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Quantifying distance of edge influence: a comparison of methods and a new randomization method

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Abstract. Despite many studies on edge influence in forests, there is no common method for estimating distance of edge influence (DEI, = edge width). We introduce a new randomization method (RTEI) for estimating DEI that tests the significance of edge influence compared to the reference forest. Using artificial datasets we compared DEI as estimated by nine different methods and examined effects of sampling design and the nature of the edge response. DEI estimates varied widely among methods; parametric, randomization and curve-fitting analyses produced the lowest, intermediate and greatest values, respectively. Sampling design and the nature of the edge response affected estimates of DEI differently among methods. RTEI was the only method that was generally invariable to sampling design while being sensitive to variation in the reference ecosystem but not at the edge. A standard method of quantifying DEI is important for comparing edge responses among different studies for conservation research.

Key words: artificial data; curve-fitting; distance of edge influence; edges; nature of the edge response; piecewise regression; randomization test; sampling design.

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Introduction

The prevalence and ecological importance of edges (the interface between different ecosystem types) in forested landscapes is widely acknowledged (Harper et al. 2005). Negative consequences, such as forest degradation and the loss of biodiversity in fragmented landscapes, have led to much interest in edges in landscape ecology and conservation biology. However, at present there is no universally accepted method for quantifying the distance of edge influence (DEI), which is defined as the distance from the edge towards the interior forest over which a given variable is found to be significantly different from the interior forest. There is wide variation in reported DEI. For example, DEI values greater than 100 m have been reported in several studies (e.g., Laurance et al. 1998, Chen et al. 1992), while others have found that DEI is less than 15 m for similar response variables in the same ecosystems (e.g., Williams-Linera 1990, Nelson and Halpern 2005). Although DEI is expected to vary among response variables and forest types, the method used for the statistical quantification of DEI may also contribute to this variation. The effect of the method of analysis on DEI has rarely been considered. To our knowledge, there are no published studies that have compared different methods for measuring the statistical or ecological significance of edge influence. Quantification of DEI is important for comparing edge influence for different response variables and among studies in order to understand the ecological importance of edge influence.

The distance of edge influence, also known as edge width, has been estimated using many different analytical methods that can be summarized into four groups: parametric, non-parametric, curve-fitting and randomization. Parametric statistical analyses include analysis of variance (ANOVA) in which distance is the independent variable and post hoc comparisons are used to determine the set of distances that are significantly different from the reference or interior forest (distances furthest away from the edge) (Wales 1972, Ferreira and Laurance 1997, Gelhausen et al. 2000, Oosterhoorn and Kappelle 2000, MacQuarrie and Lacroix 2003). The other commonly-used parametric analysis involves paired t-tests between different distances from the edge (Brothers 1993, Oliveira et al. 2004). Since parametric tests require assumptions that may not be met by ecological data, other researchers have used non-parametric equivalents to these tests including Kruskal-Wallis followed by Dunn's post-hoc test (MacQuarrie and Lacroix 2003) or by modal distance (Matlack 1994), and Wilcoxon Rank Sum tests (Brothers 1993, Euskirchen et al. 2001). For curve-fitting techniques, curves describing an exponential rise or fall to an asymptote (which is equivalent to the reference or interior forest) are usually fit to the data and the DEI is then defined as the distance at which the curve reaches 2/3 of the difference between the edge and the interior (Chen et al. 1992) or where the curve intersects the 95% confidence interval of the interior forest asymptote (Laurance et al. 1998). Williams-Linera (1990) and Toms and Lesperance (2003) used piecewise linear regression and defined the DEI as the breakpoint in the curve. Randomization tests are becoming increasingly popular for different types of spatial analyses (e.g., Perry and Dixon 2002, Fagan et al. 2003, Lichstein 2007). A randomization technique used for estimating the DEI, the critical values approach (Harper and Macdonald 2001), considered the confidence interval (critical values) of interior forest values determined using randomization. It is unclear how the differences among analytical approaches affect the estimation of DEI. In order to compare ecological responses at edges among different studies, forest types or response variables, it is imperative to understand how the method of analysis affects the estimation of DEI.

We developed an analytical approach to estimate DEI that incorporates quantification of the inherent variability for a given distance from the edge and in reference or interior forest. We then compared this method to others using artificial datasets. Our objectives were to introduce a new randomization method to estimate DEI and to compare different methodological approaches to estimating DEI as affected by variation in sampling design and the nature of the edge response (direction and shape of the response with distances from the edge).

Methods

Our proposed new method for estimating distance of edge influence (DEI), the randomization test of edge influence (RTEI), is a modification of our previous Critical Values Approach (Harper and Macdonald 2001). The RTEI method includes randomization of the values at the edge as well as the values in the reference ecosystem (e.g., interior forest). This method can be used for sampling designs that include plots in the reference ecosystem that are either associated with or independent from plots at or near the edge (blocking vs. no blocking). We then compare the RTEI method with other common methods from the literature. For this, we constructed 102 artificial data sets in which we varied aspects of the sampling design and characteristics of the edge-to-interior transition. We analyzed these artificial data sets using nine different analytical methods and compared the resulting DEI values.

Description of the RTEI method

The conceptual basis for the RTEI method is to test the significance of the magnitude of edge influence (MEI) for different distances from the edge using randomization tests of the data at a given distance from the edge and in the reference (i.e., 'interior') forest. We use a standardized form of MEI (Harper et al. 2005):

$$MEI = \frac{\bar{e} - \bar{r}}{\bar{e} + \bar{r}} \quad (1)$$

where $\bar{e}$ is the average of the response variable at a given distance from the edge and $\bar{r}$ is the average of the reference data set. MEI varies between -1 and $+1$ and MEI is 0 when the average value at the edge is identical to the average value in the reference area. MEI has the advantage that it standardizes edge influence across variables with widely varying scales of measurement. Following testing of MEI at each distance from the edge, we then estimate DEI as the set of distances over which MEI is significantly different than zero.

A key component of our method is the designation of a reference system, which researchers can choose based on their question of interest. For example, forest structure at lakeshore edges could be compared to the adjacent interior riparian forest or to the more distant upland interior forest (Harper and Macdonald 2001). Although it may be difficult to predict a priori whether or not reference plots are influenced by edges, researchers could select possibilities based on results of similar studies and knowledge of the ecosystem. Site availability limitations may also mean that the reference system is not entirely unaffected by edge influence.

The RTEI method is appropriate for a sampling design that consists of edge ('treatment') data collected at different distances from the edge along multiple replicate transects established perpendicular to edges (the 'edge treatment' data) along with data collected within the designated reference system. When the data collection sites in the reference forest are spatially paired with each edge transect, the RTEI method with blocking should be used. Blocking is most commonly done by having the reference data collected along the same transects as the edge data but at distances far enough from the edge to be considered the reference 'interior' condition. Alternatively, an unblocked design might be used in which reference data are collected at a variety of locations in the reference ecosystem without any particular spatial association with the edge transects.

Use of the RTEI method was first introduced in Mascarúa-López et al. (2006) as an updated version of the critical values approach (CVA, Harper and Macdonald 2001, 2002). The CVA method compared the mean value at the edge to critical values based on randomization of reference data; however, this method does not account for the range of variation among sample locations at a given distance from the edge and in some instances might lead to Type I error. The RTEI method compares the mean difference between reference values and values at a given distance from the edge to a distribution of differences created by randomizing the entire data set (reference values and values for a given distance from the edge). The null hypothesis is that MEI is 0, i.e., there is no difference in the value of a response variable between a given distance from the edge and the reference forest.

The RTEI analysis is done separately for each response variable and for each distance d from the edge. The sampling design is x sample points at distance d from the edge and y reference sample points; x is usually the number of transects perpendicular to the edge. When there is blocking, we consider z as the number of reference sample points for each transect ($y = x \times z$). The RTEI method proceeds as follows:

1. Calculation of the observed magnitude of edge influence: Calculate observed MEI at distance d using the samples for the edge and for the reference forest (Observed MEI).
2. Calculation of randomized MEI:

   a. Without blocking: Create a data set that includes all edge data at distance d and all reference data for a total sample size of $x + y$. Randomly select x values from the entire data set. Calculate MEI using these x values as the 'edge' sample and the remaining y values as the 'reference' sample (Randomized MEI). This is equivalent to randomly rearranging your sample points on the landscape (x of the possible $x + y$ sample points randomly become the "edge" sample).
   b. With blocking: Create a data set for each transect that includes the edge sample point at distance d and all reference sample points for that transect for a total of $1 + z$ sample points, then randomly select one of these to be the 'edge' sample point. Calculate MEI (Randomized MEI) using the randomly selected 'edge' sample points from each transect as the 'edge'

sample with the remaining sample points as the 'reference' sample. This is equivalent to randomly rearranging your sample points within a transect (one of the $1 + z$ possible sample points from each transect becomes the "edge" sample point). Because randomization is done within each transect (block), the transect is the experimental unit. Thus multiple sample points in the 'reference' forest for a given transect are effectively dealt with as subsamples.

3. Repeat step 2 many times. We use 5000 permutations which is the recommended minimum number for randomization tests at a significance level of 1% (Crowley 1992). This creates a distribution of 5000 Randomized MEIs.
4. Determine the percentile of the Observed MEI within the distribution of the Randomized MEIs. The p-value is equal to this percentile for a one-tailed test, or to two times this percentile for a two-tailed test.
5. If the p-value is lower than the pre-defined significant level (α), then reject the null hypothesis and conclude that MEI is significantly different than zero at distance d (i.e., the population mean value of the response variable at distance d from the edge is significantly different than the population mean value in the reference system).

The steps are repeated for the other distances from the edge. DEI is then estimated as the set of distances over which MEI is significant.

We recommend using exact permutation (all possible permutations) when the sample size is low such that the maximum possible number of permutations is less than the number desired. The maximum number of permutations with no blocking is $(x + y)!/(x!y!)$ and with blocking is $(1 + z)^x$. In this case, for steps 2 and 3 above, all possible combinations of x and y sample points from the entire data set (step 2a) or of $1 + z$ sample points from each transect (step 2b) are used to construct the distribution of randomized MEIs.

Comparison of DEI methods using artificial data sets

Artificial data sets were constructed to compare values of DEI as estimated using RTEI and other common methods. The sampling design was a blocked design that could be analyzed using any of the methods and which consisted of values at different distances from the edge along transects where distances equal to or greater than 100 m from the edge were assumed to be in the reference forest. We varied parameters of the sampling design including number of transects, edge distances and number of reference sample points per transect as well as the spacing of distances from the edge (Table 1; the artificial datasets are described in Appendix A). We also altered parameters that affect the nature of the edge response as follows: positive vs. negative edge influence; the pattern of response with distance from the edge (linear, non-monotonic, abrupt, exponential rise to a maximum for negative edge influence or exponential decay to a minimum for positive edge influence); the variation among replicate edge sample points at a given distance from the edge; the variation among reference sample points within a transect; and the variation among transects for the reference sample points (average of the subsamples per transect when there were multiple reference sample points per transect). The mean value of the hypothetical variable was 50 in the reference area for all datasets and either 90 or 10 right at the edge (or at 20 m for the non-monotonic transition pattern) for positive and negative edge influence, respectively. While varying aspects of the sampling design options and edge characteristics one at a time, the following standards were most often used: positive edge influence with exponential decay to a minimum, 10 transects, 7 distances concentrated at the edge, 3 or 5 reference subsamples associated with each edge transect and moderate variation among transects for edge and reference sample points and among reference forest subsamples within a transect.

For comparison to the RTEI method (with and without blocking), we chose seven different published methods used to estimate DEI for vegetation data using one-dimensional data collected along transects for a total of nine types of analysis. Although the artificial data sets

Table 1. Description and options for parameters of the sampling design and the nature of the edge response that were varied in the artificial data sets used in the study.

Parameters	Description	Options
Sampling design		
No. transects	No. transects perpendicular to the edge	3, 5, 7, 10, 15, 20
No. edge distances	No. distances from the edge sampled along each transect	1, 3, 5, 7, 10
Distance spacing	Spacing of distances from the edge sampled along each transect	equal, concentrated at edge, gap in middle*
No. reference subsamples	No. subsamples per transect in the reference forest†	1, 3, 5
Nature of the edge response		
Type of edge influence	Direction of magnitude of edge influence	positive, negative
Transition pattern	Pattern of the trend along the edge-to-reference gradient	linear, non-monotonic, abrupt, exponential‡
Edge variation	Variation among transects at each distance from the edge	none, moderate, high§
Subsample reference variation	Variation among subsamples in the reference forest for each transect	none, moderate, high§
Sample reference variation	Variation among transects in the reference forest values (mean of the subsamples)	none, moderate, high§

Note: Details for each of the 102 artificial datasets are in Appendix A.

*Distances are concentrated at and away from the edge, the gap consists of no distances sampled between 20 and 50 m.

†These would be located along the same transects as the edge samples for a blocked design, but could be anywhere if there is no blocking.

‡Linear: gradient from a hypothetical value of 90 at 0 m to a value of 50 at 60 m then level at 50 thereafter; non-monotonic: value of 60 at 0 m, linear increase to a maximum value of 90 at 20 m, then linear decline to 50 at 60 m then level at 50; abrupt: value of 90 from 0 m to 30 m then immediate change to a value of 50 and level at 50 thereafter; exponential: exponential decay for positive edge influence: $y = 50 + 40e^{-0.05x}$, exponential rise to maximum for negative edge influence: $y = 10 + 40(1 - e^{-0.05x})$, for both reaching 95% of difference between edge and reference at 60 m; always the mirror image for negative edge influence.

§None: all values the same, moderate: coefficient of variation = 25, high: coefficient of variation = 50.

followed a blocked sampling design we analyzed them with RTEI both with and without blocking to determine if including blocking in the analysis affects the results. Three analyses use randomization tests: (1) RTEI with blocking, (2) RTEI without blocking and (3) CVA (described above, Harper and Macdonald 2001). We wrote an Add-In in Excel using VisualBasic to conduct the analyses for RTEI. We used the program in Harper and Macdonald (2001) for CVA. For all randomization methods we used 5000 permutations. We also included two analyses based on parametric tests: (4) ANOVA with post hoc Tukey comparisons (Wales 1972, Ferreira and Laurance 1997, Oosterhoorn and Kappelle 2000, MacQuarrie and Lacroix 2003); and (5) paired t-tests in which each value at a given distance from the edge was compared with the average of reference values paired along the same transect (Brothers 1993, Oliveira et al. 2004). For the ANOVA, distance was the independent variable and reference subsamples were considered those to be at distances of 100 m or greater from the edge; we determined edge influence to be significant for a given distance if the sample of values at that distance was significantly different from more than half of the reference distances. (6) Wilcoxon Rank Sum tests were also conducted in which each value at a given distance from the edge was paired with the average of reference values for the same transect (Brothers 1993, Euskirchen et al. 2001). Parametric and nonparametric analyses were conducted using SPSS 15.0 for Windows (SPSS Inc. 2006). The last three analyses were all curve-fitting techniques for which we used SigmaPlot version 10.0 (Systat Software Inc. 2006). For (7) piecewise regression (Williams-Linera 1990, Toms and Lesperance 2003), two and three-segment regressions were fit to the data; three-piece regression was used only if the addition of the third term was significant. DEI was considered to be the breakpoint between two pieces or a zone between two breakpoints in a three-piece regression. Exponential curves were used for (8) exponential 2/3 rule (Chen et al. 1992) in which DEI is the distance at which the value was 2/3 of the difference between the value right at the edge (0 m) and the value at the sampling distance furthest from the edge, and (9) exponential with CI intersection (Laurance et al. 1998), in which DEI is the distance at which the curve intersects the 95% CI of all the reference data. For these exponential curve-fitting methods, we attempted to fit three different curves to each data set:

$$y = y_0 + ae^{-bx} \qquad (2)$$

$$y = y_0/(1 + ae^{-bx}) \qquad (3)$$

$$y = y_0 + a(1 - e^{-bx}) \qquad (4)$$

where x is the distance from the edge, y is the response variable, y_0 is the intercept or fitted value at the edge and a and b are constants. All these equations result in an asymptote with infinite distance from the edge. We chose the curve with the highest R^2 value or Eq. 2 if there was a tie. A significance level of $\alpha = 0.05$ was used for all analyses.

Results

RTEI method

Estimates of DEI from the application of the RTEI method ranged from not significant to 60 m and varied with both sampling design and nature of the edge response (Appendix B). DEIs calculated using the blocking vs. no blocking RTEI method were usually the same or the estimate with blocking was sometimes slightly lower. Exact permutation was only appropriate (there were less than 5000 permutations possible) for eight data sets with the blocking method (data sets 15, 16, 29, 30, 43, 44, 57, 58) and three with the no blocking method (2, 3, 15). Usually (8 of 11 data sets) DEI estimates with exact permutation were slightly lower than comparable results with 5000 randomized permutations.

Sampling design affected DEI estimates, including an apparent increase in DEI with the number of transects up to a threshold of about seven or ten transects (Fig. 1). The threshold number of transects was less when there were more reference subsamples (Fig. 1A) or when there was less variation among reference subsamples (Fig. 1B). When there was no variation among reference subsamples, DEI estimates were the same regardless of the number of transects for the blocked analysis method (Fig. 1B), but varied unpredictably with number of transects when the analysis method with no blocking was used (Fig. 1C). The DEI estimate decreased with the number of reference subsamples only when there were fewer than ten transects (Fig. 1A). The number of distances being sampled did not appear to affect the DEI estimate as long as the distances sampled extended beyond the DEI (Appendix B). Two distance spacings, equal and concentrated, yielded identical DEI estimates. However, when the spacing of distances included a gap in the middle of the transect the DEI

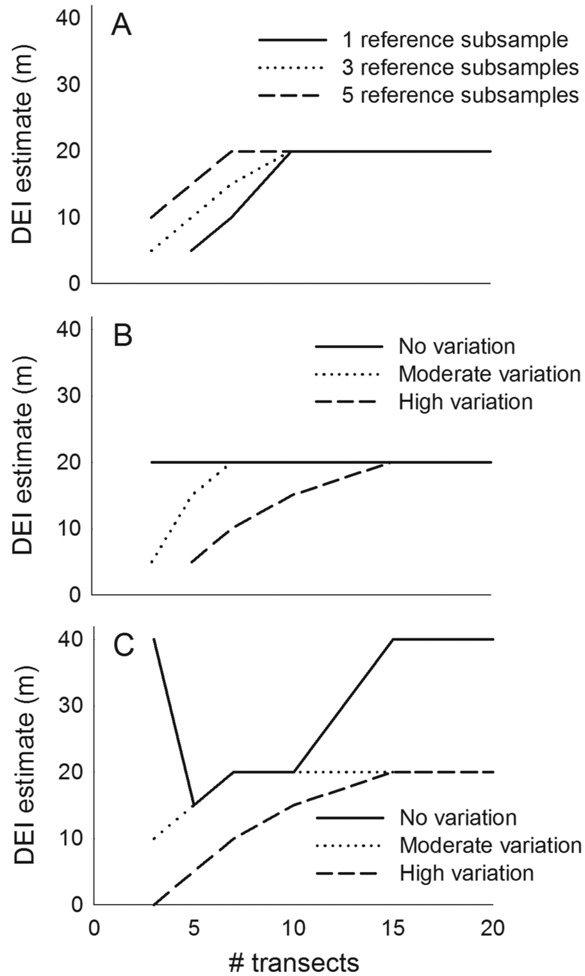

Fig. 1. Estimates of DEI using the RTEI method as a function of the number of transects for: (A) different numbers of reference subsamples per transect for RTEI with blocking, (B) different levels of variation among subsamples of the reference forest for RTEI with blocking and (C) different levels of subsample reference variation for RTEI with no blocking. All DEIs presented start at 0 m. In (A) there was no significant DEI when there was only one reference subsample and 3 transects. Comparable results for no blocking as for (A) were only slightly different and can be found in Appendix B.

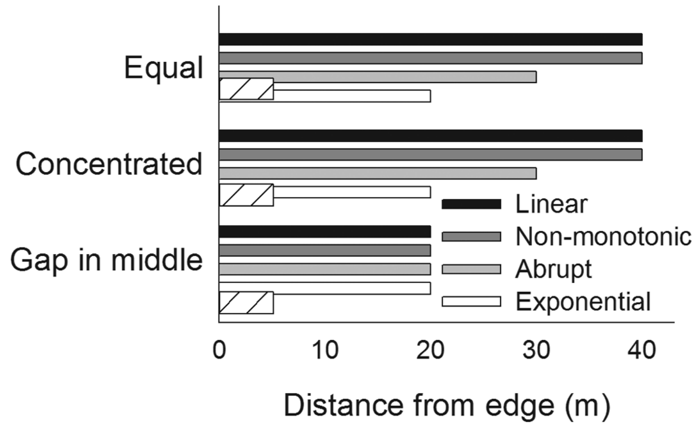

Fig. 2. Estimates of DEI using RTEI for different spacing of sample points along the transect (equal, concentrated and gap in middle) and for different transition patterns (linear, non-monotonic, abrupt, exponential). The hatched area indicates that DEI starts at 5 m rather than 0 m. Results were for the same for the RTEI method with blocking as for the method with no blocking except that the DEI estimate for non-monotonic for gap in middle for blocking started at 0 m rather than 5 m.

estimate was always 20 m regardless of the transition pattern (Fig. 2).

In terms of the nature of the edge response, positive vs. negative edge influence sometimes resulted in slightly different DEI estimates, usually for the non-monotonic transition pattern (Appendix B). For equal and concentrated sampling designs, non-monotonic and linear response patterns yielded the highest DEI estimates, followed by abrupt and then exponential. Estimates of DEI were influenced by the amount of variation among sample points at the edge and in the reference area (Fig. 3). With more edge variation among transects at a given edge distance, DEI estimates were generally lower, but only when variation among reference subsamples or among transects for the reference sample points was high or when there was no reference variation. Overall, higher variation among reference subsamples within a transect or transects for the reference sample points resulted in lower estimates of DEI. These trends were much more pronounced when there were fewer reference sample points (Appendix B).

Comparison of methods

In general the RTEI methods (blocked and unblocked) resulted in moderate to low estimates of DEI compared to other methods while the curve-fitting techniques resulted in the highest estimates of DEI (Table 2). The parametric and nonparametric methods tended to result in lower estimates of DEI than other methods. The DEI estimates produced by the CVA method were mostly intermediate in value. Estimates usually differed among methods by 30–60 m but the range was greater than 100 m for some data sets (Appendix B).

DEI estimates were greater for the RTEI method than for other methods when there was no variation at the edge or in the reference data but were relatively low when there was high subsample reference variation. The CVA method always resulted in the greatest estimates of DEI when there was no subsample reference variation. Most of the DEI estimates for the ANOVA method were the lowest. Paired t-tests were usually ranked low to intermediate with relatively high estimates when the edge response pattern was linear and there was equal spacing of relatively few edge distances. DEI estimates from Wilcoxon tests ranked similar to those for t-tests but with relatively high estimates when there were few edge distances or no variation among transects in the reference forest, and low estimates with variation among transects at the edge or in the reference forest. Both the piecewise regression and exponential CI methods had most DEI estimates ranked very high. The exponential 2/3 rule method gave slightly lower estimates of

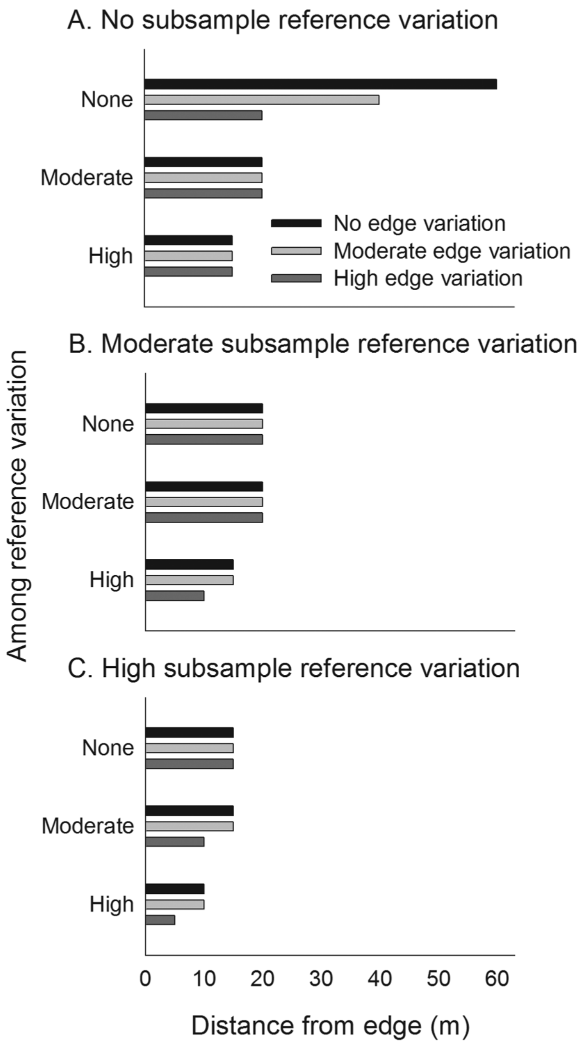

Fig. 3. Estimates of DEI using RTEI for different levels of sample reference variation and edge variation for (A) no, (B) moderate and (C) high subsample reference variation. Results are presented for the RTEI method with blocking, results for the no blocking method were only slightly different and can be found in Appendix B.

DEI than these two methods, with most rankings of intermediate to high. Many of the lower DEI estimates for these methods occurred when the transition pattern was linear with equal sampling distances.

Although the RTEI, CVA, Wilcoxon and exponential 2/3 rule methods worked well, we encountered some problems conducting the analyses for the other methods. Neither parametric method worked when there was no edge or sample reference variation. Following a significant ANOVA, the pairwise Tukey tests were sometimes not significant or they showed a significant difference between the edge and some reference distances (>100 m) but not others. For piecewise regressions, DEI estimates could not be provided for one dataset because there was no convergence; similarly many three-piece regressions did not converge. For some other datasets the breakpoints were not significant. Although exponential curves could always be fit, when there was no reference variation the CI was infinitely small and did not intersect the asymptotic exponential curve; in these cases there could be no defined DEI for the exponential CI method.

The methods behaved differently as we modified the parameters of the sampling design (Table 3). With an increasing number of transects, DEI increased to a threshold for some methods, but remained unchanged for others. Although DEI estimates were generally lower with one or three edge distances, DEI continued to increase with more edge distances only for the CVA method. Most methods exhibited little change in DEI estimates for different distance spacings, but the estimates for piecewise regression and the exponential CI methods were more variable with different distance spacings when there was a non-monotonic transition pattern. For the final sampling design parameter of the number of reference subsamples, DEI estimates were generally unaffected. However, DEI appeared to increase with more reference subsamples for the RTEI method when there was high edge variation and for the exponential CI method. DEI estimates were also more variable among analyses with different numbers of reference subsamples for ANOVA and piecewise regression when there was high or no sample reference variation, respectively. For CVA, DEI estimates were always greatest when there was only one reference sample point per transect.

The different methods were also influenced differently by varying the nature of the edge response. DEI estimates were generally similar for positive vs. negative edge influence for all methods except for the two exponential methods for which estimated DEI was sometimes very different (1–4 m compared with 39–76 m, Table 3). Estimated DEI varied with the transition pattern (shape) of the edge response with the

Table 2. Frequency distribution of ranks for DEI estimates for the 102 artificial datasets using different methods as well as the number of times the method produced a non-significant result (ns), was not applicable (N/A, DEI could not be estimated) or produced a DEI estimate that did not start at zero (other).

Rank	RTEI blocking	RTEI no blocking	CVA	ANOVA	Paired t-tests	Wilcoxon tests	Piecewise regression	Exp. 2/3 rule	Exp. CI
1	2	2	28	0	0	3	24	1	48
2	1	1	1	0	1	3	58	5	34
3	8	5	18	1	3	2	11	56	10
4	36	30	50	12	25	21	0	28	2
5	39	39	4	4	19	20	2	4	1
6	8	16	0	2	11	10	0	3	0
7	2	2	0	2	26	22	0	3	1
8	0	0	1	4	1	9	0	2	0
9	0	1	0	45	0	1	0	0	0
ns	2	1	0	21	1	4	4	0	0
N/A	0	0	0	5	5	0	1	0	6
other	4	5	0	6	10	7	2	0	0

Notes: DEI estimates were ranked from the highest with a rank of 1 to the lowest; ties were given the same rank. Values in the table are the number of artificial data sets for which a given method was given a specific rank. Exp. = exponential.

Table 3. Summary of how DEI estimates varied in relation to the different aspects of the sampling design and nature of the edge response, as determined by analysis of 102 artificial datasets by different methods.

Aspect	RTEI*	CVA	ANOVA	Paired t-tests	Wilcoxon tests	Piecewise regression	Exp. 2/3 rule	Exp. CI
Sampling design								
No. tr†	I ≤ 7 tr	N	I ≤ 15 tr	I ≤ 15 tr	I ≤ 15 tr	N	N	I
No. edge dist	L > 1 dist	I	L > 3 dist	L > 1 dist	L > 1 dist	L > 1 dist	L > 3 dist	L > 3 dist
Distance spacing	L	L	L	L	L	L but V for nm	L	L but V for nm
No. ref subsamples	N but I for high edge var‡	greater for 1	L but V for high sample ref var	N	N‡	L but V for no sample ref var	N	I
Nature of the edge response								
Type (−ve vs. +ve)	L	N‡	L‡	L	L	L	V	V
Transition pattern§	a < e < l = n	a = e < l = n	e < l < a = n	e < l < a = n	e < l = a < n	e < a < l < n	e < l < a < n	e < l < a < n
Edge var	N‡ but D for no ref var	N‡	D	D	D	N	N	L
Subsample ref var	D	D	V	N	N‡	L but I for no sample ref var	L	D‡
Sample ref var	D	N‡	D‡	D	D	V but N for no ss ref var	N but L for high ss ref var	D‡

Notes: We assessed trends in individual parameters while keeping other aspects of the sampling design and nature of the edge response constant. N = no change, I = increase, D = decrease, L = little change, V = variable; the latter two indicate change in no consistent direction, little change and variable indicate that the difference between estimates was less or more than the interval between sampled distances, respectively. See the Results and Table 1 for further information. Other abbreviations are as follows: dist = distances, exp. = exponential, ref = reference, sam = sample, ss = sub-sample, tr = transects, var = variation.

*Trends for the RTEI method with no blocking. These were usually the same as with blocking.

†Results presented for 5 reference subsamples and moderate subsample reference variation.

‡General trend that has one or two exceptions.

§Results presented for concentrated distance sampling; l = linear, n = non-monotonic, a = abrupt, e = exponential.

lowest values almost always for the exponential transition pattern and the highest values always for the non-monotonic pattern; results did not vary much among different methods.

DEI estimates were affected by the amount of variation among the edge and reference sample points and these effects differed among methods. Increasing variation among edge sample points had little or no change in DEI for the randomization methods and the curve-fitting methods (except for the RTEI method when there was no reference variation), but decreased DEI estimates for the parametric and non-parametric methods. Only the RTEI and exponential CI methods resulted in DEI estimates that decreased with variation among reference subsamples and among transects for the reference forest. Estimates produced by CVA decreased with greater variation among reference subsamples and those produced by the parametric and nonparametric methods decreased with greater variation among transects for the reference forest.

Discussion

The estimate of DEI can greatly depend on the method of analysis. Different methods for estimating DEI produced very different results for the same data; estimates were highest for curve-fitting methods, lowest for parametric and non-parametric methods and intermediate for randomization methods. This is consistent with results found by Harper et al. (2005) with the largest DEI estimates produced by the exponential CI (Laurance et al. 1998) or a similar method (Burton 2002) and some of the smallest estimates determined using CVA (Harper and Macdonald 2002), ANOVA (Burke and Nol 1998, Sizer and Tanner 1999, Rheault et al. 2003) or Wilcoxon tests (Euskirchen et al. 2001). Overall, our results suggest that some of the differences in DEI among studies may actually be due to the method of analysis; however, regional differences and differences in edge characteristics are obviously also contributing factors.

An ideal method for assessing edge influence should provide consistent DEI estimates for different sampling approaches but reflect differences in the nature of the edge response. RTEI and the exponential 2/3 rule method produced the most consistent DEI estimates with variable sampling designs with at least 7 transects (with moderate subsample reference variation) and 3 edge distances. DEI estimates produced by other methods were directly related to the number of edge distances sampled, required at least 15 transects before DEI estimates stabilized, were highly variable for a non-monotonic transition pattern or increased with an increasing number of reference subsamples. Therefore, the results of DEI in studies that use these other methods depend on the sampling design. As for the nature of the edge response, DEI should ideally be consistent with different levels of edge variation but sensitive to reference variation since the significance of edge influence should be assessed within a context of inherent variation in the reference forest. Only RTEI and exponential CI followed this pattern most of the time.

Overall, RTEI was the only method for estimating DEI that was generally invariable with sampling design and was sensitive to reference variation but not edge variation. DEI estimates obtained using the RTEI method were relatively consistent as long as sampling included 7–15 or more edge transects (depending on the level of subsample reference variation, see Results) with sampling at 3 or more distances from the edge that extend beyond the expected DEI. However, one exception is that more reference subsamples seem to be needed if there is high edge variation. The only situation where DEI estimates produced by RTEI were not consistent with increasing edge variation was when there was no variation among transects for the reference forest or no variation among subsamples on a given reference transect, a very unlikely situation in field studies.

The RTEI method is very flexible and can be used for blocked or unblocked sampling designs and allows for the incorporation of any type of reference system desired. The RTEI method was also one of the methods able to detect a non-monotonic transition pattern by estimating a DEI that did not start at zero. Although not shown here, RTEI can also accommodate sampling across the edge into both adjacent ecosystems as advocated by Ewers and Didham (2006), and can be used to test the significance of edge influence in comparison with both adjacent ecosystems as references (Burley et al. 2010). We plan to expand the RTEI method into a suite of methods that will include different options such as comparing different edge types and responses at different times since edge creation and a test for the interaction of edge influence (Harper and Macdonald 2002, Harper et al. 2004, 2007).

The use of a standard method for quantifying DEI will allow for comparisons of DEI among response variables, ecosystems, edge types and studies. Quantification of DEI is important for understanding the ecological importance of edge influence; determining which response variables have higher or lower DEI could provide insight into processes at edges. Understanding the ecological effects of edges in different ecosystems will assist in determining which ones are more sensitive to edge creation and landscape fragmentation. In addition, a consistent method of estimating DEI is necessary for quantifying the area of edge influence for different regions and different scenarios of landscape pattern for conservation planning. The variation in DEI estimates due to the analysis has important implications for conservation. For example, the range of DEI estimates (15–67 m) from dataset 79 (which has moderate edge and reference variation) would result in an area unaffected by edge influence ranging from 76 to 95% for a circular 100 ha forest remnant (using the Core-Area Model, Laurance 1991) and a width of unaffected forest from 0 to 90 m for a 120 m wide corridor.

We advocate using our RTEI method as a standard method. We realize that the choice of method can also be personal preference or may depend on the specific objectives or sampling design. The parametric and nonparametric methods should only be used with at least 15 transects and caution should be used when comparing DEI estimates for data sets with different amounts of edge variation. We do not recommend using curve-fitting methods since DEI estimates are sensitive to either variation in the reference data or the sampling design. The large difference in DEI estimates for positive vs. negative edge influence for the exponential methods is also a concern. Without a common method for analysis, comparisons among different studies are inadvisable. At the very least, researchers should acknowledge that their choice of method is a factor affecting their estimate of DEI.

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Appendix A

Table A1. Description of the 102 artificial datasets including parameters for sampling design as explained in Table 1.

No.	No. transects	Distances from the edge*	No. reference subsamples†
1	3	0, 5, 10, 15, 20, 40, 60	1
2	5	0, 5, 10, 15, 20, 40, 60	1
3	7	0, 5, 10, 15, 20, 40, 60	1
4	10	0, 5, 10, 15, 20, 40, 60	1
5	15	0, 5, 10, 15, 20, 40, 60	1
6	20	0, 5, 10, 15, 20, 40, 60	1
7	10	0, 5, 10, 15, 20, 40, 60	1
8	10	0, 5, 10, 15, 20, 40, 60	1
9	10	0, 5, 10, 15, 20, 40, 60	1
10	10	0, 5, 10, 15, 20, 40, 60	1
11	10	0, 5, 10, 15, 20, 40, 60	1
12	10	0, 5, 10, 15, 20, 40, 60	1
13	10	0, 5, 10, 15, 20, 40, 60	1
14	10	0, 5, 10, 15, 20, 40, 60	1
15	3	0, 5, 10, 15, 20, 40, 60	3
16	5	0, 5, 10, 15, 20, 40, 60	3
17	7	0, 5, 10, 15, 20, 40, 60	3
18	10	0, 5, 10, 15, 20, 40, 60	3
19	15	0, 5, 10, 15, 20, 40, 60	3
20	20	0, 5, 10, 15, 20, 40, 60	3
21	10	0, 5, 10, 15, 20, 40, 60	3
22	10	0, 5, 10, 15, 20, 40, 60	3
23	10	0, 5, 10, 15, 20, 40, 60	3
24	10	0, 5, 10, 15, 20, 40, 60	3
25	10	0, 5, 10, 15, 20, 40, 60	3
26	10	0, 5, 10, 15, 20, 40, 60	3
27	10	0, 5, 10, 15, 20, 40, 60	3
28	10	0, 5, 10, 15, 20, 40, 60	3
29	3	0, 5, 10, 15, 20, 40, 60	5
30	5	0, 5, 10, 15, 20, 40, 60	5
31	7	0, 5, 10, 15, 20, 40, 60	5
32	10	0, 5, 10, 15, 20, 40, 60	5
33	15	0, 5, 10, 15, 20, 40, 60	5
34	20	0, 5, 10, 15, 20, 40, 60	5
35	10	0, 5, 10, 15, 20, 40, 60	5
36	10	0, 5, 10, 15, 20, 40, 60	5
37	10	0, 5, 10, 15, 20, 40, 60	5
38	10	0, 5, 10, 15, 20, 40, 60	5
39	10	0, 5, 10, 15, 20, 40, 60	5
40	10	0, 5, 10, 15, 20, 40, 60	5
41	10	0, 5, 10, 15, 20, 40, 60	5
42	10	0, 5, 10, 15, 20, 40, 60	5
43	3	0, 5, 10, 15, 20, 40, 60	5
44	5	0, 5, 10, 15, 20, 40, 60	5
45	7	0, 5, 10, 15, 20, 40, 60	5
46	10	0, 5, 10, 15, 20, 40, 60	5
47	15	0, 5, 10, 15, 20, 40, 60	5
48	20	0, 5, 10, 15, 20, 40, 60	5
49	10	0, 5, 10, 15, 20, 40, 60	5
50	10	0, 5, 10, 15, 20, 40, 60	5
51	10	0, 5, 10, 15, 20, 40, 60	5

Table A1. Continued.

No.	No. transects	Distances from the edge*	No. reference subsamples†
52	10	0, 5, 10, 15, 20, 40, 60	5
53	10	0, 5, 10, 15, 20, 40, 60	5
54	10	0, 5, 10, 15, 20, 40, 60	5
55	10	0, 5, 10, 15, 20, 40, 60	5
56	10	0, 5, 10, 15, 20, 40, 60	5
57	3	0, 5, 10, 15, 20, 40, 60	5
58	5	0, 5, 10, 15, 20, 40, 60	5
59	7	0, 5, 10, 15, 20, 40, 60	5
60	10	0, 5, 10, 15, 20, 40, 60	5
61	15	0, 5, 10, 15, 20, 40, 60	5
62	20	0, 5, 10, 15, 20, 40, 60	5
63	10	0, 5, 10, 15, 20, 40, 60	5
64	10	0, 5, 10, 15, 20, 40, 60	5
65	10	0, 5, 10, 15, 20, 40, 60	5
66	10	0, 5, 10, 15, 20, 40, 60	5
67	10	0, 5, 10, 15, 20, 40, 60	5
68	10	0, 5, 10, 15, 20, 40, 60	5
69	10	0, 5, 10, 15, 20, 40, 60	5
70	10	0, 5, 10, 15, 20, 40, 60	5
71	10	0	3
72	10	0, 33, 67	3
73	10	0, 20, 40, 60, 80	3
74	10	0, 15, 30, 45, 60, 75, 90	3
75	10	0, 10, 20, 30, 40, 50, 60, 70, 80, 90	3
76	10	0, 10, 20, 30, 40, 50, 60, 70, 80, 90	3
77	10	0, 10, 20, 30, 40, 50, 60, 70, 80, 90	3
78	10	0, 10, 20, 30, 40, 50, 60, 70, 80, 90	3
79	10	0, 5, 10, 15, 20, 30, 40, 50, 60, 80	3
80	10	0, 5, 10, 15, 20, 30, 40, 50, 60, 80	3
81	10	0, 5, 10, 15, 20, 30, 40, 50, 60, 80	3
82	10	0, 5, 10, 15, 20, 30, 40, 50, 60, 80	3
83	10	0, 5, 10, 15, 20, 50, 55, 60, 65, 70	3
84	10	0, 5, 10, 15, 20, 50, 55, 60, 65, 70	3
85	10	0, 5, 10, 15, 20, 50, 55, 60, 65, 70	3
86	10	0, 5, 10, 15, 20, 50, 55, 60, 65, 70	3
87	10	0	3
88	10	0, 33, 67	3
89	10	0, 20, 40, 60, 80	3
90	10	0, 15, 30, 45, 60, 75, 90	3
91	10	0, 10, 20, 30, 40, 50, 60, 70, 80, 90	3
92	10	0, 10, 20, 30, 40, 50, 60, 70, 80, 90	3
93	10	0, 10, 20, 30, 40, 50, 60, 70, 80, 90	3
94	10	0, 10, 20, 30, 40, 50, 60, 70, 80, 90	3
95	10	0, 5, 10, 15, 20, 30, 40, 50, 60, 80	3
96	10	0, 5, 10, 15, 20, 30, 40, 50, 60, 80	3
97	10	0, 5, 10, 15, 20, 30, 40, 50, 60, 80	3
98	10	0, 5, 10, 15, 20, 30, 40, 50, 60, 80	3
99	10	0, 5, 10, 15, 20, 50, 55, 60, 65, 70	3
100	10	0, 5, 10, 15, 20, 50, 55, 60, 65, 70	3
101	10	0, 5, 10, 15, 20, 50, 55, 60, 65, 70	3
102	10	0, 5, 10, 15, 20, 50, 55, 60, 65, 70	3

*Distances from the edge incorporates both the number of sample points along the transect and their spacing.

†For curve-fitting methods, these were located at 100 m from the edge for 1 distance, 100, 150 and 200 m from the edge for 3 distances and 100, 150, 200, 250 and 300 m from the edge for 5 distances.

Table A2. Description of the 102 artificial datasets including parameters for nature of the edge response as explained in Table 1.

No.	Type of edge influence	Transition pattern	Edge variation	Subsample reference variation	Sample reference variation
1	positive	exponential	moderate	none	moderate
2	positive	exponential	moderate	none	moderate
3	positive	exponential	moderate	none	moderate
4	positive	exponential	moderate	none	moderate
5	positive	exponential	moderate	none	moderate
6	positive	exponential	moderate	none	moderate
7	positive	exponential	none	none	none
8	positive	exponential	moderate	none	none
9	positive	exponential	high	none	none
10	positive	exponential	none	none	moderate
11	positive	exponential	high	none	moderate
12	positive	exponential	none	none	high
13	positive	exponential	moderate	none	high
14	positive	exponential	high	none	high
15	positive	exponential	moderate	moderate	moderate
16	positive	exponential	moderate	moderate	moderate
17	positive	exponential	moderate	moderate	moderate
18	positive	exponential	moderate	moderate	moderate
19	positive	exponential	moderate	moderate	moderate
20	positive	exponential	moderate	moderate	moderate
21	positive	exponential	none	moderate	none
22	positive	exponential	moderate	moderate	none
23	positive	exponential	high	moderate	none
24	positive	exponential	none	moderate	moderate
25	positive	exponential	high	moderate	moderate
26	positive	exponential	none	moderate	high
27	positive	exponential	moderate	moderate	high
28	positive	exponential	high	moderate	high
29	positive	exponential	moderate	none	moderate
30	positive	exponential	moderate	none	moderate
31	positive	exponential	moderate	none	moderate
32	positive	exponential	moderate	none	moderate
33	positive	exponential	moderate	none	moderate
34	positive	exponential	moderate	none	moderate
35	positive	exponential	none	none	none
36	positive	exponential	moderate	none	none
37	positive	exponential	high	none	none
38	positive	exponential	none	none	moderate
39	positive	exponential	high	none	moderate
40	positive	exponential	none	none	high
41	positive	exponential	moderate	none	high
42	positive	exponential	high	none	high
43	positive	exponential	moderate	moderate	moderate
44	positive	exponential	moderate	moderate	moderate
45	positive	exponential	moderate	moderate	moderate
46	positive	exponential	moderate	moderate	moderate
47	positive	exponential	moderate	moderate	moderate
48	positive	exponential	moderate	moderate	moderate
49	positive	exponential	none	moderate	none
50	positive	exponential	moderate	moderate	none
51	positive	exponential	high	moderate	none
52	positive	exponential	none	moderate	moderate
53	positive	exponential	high	moderate	moderate
54	positive	exponential	none	moderate	high
55	positive	exponential	moderate	moderate	high
56	positive	exponential	high	moderate	high
57	positive	exponential	moderate	high	moderate
58	positive	exponential	moderate	high	moderate
59	positive	exponential	moderate	high	moderate
60	positive	exponential	moderate	high	moderate
61	positive	exponential	moderate	high	moderate
62	positive	exponential	moderate	high	moderate
63	positive	exponential	none	high	none
64	positive	exponential	moderate	high	none
65	positive	exponential	high	high	none
66	positive	exponential	none	high	moderate

Table A2. Continued.

No.	Type of edge influence	Transition pattern	Edge variation	Subsample reference variation	Sample reference variation
67	positive	exponential	high	high	moderate
68	positive	exponential	none	high	high
69	positive	exponential	moderate	high	high
70	positive	exponential	high	high	high
71	positive	N/A	moderate	moderate	moderate
72	positive	linear	moderate	moderate	moderate
73	positive	linear	moderate	moderate	moderate
74	positive	linear	moderate	moderate	moderate
75	positive	linear	moderate	moderate	moderate
76	positive	exponential	moderate	moderate	moderate
77	positive	non-monotonic	moderate	moderate	moderate
78	positive	abrupt	moderate	moderate	moderate
79	positive	linear	moderate	moderate	moderate
80	positive	exponential	moderate	moderate	moderate
81	positive	non-monotonic	moderate	moderate	moderate
82	positive	abrupt	moderate	moderate	moderate
83	positive	linear	moderate	moderate	moderate
84	positive	exponential	moderate	moderate	moderate
85	positive	non-monotonic	moderate	moderate	moderate
86	positive	abrupt	moderate	moderate	moderate
87	negative	N/A	moderate	moderate	moderate
88	negative	linear	moderate	moderate	moderate
89	negative	linear	moderate	moderate	moderate
90	negative	linear	moderate	moderate	moderate
91	negative	linear	moderate	moderate	moderate
92	negative	exponential	moderate	moderate	moderate
93	negative	non-monotonic	moderate	moderate	moderate
94	negative	abrupt	moderate	moderate	moderate
95	negative	linear	moderate	moderate	moderate
96	negative	exponential	moderate	moderate	moderate
97	negative	non-monotonic	moderate	moderate	moderate
98	negative	abrupt	moderate	moderate	moderate
99	negative	linear	moderate	moderate	moderate
100	negative	exponential	moderate	moderate	moderate
101	negative	non-monotonic	moderate	moderate	moderate
102	negative	abrupt	moderate	moderate	moderate

Appendix B

Table B1. Estimated values for distance of edge influence (DEI in m from 0 m to the distance given, unless otherwise indicated) results analyzed by different methods for the 102 artificial datasets.

Data set	RTEI blocking	RTEI no blocking	Critical values approach	ANOVA	Paired t-tests	Wilcoxon tests	Piecewise regression	Exp. 2/3 rule	Exp. with CI
1	ns	ns	60	ns	40–40	ns	29	22	21
2	5	5	60	0	5	5	29	22	25
3	10	10	60	5	10	10	29	22	29
4	20	15	60	10	15	15	41	22	33
5	20	20	60	10	20	20	29	22	37
6	20	20	60	15	20	20	29	22	39
7	60	60	60	N/A	N/A	60	41	22	no CI
8	20	40	60	10	20	20	41	22	no CI
9	5	5	60	ns	5	5	ns	22	no CI
10	20	20	60	20	20	20	41	22	33
11	5	0	60	ns	5	0	ns	22	33
12	15	15	60	20	15	10	41	22	19
13	10	10	60	5	10	10	41	22	19
14	0	0	60	ns	0	0	ns	22	19
15	5	5–5	20	ns	40–40	ns	30	22	27
16	10	15	20	0	5	5	30	22	32
17	15	15	20	5	10	10	30	22	35
18	20	20	20	5	15	15	30	22	38
19	20	20	20	10	20	20	30	22	42
20	20	20	40	15	20	20	41	22	45
21	20	20	20	N/A	N/A	60	30	23	48
22	20	20	20	10	20	20	30	23	48
23	5	15	20	ns	5	5	30	23	48
24	20	20	20	20	20	20	30	22	38
25	15	15	20	ns	5	0	30	22	38
26	15	20	20	10	15	10	30	22	28
27	15	15	20	0	10	10	30	22	28
28	10	15	20	ns	0	0	30	22	28
29	20	40	60	ns	40–40	ns	N/A	22	40
30	20	15	60	0	5	5	42	22	43
31	20	20	60	5	10	10	42	22	46
32	20	20	60	10	15	15	42	22	49
33	20	40	60	10	20	20	42	22	53
34	20	40	60	15	20	20	42	22	56
35	60	60	60	N/A	N/A	60	42	22	no CI
36	40	40	60	10	20	20	42	22	no CI
37	20	20	60	ns	5	5	42	22	no CI
38	20	40	60	20	20	20	42	22	49
39	20	20	60	ns	5	0	42	22	49
40	15	20	60	5	15	10	42	22	36
41	15	20	60	0	10	10	42	22	36
42	15	20	60	ns	0	0	42	22	36
43	10	5	20	ns	40–40	ns	42	22	32
44	15	15	20	0	5	5	42	22	36
45	20	20	20	0	10	10	42	22	39
46	20	20	20	5	15	15	42	22	43
47	20	20	20	20	20	20	42	22	47
48	20	20	20	20	20	20	42	22	49
49	20	20	20	N/A	N/A	60	106	23	51
50	20	20	20	15	20	20	106	23	51
51	20	20	20	ns	5	5	106	23	51
52	20	20	20	20	20	20	42	22	43
53	20	15	20	ns	5	0	42	22	43
54	15	20	20	15	15	15	30	22	34
55	15	20	20	10	10	10	30	22	34
56	10	15	20	ns	0	0	30	22	34
57	0	ns	5	ns	40–40	ns	30	21	22
58	5	5	10	ns	5	5	30	21	26
59	10	10	15	0	10	10	30	21	30
60	15	15	20	0	15	15	30	21	33
61	20	20	20	5	20	20	30	22	38

Table B1. Continued.

Data set	RTEI blocking	RTEI no blocking	Critical values approach	ANOVA	Paired t-tests	Wilcoxon tests	Piecewise regression	Exp. 2/3 rule	Exp. with CI
62	20	20	20	10	20	20	42	22	41
63	15	15	20	N/A	N/A	60	127	23	38
64	15	15	20	10	20	20	127	23	38
65	15	15	20	ns	5	5	127	23	38
66	15	15	20	5	20	20	30	21	33
67	10	10	20	ns	5	0	30	21	33
68	10	10	15	0	15	10	42	22	28
69	10	10	15	0	10	10	42	22	28
70	20	20	20	ns	0	0	42	22	28
71	0	0	0	0	0	0	ns	1	2
72	33	33	33	0	33	33	66	1	4
73	40	40	40	20	40	20	60	37	64
74	30	30	45	15	30	30	60	38	64
75	40	40	50	20	40	30	60	39	63
76	20	20	30	0	10	10	41	22	44
77	5–40	5–40	50	20–30	10–40	10–40	20–60	76	81
78	30	30	30	30	30	30	54	43	66
79	40	40	50	15	40	30	60	39	67
80	20	20	30	5	15	15	34	22	44
81	5–40	5–40	50	15–30	5–40	5–40	90	88	102
82	30	30	30	30	30	30	55	43	71
83	20	20	50	15	20	20	60	34	58
84	20	20	20	5	15	15	29	22	44
85	20	5–20	50	15–20	5–20	5–20	73	65	76
86	20	20	20	20	20	20	56	38	62
87	0	0	0	0	0	0	107	42	76
88	33	33	33	33	33	33	59	39	67
89	40	40	40	20	20	20	60	39	65
90	20	30	45	30	30	30	60	39	65
91	40	40	50	30	40	40	60	39	64
92	20	20	30	10	20	20	41	22	44
93	10–40	50	50	10–40	10–40	10–40	20–60	78	81
94	30	30	30	30	30	30	54	43	66
95	40	40	50	30	40	40	60	40	67
96	20	20	30	15	20	20	34	22	44
97	5–40	40	40	5–40	5–40	5–40	82	148	127
98	30	30	30	30	40	30	55	45	71
99	20	20	50	20	20	20	60	35	59
100	20	20	20	15	20	20	29	22	44
101	5–20	50	50	5–20	5–20	5–20	73	70	77
102	20	20	15	20	15	20	56	39	62

Notes: See Table 1 and Appendix A for the description of the artificial datasets and the methods section for the description of the methods. ns = no distances significantly different from the reference; N/A = not applicable; exp. = exponential. DEI could not be calculated because the analysis did not work; see the text for details.