Predictors of zoonotic potential in helminths

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1 Abstract

2 Helminths are parasites that cause disease at considerable cost to public health and present a 3 risk for emergence as novel human infections. Although recent research has elucidated 4 characteristics conferring a propensity to emergence in other parasite groups (e.g. viruses), the 5 understanding of factors associated with zoonotic potential in helminths remains poor. We 6 applied an investigator-directed learning algorithm to a global dataset of mammal helminth traits 7 to identify factors contributing to spillover of helminths from wild animal hosts into humans. We 8 characterized parasite traits that distinguish between zoonotic and non-zoonotic species with 9 greater than 88% accuracy. Results suggest that helminth traits relating to transmission (e.g. 10 definitive and intermediate hosts) and geography (e.g. distribution) are more important to 11 predicting zoonotic species than morphological or epidemiological traits. Whether or not a 12 helminth causes infection in companion animals (cats and dogs) is the most important predictor 13 of propensity to cause human infection. Finally, we identified helminth species with high 14 modeled propensity to cause zoonosis (over 70%) that have not previously been deemed to be 15 of risk. This work highlights the importance of prioritizing studies on the transmission of 16 helminths that infect pets and points to the risks incurred by close associations with these 17 animals.

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20 Keywords: macroparasite, parasite trait, zoonosis, pet, intermediate host

21 Introduction

22 Understanding the factors that contribute to the emergence of novel infectious diseases 23 is a central concern to global public health [1]. Since most outbreaks of novel pathogens among 24 humans are due to spillover from animal hosts [2-4], identifying factors associated with the 25 propensity for transmission to humans is of high priority. Research in this area is particularly 26 urgent because the rate of human-wildlife contacts is increasing with changes to natural 27 landscapes and global climate [5], providing ample opportunities for human exposure to novel 28 hosts and pathogens [6, 7]. Identifying species that are potentially parasitic or pathogenic in 29 humans (i.e., those with high zoonotic potential) would enhance our understanding of the factors 30 underpinning spillover transmission from animal reservoirs, and enable preemptive approaches 31 to disease control.

32 One approach to evaluating zoonotic potential is to analyze pathogen and host traits 33 [e.g. 8]. Particularly, features distinguishing zoonotic from non-zoonotic parasites and their 34 reservoir host species can be used to predict which species are most likely to present high risk 35 of zoonotic exposure to people [9]. For example, work by Han, Schmidt [10] identified 'fast' life 36 history strategy (short-lived, short generation time) as a key predictor of the rodent species most 37 likely to be reservoirs of novel zoonotic pathogens. Trait analysis of zoonotic viruses revealed 38 that viruses which can replicate in cytoplasm are more likely to infect humans [11] and viruses 39 which infect nonhuman primates predict the transmissibility of a virus between humans [12]. 40 Patterns in genome sequences of viruses have also yielded predictions on which hosts are 41 likely to be reservoirs of zoonosis and which arthropods are likely to be their vectors [13]. These 42 findings are of scientific interest concerning the current theoretical debate about why some 43 parasite species are more prone to spillover [14-16].

Parasitic helminths are a group of parasites that remains poorly studied in comparison to
 viruses and bacteria, but may pose considerable future risk of human transmissibility. Helminths

46 are macroparasites, primarily known for chronic infections of the gastrointestinal tract, typically 47 caused by tapeworms (cestodes), roundworms (nematodes), or flatworms (trematodes), 48 although helminths can infect nearly all human tissues [17]. Helminths are also known to be 49 vectors for other zoonoses, such as the fever-causing bacteria Neorickettsia sennestu 50 transmitted by a trematode ingested via raw fish consumption [18]; although helminth vectoring 51 remains understudied [19]. Human-helminth associations have ancient origins [reviewed in 20]. 52 but the relatively recent domestication of animals for food and companionship significantly 53 increased the number of parasites shared between humans and (domesticated) animals [21]. 54 The agricultural revolution and associated practices, such as storage of crops in granaries, likely 55 created new links between humans and wildlife, providing additional opportunities for helminth 56 species to infect human hosts [22]. To this day, zoonotic helminths continue to emerge within 57 human populations, a process that may be further accelerated with the global trade of livestock, 58 climate change and growth in the demand for animal protein for human consumption [23].

59 Helminths are distinct from other human parasites, such as viruses and bacteria, in that 60 they commonly have complex life cycles that rely on one or more intermediate hosts [24, 25]. 61 These intermediate hosts are necessary for the development of juvenile life stages (eggs and 62 larvae) and transmission to the definitive host, where the animal matures, reproduces and 63 produces propagules [26]. Intermediate hosts include a wide range of aquatic, terrestrial, wild 64 and domesticated animals [26], yet it is unknown how intermediate host identities are linked to 65 risk of helminthiasis in humans. In addition, transmission may occur directly (i.e., trophically, 66 vertically) and/or indirectly (i.e., via environment or arthropod vector). From a public health 67 perspective, most chronic infections are caused by soil-transmitted helminths [27], however, the 68 transmission modes of most zoonotic helminths have not previously been summarized. Thus, 69 identifying helminth biological and ecological traits that are linked to zoonosis can help to

improve our understanding of the factors that drive zoonotic potential in helminths and to better
 manage risk of transmission to humans.

72 In addition to intrinsic biological and ecological traits such as identity of definitive and 73 intermediate hosts, transmission to humans also may be influenced by socio-economic factors 74 specific to regions where the parasites are found. Currently, most helminth infections in humans 75 are found in low and middle income countries of the tropics [27, 28], where disease prevention 76 and healthcare infrastructure vary greatly. Numerous parasitic worms such as hookworms 77 (genera Ancylostoma and Necator) are considered neglected tropical diseases which could be 78 eliminated with sufficient drug administration and effective interventions [28]. Further, given the 79 generally high animal biodiversity of tropical regions, it also may be that there are more host 80 species of potential zoonoses in this part of the world [29], although previous work indicates that 81 temperate regions contain more zoonotic helminths than tropical regions [9]. Thus, we 82 conjectured that geographic traits of helminths might be important factors for predicting the 83 probability that a species might infect humans. Despite the high variation in medical, 84 educational, and economic burden of human helminth infections worldwide [28], how the 85 different epidemiological and geographic factors relate to helminth zoonotic potential has been 86 unclear.

87 We investigated which traits of helminths are predictors of disease in humans. We 88 compiled a global dataset from existing databases and the published literature on more than 89 700 mammal helminth parasite species to examine the frequency of biological (transmission, 90 morphology), epidemiological, and geographical traits. We used boosted regression trees, an 91 ensemble learning technique, to navigate the high dimensionality of these data. These and 92 similar machine learning methods are rapidly developing approaches that can be applied to 93 hetereogeneous covariates and are often robust to nonlinear interactions hidden in the data [30, 94 31]. Among over 70 variables, our machine learning approach identified key trait patterns

95 predicting helminth zoonosis. Specifically, whether a helminth species is zoonotic was best 96 predicted by three characteristics: (1) whether one of the hosts is a companion animal (i.e. dog, 97 cat), (2) whether an intermediate host is a fish (member of Chordata phylum), and (3) the 98 number of unique locations in which the helminth species has been detected. More generally, 99 this study adds to the growing body of literature used to inform strategies for preventing 100 helminth infection and mitigating risk of novel zoonoses.

101

102 Methods

103 Data compilation

104 We used the Global Mammal Parasite Database (GMPD) [32], which consists of over 700 105 species of helminths, representing three main phyla (Acanthocephala, Nematoda, and 106 Platyhelminthes) of parasitic helminths that infect wild mammals. Most emerging zoonotic 107 diseases originate from mammals [33] and therefore a mammal-focused analysis is well-suited 108 to identifying zoonotic risk factors. For each helminth species, we searched primary literature for 109 evidence of human infection originating from animal hosts to assign a binary response indicating 110 whether or not the helminth species is zoonotic. We acquired morphological information of 111 adults and eggs from Benesh, Lafferty [34] and Dallas, Gehman [35] databases, both of which 112 gathered information from the literature. To fill in gaps, we followed Dallas, Gehman [35] and 113 searched for missing morphological information from veterinary and parasitology references 114 (e.g. Taylor, Coop [36]), taxonomy references [26, 37], and primary literature. We extracted 115 minimum, mean, and maximum body length and width (in millimeters) of adult helminths from 116 the descriptions of each parasite species. We also extracted minimum, mean, and maximum 117 egg length and width (in millimeters). We compiled records of male and female body sizes when 118 that information was available. We recorded site of infection in the definitive host body when it 119 was provided.

120 We supplemented transmission information within the above references by extracting the 121 following: common name(s) of definitive and intermediate hosts, whether the species has a free-122 living propagule stage (a binary variable), and if so, the stage of the free-living propagule as 123 egg, larva, or both (as can occur in species that pass through more than one intermediate host), 124 and the medium in which free-living stage(s) persist (soil, water, or both). We used the common 125 names of intermediate hosts to note the class or phyla to which the intermediate animal host 126 belongs, whether any of the host (definitive or intermediate) are domesticated animals (livestock 127 and pets), or companion pet animals (predominantly cats and dogs). For each species we noted 128 the transmission mode(s) to the definitive host as vertical (from parent to offspring), 129 environmental (propagules acquired from the soil, water, or both), vector (via biting arthropod), 130 or trophic (via consumption of intermediate host).

131 The GMPD provides geographical coordinates for each helminth species, which we 132 augmented with host-helminth occurrence data from London Natural History Museum (LNHM) 133 [38] available via R package helminthR [39]. Coordinates in the GMPD are from reported study 134 site coordinates, or centroids of the reported study area [32]. Helminth occurrences in LNHM 135 are georeferenced as centroids to the country or state (for the USA) level. In several instances 136 coordinates were not provided by the databases, which we then georeferenced based on the 137 location name using the *geocode* function [package ggmap; 40]. Some location names were 138 obscure, such as the portion of a continent (e.g. southern South America) or body of water (e.g. 139 southwest Atlantic), which we did not georeference. Next, based on the occurrence points of 140 each species, we calculated the number of unique locations and latitudinal range (minimum and 141 maximum), assigned a binary variable to indicate whether the species occurrences fall within 142 the tropical latitudes (between 23° 27' N and 23° 27' S), and guantified the number of 143 occurrences within tropical latitudes. We note that the number of unique locations reflects 144 geographic distribution and sampling effort. From occurrence data we also calculated the 145 number of countries, terrestrial ecoregions of the world (as defined by Olson, Dinerstein [41]).

146 and terrestrial zoogeographic realms (as defined by Holt, Lessard [42]) from which each 147 helminth species has been reported. Further, following Byers, Schmidt [43] we calculated range 148 size for each helminth species as the total area of the ecoregions in which the species has been 149 found. Finally, we calculated the mean gross domestic product (GDP) and human population 150 size of the countries (provided by package rworldmap in R [44]) in which the species has been 151 documented. Our final dataset consisted of 737 globally distributed helminth species 152 (supplemental materials Fig. S1) and 73 trait variables describing helminth species that we 153 included in our analyses. We classified the traits into one of four categories: transmission, 154 epidemiological, morphological, or geographical traits (see Table 1). For full descriptions of each 155 variable see supplementary materials. 156 157 Predictive model 158 We used boosted regression trees (BRT), a regression approach that permits missing data. 159 variable interactions, collinearity, and non-linear relationships between the response and 160 explanatory variables, which can be of mixed types [30, 45]. We fit a logistic-like predictive 161 model with the zoonotic status of the helminths (0: not zoonotic, 1: zoonotic) as the response 162 variable and the 73 traits as explanatory variables. Prior to analysis, we log transformed body 163 size variables, which were right skewed. We randomly selected 80% of the data as the training 164 set and reserved 20% for testing. Boosted regression trees were trained using the gbm package 165 in R [46] with Bernoulli distributed error. We ran permutations of the model with different learning rates $(1 \times 10^{-5} \text{ to } 1 \times 10^{-2})$ and tree depths (1 to 3) using the training set to identify 166 167 optimal learning parameters yielding the highest predictive performance (see supplementary 168 materials Fig. S2). The learning conditions that were identified as yielding highest accuracy as 169 assessed by the model AUC score (area under the receiver operating characteristic curve) 170 included setting the maximum number of trees to 50,000, a learning rate of 0.001, and an 171 interaction depth of 3. We used permutation procedures to compute relative importance scores

172 for each predictor variable using Friedman's algorithm [45]. We also build partial dependence 173 plots, showing the marginal effect of each variable on the predicted outcome of the primary 174 model [30, 45] (Fig. 1). Based on the results of the primary model, we ranked helminth species 175 by their mean predicted probability of being transmissible to humans (Fig. 2).

- 176 Finally, we repeated the above analysis using only the top 15 most important variables 177
- 178 To further evaluate the relative importance of trait category, we ran additional submodels, also

predicted by the primary model trained on all 73 variables, and permuted the model 100 times.

- 179 permuted 100 times, with one of the four trait categories (transmission, epidemiology,
- 180 morphology, geography) excluded (Fig. 3 and 4). We used R programming for all analyses [47].
- 181

182 Results

183 We examined 737 globally distributed helminth species of which 137 are known to infect 184 humans. Our boosted regression ensemble of models trained on 73 helminth traits distinguished 185 zoonotic versus nonzoonotic species in the test dataset with 88% accuracy (AUC \pm SE = 0.88 \pm 186 0.01) and identified several predictors of zoonotic helminths (Fig. 1). The most important 187 variable for accurately predicting zoonotic helminths was whether the helminth species is known 188 to infect a companion animal, followed by whether fish serve as intermediate hosts, and the 189 number of locations in which the helminth species has been documented. The fourth and fifth 190 most important traits predicting zoonotic status in helminths related to the size of terrestrial 191 zoogeographic regions observed for each helminth species (Fig. 1). Generally, the most 192 important traits were related to geography and transmission, while epidemiological and 193 morphological traits were least important (for the relative influence values of all 73 variables see 194 supplementary materials Table S1).

195 While not currently known to cause human infection, BRT models identified 3 mammal-196 borne helminth species as likely to be zoonotic with >70% probability (Fig. 2) (in descending 197 order): Paramphistomum cervi, Schistocephalus solidus, and Taenia pisiformis.

198 Additional ensembles of BRT models restricted to the top 15 most important variables (as 199 identified by the primary models with 73 traits included, see Fig. 1) predicted the testing data 200 with higher accuracy (AUC = 0.91) compared to the primary models trained on all 73 traits (AUC 201 = 0.89). The restricted submodels trained on the 15 variables generally agreed on the ranking of 202 the importance of variables with the primary models (Fig. 3). Submodels trained on data without 203 one of the trait categories (i.e., leave-one-out) indicated that model trained on data without 204 morphological traits performed slightly worse (AUC = 0.90) compared to submodels with all trait 205 categories included (AUC = 0.91; Fig. 3), suggesting that including these features improved the 206 predictive accuracy of our models. Models trained on data with epidemiological traits left-out 207 performed best (AUC = 0.92; Fig. 3). Finally, models trained on data without geographical traits 208 or transmission traits performed worse than models with other categories left out (AUC = 0.87, 209 AUC = 0.89 respectively; Fig. 3). In submodels, companion animal host was the most important 210 variable, except for the submodel that excluded transmission traits (Fig. 4). For AUC scores and 211 the relative influence values of the variables in submodels see supplementary materials (Table 212 S2).

213

214 **Discussion**

215 Identifying pathogen traits associated with a propensity to spillover into humans is key 216 for understanding and predicting emergence of novel human diseases originating from wildlife. 217 We applied a machine learning algorithm to a large dataset of mammal helminths to identify 218 characteristics distinguishing zoonotic and non-zoonotic species, and to predict which species 219 currently classified as non-zoonotic have a high risk of 'spilling over' to humans in the future. 220 Our results indicate that helminths that infect companion animals (dogs and cats) and utilize fish 221 as intermediate hosts are more likely to cause human infection compared to other mammal-222 borne helminths. The third strongest predictor of the ability to cause human infection was the 223 number of occurrences of helminth species, which indicates that widespread geographic

distribution might provide important transmission exposure to human hosts; however, we note
that this variable might also reflect sampling effort (see below). Overall, these results suggest
that the zoonotic potential of helminth species is related to the identity of both definitive and
intermediate hosts that come in direct and indirect contact with people, thereby providing
abundant opportunities for parasite transmission. Further, our findings highlight the importance
of transmission strategies in the ability of mammalian helminths to infect humans.

230 Particularly interesting is the predicted association between helminth zoonosis and 231 companion animals (predominantly cats and dogs in this study). Domestic cats and dogs are 232 hosts to numerous parasitic helminth species [36, 48] and represent an important link between 233 humans and wildlife for zoonosis [49]. Indeed, the role of cats and dogs in helminthiasis have 234 been well-documented for several parasites including the zoonotic tapeworm Echinococcus 235 multilocularis (see Richards et al. in this issue) and roundworm Toxocara cati [49]. While many 236 domesticated cats and dogs are "free-range" (i.e., not owned and cared for by humans), these 237 animals are ubiquitous and tend to live near humans for provisioned food and shelter. Further, 238 they hunt wild animals, consume animal parts (e.g. entrails) discarded by humans, and can 239 overlap with wildlife habitat and territories [50], even in urban areas where numerous wild 240 animals such as racoons, foxes, and covotes thrive [51, 52]. The direct trophic interactions and 241 indirect contacts dog and cats have with wildlife provide numerous opportunities for 242 transmission of helminth parasites from wild to domestic animals, and eventually to humans. 243 Additionally, the human-pet-wildlife interface has been around for centuries as it surfaced 244 thousands of years ago with the domestication of cats 10.000 years ago and dogs 16.000 years 245 ago [53, 54]. Therefore, there has been ample opportunity for host-jumping and host-switching 246 events from wildlife to pets and humans, a process which is expected to accelerate with the 247 increasing size of the human population, associated companion animals, and activities that 248 impose close contact with wildlife.

249 Fish (freshwater or marine) as an intermediate host was identified as the third most 250 important trait for predicting zoonosis. This finding is not surprising as fish are well-documented 251 intermediate hosts to non-zoonotic parasitic worms that inflict humans [55]. One of the best-252 known examples of zoonotic parasites transmitted by fish is nematode Anisakis simplex, which 253 have a complex life cycle with marine mammals as definitive host and high incidence among 254 human populations that eat raw fish [56]. Fish-borne helminths are transmitted via consumption 255 of raw, undercooked, or improperly preserved fish [57] and therefore fish represent an important 256 direct trophic link between humans and wildlife. While wild fish are a source of parasitic 257 helminths [55, 58], recent work indicates that farmed fish are also linked to zoonosis [59, 60]. 258 Parasitic worm infections stemming from fish ingestion are increasing, likely due to the 259 significant increase in demand for fish meat associated with changes in dietary habits and 260 population growth [61]. Our finding elucidates fish as a key group of intermediate hosts linked to 261 helminthiasis and the importance of monitoring fish intended for human consumption for 262 parasitic worms to prevent and control zoonosis.

263 We also identified several geographical traits as important to predicting zoonotic 264 helminths. Specifically, the number of unique locations around the world, the number of 265 zoological realms in which helminths have been found, and the number of locations within the 266 tropics were relatively important predictors. Overall, these findings suggest that mammalian 267 parasitic helminths that are geographically widespread and able to persist in a range of habitat 268 types are also more likely to be zoonotic than their more ecological specialized counterparts, 269 possibly due to their ability to persist in different environmental conditions and exposure to 270 humans in varying environments.

271 It is important to note that study effort (and attendant bias) is likely interwoven through 272 several traits we included in this study. Particularly, the number of unique record locations might 273 not only capture distribution but also number of samples and therefore sampling effort. Indeed, 274 previous work shows that variation in sampling effort among parasitic species can predict the

275 number of localities in which the species are documented [62]. Companion animal (pet host) 276 trait might also reflect disproportionate study effort given the high access and relative ease of 277 sampling. Furthermore, veterinary diagnostics (e.g. fecal floats, snap tests) more frequently 278 performed on companion animals in high income countries might lead to higher discovery rate 279 of helminth species in these places. We found that submodels which included or excluded the 280 number of occurrences resulted in companion animal (pet host) remaining the most important 281 predictor of zoonotic status among the helminths, lending some assurance of the strong 282 statistical association between zoonotic status and pet host despite the influence of sampling 283 effort in helminth data.

284 Our model predicted several helminth species that are currently not known to infect 285 humans to have high probability (70% or higher) of causing zoonosis. The helminth species with 286 highest probability of causing human infection was a flatworm, Paramphistomum cervi, followed 287 by Schistocephalus solidus, and Taenia pisiformis. Paramphistomum cervi is environmentally 288 transmitted and requires a snail intermediate host that is accidentally ingested by wild mammals 289 and livestock ruminants (e.g. sheep and cattle), the definitive hosts [63]. Given that livestock 290 can share species of gastrointestinal helminths with farmers [64], Paramphistomum cervi may 291 be a likely candidate for spillover to humans. On the other hand, the flatworm Schistocephalus 292 solidus infects a copepods, fish, and fish-eating water birds [65], all of which have the potential 293 to provide trophic transmission to human host. Taenia pisiformis also appears likely to have the 294 pathway to directly infect humans since it utilizes rabbit intermediate hosts and carnivores 295 including cats and dogs as definitive hosts [66]. Indeed, consumption of wild rabbits by humans 296 is popular in some European countries [e.g. Spain; 67] and might facilitate host-switching to 297 humans for Taenia pisiformis. Identifying the three species of helminths and their traits serves 298 as an initial step in focusing efforts on surveillance and empirical work investigating the zoonotic 299 potential of these species.

300 In conclusion, we focused our study on parasitic helminth traits and used boosted 301 regression trees to quantify how the different transmission, geographic, morphological and 302 epidemiological factors relate to helminths' zoonotic potential. Our work suggests that helminths 303 found in cats and dogs are more likely to infect humans, and that consumption of fish by 304 humans may pose a greater risk of spillover. While our study examined over 700 mammalian 305 helminth species, many more parasitic worms are found in wildlife, and most are poorly 306 described with little known about their life cycles [68]. Key life cycle details, such as intermediate 307 host(s), are often assumed based on relation to better-studied species in the same genus. 308 Large gaps in our understanding of life cycles and transmission dynamics exist for most 309 parasitic worms, including those known to infect humans. Experimental infection work is largely 310 lacking, while detailed studies of life cycles are no longer common [68] as molecular studies 311 have eclipsed traditional experimental biology. Despite these knowledge gaps, the machine 312 learning approach we took point to key insights about zoonotic helminths. In particular, our 313 results highlight the importance of the interface between wildlife, companion animals, and 314 humans in determining risk of parasitic worm infections, which continue to cause significant 315 disease burden in developing countries [69], where semi-feral dogs and cats are generally not 316 treated for parasites and will likely continue to serve as a source of novel helminthiases. 317

318

319 Acknowledgements

We would like to thank J. Walker, C. Sanchez, and J. Vaz for helpful hints in compiling data and
C. Cleveland for feedback on early version of the manuscript. We are also grateful to the UGA
Library staff and Interlibrary Loan staff for the facilitating delivery of various articles for
compilation of the trait data.

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bioRxiv preprint doi: https://doi.org/10.1101/2021.03.28.437423; this version posted March 29, 2021. The copyright holder for this preprint (which was not certified by peer review) is the author/funder. All rights reserved. No reuse allowed without permission.

326 Funding

- 327 This work was supported by the NSF Ecology and Evolution of Infectious Diseases program
- 328 (DEB 1717282 to BAH and JD). AAM was also supported by NIH/NIGMS K12 Postdoctoral
- 329 Fellowship at Emory University (Project 5K12GM000680-19).

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Table 1. Top 15 most important variables used to predict helminth zoonoses status.

Colors of the rows correspond to the four trait categories: geographical traits are in pink,

transmission traits are in green, morphological traits are in blue and epidemiological traits are in orange. Color scheme also applies to Fig. 3 and 4.

Variable	Description
Transmission	
Pet host	Binary variable indicating whether the host (final or intermediate) is a companion animal (predominantly dog and cat)
Fish intermediate host	Binary variable indicating whether an intermediate host is a fish
Geography	
Number of locations	Number of distinct locations (based on coordinates) a helminth species was observed in
Number of zoogeographic realms	Number of terrestrial zoogeographic realms (as defined in Holt et al 2013) a helminth species was located in
Number of tropical sites	Number of tropical sites the parasites was observed in
Number of ecoregions	Number of terrestrial ecoregions (as defined by World Wildlife Fund)
Number of countries	Number of countries the helminth parasite was observed in
Morphology	
Male length (mean)	Mean male length in millimeters
Female length (max)	Maximum female length in millimeters
Egg width (max)	Maximum egg width in micrometers
Female length (min)	Minimum female length in millimeters
Male length (min)	Minimum male length in millimeters
Female width (max)	Maximum female width in millimeters
Epidemiology	
Human population (mean)	Mean human population of the countries in which the helminth species is found
Gross domestic product (mean)	Mean gross domestic product (GDP) of the countries in which the helminth species occurs

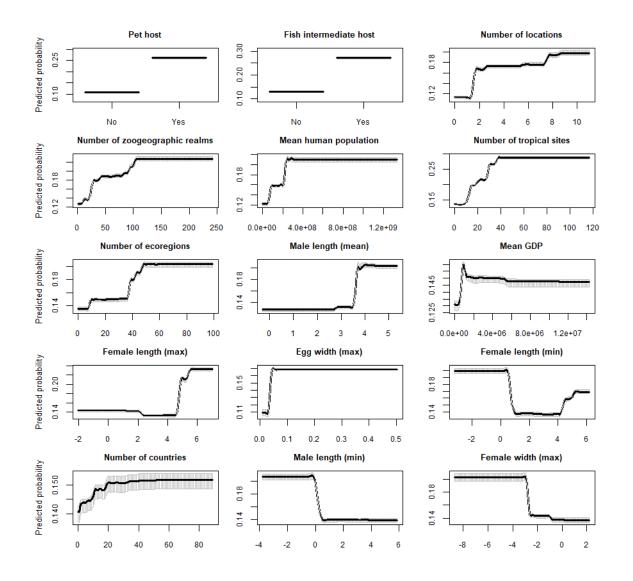


Figure 1. **Partial dependence plots for top 15 most important variables.** Plots are based on permutations of the primary boosted regression tree model that included 73 variables. Importance of the variables is ordered from left to right, then top to bottom. Black lines represent the median predicted probability, while shaded regions represent the corresponding 95% confidence interval across 100 permutations of the model.

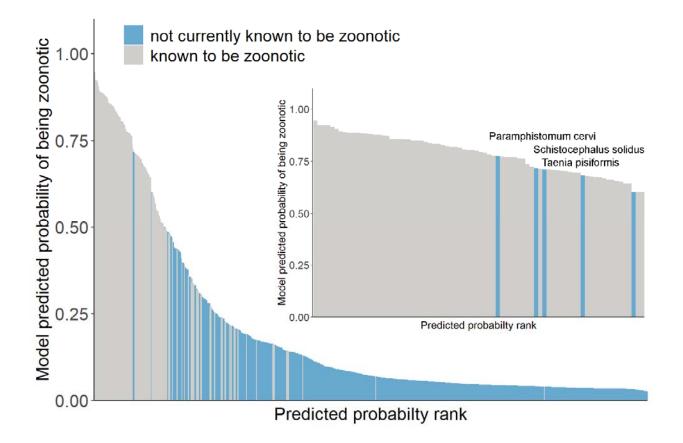


Figure 2. Predicted zoonotic helminth risk index. Average model-predicted probability of being zoonotic as ranked by the primary boosted regression tree model. Blue bars represent species not known to be transmissible to humans from wildlife and gray bars are species known to be transmissible to humans from wild hosts and are confirmed by the model to be zoonotic. Inset: zoonoosis risk of helminth species with model-predicted probabilities greater than 70%. Names of top 3 species not currently known to be zoonotic appear above the bars and include *Paramphistomum cervi, Schistocephalus solidus,* and *Taenia pisiformis* (in descending order).

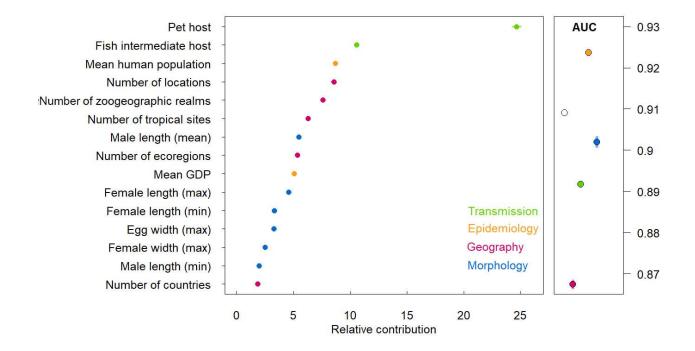


Figure 3. Variable importance values by permutation, averaged over 100 models trained on all four categories of traits (left panel), show relative importance of transmission traits (green), epidemiological traits (orange), geographical traits (maroon), and morphological traits (blue). Average model accuracy for each submodel trained on all four trait categories (white symbol), all trait categories except: morphological traits (blue), epidemiological traits (orange), transmission traits (green), or geographical traits (maroon). Error bars represent the standard deviation from 100 model permutations.

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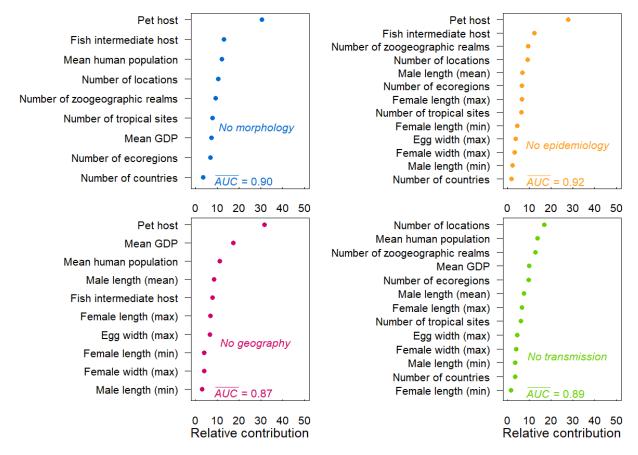


Figure 4. Variable importance values averaged over 100 model permutations trained on all categories of traits except: morphology (top left - blue), epidemiological traits (top right - orange), geography (bottom left - maroon), and transmission (bottom right- green).