

# Climate and Weather Data

STEG Virtual Course on “Data in Macro Development”

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University of Virginia and CEPR

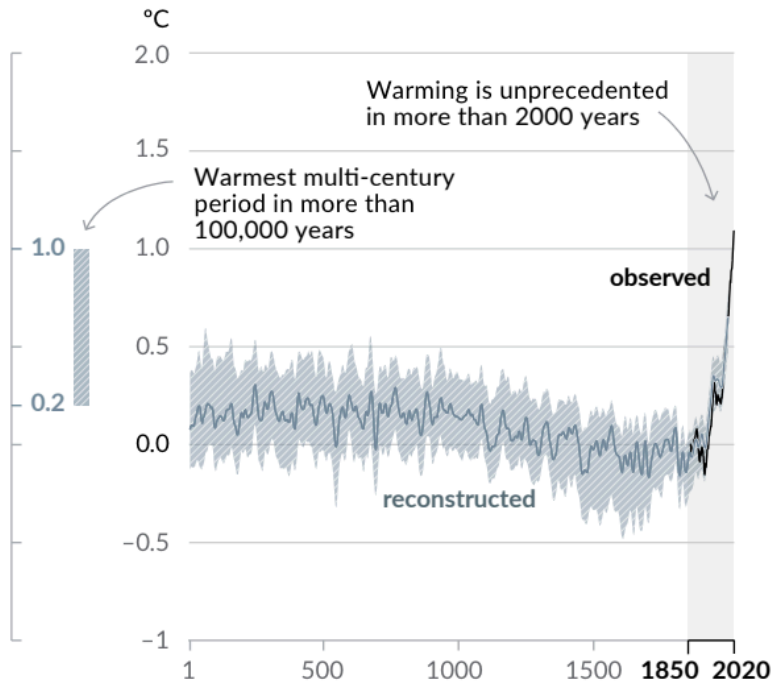
May 31<sup>st</sup>, 2024



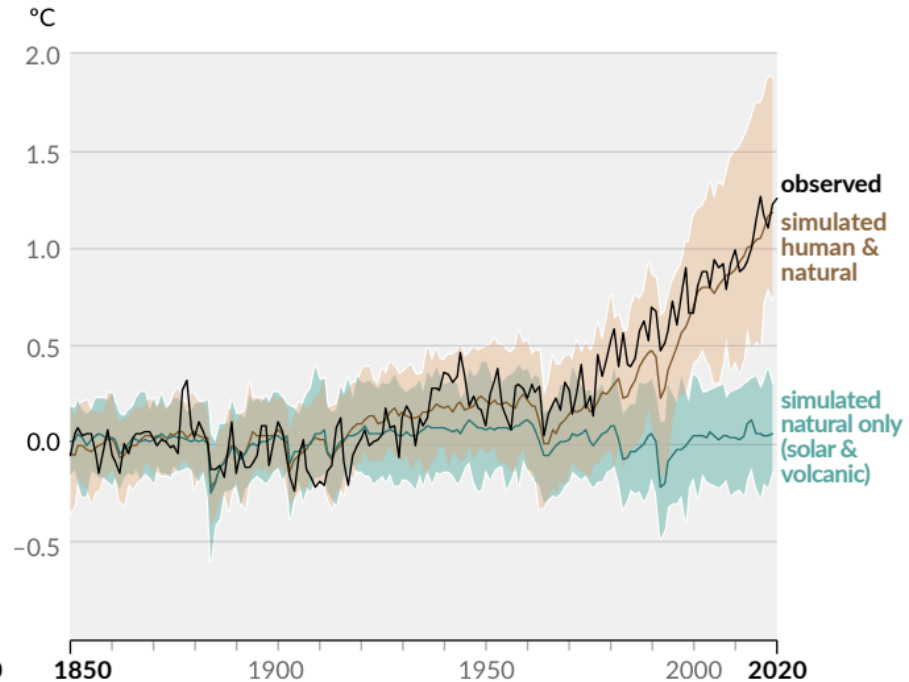
# Human influence has warmed the climate at an unprecedented rate.

## Changes in global surface temperature relative to 1850–1900

(a) Change in global surface temperature (decadal average) as **reconstructed** (1–2000) and **observed** (1850–2020)



(b) Change in global surface temperature (annual average) as **observed** and simulated using **human & natural** and **only natural** factors (both 1850–2020)





# A Global Challenge that is Experienced Locally



↑ Extreme Heat



↑ Intense Rainfall



↑ Wildfires



↑ Droughts



↑ Intense Storms



↑ Relative Sea Level Rise

# The Challenge

## Global greenhouse gas emissions and warming scenarios



- Each pathway comes with uncertainty, marked by the shading from low to high emissions under each scenario.
- Warming refers to the expected global temperature rise by 2100, relative to pre-industrial temperatures.

Annual global greenhouse gas emissions  
in gigatonnes of carbon dioxide-equivalents

150 Gt

100 Gt

50 Gt

0

Greenhouse gas emissions  
up to the present

1990 2000 2010 2020 2030 2040 2050 2060 2070 2080 2090 2100

**No climate policies**

4.1 – 4.8 °C

→ expected emissions in a baseline scenario if countries had not implemented climate reduction policies.

**Current policies**

2.7 – 3.1 °C

→ emissions with current climate policies in place result in warming of 2.7 to 3.1°C by 2100.

**Pledges & targets (2.4 °C)**

→ emissions if all countries delivered on reduction pledges result in warming of 2.4°C by 2100.

**2°C pathways**

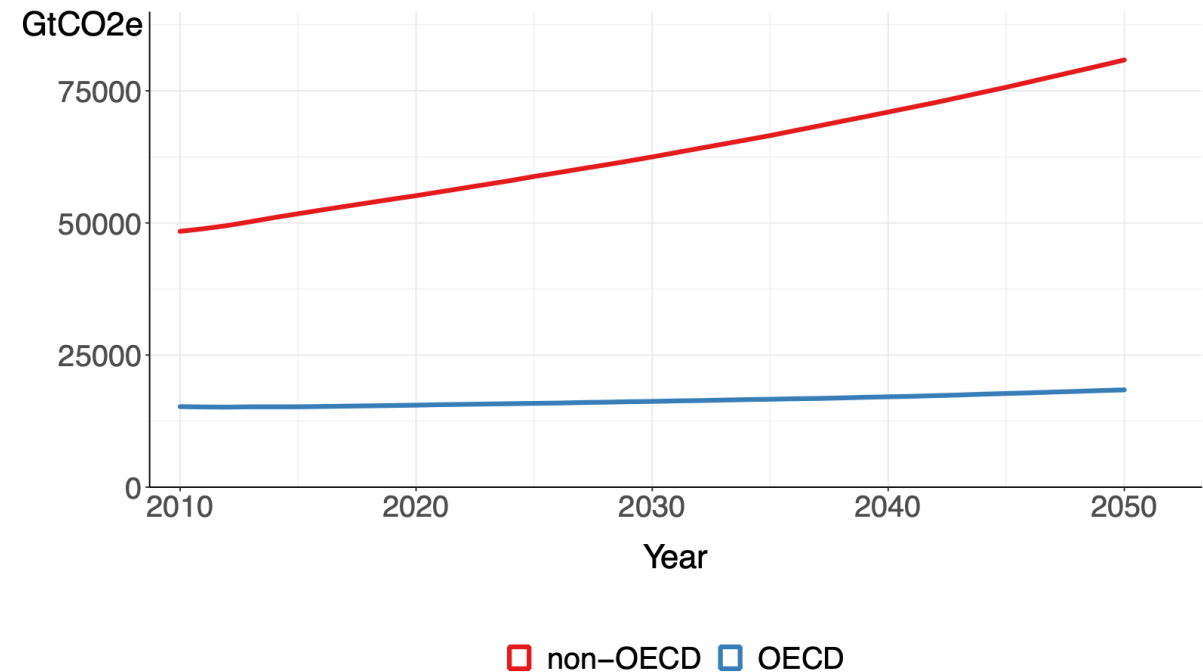
**1.5°C pathways**



# A Changing Composition

- Developed economies got us into this mess.
- LMICs:
  - currently generate 2/3 of emissions
  - account for almost all emissions growth
  - are rightly focused on alleviating poverty and increasing relative living standards.
- Emissions will continue to increase unless decoupled from growth.
- **Fundamental Question:** How do we balance growth and the externalities from growth?

GHG Emissions by regions: Baseline Scenario 2010–2050



# Decarbonization and Growth

- Low-carbon “frontier” growth opportunities largely will come from developed economies — a “new industrial revolution”. (Acemoglu et al., 2012; Aghion et al., 2016; Van Reenen et al. 2020; Stern and Valero, 2021)
- No guarantees (Besley and Persson, 2023).
- To what degree will LMICs “catch up”?
  - We need to understand constraints to financing, adoption, transfer, and integration.
  - It doesn’t matter where emissions reductions occur (Glennerster and Jayachandran, 2024)

# How will climate change affect growth and development?

$$Y_{it} = A_{it}F(L_{it}, K_{it})$$

- Clear channels through which climate change could affect labor, capital, and efficiency.
- More scope for growth effects in LMICs.
- Less scope (imo) for growth effects in developed economies.
- Understanding opportunities for adaptation is critical, but not free.



# What Do We Know?

## BREAD-IGC Virtual PhD Course on Environmental Economics, September/November 2023

Past Webinar • Online • From 14 Sep 2023 at 16:00 to 16 Nov 2023 at 17:30 • Sustainable Growth, Energy and Climate change

### Economic impact of climate change Renewables

9 Nov 2023 at 16:00



**Michael Greenstone**

Milton Friedman Professor of Economics, University of Chicago

### Sea level rise

16 Nov 2023 at 16:00



**Clare Balboni**

Assistant Professor, London School of Economics and Political Science

### Climate adaptation

28 Sep 2023 at 16:00



**Esther Duflo**

Abdul Latif Jameel Professor of Poverty Alleviation and Development Economics, Massachusetts Institute of Technology



**Allan Hsiao**

Assistant Professor, Economics and Public Affairs, Princeton University

5 Oct 2023 at 16:00



**John Van Reenen**

Ronald Coase School Professor, London School of Economics and Political Science

### Climate migration

19 Oct 2023 at 16:00



**Gharad Bryan**

Associate Professor, London School of Economics and Political Science (LSE)



**Melanie Morten**

Assistant Professor, Stanford University

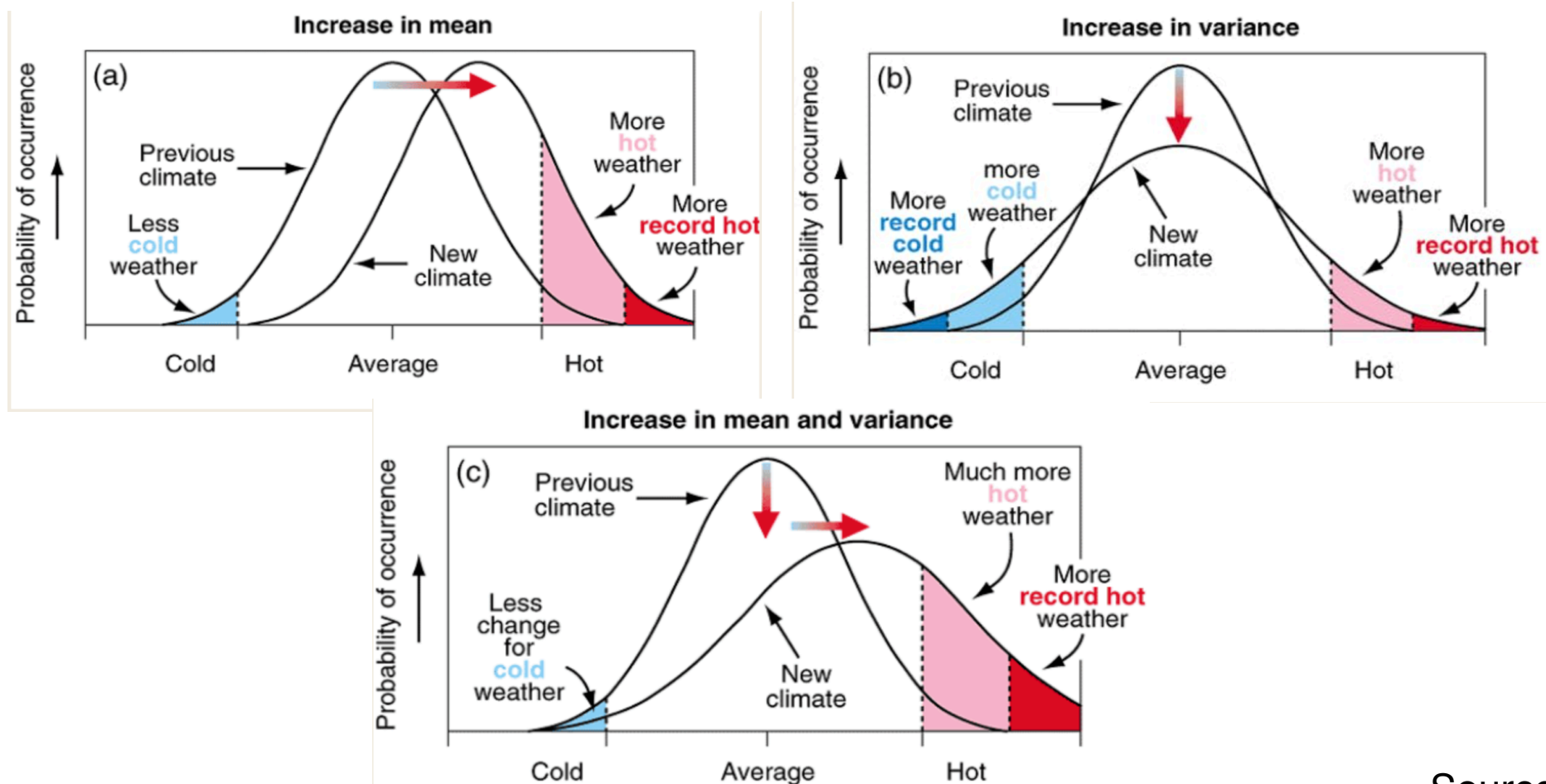


**Mar Reguant**

Professor of Economics, Northwestern University

# Weather vs. Climate

“Climate is what you expect, weather is what you get.”— Mark Twain



# A Brief History of Meteorology

- **650 BC** The Babylonians tried to predict short-term weather changes based on the appearance of clouds and optical phenomena
- By **300BC** Chinese astronomers had developed a calendar dividing the year into 24 festivals (each associated with a different type of weather).
- In **340BC** Aristotle wrote *Meteorologica*, which provided various theories about the formation of weather. Many of these theories were erroneous, but it took until the 17th century to realize this.
- (**16th-19th Ce**) Many advances in our understanding with the invention of the thermometer, hygrometer, and barometer, etc.
- Modern advances in computation and satellites has led to an explosion of data and massive improvements in weather forecasting accuracy.
- **Core motivations:** Agriculture, navigation, military operations, public health, scientific curiosity.



# Development Economists Have Been Talking about the Weather for a Long Time

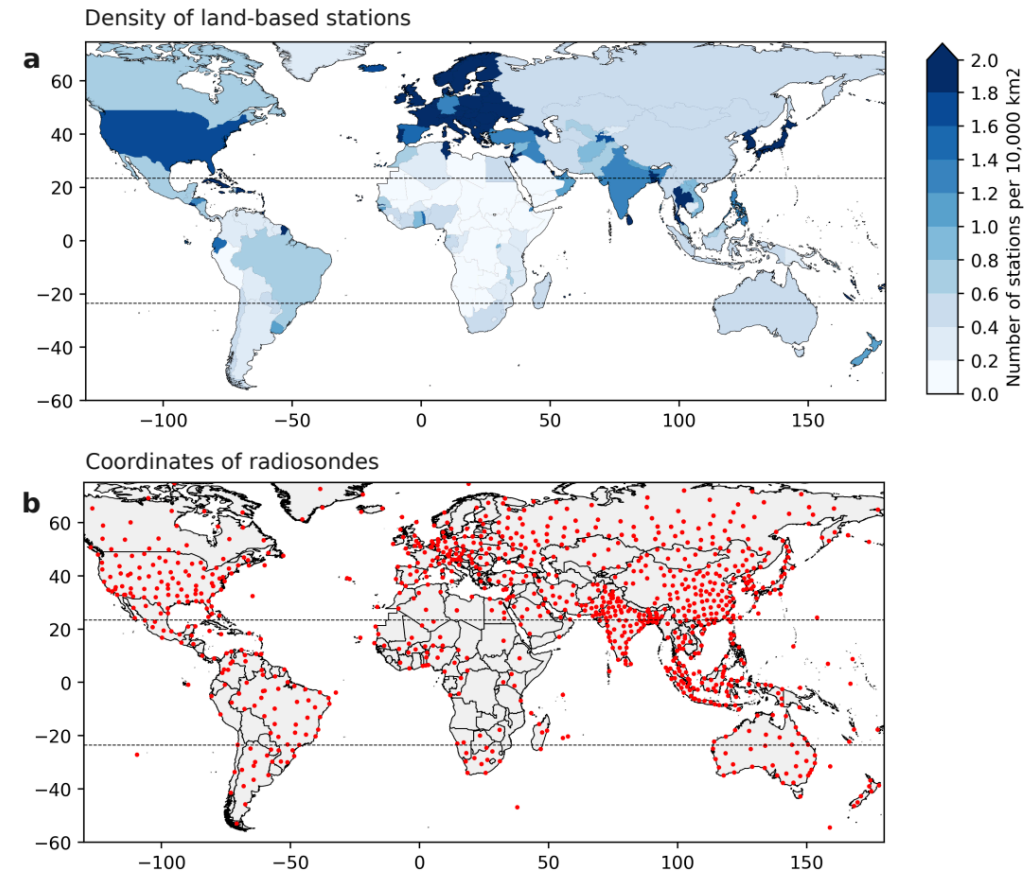
- Unpredictable weather is a dominant risk for those living in rural parts of developing countries.
- Key questions:
  - How do individuals manage risk?
  - How are expectations formed?
  - What are the barriers to mitigating risk?
  - How does the economic and policy environment help/hinder?
  - What are the aggregate consequences of risk?

# An Exciting Time for Macro-Development

- Many of the remaining important questions are macro.
  - How do we aggregate micro-estimates?
  - What about general equilibrium effects?
  - Short-run vs. long-run elasticities?
  - How are expectations about climate change formed?
- Much of the existing literature is “model free”.
- We need more structure to answer these questions.
- Important to match historical aggregate patterns and trends.
- Opportunities for micro-to-macro ([Donovan 2021](#); [Buera et al., 2023](#))
- Learning about the transition path is more useful at this point.

# Weather Station Data

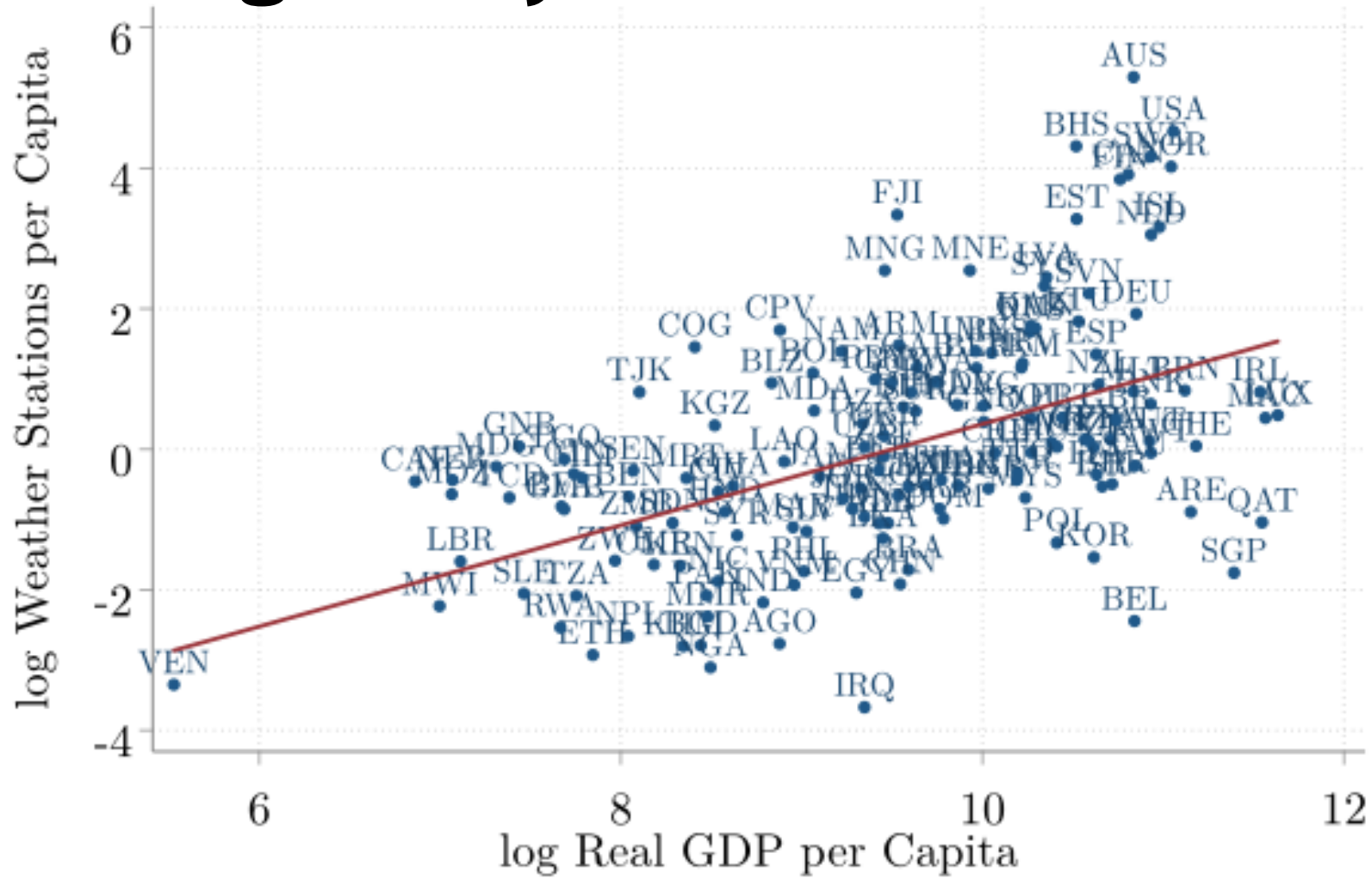
- Access to weather data is not equal.
  - Variation in distribution of stations, quality of data, and accessibility across and within countries.
  - There is an urban bias
  - Some countries have good historical data, but it's not accessible outside of national meteorological agencies.
  - Conflict results in large gaps in the record, e.g., the Rwandan genocide resulted in the loss of 15 years of data.



Source: Shrader and Linsenmeier (2023)

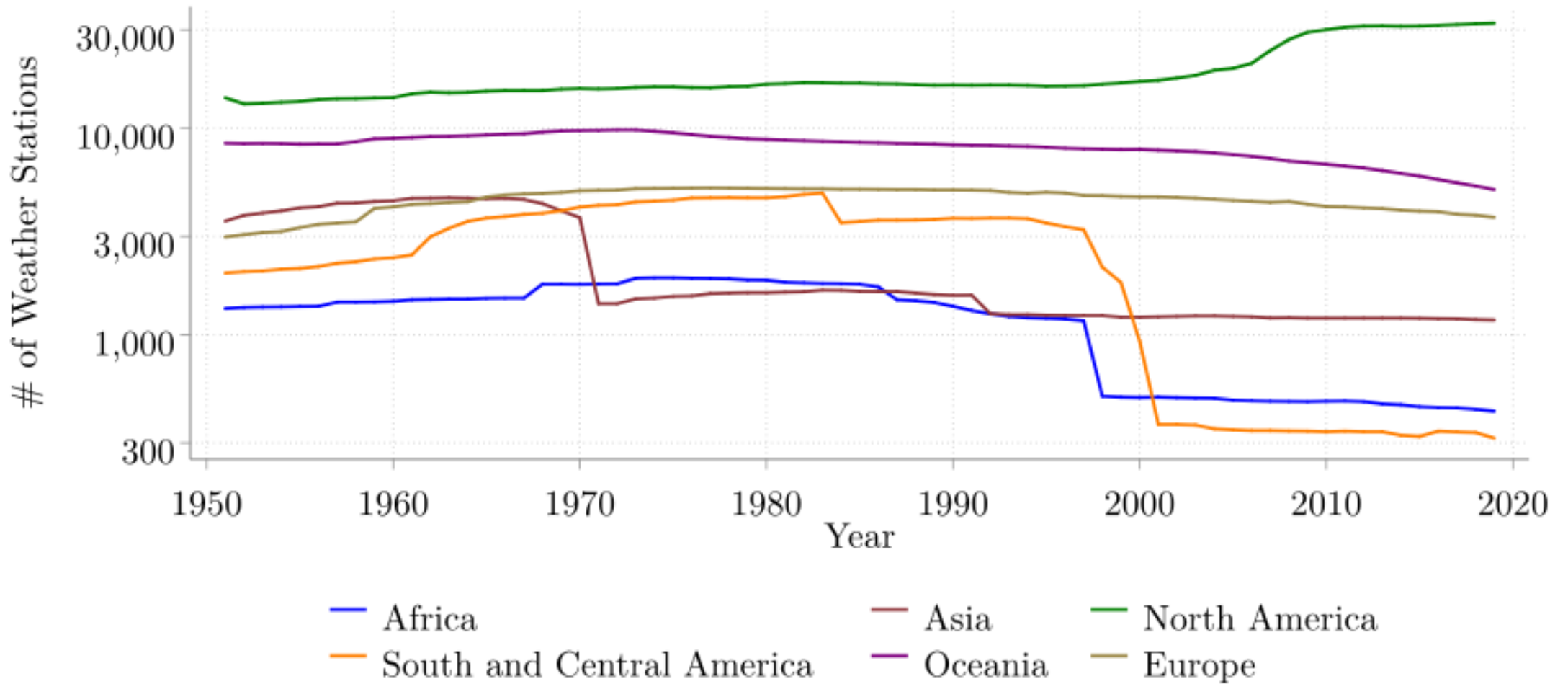


# Endogeneity across Countries



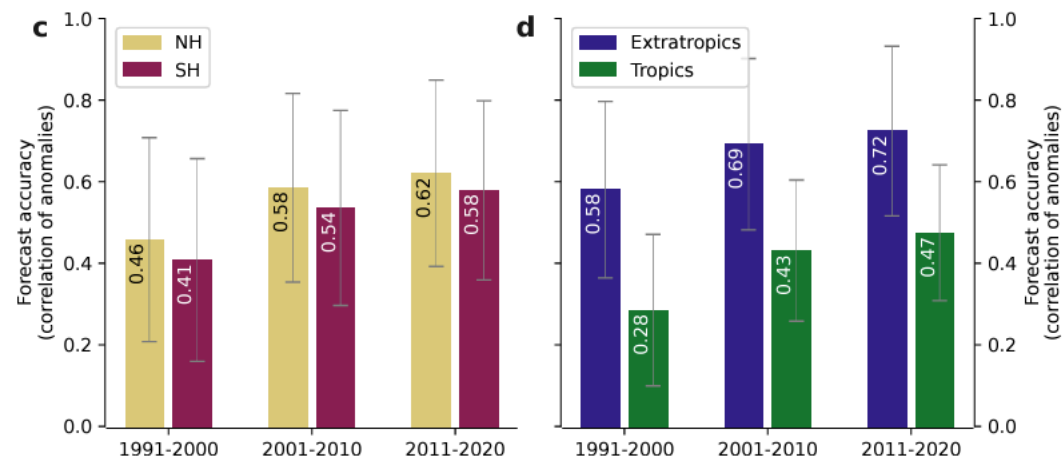
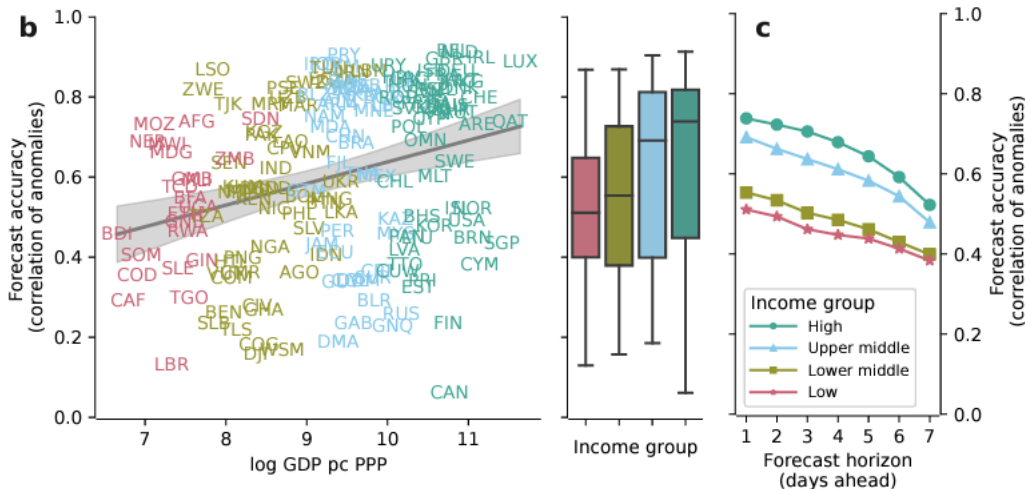
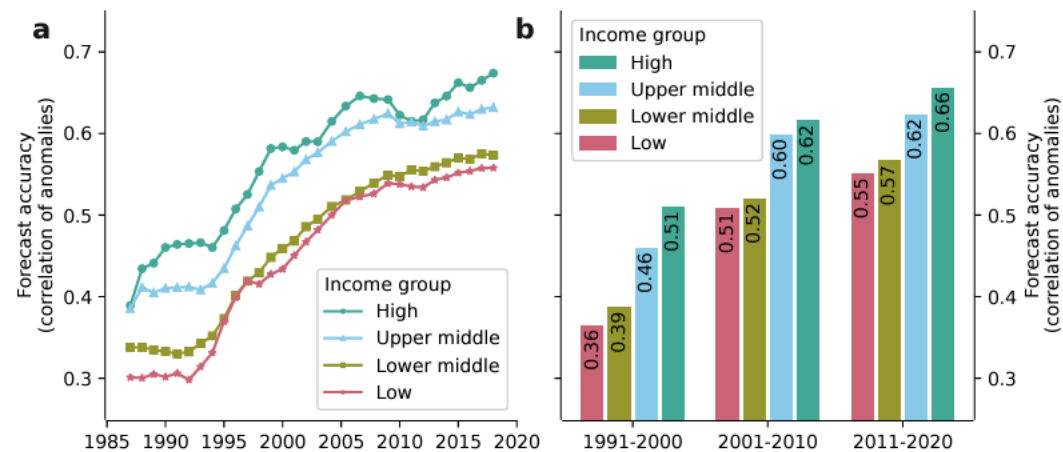
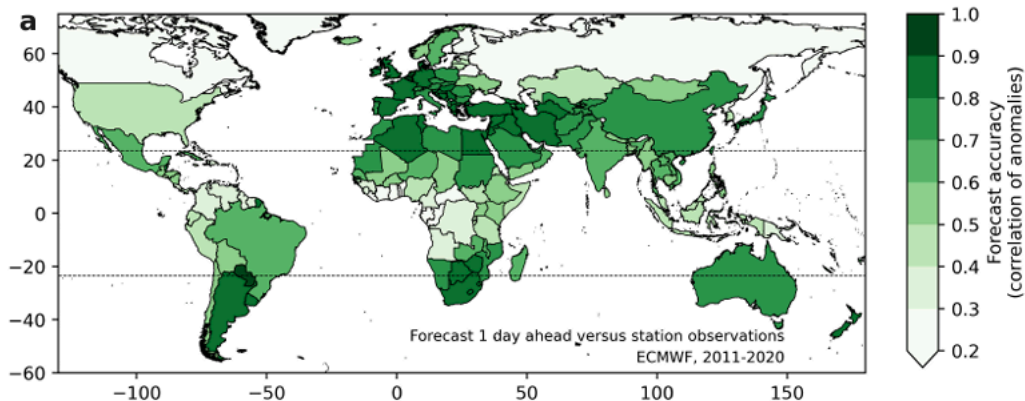
Source: Own calculations using GCHN and PWT data

# Endogeneity over Time



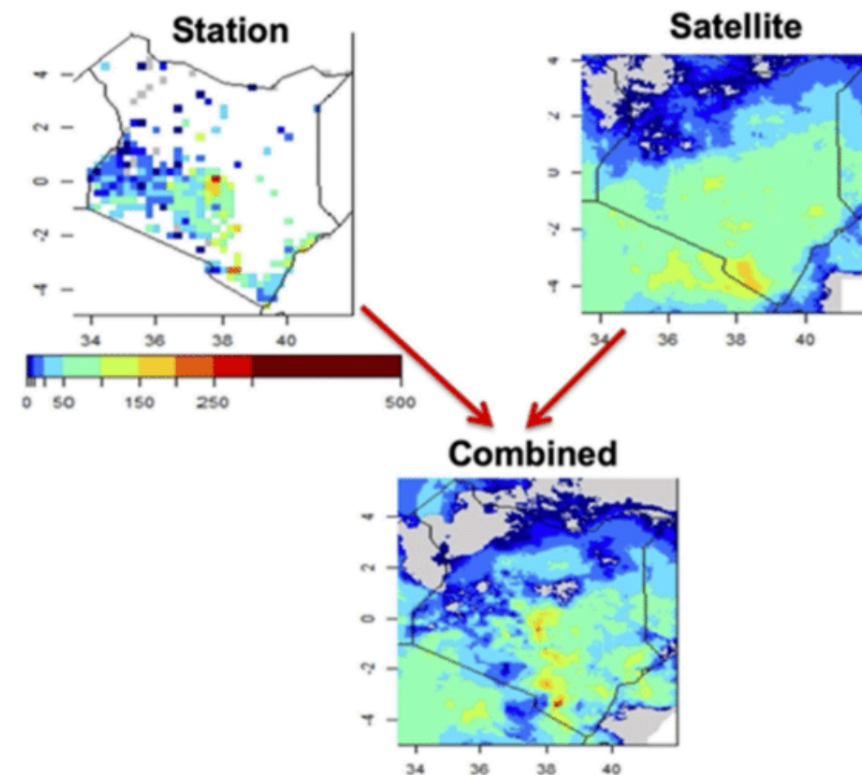
Source: Own calculations using GCHN and PWT data

# Weather Forecasting Accuracy



# Satellite Data

- Satellite data alleviates the issues with observational stations.
- However, measurements are largely based on radiance.
- Radiance  $\neq$  Precipitation or Temperature.
- Lots of assumptions (but physical ones).
- Be careful aware of prediction error/model uncertainty (Proctor, Carleton and Sum, 2023)
- Best practice = combination of satellite and in-situ observations



Source: Dinku et al., (2022)

# Reanalysis Data

- Reanalysis data combines in-situ observations, satellite data, and climate models.
  - Provides a consistent best-estimate of weather realizations over time and space.
  - Available for every hour at multiple atmospheric levels.
- Reanalysis fills in the missing jigsaw pieces using structural models based on the laws of physics.
- Limitations are well understood; biases are well known (although identified relative to in-situ observations).
- More physically reasonable for places with low station density, but potentially less accurate in places with in-situ measurements.



Source: Copernicus ECMWF

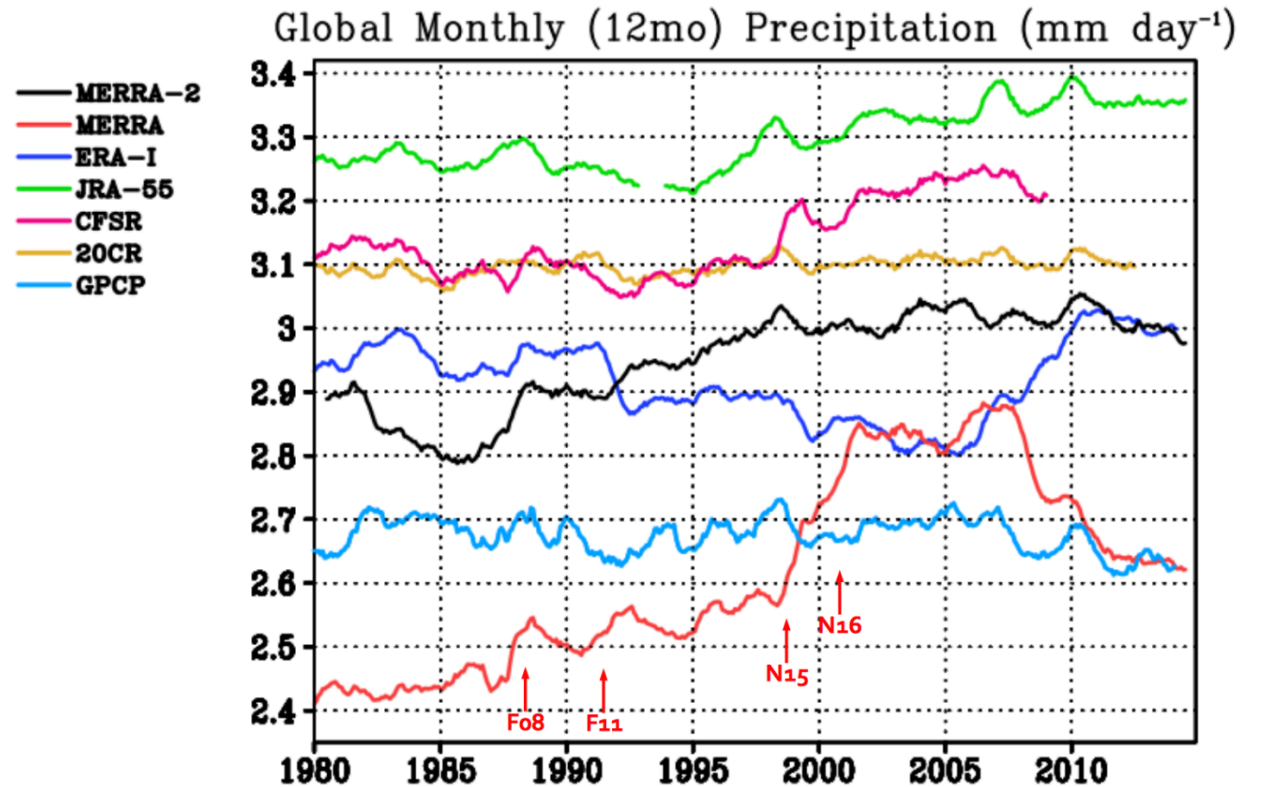
# Working with Weather and Climate Data

- There is no universally correct weather or climate data product.
- [Auffhammer et al. \(2013\)](#) provides an excellent discussion of the trade-offs.
- More often than not, you will work with gridded data:
  - Interpolated datasets (UDEL, BEST, PRISM) vs. reanalysis data (ERA5)
  - Interpolated data is simple and works best in places with good station density.
- Research what data products are most appropriate for your region and question of interest.
  - Right variables? Suitable resolution? Are biases reasonable for variables and region of interest?



# Hydrological Variables vs. Temperature

- Precipitation:
  - Highly heterogeneous over time and space
  - Very difficult to measure accurately.
- Temperature:
  - Relatively uniform over time and space
  - Can be interpolated with reasonable confidence.
- **Take-home:** There is way more uncertainty about hydrological variables.



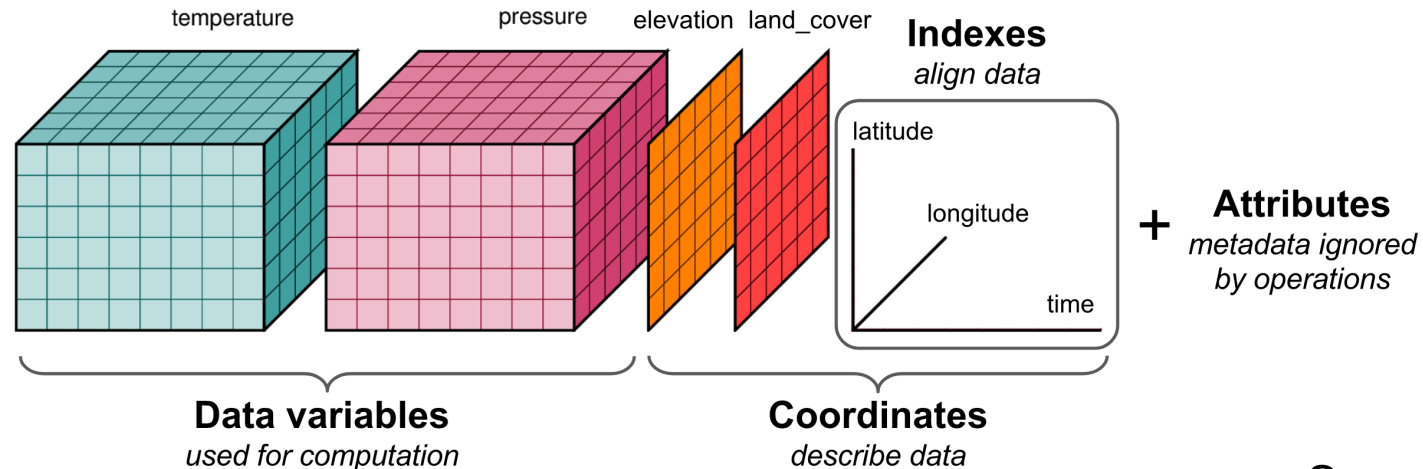
Data from [Bosilovich et al. \(2015\)](#). Gridded data products disagree on average global monthly precipitation by up to 40% and aren't always consistent!

# Processing Weather and Climate Data

- There are usually three types of input you'll work with,
  1. **Climatic data:** gridded data providing information on temperature, precipitation, vectors of wind speed, surface pressure, etc.
  2. **Shapefiles:** polygons of the administrative boundaries of interest, e.g., country, state, districts, counties, etc.
  3. **Secondary Weights:** gridded data on population, land use, etc.

# Multidimensional Data

- Climatic data is often stored as multidimensional arrays and saved as **NetCDF** files.
  - NetCDF files are “self-describing”.
  - Metadata provides detailed information about the data’s structure and content.
  - Data are indexed by latitude, longitude, atmospheric level, and time.
  - Variables are then assigned to these dimensions, e.g., for a given elevation, hourly temperature is stacked at each latitude and longitude over time.



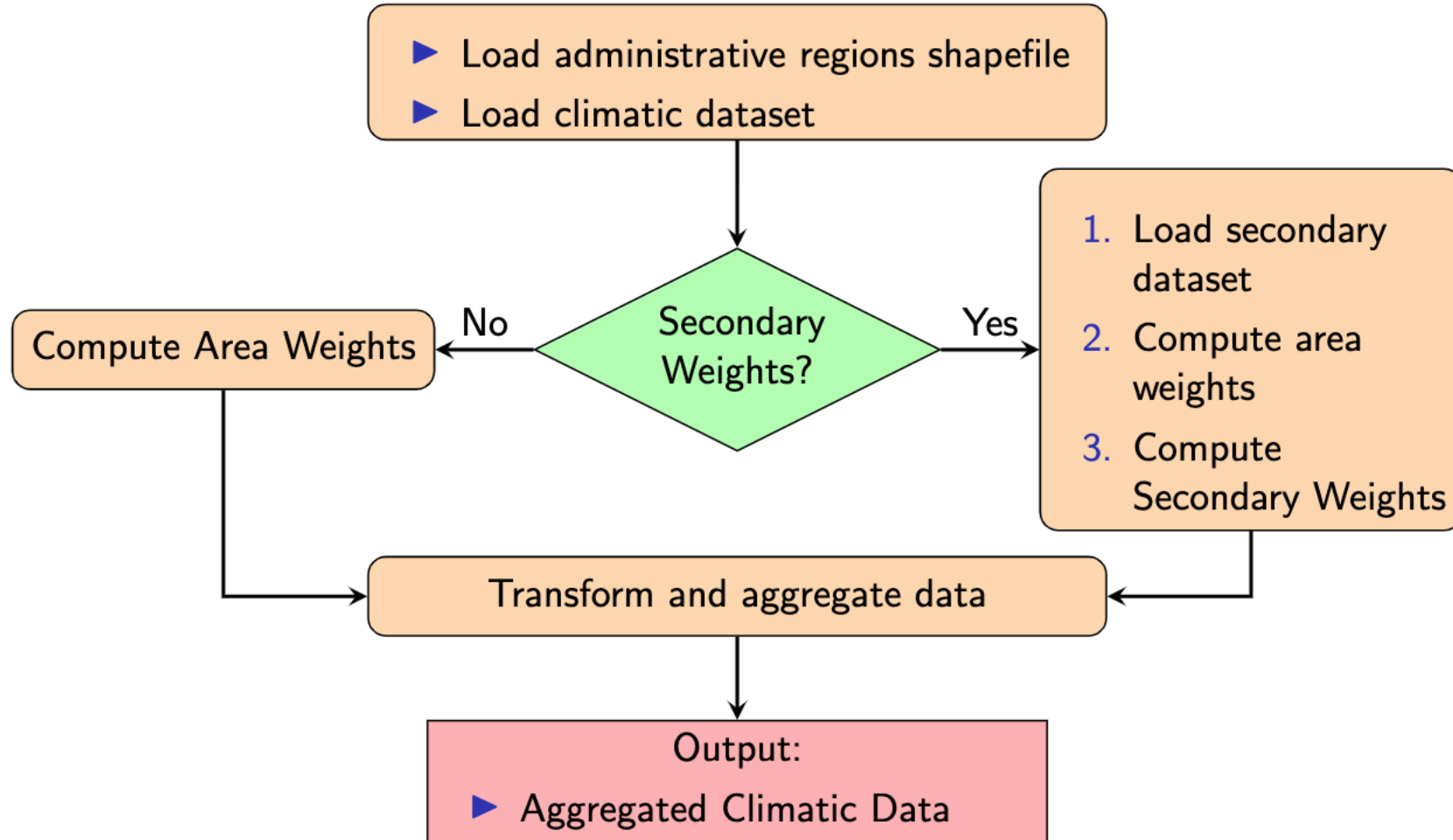
# The Choice Set

- For any given research project, you need to decide:
  - What type of weather and climate you want to work with.
  - What temporal scale are you working at (daily, monthly, annual, multi-year).
    - Often constrained by economic data.
  - What region and level of spatial aggregation you are studying
  - Whether you are going to use spatial weights (if aggregating)
  - Whether you are going to aggregate-before-transforming the data or transform-before-aggregating
    - Often, you'll want to "transform-before-aggregating"

# A New Tool: AggFly

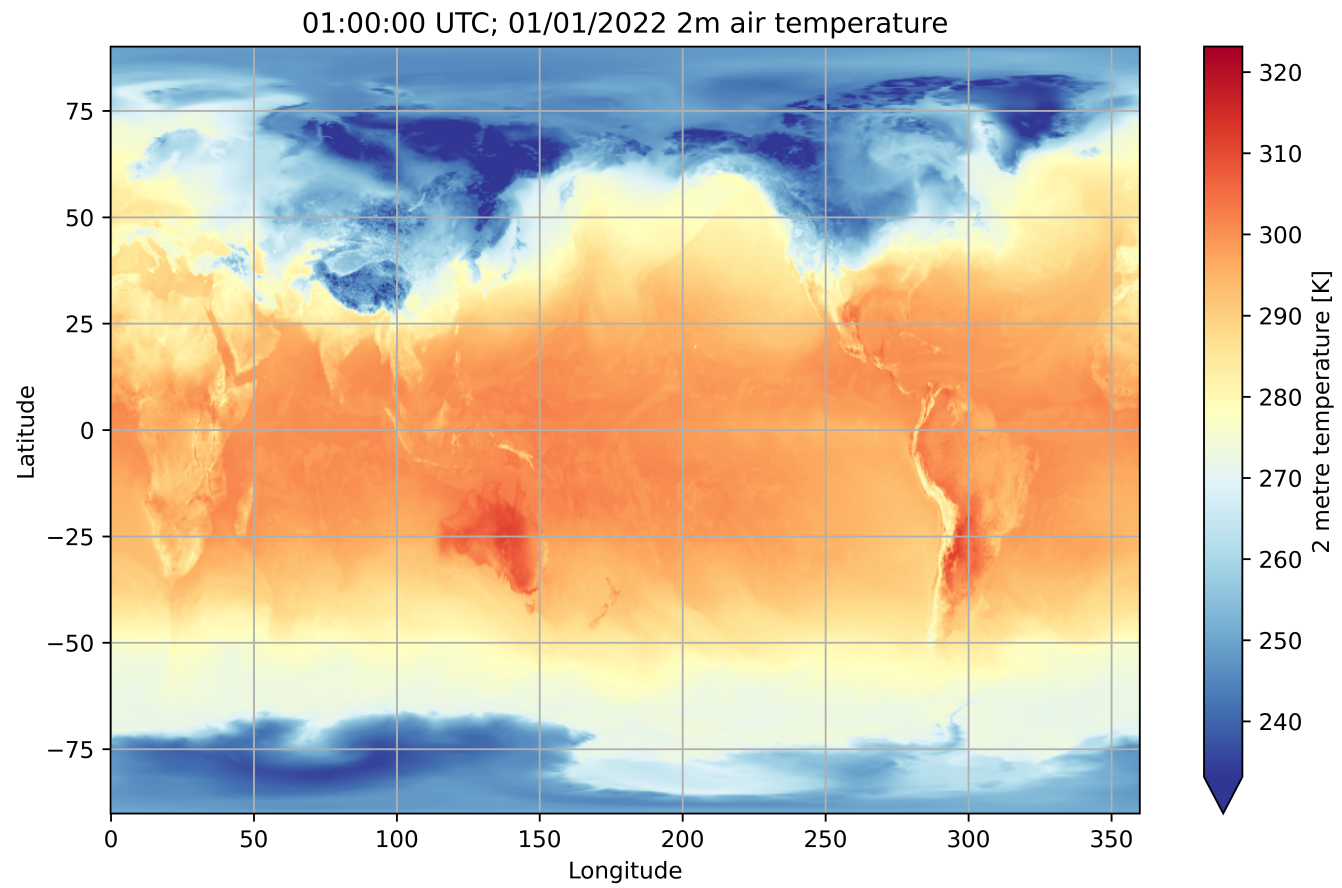
- A new python package designed by the amazing Dylan Hogan (Columbia University, PhD *forthcoming*)
  - Aggregates climatic data over different spatial and temporal scales.
  - Efficiently automates computational and memory-intensive geospatial operations (a common barrier to entry).
  - Allows for secondary weights.
  - Constructs a wide variety of different functional forms (helpful if transforming-before-aggregating)
  - Kicks out “ready-to-use” aggregated climatic data.
  - Documentation and examples coming out soon.
- Tamma Carleton (UCSB) has put together a similar package in R (`stagg`)

# Workflow

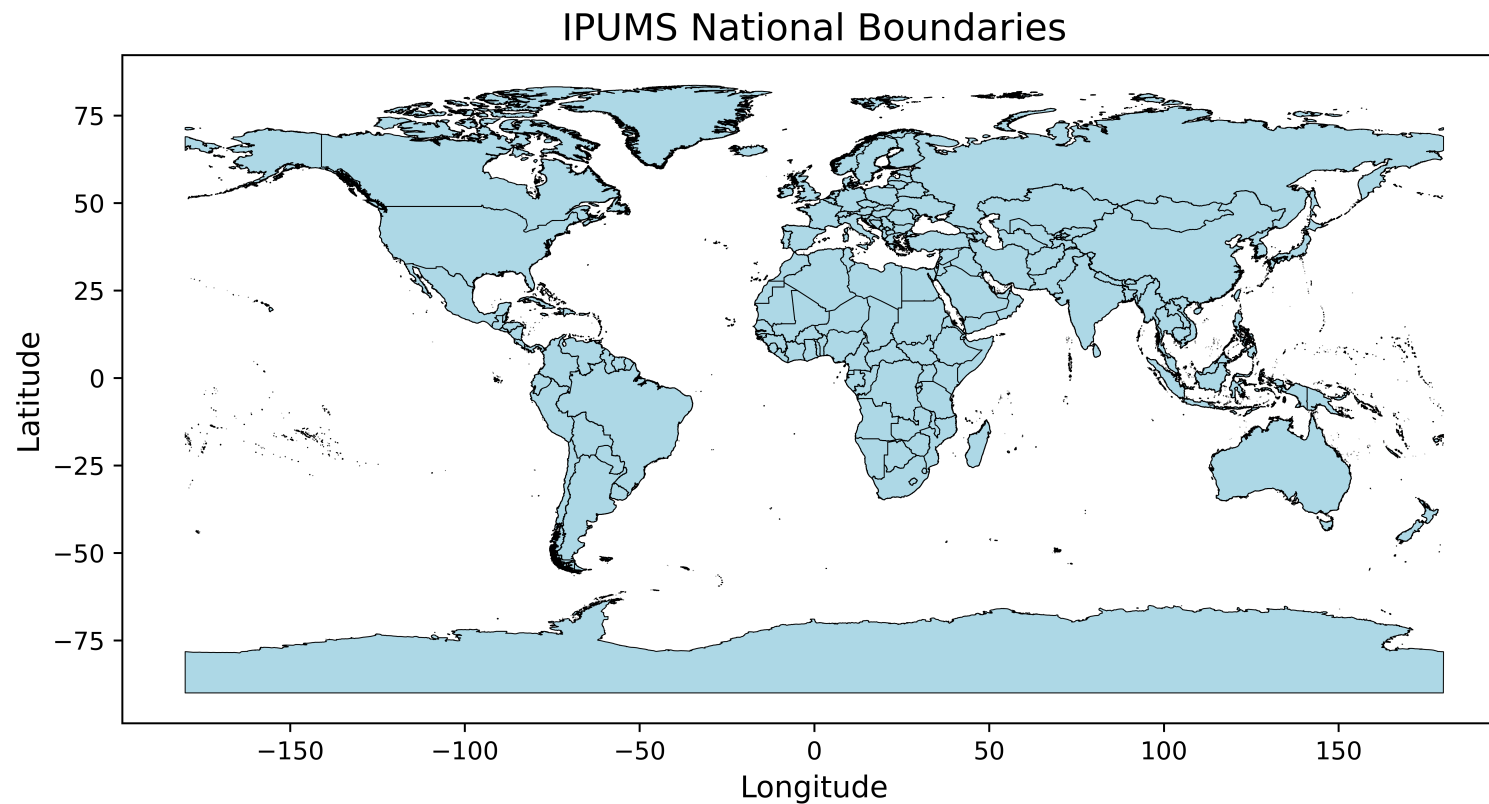




# Gridded Weather data

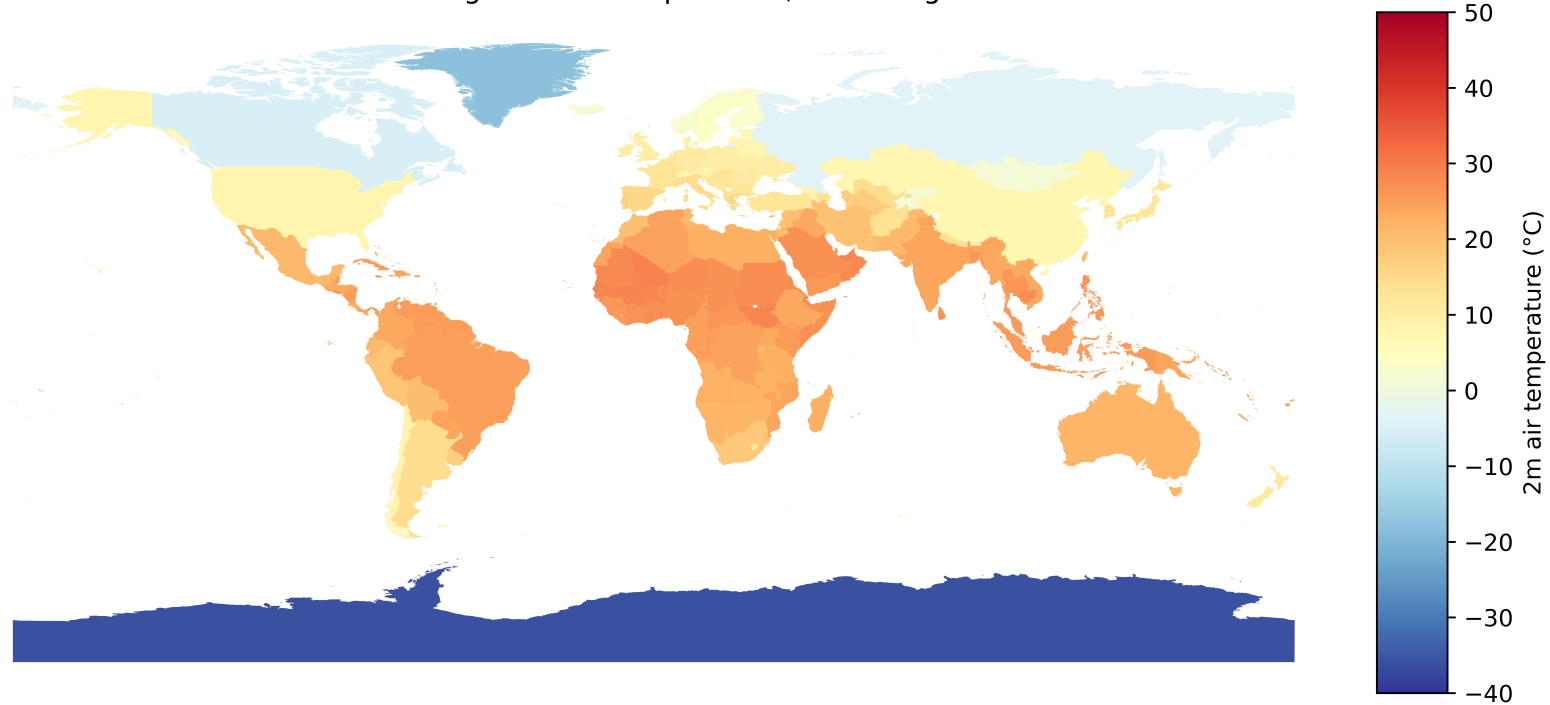


# + Administrative Boundary Shapefiles



# = Area-Weighted Weather Data

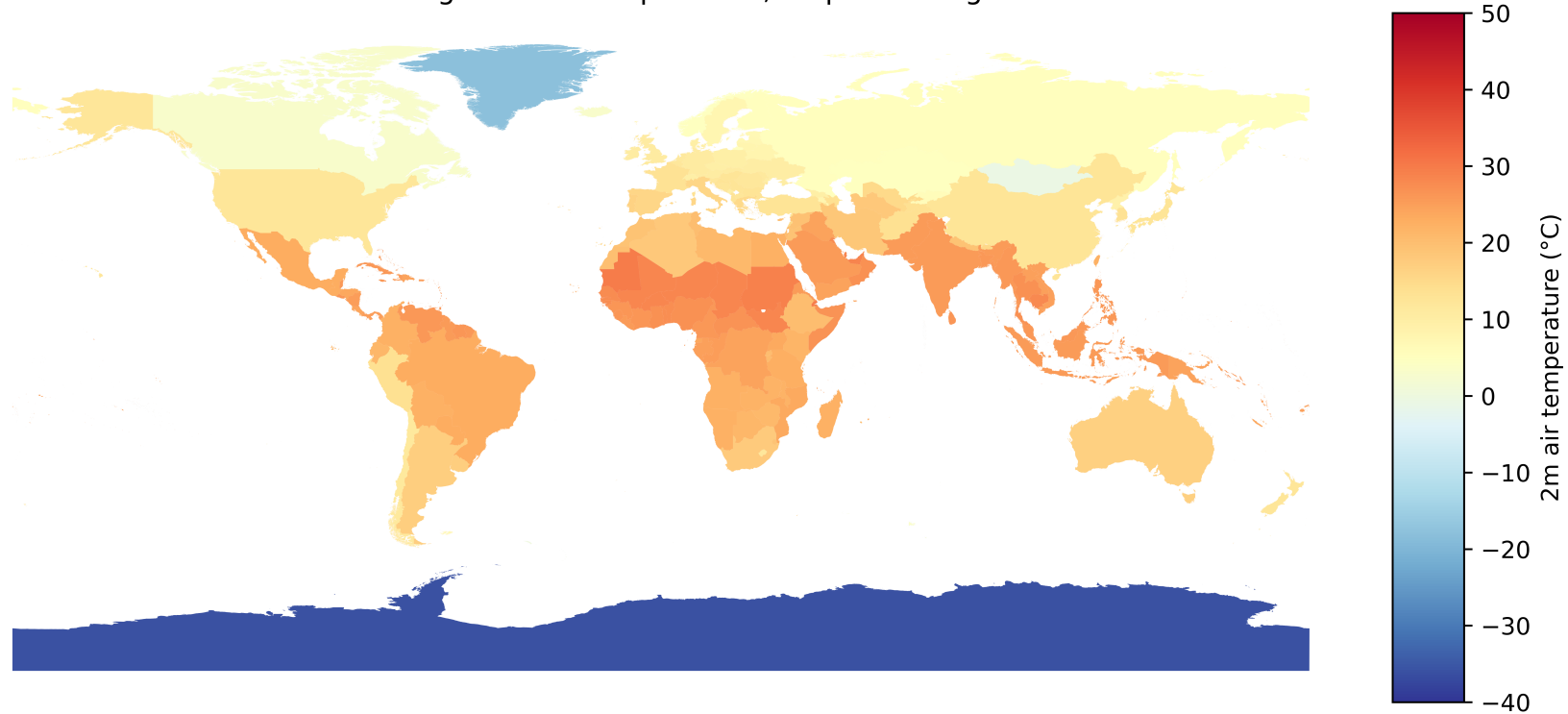
2022 Average 2m air temperature, area weighted



Data: ERA5 from the Copernicus Climate Data Store

# = Crop Area-Weighted Weather Data

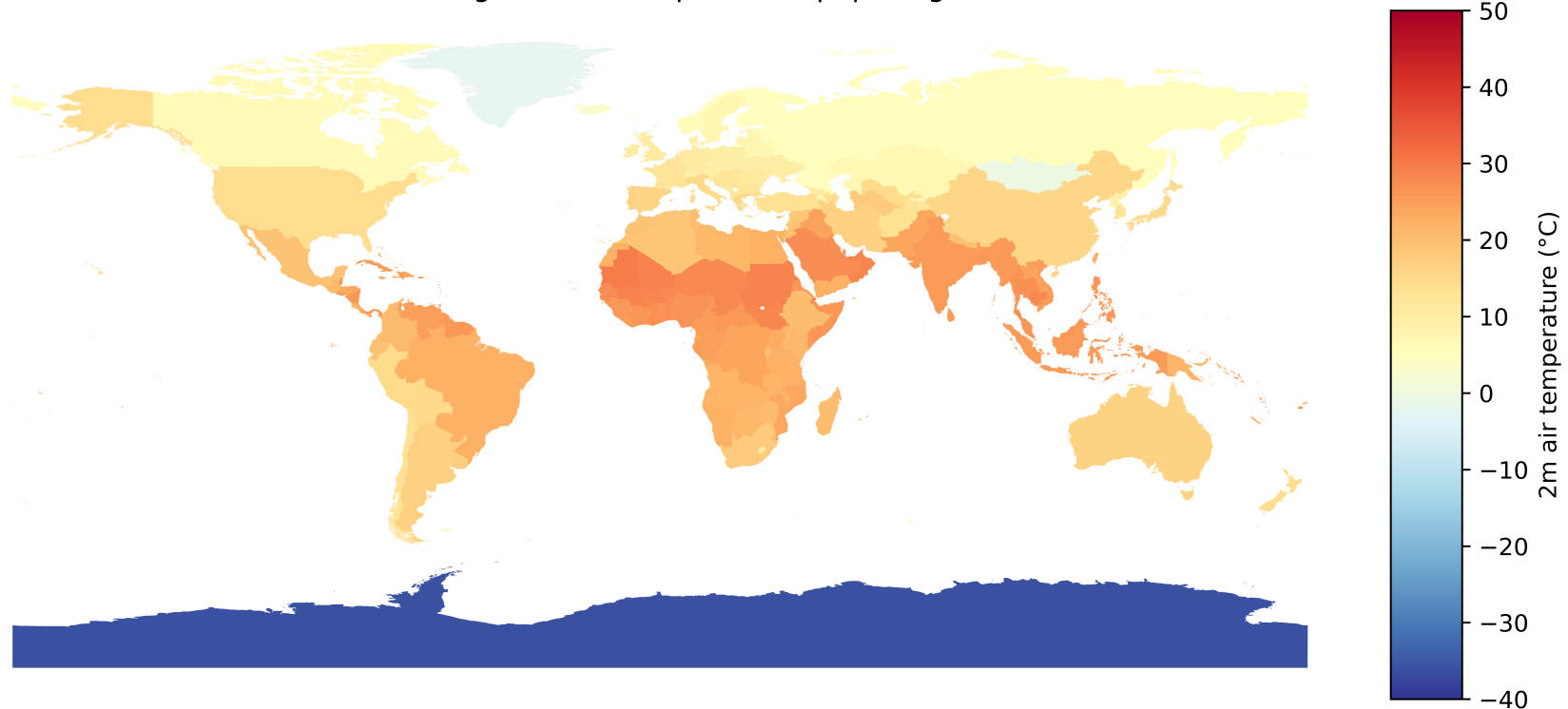
2022 Average 2m air temperature, croparea weighted



Data: ERA5 from the Copernicus Climate Data Store

# = Population-Weighted Weather Data

2022 Average 2m air temperature, pop weighted



Data: ERA5 from the Copernicus Climate Data Store

# Weights

- Area weights:
  - `AggFly` uses area weights as standard.
  - Accounts for differences in the sizes of grid cells and intersecting boundaries (partial coverage).
- Secondary weights:
  - Weights based on specific variables like population or crop coverage
  - Useful for studies focusing on health, or agricultural productivity, etc.
  - Population weights example: cells with higher population contribute more than the computation of average temperature.



# Current Output

- `AggFly` currently constructs aggregated climatic variables such as:
  - **Mean:** e.g. mean temperature over specified time period.
  - **Sum:** e.g. total precipitation over specified time period.
  - **Min:** e.g. minimum temperature over specified time period.
  - **Max:** e.g. maximum temperature over specified time period.
  - **Polynomials:** e.g. the sum of polynomials of daily temperature up to the  $n^{\text{th}}$  degree.
  - **Degree Days:** e.g. the sum of daily temperatures exceeding a base threshold.
  - **Bins:** e.g. the number of days that average temperature was in a given 3 degree Celsius interval in each year.

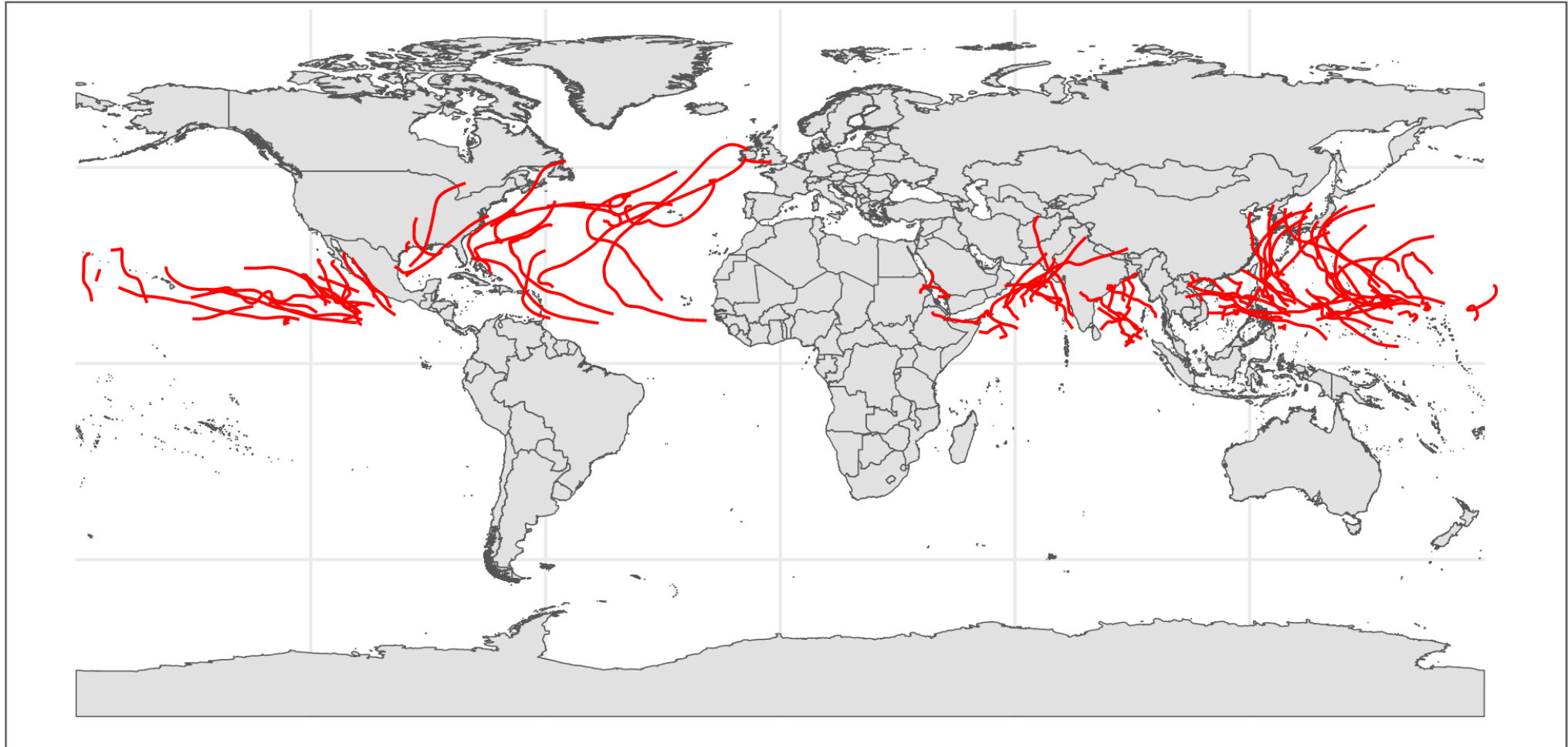
# Tropical Cyclones

- ~35% of the global population is affected by tropical cyclones (Hurricanes, tropical cyclones, typhoons) ([Hsiang and Jina, 2014](#)).
- Tropical cyclones: large storms that form over the oceans and cause physical damage and loss of life via intense winds, heavy rainfall, and ocean surges.
- It's important to construct physical indexes of disaster exposure.
  - Self-reported damages are endogenous (concerns about coverage, quality, and amount of damage itself, etc.)
  - There is lots of nice natural random variation to exploit in terms of formation, cyclone path, and intensity.

# Historical Tropical Cyclone Data

- NOAA's International Best Track Archive for Climate Stewardship (IBTrACS) database provides the most comprehensive collection of tropical storms globally.
- Provides information on path of the storms':
  - minimum central surface air pressure
  - maximum sustained wind speedsat 6 hour intervals.

# IBTrACS storm paths (2019)



# Wind Field Models

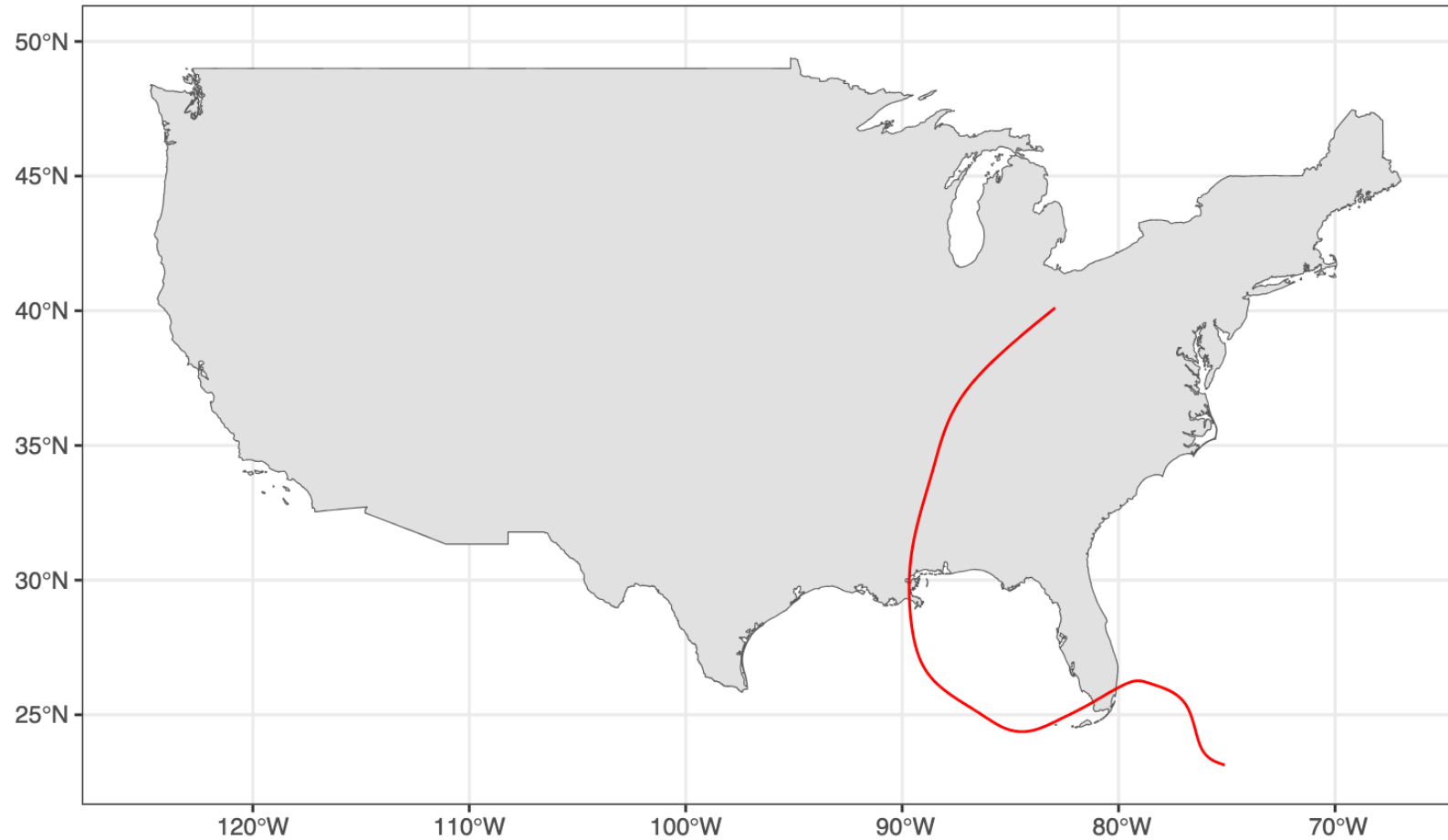
- Storm tracks aren't sufficient.
- Tropical cyclones can have meaningful effects hundreds of km away from the center of the storm.
- To account for this we need to combine information from storm tracks with a wind field model.
  - e.g. the `stormwindmodel` package in R.
- Provides estimates of maximum sustained windspeed relative to the hurricane center.

# The Willoughby Model

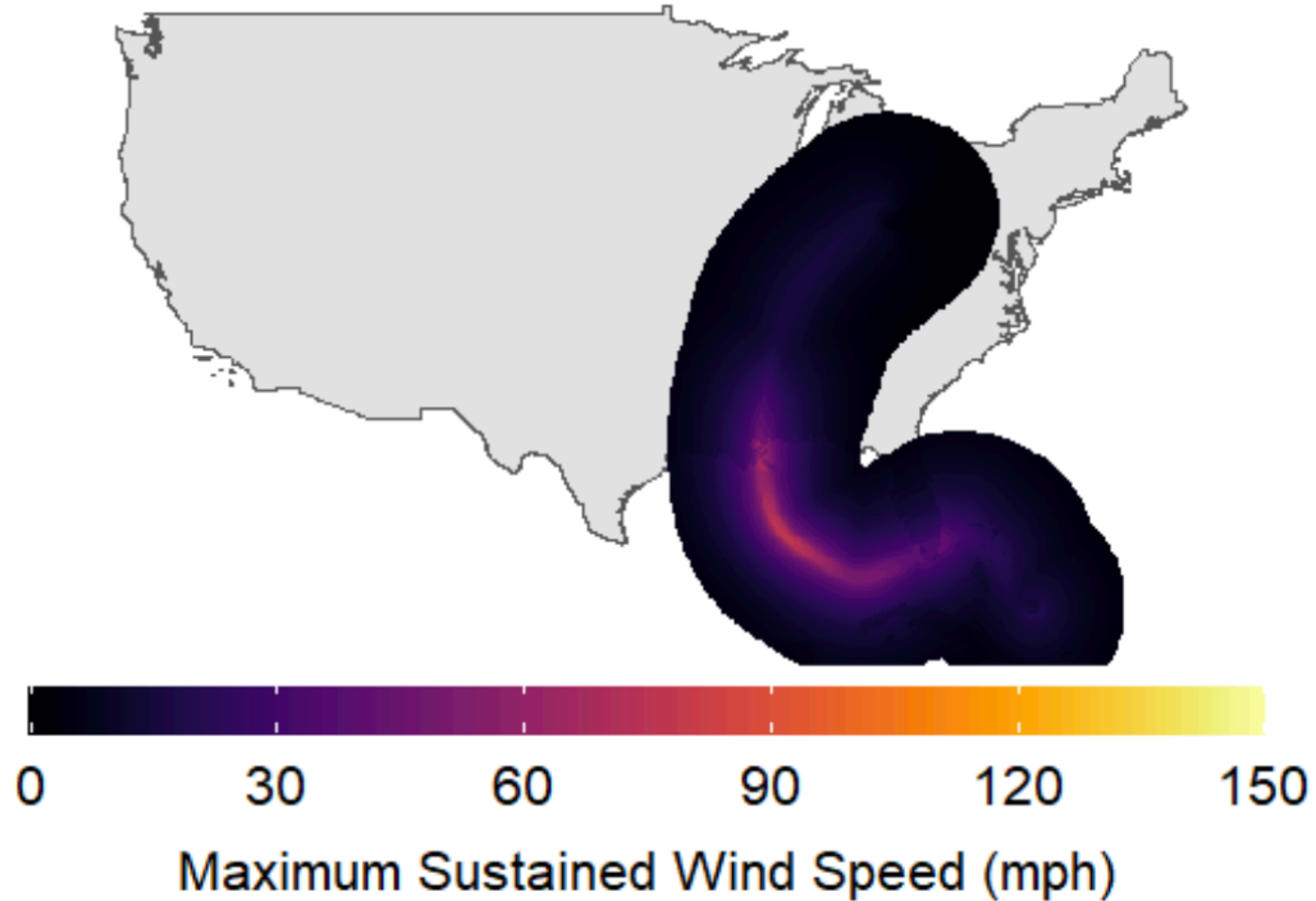
- A parametric model of radial and azimuthal wind profiles.
  - **Radial wind profile:** how does wind speed change as you move away from the center
  - **Azimuthal wind profile:** how does wind speed change as you move around, holding distance fixed (influenced by earth's rotation, storm motion, etc.)
- Provides a simplified yet accurate representation of the wind field in hurricanes.
- Key components:
  - Maximum windspeed.
  - Radius of maximum winds.
  - Shape parameters that constrain how quickly windspeed decay as you move away from the center.



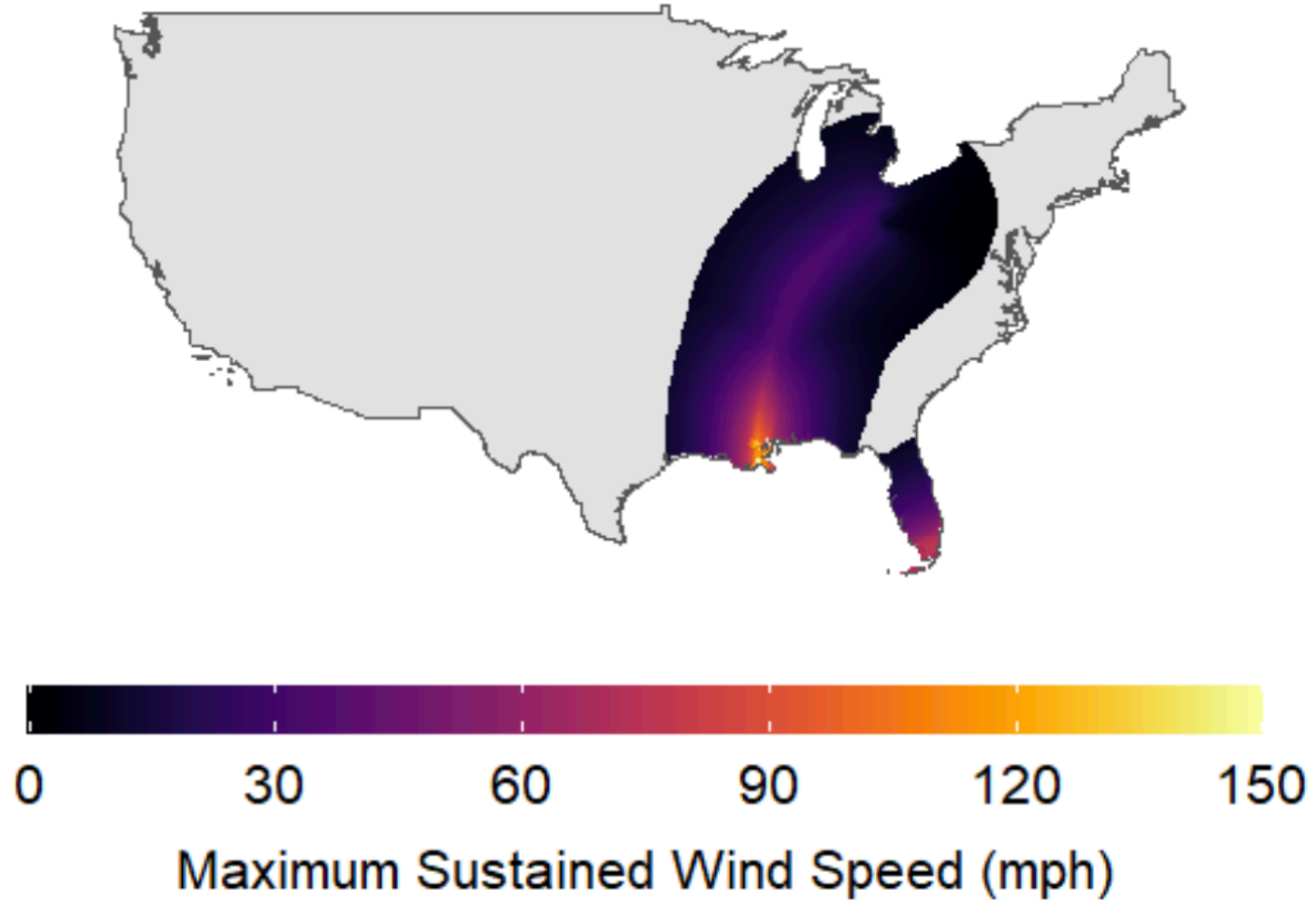
# Hurricane Katrina (2005)



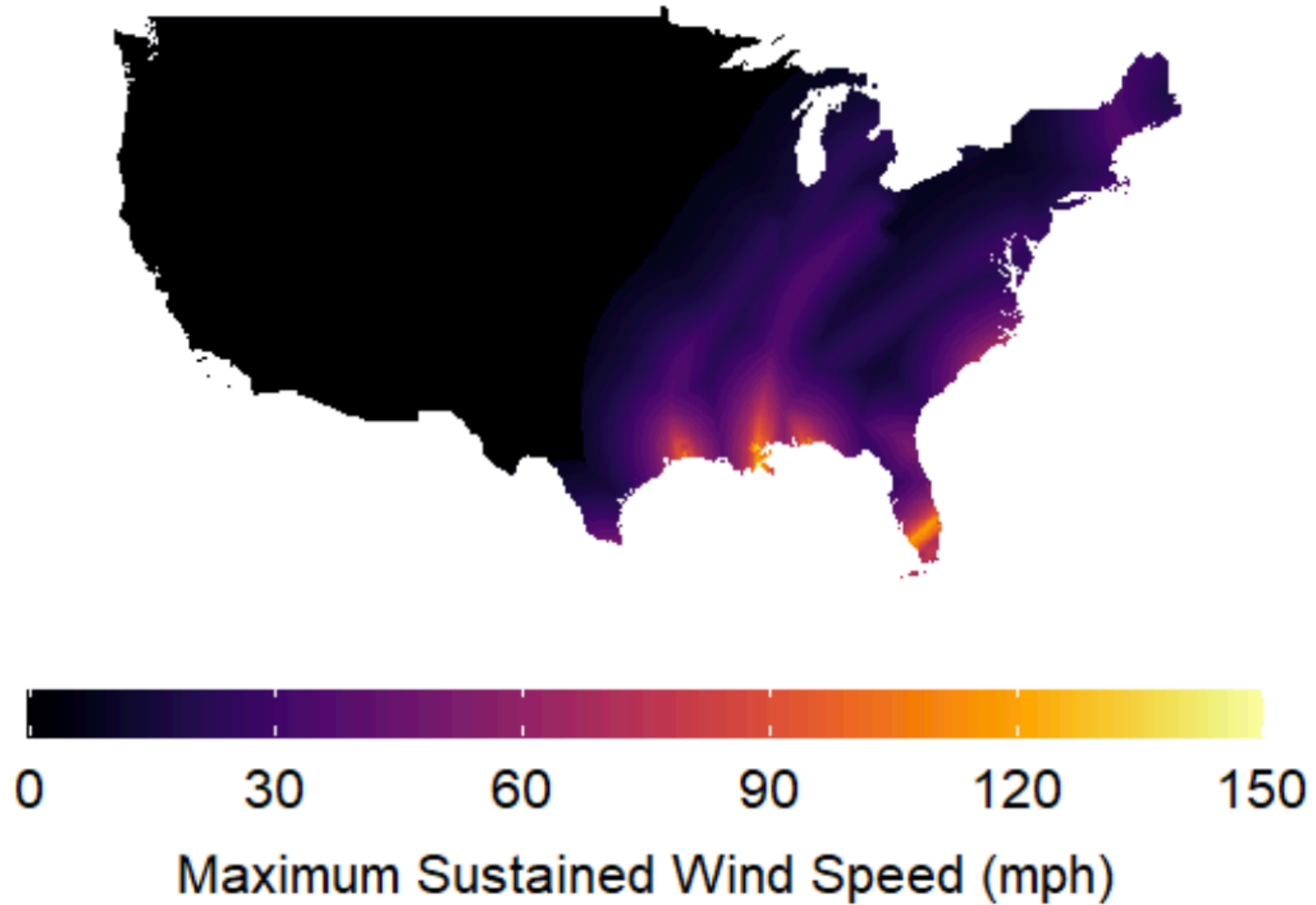
# Hurricane Katrina (2005)



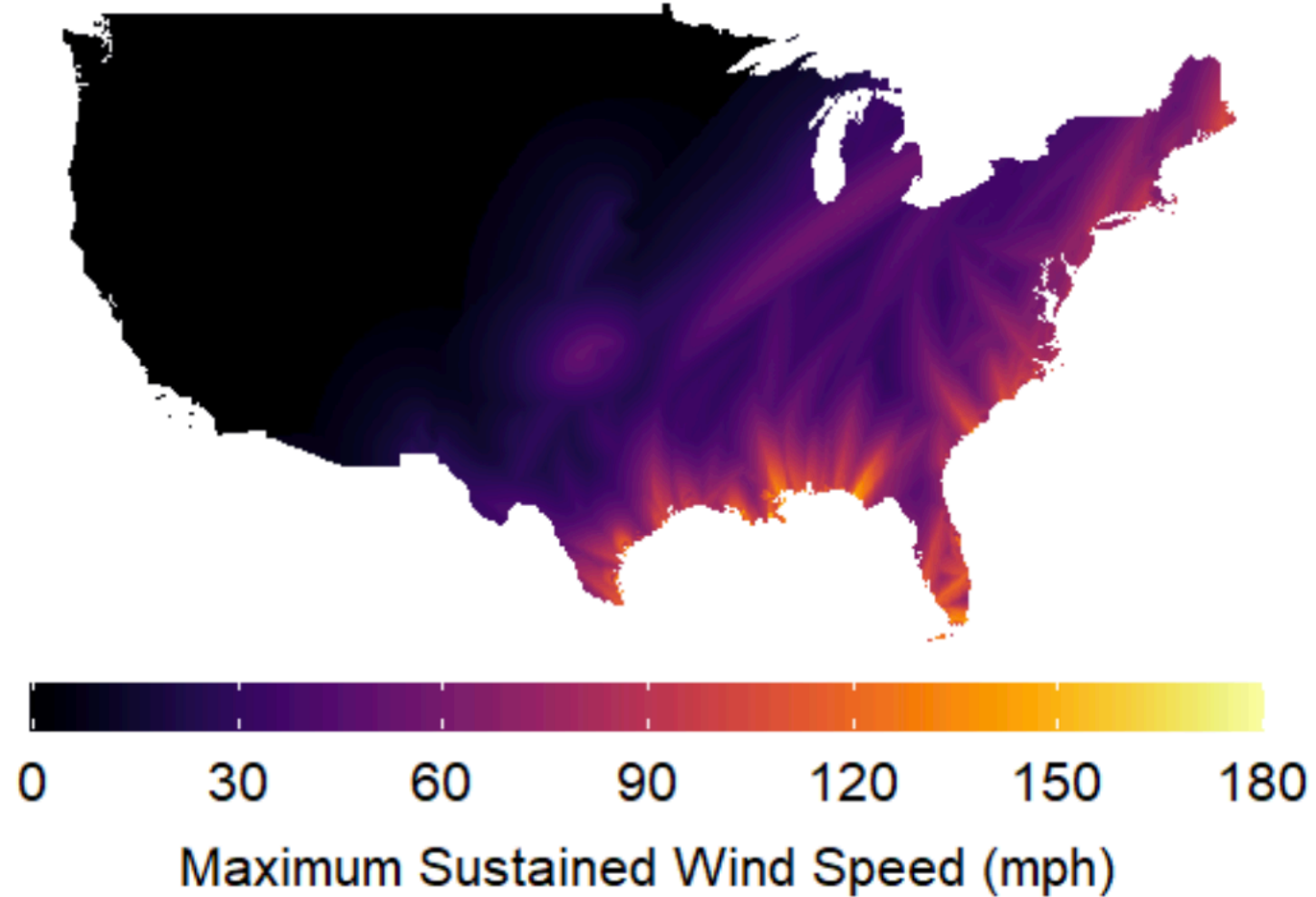
# Hurricane Katrina (2005)



# All Hurricanes (2005)



# All Hurricanes (1969-2019)

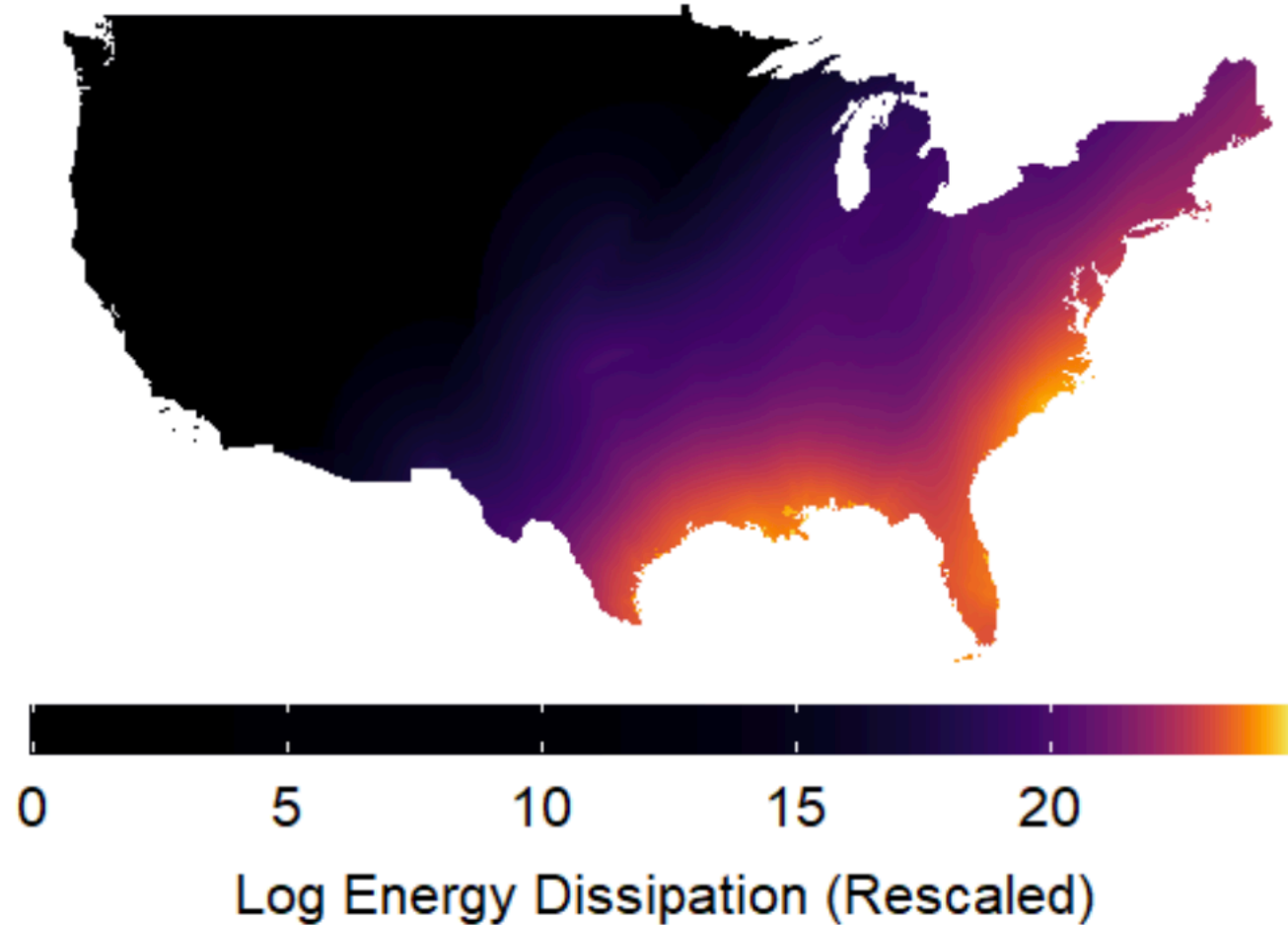


# An Alternative Measure of Exposure

- Max windspeed doesn't account for the amount of energy dissipated:
  - Slower moving storms are more damaging because locations are exposed to high windspeed for longer.
  - Multiple storms vs. max across storms.
- Storm damage increases following a power rule (approximately) equal to the cube of max wind speed ([Emmanuel, 2005](#))
- Energy dissipated ( $\text{m}^3/\text{s}^2$ ) can be calculated by summing “energy” over time within a cell.

$$\text{Energy Dissipation}_i = \sum_t (V_{\max}(t))^3 * \Delta t$$

# “Energy” — All Hurricanes (1969-2019)



# Conclusions

- Weather and climate are important for decision-making and economic outcomes, especially in LMICs.
- Vast improvements in measurement and availability of data.
- It's important to understand the data you are using:
  - Measurement can be endogenous even when physical realizations aren't
  - Non-linearities are important.
  - Think carefully about your context and what data would be most appropriate.
  - Understand strengths and limitations.
  - Be clear about trade-offs.
  - New tools will make it increasingly easier to process data