

1 **The influence of landscape context on short- and long-term forest change**
2 **following a severe ice storm**

3 Jed Immanuel Lloren^{1,5*}, Lenore Fahrig², Joseph R. Bennett^{2,3}, Thomas A. Contreras⁴, and Jenny
4 L. McCune^{2,5}

5
6 ¹Department of Biology, Carleton University, Ottawa, ON, K1S 5B6

7 ²Geomatics and Landscape Ecology Research Laboratory, Department of Biology, Carleton
8 University, Ottawa, ON, K1S 5B6

9 ³Institute of Environmental Science, Carleton University, Ottawa, ON, K1S 5B6

10 ⁴Biology Department, Washington and Jefferson College, Washington, PA, USA, 15301

11 ⁵Current address: Department of Biological Sciences, University of Lethbridge, Lethbridge, AB,
12 T1K 3M4

13 *Corresponding author: Jed Immanuel Lloren, jed.i.lloren@gmail.com, ORCID 0000-0002-
14 1925-9579

15
16 **Abstract**

- 17 1. When deforestation results in small forest fragments surrounded by a non-forest matrix,
18 forest stands within these fragments experience changes in structure and community
19 composition. They also continue to experience natural disturbances like hurricanes and

20 ice storms. It is unclear whether the landscape context of forest stands influences plant
21 community response to natural disturbances.

22 2. Using data from surveys of forested plots in the years immediately following and 19
23 years after a severe ice storm, we measured changes in woody stem density, species
24 richness, and beta diversity.

25 3. Plots with greater storm damage had greater gains in stems and species, and greater shifts
26 in community composition. In addition, there were interactions between the degree of
27 storm damage and landscape context. The short-term effects of storm damage were
28 magnified in plots with less forest on the surrounding landscape and farther from the
29 forest edge. In plots with high damage, a return towards pre-storm conditions over the
30 long-term occurred more often in plots farther from the forest edge compared to those
31 close to the edge.

32 4. Synthesis: Future climate scenarios predict increases in severe weather and
33 accompanying ecosystem disturbance. Our results show that it is important to consider
34 landscape context when assessing the response of forest communities to such
35 disturbances.

36

37 **Keywords:** community composition; deforestation; fragmentation; landscape matrix;
38 recovery; natural disturbance; species richness; succession

39

40 **1. Introduction**

41 Human dominance of landscapes has resulted in the loss and fragmentation of forests around the
42 world (Lindenmayer and Fischer 2006, Riitters et al. 2016). The conversion from large,

43 contiguous forests to small patches embedded in a matrix of agricultural and urban land results in
44 changes in forest structure, diversity, and species composition that are predictable based on
45 landscape context and plant traits (e.g. Metzger 2000, Dupré and Ehrlen 2002, Kolb and
46 Diekmann 2005, McCune and Vellend 2015). For example, McCune and Vellend (2015) found
47 that, over a four-decade period, forest stands with low amounts of forest in the surrounding
48 landscape were more likely to be colonized by exotic, annual, shade-intolerant species than
49 stands embedded in large areas of forest. In addition to the changes forests undergo as a result of
50 anthropogenic deforestation, they also continue to respond to natural disturbances such as fire,
51 hurricanes, and ice storms. It is important to understand how reduction of forest cover on a
52 landscape influences forest response to natural disturbances to be able to predict how forest
53 ecosystems will change in the future with further forest loss and changes in climate (Laurance
54 and Cochrane 2001, Catterall et al. 2008, Smart et al. 2014). But few studies have attempted to
55 measure these potential interactions, particularly over the timescales necessary to document
56 long-term compositional changes in forest communities.

57

58 There is a large literature regarding forest change following natural disturbances. Firstly,
59 disturbances that create gaps in forest canopies often result in greater stem density and increased
60 species richness compared to pre-storm conditions or undisturbed areas (Peterson 2000, von
61 Oheimb et al. 2007, Fisher et al. 2013, Smart et al., 2014). An increase in light and nutrient
62 availability following the loss of larger canopy trees results in increased growth of existing
63 saplings and/or allows colonization by new species (Whitney and Johnson 1984, Canham 1989,
64 Arian and Lechowicz 2007, Xi and Peet 2011). Alternatively, recovery following canopy damage

65 can proceed mainly by root sprouting of residual mature trees, resulting in little or no change in
66 species richness (Chazdon 2003, Dietze and Clark 2008, Plotkin et al. 2013).

67

68 Beta diversity, defined as the variability in community composition among sites (Whittaker
69 1972), can also be altered by natural disturbances (Liebsch et al. 2008, Myers et al. 2015).

70 Severe disturbance can result in lower beta diversity if species that are more susceptible to
71 damage cannot survive the disturbance or adapt to post-disturbance conditions, leaving only a
72 subset of less susceptible species to accumulate in communities (e.g. Heydari et al. 2017).

73 However, beta diversity may increase in cases where dominant species are most affected by the
74 disturbance, leaving more resources available for uptake by a more diverse group of subordinate
75 species (Silva Pedro et al. 2016).

76

77 Finally, natural disturbances can affect forest succession. In some cases, large natural
78 disturbances set succession back to an earlier stage by killing larger, late-seral species and
79 therefore favouring younger, pioneer species (Kosugi et al. 2016). In other cases, disturbance
80 accelerates succession, by removing lingering early-seral species that had been slowing the rise
81 to dominance of late-seral species (Abrams and Scott 1989, Rhoads et al. 2002, Zhao et al. 2006,
82 Allen et al. 2012). Clearly, the impact of natural disturbances on forest communities is complex,
83 and depends on the disturbance type, frequency and severity, as well as the composition and
84 successional stage of the forest at the time of the disturbance (Everham and Brokaw 1996,
85 Turner et al. 1998, Tremblay et al. 2005).

86

87 Landscape context – by which we mean the amount of forest surrounding a focal forest stand and
88 the proximity of the stand to the nearest forest-matrix edge – could affect forest response to
89 natural disturbance in two ways. First, it can change the frequency of natural disturbances, or the
90 degree of damage they cause. For example, small isolated forest fragments may experience forest
91 fires less frequently due to the inability of fire to spread across non-forested areas (Weir et al.
92 2000), but they may experience greater damage from hurricanes due to a greater area of forest
93 being closer to forest edges, which are more susceptible to damage from high winds (Schwartz et
94 al. 2017). Second, landscape context could influence the short- and long-term response of forest
95 communities to natural disturbances by affecting the mechanisms by which communities respond
96 to disturbance - specifically, by affecting regeneration (Catterall et al. 2008). The density of
97 seeds and seedlings of matrix-associated generalist, shade-intolerant, and exotic species is
98 predicted to increase in landscapes with smaller areas of forest, and at sites within forest patches
99 that are closer to the forest-matrix boundary (Garwood 1989). Therefore, canopy gaps may be
100 more likely to be colonized by generalist or exotic species in forest stands in landscapes where
101 non-forest habitat predominates, and closer to the boundary between the forest and the
102 agricultural matrix, compared to forest stands in high-forest landscapes or located far from the
103 forest-matrix edge (Kupfer et al. 1997, Catterall et al. 2008, Laurance and Curran 2008, Smart et
104 al. 2014). Canopy gaps may also experience a greater increase in stem density at sites surrounded
105 by less forest and closer to the forest-matrix edge due to this higher density of seeds or seedlings
106 of light-loving, matrix-associated species when compared to sites far from the forest-matrix edge
107 or in landscapes dominated by unbroken forest. This second potential influence of landscape
108 context is more difficult to test, because the response of plant communities to disturbance
109 typically unfolds over decades; therefore, data on species richness and community composition

110 over long timescales are required, ideally both before and after the occurrence of a natural
111 disturbance.

112

113 In this study, we use detailed forest surveys conducted immediately following, three years, and
114 nineteen years after a severe ice storm to measure changes in stem density, species richness, and
115 composition over time, and to test for an effect of landscape context on these changes. Ice storms
116 occur when warm fronts moving across cold landscapes cause the formation of thick ice layers
117 on the surface of objects, and they are a relatively frequent disturbance of temperate forests in
118 northeastern North America (Lemon 1961). In early January 1998, an exceptional ice storm hit a
119 large area of Canada and the northeastern United States (Regan 1998). In the region near Ottawa,
120 Canada, where our study takes place, 60-80mm of ice accumulated on tree branches and other
121 surfaces, causing losses of branches and entire trees to breakage (Kerry et al. 1999). Land use in
122 this region is primarily agricultural, with forests confined to patches surrounded by crop fields or
123 pastures. If landscape context has a significant influence on the post-storm response of forests in
124 this area, we predicted that the short- and/or long-term effects of the storm on stem density,
125 species richness, and community composition would be moderated by (1) the amount of forested
126 area in the landscape surrounding each forest stand, or (2) the distance of the measured stand
127 from the nearest forest-matrix edge. Specifically, we tested for interactions between the amount
128 of damage caused by the ice storm and these two landscape context variables in predicting
129 changes in stem density, species richness, and community composition over time. We
130 hypothesized that increases in stem density, species richness, and shifts in composition would be
131 greater with greater ice storm damage, and that this effect would be magnified in stands located
132 in low-forest landscapes, or closer to the forest-matrix edge.

133

134 **2. Materials and methods**

135 *2.1. Study area*

136 We conducted this study in forests near Ottawa, Ontario, Canada (45°25'N 75°41'W), within the
137 Great Lakes-St. Lawrence forest region (Fig. 1; Crins et al. 2009, Ontario Ministry of Natural
138 Resources and Forestry 2018). Forests here are dominated by hardwoods, including sugar maple
139 (*Acer saccharum*), beech (*Fagus grandifolia*), and Eastern hop-hornbeam (*Ostrya virginiana*).
140 On average, 758mm of rain and 224cm of snow fall in the area each year; the annual mean
141 temperature is 6.38°C (Environment and Natural Resources 2017). The topography is gentle,
142 with elevations ranging from 71m to 122m above sea level on flat to nearly flat slopes. The study
143 sites are patches of deciduous or mixed forests located in rural areas, mostly surrounded by crop
144 fields or pastures, except for one site which is situated in a municipal park now surrounded by
145 recent suburban development. All forests in this region have experienced some level of selective
146 harvest for firewood or timber. In 1998, the stands in our study ranged from 16.9cm to 22.4cm in
147 mean diameter at breast height (DBH) of all trees greater than 10cm DBH, with maximum DBH
148 ranging from 17.8cm to 118.5cm.

149

150 *2.2. Data collection*

151 In 1997, Contreras (2002) identified 29 non-overlapping 1km² landscapes with forest cover of
152 each landscape ranging from 7% to 95% of the total area. He chose 10 sampling plot locations
153 within each landscape, both forested and non-forested. Each plot measured 12.5m by 25m.
154 During the summer of 1998, after the ice storm, surveyors attempted to re-locate the plots with
155 varying amounts of success. Surveyors in 1998 marked the plots with flagging and metal tags.

156 Each summer, from 1998 to 2001, researchers surveyed these plots using the same protocol as
157 the 1997 surveys (Brommit et al. 2004, Charbonneau and Fahrig 2004, Darwin et al. 2004).
158 Because we could only be certain of high plot relocation accuracy from 1998 onwards, we used
159 the 1998 survey as the baseline for measuring change over time. Although the ice storm caused
160 significant canopy loss, most individuals were still standing and therefore measured in 1998.
161 Therefore we consider the 1998 data a valid baseline for measuring the changes that followed the
162 ice storm.

163
164 In 1998, surveyors measured the percent crown loss due to the ice storm for all trees in each plot
165 (Darwin et al. 2004). They then calculated the plot damage index (pdi) as the percent crown loss
166 multiplied by the basal area of each tree, summed across all individuals and divided by the total
167 basal area of all trees in the plot, according to the following equation:

$$Plot\ Damage\ Index\ (pdi) = \frac{\Sigma[\pi r^2(\% \text{ crown loss})]}{100 \times [\Sigma\pi r^2]}$$

168
169 where r is the radius of each tree at breast height (1.3m).

170
171 In the summer of 2017, we used GPS coordinates and field notes to re-locate and re-survey a
172 subset of the forest plots established in 1998. We re-surveyed only plots within 40km of
173 downtown Ottawa that had not been clear cut between 2001 and 2017, and where we could
174 obtain permission from landowners. We surveyed a total of 69 plots in 17 landscapes (Fig 1). At
175 44 of these plots, fragments of tags or flagging indicated we were definitively at the site of the
176 previous re-surveys. For the others, we used the GPS coordinates from 2001 (5-10m accuracy).

177

178 In accordance with the earlier surveys, we delineated a 12.5m by 25m rectangular plot within
179 which we identified to species and counted all trees of at least 10cm diameter at breast height
180 (DBH). Within this larger plot, we delineated a 6.25m by 12.5m shrub-sapling plot in which we
181 identified and counted all shrubs and saplings less than 10cm DBH and at least one metre in
182 height. We standardized plant species names following Reznicek et al. (2011). To ensure
183 consistency throughout years, we lumped some species to genus level where accuracy of
184 previous surveys was in doubt.

185
186 Using aerial photos from 1999 (City of Ottawa 2018) and 2015 (DigitalGlobe 2010, 2015a,
187 2015b, 2016), we digitized the forests within which our plots were located in ArcMap version
188 10.6 (ESRI 2011). Forests were easily distinguished from cropland and urban land, and also from
189 shrubland, which is rare in the region. We measured the total amount of forest (area in hectares)
190 surrounding each plot within 200m, 500m, and 1000m of the plot in each year. We chose these
191 distances based on previous research in which landscape context within 500m was correlated
192 with plant community metrics (McCune et al. 2017, McCune and Vellend 2015), but recognizing
193 that the strongest effects might occur at larger or smaller distances (Jackson and Fahrig 2015).
194 We also measured the distance of each plot from the nearest forest edge (i.e. the forest-matrix
195 boundary; Fig. 1B). We measured these landscape context factors in two years because there
196 have been significant changes in forest cover in the study area since 1998, mostly in the form of
197 deforestation. Based on our experience in the field, the most recent forest cover estimates which
198 we based on satellite imagery ranging from 2010-2015 were accurate for our sites in 2017.

199

200 2.3. *Analyses*

201 2.3.1. Region-wide responses

202 We first tested for changes across all plots over time. To test for changes in woody stem density
203 and species richness, we used a linear mixed effects model for each response variable, with plot
204 within landscape as a random effect. To determine whether there were any significant differences
205 between years in (1) stem density and (2) species richness, we compared a model with ‘year’ as a
206 predictor to one with only the random effect using a likelihood ratio test. We used a post-hoc test
207 with adjusted p-values using Bonferroni correction to analyze pairwise differences between
208 years. To determine changes in beta diversity in the years following the ice storm, we used non-
209 metric multidimensional scaling (NMDS) ordination based on Bray-Curtis dissimilarities to
210 visualize the range of woody plant community composition occupied by all the plots in each year
211 (Bray and Curtis 1957, McCune and Grace 2002). We then used a test of difference in
212 multivariate dispersions (PERMDISP; Anderson et al. 2006) with pairwise comparisons between
213 years to determine whether beta diversity changed significantly between years. We ran the
214 ordination and the PERMDISP analysis on the matrix of pairwise dissimilarities of plots based
215 on the Bray-Curtis dissimilarity metric calculated on square-root transformed stem counts for
216 each species in each plot. Canopy and understory layers have been found to have differing
217 responses to disturbance (e.g. Bače et al. 2017), so we tested three subsets of data: trees only
218 (≥ 10 cm DBH), shrubs and saplings only (< 10 cm DBH and > 1 m tall), and an overall community
219 assessment which combined both subsets. Surveyors did not count all the tree stems in 2000;
220 therefore we omitted that year.

221

222 To determine which species became more frequent and/or abundant on the landscape 3 years and
223 19 years after the storm we used an indicator species analysis (ISA). ISA computes an ‘indicator

224 value' for each species based on its relative abundance and relative frequency in different
225 experimental groups and uses permutation to test for significance (Dufrêne and Legendre 1997).
226 While ISA is most often used to determine which species are indicators of specific habitat types
227 or experimental treatments (McCune and Grace 2002), it can be used in the same way to
228 determine which species are indicators of different points in time (e.g. McCune and Vellend
229 2013). We hypothesized that shade-intolerant species would increase following the ice storm as
230 they took advantage of canopy gaps, and then decline again as gaps closed and shade-tolerant
231 species recovered. We determined the shade tolerance of each species based on Niinemets and
232 Valladares (2006).

233

234 2.3.2. Plot-level responses

235 We then tested for effects of ice storm damage, landscape context (i.e. forest amount and
236 distance to nearest forest-matrix edge), and interactions between ice storm damage and each of
237 the two landscape context variables on plot-level changes in stem density, species richness, and
238 species composition. We carried out these tests on all size classes (trees and shrubs/saplings),
239 and on the shrub/sapling size class alone. As the results for these two sets were qualitatively
240 nearly identical, for simplicity we report only the results for the total community. We first
241 plotted stem density and species richness over time for each plot. We also plotted the Bray-Curtis
242 dissimilarity of each plot in 1999, 2001, and 2017 compared to the same plot itself in 1998 to
243 track plot-level shifts in species composition over time, based on the square-root transformed
244 stem counts for all woody species.

245

246 We defined the change in stem density, the change in species richness, and the Bray-Curtis
247 dissimilarity of each plot in 2001 compared to 1998 as the short-term change following the ice
248 storm, and the changes in 2017 compared to 1998 as the long-term change. This resulted in 6
249 response variables (Table 1). We then built a model for each response variable with predictors
250 ice storm damage (pdi), amount of forest, distance to the nearest forest edge, and interactions
251 between pdi and each of the two landscape context variables. In addition, we included covariates
252 that might also influence the response (Table 1). For change in stem density and species richness,
253 we included starting stem density (number of stems in 1998) or starting species richness,
254 respectively, because starting conditions could influence the likelihood that a plot experiences
255 increases or decreases in the number of stems or species. We also included an index of plot
256 wetness, which we calculated as the average wetness coefficient of all woody species in the plot
257 in 2017, weighted by their abundances. We compiled the wetness coefficient for each species
258 from the Michigan Floristic Quality Assessment System (Reznicek et al. 2014) and available
259 online (Reznicek et al. 2011). Wetness coefficients range from 5 to -5, where species with a
260 score of 5 are obligate upland species, and those rated -5 are obligate wetland species (Oldham et
261 al. 1995). Forest response to disturbance can vary in xeric versus mesic sites (Whitney and
262 Johnson 1984). For change in species composition, we included as covariates the starting species
263 richness, and starting species composition, based on the score of each site in 1998 on the NMDS
264 axis with the greatest variation. We did not include wetness index in these models due to a very
265 strong correlation between starting composition and wetness index (see below). We also
266 included average DBH as a covariate for changes in species composition, because shifts in
267 species composition in response to natural disturbances can vary in stands of different ages
268 (Peterson 2000).

269

270 Before building each model, we examined the correlations between all explanatory variables.

271 Due to high correlations between forest amount measured within different distances of the plots,

272 we used only the 1000m measurement because it provided the greatest explanatory power in a

273 comparison of univariate models. For the long-term response, we used the forest amount and

274 distance to edge calculated for 2015, while for the short-term response, we used the forest

275 amount and distance to edge calculated for 1999. No two explanatory variables in the final

276 candidate models had a correlation coefficient greater than 0.53 (Table A1, Supporting

277 Information).

278

279 We modelled change in stem density and change in species richness using linear models.

280 Because the Bray-Curtis dissimilarity metric takes values between 0 and 1 (McCune and Grace

281 2002), we used generalized linear models (GLM) with a beta distribution and a logit link to

282 model changes in community composition. We standardized all response variables prior to

283 building GLMs by subtracting the mean and dividing by the standard deviation. For the linear

284 models we used the 'arm' package in R to standardize by centering and dividing by twice the

285 standard deviation. We checked for spatial autocorrelation in the residuals of all models using

286 spline correlograms. Because we found no evidence of spatial autocorrelation, we treated plots in

287 the same 1km² landscape as independent (Dormann et al. 2007). For each response variable, we

288 built a model with all our candidate predictors. We then identified the minimum adequate model

289 using backwards stepwise selection and AIC. If a predictor or an interaction was not included in

290 the minimum adequate model, we considered the predictor not to be significantly related to the

291 response and we did not consider it further. After we had fit the minimum adequate model for

292 each response variable, we performed marginal fitting of terms ('drop1' test) by dropping each
293 of the terms from the minimum adequate model to determine which predictors and interactions
294 had a significant effect on the response variable once all other variables in the minimum model
295 were accounted for. We visualized the relationships between each predictor in the minimum
296 model and the response variable using partial residual plots. These plots show the conditional
297 effect of each predictor on the response variable by holding all other predictors constant at their
298 median. That is, the y-axis value for each data point is adjusted to remove the fitted effect of the
299 other predictors in the model (Breheny and Burchett 2017).

300

301 We conducted all analyses using R version 3.3.3 (R Core Team 2017). We used the package
302 'multcomp' to perform post-hoc tests (Hothorn et al. 2008), and the 'vegan' package for
303 ordinations and the PERMDISP analysis (Oksanen et al. 2017). We ran the indicator species
304 analysis using the 'labdsv' package, with 10,000 permutations (Roberts 2016). We used the
305 'nlme' package to fit linear models (Pinheiro et al. 2017), and packages 'betareg' and
306 'glmmTMB' to fit GLMs (Cribari-Neto and Zeileis 2010, Brooks et al. 2017). We used the
307 packages 'arm' to standardize predictor variables (Gelman and Su 2018), 'MASS' for stepwise
308 model selection and marginal fitting of terms (Venables and Ripley 2002), 'ncf' for spatial
309 correlograms (Bjornstad 2018), and 'visreg' to create partial residual plots (Breheny and
310 Burchett 2017).

311

312 **3. Results**

313 *3.1. Region-wide responses*

314 Stem density varied between years for trees, shrubs/saplings, and all woody stems combined
315 (See Table A2, A3, Supporting Information). The greatest change was in the shrub/sapling layer,
316 where stem density increased considerably after the storm, and then declined to levels similar to
317 1999 by 2017 (Fig. 2A). Species richness also changed significantly between years, primarily in
318 the shrub/sapling layer (Table A4, A5, Supporting Information). Shrub/sapling species richness
319 increased significantly by 1999 and has remained significantly higher than 1998 levels (Fig 2B).
320 There were no significant changes in beta diversity across all plots for any subset (Table A6, Fig.
321 A1, Supporting Information).

322

323 There were no significant indicator species for trees: no tree species was significantly more
324 frequent and/or abundant in 2001 or in 2017 compared to 1998 (Table A7, Supporting
325 Information). In the shrub/sapling layer, choke cherry (*Prunus virginiana*), beaked hazelnut
326 (*Corylus cornuta*), ash (*Fraxinus americana/pennsylvanica*) and nannyberry (*Viburnum lentago*)
327 were indicators of 2001 compared to 1998. Saplings of the shade tolerant tree sugar maple (*Acer*
328 *saccharum*) and the moderately shade tolerant shrub bristly gooseberry (*Ribes cynosbati*) were
329 also indicators of 2001 (Table A7). By 2017, chokecherry, hazelnut, and sugar maple were still
330 more frequent and abundant in the shrub/sapling layer than they had been in 1998, but
331 nannyberry and gooseberry were no longer indicators. However, the shade tolerant blue beech
332 (*Carpinus caroliniana*) and alternate leaved dogwood (*Cornus alternifolia*) were more frequent
333 and abundant in the 2017 shrub/sapling layer compared to 1998 (Table A7).

334

335 3.2. Plot-level responses

336 Plot-level trajectories in stem density, species richness, and species composition were highly
337 variable across plots, and even between plots located in the same 1km² landscape (Fig. A2, A3,
338 Supporting Information; Fig. 3). While stem density tended to peak two years after the ice storm,
339 and then decline towards 1998 levels, changes in species richness and composition were more
340 variable, and did not tend to return towards 1998 levels.

341

342 3.2.1 Short-term changes in stem density and species richness

343 The degree of canopy loss (pdi) was a significant predictor of changes in stem density and
344 species richness from 1998 to 2001, with more heavily damaged plots gaining more stems and
345 species (Table 2, Fig. 4A). Landscape context was also a significant predictor of short-term
346 changes in stem density and species richness, with plots having more forest in the surrounding
347 landscape tending to gain fewer stems and species (Table 2, Fig. 4B). Models for short-term
348 change in stem density and species richness did not include interactions between the amount of
349 ice storm damage and landscape context.

350

351 3.2.2 Long-term changes in stem density and species richness

352 By 2017, the difference in stem density compared to 1998 was negatively related to ice storm
353 damage, with more damaged plots having gained fewer stems, all else being equal (Table 2). The
354 number of stems gained between 1998 and 2017 declined with greater amounts of forest within
355 1000m of the plot, and with a higher starting density. The change in species richness between
356 1998 and 2017 was no longer predictable based on ice storm damage once other predictors were
357 taken into account, but was strongly related to starting species richness, with plots having lower
358 species richness in 1998 tending to gain more species by 2017 (Table 2, Fig. 5D). The models for

359 long-term change in stem density and species richness both included an interaction between plot
360 damage and distance to the forest edge: plots farther from the forest-matrix edge showed a
361 negative relationship between ice storm damage and long-term gain in stems and species (Table
362 2, Fig. 5E).

363

364 3.3.3 Changes in community composition

365 The models of short- and long-term change in community composition both included interactions
366 between ice storm damage and landscape context (Table 2, Fig. 6, Fig. 7). In the short-term,
367 there was a positive relationship between greater damage and a larger shift in species
368 composition, particularly in plots surrounded by lower amounts of forest and in plots farther
369 from the forest edge (Fig. 6). Changes in species composition in the short-term were smaller in
370 plots with lower species richness in 1998, and plots surrounded by higher amounts of forest
371 within 1000m (Fig. 6).

372

373 Over the long-term, changes in composition were smaller in plots with greater ice storm damage,
374 and in plots surrounded by greater amounts of forest (Fig. 7). Plots with starting composition on
375 the lower end of the main ordination axis tended to shift less in composition over the long term –
376 these plots are drier sites dominated by sugar maple. The minimum adequate model for long-
377 term shifts in composition included an interaction between plot damage and distance to the forest
378 edge (Fig. 7E; Table 2). Plots that sustained high levels of damage in the ice storm were more
379 similar in composition to their 1998 composition if they were farther from the forest edge (Fig.
380 7E).

381

382 **4. Discussion**

383 Our results confirm the relatively well-known effects of both natural disturbance and landscape
384 context on forest communities. More importantly, we found interactions between these two
385 drivers of change. This supports our prediction that landscape context can moderate plant
386 community response to a natural disturbance and emphasizes the importance of landscape
387 context when assessing plant community response to natural disturbance in fragmented
388 landscapes (Laurance and Cochrane 2002, Chazdon 2003, Catterall et al. 2008, Smart et al.
389 2014).

390

391 *4.1 Effects of storm damage*

392 Across all plots, the density of shrubs and saplings increased dramatically by 2001, as
393 documented by Darwin et al. (2004). By 2017, 19 years after the storm, average stem density of
394 shrubs and saplings had declined nearly to original levels. This peak and subsequent decline in
395 the density of shrubs and saplings is a common finding in studies of forests after natural
396 disturbances, although the timing of the peak varies between regions (White et al. 1985,
397 Tremblay et al. 2005, Zhao et al. 2006, Heartsill Scalley et al. 2010, Kosugi et al. 2016).

398

399 Short-term increases in total stem density were greater with greater storm damage (Table 2).
400 Greater canopy damage likely resulted in increased resource availability to understory seedlings
401 and small shrubs and saplings, facilitating their growth (e.g. Peterson and Pickett 1995).
402 However, the difference in stem density between 2017 and 1998 was *negatively* correlated with
403 ice storm damage, all else being equal. It is possible that intense sprouting of damaged canopy

404 trees in heavily damaged sites (Brommit et al. 2004) actually resulted in faster canopy closure in
405 those sites and therefore less opportunity for sustained stem recruitment over the long-run.

406

407 Unlike stem density, average species richness did not return to pre-storm levels by 2017. Two
408 things may have contributed to this pattern. First, it may take longer than the 19 years in our
409 study for species richness to return to pre-storm conditions (eg. Metzger et al. 2009, Kosugi et al.
410 2016, Liu et al. 2017). For example, in a 60-year study of two forests in Japan following a
411 typhoon, Kosugi et al. (2016) found that species richness peaked 37 years after the storm, before
412 declining gradually. Alternatively, the ice storm may have allowed colonization by new species
413 that are able to establish permanently. In contrast to our prediction, species that increased
414 significantly in abundance or frequency included both shade-tolerant and intolerant species. Sheil
415 (2001) found that over a 54-year observation of five plots that experienced canopy loss, an
416 increase in the number of shade-tolerant species resulted in an increase in species richness that
417 was sustained over time. Canopy damage can allow shade-intolerant species to grow and/or
418 colonize, but it can also provide more light for shade-tolerant, sub-canopy species which allows
419 them to grow into the shrub/sapling size class, and hence be measured (e.g. Batista and Platt
420 2003, Zhao et al. 2006).

421

422 Greater canopy damage was correlated with a larger short-term increase in species richness.
423 Many studies have found that natural disturbances increase forest diversity (e.g. Heartsill Scalley
424 et al. 2010, Fischer et al. 2013, Kosugi et al. 2016). By 2017, canopy damage was no longer a
425 significant predictor of the change in species richness since the storm, once other predictors were

426 accounted for. Some of the species that were able to grow/colonize following the storm have
427 likely not been able to survive as the canopy has closed.

428

429 The species composition of forests across our study area as a whole was not changed by the ice
430 storm: there was no evidence of biotic homogenization and no shift in composition across all 69
431 forest plots. However, compositional change at the plot level has been considerable. Although
432 some plots are returning towards the composition of pre-storm communities, most plots are not
433 (Fig 3). Heartsill Scalley et al. (2010) similarly found that differences in community composition
434 initiated by a hurricane in a Puerto Rican forest were still evident 15 years later. However,
435 Plotkin et al. (2013) found that community composition had returned nearly to the starting point
436 by 5-10 years after a simulated hurricane. The forest communities in our study area are dynamic
437 at the local scale, yet in aggregate they are steady, aligning with the ‘shifting mosaic steady state’
438 theory of Bormann and Likens (1979), except applied to species composition rather than
439 biomass. Historical ecologists have cautioned that local-scale trajectories cannot be extrapolated
440 from regional patterns (e.g. Swetnam et al. 1999). The reverse is also true: local-scale change in
441 species composition in response to a large disturbance cannot be extrapolated to infer change in
442 species composition at a regional scale.

443

444 At the plot level, short-term shifts in community composition were greater with greater canopy
445 damage. Zhao et al. (2006) found the same effect in hurricane damaged forests in South
446 Carolina. Interestingly, we found long-term shifts in composition tended to be smaller with
447 greater canopy loss. We speculate that heavily damaged plots may have been shifted back to an
448 earlier seral stage by the ice storm, and after 19 years have returned towards their starting

449 composition, whereas less damaged plots have proceeded along ‘natural’ successional pathways
450 away from their starting composition.

451

452 4.2 *Effects of landscape context*

453 Landscape context affected post-storm changes in stem density. Plots surrounded by more forest
454 gained fewer stems in the short- and long-term, independent of the degree of storm damage.
455 Forest stands in small forest fragments surrounded by open, agricultural land likely have a
456 greater number of shade-intolerant, edge- or open-habitat adapted species as seedlings and/or in
457 the seedbank – due to a greater abundance of such species in low-forest landscapes – which
458 quickly take advantage of canopy gaps leading to a greater increase in stem density (Kupfer et al.
459 1997, Catterall et al. 2008, Laurance and Curran 2008, Smart et al. 2014).

460

461 As with stem density, short-term gain in species richness was greater in plots with smaller
462 amounts of forest in the surrounding landscape. This pattern is consistent with the prediction that
463 a greater number of edge- or open-habitat adapted species are found in the understory and/or the
464 seedbank of forest plots with more open land in the surrounding landscape, in addition to shade-
465 tolerant forest species, leading to a greater diversity of species able to colonize (Kupfer et al.
466 1997). While we lack data on seedling and seedbank composition, the abundance-weighted mean
467 shade tolerance of species in the shrub/sapling layer in 1998 was significantly positively
468 associated with forest amount within 1000m, supporting our prediction of a greater availability
469 of propagules of matrix-associated shade-intolerant species in low-forest landscapes (see
470 Supporting Information, Table A8).

471

472 Landscape context affected both short- and long-term compositional change. Plots in landscapes
473 with less forest became less similar to their starting composition over time compared to plots
474 embedded in more extensively forested landscapes. This is consistent with our prediction that
475 plots in landscapes with less forest were more susceptible to colonization by new shade-
476 intolerant, disturbance-tolerant species associated with the open habitats of the non-forest matrix,
477 which is an ongoing process (e.g. McCune and Vellend 2015). While the distance to the forest
478 edge was also a predictor in models of both short- and long-term shifts in species composition, it
479 was not significant once accounting for other predictors in the minimum models, but was
480 important as a moderator of the effects of storm damage (see below).

481

482 The long-term change in composition was also affected by starting composition, with plots in
483 drier forests dominated by sugar maple showing smaller shifts in composition (Fig. 7D). This
484 matches the results of Whitney and Johnson (1984) who found that xeric sites showed the least
485 compositional change after an ice storm in Virginia. They suggested this was because xeric sites
486 have similar species in both the canopy and understory. Indeed, in our dataset the compositional
487 similarity between the tree layer and the shrub-sapling layer within the same plot was greater for
488 drier plots (See Supporting Information, Figure A4).

489

490 4.3 *Interactions between storm damage and landscape context*

491 The models for four out of six response variables included interactions between the amount of
492 canopy loss from the ice storm and one or both measures of landscape context. In particular,
493 these interactions had a strong influence on short-term shifts in community composition, even
494 after other important predictors had been accounted for.

495
496 The positive correlation between canopy damage and short-term shifts in composition was
497 steeper in plots with low amounts of surrounding forest. This result is consistent with the idea
498 that forest stands in small forest fragments surrounded by a lot of open, agricultural lands
499 experience greater propagule pressure from disturbance-tolerant, open-habitat species (Kupfer et
500 al. 1997, Chazdon 2003, Catterall et al. 2008, Smart et al. 2014, McCune and Vellend 2015).
501 When a disturbance damages the canopy, these stands see even greater shifts in composition due
502 to a greater likelihood of these open-habitat species colonizing and/or maturing from seedlings
503 into the shrub/sapling layers. In contrast to our hypothesis, the positive relationship between
504 storm damage and compositional shifts was actually steeper in plots most distant from the forest
505 edge, rather than closer to it. We found this surprising at first, as we expected plots closer to
506 edges would tend to be colonized by more shade-intolerant, edge-loving species. However,
507 because plots close to the forest edge already had a significant component of shade-intolerant,
508 edge-loving species, an increase in such species due to storm damage would not cause as great a
509 shift in composition as for plots far from the forest edge, where such species were not already
510 present, or were present only as suppressed seedlings.

511
512 Models of long-term changes in stem density, species richness, and community composition all
513 included interactions between the amount of storm damage and distance to the forest-matrix
514 edge. Among plots with the greatest amounts of storm damage, those far from the forest edge
515 had the lowest long-term gains in stems and species, and the smallest shifts in species
516 composition compared to 1998 levels. It seems that the long-term establishment of matrix-

517 associated species whose colonization was facilitated by natural disturbance is less likely to
518 occur in stands farther away from the matrix.

519

520 *4.4 Conclusion*

521 The variation explained by the models ranged from 16% to 30%. We acknowledge that, in
522 addition to the predictors in our models, other unmeasured factors such as anthropogenic
523 disturbances (e.g. selective logging) or natural disturbances (e.g. grazing, disease) likely affected
524 the responses. Nevertheless, our study illustrates that human disturbance in the form of forest
525 fragmentation via deforestation can influence how forest stands respond to natural disturbances.
526 The impacts of the reduced forest area and increased proximity to non-forested matrix on
527 remaining forest communities are not just direct, but also indirect. Stands located in landscapes
528 with little forest, but relatively far from the forest edge experienced the greatest changes in
529 community composition with storm damage. However, over the long term, heavily damaged
530 stands far from the forest edge were more likely to return towards pre-storm conditions. If
531 climate change continues along its projected trajectory, severe winter ice storms are predicted to
532 become more frequent in eastern Ontario and the northeastern United States (Klima and Morgan
533 2015). This may lead to a permanent shift in composition throughout forest fragments, even in
534 sites far from forest edges.

535

536 **Acknowledgements**

537 We thank the field technicians who helped carry out surveys from 1997-2001. Erin C. O'Boyle
538 assisted with the 2017 surveys and with digitizing aerial photos. The City of Ottawa and 31
539 private landowners gave permission to conduct surveys on their property. The Geomatics and

540 Landscape Ecology Laboratory discussion group at Carleton University and three anonymous
541 reviewers provided helpful comments. This study was funded by Natural Sciences and
542 Engineering Research Council grants to L.F., J.R.B., and J.L.M.

543

544 **Authors' contributions**

545 L.F. and T.A.C. designed the original sampling methodology; T.A.C. collected data prior to
546 2000; J.L.M. conceived the study; J.I.L. and J.L.M. collected the data from 2017, analyzed the
547 dataset, and led the writing of the manuscript; all authors contributed critically to the drafts and
548 gave final approval for publication.

549

550 **Data accessibility**

551 We intend to archive our data on the Dryad Digital Repository.

552

553 **References**

554 Abrams MD, Scott ML (1989) Disturbance-mediated accelerated succession in two Michigan
555 forest types. *Forest Sci* 35:42-49 DOI: 10.1093/forestscience/35.1.42

556 Allen, MS, Thapa V, Arévalo JR, Palmer MW (2012) Windstorm damage and forest recovery:
557 accelerated succession, stand structure, and spatial pattern over 25 years in two Minnesota
558 forests. *Plant Ecol* 213(11):1833-1842 DOI: 10.1007/s11258-012-0139-9

559 Ariei K, Lechowicz MJ (2007) Changes in understory light regime in a beech-maple forest after a
560 severe ice storm. *Can J For Res* 37:1770-1776 DOI: 10.1139/X07-024

561 Anderson MJ, Ellingsen KE, McArdle BH (2006) Multivariate dispersion as a measure of beta
562 diversity. *Ecol Lett* 9:683-693 DOI: 10.1111/j.1461-0248.2006.00926x

563 Bače R, Schurman JS, Brabec M, Čada V, Després T, Janda P, Lábusová J, Mikoláš M,
564 Morrissey RC, Mrhalová H, Nagel TA, Nováková MH, Seedre M, Synek M, Trotsiuk V,
565 Svoboda M (2017) Long-term responses of canopy-understory interactions to disturbance
566 severity in primary *Picea abies* forests. J Veg Sci 28:1128-1139 DOI: 10.1111/jvs.12581

567 Batista WB, Platt WJ (2003) Tree population responses to hurricane disturbance: syndromes in a
568 south-eastern USA old-growth forest. J Ecol 91(2):197-212

569 Bjornstad ON (2018) ncf: spatial covariance functions. R package version 1.2-5

570 Bormann FH, Likens GE (1979). Catastrophic disturbance and the steady state in northern
571 hardwood forests: A new look at the role of disturbance in the development of forest
572 ecosystems suggests important implications for land-use policies. American Scientist, 67:
573 660-669

574 Bray JR, Curtis JT (1957) An ordination of the upland forest communities of southern
575 Wisconsin. Ecol Monogr 27:325-349 DOI: 10.2307/1942268

576 Breheny P, Burchett W (2017) Visualization of regression models using visreg. The R Journal
577 9:56-71 DOI: 10.32614/RJ-2017-046

578 Brommit AG, Charbonneau NC, Contreras TA, Fahrig L (2004) Crown loss and subsequent
579 branch sprouting of forest trees in response to a major ice storm. J Torrey Bot Soc 131:169-
580 176 DOI: 10.2307/4126918

581 Brooks ME, Kristensen K, van Benthem KJ, Magnusson A, Berg CW, Nielsen A, Skaug HJ,
582 Maechler M, and Bolker BM (2017) glmmTMB balances speed and flexibility among
583 packages for zero-inflated generalized linear mixed modeling. The R Journal, 9(2), 378-400
584 DOI: 10.32614/RJ-2017-066

585 Canham CD (1989) Different responses to gaps among shade-tolerant tree species. *Ecology*
586 70:548-550 DOI: 10.2307/1940200

587 Catterall CP, McKenna S, Kanowski J, Piper SD (2008) Do cyclones and forest fragmentation
588 have synergistic effects? A before-after study of rainforest vegetation structure at multiple
589 sites. *Austral Ecol* 33:471-484 DOI: 10.1111/j.1442-9993.2008.01902.x

590 Charbonneau NC, Fahrig L (2004) Influence of canopy cover and amount of open habitat in the
591 surrounding landscape on proportion of alien plant species in forest sites. *Écoscience*
592 11:278-281 DOI: 10.1080/11956860.2004.11682833

593 Chazdon RL (2003) Tropical forest recovery: legacies of human impact and natural disturbances.
594 *Perspect Plant Ecol Evol Syst* 6:51-71 DOI: 10.1078/1433-8319-00042

595 City of Ottawa (2018) 1999 Orthorectified Ottawa Air Photos [Data file].
596 [https://library.carleton.ca/find/gis/geospatial-data/ottawa-orthophotos-1928-2017-](https://library.carleton.ca/find/gis/geospatial-data/ottawa-orthophotos-1928-2017-intermittent)
597 [intermittent](https://library.carleton.ca/find/gis/geospatial-data/ottawa-orthophotos-1928-2017-intermittent)

598 Contreras TA (2002) Changes in the abundance and distribution of woody plants related to
599 dispersal mechanisms along a forest cover gradient. Ph.D. thesis, Carleton University

600 Cribari-Neto F, Zeileis A (2010) Beta Regression in R. *Journal of Statistical Software* 34(2), 1-
601 24. URL <http://www.jstatsoft.org/v34/i02/> DOI: 10.18637/jss.v034.i02

602 Crins WJ, Gray PA, Uhlig PWC, Wester MC (2009) The Ecosystems of Ontario, Part 1:
603 Ecozones and Ecoregions. Ontario Ministry of Natural Resources, Peterborough, Ontario

604 Darwin AT, Ladd D, Galdins R, Contreras TA, Fahrig L (2004) Response of forest understory
605 vegetation to a major ice storm. *J Torrey Bot Soc* 131:45-52 DOI: 10.2307/4126927

606 Dietze MC, Clark, JS (2008) Changing the gap dynamics paradigm: vegetative regeneration
607 control on forest response to disturbance. *Ecol Monogr* 78(3):331-347 DOI: 10.1890/07-
608 0271.1

609 DigitalGlobe. 2010. World Imagery [Basemap]. World Imagery, Vivid-Canada. April 14, 2010.
610 DigitalGlobe. 2015a. World Imagery [Basemap]. World Imagery, Vivid-Canada. April 4, 2015.
611 DigitalGlobe. 2015b. World Imagery [Basemap]. World Imagery, Vivid-Canada. June 19, 2015.
612 DigitalGlobe. 2016. World Imagery [Basemap]. World Imagery, Vivid-Canada. April 20, 2015.

613 Dormann CF, McPherson JM, Araújo MB, Bivand R, Bolliger J, Carl G, Davies RG, Hirzel A,
614 Jetz W, Kissling D, Kühn I, Ohlemüller R, Peres-Neto PR, Reineking B, Schröder B, Schurr
615 FM, Wilson, R (2007) Methods to account for spatial autocorrelation in the analysis of
616 species distributional data: a review. *Ecography* 30:609-628 DOI: 10.1111/j.2007.0906-
617 7590.05171.x

618 Dufrêne M, Legendre P (1997) Species assemblages and indicator species: a need for a flexible
619 asymmetrical approach. *Ecol Monogr* 67:345-366 DOI: 10.1890/0012-
620 9615(1997)067[0345:SAAIST]2.0.CO;2

621 Dupré C, Ehrlén J (2002) Habitat configuration, species traits and plant distributions. *J Ecol*
622 90:796-805 DOI: 10.1046/j.1365-2745.2002.00717.x

623 Environment and Natural Resources (2017) Canadian climate normal 1981-2010 station data.
624 http://climate.weather.gc.ca/climate_normals/results_1981_2010_e.html?stnID=4337.
625 Accessed 15 June 2017

626 ESRI (2011) ArcGIS Desktop: Release 10. Redlands, CA: Environmental Systems Research
627 Institute

628 Everham EM, Brokaw NVL (1996) Forest damage and recovery from catastrophic wind. *Bot*
629 *Rev* 62:113–85 DOI: 10.1007/BF02857920

630 Fischer A, Marshall P, Camp A (2013) Disturbances in deciduous temperate forest ecosystems of
631 the northern hemisphere: their effects on both recent and future forest development.
632 *Biodivers Conserv* 22(9):1863-1893 DOI: 10.1007/s10531-013-0525-1

633 Garwood NC (1989) Tropical soil seed banks: A review. In *Ecology of Seed Soil Banks*, ed. MA
634 Leck, VT Parker, and RL Simpson, 149–209. San Diego: Academic Press.

635 Gelman A, Su Y (2018) arm: data analysis using regression and multilevel/hierarchical models.
636 R package version 1.10-1

637 Heartsill Scalley T, Scatena FN, Lugo AE, Moya S, Estrada Ruiz CR (2010) Changes in
638 structure, composition, and nutrients during 15 yr of hurricane induced succession in a
639 subtropical wet forest in Puerto Rico. *Biotropica*, 42(4):455-463

640 Heydari M, Omidipour R, Abedi M, Baskin C (2017) Effects of fire disturbance on alpha and
641 beta diversity and on beta diversity components of soil seed banks and aboveground
642 vegetation. *Plant Ecol Evol* 150:247-256 DOI: 10.5091/plececo.2017.1344

643 Hothorn T, Bretz F, Westfall P (2008) Simultaneous inference in general parametric models.
644 *Biom J* 50:346-363 DOI: 10.1002/bimj.200810425

645 Jackson HB, Fahrig L (2015) Are ecologists conducting research at the optimal scale? *Global*
646 *Ecology and Biogeography* 24:52-63.

647 Kerry M, Kelk G, Etkin D, Burton I, Kalthok S (1999) Glazed over: Canada copes with the ice
648 storm of 1998. *Environment* 41:6-11 DOI: 10.1080/00139159909604608

649 Klima K, Morgan GM (2015) Ice storm frequencies in a warmer climate. *Clim Change* 133:209-
650 222 DOI: 10.1007/s10584-015-1460-9

651 Kolb A, Diekmann M (2005) Effects of Life-History Traits on Responses of Plant Species to
652 Forest Fragmentation. *Conserv Biol* 19:929-938 DOI: 10.1111/j.1532-1739.2005.00065.x

653 Kosugi R, Shibuya M, Ishibashi S (2016) Sixty-year post-windthrow study of stand dynamics in
654 two natural forests differing in pre-disturbance composition. *Ecosphere*, 7(11) DOI:
655 10.1002/ecs2.1571

656 Kupfer JA, Runkle JR, Malanson GP (1997) Factors influencing species composition in canopy
657 gaps: the importance of edge proximity in Hueston Woods, Ohio. *Prof Geogr* 49(2):165-178
658 DOI: 10.1111/0033-0124.00067

659 Laurance WF, Cochrane MA (2001) Special section: Synergistic effects in fragmented
660 landscapes. *Conserv Biol* 15(6):1488-1489 DOI: 10.1046/j.1523-1739.2001.01088.x

661 Laurance WF, Curran TJ (2008) Impacts of wind disturbance on fragmented tropical forests: a
662 review and synthesis. *Austral Ecol* 33(4):399-408 DOI: 10.1111/j.1442-9993.2008.01895.x

663 Lemon PC (1961) Forest ecology of ice storms. *Bull Torrey Bot Club*, 21-29 DOI:
664 10.2307/2482410

665 Liebsch D, Marques MCM, Goldenberg R (2008) How long does the Atlantic rain forest take to
666 recover after a disturbance? changes in species composition and ecological features during
667 secondary succession. *Biol Cons* 141:1717-1725 DOI: 10.1016/j.biocon.2008.04.013

668 Lindenmayer DB, Fischer J (2006) *Habitat fragmentation and landscape change: an ecological
669 and conservation synthesis*. Island Press, Washington DC

670 Liu X, Liu X, Skidmore A, Garcia C (2017) Recovery of woody plant species richness in
671 secondary forests in China: a meta-analysis. *Sci rep* 7:10614 DOI: 10.1038/s41598-017-
672 10898-7

673 McCune B, Grace JB (2002) Analysis of ecological communities. MjM Software, Gleneden
674 Beach DOI: 10.1016/S0022-0981(03)00091-1

675 McCune JL, Van Natto A, MacDougall AS (2017) The efficacy of protected areas and private
676 land for plant conservation in a fragmented landscape. *Landscape Ecology* 32:871-82.

677 McCune JL, Vellend M (2013) Gains in native species promote biotic homogenization over four
678 decades in a human-dominated landscape. *Journal of Ecology* 101:1542-1551.

679 McCune JL, Vellend M (2015) Using plant traits to predict the sensitivity of colonizations and
680 extirpations to landscape context. *Oecologia* 178:511-524 DOI: 10.1007/s00442-014-3217-y

681 Metzger, J. P. 2000. Tree functional group richness and landscape structure in a Brazilian
682 tropical fragmented landscape. *Ecological Applications* 10:1147-1161 DOI: 10.1890/1051-
683 0761(2000)010[1147:TFGRAL]2.0.CO;2

684 Metzger JP, Martensen AC, Dixo M, Bernacci LC, Ribeiro MC, Godoy Teixeira AM, Pardini R
685 (2009) Time-lag in biological responses to landscape changes in a highly dynamic Atlantic
686 forest region. *Biol Cons* 142:1166-1177 DOI: 10.1016/j.biocon.2009.01.033

687 Myers JA, Chase JM, Crandall RM, Jiménez I (2015) Disturbance alters beta-diversity but not
688 the relative importance of community assembly mechanisms. *J Ecol* 103: 1291-1299 DOI:
689 10.1111/1365-2745.12436

690 Niinements O, Valladares F (2006) Tolerance to shade, drought, and waterlogging of temperate
691 Northern Hemisphere trees and shrubs. *Ecol Monograph* 76:521-547 DOI: 10.1890/0012-
692 9615(2006)076[051:TTSDAW]2.0.CO;2

693 Oksanen J, Guillaume Blanchet F, Friendly M, Kindt R, Legendre P, McGlenn D, Minchin PR,
694 O'Hara RB, Simpson GL, Solymos P, Stevens MHH, Szoecs E, Wagner H (2017) *Vegan*:
695 community ecology package. R package version 2.4-4

696 Oldham MJ, Bakowsky WD, Sutherland DA (1995) Floristic Quality Assessment System for
697 Southern Ontario. Natural Heritage Information System, Ontario Ministry of Natural
698 Resources, Peterborough DOI: 10.13140/RG.2.2.35685.91360

699 Ontario Ministry of Natural Resources and Forestry (2018) Ontario's forest regions.
700 <https://www.ontario.ca/page/forest-regions>. Accessed 31 December 2018

701 Peterson CJ (2000) Damage and recovery of tree species after two different tornadoes in the
702 same old growth forest: a comparison of infrequent wind disturbances. *Forest Ecol Manag*
703 135:237-252 DOI: 10.1016/S0378-1127(00)00283-8

704 Peterson CJ, Pickett STA (1995) Forest regeneration: a case study in an old-growth forest
705 catastrophic blowdown. *Ecology* 76:763-774 DOI: 10.2307/1939342

706 Pinheiro J, Bates D, DebRoy S, Sarkar D, and R Core Team (2017) nlme: linear and nonlinear
707 mixed effects models. R package version 3.1-131

708 Plotkin AB, Foster D, Carlson J, Magill A (2013) Survivors, not invaders, control forest
709 development following simulated hurricane. *Ecology* 94(2):414-423 DOI: 10.1890/12-
710 0487.1

711 R Core Team (2017) R: a language and environment for statistical computing and graphics. R
712 Foundation for Statistical Computing, Vienna, Austria. <https://www.r-project.org/>

713 Regan M (1998) Canadian ice storm 1998. *WMO Bulletin* 47:250-256

714 Reznicek AA, Voss EG, Walters BS (2011) Michigan Flora Online. University of Michigan.
715 <http://michiganflora.net>. Accessed 14 January 2007

716 Reznicek AA, Penskar MR, Walters BS, Slaughter BS (2014) Michigan Floristic Quality
717 Assessment Database. Herbarium, University of Michigan, Ann Arbor MI and Natural
718 Features Inventory, Michigan State University, Lansing, MI.

719 Rhoads AG, Hamburg SP, Fahey TJ, Siccama TG, Hane EN, Battles J, Cogbill C, Randall J,
720 Wilson G (2002) Effects of an intense ice storm on the structure of a northern hardwood
721 forest. *Can J For Res* 32(10):1763-1775 DOI: 10.1139/x02-089

722 Riitters K, Wickham J, Costanza JK, Vogt P (2016) A global evaluation of forest interior area
723 dynamics using tree cover data from 2000 to 2012. *Landsc Ecol* 31(1):137-148 DOI:
724 10.1007/s10980-015-0270-9

725 Roberts DW (2016) labdsv: ordination and multivariate analysis for ecology. R package version
726 1.8-0

727 Schwartz NB, Uriarte M, DeFries R, Bedka KM, Fernandes K, Gutiérrez-Vélez V, Pinedo-
728 Vasquez MA (2017) Fragmentation increases wind disturbance impacts on forest structure
729 and carbon stocks in a western Amazonian landscape. *Ecol Appl* 27(6):1901-1915 DOI:
730 10.1002/eap.1576

731 Sheil D (2001) Long-term observations of rain forest succession, tree diversity and responses to
732 disturbance. *Plant Ecol* 155:183-199 DOI: 10.1023/A:1013243411819

733 Silva Pedro M, Rammer W, Seidl R (2016) A disturbance-induced increase in tree species
734 diversity facilitates forest productivity. *Landsc Ecol* 31:989-1004 DOI: 10.1007/s10980-
735 015-0317-y

736 Smart SM, Ellison AM, Bunce RGH, Marrs RH, Kirby KJ, Kimberly A, Scott AW, Foster DR
737 (2014) Quantifying the impact of an extreme climate event on species diversity in
738 fragmented temperate forests: the effect of the October 1987 storm on British broadleaved
739 woodlands. *J Ecol* 102:1273-1287 DOI: 10.1111/1365-2745.12291

740 Swetnam TW, Allen CD, Betancourt JL (1999) Applied historical ecology: using the past to
741 manage for the future. *Ecol Appl* 9(4):1189–1206 DOI: 10.1890/1051-
742 0761(1999)009[1189:AHEUTP]2.0.CO;2

743 Tremblay M, Messier C, Marceau DJ (2005) Analysis of deciduous tree species dynamics after a
744 severe ice storm using SORTIE model simulations. *Ecol Modell* 187(2-3): 297-313 DOI:
745 19.1016/j.ecolmodel.2005.01.038

746 Turner MG, Baker WL, Peterson CJ, Peet RK (1998) Factors influencing succession: lessons
747 from large, infrequent natural disturbances. *Ecosystems*, 1(6): 511-523 DOI:
748 10.1007/s100219900047

749 Venables WN, Ripley BD (2002) *Modern applied statistics with S*. Fourth Edition. Springer,
750 New York

751 Von Oheimb G, Friedel A, Bertsch A, Härdtle W (2007) The effects of a windthrow on plant
752 species richness in a Central European beech forest. *Plant Ecol* 191:47-65 DOI:
753 10.1007/s11258-006-9213-5

754 Weir JMH, Johnson EA, Miyanishi K (2000) Fire frequency and the spatial age mosaic of the
755 mixed-wood boreal forest in western Canada. *Ecol Appl* 10(4): 1162-1177. DOI:
756 10.1890/1051-0761(2000)010[1162:FFATSA]2.0.CO;2

757 White PS, MacKenzie MD, Busing RT (1985) Natural disturbance and gap phase dynamics in
758 southern Appalachian spruce-fir forests. *Can J For Res* 15:233-240. DOI: 10.1139/x85-041

759 Whitney HE, Carter Johnson W (1984) Ice storms and forest succession in southwestern
760 Virginia. *Bull Torrey Bot Club* 111:429-437. DOI: 10.2307/2995892

761 Whittaker RH. 1972. Evolution and measurement of species diversity. *Taxon* 1: 213-251.

762 Xi W, Peet RK (2011) The complexity of catastrophic wind disturbance on temperate forests. In
763 Lupo A (ed) Recent hurricane research: climate, dynamics, and societal impacts. InTech,
764 Vienna, pp 503-534. DOI: 10.5772/16167

765 Zhao D, Allen B, Sharitz RR (2006) Twelve year response of old-growth southeastern
766 bottomland hardwood forests to disturbance from Hurricane Hugo. Can J For Res 36:3136-
767 3147. DOI: 10.1139/x06-204

768

769 **Tables**

770 Table 1: candidate predictor variables used to model each response variable

response	candidate predictors	predictor type
change in stem density (<i>short-term</i> = stem density 2001 – density 1998; <i>long-term</i> = density 2017 – density 1998)	ice storm damage (pdi)	disturbance
	total forest area within 1000m	landscape context
	distance to nearest forest edge	landscape context
	pdi x forest area	disturbance x landscape context
	pdi x distance to edge	disturbance x landscape context
	stem density 1998	covariate
change in species richness (SR) (<i>short-term</i> = SR 2001 – SR 1998; <i>long-term</i> = SR 2017 – SR 1998)	wetness index	covariate
	ice storm damage (pdi)	disturbance
	total forest area within 1000m	landscape context
	distance to nearest forest edge	landscape context
	pdi x forest area	disturbance x landscape context
	pdi x distance to edge	disturbance x landscape context
change in community composition (<i>short-term</i> = Bray-Curtis dissimilarity, 2001 vs. 1998; <i>long-term</i> = Bray-Curtis dissimilarity, 2017 vs. 1998)	species richness 1998	covariate
	wetness index	covariate
	ice storm damage (pdi)	disturbance
	total forest area within 1000m	landscape context
	distance to nearest forest edge	landscape context
	pdi x forest area	disturbance x landscape context
pdi x distance to edge	starting composition	disturbance x landscape context
	average DBH 1998	covariate
	species richness 1998	covariate

771

772

773 Table 2: Model parameters for predictors included in the minimum adequate model obtained for each response v
 774 drop1 tests. Estimates are standardized partial regression coefficients.

Response	Predictor	Estimate	SE	p (dr
short-term change in stem density	<i>pdi</i>	30.96	12.67	0.017
	<i>forest amount</i>	-31.78	13.12	0.018
	wetness index	19.01	12.11	0.121
long-term change in stem density	<i>pdi</i>	-34.12	15.04	0.027
	forest amount	-25.65	14.92	0.091
	distance to edge	-8.01	13.91	0.566
	<i>stem density 1998</i>	-61.46	13.95	<0.001
	<i>pdi x distance to edge</i>	-51.10	34.74	0.146
short-term change in species richness	<i>pdi</i>	2.21	0.62	<0.001
	<i>forest amount</i>	-1.33	0.62	0.034
long-term change in species richness	<i>pdi</i>	-0.50	0.73	0.498
	forest amount	-1.07	0.75	0.161
	distance to edge	0.01	0.72	0.990
	<i>species richness 1998</i>	-2.18	0.67	0.002
	<i>pdi x distance to edge</i>	-2.87	1.72	0.101
short-term change in community composition	<i>pdi</i>	0.22	0.11	0.050
	forest amount	-0.21	0.11	0.068
	distance to edge	0.07	0.10	0.459
	average DBH 1998	0.16	0.09	0.089
	<i>species richness 1998</i>	0.24	0.10	0.016
	<i>pdi x forest amount</i>	-0.30	0.10	0.005
	<i>pdi x distance to edge</i>	0.28	0.12	0.019
long-term change in community composition	<i>pdi</i>	-0.20	0.10	0.052
	<i>forest amount</i>	-0.22	0.11	0.048
	distance to edge	-0.00	0.10	0.973
	starting composition	0.19	0.10	0.054
	<i>pdi x distance to edge</i>	-0.17	0.12	0.141

775 * predictors that explain a significant amount of variation in the response once all other predictors in the models
776 ($p < 0.05$ in drop1 tests) are italicized
777 † adjusted R^2 for linear models, pseudo- R^2 for models of change in community composition

778

779 **Figures**

780 Figure 1. (A) Map outlining the boundaries of the study region. Forests within greater city limits
781 in 2015 (green shading), agricultural land use (yellow), urban development (grey), and black
782 squares showing the locations of the 17 landscapes. (B) One 1km² landscape showing study plots
783 (black circles). Dotted lines illustrate the distance to the nearest forest edge for two plots, with
784 one (i) having a smaller distance than the other (ii). (C) The location of the study area (red
785 shading) within the province of Ontario (white), and in relation to the surrounding areas in
786 Canada (hatched) and the United States (grey).

787

788 Figure 2. Comparison of average (A) density and (B) species richness of the shrub/sapling layer
789 in each year. Error bars are ± 2 SE. Letters above the error bars indicate significant differences
790 between years.

791

792 Figure 3. The trajectory over time of the Bray-Curtis dissimilarity of each plot compared to its
793 starting composition in 1998. Dissimilarity values closer to zero indicate greater similarity in
794 composition. Plots are grouped according to the 1km² landscape in which they are located.
795 Landscapes are ordered from top left to bottom right based on increasing average area of forest
796 within 1000m of each plot in 1999. damage = a factorial representation of plot damage index
797 (pdi) where dotted lines indicate plots with pdi lower than the median and solid lines indicate
798 plots with pdi higher than the median.

799

800 Figure 4. Partial residual plots based on the minimum adequate model for the change in species
801 richness from 1998 to 2001 (see Table 2). Note that for each panel, all other variables in the
802 model are held at the median. ** indicates $p < 0.05$ in drop1 test, * indicates $0.1 > p > 0.05$ in drop1
803 test.

804

805 Figure 5. Partial residual plots based on the minimum adequate model for the change in species
806 richness from 1998 to 2017 (see Table 2). Note that for each panel, all other variables in the
807 model are held at the median. Panel E illustrates the interaction between plot damage index and
808 distance to forest edge – the continuous variable distance to forest edge has been divided into 3
809 categories by taking cross-sections at the 10th, 50th, and 90th percentiles. Confidence bands are
810 omitted for clarity. ** indicates $p < 0.05$ in drop1 test, * indicates $0.1 > p > 0.05$ in drop1 test.

811

812 Figure 6. Partial residual plots based on the minimum adequate model for the change in
813 community composition from 1998 to 2001 (see Table 2). Note that for each panel, all other
814 variables in the model are held at the median. Panels F and G illustrate the interactions between
815 plot damage index and forest amount, and plot damage index and distance to nearest forest edge,
816 respectively – the continuous variables distance to forest edge and forest amount have been
817 divided into 3 categories by taking cross-sections at the 10th, 50th, and 90th percentiles.
818 Confidence bands are omitted for clarity. ** indicates $p < 0.05$ in drop1 test, * indicates
819 $0.1 > p > 0.05$ in drop1 test.

820

821

822 Figure 7. Partial residual plots based on the minimum adequate model for the change in
823 community composition from 1998 to 2017 (see Table 2). Note that for each panel, all other
824 variables in the model are held at the median. Panel E illustrates the interaction between plot
825 damage index and distance to the nearest edge – the continuous variable distance to forest edge
826 has been divided into 3 categories by taking cross-sections at the 10th, 50th, and 90th percentiles.
827 Confidence bands are omitted for clarity. ** indicates $p < 0.05$ in drop1 test, * indicates
828 $0.1 > p > 0.05$ in drop1 test.

829

830

831

832

833

834

835

836

837

838

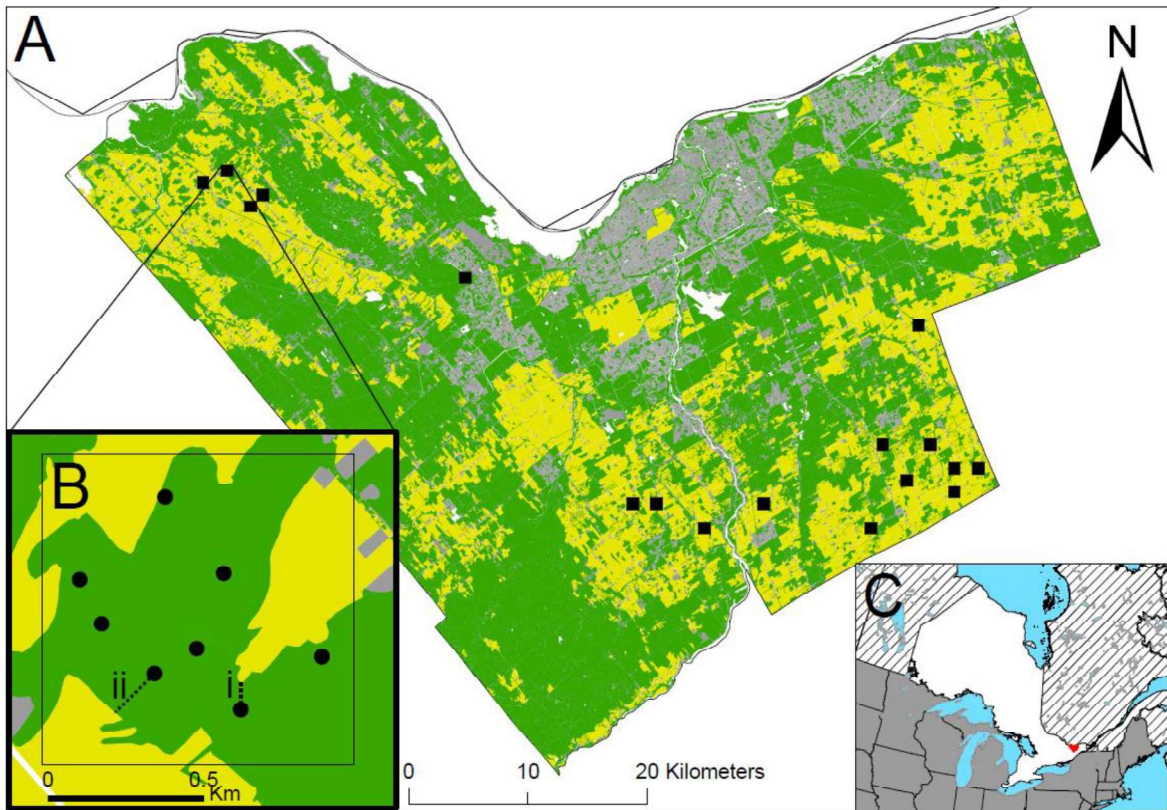
839

840

841

842

843 Figure 1.



844

845

846

847

848

849

850

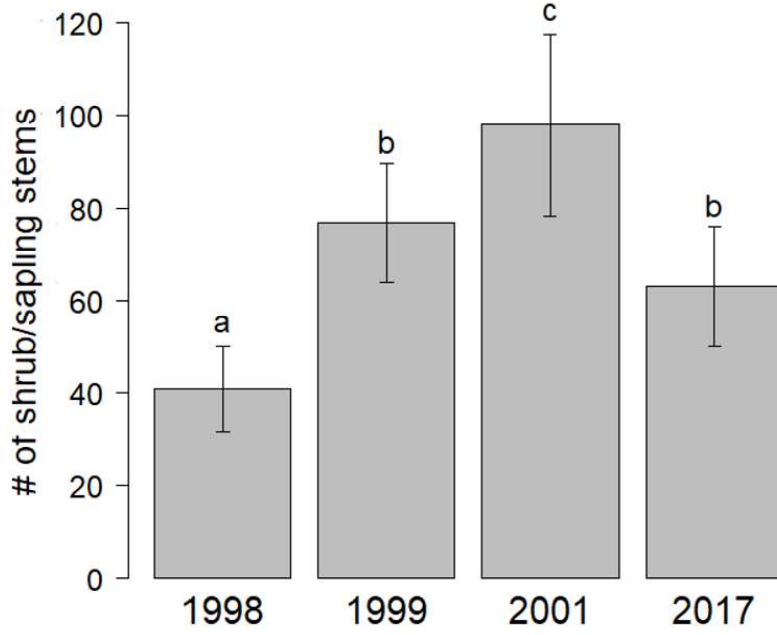
851

852

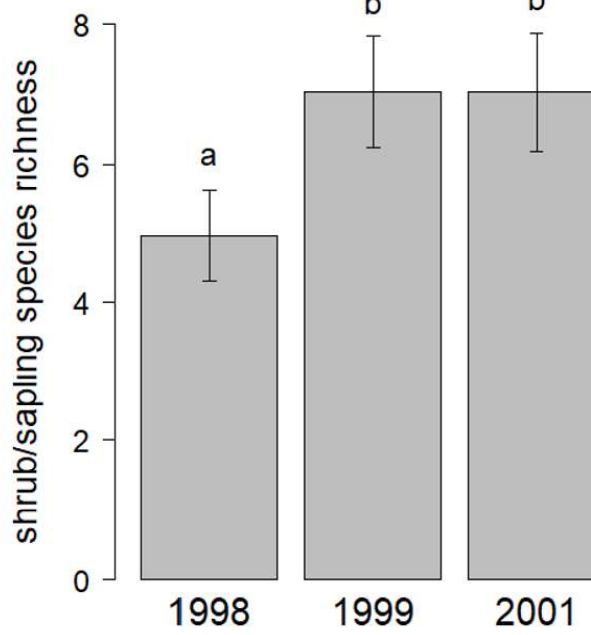
853

854

A



B



855 Figure 2.

856

857
858
859
860
861
862
863
864
865
866
867
868
869
870
871
872
873
874
875

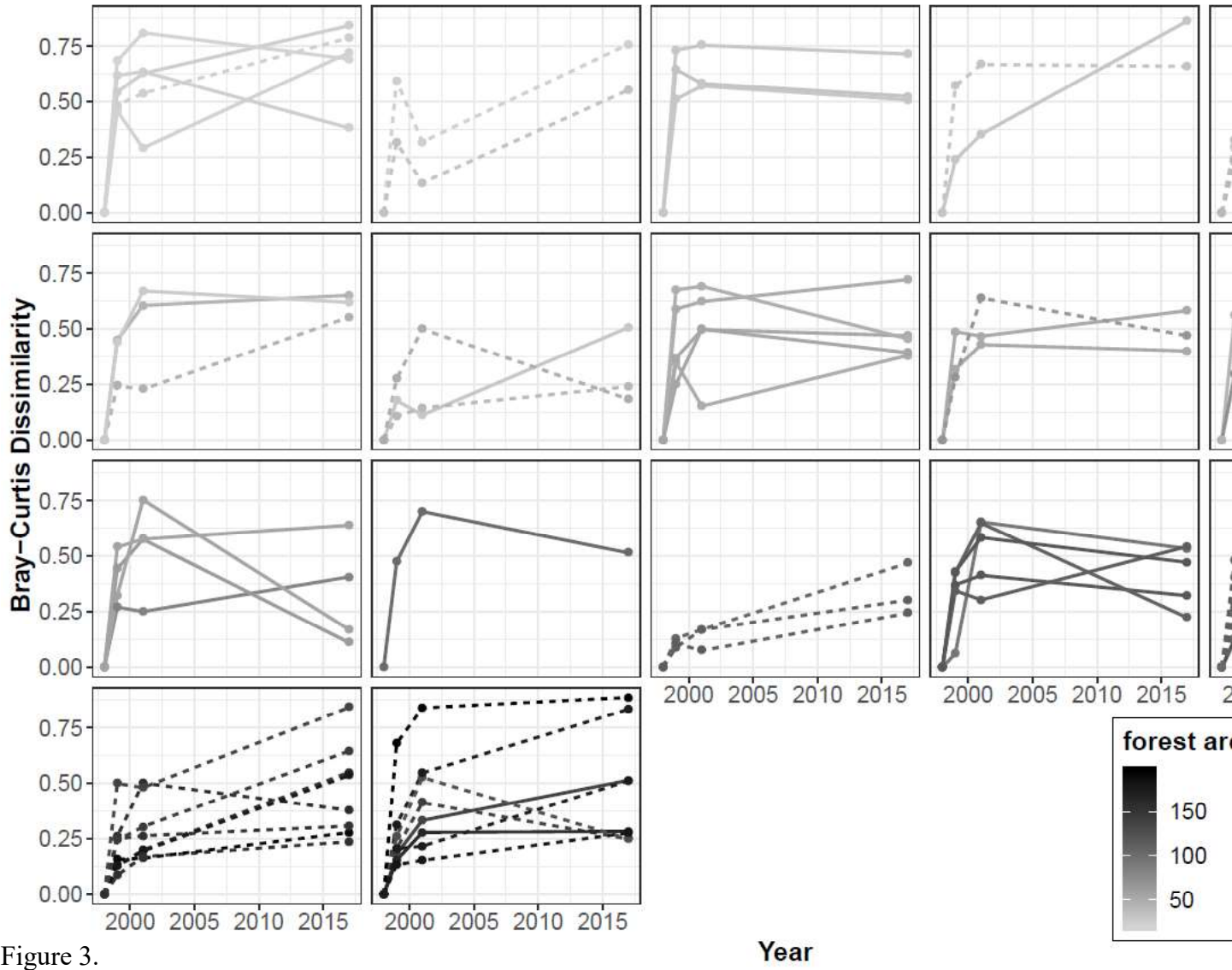


Figure 3.

876
877
878
879
880
881
882
883
884
885
886
887
888

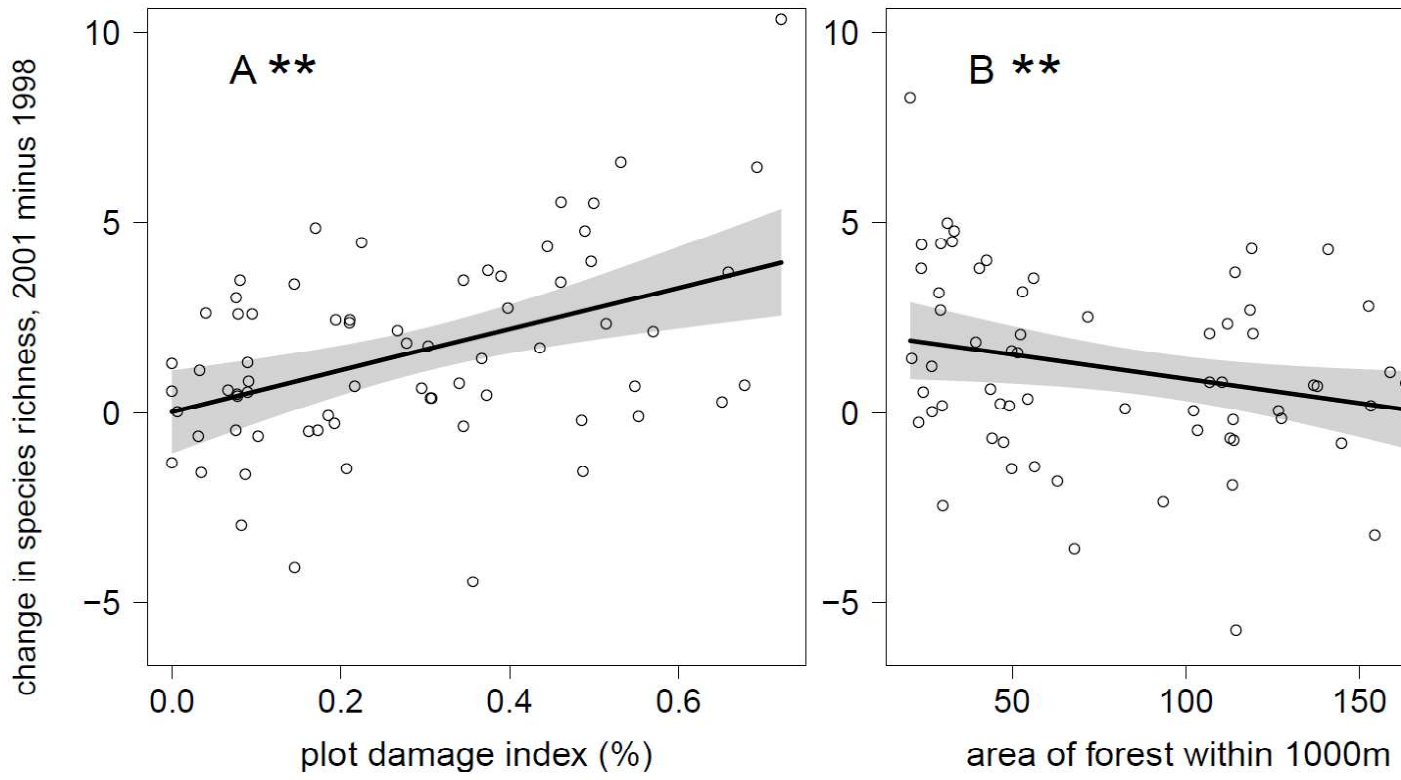


Figure 4

889

890

891

892

893

894

895

896

897

898

899

900

901

902

903

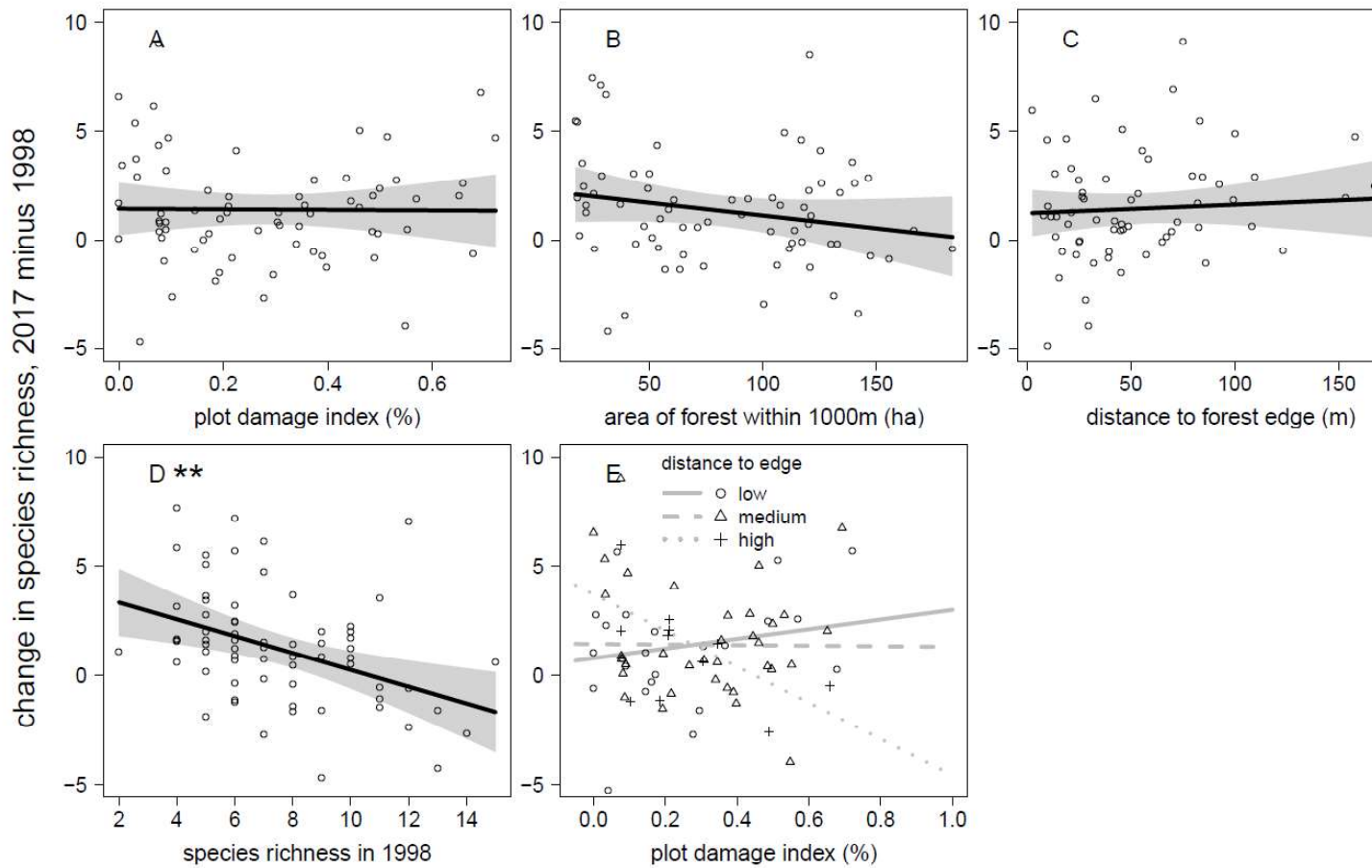


Figure 5

904
905
906
907
908
909
910
911
912
913
914
915
916

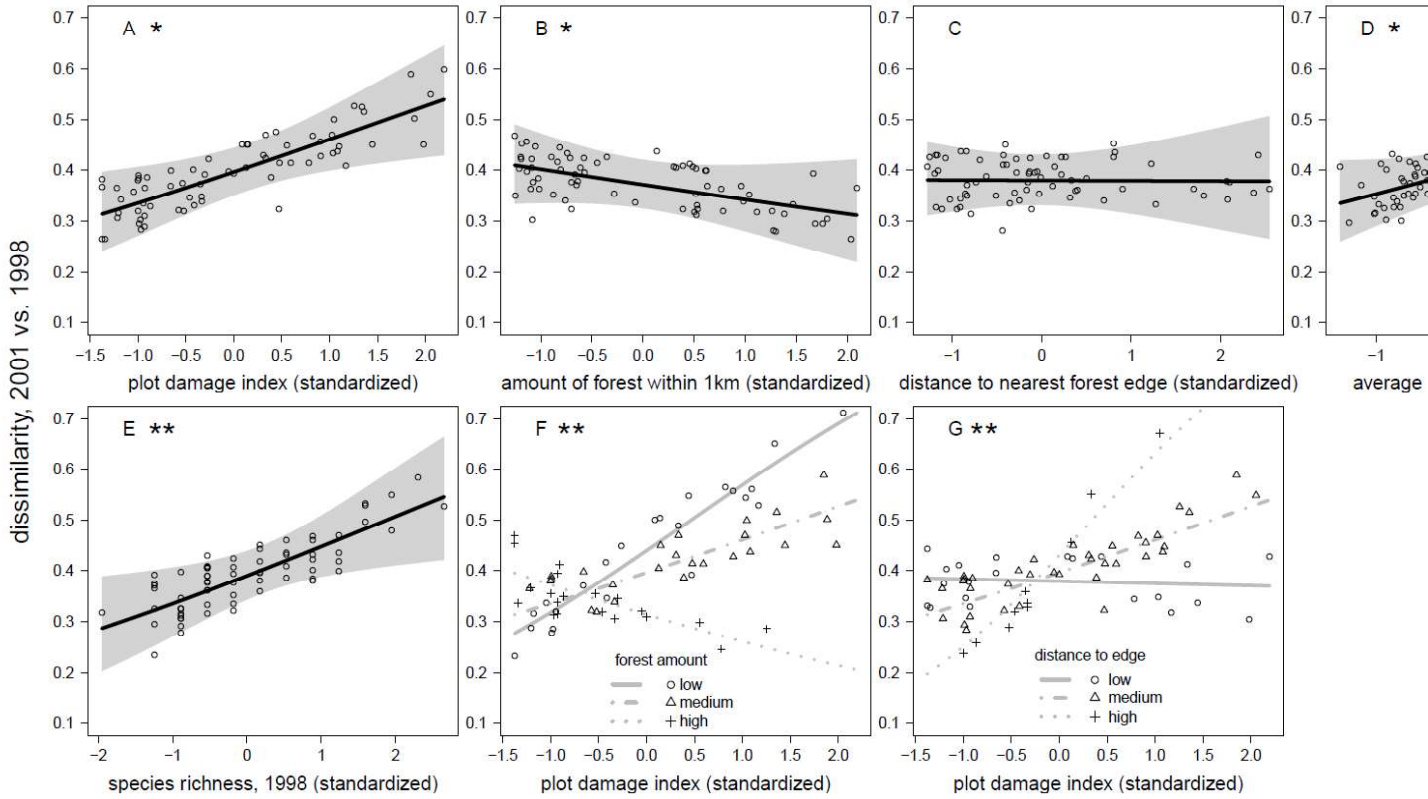


Figure 6.

917
918
919
920
921
922
923
924
925
926
927
928
929
930
931
932
933
934
935
936

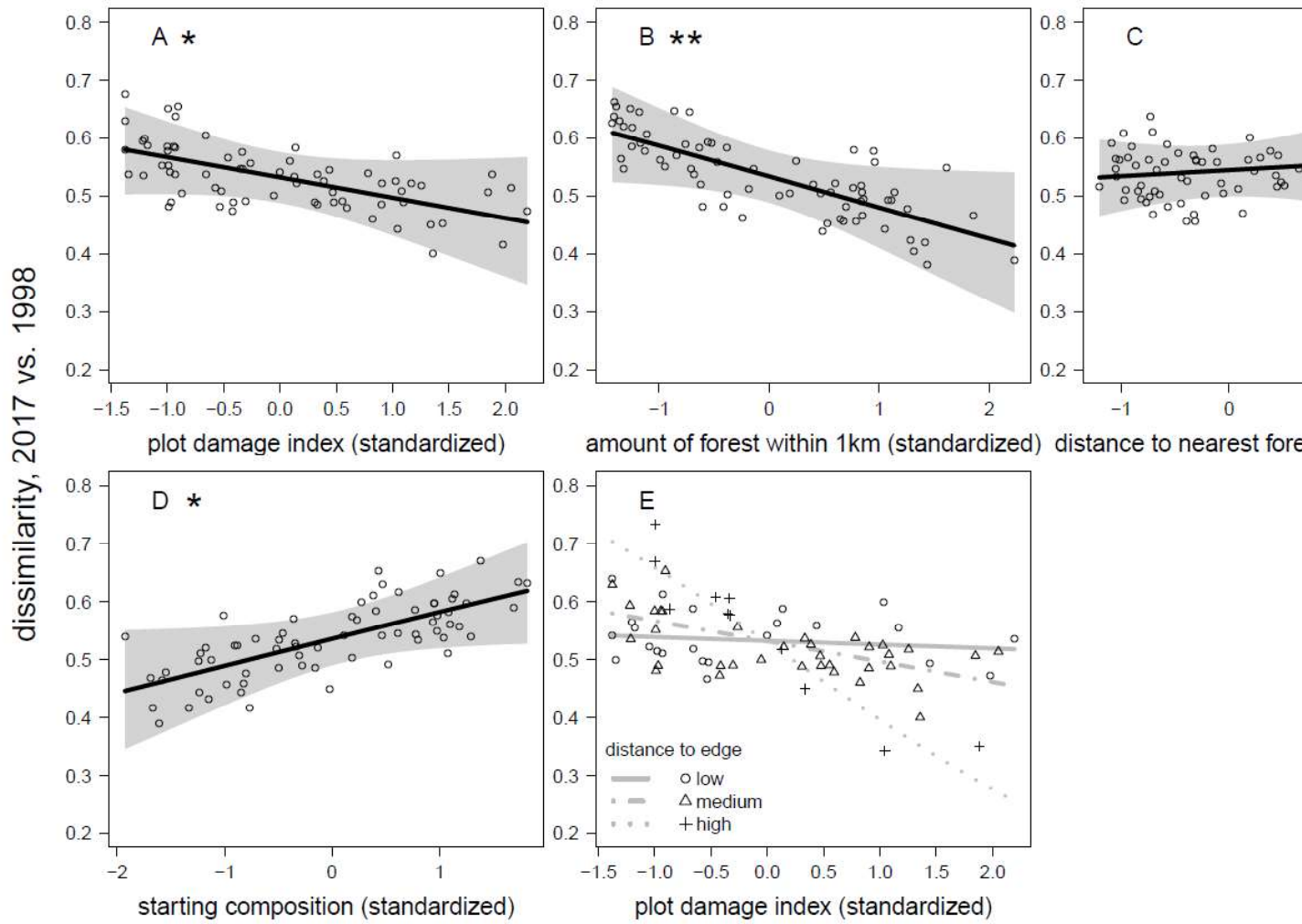


Figure 7