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Moving From Fear to Hope Through Projections, Radiative Constraints, and Diurnal Controls:
Earth's Warmest Surface Temperatures

A dissertation submitted in partial satisfaction of the
requirements for the degree Doctor of Philosophy

in

Earth Sciences

by

Anthony Wilson

Committee in charge:

Arthur Miller, Co-Chair
Nicholas Lutsko, Co-Chair
Ivan Evans
Sasha Gershunov

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University of California San Diego

2026

DEDICATION

To my Uncle Jesse, who provided the foundation, and my Uncle Edward, who provided the house for my family, and my Aunt Ella Sue, the Matriarch who made the house a home. This is in your honor and in honor of the many generations before of Uncle Jesses, Uncle Edwards, Aunt Ella Sues.

EPIGRAPH

"I am a writer and my faith in the world of art is intense, but not irrational, nor naïve - because art takes us and makes us take a journey beyond price, beyond cost, into bearing witness to the world as it is and as it should be. Art invites us to know beauty and to solicit it, summon it, from even the most tragic of circumstances."

"I know the world is bruised and bleeding, and though it is important not to ignore its pain, it is also critical to refuse to succumb to its malevolence. Like failure, chaos contains information that can lead to knowledge - even wisdom. Like art"

Toni Morrison

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PREFACE

This dissertation contains an introductory chapter and three manuscript-style chapters on physical constraints governing Earth's hottest surface and near-surface air temperatures. The first manuscript chapter, now Chapter 2, examines CMIP6 projections of the hottest surface-temperature extremes and is currently in revision for *Geophysical Research Letters*. Chapter 3 develops radiative constraints on the warmest daily-mean surface temperatures. Chapter 4 develops a reduced-order diurnal-cycle framework for extreme daily-maximum temperatures.

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PUBLICATIONS

- Wilson, A., Lutsko, N., Faggiani Dias, D., and Miller, A. J. (2026, submitted): *Projections of Earth's Hottest Surface Temperatures in CMIP6*. Submitted to *Geophysical Research Letters*. The dissertation author was the primary investigator and first author of this manuscript.
- Wilson, A., Lutsko, N., and Miller, A. J. (in prep.): *Radiative Constraints on Earth's Warmest Daily-Mean Surface Temperatures*. In preparation for submission to *Climate Dynamics*. The dissertation author was the primary investigator and first author of this manuscript.
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FIELDS OF STUDY

Major Field: Earth Sciences

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ABSTRACT OF THE DISSERTATION

Moving From Fear to Hope Through Projections, Radiative Constraints, and Diurnal Controls:
Earth's Warmest Surface Temperatures

by

Anthony Wilson

Doctor of Philosophy in Earth Sciences

University of California San Diego, 2026

Arthur Miller, Co-Chair
Nicholas Lutsko, Co-Chair

Extreme land temperatures are among the most direct and consequential expressions of climate change, with impacts on human health, ecosystems, infrastructure, and the habitability of hot regions. Yet the physical controls on Earth's hottest surface and near-surface air temperatures remain incompletely understood, especially in the dry subtropical environments where record-setting heat most often occurs. This dissertation addresses that problem by linking climate-model projections, radiative-transfer theory, and reduced-order land-atmosphere modeling.

First, I analyze CMIP6 simulations to evaluate how the hottest land temperatures change

under greenhouse forcing. The results show that annual hottest daily-mean and daily-maximum temperatures over tropical land warm about 30–40% faster than the tropical land mean. The geography of record-like heat remains concentrated in subtropical arid and semi-arid regions, particularly the Middle East and South Asia, while the likelihood of exceeding a fixed historical hottest-land benchmark increases by about 35% per 1 °C of tropical land warming.

Second, I develop a daily-mean radiative framework for Earth’s warmest dry states using a simplified surface–atmosphere energy balance constrained by line-by-line radiative-transfer calculations. The hottest present-day daily-mean states occur in hot, dry columns that remain close to a top-of-atmosphere radiative balance. Even when the lower atmosphere is strongly infrared opaque, outgoing longwave radiation continues to increase with temperature. Doubling CO₂ shifts this balance toward warmer conditions by reducing longwave emission at fixed temperature, but it does not remove the radiative constraint.

Third, I examine daily-maximum temperatures with a diurnal-cycle model for the surface skin layer and a deep convective boundary layer. The model shows that the surface skin can become tens of kelvin warmer than both near-surface air and the bulk boundary layer during the afternoon maximum. This separation arises from the contrast between the shallow thermal inertia of the land surface and the much larger heat capacity of the boundary layer. Together, these results clarify why Earth’s warmest temperatures occur in hot, dry desert environments, why satellite-observed skin temperatures can greatly exceed standard air-temperature measurements, and how greenhouse forcing alters both daily-mean and daily-maximum heat extremes.

Chapter 1

Introduction

1.1 Motivation and Scope

Extreme heat is one of the clearest and most consequential manifestations of a warming climate. Observed and projected increases in the frequency, intensity, and duration of heat extremes affect mortality, labor capacity, infrastructure reliability, agriculture, and ecosystems (Seneviratne et al., 2021; Perkins-Kirkpatrick and Lewis, 2020; Vicedo-Cabrera et al., 2021; Stillman, 2019; Dunne et al., 2013). The physical hazards associated with heat are not controlled by temperature alone: humidity, exposure, acclimatization, behavior, infrastructure, and vulnerability all matter for impacts (Sherwood and Huber, 2010a; Raymond et al., 2020; Coffel et al., 2018). Nevertheless, dry-bulb temperature extremes remain a fundamental part of the climate system’s upper tail. They describe how hot the land–atmosphere system itself can become, independent of the additional physiological burden imposed by humidity, and they provide a direct way to ask how far surface heating can be pushed by greenhouse forcing.

This dissertation asks a deliberately physical question: what controls Earth’s warmest surface and near-surface temperatures, and how do those controls change under increased greenhouse forcing? The goal is not to produce a complete assessment of heat risk. Instead, the dissertation focuses on the physical upper envelope of dry heat: where the hottest land temperatures occur, how comprehensive climate models project those extremes to change, why hot dry columns remain radiatively constrained, and how daily-mean radiative states are translated into

daily-maximum temperatures by land-surface and boundary-layer processes.

This framing matters because “extreme heat” is not a single quantity. A record daily maximum, a warm daily mean, a hot nighttime minimum, a humid heat-stress event, and a remotely sensed land-surface skin-temperature maximum can occur in different places and can be controlled by different processes. Human-health studies often emphasize humid heat stress, heat index, wet-bulb temperature, nighttime cooling, exposure, and vulnerability. Those quantities are essential for impacts, but they answer a different question from the one emphasized here. This dissertation treats the hottest dry-bulb and surface-temperature states as a specific object of study rather than as a complete proxy for all heat-related hazards.

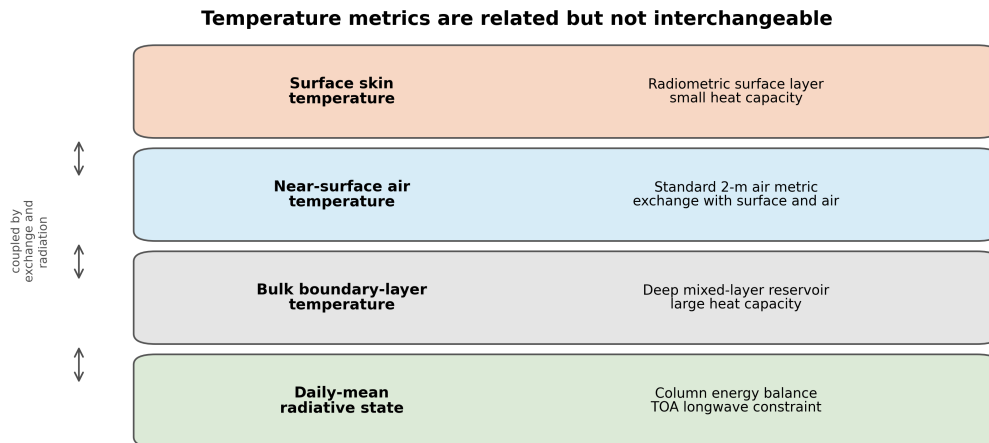


Figure 1.1. Conceptual distinction among temperature metrics used throughout the dissertation. Surface skin temperature, standard near-surface air temperature, bulk boundary-layer temperature, and daily-mean radiative state are related by surface exchange and radiation, but they are not interchangeable. This distinction motivates the separation between the CMIP6 projection analysis, the daily-mean radiative-transfer analysis, and the reduced-order diurnal-cycle framework.

1.2 Prior Work and Open Questions

Previous work has established several important controls on extreme heat. Land regions warm more rapidly than the ocean, and the warmest extremes can amplify relative to

mean temperature under greenhouse forcing (Seneviratne et al., 2021; Byrne, 2021). Soil-moisture depletion and land–atmosphere coupling can intensify hot extremes by suppressing latent heat flux and shifting available energy into sensible heating (Seneviratne et al., 2010; Fischer et al., 2007; Miralles et al., 2019). Satellite observations show that land-surface skin temperatures can greatly exceed near-surface air temperatures, with the hottest remotely sensed surfaces occurring in arid regions such as the Lut and Sonoran deserts (Mildrexler et al., 2011a; Zhao et al., 2021a). Station-based and WMO-evaluated records further show that near-surface air-temperature extremes are concentrated in hot dry environments, but also that individual records require careful evaluation of instrumentation, siting, exposure, and meteorological context (El Fadli et al., 2013; Merlone et al., 2019b; World Meteorological Organization, 2019).

These studies provide the foundation for the dissertation, but they also leave a gap. Much of the extreme-heat literature is organized around impacts, event attribution, regional heat waves, humid heat stress, or changes in percentile-based extremes. Those approaches are important, but they do not fully isolate the physical controls on the hottest dry states of the climate system. Conversely, idealized theories of radiative limits clarify how hot atmospheres emit to space, but they do not by themselves predict the geography of model-projected extreme heat or the difference between daily-mean and daily-maximum temperature. The contribution of this dissertation is to connect these perspectives across a hierarchy of tools.

Radiative theory is especially important for interpreting the hottest daily-mean states. In a daily-mean framework, a hot dry column must balance absorbed solar radiation with outgoing longwave radiation. Even when the lower atmosphere is strongly infrared-opaque, outgoing longwave radiation can continue to increase with temperature because emission to space occurs through spectral windows and from vertically distributed atmospheric layers (Pierrehumbert, 2010; Koll and Cronin, 2018; Jeevanjee et al., 2021). This analytical work is central to the interpretation developed here: the hottest dry states are not unconstrained simply because the lower atmosphere is optically thick. Instead, greenhouse forcing shifts a radiative balance that remains limited by spectrally distributed longwave emission.

Boundary-layer and land-surface theory provide the complementary subdaily perspective. Daily-maximum temperature is usually an afternoon quantity, so it depends on how solar heating is partitioned among a shallow surface layer, the near-surface air, and the deeper convective boundary layer. Classic surface-energy-balance and boundary-layer theory show that turbulent exchange, surface heat capacity, entrainment, boundary-layer depth, and subsurface heat storage all influence the daytime maximum (Brutsaert, 1982; Stull, 1988; Garratt, 1992). Thus, a daily-mean radiative constraint can set the background state, but it cannot by itself determine the observed or modeled daily maximum at two meters.

1.3 Tools, Datasets, and Why They Are Used

The dissertation uses three levels of model complexity (Fig. 1.2). Each level is chosen because it answers a different part of the physical question. Comprehensive climate models are used to study the forced climate response and the geography of hottest-land extremes. Line-by-line radiative-transfer calculations are used to isolate the spectral longwave physics of hot dry columns. A reduced-order diurnal-cycle model is used to interpret how a daily-mean radiative state is expressed as a daily-maximum surface and near-surface air temperature.

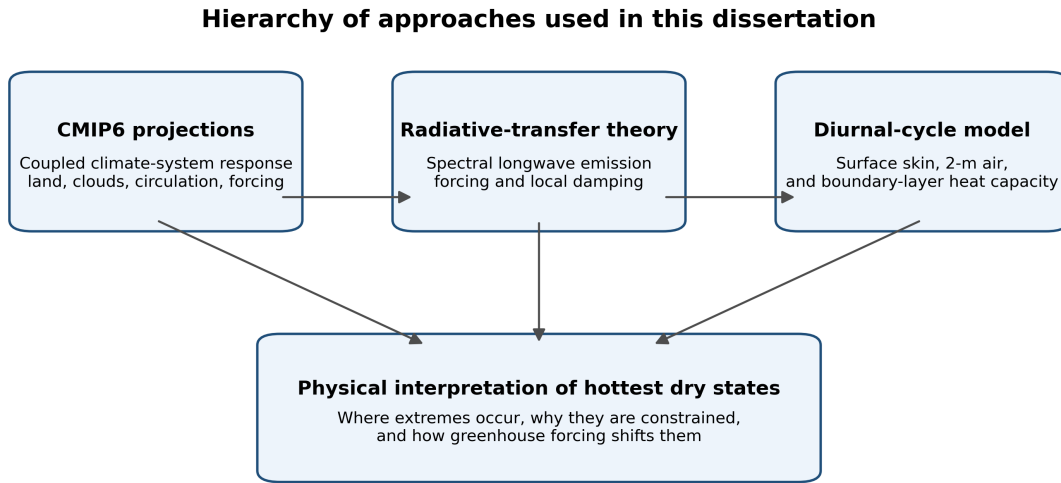


Figure 1.2. Hierarchy of approaches used in the dissertation. CMIP6 simulations provide the comprehensive climate-system response, line-by-line radiative-transfer calculations isolate the daily-mean radiative constraint, and a reduced-order diurnal-cycle model connects that background state to daily-maximum temperature. The dissertation contribution is the synthesis across these levels rather than any single tool in isolation.

A CMIP model is a comprehensive numerical climate model participating in the Coupled Model Intercomparison Project. These models solve discretized equations for atmosphere, ocean, land, and sea ice, together with parameterizations for unresolved processes such as clouds, turbulence, convection, radiation, and land-surface exchange (Eyring et al., 2016). They are appropriate for Chapter 2 because the geography and forced evolution of extreme heat depend on coupled climate processes that cannot be represented by a single-column theory alone. At the same time, CMIP models differ in resolution, land-surface schemes, soil hydrology, vegetation treatment, turbulent exchange, and cloud parameterizations. These differences are not incidental for extreme heat: the partitioning of energy between latent and sensible heat, the representation of dry soils, and the depth and mixing of the boundary layer can all affect the hottest simulated temperatures. For this reason, Chapter 2 evaluates historical model performance before interpreting projections.

Observational products are used as benchmarks, not as perfect truth. Station coverage

is sparse in many of the world’s hottest desert regions, and gridded products necessarily combine observations with interpolation, homogenization, and assumptions about spatial covariance (Rohde and Hausfather, 2020; Hersbach et al., 2020a). Reanalysis products provide physically complete gridded fields, but they are constrained by model physics and data assimilation choices rather than direct observations alone. Satellite products provide global spatial coverage of land-surface skin temperature, but they do not directly measure standard two-meter air temperature. These differences explain why the dissertation distinguishes among station-like air temperature, gridded near-surface air temperature, and remotely sensed skin temperature.

Line-by-line radiative transfer is used because the radiative behavior of very hot dry columns depends on spectral detail. In such columns, some infrared bands are strongly opaque, but other spectral regions and emission levels continue to contribute to outgoing longwave radiation. Bulk gray-atmosphere models are useful pedagogically, but they cannot capture the detailed spectral cancellation and window-region behavior emphasized in recent analytical work (Koll and Cronin, 2018; Jeevanjee et al., 2021). Chapter 3 therefore uses line-by-line calculations based on spectroscopic absorption data and continuum absorption parameterizations (Clough et al., 1992, 2005; Gordon et al., 2017; Mlawer et al., 2012). This tool is not meant to replace a climate model; it is used to isolate the local clear-sky radiative forcing and feedback structure of the hottest daily-mean states.

The reduced-order diurnal-cycle model is used for a different reason. Daily-maximum temperature depends on transient energy storage and exchange over the course of a day. A comprehensive model includes these processes but makes it difficult to identify the controlling terms. A reduced-order model sacrifices completeness in order to expose the roles of surface thermal inertia, turbulent coupling, and boundary-layer heat capacity. This makes it useful for interpretation, but it also means that its quantitative values should be viewed as benchmarks rather than complete predictions.

1.4 Reproducibility and Methodological Assumptions

A central aim of the dissertation is to make the methodological choices traceable. Chapter 2 specifies the CMIP6 variables, experiments, time periods, model subsets, historical benchmark products, and preprocessing steps used to compare models and observations. Chapter 3 describes the construction of the daily-mean radiative-transfer profiles, the temperature and humidity assumptions, the CO₂ perturbation, and the diagnosed forcing and feedback metrics. Chapter 4 states the parameter choices used in the reduced-order diurnal model, including surface heat capacity, boundary-layer heat capacity, turbulent exchange, and imposed solar forcing.

The assumptions behind these methods are part of the scientific argument. CMIP6 projections are physically comprehensive but model-dependent. Observational products are essential for evaluation but uncertain in remote hot regions. Line-by-line calculations provide detailed clear-sky radiative physics but require prescribed atmospheric profiles, humidity structure, surface properties, and cloud-free conditions. Reduced-order diurnal models clarify mechanism but neglect horizontal advection, heterogeneous surfaces, mesoscale circulations, and many details of land-atmosphere exchange. These limitations do not invalidate the approach; they define what each tool can and cannot claim.

1.5 What Is New Here

The dissertation makes three connected contributions. First, it evaluates how the hottest land-temperature tail behaves in CMIP6 simulations, including both historical model skill and future changes in annual hottest-land temperature. Second, it develops a daily-mean radiative interpretation of hot dry states, showing that increased CO₂ shifts but does not remove the top-of-atmosphere longwave constraint. Third, it introduces a reduced-order diurnal framework that explains why surface skin temperature, near-surface air temperature, and bulk boundary-layer temperature can respond differently even when they are linked to the same background radiative state.

The novelty lies in the synthesis. Chapter 2 asks what comprehensive models project. Chapter 3 asks why the hottest daily-mean states remain radiatively constrained. Chapter 4 asks how that constraint is translated into a daily maximum. Together, the chapters show that Earth’s hottest dry extremes are both radiatively constrained and locally amplified: greenhouse forcing shifts the background energetic state, while land-surface and boundary-layer processes determine how that shift appears in the hottest daily maximum.

1.6 Dissertation Roadmap

Chapter 2 uses CMIP6 simulations to evaluate historical model performance and project changes in the hottest land temperatures under SSP2-4.5 and abrupt CO₂ forcing. It focuses on the geography of hottest-land grid cells, the amplification of annual hottest daily-mean and daily-maximum temperatures relative to tropical land mean warming, and the changing likelihood of exceeding a fixed historical hottest-land benchmark.

Chapter 3 develops a daily-mean radiative constraint on hot dry states using line-by-line radiative-transfer calculations and a reduced surface–atmosphere energy-balance framework. It diagnoses fixed-state CO₂ forcing and local radiative feedback across paired surface skin and near-surface air temperatures, connecting the results to analytical work on spectrally resolved emission from warm optically thick atmospheres.

Chapter 4 extends the analysis to the diurnal cycle by modeling the coupled evolution of a shallow surface skin layer and a deeper dry convective boundary layer. This chapter provides a physical bridge between daily-mean radiative limits and the daily-maximum temperatures analyzed in comprehensive climate models.

Chapter 5 synthesizes the results, discusses limitations and uncertainty, and outlines future directions. The central message is that extreme dry heat is serious but physically interpretable. Understanding its controls helps turn projections of hotter extremes into testable statements about radiative constraints, land-surface coupling, and boundary-layer dynamics.

Chapter 2

Projections of Earth’s Hottest Surface Temperatures in CMIP6

Key Points

- CMIP6 captures the broad spatial pattern of $p99(T_{\max})$ vs Berkeley Earth, supporting projections of record-like heat.
- Tropical extremes amplify: T_{DM} and T_{DX} warm $\sim 30\text{--}40\%$ faster than T_{TL} in SSP2-4.5 and abrupt $4\times\text{CO}_2$.
- Annual hottest-land “record-like” exceedances become common under SSP2-4.5, with odds increasing $\sim 35\%$ per 1°C of tropical land warming.

Abstract

Extreme land heat threatens health, infrastructure, and ecosystems worldwide. Using CMIP6 simulations, we evaluate historical extremes against Berkeley Earth and project future changes under SSP2-4.5 and abrupt-4xCO₂. Historical fidelity is assessed from the spatial pattern of the 99th percentile of daily maximum temperature ($p99 T_{\max}$) over land using centered RMSE, mean bias, and spatial R^2 . We analyze three annual tropical land indices: tropical land-mean temperature (T_{TL}), daily-mean temperature on the hottest day each year (T_{DM}), and the maximum daily-maximum temperature (T_{DX}). Across models, T_{DM} and T_{DX} warm 30–40%

faster than T_{TL} in transient trends and equilibrium responses, consistent with amplified upper-tail warming. Hotspot-frequency maps of the annual global land maximum show persistence in subtropical arid and semi-arid regions, especially the Middle East and South Asia. We define a fixed-threshold record-like benchmark for hottest-land temperature and relate exceedance likelihood to tropical land warming; pooled fits show exceedance odds rise $\sim 35\%$ per 1°C .

Plain Language Summary

Hot days are becoming more common as the planet warms. We use 21 CMIP6 models to study extreme heat over land, focusing on the hottest daytime temperature each year (T_{DX}). We analyze a mid-range future scenario (SSP2-4.5) and an experiment where carbon dioxide is quadrupled, sampling both transient and equilibrium responses. In both cases, hottest-day temperatures over tropical land rise faster than tropical-mean land temperature, showing that extremes intensify faster than the background climate. We also evaluate how well models reproduce the observed spatial pattern of past extreme heat using the Berkeley Earth dataset. Many models capture the broad pattern, but others have large warm or cold biases and place the hottest regions incorrectly. Tracking the single hottest land grid cell each year shows strong spatial persistence: record-setting heat remains concentrated in subtropical arid and semi-arid regions, especially the Middle East and adjacent South Asia. Finally, a fixed-threshold “record-like” benchmark indicates that exceeding the late-20th-century hottest-land temperature becomes more common as tropical land warms. These results show that mean warming alone does not determine where the most dangerous heat will occur or how often record-breaking extremes will happen there.

2.1 Introduction

Extreme heat is one of the most direct impacts of climate change, affecting human health and productivity, agriculture, and ecosystems (Vicedo-Cabrera et al., 2021; Dunne et al., 2013;

Schlenker and Roberts, 2009; Zhao et al., 2017; Stillman, 2019). A large body of literature now investigates extreme heat, including the controls on moist and dry heatwaves, projected changes in a warming climate, and the contributions of meteorological factors and land-surface interactions (Seneviratne et al., 2021; Perkins-Kirkpatrick and Lewis, 2020; Raymond et al., 2020; Coffel et al., 2018; Fischer et al., 2007; Miralles et al., 2019). This work is increasingly being used by public health researchers to help stakeholders prepare for more intense heat extremes (Lutsko, 2019).

One topic that has received less attention is the very warmest surface temperatures on Earth. While it is known that parts of the tropics are approaching thermal habitability limits (Sherwood and Huber, 2010a; Raymond et al., 2020; Coffel et al., 2018), the upper bound of these temperatures has not been investigated in detail. Changes in maximum temperatures reveal how the tail of the global temperature distribution evolves and serve as a vivid indicator of a warming climate. Here, we use state-of-the-art climate models to examine how these warmest temperatures are projected to change over the 21st century.

Earth's warmest surface temperatures are typically found in subtropical deserts, where daily-mean temperatures can reach up to $\sim 44^{\circ}\text{C}$ and daily-maximum temperatures the mid- $50\text{s}^{\circ}\text{C}$ (Mildrexler et al. (2011a); Stachelski (2013), Figure 1). Surface, or skin, temperatures can be even warmer, with satellites measuring values as high as 80.8°C Zhao et al. (2021a). Subtropical deserts have all the ingredients needed to generate extreme temperatures: high levels of insolation, extreme surface dryness and the relatively low surface emissivity of sand. Low moisture levels are crucial for generating high temperatures, as latent heat fluxes can efficiently cool the surface Seneviratne et al. (2010), while sand's relatively weak emissivity ($\sim 0.85\text{-}0.9$, compared to >0.9 for most other surface types, e.g., Ogawa and Schmugge (2004); Jin and Liang (2006); Huang et al. (2016); Chen et al. (2019)) requires warmer temperatures to achieve the same emission as other surfaces.

Measuring these extreme temperatures is difficult because they often occur in remote deserts (e.g., the Sahara, Gobi, Sonoran, and Lut), where station coverage is sparse. Satellites

provide continuous monitoring of skin temperature but not near-surface air temperature; the 80.8°C estimate is therefore based on a relatively short satellite record (July 2002–December 2019; Zhao et al., 2021a). Historical air-temperature records include disputed measurements of 56.7°C (Death Valley, 1913) and 57.8°C (‘Aziziya, 1922) (Spencer et al., 2026; El Fadli et al., 2013), while more recent values near 54°C have been reported in Kuwait and Pakistan (Merlone et al., 2019b; World Meteorological Organization, 2019).

Studying extreme temperatures also poses methodological challenges because they are, by definition, rare events, making it difficult to obtain robust statistics for trend detection and model evaluation. Moreover, focusing on these extremes adds an additional dimension of complexity: the locations where maximum temperatures occur may themselves shift, requiring models to correctly capture spatial changes as well as the physical drivers of temperature extremes.

To address these issues, we first evaluate the ability of state-of-the-art climate models to simulate the observed spatial pattern of historical extreme land heat. We then examine how strongly the hottest land temperatures amplify relative to tropical-mean land warming under both transient (SSP2-4.5) and equilibrium (abrupt-4×CO₂) forcing, and where the world’s hottest land-temperature hotspots occur. Finally, we quantify changes in exposure using a fixed-threshold “record-like” metric based on the annual hottest-land temperature, and estimate how exceedance likelihood scales with tropical land warming in pooled fits. Together, these analyses clarify where record-setting heat is most likely to recur and how rapidly record-like extremes become more common as the climate warms.

2.2 Methods

2.2.1 Datasets and preprocessing

We analyze daily near-surface air temperature extremes in observations and CMIP6 models. Observed daily maximum near-surface air temperature (t_{asmax}) is taken from Berkeley Earth (Rohde and Hausfather, 2020). Unless otherwise noted, historical evaluation uses

1980–2014 to match the satellite-era reference period and to maximize overlap with the CMIP6 historical experiment.

Model simulations are drawn from CMIP6 (Eyring et al., 2016). We define a core ensemble of $N_{\text{core}} = 21$ models (Table 1; Table S1), and this same set is used for the historical skill metrics (Table 1) and for the primary multi-model analyses in Fig. 1. For projections, we analyze SSP2-4.5 simulations over 2015–2100.

A CMIP6 model is a comprehensive coupled climate model that represents the atmosphere, ocean, land surface, and sea ice on a numerical grid, together with parameterizations for unresolved processes such as turbulence, clouds, radiation, convection, snow, vegetation, and soil hydrology. This matters for the present analysis because the hottest land temperatures are strongly affected by land-surface parameterizations. Different models make different assumptions about soil water availability, rooting depth, stomatal resistance, surface albedo, roughness length, and the partitioning of available energy into latent and sensible heat. These choices can influence both the magnitude and geography of simulated dry heat extremes. For this reason, the analysis below treats CMIP6 as an ensemble of physically based but imperfect model realizations, and historical pattern evaluation is used as a prerequisite for interpreting future projections.

Several analyses require different underlying daily variables and/or complete time coverage, so the effective sample size varies by diagnostic. In Fig. 2 we analyze three indices derived from daily temperature: the tropical land-mean temperature (T_{TL}), the daily-mean temperature on the hottest day (T_{DM}), and the annual maximum daily maximum temperature (T_{DX}). Because availability of the processed SSP2-4.5 time series differs by index, the projection sample sizes are $N_{TL} = 24$, $N_{DM} = 21$, and $N_{DX} = 17$ (Table S1), and we report the corresponding N in the figure legend. For equilibrium warming (Fig. 2c), we further restrict to models with both abrupt- $4\times\text{CO}_2$ and the corresponding piControl simulations available for the index; the final sample size is reported in the panel.

In Fig. 3, the record-exceedance analysis requires both daily t_{asmax} and daily t_{as} over

historical and SSP2-4.5 in order to define the fixed historical record and relate exceedances to a warming predictor. This yields $N = 17$ models (Table S1); any additional model-specific exclusions (e.g., insufficient years in the regression fit window) are noted alongside the analysis output and do not alter the data-availability subset.

All temperatures are converted to degrees Celsius ($^{\circ}\text{C}$; Kelvin minus 273.15). Unless otherwise stated, analyses are restricted to land grid boxes within 45°S – 45°N . Land points are identified using a land mask on each model grid. When comparing model fields with observations, model data are bilinearly interpolated to the Berkeley Earth latitude–longitude grid prior to computing spatial metrics.

We use the following temperature indices throughout:

1. T_{TL} : annual-mean near-surface temperature averaged over tropical land (45°S – 45°N). We denote the tropical-land spatial mean with an overline, $\overline{T}_{TL}$, and define tropical land warming relative to a baseline period as

$$\Delta\overline{T}_{TL} = \overline{T}_{TL} - \overline{T}_{TL}^{\text{ref}},$$

where $\overline{T}_{TL}^{\text{ref}}$ is the mean over 2005–2014 unless stated otherwise.

2. T_{DM} : annual maximum of daily-mean near-surface air temperature (computed from daily tas).
3. T_{DX} : annual maximum of daily-maximum near-surface air temperature (computed from daily tasmax).
4. T^* : annual hottest-land temperature, defined as the annual maximum of the daily maximum over all land grid boxes within 45°S – 45°N . In practice, we compute the spatial maximum of daily tasmax over land and then take the annual maximum of that daily series.

2.2.2 Historical model evaluation

We evaluate historical model fidelity using the climatological 99th percentile of daily maximum temperature, denoted $T_{DX,99}$, computed from daily `tasmax` over 1980–2014. For each model and for Berkeley Earth, $T_{DX,99}$ is computed at each land grid box and then compared on the common Berkeley Earth grid.

We summarize spatial agreement using three complementary pattern metrics computed over all land grid boxes (N points). Let M_i and O_i denote the model and observed $T_{DX,99}$ at grid box i , and let primes denote anomalies relative to the spatial mean (i.e., $M'_i = M_i - \bar{M}$ and $O'_i = O_i - \bar{O}$):

- **Spatial bias:**

$$\text{Bias} = \frac{1}{N} \sum_{i=1}^N (M_i - O_i).$$

- **Centered RMSE (cRMSE):**

$$\text{cRMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N (M'_i - O'_i)^2}.$$

- **Spatial pattern R^2 (squared spatial correlation):**

$$R^2 = \frac{\text{Cov}(M', O')^2}{\text{Var}(M') \text{Var}(O')},$$

where covariance and variance are taken across grid boxes.

Together, these metrics separate (i) systematic warm/cool offsets (Bias), (ii) mismatch in the amplitude of the spatial pattern (cRMSE), and (iii) agreement in pattern structure (R^2). Model skill values are reported in Table S2 and are used to contextualize inter-model spread in projections.

2.2.3 GLM scaling of record-like exceedance likelihood

To quantify how the likelihood of a record-like hottest-land year changes with warming, we use a fixed-threshold exceedance definition based on the historical period. We define a historical benchmark

$$T_{\text{hist}}^* = \max_{y \in [1980, 2014]} T^*(y),$$

where y indicates year, and an annual exceedance indicator

$$I(y) = \begin{cases} 1, & T^*(y) > T_{\text{hist}}^*, \\ 0, & \text{otherwise.} \end{cases} \quad (2.1)$$

This fixed threshold yields an impacts-style interpretation (how often future climate exceeds a late-20th-century record) and avoids the progressively tightening target that occurs under running-maximum “new record” definitions.

We relate exceedance probability to tropical land warming using a pooled logistic model fit over 2015–2100:

$$\text{logit } P[I(y) = 1] = \alpha_0 + \alpha_1 \Delta \bar{T}_{TL}(y), \quad (2.2)$$

where $\Delta \bar{T}_{TL}(y)$ is tropical land-mean tas anomaly relative to 2005–2014. The slope α_1 is reported as an odds ratio $\text{OR} = \exp(\alpha_1)$ per 1°C of tropical land warming. To stabilize the pooled fit given inter-model heterogeneity, we apply ridge regularization (L2 penalty) and estimate uncertainty by bootstrapping the model ensemble (resampling models with replacement and re-fitting the pooled model), reporting the 10th–90th percentile envelope of predicted probabilities.

For interpretability, we also summarize the expected number of exceedance-years over a future window (e.g., 2026–2100) by summing fitted annual probabilities, $E = \sum_y P[I(y) = 1]$, computed separately for each model’s warming trajectory and then summarized across models.

2.3 Results

2.3.1 Model performance for extreme land surface temperatures

Table 2.1 reports these metrics for the 21-model core ensemble; the final two rows show the multi-model mean and multi-model median. We use the median as a more robust benchmark because a small number of outliers can skew mean-based summaries.

Table 2.1. Performance of 21 CMIP6 models in simulating the spatial pattern of extreme land heat. Centered RMSE (cRMSE; °C), mean bias (°C), and spatial R^2 are computed by comparing the historical $p99(T_{\max})$ field (1980–2014) with Berkeley Earth over land grid cells. For illustrative purposes, cells are shaded green when a model outperforms the multi-model median (lower cRMSE, higher R^2) and when the magnitude of bias is less than 0.5°C, and shaded red otherwise. The final two rows show the multi-model mean and multi-model median.

Model	RMSE (°C)	Mean Bias (°C)	Spatial R^2
ACCESS-CM2	2.445	-0.280	0.851
ACCESS-ESM1-5	3.630	+1.350	0.686
AWI-CM-1-1-MR	2.548	+0.531	0.850
CAMS-CSM1-0	2.538	+1.798	0.849
CMCC-ESM2	2.300	+0.670	0.863
CNRM-CM6-1	2.535	-0.779	0.874
CNRM-CM6-1-HR	2.971	-1.575	0.841
CNRM-ESM2-1	2.489	-0.051	0.878
CanESM5	3.732	+3.060	0.782
EC-Earth3	2.277	+0.449	0.881
EC-Earth3-CC	2.328	+0.889	0.875
EC-Earth3-Veg	2.305	+0.247	0.879
EC-Earth3-Veg-LR	2.281	-0.160	0.877
GFDL-CM4	2.239	-1.143	0.903
GFDL-ESM4	2.266	-0.431	0.896
INM-CM4-8	3.261	+0.625	0.766
INM-CM5-0	2.917	+0.428	0.806
IPSL-CM6A-LR	2.774	-3.026	0.845
NorESM2-LM	2.489	+0.519	0.809
NorESM2-MM	2.305	+0.190	0.839
TaiESM1	2.296	-6.471	0.873
Multi-Model Mean	2.616	-0.150	0.844
Multi-Model Median	2.489	+0.247	0.851

There is substantial inter-model spread across all three metrics. Several models show relatively high skill, with cRMSE $\sim 2\text{--}3$ °C and high spatial correlations ($R^2 \geq 0.85$), indicating they capture the large-scale pattern of extreme heat reasonably well. Other models exhibit larger

systematic biases (both warm and cold) and weaker spatial correlations. Where local biases are largest, they often occur in semi-arid and arid regions, suggesting that errors in land-surface processes and land-atmosphere coupling may contribute. Because these metrics are evaluated on native (typically coarse) model grids, they reflect grid-box mean extremes; local extremes could differ at higher resolution. To document the full range of modeled spatial patterns and biases, we provide a supplementary multi-panel “stamp” figure showing $p99(T_{\max})$ on each model’s native grid and the corresponding bias relative to Berkeley Earth after regridding (Fig. S4). We also summarize overall performance with a composite skill score that combines cRMSE, $|\text{bias}|$, and spatial R^2 (Fig. S5).

By contrast, several models exhibit larger systematic errors. CanESM5 and ACCESS-ESM1-5 show pronounced warm biases, whereas IPSL-CM6A-LR and especially TaiESM1 are strongly cold-biased relative to Berkeley Earth. These models also tend to have weaker spatial correlations.

This is also reflected in the composite model skill score (Fig. S5), which combines cRMSE, $|\text{bias}|$, and spatial R^2 into a single ranking. In that summary, GFDL-ESM4 and several EC-Earth3 variants cluster among the highest-skill models, whereas CanESM5 and ACCESS-ESM1-5 rank near the bottom, consistent with their larger mean biases and weaker spatial agreement.

2.3.2 Geography of Record-Setting Heat

Before quantifying trends, we examine where the most extreme land temperatures occur in observations and in model projections. Record temperatures may also reflect shifts in the *location* of the global land maximum if the hottest regions broaden or migrate under warming.

We diagnose hotspot locations using the hotspot-frequency maps in Fig. 2.1. For each year, we identify the single land grid cell with the global maximum of annual $T_{\max}$ and count how often each grid cell attains this maximum. In Berkeley Earth (1980–2014), hotspots cluster over the Middle East/Persian Gulf and adjacent northwestern South Asia, with fewer events

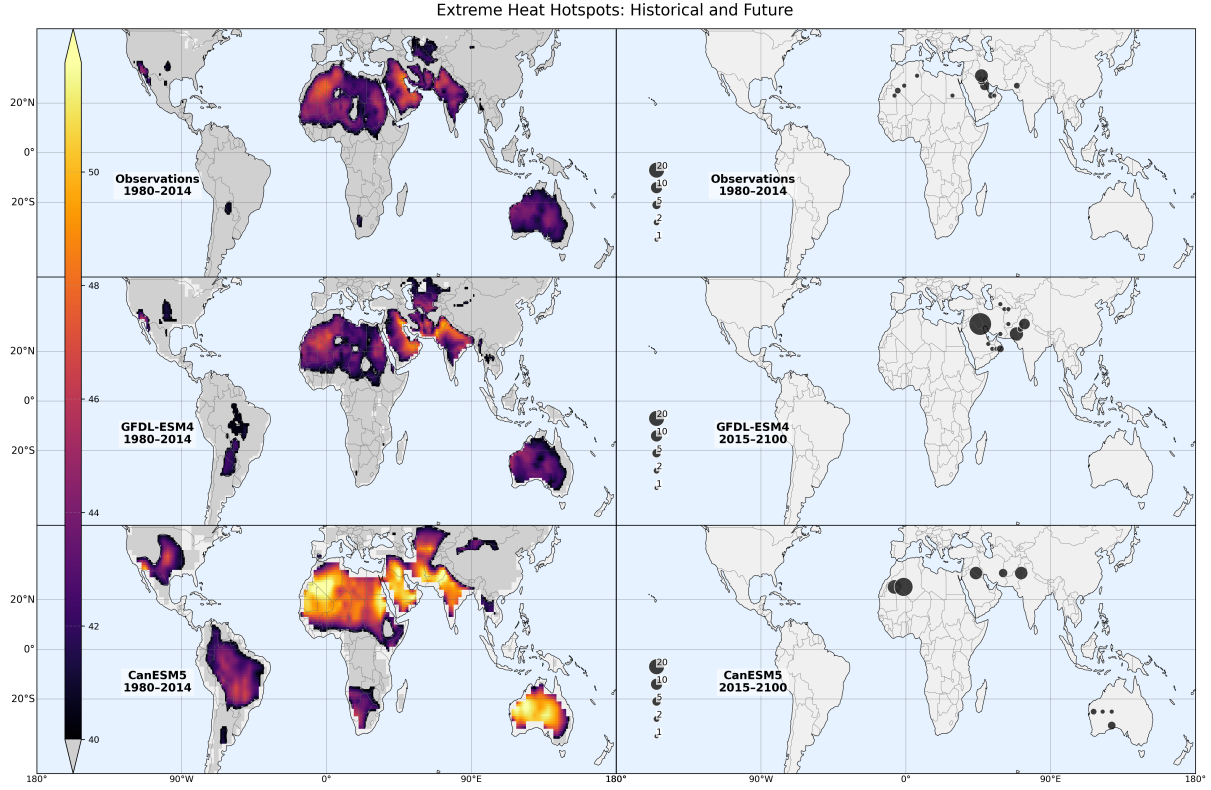


Figure 2.1. Observed and simulated spatial patterns of extreme land heat. Left column: $p99(T_{\max})$ (99th percentile of daily maximum temperature; shading) with the 40°C isotherm contoured in black. Top row shows Berkeley Earth over 1980–2014; middle row shows GFDL-ESM4 (high skill in Table 2.1) and bottom row shows CanESM5 (strong warm bias) over 1980–2014. Right column: hotspot frequency, defined as the number of years in which a grid cell attains the *global land maximum* of annual $T_{\max}$ (marker size; 35 years for observations, 86 years for projections). Top row is for observations and bottom rows show SSP2-4.5 projections over 2015–2100 for each example model.

over North Africa and Australia, indicating strong spatial persistence. Regions that are broadly hot in $p99(T_{\max})$ do not necessarily dominate hotspot frequency because this metric isolates the single hottest grid cell each year. Figure S2 shows hotspot-frequency maps for each core model over the historical period.

The middle and bottom right rows of Fig. 2.1 illustrate projected behavior for two models with contrasting historical skill. GFDL-ESM4 maintains a concentrated hotspot distribution dominated by the Middle East and nearby South Asia, whereas CanESM5 produces a more dispersed pattern, with frequent maxima over western Australia and increased occurrence over the

western Sahara. Across the full ensemble, comparing Fig. S2 (historical) and Fig. S3 (SSP2-4.5) shows that dominant hotspot regions change little: the global land maximum remains anchored in a small set of subtropical arid and semi-arid regions, with differences mainly in how dispersed the hotspots become. Consistent with the historical evaluation (Table 2.1), higher-skill models tend to place hotspots closer to the observed Middle East–South Asia corridor, whereas lower-skill models more often introduce prominent maxima in regions that are less favored in the observations.

2.3.3 Transient and equilibrium trends of tropical land extremes

Figure 2.2 summarizes how tropical land temperature responds to warming in the mean state and in the far tail. We consider three annual indices: tropical land-mean temperature T_{TL} , the daily-mean temperature on the hottest day each year T_{DM} , and the annual maximum daily-maximum temperature T_{DX} (Methods). Panel (a) shows SSP2-4.5 projections (2015–2100) as anomalies relative to 2005–2014. For additional context on inter-model spread, Fig. S1 shows the corresponding per-model trajectories and model-by-model trend estimates for a common-model set.

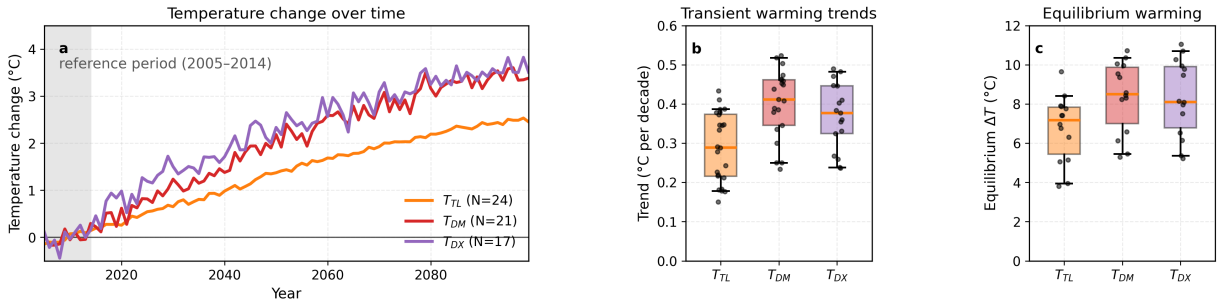


Figure 2.2. Multi-model response of tropical land temperatures in CMIP6 (all changes in °C). (a) Annual evolution of tropical land-mean temperature T_{TL} , the daily-mean temperature on the hottest day each year T_{DM} , and the annual maximum daily-maximum temperature T_{DX} under SSP2-4.5, shown as anomalies relative to 2005–2014. Sample sizes differ across indices due to data availability and completeness (Table S1): $N = 24$ for T_{TL} , $N = 21$ for T_{DM} , and $N = 17$ for T_{DX} . (b) Transient warming trends for each index over 2015–2100 in °C per decade. (c) Equilibrium warming in abrupt- $4\times\text{CO}_2$ experiments, defined as the difference between the late-time mean of abrupt- $4\times\text{CO}_2$ (last 30 years) and the corresponding piControl (°C); this panel uses the subset of models with both experiments available for the relevant index.

All three indices warm substantially over the 21st century. In the multi-model mean, T_{TL} increases by about ~ 2.5 °C by 2100, whereas the hottest-day metrics increase by ~ 3 – 3.5 °C. Interannual variability is larger for T_{DM} and T_{DX} than for T_{TL} , but the forced warming signal is clear.

Sample sizes differ across indices because complete processed time series are not available for all models (Table S1): T_{TL} uses $N = 24$ models, T_{DM} uses $N = 21$, and T_{DX} uses $N = 17$. These differences primarily reflect data availability requirements (daily-mean temperature for T_{TL} and T_{DM} versus daily-maximum temperature for T_{DX}), as well as completeness of the SSP2-4.5 record. All calculations are performed on native model grids, so the plotted values represent grid-box mean extremes; local extremes could differ at higher spatial resolution.

Panels (b) and (c) compare transient and equilibrium responses. Panel (b) shows per-model warming trends over 2015–2100, while panel (c) shows the equilibrium response in abrupt-4 $\times$ CO₂, defined as the difference between the late-time mean of abrupt-4 $\times$ CO₂ and the corresponding piControl (Methods). In both frameworks, extremes warm faster than the mean: T_{DM} and T_{DX} exhibit larger trends and larger equilibrium warming than T_{TL} , while T_{DM} and T_{DX} are similar to each other, suggesting broadly consistent mechanisms controlling the hottest-day mean and the annual maximum of daily maxima.

The ratio of extreme to mean warming implies that the hottest-day indices increase roughly 30–40% faster than T_{TL} , consistent with theoretical expectations for land extremes under warming associated with moisture limitation and land–atmosphere coupling (Byrne, 2021). This scaling provides a useful baseline for interpreting record-breaking behavior: if record temperatures track the far tail, then record magnitudes should increase faster than the tropical land mean by a comparable factor. In subsequent analyses, we also explore whether model performance in the historical spatial pattern (Table 2.1) can be used to weight the multi-model response across these three indices, rather than treating all models equally.

2.3.4 Scaling of record-like extreme heat with tropical land warming

A key implication of percentile-dependent warming over land is that exceedances of a *fixed* historical extreme should become increasingly common as warming accumulates. In the tropical band, our CMIP6 ensemble shows clear tail amplification over land consistent with the theoretical expectation summarized by Byrne (2021): the scaling factor $S_x = \Delta T^x / \Delta \bar{T}$ rises above unity in the upper tail (Fig. S6), reaching $S_{99} \approx 1.27$ over land compared with $S_{99} \approx 1.08$ over ocean. This amplified warming of high percentiles motivates an impacts-style “record-like” metric that asks how often future climate surpasses a familiar late-20th-century benchmark.

We define $T^*(y)$ as the annual hottest-land temperature in year y , computed as the annual maximum of the daily land maximum of `tasmax` (land within 45°S–45°N). We then define a fixed historical benchmark from the 1980–2014 period and an exceedance indicator,

$$I(y) = \begin{cases} 1, & T^*(y) > T_{\text{hist}}^*, \\ 0, & \text{otherwise,} \end{cases} \quad T_{\text{hist}}^* = \max_{y \in [1980, 2014]} T^*(y). \quad (2.3)$$

Unlike a “new record” (running-maximum) definition, this fixed-threshold formulation does not tighten the target over time; instead it directly measures the increasing frequency of exceeding a historical record-like extreme.

To quantify how exceedance likelihood scales with warming, we relate $I(y)$ to tropical land-mean warming $\Delta \bar{T}_{\text{TL}}(y)$ (30°S–30°N land mean `tas`, baseline 2005–2014) using a pooled ridge-regularized logistic regression over 2015–2100. The pooled fit yields an odds ratio of $\text{OR} \approx 1.35$ per $1^\circ\text{C}_{\text{TL}}$, implying that each additional degree of tropical land warming increases the odds of exceeding the 1980–2014 hottest-land benchmark by $\sim 35\%$. In other words, tail amplification documented in Supporting Information Fig. S1 translates into a rapid increase in the frequency with which the climate exceeds a fixed historical extreme. Summing fitted annual exceedance probabilities over 2026–2100 gives an expected ~ 42 exceedance-years in the multi-model mean (out of 75), indicating that surpassing the late-20th-century hottest-land

record becomes a common outcome later in the century under SSP2-4.5.

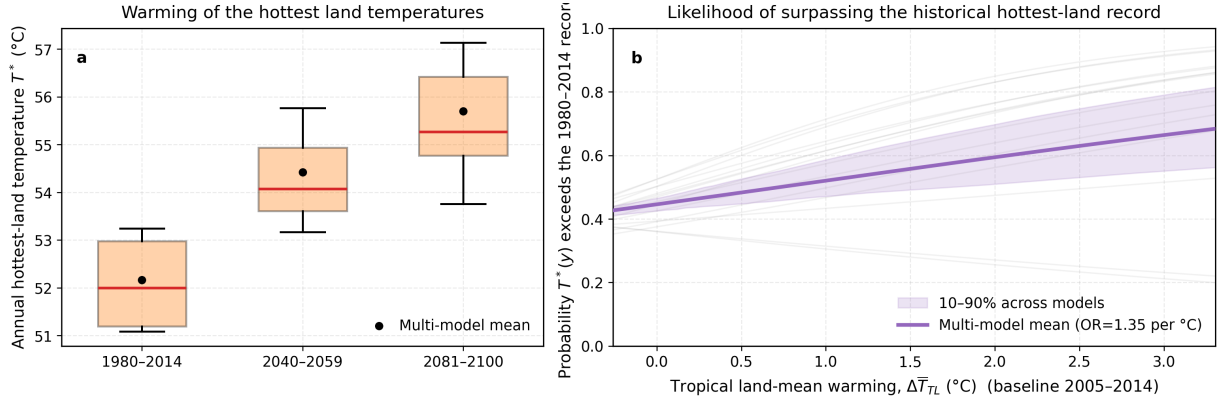


Figure 2.3. Fixed-threshold exceedance of the historical hottest-land benchmark. (a) Model spread of the annual hottest-land temperature T^* across time slices. (b) Probability that $T^*(y)$ exceeds the historical benchmark $T_{\text{hist}}^* = \max_{1980-2014} T^*(y)$ (Eq. 2.1) as a function of tropical land warming $\Delta\bar{T}_{\text{TL}}$ relative to 2005–2014. Thin curves show individual-model ridge-logit fits; the thick curve shows the pooled multi-model ridge-logit fit (2015–2100). Shading indicates the 10th–90th percentile range across bootstrap resamples of the model ensemble.

2.4 Discussion

The analysis in this chapter focuses deliberately on the hottest dry-bulb land temperatures rather than on a comprehensive heat-health metric. This scope is important because several physically related heat metrics answer different questions. Annual maximum daily-maximum temperature emphasizes the upper tail of daytime sensible heating and is closely tied to surface energy balance, soil dryness, boundary-layer mixing, and regional aridity. By contrast, heat index and wet-bulb temperature include humidity and are more directly related to human thermoregulation (Sherwood and Huber, 2010a; Raymond et al., 2020; Coffel et al., 2018). Multi-day heatwave metrics emphasize persistence, circulation anomalies, and soil-moisture memory, while annual maximum daily-minimum temperature emphasizes nighttime cooling, longwave emission, cloudiness, humidity, and boundary-layer stability. These quantities are all important, but they are not interchangeable.

This distinction helps clarify the role of human impacts in motivating the study. Extreme

dry-bulb temperature is relevant to heat risk, infrastructure stress, ecosystems, and agriculture, but it is not the most direct measure of human physiological heat stress. If the primary goal were a heat-health assessment, the analysis would need to include humidity-aware metrics such as heat index or wet-bulb temperature, population exposure, acclimatization, vulnerability, and nighttime recovery. The objective here is narrower and more physical: to understand how the hottest land temperatures simulated by CMIP6 change under greenhouse forcing and where the annual global land-temperature maximum is likely to occur. The results should therefore be interpreted as a contribution to the physical climatology of the hottest dry states rather than as a complete assessment of human heat burden.

Additional model-derived metrics such as annual maximum five-day temperature or annual maximum daily-minimum temperature would be valuable extensions. They would help connect the present analysis to heatwave duration and nighttime recovery, and they may reveal geographic patterns that differ from those of T_{DX} . However, including those metrics for all models would substantially expand the dimensionality of the analysis: each would require separate historical evaluation, future trend analysis, hotspot mapping, model-subset accounting, and uncertainty assessment. In a short-format paper, such additions could obscure the main physical result. For the dissertation, they are best viewed as a clear topic for future work rather than a prerequisite for interpreting the daily-maximum results.

Observational uncertainty is a separate and important limitation. The comparison against Berkeley Earth evaluates how well models reproduce one gridded observational estimate of historical extreme temperature, but it does not eliminate uncertainty in the observations themselves. This matters because the hottest regions are often data sparse, and gridding can smooth or displace local extremes. A useful next step would be an observation–observation comparison, for example contrasting Berkeley Earth and ERA5 over the same period, land mask, and grid-cell diagnostics used here (Rohde and Hausfather, 2020; Hersbach et al., 2020a). Such a comparison would provide a practical estimate of observational and gridding uncertainty that could be included alongside the model metrics in Table 2.1. In that framing, ERA5 would not need to be

compared separately against every model; rather, the Berkeley–ERA5 difference would indicate the scale of benchmark uncertainty against which model biases should be judged.

These limitations do not change the main conclusion of the chapter. The CMIP6 ensemble indicates that the upper tail of tropical-land temperature warms faster than the tropical-land mean and that the annual hottest land locations remain concentrated in subtropical arid and semi-arid regions. But they do affect how the results should be used. The projections are strongest as statements about physical amplification of dry-bulb extremes and the persistence of desert hotspot regions. They should not be interpreted as a complete ranking of future human heat danger, nor as a definitive estimate of point-scale record temperatures in sparsely observed regions.

2.5 Conclusion

CMIP6 models project that the hottest land temperatures intensify faster than mean tropical land warming, but the magnitude and spatial fidelity of this amplification vary across models (Table 2.1). In several cases, strong spatial agreement coexists with a sizable mean bias, so both pattern skill and bias magnitude matter when interpreting projections.

Hotspot locations are relatively stable: the annual global land maximum most often occurs within a subtropical corridor spanning North Africa, the Arabian Peninsula/Middle East, and South Asia (Fig. 2.1; Figs. S3–S4). Across the ensemble, extremes warm more than the mean: T_{DM} and T_{DX} increase faster than T_{TL} in both transient and equilibrium frameworks (Fig. 2.2). Consistent with this amplification, exceedances of a fixed 1980–2014 “record-like” benchmark become increasingly common under SSP2-4.5, with pooled fits indicating $\sim 35\%$ higher odds per 1°C of tropical land warming (Fig. 2.3).

Data and Code Availability

CMIP6 model output is available through the Earth System Grid Federation (ESGF) at <https://esgf-node.llnl.gov/search/cmip6/>. Berkeley Earth surface temperature data can be accessed at <http://berkeleyearth.org/data/>. ERA5 reanalysis data were obtained from the Copernicus Climate Data Store: *ERA5 hourly data on single levels from 1940 to present* (C3S), DOI: 10.24381/cds.adbb2d47.

Code and analysis workflows used in this study are archived on Zenodo at <https://doi.org/10.5281/zenodo.17009316>. The GitHub repository is available at <https://github.com/a4wilson/extreme-heat-cmip6>. Figures were produced using Python libraries including Matplotlib and xarray (Byrne, 2021).

Supplemental Material for Chapter 1

Table 2.2. CMIP6 model membership and analysis-specific usage. The *core ensemble* ($N_{\text{core}} = 21$) is used for the historical skill metrics in Table 2.1 and for Figure 2.1. Figure 2.2 uses index-specific subsets because availability of the processed time series differs by index: $N_{TL} = 24$, $N_{DM} = 21$, and $N_{DX} = 17$ (SSP2-4.5). Equilibrium warming (Fig. 2c) additionally requires both abrupt-4 $\times$ CO₂ and the corresponding piControl for the relevant index; the final N is reported in Fig. 2c. Figure 3 requires both daily tasmax and daily tas over historical and SSP2-4.5, yielding $N = 17$ models.

Model	Institution	Core (Tbl 1, Fig 1)	Fig 2 TTL	Fig 2 TDM	Fig 2 TDX	Fig 2c Equil [†]	Fig 3
ACCESS-CM2	CSIRO	y	y	y	y	y	y
ACCESS-ESM1-5	CSIRO	y					
AWI-CM-1-1-MR	AWI	y	y	y	y	y	y
CAMS-CSM1-0	CAMS	y	y	y	y		y
CMCC-ESM2	CMCC	y	y	y	y	y	y
CNRM-CM6-1	CNRM	y	y	y	y	y	y [‡]
CNRM-CM6-1-HR	CNRM	y	y	y			
CNRM-ESM2-1	CNRM	y	y	y	y	y	y
CanESM5	CCCma	y	y	y	y	y	y
EC-Earth3	EC-Earth Consortium	y	y	y	y	y	y
EC-Earth3-CC	EC-Earth Consortium	y	y				y
EC-Earth3-Veg	EC-Earth Consortium	y	y	y	y		y
EC-Earth3-Veg-LR	EC-Earth Consortium	y	y	y	y		y
GFDL-CM4	NOAA-GFDL	y	y	y	y	y	y
GFDL-ESM4	NOAA-GFDL	y	y	y	y	y	y
INM-CM4-8	INM	y	y	y	y	y	y
INM-CM5-0	INM	y	y	y	y	y	y
IPSL-CM6A-LR	IPSL	y	y	y	y	y	y
NorESM2-LM	NORCE	y	y			y	
NorESM2-MM	NORCE	y	y	y	y	y	y
TaiESM1	AS-RCEC	y	y	y	y	y	
Additional models used beyond the core ensemble							
CMCC-CM2-SR5	CMCC		y	y			
HadGEM3-GC31-LL	UKMO		y	y			
IITM-ESM	IITM		y				
UKESM1-0-LL	Met Office		y	y			

[†]Equilibrium (Fig. 2c) denotes the *candidate set* for which the analysis attempts to compute equilibrium warming; the final subset additionally requires both abrupt-4 $\times$ CO₂ and piControl to be present for the index and may exclude outliers as described in the figure caption / code output.

[‡]In the Fig. 3 run shown in the log, CNRM-CM6-1 was loaded but later skipped in the regression fit due to insufficient years in the fit window; the model remains part of the data-availability subset.

Per-model tropical land indices in SSP2-4.5

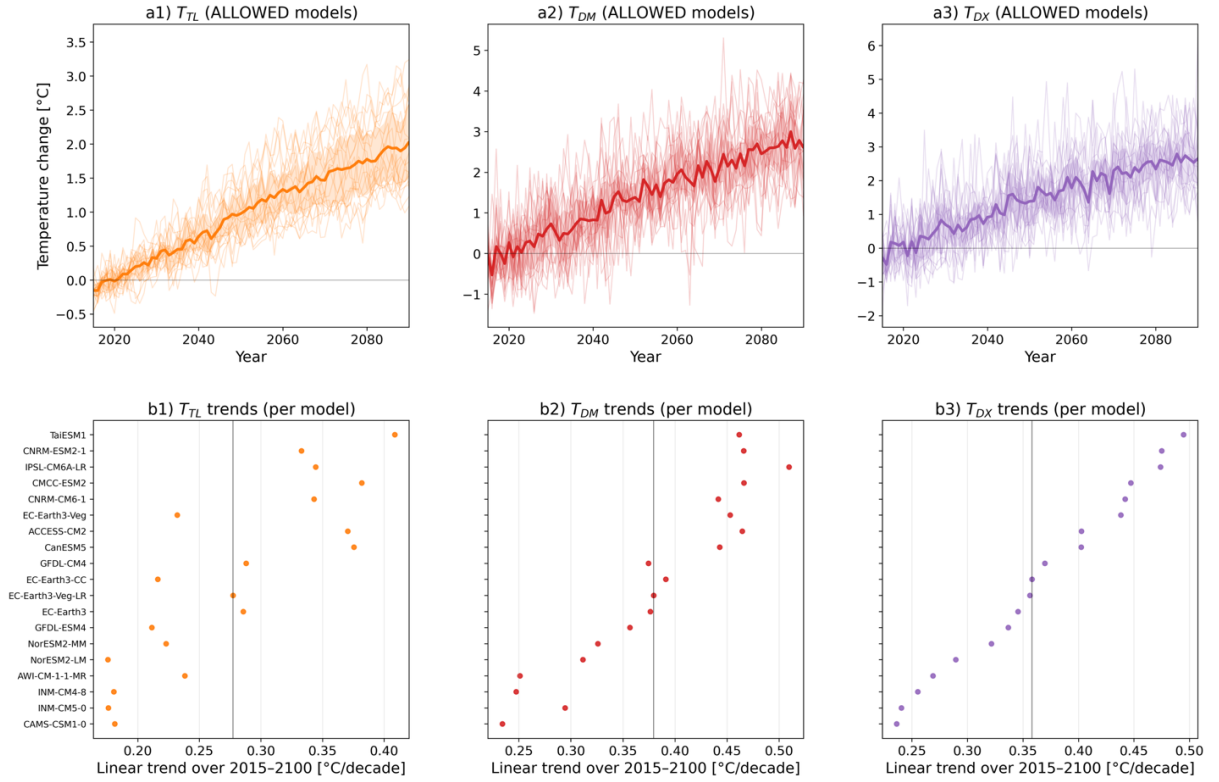


Figure 2.4. Per-model tropical land temperature indices under SSP2-4.5 for the common-model set. (a1–a3) Time evolution of T_{TL} , T_{DM} , and T_{DX} shown as anomalies relative to the 2015–2024 mean (baseline chosen because SSP2-4.5 begins in 2015 for most models). Thin lines show individual models; the thick line is the multi-model mean and shading denotes the interquartile range. (b1–b3) Linear trends over 2015–2100 computed separately for each model (sorted by T_{DX} trend).

Figure S2. Hottest-of-hot locations (historical)

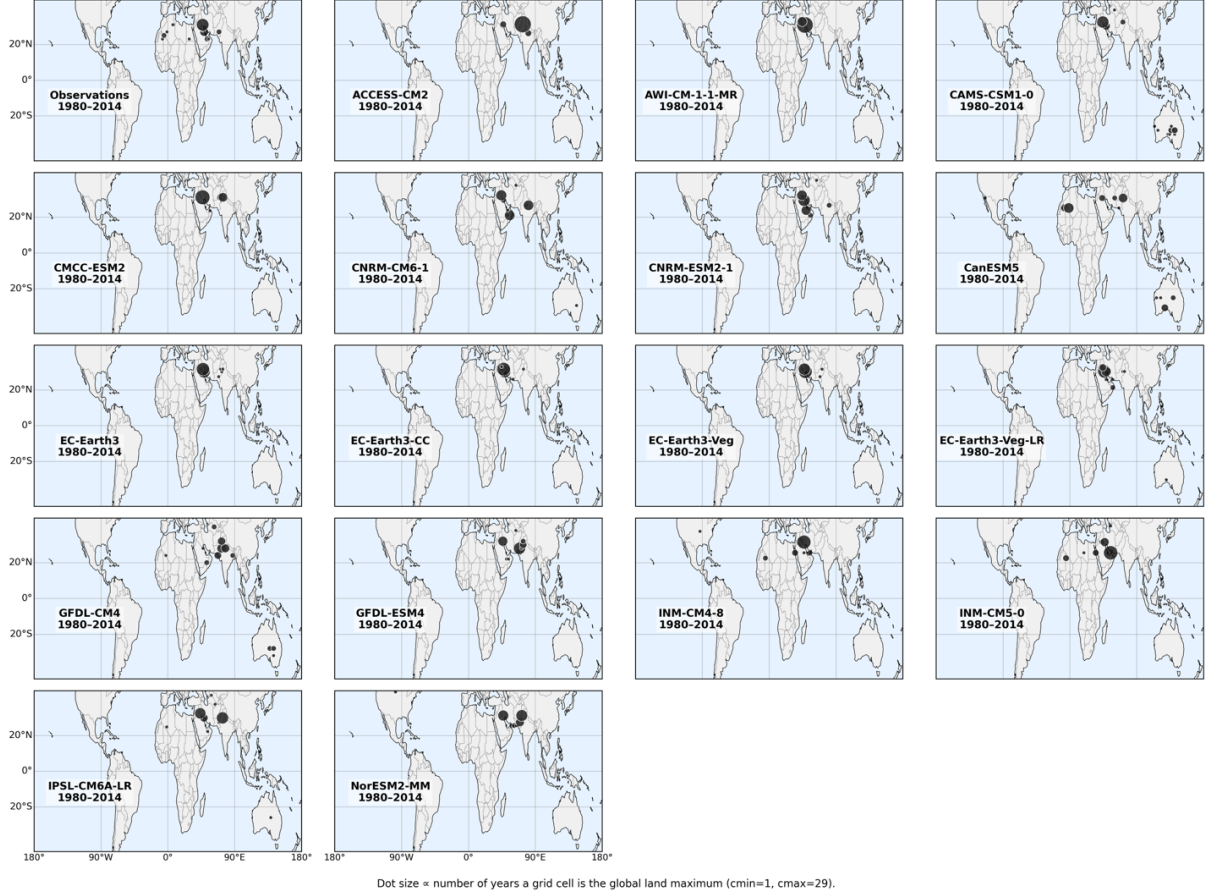


Figure 2.5. Hottest-of-hot hotspot locations in observations and historical CMIP6 simulations (1980–2014). Dot size indicates the number of years in which a grid cell attains the global land maximum of annual $T_{\max}$ (one location per year). The observational panel uses Berkeley Earth; model panels use each model’s historical simulation.

Figure S3. Hottest-of-hot locations (future; ssp245)

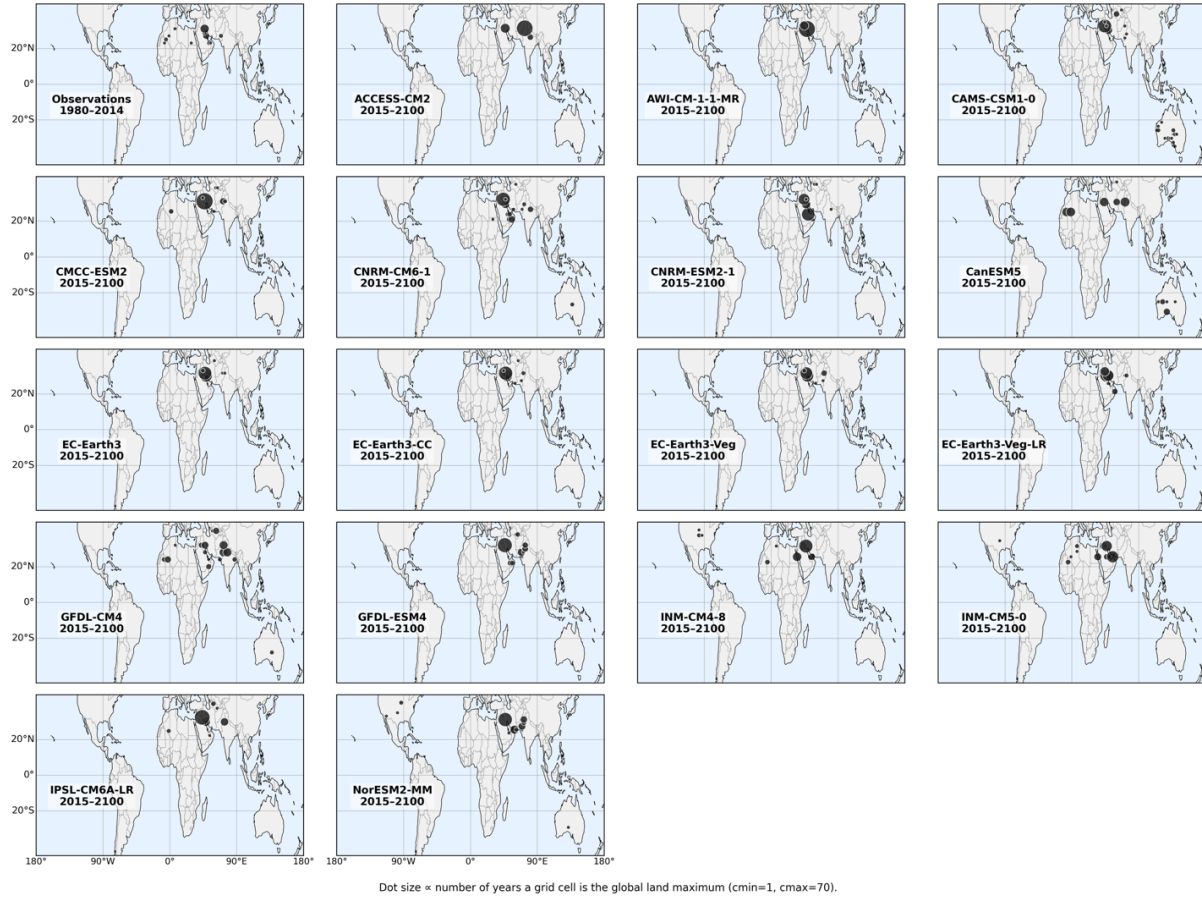


Figure 2.6. Hottest-of-hot hotspot locations in observations and SSP2-4.5 projections (2015–2100). Dot size indicates the number of years in which a grid cell attains the global land maximum of annual $T_{\max}$ (one location per year). The observational panel is shown for reference (1980–2014), and model panels show SSP2-4.5 over 2015–2100.

CMIP6 extreme heat patterns (historical 1980–2014): model $p99(T_{\max})$ and bias vs Berkeley

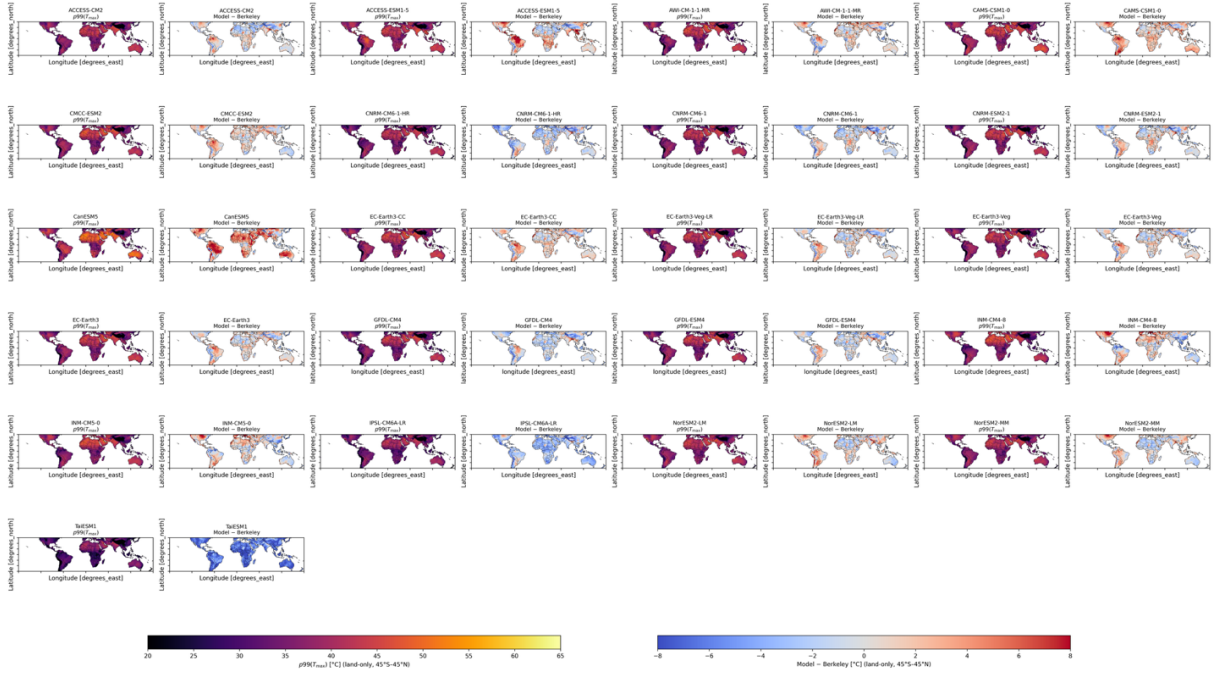


Figure 2.7. Spatial patterns of $p99(T_{\max})$ and associated model biases across the CMIP6 ensemble (1980–2014). For each model, the left panel shows the simulated $p99(T_{\max})$ on the native model grid and the right panel shows the corresponding bias relative to Berkeley Earth (model minus Berkeley Earth), after regridding Berkeley Earth to the model grid. Maps are restricted to land within 45°S–45°N and use common color scales across models (°C) to facilitate comparison.

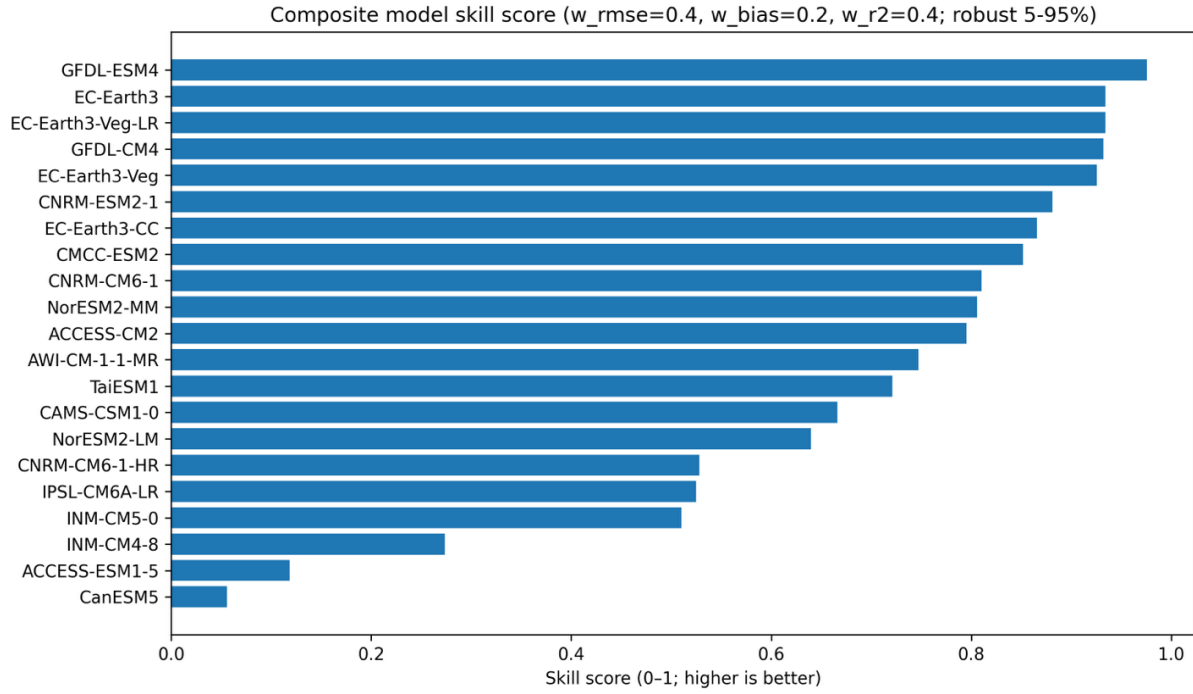


Figure 2.8. Composite skill score for simulated $p99(T_{\text{max}})$ (1980–2014), ranked across models. The score combines centered RMSE (cRMSE), absolute mean bias, and spatial R^2 for land grid cells within 45°S – 45°N , computed relative to Berkeley Earth after regridding Berkeley Earth to each model grid. Each metric is robustly normalized across models using a 5th–95th percentile transformation and clipped to $[0, 1]$ such that larger values indicate better performance. The composite score is the unweighted mean of the three normalized components, yielding $S \in [0, 1]$.

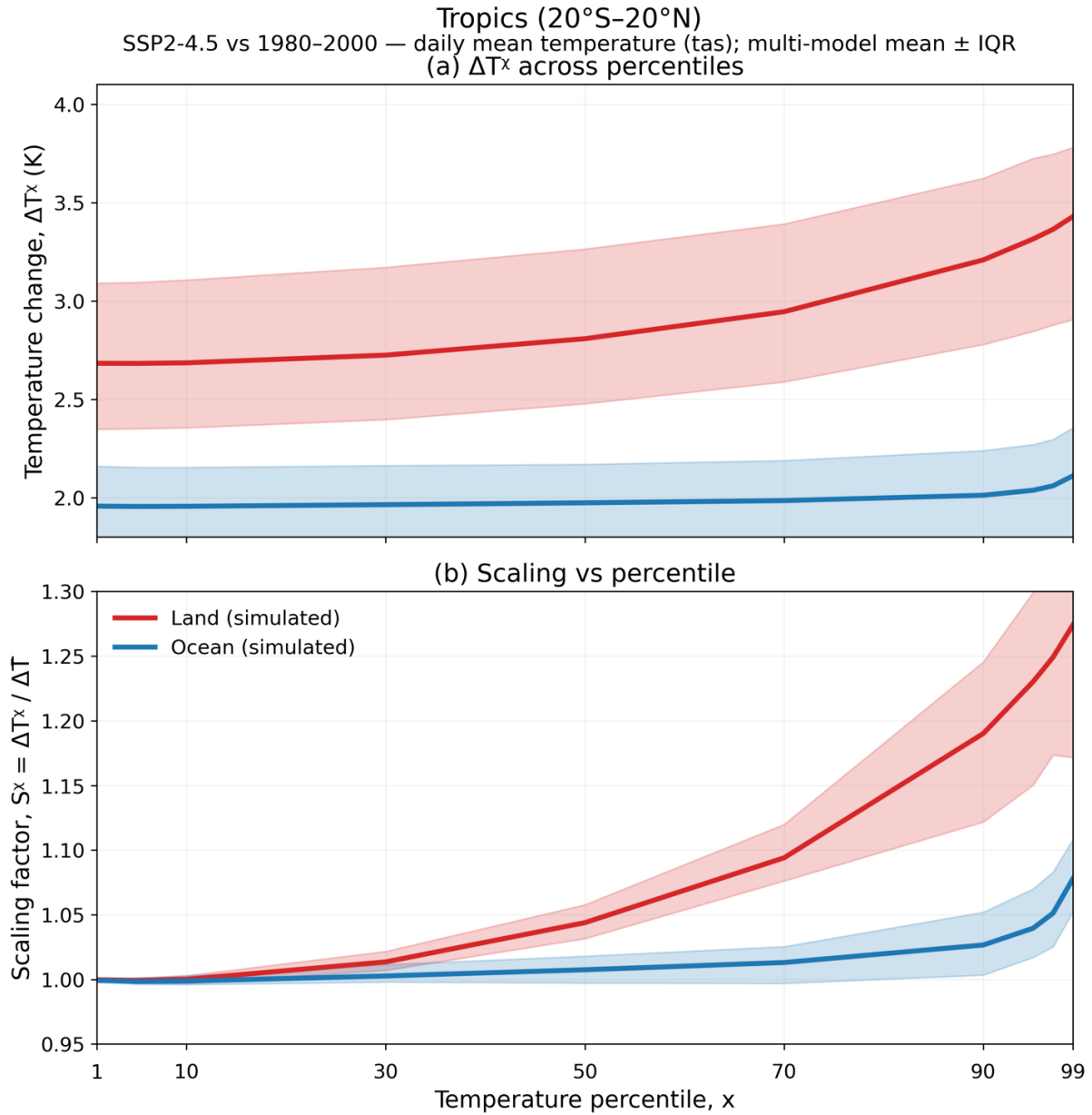


Figure 2.9. Percentile-dependent warming in the tropics under SSP2-4.5. Using daily-mean near-surface temperature (tas) averaged over 20°S–20°N, panel (a) shows the simulated temperature change ΔT^x as a function of percentile x for land (red) and ocean (blue), comparing SSP2-4.5 to the 1980–2000 baseline. Panel (b) shows the corresponding scaling factor $S^x = \Delta T^x / \Delta T$, where ΔT is the change in the tropical-mean tas. Solid lines denote the multi-model mean and shading indicates the interquartile range across models.

Chapter 3

Radiative Constraints on Earth's Warmest Daily-Mean Surface Temperatures

Abstract

Earth's warmest daily-mean near-surface air temperatures occur in subtropical deserts, yet the physical processes that set their upper bound remain incompletely understood. Here we combine observational constraints, a simplified daily-mean surface–atmosphere energy-balance framework, and line-by-line radiative-transfer calculations to diagnose the radiative structure of extreme hot states across paired surface skin and near-surface air temperatures. We find that the hottest present-day daily-mean temperatures occur in warm, dry columns that lie close to a top-of-atmosphere radiative constraint. In these states, outgoing longwave radiation continues to increase with temperature, even though the lower atmosphere is already strongly infrared-opaque. Doubling CO_2 does not fundamentally alter this structure. Instead, increased CO_2 produces a positive fixed-state forcing that shifts the same radiative balance toward warmer conditions, with the largest forcing occurring in the hottest and driest part of the domain. At the same time, the local radiative feedback remains positive across the physically allowed range of paired temperatures, so additional warming continues to be opposed by increased longwave emission to space. These results suggest that Earth's hottest daily-mean temperatures are governed primarily by radiative control, and that higher CO_2 warms these extremes by shifting, rather than removing, the radiative constraint.

Purpose: The abstract serves both as a general introduction to the topic and as a brief, non-technical summary of the main results and their implications. The abstract must not include subheadings (unless expressly permitted in the journal’s Instructions to Authors), equations or citations. As a guide the abstract should not exceed 200 words. Most journals do not set a hard limit however authors are advised to check the author instructions for the journal they are submitting to.

3.1 Introduction

Earth’s warmest surface temperatures are typically found in subtropical deserts, where daily-mean temperatures can reach up to $\sim 44^{\circ}\text{C}$ and daily-maximum temperatures the mid- $50\text{s}^{\circ}\text{C}$ (Mildrexler et al. (2011b), Figure 3.1). Surface, or skin, temperatures can be even warmer, with satellites measuring values as high as 80.8°C Zhao et al. (2021b). Subtropical deserts have all the ingredients needed to generate extreme temperatures: high levels of insolation, extreme surface dryness and the relatively low surface emissivity of sand Garratt (1992); Mildrexler et al. (2011b); Zhao et al. (2021b). Low moisture levels are crucial for generating high temperatures, as latent heat fluxes can efficiently cool the surface Brutsaert (1982); Stull (1988), while sand’s relatively weak emissivity ($\sim 0.85\text{--}0.9$, compared to >0.9 for most other surface types, e.g., Ogawa and Schmugge (2004); Jin and Liang (2006); Huang et al. (2016); Chen et al. (2019)) requires warmer temperatures to achieve the same emission as other surfaces.

Measuring extreme temperatures is difficult, because they tend to occur in remote, sparsely populated regions, such as the Sahara, Gobi, Sonoran and Lut Deserts World Meteorological Organization (2023); Merlone et al. (2019a). Without large population bases, there is little motivation to maintain weather stations in these places. Satellites now provide continuous monitoring of ground temperatures, but not of near-surface air temperatures, which are more relevant for human activities and heat exposure Sherwood and Huber (2010b); Carleton and Hsiang (2016). So we can be reasonably confident in the 80.8°C value for skin temperatures, though this comes

from only 17.5 years of data (July 2002 – December 2019, Zhao et al. (2021b)). By contrast, the warmest near-surface air temperatures were recorded in 1913 (56.7°C in Death Valley, California) and in 1922 (57.8°C in 'Aziziya, Libya), and both measurements have been disputed. More recently, temperatures of 54°C have been recorded in Kuwait and Pakistan Merlone et al. (2019a).

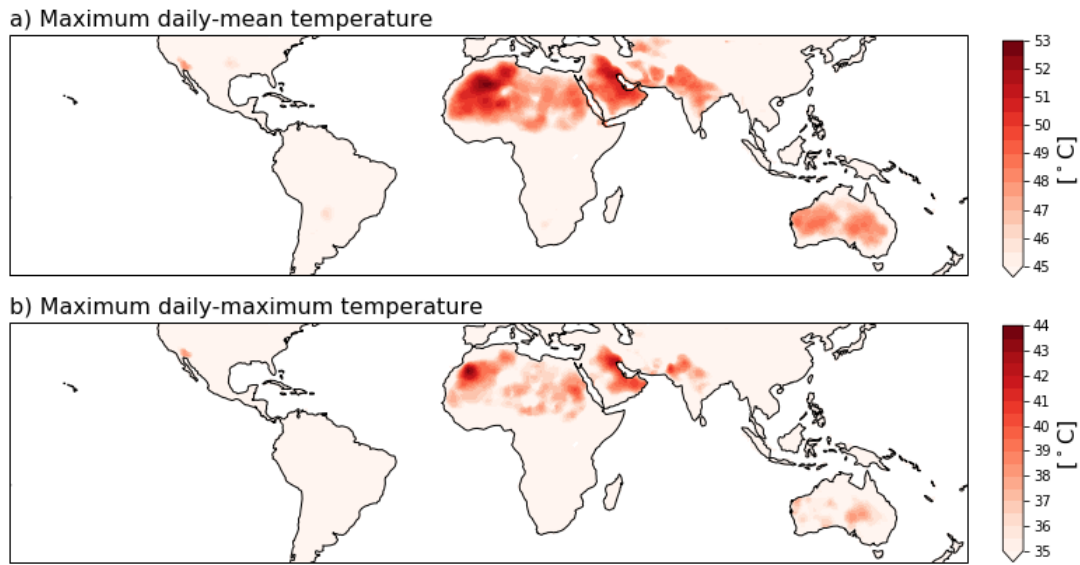


Figure 3.1. Warmest daily-mean temperatures (a) and daily-maximum temperatures (b) for latitudes between 45°S and 45°N over the period 2010-2019, as recorded by the Berkeley Earth Surface Temperatures dataset (see Methods).

Apart from these measurement issues, relatively little attention has been paid to what sets Earth’s warmest surface temperatures – why 55°C, and not 65°C, or 45°C? And why are the highest skin temperatures roughly 25°C warmer? Answering these questions would allow us to place upper limits on the potential severity of extreme heat waves in the tropics – in today’s climate and in the future. Many of climate change’s worst impacts are associated with extreme heat (e.g., Carleton and Hsiang (2016)), so it is important to constrain just how warm near-surface temperatures can get. A related concern is whether increased CO₂ concentrations lead to a simple shift in temperature distributions towards warmer means, or if the shapes of the distributions change, which could imply larger, more uncertain changes in extreme temperatures

Mearns et al. (1984).

In this study, we provide the first detailed calculations of what sets Earth’s warmest surface and skin temperatures, for both daily-mean temperatures. We do this using energy balance models for Earth’s surface, boundary layer and top-of-atmosphere (TOA), under the assumption that extreme temperatures occur when the atmosphere is close to local radiative equilibrium (see next section), following standard idealized approaches in physical climate theory and boundary-layer meteorology North et al. (1981); Hartmann (2016); Pierrehumbert (2010); Stull (1988). These calculations build on earlier work by Garratt (1992) and Pierrehumbert (2010); however, their calculations were highly idealized and did not include realistic meteorological conditions for extreme heat events, nor did they consider how these extreme temperatures respond to higher CO₂ concentrations. Here, we focus particularly on accurately characterizing the typical meteorological conditions of extreme temperature events and on understanding the radiative factors that control extreme temperatures. The latter requires calculations with a line-by-line (LBL) radiative transfer model, the benchmark approach for spectrally resolved clear-sky longwave transfer, which we also use to understand how extreme temperatures change at higher CO₂ concentrations Goody and Yung (1989); Clough et al. (1992, 2005).

This approach allows us to address our two key questions: (Q1) What sets the present-day upper bound on the hottest daily-mean near-surface air temperatures? (Q2) How do these hottest daily-mean states respond to increased CO₂ levels? Our research extends the results of previous idealized work by using meteorological conditions representative of observed extreme-heat events and by explicitly evaluating the response to higher CO₂. We can then assess whether those future-climate responses are consistent with the radiative framework developed for the present-day climate.

In Section 2, we introduce the 1D energy balance model, the observations and assumptions used to implement it, and the line-by-line radiative calculations that are used to compute the emissivities. In Section 3, we present our results for both air temperature and skin temperature along with key diagnostics of forcings and feedbacks. Section 4 presents our conclusions.

3.2 Methods

3.2.1 Overview

We combine observations, a simplified energy-balance framework, and line-by-line (LBL) radiative-transfer calculations North et al. (1981); Hartmann (2016); Goody and Yung (1989); Clough et al. (1992) to study two questions about Earth’s hottest daily-mean temperatures. First, we ask what sets the present-day upper bound on the hottest daily-mean near-surface air temperatures. Second, we ask how these hottest daily-mean temperatures respond to increased CO₂ concentrations. We begin with an idealized daily-mean surface–atmosphere energy-balance model appropriate for hot, dry desert conditions Garratt (1992); Pierrehumbert (2010). We then use radiosonde observations to characterize the vertical structure of representative extreme-heat environments and construct idealized atmospheric columns for the radiative-transfer calculations University of Wyoming, Department of Atmospheric Science (2025); World Meteorological Organization (2023). These columns are used in the LBL model to diagnose the emissivities and radiative-response metrics that appear in the 1D energy-balance equations. Finally, we use radiosonde data, ERA5 reanalysis, and published estimates for desert surfaces to choose representative values for the remaining bulk parameters University of Wyoming, Department of Atmospheric Science (2025); Hersbach et al. (2020b); Ogawa and Schmugge (2004); Jin and Liang (2006); Huang et al. (2016); Chen et al. (2019).

3.2.2 Daily-mean temperature framework

For daily-mean temperatures, we use a one-layer energy-balance model, a standard idealization in climate dynamics, in which the atmosphere is represented by a single temperature, T_a , and the surface temperature is denoted T_s North et al. (1981); Hartmann (2016); Pierrehumbert (2010). We define T_a as the temperature 1 km above the surface. Under the assumption that temperatures follow a dry adiabat in the lower troposphere, as expected for a strongly heated and well-mixed dry convective boundary layer, the near-surface air temperature is then given by

$T_a + 9.76$ K Wallace and Hobbs (2006); Stull (1988).

Under the assumption that extreme temperatures occur close to local radiative equilibrium, the daily-mean top-of-atmosphere (TOA) and surface energy budgets are written as Garratt (1992); Hartmann (2016); Pierrehumbert (2010)

$$Q = \epsilon_{t,s}\epsilon_g\sigma T_s^4 + \epsilon_{t,a}\sigma T_a^4, \quad (3.1)$$

$$(1 - \beta)Q = \epsilon_g\sigma T_s^4 - \epsilon_g\epsilon_s\sigma T_a^4 + \rho_a c_{p,a} C_d |\mathbf{v}| (T_s - T_a - 9.76 \text{ K}), \quad (3.2)$$

where Q is net absorbed solar radiation at the top of the atmosphere, β is the fraction of absorbed solar radiation taken up by the atmosphere rather than the surface, ϵ_g is the surface emissivity, $\epsilon_{t,s}$ is the surface contribution to TOA emissivity, $\epsilon_{t,a}$ is the atmospheric contribution to TOA emissivity, and ϵ_s is the atmospheric emissivity into the surface. The final term in the surface budget represents the sensible heat flux between the surface and the lower atmosphere using a standard bulk-aerodynamic exchange formulation Brutsaert (1982); Stull (1988); Garratt (1992).

These equations can be solved for T_s and T_a , but the emissivities $\epsilon_{t,s}$, $\epsilon_{t,a}$, and ϵ_s depend on temperature and humidity and must therefore be diagnosed from the radiative-transfer calculations. The remaining bulk parameters are constrained from a combination of radiosonde observations, reanalysis fields, and published estimates for desert environments.

3.2.3 Observed structure of extreme-heat environments

To characterize the typical meteorology of extreme heat events, we use radiosonde data from four long-term meteorological stations deployed at airports in subtropical desert environments: Al Qaisumah-Hafar Al Batin in Saudi Arabia (station label: OEPA, 28.33°N, 46.12°E), King Khalid International Airport in Saudi Arabia (OERK, 24.96°N, 46.70°E), Ahvaz International Airport in Iran (OIAW, 31.20°N, 48.45°E), and Dr. Babasaheb Ambedkar International Airport in India (VANP, 21.09°N, 70.06°E), obtained from the University of Wyoming upper-

air sounding archive (University of Wyoming, Department of Atmospheric Science, 2025). For stations OEPA, OERK, and OIAW, we use data from the warmest days over the period 2000–2020. For VANP, we use data from 29 April 2022, during an intense heatwave over India and Pakistan. While these days may not represent the absolute warmest temperatures experienced on Earth, we take them as representative of extremely warm conditions. Because the stations are located at different altitudes, the calculations below assume a reference surface at sea level with a total overlying atmospheric pressure of 1000 hPa.

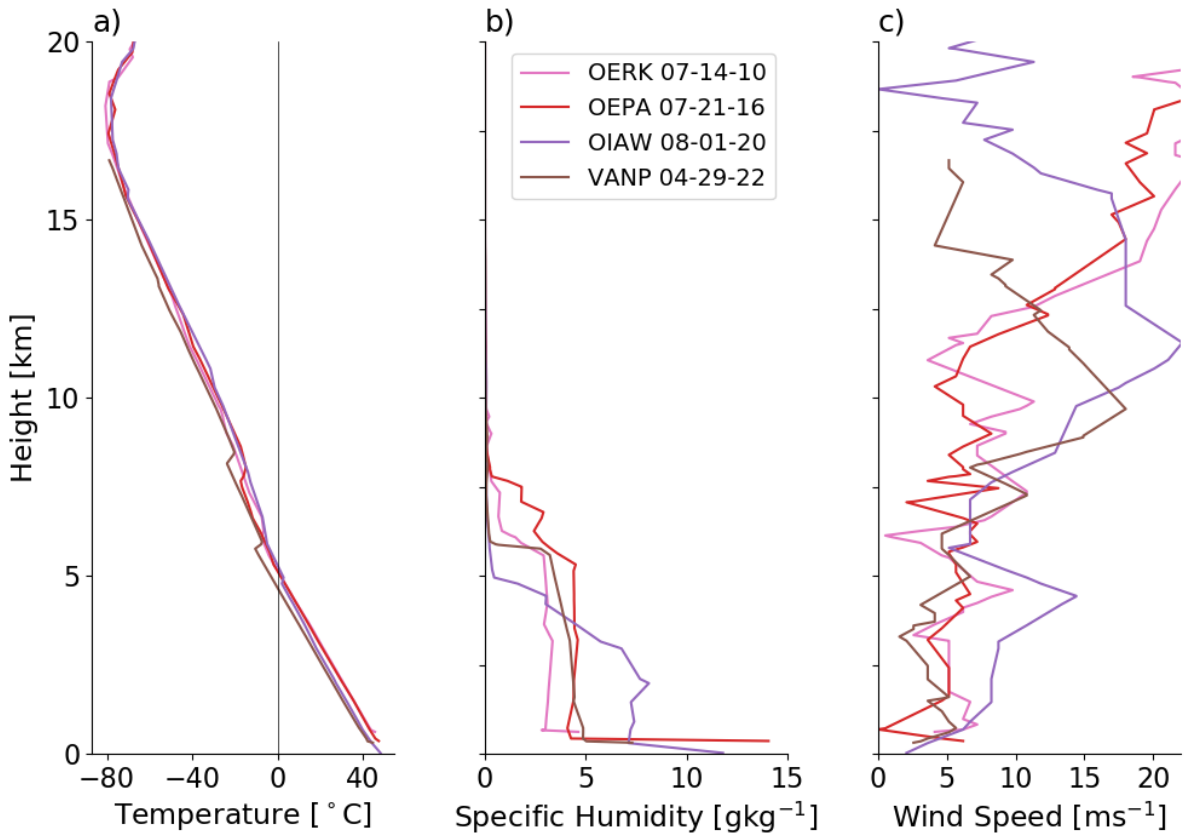


Figure 3.2. Daily-averaged temperature (a), specific humidity (b), and wind speed (c) profiles on the very hot days recorded at the four radiosonde stations.

The radiosonde data show that days with extremely warm temperatures typically feature deep, well-mixed boundary layers extending up to 5–7 km, consistent with previous observations and modeling of Saharan and desert convective boundary layers Gamo (1996); Messenger et al. (2010); Ryder et al. (2015) (Fig. 3.2a). Temperatures follow the dry adiabat up to the

top of the boundary layer, above which there is an inversion and then smaller lapse rates, likely reflecting the capping structure and residual-layer dynamics typical of deep desert boundary layers Stull (1988); Messenger et al. (2010); Ryder et al. (2015). Specific humidities are in the range of $5\text{--}10\text{ g kg}^{-1}$ in the boundary layer (Fig. 3.2b), while the free troposphere is much drier. The winds are noisy, but near-surface winds tend to be relatively weak, with absolute values of about $2\text{--}6\text{ m s}^{-1}$ (Fig. 3.2c). These winds help determine the sensible heat flux between the surface and the lower atmosphere through the aerodynamic exchange coefficient; faster winds therefore reduce surface–air temperature differences even though the wind itself is not a direct heat source Brutsaert (1982); Stull (1988).

These observed profiles provide the basis for the idealized atmospheric columns used in the radiative-transfer calculations, following the common single-column strategy of prescribing thermodynamic structure before evaluating radiative fluxes Goody and Yung (1989); Pierrehumbert (2010). In particular, they motivate a deep dry-adiabatic lower troposphere, a boundary-layer inversion near 6 km, a very dry free troposphere, and relatively weak near-surface winds.

3.2.4 Construction of the radiative-transfer profiles

For each paired surface and atmospheric temperature state (T_s, T_a) , we construct an idealized atmospheric column intended to represent the thermodynamic structure of extremely hot subtropical desert environments. The profile is prescribed rather than interactively simulated, but its structure is chosen to be representative of the hot-day radiosonde observations shown in Fig. 3.2, following the common single-column strategy of prescribing thermodynamic structure before evaluating radiative fluxes Goody and Yung (1989); Pierrehumbert (2010).

The lower troposphere is prescribed to follow a dry adiabat, consistent with strongly mixed dry convective boundary layers over hot land surfaces Wallace and Hobbs (2006); Stull (1988); Gamo (1996) up to 6 km. At 6 km, a 2 K inversion is imposed to represent the top of the boundary layer. Above the inversion, temperature decreases with a free-tropospheric lapse rate of 7.5 K km^{-1} until a tropopause temperature floor of 190 K is reached. Above that

level, temperature increases with a stratospheric lapse rate of 3.5 K km^{-1} . The atmospheric temperature T_a is prescribed at the model level corresponding to approximately 1 km above the surface.

Humidity is prescribed using an idealized vertical profile intended to mimic the hot-day radiosonde structure. Specific humidity is held constant below 4 km, decreases linearly from 4 to 6 km, and is set to a very dry constant value above 6 km. The profile shape is fixed, but its amplitude is scaled so that near-surface humidity corresponds to a prescribed near-surface relative humidity of 10% for the thermodynamic state under consideration.

3.2.5 Parameter choices and environmental constraints

We estimate the representative parameter values by combining hot-day radiosonde profiles with ERA5 reanalysis-based radiative constraints and published estimates for desert conditions University of Wyoming, Department of Atmospheric Science (2025); Hersbach et al. (2020b); Garratt (1992). ERA5 provides the single-level shortwave-radiation fields needed to estimate both absorbed solar radiation at the top of the atmosphere and the partitioning of absorbed solar radiation between the atmosphere and the surface Hersbach et al. (2020b). The radiosonde observations are used to characterize the vertical structure of extreme-heat environments, including the boundary-layer depth, temperature and humidity stratification, and representative near-surface wind speeds. The resulting prescribed parameter choices used in the daily-mean analysis are summarized in Table 3.1.

Maps of daily-mean top net solar radiation over representative subtropical desert environments suggest typical values of about $340\text{--}380 \text{ W m}^{-2}$, and we adopt a relatively high representative value of $Q = 365 \text{ W m}^{-2}$. We estimate β by comparing absorbed solar radiation at the top of the atmosphere with net absorbed solar radiation at the surface over the same representative hot-desert environments, which gives typical values in the range 0.1–0.3. We therefore adopt a representative value of $\beta = 0.2$.

We take a relatively low surface emissivity of $\epsilon_g = 0.8$, representative of sandy desert

Table 3.1. Representative parameter values used in the daily-mean surface–atmosphere energy-balance calculations.

Parameter	Adopted value	Basis
Net absorbed solar radiation, Q	365 W m^{-2}	Representative high daily-mean value from ERA5 subtropical desert environments.
Atmospheric short-wave absorption fraction, β	0.2	Typical range 0.1–0.3 from comparison of TOA and surface absorbed shortwave radiation.
Surface emissivity, ϵ_g	0.8	Low-emissivity sandy desert surface.
Air density, ρ_a	1.106 kg m^{-3}	Ideal-gas estimate using $P = 10^5 \text{ Pa}$ and $T = 315 \text{ K}$.
Air heat capacity, $c_{p,a}$	$1005 \text{ J kg}^{-1} \text{ K}^{-1}$	Standard dry-air value.
Bulk drag coefficient, C_d	10^{-3}	Lower-end value for weakly rough desert surfaces.
Near-surface wind speed, $ \mathbf{v} $	$2\text{--}6 \text{ m s}^{-1}$	Range from hot-day radiosonde profiles.

conditions and consistent with satellite-based estimates of low broadband emissivity over sandy/arid surfaces Ogawa and Schmugge (2004); Jin and Liang (2006); Huang et al. (2016); Chen et al. (2019). A typical atmospheric density is estimated from the ideal gas law as $\rho_a = P/(R_d T)$, where P is pressure, R_d is the dry gas constant, and T is temperature. Taking $P = 10^5 \text{ Pa}$, $R_d = 287 \text{ J kg}^{-1} \text{ K}^{-1}$, and $T = 315 \text{ K}$, corresponding to an extreme surface-air temperature, gives $\rho_a \approx 1.106 \text{ kg m}^{-3}$. For the atmospheric heat capacity, we take $c_{p,a} = 1005 \text{ J kg}^{-1} \text{ K}^{-1}$.

Bulk drag coefficients over land are commonly of order 10^{-3} to 10^{-2} , depending on roughness and stability Brutsaert (1982); Stull (1988). Because the boundary layer appears weakly mixed and surface roughness is low over deserts, we adopt a lower-end value of $C_d = 10^{-3}$. Finally, we consider near-surface wind speeds $|\mathbf{v}| \in [2, 6] \text{ m s}^{-1}$, consistent with the hot-day radiosonde profiles.

3.2.6 Line-by-line radiative calculations

The key unknowns in the daily-mean energy-balance equations are the emissivities, which depend on spectrally resolved gaseous absorption and surface emission Goody and Yung (1989); Pierrehumbert (2010). We estimate them with the PyRADS line-by-line longwave radiative-transfer model by evaluating radiative fluxes over a grid of (T_s, T_a) states using atmospheric columns constructed as described above Koll and Cronin (2019); Goody and Yung (1989); Clough et al. (1992).

A line-by-line model computes radiative absorption and emission by resolving the spectrum into many narrow wavenumber intervals rather than using a small number of broadband gray coefficients. At each wavenumber, molecular absorption depends on the absorber amount, pressure, temperature, and spectroscopic line parameters. The model then integrates over wavenumber to obtain broadband longwave fluxes. This approach is more computationally expensive than a gray or band model, but it is appropriate here because the central question concerns hot, dry atmospheres in which spectral windows, CO₂ bands, water-vapor lines, and continuum absorption can contribute differently to the top-of-atmosphere flux. The line-by-line calculation is therefore used as a diagnostic tool for the radiative constraint, not as a complete climate model.

The spectral calculations are performed over the range 0.1–3500 cm^{−1} with spectral resolution 0.1 cm^{−1}. The optical-thickness calculations include H₂O and CO₂ line absorption together with the H₂O continuum, implemented using the MT_CKD continuum routines Gordon et al. (2017); Mlawer et al. (2012). Present-day and doubled-CO₂ calculations are performed using CO₂ volume mixing ratios of 360 ppm and 720 ppm, respectively, following the standard doubled-CO₂ forcing experiment convention Myhre et al. (1998); Gregory et al. (2004). In the optical-thickness calculation, CO₂ is treated as a dilute trace gas.

The calculations are performed over the discrete state-space grid

$$T_s = 304, 305, \dots, 359 \text{ K}, \quad (3.3)$$

$$T_a = 300, 301, \dots, 355 \text{ K}, \quad (3.4)$$

retaining only the physically allowed region with $T_s \geq T_a$.

3.2.7 Radiative diagnostics and CO₂-response metrics

The LBL calculations are used to diagnose the radiative quantities appearing in the energy-balance model and in the CO₂ response analysis, consistent with standard forcing–feedback diagnostics based on TOA radiative flux changes Gregory et al. (2004); Forster et al. (2016). The surface contribution to TOA emissivity, $\epsilon_{t,s}$, is diagnosed as the fraction of spectrally integrated surface thermal emission that reaches the top of the atmosphere:

$$\epsilon_{t,s} = \frac{\int B_{\text{surf}}(\nu) \exp[-\tau_{\text{top}}(\nu)] d\nu}{\sigma T_s^4}, \quad (3.5)$$

where $B_{\text{surf}}(\nu)$ is the surface Planck function and $\tau_{\text{top}}(\nu)$ is the total optical thickness of the column.

The atmospheric contribution to TOA emissivity, $\epsilon_{t,a}$, is then obtained as the residual contribution to the TOA longwave flux after subtracting the surface contribution:

$$\epsilon_{t,a} = \frac{F_{\text{TOA}} - \epsilon_{t,s} \sigma T_s^4}{\sigma T_a^4}, \quad (3.6)$$

where T_a is the atmospheric temperature at the prescribed 1 km level. The atmospheric emissivity into the surface, ϵ_s , is diagnosed from the difference between surface blackbody emission and the net longwave flux at the surface:

$$\epsilon_s = \frac{\sigma T_s^4 - F_{\text{sfc}}}{\sigma T_a^4}. \quad (3.7)$$

To evaluate the response to increased CO₂, we compute the fixed-state CO₂ forcing as the negative of the change in top-of-atmosphere longwave flux between the 360 ppm and 720 ppm calculations at fixed (T_s, T_a) , analogous to an instantaneous clear-sky longwave forcing diagnostic Myhre et al. (1998); Gregory et al. (2004); Forster et al. (2016):

$$F_{\text{CO}_2}(T_s, T_a) = - \left[F_{\text{TOA}}^{720}(T_s, T_a) - F_{\text{TOA}}^{360}(T_s, T_a) \right]. \quad (3.8)$$

Local radiative feedback is diagnosed from discrete finite differences of the 360 ppm TOA flux field across neighboring states in (T_s, T_a) space. In the current implementation, the feedback field is computed from differences between adjacent diagonal grid points in state space, so it should be interpreted as a local directional radiative sensitivity rather than as a full vector gradient.

These diagnostics are used to characterize how daily-mean extreme-temperature states respond to increased CO₂ across (T_s, T_a) space. In particular, the fixed-state forcing and local radiative sensitivity provide a compact description of how the daily-mean radiative balance shifts under higher CO₂, and they form the basis for decomposing the response into a fixed-state forcing term and a local radiative feedback term across extreme-temperature state space.

3.3 Results

3.3.1 Daily-mean radiative structure of extreme-temperature states

We first examine the daily-mean radiative structure of the warmest states in the idealized subtropical-desert framework. Figure 3.3 shows the line-by-line radiative calculations across paired near-surface air and surface skin temperatures for both present-day CO₂ (360 ppm) and doubled-CO₂ (720 ppm) conditions. In the 360 ppm calculations, the surface contribution to top-of-atmosphere (TOA) emission decreases as the column becomes warmer, while the atmospheric contribution varies more modestly across the same range of temperatures. The total outgoing longwave flux nevertheless continues to increase with warming. Thus, even though

the atmosphere is already optically thick over much of the relevant infrared spectrum, the hottest daily-mean states remain radiatively constrained by the need to emit additional energy to space as temperature increases (Pierrehumbert, 2010; Koll and Cronin, 2018; Jeevanjee et al., 2021).

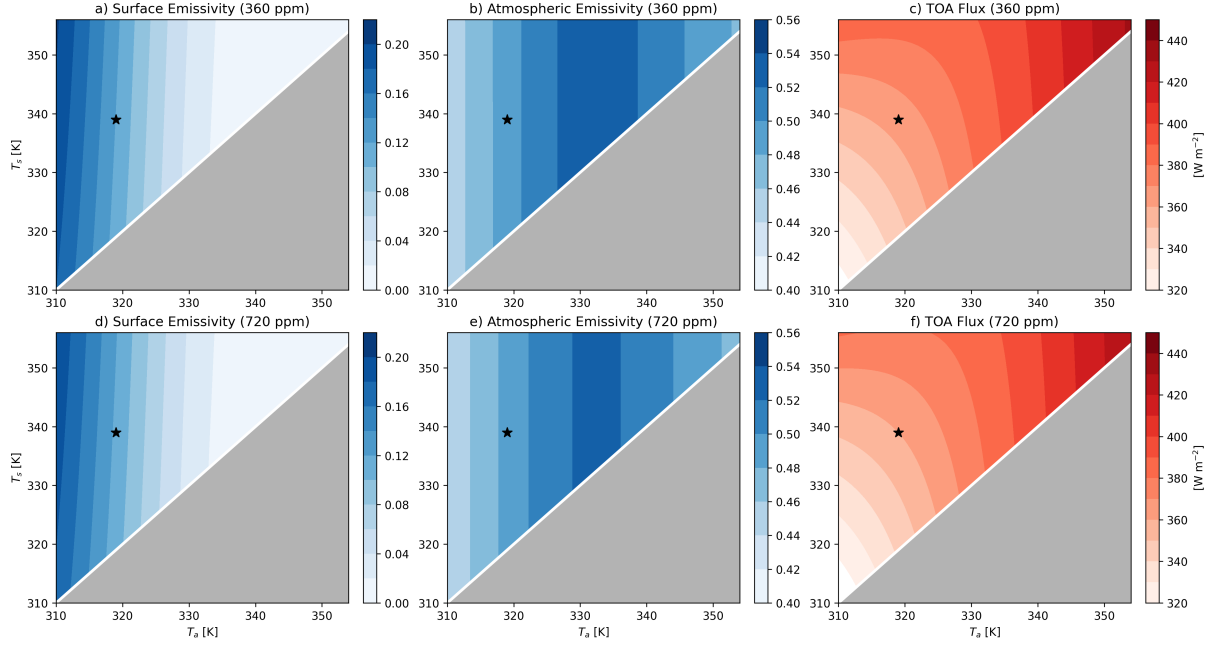


Figure 3.3. Daily-mean radiative structure across paired near-surface air and surface skin temperatures for 360 ppm CO₂ (top row) and 720 ppm CO₂ (bottom row). Panels show the surface contribution to top-of-atmosphere emissivity $\epsilon_{t,s}$, the atmospheric contribution to top-of-atmosphere emissivity $\epsilon_{t,a}$, and the top-of-atmosphere outgoing longwave flux. The black star marks the representative present-day subtropical desert extreme state used as a benchmark throughout the analysis. The gray region indicates states outside the physically allowed domain considered here.

The magnitude of the diagnosed radiative coefficients is summarized in Table 3.2. The surface contribution to TOA emissivity is small compared with the atmospheric contribution over most of the domain, consistent with strong infrared opacity above hot desert surfaces. At the same time, the diagnosed downward longwave coupling between the atmosphere and the surface remains large. Because ϵ_s is defined using the prescribed 1 km atmospheric temperature rather than the full emitting-temperature profile, it should be interpreted as an effective coupling coefficient rather than as a material emissivity bounded by one. This distinction is important for interpreting the small part of the range in which $\epsilon_s > 1$.

The benchmark state marked by the black star lies near the warm edge of the physically allowed domain but not at a singular point in the radiative calculation. This is useful because it indicates that the representative hot-desert state is part of a broader continuum of allowable warm states, rather than an isolated numerical solution. Across this continuum, the surface and lower atmosphere warm together, but they do not contribute equally to emission to space. The direct surface contribution is limited by atmospheric absorption, while the atmospheric contribution remains the dominant term in the TOA budget. The relevant constraint is therefore not simply the Stefan–Boltzmann emission of the surface skin, but the combined ability of the surface–atmosphere column to emit longwave radiation through spectral windows and from vertically distributed emitting levels.

This distinction is important for interpreting the role of the physically excluded region. States with surface temperature lower than the prescribed near-surface atmospheric temperature are not representative of the dry daytime environments targeted here, where strong solar heating and weak evaporative cooling favor a warm surface relative to the overlying air. Excluding these states focuses the analysis on the part of phase space relevant to the warmest dry land temperatures. Within that allowed domain, the TOA longwave flux remains a smooth function of both T_s and T_a , which supports the use of local radiative sensitivities to diagnose how the constraint shifts under increased CO_2 .

Table 3.2. LBL-diagnosed radiative coefficients in the daily-mean analysis. Reported ranges are over the physically allowed domain with $T_s \geq T_a$. The coefficient ϵ_s is an effective atmospheric longwave-coupling coefficient defined relative to the prescribed 1 km atmospheric temperature.

Quantity	Meaning	360 ppm	720 ppm
$\epsilon_{t,s}$	Surface contribution to TOA emissivity	0.0004–0.276	0.0004–0.268
$\epsilon_{t,a}$	Atmospheric contribution to TOA emissivity	0.412–0.528	0.410–0.523
ϵ_s	Effective atmospheric coupling to the surface	0.751–1.029	0.758–1.029

The doubled- CO_2 calculations preserve the same qualitative structure, but shift the radiative balance over the same extreme-temperature domain. At fixed paired temperatures, the 720 ppm columns emit less longwave radiation to space than the corresponding 360 ppm columns, implying a positive fixed-state CO_2 forcing. This forcing is largest in the warmest and driest part of the domain. However, the TOA longwave flux still increases with temperature, so the response to higher CO_2 is not an unconstrained warming; it is a shift to warmer states that must still satisfy the TOA energy balance.

The spatial structure of this response also emphasizes that the CO_2 perturbation should be interpreted as a state-dependent forcing. The same increase in CO_2 does not produce an identical radiative perturbation at every point in (T_s, T_a) space because the Planck spectrum, spectral-line absorption, and atmospheric temperature structure vary across the domain. In the warmest states, a larger fraction of thermal emission is concentrated in spectral regions where additional absorption can still reduce TOA flux, while the high absolute temperature also increases the longwave flux that must be balanced. The result is a forcing pattern that is strongest precisely where the daily-mean energy balance is already closest to the upper envelope of present-day dry heat.

The daily-mean extreme-temperature problem is therefore limited primarily by the need to balance absorbed solar radiation with longwave emission to space. In terms of Eq. (1), the key limiting terms are the surface and atmospheric contributions to TOA longwave emission, $\epsilon_{t,s}\epsilon_g\sigma T_s^4$ and $\epsilon_{t,a}\sigma T_a^4$. In the hottest dry conditions, the atmosphere is already strongly infrared-opaque, so further warming is only possible if TOA longwave emission also increases. This is the central radiative constraint on the warmest daily-mean states in the model.

3.3.2 Fixed-state CO_2 forcing and local radiative feedback

The differences between the 360 ppm and 720 ppm calculations can be summarized more directly in terms of fixed-state CO_2 forcing and local radiative feedback. Figure 3.4 shows these quantities across the same paired near-surface air and surface skin temperatures used in

Fig. 3.3. The fixed-state forcing is positive throughout the physically allowed domain, reflecting the reduction in TOA outgoing longwave flux when CO_2 is increased at fixed temperature. The largest forcing occurs in the hottest and driest part of the domain, indicating that the radiative impact of increased CO_2 is strongest in the same conditions that produce the warmest daily-mean temperatures.

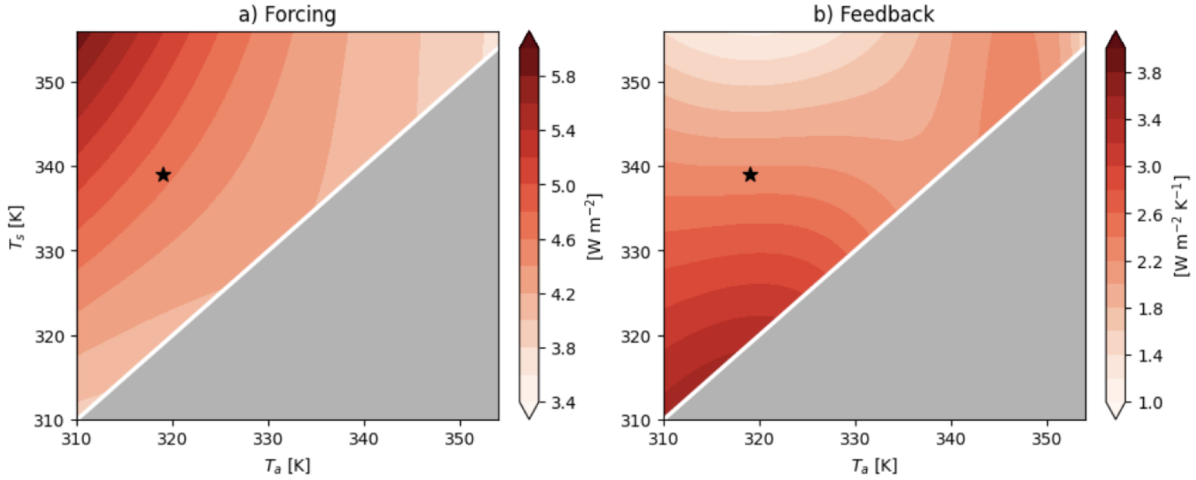


Figure 3.4. Fixed-state CO_2 forcing and local radiative feedback across paired near-surface air and surface skin temperatures. Panel (a) shows the fixed-state CO_2 forcing, defined as the reduction in top-of-atmosphere outgoing longwave flux between the 360 ppm and 720 ppm calculations at fixed paired temperatures. Panel (b) shows the local radiative feedback parameter diagnosed from discrete finite differences of the 360 ppm top-of-atmosphere flux field across neighboring states in (T_s, T_a) space. The black star marks the representative present-day subtropical desert extreme state used as a benchmark throughout the analysis. The gray region indicates states outside the physically allowed domain considered here.

The local radiative feedback remains positive across the plotted domain. Outgoing longwave radiation therefore continues to increase with warming even for the warmest present-day states. The magnitude of this feedback varies across the domain, but it does not change sign in the range considered here. The CO_2 response can therefore be interpreted as a competition between a positive fixed-state greenhouse forcing and a positive local radiative damping. Higher CO_2 shifts the daily-mean radiative balance toward warmer extreme states, while the increase in outgoing longwave emission with temperature continues to limit the magnitude of that shift (Myhre et al., 1998; Gregory et al., 2004; Forster et al., 2016).

This result connects directly to recent analytical work on the radiative physics of hot, optically thick atmospheres. Koll and Cronin (2018) showed that even very warm atmospheres need not approach a hard runaway limit, because emission to space can continue through spectral windows and from vertically distributed layers whose temperatures increase with surface warming. Related work by Jeevanjee et al. (2021) emphasized that spectral structure can produce compensating changes among different parts of the longwave spectrum, so that the net feedback of a warm column is not determined by the opacity of any single band. The feedback field in Fig. 3.4 is consistent with that analytical picture: the lower atmosphere is highly opaque in many bands, but the integrated TOA flux still has a positive temperature derivative over the extreme-temperature states considered here.

The smallness of the diagnosed sensitivity also follows from this forcing–feedback interpretation. A doubled- CO_2 perturbation produces a finite fixed-state reduction in OLR, but the perturbation is applied to a background state in which the column already emits very large longwave fluxes. Restoring TOA balance therefore requires only a modest temperature shift, because the same high-temperature state also has substantial radiative damping. In other words, the hottest dry columns are sensitive to greenhouse forcing, but they are not weakly constrained. Their response is limited by the same Planck-weighted and spectrally distributed emission processes identified in the analytical theories of Koll, Jeevanjee, and collaborators.

This connection is important for interpreting the spatial pattern in Fig. 3.4. The largest fixed-state forcing occurs in the hottest and driest corner of the domain, but this does not imply that these states should warm without bound or display exceptionally large local sensitivity. The feedback panel shows why: the radiative damping remains positive in the same part of state space. The forcing and feedback fields therefore work together to produce a finite displacement of the radiative constraint rather than a qualitative breakdown of the constraint. This is the physical basis for the conclusion that the doubled- CO_2 sensitivity of the daily-mean extreme state is relatively small despite the large absolute temperatures involved.

3.4 Discussion

The radiative framework developed here is intentionally simple, but it clarifies why the hottest daily-mean temperatures should be viewed as constrained states rather than arbitrary extrapolations of mean warming. In the hottest dry environments, evaporation is weak and the surface energy budget is dominated by absorbed solar radiation, sensible heat exchange, and longwave emission. The top-of-atmosphere energy balance therefore becomes a useful organizing principle: a daily-mean state can persist only if the atmospheric column emits enough longwave radiation to balance absorbed sunlight. This does not imply a sharp universal maximum temperature, because albedo, emissivity, atmospheric humidity, lapse rate, clouds, and circulation all vary. It does imply that the warmest states must satisfy a radiative closure condition.

A key result is that strong infrared opacity does not make outgoing longwave radiation independent of temperature. Even when the lower atmosphere is optically thick, emission to space occurs through spectral windows and from vertically distributed levels. As the surface and lower atmosphere warm, emission from these regions still increases. This behavior is important because it prevents the warmest dry states from being controlled only by near-surface saturation of infrared absorption. The atmosphere can be optically thick in some spectral bands and still have a positive local longwave feedback when the full spectrum and vertical structure are considered.

The CO₂ perturbation experiments should be interpreted in this context. Doubling CO₂ reduces outgoing longwave radiation at fixed temperature, creating a positive fixed-state forcing. The system can compensate only by shifting toward warmer states, changing the vertical temperature structure, changing other radiatively active constituents, or changing absorbed solar radiation through clouds and surface properties. In the idealized calculations here, the dominant response is a shift of the dry radiative constraint toward warmer surface and near-surface air temperatures. This connects the chapter directly to the CMIP6 results in Chapter 1: greenhouse

forcing raises the background energetic state on which the hottest land-temperature extremes occur.

The framework also helps explain why daily-mean and daily-maximum extremes should not be conflated. A daily-mean radiative balance constrains the integrated heating and cooling of the column over a full day. The daily maximum, however, depends on the transient partitioning of energy during the afternoon, when solar forcing is large and the surface skin, near-surface air, and boundary layer can be far from thermal equilibrium with one another. Thus the daily-mean theory provides the background state for extreme heat, but additional subdaily physics are required to translate that state into a maximum temperature. This motivates the diurnal-cycle model developed in Chapter 3.

There are several limitations. The calculations are clear-sky and use idealized hot, dry profiles, so they do not represent the full range of cloud, aerosol, and circulation effects that occur in comprehensive models. Surface emissivity and albedo are treated as prescribed parameters even though real deserts are heterogeneous in soil type, mineralogy, roughness, and vegetation cover. Atmospheric humidity is also idealized, despite the strong influence of water vapor on infrared opacity and on the distinction between dry heat and humid heat stress. Finally, the energy-balance framework is local and column-based, while real heat extremes are affected by horizontal advection, subsidence, soil-moisture history, and synoptic circulation.

Despite these limitations, the value of the framework is that it identifies the radiative terms that any more complete model must satisfy. Comprehensive climate models can simulate complex interactions among circulation, land surface, clouds, and radiation, but their output can be difficult to interpret mechanistically. The reduced framework in this chapter provides a diagnostic lens: it asks whether the hottest simulated states are consistent with plausible absorbed solar radiation, surface emissivity, atmospheric emissivity, and longwave response. In that sense, the model is best understood as a physical constraint on the upper envelope of daily-mean dry heat, not as a replacement for comprehensive simulations.

3.5 Conclusions

This study asked what sets the upper bound on Earth’s hottest daily-mean near-surface air temperatures and how that bound changes when CO_2 is increased. We addressed these questions using a deliberately simple framework: observationally constrained hot-desert columns, a daily-mean surface–atmosphere energy balance, and line-by-line radiative-transfer calculations. The goal was not to simulate every process involved in an observed heat wave, but to isolate the radiative constraint that must be satisfied by the warmest dry states.

The main result is that the hottest present-day daily-mean states are close to a TOA radiative constraint. In the representative subtropical-desert environment, the lower atmosphere is already strongly infrared-opaque, so the surface contribution to TOA emission is small and the atmospheric contribution dominates the longwave cooling to space. Nevertheless, outgoing longwave radiation continues to increase with temperature. This positive local radiative feedback is what prevents the warmest states from warming without bound in the daily-mean framework.

Doubling CO_2 shifts this balance but does not remove the constraint. At fixed surface and atmospheric temperatures, higher CO_2 reduces outgoing longwave radiation and therefore produces a positive fixed-state forcing across the extreme-temperature domain. The forcing is largest in the hottest and driest states, implying that CO_2 has a particularly strong radiative effect under the same conditions that favor the largest daily-mean temperatures. But because the local radiative feedback remains positive, the response is a finite shift toward warmer extreme states rather than a breakdown of the radiative limit.

These results suggest that Earth’s hottest daily-mean temperatures are not set by an arbitrary thermodynamic ceiling. They are set by the requirement that absorbed solar radiation be balanced by outgoing longwave radiation at the top of the atmosphere, together with the way that hot, dry atmospheric columns transmit and emit infrared radiation. Future work should test the robustness of this constraint in comprehensive climate models and in broader observational

samples, and should examine how it varies with surface type, soil moisture, boundary-layer structure, clouds, aerosols, and large-scale circulation.

Acknowledgements

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Chapter 4

A Diurnal-Cycle Framework for Extreme Daily-Maximum Temperatures

Abstract

The warmest near-surface air temperatures on Earth occur over hot, dry land surfaces, where intense solar heating, weak evaporative cooling, and deep convective boundary layers combine to produce large daytime temperature extremes. Previous daily-mean radiative calculations suggest that the upper envelope of dry heat is constrained by the requirement that the atmospheric column balance absorbed solar radiation with outgoing longwave radiation. However, daily-maximum temperature is not determined by this daily-mean constraint alone. It also depends on how daytime heating is partitioned among the surface skin, the near-surface air, and the deeper boundary layer. Here we develop a preliminary reduced-order framework for the diurnal cycle of extreme dry heat. The model linearizes coupled surface and boundary-layer energy budgets about a daily-mean radiative state and uses line-by-line radiative coefficients to represent longwave exchange. The calculations show that the surface skin can become tens of kelvin warmer than both the near-surface air and the bulk boundary layer at the time of daily maximum. At a representative benchmark state, the diagnosed surface skin reaches 359.3 K, while the near-surface air is 333.8 K and the bulk boundary-layer air is 319.0 K. A doubled- CO_2 diagnostic gives a skin-like warming of 4.42 K and a near-surface-air warming proxy of 3.86 K at the same state. These results suggest that greenhouse forcing shifts the background

radiative state, while surface thermal inertia, turbulent exchange, and boundary-layer depth determine how that shift appears in daily-maximum near-surface air temperature. The framework is intentionally idealized, but it provides a physically interpretable bridge between daily-mean radiative limits and observed daily-maximum dry heat extremes.

4.1 Introduction

The largest near-surface air temperatures on Earth occur in hot, dry subtropical land regions. These extremes are shaped by strong solar heating, low evaporative cooling, clear skies, dry soils, and deep convective boundary layers. Station-based records document near-surface air temperatures exceeding 50°C in desert environments, while satellite retrievals show that land-surface skin temperatures can become substantially hotter than the air above them (Merlone et al., 2019a; Mildrexler et al., 2011b; Zhao et al., 2021b). Observations and theory of dry convective boundary layers show that desert heat extremes are coupled to surface exchange, entrainment, and boundary-layer growth, rather than to radiative transfer alone (Stull, 1988; Garratt, 1992; Gamo, 1996; Messenger et al., 2010; Ryder et al., 2015). Understanding the physical limits on these temperatures is important both for climate dynamics and for the impacts of extreme heat on human and natural systems (Mearns et al., 1984; Carleton and Hsiang, 2016).

A useful starting point is the daily-mean radiative constraint on hot, dry states. In a daily-mean framework, the warmest dry climates must balance absorbed solar radiation with outgoing longwave radiation. Even in very hot states, outgoing longwave radiation continues to increase with temperature because of the spectral structure of atmospheric absorption and emission (Koll and Cronin, 2018; Jeevanjee et al., 2021). Increasing CO₂ shifts this balance by reducing outgoing longwave radiation at fixed temperature, following the standard radiative-forcing logic used in global climate analysis (Myhre et al., 1998; Gregory et al., 2004; Forster et al., 2016). This daily-mean perspective provides a clean energetic constraint on extreme dry heat.

Daily-maximum temperature, however, requires additional physics. The maximum usually occurs during the afternoon, when the surface energy budget is far from its daily average. The land surface has a small effective heat capacity and responds rapidly to solar forcing. The convective boundary layer has a much larger heat capacity and responds more slowly. The near-surface air temperature measured near two meters lies between these two limits because it is coupled to both the hot surface and the overlying mixed layer. Classic surface-energy-balance and boundary-layer theory therefore imply that daily-maximum air temperature depends on surface thermal inertia, turbulent exchange, boundary-layer depth, and radiative cooling, not only on top-of-atmosphere radiative balance (North et al., 1981; Stull, 1988; Brutsaert, 1982; Hartmann, 2016).

This distinction is especially important in deserts. Previous work on extreme maximum land-surface temperatures emphasized that intense solar heating and weak evaporative cooling can produce very large skin-temperature maxima (Garratt, 1992). Observations over hot desert regions also show that daytime boundary layers can become several kilometers deep, distributing sensible heat through an unusually large atmospheric reservoir (Gamo, 1996; Messenger et al., 2010; Ryder et al., 2015). These conditions naturally produce separation among surface skin temperature, near-surface air temperature, and bulk boundary-layer temperature.

Here we develop a preliminary reduced-order framework for this daily-maximum problem. The goal is not to replace comprehensive land-atmosphere models or to provide a fully calibrated prediction of observed heat records. Instead, we ask how the daily-mean radiative constraint on hot, dry states is translated into daily-maximum surface and air temperatures. The model represents the surface skin and the convective boundary layer as two coupled thermal reservoirs, linearized about the daily-mean state. It uses radiative coefficients diagnosed from line-by-line calculations and explores how increased CO₂ affects skin-like and air-like daily-maximum responses.

The framework also clarifies the distinction between dry heat extremes and humid heat stress. The highest dry-bulb temperatures occur mainly under low-relative-humidity conditions,

while the highest wet-bulb temperatures require much moister environments and are constrained by moist thermodynamics and human adaptability limits (Sherwood and Huber, 2010b). The present study therefore focuses on the physical controls on dry daily-maximum temperature rather than on humid heat stress.

4.2 Methods

4.2.1 Daily-maximum temperature framework

We model the diurnal cycle by linearizing coupled surface and boundary-layer energy budgets about a daily-mean state. The prognostic variables are the diurnal anomalies in surface skin temperature, T'_s , and bulk boundary-layer air temperature, T'_a . The governing equations are

$$\begin{aligned} \rho_a H_a c_{p,a} \frac{dT'_a}{dt} = & 4\sigma T_s^3 T'_s (1 - \epsilon_{a,s}) - 4\epsilon_s \sigma T_s^3 T'_s (\epsilon_s + \epsilon_a) \\ & + V(1 + k) (T'_s - T'_a - \Delta T_0), \end{aligned} \quad (4.1)$$

$$\begin{aligned} \rho_s H_s c_{p,s} \frac{dT'_s}{dt} = & (1 - \beta) Q' - 4\epsilon_g \sigma T_s^3 T'_s + 4\epsilon_g \epsilon_s \sigma T_a^3 T'_a \\ & - V (T'_s - T'_a - \Delta T_0) + F_s. \end{aligned} \quad (4.2)$$

Here ρ_a and ρ_s are the densities of air and the effective surface layer, $c_{p,a}$ and $c_{p,s}$ are their heat capacities, H_a is the boundary-layer depth, H_s is the effective thermal skin depth of the surface, V is the bulk turbulent exchange coefficient, and k relates entrainment heating at the boundary-layer top to the surface sensible heat flux. The parameter ΔT_0 represents the background daytime skin–air disequilibrium about which the equations are linearized. In the baseline calculations, $\Delta T_0 = 9.75$ K.

The first equation is the heat budget of the bulk boundary layer. It includes radiative terms associated with surface-emitted longwave radiation and atmospheric longwave exchange, as well as turbulent and entrainment-related heating. The second equation is the heat budget of the surface skin layer. It includes absorbed solar forcing, linearized longwave cooling, down-

ward atmospheric longwave exchange, turbulent heat loss to the air, and subsurface heat storage.

This model is intentionally reduced order. It does not attempt to simulate the full land surface or atmospheric boundary layer. Instead, it keeps only the reservoirs and exchanges most directly relevant to the daily maximum: a shallow surface layer with small heat capacity, a much deeper air reservoir with large heat capacity, turbulent coupling between them, and longwave radiative exchange. The purpose of this simplification is interpretability. By reducing the system to a small number of terms, the model makes clear why a daily-mean radiative response cannot be translated directly into a daily-maximum two-meter air-temperature response without considering surface thermal inertia and boundary-layer heat capacity.

4.2.2 Diurnal forcing and parameter choices

The imposed solar forcing is represented by a prescribed diurnal anomaly about the daily mean,

$$Q' = -Q \cos\left(\frac{\pi t}{24 \text{ hours}}\right), \quad (4.3)$$

where Q is the characteristic amplitude of absorbed solar radiation. This idealized form isolates the leading harmonic of the diurnal heating cycle. It does not attempt to represent clouds, aerosols, changing solar zenith angle, or site-specific albedo variations.

The baseline parameters are chosen to represent hot subtropical desert conditions. We use $\rho_s = 1400 \text{ kg m}^{-3}$, $c_{p,s} = 1000 \text{ J kg}^{-1} \text{ K}^{-1}$, and $H_s = 0.1 \text{ m}$ for the effective surface layer. The boundary-layer depth is taken to be of order 6–8 km, consistent with observations of very deep dry convective boundary layers in desert regions (Gamo, 1996; Messenger et al., 2010; Ryder et al., 2015). We set $k = 0.2$ and set the anomalous subsurface heat-flux term F_s to zero in the preliminary calculations. The turbulent exchange coefficient V should be interpreted as an effective bulk coupling that depends on wind speed, roughness length, stability, and surface heterogeneity (Garratt, 1977; Stull, 1988).

These values are not intended as a final calibration. Surface thermal inertia varies with

Table 4.1. Baseline parameters used in the preliminary diurnal-cycle calculations. Values are intended to be representative of hot subtropical desert conditions rather than uniquely optimized.

Symbol	Meaning	Baseline value
ρ_s	Effective surface-layer density	1400 kg m ⁻³
$c_{p,s}$	Effective surface-layer heat capacity	1000 J kg ⁻¹ K ⁻¹
H_s	Effective thermal skin depth	0.1 m
H_a	Convective boundary-layer depth	6–8 km
k	Entrainment-to-surface-flux parameter	0.2
ΔT_0	Background daytime skin–air offset	9.75 K
F_s	Anomalous subsurface heat flux	0 W m ⁻²

soil type, soil moisture, vegetation, and the effective depth of daytime heat storage. Turbulent exchange varies with wind speed and stability. The parameter set in Table 4.1 instead defines a transparent baseline case for interpreting the mechanism.

4.2.3 Radiative coefficients

The diurnal-cycle model uses radiative coefficients diagnosed from the daily-mean line-by-line calculations. Line-by-line radiative transfer is appropriate because hot, dry states are sensitive to the spectral structure of water-vapor absorption, CO₂ absorption, atmospheric continuum absorption, and thermal-infrared windows (Goody and Yung, 1989; Clough et al., 1992, 2005; Gordon et al., 2017; Mlawer et al., 2012). The calculations are interpreted in terms of effective longwave coefficients rather than individual spectral lines.

Surface emissivity is also important in desert environments. Mineral surfaces have spatially and spectrally variable thermal-infrared emissivity, as shown by remote-sensing datasets and observations over arid regions (Ogawa and Schmugge, 2004; Jin and Liang, 2006; Hulley et al., 2015; Huang et al., 2016; Masiello et al., 2014). Emissivity variations over the Sahara and Sahel can affect atmospheric heating and circulation (Chen et al., 2019). In the present framework, these effects enter through bulk diagnosed coefficients. Future work should test sensitivity to spectrally varying surface emissivity more explicitly.

The diurnal model requires two additional radiative quantities associated with the boundary-

layer top. The first is $\epsilon_{a,s}$, the absorptivity below the boundary-layer top for surface-emitted thermal radiation. The second is ϵ_a , an effective atmospheric emissivity relevant for longwave exchange with the boundary layer. Ideally, ϵ_a would be diagnosed from downward longwave fluxes at the boundary-layer top. Because the present implementation does not output downward fluxes at arbitrary interior levels, we approximate ϵ_a using the atmospheric contribution to top-of-atmosphere emissivity, $\epsilon_{t,a}$. This approximation is physically motivated by the fact that absorption and emission are controlled by the same opacity structure under local thermodynamic equilibrium (Goody and Yung, 1989; Pierrehumbert, 2010).

4.2.4 Near-surface air temperature diagnostic

The two-layer system predicts a surface skin anomaly and a bulk boundary-layer anomaly. Observed daily-maximum temperature, however, is conventionally measured near two meters above the surface (World Meteorological Organization, 2023). The near-surface air temperature is therefore treated as a diagnostic quantity that lies between the surface skin and the bulk mixed layer. This distinction is essential because station-based air-temperature records and satellite skin-temperature records are related but not interchangeable (Mildrexler et al., 2011b; Merlone et al., 2019a; Zhao et al., 2021b).

In the preliminary implementation, the near-surface response is inferred from the modeled skin–boundary-layer separation and the assumed surface-layer coupling. A more complete framework would include a separate surface-layer temperature equation or fit the diagnostic relationship directly to observed two-meter temperature and skin-temperature diurnal cycles. Reanalysis products, satellite retrievals, station observations, and radiosonde archives provide possible validation datasets (Hersbach et al., 2020a; Copernicus Climate Change Service, 2018; Hersbach et al., 2020b, 2023; University of Wyoming, Department of Atmospheric Science, 2025).

4.3 Results

4.3.1 Response to increased CO₂

We first combine the daily-mean radiative response with the daily-maximum skin–air separation mechanism to explore how extreme daily-maximum temperatures may respond to higher CO₂. Figure 4.1 summarizes the preliminary response across the same paired temperature domain. Panel (a) shows the skin-like warming expected from the radiative framework. Panel (b) shows the difference between the air-like and skin-like warming responses. Panel (c) shows the present-day skin–air separation.

The radiative framework provides the baseline warming response. Across the plotted domain, the skin-like quantity warms by several kelvin under doubled CO₂, with the largest warming occurring in the warmest states. At the benchmark state, the fixed-state CO₂ forcing is 4.65 W m^{-2} , corresponding to a skin-like warming of 4.42 K and a near-surface-air warming proxy of 3.86 K (Table 4.2). Thus the air-like response is slightly smaller than the skin-like response at this state.

This difference is not large enough to overturn the radiative-control interpretation, but it shows why daily-maximum air temperature should not be assumed to equal surface skin temperature. Increased CO₂ shifts the background radiative state, while the diurnal-cycle structure controls how that shift is partitioned among skin temperature, near-surface air temperature, and bulk boundary-layer temperature. In regions of state space where present-day skin–air separation is already large, changes in surface heat capacity, turbulent exchange, boundary-layer depth, or soil moisture could substantially influence the daily-maximum air-temperature response.

4.3.2 Daily-maximum structure of surface skin and air temperatures

We then examine the daily-maximum temperature structure across paired daily-mean near-surface air and surface skin temperatures. Figure 4.2 summarizes the preliminary diagnostics. Panel (a) shows the absorptivity below the boundary-layer top, $\epsilon_{a,s}$. The absorptivity is

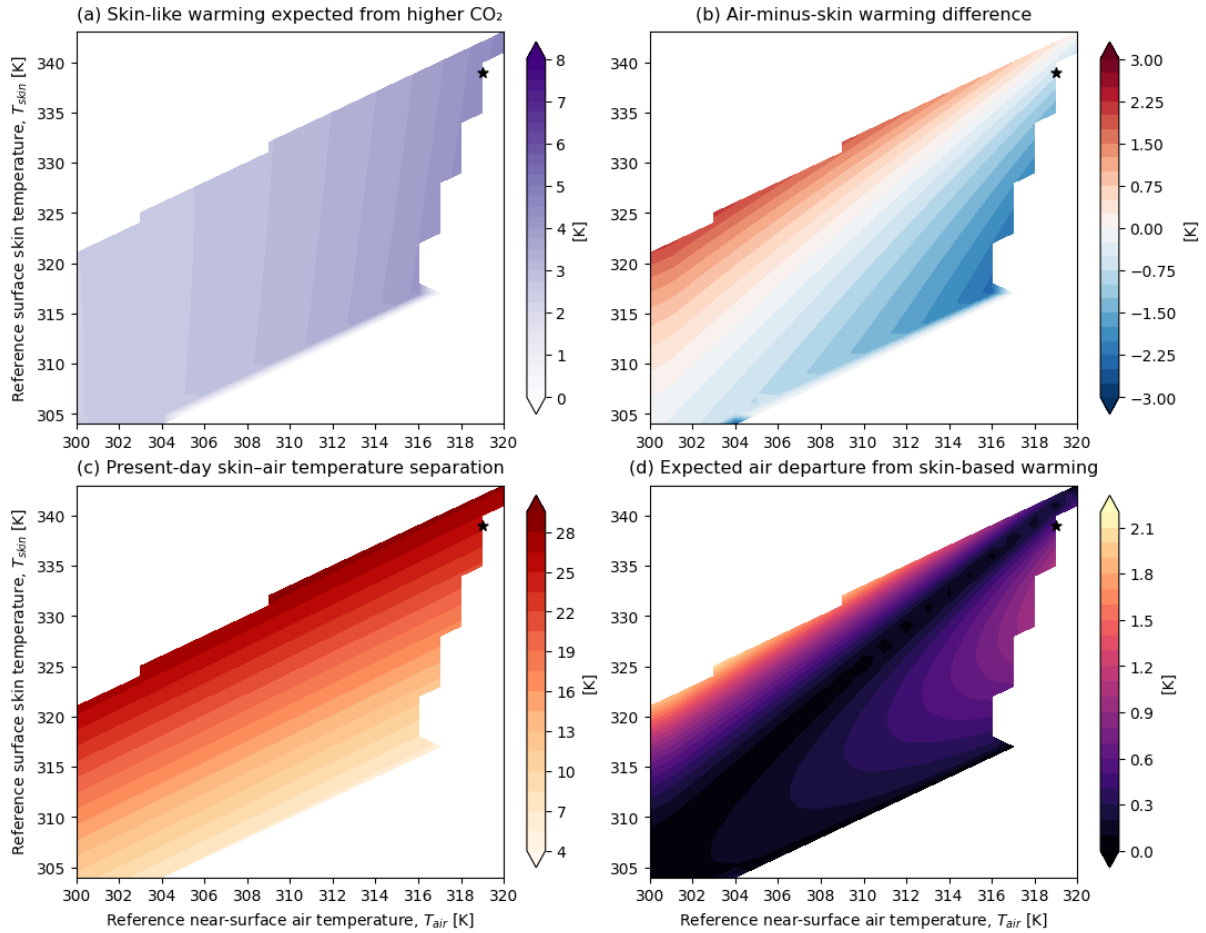


Figure 4.1. Preliminary response of daily-maximum temperature structure to increased CO_2 . Panel (a) shows the skin-like warming expected from the radiative framework. Panel (b) shows the difference between the air-like and skin-like warming responses. Panel (c) shows the present-day skin-air temperature separation. The gray region indicates states outside the physically allowed domain considered here.

large across much of the plotted domain, indicating that the lower atmosphere is strongly coupled radiatively to the hot land surface. Panels (b) and (c) show that the surface skin remains substantially warmer than both the bulk boundary-layer air and the near-surface air at the time of daily maximum.

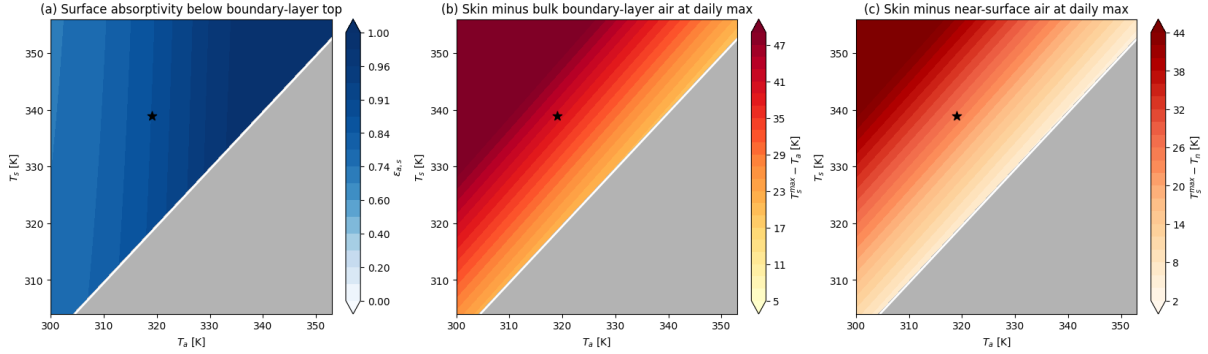


Figure 4.2. Preliminary daily-maximum diagnostics across paired near-surface air and surface skin temperatures. Panel (a) shows the surface-emission absorptivity below the top of the boundary layer, $\epsilon_{a,s}$. Panel (b) shows the difference between the daily-maximum surface skin temperature and the bulk boundary-layer air temperature. Panel (c) shows the difference between the daily-maximum surface skin temperature and the near-surface air temperature. The gray region indicates states outside the physically allowed domain considered here.

The largest separation occurs between the surface skin and the bulk boundary-layer air. Across the plotted domain, the surface skin can exceed the bulk boundary-layer temperature by several tens of kelvin, with the largest differences occurring in the hottest and driest states. This is consistent with the contrast between the small effective heat capacity of the surface and the much larger heat capacity of the convective boundary layer. The near-surface air is more strongly coupled to the skin than the bulk boundary-layer air, but it still remains substantially cooler than the skin at the time of maximum temperature.

Table 4.2 gives representative diagnosed values from the same calculations. At the benchmark state, the preliminary diurnal model gives a daily-maximum surface skin temperature of 359.3 K, while the diagnosed near-surface air temperature at that time is 333.8 K. The resulting skin–near-surface-air separation is 25.4 K, and the skin–bulk-boundary-layer separation is 40.3 K. These values make the mechanism in Fig. 4.2 concrete: the surface skin becomes

extremely hot, but the measured near-surface air temperature remains buffered by surface-layer and boundary-layer coupling.

Table 4.2. Representative diagnosed values from the preliminary daily-maximum framework. The benchmark state is the black-star state used in Figs. 4.1 and 4.2, with daily-mean $T_s = 339$ K and $T_a = 319$ K. Domain summaries are computed over the valid radiative-response states used for Fig. 4.1.

Quantity	Benchmark value	Domain mean	Interpretation
$\epsilon_{a,s}$	0.88	–	Fraction of surface thermal emission absorbed below the boundary-layer top
$T_{s,\max}$	359.3 K	–	Daily-maximum surface skin temperature in the preliminary diurnal model
$T_a(T_{s,\max})$	319.0 K	–	Bulk boundary-layer air temperature at the time of maximum skin temperature
$T_{2m}(T_{s,\max})$	333.8 K	–	Diagnosed near-surface air temperature at the time of maximum skin temperature
$T_{s,\max} - T_{2m}$	25.4 K	17.1 K	Skin–near-surface-air separation
$T_{s,\max} - T_a$	40.3 K	–	Skin–bulk-boundary-layer separation
CO ₂ forcing	4.65 W m ^{−2}	4.67 W m ^{−2}	Fixed-state reduction in outgoing longwave radiation
Predicted skin-like warming	4.42 K	2.83 K	Radiative warming response of the surface-like state
Predicted bulk-air-like warming	3.77 K	2.63 K	Radiative warming response of the air-like state
Predicted near-surface-air warming	3.86 K	2.89 K	Proxy daily-maximum near-surface-air warming
Air-minus-skin difference	−0.56 K	0.06 K	Departure of near-surface-air warming from skin-like warming

4.3.3 Relationship to moist heat stress

The framework developed here applies most directly to the warmest dry-temperature states, which occur in hot and arid environments. These states are distinct from the condi-

tions that produce the highest wet-bulb temperatures. Figure 4.3 compares daily-mean wet-bulb temperature with daily-mean near-surface air temperature, colored by relative humidity. The warmest dry-temperature states occur predominantly at low relative humidity, whereas the largest wet-bulb temperatures occur in much more humid environments.

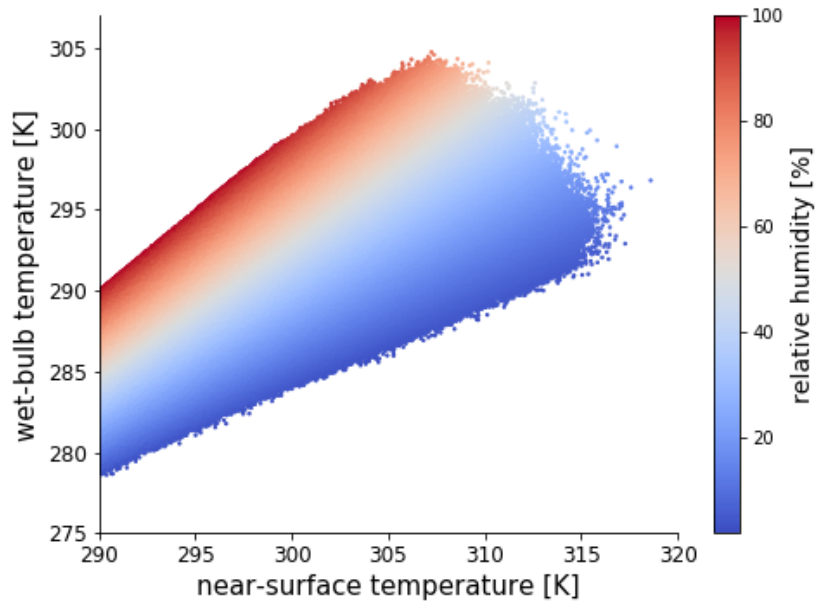


Figure 4.3. Daily-mean wet-bulb temperature as a function of daily-mean near-surface air temperature, colored by relative humidity. The highest near-surface temperatures occur predominantly under low-relative-humidity conditions, whereas the highest wet-bulb temperatures occur in warm, humid environments.

This distinction matters because dry-temperature extremes and moist heat-stress extremes are not governed by the same limiting processes. The highest wet-bulb temperatures are strongly tied to humidity and moist thermodynamics, while the hottest dry-temperature states considered here occur where the atmosphere is dry, latent cooling is limited, and the land surface can become extremely hot. The model developed here should therefore be interpreted as a framework for dry heat extremes rather than a general theory of humid heat stress (Sherwood and Huber, 2010b).

4.4 Discussion

The preliminary diurnal-cycle framework highlights why daily-maximum temperature cannot be inferred from a daily-mean radiative constraint alone. The daily-mean calculation constrains the energetic background state, but the daily maximum depends on transient coupling among the surface skin, near-surface air, and deeper boundary layer. In hot desert environments, the surface can become much warmer than the air above it, creating a large potential sensible heat flux. The measured near-surface air temperature then depends on how efficiently that heat is mixed upward and how much heat capacity the boundary layer provides (Garratt, 1977; Stull, 1988; Garratt, 1992).

This interpretation gives the reduced-order parameters a direct physical meaning. The surface heat capacity H_s controls how rapidly the skin responds to the imposed solar cycle. The exchange coefficient V controls how efficiently the surface anomaly is communicated to the air. The boundary-layer heat capacity H_a controls the dilution of sensible heating through the mixed layer, and the coupling coefficient k controls how strongly the near-surface diagnostic follows the modeled surface–boundary-layer contrast. The benchmark calculation is therefore not meant to be a universal desert prediction. It is a reference point that shows how physically plausible parameter choices can translate a radiatively constrained daily-mean state into distinct skin, near-surface-air, and boundary-layer maxima.

This synthesis helps reconcile a slowly increasing radiative limit with potentially larger or more spatially variable changes in modeled daily-maximum extremes. The radiative calculation isolates how much warming is needed to restore longwave balance after greenhouse forcing. Comprehensive climate models include additional changes in soil moisture, cloudiness, aerosols, circulation, wind speed, boundary-layer depth, vegetation, and land-surface properties. These factors can alter the diurnal amplification between daily-mean state and daily maximum. Thus, differences between the radiative-limit response and model-projected daily-maximum extremes need not imply that the radiative constraint is irrelevant; they may instead reflect changes

in surface and boundary-layer coupling.

Several limitations should be emphasized. First, the model neglects horizontal advection, which can be important during observed heat waves. Second, it assumes a simple sinusoidal solar forcing and ignores clouds and aerosols. Third, it uses a simplified turbulent exchange term rather than a full surface-layer similarity formulation. Fourth, it sets the anomalous subsurface heat flux to zero, even though heat storage and release in the ground can affect the timing and amplitude of the surface temperature cycle. Fifth, near-surface air temperature is treated diagnostically rather than prognostically. Finally, the approximation of ϵ_a using the atmospheric contribution to top-of-atmosphere emissivity should be replaced by direct interior-level flux diagnostics in future radiative-transfer calculations.

The distinction between skin temperature, near-surface air temperature, and bulk boundary-layer temperature is also important for interpreting observations. Satellite products observe radiometric skin temperature, station networks measure air temperature near two meters, and reanalyses estimate both through a combination of model physics and data assimilation. During ordinary conditions these quantities may covary closely enough that their differences are secondary. During extreme dry heat, however, the differences can become central to the problem. A shallow surface layer can heat rapidly under intense sunlight, while the near-surface air responds through turbulent exchange and the deeper boundary layer responds through entrainment and vertical mixing. This is why the hottest satellite-observed land-surface temperatures can be far above the hottest standard air-temperature records.

The framework suggests that future projections of daily-maximum dry heat should be interpreted through both radiative and boundary-layer changes. Greenhouse forcing warms the background state, but changes in boundary-layer depth, soil moisture, surface roughness, and sensible heat exchange can alter how much of that warming appears in the daily maximum at two meters. For example, a deeper boundary layer increases the heat capacity of the air reservoir and can damp the near-surface air response for a given surface heat input, whereas drier soils and weaker evaporative cooling can increase sensible heating and amplify the daytime maximum.

These competing effects help explain why the hottest-day response in comprehensive models can differ from the mean land-temperature response.

The main sensitivities expected from this framework are also physically interpretable. Increasing surface thermal inertia should reduce the amplitude of the skin-temperature cycle and delay the afternoon maximum. Increasing turbulent exchange should reduce the skin-air separation but transfer more heat into the boundary layer. Increasing boundary-layer depth should distribute the same heat input through a larger air mass and therefore weaken the bulk-air temperature response. These signs are not artifacts of the numerical implementation; they follow from the reservoir structure of the model and are consistent with the standard mixed-layer view of daytime boundary-layer evolution (Stull, 1988; Gamo, 1996).

This distinction also reinforces why the present work should not be read as a full heat-health analysis. The most severe human heat stress often involves humidity, warm nights, event duration, and limited physiological recovery. A daily-maximum dry-bulb framework isolates one physically important piece of the heat problem: the upper envelope of daytime dry heating. Future work could connect this framework to heat-index or wet-bulb projections by adding a moisture budget and by diagnosing how humidity modifies near-surface thermodynamic comfort. That extension would be valuable, but it would address a different problem from the one solved here.

These limitations are acceptable for the present framework because the goal is to develop a physically interpretable model and identify the relevant controls. They would not be sufficient for a final predictive theory of daily-maximum temperature. The next step should be direct validation against observations and reanalysis. A useful strategy would be to composite the hottest days in major subtropical desert regions using station observations, satellite skin temperatures, ERA5 fields, and radiosonde profiles, then fit the effective parameters H_s , V , H_a , and k (Hersbach et al., 2020a; Copernicus Climate Change Service, 2018; Hersbach et al., 2023; University of Wyoming, Department of Atmospheric Science, 2025). This would test whether the reduced-order model captures the amplitude and timing of observed daily-maximum tem-

perature cycles.

A practical validation workflow would begin with observed hot-day composites rather than with individual record events. For each region, one could identify the upper tail of daily-maximum air temperature, extract the corresponding satellite skin temperature and reanalysis boundary-layer fields, and compare the observed phase and amplitude of the skin–air separation with the model solution. Radiosonde profiles would then provide an independent check on mixed-layer depth and lower-tropospheric temperature structure. This workflow would directly address the largest uncertainty in the present chapter: whether the inferred effective parameters remain stable across real hot-desert environments or vary systematically with soil moisture, wind speed, surface roughness, and synoptic setting.

4.5 Conclusions

We developed a preliminary reduced-order framework for connecting the daily-mean radiative constraint on extreme dry heat to the diurnal cycle of daily-maximum temperature. The model represents the surface skin and convective boundary layer as coupled thermal reservoirs and uses line-by-line radiative coefficients to represent longwave exchange. The framework is intentionally idealized, but it identifies the processes that connect daily-mean radiative limits with daily-maximum near-surface air temperature.

The main result is that the surface skin, near-surface air, and bulk boundary layer can become substantially separated during the daytime maximum. At a representative benchmark state, the diagnosed surface skin reaches 359.3 K, while the near-surface air is 333.8 K and the bulk boundary-layer air is 319.0 K. This implies skin–air separations of tens of kelvin, showing that daily-maximum air temperature is mediated by surface-layer and boundary-layer coupling rather than being identical to the surface skin temperature.

The preliminary CO₂ response is similarly two-part. Higher CO₂ shifts the background radiative balance toward warmer states, but the expression of that warming in daily-maximum

air temperature depends on the diurnal-cycle structure. At the benchmark state, the skin-like warming is 4.42 K, while the near-surface-air warming proxy is 3.86 K. Thus increased CO₂ shifts rather than removes the radiative constraint, while surface thermal inertia, turbulent exchange, and boundary-layer depth determine how that shift appears in measured near-surface air temperature.

These results help explain why the daily maximum of near-surface air temperature cannot be inferred from a daily-mean radiative limit alone. The radiative constraint determines the background energetic state of the column, but the afternoon maximum depends on how that energy is partitioned among the surface skin, the surface layer, and the deeper boundary layer. In the dry, weakly evaporative environments emphasized in this dissertation, sensible heat exchange is the main pathway by which surface heating is communicated to the air. The strength and timing of this exchange therefore regulate whether a warmer radiative state appears primarily as a hotter surface skin, a hotter two-meter air temperature, or a deeper warming of the convective boundary layer.

The framework also clarifies the relationship between Chapters 1 and 2. Chapter 1 shows that the hottest dry-bulb temperatures in CMIP6 warm strongly over the 21st century and remain geographically tied to subtropical dry regions. Chapter 2 shows that the warmest daily-mean states are constrained by the ability of hot, dry atmospheric columns to emit longwave radiation to space. The present chapter provides the subdaily link between those results: once the daily-mean radiative state is shifted by greenhouse forcing, the realized daily maximum depends on boundary-layer heat capacity, turbulent coupling, and surface thermal inertia. This provides a physical interpretation for why daily-maximum extremes may warm differently from broader mean-temperature metrics.

Because the model is reduced order, the quantitative values reported here should be viewed as benchmarks rather than final predictions. A complete predictive theory would require direct evaluation against station observations, satellite land-surface temperature, reanalysis boundary-layer diagnostics, and radiosonde profiles during observed extreme-heat events.

Nevertheless, the central qualitative result is robust within the framework: greenhouse forcing shifts the energetic constraint toward warmer states, but the conversion of that shift into an observed daily-maximum air temperature is controlled by the diurnal boundary-layer problem. This is the key physical bridge from the daily-mean radiative limits developed in Chapter 2 to the hottest daily-maximum temperatures analyzed in Chapter 1.

Chapter 5

Synthesis and Future Directions

This dissertation examined Earth’s warmest surface and near-surface temperatures from three complementary perspectives: comprehensive climate-model projections, daily-mean radiative constraints, and a reduced-order diurnal-cycle framework. The central result is that the hottest temperatures are not controlled by mean warming alone. They emerge from the interaction of radiative forcing, dry atmospheric structure, land-surface properties, turbulent exchange, and boundary-layer heat capacity. This synthesis chapter summarizes the main contributions, connects the three papers, and outlines directions for future work.

5.1 Main Contributions

The first contribution is an assessment of how the hottest land temperatures change in CMIP6 simulations. Chapter 2 showed that annual hottest daily-mean and daily-maximum temperatures over tropical land warm faster than the tropical land mean. This tail amplification appears in both transient SSP2-4.5 simulations and abrupt CO₂ experiments. The chapter also showed that the geography of the hottest annual land grid cells is spatially persistent, with hotspots concentrated in a subtropical corridor spanning North Africa, the Arabian Peninsula and Middle East, and South Asia. These regions combine strong insolation, low evaporative cooling, dry soils, and favorable surface properties, so they remain central to the global upper tail even as the climate warms.

A second contribution is the explicit connection between model evaluation and projection interpretation. The CMIP6 analysis does not simply ask how hot models become in the future; it first asks whether models reproduce the observed spatial pattern and magnitude of historical extreme heat. This distinction matters because a model can reproduce the broad desert-hotspot pattern while still having substantial warm or cold biases, and a model can project strong future warming even if its historical maximum-temperature geography is imperfect. Evaluating pattern skill and bias together provides a more cautious basis for interpreting record-like projections.

The third contribution is a daily-mean radiative framework for very hot, dry atmospheric columns. Chapter 3 showed that the warmest daily-mean states can be interpreted as radiatively constrained states in which absorbed solar radiation is balanced by outgoing longwave radiation. Even in hot, optically thick lower atmospheres, outgoing longwave radiation continues to increase with temperature because emission occurs across spectral windows and from vertically varying parts of the column. Increasing CO₂ shifts the radiative balance toward warmer states by reducing outgoing longwave radiation at fixed temperature, but it does not eliminate the basic top-of-atmosphere energy constraint.

The fourth contribution is a diurnal interpretation of daily-maximum temperature. Chapter 4 showed that daily-maximum surface skin temperature, near-surface air temperature, and bulk boundary-layer temperature should not be treated as interchangeable. The surface skin has a shallow heat capacity and can respond rapidly to daytime solar forcing; the convective boundary layer has a much larger heat capacity and integrates heating over a deeper air mass. As a result, the skin can become tens of kelvin warmer than both the near-surface air and the bulk boundary layer during the afternoon maximum. This separation helps explain why satellite-observed land-surface skin temperatures can be far hotter than standard two-meter air-temperature records.

5.2 Connecting the Chapters

The chapters form a hierarchy of complexity. Chapter 2 begins with the full climate-system response in CMIP6 models. Those simulations include large-scale circulation, clouds, land-surface feedbacks, soil moisture, and model-specific parameterizations, but their complexity makes it difficult to identify the controlling mechanisms of the hottest states. Chapter 3 therefore simplifies the problem to a daily-mean surface–atmosphere column and asks how radiative transfer constrains the upper envelope of dry heat. Chapter 4 then adds the diurnal cycle and separates the thermal reservoirs that determine the daily maximum.

Viewed together, the results suggest a two-step interpretation of extreme dry heat. First, radiative forcing and large-scale climate change shift the background state: the warmest dry columns become warmer because the atmosphere emits less longwave radiation at fixed temperature when greenhouse gases increase. Second, local land–atmosphere processes determine how that warmer background state appears in a daily maximum. Surface thermal inertia, sensible heat exchange, boundary-layer depth, and the phase of solar forcing determine the partitioning among skin temperature, near-surface air temperature, and mixed-layer temperature. This is why the daily-mean and daily-maximum responses can be related but not identical.

This interpretation also clarifies why dry-bulb extremes are connected to, but distinct from, human heat risk. The hottest dry-bulb temperatures often occur in very dry regions, whereas the most dangerous humid heat stress can occur in moister environments where evaporation and humidity limit human thermoregulation (Sherwood and Huber, 2010a; Raymond et al., 2020; Coffel et al., 2018). Similarly, nighttime minima and multi-day heatwaves are crucial for impacts, but they emphasize persistence, humidity, cloudiness, and nocturnal cooling rather than the single-day upper envelope of dry daytime temperature. The dissertation therefore treats dry-bulb maximum temperature as a physically specific climate quantity, not as a complete heat-health metric.

5.3 Implications

One implication is that changes in mean land temperature are insufficient for understanding changes in the hottest extremes. Chapter 2 found that the hottest daily-mean and daily-maximum indices warm faster than tropical land mean temperature. This means that projections based only on mean warming can understate changes in the upper tail. The amplification of extremes also affects the probability of exceeding fixed historical benchmarks: as the background distribution shifts and the tail warms faster than the mean, events that were historically rare become increasingly common.

A second implication is that model evaluation should consider both spatial pattern and absolute bias. For record-like heat, the location of the maximum matters because the annual global maximum can be determined by relatively small differences among hot desert regions. Biases in surface properties, soil moisture, boundary-layer mixing, or regional circulation can shift the simulated hottest location even if the global mean climate is well represented. Observational uncertainty further complicates this evaluation, especially in remote arid regions where station density is low. Comparisons between Berkeley Earth, ERA5, and other products should therefore be interpreted as part of the uncertainty budget rather than as a purely technical preprocessing detail.

A third implication is that surface skin temperature and near-surface air temperature should be interpreted separately. Satellite skin-temperature records are invaluable for mapping land-surface extremes, but they do not directly measure the air temperature experienced at standard screen height. Conversely, two-meter air temperature does not capture the full radiative and thermal state of the land surface. The very large skin–air separations suggested by Chapter 4 imply that future work should use both quantities when diagnosing the physical limits of hot desert environments.

5.4 Limitations

The dissertation intentionally focuses on dry-bulb temperature extremes, which means that it does not provide a complete assessment of heat impacts. Humidity, human exposure, urban form, acclimatization, socioeconomic vulnerability, and access to cooling all strongly shape heat risk. A heat-health analysis would need to consider heat index or wet-bulb temperature, nighttime minima, event duration, population exposure, and vulnerability. Those variables are not secondary details for impacts; they define a different research question from the one addressed here.

The CMIP6 analysis is also limited by model availability and observational uncertainty. Daily maximum temperature, daily mean temperature, and abrupt-forcing experiments are not available for all models in consistent form, so different parts of the analysis use different model subsets. Observational benchmarks are uncertain in the hottest regions because station coverage is sparse and gridded products may smooth or shift local extremes. These uncertainties do not undermine the main conclusion that extremes warm faster than the mean, but they do affect quantitative estimates of bias, hotspot location, and record-like exceedance probability.

The idealized models in Chapters 3 and 4 are deliberately simplified. The radiative calculations use idealized hot, dry atmospheric structures and focus on clear-sky longwave behavior. The diurnal model reduces the land–atmosphere system to a small number of effective heat reservoirs and exchange coefficients. These simplifications make the models interpretable, but they omit clouds, advection, spatial heterogeneity, soil-moisture evolution, entrainment variability, and detailed surface-layer stability. The models should therefore be read as mechanistic frameworks rather than final predictive tools.

These assumptions affect how broadly the analytic conclusions should be interpreted. The radiative calculations support the conclusion that hot, dry daily-mean states remain constrained by spectrally distributed longwave emission, but they do not prove that real heat waves are controlled by radiation alone. Clouds, aerosols, horizontal heat advection, soil-moisture

anomalies, and circulation can all shift the realized temperature away from the idealized clear-sky column. Similarly, the diurnal model supports the conclusion that surface thermal inertia and boundary-layer heat capacity can separate skin, near-surface air, and bulk-air temperatures, but the exact magnitude of that separation will depend on local soil properties, wind speed, surface roughness, entrainment, and heterogeneity. The broader conclusion is therefore not that the reduced-order models predict a unique maximum temperature. Rather, it is that they identify mechanisms that comprehensive models and observations should be tested against.

5.5 Future Directions

A natural next step is to extend the CMIP6 analysis to additional heat metrics while keeping the physical question clear. Annual maximum five-day mean temperature and annual maximum daily minimum temperature would help connect hottest-land projections to heatwave persistence and nighttime recovery. Heat index, wet-bulb temperature, or other humidity-aware metrics would be needed for a direct human-health analysis. These metrics should be analyzed as complementary quantities rather than as replacements for daily-maximum dry-bulb temperature, because they emphasize different mechanisms and may identify different geographic hotspots.

A second direction is to quantify observational uncertainty more systematically. One practical approach is to compare Berkeley Earth with ERA5 and other gridded products over the historical period, focusing on the same tropical-land mask and hottest-grid-cell diagnostics used in Chapter 2. The resulting product-to-product spread would not provide a perfect error estimate, but it would give a useful scale for observational and gridding uncertainty. This comparison could be reported alongside the existing model-skill metrics and would help distinguish robust model biases from benchmark uncertainty.

A third direction is to validate the reduced-order diurnal framework against observations and reanalysis. The model parameters in Chapter 4 could be estimated from composites of the

hottest days in major desert regions using station observations, satellite skin temperature, ERA5 surface fluxes, and radiosonde profiles. Such a comparison would test whether the diagnosed skin–air–boundary-layer separation is realistic and whether the effective heat capacities and exchange coefficients vary systematically across deserts.

Finally, the radiative and diurnal frameworks could be coupled to land-surface and boundary-layer models of intermediate complexity. Such models would retain enough process detail to represent soil moisture, entrainment, and stability while remaining simple enough to interpret physically. This would help bridge the gap between the comprehensive CMIP6 projections of Chapter 2 and the reduced-order mechanisms developed in Chapters 3 and 4.

5.6 Concluding Remarks

Earth’s hottest temperatures are produced by an unusual combination of strong radiative forcing, atmospheric dryness, limited evaporative cooling, and land-surface properties that favor large sensible heating. Greenhouse forcing shifts these hot states warmer, but the expression of that shift depends on whether one considers daily-mean temperature, daily-maximum near-surface air temperature, or surface skin temperature. The central message of this dissertation is therefore that the upper tail of land temperature is both radiatively constrained and locally amplified. Understanding future extremes requires both perspectives: the global energy constraint that sets the background and the land–atmosphere physics that shapes the hottest days.

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