

1 **Multi-site sampling and risk prioritization reveals the public health relevance of antibiotic**
2 **resistance genes found in wastewater environments**

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24 **Abstract**

25 The spread of bacterial antibiotic resistance across human and environmental habitats is a global
26 public health challenge. Wastewater has been implicated as a major source of antibiotic
27 resistance in the environment, as it carries resistant bacteria and resistance genes from humans
28 into natural ecosystems. However, different wastewater environments and antibiotic resistance
29 genes in wastewater do not all present the same level of risk to human health. In this study, we
30 investigate the public health relevance of antibiotic resistance found in wastewater by combining
31 metagenomic sequencing with risk prioritization of resistance genes, analyzing samples across
32 urban sewage system environments in multiple countries. We find that many of the resistance
33 genes commonly found in wastewater are not readily present in humans. Ranking antibiotic
34 resistance genes based on their potential pathogenicity and mobility reveals that most of the
35 resistance genes in wastewater are not clinically relevant. Additionally, we show that residential
36 wastewater resistomes pose greater risk to human health than those in wastewater treatment plant
37 samples, and that residential wastewater can be as risky as hospital effluent. Across countries,
38 differences in antibiotic resistance in residential wastewater can, in some cases, reflect
39 differences in antibiotic drug consumption. Finally, we find that the flow of antibiotic resistance
40 genes is influenced by geographical distance and environmental selection. Taken together, we
41 demonstrate how different analytical approaches can provide greater insights into the public
42 health relevance of antibiotic resistance in wastewater.

43

44 **Keywords**

45 Antibiotic resistance; metagenomics; wastewater; microbiome; public health; risk assessment

46 **1. Introduction**

47
48 The spread of antibiotic resistant bacteria and resistance genes is a global public health challenge
49 (The Review on Antimicrobial Resistance, 2014; World Health Organization, 2014; Zaman et
50 al., 2017). Antibiotic resistance genes (ARGs) confer resistance to antibiotics and are present in
51 both bacterial pathogens and the broader environment (Allen et al., 2010; Baquero et al., 2008;
52 D’Costa et al., 2011; Huijbers et al., 2015; Lee et al., 2018). The transfer of these genes between
53 bacteria through horizontal gene transfer is of particular concern, as it can facilitate the
54 transmission of ARGs from environmental reservoirs to human pathogens (Allen et al., 2010;
55 Cantón, 2009; Forsberg et al., 2012; Martínez, 2018; Pehrsson et al., 2016). While current efforts
56 to monitor antibiotic resistance are largely limited to clinical settings (“EARS-Net,” 2010, p.,
57 “GLASS,” 2015, “NARMS,” 2018), government agencies have begun to recognize the
58 importance of antibiotic resistance in the environment (Gaze and Depledge, 2017; Wellcome
59 Trust et al., 2018). As health officials explore the need for environmental surveillance of
60 antibiotic resistance, it is critical to understand the human health relevance of ARGs found in
61 different environments.

62
63 Efforts to monitor antibiotic resistance in the environment face the challenge of interpreting the
64 threat that environmental resistomes pose to human health (Huijbers et al., 2015). Environmental
65 bacteria are difficult and costly to culture (Larsson et al., 2018; Wellcome Trust et al., 2018). As
66 such, the ability to identify the evolution, transmission, and host range of resistance genes is
67 limited (Larsson et al., 2018). To overcome this challenge, studies have employed metagenomic
68 sequencing to measure antibiotic resistance in the environment (Martínez et al., 2015; Ng et al.,
69 2017; Rowe et al., 2017). These studies often establish the presence of resistance genes in an
70 environment as a risk to human health. Antibiotic resistance genes, however, do not all pose the
71 same risk, and the presence of certain genes may be more indicative of the organisms harboring
72 these genes than of a real public health threat (Martínez et al., 2015). In order for resistance
73 genes to be of relevance to human health, they should reside on mobile genetic elements and be
74 hosted by human bacterial pathogens (Bengtsson-Palme and Larsson, 2015; Martínez et al.,
75 2015). Most resistance genes in the environment, however, are unlikely to be found in human-
76 associated bacteria, as they often occupy different habitats and are phylogenetically distant
77 (Bengtsson-Palme and Larsson, 2015; Larsson et al., 2018; Martínez et al., 2015). Therefore,
78 studies need to move beyond reporting the presence and abundance of ARGs in an environment
79 and also assess their relevance to human health (Bengtsson-Palme and Larsson, 2015; Huijbers et
80 al., 2015; Martínez et al., 2015; Topp et al., 2018).

81
82 Wastewater has been proposed as an important source of environmental antibiotic resistance
83 (Marti et al., 2013; Munir et al., 2011; Rizzo et al., 2013; Rodriguez-Mozaz et al., 2015), as well
84 as an environment for monitoring the prevalence of antibiotic resistance in humans (Fahrenfeld
85 and J. Bisceglia, 2016; Gaze and Depledge, 2017; “COMPARE,” 2016). Previous studies of
86 antibiotic resistance in wastewater have primarily focused on hospital effluents and wastewater
87 treatment plants (WWTPs), locations which are widely viewed as hotspots for antibiotic resistant
88 bacteria and horizontal gene transfer (Harris et al., 2014; Ng et al., 2017; Rizzo et al., 2013;
89 Rodriguez-Mozaz et al., 2015; Varela et al., 2014). WWTPs serve as the interface between
90 human society and the environment, as wastewater from various sources meet at WWTPs and
91 undergo treatment processes before being released into the environment. Despite the efforts to

92 remove human-associated bacteria, ARGs are still prevalent in WWTP effluents (Ju et al., 2018;
93 Rizzo et al., 2013; Rodriguez-Mozaz et al., 2015). Hospital wastewater has also been proposed
94 as an important source of environmental antibiotic resistance due to the high levels of antibiotic
95 use and resistant bacteria amongst hospital patients (Harris et al., 2014; Wellcome Trust et al.,
96 2018). Abundances of ARGs in hospital effluents have been found to be higher than in
97 downstream environments such as WWTPs and surface water (Buelow et al., 2018; Ng et al.,
98 2017; Rodriguez-Mozaz et al., 2015; Rowe et al., 2017). However, hospitals contribute less than
99 1% of the total amount of municipal wastewater at WWTPs and have been found to have little
100 influence on the levels of antibiotic resistance observed at WWTPs (Buelow et al., 2018; Harris
101 et al., 2014; Kümmerer, 2004; Varela et al., 2014). Thus, it remains unclear which wastewater
102 environments should be the focus for monitoring environmental ARGs.

103
104 In this study, we combine multi-site sampling of upstream and downstream wastewater with risk
105 prioritization of ARGs to evaluate the public health relevance of antibiotic resistance found in
106 wastewater environments. We show that many ARGs found in wastewater are not human-
107 associated and most genes in wastewater are likely not of risk to human health. We also find that
108 the abundance of ARGs in wastewater for certain classes of antibiotics mirrors antibiotic
109 consumption across countries. Lastly, by comparing resistomes sampled within and across
110 countries, we show that the diversity of resistance genes is shaped by environmental selection
111 and geography. Taken together, this study provides evidence for the hypothesis that different
112 genes and environments pose different risks to human health and illustrates the complexities in
113 interpreting the public health relevance of resistomes.

114 115 **3. Results and Discussion**

116 117 **3.1 Residential wastewater resistomes are a complex mixture of human-associated and** 118 **environmental antibiotic resistance genes**

119 To understand patterns of antibiotic resistance across human-associated environments, we
120 compared the metagenomes of residential wastewater with those from similar wastewater
121 environments and the human gut microbiome. We collected and sequenced wastewater from 13
122 residential manholes in and surrounding the urban areas of Boston, MA; Seoul, South Korea; and
123 Kuwait City, Kuwait (Table S1; Materials and Methods). We also collected untreated wastewater
124 from the influent of WWTPs in the US and Kuwait. To compare residential wastewater with
125 other wastewater environments and human feces, we downloaded and reprocessed publicly
126 available metagenomic data of adult fecal samples in the US and South Korea and a hospital
127 effluent in the U.K. (Materials and Methods). We used ShortBRED with the SARG database to
128 quantify the abundance of antibiotic resistance genes (ARGs) from metagenomic data (Material
129 and Methods).

130
131 Residential wastewater contains more ARGs than human feces and WWTP influent but less than
132 hospital effluent. The median number of ARGs in residential wastewater was 161 (Figure 1A). In
133 comparison, hospital effluent and WWTP influent samples had median ARG counts of 238.5 and
134 125.5 genes, respectively (Figure 1A). All types of wastewater samples contained more ARGs
135 than fecal samples, which had medians of 50 genes in South Korea and 29.5 genes in the US. We
136 found similar trends in abundance measurements (Figure 1B). Previous studies have implicated
137 both hospital effluent and WWTPs as hotspots for antibiotic resistance, with hospital effluent
138 harboring more ARGs than WWTPs (Ng et al., 2017; Rizzo et al., 2013; Rowe et al., 2017). Our

139 results are consistent with these expectations. The higher levels of antibiotic resistance in
140 residential wastewater than at WWTPs suggest that residential wastewater is also a major
141 reservoir of resistance genes and is a source of antibiotic resistance for WWTPs.

142
143 To identify common characteristics of antibiotic resistance in residential wastewater, we looked
144 for genes shared across catchment sites and found a set of 42 genes present in at least one sample
145 from each residential manhole (Figure 1A). These 42 ‘core genes’ accounted for the majority of
146 ARG abundance in residential wastewater (Figure 1B). All of these core genes were also
147 observed at high abundances in hospital effluent and WWTP influent (Figure 1A, 1B). In human
148 fecal samples, these core wastewater ARGs made up approximately 90% of the total ARG
149 abundance (median = 96.2% and 90.8% in US and South Korean individuals, respectively),
150 confirming that the majority of ARGs found in the human gut microbiome are also found in
151 wastewater (Figure 1B). Three South Korean fecal samples had high abundance of ARGs
152 (>50%) that were not part of the core set, with many of these genes conferring multidrug or beta-
153 lactam resistance (Figure S1).

154
155 However, not all of the core wastewater genes are found in human feces, suggesting that many of
156 the ARGs measured in wastewater may not be directly relevant to human health. Individual fecal
157 samples only carried approximately half of the 42 core wastewater genes at a time (median = 22
158 and 18 genes for South Korean and US samples, respectively; Figure 1C). Few core wastewater
159 genes were ubiquitously present in human feces, as only a fifth to a third of the core wastewater
160 genes were found in more than 90% of individuals (14 genes in more than 90% of South Korean
161 fecal samples; 9 in US feces). In fact, 10 of the 42 core genes were not observed in any human
162 fecal sample, suggesting that they are of environmental origin (Figure 1C). Since the transfer of
163 genes from environmental bacteria to human pathogens is less frequent than between human-
164 associated bacteria (Bengtsson-Palme and Larsson, 2015), these 10 core genes likely do not pose
165 an immediate threat to human health. Therefore, not all ARGs identified in wastewater are likely
166 to have equal relevance to human health. Some may reflect genes carried by most humans while
167 others are likely to be derived from the environment.

168 169 **3.2 Most ARGs in wastewater are not clinically-relevant, and upstream wastewater** 170 **captures more human-related resistomes**

171 To better understand how the presence of ARGs in residential wastewater relates to human
172 health risks, we categorized genes based on their potential pathogenicity. We used the method
173 described in Zhang et al. (in preparation), which ranks the risk of gene variants based on the
174 variant’s observed host pathogenicity, mobility, host range, and anthropogenic prevalence
175 (Materials and Methods). Variants classified into the top two ranks with this method are variants
176 which have been previously observed on plasmids and in a phylogenetically diverse range of
177 hosts, including human pathogens. We therefore refer to the variants in these two ranks as
178 clinically-relevant, as there exists published evidence of these mobile genes posing a substantial
179 risk for the dissemination of resistance (Martínez et al., 2015).

180
181 Most of the ARGs found in wastewater and humans are not clinically-relevant, and the majority
182 of the core wastewater genes are also not clinically-relevant. We found that clinically-relevant
183 variants make up less than 50% of the total antibiotic resistance gene abundance in all of the
184 wastewater and human samples we surveyed (Figure 2, S2). These results also held when we

185 looked at the top three ranks, which represents all mobile ARGs (Figure S3). Among the 42 core
186 wastewater genes, clinically-relevant variants were found for only 11 of the core wastewater
187 genes and represented less than 15% of the total ARG abundance in residential wastewater
188 (Figure 2, light red). These results directly support the hypothesis proposed by Martínez et al.
189 (2015), in which the number of antibiotic resistance genes that are actually acquired by human
190 pathogens and lead to clinical complications are low compared to the number of sequences
191 classified as resistance genes in metagenomic studies. Thus, simply quantifying the presence and
192 abundance ARGs in a given sample does not necessarily measure the health relevance of that
193 sample's resistome.

194
195 All types of upstream wastewater harbor more clinically-relevant ARGs than the influent of
196 WWTPs. We compared the presence and abundance of clinically-relevant variants in residential
197 wastewater to the traditionally studied environment of wastewater treatment plants. In both
198 countries (Kuwait and US) where we sampled upstream and downstream wastewater, residential
199 wastewater had higher abundances of clinically-relevant variants than the respective WWTP
200 influent (Figure 2). At the same time, WWTP influent contained fewer variants found in human
201 feces than residential wastewater. We focused on the US where data was available for human
202 fecal, residential wastewater, and WWTP influent samples. We found that of the 29 clinically-
203 relevant variants present in at least one healthy fecal sample, 90% (n = 26) were present in
204 residential wastewater. In contrast, only 76% (n = 22) were found in WWTP influents. More
205 generally, 82% (n = 270) of all of the variants found in fecal samples (n = 328) were observed in
206 residential wastewater, whereas only 59% (n = 195) of them were identified downstream in the
207 WWTP influents. The microbial composition of human waste is known to decrease in similarity
208 to the human fecal microbiota as it progresses through the sewage system (Pehrsson et al., 2016).
209 Our results suggest this decrease also occurs for resistomes, both clinically-relevant and non-
210 clinically-relevant ones, as upstream sampling better reflects the collection of microbes and
211 antibiotic resistance in the contributing human population.

212
213 Although hospital effluent has more overall ARGs and is traditionally thought of as a unique
214 hotspot for environmental antibiotic resistance, we found that residential wastewater can harbor
215 as many clinically-relevant variants as hospital effluent. U.K. hospital effluent had abundances
216 of clinically-relevant variants ranging from 821 to 1555 RPKM (Figure 2). By comparison, the
217 residential wastewater of South Korea and Kuwait had abundances of clinically-relevant variants
218 ranging from 478 to 933 RPKM and 200 to 850 RPKM, respectively (Figure 2). Previous studies
219 implicating hospital wastewater as a major source of environmental antibiotic resistance have
220 largely compared hospital wastewater with environments further downstream such as wastewater
221 treatment plants or surface water (Buelow et al., 2018; Ng et al., 2017; Rodriguez-Mozaz et al.,
222 2015; Rowe et al., 2017). Our results thus challenge the prevailing hypothesis that hospital
223 effluent represents the most concerning source of environmental antibiotic resistance genes and
224 suggests that all upstream wastewater may serve as important reservoirs of clinically-relevant
225 genes.

227 **3.3 Antibiotic resistance patterns across countries can reflect human activity**

228 To assess whether ARGs in residential wastewater reflect population-level antibiotic
229 consumption, we compared the abundance of antibiotic resistance genes with available

230 consumption data from the IQVIA MIDAS database (Klein et al., 2018). We limited our analysis
231 to South Korea and the US, where consumption data included both hospital and non-hospital use.

232
233 For certain antibiotic classes, resistance across countries reflects antibiotic consumption patterns.
234 Consumption of aminoglycoside and beta-lactam antibiotics is higher in South Korea than the
235 US, as reflected by the median abundance of resistance genes to these antibiotics in the
236 respective residential wastewater and fecal samples (Figure 3A, top and bottom row). South
237 Korean samples also had higher abundances of chloramphenicol resistance than US samples.
238 While differences in current antibiotic consumption is negligible, historical consumption of
239 chloramphenicol was higher in South Korea. Unlike the US, which phased out chloramphenicol
240 use in the 1960s, South Korea continued its usage until 2013. The presence of chloramphenicol
241 resistance may therefore be the result of persistent resistance, as previous studies have found that
242 resistance genes can persist for a long time after their introduction into the microbial flora
243 (Forslund et al., 2013). However, this hypothesis needs further validation with better
244 consumption data and direct antibiotic susceptibility testing. These resistance patterns were also
245 observed in the human fecal samples (Figure 3A, middle row) and were more evident in
246 clinically-relevant genes than non-clinically-relevant ones (Figure S4).

247
248 Other antibiotic classes, however, have resistance patterns which do not reflect known country-
249 level differences in antibiotic consumption. Sulfonamide-trimethoprim consumption is higher in
250 the US than South Korea, but resistance to sulfonamide and trimethoprim, both separately and
251 combined, were higher in South Korean samples (Figure 3B). Similarly, tetracycline
252 consumption is higher in the US than South Korea but median abundance of tetracycline
253 resistance genes showed the opposite trend. These inconsistencies emphasize how multiple
254 factors contribute to the antibiotic resistance observed in the environment (Collignon et al.,
255 2018). Other factors, such as antibiotic use in agriculture and environmental contamination with
256 antibiotics, can also drive resistance but data on them is limited (Berendonk et al., 2015; Hoelzer
257 et al., 2017). As efforts are made to fully understand the public health relevance of
258 environmental antibiotic resistance, more comprehensive data on antibiotic use across sectors as
259 well as better approaches to measuring antibiotic resistance in the environment are needed.

260
261 **3.4 Flow of antibiotic resistance genes varies across geographic scales**
262 The composition of resistomes differs between residential catchment sites within a city. Pairs of
263 samples from different residential manholes in the same city had higher beta diversity than
264 sample pairs from the same manhole (median JSD = 0.30 vs. 0.27, respectively; $p < 0.01$,
265 PERMANOVA; Figure 4A). Samples from the same manhole were collected one after another
266 with ~5 minute breaks in between (Materials and Methods). Therefore, different sets of humans
267 likely contributed to the ARGs in each sample, resulting in the observed differences between
268 these samples (Ort et al., 2005). Across manholes, however, the physical conditions of the
269 wastewater environment are also different, with levels of oxygen and temperature often varying
270 between sites (Wellcome Trust et al., 2018). These variations likely contribute to differences in
271 microbial composition and consequently, ARG composition (Huisman et al., 2004; Pehrsson et
272 al., 2016; Vollertsen and Hvitved-Jacobsen, 1999). As expected, beta diversity between samples
273 from different countries are higher than all within-city comparisons (median JSD = 0.53; $P <$
274 0.01, PERMANOVA; Figure 4A). Thus, these differences in resistome composition may reflect
275 selection resulting from different environmental conditions in individual manholes.

276
277 Despite differences in the overall resistome composition between different catchments, the
278 nucleotide diversity of individual ARGs remain similar across manholes in the same city. We
279 aligned metagenomic reads against representative nucleotide sequences to identify single
280 nucleotide polymorphisms for each antibiotic resistance gene (Materials and Method). We then
281 calculated F_{ST} values to quantify genetic diversity between samples for each gene that had
282 sufficient coverage and polymorphisms ($N = 35$; Materials and Method). F_{ST} is a measure of
283 genetic differentiation, with values ranging from 0 to 1 where 0 represents no substructure and 1
284 means completely different alleles between the subpopulations (Wright, 1951). Overall, pairs of
285 samples from different manholes within the same city did not have significantly different F_{ST}
286 values than pairs of samples from the same manhole (median $F_{ST} = 0.075$ versus 0.083,
287 respectively; $P = 0.06$, PERMANOVA). That is, variants of a gene present across multiple
288 locations within a city were as similar to each other as those found in consecutive samples taken
289 from one manhole. As expected, genes were more dissimilar across countries, suggesting that
290 there exists barriers to the distribution of ARGs across larger geographic distances (median $F_{ST} =$
291 0.14 across country versus median $F_{ST} = 0.08$ within country; $P < 0.01$, PERMANOVA; Figure
292 4B). To understand how the composition of these genes differ across catchment sites and across
293 geography, we evaluated the beta diversity of these 35 genes between samples. Similar to the
294 results for the overall resistome composition, beta diversity was highest between countries and
295 was higher between different catchments in the same city than within the same catchment
296 (Figure S5). Taken together, these results suggest that while individual manhole environments
297 play a role in selecting for abundances of genes, specific gene variants themselves likely have
298 few barriers to distribution at smaller geographical scales.
299

300 4. Conclusion

301
302 Urban sewage systems play a major role in the dissemination of antibiotic resistance from
303 humans to the environment. In this study, we evaluated the presence of antibiotic resistance
304 genes across wastewater environments, assessing their relevance and risk to human health and
305 identifying patterns across geography. We sampled upstream residential wastewater, an
306 understudied part of the sewage system that is close to the human waste sources, across multiple
307 countries and compared it with other wastewater environments to highlight challenges in the
308 evaluation of antibiotic resistance in wastewater. We found that a substantial proportion of the
309 antibiotic resistance genes commonly found in wastewater are not present in human feces and do
310 not pose an immediate threat to human health, suggesting that evaluating an environment's risk
311 to human health should not rely solely on measuring the presence of resistance genes. While
312 WWTPs and hospital effluents are traditionally viewed as antibiotic resistance hotspots, we
313 showed that residential wastewater may also be a major source of environmental resistance,
314 containing higher abundances of ARGs than WWTP samples and at times reaching comparable
315 levels of risk as hospital effluent. Although some classes of antibiotics exhibited similar patterns
316 between consumption and resistance across countries, others did not, highlighting that the
317 relationship between environmental antibiotic resistance and population-level human antibiotic
318 consumption is complex. Finally, we demonstrated that despite some differences due to
319 environmental selection between manholes, gene flow readily occurs within a city but larger
320 geographical distances serve as a barrier to gene flow.
321

322 Overall, our study highlights the challenges in evaluating the public health relevance of antibiotic
323 resistance genes found in wastewater environments and provides preliminary insights on how to
324 address these challenges. Targeting specific genes (e.g., human-associated genes, clinically-
325 relevant genes) and evaluating resistomes at different scales (e.g., nucleotide diversity,
326 compositional differences) reveals relationships between antibiotic resistance found in the
327 environment and human health. As wastewater becomes a focal point in efforts to monitor
328 population-level antibiotic resistance, targeted approaches such as those presented here can be
329 incorporated into surveillance efforts to yield more actionable public health insights.

330 **2. Material and Methods**

331

332 **2.1 Wastewater collection and processing.**

333 Grab wastewater samples (250 mL) were taken from the manholes at 13 different residential
334 catchment sites in Boston, MA (3 neighborhoods); Cambridge, MA (4 neighborhoods); Seoul,
335 South Korea (3 neighborhoods); and the surrounding areas of Kuwait City, Kuwait (3
336 neighborhoods). We also collected raw wastewater samples at a pump station directly feeding
337 into a WWTP in Chelsea, MA and at a WWTP in Sulaibiya, Kuwait (Table S1). The pump
338 station in Chelsea serves parts of the Boston metropolitan area while the Sulaibiya WWTP serves
339 parts of Kuwait City and its surrounding area. We consider samples from these two locations as
340 WWTP influent samples as they are untreated. WWTP influent samples were collected using a
341 sampling pole while samples from manholes were collected using a commercial peristaltic pump
342 (Boxer) at a sampling rate of 50 mL/min. 30 ml of collected wastewater were filtered through
343 0.2- μ m PTFE membrane filters (Millipore). PTFE membrane filters were kept in RNAlater at -
344 80 degrees Celsius until DNA extraction. The lab filtration system consisted of a Masterflex
345 peristaltic pump (Pall), Masterflex PharMed BPT Tubing (Cole-Palmer), 47 mm PFA filter
346 holders (Cole-Palmer) and 47mm PTFE Omnipore filter membranes (Millipore).

347

348 **2.2 DNA extraction and shotgun metagenomic sequencing.**

349 0.2- μ m filter membranes were thawed on ice. RNAlater was removed and filters were washed
350 with phosphate-buffered saline (PBS) buffer twice. Metagenomic DNA was extracted from each
351 filter using the Power Water extraction kit (MO BIO Laboratories Inc.), according to
352 manufacturer's instructions. Sample concentrations were quantified with the Quant-iT PicoGreen
353 dsDNA Assay (Life Technologies) and normalized to equal concentration. Paired-end libraries
354 were prepared with 100-250 pg of DNA using the Illumina Nextera XT DNA Library
355 Preparation Kit according to the manufacturer's instructions. Insert sizes and concentrations for
356 each library were determined with an Agilent Bioanalyzer DNA 100 kit (Agilent Technologies).
357 Libraries were finally sequenced on the Illumina NextSeq platform at the MIT Biomicro Center
358 to generate 2 x 150 bp paired reads. Approximately 10 million reads were generated for each
359 sample (~5 million for each pair).

360

361 **2.3 Shotgun metagenomic sequencing data processing.**

362 Raw paired-end DNA sequences (FASTQ reads) were quality controlled prior to any analysis.
363 Low-quality reads and adaptor sequences were removed using Trimmomatic version 0.36 with
364 the ILLUMINACLIP parameters: NexteraPE-PE.fa:2:30:10 SLIDINGWINDOW:4:20
365 MINLEN:50 (Bolger et al., 2014). To remove sequences resulting from human contamination,
366 we used Bowtie 2 version 2.3.0 in default mode (Langmead and Salzberg, 2012). We aligned
367 trimmed reads to the human reference genome (GRCh38) and removed the reads that mapped
368 from downstream analyses.

369

370 **2.4 Comparison of wastewater resistomes to published fecal and wastewater samples**

371 For comparison with hospital effluent wastewater and human feces, whole metagenome shotgun
372 reads were downloaded from ENA or SRA. Hospital effluent wastewater sequences was
373 obtained from Rowe et al. (2017), ENA accession PRJEB12083; Human fecal samples were
374 obtained from Lim et al. (2014), ENA accession ERP002391, for South Korea and Obregon-Tito
375 et al. (2015), SRA accession PRJNA268964, for the United States. Raw FASTQ reads from

376 these samples were processed as above and all further analyses were performed together with
377 sequences generated in this study.

378

379 **2.5 Quantification of antibiotic resistance genes**

380 To identify and quantify the abundance of antibiotic resistance genes in each quality-controlled
381 metagenomic sample, we used ShortBRED version 0.9.5 (Kaminski et al., 2015). ShortBRED
382 first clusters proteins based on shared amino acid identity and identifies unique marker
383 sequences for each cluster that distinguish them from close homologues. ShortBRED then
384 quantifies the abundance of each protein cluster by mapping reads to those unique markers.
385 Since antibiotic resistance genes can share homology with genes of non-resistance functions,
386 ShortBRED provides greater accuracy than mapping reads to the entire protein sequence.

387

388 We generated ShortBRED markers from the Structured ARG (SARG) reference database (Yang
389 et al., 2016). The SARG database contains 4,049 amino acid sequences and was constructed by
390 integrating the ARDB and CARD databases (Yang et al., 2016). We used 100% identity for
391 clustering and mapped the clustered sequences to the Integrated Microbial Genomes database
392 version 3.5 to generate the set of unique markers (Kaminski et al., 2015). We used the
393 parameters: --id 1.0 --clustid 1.0 --qclustid 1.0. In total, ShortBRED generated 9,807 marker
394 sequences. Finally, these marker sequences were used to quantify antibiotic resistance gene
395 abundance in metagenomes by mapping paired FASTQ reads to them at 99% sequence identity.
396 Abundances were normalized to reads per kilobase per million reads (RPKM).

397

398 **2.6 Risk Ranking of Antibiotic Resistance Genes**

399 We used ARG Ranker to prioritize antibiotic resistance genes based on their risk relevance to
400 human health (Zhang et al., in preparation; https://github.com/caozhichongchong/arg_ranker).
401 Building off of the risk ranking criteria outlined in Martínez et al. (2015), ARG Ranker takes the
402 genes in the SARG database and assesses their prevalence in publicly available whole genome
403 and metagenomic sequences. Since transferability is a major bottleneck that determines an
404 ARG's risk potential, genes found on the plasmids of previously-sequenced pathogen isolates are
405 ranked higher in risk potential (Rank 1-3) than genes not found in plasmids (Rank 4-5). Amongst
406 these mobile genes (Rank 1-3), those with a phylogenetically diverse range of hosts are ranked
407 higher (Rank 1-2) than those with a less phylogenetically diverse range of hosts (Rank 3). We
408 consider the genes in the top two ranks as clinically-relevant as they have the greatest potential
409 for transfer between host and environments. Abundance in anthropogenic environments versus
410 natural environments differentiate genes between the top two ranks, with genes having higher
411 abundances being ranked higher.

412

413 **2.7 Identification of single nucleotide variants**

414 We used a combination of Bowtie 2 and metaSNV to identify and quantify single nucleotide
415 variants. We first aligned metagenomic reads to a nucleotide database of representative sequence
416 for antibiotic resistance genes using Bowtie 2 version 2.3.0 (Langmead and Salzberg, 2012).
417 This database included a single nucleotide reference sequence for each gene found by
418 ShortBRED. In total, 264 ARGs were assessed. We used the nucleotide sequences from the
419 CARD database that shared > 99% similarity with the SARG database (n = 3136), as the SARG
420 database only included amino acid sequences and was constructed using CARD (Jia et al., 2017).

421 We called and filtered variants with metaSNV version 2.0 using the default setting (Costea et al.,
422 2017).

423

424 **2.8 Statistical analyses**

425 Beta diversity between residential wastewater samples was calculated at gene level using the
426 Jensen-Shannon distance (JSD). Differences in antibiotic resistance gene composition across
427 manholes and countries was evaluated using the PERMANOVA test implemented in the Python
428 package *scikit-bio* v0.4.2 (`skbio.stats.distance.permanova`).

429

430 Nucleotide diversity was measured using Wright's F_{ST} (Wright, 1951), as implemented in
431 metaSNV v.2.0 with the flag: `-div`. We only analyze genes present in all three countries ($n = 35$).
432 Comparisons between manholes and between countries were made using the PERMANOVA test
433 implemented in the Python package *scikit-bio* v0.4.2 (`skbio.stats.distance.permanova`).

434 **Code and data availability**

435 All custom scripts generated in Python to analyze the data in this paper are available through
436 GitHub (https://github.com/chengdai/amr_risk). Metagenomics sequencing data generated in this
437 study are available at NCBI Short Read Archive under Bioproject PRJNA524435.

438

439 **Supplementary Data**

440 Supplementary data related to this article can be found in the online version.

441

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451

452 **Conflicts of Interest**

453 M.G.M. and N.G. are co-founders and shareholders of Biobot Analytics. N.E. is currently
454 employed by and is a shareholder of Biobot Analytics. E.J.A. is a co-founder and shareholder of
455 Finch Therapeutics and is also a shareholder of Biobot Analytics.

456

457 **Author contributions**

458 C.L.D., C.D., and E.J.A. designed this study. M.G.M., N.G., S.P. collected the raw samples. N.E.
459 helped select the sites for sampling. M.G.M. processed the samples for sequencing. C.L.D.
460 analyzed the data. C.D., A.Z., and S.I. assisted with data analysis. C.L.D., C.D., and E.J.A. wrote
461 the paper. All authors reviewed and edited the paper. This study was conceived by E.J.A., C.R.,
462 and K.J.

463

464 **References**

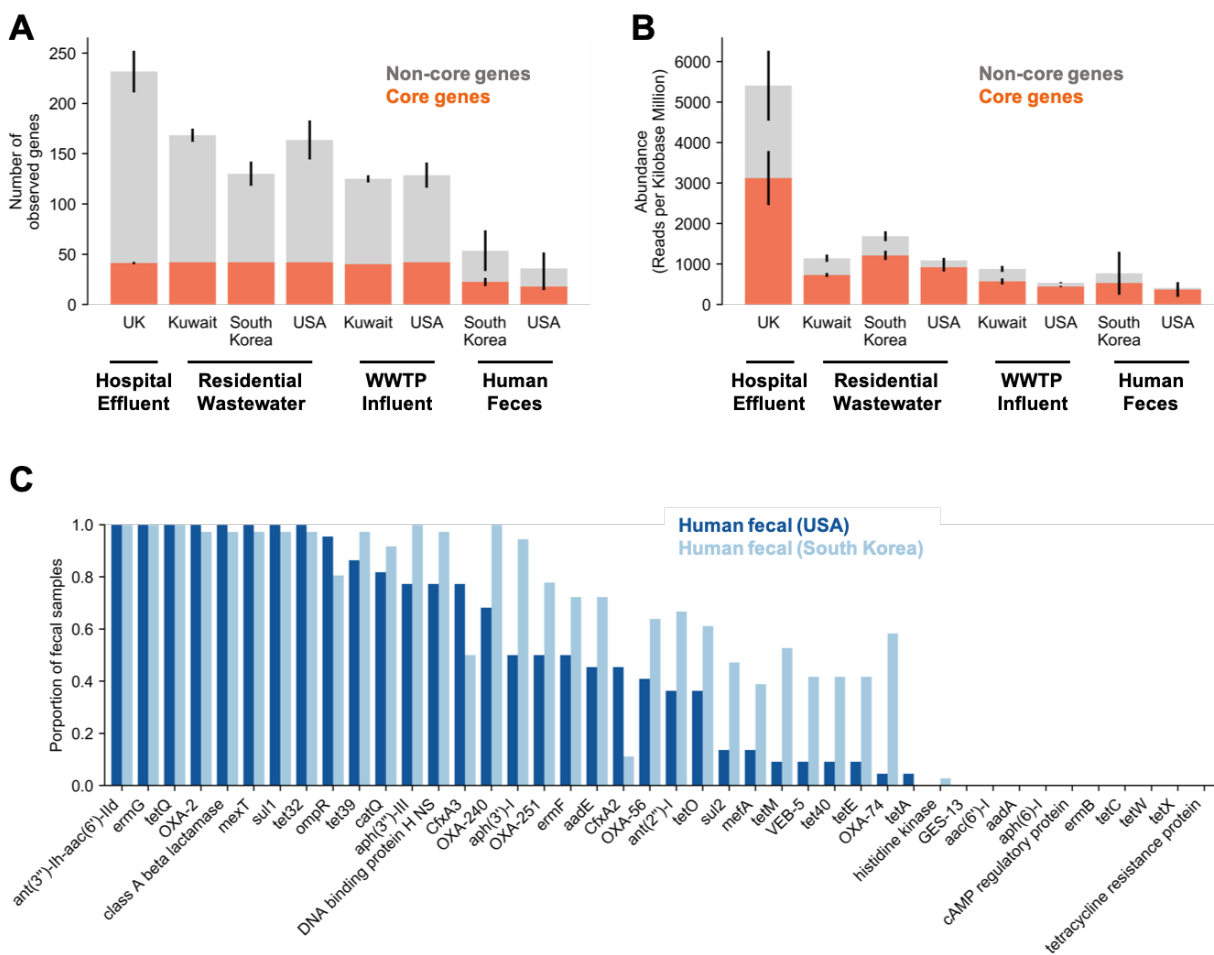
- 465 Allen, H.K., Donato, J., Wang, H.H., Cloud-Hansen, K.A., Davies, J., Handelsman, J., 2010.
466 Call of the wild: antibiotic resistance genes in natural environments. *Nat. Rev. Microbiol.*
467 8, 251–259. <https://doi.org/10.1038/nrmicro2312>
- 468 Baquero, F., Martínez, J.-L., Cantón, R., 2008. Antibiotics and antibiotic resistance in water
469 environments. *Curr. Opin. Biotechnol., Energy biotechnology / Environmental*
470 *biotechnology* 19, 260–265. <https://doi.org/10.1016/j.copbio.2008.05.006>
- 471 Bengtsson-Palme, J., Larsson, D.G.J., 2015. Antibiotic resistance genes in the environment:
472 prioritizing risks. *Nat. Rev. Microbiol.* 13, 396. <https://doi.org/10.1038/nrmicro3399-c1>
- 473 Berendonk, T.U., Manaia, C.M., Merlin, C., Fatta-Kassinos, D., Cytryn, E., Walsh, F.,
474 Bürgmann, H., Sørum, H., Norström, M., Pons, M.-N., Kreuzinger, N., Huovinen, P.,
475 Stefani, S., Schwartz, T., Kisand, V., Baquero, F., Martinez, J.L., 2015. Tackling
476 antibiotic resistance: the environmental framework. *Nat. Rev. Microbiol.* 13, 310–317.
477 <https://doi.org/10.1038/nrmicro3439>
- 478 Bolger, A.M., Lohse, M., Usadel, B., 2014. Trimmomatic: a flexible trimmer for Illumina
479 sequence data. *Bioinformatics* 30, 2114–2120.

- 480 <https://doi.org/10.1093/bioinformatics/btu170>
- 481 Buelow, E., Bayjanov, J.R., Majoor, E., Willems, R.J., Bonten, M.J., Schmitt, H., van Schaik,
482 W., 2018. Limited influence of hospital wastewater on the microbiome and resistome of
483 wastewater in a community sewerage system. *FEMS Microbiol. Ecol.* 94.
484 <https://doi.org/10.1093/femsec/fiy087>
- 485 Cantón, R., 2009. Antibiotic resistance genes from the environment: a perspective through newly
486 identified antibiotic resistance mechanisms in the clinical setting. *Clin. Microbiol. Infect.*
487 *Off. Publ. Eur. Soc. Clin. Microbiol. Infect. Dis.* 15 Suppl 1, 20–25.
488 <https://doi.org/10.1111/j.1469-0691.2008.02679.x>
- 489 Collignon, P., Beggs, J.J., Walsh, T.R., Gandra, S., Laxminarayan, R., 2018. Anthropological
490 and socioeconomic factors contributing to global antimicrobial resistance: a univariate
491 and multivariable analysis. *Lancet Planet. Health* 2, e398–e405.
492 [https://doi.org/10.1016/S2542-5196\(18\)30186-4](https://doi.org/10.1016/S2542-5196(18)30186-4)
- 493 Costea, P.I., Munch, R., Coelho, L.P., Paoli, L., Sunagawa, S., Bork, P., 2017. metaSNV: A tool
494 for metagenomic strain level analysis. *PLOS ONE* 12, e0182392.
495 <https://doi.org/10.1371/journal.pone.0182392>
- 496 D’Costa, V.M., King, C.E., Kalan, L., Morar, M., Sung, W.W.L., Schwarz, C., Froese, D.,
497 Zazula, G., Calmels, F., Debruyne, R., Golding, G.B., Poinar, H.N., Wright, G.D., 2011.
498 Antibiotic resistance is ancient. *Nature* 477, 457–461.
499 <https://doi.org/10.1038/nature10388>
- 500 European Antimicrobial Resistance Surveillance Network (EARS-Net) [WWW Document],
501 2010. . *Eur. Cent. Dis. Prev. Control.* URL [http://ecdc.europa.eu/en/about-](http://ecdc.europa.eu/en/about-us/partnerships-and-networks/disease-and-laboratory-networks/ears-net)
502 [us/partnerships-and-networks/disease-and-laboratory-networks/ears-net](http://ecdc.europa.eu/en/about-us/partnerships-and-networks/disease-and-laboratory-networks/ears-net) (accessed
503 1.11.19).
- 504 Fahrenfeld, N., J. Bisceglia, K., 2016. Emerging investigators series: sewer surveillance for
505 monitoring antibiotic use and prevalence of antibiotic resistance: urban sewer
506 epidemiology. *Environ. Sci. Water Res. Technol.* 2, 788–799.
507 <https://doi.org/10.1039/C6EW00158K>
- 508 Forsberg, K.J., Reyes, A., Wang, B., Selleck, E.M., Sommer, M.O.A., Dantas, G., 2012. The
509 shared antibiotic resistome of soil bacteria and human pathogens. *Science* 337, 1107–
510 1111. <https://doi.org/10.1126/science.1220761>
- 511 Forslund, K., Sunagawa, S., Kultima, J.R., Mende, D.R., Arumugam, M., Typas, A., Bork, P.,
512 2013. Country-specific antibiotic use practices impact the human gut resistome. *Genome*
513 *Res.* 23, 1163–1169. <https://doi.org/10.1101/gr.155465.113>
- 514 Gaze, W., Depledge, M., 2017. Antimicrobial Resistance: Investigating the Environmental
515 Dimension. United Nations Environment Programme.
- 516 Global Antimicrobial Resistance Surveillance System (GLASS) [WWW Document], 2015. .
517 WHO. URL <http://www.who.int/glass/en/> (accessed 1.11.19).
- 518 Global Sewage Surveillance Project [WWW Document], 2016. . COMPARE. URL
519 <https://www.compare-europe.eu/Library/Global-Sewage-Surveillance-Project> (accessed
520 1.11.19).
- 521 Harris, S., Morris, C., Morris, D., Cormican, M., Cummins, E., 2014. Antimicrobial resistant
522 *Escherichia coli* in the municipal wastewater system: Effect of hospital effluent and
523 environmental fate. *Sci. Total Environ.* 468–469, 1078–1085.
524 <https://doi.org/10.1016/j.scitotenv.2013.09.017>
- 525 Hoelzer, K., Wong, N., Thomas, J., Talkington, K., Jungman, E., Coukell, A., 2017.

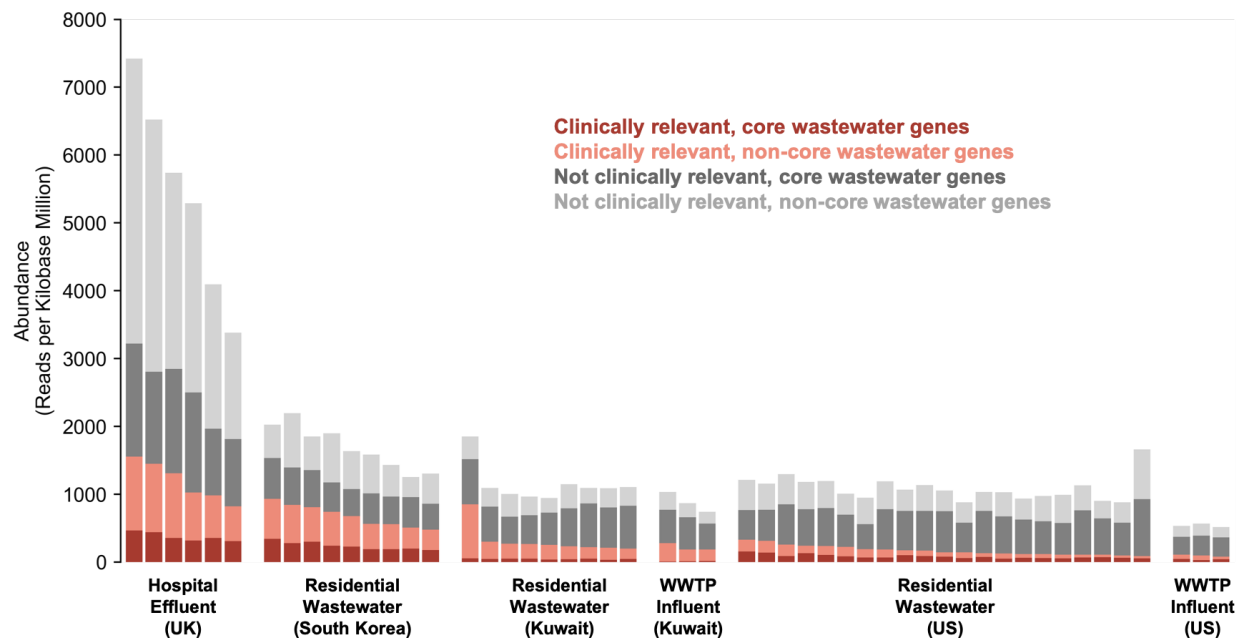
- 526 Antimicrobial drug use in food-producing animals and associated human health risks:
527 what, and how strong, is the evidence? *BMC Vet. Res.* 13.
528 <https://doi.org/10.1186/s12917-017-1131-3>
- 529 Huijbers, P.M.C., Blaak, H., de Jong, M.C.M., Graat, E.A.M., Vandenbroucke-Grauls, C.M.J.E.,
530 de Roda Husman, A.M., 2015. Role of the Environment in the Transmission of
531 Antimicrobial Resistance to Humans: A Review. *Environ. Sci. Technol.* 49, 11993–
532 12004. <https://doi.org/10.1021/acs.est.5b02566>
- 533 Huisman, J.L., Gasser, T., Gienal, C., Kühni, M., Krebs, P., Gujer, W., 2004. Quantification of
534 oxygen fluxes in a long gravity sewer. *Water Res.* 38, 1237–1247.
535 <https://doi.org/10.1016/j.watres.2003.11.012>
- 536 Jia, B., Raphenya, A.R., Alcock, B., Waglechner, N., Guo, P., Tsang, K.K., Lago, B.A., Dave,
537 B.M., Pereira, S., Sharma, A.N., Doshi, S., Courtot, M., Lo, R., Williams, L.E., Frye,
538 J.G., Elsayegh, T., Sardar, D., Westman, E.L., Pawlowski, A.C., Johnson, T.A.,
539 Brinkman, F.S.L., Wright, G.D., McArthur, A.G., 2017. CARD 2017: expansion and
540 model-centric curation of the comprehensive antibiotic resistance database. *Nucleic
541 Acids Res.* 45, D566–D573. <https://doi.org/10.1093/nar/gkw1004>
- 542 Ju, F., Beck, K., Yin, X., Maccagnan, A., McArdeell, C.S., Singer, H.P., Johnson, D.R., Zhang,
543 T., Bürgmann, H., 2018. Wastewater treatment plant resistomes are shaped by bacterial
544 composition, genetic exchange, and upregulated expression in the effluent microbiomes.
545 *ISME J.* 1. <https://doi.org/10.1038/s41396-018-0277-8>
- 546 Kaminski, J., Gibson, M.K., Franzosa, E.A., Segata, N., Dantas, G., Huttenhower, C., 2015.
547 High-Specificity Targeted Functional Profiling in Microbial Communities with
548 ShortBRED. *PLOS Comput. Biol.* 11, e1004557.
549 <https://doi.org/10.1371/journal.pcbi.1004557>
- 550 Klein, E.Y., Van Boeckel, T.P., Martinez, E.M., Pant, S., Gandra, S., Levin, S.A., Goossens, H.,
551 Laxminarayan, R., 2018. Global increase and geographic convergence in antibiotic
552 consumption between 2000 and 2015. *Proc. Natl. Acad. Sci. U. S. A.* 115, E3463–E3470.
553 <https://doi.org/10.1073/pnas.1717295115>
- 554 Kümmerer, K., 2004. Resistance in the environment. *J. Antimicrob. Chemother.* 54, 311–320.
555 <https://doi.org/10.1093/jac/dkh325>
- 556 Langmead, B., Salzberg, S.L., 2012. Fast gapped-read alignment with Bowtie 2. *Nat. Methods* 9,
557 357–359. <https://doi.org/10.1038/nmeth.1923>
- 558 Larsson, D.G.J., Andremont, A., Bengtsson-Palme, J., Brandt, K.K., de Roda Husman, A.M.,
559 Fagerstedt, P., Fick, J., Flach, C.-F., Gaze, W.H., Kuroda, M., Kvint, K., Laxminarayan,
560 R., Manaia, C.M., Nielsen, K.M., Plant, L., Ploy, M.-C., Segovia, C., Simonet, P.,
561 Smalla, K., Snape, J., Topp, E., van Hengel, A.J., Verner-Jeffreys, D.W., Virta, M.P.J.,
562 Wellington, E.M., Wernersson, A.-S., 2018. Critical knowledge gaps and research needs
563 related to the environmental dimensions of antibiotic resistance. *Environ. Int.* 117, 132–
564 138. <https://doi.org/10.1016/j.envint.2018.04.041>
- 565 Lee, J.H., Park, K.S., Jeon, J.H., Lee, S.H., 2018. Antibiotic resistance in soil. *Lancet Infect. Dis.*
566 18, 1306–1307. [https://doi.org/10.1016/S1473-3099\(18\)30675-3](https://doi.org/10.1016/S1473-3099(18)30675-3)
- 567 Lim, M.Y., Rho, M., Song, Y.-M., Lee, K., Sung, J., Ko, G., 2014. Stability of Gut Enterotypes
568 in Korean Monozygotic Twins and Their Association with Biomarkers and Diet. *Sci.
569 Rep.* 4, 7348. <https://doi.org/10.1038/srep07348>
- 570 Marti, E., Jofre, J., Balcazar, J.L., 2013. Prevalence of Antibiotic Resistance Genes and Bacterial
571 Community Composition in a River Influenced by a Wastewater Treatment Plant. *PLOS*

- 572 ONE 8, e78906. <https://doi.org/10.1371/journal.pone.0078906>
- 573 Martínez, J.L., 2018. Ecology and Evolution of Chromosomal Gene Transfer between
574 Environmental Microorganisms and Pathogens. *Microbiol. Spectr.* 6.
575 <https://doi.org/10.1128/microbiolspec.MTBP-0006-2016>
- 576 Martínez, J.L., Coque, T.M., Baquero, F., 2015. What is a resistance gene? Ranking risk in
577 resistomes. *Nat. Rev. Microbiol.* 13, 116–123. <https://doi.org/10.1038/nrmicro3399>
- 578 Munir, M., Wong, K., Xagorarakis, I., 2011. Release of antibiotic resistant bacteria and genes in
579 the effluent and biosolids of five wastewater utilities in Michigan. *Water Res.* 45, 681–
580 693. <https://doi.org/10.1016/j.watres.2010.08.033>
- 581 National Antimicrobial Resistance Monitoring System for Enteric Bacteria (NARMS) [WWW
582 Document], 2018. . Cent. Dis. Control Prev. URL <https://www.cdc.gov/narms/index.html>
583 (accessed 1.11.19).
- 584 Ng, C., Tay, M., Tan, B., Le, T.-H., Haller, L., Chen, H., Koh, T.H., Barkham, T.M.S.,
585 Thompson, J.R., Gin, K.Y.-H., 2017. Characterization of Metagenomes in Urban Aquatic
586 Compartments Reveals High Prevalence of Clinically Relevant Antibiotic Resistance
587 Genes in Wastewaters. *Front. Microbiol.* 8. <https://doi.org/10.3389/fmicb.2017.02200>
- 588 Obregon-Tito, A.J., Tito, R.Y., Metcalf, J., Sankaranarayanan, K., Clemente, J.C., Ursell, L.K.,
589 Zech Xu, Z., Van Treuren, W., Knight, R., Gaffney, P.M., Spicer, P., Lawson, P., Marin-
590 Reyes, L., Trujillo-Villarreal, O., Foster, M., Gujja-Poma, E., Troncoso-Corzo, L.,
591 Warinner, C., Ozga, A.T., Lewis, C.M., 2015. Subsistence strategies in traditional
592 societies distinguish gut microbiomes. *Nat. Commun.* 6, 6505.
593 <https://doi.org/10.1038/ncomms7505>
- 594 Ort, C., Schaffner, C., Giger, W., Gujer, W., 2005. Modeling stochastic load variations in sewer
595 systems. *Water Sci. Technol.* 52, 113–122. <https://doi.org/10.2166/wst.2005.0122>
- 596 Pehrsson, E.C., Tsukayama, P., Patel, S., Mejía-Bautista, M., Sosa-Soto, G., Navarrete, K.M.,
597 Calderon, M., Cabrera, L., Hoyos-Arango, W., Bertoli, M.T., Berg, D.E., Gilman, R.H.,
598 Dantas, G., 2016. Interconnected microbiomes and resistomes in low-income human
599 habitats. *Nature* 533, 212–216. <https://doi.org/10.1038/nature17672>
- 600 Rizzo, L., Manaia, C., Merlin, C., Schwartz, T., Dagot, C., Ploy, M.C., Michael, I., Fatta-
601 Kassinos, D., 2013. Urban wastewater treatment plants as hotspots for antibiotic resistant
602 bacteria and genes spread into the environment: A review. *Sci. Total Environ.* 447, 345–
603 360. <https://doi.org/10.1016/j.scitotenv.2013.01.032>
- 604 Rodriguez-Mozaz, S., Chamorro, S., Martí, E., Huerta, B., Gros, M., Sánchez-Melsió, A.,
605 Borrego, C.M., Barceló, D., Balcázar, J.L., 2015. Occurrence of antibiotics and antibiotic
606 resistance genes in hospital and urban wastewaters and their impact on the receiving
607 river. *Water Res.* 69, 234–242. <https://doi.org/10.1016/j.watres.2014.11.021>
- 608 Rowe, W.P.M., Baker-Austin, C., Verner-Jeffreys, D.W., Ryan, J.J., Micallef, C., Maskell, D.J.,
609 Pearce, G.P., 2017. Overexpression of antibiotic resistance genes in hospital effluents
610 over time. *J. Antimicrob. Chemother.* 72, 1617–1623. <https://doi.org/10.1093/jac/dkx017>
- 611 The Review on Antimicrobial Resistance, 2014. Antimicrobial Resistance: Tackling a crisis for
612 the health and wealth of nations.
- 613 Topp, E., Larsson, D.G.J., Miller, D.N., Van den Eede, C., Virta, M.P.J., 2018. Antimicrobial
614 resistance and the environment: assessment of advances, gaps and recommendations for
615 agriculture, aquaculture and pharmaceutical manufacturing. *FEMS Microbiol. Ecol.* 94.
616 <https://doi.org/10.1093/femsec/fix185>
- 617 Varela, A.R., André, S., Nunes, O.C., Manaia, C.M., 2014. Insights into the relationship between

- 618 antimicrobial residues and bacterial populations in a hospital-urban wastewater treatment
619 plant system. *Water Res.* 54, 327–336. <https://doi.org/10.1016/j.watres.2014.02.003>
- 620 Vollertsen, J., Hvitved-Jacobsen, T., 1999. Stoichiometric and kinetic model parameters for
621 microbial transformations of suspended solids in combined sewer systems. *Water Res.*
622 33, 3127–3141. [https://doi.org/10.1016/S0043-1354\(99\)00033-0](https://doi.org/10.1016/S0043-1354(99)00033-0)
- 623 Wellcome Trust, Center for Disease Control, UK Science & Innovation Network, 2018.
624 Initiatives for Addressing Antimicrobial Resistance in the Environment: Current
625 Situation and Challenges.
- 626 World Health Organization (Ed.), 2014. Antimicrobial resistance: global report on surveillance.
627 World Health Organization, Geneva, Switzerland.
- 628 Wright, S., 1951. The genetical structure of populations. *Ann. Eugen.* 15, 323–354.
- 629 Yang, Y., Jiang, X., Chai, B., Ma, L., Li, B., Zhang, A., Cole, J.R., Tiedje, J.M., Zhang, T., 2016.
630 ARGs-OAP: online analysis pipeline for antibiotic resistance genes detection from
631 metagenomic data using an integrated structured ARG-database. *Bioinforma. Oxf. Engl.*
632 32, 2346–2351. <https://doi.org/10.1093/bioinformatics/btw136>
- 633 Zaman, S.B., Hussain, M.A., Nye, R., Mehta, V., Mamun, K.T., Hossain, N., 2017. A Review on
634 Antibiotic Resistance: Alarm Bells are Ringing. *Cureus* 9, e1403.
635 <https://doi.org/10.7759/cureus.1403>
- 636 Zhang, An-ni, Li, L.-G., Tiedje, J., Alm, E.J., Zhang, T., n.d. Whom to Fight: Top Risk
637 Antibiotic Resistances for Global Action. Prep.



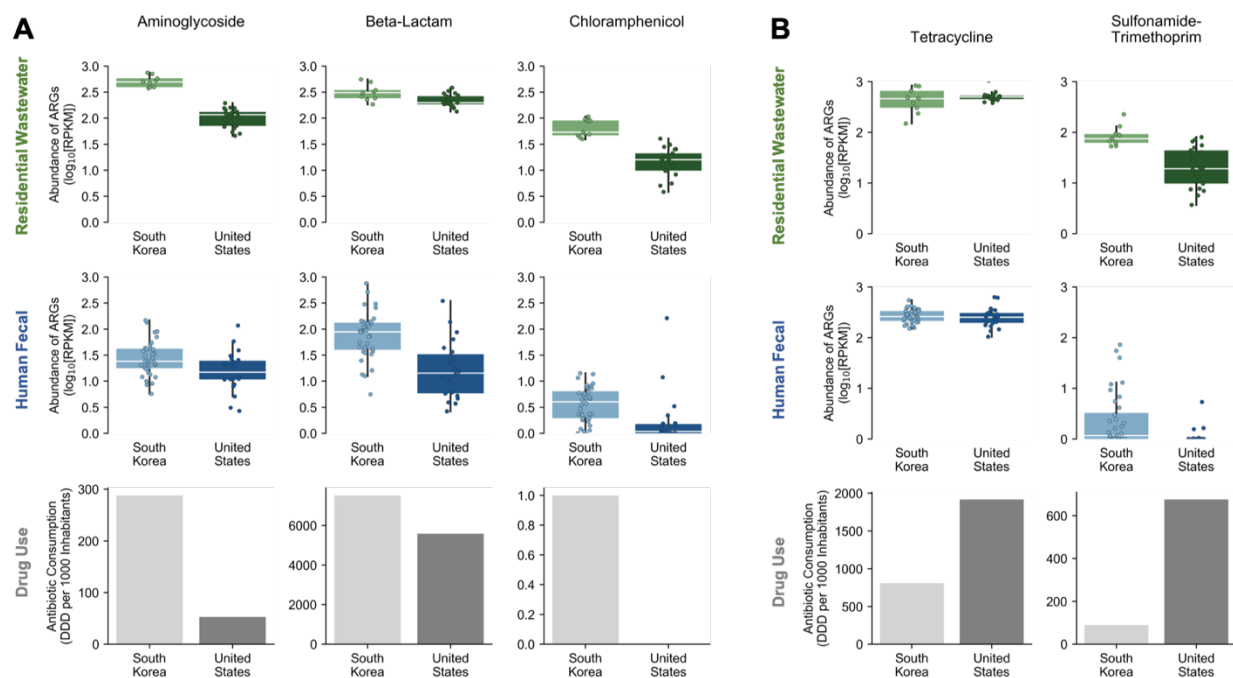
638
 639 **Figure 1. Presence and abundance of antibiotic resistance genes across environments**
 640 (A) Number of antibiotic resistance genes observed per environment. Orange coloring represent the core
 641 wastewater genes (n = 42) while grey colorings represent the remaining non-core genes. Error bars for
 642 each coloring (orange and grey) represent the standard deviations in the number of genes present for that
 643 category.
 644 (B) Abundance of antibiotic resistance genes observed per environment in reads per kilobase millions.
 645 Coloring and error bars represent the same as in (A).
 646 (C) Proportion of the human fecal samples in South Korea (n = 36) and the US (n = 22) with each core
 647 wastewater gene.



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650 **Figure 2. Risk prioritization of antibiotic resistance genes in wastewater environments**

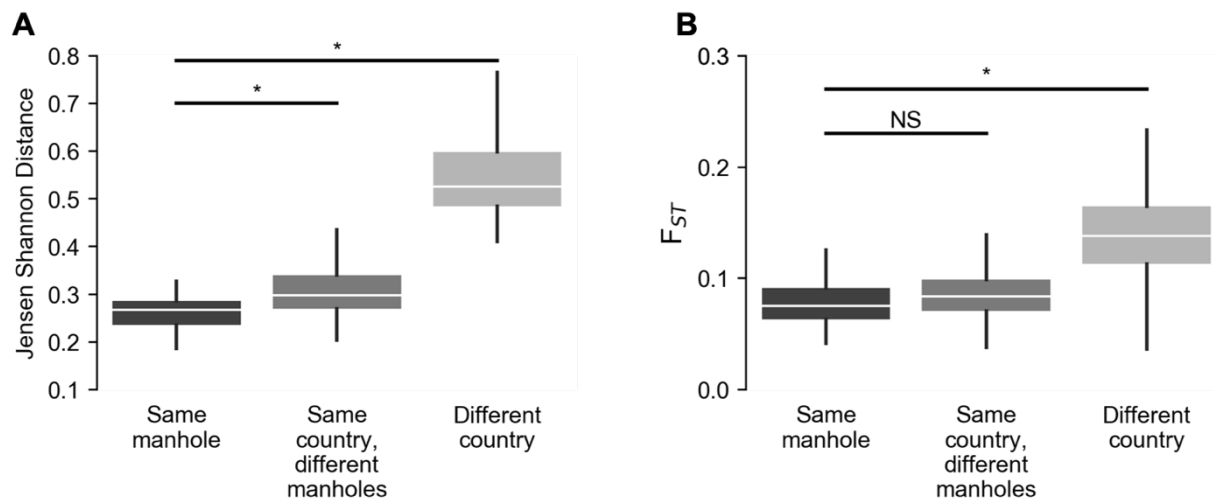
651 Abundance of antibiotic resistance gene in each wastewater environment, categorized by risk. Proportions
652 in shades of red represent abundances of clinically-relevant antibiotic resistance genes while shades of
653 grey represent non-clinically-relevant genes. Within each coloring (red and grey), genes in the core set of
654 wastewater genes are shaded darker (i.e., dark red = genes which are clinically relevant and core; dark
655 grey = genes which are not clinically relevant and core). Samples within each environment are ranked in
656 descending order based on total abundance of clinically relevant genes. Genes are defined as clinically-
657 relevant if they have previously been observed on plasmids and have a phylogenetically diverse range of
658 hosts. Abundances are measured in reads per kilobase million.



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661 **Figure 3. Antibiotic resistance and antibiotic consumption across geography by drug class**

662 Patterns of antibiotic resistance in residential wastewater (top panels) and human feces (middle panels)
663 and patterns antibiotic consumption (bottom panels) between South Korea and the United States.
664 Antibiotic resistance and antibiotic consumption pattern show concordance for some classes of antibiotics
665 (A) but not for others (B). Antibiotic resistance is represented in log abundances of reads per kilobase
666 million (RPKM) while antibiotic consumption is represented in defined daily dose (DDD) per 1,000
667 inhabitants. Each point represents one sample. The y-axis range for each antibiotic consumption plot is
668 different. Data for antibiotic consumption (2015) was obtained from the IQVIA MIDAS database (Klein
669 et al., 2018; <https://resistancemap.cddep.org/AntibioticUse.php>).



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672 **Figure 4. Beta diversity and nucleotide diversity of antibiotic resistance genes across different**
673 **geographical scales**

674 (A) Beta diversity in Jensen Shannon Distance of resistomes between samples at different scales of
675 geographical comparisons. *P < 0.01

676 (B) Nucleotide diversity of resistomes between samples at different scales of geographical comparisons.

677 Nucleotide diversity between each pair of samples was measured in terms of the average F_{ST} of genes with
678 sufficient coverage and polymorphism (n = 35; Material and Methods). *P < 0.01. NS = not significant.