Lightning Talks

ESSM Extreme Heat Workshop Day 1

National Integrated Heat Health Information System (NIHHIS)

Decision-maker Use Cases & Climate Information Needs

NIHHIS

Improving climate & health services by understanding decision-maker demand and integrating information across timescales and disciplines.

Urban Heat Island Intensity Maps	Urban-scale Climate Modeling	Climate Attribution	Wet Bulb Globe Temp. Predictions
S2S Temperature Predictions	Annual Temperature Predictions	Scenario-based Climate Info	Heat Index Predictions

Long term assessment of risk of cancellation, Heat island route mapping, WBGT extended prediction

Decadal climate predictions sensitive to critical thresholds for grid resilience

Allocating limited funds to summer cooling and winter heating subsidies.

Informing energy customers with predicted monthly climate & cost estimates

Combining UHI information and CDC & Census Social Vulnerability

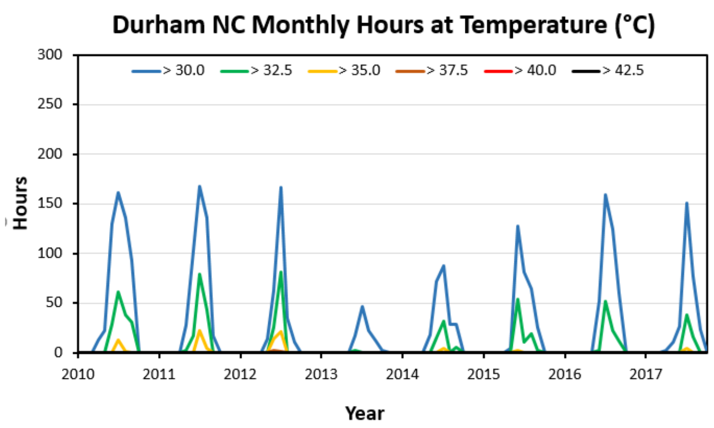
Urban-scale modeling to understand effectiveness of interventions

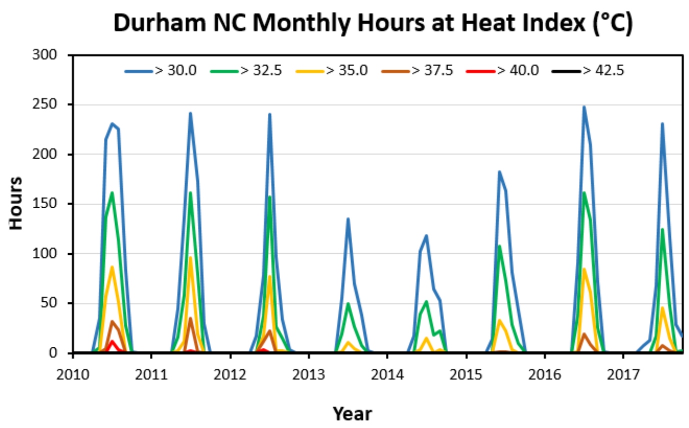
Statistical downscaling of climate predictions via UHI maps

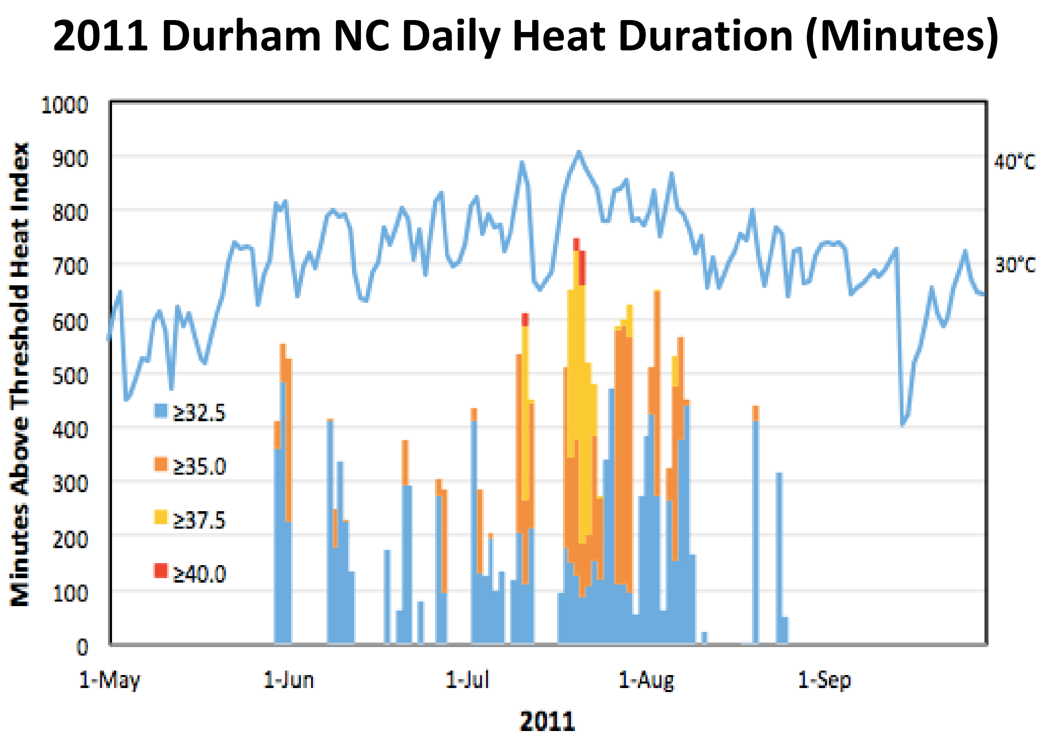
***Sources**: NIHHIS: Chicago Workshop Requirements Annex, RGB Workshop Report, Northeast Workshop Report; GHHIN Forum 2018 Report; NCA4; SASCOF Colombo Report; Personal communications.*

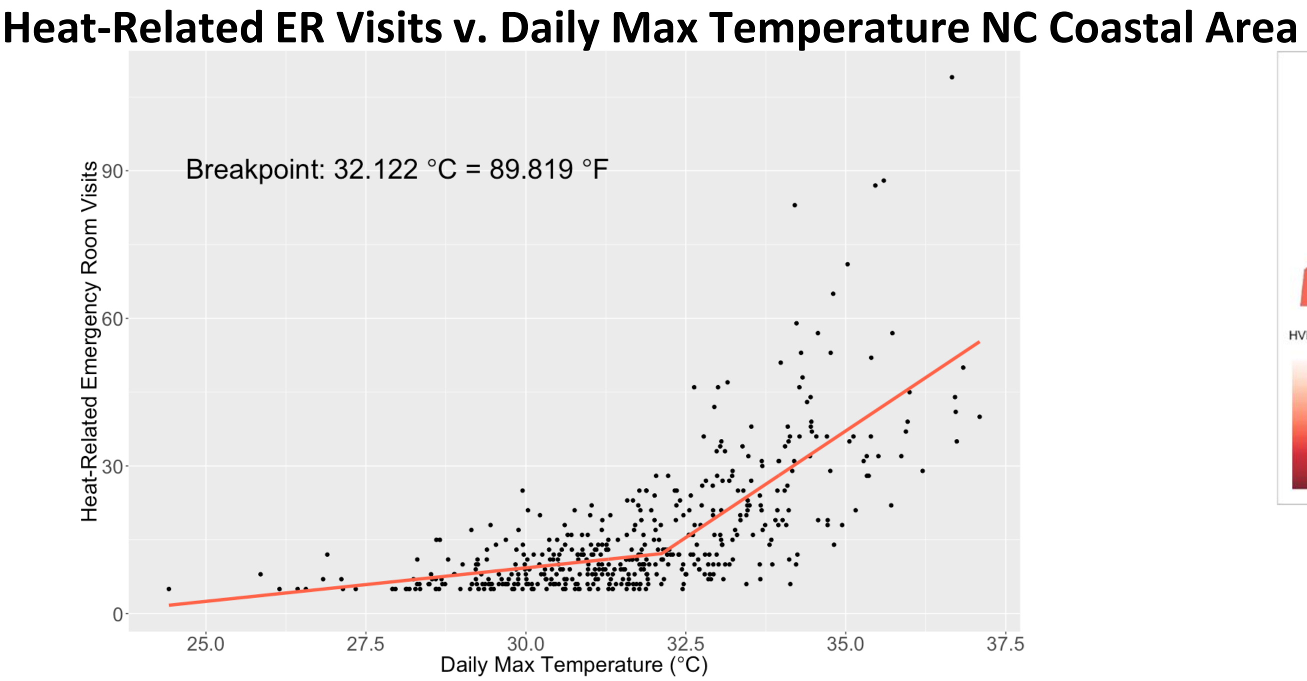
Combining heat exposure indices and with socioeconomic data to build a heat vulnerability index for the Southeast United States

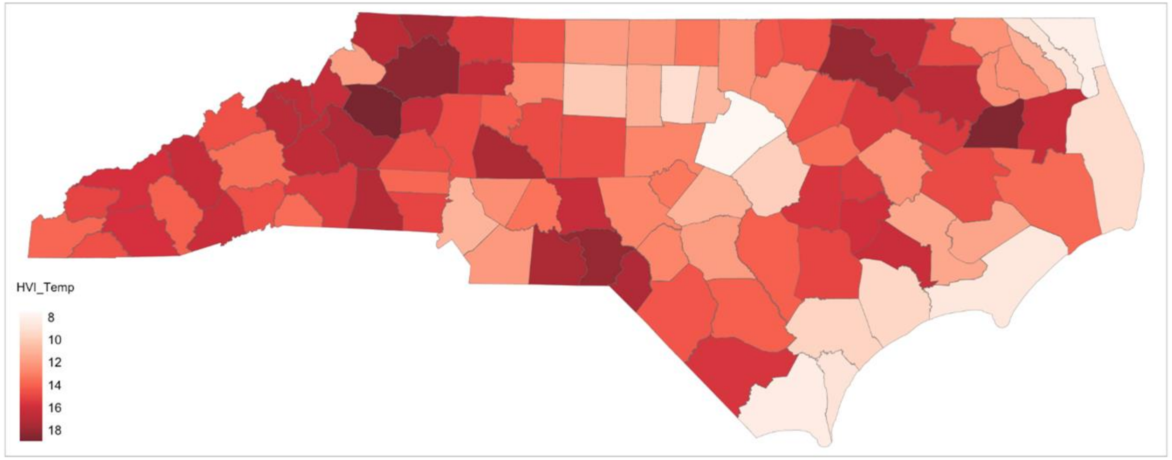
Howard J. Diamond, NOAA OAR/ARL











Combined Index for July 1, 2012: HVI*Maximum Temperature/Threshold Temperature

When Extreme Heat Meets With Dry Spell: How Does Air Quality Respond ?

Yuxuan Wang, University of Houston

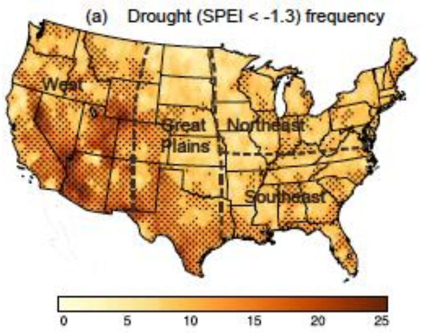
Temperature increase — **Heatwaves**

Soil moisture decrease — **Droughts**

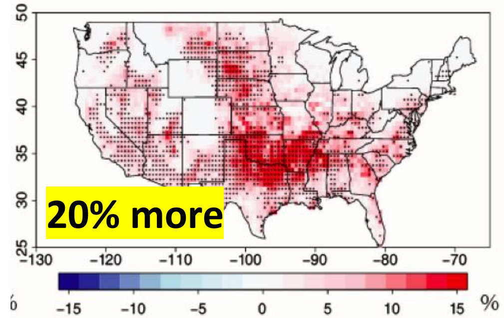
Compound Extremes ← **Extreme Air pollution**

Drought frequency

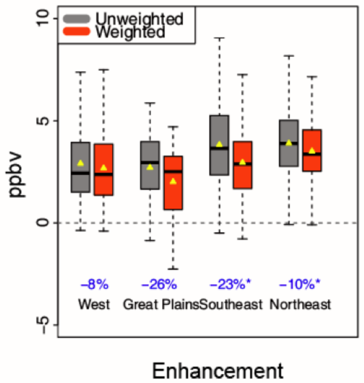
Mar-Oct 1990-2014



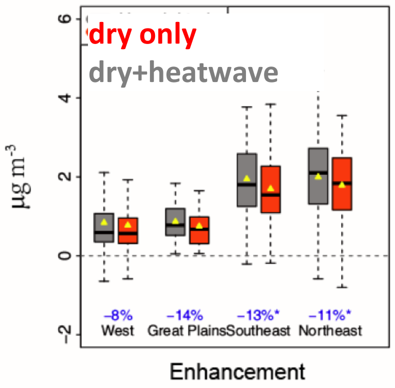
More heatwaves w/ drought



Ozone



$PM_{2.5}$



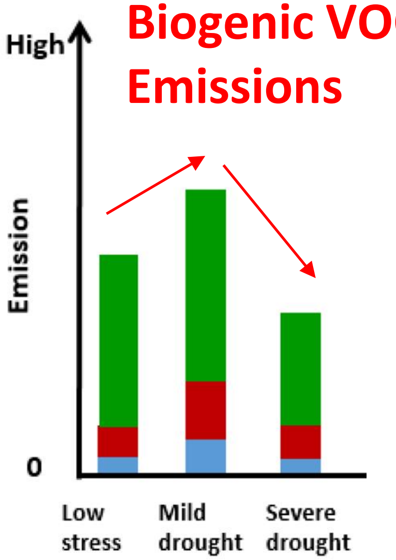
Mean Enhancements

O_3: 3.4 ppbv (dry)
20% more (dry+heat)

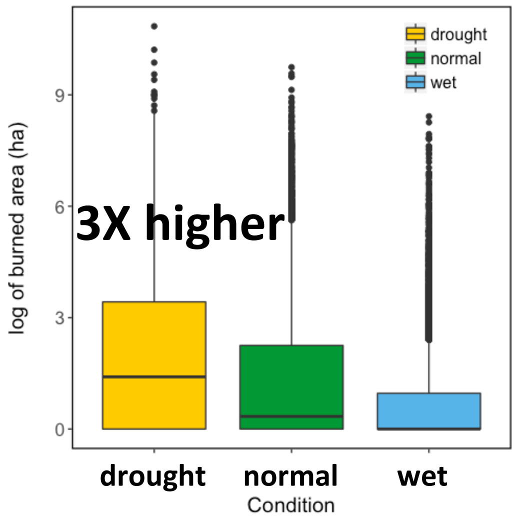
$PM_{2.5}$: 1.7 μg/m^3 (dry)
12% more (dry+heat)

Wang Y. et al., ACP, 2017

Biogenic VOC Emissions

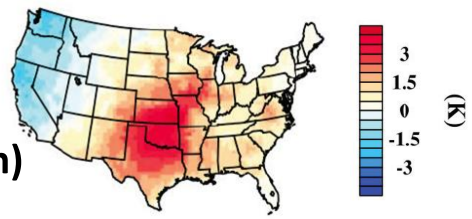


Wildfire Emissions

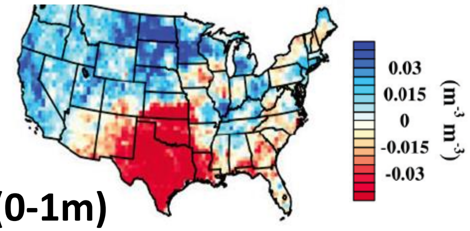


2011 SUS Drought

T (2m)

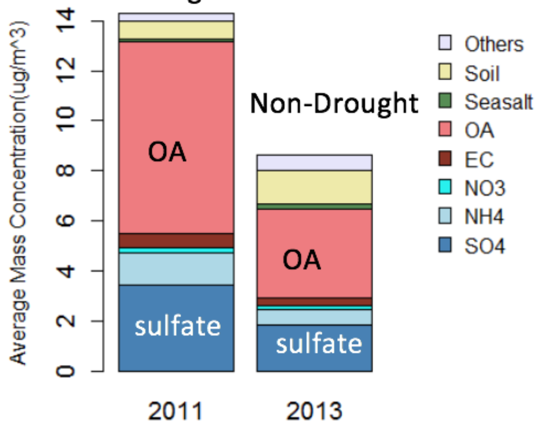


SWC (0-1m)



NOAA Drought Task Force

75% higher $PM_{2.5}$



Wang Y. et al., JAS, 2015; Zhao, Wang, et al., ES&T, 2019

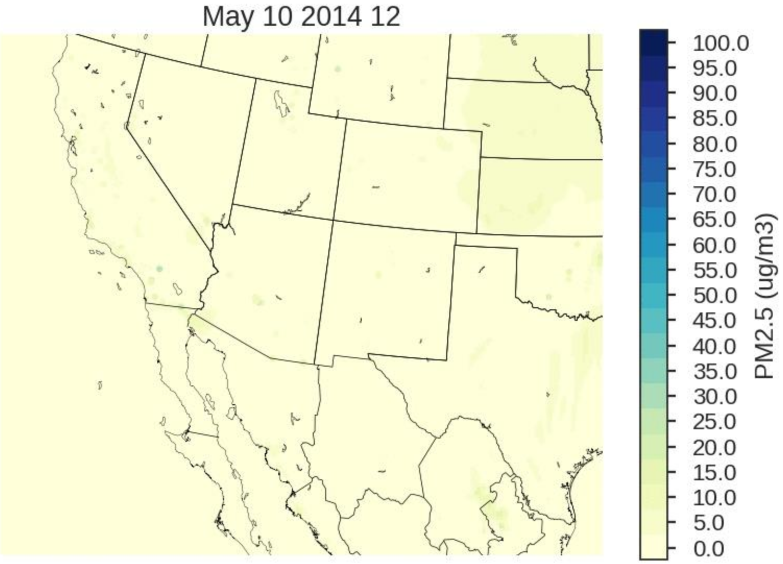
Potential Impacts of Extreme Heat on Air Quality Forecasting

Modeling Windblown Dust

FENGSHA dust emission algorithm

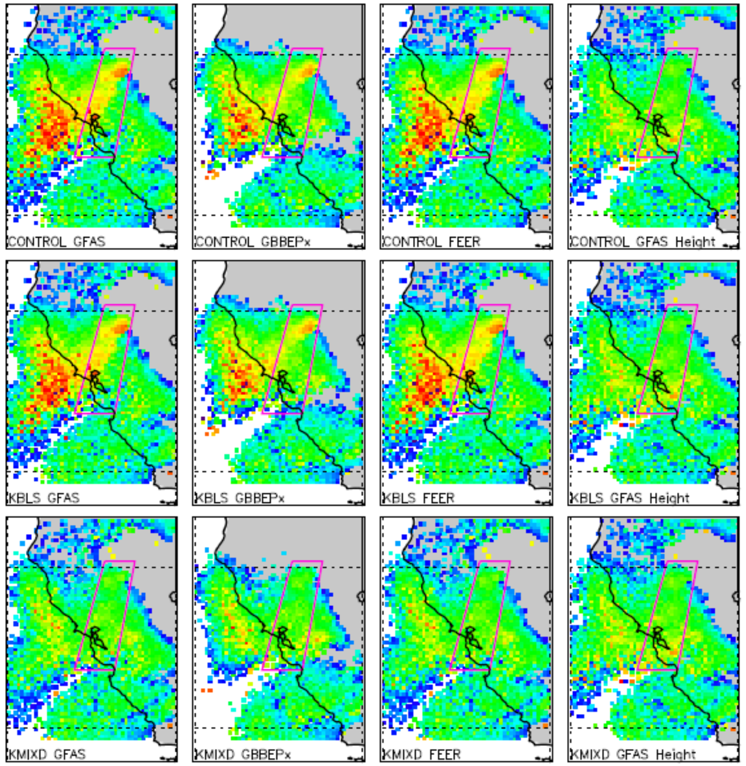
NWS NAQFC

GEFS-Aerosol



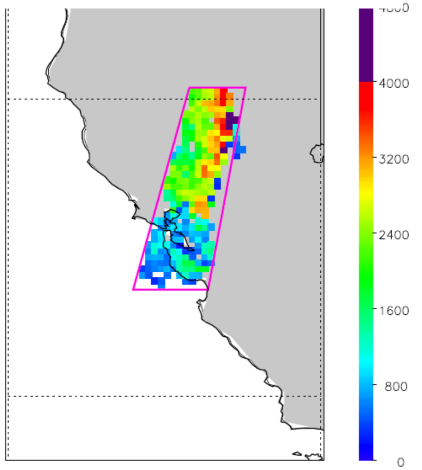
Daniel Tong
Barry Baker
Rick Saylor
NOAA/OAR/ARL

Fire Radiative Power
Atmospheric Stability
Wind Direction
Plume Rise & PBL Depth
Fuel Source
Fire Location and Duration

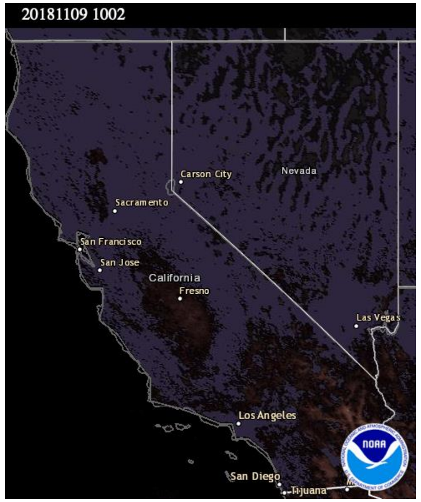


Modeling Smoke from Wildfires

MISR Plume Height (NASA)



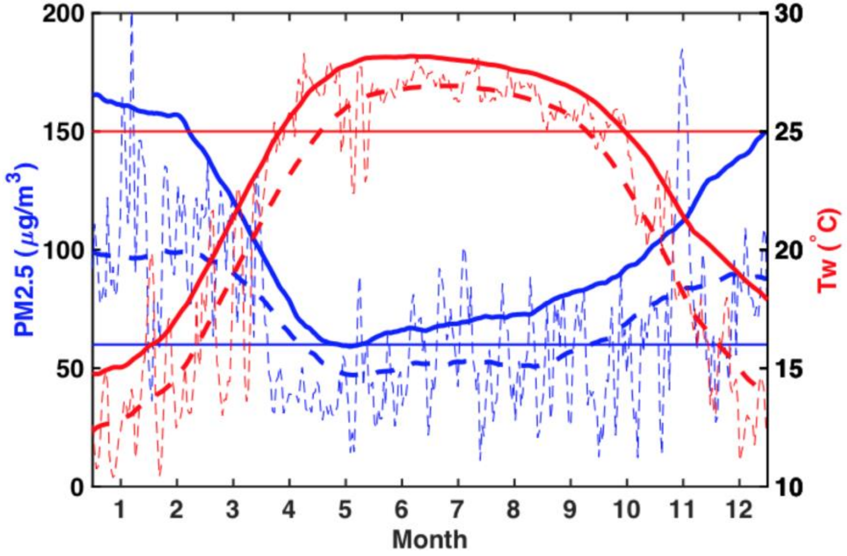
GOES-R Fire Obs



Compound risks of heat and haze extreme in South Asia

Xu, Yangyang (Texas A&M University)

NOAA workshop on heat extremes, Nov, 2019



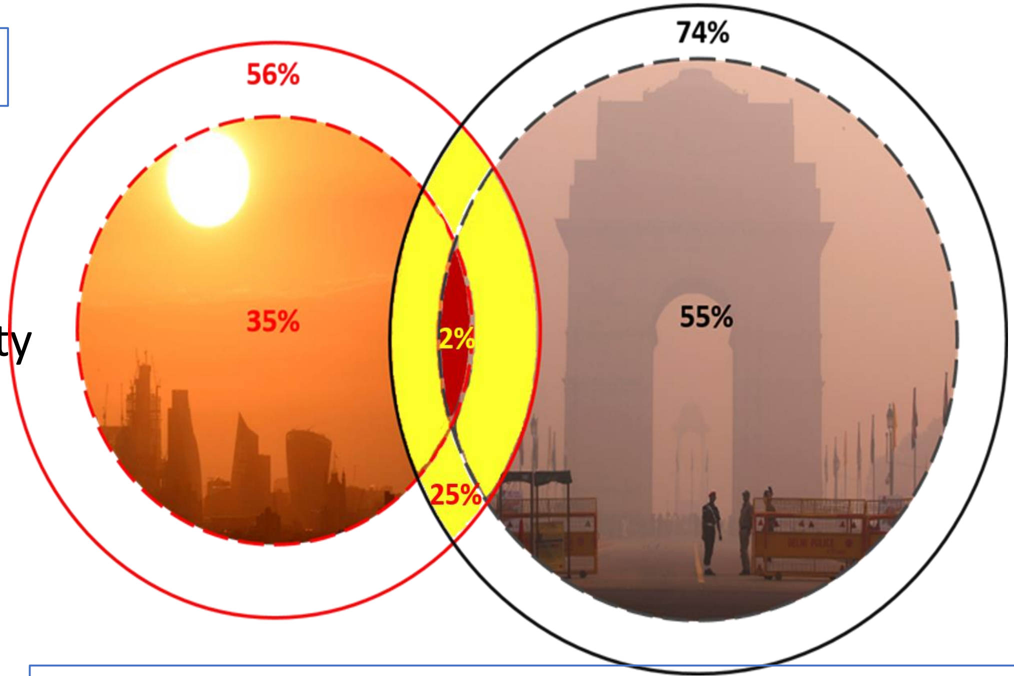
- **Motivation**:

  First large-scale assessment of
  the co- occurrence of heat extreme and haze extreme
  the **future** evolution and
  the **human** exposure

1997-2004 (Decade 2000) and 2046-2054 (Decade 2050).

- **Methods**:

  2 sets of high-resolution WRF_Chem decadal-long simulation [Kumar, 2018]
  that is evaluated thoroughly based on in situ measurement of air quality and also bias-corrected against meteorological reanalysis.



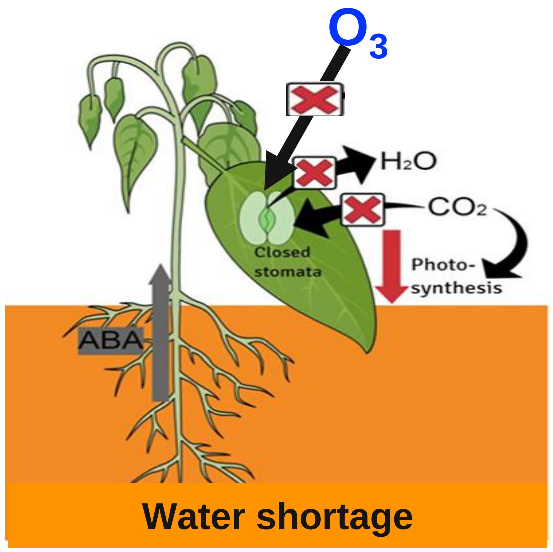
- **Results**:

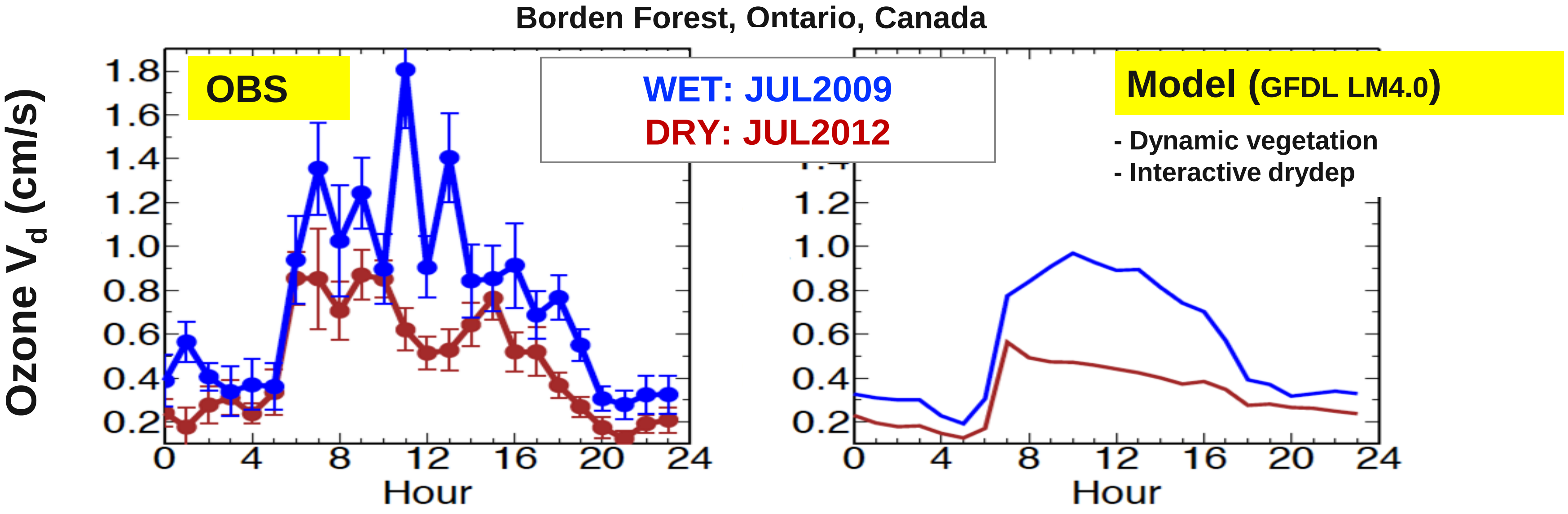
  Worrying Future Outlook…
  But useful for raising the awareness and anticipating scale of adaptation

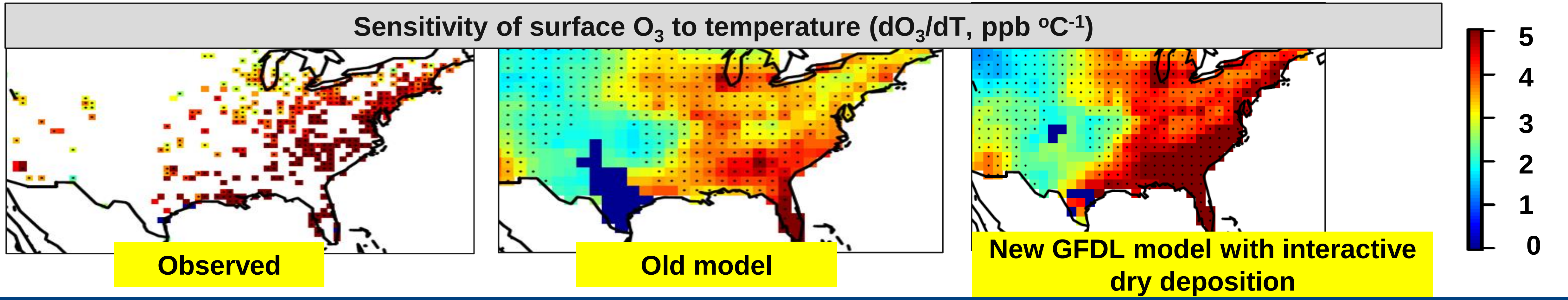
Land fraction with more than 60 days of exposure

Reduced ozone removal by water stressed vegetation exacerbates air pollution during heatwaves

(Meiyun Lin, NOAA GFDL/Princeton)



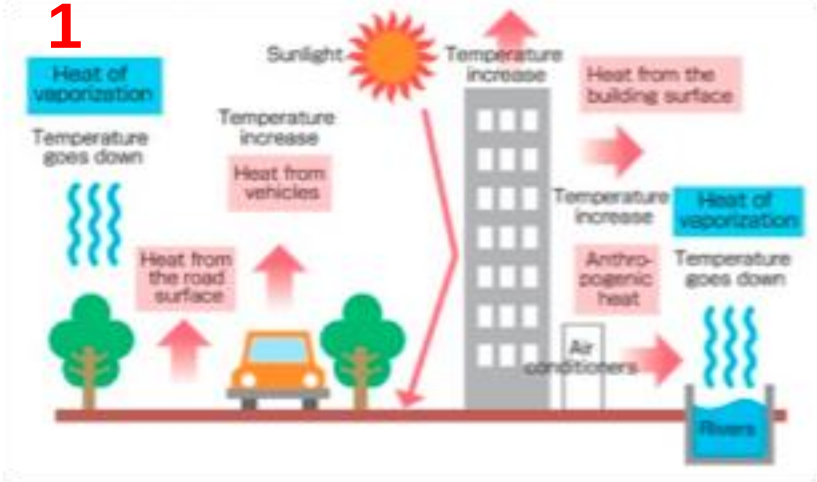




Urban Heat Island Mapping & Modeling Campaigns

David.Herring@noaa.gov | Vivek Shandas, PhD (vs@capastrategies.com)

1



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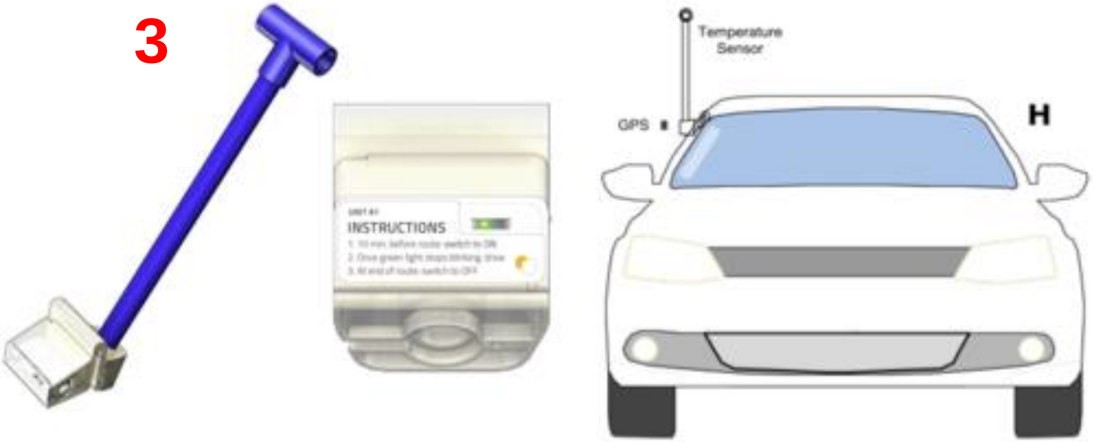

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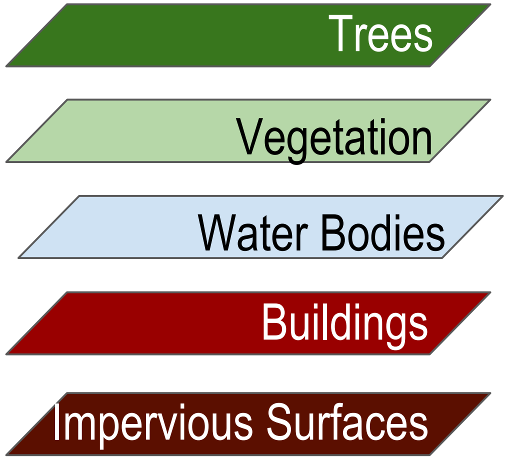

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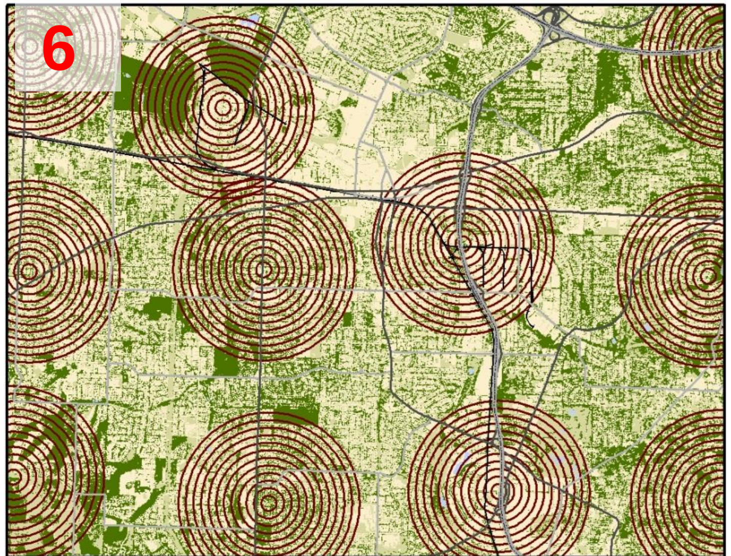

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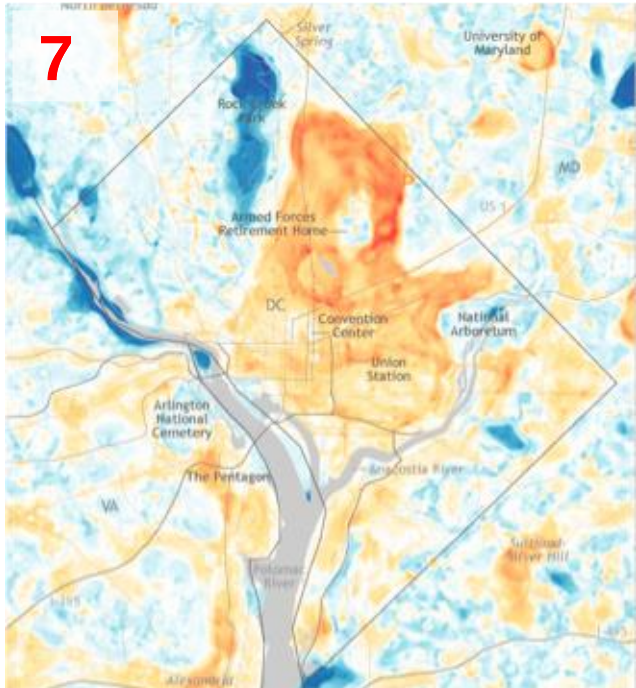


An Experimental Real-time Global Monitoring and Forecasting System for Excess Heat and Health

Augustin Vintzileos

University of Maryland - ESSIC

The Monitoring & Forecasting System:

Heat and Health Formula (Nairn and Fawcett, 2014):

$$EHI_{sig} = \frac{1}{3}(T_i + T_{i-1} + T_{i-2}) - T_{95\%}$$

$$EHI_{acclim} = \frac{1}{3}(T_i + T_{i-1} + T_{i-2}) - \frac{1}{30}\sum_{k=i-32}^{i-3} T_k$$

$$EHF = max(0, EHI_{sig}) \times max(1, EHI_{accl})$$

Model: CFSv2 (used for the forecasting component)

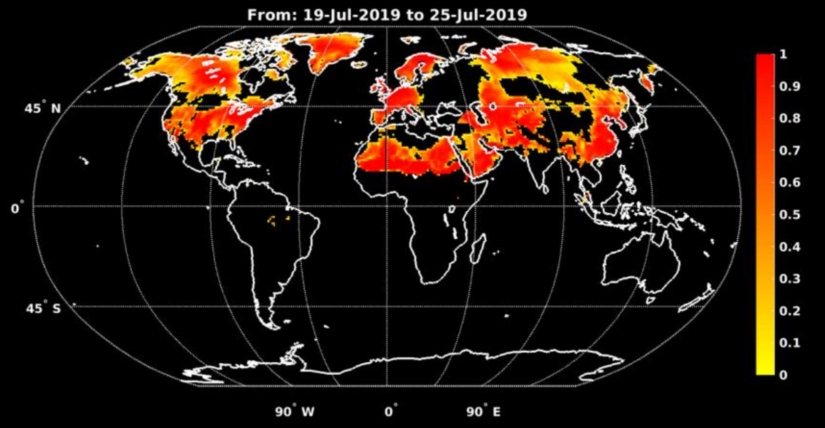
- 16 member ensemble forecasts
- Reforecast 1999-2010

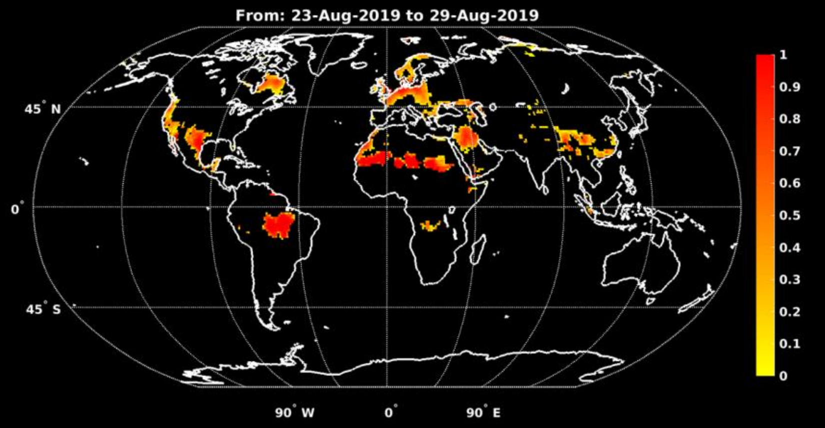
Bias correction

- Quantile mapping
- Correction basis: ERA-Interim 1999-2010

Daily Real-time Monitoring and Forecast:

excess-heat.org

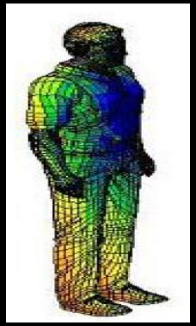




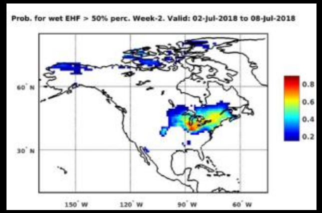
Quantile of the maximum daily EHF within the selected period

Future Work

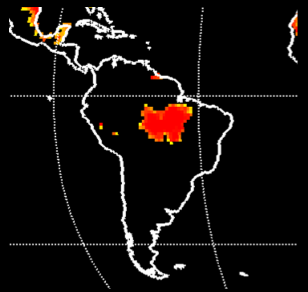
Define impacts of heat on health using thermal manikins (e.g., IESD-Fiala model)



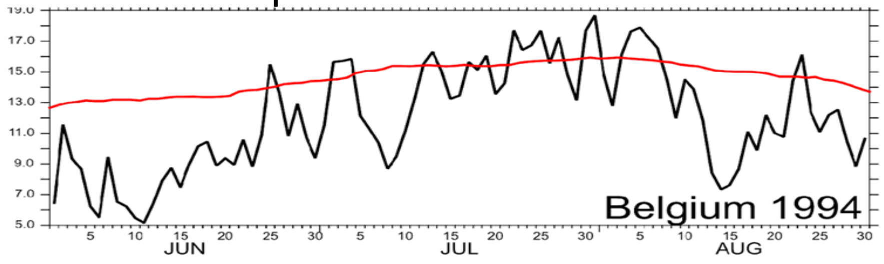
Very high resolution (~500 meters) downscaling with the WRF



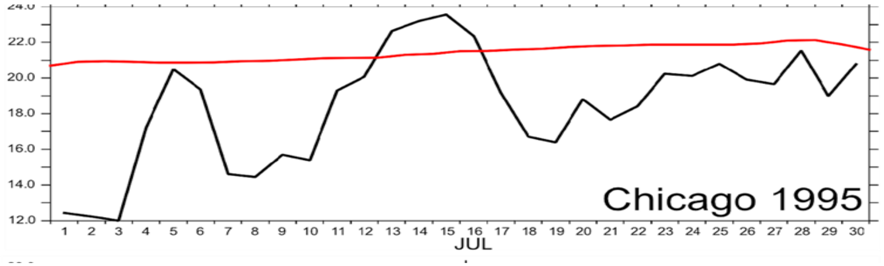
Probabilistic attribution of individual heat waves to climate variability and climate change



compound heat wave

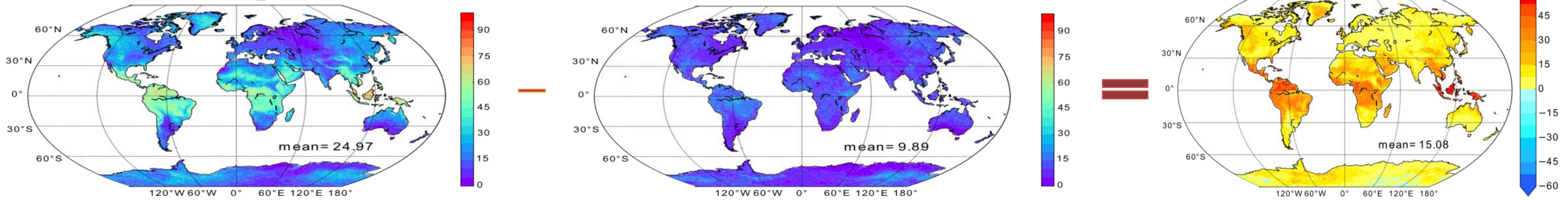


"normal" heat wave



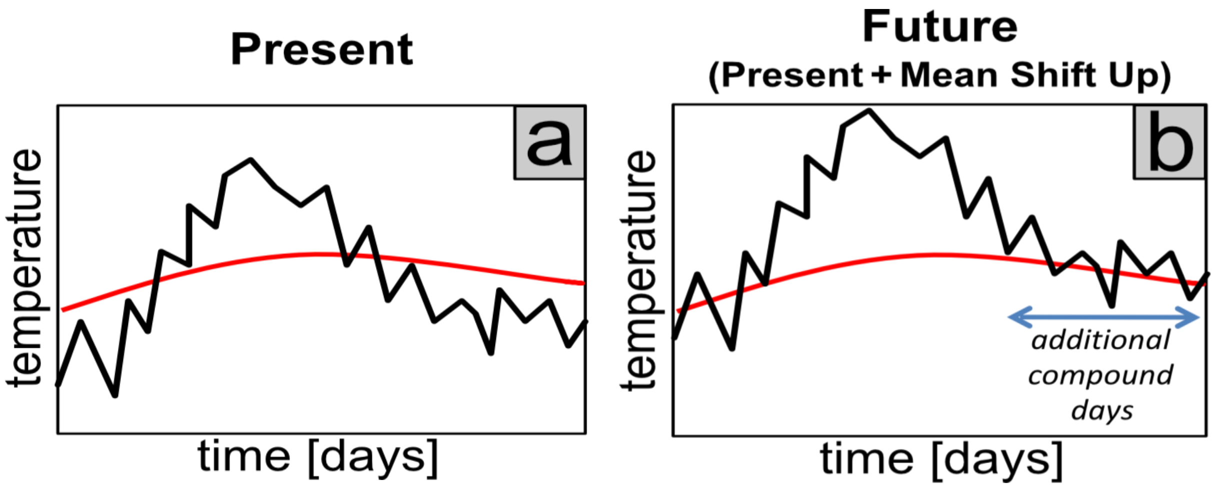
% = (Compound Days)/(All Heat Wave Days)*100

2xCO_2 Control



Baldwin et al 2019, *Earth's Future*

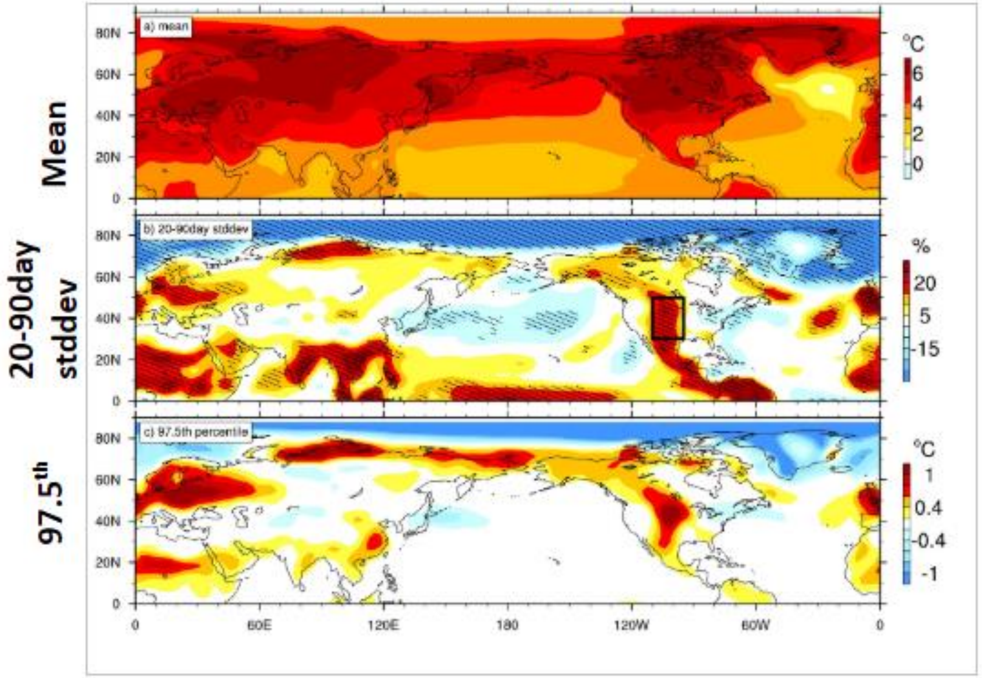
"Temporally Compound Heat Wave Events and Global Warming: An Emerging Risk"



Understanding Future Change in Subseasonal Temperature Variability and Heat Waves

Haiyan Teng
National Center for Atmospheric Research

CESM1 TAS 2070-2100 wrt 1980-2010

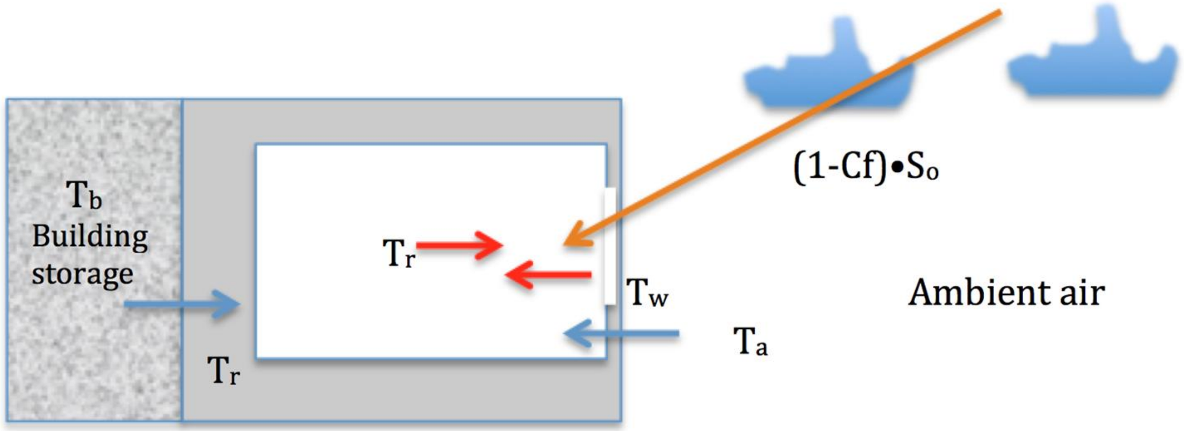


- Change in variability vs. mean
- Amplification of planetary waves ?
- Enhanced atmosphere-land feedback ?

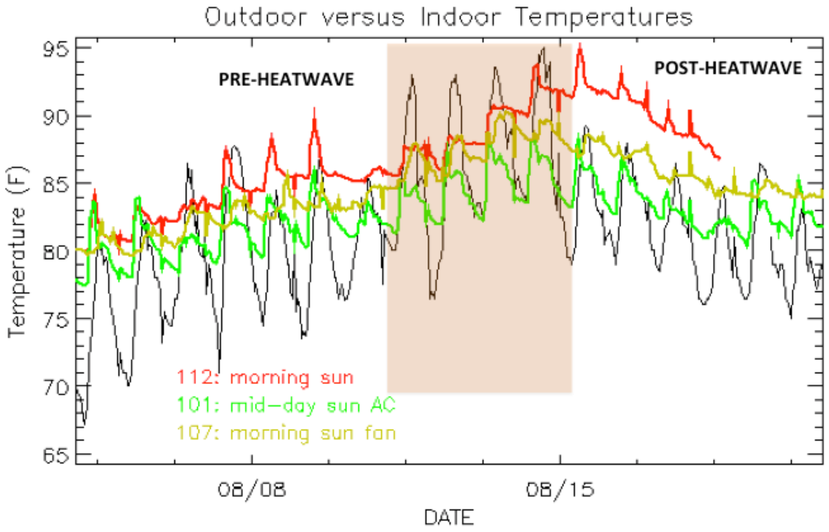
U.S. DEPARTMENT OF ENERGY
Office of Science
NOAA
CGD Climate & Global Dynamics

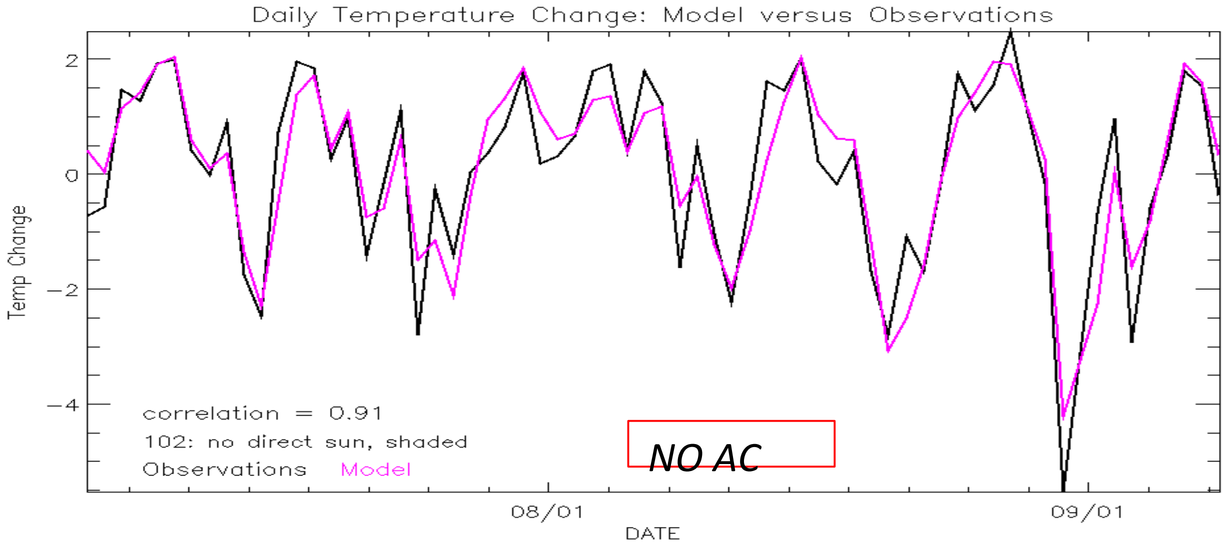
Brian Vant-Hull
CREST Institute
City College of New York

Indoor Heat Waves



During heat waves those most at risk tend to be indoors, which can be treated as greenhouses with temperatures driven by outdoor weather.
Results from the Harlem Heat Project





Lightning Talks

ESSM Extreme Heat Workshop Day 2

Conclusions:

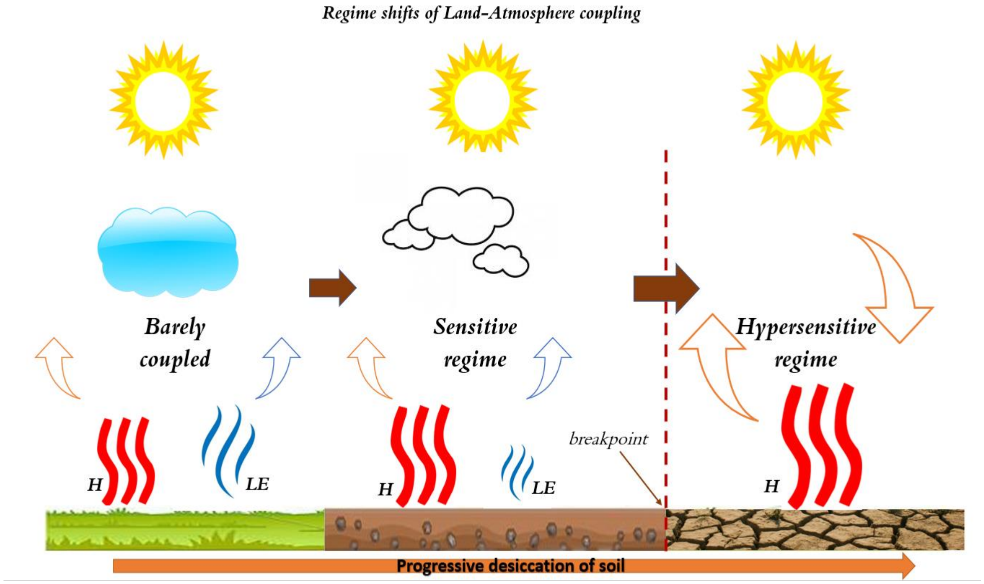
- There has been no detectable change in land-based emission of CH_4 in the Arctic tundra south of Barrow despite large temperature changes.
- There have been significant increases in late summer to early winter time fluxes of CO_2 at Barrow.

How dry soil moisture extremes exacerbate heatwaves over the contiguous United States

by
David Benson & Paul Dirmeyer (GMU/COLA)
NOAA Grant: NOAA / NA160AR4310095

Background

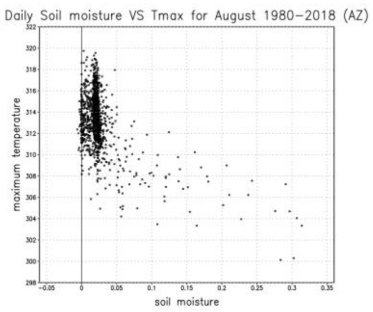
- This study shows that there are certain thresholds of soil moisture below which there is a shift in the sensitivity of the atmospheric temperature to soil moisture

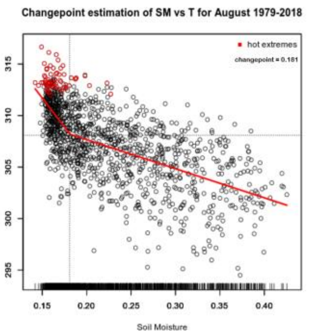


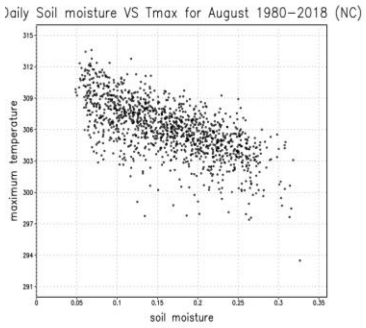
Data & Methods

- ERA 5 reanalysis investigated over the US and fluxnet data
- The relationship between extremely dry soil moisture and hot temperature extremes is shown to be piecewise linear

Results







Discussion

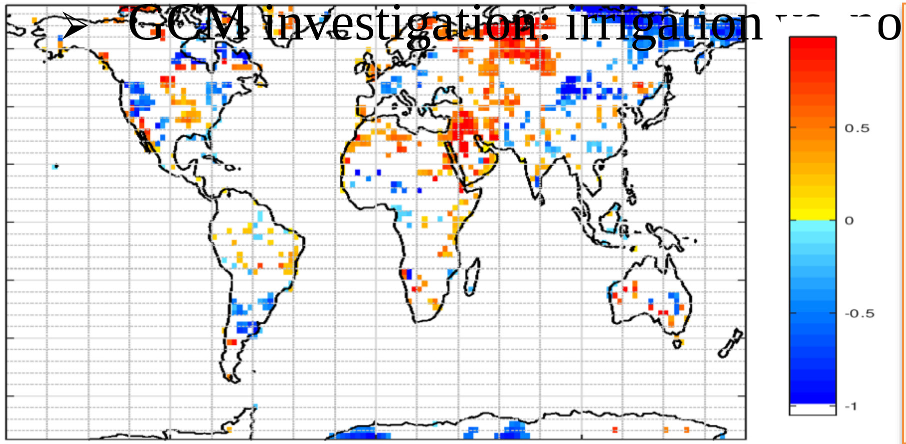
- There are significant physical processes that determine the changepoints
- These changepoints can serve as indicators for a shift from sensitive to hypersensitive response of the atmosphere to the land
- Accurate prediction of regime shifts can lead to improvements in predicting heatwave events exacerbated by L-A feedback

Benson, D. O. & Dirmeyer, P. A. (2019) Characterizing the relationship between temperature and soil moisture extremes and their role in the exacerbation of heatwaves over the contiguous United States (In preparation)

Effect of Irrigation on Humid Heat Extremes

Nir Y Krakauer (CCNY), BI Cook and MJ Puma (NASA-GISS)

- Expansion of irrigation has lead to regional cooling, particularly during the hottest days
  - What about humidity?
  - Wet-bulb temperature (T_w – can be thought of as combination of temperature and humidity) sets a heat stress adaptability limit
- GCM investigation: irrigation vs. no irrigation in GISS ModelE



Irrigation minus No-irrigation 90th-percentile daily-maximum T_w for warmest month (K). Only differences that are over land and significant at 95% are shown. Irrigation reduces maximum T over most of the hot land areas, but increases humidity and hence maximum T_w over many of them, notably the central USA

Henry Koerner, *It Isn't the Heat, It's the Humidity* (1947-8). Carnegie Museum of Art, Pittsburgh.

Messages:

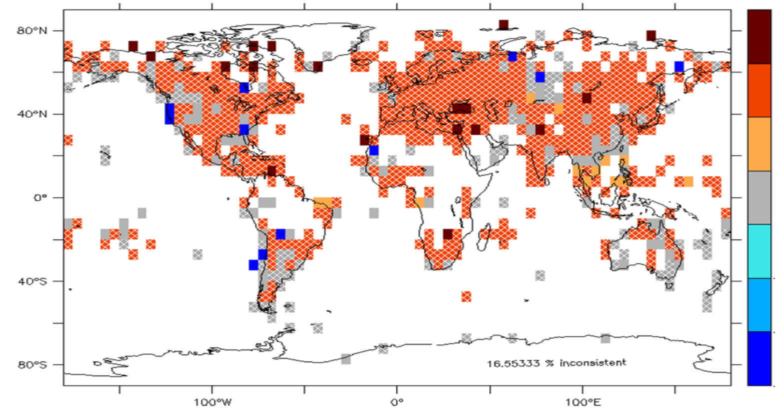
- Land management affects heat extremes
- Extreme-heat research needs to consider humidity, not just T – irrigation reduces T but worsens humidity

mail@nirkrakauer.net

MS in prep for ERL

Detection of anthropogenic influence on a summertime heat stress index

Thomas Knutson
NOAA/OAR/GFDL



Wet Bulb Globe Temperature Trend Assessment (1973-2012):

Detectable anthro. increase, greater than modeled (2%)

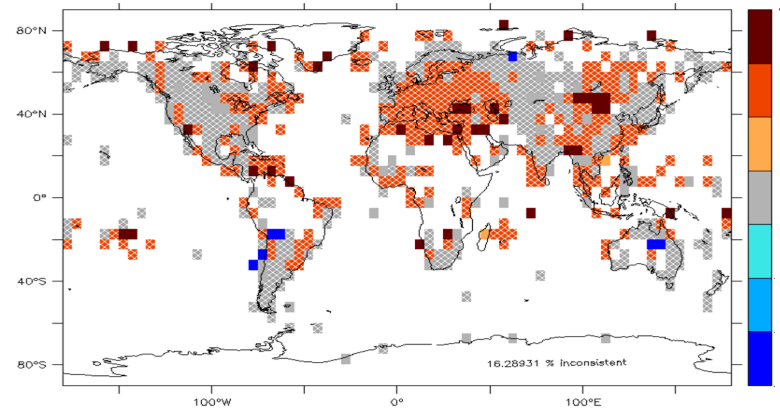
Detectable anthro. increase, consistent with modeled (67%)

Detectable increase, less than modeled (3%)

No detectable trend; (27%)

Detectable decrease, less than modeled (0%)

Detectable decrease, consistent with modeled (0%)



Surface Air Temperature Trend Assessment (1973-2012):

Detectable decrease, greater than modeled (2%)

Detectable anthro. increase, greater than modeled (6%)

Detectable anthro. increase, consistent with modeled (41%)

Detectable increase, less than modeled (<1%)

No detectable trend; (51%)

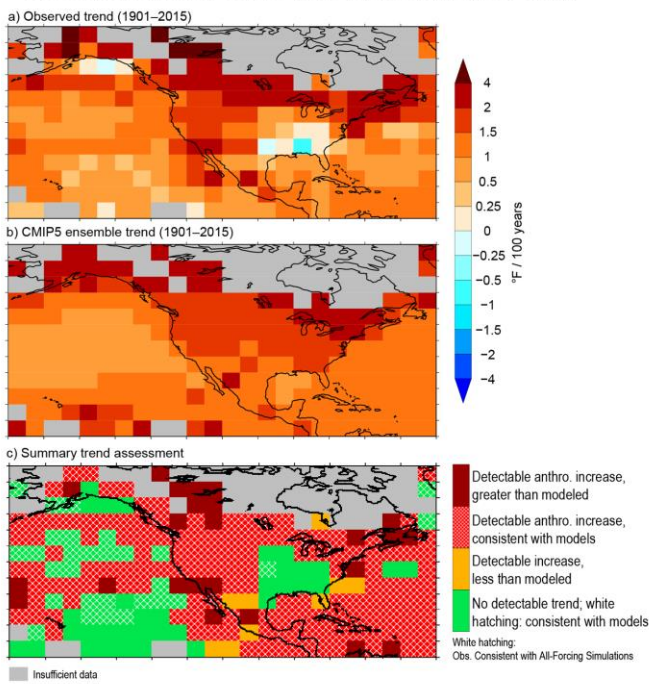
Detectable decrease, less than modeled (0%)

Detectable decrease, consistent with modeled (0%)

Detectable decrease, greater than modeled (1%)

Some remaining issues for U.S.:

Assessment of Annual Surface Temperature Trends (1901–2015)

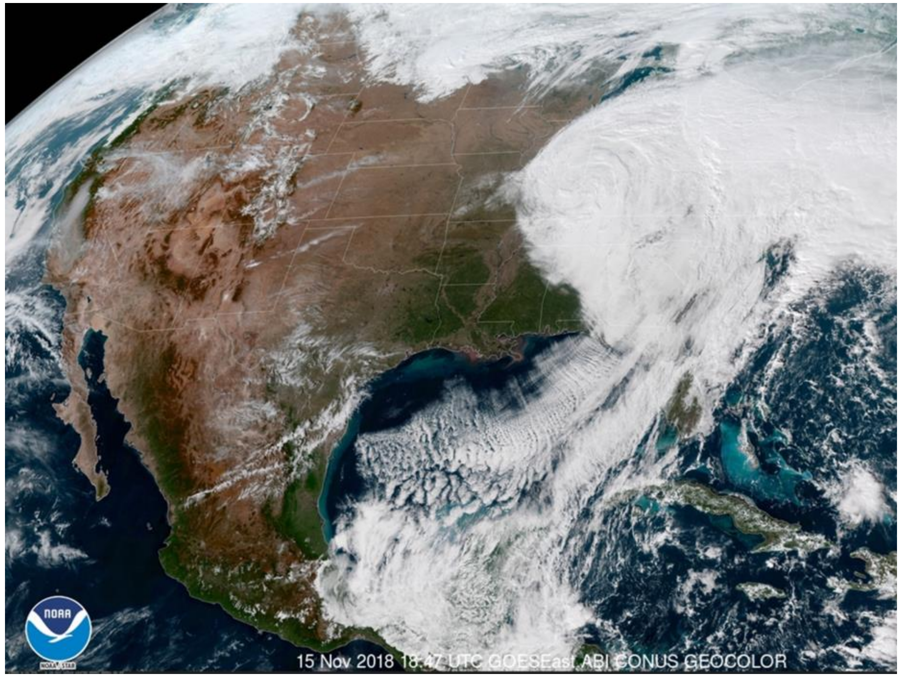


Sources: Knutson and Ploshay, 2016, *Climatic Change*;
NCA4: Climate Science Special Report (2017)
Adapted from Knutson et al. *J. Climate* 2013

How does Extratropical cyclone activity impact extreme heat?

Stony Brook University
School of Marine and Atmospheric Sciences

Edmund Chang, Stony Brook University



- Cyclones bring clouds
- Fewer or weaker cyclones bring less clouds
- Less clouds imply more solar radiation reaching surface and higher maximum temperature
- Several studies have shown that in observations maximum temperature in summer is negatively correlated with level of cyclone activity

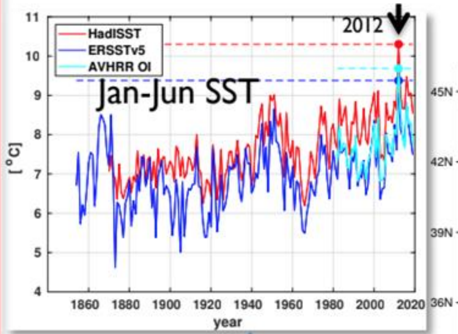
- GCM's simulate much weaker correlations than those observed (Chang et al. 2016; Ma 2019)
- CMIP5 models project weaker cyclone activity in summer under changing climate, potentially less clouds from cyclones
    - This could potentially accentuate warming

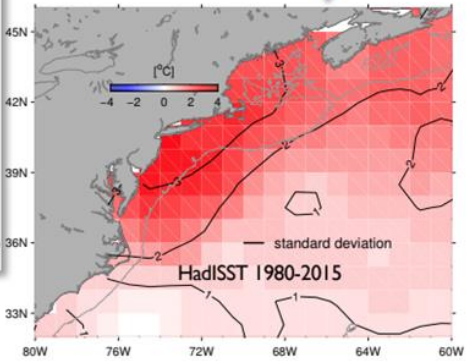
The 2012 extreme heat in NW Atlantic: from understanding to predictability

Ke Chen (kchen@whoi.edu), Woods Hole Oceanographic Institution

1. Characteristics and impacts

Exceeding 3 STDs

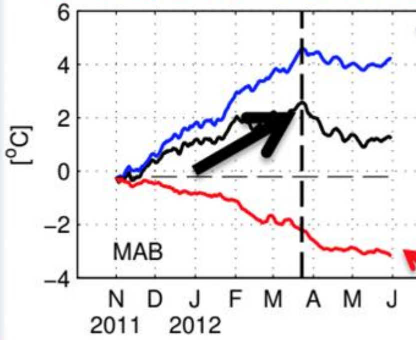




Highest on record

- Earlier and more intense spring bloom
- Higher zooplankton biomass
- Earlier landing and larger catch of lobster
- Northward shift of butterfish, black sea bass, Atlantic cod

2. Temperature anomaly (no seasonal cycle) budget

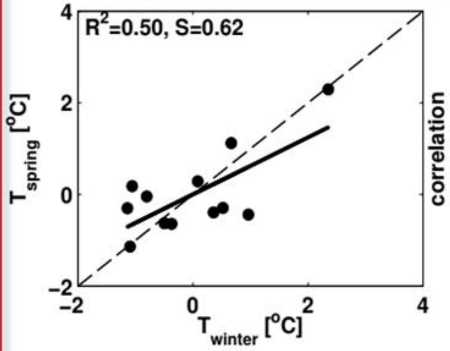


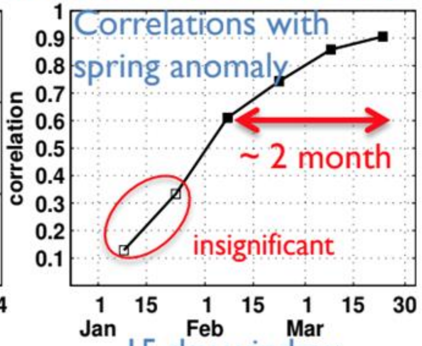
Cumulative air-sea heat flux

- Anomalous air-sea flux, associated with jet stream variability
- Ocean advection secondary

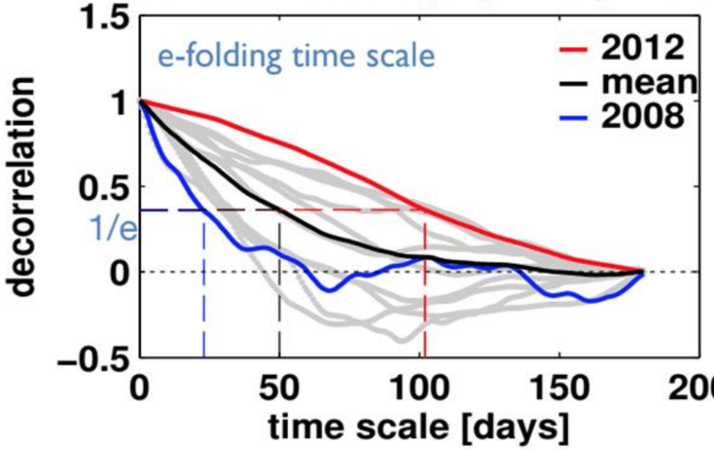
Ocean advection

3. Interannual variability and predictability





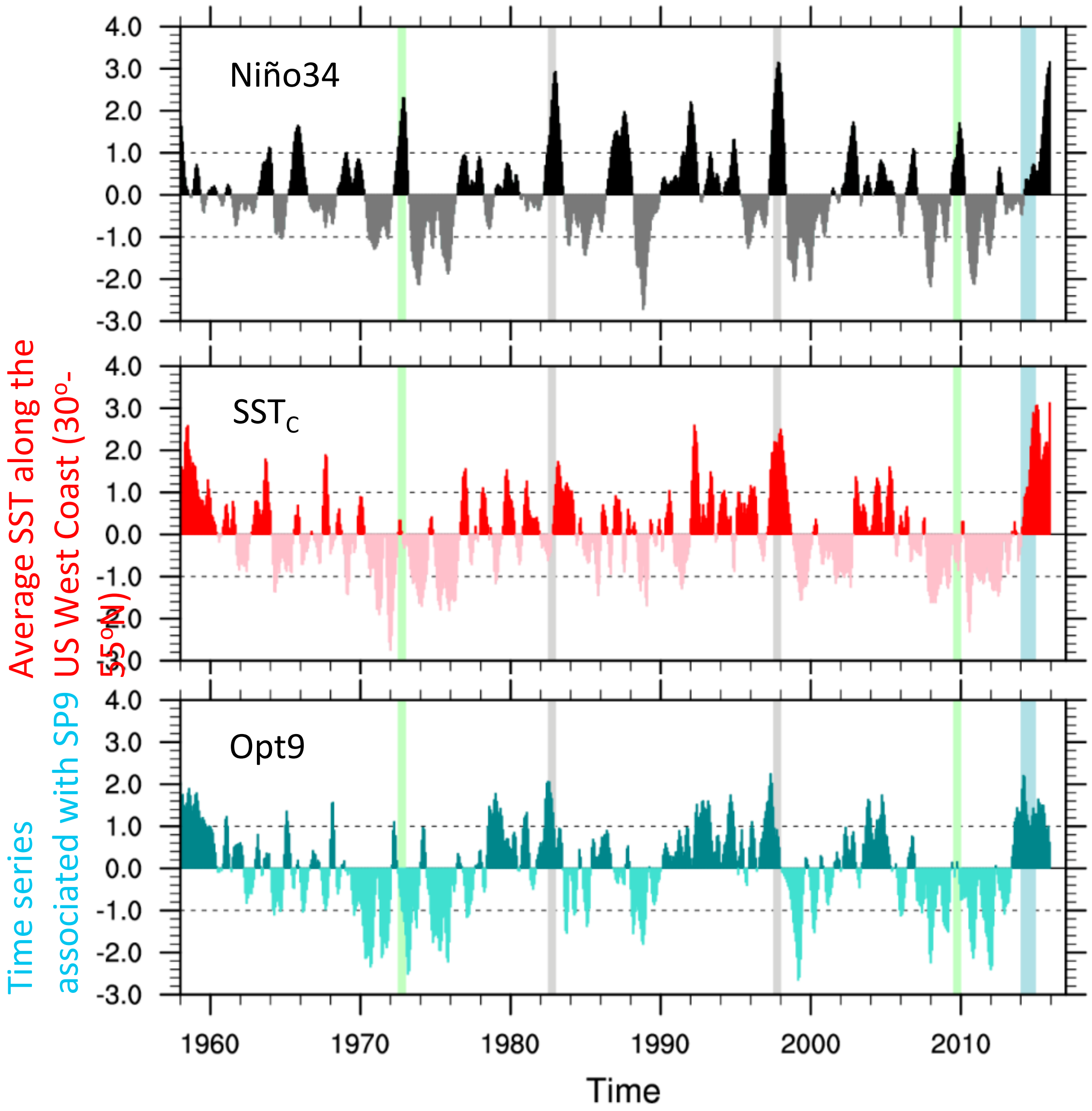
Decorrelation Scale of Jan-Jun Daily Anomaly



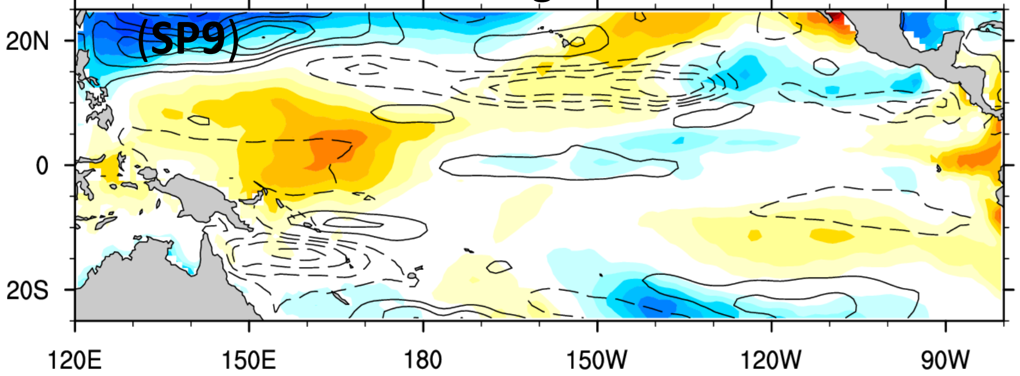
- 50-day mean decorrelation scale, consistent with the 2-month scale
- Strong interannual variability: oceanic and atmospheric fluxes change dramatically from year to year
- Deterministic prediction of NW Atlantic is challenging, but is an exciting research topic

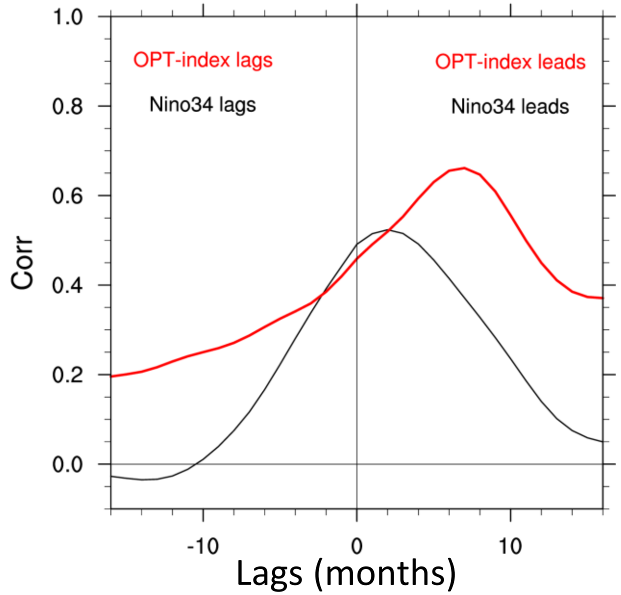
Which El Niño Flavors are Most Important for US West Coast Extreme Marine Warming?

Antonietta Capotondi
NOAA/ESRL Physical Sciences Division



Patterns of SST (shading) and SSH (contours) that are most conducive to US West Coast warming at 9 months lead time (SP9)



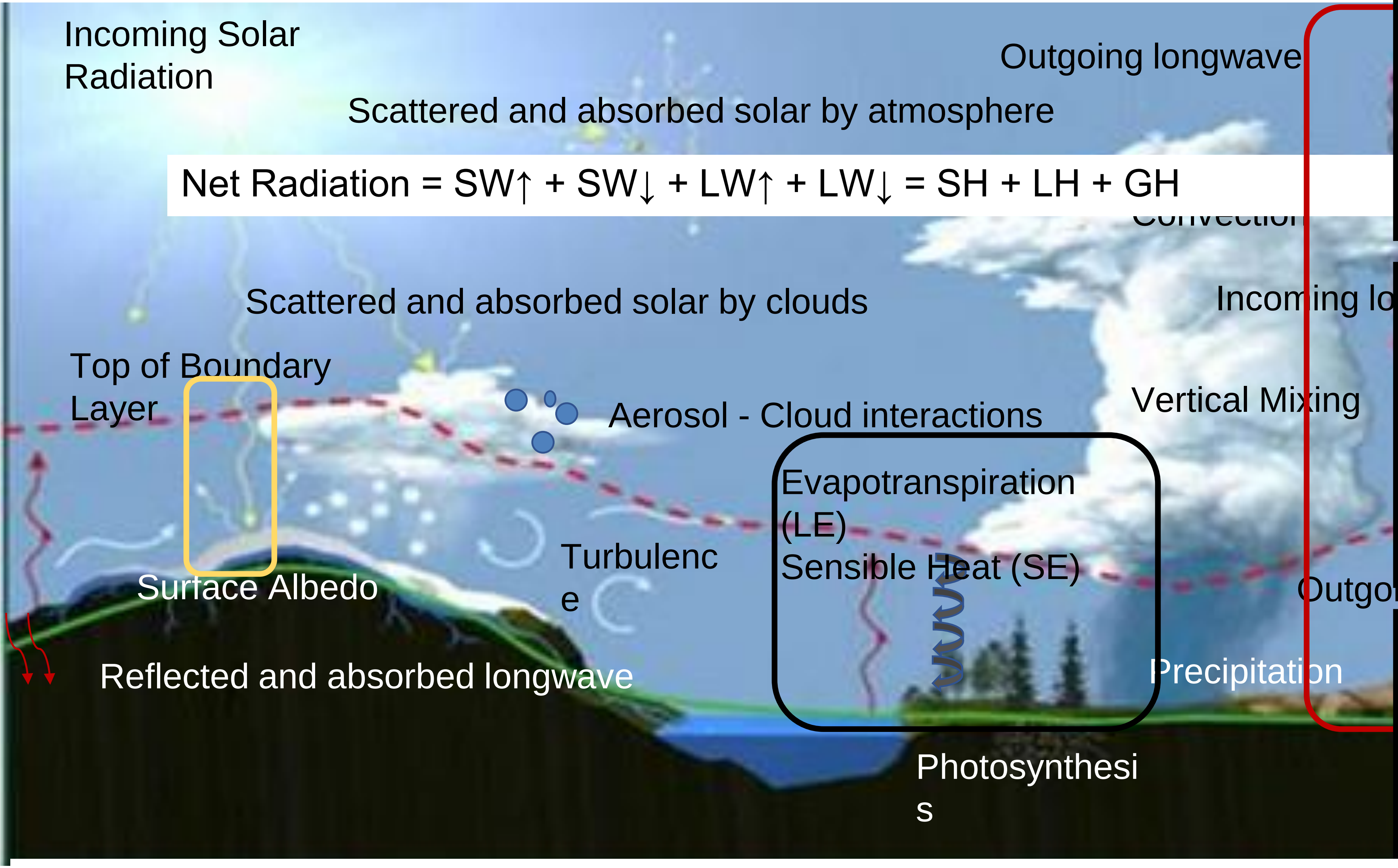


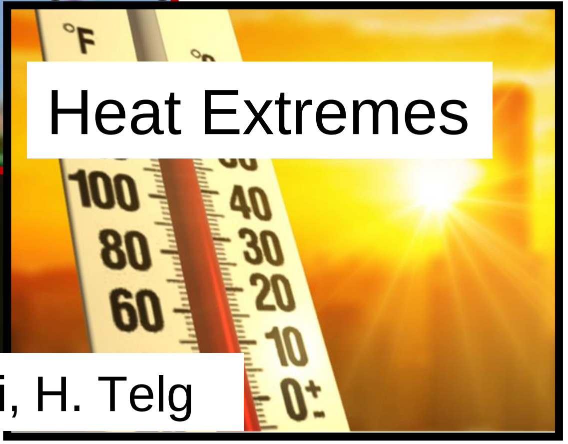
Lag-Correlations between Niño3.4 and SST_C (black) and Opt9 and SST_C (red)

Largest corr. with Niño34 is ~0.5 with Niño34 leading by 2-3 months

Largest corr with Opt9 is ~0.65 with Opt9 leading by 7 months

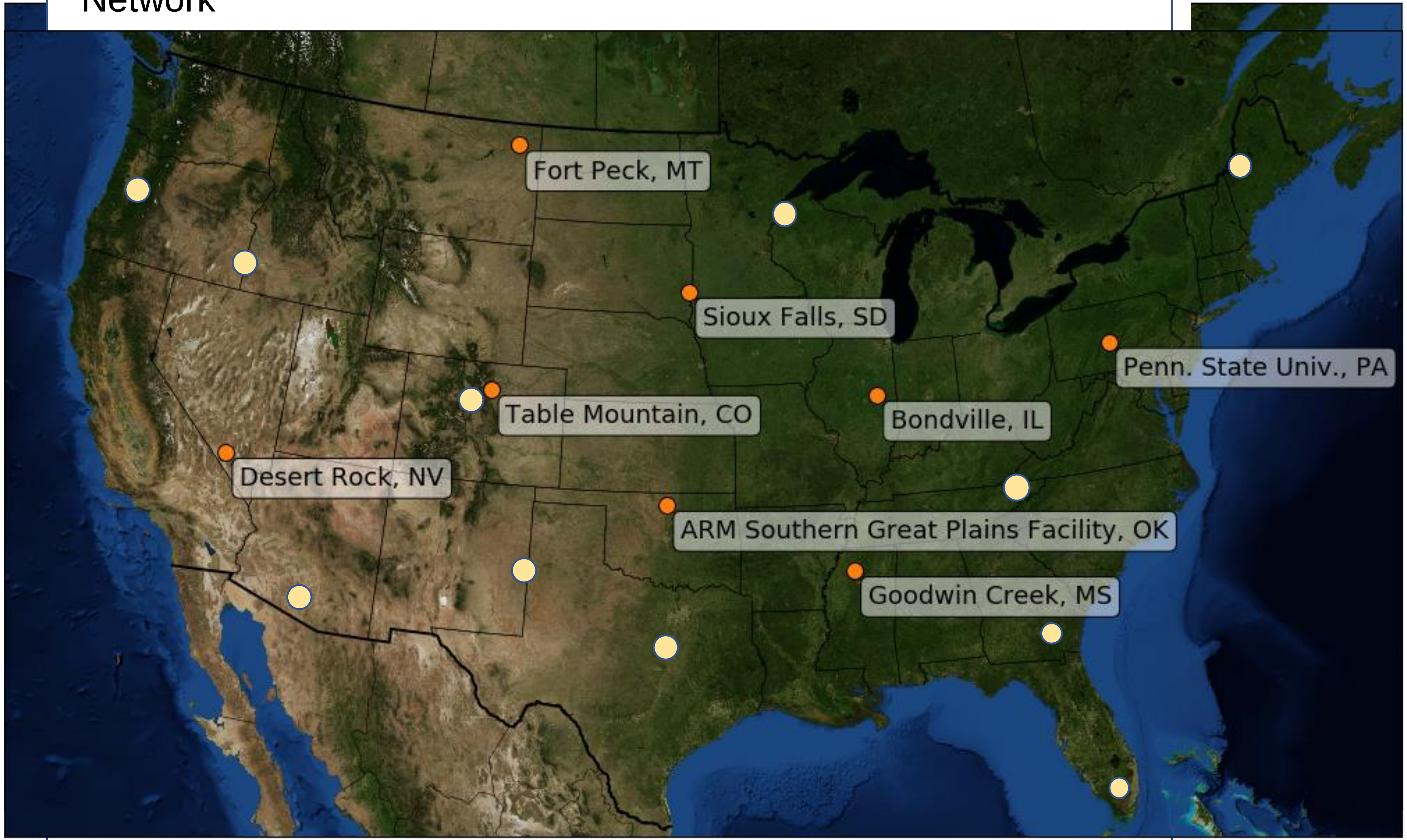
Net Radiation is the driver weather and climate





Why a Surface Energy Budget Network? K. Lantz, J. Augustine, T. Meyers, D. Stanitski, H. Telg

Expanded SURFRAD Stations Network



Integrated Approach – Modeling and Observations (ground and satellite)

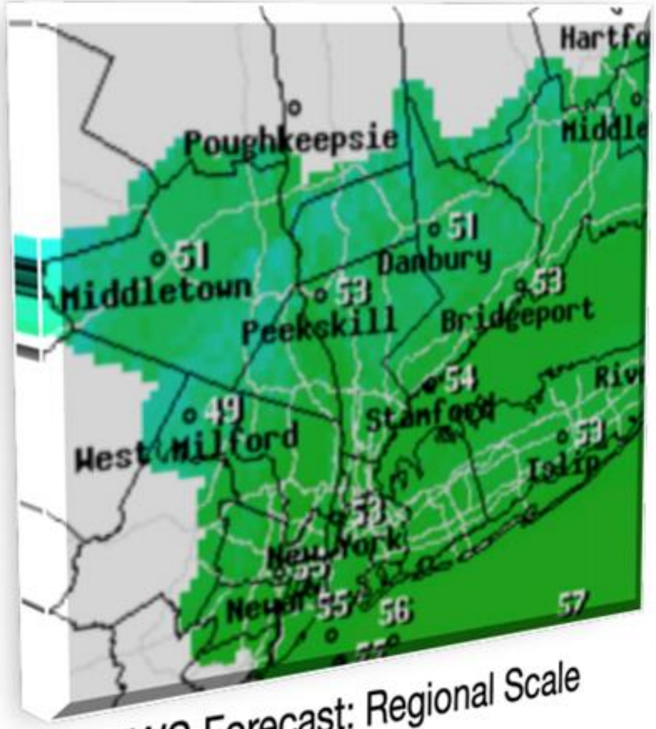
Foundational long-term observations across time (diurnal, seasonal, decadal) and spatial scales (synoptic to local)

Connections - Land Atmospheric Interactions and Feedbacks

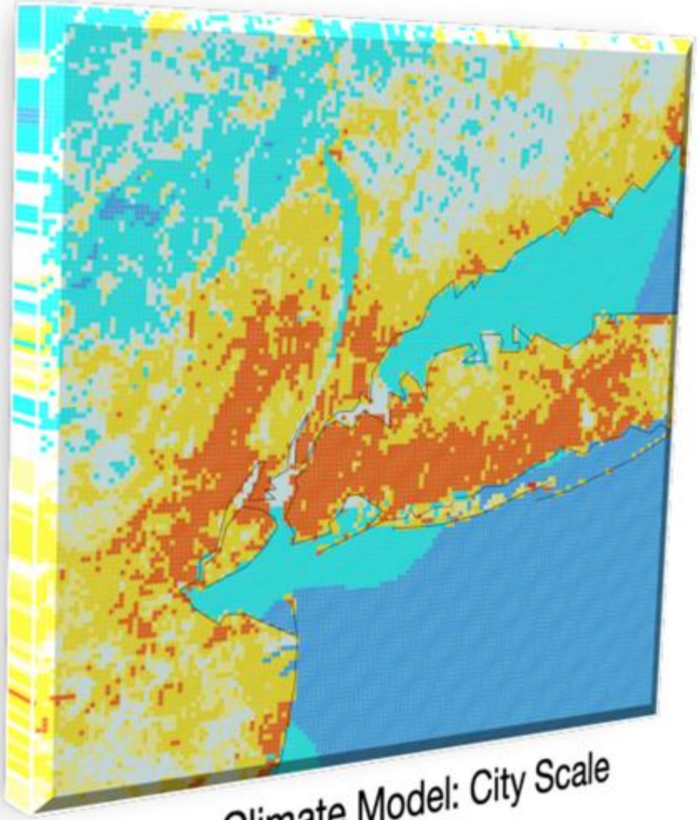
Predictive capabilities

Remote sensing solutions to combat extreme heat at relevant spatio-temporal scales

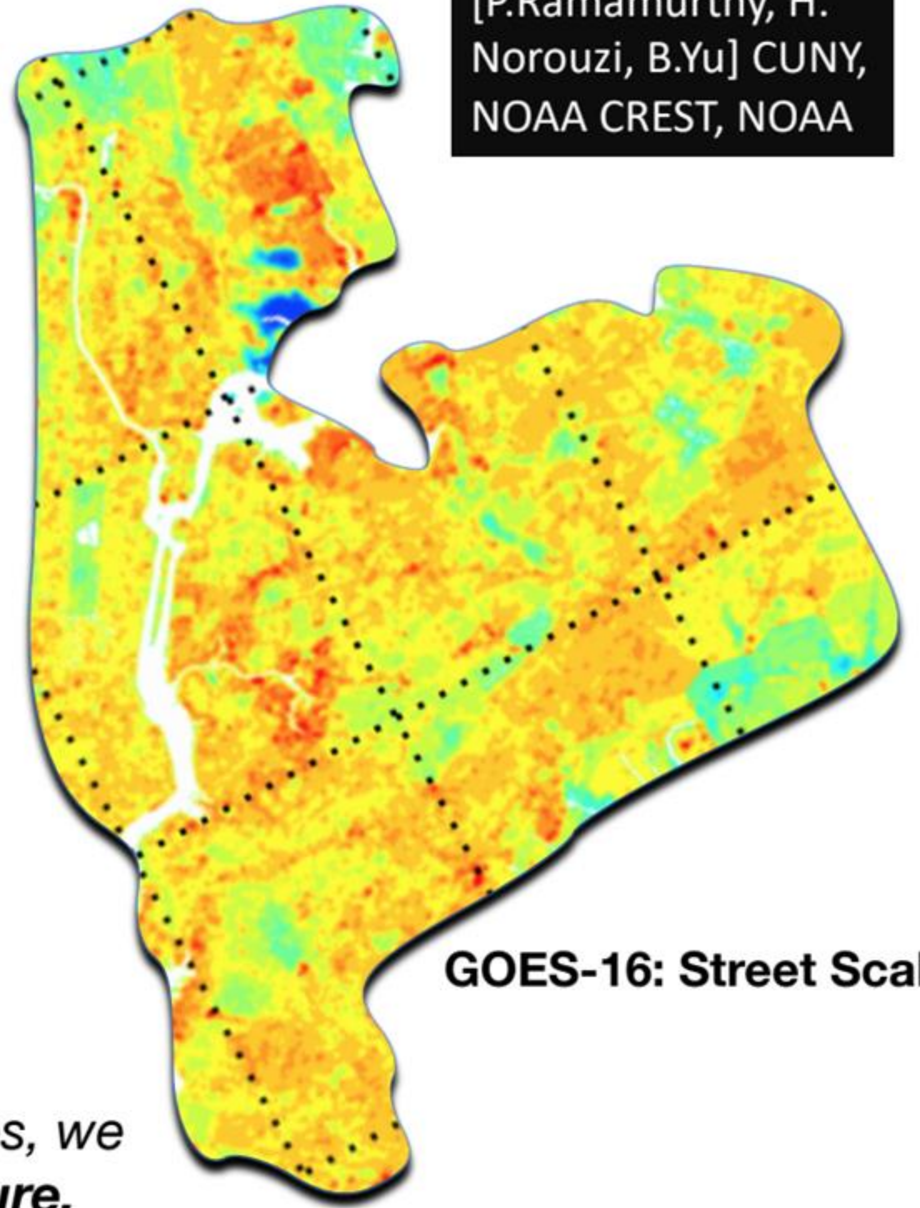
[P.Ramamurthy, H. Norouzi, B.Yu] CUNY, NOAA CREST, NOAA



NWS Forecast: Regional Scale



Urban Climate Model: City Scale

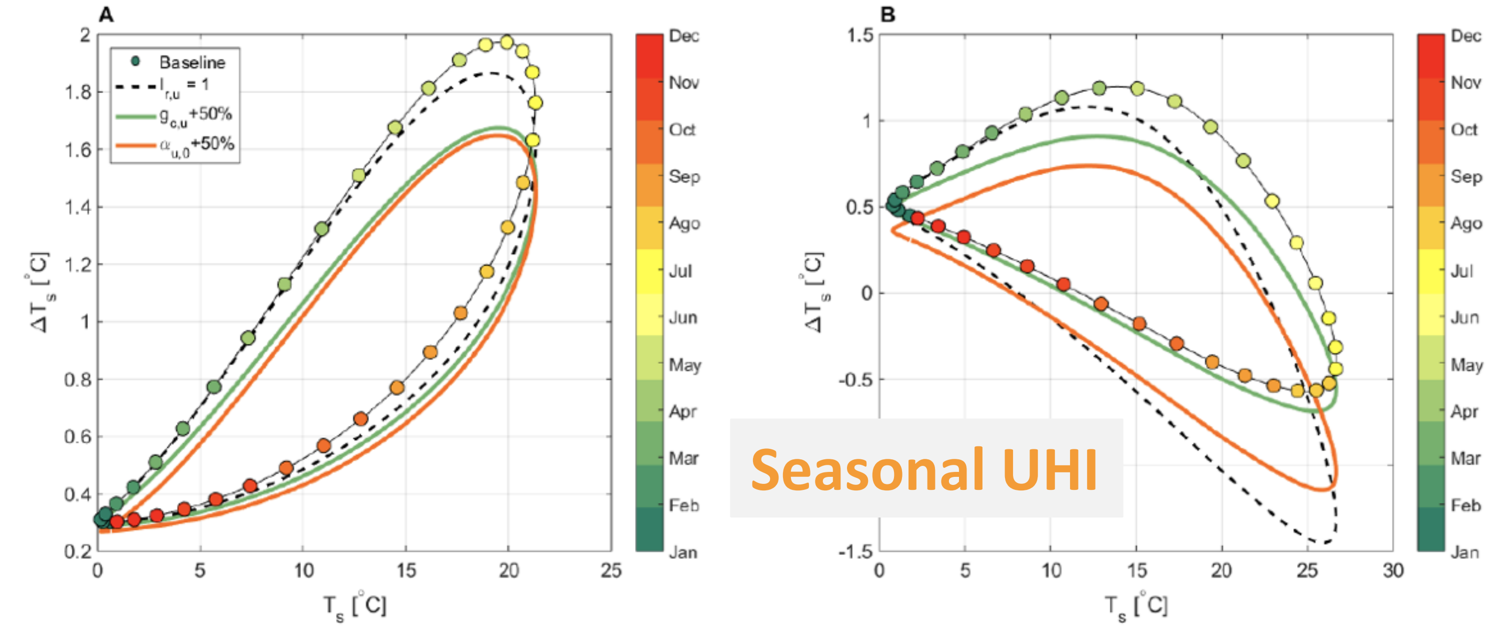


GOES-16: Street Scale

*Using ground based observations & machine learning techniques, we will able to predict/nowcast high resolution urban **air temperature, humidity and heat index***

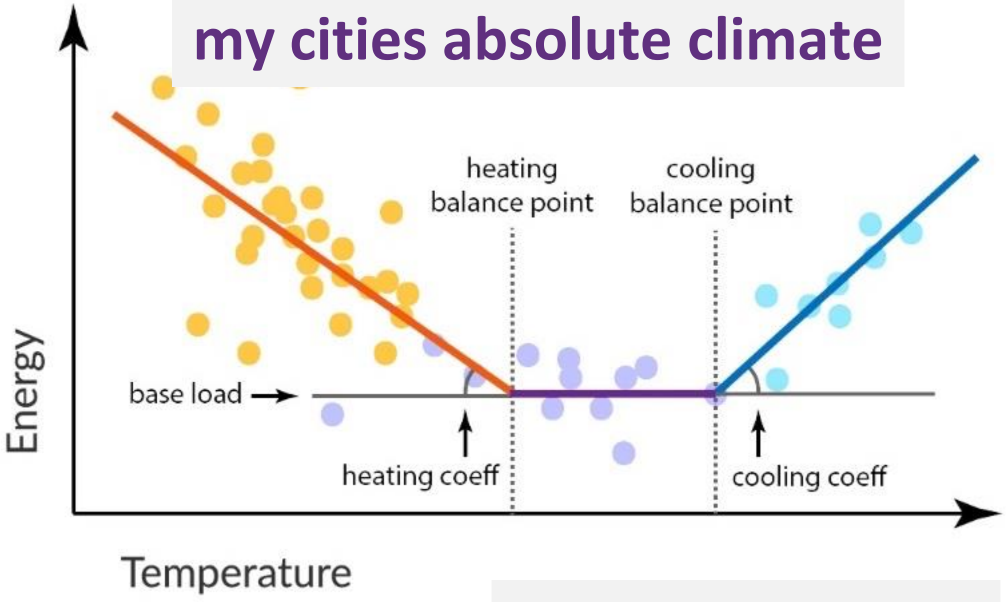
Ramamurthy et. al. 2016; Ramamurthy et. al. 2017; Hrisko et. al. 2019

Elie Bou-Zeid, Civil and Environmental Engineering
Princeton University

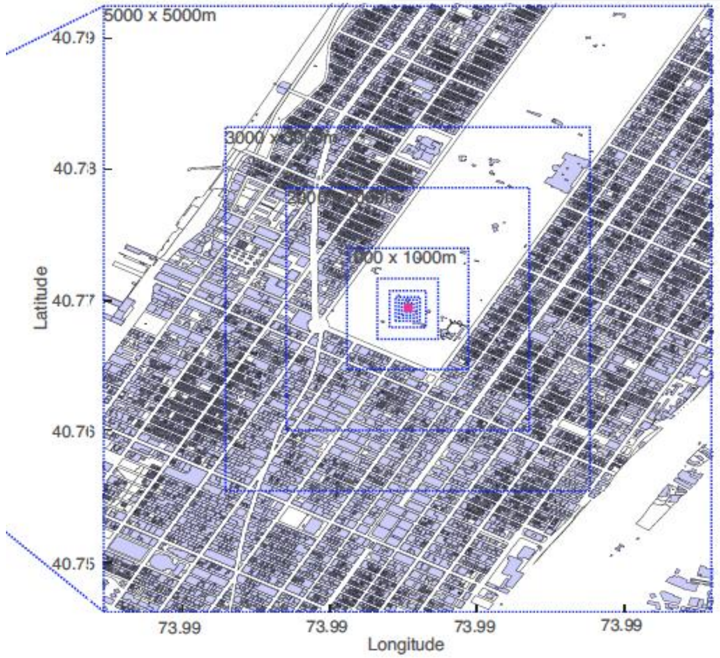


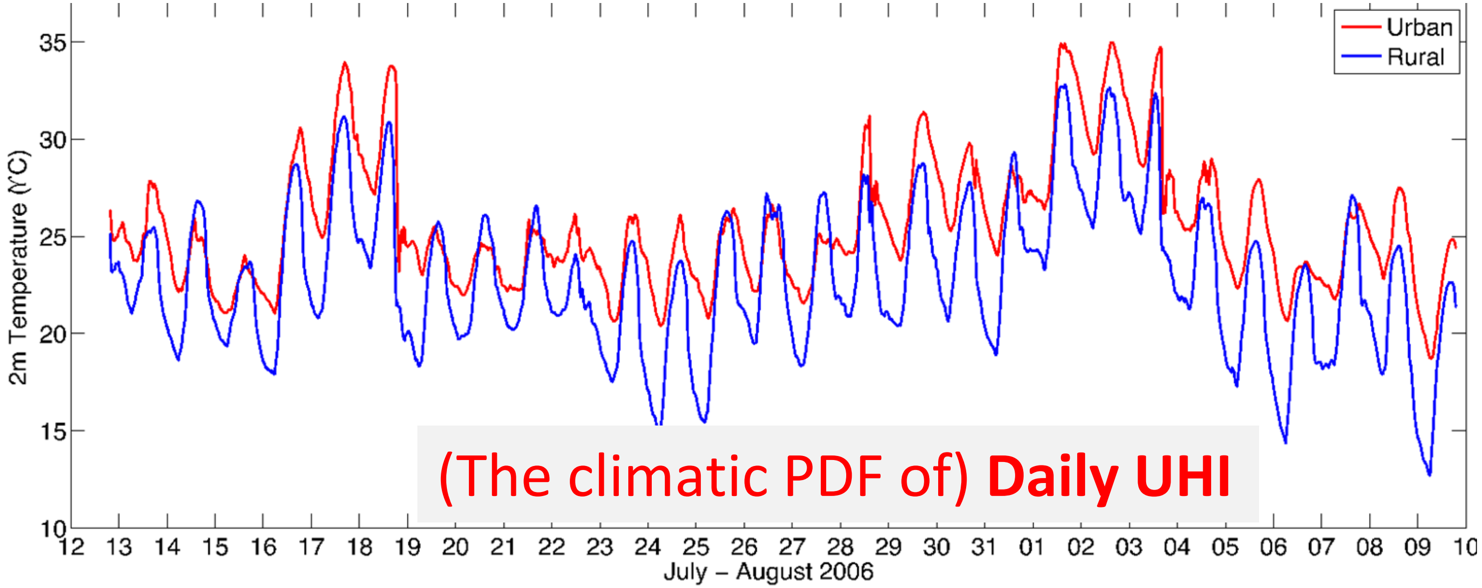
Seasonal UHI

Local: Beyond UHI, my cities absolute climate



But what is local?





(The climatic PDF of) **Daily UHI**