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Drivers of thermal tolerance breadth of plants across contrasting biomes: do mean or seasonality in climate indices matter more?

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Figures x 6 Tables x 2 Supplementary tables x 3

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Abstract

- 1. The Climate Variability Hypothesis (CVH) predicts that species from environments with more variable temperatures should have *wide* thermal tolerance breadth. We addressed this question in plants and asked which climate predictors (e.g., temperature, precipitation, variability/seasonality) best predict species thermal limits.
- Measures of low (T_{crit-cold}) and high (T_{crit-hot}) photosystem II thermal thresholds were used to determine thermal tolerance breadth (TTB), along with ice nucleation temperature (NT) of 69 plant species in alpine, desert and temperate biomes.
- 3. Tolerance metrics T_{crit-cold}, NT and T_{crit-hot} all differed among biomes. Notably, desert species had the most cold and heat tolerant leaves with the widest TTB. Alpine and temperate biomes had similar TTB and each biome TTB exceeded their climate thermal ranges. Overall, climate drivers explained the most variation (~50%) in TTB and NT, with species a second strong predictor. The climate variables best explaining tolerance differed for cold and heat: species from more variable (higher temperature seasonality) environments (alpine and desert) were more cold tolerant, whereas mean annual temperature (MAT) was the best predictor of T_{crit-hot} with species in higher MAT environments having higher heat tolerances. TTB and NT were explained by both seasonality and MAT. Unexplained variation could be due to microclimate-driven plasticity, leaf traits or thermoregulatory mechanisms.
- Our results provide some support for the CVH. Depending on the thermal limits examined, climate means and seasonality remain important predictors of plant thermal tolerance.

Key words: Climate variability hypothesis, thermal tolerance breadth, heat tolerance, freezing tolerance, climate, ice nucleation temperatures

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1 Introduction

2 Desert and alpine plant species live at the thermal limits of biological processes. Unlike those in 3 temperate regions, plants living in extreme environments are exposed to both very low and very 4 high temperatures and thus to wide thermal range and highly variable thermal regimes, both 5 among days and seasons. Given the important influence of temperature in shaping species 6 distributions (Tattersall et al., 2012; Garcia-Pichel et al., 2013) the innate thermal tolerance 7 limits (lowest and highest temperature that a species can withstand) and thermal tolerance 8 breadths (range of temperature between upper and lower thermal tolerance limits) of species are 9 predicted to correlate with the temperature variation characterising their environment. The 10 climate variability hypothesis (CVH; Janzen, 1967) predicts that species with wide thermal 11 tolerance ranges are likely to evolve in environments with *variable* temperatures compared to 12 thermal specialists with *narrow* tolerance ranges that evolved in thermally *stable* environments. 13 This hypothesis is a cornerstone of thermal ecology, but has to date been primarily explored in animals (Addo-Bediako et al., 2000; Compton et al., 2007; Calosi et al., 2010; Baudier et al., 14 15 2018).

16 Cold and heat tolerance thresholds are rarely studied concomitantly. Cold tolerance studies 17 predominate in alpine environments where plants can withstand very low temperatures and tolerate extracellular ice formation and the resulting cytoplasmic dehydration (Sakai & Larcher, 18 19 1987; Larcher, 2003). Heat tolerance studies, historically, are primarily focussed on warm and 20 desert environments (Geange et al., 2021). Mechanisms for tolerating extreme heat have been 21 demonstrated in a range of desert species, including heat avoidance through increased 22 transpiration (Aparecido et al., 2020) with microhabitat conditions setting the scene for heat 23 tolerance (Curtis *et al.*, 2016), whereas in other cases, these differences disappear under common 24 garden conditions (Downton et al., 1984; Knight & Ackerly, 2002; Knight & Ackerly, 2003). In 25 spite of great progress, a recent systematic review revealed that less than 5% of more than 3000 26 studies examining thermal tolerance of plants considered both heat and cold tolerance thresholds 27 together (Geange *et al.*, 2021). The current focus on either cold or heat tolerance overlooks the 28 fact that plants in extreme biomes can experience both cold and heat stress.

Temperature increases associated with climate change have motivated an increase in studies on plant heat tolerance, particularly in relation to climate variability and the occurrence of aseasonal extreme events (Rummukainen, 2012; Seneviratne *et al.*, 2012). However, *in situ* field sampling

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32 studies rarely encompass multiple biomes or a broad range of thermal environments across 33 landscapes. There remains a critical gap in our understanding of how plants in extreme *vs*. 34 benign environments tolerate both heat and cold stress *in situ*, which limits our capacity to 35 predict where the most thermally sensitive species occur.

36 Differing patterns of climate among contrasting biomes provide an opportunity to explore the 37 role of climate variability in upper and lower thermal thresholds and on thermal tolerance 38 breadth. Of the few studies that have compared thermal thresholds among biomes, Smillie and 39 Nott (1979) found that heat tolerance was lower in alpine species, followed by temperate and 40 tropical species. In a rare study considering both upper and lower thermal thresholds together, 41 Cunningham and Read (2006) show that, in common garden conditions, temperate origin species 42 have lower heat and higher cold tolerance than tropical species. Meta-analytical studies across a 43 wide range of species and biomes suggest that heat tolerance decreases and cold tolerance 44 increases with latitude; however, these shifts in tolerance do not keep pace with an observed 45 latitudinal temperature gradient (Lancaster & Humphreys, 2020). Further, predictors of thermal 46 tolerance variation with latitude may include mean temperature of the warmest month and mean 47 annual temperature (O'Sullivan et al., 2017; Lancaster & Humphreys, 2020), though threshold-48 based predictors (e.g. number of days over 35 degrees per year; Maher et al., 2019) are 49 increasingly being explored as drivers of heat tolerance (Mora *et al.*, 2015). Given that water 50 status influences plant heat tolerance (Curtis et al., 2016; Marchin et al., 2022) and freezing 51 tolerance (Sierra-Almeida et al., 2016), precipitation parameters are also likely to affect thermal 52 thresholds. In addition, upper and lower thermal thresholds can vary in relation to the methods 53 used (Lancaster & Humphreys, 2020; Perez et al., 2021), influencing the ability of large-scale 54 meta-analyses to capture such sources of variation and likely limiting their power to reach 55 generalisable conclusions about any association between thermal limits and climate variables. 56 Finally, although we have evidence that climate variables influence heat and cold thermal 57 thresholds independently, the climate predictors of the difference between these thresholds, 58 thermal tolerance breadth, are unknown. If we can reveal general patterns underlying variation 59 and the climate drivers of physiological thermal tolerance thresholds among co-occurring species 60 within and among biomes, we can strengthen predictions of which and where species are likely 61 to be most vulnerable to changing thermal conditions.

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Here we assess leaf-level thermal tolerance breadth (TTB) of plant species in extreme and benign 62 63 environments and the climate drivers of these thresholds to test the CVH. We used chlorophyll 64 fluorescence to determine the low and high photosystem II (PSII) thermal thresholds and thermal 65 tolerance breadth of 22 alpine, 24 desert and 23 temperate rainforest species (temperate hereafter) during the growing season. We also determined ice nucleation temperatures to 66 67 examine freezing tolerance in all species. To determine relationships between climate variability and physiological thresholds, we extracted long term climate parameters for each sampling 68 69 locality. First, we hypothesised that the physiological thermal limits will be skewed towards the 70 extremes of the environments; colder temperatures in the alpine; and warmer temperatures in the 71 desert respectively, with temperate species having milder cold and heat tolerance thresholds. 72 Second, we tested if species from more thermally variable biomes have high thermal tolerance to 73 both heat and cold, and thus wider thermal tolerance breadth, in accordance with the CVH. 74 Thirdly, we assessed whether the variation in tolerance thresholds and TTB is explained by 75 climate variability (e.g., seasonality), supporting the CVH, rather than mean climate values.

76 Materials and Methods

77 Study locations

Sites used in this study were designated to one of three biomes in New South Wales,
Australia: alpine (Kosciuszko National Park), desert (Gundabooka National Park), and wet
temperate (Illawarra Region: Royal National Park, Illawarra State Conservation Area and Bass
Point Conservation Area) (Fig. 1).

82 Species selection

A total of 69 species (22 alpine, 24 desert and 23 wet temperate species; **Table S1**) were selected to encompass a representative sample of growth forms and plant families and where possible, included congeneric and/or confamilial species between two or more biomes. We included community dominants and a range of less abundant species to represent a cross section of species occupying each biome. Species replicates were sampled across days within each sampling period to incorporate daily variation in thermal tolerance thresholds.



Fig. 1: Locations of study sites across three biomes in NSW, Australia. Desert sites (red) in Gundabooka National Park (GNP), temperate sites (green) in the Illawarra Region, and alpine sites (blue) in Kosciuszko National Park (KNP). GNP sites span open eucalypt woodland, mulga and chenopod shrublands between elevations of 100 to 224 m a.s.l. KNP sites encompassed feldmark, herbfields and sphagnum bog vegetation formations between 1792 and 1855 m a.s.l. In the wet temperate environments, collections were conducted across the Illawarra Subtropical Rainforest including the Tall Open Forest and Rainforest communities between 100 and 400 m a.s.l. MAT = mean annual temperature, MAP = mean annual precipitation.

89 Leaf sample collection

90 Mature, fully expanded leaves were harvested from five to seven individuals per species. For 91 shrubs and trees, small branches were collected from the northern facing side of the plant at a 92 height of 1-1.5 m. For smaller growth forms, entire individuals or rosettes were collected. 93 Samples were kept in cool sealed plastic bags with moistened paper towel until they were 94 processed (approx. 1-2 hours after collection). In the field laboratory, leaves (size ranging 0.25 cm^2 to 5 cm^2) were cut (or combined) to fit an approximate area of 1 cm^2 and kept on wet florist 95 96 foam in humid dark containers until thermal tolerance assays were performed. Measurements 97 occurred during January 2020, March 2020 and December 2020 for the desert, wet temperate and

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alpine biomes, respectively. Sampling periods were selected to capture peak growing season in

99 each region.

100 Thermal tolerance assays

101 The photosynthetic machinery, specifically photosystem II (PSII), embedded in the thylakoid membrane has long been recognised as a thermally sensitive structure (Schreiber & Berry, 1977; 102 103 Berry & Bjorkman, 1980; Seemann et al., 1984). The temperature at which the PSII are 104 disrupted causes a rise in minimal chlorophyll a fluorescence (F_0) as a leaf is heated or cooled 105 (Schreiber & Berry, 1977; Neuner & Pramsohler, 2006). This critical temperature indicates a 106 threshold beyond which physiological and photochemical systems become increasingly impaired 107 and damage can occur, if temperatures are sustained. Freezing tolerance is tied to the 108 temperatures at which ice formation occurs (ice nucleation, IN), the measuring of which is 109 required to understand whether temperature dependent damage to photosynthetic machinery 110 occurs in association with ice formation.

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112 Lower and upper thresholds of PSII (T_{crit-cold} and T_{crit-hot})

113 The critical low and high temperature thresholds of PSII (T_{crit-cold} and T_{crit-hot}) were measured 114 using T- F_0 curves, i.e., the rise in F_0 (Neuner & Pramsohler, 2006; Arnold et al., 2021) with set 115 heating or cooling rates. One leaf per individual (or several small leaves abutting one another) 116 was used for each of the heating and cooling assays with n = 5-7 replicates per species. For each 117 assay run, 45 samples were secured with double-sided tape to paper on a peltier plate (CP-118 121HT; TE-Technology, Inc., Michigan, USA), used to cool or heat samples at a set rate using 119 LabView-based control software (National Instruments, Texas, USA) and adapted code from 120 TE-Technology, Inc. A vacuum sealed double-glazed glass was placed on top of the leaf samples 121 on the plate to avoid water condensation, particularly at freezing temperatures, and compress 122 samples to ensure maximum leaf contact with the Peltier plate (see Arnold et al., 2021 for more 123 details).

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125 Chlorophyll fluorescence was measured with a Pulse Amplitude Modulated (PAM) chlorophyll 126 fluorescence imaging system (Maxi-Imaging-PAM; HeinzWalz GmbH, Effeltrich, Germany) 127 mounted above the Peltier plate. Leaves were dark-adapted first and the PSII photochemistry 128 maximum quantum efficiency (F_V/F_M) measured to check starting function of leaves before 129 another dark adaption for 15min prior to assay. Circular areas of interest were created in the

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130 middle of leaf samples avoiding edges for F₀ measurements using the Maxi-Imaging-PAM 131 software. During temperature ramping, F₀ was measured every 20 s with a weak blue low frequency (1 Hz) pulse modulated measuring light (0.5 μ mol photons m⁻² s⁻¹). Leaf temperatures 132 133 were simultaneously measured with 40-gauge type-T thermocouples (OMEGA Engineering, 134 Singapore) attached to undersides of leaves and logged with a multi-channel DT85 Datataker 135 datalogger (Lontek, Australia). For hot T-F₀ measurements, samples were heated to 60°C at a 136 rate of 30°C h⁻¹(0.5°C/min). For cold T-F₀ measurements, the leaves were cooled down to -20°C or -25°C when logistically possible, at a rate of 15°C h⁻¹(0.25°C/min). Temperature rates were 137 138 selected as moderate temperature changes per Arnold et al., (2021). The starting temperature of 139 each heating/cooling assay depended on average field lab temperature, generally 15°C for alpine 140 and temperate, and 20°C for desert measurements.

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142 $T_{crit-cold}$ and $T_{crit-hot}$ were determined as inflection points on the T- F₀ curves, using the *segmented* 143 R package. For further description of T- F₀ curve see Arnold et al., (2021). $T_{crit-cold}$ and $T_{crit-hot}$ 144 were used to represent the lower and upper bounds of the PSII thermal tolerance breadth, TTB 145 (TTB = $T_{crit-hot} - T_{crit-cold}$).

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147 *Ice nucleation temperatures*

The ice nucleation temperature was estimated by analysing the freezing exotherms of leaf tissue, using the leaf temperature data collected during $T_{crit-cold}$ measurements. Temperature data collected for each leaf sample was plotted against time to visualize the freezing exotherms (small peak in temperature). The temperature at which the exotherm began was recorded as the nucleation temperature (Larcher, 2003).

153 Climate variables for sampling locations

154 Climate data were obtained from gridded datasets at 1 km resolution based on spatial 155 interpolations of long-term (1981-2010) conditions accessed from the CHELSA v2.1 database 156 (Karger *et al.*, 2017). For each species, a suite of climate variables including means, minimum, 157 maximum and seasonality variables for temperature and precipitation were extracted for each 158 species at leaf collections sites (see **Table S2** for complete list and sampling location 159 coordinates).

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161 Statistical analyses

To test the Climate Variability Hypothesis ability to predict photosystem thermal tolerance, we
examined climate by two designations. First, as a-prior categorical variable 'biome' (aims 1 &
2), and secondly, by a comprehensive selection of continuous climate variables (aim 3).

165 Differences in thermal tolerance metrics among biomes were tested with Linear Mixed Models 166 (LMMs, Bates et al., 2015) from the *lme4* package and post-hoc Tukey's Honest Significant 167 Differences were used to compare biome means. Models included biome (alpine, desert and 168 temperate) as fixed terms and species as a random term. Growth form as a random effect did not 169 significantly improve models thus was excluded. Because the aim of this study was to test the 170 Climate Variability Hypothesis in relation to thermal tolerance limits and TTB, other variables 171 such as local air and leaf temperatures or finer scale environmental characteristics such as aspect 172 were not included in models. Plant evolutionary history was considered in analysis, see below.

173 LMMs were also used to determine the relative contribution of climate variables to the variation 174 in each thermal tolerance metric. For the contribution of climate variables, LMMs included the 175 climate variables as fixed terms and species as a random term. Several of our climate variables 176 were strongly correlated and to avoid collinearity, we excluded some of those variables. All full 177 models included mean annual temperature (MAT, °C), mean annual precipitation (MAP, mm), temperature seasonality (BIO4, standard deviation of the monthly mean temperatures) and 178 179 precipitation seasonality (standard deviation of the monthly precipitation estimates expressed as 180 a percentage of the annual mean of those estimates). The best models were selected by backward 181 selection using the function *step* from the *emdi* package (Kreutzmann *et al.*, 2019). The package 182 *ImerTest* (Kuznetsova *et al.*, 2017) was used with *Ime4* to calculate LMM degrees of freedom 183 and P-values. The MuMIn package (Johnson, 2014) was used to calculate the variance explained by fixed effects, (marginal R^2 , mR^2) and the variance explained by both fixed and random effects 184 (conditional R^2 , cR^2). The Intraclass Correlation Coefficient (ICC) describes the proportion of the 185 186 total variance in the data that is explained by the random effects alone.

Prior to model fitting we assessed if the shared evolutionary history across our 69 species may also explain differences in thermal tolerance measures. We generated a phylogenetic tree using the R package *V.phylomaker* (Jin & Qian, 2022) and calculated the phylogenetic signal and statistical significance for each $T_{crit-cold}$, $T_{crit-hot}$, TTB and nucleation temperature using Pagel's λ

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and Blombergs's K (**Table S3**) with the *phylosignal* package (Keck et al., 2016). No evidence of

192 phylogenetic signal was present and thus phylogenetic non-independence was not detected

193 therefore, we did not include the phylogenetic structure in any of our models. All analyses and

194 visualizations were carried out in R version 3.6.1 (R Core Team, 2018).

195 **Results**

Biome differences in thermal tolerance

197 There were significant differences among biomes in all the individual thermal tolerance metrics 198 measured on plant species (Fig. 2a-d, Table 1). Unexpectedly, desert species exhibited the most 199 extreme cold thresholds (-13.3 \pm 0.5°C), followed by alpine (-11.0 \pm 0.5°C) and then temperate 200 species (-8.8 \pm 0.5 °C), all of which differed significantly from one another (Fig. 2a, Table 1). As 201 predicted, desert species had significantly higher heat tolerance (49.3 \pm 0.6°C), followed by 202 temperate (46.6 \pm 0.6°C), then alpine (43.1 \pm 0.6°C) species (Fig. 2b, Table 1). Similar to T_{crit}-203 _{cold} values, nucleation temperatures were coldest in desert species (-16.0 \pm 0.6°C), followed by 204 alpine (-10.8 \pm 0.6°C) and warmest in temperate species (-7.5 \pm 0.6°C); again, these differed 205 significantly from one another (Fig. 2c, Table 1). Interestingly, T_{crit-cold} values for alpine and 206 temperate species were very close to their nucleation temperature, whereas in desert species, ice 207 formation occurred at markedly lower temperatures than T_{crit-cold} (Fig. 2a, c).



Fig. 2: Heat ($T_{crit-hot}$) and cold ($T_{crit-cold}$) thresholds, ice nucleation temperatures (NT) and thermal tolerance breadth (TTB) for desert (n = 24 spp), temperate (n = 23 spp) and alpine (n = 22 spp) biomes. Circles represent individual replicates, triangles represent biome means across species; letters denote significant differences between biomes tested using linear mixed models and post-hoc Tukey's Honest Significant Differences test for comparing means with significance at 0.05 alpha level.

- 208 At a species level, temperate species *Oplismenus hirtellus* was the least cold tolerant (-4.0°C,
- 209 T_{crit-cold}), whereas two alpine species *Epacris paludosa* and *Hovea montana* were the most cold
- 210 tolerant (-18.5°C T_{crit-cold}) and the desert species *Atriplex stipitata* had the most extreme
- 211 nucleation temperature (-20.5°C). The alpine species *Pimelea ligustrina* was the least heat
- 212 tolerant (38.1°C, T_{crit-hot}) and the desert species *Rhagodia spinescens* was the most heat tolerant
- 213 $(T_{crit-hot} = 54.9^{\circ}C, Fig. 3, Table S1).$





Fig. 3: Thermal tolerance breadth (TTB = $T_{crit-hot}-T_{crit-cold}$) for all the studied species. Species are sorted top to bottom from widest to narrowest TTB. Red circles and lines represent desert species (n = 24 spp), green triangles and lines represent wet temperate species (n = 23 spp) and blue squares and lines represent alpine species (n = 22 spp). Black horizontal lines represent the standard error. The vertical dashed line represents 0°C. Each TTB, $T_{crit-hot}$ and $T_{crit-cold}$ value is from n = 5-6 replicates per species.

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Biome	T _{cr}	it-hot	$\mathbf{T}_{\mathbf{crit-cold}}$		NT		ТТВ	
	Estimate	Std.Error	Estimate	Std.Error	Estimate	Std.Error	Estimate	Std.Error
Alpine	43.1	0.6	-11.0	0.5	-10.8	0.6	54.1	0.9
Desert	49.3	0.6	-13.3	0.5	-16.0	0.6	62.6	0.8
Temperate	46.6	0.6	-8.8	0.5	-7.5	0.6	55.4	0.9
	Variance		Variance		Variance		Variance	
Species	5.0		5.2		7.4		12.3	
Residual	14.9		7.7		7.1		23.0	

Table 1: Linear mixed model output for all thermal limits considering biome as a fixed effect and species as random effect. Model biome mean estimates were significant with P values of <0.001.

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217 The thermal tolerance breadth (TTB) was significantly wider in desert species ($62.6 \pm 0.8^{\circ}$ C) 218 than temperate $(55.4 \pm 0.9^{\circ}\text{C})$ or alpine species $(54.1 \pm 0.6^{\circ}\text{C})$ (Fig. 2d, Table 1). However, 219 there was also considerable variation among species within biomes (Fig. 3). Within the desert 220 biome TTB was more similar across species (lower variability), (56.2 to 70.3 °C TTB, Δ 14.1 °C), compared to the alpine biome which had the greatest variation among species (45.9 to 63.1°C 221 TTB, $\Delta 17.2^{\circ}$ C) followed by the wet temperate species (44.8 and 60.4°C TTB, $\Delta 15.6^{\circ}$ C). For 222 223 species from all three biomes. TTB was much wider than the extreme temperature range 224 calculated for the sampling sites, thus most thermal thresholds lay well beyond the minimum and 225 maximum temperatures expected for each species in their local environment. The only notable 226 exception was for the alpine biome species, where the cold threshold was closer to the minimum 227 temperatures representing our alpine sites (Fig. 4).

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Fig. 4: Mean thermal tolerance breadth (TTB, solid lines) for alpine, temperate and desert species and their respective mean thermal range ($T_{range} = mean MaxT$ - mean MinT based on the locations of the sample sites, see **Table S2**). Black lines represent standard errors.

228 Contribution of climate variables to the variation on thermal tolerance metrics

We investigated the relationship between climate variables at the site of plant sampling and each of the thermal tolerance traits using backward model selection to identify the most parsimonious linear mixed models. None of the precipitation variables included in our models explained considerable variation in thermal tolerance thresholds. Whereas the best models included either mean annual temperature or temperature seasonality or both.

234 $T_{crit-cold}$ was best explained by temperature seasonality (19% of the variation in $T_{crit-cold}$), although 235 a much larger proportion of the variation in T_{crit-cold} was explained by species (32%, **Table 2**). 236 There was a negative relationship between T_{crit-cold} and temperature seasonality, indicating that 237 species from environments with greater seasonality, our alpine and desert sites, had a more 238 extreme T_{crit-cold} than species from the less seasonal wet temperate rainforest (Fig. 5a). By 239 contrast, rather than seasonality, T_{crit-hot} was best explained by mean annual temperature (MAT, 240 23%), with a much smaller proportion of the variation in this variable explained by species 241 (19%, **Table 2**). There was a positive relationship between T_{crit-hot} and site MAT (**Fig. 5b**), such 242 that species from, on average, warmer environments, also had higher T_{crit-hot}.



Fig. 5: Climatic variables that best predicted the variation in thermal thresholds across all biomes. Environmental variables are temperature seasonality (°C) and mean annual temperature (MAT, °C). Best models included: for $T_{crit-cold}$, seasonality; for $T_{crit-hot}$, MAT; for TTB both seasonality and MAT. See **Table 2** for statistics. Solid circles are species means, open circles are individual replicates which are jittered around mean x axis points.

TTB was best predicted by seasonality and mean annual temperature (**Table 2**), although a similar proportion of the variance was explained by the species effect compared to climate variables (29% and 24% respectively). There was a positive relationship between TTB and seasonality as well as with mean annual temperature (**Fig. 5c,d**). Notably, TTB was wider in species from desert biomes, which experience considerably greater seasonality and MAT than those in alpine and temperate environments.

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Table 2: Best models predicting climatic drivers of physiological thermal limits across all species. Linear mixed model fit using a restricted maximum likelihood approach and t-tests using Satterthwaite's method. Climatic conditions at the sites where leaf samples were collected were included as fixed effects and species as a random effect. These models were selected using a backward model selection using the function *step* from the *emdi* package in R. Along with species, mean annual temperature (MAT) and temperature seasonality were significant predictors in our models.

		T _{crit-cold} ~	 Seasonality 	+(1 Sp)	ecies)			
	Estimate	SE	t-value	Df	P-value	mR ²	ICC	cR ²
Intercept	-4.20	1.21	-3.48	70	< 0.001			
Seasonality	-1.41	0.24	-5.82	70	< 0.001			
	Varianc		Ν			0.19	0.32	0.52
	e							
Species	5.25		69					
Residual	7.66	2.76						
		T _{crit-h}	$ot \sim MAT + ($	1 Specie	es)			
	Estimate	SE	t-value	Df	P-value	mR ²	ICC	cR ²
Intercept	41.00	0.81	50.24	61	< 0.001			
MAT	0.38	0.05	7.22	63	< 0.001			
	Varianc		Ν			0.23	0.19	0.43
	e							
Species	5.22		69					
Residual	14.87							
	T	ГВ ~ Seas	sonality + MA	T + (1)	Species)			
	Estimate	SE	t_vəluo	DF	P-value	$\mathbf{m}\mathbf{R}^2$	ICC	$\mathbf{c}\mathbf{R}^2$
	Estimate	SE	t-value	Dr	I-value	IIII	ICC	UN
Intercept	42.39	2.11	20.06	67	<0.001	IIIX	icc	UN
Intercept Seasonality	42.39 1.88	2.11 0.07	20.06 4.91	67 68	<0.001 <0.001	mx		CK
Intercept Seasonality MAT	42.39 1.88 0.42	2.11 0.07 0.07	20.06 4.91 5.51	67 68 64	<0.001 <0.001 <0.001		ice	CK
Intercept Seasonality MAT	42.39 1.88 0.42 Varianc	2.11 0.07 0.07	20.06 4.91 5.51 N	67 68 64	<0.001 <0.001 <0.001	0.29	0.24	0.53
Intercept Seasonality MAT	42.39 1.88 0.42 Varianc e	2.11 0.07 0.07	20.06 4.91 5.51 N	67 68 64	<pre></pre>	0.29	0.24	0.53
Intercept Seasonality MAT Species	42.39 1.88 0.42 Varianc e 13.14	2.11 0.07 0.07	20.06 4.91 5.51 N 69	67 68 64	<0.001 <0.001 <0.001	0.29	0.24	0.53
Intercept Seasonality MAT Species Residual	42.39 1.88 0.42 Varianc e 13.14 22.94	2.11 0.07 0.07	20.06 4.91 5.51 N 69	67 68 64	<0.001 <0.001 <0.001	0.29	0.24	0.53
Intercept Seasonality MAT Species Residual	Estimate 42.39 1.88 0.42 Varianc e 13.14 22.94	3E 2.11 0.07 0.07	20.06 4.91 5.51 N 69 C + Seasonali	67 68 64 ty + (1 S	<pre></pre>	0.29	0.24	0.53
Intercept Seasonality MAT Species Residual	Estimate 42.39 1.88 0.42 Varianc e 13.14 22.94 N Estimate	3E 2.11 0.07 0.07	20.06 4.91 5.51 N 69 C + Seasonali t-value	67 68 64 ty + (1 S DF	<pre></pre>	0.29 mR ²	0.24	0.53
Intercept Seasonality MAT Species Residual Intercept	Estimate 42.39 1.88 0.42 Varianc e 13.14 22.94 N Estimate 3.15	3E 2.11 0.07 0.07 T ~ MAT SE 1.52	20.06 4.91 5.51 N 69 C + Seasonali t-value 2.06	67 68 64 ty + (1 S DF 65	<pre></pre>	0.29 mR ²	0.24 ICC	0.53
Intercept Seasonality MAT Species Residual Intercept MAT	Estimate 42.39 1.88 0.42 Varianc e 13.14 22.94 Stimate 3.15 -0.14	3E 2.11 0.07 0.07 IT ~ MAT SE 1.52 0.05	20.06 4.91 5.51 N 69 C + Seasonali t-value 2.06 -2.68	67 68 64 ty + (1 S DF 65 66	<pre></pre>	0.29	0.24 ICC	0.53
Intercept Seasonality MAT Species Residual Intercept MAT Seasonality	Estimate 42.39 1.88 0.42 Varianc e 13.14 22.94 Santa Santa -0.14 -2.60	2.11 0.07 0.07 T ~ MAT <u>SE</u> 1.52 0.05 0.27	$ \begin{array}{r} 1.1 \\ 20.06 \\ 4.91 \\ 5.51 \\ N \\ 69 \\ \hline F + Seasonali \\ t-value \\ 2.06 \\ -2.68 \\ -9.38 \\ $	67 68 64 ty + (1 S DF 65 66 65	<pre></pre>	0.29 mR ²	0.24 ICC	0.53
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Intercept Seasonality MAT Species Residual Intercept MAT Seasonality	Estimate 42.39 1.88 0.42 Varianc e 13.14 22.94 N Estimate 3.15 -0.14 -2.60 Varianc e	SE 2.11 0.07 0.07 1.07 SE 1.52 0.05 0.27	20.06 4.91 5.51 N 69 C + Seasonali t-value 2.06 -2.68 -9.38 N	67 68 64 ty + (1 S DF 65 66 65	<pre></pre>	0.29 mR ² 0.45	0.24 ICC 0.27	0.53 cR ² 0.72
Intercept Seasonality MAT Species Residual Intercept MAT Seasonality Species	Estimate 42.39 1.88 0.42 Varianc e 13.14 22.94 N Estimate 3.15 -0.14 -2.60 Varianc e 7.22	2.11 0.07 0.07 T ~ MAT SE 1.52 0.05 0.27	20.06 4.91 5.51 N 69 C + Seasonali t-value 2.06 -2.68 -9.38 N 69	67 68 64 ty + (1 S DF 65 66 65	<pre></pre>	0.29 mR ² 0.45	0.24 ICC 0.27	0.53 cR ² 0.72

Unlike the cold PSII thermal threshold, both mean annual temperature (MAT) and seasonality explained a considerable proportion of variation (45%) among ice nucleation (NT) temperatures while species had comparatively less of an effect (27%) (**Table 2**). There was a negative

252 relationship between nucleation temperature and temperature seasonality, indicating that species

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from environments with higher seasonality froze at lower temperatures than species in environments where temperature is more stable (**Fig. 6a**). There was also a negative relationship between nucleation temperature and MAT, where desert species froze at more extreme temperatures than most species in colder climates (**Fig. 6b**).



Fig. 6: Climatic variables (temperature seasonality and mean annual temperature (MAT)) that best explained the variation in ice nucleation temperature (NT), see **Table 2** for statistics.

257 Discussion

258 The climate variability hypothesis (CVH) predicts that species will evolve wider thermal 259 tolerance breadths in environments with more variable temperatures and thermal specialisation 260 (narrow TTB) in thermally stable environments, a concept largely supported in animals (i.e 261 Compton *et al.*, 2007; Sunday *et al.*, 2011). Of the few studies testing this hypothesis on plants, 262 investigations have included phenotypic plasticity increases with latitude (Molina-Montenegro & 263 Naya, 2012), species distribution ranges with seasonality across elevation (Mumladze et al., 264 2017) and the breadth of photosynthetic thermal response with environmental temperature 265 variability (Perez et al., 2023). Here we explored the CVH by sampling for thermal tolerance 266 metrics including TTB on species growing in three contrasting biomes, two extreme and more 267 variable, one benign and more thermally stable.

Using the CVH framework, we hypothesised that the thermal tolerance limits of alpine and desert species would be skewed to their respective habitat extremes (aim 1). These more skewed

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270 tolerances in the thermally extreme environments would also drive wider TTB than the more 271 benign temperate thermal environment (aim 2). We found that variation in tolerance breadth in 272 the more seasonal desert and alpine environments was indeed wider than temperate species, with 273 desert TTB values skewed towards higher temperatures, alpine TTB values skewed towards 274 colder temperatures and wet temperate TTB sitting in between. However, the mean tolerance 275 breadths of alpine and temperate species were not statistically different, while desert species had 276 both greater heat and cold thresholds. When looking at the climate drivers of tolerance breadth, 277 we found that not only thermal seasonality, but also mean annual temperature and predicted 278 TTB, providing some, but not conclusive support for the CVH (aim 3). When we explored the 279 climate drivers of thermal thresholds, we found that temperature seasonality, our proxy for 280 climate variability, and MAT both contributed to explaining the variation in TTB: seasonality 281 best explained the variation in T_{crit-cold}, whereas MAT was the strongest predictor of T_{crit-hot}. 282 Below we explore our findings in terms of physiology and the ecological implications of these 283 results for species persistence in a changing climate.

284 TTB exceeds thermal ranges in each biome and varies within biomes

285 Thermal tolerance breadth values reported here are notably wide; wider than the thermal ranges 286 in each environment and larger than TTB in other organisms. For instance, across a range of 287 marine and terrestrial ectotherm taxa, the widest recorded TTB was 60°C in terrestrial arthropods 288 (Sunday et al., 2011), while the widest TTB in our dataset was 70°C in the desert species 289 *Rhagodia spinescens*, with several other desert species also exceeding 60°C. Within each biome, 290 we found species with a range of wide and narrow TTB (Fig. 3). For example, several alpine 291 species across growth forms had relatively narrow TTB, such as the snow bed species 292 *Psychrophila introloba* (45°C TTB) and the treeline species *Eucalyptus pauciflora* subsp. 293 *niphophila* (47°C TTB). The narrow TTB of some alpine species is mainly driven by their low 294 heat tolerance ($T_{crit-hot}$ = around 40°C), while other co-occurring species (*Hovea montana* and 295 Epacris paludosa) had TTB similar to desert species (around 63°C) driven by extreme cold 296 tolerance (around -18°C). This within-biome variation in TTB might be due to variation in 297 microclimate 'preferences' of species within biomes, which vary depending on species growth 298 forms, topography and different transpirational cooling limitations (Curtis et al., 2016; Curtis et 299 al., 2019; Aparecido et al., 2020).

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300 Although thermal seasonality was greater in alpine than temperate regions sampled here, the 301 average TTB for these two biomes is remarkably similar (Fig. 2d). Temperate species can 302 tolerate colder temperatures than expected, and it is possible that their wide thermal tolerance is a 303 legacy of exposure to climate extremes through geological time (Byrne *et al.*, 2008). The climate 304 legacy effect on thermal tolerance seems to be stronger for cold than heat tolerances (Bennett et 305 al., 2021) and might explain why some temperate and desert species have greater freezing 306 tolerance than expected by their current climate. Although metrics based on air temperatures for 307 our alpine biome (e.g., MAT, temperature seasonality) confirm that thermal range and 308 seasonality are high in this biome, mountain plants spend 4-5 months under the insulating cover 309 of snow, which stabilizes temperatures (Briceño et al., 2014). This dampening of climate 310 extremes might contribute to the similarity between alpine and temperate species TTB.

311 Heat and cold thermal limits vary among biomes

312 Plants exposed to drought and/or freezing share a similar physiological response: cell 313 dehydration (Anisko & Lindstrom, 1996; Blake & Hill, 1996; Lintunen et al., 2013). The 314 physiological response to drought conditions may partially explain our somewhat 315 counterintuitive result that desert species were more freezing tolerant (more extreme T_{crit-cold} and 316 nucleation temperature) than either alpine or temperate species. Plants can use osmotic 317 adjustments to offset water loss from cells along the water potential gradient caused by both 318 drying and freezing (Siminovitch & Cloutier, 1983; Larcher, 2003). Thus, the ability of desert 319 species to cope with dehydration induced by long periods of drought might also confer the ability 320 to cope with freezing, despite the fact that these desert species are unlikely to ever be exposed to 321 such extreme freezing temperatures. In addition, leaf adaptations to aridity such as smaller 322 leaves, thick cuticles, smaller, more densely packed cells, thicker cell walls with small capillary 323 structures and small xylem vessel diameter (Dörken et al., 2020) also can prevent ice formation, 324 which increases supercooling capacity and freezing tolerance (Lintunen et al., 2013). This may 325 reflect that species living in environments where freezing temperatures are rare use supercooling 326 as a mechanism to avoid freezing damage, while in alpine environments species tolerate ice 327 formation. Indeed, the desert species studied here generally had nucleation temperatures much 328 lower than their $T_{crit-cold}$, from which we can infer a high supercooling capacity that effectively 329 serves to delay freezing. Indeed, Andean alpine species' low ice nucleation temperatures at the 330 end of the growing season are attributed to low soil moisture, thus potential water stress, rather 331 than low temperatures. (Sierra-Almeida et al., 2016). Likewise, drought exposure can influence

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heat tolerance through raising intracellular sugar contents which stabilize thylakoid membranes, increasing heat tolerance (Huve *et al.*, 2006; Brestic *et al.*, 2012). The extreme freezing tolerance and high heat tolerances found in our desert species might reflect a secondary outcome of plant adaptation to aridity.

336 The relatively high heat tolerance of some of our alpine species is at first counterintuitive, as 337 alpine areas are conventionally seen as primarily cold environments. Yet, alpine plants can be 338 exposed to very high temperatures, especially those with prostrate growth forms (Körner, 2003). 339 Studies on leaf temperature in alpine species in Europe have shown that leaf temperature can 340 reach up to 50°C in summer, especially on calm sunny days, with leaf heat tolerance higher than 341 50°C (Buchner & Neuner, 2003). Maximum leaf temperature has been measured at 38°C in early 342 summer in one Australian alpine species (Danzey et al., 2021 unpublished data) and may be 343 higher in suitable hot and still conditions in late summer. Therefore, thermal thresholds could be 344 breached in alpine species if the combination of heat with other environmental stress, such as 345 high light, decreased heat tolerances, as found for some European alpine species (Buchner & 346 Neuner, 2003; Buchner et al., 2015).

347 Heat and cold thermal limits relate to different macroclimatic temperature variables

348 Predicting organismal responses to changing temperature regimes is a significant global 349 challenge and it requires a mechanistic understanding of how temperature affects species physiology and distributions. Although the physiological mechanisms underpinning freezing and 350 351 cold tolerance (see Guy, 2003 for a review) and heat tolerance (Wahid et al., 2007) have been 352 established in model plants, responses in species exposed to natural conditions remain 353 understudied. While the thermal limits of plants have recently been shown to broadly vary with 354 latitude (O'Sullivan et al., 2017; Lancaster & Humphreys, 2020), comparisons employing 355 standard techniques across multiple biomes remain rare, particularly for both heat and cold 356 tolerance concomitantly (Geange *et al.*, 2021). Importantly, our capacity to predict thermal 357 tolerance from key bioclimate parameters such as MAT and MAP remains complex. In our 358 cross-biome dataset, we found that neither mean annual temperature or precipitation explained 359 variation in cold tolerance (T_{crit-cold}), which was instead strongly predicted by thermal 360 seasonality. For heat tolerance, again climate precipitation was not a significant driver, aligning 361 with the findings for Australian Acacia species in an experimental heatwave (Andrew et al.,

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362 2023). On the other hand, mean annual temperature explained 23% of the variance in $T_{crit-hot}$, 363 which contrasts a common garden study of 123 taxonomically diverse species, for which climate 364 variables generally had very weak predictive power (<5%) for heat tolerance (Perez & Feeley, 365 2021).

366 Despite some clear macroclimatic patterns in our study, a large proportion of the variation in 367 cold and, to a lesser extent, heat tolerance was explained by species (32% and 19%, 368 respectively). The contribution of species could reflect micro-climate adaptation among species 369 or differences in species' leaf traits that contribute to within-species variation in leaf temperature, 370 the signal of which may be amplified when sampled in situ. Mahan and Upchurch (1988) 371 proposed that the lower limit of temperature for a plant is controlled by its environment, while 372 the upper limit can be controlled by the plant, suggesting that plants are "limited homeotherms". 373 Recent studies have shown that what drives variation in heat tolerance is leaf temperature, rather 374 than large scale measures of air temperature (Perez & Feeley, 2020; Cook et al., 2021). Leaves 375 can avoid heat stress through different mechanisms that decouple leaf from air temperature such 376 as anatomical traits (Leigh et al., 2012; Leigh et al., 2017; Tserej & Feeley, 2021), patterns of 377 display such as leaf inclination (Ball et al., 1988) and transpirational cooling through stomatal 378 conductance and can vary among co-existing species (Urban et al., 2017; Drake et al., 2018; 379 Deva et al., 2020; Marchin et al., 2022). The thermoregulatory patterns and physical properties 380 of leaves can differ greatly among species, such that different species exhibit different leaf 381 temperatures even when they co-exist in close proximity. Leaf to air temperature decoupling 382 (Blonder et al., 2020) might also explain why relationships between heat tolerance and latitude 383 are negligible or smaller than expected for the temperature span considered (Curtis *et al.*, 2016; 384 O'Sullivan *et al.*, 2017; Lancaster & Humphreys, 2020).

385 Species' TTB is a more holistic measure of species thermal limits given that it encompasses both 386 lower and upper limits. Unlike for animals, global patterns of variation in the TTB of plants have 387 received little attention. Despite the existence of large thermal tolerance datasets, the lack of 388 paired, concurrently measured low and high thermal thresholds measurements for a given species 389 constrains our ability to adequately assess TTB globally. We found that TTB was best predicted 390 by the combination of seasonality and mean annual temperature: species exposed to the high 391 seasonality and mean annual temperatures in our desert biome had wider thermal tolerance 392 breadth. However, species played an equal role in explaining variation in TTB and the capacity

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393 for species to respond to increasingly extreme high temperatures and greater climate variability 394 by broadening their TTB is unknown. Previous research generally suggests that plant niche 395 thermal evolution is constrained by heat tolerance (Aruajo et al 2013) as evident through reduced 396 variation in heat tolerance across landscapes (Lancaster and Humphreys, 2020). However, we 397 found the reverse, with heat tolerance having greater variability (~30°C) than cold tolerance 398 (~20°C) across our diverse biomes. Future studies could examine whether wider TTB or more 399 extreme thermal thresholds in fact equate to greater plasticity to warming and future climate 400 extremes.

401 Narrow thermal physiological limits have been identified as an aspect of species vulnerability to 402 climate change (Williams et al., 2008; Pacifici et al., 2015). The use of PSII thermal tolerance 403 metrics determined at the leaf-level, however, requires careful interpretation. When plants reach 404 their critical thermal limits, damage to PSII can occur, leading to decreased electron transport 405 rate and photosynthetic failure, thus compromising leaf survival. If this risks whole plant 406 survival, however is less clear. In 21 species, heat tolerance thresholds have been correlated with 407 carbon assimilation limits (Perez et al, 2021) which influence plant productivity. To further 408 unpick these patterns, we need to better understand the relationship between physiological 409 thermal limits with plant survival and fitness and how plastic these metrics are over space, time 410 and across the plant life cycle – for example, thermal tolerance of seedlings may be more critical 411 than that of adults.

412 Conclusion

413 Thermal tolerance breadth (TTB), a parameter broadly used in animal thermal biology literature, 414 has not previously been measured using a consistent method in such a diverse range of plant 415 species and environments. Here we concomitantly measured the lower (T_{crit-cold} and NT) and 416 upper (T_{crit-hot}) thermal thresholds of PSII and quantified the TTB of 69 plant species across three 417 biomes: two climatically extreme (alpine and desert) and one more stable (wet temperate). Our 418 results show partial support for the climate variability hypothesis. Looking at climate from a 419 discreet biome category perspective, TTB only partially supported the CVH with the climatically 420 variable desert biome having the widest but only significantly different TTB. Using coarse 421 climate variables at sampling locations, we found support for CVH with temperature seasonality 422 predicting cold tolerance, TTB and NT but was lacking in heat tolerance (MAT not seasonality

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423 was the significant predictor) with species explaining substantial portions of variation. 424 Interestingly we found that leaf-level TTB was extremely wide, much wider than the air 425 temperature extremes to which plants are exposed in these biomes. It is important to remember, 426 however, that these measured thermal limits represent a point beyond optimal photosynthetic 427 function and consistent temperatures inside these limits could have far-reaching effects, 428 depending on species life history, morphological traits and plasticity, as well as microclimatic 429 and temporal heterogeneity. Incorporating species traits, leaf temperature and microhabitat 430 information over space and time in future work is important next step to improving predictive 431 power of thermal tolerance metrics for understanding vulnerability of different vegetation 432 communities to climate extremes.

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444 Author Contribution

- 445 VFB, AMC, SKCJ, ABN, LABR and AL designed the study, PAA, RVG, VGB and AMC
- 446 collated and analysed the data, all authors contributed to data collection, interpretation of results447 and writing.
- 448 **Conflict of interest**
- 449 The authors have no conflicts of interest to disclose.

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453 **Ethics information**

- 34
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