# Global multi-model projections of local urban climates

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C F


PM2.5

# Climate-driven urban risks will worsen in the future because of …

Urban development

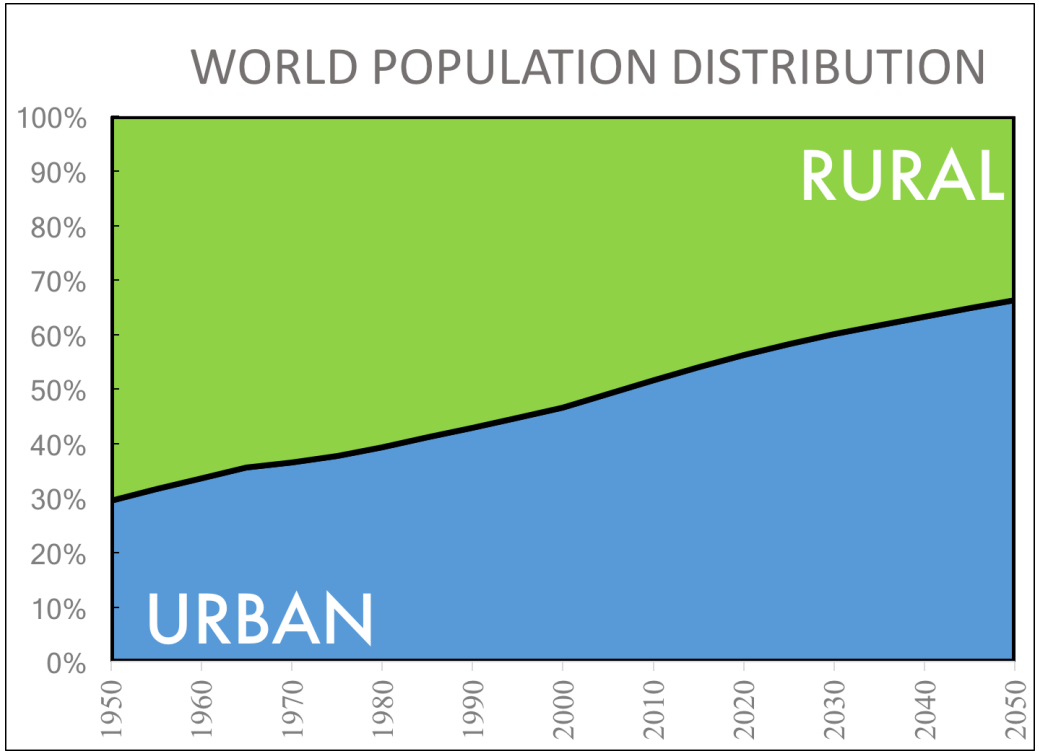
+

Climate change

# Human-perceived impacts

2-3 %
of Earth's land surface

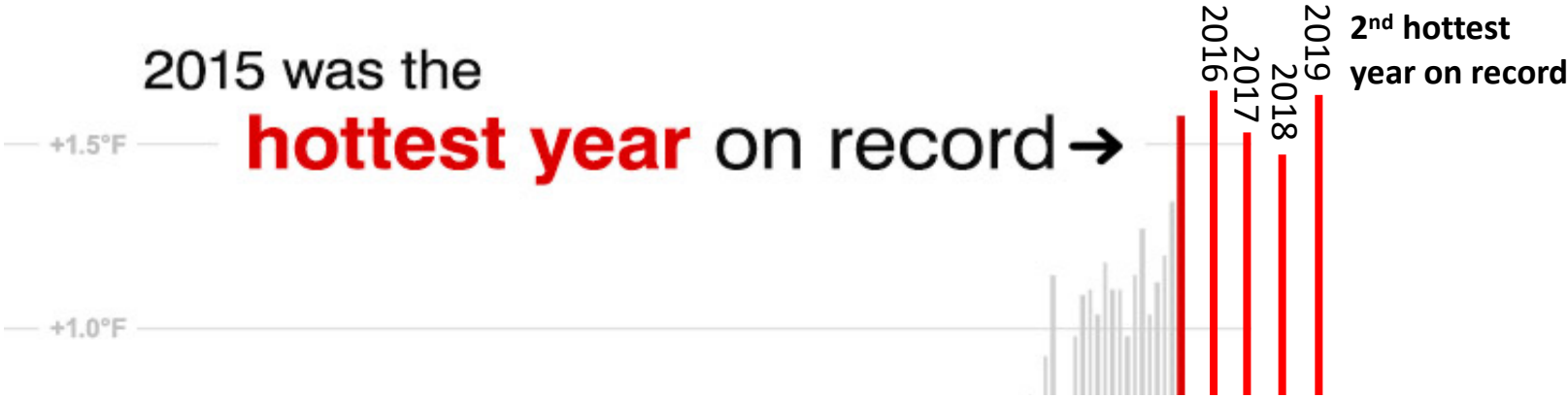
>50 %
of world population




Source: UN HABITAT

# Heat

- Profound impacts
  - Health
  - Energy
  - Productivity
- Connected to other urban environmental problems




National Oceanic and Atmospheric Administration
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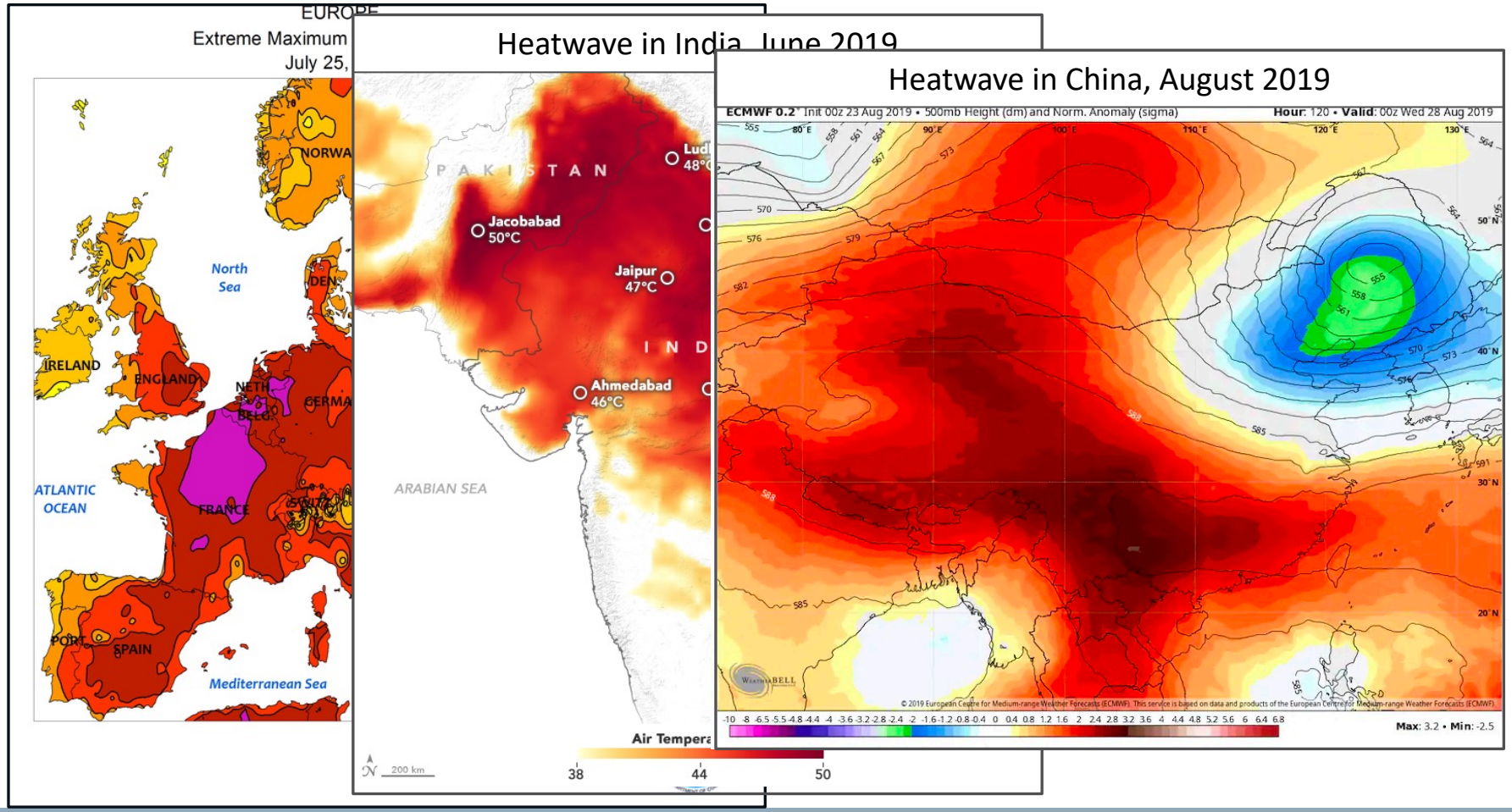
# 2020 was Earth's 2nd-hottest year, just behind 2016

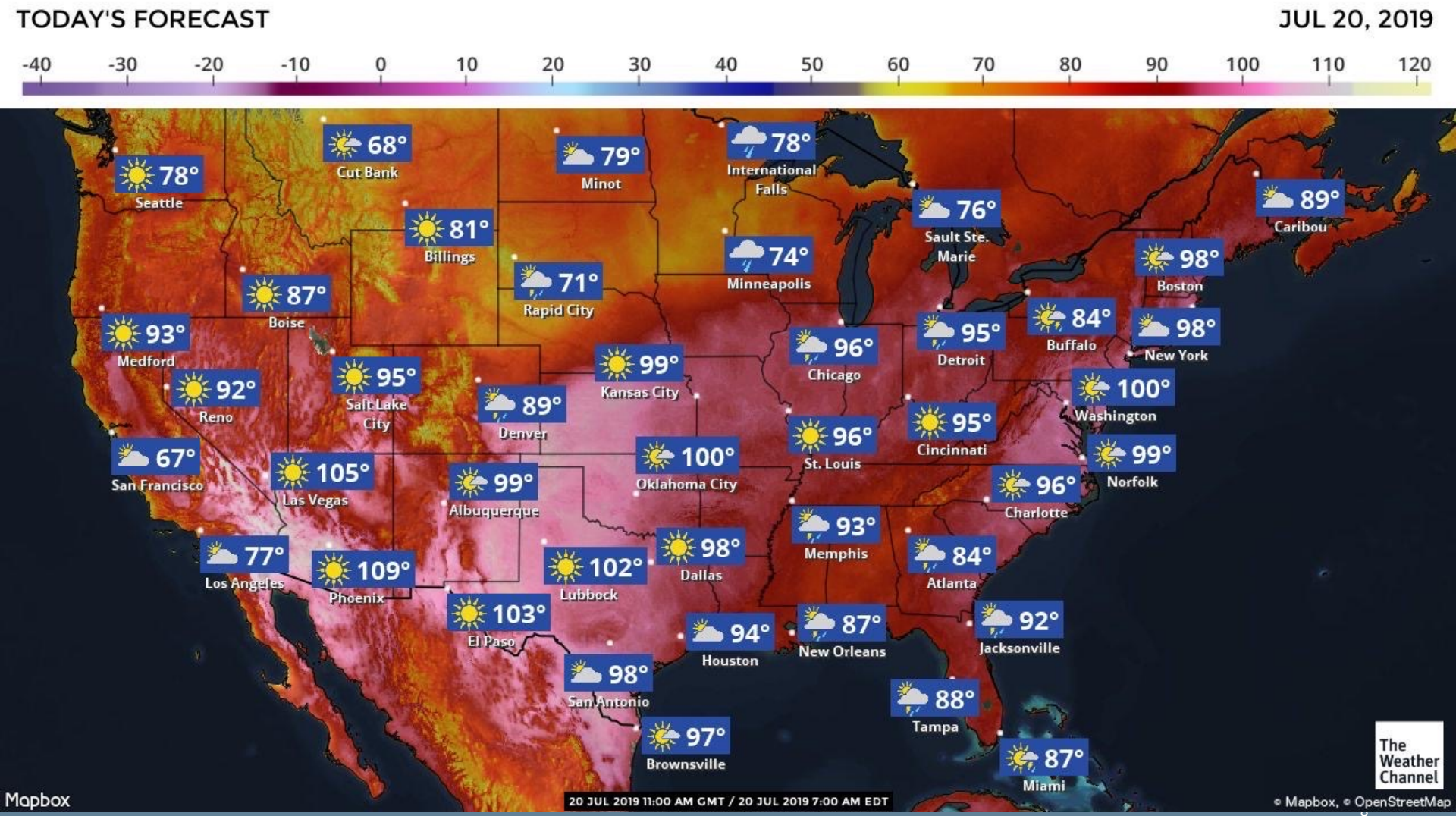
Climate Satellites | global average temperatures State of the Climate temperature rankings SHARE

January 14, 2021 — It's official: 2020 ranks as the second-hottest year on record for the planet, knocking 2019 down to third hottest, according to an analysis by NOAA scientists.

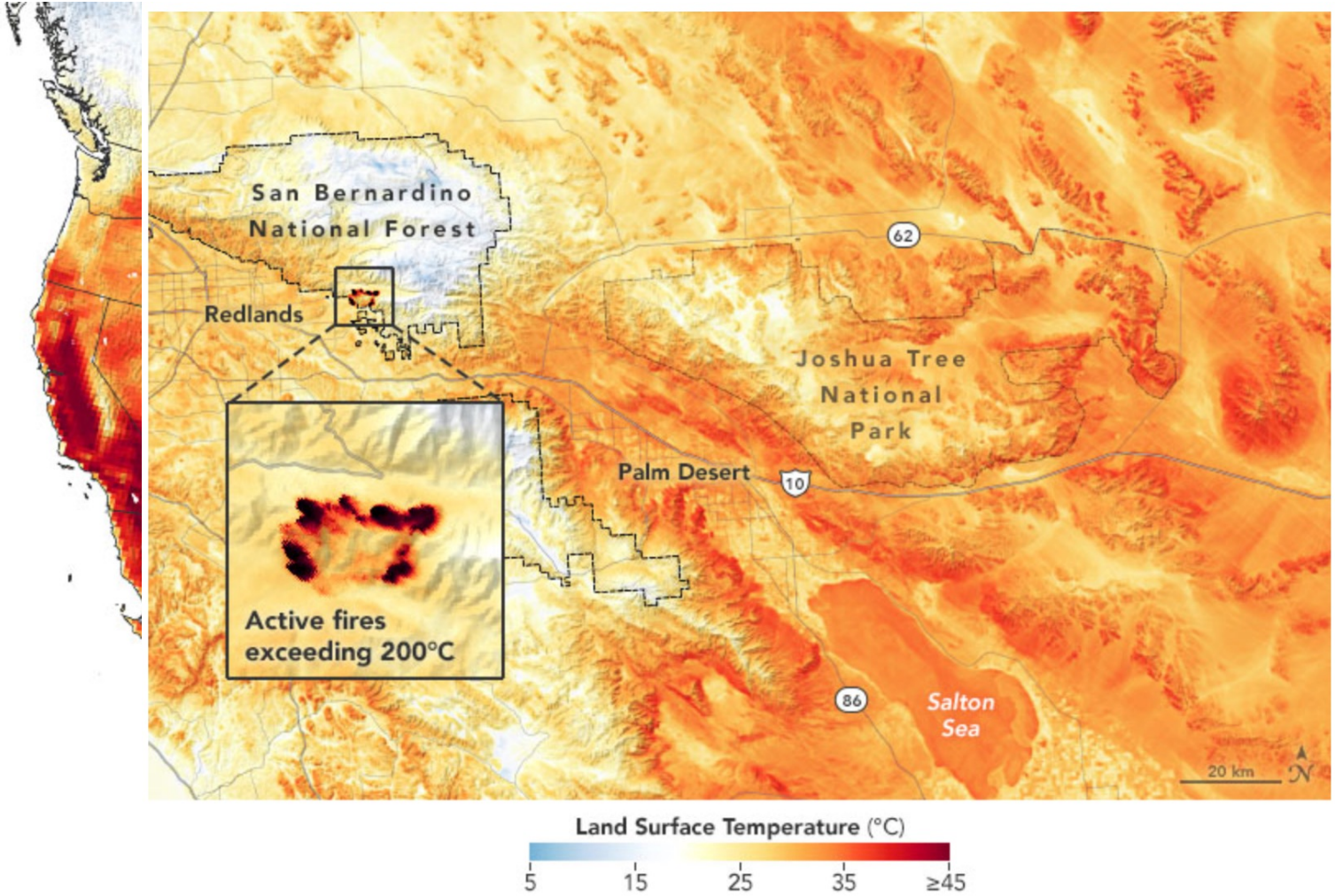
Courtesy: Dr. Xuhui Lee; Data and graphic sources: NYT, NOAA

# Heatwaves 2019



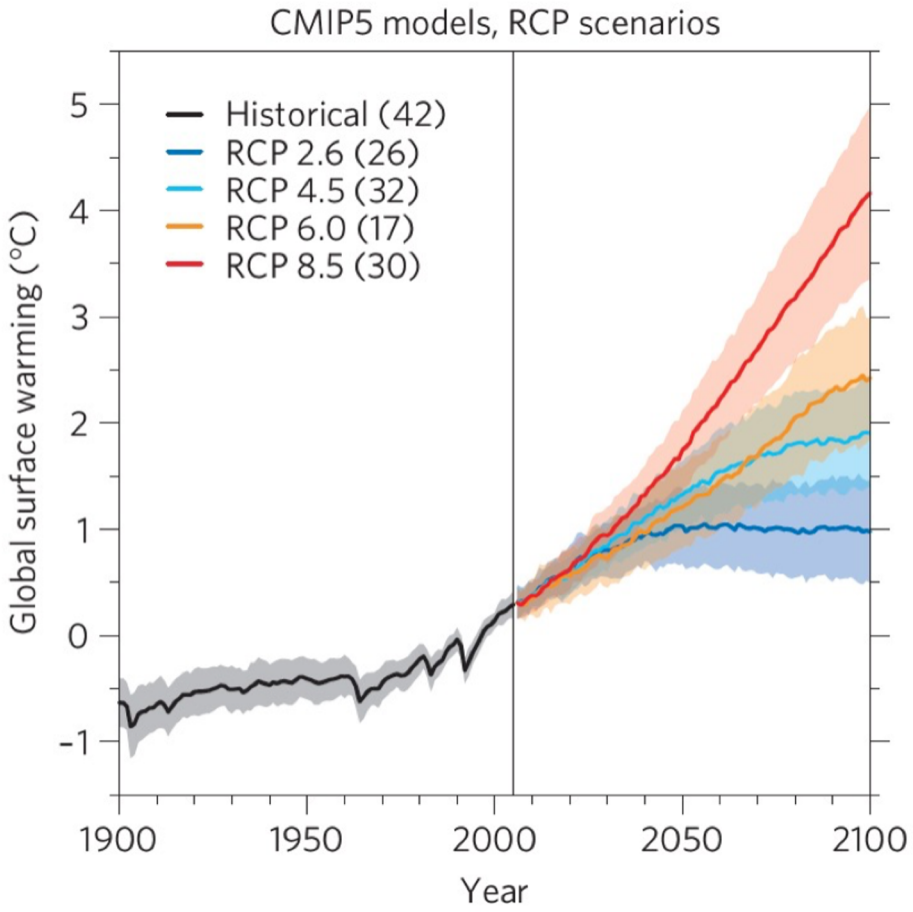

TODAY'S FORECAST
JUL 20, 2019
-40 -30 -20 -10 0 10 20 30 40 50 60 70 80 90 100 110 120
78° Seattle
68° Cut Bank
79° Minot
78° International Falls
76° Sault Ste. Marie
89° Caribou
81° Billings
74° Minneapolis
98° Boston
87° Boise
71° Rapid City
93° Medford
84° Buffalo
98° New York
95° Detroit
96° Chicago
99° Kansas City
95° Salt Lake City
92° Reno
89° Denver
100° Washington
95° Cincinnati
96° St. Louis
67° San Francisco
105° Las Vegas
100° Oklahoma City
99° Norfolk
99° Albuquerque
96° Charlotte
93° Memphis
77° Los Angeles
109° Phoenix
102° Lubbock
98° Dallas
84° Atlanta
103° El Paso
94° Houston
87° New Orleans
92° Jacksonville
98° San Antonio
88° Tampa
97° Brownsville
87° Miami
The Weather Channel
Mapbox
20 JUL 2019 11:00 AM GMT / 20 JUL 2019 7:00 AM EDT
© Mapbox, © OpenStreetMap

September 6, 2020




Source: NOAA

# CMIP5 projections of global surface climate




Source: Knutti & Sedlacek, *Nature Climate Change* 2013

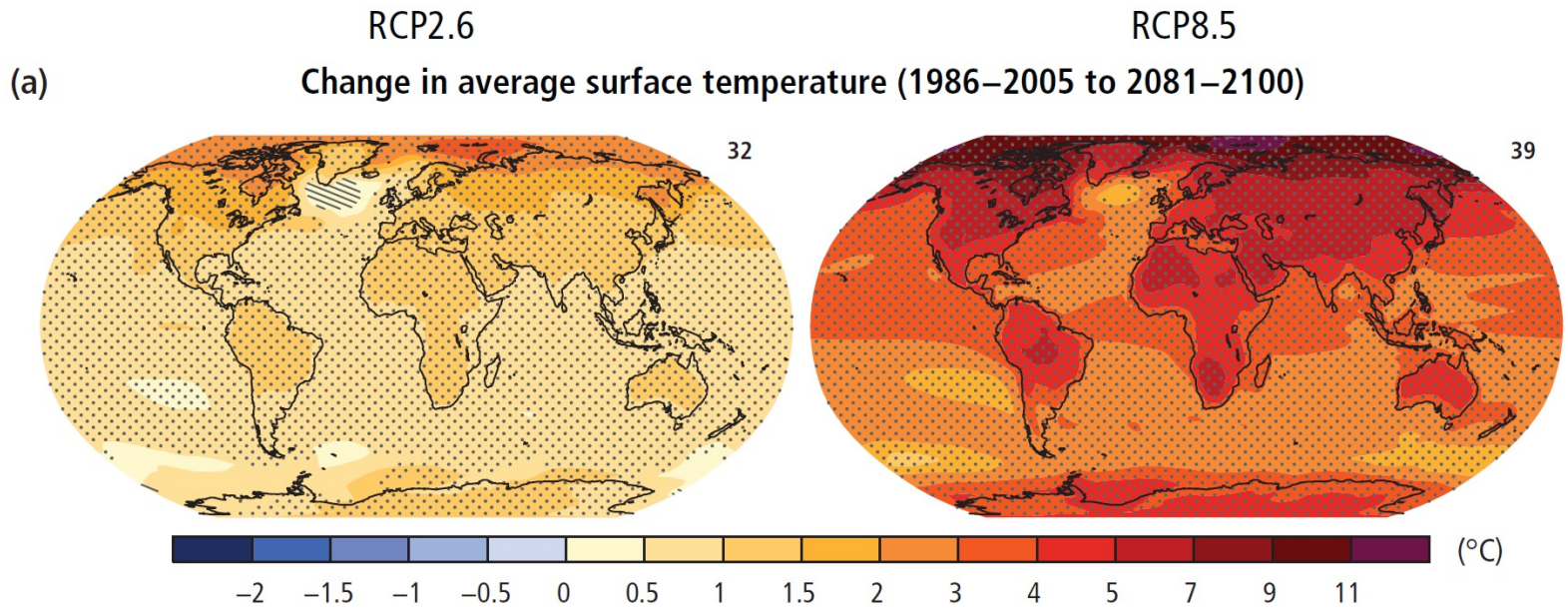
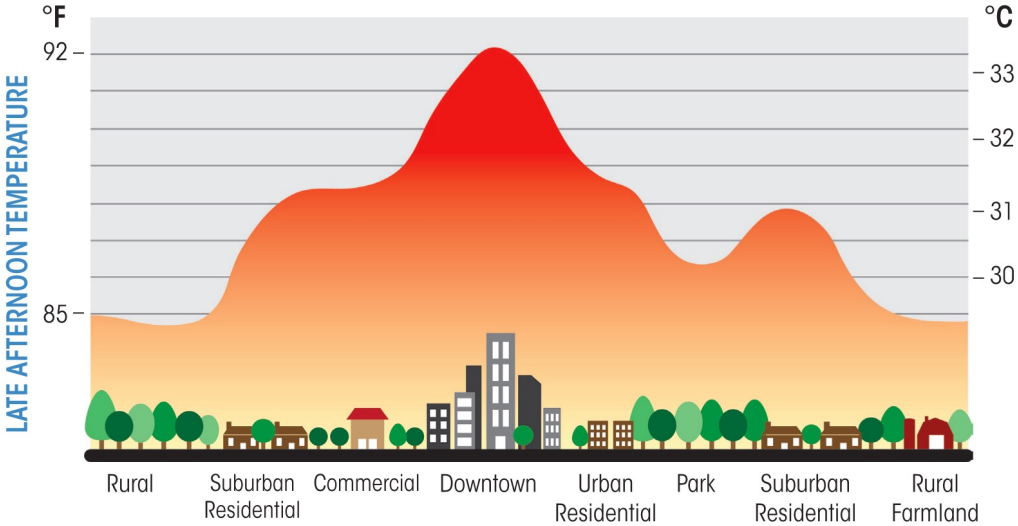



**Figure SPM.7 |** Change in average surface temperature **(a)** and change in average precipitation **(b)** based on multi-model mean projections for 2081–2100 relative to 1986–2005 under the RCP2.6 (left) and RCP8.5 (right) scenarios. The number of models used to calculate the multi-model mean is indicated in the upper right corner of each panel. Stippling (i.e., dots) shows regions where the projected change is large compared to natural internal variability and where at least 90% of models agree on the sign of change. Hatching (i.e., diagonal lines) shows regions where the projected change is less than one standard deviation of the natural internal variability. *{2.2, Figure 2.2}*

Source: IPCC 2014

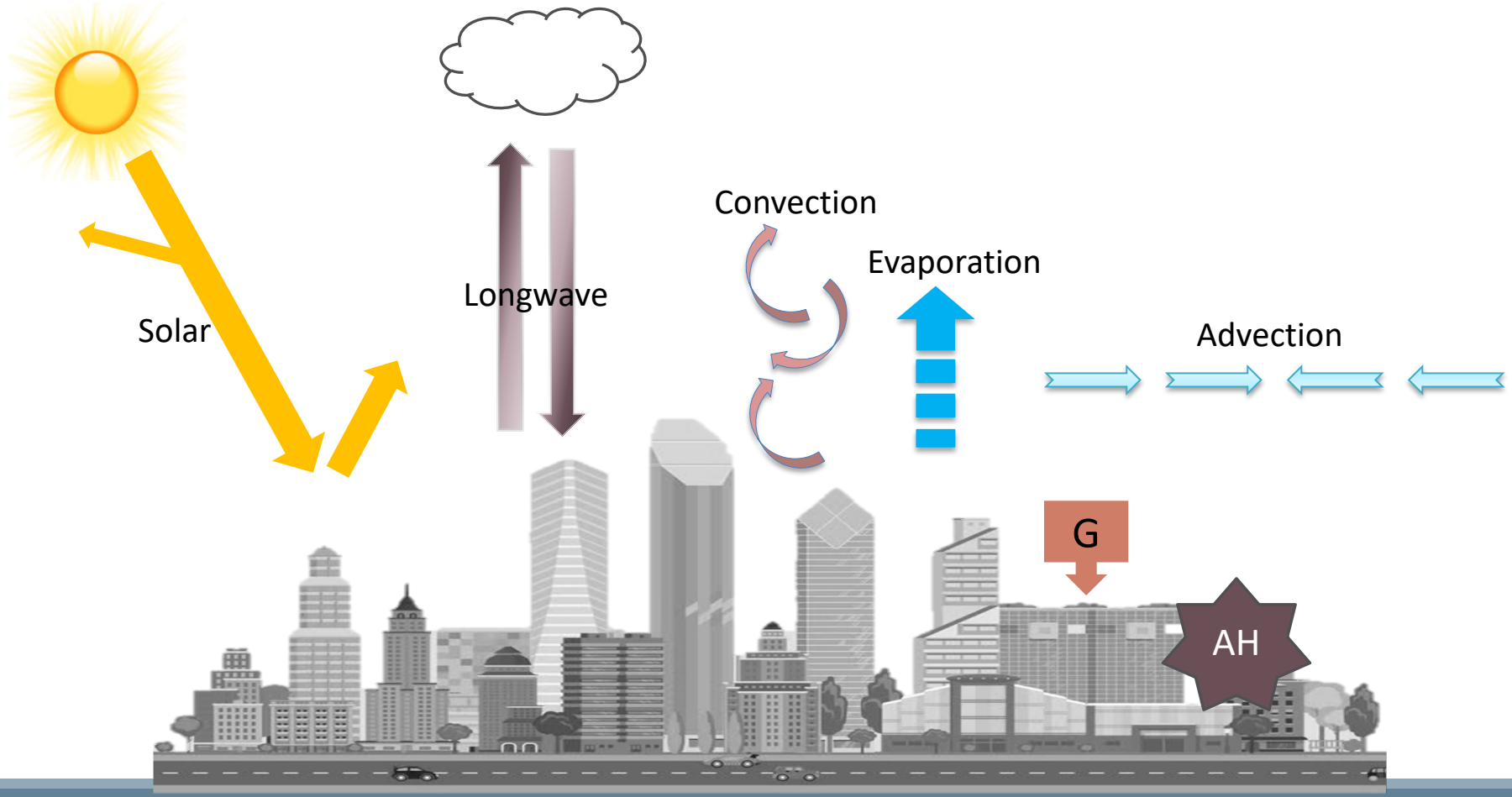
# Urban warmth

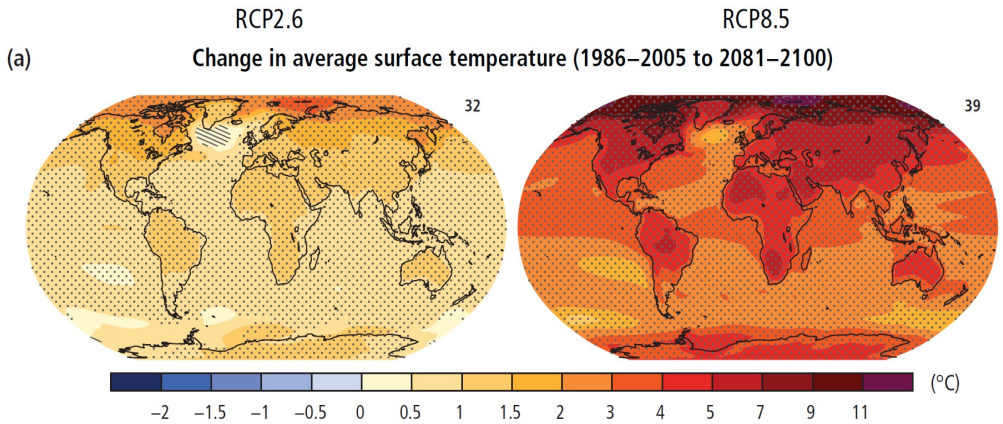

Urban Heat Island (UHI) effect

Source: C3 Headlines

# Urban Land – Atmosphere Interactions



# Can we provide robust multi-model urban projections?

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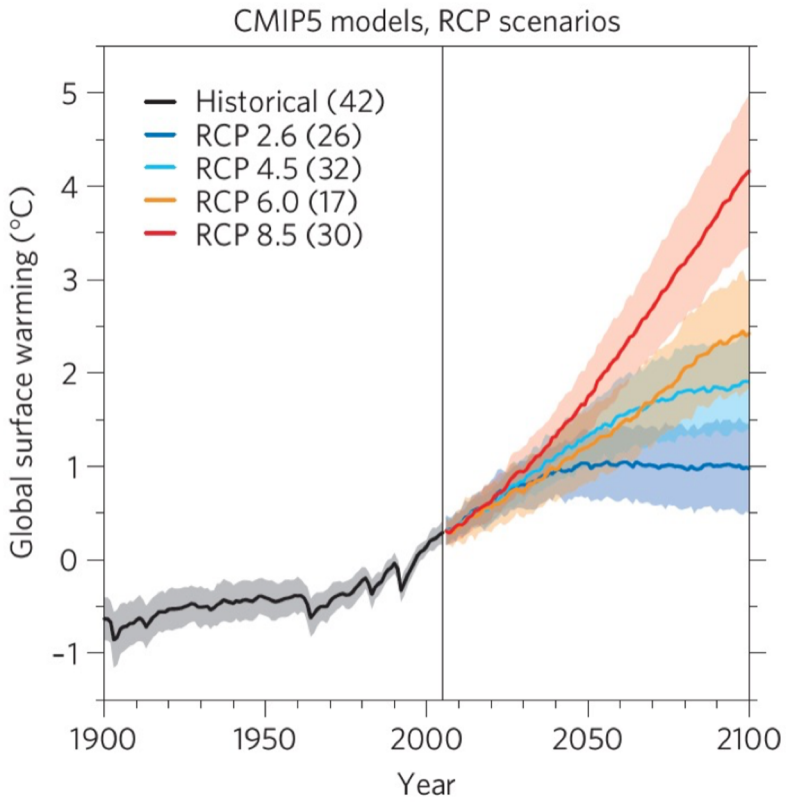
Source: Knutti & Sedlacek, *Nature Climate Change* 2013

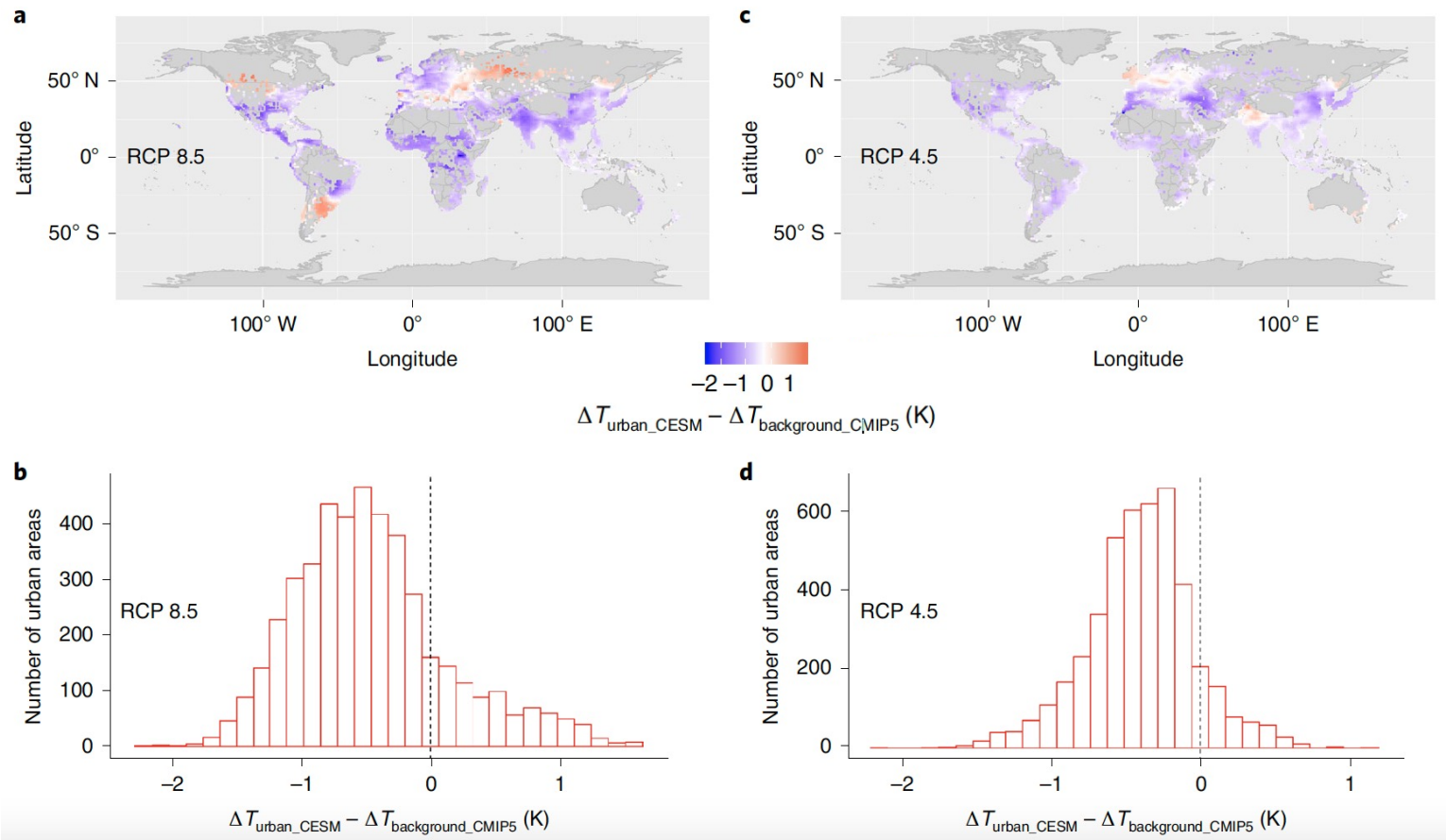
# Near-universal lack of urban representation in global-scale Earth system models




Traditional projections of “global surface climate” are essentially global “non-urban” surface climate.

Source: Knutti & Sedlacek, *Nature Climate Change* 2013

# Traditional CMIP multi-model projections fail to capture urban warming signals

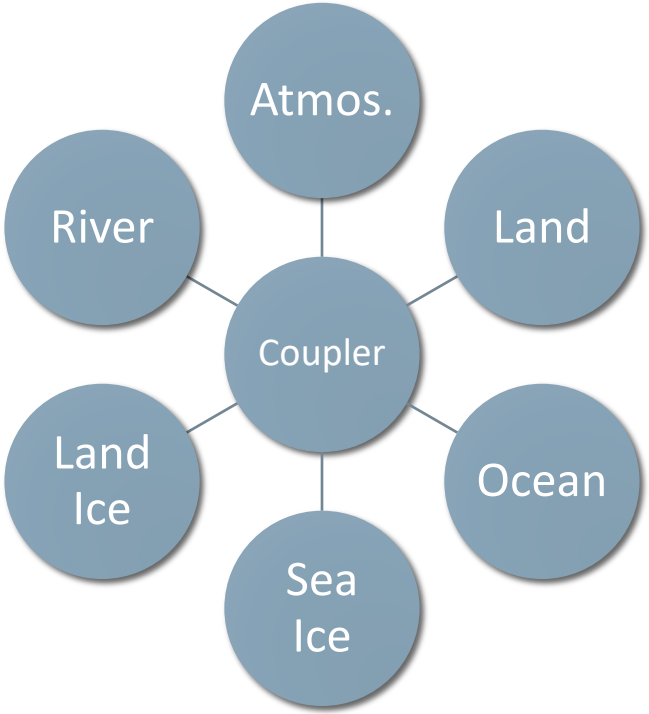


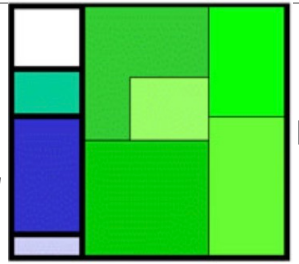

Source: Zhao et al. *Nature Climate Change* (2021)

# Modeling urban heat

- Dynamic modeling
  - Process-based
  - Trying to “resolve” the physics, chemistry and dynamic processes
  - Computationally Expensive
- Statistical modeling
  - Empirical
  - Trying to establish the statistical relationship
  - Computationally-efficient
  - Interpolation vs. extrapolation
- Hybrid modeling
  - Process-based dynamic modeling + data-driven statistical modeling

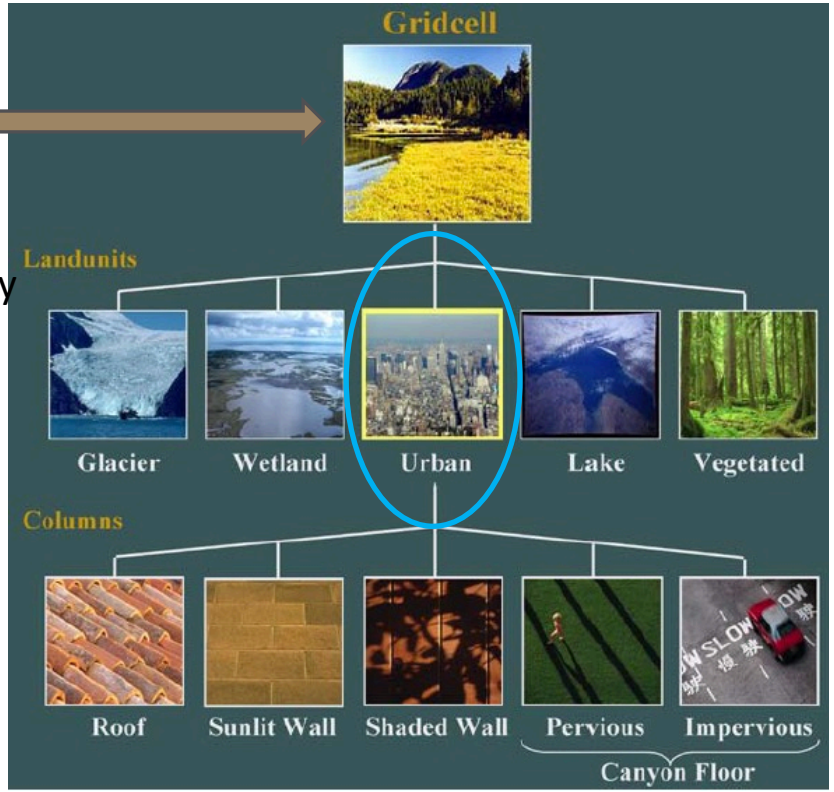
# Community Earth System Models (CESM)



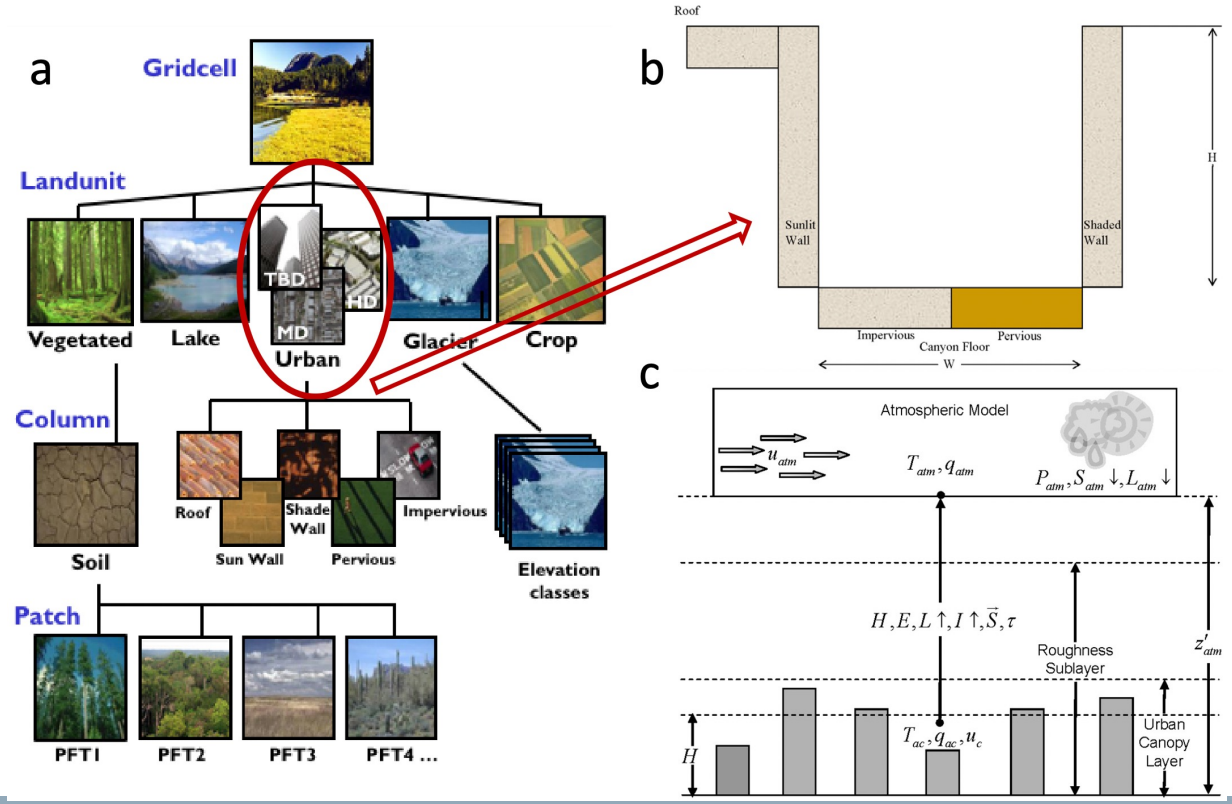
Surface heterogeneity

Sub-grid modeling



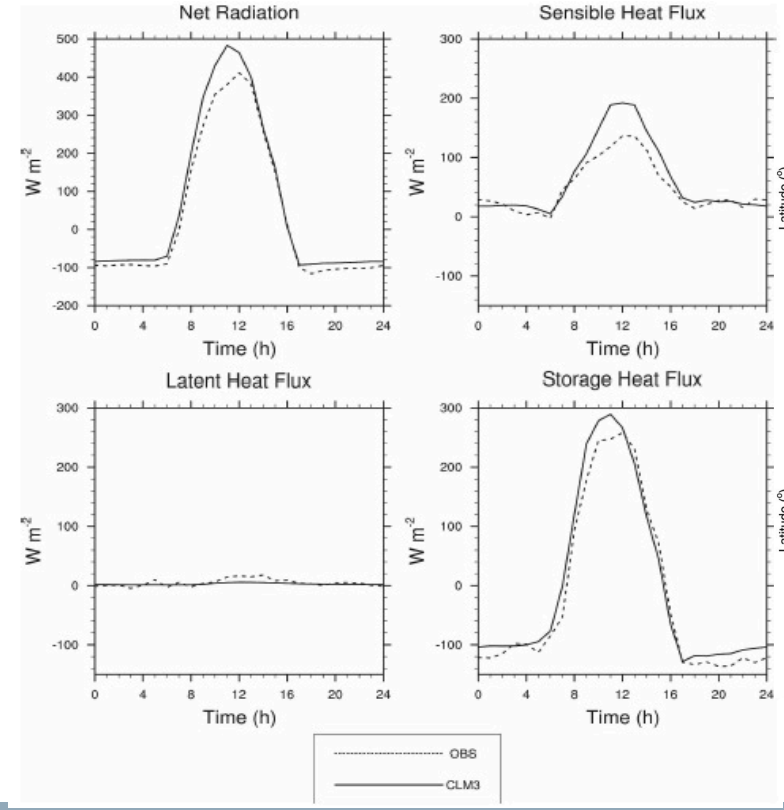

Source: http://www.cesm.ucar.edu/models/clm/surface.heterogeneity.html

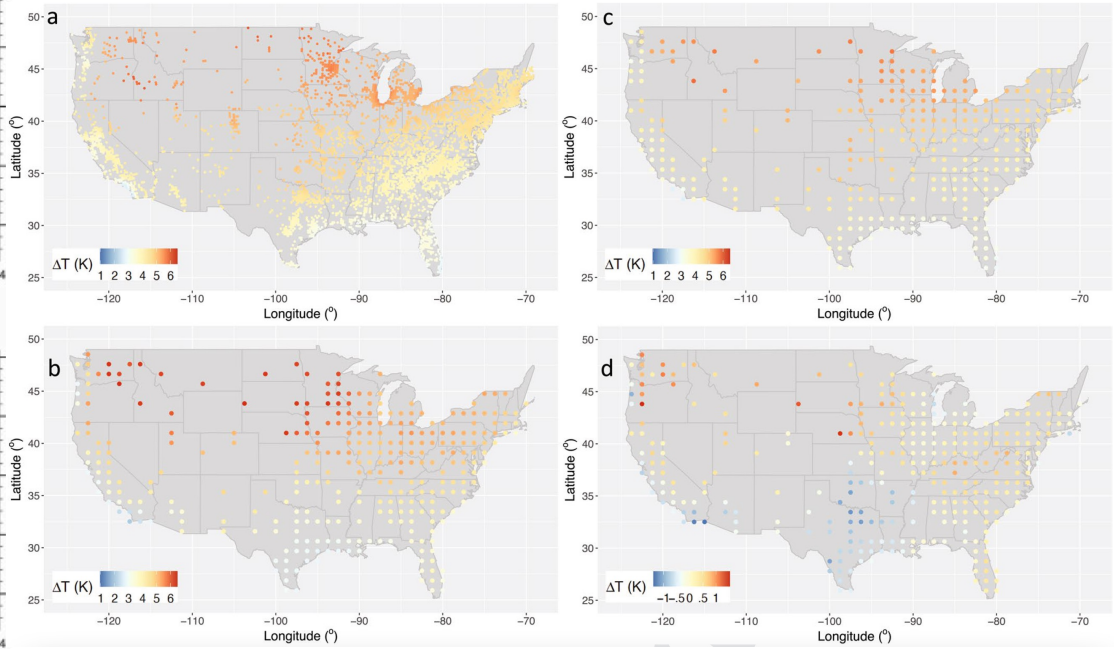
# Dynamic process-based urban parameterization in CESM




Source: http://www.cesm.ucar.edu/models/clm/human.html

# Evaluation of the CESM urban modeling




Source: Oleson et al. 2008

Source: Zhao et al. *Nature Climate Change* (in press)

# Methods

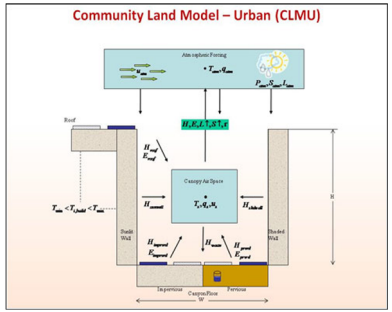
Earth System Modeling combined with Physics Guided Machine Learning (PGML)

Urban Climate Emulator

- Process-based climate modeling + Data-driven machine learning approach
- Computationally efficient & global-scale

Atmospheric forcings:

$K_{\downarrow}, L_{\downarrow}, P_r, P, T_a, Q, U, V, CO_2$



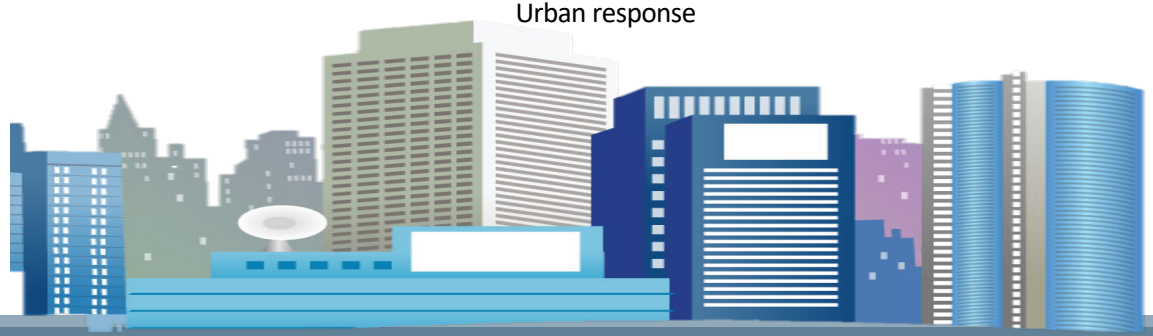

Dynamic modeling

High dimensional surface dataset

Machine Learning

Reduced-order emulator

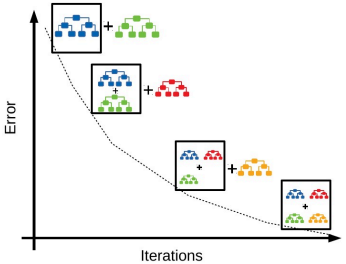
Urban response



# The urban climate emulator framework

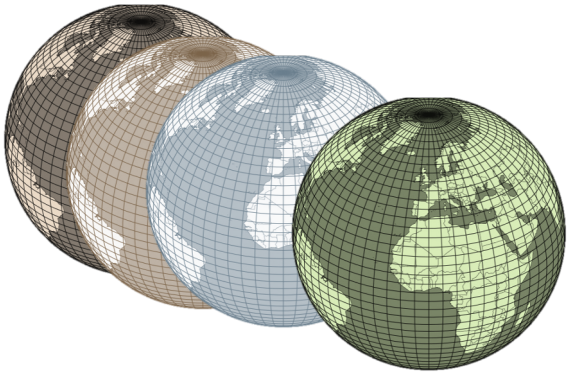

CESM

Train & Validate



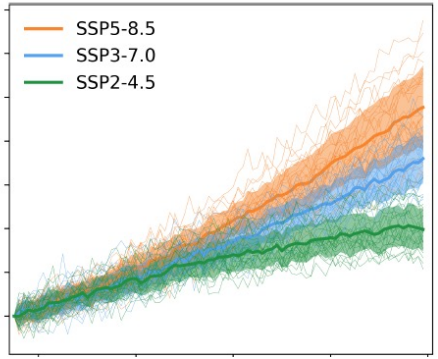

ML regressors

$$R_{\text{urb}} = f_{\text{lat,long}}(\mathbf{AF}, m, I)$$

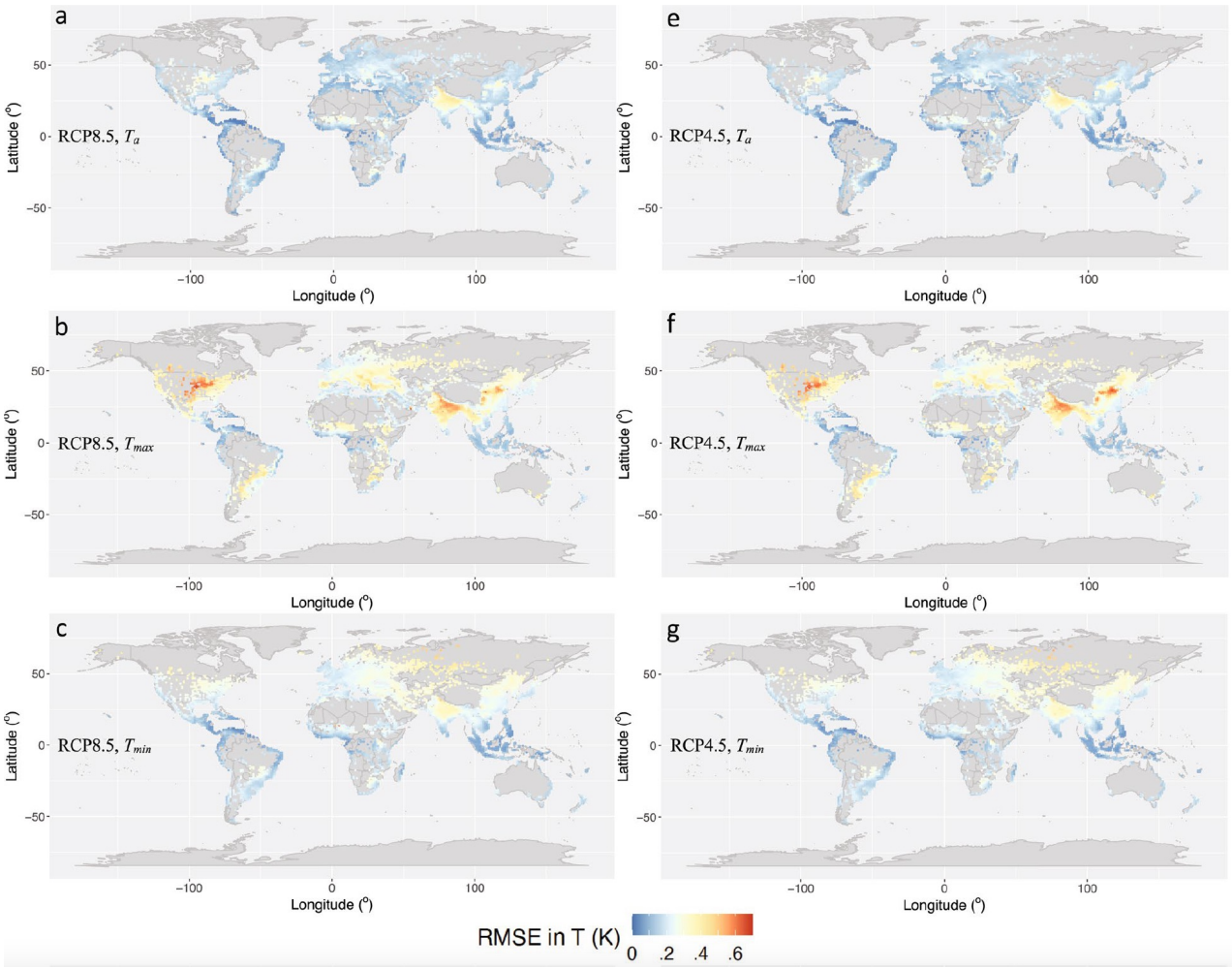


Other CMIP models


Emulator




Multi-model projections




# Emulator Accuracy

Validated on never-seen data

Source: Zhao et al. *Nature Climate Change* (2021)

# Robust projections of urban warming

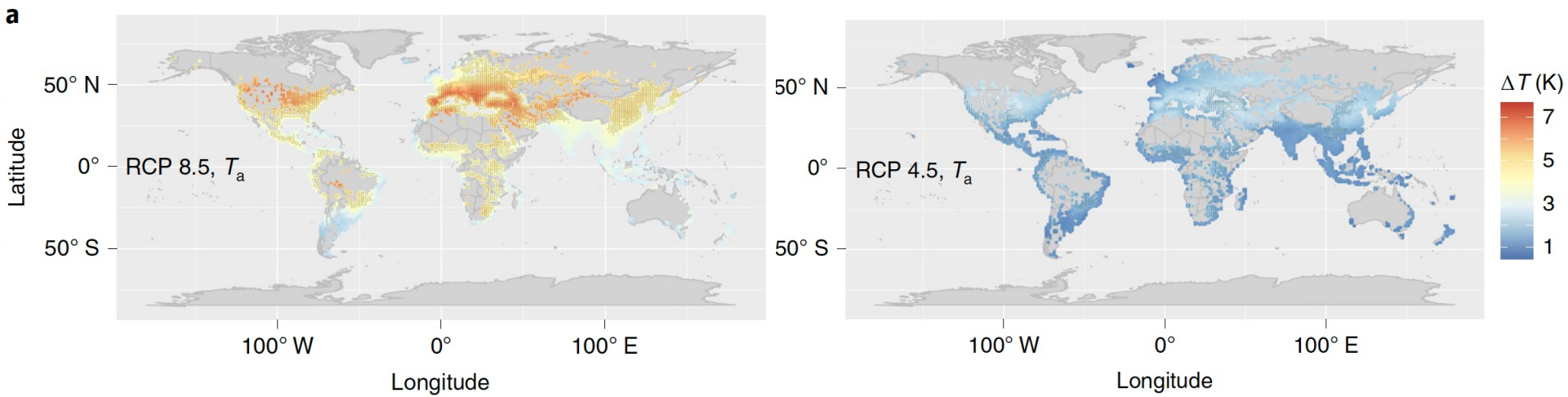



**Figure: Multi-model ensemble mean urban warming for JJA under RCP 8.5 and RCP 4.5.** Stippling indicates significant change ($\Delta T \geq 4$ K under RCP8.5 and $\Delta T \geq 1.5$ K under RCP45) with high inter-model robustness (SNR > 2.5).

Source: Zhao et al. *Nature Climate Change* (2021)

# Robust projections of urban drying

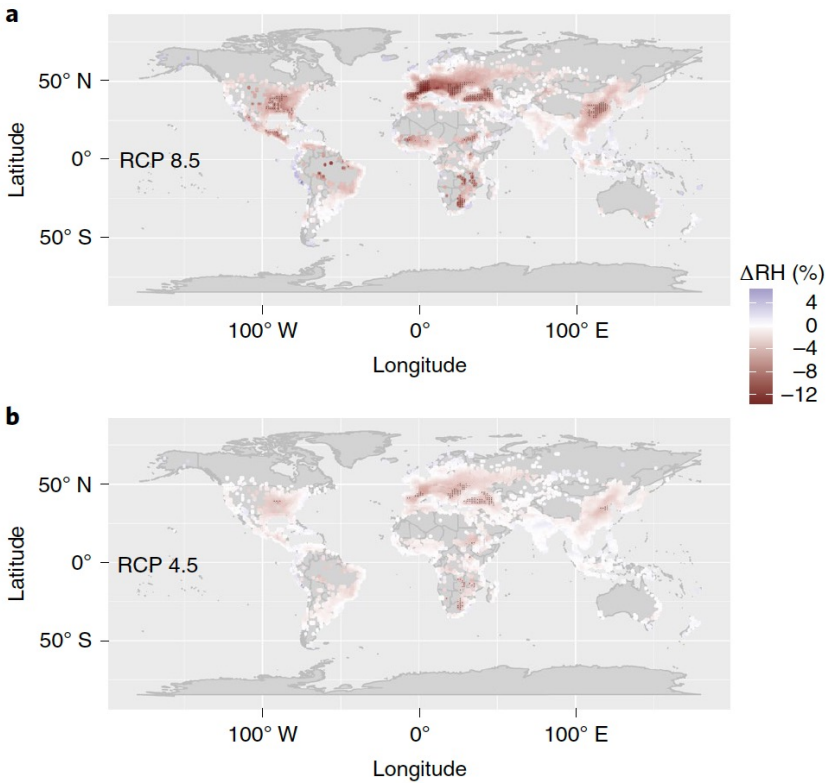



**Fig. 4 | Multi-model mean urban relative humidity change for JJA. a**,**b**, Seasonal mean urban RH changes between 2006–2015 and 2091–2100 under RCP 8.5 (**a**) and RCP 4.5 (**b**). Stippling indicates substantial change (abs(ΔRH) > 5% under RCP 8.5 or abs(ΔRH) > 2.5% under RCP 4.5) with high inter-model robustness (SNR > 1).

Source: Zhao et al. *Nature Climate Change* (2021)

# Future urban heatwaves

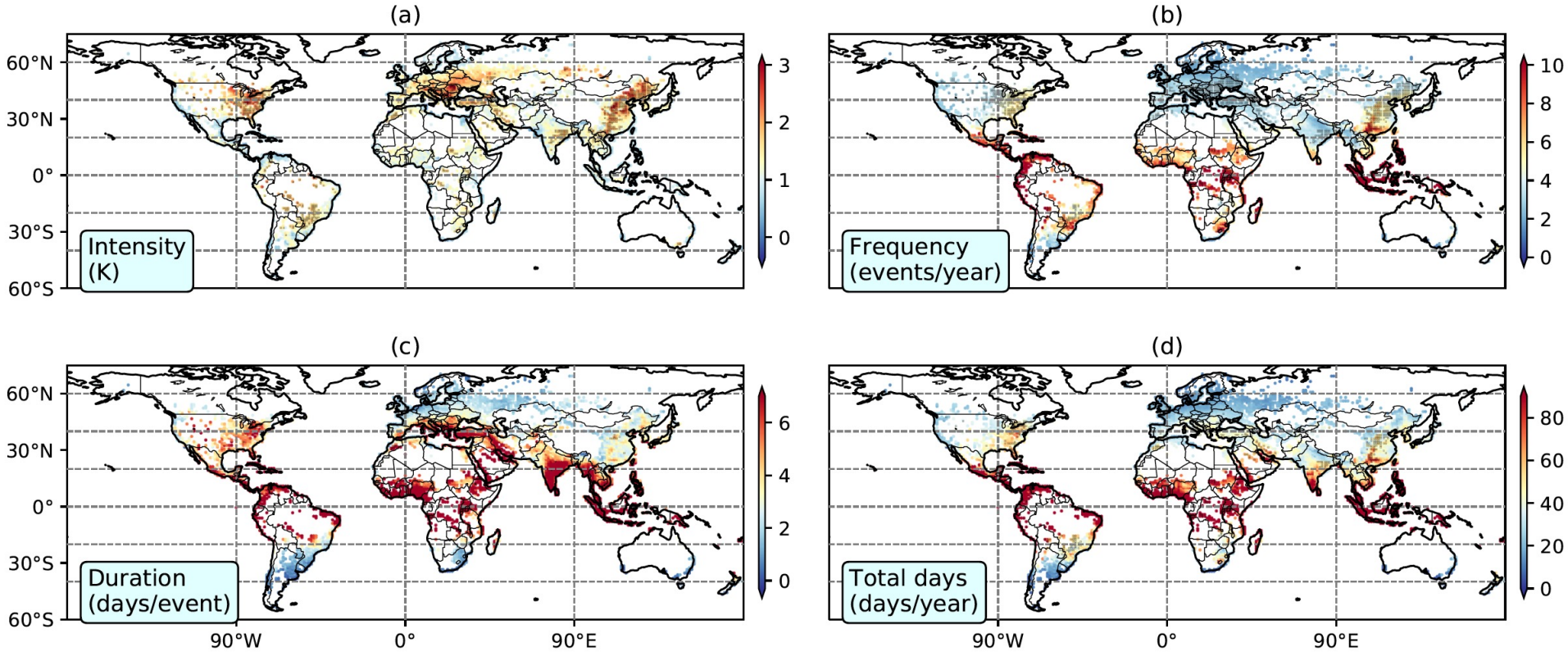
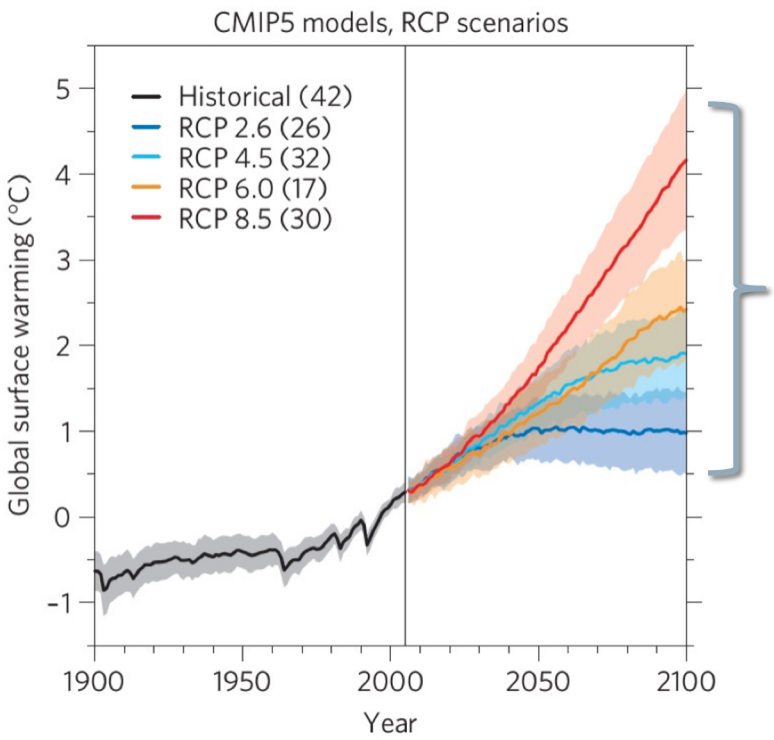



**Figure: Multi-model ensemble mean change in average UHW intensity (K), frequency (events per year), duration (days per event), and total days (days per year) in 2061–2070 relative to 2006–2015.** Stippling indicates substantial change (intensity > 1.5 K) with high inter-model robustness (SNR > 2.0).

Source: Zheng et al. *Nature Communications* 2021 (in press)

# Understanding the uncertainties




Internal variability

+

Structural uncertainty

+

Parameter uncertainty

+

Scenario uncertainty

Dominant source of uncertainty at the time horizons of multiple decades or longer

# Understanding the uncertainties

Structural uncertainty: emulated multi-model urban projections

$$\sigma_{CMIP}$$

Internal variability: CESM Large Ensemble (CESM-LE) simulations

$$\sigma_{CESM}$$

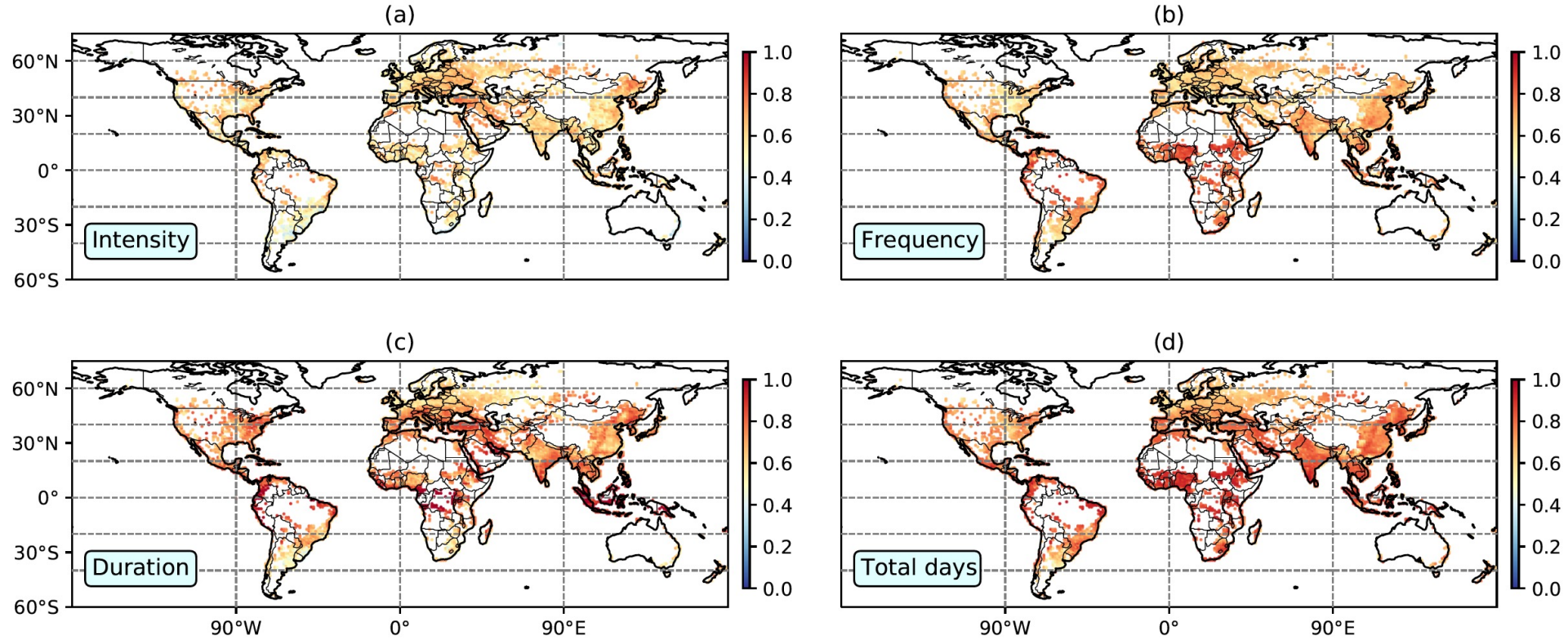



**Figure 3. Relative contribution of the model structural variability in UHW projections.** Each colored point represents a decadal mean structural uncertainty fraction (SUF) defined as $\frac{\sigma_{CMIP}}{\sigma_{CMIP}+\sigma_{CESM}}$

Source: Zheng et al. *Nature Communications* 2021 (in press)

# Grey-swan urban heatwaves

Seemingly unlikely
0.01% UHW

23.7%

4.2%

1.6%

14.8%

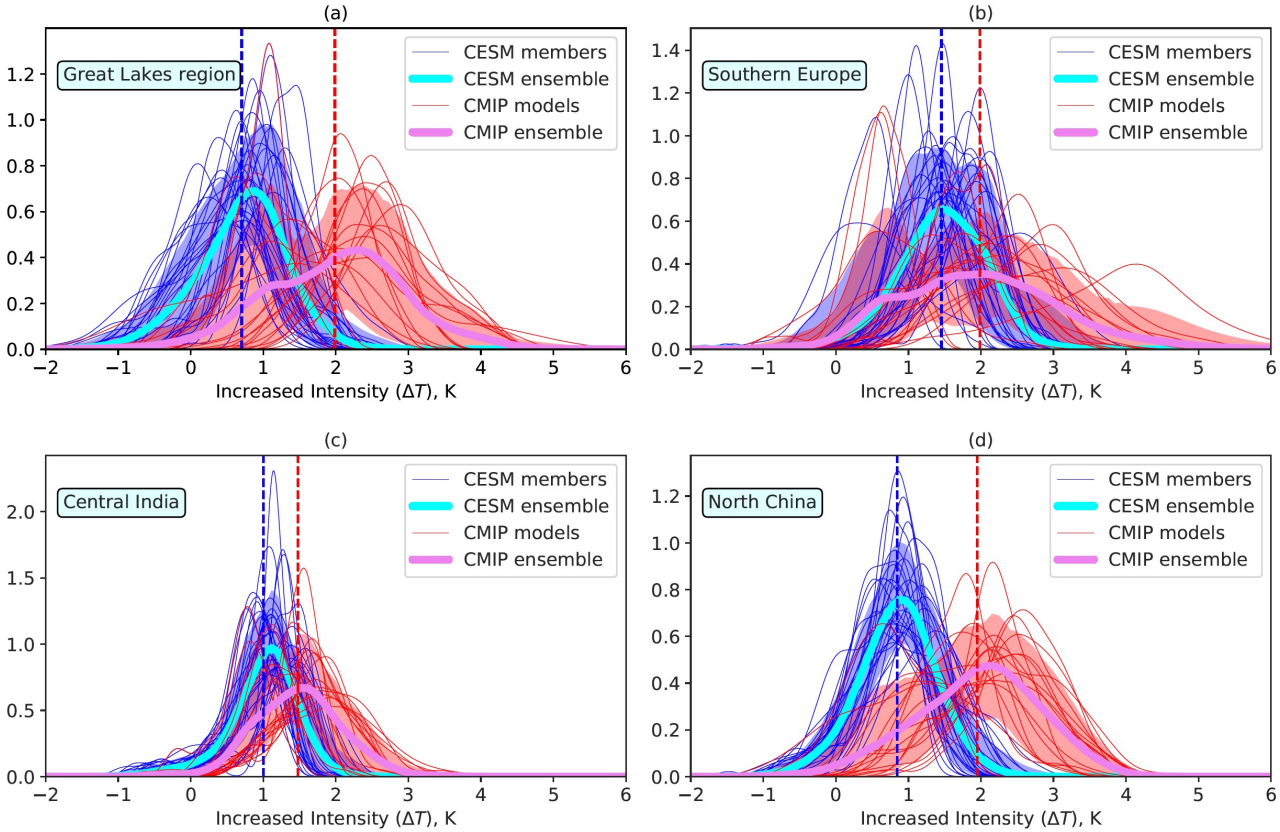



**Figure: Spatial distribution of changes in urban heat waves intensity by 2061 – 2070.** The thick lines mark the CMIP5 multi-model mean (thick violet lines) and CESM-LE multi-member mean (thick cyan lines).

Source: Zheng et al. *Nature Communications* 2021 (in press)

# Thank you!

Comments & questions?