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1 **Dynamic and integrative approaches to understanding pathogen spillover**

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19 **Running head:** Approaches to pathogen spillover

20

21 **Keywords:** cross-species transmission; epidemics; pandemics; zoonotic; surveillance;
22 interventions

23 Introduction

24 Pathogen spillover is the process by which a pathogen is transmitted from a reservoir host
25 species to a recipient host species [1,2]. The term is sometimes used more broadly, particularly in
26 public discourse, blending in elements of onward transmission in the novel host species or even
27 pathogen adaptation to the novel host [3,4]. This theme issue focuses on pathogen spillover *sensu*
28 *stricto*, except where explicitly noted. Many of the examples considered pertain to zoonotic
29 spillover (i.e., from wildlife or domestic animals to humans), given recent epidemics (e.g., Ebola
30 virus [5]) and pandemics (e.g., H1N1 influenza virus [6]); however, we emphasize the general
31 methods and mechanisms involved in understanding spillover between any two species, such as
32 those that threaten wildlife conservation (e.g., *Mycoplasma ovipneumoniae* from domestic sheep
33 to bighorn sheep [7]) and the agricultural sector (e.g., *Brucella abortus* from elk to cattle [8]).

34 Spillover requires the spatial and temporal alignment of several hierarchical factors that
35 must occur for a pathogen to be transmitted from a reservoir or source host to a recipient host of
36 a different species [9]. These factors include reservoir host distribution and abundance, pathogen
37 prevalence and shedding from reservoir hosts; pathogen survival in the environment or arthropod
38 vector; recipient host contact with the infectious agent, reservoir host, or arthropod vector; and
39 susceptibility of the recipient host. Following spillover, another suite of factors determines
40 whether a pathogen is transmitted within the recipient host population [e.g., 7]. Research on
41 pathogen spillover is often focused on a single component of this process through the lens of a
42 particular discipline. For example, the distribution of reservoir hosts is often studied through
43 ecology, contact between reservoirs and humans is often studied via epidemiology or
44 anthropology, and the pathogenesis of zoonoses in humans is often studied with medical
45 microbiology and immunology. While each factor must be studied and quantified, spillover is the
46 emergent property of these collective processes. Studying each factor in isolation fails to account
47 for the hierarchical and often non-linear dynamics of the spillover system [9]. Pathogen
48 surveillance, epidemic preparedness, and management interventions would all benefit from
49 integrative approaches that consider multiple components of pathogen spillover [1].

50 This theme issue stemmed from a 2018 workshop on cross-species transmission of
51 pathogens, where participants from interlinked fields including ecology, mathematical modeling,
52 epidemiology, virology, and immunology discussed how to better understand and predict
53 pathogen spillover. Here, we bring together a diverse set of perspectives—including empirical
54 research, theory, and synthetic reviews—to highlight cutting-edge research and to provide a
55 roadmap for quantifying and integrating host–pathogen dynamics at each step in the spillover
56 process. Manuscripts are organized around three approaches. The first set of manuscripts focuses
57 on integrating data streams to understand spillover dynamics and predict risk. The second set of
58 manuscripts focuses on in-depth analysis of each of the factors affecting cross-species
59 transmission: infection dynamics in reservoir hosts, pathogen survival in the environment,
60 recipient host exposure, dose–response relationships, and establishment of infection in recipient
61 hosts. The final set of manuscripts focuses on applied perspectives, with an emphasis on
62 surveillance and interventions. Here, we summarize these contributions to highlight key insights,
63 methodologies, and future directions to improve our understanding of pathogen spillover.

64

65 Integrating data streams to understand spillover dynamics

66 Because spillover is the outcome of multiple ecological, epidemiological, and immunological
67 factors aligning in space and time [9,11], predictive frameworks aim to integrate data pertinent to

68 these factors to quantify the relative importance of these processes and to estimate risk. Cross et
69 al. [this issue] review approaches for estimating spatiotemporal variation in spillover risk,
70 focusing on the wildlife–livestock interface. The authors highlight the challenges inherent in
71 either correlating observed spillover events with relevant covariates or integrating data on host
72 density, distribution, and pathogen prevalence using mechanistic models. They highlight that
73 mechanistic approaches may be especially useful in systems where spillovers are infrequent,
74 rarely observed, or hard to differentiate from within-species transmission; however, linking
75 datasets on different factors in the spillover pathway requires that such datasets be related to a
76 common spatial and temporal resolution. The authors use case studies of brucellosis in the
77 Greater Yellowstone Ecosystem [12] and of avian influenza virus in China and North America
78 [13] to emphasize potential solutions to these challenges for estimating spillover risk.

79 Emphasizing that statistical modeling efforts may struggle to detect nonlinear and
80 stochastic relationships inherent in pathogen spillover, Childs et al. [this issue] provide a strong
81 test of theory governing how hierarchical barriers control cross-species transmission [9]. The
82 authors focus their case study on yellow fever, a mosquito-borne viral disease of historical
83 importance in South America that persists in the region largely in sylvatic cycles that
84 occasionally spill over to infect humans [14,15]. Specifically, they use mechanistic models that
85 incorporate spatial ecological and immunological data from Brazil across 16 years to predict
86 yellow fever spillover in humans. The authors show that a mechanistic model of spillover risk,
87 based on the ecology of mosquito vectors and non-human primate reservoirs, best predicts
88 spillover events compared to models that also include human population size and immunity. This
89 result arises because spillover occurs even in areas with low human population density and high
90 vaccination coverage (e.g., parts of the Amazon), so population density and vaccination coverage
91 tend to inflate the predicted risk in locations with low ecological suitability. This integrated
92 approach also highlights a key research gap—cyclical dynamics of susceptible primate
93 populations—that could further improve prediction. This work illustrates that mechanistically
94 modeling the interactions among the environment, viruses, vectors, non-human primates, and
95 humans can predict rare and seemingly stochastic spillover events with high accuracy.

96 Washburne et al. [this issue] study the general statistical problems that can arise when
97 aiming to forecast spillover risk. The authors highlight that any such statistical efforts will
98 compile a dataset of explanatory variables expected to relate to pre-spillover processes (e.g.,
99 infection prevalence in reservoirs, human vaccination coverage) that are aligned with one of two
100 response variables: the presence and absence of spillover or the number of spillover events at
101 some spatial and temporal resolution (e.g., spatiotemporal counts of yellow fever spillovers
102 [Childs et al., this issue]). The authors show how modeling cross-species transmission as a
103 percolation process, in which pathogens move from infected reservoirs to recipient hosts along a
104 graph representing various spillover pathways [16,17], reveals first principles for how such
105 datasets will behave and how common statistical tools can produce misleading inferences and
106 poor predictions. For example, percolation theory reveals an inherent nonlinearity in modeling
107 spillover counts, in which statistical inferences are driven by the dominant reservoir sources of
108 infection and the most limiting barriers to cross-species transmission; this nonlinearity can mask
109 the influence of alternative reservoir species or barriers, both of which could be modified
110 through interventions but whose sensitivity as a management tool will appear reduced under
111 linear models. Percolation models provides a conceptual framework to connect statistical and
112 mechanistic models with applications to limit risk by illuminating unexpected statistical
113 principles governing pathogen spillover and the nonlinear impacts of management actions.

114

115 **Individual factors affecting pathogen spillover**

116 The theme issue's second section uses empirical research, theory, and synthetic reviews to
117 understand the processes operating at each stage of pathogen spillover, from infection dynamics
118 within the reservoir hosts to susceptibility and establishment of infection in the recipient host.
119 For the former, the distribution and intensity of infection in reservoir hosts over space and time is
120 the first determinant of spillover risk [9]. Data on these spatiotemporal dynamics helps elucidate
121 how pathogens circulate in reservoir hosts and when and where to expect pathogen excretion to
122 be greatest [18]. However, such field data can be expensive and difficult to collect, and
123 researchers inevitably must tradeoff between the extent and intensity of spatial versus temporal
124 sampling. Sampling is thus often opportunistic and fails to adequately describe spillover.
125 Plowright et al. [this issue] review factors that influence spatial and temporal variation in
126 infection in reservoirs and describe sampling designs that can increase the quality and quantity of
127 this information. Although the standard prescription from sampling theory is to sample randomly
128 in space and time [19], probabilistic sampling designs are rare in the study of wildlife disease
129 given logistical challenges and non-random distributions of hosts. The authors highlight how
130 stratified random sampling designs or adaptive sampling designs can help capture spatiotemporal
131 pulses of infection when researchers have little *a priori* data on concentrations of infection or
132 spillover events in space and time. These sampling designs can be integrated into modelling
133 approaches and used to better quantify pathogen shedding from reservoirs. Accordingly,
134 Glennon et al. [this issue] present a case study for how to use mechanistic models to differentiate
135 among transmission processes for henipaviruses in straw-colored fruit bats (*Eidolon helvum*).
136 Using this virulent zoonosis as a case study, the authors generalize standard frameworks
137 common in epidemiological modeling [20]. Given that henipavirus infection dynamics in bats
138 are poorly understood, the authors study all possible transitions among infection states in bats to
139 produce 46 potential models. Using likelihood-based methods, they fit these models to
140 longitudinal data from captive bats to show strong support for reinfection after virus clearance
141 and cycles of recurrent latent infection: key areas for future empirical work. This inclusive
142 approach to confronting epidemiological models with longitudinal data in poorly understood
143 reservoir host systems holds promise for elucidating spatiotemporal risk of pathogen spillover.

144 Following pathogen shedding from reservoir hosts, spillover risk is influenced by the
145 duration of pathogen survival and possible reproduction outside the host in the environment [9].
146 For pathogens such as avian influenza virus, persistence in the environment (e.g., ponds) can also
147 facilitate viral reassortment when strains co-occur, promoting coinfections during environmental
148 exposure [21,22]. Pepin et al. [this issue] review and discuss how genomics, experimental
149 ecology, and epidemiological modeling can be leveraged to understand viral reassortment in
150 environmental reservoirs. Although no gold-standard for capturing, isolating, and identifying
151 avian influenza virus diversity from the environment exists, environmental metagenomics and
152 field-based viral diagnostics (e.g., field-based nucleic acid extraction, PCR, and sequencing) hold
153 promise for characterizing this context of viral reassortment [23,24]. The authors note how
154 standardizing such field protocols and coupling these data streams with quantitative disease
155 models and natural transmission studies should dramatically improve our understanding of viral
156 co-occurrence and reassortment and thus this additional process in the pathway to spillover.

157 Exposure of recipient hosts to pathogens (e.g., those persisting in the environment) can
158 take a variety of forms; however, in a more general sense, exposure often occurs at elevated rates
159 near boundaries between ecosystems [25]. Borremans et al. [this issue] review how ecosystem

160 boundaries can promote spillover by applying ecological theory to understand landscape
161 permeability across ecosystems. The authors highlight that the traits of hosts and pathogens are
162 critical for determining effects of ecosystem boundaries on cross-species transmission. Properties
163 of ecosystem boundaries can also promote or inhibit exposure; for example, edge effects can
164 affect species composition, diversity, and population size between ecosystems, as can features of
165 landscape configuration such as patch size and perimeter-to-area ratio [26]. By considering the
166 analogy between parasite flow and resource flow and by applying concepts from movement
167 ecology, Borremans et al. [this issue] connect contact rates and spillover risk across ecosystem
168 boundaries to generalize between pathogens and integrate into broader ecological theory.

169 Following the complex interactions between reservoir hosts, vectors, pathogens, the
170 environment, and recipient hosts, a crucial juncture in any potential spillover event is the point
171 when a recipient host is challenged with a given dose of pathogen (through a particular route and
172 sometimes over a particular duration) and a successful infection does or does not ensue [9].
173 Lunn et al. [this issue] describe how the dose–response relationship, which quantifies the
174 probability of successful infection in the recipient host as a function of challenge dose, can act as
175 a filter on the aforementioned upstream dynamics to shape pathogen spillover risk. The authors
176 integrate recent developments in the dose–response literature, as well as re-analyzing data from
177 animal challenge experiments with Nipah virus and Middle East respiratory syndrome
178 coronavirus [27,28], to highlight challenges and opportunities arising at the intersection of
179 infectious disease ecology, microbial risk assessment, and virology. Lunn et al. [this issue] call
180 for closer interactions between these fields and for a new generation of pathogen transmission
181 models that link dose–response data to epidemiological dynamics. Gostic et al. [this issue] next
182 provide an example of the epidemiological insights such an approach can yield. They present a
183 modeling analysis of dose–response experiments for *Leptospira interrogans*, a globally
184 important bacterial zoonosis for which environmental exposure to soil or water contaminated by
185 urine of infected reservoir hosts is the primary transmission route [29]. By conducting well-
186 designed challenge experiments across a range of exposure routes, and then developing a
187 mechanistic model to identify and quantify the key barriers to infection, Gostic et al. [this issue]
188 show that intact skin is the crucial defense against leptospiral infection and that skin abrasions or
189 wounds can increase recipient host infection risk by at least a million-fold. This close integration
190 of experimental and modeling approaches isolates a potent and well-defined risk factor for
191 infection with *Leptospira*, opening the door to targeted interventions to reduce spillover risk.

192 Once a pathogen has crossed these within-host barriers to replicate and disseminate in the
193 recipient host, the outcome of infection may range from subclinical illness to death and from
194 dead-end spillover to sustained onward transmission [9]. Bonneaud et al. [this issue] focus on the
195 conditions favoring pathogen emergence, from the initial jump into the recipient host to their
196 adaption in the novel host environment [30]. The authors highlight that our current understanding
197 of host shifts stems primarily from viral infections, limiting generalizations to other pathogen
198 taxa given substantial differences in ecology and life history [31]. They propose several non-
199 mutually exclusive hypotheses to explain why novel bacterial pathogens may be less likely to
200 specialize on their novel hosts and then test these with a mathematical model. The authors
201 demonstrate that high levels of phenotypic plasticity, low rates of evolution, and the ability to
202 recombine should reduce propensity to specialize, suggesting that novel bacterial infections may
203 be more likely to result in transient spillovers or increased host ranges than in host shifts.

204 Wasik et al. [this issue] in turn describe the within-host barriers that pathogens, and
205 viruses in particular, must overcome to replicate and spread in new host populations to cause

206 onward transmission. They present three well-documented examples of viruses that have crossed
207 these barriers to cause epidemics or pandemics in the new host species: influenza A viruses [32],
208 human immunodeficiency virus [33], and canine parvovirus [34]. The authors emphasize the role
209 of integrated models that consider all the steps required to go from exposure to spillover to
210 epidemic or pandemic. Guth et al. [this issue] expand upon these ideas through a comparative
211 study of host and viral traits that predict virulence and the capacity for onward transmission in
212 recipient hosts (i.e., humans). By expanding a previous global dataset of viral zoonoses [35], the
213 authors show that increasing reservoir host phylogenetic distance from humans positively
214 correlates with human mortality but negatively correlates with human-to-human transmissibility,
215 suggesting that the virulence induced by reservoirs at high phylogenetic distance may limit viral
216 capacity for onward transmission [36]. In particular, distantly related reservoirs, such as bats,
217 harbor highly virulent zoonotic viruses with a lower capacity for onward transmission in
218 recipient human hosts, building upon prior work describing bats as special reservoirs [37].

219

220 **Applications for management of spillover**

221 The theme issue's final section focuses on applied perspectives to detect early spillover events
222 (i.e., surveillance) and the role of interventions focused upstream in the spillover pathway. In
223 particular, early detection is critical for minimizing the spread of zoonotic pathogens following
224 an initial spillover event [38]. A first series of manuscripts emphasize different approaches to the
225 surveillance of zoonoses. Schmidt et al. [this issue] use machine learning tools (e.g., boosted
226 regression trees [39]) to predict which mammal species are more likely to play roles in Ebola
227 virus spillover events. The authors show that large-bodied, frugivorous mammals with slow life
228 histories are likely host species, implicating some insectivorous bats, Old World monkeys, and
229 forest antelopes as possible Ebola virus reservoirs. Predictions such as these can help prioritize
230 future wildlife surveillance efforts [e.g., Plowright et al. 2019]. Kuisma et al. [this issue] in turn
231 describe a community-based surveillance effort focused on wildlife mortality reporting and
232 oriented to early detection of Ebola virus disease outbreaks. Spanning over a decade and
233 covering 50,000 km² of challenging terrain in the Congo basin, this program has reached
234 hundreds of villages and thousands of hunters and forest gatherers. The program has educated
235 community members in wildlife carcass reporting and behavioral risk reduction as well as built
236 capacity for safe carcass sampling by trained local responders. This region was not confronted
237 with an Ebola virus outbreak during the period described here, and all reported carcasses tested
238 negative. Nevertheless, given the well-recognized fact that early intervention can avert massive
239 human and economic costs of widespread epidemics, the low-cost and scalable surveillance
240 program described by the authors could provide key early detection capability more generally.

241 Two other contributions focus on zoonotic pathogen surveillance efforts in domestic
242 animals and human populations. Mwangi et al. [this issue] present a real-time surveillance
243 system that leverages the existing mobile phone network and shows immense potential to
244 improve adaptive management of spillover. This surveillance system has been implemented in
245 1,500 households across rural Kenya where participants are asked to report symptom syndromes
246 in their livestock. Zoonotic diseases such as Rift Valley fever present with severe clinical signs
247 in domestic animal populations, but lack of active surveillance can miss these sentinels [40]. The
248 authors demonstrate that illnesses were more likely to be reported on mobile phones compared to
249 standard routine household animal surveys. They also show that more severe symptoms are
250 likely to be reported, highlighting the utility of this surveillance method for diseases such as Rift
251 Valley fever. Das et al. [this issue] similarly describe implementation of a surveillance system in

252 hospitals in Bangladesh that screen symptomatic patients for potential zoonoses. Most patients
253 did not have a laboratory diagnosis for their illness, indicating that unidentified pathogens are
254 likely spilling over in human populations. Broad-scale, sustainable human surveillance programs
255 such as outlined by the authors can play a critical role in early detection of zoonotic spillovers.

256 Following these approaches to surveillance, interventions can accordingly focus upstream
257 or downstream in the pathway to spillover, given available data and resources, to limit cross-
258 species transmission. At the wildlife–livestock interface, managing pathogen spillover is a main
259 goal for animal husbandry, conservation, and food security [41]. Yet managers are often forced
260 to make control decisions on the basis of limited evidence about intervention efficacy. Manlove
261 et al. [this issue] develop a spatially explicit, stochastic model of pathogen transmission within
262 and between wildlife reservoirs and livestock recipient hosts to improve evidence-based decision
263 making. By varying host movement patterns and epidemic growth rates, the authors show that
264 biosecurity, containment, and retroactive vaccination of the reservoir are the most effective for
265 limiting the spatial spread and magnitude of spillover risk for fast-moving epidemics in
266 mobile hosts. By contrast, prophylactic vaccination and depopulation of the reservoir host were
267 more successful for fast-moving epidemics with low rates of host movement. This framework
268 provides general intuition for how to manage different pathogens at the wildlife–livestock
269 interface, and a flexible platform for more rigorously investigating disease control strategies.

270 Ultimately, one of the primary goals of research focused on pathogen spillover is to
271 design interventions that can reduce or eliminate disease burden in recipient hosts. Sokolow et al.
272 [this issue] explore how ecological interventions, which target the ecological context in which
273 cross-species transmission occurs, can complement more traditional biomedical and veterinary
274 interventions (e.g., vaccination, culling). The authors provide case studies to illustrate the
275 potential for ecological interventions that target the reservoir host (sometimes indirectly, such as
276 through the restoration of natural enemy populations [42]), pathogen survival in the environment,
277 contact between reservoir and recipient hosts, or other aspects of risk in the recipient species.
278 The authors also present a simple mechanistic model, parameterized for two example systems,
279 that shows how nonlinear effects can produce counterintuitive results when comparing potential
280 intervention strategies and highlights the importance of a detailed understanding of underlying
281 ecological dynamics when designing and assessing interventions. Lastly, the authors draw
282 attention to the importance of social, economic, and political considerations to intervention
283 success, as these can derail even the most efficient or cost-effective intervention. In particular,
284 aligning the benefits of an intervention with the costs incurred is crucial to motivate ecological
285 interventions and may require working across sectors for successful implementation.

286

287 **Future directions and conclusions**

288 Pathogen spillover is the result of a complex series of events that result in the successful
289 establishment of infection in a recipient host [9]. As highlighted in the final paper of this theme
290 issue, developing actionable forecasts of risk is further complicated by the various phylogenetic,
291 spatial, and temporal scales over which we study and predict spillover [Becker et al., this issue].
292 The authors here contextualize a diverse range of approaches to pathogen spillover within these
293 scales to illustrate critical areas of pragmatic overlap. By focusing on an ecological perspective,
294 the authors outline a research pipeline that connects pathogen discovery and macroecological
295 analyses with spatiotemporal surveillance in reservoir and recipient hosts. Through several case
296 studies (e.g., Lyme disease [43], Hendra virus [44], *Plasmodium knowlesi* [45]), the authors

297 further demonstrate how ecologically focused research has facilitated predicting spillover of
298 particular pathogens in space and time and facilitated design of intervention strategies. This
299 synthesis shows how greater integration of macroecology, pathogen discovery, and surveillance
300 could ultimately generate more actionable predictions and interventions to limit spillover risks.

301 Recent epidemics, pandemics, and disease emergence events all underscore the need to
302 improve approaches to predict and prevent pathogen spillover. This theme issue highlights a
303 range of methods and their commonalities through diverse host–pathogen systems for which
304 researchers are assessing factors driving spillover risk across varying phylogenetic, spatial, and
305 temporal scales. Contributing manuscripts further emphasize how developing a mechanistic
306 understanding of the hierarchical factors affecting spillover can facilitate quantifying the drivers
307 of cross-species transmission, deriving generalizable theory, and making robust predictions, even
308 for seemingly rare and idiosyncratic spillover events. Importantly, such insights can improve our
309 ability to deploy surveillance efforts, design interventions at early stages of the pathway to
310 spillover, and manage disease cases in recipient hosts, thereby limiting or preventing further
311 outbreaks. Continued study of pathogen spillover as a repeated and hierarchical phenomenon will
312 only improve our ability to predict, prevent, and manage cross-species transmission risks.

313

314 **Data accessibility**

315 This manuscript has no additional data.

316

317 **Competing interests**

318 We declare no competing interests.

319

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341

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346

347 **Author contributions**

348 All authors contributed to the development of ideas and to the writing of this manuscript.

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