

Disease ontogeny overshadows effects of climate and species interactions on population dynamics in a nonnative forest disease complex

Jeffrey R. Garnas^{a,b}

David R. Houston^c

Matthew P. Ayres^a

Celia Evans^d

^aDepartment of Biological Sciences, Dartmouth College, Hanover, NH 03755

^bCurrent Address: Zoology and Entomology, Forestry and Agricultural Biotechnology Institute, University of Pretoria, Pretoria 0002, South Africa

^cUS Forest Service retired, Danville, VT 05828

^dDepartment of Science, Paul Smith's College, Paul Smith, NY 12970

Corresponding author:

Jeff Garnas

Forestry and Agriculture Biotechnology Institute (FABI)

University of Pretoria

Pretoria 0002, South Africa

Phone/Fax: (27)12-420-3854 / (27)12-420-3960

Email: jeff.garnas@fabi.up.ac.za

Subject classification: Population Ecology

Abbreviations: BBD, beech bark disease; DD, density dependence

Pages: 29; **Figures:** 4; **Tables:** 0

ABSTRACT

1
2 Biotic threats to trees often arise from interactions among two or more species, frequently
3 insects and fungi, that function together to defeat host defenses, secure resources and colonize new
4 hosts. Feedbacks among plant enemies can have large effects on host population and disease
5 dynamics, either by promoting stabilizing negative feedbacks or contributing to positive feedbacks
6 that can destabilize populations and permit outbreaks. Feedbacks can be rapid and direct (e.g.,
7 within trees or among years) or can arise from slowly developing changes in host resource quantity
8 or quality at the scale of forest stands or landscapes. Climate may also influence system dynamics by
9 altering feedbacks within or among species or through density independent effects. We evaluated
10 major drivers of population dynamics of beech bark disease (BBD), an important forest disease in
11 eastern deciduous forests of North America, using data from 28 study sites in the eastern United
12 States monitored for up to 14 years between 1979 and 1992. Both primary causal agents of BBD –
13 the introduced felted beech scale (*Cryptococcus fagisuga*) and native fungi (*Neonectria* spp.) – showed
14 strong simple density dependence in all study populations. Surprisingly, densities of scale insects
15 and fungi had little or no effects on population growth rates of the other, despite their habit of living
16 in close physical relationships. For both insects and fungi, ecologically important features of the
17 density dependent functions (slope, carrying capacity and density independent variance) were
18 variable across sites. Climatic effects on density-dependent functions (and scatter around them)
19 were evident but generally weak and variable. The most striking predictor of patterns in density
20 dependence was duration since establishment of BBD in the region. Apparently BBD alters forests
21 over decades in ways that strengthen self-regulation among causal agents without eliminating or
22 even dramatically reducing host populations.

23

24 **Keywords:** density dependence | climate | biotic feedbacks | beech bark disease | insect-fungal

25 interactions

26

27

INTRODUCTION

28 The global transfer of pests and pathogens has led to numerous devastating examples of forest
29 disease outbreaks in the United States and worldwide, including Chestnut blight, Dutch elm disease,
30 and pine pitch canker, among others (Brasier 1991, Storer et al. 1997, Paillet 2002). Despite
31 comprehensive efforts to limit their introduction and spread, rates of establishment of exotic insects
32 and pathogens have been increasing nearly exponentially for 200 years (Liebhold et al. 1995) and
33 pose increasing threats to forests worldwide (Seppälä et al. 2009). On the other hand, notable pests
34 are only a subset of the many forest organisms that have become established in novel ecosystems
35 following recent introductions and range extensions. Apparently, ecological controls regularly limit
36 the abundance of newly arrived organisms, but general theoretical principles for predicting
37 pestilence have been elusive (Parker and Gilbert 2004, Dukes et al. 2009). One appealing possibility
38 is that species interactions within the newly formed assemblages are crucial (Burdon et al. 2006).

39 Of the herbivores and pathogens that cause damage to forest trees, many have strong (frequently
40 symbiotic) associations with other organisms that exploit plants (Lombardero et al. 2003, Six and
41 Klepzig 2004, Klepzig et al. 2009). For example, many bark and wood-feeding insects harbor
42 microbial symbionts that aid in nutrition (Hoffstetter et al. 2006, Klepzig et al. 2009). Where such
43 reciprocally beneficial interactions arise, there could be increased tendency for pestilence due to the
44 intrinsic instabilities associated with mutualisms (May 1982, Dean 1983, Bleiker and Six 2007).
45 However, if co-occurring plant-feeding organisms compete or share predators, populations are more
46 likely to be constrained and pestilence therefore less likely (Holt and Lawton 1994, Chesson 2000).

47 An alternative general explanation for variable tendencies toward pestilence is feedback from
48 changes in host resources. For example, the abundance of introduced organisms may decline with
49 time since occupancy due to decreased quantity and/or quality of host plants. Impacts on forests
50 will be least when this negative feedback arises quickly and with only modest declines in host

51 abundance. In the absence of rapid stabilizing feedback from declining resources, the transient
52 dynamics in insect abundance can be lengthy and consequential (Tobin and Bjørnstad 2003) and the
53 new state of the system uncertain (Anderson and May 1979).

54 Climate provides another potential explanation for variable outcomes from new plant-feeding
55 organisms in forest systems (Berryman et al. 1987, Estay et al. 2009). Furthermore, climate warming
56 seems to be exacerbating undesirable invasions by increasing the extent of forests that are
57 climatically suitable for potential new pests (Seppälä et al. 2009). Climate is a frequent example of
58 “density-independent effects” or demographic forces that are not themselves influenced by
59 abundance (Berryman 2002; exogenous effects *sensu* Turchin 2003). Accordingly, analytical
60 treatments of climate effects have commonly subsumed climate within the error term of per capita
61 population growth (R) as a function of abundance. However, climate can also influence intrinsic
62 growth rates (r), carrying capacity (K) and/or variability around the density dependent function
63 (Royama 1992), though studies addressing such impacts are comparatively rare. Furthermore,
64 geographic patterns in climatic effects on insect populations are likely (e.g., increased importance of
65 winter cold in poleward populations; Ungerer et al. 1999). When climate effects are strong, they can
66 synchronize population fluctuations over large areas (Moran 1953, Peltonen et al. 2002). When
67 there are close associations among plant-feeding species (e.g., symbioses), climatic effects on the
68 system could be (1) more pronounced because there are more avenues for autecological impacts on
69 one or the other species, or (2) more buffered because the assemblage is more environmentally
70 tolerant than the species by themselves (Klepzig and Six 2004).

71 Empirical study of how the abundance of non-native organisms is influenced by species
72 interactions, resource depletion, and climate requires measurements of population dynamics across a
73 climatically variable region, but such data are rarely available. We were able to compare alternative
74 theoretical models of population dynamics via analysis of spatially replicated time series abundance

75 data for a conspicuous but poorly studied non-indigenous pest assemblage in North America: beech
76 bark disease (BBD). The spread of BBD through northeastern North America, while undesirable,
77 presents a natural experiment for better understanding the population dynamics of newly interacting
78 organisms associated with forest disease.

79 MATERIALS AND METHODS

80 *Beech bark disease in North America*

81 Beech bark disease (BBD) in North America is a bark cankering disease of *Fagus grandifolia* Ehrh.
82 arising from the interaction between an introduced scale insect (the felted beech scale -- *Cryptococcus*
83 *fagisuga* Lind.) and two species of ascomycete fungi of the genus *Neonectria* (*N. faginata* [Lohman et
84 al.] Castl. & Rossman and *N. ditissima* [Tul. & C. Tul.] Samuels & Rossman; Castlebury et al. 2006).
85 Scale insects feed on cell contents of periderm cells. *Neonectria* spp. only infect beech in the presence
86 of scale insects, exploiting the feeding behavior of the insects to gain access to phloem resources
87 (Houston 1994). Although the effects of *Neonectria* on the scale insects are less clear, it has been
88 generally assumed that cankers and wound callous caused by *Neonectria* infection provide microsites
89 in which scale insects can feed, overwinter, and avoid being displaced by stemflow during rains
90 (Shigo 1964, Houston et al. 1979). Both species are obligatorily sedentary after a brief dispersal
91 opportunity by propagules (ascospores or crawlers). Individual host trees typically harbor persistent
92 populations for many years, frequently of both species living in intimate association within the same
93 bark wounds. While impacts have been dramatic (approximately 50% mortality of adult trees during
94 the first 10 years of infection; Houston et al. 2005), beech remains one of the most abundant forest
95 trees, even in the longest affected regions (Garnas 2012).

96 *Study sites and sampling design*

97 We analyzed time series abundance data of the two BBD agents that were collected with the
98 same protocol for 14 years across 28 sites distributed across about 200,000 km² (Supplementary

99 materials Appendix, Fig. A1). Sites were selected by one of us (DRH) and colleagues in 1978-83 to
100 encompass the geographic range of BBD at the time, and to capture a gradient of temporal
101 development of the disease (Table A1). Based on county-level estimates of the year of initial scale
102 insect colonization (Morin et al. 2007), plots closest to the initial point of scale insect establishment
103 in Halifax, Nova Scotia had been affected for about 44 years at the time of initial sampling, while
104 others had yet to become infested (duration [$\bar{x} \pm SD$] = 19 ± 15 years). All plots retained in the
105 analysis became colonized during the course of the study. Preliminary analyses using a subset of
106 these data were reported in Houston et al. (2005).

107 Field crews established plots by finding and marking 50-266 trees per plot, and revisited them
108 each summer through 1992 (though not all plots were continuously monitored, there were few
109 missing years; Table A1). All sites were approximately 1.5 hectares, which allowed us to use the
110 number of trees sampled as a proxy for beech stem density. Population estimation and sampling
111 protocols were identical across sites and years (described in detail in Houston et al. 2005). Briefly,
112 each year field crews measured diameter at breast height (DBH) and crown class (Avery and
113 Burkhart 2002), and estimated tree-specific population densities of insects and fungi using visual
114 assessments of waxy secretions produced by scale insects and red fruiting bodies (perithecia)
115 produced by *Neonectria*. Wax is produced by all feeding beech scale insects and is a reliable proxy for
116 insect population density (Ehrlich 1934). Hyphal growth within phloem tissue could not be
117 assessed, but external perithecia are produced annually on most infected trees so the abundance of
118 perithecia is a reasonable proxy for fungal abundance (Houston et al. 2005). Separate estimates of
119 population densities using the same ordinal scales (0-5 for insects and 0-4 for *Neonectria*; Table A2)
120 were made at three heights on the bole of each tree (0-2, 2-4 and 4+ meters above the ground). We
121 also quantified “tarry spots,” areas of bark in early stages of infection identified by dark, weeping

122 and/or stained spots which in many cases indicate incipient *Neonectria* infection. Tarry spots were
123 quantified using four abundance classes: 0 (none); 1 (1-5); 2 (6-10); or 3 (> 10).

124 *Climate data acquisition*

125 Records of daily precipitation, snowfall, maximum and minimum temperatures were obtained
126 for 1978 to 1992 from the National Oceanic and Atmospheric Administration (NOAA)
127 (<http://cdo.ncdc.noaa.gov/CDO/cdo>). We initially considered all stations within 0.5 degrees of
128 latitude from each plot. All plots (with the exception of NY610 which was excluded from analyses
129 involving climate variables) were within 8 to 55 km of a climate station (\bar{x} = 24 km) with generally
130 complete records during our study years. In cases of missing years for one or more variables at an
131 otherwise ideal nearby climate station, we substituted estimates based on records from the next
132 closest station. Climate stations with >3 consecutive days of missing records for any variable were
133 excluded; we used linear interpolation from surrounding days to estimate temperatures for
134 occasional missing records of 1-3 days. We corrected for adiabatic effects by adjusting daily
135 temperatures (up or down) by 0.5 °C per 100 m (Tran et al. 2007) of difference in elevation between
136 plots and weather stations (maximum difference = 636 m, mean = 194 m).

137 *Data analyses*

138 We began by examining our data with respect to its generic temporal and spatial autocorrelational
139 structure. For temporal patterns, we evaluated the autocorrelation (ACF) and partial correlation
140 (PACF) functions for each population at each site as well as cross-correlations between the scale
141 insects and fungus. Our time series were short for such analyses (Turchin 2003), but we could take
142 advantage of the spatial replication of time series to test for patterns in the correlation structure that
143 were consistent among sites. We evaluated spatial auto- and cross-correlations among sites with
144 spline correlograms from spatially explicit population growth rates for both insects and fungi
145 (Bjørnstad 2009).

146 More explicit tests of our biological hypotheses were permitted by analyses of population growth
147 rate (R) for both insects and fungi using the formula $R_t = \ln(N_{t+1}/N_t)$, where N_t and N_{t+1} correspond
148 to mean population estimates (across height zones) on each tree in the focal and following year
149 respectively. Analyses were based on tree-specific population estimates because this is the scale at
150 which we hypothesize demographic effects (Ylloja et al 1999). This approach assumes that
151 immigration and emigration rates are balanced, or that dispersal among trees has a negligible effect
152 on population dynamics (Royama 1992). Spatially explicit sampling conducted in 2006-2008 at
153 multiple spatial scales throughout the eastern United States indicated a very limited role for dispersal,
154 as extinction at the scale of trees and sites is very rare, and re-colonization from the same tree from
155 year to year typically swamps effects of among-tree dispersal (Garnas 2012). Because population
156 densities were estimated using ordinal classes, and because there are no clear *Neonectria* "individuals",
157 we treat R as an analog to traditional per capita rates. Abundance classes correspond roughly to the
158 natural logarithm of percent cover of scale insects and fungi on trees (as confirmed in post hoc
159 examination in the field) and so scale approximately to continuous variables. Nonetheless, we
160 interpret growth rate parameters cautiously as influencing transitions among abundance classes. Our
161 interpretations emphasize the relative contribution of various biotic and abiotic forces in driving
162 interannual variation in population growth rate, and in how density dependent functions vary
163 spatiotemporally. We excluded tree-year combinations where N_t or $N_{t-1} = 0$ because sampling was
164 sufficiently thorough such that zeros represent the absence of a population on that tree in that year
165 (frequently from local extinction events). Scale insects were common in most sites, present on 3,202
166 trees across 24 plots, each sampled between 6 and 14 times. *Neonectria* was considerably rarer but we
167 were still able to calculate R_t for 629 trees in 18 sites. Preliminary analyses included tarry spots in
168 estimates of fungal abundance but this variable had little or no effect and was dropped from
169 analyses.

170 We tested for the strength and importance of density dependent effects and of feedback from
 171 associated disease agent populations using the general linear model:

$$172 \quad R_t = F(\text{Site}, N_b, N_{t-1}, A_b, A_{t-1}, \text{Site} \times [N_b, N_{t-1}, A_b, A_{t-1}]) + \varepsilon \quad [1]$$

173 where N is the population density of the focal species (either scale insects or *Neonectria*) and A is
 174 the density of the associated disease agent (*Neonectria* in the case of scale insects, and vice versa) at
 175 time t and $t-1$. *Site* was treated as a main categorical effect and crossed with all other terms; no
 176 additional interactions or higher order terms were considered. The relationship between R and N_t
 177 for each population showed some nonlinearity due to frequent cases of trees with stable, low
 178 population densities. We explored various transformations of the dependent variable (e.g., $\ln[N_t]$,
 179 $N_t^{1/2}$) as well as a nonlinear model (May 1976), but neither approach substantially improved the
 180 model fit. Because our data did not strictly meet the assumptions of the statistical model, we treated
 181 our F-tests as approximations and relied primarily on model selection to identify important variables
 182 with the potential for strong and/or broad-scale effects. We employed Pollard's randomization test
 183 as a distribution-free assessment of density dependence relative to a random walk of population
 184 abundance over time (Pollard et al. 1987, Woivod and Hanski 1992).

185 For each site independently, and for both insects and fungi, we estimated the slope, carrying
 186 capacity (K , the model x-intercept), and the mean squared error (MSE) from the model $R = b_0 + b_1 N_t$
 187 $+ \varepsilon$. These measures varied considerably by site, and preliminary analyses suggested latitudinal
 188 patterns and spatially autocorrelated dynamics. We analyzed each of three parameters from the
 189 density dependent function: slope (b_1), K ($-b_1/b_0$) and variability unexplained by density (MSE)
 190 independently for insects and fungi in two complementary ways. First, we compared models
 191 containing explanatory variables from four distinct categories in an order corresponding to our *a*
 192 *priori* understanding of the relative importance of each in driving BBD dynamics (Table A3). All
 193 model comparison was performed using Akaike's Information Criteria, employing a correction for

194 small sample size (Anderson 2008). We retained variables with parsimonious explanatory power
195 within each of four categories of theoretical possibilities: densities of the associated population
196 (fungi for insects and insects for fungi), resource quality and abundance, climatic effects, and disease
197 ontogeny (duration of regional infection with BBD). Table A3 lists and justifies the variables that
198 we considered. Our model selection was hierarchical in that once a predictor was determined to be
199 important (significant p-value [because null hypotheses were plausible], biologically relevant effect
200 size, and a reduction in AIC_c of >2), we retained it in the model unless there was strong evidence
201 from subsequent analyses of a superior alternative (Anderson 2008). To be certain that we had not
202 missed any conspicuously better models, we also evaluated all possible regressions. Since null
203 hypotheses embedded within the model selection exercise were nontrivial (e.g., minimum winter
204 temperature may or may not influence insect or fungal survival) we favored models where regression
205 coefficients were statistically distinguishable from zero.

206 To assess the relative importance of exogenous effects contributing to the variation around the
207 density dependent relationship across sites, we repeated the model selection process using the
208 residuals (ϵ_i) from the following regression model: $R_t = Site + N_t + Site \times N_t + \epsilon$, again for both
209 insects and fungi. In this case only predictor variables that varied interannually were relevant, so the
210 candidate drivers were climate and the abundance of the associated species (fungal densities in the
211 case of scale insect population growth rate, and vice versa). Because the effects of climate may also
212 vary geographically, we also tested models of exogenous effects both alone and crossed with
213 latitude. The inclusion of this interaction term frequently improved overall model fit but gains were
214 modest at best ($<2\%$ increase in variance explained) so we only report models containing main
215 effects.

216 Model selection, including comparisons of all possible models, was performed using JMP 5.1
217 and R 2.6.2 (Giraudoux 2008, R Development Team 2008, JMP[®] v. 5.1). Residuals from all models

218 were assessed for both univariate and multivariate normality and homogeneity of variance. We
219 avoided multicollinearity by avoiding models that included correlated variables.

220 RESULTS

221 *Simple density dependence*

222 There was strong evidence for simple density dependence for scale insects (Fig. 1, left) and
223 *Neonectria* (Fig. 1, right) across all sites and for all sites combined. Insect population density at time t
224 was by far the best predictor of tree-specific population growth rate for scale insects, alone
225 explaining 17% of the variation (Table A4). *Neonectria* contributed little to estimates of insect
226 abundance (0.5%) and its effects were small and variable in direction across sites (slope estimate, all
227 sites = -0.03 ± 0.008 for *Neonectria*[N_t] versus -0.29 ± 0.004 for Insect[N_t]). Lagged effects from
228 either scale insects or *Neonectria* contributed even less and were dropped from models of insect R .
229 Autocorrelation functions (ACF) and partial correlation functions (PACF) likewise showed no
230 evidence of lagged density dependence for either insects or fungi (Fig. A2). There was also no
231 evidence for lagged cross-correlations between scale insect and *Neonectria* populations, though there
232 was a modest positive correlation coefficient of 0.20 ± 0.13 at time 0 (no lag; Fig. 3S). Of the best
233 supported models for insect R , the simplest also contained Site and the Site \times Insect(N_t) interaction
234 in addition to Insect(N_t) main effect, indicating that the density dependent relationship differed in
235 slope and relative position across sites (full model: $F_{49, 25603} = 185.0$; $P < 0.0001$; $R^2 = 0.26$).
236 Pollard's randomization test validated the statistical case for simple density dependence in scale
237 insects ($P < 0.01$ for all sites individually, and for all sites combined).

238 *Neonectria* populations likewise showed evidence for simple endogenous regulation that varied by
239 site, with little impact of co-occurring scale insect densities. Interannual variation in population
240 growth rate for fungi were best explained with a model containing *Neonectria*(N_t) and Site ($F_{40,1658} =$
241 25.37 ; $P < 0.0001$; $R^2 = 0.38$; Fig. 1 right). The contribution of Insect(N_t) was small and highly

242 variable, and while statistically significant in the full model (eq. 1; $F_{1,1418}$; $P < 0.0001$), added little
243 explanatory power to overall fungal dynamics. The same was true for year $t-1$ lags for both insects
244 and fungi. Models containing Site \times *Neonectria*(N_t) interaction were nearly indistinguishable from the
245 simpler model without the term ($\Delta AIC_c = 2.67$), though the preferred model containing the
246 interaction was over three times as likely as a ratio of AIC weights. Empirically, estimates of the
247 density dependent slopes did in fact differ by site, ranging from -1.45 and -0.35 ($\bar{x} \pm SE = -0.66 \pm$
248 0.07) and the interaction was significant ($F_{17,1418} = 1.9$, $P = 0.009$), so we chose to retain it in the final
249 model. For *Neonectria*, Pollard's test confirmed the existence of density dependence in 13 of 16 sites
250 as well as for all sites combined. Regression slopes failed to differ from random in one site each in
251 Maine, Connecticut and Vermont ($P = 0.25$, 0.07 and 0.50 respectively). In all three of these sites,
252 *Neonectria* was comparatively rare and small sample size was likely a factor; given the overall trend,
253 we included estimates of density dependent parameters for fungi from all 16 sites in the remainder
254 of our analyses.

255 *Biotic and abiotic effects on density dependent functions across sites*

256 The variability among sites in the parameters of density dependent functions (DD slope,
257 equilibrium abundance [K] and MSE) revealed by the above analyses were explained reasonably well
258 by subsequent analyses, described below. For both BBD organisms, density dependent slope and
259 carrying capacity (K) were the most generally predictable; simple models containing 1-3 predictors
260 explained 41-79% of variation in these two parameters. For scale insects, the top model also
261 explained a large proportion of variation among sites in MSE ($R^2=0.62$). Following our ordered
262 modeling approach, we treat each broad category of biotic and abiotic effects below.

263 Disease agent associates

264 Variability in the population density of insects and *Neonectria* showed little to no influence on any
265 of the aspects of density dependence we considered. We therefore rejected the hypothesis that

266 associated species influence the strength or shape of population regulation in the BBD system.
267 *Neonectria* densities did not affect strength or form of the scale insect density dependent relationship,
268 or vice versa. When entered alone into models predicting the slope of insect density dependence,
269 carrying capacity and MSE, in no case was the “*Neonectria*” predictor significant, and explained only
270 3%, 1% and 0.1% of variation respectively. *Neonectria* also failed to appear as a predictor in any of
271 the top models identified using the all possible models approach (Table A4). Scale insect density
272 was a similarly poor predictor of fungal dynamics, explaining very little variation in the slope,
273 carrying capacity and MSE for *Neonectria* (<1%, <1% and 2% respectively). Accordingly, scale insect
274 density was virtually absent from top models for *Neonectria*, with the single exception being that
275 predicting MSE where the explanatory power of top models was low in general ($R^2 = 0.03$).

276 Resource availability

277 Variation in resource availability influenced various aspects of the density dependence for both
278 scale insects and fungi. Mean tree size (diameter at breast height, or DBH) and the total number of
279 trees (a proxy for density in plots of approximately equal size) were present among the top three
280 models for several response variables for both scale insects and *Neonectria* (Table A4). Both were
281 positively associated with density dependent slope for scale insects (parameter estimates: DBH =
282 0.02 ± 0.005 ; tree count = 0.001 ± 0.0005). Though later displaced by better performing variables,
283 the model containing only these two factors was highly significant and had reasonable predictive
284 power ($F_{2,21} = 8.8$, $P = 0.001$, $R^2 = 0.46$). DBH was a component of all three top models predicting
285 scale insect K, and was the dominant predictor in the selected model (Table 5, Fig. 3c). Tree count
286 appeared as a weakly negative predictor (-0.002 ± 0.001) in a candidate model identified by all
287 possible regressions predicting the density dependent slope for *Neonectria*, but was displaced by
288 simpler models with higher AIC_c weights ($w_i = 0.68$ versus 0.19; simpler model ~ 3.5 times as likely;
289 Table A4). Finally, DBH was the single best predictor of MSE for *Neonectria* ($F_{1,13}=0.87$; $P=0.37$;

290 $R^2 = 0.06$ Fig. 3d), though explanatory power was low and several other models were effectively
291 equivalent ($\Delta AIC_c < 2$; Table A4 and S5).

292 Climate effects

293 Climate moderately influenced aspects of the density dependent function for scale insects and
294 *Neonectria*. Of the ten climate variables considered, several showed some explanatory power.
295 Among them, four – early precipitation, late precipitation, thermal sum, and the number of days
296 with snow cover > 10 cm (herein, “snow cover”) – appeared in a subset of the final models. For
297 scale insects, higher early season precipitation correlated negatively with density dependent slope
298 (mean parameter estimate [\pm SE] = -0.02 ± 0.01 ; Fig. 2b). Inclusion of early precipitation in this
299 model along with the duration of BBD infection (with its squared term) marginally improved fit and
300 explained an additional 9% of the variation, though models with or without the variable were not
301 easily distinguishable based on information theory ($\Delta AIC_c = 2.04$; Table A4). Scale insect carrying
302 capacity was also negatively associated with early precipitation (-0.05 ± 0.3 ; Fig. 3d). Variation in
303 MSE for scale insects was best predicted by early precipitation, thermal sum and duration of
304 infection ($F_{3,19} = 10.5$; $P = 0.0002$; $R^2 = 0.62$). In this model, thermal sum was negatively associated
305 with MSE (-0.0003 ± 0.0001 ; Fig. 2e) while early precipitation showed a positive association (0.007
306 ± 0.003 ; Fig. 3f).

307 Climate influenced density dependence in *Neonectria*, again to a moderate degree. Several climate
308 predictors showed explanatory power with respect to site level variation in the parameters of the
309 density dependent function, though only two were retained in the final models (Table A4). Late
310 precipitation was associated with increased carrying capacity for *Neonectria* (slope \pm SE = $0.23 \pm$
311 0.05) and together with duration of infection with its squared term formed the best model ($F_{3,12} =$
312 13.7 ; $P = 0.0005$; $R^2 = 0.79$; Fig. 3c). Early precipitation was positively correlated (0.014 ± 0.007)

313 with overall variation around the density dependent function, though the relationship was rather
314 weak ($F_{1,87} = 4.2$; $P = 0.046$; $R^2 = 0.05$; Fig. 3e).

315 Our analyses of spatial synchrony in population fluctuations for both insects and fungi provided
316 additional support for a moderate climate signal in the BBD system. The spatial scale of synchrony
317 exceeded that which could be easily explained by dispersal or mobile predators; spatial
318 autocorrelation in population growth was evident out to about 92 km for both scale insects and
319 *Neonectria* (Fig. S4). While long-distance movement via wind currents occurs for both scale insects
320 and fungi, the only comprehensive study on the scale of dispersal found that over 99% of scale
321 insect crawlers dispersed locally, falling from within a meter up to 12-15 m from the inoculum
322 source (Wainhouse 1980). For neither species did we find evidence of anisotropy (directional bias in
323 spatial autocorrelation which – if evident along lines of latitude – would implicate a role for climate).

324 Forest change and disease ontogeny

325 The number of years that stands were colonized by BBD was the strongest and most general
326 predictor of variation in density dependence for insects and fungi (Fig. 2 and 3). There was a clear,
327 nonlinear relationship between duration of infection and density dependent slope for scale insects,
328 with the longest affected stands exhibiting the most negative slope (Fig. 2a). Density dependent
329 slope for *Neonectria* was also best predicted by duration of infection and duration² ($F_{2,13} = 4.66$; $P =$
330 0.017 ; $R^2 = 0.417$; Fig. 3a). Together with late precipitation, duration and duration² also provided
331 the best fit for *Neonectria* carrying capacity, with the highest values at intermediate duration of
332 infection, roughly coincident with the center of the range. The best model predicting scale insect
333 MSE also contained duration of infection; in this case the relationship was linear, but rather weak
334 (Fig. 2g). Finally, though not among the top three models based on AIC_c , there was a significant
335 univariate, linear relationship between the duration of infection and scale insect K (not shown).

336 Scale carrying capacity generally declined with increasing duration of infection ($F_{1,21} = 5.97$; $P = 0.02$;
337 $R^2 = 0.22$, though only marginally after removing two outliers [$P = 0.07$]).

338 *Contribution of climate and associated species densities to exogenous variation*

339 Climate was a moderately weak predictor of variation in population growth rate around the
340 density dependent function for both insects and *Neonectria*, explaining only 8 to 10% of variation
341 (Fig. 2h-i and Fig. 3e). In addition, relationships between residual (exogenous) variation and climate
342 metrics varied unpredictably in strength and direction across sites. Pooling across sites, years with
343 comparatively high spring precipitation were positively associated with population growth rates for
344 both insects (0.014 ± 0.007) and fungi (0.36 ± 0.33 ; Table A4). For scale insects, the top model
345 containing the early precipitation and snow cover was indistinguishable from slightly more complex
346 models ($AIC_c < 2$), accounting for 7% of the variation in residual error ($F_{2,155} = 5.75$; $P = 0.004$; R^2
347 $= 0.07$). Top models explaining residual error for *Neonectria* contained various combinations of early
348 precipitation, minimum winter temperature and thermal sum variables (Table A4); of these, we
349 favored the model containing only early precipitation as most ecologically parsimonious (Fig. 3e).

350 DISCUSSION

351 Where two or more organisms interact, an understanding of the nature and scale of feedbacks is
352 essential to predicting and understanding dynamics. Our results demonstrate that interannual
353 variation in abundance of both scale insects and *Neonectria* is effectively independent of local, within-
354 tree densities of the associated species within the established range of BBD. Population dynamics
355 for both organisms were best explained with models allowing only for simple density dependence
356 that varied by site, and we therefore reject the hypothesis of coupled dynamics among BBD
357 associates. This result was particularly surprising for *Neonectria*, which depends on scale insect
358 feeding to gain access to host tree tissues, and suggests that either beech trees typically support
359 densities of scale insects sufficiently high relative to the fungus that infection sites are not limiting,

360 or that trees harbor persistent fungal infection such that interannual fluctuations in the abundance of
361 scale insect are irrelevant to short term *Neonectria* dynamics. This pattern might be different during
362 the first wave of BBD infestations, a stage in the invasion process that was not well represented in
363 our data, but it would be somewhat surprising if scale insects are more limiting for fungi during the
364 years when scale insects are most abundant (Ehrlich 1934). Given the length of our time series, we
365 cannot exclude the possibility that the relevant time scale for the feedback is greater than we were
366 able to evaluate, but there was no temporal signal out to 6 years. In addition, fluctuations in the
367 local abundance of *N. ditissima* (which unlike the dominant *N. faginata* is not obligatorily associated
368 as a forest pathogen either with beech trees or scale insects) may also be driven in part by dynamics
369 on alternate hosts..

370 Density dependence was clearly variable across sites for both scale insects and *Neonectria*, adding
371 to accumulating evidence that the form and strength of the endogenous relationship is spatially
372 variable for many species (Peltonen et al. 2002, Post 2005). Density dependent slopes and carrying
373 capacities (and MSE for scale insects) were surprisingly well predicted using simple models selected
374 from a pool of variables describing aspects of resource availability, climate and disease history. The
375 most general predictor was the duration of infection with BBD. Such relationships were often
376 nonlinear, indicative of threshold effects. For scale insects, duration of infection predicts a modest,
377 linear decline in carrying capacity, together with a sharp increase in the strength of density
378 dependence in the longest-affected stands (Fig. 4 left). Density dependent functions for *Neonectria*
379 were nearly identical between the most recently and the longest affected stands, while sites of
380 intermediate duration of infection had weaker density dependence and dramatically increased
381 carrying capacity (Fig. 4 right). One possible explanation for the prominence of duration of
382 infection as a predictor of density dependence in BBD populations is that the disease itself has
383 altered the forest and so influenced its own dynamics. Williams and Liebhold (2000) found that

384 density dependence was strongest at the edge of an outbreak for the spruce budworm, which they
385 attributed to reduced predation effects in the higher quality habitat at the epicenter. At least for
386 scale insects, it is very likely that habitat quality has been degraded in the longest-affected regions.
387 Mean tree diameter correlates negatively with duration of infection at the landscape scale (Garnas
388 2012), and was the dominant predictor of scale insect carrying capacity. While the positive
389 correlation between mean tree diameter and scale insect K does not demonstrate causation, this is an
390 attractive interpretation because it has been commonly noted that larger trees have higher
391 susceptibility to scale insect attack because increased fissuring of bark creates suitable microhabitats
392 (Gove and Houston 1996). An alternative interpretation is that the relative frequency of susceptible
393 genotypes has declined over time. Habitat suitability for *Neonectria* appears to peak approximately 2-
394 3 decades after the arrival of scale insects. Other work has suggested that *Neonectria* infection trails
395 the arrival of scale insects by approximately 1-10 years (Ehrlich 1934, Houston 1994). It is not
396 difficult to imagine that the buildup of *Neonectria* takes some time after it first appears and that
397 conditions remain optimal or improve for a period once fungal infection begins. In the longest-
398 affected stands, however, habitat quality appears to deteriorate for both scale insects and *Neonectria*.

399 Overall, the contribution of climate to population dynamics was minimal within the core range
400 of BBD where plots were monitored (though recent work suggests that historically, scale insects
401 have been limited by low winter temperatures in northwestern Maine; M. Kasson, personal
402 communication). Spring precipitation was associated with stronger density dependence and reduced
403 carrying capacity for scale insects and with increased total variability around the density function
404 (MSE), but effect sizes were low. Sites with higher late Summer/Fall precipitation had higher
405 carrying capacities for *Neonectria*. Predictors that relate directly to insect or fungal growth rate
406 (thermal sum) or to overwintering survival (minimum winter temperature) were conspicuously
407 absent from most top models. Similarly, resource related predictors showed some association with

408 aspects of the density dependent functions (i.e., DBH positively associated with carrying capacity for
409 scale insects) but overall were overshadowed by the effect of duration of infection with BBD. In
410 fact, duration of infection was negatively correlated with tree size ($r = -0.63$, $P = 0.001$), which
411 provides an alternate model to predict scale K.

412 The modest contribution of climate to population dynamics was striking because we tested
413 across a large geographic extent and allowed for a broad spectrum of possibilities (including
414 interannual fluctuations around density dependent functions and changes in the density dependent
415 functions themselves). Furthermore, support for the climatic patterns that emerged from the
416 modeling was not necessarily compelling. For example, early precipitation was related to per capita
417 population change in both scale insects and fungi, but the direction of the effect varied among sites
418 and did not conform to hypothesized mechanisms (Houston and Valentine 1988). Snow cover was
419 positively associated with scale insect growth, which we had hypothesized might be related to the
420 role of snowpack as a thermal refuge during cold weather (Houston and Valentine 1988; Dukes et al.
421 2009), but the case for this theoretical mechanism was weakened by the absence of consistent
422 relationships with minimum winter temperature.

423 At the outset of this study, we had predicted coupled population dynamics between BBD
424 associates. This is clearly not the case. Important feedbacks likely do exist, but at a much larger
425 spatiotemporal scale than we had originally hypothesized. A plausible hypothesis to explain
426 observed patterns is that temporal patterns in disease development correspond to asynchronous
427 peaks in host tree suitability for scale insects and fungi. In this framework, BBD may best be
428 understood as a system where the density dependent relationship is itself regulated by slow-
429 developing, endogenous feedbacks linked to large scale forest change caused by disease and by
430 management in response to outbreak mortality. Once peaks of high host and habitat suitability have
431 passed (as they have for much of the northeastern forest), both scale insects and *Neonectria* are

432 apparently regulated at relatively low densities. Whether the current condition represents a new
433 equilibrium or a trough in a very long cycle (as would be the case if beech must simply age into
434 higher susceptibility for a new outbreak to occur; Houston 1975), is an interesting and open
435 question with important consequences to the structure and function of the eastern deciduous forest.

436 ACKNOWLEDGEMENTS

437 We wish to acknowledge the many people who established plots and took data. Special Mike
438 Ferrucci, Manfred Mielke, and Bill Jackson (USFS); Barbara Burns (VT Dept. Forests, Parks and
439 Recreation); and Barry Towers, Gary Laudermilch, Edwin Blumenthal, and Norman Kauffman
440 DCNR, PA Bureau of Forestry). This work was partially supported by the USDA Forest Service
441 Northeastern Research Station, grant 04-JV-11242328-122.

442 LITERATURE CITED

- 443 Anderson, D. R. 2008. Model based inference in the life sciences: A primer on evidence. - Springer.
- 444 Anderson, R. M. and May, R. M. 1979. Population biology of infectious-diseases .1. - Nature 280:
445 361-367.
- 446 Avery, T. E. and Burkhart, H. E. 2002. Forest measurements. - McGraw-Hill.
- 447 Berryman, A. A., et al. 1987. Natural regulation of herbivorous forest insect populations. - Oecologia
448 71: 174-184.
- 449 Berryman, A. A., et al. 2002. Population regulation, emergent properties, and a requiem for density
450 dependence. - Oikos 99: 600-606.
- 451 Bjørnstad, O. N. 2009. Ncf: Spatial nonparametric covariance functions. - R package version 1.1-1.
452 <http://onb.ent.psu.edu/onb1/R>.
- 453 Bleiker, K. P. and Six, D. L. 2007. Dietary benefits of fungal associates to an eruptive herbivore:
454 Potential implications of multiple associates on host population dynamics. - Environmental
455 Entomology 36: 1384-1396.

- 456 Brasier, C. M. 1991. *Ophiostoma novo-ulmi* sp. nov., causative agent of current Dutch Elm disease
457 pandemics. - Mycopathologia 115: 151-161.
- 458 Burdon, J. J., et al. 2006. The current and future dynamics of disease in plant communities. - Annual
459 Review of Phytopathology 44: 19-39.
- 460 Castlebury, L. A., et al. 2006. Phylogenetic relationships of *Neonectria/Cylindrocarpon* on *Fagus* in
461 North America. - Canadian Journal of Botany 84: 1417-1433.
- 462 Chesson, P. 2000. Mechanisms of maintenance of species diversity. - Annu. Rev. Ecol. Syst. 31: 343-
463 366.
- 464 Dean, A. M. 1983. A simple model of mutualism. - The American Naturalist 121: 409-417.
- 465 Dukes, J. S., et al. 2009. Responses of insect pests, pathogens, and invasive plant species to climate
466 change in the forests of northeastern North America: What can we predict? - Canadian
467 Journal of Forest Research 39: 231-248.
- 468 Ehrlich, J. 1934. The beech bark disease: A *Nectria* disease of *Fagus*, following *Cryptococcus fagi* (Baer.).
469 - Canadian Journal of Research 10: 593-692.
- 470 Estay, S. A., et al. 2009. Predicting insect pest status under climate change scenarios: Combining
471 experimental data and population dynamics modeling. - Journal of Applied Entomology 133:
472 491-499.
- 473 Garnas, J., et al. 2011. Subcontinental impacts of an invasive tree disease on forest structure and
474 dynamics. Journal of Ecology 99:532–541. doi: 10.1111/j.1365-2745.2010.01791.x.
- 475 Giraudoux, P. 2008. Pgirness: Data analysis in ecology. R package version 1.3.7.
476 <http://perso.orange.fr/giraudoux/SiteGiraudoux.html>
- 477 Gove, J. H. and Houston, D. R. 1996. Monitoring the growth of American beech affected by beech
478 bark disease in Maine using the Kalman filter. - Environmental and Ecological Statistics 3:
479 167-187.

- 480 Hofstetter et al. 2006. Antagonisms, mutualisms and commensalisms affect outbreak dynamics of
481 the southern pine beetle. *Oecologia* 147: 679-691
- 482 Holt, R. D. and Lawton, J. H. 1994. The ecological consequences of shared natural enemies. -
483 *Annual Review of Ecology and Systematics* 25: 495-520.
- 484 Houston, D. R. 1975. Beech bark disease - aftermath forests are structured for a new outbreak. -
485 *Journal of Forestry* 73: 660-663.
- 486 Houston, D. R., et al. 1979. Beech bark disease - patterns of spread and development of the
487 initiating agent *Cryptococcus fagisuga*. - *Canadian Journal of Forest Research* 9: 336-344.
- 488 Houston, D. R. and Valentine, H. T. 1988. Beech bark disease - the temporal pattern of cankering in
489 aftermath forests of Maine. - *Canadian Journal of Forest Research* 18: 38-42.
- 490 Houston, D. R. 1994. Major new tree disease epidemics - beech bark disease. - *Annual Review of*
491 *Phytopathology* 32: 75-87.
- 492 Houston, D. R., et al. 2005. Spatial and temporal development of beech bark disease in the
493 northeastern United States. - In: C. A. Evans, Lucas, Jennifer A. and Twery, Mark J. (ed)
494 *Beech Bark Disease: Proceedings of the Beech Bark Disease Symposium*. US. Department of
495 *Agriculture, Forest Service, Northeastern Research Station*, pp. 43-47.
- 496 JMP[®]. Version 5.7.1. 1989-2007. SAS Institute Inc., Cary, NC.
- 497 Klepzig, K. D. and Six, D. L. 2004. Bark beetle-fungal symbiosis: Context dependency in complex
498 associations. - *Symbiosis* 37: 189-205.
- 499 Klepzig, K. D., et al. 2009. Symbioses: A key driver of insect physiological processes, ecological
500 interactions, evolutionary diversification, and impacts on humans. - *Environmental*
501 *Entomology* 38: 67-77.
- 502 Liebhold, A. M., et al. 1995. Invasion by exotic forest pests - a threat to forest ecosystems. - *Forest*
503 *Science* 41: 1-49.

- 504 Lombardero, M. J., et al. 2003. Strong indirect interactions of *Tarsonemus* mites
505 (Acarina:Tarsonemidae) and *Dendroctonus frontalis*. - *Oikos* 104: 208.
- 506 May, R. M. 1976. Simple mathematical models with very complicated dynamics. - *Nature* 261: 459-
507 467.
- 508 May, R. M. 1982. Mutualistic interactions among species. - *Nature* 296: 803-804.
- 509 Moran, P. A. P. 1953. The statistical analysis of the Canadian lynx cycle. 2. Synchronization and
510 meteorology. - *Aust J Zool* 1: 291-298.
- 511 Morin, R. S., et al. 2007. Spread of beech bark disease in the eastern United States and its
512 relationship to regional forest composition. - *Canadian Journal of Forest Research* 37: 726-
513 736.
- 514 Paillet, F. 2002. Chestnut: History and ecology of a transformed species. - *Journal of Biogeography*
515 29: 1517-1530.
- 516 Parker, I. M. and Gilbert, G. S. 2004. The evolutionary ecology of novel plant-pathogen interactions.
517 - *Annual Review of Ecology Evolution and Systematics* 35: 675-700.
- 518 Peltonen, M., et al. 2002. Spatial synchrony in forest insect outbreaks: Roles of regional stochasticity
519 and dispersal. - *Ecology* 83: 3120-3129.
- 520 Pollard, E., et al. 1987. The detection of density-dependence from a series of annual censuses. -
521 *Ecology* 68: 2046-2055-2046-2055.
- 522 Post, E. 2005. Large-scale spatial gradients in herbivore population dynamics. - *Ecology* 86: 2320-
523 2328.
- 524 R development core team. 2009. R: A language and environment for statistical computing. R
525 foundation for statistical computing, Vienna, Austria. <http://www.R-project.org>.
- 526 Royama, T. 1992. Analytical population dynamics. - Chapman & Hall.

- 527 Seppälä, R., A. Buck, and P. Katila. (eds.) 2009. Adaptation of forests and people to climate change:
528 A global assessment report. - In: Presented to United Nations Forum on Forests (UNFF).
529 International Union of Forest Research Organizations, p. 224.
- 530 Shigo, A. L. 1964. Organism interactions in beech bark disease. - *Phytopathology* 54: 263-269.
- 531 Six, D. L. and Klepzig, K. D. 2004. *Dendroctonus* bark beetles as model systems for studies on
532 symbiosis. - *Symbiosis* 37: 207-232.
- 533 Storer, A. J., et al. 1997. Pitch canker disease of pines - current and future impacts. - *Journal of*
534 *Forestry* 95: 21-26.
- 535 Tobin, P. C. and Bjørnstad, O. N. 2003. Spatial dynamics and cross-correlation in a transient
536 predator-prey system. - *Journal of Animal Ecology* 72: 460-467.
- 537 Tran, J., et al. 2007. Impact of minimum winter temperatures on the population dynamics of
538 *Dendroctonus frontalis*. - *Ecological Applications* 17: 882-899.
- 539 Turchin, P. 2003. Complex population dynamics: A theoretical/empirical synthesis. - Princeton Univ
540 Press.
- 541 Ungerer, M. J., et al. 1999. Climate and the northern distribution limits of *Dendroctonus frontalis*
542 Zimmermann (Coleoptera: Scolytidae). - *Journal of Biogeography* 26: 1133-1145.
- 543 Wainhouse, D. 1980. Dispersal of 1st instar larvae of the felted beech scale, *Cryptococcus fagisuga*. -
544 *Journal of Applied Ecology* 17: 523-532.
- 545 Williams, D. W. and Liebhold, A. M. 2000. Spatial synchrony of spruce budworm outbreaks in
546 eastern North America. - *Ecology* 81: 2753-2766.
- 547 Woiwod, I. P. and Hanski, I. 1992. Patterns of density dependence in moths and aphids. - *Journal of*
548 *Animal Ecology* 61: 619-629.
- 549 Ylloja, T., et al. 1999. Host-driven population dynamics in an herbivorous insect. - *Proceedings of*
550 *the National Academy of Sciences of the United States of America* 96: 10735-10740.

- 551
- 552 Supplementary material (available as Appendix E6938 at www.oikosoffice.lu.se/appendix).
- 553 Appendix Tables A1-A5, Figures A1-A5

FIGURE CAPTIONS

Figure 1. Density dependent relationships in three sites (left column: scale insects, right column: *Neonectria*). Rows correspond to sites ME103, NY611 and WV821 respectively, randomly selected for illustration. Grey lines are OLS regressions for each site.

Figure 2. Bivariate relationships between population parameters for scale insects (slope, carrying capacity, MSE and error residuals around the density dependent function) and explanatory variables from the top models identified by AIC_c. For models with two or more predictors, dependent variables were corrected for the effects of all other variables in the model; grey lines are 1st or 2nd-order regression lines.

Figure 3. Bivariate relationships between population parameters for *Neonectria* (slope, carrying capacity, MSE and error residuals around the density dependent function) and explanatory variables from the top models identified by AIC_c. For models with two or more predictors, dependent variables were corrected for the effects of all other variables in the model; grey lines are 1st or 2nd-order regression lines.

Figure 4. Density dependent functions by regional duration of infestation for scale insects (left) and infection for fungi (right).

Figure 1

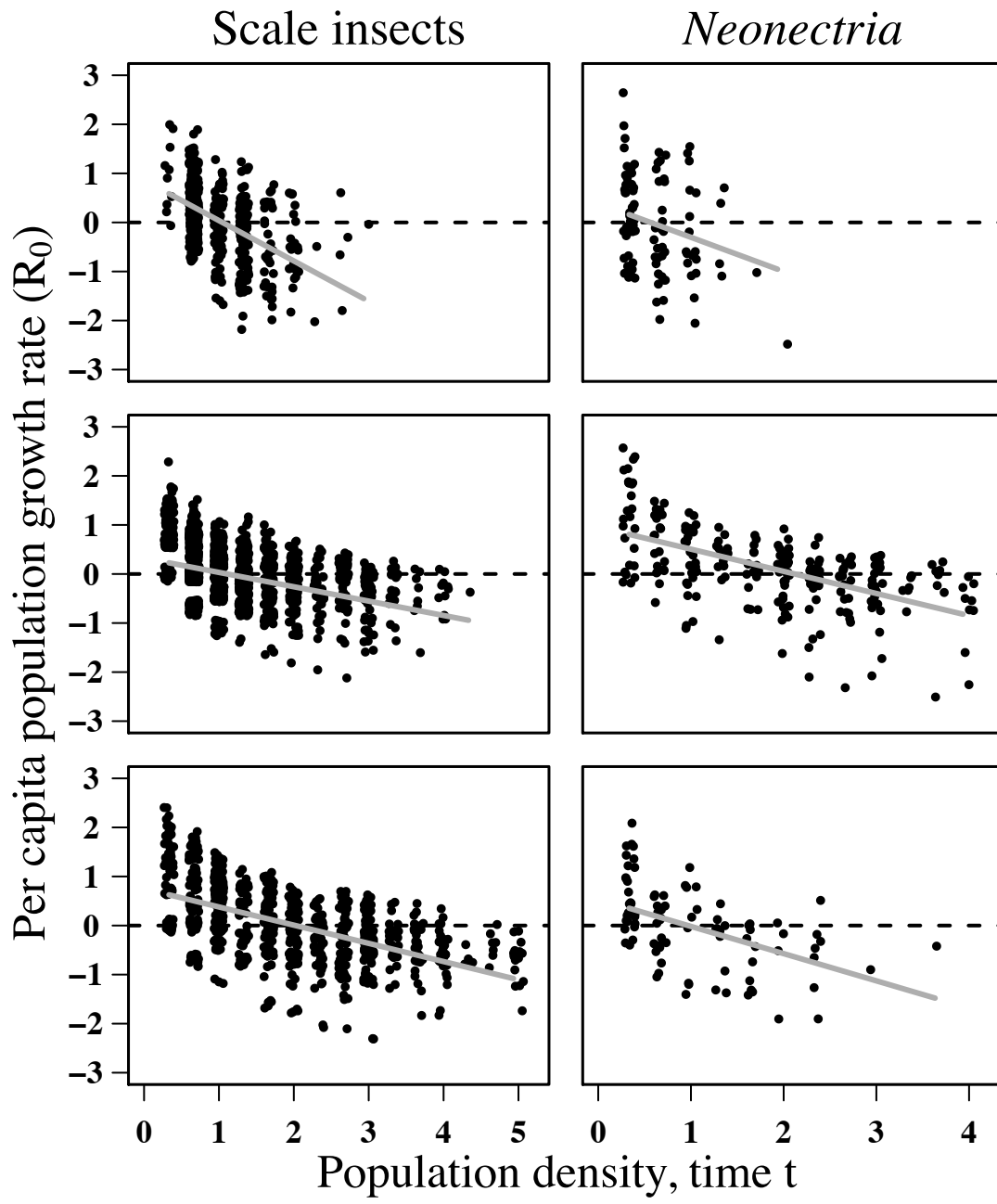


Figure 2

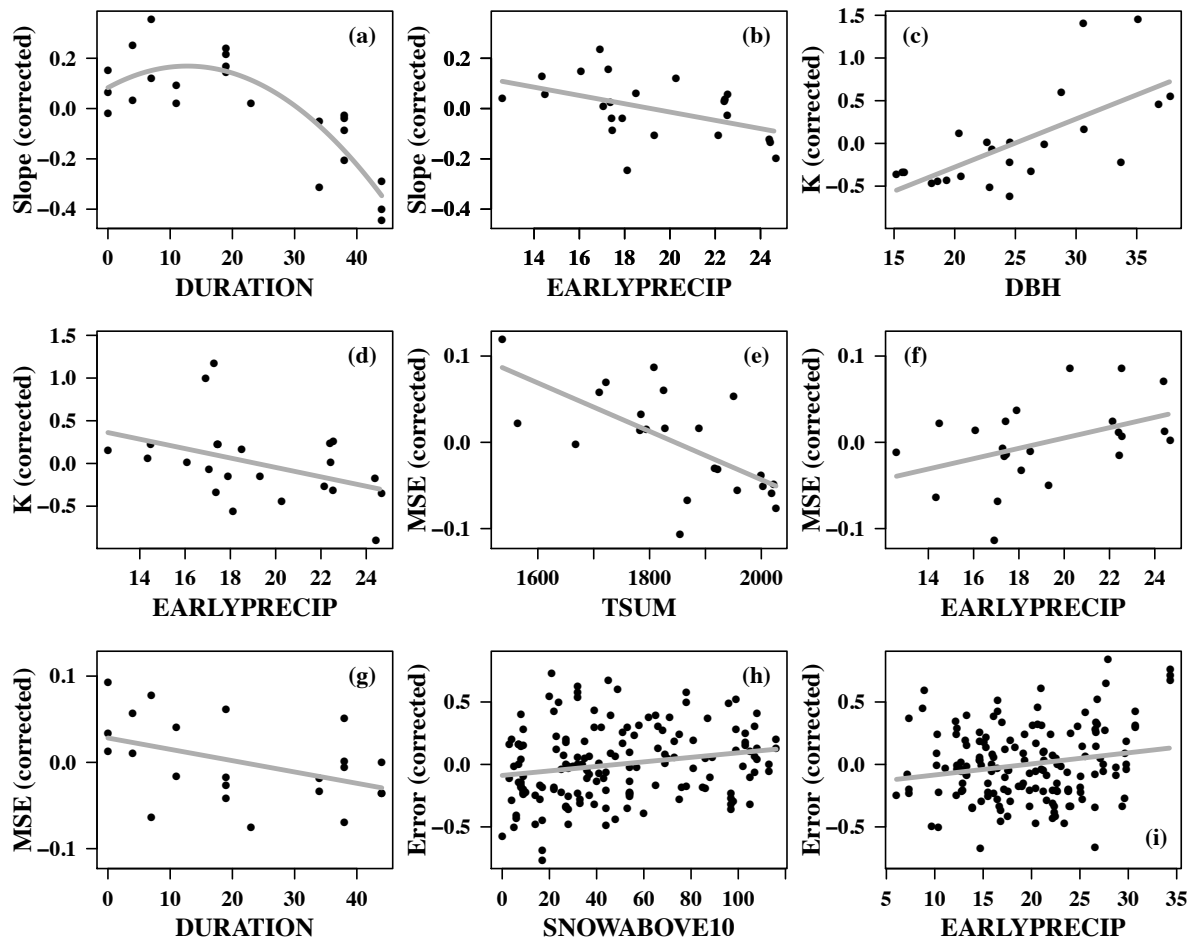


Figure 3

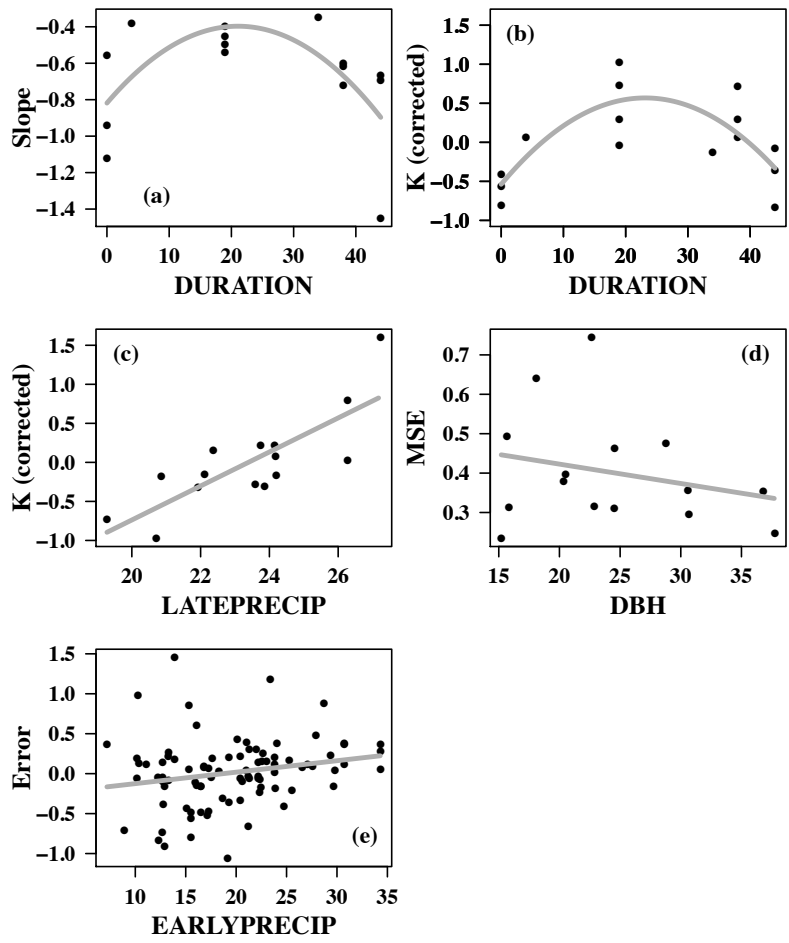


Figure 4

