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1	Host specificity in variable environments		
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13	Highlights		
14	• Increasing interests in emerging infectious diseases and parasite spillover coincide with a		
15	rise of studies reporting and comparing host specificity for multihost parasite. Intuitively,		
16	higher host specificity means less spillover risk but to date, a systematic consensus on such a		
17	relationship is lacking.		
18	• Host specificity can vary in space and time due to changing compositions of potential host		
19	species and constraints in environmental conditions. Eco-evolutionary dynamics and		
20	contemporary conditions synergistically determine 'realized' host specificity across regional		
21	scales.		
22	• Modelling advances to capture spatiotemporal variation in the distributions and biotic		
23	interactions of species provide the basis to quantify variation in realized host specificity and		
24	progress towards determining how this relates to spillover risk.		
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27			

28 Abstract

29 Host specificity encompasses the range and diversity of host species that a parasite is capable

- 30 of infecting and is considered a crucial measure of a parasite's potential to shift hosts and
- 31 trigger disease emergence. Yet empirical studies rarely consider that regional observations
- 32 only reflect a parasite's 'realized' host range under particular conditions: the true
- 33 'fundamental' range of host specificity is typically not approached. We provide an overview
- of challenges and directions in modelling host specificity under variable environmental
- 35 conditions. Combining tractable modelling frameworks with multiple data sources that
- 36 account for the strong interplay between a parasites' evolutionary history, transmission mode
- and environmental filters that shape host-parasite interactions will improve efforts to quantify
- 38 emerging disease risk in times of global change.
- 39

Key words: disease spread; pathogen spillover; co-speciation; host shifting; host-parasite
interactions; realized host specificity

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44 Host specificity in times of emerging infectious diseases

The diversity of infectious disease affecting humans and animals are strongly determined by
parasites capable of infecting multiple host species. Estimates that up to 70% of human
parasites are zoonotic (i.e. shared by humans and at least one other animal species; see
Glossary) showcase that multi-host parasites, as opposed to those that only infect a single
host species, are the rule rather than the exception [1, 2]. Frequent identification of Emerging
Infectious Diseases (EIDs) highlights the global importance of contemporary host shifting
that can result in infection of novel and often immunologically naïve hosts [3, 4].

52 Host specificity, representing the number and/or diversity of host species a parasite is capable of infecting, is considered a key indicator of its propensity to shift hosts [5]. Host 53 specificity is a topic of considerable interest in the fields of disease ecology and One Health 54 that is quickly becoming a key feature of research agendas (Figure 1). Much of this work is 55 aimed at delineating possible EID reservoirs by attempting to identify parasites that may be 56 capable of shifting between wildlife and human hosts [6-8]. Wildlife parasitology research 57 58 has uncovered a broad spectrum of host specificity 'strategies' for an impressive diversity of 59 parasites. These range from haemosporidian blood parasites and feather mites that associate

- with only a small number of closely-related host species [9, 10] to rabies viruses that are
 seemingly capable of infecting virtually any mammalian species they encounter [11].
- 62

Intuitively, one may assume that among multi-host parasites, those that exhibit low host 63 specificity (i.e. high levels of host generalism) are more capable to shift hosts [12]. Indeed, 64 numerous studies have identified so-called 'generalist' parasites that seem capable of 65 infecting a broad spectrum of phylogenetically and sometimes ecologically dissimilar host 66 67 species [5, 13, 14]. Yet whether low host specificity meaningfully reflects a higher risk for 68 EID-related spillover remains unresolved [15, 16]. This is largely because there are multiple facets of host specificity, many of which are not captured by common metrics, and there are 69 idiosyncratic ways in which different host species contribute to a parasite's specificity [17]. 70 Moreover, there is a great deal of uncertainty about whether any retrospective summary of 71 observed host ranges into host specificity measures, which basically reflect the accumulation 72 of historical host-parasite interactions, translate into a parasite's potential for contemporary 73 74 host shifting [18].

75

Here, we summarize the state of current research on host specificity and highlight how such work can play a role in advancing our ability to quantify host shifting capacity. We extend previous reviews of how novel species communities may relate to shifting host ranges and variation in parasite transmission dynamics [4, 17, 19] by discussing challenges in the use of host specificity metrics and outlining frameworks that align common data structures to relevant modelling tools.

82

83 The eco-evolutionary backbone of host specificity

Specialization of species in parasitic or mutualistic interactions is assumed to be tightly 84 linked to the levels of adaptation exhibited by interacting partners [20]. Host-parasite 85 interactions often require highly tuned transmission modes and adaptations by the parasite to 86 87 survive and reproduce in the host environment [21]. It therefore comes as little surprise that much of the emphasis surrounding investigation of host-parasite interactions has been placed 88 on host-parasite co-evolution. Co-speciation, whereby a parasite species evolves into two 89 distinct species in response to host speciation, has long been used to explain apparent 90 congruence in host and parasite phylogenies. The prevailing reasoning is that a parasite's 91 92 evolutionary history sets the stage for host specificity by introducing phylogenetic and

ecological barriers to host shifting [22, 23]. Host shifting requires parasites to be exposed to
new hosts that exhibit certain levels of physiological and/or behavioural overlap with
previous hosts (ecological fitting), as this allows circumvention of barriers caused by
variation in host competence or immunity [22, 24].

An expanded line of thought, primarily derived from studying mutualisms such as
animal-plant interactions, suggests that host shifting is probabilistic and relies on opportunity
for hosts and parasites to interact under variable environmental conditions [4, 25]. A
prominent example involves herbivorous insects introduced as biocontrol agents into
different environments, which showcases that regional host ranges are largely determined by
local environmental conditions such as plant community composition, relative abundance and
phenology in response to climate variation [26, 27].

By analogy, we argue that similar environmental forces will also be important for 104 shaping host-parasite interactions [4, 28-30]. This idea that a parasite's capacity for host 105 106 shifting can vary in response to environmental conditions (Figure 2) presents a new forefront of research on spillover risk in times of global change [4, 31-34]. Fortunately, a burst in 107 108 analytical tools designed to explore spatiotemporal variation in species interactions [35-37] make it possible to characterize how host specificity changes across environmental gradients. 109 110 Consistent frameworks are now needed to disentangle the evolutionary and ecological aspects 111 of host-parasite interactions that should be considered when judging host specificity. 112

113 A niche perspective on host specificity

114 Developing a framework to assess host specificity, and to begin relating specificity to potential spillover risk, relies first on developing a consistent definition for host specificity. 115 116 This is particularly necessary when considering the staggering diversity of advocated indices and metrics (Table 1). The most common of these focus on the range of hosts a parasite is 117 observed to infect and in which it can persist and/or complete its life cycle. The simplest way 118 to do this is to count the number of host species a parasite infects [10]. But this provides little 119 information about the diversity of host 'habitats' that comprise a parasite's niche. Authors 120 have more recently recognized that adapting ecological niche concepts to host specificity can 121 improve understanding of a parasite's host range using concepts from a widely-supported 122 123 theoretical framework [13, 32]. An important aspect of niche theory distinguishes between potential resources (resources that a species could utilise if it encountered them) and 124 surrounding conditions that determine whether resources are available and can be utilized 125

(environmental filtering). Recent advances in ecological niche modelling have capitalized
on the concept of potential resources to expand our understanding of niche filling by
differentiating between a species' fundamental niche and its realized niche. Here, the
fundamental niche refers to resources that can be used in the absence of any restrictive
conditions, while the realized niche refers to regional consumer-resource dynamics that are
observed under local environmental conditions [38].

Translated to multi-host parasites, the fundamental niche describes a parasite's 132 capacity to explore different host species independently of conditions that may restrict its 133 134 exposure to these potential hosts. The realized niche, in turn, is based on the regional diversity of host species a parasite is actually observed to infect [39](Figure 2). 135 Biogeographic structuring of host assemblages across regional scales will constrain 136 opportunities for host-parasite interactions. In other words, variation in the diversity of 137 potential hosts occurring in regional species pools can ensure that a parasite's fundamental 138 host specificity is not completely realized [40]. Empirical support for this can be derived 139 from a number of field studies from diverse host-parasite systems. Biogeographic structure in 140 141 host species distributions likely narrows the realized host specificity of chewing lice infecting toucans, particularly when closely related host species are spatially disconnected [41]. Host 142 143 range expansions by relatively fast evolving (RNA) rabies viruses depend on local compositions of bat assemblages, as different virus lineages often cannot cross species 144 145 barriers to infect distantly related host species [11]. Regional climate conditions that influence vector habitats are associated with observed host specificities for widespread avian 146 malaria parasites [34]. Experimental studies that artificially increase the host range accessible 147 to a parasite further support the concept of fundamental vs realized host specificity: the set of 148 hosts that can be infected experimentally can be much larger than the actual range observed 149 under natural conditions, even for parasites that are only observed to infect a single host 150 species [42]. This increasing recognition that local variation changes the suite of hosts to 151 which a parasite is exposed and pre-existing capacity enables host shifting upon newly 152 arising opportunities has been raised by a number of recent studies that collectively 153 contribute to a meta-theory called the Stockholm Paradigm [32]). 154

155

156 Inferring host specificity

Ecological dynamics impact the host specificity of parasites across local and regional scales[43, 44]; this has important ramifications for formulating concepts to gather inferences about

explanatory mechanisms. Identifying factors that influence opportunities for novel host-159 parasite interactions, and how these shape realized host specificity, are vital steps to begin 160 uncovering the true fundamental host specificity (see **Box 1**). This requires an understanding 161 of how host communities are shaped and how resources are utilised, both of which have 162 strong parallels in community ecology. A growing consensus states that a suite of factors 163 such as evolutionary contingencies, speciation, adaptive plasticity, dispersal capacity, 164 environmental filters and biotic interactions [45-48] act in concert with stochastic processes 165 [49] to shape communities. Accounting for plasticity in resource utilisation helps to align 166 167 ecological modelling approaches to reality for understanding shifts in species' habitat use, 168 geographical ranges, or trophic interactions across environmental gradients [20, 50]. Moreover, tractable modelling concepts that can untangle the effects of environmental 169 170 forcing and species interactions on resource utilisation have recently been developed [51-54]. Note that in most situations, sufficient empirical and experimental evidence is 171 172 necessary to infer aspects of fundamental host specificity (see Box 2 for some considerations about matching data to study questions and models). We now outline a number of important 173 174 modelling approaches that are available to begin understanding how host specificity is shaped across scales. 175

176

177 Trait-based approaches to host specificity

Trait-based approaches, which group species of interest according to attributes such as
phylogenetic relationships, body size, diet, climate tolerance or distributions, are increasingly
adopted to study species ecological preferences and their potential responses to global change
[55, 56]. In the context of host specificity, there are at least two trait-based approaches that
have received considerable attention recently.

First, indices of functional and phylogenetic diversity are used to delineate host 183 specificity according to the observed (or estimated) variation in traits exhibited by competent 184 host species [5]. Often, such measures are based on pair-wise distances that are calculated 185 186 among all possible combinations of viable host species [57, 58]. For instance, phylogenetic 187 trees, which depict evolutionary relationships among host species, can be used to generate indices of phylogenetic host specificity [17, 59, 60]. In a similar way, distance-based 188 diversity measures can be generated using host species' ecological traits [14, 61], with 189 supporting computational algorithms readily available in open-source software such as R 190 [62]. The central aim when using these measures is to determine whether the distribution of 191 pairwise distances between infected host species (observed distances) is different to a 192

distribution of distances between potential host species (expected distances). Here, an 193 observed distance distribution that is statistically smaller than expected indicates that infected 194 hosts are more closely related than expected by chance. It is worth noting that such metrics 195 largely depend on sample size (i.e. the number of host species recorded) and thus are 196 potentially subject to sampling bias [63]. Null model permutation approaches [64] and more 197 198 recently, hierarchical models [40], have been proposed to account for sampling bias while comparing observed and expected distance distributions. Recent studies have put these ideas 199 200 into practice by demonstrating that host functional traits are as important as phylogenetic 201 relationships for assessing whether primates share the same parasites [15] and by showing that host phylogenetic relationships appear to strongly shape the host ranges of avian malaria 202 lineages [14]. Moreover, a recent multi-taxa study deciphered that phylogenetic specialization 203 among prospective hosts is more pronounced for helminths and viruses than for other parasite 204 groups [65]. Finally, similar trait-based measures were used to show that fleas with certain 205 traits are more likely to infest the same subsets of phylogenetically and functionally related 206 mammalian host species [66], showcasing that evolutionary history and ecological fitting 207 208 synergistically drive the realized host specificity of these ectoparasites.

Trait-based regression models have also gained popularity for analysing whether the 209 210 presence-absence of parasites in a suite of host species is linked to host traits [6-8]. Such approaches are of relevance for host specificity measures as model-based estimates of a 211 parasite's associations with particular host traits can enable projections onto unmeasured host 212 species, enabling prediction of unknown interactions [67]. Generalised linear models (GLMs; 213 214 readily estimated using Maximum Likelihood or Bayesian frameworks through available R packages; [68-70]) or machine-learning regression trees [71] are the methods of choice as 215 they estimate associations using data from a variety of outcome distributions. Prominent 216 examples have found that higher proportions of zoonotic viruses occur in mammals that are 217 closely related to humans [8], whereas studies of rodents have shown that hosts with faster 218 life histories have higher occurrences of zoonotic viruses [6]. Another study found that the 219 220 intensity of helminth parasite sharing between humans, domestic animals and wildlife appeared to be predominantly driven by dietary traits of wildlife species [7]. At the species 221 222 level (i.e. presence-absence of a particular parasite in a suite of host species), however, we stress again that such regressions are only useful if the underpinning data include sufficient 223 numbers of both presence and absence records to allow meaningful inference. 224

225

226 Network approaches to study host-parasite interactions

Ecological networks summarize biotic interactions among groups of species that live in 227 trophic or symbiotic relationships [72]. Amongst the many useful insights gained from such 228 community-scale analysis, they allow users to draw conclusions about the preference 229 (specialization) of species towards a suite of potential partners [73]. Networks can be 230 231 constructed as bipartite graphs that denote whether species interact or not (e.g., binary 'presence-absence' data of interactions between combinations of host and parasite species) or 232 the frequencies of interactions (e.g., the number/proportion of individuals from a given pool 233 234 of host species infected with the concerned parasites). A simple measure of a parasite's specialization derived from binary networks can be the proportion of host species infected 235 [74], an index that resembles host specificity without taking link strengths into account. This 236 measure can be linked at the community scale when used in combination with null model 237 analysis [75], allowing users to ask which parasites are more or less specialist. In contrast, 238 239 many network measures of species-level host specificity, such as the species-specific specialization index d' [76], are based on both the link distributions as well link strengths. 240 241 Such community-scale analysis acknowledges the fact that every single interaction is embedded in a network of species interactions and depicts a parasite's 242 243 preference/specialization on particular hosts relative to both the overall host availability and 244 the host utilisation by other parasites. Such an approach was recently used to explore network compositions of fish parasites and mammalian fleas across a number of regions [74]. The 245 authors showed that specialist parasites tended to interact with hosts that harboured high 246 richness of parasites, and that hosts with high parasite richness also tended to be more 247 abundant. However, given the fact that network specificity indices are commonly derived 248 from a finite set of community-scale observations, their utility for predicting fundamental 249 host specificity needs to be carefully evaluated. This is because host specificity is a species-250 specific attribute, and we argue that host specificity is not necessarily shaped by the 251 specificities of other parasites in the community. Moreover, networks assembled under 252 253 particular regional conditions will only yield measures of realized host specificity and thus do 254 not necessarily provide accurate insights about host specificity under novel (unsampled) environmental conditions. Nevertheless, advances in techniques to model how ecological 255 network properties respond to environmental variation [36, 77] may provide promising 256 opportunities to estimate fundamental host specificity in future research. 257 Ecological network concepts have also been employed to detect the centrality of key 258

259 host species and/or the modularity of interaction compositions in observed host-parasite

260 networks [78]. These approaches aggregate host-parasite interactions into adjacency matrices

- to depict focal species that share similar sets of interactions (i.e. two host species that are
- infected by similar parasites may be connected within the network; [78, 79]). This of course
- comes at the cost of losing information about species identity, but can nevertheless be helpful
- for identifying roles that different host species may play for facilitating parasite spread or for
- 265 understanding whether host-parasite interactions exhibit a modular or nested structure.
- 266

267 Identifying environmental filters related to realized host specificity

268 Despite the examples outlined above, few studies have examined how changes in host specificity relate to spatiotemporal changes in environmental conditions [80, 81]. Capturing 269 the complex ways in which environmental filtering can affect realized host specificity is a 270 looming challenge that calls for integrative approaches to consolidate the synergies between 271 species distributions and biotic interactions [46]. For example, if variation in realized host 272 273 specificity is linked to changes in regional host composition [40], a comprehensive understanding of how environmental filters impact realized host specificity requires 274 275 disentangling their effects on host species occurrence and on host-parasite interactions (i.e. by influencing epidemiological factors such as host susceptibility, parasite survival and 276 277 transmission potential). Some first step towards capturing this process have been taken by applying statistical models that estimate how realized host specificity changes in relation to 278 the variation in host community compositions [40, 82] and environmental filters such as 279 climate [34]. These approaches expand on the trait-based methods described above by 280 281 comparing suites of ecological and/or phylogenetic distances among infected pairs of host species to distances that describe all potential host species within each region that a parasite 282 occupies. Results have provided promising new insights. For example, Wells et al. [40] 283 showed that helminth parasites generally exhibited the lowest phylogenetic host specificity in 284 regional 'hotspots' that showed high variation in prospective host diversity; despite being 285 286 globally distributed, some parasites still infected less functionally diverse hosts than 287 expected, indicating limited potential to infect hosts from different ecological niches. Fecchio et al. [34] showed that avian malaria parasites are more constrained in their capacity to 288 289 exploit a diversity of host species in regions with pronounced rainfall seasonality and wetter dry seasons. Other recent developments can account for biotic interactions within 290 multivariate community models, which can be helpful to understand how host-parasite 291 interactions may change across environmental gradients [52]. While we are unaware of these 292 293 models being used to assess changes in realized host specificity, their ability to detect

associations among different parasites opens exciting avenues for uncovering how hostspecificity is shaped across regional scales.

296

The need to capture uncertainty: probabilistic tools and an outlook on forecasting host shifting

Because observational data dominates the host specificity literature, the above sections stress 299 that taking advantage of contemporary modelling tools for best-possible inference offers 300 301 significant improvements over simply drawing conclusions from finite observations at hand. 302 We also urge the use of probabilistic methods when applying such tools, as they can 303 distinguish drivers of host-parasite interactions from underlying observation processes to obtain model-based estimates [83-85]. Probabilistic sampling approaches have a number of 304 305 benefits that make them suitable to host specificity research, including: (1) Capturing uncertainty and sampling bias in infection and host-parasite association data, and allowing for 306 307 random data imputation/augmentation (i.e. for poorly sampled host species there might be a certain probability this species is infected, even if records of such associations are missing); 308 (2) Utilising a diversity of data sources such as host-parasite association data, trait variables 309 310 and spatiotemporal environmental data in consistent model frameworks; (3) Capturing the hierarchical nature of realized host specificity by conceptualizing conditional dependencies 311 such as 'the probability a host species contributes to realized host specificity, conditional on 312 its presence and compatibility under regional conditions'. The ability to capture uncertainties 313 is particularly imperative for forecasting the possible infection of a novel host species under 314 future or as yet unexplored environmental conditions, which is the basis for mitigating the 315 public and animal health risks posed by EIDs. Given the importance of plasticity in host 316 specificity, quantitative solutions require developing and applying tractable forecasting tools 317 318 to answer questions such as 'how likely is a parasite to shift from one host species to another under XYZ regional conditions?'. This can be a challenging task for a large range of parasites 319 320 that affect only a small number of host species and/or for which retrospective data on host shifting events are rare. 321

Despite these challenges, novel modelling frameworks offer a foundation for prediction about when and in which host species a parasite may occur. Correlative approaches in species distribution and ecological niche modelling, for example, aim to estimate species persistence under a range of surveyed environmental conditions (aiming to describe the pattern but not necessarily the underlying mechanism) and then project species

distributions across larger environmental space [86]. The trait-based regression models 327 discussed above fall into this category, and may be useful for prediction as they generally 328 have moderate data needs, including the presence-absence of host-parasite associations and 329 information about host traits and environmental conditions. However, projecting models to 330 estimate a parasite's fundamental host range (and to predict host shifting events) across 331 gradients of substantial spatiotemporal change might significantly violate model assumptions 332 and could be hampered by poor transferability [87]. Only for parasites with invariable 333 realized host specificity across environmental gradients would one expect to obtain 334 335 reasonable accuracy in projected host specificity under unsampled conditions. This raises the need for detailed sampling regimes that cover much (if not all) of the parasite's known 336 distribution. In light of the potential drawbacks of correlative predictions, a key aim for future 337 research could be to use historical data on true host shifting events to see if any patterns of 338 realized host specificity prior to the shift could have been informative for prediction. Using 339 340 such hindcasting approaches to evaluate our capacity to forecast future EIDs could tell us whether any of our metrics have any real value, or whether other situational aspects (such as 341 342 rapid changes in contact rates, the emergence of new host-host contacts or the stochastic emergence of new strains) are more important. 343

344 In contrast to correlative approaches, processed-based methods explicitly model the important processes underlying patterns [88, 89]. In terms of host-parasite interactions, such 345 models may aim to predict and reproduce host shifting events from a suite of eco-346 epidemiological factors that jointly drive system dynamics, including variation in contact 347 opportunities among host species and spatiotemporal environmental variation. Perhaps a 348 promising move towards predicting fundamental host specificity and forecasting EIDs could 349 be the establishment of so-called hybrid models. Hybrid models synthesise correlative and 350 process-based models by combining static projections from correlative approaches with 351 simulation of key processes; in species distribution modelling, these processes include 352 aspects such as species abundances, the realistic co-occurrence of interacting species and 353 354 dispersal events [90]. Hybrid models can improve the transferability of correlation-based approaches by more realistically accounting for key processes while avoiding specification of 355 a large number of parameters [91]. For our purposes, such models could aim to capture the 356 most essential dynamics underlying host shifting, such as possible range shifts of key hosts, 357 expected variation in host community composition in relation to climate change [92] or the 358 emergence of species invasion 'hotspots' [93]. 359

360

361 **Concluding Remarks**

A large body of research on human, animal and plant parasites uses host specificity to gauge 362 the risk of EIDs and spillover events. However, in times of global change and the large-scale 363 spread of parasites across former geographic barriers, drawing conclusions about a parasite's 364 host shifting capacity using simple specificity indices may not be suitable to predict such 365 events under novel conditions. Host specificity cannot be considered a fixed trait, as 366 environmental conditions cause considerable variation in realized host specificity. The task of 367 predicting host shifting events must rely on tractable modelling frameworks that sit at the 368 core of ecological forecasting [94]. Ultimately, accounting for plasticity and uncertainty in a 369 parasite's realized host specificity may be a worthy step to better predict disease emergence 370 and host shifting events (see **Outstanding questions**). But identifying the multifaceted 371 processes involved in multi-host parasite transmission is laborious and will require 372 considerable empirical and quantitative research. Along the way towards understanding such 373 complexities, we should not ignore the fact that disease emergence inevitably means parasites 374 often have a hidden potential to infect novel host species. Initial conclusions based on 375 realized host specificity alone need to be carefully revisited as more data becomes available. 376 This will leverage our growing understanding about which parasites are capable of crossing 377 378 the species barrier and causing unwanted diseases.

379

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383

384

385 **Outstanding questions**

Are there generalities about the plasticity in host specificity in response to environmental
conditional for parasites from different taxonomic groups and/or with different transmission
modes?

Do strong host-parasite co-evolutionary histories constrain the plasticity in host specificity
and potential for host shifting across environmental gradients?

- Can integrated model frameworks and validation procedures for inferring fundamental host 391 392 specificity allow us to better predict future host shifting events? 393 394 395 396 397 References 398 1. Taylor, L.H. et al. (2001) Risk factors for human disease emergence. Philos. Trans. Royal 399 400 Soc. B 356, 983-989. 2. Jones, K.E. et al. (2008) Global trends in emerging infectious diseases. Nature 451, 990-401 994. 402 3. Woolhouse, M.E.J. and Gowtage-Sequeria, S. (2005) Host range and emerging and 403 reemerging pathogens. Emerg. Infect. Dis. 11, 1842-1847. 404 4. Nylin, S. et al. (2018) Embracing colonizations: a new paradigm for species association 405 dynamics. Trends Ecol. Evol. 33, 4-14. 406 5. Poulin, R. and Mouillot, D. (2003) Parasite specialization from a phylogenetic perspective: 407 a new index of host specificity. Parasitology 126, 473-480. 408 6. Han, B.A. et al. (2015) Rodent reservoirs of future zoonotic diseases. Proc. Natl. Acad. 409 410 Sci. U. S. A. 112, 7039-7044. 411 7. Wells, K. et al. (2018) Global spread of helminth parasites at the human-domestic animalwildlife interface. Global Change Biol. 24, 3254-3265. 412 413 8. Olival, K.J. et al. (2017) Host and viral traits predict zoonotic spillover from mammals.
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657 Glossary

- Ecological fitting: Species association enabled by pre-existing capacity without genetic change. (e.g. a certain suite of potential host traits enables infection by a parasite upon encounter).
- Emerging infectious disease (EID): Infectious disease that recently appeared in a population or is recognized as a 'novel' disease with rapid spread.
- Environmental filtering: Environmental conditions that constrain resource utilisation by a
 species (e.g. the use of different host species by a parasite).
- Fundamental niche (e.g. fundamental host range): For parasites, the set of all host
 species, whether known to be infected or not, that would serve a parasite as hosts under any
 environmental condition. The overall fundamental host range cannot necessarily be
 determined empirically, as only the existing (realized) host range across the accessible host
 species pool can be surveyed.
- Host shifting: The event of colonizing of a novel host species by a parasite, involving host
 range expansion (here defined as colonization of a novel host without losing the ancestral
 host opposed to considerations that parasites may shift from one host to another without
 range expansion).
- Host specificity: Measures of the number and/or diversity of host species a parasite is
 capable of infecting.
- Niche: Broadly and indistinctly defined environmental space suitable for a species to
 survive and reproduce. For parasites, the host range broadly refers to the main component of
 their niche.
- Potential resources: The range of resources that a species could utilise if it encountered
 them. In terms of host species, this is equivalent to fundamental host specificity, representing
 the full (unknown) range of hosts species a parasite is capable of infecting.
- Realized niche (e.g. realized host range): A set of host species observed to be infected by
 a parasite in a specific regional and spatiotemporal context.
- Spillover: Cross-species transmission of a parasite into a host population not previously
- 685 infected. In contrast to 'host shifting', 'spillover' often refers to infection of novel
- 686 *populations* but not necessarily novel *species* (i.e. no host range expansion). The term appears
- to be most commonly used to describe cross-species transmission from wildlife to humans.
- **Stockholm Paradigm**: Hypothetical concept arguing that host range expansions by
- parasites result from the interplay between novel host-parasite opportunities in response to

shifting community assembly and phylogenetic and/or ecological barriers that limit parasitespread to novel hosts.

• Transferability (models): Whether a model (and its parameter estimates) derived from a
particular set of spatiotemporal conditions is transferable to other conditions and can be
generalized. In terms of resource utilisation, a transferable model would allow accurate
predictions of resource use from a model built using data from elsewhere.

• Transmission: The transfer of a parasite between different host individuals or other entities
(such as relevant vectors). A term typically used in epidemiological studies.

• Zoonosis (zoonotic): An infectious disease of humans caused by parasites acquired from an animal reservoir (host individual/ population/ species infected with a parasite and acting as a source for further infection and parasite spillover).

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703 **Box 1: Drivers of contemporary host specificity**

Host community composition is influenced by various biotic and environmental filters that
can collectively lead to dramatic variation in a parasite's realized host specificity. Here we
outline a number of these situations, though it is important to note that this list is by no means
exhaustive.

Anthropogenic invasion of key hosts: Changes in host community composition 708 • caused by anthropogenic invasions can lead to important changes in parasite realized 709 host specificities. For example, the rapid expansion of chytrid fungus, the parasite 710 responsible for threatening declines of many amphibians globally, largely occurred 711 along wildlife trade routes [95]. In addition, invasive commensal rats have been 712 crucial for the global spread of parasitic helminths that have 'hitch-hiked' their way to 713 encountering novel host species [33], ultimately shaping parasite biogeographic 714 distributions [31]. 715

Changing community compositions leading to new transmission dynamics: The
 population structure of a parasite depends on the diversities and relative abundances
 of different host species infected [17]; host abundance is itself a plastic trait that
 typically varies across environmental gradients, strongly contributing to plasticity in
 realized host specificity [96, 97]. Following the examples above, introduced species
 may not only serve as potential vehicles for introduced parasites, but may also directly

alter existing local host-parasite interactions by changing the abundance of endemic
host species [19], hence inducing cascading effects on host-parasite interactions.

Habitat encroachment and the human-wildlife interface: As a consequence of
 habitat conversion and fragmentation, humans and domestic species are in frequent
 contact with wildlife species. Cat fleas, intestinal helminths, and canine distempter
 virus are among the increasing number of parasites observed to expand their host
 ranges to include a diversity of wild mammals following such novel human-wildlife
 encounters [7, 98, 99].

- Expanding dietary range of a key host: Biotic interactions among key host species
 play a large role in driving plasticity in host specificity. For example, within its exotic
 range in Australia, the presence of dingos and dingo/dog hybrids that feed on a large
 range of endemic wildlife has enabled the establishment of stable transmission cycles
 of the tapeworm *Echinococcus granulosus* through wild dogs and endemic wildlife
 [100], illustrating how host shifting into novel communities may be facilitated by
 particular regional conditions.
- Exposure of parasites to competitors or facilitators: Parasites themselves can also
 exhibit important biotic interactions. Antagonistic and synergistic effects in multi host, multi-parasite systems affect both the co-occurrence of co-infecting parasites
 within the same host individuals [53, 101] as well as eco-epidemiological
 transmission dynamics [102].
- Climate-related changes in the host affinity of vectors: Climate-driven changes in the feeding patterns of important vectors may facilitate opportunities for vector-borne parasites to contact novel host species. For instance, warming climate influences the human-feeding habits of rickettsiae-vectoring tick species, leading to human spillover events [103]. Climate in combination with habitat changes can also affect the host range of tick-borne *Borrelia* bacteria, the cause of Lyme disease [104, 105].
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750 Box 2: A data primer on host shifting and specificity

Any conclusion on fundamental host specificity depends on a sufficiently large number of
individuals and potential host species examined for robust inference. At their most basic
level, host specificity analyses rely on binary vectors describing the confirmed presence or
absence of infection by a particular parasite from a diversity of sampled host species. Ideally,

the scope of the study should be narrow enough that the sampled species will all be suitable 755 potential hosts for the selected parasite (occurring within the parasite's geographical 756 distribution and exhibiting some level of possible exposure). Yet even with good foresight 757 and selection of possible hosts, these presence-absence vectors are surprisingly difficult to 758 acquire. For example, if data from multiple studies are compiled to represent a suite of known 759 760 host-parasite associations, such data are usually strongly susceptible to bias. This is because such databases typically contain presence-only records. For host specificity inferences 761 762 beyond simple diversity metrics of the observed host species, the absence records 763 (representing species not found to be host after a reasonable sampling effort) are just as important as presence records and should be included where possible. An option to make 764 presence-only data accessible to analysis could be the utilisation of pseudo presence-absence 765 data, in which infected host species are recorded as 'viable' and uninfected species (i.e. those 766 species present in a pool of potential host species but not recorded to be infected) as 'non-767 viable' hosts. 768

Without detailed information on sampling efforts such as the number of host 769 770 individuals screened for a parasite, there is uncertainty whether parasites are truly absent from a host species that is reported to be uninfected, challenging the estimate of host range 771 772 [106, 107]. Such absences can represent 'false zeros' (missing observations of interactions) 773 when small sample sizes and a naturally low parasite prevalence result in limited detection 774 probability. A simple proxy of sampling bias could be a measure of research effort, such as the number of scientific publications linked to a particular potential host species (see e.g. 775 776 [99]). However, conservative interpretation is warranted as indices of research effort are only coarse proxies of the true underlying sampling bias (i.e. the number of publications does not 777 778 necessarily reflect the true sampling efforts of how many host individuals have been surveyed 779 for a parasite).

780 Preferably, individual-level data (i.e. detailed data on the number of individuals examined and infected) will be available so that biological patterns and processes can be 781 782 distinguished from sampling bias arising from unequal and small sample sizes [83, 85, 108]. If detailed information from empirical field surveillances (such as the number of infected and 783 784 uninfected host individuals captured) are available, the prevalence of parasites in different sympatric host species can be estimated. If combined with further information on host species 785 occurrence and density (which are often available or can be estimated from trap or survey 786 data), such estimates provide valuable information on the relative importance of different 787 788 host species as parasite reservoirs. These relative importances can be used to weight the

contributions of different host species to a parasite's realized host specificity, aligning to theconcept that host species may have different reservoir capacities. Incorporating measures on

- 791 host presence and abundance might be of particular relevance if host abundances are subject
- to strong fluctuations [13, 109] and/or migration that drives the connectivity of
- 793 geographically disparate host assemblages [48, 110].

For parasites with complex life cycles, it can also be important to consider details of parasite life histories. For some helminths, for example, different sets of host species are utilised to complete different parts of the life cycle (i.e. predatory carnivorous species that serve as definite host versus herbivorous species that serve as intermediate hosts). In addition, detailed molecular data can provide valuable insight into whether different sympatric host species share the same strains or populations of a parasite [111], eventually narrowing down the pool of host species relevant for analysis.

Table 1. Overview of selected components and methods to define host specificity.

Method	Methodological approach	Example/Reference
Number of host species	Count of the number of	[112]
infected	infected host species. This	
	basic count ignores host	
	species attributes such as	
	phylogenetic or ecological	
	relationships.	
Diversity indices capturing	Diversity measures based on	[5], [113]
variation in host community	the abundance and/or	
composition (e.g. Shannon-	attributes attributed to the	
Wiener, phylogenetic	range of observed host	
diversity, UniFrac)	species (i.e. phylogenetic	
	diversity).	
Geographic specificity and	Measures of the	[114], [17]
host range turnover (β-	dissimilarity of a parasite's	
diversity)	host ranges in different	
	regions, resembling β -	
	diversity measures.	
Distance-based phylogenetic	Measures of the distances	[115], [15]
and/or functional specificity	between pairs of host	
	species in terms of	
	phylogenetic or functional	
	relationships. Distance	
	measures can be weighted	
	by prevalence to give greater	
	weight to commonly	
	infected host species.	
Network indices of	Calculated from bipartite	[76]
specialization (d')	host-parasite interaction	
	networks, these indices	
	measure of a parasite's	
	interactions with a range of	

	potential host species (i.e.	
	the sampled host species	
	pool), weighted relative to	
	the host interactions	
	displayed by other parasites	
	in the community.	
Degree of matching between	Measures of the matching	[116]
host and parasite	between host and parasite	
phylogenies	phylogenies, used for	
	depicting community-level	
	patterns of possible co-	
	evolution. Specificity	
	inferences are drawn based	
	on how tightly parasite	
	evolution is linked to host	
	evolution.	
Host competence	The spread of parasites	[117], [118]
heterogeneity	through host assemblages	
	can be largely determined by	
	their variation in potential	
	hosts' competence and	
	reservoir potential. Such	
	measures have been rarely	
	used to measure host	
	specificity to date, but could	
	be especially useful to	
	express plasticity in host	
	specificity.	





Figure 1. Rise in the proportion of peer-reviewed research articles mentioning 'host

- specificity' for select groups of parasites over time. Colours of bars represent the total
- 833 number of unique peer-reviewed journals mentioning 'host specificity' for each parasite
- group in each year. Articles were accessed by searching the NCBI PubMed database on 2^{nd}
- 835 April 2019.



Figure 2. Illustration of how environmental filters across a parasite's geographical range may impact the parasite's realized host specificity. Hosts are sampled for the parasite across an environmental gradient that influences opportunity for the parasite to interact with each potential host species. Density plots depict the probabilities that observed host pairwise phylogenetic distances differ from those expected (representing the entire host pool that occurs at a given location) for each site. More negative measures (darker purple tones) indicate a parasite infects hosts that are more closely related than expected, indicating specialism; more positive measures (warmer yellow tones) indicate generalism.