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# **A conserved interdomain microbial network underpins cadaver decomposition despite environmental variables**

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Supplementary Information for

**A conserved interdomain microbial network underpins cadaver decomposition despite environmental variables**

Zachary M. Burcham<sup>1,2</sup>, Aerial D. Belk<sup>1,3</sup>, Bridget B. McGivern<sup>4</sup>, Amina Bouslimani<sup>5</sup>, Parsa Ghadermazi<sup>6</sup>, Cameron Martino<sup>7</sup>, Liat Shenhav<sup>8,9,10</sup>, Anru R. Zhang<sup>11,12</sup>, Pixu Shi<sup>11</sup>, Alexandra Emmons<sup>1</sup>, Heather Deel<sup>1</sup>, Zhenjiang Zech Xu<sup>13</sup>, Victoria Nieciecki<sup>1,14</sup>, Qiyun Zhu<sup>7,15,16</sup>, Michael Shaffer<sup>4</sup>, Morgan Panitchpakdi<sup>5</sup>, Kelly C. Weldon<sup>5</sup>, Kalen Cantrell<sup>17</sup>, Asa Ben-Hur<sup>18</sup>, Sasha C. Reed<sup>19</sup>, Greg C. Humphry<sup>7</sup>, Gail Ackermann<sup>7</sup>, Daniel McDonald<sup>7</sup>, Siu Hung Joshua Chan<sup>6</sup>, Melissa Connor<sup>20</sup>, Derek Boyd<sup>21,22</sup>, Jake Smith<sup>21,23</sup>, Jenna M.S. Watson<sup>21</sup>, Giovanna Vidoli<sup>21</sup>, Dawnie Steadman<sup>21</sup>, Aaron M. Lynne<sup>24</sup>, Sibyl Bucheli<sup>24</sup>, Pieter C. Dorrestein<sup>5</sup>, Kelly C. Wrighton<sup>4</sup>, David O. Carter<sup>25</sup>, Rob Knight<sup>7,17,26,27</sup>, Jessica L. Metcalf<sup>1\*</sup>

Corresponding author: [jessica.metcalf@colostate.edu](mailto:jessica.metcalf@colostate.edu)

**The PDF file includes:**

Legends for Supplementary Tables 1 to 9, 14 to 16, and 25 to 39  
Supplementary Tables 10 to 13 and 17 to 24  
Supplementary Text

**Other Supplementary Material for this manuscript includes the following:**

Supplementary Tables 1 to 9, 14 to 16, and 25 to 39 (separate file)

**Supplementary Text**

Full details of mathematical models in joint-robust principal component analysis

30 **SUPPLEMENTARY TABLES AND LEGENDS**

31

32 **Supplementary Table 1. (separate file)**

33 Sample metadata. Table includes data taken during intake and over the course of the study.

34

35 **Supplementary Table 2. (separate file)**

36 ANCOM-BC differential abundance analysis results of cadaver skin metabolite log-ratio change  
37 over decomposition stages. Initial day 0 samples were used as the reference level and the  
38 intercept. Results include log-ratio changes of day 0 metabolites to early, active, and advanced  
39 decomposition stages, P-values, Holm–Bonferroni-corrected P-values (Q-values), standard  
40 errors, and W-values.

41

42 **Supplementary Table 3. (separate file)**

43 ANCOM-BC differential abundance analysis results of cadaver-associated soil metabolite log-  
44 ratio change over decomposition stages. Initial day 0 samples were used as the reference level  
45 and the intercept. Results include log-ratio changes of day 0 metabolites to early, active, and  
46 advanced decomposition stages, P-values, Holm–Bonferroni-corrected P-values (Q-values),  
47 standard errors, and W-values.

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49 **Supplementary Table 4. (separate file)**

50 List of samples used to generate shotgun metagenomic data.

51

52 **Supplementary Table 5.**

53 Assembly statistics and GTDB taxonomic classification of genomic bins (metagenome-  
54 assembled genomes; MAGs) co-assembled from the metagenomic samples. Table includes  
55 completeness and contamination of each MAG.

56

57 **Supplementary Table 6. (separate file)**

58 TPM-normalized count abundance of MAGs within metagenomic samples.

59

60 **Supplementary Table 7. (separate file)**

61 Linear mixed-effects model statistics for testing response variable change of ATP per C-mol  
62 amino acids calculated from metagenomic data over ADD at each facility and a random intercept  
63 for each individual body to account for repeated measures to test whether the metabolism  
64 efficacy shifts within each facility. Formula: “ATPm ~ ADD + (1|body ID)”.

65

66 **Supplementary Table 8. (separate file)**

67 Linear mixed-effects model statistics for testing response variable change of ATP per C-mol  
68 carbohydrates calculated from metagenomic data over ADD at each facility and a random  
69 intercept for each individual body to account for repeated measures to test whether the  
70 metabolism efficacy shifts within each facility. Formula: “ATPm ~ ADD + (1|body ID)”.

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72 **Supplementary Table 9. (separate file)**

73 Linear mixed-effects model statistics for testing response variable change of ATP per C-mol  
74 lipids calculated from metagenomic data over ADD at each facility and a random intercept for

75 each individual body to account for repeated measures to test whether the metabolism efficacy  
 76 shifts within each facility. Formula: “ATPm ~ ADD + (1|body ID)”.

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 78 **Supplementary Table 10.**

79 Kruskal-Wallis rank sum test statistics for comparison of  $\beta$ NTI distance values between  
 80 decomposition stages at each facility. The tests used were Kruskal-Wallis rank sum tests.

Test	Metric	Facility	Chi-squared	df	p-value
Kruskal Wallis	$\beta$ NTI	FIRS	524.89	2	<2.2E-16
Kruskal Wallis	$\beta$ NTI	STAFS	132.37	2	<2.2E-16
Kruskal Wallis	$\beta$ NTI	ARF	123.48	2	<2.2E-16

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 82 **Supplementary Table 11.**

83 Dunn multiple comparison with Benjamini-Hochberg adjustment test statistics for comparison of  
 84  $\beta$ NTI distance values between decomposition stages at each facility.

Test	Metric	Facility	Comparison	Z	P.unadj	P.adj
Dunn	$\beta$ NTI	FIRS	AC-AD to EA-AC	17.59	2.73E-69	4.1E-69
Dunn	$\beta$ NTI	FIRS	AC-AD to PL-EA	20.80	3.97E-96	1.19E-95
Dunn	$\beta$ NTI	FIRS	EA-AC to PL-EA	9.93	3.18E-23	3.18E-23
Dunn	$\beta$ NTI	STAFS	AC-AD to EA-AC	7.65	1.99E-14	2.99E-14
Dunn	$\beta$ NTI	STAFS	AC-AD to PL-EA	8.92	4.6E-19	1.38E-18
Dunn	$\beta$ NTI	STAFS	EA-AC to PL-EA	6.85	7.41E-12	7.41E-12
Dunn	$\beta$ NTI	ARF	AC-AD to EA-AC	2.78	5.58E-03	5.58E-03
Dunn	$\beta$ NTI	ARF	AC-AD to PL-EA	10.98	4.62E-28	1.39E-27
Dunn	$\beta$ NTI	ARF	EA-AC to PL-EA	9.64	5.54E-22	8.32E-22

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 86 **Supplementary Table 12.**

87 Kruskal-Wallis rank sum test statistics for comparison of metabolic resource overlap (MRO) and  
 88 metabolic interaction potential (MIP) values between decomposition stages at each facility. The  
 89 tests used were Kruskal-Wallis rank sum tests.

Test	Metric	Facility	Dataset	Chi-squared	df	p-value
Kruskal Wallis	MRO	FIRS	Co-occurrence	4.1188	1	0.04241
Kruskal Wallis	MIP	FIRS	Co-occurrence	61.795	1	3.811E-15
Kruskal Wallis	MRO	STAFS	Co-occurrence	181.24	2	<2.2E-16
Kruskal Wallis	MIP	STAFS	Co-occurrence	190.67	2	<2.2E-16
Kruskal Wallis	MRO	ARF	Co-occurrence	3.5887	2	0.1662
Kruskal Wallis	MIP	ARF	Co-occurrence	134.88	2	<2.2E-16
Kruskal Wallis	MRO	FIRS	Null/Random	0.3648	1	0.5459
Kruskal Wallis	MIP	FIRS	Null/Random	0.2267	1	0.634
Kruskal Wallis	MRO	STAFS	Null/Random	0.4032	2	0.8174
Kruskal Wallis	MIP	STAFS	Null/Random	4.3567	2	0.1132

Kruskal Wallis	MRO	ARF	Null/Random	3.2102	2	0.2009
Kruskal Wallis	MIP	ARF	Null/Random	1.0856	2	0.5811

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**Supplementary Table 13.**

Dunn's multiple comparison with Benjamini-Hochberg adjustment test statistics for comparison of metabolic resource overlap (MRO) and metabolic interaction potential (MIP) values between decomposition stages at each facility.

Test	Metric	Facility	Comparison	Z	P.unadj	P.adj
Dunn	MRO	STAFS	Active-advanced	13.46	2.62E-41	7.85E-41
Dunn	MRO	STAFS	Active-early	6.63	3.42E-11	3.42E-11
Dunn	MRO	STAFS	Advanced-early	-6.84	8.2E-12	1.23E-11
Dunn	MIP	STAFS	Active-advanced	-10.24	1.36E-24	2.04E-24
Dunn	MIP	STAFS	Active-early	-13.14	1.84E-39	5.53E-39
Dunn	MIP	STAFS	Advanced-early	-2.91	3.65E-3	3.65E-3
Dunn	MRO	ARF	Active-advanced	-0.8	0.42	0.42
Dunn	MRO	ARF	Active-early	-1.89	0.06	0.18
Dunn	MRO	ARF	Advanced-early	-1.09	0.28	0.42
Dunn	MIP	ARF	Active-advanced	0.05	0.96	0.96
Dunn	MIP	ARF	Active-early	10.08	6.51E-24	1.95E-23
Dunn	MIP	ARF	Advanced-early	10.03	1.11E-23	1.67E-23

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**Supplementary Table 14. (separate file)**

Number of predicted exchanges for cross-fed compounds at each facility during late decomposition. Late decomposition was defined as the advanced decomposition stage at STAFS and ARF and the active decomposition stage at FIRS.

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**Supplementary Table 15. (separate file)**

Linear mixed-effects model statistics for testing response variable change of Generalized UniFrac PC1 distances calculated from 16S rRNA gene data over ADD at each facility with sampling site (i.e., soil adjacent to hip vs. soil control) as an independent variable (fixed effect) and a random intercept for each individual body to account for repeated measures. The models measure the sampling site and ADD variables individually and the interaction between the variables. The interaction between the variables was used to test whether the sampling sites respond differently to decomposition. Formula: “diversity metric ~ ADD \* sampling site + (1|body ID)”.

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**Supplementary Table 16. (separate file)**

Linear mixed-effects model statistics for testing response variable change of ASV richness calculated from 16S rRNA gene data over ADD at each facility with sampling site (i.e., soil adjacent to hip vs. soil control) as an independent variable (fixed effect) and a random intercept for each individual body to account for repeated measures. The models measure the sampling site and ADD variables individually and the interaction between the variables. The interaction

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117 between the variables was used to test whether the sampling sites respond differently to  
 118 decomposition. Formula: “diversity metric ~ ADD \* sampling site + (1|body ID)”.

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 120 **Supplementary Table 17.**

121 Permutational multivariate analysis of variance model statistics using vegan-R adonis in QIIME2  
 122 v. 2022.2 (permutations = 5000) with the combined multi-omics Joint-RPCA distance matrix as  
 123 the response variable. Formula: “distance matrix ~ decomp\_group \* climate \* facility \* season”.

	Df	SumsOfSqs	MeanSqs	F.Model	R2	Pr(>F)
decomp_group	3	0.5099	0.1700	63.8083	0.0958	0.0002
climate	1	1.2560	1.2560	471.5303	0.2359	0.0002
facility	1	1.0828	1.0828	406.5141	0.2034	0.0002
season	3	0.8440	0.2813	105.6233	0.1585	0.0002
decomp_group:climate	3	0.0528	0.0176	6.6015	0.0099	0.0002
decomp_group:facility	3	0.0223	0.0074	2.7856	0.0042	0.0006
decomp_group:season	9	0.1156	0.0128	4.8220	0.0217	0.0002
climate:season	2	0.0668	0.0334	12.5446	0.0126	0.0002
facility:season	3	0.3794	0.1265	47.4766	0.0713	0.0002
decomp_group:climate:season	6	0.0084	0.0014	0.5282	0.0016	0.9756
decomp_group:facility:season	9	0.1065	0.0118	4.4426	0.0200	0.0002
Residuals	330	0.8790	0.0027	NA	0.1651	NA
Total	373	5.3234	NA	NA	1.0000	NA

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 125 **Supplementary Table 18.**

126 Permutational multivariate analysis of variance model statistics using vegan-R adonis in QIIME2  
 127 v. 2022.2 (permutations = 5000) with the 16S rRNA gene abundances RPCA distance matrix as  
 128 the response variable. Formula: “distance matrix ~ decomp\_group \* climate \* facility \* season”.

	Df	SumsOfSqs	MeanSqs	F.Model	R2	Pr(>F)
decomp_group	3	0.2827	0.0942	36.8614	0.0873	0.0002
climate	1	0.6330	0.6330	247.5760	0.1954	0.0002
facility	1	0.5326	0.5326	208.3075	0.1644	0.0002
season	3	0.4822	0.1607	62.8620	0.1489	0.0002
decomp_group:climate	3	0.0329	0.0110	4.2953	0.0102	0.0002
decomp_group:facility	3	0.0717	0.0239	9.3497	0.0221	0.0002
decomp_group:season	9	0.0334	0.0037	1.4535	0.0103	0.0638
climate:season	2	0.0787	0.0394	15.3978	0.0243	0.0002
facility:season	3	0.1762	0.0587	22.9734	0.0544	0.0002
decomp_group:climate:season	6	0.0361	0.0060	2.3502	0.0111	0.0022
decomp_group:facility:season	9	0.0356	0.0040	1.5455	0.0110	0.0496
Residuals	330	0.8438	0.0026	NA	0.2605	NA
Total	373	3.2390	NA	NA	1.0000	NA

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131 **Supplementary Table 19.**

132 Permutational multivariate analysis of variance model statistics using vegan-R adonis in QIIME2  
 133 v. 2022.2 (permutations = 5000) with the 18S rRNA gene abundances RPCA distance matrix as  
 134 the response variable. Formula: “distance matrix ~ decomp\_group \* climate \* facility \* season”.

	Df	SumsOfSqs	MeanSqs	F.Model	R2	Pr(>F)
decomp_group	3	0.1078	0.0359	16.3211	0.0347	0.0002
climate	1	0.5048	0.5048	229.2283	0.1627	0.0002
facility	1	0.2779	0.2779	126.2109	0.0896	0.0002
season	3	0.8685	0.2895	131.4546	0.2799	0.0002
decomp_group:climate	3	0.0346	0.0115	5.2303	0.0111	0.0002
decomp_group:facility	3	0.0289	0.0096	4.3744	0.0093	0.0002
decomp_group:season	9	0.0913	0.0101	4.6081	0.0294	0.0002
climate:season	2	0.2433	0.1217	55.2429	0.0784	0.0002
facility:season	3	0.1768	0.0589	26.7664	0.0570	0.0002
decomp_group:climate:season	6	0.0172	0.0029	1.3019	0.0055	0.1882
decomp_group:facility:season	9	0.0250	0.0028	1.2638	0.0081	0.1822
Residuals	330	0.7267	0.0022	NA	0.2342	NA
Total	373	3.1029	NA	NA	1.0000	NA

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 136 **Supplementary Table 20.**

137 Permutational multivariate analysis of variance model statistics using vegan-R adonis in QIIME2  
 138 v. 2022.2 (permutations = 5000) with the MAG abundances RPCA distance matrix as the  
 139 response variable. Formula: “distance matrix ~ decomp\_group \* climate \* facility \* season”.

	Df	SumsOfSqs	MeanSqs	F.Model	R2	Pr(>F)
decomp_group	3	0.3455	0.1152	72.3992	0.1023	0.0002
climate	1	0.9660	0.9660	607.3127	0.2860	0.0002
facility	1	1.0219	1.0219	642.4532	0.3025	0.0002
season	3	0.1352	0.0451	28.3228	0.0400	0.0002
decomp_group:climate	3	0.0200	0.0067	4.1916	0.0059	0.0002
decomp_group:facility	3	0.0111	0.0037	2.3341	0.0033	0.0128
decomp_group:season	9	0.0385	0.0043	2.6874	0.0114	0.0002
climate:season	2	0.0217	0.0109	6.8337	0.0064	0.0002
facility:season	3	0.2036	0.0679	42.6605	0.0603	0.0002
decomp_group:climate:season	6	0.0135	0.0022	1.4100	0.0040	0.1194
decomp_group:facility:season	9	0.0762	0.0085	5.3231	0.0226	0.0002
Residuals	330	0.5249	0.0016	NA	0.1554	NA
Total	373	3.3780	NA	NA	1.0000	NA

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142 **Supplementary Table 21.**

143 Permutational multivariate analysis of variance model statistics using vegan-R adonis in QIIME2  
 144 v. 2022.2 (permutations = 5000) with the MAG gene abundances RPCA distance matrix as the  
 145 response variable. Formula: “distance matrix ~ decomp\_group \* climate \* facility \* season”.

	Df	SumsOfSqs	MeanSqs	F.Model	R2	Pr(>F)
decomp_group	3	0.8410	0.2803	34.4509	0.1090	0.0002
climate	1	1.6593	1.6593	203.9138	0.2151	0.0002
facility	1	1.0324	1.0324	126.8717	0.1338	0.0002
season	3	0.4349	0.1450	17.8133	0.0564	0.0002
decomp_group:climate	3	0.1043	0.0348	4.2718	0.0135	0.0008
decomp_group:facility	3	0.0154	0.0051	0.6310	0.0020	0.7473
decomp_group:season	9	0.1991	0.0221	2.7190	0.0258	0.0002
climate:season	2	0.0702	0.0351	4.3162	0.0091	0.0010
facility:season	3	0.5085	0.1695	20.8298	0.0659	0.0002
decomp_group:climate:season	6	0.0183	0.0031	0.3754	0.0024	0.9802
decomp_group:facility:season	9	0.1469	0.0163	2.0062	0.0190	0.0100
Residuals	330	2.6854	0.0081	NA	0.3480	NA
Total	373	7.7158	NA	NA	1.0000	NA

146 **Supplementary Table 22.**

147 Permutational multivariate analysis of variance model statistics using vegan-R adonis in QIIME2  
 148 v. 2022.2 (permutations = 5000) with the MAG gene module abundances RPCA distance matrix  
 149 as the response variable. Formula: “distance matrix ~ decomp\_group \* climate \* facility \*  
 150 season”.

	Df	SumsOfSqs	MeanSqs	F.Model	R2	Pr(>F)
decomp_group	3	0.2805	0.0935	22.0621	0.0893	0.0002
climate	1	0.5196	0.5196	122.6151	0.1654	0.0002
facility	1	0.2022	0.2022	47.7039	0.0644	0.0002
season	3	0.1448	0.0483	11.3934	0.0461	0.0002
decomp_group:climate	3	0.0528	0.0176	4.1555	0.0168	0.0002
decomp_group:facility	3	0.0176	0.0059	1.3833	0.0056	0.1944
decomp_group:season	9	0.0664	0.0074	1.7405	0.0211	0.0138
climate:season	2	0.0680	0.0340	8.0263	0.0217	0.0002
facility:season	3	0.2676	0.0892	21.0527	0.0852	0.0002
decomp_group:climate:season	6	0.0304	0.0051	1.1942	0.0097	0.2603
decomp_group:facility:season	9	0.0927	0.0103	2.4307	0.0295	0.0006
Residuals	330	1.3984	0.0042	NA	0.4452	NA
Total	373	3.1411	NA	NA	1.0000	NA

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154 **Supplementary Table 23.**  
 155 Permutational multivariate analysis of variance model statistics using vegan-R adonis in QIIME2  
 156 v. 2022.2 (permutations = 5000) with the soil metabolites abundance with predicted chemical  
 157 abundances RPCA distance matrix as the response variable. Formula: “distance matrix ~  
 158 decomp\_group \* climate \* facility \* season”.

	Df	SumsOfSqs	MeanSqs	F.Model	R2	Pr(>F)
decomp_group	3	0.0278	0.0093	1.4870	0.0090	0.1442
climate	1	0.0591	0.0591	9.4983	0.0191	0.0004
facility	1	0.0740	0.0740	11.8883	0.0240	0.0002
season	3	0.4316	0.1439	23.1200	0.1397	0.0002
decomp_group:climate	3	0.0126	0.0042	0.6745	0.0041	0.7165
decomp_group:facility	3	0.0399	0.0133	2.1376	0.0129	0.0286
decomp_group:season	9	0.0581	0.0065	1.0371	0.0188	0.4095
climate:season	2	0.0725	0.0363	5.8288	0.0235	0.0002
facility:season	3	0.1279	0.0426	6.8544	0.0414	0.0002
decomp_group:climate:season	6	0.0164	0.0027	0.4383	0.0053	0.9644
decomp_group:facility:season	9	0.1153	0.0128	2.0593	0.0373	0.0058
Residuals	330	2.0533	0.0062	NA	0.6648	NA
Total	373	3.0885	NA	NA	1.0000	NA

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 160 **Supplementary Table 24.**  
 161 Test statistics for comparison of Joint-RPCA PC values from Axes 1 through 4 on metadata  
 162 variables season, climate, decomposition stage, and facility. The tests used were two-tailed  
 163 Kruskal-Wallis H tests and Mann-Whitney U tests and no multiple comparison adjustments.

Test	Axis	Factor	n_groups	test-statistic	test-statistic-value	p-value
Kruskal Wallis	1	season	4	H	218.48692	4.26E-47
Mann-Whitney U	1	climate	2	U	6429	0.00030241
Kruskal Wallis	1	facility	3	H	14.1469549	0.00084728
Kruskal Wallis	1	decomp_group	4	H	8.57783592	0.03546368
Kruskal Wallis	2	decomp_group	4	H	111.845888	4.40E-24
Kruskal Wallis	2	season	4	H	83.7979755	4.70E-18
Kruskal Wallis	2	facility	3	H	63.879984	1.34E-14
Mann-Whitney U	2	climate	2	U	11962	0.00021862
Kruskal Wallis	3	facility	3	H	280.164284	1.46E-61
Mann-Whitney U	3	climate	2	U	748	1.00E-28
Kruskal Wallis	3	decomp_group	4	H	13.2926913	0.00404456
Kruskal Wallis	3	season	4	H	6.05613856	0.10891068
Kruskal Wallis	4	facility	3	H	267.377664	8.70E-59
Mann-Whitney U	4	climate	2	U	18259	2.89E-33
Kruskal Wallis	4	season	4	H	12.1795546	0.00679272

Kruskal Wallis	4	decomp_group	4	H	9.09038997	0.02811293
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**Supplementary Table 25. (separate file)**

Joint-RPCA PC2 correlations calculated between network feature nodes that correspond with late (i.e., active and advanced) decomposition soil.

**Supplementary Table 26. (separate file)**

Joint-RPCA PC2 correlations calculated between network feature nodes in initial, non-decomposition and early decomposition soil.

**Supplementary Table 27. (separate file)**

16S rRNA gene ASVs assigned to the same taxonomy as decomposer network taxa. Table includes the phylogenetic tree labels in Figure 4E, 150bp length ASVs and trimmed 100bp length ASVs used to explore ASV presence in other studies.

**Supplementary Table 28. (separate file)**

Presence of universal decomposers in possible human and terrestrial source environments in a few other studies. Table shows the average relative abundance of each decomposer ASV across each sample type. Average relative abundances were then summed for each decomposer genus.

**Supplementary Table 29. (separate file)**

Cross-feeding statistics for MAGs predicted as cross-feeders during late decomposition. Table includes GTDB taxonomic classification, number of reactions each MAG was considered the compound receiver and/or donor, and the percent responsible for all donations and acceptances during late decomposition. Late decomposition was defined as the advanced decomposition stage at STAFS and ARF and the active decomposition stage at FIRS.

**Supplementary Table 30. (separate file)**

Cross-feeding exchanges for *Oblitimonas alkaliphila* during late decomposition. *Oblitimonas alkaliphila* was not a predicted cross-feeder at FIRS during this timeframe. Table includes MAG ID and taxonomic classification of genomes involved in exchange, compounds exchanged, and computed interaction metrics.

**Supplementary Table 31. (separate file)**

Cross-feeding exchanges for L-arginine or ornithine during late decomposition. Table includes MAG ID and taxonomic classification of genomes involved in exchange, compounds exchanged, and computed interaction metrics.

**Supplementary Table 32. (separate file)**

Model validation results from predicting an independent test set of samples using the 16S rRNA gene at the SILVA database level-7 taxonomic rank random forest regression models for the skin of the hip and soil adjacent the hip. Errors are represented by MAE in ADD.

**Supplementary Table 33. (separate file)**

208 Presence of universal decomposers in a few other studies focused on mammalian decomposition  
209 environments. A search for the 35 universal PMI decomposer ASVs was conducted within each  
210 dataset. The relative abundance of each decomposer ASV was first averaged across all samples  
211 within a specific metadata category. The average relative abundances were then summed across  
212 each decomposer genus. Prevalence tables were constructed by summing the number of samples  
213 across a specific metadata category in which each universal decomposer ASV was present.  
214

215 **Supplementary Table 34. (separate file)**

216 The average ADD per calendar day calculated for each cadaver at each facility. The average  
217 ADD per calendar day was calculated by dividing the final maximum ADD values by the total  
218 number of days (i.e., 21). The average ADD per day was calculated for each cadaver, season and  
219 facility, each climate type, and as a study-wide average.  
220

221 **Supplementary Table 35. (separate file)**

222 The average ADD per calendar day calculated for each cadaver at each facility for the  
223 independent test set. The average ADD per calendar day was calculated by dividing the final  
224 maximum ADD values by the total number of sampling days. The average ADD per day was  
225 calculated for each cadaver, facility, and as a study-wide average.  
226

227 **Supplementary Table 36. (separate file)**

228 Metabolite identification information for metabolites that had a predicted chemical formula or  
229 matched to a compound in the database library. When available, chemical formulas in the  
230 database library took precedence over predicted chemical formulas for calculating NOSC and  
231 major biochemical classes based on the molar H:C and O:C ratios.  
232

233 **Supplementary Table 37. (separate file)**

234 Soil metabolite feature table normalized with sum normalization then scaled with pareto scaling.  
235 Table includes chemical formulas and major biochemical classes based on the molar H:C and  
236 O:C ratios.  
237

238 **Supplementary Table 38. (separate file)**

239 Skin metabolite feature table normalized with sum normalization then scaled with pareto scaling.  
240 Table includes chemical formulas and major biochemical classes based on the molar H:C and  
241 O:C ratios.  
242

243 **Supplementary Table 39. (separate file)**

244 Sample metadata for machine learning independent test set. Table includes data taken during  
245 intake and over the course of the study.  
246

**SUPPLEMENTARY TEXT**

## Methods

1

2 **Preprocessing.** Prior to joint factorization, we first split the data into training  $j_{train}$  and  
 3 testing  $j_{test}$  samples set from the total set of shared samples  $k$  across all  $N$  input data matrix  
 4  $X_{ij}^1, X_{ij}^2, \dots, X_{ij}^N$ . Each matrix  $X_{ij}^k$  is then transformed, through the robust centered log-  
 5 ratio transformation (robust-clr) to center the data around zero and approximate a normal  
 6 distribution [1].

$$rclr(x) = \left[ \log \frac{x_1}{g_r(x)}, \dots, \log \frac{x_D}{g_r(x)} \right] \quad (1)$$

$$g_r(x) = \left( \prod_{i \in \Omega_x} x_i \right)^{1/|\Omega_x|} \quad (2)$$

7 where  $x_i$  is the abundance of feature (e.g., microbe, metabolite, or gene)  $i$ ,  $\Omega_x$  is the set of  
 8 observed microbes in sample  $x$  and  $g_r(x)$  is the geometric mean only defined on microbes  
 9 with abundance  $> 0$ . Unlike the traditional clr transformation, the robust-clr handles the  
 10 sparsity often found in biological data without requiring imputation. The rclr transformation  
 11 is applied to the training and test set matrices  $rclr(X_{ij_{train}}^k)$  and  $rclr(X_{ij_{test}}^k)$  independently  
 12 to give  $Y_{ij_{train}}^k$  and  $Y_{ij_{test}}^k$ .

13

14 **Joint matrix factorization.** The joint factorization used here is built upon the OptSpace  
 15 matrix completion algorithm which is a singular value decomposition (SVD) optimized on a  
 16 local manifold [2, 1].

$$\min_{U_{shared}, V^k} \frac{\sum_{k=1}^N \left| \Lambda \left( Y^k - U_{shared} S V^{kT} \right) \right|_2^2}{N} \quad (3)$$

17 where  $U_{shared}$  is the matrix being estimated across the shared samples of all input matrices,  
 18  $V^k$  are the matrices being estimated corresponding to each respective to input matrix, and  $S$   
 19 is analogous to a matrix of shared eigenvalues across all input matrices. For each matrix  $Y^k$   
 20 the observed values and  $\Lambda$  is a function such that the errors between  $Y^k$  and  $U_{shared} S V^{kT}$   
 21 are only computed on the nonzero entries and then averaged for each matrix, such that the  
 22 minimized shared estimated matrices  $U_{shared}$  and  $S$  are optimized across all matrices. The  
 23 minimization is performed across iterations by gradient decent. To ensure the rotation of  
 24 the estimated matrices are consistent,  $U_{shared}$  and  $S$  are recalculated at each iteration by

$$U_{shared} S U_{shared} = SVD \left( \frac{\sum_{k=1}^N U^k U^{kT}}{N} \right) \quad (4)$$

25

26 where  $U^k$  is the update for each estimated matrix during that iteration. For each  $V^k$   
 27 iteration update we define  $W^k$  given by

$$\mathbf{W}^k = (\mathbf{S}\mathbf{V}^{kT})^T \quad (5)$$

28 In order to prevent over fitting of the joint-factorization cross validation of the reconstruction  
 29 can be performed. In this case, all of the previously described minimization is performed on  
 30 only the training set data. The test set data is then projected into the same space using the  
 31 training set data estimated matrices and the reconstruction of the test data is calculated,  
 32 given by:

$$cross-validation\ error = \frac{\sum_{k=1}^N \left| \Lambda \left( \mathbf{Y}_{test}^k - (\mathbf{Y}_{test}^k \mathbf{V}_{train}^{kT}) \mathbf{W}_{train} \right) \right|_2^2}{N} \quad (6)$$

33 Through this it can be ensured that the minimization error of the training data estimations  
 34 also minimizes that of the test set data, which is not incorporated into those estimates on  
 35 each iteration. After the training data estimates are finalized the test set samples can again  
 36 be projected into the final output to prevent those samples from being lost. The covariance  
 37 of all features across all input matrices is calculated from the final estimated matrices by

$$feature\ covariance\ matrix = \begin{bmatrix} \mathbf{W}_1 \\ \mathbf{W}_2 \\ \dots \\ \mathbf{W}_N \end{bmatrix} \begin{bmatrix} \mathbf{W}_1 \\ \mathbf{W}_2 \\ \dots \\ \mathbf{W}_N \end{bmatrix}^T \quad (7)$$

38 Finally, here we treat the Joint-RPCA with only one input matrix  $X_{ij}^1$  as the original RPCA  
 39 [1] but with the additional benefit of the addition of cross-validation for comparison across  
 40 other methods.

41

## 42 References

- 43 [1] C. Martino, J. T. Morton, C. A. Marotz, L. R. Thompson, A. Tripathi, R. Knight,  
 44 K. Zengler, A novel sparse compositional technique reveals microbial perturbations,  
 45 mSystems 4 (2019).
- 46 [2] R. H. Keshavan, S. Oh, A. Montanari, Matrix completion from a few entries, in: 2009  
 47 IEEE International Symposium on Information Theory.