Effects of cost surface uncertainty on current density estimates from circuit theory

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Background Conservation practitioners are often interested in developing land use plans that increase landscape connectivity, which is defined as the degree to which the landscape facilitates or impedes movement among resource patches. Landscape connectivity is often estimated with a cost surface that indicates the varying costs experienced by an organism in moving across a landscape. True, or absolute costs are rarely known however, and therefore assigning costs to different landscape elements is often a challenge in creating cost surface maps. As such, we consider it important to understand the sensitivity of connectivity estimates to uncertainty in cost estimates. **Methods** We used simulated landscapes to test the sensitivity of current density estimates from circuit theory to varying relative cost values, fragmentation, and number of cost classes (i.e., thematic resolution). Current density is proportional to the probability of use during a random walk. Using Circuitscape software, we simulated electrical current between pairs of nodes to create current density maps. We then measured the correlation of the current density values across scenarios. **Results** In general, we found that cost values were highly correlated across scenarios with different cost weights (mean correlation ranged from 0.87 to 0.92). Changing the spatial configuration of landscape elements by varying the degree of fragmentation reduced correlation in current density across maps. We also found that correlations were more variable when the range of cost values in a map was high. **Discussion** The low sensitivity of current density estimates to relative costs weights suggests that the measure may be reliable for land use applications even when there is uncertainty about absolute cost values, provided that the user has the costs correctly ranked. This finding should facilitate the use of cost surfaces by conservation practitioners interested in estimating connectivity and planning linkages and corridors.

1 **Effects of cost surface uncertainty on current density**

2 **estimates from circuit theory**

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23 **Abstract**

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28 impedes movement among resource patches. Landscape connectivity is often estimated with a

29 cost surface that indicates the varying costs experienced by an organism in moving across a

30 landscape. True, or absolute costs are rarely known however, and therefore assigning costs to

31 different landscape elements is often a challenge in creating cost surface maps. As such, we

32 consider it important to understand the sensitivity of connectivity estimates to uncertainty in cost

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35 **Methods**

36 We used simulated landscapes to test the sensitivity of current density estimates from circuit

37 theory to varying relative cost values, fragmentation, and number of cost classes (i.e., thematic

38 resolution). Current density is proportional to the probability of use during a random walk. Using

39 Circuitscape software, we simulated electrical current between pairs of nodes to create current

40 density maps. We then measured the correlation of the current density values across scenarios.

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42 **Results**

43 In general, we found that cost values were highly correlated across scenarios with different cost

44 weights (mean correlation ranged from 0.87 to 0.92). Changing the spatial configuration of

45 landscape elements by varying the degree of fragmentation reduced correlation in current density

46 across maps. We also found that correlations were more variable when the range of cost values

47 in a map was high.

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49 **Discussion**

50 The low sensitivity of current density estimates to relative costweights suggests that the measure

51 may be reliable for land use applications even when there is uncertainty about absolute cost

52 values, provided that the user has the costs correctly ranked. This finding should facilitate the use

53 of cost surfaces by conservation practitioners interested in estimating connectivity and planning

54 linkages and corridors.

55

Introduction

57 Habitat loss and fragmentation can lead to increased extinction risk of populations by limiting

58 landscape connectivity, which is defined as the degree to which landscape structure facilitates or

59 impedes movement among resource patches (Taylor et al. 1993). Exploring the impacts of

60 changes in landscape connectivity is a significant conservation research focus, because

61 enhancements to connectivity have the potential to help mitigate extinction risk (Crooks et al.

62 2017). For example, the creation of a connected network of protected areas in India resulted in a

63 2385 km^2 increase of critical habitat for tigers (*Panthera tigris*) (Gubbi et al. 2015).

64   In recent years, evaluating landscape connectivity has often been done through the use of a

65 cost surface, which is a 2-dimensional depiction of a landscape where the landscape elements are

66 assigned relative costs that are meant to represent what organisms experience as they move

67 through the landscape (Koen et al. 2012). Typically, higher costs indicate higher risk, and

68 therefore lower probability of moving successfully through the element. Cost surfaces are

69 generally depicted as a raster of pixels, where each pixel is assigned a cost. Different movement

70 models, such as circuit theory or least cost path analysis (Adriaensen et al. 2003, McRae 2006),

71 are then used to estimate connectivity between locations based on the raster of cost values. Cost

72 assignment is often driven by species-specific considerations, because connectivity is generally a

73 species-specific construct (Taylor et al. 1993).

74   A challenge in developing accurate cost surfaces, and therefore in modelling connectivity, is

75 uncertainty in assigning costs to different landscape elements. True costs are rarely known, and

76 therefore a variety of methods are used to estimate them, including expert opinion, empirical

77   movement data, and gene flow (Spear et al. 2010, Koen et al. 2012). The accuracy of cost values

78   may be evaluated through comparison with field data (Cushman et al. 2006, Lee-Yaw et al.

79   2009), but even in such cases, it is often the relative, rather than absolute costs that are learned.

80   Given uncertainty in cost values, it seems important to understand the sensitivity of different

81   connectivity estimates to variations in the estimated costs (Adriaensen et al. 2003). For example,

82   Rayfield et al. (2009) found that the sensitivity of placing least-cost routes is positively related to

83   the amount of habitat fragmentation and inversely related to the hospitality of the matrix. Beier,

84   Majka, & Newell (2009) demonstrated that if a model has the correct rank order of costs, the

85   placement of a least-cost path is robust to uncertainty. They recommended that users undertake

86   sensitivity analyses when developing cost surfaces. Koen et al. (2012) showed that accumulated

87   cost of least-cost paths and effective resistance estimates from circuit theory (McRae et al. 2008)

88   are more sensitive to changes in cost surface than least-cost paths measured as Euclidean

89   distance. Most recently, Zeller et al. (2017) showed that current density measures from circuit

90   theory are sensitive to landscape definition, including spatial grain, thematic resolution, and the

91   number of geospatial layers. Varying these aspects of landscape definition can alter the spatial

92   pattern of current density.

93   Circuit theory is used to measure landscape connectivity via the analogous relationship

94   between electricity travelling through a circuit and a random walk (Doyle & Snell 1984). The

95   circuit theory model has increased in popularity in recent years, following the development of

96   the Circuitscape software package (McRae et al. 2008). Circuit theory differs from least-cost

97   path analysis in that multiple paths from a destination to a source are modeled rather than the

98   single, least-cost route, and the probability of moving through any pixel on a map is estimated.

99   This method may be preferable in cases where the assumption of travelling on the least-cost path

100   is difficult to meet (Adriaensen et al. 2003), such as animals requiring knowledge of the optimal

101   route (Marrotte & Bowman 2017). For example, gene flow is often modelled using circuit theory

102   (McRae & Beier 2007).

103   Circuit theory analyses provide two outputs of particular interest for connectivity studies.

104   The first output is effective resistance, which is a pairwise measure of cost distance between

105   nodes and is measured as the voltage induced by passing 1 amp current between nodes (Doyle &

106   Snell 1984, McRae et al. 2008). This is equivalent to commute time, or the expected time needed

107   to get from source to destination and back again. Effective resistance is often used to model

108   genetic connectivity between individuals or populations (e.g., McRae & Beier 2007, Lee-Yaw et

109   al. 2009, Spear et al. 2010), but is not a mappable quantity. The second output, current density, is

110   a localized measure of movement probability at a spatially-referenced point that can be

111   interpreted as the probability of a location being used during a random walk between a source

112   and destination node. Current density can be mapped and is thus particularly useful for

113   applications where mapped routes are of interest, such as in natural heritage planning (Koen et

114   al. 2014), modelling animal movement routes (Walpole et al. 2012, Marrotte et al. 2020), or

115   forecasting migration arising from shifts in climate (Lawler et al. 2013). Recently, Marrotte et al.

116   (2017) used current density to estimate at-site genetic connectivity of sampled nodes.

117   Multiple sources of uncertainty exist when developing a cost surface to estimate current

118   density, including uncertainty about relative cost weights of different landscape elements, and

119   the thematic resolution (i.e., number of classes) of the cost surface map. Uncertainty in assigning

120   costs has been identified as a difficult and often subjective problem in modeling connectivity

121   (Peterman 2018, Grafius et al. 2017, Etherington 2016). Variability in the relative cost weights

122   assigned to particular landscape elements might affect current density, and since absolute costs

123   are often unknown, the sensitivity of current density estimates to this variation is an important

124   consideration. If current density estimates are highly sensitive to such variation, then a priority

125   must be placed by users on accurate estimation of relative or absolute costs. On the other hand, if

126   current density is insensitive to variation in relative cost weights, then current estimates should

127   be robust to uncertainty. Beier, Majka, & Newell (2009) showed that, provided rank order is

128   correct, least-cost route placement will be correct, but we are unaware of similar analysis

129   evaluating current density. A contrast to the rank order of costs being correct occurs where the

130   spatial arrangement of costs is varied, while other aspects of the cost surface are maintained.

131   Varying spatial arrangement of costs can influence the placement of a least-cost route (Rayfield

132   et al. 2009), and we anticipate a similar effect for circuit theory analysis. There might also be an

133   influence of the range of relative cost weights on current density estimates. Beier et al. (2009)

134   referred to this concept as dispersed versus compressed cost values, finding that least-cost path

135   analysis was robust to this type of uncertainty. Finally, landscape definition, including spatial

136   and thematic resolution, and the number of geospatial data layers employed, can affect estimates

137   of current density. Zeller et al. (2017) found that varying these characteristics of landscape

138   models produced different estimates of where the highest current density pixels occurred.

139   We evaluated the effects of varying relative cost weights, the range of cost weights, the

140   spatial arrangement of cost classes, and thematic resolution on current density estimates from

141   circuit theory. We predicted that, as with least-cost paths (Beier et al. 2009), current density

142   would not be sensitive to relative cost weights or the range of cost weights provided that the rank

143   order of the costs was not changed. We further predicted that changing the spatial arrangement of

144   relative cost weights would affect current density. Finally, we predicted that current density

145   would not be sensitive to thematic resolution if the rank order of costs was maintained across

146   themes.

147

Materials & Methods

149   We generated cost surface maps to test the sensitivity of current density estimates to changing

150   cost values, range of cost values, varying spatial arrangement, and the number of cost classes (or

151   thematic resolution). We started with eight cost surfaces using values from Rayfield et al. (2009),

152   who selected cost scenarios that represented the range of values used in connectivity studies. We

153   generated eight cost surface scenarios, each with three levels (low, medium, and high cost; Table

154   1). We also generated two additional scenarios using alternative low-cost values (0.1, 10) that

155   were not used by Rayfield et al. (2009). For all simulated maps, we assigned 25% of cells low

156   cost values, 25% medium cost values, and 50% high cost values.

157   We first used these 10 cost scenarios to evaluate the effects of relative cost weight and the

158   range of cost weights on current density estimates. We did this at three different levels of

159   fragmentation, high, medium, and low (Fig. 1). In the highly fragmented treatment, each pixel

160   was randomly assigned to one of the three cost values. We produced 10 different high

161   fragmentation maps – one for each cost scenario. Medium fragmentation maps were produced by

162   placing 12 blocks of contiguous cost values within each map (10 maps in total), and low

163   fragmentation maps had 3 contiguous blocks (again, 10 maps in total) (Fig. 1). We used

164   Spearman rank correlations to compare current density values across all 10 cost scenarios within

165   fragmentation levels. As a contrast to varying the relative cost weights, we used the same 10

166   scenarios and 3 fragmentation levels to explore the effects of changing spatial arrangement of

167   cost classes on current density estimates. Changing spatial arrangement of costs is one form of

168   rearranging cost ranks, allowing us to compare different configurations of cost surfaces with the

169   same overall costs and proportions of classes (50% high, 25% medium, and 25% low). For this

170   analysis we used Spearman rank correlations to compare current density values between

171   fragmentation levels.

172   The range of cost values on a map might affect current density estimates by compressing

173   or dispersing the costs (Beier et al. 2009). If this is the case, the effects might be caused by the

174   high cost classes, since low costs are bounded by 0 in our design, and high costs have no such

175   bound (Koen et al. 2012). To test this idea, we evaluated the effect of the absolute value of the

176   difference in the range of costs between scenarios on the Spearman correlation between

177   scenarios for the simulated landscapes (Table 1). We also tested for a relationship between the

178   maximum current density from each scenario and the range of costs. We tested for this

179   relationship only within each fragmentation level (high, medium, and low).

180   We also sought to investigate our questions related to the effect of relative cost weights

181   and the range of cost weights on a real-world landscape, so we tested the effects of varying cost

182   weights on current density estimates in a 107-km² urban study area encompassing Oakville,

183   Ontario. The area was a highly fragmented urban landscape, consisting of 10% low, 14%

184   medium and 76% high cost values. Designation of cost values for the urban study area followed

185   the methodology of Bowman & Cordes (2015) using the Southern Ontario Land Resource

186   Information System (SOLRIS) database (Ontario Ministry of Natural Resources 2008). We

187   varied costs in the urban landscape using the same 10 cost structures employed in the simulated

188   landscapes, producing 10 different maps. The resolution of the map was 15 m.

189   We created an additional 20 simulated maps to test the effect of thematic resolution (3, 6, 12

190   cost classes per map) on current density (Fig. 2). We started with the low fragmentation scenario

191   with the 3 thematic categories that we had already created. To generate 6 cost categories, we

192   divided the original three cost values from the low fragmentation map into portions reflecting

193   45% and 55% of the costs per theme. These 6 subcategories were then divided by 48% and 52%

194   to further stratify the cost surface map into 12 cost categories (Table 2). These proportions were

195   selected to maintain the rank order of the original 3 class map, while also varying thematic

196   resolution. We then compared outputs across these 3 different scenarios (3, 6, or 12 categories).

197   All simulated maps were 140 x 140 cells, consisting of 100 x 100 cells with a 20-cell buffer,

198   to accommodate edge effects (Koen et al. 2010) on the nodes. Koen et al. (2014) showed that a

199   buffer equal to 20% of the width of the study area would largely remove the effect of node bias

200   in circuit analyses. The urban study area was comprised of 476,527 cells with an additional

201   726,423 cells to accommodate the required buffer equal to 20% the width of the area.

202   We used Circuitscape v4.0 (McRae et al. 2013) to construct a current density map by

203   simulating electrical current flow iterated between all pairs of nodes on a rasterized surface. We

204   connected the eight neighbouring cells as an average cost using the pairwise mode and extracted

205   the cumulative current density map. The current density within a pixel, as a result of simulated

206   electrical current flowing across the surface is proportional to the probability of animal

207   movement (McRae et al. 2008). To model omnidirectional movement in the simulated

208   landscapes, we distributed 20 nodes in equal numbers among four sides of the surface in the 20-

209   cell buffer, using the same stratified placement of nodes for all scenarios. Due to the increased

210   size and more complex shape of the Oakville study area, 100 nodes were distributed in a

211   stratified placement around the buffered cost surface. See Marrotte et al. (2017), Bowman &

212   Cordes (2015) and Koen et al. (2014) for additional descriptions of the point-based

213   omnidirectional methodology used.

214   We note that circuit theory users will most often be interested in relative, rather than

215   absolute differences in current density. In fact, current density outputs are often standardized for

216   ease of comparison across landscapes (e.g., Bowman and Cordes 2015). Therefore, our method

217   of comparing current density outputs was aimed at evaluating relative differences in the

218   distribution of current across maps. In ArcMap v10.5 (ESRI 2016), we produced a polygon over

219   the generated study area and randomly selected 1000 data points within this polygon. We then

220   measured the correlation of the current density values of these randomly selected data points

221   across all maps by creating a Spearman rank correlation coefficient matrix in R v3.4.1 (R Core

222   Team 2014). We compared the mean correlation coefficients and the range of correlations across

223   scenarios of interest.

224

225   **Results**

226   In our simulated landscapes, the three fragmentation levels had equivalent costs for any given

227   cost scenario, varying only in the spatial arrangement of these costs. Mean (range) current

228   density for each of the three levels was 1.36 amperes for high fragmentation (1.25 to 1.59; n = 10

229   scenarios), 1.37 amperes for medium fragmentation (1.27 to 1.49), and 1.0 ampere for low

230   fragmentation (0.54 to 1.25). The 6 and 12 class surfaces had mean values of 1.20 amperes (1.11

231   to 1.26) and 1.21 amperes (1.13 to 1.26), respectively. The urban landscape had a mean (range)

232   current density of 3.95 amperes (3.78 to 4.31; n = 10 scenarios).

233   We found that current density values were highly correlated within fragmentation levels

234   across cost scenarios (Table 1; Fig. 3). High, medium, and low fragmentation levels had mean

235   Spearman correlation coefficients (range) of 0.87 (0.65, 1.00), 0.90 (0.80, 1.00), and 0.90 (0.74,

236   1.00) (n = 45 comparisons for each analysis), respectively. Similarly, the urban study area (Fig.

237   4) had a mean Spearman correlation coefficient (range) of 0.85 (0.62, 1.00) (n = 45

238   comparisons).

239   When the rank order of costs was not maintained, by changing the spatial arrangement of

240   the costs, correlations were reduced. The correlation coefficients for comparisons between

241   fragmentation levels (range) were -0.03 (-0.17, 0.06) for the comparison of low and medium

242   fragmentation, -0.07 (-0.10, -0.04) for medium and high, and -0.02 (-0.12, 0.10) for low and high

243   levels of fragmentation (n = 100 for each comparison) (Fig 3).

244   In simulated landscapes, the correlation between current density values was affected by

245   the range of cost values (Fig. 5). In general, correlations were more variable when the range of

246   cost values was broader, although, correlations always exceeded R_S = 0.65. A broad range of

247   cost values occurred when the highest cost class was especially high, and this led to the

248   occurrence of especially high current density values (Fig. 6). Maximum current density in a

249   simulated landscape was correlated with cost range: R_S = 0.85, 0.80, and 0.57 for high, medium,

250   and low fragmentation levels, respectively (n = 10 for each comparison). High current density

251   was associated with especially high cost classes, leading to overall high variability in current

252   density, reducing correlations with other cost scenarios. Maximum current density in the urban

253   landscape was also correlated with cost range (R_S = 0.78, n = 10 scenarios; Fig. 6).

254   Within scenarios with 6 or 12 thematic classes, current density was highly correlated

255   across cost values: R_S (range) = 0.90 (0.74, 1.00) and 0.92 (0.80, 1.00), for 6 and 12 cost classes,

256   respectively (n = 45 comparisons for each analysis). Comparing scenarios with different thematic

257   resolution, the Spearman correlation coefficients (range) were 0.87 (0.69, 0.97) for 3 and 6

258   classes, 0.89 (0.75, 0.98) for 6 and 12, and 0.85 (0.71, 0.97) for 3 and 12 (n = 100 for each

259   analysis) (Fig. 7).

260 **Discussion**

261   We applied circuit theory to measure the sensitivity of current density estimates to varying cost

262   surfaces, including the relative cost weights, the range of cost weights, the spatial arrangement of

263   the classes throughout the landscape (fragmentation), and the number of classes (thematic

264   resolution). Given that the placement of least cost routes is robust to uncertainty in relative cost

265   weights and the range of costs (Beier, Majka, & Newell 2009), we suspected that varying cost

266   weights would not substantially alter current density patterns from circuit theory when relative

267   ranks of costs were held constant. For a given level of fragmentation, current density was highly

268   correlated across landscape models despite differences in cost values. Thus, relative current

269   density estimates were not sensitive to cost value. This was true both for simulated landscapes

270   and a real-world urban landscape. The range of cost values had some effect on current density

271   however, as there was an inverse relationship between the ranges of cost values in a landscape

272   and the amount of correlation in current density of landscapes. We did find that changing the

273   spatial arrangement of cost classes had a high impact on current density, as shown by the low

274   correlation between different levels of fragmentation in our maps. Current density is sensitive to

275   landscape configuration. However, high correlations between current density estimates arising

276   from scenarios with varying numbers of classes suggests that thematic resolution itself has little

277   impact on current density, provided that the rank order of the costs is maintained across themes.

278   Our finding of low sensitivity to varying relative cost weights in circuit theory concurs

279   with Beier et al. (2009)'s finding with least cost paths, in that provided the costs had a consistent

280   rank order, the current density maps were quite similar. This is a useful result, insofar as true

281   costs are often unknown by users (Grafius et al. 2017, Bishop-Taylor et al. 2015, Yumnam et al.

282   2014). Therefore, where users have insight about the relative costs of elements in the landscape,

283   current density outputs should be reliable. This is helpful for applications where current density

284   is employed in natural heritage planning or designing wildlife linkages (e.g., Marrotte et al.

285   2017, Bowman & Cordes 2015).

286   The range of cost values used in a map did affect the correlation between current density

287   values. As the range increased, current tended to be more highly pinched, whereas it spread more

288   as the range decreased (e.g., Fig. 3). This observation is further supported by the overall increase

289   in the variation of correlation results as the absolute cost value range increased (Fig. 5). The cost

290   range influenced current density through the effect of high cost weights. In our simulations, cost

291   was limited by 0 at the lower end, but was variable across scenarios at the upper end (e.g., Koen

292   et al. 2012). It was surfaces with the highest cost that also had the broadest range of costs (i.e. the

293   costs were more dispersed), and these surfaces produced higher current density values than

294   comparable surfaces with a narrower (i.e., compressed) cost ranges (Fig. 6). We are reminded

295   with this observation that high current density is a result of high cost weights (e.g., Marrotte et

296   al. 2017). Despite variation in current density values however, the Spearman correlations

297   between landscapes were always rather high within the fragmentation scenarios, such that there

298   was always agreement among maps, even where the range of cost values was high. The lowest

299   correlation between any pair of maps within fragmentation levels was $R_S = 0.65$.

300   Our findings also concur with those of Rayfield et al. (2009), who found that the location

301   of least-cost paths varied with fragmentation. In particular, they showed that routes were more

302   sensitive to higher amounts of fragmentation, or lower quality matrix. We found that altering the

303   configuration of the landscape, while holding overall costs constant, affected the distribution of

304   current density. We consider that the low correlation across fragmentation scenarios was due to

305   the changing spatial arrangement of landscape elements, which altered the location of low and

306 high cost routes. Changing the spatial arrangement served to change the rank order of the cost

307 categories, so this treatment served to show the effect of altering rank order.

308   We add to the work of Zeller et al. (2017), who found that current density estimates were

309 sensitive to landscape definition, which they varied by changing the data source, thematic

310 resolution, and spatial grain. We did not explore the effect of spatial grain in our study, but Koen

311 et al. (2019) have recently shown that reducing tile size can reduce accuracy of current density

312 maps compared to untiled maps of larger extent. Our findings suggest that current density

313 estimates are not particularly sensitive to thematic resolution, or relative cost weights, provided

314 that the rank order of the costs does not vary. Coarsening of thematic resolution reduces detail, as

315 similar categories are merged, but this can come with the potential benefit of increasing accuracy

316 of ranking cost weights of the categories. More categories likely lead to increased error in

317 ranking costs. Therefore, we recommend that users strike a balance between adequate detail and

318 accurately ranked costs.

319   Our results suggest that current density is an effective tool for conservation planning, as it

320 is robust to uncertainty in absolute cost values and sensitive to habitat fragmentation.

321 Fragmentation is an increasing conservation concern as the human footprint continues to expand;

322 a recent global analysis revealed animal movements are reduced by approximately 50% in areas

323 with a high human footprint (Tucker et al. 2018). Thus, understanding the movement of animals

324 in and across complex landscapes will be imperative for effective conservation of biodiversity in

325 the age of the Anthropocene. Our findings also suggest that when planning landscape

326 connectivity applications, managers and researchers should put more effort toward establishing

327 confidence in the rank order of costs, than reducing uncertainty in relative or absolute cost

328 weights.

329

Conclusions

331 We tested the hypothesis that current density estimates from circuit theory are not sensitive to

332 absolute values of underlying cost surfaces, provided that the rank order of the costs is accurate.

333 We compared a variety of cost surfaces with different costs, where rank order of costs was held

334 constant, and found a high correlation among resulting current density estimates. Our findings

335 suggest that knowledge of the absolute values of cost surfaces may not be required, provided that

336 rank orders of costs are known. This finding should facilitate the use of cost surfaces by

337 conservation practitioners interested in estimating connectivity and planning linkages and

338 corridors.

339

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343

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425

Cost scenarios used to compare across simulated and urban landscapes with 3 cost categories.

Table 1. Cost values assigned to each cost category (low, medium, high).

Scenario	Low	Medium	High	Range
C1	0.1	0.5	1	0.99
C2	1	1.5	2.25	1.25
C3	1	1.5	150	149
C4	1	2	3	2
C5	1	2	200	199
C6	1	5	7.5	6.5
C7	1	5	500	499
C8	1	100	150	149
C9	1	100	10 000	9 999
C10	10	100	1000	990

Cost scenarios used to compare across 6 and 12 category thematic resolutions while maintain rank order of costs in comparison to a 3 category cost surface.

Table 2. Cost values assigned to each category for thematic resolutions with 6 and 12 categories.

	Six categories						Twelve Categories											
	Lower		Medium		Higher		Lower				Medium				Higher			
C1	0.045	0.055	0.225	0.275	0.45	0.55	0.0216	0.0234	0.0264	0.0286	0.108	0.117	0.132	0.143	0.216	0.234	0.264	0.286
C2	0.45	0.55	0.675	0.825	1.0125	1.2375	0.216	0.234	0.264	0.286	0.324	0.351	0.396	0.429	0.486	0.5265	0.594	0.6435
C3	0.45	0.55	0.675	0.825	67.5	82.5	0.216	0.234	0.264	0.286	0.324	0.351	0.396	0.429	32.4	35.1	39.6	42.9
C4	0.45	0.55	0.9	1.1	1.35	1.65	0.216	0.234	0.264	0.286	0.432	0.468	0.528	0.572	0.648	0.702	0.792	0.858
C5	0.45	0.55	0.9	1.1	90	110	0.216	0.234	0.264	0.286	0.432	0.468	0.528	0.572	43.2	46.8	52.8	57.2
C6	0.45	0.55	2.25	2.75	3.375	4.125	0.216	0.234	0.264	0.286	1.08	1.17	1.32	1.43	1.62	1.755	1.98	2.145
C7	0.45	0.55	2.25	2.75	225	275	0.216	0.234	0.264	0.286	1.08	1.17	1.32	1.43	108	117	132	143
C8	0.45	0.55	45	55	67.5	82.5	0.216	0.234	0.264	0.286	21.6	23.4	26.4	28.6	32.4	35.1	39.6	42.9
C9	0.45	0.55	45	55	4500	5500	0.216	0.234	0.264	0.286	21.6	23.4	26.4	28.6	2160	2340	2640	2860
C10	4.5	5.5	45	55	450	550	2.16	2.34	2.64	2.86	21.6	23.4	26.4	28.6	216	234	264	286

Figure 1

Simulated cost surfaces with 3 levels of fragmentation.

Cost surfaces with 100 × 100 pixels and a 20-pixel buffer around the perimeter (140 × 140 cells total). All maps had a total ratio of 25% low cost (white), 25% medium cost (grey), and 50% high cost (black). Treatments included (A) High fragmentation (randomized), (B) Medium fragmentation, and (C) Low fragmentation. Each cell was assigned a weight corresponding to its cost. For each level of fragmentation, we generated 10 maps with varying cost weights.

A)

B)

C)
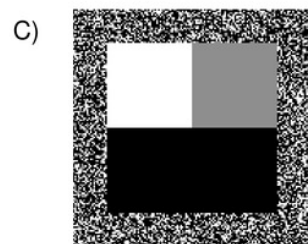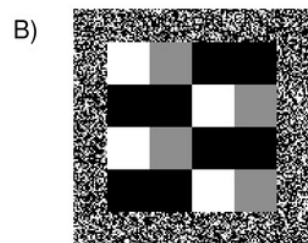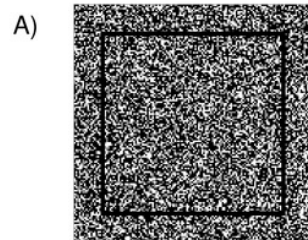
Figure 2

Simulated cost surfaces with varying thematic resolution (3, 6, and 12 categories).

Cost surfaces with 100 × 100 pixels and a 20-pixel buffer around the perimeter (140 × 140 cells total). All maps had a total ratio of 25% low cost (white), 25% medium cost (grey), and 50% high cost (black). Treatments included 3 levels of thematic resolution (A) 3 categories, (B) 6 categories, and (C) 12 categories. Each cell was assigned a weight corresponding to its cost. For each level of thematic resolution, we generated 10 maps with varying cost weights.

A)

B)

C)
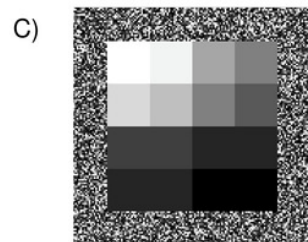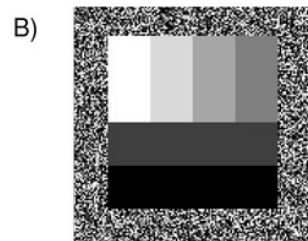
Figure 3

Example current density maps for cost surfaces at 3 levels of fragmentation.

Examples of current density maps at a resolution of 140 x 140 cells for landscapes with different fragmentation levels (high, medium, and low), different cost classes, and a 20-pixel buffer. Panels A, C and E had a costs of 7.5 (high), 5, and 1 (low), whereas B, D, and F had costs of 1000, 100, 10, respectively. Highest current density is indicated by red. Node locations are indicated by areas of high current density around perimeters, especially evident in panels A and F.
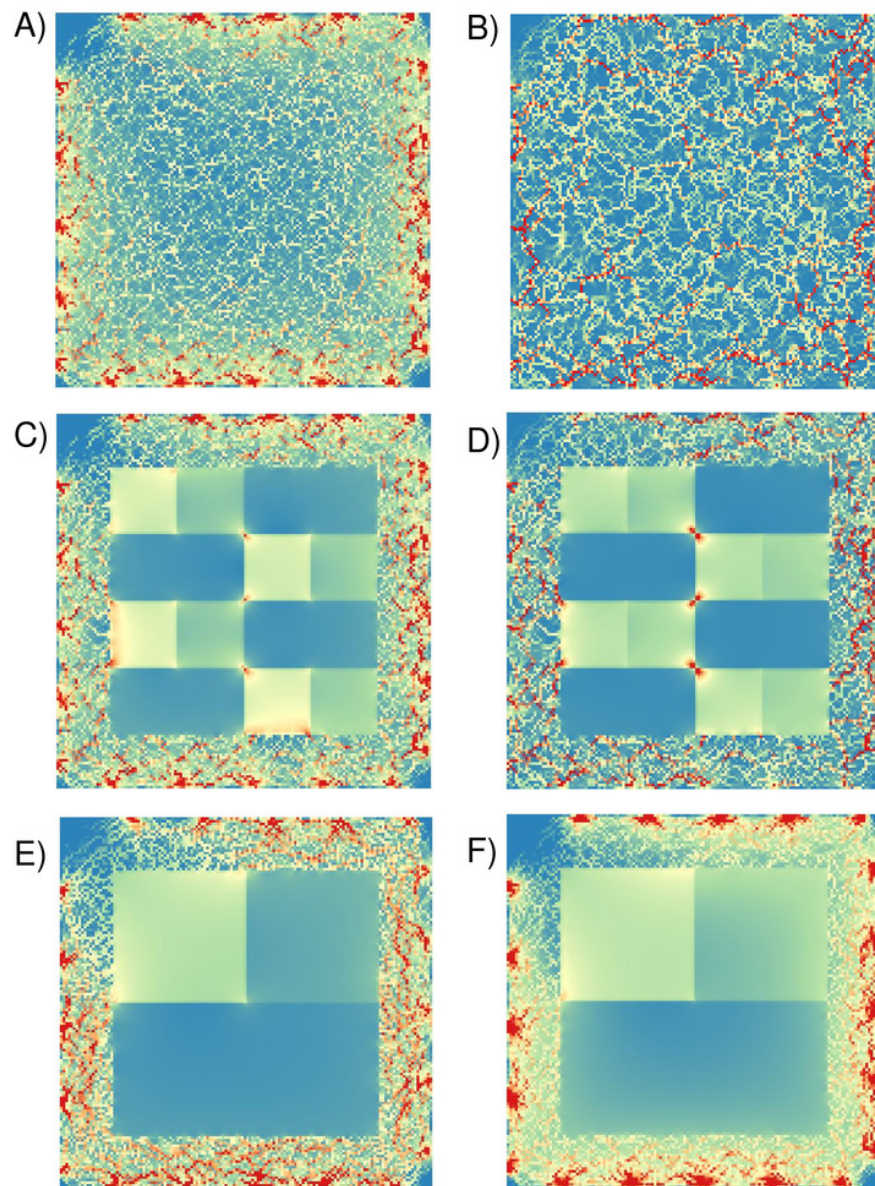
Figure 4

Example current density maps from an urban landscape.

Two examples of current density maps for an urban study area in Oakville, Ontario. Panel A had costs of 1 (low), 2, and 3 (high), and B had costs of 1, 100, and 150. The Spearman rank correlation was 0.68, lowest of all comparisons for this landscape (mean (range) RS = 0.85 (0.62-1.00) n = 45 comparisons).
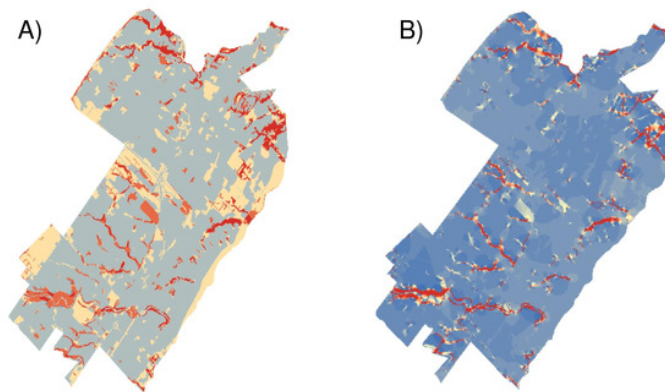
Figure 5

Effect of the range of cost values on correlation of current density across landscapes

Effect of the absolute value of the difference in the range of cost values in a landscape ($\log_{10}$-transformed) on the Spearman correlation between current density estimates in pairs of landscapes: (A) high, (B) medium, and (C) low fragmentation.
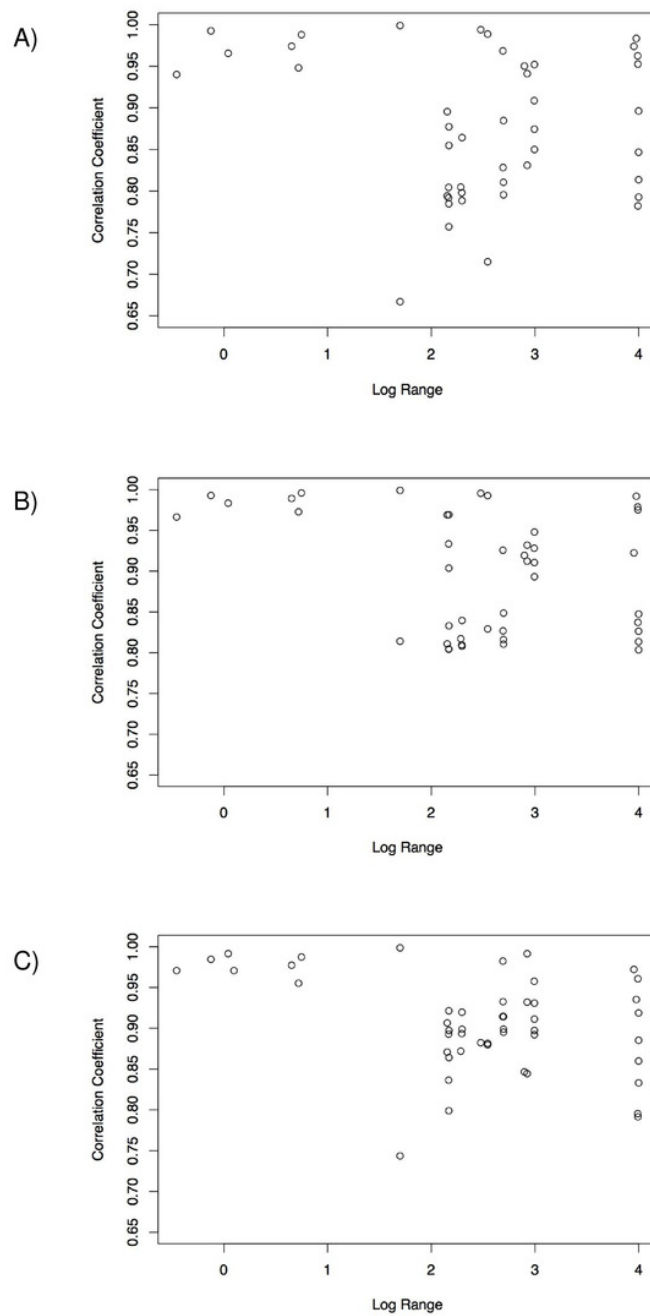
Figure 6

Effect of cost range on current density

Effect of the absolute value of the difference in the range of cost values in a landscape ($\log_{10}$-transformed) on mean and maximum current density estimates cross 10 different cost scenarios. We have shown here (A) the medium fragmentation scenarios in a simulated landscape, and (B) the real, urban landscape.
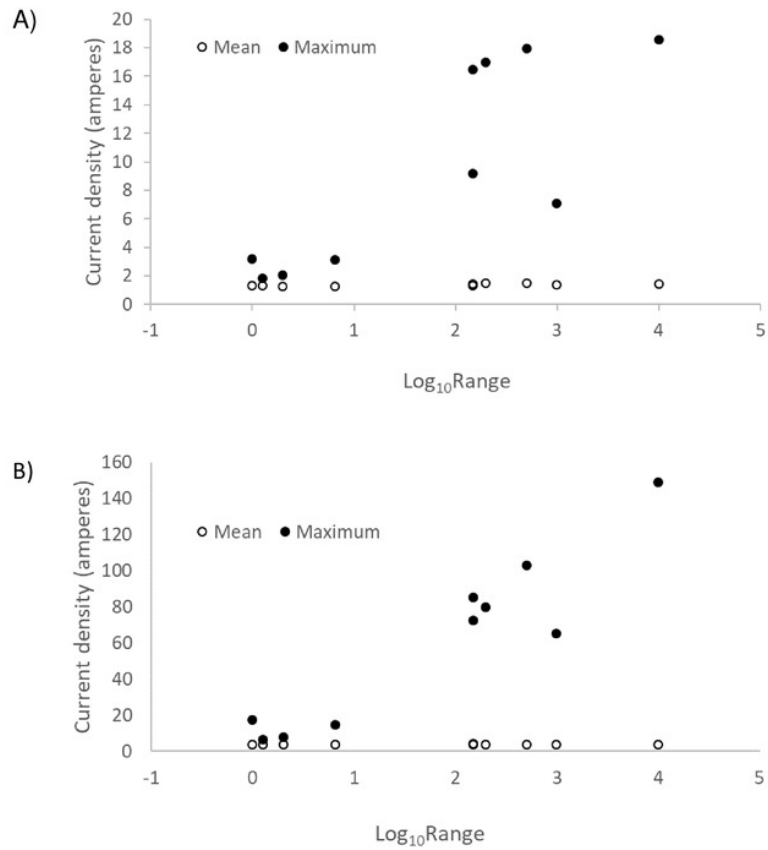
Figure 7

Examples of current density maps with different thematic resolutions

Figure 7. Examples of current density maps at a resolution of 140 x 140 cells for landscape depictions with different thematic resolutions (3 (top row), 6, or 12 (bottom row) categories), different costs, and a 20-pixel buffer. Panels A, C and E had costs of 1 (low), 5, and 7.5 (high), whereas B, D, and F had costs of 10, 100, 1000, respectively. Highest current density is indicated by red. Node locations are indicated by areas of high current density around perimeters.