Remote sensing restores predictability of ectotherm body temperature in the world’s forests

Remote sensing and body temperature

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BIOSKETCH

Adam C. Algar’s research asks how organisms respond ecologically and evolutionarily to climate across spatial scales.

Kate Morley’s MSc integrated remote sensing data into macrophysiology.

Doreen S. Boyd’s main research interests are in the optimal exploitation of remote sensing systems to understand ecosystem services provided by terrestrial systems.
AIM: Rising global temperatures are predicted to increase ectotherms’ body temperatures, benefitting some species but threatening others. Biophysical models predict a key role for shade in buffering these effects, but the difficulty of measuring shade across broad spatial extents limits predictions of ectotherms’ thermal futures at the global scale. Here, we extend biophysical models of ectotherm body temperature to include effects of forest canopy shade, via leaf area index, and test whether considering remotely-sensed canopy density improves predictions of body temperature variation in heavily shaded habitats.

LOCATION: Worldwide.


MAJOR TAXA STUDIED: Lizards.

METHODS: We test predictions from biophysical ecological theory for how body temperature should vary with microclimate for 269 lizard populations across open, semi-open, and closed habitats worldwide. We extend existing biophysical models to incorporate canopy shade effects via leaf area index, test whether body temperature varies with canopy density as predicted by theory, and evaluate the extent to which incorporating canopy density improves model performance in heavily-shaded areas.

RESULTS: We find that body temperatures in open habitats, like deserts, vary with air temperature and incident solar radiation as predicted by biophysical equations, but these relationships break down in forests, where body temperatures become unpredictable. Incorporating leaf area index into our models revealed lower body temperatures in more heavily shaded environments, restoring the predictability of body temperature in forests.

CONCLUSIONS: Although biophysical ecological theory can predict ectotherm body temperature in open habitats, like deserts, these relationships decay in closed forests. Models incorporating remotely-sensed data on canopy density improved predictability of body temperatures in these habitats, providing an avenue to incorporate canopy shade effects into predictions of animals’ vulnerability to climate change. These results highlight the thermal threat of changes in canopy structure and loss of forest cover for the world’s ectotherms.
KEYWORDS

biophysical ecology, body temperature, canopy cover, land cover change, leaf area index, lizards, macrophysiology, operative temperature, remote sensing, thermal ecology
INTRODUCTION

The implications of higher body temperatures in a warming world may be felt across all scales of life, from metabolic rates (Dillon, Wang, Huey, 2010), to organismal behavior (Kearney, Shine, Porter, 2009; Sinervo, 2010), evolutionary fitness (Kingsolver, Diamond, Buckley, 2013), species’ distributions (Parmesan et al., 1999), and ecosystem dynamics (Cramer et al., 2001). Warm-adapted species will benefit from hotter conditions, making a wider range of habitats available and encouraging range expansion (Deutsch et al., 2008; Huey et al., 2009; but c.f. Logan, Huynh, Precious, Calsbeek, 2013). In contrast, many species are already operating with slim thermal safety margins, especially in biodiverse tropical environments (Deutsch et al., 2008; Huey et al., 2009; Khaliq, Hof, Prinzinger, Böhning-Gaese, Pfenninger, 2014; Sunday et al., 2014), suggesting that future temperature increases will reduce activity times (Kearney et al., 2009), lower fitness (Kingsolver et al., 2013), and increase the chance of extinction (Sinervo et al., 2010). These effects may be especially severe in closed-canopy forests, where species tend to be cool-adapted (Deutsch et al., 2008; Huey et al., 2009; Sunday, Bates, Dulvy, 2012). The effects of future warming on ectotherm thermal vulnerability are often predicted using biophysical models of heat flux (Deutsch et al., 2008; Kearney et al., 2009; Sinclair et al., 2016), but how well these models actually capture relationships between microclimate and body temperature at the global scale over which predictions are made is largely untested. Furthermore, these models do not currently incorporate the effects of forest canopy shade on body temperatures, limiting their capacity to capture effects of global change on forest-dwelling species.

Predicting the effects of climate warming and variability on organisms relies on understanding the link between environmental conditions and body temperature ($T_b$). Although ectotherms must gain their heat from the surrounding environment, standard climate variables, like mean annual air temperature, are poor predictors of $T_b$ worldwide (Meiri et al., 2013), not least because long-term climate averages do not accurately reflect the microclimates experienced by individual organisms (Kearney, Isaac, Porter, 2014; Kearney, Shamakhy, et al., 2014). $T_b$ may also deviate from air temperature, even when measured locally, for two reasons. Firstly, by behaviourally
thermoregulating, ectotherms can alter their $T_b$ (Bogert, 1949; Huey, 1974; Huey & Slatkin, 1976).

Secondly, even for thermoconformers, $T_b$ is not just a function of air temperature, but also depends on the radiation absorbed and emitted by an animal, along with heat transfer via conduction and convection and evaporative water loss (Porter & Gates, 1969; Gates, 1980; Bakken, Santee, Erskine, 1985; Campbell & Norman, 1998). The temperature that a non-thermoregulating animal would reach at equilibrium in a particular environment is known as operative temperature (Bakken et al., 1985).

Shade plays a key role in determining operative temperature and species’ thermal vulnerability to climate change. By reducing the amount of solar radiation reaching an animal, shade can make the difference between lethal and favorable body temperatures (Kearney et al., 2009; Sears et al., 2011; Sunday et al., 2014) and alters the relative importance of different microclimate components: in full sun, $T_b$ will be sensitive to the intensity of incoming solar radiation, but in full shade, $T_b$ should track air temperature (Gates, 1980; Campbell & Norman, 1998; Buckley, 2008; Sears, Raskin, Angilletta, 2011). Shade will become increasingly important under future climate change, especially in tropical regions, as animals must increasingly seek out cooler microhabitats to buffer against rising temperatures (Kearney et al., 2009; Sunday et al., 2014). Despite its importance for the thermal future of biodiversity, shade remains a significant challenge for predicting body temperature through space and time. Currently, most models designed to predict operative and body temperatures of animals predict a broad envelope of possible operative temperatures that encompasses full sun and full shade or must assume a specific, spatially invariant, shade level (Kearney et al., 2009; Sunday et al., 2014; Buckley, Ehrenberger, Angilletta, 2015). While shade from topographical features can be modelled directly, provided detailed topographical information is available (Sears et al., 2011), quantitative measures of shade from other sources—such as the forest canopy, which can greatly alter sub-canopy thermal environments (George, Thompson, Faaborg, 2015; Frey et al., 2016; Lenoir, Hattab, Pierre, 2017)—is lacking from most models. Thus, current biophysical models, while effective in open habitats, are likely to break down in forests, where shade is extensive (but not complete), limiting our ability to accurately predict the thermal futures of species inhabiting these biodiverse environments.
In this paper, we extend existing biophysical models of ectotherm body temperature (Gates, 1980; Campbell & Norman, 1998; Buckley, 2008; Sears et al., 2011) to incorporate shade effects of the forest canopy, allowing for more precise predictions of ectotherm body temperature in forested environments using readily available remote sensing data on canopy density. Firstly, we model the expected relationships between body temperature, air temperature, solar radiation, and wind speed, ignoring canopy effects, and predict that model performance will decline across major habitat types with increasing shade levels, from barren lands to forests. Next, we use our extended model to evaluate whether incorporating remote sensing data to capture shade effects can improve model fit in heavily shaded forests.

**METHODS**

**Predicted relationships between body temperature and microclimate**

We generated predictions of how body temperature of a non-thermoregulating lizard will vary with microclimate (air temperature, incident solar radiation, and wind speed) in full sun by modelling operative temperature ($T_e$) using biophysical principles (Gates, 1980; Campbell & Norman, 1998), following Sears et al. (2011) and Buckley (2008):

$$T_e = T_{air} + \frac{R_{solar} + R_{lw} - \varepsilon_s \sigma(T_{air} + 273)^4}{4\sigma(T_{air} + 273)^3 + c_p \left(1.4 + 0.135 \sqrt{\frac{v}{d}} \right)}$$  \hspace{1cm} \text{Eq. 1}$$

where $T_{air}$ is air temperature, $R_{solar}$ is absorbed incoming solar radiation, $R_{lw}$ is absorbed longwave radiation, $\varepsilon_s$ is animal emissivity, $\sigma$ is the Stefan-Boltzmann constant, $c_p$ is the specific heat of air, $d$ is the characteristic dimension of the animal and $v$ is wind speed. The forest canopy will reduce the amount of solar radiation reaching an animal (Campbell & Norman, 1998), thereby lowering body temperature. We modelled the solar radiation incident on an animal as a function of the direct (beam) radiation, diffuse radiation, and the radiation reflected from the ground, following Buckley (2008) and Sears et al. (2011):

$$R_{solar} = \alpha_s \left(F_p S_p + F_d S_d + F_r S_r \right)$$  \hspace{1cm} \text{Eq. 2}$$
where \( \alpha_s \) is the lizard’s absorptivity of solar radiation, \( F_p, F_d, \) and \( F_g \) are view factors between the lizard and direct solar radiation (\( S_p \)), diffuse solar radiation (\( S_d \)), and reflected solar radiation (\( S_r \)), respectively. Direct and diffuse solar radiation are reduced under the forest canopy; we modelled direct solar radiation reaching an animal under the canopy (\( S_{p,sub} \)) using equations in Campbell and Norman (1998):

\[
S_{p,sub} = \omega_p S_p
\]  
Eq 3

where \( \omega_p \) is the proportion of direct solar radiation that makes it through the canopy, which is an exponential function of LAI (Campbell & Norman, 1998):

\[
\omega_p = \exp(-\sqrt{\alpha_c K_{b,z} LAI})
\]  
Eq 4

where \( \alpha_c \) is the average absorptivity of the canopy and \( K_{b,z} \) is the extinction coefficient for direct solar radiation at zenith angle \( z \). Following Campbell and Norman (1998), we modelled the diffuse solar radiation under the canopy (\( S_{d,sub} \)) through numerical integration across all zenith angles (\( z \)):

\[
S_{d,sub} = S_d 2 \int_0^\pi \exp(-\sqrt{\alpha_c K_{b,z} LAI}) \sin z \cos z \, dz
\]  
Eq 5

The forest canopy also affects the amount of long-wave radiation reaching an animal from above (Webster et al., 2017). In the absence of a canopy, long-wave radiation from the air (\( L_a \)) is calculated as (Campbell & Norman, 1998; Buckley, 2008; Sears et al., 2011):

\[
L_a = \varepsilon_{ac} \sigma (T_{air} + 273)^4
\]  
Eq 6

where \( \varepsilon_{ac} \) is clear-sky emissivity. Under a canopy, long-wave radiation (\( L_{a,sub} \)) comes from the sky and from the canopy, in proportion to the amount of clear sky (Webster, Rutter, Jonas, 2017):

\[
L_{a,sub} = V_s L_a + (1 - V_s) \varepsilon_c \sigma (T_{can} + 273)^4
\]  
Eq 7

where \( T_{can} \) is canopy temperature, \( \varepsilon_c \) is canopy emissivity and \( V_s \) is a view factor denoting the proportion of long-wave radiation from clear sky. In Eq 4, the proportion of direct solar radiation reaching an animal through the canopy (\( \omega_p \)) was modelled as a function of LAI (also see Essery, Pomeroy, Ellis, Link, 2008). As \( \omega_p \) represents the proportion of radiation non-intercepted by the canopy, we derived the proportion of clear sky (\( V_s \)) using Equation 4 but assuming black leaves (\( \alpha_c^{-1} \)):

\[
V_s = \exp(-K_{b,z} LAI)
\]  
Eq 8
The forest canopy will also reflect longwave and reflected solar radiation from the substrate back downward, with the process repeating, attenuated by the absorptivity of the canopy and the ground, (Mahat & Tarboton, 2012), but we do not include this process here. We can now rewrite Eq 1 to include the radiation reaching animals below the canopy as:

\[
T_{e,\text{sub}} = T_{\text{air}} + \frac{R_{\text{solar,sub}} + R_{\text{lw,sub}} - \varepsilon_s \sigma (T_{\text{air}} + 273)^4}{4 \sigma (T_{\text{air}} + 273)^3 + c_p \left( 1.4 + 0.135 \frac{v}{\sqrt{d}} \right)}
\]

Eq 9

We used Eq 9 to model the predicted relationships between \(T_b\) and \(T_{air}\), solar radiation, wind speed and LAI. Full model details and parameter values are given in Appendix S1 in Supporting Information. We varied each environmental variable across the range of values observed in our empirical data to generate predictions of the shape of the relationships between each variable and \(T_b\). We modelled the relationships between \(T_b\) and \(T_{air}\), solar radiation, and wind speed at five different LAI levels to visualize interactive effects between these variables. We stress that our aim was not to predict the absolute values of \(T_b\) in our empirical dataset, but rather the relationships that emerge between \(T_b\), microclimate, and LAI.

**Empirical data**

We tested whether global relationships between ectotherm body temperature, microclimate and LAI matched those predicted by our biophysical model using a dataset, collected from the literature, of mean body temperatures for 269 diurnal, non-fossorial mainland lizard populations (179 species; Fig. S1.1) sampled between 1990 and 2010, building on an existing database (Clusella-Trullas, Blackburn, Chown, 2011; Meiri et al., 2013). A list of data sources is found in Appendix 1. Following Meiri et al. (2013), we did not set a minimum sample size, pooled data across sexes and life stages, and excluded temperatures or populations sampled at night. We limited our data to post-1990 to limit confounding effects of substantial 20th century land cover change on our estimates of canopy structure (see below). For each population, we extracted the mean daytime (06:00–18:00 local time) air temperature 1cm above ground (averaged across rock, soil, and sand), air temperature at 1.2m, solar radiation, and wind speed at 1cm from the microclim dataset (Kearney, Isaac, et al., 2014) for the sampling months
reported for each study. We extracted microclimate data values in full sun for open and semi-open
habitats and in full shade for closed forests. We assigned each population to one of these habitat types
based on the geographical coordinates reported for a population. While this may not capture
microhabitat preferences perfectly (e.g. forest gap or edge specialists), this is likely to add noise to our
analysis rather than bias it. We made these assignations (Table S1.2) based on combining categories
included in the global land cover consensus product (Tuanmu & Jetz, 2014) and finding the land
cover (closed, semi-open, open) with the highest probability of occurring at each location, resulting in
27 closed, 123 semi-open, and 119 open habitat populations (Fig. S1.1).

We determined whether species were ground-dwelling, arboreal or semi-arboreal (use ground and
trees, or use shrubs) from the literature, using the source paper for the $T_b$ data where possible and
other literature or expert knowledge where necessary. Data sources are given in Appendix 1 and the
accompanying dataset. For ground-dwellers, we used air temperature and wind speed at 1cm for all
analyses, for arboreal species we used air temperature and wind speed at 1.2m and for semi-arboreal
species, we used the average of 1cm and 1.2m. We inferred wind speed at 1.2m using the equations
given for this purpose in Kearney, Isaac, et al. (2014). We did not consider variation in substrate
temperature because in our empirical dataset (see below), air and soil temperature were highly
correlated ($r=0.94$, $P<0.001$). If sampling months were not reported we used a summer average
(northern hemisphere: April–September, southern hemisphere: October–March) instead. For
populations whose coordinates fell in the ocean (likely due to georeferencing error), we used
conditions from the nearest piece of land, provided it was within 1 grid cell (at 0.1667 x 0.1667 DD
resolution) of the original coordinates.

We also extracted leaf area index (LAI) for each population’s location. We used the mean of 8-day
MODIS reprocessed composites of LAI (Yuan, Dai, Xiao, Ji, Shangguan, 2011) across the sampling
months at 30 arc-sec spatial resolution, averaged from 2001-2010. LAI data are freely available from
http://globalchange.bnu.edu.cn/research/lai/. There is a partial temporal mismatch between our $T_b$ data
(1990-2010) and our LAI data (2001-2010) that represents a tradeoff between limiting effects of land cover change on LAI estimates for lizard sampling locations and maintaining sample size.

**Testing for predicted relationships**

We initially fit regression models that excluded LAI and modelled T\(_b\) as linear functions of air temperature and solar radiation and quadratic functions of wind speed to approximate the predicted non-linearity in the T\(_b\) wind speed relationships (Eqs 1 and 9). Wind speed data were right-skewed, so we fifth-root transformed this variable to reduce high leverage of large values. We did not use a log-transformation to avoid taking the logarithm of zero. We removed non-significant terms from our model sequentially, based on P-value, starting with quadratic terms. Next, we added LAI to our full regression model, including a quadratic term to capture non-linearity, as well as interactions with wind speed and solar radiation. We removed non-significant terms as above, beginning with interactions, then quadratic terms. LAI was also right-skewed so we square-root transformed it to reduce influence of a few large values. We repeated regressions for all data habitats pooled and each habitat (open, semi-open, closed) separately.

We fit all regressions using the `lmekin` function in the `coxme` package (Therneau, 2015) in R 3.4.3 (R Core Team, 2018) to simultaneously incorporate spatial and phylogenetic non-independence into our regressions (Freckleton & Jetz, 2009). Based on Tonini, Beard, Ferreira, Jetz, Pyron's (2016) consensus tree, we used shared branch length between species (or populations, see below) as our measure of phylogenetic covariance and the inverse of distance between locations as our spatial covariance matrix. We also considered an alternative phylogenetic covariance structure by transforming the tree using Pagel’s \(\lambda\) of T\(_b\) and then recalculating shared branch lengths. Where multiple populations of the same species from different locations were included in our data, we replaced a species’ terminal branch with a randomly resolved clade whose crown node depth was chosen from a random uniform distribution with a maximum length equal to the original terminal branch. Populations were added to the tree prior to pruning species not included in our analysis and thus are represented as branching events which occurred after a species diverged from its sister. After
fitting regressions, we calculated the marginal ($R^2_m$) and conditional ($R^2_c$) $R^2$ values (Nakagawa & Schielzeth, 2013). $R^2_m$ is the proportion of variance explained by environmental variables and $R^2_c$ is the variance explained by environment, space and phylogeny.

Geographical bias

Our $T_b$ data were highly geographically biased toward South America (Fig. S1.1). To determine how this may have affected our results, we randomly sub-sampled the South American data and refit the final model for each habitat type and all habitat types combined. For each regression, we reduced the number of South American data points so that they were equal in number to the next highest continent (Table 1). We repeated this process 1000 times and computed the number of times we detected a significant (P<0.05) relationship in the direction matching that found in the original regression. We did not geographically subsample closed habitats because only three populations were not from South America.

RESULTS

Biophysical predictions

The model based on environmental biophysical principles for a non-thermoregulating lizard in full sun (LAI=0); Eq. 9) predicts that $T_b$ will increase linearly with air temperature and solar radiation, and that it will decline proportionally to the inverse of the square root of wind speed (Fig. 1). $T_b$ is predicted to decline in a nearly exponential fashion with increasing LAI (Fig 1) and to have interactive effects on $T_b$ with wind speed and solar radiation, but not air temperature (Fig 2). As LAI increases, solar radiation above the canopy and wind speed both are predicted to have diminishing influence on $T_b$ (Fig. 2).

Microclimate–$T_b$ relationships

As predicted, and after accounting for phylogenetic and spatial autocorrelation, we found positive, global relationships between $T_b$ and air temperature (slope±s.e.=0.21±0.03, P=6.5×10^-10, Table S1.3)
Contrary to our prediction, we found no relationship between $T_b$ and wind speed (linear slope $\pm$ s.e. = -2.6$\pm$2.4, $P=0.27$, Table S1.3). Although relationships with air temperature and solar radiation were significant, these variables explained just 13% of the variance in $T_b$ worldwide (Table S1.3). Regression results using a Pagel’s $\lambda$ transformed tree were nearly identical with no changes in direction of coefficients, $R^2_m$, or significance (Table S1.4).

As predicted by biophysical models, $T_b$ in open habitats, where there is less extensive shade, was significantly related air temperature and solar radiation ($P<0.005$ for both; Fig. 3; Table S1.5). We found no relationship with wind speed ($P=0.11$; Fig. 3; Table S1.5). In total, temperature and solar radiation explained 35% of the variance in $T_b$ (Table S1.5). The variance explained by microclimate declined to 10% in semi-open habitats (Table S1.6), where there was no relationship between $T_b$ and solar radiation or wind speed ($P>0.7$ for both; Table S1.6), but the significant relationship with air temperature was retained (slope $\pm$ s.e. = 0.18$\pm$0.05, $P=0.0003$, Fig. 3). These relationships did not change when a Pagel’s $\lambda$-transformed phylogeny was used (Table S4).

In shade-dominated closed forests, we found no significant relationships between $T_b$ and air temperature, solar radiation, or wind speed (Fig. 3; Table S1.7; $P>0.25$ in all cases). The low sample size (n=27) in closed forests compared to semi-open (n=123) and open habitats (n=119) results in low statistical power. In closed forests, to achieve significance at $P<0.05$ with statistical power of 0.8, we would have needed sample sizes of 569 (air temperature), 362 (solar radiation), or 193 (wind speed), suggesting that the lack of relationships in closed forests is not simply a function of lower power compared to open and semi-open habitats. The variance in $T_b$ explained by microclimate including air temperature, solar radiation and a linear wind speed term was only 8% (Table S1.7). These results were insensitive to using a Pagel’s $\lambda$-transformed phylogeny (Table S4).

**LAI and $T_b$ relationships**
We found no global relationship between $T_b$ and LAI, either as a main effect or as interactions with solar radiation and wind speed when all land cover types were pooled (P>0.25 in all cases; Fig. 4; Table S1.3). However, as predicted, $T_b$ was negatively related to LAI in closed habitats (Fig. 4; Table S1.3; slope±s.e.=−5.0±0.2.3, P=0.03), We found no significant interactions between LAI and wind speed or solar radiation in these habitats (Table S1.3). Including LAI in regressions of $T_b$ on micro-environmental conditions in closed forests almost tripled the variance explained by microclimate ($T_{air}$, solar radiation and linear wind speed) alone from 7% to 19% (Fig. 4; Table S1.7). In contrast, LAI explained very little additional variance in $T_b$ in semi-open and open habitats or when all data were pooled (<2%; Fig. 4; Tables S1.3, S1.6, S1.7), signifying it is of little to no importance for $T_b$ in these habitats. None of these regression results were affected by using a Pagel’s $\lambda$-transformed phylogeny (Table S1.4).

Geographical bias.

Subsampling our South America data revealed that relationships between $T_b$ and air temperature were robust to geographical bias in our dataset (Table 1). Relationships with solar radiation were variable when all habitat types were pooled, but their direction was consistent in open habitats, though only significant 11% of the time (Table 1).

**DISCUSSION**

We identified a systematic decay in the ability of existing biophysical models to predict global variation in body temperature ($T_b$) across major habitat types as a function of shade availability, from open habitats where models performed well to closed forests where $T_b$ was unpredictable.

Relationships between body temperature, air temperature and solar radiation matched predictions from classic biophysical models in open habitats across the globe, but the same models failed in forests because even estimates of air temperature from full shade fail to accurately capture thermal conditions under the canopy. By extending biophysical models of ectotherm heat flux to incorporate the interception of solar radiation by the forest canopy, we showed it is possible to predict ectotherm body temperature variation in forests using readily available remote sensing data. As predicted by our
model, we found that in closed forests, body temperatures cooled with increasing canopy density. Moreover, including LAI in $T_b$–microclimate regressions almost tripled the variance explained by in closed forests, revealing potential to improve predictions of body temperatures of forest species under future climate change and highlighting the importance of future canopy thinning and loss for the thermal future of forest ectotherms.

The relative importance of different microclimate variables for $T_b$ varied across major habitat types. In open habitats, $T_b$ was sensitive to air temperature and solar radiation, as predicted by biophysical models (Gates, 1980; Campbell & Norman, 1998; Buckley, 2008; Sears et al., 2011). These relationships reflect proximate effects of microclimate on heating and cooling of organisms where shade is too rare or unevenly distributed to permit efficient thermoregulation to lower temperatures (Huey, 1974; Huey & Slatkin, 1976; Sears et al., 2016), but also capture longer-term adaptive responses that have resulted in higher preferred temperatures in open environments, especially if these environments are also drier (Clusella-Trullas et al., 2011). Contrary to biophysical predictions, we found no relationship with wind speed in open habitats which could either reflect lower accuracy of wind data, or perhaps reduced activity of lizards in windier conditions (e.g. Logan, Fernandez, Calsbeek, 2015). The sensitivity of the solar radiation (but not air temperature) relationship to sub-sampling of the South American data indicate that it has a weaker effect than temperature and thus its detectability may be more prone to a loss of statistical power. However, it is also possible that the effects of solar radiation are stronger in South America than elsewhere. Liolaemus, which comprise much of our South American data, span exceptionally large elevational and latitudinal gradients gradient (Pincheira-Donoso, Tregenza, Witt, Hodgson, 2013) and thus may experience exceptional variation in solar radiation; this additional variation could make detecting effects of this variable easier in South America than elsewhere.

In semi-open habitats, we found no relationship between $T_b$ and wind speed or solar radiation. In these habitats, sun and shade should both be abundant across the landscape. By shuttling in and out of the sun, thermoregulating individuals can maintain body temperatures at, or close to, preferred levels.
Incorporating a remotely-sensed measure of canopy LAI greatly improved the $R^2$ of our regression models in closed forests, indicating that it does capture valuable additional information on thermal environment which is missing from global microclimate variables. Lizards had cooler body temperatures in forests with denser canopies (higher LAI), as predicted by our extended biophysical model. However, we did not find a curvilinear relationship, as predicted, suggesting that there are
additional factors that could be usefully incorporated into our model. For example, arboreality will expose species to different thermal conditions from ground level to the canopy (Bakken, 1989; Scheffers et al., 2013; Spicer et al., 2017). Although we attempted to account for the major temperature differences between ground-dwelling and arboreal lizards, more precise data on perch height and type could improve predictions of $T_b$ in treed environments. Also, our model did not include long-wave radiation from the ground that may have been reflected back downwards toward the animal by the canopy (Mahat & Tarboton, 2012), surface conduction; or variation in latent heat loss. Another possibility is that our results reflect both proximate effects of LAI on forest-lizard $T_b$ and adaptive outcomes of living in these environments as sub-canopy lizards in cooler, closed, environments have adapted to prefer, and function at, lower body temperatures (Ruibal, 1961; Hertz, 1974; Huey et al., 2009; Munoz et al., 2016). The increase in $T_b$ as LAI decreased is consistent with more solar radiation reaching sub-canopy microenvironments, raising sub-canopy temperatures (Hardwick et al., 2015) and allowing for opportunistic thermoregulation to higher $T_b$ (Otero, Huey, Gorman, 2015), which would permit the occurrence of species adapted to warmer thermal conditions in gaps and edges (Ruibal, 1961; Munoz et al., 2016).

The reliance of $T_b$ on canopy density in forests highlights the thermal threat of land use and canopy change for ectotherms. Previous biophysical modelling efforts at broad scales have predicted that in a warming world, shade will become increasingly important for ectotherms (Kearney et al., 2009; Sunday et al., 2014). Our results provide empirical evidence of the effect of canopy-shade on body temperature at the scale of these modelled predictions, suggesting that canopy loss would reduce the buffering capacity of shaded environments, further raising body temperatures. In addition to wholesale canopy loss, more subtle changes in canopy density could also raise $T_b$ and narrow thermal safety margins for forest ectotherms, as well as open new opportunities for more warm-adapted species (Huey et al., 2009; but c.f. Logan et al., 2013). In tropical forests, drought causes increased tree mortality along with losses of water content, photosynthetic activity (greenness), and canopy volume (Phillips et al., 2010; Xu et al., 2011; Saatchi et al., 2013; Zhou et al., 2014), leading to increases in the light incident to the forest floor (Slik, 2004). Thus, the increases in drought intensity...
and/or frequency predicted by global climate models (Dai, 2013; Trenberth et al., 2014) will have
indirect effects on $T_b$ via alterations in canopy density, reducing thermal safety margins and the
potential for vegetation shade to act as thermal microrefugia (Lenoir et al., 2017) as global
temperatures continue to rise. These potential indirect effects of drought highlight the importance of
precipitation dynamics, and not just air temperature, for ectotherm thermal niches (Clusella-Trullas et
al., 2011).

Even the relatively coarse-grained, satellite-derived, LAI product used here tripled the fit of $T_b$–
microclimate models in forests, capturing the importance of shade for ectotherms in these
environments. At narrower spatial extents, the potential for remote sensing to improve understanding
of shade variation and predict thermal habitat quality is even greater. Remote sensing using LiDAR
and hyperspectral sensors on airborne platforms capture variation in canopy and sub-canopy
vegetation structure at centimeter scales and thus can provide information at scales relevant to
individual organisms’ movement (George et al., 2015; Frey et al., 2016; Lenoir et al., 2017), and
potentially allow for precise estimates of an individual organism’s exposure to sun. These products
can not only capture the total shade available, but also its spatial configuration, which can have
important implications for thermoregulation (Sears & Angilletta, 2015; Sears et al., 2016). Remote
sensing data can also improve temporal resolution of predictions of thermal vulnerability in response
to land cover change and drought dynamics. Even at the coarser spatial resolutions used here, we have
found that canopy structure leaves a predictable signature on lizard body temperatures across the
globe, demonstrating the potential of remote sensing products, when properly calibrated, to narrow
the predictive envelope of purely biophysical models and provide more precise predictions of $T_b$ in
free-living ectotherms across broad spatial extents. Moreover, the sensitivity of $T_b$ to canopy density
suggests that changes in forest cover, whether from wholesale land cover change or more subtle
alterations of canopy structure, may intensify the thermal challenges faced by organisms in the
Anthropocene.

REFERENCES


microclimate based on long-term monthly climate averages. *Scientific Data, 1*, 140006.


Webster, C., Rutter, N. & Jonas, T. (2017) Improving representation of canopy temperatures for


**DATA ACCESSIBILITY**

All data used in these analyses will be deposited in FigShare or Dryad upon manuscript acceptance.
Table 1. Consistency of final regression results after randomly sub-setting South American data. N is the number of South American points retained and is equal to the maximum number of points from any other continent. Subsampling and regressions were repeated 1000 times. Sub-setting was not done for closed habitats as only 3 points were outside South America. Columns show the number of regressions coefficients—out of 1000—that matched the sign of the regression on all data, the number of regressions with a significant (P<0.05) coefficient and the means and standard deviations (s.d.) of $R^2_m$ and $R^2_c$. $R^2_m$ (marginal $R^2$) is the variance explained by predictors and $R^2_c$ (conditional $R^2$) is the variance explained by predictors, space and phylogeny. $T_b$ is body temperature, Tair is air temperature, SOL is solar radiation, and LAI is the square root of leaf area index.

<table>
<thead>
<tr>
<th>Habitat</th>
<th>Model</th>
<th>Tair</th>
<th>SOL</th>
<th>$R^2_m$</th>
<th>$R^2_c$</th>
<th>+ P&lt;0.05</th>
<th>+ P&lt;0.05</th>
<th>mean</th>
<th>s.d.</th>
<th>mean</th>
<th>s.d.</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>All</td>
<td>$T_b$~Tair +SOL</td>
<td>1000</td>
<td>1000</td>
<td>447</td>
<td>2</td>
<td>0.16</td>
<td>0.04</td>
<td>0.45</td>
<td>0.26</td>
<td>28</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Semi</td>
<td>$T_b$~ Tair</td>
<td>1000</td>
<td>810</td>
<td></td>
<td>0.08</td>
<td>0.04</td>
<td>0.39</td>
<td>0.33</td>
<td>20</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Open</td>
<td>$T_b$~Tair +SOL+WS</td>
<td>1000</td>
<td>1000</td>
<td>970</td>
<td>113</td>
<td>0.40</td>
<td>0.06</td>
<td>0.57</td>
<td>0.18</td>
<td>11</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Fig. 1. Predicted relationships between body temperature ($T_b$), microclimate, and leaf area index (LAI). Predictions are based on a biophysical model of body temperature for a non-thermoregulating lizard (Eq. 9). Parameters for model predictions are given in Appendix 1 and Table S1.1. Relationships with air temperature, solar radiation and wind speed were modelled in full sun (LAI=0). The grey axes and lines for wind speed and LAI show predicted relationships after a fifth root transformation of wind speed and a square root transformation of LAI to allow comparison with patterns in Fig. 4.
Fig. 2. Predicted effect of LAI on the body temperature ($T_b$) – microclimate relationship for a non-thermoregulating lizard at equilibrium with its environment. The arrows depict direction of increasing LAI, from low (red) to high (blue). Relationships were modelled using Eq. 9 and all parameters are given in Appendix S1 and Table S1.1. LAI is predicted to have an interactive effect on $T_b$ with solar radiation and wind speed but not air temperature.
Fig. 3. Relationship between body temperature ($T_b$) and microclimate for lizards in all habitats and divided by major habitat types that vary in shade availability. Microclimate conditions are daytime averages across the months of $T_b$ collection. Significant (P<0.05) relationships after accounting for spatial and phylogenetic relationships are shown as black regression lines. The variance in $T_b$ explained by microclimate (with linear wind speed) was lowest in closed (0.07%, n=27) and semi-open habitats (11%, n=123), highest in open habitats (36%, n=119), and low in the combined data (0.13, n=269). Wind speed was fifth root transformed to reduce skew and leverage of extreme points.
Fig. 4. Relationship between lizard body temperature ($T_b$) and leaf area index (LAI) in closed, semi-open, and open habitats and all habitats pooled. The relationship was significant ($P=0.03$) in closed (forest) habitats and was in the direction (negative) predicted by theory, though not curvilinear (see Fig. 1). The bottom panel shows the unique variance explained by environment predictors (marginal $R^2$) without and with LAI. LAI had little effect on model fit apart from in closed forests.
APPENDIX 1 – Data Sources


Supplementary Methods

Modelling operative temperature ($T_e$) in full sun

We derived the expected relationships between $T_b$ of a non-thermoregulating lizard at equilibrium with its environment and air temperature, solar radiation, wind speed and shade level by modelling $T_e$ for a theoretical lizard on a flat surface and varying each of these variables individually or jointly, assuming $T_b = T_e$ for a non-thermoregulating lizard at equilibrium. Initial parameters for these calculations are given in Table S1.1. Solar radiation was manipulated by varying latitude while controlling for time of day and year.

We modelled $T_e$ on a flat surface following Buckley (2007) and Sears et al. (2011), using the equation:

$$T_e = T_{air} + \frac{R_{solar} + R_{lw} - \varepsilon_s \sigma (T_{air} + 273)^4}{4\sigma (T_{air} + 273)^3 + c_p \left(1.4 + 0.135 \frac{v}{d}\right)}$$  \hspace{1cm} \text{Eq S1}

where $T_{air}$ is air temperature in degrees Celsius, $R_{solar}$ is absorbed incoming solar (short-wave) radiation, $R_{lw}$ is absorbed long-wave radiation, $\varepsilon_s$ is animal emissivity which we set at 0.965, following Buckley (2007), $\sigma$ is the Stefan-Boltzmann constant ($5.67 \times 10^{-8}$ W m$^{-2}$ K$^{-4}$; Buckley 2007), $c_p$ is the specific heat of air ($29.3$ J mol$^{-1}$ K$^{-1}$) (Buckley, 2007), $d$ is the characteristic dimension of the animal, and $v$ is wind velocity. We set $d$ equal to the snout-vent length of our theoretical lizard, which assumes the animal is parallel to wind direction (Campbell & Norman, 1998).

We calculated the absorbed long-wave radiation following Buckley’s (2007) equation A23:

$$R_{lw} = \alpha_L (F_a L_a + F_g L_g)$$  \hspace{1cm} \text{Eq S2}

$\alpha_L$ is absorptivity in the long-wave (thermal) waveband, set to 0.965, following Buckley (2007). $F_a$ and $F_g$ are view factors for long-wave radiation from the air and ground, respectively, both set to 0.5 (Buckley, 2007; Sears et al., 2011). $L_a$ is the long-wave radiation from the air, calculated using Buckley’s (2007) Eq A21:
\[ L_a = \varepsilon_{ac} \sigma(T_{air} + 273)^4 \]  
Eq S3

\varepsilon_{ac} is clear-sky emissivity which was calculated using Buckley’s (2007) equation A12:

\[ \varepsilon_{ac} = 9.2 \times 10^{-6}(T_{air} + 273)^2 \]  
Eq S4

\[ L_g = \varepsilon_s \sigma(T_s + 273)^4 \]  
Eq S3

where \( T_s \) is the ground surface temperature in degrees Celsius and \( \varepsilon_s \) is the emissivity of the ground.

According to Campbell and Norman (1998), emissivity is between 0.95 and 1.0 for most natural surfaces, so we use 0.965, which matches the emissivity of our theoretical lizard.

Solar (short-wave) radiation absorbed by an animal in full sun was modelled following Buckley’s (2007) equation A23 (with slightly different notation):

\[ R_{solar} = \alpha_s (F_pS_p + F_aS_d + F_rS_r) \]  
Eq S4

In Eq S4, \( \alpha_s \) is the absorptivity of solar radiation, set to 0.9 for lizards (Gates, 1980; Buckley, 2007).

\( F_p, F_a, \) and \( F_r \) are view factors between the lizard and direct solar radiation (\( S_p \)), diffuse solar radiation (\( S_d \)), and reflected solar radiation (\( S_r \)), respectively. \( F_r \) was set to 0.5 (Buckley, 2007; Sears et al., 2011), as was \( F_d \) (Sears et al., 2011). Buckley (2007) set \( F_d \) to 0.8, but this slight difference would not affect our conclusions about the shape and direction of the relationships between \( T_e \) and microclimate.

\( F_p \) was modelled following Sears et al.’s (2011) Equation 5 and assumes the lizard is a cylinder with rounded ends:

\[ F_p = 1 + \frac{4h \sin \Theta}{\pi w} - \frac{4h^2}{w^2} \]  
Eq S5

where \( h \) is the SVL of the lizard (length of cylinder) and \( w \) is the body width (diameter of cylinder). \( \Theta \) is the angle between the solar beam and the animal’s longitudinal axis, which we assumed to be 90º.

Direct solar radiation reaching the Earth’s surface (\( S_p \)) in full sun was calculated following Sears et al.’s (2011) equations 6 and 9:
\[ S_p = \bar{S}_0 \left( 1 + 2 \times \cos \left( \frac{2\pi f}{365} \right) \right) \tau^m \cos z \quad \text{Eq S6} \]

where \( \bar{S}_0 \) is the solar constant (1360 W m\(^{-2} \)), \( f \) is the Julian day, \( z \) is the zenith angle, \( \tau \) is the optical transmittance of the atmosphere. \( \tau \) values between 0.6 and 0.7 are typical of clear days (Gates, 1980; Campbell & Norman, 1998), so we set \( \tau = 0.65 \). \( m \) is the optical air mass number, given by Sears et al. (2011), following Campbell & Norman (1998), as:

\[ m = \frac{101.3 e^{\frac{a}{100}}}{101.3 \cos z} = \frac{e \frac{a}{100}}{\cos z} \quad \text{Eq S7} \]

where \( a \) is elevation in meters above sea level. We calculated zenith angle, assuming a flat surface with no surrounding topography, as a function of latitude, longitude and hour following Sears et al. (2011) and Campbell & Norman (1998):

\[ z = \cos^{-1} \left( \sin \Phi \sin \delta + \cos \Phi \cos \delta \cos h \right) \quad \text{Eq S8} \]

where \( \Phi \) is latitude, \( \delta \) is solar declination, and \( h \) is the hour angle of the sun. We calculated declination using Campbell & Norman’s (1998) equation 11.2:

\[ \delta = 0.39785 \sin(278.97 + 0.9856 f + 1.9165 \sin(356.6 + 0.9856 f)) \quad \text{Eq S9} \]

We calculate hour angle of the sun as:

\[ h = 15(t - 12 + L_{\text{cor}} + E_T) \quad \text{Eq S10} \]

where \( t \) is time of day, \( L_{\text{cor}} \) is a longitudinal correction and \( E_T \) is the time equation, calculated from Sears et al. (2011) and Campbell & Norman (1998) as:

\[ E_T = 3600^{-1} \left( -104.7 \sin f + 596.2 \sin 2f + 4.3 \sin 3f - 12.7 \sin 4f \right. \\
\left. -429.3 \cos f - 2.0 \cos 2f + 19.3 \cos 3f \right) \quad \text{Eq S11} \]

where \( f = 279.575 + 0.9856 f \). The longitudinal correction \( L_{\text{cor}} \) is the longitude plus 4 minutes for each degree east of a standard meridian (minus 4 minutes for each degree west), where standard meridians are located at 0°, 15°, 30°, . . . , 345° (Campbell & Norman, 1998).
Diffuse solar radiation ($S_d$) was modelled following Buckley (2007) and Campbell and Norman (1998):

$$S_d = 0.3S_0(1 - \tau^m)\cos z \quad \text{Eq S10}$$

Reflected solar radiation ($S_r$) was modelled as a function of surface (ground) albedo ($\alpha$) and the direct and diffuse solar radiation (Campbell & Norman, 1998; Buckley, 2007; Sears et al., 2011):

$$S_r = \alpha(S_p + S_d) \quad \text{Eq S10}$$

Modelling operative temperature ($T_e$) under the forest canopy

Shade has previously been incorporated into $T_e$ models by reducing the amount of solar radiation reaching an animal:

$$T_e = T_{air} + \frac{(1 - S)R_{solar} + R_{iwe} - \varepsilon_r\sigma(T_{air} + 273)^4}{4\sigma(T_{air} + 273)^3 + c_p\left(1.4 + 0.135\sqrt{\nu}\right)} \quad \text{Eq S12}$$

where $S$ is the proportion of an animal in the shade (Sears et al., 2011). However, shade imposed by a forest canopy will affect both solar radiation and long-wave radiation (Campbell, 1986; Campbell & Norman, 1998; Webster et al., 2017). The direct solar radiation reaching an animal in full sun ($S_p$) was modelled using Equation S4. However, under a forest canopy, only a proportion of the potential direct solar radiation will penetrate the canopy. We modelled the direct solar radiation reaching below the canopy ($S_{p,sub}$) following Campbell and Norman (1998):

$$S_{p,sub} = \omega_p S_p \quad \text{Eq S13}$$

where $\omega_p$ is the proportion of direct solar radiation that makes it through the canopy, which is an exponential function of LAI (Campbell & Norman, 1998):

$$\omega_p = \exp\left(-\sqrt{\alpha_c K_{b,z} LAI}\right) \quad \text{Eq S14}$$

where $\alpha_c$ is the average absorptivity of the canopy, set to 0.8 (Page 248 in Campbell & Norman, 1998), $K_{b,z}$ is the extinction coefficient for direct solar radiation at zenith angle $z$. $K_{b,z}$ was modelled as a function of $z$, assuming a spherical leaf angle distribution (Campbell & Norman, 1998):
\[ K_{b,z} = \frac{\sqrt{1 + \tan^2 z}}{2.00132} \]  
Eq S15

Diffuse solar radiation below the canopy \((S_{d,sub})\) was found by numerically integrating Equation 15.5 in Campbell and Norman (1998):

\[ S_{d,sub} = S_d 2 \int_0^\pi \exp(-\sqrt{\alpha_c K_{b,z} LAI}) \sin z \cos z dz \]  
Eq S16

We then modelled the solar radiation reflected from the ground under the canopy \((S_{r,sub})\) as:

\[ S_{r,sub} = \alpha(S_{p,sub} + S_{d,sub}) \]  
Eq S17

and total solar radiation reaching the animal under the canopy \((R_{solar,sub})\) as:

\[ R_{solar,sub} = \alpha_s(F_p S_{p,sub} + F_d S_{d,sub} + F_r S_{r,sub}) \]  
Eq S18

The forest canopy will also affect the long-wave radiation incident on an animal if the canopy is a different temperature than the air (Webster et al., 2017). We modelled the below-canopy long-wave radiation \((L_{a,sub})\) following Webster et al. (2017), but accounting for canopy emissivity \((\epsilon_c)\):

\[ L_{a,sub} = V_s L_a + (1 - V_s) \epsilon_c \sigma(T_{can} + 273)^4 \]  
Eq S19

where \(T_{can}\) is canopy temperature in °C, \(V_s\) is a view factor delineating proportion of radiation comes from clear sky and \(\epsilon_c\) is set to 0.99 (Page 273 in Campbell & Norman, 1998). We modelled \(T_{can}\) using the empirical relationship derived by Webster et al. (2017):

\[ T_{can} = 2.36 + 0.88T_{air} + 0.0073(S_{p,sub} + S_{d,sub} + S_{r,sub}) \]  
Eq S20

\(V_s\) varies between 0 and 1, where 0 indicates complete canopy cover and 1 no canopy cover. We modelled \(V_s\) as an exponential function of LAI. When LAI is zero, \(V_s\) is 1.0 as all long-wave radiation from the air comes from the sky (there is no canopy). As LAI increases leaves block the sky, decreasing \(V_s\). The proportion of direct (beam) solar radiation that penetrates the canopy \((\alpha_p)\) is given in Eq S14. This reflects value reflects the amount of direct light reaching the ground between and through leaves (as determined by \(\alpha_c\), canopy absorptivity). Thus, we modelled \(V_s\) based on Eq S14, assuming black leaves \((\alpha_c=1.0)\):
\[ V_s = \exp(-K_{b,x}LAI) \]  

Eq S14

We used these equations to model the expected relationships between air temperature, solar radiation, LAI and wind speed. Parameters used in models, but not defined above are given in Table S1.1.

References


Table S1.1. Parameter values not given in the supplementary text above for modelling operative temperature of a lizard on a flat surface. Air temperature, wind speed, shade level and latitude (as a proxy for solar radiation) were varied between the given ranges to derive predicted relationships with lizard body temperature. Variable ranges were based on ranges in our global data set.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Default</th>
<th>Range</th>
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</thead>
<tbody>
<tr>
<td>Air Temperature (°C)</td>
<td>20</td>
<td>7.7–36.4</td>
</tr>
<tr>
<td>Substrate Temperature (°C)</td>
<td>20</td>
<td>–</td>
</tr>
<tr>
<td>Wind speed (m s$^{-1}$)</td>
<td>5</td>
<td>0.14–4.51</td>
</tr>
<tr>
<td>Latitude (DD)</td>
<td>34.0</td>
<td>25.5–47.5</td>
</tr>
<tr>
<td>Longitude (DD)</td>
<td>-111.0</td>
<td>–</td>
</tr>
<tr>
<td>Hour (local time)</td>
<td>11:00</td>
<td>–</td>
</tr>
<tr>
<td>Julian Day</td>
<td>10</td>
<td>–</td>
</tr>
<tr>
<td>LAI</td>
<td>0</td>
<td>0–6.4</td>
</tr>
<tr>
<td>Surface albedo</td>
<td>0.2</td>
<td>–</td>
</tr>
<tr>
<td>Elevation (m.a.s.l.)</td>
<td>100</td>
<td>–</td>
</tr>
<tr>
<td>Snout-Vent Length (cm)</td>
<td>10</td>
<td>–</td>
</tr>
<tr>
<td>Body Diameter (cm)</td>
<td>2</td>
<td>–</td>
</tr>
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</table>
Table S1.2. Reclassification of land cover categories in Tuanmu & Jetz (2014) into closed, semi-open and open habitat types.

<table>
<thead>
<tr>
<th>Class</th>
<th>Description</th>
<th>Habitat type</th>
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<tbody>
<tr>
<td>1</td>
<td>Evergreen/Deciduous Needleleaf Trees</td>
<td>Closed</td>
</tr>
<tr>
<td>2</td>
<td>Evergreen Broadleaf Trees</td>
<td>Closed</td>
</tr>
<tr>
<td>3</td>
<td>Deciduous Broadleaf Trees</td>
<td>Closed</td>
</tr>
<tr>
<td>4</td>
<td>Mixed/Other Trees</td>
<td>Semi-Open</td>
</tr>
<tr>
<td>5</td>
<td>Shrubs</td>
<td>Semi-Open</td>
</tr>
<tr>
<td>6</td>
<td>Herbaceous Vegetation</td>
<td>Open</td>
</tr>
<tr>
<td>7</td>
<td>Cultivated and Managed Vegetation</td>
<td>Open</td>
</tr>
<tr>
<td>8</td>
<td>Regularly Flooded Vegetation</td>
<td>Open</td>
</tr>
<tr>
<td>9</td>
<td>Urban/Built-up</td>
<td>Open</td>
</tr>
<tr>
<td>10</td>
<td>Snow/Ice</td>
<td>-</td>
</tr>
<tr>
<td>11</td>
<td>Barren</td>
<td>Open</td>
</tr>
<tr>
<td>12</td>
<td>Open Water</td>
<td>-</td>
</tr>
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</table>
Table S1.3. Regression of $T_b$ on microclimate and canopy structure for global data and all habitats. For each variable the sign of the coefficient and P-value are given. P<0.05 are in bold. All regressions accounted for spatial and phylogenetic autocorrelation. $R^2_m$ (marginal $R^2$) is the variance explained by predictors and $R^2_c$ (conditional $R^2$) is the variance explained by predictors, space and phylogeny. $T_b$ is body temperature, Tair is air temperature, SOL is solar radiation, WS is the fifth root of wind speed and LAI is the square root of leaf area index.

<table>
<thead>
<tr>
<th>Model</th>
<th>Tair</th>
<th>SOL</th>
<th>WS</th>
<th>WS$^2$</th>
<th>LAI</th>
<th>LAI$^2$</th>
<th>LAI×SOL</th>
<th>LAI×WS</th>
<th>$R^2_m$</th>
<th>$R^2_c$</th>
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<tbody>
<tr>
<td>No LAI</td>
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<td></td>
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<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>$T_b$~Tair +SOL+WS+WS$^2$</td>
<td>+;</td>
<td>3e-6</td>
<td>+; 0.01</td>
<td>−; 0.54</td>
<td>+; 0.61</td>
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<td>0.42</td>
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<tr>
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<td>+;</td>
<td>2e-6</td>
<td>+;0.01</td>
<td>−; 0.27</td>
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<td></td>
<td></td>
<td></td>
<td>0.13</td>
<td>0.42</td>
</tr>
<tr>
<td>$T_b$~Tair +SOL</td>
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<td>7e-10</td>
<td>+; 0.02</td>
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<td></td>
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<td></td>
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<td>0.38</td>
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<tr>
<td>With LAI</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$T_b$~Tair+SOL+WS+WS$^2$+LAI+LAI$^2$+LAI×SOL</td>
<td>+;</td>
<td>6e-6</td>
<td>+; 0.34</td>
<td>−; 0.36</td>
<td>+; 0.44</td>
<td>−; 0.27</td>
<td>+; 0.42</td>
<td>+; 0.49</td>
<td>0.14</td>
<td>0.43</td>
</tr>
<tr>
<td>LAI×SOL+LAI×WS</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$T_b$~Tair+SOL+WS+WS$^2$+LAI+LAI$^2$+LAI×SOL</td>
<td>+;</td>
<td>5e-6</td>
<td>+; 0.35</td>
<td>−; 0.46</td>
<td>+; 0.52</td>
<td>−; 0.37</td>
<td>+; 0.44</td>
<td>+; 0.50</td>
<td>0.14</td>
<td>0.42</td>
</tr>
<tr>
<td>$T_b$~Tair+SOL+WS+WS$^2$+LAI+LAI$^2$</td>
<td>+;</td>
<td>2e-6</td>
<td>+; 0.02</td>
<td>−; 0.51</td>
<td>+; 0.57</td>
<td>−; 0.46</td>
<td>+; 0.54</td>
<td></td>
<td>0.14</td>
<td>0.40</td>
</tr>
<tr>
<td>$T_b$~Tair+SOL+WS+WS$^2$+LAI</td>
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<td>3e-6</td>
<td>+; 0.02</td>
<td>−; 0.50</td>
<td>+; 0.57</td>
<td>−; 0.64</td>
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<td>0.13</td>
<td>0.42</td>
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<tr>
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<td>+;</td>
<td>2e-6</td>
<td>+; 0.03</td>
<td>−; 0.27</td>
<td>−; 0.69</td>
<td></td>
<td></td>
<td></td>
<td>0.13</td>
<td>0.41</td>
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</table>
**Table S1.4.** Results of final regressions of $T_b$ on microclimate and canopy structure using a Pagel’s lambda transformed phylogenetic variance-covariance matrix. For each variable the sign of the coefficient and P-value are given. P<0.05 are in bold. All regressions accounted for spatial and phylogenetic autocorrelation. $R^2_m$ (marginal $R^2$) is the variance explained by predictors and $R^2_c$ (conditional $R^2$) is the variance explained by predictors, space and phylogeny. $T_b$ is body temperature, Tair is air temperature, SOL is solar radiation, WS is the fifth root of wind speed and LAI is the square root leaf area index.

<table>
<thead>
<tr>
<th>Model</th>
<th>Tair</th>
<th>SOL</th>
<th>WS</th>
<th>LAI</th>
<th>$R^2_m$</th>
<th>$R^2_c$</th>
</tr>
</thead>
<tbody>
<tr>
<td>All</td>
<td>$T_b$~Tair +SOL</td>
<td>$+; 6e^{-10}$</td>
<td>$+; 0.02$</td>
<td></td>
<td>0.13</td>
<td>0.40</td>
</tr>
<tr>
<td>Closed</td>
<td>$T_b$~LAI</td>
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</tr>
<tr>
<td>Semi</td>
<td>$T_b$~Tair</td>
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<td></td>
<td>$-; 0.03$</td>
<td>0.15</td>
</tr>
<tr>
<td>Open</td>
<td>$T_b$~Tair +SOL</td>
<td>$+; 1e^{-15}$</td>
<td>$+; 4e^{-3}$</td>
<td></td>
<td>0.35</td>
<td>0.52</td>
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</table>
Table S1.5. Regression of $T_b$ on microclimate and canopy structure for open habitats in the global data. For each variable the sign of the coefficient and $P$-value are given. $P<0.05$ are in bold. All regressions accounted for spatial and phylogenetic autocorrelation. $R^2_m$ (marginal $R^2$) is the variance explained by predictors and $R^2_c$ (conditional $R^2$) is the variance explained by predictors, space and phylogeny. $T_b$ is body temperature, $T_{air}$ is air temperature, SOL is solar radiation, WS is the fifth root of wind speed and LAI is the square root leaf area index.

<table>
<thead>
<tr>
<th>Model</th>
<th>Tair</th>
<th>SOL</th>
<th>WS</th>
<th>WS^2</th>
<th>LAI</th>
<th>LAI^2</th>
<th>LAI×SOL</th>
<th>LAI×WS</th>
<th>$R^2_m$</th>
<th>$R^2_c$</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>No LAI</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$T_b\sim T_{air} + SOL + WS + WS^2$</td>
<td>; 2e-7</td>
<td>+;</td>
<td>5e-4</td>
<td>-;</td>
<td>0.08</td>
<td>+;</td>
<td>0.10</td>
<td></td>
<td>0.37</td>
<td>0.64</td>
</tr>
<tr>
<td>$T_b\sim T_{air} + SOL + WS$</td>
<td>; 2e-9</td>
<td>+;</td>
<td>0.001</td>
<td>-;</td>
<td>0.11</td>
<td></td>
<td></td>
<td></td>
<td>0.36</td>
<td>0.58</td>
</tr>
<tr>
<td>$T_b\sim T_{air} + SOL$</td>
<td>; 1e-15</td>
<td>+;</td>
<td>0.004</td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td>0.35</td>
<td>0.53</td>
</tr>
<tr>
<td><strong>With LAI</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$T_b\sim T_{air} + SOL + WS + WS^2 + LAI + LAI^2 + LAI×SOL$</td>
<td>+;</td>
<td>1e-6</td>
<td>+;</td>
<td>0.38</td>
<td>-;</td>
<td>0.16</td>
<td>+;</td>
<td>0.17</td>
<td>-;</td>
<td>0.64</td>
</tr>
<tr>
<td>LAI×SOL + LAI×WS</td>
<td>+;</td>
<td>7e-7</td>
<td>+;</td>
<td>0.26</td>
<td>-;</td>
<td>0.07</td>
<td>+;</td>
<td>0.05</td>
<td>-;</td>
<td>0.07</td>
</tr>
<tr>
<td>$T_b\sim T_{air} + SOL + WS + WS^2 + LAI + LAI^2 + LAI×SOL$</td>
<td>+;</td>
<td>5e-8</td>
<td>+;</td>
<td>0.002</td>
<td>-;</td>
<td>0.08</td>
<td>+;</td>
<td>0.10</td>
<td>-;</td>
<td>0.08</td>
</tr>
<tr>
<td>$T_b\sim T_{air} + SOL + WS + WS^2 + LAI$</td>
<td>+;</td>
<td>4e-9</td>
<td>+;</td>
<td>0.002</td>
<td>-;</td>
<td>0.08</td>
<td>+;</td>
<td>0.11</td>
<td>-;</td>
<td>0.21</td>
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Table S1.6. Regression of $T_b$ on microclimate and canopy structure for semi-open habitats in the global data. For each variable the sign of the coefficient and P-value are given. P<0.05 are in bold. All regressions accounted for spatial and phylogenetic autocorrelation. $R^2_m$ (marginal $R^2$) is the variance explained by predictors and $R^2_c$ (conditional $R^2$) is the variance explained by predictors, space and phylogeny. $T_b$ is body temperature, Tair is air temperature, SOL is solar radiation, WS is the fifth root of wind speed and LAI is the square root leaf area index.

<table>
<thead>
<tr>
<th>Model</th>
<th>Tair</th>
<th>SOL</th>
<th>WS</th>
<th>WS²</th>
<th>LAI</th>
<th>LAI²</th>
<th>LAI×SOL</th>
<th>LAI×WS</th>
<th>$R^2_m$</th>
<th>$R^2_c$</th>
</tr>
</thead>
<tbody>
<tr>
<td>No LAI</td>
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<td></td>
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<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$T_b=\text{Tair }+\text{SOL }+\text{WS }+\text{WS}^2$</td>
<td>+; 0.01</td>
<td>+; 0.70</td>
<td>−; 0.36</td>
<td>+; 0.38</td>
<td>0.11</td>
<td>0.13</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$T_b=\text{Tair }+\text{SOL }+\text{WS}$</td>
<td>+; 0.004</td>
<td>+; 0.85</td>
<td>−; 0.71</td>
<td>0.10</td>
<td>0.14</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$T_b=\text{Tair }+\text{WS}$</td>
<td>+; 0.004</td>
<td>−; 0.73</td>
<td>0.10</td>
<td>0.14</td>
<td></td>
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<td></td>
</tr>
<tr>
<td>$T_b=\text{Tair}$</td>
<td>+; 3e-4</td>
<td>0.10</td>
<td>0.15</td>
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<td></td>
</tr>
<tr>
<td>With LAI</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$T_b=\text{Tair }+\text{SOL }+\text{WS }+\text{WS}^2+\text{LAI }+\text{LAI}^2$</td>
<td>+; 0.01</td>
<td>+; 0.72</td>
<td>−; 0.39</td>
<td>+; 0.37</td>
<td>+; 0.89</td>
<td>+; 0.59</td>
<td>−; 0.75</td>
<td>−; 0.80</td>
<td>0.11</td>
<td>0.19</td>
</tr>
<tr>
<td>LAI×SOL</td>
<td>+; 0.01</td>
<td>+; 0.72</td>
<td>−; 0.39</td>
<td>+; 0.37</td>
<td>+; 0.89</td>
<td>+; 0.59</td>
<td>−; 0.75</td>
<td>−; 0.80</td>
<td>0.11</td>
<td>0.19</td>
</tr>
<tr>
<td>$T_b=\text{Tair }+\text{SOL }+\text{WS }+\text{WS}^2+\text{LAI }+\text{LAI}^2+\text{LAI×SOL}$</td>
<td>+; 0.009</td>
<td>+; 0.71</td>
<td>−; 0.35</td>
<td>+; 0.35</td>
<td>−; 1.0</td>
<td>+; 0.60</td>
<td>−; 0.72</td>
<td>0.11</td>
<td>0.19</td>
<td></td>
</tr>
<tr>
<td>$T_b=\text{Tair }+\text{SOL }+\text{WS }+\text{WS}^2+\text{LAI }+\text{LAI}^2$</td>
<td>+; 0.009</td>
<td>+; 0.89</td>
<td>−; 0.31</td>
<td>+; 0.32</td>
<td>−; 0.40</td>
<td>+; 0.45</td>
<td>0.11</td>
<td>0.18</td>
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<td></td>
</tr>
<tr>
<td>$T_b=\text{Tair }+\text{SOL }+\text{WS }+\text{WS}^2+\text{LAI}$</td>
<td>+; 0.01</td>
<td>+; 0.83</td>
<td>−; 0.33</td>
<td>+; 0.35</td>
<td>−; 0.69</td>
<td>0.11</td>
<td>0.14</td>
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</tr>
<tr>
<td>$T_b=\text{Tair }+\text{SOL }+\text{WS }+\text{LAI}$</td>
<td>+; 0.006</td>
<td>+; 0.92</td>
<td>−; 0.71</td>
<td>−; 0.86</td>
<td>0.10</td>
<td>0.15</td>
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<td></td>
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</tr>
<tr>
<td>$T_b=\text{Tair }+\text{WS }+\text{LAI}$</td>
<td>+; 0.004</td>
<td>−; 0.72</td>
<td>−; 0.86</td>
<td>0.10</td>
<td>0.15</td>
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</table>
Table S1.7. Regression of $T_b$ on microclimate and canopy structure for closed habitats in the global data. For each variable the sign of the coefficient and P-value are given. P<0.05 are in bold. All regressions accounted for spatial and phylogenetic autocorrelation. $R^2_m$ (marginal $R^2$) is the variance explained by predictors and $R^2_c$ (conditional $R^2$) is the variance explained by predictors, space and phylogeny. $T_b$ is body temperature, $Tair$ is air temperature, SOL is solar radiation, WS is the fifth root of wind speed and LAI is the square root leaf area index.

<table>
<thead>
<tr>
<th>Model</th>
<th>$Tair$</th>
<th>SOL</th>
<th>WS</th>
<th>$WS^2$</th>
<th>LAI</th>
<th>LAI$^2$</th>
<th>LAI×SOL</th>
<th>LAI×WS</th>
<th>$R^2_m$</th>
<th>$R^2_c$</th>
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</thead>
<tbody>
<tr>
<td>No LAI</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$T_b$~$Tair$+$SOL$+$WS$+$WS^2$</td>
<td>+; 0.60</td>
<td>+; 0.80</td>
<td>+; 0.58</td>
<td>-; 0.65</td>
<td></td>
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</tr>
<tr>
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<td>+; 0.54</td>
<td>+; 0.44</td>
<td>+; 0.29</td>
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<td>+; 0.35</td>
<td>+; 0.35</td>
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<td>0.06</td>
<td>0.13</td>
</tr>
<tr>
<td>$T_b$~ WS</td>
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<td></td>
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<td>0.03</td>
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<td>With LAI</td>
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<td></td>
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<td></td>
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<td></td>
</tr>
<tr>
<td>$T_b$~$Tair$+$SOL$+$WS$+$WS^2$+$LAI$+$LAI^2$</td>
<td>−; 0.91</td>
<td>+; 0.32</td>
<td>−; 0.47</td>
<td>−; 0.67</td>
<td>−; 0.53</td>
<td>−; 0.88</td>
<td>−; 0.39</td>
<td>+; 0.08</td>
<td>0.28</td>
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</tr>
<tr>
<td>LAI×SOL+LAI×WS</td>
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</tr>
<tr>
<td>$T_b$~$Tair$+$SOL$+$WS$+$WS^2$+$LAI$+$LAI^2$+LAI×WS</td>
<td>+; 0.75</td>
<td>+; 0.34</td>
<td>−; 0.52</td>
<td>−; 0.72</td>
<td>−; 0.16</td>
<td>−; 0.71</td>
<td></td>
<td>+; 0.10</td>
<td>0.27</td>
<td>0.27</td>
</tr>
<tr>
<td>$T_b$~$Tair$+$SOL$+$WS$+$WS^2$+LAI$+LAI^2$</td>
<td>+; 1.00</td>
<td>+; 0.95</td>
<td>+; 0.42</td>
<td>−; 0.47</td>
<td>−; 0.73</td>
<td>−; 0.89</td>
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<td>0.20</td>
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<tr>
<td>$T_b$~$Tair$+$SOL$+$WS$+$WS^2$+LAI</td>
<td>−; 0.98</td>
<td>+; 0.92</td>
<td>+; 0.40</td>
<td>−; 0.45</td>
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<td>−; 0.04</td>
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<td>0.20</td>
</tr>
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<td>$T_b$~$Tair$+$SOL$+$WS$+$LAI$</td>
<td>+; 0.90</td>
<td>+; 0.40</td>
<td>+; 0.32</td>
<td></td>
<td>−; 0.05</td>
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<td></td>
<td>0.19</td>
<td>0.19</td>
</tr>
<tr>
<td>$T_b$~$SOL$+$WS$+$LAI$</td>
<td>+; 0.37</td>
<td>+; 0.31</td>
<td></td>
<td>−; 0.03</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.20</td>
<td>0.20</td>
</tr>
<tr>
<td>$T_b$~$WS$+$LAI$</td>
<td>+; 0.35</td>
<td></td>
<td>−; 0.03</td>
<td></td>
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<td></td>
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<td>0.18</td>
<td>0.18</td>
</tr>
<tr>
<td>$T_b$~LAI</td>
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<td>−; 0.03</td>
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</tr>
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</table>
Figure S1.1. Location of lizard populations (n=269) with $T_b$ data, overlaid over our habitat classification.