Climate Change and how Machine Learning can help

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Maties Machine Learning (MML)

Stellenbosch University, 2019

WHY — Why should you care?

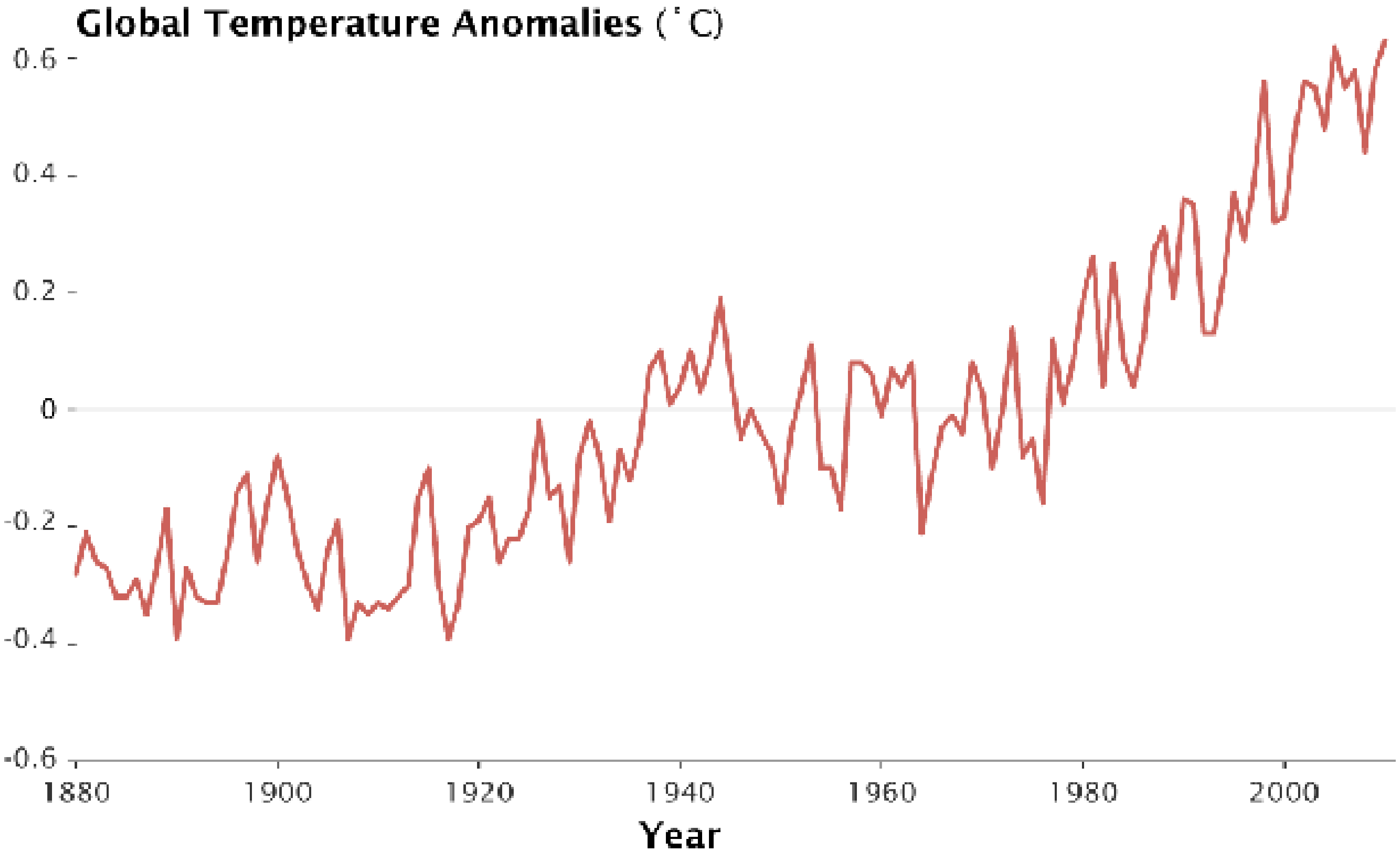
HOW — How did this happen?

WHEN — When will things turn bad, how long do we have to act?

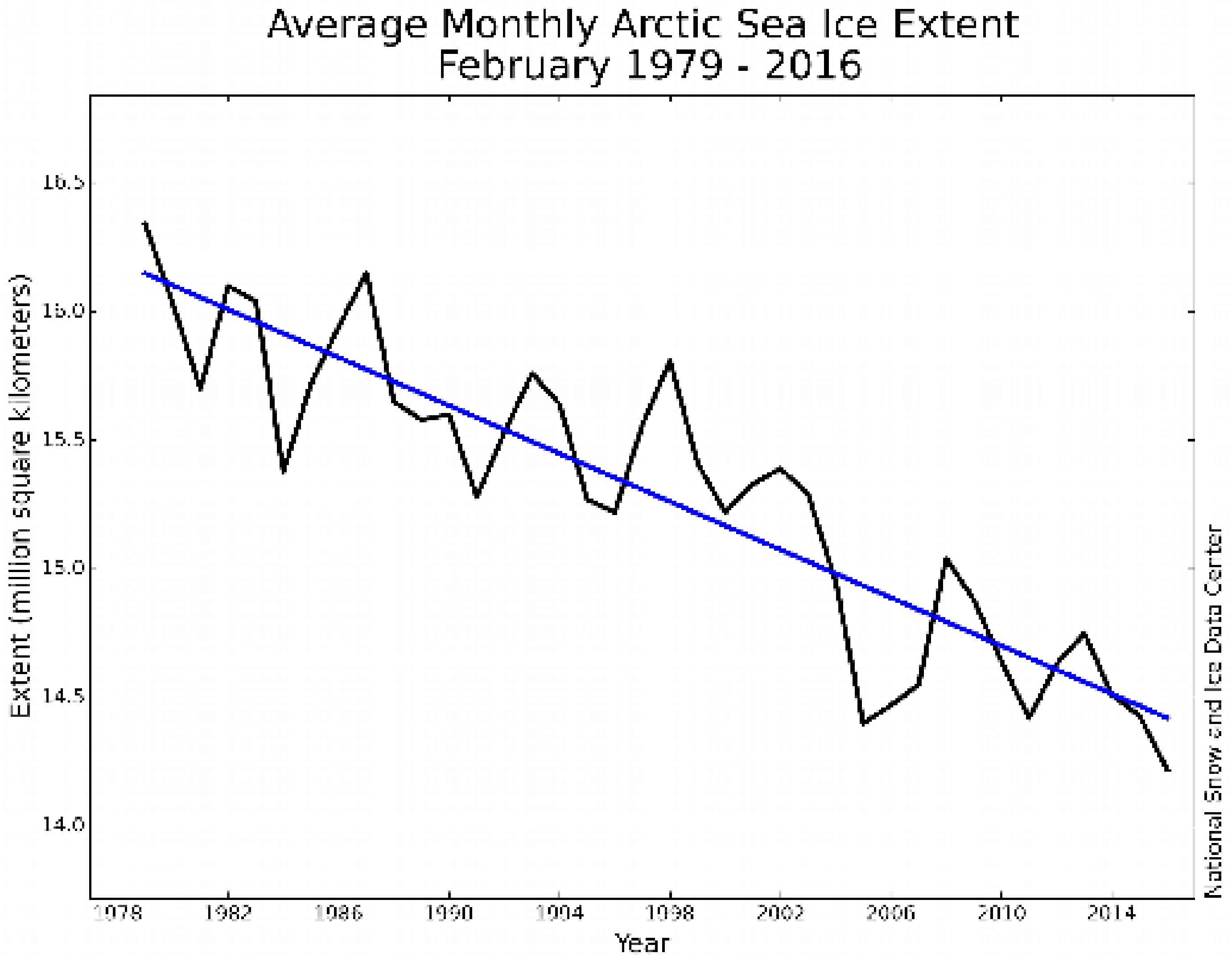
WHAT — What can we (ML) do to help?

WHY

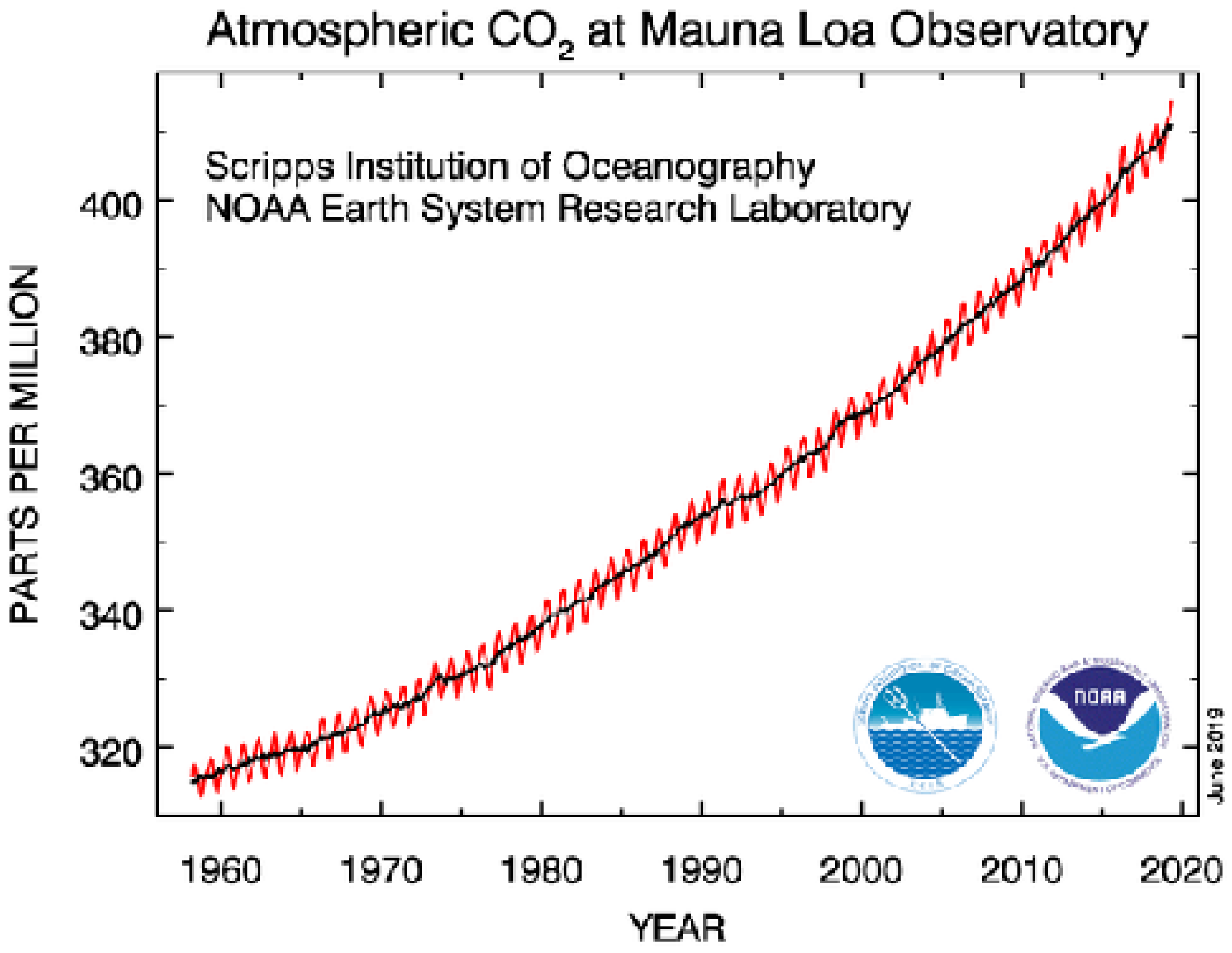
Earth's temperature is rising



Poles are melting

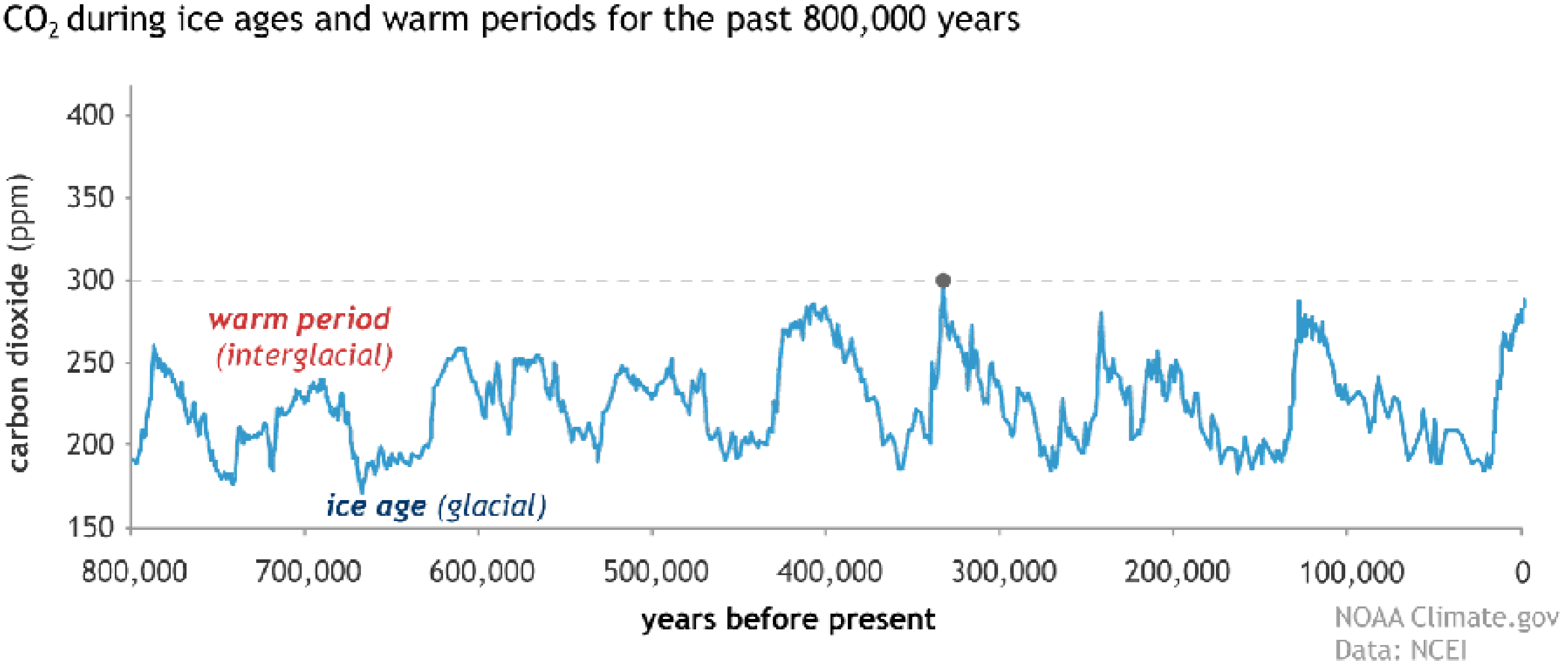


…and this correlates with atmospheric CO2 levels

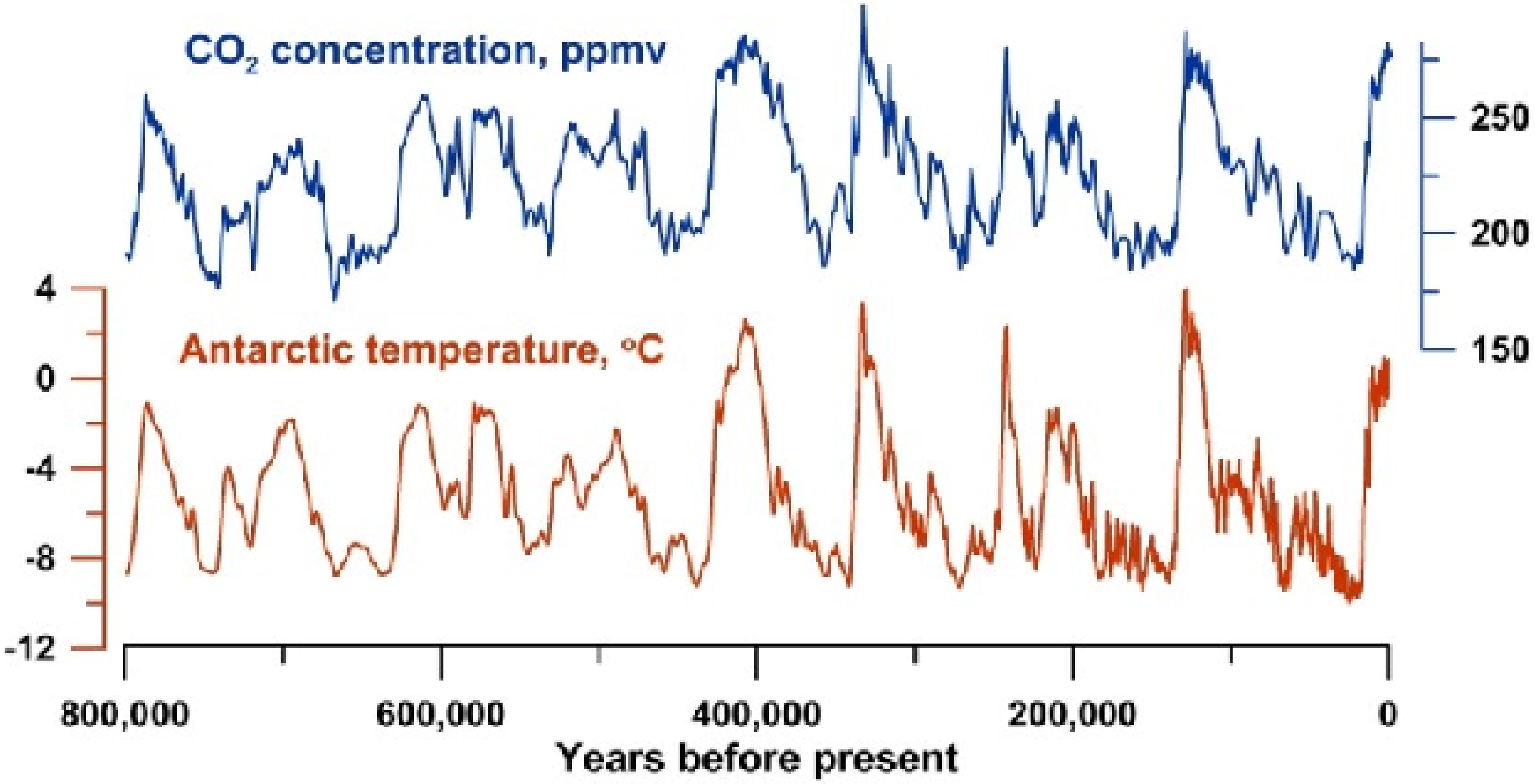


Is this normal?

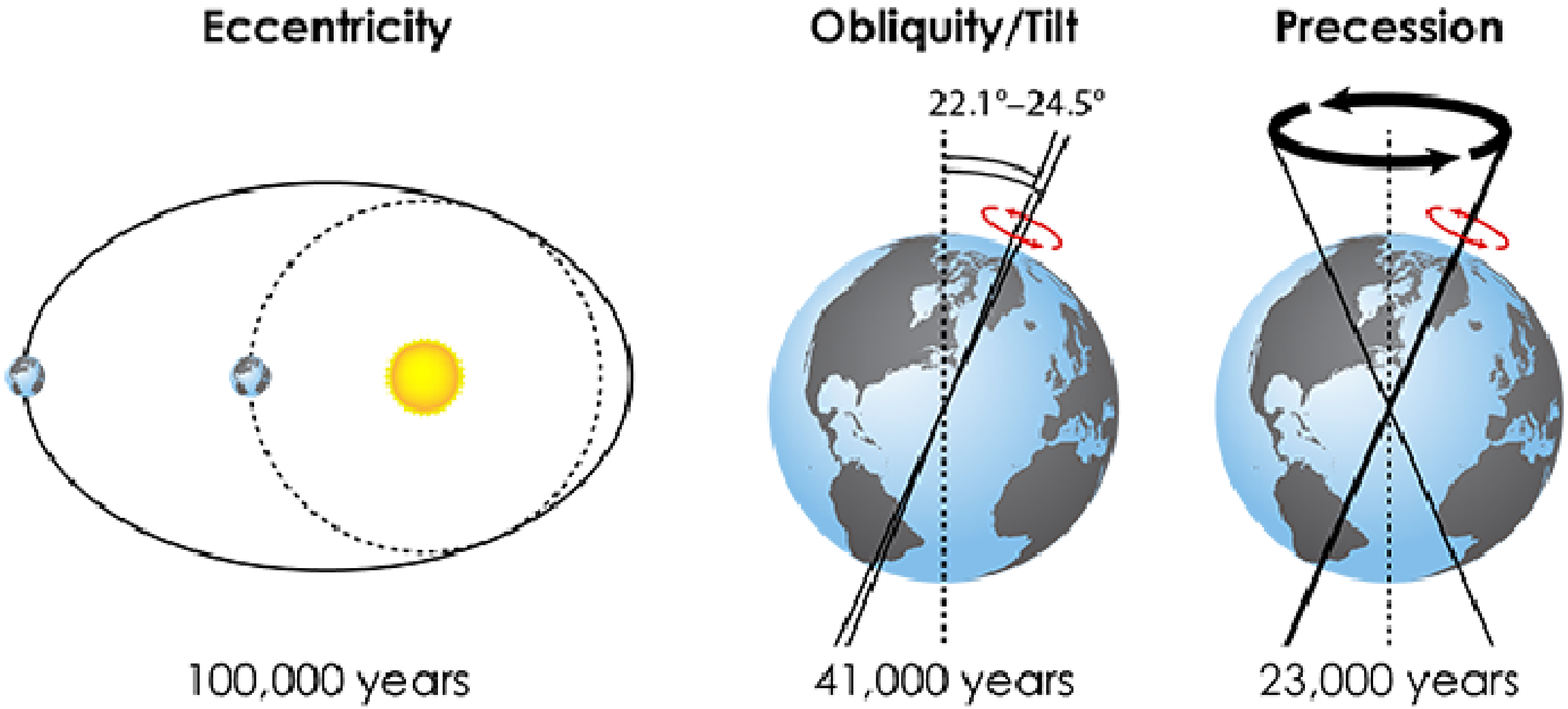
Variability in CO2 levels



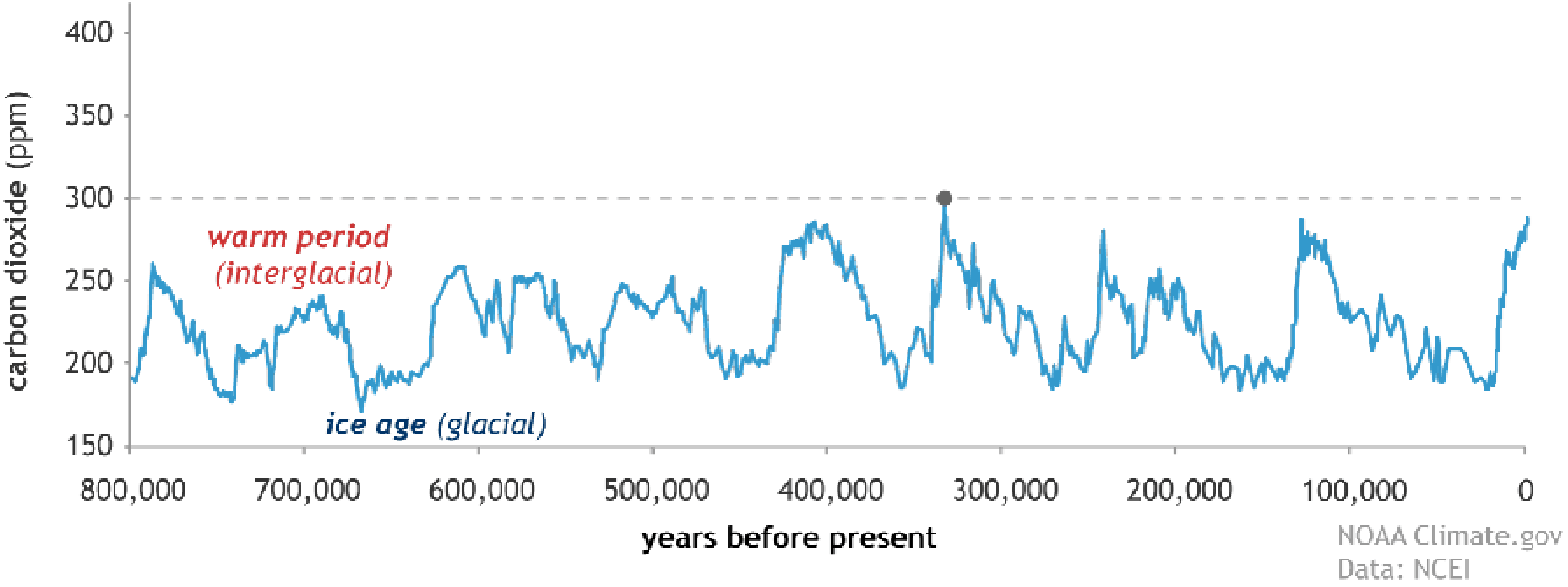
Temperature and CO_2 from Antarctic ice cores over the past 800,000 years



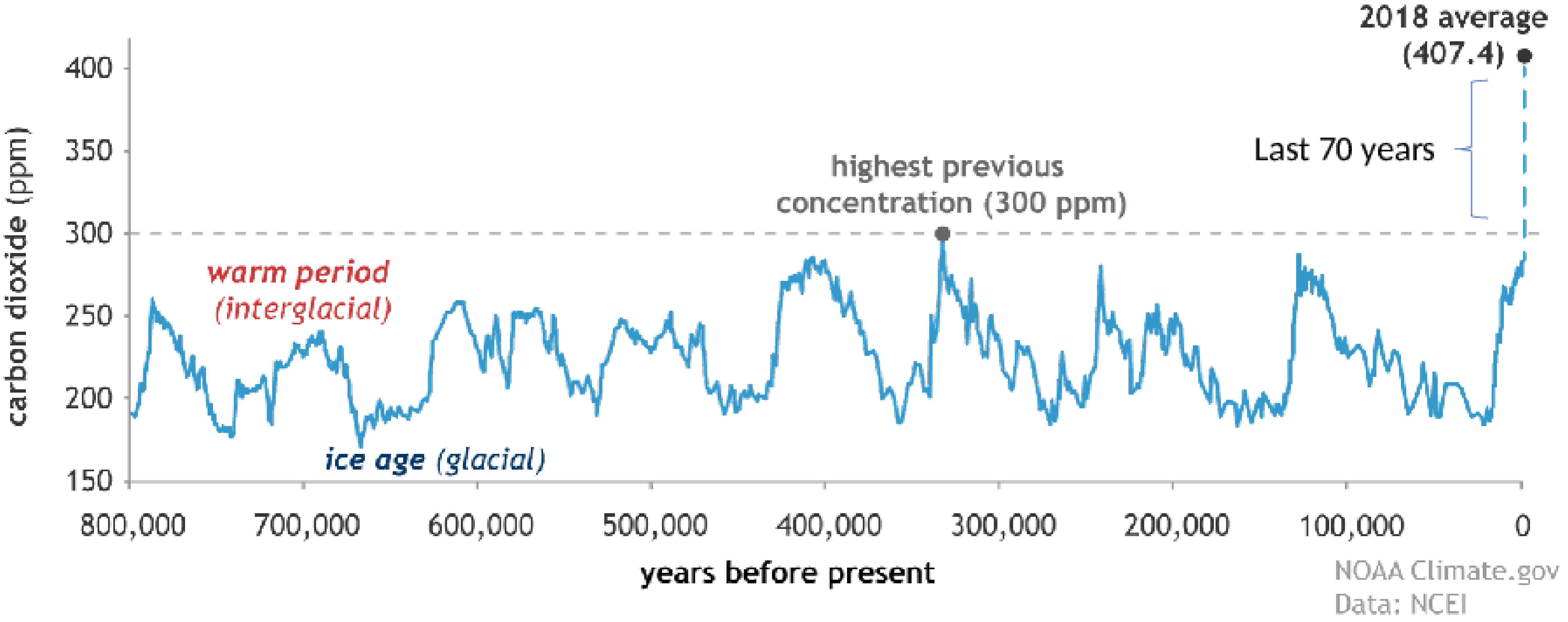
Milankovitch cycles

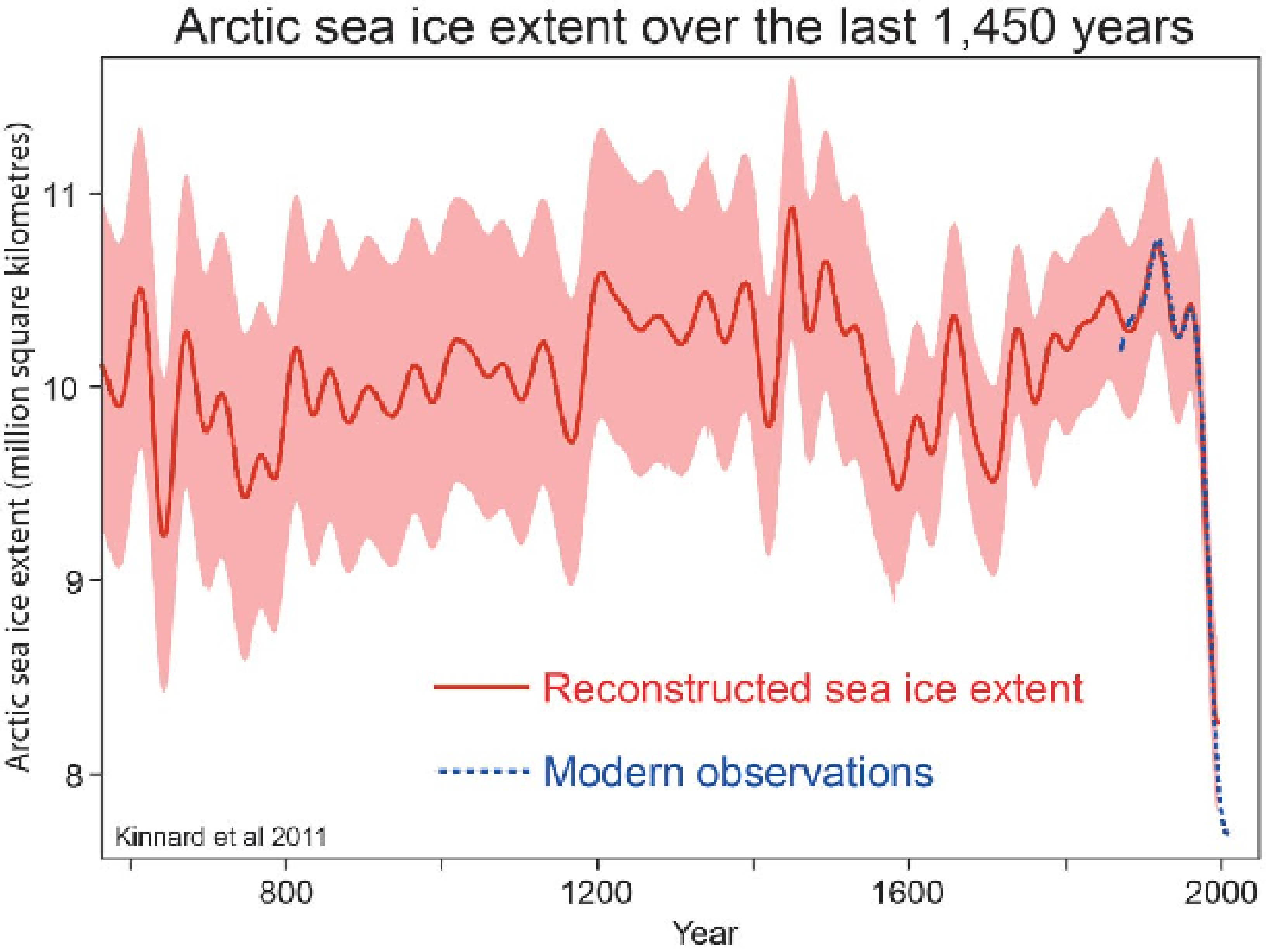


CO_2 during ice ages and warm periods for the past 800,000 years



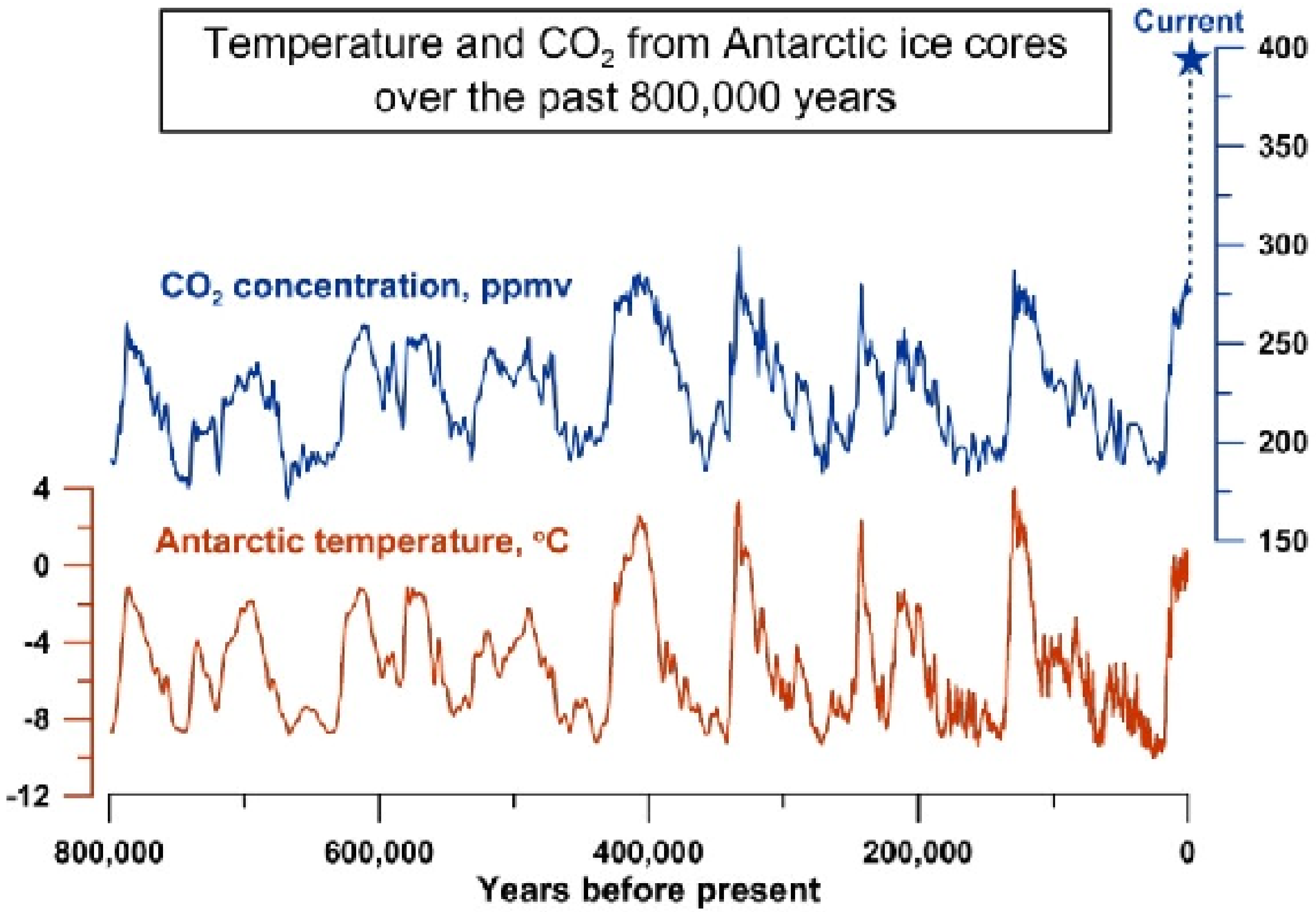
CO_2 during ice ages and warm periods for the past 800,000 years





Arctic sea ice extent over the last 1,450 years
Arctic sea ice extent (million square kilometres)
11
10
9
8
800
1200
1600
2000
Year
Reconstructed sea ice extent
Modern observations
Kinnard et al 2011

We expect a rise of 1-1.5 degrees?



Oceans absorb heat first

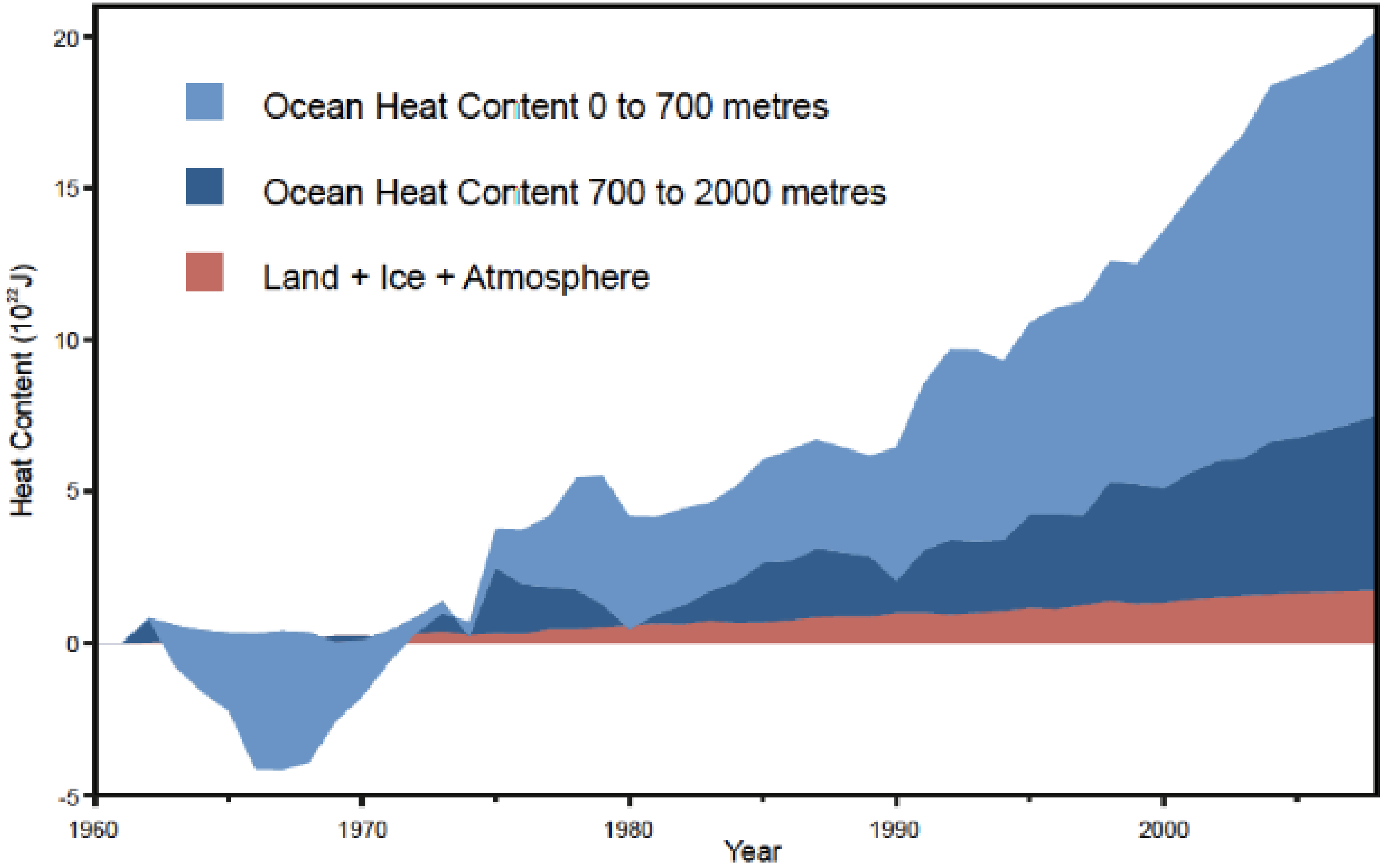
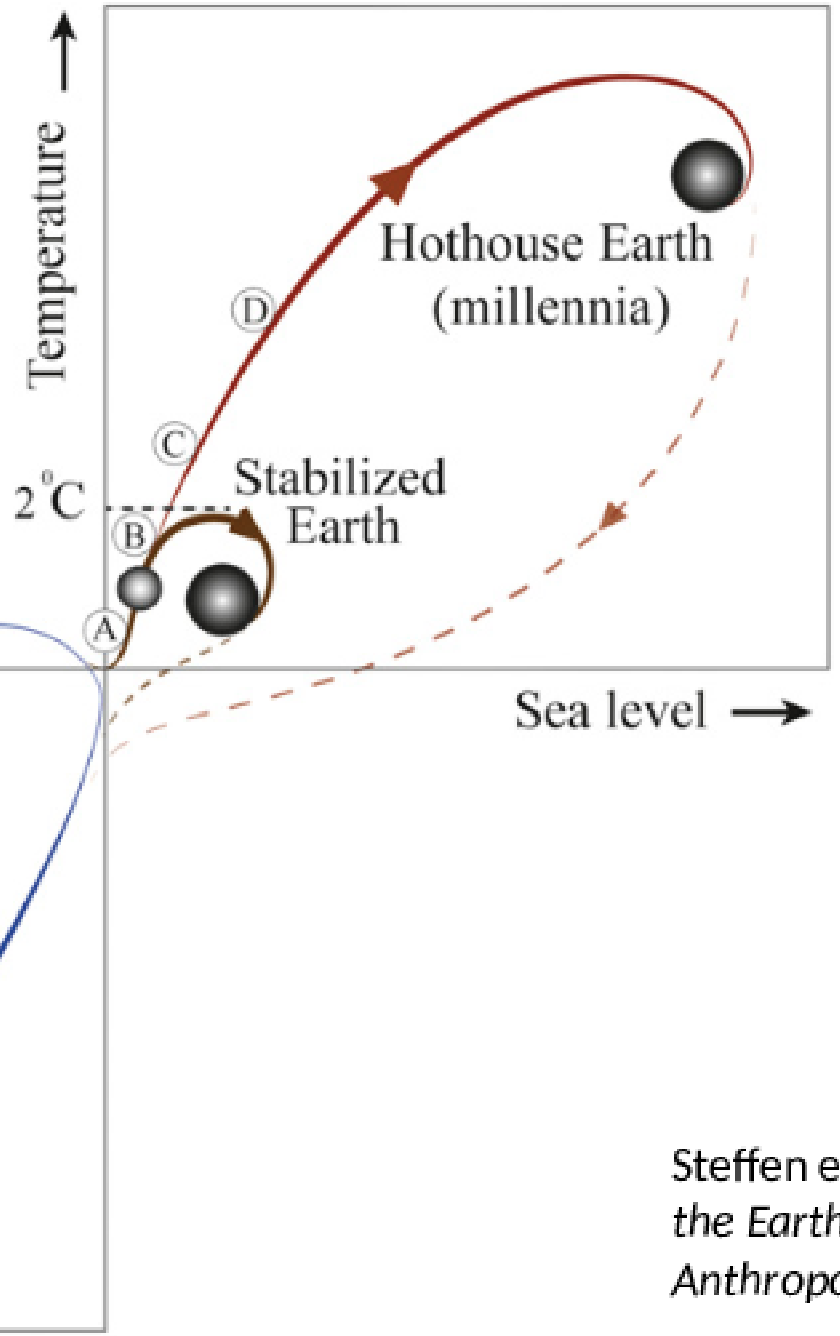


Figure 1 Land, atmosphere, and ice heating (red), 0-700 meter OHC increase (light blue), 700-2,000 meter OHC increase (dark blue)

Possible Futures

What is so significant about 2 degrees?



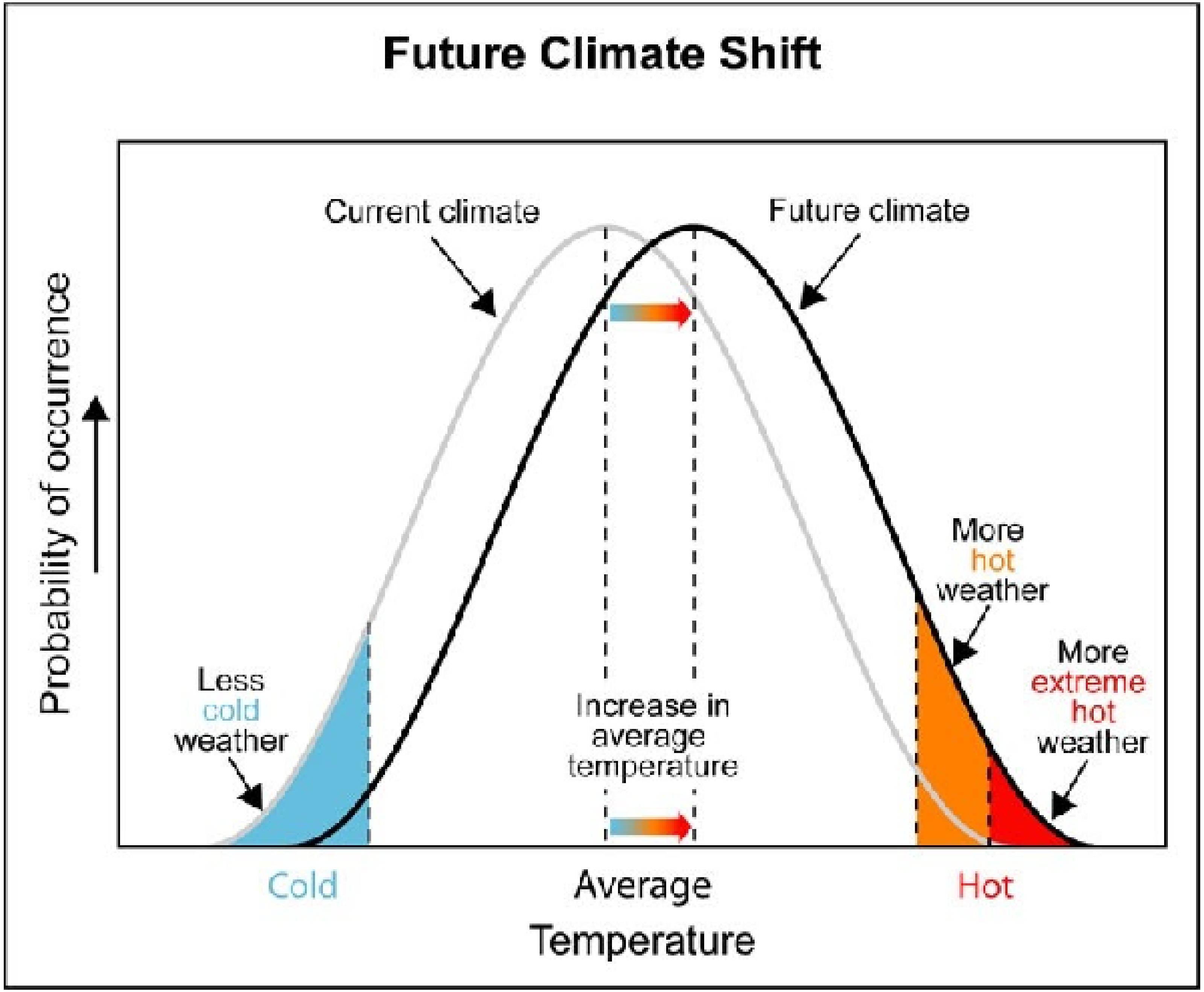
Steffen et al. *Trajectories of the Earth System in the Anthropocene*, PNAS, 2018.

Probability of extreme events

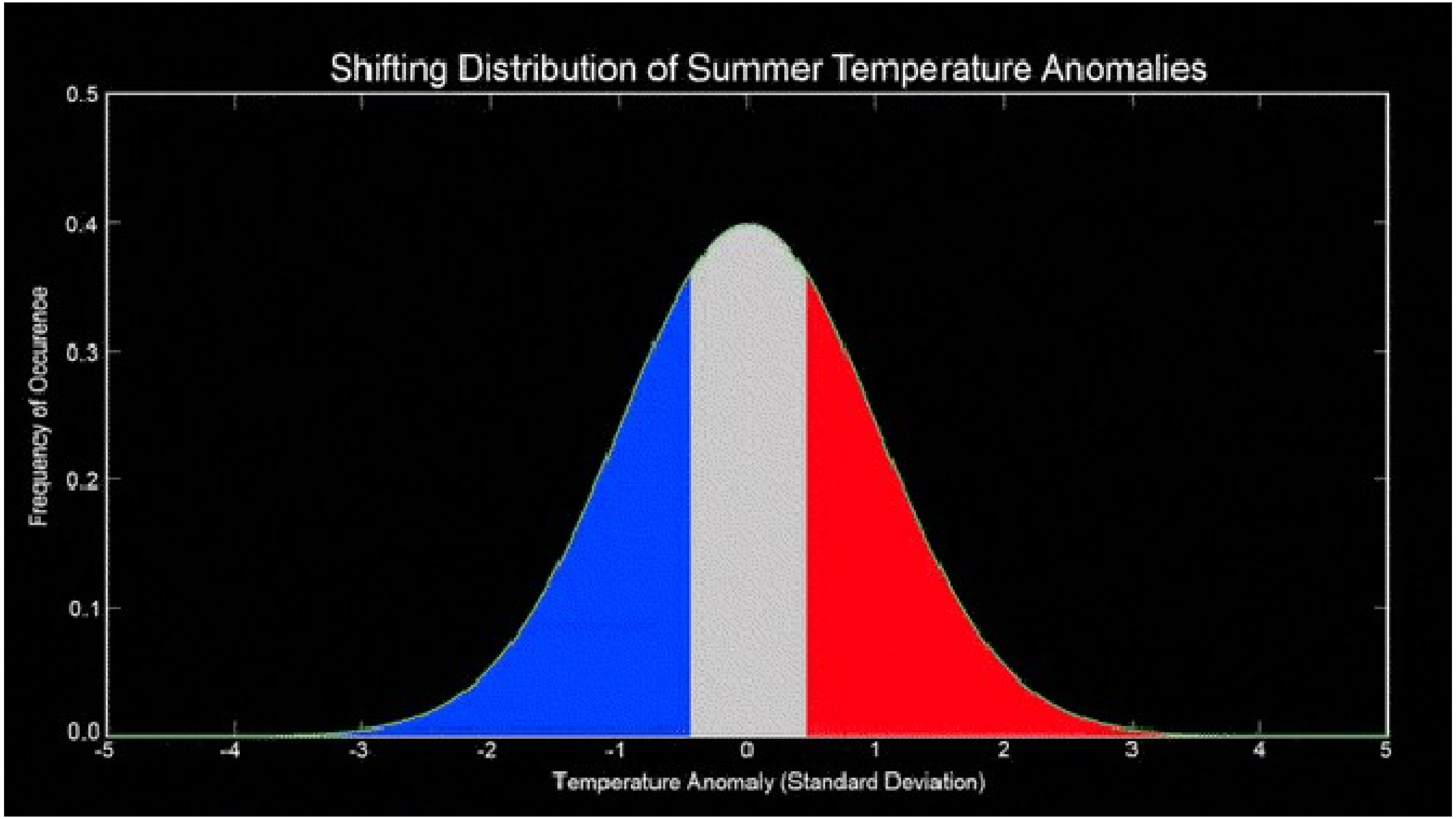
Climate sensitive systems

Amplifying feedback loops

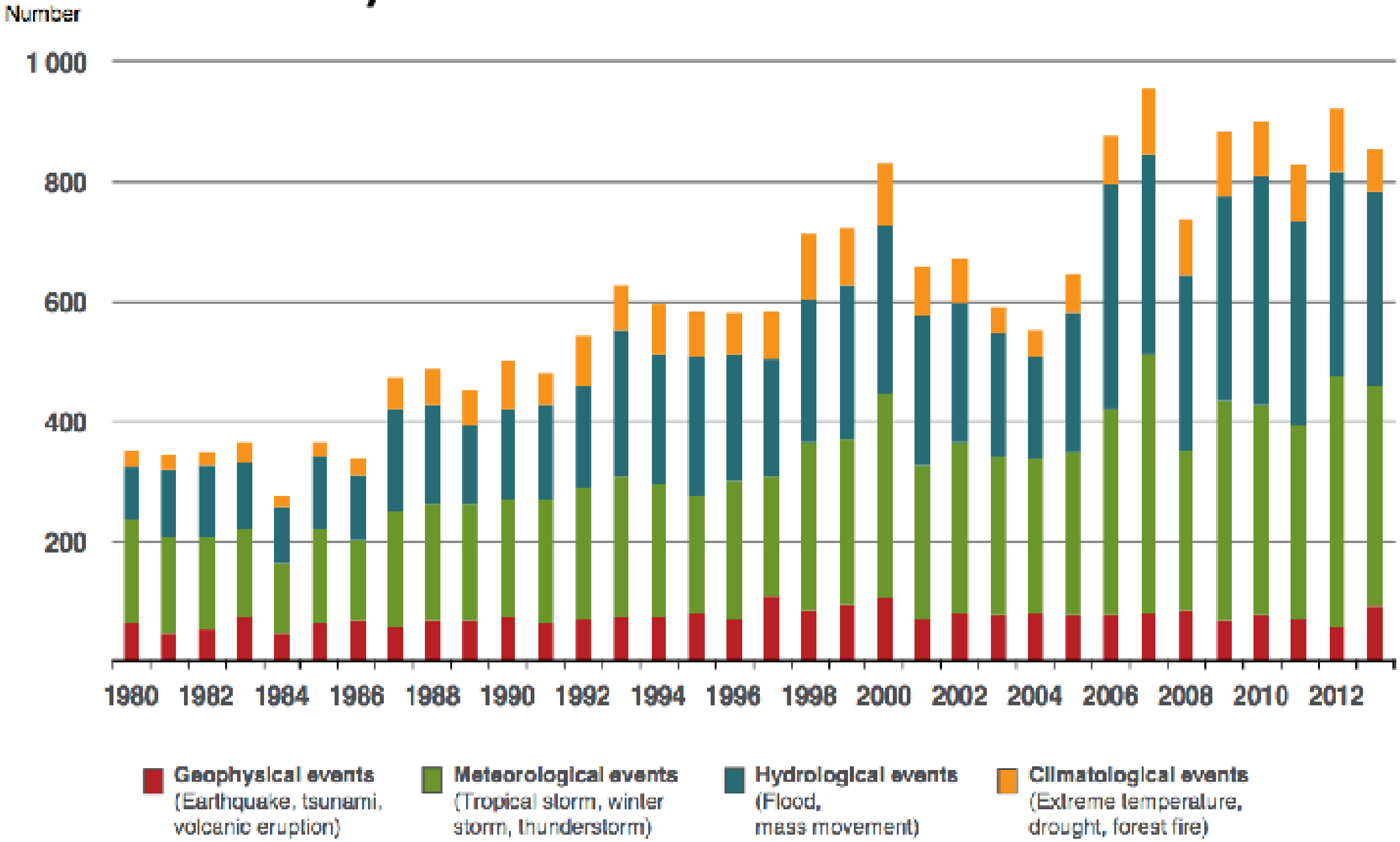
Probability of extreme events



NASA Global Climate Data

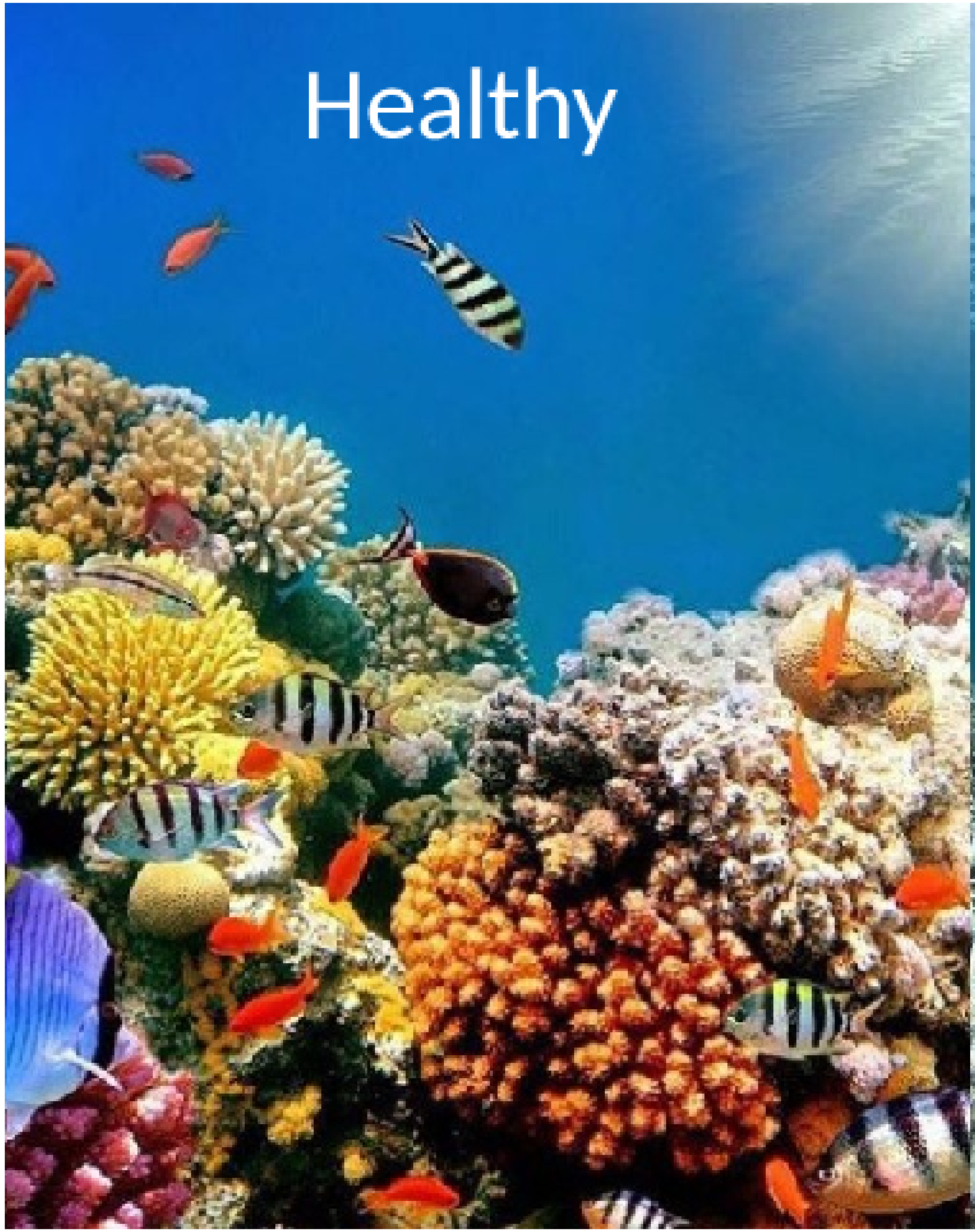


History of extreme weather events



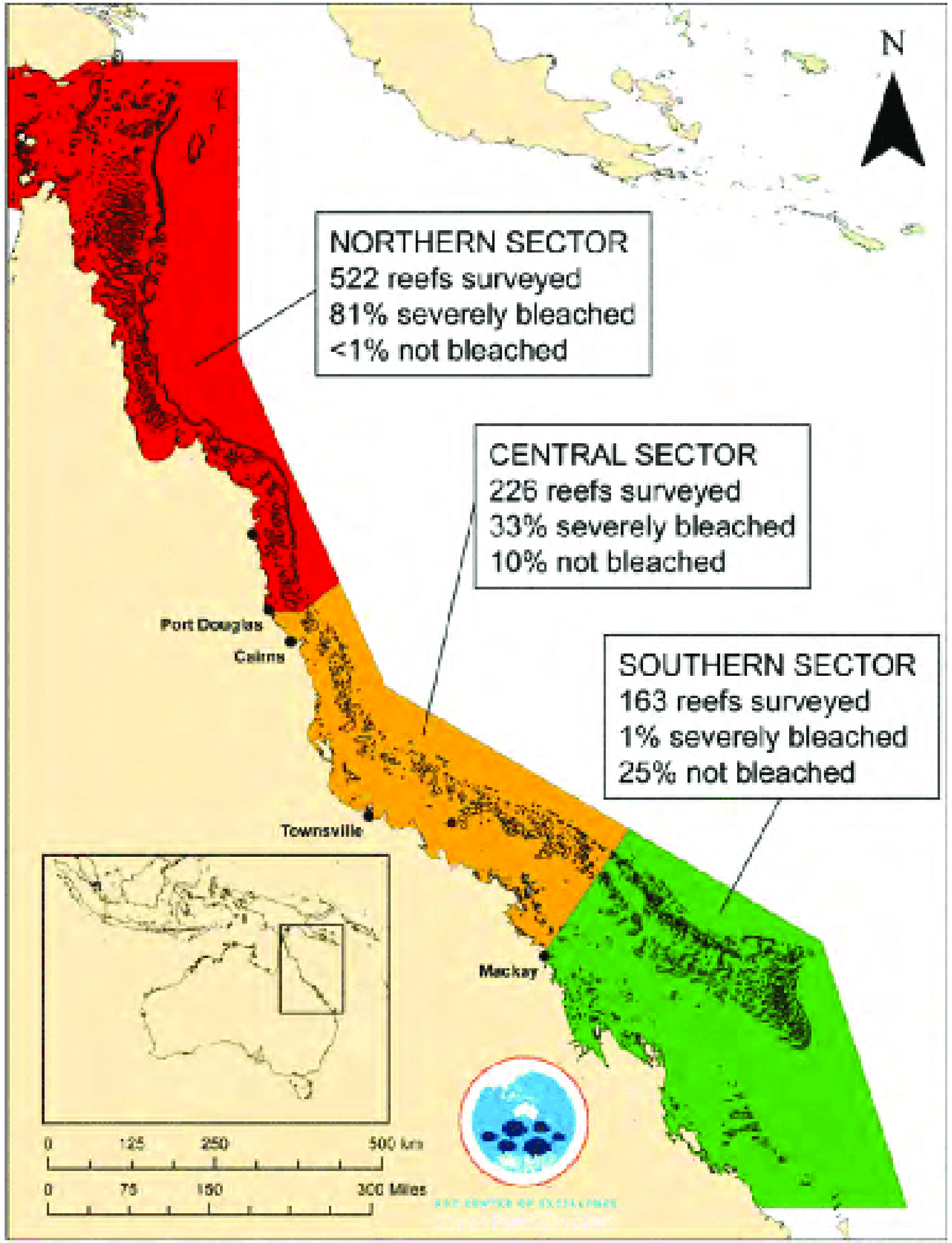
Climate sensitive systems

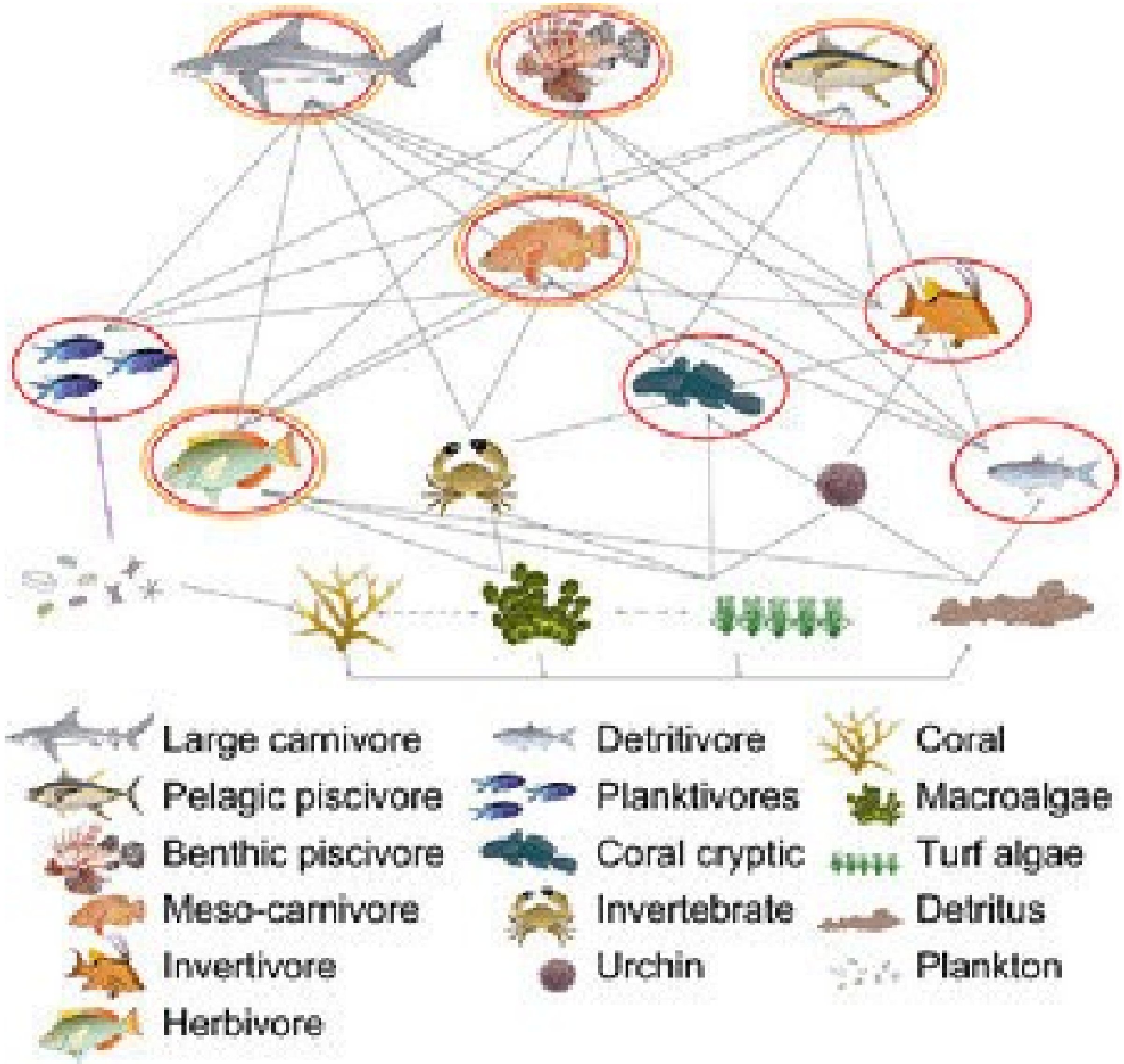
CORAL REEF


Healthy


Bleached

Coral bleaching in the Great Barrier Reef

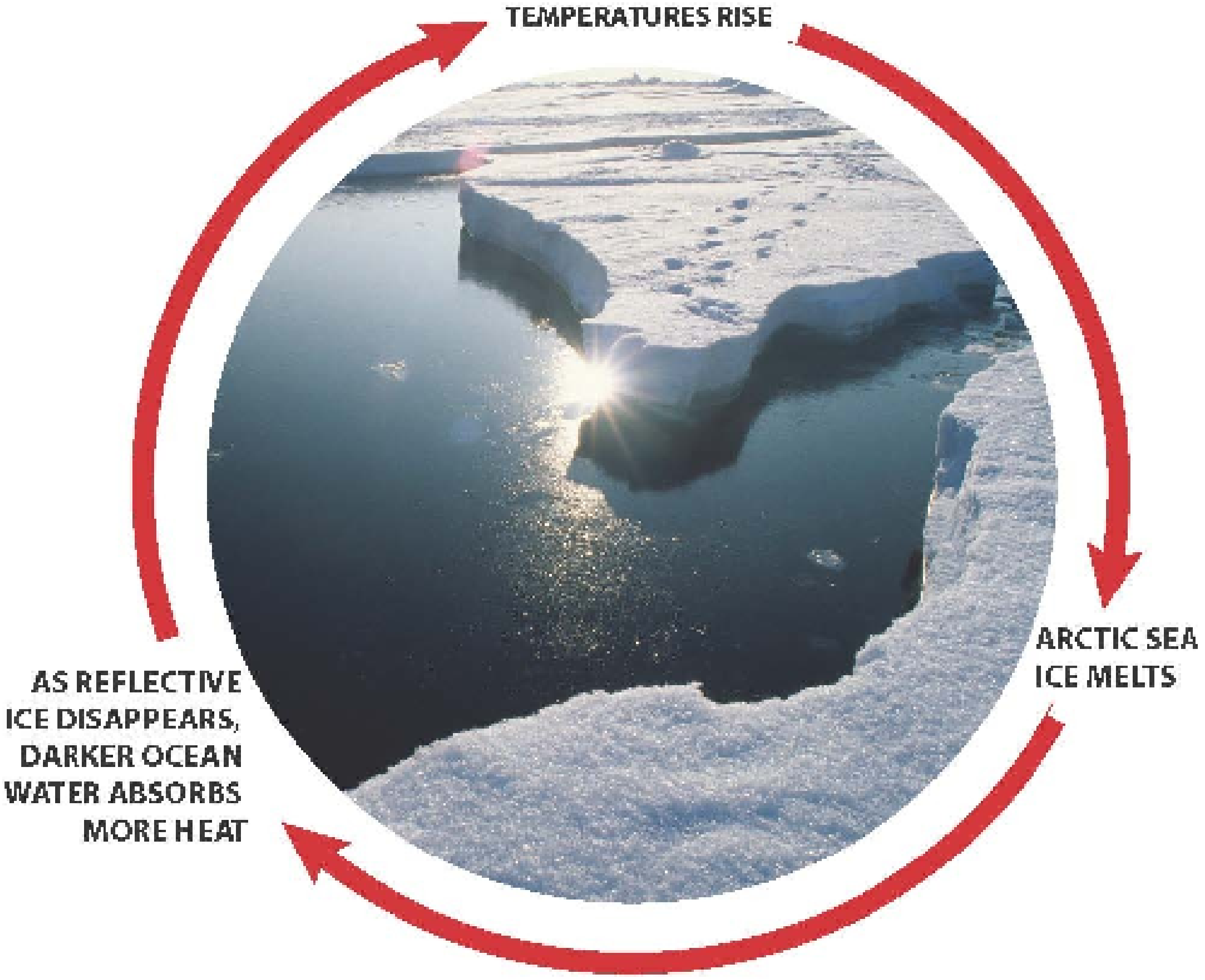




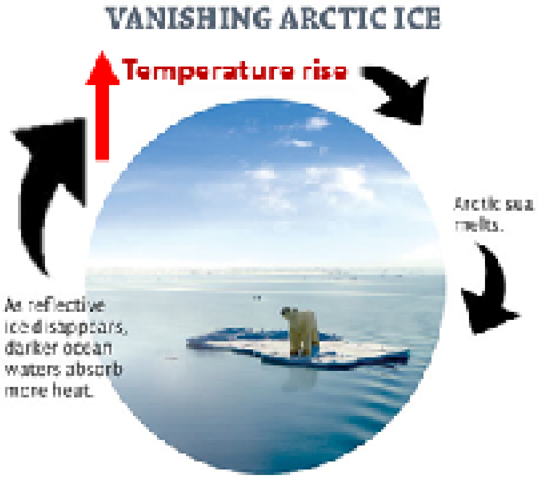
¼ of all ocean species depend on coral reefs

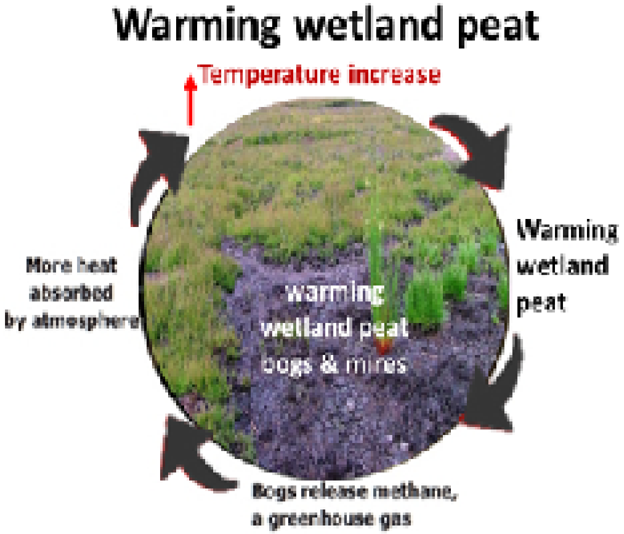
Plaisance et al., (2011) The Diversity of Coral Reefs: What Are We Missing? PLoS ONE

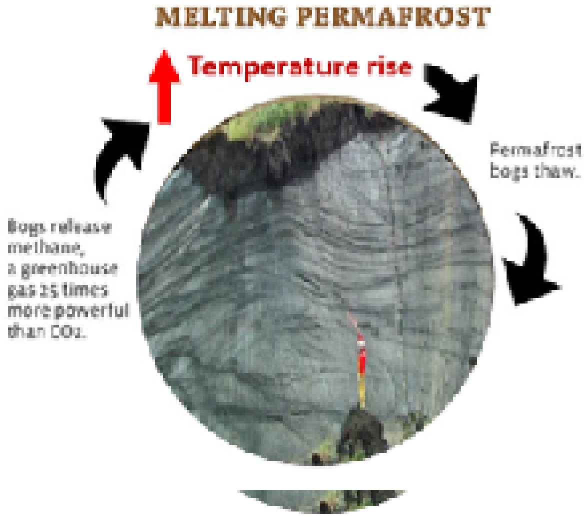
Amplifying feedback loops



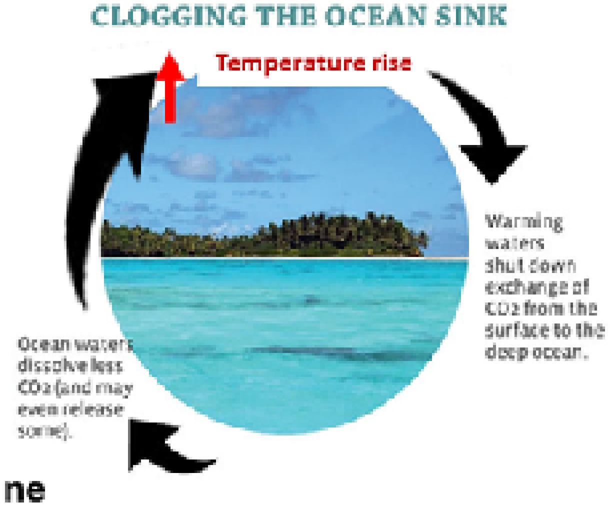
Ice albedo feedback loop

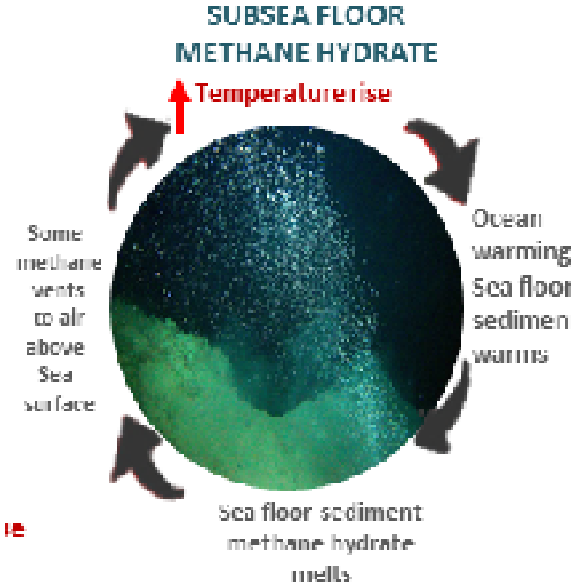

VANISHING ARCTIC ICE
Temperature rise
Arctic sea ice melts.
As reflective ice disappears, darker ocean waters absorb more heat.

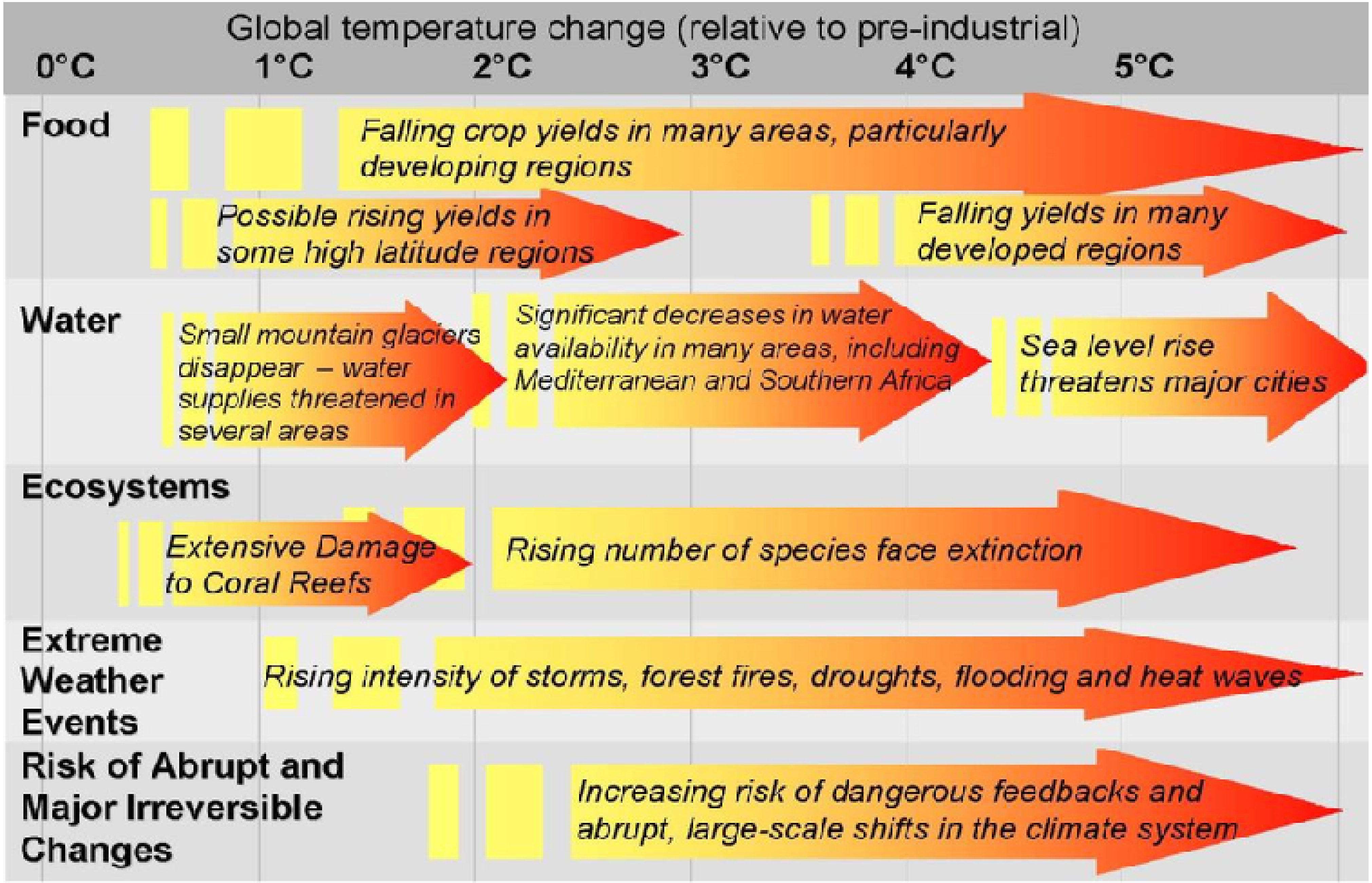

Warming wetland peat
Temperature increase
Warming wetland peat
warming wetland peat bogs & mires
More heat absorbed by atmosphere
Bogs release methane, a greenhouse gas


MELTING PERMAFROST
Temperature rise
Permafrost bogs thaw.
Bogs release methane, a greenhouse gas 25 times more powerful than CO_2.


AMAZON RAINFOREST DIE-OFF
Temperature rise
Drought and wildfires increase in the Amazon.
More trees die and decompose, or burn, releasing CO_2.
Fewer rainforest trees mean less water is pumped into the atmosphere.
Rainfall decreases.


CLOGGING THE OCEAN SINK
Temperature rise
Warming waters shut down exchange of CO_2 from the surface to the deep ocean.
Ocean waters dissolve less CO_2 (and may even release some).

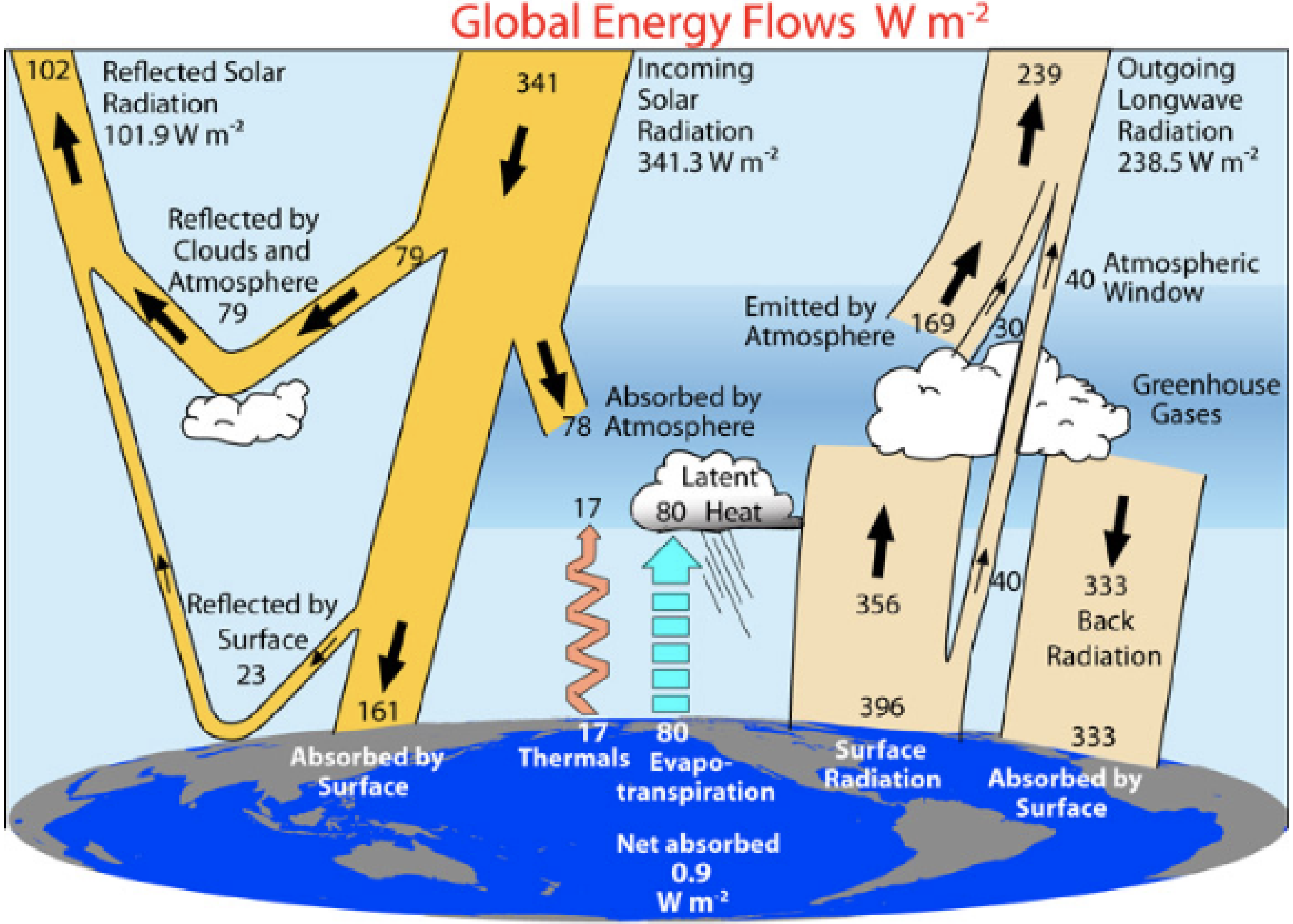

SUBSEA FLOOR METHANE HYDRATE
Temperature rise
Ocean warming
Sea floor sedimen warms
Sea floor sediment methane hydrate melts
Some methane vents to air above Sea surface



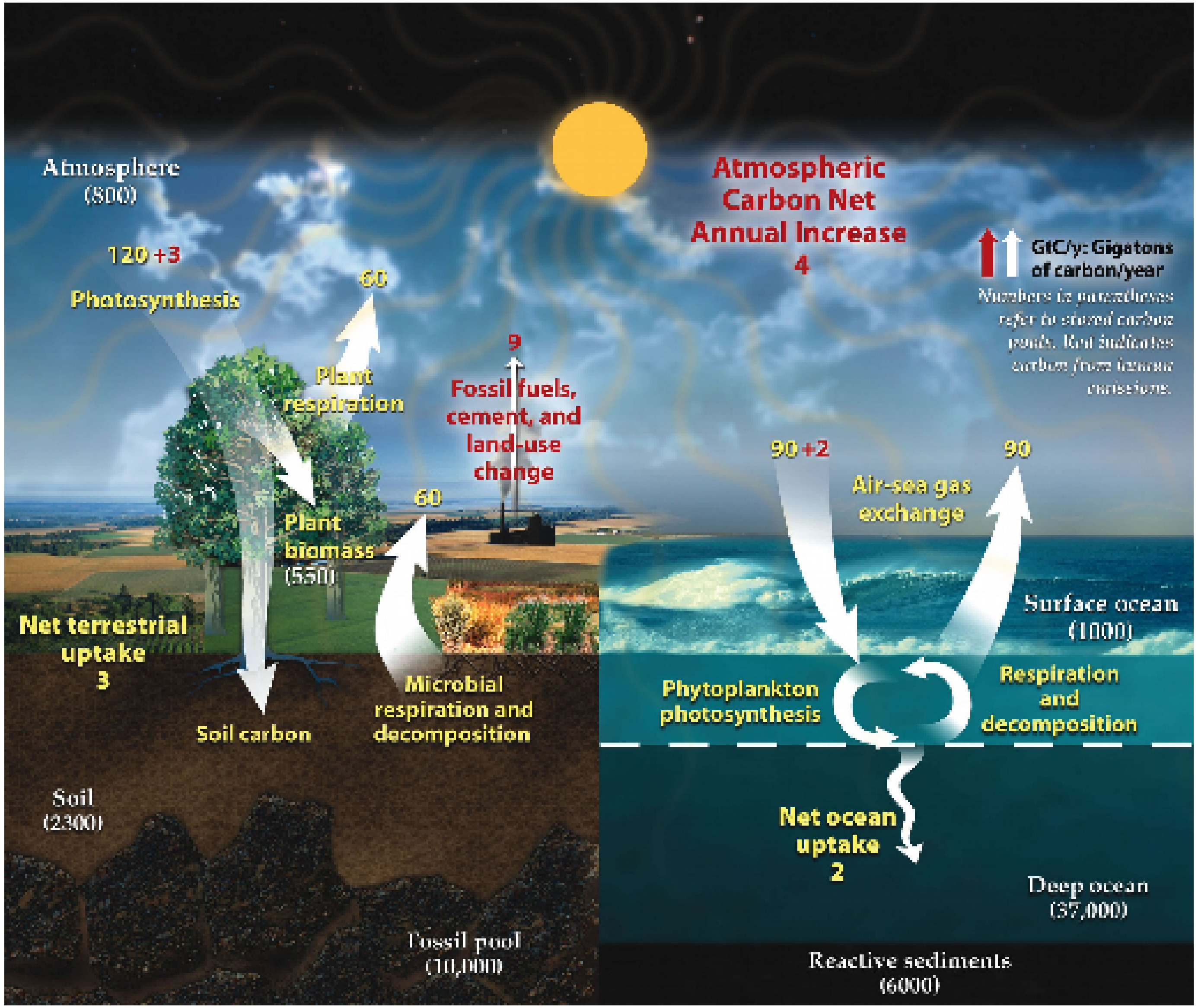
Global temperature change (relative to pre-industrial)
0°C
1°C
2°C
3°C
4°C
5°C
Food
Falling crop yields in many areas, particularly developing regions
Possible rising yields in some high latitude regions
Falling yields in many developed regions
Water
Small mountain glaciers disappear – water supplies threatened in several areas
Significant decreases in water availability in many areas, including Mediterranean and Southern Africa
Sea level rise threatens major cities
Ecosystems
Extensive Damage to Coral Reefs
Rising number of species face extinction
Extreme Weather Events
Rising intensity of storms, forest fires, droughts, flooding and heat waves
Risk of Abrupt and Major Irreversible Changes
Increasing risk of dangerous feedbacks and abrupt, large-scale shifts in the climate system

HOW

Global energy system is very complex

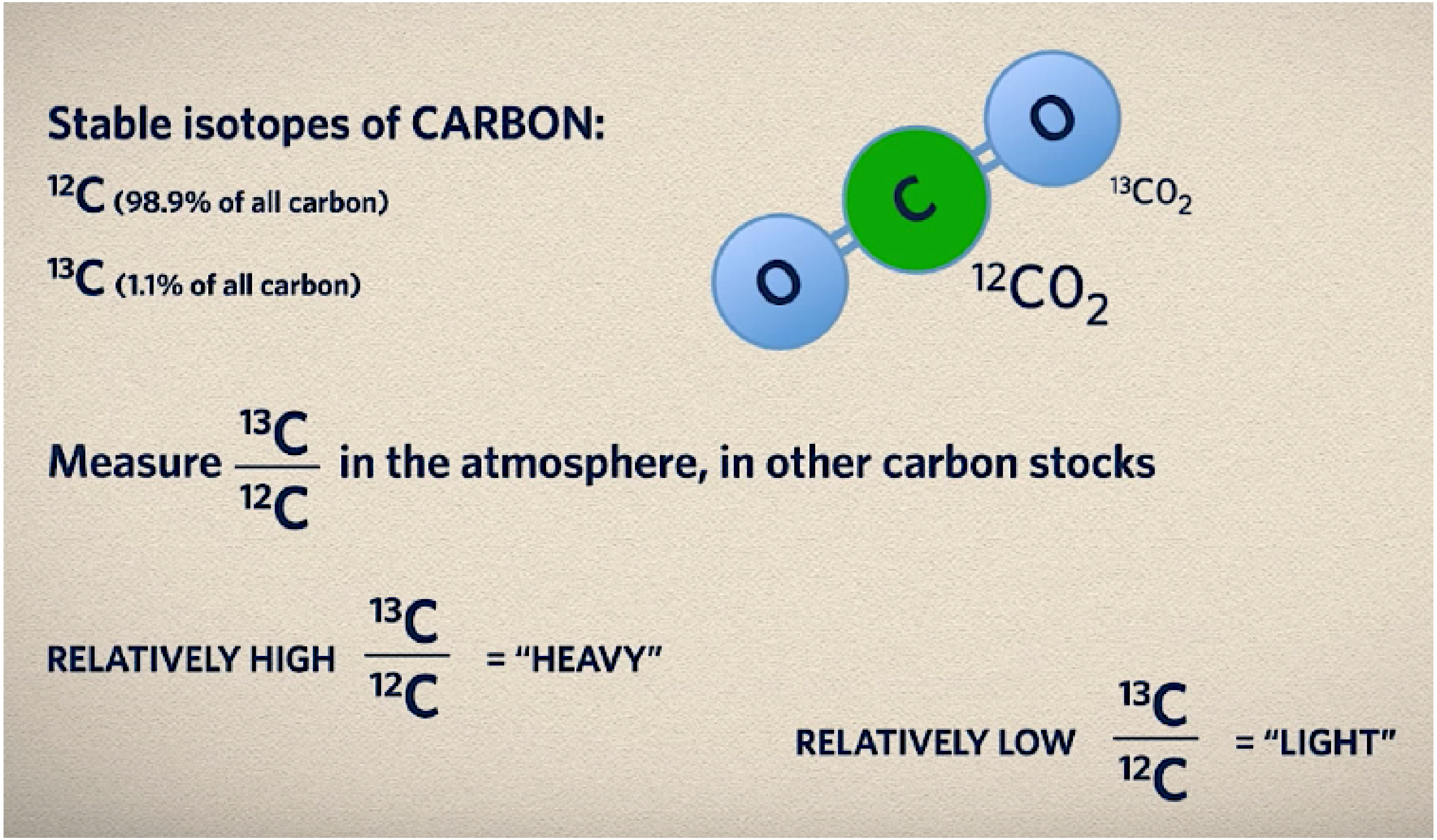


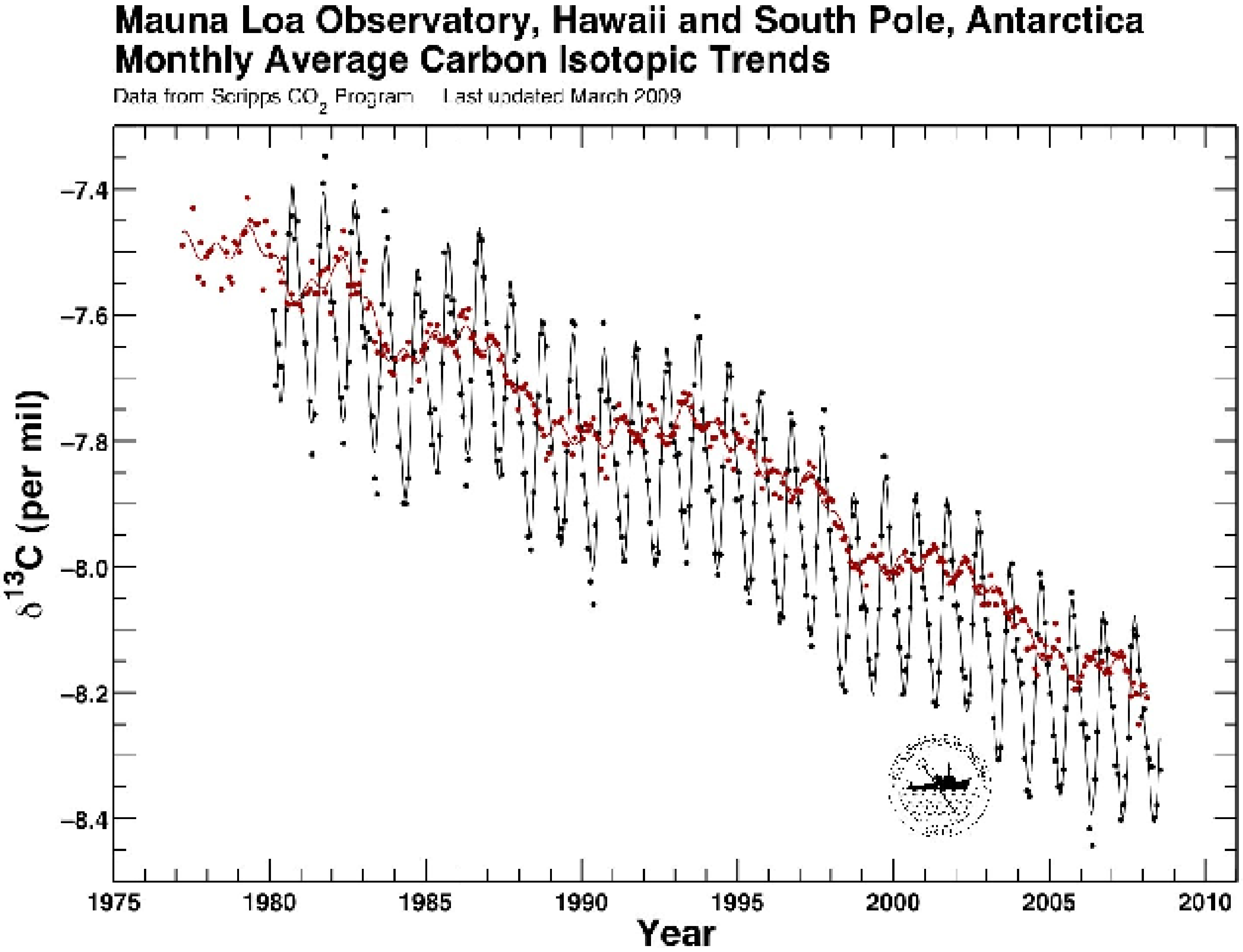
Global carbon cycle is very complex



How do we know humans are to blame?

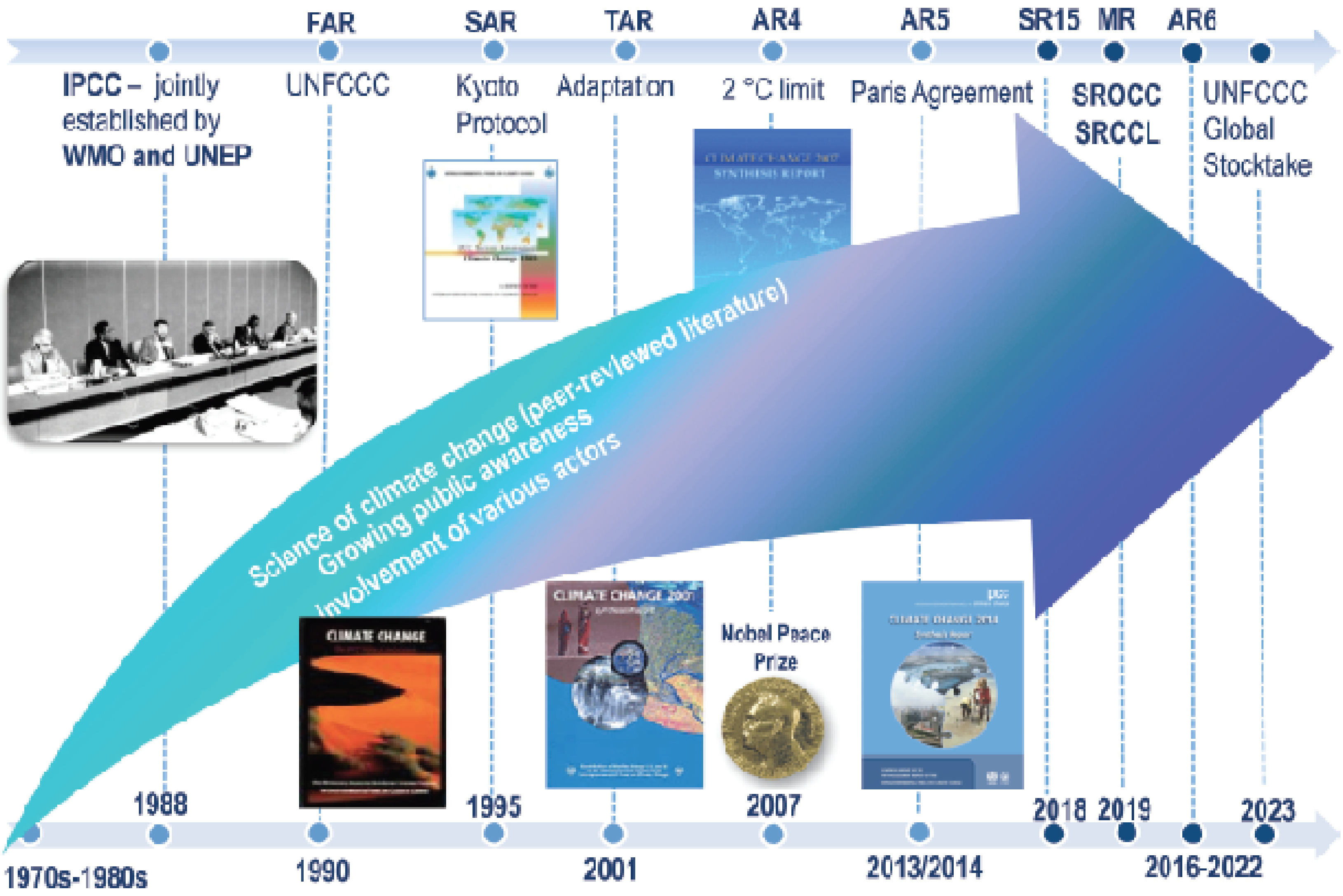
Carbon isotope ratio in the atmosphere



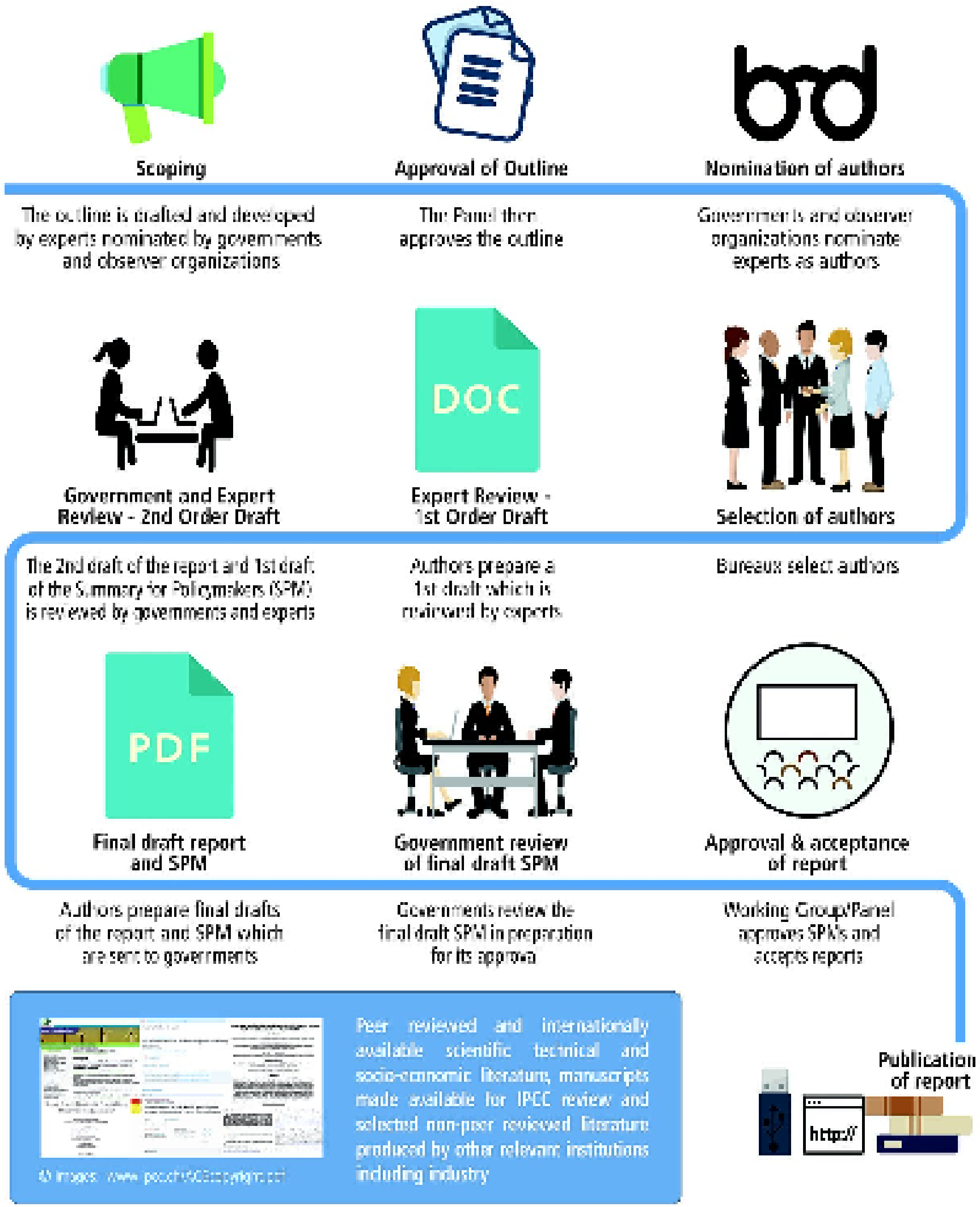


Mauna Loa Observatory, Hawaii and South Pole, Antarctica
Monthly Average Carbon Isotopic Trends
Data from Scripps CO_2 Program   Last updated March 2009
$\delta^{13}C$ (per mil)
-7.4
-7.6
-7.8
-8.0
-8.2
-8.4
1975
1980
1985
1990
1995
2000
2005
2010
Year

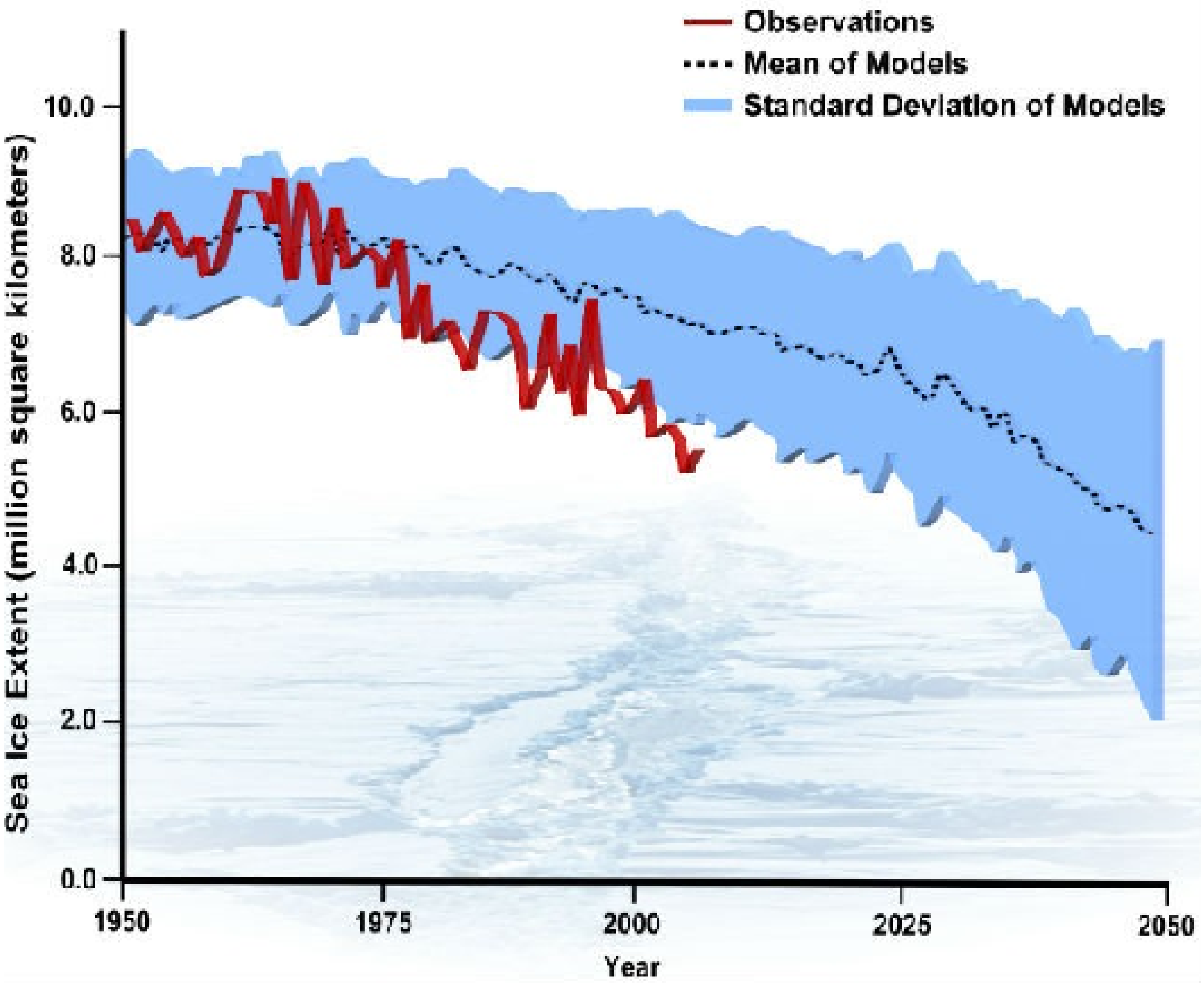
Intergovernmental Panel on Climate Change (IPCC)



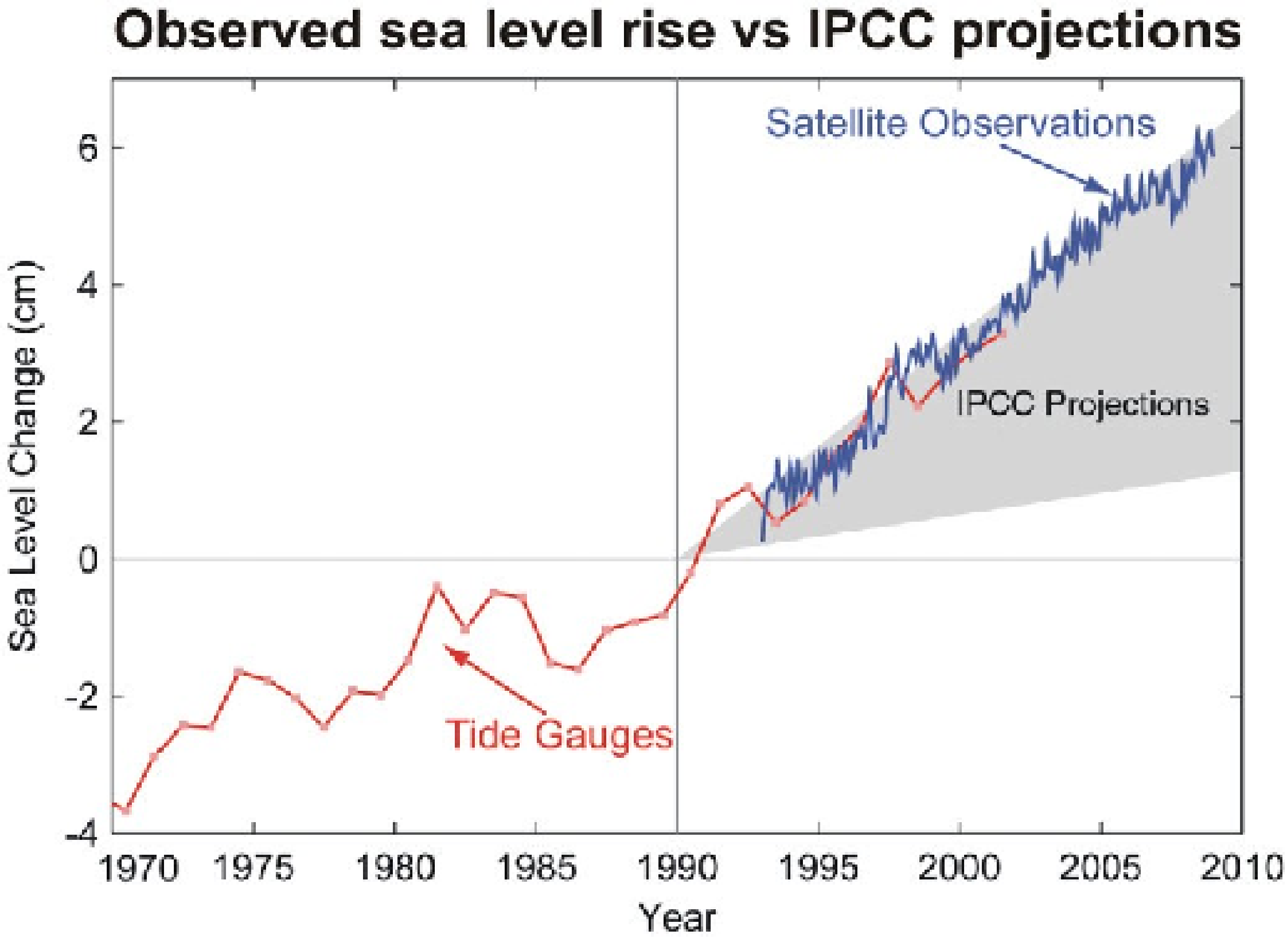
Process of preparing reports



Arctic September Sea Ice Extent: Observations and Model Runs



In a climate system with net positive feedback, climate response is likely to be greater than expected



Copenhagen Diagnosis 2009

http://sks.to/model

Human attribution from the IPCC 1st, 2nd, 3rd, 4th assessment reports

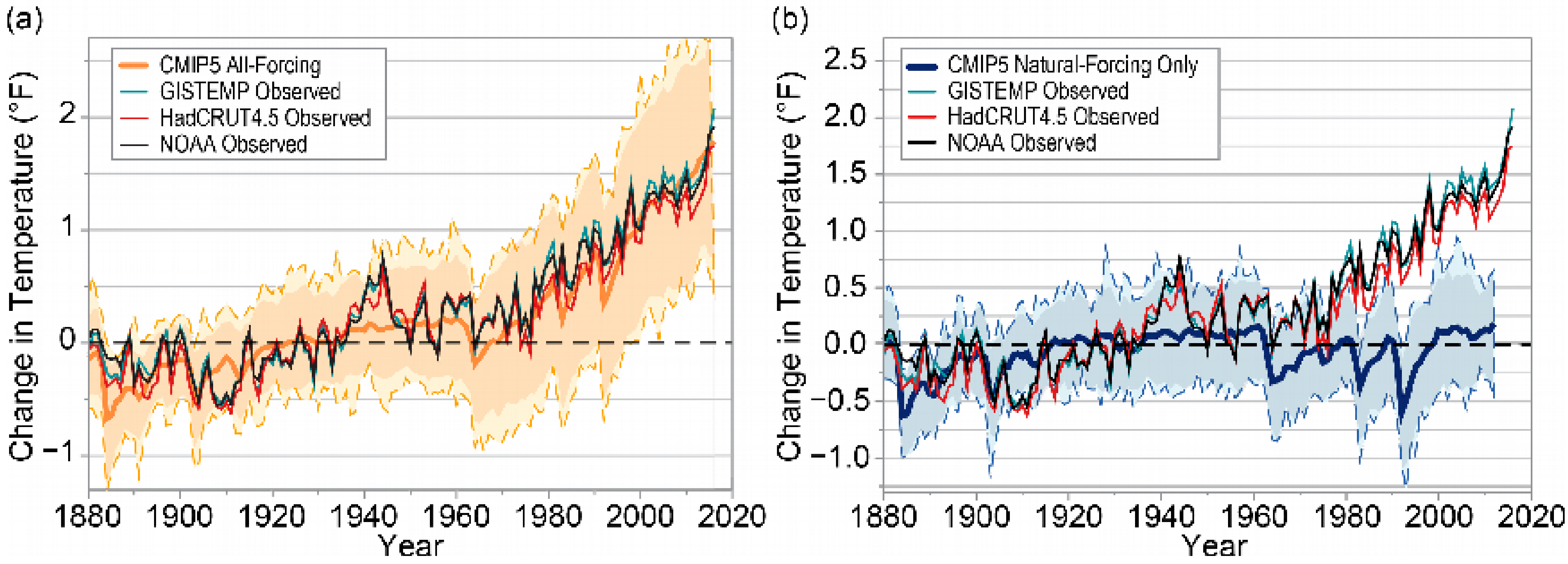
» **IPCC, 1990:** "by increasing [greenhouse gas] concentrations... **humankind is capable of** raising the global-average annual-mean surface-air temperature"

» **IPCC, 1995:** "The balance of evidence suggests a **discernible human influence** on global climate"

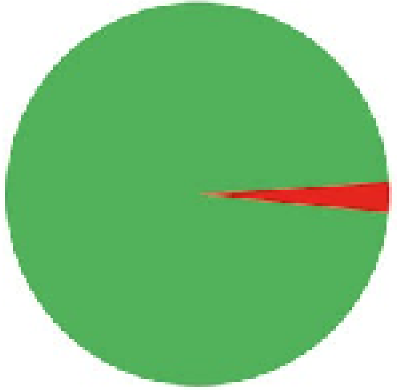
» **IPCC, 2001:** "most of the observed warming over the last 50 years **is likely to have been due to the increase in greenhouse gas concentrations**"

» **IPCC, 2007:** "Most of the observed increase in global average temperatures since the mid-20th century is **very likely due to the observed increase in anthropogenic greenhouse gas concentrations.**"

Global Mean Temperature Change

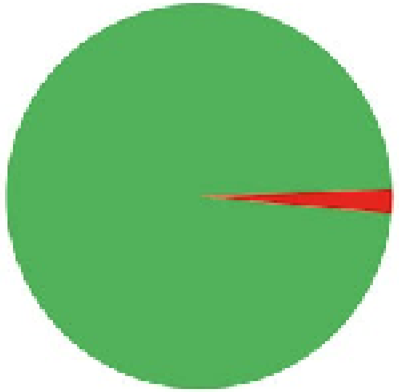


The Scientific Consensus on Climate Change



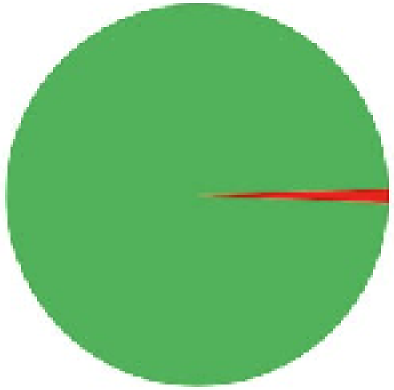
97%

Doran and
Zimmerman 2009
79 scientists



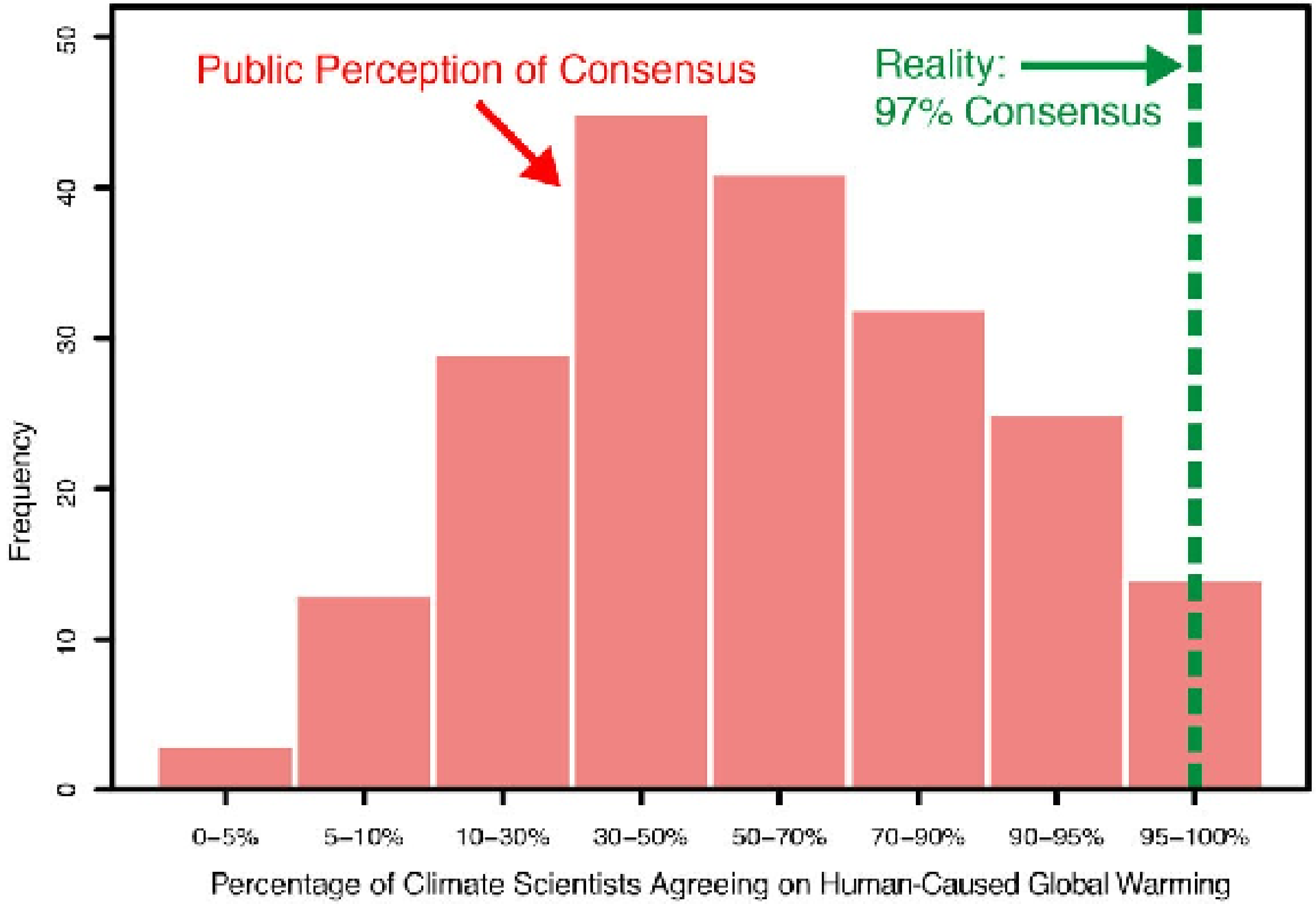
97.5%

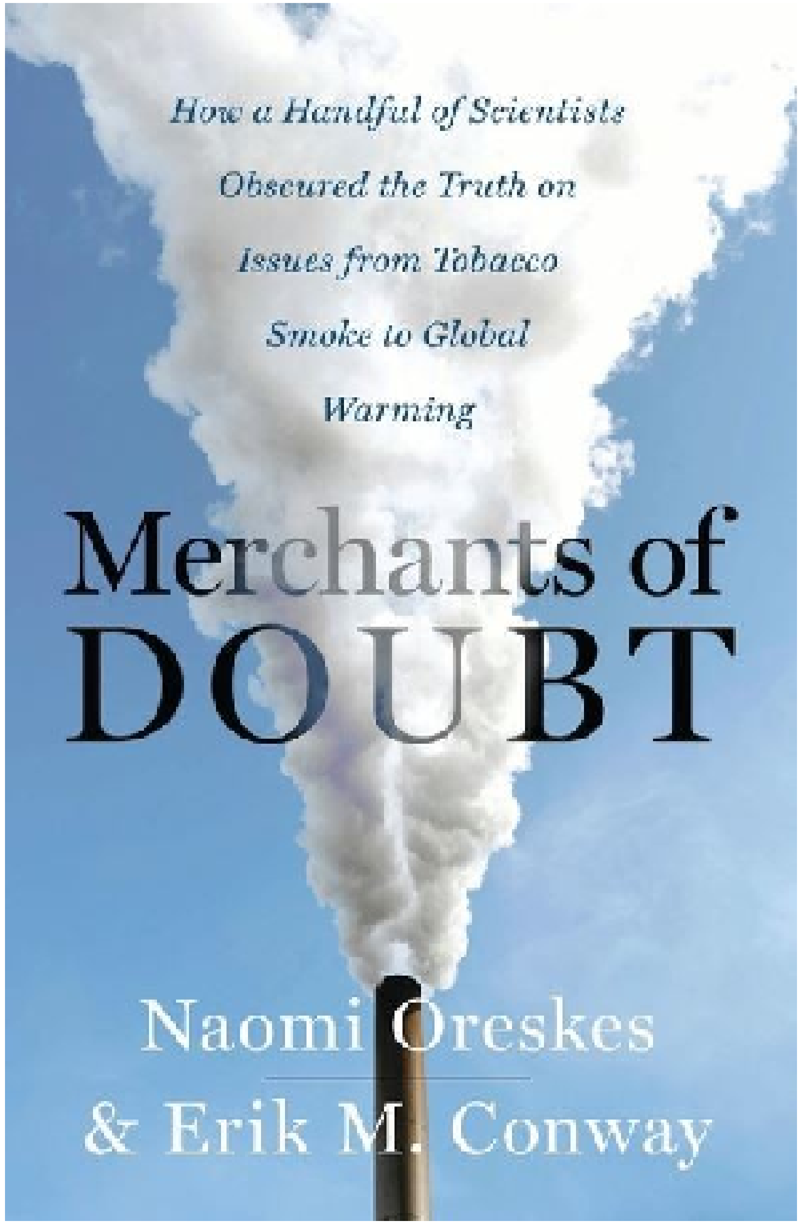
Anderegg et al 2010
908 scientists

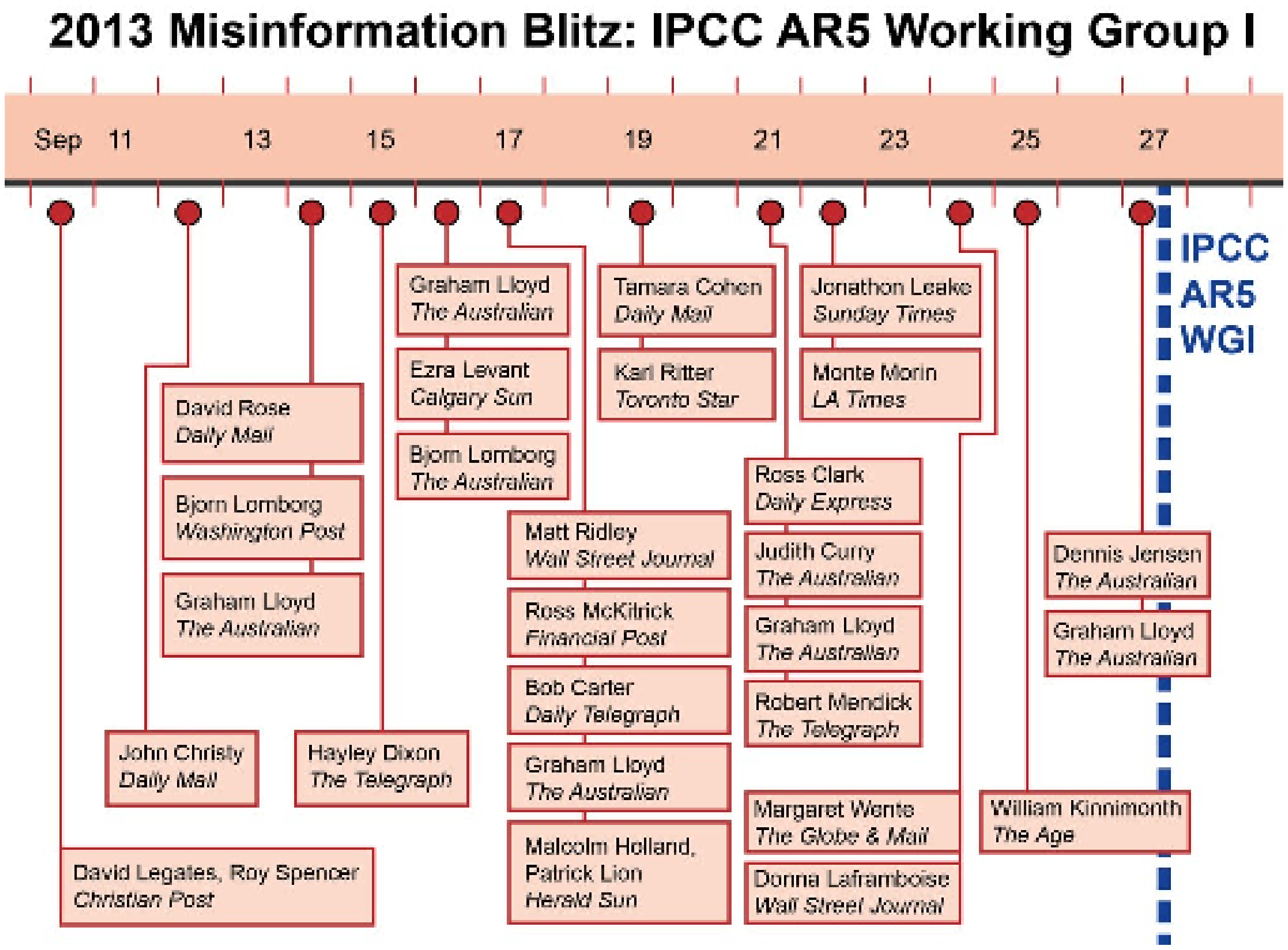


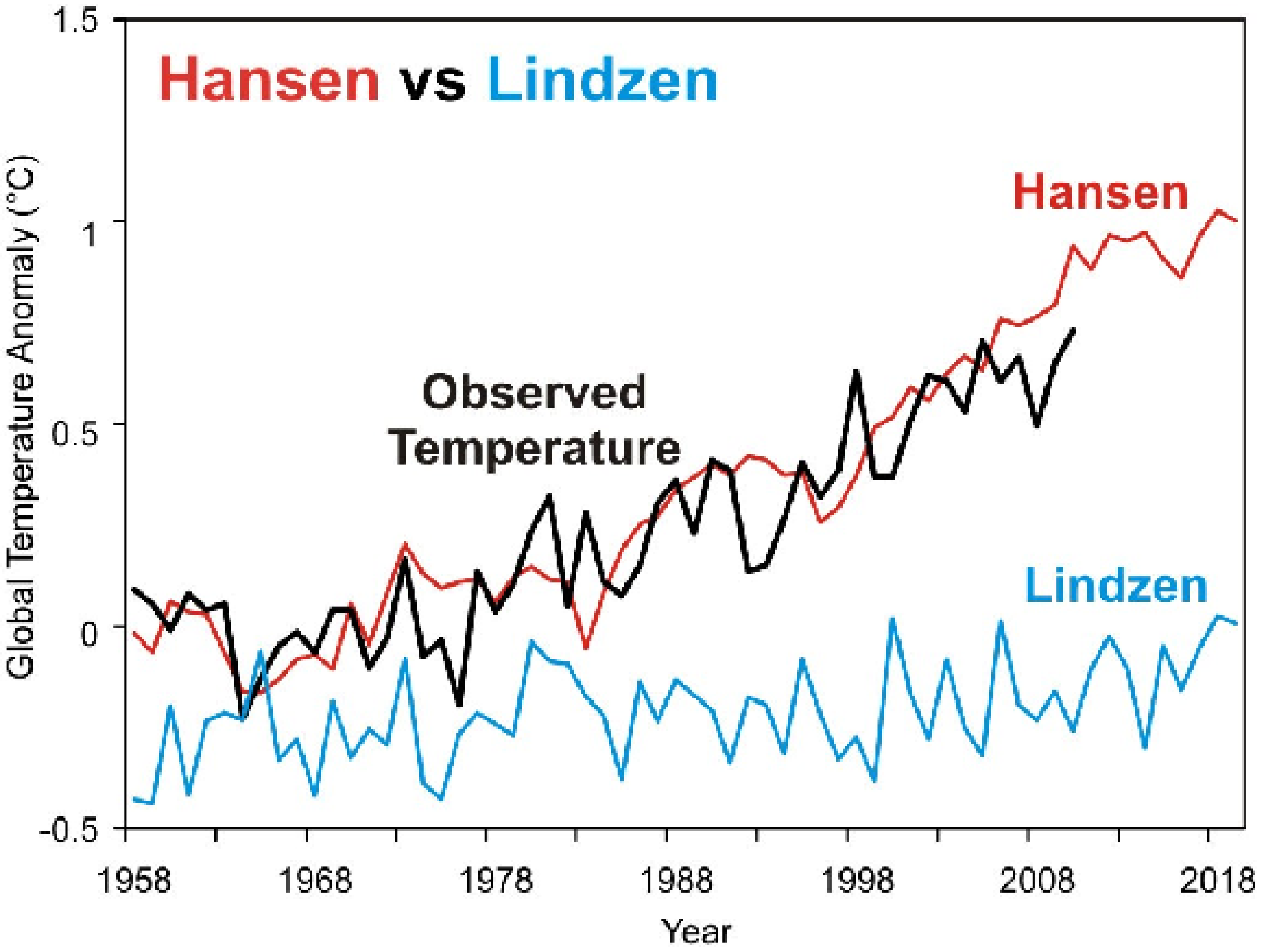
98.5%

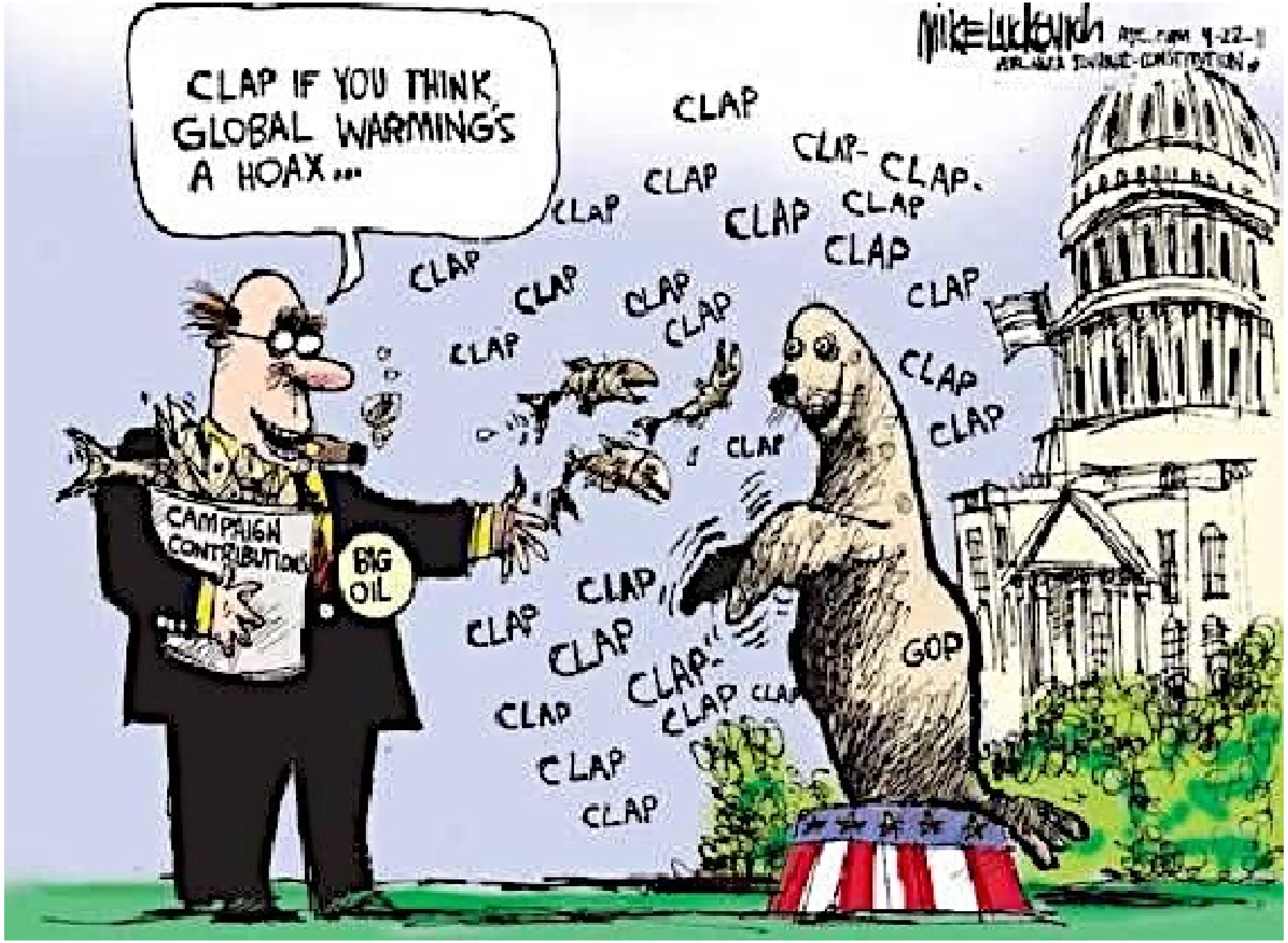
Cook et al 2013
10,306 scientists


Public Perception of Consensus
Reality:
97% Consensus
Frequency
0
10
20
30
40
50
0–5%
5–10%
10–30%
30–50%
50–70%
70–90%
90–95%
95–100%
Percentage of Climate Scientists Agreeing on Human-Caused Global Warming


How a Handful of Scientists Obscured the Truth on Issues from Tobacco Smoke to Global Warming
Merchants of DOUBT
Naomi Oreskes
& Erik M. Conway


2013 Misinformation Blitz: IPCC AR5 Working Group I
Sep 11 13 15 17 19 21 23 25 27
IPCC AR5 WGI
David Legates, Roy Spencer Christian Post
John Christy Daily Mail
David Rose Daily Mail
Bjorn Lomborg Washington Post
Graham Lloyd The Australian
Hayley Dixon The Telegraph
Graham Lloyd The Australian
Ezra Levant Calgary Sun
Bjorn Lomborg The Australian
Matt Ridley Wall Street Journal
Ross McKitrick Financial Post
Bob Carter Daily Telegraph
Graham Lloyd The Australian
Malcolm Holland, Patrick Lion Herald Sun
Tamara Cohen Daily Mail
Karl Ritter Toronto Star
Ross Clark Daily Express
Judith Curry The Australian
Graham Lloyd The Australian
Robert Mendick The Telegraph
Jonathon Leake Sunday Times
Monte Morin LA Times
Margaret Wente The Globe & Mail
Donna Laframboise Wall Street Journal
William Kininmonth The Age
Dennis Jensen The Australian
Graham Lloyd The Australian

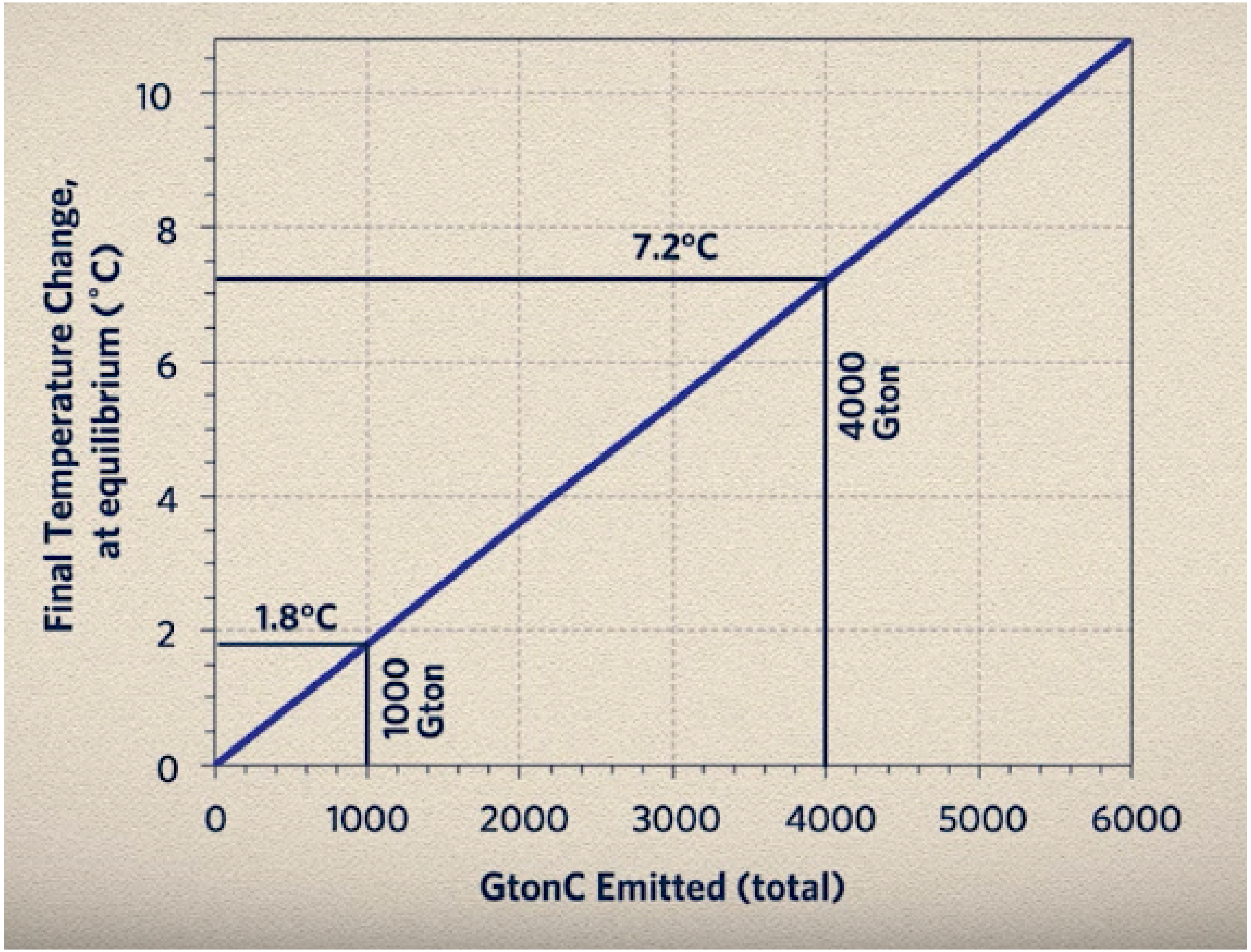

Hansen vs Lindzen
Hansen
Observed Temperature
Lindzen
Global Temperature Anomaly (°C)
1.5
1
0.5
0
-0.5
1958
1968
1978
1988
1998
2008
2018
Year

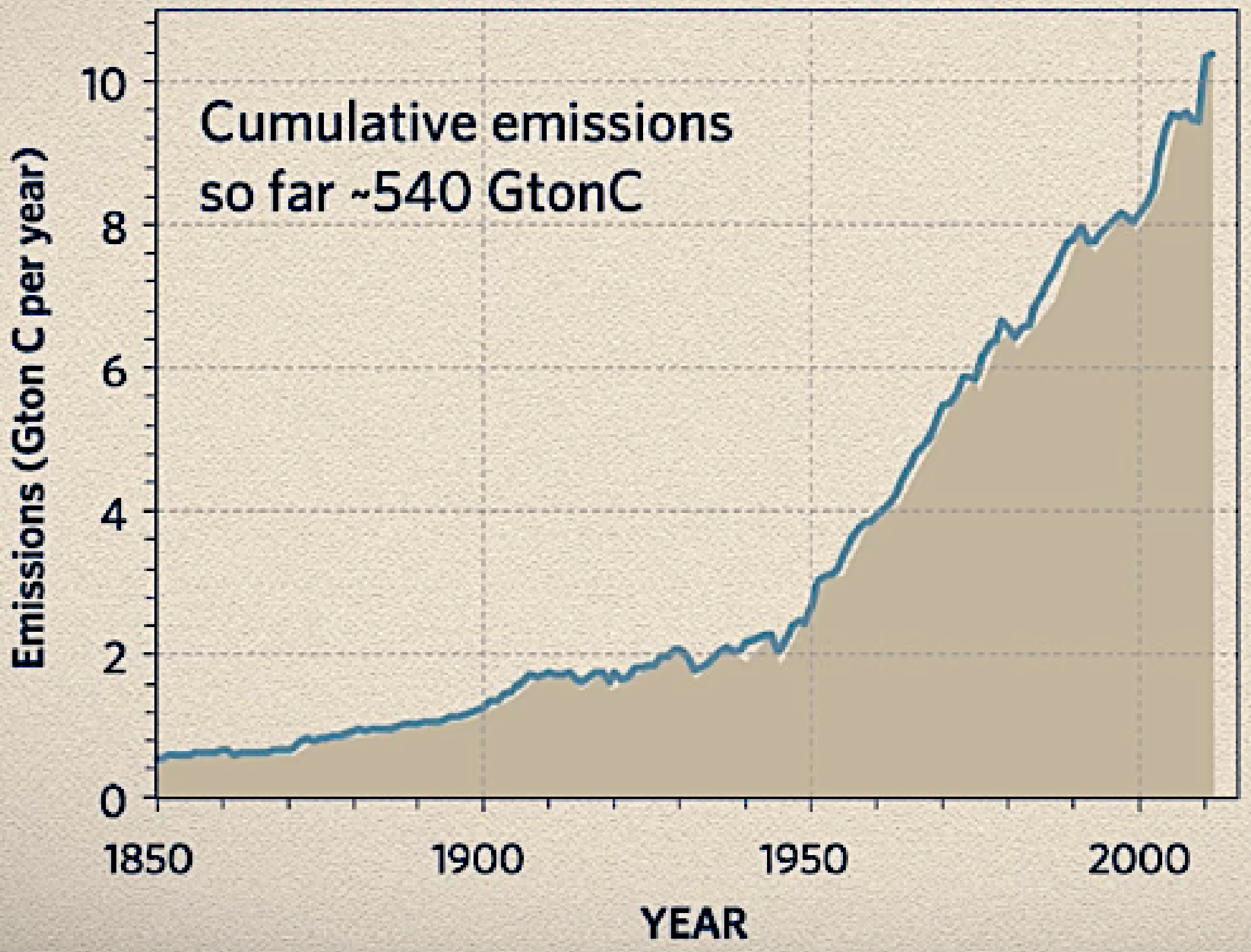

CLAP IF YOU THINK GLOBAL WARMING'S A HOAX...
CAMPAIGN CONTRIBUTIONS
BIG OIL
GOP

Cagle.com

WHEN

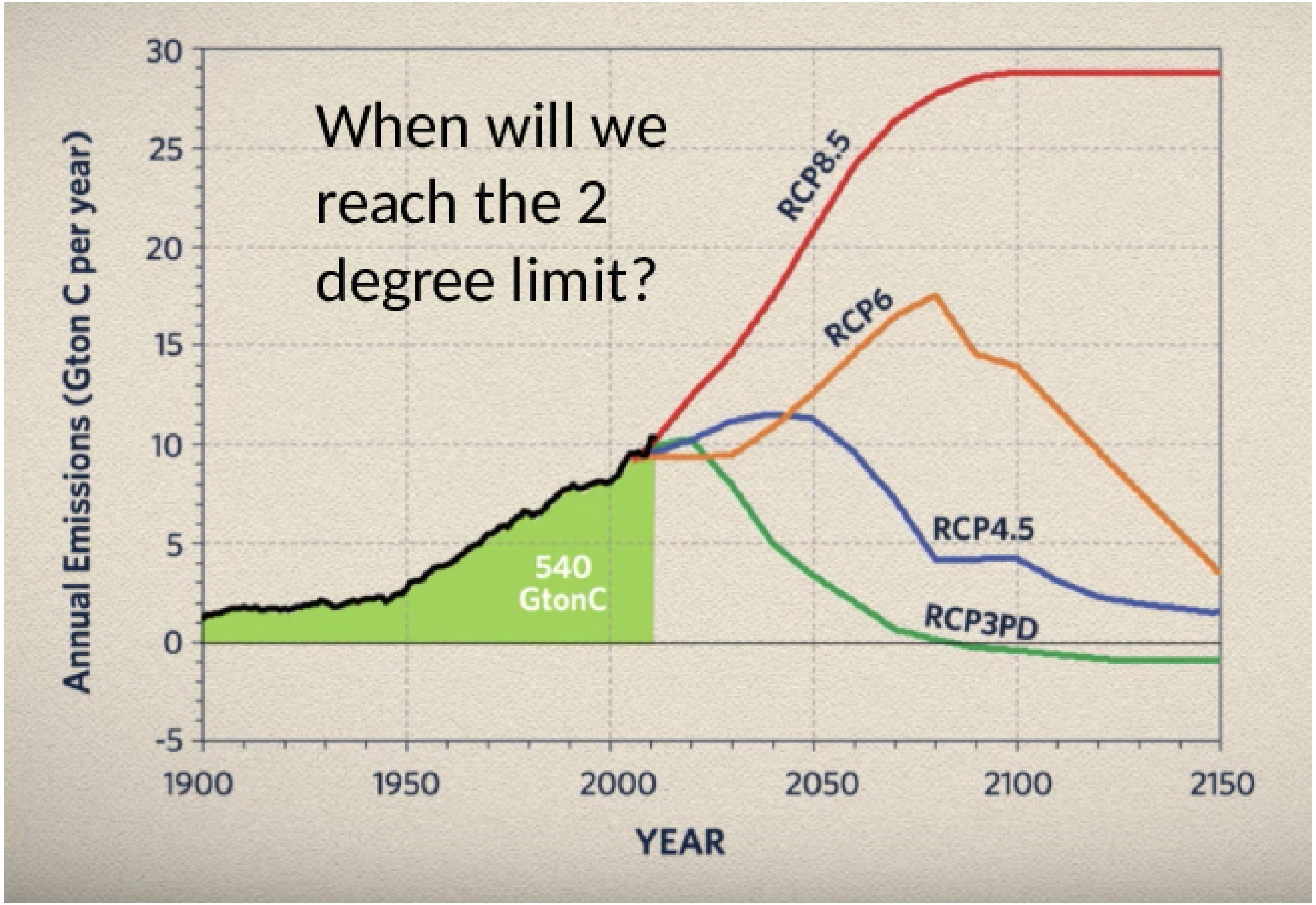
Relationship between CO2 and temperature

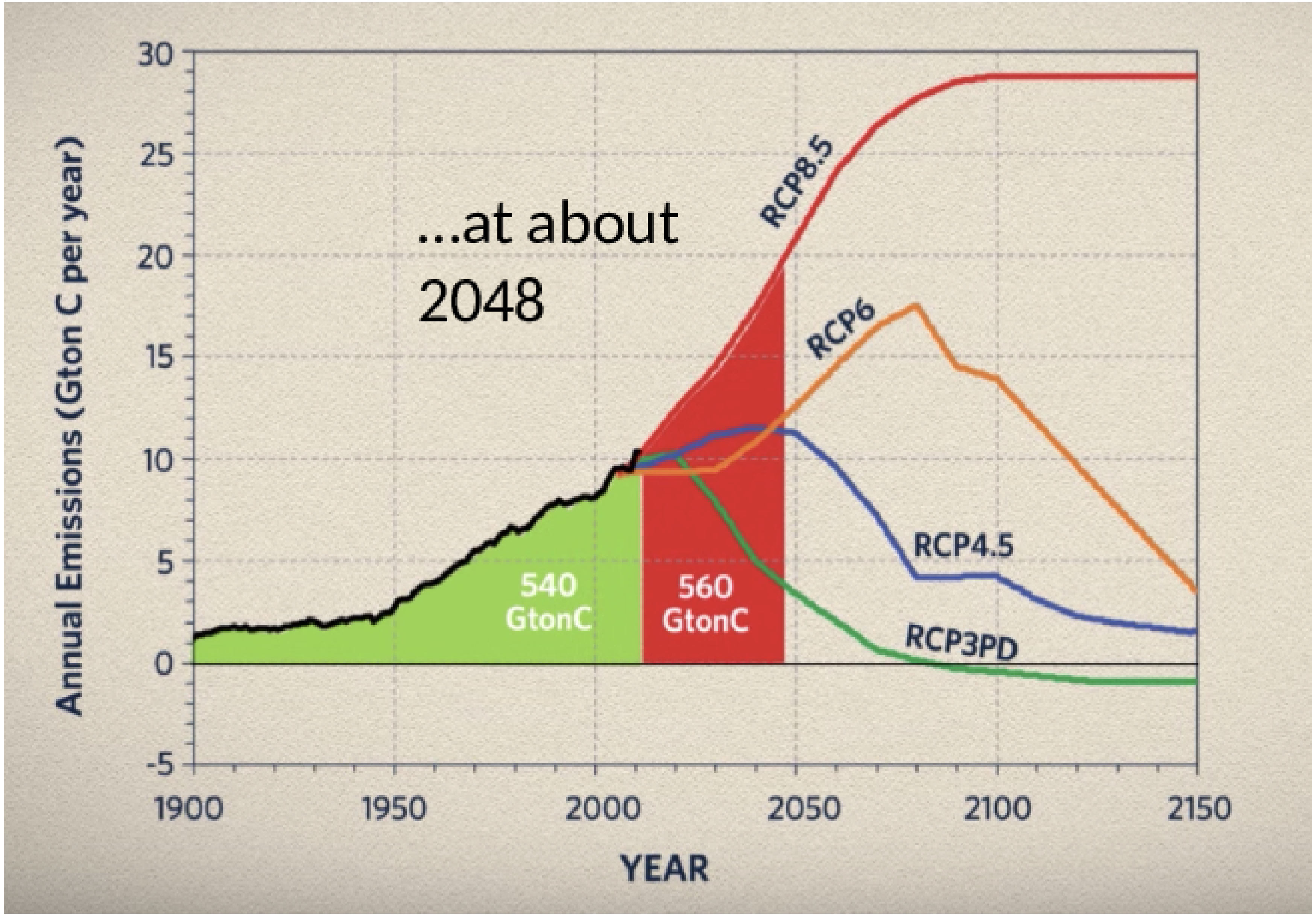


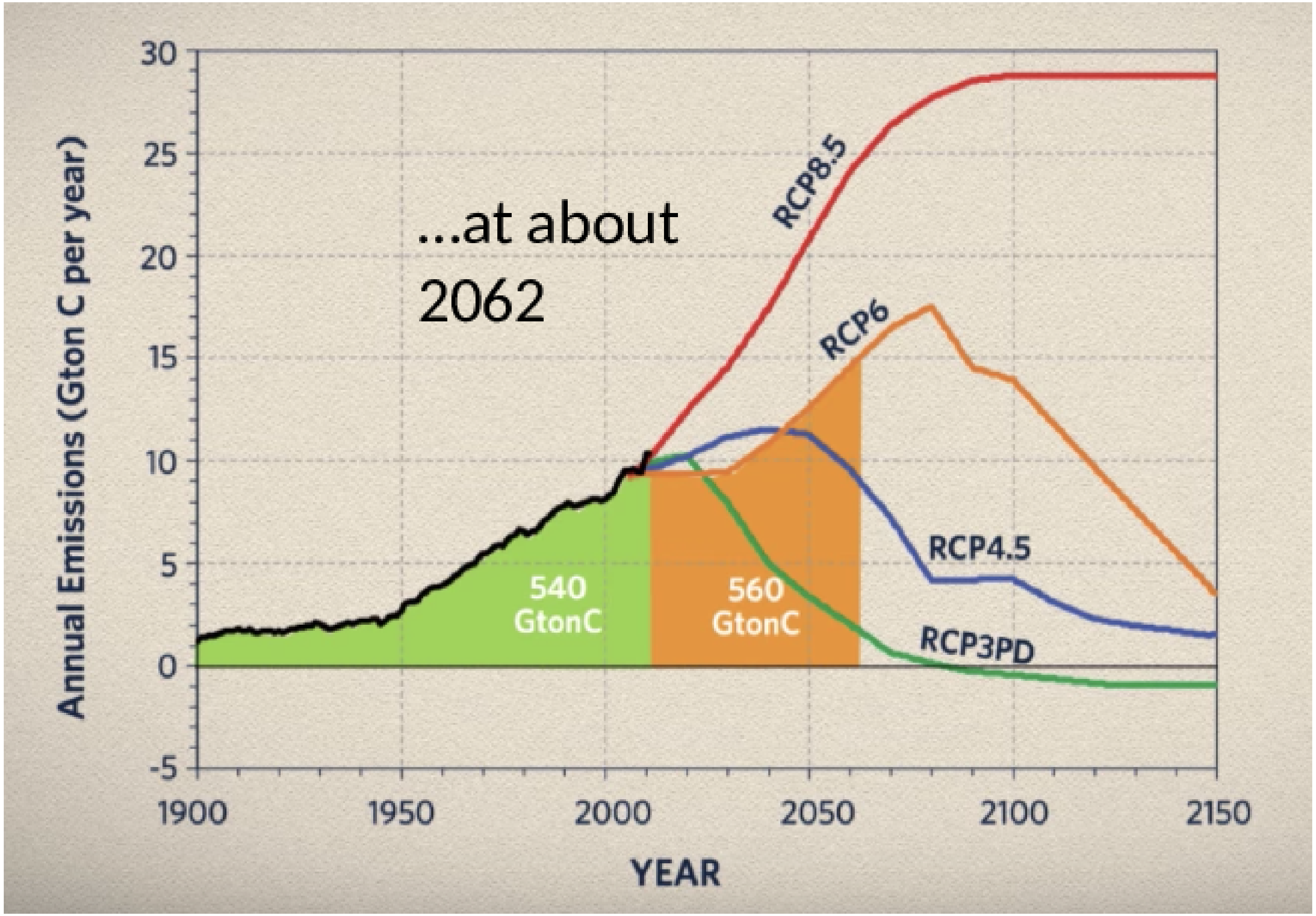


About 1100 GtonC gets us about 2°C

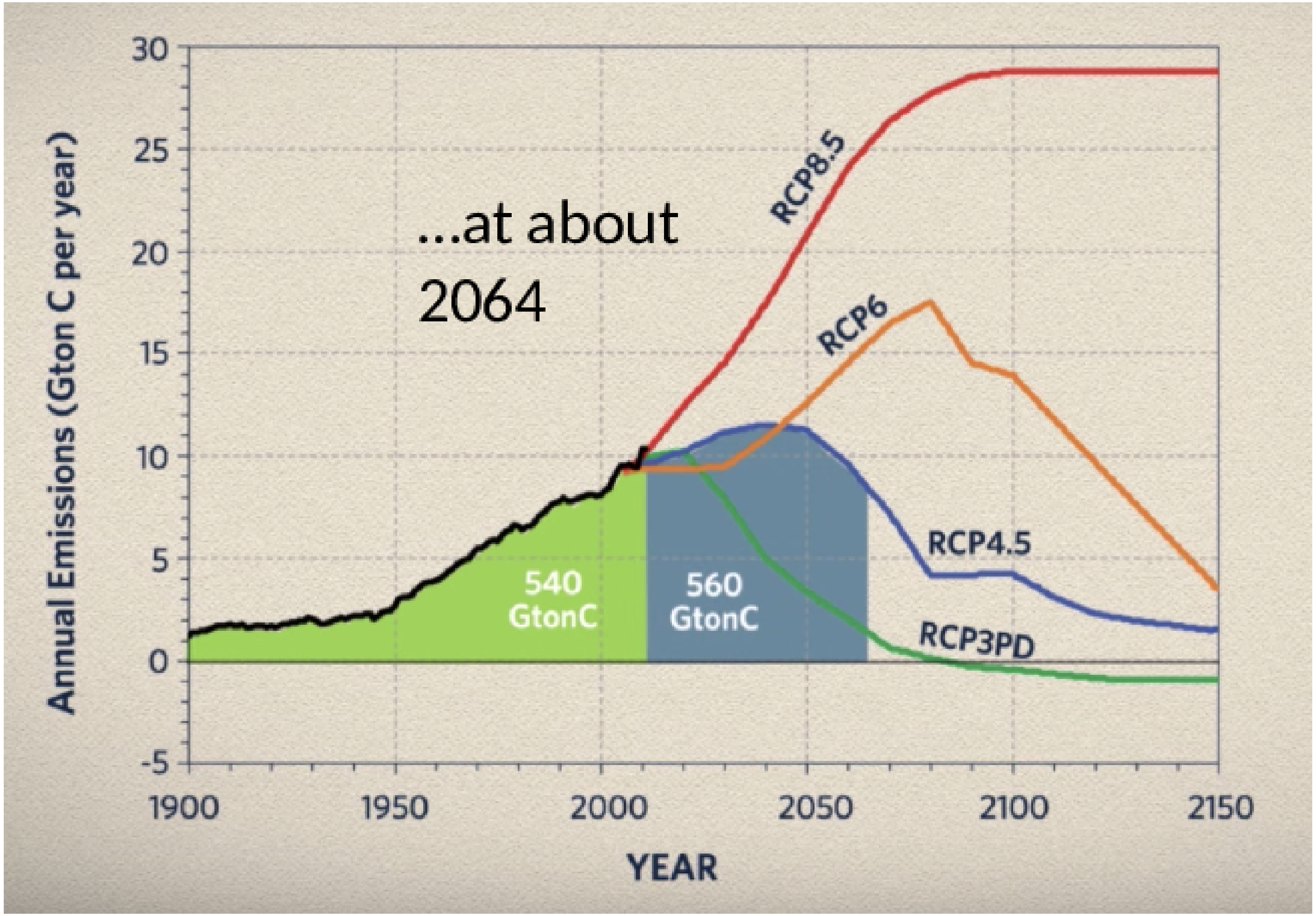
Representative concentration pathways (RCPs)



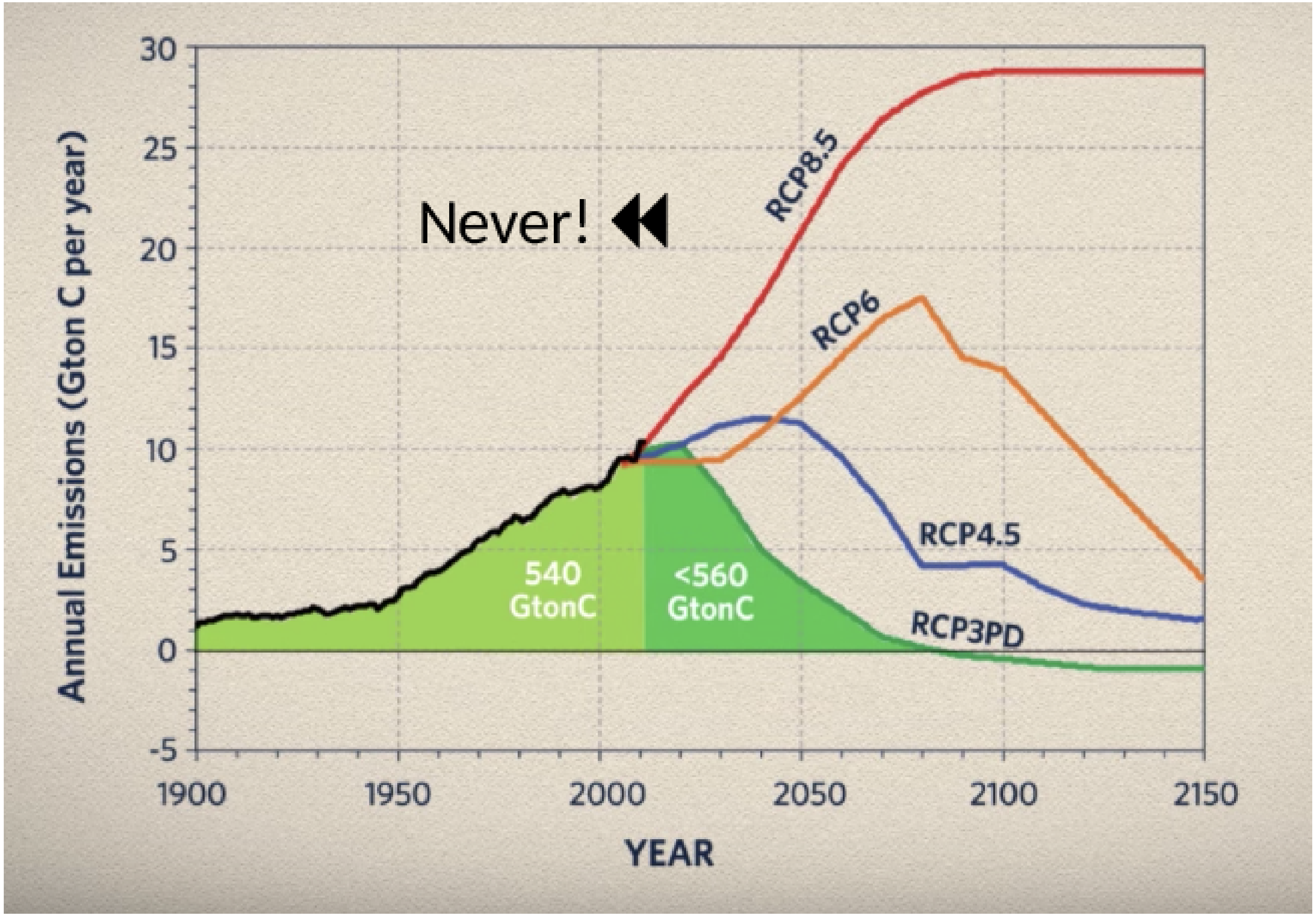

...at about
2048
Annual Emissions (Gton C per year)
30
25
20
15
10
5
0
-5
1900
1950
2000
2050
2100
2150
YEAR
RCP8.5
RCP6
RCP4.5
RCP3PD
540
GtonC
560
GtonC



...at about
2062
RCP8.5
RCP6
RCP4.5
RCP3PD
540
GtonC
560
GtonC
Annual Emissions (Gton C per year)
YEAR
30
25
20
15
10
5
0
-5
1900
1950
2000
2050
2100
2150



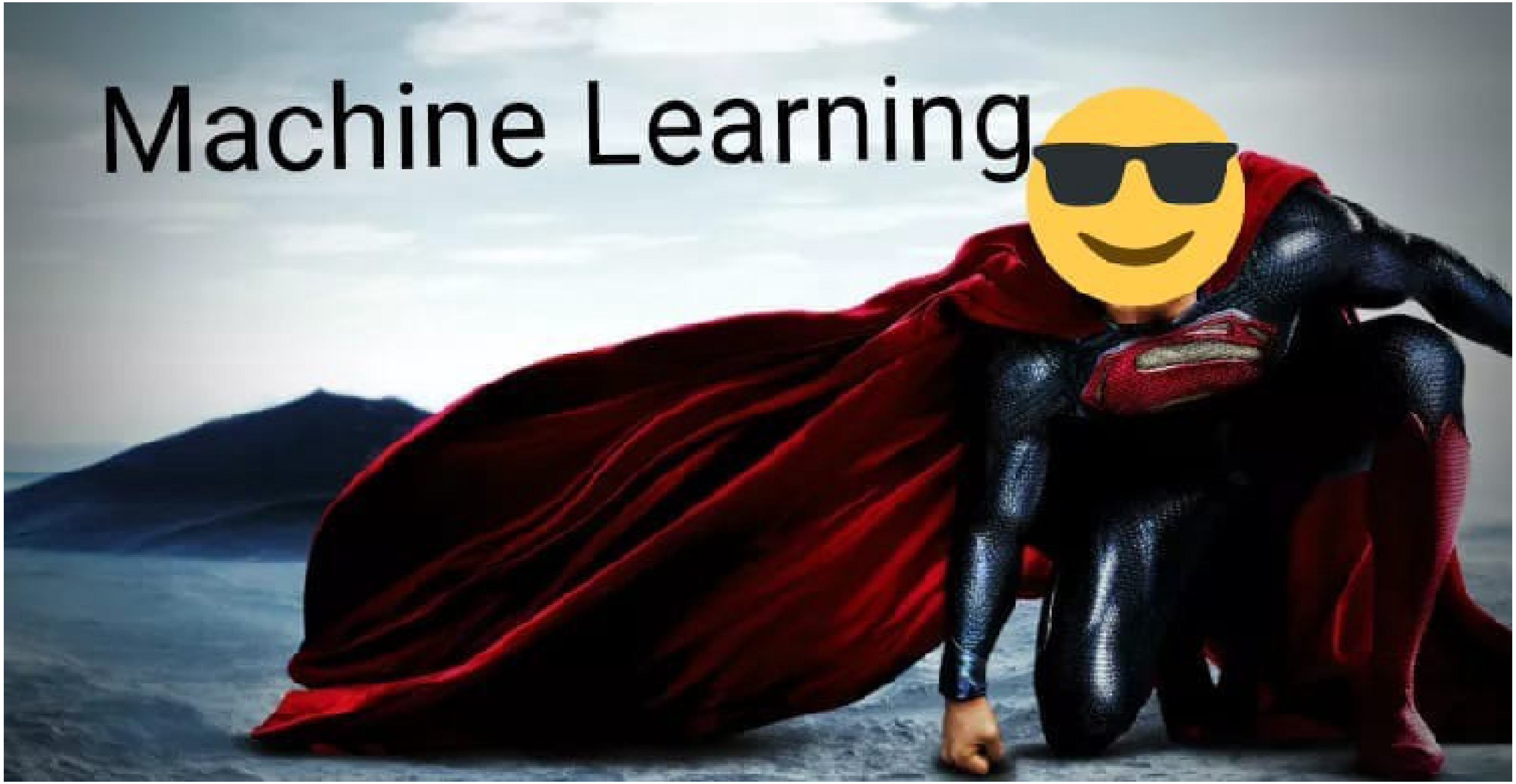
...at about
2064
RCP8.5
RCP6
RCP4.5
RCP3PD
540
GtonC
560
GtonC
Annual Emissions (Gton C per year)
YEAR
30
25
20
15
10
5
0
-5
1900
1950
2000
2050
2100
2150

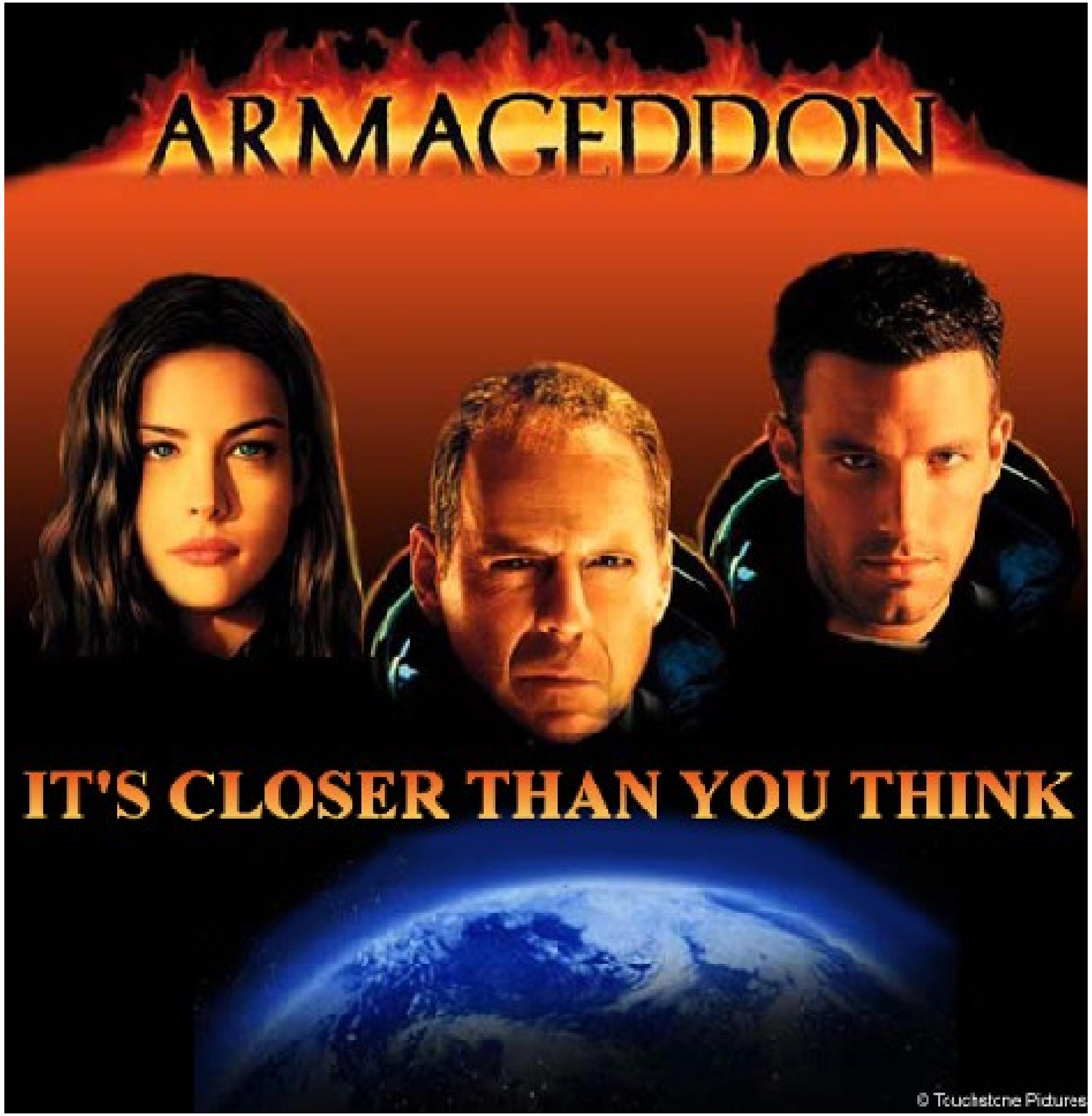


Never!
Annual Emissions (Gton C per year)
30
25
20
15
10
5
0
-5
1900
1950
2000
2050
2100
2150
YEAR
RCP8.5
RCP6
RCP4.5
RCP3PD
540
GtonC
<560
GtonC

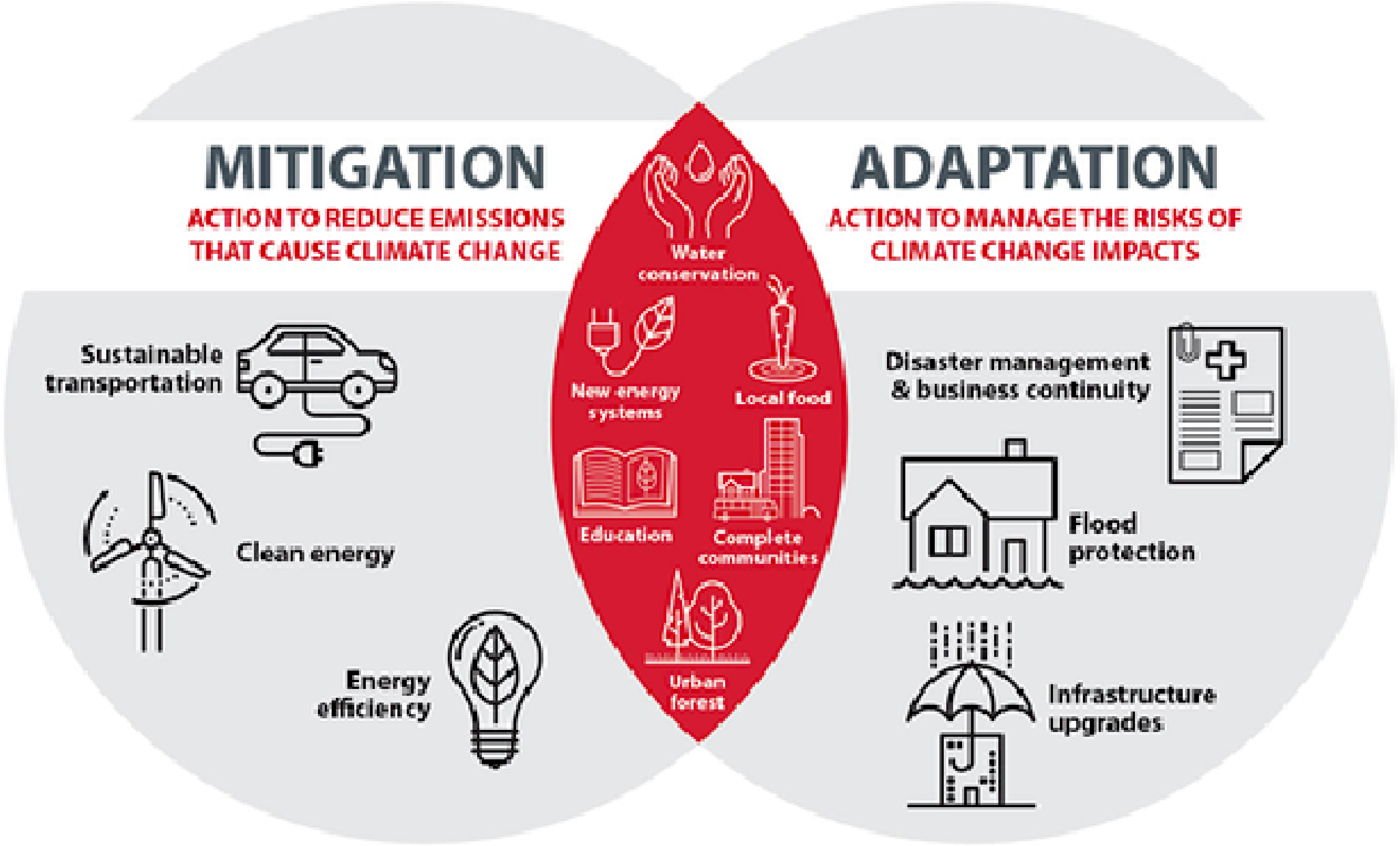
WHAT

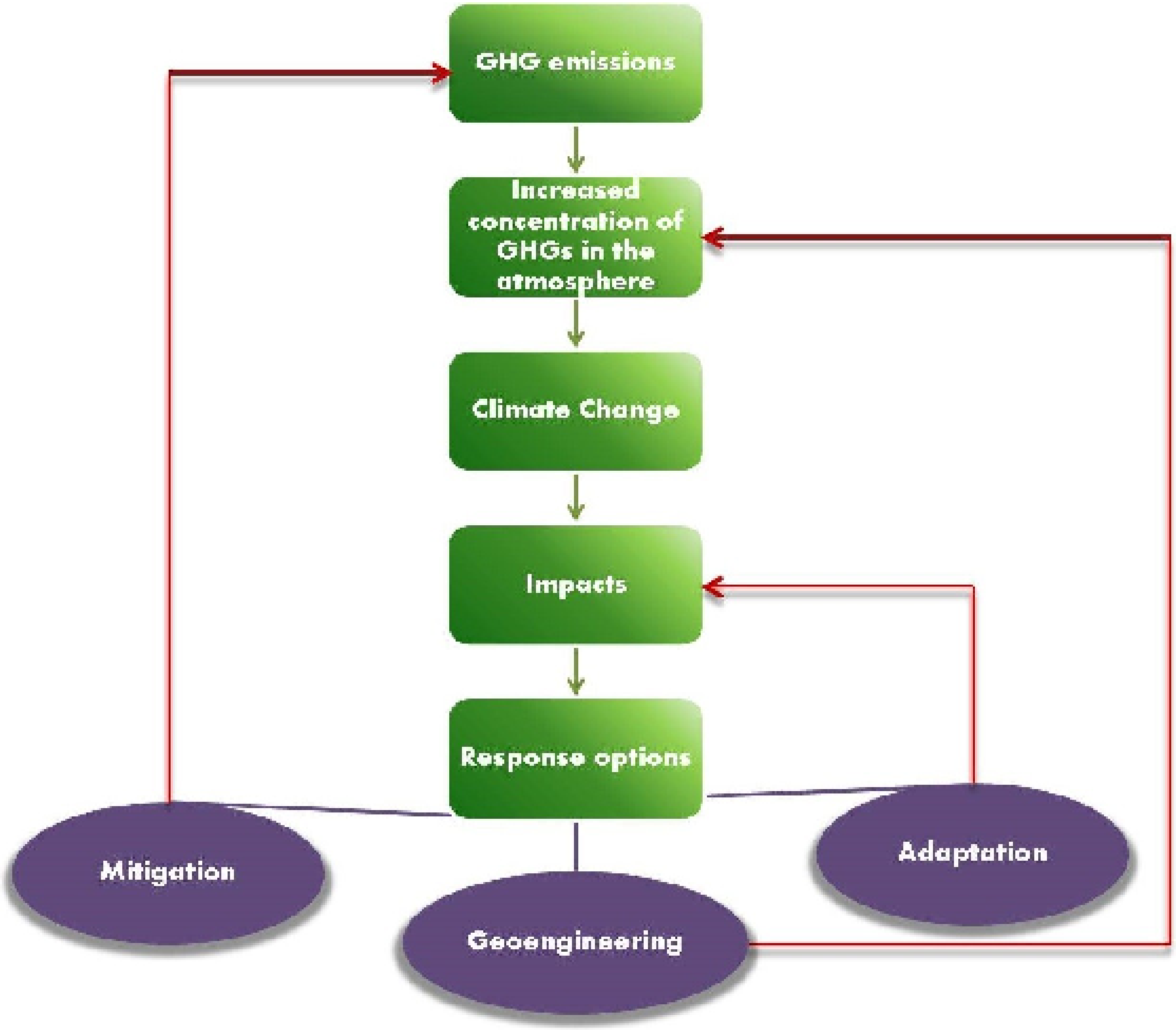
Save the planet




ARMAGEDDON
IT'S CLOSER THAN YOU THINK
© Touchstone Pictures

Building Climate Resilience




GHG emissions
Increased concentration of GHGs in the atmosphere
Climate Change
Impacts
Response options
Mitigation
Geoengineering
Adaptation

Tackling Climate Change with Machine Learning

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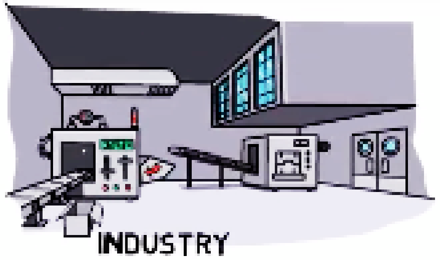
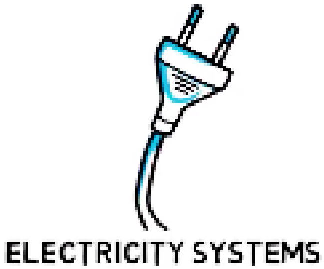
Abstract

Climate change is one of the greatest challenges facing humanity, and we, as machine learning experts, may wonder how we can help. Here we describe how machine learning can be a powerful tool in reducing greenhouse gas emissions and helping society adapt to a changing climate. From smart grids to disaster management, we identify high impact problems where existing gaps can be filled by machine learning, in collaboration with other fields. Our recommendations encompass exciting research questions as well as promising business opportunities. We call on the machine learning community to join the global effort against climate change.

- Reducing waste in supply chains
- Reduce material via
- new constructions
- Reduce factory energy consumption



How ML can help



- Forecasting power generation and demand
- Accelerating material science
- Advancing research of nuclear fusion

- Enhance precision agriculture
- Tracking deforestation
- Automated afforestation
- Fire management

- Understand transportation patterns and optimise routing
- Electric autonomous vehicles
- Model demand

- Model energy consumption
- Low-emission infrastructure
- Smart buildings

	Computer vision	NLP	Time-series analysis	Unsupervised learning	RL & Control	Causal inference	Uncertainty quantification	Transfer learning	Interpretable ML	Other
Electricity Systems	1	1.1	1.1 1.2	1	1.1		1.1 1.2	1.3	1.1	1.1
Transportation	2.1 2.2 2.4		2	2.1 2.4	2	2.1 2.4	2	2.1 2.4	2	
Buildings & Cities	3.2	3.3	3	3	3.1	3.1	3.3	3		
Industry	4.1 4.3		4.3	4.3	4	4.2 4.3		4.2 4.3	4.3	
Farms & Forests	5.1 5.3 5.4				5.2			5.4		
CO_2 Removal			6.3				6.3	6.3		6.2
Climate Prediction	7.1		7				7.3		7	
Societal Impacts	8.1 8.4	8.4	8.2 8.3		8.2	8.3	8.2	8.1	8.3	
Solar Geoengineering			9.3		9.4		9.3 9.4			9.2
Tools for Individuals	10.1	10.1	10.2	10.3	10.2	10.1			10.2	10.2
Tools for Society		11.1	11.2 11.1	11.3	11.2 11.1	11.1 11.3	11.1	11	11.1	11.1 11.3
Education		12.2			12.1					
Finance		13.2	13				13.2			

Table 1: Climate change solution domains, along with areas of ML that are relevant to each. Rows of the table correspond to sections of this paper. This table should not be seen as comprehensive.

- ***High Leverage*** denotes bottlenecks that domain experts have identified in climate change mitigation or adaptation and that we believe to be particularly well-suited to tools from ML. These solutions may be especially fruitful for ML practitioners wishing to have an outsized impact, though applications not marked with this flag are also valuable and should be pursued.
- ***Long-term*** denotes solutions that will have their primary impact after 2040. Such solutions are neither more nor less important than short-term solutions – both are necessary.
- ***High Risk*** denotes solutions that are risky in one of the following ways: (i) the technology involved is uncertain and may ultimately not succeed, (ii) there is uncertainty as to the impact on GHG emissions (for example, the Jevons paradox may apply[4]), or (iii) there is the potential for unwanted side effects (negative externalities).

- **Learn.** Identify how your skills may be useful – we hope this paper provides a starting point.
- **Collaborate.** Find collaborators, who may be researchers, entrepreneurs, established companies, or policy-makers. Remember that for every domain we have discussed here, there are experts in that area who understand its opportunities and pitfalls, even if they do not necessarily understand ML.
- **Listen.** Listen to what your collaborators say is needed, and gather input more broadly as well to make sure your work will have the desired impact. Groundbreaking technologies have an impact, but so do well-constructed solutions to mundane problems.
- **Deploy.** Ensure that your work is deployed where its impact can be realized.

Example

Andrew Ng talk at ICML workshop on ML for CC

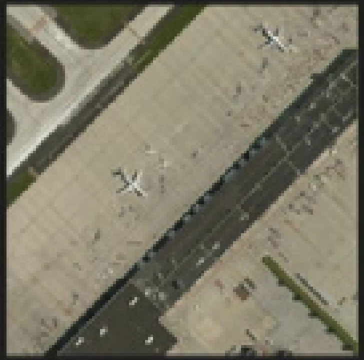

QUE.
ONT.
WASH.
MONT.
MINN.
N.B.
Ottawa
S.D.
WIS.
MICH.
IDAHO
Toronto
VT.
MASS.
OHIO
N.J.
MD.
MO.
KY.
VA.
TENN.
N.C.
ARK.
S.C.
ALA.
GA.
LA.
FLA.
Gulf of
Mexico
Miami
Monterrey
CUBA
Mexico

Mitigation Wind Turbine Detection

S3L & Stanford ML Group

Data:

- Train model on 100K images
  - ~50K USGS positives
- Run detection on 1.8M images

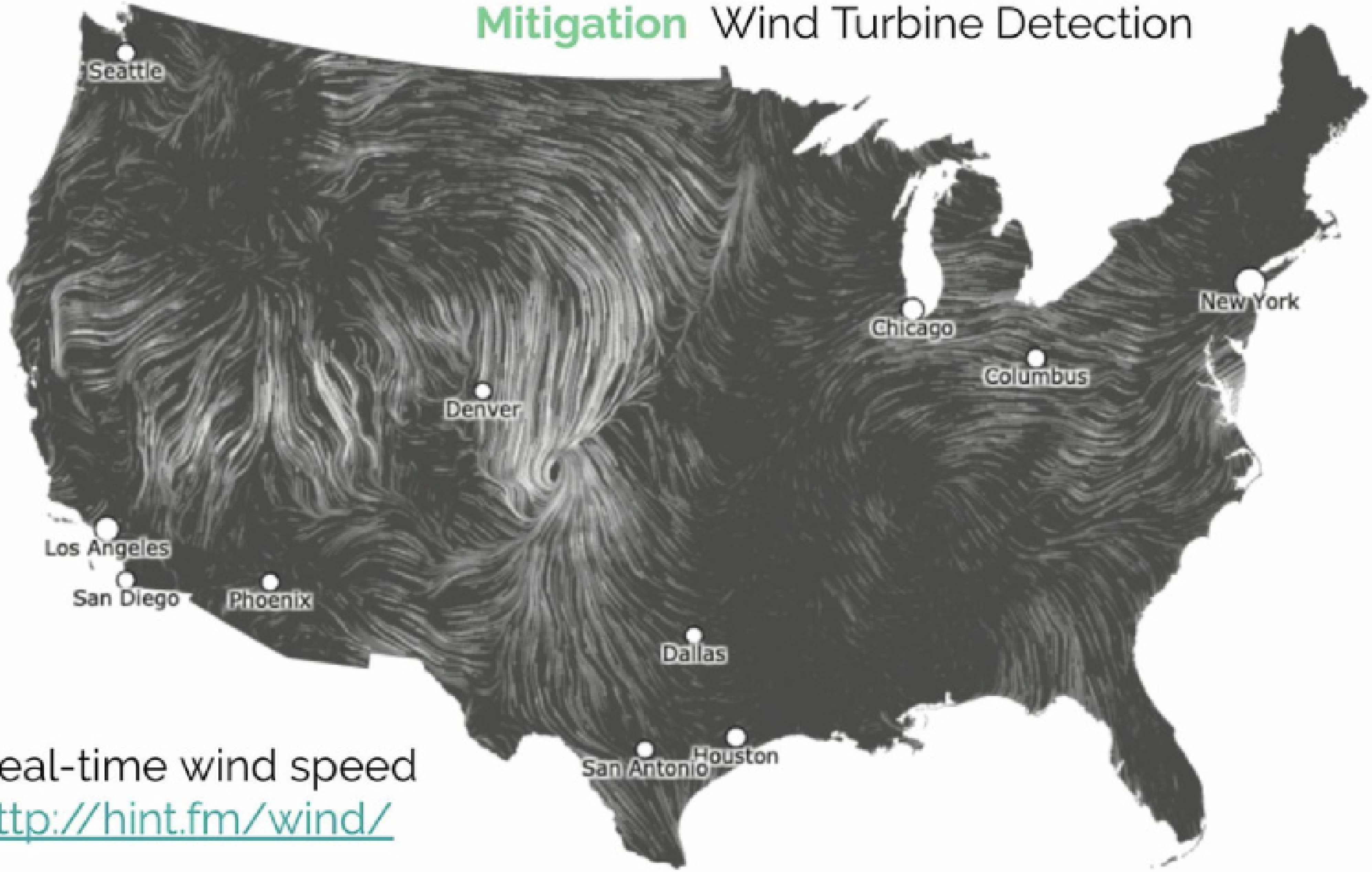




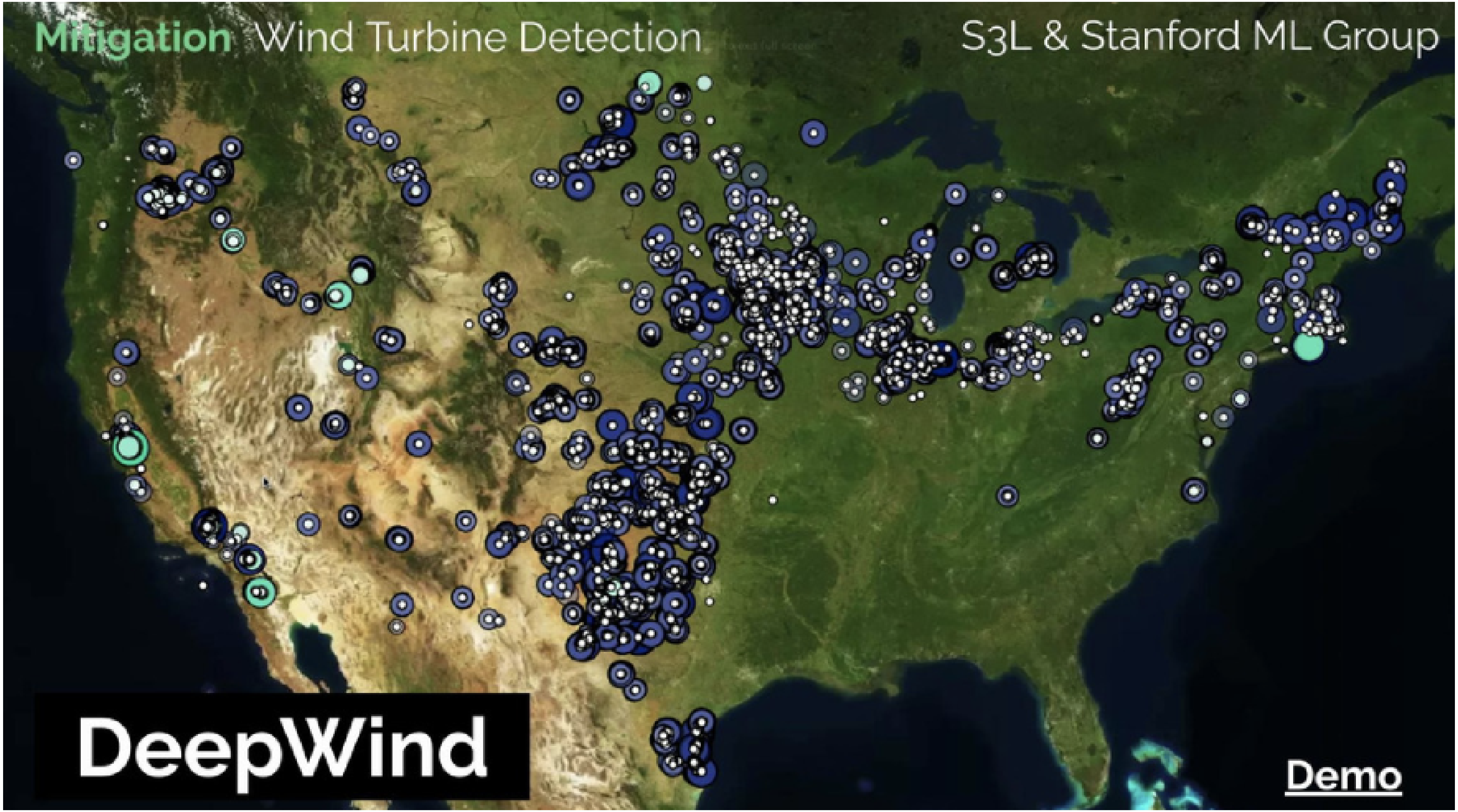
Baseline Model:
DenseNet-121

Weakly Supervised Localization: GradCAM

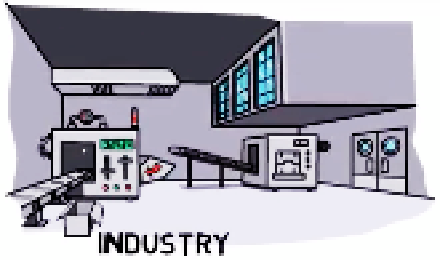
Mitigation Wind Turbine Detection



Real-time wind speed
http://hint.fm/wind/


Mitigation Wind Turbine Detection
S3L & Stanford ML Group
DeepWind
Demo

How ML can help



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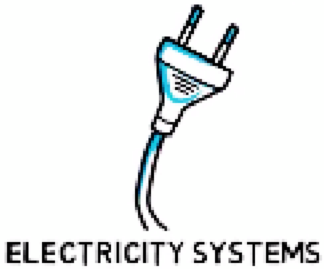

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Remember to be conscious of our own impact

Consumption	CO_2e (lbs)
Air travel, 1 passenger, NY↔SF	1984
Human life, avg, 1 year	11,023
American life, avg, 1 year	36,156
Car, avg incl. fuel, 1 lifetime	126,000
Training one model (GPU)	
NLP pipeline (parsing, SRL)	39
w/ tuning & experimentation	78,468
Transformer (big)	192
w/ neural architecture search	626,155

Strubel et al., *Energy and Policy Considerations for Deep Learning in NLP* (2019)

WHY

Large scale risk to our and other species' survival.

HOW

We (humans) did this.

WHEN

Now.

WHAT

Help with mitigation and adaptation.

At least get a Spekboom! ⏪

Hectare for hectare **ten times more effective than the Amazon rainforest** at removing carbon dioxide from the atmosphere and they **live up to 200 years.**

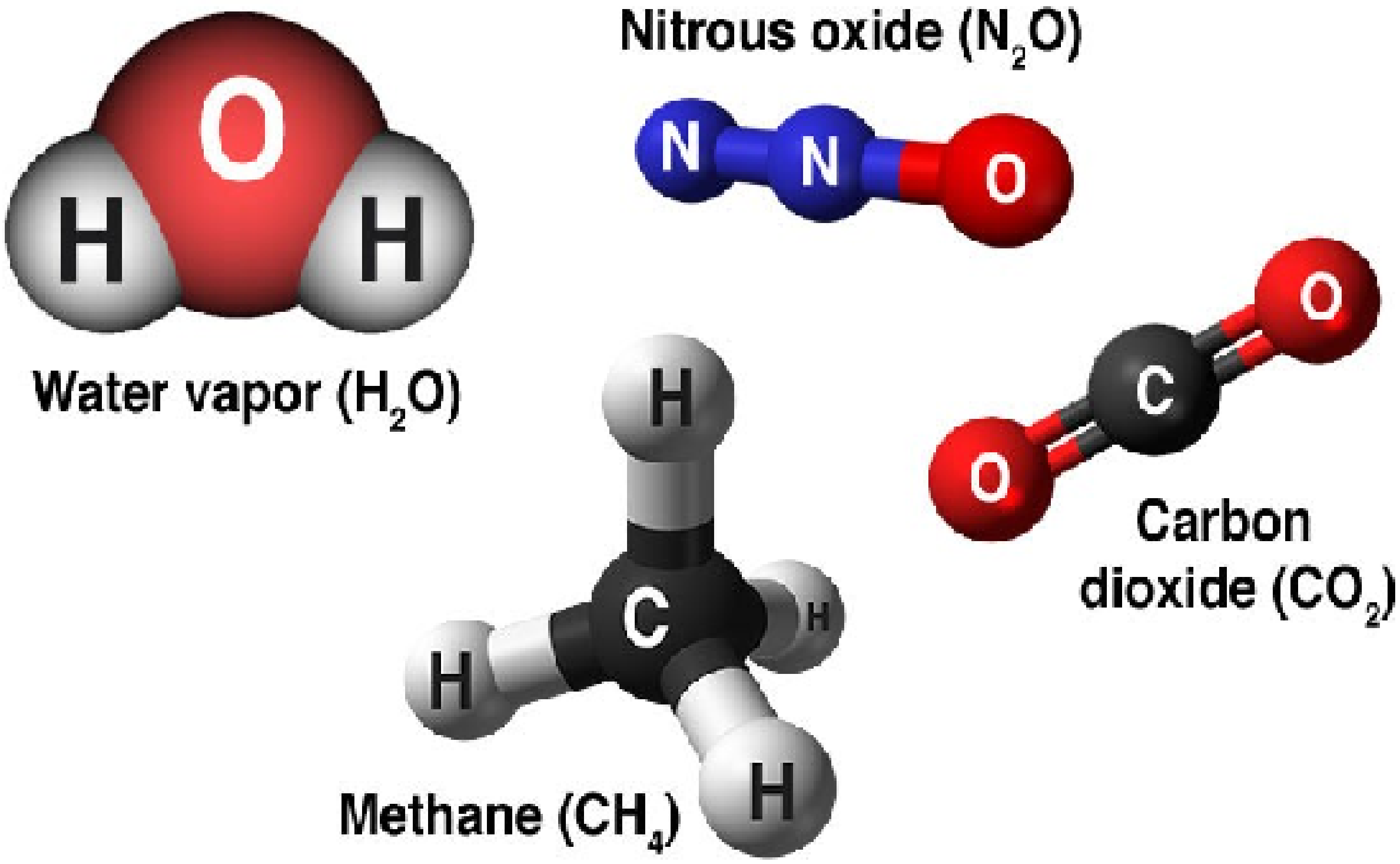
PROUDLY SOUTH AFRICAN

Thank you!

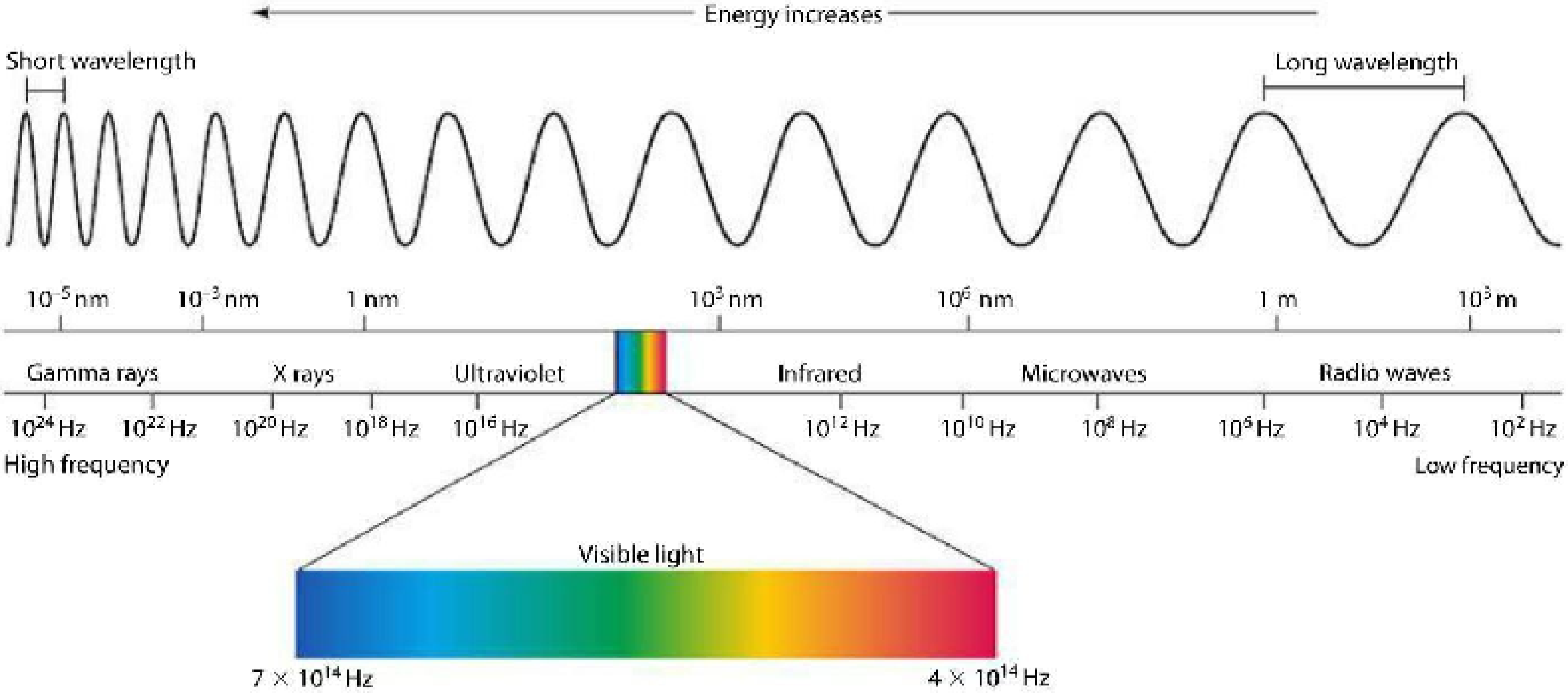
References and Resources

- Climate Change AI: https://www.climatechange.ai/
- Skeptical Science: https://skepticalscience.com/
- IPCC: https://www.ipcc.ch/
- Climate Literacy: https://www.youtube.com/user/climateliteracy
- NASA Global Climate Change: https://climate.nasa.gov/
- A Guide to CC by Neil Kakkar: https://neilkakkar.com/climate-change.html
- Codecentric blog by Paul Strobel: https://blog.codecentric.de/en/2019/09/how-to-tackle-climate-change-with-machine-learning-electricity-systems/#post-69396

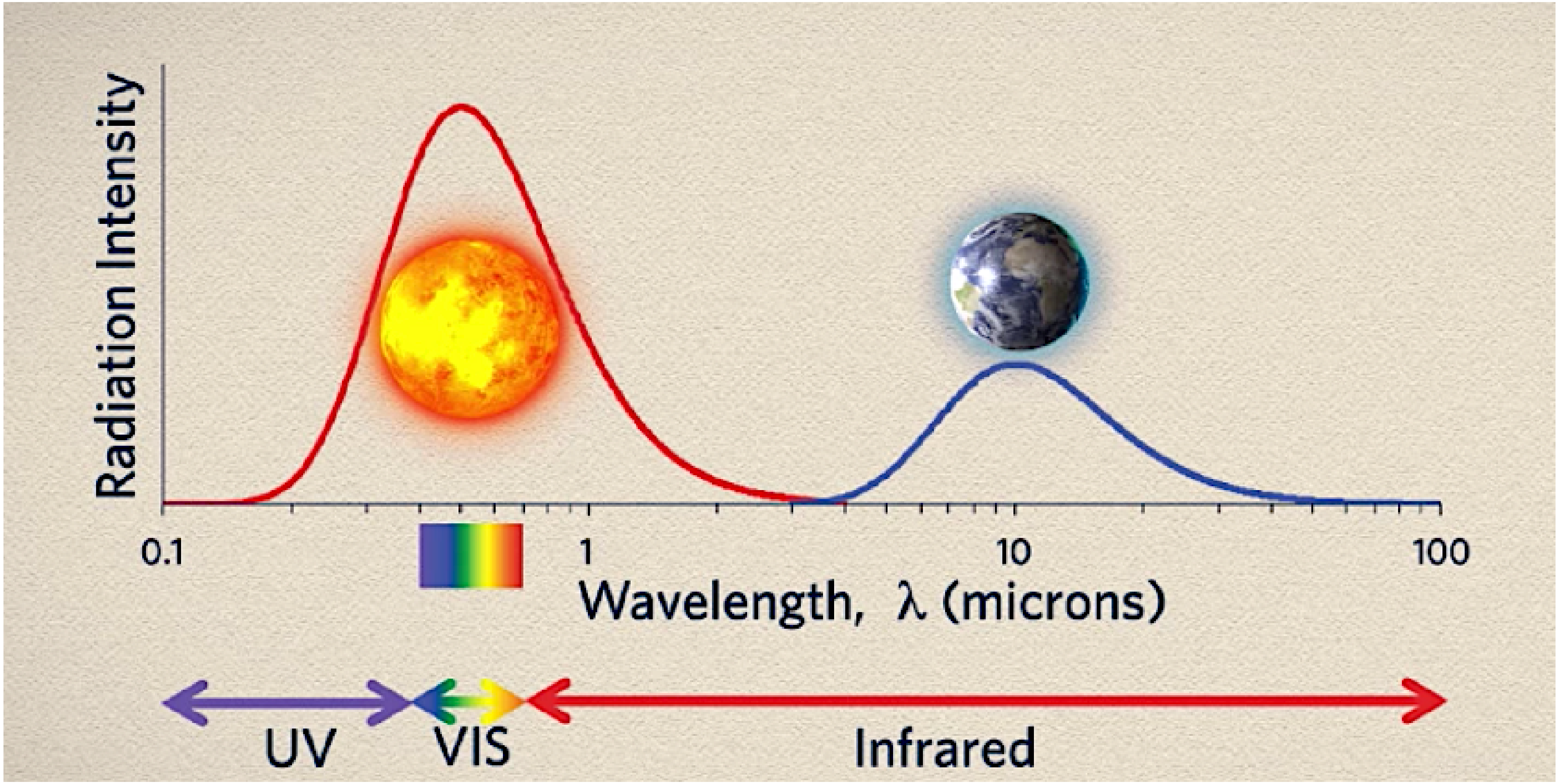
- “We do not inherit the earth from our ancestors. We borrow it from our children.” – Native American Proverb
- “If you really think that the environment is less important than the economy, try holding your breath while you count your money.” — Guy McPherson
- “The general population doesn’t know what’s happening, and it doesn’t even know that it doesn’t know.” – Noam Chomsky

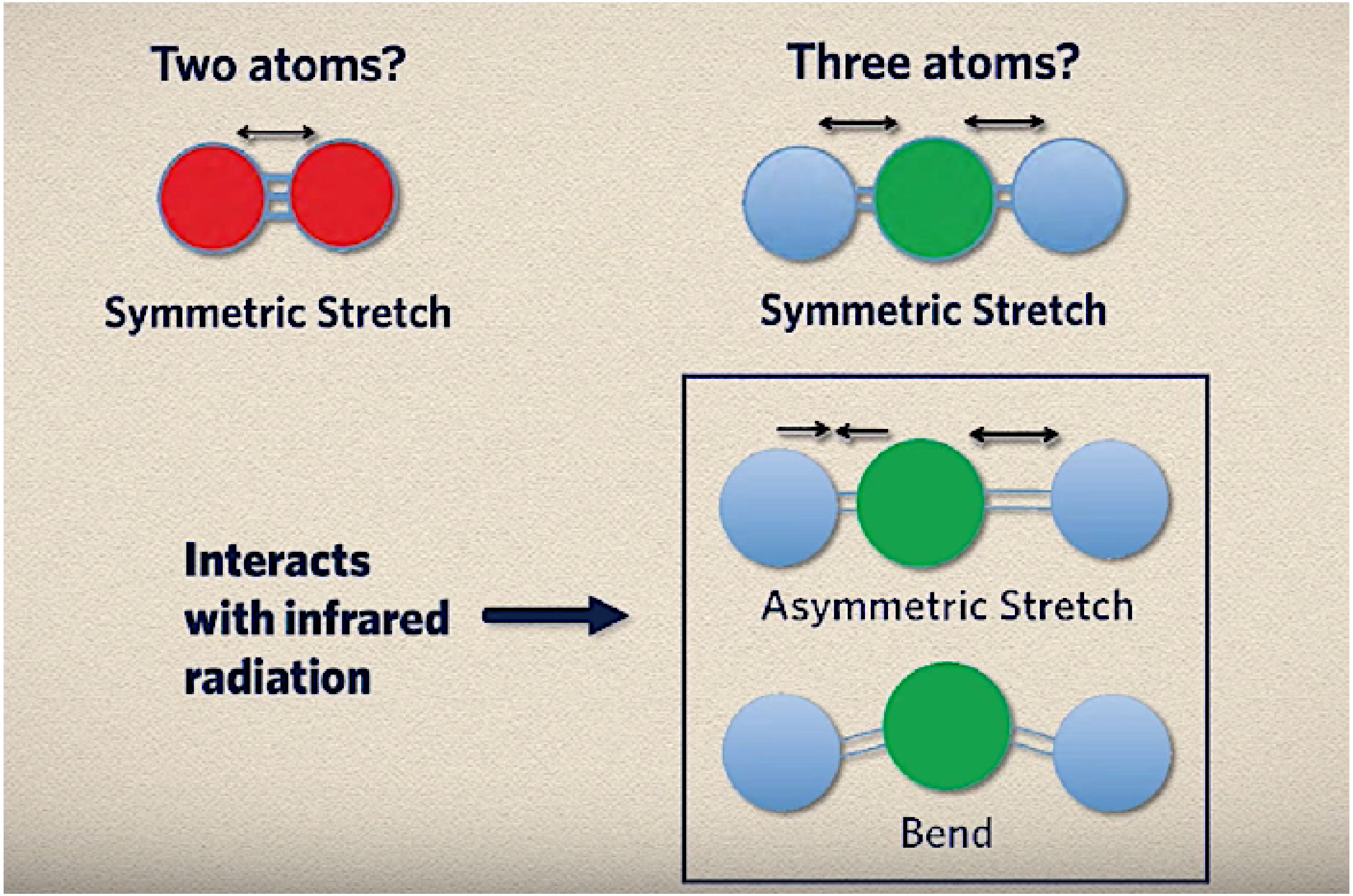


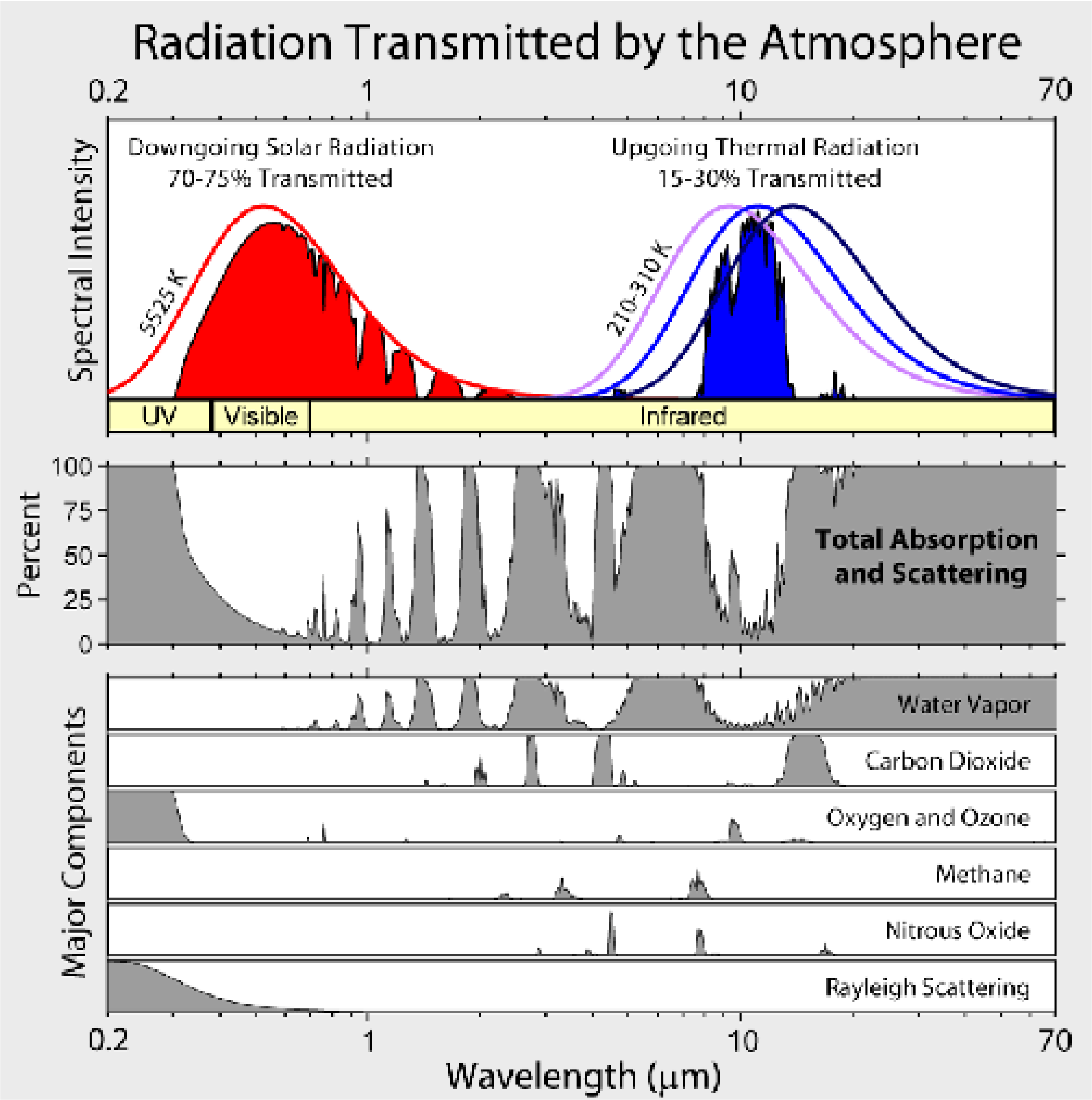
Nitrous oxide (N_2O)
N
N
O
O
H
H
Water vapor (H_2O)
O
C
O
Carbon
dioxide (CO_2)
H
C
H
H
H
Methane (CH_4)

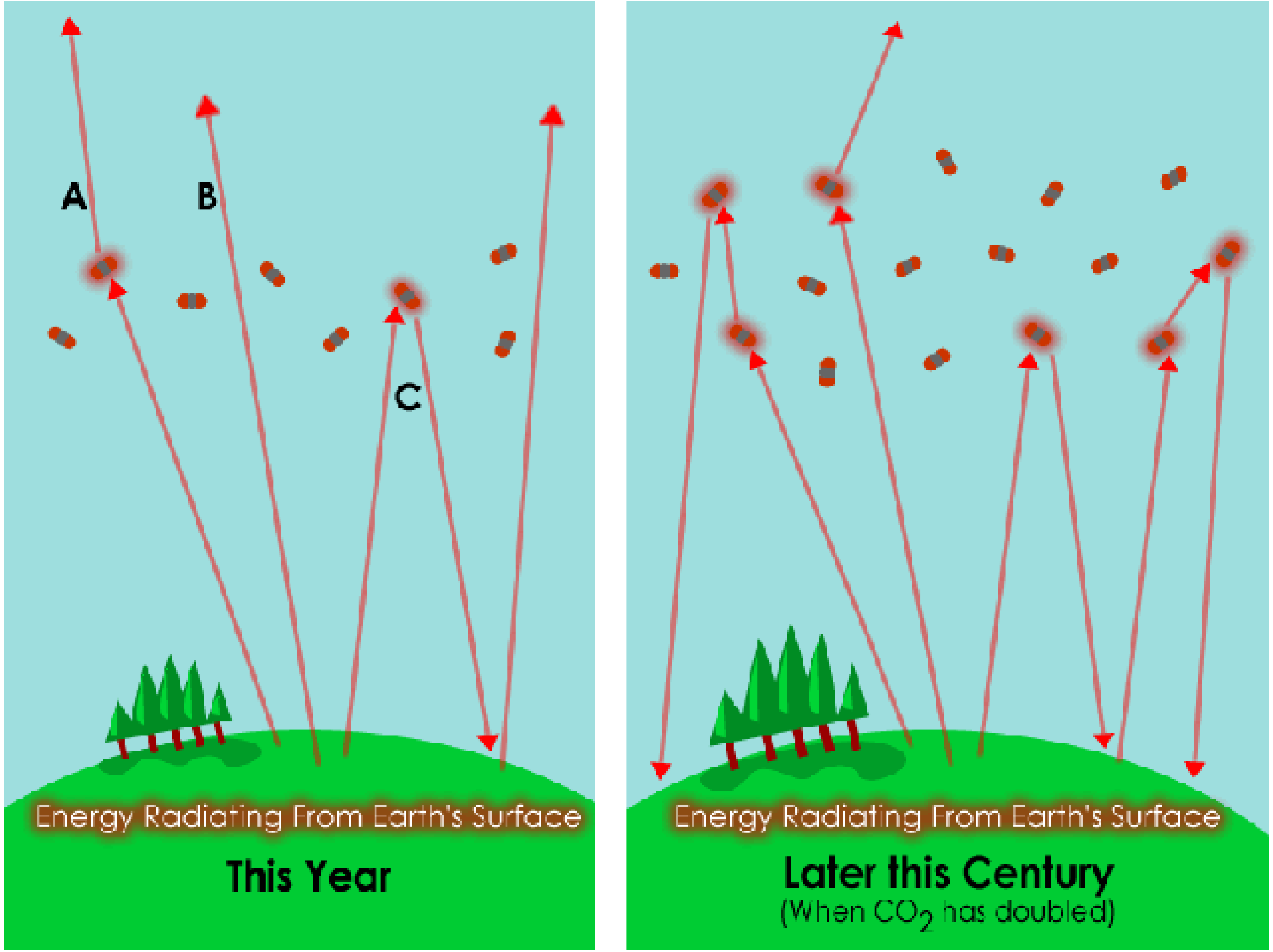


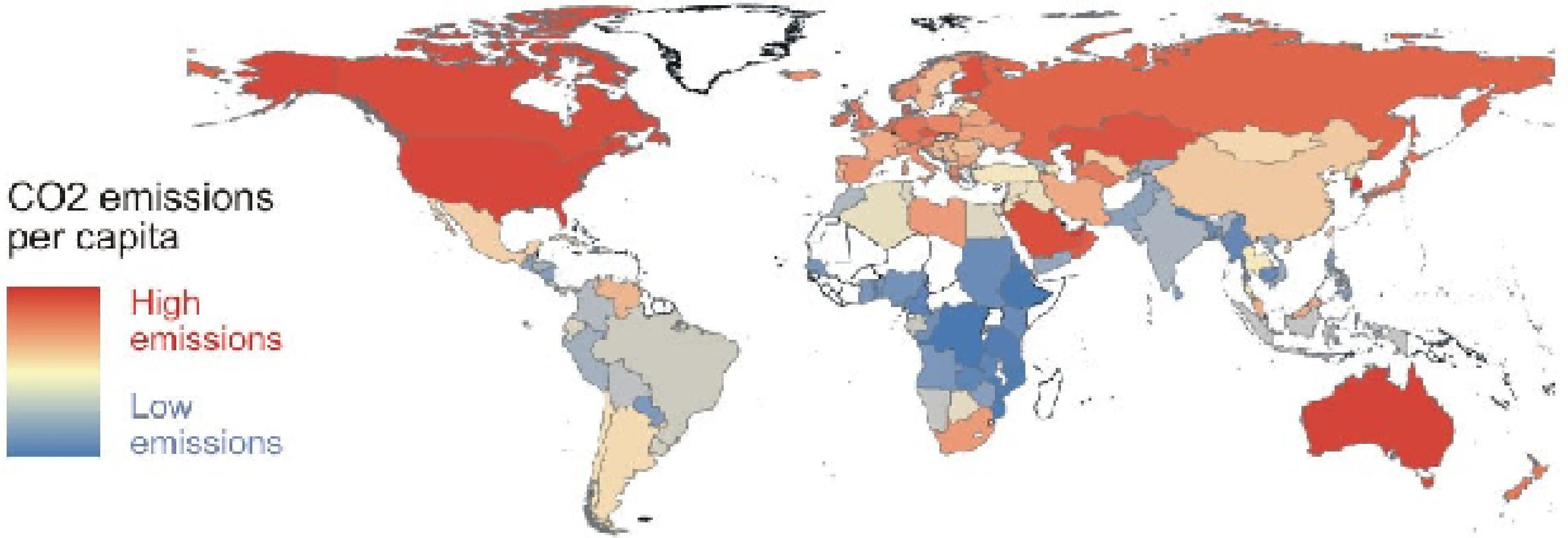
Energy increases
Short wavelength
Long wavelength
10−5 nm
10−3 nm
1 nm
10³ nm
10⁶ nm
1 m
10³ m
Gamma rays
X rays
Ultraviolet
Infrared
Microwaves
Radio waves
10²⁴ Hz
10²² Hz
10²⁰ Hz
10¹⁸ Hz
10¹⁶ Hz
10¹² Hz
10¹⁰ Hz
10⁸ Hz
10⁶ Hz
10⁴ Hz
10² Hz
High frequency
Low frequency
Visible light
7 × 10¹⁴ Hz
4 × 10¹⁴ Hz


Radiation Intensity
0.1
1
10
100
Wavelength, λ (microns)
UV
VIS
Infrared

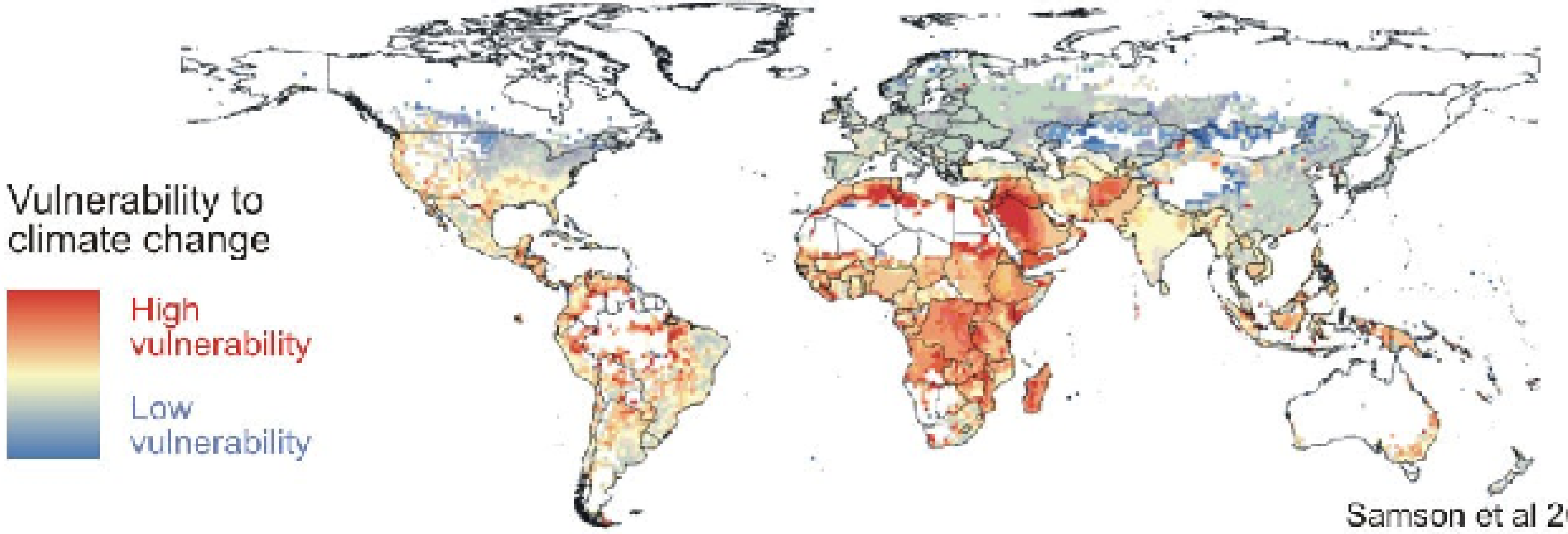

Two atoms?
Three atoms?
Symmetric Stretch
Symmetric Stretch
Interacts with infrared radiation
Asymmetric Stretch
Bend


Radiation Transmitted by the Atmosphere
0.2
1
10
70
Spectral Intensity
Downgoing Solar Radiation
70-75% Transmitted
Upgoing Thermal Radiation
15-30% Transmitted
5525 K
210-310 K
UV
Visible
Infrared
Percent
100
75
50
25
0
Total Absorption and Scattering
Major Components
Water Vapor
Carbon Dioxide
Oxygen and Ozone
Methane
Nitrous Oxide
Rayleigh Scattering
Wavelength (μm)


A
B
C
Energy Radiating From Earth's Surface
This Year
Energy Radiating From Earth's Surface
Later this Century
(When CO_2 has doubled)

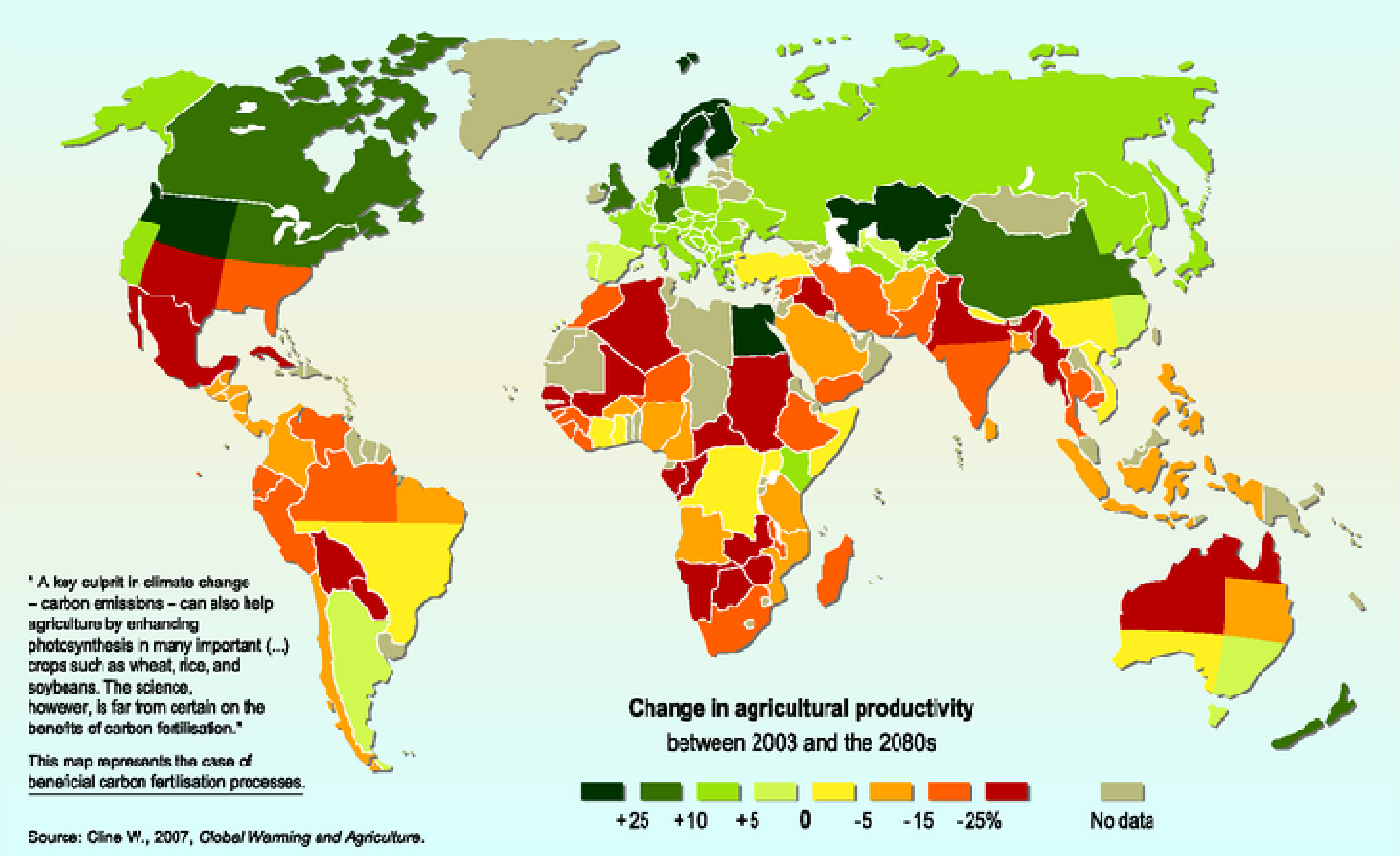


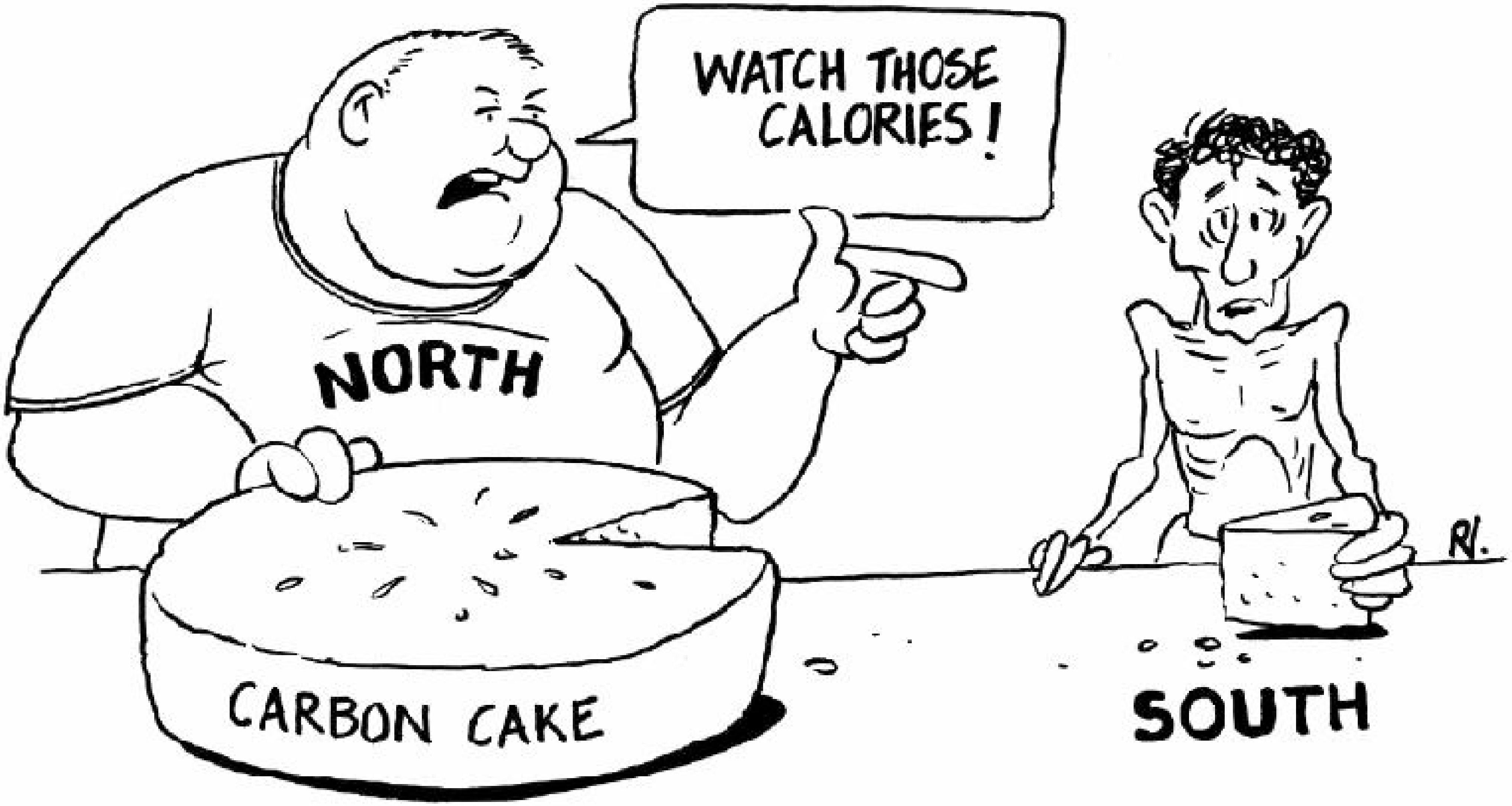
Those who contribute the least greenhouse gases
will be most impacted by climate change



Samson et al 2011

Projected impact of climate change on agricultural yields




WATCH THOSE CALORIES!
NORTH
CARBON CAKE
SOUTH
RI.