Edge effects in fragmented landscapes: a generic model for delineating area of edge influences (D-AEI)

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Abstract

We developed a generic model for delineating area of edge influences D-AEI for quantifying edge effects within a landscape by combining remote sensing, geographic information systems (GIS), moving window (3 × 3), and computer programming techniques. Our model provided a more realistic assessment of edge effects than those based on traditional methods. Unique characteristics of the D-AEI model included: (1) preservation of the spatial characteristics of the landscape structure; (2) incorporation of the most critical parameters controlling edge effects, such as edge orientation, edge contrast, prevailing direction of edge effects, decay value, and interior approximation; and (3) ability to quantify edge effects for various variables at multiple scales. The model is flexible so that the users can define key parameters and generate ecologically relevant output based on environmental and spatial characteristics of the study area and the study purpose. Our results demonstrated that: (a) edge effects were not symmetrically distributed in all directions around clearcuts; (b) AEI was not necessarily continuous around patches; and (c) boundary dynamics and multiple edge effects were clearly reflected across the landscape. Results from this research are important for current and future resource assessments, biological conservation and wildlife habitat management, biodiversity studies of flora and fauna, microclimatic research, future studies on edges and their importance in landscape design and analysis. The model has potential for broader applications in other research areas where human and natural disturbances are evident, at multiple scales from watershed, forest management district, to region. © 2000 Elsevier Science B.V. All rights reserved.

Keywords: Edge effects; Edge orientation; Edge contrast; Fragmentation; Ecological modeling

1. Introduction

Edge effects are the most significant consequences of fragmentation resulting from natural and human-caused disturbances. Therefore, the area influenced by edges (AEI) is an important measurement for ecological studies and natural resource management (Chen et al., 1996). Clearcuts, road construction, and wildfire can generate a considerable amount of edge within the remaining forest by changing the microclimatic environment (Franklin and Forman, 1987; Li et
al., 1993; Chen et al., 1996), the composition of plant and animal communities (Yahner, 1988; Haefner et al. 1991), wildlife habitat (Johnson, 1991; Johnson et al., 1991), and the spatial patterns of entire landscapes. Edge effects are especially influential when fragments are small or irregularly shaped, or when the gradient between natural and modified habitats is steep (Thomas et al., 1979; Ranney et al., 1981).

Fragmentation has been suggested to be the primary cause of reduction in biological diversity and the collapse of primary productivity in the tropical rainforests (Laurance et al., 1997). Wildlife managers have been applying landscape design for many years, often by manipulating artificial edges to create more or less edge habitat for plant and animal species (Leopold, 1933; Thomas et al., 1979; Noss, 1983). Larger-scale approaches, at the levels of ecosystems and landscapes, are the only way to conserve existing biodiversity (Franklin, 1993). Certain species of plants and animals are primarily found and preserved in interior forest environments while others favor open, or edge environments (Brown, 1985; Rosenburg and Raphael, 1986; Fraver, 1994; Matlack, 1994; Zheng et al., 1995). Furthermore, the area of continuous interior forest must be larger than a certain size to be considered suitable habitat and to maintain a viable population of some threatened or endangered species. Finally, field data also support assumptions that extinction rates are higher in smaller habitat patches and for smaller local populations (Hanski, 1994).

Development of remote sensing techniques during the last three decades has provided a powerful and reliable tool for monitoring landscape dynamics and modeling ecosystems across large areas (Parton, 1992; Prentice et al., 1992; Running and Hunt, 1993; Neilson, 1995). Remote sensing techniques, in combination with spatial modeling and geographic information systems (GIS), have improved our ability to assess rates, patterns, and directions of regional changes across entire landscapes (Hall et al., 1991; Spies et al., 1994; Cohen et al., 1995; Zheng et al., 1997). For example, changes in land-use patterns and clearcuts in forestlands over time can be identified from remotely sensed data and other sources. Consequently, the edge effects of clearcuts on surrounding forests can be evaluated for the entire area using buffering capabilities (McGarical and Marks, 1995; Gustafson and Crow, 1996).

The field of ecological and environmental modeling has developed enormously in the last two or three decades, especially since the early 1990s, indicating a much greater recognition of the importance of quantification in ecology (Jørgensen, 1997). Delineating area of edge influences (DAEI) has been one of the major research topics in ecology, yet most modeling efforts concerning edge effects are performed for point or linear features in a landscape. Fractal geometry has been widely used for ecological analyses in characterizing edge complexity (Burrough, 1981; Loehle, 1983; Bradbury et al., 1984). Fractal dimensions have been computed for a variety of landscape and other environmental data in landscape analysis (Burrough, 1983; Krummel et al., 1987). Brunt and Conley (1990) developed simulations to assess how the squared euclidean distance algorithm behaved with five factors influencing edge detection. Haefner et al. (1991) used Monte Carlo simulation to compare four methods to modeling the edge effects on organisms growing within a small area. Laurance and Yensen (1991) used a core-area model to estimate the total area of pristine habitat contained within a fragmented area and to predict the amount of unaltered habitat preserved within any hypothetical fragment using edge-related measurements. However, these models were not developed to demonstrate realistic patterns of edge effects across the landscape. Numerous studies have demonstrated that spatial characteristics of a landscape, such as patch size, patch shape, patch density, and patch arrangement, are the basic features controlling ecological processes within a landscape (Forman and Godron, 1986; Franklin and Forman, 1987; Milne, 1988; Ripple et al., 1991). However, traditional approaches assume depth of edge influence (DEI) is constant regardless of edge orientation, sharpness of the edge, and variable of interest (Harris, 1984; Franklin and Forman, 1987; Morrison, 1990; Ripple et al., 1991; McGarical and Marks, 1995; Gustafson and Crow, 1996). Consequently, AEI delineated using the buffering function of GIS is
often symmetric and continuous around a target patch, and multiple edge effects cannot be assessed.

Accurate identification of AEI at the landscape level is currently lacking in landscape ecology studies because several difficulties exist for evaluating edge effects at such scales. First, the effect of edge differs according to the variable under examination (Chen et al., 1996). For example, wind can penetrate twenty times further than light into old-growth Douglas-fir (*Pseudotsuga menziesii* (Mirb.) Franko) forests in the Pacific Northwest, USA (Chen et al., 1995). Effects of clearcut edges on avian species may extend even deeper into the adjacent forests. Studies have indicated that in different habitats and for different taxa, edge effects may penetrate from 15 m (Ranney et al., 1981) to 5 km (Janzen, 1986). Second, edge effects vary with forest composition and height. In general, the sharper the difference (i.e. higher contrast) between the two adjacent patches, the stronger the edge effects is. Third, physical characteristics such as edge orientation, prevailing direction of edge effects, and topography also influence the depth of edge effects (Chen et al., 1993, 1996).

Evaluating edge effects within remnant forests and identifying AEI of a landscape are particularly important for current and future resource assessments, biodiversity studies, landscape design and analysis, and wildlife habitat management. Thus, there is a need for a generic edge model in a fragmented landscape that can provide more accurate and realistic measurements of AEI than those delineated based on traditional approaches that are mainly based on distance from clearcuts. Such information is critical for managers seeking to integrate the considerations of economic development, environmental protection, reserve design, and maintenance of sustainable ecosystems across an integrated region.

We synthesize that traditional methods do not adequately reflect some important factors influencing edge effects in the real world. In this study we developed a generic model for quantifying edge effects at landscape or broader scales by combining remotely sensed data, GIS, and programming. Our objective was to develop a model that: (1) preserved the spatial characteristics of the landscape structure; (2) incorporated several critical parameters (defined later in their context) that control edge effects such as edge orientation, edge contrast, prevailing direction of edge effects, decay value, and interior approximation (IA); and (3) allowed users more control in dealing with various variables across the landscape. We also sought to examine the relationships among decay value, IA values, and estimates of edge effects using the model we developed.

2. Model development and implementation

2.1. Development

Edge effects occur where two distinct patches or communities meet. Although edge effects are two-way exchanges in terms of energy flow and movement of materials, edge effects from clearcuts into interior forests are the primary concern in our study because these influences are commonly considered the most meaningful and significant for ecological and biological studies (Laurance and Yensen, 1991; Chen et al., 1992). In this study, we focused on predicting the extent of the effects of clearcuts into adjoining land cover types.

A 3 x 3 pixel moving window was used in model development. For any given non-clearcut pixel placed in the center of the window, spatial characteristics of each of its eight neighboring pixels were examined and recorded. This method demonstrates several advantages based on the fact that the pixel (i.e. grain) is the minimum mapping unit for landscape level simulation. First, for the centered pixel, orientations of its surrounding pixels within the 3 x 3 window can be recorded (in degrees, e.g. N = 0 or 360, NE = 45, E = 90, SE = 135, S = 180, SW = 225, W = 270, and NW = 315, Fig. 1a). Different edge effects can thus be determined and multiple edge effects can be calculated. Second, it preserves the most important spatial features of landscape configuration, such as the size, shape, and arrangement of a clearcut patch. For example, when a clearcut patch contains one pixel, eight surrounding pixels can be affected (Fig. 1b). The number of affected
surrounding pixels increases to ten when a clearcut patch contains two pixels (Fig. 1c). If arrangement of a two-pixel clearcut patch is in a diagonal direction, 12 surrounding pixels can possibly be affected (Fig. 1d). Third, a landscape with a higher density of clearcut patches (or a more fragmented landscape) is expected to contain more AEI than a less fragmented landscape of the same size. As the window moves across the landscape pixel by pixel, all such spatial information and features are captured and reflected during the simulation.

The only required input layer for the model is a pixel-based landscape coverage (raster file) which contains clearcuts and other vegetation types for an area. Required resolution of the input file will vary depending on the edge-effect variable under consideration. For example, an input file with 30-m pixel resolution was used for general model development, while a subset of the input file was rescaled to a pixel resolution of 1 m to detect edge effects of radiation in this study. Actual values contained in the coverage were tree height ($h_{\text{pixel}}$) in meters based on ground surveyed data for corresponding vegetation types. Edge contrast for each pixel, relative measurement between the pixel and the highest pixel value in the study area for any variable of interest, was calculated as:

$$\text{contrast} = \frac{h_{\text{pixel}}}{H_{\text{max}}} \quad (1)$$

where $H_{\text{max}}$ was the maximum tree height within the landscape. If a pixel had a value of 0, there was no edge effect based on the model design (Fig. 2). In this study, we assigned a value of 20 to represent the maximum tree height of the study area based on our field sampling, and 0 to represent water and wetland.

Edge orientation ($\theta$), edge-facing to the azimuth, was also determined by the moving window. Any pixel classified as non-clearcut (except water) was placed in the center of the window. Edge effects, if any, resulting from adjacent clearcut pixel(s) were examined and recorded according to its orientation, a critical variable in determining the DEI and thus, the AEI. Edge effects with different $\theta$ values can be expressed using a cosine function:

$$EF_i = \Sigma EF_i / EF_{\text{max}}$$
\[
\cos \left[ 2\pi (x + (360 - x))/360 + (2\pi/N)i \right] \tag{2}
\]

where \( x \) is the prevailing direction of the edge effect defined by users before simulation (in degrees), \( N \) is the number of directions identified in the model, and \( i \) varies from 0 to \( N-1 \) with an increment of 1. In this study there were eight directions in a 3 \( \times \) 3 window, so the increment was \( \pi/4 \) (radians) and \( i \) varied from 0 to 7. The first value of \( i \) \((i = 0)\) was always assigned to the prevailing direction of edge effects defined by users and the cosine values for the other seven directions were calculated clockwise as \( i \) increased.

This design ensures that influence from the prevailing direction of edge effects across the landscape is always equal to 1 \((i = 0, \text{maximum edge influence in terms of orientation})\) and the influence from the opposite of the prevailing direction always equals \( 1/(N-2, \text{minimum edge influence}). \)

Eq. (2) can be simplified to:

\[
\cos[2\pi(1 + i/N)], \quad i = 0, 1, \ldots N-1 \tag{3}
\]

We then rescaled all cosine values to 0–1 using:

\[
(\text{Eq. (3) + 1)/2} \tag{4}
\]

However, we believe that edge effects coming from the opposite of the prevailing direction of edge influence, in most cases, should not be 0 in a real landscape. Thus, the model provides users with an option to define the minimum value for the opposite orientation of the prevailing direction \((\text{MIN}_{\text{def}})\) by:

\[
\theta_{\text{value}} = \text{Eq. (4) * (1 - MIN}_{\text{def}}) + \text{MIN}_{\text{def}} \tag{5}
\]

A set of \( \theta_{\text{value}} \) can be determined after the prevailing direction of edge effects is defined. These values are used for differentiating edge effects from different orientations (eight directions) during the simulation.

Significance of edge influence (SEI), measurement of the magnitude of edge influences between the edge and interior forest, is related to a series of factors such as edge orientation, edge contrast, and other potential scalers \((S_i, \ i = 1, 2, \ldots, \text{Eq. (6)})\). In this study the model incorporated the first two factors. Distance (dist) from a non-clearcut pixel to its surrounding clearcut pixel(s) in a 3 \( \times \) 3 window can be obtained based on pixel resolution (i.e. distances from four cardinal directions equal pixel resolution and distance from four diagonal directions can be calculated according to the Pythagorean theorem). With SEI, dist, and the decay value \( K \) (changing ratio from edge into interior forest over distance), the edge effect \((\text{EF}_i)\) from one of the eight surrounding pixels \((i)\) can be calculated from Eq. (7). Consequently, multiple edge effects \((\text{EF}_m, i > 1)\), is determined by Eq. (8).

\[
\text{SEI} = \text{SEI}_{\text{max}} \times \text{contrast} \times \theta_{\text{value}} \times S_1, S_2, \ldots \tag{6}
\]

\[
\text{EF}_i = \text{SEI} \times e^{-K \times \text{dist}} \tag{7}
\]

\[
\text{EF}_m = \sum_{i=1}^{8} \text{EF}_i \tag{8}
\]

\[
\text{Value}_{\text{EF}_m} = \text{EF}_m / (\text{EF}_m)_{\text{max}} \tag{9}
\]

2.2. Implementation and ecological implications

In the current version of the D-AEI, the maximum tree height could be up to 99 m. Users are provided with an opportunity to produce better, more ecologically meaningful output based on environmental and spatial characteristics of the study area and the study purpose by defining several key parameters (Table 1).

The first parameter is the decay value \((K)\). It determines the rate of change from clearcut to the interior forest for a specific variable (Chen et al., 1993). The larger this value is, the faster it changes. In reality, the \( K \) values can vary significantly from one variable to another. For example, the amount of sunlight can change from full sunlight in the clearcuts to values approximating those of interior forest within several meters (Chen et al., 1995). Thus, a higher value of \( K \) (0.5) should be used (rapid change over a short distance). Conversely, edge effects concerning some avian species may extend into the interior forest...
Table 1
Requested inputs for D-AEI model (delineating area of edge influences).

| Name of input file: infile.dat |
| Name of output file: test3.out |
| Number of ROWs integer: 100 |
| Number of COLs, i: 100 |
| Decay value \((K)\), float: 0.025 |
| Maximum tree height (m), f: 20.0 |
| Interior approximation (IA) value (0–1), f: 0.01 |
| Prevailing direction of edge effect (in degrees), i: 270 |
| Pixel size (m), f: 30.0 |
| Class number for clearcut, f: 1.0 |
| Minimum value for edge orientation (0–1), f: 0.5 |
| Output format, 1 presentation, 2 probability: 1 |

If format = 1, class code for edge = ?, i: 50

Fig. 3. Theoretical relationships between magnitude of edge effects and distance from edge as functions of decay values \((K)\). A high \(K\) value indicates that edge effects from the clearcut decrease quickly over a short distance into the forest, while a low \(K\) value indicates a slow decrease over a long distance.

by much longer distance, indicating that a lower value of \(K\) should be applied, such as 0.001 (slow change over long distance). Fig. 3 illustrates some theoretical relationships between degree of edge effects (0–1) and distance from edge using different \(K\) values. Significant differences in edge effects over distance were evident among different \(K\) values.

The second parameter needed to be defined in the D-AEI model is the interior approximation (IA), ranging from 0 to 1. The smaller the IA value, the closer the condition is to that under interior forests. This design allows us to define the precision necessary for determining whether a variable has reached interior forest levels and whether the simulation needs to be terminated. Because transitional changes of biotic and abiotic variables from clearcuts to interior forest always occur gradually, we must make an arbitrary decision to stop the simulation. For example, if air temperature within a clearcut patch is 15°C while air temperature under interior forest is 10°C, giving an IA value of 0.1 indicates that air temperatures < 10.5°C (error < 10% of the air temperature difference between clearcut and interior forest) could be considered as ‘the interior forest’, and the simulation should be terminated.

The third user-defined parameter is prevailing direction of edge effects for the area because this variable can substantially affect the AEI given different orientations. Furthermore, this environmental variable can be completely different from one region to another. In this study west (270°) was assigned as the prevailing direction of edge effects because this is the dominant wind direction for the region (it might also differ with variables, e.g. 180° for radiation in the Northern Hemisphere). As a result, for any given non-clearcut pixel centered in a 3×3 window, edge effects from the west are always considered to have the greatest edge influence while the edge effects from the east (the opposite of the prevailing direction) has the least influence.

The fourth parameter is the minimum value for edge orientation (\(\text{MIN}_{\text{def}}\) 0–1). In this study, a value of 1 indicates that edge effects from all directions are the same strength. A value of 0 indicates that the area has strong, consistent edge effects from the prevailing direction and no effects of edges exists from the opposite direction. A \(\text{MIN}_{\text{def}}\) value of 0.5 was used in this study to illustrate that the depth of edge influence from the direction opposite to the prevailing direction is half of that from the prevailing direction of edge effect.

The last parameter defined for the D-AEI model refers to its optional output format. Two output formats are provided by the model. The first is the presentation format that aggregates all
edge-affected pixels into the same class for spatial demonstration. In this case, one is given an option to select a class number that does not exist in the original input file, for the simulated AEI across the landscape. The other format outputs a probability, ranging from the IA value to one that indicates degree of similarity of the pixel to either clearcut or interior conditions. Output pixel values close to 1 indicate that the conditions are similar to those within clearcuts, while pixel values close to 0 indicate conditions approximate those under interior forest. The significance of this output lies in its ability to reconstruct actual values for the simulated edge pixels if the conditions under clearcuts and interior forests are known. For example, if one knows that air temperatures are 15°C under clearcut and 10°C under interior forest, the pixel values of air temperatures within the simulated AEIs can be interpolated using the calculated probabilities.

2.3. Model tests

We used the northern portion of the Chequamegon National Forest (CNF), WI, USA, to illustrate the potential applications and merits of the D-AEI model, since we have abundant ground surveyed vegetation and land cover data for this area. A 1987 LANDSAT5 TM image (30-m resolution) of the area was used to generate a land cover map (Wolter et al., 1995), which was recoded into the following categories based on tree height characteristics: wetland, clearcuts, grass and shrub, mixed forest, jack pine and oak, red pine, hardwood, and others. The tree height for each class was calculated from ground observed data. A subscene of CNF containing 100 rows and 100 columns (900 ha) was used in model testing (Fig. 4). Since edge effects of some variables (such as radiation) only exist over a short distance, 30-meter TM data are too coarse to detect edge effects for these variables across a landscape. Therefore, a subset (20 × 20, 36 ha, northwest corner of the subscene) was extracted and rescaled to 1-m resolution for simulating edge effects of radiation (Fig. 4).

The model was tested for the above landscapes to explore the importance of key parameters by: (1) keeping the decay value constant (0.025) while assigning different IAs for stopping the simulation (0.1–0.001); the outputs from step 1 were then compared to output from a conventional buffering method; (2) holding the IA constant (0.01) while modifying the decay values (0.5–0.005); and (3) running the model using different combinations of K and IA to examine the combined impact on estimates of edge effects across the landscape.

To simplify data processing for the most outside rows and columns in a 3 × 3 window, the model starts simulation at row (I)2 and column (J)2 for a matrix of I × J (both I and J start at 1); and ends the simulation at I − 1 and J − 1. As a result, the size of the study extent in the output file is always two rows and two columns less than those in the input file (e.g. in this study all output files with 30-m pixel resolution have a size of 98 × 98, while the outputs with 1-m resolution have a size of 598 × 598).

3. Modeling results

Changes in both K and IA values had exponential effects on estimating edge areas across the entire landscape. Forest lands accounted for 63.7% (550.5 ha) of the simulation area. Total interior forest habitats decreased to 522 ha, or 5.1% less than original forest habitat when IA was set to 0.1. The area of interior forest habitat decreased further to 212.7 ha (61.4%) as the value was changed to 0.001 (Fig. 5, a constant K value was used). Total AEI increased from 5.7 ha (0.63% of entire landscape) to 745.9 ha (82.9% of entire landscape) when decay values varied from 0.1 to 0.005 (Fig. 6, a constant IA value was used). Our results indicated that changing decay values resulted in a faster rate of increase of AEI (or decreasing interior forest habitat) than did changing IA values (Table 2).

The coupling influence of different combinations of IA and K values is greater on estimating total AEI than on total interior forest area. This is because total AEI includes all land cover types except clearcuts and water/wetland, while only forest cover types are considered when total inte-
Fig. 4. Landsat TM land cover map (1987) for the study area, Chequamegon National Forest, WI, USA. A subscene with a pixel resolution of 30 m was used for model development and testing. A subset of the subscene (northwest corner) was used and rescaled to 1-m resolution for detecting area of edge effects for radiation.
Fig. 5. Comparison of AEIs and landscape patterns estimated from a conventional method (GIS buffer) and D-AEI model simulations. During the D-AEI simulation, decay value ($K$) stayed constant (0.025), while the IA values varied from 0.1 to 0.001.
Fig. 6. Comparison of AEIs and landscape patterns estimated from model simulations. During the simulation IA values were set as constant (0.01), while \( K \) varied from 0.5 (fast change over short distance) to 0.005 (slow change over long distance).
AEI obtained from the D-AEI model differed from that generated through a conventional buffering method, both spatially and statistically. The buffering method resulted in AEIs that were continuously and symmetrically distributed around clearcut patches (Fig. 5). Although the contrast between clearcuts and grass/shrub cover types was small, many grass/shrub pixels were buffered as AEIs simply because they were adjacent to clearcut pixels. This shortcoming is addressed in the D-AEI model. Our results indicated that: (1) AEI around a clearcut patch was not necessarily continuous when the edge contrast was small; (2) edge effects from clearcuts were not evenly distributed in all directions; more non-clearcut pixels were identified as AEIs on the eastern side of clearcuts than those identified on the western side of clearcuts (because the west side was defined as the prevailing direction of edge effects); and (3) more forest lands were classified as AEIs because of higher edge contrast. Across the landscape, spatial patterns and land cover composition resulting from the D-AEI model differed significantly from the buffering method (Fig. 7). Our model provided results that were more

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*Theoretically, a combination of higher K and IA values may result in no or very little AEI, while a combination of lower K and IA values may convert all non-clearcut area into AEI. In this study clearcut accounts for about 12.9% of the study area.

rior forest area is calculated. The degree of difference depends on the proportion of forest land within the entire study area. Theoretically, a combination of high decay value (0.5) and high IA (0.1) should result in no (or a very small amount) AEI across the landscape, while a combination of low decay value (0.001) and low IA (0.005) may turn all non-clearcut areas into AEI (Table 2).

Fig. 7. Area (percentage of the entire study area) of major land cover types within a controlled landscape, buffered landscape, and D-AEI simulated landscapes (K = 0.025, and IA values varied from 0.1 to 0.001). Significant differences were observed both statistically and spatially.
realistic and a significant improvement over results obtained from the traditional methods.

Edge effects of variables with small DEI (e.g. radiation) values could not be detected using our original input data (30-m pixel resolution) and a decay value of 0.5 (Fig. 6), probably because the effects existed only within several meters. To simulate the edge effects of such variables we made a subset of the original input and rescaled it to 1-m pixel resolution. Results suggested that the edge effects of radiation can reach a distance of 3 m into interior forest when an IA value of 0.1 was used. The distance increased to 12–13 m with an IA value of 0.001. During these simulations, a constant decay value of 0.5 was used, while IA values varied from 0.1–0.001 (Fig. 8).

4. Discussion

The D-AEI model developed in this study includes several critical features that are lacking in traditional approaches in evaluating edge effects for research and management purposes. First, the degree of edge effect, i.e. the rapidity and magnitude of change from the edge into the interior area, is based on edge contrast between two distinct communities. This is critically important because edge effects between a fresh clearcut and tall forest may be significantly different from those between a clearcut and young stand (Chen et al., 1992). In addition, the inclusion of edge contrast in studying edge effects provides further opportunities to understand the importance of different edge types (e.g. old-field edges, partial cut-forest edges), edge dynamics (i.e. sealing process of an edge, Oliver and Larson (1990)), and alternative silvicultural treatments. We used tree height in this study to determine edge contrast; yet it can be defined using any other relevant variable (e.g. stand density, age, leaf area index, productivity, or other measurements) that coincides with the study objectives. Finally, although the model is originally designed to simulate edge effects from clearcuts into forests, it can also be used for other research purposes such as detecting edge effects caused by roads, power lines, streams (i.e. delineating riparian zones) at small scales, and delineating ecotones at broader spatial scales if adequate information for quantifying edge effects is available.

Another strength of the D-AEI model is its scale-free property. The model operates on spatial data with any given resolution and, thus, the depth of edge influences for different variables can be accurately calculated by selecting a suitable grain size. This is essential for practical and meaningful predictions of edge effects in a landscape, because DEI values vary greatly among ecological variables. For example, DEI for solar radiation is only several meters and cannot be identified when the grain size is 30 m. Meanwhile, there is less need to use a high-resolution input to delineate edge effects for wind speed or bird communities, which can extend several kilometers (Chen et al., 1996), especially when a large landscape is analyzed. Finally, this flexible requirement for grain size allows us to use readily available databases (such as Landsat TM or AVHHR data), in which the resolution is pre-determined.

The D-AEI model was designed to simulate edge effects for any variable by changing two parameters of an exponential model: the $K$ and $IA$ values. Selection of these two parameters can be based on previously reported values, or they can be estimated using field data. Comparisons made using different $K$ and $IA$ values can assist researchers and managers to perform sensitivity analysis of the edge effects for different interspersion processes during fragmentation. Thus, the model can be used as a decision-making tool when alternative landscape mosaics are created through different management scenarios.

Satellite data were used for model development in this study but they are not the only source of input for model simulation. Data from existing maps or field inventories at different scales can also be used as model input. Simulated output from the model can easily be converted to other formats such as Arc/Info grid, Imagine image, and postscript files.

Two limitations of the model developed include: (1) lack of control in temporal dynamics since edge effects across a landscape at one time
Fig. 8. Simulated edge effects of radiation in the study area using 1-m resolution input. The depth of edge influence (DEI) was 2–3 m when IA = 0.1. The DEI increased to 11–12 m when IA = 0.001. In all cases, the K value was set to 0.5.
maybe different from that at another time of the day (or year); (2) the current D-AEI can only simulate the edge effects from one type (e.g. clearcuts, or non-forest) to other types (or forest) at one time. Future improvement of the D-AEI model needs to be expanded to include edge effects between any two different communities. Despite these limitations the model can be used to estimate multiple edge effects including consideration of edge orientation and contrast, and to assess different spatial patterns of the landscape for any variable of interest. Proper use of the model will provide more realistic delineation of AEI in fragmented landscapes for both research purposes and development of management plans.

Linkages between the D-AEI model and other landscape models (e.g. Li et al. (1993), Gustafson and Crow (1996), Mladenoff et al. (1996)) can readily be made to further explore and enhance our current efforts to understand pattern–process relationships and future management of the landscape. For example, a timber harvest allocation model (HARVEST) was developed to predict the potential effects of different arrangements of harvesting units in the landscape on forest interior environment (Gustafson and Crow, 1994, 1996). Using a constant IA value the authors demonstrated that the core area (i.e. interior forest) differed significantly when different allocation scenarios were applied. Linking D-AEI to HARVEST would not only allow us to produce asymmetric core areas, but also address the importance of multiple edge effects during fragmentation. As another example LANDIS was developed to simulate the effects of disturbance and stand change on overall landscape dynamics (Mladenoff et al., 1996). The model predicts different patterns of seed dispersal, species establishment, and shade tolerance across a landscape. Linkages with D-AEI would help us to understand the importance of AEI as an independent landscape element and its role in the overall landscape mosaic. Thus, D-AEI provides a new perspective for revisiting our understanding of landscape structure, landscape pattern, and spatial heterogeneity (Li and Reynolds, 1995) both in theory and practice.

5. Conclusions

D-AEI examines edge effects across an entire landscape with more realistic output of understanding edge effects than those provided by traditional approaches. The model incorporates edge orientation, edge contrast, prevailing direction of edge influences, decay value, and other parameters that are critical in controlling edge effects at the landscape level, while preserving several traditional characteristics of landscape structure such as patch size, shape, and spatial arrangement. These improvements may significantly strengthen edge related studies and analyses. The model offers a new tool for various ecological studies involving landscape analysis, particularly in regional resource assessment, biological conservation, and biodiversity research at landscape or broader scales. The model is quite genetic and can be incorporated into other more comprehensive ecosystem models.

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