A global deep-sea small protein atlas reveals a reservoir of noncanonical antimicrobial peptides

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Abstract

Small proteins encoded by small open reading frames (smORFs; ≤ 100 aa) represent a largely unexplored dimension of microbial diversity, especially in the deep sea. By analyzing 708 metagenomes from five major deep-sea biomes (hadal trenches, cold seeps, hydrothermal vents, abyssal plains, and seamounts), we constructed the Deep-Sea Small Protein Atlas, comprising 88.7 million smORFs with exceptional novelty and strong habitat specificity. Deep-learning predictions identified 5.47 million candidate antimicrobial peptides (c_AMPs), revealing a peptide space far larger and structurally distinct from known AMPs. Deep-sea c_AMPs are longer, enriched in nonpolar and acidic residues, and exhibit low charge and high intrinsic disorder, suggesting non-membranolytic modes of action. We synthesized 131 representative peptides, of which 87% were antimicrobial, with MICs as low as 1.25 μM, broad-spectrum antibacterial and even antifungal efficacy, and minimal mammalian cytotoxicity. Transcriptomics, TEM imaging, and peptide–protein modeling showed that representative peptides preserve membrane integrity while disrupting intracellular processes such as translation and metabolism, supporting intracellular, non-lytic mechanisms. This work uncovers a vast reservoir of previously unrecognized deep-sea small proteins and structurally unconventional AMPs, providing a foundational resource for discovering next-generation peptide therapeutics.

41 # Introduction

42 The deep sea, comprising cold seeps, hydrothermal vents, hadal trenches, abyssal plains,
43 and seamounts, represents Earth's largest and least explored biome, extending below
44 200 meters and encompassing nearly three-quarters of the ocean's volume[1]. These
45 environments are defined by extreme physicochemical conditions: perpetual darkness,
46 low temperatures (0–4°C, except for hydrothermal systems that exceed 100°C), and
47 immense hydrostatic pressure reaching up to 110 MPa in the deepest trenches. Such
48 harsh conditions have driven the evolution of unique microbial communities with
49 specialized physiological traits and metabolic architectures[1]. Deep-sea microorganisms
50 are prolific producers of bioactive molecules that mediate competition and
51 environmental adaptation, as exemplified by the discovery of unique biosynthetic gene
52 clusters in cold-seep microbiome[2, 3]. Among these adaptations, small proteins encoded
53 by small open reading frames (smORFs; ≤ 100 amino acids) have emerged as a
54 particularly intriguing but underexplored molecular class[4]. Across diverse organisms,
55 smORFs play critical roles in gene regulation[5], stabilization of large protein complexes[6],
56 signal transduction[7], protein transport[8], stress responses[9], and antimicrobial defense[10].
57 Despite this functional breadth, the diversity, ecological distribution, and biological
58 roles of smORFs in deep-sea ecosystems remain largely unknown.

59 Antimicrobial peptides (AMPs) represent one biologically important subset of smORF-
60 encoded proteins. These peptides exhibit activity against bacteria, fungi, and viruses[10,
61 11], and are characterized by properties such as reduced propensity for resistance
62 development[12, 13], increased target specificity, and often lower cytotoxicity compared
63 with conventional antibiotics. However, the systematic discovery of AMPs has been
64 historically constrained by technical limitations, including biased biochemical
65 enrichment, incomplete mass spectrometry reference databases[14], and challenges in
66 distinguishing genuine short coding sequences from spurious predictions[15]. Recent
67 advances in ribosome profiling[16], proteomics[17], comparative genomics[18], and artificial
68 intelligence[19] have transformed our ability to identify small proteins at scale. For

example, the Global Microbial Small Protein Catalog (GMSC) contains nearly one billion non-redundant smORFs from 75 environments[4], while the AMPSphere database reports 863,498 predicted AMPs, more than half of which show antimicrobial activity upon synthesis[20]. Similar large-scale efforts in the human gut[19] and marine biofilms[21] have further demonstrated the abundance and functional potential of environmental AMPs. Yet, despite representing Earth's largest reservoir of microbial novelty[22, 23], the deep sea remains conspicuously underrepresented in these global surveys. Most existing studies rely on cultivation-dependent approaches[24-28], which capture only a small fraction of deep-sea microbial diversity, leaving the vast majority of deep-sea smORFs and AMP-like peptides unexplored.

AMPs operate through diverse mechanisms of action. Classical membrane-disruptive pathways involve electrostatic interactions between cationic peptides and anionic bacterial surface components such as lipopolysaccharides[29], followed by membrane destabilization through barrel-stave, toroidal pore, or carpet-like mechanisms[30]. Increasing evidence, however, indicates that many AMPs act through non-membranolytic mechanisms[31], including inhibition of cell-wall synthesis, replication, transcription, translation, or other essential intracellular processes[32-34]. Such mechanistic diversity expands the functional landscape of antimicrobial peptides and offers opportunities to develop next-generation therapeutics with improved specificity and reduced host toxicity[32]. Given the extreme physicochemical constraints of deep-sea environments, it remains unclear whether deep-sea-derived AMPs follow classical lytic paradigms or instead encode fundamentally distinct modes of action.

Here, we present the Deep-Sea Small Protein Atlas, a comprehensive resource that systematically maps smORFs and antimicrobial peptides across five major deep-sea biomes. By integrating large-scale metagenomic data with advanced computational annotation and deep-learning-based peptide prediction, we construct non-redundant, habitat-resolved smORF catalogs that uncover a vast and previously inaccessible diversity of microbial small proteins and previously undescribed AMP candidates. We

further combine targeted peptide synthesis with antimicrobial assays, transcriptomics, structural modeling, and ultrastructural imaging to interrogate the biological activities and mechanistic potential of representative smORF-derived AMPs. Together, this atlas establishes a foundational framework for understanding small-protein-mediated adaptation in extreme environments and expands the structural and mechanistic repertoire available for next-generation peptide therapeutics.

Results

A vast and previously uncharted deep-sea small-protein landscape

We constructed a large-scale atlas of microbial smORFs from 708 metagenomic samples across five ecologically distinct deep-sea ecosystems **(Fig. 1a; Supplementary Table 1)**. Within each ecosystem, smORFs (≤ 100 aa) were predicted from assembled contigs using a unified workflow and subsequently dereplicated to generate five non-redundant habitat-specific catalogs (**Methods; Fig. 1b**). In total, we identified 88.7 million predicted smORFs, including 49.9 million from hadal trenches, 32.5 million from cold seeps, 3.8 million from hydrothermal vents, 0.8 million from abyssal plains, and 1.8 million from seamounts, representing the most comprehensive deep-sea small-protein resource available to date (**Supplementary Fig. 1; Supplementary Table 2**).

Deep-sea smORFs exhibited exceptionally high novelty relative to existing reference databases. On average, only 23.8% and 4.3% (range: 2.9–29.1%) of deep-sea smORFs displayed detectable homology to entries in sORFdb[35] and SmProt[36], respectively **(Fig. 1c)**. Even when compared with GMSC[4], the largest microbial smORF dataset currently available, an average of 26.8% (range: 19.3–34.9%) of deep-sea smORFs remained unmatched. In total, 23.8 million smORFs showed no similarity to any tested database, greatly expanding the known sequence space of small proteins. Functional and taxonomic annotations further underscored this novelty. Approximately 53.6% (range: 47.8–59.2%) of smORFs lacked KEGG, eggNOG, CAZy, or Pfam annotations **(Fig.**

124 **1d; Supplementary Table 2)**, and nearly half (43.3%; range: 36.4–49.6%) could not
125 be assigned to any taxonomic lineage across the five ecosystems (**Supplementary Fig.**
126 **2**). In line with estimates that ~90% of deep-sea microbial taxa remain undescribed[22,
127 37], the Deep-Sea Small Protein Atlas provides a foundational resource for uncovering
128 previously unknown adaptive mechanisms, ecological functions, and bioactive
129 molecules within Earth's largest and least explored biosphere.

130 **Habitat specificity and distinct metabolic adaptations across deep-sea smORFs**

131 Environmental heterogeneity across the five deep-sea biomes imposes strong selective
132 pressures that shape the diversity and distribution of smORFs. Pairwise comparisons
133 showed that smORFs are overwhelmingly habitat-specific: on average, 86.4% (62.9–
134 97.8%) of smORFs were restricted to a single biome, whereas only 4.4% (0.1–35.0%)
135 were shared between any two habitats (**Fig. 2a; Supplementary Table 3**). Sharing was
136 lowest between hydrothermal vents and abyssal plains (0.1%), reflecting the sharp
137 ecological segregation associated with hydrothermal chemistry[38]. Consistently, within-
138 habitat sharing was minimal, with only 2.5% of smORFs shared in hadal trench samples,
139 2.2% in cold seeps, 4.7% in hydrothermal vents, 37.1% in abyssal plains, and 21.2% in
140 seamounts. The most physiochemically extreme habitats (hadal trenches, cold seeps,
141 and hydrothermal vents) harbored the highest proportions of unique smORFs (> 95.3%),
142 likely driven by steep redox gradients, high hydrostatic pressure, and strongly reducing
143 conditions[38-41]. By contrast, the more stable, oxygenated abyssal plains and seamounts[42,
144 43] exhibited comparatively higher levels of smORF sharing.

145 Despite this pronounced habitat specialization, the atlas revealed a conserved core of
146 902 smORFs present across all biomes (**Supplementary Table 4**). Functional
147 annotation showed enrichment in essential cellular processes, including translation,
148 ribosomal structure and biogenesis (25.8%), transcription (19.1%), and energy
149 production and conversion (10.1%) (**Fig. 2b; Supplementary Table 5**). These findings
150 highlight a dual organizational structure within the deep-sea smORFome: a vast, highly
151 specialized set of habitat-restricted smORFs shaped by localized selection pressures,

152 and a small, deeply conserved core required for fundamental cellular processes across
153 extreme physicochemical regimes.

154 Taxonomic profiling further underscored this pattern of habitat structuring while
155 revealing remarkable phylogenetic breadth. Using MMseqs2-based classification[44]
156 with GTDB R220 [45], 46,303,778 smORFs were taxonomically assigned, spanning 18
157 archaeal and 169 bacterial phyla (**Supplementary Table 6**). Over half of all annotated
158 smORFs were species-specific, with 81.8–89.7% of archaeal and 62.0–68.8% of
159 bacterial assignments mapping to species-level lineages (**Supplementary Fig. 3**).
160 Distinct habitat-level taxonomic signatures were evident: *Nitrososphaeria* dominated
161 archaeal smORFs in hadal trenches (38.0%), abyssal plains (79.3%), and seamounts
162 (89.9%), whereas *Methanosarcinia* (22.0%) and *Thermoprotei* (14.6%) predominated
163 in cold seeps and hydrothermal vents, respectively (**Fig. 2c; Supplementary Table 7**).
164 Among bacteria, *Alphaproteobacteria* were most abundant in hadal trenches (15.2%)
165 and abyssal plains (17.4%), while *Gammaproteobacteria* predominated in cold seeps
166 (12.5%), hydrothermal vents (15.5%), and seamounts (19.7%). These lineage-specific
167 patterns are consistent with known biogeographic distributions[41, 43, 46] and reflect
168 microbial adaptation to highly contrasting redox, pressure, and energy landscapes.
169 Collectively, the atlas demonstrates how local physicochemical regimes act as
170 dominant selective forces shaping the evolution, diversification, and ecological
171 partitioning of small proteins across the deep-sea biosphere[39, 47-49].

172 Functional annotation further revealed metabolic specializations that distinguish deep-
173 sea smORFs from global small-protein repertoires. On average, 46.4% of smORFs per
174 habitat were assigned to COG categories[50] (37.7 million total; **Supplementary Table**
175 **2**). Among these, ~20.5% belonged to poorly characterized functions (S), highlighting
176 the deep sea as a rich reservoir of uncharacterized protein functions. Annotated
177 smORFs were enriched in categories C, J, K, E, and L, corresponding to energy
178 metabolism, amino acid metabolism, and core informational processes
179 (**Supplementary Figs. 4-5; Supplementary Table 8**). Consistent with GMSC

180 database[4], information-processing functions constituted a major fraction of annotated
181 smORFs; however, the disproportionate representation of metabolic categories
182 distinguishes the deep-sea smORFome from global trends[4] and highlights the role of
183 smORFs in mediating physiological adaptation to extreme environments[1, 3].

184 Protein feature analysis showed that ~12.6% of smORFs encode transmembrane helices
185 and ~1.6% contain signal peptides (**Fig. 2d; Supplementary Table 9**), suggesting that
186 membrane-associated or secreted small proteins are widespread. These features were
187 more common in bacterial than archaeal smORFs (**Supplementary Fig. 6**), likely
188 reflecting both limited characterization of archaeal secretion systems and distinct
189 ecological strategies. Approximately 1.1% of smORFs encoded Sec/Tat signal peptides
190 and 0.5% encoded lipoprotein signal motifs **(Supplementary Fig. 7**), consistent with
191 roles in cell–cell communication, nutrient acquisition, syntrophy, or environmental
192 sensing[5, 51, 52]. Together, these findings reveal a deep-sea smORF repertoire enriched in
193 metabolic and secreted functions that support microbial survival, interaction, and
194 ecosystem functioning under extreme conditions.

195 **Unconventional, structurally flexible, and uncharacterized deep-sea c_AMPs**

196 Using four independent deep-learning-based prediction tools, we identified 5,469,335
197 candidate antimicrobial peptides (c_AMPs) from the Deep-Sea Small Protein Atlas
198 (**Supplementary Fig. 8**). This represents an expansion of ~152-fold and ~1,654-fold
199 relative to the experimentally validated AMPs in DRAMP v4.0 [53] and APD v3 [54],
200 respectively. The deep-sea repertoire also exceeds computationally predicted AMP
201 collections by ~6-fold (AMPSphere[20]), ~127-fold (encrypted peptides (EPs) from the
202 human proteome[55]), and ~16,039-fold (marine biofilm-derived AMPs[21]). Sequence-
203 level homology was minimal: only 0.03% and 0.21% of deep-sea c_AMPs showed
204 similarity to DRAMP or APD entries, respectively (**Fig. 3a**). On average, 96.25% of
205 c_AMPs were absent from all three major computational AMP resources (AMPSphere,
206 EPs, and marine biofilms), and overall fewer than 14.32% had detectable homology to
207 any known peptide. These results reveal a largely unexplored antimicrobial sequence

space with substantial biotechnological potential.

Amino acid composition profiling uncovered a distinct biochemical signature. Deep-sea c_AMPs were enriched in A (alanine), D (aspartic acid), E (glutamic acid), N (asparagine), Q (glutamine), S (serine), and T (threonine), but depleted in C (cysteine), K (lysine), R (arginine), and W (tryptophan) relative to DRAMP, APD, EPs and marine biofilm datasets (**Fig. 3b; Supplementary Table 10**). The enrichment of acidic residues (D, E) contrasts sharply with canonical membrane-disruptive AMPs, typically cationic and enriched in K and R that facilitate electrostatic interactions with negatively charged microbial membranes[20, 21, 55], suggesting that these peptides likely employ fundamentally different interaction modes with microbial cells. Correspondingly, deep-sea c_AMPs exhibited near-neutral net charge (~0 at pH 7) and substantially lower isoelectric points (pI ~7) compared with reference AMPs (+2 to +7; pI 9–11.5, $P < 0.0001$; **Fig. 3c; Supplementary Tables 11–12**). Such electrostatic profiles imply a reduced dependence on charge-mediated membrane disruption, instead pointing toward alternative mechanisms, including metal ion coordination, protein–protein interaction, or intracellular pathway modulation[56-58].

Multiple residue-level features further support a shift toward noncanonical structural paradigm. Elevated alanine content (**Fig. 3b**) suggests a bias toward flexible, low-complexity scaffolds[59], whereas marked cysteine depletion reduces reliance on disulfide-stabilized β-sheet structures, favoring linear or intrinsically disordered conformations[60]. Predicted structural ensembles showed predominantly extended coils with short, transient α-helical segments (**Fig. 3d**), consistent with increased conformational plasticity. Such structural flexibility has been linked to non-membrane-disruptive antimicrobial modes, including selective intracellular targeting and specific molecular recognition[61, 62]. These observations align with our TEM imaging and transcriptomic analyses (see below), which showed antimicrobial activity without classical membrane permeabilization.

Physicochemical profiling reinforced the unique nature of deep-sea c_AMPs. They

236 were longer (~67 aa) and heavier (~7 kDa) than reference AMPs (17–29 aa; 2–4 kDa),
237 showed moderate hydrophobicity (GRAVY ≈ 0.01 vs. −0.30 to −0.47), and exhibited
238 significantly reduced hydrophobic moments (~0.38 vs. 0.72–0.77; $P < 0.0001$),
239 indicative of weak α-helical amphipathicity (**Supplementary Fig. 9; Supplementary**
240 **Tables 11–12**). Deep-sea peptides also displayed higher disorder propensity, enhanced
241 polyproline II (PPII) tendency, and greater linear moment values ($P < 0.05$; **Fig. 3c;**
242 **Supplementary Fig. 9**), features associated with increased structural flexibility, which
243 may expand the repertoire of potential molecular targets. Reduced amphiphilicity and
244 net charge could also decrease nonspecific cytotoxicity, a beneficial trait for therapeutic
245 peptides. Together, these findings suggest that deep-sea c_AMPs represent a previously
246 unrecognized class of antimicrobial peptides, characterized by low charge, intrinsic
247 disorder, conformational adaptability, and diminished amphipathicity.

248 **Broad-spectrum antibacterial and antifungal activity with minimal cytotoxicity**

249 To experimentally validate computational predictions in the Deep-Sea Small Protein
250 Atlas, we synthesized 131 representative c_AMPs and evaluated their antimicrobial
251 properties. Each peptide was screened at 125 μM, a benchmark concentration
252 commonly used in AMP discovery studies[19], against nine representative
253 microorganisms, including Gram-positive bacteria (*Priestia filamentosa* and
254 *Staphylococcus aureus* RN450), Gram-negative bacteria (*Escherichia coli* DH5α, *E.*
255 *coli* BW25113, *Klebsiella pneumoniae* ATCC 13883, *Vibrio parahaemolyticus*
256 VP.1997, *Halomonas bluephagenesis* TD01, and *Acinetobacter pittii*), and the yeast
257 *Saccharomyces cerevisiae* BY4741. A total of 114 peptides (87.0%) inhibited the
258 growth of at least one microorganism (**Supplementary Fig. 10; Supplementary Table**
259 **13**), demonstrating an exceptionally high validation rate compared with previous AMP
260 discovery efforts.

261 Minimum inhibitory concentration (MIC) assays identified several highly potent
262 peptides, including plain-4/sm-4, hydrothermal vent-19, and hydrothermal vent-35,
263 with activities down to 1.25 μM, comparable to the positive controls nisin and melittin[63,

264 [64] (**Fig. 4a; Supplementary Tables 14–15**). Susceptibility varied across strains, with
265 the highest numbers of active peptides observed for *P. filamentosa* (38 hits), *H.*
266 *bluephagenesis* (31), *A. pittii* (16), and *S. aureus* (12). Several peptides displayed broad-
267 spectrum properties, including 22/131 active against both Gram-positive and Gram-
268 negative species and 7/131 active across multiple species within the same Gram group
269 (**Supplementary Table 15**). Representative c_AMPs achieved complete bactericidal
270 activity (≥ 99.9% killing) at 1 × – 4 × MIC against *P. filamentosa*, *H. bluephagenesis*,
271 *V. parahaemolyticus*, *A. pittii*, and *E. coli* DH5*α* **(Fig. 4b; Supplementary Figs. 11–**
272 **13; Supplementary Table 16**), confirming strong and reproducible antimicrobial
273 efficacy.

274 Consistent with ecological expectations, no c_AMPs inhibited *S. cerevisiae* under
275 fermentative conditions (YPD), potentially reflecting weaker evolutionary pressure to
276 target fungi, an infrequent component of deep-sea communities (< 1–4%)[65, 66].
277 However, subtle growth defects emerged during the ethanol-dependent secondary
278 growth phase (**Supplementary Fig. 14**). Under respiratory conditions (YPEG; ethanol
279 + glycerol), cold seep-38 displayed strong antifungal activity (MIC = 8 μM) (**Fig. 4a**).
280 Because ethanol metabolism requires functional mitochondria, these observations
281 suggest that cold seep-38 may interfere with mitochondria-associated pathways,
282 consistent with downstream transcriptomic responses described below.

283 To evaluate biosafety, we assessed eight deep-sea c_AMPs (hadal trench-22, cold seep-
284 3, cold seep-9, cold seep-38, hydrothermal vent-9, hydrothermal vent-19, hydrothermal
285 vent-36, and plain-4/sm-4) in mammalian cell lines, including a non-tumorigenic line
286 (HEK293T) and two cancer lines (HepG2, HeLa). All peptides exhibited low
287 cytotoxicity, with no significant dose-dependent effects observed in HeLa cells across
288 the tested concentration range (**Fig. 4c; Supplementary Table 17**). The cold seep-9
289 showed mild dose-dependent toxicity toward HEK293T cells, whereas cold seep-38
290 displayed stronger, cell line–specific effects in HEK293T and HepG2 but minimal
291 impact on HeLa cells. Given the differing energy demands and mitochondrial

292 abundance across these cell types[67], this cell line–specific response suggests that its
293 activity may be linked to cellular energy metabolism and particularly mitochondria
294 related function, consistent with the antifungal assays[68].

295 **Diverse but predominantly non-lytic, intracellular antimicrobial strategies**

296 Mechanistic profiling of representative deep-sea–derived c_AMPs revealed a coherent
297 signature across peptides and taxa, most notably cold seep-9, hydrothermal vent-19,
298 and cold seep-38, which showed the strongest *in vitro* activity against *A. pittii*, *P.*
299 *filamentosa*, *V. parahaemolyticus*, and *S. cerevisiae*. Despite their structural diversity
300 and the phylogenetic differences of the target organisms, these peptides consistently
301 induced non-lytic antimicrobial responses characterized by modest perturbation of
302 membrane permeability and pronounced intracellular effects on translation,
303 proteostasis, and metabolic homeostasis, rather than catastrophic membrane lysis. To
304 dissect these mechanisms, we performed transcriptomic profiling following AMP
305 exposure, a widely used strategy for resolving intracellular targets and stress
306 responses[31, 69]. Based on MIC results (**Fig. 4**), we selected four peptide–microbe
307 combinations: *A. pittii* treated with cold seep-9 (MIC = 5 μM), *P. filamentosa* treated
308 with hydrothermal vent-19 (MIC = 1.25 μM), *V. parahaemolyticus* treated with
309 hydrothermal vent-19 (MIC = 1.25 μM), and *S. cerevisiae* treated with cold seep-38
310 (MIC = 8 μM). Across all organisms, only a restricted number of genes were
311 significantly altered (|log2FC| ≥ 1 for bacteria, ≥ 0.5 for yeast; FDR < 0.05; **Fig. 5a**),
312 consistent with targeted rather than global stress responses. DEG counts ranged from
313 127 in *A. pittii* to only 13 in *S. cerevisiae* (**Supplementary Tables 18-21**), reflecting
314 organism- and pathway-specific peptide sensitivity.

315 In *A. pittii*, 120 of 127 DEGs were associated with metabolic pathways
316 (**Supplementary Fig. 15a; Supplementary Table 18**). Carbon metabolism (21 DEGs)
317 and amino acid metabolism (19 DEGs) were prominently affected. Two pathways
318 showed the strongest perturbation: benzoate degradation (13/35 genes; **Supplementary**
319 **Fig. 15a, 16b**) and branched-chain amino acid degradation (9/28 genes;

320 **Supplementary Fig. 15a, 16c**). GO enrichment **(Fig. 5b)** highlighted a strong
321 overrepresentation of membrane-localized proteins, particularly those associated with
322 the cell envelope and transport processes. The transporters comprised systems
323 mediating the uptake or export of carbon sources (e.g., *quiX*), amino acids (including
324 multiple MFS and DMT family transporters), and ions (e.g., members of the RcnB
325 family (**Supplementary Table 18**). Although cold seep-9 lacks predicted
326 transmembrane helices (**Supplementary Fig. 16d**), AlphaFold3 modeling suggested a
327 physically plausible interaction with an ABC transporter permease (ipTM = 0.67, pTM
328 = 0.73; **Fig. 5c**), pointing to a mechanism involving modulation of membrane-
329 associated transport rather than membrane insertion. Collectively, these findings
330 suggest that cold seep-9 modestly perturbs membrane permeability, leading to
331 disruption of carbon, nitrogen, and ion homeostasis and broadly impairing metabolic
332 balance.

333 In *P. filamentosa*, translation-related genes were strongly downregulated (28/57
334 ribosomal genes), alongside genes involved in flagellar assembly (15/35) (**Fig. 5d;**
335 **Supplementary Fig. 15b; Supplementary Table 19**). Both large and small ribosomal
336 subunits exhibited extensive downregulation (**Fig. 5e**). Aminoacyl-tRNA ligases (*thrS*
337 etc), tRNA-modifying enzymes (including *truA* and *truB*), and aminotransferases (*gatC*)
338 were also repressed (**Supplementary Table 19**), indicating substantial impairment of
339 translational capacity. AlphaFold3 modeling predicted a high-confidence interaction
340 between hydrothermal vent-19 and TruA (ipTM = 0.87, pTM = 0.90), a key tRNA
341 pseudouridine synthase (**Fig. 5f**), providing a mechanistic basis for translation
342 inhibition. Altogether, these results suggest that hydrothermal vent-19 likely exerts its
343 antibacterial activity primarily by disrupting protein translation, thereby impairing
344 multiple cellular processes including flagellum biogenesis, ultimately compromising
345 bacterial viability. Consistent with the well-documented flagellar shedding phenotype
346 observed following AMP treatment[70], TEM imaging revealed flagellar loss in
347 hydrothermal vent-19–treated cells (**Fig. 5g**). Additional AMPs exhibited distinct
348 phenotypes: cold seep-32 caused cell enlargement with pale cytoplasmic density,

349 whereas cold seep-37 induced elongation and cytoplasmic leakage, highlighting
350 mechanistic diversity among deep-sea peptides.

351 In *V. parahaemolyticus*, hydrothermal vent-19 triggered upregulation of ribosomal
352 genes (17/56) and components of the bacterial secretion system (12/58) (**Fig. 5h;**
353 **Supplementary Fig. 14c; Supplementary Table 20**), critical for virulence[71]. This
354 response contrasts with the downregulation observed in Gram-positive *P. filamentosa*,
355 suggesting that organism-specific regulatory architectures shape transcriptional outputs
356 despite potentially shared molecular targets. Supporting this, hydrothermal vent-19 also
357 displayed a predicted interaction with TtcA (ipTM = 0.8, pTM = 0.84; **Fig. 5i**), a tRNA
358 thiolation enzyme involved in tRNA modification that contributes to efficient
359 translation, particularly under stress conditions. Together, these data indicate that
360 hydrothermal vent-19 primarily targets translation machinery, with downstream
361 consequences that differ between Gram-positive and Gram-negative bacteria.

362 The limited DEGs in *S. cerevisiae* **(**n = 13; |log2FC| ≥ 0.5, FDR < 0.05; **Supplementary**
363 **Fig. 15d; Supplementary Table 21)** is consistent with the observation that cold seep-
364 38 treatment resulted in only slight growth reduction during the secondary growth phase
365 in YPD, when ethanol becomes the primary carbon source **(Supplementary Figs. 14,**
366 **15d)**. The complete growth inhibition under YPGE condition **(Fig. 4a)** prompted us to
367 further investigate potential transcriptional changes, revealing that cold seep-38 induces
368 mild rather than extensive transcriptional perturbation. KEGG enrichment revealed
369 perturbation of carbon and energy metabolism, with *PCK1*, a key gluconeogenic and
370 ethanol-utilization gene (**Supplementary Figs. 15d, 17**), significantly downregulated.
371 Removal of the peptide fully restored respiratory growth (**Supplementary Fig. 18**),
372 indicating a reversible inhibitory mechanism. The peptide's cell-line–specific
373 cytotoxicity (**Fig. 4c**) further supports a connection to mitochondrial or energy-linked
374 processes, raising the possibility that cold seep-38 may function as a reversible
375 modulator of central carbon metabolism with broader implications for
376 immunometabolism and cancer biology (**Supplementary Fig. 19**).

Discussion

This study provides three conceptual advances: (i) the first global atlas of deep-sea small proteins; (ii) the discovery of a structurally distinct class of noncanonical c_AMPs; and (iii) experimental evidence that representative peptides act predominantly through intracellular, non-lytic mechanisms. The Deep-Sea Small Protein Atlas uncovers an expansive and previously inaccessible repertoire of bioactive peptides, over 85% of which show no detectable similarity to existing AMP databases, greatly expanding the known sequence space of natural antimicrobials. Representative c_AMPs demonstrated broad antimicrobial efficacy across Gram-positive and Gram-negative bacteria and even a mitochondrial-dependent yeast strain, suggesting that their primary targets may lie beyond the cell membrane. Such breadth of activity is consistent with mechanisms that are not strictly dependent on membrane composition[32]. Indeed, transcriptomic analyses revealed perturbations in translation, proteostasis, and metabolic pathways rather than gene expression patterns characteristic of classical membrane lysis, indicating that intracellular pathways are likely the dominant targets of these peptides under deep-sea environmental conditions such as high hydrostatic pressure, extreme temperature, and nutrient limitation.

A distinctive feature of the deep-sea c_AMPs is their predicted intrinsic disorder. Unlike canonical AMPs that fold into amphipathic α-helices, these peptides appear structurally plastic, favoring extended or low-complexity conformations. Intrinsically disordered peptides can undergo environment-dependent structural transitions[72] and may interact with membranes through transient, peripheral contacts rather than inserting into bilayers to form stable pores. The behavior of cold seep-9 exemplifies this: despite lacking predicted transmembrane helices, it alters membrane permeability sufficiently to disrupt carbon, nitrogen, and ion homeostasis while maintaining overall membrane integrity. Analogous to disordered C-terminal motifs in endocytic adaptors, which generate steric pressure to drive membrane curvature[73], deep-sea peptides may exert functional effects without requiring stable secondary structure.

405 Functionally, representative c_AMPs inhibited diverse microorganisms, yet TEM
406 imaging revealed no evidence of catastrophic membrane damage. Cells maintained
407 intact envelopes but exhibited altered intracellular organization and transcriptional
408 responses. These observations contrast sharply with membrane-disruptive AMPs, such
409 as polymyxins and many amphipathic helical peptides[19, 20], which kill by compromising
410 membrane integrity. While membrane lysis is effective, it often correlates with
411 cytotoxicity in mammalian cells[74] due to nonspecific interactions with eukaryotic
412 membranes. In contrast, several antimicrobial peptides can cross membranes without
413 causing detectable damage and modulate intracellular processes[32], an emerging but still
414 poorly understood antimicrobial strategy. The deep-sea peptides characterized here
415 appear to fall within this underexplored mechanistic class.

416 Together, these findings reveal a vast diversity of previously uncharacterized small
417 proteins encoded by extreme marine ecosystems. The c_AMPs uncovered here possess
418 a unique combination of low net charge, intrinsic disorder, structural plasticity, and
419 intracellular, non-lytic mechanisms of action, collectively expanding the conceptual
420 landscape of natural antimicrobial strategies. These results challenge the prevailing
421 emphasis on membrane-disruptive paradigms and suggest that environmental extremes
422 such as those in the deep sea may drive the evolution of fundamentally distinct
423 antimicrobial modalities.

424 At the same time, our mechanistic analyses were restricted to a subset of short,
425 synthesizable peptides, and it remains unknown whether longer or more complex
426 c_AMPs share similar structural or mechanistic properties. Future work will require
427 pinpointing precise intracellular targets, determining peptide–protein interaction
428 structures at atomic resolution, exploring functional diversity across peptide families,
429 and evaluating pharmacokinetics and therapeutic potential *in vivo*. By enabling
430 systematic discovery and mechanistic exploration, the Deep-Sea Small Protein Atlas
431 provides a foundational resource for identifying next-generation peptide antibiotics
432 inspired by Earth's most remote and evolutionarily unique environments.

433 # Materials and Methods

434 ## Metagenomic dataset and processing

435 Metagenomic datasets included 308 samples (40 water samples and 268 sediment
436 samples) from hadal trenches in the Pacific Ocean (Mariana, Kermadec, Atacama, Kuril,
437 Izu-Bonin, and Japan Trenches), 174 cold seep sediment samples collected from 17
438 globally distributed seep sites, 160 hydrothermal vent samples (three hydrothermal
439 chimney samples, seven rock samples, 28 microbial mat samples, 38 water samples,
440 and 84 sediment samples) from the Pacific, Atlantic, Indian, and Arctic Oceans
441 (Brothers Volcano, Guaymas Basin, Juan de Fuca Ridge, Gakkel Ridge, Manus Basin,
442 the Southern Mariana Trough, and the Mid Cayman Rise), 56 seamount sediment
443 samples from the Pacific Ocean (Northwest Pacific Ocean, Takuyo-Daigo Seamount,
444 Takuyo-Daisan Seamount, and seamounts along the Yap and Mariana trenches), and 10
445 abyssal plain sediment samples from the Pacific Ocean **(Supplementary Fig. 1a and**
446 **Supplementary Table 1)**. A total of 115 cold seep sediment metagenomic datasets were
447 generated by our group and reported in our previous publications[23, 75-82], whereas the
448 remaining datasets were retrieved from the National Center for Biotechnology
449 Information Sequence Read Archive (NCBI-SRA) and the European Bioinformatics
450 Institute European Nucleotide Archive (EBI-ENA). Detailed information, including
451 associated publications, sample metadata, sequencing platforms, and accession
452 numbers, is provided in **Supplementary Table 1**. For each sample, metagenomic reads
453 were quality-filtered using fastp[83] (v0.23.2, default parameters), and clean reads were
454 assembled using MEGAHIT[84] (v1.2.9, default parameters). In total, 1,058,734,804
455 contigs were generated (> 200 bp), including 807,712,620 from hadal trenches,
456 59,011,641 from cold seeps, 125,126,723 from hydrothermal vents, 15,953,963 from
457 abyssal plains, and 50,929,857 from seamounts (**Fig. 1b and Supplementary Table 2**).
458 All assembled contigs were used for subsequent smORF prediction.

459 **Non-redundant smORF catalog construction and cross-habitat analyses**

460 smORFs were predicted from assembled contigs using smorFinder[85] (v1.0.0, default
461 parameters) and GMSC-mapper[4] (v0.0.1a0, parameters: --no-habitat --no-taxonomy).
462 The predicted smORFs were first deduplicated at 100% amino acid identity and 100%
463 coverage using CD-HIT[86] (v4.8.1, parameters: -c 1 -aS 1 -g 1 -d 0). All non-singleton
464 sequences were subsequently clustered at 90% amino acid identity and coverage with
465 MMseqs2 (v13.45111)[87] using the easy-linclust module (parameters: -c 0.9 -min-seq-
466 id 0.9). Singletons removed during the 100% identity deduplication step were further
467 evaluated to retain potentially meaningful homologs. These sequences were aligned
468 against MMseqs2 cluster representatives using DIAMOND[88] (v2.1.8, parameters: --id
469 90 --query-cover 90 --subject-cover 90 -e 1e-5). Homologous singletons were merged
470 with the non-singleton sequences identified earlier to generate the final non-redundant
471 smORF catalogs for each deep-sea habitat. The overall workflow is summarized in **Fig.
472 1b**. To assess smORF sharing across habitats, pairwise comparisons between smORF
473 catalogs were performed using DIAMOND (v2.1.8, parameters: --id 100 --query-cover
474 100 --max-target-seqs 1). smORFs with hits meeting this criterion were considered
475 shared.

476 **Taxonomic and functional annotation of smORFs**

477 Taxonomic assignment of smORFs was performed using MMseqs2 [44] (v13.45111,
478 taxonomy module; parameter: --tax-lineage 1) against the GTDB reference database[45]
479 (R220). Functional annotation was conducted using eggNOG-mapper[89] (v2.1.9, default
480 parameters), based on eggNOG 5.0 orthology predictions and integrated databases
481 including Pfam 33.1, KEGG, EC numbers, GO terms, and CAZy families[90]. Given the
482 short length of smORFs, these eggNOG-based functional assignments should be
483 interpreted as tentative annotations. Signal peptides were predicted with SignalP 6.0
484 (fast model)[91], which identifies classical Sec/SPI signal peptides (SP), twin-arginine
485 translocation (TAT) signals, lipoprotein signal peptides (LIPO and TATLIPO), and

486 PILIN (Sec/SPIII), a specialized class of Sec pathway signal peptides. Transmembrane
487 helices were predicted with TMHMM[92] (v2.0, default parameters), allowing the
488 determination of their number and topology.

489 **AMP prediction and physicochemical feature analysis**

490 AMPs were predicted by ampir (https://ampir.marine-omics.net/; precursor peptide
491 model), Macrel[93] (v 1.5.0, default parameters), amPEPpy[94] (v 1.1.0, parameter: --seed
492 2012), and AMPLify[95] (v 2.0.0, parameter: -m imbalanced). Any peptide predicted as
493 an AMP by at least one method was retained, and the combined outputs were merged
494 to generate a comprehensive c_AMP catalog for each habitat. The amino acid
495 composition of deep-sea c_AMPs was compared with experimentally validated AMPs
496 from DRAMP[53] (v4) and APD3 [54], as well as predicted datasets including AMPSphere[20],
497 EPs from the human proteome[55], and AMPs identified from marine biofilms[21].
498 Additional physicochemical features were computed using custom Python scripts
499 (Figshare: https://doi.org/10.6084/m9.figshare.30692342), including peptide length,
500 molecular weight, isoelectric point (pI), net charge at pH 7 (NetCharge_pH7), GRAVY
501 (grand average of hydropathy), amphiphilicity index, hydrophobic moment, linear
502 moment, polyproline II (PPII) propensity, and disorder propensity. For visualization,
503 2,000 AMPs were randomly selected from each habitat-specific catalog and each
504 reference database.

505 **Protein structure and peptide-protein interaction prediction**

506 Three-dimensional structures of 131 selected c_AMPs were predicted using
507 AlphaFold[96] (v2.0; parameter: full_dbs), and model confidence was evaluated using
508 pLDDT scores. Peptide–protein complex structures (targets: tRNA modifying enzymes
509 TruA and TtcA) were generated using AlphaFold3 [97], and prediction quality were
510 assessed using ipTM and pTM scores. All structural models were visualized and
511 exported as images using PyMOL (http://www.pymol.org).

512 **Assessment of deep-sea smORF and c_AMP novelty**

513 Each smORF catalog was compared against established small-protein reference
514 databases, including sORFdb[35], SmProt 2 [36], and GMSC[4], to evaluate the homology
515 and novelty of the identified deep-sea smORFs. Deep-sea c_AMPs were additionally
516 compared with experimentally validated AMPs from DRAMP[53] and APD3 [54], as well
517 as predicted AMP datasets including AMPSphere[20], EPs[55], and marine biofilm AMPs
518 [21]. All pairwise comparisons were performed using DIAMOND[88] (v2.1.8, parameters:
519 --more-sensitive --evalue 1e-5).

520 **Deep-sea c_AMP selection for synthesis and testing**

521 A total of 131 c_AMPs from the five deep-sea habitats were synthesized by solid-phase
522 peptide synthesis using the Fmoc strategy by Sangon Biotech (Shanghai) Co., Ltd.
523 Peptide molecular weights were verified by mass spectrometry, and purity (> 90%) was
524 confirmed by high-performance liquid chromatography. The selection criteria for these
525 peptides are described below.

526 Deep-sea c_AMPs were initially filtered by peptide length, excluding sequences longer
527 than 40 amino acids, as conventional Fmoc-based solid-phase peptide synthesis often
528 yields lower efficiencies and requires repeated recoupling steps for longer peptides[98, 99].
529 Two complementary groups of c_AMPs were then selected for downstream synthesis
530 and functional testing: (i) peptides predicted to have high antimicrobial potential, and
531 (ii) peptides randomly selected to represent taxonomic diversity across habitats. For the
532 first group, we employed EvoGradient[100] to predict and virtually evolve candidate
533 bioactive peptides, an explainable deep learning framework integrating convolutional
534 neural network (CNN)[101], long short-term memory networks (LSTM)[102], attention
535 networks[103] and Transformer models[103]. Peptides with high predicted antimicrobial
536 activity were subsequently filtered based on solubility (> 0.5) using the criteria
537 implemented in Protein–Sol[104]. This resulted in the selection of five peptides from
538 abyssal plains, five from seamounts (one overlapping with the abyssal plain group), 16

539 from cold seeps, 18 from hydrothermal vents, and 18 from hadal trenches (one
540 overlapping with the abyssal plain group). For the second group, c_AMPs were selected
541 according to their taxonomic classification at a defined rank to ensure representation
542 across taxonomic levels, retaining at least one peptide per rank. This yielded five
543 c_AMPs from abyssal plains, four from seamounts, 21 from cold seeps, 21 from
544 hydrothermal vents, and 20 from hadal trenches (one overlapping with the abyssal plain
545 group).

546 **Bacterial and fungal inhibition experiment**

547 Nine representative strains were selected for initial antimicrobial screening, including
548 Gram-positive bacteria *P. filamentosa* and *S. aureus* (ATCC RN450); Gram-negative
549 bacteria *E. coli* strains (DH5*α* and BW25113), *K. pneumoniae* (ATCC 13883), *V.*
550 *parahaemolyticus* (VP.1997; ATCC 17802), *H. bluephagenesis* (TD01), and *A. pittii*;
551 and the yeast *S. cerevisiae* (BY4741). Strains were streaked onto Luria–Bertani (LB)
552 agar medium and incubated overnight at 37°C, except *H. bluephagenesis,* which was
553 cultured on LB agar supplemented with 6 × NaCl (60 g L^{-1} NaCl); *S. aureus*, which
554 was grown on Mueller–Hinton (MH) agar; and *S. cerevisiae*, which was grown on yeast
555 extract–peptone–dextrose (YPD) agar at 30°C. Single colonies were inoculated into
556 appropriate liquid media and cultured overnight at 220 r.p.m. (37°C for bacteria; 30°C
557 for *S. cerevisiae*). Overnight bacterial cultures were diluted 1:100 (v/v) into fresh
558 medium and grown for 3 h to mid-exponential phase; *S. cerevisiae* cultures were diluted
559 to an OD_{600} of 0.1 and grown for 6 h to reach mid-exponential phase. Bacterial
560 suspensions were adjusted to an OD_{600} of 0.0002, and *S. cerevisiae* suspensions were
561 adjusted to an OD_{600} of 0.02 (≈ 2×10^5 CFU mL^{-1} in YPD or yeast extract–peptone–
562 ethanol–glycerol (YPEG) medium) and used as inocula for testing 131 synthesized
563 c_AMPs.

564 Freeze-dried c_AMPs was dissolved in double-distilled water to 0.4 mmol L^{-1}. Three
565 experimental groups were established in 96-well plates: (1) blank control, 100 μL fresh
566 medium; (2) microbial control, 50 μL fresh medium and 50 μL bacterial or yeast

567 suspension; and (3) c_AMPs treatment, 50 μL microbial suspension and 50 μL c_AMP
568 solution (final concentration 125 μmol L^{-1}). Each well contained a final volume of 100
569 μL and a microbial density of 1×10^5 CFU mL^{-1}. Plates were incubated at 37°C for
570 bacteria (30°C for *S. cerevisiae*) with shaking at 220 r.p.m for 16 h. OD_{600} values were
571 normalized by $(OD_{600,\ experiment} - OD_{600,\ blank}) / (OD_{600,\ control} - OD_{600,\ blank})$. The c_AMPs
572 were considered effective if they reduced bacterial or yeast growth by > 75% relative
573 to controls. All assays were performed with three biological replicates, each including
574 three technical replicates.

575 **Minimum inhibitory concentration determination**

576 MICs of c_AMPs were determined by the broth microdilution method[19]. Briefly,
577 microbial inocula were prepared as described for the inhibition experiment. A twofold
578 serial dilution of each c_AMP (160–2.5 μM) was prepared in fresh medium, and 50 μL
579 of each dilution was mixed with 50 μL of microbial inoculum in 96-well plates,
580 resulting in final peptide concentrations ranging from 80 to 1.25 μM and a microbial
581 density of 1×10^5 CFU mL^{-1}. Wells containing medium only (blank control) and
582 microbial cultures without peptide (growth control) were included on each plate. The
583 MIC was defined as the lowest peptide concentration with no detectable growth after
584 16 h incubation (37°C for bacteria; 30°C for *S. cerevisiae*). All assays were performed
585 in triplicate with three independent biological replicates.

586 **Minimum bactericidal concentration determination**

587 Minimum bactericidal concentrations (MBCs) of bioactive c_AMPs were determined
588 according to the European Committee on Antimicrobial Susceptibility Testing
589 (EUCAST) guidelines for bactericidal activity assessment. Briefly, bacterial cultures
590 were prepared as described for MIC determination. After 16 h exposure to c_AMPs, 50
591 μL of culture from each well was spread onto LB agar plates lacking antimicrobial
592 agents and incubated at 37°C for 18–24 h. *H. bluephagenesis* was plated onto LB agar
593 supplemented with 6 × NaCl (60 g L^{-1} NaCl), *S. aureus* onto MH agar, and *S. cerevisiae*

594 onto YPD or YPEG agar at 30°C. CFUs were enumerated, and the bactericidal rate was
595 calculated as: Bactericidal rate (%) = $(1 - CFU_{sample} / CFU_{control}) \times 100$. The MBC was
596 defined as the lowest peptide concentration resulting in ≥ 99.9% reduction in CFUs
597 compared to the untreated control (corresponding to ≤ 0.1% survival). All assays were
598 performed in triplicate.

599 **Cytotoxicity determination**

600 Cytotoxicity was evaluated using the Cell Counting Kit-8 (C6005; NCM Biotech).
601 HEK293T cells were cultured in Dulbecco's Modified Eagle Medium (DMEM)
602 supplemented with 10% fetal bovine serum (FBS) at 37°C in 5% CO_2 for 24 h. Cells
603 were then subcultured, diluted to 1×10^5 cells mL^{-1}, and 50 μL suspension was
604 transferred to each well of a 96-well microplate. After 24 h, DMEM containing different
605 concentrations of c_AMPs was dispensed to each well. Cells were treated with c_AMPs
606 for 48 h. Subsequently, 10 μL of CCK-8 solution was added to each well and incubated
607 for 30 min at 37°C, after which absorbance at 450 nm was measured using a microplate
608 reader. Relative cell viability was calculated as $(OD_{450\ sample} - OD_{450\ blank}) / (OD_{450\ control}$
609 $- OD_{450\ blank})$. All assays were performed with three biological replicates. The same
610 procedure was applied to HepG2 and HeLa cells.

611 **Transmission electron microscopy examination**

612 *P. filamentosa* cells were treated with three deep-sea c_AMPs (cold seep-32, cold seep-
613 37, and hydrothermal vent-19) at a final concentration of 1 × MIC. In contrast, the
614 control group received phosphate-buffered saline (PBS) under the same conditions.
615 After incubation at 37°C for 2 h following previous studies[105], bacterial suspensions
616 were collected by centrifugation (6,000 r.p.m, 1 min, 4°C) and washed twice with PBS.
617 Cell pellets were resuspended and immediately processed for ultrathin sectioning for
618 observation. Samples were mounted on copper grids, negatively stained with 1% (w/v)
619 uranyl acetate for 15 s, air-dried, and examined using a transmission electron
620 microscope (TEM; Thermo Fisher Scientific Helios 5 UC) operated at 80 kV.

621 Morphological alterations in cell walls and membranes were compared between
622 peptide-treated and control cells.

623 **RNA sequencing and analysis**

624 To investigate transcriptional responses induced by representative c_AMPs, *P.*
625 *filamentosa* was treated with hydrothermal vent-19 (1 × MIC), *V. parahaemolyticus*
626 with hydrothermal vent-19 (1 × MIC), *A. pittii* with cold seep-9 (1 × MIC), and *S.*
627 *cerevisiae* with cold seep-38 (1 × MIC) for 4 h, each with three biological replicates.
628 PBS was used as the control. Total RNA was extracted using TRIzol® reagent
629 (Invitrogen) following the manufacturer's instructions and treated with DNase I
630 (TaKaRa) to remove residual genomic DNA. RNA integrity and purity were assessed
631 using an Agilent 2100 Bioanalyzer (Agilent Technologies) and a NanoDrop ND-2000
632 spectrophotometer (Thermo Fisher Scientific). High-quality RNA samples ($OD_{260/280}$ =
633 1.8–2.2, $OD_{260/230} \geq 2.0$, RIN ≥ 6.5, 28S:18S ≥ 1.0, and total RNA ≥ 10 μg) were used
634 for library construction.

635 For prokaryotic samples, rRNA was removed using the Ribo-Zero rRNA Removal Kit
636 (Epicenter), and strand-specific libraries were constructed from 5 μg of total RNA
637 following standard protocols. RNA was fragmented, reverse-transcribed into cDNA,
638 end-repaired, adenylated, and ligated to indexed adaptors. Libraries were size-selected
639 for 200–300 bp cDNA fragments using 2% Low Range Ultra Agarose and PCR-
640 amplified with Phusion DNA polymerase (NEB). For the eukaryotic sample (*S.*
641 *cerevisiae*), poly (A) + mRNA was purified using oligo (dT) magnetic beads,
642 fragmented, and processed using the same workflow. Final libraries were quantified
643 using a TBS380 fluorometer (Turner Biosystems) and sequenced on the MGI-T7
644 DNBSEQ platform (Shanghai BIOZERON Biotech) with 150 bp paired-end reads.

645 Raw reads were processed using Trimmomatic[106] (v0.36; parameters:
646 SLIDINGWINDOW:4:15 MINLEN:75) to remove adaptors, low-quality bases, and
647 short reads. Reads containing more than 10% ambiguous bases (N) were discarded.

648 Quality-controlled reads were further filtered against the rRNA database[107] (Rfam)
649 using sortmeRNA[108] (v2.1) to remove rRNA contaminants. For bacterial samples, clean
650 reads were aligned to the respective reference genomes using Rockhopper[109]. For *S.*
651 *cerevisiae*, reads were aligned to the reference genome using HISAT2 [110], and gene-
652 level counts were obtained using featureCounts (http://subread.sourceforge.net/). Gene
653 expression levels were normalized as reads per kilobase of transcript per million
654 mapped reads (RPKM)[111]. Differential expression and functional enrichment analyses
655 were performed on the CFViSA[112] platform. DEGs between treatment and control
656 groups were identified using edgeR[113] with thresholds of $|\log_2(\text{fold change})| \geq 1$ and
657 false discovery rate (FDR) < 0.05. GO enrichment analysis was performed using
658 Goatools[114], and KEGG pathway enrichment was conducted using KOBAS[115]. GO
659 terms[116] and KEGGpathways[117] with Bonferroni-corrected $P < 0.05$ were considered
660 significantly enriched.

661 **Statistical analysis**

662 Statistical analyses were performed using R v4.2.3. Data normality was assessed using
663 the Shapiro–Wilk test prior to downstream analyses. The Kruskal–Wallis rank-sum test
664 was used to compare physicochemical properties across deep-sea c_AMPs and
665 reference AMP datasets. Pairwise comparisons were conducted using Wilcoxon rank-
666 sum tests, and *P* values were adjusted using the Bonferroni correction. Corrected $P <$
667 0.05 was considered statistically significant.

668 **Data availability**

669 All transcriptome sequencing data generated in this study have been deposited in
670 Genome Sequence Archive (GSA) under accession number PRJCA052490. Sequence
671 files for smORF and c_AMP datasets from the five deep-sea habitats have been
672 deposited on Figshare (DOI: 10.6084/m9.figshare.30692342).

Code availability

Original codes have been deposited at Figshare (DOI: 10.6084/m9.figshare.30692342). All computational tools used in this study were executed with default parameters unless otherwise specified, as detailed in the Methods.

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Acknowledgements

This work was supported by National Key R & D Program of China (2022YFC2805505, 2024YFA0916503); National Natural Science Foundation of China (42376115, 42406109, 32122050, 32370074); Natural Science Foundation of Fujian Province (2023J06042, 2025J011005); Scientific Research Foundation of Third Institute of Oceanography, MNR (2025013); and Hubei Hongshan Laboratory (CDSJ, 2025hsqd014). We thank Tianxueyu Zhang and Ruiqi Lin for assistance with data collection, Hai Zhang, Chen Ling, Xianming Deng for providing strains, and Qiang Zheng, Weipeng Zhang, Fabai Wu, and Rui Cheng for helpful discussions.

Author contributions

X.D. and Z.L. conceived and designed the study. Q.J. and Y.H. carried out the omics analyses. Z.L. and C.Y. performed the experiments. Y.D., F.L., Z.H. and C.S. contributed to methodological development and discussions. Q.J., Y.H., X.D. and Z.L. wrote the manuscript with input from all authors. All authors reviewed and approved the final manuscript.

Competing interests

The authors declare no competing interests.

Figure legends

Figure 1. A global atlas of deep-sea small proteins with unprecedented diversity and novelty. (a) Geographic distribution of the deep-sea sampling sites included in this study. Circles denote metagenomic sampling locations, and squares indicate the number of samples collected at each site. Sampling and sequencing metadata for all datasets are provided in **Supplementary Table 1**. The world map was generated using Ocean Data View (ODV 5.1.7). **(b)** Workflow for predicting smORFs and candidate antimicrobial peptides (c_AMPs). Details are provided in methods. **(c)** Comparative homology landscape showing the novelty of deep-sea smORFs relative to existing small-protein databases. For each habitat, the proportions of smORFs with detectable homologs versus novel smORFs lacking database matches are shown. Some smORFs map to multiple databases; therefore, counts are not additive across databases. Detailed homology statistics are reported in **Supplementary Table 2**. **(d)** Functional annotation of smORF catalogs from the five deep-sea habitats, based on KEGG, eggNOG, CAZy, and Pfam databases. Summary statistics provided in **Supplementary Table 2**.

Figure 2. Habitat-specific patterns of deep-sea smORFs. (a) Shared smORFs across the five deep-sea habitats. Ribbon widths represent the proportion of smORFs shared between habitats, with numerical labels indicating the percentage of each habitat's smORF catalog that is shared with others. Owing to the large disparities in smORF catalog sizes among habitats, truncated axes are used to improve visualization. Detailed pairwise comparisons are provided in **Supplementary Table 3**. **(b)** Functional annotation of shared small proteins based on the COG database. COG categories are grouped into four major functional classes. Colors correspond to individual COG categories within these groups. **(c)** Taxonomic annotation of smORFs across the five habitats. Stacked bar charts show the relative abundance of archaeal and bacterial taxa at class level. Taxonomic assignment was performed using GTDB release R220. Detailed habitat-specific taxonomic profiles are provided in **Supplementary Tables 6–7**. **(d)** Proportions of smORF-derived proteins predicted to contain transmembrane

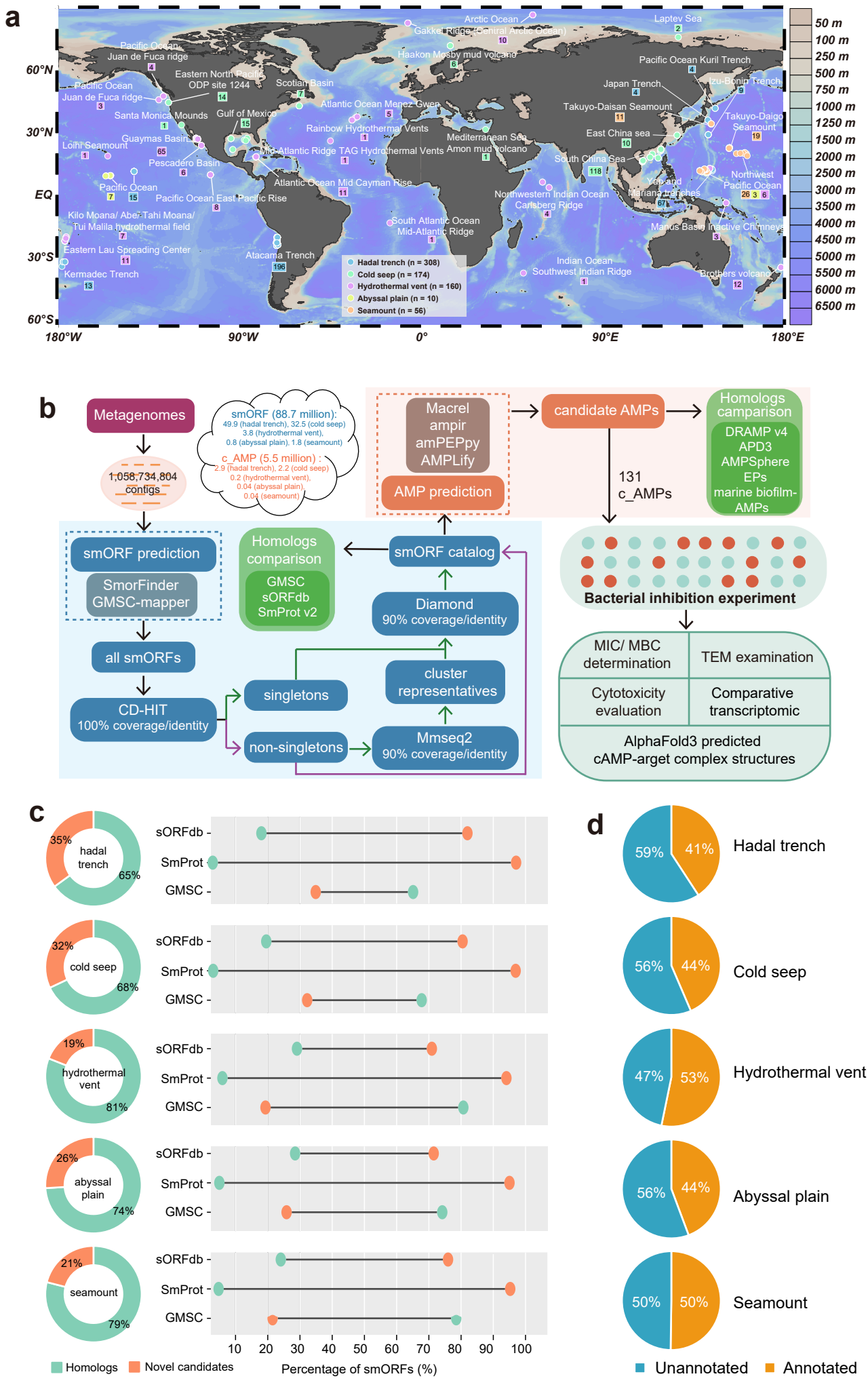
988 domains or signal peptides across habitats. Values shown in the radial plots indicate the
989 percentage of small proteins carrying the corresponding structural feature in each
990 habitat. Detailed information is provided in **Supplementary Table 9**.

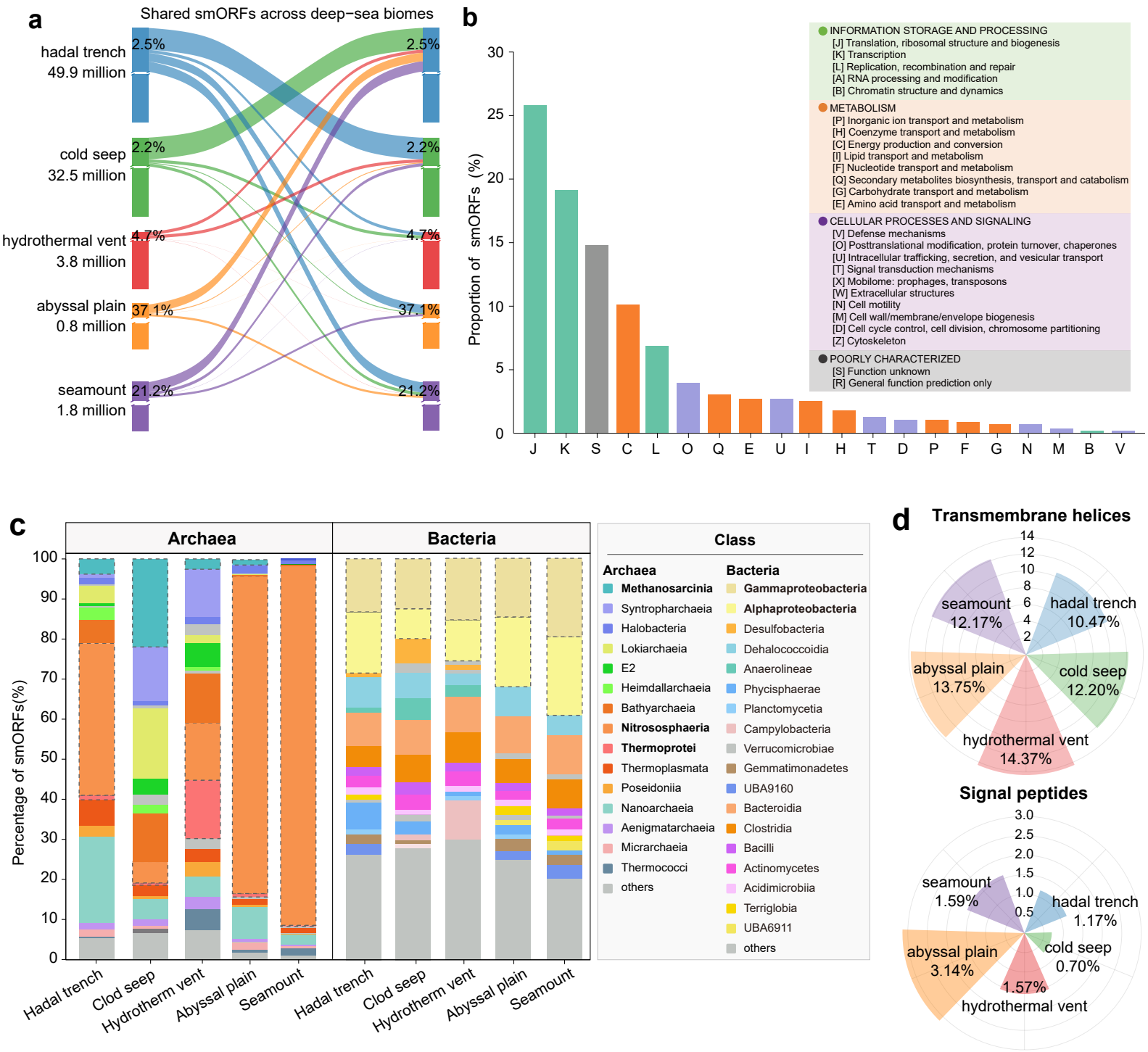
991 **Figure 3. Defining a new structural and biophysical class of deep-sea antimicrobial**
992 **peptides (c_AMPs). (a)** Novelty assessment of c_AMPs identified across the five
993 deep-sea habitats, benchmarked against experimentally validated AMP databases and
994 large-scale predicted AMP resources. Bubble plots summarize the proportion of
995 homologous (light color) versus novel sequences (dark color). **(b)** Normalized amino-
996 acid composition profiles of deep-sea c_AMPs compared with reference AMP datasets.
997 Detailed information is provided in **Supplementary Table 10**. **(c)** Multidimensional
998 comparison of physicochemical descriptors across habitats and reference datasets.
999 Detailed physicochemical properties and statistical data are provided in
1000 **Supplementary Tables 10-12. (d)** Representative AlphaFold2-predicted structures
1001 illustrating the conformational diversity of c_AMPs from different habitats. Model
1002 confidence is reported as per-residue pLDDT scores, highlighting ordered secondary-
1003 structure elements (α-helices, β-sheets) alongside flexible or disordered regions.

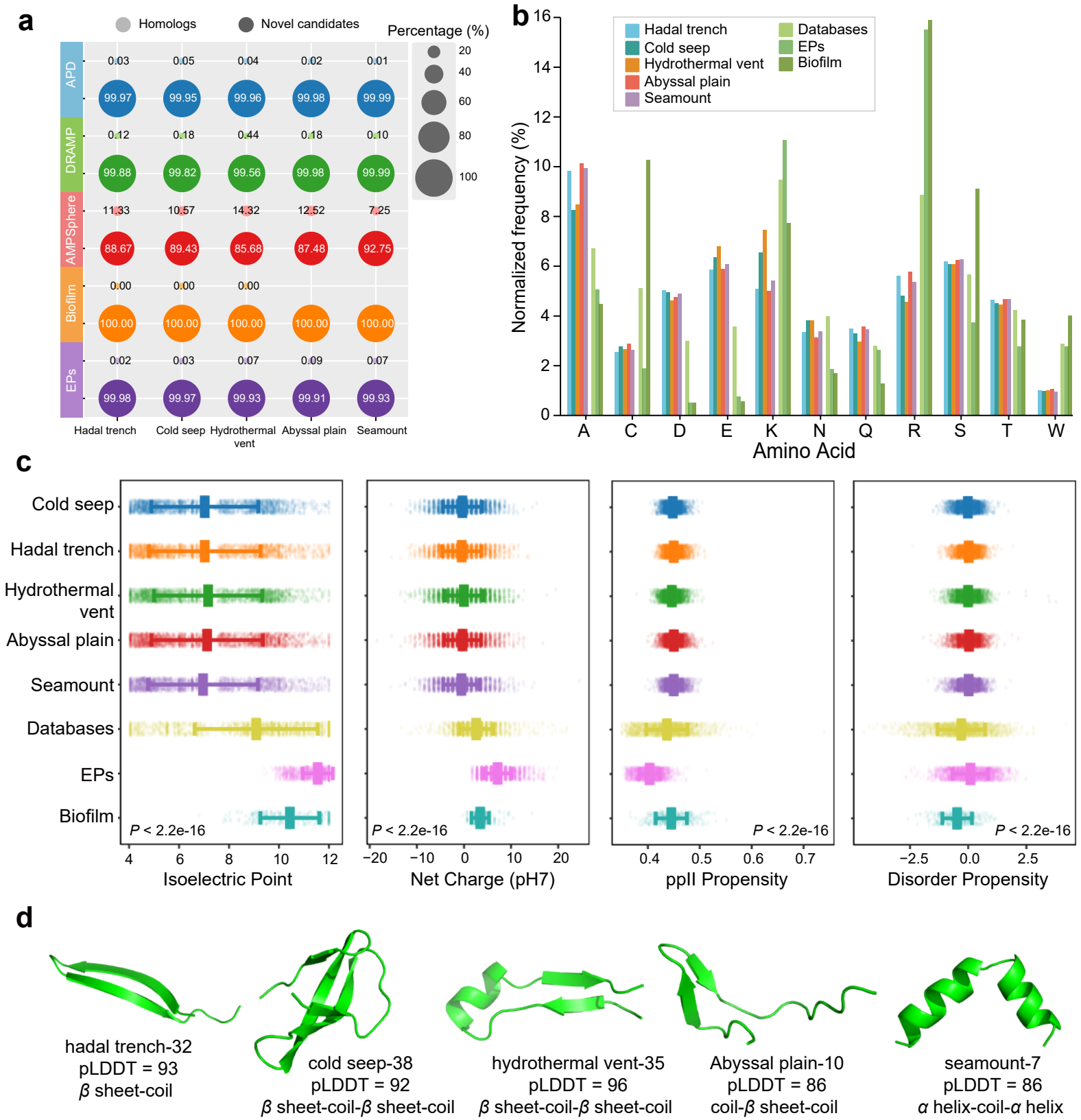
1004 **Figure 4. Functional validation of representative deep-sea c_AMPs. (a)** Broad-
1005 spectrum inhibitory activity of synthetic c_AMPs against four non-pathogenic and five
1006 pathogenic microorganisms. MICs were determined using two-fold serial dilutions
1007 (2.5–125 μM) in 96-well plates containing ~1×10^5 CFU/mL. MIC values represent the
1008 mean concentration across three independent dilution series. Gram-positive (+) and
1009 Gram-negative (−) species are indicated. Detail information on MICs is provided in
1010 **Supplementary Tables 14-15**. **(b)** Bactericidal activity of representative c_AMPs at
1011 1× MIC against *P. filamentosa*, *H. bluephagenesis*, *V. parahaemolyticus*, *A. pittii*, and
1012 *E. coli* DH5α. The minimum bactericidal concentration (MBC) was defined as the
1013 lowest concentration yielding ≥ 99.9% killing (≤ 0.1% survival). Representative plate
1014 images are shown. All assays were performed in triplicate. Detail information on MBCs
1015 is provided in **Supplementary Table 16**. **(c)** Cytotoxicity of synthetic c_AMPs toward

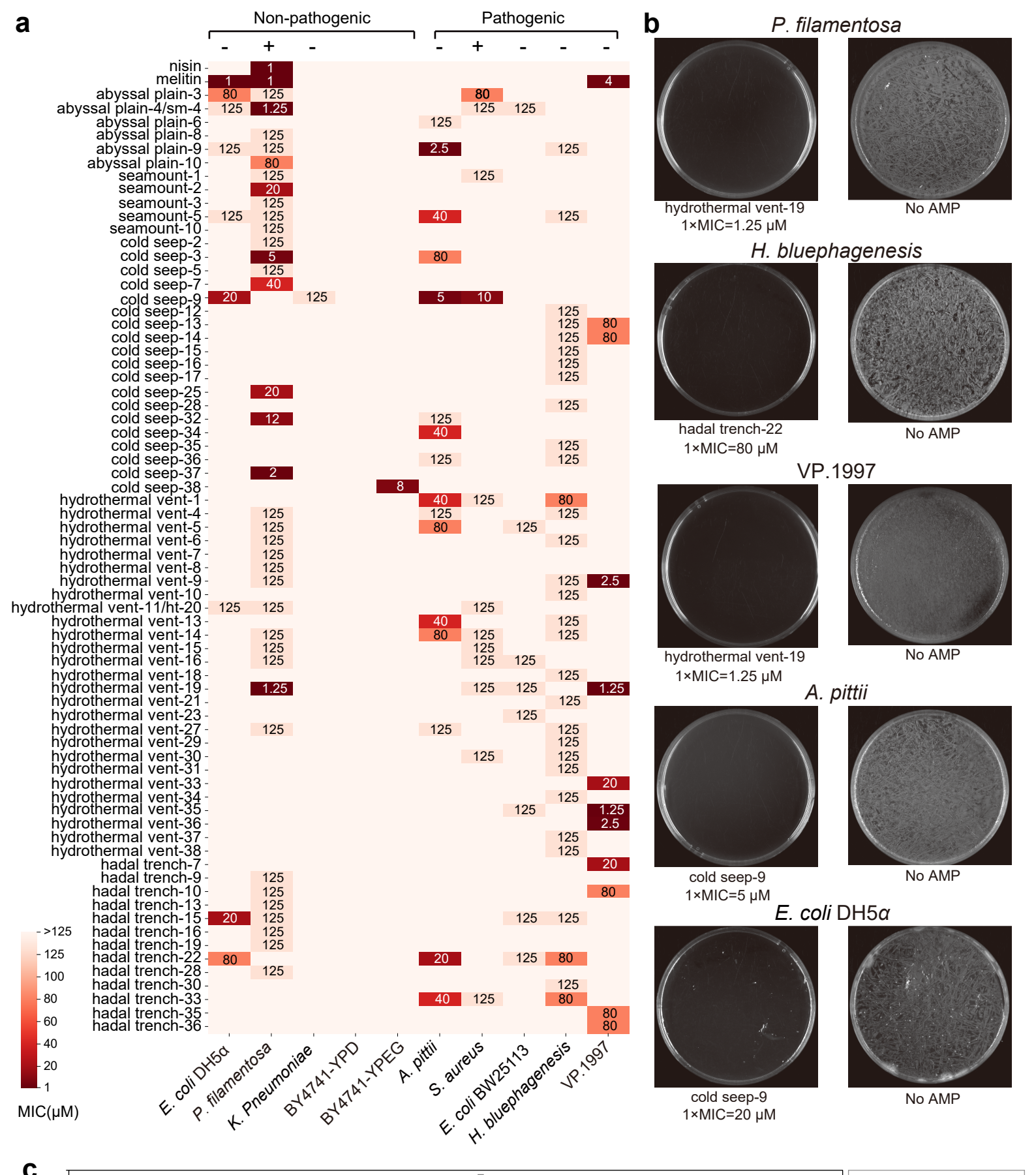
1016 mammalian cells (HEK293T, HepG2, HeLa) at 1–2 × MIC, assessed using standard
1017 metabolic-activity assays. Data represent mean ± SD from independent experiments.
1018 Detail data are provided in **Supplementary Table 17**.

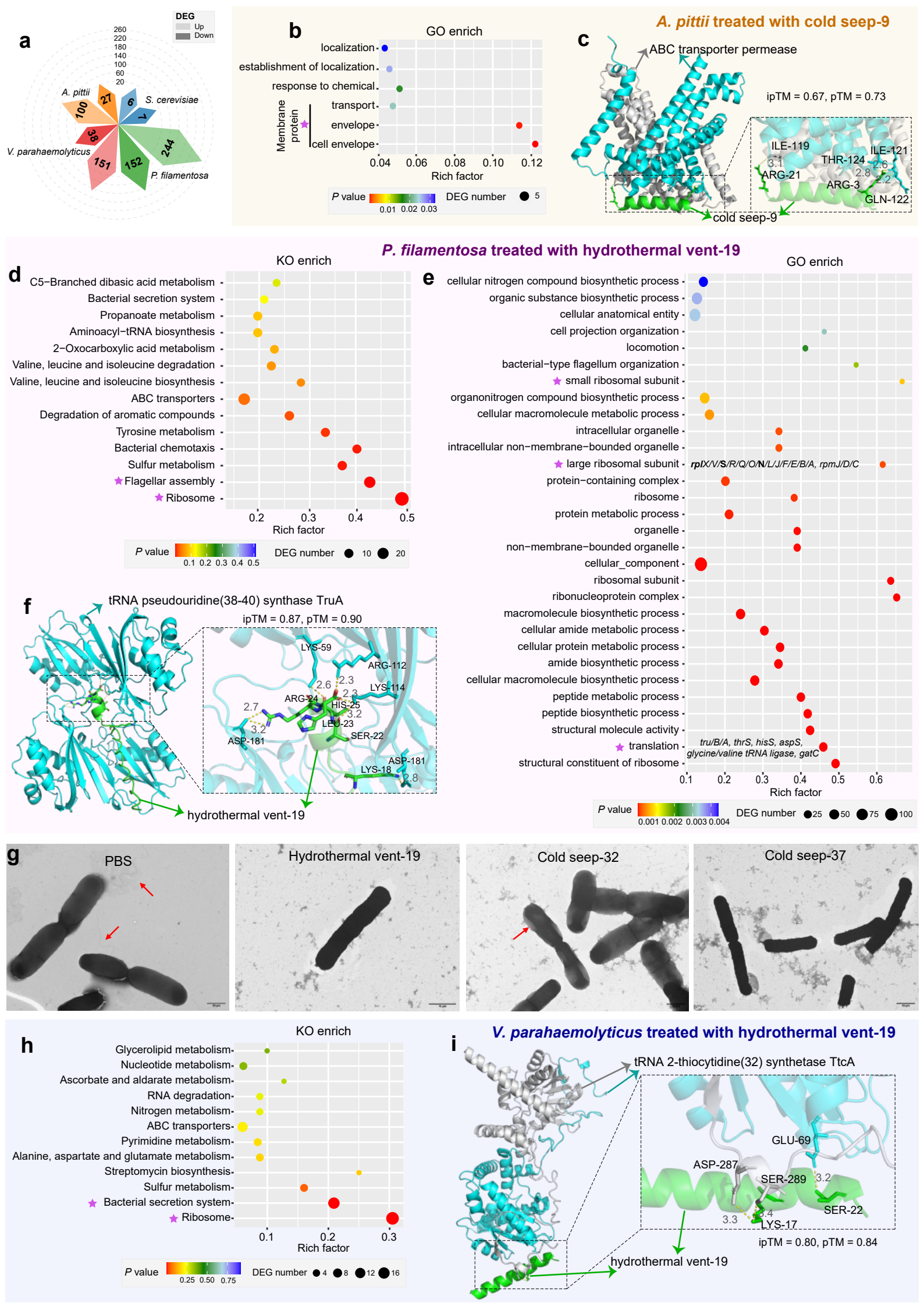
1019 **Figure 5. Mechanistic insights into deep-sea c_AMP activity across multiple**
1020 **microorganisms. (a)** Diamond plots showing differentially expressed genes (DEGs) in
1021 four microorganisms treated with representative c_AMPs. Numbers within each sector
1022 indicate total DEGs, with light and dark colors marking significantly up- and
1023 downregulated genes, respectively. Detailed lists of up- and down-regulated genes for
1024 each treatment group are presented in **Supplementary Tables 18–21**. **(b–c)** Proposed
1025 mechanism of action of cold seep-9 in *A. pittii*, including GO enrichment analysis of
1026 DEGs ($P < 0.05$) (b) and a structural model of an ABC transporter permease subunit
1027 (light blue/gray) bound to cold seep-9 (green) (c). Protein–peptide complexes were
1028 generated using AlphaFold3, and model quality was assessed using ipTM and pTM
1029 scores. Insets highlight predicted interaction interfaces between the peptide and the
1030 permease. **(d–f)** Proposed mechanism of action of hydrothermal vent-19 in *P.*
1031 *filamentosa*, including KEGG KO enrichment analysis of DEGs (d), GO enrichment
1032 analysis ($P < 0.005$) (e), and an AlphaFold-based structural model of tRNA
1033 pseudouridine synthase TruA (light blue) bound to hydrothermal vent-19 (green) (f),
1034 with predicted peptide–protein interaction residues indicated. **(g)** Transmission electron
1035 microscopy (TEM) images of *P. filamentosa* treated with hydrothermal vent-19, cold
1036 seep-32, and cold seep-37 at 1× MIC. All TEM experiments were performed in
1037 triplicate. Scale bars: 10 μm. **(h–i)** Proposed mechanism of action of hydrothermal vent-
1038 19 in *V. parahaemolyticus*, including KEGG KO enrichment analysis showing
1039 significantly enriched pathways (h) and a structural model of tRNA 2-thiocytidine (32)
1040 synthetase (TtcA; light blue) bound to hydrothermal vent-19 (green), highlighting
1041 predicted interaction residues (i). All structural models were visualized using PyMOL.


a
Arctic Ocean
Gakkel Ridge (Central Arctic Ocean)
Laptev Sea
Haakon Mosby mud volcano
Pacific Ocean Kuril Trench
Pacific Ocean
Juan de Fuca ridge
Eastern North Pacific
ODP site 1244
Scotian Basin
Japan Trench
Izu-Bonin Trench
Takuyo-Daisan Seamount
Takuyo-Daigo Seamount
Santa Monica Mounds
Gulf of Mexico
Atlantic Ocean Menez Gwen
Rainbow Hydrothermal Vents
East China sea
Loihi Seamount
Guaymas Basin
Mediterranean Sea
Amon mud volcano
Mid-Atlantic Ridge TAG Hydrothermal Vents
South China Sea
Pescadero Basin
Northwest Pacific Ocean
Pacific Ocean
Pacific Ocean East Pacific Rise
Atlantic Ocean Mid Cayman Rise
Northwestern Indian Ocean Carlsberg Ridge
Yap and Mariana trenches
Kilo Moana/ Abe/ Tahi Moana/ Tui Malila hydrothermal field
South Atlantic Ocean Mid-Atlantic Ridge
Manus Basin Inactive Chimney
Eastern Lau Spreading Center
Atacama Trench
Kermadec Trench
Indian Ocean Southwest Indian Ridge
Brothers volcano
Hadal trench (n = 308)
Cold seep (n = 174)
Hydrothermal vent (n = 160)
Abyssal plain (n = 10)
Seamount (n = 56)
60°N
30°N
EQ
30°S
60°S
180°W
90°W
0°
90°E
180°E
50 m
100 m
250 m
500 m
750 m
1000 m
1250 m
1500 m
2000 m
2500 m
3000 m
3500 m
4000 m
4500 m
5000 m
5500 m
6000 m
6500 m
b
Metagenomes
1,058,734,804 contigs
smORF (88.7 million):
49.9 (hadal trench), 32.5 (cold seep) 3.8 (hydrothermal vent), 0.8 (abyssal plain), 1.8 (seamount)
c_AMP (5.5 million) :
2.9 (hadal trench), 2.2 (cold seep) 0.2 (hydrothermal vent), 0.04 (abyssal plain), 0.04 (seamount)
Macrel
ampir
amPEPpy
AMPLify
AMP prediction
candidate AMPs
Homologs camparison
DRAMP v4
APD3
AMPSphere
EPs
marine biofilm-AMPs
131 c_AMPs
smORF prediction
SmorFinder
GMSC-mapper
Homologs comparison
GMSC
sORFdb
SmProt v2
smORF catalog
Diamond
90% coverage/identity
Bacterial inhibition experiment
all smORFs
cluster representatives
CD-HIT
100% coverage/identity
singletons
non-singletons
Mmseq2
90% coverage/identity
MIC/ MBC determination
TEM examination
Cytotoxicity evaluation
Comparative transcriptomic
AlphaFold3 predicted cAMP-arget complex structures
c
hadal trench
35%
65%
cold seep
32%
68%
hydrothermal vent
19%
81%
abyssal plain
26%
74%
seamount
21%
79%
sORFdb
SmProt
GMSC
10
20
30
40
50
60
70
80
90
100
Homologs
Novel candidates
Percentage of smORFs (%)
d
Hadal trench
59%
41%
Cold seep
56%
44%
Hydrothermal vent
47%
53%
Abyssal plain
56%
44%
Seamount
50%
50%
Unannotated
Annotated


a
Shared smORFs across deep−sea biomes
hadal trench
49.9 million
cold seep
32.5 million
hydrothermal vent
3.8 million
abyssal plain
0.8 million
seamount
1.8 million
2.5%
2.2%
4.7%
37.1%
21.2%
b
Proportion of smORFs (%)
J K S C L O Q E U I H T D P F G N M B V
INFORMATION STORAGE AND PROCESSING
[J] Translation, ribosomal structure and biogenesis
[K] Transcription
[L] Replication, recombination and repair
[A] RNA processing and modification
[B] Chromatin structure and dynamics
METABOLISM
[P] Inorganic ion transport and metabolism
[H] Coenzyme transport and metabolism
[C] Energy production and conversion
[I] Lipid transport and metabolism
[F] Nucleotide transport and metabolism
[Q] Secondary metabolites biosynthesis, transport and catabolism
[G] Carbohydrate transport and metabolism
[E] Amino acid transport and metabolism
CELLULAR PROCESSES AND SIGNALING
[V] Defense mechanisms
[O] Posttranslational modification, protein turnover, chaperones
[U] Intracellular trafficking, secretion, and vesicular transport
[T] Signal transduction mechanisms
[X] Mobilome: prophages, transposons
[W] Extracellular structures
[N] Cell motility
[M] Cell wall/membrane/envelope biogenesis
[D] Cell cycle control, cell division, chromosome partitioning
[Z] Cytoskeleton
POORLY CHARACTERIZED
[S] Function unknown
[R] General function prediction only
c
Archaea
Bacteria
Percentage of smORFs(%)
Hadal trench
Clod seep
Hydrotherm vent
Abyssal plain
Seamount
Class
Archaea
Methanosarcinia
Syntropharchaeia
Halobacteria
Lokiarchaeia
E2
Heimdallarchaeia
Bathyarchaeia
Nitrososphaeria
Thermoprotei
Thermoplasmata
Poseidoniia
Nanoarchaeia
Aenigmatarchaeia
Micrarchaeia
Thermococci
others
Bacteria
Gammaproteobacteria
Alphaproteobacteria
Desulfobacteria
Dehalococcoidia
Anaerolineae
Phycisphaerae
Planctomycetia
Campylobacteria
Verrucomicrobiae
Gemmatimonadetes
UBA9160
Bacteroidia
Clostridia
Bacilli
Actinomycetes
Acidimicrobiia
Terriglobia
UBA6911
others
d
Transmembrane helices
seamount 12.17%
hadal trench 10.47%
abyssal plain 13.75%
cold seep 12.20%
hydrothermal vent 14.37%
Signal peptides
seamount 1.59%
hadal trench 1.17%
abyssal plain 3.14%
cold seep 0.70%
1.57%
hydrothermal vent


a
Homologs
Novel candidates
Percentage (%)
20
40
60
80
100
APD
DRAMP
AMPSphere
Biofilm
EPs
0.03 0.05 0.04 0.02 0.01
99.97 99.95 99.96 99.98 99.99
0.12 0.18 0.44 0.18 0.10
99.88 99.82 99.56 99.98 99.99
11.33 10.57 14.32 12.52 7.25
88.67 89.43 85.68 87.48 92.75
0.00 0.00 0.00
100.00 100.00 100.00 100.00 100.00
0.02 0.03 0.07 0.09 0.07
99.98 99.97 99.93 99.91 99.93
Hadal trench
Cold seep
Hydrothermal vent
Abyssal plain
Seamount
b
Hadal trench
Cold seep
Hydrothermal vent
Abyssal plain
Seamount
Databases
EPs
Biofilm
Normalized frequency (%)
Amino Acid
A C D E K N Q R S T W
c
Cold seep
Hadal trench
Hydrothermal vent
Abyssal plain
Seamount
Databases
EPs
Biofilm
P < 2.2e-16
Isoelectric Point
Net Charge (pH7)
ppII Propensity
Disorder Propensity
d
hadal trench-32
pLDDT = 93
β sheet-coil
cold seep-38
pLDDT = 92
β sheet-coil-β sheet-coil
hydrothermal vent-35
pLDDT = 96
β sheet-coil-β sheet-coil
Abyssal plain-10
pLDDT = 86
coil-β sheet-coil
seamount-7
pLDDT = 86
α helix-coil-α helix


a
Non-pathogenic
Pathogenic
E. coli DH5α
P. filamentosa
K. Pneumoniae
BY4741-YPD
BY4741-YPEG
A. pittii
S. aureus
E. coli BW25113
H. bluephagenesis
VP.1997
MIC(μM)
>125
125
100
80
60
40
20
1
b
P. filamentosa
hydrothermal vent-19
1×MIC=1.25 μM
No AMP
H. bluephagenesis
hadal trench-22
1×MIC=80 μM
No AMP
VP.1997
hydrothermal vent-19
1×MIC=1.25 μM
No AMP
A. pittii
cold seep-9
1×MIC=5 μM
No AMP
E. coli DH5α
cold seep-9
1×MIC=20 μM
No AMP
c
Cell viability (%)
Hek293T
HepG2
Hela
hadal trench-22 1×MIC
hadal trench-22 2×MIC
cold seep-3 1×MIC
cold seep-3 2×MIC
cold seep-9 1×MIC
cold seep-9 2×MIC
cold seep-38 1×MIC
cold seep-38 2×MIC
hydrothermal vent-9 1×MIC
hydrothermal vent-9 2×MIC
hydrothermal vent-19 1×MIC
hydrothermal vent-19 2×MIC
hydrothermal vent-36 1×MIC
hydrothermal vent-36 2×MIC
abyssal plain-4/sm-4 1×MIC
abyssal plain-4/sm-4 2×MIC
No AMP
DMSO


a
DEG
Up
Down
A. pittii
S. cerevisiae
V. parahaemolyticus
P. filamentosa
b
GO enrich
localization
establishment of localization
response to chemical
transport
envelope
cell envelope
Membrane protein
Rich factor
P value
DEG number
c
A. pittii treated with cold seep-9
ABC transporter permease
ipTM = 0.67, pTM = 0.73
ILE-119
ILE-121
THR-124
ARG-21
ARG-3
GLN-122
cold seep-9
P. filamentosa treated with hydrothermal vent-19
d
KO enrich
C5−Branched dibasic acid metabolism
Bacterial secretion system
Propanoate metabolism
Aminoacyl−tRNA biosynthesis
2−Oxocarboxylic acid metabolism
Valine, leucine and isoleucine degradation
Valine, leucine and isoleucine biosynthesis
ABC transporters
Degradation of aromatic compounds
Tyrosine metabolism
Bacterial chemotaxis
Sulfur metabolism
Flagellar assembly
Ribosome
Rich factor
P value
DEG number
e
GO enrich
cellular nitrogen compound biosynthetic process
organic substance biosynthetic process
cellular anatomical entity
cell projection organization
locomotion
bacterial−type flagellum organization
small ribosomal subunit
organonitrogen compound biosynthetic process
cellular macromolecule metabolic process
intracellular organelle
intracellular non−membrane−bounded organelle
large ribosomal subunit
rplX/V/S/R/Q/O/N/L/J/F/E/B/A, rpmJ/D/C
protein−containing complex
ribosome
protein metabolic process
organelle
non−membrane−bounded organelle
cellular_component
ribosomal subunit
ribonucleoprotein complex
macromolecule biosynthetic process
cellular amide metabolic process
cellular protein metabolic process
amide biosynthetic process
cellular macromolecule biosynthetic process
peptide metabolic process
peptide biosynthetic process
structural molecule activity
translation
tru/B/A, thrS, hisS, aspS, glycine/valine tRNA ligase, gatC
structural constituent of ribosome
Rich factor
P value
DEG number
f
tRNA pseudouridine(38-40) synthase TruA
ipTM = 0.87, pTM = 0.90
LYS-59
ARG-112
LYS-114
ARG-24
HIS-25
LEU-23
SER-22
ASP-181
LYS-18
hydrothermal vent-19
g
PBS
Hydrothermal vent-19
Cold seep-32
Cold seep-37
h
KO enrich
Glycerolipid metabolism
Nucleotide metabolism
Ascorbate and aldarate metabolism
RNA degradation
Nitrogen metabolism
ABC transporters
Pyrimidine metabolism
Alanine, aspartate and glutamate metabolism
Streptomycin biosynthesis
Sulfur metabolism
Bacterial secretion system
Ribosome
Rich factor
P value
DEG number
i
V. parahaemolyticus treated with hydrothermal vent-19
tRNA 2-thiocytidine(32) synthetase TtcA
GLU-69
ASP-287
SER-289
SER-22
LYS-17
ipTM = 0.80, pTM = 0.84
hydrothermal vent-19