Seasonal Prediction of Particularly-Impactful Hot Days

Patrick T. Brown[1], Max Evans[2], Ankur Mahesh[2], Himanshu Gupta[2], Ken Caldeira[3]

@PatrickTBrown31

[1] *San José State University, Department of Meteorology and Climate Science*
[2] *ClimateAi, San Francisco, CA*
[3] *Carnegie Institution for Science, Department of Global Ecology*

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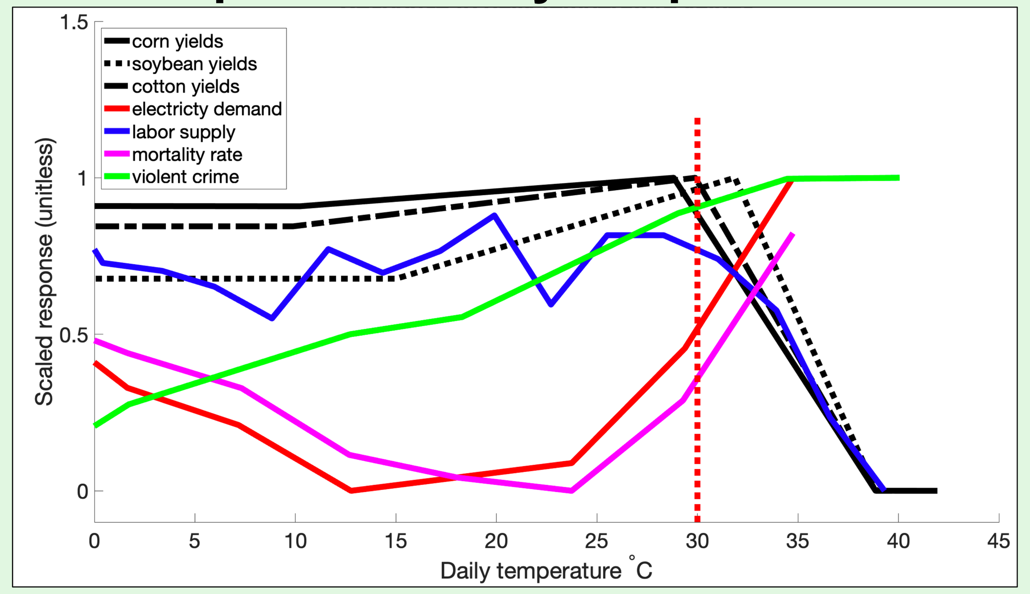
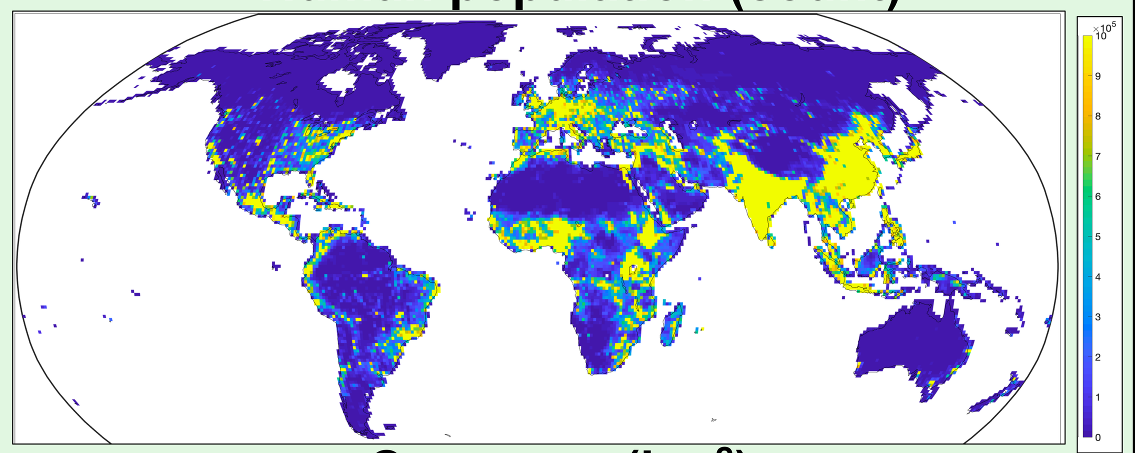
- Several sectors of the socioeconomy are particularly sensitive to time spent above temperatures of ~30°C

Response to daily temperatures

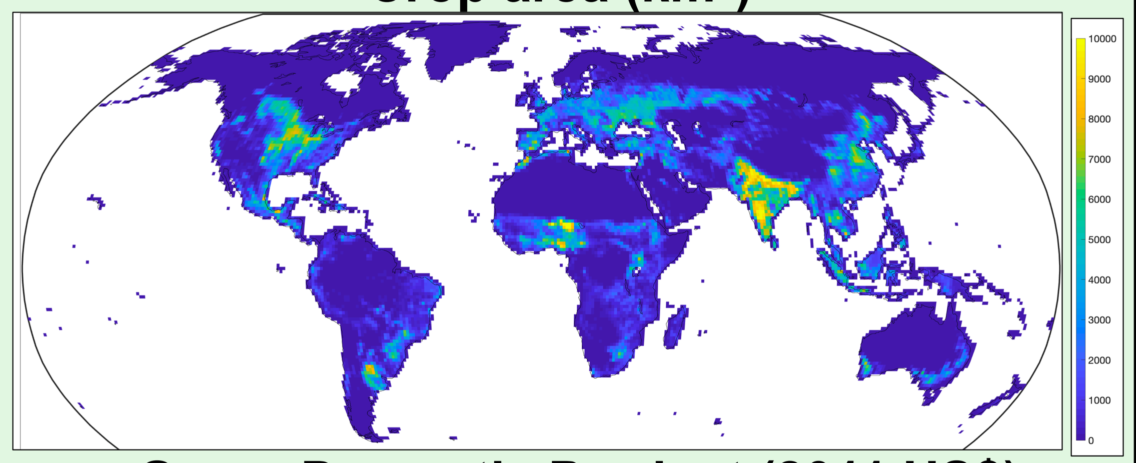


- Assets are not equally distributed in space so heat waves in some locations are more impactful than heat waves in other locations

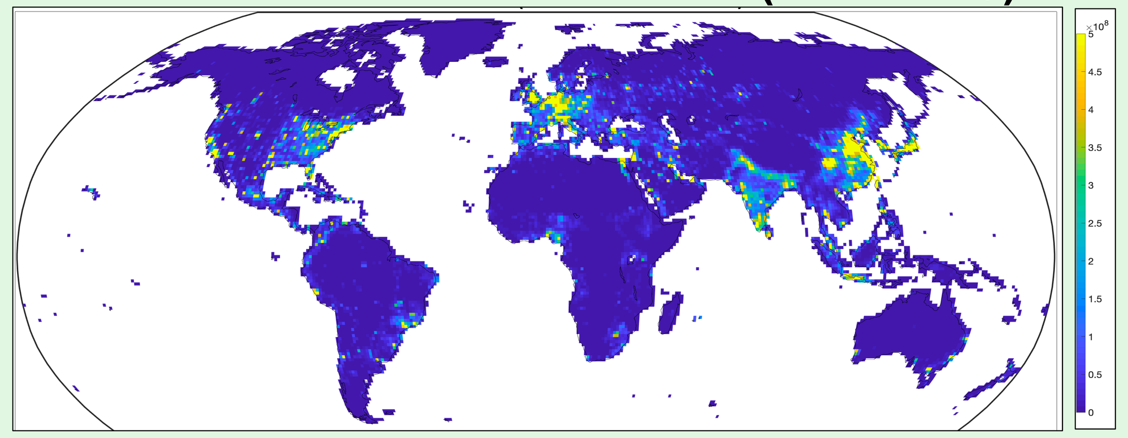
Human population (count)



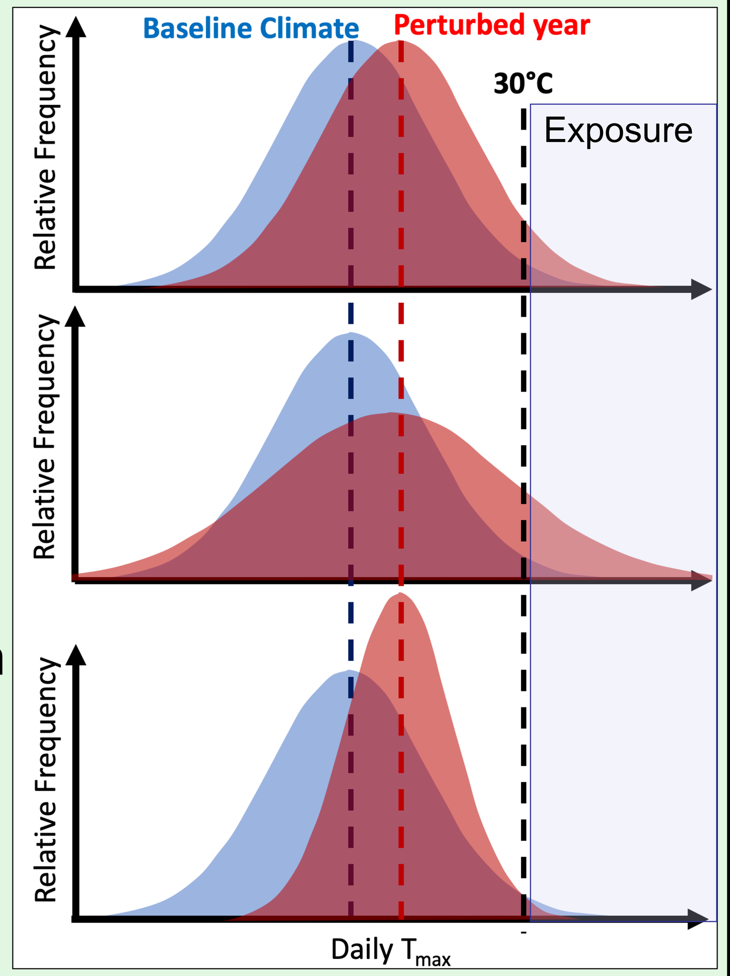
Crop area (km²)



Gross Domestic Product (2011 US$)



- Asset exposure to >30°C days is not necessarily the direct result of shifts in mean temperature
- We aim to predict fluctuations in the warm-season exposure of assets to days where T_{max} is > 30°C
- Warm-season is defined as
  - May - October for the Northern Hemisphere
  - November - April for the Southern Hemisphere



Empirical, data-driven approach

Predictor
- Globally-gridded surface air temperature field
- Monthly-mean from month antecedent to predictand season
  - April for Northern Hemisphere forecast of warm-season
  - September for Southern Hemisphere forecast of warm-season

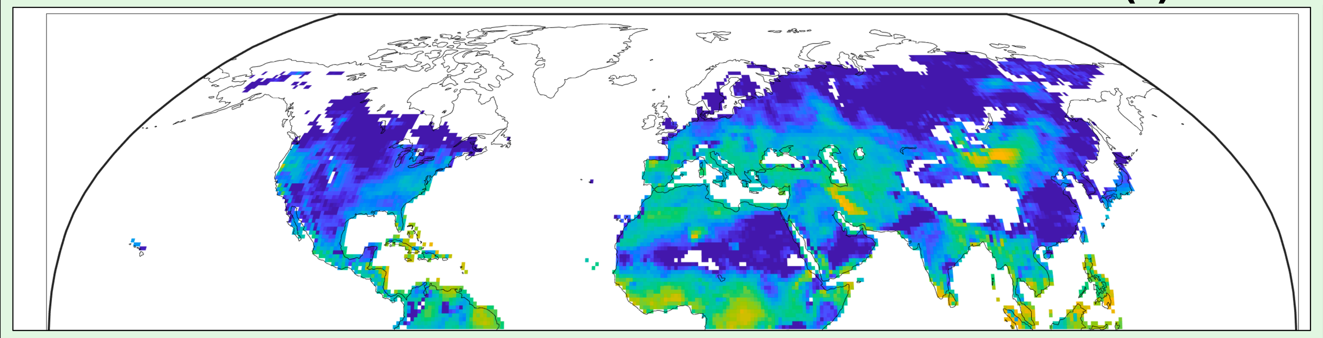
Model
- Partial Least Squares Regression
- 3 PLSR components used

Predictand
- Number of days within a warm-season where T_{max} >30°C
- Target local anomalies at 1° × 1° spatial scale
- Target global amalgamation of
  - Crop area-days
  - People-days
  - GDP-days

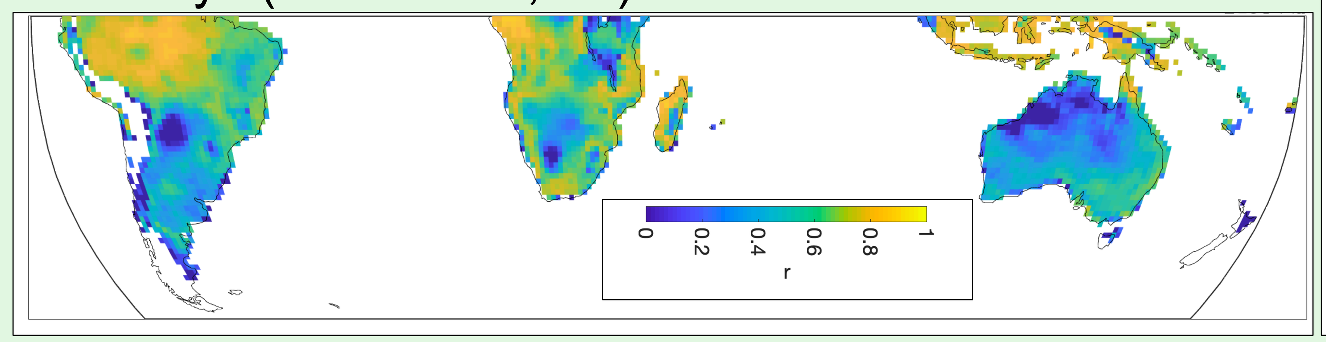
Predictand ← Predictor field →

$$\begin{bmatrix} Target_{t_3}\\ Target_{t_4}\\ Target_{t_5}\\ \dots\\ Target_{t_n}\end{bmatrix} = \begin{bmatrix} 1 & SAT_{t_2,loc_1} & \dots & SAT_{t_2,loc_k} & \dots & SAT_{t_1,loc_1} & \dots & SAT_{t_1,loc_k}\\ 1 & SAT_{t_3,loc_1} & \dots & SAT_{t_3,loc_k} & \dots & SAT_{t_2,loc_1} & \dots & SAT_{t_2,loc_k}\\ 1 & SAT_{t_4,loc_1} & \dots & SAT_{t_4,loc_k} & \dots & SAT_{t_3,loc_1} & \dots & SAT_{t_3,loc_k}\\ \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots\\ 1 & SAT_{t_{n-1},loc_1} & \dots & SAT_{t_{n-1},loc_k} & \dots & SAT_{t_{n-2},loc_1} & \dots & SAT_{t_{n-2},loc_k}\end{bmatrix} \cdot \begin{bmatrix} b_0\\ b_1\\ b_2\\ \dots\\ b_{n\cdot k}\end{bmatrix} + \begin{bmatrix} r_{t_3}\\ r_{t_4}\\ r_{t_5}\\ \dots\\ r_{t_n}\end{bmatrix}$$

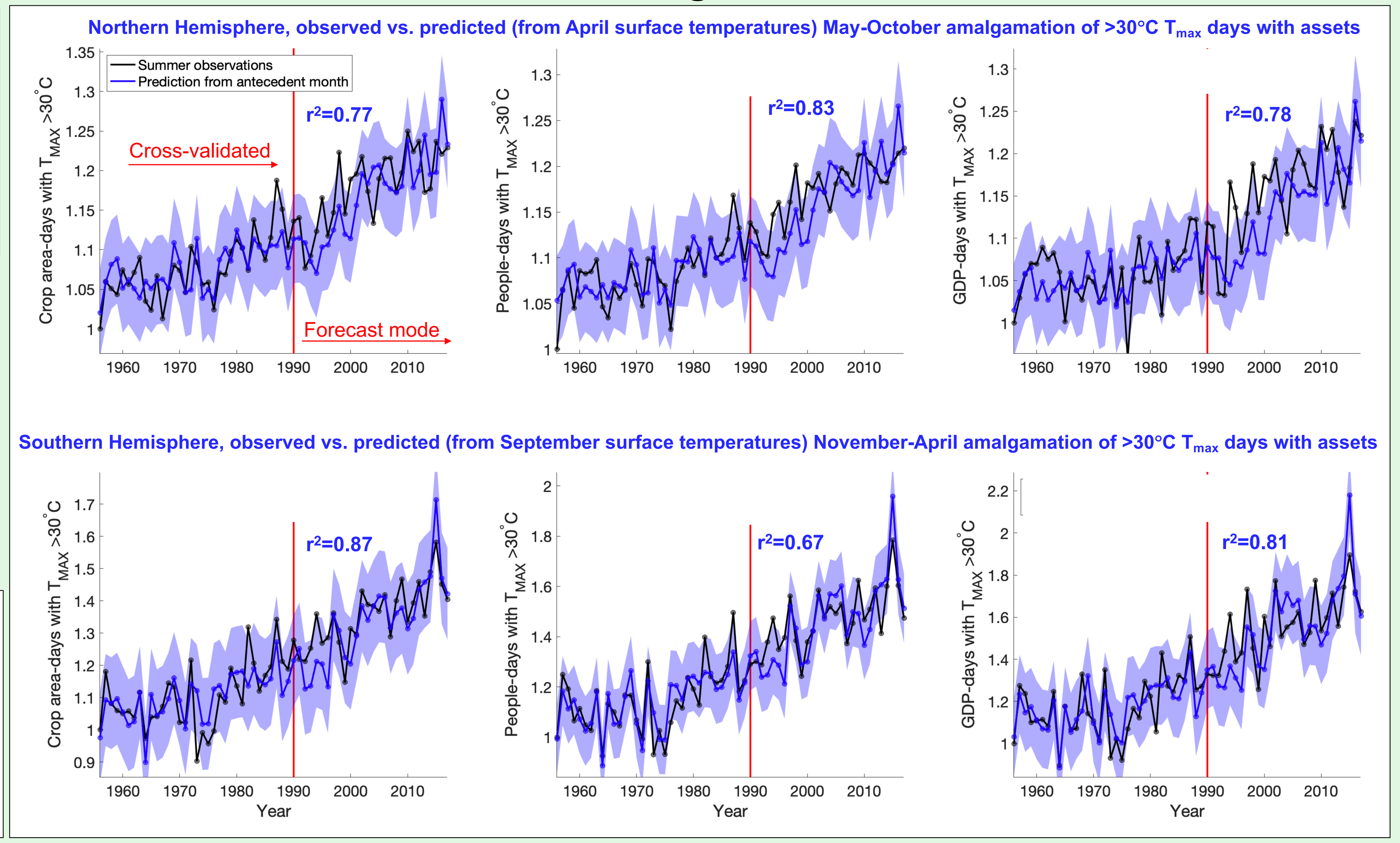
Local 1° × 1° warm-season hindcast skill (r)



- Hindcast skill for the anomalous number of days within a warm-season where T_{max} >30°C
  - Reasonable skill is exhibited at some local 1° × 1° land locations (maps, ↑↓)
  - Substantial skill is exhibited on the global-amalgamation of the exposure of assets to hot days (time series, ⟶)



Global amalgamation hindcasts



Modes of variability used for predicting subsequent frequency of T_{max} days > 30°C

- Out-of-sample hindcasts suggest predictive skill that originates from the antecedent state of global warming as well as from internal modes of variability
  - El Niño-Southern Oscillation (ENSO)
  - Interdecadal Pacific Oscillation (IPO)
  - North Atlantic Oscillation (NAO)