriculture, water) assume the cell values of the raster layer of SOG features. Conversely, if the statement is evaluated as false, land cover types would remain unchanged, an indication that between 1975 and 2015, SOG features have not disturbed the landscape. For instance, any pixel of the land cover image which represents forest but finds itself underneath the shale gas feature was converted into developed land, an indication that an area which was once covered by forest was taken over by a shale gas feature (either access road, pipeline or well pads), as at December 2017. In a situation where a raster layer of SOG features overlay pixels of a non-forest category of land, that non-forest category would change into developed land. According to the condition statement, if the raster layer of SOG features overlays a developed land category, no change would be measured.

Whereas this GIS-based ‘if-else’ analysis could accurately evaluate the cumulative quantity of landscape change from the construction of SOG infrastructural development, it is likely that the quantity of change would be slightly overestimated when calculating the change in individual land cover classes. For instance, an overestimation of the quantity of forest change could occur if the 1975 forest cover at a location changed into another category before the construction of the SOG infrastructure. The final land cover image, which is a composite of the classified 1975 Landsat and the SOG features was generated for each of the four shale gas plays of northeastern BC for further analysis. Shapefiles of the four shale gas plays were used as regions of interest to clip out the four study locations from the final land cover image. This step was performed to acquire separate final land cover images for each of the four shale gas plays. A comparison was made between the shale gas plays in terms of the amount and pattern of forest cover loss, using the 1975 classified Landsat image and the final land cover image.

A t-test was performed using samples of forest cover patches to find out if there was a statistically significant difference in the area of forest cover patches in 1975 and after 1975 when the shale oil and gas wells increased by more than 85%. The same samples of forest cover patches were compared for the two periods in each of the shale gas plays. For instance, selected patches of forest cover labelled a, b, c,…etc. were compared at two different times (in 1975 and after 1975) to derive and test the statistically significant differences in their sizes. The statistical test was performed at a 95% confidence interval. In the Cordova basin, 57 out of 112 forest patches affected by the SOG infrastructure development were randomly selected for the statistical test. A sample of 42 out of 86 patches of forest cover affected by the SOG infrastructural development was randomly selected in the Horn River Basin. In the Liard Basin, 45 out of 89 patches of forest cover were randomly selected. A sample of 51 out of 105 forest cover patches affected by SOG infrastructure development in the Montney shale gas play was randomly selected. A Shapiro-Wilk normality test showed that the samples of forest cover patches selected do not follow a normal distribution (see Appendix 4 Table VI). To test for the robustness of the parametric t-test and the impacts of the sensitivity in the distribution of the data samples, a non-parametric test was performed using the Wilcoxon signed rank test.

5.2.5 Forest fragmentation analysis

In this study, assessing forest fragmentation includes (i) measuring the composition of patches/cover, (ii) measuring the patch size and patch size pattern, (iii) measuring patch shape and patch shape pattern, and (iv) measuring patch connectivity in the forest cover. FRAGSTATS metrics developed by McGarigal and Marks (1995) and further upgraded in a later version by McGarigal et al. (2012), were used to calculate the amount of fragmentation in the landscape for (i) the 1975 classified Landsat images for the four shale gas plays and (ii) the final land cover for the four shale gas features. Metrics, namely: number of patches, mean patch size, the coefficient of variation of patch size, mean shape index, the coefficient of variation of patch shape index, and aggregation index at the class level were used to calculate the amount of forest fragmentation for the two datasets for each of the four shale gas plays. The GIS-based Landscape Fragmentation Tool (LFT) (Vogt et al., 2007) was used to create the forest fragmentation categories of core, edge, patch and perforated forest. Tables 5.2 and 5.3 show some of the metrics and categories of forest fragmentation used and their descriptions.

Table 5.2 FRAGSTATS metrics and their descriptions

Metrics	Description
Number of patches (NP)	The total number of patches in a class. An increasing number of patched means the forest is getting fragmented. This metric is unitless and used in conjunction with other metrics.
Mean Patch Area/Size (Arean_MN)	Average patch size or area in a class. A decreasing patch size means the forest is getting fragmented and vice versa.
Patch size coefficient of variation (AREA_CV)	It measures relative variability about the mean (that is, variability as a percentage of the mean), not absolute variability. The larger the Area_CV the larger the variabilities within patch sizes.
Mean shape index (Shape_MN)	The shape index measures the complexity of patch shape compared to a standard shape (square) of the same size. The value is 1 when the patch is square and increases without limit as patch shape becomes more irregular.
The coefficient of variation of forest patch shape Index (SI_CV)	It measures variability (standard deviation) in the patch shape expressed as a percentage of the mean shape index. The higher the SI_CV, the larger the variabilities in the patch shape.
Aggregation index (AI)	It measures aggregation. AI equals 0 when the focal patch type is maximally disaggregated and equals 100 when the patch type is maximally aggregated into a single, compact patch.

The information in the table is from McGarigal et al. (2012)

Table 5.3 Categories of forest fragmentation

Category of fragmentation	Description
Patch forests (PF)	They are small fragments that are completely degraded (does not contain any forest pixels) by the "edge effect*". An increasing PF means an increasing fragmentation and degradation of forest cover.
Edge forest (EF)	EF occurs within the "edge effect" zone along the outside edge of a non-patch tract. An increasing EF shows an increasing amount of forest fragmentation.
Core forest (CF)	CF occurs outside of the "edge effect" zone, and so it is not degraded by fragmentation. An increasing CF shows a decreasing amount of fragmentation.
Perforated forest (PFF)	PFF occurs within the "edge effect" zone along the edge of a small clearing in a non-patch tract. An increasing PFF means an increasing amount of fragmentation.

Note: the information in the table is based on Vogt et al. (2007). *Edge effect zone is a 100m distance between the forest and the non-forest area. Beyond this distance, shale oil and gas activities and other land uses could degrade the forest cover. The 100m was chosen for general purposes (see Drohan et al., 2012).

5.3 Results

5.3.1 Shale oil and gas-induced forest cover change

The overall accuracy achieved for the classified Landsat image is 96.623%, and the margin of error for the selected sample of ground truth used in the accuracy assessment is ±4.624 (see Appendix 4 for details). The forest cover has remained the most extensive land cover class among all the land categories and in all the BCOGC's management areas (Table 5.4). The Liard basin had more forest cover (91%) than all the other management areas. By December 2017, the Liard had lost the least (-0.14%) quantity of forest cover as compared to that of the other three management areas (see Table 5.5). The largest forest cover loss (-0.36%) occurred in the Montney area followed by the Cordova, Horn, and Liard management areas, respectively (Table 5.5). At a 95% confidence interval, the t-test show that the *P*-values (Cordova = 0.015, Horn = 0.0002, Liard = 0.021, Montney = 0.002) are less than the alpha value of 0.05 (see Appendix 4 Table II–

V). The Wilcoxon signed rank test re-affirms the robustness of the t-test, even though the samples used for the t-test do not follow a normal distribution (see Appendix 4 Table VI).

A total of 1.05% (computed from Table 5.5) of the forest cover has been lost from all the management areas, and this is attributed to the SOG infrastructure development. Apart from the forest land class, the barren land category also reduced in size, and it is the second largest land class to convert to developed land as a result of SOG infrastructure development (see Table 5.5). Table 4.5 shows that the conversion from barren land to developed land occurred mainly in the Cordova shale gas play.

Information in Table 5.5 also shows how much the developed land category has increased due to shale oil and gas infrastructure development. This increment is at the expense of all land categories within the shale gas plays. The Cordova shale gas play is the formation with the largest part of its surface area covered by the SOG infrastructure. It is also the formation with the second largest amount of forest cover loss (see Table 5.6). Figure 5.2 shows the overall change and transition in each of the shale gas play in northeastern BC. The most developed shale gas play (Montney) has more SOG features (infrastructure) than any of the other three management areas as shown in Figure 5.3.

Table 5.4 Relative proportions of land categories in the respective management areas before and after shale oil and gas features

Land Category	Montney		Horn		Liard		Cordova	
	% of category before SOG	**% of category after SOG**	**% of category before SOG**	**% of category after SOG**	**% of category before SOG**	**% of category after SOG**	**% of category before SOG**	**% of category after SOG**
Water	5.24	5.23	1.799	1.790	2.797	2.796	2.5115	2.5112
Forest	84.91	84.55	87.98	87.74	91.19	91.05	77.56	77.25
Barren	5.26	5.24	9.40	9.38	4.96	4.95	19.73	19.67
Agriculture	1.92	1.91	0.1892	0.1891	0.3800	0.3796	0.08000	0.07996
Developed	2.66	3.06	0.63	0.90	0.67	0.82	0.12	0.48

Note: SOG is shale oil and gas. The percentage of categories 'after' oil and gas activities also represent the persistence of the category after the construction of oil and gas well pads, access roads, and pipelines.

Table 5.5 Relative changes in categories of land attributed to shale oil and gas features in the respective management areas

Category of land	% change in categories after SOG development in the shale gas plays			
	Montney	**Horn**	**Liard**	**Cordova**
Water	-0.01	-0.009	-0.001	-0.0003
Forest	**-0.36**	**-0.25**	**-0.14**	**-0.30**
Barren	-0.02	-0.02	-0.01	-0.06
Agriculture	-0.01	-0.0001	-0.0004	-0.00004
Developed	0.40	0.27	0.15	0.36

Note: SOG is shale oil and gas. The values in the table also represent the proportion of land categories that transitioned to developed land.

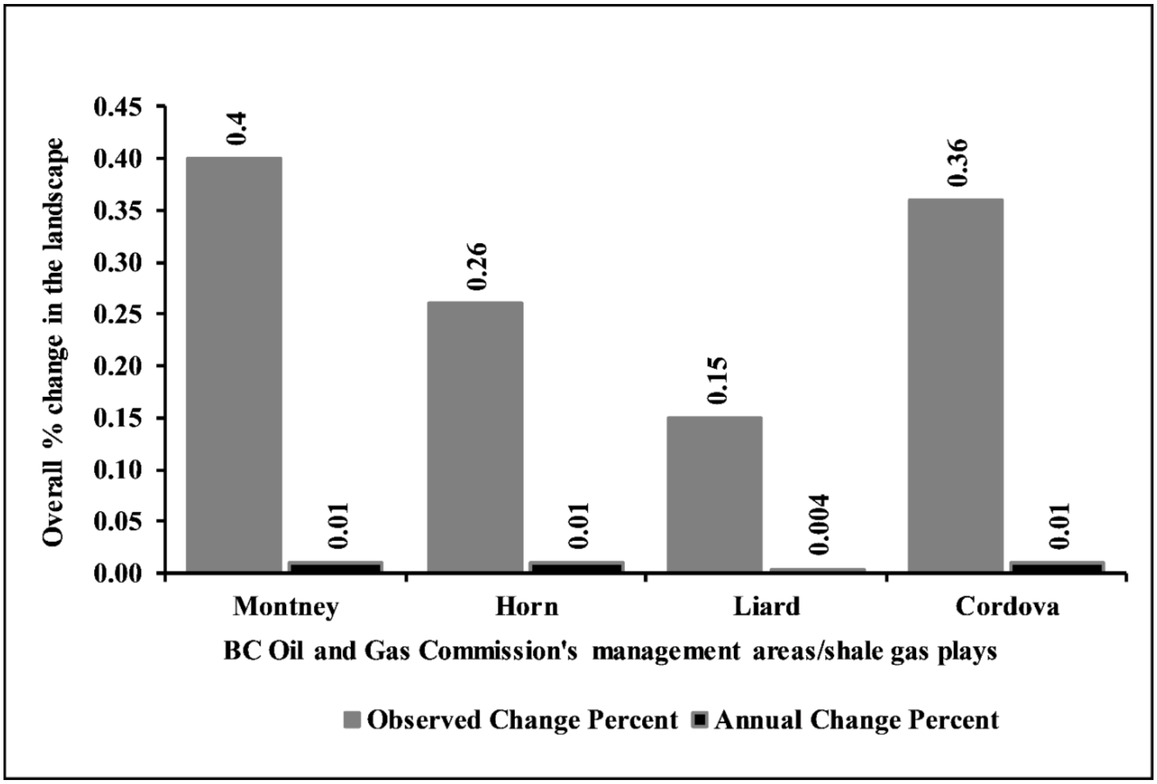

Figure 5.2 Overall percentage change in the shale gas plays after shale oil and gas activities, 1975-2017.
The percentage change amounts to the portions of the landscape that converted from all land categories to developed land in the shale gas plays.

Table 5.6 Total area of shale gas play, the total surface area covered by shale oil and gas (well pads, pipelines, and roads only) as at 2017, and the corresponding amount of forest change

Shale gas play	Total Area (ha) of formation/play	Area of land (ha) for SOG infrastructure, 2017	% of surface area covered by SOG infrastructure, 2017	% of forest change from SOG infrastructure
Horn	1,146,183	5,386	0.46	-0.25
Liard	934,972	4,034	0.43	-0.14
Cordova	268,996	3,236	1.20	-0.30
Montney	298,4899	12,450	0.41	-0.36

Note: SOG is shale oil and gas. The percentage of surface area covered by SOG infrastructure, 2017 was calculated from the data acquired from BC Oil and Gas Commission and the digitizing process._% of forest change from SOG infrastructure was calculated from the if-else conditional analysis.

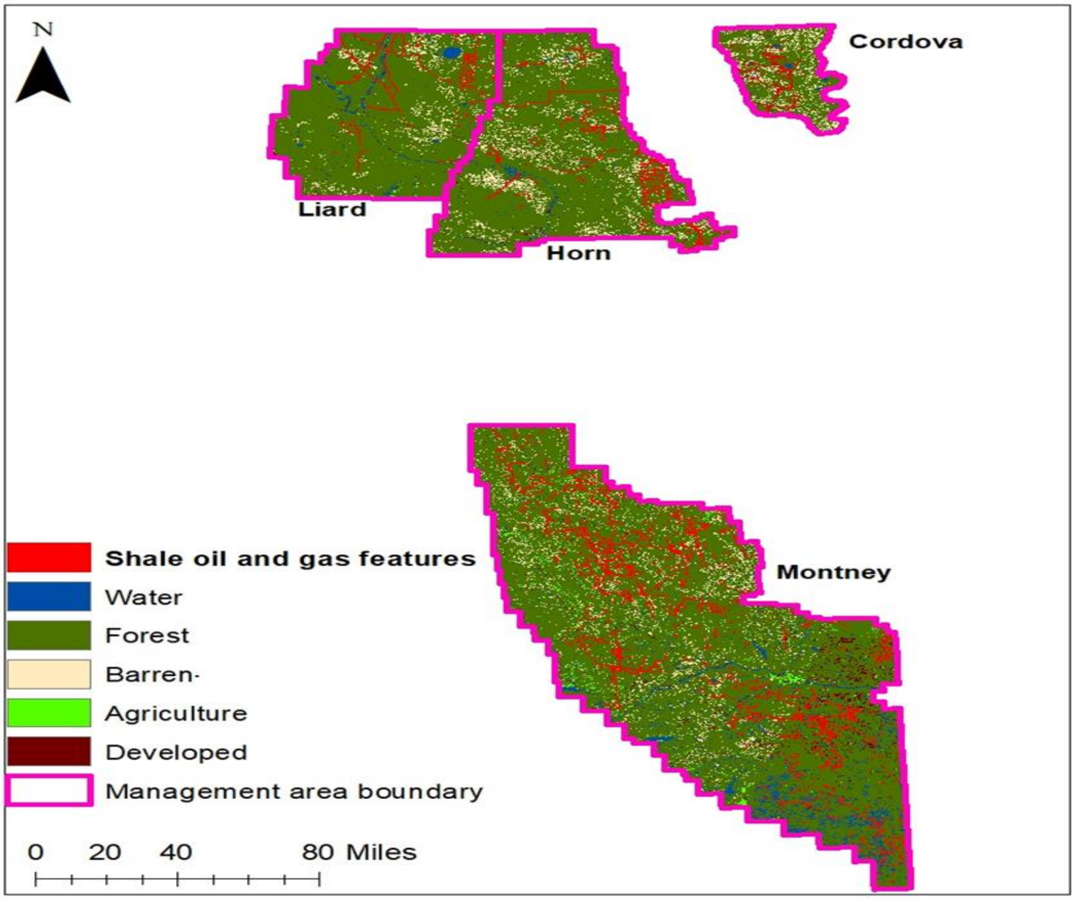

Figure 5.3 shale oil and gas features (infrastructure) and mapped land cover classes of 1975

5.3.2 Fragmentation of forest after oil and gas infrastructure development

The Cordova management area had the largest core forest before and after years of SOG infrastructure development. Table 5.7 shows that Montney is the area with the least quantity of core forest and, however, still measured the largest loss in core forest and the largest increase in the forest edge as compared to the other three shale gas plays. The Laird management area received the least impacts from shale oil and gas activities as all the measures of fragmentation has shown (see Tables 5.7 and 5.8). Also, it has the least increment in the edge forest.

Table 5.7 Forest fragmentation before and after shale oil and gas infrastructure in the BC shale gas plays, 1975-2017

Category of fragmentation	**Shale gas play/Year**							
	Cordova		**Horn**		**Liard**		**Montney**	
	1975	**After 1975**	**1975**	**After 1975**	**1975**	**After 1975**	**1975**	**After 1975**
Patch	0.055	0.056	0.0530	0.0537	0.058	0.059	0.198	0.201
Perforated	1.370	1.373	1.016	1.020	0.998	0.999	2.899	2.903
Edge	3.544	3.55	4.621	4.629	3.99924	3.999242	11.233	11.248
Core	95.030	95.019	94.310	94.301	94.945	94.943	85.666	85.652

Table 5.8 Percentage change in categories of forest fragmentation, after shale oil and gas Infrastructure, 1975-2017

	Shale gas play			
Category of fragmentation	**Cordova**	**Horn**	**Liard**	**Montney**
Patch	0.001	0.0007	0.001	0.003
Perforated	0.003	0.004	0.001	0.004
Edge	0.006	0.008	0.000002	0.015
Core	-0.011	-0.009	-0.002	-0.014

The results from Table 5.9 show that forest patches have increased in number in all the management areas, especially in the Montney. Patch sizes of the forest cover have also reduced after the construction of shale gas infrastructure, and the sizes are more irregular in pattern mostly within the Montney than the other three management areas (see Area_CV in Tables 5.9 and 5.10). Also, from Table 5.9, after the oil and gas infrastructure construction, the shape of the forest patches within the various management areas became more irregular than square-shaped patches. Among the management areas, the Montney is the landscape with most variabilities in the patch shape. That is, there is a vast difference between the most regular square-shaped patches and the most irregularly shaped patches. The forest patches in the Liard and Horn are the most maximally aggregated. The patches in these management areas are close to being a single patch of forest in their respective landscapes. However, the Horn and Cordova are similar in the amount of fragmentation as shown in Tables 5.7, 5.8, 5.9, and 5.10.

Table 5.9 Composition and configuration of forest patches before/after oil and gas Infrastructure in the BC shale management areas, 1975-2017

Management Areas	NP		Area_MN		Area_CV		Shape_MN		Shape_CV		AI	
	1975	**After 1975**	**1975**	**After 1975**	**1975**	**After 1975**	**1975**	**After 1975**	**1975**	**After 1975**	**1975**	**After 1975**
Cordova	2081	2090	100.22	99.41	4486.1	4493.5	1.175	1.143	106.7	112.44	98.65	91.68
Horn	3640	2644	376.84	275.7	4811.3	4810.8	1.183	1.1479	105.3	110.92	99.22	95.21
Liard	1482	1483	574.67	573.5	2419.1	2419.9	1.124	1.2092	95.73	101.15	99.50	96.89
Montney	1760	5754	1440.2	438.6	3061.8	5490.1	1.214	1.1659	253.3	198.48	91.75	90.22

Table 5.10 Changes in the composition and configuration of forest patches after well pads, access roads, and pipelines in the BC shale oil and gas management areas, 1975-2017

Management Areas	Change in NP	Change in Area_MN	Change in Area_CV	Change in Shape_MN	Change in Shape_CV	Change in A1
Cordova	9	-0.81	7.4	-0.032	5.74	-6.97
Horn	-996	-101.14	-0.5	-0.035	5.62	-4.01
Liard	1	-1.17	0.8	0.085	5.42	-2.61
Montney	3994	-1001.6	2428.3	-0.0481	-54.82	-1.53

5.4 Discussion

5.4.1 Shale gas feature changes in the forest cover

This study which assesses change in the forest cover from the impacts of SOG infrastructure finds that the shale oil and gas features impacts are more in the management areas with lesser forest cover. For instance, in the Cordova and Montney areas, forest forms 77% and 84% of the management areas, respectively. These two areas have smaller forest cover than the Liard and Horn management areas. However, the forest areas of the Cordova and Montney management areas received the most impacts from the SOG infrastructure development. This pattern of forest change suggests that forest loss from SOG infrastructure development occurred mainly in the shale gas management areas where there are lesser quantities of forest cover on the landscape. Also, this pattern of forest change resulting from anthropogenic land use could be a forest management decision to conserve management areas that have more forest and devoid of considerable losses in forest cover. Such a forest management decision is in accordance with the International Boreal Conservation Science Panel (IBCSP) which recommends that at least fifty percent of the intact boreal forest of Canada should be conserved and that industrial activities taking place within the boreal forest zone should follow the highest global sustainability standards (Badiou et al., 2013). Nonetheless, the reason for this forest pattern from shale oil and gas infrastructure development could be better understood if the specific forest conservation or land management context of each of these shale gas plays is known.

With 1.2% of the surface area of the landscape of the Cordova basin covered with shale oil and gas well pads, roads and pipelines, this basin had 0.3% loss of forest cover. The Horn management area has the second highest surface area coverage of the shale oil and gas features and the second lowest percentage of change in the forest cover. However, it is expected that the landscape with more SOG infrastructure would have more changes in its forest landscape. This pattern of forest change suggests that even though the Cordova has the largest part of its landscape covered with SOG infrastructure as compared to the Liard, Montney and Horn, most of the infrastructures constructed have contributed to a smaller change in the forest cover. The implication of this pattern of linkage between the quantity of surface features and the amount of forest change is that the relationship between the SOG features and the quantity of change they contribute transcends being just linear. This pattern also conveys to land change modellers that different forms of relationships should be taken into consideration when predicting future changes in forest cover.

The changes in the barren land could explain these differences in the ratio of the proportion of change in forest cover to the proportion of surface area covered by shale oil and gas features. As compared to the other three management areas, the Cordova management area has the largest surface area covered by shale gas infrastructure but a lesser change in forest cover. Nonetheless, the Cordova had the most extensive barren land as compared to the Montney, Liard, and the Horn basins. Also, the Cordova had the largest change in its barren land from the SOG infrastructure development. The results, therefore, imply that the impacts of shale oil and gas infrastructure development in the Cordova Management area are shared between the forest and the barren land. In contrast, in the Montney, Liard, and Horn, lesser changes were measured in the other categories of land apart from the forest. Hence, in the Montney, Liard and Horn basins, impacts from shale oil and gas are concentrated in the forest landscape.

The amount of forest cover loss from SOG infrastructure development is less than 1% in each of the four shale gas plays (Liard, Montney, Cordova, and Horn), and this is similar to findings of land change due to shale gas infrastructure development in other locations such as Carroll County-Ohio and Washington County-Pennsylvania. However, within all the shale gas plays a total of 1.05% forest cover loss was measured, a percentage of reduction in forest cover which is higher than the average percentage of reduction in forest cover from other shale oil and gas industrial locations (see Donnelly et al., 2017; Preston & Kim, 2016; Slonecker et al., 2012). Even though the reduction in forest cover in each of the four shale gas plays is practically minimal, the t-test and the Wilcoxon signed-rank test results suggest that there is a significant difference in the areas of forest cover patches of 1975 and that of after 1975. Moreover, these statistical tests suggest that the changes in the forest cover measured in the shale gas plays are not solely as a result of random chance.

One notable feature of the results from northeastern BC's four shale gas management areas is the negligible percent change in the agriculture land from shale oil and gas infrastructural development. The minimal change in this land category is an indication that there are fewer shale gas well pads, access roads, and pipelines constructed on agriculture lands within the shale gas management areas. However, agriculture lands account for less than 2% of the total landscape in each of the four management areas. The minor change in the agriculture land from shale oil and gas infrastructure construction is because the industry is not constructing on the meagre amount of agricultural land found in the management areas. This result is inconsistent with the findings from the shale gas plays of Pennsylvania, Ohio, and Virginia in the United States where shale oil and gas activities are concentrated on the agriculture lands (see Donnelly et al., 2017; Preston & Kim, 2016; Drohan et al., 2012). For instance, in the Williston Basin, shale oil and gas activities have converted about 49% of the agricultural lands to developed lands (Preston & Kim, 2016). Similarly, in Allegheny and Susquehanna Counties of Pennsylvania where the impacts from shale oil and gas infrastructures are shared between agriculture and forest, the agriculture land constitutes 5% and 28% of the landscape in the two counties, respectively (Slonecker et al., 2012). The impacts from the construction of shale oil and gas infrastructure on the forest landscape of the BC's shale gas management areas might have been minimal if there were other land categories more extensive enough to receive some of the impacts as seen in other shale oil and gas industrial locations.

5.4.2 Shale gas feature-induced forest fragmentation

The conditions of the core forest and the edge are essential criteria for measuring forest fragmentation, especially in areas where there are increasing human activities (Pfeifer et al., 2017). The results of this study indicate that the Montney management area has the most fragmented forest landscape. The Montney is more likely to receive most of the impacts of fragmentation such as brood parasitism, the spread of invasive species, altered light, augmentation of carbon emissions, predation and a threat to biodiversity (Brinck et al., 2017; Rogan et al., 2016; Abrahams et al., 2015; Pătru-Stupariu et al., 2015), especially since it is found in the ecologically sensitive boreal forest zone. This tendency of a higher level of fragmentation in the Montney is likely due to the higher intensity of SOG infrastructure development. Empirical studies have shown that areas with higher intensity of human activities are more likely to be fragmented than areas with lesser human activities and pressure (Pătru-Stupariu et al., 2015; Peres et al., 2010).

The results also show that the Liard is the least fragmented and has the least reduction in forest cover. Conversely, the Montney, which recorded the highest amount of forest loss had the highest amount of forest fragmentation. The reason for this forest fragmentation pattern may be related to, among other factors, but most importantly the amount of forest cover change from SOG infrastructural development in the two shale gas plays. The results suggest that shale gas plays with higher forest loss from SOG infrastructure development is likely to have a higher amount of changes in the composition and spatial pattern of the forest patches.

Turner et al. (1995; 1993) have argued that the landscape pattern does fundamentally relate to land use. Here, the differences in the intensity of shale oil and gas land use between the Montney, Liard, Cordova and the Horn management areas demonstrate the pattern-process linkage. However, the change patterns and processes relationships are not fully established because of the complex interactions between human activities and other environmental factors. For instance, in the case of the findings from the shale oil and gas management areas in BC, the overall change and fragmentation in the forest landscape from the infrastructure development are less likely to be fully captured. There are indirect changes that could occur in the landscape as the landscape loses forest cover due to shale oil and gas development. These indirect changes could include soil erosion and loss of topsoil, which the methods used in this study and other similar studies could not assess (e.g., in Donnelly et al., 2017; Preston & Kim; 2016, Abrahams et al., 2015). This example from northeastern BC supports the assertion by Nagendra, Munroe, and Southworth (2004) that the explicit theoretical linkages between patterns and processes of land change are relatively underdeveloped. The conceptual understanding of forest change from SOG infrastructure development does not fully capture indirect changes. Therefore, this study argues that the current geospatial methods used in assessing the pattern of forest change resulting from shale gas infrastructure development and other land use specific land changes only reveal a partial change in the forest landscape and that there could be other indirect changes which are left unmeasured.

5.4.3 Implications for land management

The results from this study could improve land management in northeastern BC, especially within the shale gas management areas designated by the BC Oil and Gas Commission. First and foremost, the overall reduction of more than 1% in the forest cover due to the construction of well pads, pipelines, and access roads implies that many shale oil and gas regions in North America are undertaking the shale gas activities in a more sustainable manner than in the four shale gas plays in BC. For instance, in the shale gas regions of Washington County, PA and Carroll County, Ohio, the reduction in forest cover are less than 1%. The results from this study, therefore, serve as a spatial model for decision making regarding why there would be the need to undertake shale gas exploration on other land cover types such as the agriculture and barren land. Whereas directing the shale oil and gas activities to the agriculture land could impact livelihoods, reducing impacts on the forest cover could also protect the already endangered caribou species in the boreal forest of BC. Also, an initiative to utilize the agriculture lands for shale gas activities may need to be balanced with the provision of alternative livelihoods for people whose lives depend on the pasture production, the main activities on the BC's agriculture lands.

Secondly, the results from this study suggest to forest managers the need to make an effort to improve the restoration of orphan well pad sites. For instance, in the Montney management area, there has been a considerable reduction in the forest cover. As well, this management area has the most fragmented forest from the construction of SOG infrastructure. This area-specific information could assist forest managers in their efforts to reduce the industrial footprints in the boreal forest. For example, with this information, forest managers are able to decide whether or not additional anthropogenic disturbances in the Montney are socio-ecologically sustainable.

The findings from this study could direct land managers to undertake further field studies to learn about why the Cordova management area has more shale gas features on its land surface and yet did not record the highest reduction in the forest cover in the area. These questions could be answered from the proposed field studies. Is the forest cover not shrinking because gas-charged rocks are not underneath the forest? Does the quantity of other land categories have implications on the rate at which forest lands are used for shale gas activities? Such studies could improve our understanding of the need and possibility of having an area-specific initiative to maintain a large quantity of forest cover in all the management areas. The differences in the quantities of land change among the different land categories in the management areas are evidence-based information for land managers to note that there could be a non-linear relationship between the quantity of shale gas features on the landscape and the quantity of forest change.

5.5 Conclusion

This study compares and contrasts the quantity and pattern of forest change from shale oil and gas infrastructure (well pads, access roads, and pipelines) in the Montney, Liard, Horn, and Cordova shale gas plays in northeastern BC. The study finds that the shale oil and gas plays with a larger quantity of forest change resulting from shale oil and gas infrastructure construction have a higher amount of forest fragmentation and the vice versa. Also, the study finds that shale gas plays with larger quantities of forest cover were the areas with lesser amounts of forest cover loss and fragmentation.

From the results, this study concludes that the amount of surface area of the landscape covered with shale oil and gas infrastructure is less likely to determine the quantity and pattern of forest change; the amount of shale oil and gas infrastructure could not create any regular pattern of forest change. In other words, the amount of infrastructure on the landscape of the four management areas could not fully correspond to the quantity of forest change in the northeastern BC. The fact that a management area or shale gas play has a larger quantity of infrastructure on its landscape does not mean that it would measure the larger quantity of forest change. Whereas factors such as the site of the shale rocks and the demand for shale oil and gas could influence a larger scale and extensive exploitation of SOG to contribute more changes in the environment, local decisions and conservation objectives in the management areas could reduce the impacts on the forest ecosystem.

This study concludes that the pattern of shale gas land use and its impacts on the forest cover in the management areas match the amount of forest fragmentation. The linkage between the amount of forest change (from spatial variation in the land use) and forest fragmentation measured by the forest patch pattern and composition has been echoed in the results from the Montney, Liard, Horn, and Cordova areas. However, the quantity of surface area covered by shale gas features has a more complicated relationship with the amount of forest change that could be contributed by the features. Whereas the relationship between a given quantity of shale gas features and the overall change in the landscape could be fairly linear, specifically drawing a linear relationship between the quantity of shale gas features and the amount of forest cover change could be misleading. Drawing a linear connection between the two could be misleading because the findings from this study show that the relationship between the surface area of land covered by the shale gas features and forest change is more complex than a linear relationship.

The reliability of the results from this study depends on the accuracy level of the classified land cover data and the ability to identify and include all constructed well pads, pipelines, and access roads in the landscape. The overall accuracy and margin of error for the classified Landsat image suggest that the samples of ground truth points selected are representative of the area of land classes and that there is a good agreement between the selected points and the mapped land classes. Furthermore, this accuracy level suggests that the approaches (random forests and the unified land classification) used in the Landsat image classification could be used in classifying and measuring land change in other boreal forest environments.

Whereas the amount and pattern of land change from shale oil and gas infrastructure construction are necessary for understanding the direct emergent pattern of land change, indirect or secondary retrospective changes resulting from the changes contributed by the shale oil and gas infrastructure development could not be assessed. This difficulty in assessing the secondary changes is due to the complex relationship between anthropogenic land use processes and environmental factors (both geomorphic and biophysical) in the forest landscape which prevents explicit and direct linkage between land use processes and the overall change patterns. Future research could be directed towards finding improved trajectories for measuring both primary and secondary patterns of land change resulting from shale oil and gas infrastructure construction in the forest landscape.

Appendix 4 Supplemental information

A4 Table I Error matrix of estimated area proportions for the 1975 treatment area Landsat image with 500 ground truth samples.

		Reference Data							
	Class	**Water**	**Forest**	**Barren**	**Agriculture**	**Developed**	**Total**	**User's accuracy (%)**	**Commission errors (%)**
Classified image	Water	0.026	0	0.001	0	0	0.027	97.701	2.299
	Forest	0.007	0.861	0	0.007	0.007	0.881	97.692	2.308
	barren	0	0.0002	0.009	0.0002	0.0001	0.009	93.333	6.667
	Agriculture	0	0.004	0.0009	0.061	0	0.067	92.249	7.751
	Developed	0	0	0	0.0003	0.009	0.010	97.000	3.000
	Total	0.033	0.865	0.0109	0.069	0.016	1		
	Producer's accuracy (%)	79.320	99.480	84.886	89.361	57.691	Overall Accuracy= 96.623%		
	Omission errors (%)	20.680	0.520	15.114	10.639	42.309	Margin of Error (ME)*= ± 4.624%		

*The ME was calculated based on a 95% confidence interval (critical value= 1.96), and it shows how the ground truth samples for each of the land classes are representative of the areas of the land classes and total sample (500) in determining the overall accuracy. Cell entries are expressed as the estimated area proportion of the cells of the error matrix.

A4 Table II T-test: paired two-sample for patches of forest cover selected from the Cordova shale gas play in 1975 and after 1975 (ending in 2017)

Measurements	**1975**	**After 1975**
Mean	7.098	0.458
Variance	397.607	0.160
Observations	57	57
Pearson Correlation	0.002	
Hypothesized Mean Difference	0	
df	56	
t Stat	2.514	
P(T<=t) one-tail	0.007**	
t Critical one-tail	1.673	
P(T<=t) two-tail	0.015**	
t Critical two-tail	2.003	

**In both the one- and two-tail tests, the difference in the area of forest cover patches is statistically significant at a 95% confidence interval

A4 Table III T-test: paired two-sample for patches of forest cover selected from the Horn shale gas play in 1975 and after 1975 (ending in 2017)

Measurements	**1975**	**After 1975**
Mean	18.999	11.928
Variance	5286.153	5257.286
Observations	42	42
Pearson Correlation	0.988	
Hypothesized Mean Difference	0	
df	41	
t Stat	4.081	
P(T<=t) one-tail	0.0001**	
t Critical one-tail	1.683	
P(T<=t) two-tail	0.0002**	
t Critical two-tail	2.020	

**In both the one- and two-tail tests, the difference in the area of forest cover patches is statistically significant at a 95% confidence interval

A4 Table IV T-test: paired two-sample for patches of forest cover selected from the Liard shale gas play in 1975 and after 1975 (ending in 2017)

Measurements	**1975**	**After 1975**
Mean	43.793	14.123
Variance	14023.241	7777.071
Observations	45	45
Pearson Correlation	0.710	
Hypothesized Mean Difference	0	
df	44	
t Stat	2.384	
P(T<=t) one-tail	0.011**	
t Critical one-tail	1.680	
P(T<=t) two-tail	0.021**	
t Critical two-tail	2.015	

**In both the one- and two-tail tests, the difference in the area of forest cover patches is statistically significant at a 95% confidence interval

A4 Table V T-test: paired two-sample for patches of forest cover selected from the Montney shale gas play in 1975 and after 1975 (ending in 2017)

Measurements	**1975**		**After 1975**
Mean	2.305		0.264
Variance	21.283		0.103
Observations	51		51
Pearson Correlation		0.167	
Hypothesized Mean Difference		0	
Df		50	
t Stat		3.189	
P(T<=t) one-tail		0.001**	
t Critical one-tail		1.676	
P(T<=t) two-tail		0.002**	
t Critical two-tail		2.009	

**In both the one- and two-tail tests, the difference in the area of forest cover patches is statistically significant at a 95% confidence interval

A4 Table VI Results of the Shapiro-Wilk normality test and Wilcoxon signed rank test

Shale gas play	**Tests (test statistic)**	***P*-value***
Cordova	Shapiro-Wilk normality test (W = 0.33042)	1.12e-14
	Wilcoxon signed rank test (V = 1653)	5.24e-11
Horn	Shapiro-Wilk normality test (W = 0.58808)	1.199e-09
	Wilcoxon signed rank test (V = 903)	1.705e-08
Liard	Shapiro-Wilk normality test (W = 0.3693)	1.197e-12
	Wilcoxon signed rank test (V = 1035)	5.352e-09
Montney	Shapiro-Wilk normality test (W = 0.45943)	1.935e-12
	Wilcoxon signed rank test (V = 1289)	4.519e-09

***At a 95% confidence interval, the *p*-values of all the Shapiro-Wilk normality test are less than the alpha value of 0.05, an indication that the samples selected from the shale gas plays do not follow a normal distribution. Also, at a 95% confidence interval, the *p*-values of all the Wilcoxon signed rank tests are less than the alpha value of 0.05

CHAPTER SIX

Summary of major findings, conclusions, study limitations, and future studies

6.1 Major findings and conclusions

Chapter two of the dissertation assesses forest change in the study area in northeastern BC. As well as measuring a net loss in the forest cover, the chapter of the dissertation also finds that most of the forest losses are within the timber harvest land base (THLB). However, the forest cover in the study area mostly recovered from the barren land class. The net loss in the forest cover is likely to be a result of the following factors. First, over the past few decades, there has been an increase in the allowable annual cut and the actual volume of timber harvested every year, as shown in the literature used in supporting the findings of the study. The second factor is the recovery of the forest cover from the barren land, especially during the period between 2000 and 2015. Between 2000 and 2015, harvested cutblocks increased, but the higher coniferous forest recovery is likely due to the BC government regulation which requires replanting of at least 80% of harvested timber. That is, the peak period (2005-2015) of forest regrowth from replanting falls within the period between 2000 and 2015 when forest cover recovery was higher as compared to the period between 1985 and 2000.

The loss of forest cover and the corresponding amount of forest cover fragmentation provides a context for forest managers to improve the rate of forest recovery from the harvested cutblocks while limiting the rate of forest harvesting in the ecologically sensitive zone (e.g., woodland caribou range). Land managers could limit the activities that are likely to create barren land. Also, land managers could use the results of the study in this chapter as ancillary information to determine the additional anthropogenic influences that are socioeconomically and ecologically sustainable considering the period of the higher amount of forest loss and higher amount of fragmentation. A higher forest cover recovery rate in 2000-2015 showed a period of a lower amount of forest fragmentation. Conversely, the period between 1985 and 2000 showed a higher amount of forest cover recovery and fragmentation. These two contrasting land characteristics lead to the conclusion that forest cover is less likely to be fragmented with the recovery of the forest from land use induced land classes.

The third chapter of this study assessed the quantity of forest loss and fragmentation in the forest cover between 1975 and 2017. Whereas there have been concerns about the oil and gas land change legacy, the quantity of forest cover loss measured from the SOG infrastructure construction is less than 1%; that is, the amount of forest change is similar to that of other locations (Pennsylvania, Ohio, and Williston Basin). The amount of change measured between 1995 and 2017 shows that there have been more changes in the forest cover in the years following 1995 than that of years before 1995. The coincidence between the period after 1995 and the shale gas boom in years after 1995 suggests to land managers that there would be the need for them to allocate some of the shale gas infrastructures on other categories of land during the shale gas activity boom.

Whereas chapter three of the study measures and assesses the cumulative forest change from all the selected shale gas infrastructure (well pads, pipelines, and access roads), chapter four compares and contrasts the quantity of forest change from each of the selected infrastructure. The quantity of forest cover loss (0.234%) measured in chapter two is mostly as a result of SOG well pad construction (forest loss from well pads = 0.163%), as shown in chapter four.

Chapter four shows that even though well pads cover a larger surface area of the study area than that of the roads and pipelines, the difference in the amount of forest cover loss between the well pads and the linear features is minimal. These dynamics of the quantity of infrastructure and amount of forest cover loss is an indication that the linear features would likely impact the forest cover more than any other infrastructure type when more of these linear SOG features are constructed in the future. This chapter also connotes to land managers that the pipelines in northeastern BC contributed to ecologically significant forest fragmentation by increasing the edge forest. In the future, pipelines are likely to increase the amount of forest fragmentation in the forest cover as in Ohio and Pennsylvania.

In chapter three the study finds that the SOG infrastructure construction has mostly impacted the core forest. However, insights from chapter four show that well pads contributed to more of the core forest fragmentation than any other infrastructure. The shale oil and gas land use dynamics in chapters three and four of the study leads to the conclusion that, among the shale oil and gas features, well pads contributed more to core forest fragmentation than access roads and pipelines. Furthermore, the forest fragmentation dynamics from chapters three and four lead to the conclusion that the construction of well pads targets caribou habitats since these habitats are mostly within the core forest areas of the study area.

Chapter five shows the spatial disparities within the study area, where studies in chapters two, three, and four were conducted. In chapter five, the study compared and contrasted the forest loss and fragmentation pattern in the four shale gas plays of British Columbia. This chapter of the study finds that the Montney is the most fragmented shale gas play, and the largest quantity of forest loss was recorded in the Montney as compared to the Liard, Cordova, and horn basin. The shale oil and gas land use process in the Montney is likely to account for the amount of forest cover loss and fragmentation. This conclusion is based on the fact that among the four shale gas plays, the Montney is the most developed as indicated in the literature.

The findings from the four shale gas plays in chapter five demonstrate that within the northeastern BC area, spatial variations in land use, the amount of forest cover and other land categories, and the distribution of shale gas well pads, access roads, and pipelines account for the pattern of forest change. The shale gas play with the largest amount of forest loss has been the most fragmented forest cover and vice versa. This pattern of forest cover loss and fragmentation echoes the findings from chapters two, three, and four which show that time points and location with the larger amount of human-induced land classes have a larger amount of forest fragmentation.

In chapter two, it was found that the period with the highest amount of forest cover loss has a higher amount of forest fragmentation and vice versa. Similarly, in chapter two, the period with higher forest cover regrowth has a lower amount of fragmentation and vice versa. In chapter three, the study finds that the location (treatment or control area) with the largest amount of non-human induced barren land has a lower amount of forest fragmentation. In the same chapter, the study finds that the period of higher intensity of SOG development (i.e., after 1995) recorded a faster forest change as compared to the period before (i.e., before 1995) the higher intensity of SOG development. In chapter four, the study finds that the largest contributor to forest loss (well pads) has also contributed to the largest amount of forest fragmentation. These dynamics of land use and forest change reaffirms how different levels of land use processes contribute to land change patterns and in broader terms contribute to global environmental change.

6.2 Study limitations

The main limitation of this study is the resolution of the Landsat data, which does not allow a full land cover change analysis. This limitation is mainly associated with the change analysis in chapter two, where in the 30m resolution Landsat images, some of the roads and other linear features passing through the forest cover are not apparent. This image-resolution related limitation is likely to be more pronounced in chapter two of the study which measures land changes in the forest landscape using only the 30 m by 30 m Landsat images. Future studies that intend to do analysis such as the one in chapter two can use high-resolution Landsat images acquired at different points in time that show most of the anthropogenic disturbances. The use of high-resolution Landsat images would improve classification accuracy beyond what was achieved in this study and provide a detailed assessment of a wide range of disturbances (e.g., footprints of oil and gas land use, the built-up area, windthrows, and insects/diseases infestations) in the forest. Also, for objective one, future studies can make use of more than two periods for more insights into land changes between different time points.

The influence of image-resolution related limitation on the change analysis is likely to reduce since high-resolution data of SOG infrastructure are used to draw signatures in Landsat images to measure the actual changes resulting from SOG infrastructure development as outlined in chapters three, four, and five. The high-resolution SOG infrastructure data are produced mostly in the form of vector data digitized from high-resolution aerial images. Thus, the digitized portion of the high-resolution SOG infrastructure data has some limitations. Firstly, there are uncertainty issues regarding identifying all the SOG features in the high-resolution images, and this is mostly dependent on the spatial resolution of the source image and the researcher's experience in terms of aerial photo interpretation. Secondly, the accuracy of the digitized SOG features is determined by the ability of the researcher to labouriously digitize all the features at an appropriate scale to ensure real representation of the features. In this study, these limitations and uncertainties are likely to underestimate the quantity of the SOG, and thus, their impacts on various land categories in the study area.

In addition to the resolution related limitation, pixel homogeneity which occurs mostly in chapters three, four, and five is likely to reduce the classified image quality. For instance, resampling the 1975 and 1995 images from 60 m by 60 m and 30 m by 30 m, respectively to 10 m by 10 m would likely reduce the data quality for measuring the changes in the forest cover as well as the forest fragmentation analysis. The fragmentation analysis performed in this study and linked with the rate of forest recovery from barren land is likely to be affected by natural fragmentation, and thus, the amount of fragmentation in the two periods would partly be influenced by natural fragmentation (e.g., the amount of fragmentation contributed by wetland). Moreover, it is not certain in terms of the number and type of fragmentation metrics to use in studies, and thus certainty is likely to be ensured in this study if there were more universal and specific metrics for measurement.

The use of the current THLB boundary as a sub-unit of analysis is likely to influence the forest change results both in the THLB and outside the THLB. This is because the area of the THLB might have changed in previous years as anthropogenic activities (apart from timber harvesting) increase and intersect with it. Consequently, for future monitoring of forest change in the THLB, the analysis should also focus on changes that are likely to occur as a result of the changes in the area of the THLB.

The GIS-based conditional analysis used in assessing the amount of forest change from SOG infrastructure development is likely to slightly overestimate the forest cover change results. To use this conditional analysis in future studies, most of this limitation would likely be avoided by focusing on measuring the most recent land changes.

6.3 Recommendations for future studies in the study area

Future studies in the study area can focus on the use analysis that looks at the transition between deciduous forest and other land cover types. Over time, an area of land covered by deciduous forest cover would be taken over by coniferous forest cover, and consequently, the rate of transition would be necessary to learn about forest types and land dynamics in the boreal environment. Additionally, in the selection of the control area and treatment area, future studies can focus on areas that are far more homogenous in terms of vegetation and ecological setting than the ones selected for this study. Thus, this would ensure a better comparison in terms of land characteristics in the area where there are oil and gas activities and the area where there are no oil and gas activities.

Whereas the majority of the objectives in this dissertation focused on shale oil and gas-induced forest cover change and fragmentation, broadscale assessment of agricultural land expansion is worthy of being studied. As noted earlier, large tracts of agricultural lands were seen during the reconnaissance survey in the study area in September 2017. Even though the impacts of agricultural activities are known and understood to some extent, the footprints of agricultural lands were more apparent as compared to that of shale oil and gas activities in the study area. Thus, a comparison between the impacts from agricultural footprints and shale gas footprints in future studies would be relevant, and it will advance our understanding of the levels of human-environment relationships.

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