

1 Reservoir host community and vector density predict human tick-borne diseases across the
2 United States

3 Michael B. Mahon¹ and Jason R. Rohr¹

4

5 ¹Department of Biological Sciences, Eck Institute for Global Health, and Environmental Change
6 Initiative

7 University of Notre Dame

8 Notre Dame, IN, USA

9

10 Corresponding Author:

11 Michael B. Mahon

12 University of Notre Dame

13 Environmental Change Initiative

14 721 Flanner Hall

15 Notre Dame, IN 46556

16 Phone: 612-618-5557

17 E-mail: mmahon4@nd.edu

18 ORCID: 0000-0002-9436-2998

19

20

21 **Abstract (<150 words)**

22 In the United States, tick-borne disease cases have tripled since the 1990s and cost upwards of 10
23 billion USD annually. Tick density and densities and diversity of non-human mammalian
24 reservoir hosts are hypothesized to drive tick-borne disease dynamics and are targets for
25 interventions. Here, we relate human prevalence of four tick-borne diseases (Lyme disease,
26 monocytic ehrlichiosis, granulocytic anaplasmosis, and babesiosis) to tick and reservoir host
27 community data collected by the U.S. National Ecological Observatory Network (NEON) across
28 the contiguous U.S. We show that human disease prevalence is correlated positively with tick
29 and reservoir host densities and negatively with mammalian diversity for Lyme disease and
30 ehrlichiosis, but positively for anaplasmosis and babesiosis. Our results suggest that the efficacy
31 of tick-borne disease interventions depends on tick and host densities and host diversity. Thus,
32 policymakers and disease managers should consider these ecological contexts before
33 implementing preventative measures.

34

35 **Significance (<120 words)**

36 Tick-borne disease incidence has increased in the United States over the last three decades.
37 Because life-long symptoms can occur if reactive antibiotics are not administered soon after the
38 tick bite, prevention is imperative. Yet, control of tick-borne zoonoses has been largely
39 unsuccessful, at least partly because of a limited understanding of the ecological complexities of
40 these diseases, especially non-Lyme disease tick-borne zoonoses. We use continental-scale data
41 to quantify the relationships among four tick-borne diseases and tick and reservoir host
42 communities, revealing that disease incidence is driven by a combination of tick densities and
43 reservoir host densities and diversity. Thus, the efficacy of tick-borne disease interventions is
44 likely dependent on these ecological contexts.

45

46 **Introduction**

47 Vector-borne diseases and tick-borne diseases, specifically, are on the rise globally (1). In
48 the United States, tick-borne disease incidence has more than doubled since 2004 and Lyme
49 disease incidence has tripled since the 1990s (2, 3). There are an estimated 240,000-440,000 new
50 cases of Lyme disease annually (4). Lyme disease costs the United States >\$1 billion in
51 healthcare costs (5), and \$5 to \$10 billion in economic and societal costs annually (6), and is
52 only one of several major tick-borne disease in the U.S. Antibiotics are often ineffective at
53 preventing life-long symptoms of bacterial tick-borne diseases (e.g. Lyme disease, human
54 granulocytic anaplasmosis) if they are not prescribed soon after the tick bite (7) and, thus,
55 effective prevention of tick-borne diseases is crucial. However, control of tick-borne zoonoses
56 has been largely unsuccessful, in part because of a limited understanding of the ecological
57 complexities and drivers of these diseases (1, 8, 9).

58 Tick densities, reservoir host densities, and reservoir host diversity are hypothesized
59 drivers of tick-borne diseases (Fig. 1) (1, 10, 11). The causative agents of human Lyme disease
60 (*Borrelia burgdorferi* [*sensu lato*]), human granulocytic anaplasmosis (*Anaplasma*
61 *phagocytophilum*; hereafter anaplasmosis), and human babesiosis (*Babesia microti*) are
62 transmitted by *Ixodes scapularis* (eastern blacklegged ticks) in the eastern U.S. and *Ixodes*
63 *pacificus* (western blacklegged ticks) in the western U.S., while the causative agent of human
64 monocytic ehrlichiosis (*Ehrlichia chaffeensis*; hereafter ehrlichiosis) is transmitted by
65 *Amblyomma americanum* (lone star ticks) throughout the U.S. (12–14). Larval ticks become
66 infected following a blood-meal from an infected host, such as mammals (e.g. rodents,
67 insectivores, and scurids (15)) that can serve as reservoir hosts (organisms that maintain and
68 transmit pathogen populations (16)) for these pathogens. Importantly, reservoir competence

69 (ability for a host to transmit pathogens to uninfected vectors (16)) of mammalian host species
70 varies among these pathogens (Fig. 1; Table S1) (15, 17, 18).

71 Although there is some support for the hypotheses that densities of ticks and densities and
72 diversity of wildlife hosts drive Lyme disease dynamics, most of the support is at local rather
73 than country or continental scales (14, 15, 19) and has not incorporated human disease (e.g.
74 reported cases) (10, 11, 19) (but see (20)). Linking wildlife and densities of infected ticks to
75 human disease is difficult, because human behavior, such as avoidance and chemical deterrents
76 (21), can disrupt this link. Further, support for the hypotheses that tick densities and wildlife host
77 densities and diversity drive tick-borne diseases is lacking in systems other than Lyme disease. A
78 major impediment to understanding the drivers of tick-borne diseases was a lack of broad-scale
79 spatial datasets that combined reservoir host communities, tick densities, and tick infection
80 prevalence with human disease incidence at similar scales (22). With the establishment of the
81 U.S. National Ecological Observatory Network (NEON), there are now data on reservoir host
82 communities, tick densities, and tick infection prevalence from across the U.S. collected using
83 standardized methodologies that can be coupled with U.S. Center for Disease Control (CDC)
84 data on human tick-borne disease incidence to finally elucidate the role of wildlife factors on
85 human prevalence of tick-borne diseases.

86 The objectives of our study are to: 1) identify the combination of host and vector
87 community variables that best explain human tick-borne disease prevalence across space and
88 time, 2) evaluate the direct and indirect effects of these variables on human disease prevalence
89 mediated through density of infected ticks, and 3) evaluate the human health burden of tick-
90 borne diseases across a mammalian diversity gradient. In accordance with the dilution effect
91 hypothesis (14, 23), we expect a negative biodiversity-disease relationship (dilution) when the

92 most abundant hosts have the highest reservoir competence, because as rare host species are
93 added to communities the mean competence of the community, and thus disease risk, decreases
94 (assuming host community assembly is substitutive; i.e. competitive for niche space). We expect
95 a negative biodiversity-disease relationship (amplification) when hosts do not or weakly differ in
96 their reservoir competence because as rare hosts are added the mean competence of the host
97 community would not change, whereas host densities and disease risk could increase if assembly
98 is additive (Fig. 1; see Supplement Text for further details) (10, 14, 23). Hence, we predict that
99 increasing small mammal richness will dilute *B. burgdorferi* (causative agent of Lyme disease)
100 and *E. chaffeensis* (causative agent of ehrlichiosis), because the most abundant mammal hosts
101 are typically the most competent for these pathogens (Fig. 1, Table S1), but we expect increasing
102 small mammal richness to amplify *A. phagocytophilum* (causative agent of anaplasmosis) and *B.*
103 *microti* (causative agent of babesiosis), because small mammal hosts exhibit similarly poor
104 competencies for these pathogens (Fig. 1, Table S1).

105 To address these objectives, we linked tick density, and mammal density and diversity
106 data collected by NEON from 2014-2018 to CDC data on human cases of Lyme disease,
107 anaplasmosis, babesiosis, and ehrlichiosis gathered for the same counties and time as the NEON
108 data (see Table S2 for specific county-year replicates included in analyses; Fig. S1). Because of
109 differences in disease reporting and data availability (*Materials and Methods*), sample sizes (site-
110 year replicates) for model selection were variable ($n = 95$ for Lyme disease, $n = 116$ each for
111 anaplasmosis and ehrlichiosis, and $n = 57$ for babesiosis). To analyze correlations among
112 ecological factors and human tick-borne disease prevalence, we used generalized linear mixed
113 effects models with a binomial distribution and county as a random effect (24), and conducted
114 model selection of all main effects and biologically relevant two-way interactions among wildlife

115 variables (interactions between tick and host densities and host diversity and densities; see Table
116 S3 for competing models). To account for differences in questing height of blacklegged ticks
117 along a north-south gradient (25), we included latitude as a covariate for blacklegged tick-borne
118 diseases. Additionally, to account for potential climate-related differences in relationships
119 between wildlife variables and human disease incidence (20), all models included covariates of
120 mean annual temperature and annual precipitation. The previously described analyses did not
121 include tick infection data because these data were collected at only 13 NEON sites (*Materials*
122 *and Methods*), which would have reduced the statistical power to test our hypotheses. To
123 investigate direct and indirect effects of tick and host community metrics on human disease
124 prevalence mediated through density of infected ticks, we used sequential regressions (see Fig. 1
125 for *a priori* relationships).

126 **Results**

127 Tick density, reservoir host density, and small mammal species richness predicted human
128 disease prevalence, but the direction of effects and interactions among these variables differed
129 across diseases (Table 1, Table S3; Fig. 2). For Lyme disease and anaplasmosis, the relationship
130 between reservoir host density and human disease prevalence became more positive as tick
131 density increased (Fig. 2A,B). Thus, for Lyme disease and anaplasmosis, the reduction of a
132 single tick per 1,000 m² would reduce incidence by 29.4% and 26.1% at median host densities,
133 and 99.9% and 102.0% at high host densities (4 mice per 10,000 m² for Lyme disease and 7
134 small mammal individuals per 10,000 m² for anaplasmosis), respectively. For babesiosis and
135 ehrlichiosis, the reduction of tick density by a single individual per 1,000 m² would reduce
136 disease incidence by 27.1% and 25.8%, respectively. Like reducing ticks, decreasing reservoir
137 host densities also reduces human tick-borne diseases (Fig. 2). In fact, when other factors in the

138 model are at median values, a reduction in one tick per 1,000 m² and a reduction of one reservoir
139 host individual per 10,000 m² (lowering of deer density category for ehrlichiosis) is predicted to
140 prevent annually ~2,300 and ~2,500 total (across all four diseases) U.S. tick-borne disease cases,
141 respectively, and ~300 and ~20 U.S. Lyme disease disability-adjusted life years (DALYs) (26),
142 respectively, relative to 2017 data (Fig. S2). DALY information is unavailable for the other three
143 tick-borne diseases, which should be addressed in future research given that tick-borne diseases
144 vary in symptoms and virulence (2, 8, 26) and, thus, cases of tick-borne diseases do not represent
145 human disease burden.

146 Because of the opposing direction of the diversity-disease relationship for Lyme disease
147 and anaplasmosis, a non-monotonic relationship emerged between small mammal richness and
148 total tick-borne disease cases, such that human disease incidence was higher at the extremes of
149 small mammal richness (<8 and >14 species per 10,000 m²) than at intermediate numbers of
150 species (9–13 species; Fig. 3). A similar pattern emerged when babesiosis and ehrlichiosis were
151 included in the calculation of total human disease, likely due to low incidence of these diseases
152 (Fig. S3). Thus, while mean mammal richness at NEON sites was 8 [7.6, 8.5] species per 10,000
153 m², our model suggests that maintaining 9-13 species per 10,000 m² should result in the lowest
154 incidence of human tick-borne diseases regardless of tick and host densities (Fig. 3).

155 Specifically, the conservation of small mammal richness to 9-13 species per 10,000 m² is
156 predicted to prevent ~8,600 additional total U.S. tick-borne disease cases annually and an
157 average of 1,000, and as high as 5,700 (when tick and reservoir host densities are high),
158 additional U.S. Lyme disease-caused DALYs annually, relative to 2017 data (Fig. S2).

159 Finally, to evaluate the contribution of changes to density of infected ticks on human
160 disease prevalence (Fig. 1), we conducted sequential regressions. For Lyme disease,

161 anaplasmosis, and babesiosis, we found that human disease was positively associated with
162 density of infected ticks (Fig. 4A,D,H), which was driven by the proportion of infected ticks
163 (Fig. 4B,E,I, Table S4). For Lyme disease, the diluting relationship between small mammal
164 diversity and human disease (Fig. 4, Table S4) seemed to be mediated by the effect of small
165 mammal richness on the association between the proportion of infected ticks and reservoir host
166 density (Fig. 4C). When small mammal richness was low, the proportion of infected ticks was
167 positively related to reservoir host density, but this relationship was not different from zero when
168 small mammal richness was high (Fig. 4C). Conversely, the amplifying relationship between
169 small mammal diversity and anaplasmosis and babesiosis was a function of reservoir host
170 density increasing with small mammal richness (Fig. 4G,K), which in turn fueled an increase in
171 the proportion of infected ticks (Fig. 4F,J; Table S4). Despite observing a small mammal dilution
172 effect and a positive effect of deer densities for ehrlichiosis in the model selection analyses that
173 included all sites, we did not find evidence for these effects in the sequential regressions (Table
174 S4), likely because subsetting the data resulted in both reduced samples sizes and the exclusion
175 of sites with no deer.

176 **Discussion**

177 The incidences of tick-borne diseases are increasing globally (1). Because reactive
178 antibiotics can be ineffective at preventing long-term symptoms of these zoonoses if
179 administered too late following infection (7), prevention of these diseases is imperative. Yet,
180 preventative interventions are largely unsuccessful in reducing human disease (1, 8, 9). Here, we
181 related incidence of human tick-borne diseases to tick densities and the densities and diversities
182 of mammalian reservoir hosts across the contiguous U.S. Our results indicate that reservoir host
183 and tick densities are correlated with human disease prevalence for all four diseases. We also

184 found support for our hypothesis that reservoir host richness is associated with human disease
185 prevalence in directions that are predictable by reservoir competence of the host community.

186 We show that reservoir host and tick densities are correlated with human disease
187 prevalence for all four diseases, likely because as tick and mammal densities increase, so do the
188 density of infected ticks and transmission, as suggested by our sequential regressions. These
189 findings are consistent with previous studies showing positive relationships between reservoir
190 host densities and densities of infected ticks (14, 15). Alternatively, spatial genetic variation in
191 pathogens and host competence could have altered the strength of the relationships among
192 ecological variables and human disease incidence (20, 27). Yet, the inclusion of spatially explicit
193 covariates likely account for much of this potential variation.

194 Our results indicate that the commonly employed host- and vector-density-targeted
195 interventions should effectively reduce human disease (8, 9); however, these control measures
196 have not translated to fewer cases of human tick-borne diseases in practice (21, 28). The
197 disparity between the expectations from statistical/mathematical models and actual reductions in
198 human disease (21, 28) could be a function of the ecological contexts in which the interventions
199 have been applied, which may have influence over the effectiveness of these interventions, as
200 suggested by our results. For example, in ecological contexts with high Lyme disease risk (low
201 mammal richness, high tick and host densities), our results indicate that the targeted control of
202 both ticks and host densities would synergistically reduce Lyme disease incidence. Conversely,
203 in ecological contexts with moderate Lyme disease risk (median mammal richness, tick density,
204 and host density), our results indicate that the reduction of tick density alone would be most
205 effective in reducing Lyme disease incidence. Therefore, disease interventions targeting ticks
206 would be most effective in reducing Lyme disease, regardless of ecological context, but in high

207 risk contexts, both tick- and host-targeted interventions would prevent the greatest disease
208 incidence. Alternatively, these interventions may be ineffective, because, generally, these models
209 focus on changes to the density of infected ticks (10, 11, 19), which does not directly translate to
210 human disease, because human-tick encounters are the product of both density of infected ticks
211 and human behavior (e.g. repellents, tick checks, etc.) (9, 29).

212 Because current interventions do not change the species richness of host species, which
213 may be a driver of human disease, an alternative or complementary approach to reducing ticks
214 and reservoir hosts is to conserve or increase the number of reservoir host species. However, this
215 has been a controversial approach to managing tick-borne diseases for several reasons (10, 19,
216 22, 23, 30), such as concerns that it might increase certain tick-borne diseases while decrease
217 others (10, 19, 22). As predicted, for pathogens with variably competent hosts (i.e. coefficients of
218 variation for reservoirs > 1 , Table S3; Lyme disease and ehrlichiosis), human disease prevalence
219 was negatively correlated with small mammal richness, supporting a dilution effect. Specifically,
220 for Lyme disease, the negative relationship between small mammal richness and human disease
221 prevalence increased in magnitude as reservoir host density increased. Also, in agreement with
222 our predictions, human disease prevalence was positively correlated with small mammal richness
223 for anaplasmosis (a pathogen with similarly poor hosts, Table S3), supporting an amplification
224 effect. For babesiosis, the weak positive relationship between small mammal richness and human
225 disease prevalence became negative as reservoir host density increased, supporting an
226 amplification effect. These results imply that determining reservoir competence of a range of
227 host species for vector-borne pathogens may provide valuable insights into whether or not
228 biodiversity conservation would dilute or amplify disease risk (10, 23, 30). Thus, caution must be
229 taken when conserving mammal species as a tool for tick-borne disease control, given the non-

230 monotonic relationship between mammalian richness and total tick-borne disease cases (Fig. 3).

231 The goal of our study was to evaluate the role of ticks and reservoir host communities in
232 driving broad-scale spatial patterns of human tick-borne diseases, which was not possible until
233 the establishment of NEON. Yet, the ecological data collected by NEON are not without
234 limitations. Specifically, because NEON only employed one type of small mammal sampling
235 (e.g., nocturnal sampling with traps set on the ground), we may be lacking good information on
236 the presence and abundance of some competent reservoir hosts species, resulting in
237 underestimates of host richness and abundance. In using host abundance of the most competent
238 reservoir host for models of Lyme disease and ehrlichiosis, we may be lacking a measure of the
239 abundance of other potentially competent reservoir hosts. Yet, of the species with relatively high
240 realized reservoir competence for *B. burgdorferi* (>0.5; *Peromyscus leucopus* and *Tamias*
241 *striatus*) (15), *P. leucopus* was found in higher abundances and at more sites, so we chose this
242 species as the main reservoir host for the Lyme disease models. Further, in the western U.S., as
243 the most competent reservoir host (*Sciurus griseus*) (31) was not sampled at NEON sites, we
244 used moderately competent reservoirs (*Peromyscus boylii*, *P. truei*, and *P. maniculatus*) (31),
245 which may not fully represent the influence of *S. griseus* on *B. burgdorferi* transmission at these
246 sites. Additionally, we recognize that lizards play an important role in regulating transmission of
247 *B. burgdorferi* in the western U.S. (31), but information on the densities of these species at
248 NEON sites was not available, so we are unable to elucidate their role in our models. Finally, in
249 the limited data on reservoir competence for *E. chaffeensis*, the main reservoir hosts are
250 Ruminants (the only native ruminant in the eastern U.S. is white-tailed deer) and Leporidae
251 (rabbits/hares) (17). Yet, because of the high encounter rate between white-tailed deer and *A.*
252 *americanum* (i.e. reservoir potential) (17), white-tailed deer are still likely the major reservoir

253 hosts for *E. chaffeensis*, and as such, we selected this species as the reservoir host for the
254 ehrlichiosis models.

255 Additionally, the tick sampling methodology used by NEON may limit detections of
256 nymphal *I. scapularis* in the southeastern U.S. (32); thus, despite the regular sampling of
257 nymphal ticks at these sites, tick densities at these sites might be underestimated. Importantly,
258 although nymphal and adult ticks play different roles in human disease, the use of nymphal ticks
259 instead of pooling all tick stages does not appreciably alter the results nor interpretation of our
260 analyses (Table S5). Similarly, including NEON sites without forest land-cover in our analyses,
261 and, thus without the ecotonal habitat of the focal tick species, could have generated spurious
262 patterns, but removing these sites from the analyses did not change the results nor interpretation
263 of our analyses (Table S6). Thus, we believe that the established patterns in our results are robust
264 and ecologically sound.

265 As tick-borne disease incidence continues to rise across the U.S. (2, 4), preventative
266 measures, such as controlling ticks and reservoir host densities and diversity, are essential to
267 reduce human tick-borne disease. While individual relationships among reservoir hosts, ticks,
268 density of infected ticks, and human disease incidence have been previously supported (11, 15,
269 19, 20, 22), our study is the first to support all links among these variables at broad spatial scales,
270 supporting the promise of proactive rather than reactive approaches to tick-borne disease
271 management. Although host- and vector-targeted interventions reduce densities of infected ticks
272 (33–35), the individual use of these interventions to reduce human disease have shown some
273 shortcomings in practice (21, 28, 33, 35, 36). Our results indicate that the ecological context (tick
274 and host densities and host diversity) may influence the relative effectiveness of these control
275 measures. Further, an alternative and/or complimentary approach to traditional tick-borne disease

276 control may be the conservation of small mammal species within a feasible but specific range of
277 richness levels. Consequently, future work should investigate the effectiveness of control
278 measures targeting tick and reservoir host densities across a mammalian host richness gradient to
279 determine what levels and combinations of interventions would be most effective at preventing
280 human tick-borne diseases.

281 **Materials and Methods**

282 Study area

283 Our analyses paired site-level estimates of tick density, tick-borne pathogen prevalence,
284 and small mammal communities from 38 climatically and ecologically variable sites in the
285 National Ecological Observatory Network (NEON; Figure S1; Table S2) with county-level
286 human case counts of tick-borne diseases collected by the Center for Disease Control (CDC)
287 Notifiable Diseases Surveillance System (NNDSS) and Division of Parasitic Diseases and
288 Malaria (DPDM). The study area included 35 counties in 21 states across the contiguous United
289 States (Table S2). Due to variability in data collection across NEON sites and availability of
290 disease incidence data, not all sites or counties were included in each year of the data (see Table
291 S2 for site-year replicates).

292 NEON Data

293 Sampling protocols for ticks, tick-borne pathogens, and small mammals in this section
294 will be described briefly, as detailed information on sampling protocols are available through the
295 appropriately cited NEON sampling protocols (37, 38). NEON data used in this study were
296 downloaded on 1 November 2019; datasets used in this study are outlined in Table S7.

297 *Tick sampling*

298 Starting in 2014, at each site, tick sampling occurred in six plots that were iteratively

299 sampled. Sampling frequency was dependent on whether ticks were detected. Sampling began
300 with a sampling events every six weeks, but collection of one or more ticks prompted sampling
301 events every three weeks (37). The start of sampling at a site coincided within two weeks of the
302 onset of vegetation green-up and ended within two weeks of senescence (typically April-
303 September, but may be March-October depending on site and weather). Each tick sampling plot
304 was 40 x 40m; the perimeter of each sampling plot was sampled with a 1 x 1m drag cloth. If
305 vegetation within a sampling plot was too thick to allow dragging, flagging was used either
306 instead of dragging or in conjunction with dragging. Ticks were identified to species and life
307 stage. For each focal species and sampling event, nymph and adult abundances were pooled.
308 Tick abundances were converted to densities based on area sampled (individuals per m²) and
309 scaled to individuals per 1,000 m². We then calculated the density of focal tick species (*Ixodes*
310 *scapularis*, *Ixodes pacificus*, or *Amblyomma americanum*) as the mean number of individuals
311 collected per sampling event per sampling plot, to account for differences in the number of tick
312 sampling events across sites and years. See Fig. S1 for NEON sites at which each focal tick
313 species was sampled. Ticks were not supplementally sampled from small mammal hosts.

314 *Tick-borne pathogen prevalence*

315 Testing of pathogen prevalence in ticks occurred at 13 sites in the eastern U.S. (Table
316 S8), starting in 2014 (37). At the time of data analysis, tick pathogen prevalence was only
317 available for 2014-2017. At a given site, a subset of sampled nymphal ticks were tested annually
318 for the presence of zoonotic pathogens (Table S8). *Ixodes scapularis* (eastern blacklegged ticks)
319 were tested for *Anaplasma phagocytophilum*, *Babesia microti*, and *Borrelia burgdorferi*.
320 *Amblyomma americanum* (lone star ticks) were tested for *Ehrlichia chaffeensis*. Pathogens status
321 in nymphal ticks was tested using next-generation sequencing and 16S rRNA primers. As quality

322 control, we excluded all pathogen status results that did not also test positive for hard-tick DNA.
323 Pathogen prevalence at a site was estimated as the proportion of nymphal ticks that tested
324 positive for a given pathogen.

325 *Small mammal trapping*

326 Starting in 2014, at each site, trapping plots were arranged in three to eight plots of 100
327 live traps (Sherman) arranged in a 10 x 10 grid, with 10 m spacing (100 x 100m area) (38).
328 Trapping plots were separated by at least 135 m. NEON field technicians trapped, identified, and
329 released small mammals from each grid either one or three nights (depending on whether
330 sampling for diversity or pathogens, respectively) per month or every other month (depending on
331 site designation as core or relocatable, respectively) during the growing season within a 21 day
332 window centered on the new moon (typically April-September, but may be March-October
333 depending on site and weather). Ethical approval was obtained from IACUC (38).

334 Small mammal richness was the total number of unique species collected across all
335 sampling plots at a given site each year. Small mammal abundance for a given site each year was
336 calculated as the mean number of individuals of all species collected per trap night per sampling
337 plot (individuals per 10,000 m²), to account for differences in the number of sampling events and
338 plots across sites and years. Because captured individuals were marked, we excluded recaptures
339 from the estimates of small mammal abundance. See Table S9 for species by site matrix.
340 Similarly, the abundance of main reservoir species for *B. burgdorferi*, the white-footed mouse
341 (*Peromyscus leucopus*) in the eastern US and the brush mouse (*Peromyscus boylii*), the pinyon
342 mouse (*Peromyscus truei*), and the deer mouse (*Peromyscus maniculatus*) at sites located within
343 the range of *Ixodes pacificus* (western blacklegged tick) in the western U.S. (NEON sites:
344 ABBY, ONAQ, SOAP, and SJER), was calculated as the mean number of individuals collected

345 per trap night per sampling plot (individuals per 10,000 m²). The abundances of these four
346 species were pooled and termed “*B. burgdorferi* reservoir density”.

347 Deer density estimates

348 As white-tailed deer are the assumed main reservoir host for *E. chaffeensis* (17, 39), we
349 included deer densities as a predictor of ehrlichiosis. The most recent white-tailed deer density
350 estimates for the United States cover 2001-2005, were compiled by the Quality Deer
351 Management Association, and are hosted by U.S. Forest Service (40). Deer densities were not
352 meant to be a measure of absolute white-tailed deer density, but rather were meant to provide an
353 estimate for relative densities across the continental United States. Therefore, we grouped deer
354 density estimates into three categories: No Deer, Low Density, and High Density. The “No
355 Deer” category represents areas where white-tailed deer are absent, the “Low Density” category
356 represents deer densities (<11.6 deer/km²) that are below or on the cusp of ecologically
357 damaging, and the “High Density” category represents deer densities (>11.6 deer/km²) that are
358 ecologically damaging and are greatly above historic, pre-European settlement densities (41).

359 Human cases of tick-borne diseases

360 We obtained the annual number of reported cases of Lyme disease, anaplasmosis,
361 ehrlichiosis caused by *E. chaffeensis*, and babesiosis at the county level from the CDC NNDSS
362 and DPDM from 2014 – 2018. At the time of analysis, Lyme disease and babesiosis cases were
363 only available from 2014-2017. Tick-borne disease case definitions by the CDC includes both
364 confirmed and probable cases, to address under-reporting (42, 43). Due to differences in Lyme
365 disease case definitions between the CDC and Massachusetts Department of Health starting in
366 2016, most cases for Massachusetts are not reported to the CDC (42, 44); thus, case data from
367 Worcester, Massachusetts was limited to 2014 and 2015. Anaplasmosis, ehrlichiosis, and

368 babesiosis are not reportable conditions for all states in all years: anaplasmosis and ehrlichiosis
369 was not reported in Colorado and New Mexico across years, while babesiosis was not reported in
370 Arizona, Colorado, Georgia, Kansas, New Mexico, and Oklahoma across years. Further,
371 babesiosis was not reported from Virginia and Florida before 2017, so data from sites in these
372 states before 2017 were not included in the analyses. Tick-borne disease cases are reported in the
373 patient's county of residence, so reporting errors due to travel are possible, especially in non-
374 endemic and non-emerging areas.

375 Statistical analyses

376 All statistical analyses were conducted in R version 3.6.1 (45). For the national-scale
377 analyses, we used model selection and generalized linear mixed effects models (GLMMs) with a
378 binomial distribution to explore patterns among human cases of tick-borne disease prevalence,
379 tick densities, small mammal diversity, and reservoir species abundance. Responses for each
380 model were a binary county-level tick-borne disease case count and population. For Lyme
381 disease and anaplasmosis models, we used glmer in the lme4 package (24) and for the
382 ehrlichiosis and babesiosis models, we used bglmer in the blme package (46) with a gamma
383 covariance prior, due to issues of singular fit related to low incidence of these diseases. Predictor
384 variables included tick densities, reservoir host abundance, and small mammal richness. For
385 Lyme disease, anaplasmosis, and babesiosis, tick densities were the densities of the eastern (*I.*
386 *scapularis*) and western (*I. pacificus*) blacklegged ticks. For ehrlichiosis, tick densities were the
387 densities of the lone star tick (*A. americanum*). For the measure of reservoir host abundance, we
388 used the abundance of the primary competent reservoir host. Specifically, for Lyme disease we
389 used the abundance of the eastern reservoir (white-footed mice) and the western mammalian
390 reservoirs (pinyon, brush, and deer mice). For ehrlichiosis, we used the abundance of white-

391 tailed deer for the measure of reservoir host abundance. For both anaplasmosis and babesiosis
392 (diseases with evenly poor reservoir hosts, Table S1 (15, 18)), we used abundance of all small
393 mammals for the measure of host reservoir abundance. County was included as a random term in
394 all models, because annual observations within the same county are not independent.

395 We conducted model selection in which we fit all possible combinations of main effects
396 and biologically relevant two-way interactions of all biotic variables (interactions between host
397 density and tick density and between host density and host richness; dredge function in MuMIn
398 R package) (47). To account for differences in questing height of blacklegged ticks along a
399 north-south gradient (25), we included latitude as a covariate for blacklegged tick-borne diseases.
400 Further, to account for potential climate-related differences in relationships between wildlife
401 variables and human disease incidence (20), all models included covariates of mean annual
402 temperature and annual precipitation. Analysis of correlations among of variables indicated
403 correlation >0.6 for only a single pair of variables that jointly appear in any GLMMs:
404 temperature and latitude (Fig. S4). Despite this correlation, the inclusion of both variables in
405 models is important to capture known ecological/behavioral gradients along each variable. To
406 find best fitting models, we used a combination of the lowest Akaike's Information Criterion
407 with bias-correction (AICc) and the law of parsimony; such that competing models ($\Delta AICc < 2$)
408 with fewer degrees of freedom than models with lowest AICc were selected as the best model.
409 Likelihood ratio tests against a null model containing only the random term of county and fixed
410 effects of mean annual temperature and annual precipitation (and latitude for blacklegged tick-
411 borne disease models) were used to determine overall p-values for best models. We calculated
412 AICc weights (w) and marginal (fixed) and conditional (fixed and random effects) R^2 values
413 (48). We performed model diagnostics on residuals of best models using the DHARMA R

414 package (49), which indicated model assumptions had been met and no spatial autocorrelation.

415 For models with significant effects of small mammal richness on human disease
416 prevalence, we calculated the differences in case prevalence from 2017 (the year with the most
417 recent complete data) by subtracting the median state-level prevalence for a given disease in
418 2017 from best model-predicted prevalence. We then multiplied this relative change in
419 prevalence by the U.S. population from all states reporting anaplasmosis cases to get total change
420 in disease incidence across the U.S. These are reported in Figure 3 in the main text. Change in
421 Lyme disease incidence was then converted to change in annual disability-adjusted life years
422 (DALYs) to provide an estimate of overall disease burden from changing disease incidence.
423 Average case DALYs for Lyme disease have been estimated for patients with different Lyme
424 disease outcomes: erythema migrans (0.005 DALYs), disseminated Lyme disease (0.113
425 DALYs), and Lyme-related persisting symptoms (1.661 DALYs) (26). Relative prevalence of
426 these outcomes per Lyme disease diagnosis are 82.8% for erythema migrans, 8.6% for
427 disseminated LD, and 8.6% for persisting Lyme disease symptoms (7). Thus, the estimated
428 DALYs per Lyme disease case is 0.156.

429 To address our second objective of direct and indirect effects of tick density and reservoir
430 host metrics on human disease prevalence, we used sequential regressions rather than traditional
431 structural equation models (SEMs), because of limited data on tick infection prevalence (<30
432 replicates per pathogen). Models were fit using generalized linear models with either a normal
433 error distribution (for tick and mammal density models) or a binomial error distribution (for tick
434 and human disease prevalence models). All models were hypothesized *a priori* from national-
435 scale analyses, the ecology of these pathogens, and previous studies (10, 19, 23, 50); see Fig. 1 in
436 main text for *a priori* hypothesized links. Significance of relationships was found with type 3

437 error and p-values were adjusted using the Holm-Bonferroni sequential correction (51), by which
438 k relationships are ranked (i) by their p-values (P_i) and p-values are adjust by the equation:
439 $(k - i + 1) * P_i$. Significance levels of all models was $P < 0.05$.

440 **Acknowledgements**

441 We would like to thank the National Ecological Observatory Network for collection and maintenance
442 of ecological data. We would like to thank K.N.H. and S.P.H. at the Centers for Disease Control for
443 providing data access. We thank the Rohr lab and S.L. Rumschlag for feedback on this manuscript,
444 and A.M. Kilpatrick for discussions on community competence and tick-borne diseases. Funding was
445 provided by the University of Notre Dame and the National Science Foundation (DEB-1518681, EF-
446 1241889, IOS-1754868).

447 **References**

- 448 1. A. M. Kilpatrick, S. E. Randolph, Drivers, dynamics, and control of emerging vector-
449 borne zoonotic diseases. *Lancet* **380**, 1946–1955 (2012).
- 450 2. Centers for Disease Control and Prevention (CDC), Illnesses on the rise (2020) (April 6,
451 2020).
- 452 3. Centers for Disease Control and Prevention (CDC), Lyme and Other Tickborne Diseases
453 Increasing (2020) (April 6, 2020).
- 454 4. A. F. Hinckley, *et al.*, Lyme disease testing by large commercial laboratories in the United
455 States. *Clin. Infect. Dis.* **59**, 676–681 (2014).
- 456 5. E. R. Adrion, J. Aucott, K. W. Lemke, J. P. Weiner, Health care costs, utilization and
457 patterns of care following lyme disease. *PLoS One* **10**, 1–14 (2015).
- 458 6. S. Mac, S. R. da Silva, B. Sander, The economic burden of lyme disease and the cost-
459 effectiveness of lyme disease interventions: A scoping review. *PLoS One* **14**, 1–17 (2019).
- 460 7. A. Hofhuis, M. Harms, S. Bennema, C. C. Van Den Wijngaard, W. Van Pelt, Physician

- 461 reported incidence of early and late Lyme borreliosis. *Parasites and Vectors* **8**, 1–8
462 (2015).
- 463 8. E. Sanchez, E. Vannier, G. P. Wormser, L. T. Hu, Diagnosis, treatment, and prevention of
464 lyme disease, human granulocytic anaplasmosis, and babesiosis: A review. *J. Am. Med.*
465 *Assoc.* **315**, 1767–1777 (2016).
- 466 9. R. J. Eisen, J. Piesman, E. Zielinski-Gutierrez, L. Eisen, What Do We Need to Know
467 About Disease Ecology to Prevent Lyme Disease in the Northeastern United States? *J.*
468 *Med. Entomol.* **49**, 11–22 (2012).
- 469 10. J. R. Rohr, *et al.*, Toward common ground in the biodiversity–disease debate. *Nat. Ecol.*
470 *Evol.* (2019) <https://doi.org/10.1038/s41559-019-1060-6>.
- 471 11. R. S. Ostfeld, F. Keesing, Is biodiversity bad for your health? *Ecosphere* **8** (2017).
- 472 12. B. E. Anderson, *et al.*, *Amblyomma americanum*: A potential vector of human
473 ehrlichiosis. *Am. J. Trop. Med. Hyg.* **49**, 239–244 (1993).
- 474 13. H. Inokuma, “Vectors and Reservoir Hosts of Anaplasmatataceae” in *Rickettsial Diseases*,
475 D. Raoult, P. Parola, Eds. (2007), pp. 199–212.
- 476 14. R. S. Ostfeld, F. Keesing, Biodiversity and disease risk: The case of Lyme disease.
477 *Conserv. Biol.* **14**, 722–728 (2000).
- 478 15. R. S. Ostfeld, T. Levi, F. Keesing, K. Oggenfuss, C. D. Canham, Tick-borne disease risk
479 in a forest food web. *Ecology* **99**, 1562–1573 (2018).
- 480 16. D. T. Haydon, S. Cleaveland, L. H. Taylor, M. K. Laurenson, Identifying reservoirs of
481 infection: A conceptual and practical challenge. *Emerg. Infect. Dis.* **8**, 1468–1473 (2002).
- 482 17. B. F. Allan, L. S. Goessling, G. A. Storch, R. E. Thach, Blood meal analysis to identify
483 reservoir hosts for *Amblyomma americanum* ticks. *Emerg. Infect. Dis.* **16**, 433–440

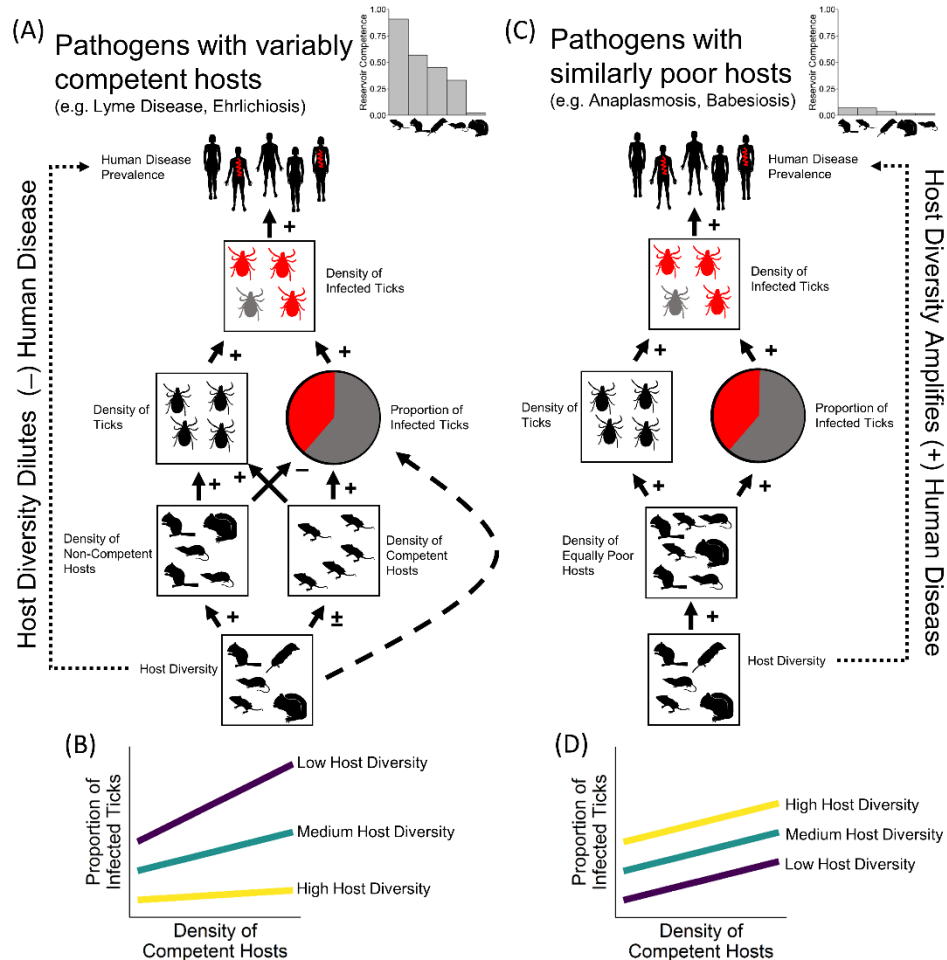
- 484 (2010).
- 485 18. F. Keesing, *et al.*, Prevalence of human-Active and variant 1 strains of the tick-borne
486 pathogen *Anaplasma phagocytophilum* in hosts and forests of Eastern North America. *Am.*
487 *J. Trop. Med. Hyg.* **91**, 302–309 (2014).
- 488 19. C. L. Wood, K. D. Lafferty, Biodiversity and disease: A synthesis of ecological
489 perspectives on Lyme disease transmission. *Trends Ecol. Evol.* **28**, 239–247 (2013).
- 490 20. K. M. Pepin, *et al.*, Geographic variation in the relationship between human lyme disease
491 incidence and density of infected host-seeking *Ixodes scapularis* nymphs in the Eastern
492 United States. *Am. J. Trop. Med. Hyg.* **86**, 1062–1071 (2012).
- 493 21. A. F. Hinckley, *et al.*, Effectiveness of Residential Acaricides to Prevent Lyme and Other
494 Tick-borne Diseases in Humans. *J. Infect. Dis.* **214**, 182–188 (2016).
- 495 22. F. W. Halliday, J. R. Rohr, Measuring the shape of the biodiversity-disease relationship
496 across systems reveals new findings and key gaps. *Nat. Commun.* **10**, 5032 (2019).
- 497 23. P. T. J. Johnson, R. S. Ostfeld, F. Keesing, Frontiers in research on biodiversity and
498 disease. *Ecol. Lett.* **18**, 1119–1133 (2015).
- 499 24. D. Bates, M. Maechler, B. Bolker, S. Walker, Fitting linear mixed-effects models using
500 lme4. *J. Stat. Softw.* **67**, 1–48 (2015).
- 501 25. I. Arsnøe, J. I. Tsao, G. J. Hickling, Nymphal *Ixodes scapularis* questing behavior
502 explains geographic variation in Lyme borreliosis risk in the eastern United States. *Ticks*
503 *Tick. Borne. Dis.* **10**, 553–563 (2019).
- 504 26. C. C. Van Den Wijngaard, *et al.*, The burden of Lyme borreliosis expressed in disability-
505 adjusted life years. *Eur. J. Public Health* **25**, 1071–1078 (2015).
- 506 27. S. S. Gervasi, D. J. Civitello, H. J. Kilvitis, L. B. Martin, The context of host competence:

- 507 A role for plasticity in host-parasite dynamics. *Trends Parasitol.* **31**, 419–425 (2015).
- 508 28. N. P. Connally, *et al.*, Peridomestic Lyme Disease Prevention. Results of a Population-
509 Based Case-Control Study. *Am. J. Prev. Med.* **37**, 201–206 (2009).
- 510 29. C. Finch, *et al.*, Integrated assessment of behavioral and environmental risk factors for
511 lyme disease infection on Block Island, Rhode Island. *PLoS One* **9** (2014).
- 512 30. A. M. Kilpatrick, D. J. Salkeld, G. Titcomb, M. B. Hahn, Conservation of biodiversity as a
513 strategy for improving human health and well-being. *Philos. Trans. R. Soc. B Biol. Sci.*
514 **372** (2017).
- 515 31. D. J. Salkeld, R. S. Lane, Community ecology and disease risk: Lizards, squirrels, and the
516 Lyme disease spirochete in California, USA. *Ecology* **91**, 293–298 (2010).
- 517 32. M. A. Diuk-Wasser, *et al.*, Spatiotemporal Patterns of Host-Seeking *Ixodes*
518 *scapularis* Nymphs (Acari: Ixodidae) in the United States. *J. Med. Entomol.* **43**, 166–
519 176 (2006).
- 520 33. J. I. Tsao, *et al.*, An ecological approach to preventing human infection: Vaccinating wild
521 mouse reservoirs intervenes in the Lyme disease cycle. *Proc. Natl. Acad. Sci. U. S. A.* **101**,
522 18159–18164 (2004).
- 523 34. M. C. Dolan, *et al.*, Control of Immature *Ixodes scapularis* (Acari: Ixodidae) on Rodent
524 Reservoirs of *Borrelia burgdorferi* in a Residential Community of Southeastern
525 Connecticut. *J. Med. Entomol.* **41**, 1043–1054 (2004).
- 526 35. T. L. Schulze, R. A. Jordan, Early Season Applications of Bifenthrin Suppress Host-
527 seeking *Ixodes scapularis* and *Amblyomma americanum* (Acari: Ixodidae) Nymphs. *J.*
528 *Med. Entomol.*, 1–4 (2019).
- 529 36. J. L. Larson, C. T. Redmond, D. A. Potter, Comparative impact of an anthranilic diamide

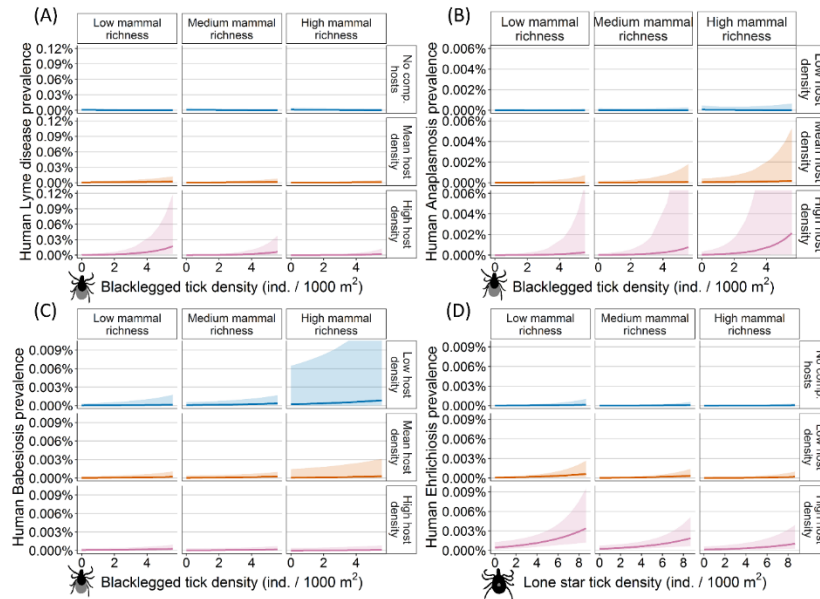
- 530 and other insecticidal chemistries on beneficial invertebrates and ecosystem services in
531 turfgrass. *Pest Manag. Sci.* **68**, 740–748 (2012).
- 532 37. K. E. Levan, K. M. Thibault, K. Tsao, Y. P. Springer, *Tos Protocol and Procedure: Tick*
533 *and Tick-Borne Pathogen Sampling, Revision K* (NEON, 2019).
- 534 38. K. M. Thibault, K. Tsao, Y. P. Springer, L. Knapp, *TOS Protocol and Procedure: Small*
535 *Mammal Sampling, Revision L* (NEON, 2019).
- 536 39. C. D. Paddock, M. J. Yabsley, *Ecological Havoc, the Rise of White-Tailed Deer, and the*
537 *Emergence of Amblyomma americanum -Associated Zoonoses in the United States* (2007).
- 538 40. B. Hanberry, P. Hanberry, Rapid digitization to reclaim thematic maps of white-tailed
539 deer density from 1982 and 2003 in the conterminous US. *PeerJ* **8**, e8262 (2020).
- 540 41. W. S. Alverson, D. M. Waller, S. L. Solheim, Forests Too Deer: Edge Effects in Northern
541 Wisconsin. *Conserv. Biol.* **2**, 348–358 (1988).
- 542 42. C. A. Nelson, *et al.*, Incidence of clinician-diagnosed lyme disease, United States, 2005–
543 2010. *Emerg. Infect. Dis.* **21**, 1625–1631 (2015).
- 544 43. C. of S. and T. Epidemiologists, Position Statements 2007 ID-03: Revision of the National
545 Surveillance Case Definition for Ehrlichiosis (Ehrlichiosis/Anaplasmosis). 7 (2007).
- 546 44. C. for D. Control, Lyme Disease Maps: Historical Data (2019) (November 1, 2019).
- 547 45. R Core Team, R: a language and environment for statistical computing (2019).
- 548 46. Y. Chung, S. Rabe-Hesketh, V. Dorie, A. Gelman, J. Liu, A nondegenerate penalized
549 likelihood estimator for variance parameters in multilevel models. *Psychometrika* **78**,
550 685–709 (2013).
- 551 47. K. Barton, MuMIn: Multi-Model Inference. (2019).
- 552 48. S. Nakagawa, P. Johnson, H. Schielzeth, The coefficient of determination R² and intra-

- 553 class correlation coefficient from generalized linear mixed-effects models revisited and
554 expanded. *J. R. Soc. Interface* **14**, 20170213 (2017).
- 555 49. F. Hartig, DHARMA: Residual Diagnostics for Hierarchical (Multi-Level / Mixed)
556 Regression Models (2019).
- 557 50. S. E. Randolph, A. D. M. Dobson, Pangloss revisited: A critique of the dilution effect and
558 the biodiversity-buffers-disease paradigm. *Parasitology* **139**, 847–863 (2012).
- 559 51. S. Holm, A Simple Sequentially Rejective Multiple Test Procedure. *Scand. J. Stat.* **6**, 65–
560 70 (1978).
- 561
- 562

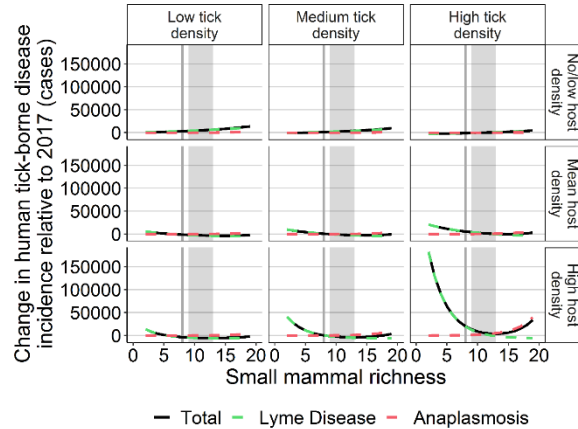
563 **Figures and Tables**



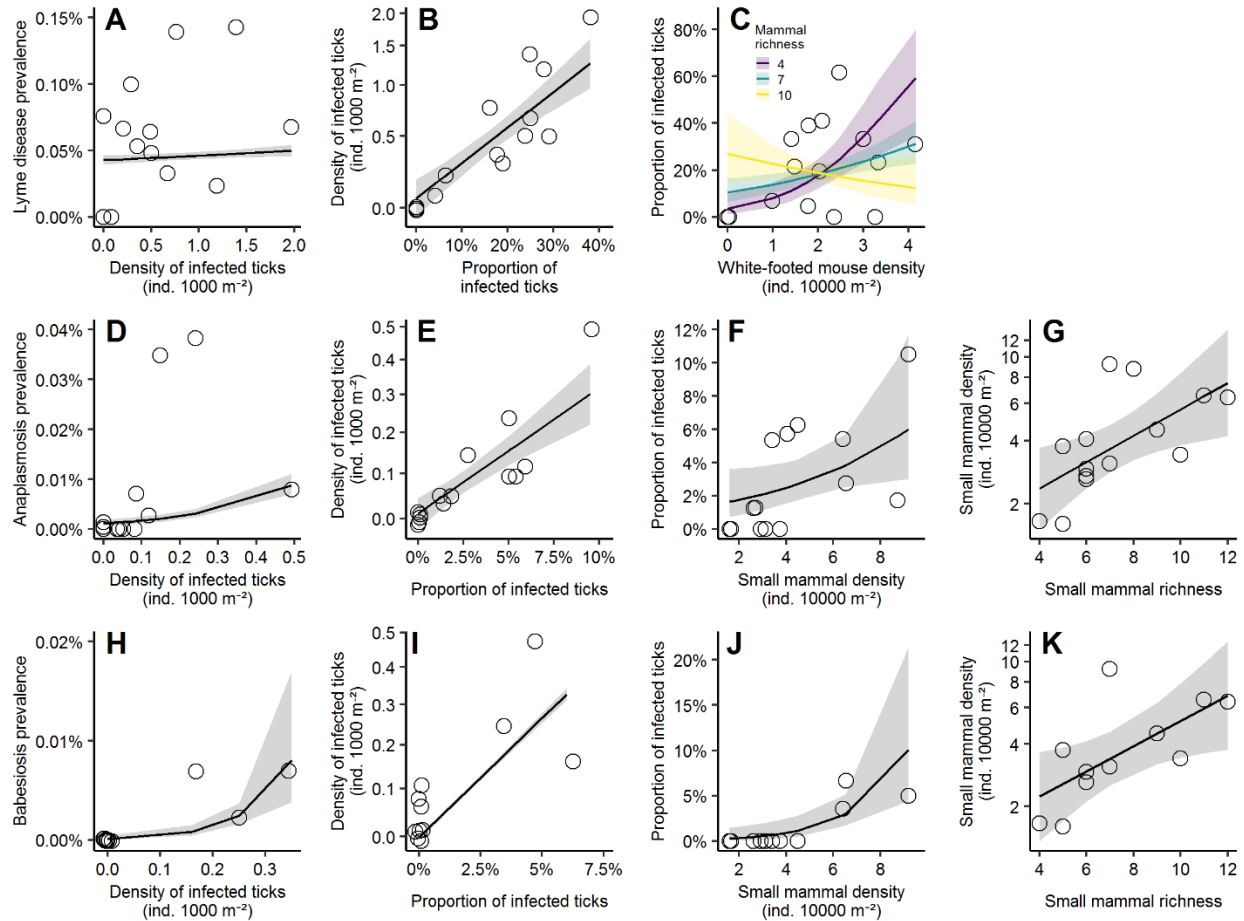
564 Figure 1. Conceptual diagram for linkages connecting wildlife to human prevalence of tick-borne
 565 diseases, per the dilution effect hypothesis. (A), hypothesized links among wildlife and human
 566 disease prevalence for pathogens with hosts that differ in reservoir competence (ability to
 567 transmit pathogen to uninfected ticks; coefficient of variation (CV) for tested *B. burgdorferi*
 568 reservoirs: 1.28, CV for tested *E. chaffeensis* reservoirs: 1.10). (B), hypothesized interaction
 569 between host diversity and competent host density, by which the effect of competent host density
 570 on tick infection prevalence is strongest when host diversity is low. (C), hypothesized links
 571 among wildlife and human disease prevalence for pathogens with hosts that are similarly poor
 572 reservoir hosts (CV for tested *A. phagocytophilum* [human strain] reservoirs: 0.80; CV for tested
 573 *B. microti* reservoirs: 0.81). (D), hypothesized additive relationship between host diversity and
 574 competent host density, such that the effect of increased host diversity in an area will increase
 575 reservoir density and, in turn, tick infection prevalence. In (A) and (C), links between density of
 576 infected ticks and human disease prevalence can be disrupted by human behavior (e.g. acaricides
 577 and avoidance). For each link in (A) and (C), signs are representative of whether relationship is
 578 positive (+), negative (-), or variable (\pm). Dotted arrows from host diversity to human disease
 579 prevalence in (A) and (C) are the overall, indirect effect of diversity on disease. Data for host
 580 reservoir competence in (A) and (C) are from ref (15, 17, 18).
 581



582 Figure 2. Human prevalence of tick-borne diseases is correlated with reservoir and vector
 583 metrics. Model predicted relationships among vector tick density, small mammal community
 584 metrics, and human prevalence of disease for A) Lyme disease, B) anaplasmosis, C) babesiosis,
 585 and D) ehrlichiosis. For (A) Lyme disease, (B) anaplasmosis, and (C) babesiosis, blacklegged
 586 ticks are both *Ixodes scapularis* and *Ixodes pacificus*. Facets of increasing small mammal
 587 richness along the top are 5, 8, and 11 species, respectively. For (A) Lyme disease, facets of
 588 increasing host density down the right side are 0, 2, and 4 mice per 10000 m², respectively. For
 589 (B) anaplasmosis and (C) babesiosis, facets of increasing host density down the right side are 3,
 590 5, and 7 small mammal individuals per 10000 m², respectively. For (D) ehrlichiosis, the facets of
 591 increasing host density down the right side are no deer, low deer density, and high deer density.
 592 Coloration for reservoir host abundance is consistent across diseases: blue lines are no/low
 593 abundance, orange lines are mean abundance, and pink lines are high abundance. Models
 594 indicate positive correlations of vector tick density with human prevalence of disease, such that
 595 human disease prevalence is predicted to be highest in areas with high vector tick density. For
 596 Lyme disease (A), anaplasmosis (B), and ehrlichiosis (D) there was a positive relationship
 597 between host abundance and disease prevalence. Accounting for differences in tick and reservoir
 598 host abundance, we found significant negative correlations between diversity and disease
 599 incidence for Lyme disease (A) and ehrlichiosis (D), but a significant positive correlation
 600 between diversity and disease for anaplasmosis (B). The observed patterns are consistent with
 601 the dilution effect hypothesis, which posits that a diluting (negative) relationship between
 602 diversity and disease is expected when hosts differ in their ability to maintain and transmit
 603 pathogens (e.g. Lyme disease and ehrlichiosis); when this condition is not met (e.g.
 604 anaplasmosis), an amplifying (positive) relationship is expected.



605
606 Figure 3. Changes in human tick-borne disease incidence. Changes in human disease incidence
607 for Lyme disease (green lines), anaplasmosis (pink lines), and the sum of the two diseases (total;
608 black solid lines) relative to incidence in the U.S. in 2017. Facets of low, medium, and high tick
609 density along the top are 0.75, 2, and 4 blacklegged ticks (*Ixodes scapularis* and *Ixodes*
610 *pacificus*) per 1000 m², respectively. Facets of host density down the right are 0, 2, and 4 mice
611 per 10000 m² and 3, 5, and 7 small mammals per 10000 m² for Lyme disease and anaplasmosis
612 respectively. Vertical dark grey line indicated median small mammal richness across NEON
613 sites. Light grey rectangle from 9 to 13 small mammal species represents the mammal richness
614 required to maintain the lowest disease incidence across tick and reservoir host densities. Figures
615 suggest that the magnitude of the relationship between small mammal richness and total tick-
616 borne disease incidence is dependent on the densities of ticks and reservoir hosts. Similarly,
617 figures suggest that the relationship between small mammal richness and total tick-borne disease
618 incidence is non-monotonic and is driven by the reductions in Lyme disease as small mammal
619 richness increases from low (<8 species) to median (8 species), then by the increase in
620 anaplasmosis as small mammal richness increases from median (8 species) to high (>13 species).
621
622



623

624 Figure 4. Mammal richness is indirectly correlated with human prevalence of tick-borne
 625 diseases. Relationships among (A) human prevalence of Lyme disease and density of *Borrelia*
 626 *burgdorferi*-infected blacklegged ticks; (B) density of infected ticks and proportion of *B.*
 627 *burgdorferi*-infected ticks; (C) proportion of infected ticks, white-footed mouse density, and
 628 small mammal richness; (D) human prevalence of anaplasmosis and density of *Anaplasma*
 629 *phagocytophilum*-infected blacklegged ticks; (E) density of infected ticks and proportion of *A.*
 630 *phagocytophilum*-infected ticks; (F) proportion of infected ticks and small mammal density; (G)
 631 small mammal density and small mammal richness; (H) human prevalence of babesiosis and
 632 density of *Babesia microti*-infected blacklegged ticks; (I) density of infected ticks and proportion
 633 of *Ba. microti*-infected ticks; (J) proportion of infected ticks and small mammal density; and (K)
 634 small mammal density and small mammal richness. Figures indicate indirect effects of small
 635 mammal species richness on human prevalence mediated through increases in proportion of
 636 infected ticks, and, in turn, density of infected ticks. Figures support predictions of a negative
 637 diversity-disease relationship (dilution) for Lyme disease (A-C), but positive diversity-disease
 638 relationships (amplification) for anaplasmosis (D-G) and babesiosis (H-K). Lines for all panels
 639 are generalized linear regression coefficients from sequential regressions (see Table S4); ribbons
 640 are model indicated standard error. Regression coefficients and statistics are described in Table
 641 S. Note: y-axis of (B), (E), (G), (I), and (K) are natural-log transformed. Points on panels are
 642 slightly jittered, but do not alter interpretation.
 643

644 Table 1. Regression coefficients and statistics from best-fit models from Table S3. Predictor
 645 variables were blacklegged tick density, lone star tick density, *B. burgdorferi* reservoir density,
 646 small mammal richness, small mammal density, and white-tailed deer density. Models included a
 647 random effect of county. All models included covariates of annual mean temperature and annual
 648 precipitation. Lyme disease models included covariates of CDC reporting type. R^2 values
 649 represent marginal/conditional (fixed/random + fixed) R^2 .
 650

Model/Variable	Estimate (SE)	DF	Chisq	P
Lyme disease ($w = 0.99$, $R^2 = 0.17/0.78$, $n = 95$, $X^2(5) = 38.323$, $p < 0.001$)				
Blacklegged tick density	-0.177 (0.12)	1	2.12	0.146
<i>B. burgdorferi</i> reservoir abundance	0.299 (0.21)	1	2.09	0.148
Small mammal richness	0.057 (0.08)	1	0.58	0.445
Blacklegged tick density* <i>B. burgdorferi</i> reservoir density	0.217 (0.05)	1	19.99	< 0.001
<i>B. burgdorferi</i> reservoir density*Small mammal richness	-0.097 (0.03)	1	12.25	< 0.001
Anaplasmosis ($w = 0.69$, $R^2 = 0.32/0.82$, $n = 116$, $X^2(4) = 17.346$, $p = 0.002$)				
Blacklegged tick density	-0.946 (0.47)	1	4.04	0.044
Small mammal density	-0.065 (0.04)	1	2.87	0.090
Small mammal richness	0.340 (0.12)	1	7.44	0.006
Black-legged tick density*Small mammal density	0.236 (0.07)	1	10.29	0.001
Babesiosis ($w = 0.51$, $R^2 = 0.73/0.74$, $n = 57$, $X^2(4) = 20.938$, $p < 0.001$)				
Blacklegged tick density	0.240 (0.12)	1	4.31	0.038
Small mammal density	0.875 (0.63)	1	1.94	0.164
Small mammal richness	0.657 (0.55)	1	1.42	0.234
Small mammal density*Small mammal richness	-0.119 (0.06)	1	3.36	0.067
Ehrlichiosis ($w = 0.22$, $R^2 = 0.44/0.46$, $n = 116$, $X^2(3) = 19.61$, $p < 0.001$)				
Lone star tick density	0.230 (0.08)	1	7.44	0.006
Deer density	1.660 (0.46)	1	12.88	<0.001
Small mammal richness	-0.197 (0.11)	1	3.37	0.066

651