THESIS

A LANDSCAPE-SCALE INVESTIGATION INTO THE RISK OF LODGEPOLE PINE MORTALITY CAUSED BY MOUNTAIN PINE BEETLE DENDROCTONUS PONDEROSAE (COLEOPTERA: CURCULIOIDAE: SCOLYTINAE)

Submitted by

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In partial fulfillment of the requirements

For the Degree of Master of Science

Colorado State University

Fort Collins, Colorado

Fall 2010

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ABSTRACT

A LANDSCAPE-SCALE INVESTIGATION INTO THE RISK OF LODGEPOLE PINE MORTALITY CAUSED BY MOUNTAIN PINE BEETLE DENDROCTONUS PONDEROSAE (COLEOPTERA: CURCULIOIDAE: SCOLYTINAE)

Mountain pine beetle (MPB), *Dendroctonus ponderosae* Hopkins, is currently causing *Pinus contorta* Douglas (LP) mortality in several areas of western United States and Canada at high levels including portions of Colorado. For decades, researchers have developed models to help land managers predict when and where MPB infestation will develop based on forest structure, tree size, tree age and geographic characteristics; these models were developed at the stand-level for stand-level analysis. Land managers and planners have become increasingly interested in predicting MPB risk and susceptibility at the landscape-scale; however attempts at landscape-scale modeling have proven difficult as continuous forest mensuration datasets are often lacking. Techniques for producing low-cost, high-resolution, landscape-scale forest composition and forest structure Geographic Information System (GIS) layers were demonstrated by this study. These GIS layers were subsequently used to assess several existing MPB risk models, at the landscape-scale, and to derive a new empirical MPB model.

The procedures outlined in this paper describe the generation of landscape-scale forest composition and structure GIS layers (predictive surfaces) based on recent innovative remote sensing and spatial statistical techniques. These techniques transform a small field sample into a continuous GIS surface utilizing multiple linear regression and binary regression trees. Information derived from satellite imagery and digital elevation models are used as auxiliary variables to assist in the prediction of response variables (basal area, proportion of lodgepole pine basal area, diameter at breast height, quadratic mean diameter, percent canopy closure, and trees per acre). A carefully designed field sample, stratified by Landsat image spectral groupings, optimized sampling faculties by maximizing between-stratum variability while minimizing within-stratum variability.

Forest composition (spatial distribution of tree species), basal area, proportion of lodgepole pine basal area, diameter at breast height, quadratic mean diameter, percent canopy closure, and trees per acre predictive surfaces were developed for Colorado's Fraser River Valley. These predictive surfaces were then used to assess the landscape-scale predictive capabilities of following MPB prediction models: Anhold et al., (1996), Amman et al. (1977), Shore and Safranyik (1992), and the USDA Forest Service National Insect and Disease Risk Map. Finally, a new MPB model is described based on geographic factors, the predictive surfaces, and recent occurrence of mountain pine beetle caused-tree mortality.

DEDICATION

To the memory of my father who gave me a lifetime of love and support without condition.

ACKNOWLEDGEMENTS

I gratefully acknowledge Robin Reich as my advisor through this process and for sharing his expertise of forestry, field sampling, and statistics with me. I am also indebted to Jose Negron and William Jacobi for serving on my graduate committee providing instrumental advice and critical feedback. I recognize the Rocky Mountain Research Station (Fort Collins, CO) of the USDA Forest Service for providing the orthorectified aerial photography and William M. Ciesla of Forest Health Management International (Fort Collins, CO) for his air-photo interpretation. I thank John Lundquist and William M. Ciesla for reviewing my manuscript and providing valuable commentary. Lastly, I thank my wife, Timi Johnson, who provided me with the encouragement and loving support I needed to complete this project. This study was financed, in part, by the USDA Forest Service, Forest Health Protection, Rocky Mountain Region (Golden, CO).

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INTRODUCTION

The mountain pine beetle (MPB), *Dendroctonus ponderosae* Hopkins (Coleoptera: Curculioidae: Scolytinae), is one of the most damaging forest insects in western North America. This widely distributed insect feeds on at least 12 native species of *Pinus* L. (Pinaceae) (Furniss and Carolin 1977). Lodgepole pine (LP), *Pinus contorta*, Douglas, is one of its favorite hosts and major outbreaks have occurred throughout its range from British Columbia to Colorado. In Colorado alone, roughly ten million lodgepole pines on over one million acres were killed by this insect between 2000 and 2006 (USDA Forest Service$_2$).

Mountain pine beetles kill trees by cutting off nutrients supplied by the tree's phloem tissue (known as girdling) and introducing several species of blue-stain fungi that invade the tree's xylem tissue. Typically, mountain pine beetles have one generation per year; adults emerge from trees between mid- and late summer to infest new trees by constructing vertical egg galleries underneath the bark. Eggs are laid along both sides of the gallery; when the larvae hatch they feed on the inner bark perpendicular to the egg galleries girdling the tree. Additionally, the beetles introduce blue-stain fungi that impede water conduction. The larvae overwinter and continue their development throughout the spring and early summer before emerging as the next generation of adult beetles in mid- to late summer. The needles on lodgepole pines that have been infested with MPB turn from green to red in the year following the initial attack and are clearly visible from the ground and from above.

Natural factors influence mountain pine beetle populations, including below-zero (F°) winter temperatures, predaceous insects, woodpeckers, and nematodes; however, these factors rarely prevent outbreaks from occurring in susceptible stands (Furniss and Carolin 1977). While direct control measures, such as the application of pesticides and the felling and debarking of infested trees, have proven ineffective at halting MPB outbreaks, silvicultural treatments that change a stand's microclimate have the greatest potential to reduce tree loss during MPB outbreaks (Fettig et al. 2007). Thinning, partial cutting, clear cutting, type conversion, and promoting diversity are examples of silvicultural tools that have been explored for improving forest health conditions and for lowering the potential of a MPB outbreak (Furniss and Carolin 1977).

Over the past several decades, models have been developed to help land managers predict risk and susceptibility of LP stands to MPB attack. These models are based on a wide range of structural, physiological, and geographic factors such as stand density (Shore and Safranyik 1992), distribution of tree diameters, tree age, (Amman et al., 1977), periodic growth ratio (Mahoney 1978), latitude, longitude, and elevation (Amman et al., 1977; Shore and Safranyik 1992). Throughout this paper I will use Shore and Safranyik's 1992 definition of *susceptibility* as *"the inherent characteristics or qualities of a stand of trees that affect its likelihood of attack and damage by a mountain pine beetle population"*; and *risk* as "*the short term expectation of tree mortality in a stand as a result of a mountain pine beetle infestation.*"

All of the models mentioned above have useful applications for LP management at the stand-level from which they were derived, but how do they function at the landscape-scale? This question has been difficult to answer as securing current and continuous forest mensuration data for geographically large risk assessments across areas of mixed land ownership has been limited by cost and technology. Only recently, new advances in computing have permitted the development of inexpensive landscape-scale datasets to support these kinds of assessments. This study attempts to examine new advances in modeling MPB risk across sizeable areas using geospatially-derived MPB risk parameters. Specifically, landscape-scale predictive surfaces of MPB susceptibility parameters (species composition, basal area, percent LP basal area, canopy closure, mean diameter at breast height, quadratic mean diameter, trees per ha) were derived across Colorado's Fraser River Valley to assesses the landscape-scale predictive capabilities of four existing MPB risk models; and a new MPB risk model was derived empirically using landscape-scale predictive surfaces of MPB susceptibility parameters. Three of the four MPB risk models chosen for the study[1], discussed in detail in subsequent sections, have and continue to be frequently applied by land managers at the stand-level; however their applications across landscape-scales have not been demonstrated. The fourth model, developed by the Forest Service for landscape-scale analyses[2], was selected for comparison against the stand-level models.

Bark beetle research in the western United States has traditionally focused on the management, biology, and ecology of economically important bark beetle species related to timber resources; with MPB nearing the top of the list. Today, societal values are

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[1] Anhold et al., (1996), Amman et. al. (1977), and Shore and Safranyik (1992).
[2] USDA Forest Service National Risk Map (2006).

shifting, and research is attempting to answer new questions about bark beetle impacts to recreation, visual corridors, threatened and endangered species, invasive species, and responses to climate change by both host and insect (Negron et al., 2008). Moreover, vegetation management research as it applies to bark beetles, long geared towards even-aged managed stands, is shifting its focus to uneven-aged stands where land management is increasingly being realized (Negron et al., 2008). It is evident that future bark beetle research will need to be conducted across large spatial scales (Negron et al., 2008); this study strives to demonstrate the production and application of landscape-scale forest composition and forest structure predictive surfaces to forest entomology and how these surfaces can help to address contemporary research needs.

RELATED RESEARCH

Spatial Statistical Models

Geospatially-explicit forest mensuration data is an essential need for land managers who are planning and prioritizing treatment areas in effort to mitigate the effects of MPB infestation. Mountain Pine Beetle models require various parameters that must be measured in the field. While this is practical for site-specific investigations, gathering data in remote locations, or across large geographical regions consisting of mixed land ownership, is seldom viable. Landscape-scale bark beetle risk assessments are increasingly favored by various groups engaged in forest management, therefore, it is paramount that scientifically credible continuous data sets are available to land managers and policy makers.

Recently, work has been published by Joy (2002), Joy et al. (2003), Reich et al. (2004), Reich et al. (2010), Reich and Bravo (2004) and Kallas et al. (2003) on spatially explicit predictive surface models. One major advantage of these models is that they provide statistically consistent estimates of the error along with associated confidence intervals, which Joy et al. (2003) contends *are more important than the estimates themselves*. Additionally, their model-based sampling design generates surfaces accounting for both large and small-scale spatial variability.

Joy (2002) and Joy et al. (2003) modeled forest structure and forest type on Arizona's northern Kaibab plateau in an effort to characterize relationships between the northern goshawk and its habitat. These authors measured total basal area, proportion of basal area by species, percent canopy closure, understory vegetation height, and presence vs. absence of understory vegetation on 177 plots. Plot locations were stratified by an unsupervised classification of Landsat imagery. Each plot, representing a 30-by-30 meter Landsat pixel, was divided into equal area 10-by-10 meter subplots to obtain estimates of small-scale variability at the sub-pixel level. Landsat imagery spectral bands and variables derived from digital elevation models (DEMs) were treated as independent random variables. Regression models were generated by fitting field data to the remote sensing data using least-squares regression equations to capture large scale variability, and the residuals were modeled using binary regression trees to capture small scale variability. Binary regression trees have been used successfully to classify digital imagery, and, because they are non-parametric in nature, have considerable benefits due to their simplicity, flexibility, and computational efficiency (Friedl and Brovey 1997). Accuracy assessment of the Joy et al. (2003) forest type classification, using a standard error or confusion matrix approach (Congalton 1991) bore an overall accuracy rate of 75% and an overall kappa statistic of 50%.

Reich et al. (2004) produced climate models for the Mexican States of Jalisco and Colima using similar techniques. Weather station data (average monthly temperature, precipitation, humidity) were modeled using variables derived from Landsat imagery and DEMs. The spatial expectations of linear regression models accounted for the large-scale variability and binary regression trees (the spatial expectations of the multiple linear regressions' modeled errors) captured small-scale variability. In other words, the broad scale tendencies within the data from the regression model were proximately 'fitted' by analyzing and classifying its residuals; in effect 'fine tuning' the model across its two-dimensional matrix. The climate models accounted between 45% and 85% of the variability observed in the climate data.

Reich and Bravo (2004) accurately identified agave (*Agave tequilana* Weber) plantations in the State of Jalisco, Mexico using k-means clustering and discriminate analysis with variables from Landsat imagery and DEMs.

Another related application of this technique is given by Kallas et al. (2003) where DEMs, precipitation grids, and site index polygons were used as independent random variables to model occurrence of root disease caused by the fungus, *Armillaria* sp. in the Black Hills of South Dakota. In this case, residuals from the regression models were kriged to capture small-scale variability.

Reich et al. (2010) describes an empirical evaluation of prediction models. These authors determined that the conventional method to establish tree size, i.e., basing tree size on minimizing the residual mean deviance, often create models with inadequate confidence intervals stemming from inaccurate variance estimates. Instead, the authors found that a binary tree-based stratified design (Breiman et al., 1984) with an appropriate cost function can provide reliable and unbiased variance estimates.

Figure 1 (below) depicts basic procedures common to the approaches by Joy (2002), Joy et al. (2003), Reich et al. (2004), Reich et al. (2010), Reich and Bravo (2004) and Kallas et al. (2003). The advantage of this methodology over "traditional" image classification technique is that a high image processing skill level and/ or *a priori* knowledge of the study area is not necessary. It is also possible to interpolate the field data to a finer spatial resolution than that of a Landsat pixel using a cluster sampling design. Most importantly, this method produces landscape-scale continuous surface models based on statistically sound procedures at a low cost; requiring only a nominal field sample and inexpensive satellite imagery.

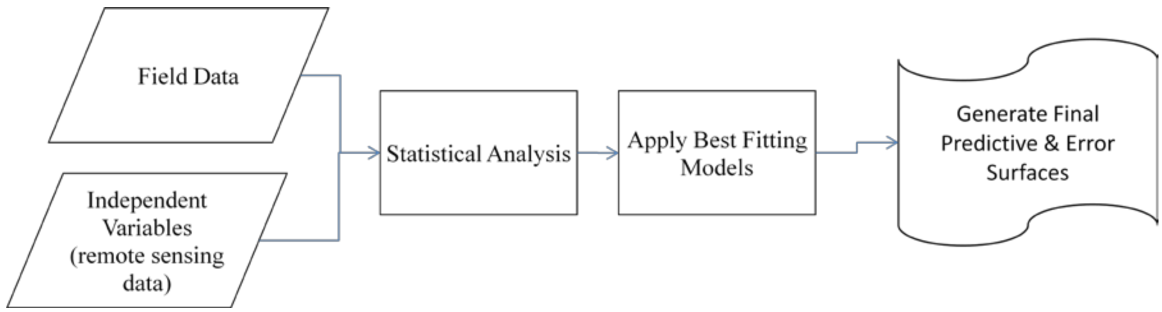

Figure 1. Generalized spatial statistical modeling workflow depicting the imputation process by which continuous surfaces are derived from field measured point data.

Mountain Pine Beetle Predictive Models

Researchers have long been working on developing MPB predictive models aimed at determining how resistant or susceptible a stand is to mountain pine beetle populations, and when and how many trees will die. Many of the models in use today were developed regionally, formulated for even-aged stands managed for timber production, and limited to the stand-scale. Additionally, most models are based solely on forest structure metrics and predict susceptibility; few models take local beetle population dynamics into account.

The MPB models evaluated during this investigation were selected over other MPB models because nearly all of their response variables could be determined, albeit indirectly, from remotely derived data (satellite imagery and DEMs). MPB models based primarily on factors that do not produce spectral responses, such as periodic growth ratio (Mahoney 1978) and phloem thickness (Berryman 1978), cannot be modeled with remotely derived variables. The following background is provided for the four MPB models applied and evaluated during this investigation:

Shore and Safranyik (1992)

The Shore and Safranyik (1992) model was derived heuristically on the basis of logic and previous experience with MPB outbreaks in British Columbia. The Shore and Safranyik system incorporates the spatial nature of MPB populations in addition to modeling susceptibility based on stand characteristics. Shore and Safranyik defined susceptibility as the characteristics of a stand of trees that affect its probability of a MPB outbreak, and risk as the short-range prospect of tree mortality in a stand based on the co-occurrence of a known MPB population(s). Applying this concept, only trees within a susceptible stand proximal to a known MPB population would be considered at risk. The authors' calculated two indices: a susceptibility index and a beetle pressure index, in order to derive a third index: the risk index. The susceptibility index is based on the percentage of pine basal area in the stand, the age of dominant and co-dominant live pine, the density of the stand, and the geographical position of the stand. The beetle pressure index is a function of MPB infestation size and its proximity to the stand being rated. A practical consequence of the Shore and Safranyik method is that when prioritizing treatment areas, a highly susceptible stand far from a MPB population can be skipped in favor of treating a moderately susceptible stand proximal to an area with a high beetle population.

Amman et al., (1977)

A model applied widely in the lodgepole pine forests of the western U.S. is described by Amman et al. (1977). This model predicts risk (the authors use the terms 'risk' and 'susceptibility' interchangeably) based on elevation, latitude, average age, and average diameter at breast height (dbh). Amman *et al.* (1977) uses Hopkins' bioclimatic law, which states that beetle development is slowed four days for each degree of increasing latitude as well as with every 400 feet of elevation. Mean age, mean diameter at breast height, and elevation/ latitude are each ranked as low, medium or high (1, 2, or 3 respectively) based on their degree of risk/ susceptibility. These rankings are then multiplied to derive risk ratings ranging from 1 to 27 (1 - 9 = low, 12 - 18 = moderate, and 27 = high). The Amman model was developed as a biological model based predominantly on observations made in Idaho and Montana.

Anhold et al., (1996)

Anhold et al., (1996) models potential for losses to MPB across the following three "zones" based on the Stand Density Index[3] (SDI): zone A (SDI = 0 to 139) represents fast-growing, non-competing trees (low susceptibility); zone B (SDI = 140 to 244) signifies the beginning of tree competition for resources (high susceptibility); and zone C (SDI = 245 and above) is where competition is high and tree vigor is low but phloem is too thin for brood production necessary to sustain a beetle outbreak. The SDI zones were derived empirically from earlier work by Anhold and Jenkins (1987) where the authors established ninety-four plots in unmanaged lodgepole pine stands, extending from northern Colorado to northern Washington, to assess the relationship between stand density and susceptibility to MPB. The authors determined that the relationship between MPB mortality and tree density was non-linear and varied significantly by SDI zone.

USDA Forest Service National Risk Map (2006)

The USDA Forest Service's Forest Health Protection Staff Unit models landscape-scale risk to insects and diseases in the *National Insect and Disease Risk Map* (Krist et. al, 2007). Risk is defined as "the expectation that, without remediation, 25 percent or more of the standing live basal area on trees greater than 1 inch in diameter

[3] Stand Density Index is defined as the number of trees per unit area that a stand would have at a standard diameter at breast height (Reineke 1933).

will die over the next 15 years". Their risk criteria for mountain pine beetle caused mortality in lodgepole pine includes quadratic mean diameter, percent basal area of host, total basal area (ft^2/ acre), and elevation/ latitude; each parameter is weighted 30%, 30%, 30%, and 10% respectively. Risk *begins* when quadratic mean diameter (QMD) reaches 6 inches, 25% of basal area is occupied by lodgepole pine, total basal equals 80 ft^2/ acre, and elevation and latitude fall within Amman et al.'s (1977) moderate risk category. Risk *peaks* when QMD reaches 8 inches, ≥ 50% of the basal area is occupied by lodgepole pine, total basal area equals 120 ft^2/ acre, and elevation and latitude fall within Amman et al.'s (1977) high risk category. Risk *decreases* when the total basal area reaches 160 ft^2/ acre and Risk *ends* when basal area exceeds 250 ft^2/ acre. Like Anhold et al., (1996) and Shore and Safranyik (1992), this model acknowledges that tree density and MPB susceptibility are non-linear. The Forest Service risk system is a multi-criterion biological model built from several stand-based models. Citations for the Forest Service model include Amman et al. (1977), Hagle et al. (2000), Randall et al. (2000), and Steele et al. (1996).

OBJECTIVES

The Amman et al. (1977) and Anhold et al., (1996) models were developed for stand-level timber management; and the Shore and Safranyik (1992) and the Amman et al. (1977) models were developed using regional datasets. Thus, this study sought to assess the performance of the models at the landscape-scale, and assess the performance of the models within different geographic settings. Another objective of this study was to demonstrate the feasibility of generating continuous landscape-scale forest composition and forest structure predictive surfaces and their application to forest entomology. Finally, this study aimed to empirically derive and evaluate a new MPB model based on variables from the predictive surfaces.

METHODS

Study Area

Finding an area of susceptible lodgepole pine adjacent to high populations of mountain pine beetles was an important prerequisite of this study. Additionally, it was necessary that the study area have large tracts of readily accessible public land for collection of the field data. Grand County's Fraser Valley, a high elevation coniferous forest in north-central Colorado, satisfied these needs. In 2003 when the study was initiated, the area was surrounded, but not yet significantly impacted, by three of the largest MPB outbreaks in Colorado (USDA Forest Service$_2$).

The study area was 55,491 ha. In size and included all forested lands bound by the Continental Divide to the east and south, 40° N latitude to the north, and 106° W longitude to the north (Figure 2). Elevations ranged from 2522 m to 4072 m. This area included portions of the Arapaho-Roosevelt National Forest, including the Fraser Experimental Forest of the USDA Forest Service Rocky Mountain Research Station, the Winter Park ski area, and the towns of Winter Park, Fraser, and Tabernash. All drainages within the study area are contained by the Fraser River watershed and make up all or part of seven subwatersheds; namely (clockwise from east to west): Meadows Creek-Ranch

Creek, Headwaters Ranch Creek, Upper Fraser River, Vasquez Creek, Middle Fraser River, Saint Louis Creek, and Crooked Creek (USDA-NRCS 2007).

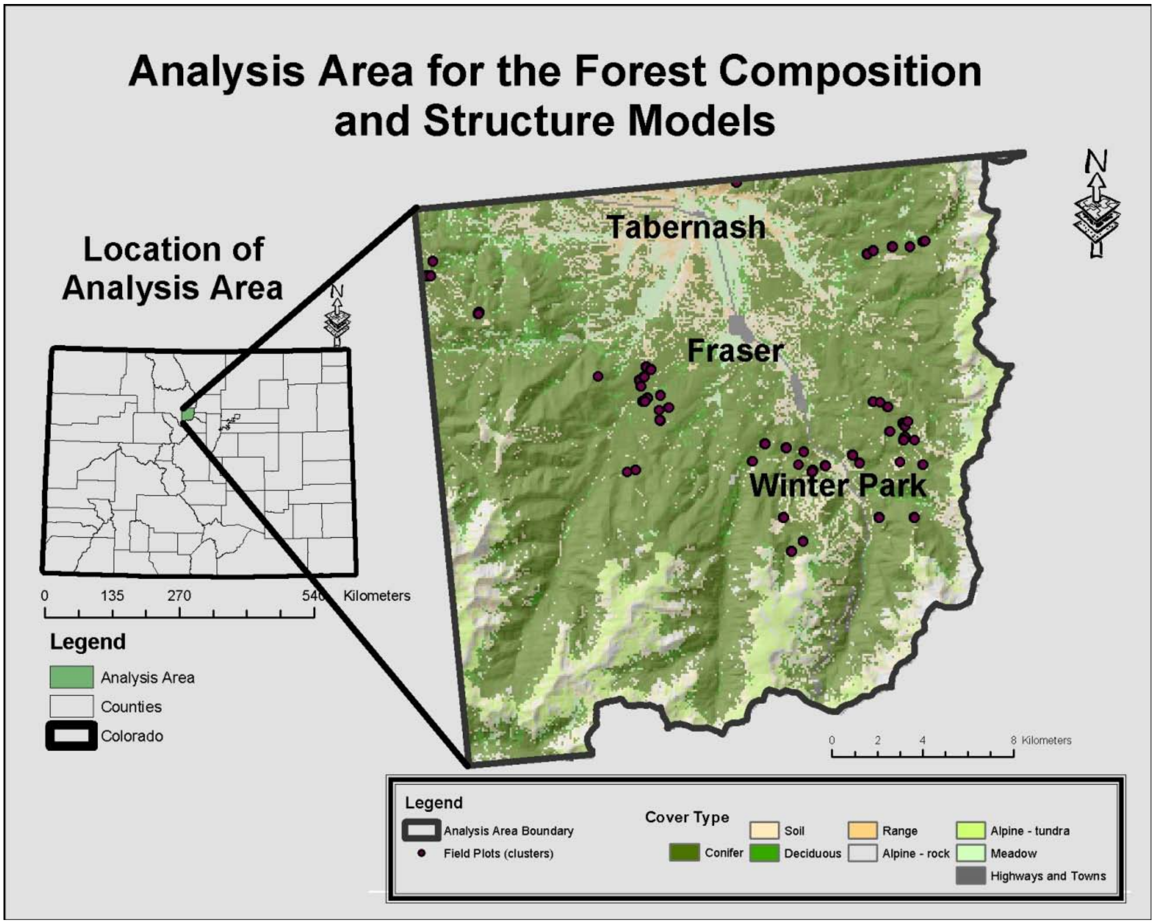

Figure 2. Map of the analysis area and field plot locations in Grand County, Colorado. Red circles designate cluster centers sampled during the field survey. Nine sample points were assigned to each of the fifty-five clusters for a total of 495 sample points overall. Field data was collected within the study area between October 1, 2003 and February 1, 2004.

Three major forest types occur within the upper Fraser Valley including: (1) lodgepole pine (*Pinus contorta*) growing primarily in pure stands between 2,760 m and 3,270 m on drier south, west, and southeast aspects; (2) Engelmann spruce (*Picea englemannii*)-subalpine fir (*Abies lasiocarpa*) mix growing between 2,730 m and 3,570 m on all aspects, but predominately on cooler north and east aspects (lodgepole pines were frequently found intermixed within these stands and on occasion growing at the highest elevations as mature trees); and (3) Deciduous trees, principally aspen (*Populus tremuloides*) and less frequently Alder (*Alnus incana*), between 2,815 m and 3,040 m (Huckaby and Moir 1998). Sagebrush, grass, and sagebrush-grass mixes were dominant below tree-line and alpine grass-forbs mixes were prevalent above tree-line. The remainder of the study area was occupied by rock, soils, water, buildings, gravel, and pavement. Only forested vegetation types were classified for this study.

Logging within the upper Fraser Valley began in 1906 to support a variety of wood fiber needs including mining and railroad construction. By the early 1930s, most logging activity within the area had ceased as market values for railroad ties declined; and the most accessible lands had been harvested and/or burned over (Troendle et al. 1987). Consequently, an even-aged forest of lodgepole pines between 75 and 100 years old now exists where these early twentieth century logging activities occurred. Where these logging activities never occurred, most stands average either 150 or 300 years old; established after a series of wildfires that took place in the mid-nineteenth and/or late seventeenth centuries (Huckaby and Moir 1995).

Field Sample

Design

The sampling scheme was based on a stratified random cluster design (Joy et al. 2003). Fifty-five cluster plots were located using an unsupervised classification of a 2003 Landsat Enhanced Thematic Mapper Plus (ETM+) quarter image of southeastern Grand County, CO. Sample size was based on previous experiences with model-based sampling designs (Reich 2003). The stratums were determined by an unsupervised classification, which groups ground reflectances into like classes based on spectral similarity using ERDAS Imagine software (IMAGINE® version 8.6, ERDAS 2003). Grouping reflectances of forest spectra into similar categories stratified the field sample to capture between-stratum variability while reducing within-stratum variability. Eleven[4] forest spectral classes were derived and were used to stratify the sample. Five cluster plots were randomly located[5] within each of the eleven 'forest' spectral classes (strata) by employing a 3 x 3 `window`, majority rule = 7 function (IMAGINE® version 8.6, ERDAS 2003). Each 30m x 30m plot contained nine 10m x 10m sub-plots corresponding to the spatial resolution of a Landsat pixel.

Data Collection

A Trimble GeoExplorer® GPS was used to navigate to each plot center with an estimated accuracy of ±10 meters post-differential correction (GPS Pathfinder® Office version 3.0, © Trimble Navigation Limited 2003). A compass and logger's tape were

[4] An iterative approach to the unsupervised classification procedure led to a determination that the conifer reflectances within the Landsat scene were best grouped into eleven distinct spectral classes.
[5] Plots were randomly located after meeting the following conditions: plots had to fall on land administered by the Forest Service and plots had to fall within 2.4 km of a primary or secondary road.

used to establish the outlying sub-plots. Canopy closure and percent slope were recorded and measured on each sub-plot. Percent canopy closure was measured using a concave spherical densitometer (Lemmon 1957) by dividing the number of grid-intersections with overlapping tree canopy by the total number of spherical densitometer grid-intersections[6]. Using variable point sampling (Avery and Burkhart 2007), a 20-basal area factor (BAF) prism was used to determine the number of 'in' trees on each sub-plot[7]. Total basal area (ft^2/ acre) was determined by multiplying the total number of 'in' trees by the BAF. Proportion of the basal area by forest type was calculated by recording which of the 'in' trees belonged to the 'LP', 'spruce-fir' or 'other' species category. Diameter at breast height[8] (dbh) was recorded for every 'in' tree. Average dbh for each sub-plot was calculated by dividing the sum of 1/dbh by the sum of $1/dbh^2$ for every 'in' tree. Trees per acre were derived by summing the tree factors[9] at each sub-plot.

For each sub-plot, the vegetation type was classified based on the proportion of 'in' trees belonging to the 'LP', 'spruce-fir' or 'other' species categories as follows:

- LP; if proportion of LP basal area $\geq .67$
- spruce/fir; if proportion of spruce/fir basal area $\geq .67$
- mixed; if proportion LP and/or spruce/fir basal area $< .67$
- where 'in' trees were absent, the sub-plot was classified as 'meadow'.

The nine sub-plots representing the pixel/ cluster were further evaluated to ensure that only one vegetation class was assigned per pixel/ plot based on the following criteria:

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[6] Four readings, one from each cardinal direction, were taken at each sub-plot and averaged together.
[7] Slope was accounted for by turning the prism at an angle parallel to the slope prior to sighting.
[8] Diameter at breast height was measured 1.37 meters above the forest floor on the uphill side of the tree.
[9] The tree factor (Ft) was calculated using the formula: Ft = BAF/BAi; where BAF = basal area factor (20) and BAi = $(0.005454)(dbh^2)$.

- If six or more sub-plots were of the same vegetation class, the majority vegetation class was assigned to all sub-plots within the plot.
- If five or fewer sub-plots were of the same vegetation class, all sub-plots within the plot were assigned to the 'mixed' class.

Spatial Statistical Modeling

Field data (dependent variables) were modeled using a combination of regression models and binary regression trees. Procedural details are further described below:

Predictor Variables

Satellite imagery and Digital Elevation Model (DEM) data served as independent variables for the forest composition and forest structure predictive models. A cloud-free Landsat-7 ETM+ satellite image (30-m spatial resolution) collected on August 26, 2002 was converted to an ESRI Stacked Grid format (ESRI, 2004) and consisted of the following six spectral bands:

- Band 1; 0.45-0.52 µm (blue)
- Band 2; 0.52-0.60 µm (green)
- Band 3; 0.63-0.69 µm (red)
- Band 4; 0.76-0.90 µm (near infra-red)
- Band 5; 1.55-1.75 µm (mid infra-red)
- Band 7; 2.08-2.35 µm (mid infra-red)

The DEM was obtained from the USGS National Elevation Dataset (USGS 1999) (30-m spatial resolution) and converted into an ESRI Grid (ESRI, 2004) file. Two additional data sets, slope and aspect, were derived from the elevation data using ESRI's ArcGIS Spatial Analyst extension (ESRI, 2004).

Thus, a total of nine auxiliary variables were used for the spatial prediction; Landsat ETM+ bands 1-6, elevation, slope and aspect. Each grid was resampled to 10 meters using the FOCALMEAN command in ArcInfo (ESRI, 2004).

Data Extraction

The value for each grid was extracted for each field sample point and added to the attribute table using Hawth's tools (Beyer 2004), a free ArcGIS extension which provides custom tools for spatial analysis, sampling, and other GIS functions. The entire data preparation process used to create a dataset used for statistical analysis is summarized in Figure 3.

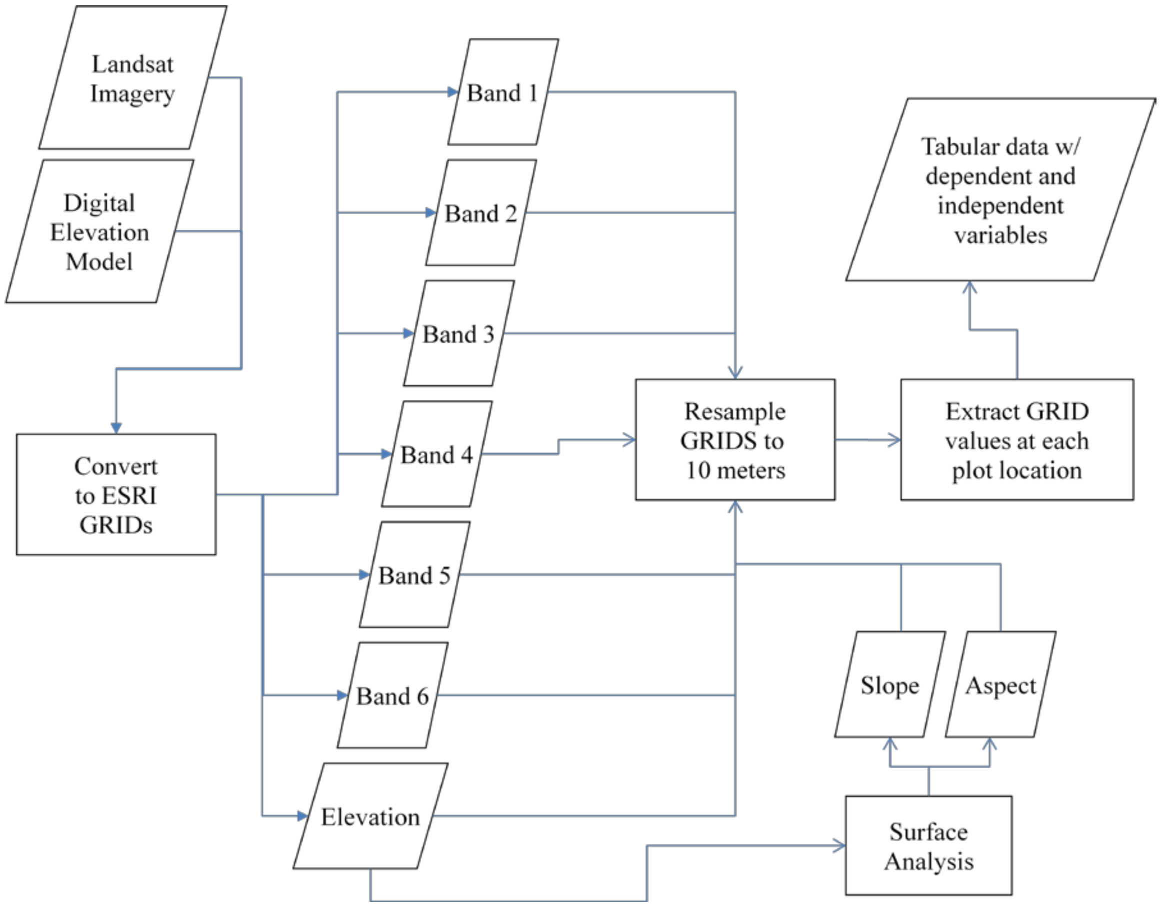

Figure 3. Flowchart depicting the data preparation procedures undertaken prior to the statistical analysis.

Forest Composition Predictive Surface

Forest composition was modeled with classification trees using S-PLUS© 2000 software (S-PLUS 2000©, Statistical Sciences 1999). Forest composition classes included *lodgepole pine*, *spruce-fir*, *mixed-forest*, and *non-forest*. The *deciduous* (aspen, willow, etc.) forest class, which was added at a later time, was derived during the initial unsupervised classification for the field sample stratification. The final forest composition surface was generated using conditional statements written in ESRI ArcMap software's Spatial Analyst extension (ESRI, 2004). The surfaces were created at a spatial resolution of 10-m.

Forest Structure Predictive Surfaces

The forest composition surface produced in the previous step was used as an additional auxiliary variable to aid the forest structure modeling. A stepwise Akaike's information criterion (AIC) method determined which auxiliary variables significantly contributed to the forest structure regression models by minimizing the AIC (Akaike, 1973). Model coefficients determined by the multi-linear regression were calculated using S-PLUS 2000© software (S-PLUS 2000©, Statistical Sciences 1999) utilizing general linear model theory (McCullagh and Nelder, 1989). The regression coefficients were used to generate a surface for describing large scale variability. MARS-L software (Reich 2008) was utilized to generate binary floating grids from the regression coefficients and auxiliary variables.

Residuals from the regression models (explaining fine-scale variability) were modeled using a tree-based stratified design (Reich et. al 2010). A tree which minimized prediction error of the variance of the mean response was selected by iteratively adjusting the number of terminal nodes (number of strata) and the minimum size of the strata until the standardized mean squared error of prediction neared 1.0 (indicating unbiased variance estimates) and a 0.95 coverage rate was achieved (Reich et. al. 2010). In addition to the predictor variables used in the regression models, the linear expectations were also considered as predictor variables in the tree-based design. Using MARS-L software (Reich 2010), a regression tree binary floating grid surface (stratified residuals) was generated based on the output of the tree-based stratification. Thus, final predictive surfaces were generated by summing the regression and error surfaces using ESRI software [(ArcGIS spatial analyst extension) (ESRI, 2004)].

As canopy closure was the first forest structure predictive surface derived, its expected values were used as predictor variables for the basal area model (as well as the remaining forest structure models). Similarly, the expected values of the basal area predictive surface were employed as predictor variables by the trees per acre model (as well as the remaining forest structure models). Next, a quadratic mean diameter surface was calculated from the basal area and trees per acre predicted surfaces using the formula:

$$Dq = \mathrm{sqrt}((TBA/TPA)/.005454)$$

where TBA is the average basal area per acre and TPA is the average trees per acre. Thus, the expected values from the canopy closure and basal area models, along with the quadratic mean diameter derivative, were used as predictor variables for the dbh model. Lastly, the expected values from the canopy closure, basal area, dbh, and trees per acre predictive surfaces were utilized for the proportion of basal area in lodgepole pine which was the final surface generated.

The final forest structure surfaces generated included total basal area, proportion-LP-basal-area, percent canopy closure, trees per acre, quadratic mean diameter, and diameter at breast height.

Forest Composition Predictive Surface Evaluation

The forest composition predictive surface was evaluated using aerial photographs acquired in 2008 by the USDA Forest Service over the Fraser Experimental Forest (Hubbard, unpublished data). Nominal scale of the air-photos was approximately 1:6,000 and the air-photos were scanned at a resolution of 1,000 DPI. Ten aerial photographs were randomly selected from the total set of 221. Forty 30m by 30m plots were randomly located on each photo using Hawth's tools (Beyer 2004) totaling 400 plots for the evaluation.

To eliminate bias, an independent, experienced aerial photo interpreter (Ciesla 2009) determined which vegetation category each of the 400 plots represented. Classes from the forest composition predictive surface were validated against photo-interpreted classes by Receiver Operating Characteristics (ROC) analysis (Zeng-Chang 2005). Area under the curve of ROC (AUC) is a contemporary method for assessing model performance; AUC is advantageous over traditional approaches (kappa statistics, areal correspondence, etc.) as the relative importance of negative versus positive outcomes is considered. Other key advantages to using AUC for evaluating model performance are: 1) sample design assumptions are not required of the field sample; and 2) true-positive and false positive rates for a discreet classifier are well-represented graphically by a single point.

To calculate the true vs. false positive rates and AUC scores (model accuracy) for each of the forest composition classes, the validation data for individual vegetation classes were arranged in binary matrix form. Agreements between the air-photo interpretations and the forest vegetation classifications were expressed as 'true positives' in the matrix. 'False positives' were expressed as the number of times the predicted class was classified differently by the air-photo interpretation; whereas 'false negatives' were the number of times the air-photo interpretation differed from the predicted category. The agreements between the air-photo interpretations and the forest vegetation classifications with respect to where a given vegetation class does not exist were expressed as 'true negatives'. The *true positive rate* was calculated using the following formula:

$$TPR = TP/(TP+FN)$$

where TPR = True Positive Rate, TP = True Positives and FP = False Positives. The *false positive rate* was calculated using the following formula:

$$FPR = FP/(FP+TN)$$

where FPR = False Positive Rate, FP = False Positives and TN = True Negatives. The AUC score for a given forest composition class was calculated using the following formula:

$$AUC = ((FPR*TPR)/2)+((1-FPR)*(1+TPR))/2$$

where AUC = Area Under Curve, TPR = True Positive Rate, and FPR = False Positive Rate. A sample true vs. false positive rate and AUC calculation using the forest composition validation data is provided in APPENDIX C.

Forest Structure Predictive Surface Evaluation and Error Surface Generation

The predictive performances of the forest structure models were evaluated using a 10-fold cross-validation (Efron and Tibshrani 1993) where the data was divided into 10 equal parts of roughly 50 observations. The models were fitted ten times omitting one part of the data each time until every observation was excluded from the model-fitting step and its response computed. Prediction errors were inferred by subtracting the cross-validated responses from the actual values obtained prior to the cross-validation (Reich et. al 2010). 95% prediction intervals were calculated during the cross-validation as were 95% intervals for the mean response of the fitted-models. The spatial realization of the regression model's prediction errors was generated using MARS-L software (Reich 2008). The spatial realization of the sample variance associated with each terminal node in the regression tree (regression tree error) was generated using MARS-L software (Reich 2008) as well. The final error surfaces depicting uncertainty in the spatial estimates, expressed as standard deviations, were calculated in ESRI ArcMap software's Spatial Analyst extension (ESRI, 2004) using the following formula:

sqrt([error-rm] + [error-rt] + MSE)

where sqrt = square root, error-rm = regression model error surface, error-rt = regression tree error surface, and MSE = mean squared error associated with the regression model (MSE is equal to the residual deviance divided by the number of degrees of freedom).

Variance estimates were tested for unbiasedness by comparing the true error to the estimated variances using the standardized mean squared error (SMSE) to test the null hypothesis of equal variance (Hevesi et al 1992). Additionally, the goodness-of-prediction statistic (G) (Agterberg 1984) was used to test the effectiveness of the fitted-models. The G-statistic measures the performance of the predicted value relative to what would be expected using the sample mean as the predicted value (Agterberg, 1984). A positive G-value is an indication that the fitted-model would outperform a model using only the sample mean. A G-value equal to one indicates a perfect fit whereas a value of zero or less indicates that the sample mean is a better predictor than the fitted-model. The mean squared error of prediction (MSEP) was calculated to measure prediction uncertainty (Reich et. al 2010).

MPB Susceptibility/ Risk Map Generation

The MPB susceptibility/ risk maps were calculated from the final predictive surfaces using the mathematical functions available in the ESRI ArcMap 9.0 *Spatial Analyst* extension (ESRI, 2004). All MPB susceptibility/ risk surfaces were generated in either English or metric units based on the original model's native units of measure.

Anhold et al., (1996)

The Anhold *et al.,* (1996) model rates susceptibility as high when stand conditions fall between Stand Density Index (SDI) values 125 – 249 and where quadratic mean diameter (QMD) is 8 inches or greater. An SDI surface was calculated using the following formula:

[Tpa] * (([Qmd_in] / 10)^1.605)

where

- [Tpa] = Trees per acre and [Qmd_in] = quadratic-mean-diameter-in-inches.

Cells meeting the Anhold et al., (1996) susceptibility criteria were coded ‘highly-susceptible’; remaining cells were coded ‘low-susceptibility’.

Amman et al. (1977)

The Amman et al., (1977) model divides risk (susceptibility) of MPB infestation into three risk categories: light, moderate and high based on elevation and latitude, average stand age, and average diameter at breast height (dbh). To produce the Amman MPB risk surface the DEM was reclassified as follows:

- 1 = elevation > 10,000 ft. (at 40° N latitude)
- 2 = elevation 9,000-10,000 ft. (at 40° N latitude)
- 3 = elevation < 9,000 ft. (at 40° N latitude)

Similarly, the dbh predictive surface was reclassified as follows:

- 1 = dbh < 7in
- 2 = dbh 7in-8in
- 3 = dbh > 8in

Average stand age was assumed to be > 80 for the study area and was given a value of 3 for the entire surface as most stands within the study area were established after extensive mid-nineteenth and/or late seventeenth century wildfires (Huckaby and Moir 1995). Thus the three surfaces were multiplied to derive risk (susceptibility) ratings ranging from 3 to 27 (3 - 9 = low, 12 - 18 = moderate, and 27 = high).

Shore and Safranyik (1992)

The Shore and Safranyik (1992) model derives an index between 1 and 100 to assess risk of MPB infestation based on a susceptibility index (SSI) and a beetle pressure index. The susceptibility index is a product of four factors: susceptible pine basal area (P), an age factor (A), a density factor (D), and a location factor (L). Hence SSI = P x A x D x L where:

- P = percent pine basal area > 15 cm. in diameter,

- A = the age of dominant/ codominant trees was assumed to be > 80 years old for the purpose of this study (Huckaby and Moir 1995) and given a value of 1.0,

- D = The trees per acre surface was multiplied by 2.47 to derive a trees per hectare predictive surface which was reclassified based on stand density weights as follows:

- a value of 0.1 was given to cells < 251 trees/ha,

- a value of 0.5 was given to cells between 251-750 trees /ha,

- a value of 1.0 was given to cells between 751-1,500 trees /ha,

- a value of 0.8 was given to cells between 1,501-2,000 trees /ha,

- a value of 0.5 was given to cells 2,001-2,500 trees /ha,

- and a value of 0.1 was given to cells > 2,501 trees /ha,

- L = 1.0, 0.7, or 0.3; because these values were based on a location algorithm tuned for British Columbia, the Amman *et al.,* (1977) elevation classes of 1, 2, and 3 were reclassified as 0.3, 0.7, and 1.0 respectively to approximate the Shore and Safranyik location factor (longitude is not a significant climatic factor for mid-continental ecosystems).

The beetle pressure index is calculated based on the number of infested trees within a stand and the numbers of infested trees outside a non-infested stand within given distances. The weights for the beetle pressure index are determined from two tables in the Shore and Safranyik (1992) paper; the fist table determines the relative size of the infestation (small, medium, or large) within 3 km of the stand (cell) being assessed; the second table determines the actual beetle pressure weight for that cell based on distance the infestation is to that cell. Forest Service aerial forest health survey data from 2003, 2004, and 2005 were converted to raster format to calculate the 2004, 2005, and 2006 beetle pressure surfaces respectively (USDA Forest Service$_2$ 2006).

Finally, the risk surface was derived using the formula:

$\text{Risk} = 2.74[S^{1.77}\, e^{-0.0177S}]\, [B^{2.78}\, e^{-2.78B}]$ where:

- e = base of natural logarithms = 2.718
- S = Susceptibility Index
- B = Beetle Pressure Index

The resulting risk surface is indexed between 1 and 100. To compare the Shore and Safranyik model to the other MPB models, their risk index was reclassified into the following categories:

- Low risk (indexed values ranging from 0.0 to 33.3)
- Moderate risk (indexed values ranging from 33.4 to 66.6)
- High risk (indexed values ranging from 66.7 to 100.0)

USDA Forest Service National Insect and Disease Risk Map

The National Risk Map risk surface was derived using scaled values of the quadratic mean diameter (QMD), percent basal area in lodgepole pine (PerBA), basal area (BA), and elevation (Elev) surfaces (Krist et. al, 2007).

Values for the QMD surface (restricted to QMD ≥ 6.0 in.), were reclassified as follows:

- QMD ≥ 7 in. = 10;
- QMD 6.0-6.9 in. = 5.

Values for PerBA surface (restricted to PERBA ≤ 20%) were reclassified as follows:

- PerBA 20-24.9% = 1;
- PerBA 25-29.9% = 2;
- PerBA 30-34.9% = 3;
- PerBA 35-39.9% = 4;
- PerBA 40-44.9% = 6;
- PerBA 45-49.9% = 8
- PerBA ≥ 50% = 10.

Values for BA surface (restricted to BA ≥ 80 sq.ft./acre) were reclassified as follows:

- BA 80-104.9 ft^2./acre = 2;
- BA 105-109.9 ft^2/acre = 6;
- BA 110-114.9 ft^2/acre = 8;

- BA 115-159.9 ft^2/acre = 10;
- BA 160-179.9 ft^2/acre = 8;
- BA 180-199.9 ft^2/acre = 6;
- BA 200-219.9 ft^2/acre = 4;
- BA 220-239.9 ft^2/acre = 3;
- BA $\geq$ 240 ft^2/acre = 2.

For the elevation (Elev) component of the National Risk Map, the Amman et al., (1977) elevation classes 1, 2, and 3 were reclassified to 0, 5, and 10 respectively. Finally, the four surfaces were weighted and added together to derive the final Risk Map risk surface using the following formula:

([QMD_in] * 0.3) + ([Perba] * 0.3) + ([BA] * 0.3) + ([Elev] * 0.1)

Similar to the Shore and Safranyik (1992) system, the National Risk Map is an index of integers 1 through 10. To compare the National Risk Map model to the other models, their indexed values were reclassified as follows:

- Low risk (indexed values 1-4)
- Moderate risk (indexed values 5-7)
- High risk (indexed values 8-10)

Evaluation of MPB Risk Models

Risk classes of the Shore and Safranyik (1992), Amman et al. (1977), Anhold et al., (1996), and Forest Service National Insect and Disease Risk Map models were compared to actual field observations mapped during 2004, 2005, and 2006 aerial surveys. Aerial survey, also referred to as aerial sketchmapping, is the technique of observing symptoms of forest damage from an aircraft and transferring the information manually onto a base map (Johnson and Ross 2008). Aerial survey data was used as the surrogate for 'ground truth' for the validation of the MPB risk models. Aerial surveys are carried out on an annual basis by the Forest Service's Forest Health Protection group where areas containing bark beetle mortality are delineated using a tablet PC linked to a GPS unit with a moving map display; the size, shape, and intensity of dead trees are recorded and the quantity of tree mortality is estimated on a per acre basis. A 2005 study by the Forest Service comparing aerial surveys to field surveys revealed that demarcations of MPB-caused LP mortality agreed with the field data 80% of the time[10] (Johnson and Ross 2008). Aerial surveys can be conducted over large areas such as the study area in a matter of hours whereas a comprehensive ground survey would take months to carry out.

Four thousand random sample points were generated across the spatial extent of the study area stratified by four MPB aerial survey mortality classes for the validation; no-mortality (0 trees per acre killed), low-mortality (0.1-1.99 trees per acre killed), medium-mortality (2.0-4.99 trees per acre killed), and high-mortality (≥ 5.0 trees per acre killed)[11]. Two thousand of these points were reserved to validate the risk models. The remaining two thousand random points were used for generating the empirical model. Forty-nine of the four thousand random points were discarded for falling outside the lodgepole pine forest type.

[10] The study measured the spatial accuracy of aerial survey delineations using three different spatial tolerances (resolutions): ± 0m, ± 50m, and ± 500m. Consumer accuracies for the MPB in LP damage category were determined to be 70% at ±0m, 80% at ±50m, and 87% at ±500m.
[11] These groupings reflect commonly accepted aerial survey beetle-kill intensity thresholds.

The validation points were used for Receiver Operating Characteristics (ROC) analysis of the MPB models as well as for calculating areal correspondence. Areal correspondence compares the 'correct' pixels, where risk and beetle mortality levels align, to 'non-correct' pixels, where risk and beetle mortality misalign using the formula:

Areal correspondence = overlapping pixels / (overlapping pixels + non-overlapping pixels).

ROC analysis was applied to the MPB risk model evaluations in the same way as it was applied to the forest composition predictive surface evaluation discussed previously. AUC scores and true versus false positives rates were calculated for each of the MPB risk models for each year (APPENDIX C provides a sample true vs. false positive rate and AUC calculation).

Empirical Derivation of a MPB Risk Model

MPB risk was empirically modeled by extracting and summarizing forest structure parameters of affected areas using the 2,000 model points described in the previous section. Classification trees using S-PLUS 2000© software (S-PLUS 2000©, Statistical Sciences 1999) were utilized to model MPB presence versus MPB absence based on these points.

Cross-validation was used to 'prune' the tree to the best-fitting number of terminal nodes by choosing the model with the least mean residual deviance. Terminal nodes of the cross-validated model were further 'snipped' to simplify the model for field applications using S-PLUS 2000© software (S-PLUS 2000©, Statistical Sciences 1999). This final Empirical Model was used for deriving a 'high susceptibility' versus 'low susceptibility' (presence vs. absence) predictive surface using conditional statements written in ESRI ArcMap software's Spatial Analyst extension (ESRI, 2004).

RESULTS AND DISCUSSION

Field Data

Field data were collected within the study area between October 1, 2003 and February 1, 2004. Elevation of the plots ranged from 2,574m to 3,310m (8,445 ft. to 10,860 ft.) with a mean elevation of 2,954m (9,692 ft.). Field data summary statistics are presented in Table 1 below. Mean basal area (152 ft2/ acre) and mean dbh (9.9 in) indicate that lodgepole pine forests within the analysis area, on average, are highly susceptible to attack by the mountain pine (Schmid 2003).

Table 1. Field data summary statistics depicting the data's minimum, maximum, and mean values along with the variance and bound on the error of estimation.

Parameter	Min	Max	Mean	Variance	Bound
Basal area ($ft.^2$/acre)	20.0	420.0	152.3	3558.5	5.4
Canopy closure (%)	6.3	96.9	58.5	324.3	1.6
Diameter at breast height (in.)	5.1	16.0	9.9	4.5	0.2
Trees per acre	25.5	1832.8	332.9	41338.9	18.3
Proportion of basal area in LP	0.00	1.00	0.85	0.57	0.02

Predictive Surfaces

All of the MPB models assessed in this study required parameters that had to be measured in the field. While practical for site-specific investigations, gathering data in remote locations or across large geographical regions crossing political and administrative boundaries is seldom feasible. The predictive surfaces derived for this study were generated from a nominal field sample and inexpensive satellite imagery. While field sampling was conducted strictly on public lands, the final surfaces were continuous regardless of administrative and land-ownership boundaries.

A model-based sample design was employed for generating sample points. Unlike probabilistic-based approaches, which are useful when the primary concern is to make an inference about the population, a model-based approach is advantageous for generating predictions across various spatial scales. The use of satellite imagery to stratify the field sample proved effectual as sampling errors were within acceptable limits. Mean basal area, trees per acre, and canopy closure decreased with increasing reflectance as higher ground reflectance correlated with less forest canopy.

Grouping the study area's forest composition categories using classification trees in lieu of 'traditional' image classification techniques produced not only a more accurate model, but was a relatively simple procedure to perform; a high level of image-processing skills was not necessary. The final forest composition predictive surface is shown in Figure 4.

Figure 5 shows the results of the forest composition accuracy assessment. Good agreement was found between the air-photo interpretation and the model's land cover classifications in the non-forest, spruce-fir, lodgepole pine, and deciduous, and categories, but not in the mixed forest category[12]. Two field sample plots fell within the aerial photographs randomly selected for the air-photo validation. The field sample and model both classified these plots as 'mixed forest' however the air-photo interpreter classified both of the plots as 'lodgepole pine'. This does not necessarily mean the air-photo interpretation was misleading or the ground observer make a mistake; instead it shows the difficulty of classifying transitional forest classes.

Forest structure predictive surfaces and cross validated error surfaces were generated for basal area, percent LP basal area, percent canopy closure, mean diameter at breast height, and trees per acre. As an example, the basal area predictive surface and its corresponding error surface are shown in Figure 6 and Figure 7. Refer to APPENDIX A for maps of all of the predictive surfaces and error surfaces generated for this study.

[12] AUC scores for the non-forest, spruce-fir, lodgepole pine, mixed forest, and deciduous classes were 0.972, 0.728, 0.756, 0.573 and 0.894 respectively.

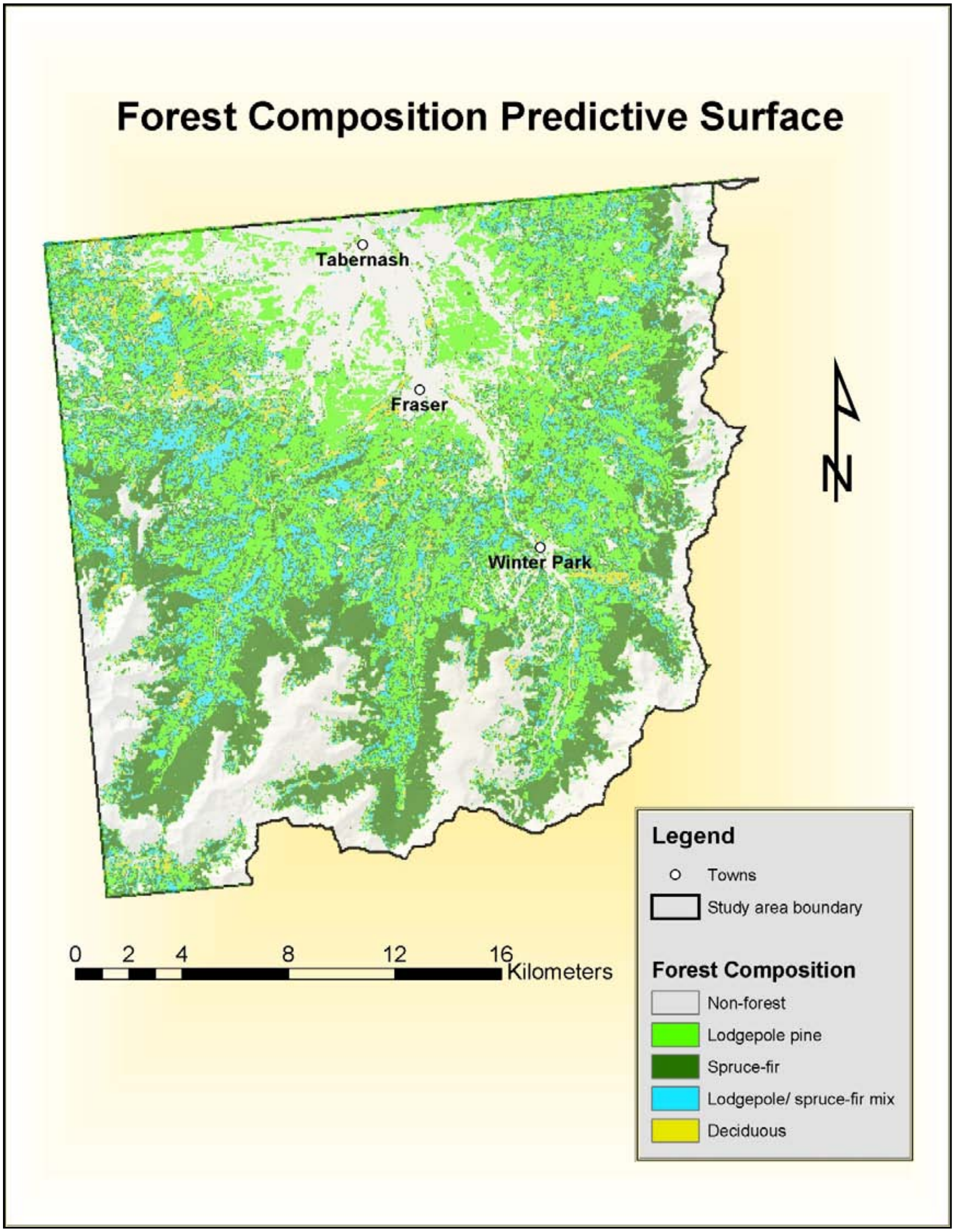

Figure 4. Forest composition predictive surface generated from the classification tree model based on field data collected between October 1, 2003 and February 1, 2004.

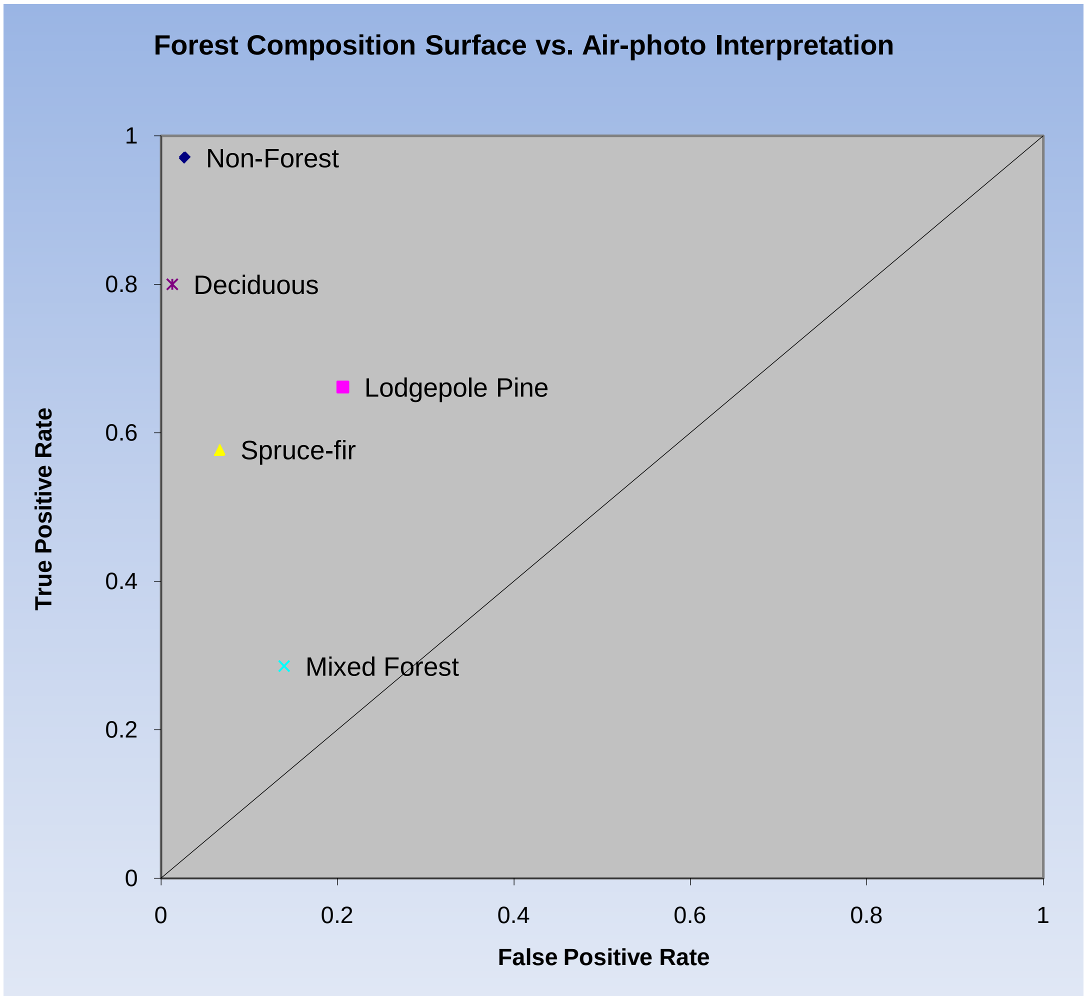

Figure 5. True versus false positive rates of the forest composition model's vegetation classes versus air-photo interpretation results[13]. The diagonal line represents what would be expected from random chance; area below the line indicates predictions are worse than random chance while area above the line indicates predictions are better than random chance.

[13] AUC scores for the vegetation classes were 0.972, 0.728, 0.756, 0.573, and 0.894 for the non-forest, lodgepole pine, spruce-fir, mixed forest, and deciduous categories respectively.

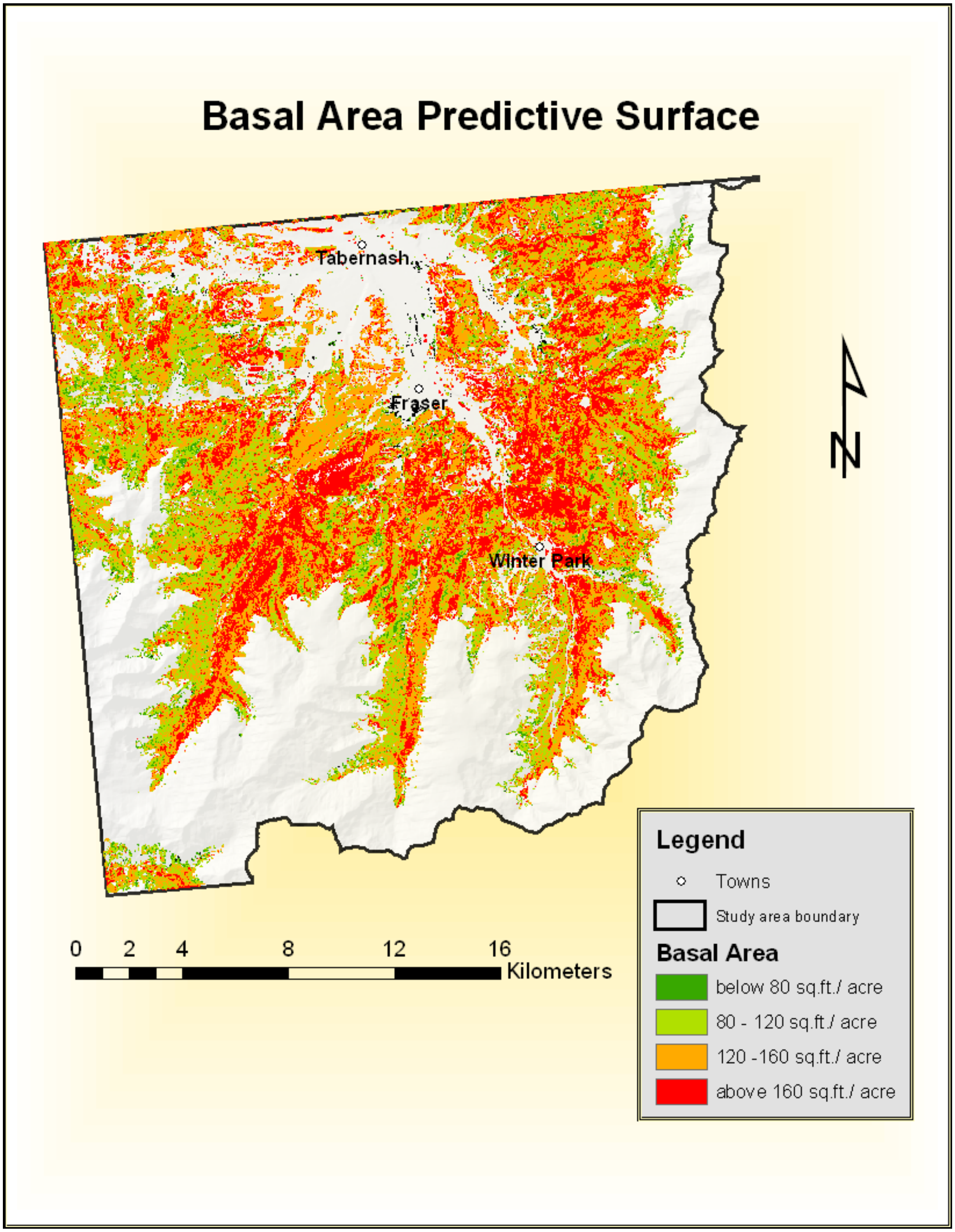

Figure 6. Basal area predictive surface of the lodgepole pine and mixed forest vegetation classes. The surface is the spatial realization of the multiple linear regression and binary regression tree models. Field data used to train the models were collected between October 1, 2003 and February 1, 2004.

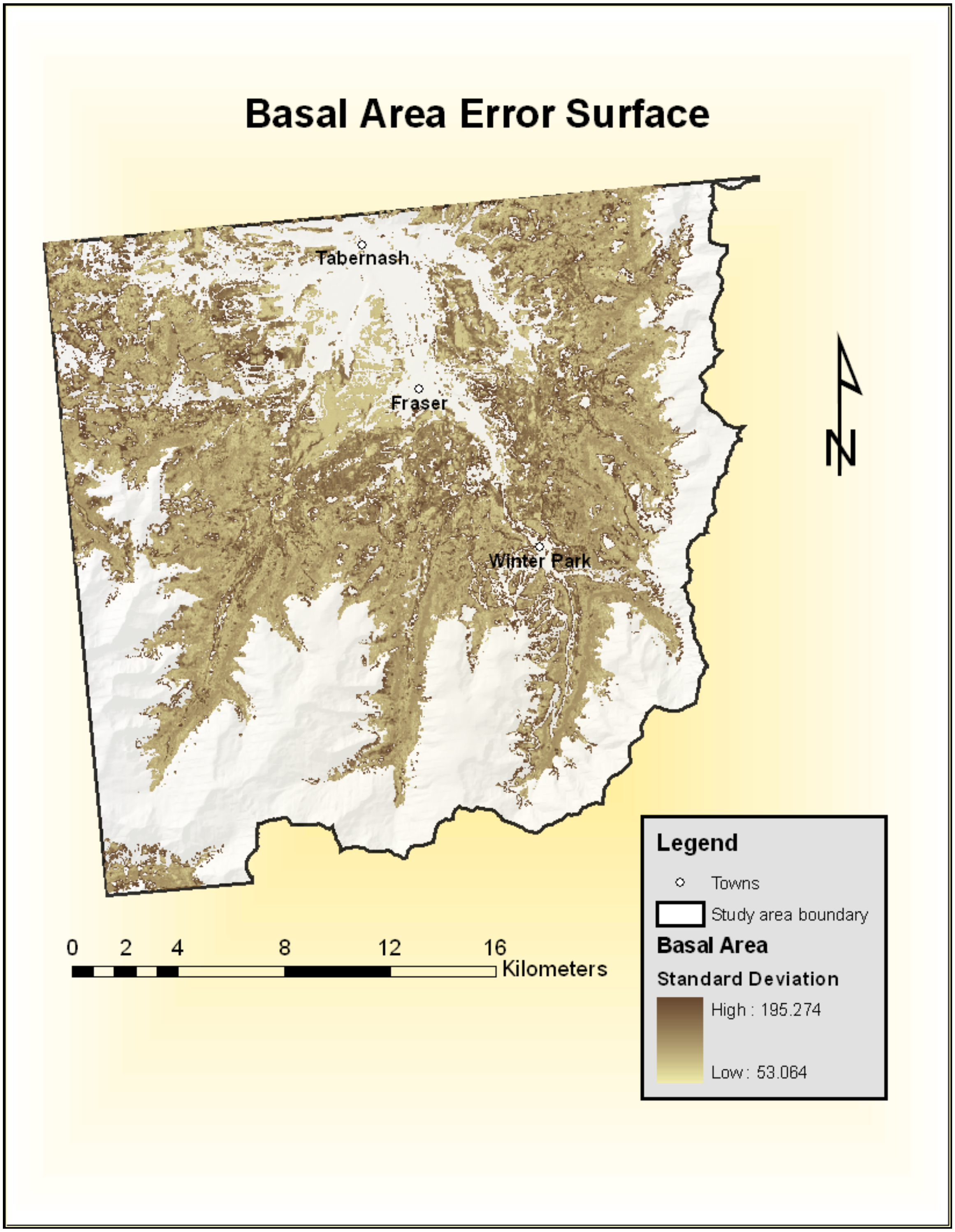

Figure 7. Basal area error surface of the lodgepole pine and mixed forest vegetation classes. The surface represents the prediction errors associated with the basal area predictive surface. The standard deviation term refers to the square root of the prediction variance. Prediction uncertainty is greater in the darker areas with higher standard deviation values.

Satellite imagery, DEM and DEM derivatives (slope, aspect), and the forest composition predictive surface were employed as explanatory variables in the forest structure regression models. Table 2 depicts the significant explanatory variables used in constructing the forest structure regression model surfaces. The regression model surfaces were used to capture the course-scale variability inherent in the forest structure parameters. All of the forest structure predictive surfaces utilized the forest composition predictive surface as an explanatory variable. Both spectral and topographical explanatory variables contributed significantly to all of the forest structure regression model surfaces. Predictor variables (canopy closure, basal area, and trees per acre) were also used as explanatory variables in the regression model surface generation.

Table 2. Multiple linear regression models describing course-scale spatial variation and the significant variables contributing to the model's formulation.

Model	Topography			Landsat TM Bands						VEG MAP[14]
	E	S	A	B1	B2	B3	B4	B5	B6	
Basal Area		▪	▪	▪	▪	▪	▪	▪	▪	▪
% Basal Area in LP	▪	▪	▪	▪		▪	▪	▪	▪	▪
Canopy Closure	▪	▪	▪	▪	▪	▪	▪	▪	▪	▪
Diameter at breast height	▪	▪	▪		▪		▪	▪	▪	▪
Trees per acre	▪	▪	▪	▪		▪	▪	▪	▪	▪

E – elevation, S – slope, A – aspect, B1 – band 1, B2 – band 2, B3 – band 3, B4 – band 4, B5 – band 5, B6 – band 6, B7 – band 7, VEG MAP – forest composition predictive surface.

[14] The forest composition model (veg map) was formulated exclusively using classification trees.

In addition to the explanatory variables used to generate the abovementioned regression models, the spatial realization of the regression models were used as predictor variables for the binary regression tree models (error models). Table 3 depicts the significant explanatory variables used to generate the residual surfaces based on results of the regression trees. Both spectral and topographical explanatory variables contributed significantly to all of the forest structure regression tree models.

Table 3. Binary regression tree models describing fine-scale spatial variation and the significant variables contributing to the model's formulation.

Model	Topography			Landsat TM Bands						TREND
	E	S	A	B1	B2	B3	B4	B5	B6	
Basal Area	▪	▪	▪	▪	▪	▪	▪		▪	▪
% Basal Area in LP	▪	▪	▪	▪		▪	▪	▪		▪
Canopy Closure	▪	▪		▪	▪		▪	▪	▪	▪
Diameter at breast height	▪			▪		▪	▪		▪	▪
Trees per acre	▪	▪		▪	▪	▪	▪	▪	▪	▪

E – elevation, S – slope, A – aspect, B1 – band 1, B2 – band 2, B3 – band 3, B4 – band 4, B5 – band 5, B6 – band 6, B7 – band 7, TREND – regression model surface.

All of the models except for the proportion-LP-basal-area were unbiased estimators as measured by the standardized mean squared error (SMSE) (Hevesi et al. 1992) (the mean ratio between the estimation error variance and the observed estimation errors); Table 4 depicts fit statistics for the forest structure models. The proportion LP basal area SMSE value (0.732) fell slightly outside of the bounds to be considered an unbiased estimator (0.87 - 1.13) as it underestimated the actual variation within the data. The reason for this underestimation of the variance was due to the homogeneous nature of the proportion LP basal area data where prediction of the mean was straightforward (explained by the high G-statistic); however spectral and topographical properties could not describe the remaining variation. G-values (Agterberg 1984) of the unbiased estimators ranged from 0.425 (canopy closure) to 0.667 (Trees per acre) indicating that the models soundly predicted the forest structure characteristics.

A key advantage to constructing error surfaces is the ability to produce small area estimations (Reich and Aguirre-Bravo 2009). The term *small area estimation* refers to using the spatial models (predictive and error surfaces) to make probabilistic inferences across various spatial scales for any given area of interest. An unbiased estimate of the mean and variance along with confidence intervals can be derived directly from the predictive surface and its associated error surface. A comparison of the spatial estimates and estimates from the field sample are shown in Table 5. Estimates by the spatial models were similar to the field sample estimates.

Table 4. Forest structure models fit statistics depicting the sample size, goodness-of-prediction statistic (G-statistic), mean squared error, standardized mean square error, and coverage rate for the model and cross validated predictions; and tree-based stratified design fit statistics including minimum the number of residuals per strata and the total number of terminal nodes per tree by parameter.

	Model				
Statistic	Canopy Closure (%)	Basal Area (sq. ft./ acre)	Trees per acre	Diameter at breast height (in.)	Proportion Basal Area in LP
Sample Size (# subplots)	493	493	493	493	493
Minsize (minimum number per strata)	60	33	42	37	2
Number terminal nodes per tree	22	30	26	18	56
G-statistic	0.425	0.594	0.666	0.502	0.943
Standardized Mean Squared Error – Model	0.916	0.935	0.960	0.895	0.619
Standardized Mean Squared Error – Prediction	1.025	1.006	1.111	0.963	0.732
Mean Squared Error Prediction	296.38	2790.96	34453.61	2.99	0.29
0.95 Coverage Rate – Model	0.97	0.96	0.95	0.97	0.97
0.95 Coverage Rate – Prediction	0.95	0.95	0.96	0.95	0.95

Table 5. Comparison of the mean, variance, variance of the mean, and bound on the error of estimation of the field data to the forest structure model and the forest structure model's prediction statistics. Model statistics were calculated from values extracted from the forest structure surface(s) at each plot location. Prediction mean was calculated by averaging all pixels (belonging to the lodgepole pine and mixed forest composition classes) within the forest structure surface(s). Prediction variance was calculated by averaging all pixels (belonging to the lodgepole pine and mixed forest composition classes) within the variance surface(s). The estimated prediction variance of the mean was calculated by dividing the sum of the prediction variances by n^2 (where n is the number of pixels within the study area belonging to the lodgepole pine and mixed forest composition classes).

	Field Sample				Model				Prediction			
	Mean	Variance	Variance of the mean	Bound	Mean	Variance	Variance of the mean	Bound	Mean	Variance	Variance of the mean	Bound
Basal area	152.3	3558.5	7.2	5.4	150.7	2082.2	4.2	4.1	143.8	4158.0	0.0018	0.084
Canopy closure	58.5	324.3	0.7	1.6	58.5	136.4	0.3	1.0	53.9	476.8	0.0002	0.029
Diameter at breast height	9.9	4.5	0.01	0.2	9.9	4.7	0.01	0.2	10.3	5.6	2.4e-06	0.003
Trees per acre	332.9	41338.9	84.0	18.3	309.3	19930.7	40.4	12.7	314.2	56134.2	0.0240	0.310
Proportion of basal area in lodgepole pine	0.85	0.57	0.00012	0.02	0.85	0.51	0.00011	0.02	0.73	0.74	3.1e-07	0.0011

Mountain Pine Beetle Activity within the Upper Fraser Valley

Tree mortality in Grand County due to MPB was limited between the 1950s and the mid-1990s (USDA Forest Service$_2$). Between 1996 and 1997, a localized outbreak situated on Table Mountain just west of Lake Granby rapidly expanded along the north, east, and south shores of the lake (approximately 12 miles north of the study area). In 1998 the infestation increased appreciably, especially along the east side of Lake Granby. At the same time two new infestations began; one in the Troublesome Creek drainage approximately 20 miles northwest of the study area and another in the Williams Creek drainage roughly 6 miles west of the study area. By 2003, these three outbreaks grew to roughly 100,000 acres in size where an estimated 900,000 trees were killed by the beetles (USDA Forest Service$_2$).

Throughout this period, the southeast portion of Grand County, which encompasses the study area, remained mostly unaffected by the beetle. In 2004, the first significant amount of tree mortality within the study area was detected when the Williams Fork infestation advanced across the St Louis Divide and spread into the St. Louis and Crooked Creek subwatersheds. By 2006, a total of 335,000 trees across 43,000 acres had been killed by MPB within the study area. Figure 8 and Figure 9 depict the number of acres affected and trees killed in Grand County and the number of acres affected and trees killed within the study area between 1994 and 2006 respectively (USDA Forest Service$_2$).

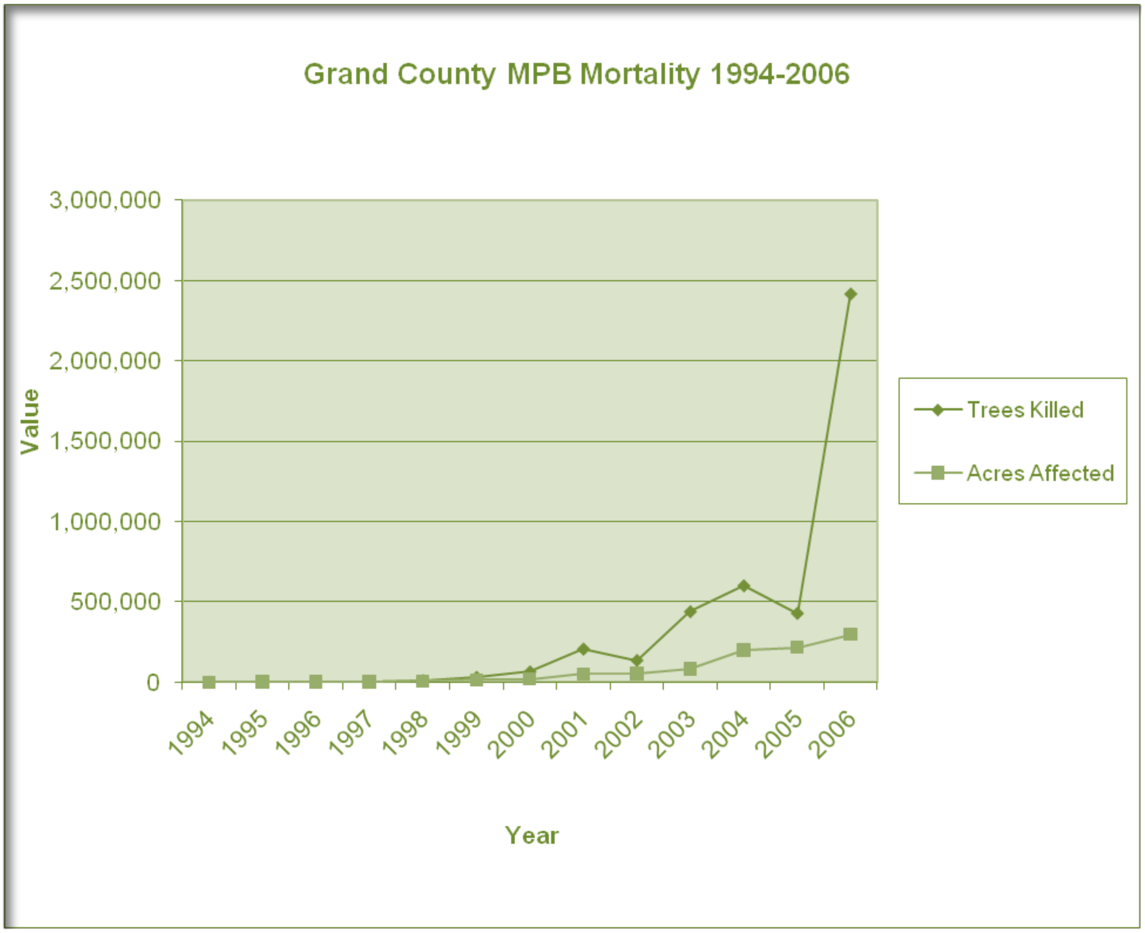

Figure 8. Number of acres affected and trees killed in Grand County between 1994 and 2006.

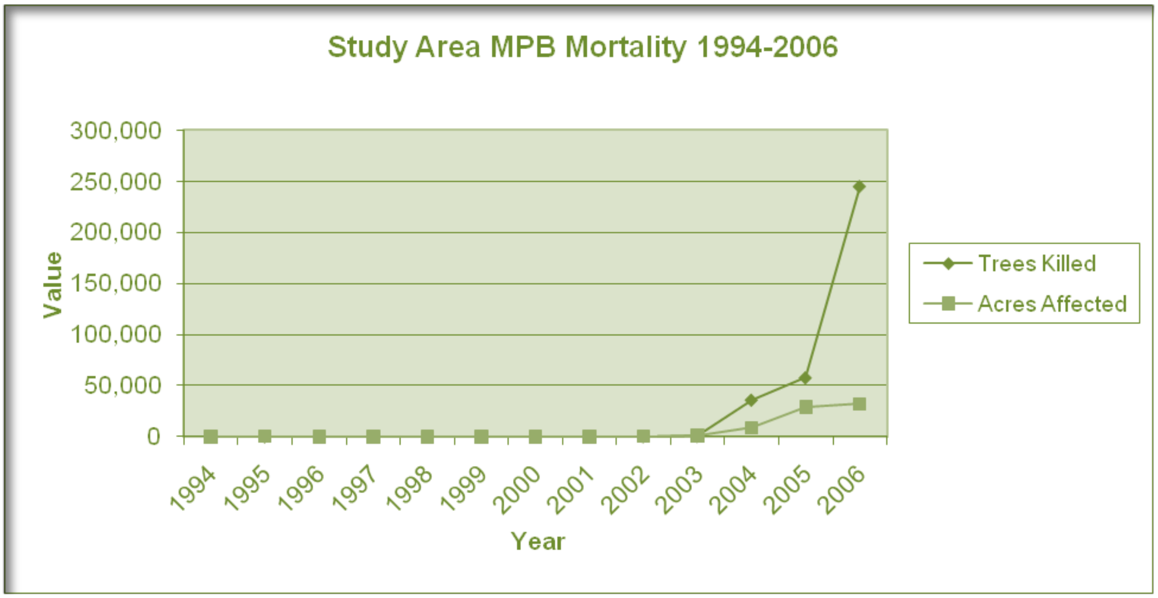

Figure 9. Number of acres affected and number of lodgepole pines killed within the study area between 1994 and 2006.

Mountain Pine Beetle Model Evaluation

Models were compared by areal correspondence and average AUC score. Areal correspondence of predicted versus observed values by year are shown in Table 6[15]. Average AUC scores for each model by listed by rank (highest to lowest AUC) are depicted in Table 7. A discussion of year-by-year results for each model follows Table 7.

[15] Aerial survey data was used as reference data for the areal correspondence analysis. A perfect areal correspondence score would be 100% for *each susceptibility category* indicating perfect agreement between the MPB predictions and the actual observed mortality.

Table 6. 2004, 2005, and 2006 areal correspondence of the five MPB models by category and overall classification accuracy. Areal correspondence is equal to the number of overlapping pixels (categorical agreement) divided by the sum of overlapping pixels and non-overlapping pixels. Aerial survey data was assumed to be the 'ground truth' for categorical comparisons. A perfect agreement for any given category would be 100%.

Model	Low Risk/ Susceptibility	Moderate Risk/ Susceptibility	High Risk/ Susceptibility
2004			
Anhold *et al.*, (1996)	87%	N/A	16%
Amman *et al.*, (1977)	40%	45%	17%
Shore and Safranyik (1992)	55%	30%	39%
National Risk Map (2006)	1%	33%	71%
Empirical model	47%	N/A	58%
2005			
Anhold *et al.*, (1996)	87%	N/A	14%
Amman *et al.*, (1977)	42%	53%	19%
Shore and Safranyik (1992)	43%	22%	52%
National Risk Map (2006)	1%	22%	68%
Empirical model	49%	N/A	63%
2006			
Anhold *et al.*, (1996)	89%	N/A	14%
Amman *et al.*, (1977)	47%	52%	23%
Shore and Safranyik (1992)	44%	23%	52%
National Risk Map (2006)	1%	27%	73%
Empirical model	54%	N/A	60%

Table 7. Average AUC score during the three-year period from 2004 to 2006 and rank by model.

Model	Average AUC score	Rank
Anhold *et al.,* (1996)	.511	4
Amman *et al.,* (1977)	.541	3
Shore and Safranyik (1992)	.560	1
National Risk Map (2006)	.497	5
Empirical model	.552	2

Anhold et al., (1996) Model Evaluation

Susceptibility maps based on the Anhold et al., (1996) MPB rating system were generated from the forest structure predictive surfaces and elevation, slope, and aspect data overlaid in a GIS by MPB polygons delineated during aerial detection surveys. The final Anhold overlaid with 2004-2006 cumulative MPB mortality are illustrated in Figure 10. All of the Anhold susceptibility maps are shown in APPENDIX B.

Anhold et al., (1996) described tree resistance to MPB attack within three density zones; Zone A, Zone B, and Zone C. Stands with relatively high (Zone C) or low (Zone A) tree densities are considered less susceptible to beetle attacks; whereas stands with intermediate relative densities (Zone B) are regarded to be more susceptible to beetle attacks. Trees growing within Zone A are characterized as fast-growing, vigorous trees with thick phloem and high resin production; while thick phloem is suitable to beetle development, the microclimate associated with the open stands of Zone A is less suited for beetle attack (Anhold et al., 1996). Trees growing within Zone B are less vigorous and slower growing because of increased competition between trees; which, combined with a more favorable microclimate (due to increased canopy closure), increases the tree's susceptibility to beetle attack. Zone C trees are even less vigorous and slower growing than Zone B trees; however their phloem is too thin for beetle development and spread. Additionally, any tree with a QMD below 8 inches is assumed to have unsuitable phloem thickness thus is regarded as having low susceptibility to bark beetle attack – regardless of its SDI zone.

The Anhold model rated most of the study area as being unsusceptible to MPB attack. Nearly half of the LP within the study area fell within the Zone C category and roughly one-quarter of the LP had an average QMD[16] below 8 inches (Table 8). Less than ten percent of the LP within the study area fell within the Zone A category and only fourteen percent fell within the susceptible Zone B. Areal correspondence for the 'low susceptibility' class was high while aerial correspondence for the 'high susceptibility' class was poor (Table 6). Figures 11-13 show Anhold false-positive rates equal to true-positive for both susceptibility categories indicating the model performed similar to what would be expected from random chance. The Anhold model had the second-poorest average AUC score during the three year period investigated (Table 7).

A clear reason for the low AUC score was that 54% of the study area was affected by MPB beetle mortality[17] while only 14% of the study area was rated as being susceptible to MPB. What was unexpected was the amount of mortality that occurred within the 'non-susceptible' zones. Examining the percentage of the Anhold susceptibility classes affected by corresponding MPB mortality classes, one would expect the highest percentage of MPB mortality to fall within the highest susceptibility class and recognize significant MPB mortality differences among the high and low susceptibility classes; however, there were no apparent differences between the predicted low and high Anhold susceptibility classes and their corresponding MPB mortality levels (Table 9).

The poor correlation between the predicted and actual MPB mortality can be attributed in part to the fact that the Anhold model was tuned for site specific conditions and was not intended to be used at the landscape-scale. For example, all pixels with an average QMD value less than 8 inches were excluded from being categorized as susceptible. The QMD forest structure surface was based on an average value for a 10-m

[16] Average per 10-m pixel.
[17] Based on total extent of the MPB polygons mapped during aerial surveys between 2004 and 2006.

cell; consequently, individual trees larger than 8 inches QMD within these cells were never accounted for. Thus, truly susceptible trees are excluded from the susceptible class by applying the model at the landscape-scale.

Moreover, susceptibility to MPB mortality is reliant upon the beetle's population pressure. When beetle population pressure is high, it is not uncommon for trees with diameters of six inches or less to be killed by beetles (Cole and Amman 1980). Thus removing the diameter criteria from the model would have increased the susceptibility area from 14% to 25% of the study area. Furthermore, an analysis of the 2004-2006 aerial survey data revealed that dense stands within the study area succumbed bark beetle mortality. Summary statistics calculated from the SDI predictive surface determined that the mean SDI value affected by the cumulative 2004-2006 MPB mortality was $302^{\pm}$ 7; well above Anhold's very dense, less susceptible Zone C threshold of SDI > 250; as well, the distribution[18] of the SDI values indicate that much of the MPB mortality had occurred within Zone C. Thus, increasing Zone C's SDI threshold in addition to removing the diameter criteria would have significantly improved the model's AUC score.

[18] 1st Quarter SDI = 218; 3rd Quarter SDI = 382; σ = 131

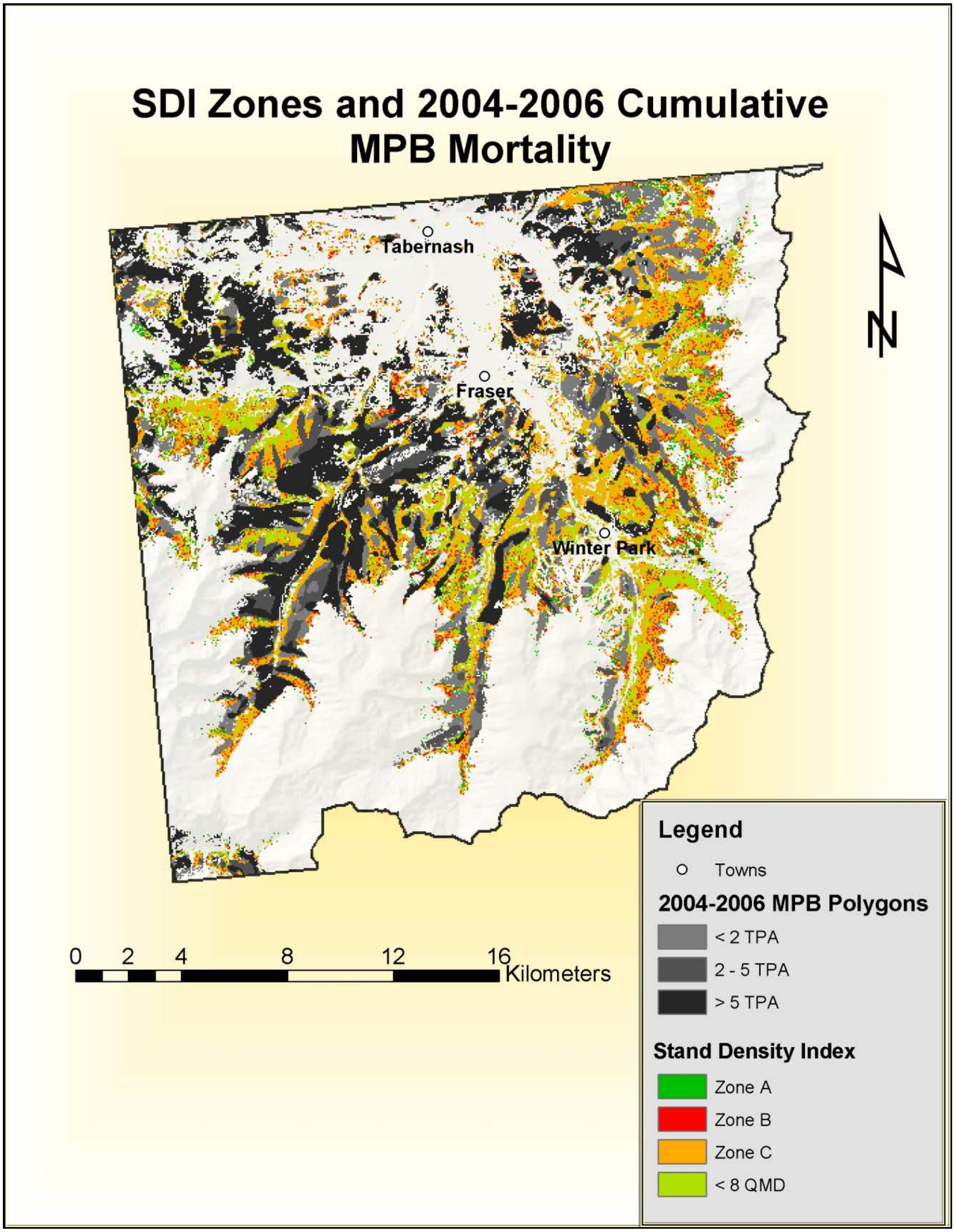

Figure 10. Stand Density Index (SDI) zones and areas < 8 in. QMD of lodgepole pine and mixed forest vegetation classes overlaid with 2004 - 2006 cumulative mountain pine beetle (MPB) mortality polygons. SDI Zone A: < 125, SDI Zone B: 125-249, SDI Zone C: > 250. TPA – trees per acre killed by mountain pine beetle (MPB).

Table 8. Percentage of study area defined by Anhold et al., (1996) susceptibility categories. Susceptibility categories are based on three stand density index (SDI) zones and quadratic mean diameter (QMD) values. Zone A = 0 to 139 SDI; zone B = 140 to 244 SDI; zone > 245 SDI.

Category	Percentage	Susceptibility
SDI Zone A	9%	Low
SDI Zone B	14%	High
SDI Zone C	49%	Low
< 8 QMD	28%	Low

Table 9. Percentage of Anhold susceptibility categories affected by corresponding 2004 MPB mortality levels and 2004-2005 and 2004-2006 cumulative MPB mortality levels. Susceptibility categories are based on three stand density index (SDI) zones and quadratic mean diameter (QMD) values. Zone A = 0 to 139 SDI; zone B = 140 to 244 SDI; zone > 245 SDI. MPB mortality and mortality levels were mapped between 2004 and 2006 during Forest Service aerial survey missions.

Anhold Susceptibility Category	Susceptibility	Area Affected (%) all mortality levels	Area Affected (%) ≥ 2 TPA	Area Affected (%) ≥ 5 TPA
		2004		
SDI Zone A	Low	16.0%	10.2%	6.1%
SDI Zone B	High	12.9%	7.9%	4.6%
SDI Zone C	Low	11.5%	7.0%	4.0%
< 8 QMD	Low	11.7%	7.3%	4.7%
		2004-2005		
SDI Zone A	Low	39.2%	15.7%	8.4%
SDI Zone B	High	35.4%	13.9%	7.2%
SDI Zone C	Low	34.9%	13.3%	6.1%
< 8 QMD	Low	31.3%	13.7%	7.6%
		2004-2006		
SDI Zone A	Low	57.9%	41.6%	30.0%
SDI Zone B	High	54.5%	40.1%	29.7%
SDI Zone C	Low	55.0%	42.3%	30.4%
< 8 QMD	Low	50.6%	38.8%	28.8%

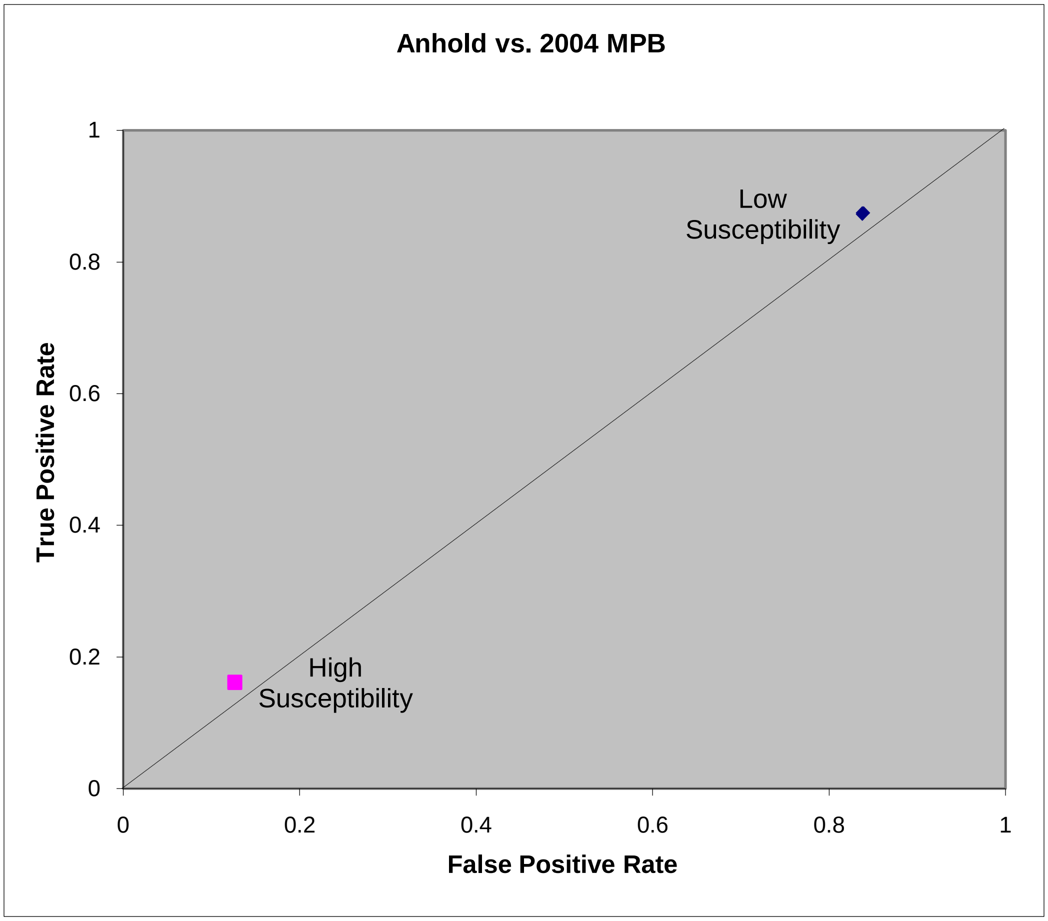

Figure 11. True versus false positive rates of the Anhold susceptibility predictions versus 2004 MPB mortality determined from USDA Forest Service aerial surveys. The diagonal line represents what would be expected from random chance; area below the line indicates predictions are worse than random chance while area above the line indicates predictions are better than random chance.

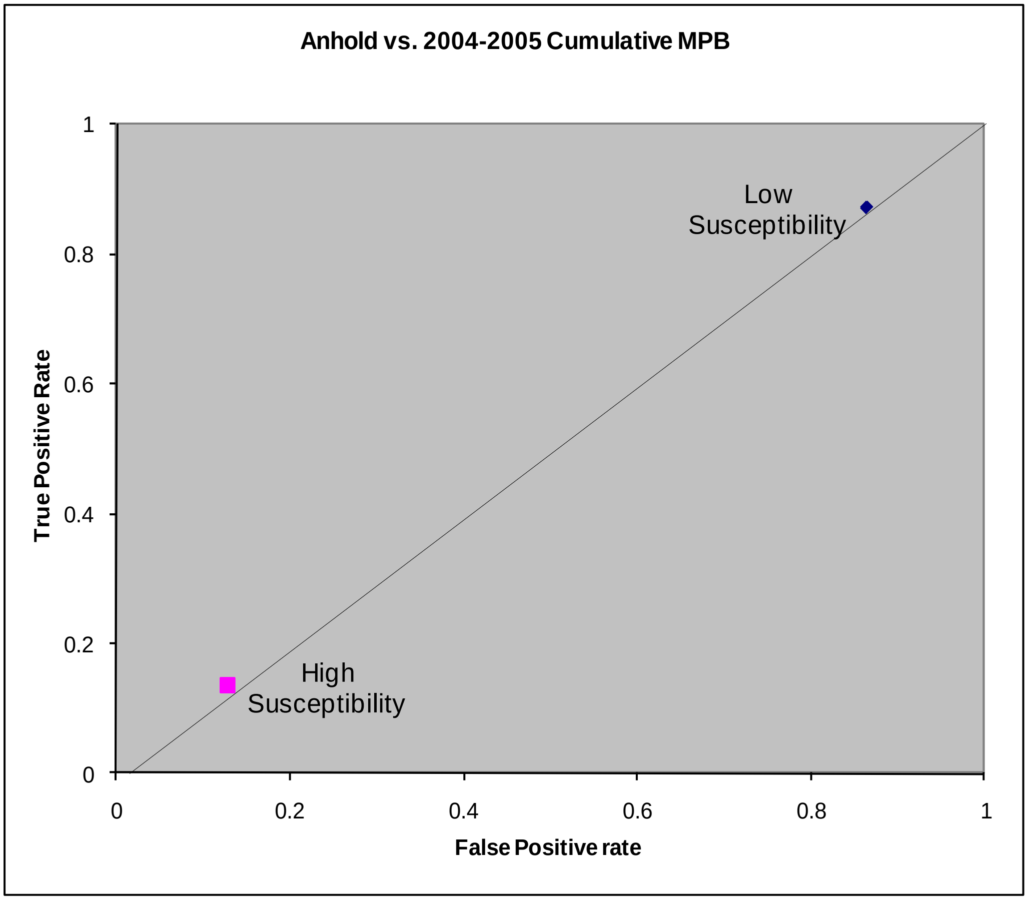

Figure 12. True versus false positive rates of the Anhold susceptibility predictions versus 2004-2005 cumulative MPB mortality determined from USDA Forest Service aerial surveys. The diagonal line represents what would be expected from random chance; area below the line indicates predictions are worse than random chance while area above the line indicates predictions are better than random chance.

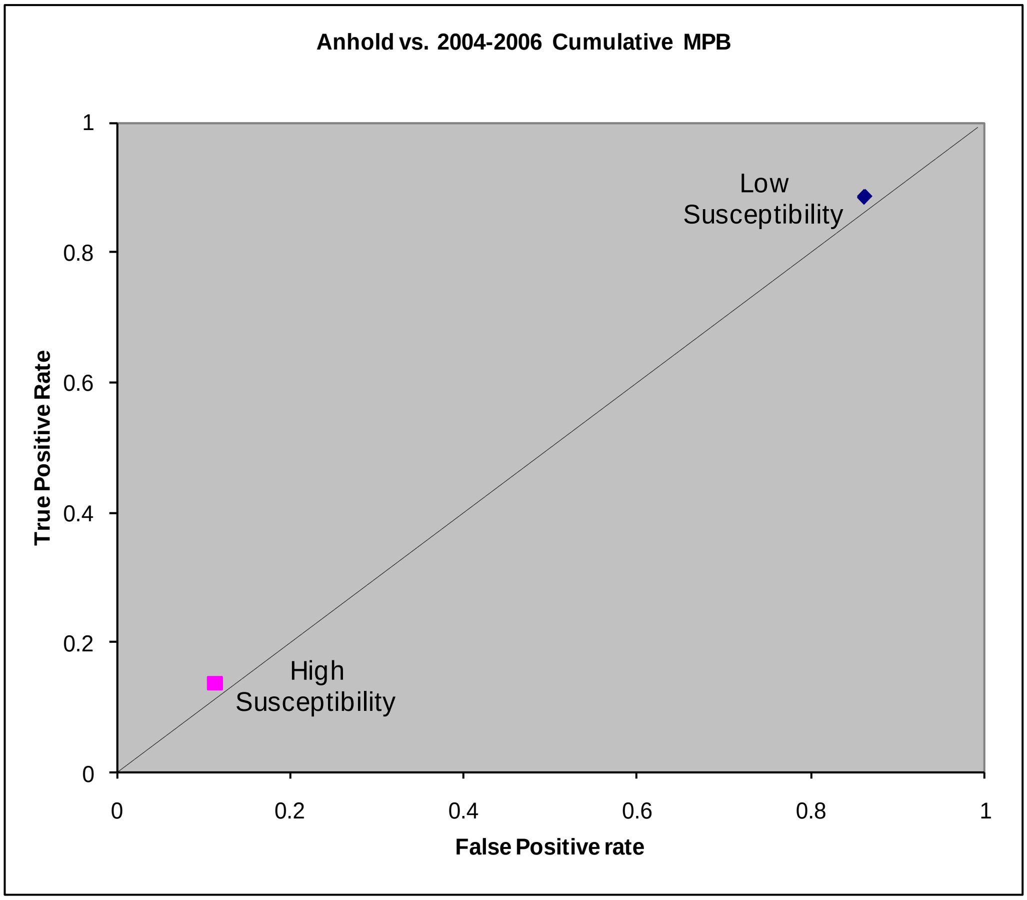

Figure 13. True versus false positive rates of the Anhold susceptibility predictions versus 2004-2006 cumulative MPB mortality determined from USDA Forest Service aerial surveys. The diagonal line represents what would be expected from random chance; area below the line indicates predictions are worse than random chance while area above the line indicates predictions are better than random chance.

Amman et al., (1977) Model Evaluation

Susceptibility maps based on the Amman et al., (1977) MPB rating system were generated from the forest structure predictive surfaces and elevation, slope, and aspect data overlaid in a GIS by MPB polygons delineated during aerial detection surveys. The final Amman susceptibility map overlaid with 2004-2006 cumulative MPB mortality are illustrated in Figure 14. All of the Amman susceptibility maps are shown in APPENDIX B.

Amman *et al.* (1977) uses the terms 'risk' and 'susceptibility' interchangeably; however Shore and Safranyik's (1992) susceptibility definition[19] was assumed for this assessment. The Amman model incorporated a greater degree of precision than the Anhold model through the inclusion of an additional category (moderate). The Amman model classified significantly more of the study area as moderate/ high risk (59%) than the Anhold model (Table 10).

Comparing the three Amman risk classes affected by MPB mortality (Table 11) shows a correlation between risk and MPB mortality levels for all three years indicating that this model possesses predictive capabilities. Areal correspondence for the Amman risk classes improved as mortality progressed over time; from 40% in 2004 to 47% in 2006 within the low risk class; 45% to 52% in the moderate 'risk' class; and 17% to 23% in the high 'risk' class (Table 6). Since the Amman model is based on susceptibility (stand characteristics) and not 'true risk' (beetle population pressure), cells were classified without consideration of MPB presence.

[19] Shore and Safranyik (1992) defines susceptibility as "the inherent characteristics or qualities of a stand of trees that affect its likelihood of attack and damage by a mountain pine beetle population".

The Amman model had the third best AUC score of the MPB models (Table 7). Like areal correspondence, true-positive vs. false-positive rates also improved over time (Figures 15-17) and indicated model performance is somewhat better than what would be expected from random chance. The low risk class had the best true-positive vs. false-positive rate than the other risk classes.

The elevation breakpoints in Amman's model appear too low based on MPB mortality mapped from aerial surveys within the study area. The elevation/ latitude component of Amman's model was tuned for LP forests growing further north in Idaho and Montana at 44° latitude. Elevation breaks for the study area's 41° latitude have never been determined empirically. Complicating matters, Amman's model was based on older climatic data which may be less applicable to a warmer environment. At the study area's 41° latitude, the Amman model classifies LP < 9,000 ft. as 'high risk', between 9,000 – 10,000 ft. as 'moderate risk', and > 10,000 ft. as 'low risk'. Results from the empirical model classification tree (see Figure 26, page 93; Empirical Model section) indicate significant elevation breakpoints occur within the study area at 9,325 and 10,343 feet. Likewise, the mean elevation of MPB mortality within the study area based on aerial survey data was calculated at 9,609 $\pm$ 9 feet; $\sigma = 594$ ft. Had Amman's model been developed at the study area's latitude using the older climatic data, it would be possible to assess whether there has been a significant increase in the elevation at which trees are susceptible to beetle attack; which may be the case as recent mild winters, earlier spring snowmelt, and higher spring and summer temperatures (Westerling *et. al, 2006*) have likely played a key role in the elevation ranges of MPB susceptibility.

Like the Anhold model, the Amman model was not developed for a landscape-scale application. However, because the Amman model classified more of the study area as moderate/ high risk than did the Anhold model, the Amman model performed better under the study area's MPB epidemic conditions.

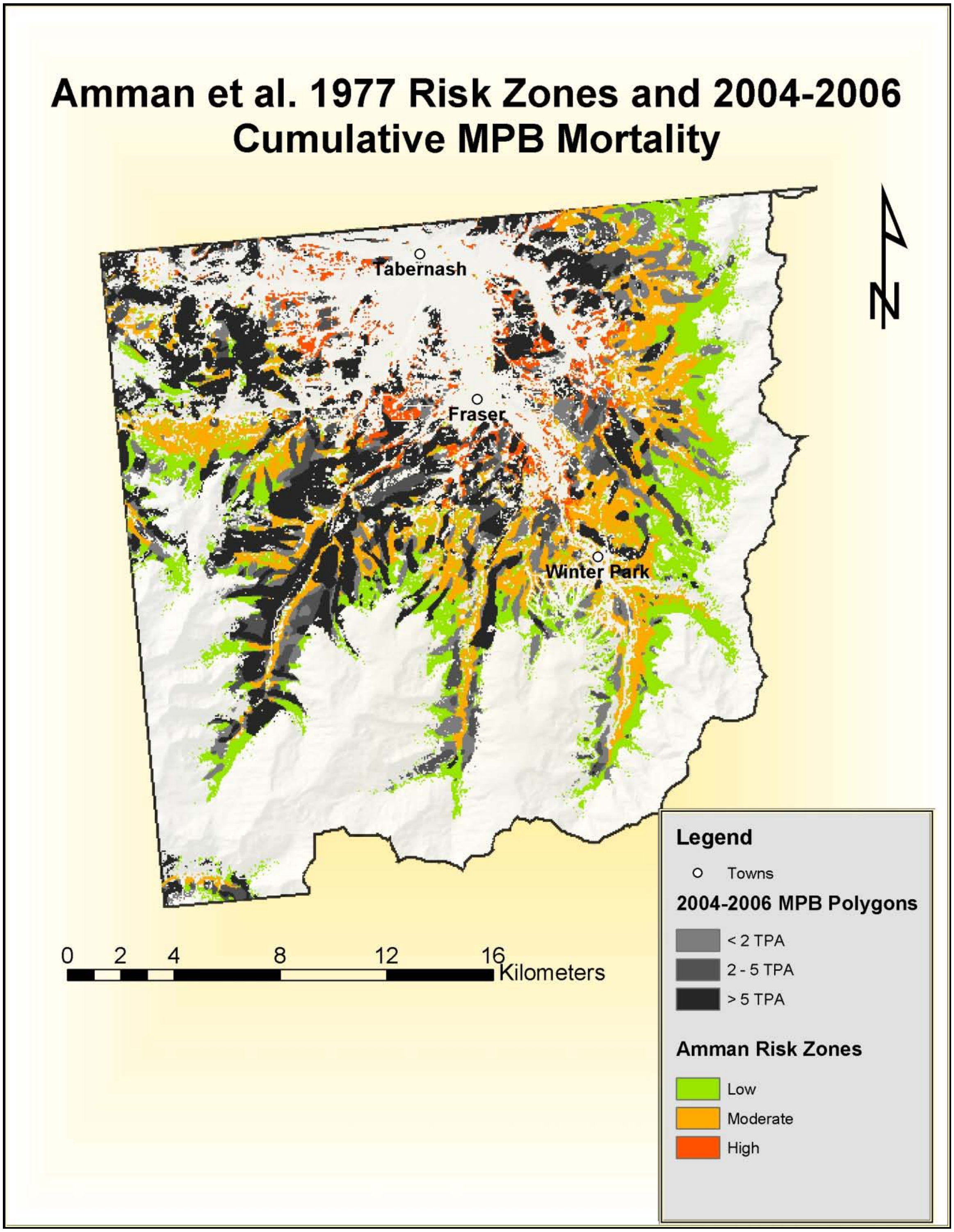

Figure 14. Lodgepole pine and mixed forest vegetation classified by Amman et al. 1997 Risk Zones overlaid with 2004 - 2006 cumulative mountain pine beetle (MPB) mortality polygons. TPA – trees per acre killed by mountain pine beetle (MPB).

Table 10. Percentage of study area defined by category based on Amman et al., (1977). The Amman model categorizes the risk of a MPB infestation into three classes: light, moderate and high; which is based on elevation (by latitude), average stand age, and average diameter.

Category	Percentage
Light Risk	41%
Moderate Risk	44%
High Risk	15%

Table 11. Percentage of Amman risk categories affected by corresponding 2004 MPB mortality levels and 2004-2005 and 2004-2006 cumulative MPB mortality levels. The Amman model categorizes the susceptibility of a MPB infestation into three risk classes: light, moderate and high; which is based on elevation (by latitude), average stand age, and average diameter. MPB mortality and mortality levels were mapped between 2004 and 2006 during Forest Service aerial survey missions.

Amman Risk Category	Area Affected (%) all mortality levels	Area Affected (%) ≥ 2 TPA	Area Affected (%) ≥ 5 TPA
2004			
Light	10.8%	6.9%	4.3%
Moderate	13.1%	8.1%	5.3%
High	14.2%	8.5%	3.2%
2004-2005			
Light	28.4%	10.5%	6.2%
Moderate	36.7%	14.4%	7.7%
High	44.0%	21.5%	7.4%
2004-2006			
Light	45.3%	31.3%	21.1%
Moderate	57.2%	44.2%	31.9%
High	67.1%	57.3%	46.6%

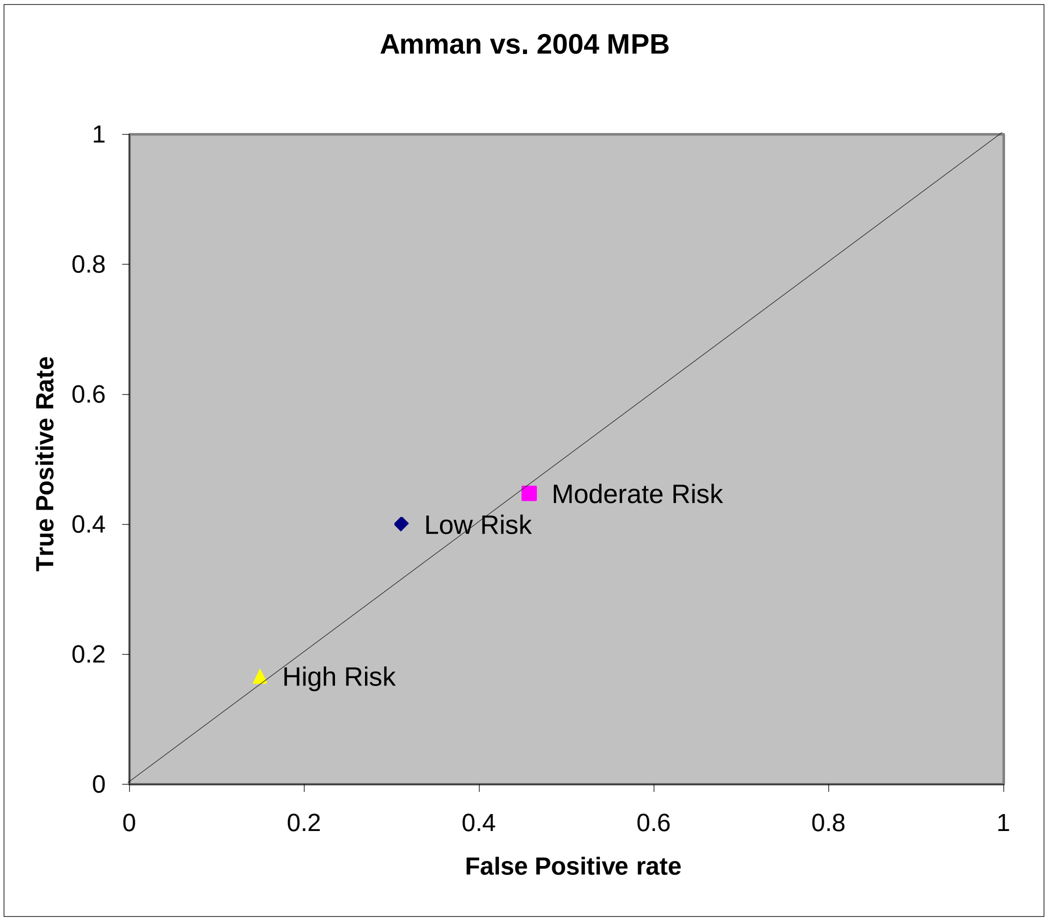

Figure 15. True versus false positive rates of the Amman risk predictions versus 2004 MPB mortality determined from USDA Forest Service aerial surveys. The diagonal line represents what would be expected from random chance; area below the line indicates predictions are worse than random chance while area above the line indicates predictions are better than random chance.

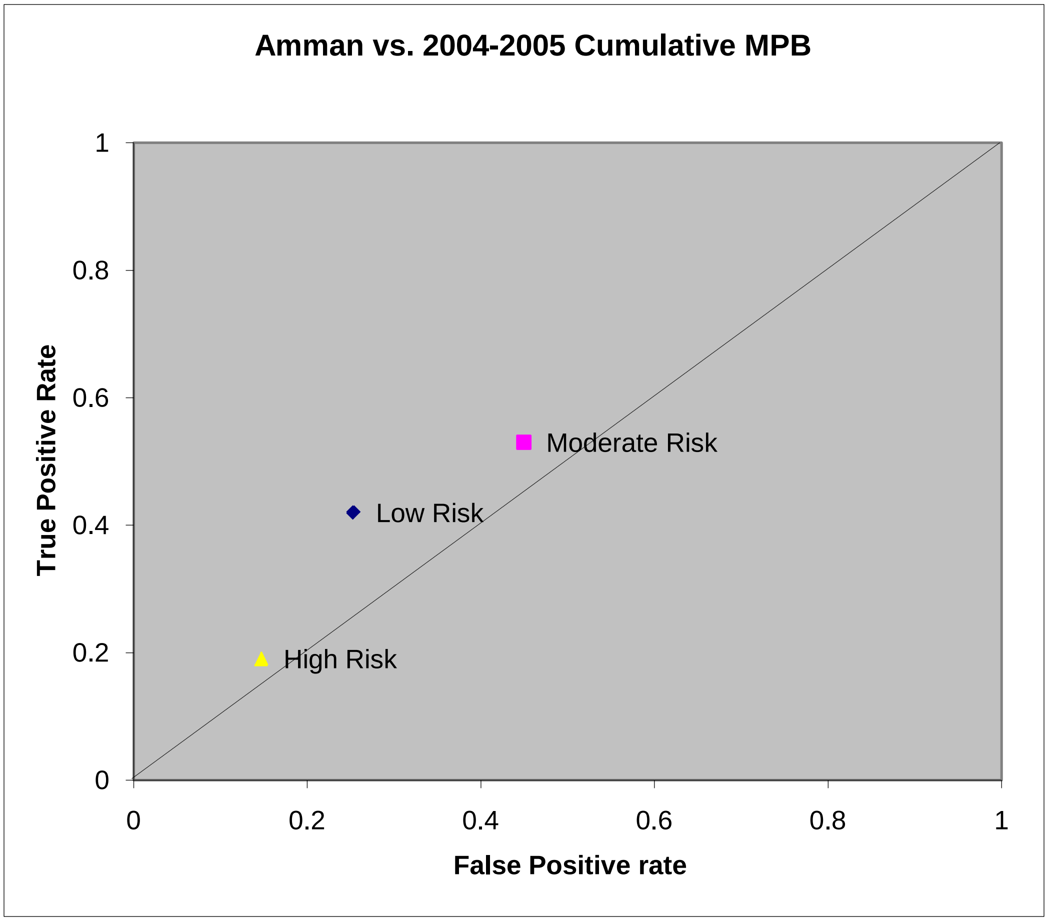

Figure 16. True versus false positive rates of the Amman risk predictions versus 2004-2005 cumulative MPB mortality determined from USDA Forest Service aerial surveys. The diagonal line represents what would be expected from random chance; area below the line indicates predictions are worse than random chance while area above the line indicates predictions are better than random chance.

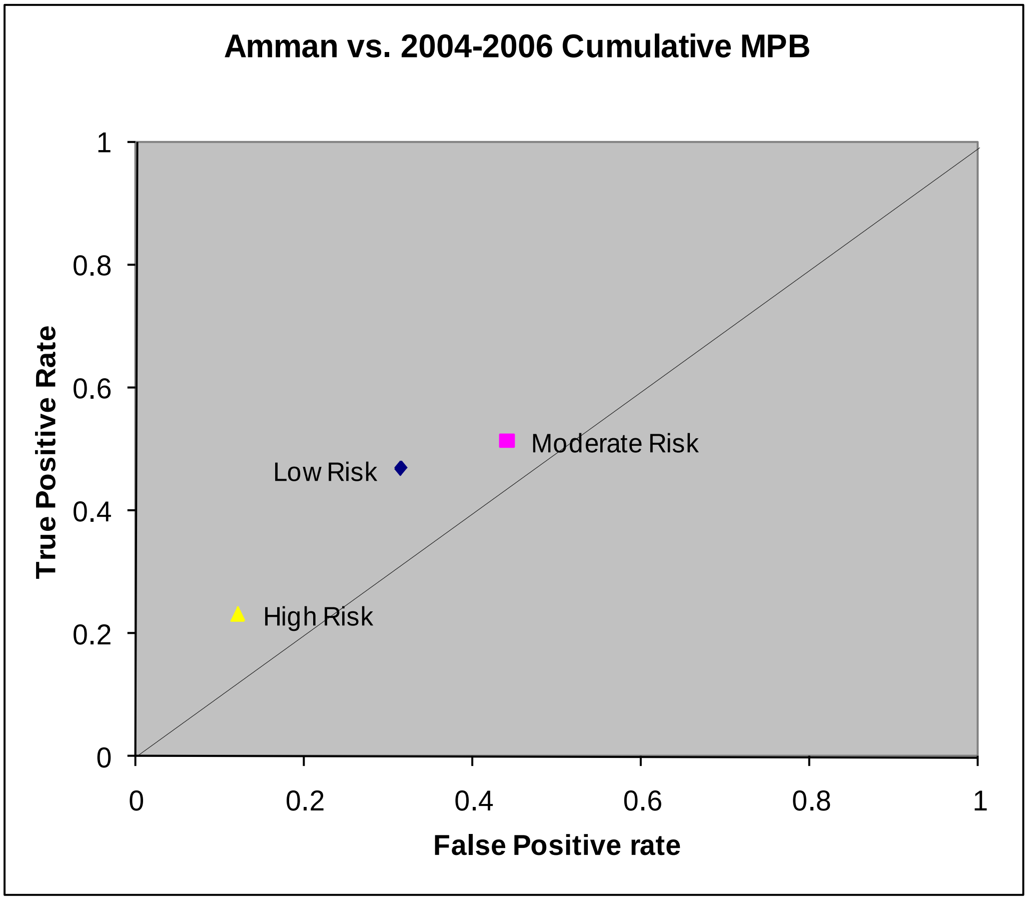

Figure 17. True versus false positive rates of the Amman risk predictions versus 2004-2006 cumulative MPB mortality determined from USDA Forest Service aerial surveys. The diagonal line represents what would be expected from random chance; area below the line indicates predictions are worse than random chance while area above the line indicates predictions are better than random chance.

Shore and Safranyik (1992) Model Evaluation

Shore and Safranyik (1992) model *susceptibility*[20] based on stand characteristics (percentage of susceptible pine basal area, age, density expressed as stems per hectare) and location (elevation and latitude); all given an equal weight of .25. Shore and Safranyik model *risk*[21] based on beetle population dynamics in conjunction with their stand susceptibility model. Because of this, the Shore and Safranyik model was evaluated by aerial survey data for *each year* instead of cumulatively. The Shore and Safranyik model had the highest degree of precision of all the models evaluated since it provides indexed risk values ranging from 0 to 100 instead of 'high', 'medium', or 'low' categories; and was most flexible of all the models evaluated as it incorporates spatial and temporal MPB occurrence(s) for risk prediction. Like the Anhold et al. (1996) model, the Shore and Safranyik system was devised for use at the stand-level scale. The final Shore and Safranyik risk map overlaid with 2006 MPB mortality is illustrated in Figure 18. All of the Shore and Safranyik of the risk maps, as well as the susceptibility and beetle pressure component maps, are shown in APPENDIX B.

The dynamicity of the Shore and Safranyik model in response to increasing beetle population pressure is illustrated in Table 12. In 2003, when most of the beetle mortality remained west of St. Louis Divide, over half (54%) of the study area's indexed risk values that were grouped into the 'low risk' category for the year 2004. That same year, an additional quarter of the study area's indexed values were grouped into the 'moderate

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[20] Defined by Shore and Safranyik as "the inherent characteristics or qualities of a stand of trees that affect its likelihood of attack and damage by a mountain pine beetle population".
[21] Defined by Shore and Safranyik as "the short term expectation of tree mortality in a stand as a result of a mountain pine beetle infestation".

risk' category. Only 21% of the study area's indexed values fell into the 'high risk' category in 2004.

After beetle activity became visually evident in the summer of 2004, the percentage of values grouped into the 2005 'low risk' category fell to 42% from the previous year whereas the percentage of 'high risk' grouped values increased to 33%. As the outbreak progressed, the percentage of 2006 'low risk' grouped values fell further to 39% and the percentage 'high risk' grouped values increased to 39%. Thus, the Shore and Safranyik system can dynamically adjusts its risk projections whenever and wherever MPB positional information is available.

The percentage of Shore and Safranyik's grouped values compared with corresponding MPB mortality classes (Table 13) show a good correlation between risk category and area affected by MPB. The Shore and Safranyik model outperformed the Amman model in this category whereby the trend remained more consistent throughout all three years of the outbreak. Since the Shore and Safranyik model takes into account current beetle population pressure, spatial predictions are adjusted based on what is known about the current infestation.

Areal correspondence between the Shore and Safranyik high and low risk 'categories' and actual high and low MPB mortality classes ranged between 39% and 55% for all of the three years evaluated (Table 6). Areal correspondence between Shore and Safranyik's 'moderate risk' grouped values and the medium MPB mortality class was lower (only 23% in 2006); however, this may have more to do with the grouping of the indexed values than with the model's capability. The Shore and Safranyik model had the best average AUC score (Table 7) and had amongst the highest true-positive vs. false-positive rates of the MPB models (Figures 19-21). The Shore and Safranyik model had the highest overall assessment scores. Because the Shore and Safranyik beetle pressure component is derived independently of the susceptibility component, the Shore and Safranyik beetle pressure component could readily be applied to other susceptibility models where imminent risk is not addressed.

As with the Amman *et al.* (1977) system, Shore and Safranyik incorporated Hopkins' bioclimatic law into their model; this component may need to be modified to account for a changing climate and may explain why the 'moderate risk' grouped values performed poorer than the 'high' and 'low' grouped values. Increasing elevation thresholds would add more cells to the 'high risk' grouped values further aligning predicted with observed mortality occurrences.

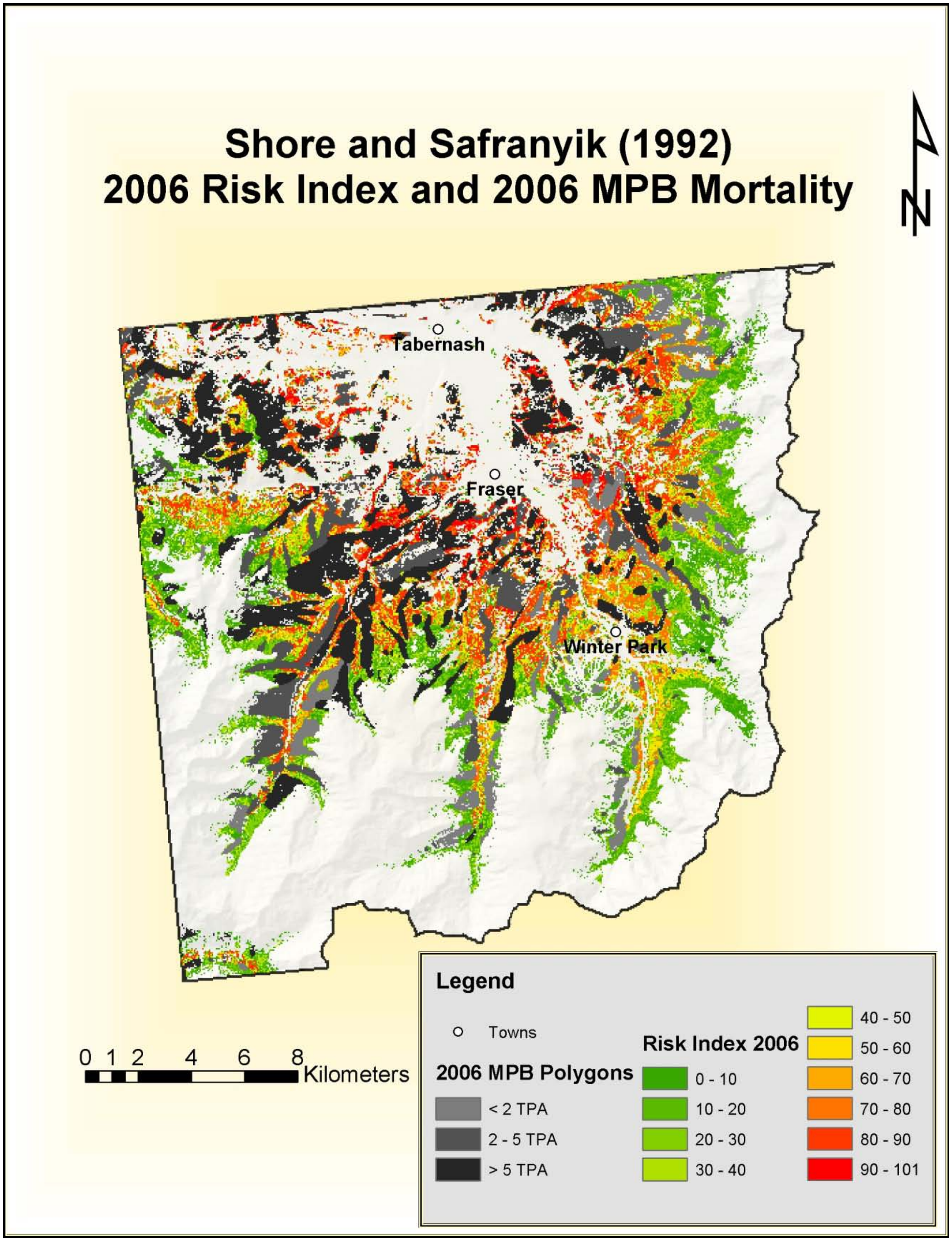

Figure 18. Lodgepole pine and mixed forest vegetation classified using the Shore and Safranyik (1992) risk index for 2006 overlaid with 2006 mountain pine beetle (MPB) mortality polygons. TPA – trees per acre killed by mountain pine beetle (MPB).

Table 12. Percentage of study area defined by category based on Shore and Safranyik (1992) risk indices for 2004, 2005, and 2006. The risk index, comprised of values between 1 and 100, is calculated from basal area, age, trees per hectare, latitude and longitude, and beetle population pressure. The risk index was reclassified for this study into the following three categories: low risk = indexed values < 33.3; moderate risk = indexed values 33.4 - 66.6; high risk = indexed values > 66.7.

Category	Percentage
2004	
Low Risk	54%
Moderate Risk	25%
High Risk	21%
2005	
Low Risk	42%
Moderate Risk	25%
High Risk	33%
2006	
Low Risk	39%
Moderate Risk	22%
High Risk	39%

Table 13. Percentage of Shore and Safranyik (1992) 2004, 2005, and 2006 risk categories affected by corresponding 2004, 2005, and 2006 mortality classes. The Shore and Safranyik model is based on a risk index, comprised of values between 1 and 100, that is calculated from basal area, age, trees per hectare, latitude and longitude, and beetle population pressure. The risk index was reclassified for this study into the following three categories: low risk = indexed values < 33.3; moderate risk = indexed values 33.4 - 66.6; high risk = indexed values > 66.7. MPB mortality and mortality levels were mapped between 2004 and 2006 during Forest Service aerial survey missions.

Shore and Safranyik Risk Category	Area Affected (%) all mortality levels	Area Affected (%) ≥ 2 TPA	Area Affected (%) ≥ 5 TPA
2004			
Low Risk	9.7%	5.8%	3.4%
Moderate Risk	12.2%	7.0%	3.9%
High Risk	19.3%	13.2%	8.8%
2005			
Low Risk	23.0%	3.8%	1.0%
Moderate Risk	28.4%	5.0%	1.8%
High Risk	38.0%	11.2%	3.6%
2006			
Low Risk	33.3%	24.2%	14.2%
Moderate Risk	40.8%	33.2%	22.0%
High Risk	50.6%	45.7%	34.0%

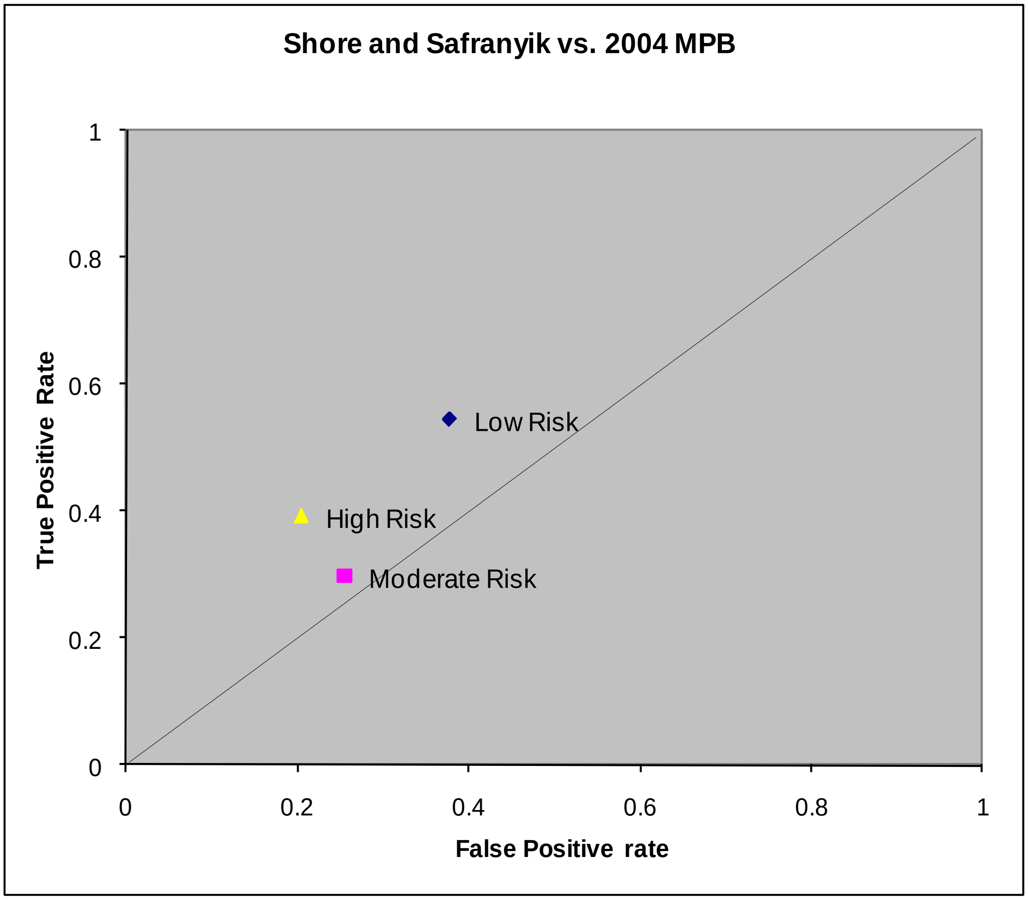

Figure 19. True versus false positive rates of the Shore and Safranyik risk predictions versus 2004 MPB mortality determined from USDA Forest Service aerial surveys. The diagonal line represents what would be expected from random chance; area below the line indicates predictions are worse than random chance while area above the line indicates predictions are better than random chance.

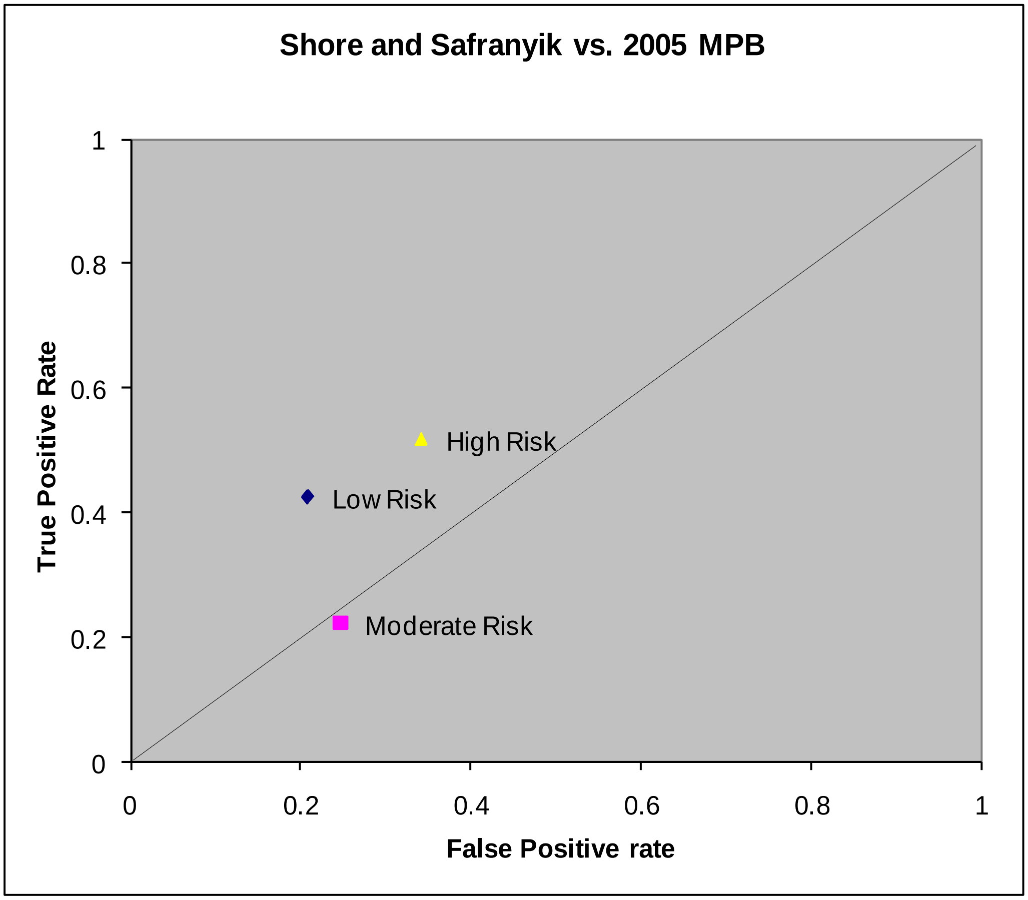

Figure 20. True versus false positive rates of the Shore and Safranyik risk predictions versus 2005 MPB mortality determined from USDA Forest Service aerial surveys. The diagonal line represents what would be expected from random chance; area below the line indicates predictions are worse than random chance while area above the line indicates predictions are better than random chance.

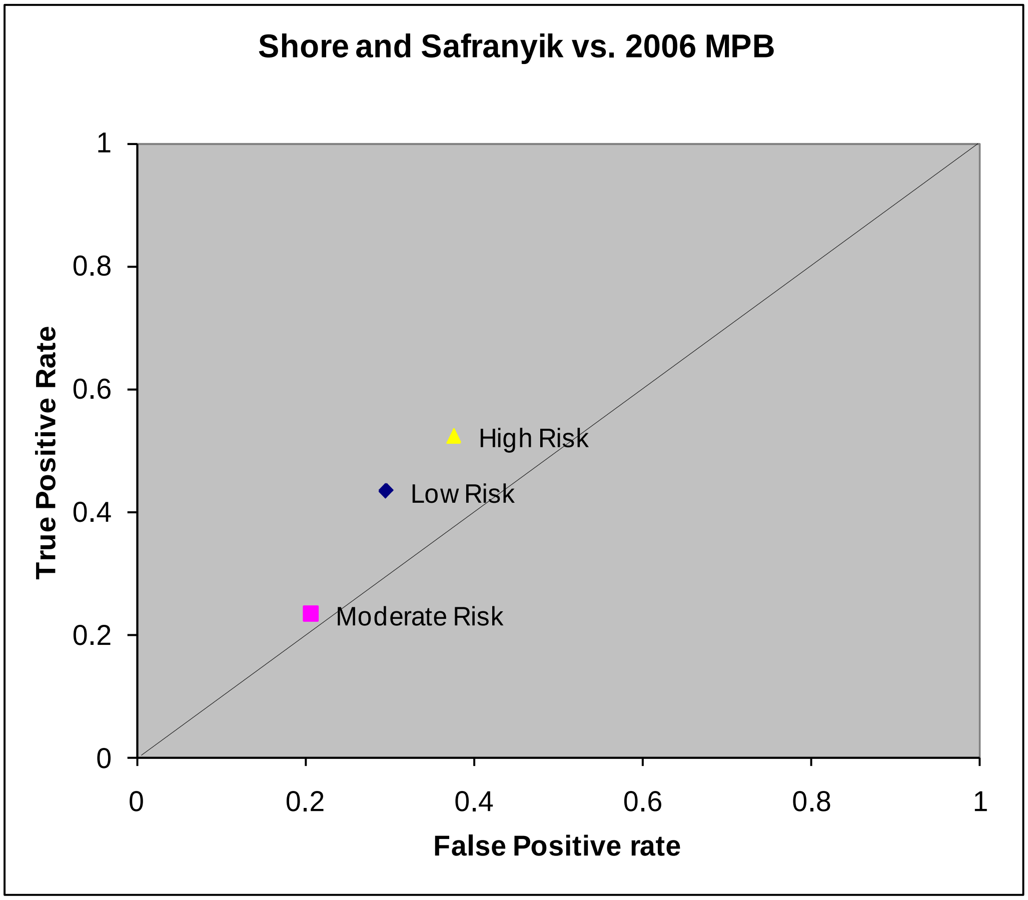

Figure 21. True versus false positive rates of the Shore and Safranyik risk predictions versus 2006 MPB mortality determined from USDA Forest Service aerial surveys. The diagonal line represents what would be expected from random chance; area below the line indicates predictions are worse than random chance while area above the line indicates predictions are better than random chance.

USDA Forest Service National Risk Map (2006) Model Evaluation

Susceptibility maps based on the USDA Forest Service National Risk Map (2006) MPB rating system were generated from the forest structure predictive surfaces and elevation, slope, and aspect data overlaid in a GIS by MPB polygons delineated during aerial detection surveys. The final Forest Service National Risk Map overlaid with 2004-2006 cumulative MPB mortality is illustrated in Figure 22. The remaining Forest Service National Risk Maps are found in APPENDIX B.

The National Risk Map integrates several stand-based MPB models and applies them at the landscape-scale. Like the Amman and Anhold models, the Forest Service model has no beetle population pressure component; thus it predicts long-term susceptibility (not short-term risk). Similar to the Shore and Safranyik model, the National Risk Map system is an index of values (ranging from 1 to 10) which herein was grouped into three classes for comparison with the other models.

The National Risk Map had the highest percentage of indexed values grouped into the 'high risk' class than any other model (71%). Additionally, 28% of the values were grouped into the 'moderate risk' class (28%) leaving only 1% in the 'low risk' class (Table 14). In comparing the percentage of the National Risk Map grouped values by corresponding MPB mortality classes (Table 15), there is a correlation between risk category and area affected by MPB; albeit not as strong and consistent over time as the Shore and Safranyik model.

Areal correspondence by susceptibility class essentially mirrored the distribution of categorical susceptibility values as a percentage of the study area (Table 6). Because most of the study area was rated as being highly susceptible, areal correspondence within the high category was good. Conversely, because less than one percent of the study area was rated lowly susceptible the areal correspondence for that category was poor. True vs. false positive values (Figures 23-25) indicate that the Forest Service model preformed no better than what would be expected by random chance. The average AUC score for the National Risk Map model was lowest of the MPB models evaluated (Table 7).

While the National Risk Map model performed poorest overall in areal correspondence and ROC analysis assessment measures, the model's performance could be misleading. Aerial survey results from 2007 through 2009 reveal that numerous stands throughout the study area have encountered tremendous rates of mortality (USDA Forest Service$_1$); thus rating 99% of the study area as being mostly susceptible may be realistic based on the current outbreak. In 2004 and 2005, when mountain pine beetles had just begun affecting the study area, the model was mostly 'incorrect' since most cells were classified as 'high risk'. As the outbreak has progressed, more and more of the 'high risk' occurrences have become 'correct' outcomes. Had the study been extended beyond 2006, the Forest Service model would have likely surpassed the areal correspondences of the other models.

Because the Shore and Safranyik system is the only model that predicts short-term risk based on beetle population pressure, it would make sense to combine the Shore and Safranyik beetle pressure index with the National Risk Map index. In this way, highly susceptible stands would only be classified as 'high risk' if they fell within the spatial proximities defined by the beetle pressure index. Conversely, highly susceptible stands further away from high beetle populations would be reduced to a lower risk classification.

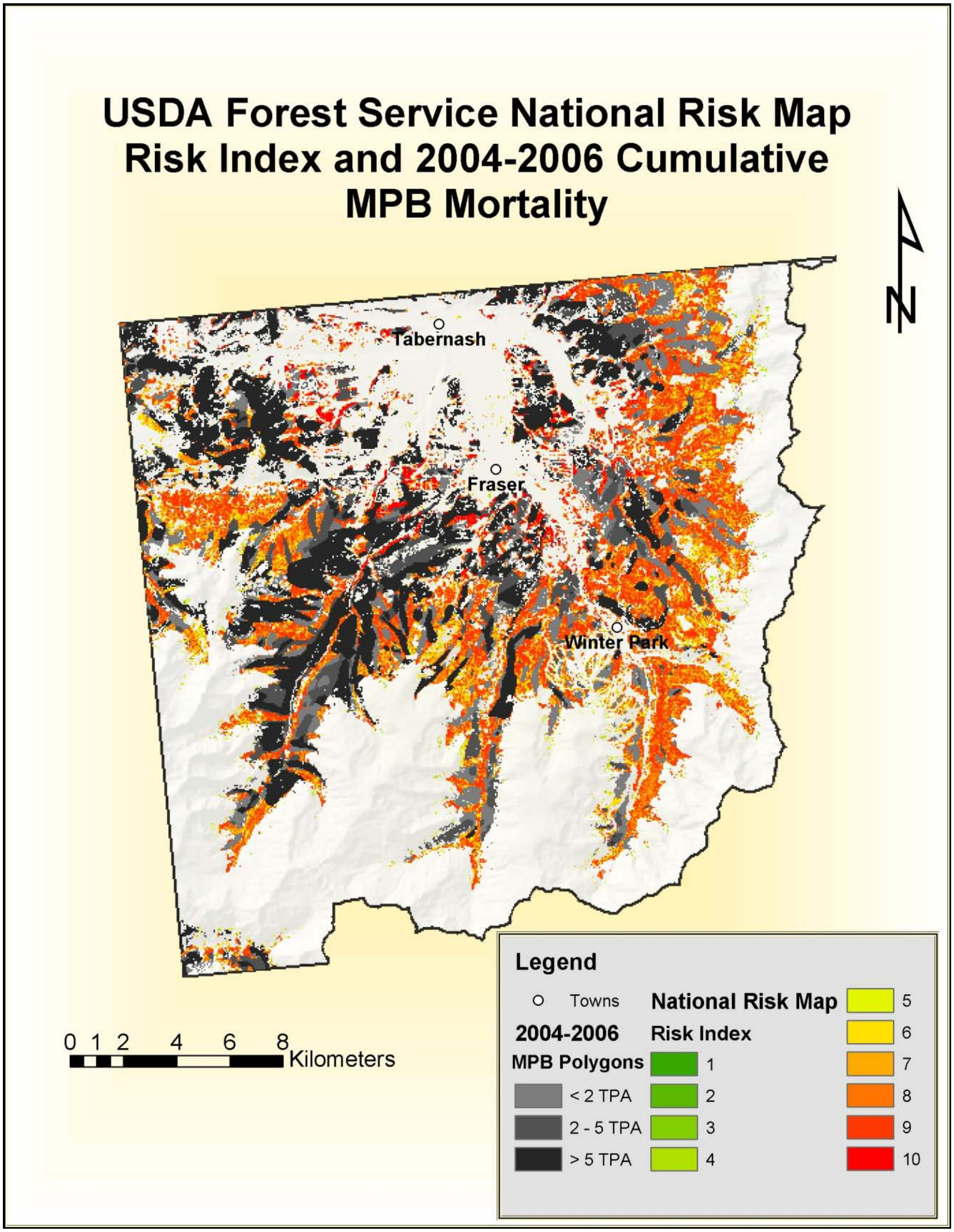

Figure 22. Lodgepole pine and mixed forest vegetation classified by the USDA Forest Service National Risk Map risk index overlaid with 2004 - 2006 cumulative mountain pine beetle (MPB) mortality polygons. TPA – trees per acre killed by mountain pine beetle (MPB).

Table 14. Percentage of study area defined by category based on the USDA Forest Service National Risk Map susceptibility indices. The index, comprised of values between 1 and 10, is calculated from quadratic mean diameter, percent basal area in lodgepole pine, basal area, and elevation. The index was reclassified for this study into the following three categories: low risk = indexed values < 4; moderate risk = indexed values 5-7; high risk = indexed values > 8.

Category	Percentage
Low Risk	1%
Moderate Risk	28%
High Risk	71%

Table 15. Percentage of USDA Forest Service National Risk Map categories affected by corresponding 2004 MPB mortality levels and 2004-2005 and 2004-2006 cumulative MPB mortality levels. The National Risk Map model is based on an index, comprised of values between 1 and 10, that is calculated from quadratic mean diameter, percent basal area in lodgepole pine, basal area, and elevation. The index was reclassified for this study into the following three categories: low risk = indexed values < 4; moderate risk = indexed values 5-7; high risk = indexed values > 8. MPB mortality and mortality levels were mapped between 2004 and 2006 during Forest Service aerial survey missions.

USDA Forest Service National Risk Map Category	Area Affected (%) all mortality levels	Area Affected (%) ≥ 2 TPA	Area Affected (%) ≥ 5 TPA
2004			
Low Risk	6.9%	5.6%	3.7%
Moderate Risk	12.3%	7.3%	4.8%
High Risk	12.5%	7.8%	4.5%
2004-2005			
Low Risk	18.2%	8.3%	4.9%
Moderate Risk	31.4%	12.6%	7.3%
High Risk	35.8%	14.4%	7.0%
2004-2006			
Low Risk	31.0%	20.3%	13.1%
Moderate Risk	48.5%	35.7%	25.2%
High Risk	56.3%	43.1%	31.7%

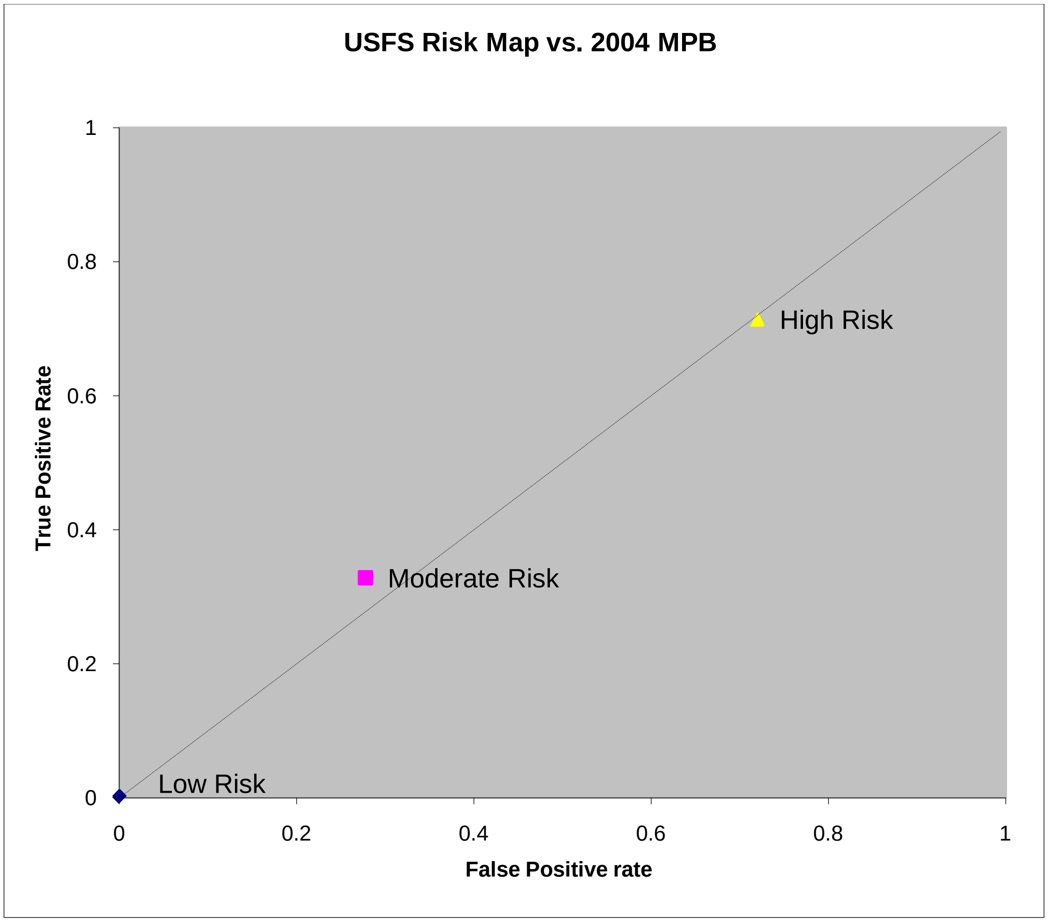

Figure 23. True versus false positive rates of the USDA Forest Service Risk Map predictions versus 2004 MPB mortality determined from USDA Forest Service aerial surveys. The diagonal line represents what would be expected from random chance; area below the line indicates predictions are worse than random chance while area above the line indicates predictions are better than random chance.

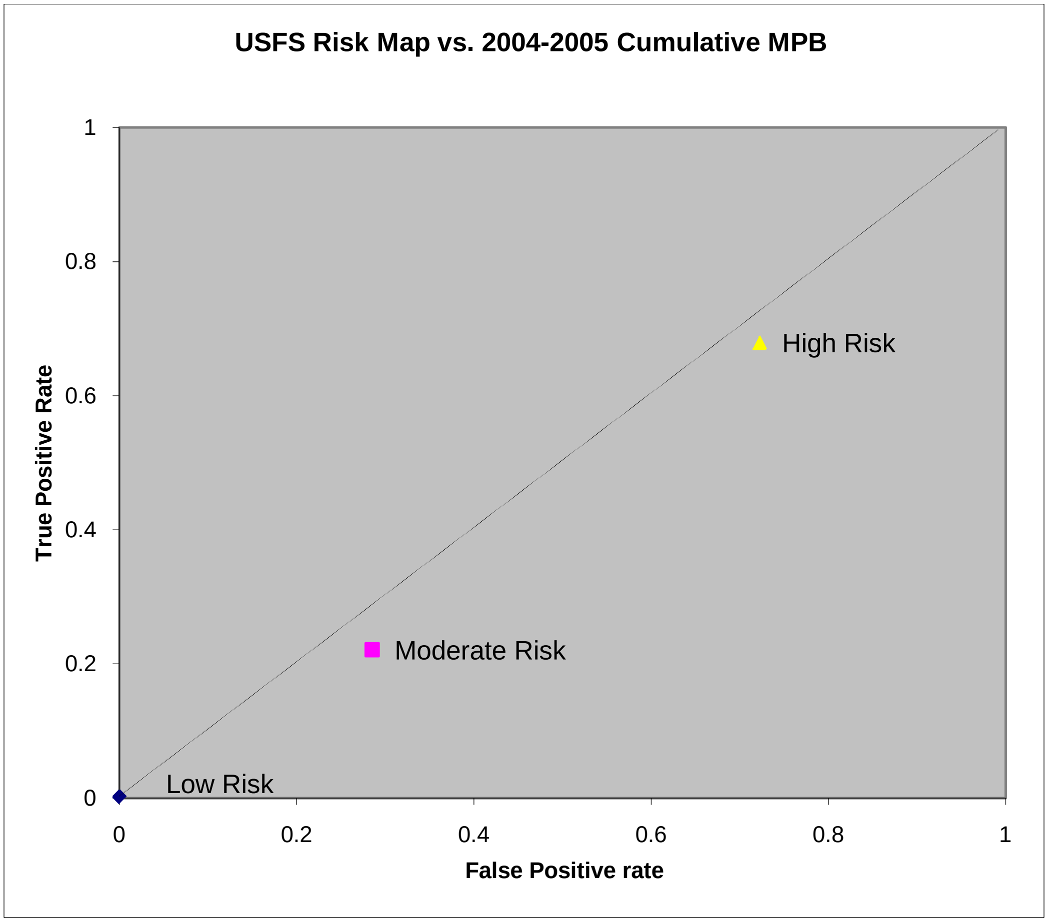

Figure 24. True versus false positive rates of the USDA Forest Service Risk Map predictions versus 2004-2005 cumulative MPB mortality determined from USDA Forest Service aerial surveys. The diagonal line represents what would be expected from random chance; area below the line indicates predictions are worse than random chance while area above the line indicates predictions are better than random chance.

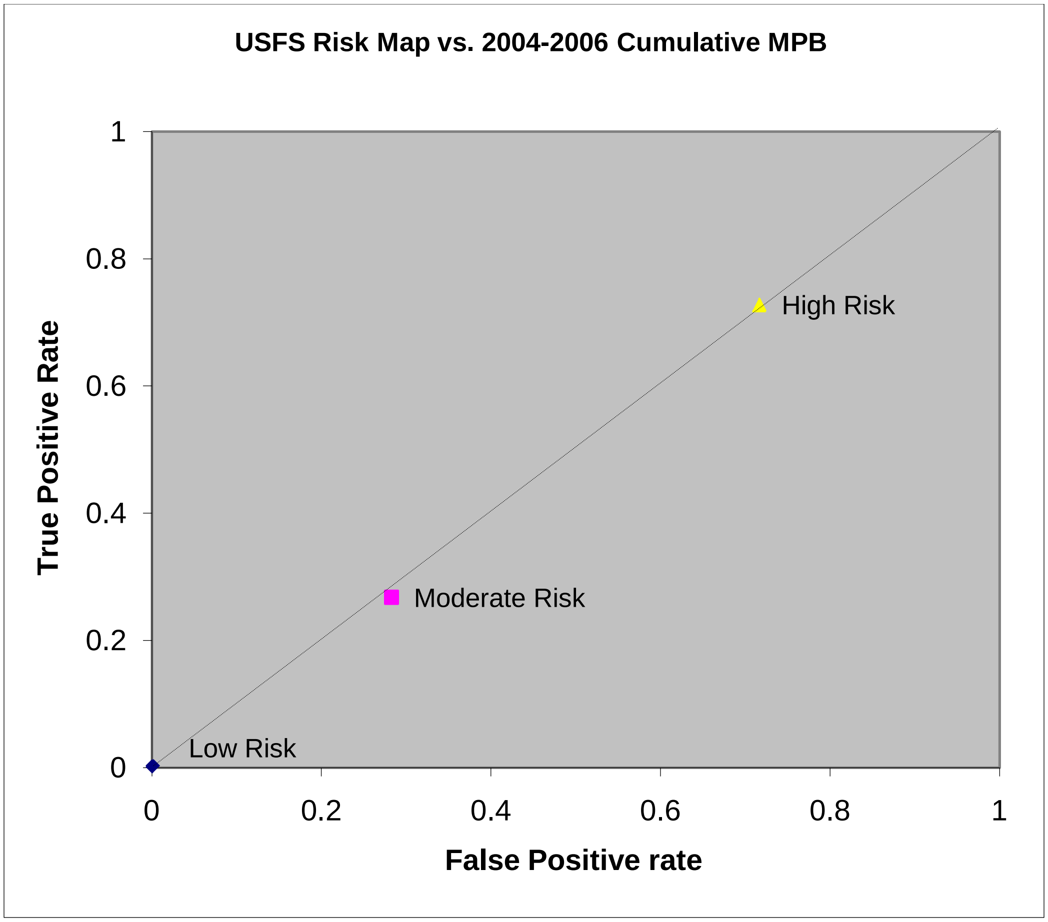

Figure 25. True versus false positive rates of the USDA Forest Service Risk Map predictions versus 2004-2006 cumulative MPB mortality determined from USDA Forest Service aerial surveys. The diagonal line represents what would be expected from random chance; area below the line indicates predictions are worse than random chance while area above the line indicates predictions are better than random chance.

Empirical Model Evaluation

The classification tree that was used to generate the empirical MPB model contained nine terminal nodes and utilized elevation, slope, percent basal area in LP, dbh, and slope as splitter variables (Figure 26). 60%, 16%, and 13% of the variability in the fitted model was accounted for by elevation, dbh, and basal area respectively. Only 6% and 5% of the variability in the fitted model was explained by percent basal area in LP and slope respectively. The final map of the empirical model's surface overlaid with 2004-2006 cumulative MPB mortality is shown in Figure 27. The final empirical model and maps of the empirical model showing MPB mortality for all years are shown in APPENDIX B.

The Empirical model classified roughly half of the study area as highly susceptible and half of the study area as having low susceptibility (Table 16). A positive correlation exists when comparing the percentage of the susceptibility classes affected by corresponding MPB mortality classes (Table 17).

Areal correspondences for the empirical model's susceptibility classes scored better than the other models (Table 6) and generally improved over time. The empirical model's AUC score was second best behind the Shore and Safranyik model (Table 7). True-positive versus false-positive rates, which also improved over time, reveals that the model performs better than what would be expected from random chance (Figures 28-30). The false positive rates of both susceptibility classes ranged between 37% and 53% over the three-year period.

The empirical model differed from the other MPB models as it was devised at the landscape scale using the spatial statistical approaches outlined within this paper.

Through developing the predictive surfaces, it was possible to explore the relationships between large-scale disturbance, forest structure, and site characteristics across the landscape. For instance, the empirical model established that the elevation breaks were not only higher than what the stand based models predicted, but that elevation was dependent on other bio-physical parameters such as slope, basal area, percent basal area, and tree diameter (Figure 26). The empirical model illustrated that stand mortality was likely even at elevations greater than 10,300 feet within dense stands of pure lodgepole pine (BA > 137 ft^2/acre and PerBA > 95%). At middle elevations between 9,300 -10,300 ft., tree mortality was more likely in large diameter trees growing on well-drained slopes (dbh > 10.2 in. and slopes > 14%). At low elevations (< 9,300 ft.), susceptibly was high regardless of density except small diameter trees less than 7.6 dbh.

Similar to what was suggested in the previous section, the Shore and Safranyik beetle pressure index could be used to improve the empirical model. In this way the short-term risk could be predicated building on the empirical model's long-term susceptibility estimate.

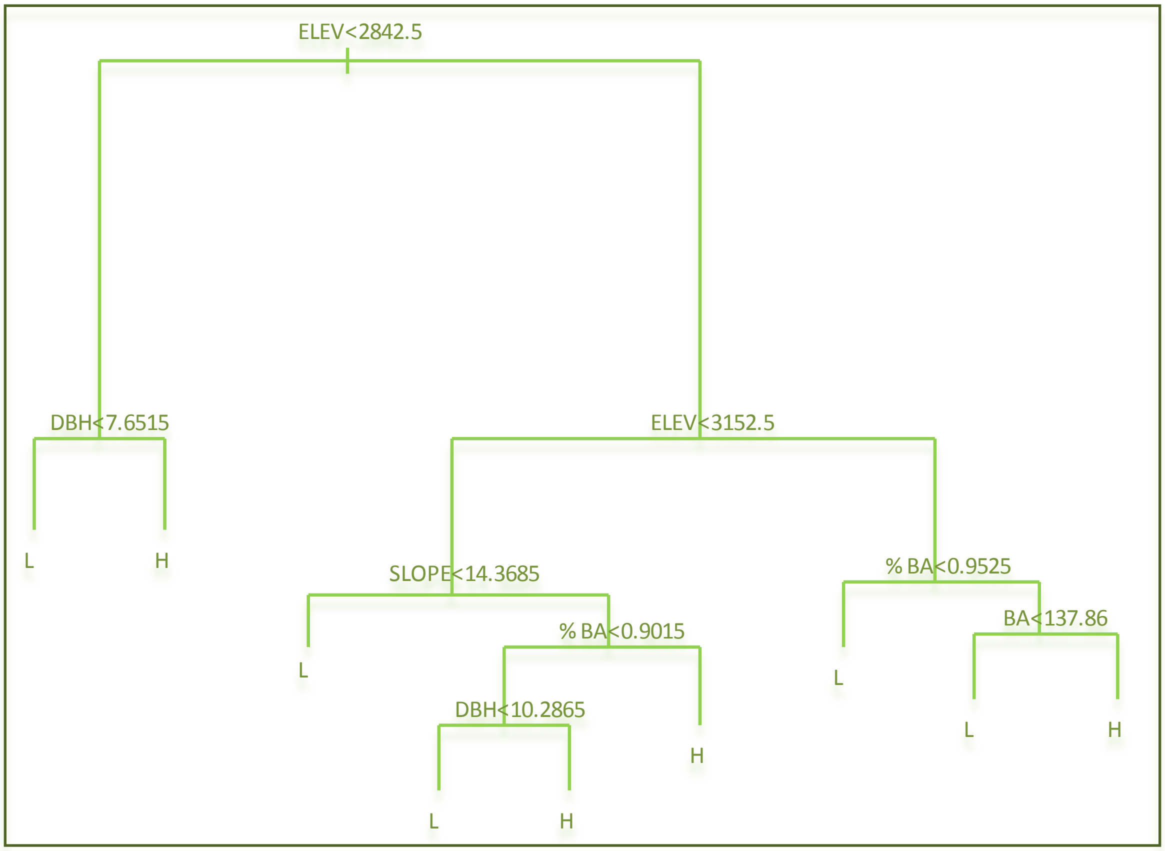

Figure 26. Empirically derived MPB model classification tree. ELEV – elevation (in meters), BA – basal area (ft^2/acre), % BA – percent basal area in lodgepole pine, DBH – diameter at breast height (inches), L – low susceptibility, H – high susceptibility.

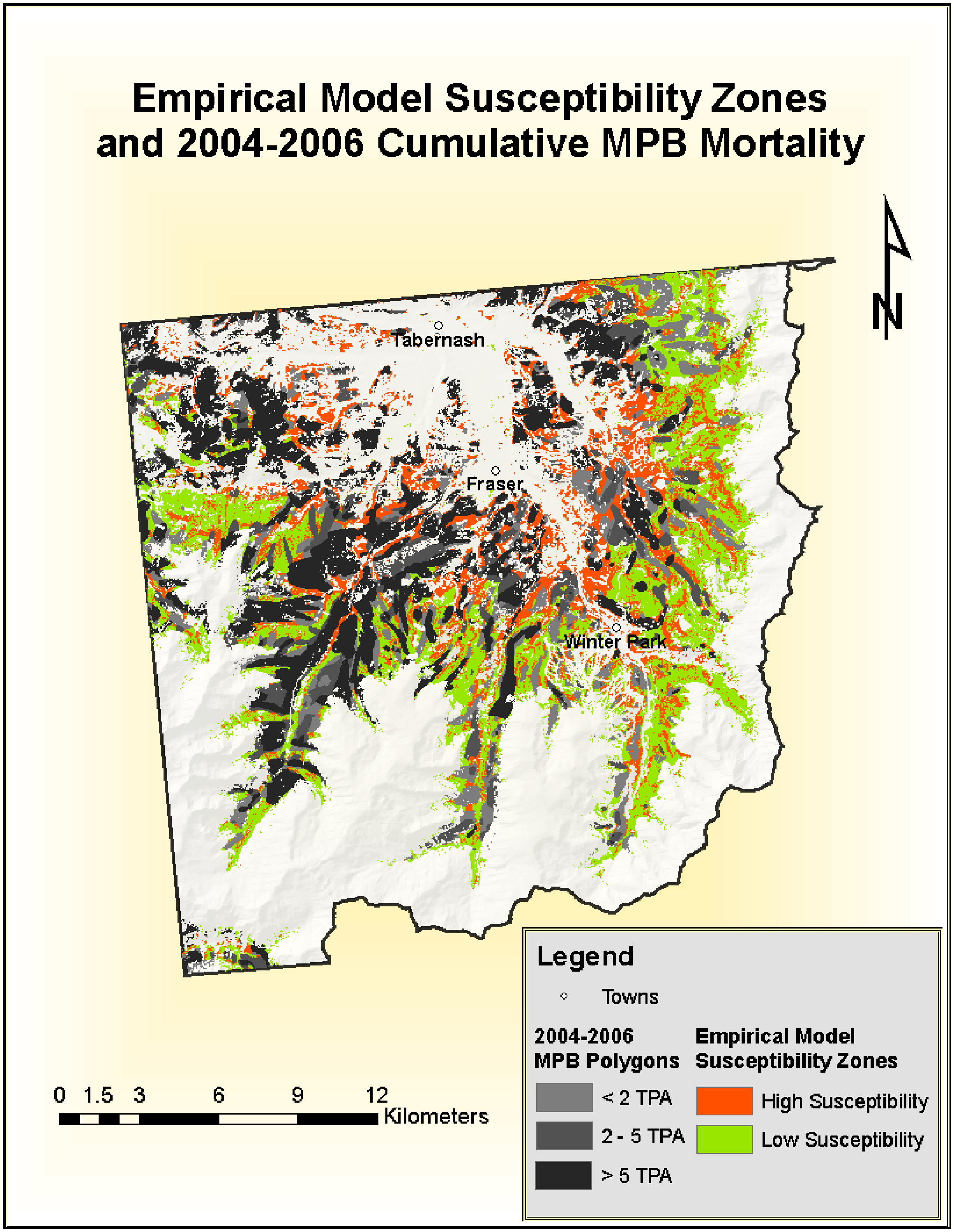

Figure 27. Lodgepole pine and mixed forest vegetation classified by the empirical model susceptibility zones overlaid with 2004-2006 cumulative mountain pine beetle (MPB) mortality polygons. TPA – trees per acre killed by mountain pine beetle (MPB).

Table 16. Percentage of study area defined by category based on the empirical model. The empirical model categorizes the susceptibility of a MPB infestation into two classes: low and high; which is based on elevation, basal area, percent basal area in lodgepole pine, diameter at breast height, and slope.

Category	Percentage
Low Susceptibility	48%
High Susceptibility	52%

Table 17. Percentage of empirical model susceptibility categories affected by corresponding 2004 MPB mortality levels and 2004-2005 and 2004-2006 cumulative MPB mortality levels. The empirical model categorizes the susceptibility of a MPB infestation into two classes: low and high; which is based on elevation, basal area, percent basal area in lodgepole pine, diameter at breast height, and slope. MPB mortality and mortality levels were mapped between 2004 and 2006 during Forest Service aerial survey missions.

Category	Area Affected (%) all mortality levels	Area Affected (%) ≥ 2 TPA	Area Affected (%) ≥ 5 TPA
2004			
Low Susceptibility	10%	6%	4%
High Susceptibility	15%	9%	5%
2004-2005			
Low Susceptibility	27%	10%	6%
High Susceptibility	41%	18%	9%
2004-2006			
Low Susceptibility	44%	31%	10%
High Susceptibility	63%	50%	12%

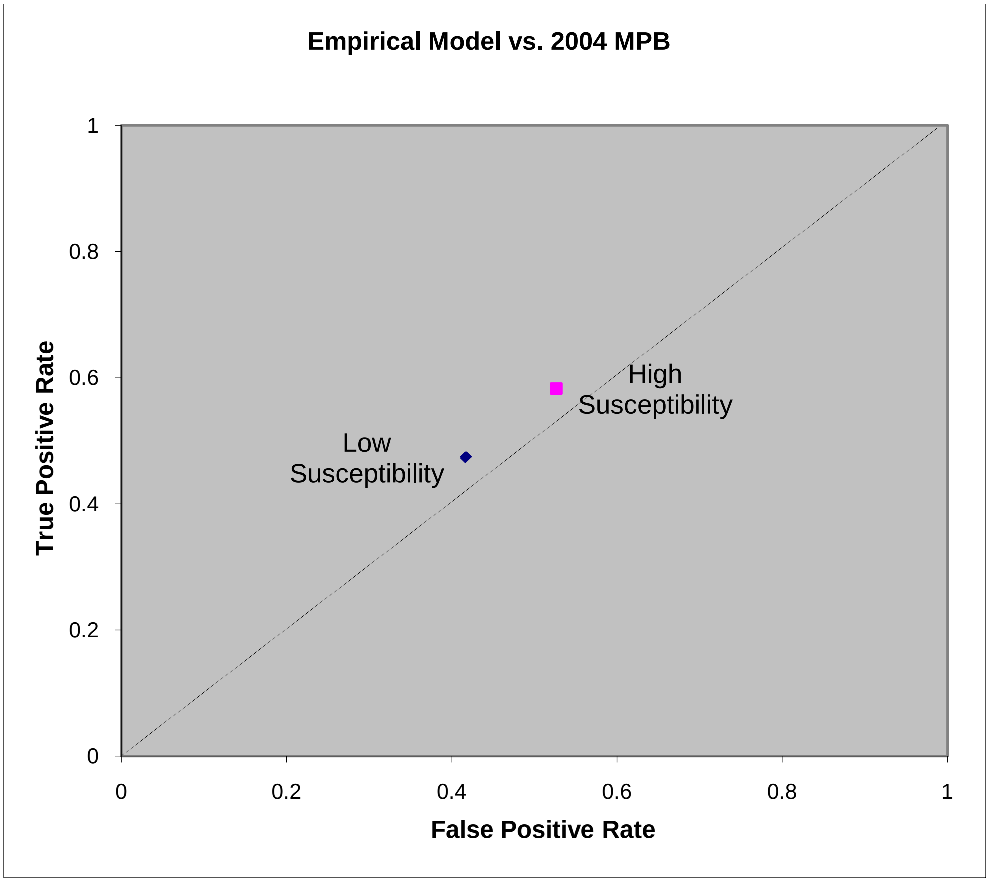

Figure 28. True versus false positive rates of the Empirical Model predictions versus 2004 MPB mortality determined from USDA Forest Service aerial surveys. The diagonal line represents what would be expected from random chance; area below the line indicates predictions are worse than random chance while area above the line indicates predictions are better than random chance.

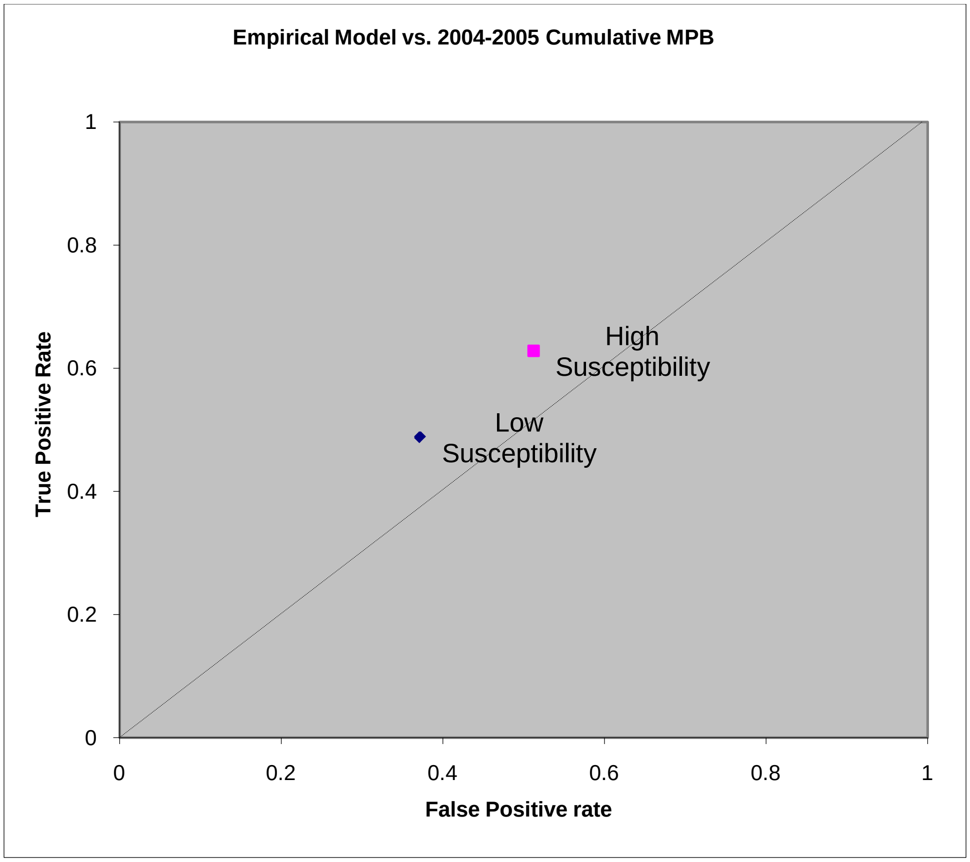

Figure 29. True versus false positive rates of the Empirical Model predictions versus 2004-2005 cumulative MPB mortality determined from USDA Forest Service aerial surveys. The diagonal line represents what would be expected from random chance; area below the line indicates predictions are worse than random chance while area above the line indicates predictions are better than random chance.

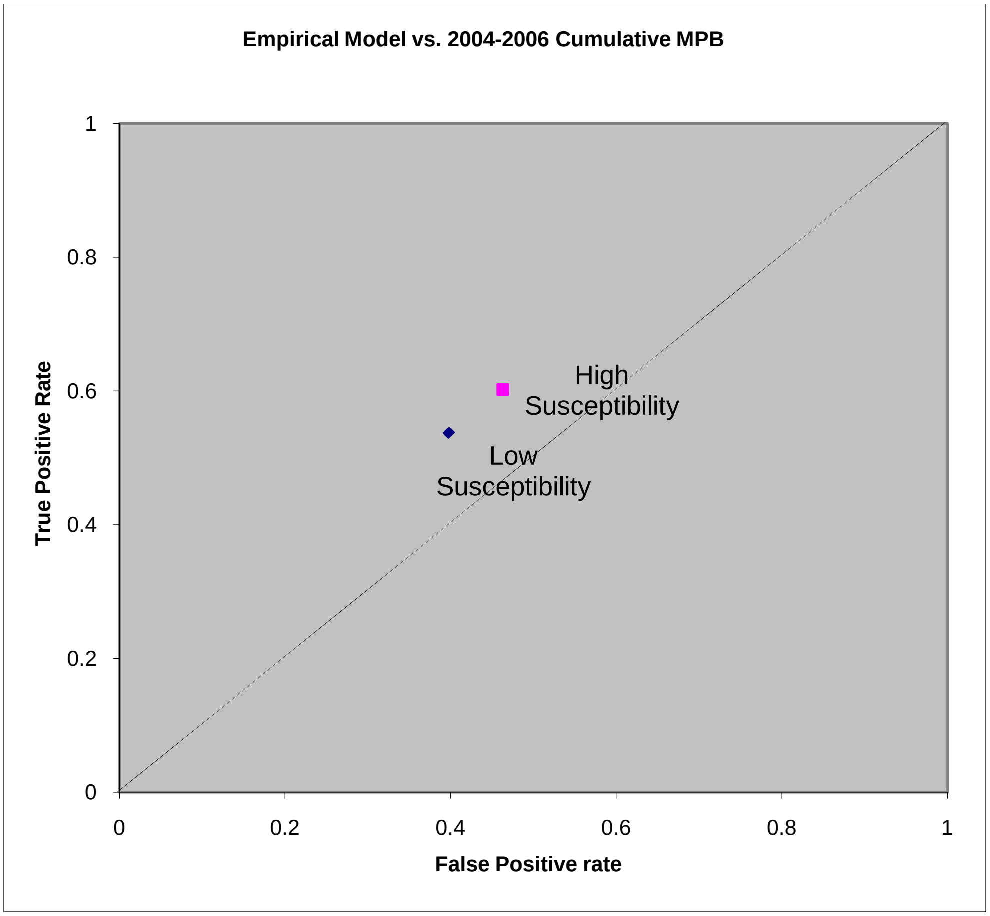

Figure 30. True versus false positive rates of the Empirical Model predictions versus 2004-2006 cumulative MPB mortality determined from USDA Forest Service aerial surveys. The diagonal line represents what would be expected from random chance; area below the line indicates predictions are worse than random chance while area above the line indicates predictions are better than random chance.

Model Enhancement

Over the last decade, large contiguous areas of lodgepole pine have succumbed to MPB mortality in the western United States and Canada. A homogeneous forested landscape consisting of old-aged and highly dense stands of lodgepole pines across southern Wyoming and north and central Colorado has experienced mortality levels not previously recorded. While the collective outcome of the outbreak in terms of overall mortality is extraordinary, MPB populations within the study area between 2004 and 2006 had not yet reached outbreak levels and therefore represented susceptible conditions in the early part of the outbreak; enough so to provide insights into how stand conditions and other variables affected model performance.

A key component lacked by all but the Shore and Safranyik model was the beetle pressure index. Generating a beetle pressure surface is straightforward; given spatial datasets consisting of MPB occurrences are readily available. Aerial survey data often provides the most comprehensive record of beetle infestation; though an inclusive and spatially attributed field sample could provide adequate information as well. As these data are available in many areas, the Shore and Safranyik system of calculating risk based on MPB population pressure could, and should, be included as a component of any MPB susceptibility model.

The elevation breakpoints of the Amman, Shore and Safranyik, and Forest Service Risk Map models need to be reevaluated. Results from the empirical model suggest the elevation threshold for susceptibility at the study area's 40° latitude should be increased by 100 meters for all lodgepole pines > 19cm dbh and by 400 meters (or more) for larger diameter trees (>26cm). Warmer temperatures may be playing a role by increasing the elevations at which beetles can successfully overwinter and reproduce. Further research is needed on elevation and MPB susceptibility in Colorado in order to better tune MPB models to what may be new climatic realities.

The Anhold model would have to be adjusted significantly to fit the occurrence of observed mortality with the study area. Removing the QMD component would negate the effects of discounting large diameter trees > 8 inches (caused by averaging cell values) thereby increasing the spatial extent of the Zone B susceptibility class. Increasing the SDI threshold of Zone C by 100 points would reconcile the model to the SDI ranges where mortality was observed. Thus, removing the diameter criterion and extending Zone C's threshold would increase the model's susceptible area from 14% to 57% and better align the model with mortality observations.

CONCLUSION

All of the objectives designed into this project were successfully met. The feasibility of generating continuous landscape-scale vegetation and vegetation-component surfaces for rating susceptibility and risk of bark beetle damage was established and applied. Precise estimates were obtained minimizing the variability associated with the sampling design by stratifying clusters spectrally using Landsat ETM+ imagery. The resultant predictive surfaces and error surfaces generated from the field sample are well suited to describe landscape-scale forest composition and structure components and to infer population parameters across various spatial scales.

The surfaces devised in this study have broad applicability to many disciplines including ecology, inventory and monitoring, and, in this case, forest entomology. Land managers interested in reducing impacts to mountain pine beetles require continuous datasets that are dependable and cost effective to obtain. The cost effectiveness of this method was established; a nominal field sample and low-cost satellite imagery were the only requirements for generating landscape-scale forest structure surfaces and their component error surfaces. The dependability of the datasets was confirmed by cross-validation and analysis of the fit statistics.

The application of employing error, or variance, surfaces to quantify prediction uncertainty was established. Aside from providing land managers with the means to determine where prediction confidence is low, error surfaces abet small area estimation so population parameters can be inferred directly from the error and predictive surfaces; which effectively negates the need to collect additional field samples. In fact, inferences can be made for areas not even sampled during the initial field collection.

A new MPB susceptibility model was modeled empirically based on tree-mortality occurrence and underlying bio-physical properties. Where conventional MPB models utilize elevation, latitude, density, and dbh to determine MPB susceptibility, the empirical model characterized how these variables interact based on stand orientation. The spatial statistical approach utilized in this study outlines how future vegetation management decisions can be taken into account at broad-scales and serves as a prototype for considering susceptibly to MPB at the landscape level - facets not adequately addressed in the current literature (Fettig et al. 2007).

Four well-known MPB susceptibility and risk models were applied to the forest structure predictive surfaces. The four models were validated against 2004-2006 MPB mortality data mapped from aerial surveys. Results of the validation showed that overall

MPB model performance was poor due to several factors including: applying models designed at the stand-level to landscape-scales; applying models tuned in British Colombia, Montana and/or Idaho to north-central Colorado; changes in the relationship between MPB susceptibility and elevation; and not accounting for MPB population pressure.

The empirical model was the best predictor of *susceptibility* as it explained the MPB mortality that occurred at higher elevations as well as the relationship between elevation, site, and forest structure. The Shore and Safranyik model was the best predictor of *risk* because of their beetle pressure index. The other MPB models (empirical model included) do not feature a risk component thus could be improved significantly by the inclusion of the Shore and Safranyik beetle pressure index.

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APPENDIX A: Predictive Surfaces and Error Surfaces

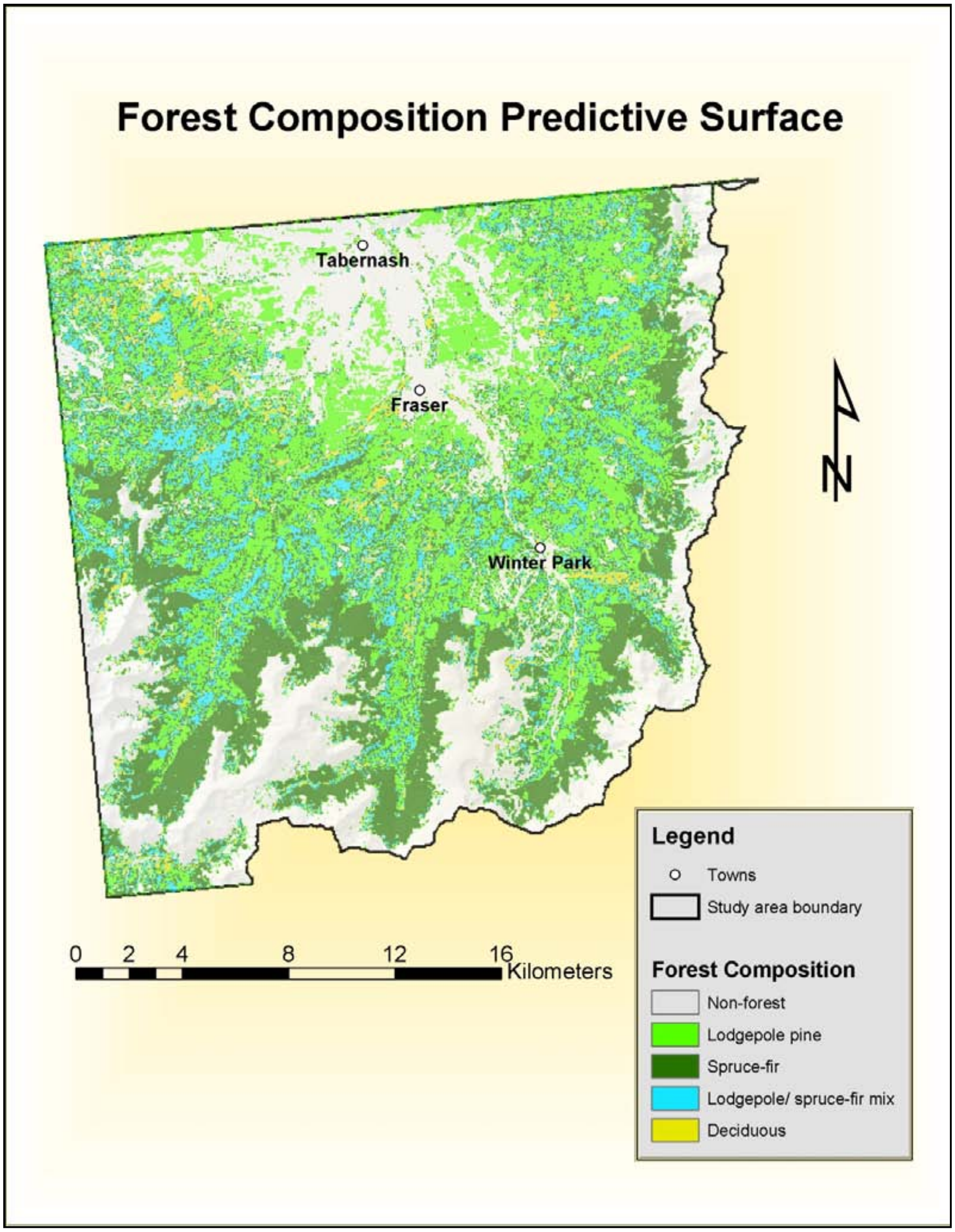

Figure A-1. Forest composition predictive surface generated from the classification tree model based on field data collected between October 1, 2003 and February 1, 2004.

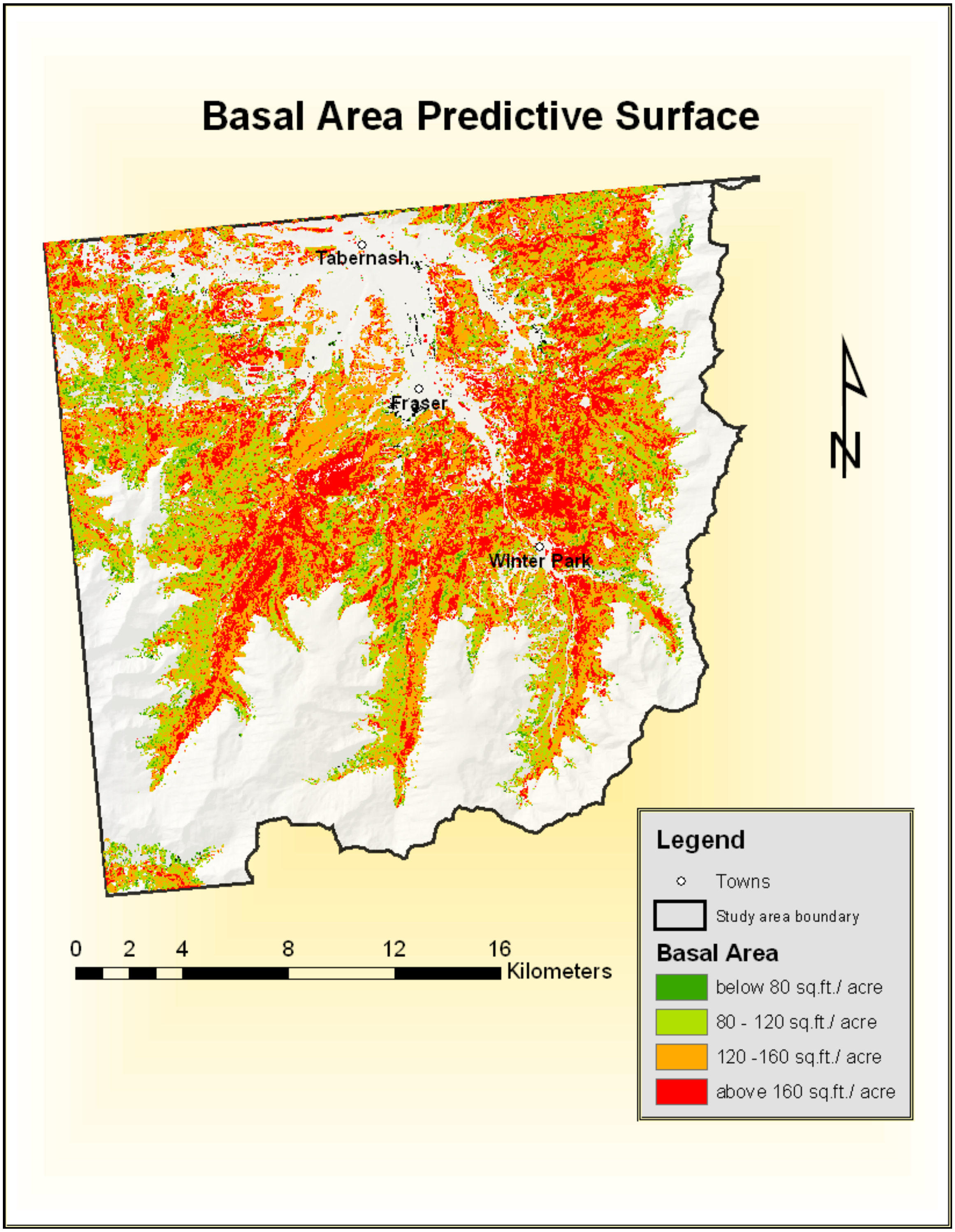

Figure A-2. Basal area predictive surface of the lodgepole pine and mixed forest vegetation classes. The surface is the spatial realization of the multiple linear regression and binary regression tree models. Field data used to train the models were collected between October 1, 2003 and February 1, 2004.

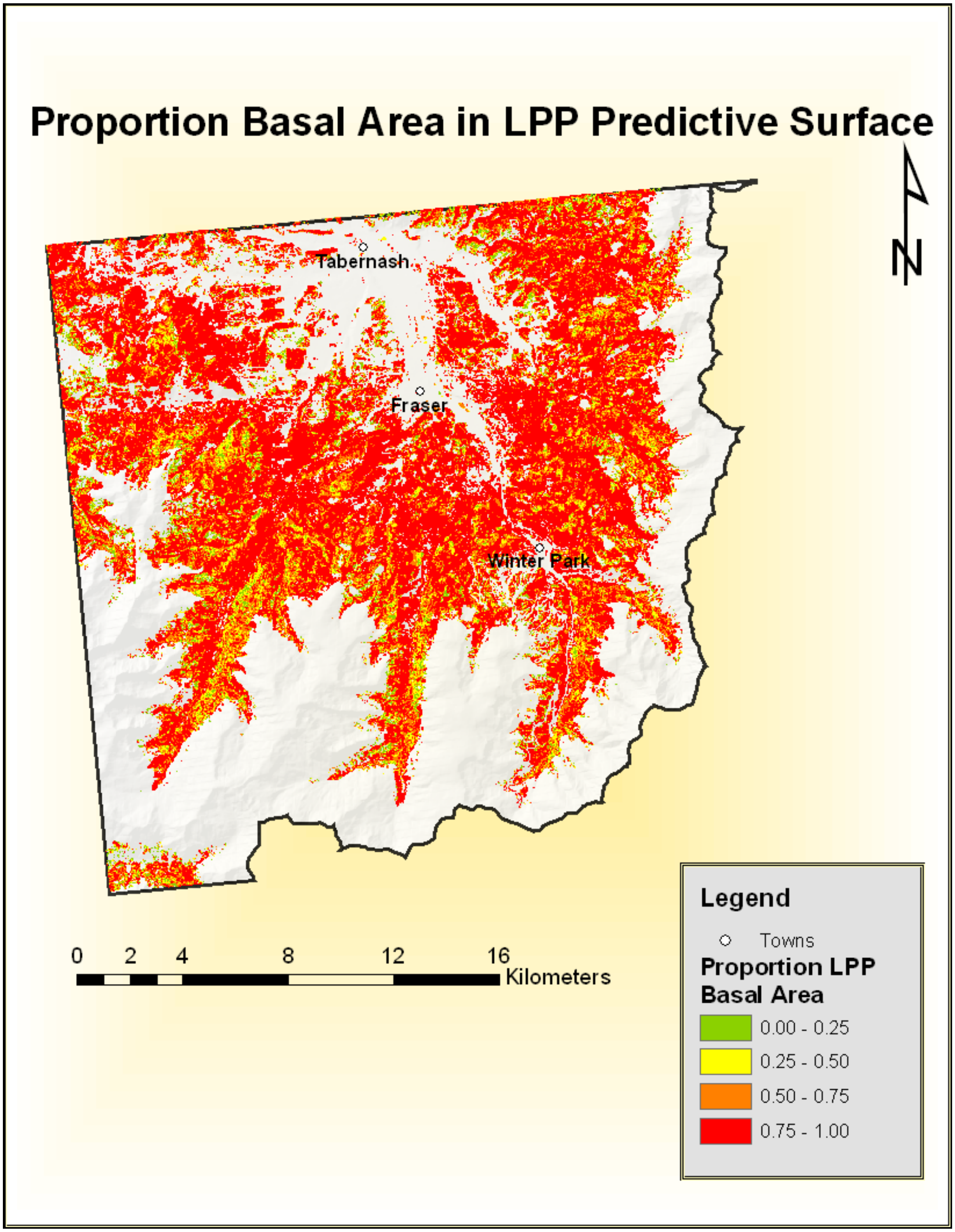

Figure A-3. Proportion of basal area in lodgepole pine predictive surface of the lodgepole pine and mixed forest vegetation classes. The surface is the spatial realization of the multiple linear regression and binary regression tree models. Field data used to train the models were collected between October 1, 2003 and February 1, 2004.

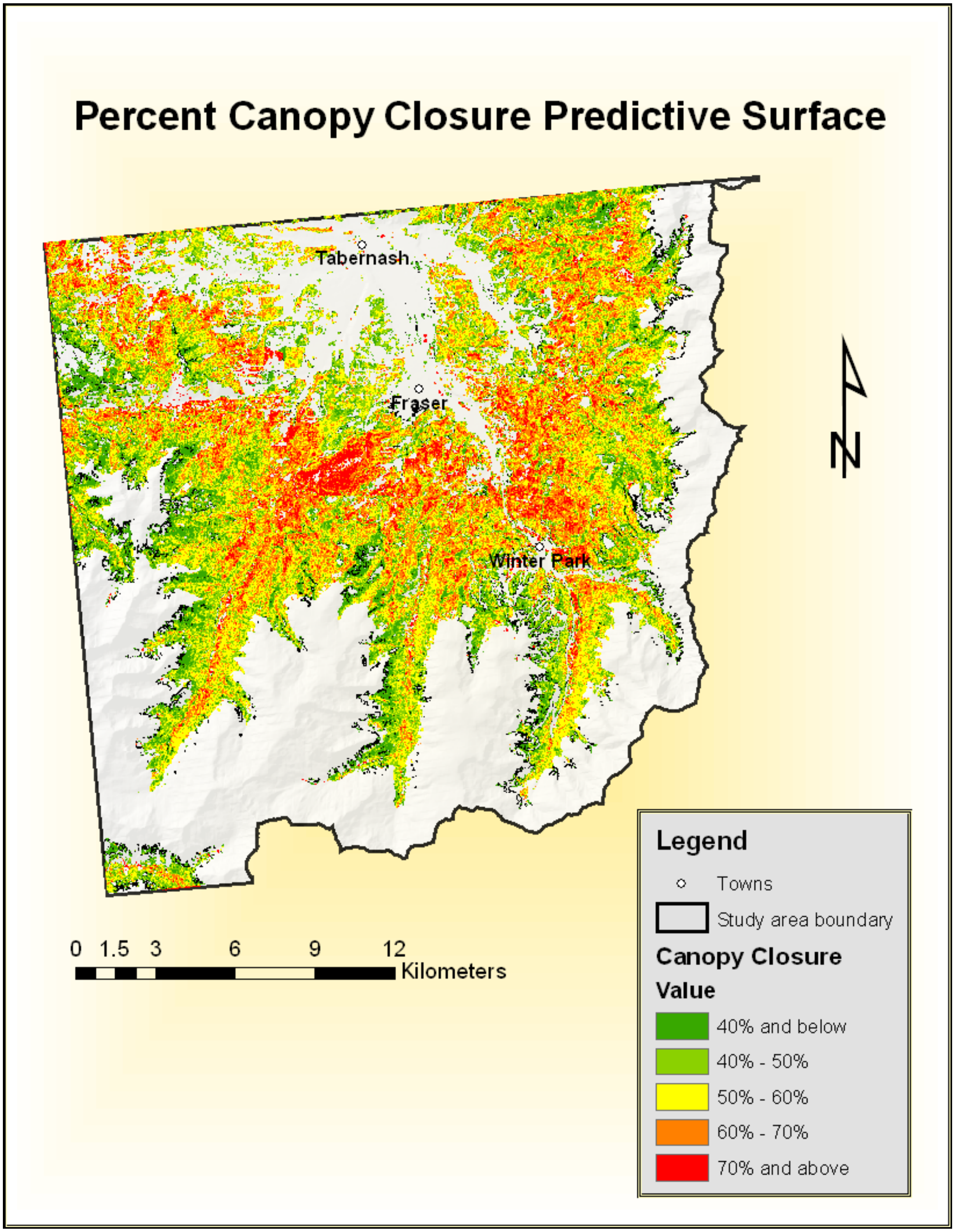

Figure A-4. Percent canopy closure predictive surface of the lodgepole pine and mixed forest vegetation classes. The surface is the spatial realization of the multiple linear regression and binary regression tree models. Field data used to train the models were collected between October 1, 2003 and February 1, 2004.

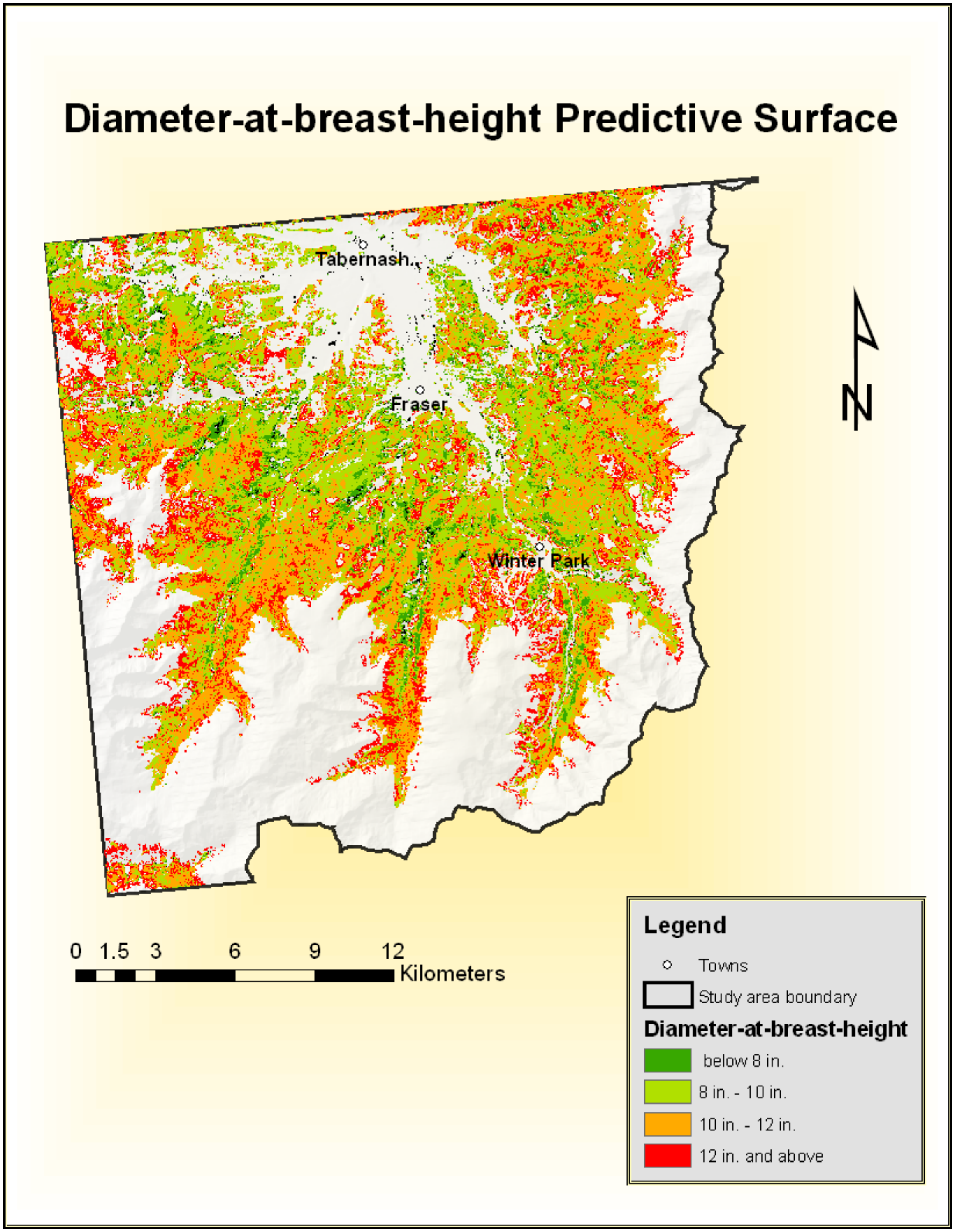

Figure A-5. Diameter at breast height predictive surface of the lodgepole pine and mixed forest vegetation classes. The surface is the spatial realization of the multiple linear regression and binary regression tree models. Field data used to train the models were collected between October 1, 2003 and February 1, 2004.

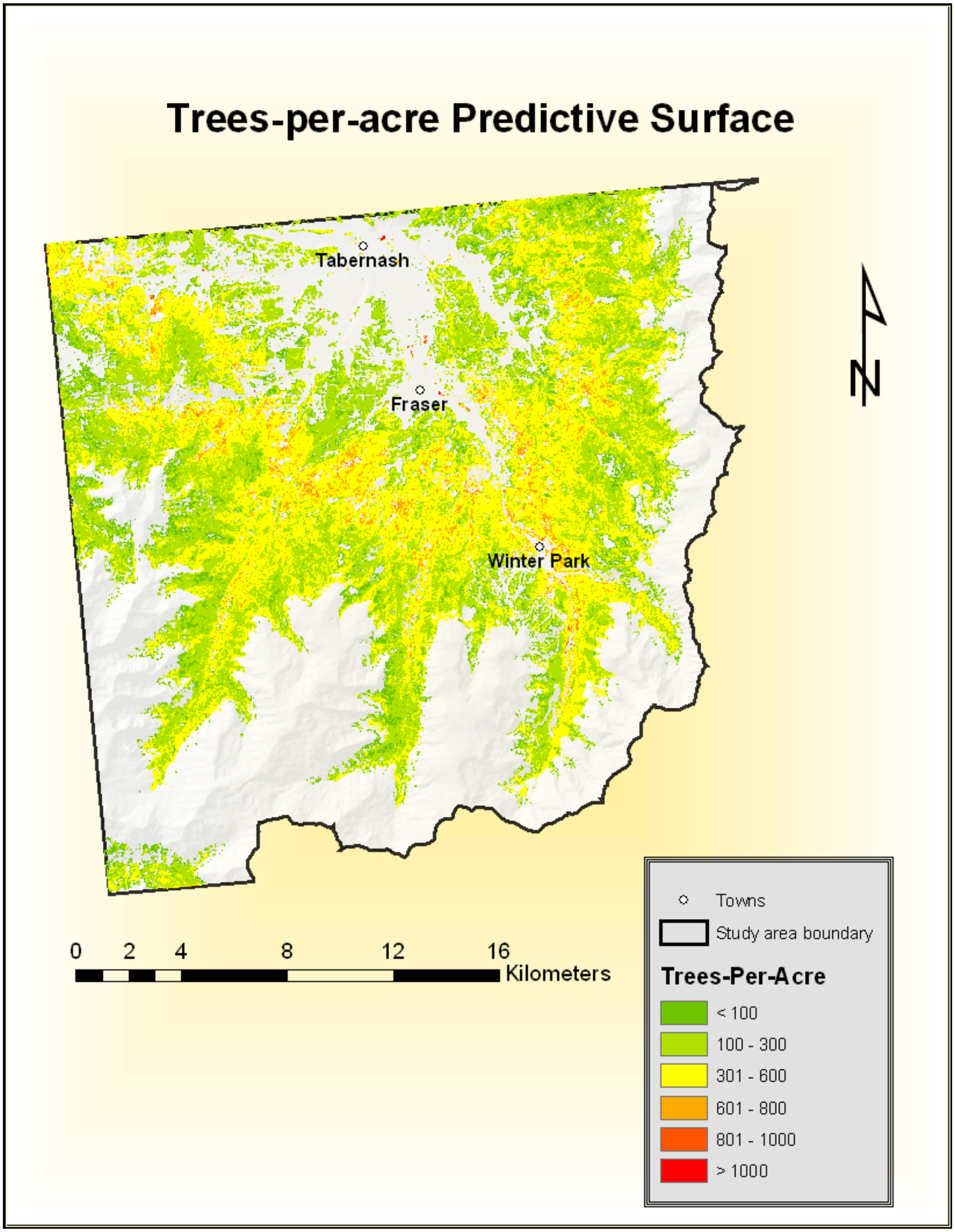

Figure A-6. Trees per acre predictive surface of the lodgepole pine and mixed forest vegetation classes. The surface is the spatial realization of the multiple linear regression and binary regression tree models. Field data used to train the models were collected between October 1, 2003 and February 1, 2004.

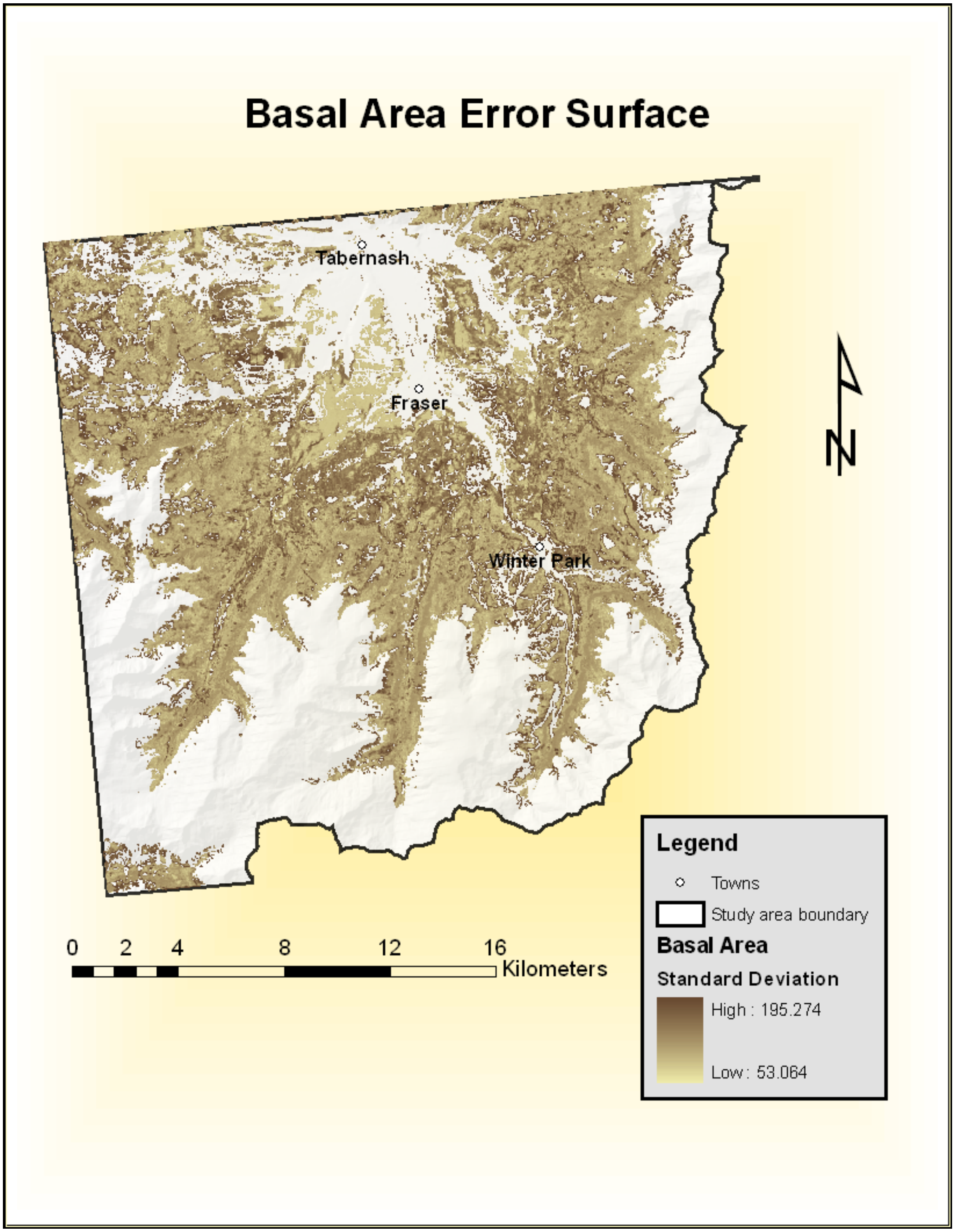

Figure A-7. Basal area error surface of the lodgepole pine and mixed forest vegetation classes. The standard deviation term refers to the square root of the prediction variance. Prediction uncertainty is greater in the darker areas with higher standard deviation values.

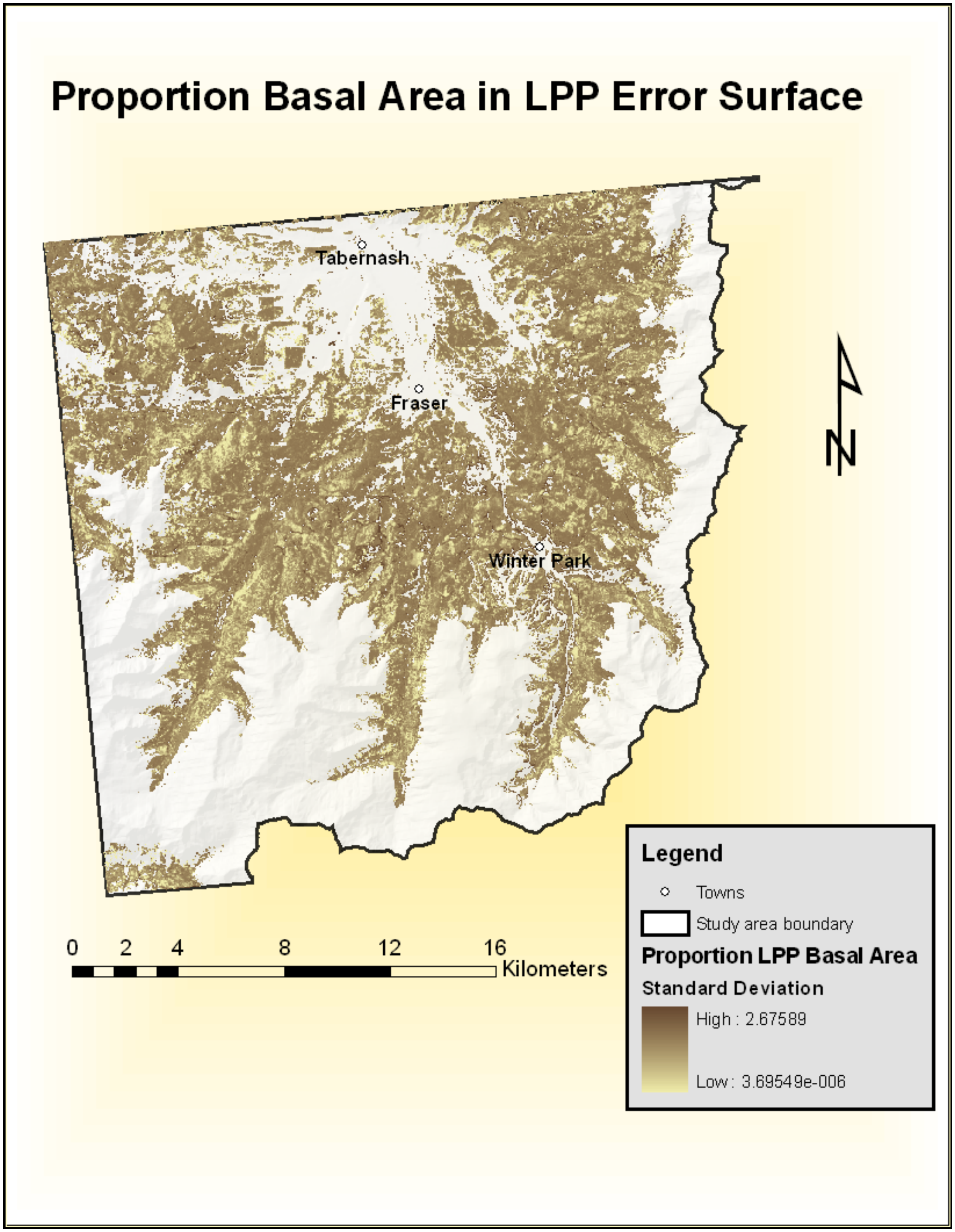

Figure A-8. Proportion basal area in lodgepole pine error surface of the lodgepole pine and mixed forest vegetation classes. The standard deviation term refers to the square root of the prediction variance. Prediction uncertainty is greater in the darker areas with higher standard deviation values.

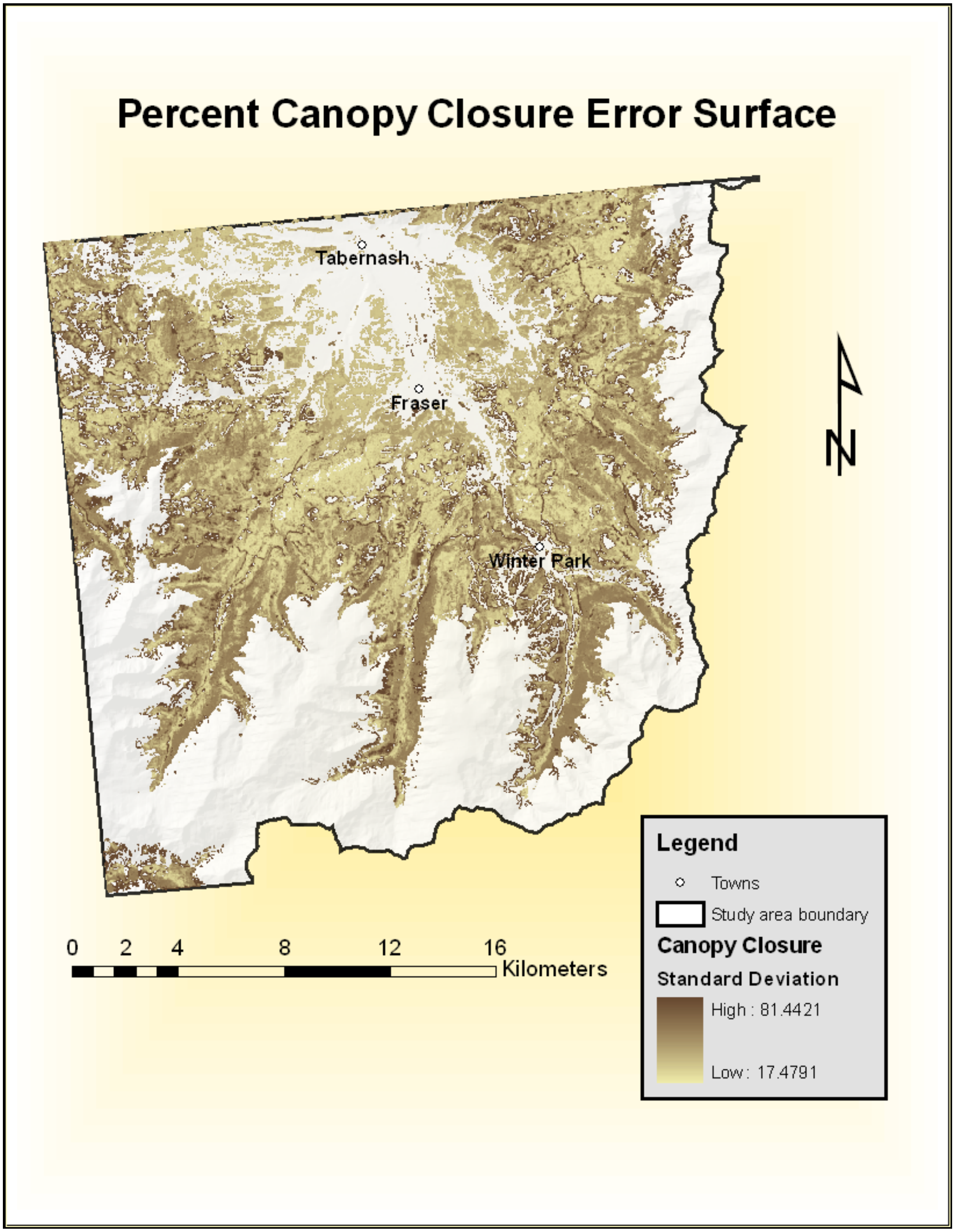

Figure A-9. Percent canopy closure error surface of the lodgepole pine and mixed forest vegetation classes. The standard deviation term refers to the square root of the prediction variance. Prediction uncertainty is greater in the darker areas with higher standard deviation values.

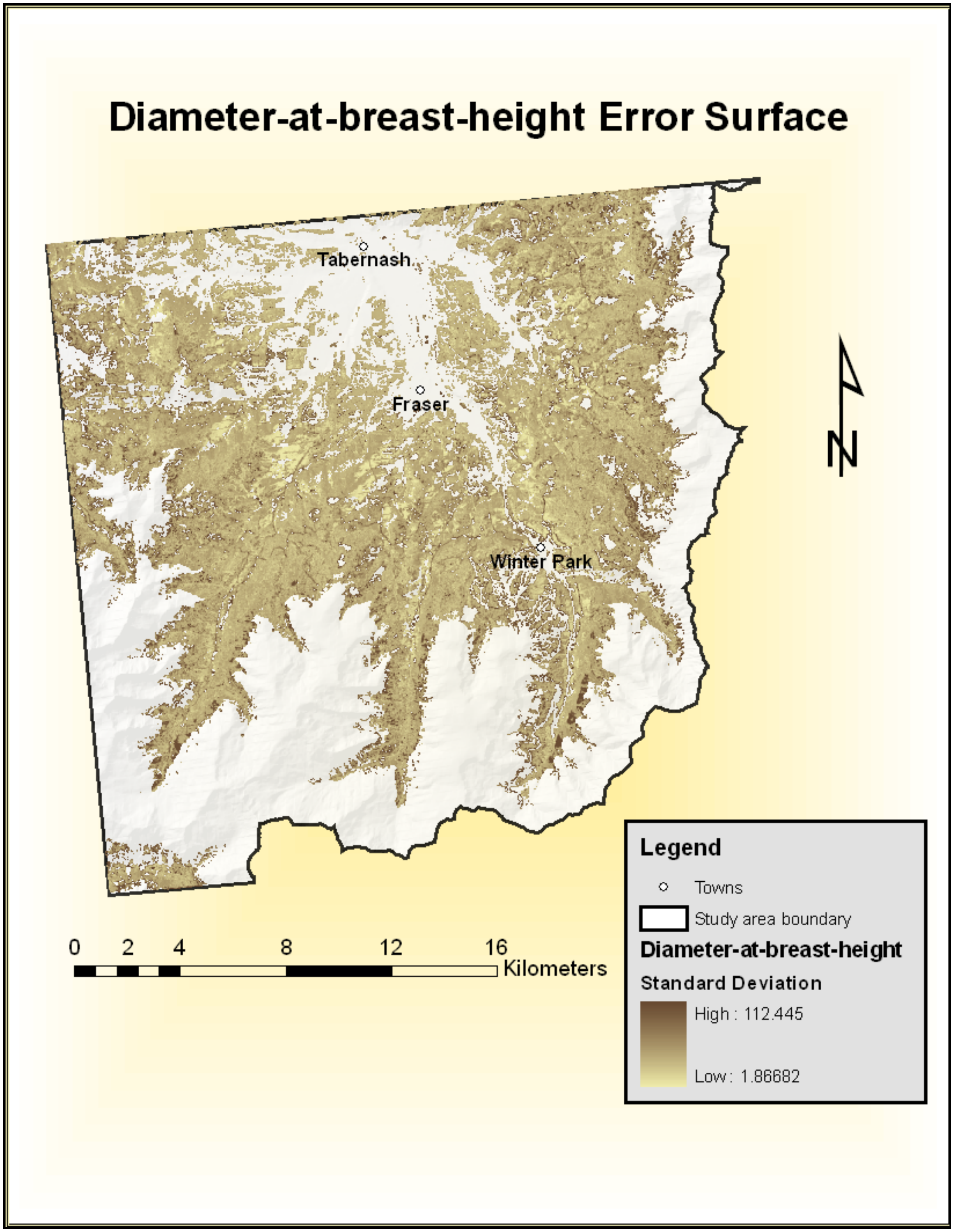

Figure A-10. Diameter at breast height (dbh) error surface of the lodgepole pine and mixed forest vegetation classes. The standard deviation term refers to the square root of the prediction variance. Prediction uncertainty is greater in the darker areas with higher standard deviation values.

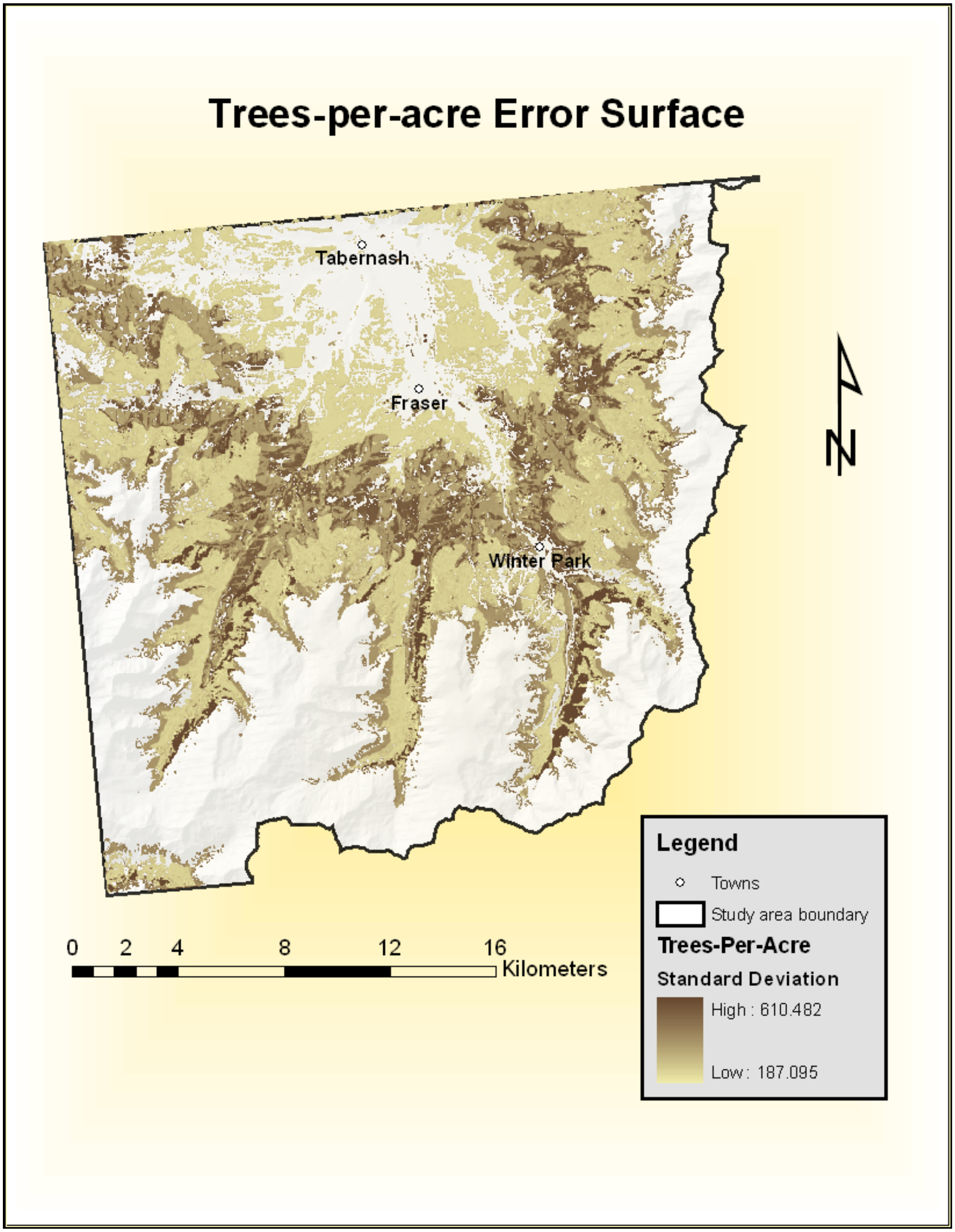

Figure A-11. Trees per acre error surface of the lodgepole pine and mixed forest vegetation classes. The standard deviation term refers to the square root of the prediction variance. Prediction uncertainty is greater in the darker areas with higher standard deviation values.

APPENDIX B: Maps of the MPB Models Overlaid with MPB Mortality

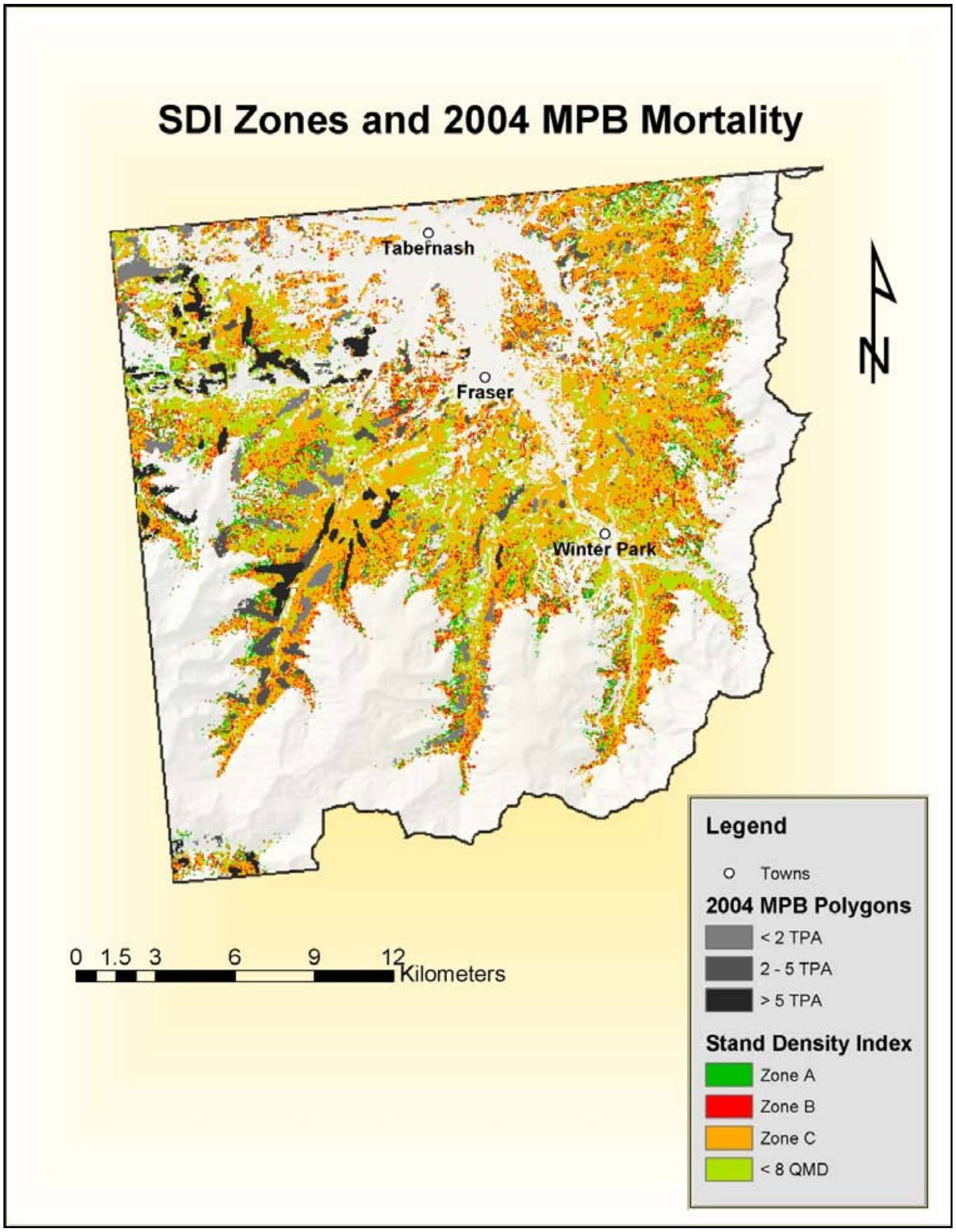

Figure B-1. Stand Density Index (SDI) zones and areas < 8 in. QMD of lodgepole pine and mixed forest vegetation classes overlaid with 2004 mountain pine beetle (MPB) mortality polygons. SDI Zone A: < 125, SDI Zone B: 125-249, SDI Zone C: > 250. TPA – trees per acre killed by mountain pine beetle (MPB).

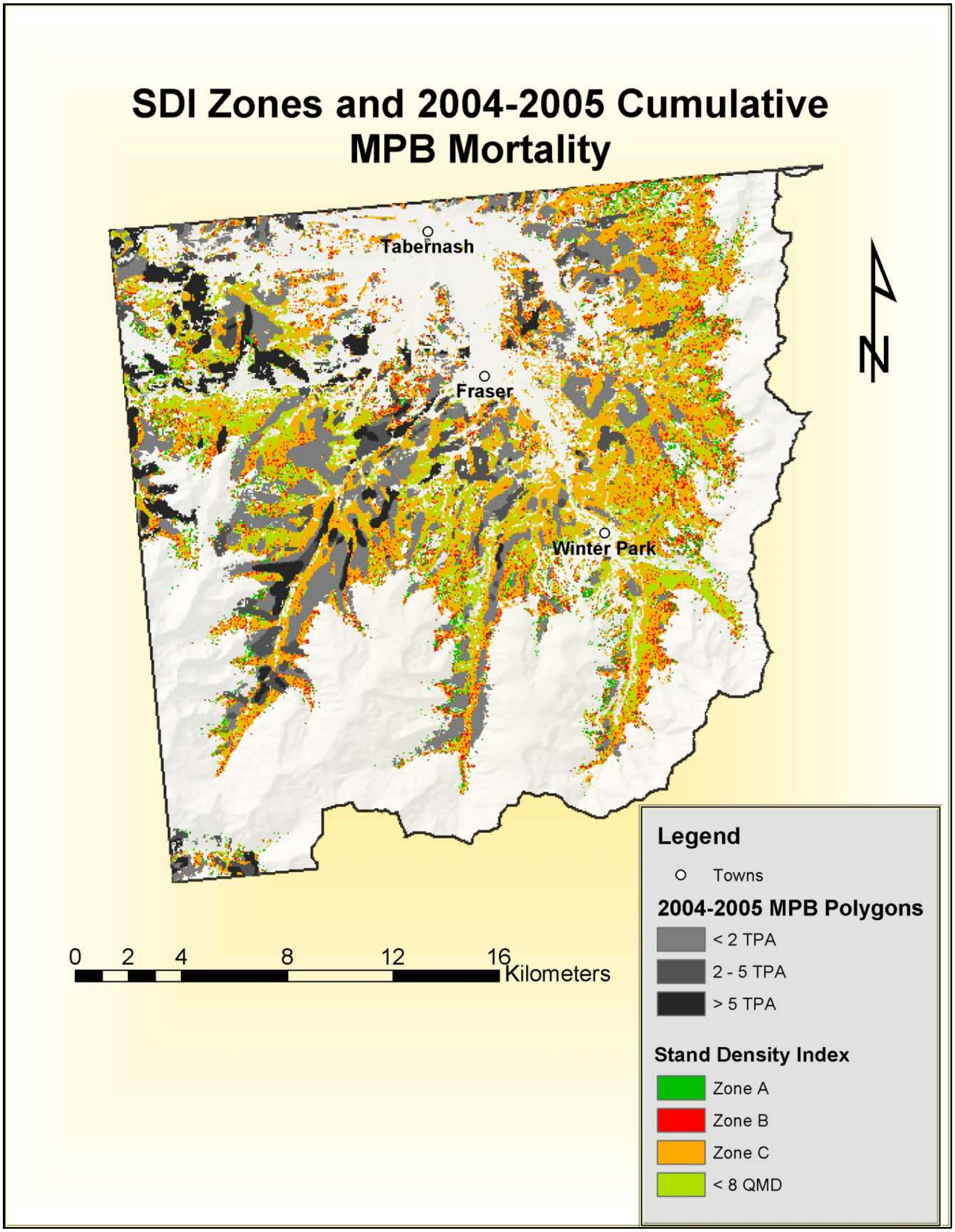

Figure B-2. Stand Density Index (SDI) zones and areas < 8 in. QMD of lodgepole pine and mixed forest vegetation classes overlaid with 2004 and 2005 cumulative mountain pine beetle (MPB) mortality polygons. SDI Zone A: < 125, SDI Zone B: 125-249, SDI Zone C: > 250. TPA – trees per acre killed by mountain pine beetle (MPB).

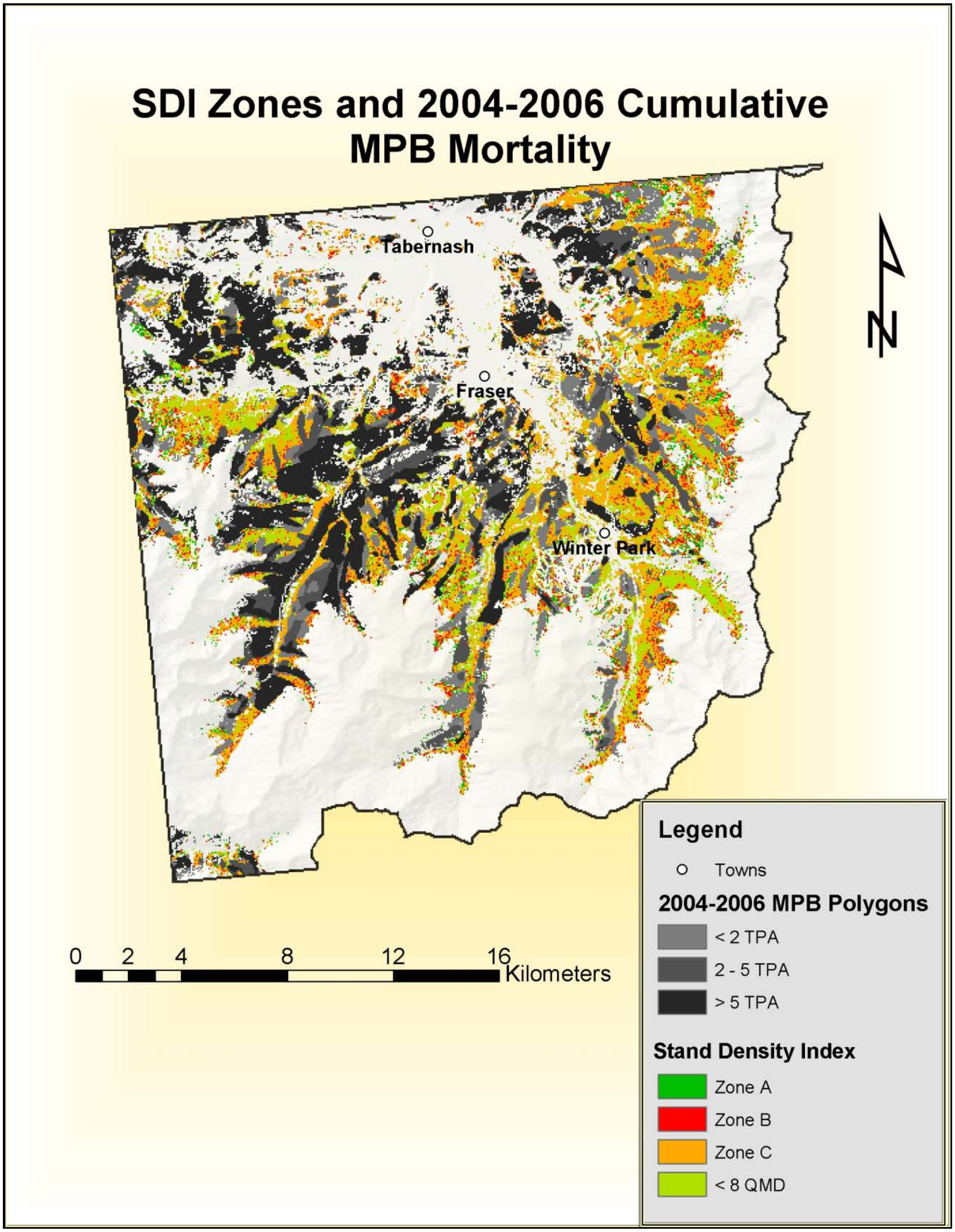

Figure B-3. Stand Density Index (SDI) zones and areas < 8 in. QMD of lodgepole pine and mixed forest vegetation classes overlaid with 2004 - 2006 cumulative mountain pine beetle (MPB) mortality polygons. SDI Zone A: < 125, SDI Zone B: 125-249, SDI Zone C: > 250. TPA – trees per acre killed by mountain pine beetle (MPB).

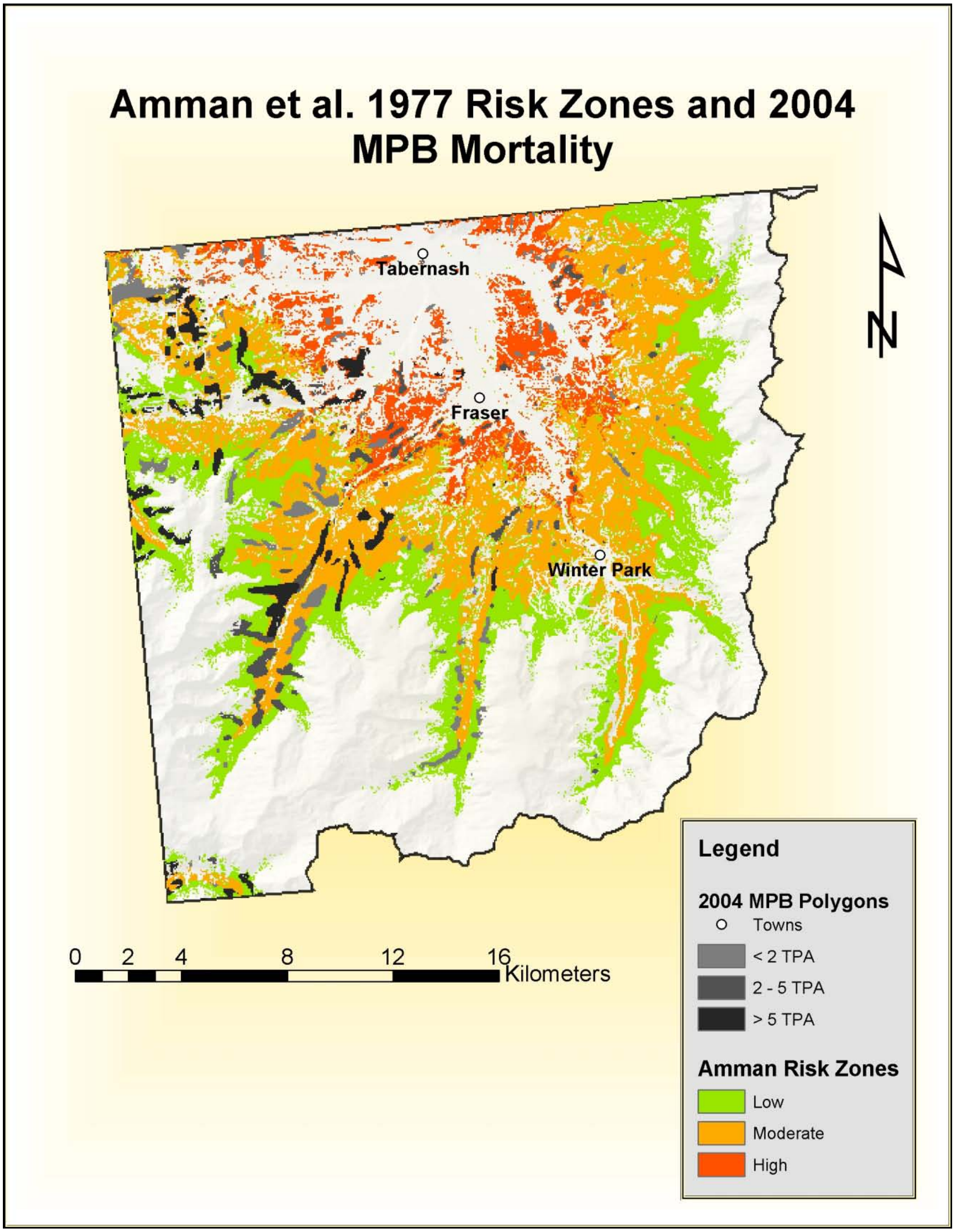

Figure B-4. Lodgepole pine and mixed forest vegetation classified by Amman et al. 1997 Risk Zones overlaid with 2004 mountain pine beetle (MPB) mortality polygons. TPA – trees per acre killed by mountain pine beetle (MPB).

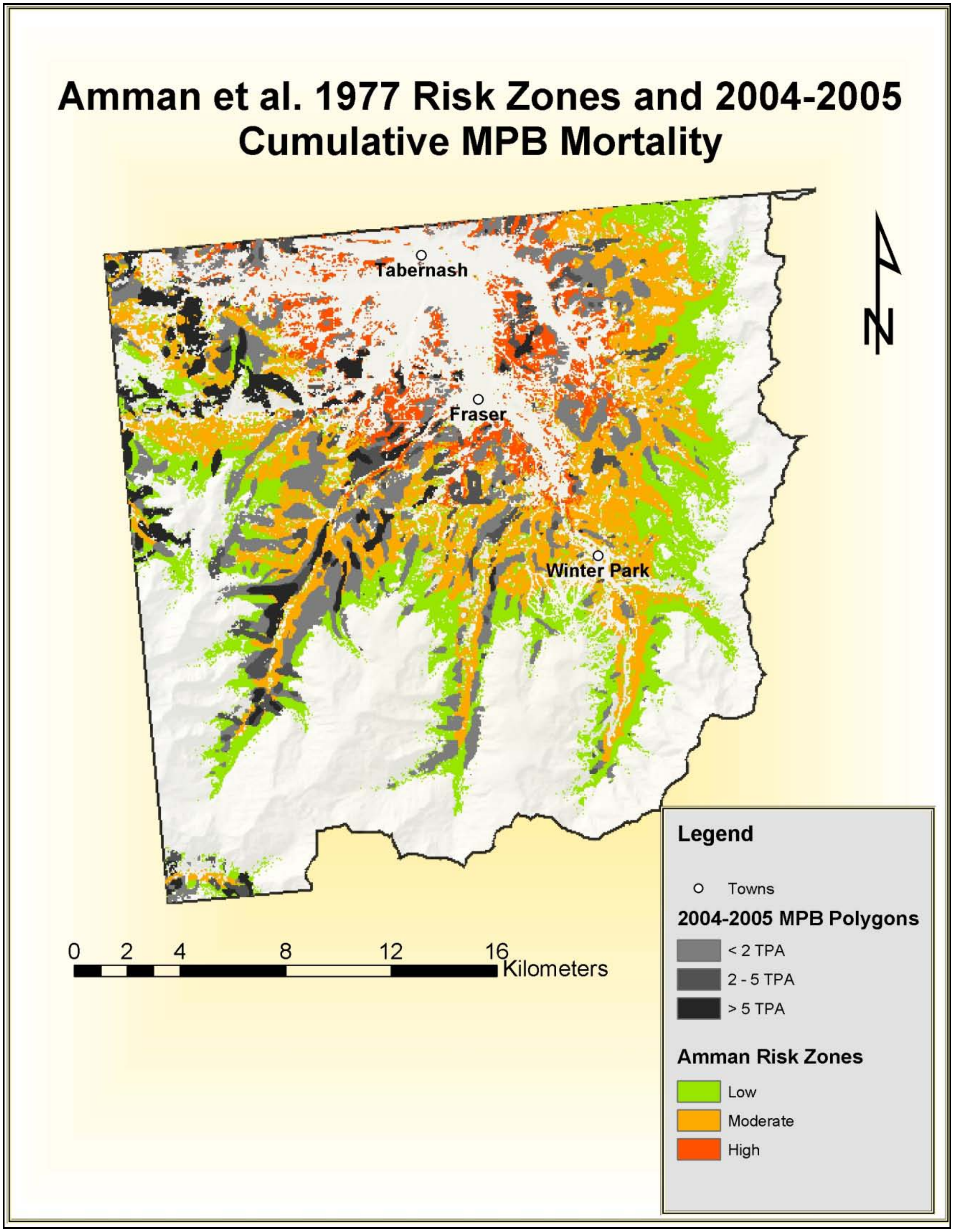

Figure B-5. Lodgepole pine and mixed forest vegetation classified by Amman et al. 1997 Risk Zones overlaid with 2004 and 2005 cumulative mountain pine beetle (MPB) mortality polygons. TPA – trees per acre killed by mountain pine beetle (MPB).

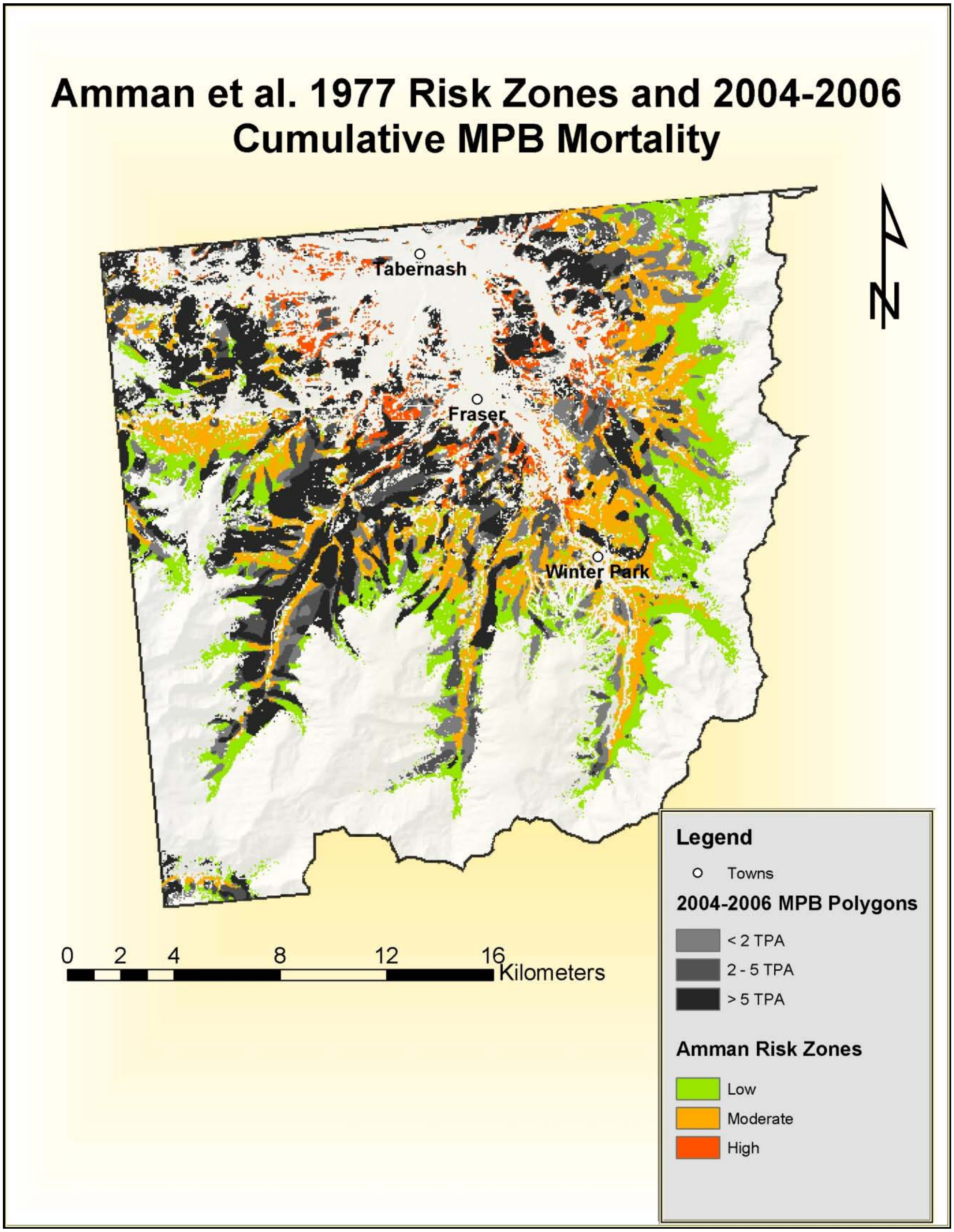

Figure B-6. Lodgepole pine and mixed forest vegetation classified by Amman et al. 1997 Risk Zones overlaid with 2004 - 2006 cumulative mountain pine beetle (MPB) mortality polygons. TPA – trees per acre killed by mountain pine beetle (MPB).

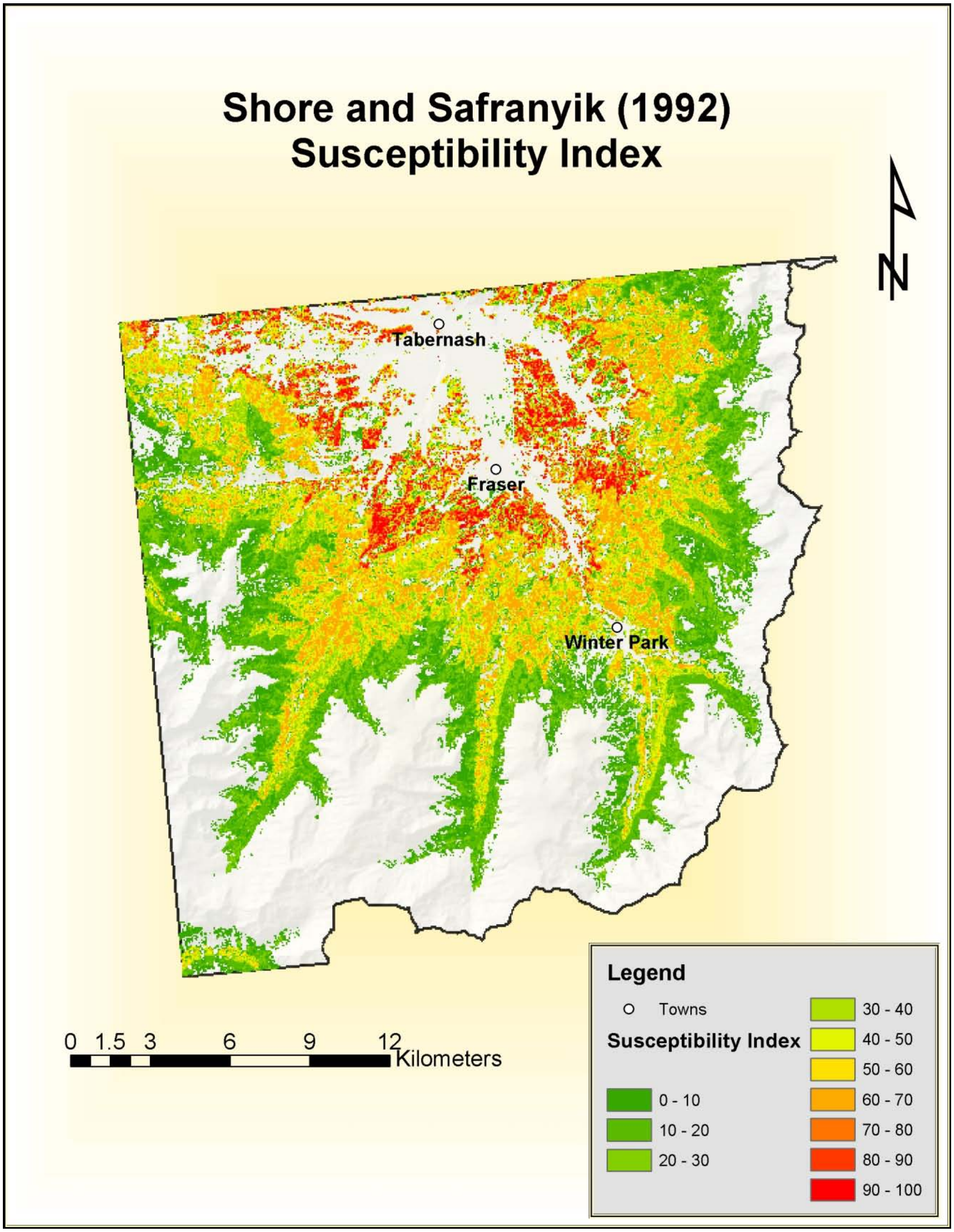

Figure B-7. Lodgepole pine and mixed forest vegetation classified using the Shore and Safranyik (1992) susceptibility index; which is based on basal area, age, trees per hectare, and latitude and longitude.

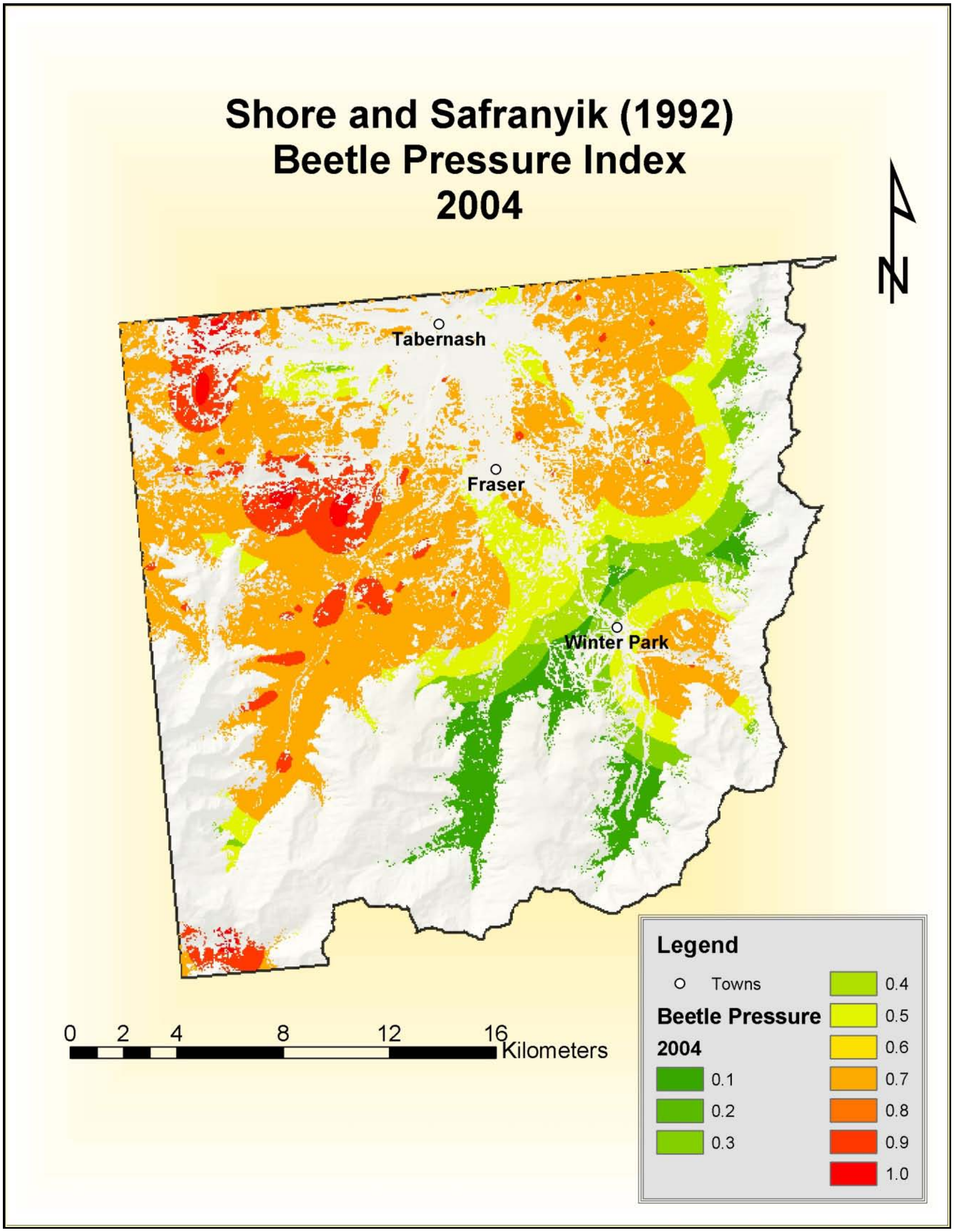

Figure B-8. Lodgepole pine and mixed forest vegetation classified using the Shore and Safranyik (1992) beetle pressure index. 2004 beetle pressure was derived from 2003 aerial survey data.

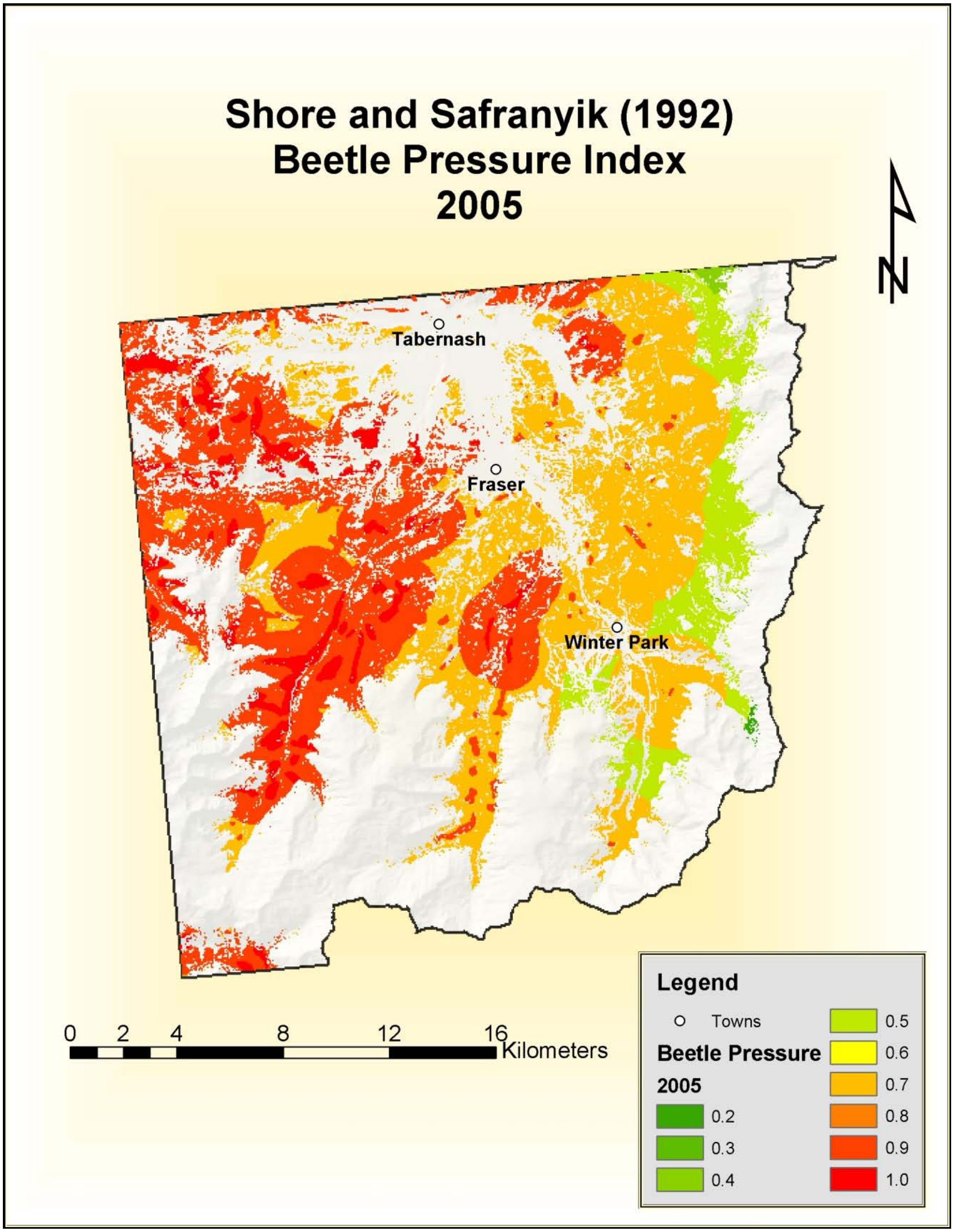

Figure B-9. Lodgepole pine and mixed forest vegetation classified using the Shore and Safranyik (1992) beetle pressure index. 2005 beetle pressure was derived from 2004 aerial survey data.

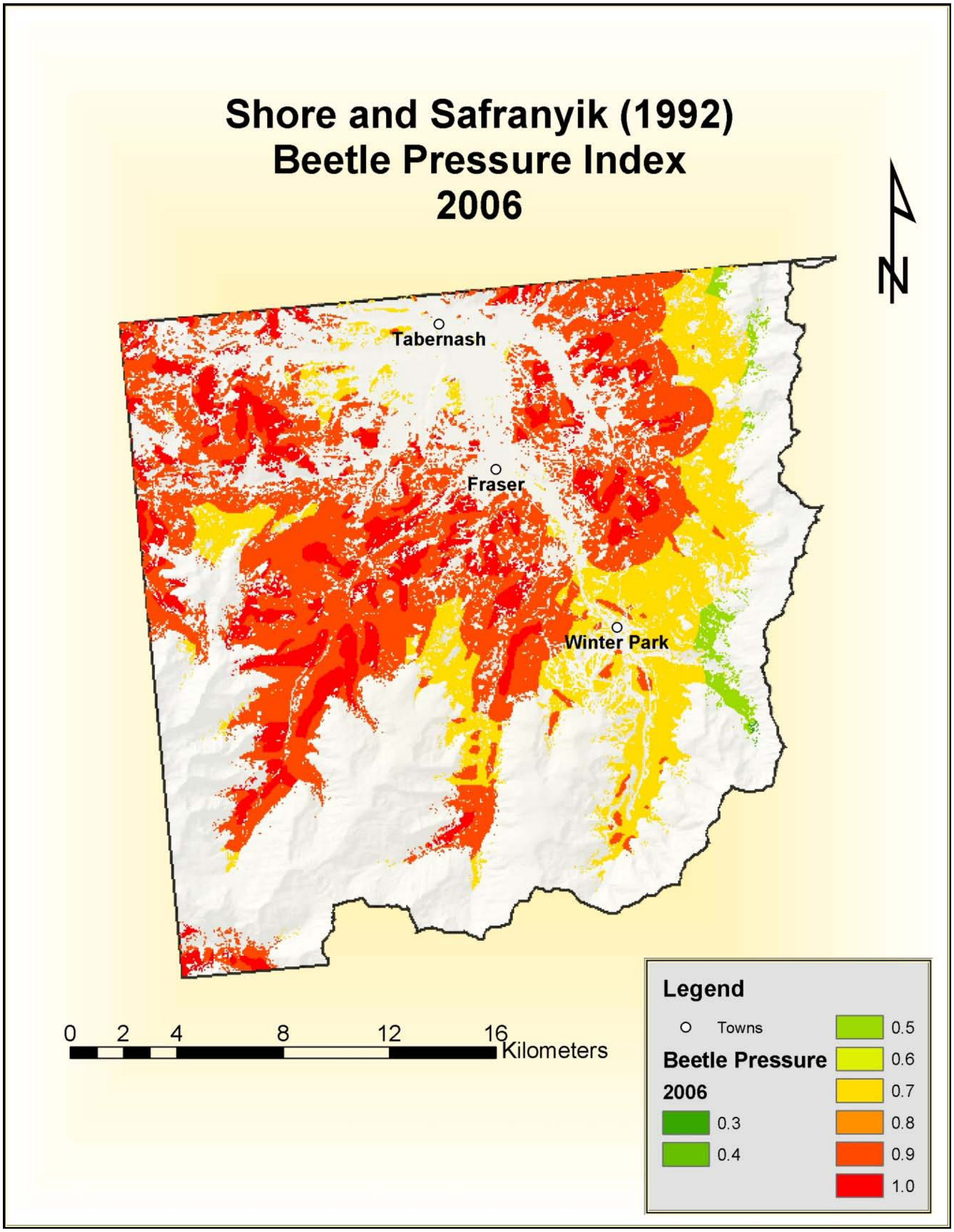

Figure B-10. Lodgepole pine and mixed forest vegetation classified using the Shore and Safranyik (1992) beetle pressure index. 2006 beetle pressure was derived from 2005 aerial survey data.

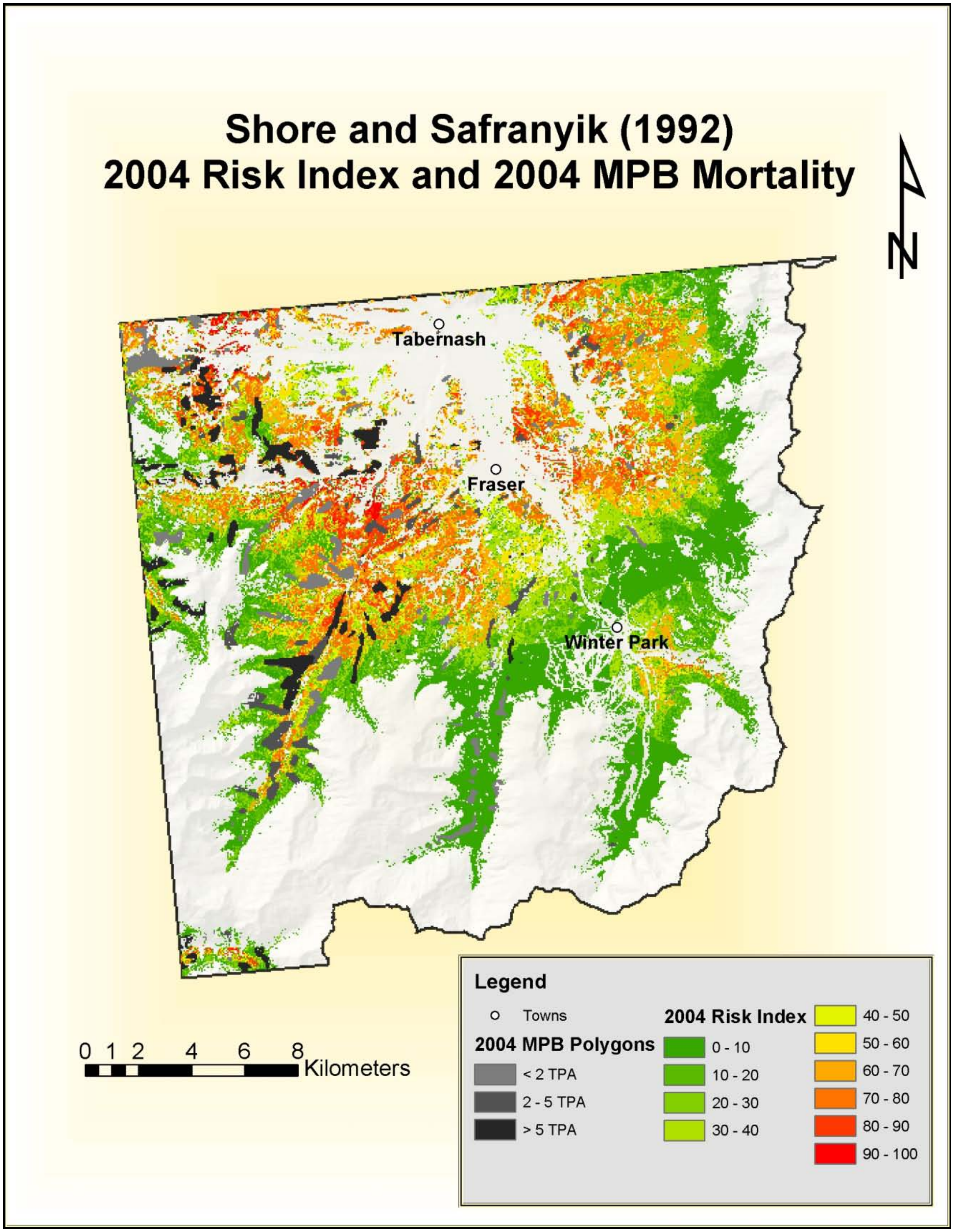

Figure B-11. Lodgepole pine and mixed forest vegetation classified using the Shore and Safranyik (1992) risk index for 2004 overlaid with 2004 mountain pine beetle (MPB) mortality polygons. TPA – trees per acre killed by mountain pine beetle (MPB).

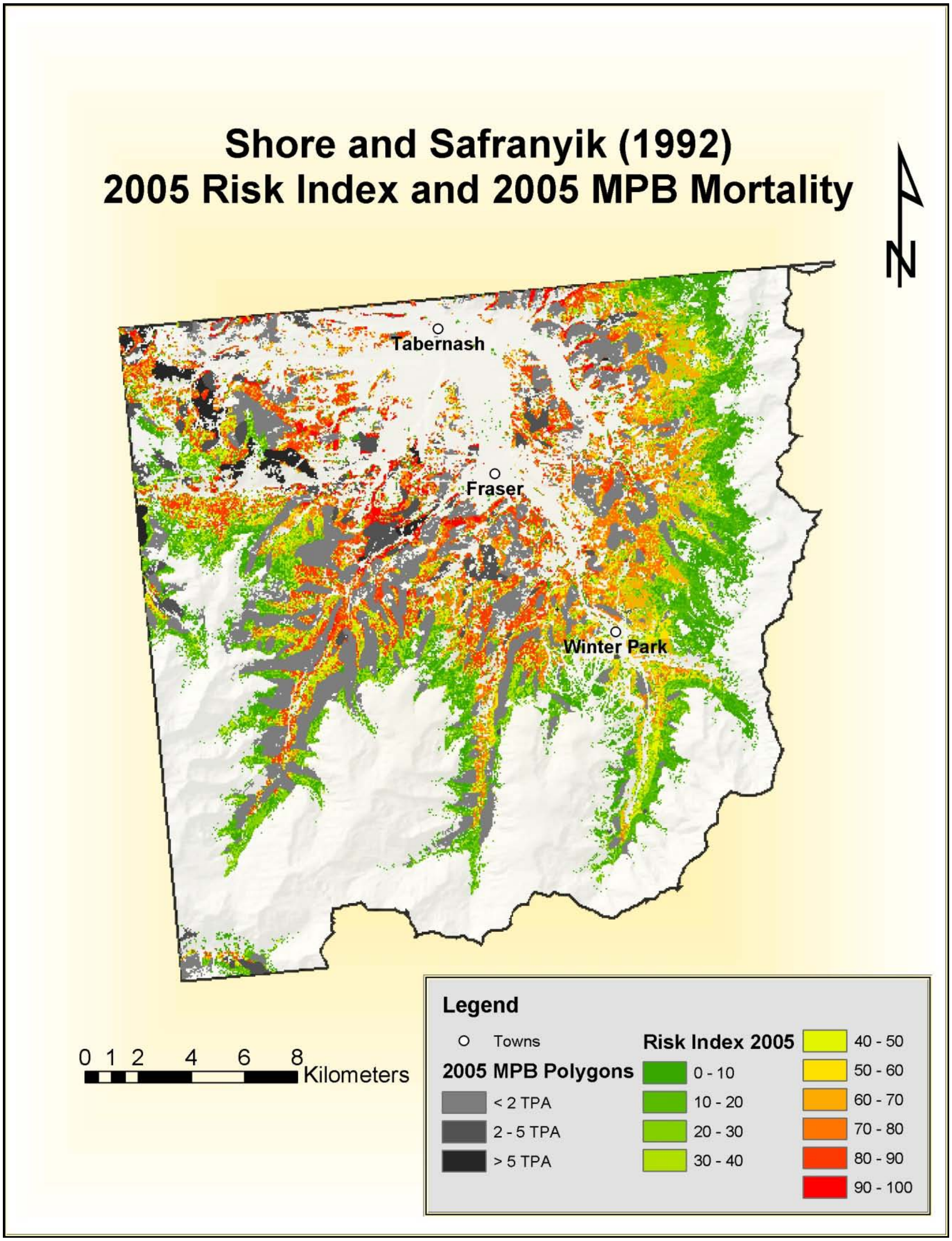

Figure B-12. Lodgepole pine and mixed forest vegetation classified using the Shore and Safranyik (1992) risk index for 2005 overlaid with 2005 mountain pine beetle (MPB) mortality polygons. TPA – trees per acre killed by mountain pine beetle (MPB).

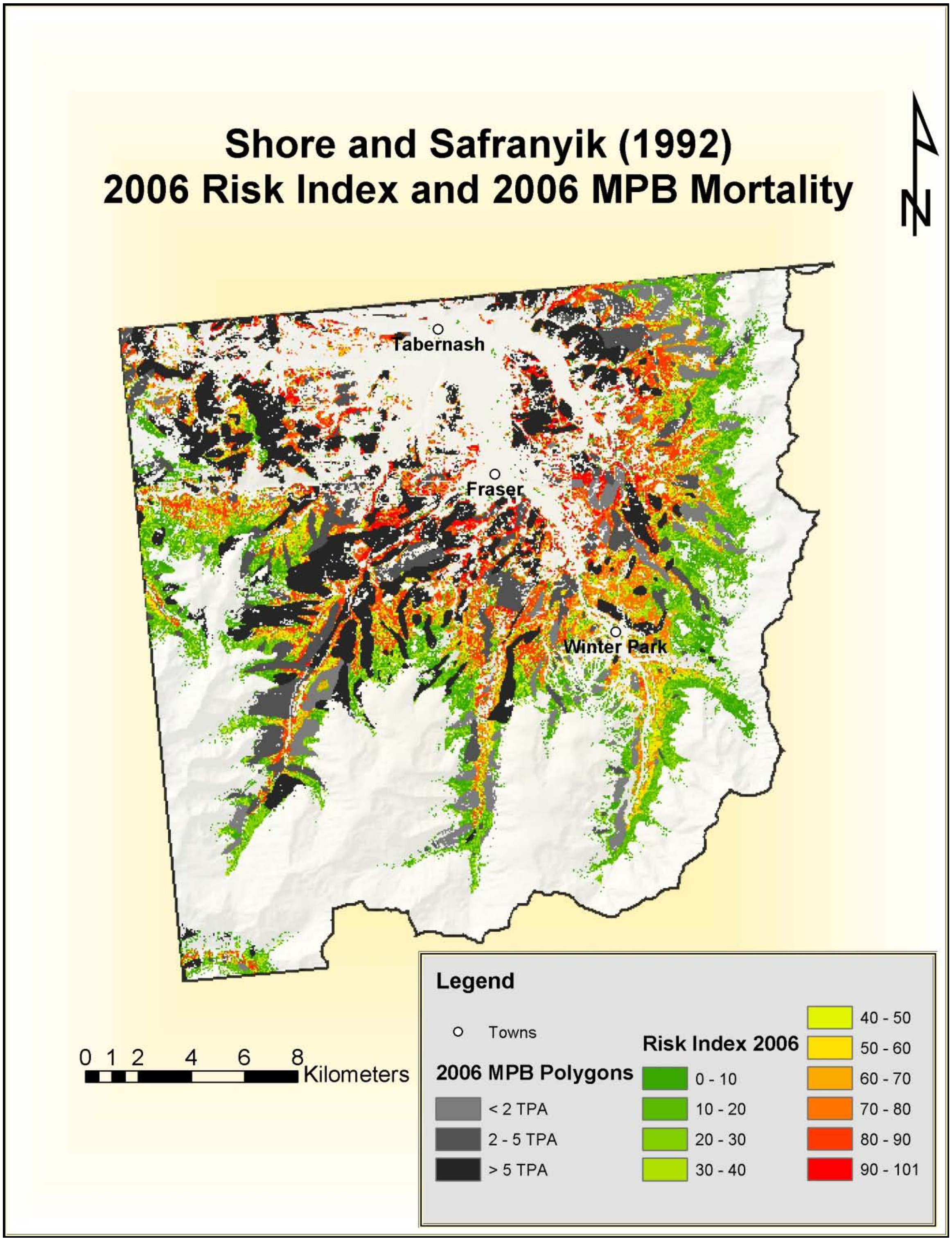

Figure B-13. Lodgepole pine and mixed forest vegetation classified using the Shore and Safranyik (1992) risk index for 2006 overlaid with 2006 mountain pine beetle (MPB) mortality polygons. TPA – trees per acre killed by mountain pine beetle (MPB).

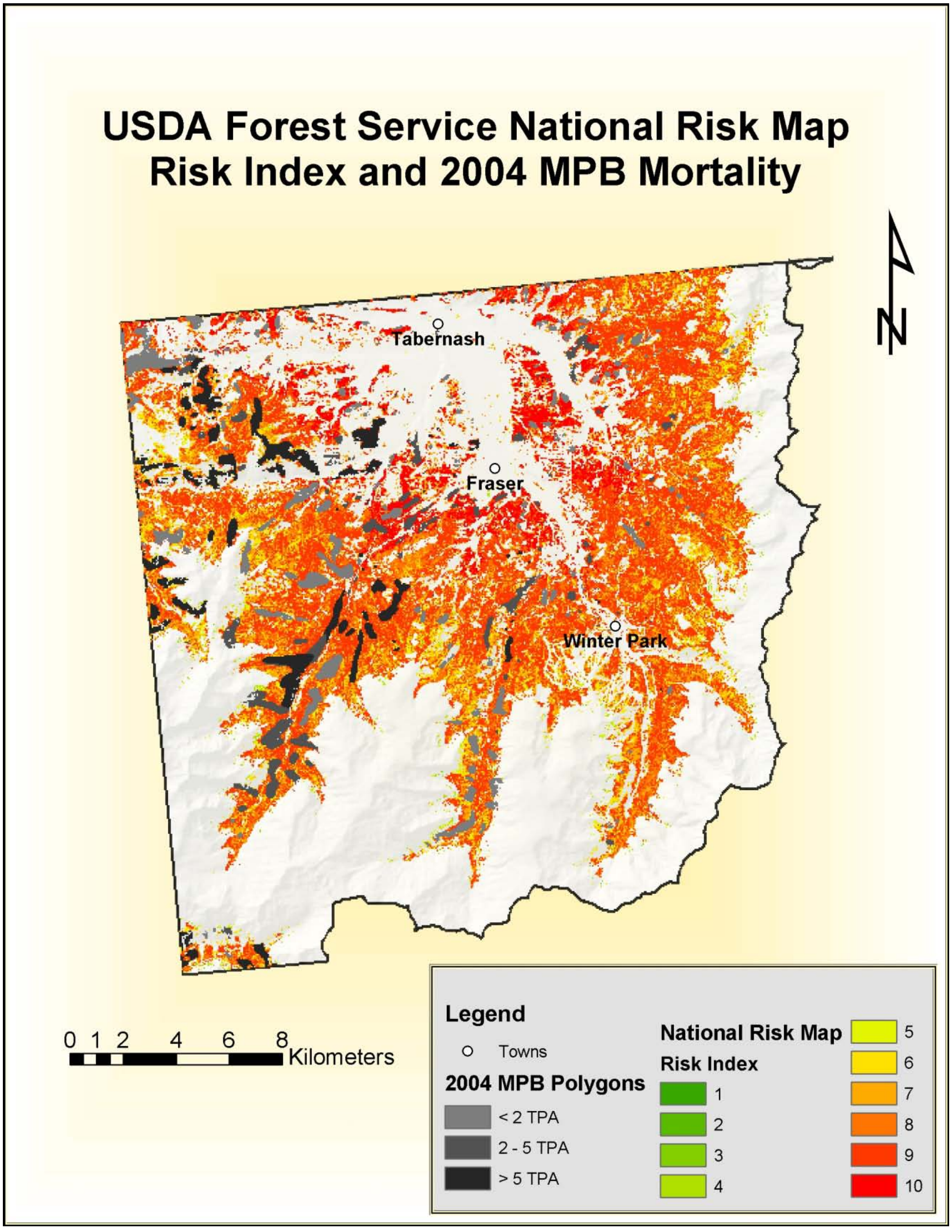

Figure B-14. Lodgepole pine and mixed forest vegetation classified by the USDA Forest Service National Risk Map risk index overlaid with 2004 mountain pine beetle (MPB) mortality polygons. TPA – trees per acre killed by mountain pine beetle (MPB).

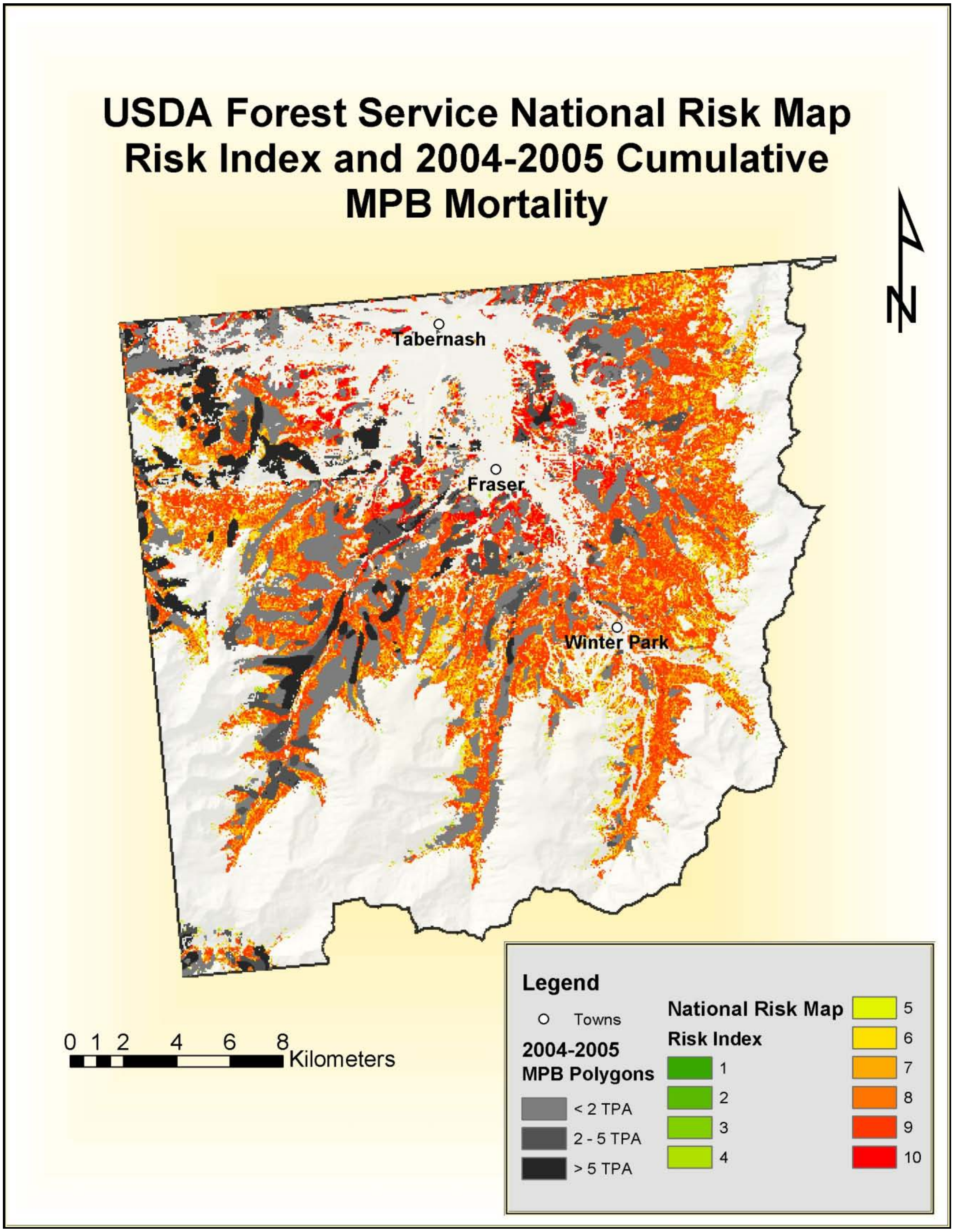

Figure B-15. Lodgepole pine and mixed forest vegetation classified by the USDA Forest Service National Risk Map risk index overlaid with 2004 - 2005 cumulative mountain pine beetle (MPB) mortality polygons. TPA – trees per acre killed by mountain pine beetle (MPB).

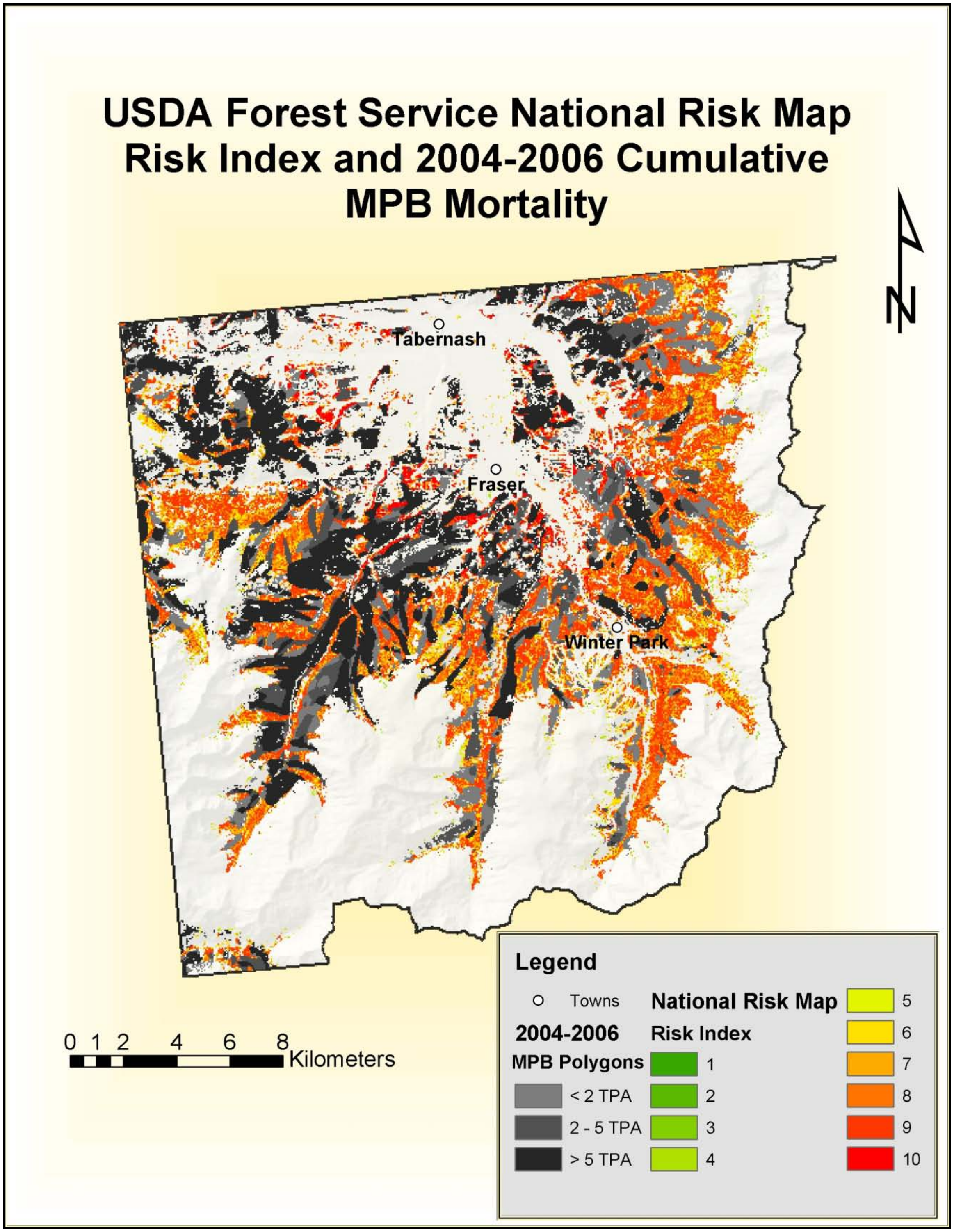

Figure B-16. Lodgepole pine and mixed forest vegetation classified by the USDA Forest Service National Risk Map risk index overlaid with 2004 - 2006 cumulative mountain pine beetle (MPB) mortality polygons. TPA – trees per acre killed by mountain pine beetle (MPB).

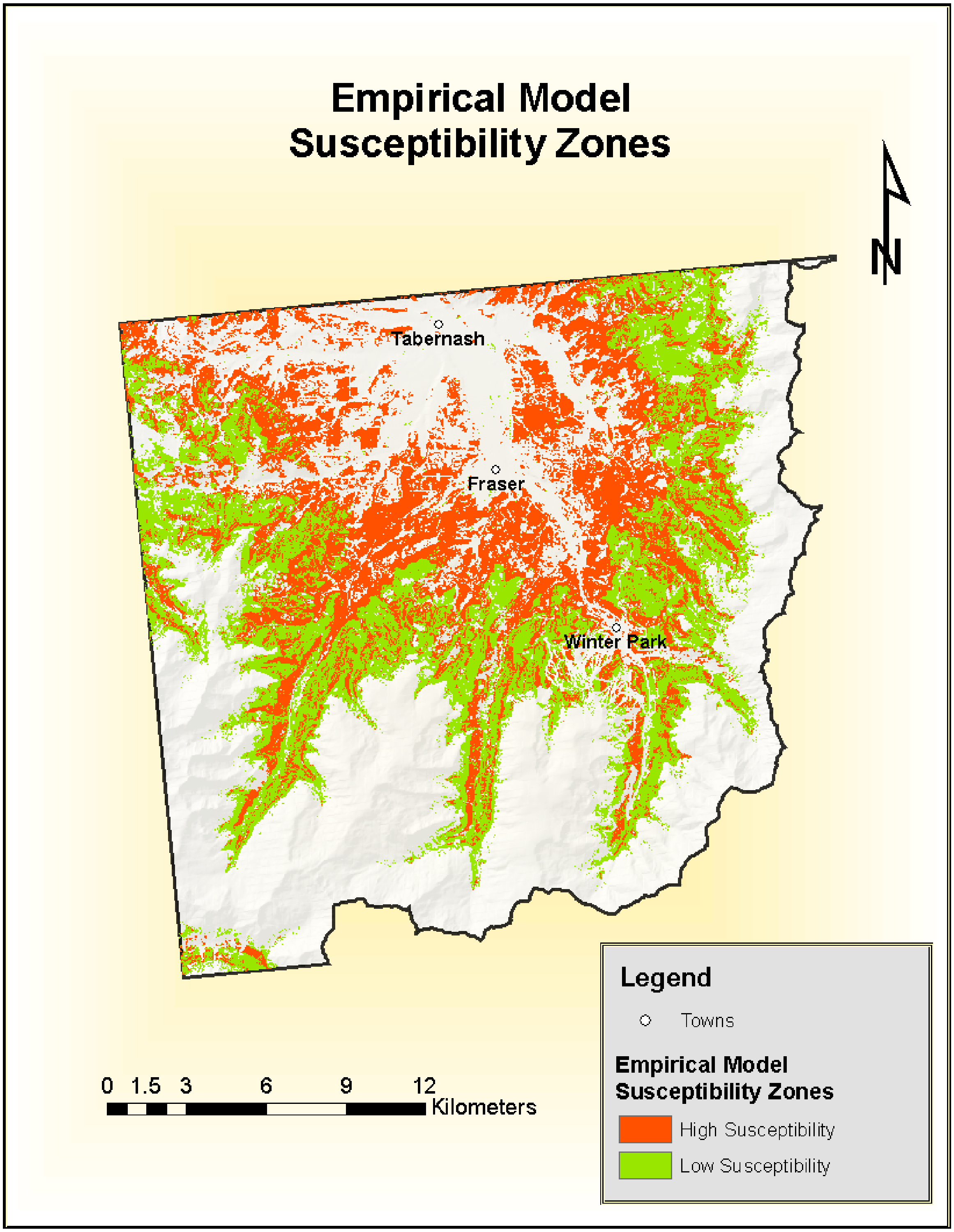

Figure B-17. Final predictive surface generated from the empirical model. The empirical model categorizes the susceptibility of a MPB infestation into two classes: low and high; which is based on elevation, basal area, percent basal area in lodgepole pine, diameter at breast height, and slope.

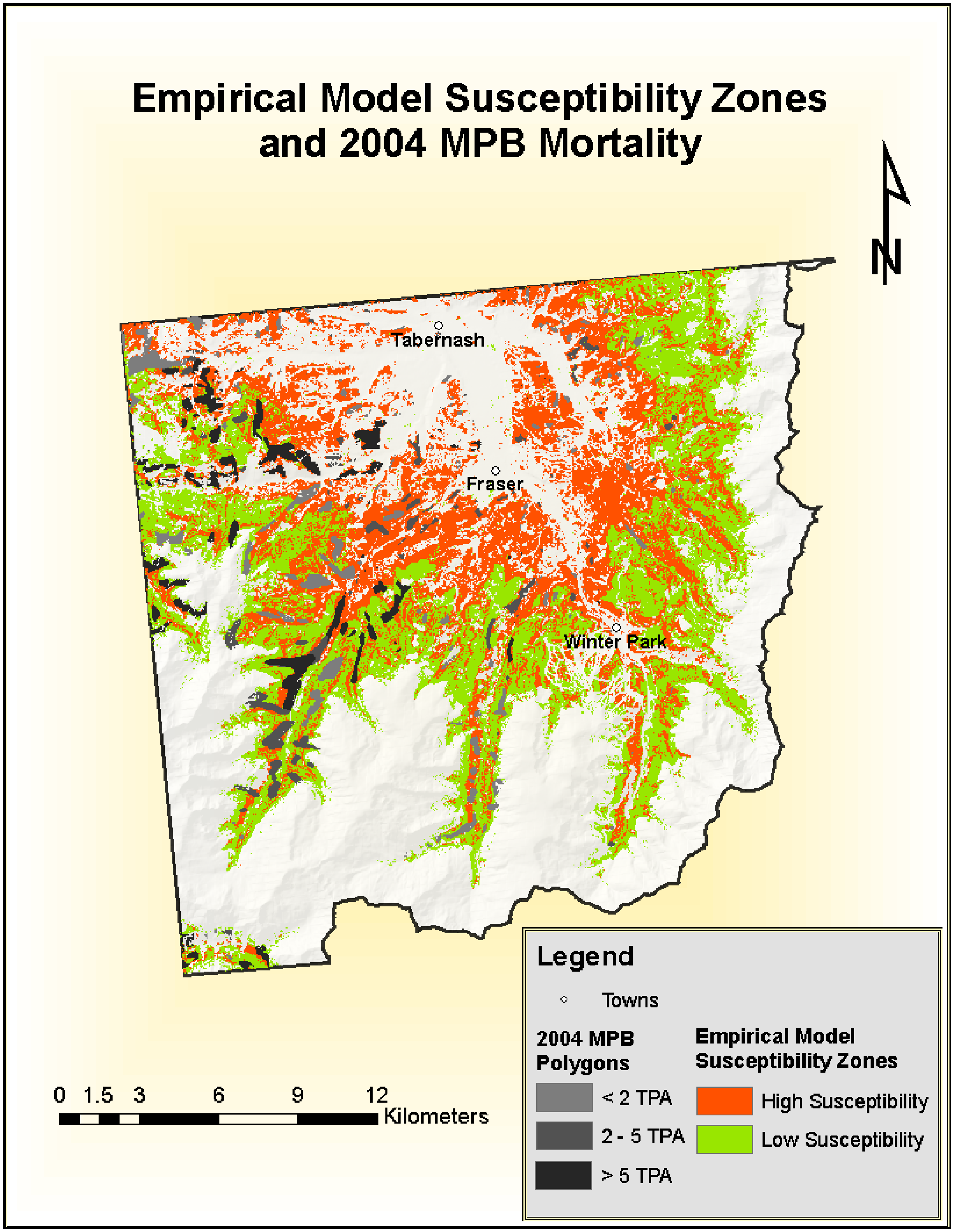

Figure B-18. Lodgepole pine and mixed forest vegetation classified by the empirical model susceptibility zones overlaid with 2004 mountain pine beetle (MPB) mortality polygons. TPA – trees per acre killed by mountain pine beetle (MPB).

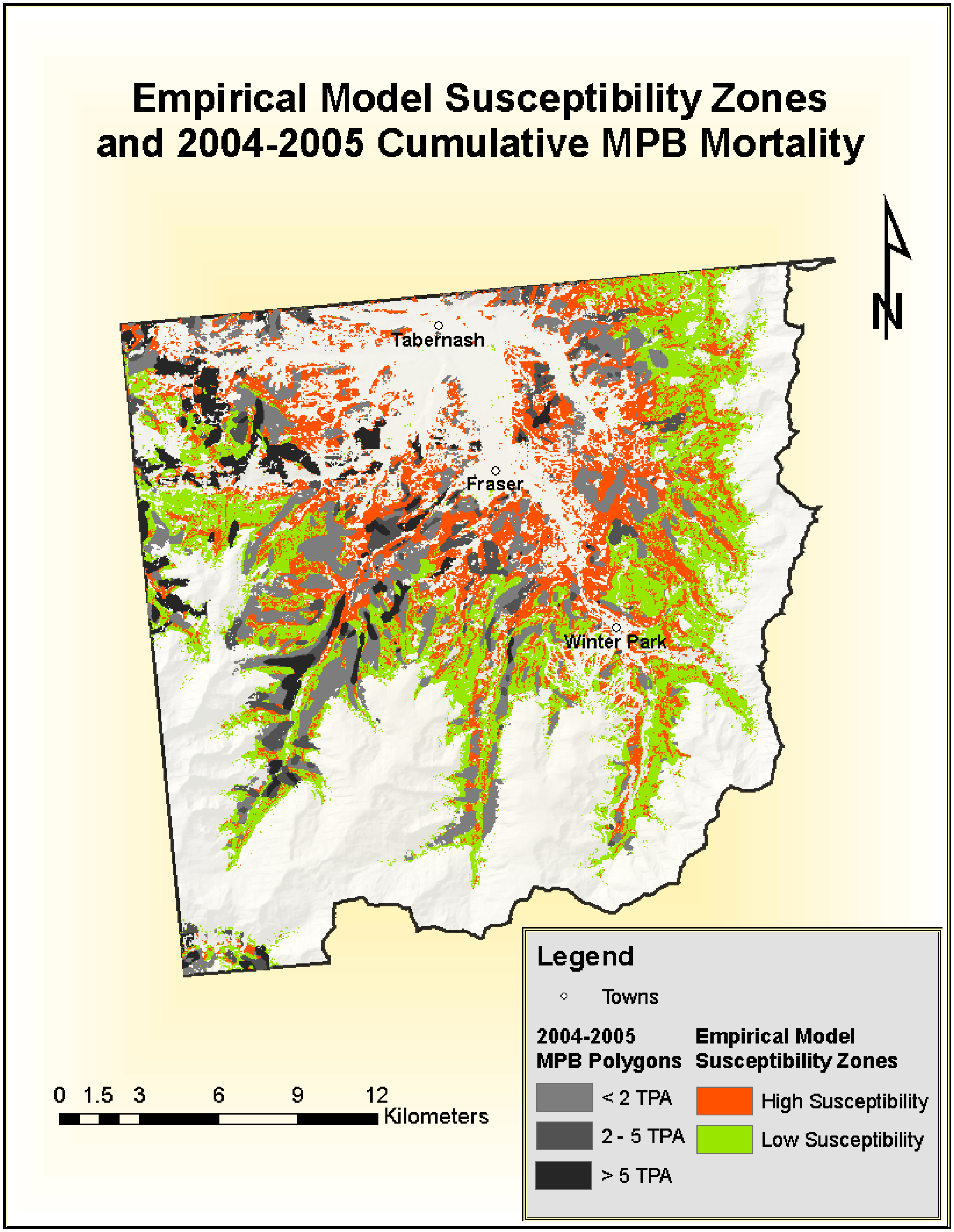

Figure B-19. Lodgepole pine and mixed forest vegetation classified by the empirical model susceptibility zones overlaid with 2004-2005 cumulative mountain pine beetle (MPB) mortality polygons. TPA – trees per acre killed by mountain pine beetle (MPB).

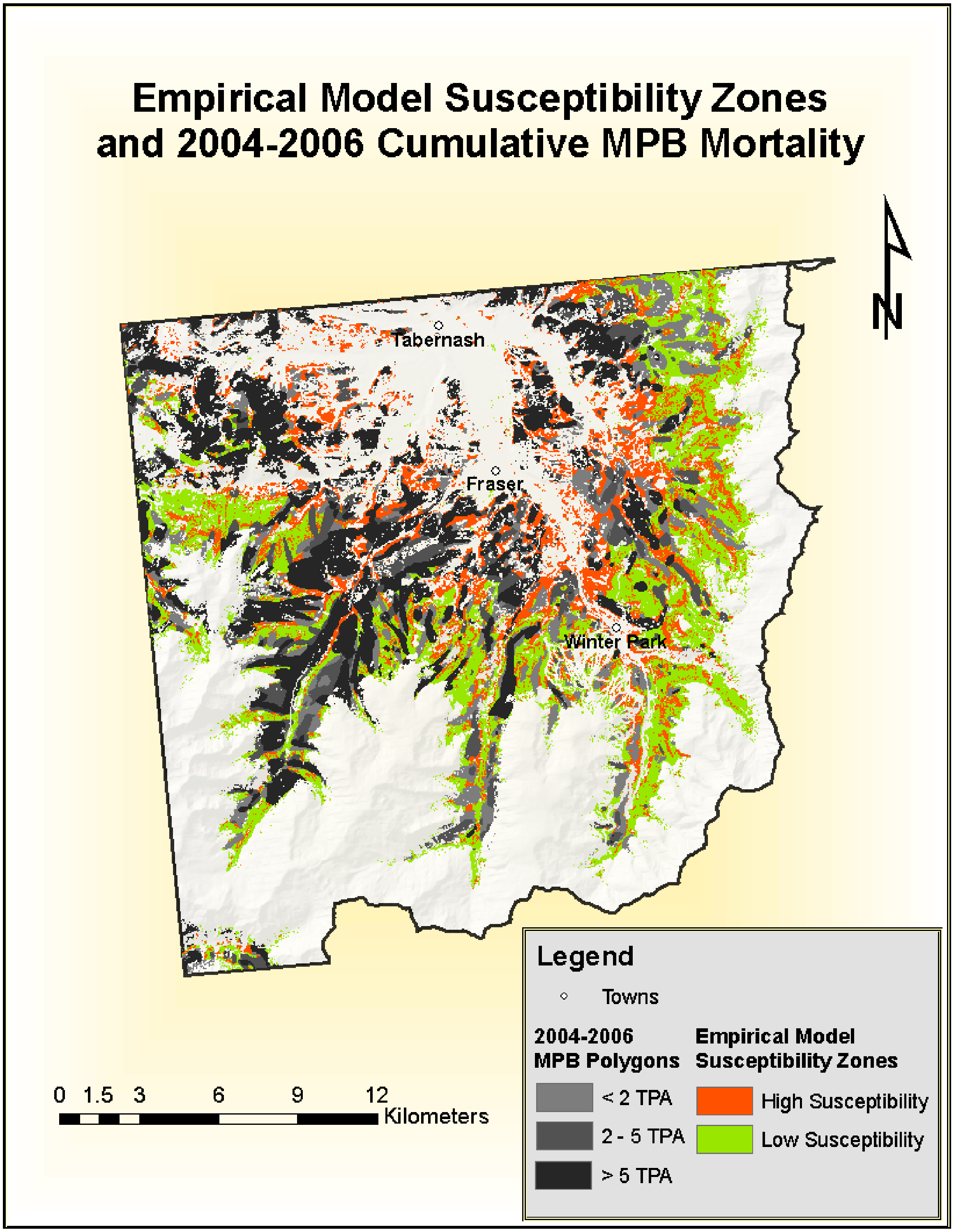

Figure B-20. Lodgepole pine and mixed forest vegetation classified by the empirical model susceptibility zones overlaid with 2004-2006 cumulative mountain pine beetle (MPB) mortality polygons. TPA – trees per acre killed by mountain pine beetle (MPB).

APPENDIX C: Sample AUC Calculation

The validation data in matrix form (color key next page):

		Air-photo Interpretation					
		NF	LP	SF	MF	D	
Predictive Surface	NF	99		2		1	102
	LP	6	88	7	32		133
	SF		24	56	14	3	97
	MC	2	31	11	18	1	63
	D				1	4	5
		107	143	76	65	9	400

NF – non-forest class, LP – lodgepole pine class, SF – spruce-fir class, MF – mixed forest class, D – deciduous class.

Binary matrix with true and false positive rates for each class (color key with formulas next page):

NF				
99	3	102		0.9705882
8	290	298		0.0268456
107	293	400		

LP				
88	45	133		0.6616541
55	212	267		0.2059925
143	257	400		

SF				
56	41	97		0.5773196
20	283	303		0.0660066
76	324	400		

MF				
18	45	63		0.2857143
47	290	337		0.1394659
65	335	400		

D				
4	1	5		0.8000000
5	390	395		0.0126582
9	391	400		

Key:

Parameter	Formula
True Positives (TP)	= Matrix Diagonal values
False Negatives (FN)	= Row Total-TP
False Positives (FP)	= Column Total-TP
True Negatives (TN)	= Total Validation Records-TP-FN-FP
True Positive Rate (TPR)	= TP/(TP+FN)
False Positive Rate (FPR)	= FP/(FP+TN)
Row/ Column Totals	= Sum of row/ column validation points
Total Validation Records	= Total number of validation points

AUC calculation for the LP class:

AUC = ((FPR*TPR)/2)+((1-FPR)*(1+TPR))/2

= ((0.2059925*0.6616541)/2)+((1-0.2059925)*(1+0.6616541))/2

= 0.727831