



**Characterization of the bacterial and fungal microbiome in  
indoor dust and outdoor air samples:  
A Pilot Study**

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3 Characterization of the microbiome in both indoor and outdoor samples, as demonstrated in this  
4 pilot, can be applied to numerous types of environmental health studies. These include studies  
5 on home microbial communities in early life and childhood allergic disease development, as well  
6 as the assessment of the microbiome in particulate air pollution and its contribution to  
7 respiratory, inflammatory and hematologic health outcomes. Furthermore, sequencing of the  
8 microbiome in outdoor air particulates may aid our understanding of how this exposure has  
9 fluctuated with the changing temperature and weather patterns associated with global warming.  
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3 1 Characterization of the bacterial and fungal microbiome in indoor dust and outdoor air samples:  
4 2 A Pilot Study

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9  
10 5 **ABSTRACT**

11 6 Environmental microbes have been associated with both protective and adverse health effects in  
12 7 children and adults. Epidemiological studies often rely on broad biomarkers of microbial exposure (i.e.  
13 8 endotoxin, 1→3, Beta-D glucan), but fail to identify the taxonomic composition of the microbial  
14 9 community. Our aim was to characterize the bacterial and fungal microbiome in different types of  
15 10 environmental samples collected in studies of human health effects. We determined the composition of  
16 11 microbial communities present in home, school and outdoor air samples by amplifying and sequencing  
17 12 regions of rRNA genes from bacteria (16S) and fungi (18S and ITS). Samples for this pilot study included  
18 13 indoor settled dust (from both a Boston area birth cohort study on Home Allergens and Asthma  
19 14 (HAA)(n=12) and a study of school exposures and asthma symptoms (SICAS) (n=1)), as well as fine and  
20 15 coarse concentrated outdoor ambient particulate (CAP) samples (n=9). Sequencing of amplified 16S,  
21 16 18S, and ITS regions was performed on the Roche-454 Life Sciences Titanium pyrosequencing platform.  
22 17 Indoor dust samples were dominated by gram-positive bacteria (Firmicutes and Actinobacteria); the  
23 18 most abundant bacterial genera were those related to human flora (Streptococcus, Staphylococcus,  
24 19 Corynebacterium and Lactobacillus). Outdoor CAPs were dominated by gram-negative Proteobacteria  
25 20 from water and soil sources, in particular the genera Acidovorax, and Brevundimonas (which were  
26 21 present at very low levels or entirely absent in indoor dust). Phylum-level fungal distributions identified  
27 22 by 18S or ITS regions showed very similar findings: a predominance of Ascomycota in indoor dust and  
28 23 Basidiomycota in outdoor CAPs. ITS sequencing of fungal genera in indoor dust showed significant  
29 24 proportions of Aureobasidium and Leptosphaerulina along with some contribution from Cryptococcus,  
30 25 Epicoccum, Aspergillus and the human commensal Malassezia. ITS sequencing detected an additional  
31 26 70 fungal genera in indoor dust not observed by culture. Microbiome sequencing is feasible for different  
32 27 types of archived environmental samples (indoor dust, and low biomass air particulate samples), and  
33 28 offers the potential to study how whole communities of microbes (including unculturable taxa) influence  
34 29 human health.

## 36 INTRODUCTION

37 Environmental exposure to microbes and their components has long been linked to numerous non-  
38 infectious health effects, both beneficial and detrimental, in children and adults. These relationships are  
39 often varied and complex. For instance, increased burden of gram-negative bacteria in the environment  
40 (as assessed by endotoxin), has been associated with an elevated risk of wheeze in early life(1,2), but  
41 with protection against later childhood asthma and allergic disease. (2-6) In occupational settings,  
42 where microbial exposures are much higher, individuals may experience airway obstruction (often  
43 termed “Monday Asthma”) in response to endotoxin from gram-negative bacteria.(7) Increased levels of  
44 global biomarkers of mold (total fungal counts, ergosterol and (1→3), Beta-D glucan), have been related  
45 to both protective(8) and adverse respiratory health outcomes.(9-11) Exposure to yeasts in early life  
46 may protect against wheeze and allergic sensitization,(12) while other taxa, including Cladosporium and  
47 Alternaria, may increase wheeze risk and later development of allergic rhinitis and asthma.(12-14)  
48 Health effects of environmental microbes extend beyond respiratory outcomes. For instance, findings  
49 from a recent controlled human chamber exposure study on the health effects of concentrated ambient  
50 particles (CAPs) suggested that the endotoxin content of the particles accounted for a significant  
51 proportion of the association of CAP exposure with increases in the peripheral white cell count(15). In  
52 the same study, short term exposure to endotoxin and fungal (1→3) Beta-D-Glucan in CAPs was also  
53 associated with increased blood pressure.(16) The hematologic, immune and physiologic responses to  
54 bacteria or fungi may depend on stage of life, dose, and host factors as well as on the form and  
55 taxonomy of the organism.

56 In studies where global biomarkers of microbes are utilized for exposure assessment, the taxonomic  
57 composition of the sample is typically unknown. Information on taxonomy may tell us more about  
58 health effects of specific groups of microorganisms, and may help us understand heterogeneity of  
59 effects of microbial components. The activity of pathogen associated molecular patterns (PAMPs)(17),  
60 airway irritants(18), and allergens(19) is known to vary widely across taxa. Furthermore, taxonomic  
61 identification will help us pose important questions about how microbial communities, rather than  
62 individual microbes, influence health. Culture-based methods yield taxonomic information, but are time  
63 consuming, inherently biased (due to selective conditions of culture media) and must be performed  
64 immediately after environmental sample collection. Independent of the potential for culture, recent  
65 advances in metagenomics allow us to characterize the microbiome and examine its taxonomic  
66 composition across different types of exposure samples collected in environmental health studies. In  
67 addition to elucidating taxonomy through sequencing, the potential function of microbes will also be  
68 critical to uncover, as metabolic pathway genes may select for particular microbes in our environment  
69 (thereby shaping the communities of microbes we are exposed to). Characterizing the genetic potential  
70 of microbes through microbiome sequencing may also yield information about microbial metabolic and  
71 biosynthesis pathways with relevance to human health.

72 Our overall aim for this pilot was to sequence the microbiome in archived environmental samples from  
73 studies that have previously shown important relationships between global biomarkers of microbial  
74 exposure and health. Specifically, we wished to 1) determine whether indoor dust samples archived  
75 long-term (up to 20 years) would be suitable for microbiome analysis 2) compare fungal taxa identified

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3 76 by culture to fungi detected by sequencing in indoor dust samples 3) determine the feasibility of  
4 77 sequencing the environmental microbiome in air samples collected from a human chamber exposure  
5 78 study on the health effects of air pollution. (To our knowledge, this is the first study to conduct  
6 79 microbiome assessment of particle exposures in a human chamber exposure study.) By amplifying and  
7 80 sequencing rRNA genes from bacteria (16S) and fungi (18S and ITS), we determined the composition of  
8 81 microbial communities present in samples from three distinct studies: home floor dust from The  
9 82 Epidemiology of Home Allergens and Asthma Study(HAA), school classroom floor dust from the School  
10 83 Inner-City Asthma Study (SICAS-1); and pre-exposure calibration samples of outdoor concentrated  
11 84 ambient particles (CAPs) from the Cardiovascular Toxicity of Concentrated Ambient Fine, Ultrafine and  
12 85 Coarse Particles in Controlled Human Exposures study. For all sample types, 16S sequencing results  
13 86 were used to impute the functional metagenome, to yield an indirect assessment of metabolic pathway  
14 87 gene abundance within the bacterial communities sequenced in indoor dust and outdoor air  
15 88 particulates.  
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## 20 90 **METHODS**

### 22 91 **Sample Collection.**

23 92 *“The Epidemiology of Home Allergens and Asthma”* birth cohort study (n=12): House dust samples, from  
24 93 children’s bedrooms or from the living room, were collected using a Eureka Mighty-Mite vacuum cleaner  
25 94 modified to hold 19 by 90-mm cellulose extraction thimble to collect house dust. For this pilot study,  
26 95 dust samples from the Home Allergens and Asthma cohort were chosen from 2 sampling time points  
27 96 (age 1 and age 12), with an over-representation of age 1 samples (as these had corresponding fungal  
28 97 culture data). All samples had at least 50mg dust remaining. For bedroom samples collected at one year  
29 98 of age, the area (2 m<sup>2</sup>) of the bedroom floor surrounding the baby’s crib was vacuumed for 5 min (n=3).  
30 99 Family room dust samples, from homes when subjects were 1 year of age (n=7) and at age 12 (n=2),  
31 100 were also collected using a Eureka Mighty-Mite vacuum. For family room dust samples, we vacuumed  
32 101 both a 1-m<sup>2</sup> area of the family room floor for 2 min and an upholstered chair commonly used by the  
33 102 parent while holding the infant (at age 1) or by index child themselves (at age 12) for 3 min. All of the  
34 103 bedroom floor and living room house dust samples collected at age 1 had corresponding fungal culture  
35 104 data (n=10). Culture methods are described in detail elsewhere.(12)

36 105 *SICAS-1* (n=1): In the classroom, vacuuming of the settled dust sample was performed for a total of 6  
37 106 minutes per sample, 3 minutes on the floor and 3 minutes on other surfaces, such as desks and chairs,  
38 107 as previously described.(20)

39 108 *“Cardiovascular Toxicity of Concentrated Ambient Fine, Ultrafine and Coarse Particles in Controlled*  
40 109 *Human Exposures”* Study (n=9): This study included 55 healthy non-smokers, aged 18-60 years, who had  
41 110 no history of cardiovascular disease.(16) Using a cross-over study design, participants blinded to the  
42 111 study condition received up to 6 separate 130-minute exposures (coarse CAPs (2.5 to 10µm)(~200  
43 112 µg/m<sup>3</sup>), fine CAPs (0.1 to 2.5 µm)(~250µg/m<sup>3</sup>), quasi-ultrafine CAPs(<0.3 µm)(~200,000 particles/cm<sup>3</sup>),  
44 113 filtered air and medical air) at least two weeks apart, with a physician in attendance. Controlled  
45 114 exposures were generated using high-flow (5,000 L/min) Harvard Ambient Particle Concentrators to  
46 115 draw ambient particles from a 1.8 m high PM10 inlet located, 10 m from a busy 4-lane downtown  
47 116 Toronto street with ~2,500 vehicles passing during the 130-minute exposure. Ambient particle  
48 117 exposures were concentrated and adjusted through a dilution control system to deliver target

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3 118 concentrations of CAPs. During the calibration phase (prior to exposing subjects), CAPs were collected  
4 119 onto 47mm, 2 µm pore size Teflon filters Teflo (R2PJ047, Pall Corporation, Ann Arbor, MI) with the  
5 120 pump set to a flow rate of 2 liters/minute while connected to the CAP airstream with the concentrator  
6 121 running (coarse or fine), to simulate the exposure conditions. The exposed surface on the filters was  
7 122 39mm. Filters collected during the calibration phase (including both coarse and fine particle fractions)  
8 123 were extracted for DNA and sequenced for the bacterial and fungal microbiome. Calibration filters  
9 124 were chosen at random for microbiome sequencing

### 13 125 **Microbiome Sequencing and Bio-informatics**

15 126 *DNA Extraction and PCR Amplification.* Indoor dust samples and filters containing CAPs were extracted  
16 127 for metagenomic DNA in a clean hood using MP Biomedicals' FastDNA™-96 Fungal/Bacterial DNA Kit. In  
17 128 each case 50mg of dust or half of the filter was included in the extraction. The extraction protocol  
18 129 includes both physical and chemical disruption of the microbial matter in order to extract all available  
19 130 DNA with a minimum of bias. The V1 through V3 hyper-variable regions (V1-V3) of 16S rRNA genes were  
20 131 amplified from the metagenomic DNA using primers 27F and 534R (27F: 5'- AGAGTTTGATCCTGGCTCAG-  
21 132 3' and 534R: 5'-ATTACCGCGGCTGCTGG-3').(21) The oligonucleotides containing the 16S primer  
22 133 sequences also contained an adaptor sequence for the Roche-454 Life Sciences Titanium  
23 134 pyrosequencing platform as well as one of 96 tag sequences unique to each sample. Analogous primers  
24 135 were designed for amplifying the 18S and ITS regions of small eukaryotes. (18S: F' –  
25 136 GACTCAACACGGGGAAACT, R' – ATTCCTCGTTGAAGAGCA) and (ITS: F' (18S-F) –  
26 137 GTAAAAGTCGTAACAAGGTTTC, R' (5.8S-1R) – GTTCAAAGAYTCGATGATTAC). Negative controls were  
27 138 included for the extraction and PCR amplification procedures. In each case there was no indication of  
28 139 contaminants intrinsic to the protocols.

30 140 *Sequence Processing and Analysis.* The DNA sequences for each targeted amplicon were assigned to the  
31 141 appropriate sample based on the unique sequence tag used in the targeted amplification and using  
32 142 Mothur's trim.seqs protocol.(22) Chimeric sequences were identified and removed with the Mothur  
33 143 implementation of UCHIME.(23) For 16S sequences, we directly aligned each sequence within the  
34 144 processed and cleaned (primers and barcodes removed) 16S fasta files to the Ribosomal Database  
35 145 Project (RDP) database using the RDP classifier version 2.8 and the 16S rRNA training set 9  
36 146 (<http://rdp.cme.msu.edu>), using a confidence cutoff of 0.5. We then attempted to further resolve the  
37 147 sequences that were unclassified at the genus level by utilizing NCBI's BLAST algorithm and their non-  
38 148 redundant nucleotide database (NCBI NRdb downloaded 06/22/2015). For 18S amplicons, we directly  
39 149 aligned each sequence within the processed and cleaned (primers and barcodes removed) 18S fasta files  
40 150 to a database maintained by SILVA ([www.arb-silva.de](http://www.arb-silva.de)), the SILVA 115 NR99 database. This reference  
41 151 database was chosen because it contains non-redundant, aligned 18S rRNA sequences. Sequences less  
42 152 than 200bp were removed from the analysis, to minimize the possibility of misclassification. Sequence  
43 153 classification was done using the least-common-ancestor methodology to identify a taxonomic  
44 154 classification for each sequence. For ITS amplicons, we directly aligned each sequence within the  
45 155 processed and cleaned (primers and barcodes removed) ITS fasta files to a database maintained by the  
46 156 Fungal Metagenomics Project (<http://www.borealfungi.uaf.edu>), the Fungal Internal Transcribed  
47 157 Spacers (ITS) rDNA sequence database fungal\_its.fa.2014-12-13.

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3 158 *Imputation of the Functional Metagenome for Bacteria.* After the 16S data was filtered for base quality,  
4 159 and the primers and barcodes removed, Mothur v.1.33.3  
5 160 ([http://www.mothur.org/wiki/Main\\_Page](http://www.mothur.org/wiki/Main_Page))(22) was employed to compare the DNA sequences to each  
6 161 other and to cluster the groups where each sequence was 97% similar to all other sequences in its  
7 162 group thereby creating operationally defined taxonomic units(24), OTUs. The bacterial taxonomy was  
8 163 then determined using the references in Greengenes 16S rRNA database version 13.5.99.(25) Then,  
9 164 PICRUSt version 1.0.0(26) normalized the OTUs by 16S rRNA copy number and predicted metagenomes  
10 165 functional content from the Kyoto Encyclopedia of Genes and Genomes (KEGG) catalogue. Finally,  
11 166 HUMAnN version 0.99(27) determined coverage and abundance of microbial pathways from the KEGG  
12 167 Ortholog results.(28) Microbial metabolic genes catalogued within the KEGG database are annotated to  
13 168 an entire range of microbial metabolic functions, from carbohydrate, amino acid, and lipid metabolism  
14 169 to xenobiotic/chemical degradation pathways (breakdown of synthetic compounds (caprolactam),  
15 170 pesticides (DDT, atrazine), and plant-derived compounds/fragrances (limonene/pinene)).

16 171 *Principal Component Analysis and Statistical Comparisons.* We performed principal component analysis  
17 172 on microbiome sequencing data using STAMP (Statistical Analysis of Metagenomic Profiles) software.  
18 173 For individual samples, we plotted scores for the first, second and third principal components to visualize  
19 174 similarity of community composition (samples of similar community composition will cluster together in  
20 175 the plot (particularly for PC1 vs. PC2 and PC1 vs. PC3), while those with markedly different composition  
21 176 are plotted far apart). For comparing the imputed functional metagenome by sample type (indoor dust  
22 177 vs. outdoor CAPs), R was used to calculate pathways that were differentially abundant ( $P < 0.001$  for  
23 178 statistical significance) using a t-test.

## 24 179 **RESULTS**

### 25 180 *Bacteria (16S Sequencing)*

26 181 Sample characteristics, including sample type, location of indoor dust sampling, size of outdoor air  
27 182 particulates (coarse vs. fine), and season of sample collection are shown in Table 1. Ninety percent of  
28 183 the samples sequenced contained at least 3000 reads for 16S rDNA sequencing. All samples analyzed  
29 184 contained at least 1000 reads; one sample contained only 419 reads and was excluded from the analysis.  
30 185 On average, 27% of sequences (range 9 to 46%) remained unclassified after alignment to the RDP  
31 186 database. After conducting a BLAST search against NCBI's NR nucleotide database, an average of 6 % of  
32 187 these unclassified sequences (range 0.2% to 16%) were identified. Overall, indoor dust samples  
33 188 showed remarkably different bacterial taxonomic profiles (PC1 vs. PC2 and PC1 vs. PC3) as compared to  
34 189 samples from outdoor air. Clustering of bacterial communities by sample type is visualized by a plot of  
35 190 principal component scores that represent underlying taxonomic distributions (Figure 1). Plant groups,  
36 191 namely Streptophyta, were also identified in the amplified 16S rRNA gene sequences.

37 192 Bacteria in indoor dust appeared to be dominated by gram-positive microbes, as represented by the  
38 193 phylum Firmicutes (the majority of which are gram-positive), as well as Actinobacteria (comprised  
39 194 entirely of gram-positive microbes) (Figure 2a). Taxonomic identification at the class and genus levels  
40 195 (Figures 1b and 1c, respectively) revealed that most of the Firmicutes dominating indoor dust samples  
41 196 originate from the taxonomic class Bacilli (with variable amounts of the genera Staphylococcus,

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3 197 Streptococcus, Lactobacillus). Two of the indoor dust samples were unique, in that the Bacilli detected  
4 198 were dominated by either Solibacillus or Brocothrix. Actinobacteria in indoor dust was comprised of  
5 199 genera related to common skin flora: Corynebacterium and Propionibacterium. All of the indoor dust  
6 200 samples contained some level of Cyanobacteria. Gram-negative bacteria (including members of the  
7 201 phyla Bacteroidetes and Proteobacteria) are also represented in indoor dust, albeit at much lower  
8 202 percentages than gram-positives (Figure 2a). For the gram-negative phylum Proteobacteria, microbes  
9 203 from the Alpha-proteobacteria and Beta-proteobacteria classes (specifically the Massilia and Paracoccus  
10 204 genera) were observed (Figure 2b and 2c). Interestingly, the school indoor dust sample contained  
11 205 Ureaplasma, a type of Mollicute (phylum Tenericutes), which was not detected in any of the house dust  
12 206 samples (Figure 2a). Mollicutes are a unique class of bacteria distinguished by the absence of a cell wall.  
13 207 In contrast to indoor dust, bacterial taxonomic composition of outdoor CAPs was dominated by gram  
14 208 negative bacteria, with large proportions of the phylum Proteobacteria, as well as some contribution  
15 209 from Bacteroidetes. Composition of the mainly gram-positive Firmicutes was much lower in outdoor  
16 210 CAPs vs. indoor dust. (Comparison by sample type at the phylum level is shown in Supplemental Figure  
17 211 1a-c). Within Proteobacteria, members of the taxonomic classes alpha, beta and gamma-proteobacteria  
18 212 were all detected in outdoor CAPs. The genera Brevundimonas (alpha-proteobacteria), Acidovorax and  
19 213 Delftia (beta-proteobacteria) were present in the majority of CAP samples. While proportions of  
20 214 gamma-proteobacteria in outdoor CAPs were generally quite low, one sample showed a large  
21 215 percentage of Escherichia. Flavobacterium, a genera within Bacteroidetes, was present in the majority  
22 216 of CAP samples. Gram-positive bacteria detectable in CAPs are represented by the phyla Firmicutes and  
23 217 Actinobacteria. While present in much lower amounts, the gram-positive micro-organisms encountered  
24 218 in CAPs included many of the taxa also detected in indoor dust: Staphylococcus, Streptococcus,  
25 219 Lactobacillus, Propionibacterium, Corynebacterium, and Nocardiodes.

26 220 For indoor dust, the top 5 most abundant genera, as calculated by ranking median abundance across  
27 221 samples, were Streptococcus, Staphylococcus, Corynebacterium, Lactobacillus and Massilia. Abundance  
28 222 of these taxa was highly variable within indoor dust samples The top 5 most abundant bacterial genera  
29 223 in outdoor CAPs were Acidovorax, Brevundimonas, Massilia, Delftia (Proteobacteria) and  
30 224 Flavobacterium (Bacteroidetes).

#### 31 225 *Fungi (ITS and 18S Sequencing).*

32 226 In sequencing runs for 18S, all analyzed samples had greater than 1,000 reads; one sample had 70 reads  
33 227 and was excluded from the analysis. For ITS, five of the outdoor CAP samples had too few reads (<1000)  
34 228 and were excluded from the analysis. Plots of principal component scores for overall fungal microbiome  
35 229 composition revealed separate clusters for indoor dust and outdoor air (Figure3a-b). In addition to  
36 230 showing the differentiation between indoor dust and outdoor air fungal communities, the ITS principal  
37 231 component plot also demonstrated distinct separation between the two types of indoor samples (school  
38 232 dust and house dust) (Figure 3a). In general, fungal community composition by ITS showed clearer  
39 233 differentiation by sample type as compared to 18S (Figure 3b). A slight overlap between indoor dust  
40 234 and outdoor CAP composition was observed, and the school dust sample clustered with house dust on  
41 235 the principal component plot.

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3 236 Trends for overall phylum and class-level distributions were similar by ITS and 18S sequencing (Figure  
4 237 4a-b, Figure 4d-e). In indoor dust samples, the fungal microbiome was dominated by Ascomycota, with  
5 238 a consistent presence (at a much lower percent composition) of Basidiomycota. Two of the indoor dust  
6 239 samples contained fungi from the phylum Glomeromycota (ITS only). Class level distributions  
7 240 demonstrated a predominance of Dothidiomycetes and Eurotiomycetes (Ascomycota) in indoor dust  
8 241 samples, along with smaller fractions of Agaricomycetes and Tremellomycetes (Basidiomycota).  
9 242 Outdoor air CAPs contained large fractions of Basidiomycota, with lower levels of Ascomycota.  
10 243 Agaricomycetes was the taxonomic class contributing most to the predominance of Basidiomycota in  
11 244 outdoor CAPs. The Ascomycota in outdoor CAPs were comprised of Dothidiomycetes (which constituted  
12 245 medium to large percentages of total CAP fungal composition) and Eurotiomycetes which were  
13 246 generally present in very low amounts.

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19 247 Genus level resolution was possible for fungal classification by ITS (Figure 4c), but not 18S (Figure 4f).  
20 248 Indoor dust samples contained fairly large percentages of the genera *Aureobasidium* and  
21 249 *Leptosphaerulina*, along with some contribution from *Cryptococcus*, *Epicoccum*, *Aspergillus* and  
22 250 *Malassezia* to fungal community composition. Outdoor CAPs included the fungal genera *Trametes*,  
23 251 *Epicoccum*, *Aspergillus*, *Cryptococcus*, *Hyphodontia* and *Hypholoma*. For a subset of house dust samples  
24 252 (n=10) a comparison of the fungi detected by culture and those observed by ITS sequencing is shown in  
25 253 Table 2. *Aureobasidium* and *Alternaria* were consistently detected in all samples by both culture and by  
26 254 ITS sequencing. *Aspergillus* and *Epicoccum* were detected more often by ITS sequencing than by  
27 255 culture.. Two relatively rare fungi, *Paecilomyces* and *Trichoderma*, were detected by culture but not by  
28 256 ITS sequencing. Although culture conditions were suitable for growing *Botrytis*, it was detected in two  
29 257 samples by ITS sequencing but not by culture. In all, ITS sequencing detected more than 70 (at  $\geq 0.1\%$   
30 258 composition) additional fungal genera in house dust samples that were not detected by culture (either  
31 259 because culture conditions were not suitable for growth of these fungi, or because they were non-viable  
32 260 at the time of culture). A table listing these taxa, along with the percentage of house dust samples with  
33 261 detectable levels of these fungi, is shown in the supplementary file (Supplemental table 1). This  
34 262 supplemental file also lists plant groupings detected within the ITS amplicons, including *Alnus* and  
35 263 *Nothofagus*.

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42 264 Overall, identification of fungi was more complete at the higher taxonomic levels by 18S sequencing (3  
43 265 to 10% unclassified sequences, for phylum and class level identification, respectively), as opposed to  
44 266 profiling by ITS (18 % to 28% unclassified sequences at phylum and class level) (Figure 3). However, ITS  
45 267 outperformed 18S sequencing for taxonomic identification at the genus level (~25% unclassified  
46 268 sequences for ITS vs. 97% for 18S).

#### 49 269 *Metabolic pathway prediction based on 16S rRNA survey results*

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52 270 The metabolic pathways that were most abundant in the imputed functional metagenome of indoor  
53 271 dust samples were pathways related to amino acid metabolism (ko00290: Valine, leucine and isoleucine  
54 272 biosynthesis), carbohydrate metabolism (ko00660: C5-Branched dibasic acid metabolism) and lipid  
55 273 metabolism (ko00061: Fatty acid biosynthesis). The top three most abundant metabolic pathways  
56 274 detected in outdoor CAPs were related to metabolism of co-factors and vitamins (ko00760: Nicotinate

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3 275 and nicotinamide metabolism), energy metabolism (ko00190: Oxidative phosphorylation) and  
4 276 carbohydrate metabolism (ko00010: Glycolysis / Gluconeogenesis). In terms of xenobiotic degradation,  
5 277 microbiota sequenced in indoor dust showed the capability of metabolizing environmental chemicals  
6 278 known to influence human health including pesticides (DDT and atrazine) and dioxin. A complete list of  
7 279 all metabolic pathways identified through imputation of the functional metagenome, along with their  
8 280 relative abundances in all samples, is shown in supplemental file 2.

11 281 We chose to compare indoor dust and filter (CAPs) samples, however the findings from this comparison  
12 282 should be treated with caution, as samples were collected from different regions and at different time  
13 283 points. We found 66 pathways that were significantly differentially abundant between the filter and the  
14 284 dust samples (Figure 5). The seven pathways classified as xenobiotics biodegradation and metabolism  
15 285 were all overrepresented in the dust samples. For instance, the caprolactam degradation pathway  
16 286 (ko00930) was almost two times more abundant in the dust samples than in the filter samples.  
17 287 Interestingly, caprolactam is used mainly for the manufacture of synthetic fibers, resins, synthetic  
18 288 leather and plasticizers [products that are prevalent in home environments].

23 289 The pathways associated with the metabolism of terpenoids and polyketides, limonene and pinene  
24 290 degradation (ko00903) and geraniol degradation (ko00281) were also found at higher abundances in  
25 291 dust samples. Limonene and pinene are aromatic compounds found in a variety of trees and herbs.  
26 292 Meanwhile, geraniol is produced by many flowering plants such as geraniums and citrus fruits. Those  
27 293 three components are often used as scents or as flavor additives. The geraniol degradation pathway  
28 294 ends with the production of 3-methylcrotonyl-CoA. This metabolite is part of the valine, leucine and  
29 295 isoleucine degradation pathway (ko00280), which was also found overrepresented in the dust samples.

## 33 296 **Discussion**

35 297 In this pilot study, we demonstrated the feasibility of microbiome assessment of archived samples  
36 298 from epidemiologic and controlled human exposure studies. We sequenced marker genes of the  
37 299 bacterial and fungal microbiome in house dust samples archived for over 20 years from a birth cohort  
38 300 study of home exposures and asthma incidence. We also successfully characterized the environmental  
39 301 microbiome in concentrated outdoor air particulate samples containing relatively low biomass.

43 302 Indoor dust samples were dominated by gram-positive micro-organisms, including a subset of bacterial  
44 303 genera known to be associated with human sources (Staphylococcus, Streptococcus, Lactobacillus,  
45 304 Corynebacterium and Priopionibacterium). Presence of these bacterial genera, which are common in  
46 305 human skin and gut flora, has been documented in other studies of the home microbiome .(29-31) The  
47 306 human contribution to bacteria within the home is further confirmed in a definitive report by Lax et  
48 307 al(32), demonstrating that abundance patterns of bacterial OTUs (operational taxonomic units) in  
49 308 samples from the home closely mirror the microbial profiles of its human residents. Humans are also  
50 309 potential sources of fungi indoors. Although we detected some known human-associated fungi, in  
51 310 particular the commensal yeast *Malassezia*, the majority of fungal taxa sequenced in our indoor samples  
52 311 were associated with soil (*Aureobasidium*, *Penicillium*), water (*Aureobasidium*) or plant  
53 312 (*Leptosphaerulina*, *Epicoccum*, *Cladosporium*, *Alternaria*) sources. This finding is consistent with work

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3 313 by Adams et al(30), in which indoor samples from a students' dormitory complex showed a consistent,  
4 314 but relatively low, abundance of the human-derived taxon *Malassezia*, with much higher percentages of  
5 315 the fungal classes *Dothidiomycetes* (*Leptosphaerulina*, *Cladoporium*, *Alternaria*) and *Eurotiomycetes*  
6 316 (*Penicillium*, *Aspergillus*). As in the Adams et al study, we also consistently detected a moderate  
7 317 percent abundance of the soil-derived genus *Cryptococcus*; in some of our indoor dust samples  
8 318 *Cryptococcus* was the third most abundant taxon at the genus level. (It is important to note that the  
9 319 majority of *Cryptococci* are non-pathogenic to humans, with the exception of a few well-known  
10 320 pathogenic species). In addition to humans, soil, plant and water-based sources, pets are another  
11 321 important microbial reservoir that may influence the composition of the home microbiome. The indoor  
12 322 microbiome of dog owners' homes shows greater microbial diversity(33), and may contain higher levels  
13 323 of *Lactobacillus Johnsonii*, a taxon that may mitigate allergic disease response.(34)Microbes found  
14 324 indoors may also be influenced by the characteristics of the home itself. Dannemiller and colleagues  
15 325 found that water leaks, longer AC use, and suburban (vs.urban) homes were associated with greater  
16 326 diversity in house dust samples.(31) Although we did not have the power to examine these  
17 327 relationships, sequencing of additional samples within the two prospective cohorts described in the  
18 328 present work (HAA and SICAS) may help us to identify characteristics in homes and schools that are  
19 329 associated with particular microbial communities.

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27 330 Bacteria detected in outdoor samples were predominately gram-negative Proteobacteria; in particular  
28 331 the taxa *Acidovorax* (associated with plant matter), *Brevundimonas*, and *Flavobacterium* (a genera  
29 332 within Bacteroidetes often detected in environmental water and soil samples). These three gram-  
30 333 negative genera showed little to no abundance in the indoor samples analyzed. However, the gram-  
31 334 positive taxa identified in these outdoor samples showed considerable overlap with genera detectable in  
32 335 indoor samples (including *Staphylococcus*, *Streptococcus* and *Corynebacterium*). Fungal distributions  
33 336 contained a predominance of the phylum Basidiomycota, which was mainly comprised of  
34 337 *Agaricomycetes* at the class level. Interestingly, characterization of fungal microbiota in a much  
35 338 different locale (Berkeley, California) also showed a high proportion of *Agaricomycetes* in outdoor air,  
36 339 with significant representations of *Dothidiomycetes* and *Tremellomycetes* as secondary taxa.(35)  
37 340 Season and particle size (fine vs. coarse CAPs) were not associated with different types of microbial  
38 341 (bacterial or fungal) communities (data not shown); however, the relatively small sample size in this  
39 342 study may have obscured our ability to detect community differences between these particle size  
40 343 fractions. A study by Cao et al of the environmental microbiome in outdoor air particulates during a  
41 344 Beijing smog event reported a higher percentage of eukaryotes in larger particulates (PM<sub>2.5-10</sub> $\mu\text{m}$ ) as  
42 345 opposed to particles < 2.5  $\mu\text{m}$  in diameter.(36) The microbial signatures found in air particulates are  
43 346 unlikely to be from whole microbial cells (which are often larger than 2 or 10 $\mu\text{m}$ ), but rather fragments  
44 347 of these micro-organisms. For both indoor and outdoor samples, 18S sequencing yielded a more  
45 348 complete taxonomic profile at the Phylum and Class level, but identified only a small percentage of the  
46 349 fungal genera. Since the 18S rRNA gene encodes for a transcribed (as well as functional) portion of  
47 350 rRNA, it shows greater conservation across fungi overall but still contains sufficient variability to  
48 351 differentiate between fungi at higher taxonomic levels. Conversely, ITS is an intronic region of rDNA,  
49 352 and is less conserved across fungal taxa. Hypervariable regions within the ITS rDNA locus serve as  
50 353 "barcodes" for specific fungal genera, with little homogeneity at higher at taxonomic levels.(37)

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3 354 Unfortunately, no bioinformatic technique exists for combining sequencing information from these two  
4 355 different rDNA regions into an overall relative abundance profile when utilizing current targeted  
5 356 sequencing technologies. The choice of which rDNA region to use will depend upon the level of  
6 357 taxonomic classification desired by the investigator. Expansion of the existing fungal databases, such as  
7 358 SILVA, UNITE and the Fungal Metagenomics Project database, will eventually increase ITS coverage, so  
8 359 that the majority of fungal taxa, from phylum to species level, will be identifiable in environmental  
9 360 samples. In a subset of our indoor dust samples, we were able to compare ITS sequence data with  
10 361 culturable fungi. While *Aureobasidium* was consistently detected in all samples by both methods,  
11 362 sensitivity of detection varied for other genera. Amplification and sequencing by ITS may capture dead  
12 363 or unculturable fungi (potentially explaining detection by ITS but not culture), and culture techniques  
13 364 may selectively grow relatively rare fungi that are missed due to inadequate sequencing read depth or  
14 365 representation in an ITS database. In all, ITS sequencing yielded a much broader survey of fungi present  
15 366 within the environmental samples studied (with an excess of 80 additional taxa detectable by ITS, as in  
16 367 contrast to the 9 detectable by culture). It is important to note that the culture methods used here for  
17 368 comparison with ITS sequencing (performed 20 years ago, prior to the advent of metagenomic  
18 369 sequencing) were originally designed to characterize indoor mold exposure in an epidemiological study,  
19 370 and were not optimized for a direct culture vs. metagenomic sequencing comparisons.

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27 371 In addition to characterizing the microbiome with respect to taxonomic composition, we were also able  
28 372 to impute the functional metagenome of bacterial communities. The role of microbial metabolic  
29 373 function/xenobiotic degradation may be of particular importance indoors, where human use of  
30 374 household chemicals may alter the microbiome. Thus far, limited information exists on the relationship  
31 375 between household chemical use and indoor bacterial and fungal levels; however, the ability of bacteria  
32 376 and fungi to degrade synthetic substrates has been clearly demonstrated in environmental  
33 377 microbiology.(38,39) Indoor chemicals (pesticides, phthalates, triclosan, fragrances and synthetic  
34 378 polymers) may exert selective pressure on microbes, with the potential to drastically alter microbial  
35 379 community composition (taxa with the ability to degrade or utilize these chemicals as substrates may  
36 380 proliferate, while others that are susceptible to their anti-microbial activity may be reduced).  
37 381 Furthermore, xenobiotic degradation by microbes may either increase or decrease toxicity of a chemical  
38 382 compound with respect to human health, depending upon the activity of the parent compound vs. its  
39 383 metabolites. In this pilot study, we were able to identify microbial metabolic pathway genes in indoor  
40 384 dust that degrade known toxic compounds (pesticides, bisphenol, dioxin), synthetic materials found  
41 385 indoors (caprolactam) and fragrance additives used in household products (limonene, pinene). Future  
42 386 work is needed to uncover whether the potential to metabolize these compounds selects for particular  
43 387 microbes indoors and to determine whether microbial metabolism of these compounds alters their  
44 388 toxicity.

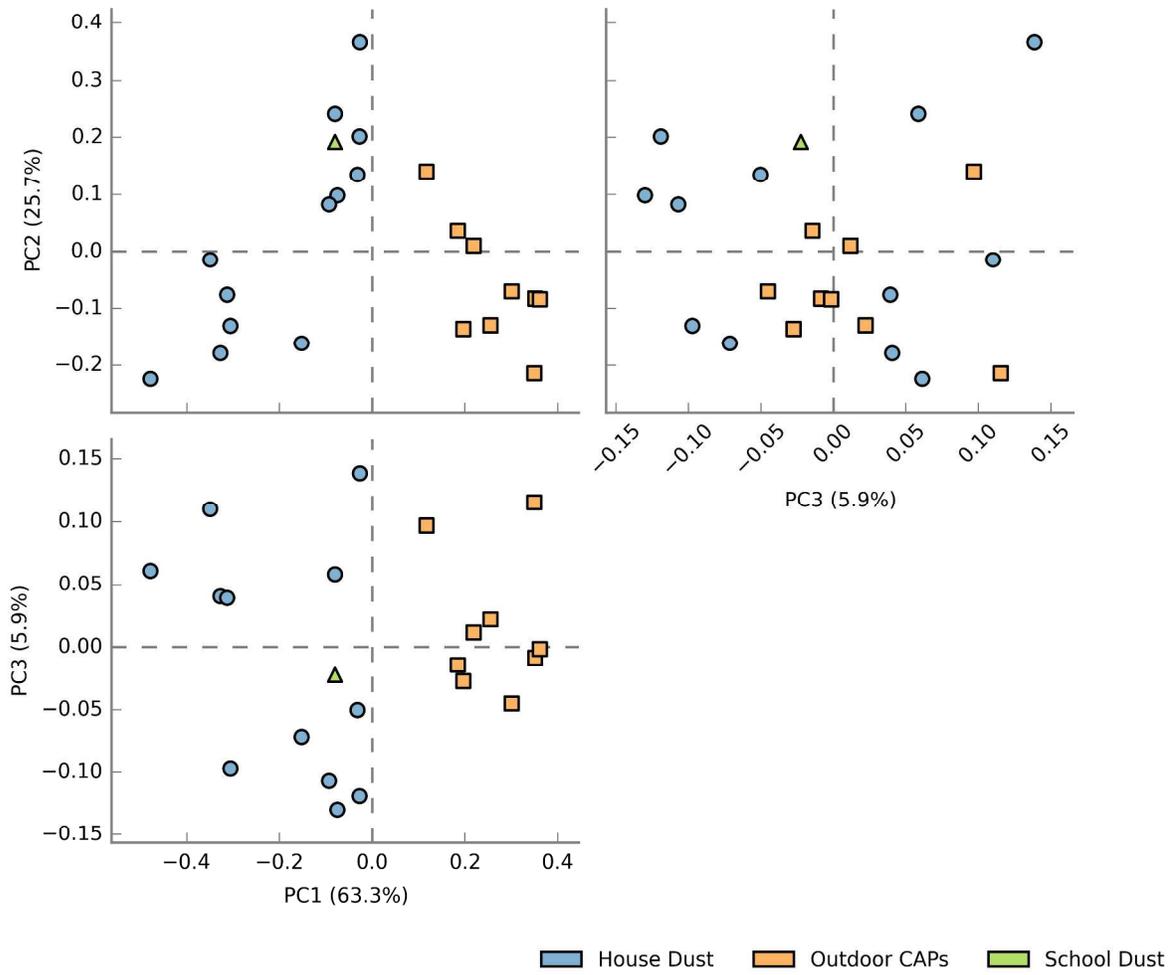
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51 389 In summary, characterization of the bacterial and fungal microbiome in the indoor dust and outdoor air  
52 390 samples presented in this work show both the potential and limitations for this type of exposure  
53 391 assessment in studies of human health effects. Methods for taxonomic identification of microbial  
54 392 communities through metagenomics approaches to DNA sequencing are more developed for bacteria  
55 393 than for fungi, where reference databases are more incomplete, and, up until recently, developed for

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3 394 purposes other than the relation of the environmental microbiome to human physiologic or health  
4 395 outcomes. While tremendous gains are made in identifying additional taxa that are not amenable to  
5 396 culture techniques, a fairly large percentage of sequences (for both environmental bacteria and fungi)  
6 397 cannot yet be assigned to a highly resolved (i.e. genus or species) taxonomic level. This limitation will be  
7 398 less of an issue as databases expand to include a greater number of micro-organisms. In all, microbiome  
8 399 sequencing provides an additional assessment of microbes in our environment that offers the option to  
9 400 identify both culturable and non-culturable as well as live and dead organisms that exist in the  
10 401 environment. Thus, one has the potential to study a more complete view of microbial communities, or  
11 402 even previously unstudied individual taxa, that may influence human health.

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16 403 **Funding sources**

17  
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424 **Figure 1. Principal component plot of bacterial (16S) community composition by sample type**  
425 **(● = house dust, ■ = outdoor CAPs, ▲ = classroom dust)**



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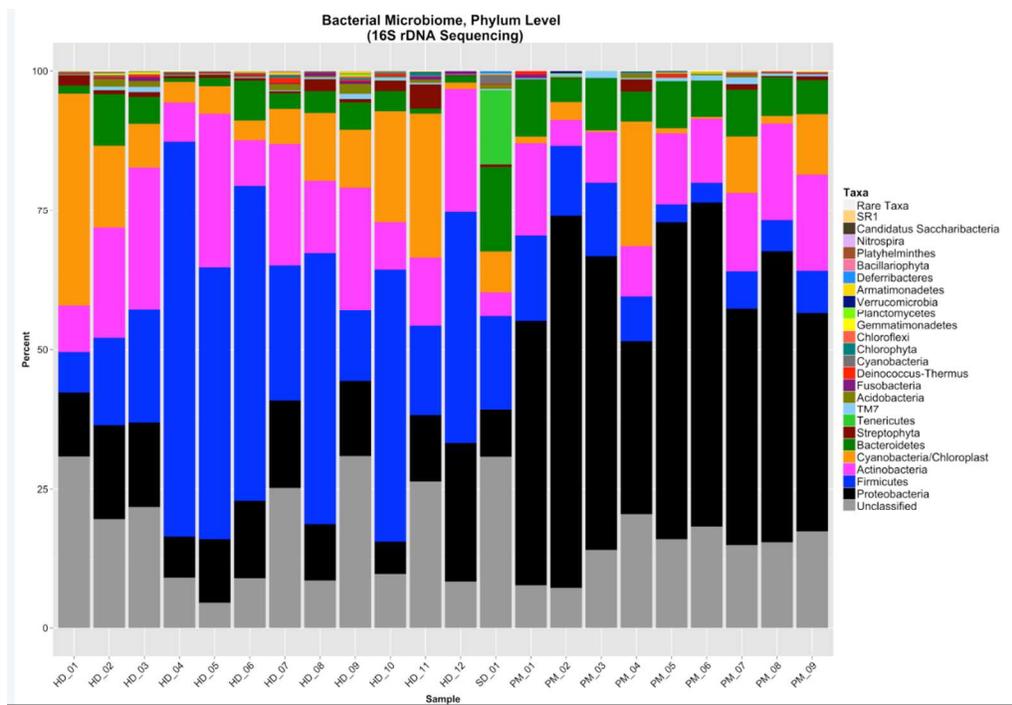
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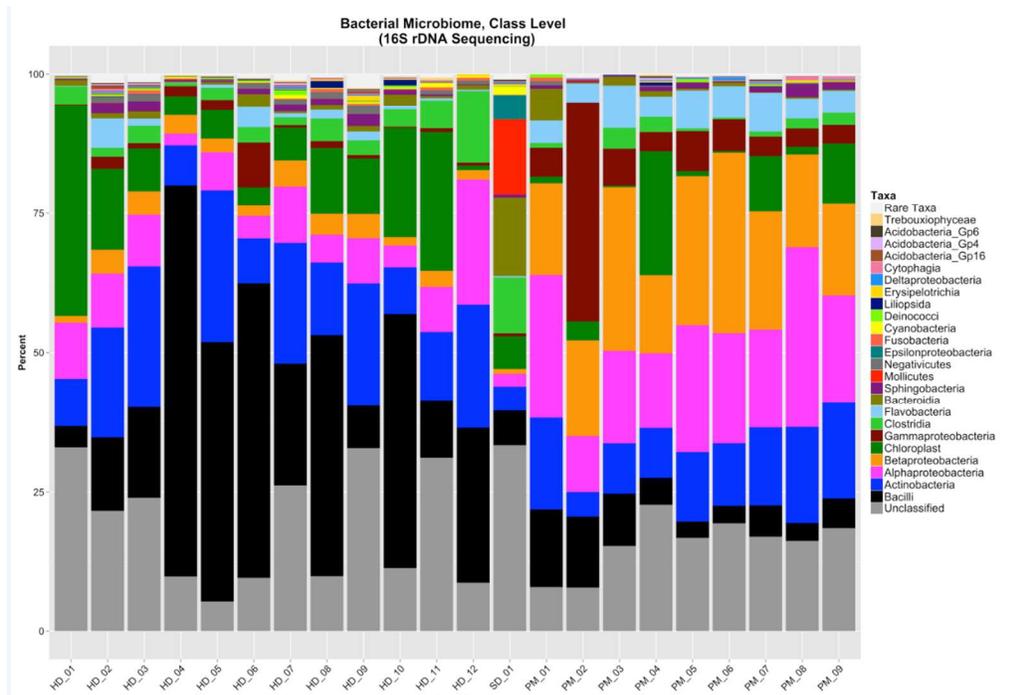
434 **Figure 2. Bacterial microbiome by 16S shown in panels a-c at three different taxonomic levels: (a)**  
 435 **Phylum (b) Class (c) Genus**

436 **(2a)**



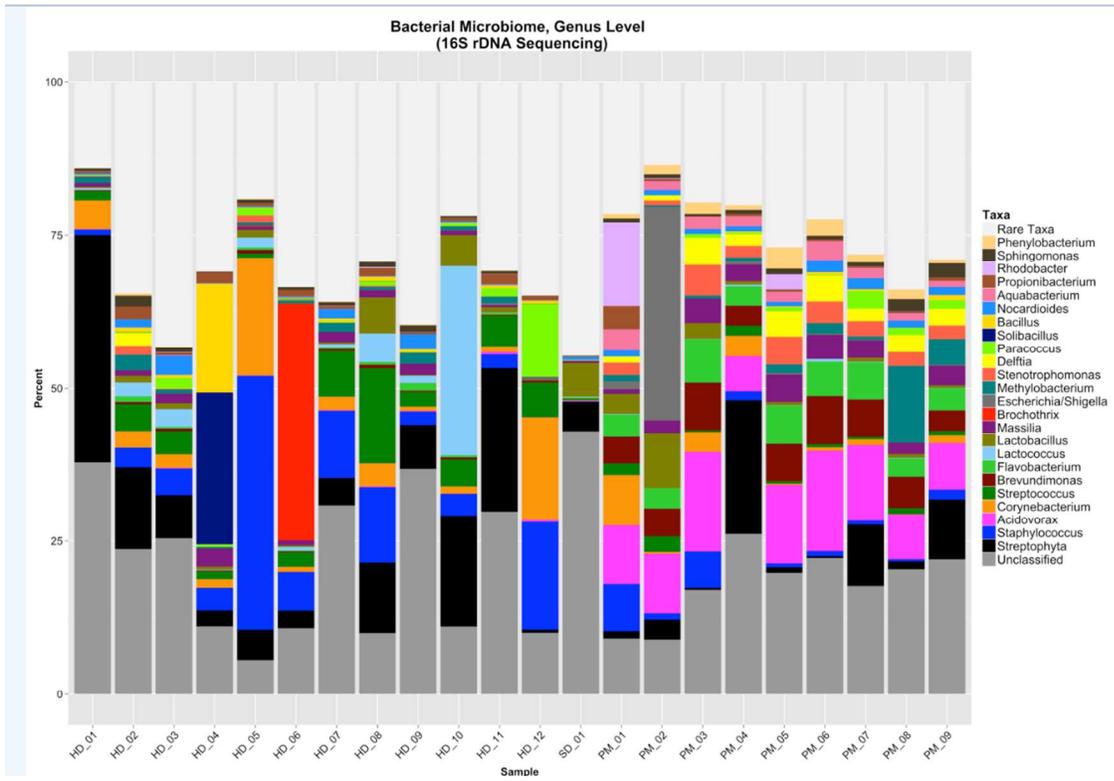
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438 **(2b)**



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440 (2c)



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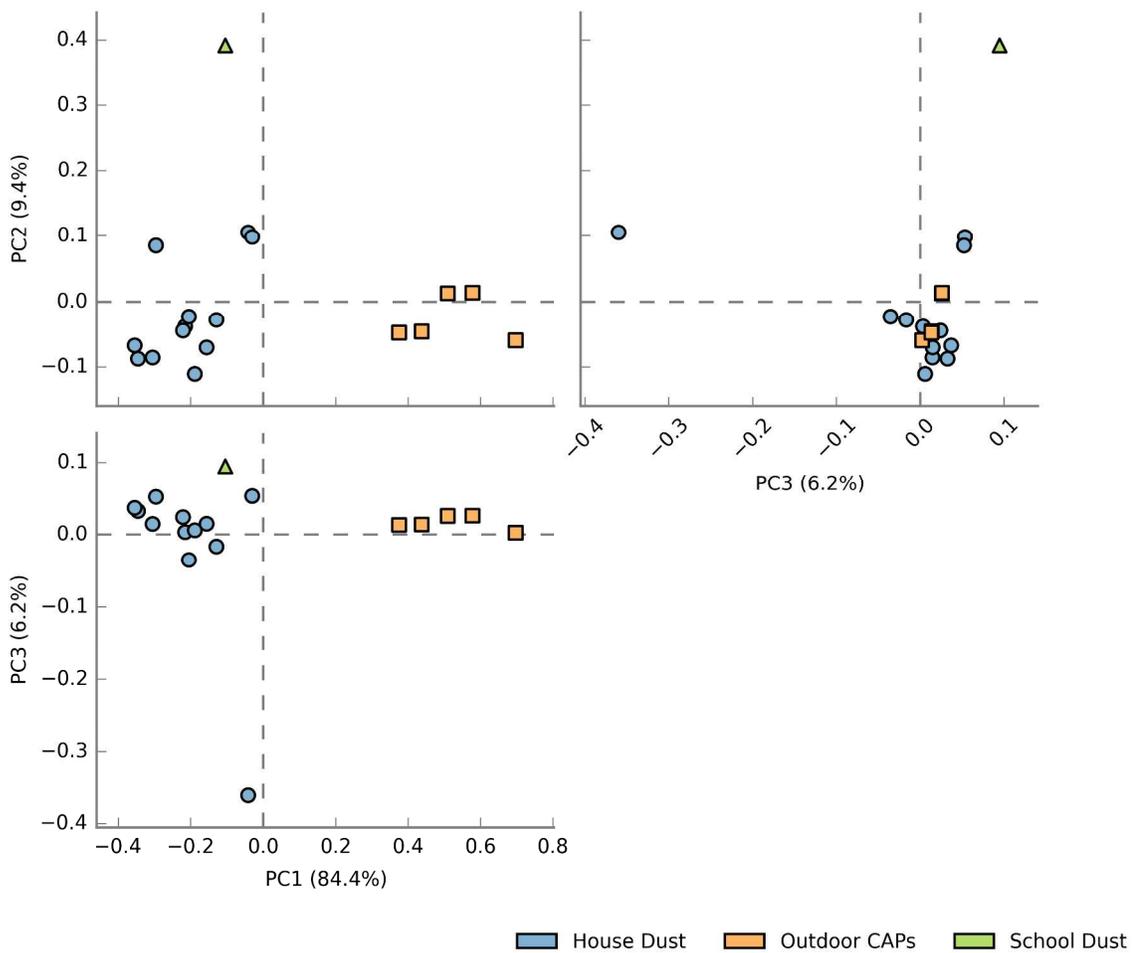
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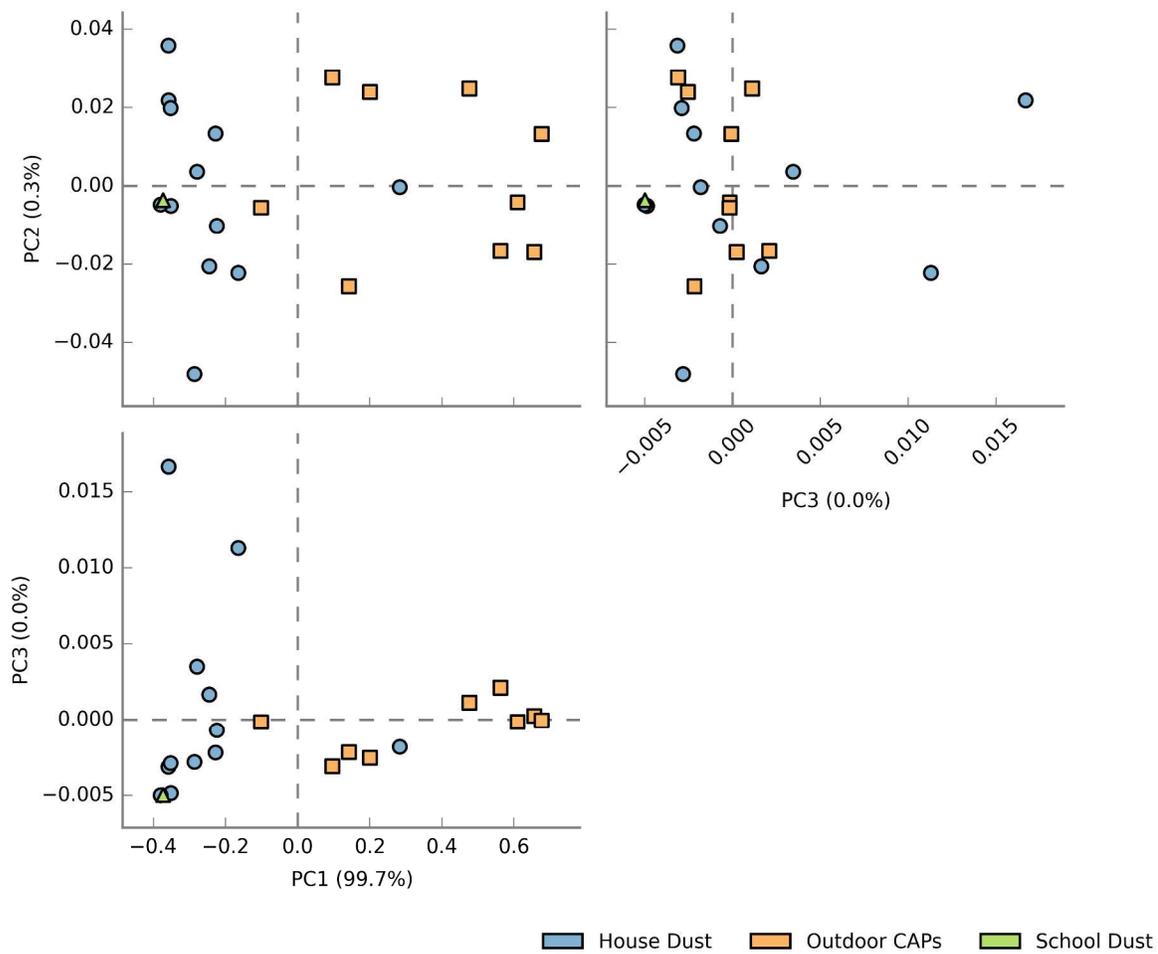
453 **Figure 3. Principal component plot for Phylum-level Fungal community composition by sample type**  
 454 **a) ITS sequencing b) 18S sequencing type**  
 455 **(● = house dust, ■ = outdoor CAPs, ▲ = classroom dust)**

457 **Panel (3a) ITS Sequencing:**



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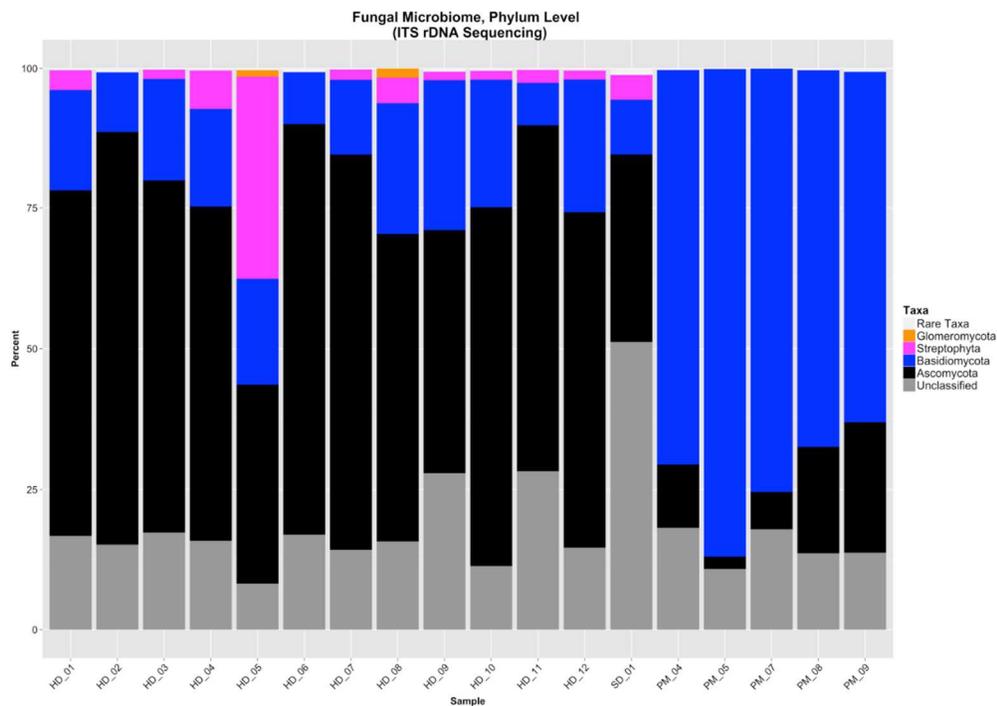
464 Panel (3b) 18S Sequencing:



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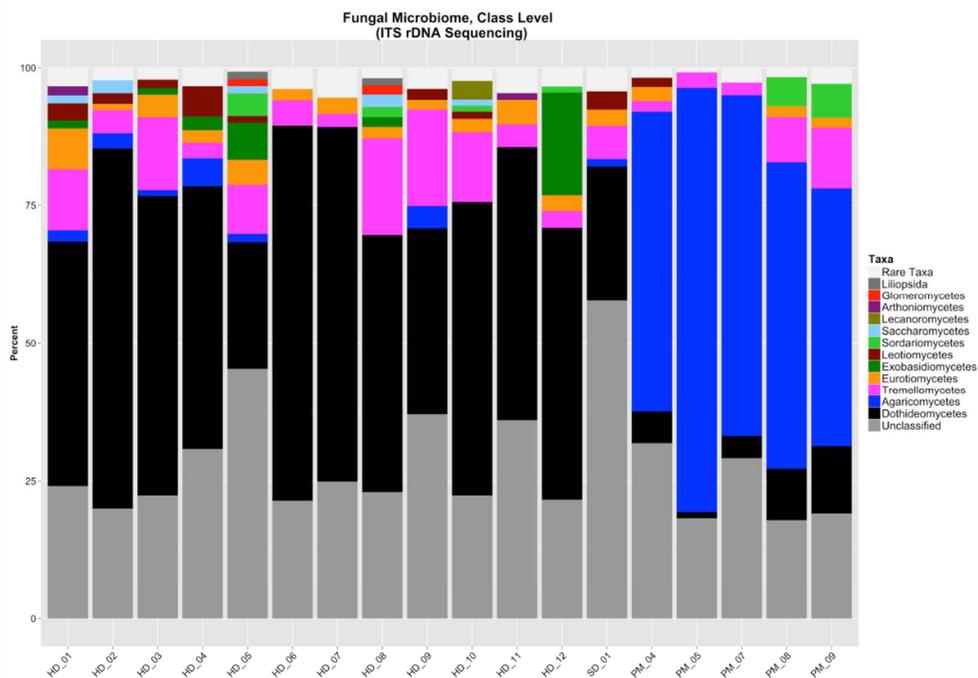
474 **Figure 4. Fungal microbiome by ITS (panels a-c) at three taxonomic levels (a) phylum (b) class (c) and**  
 475 **genus. Fungal microbiome by 18S (panels d-f) at (d)Phylum (e) Class (f) and genus levels**

476 **Panel (4a):**



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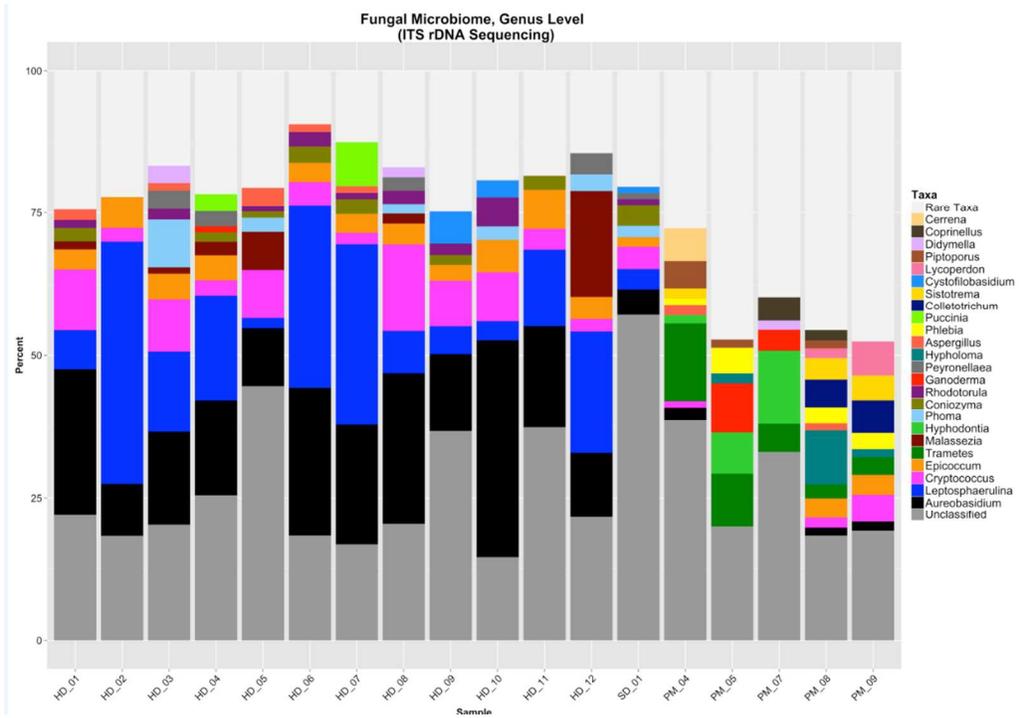
478 **Panel (4b):**



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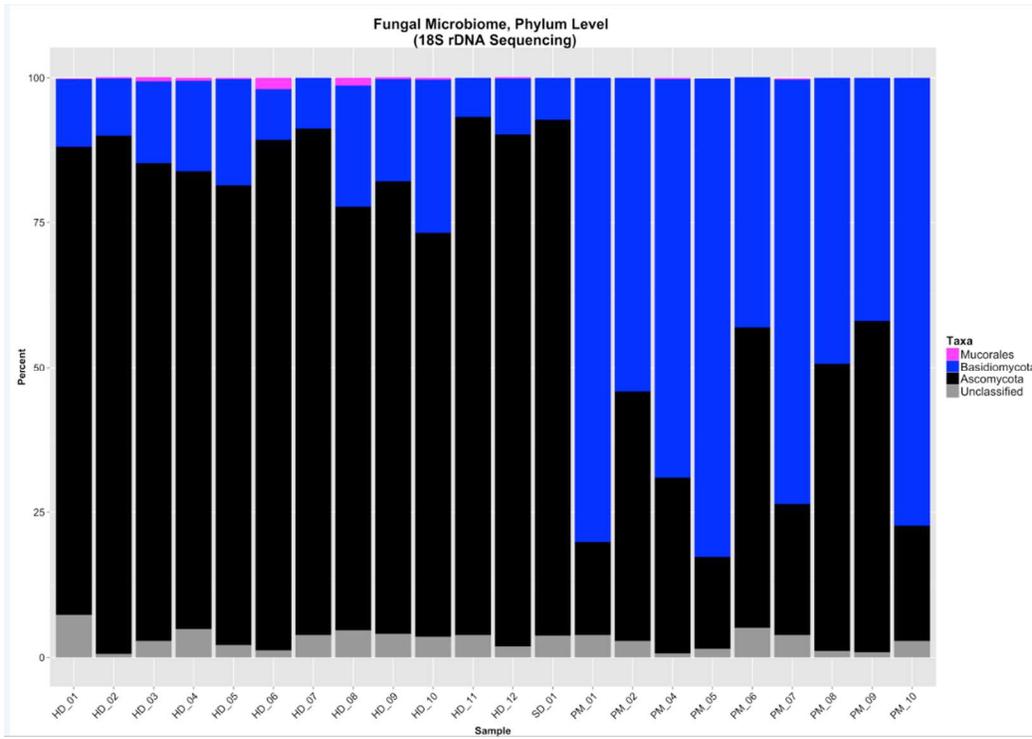
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480 Panel (4c):



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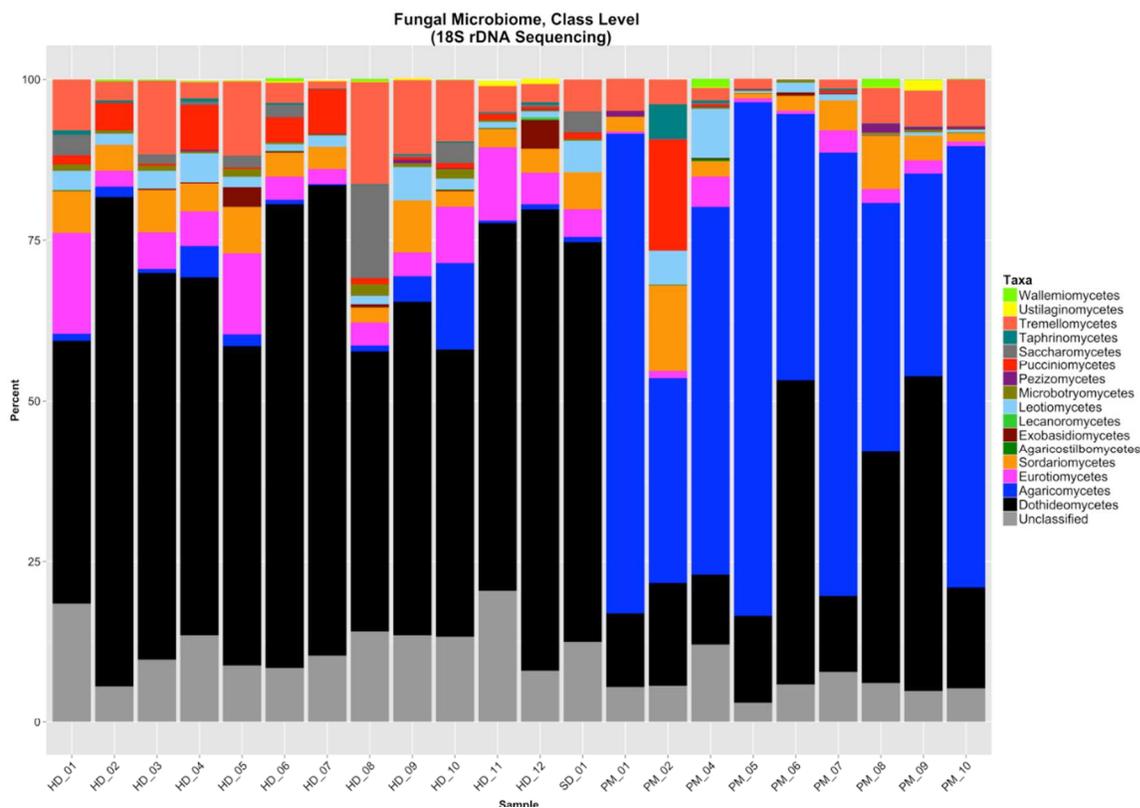
482 Panel (4d):



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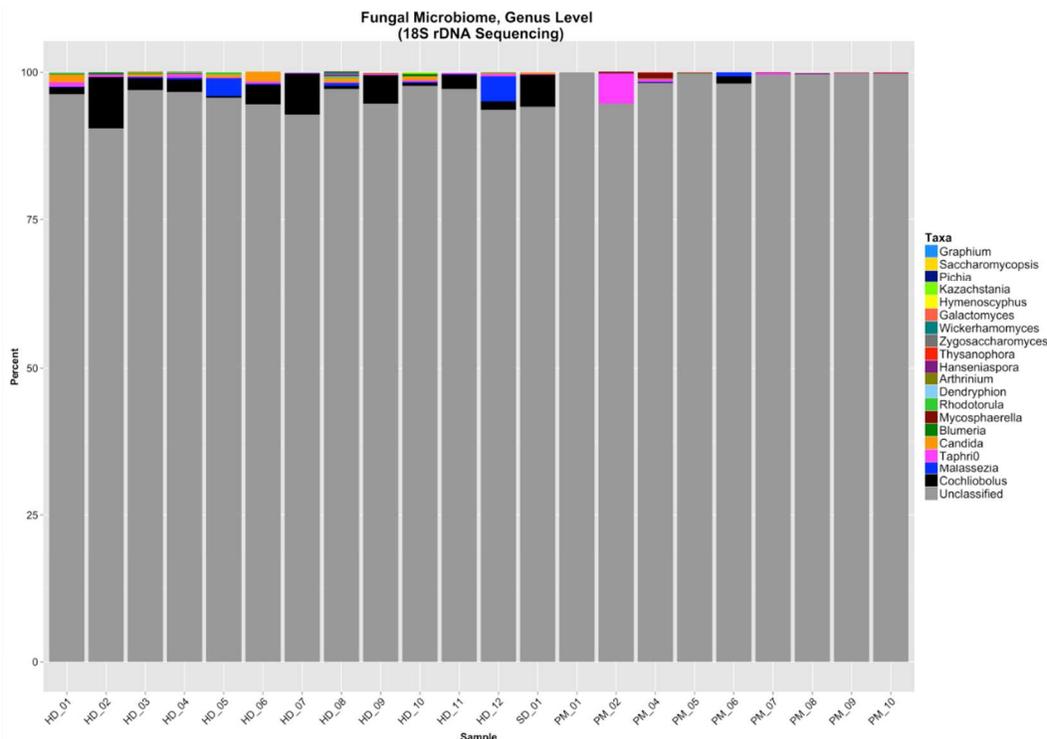
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485 Panel (4e):



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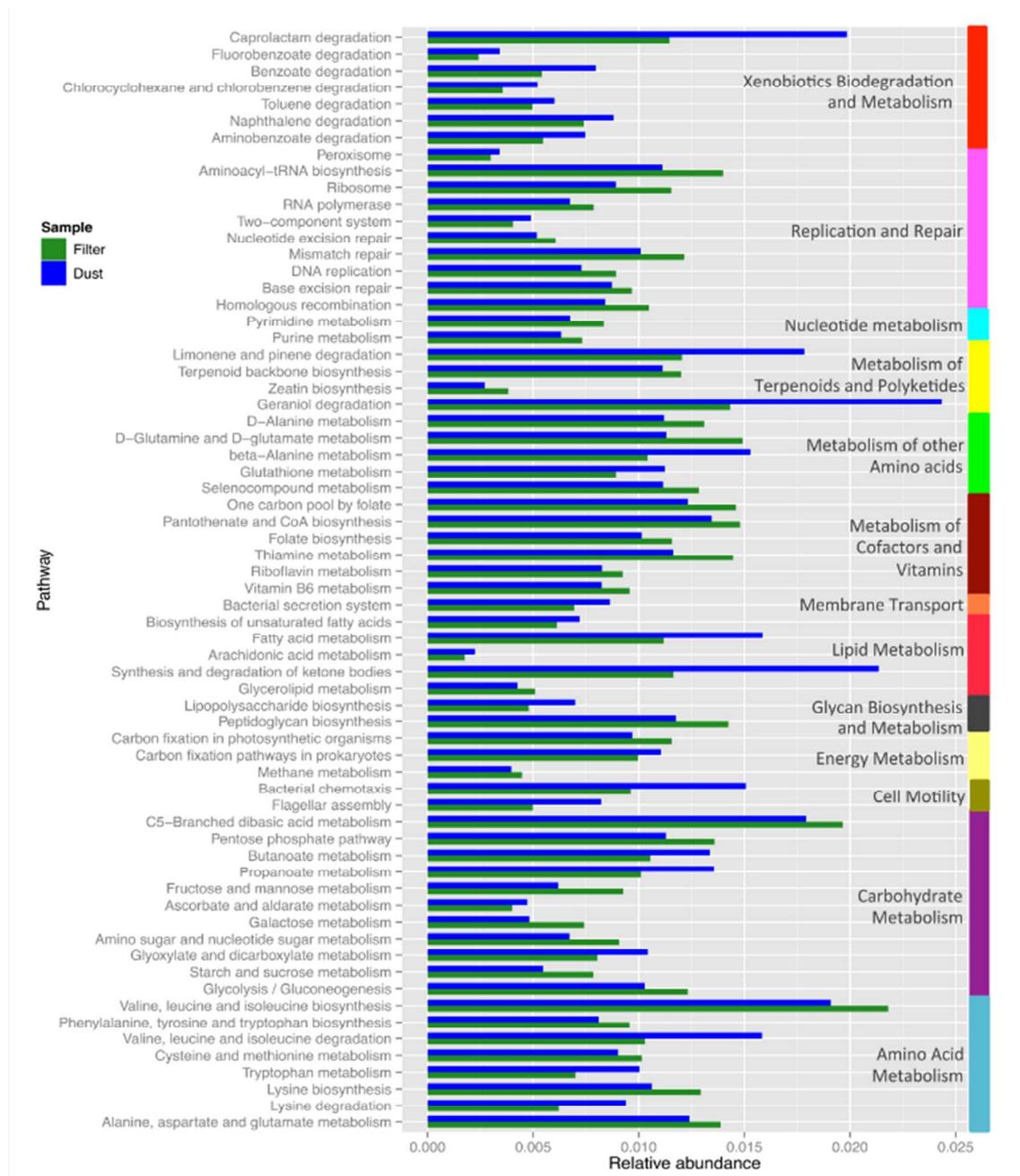
487 Panel (4f):



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489 **Figure 5. Differentially Abundant Functional Gene/Metabolic Pathways in indoor dust vs outdoor**  
 490 **CAPs (filter) samples (p<0.0001 for all comparisons)**

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Table 1. Characteristics of Environmental Samples

Sample ID	Sample Type	Sample Details	Season	Microbiome Sequencing			
				16S (Bacteria)	ITS (Fungi)	18S (Fungi)	Culture for Fungi
HD_01	House Dust	Living room floor	summer	X	X	X	X
HD_02	House Dust	Child's bedroom floor	Fall	X	X	X	X
HD_03	House Dust	Living room floor	Fall	X	X	X	X
HD_04	House Dust	Child's bedroom floor	Fall	X	X	X	X
HD_05	House Dust	Child's bedroom floor	summer	X	X	X	X
HD_06	House Dust	Living room floor	summer	X	X	X	X
HD_07	House Dust	Living room floor	Fall	X	X	X	X
HD_08	House Dust	Living room floor	Fall	X	X	X	X
HD_09	House Dust	Living room floor	Winter	X	X	X	X
HD_10	House Dust	Living room floor	Fall	X	X	X	X
HD_11	House Dust	Living room floor	Spring	X	X	X	
HD_12	House Dust	Living room floor	Spring	X	X	X	
SD_01	School Dust	Classroom		X	X	X	
PM_01	Outdoor CAPs	Coarse particles (PM2.5-10)	Fall	X		X	
PM_02	Outdoor CAPs	Coarse particles (PM2.5-10)	Spring	X		X	
PM_03	Outdoor CAPs	Fine particles (PM0.1-2.5)	Winter	X		X	
PM_04	Outdoor CAPs	Fine particles (PM0.1-2.5)	Spring	X	X	X	
PM_05	Outdoor CAPs	Coarse particles (PM2.5-10)	Fall	X	X	X	
PM_06	Outdoor CAPs	Fine particles (PM0.1-2.5)	Fall	X		X	
PM_07	Outdoor CAPs	Coarse particles (PM2.5-10)	summer	X	X	X	
PM_08	Outdoor CAPs	Coarse particles (PM2.5-10)	Fall	X	X	X	
PM_09	Outdoor CAPs	Coarse particles (PM2.5-10)	Fall	X	X	X	

**Table 2. Fungal Genera Cultured from House Dust Samples and Detection by ITS Sequencing**

ID	Alternaria		Aspergillus		Aureobasidium		Botrytis		Cladosporium		Curvularia		Epicoccum		Paecilomyces		Penicillium		Trichoderma	
	Cul	ITS	Cul	ITS	Cul	ITS	Cul	ITS	Cul	ITS	Cul	ITS	Cul	ITS	Cul	ITS	Cul	ITS	Cul	ITS
HD_01	●	●		●	●	●		●	●	●	●			●			●	●		
HD_02	●	●			●	●			●	●			●	●			●	●		
HD_03	●	●	●	●	●	●			●	●			●	●			●	●		
HD_04	●	●		●	●	●		●	●	●			●	●			●	●		
HD_05	●	●	●	●	●	●			●	●			●	●			●	●		
HD_06	●	●	●	●	●	●			●	●	●	●	●	●			●	●		
HD_07	●	●		●	●	●			●	●	●	●	●	●			●	●		
HD_08	●	●		●	●	●			●	●			●	●			●	●		●
HD_09	●	●	●	●	●	●			●	●		●	●	●	●		●	●		
HD_10	●	●		●	●	●			●	●			●	●			●	●		

Cul= Detectable by culture; ITS=Detectable by ITS sequencing at 0.1% relative abundance or greater.

(●) indicates if a fungal genera was detected in a given sample

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