

The coevolutionary mosaic of bat-betacoronaviruses spillover risk

Timothée Poisot^{1,2,‡} Peregrin Took^{3,4} Merriadoc Brandybuck^{5,4,‡}

¹ Université de Montréal ² Québec Centre for Biodiversity Sciences ³ Inn of the Prancing Pony

⁴ Fellowship of the Ring ⁵ Green Dragon Inn

‡ These authors contributed equally to the work

Correspondance to:

Timothée Poisot — timothee.poisot@umontreal.ca

This work is released by its authors under a CC-BY 4.0 license



Last revision: *April 6, 2022*

Purpose: This template provides a series of scripts to render a markdown document into an interactive website and a series of PDFs.

Motivation: It makes collaborating on text with GitHub easier, and means that we never need to think about the output.

Internals: GitHub actions and a series of python scripts. The markdown is handled with pandoc.

1 Spillover risk is not unidimensional. From the standpoint of an animal community, i.e. a pool of possible
2 hosts, there are a multiplicity of ecological factors that come into play (Plowright et al. 2017). The global
3 richness of hosts is one such component commonly mentioned/analysed (Anthony et al. 2017), but there
4 is an argument to be made that species who are not competent hosts of a specific virus genus may not
5 factor into this (Plowright et al. 2015), or that species who are assumed to share viruses at different rates
6 should be weighted accordingly (Albery et al. 2020). In mammals, key functional traits (for which
7 phylogeny is a reasonable proxy) are determinants of the spillover potential (Olival et al. 2017); these
8 include, notably, TK. Finally, especially when the pool of potential hosts spans the entire globe, there may
9 be local host pools that are highly unique; not having been observed in other locations, these can act on
10 the overall risk either by providing novel contact opportunities, reflecting unique host-environment
11 combinations (Engering et al. 2013), or facilitating rapid changes in specialism (Agosta et al. 2010). In the
12 specific case of generalist pathogens (as betacoronavirus clearly are), there is conceptual and empirical
13 support to the idea that these community- level mechanisms are even more important in driving the
14 overall risk (Power and Mitchell 2004).

15 Bats are important reservoir hosts for different classes of microorganisms (Chu 2008, Donaldson 2010, Li
16 2010), some of which can threaten human health. Especially concerning is the fact that bats are reservoirs
17 for a variety of emerging viruses (Calisher 2006), making balancing the needs for bat conservation and
18 disease prevention a potentially difficult act, especially in more densely populated areas (REF).

19 Chiropterans emerged around 64 million years ago and are one of the most diverse mammalian orders,
20 with an estimated richness of more than 12000 species, (Peixoto F et al, 2018) and 14325 known species
21 Simmons & Cirranello. They exhibit a broad variety of habitat use, behaviour, and feeding strategies,
22 resulting in their playing an essential role in the delivery of several ecosystem services (Kasso 2013),
23 including economic benefits. Over two-thirds of bats are either obligate or facultative insectivorous
24 mammals, therefore playing an important role in the regulation of insect pests that can affect crops
25 (Williams-Guillen 2011), and vectors of diseases that put a risk on human health (Gonsalves 2013).

26 Because bats are globally distributed and have a long evolutionary history, phylogeographic and
27 biogeographic approaches are required to shed light on the extant distribution of coevolutionary processes
28 between bats and the pathogens they carry. As a consequence, not all areas are facing a risk of human
29 spillover, and those who do might not be facing risks of the same nature and magnitude.

30 Yet a comprehensive assessment of the risk of spillover of betacoronaviruses from bat hosts to humans is

31 limited by the fact that we do not know the full diversity of viruses associated with every bat species.
32 Predictive models can help fill in some of these gaps, by recommending hosts based on known host-virus
33 associations BECKER REF. In this paper, we examine the biogeographic structure of
34 bats-betacoronaviruses associations, based on a curated dataset of known and predicted hosts. We turn
35 these associations into a spatially explicit additive mapping of zoonotic risk components, which reveals
36 extreme heterogeneity of risk at the global scale; furthermore, we identify the Amazon and South-Eastern
37 Asia as hotspots of phylogenetic distinctiveness of betacoronaviruses; surprisingly, current data suggest
38 that viral sharing between hosts is high in the Amazon and low in South-Eastern Asia, which has the
39 potential to result in different evolutionary dynamics between these two regions.
40 TK summary of the results

41 **Methods**

42 **Known betacoronavirus hosts**

43 We downloaded the CoV reservoir database from <https://www.viralemergence.org/betacov> on Aug. 2021.
44 This database was assembled by a combination of data mining, literature surveys, and application of an
45 ensemble recommender system classifying hosts as either “Suspected” or “Unlikely” (REF BECKER). The
46 hosts considered for this study were all hosts with a known record of a betacoronavirus, and all those with
47 a “Suspected” status in the ensemble model. This resulted in a list of TK TP unique host species.

48 **Bats occurrences**

49 We downloaded the rangemap of every extant bat species that was either classified as an empirically
50 documented or a suspected host of beta-coronaviruses (Becker et al. 2020), according to recent IUCN data
51 (IUCN 2021). The range maps were subsequently rasterized at a resolution of approximately TK TP. For
52 every pixel in the resulting raster where at least one bat host of betacoronavirus was present, we extract the
53 species pool, which was used to calculate the following risk assessment components: phylogenetic
54 diversity, bat compositional uniqueness, and predicted viral sharing risk.

55 **Bats phylogeography**

56 For every pixel, we measured Faith's Phylogenetic Diversity (Faith 1992) based on a recent synthetic tree
57 with robust time calibration, covering about 6000 mammalian species (Upham et al. 2019). Faith's PD
58 measures the sum of unique branches from an arbitrary root to a set of tips, and comparatively larger
59 values indicate a more phylogenetic diverse species pool. We measured phylogenetic diversity starting
60 from the root of the entire tree (and not from Chiroptera); this bears no consequences on the resulting
61 values, since all branches leading up to Chiroptera are only counted one per species pool, and (as we
62 explain when describing the assembly of the composite risk map), all individual risk components are
63 ranged in [0,1]. This measure incorporates a richness component, which we chose not to correct for; the
64 interpretation of the phylogenetic diversity is therefore a weighted species richness, that accounts for
65 phylogenetic over/under-dispersal in some places.

66 **Bats compositional uniqueness**

67 For every species pool, we measured its Local Contribution to Beta-Diversity (Legendre and De Cáceres
68 2013); LCBBD works from a species-data matrix (traditionally noted as Y), where species are rows and sites
69 are columns, and a value of 1 indicates occurrence. We extracted the Y matrix assuming that every pixel
70 represents a unique location, and following best practices (Legendre and Condit 2019) transformed it
71 using Hellinger's distance to account for unequal bat richness at different pixels. The correction of raw
72 community data is particularly important for two reasons: first, it prevents the artifact of richer sites
73 having higher importance; second, it removes the effect of overall species richness, which is already
74 incorporated in the phylogenetic diversity component. High values of LCBBD indicate that the pixel has a
75 community that is on average more dissimilar in species composition than what is expected knowing the
76 entire matrix, i.e. a more unique community.

77 **Viral sharing between hosts**

78 For all bat hosts of betacoronaviruses, we extracted their predicted viral sharing network (Albery et
79 al. 2020). This network stores pairwise values of viral community similarity. To project viral sharing values
80 into a single value for every pixel, we averaged the pairwise scores. High values of the average sharing
81 propensity means that this specific extant bat assemblage is likely to be proficient at exchanging viruses.

82 **Composite risk map**

83 To visualize the aggregated risk at the global scale, we combine the three individual risk components
84 (phylogenetic diversity, compositional uniqueness, and viral sharing) using an additive color model
85 (Seekell et al. 2018). In this approach, every risk component gets assigned a component in the RGB color
86 model (phylogenetic diversity is green, compositional uniqueness is red, and viral sharing is blue). In
87 order to achieve a valid RGB measure, all components are re-scaled to the [0,1] interval. This additive
88 model conveys both the intensity of the overall risk, but also the nature of the risk as colors diverge
89 towards combinations of values for three risk components.

90 **Viral phylogeography**

91 We used the following query to pull all betacoronavirus sequence data from the GenBank Nucleotide
92 database except SARS-CoV-2; (“Betacoronavirus”[Organism] OR betacoronavirus[All Fields]) NOT
93 (“Severe acute respiratory syndrome coronavirus 2”[Organism] OR sars-cov-2[All Fields]). We added a
94 single representative sequence for SARS-CoV-2 and manually curated to remove sequences without the
95 RNA-dependent RNA polymerase (RdRp) sequence or that contained words indicating recombinant or
96 laboratory strains including “patent,” “mutant,” “GFP,” and “recombinant.” We filtered over-represented
97 taxa including betacoronavirus 1, hCoV-OC43, Middle East respiratory syndrome coronavirus, Murine
98 hepatitis virus, and hCoV-HKU1. Curated betacoronavirus RdRp sequences were then aligned using
99 MAFFT v 1.4.0 (Kato and Standley 2013, Supplemental X) and a maximum likelihood tree reconstructed
100 in IQ-TREE v 1.6.12 (Nguyen et al. 2015) with ModelFinder (Kalyaanamoorthy et al. 2017) ultrafast
101 bootstrap approximation (Hoang et al. 2018) and the following parameters (STEPH WILL ADD,
102 Supplemental X).

103 **Viral evolutionary diversification**

104 We first tested the hypothesis that hotspots of viral diversification would track hotspots of bat
105 diversification. To do so, we plotted the number of known bat hosts (specifically only those included in the
106 phylogeny, so there was a 1:1 correspondence between data sources) against the “mean evolutionary
107 distinctiveness” of the associated viruses. To calculate this, we derived the fair proportions evolutionary
108 distinctiveness (Isaac et al., 2007) for each of the viruses in the tree, then averaged these at the bat species

level, projected these values onto their geographic distributions, and averaged across every bat found in a given pixel. As such, this can be thought of as a map of the mean evolutionary distinctiveness of the known viral community believed to be associated with a particular subset of bats present.

Co-distribution of hosts and viral hotspots

Subsequently, we tested the hypothesis that the biogeography of bat betacoronaviruses should track the biogeography of their hosts. To test this idea, we loosely adapted a method from Kreft & Jetz (2010), who proposed a phylogenetic method for the delineation of animal biogeographic regions. In their original method, a distance matrix - where each row or column represents a geographic raster's grid cell, and the dissimilarity values are the "beta diversity similarity" of their community assemble - undergoes non-metric multidimensional scaling (NMDS); the first two axes of the NMDS are projected geographically using a four-color bivariate map.

Here, we build on this idea with an entirely novel methodology. First, we measure the phylogenetic distance between the different viruses in the betacoronavirus tree by using the cophenetic function in 'ape'; subsequently, we take a principal components analysis of that distance matrix (readily interchangeable for NMDS in this case) to project the viral tree into an n-dimensional space. We then take the first two principal components and, as with the evolutionary distinctiveness analysis, aggregated these to a mean host value and projected them using a four-color bivariate map.

Outbreaks data geo-referencing

Finally, we provide a summary visualization of what available information describes the spillover of zoonotic betacoronaviruses of bat origin where data was available before and up through the COVID-19 pandemic. The SARS-CoV-2 outbreak was georeferenced to the initial case cluster in Wuhan, China; SARS-CoV was georeferenced based on the cave with the closest known viruses circulating in nature (Hu et al. 2017 PLoS Pathogens), and a nearby location where serological (antibody) evidence has indicated human exposure to SARS-like viruses (Wang et al. 2018 Virologica Sinica). For MERS-CoV, we presented the index cases available from a recently-published compendium of MERS-CoV cases (Ramshaw et al. 2019); these are largely if not all presumed to be camel-to-human transmission, and the precise origin point of MERS-CoV in bats is uncertain. Not shown is a recent case of a recombinant canine coronavirus

136 that showed the ability to infect humans, both because this study was published after the beginning of the
137 COVID-19 pandemic and because bats' involvement in this cycle of transmission has been marginal to
138 non-existent.

139 **Results**

140 **Host distribution**

141 Chiroptera are an hyperdiverse group, distributed in a large part of the world, and are an important
142 reservoir for different strains of betacoronaviruses (Drexler et al., 2014); this has attracted attention to
143 areas where high diversity of bats can be an important issue for human health (Calisher et al., 2006).
144 Accordingly, we collected the IUCN rangemaps for known hosts of betacoronaviruses, to illustrate where
145 hotspots of host diversity are. These results are presented in Fig xx.a. As per our current knowledge of
146 which bats are hosts of betacoronaviruses, these hotspots are primarily South-East Asia, parts of Europe,
147 and to a lesser extent sub-saharan Africa. Even the subset of chiroptera that are hosts of betacoronaviruses
148 fits the evolutionary timeline of the group. Chiropterans can be classified as Microchiroptera and
149 macrochiroptera, where macrochiroptera have an older history from an evolutionary perspective
150 compared to microchiroptera (Springer, 2013; Teeling et al., 2005). South-East Asia has a high diversity of
151 bats (Kingston, 2010), and our results show that part of that diversity includes betacoronavirus hosts. High
152 density of hosts sharing the same virus (albeit possibly different strains) calls into question the evolution
153 of the bat antiviral immune system and its co-evolution with viruses, which may result in distinct
154 immunological responses in different areas, as evidenced in other bat species (Banerjee et al., 2020)

155 **Viral evolutionary distinctiveness**

156 Higher host diversity may not result in a higher viral diversity; for this reason, we quantified and mapped
157 the evolutionary distinctiveness of betacoronaviruses, based on Viral evolutionary distinctiveness
158 largely tracks host diversity, particularly in southern China but oddly not throughout the rest of southeast
159 Asia, perhaps indicating that many distinctive viruses remain to be discovered in this region (an idea that
160 is unsurprising given the growing realization, around the emergence of SARS-CoV-2, that a unique
161 lineage of similar viruses are widespread in bats but still mostly undescribed). The most distinct

betacoronaviruses are found in South America, a region with a comparatively lower number of hosts; this suggests that the South American bat-betacoronavirus complex has been more isolated, and is probably undergoing a different co-evolutionary dynamic. Alternatively, this distinctiveness hotspot may be a product of under-sampling: South-America is one of the places where the fewest betacoronaviruses have been discovered (Anthony et al., 2017), and adding more viruses would bring the distinctiveness of known sequences down. Previous work has suggested the Americas may be a hotspot of both undiscovered bat viruses in general (Olival) and coronavirus specifically (Anthony), though not necessarily betacoronaviruses, and particularly not those in clades with notable zoonotic potential (c.f. Anthony).

Geographic Mosaic of bat-betacoronavirus risk

In order to turn the hypotheses based on the Geographic Mosaic Theory of Coevolution into a measure of risk, we overlapped three components: viral sharing, i.e. the chance that two bats will share viruses overall; Local Contribution to Beta Diversity, i.e. the fact that a bat community is compositionally unique compared to the average compositional similarity across the entire system; finally, the phylogenetic diversity, i.e. how dispersed the bats in a location are within the tree of life. These results are presented using an additive color mapping in Figure xx, and lead to the definition of broad biogeographic regions of risk, where the same color represents the same type of risk. Pairwise maps of the three components are present in supplementary materials.

From the perspective of spillover risk, the most important combination of factors is a high phylogenetic diversity of hosts with low viral sharing; this, essentially, means that very different betacoronavirus could co-exist within the same place. This is particularly the case given that betacoronaviruses often evolve and even achieve host shifts through recombination, which requires the co-occurrence of sufficiently distinct viruses to be a major driver of emergence. In Fig. xx, this corresponds to yellow to pale green areas, which are essentially limited to South-Eastern Asia, and to some part of Sub-Saharan Africa. Adopting a geographic mosaic theory perspective on risk, other regions of the world are of lesser concern.

Available data on bat betacoronavirus spillover into humans (TP overlay on the figure) is limited and circumstantial at best for these purposes, but our risk maps suggest that the areas predicted by prior expectations about host biogeography correspond loosely to those where previous emergence events have been recorded. Areas with high bat diversity and high turnover may facilitate the evolutionary radiation of

190 viruses, matching previous findings that the diversification of bat coronaviruses is driven largely by host
191 shifts (inter-genus or higher levels of cross-species transmission) and, to a lesser degree, cospeciation and
192 sharing (intra-genus cross-species transmission; Anthony et al. 2017). This diversification - while not an
193 actual risk factor for spillover itself - likely increases the random chance of a virus with the raw genomic
194 components required for the potential to infect humans.

195 **Global distribution of spillover risk**

196 Based on the previous result, we extracted the yellow component of the risk map (TP add methods), to
197 provide a single measure of risk varying between 0 and 1. This measure is presented in Fig. xxA. However,
198 this maps the potential risk, which must be weighed by the potential for contacts with humans. As a proxy
199 for this measure, we used the proportion of build/urban land from the EarthEnv dataset: this is a
200 reasonable proxy for the density of humans per unit area, which increases the probability of pathogen
201 spread more widely (Hazarie et al., 2021). Since human activity is required to amplify the frequency of
202 virus encounters and thus create areas of viral amplification, mapping the potential risk against measures
203 of land use is required to generate a more actionable assessment of risk. This map is presented in Fig. xxB.
204 Most of South America and Europe are at low risk, as although densely populated, settlements tend to be
205 in areas with lower potential risk. However, this mapping reveals that South-East Asia, the Indian
206 subcontinent, and parts of sub-Saharan Africa, are at high risk due to the overlap between built areas and
207 bat communities representing more opportunities for cross-species transmission of betacoronaviruses.

208 **Discussion**

209 Driven by the need to understand the ecological factors involved in the emergence of viral pathogens, we
210 spatially mapped bat-betacoronavirus interactions worldwide, using (i) a database of known betacov
211 hosts(Becker et al., 2020), and (ii) range maps for the hosts according to IUCN (IUCN 2021). To reflect the
212 fact that the risk posed by viruses has many ecological origins, we quantified the phylogenetic diversity of
213 hosts, their compositional uniqueness, and the expected viral sharing. Because these components of risk
214 matter when contrasted to human density, we compared them to a proxy, namely the proportion of each
215 pixel that is covered by urban or built land. This provides a synthetic risk map, allowing to identifying of
216 hotspots where the bat-betacoronavirus system may originate viruses in humans. SE Asia is one of the

217 regions with the highest risk since, according to our results, several of its conditions could increase the
218 risk of transmission of the virus.

219 Bats are found worldwide and are one of the most diverse groups among mammals (Moratelli & Calisher,
220 2015). Previous research (Anthony et al., 2017; Mollentze & Streicker, 2020) states that locally diverse bat
221 communities could maintain more viruses and hence, a higher probability of having a pathogen that could
222 represent a risk for human health. This probability involves multiple factors, among which the relatedness
223 of hosts (which can make the jumps easier (Longdon et al., 2011; Mollentze et al., 2020; Wolfe et al., 2007),
224 and the overall tendency of hosts within a locality to share viruses, which may limit viral diversity because
225 of within-host competition (Leeks et al., 2018; Sallinen et al., 2020). Species richness, therefore, is not a
226 sufficient measure of viral risk. This is exemplified in our results, where both South America and
227 South-Eastern Asia have a high species richness of betacov hosts, but only the latter region has a high risk.
228 Specifically, because previous studies propose that Asia is important when it comes to understanding the
229 evolutionary origin of various mammalian taxa (Beard C K, 1988). Including bats (Yu et al., 2014), which
230 could support the relationship between evolutionary time and the development of an immune system
231 with characteristics that allow them to be better adapted to infection by emerging viruses (Gorbunova et
232 al., 2020; Irving et al., 2021) may be related to a wide variety of diets (Jones et al., 2022; Moreno Santillán
233 et al., 2021; Banerjee et al., 2020; Schneeberger et al., 2013).

234 Our study focuses largely on the biogeography of hosts. Yet, we know that viruses with high host
235 plasticity, that is, the ability of a given virus to adapt to various taxonomic orders and ecological groups
236 (Kreuder Johnson et al., 2015); are more likely to amplify viral spillover, followed by secondary
237 human-to-human transmission, and geographical spread (Hazarie et al., 2021). High viral host plasticity is
238 an especially important trait for RNA viruses such as betacov (Kreuder Johnson et al., 2015; Haddad et al.,
239 2021). Indeed, our analysis of viral sequences reveals that Latin America is a hotspot of viral
240 distinctiveness, suggesting that this part of the bats-betacov system may be undergoing independent
241 evolutionary dynamics (related species sharing viruses that are different from the rest of the global pool).
242 The other hotspot of viral distinctiveness is S.E. Asia, in which richness is high but sharing is low; this
243 suggests a different type of evolutionary dynamics (unrelated viruses coevolving with evolutionarily
244 distinct hosts, generating high diversity locally).

245 This diversity of hosts and how the exchange of viruses occurs between species, is largely affected by the
246 different environmental changes, as the case of sarbecovirus bats reservoirs (Muylaert et al., 2021) where

247 they are affected by the area of the cave or the alteration of the forest, which could result in modifications
248 of host distribution. Additionally, our results highlight the importance of Asia as a betacov hotspot, which
249 is consistent with recent studies (Muylaert et al., 2021), where projections on this area suggest that new
250 future events of sarbecovirus viral exchange might be easily spread among species or humans.

251 There are several factors that drive changes in the diversity of bats (Alves et al., 2018), but human
252 activities' effects on the ecosystem (like modifications of land use) could significantly decrease it.
253 Therefore, it can be suggested that changes in the diversity of betacovs in bats are linked to their
254 biogeographic variation, and human population density and other anthropogenic factors are decisive
255 moderators for its implications in public health. With the increase of contact between humans and
256 potential hosts, we also increase the risk of emergence of novel diseases (Johnson et al., 2020), as previous
257 studies on RNA viruses suggest the importance of host phylogeography at the time of virus dispersal
258 (Gryseels et al., 2017).

259 One of these scenarios where interaction between bats and humans can occur can be seed dispersal in
260 tropical agroecosystems. It opens the discussion of whether the fruits thrown by bats not only disperse
261 seeds but could also be a source of indirect interaction between viruses of bat origin and humans
262 (Deshpande et al., 2022) . This represents a challenge for conservation strategies and disease ecology since
263 we have areas with potential zoonotic viruses and bat-human interaction. However, it must still be taken
264 into account the quantification of real exposure from several scenarios, where there can be directly or
265 indirectly bat - human interaction.

266 Comparing scenarios of high viral exchange vs low viral exchange, open the discussion to consider if the
267 best scenario is where viruses easily adapted to multiple hosts but with low virulence or easily ignored by
268 the immune system of the host, or where we have viruses specialized to a specific host, but highly virulent
269 when invade a new host. Accordingly, the understanding of viral-host interactions from a taxonomic and
270 phylogenetic contributes to improving zoonoses surveillance programs.

271 **Acknowledgements:** We acknowledge that this study was conducted on land within the traditional
272 unceded territory of the Saint Lawrence Iroquoian, Anishinabewaki, Mohawk, Huron-Wendat, and
273 Omàmiwininiwak nations. This work was supported by funding to the Viral Emergence Research
274 Initiative (VERENA) consortium including NSF BII 2021909 and a grant from Institut de Valorisation des
275 Données (IVADO). This research was enabled in part by support provided by Calcul Québec
276 (www.calculquebec.ca) and Compute Canada (www.computeCanada.ca). NF is funded by the NSERC

277 BIOS² CREATE program. TP and NF are funded by the Courtois Foundation. RLM was supported by
278 Bryce Carmine and Anne Carmine (née Percival), through the Massey University Foundation.