

1 **Title: Thermal filtering reveals a cryptic reservoir of thermotolerant yeasts in Sub-**
2 **Antarctic soils**

3 Luis A. Saona^{1,2,3}, Macarena Las Heras⁴, José Benavides-Parra^{1,5}, Javiera I. Cajas⁵, Fernanda Jeria-Osorio⁵, Julian
4 F. Quintero-Galvis^{2,6}, Jennifer Molinet⁷, and Pablo Villarreal^{5,8*}

5 ¹ *Facultad de Química y Biología, Departamento de Biología, Universidad de Santiago de Chile, Santiago,*
6 *9170022, Chile.*

7 ² *ANID-Millennium Nucleus of Patagonian Limit of Life (LiLi), Valdivia, Chile.*

8 ³ *Centro Científico y Tecnológico de Excelencia Ciencia & Vida, Fundación Ciencia & Vida, Huechuraba,*
9 *Santiago, Chile.*

10 ⁴ *Facultad de Medicina, Centro de Genética y Genómica, Clínica Alemana Universidad del Desarrollo,*
11 *Santiago, Chile.*

12 ⁵ *ANID-Millennium Science Initiative-Millennium Institute for Integrative Biology (iBio), Santiago, Chile.*

13 ⁶ *Departamento de Ciencias, Facultad de Artes Liberales, Universidad Adolfo Ibáñez, Santiago, Chile.*

14 ⁷ *Facultad de Ingeniería, Instituto de Ciencias Aplicadas, Centro de Investigación e Innovación, Universidad*
15 *Autónoma de Chile, Santiago, Chile*

16 ⁸ *Centro de Genómica y Bioinformática, Facultad de Ciencias, Ingeniería y Tecnología, Universidad Mayor,*
17 *Santiago, Chile.*

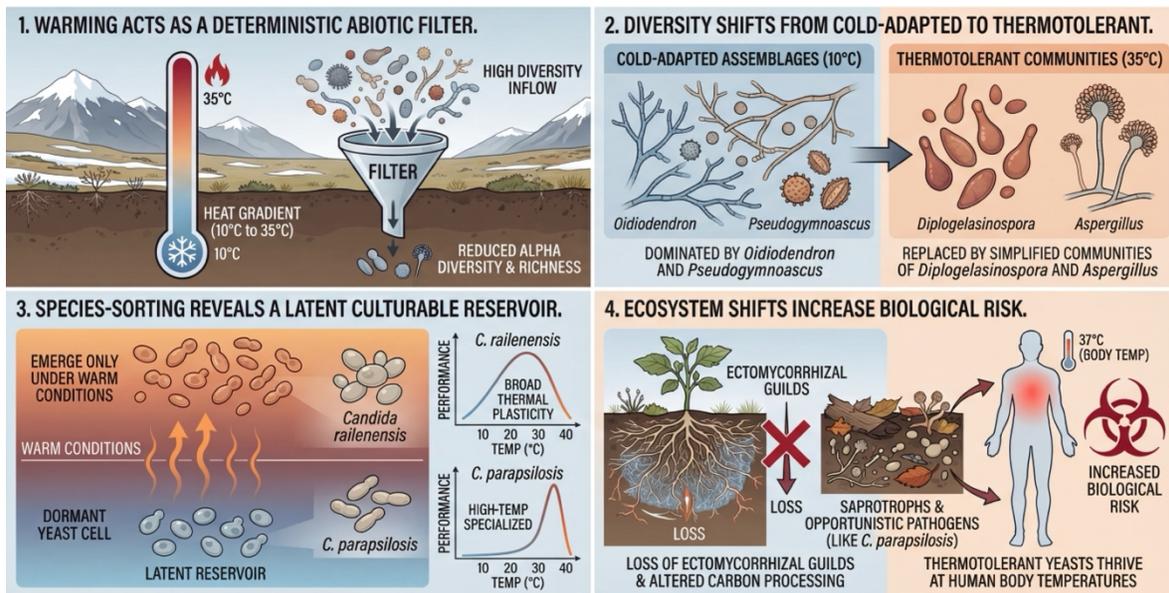
18 **Corresponding author.*

19 *Email address: pablo.villarreal@umayor.cl*

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22 Graphical Abstract



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25 **Abstract**

26 Global climate change is accelerating ecological transformation in Sub-Antarctic ecosystems, where resident
27 biota exhibit narrow thermal tolerances. While microbial responses to warming are increasingly documented,
28 the role of soil yeasts, key players in organic matter decomposition, remains poorly understood. Here, we
29 show that warming acts as a deterministic filter, triggering a profound community restructuring that favors a
30 cryptic reservoir of thermotolerant taxa. Using species-sorting and thermal profiling, we found that elevated
31 temperatures (up to 35°C) significantly reduced alpha diversity and richness. This filtering shifted communities
32 from cold-adapted assemblages to simpler, thermotolerant lineages. Thermal sorting revealed hidden
33 culturable diversity, notably an increase in *Candida* spp., with *Candida railenensis* and *Candida parapsilosis*
34 found only under warm conditions. Physiological profiling showed *C. railenensis* had broad thermal plasticity,
35 while *C. parapsilosis* was high-temperature specialized. Additionally, warming nearly eliminated
36 ectomycorrhizal guilds and increased saprotrophs, suggesting shifts in carbon processing and organic matter
37 decomposition. Furthermore, our results indicate that sustained warming reduces functional redundancy and
38 broadens reservoirs for opportunistic pathogens such as *C. parapsilosis*, which thrive near human body
39 temperatures. These findings highlight the importance of including yeasts in climate models to predict future
40 biogeochemical changes and biological risks in warming cold ecosystems.

41 **Keywords:** Global climate change, yeasts, Sub-Antarctic, microcosms, diversity, thermotolerance

42

43 Introduction

44 Global climate change is accelerating ecological transformation at an unprecedented rate across
45 biomes. One of the primary anthropogenic stressors is the ongoing rise in temperature, which directly alters
46 ecosystem dynamics and indirectly influences water availability, nutrient flows, and biodiversity patterns
47 (Pendlebury & Barnes-Keoghan, 2007, Berdugo *et al.*, 2018, Delgado-Baquerizo *et al.*, 2018, Intergovernmental
48 Panel on Climate, 2023). While these effects are increasingly well-documented in temperate forests and the
49 polar cryosphere (Meir, Cox & Grace, 2006), high-latitude and Sub-Antarctic ecosystems remain comparatively
50 understudied. These regions are especially vulnerable due to their historical climatic stability and the narrow
51 thermal tolerance of their resident biota (Saona *et al.*, 2025, Zhang *et al.*, 2025). Recent studies in South
52 America indicate that temperatures will increase and aridification will progress, posing significant risks to soil
53 structure, vegetation productivity, and biogeochemical cycles (Barnes-Keoghan & Pendlebury, 2023). In this
54 context, understanding how microbial communities, especially assemblages and their metabolic functions,
55 respond to such shifts is essential for predicting broader ecosystem trajectories under global warming
56 scenarios (Delgado-Baquerizo *et al.*, 2016, Delgado-Baquerizo *et al.*, 2018, Abs, Chase & Allison, 2023).

57 Microorganisms play a central role in terrestrial ecosystems, driving decomposition, nutrient cycling,
58 and plant-soil feedback (Jansson & Hofmockel, 2020). Their diversity, rapid life cycles, and metabolic plasticity
59 make them highly responsive to environmental fluctuations, including those induced by temperature shifts
60 (Knight *et al.*, 2024). However, the relationship between microbial community structure and ecosystem
61 function is not necessarily linear (Allison & Martiny, 2008). Recent evidence shows that microbial composition,
62 functional traits, and evolutionary processes can interact to modulate ecosystem-level outcomes in complex
63 ways (Yurkov & Pozo, 2017, Rodriguez Amor & Dal Bello, 2019, Diaz-Colunga *et al.*, 2022).

64 Warming can act as a selective pressure, altering community assembly trajectories and shifting
65 ecosystem states toward lower functional redundancy or reduced resilience by favoring thermotolerant
66 lineages over cold-adapted specialists (Yurkov & Pozo, 2017, Yurkov, 2018, Smith *et al.*, 2022). Moreover,
67 microbial communities may exhibit eco-evolutionary feedback, in which shifts in community structure
68 influence adaptive dynamics, a phenomenon particularly relevant under continuous climatic pressures.
69 (Yurkov, 2018, Runnel *et al.*, 2025).

70 Microbial restructuring is not merely a taxonomic shift, it poses profound risks to ecosystem stability
71 and biosecurity (Cavicchioli *et al.*, 2019). The replacement of specialized, cold-adapted taxa by thermotolerant
72 lineages can disrupt delicate plant-soil feedbacks and alter nutrient-cycling rates, potentially destabilizing
73 carbon storage in these vulnerable biomes (Delgado-Baquerizo *et al.*, 2016, Delgado-Baquerizo *et al.*, 2018).
74 Furthermore, the deterministic selection of latent, heat-tolerant microorganisms, including taxa with
75 opportunistic pathogenic potential, raises significant concerns about the emergence of fungal diseases in a
76 warming world (Casadevall, Kontoyiannis Dimitrios & Robert, 2019). Understanding these community-level
77 reorganizations is therefore vital for assessing the resilience of Sub-Antarctic forests and their capacity to
78 maintain essential ecological services under future climate scenarios.

79 Within this context, the species sorting framework provides a robust conceptual basis for
80 understanding community reassembly along environmental gradients. This process often relies on selecting
81 taxa from a microbial seed bank, a reservoir of dormant or low-abundance organisms that can rapidly
82 resuscitate when environmental conditions favor their specific traits (Litchman & Thomas, 2022). The success
83 of these organisms is governed by their Thermal Performance Curves (TPCs), which define the physiological
84 limits and optimal growth temperatures of each taxon (Alster, Weller & von Fischer, 2018, Ramond, Galand &
85 Logares, 2025). While these dynamics have been studied in other microbes, the role of yeasts as a "cryptic
86 reservoir" of diverse thermal traits remains largely unexplored (Burman & Bengtsson-Palme, 2021, Wieczynski
87 *et al.*, 2021, Smith *et al.*, 2022). Furthermore, the deterministic selection of these latent microorganisms raises
88 significant concerns: warming may favor the emergence of opportunistic pathogens, whose TPCs allow them
89 to thrive as thermal thresholds are exceeded.

90 To understand this pattern, we studied yeast communities in rhizosphere soils from a Sub-Antarctic
91 environment along a thermal gradient. We tested the hypothesis that warming constrains stochastic assembly,
92 shifting the balance toward a deterministic regime in which the thermal niches of constituent taxa, defined
93 by their TPCs, strictly predict community composition. Using a dual approach of ITS2 metabarcoding and
94 culture-dependent thermal profiling, we linked taxonomic shifts directly to physiological limits. We show that
95 yeast diversity and composition are significantly altered by temperature. These changes are consistent with
96 the species-sorting paradigm: warming acts as an abiotic filter, favouring yeasts with high thermal tolerance

97 and reshaping communities through deterministic rather than stochastic processes. Our results expand
98 understanding of microbial assembly under climate stress and highlight the importance of including yeasts in
99 global change frameworks. Microorganisms and specialized yeasts also inform discussions of microbial
100 functional similarity and redundancy, especially in ecosystems where warming exceeds microbial tolerance.
101

102 **Materials and Methods**

103 ***Sample collection***

104 Rhizosphere samples were obtained from the Karukinka Natural Park in the Sub-Antarctic region
105 (53°42'S 69°18'O). Five squares of 10 x 10 meters were established (**Figure S1**). Each of these squares was at
106 least 1 km apart. In each square, five soil samples (50 g each) were randomly collected from the top 10 cm of
107 soil and combined in a sterile plastic bag. All samples were stored in 50 mL tubes and maintained at -80 °C
108 until the analysis.

109 ***Species-sorting analysis***

110 For each sampling, three independent replicates of 5 g were generated. Each replicate was incubated
111 at one of four temperatures (10, 20, 30, and 35 °C) for eight weeks (**Figure S1**). This thermal gradient was
112 selected to represent conditions ranging from current Sub-Antarctic soil temperatures to extreme thermal
113 stress scenarios, aiming to trigger and capture the latent functional diversity reservoir that may respond to
114 abrupt warming events. During incubation, soil microcosms were periodically rehydrated with sterile
115 deionized water to maintain moisture levels (Smith *et al.*, 2022). Immediately after the 8-week incubation, 1
116 g of soil from each replicate was stored at -20 °C for subsequent DNA extraction and metabarcoding analyses.
117 The remaining soil (~4 g) from each replicate was processed for culture-based isolation as follows: samples
118 were washed with phosphate-buffered saline (PBS), and the suspension was plated onto YPD agar (1% yeast
119 extract, 2% peptone, 2% glucose, 2% agar) supplemented with 100 µg/mL chloramphenicol. Plates were
120 incubated at both 20 °C and the corresponding sorting temperature (10, 20, 30, or 35 °C). Once colonies
121 developed, the five most abundant morphologically distinct colony types per plate were selected. As a control,
122 yeasts were also directly isolated from untreated soil samples and incubated at 20 °C. Isolates were preserved
123 at -80 °C in 20% glycerol until subsequent molecular identification.

124

125

126 ***DNA extraction and sequencing***

127 DNA was extracted from each rhizosphere sample using the Zymo Quick-DNA bacterial/fungal
128 extraction kit according to the manufacturer's instructions. The DNA obtained was quantified using the
129 Invitrogen™ Qubit™ 4 Fluorometer, and samples containing more than 2 ng/μl of DNA were used to generate
130 the ITS amplicon library. The extracted DNA was used as a template to amplify the internal nuclear ribosomal
131 transcribed spacer 2 (ITS2 region), using forward ITS3 (5'-GCATCGATGAAGAACGCAGC-3') and reverse ITS4 (5'-
132 TCCTCCGCTTATTGATATAT-3') primers (White *et al.*, 1990). The PCR conditions used for ITS amplification were
133 as follows: denaturation at 95 °C for 3 min, followed by 25 cycles of 95 °C for 30 s (denaturation), 55 °C for 30
134 s (annealing), and 72 °C for 30 s (extension). A final annealing step was performed at 72 °C for 5 min. Libraries
135 were prepared using the Illumina DNA Prep Kit according to the manufacturer's protocol. The libraries were
136 then sequenced on the Illumina MiSeq using a Mid-Output Kit with 300-bp paired-end reads at the University
137 of Chile sequencing facility. The total number of raw reads obtained is shown in **Table S1**.

138

139 ***Processing of ITS2 amplicon sequence data***

140 Raw 300-bp paired-end reads from the MiSeq run were first demultiplexed and primers removed in
141 QIIME 2 (v2022.8) (Bolyen *et al.*, 2019) using the Cutadapt plugin, yielding 45 sample-specific FASTQ pairs.
142 Demultiplexed reads were then imported into R (v4.1.2) and processed with DADA2 (v1.20) (Callahan *et al.*,
143 2016). To ensure high-quality data, sequences were filtered, allowing a maximum of expected errors (maxEE =
144 2) for both forward and reverse reads. The first 1 and 5 nucleotides were removed from the start of forward
145 and reverse reads, respectively (trimLeft = c(1,5)). No fixed truncation length was applied to preserve the
146 natural length variation of the ITS2 region. Error models were learned using 1 million reads, amplicon sequence
147 variants (ASVs) were inferred, and chimeras were removed using the consensus method.

148 Each ASV was taxonomically classified against the UNITE database (v8.3) using a naïve Bayes classifier in QIIME
149 2's feature-classifier, yielding species-level assignments where possible. The resulting abundance table
150 containing 4,672 ASVs, taxonomy, and sample metadata (**Table S2**) was imported into phyloseq (v1.38)
151 (McMurdie & Holmes, 2013) and merged into a single object for downstream analyses.

152 Initial data filtering was performed to remove low-quality or low-prevalence taxa. ASVs with a mean
153 read count below 1×10^{-5} across all samples were removed. A prevalence filter was also applied, retaining only
154 ASVs present in at least 5% of the samples with more than two reads. Finally, samples with fewer than 1,000
155 total reads were excluded, resulting in a final dataset of 1,033 ASVs across 45 samples (**Table S3**). The core
156 microbiome, defined as the set of ASVs shared across all temperature conditions (T0, 10°C, 20°C, 30°C, and
157 35°C), was identified and is detailed in **Table S4**.

158 Alpha diversity was calculated on the filtered phyloseq object using the *estimate_richness* function
159 from the phyloseq package. We assessed richness using Observed ASVs and diversity using the Shannon and
160 Simpson indices. To test for significant differences in alpha diversity metrics among temperature treatments,
161 we performed an analysis of variance (ANOVA). The normality of residuals was confirmed using the Shapiro-
162 Wilk test. A post-hoc Tukey's Honestly Significant Difference (HSD) test was used to identify pairwise
163 differences among temperature groups.

164 Beta diversity was analyzed to assess shifts in community composition. We performed a Redundancy
165 Analysis (RDA) on a Hellinger-transformed ASV abundance matrix using the vegan package. Temperature was
166 set as the sole constraining variable. The significance of the overall model and of each constrained axis was
167 determined using a permutation-based ANOVA (*anova.cca* function with 999 permutations).

168 Taxonomic composition was visualized using stacked bar charts generated with ggplot2 (Wickham,
169 2016), showing the relative abundance of the most prevalent genera across the temperature treatments. A
170 Venn diagram was generated using the *ps_venn* function to illustrate the number of shared and unique ASVs
171 among the five temperature conditions.

172 Functional guild assignment was performed using FUNGuild (v1.2) (Nguyen *et al.*, 2016). The ASV
173 table and taxonomy were used as input to assign ecological guilds to each taxon. Guild assignments were
174 manually curated to consolidate complex or ambiguous classifications into broader, more informative
175 categories (Saona *et al.*, 2025). Functional community structure was visualized with stacked bar charts. To test
176 if functional profiles were significantly structured by temperature, we conducted an RDA on the Hellinger-
177 transformed guild abundance matrix, followed by a permutational ANOVA as described for the taxonomic beta
178 diversity.

179 ***Taxonomic identification***

180 To identify isolates at the species level, we sequenced the internal transcribed spacer (ITS) region
181 ITS1-5.8S-ITS2) using primers ITS1 and ITS4 (White *et al.*, 1990). DNA extraction will be performed as previously
182 described (Villarreal *et al.*, 2022). PCR fragments will be generated using primers ITS1 and ITS4. PCR thermal
183 profile was 96 °C 2 min, followed by 35 cycles of 96 °C for 30 s, 51 °C for 45 s, 72 °C for 120 s, and a final
184 extension step at 72 °C for 7 min. Nucleotide sequences of the PCR products were determined by Sanger
185 sequencing in both directions at Macrogen (Macrogen Inc., Seoul, Korea). The sequences obtained were
186 analyzed with the PhyKit toolkit (Steenwyk *et al.*, 2021) and compared to the NCBI database using BLAST. To
187 investigate the modulation and relationships among the species resulting from the applied temperature,
188 phylogenetic analysis of the ITS1/ITS4 sequences of the selected isolates was performed using the R package
189 phytools (Revell, 2024).

190

191 ***High-throughput physiological traits profiling***

192 The optimum growth temperature for each isolate was obtained by measuring the thermal
193 performance curve (TPC, the relationship between fitness-related trait performance and temperature) of its
194 maximal growth rate at ten temperatures (12, 15, 18, 20, 25, 30, 32, 35, 37, and 40 °C) in YPD medium. For
195 this, high-throughput phenotyping in 96-well microculture plates was performed as previously described
196 (Villarreal *et al.*, 2022). Briefly, cells were pre-cultivated in 200 µL YPD medium without agitation at 20 °C for
197 48 h. For the experimental run, each well was inoculated with 10 µL of pre-inoculum to an optical density
198 (OD_{600nm}) of 0.03-0.1 in 200 µL of YPD medium. Four independent OD measurements were taken per strain.
199 The maximum growth rate (μ_{max}) was determined as previously described (Ibstedt *et al.*, 2015). For this, μ_{max}
200 was calculated following a smoothing procedure on ln-transformed OD-values and using the discrete
201 derivative, as previously described (Warringer & Blomberg, 2003, Perez-Samper *et al.*, 2018, Molinet *et al.*,
202 2022) in R version 4.3.1.

203

204 ***Modeling Thermal Performance Curves***

205 We fitted TPCs to μ_{\max} of each strain using the cardinal temperature model with inflection (CTMI) as
206 previously described (Salvadó *et al.*, 2011, Molinet & Stelkens, 2025), using equation 1.

207

$$208 \quad P = 0 \quad \text{if } T \leq CT_{\min} \text{ or } T \geq CT_{\max}$$

$$209 \quad P = P_{\text{opt}} \times (D/E) \quad \text{if } CT_{\min} < T < CT_{\max}$$

$$210 \quad D = (T - CT_{\max}) \times (T - CT_{\min})^2 \quad (1)$$

$$211 \quad E = (T_{\text{opt}} - CT_{\min}) \times [(T_{\text{opt}} - CT_{\min}) \times (T - T_{\text{opt}}) - (T_{\text{opt}} - CT_{\max}) \times (T_{\text{opt}} + CT_{\min} - 2T)]$$

212

213 Where:

214 CT_{\max} is the temperature above which no growth occurs.

215 CT_{\min} is the temperature below which no growth occurs.

216 T_{opt} is the temperature at which P_{\max} equals its optimal value (P_{opt}).

217

218 CTMI parameters were estimated using nonlinear regression in R version 4.3.1. Thermal tolerance
219 and Thermal breadth (T_{br}) were obtained using the `calc_params` function from the `rTPC` package (Padfield,
220 O'Sullivan & Pawar, 2021), where thermal tolerance corresponds to CT_{\max} minus CT_{\min} , and T_{br} is the
221 temperature range across which performance is above 80% of optimal. The adequacy of fit of TPCs was
222 checked by the proportion of variance explained by the model (R^2). We considered thermal parameters to
223 differ significantly among strains if their 95% CI did not overlap. To compare TPCs between strains and to
224 estimate the mean and 95% CI of each strain TPC, we used parametric bootstrapping, implemented in the `boot`
225 package (v1.3-28.1).

226

227 ***Phylogenetic and non-phylogenetic comparisons***

228 The molecular phylogeny of 12 yeast species was reconstructed from ITS sequences aligned using
229 MAFFT v7.0. Maximum likelihood (ML) inference was performed in IQ-TREE v2.0 (Nguyen *et al.*, 2014),
230 employing the TVMe+G4 substitution model selected via the Bayesian Information Criterion (BIC). To facilitate
231 comparative analyses, the resulting tree was ultrametricized using penalized likelihood smoothing (Paradis,
232 2013) with a correlated evolutionary rate model, implemented in the R package *ape* (Paradis & Schliep, 2019).

233 We assessed the phylogenetic signal of six derived thermal tolerance traits (T_{\min} , T_{\max} , T_{opt} , P_{\max} ,
234 Tolerance, and T_{br}) using three complementary metrics: Blomberg's K statistic (Blomberg, Garland & Ives,
235 2003), which compares observed phenotypic similarity with that expected under a Brownian motion (BM)
236 model, where $K = 1$ indicates neutral evolution, $K < 1$ suggests evolutionary lability, and $K > 1$ indicates
237 phylogenetic conservatism; (2) Pagel's λ parameter (Pagel, 1999), which assesses the degree of phylogenetic
238 dependence of a trait, where $\lambda = 0$ indicates evolutionary independence and $\lambda = 1$ indicates Brownian
239 evolution; and (3) Moran's I index (Gittleman & Kot, 1990), which measures the phylogenetic autocorrelation
240 of traits (Paleo-López *et al.*, 2016, Quintero-Galvis *et al.*, 2018). The statistical significance of K and λ was
241 assessed using 999 random permutations of trait values at the tree tips. To identify the mode of trait evolution,
242 we compared the fit of four evolutionary models, Brownian Motion (BM), White Noise (WN), Ornstein-
243 Uhlenbeck (OU), and Early Burst (EB), calculating Akaike weights based on sample-size corrected AIC (AICc) to
244 determine the best-fitting model. Additionally, we visualized evolutionary trajectories through phenograms
245 and disparity-through-time (DTT) plots. These analyses were conducted using the *phytools* (Revell, 2012) and
246 *geiger* (Harmon *et al.*, 2008) packages in R v4.3.0.

247 To test for relationships between thermal traits while accounting for non-independence due to shared
248 ancestry, we fitted PGLS models using the *pgls* function in the *caper* package (Swenson, 2014). Models
249 incorporated thermal parameters, grouping factors, and acclimation duration as predictors, with the λ
250 parameters estimated via maximum likelihood to control for phylogenetic signal. Finally, we replicated the
251 signal analysis using the thermal performance curves variables (mean growth rate, mean lag phase duration,
252 and mean maximum optical density [OD_{\max}]) measured across the thermal gradient (10, 20, 30, and 35°C).

253

254 **Statistical analysis**

255 The experimental data and calculated parameters are expressed as the mean of four replicas with the
256 corresponding standard deviation. All data were statistically analyzed with R software version 4.3.1 using a
257 one-way ANOVA and Tukey test for mean comparisons with a *p-value* of 0.05. Heat maps were performed
258 using the R software (Team, 2014) and the “pheatmap” package (stats 3.6.0), and plotted using the “ggplot2”

259 package. Principal component analysis (PCA) was performed in R software using the “prcomp” package (stat
260 3.6.0), and plotted with the “ggbiplot” package (Team, 2014).

261

262 ***Data availability statement***

263 The data and code supporting the findings of this study are openly available at Zenodo
264 (<https://doi.org/10.5281/zenodo.18494565>). Raw reads have been deposited in the Sequence Read Archive
265 (SRA) database of the National Center for Biotechnology Information (NCBI) under the BioProject ID
266 PRJNA1402372.

267 Results

268 Thermal stress reduces yeast richness and reshapes community composition

269 To evaluate the thermal resilience of the specialized yeast communities found in Sub-Antarctic soils,
270 we exposed native samples to a controlled temperature gradient (10°C to 35°C). This experimental setup
271 allowed us to pinpoint specific thresholds at which warming-related stress disrupts community assembly.

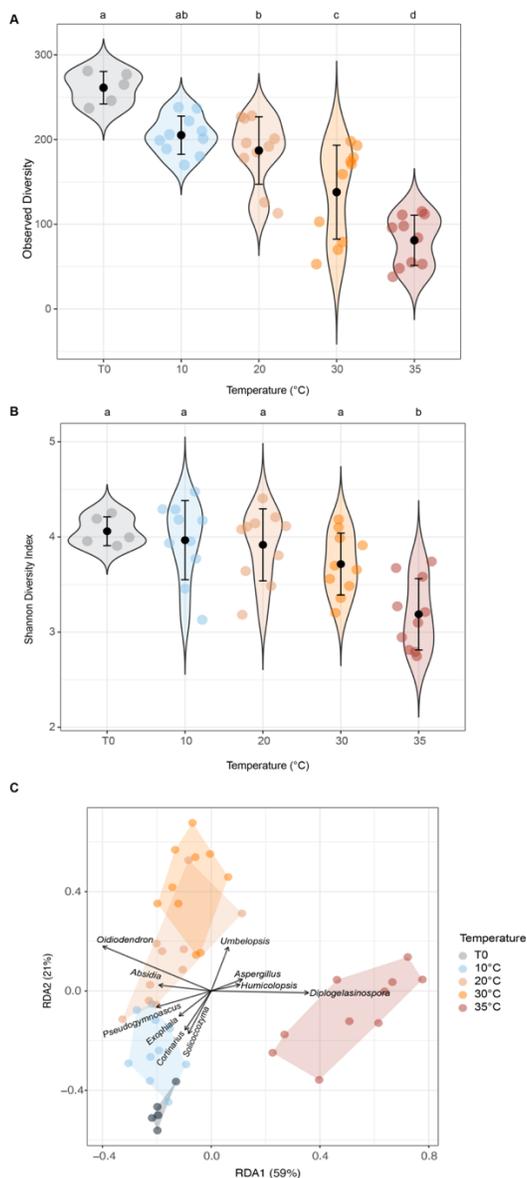
272 Incubation of sub-Antarctic soil yeast communities across a thermal gradient resulted in significant
273 alterations in their alpha diversity (**Figure 1A-B**). Both the number of observed ASVs (richness) and the
274 Shannon diversity index showed a clear and significant decreasing trend with increasing temperature (**Figure**
275 **1A-B**). The highest richness was recorded at the initial time point (T0), with an average of 261 ASVs (**Figure**
276 **1A**). This value remained relatively stable at 10°C and 20°C but declined significantly at 30°C (mean = 138 ASVs;
277 Tukey's HSD, p -value < 0.001), and reached its minimum at 35°C (mean = 81 ASVs; p -value < 0.001). A similar
278 pattern was observed for the Shannon diversity index (ANOVA, $F_{4,40} = 8.52$, p -value < 0.001). While diversity at
279 10°C, 20°C, and 30°C was not statistically different from the T0 communities, the 35°C treatment caused a
280 drastic and significant reduction in diversity compared to all other conditions (Tukey's HSD, p -value < 0.05)
281 (**Figure 1B**). In contrast, the Simpson diversity index did not show a statistically significant difference across
282 treatments (ANOVA, p -value = 0.066), suggesting that richness and evenness declined under stress, primarily
283 due to the loss of rare taxa, while the relative dominance of abundant taxa remained stable until the highest
284 temperature stress was reached.

285 Then, to evaluate the role of temperature as a deterministic driver of community assembly, we
286 performed a Redundancy Analysis (RDA) constrained by temperature, together with a PERMANOVA. Yeast
287 community structure was strongly and significantly shaped by temperature (PERMANOVA, $F_{4,40} = 2.43$, p -value
288 = 0.001). An RDA constrained by temperature explained 19.6% of the total variance in community composition.
289 The first two RDA axes captured most of this constrained variance (RDA1: 59%; RDA2: 21%), clearly separating
290 the samples along the temperature gradient (**Figure 1C**). The first axis (RDA1) primarily distinguished the
291 extreme warming condition, separating the 35°C samples (positive scores) from the rest of the thermal
292 gradient. The second axis (RDA2) resolved the variation among the non-extreme temperatures, separating the
293 cold-adapted communities (Time 0 and 10°C) on the negative side from those incubated at intermediate

294 temperatures (20°C and 30°C) on the positive side. A clear taxonomic turnover drove this separation. Genera
295 such as *Pseudogymnoascus*, *Exophiala*, *Cortinarius*, and *Solicoccozyma* were strongly associated with the
296 cooler conditions (Time 0 and 10°C). In contrast, genera such as *Diplogelasinospora*, *Aspergillus*, and
297 *Humicolopsis* were highly influential in structuring communities at elevated temperatures (30°C and 35°C).

298 Overall, these results demonstrate that warming acts as a powerful deterministic filter, restructuring
299 Sub-Antarctic yeast communities. By selectively modifying the rare biosphere, which comprises specialized
300 cold-adapted taxa, while favoring a resilient group of persistent residents, thermal stress drives a non-uniform
301 erosion of diversity. This selective sorting process shapes niche occupation along the thermal gradient,
302 triggering profound taxonomic turnover that replaces historically stable cold-associated assemblages with
303 thermotolerant groups.

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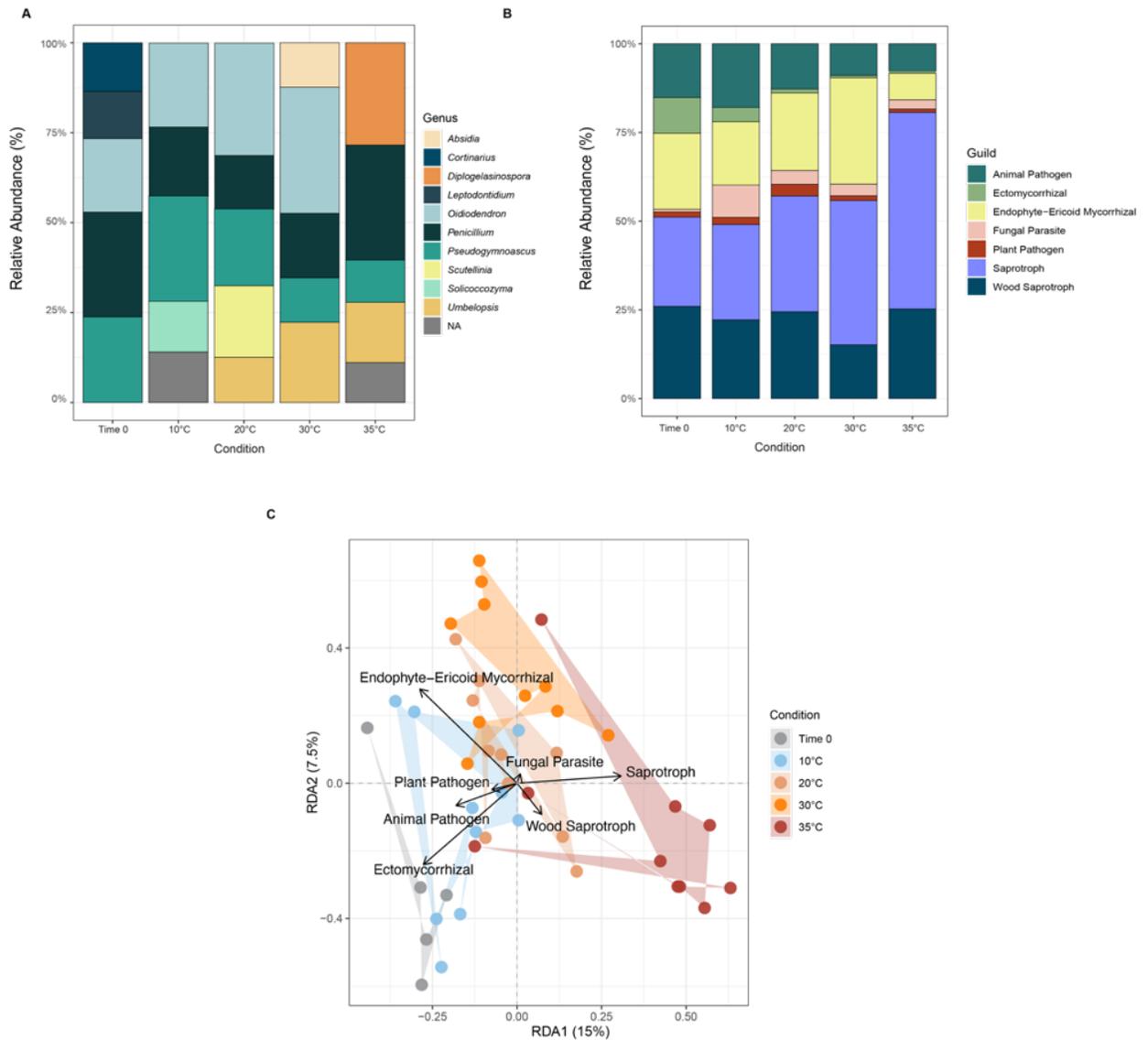
Figure 1. Effects of temperature on yeast community diversity and structure. (A) Observed diversity (number of ASVs) and (B) Shannon diversity index across the temperature gradient (Time 0, 10°C, 20°C, 30°C, and 35°C). Letters above the violin plots indicate significant differences between groups based on a Tukey's HSD post-hoc test (p -value <0.05). The central black bar represents the standard deviation of the distribution around the mean. (C) Redundancy Analysis (RDA) of Hellinger-transformed yeast community composition constrained by temperature. Points represent individual samples, colored by temperature treatment. Polygons enclose all samples from a given treatment. Arrows indicate the top 10 most influential genera driving the community separation. The percentage of variance explained by each axis is shown in parentheses.

319 **Taxonomic and functional profiles shift towards warm-associated taxa**

320 The shift in community structure was reflected in the overall taxonomic profiles at the genus level
321 **(Figure 2A)**. While the initial T0 community was diverse, warming induced a progressive shift towards a
322 community heavily dominated by *Diplogelasinospora* at 35°C. A Venn diagram analysis revealed that despite
323 this turnover, a core microbiome of 114 ASVs was shared across all temperature conditions **(Figure S2, Table**
324 **S4)**.

325 An analysis of these 114 core taxa showed that temperature was also associated with consistent
326 changes within this stable portion of the community **(Figure S2A, Table S4)**. Core members of genera such as
327 *Pseudogymnoascus* and *Penicillium* were abundant at lower temperatures but declined in relative abundance
328 under warming conditions. Conversely, core taxa from genera like *Humicolopsis* and *Absidia*, while present
329 initially, increased in relative abundance at 30°C and 35°C **(Figure S2B)**. These patterns indicate that
330 temperature influenced the relative contributions of taxa even within the shared core community.
331 Functionally, yeast communities were dominated by Saprotrophs and Wood Saprotrophs across all
332 temperatures **(Figure 2B)**, although the relative proportions of other guilds shifted along the thermal gradient.
333 Ectomycorrhizal fungi, present in the T0 and 10°C treatments, were nearly absent at 30°C and 35°C.
334 Consistently, the RDA based on functional guild profiles showed that temperature significantly structured
335 community functional profiles (PERMANOVA, $F_{4,40} = 3.50$, $p\text{-value} = 0.001$), explaining 18.5% of the variance
336 **(Figure 2C)**. Lower temperature communities were associated with Ectomycorrhizal guilds, whereas higher
337 temperatures were associated with increased contributions of Saprotroph and Wood Saprotroph functions.

338 Overall, these results show that increasing temperature was associated with coordinated shifts in
339 both taxonomic composition and functional profiles of yeast communities. Changes in genus-level dominance,
340 functional guild composition, and relative abundances within a shared core microbiome were consistent along
341 the thermal gradient.



342

343 **Figure 2. Taxonomic and functional shifts in yeast communities under thermal gradient.** (A) Relative
 344 abundance of the most prevalent fungal genera across all temperature treatments. (B) Relative abundance of
 345 functional guilds, assigned by FUNGuild, across the temperature gradient. (C) Redundancy Analysis (RDA) of
 346 Hellinger-transformed functional guild profiles constrained by temperature, with arrows indicating the major
 347 guilds driving community separation.

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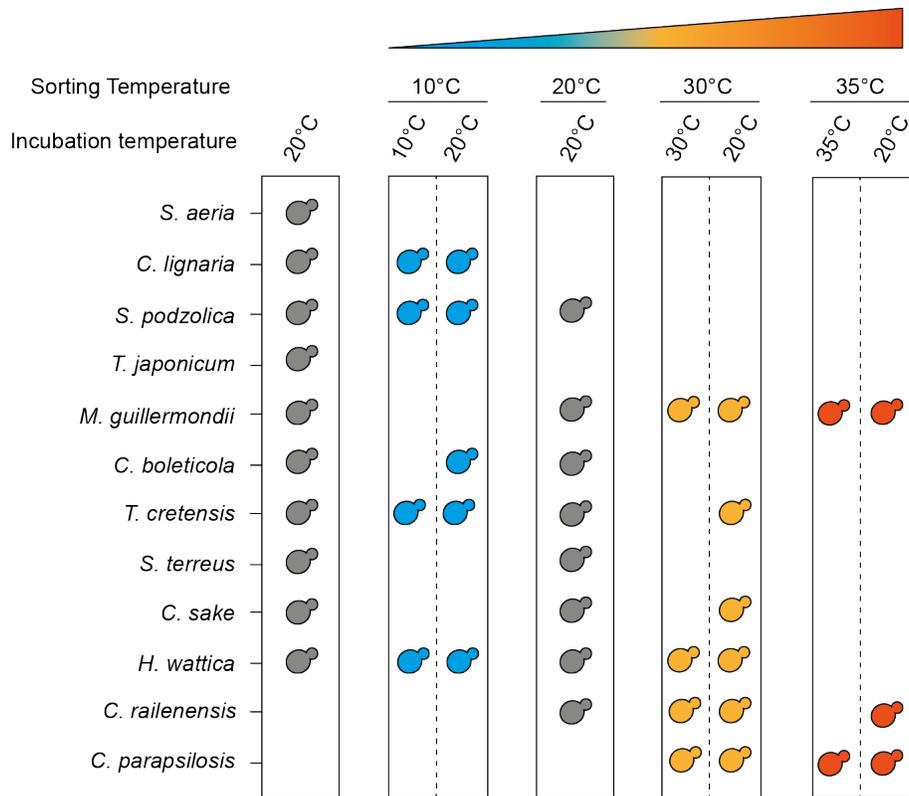
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354 Thermal sorting reveals hidden yeast diversity

355 To establish a mechanistic link between taxonomic turnover and individual physiological traits, we
356 complemented our molecular analysis with a detailed characterization of the culturable yeast assemblages
357 (**Figure S1, Figure 3**). This culture-dependent approach was essential for distinguishing between the
358 environmental presence of DNA sequences and the metabolic viability of the constituent taxa. By isolating
359 yeasts from microcosms across the thermal gradient (10°C to 35°C), we were able to directly assess whether
360 the shifts observed in the molecular data correspond to the resuscitation and active growth of thermotolerant
361 lineages from the seed bank. Samples obtained from tubes exposed to increasing sorting temperatures (10°C,
362 20°C, 30°C, and 35°C) were incubated under two conditions: (i) at the same temperature used for sorting, and
363 (ii) under a control incubation at 20°C (**Figures S1, Figure 3**). This approach allowed us to distinguish between
364 two ecological responses: the ability of yeasts to tolerate a transient exposure to elevated temperature during
365 the sorting process, and their capacity to maintain active growth and reproduction under sustained warming
366 conditions.

367 At time 0, following incubation at 20°C, culturable yeasts recovered from rhizosphere soils of the
368 Karukinka Natural Park revealed a diverse assemblage of ten species, including *Solicoccozyma aeria*,
369 *Solicoccozyma terreus*, *Saitozyma podzolica*, *Coniochaeta lignaria*, *Teunomyces cretensis*, *Meyerozyma*
370 *guilliermondii*, *Candida boleticola*, *Holtarmanniella wattica*, *Trichosporon japonicum*, and *Candida sake*
371 (**Figure 3**). This assemblage comprised both basidiomycetous and ascomycetous yeasts, encompassing taxa
372 typically associated with cold, organic-rich soils, plant-associated niches, and decomposer lifestyles. The
373 recovery of this taxonomically and ecologically heterogeneous culturable community from the rhizosphere
374 establishes a baseline diversity before thermal filtering. It provides a reference point for evaluating
375 temperature-driven shifts in yeast composition and growth performance.

376



377

378 **Figure 3. Thermal sorting reveals latent diversity within sub-Antarctic yeast communities.** Yeast species
 379 isolated from soil samples subjected to sorting at increasing temperatures (10°C, 20°C, 30°C, and 35°C) and
 380 subsequently incubated either at the same temperature (Sorting Temperature) or under control conditions
 381 (20°C).

382 After sorting, the composition of culturable yeasts showed a clear non-random pattern along the
 383 thermal gradient (**Figure 3, Table S5**). Low-temperature treatments (10 °C and 20 °C) were dominated by taxa
 384 such as *C. lignaria*, *T. cretensis*, and *S. podzolica*. These species exhibited a stenothermal response, showing
 385 reduced recovery as temperatures increased and complete exclusion at 35 °C. In contrast, some taxa, such as
 386 *H. wattica*, displayed remarkable thermal plasticity, persisting across intermediate and high-temperature
 387 regimes (10-30 °C). Interestingly, *C. sake* and *T. cretensis* were recovered after sorting at 30 °C, but only when
 388 cultivated at 20 °C, highlighting their ability to tolerate incubation at 30 °C rather than to grow at that
 389 temperature. *M. guillermondii* exhibits an exceptional resilience to warming conditions, being isolated from
 390 conditions ranging from 20 °C to 35 °C (**Figure 3, Table S4**). These results suggest that these species possess
 391 broader thermal niches, allowing them to maintain activity as the environment warms.

392 Finally, the thermal sorting process revealed a fraction of "hidden" yeast diversity that was
393 undetectable in the baseline community. This emergence followed two distinct patterns. First, *Candida*
394 *railenensis* appeared as a latent taxon with a broad thermal niche. This species was successfully isolated from
395 soils incubated at 20-35 °C, suggesting it is a rare biosphere member that thrives when competitive pressure
396 from cold-adapted specialists is removed. Second, in contrast to this broad emergence, *Candida parapsilosis*
397 exhibited a strict high-temperature requirement, being exclusively retrieved at the most extreme conditions
398 of 30 and 35 °C. This specific recruitment of latent taxa drove marked compositional turnover at the genus
399 level (**Figure S3**). The relative contribution of *Candida* species to the culturable community increased
400 progressively along the thermal gradient. While *Candida* isolates constituted a minor fraction at lower
401 temperatures (20% at 10 °C), their prevalence increased under warming conditions, ultimately making them
402 the dominant group at 35 °C, where they represented 67% of the recovered isolates (**Figure S3**).

403 Together, these results indicate that warming does not simply reduce diversity; it reorders the
404 community by filtering out cold specialists and "unlocking" a cryptic reservoir of thermotolerant species, such
405 as *Candida* spp., that occupy distinct thermal niches, from the broadly adaptable *C. railenensis* to the heat-
406 specialized *C. parapsilosis*.

407

408 **Yeast species display extensive variation in thermal performance across a temperature gradient**

409 To determine whether the temperature-dependent shifts observed in the cultivable yeast community
410 were associated with intrinsic differences in thermal tolerance and growth capacity, we quantified thermal
411 performance curves (TPCs) for all recovered yeast species across a broad temperature gradient (**Figure S4**).
412 This approach allowed us to link community-level sorting patterns (**Figure 3**) to species-specific traits,
413 including optimum growth temperature (T_{opt}), maximum growth rate (P_{max}), and thermal breadth (**Table S6**).

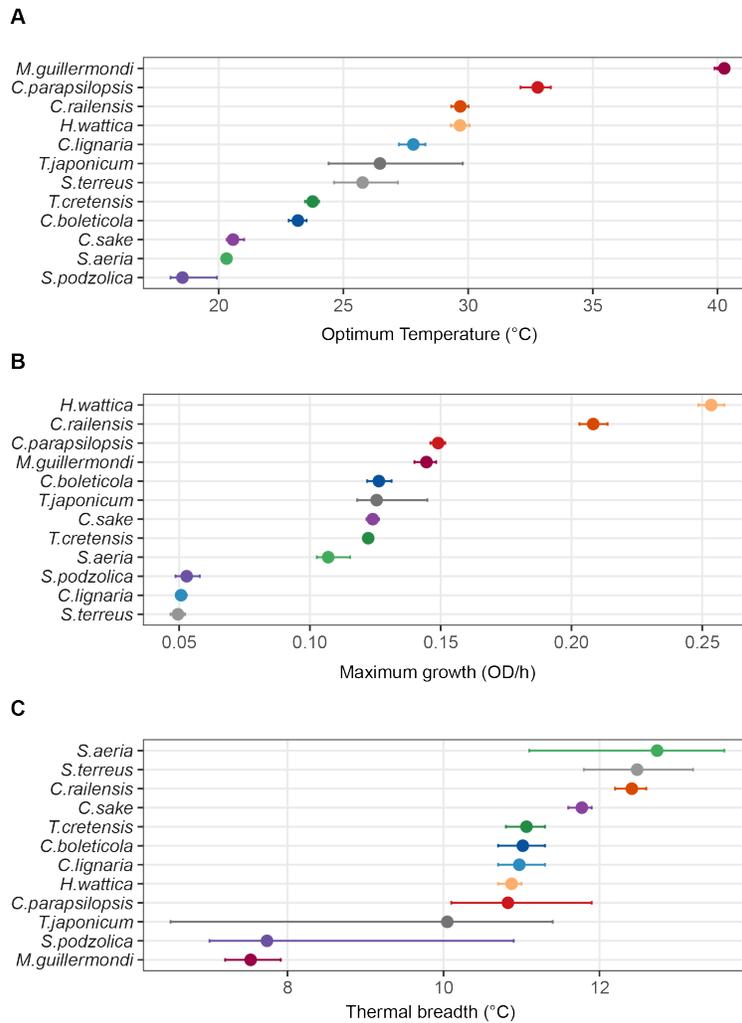
414 The TPC profiling revealed a stark physiological divergence that mirrors the ecological turnover.
415 Species that were filtered out by warming, such as *S. podzolica*, *S. aerea*, and *C. sake*, exhibited significantly
416 lower thermal optima ($T_{opt} < 25$ °C) (**Figure 4A, Table S6**). Their performance curves declined abruptly beyond

417 this threshold (**Figure S4**), providing a mechanistic explanation for their inability to persist at 30 °C and 35 °C.
418 In contrast, the taxa that dominated under warming displayed distinct warm-adapted signatures. *M.*
419 *guilliermondii* and *C. parapsilosis* exhibited the highest thermal optima of the assemblage, with T_{opt} values
420 reaching approximately 40 °C and 32°C, respectively (**Figure 4, Table S5**). This high thermal preference explains
421 their competitive advantage and dominance at the upper end of the experimental gradient.

422 Analysis of maximum growth (P_{max}) revealed that thermal dominance was not strictly coupled with
423 growth speed (**Figure 4B**). While *H. wattica* exhibited the highest potential growth rate of the entire
424 community ($\mu_{max} = 0.25$ OD/h), its lower T_{opt} (< 30 °C) limited its success under extreme warming. Meanwhile,
425 the dominant *Candida* species at high temperatures maintained moderate but sustained growth rates. This
426 suggests that in this system, having a compatible thermal niche is a stronger predictor of persistence than
427 peak growth potential alone.

428 Finally, the shape of the thermal curves highlighted contrasting survival strategies among the warm-
429 tolerant taxa (**Figure 4C**). *C. railenensis* displayed one of the widest thermal breadths (> 12 °C). This broad
430 physiological plasticity supports its characterization as a thermal generalist, capable of maintaining high
431 performance across the shifting conditions from 20 °C to 35 °C. Conversely, and surprisingly given its wide
432 ecological recovery, *M. guilliermondii* exhibited the narrowest thermal breadth of the isolates (7 °C) (**Figure**
433 **4C**), similar to the cold-stenotherm *S. podzolica*. Coupled with its high T_{opt} , this profile indicates that *M.*
434 *guilliermondii* is a warm-specialist. Its presence at lower temperatures (20 °C) in the sorting experiments likely
435 reflects a capacity for sub-optimal survival rather than broad physiological adaptation. In contrast, its
436 explosive dominance at 35 °C aligns with its specialized peak performance.

437 Collectively, these physiological fingerprints confirm that the community reordering was not
438 stochastic. Warming acted as a filter, selecting for two distinct warm-response strategies: the plastic
439 generalism of *C. railenensis* and the high-temperature specialization of *M. guilliermondii* and *C. parapsilosis*.



440

441 **Figure 4. Thermal performance profiles of yeast species isolated from sub-Antarctic soils.**
 442 (A) Optimum growth temperature (T_{opt}) calculated from fitted thermal performance curves. (B) The maximum
 443 growth rate (P_{max}) was obtained for each species. (C) Thermal breadth, defined as the temperature range over
 444 which each species maintained at least 80% of its maximum growth rate.
 445

446 **Reduced phylogenetic structuring reflects environment-driven thermal traits**

447 Phylogenetic signal analyses revealed a consistent absence of phylogenetic structure in all assessed
 448 thermal parameters (**Table S6**). Blomberg's K statistic was extremely low and not significant for any trait ($K =$
 449 0.041 , $p > 0.41$ in all cases), indicating that the similarity between closely related species is much lower than
 450 expected under a Brownian evolution model. Consistently, Pagel's λ parameter was practically zero for all traits
 451 ($\lambda < 0.001$, $p = 1.00$ for T_{max} , Thermal Breadth, Tolerance, T_{min} , and T_{opt} ; $\lambda = 0$ for P_{max}), suggesting that phylogeny
 452 does not explain the observed variation in thermal tolerances. Moran's I index confirmed this pattern, with

453 low and mostly non-significant values ($I = 0.037\text{--}0.171$, $p > 0.09$), except for T_{\min} ($I = 0.171$, $p = 0.028$) (**Figure**
454 **S5A**) and P_{\max} ($I = 0.350$, $p < 0.001$), which showed a weak but significant positive phylogenetic autocorrelation
455 (**Figure S5C**).

456 Comparison of evolutionary models provided conclusive evidence that thermal traits evolve
457 independently of phylogenetic history. The White Noise model fit substantially better than the Brownian
458 model for all traits, with Akaike weights greater than 98% for five of the six traits analyzed ($T_{\max} = 100.0\%$,
459 Thermal Breadth = 98.6%, tolerance = 98.8%, $T_{\min} = 98.5\%$, $T_{\text{opt}} = 99.9\%$). Only P_{\max} showed moderate support
460 for the White Noise model (weight = 28.7%), although this remained the highest-ranked model. The differences
461 in AICc between models ($\Delta\text{AICc} = 50.8\text{--}100.8$) indicate that the phylogenetic models (Brownian Motion,
462 Ornstein-Uhlenbeck, Early Burst) are substantially less plausible than the independent evolution model. PGLS
463 models confirmed the absence of phylogenetic structure in trait relationships ($\lambda < 0.05$ in all models). T_{\min}
464 showed a significant positive relationship with T_{\max} ($\beta = 0.65$, $t = 5.4$, $p < 0.001$), independent of phylogeny.
465 The results were qualitatively identical using ordinary linear regression ($\beta = 0.68$, $p < 0.001$), validating that
466 the relationships are not confounded by shared evolutionary history.

467 Phylogenetic signal analyses of three growth curve traits (growth rate, lag phase, and maximum
468 optical density) evaluated at four temperatures (10, 20, 30, and 35°C) revealed a generalized absence of
469 phylogenetic structure under most thermal conditions (**Table S7**). Even under cold stress (10 °C), $K = 0.239\text{--}$
470 0.371 and Pagel λ values ($\lambda \leq 0.001$) remained non-significant ($P > 0.07$). However, the maximum optical density
471 (mean OD_{\max}) at 10 °C showed a unique trend: it was the only instance where the Brownian model marginally
472 outperformed White Noise, suggesting a weak phylogenetic constraint on biomass production under cold
473 conditions. Conversely, at optimal (20 °C) and heat-stress (30–35 °C) temperatures, phylogenetic signal was
474 completely absent, confirming that physiological responses to warming evolve independently across lineages.

475

476

477

478 **Discussion**

479 Our findings demonstrate that warming acts as a potent deterministic filter in Sub-Antarctic soils,
480 fundamentally reshaping yeast communities by unlocking a cryptic reservoir of thermotolerant taxa. This shift
481 is characterized by a significant decline in alpha diversity and a clear, temperature-dependent separation in
482 community composition (RDA and PERMANOVA), indicating that thermal stress reduces richness primarily by
483 excluding rare, cold-adapted taxa. Such a pattern provides direct evidence for the species-sorting paradigm,
484 in which environmental stressors act as deterministic filters that select for taxa with thermal tolerance (He *et*
485 *al.*, 2021, Chen *et al.*, 2022, Litchman & Thomas, 2022, Smith *et al.*, 2022). While temperature is a universal
486 constraint on microbial metabolism (Delgado-Baquerizo *et al.*, 2016, Berdugo *et al.*, 2018), our results
487 underscore that in historically stable Sub-Antarctic ecosystems, it triggers an abrupt taxonomic turnover that
488 favors opportunistic lineages, most notably within the genus *Candida*, as long-standing thermal barriers are
489 breached.

490 In line with the expected outcome that thermal niches would dictate community structure, the
491 observed taxonomic turnover confirms that warming acts as a precise deterministic filter. While we expected
492 cold-adapted residents to dominate the baseline conditions, their systematic replacement by thermotolerant
493 opportunists at higher temperatures provides a clear view of species sorting in action. At lower temperatures,
494 the community was indeed characterized by psychrotolerant taxa such as *Cortinarius* and *Solicoccozyma*,
495 typical of cold high-latitude soils (Timling *et al.*, 2014, Treseder & Lennon, 2015, Saona *et al.*, 2025).
496 Conversely, as temperature increased, we observed a shift toward *Diplogelasinospora* and *Aspergillus*, which
497 became dominant due to their faster growth and greater resource utilization under thermal stress (Delgado-
498 Baquerizo *et al.*, 2018). Our culture-dependent physiological profiling confirms the mechanistic basis for what
499 was seen in the metabarcoding: the rapid exclusion of cold-associated species like *S. podzolica* and *S. aeria* is
500 directly explained by their physiological constraints, such as sharp performance declines and low T_{opt} (< 25 °C).
501 These findings validate our prediction that thermal sensitivity is a conserved microbial trait that dictates
502 community boundaries under climate change (Alster, Weller & von Fischer, 2018, Molinet & Stelkens, 2025).

503 While these results provide critical insights, it is important to acknowledge the inherent methodological biases
504 associated with yeast isolation. The selection of specific culture conditions may influence the observed
505 proportions and diversity of culturable species, as not all taxa may be equally recoverable in the laboratory.
506 Nonetheless, the strong congruence between our physiological data and broader molecular patterns suggests
507 that these isolates serve as a robust proxy for the community's response to warming.

508 The divergence in physiological strategies among the emerging dominant taxa reveals a sophisticated
509 mechanism of niche occupancy within the cryptic reservoir. Rather than a uniform response to heat, the
510 "unlocking" of this hidden diversity relies on a dual pathway: niche expansion by plastic generalists such as *C.*
511 *railenensis* and competitive exclusion at high-temperature peaks by specialists such as *M. guilliermondii* and
512 *C. parapsilosis*. This multi-faceted response suggests that the Sub-Antarctic microbial seed bank is pre-adapted
513 to a variety of warming scenarios, from gradual shifts to extreme heat events. While generalists provide the
514 community with initial flexibility to colonize newly available thermal spaces, specialists ensure dominance
515 once thermal thresholds are breached, effectively out-competing cold-adapted residents. Such a combination
516 of thermal breadth and performance limits explains why warming-induced assembly is so rapid and difficult
517 to reverse, as these taxa do not merely survive the heat, they are physiologically primed to exploit it (Boixel
518 *et al.*, 2019, Wieczynski *et al.*, 2021).

519 A critical finding of this study is that extreme warming unlocked a cryptic reservoir of yeast diversity
520 undetectable under ambient conditions. The emergence of *Candida* species at 30 °C and 35 °C, taxa likely
521 belonging to the rare biosphere at lower temperatures, supports the hypothesis that soils harbor latent
522 functional diversity capable of responding rapidly to fluctuations (Smith *et al.*, 2022). These conditionally rare
523 taxa likely persist in low abundance or dormancy within the cold sub-Antarctic soil, providing a "seed bank"
524 for ecosystem resilience (Jansson & Hofmockel, 2020, Eisenhauer *et al.*, 2023). However, this effect comes at
525 a cost: the awakening of this reservoir led to a marked homogenization of the culturable community, shifting
526 from a diverse assemblage to one heavily dominated by opportunistic *Candida* species. This transition
527 suggests that while functional processes might be maintained, the phylogenetic structure and functional

528 redundancy of the community could be compromised under sustained warming (Eisenhauer *et al.*, 2023,
529 Ramond, Galand & Logares, 2025).

530 The marked dominance of *Candida* species in our warming microcosms provides empirical evidence
531 for the ongoing erosion of the mammalian thermal barrier (Garcia-Solache & Casadevall, 2010, Robert,
532 Cardinali & Casadevall, 2015). According to the hypothesis proposed by Casadevall, the endothermic nature
533 of mammals (37 °C) has historically served as a robust evolutionary shield against most environmental fungi
534 (Casadevall, 2012). However, our results demonstrate that anthropogenic warming exerts selective pressure,
535 training environmental assemblages to tolerate higher thermal optima (Casadevall, Kontoyiannis & Robert,
536 2019, Nnadi & Carter, 2021). This process effectively narrows the thermal gap between the environment and
537 endothermic hosts (Smith *et al.*, 2025).

538 Finally, the absence of phylogenetic signals in thermal tolerance traits and growth curve parameters
539 suggests that these characters are evolutionarily highly labile and respond more to local selective pressures
540 than to the conservation of ancestral values. This pattern contrasts with the widely documented expectation
541 of thermal niche conservatism in other taxa (Wiens *et al.*, 2010), where closely related species are expected
542 to maintain similar physiological phenotypes inherited from common ancestors. Our results suggest that the
543 yeast species examined in this study possess an exceptional capacity to adapt their thermal limits to the
544 environmental conditions of their current habitats. The independent evolution of T_{min} , T_{max} , and T_{opt} among
545 lineages implies that closely related species can occupy dramatically different thermal niches, likely reflecting
546 an ability to adapt to microhabitats with different thermal regimes, phenotypic plasticity, or divergent
547 selection along different thermal gradients (Buckley & Kingsolver, 2021). Each lineage has independently
548 optimized its growth rate, acclimation lag, and ability to reach high biomass (OD_{max}) in response to the specific
549 thermal conditions of its current ecological niche. The weak signal detected in P_{max} could indicate conserved
550 physiological limitations in the underlying metabolic machinery, while the upper and lower thermal limits are
551 more plastic. This evolutionary lability has important implications for predicting responses to climate change,
552 suggesting that the analyzed species may have a greater capacity for rapid evolutionary responses to new

553 thermal regimes than taxa with conserved thermal niches. The independent evolution of thermal tolerances
554 has likely facilitated the coexistence of related species across environmental gradients, allowing for the
555 partitioning of thermal resources (e.g., specialization in warm vs. cold microhabitats within the same
556 ecosystem).

557 Overall, our findings highlight temperature as a central deterministic driver of microbial community
558 assembly in Sub-Antarctic soils. By filtering cold-specialized taxa and promoting the resuscitation of
559 thermotolerant lineages from the rare biosphere, warming reshapes yeast diversity and selects for specific
560 life-history strategies. The transition from complex, cold-adapted communities to simplified assemblages
561 dominated by opportunistic generalists could have profound implications for soil processes, including
562 decomposition rates and nutrient turnover (Zhou *et al.*, 2023). Moreover, we hypothesize that the selective
563 proliferation of these thermotolerant opportunistic lineages under sustained warming may expand the
564 environmental reservoir of emerging fungal pathogens, potentially posing new health risks to resident biota
565 and wildlife as historical thermal barriers are breached. Understanding this thermally driven restructuring and
566 the physiological mechanisms behind it is essential for predicting the functional trajectory of high-latitude
567 ecosystems in a warming world.

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569

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579

580 **Author Contributions**

581 **Conceptualization:** JM and PV. **Formal analysis:** LAS, MLHP, JBP, FJ, JFQG, JM, and PV. **Investigation:** LAS, JFQG,
582 JM, and PV. **Writing—original draft:** LS, JM, and PV. **Writing – review & editing:** LAS, JFQG, JM, and PV.

583 **Conflict of interest**

584 The authors declare no conflicts of interest.

585

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587 **References**

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Supplementary Information

Supplementary Figures

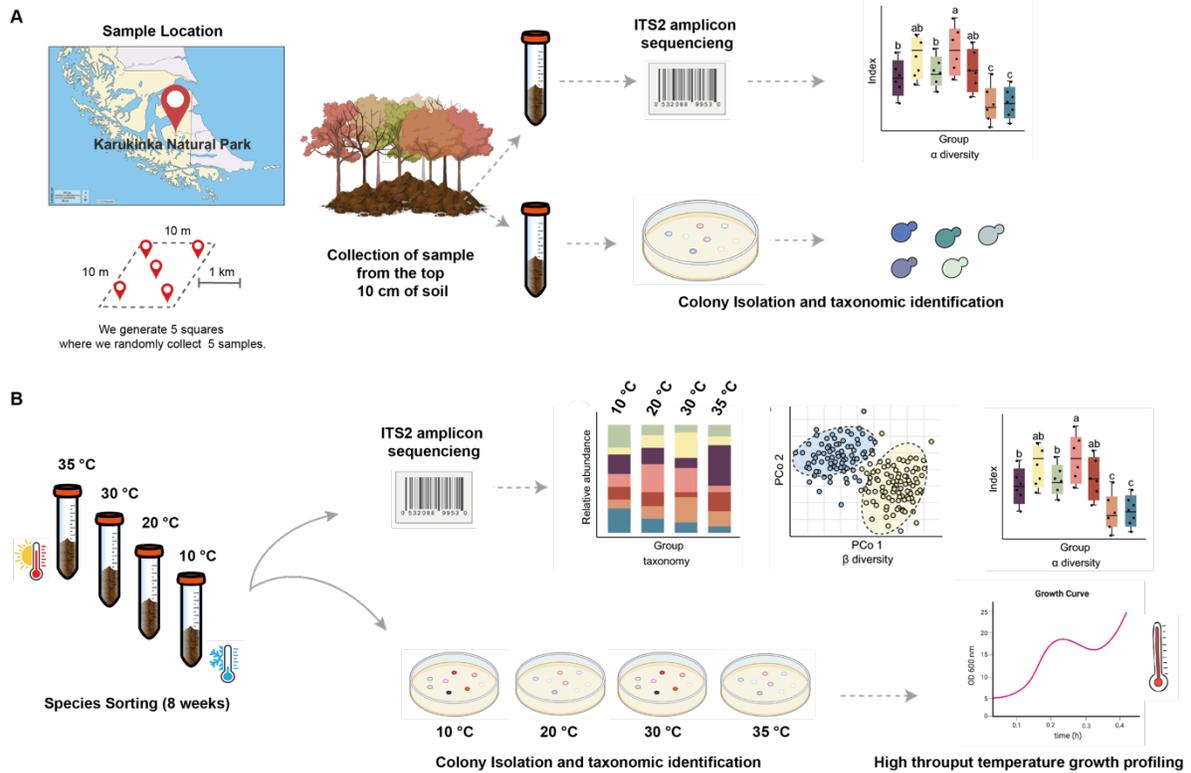


Figure S1. Experimental design used to evaluate the impact of temperature on culturable yeast communities. (A) Soil samples were collected from the top 10 cm of soil at Karukinka Natural Park (Tierra del Fuego, Chile) using five 10 × 10 m plots, each with five randomly selected sampling points. (B) Samples were incubated at 10, 20, 30, and 35 °C for eight weeks to assess species sorting across the thermal gradient. Yeasts were then isolated for taxonomic identification and subjected to ITS2 amplicon sequencing and temperature growth profiling.

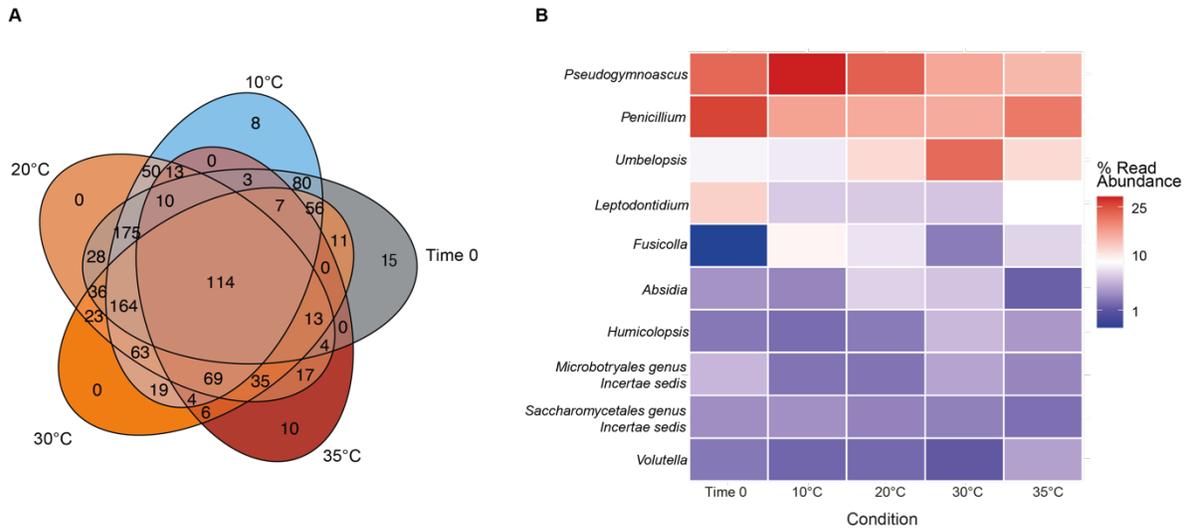


Figure S2. Overlap and relative abundance of dominant fungal genera across the temperature gradient. (A) Venn diagram showing the number of shared and unique fungal ASVs detected at each incubation temperature (Time 0, 10 °C, 20 °C, 30 °C, and 35 °C). (B) Heatmap representing the relative read abundance (% of total reads) of the top ten most abundant fungal genera across temperature treatments. Warmer colors indicate higher relative abundance.

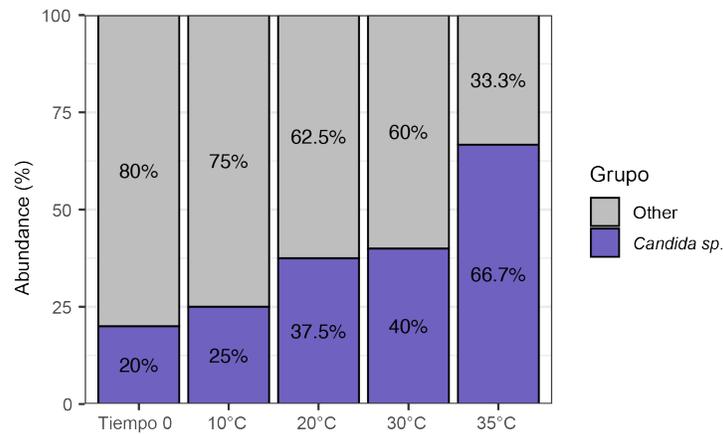


Figure S3. Relative abundance of *Candida* spp. across the thermal gradient. Stacked bar plots showing the proportion of *Candida* isolates (purple) and other yeasts (gray) recovered from Sub-Antarctic soil communities incubated at different temperatures (10 °C to 35 °C). Each bar represents the relative abundance within culturable communities at each temperature

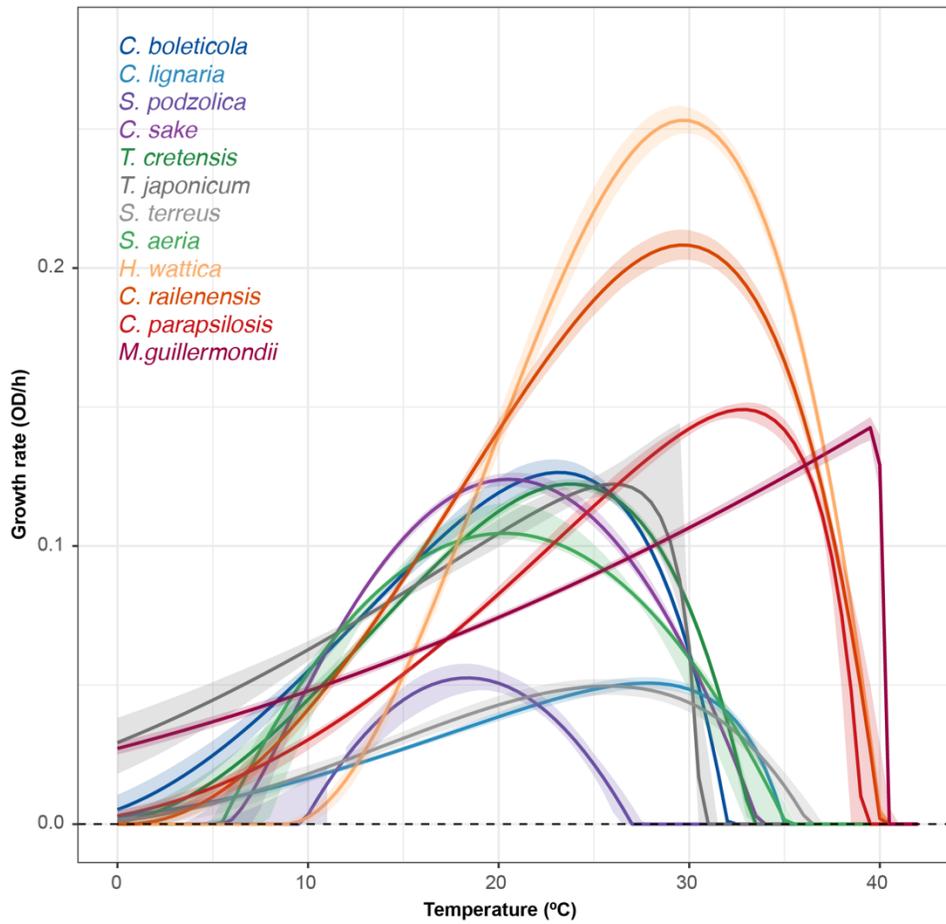


Figure S4. Thermal performance curves (TPCs) of yeast species isolated from sub-Antarctic soils. TPCs were constructed using the CTMI fitting maximum growth rate values as a function of temperature for each species, using four independent replicates.

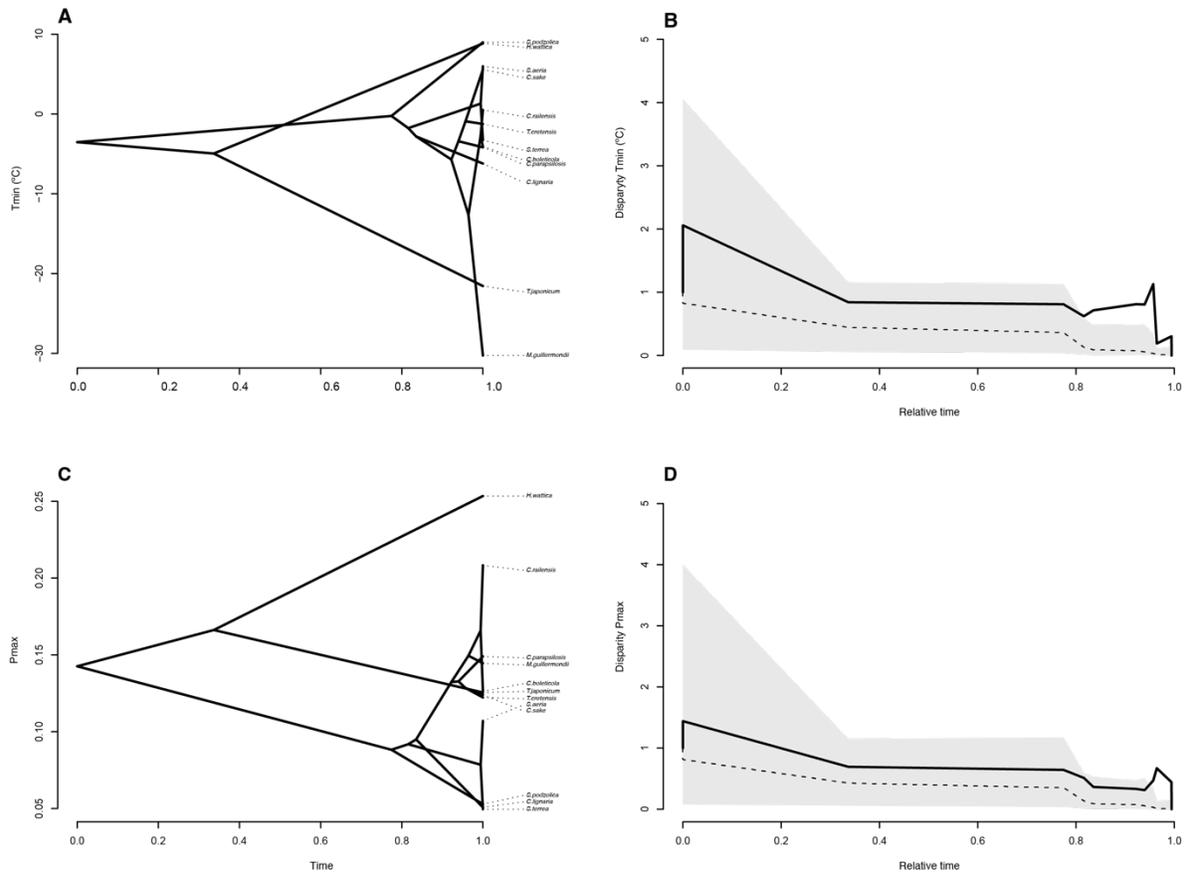


Figure S5. Phylogenetic trait evolution and disparity-through-time. Phenogram projecting the phylogenetic history of the studied taxa in relation to (A) T_{min} (Minimum temperature, °C), (C) P_{max} . The disparity-through-time plots for (B) T_{min} and (D) P_{max} . A simulation of the expectation of trait values assuming random walking evolution (dashed line), compared with what is observed (continuous line) in the trait of interest (percentage change in thermogenic capacity after cold acclimation). The gray area represents the 95% CI after 1000 simulations.

Supplementary Tables

Supplementary Table 1. Total number of raw reads

Supplementary Table 2. All ASV abundance table, taxonomy, and sample metadata

Supplementary Table 3. Filtered ASV abundance table, taxonomy, and sample metadata.

Supplementary Table 4. Core ASV abundance table.

Supplementary Table 5. Thermal sorting assay.

Supplementary Table 6. Thermal performance profiles of yeast species isolated from sub-Antarctic soils.

Supplementary Table 7. Phylogenetic models of traits.

Supplementary Table 8. Phylogenetic models using thermal performance curve variables.