Swine Growth Promotion with Antibiotics or Alternatives Increases Antibiotic Resistance Gene Mobility Potential in the Fecal Microbiome

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Running Title: Growth Promotion Mobilizes Antimicrobial Resistance

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Abstract

The use of antimicrobials in animal production has been shown to increase the abundance of antibiotic resistance genes (ARGs) in microbiomes and it is recommended by international health organizations that the use of antimicrobial growth promoters would be restricted. Consequently, the use alternative growth promoters is increasing, however, their influence on the collection of ARGs (the resistome) in the animal microbiome is understudied. We investigated the impact of different growth promoters on the pig fecal resistome and microbiome. The growth promoters were carbadox (antibiotic), copper sulfate and zinc oxide (metal) or mushroom powder (natural product). Six pens of seven weanling piglets per treatment were used in a growth trial and after 33 days, fecal samples were taken from one median weight female and male pig per pen. Samples from the same pen were pooled, and DNA was isolated. The community composition was investigated by 16S rRNA gene sequencing and relative ARG and mobile genetic element (MGE) abundances were measured using qPCR array with 382 primers. Only modest shifts were observed in community structure and resistome in response to growth promoters, but more ARGs were co-occurring with MGEs in growth promoter group samples than in the control group samples. The taxonomic structure could not be linked to resistome structure in the growth promoter groups. The ARG–MGE co-occurrence patterns suggest that replacing the use of antibiotics with alternative growth promoters might be an insufficient antibiotic resistance mitigation strategy and active selection against ARGs will require a more comprehensive approach.

Importance

Due to increasing antimicrobial drug resistance of pathogenic bacteria, international organizations are advising livestock and poultry industries to limit the use of antimicrobials in growth promotion. Together with growing consumer concerns towards antimicrobials, the

markets are favorable to alternative growth promoters. Since the interest towards enhancing animal productivity and health through microbiomes is also increasing, it is important to study the linkages between the resistome and bacterial community structure to avoid enriching ARGs in animal microbiomes. Our study explores the influences of different growth promoters on the bacterial community and resistome compositions and we show that resistance gene mobility should be taken into account when considering the changes in agricultural antibiotic use policies.

Introduction

Antibiotics have been used in pork production to prevent diseases and to increase productivity since the 1940's (1, 2). Due to the established connection of antibiotic use in animals and the emergence of antibiotic resistance in pathogenic bacteria (e.g. 3), in 2017, the use of medically important antibiotics as growth promoters was prohibited in the U.S. (4) Additionally, a report to the Secretary General of the United Nation suggests that antibiotic growth promoters should be completely phased out from livestock production (5). Currently, the livestock industry is adapting to reduced antibiotic use for growth promotion and because consumer concerns towards antibiotic use in animal agriculture are increasing, the markets are favorable to antibiotic alternatives (6, 7).

Despite the increasing restrictions, some antibiotics can still be used for growth promotion of animals, but interest towards antibiotic-alternative growth promoters is increasing rapidly. Among the antibiotics that are still allowed for growth promotion, carbadox is used in pigs mainly to control dysentery and bacterial enteritis. Carbadox can cause short-term but also long-lasting alterations in the microbiome (8) and can promote the mobility of antibiotic resistance genes (ARGs) through transduction (9). Numerous antibiotic alternatives are currently under study for their efficacy to promote animal growth and gastrointestinal health. Of special interest among natural products that can be used in growth promotion are medicinal mushrooms.

Cordyceps militaris and *Ophiocordyceps sinensis* (formerly *C. sinensis*) produce many bioactive compounds, such as Cordycepin and Beta-Glucan, which have antimicrobial effects and can enhance the immune system (10). Zinc (Zn) and copper (Cu) are important trace elements for all organisms and livestock animals commonly receive feed supplements that ensure their required concentration in the feed. Higher concentrations of Zn and Cu can be used for controlling various bacterial infections in livestock animals, such as diarrheal diseases (7) and also for growth promotion (7, 11, 12). However, use of Zn oxide has shown to select zoonotic methicillin resistant *Staphylococcus aureus* (MRSA) and multiresistant *E. coli* (13–16). In-feed supplemented Cu can increase the prevalence of erythromycin resistance in gram-positive bacteria (17) and various plasmid-mediated resistance genes in microbiomes (16, 18). Thus, it seems that alternative growth promoters may also select ARGs similarly as the antibiotics they are meant to replace.

Several studies have found that metals and growth promotion antimicrobials can select for antibiotic resistance and promote horizontal gene transfer, but the capability of natural products to select resistance and increase resistance gene mobility is currently understudied. It has also shown that the taxonomic composition may explain resistance composition (19, 20). Since growth promoters alter the gut microbial community composition, it has been proposed that the microbiota composition could be manipulated to act as a “growth promoter” by inducing populations favorable to animal growth and gut health (21). Therefore, it would be important to determine if the populations linked to induced animal growth carry resistance genes and mobile genetic elements (MGEs). However, making connections between taxonomic data and resistance gene data can be challenging, since microbiome datasets are compositional and rarely meet assumptions of normality that many statistical tests require (22, 23). In addition, it has been pointed out that different normalization strategies could influence the results derived from sequence data (24, 25).

In order to examine the influence of carbadox, cordyceps mushroom powder and pharmacological concentrations of Zn and Cu on the community composition and resistome (26), we took fecal samples from pigs that were administered these growth promoters, extracted DNA, analyzed 16S rRNA gene sequences and quantified genes related to resistance and gene transfer with 382 primer pairs using high-throughput qPCR array (27, 28). We also compared two 16S rRNA gene sequence normalization strategies using statistical analyses that are suitable for compositional data. Our results suggest that inclusion of ARGs into MGEs led to uncoupling of bacterial community composition and resistome composition in response to growth promotion, highlighting the importance of MGEs in shaping the resistomes under the influence of antimicrobial agents.

Results

Samples and data quality control

Samples were collected from pigs that had been assigned into non-treatment control group (NTC = no antibiotic or alternative growth promoters), or one of the growth promoter groups (AB = carbadox, M = mushroom powder mixture of *C. militaris* and *O. sinesis*, ZnCu = Zn oxide and Cu sulfate). Each treatment group consisted of six pens and each pen had seven pigs. The DNA for 16S rRNA gene sequencing was extracted from combined fecal samples of one medium weight female and male per pen. After quality filtering, a total of 741,785 sequences were obtained. For 22 samples sequences per sample ranged from 11,392 to 67,072. Two samples were discarded due to low number of sequences, resulting in five samples in the NTC and AB groups. The data analysis for 16S rRNA gene sequencing was completed using two different methods: rarefication and subsampling or total sum scaling (TSS). The TSS normalized 16S rRNA gene sequence data had 132 observed taxonomical units (OTUs), while rarefied and subsampled 16S rRNA gene sequence data 127 OTUs. The same DNA samples were used for

qPCR array analysis to examine how the treatments altered the resistome. One hundred and thirty-six assays out of 382 assays (Table S1) targeting antibiotic resistance genes (ARGs) or mobile genetic elements (MGEs) were positive. See materials and methods for qPCR data processing and Ct value adjustment for four assays that had unspecific amplification.

The profiles of most abundant genera and genes were similar in different treatment groups

To take into account the influence of normalization of 16S rRNA gene sequence reads on the results, we used two different normalization methods. Only small differences were discovered between TSS normalized and rarefied and subsampled OTUs among the most abundant genera (Fig. 1A and B). The TSS normalized OTUs and rarefied and subsampled OTUs correlated significantly ($\rho = 0.97$, $p < 0.05$) (Fig. S1), indicating the agreement of the overall community composition of the two normalization methods. *Prevotella* was the most abundant genera in all treatments and all samples had several short chain fatty acid producers (Fig. 1A and B). Very few OTUs were found only in one treatment group with both normalization methods and a majority of the OTUs were found in all treatment groups, however more OTUs were found in all treatment groups using TSS normalization than rarefied and subsampled normalization (Fig. 1D and E).

The different treatment groups also had similar resistome profiles (Fig. 1C). The NTC had the highest number of positive assays (110), the AB group had 106 positive assays, The M group had 100 positive assays and the ZnCu group had 103 positive assays. Twenty-eight genes were detected in only one treatment group, but most genes were found in all treatment groups (Fig. 1F). Out of the positive assays, 108 targeted ARGs and 28 MGEs. Among the detected ARGs, altogether 63 conferred resistance to aminoglycosides, MLSBs or tetracyclines and the most common resistance mechanism was antibiotic deactivation (Fig. S2A and B). Among MGEs, most positive assays targeted insertion sequences (12) or transposases (7) (Fig. S2C).

Growth promoters favored different genera, ARGs and MGEs

Generalized linear models (GLMs) were used for testing which genera, ARGs and MGEs differed in abundance between treatments. Mostly only minor differences in abundance of different genera were found between treatment groups (Fig. S3A and B). Compared to all other growth promoters, carbadox favored unclassified *Veillonellaceae* in feces and decreased the abundance of *Streptococcus*, whereas Zn and Cu decreased the abundance of *Bifidobacterium* and *Campylobacter* ($p < 0.05$, gamma distribution GLMs [TSS OTUs] and negative binomial GLMs [rarefied and subsampled OTUs]) (Fig. 2A and B, Table S2 and S3). Mushroom powder decreased the abundance of fecal *Roseburia* and favored *Campylobacter* comparted to other treatments ($p < 0.05$, gamma distribution GLMs [TSS OTUs] and negative binomial GLMs [rarefied and subsampled OTUs]) (Fig. 2A and B, Table S2 and S3). *Streptococcus* were more abundant in M and ZnCu group samples compared to other groups ($p < 0.05$, gamma distribution GLMs [TSS OTUs] and negative binomial GLMs [rarefied and subsampled OTUs]) (Fig. 2A and B, Table S2 and S3). More ARGs and MGEs were differentially abundant in NTC group and M group compared to ZnCu and AB groups (Fig. S3C). Compared to other growth promoters, carbadox and Zn and Cu increased the relative abundance of *vat(E),* mushroom powder increased the relative abundance of *tetW*, and Zn and Cu favored *tetM* ($p < 0.05$, gamma distribution GLMs) (Fig. 2C, Table S4). Interestingly, carbadox treatment decreased the relative abundance of six antibiotic resistance genes of the most abundant and differentially abundant ARGs and MGEs compared to other treatments or to NTC group ($p < 0.05$, gamma distribution GLMs) (Fig. 2C, Table S4).

Both OTU normalization methods yielded similar results for differential OTU abundance in the treatment groups (Fig. 2A and B). The exceptions were that *Phascolarctobacterium* was among the differentially abundant genera when TSS normalization was used, whereas *Faecalibacterium* was differentially abundant when rarefying and subsampling was used (Fig.

2A and B) and that more genera were differentially abundant when TSS normalization was used (Table S2 and Table S3).

Growth promoters had modest influences on overall bacterial community composition and resistome

With both TSS normalized OTUs and rarefied and subsampled OTUs, the treatment group explained 24% of the variability in community composition (PERMANOVA, $R^2 = 0.239$, $p < 0.05$). With ARGs and MGEs, the treatment group explained 27% of the variability (PERMANOVA, $R^2 = 0.267$, $p < 0.05$). The number of sequences per sample was also included as a variable in the PERMANOVA model with both normalization methods, but the library size did not have influence on the community variability in our samples ($p > 0.05$).

The different growth promoters altered the community composition and resistome only slightly, since in all non-metric multidimensional scaling (NMDS) ordinations the samples belonging to different treatment groups clustered close to each other with mostly overlapping centroid confidence intervals (Fig. 3A, B and D). In ordinations of TSS normalized and rarefied and subsampled OTU-tables, the ZnCu group tended to cluster further away from the other samples indicating more dissimilar community composition (Fig. 3A and B), however there were no significant differences between treatment groups among pairwise PERMANOVA comparisons. In the ordination of the ARG and MGE data, there was no separation between ZnCu group and the other groups, instead the M group clustered slightly separately (Fig. 2D) and in the pairwise comparisons using the ARG and MGE data, M vs. AB group explained 32% of the variance (PERMANOVA, $R^2 = 0.321$, $p < 0.05$), but in all the other pairwise comparisons the differences were nonsignificant ($p > 0.05$)

Taxonomic variation did not explain resistome variation in growth promoter group samples

The OTU ordinations were correlated against each other and against the ARG and MGE NMDS ordination using Procrustes analysis to determine if the taxonomic variation explains resistome variation. The two OTU NMDS ordinations had reasonably high (0.7) and significant ($p < 0.05$) correlation and the Procrustes residual error remained lower than 0.25 in all samples except one (Fig. 3C). The correlation between the rarefied and subsampled OTU ordination (which did not include all the data due to subsampling) and the ARG and MGE ordination was moderately high (0.6, $p < 0.05$) and there was no pattern in Procrustes residual errors across different samples (Fig. 3F). Contrariwise, the correlation between the TSS normalized OTU ordination (that included all quality filtered data) and the ARG and MGE ordination was nonsignificant ($p > 0.05$) and Procrustes residual errors were high in most samples not belonging to NTC group, in which the residual errors were mostly equal or less than the first quantile residual value (Fig. 3E). The Procrustes analyses performed on TSS normalized OTUs and resistome implies that taxonomic variation explained resistance variation in NTC samples with less error. However, growth promoters altered the resistome, resulting higher residual errors in samples belonging to AB, M and ZnCu groups and thus the overall correlation between TSS normalized OTU ordination and ARG and MGE ordination was not significant (Procrustes analysis, $p > 0.05$).

The links between bacterial community structure and resistome were further examined with Mantel's test using Spearman's rank correlation. The correlation coefficients between distance matrix of TSS normalized OTUs and ARGs and MGEs distance matrix as well as the distance matrix of rarefied and subsampled OTUs and ARGs and MGEs distance matrix were low ($\rho = 0.25$ and $\rho = 0.23$, respectively, $p < 0.05$), which suggests that the phylogenetic composition did not govern the resistome composition when all samples were included in the

analysis. We also used Mantel's test for all treatment groups individually. With NTC group and both OTU normalization methods, the bacterial community distance matrix correlated significantly with the distance matrix obtained from ARGs and MGEs (ρ = 0.66 [TSS OTUs] and ρ = 0.62 [rarefied and subsampled OTUs], $p < 0.05$). With all growth promoter groups and both OTU normalization methods, the correlations between OTU and ARG and MGE distance matrixes were nonsignificant, giving more evidence that the growth promoters shaped the resistance composition and thus taxonomic variation did not explain the resistance variation in the growth promoter group samples. It should be denoted that we had only five or six samples in each treatment group, however, the results were consistent, since the correlations between taxonomic structure and resistome were reasonably high and significant in NTC group and nonsignificant in all other groups.

Growth promoters increased the co-occurrences of ARGs and MGEs

A correlation matrix between ARG and MGE relative abundances was visualized using network analysis to examinine if the growth promoters selected resistance genes into mobile genetic elements. The network of NTC group was simpler compared to growth promoter group networks as the number of correlating ARGs and MGEs increased in response to growth promotion (Fig. 4). There were no integrons co-occurring with resistance genes in the NTC group network, but integrons were present in all the growth promoter group networks (Fig. 4) and co-occurred with many ARGs. AB and M group networks had more aminoglycoside resistance genes than other networks and M group also had the most multidrug resistance genes, but the least tetracycline resistance genes, whereas AB group network had the most vancomycin resistance genes (Fig. 4).

Transposase gene for insertion sequence-like element IS1216 was the best predictor for resistance and community composition

We used machine learning approaches to identify drivers of change in community composition. First, a cluster analysis was performed on a combined data table of TSS normalized OTUs and ARGs and MGEs using *t*-distributed stochastic neighbor embedding (t-SNE) algorithm (29) and HDBSCAN algorithm (30). Then, a classification random forests model (31, 32) was used for identifying the predictors for the clustering pattern. Three clusters were identified after dimension reduction. Most of the samples belonged to cluster 2, while cluster 1 had two ZnCu samples, one M group sample and one AB group sample, and cluster 3 contained only three ZnCu samples (Fig. 5A). According to the partial dependence plot that shows the most important predictors found by the classification random forests model, clusters 1 and 3 were separated from cluster 2 due to higher abundance of transposase gene linked to IS1216 element and from each other because the abundance of *tetO* was lower in cluster 3 (Fig. 5B). Five of the nine best predictors for clustering pattern were MGEs and ARGs and four were bacterial genera (Fig. 5B). Interestingly, most of the samples belonging to clusters 1 and 3 originate from animals, which were kept in pens that were close to each other (five out of seven) (Fig. 5C). Unfortunately, we could not analyze the possible influence of the pen location, since we had only one sample from each pen and only 21 samples in the statistical analysis using both taxonomy and resistome data. In addition, only one of the ZnCu group samples belongs to the cluster 2 with most of the samples and since all the other ZnCu samples clustered to clusters 1 and 3. Thus, growth promotion with Zn and Cu might cause more alterations in the community composition and resistome than the other growth promoters examined in this study.

Discussion

Our study explores the influences of antibiotic and alternative growth promoters on the pig fecal resistome, resistome mobility, and bacterial community composition. We did not have an alternative growth promoter that would not have antimicrobial effects in our study; however, the abundances of ARGs and MGEs were on similar level in the non-treatment control group and the growth promoter groups. Our results indicate that it is unlikely that changing the substance that is used for growth promotion would reduce antimicrobial resistance in the pig fecal microbiome at least in a short period of time (33 days in this study). Gut bacteria, especially gram-negative species, are known to carry many ARGs and MGEs and the gastro-intestinal tract is suspected to be a major hotspot for horizontal gene transfer (33, 34). These observations have also been made with individuals without antibiotic exposure (35, 36).

Interestingly, many ARGs were less abundant in the AB group than in the NTC group and alternative growth promotion groups. A potential explanation for this could be that carbadox is a broad acting antibiotic and effects most bacterial populations equally when carbadox resistance is not present (8). Overall, we did not observe large shifts among genera as a result of growth promotion feed additives. *Bifidobacteria*, which have been previously linked to lower antibiotic resistance level (37, 38), were somewhat more abundant in the NTC and M group samples; however, in this study the ARG abundances in samples belonging to different groups were similar. It is possible that the shifts in the community composition caused by growth promoters were small with high variability and thus the changes in the community structure are difficult to capture with community-wide molecular approaches.

We were able to link the resistome structure to taxonomic structure only in the NTC group samples. In all other samples we did not find the connection between resistome and community composition. Some have reported that community composition predicts resistance profile (19, 20, 39), while others have reported that under the presence of a selective pressure

phylogeny and resistance profile become uncoupled (40). Our network analysis revealed that growth promoters increased linkages between ARGs and MGEs. It seems possible that the growth promoters would have increased the horizontal gene transfer mechanisms in the pig gut microbiome and thus more ARGs were incorporated into MGEs in the resistome of growth promoter group pigs than in the resistome of NTC group pigs. Another possible scenario is that bacteria carrying more complex MGEs would have tolerated the growth promoters better than bacteria carrying simpler MGEs, possible due to more variability in stress response mechanisms (16, 41). Despite the mechanism, more ARGs co-occurring with MGEs in response to growth promotion could indicate more persistent resistance gene collection (42).

Taken alone, the rarefied and subsampled OTU data and TSS normalized OTU data mostly agreed; however, in Procrustes analysis, the rarefied and subsampled OTU data correlated significantly with the resistome data when all samples were used, although the same analysis using the TSS normalized data as input showed that the taxonomic data did not explain resistance. It is important to understand that rarefying and subsampling captures the most abundant OTUs for each sample (25) and discards rare OTUs. Additionally, OTU abundances in different samples are slightly adjusted. If the sample size and differences in OTU abundances are small before the procedure, the shifts might change the outcome if OTU data is used in comparison with data obtained using a different method. Thus, researchers making connections between taxonomic data and resistome observations should use multiple methods to confirm their findings.

Although the shifts in community composition and resistome were modest and mostly nonsignificant, we were able to find differences in community structures with machine learning methods. The differences we observed did not precisely follow the experimental grouping, and therefore they were not found with commonly used ordination methods or differential abundance analysis. The transposase gene linked to IS1216 element that was the driver for the clustering

result has been previously associated to Gram-positive bacteria (40, 43) and since this element was abundant in seven samples belonging to two smaller clusters in our analysis, it is tempting to speculate that the populations in the larger cluster were more dominated by Gram-negative bacteria, which are known to spread easily within pig herds. Since the clustering pattern somewhat followed the locations of experimental pens, it could indicate that spreading of bacteria between animals may be one of the factors shaping microbiomes and resistomes. However, evaluating the ARG disseminating potential of bacteria spreading between the animals is not possible with our experimental design and would require further studies.

Conclusions

Under this experimental design, the withdrawal of antibiotics did not decrease antibiotic resistance, however, we did not observe enrichment of antimicrobial resistance in response to growth promotion either. Instead our results show that growth promoters increased the connections between ARGs and MGEs, which indicates that all tested growth promoters can increase and maintain resistance gene mobility. Only modest changes in the community composition and resistome and increased linkages between ARGs and MGEs suggests that MGEs may be even more important vehicles in dissemination of antimicrobial resistance under the influence of growth promoters than the selection pressure caused by used substances. Therefore, we suggest that more attention should be paid to resistance gene mobility potential in antimicrobial resistance surveillances.

Materials and methods

Animal experiment statement

All procedures involving animal use were approved by the Purdue University Animal Care and Use Committee (protocol #1303000841), and animal care and use standards were based upon the Guide for the Care and Use of Agricultural Animals in Research and Teaching (44).

Samples and DNA

The pig fecal samples were obtained from growth promoter experiment where 210 weanling pigs ((Duroc × (York × Landrace)) avg. 19 d of age and 5.8 kg were used in a 33-day trial. The experiment had 7 pigs in each pen and 6 pens per each treatment. Feed amendment treatments were: 1) non-treatment control (NTC); 2) antibiotic growth promoter (carbadox, 55 ppm) (AB); 3) mushroom powder (mixture of *C. militaris* and *O. sinesis*, 300 ppm) (M); 4) carbadox and mushroom powder mixture (results are not included in this study); 5) copper sulfate (125 ppm) and zinc oxide (3000 ppm d 0-7, 2000 ppm d 7-35) (ZnCu). After 33 days, fecal samples were taken from 1 median weight female and male per pen. Samples from the same pen were pooled, and DNA was extracted using the DNeasyPowerLyzer PowerSoil DNA Isolation Kit (Qiagen) according to the manufacturer's protocol. Extracted DNA was stored at −20 °C before 16S sequencing and qPCR array.

16S sequencing and quantitative PCR array

The 16S rRNA gene library was constructed as described (45). Briefly, the V4 region of the bacterial 16S rRNA gene was amplified with the 515R (GTGCCAGCMGCCGCGGTAA) / 806R (GGACTACHVGGGTWTCTAAT) primers. 16S rRNA gene libraries were also prepared for a known mock community (20 Strain Even Mix Genomic Material; ATCC® MSA–1002TM) and a no-template control (water). The amplified DNA from one 96-well plate was normalized using a SequalPrep Normalization Plate (Invitrogen), and pooled into a single library. Library

concentrations were determined using the KAPA Library Quantification Kit (Roche) and the average fragment length was determined using a high sensitivity kit with the Bioanalyzer (Agilent). The pooled samples, mock community, and water were sequenced with Illumina MiSeq v2 (500 cycles). Sequences were demultiplexed using oligonucleotide bar code sequences and Illumina software.

Quantitative PCR reactions and raw data processing were conducted using WaferGen SmartChip Real- time PCR system as reported previously (46). The qPCR reactions were performed using 384 primer sets (assays) (Table S1) (27). One sample from M group (2_M) was not included in the qPCR array analysis due to technical error. Samples from pigs that received both mushroom powder and carbadox were also excluded and therefore the results from 16S rRNA amplicon sequencing are not presented in this study.

16S sequence analysis and qPCR array data processing

The 16S rRNA amplicon sequences were analyzed using mothur (v 1.39.3) (45): contigs were made from paired forward and reverse raw reads, aligned to reference sequences (SILVA database release 132) (47), screened and filtered to remove low quality reads (ambiguous bases allowed = 0, maximum read length = 275, homopolymers allowed = 8), classified with reference to known taxonomic classifications (RDP training set 16) (48) and clustered into OTUs. The sequences clustered into 137 different OTUs at the 3% dissimilarity level. One NTC group sample (11_NTC) and one AB group sample (16_AB) were discarded due to low number of obtained sequences. 16S sequences were normalized using two different methods: total sum scaling (TSS) using R and rarefying and subsampling using mothur. To produce the rarefied and subsampled OTU table, the data were subsampled to 7,500 reads per sample according to rarefication curves (Fig. S6). The rarefied and subsampled OTU table and only quality filtered OTU table (for TSS) were imported into R. After removing the results of samples from animals that received both mushroom powder and carbadox, 132 different OTUs remained in the TSS

372 normalized OTU table and 127 different OTUs in the rarefied and subsampled OTU table. The
373 TSS normalization was carried out in R by dividing each OTU read count by the total number of
374 reads in that sample and all the NA observations (zero sequences) were replaced with 1.490935e-
375 07, which was 100-fold lower than the lowest observed relative abundance.

376 In the qPCR array, assays "16S old 1_1", "blaOXY-1_1118", "cmlV_911",
377 "czcA_1536", "fabK_1520", "intI1F165_clinical_359" and "tetPA_1507" were positive in the
378 negative control, however the Ct-values in the negative control were mostly higher than in
379 experimental samples (Table S5). Assay "tetPA_1507" was detected only in the negative control
380 and the Ct-values of assay "czcA_1536" were removed from the results since they were lower in
381 the negative control than in samples. Assay "16S old 1_1" results were removed and not used in
382 normalization since DNA amplification was more efficient in assay "16S new 2_2". The Ct-
383 values of the remaining four assays that were positive in the negative control were adjusted as
384 follows: The Ct values of each of these assays in each sample were subtracted from Ct value of
385 the assay in the negative control. The resulting numbers were then subtracted from 27, which
386 was the Ct value was used as the cutoff between true positive values and primer-dimer
387 amplification. Next, all the Ct values that were higher than 27 were set to "NA". After this, all
388 the assays that were undetected in all the samples were removed, resulting in 136 assays out of
389 382 targeting to AGRs or MGEs being included in the data table. The ΔCt values, ΔΔCt values
390 and relative gene abundances were calculated from these Ct values as previously described (27).
391 Genes under the detection limit were given a ΔCt value of 20, which was higher than any
392 observed ΔCt (17.4).

393 ## Statistical analyses

394 R version 3.5.1 (2018-07-02) was used for data exploration, visualization and for all
395 statistical analyses. Analysis of differential abundances of taxa and ARGs and MGEs were
396 carried out using gamma distribution GLMs with TSS normalized OTUs and ARGs and MGEs

(relative abundances) and negative binomial GLMs with rarefied and subsampled OTUs (abundance). Gamma distribution model was selected because the relative abundance values (TSS normalized OTUs and ARGs and MGEs) did not fit to normal distribution but followed the gamma distribution. Negative binomial models were selected for rarefied and subsampled OTUs because of the overdispersion in the abundance data. With both model types, p-values were obtained with Tukey's post-hoc test and adjusted with False discovery rate control (49) using *glht* function in the multcomp package (50).

The community and resistome compositions were analyzed using vegan package (51). PERMANOVA was used to examine the shifts in community composition and resistome between treatment groups with function *adonis* and 9,999 permutations. Nonmetric multidimensional scalings (NMDS) were completed using the Bray−Curtis dissimilarity index with function *metaMDS*. Procrustes analysis with the *protest* function was used to examine the agreement of ordinations of TSS normalized OTUs and rarefied and subsampled OTUs as well as ordination of ARGs and MGEs and both OTU ordinations separately. Mantel's test and Spearman's rank correlation was used to analyze the links between microbial community structure and resistome: first, Bray-Curtis dissimilarity indexes were calculated for TSS normalized OTUs, rarefied and subsampled OTUs and for ARGs and MGEs with function *vegdist*. Then the *mantel* function was applied for the dissimilarity indexes of TSS normalized OTUs and ARGs and MGEs as well as rarefied and subsampled OTUs and ARGs and MGEs. Mantel's tests between both OTU dissimilarity matrices and dissimilarity matrix of ARGs and MGEs were also run for all the treatment groups separately.

To examine if the treatments selected resistance genes into mobile genetic elements, a correlation matrix between ARG and MGE relative abundances was visualized using network analysis with Gephi (52). Spearman's rank correlations between ARGs and MGEs within treatment groups and their *p*-values used in network analysis were obtained with package psych

(53) using False discovery rate control (49). Only ARG-MGE-pairs that were detected at least in three samples with a strong positive correlation ($\rho > 0.8$, $p < 0.05$) were included.

The factors influencing the shifts in taxonomic structure and resistome were analyzed with machine learning algorithms as previously described (54). First, dimension reduction was executed on a combined data table of TSS normalized OTUs and ARGs and MGEs using t-SNE algorithm (29) and the R package Rtsne (55), with 50,000 iterations and "perplexity" set to 5. Then, clusters in the two-dimensional data were identified using HDBSCAN algorithm (30) in the package dbscan (56). The minimum number of members in clusters ("minPts") was set to 3. Classification random forest model (31) was used with partial dependence plot function in edarf package (57) for identifying the most important predictors for the clustering pattern. The forests were grown to 10,000 trees using the ranger package (58) and the best predictors were screened using Gini index by adding predictors one at a time in the order of decreasing importance (59). The final model was then selected according to the highest Cohen's Kappa (comparison of observed accuracy and expected accuracy).

Data availability

Raw reads from 16S rRNA gene amplicon sequencing are deposited under BioProject accession number PRJNA605462 at NCBI. The R code, mothur commands and all datasets used in statistical analyses are available at https://github.com/sjmuurine/ZnCu.

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Figures and figure legends

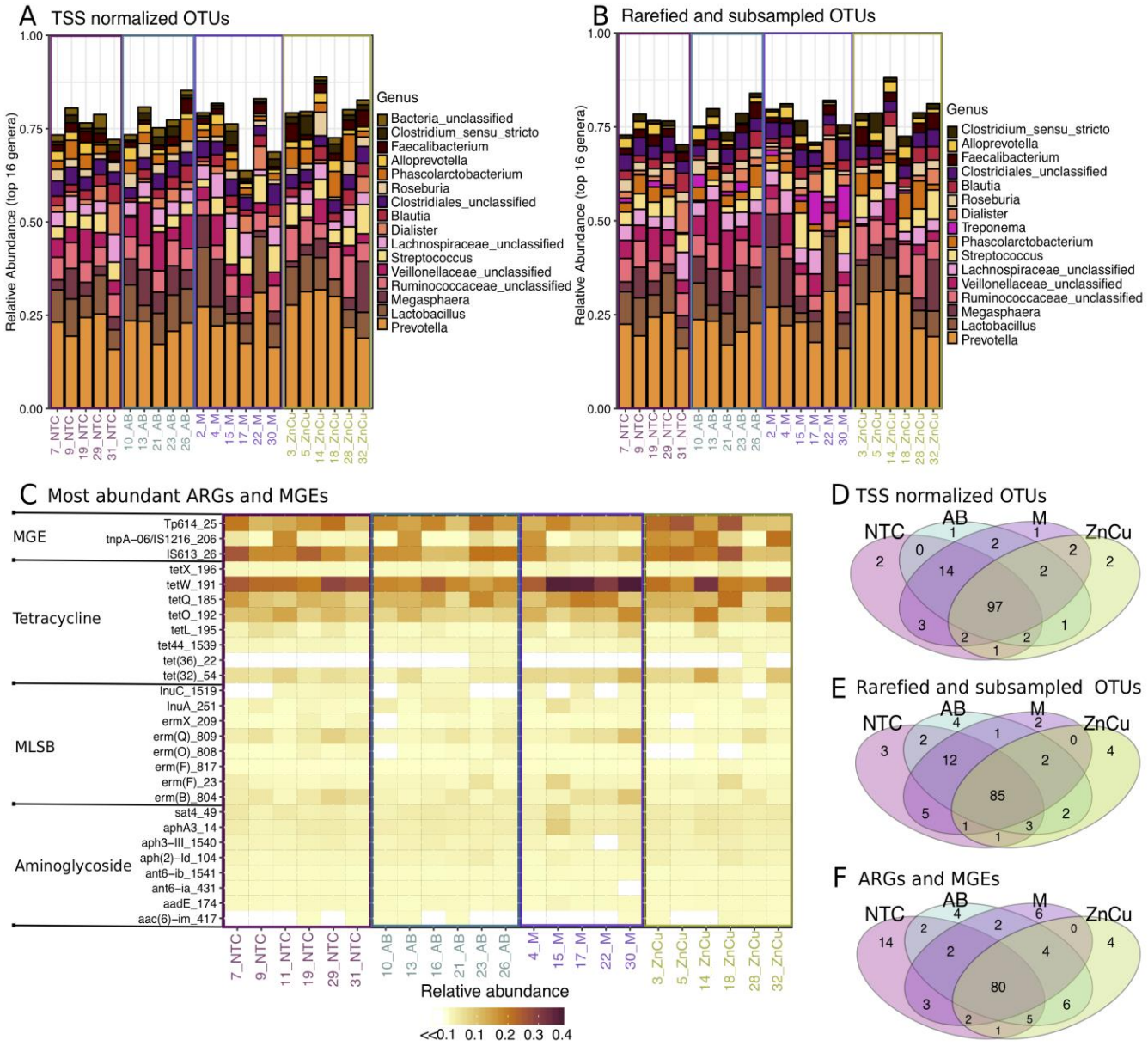


Fig. 1. Comparison of most abundant genera, ARGs and MGEs in different treatment groups. Samples on x-axis are grouped according to the treatments and color-coded. Sample names are as follows: NTC= Non-treatment control, AB= Carbadox (antibiotic), M= Mushroom powder and ZnCu= zinc oxide and copper sulfate. The number in front of the group code denotes the number of the pen. (A) Stacked bar plot showing 16 most abundant genera in OTUs normalized using total sum scaling (TSS). (B) Stacked bar plot showing 16 most abundant genera in rarefied and subsampled OTUs. (C) Most abundant genes related to antibiotic resistance and mobile

639 genetic elements (n=27). Each row represents results of each primer set (assay) (Table S1)
640 displayed on the y-axis. Assays are grouped according to the antibiotic group which the target
641 genes confer resistance. MLSB is abbreviation for Macrolide−Lincosamide−Streptogramin B
642 resistance and MGE for mobile genetic elements. One sample from mushroom powder group
643 was left out from the qPCR array analysis due to a technical error. (D) Venn diagram showing
644 the OTUs that are shared between samples belonging into different treatment groups when TSS
645 normalization was used. (E) Venn diagram showing the OTUs that are shared between samples
646 belonging into different treatment groups when Rarefying and subsampling was used. (F) Venn
647 diagram showing the ARGs and MGEs that are shared between samples belonging into different
648 treatment groups.

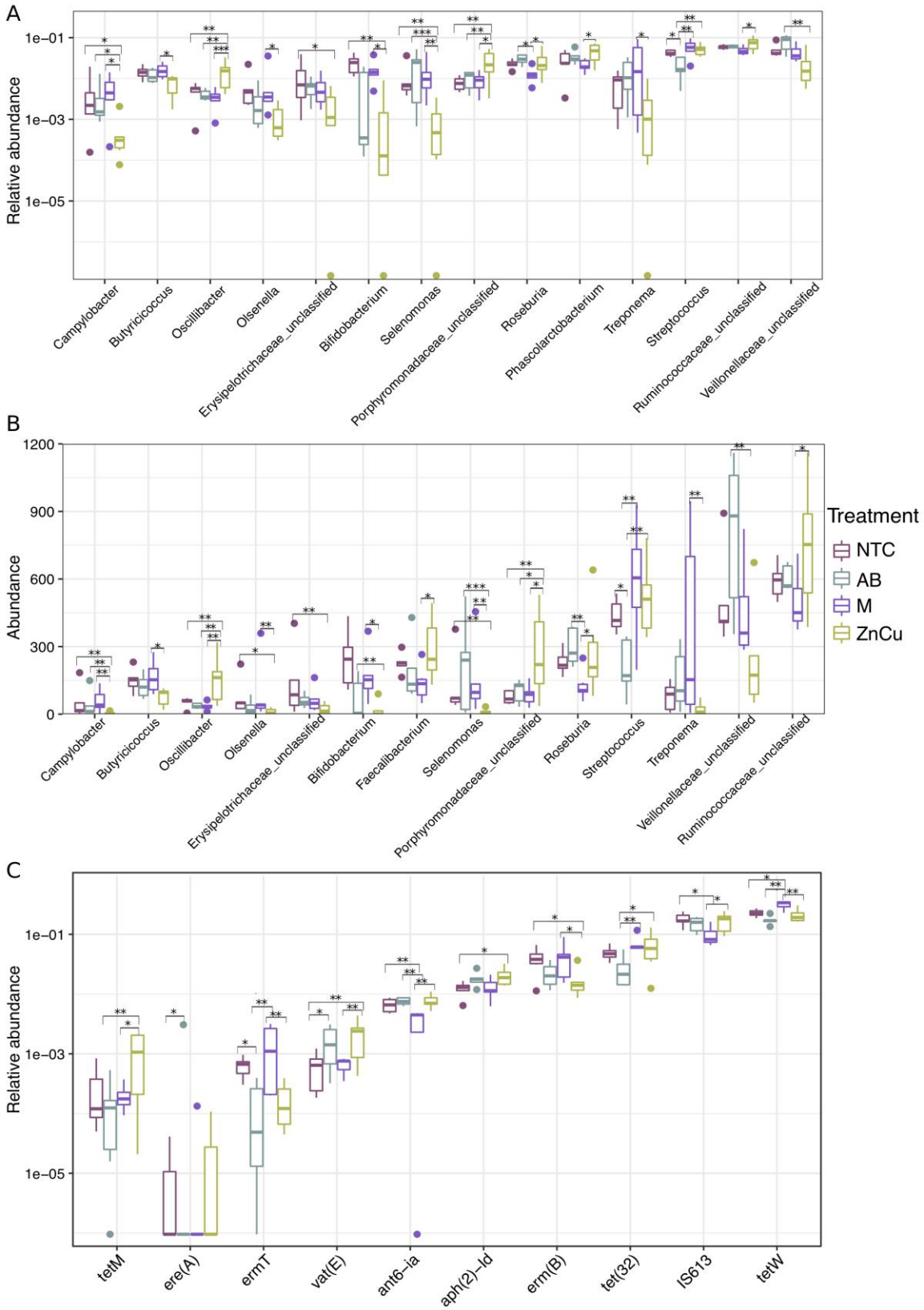


Fig. 2. Boxplots showing the most abundant genera, ARGs and MGEs with statistically significant differences between treatment groups labeled on right. NTC= Non-treatment control, AB= Carbadox (antibiotic), M= Mushroom powder and ZnCu= zinc oxide and copper sulfate.

653 The asterisks "*", "**" and "***" denote statistical significance levels at $p < 0.05$, $p < 0.01$ and
654 $p < 0.001$, respectively. (A) Most abundant genera in TSS normalized OTUs (n=14), (B) Most
655 abundant genera in rarefied and subsampled OTUs (n=14), (C) Most abundant genes related to
656 resistance and transfer (n=10). See Fig. S3A, B and C for all differentially abundant genera and
657 ARGs and MGEs and Table S2, S3 and S4 for fold changes of the differently abundant genera
658 and ARGs and MGEs.
659

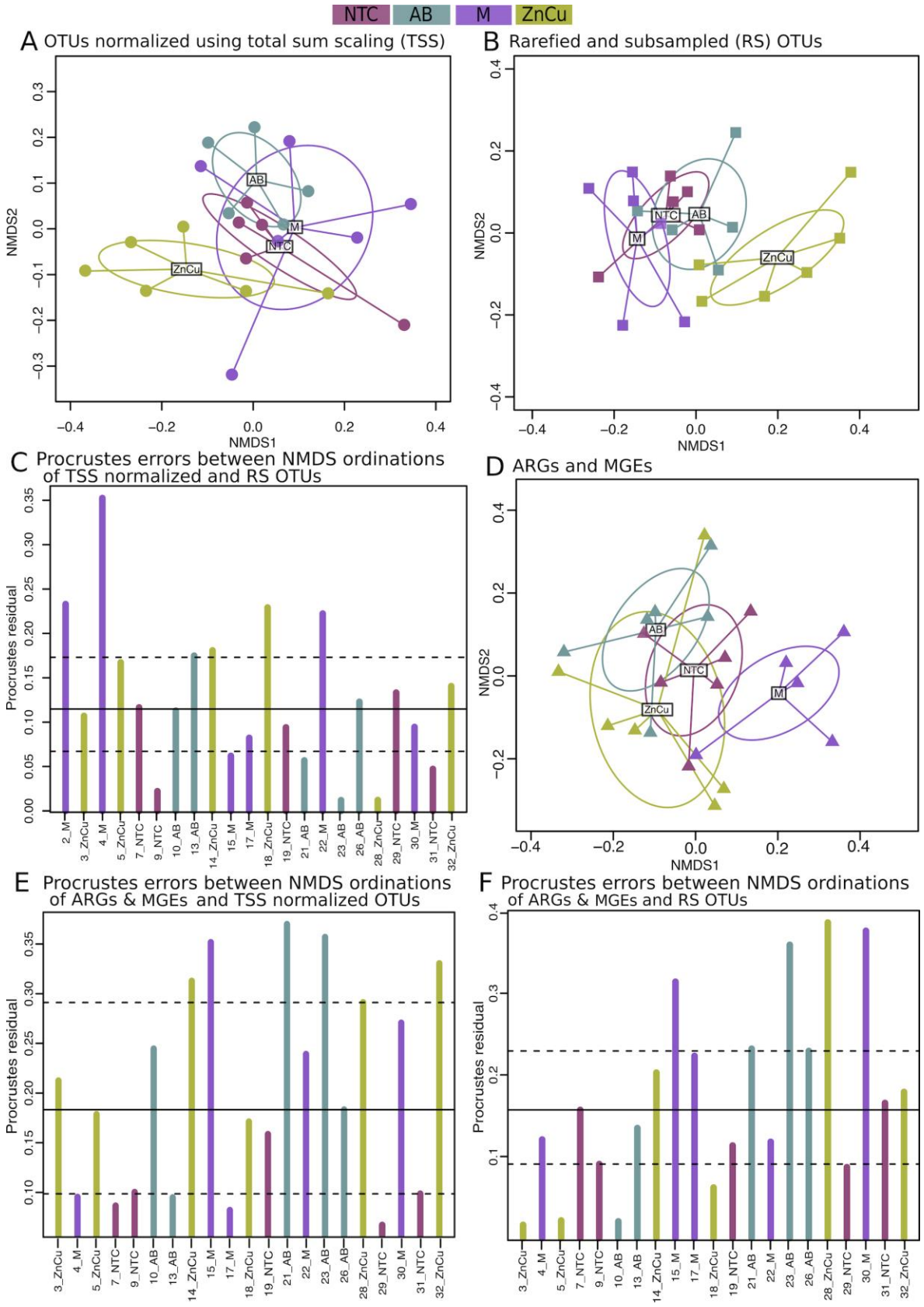
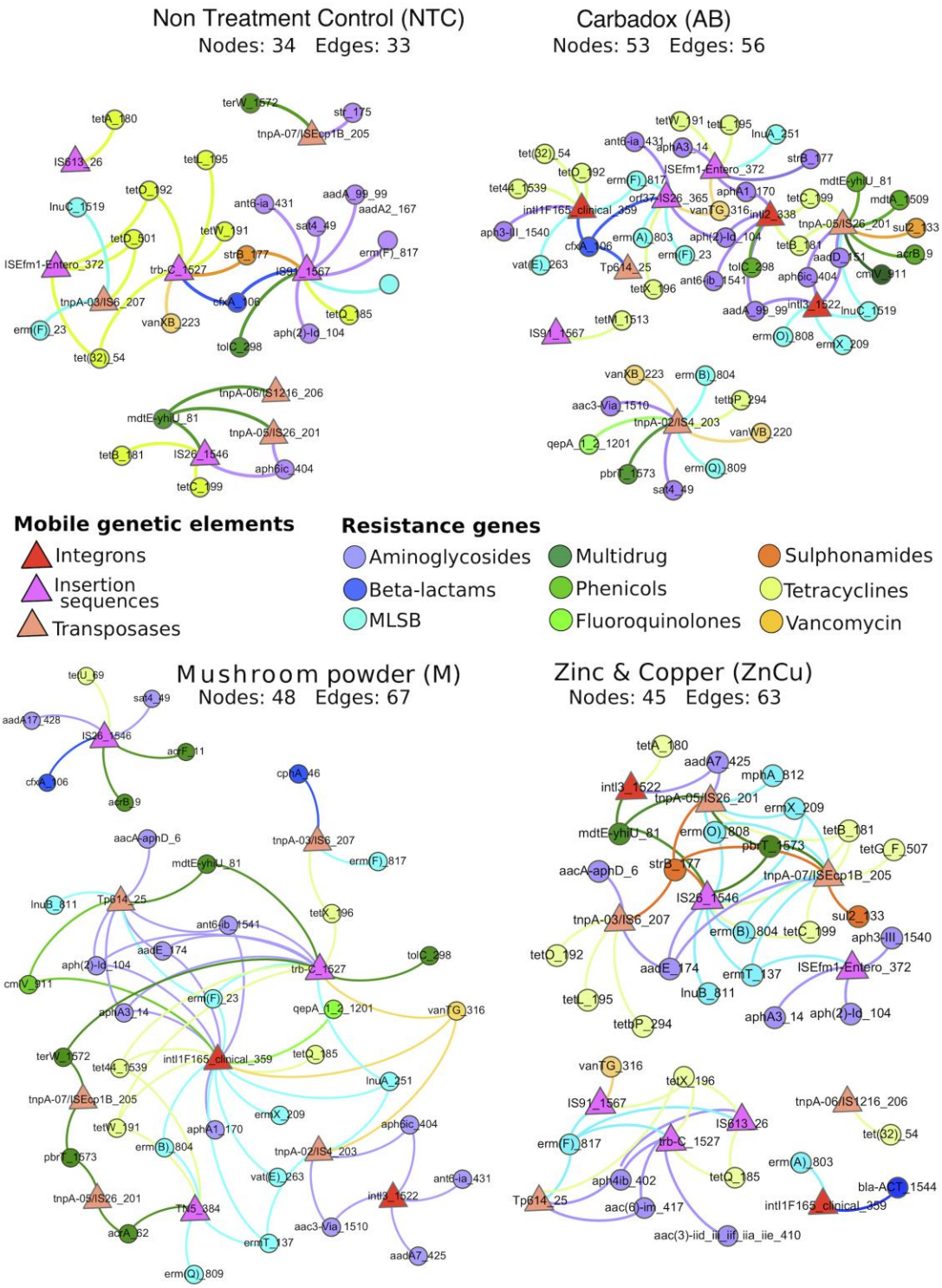


Fig. 3. NMDS ordinations of TSS normalized OTUs, rarefied and subsampled OTUs and ARGs & MGEs and Procrustes errors between them. Sample names are as follows: NTC= Non-

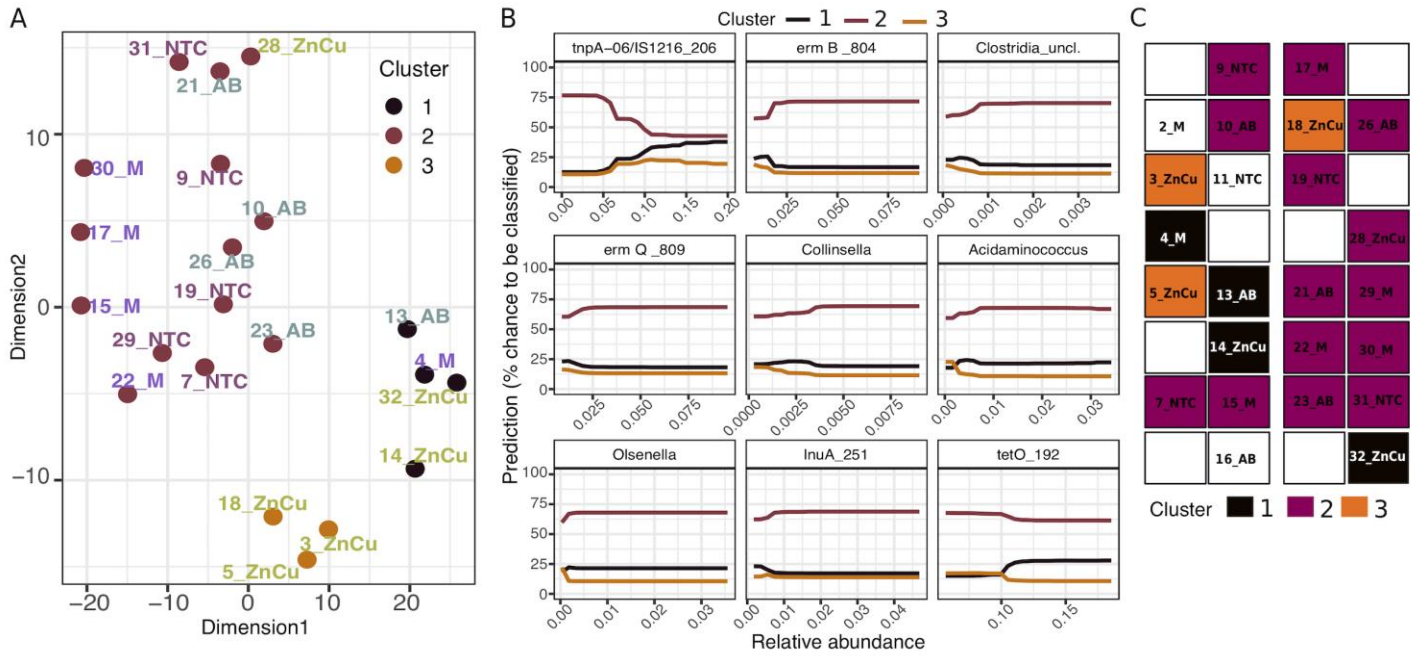
663 treatment control, AB= Carbadox (antibiotic), M= Mushroom powder and ZnCu= zinc oxide and
664 copper sulfate. The number in the sample name denotes the number of the pen. (A) NMDS
665 ordination of TSS normalized OTUs. (B) NMDS ordination of rarefied and subsampled (RS)
666 OTUs. (C) Procrustes errors between NMDS ordinations of TSS normalized OTUs and rarefied
667 and subsampled OTUs. (D) NMDS ordination of ARGs and MGEs. (E) Procrustes errors
668 between NMDS ordinations of TSS normalized OTUs and ARGs & MGEs. (F) Procrustes errors
669 between NMDS ordinations of rarefied and subsampled OTUs and ARGs & MGEs. The
670 Procrustes residual error line plots (C, E and F) allow residual error size comparisons. The bars
671 show the difference in the community structures between the two normalization methods (C) as
672 well as the differences in community structure and resistome structure in samples belonging to
673 different treatment groups (E and F). Horizontal lines denote the median (solid), 25% and 75%
674 quantiles (dashed).



675

676 Fig. 4. Network analysis showing co-occurrence patterns between ARGs and MGEs within the
677 samples in different treatment groups. Nodes of the MGEs are triangles, and circle resistance
678 gene nodes are colored according to the antibiotic they confer resistance. Edges between
679 resistance gene nodes and mobile genetic element nodes have the color of the resistance gene

680 node. Nodes have equal sizes, edges have equal weights, and distance between the nodes is
681 irrelevant.



682

683 Fig. 5. t-SNE analysis of a dataset containing ARGs, MGEs and TSS normalized OTUs (all
684 relative abundances) and the distribution of the pens where experimental pigs were kept. (A) The
685 clustering pattern of the samples. (B) Partial dependence plot of cluster numbers and the most
686 important predictors in the order of decreasing importance. The partial dependence plot shows
687 the effect of each predictor on the model outcome one by one, meanwhile the other predictors are
688 fixed to their average value. (C) The physical distribution of the of the experiment pens.

689 ## Supporting information legends

690

691 Table S1. List of the used primer sets.

692

693 Fig. S1. Correlation between rarefied and subsampled OTUs and TSS normalized OTUs.

694

Fig. S2 Composition of positive assays grouped by (A) antibiotic group the targeted gene confers resistance, (B) resistance mechanism and (C) mobile genetic element group.

Fig. S3. Differentially abundant genera and genes. Samples on x-axis are grouped according to the treatments. Sample names are as follows: NTC= Non-treatment control, AB= Carbadox (antibiotic), M= Mushroom powder and ZnCu= zinc oxide and copper sulfate. The number in front of the group code denotes the number of the pen. Each row represents abundance of each genus or the results of each primer set (assay) (Table S1) displayed on the y-axis. Only genera and genes with statistically significant differences between treatment groups are shown (A) Differentially abundant genera with TSS normalization. See Table S2 for fold changes. (B) Differentially abundant genera with Rarefying and subsampling. See Table S3 for fold changes. (C) Differentially abundant ARGs and MGEs. See Table S4 for fold changes.

Table S2. Pairwise comparisons of gamma distribution GLMs of relative abundances of each genera between treatment groups. TSS normalized OTU table was used as the input.

Table S3. Pairwise comparisons of negative binomial GLMs of abundances of each genera between treatment groups. Rarefied and subsampled OTU table was used as the input.

Table S4. Pairwise comparisons of gamma distribution GLMs of relative abundances of each ARG or MGE between treatment groups.

Fig. S4. Rarefaction curves. OTU collection curves determined from sequence analysis. Each line represents one sample. Vertical line shows the subsampling cutoff: 7500 sequences

720 Table S5. Assays that had unspecific amplification. Ct values in the negative control and mean

721 Ct-values in samples.

722