

1 Title

2 **Ecological selection for small microbial genomes along a temperate-to-thermal soil gradient**

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17 Keywords

18 microbial ecology, genome size, genome reduction, thermophile, *Centralia*, coal seam fire,

19 metagenome, disturbance, extreme environment

20 Summary

21 Small bacterial and archaeal genomes provide insights into the minimal requirements for life¹
22 and seem to be widespread on the microbial phylogenetic tree². We know that evolutionary
23 processes, mainly selection and drift, can result in microbial genome reduction^{3,4}. However, we
24 do not know the precise environmental pressures that constrain genome size in free-living
25 microorganisms. A study including isolates⁵ has shown that bacteria with high optimum growth
26 temperatures, including thermophiles, often have small genomes⁶. It is unclear how well this
27 relationship may extend generally to microorganisms in nature^{7,8}, and in particular to those
28 microbes inhabiting complex and highly variable environments like soil^{3,6,9}. To understand the
29 genomic traits of thermally-adapted microorganisms, here we investigated bacterial and
30 archaeal metagenomes from a 45°C gradient of temperate-to-thermal soils overlying the
31 ongoing Centralia, Pennsylvania (USA) coal seam fire. There was a strong relationship between
32 average genome size and temperature: hot soils had small genomes relative to ambient soils
33 (Pearson's $r = -0.910$, $p < 0.001$). There was also an inverse relationship between soil
34 temperature and cell size (Pearson's $r = -0.65$, $p = 0.021$), providing evidence that cell and
35 genome size in the wild are together constrained by temperature. Notably, hot soils had
36 different community structures than ambient soils, implicating ecological selection for thermo-
37 tolerant cells that had small genomes, rather than contemporary genome streamlining within
38 the local populations. Hot soils notably lacked genes for described two-component regulatory
39 systems and antimicrobial production and resistance. Our work provides field evidence for the
40 inverse relationship between microbial genome size and temperature requirements in a
41 diverse, free-living community over a wide range of temperatures that support microbial life.

42 Our findings demonstrate that ecological selection for thermophiles and thermo-tolerant
43 microorganisms can result in smaller average genome sizes *in situ*, possibly because they have
44 small genomes reminiscent of a more ancestral state.

45
46

47 Main text

48 Genome streamlining is a reduction in genome size to increase cellular efficiency, and it
49 evolves by means of selection³. A comparative analysis of changes in microbial genomes sizes
50 with optimal growth temperature found a negative relationship that was independent of
51 phylogeny and environment⁶. This led to the conclusion that thermophiles are examples of
52 free-living microorganisms subject to genome streamlining^{6,10,11}. These results were exciting
53 because they suggested that high temperature can select on genome size, providing insights
54 into environmental conditions that may propel efficiency. For the comparative analysis⁶ and
55 cited studies therein, temperature optimum, genome size, 16S rRNA gene sequences, and
56 habitat were available for a curated collection 115 bacterial and archaeal isolates^{5,12}. Given
57 biases of cultivation¹³, an outstanding question was whether the relationship between growth
58 temperature and genome size would prove to be general for wild microbial communities.

59 Fortuitously, the fire-impact gradient at the Centralia ecosystem provides an
60 opportunity to investigate relationships between temperature and microbial genome traits.
61 Centralia, Pennsylvania is the site of a slow-burning, near-surface coal seam fire that ignited in
62 1962. The heat from the fire vents through overlying soils, causing surface soil temperatures to
63 reach as high as > 400°C¹⁴, but more recently in the range of 40 - 75°C^{15,16}. However, the soils
64 in Centralia were previously temperate, with no known exposure to prolonged high

65 temperatures. Therefore, Centralia offers an interesting model for the examining the eco-
66 evolution of microbial communities ¹⁷.

67 We recently used 16S rRNA gene amplicon sequencing to assess compositional changes
68 in Centralia soil microbial communities along an ambient-to-thermal temperature gradient ¹⁶.
69 Surface soils overlying the coal seam fire were collected to include soils that were hot from fire
70 (“fire-affected”), soils that were previously hot but had since recovered to ambient
71 temperatures (“recovered”) and reference soils that had never been impacted by the fire. As
72 expected, fire-affected soils had starkly different community structure from ambient soils.
73 However, after the fire advanced, soils reasonably recovered towards reference community
74 structure. This suggested a considerable capacity of soil microbiomes for resilience, even after
75 exposure to a severe and unanticipated stressor, and prompted us to next ask what microbial
76 attributes underlay the observed changes in community structure in fire-affected soils.

77 Moving forward, we assessed average genome size along the Centralia fire gradient
78 (**Table S1**). From twelve metagenomes (six fire-affected, five recovered, and one reference),
79 we used MicrobeCensus ¹⁸ to calculate average genome size across a soil temperature range of
80 45 °C. Average genome sizes were negatively and strongly correlated with temperature (**Figure**
81 **1A**, Pearson’s $r = -0.910$, $p < 0.001$). In addition to MicrobeCensus, we used three other distinct
82 and complementary methods to assess changes in genome size with soil temperature and
83 found them all to be in agreement (**Figure S1**). To the best of our knowledge, this is the first
84 report of decreases in genome size across an *in situ* temperature gradient that supports the
85 broad range of physiological requirements from mesophiles to thermophiles.

86 We next compared the average genome sizes estimated from *Centralia* metagenomes
87 to those from 22 publicly available soil metagenomes (**Figure 2, Table S2**). Generally, hot soils
88 in *Centralia* had small genomes relative to other soils, while ambient soils in *Centralia* were
89 closer to the average size observed among this set. Intriguingly, permafrost soils also harbored
90 small average genomes and were comparable to the hottest *Centralia* sites. These results
91 support comparably small genome sizes in *Centralia* soils and also provide a range of expected
92 soil genome sizes more generally.

93 It was hypothesized that small cells may be selected to attain minimal cellular
94 maintenance costs at high temperatures, and that small cells indirectly select for small
95 genomes ⁶. Because we had microscope images from soil cell counts in *Centralia*¹⁶, we re-
96 analyzed the images to extract size information. We found that average cell sizes were also
97 negatively correlated with temperature (**Figure 1B**, Pearson's $r = -0.65$, $p = 0.021$). Accordingly,
98 cell size had a direct relationship with genome size (**Figure 1C**, Pearson's $r = 0.64$, $p = 0.025$).
99 These results agree with reported *in situ* relationships between cell size and temperature in
100 aquatic systems. For example, an experiment investigating a 6°C increase in water temperature
101 confirmed that smaller cells with lower nucleotide content were selected at warmer
102 temperatures ⁷, providing support that even slight warming may enrich for microorganisms
103 with small genomes. An observational study of marine microbial genome size along a
104 latitudinal gradient (10.7°C range) also supports this hypothesis ⁸. Our results extend the cell
105 size-temperature trend to soils and also to a temperature range encompassing 45 °C.

106 To understand the selective outcomes of high temperature on the functions of these
107 small genomes, we next asked if there were functional genes that were characteristically

108 enriched or depleted with increasing temperature. We used shotgun metagenome annotations
109 from the KEGG module (KM) database¹⁹. KMs are groups of KEGG Orthologs (KOs) that
110 represent complexes, functional sets, metabolic pathways, or signatures. Eighty-one percent of
111 KOs detected in *Centralia* metagenomes were detected in all soils, and many patterns with
112 temperature were attributable to changes in normalized KO abundance rather than in KO
113 detection. In total, 284 (out of 541 detected; 52.50%) were correlated with temperature (**Figure**
114 **3, Table S3**).

115 Twenty-seven KMs were positively correlated with temperature (Pearson's $R > 0.656$,
116 false discovery rate adjusted p-value < 0.05 ; **Figure 3A**). Specifically, dissimilatory sulfate
117 reduction (M00596), dissimilatory nitrate reduction (M00530) and denitrification (M00529)
118 were enriched in hot soils (**Figure 3A, cluster iii; Figure 4A**). These are anaerobic processes
119 aligned with known and expected environmental conditions in *Centralia*. Fire-affected soils
120 from active vents have higher moisture than reference and recovered soils (Pearson's $r = 0.714$,
121 $p < 0.01$), which likely promote inundated and anaerobic microhabitats therein. Prior work in
122 *Centralia* has indicated an importance of these metabolisms in hot soils, noting that sulfur,
123 sulfate, nitrate and ammonium were commonly elevated at vents^{14,15}. These results also agree
124 with observations of thermophile metabolisms in other terrestrial and geothermal
125 environments, including a prevalence of denitrification and dissimilatory nitrate reduction^{20,21},
126 highly active nitrogen cycles in hot springs²², and increased dissimilatory organic sulfur
127 mineralization²³. Notably, these anaerobic KMs grouped in their response patterns with several
128 archaeal proteins (**Figure 3A cluster iii**; Archaeal ribosome M00179, polymerase M00184, and
129 exosome M00390). We also observed an increase in Crenarchaeota in fire-affected soils¹⁶, an

130 archaeal phylum that includes sulfate reducers²⁴. Additional results describing patterns and
131 thresholds of KM enrichment with temperature are provided in Supporting Materials. Together,
132 these data suggest that the pathways enriched in small genomes from hot soils offer functions
133 attuned to the *Centralia* habitat.

134 Temperature was negatively correlated with 257 KMs (47.5% out of 541 total KMs
135 detected, Pearson's $R < -0.6$, false discovery rate adjusted p-value < 0.05 ; **Figure 3B**). In general,
136 these depleted KMs were detected across recovered soils and the reference soil. There were
137 two noteworthy categories of KMs that were consistently depleted in hot soils: antimicrobial
138 resistance and production and two component regulatory systems (**Figure 4B**). Together, these
139 two KM categories comprised 32.7% of KMs negatively correlated with temperature (84 out of
140 257). This trend was striking, but we also note that some KMs belonging to these categories had
141 no relationships with temperature and that these KM categories were always detected in fire-
142 affected soils.

143 Thirty-nine modules for antimicrobial production and resistance mechanisms were
144 negatively correlated with temperature (**Figure 4B**), which agrees with a prior analysis of
145 antibiotic resistance genes in this system²⁵. Among these modules were resistance to
146 vancomycin, tetracycline, fluoroquinolone, aminoglycoside, nisin, erythromycin, streptomycin
147 and beta-lactam, and several multidrug efflux pumps. The small genomes of host-associated
148 symbionts often lack antimicrobial genes²⁶. However, the *Pelagibacter* clade, which is a model
149 free-living population that has streamlined genomes, has a conserved multidrug transporter
150 across sequenced genomes²⁷. It could be that thermophiles have fewer genes encoding
151 resistance to described antimicrobials, as evidenced by the challenges inherent in developing

152 specific selectable antibiotic resistance markers for thermophiles^{28,29}. A related consideration
153 is that, like most databases, KEGG is biased towards genomes and annotations from fast-
154 growing mesophiles and may have missed annotation of under-described thermophile
155 antimicrobials. To clarify whether the observed decrease in antimicrobial production and
156 resistance was due to unannotated novelty or a true deficit of these functions in thermal sites,
157 annotation-independent methods could be used to identify antimicrobial-related biosynthetic
158 gene clusters from Centralia metagenomes^{30,31}. In addition, functional screens of Centralia
159 isolates could be performed for antibiotic production and resistances. If there is a true deficit in
160 genes encoding antimicrobial production and resistance, it could be that the thermal conditions
161 present a strong environmental filter that reduces competition among the populations tolerant
162 of the heightened temperature. Our previous work reported decreased richness and
163 phylogenetic diversity fire-affected Centralia soils¹⁶, suggesting that there is a smaller pool of
164 potential competitors inhabiting the hot soils.

165 Additionally, forty-nine detected two-component regulatory system modules were also
166 negatively correlated with temperature (Pearson's $R < -0.6$, **Figure 4B**). Two-component
167 systems consist of a sensor kinase and a response regulator and allow for transcriptional
168 responses to environmental stimuli³². This simple regulatory system allows bacteria to respond
169 to multiple stimuli: the involved genes duplicate, the sensors evolve sensitivity to additional
170 stimuli, and additional genes are transcribed^{32,33}. Previous studies suggested that smaller
171 genomes have fewer regulatory components³⁴, and this relationship is often observed in
172 streamlined genomes^{3,8}. Our results agree with observations of generally less regulation with
173 smaller genomes^{4,11,27,35,36} and also suggest that thermophiles may have lower regulatory

174 needs. It has been proposed that thermophiles with “streamlined” genomes may be more
175 likely to utilize global regulatory systems that mediate transcriptional responses to co-occurring
176 environmental stimuli ¹¹. The degree of environmental variability is also predicted to influence
177 the relative benefit an organism gains from investing in sensing its environment ³⁷. As a
178 common case study in genome reduction, obligate endosymbionts are thought to have drifted
179 towards small genomes in part because environmental conditions are stable and thus sensing
180 requirements are minimal (e.g., ³). Furthermore, in *Centralia*, seasonal temperature
181 fluctuations in fire-affected soils are equivalent to those in ambient soils (**Figure S2**), providing
182 evidence that the soils experience similar environmental stability in temperature, albeit at
183 different ranges. This suggests that small genomes are not necessarily conditional on very
184 stable environments ³. Future work should investigate whether two-component regulatory
185 systems are consistently less prevalent among thermophiles, and, if so, whether their absence
186 is reminiscent of an ancestral state.

187 Our field study supports and reinforces cultivation-dependent observations that
188 suggested bacteria and archaea with small genome sizes have higher growth temperatures ⁶.
189 Because our study considers ecological succession, as evidenced by the turnover in community
190 membership between ambient and hot soils¹⁶, these data indicate that environmental
191 microorganisms with relatively higher temperature requirements also are likely to have small
192 genomes and cell sizes. Surprisingly, it also suggests that microbial populations inhabiting
193 complex environments, like soils, may generally reflect similar overarching traits in genome size
194 as those observed in laboratory studies, which are necessarily biased towards fast-growing
195 organisms that often are of medical, industrial, or agricultural interest (e.g., ³⁸). In addition, this

196 work expands upon previous reports of smaller genomes with higher temperatures^{7,8} to
197 consider a range of *in situ* temperatures at which a variety of microbes compete in non-optimal
198 conditions. For example, we would expect mesophiles growing near their upper temperature
199 ranges and thermophiles growing near their lower temperature ranges to co-occur at some
200 sites in Centralia. Therefore, these results are relevant to the experiences of many wild
201 microorganisms that cope with dynamic environments.

202 Our results add evidence that supports both smaller genomes and cells, on average,
203 with higher temperatures but also offer a key point of distinction. Though the taxa enriched in
204 Centralia hot soils characteristically had smaller genomes and cells, there is no evidence for
205 contemporary genome streamlining in Centralia. Rather, we suspect that these thermo-tolerant
206 cells were resuscitated from the vast dormant pool in soil. This is supported by three lines of
207 evidence. First, there was turnover in community membership across hot and ambient
208 Centralia soils¹⁶, providing evidence against contemporary streamlining within local lineages.
209 Second, there was striking comparability in average genome size of hot Centralia soils to
210 ancient permafrost soils, which largely contain an inactive and very old dormant pool. Third,
211 many other studies have described thermophile persistence and resuscitation from non-
212 thermal environments, suggesting that these lineages are widespread but typically inactive^{21,39–}
213⁴³. Therefore, we posit that Centralia small genomes are characteristic of an ancestral trait of
214 previously dormant thermophiles in the soil and not the outcome of genome streamlining.

215 In conclusion, we found a strong negative relationship between average microbial
216 genome size and temperature in Centralia soils along a mesophile-to-thermophile gradient,
217 spanning 45°C. We also found that cells were smaller in hot soils, supporting the hypothesis

218 that thermo-tolerant bacteria have smaller cell size, which indirectly selects for small genomes
219 ⁶. By KEGG annotations, *Centralia* metagenomes at hot temperatures were best defined by
220 what they lacked rather than enriched modules of distinctive metabolisms. Specifically,
221 environmental sensing mechanisms, such as two-component regulatory systems, and
222 antimicrobial production and resistance mechanisms were in lower abundance in hot soils. In
223 addition, there were a few modules enriched at high temperatures that met expectations for
224 the hot anaerobic environment at active vents, including nitrogen and sulfur metabolism. Our
225 results show that the relationship that was observed between growth temperature and
226 genome size for cultivable isolates also holds true in a complex, *in situ* microbial community
227 that inhabits a complex and variable soil environment. We suggest that, for thermo-tolerant
228 organisms, the relationship between temperature and genome size indicates the precursory
229 microbial condition of small genomes, reminiscent of ancient lineages, rather than
230 contemporary genome streamlining.

231

232 Materials and Methods

233 *DNA extraction and metagenome sequencing*

234 DNA for metagenome sequencing was manually extracted using a phenol chloroform extraction
235 ⁴⁴ and then purified using the MoBio DNEasy PowerSoil Kit (MoBio, Solana Beach, CA, USA)
236 according the manufacturer's instructions. Total DNA sequencing was performed on all 12
237 samples by the Department of Energy's Joint Genome Institute (Community Science Project)
238 using an Illumina HiSeq 2500. Libraries were prepared with a targeted insert size of 270 base

239 pairs. Samples had between 19Gbp and 50Gbp of sequence data. Additional methodology
240 details are provided in Supporting Materials.

241

242 *Quality control, assembly and annotation*

243 Assembly was performed by the Joint Genome Institute according to their standard operating
244 procedure (Supporting Materials). To use all sequencing data, we worked with assembled and
245 unassembled reads processed by Integrated Microbial Genomes (IMG) using their standard
246 annotation pipeline⁴⁵. After comparing several annotation methods (Supporting Materials), we
247 chose to use the KEGG Orthology database for analyzing the *Centralia* data due to its inherent
248 structure and ability to integrate metabolic pathways. KEGG Ortholog (KO) abundances were
249 relativized to the median abundance in each site of a set of 36 single copy genes published
250 previously⁴⁶ (see Supporting Materials). One single copy gene (K01519) was an outlier in 7 out
251 of 12 samples as assessed by Grubb's test for outliers and removed. We analyzed patterns in
252 KEGG Modules (KMs)¹⁹, a set of manually defined functional units made up of multiple KOs. KM
253 abundances were calculated based on the median abundance of their constituent KOs that
254 were present in the metagenomes. KMs were included in analysis if 50% or more of their
255 constituent KOs were identified in the dataset. Approximately one third of the open reading
256 frames per sample were able to be annotated with KEGG (**Table S1**). As a caveat to the study,
257 unannotated open reading frames can result from erroneous reads and mis-assemblies but also
258 could be novel and or divergent genes critical for microbial processes. Thus, new annotations
259 could impact the overarching patterns described here.

260

261 *Average genome and cell size*

262 Average genome size was calculated from the quality filtered DNA sequences using
263 MicrobeCensus (“run_microbe_census.y -n 2000000”), which estimates average genome size
264 by calculating the percent of sampled reads that match to a set of single copy genes¹⁸. We also
265 used three additional methods to calculate average genome size (see Supporting Materials),
266 and all were in agreement in revealing the negative relationship between temperature and
267 average genome size. To calculate cell size, we re-analyzed microscope images previously used
268 to count microbial cells for community size quantifications in the same soils¹⁶. We hand-
269 curated a debris-free subset from the images and measured 44 - 910 cells from 3 - 9 replicate
270 fields for each soil. The major and minor axes of cells were measured using a FIJI macro in
271 ImageJ (Version: 2.0.0-rc-65/1.51s Build: 961c5f1b7f). We found that cell size range and
272 deviations (**Table S4**) were consistent with those previously reported⁴⁸.

273

274 *Comparisons with other soil metagenomes*

275 All metagenomic data sets for comparison were obtained from MG-RAST
276 (<http://metagenomics.anl.gov/>). The MG-RAST database was searched with the following
277 criteria: material = soil, sequence type = shotgun, public = true. The resulting list of
278 metagenome data sets were ordered by number of base pairs (bp). Metagenomic data sets
279 with the most bp were included if they were sequenced using Illumina (to standardize
280 sequencing errors), had an available FASTQ file (for internal quality control), and contained <
281 30% low quality as determined by MG-RAST. Within high quality Illumina samples, priority for
282 inclusion was given to projects with multiple samples. When a project had multiple samples,

283 data sets with the greatest bp were selected. This search yielded 22 data sets from 12 locations
284 and five countries (**Table S2**). Sequences from MG-RAST data sets were quality checked using
285 FastQC (v0.11.3,⁴⁹ and quality controlled using the FASTX toolkit (fastq_quality_filter, "-Q33 -q
286 30 -p 50"). Average genome size for each dataset was calculated from the quality filtered DNA
287 sequences using MicrobeCensus with default parameters.

288

289 *Statistical analyses*

290 Statistics for the metagenome datasets were performed in the R environment for
291 statistical computing⁵⁰. The stats package was used for calculating Pearson's correlations⁵⁰. The
292 outliers package⁵¹ was used for identifying outlying KOs. The ggplot2 package was used for
293 visualization⁵². Heat maps were created with heatmap2 from the gplots package⁵³.

294

295 *Data and workflows*

296 All analysis workflows are available on GitHub (ShadeLab/PAPER_SorensenInPrep).

297 Metagenome data are available on IMG under the GOLD Study ID GS0114513.

298

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421

422 Contributions

423 AS and TCT conceived the study and conducted field work. JWS and TKD performed analyses,
424 with direction and oversight by AS. JWS, AS and TKD contributed writing. All authors discussed
425 results, and commented on and edited the manuscript.

426

427 Competing financial interests

428 The authors declare no competing financial interests.

429

430 Figure Legends

431 Figure 1. Changes in average genome and cell sizes across the soil temperature gradient in
432 Centralia. (A) Average genome size in each metagenome was calculated using MicrobeCensus
433 and plotted against site temperature. (B) Average cell length was measured from 44-910 cells
434 from 3-9 replicate fields for each soil and plotted against soil temperature. (C) Average genome
435 size had a direct relationship with average cell size.

436

437 Figure 2. Average genome size in soil metagenomes, estimated using MicrobeCensus.¹⁸

438 Samples are ordered by average genome size and colored by sample location.

439

440 Figure 3. Heatmap of KEGG modules correlated with temperature (false discovery rate adjusted
441 p-value < 0.05). Modules (rows) are centered and standardized across Centralia metagenomes
442 (columns), with warm colors showing relative enrichment and cool colors showing relative
443 depletion. Modules with significant relationships with temperature are shown. Sites are
444 arranged by increasing temperature from left to right. (A) 27 KEGG modules were positively
445 correlated with temperature (Pearson's R range = 0.646 to 0.933). (B) 257 KEGG modules were
446 negatively correlated with temperature (Pearson's R range = -0.642 to -0.925). A third of the
447 KEGG modules negatively correlated with temperature were either two-component regulatory

448 systems (TCRS, blue dendrogram tips), antimicrobial resistance or production (ARP, gray tips),
449 or both (black tips). Note differences in color gradient ranges across panels A and B.

450

451 Figure 4. KEGG modules that had notable enrichments or depletions with temperature. (A) The
452 median abundances of KEGG modules for denitrification (red), dissimilatory nitrate reduction
453 (green) and dissimilatory sulfate reduction (blue) were all positively correlated with
454 temperature. (B) Pearson's correlation values for all detected modules classified as antibiotic
455 resistance and production (gray density, $n = 62$ detected modules) or two-component
456 regulatory systems (blue density, $n = 89$ detected modules). The black vertical line
457 distinguishes correlation values that are significant at a false discovery rate adjusted p -value $<$
458 0.05 (left), and all of these had a strong and negatively relationship with temperature. In total,
459 there were 39 antimicrobial resistance and production modules and 49 two-component
460 regulatory system modules that significantly decreased with temperature.

461

462 Supporting Figures

463 Figure S1. Complementary methods used to assess changes in average genome size across the
464 soil temperature gradient in Centralia. (A) Odds ratios were calculated for 35 single-copy gene
465 KEGG Orthologs in each site and plotted against site temperature. Reported correlation is
466 between all single copy gene odds ratios and temperature, and all $p < 0.001$. (B) Average
467 genome size in each site was calculated based on phylum level abundances from 16S rRNA gene
468 amplicon data, using weighted average genome sizes of each phylum present in JGI IMG

469 (accessed 19 June 2017, correlation $p < 0.001$). (C) Average MAG size at each site was calculated
470 based on presence/absence of 104 MAGs (correlation $p = 0.029$).

471

472 Figure S2. Annual temperature fluctuations at three fire-affected (circles) and two ambient
473 (triangles) Centralia sites, measured using *in situ* temperature loggers (HOBOS) that were buried
474 5 - 10 cm below the surface. Temperature loggers were deployed after the soils were collected
475 for this study.

476

477 Supporting Tables

478 Table S1. Sequence summary information for *Centrاليا* metagenomes. Soils were collected 03-
479 07 October 2014. Asterisks indicate that the site was actively venting at the time of soil
480 collection.

481 Table S2. MG-RAST metadata for soil metagenomes used in this study.

482 Table S3. KEGG Modules significantly correlated with temperature (false-discovery-rate
483 adjusted p-value <0.05)

484 Table S4. Cell size measurements from microscope images.

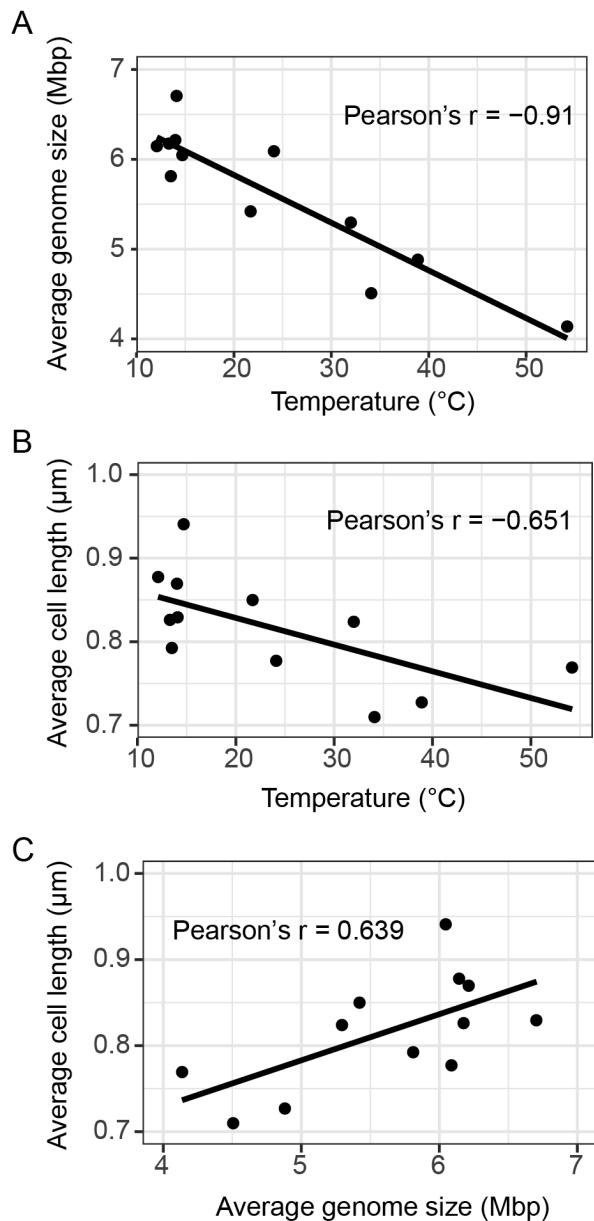
485 Table S5. Single-copy KEGG Orthologs' odds ratios correlations with temperature.

486 Table S6. Lineage, completeness and contamination of Metagenome Assembled Genomes as
487 estimated by CheckM

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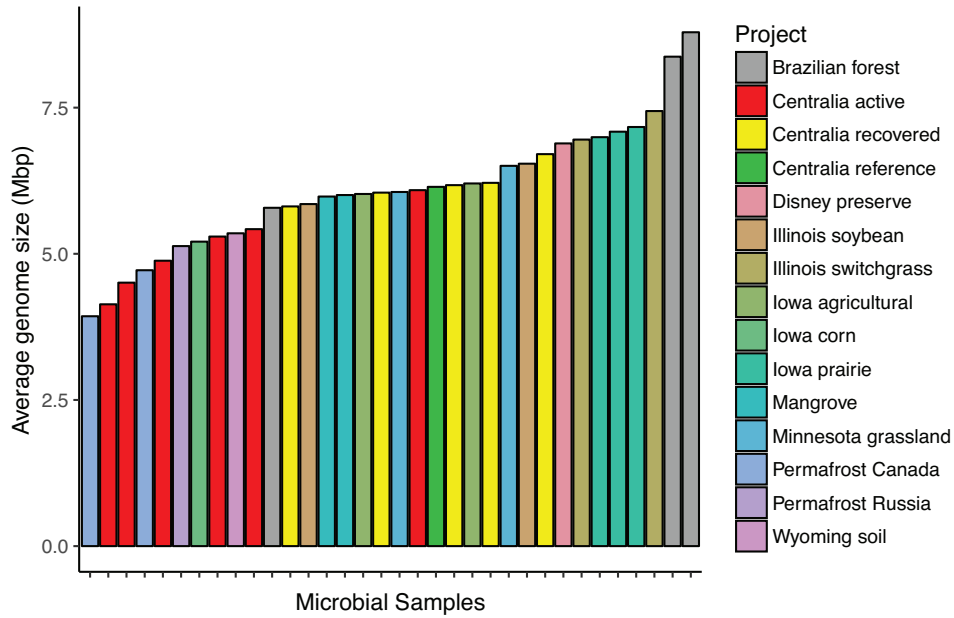
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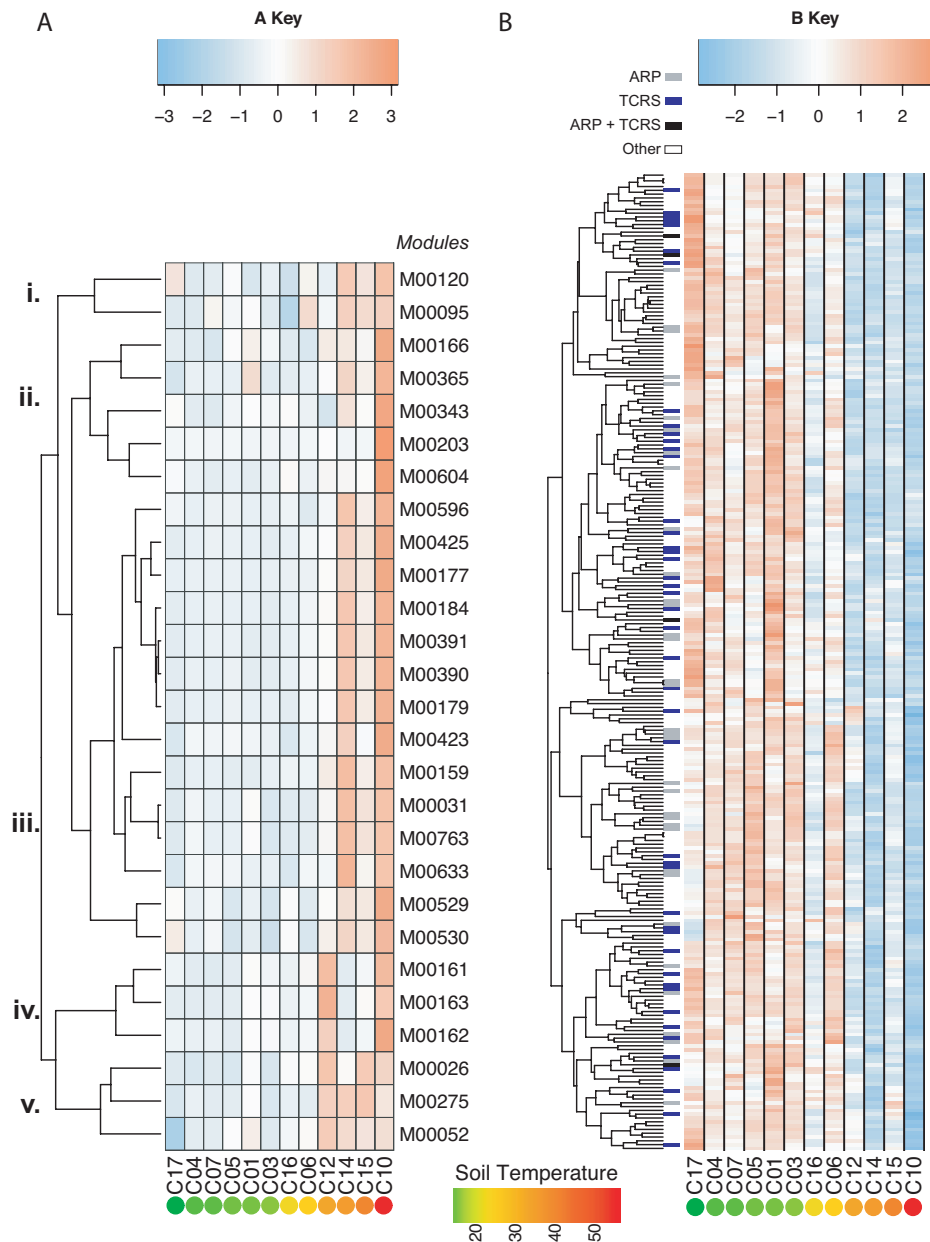
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500
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515



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521 resistance and production (gray density, n = 62 detected modules) or two-component
522 regulatory systems (blue density, n = 89 detected modules). The black vertical line
523 distinguishes correlation values that are significant at a false discovery rate adjusted p-value <
524 0.05 (left), and all of these had a strong and negatively relationship with temperature. In total,
525 there were thirty-nine antimicrobial resistance and production modules and forty-nine two-
526 component regulatory system modules that significantly decreased with temperature.
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