Climate Informatics

Recent Advances and Challenge Problems for Machine Learning in Climate Science

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August 2005: Hurricane Katrina – Reuters

October 2012: Hurricane Sandy – Reuters


August 2013: Rim Fire, California – Reuters

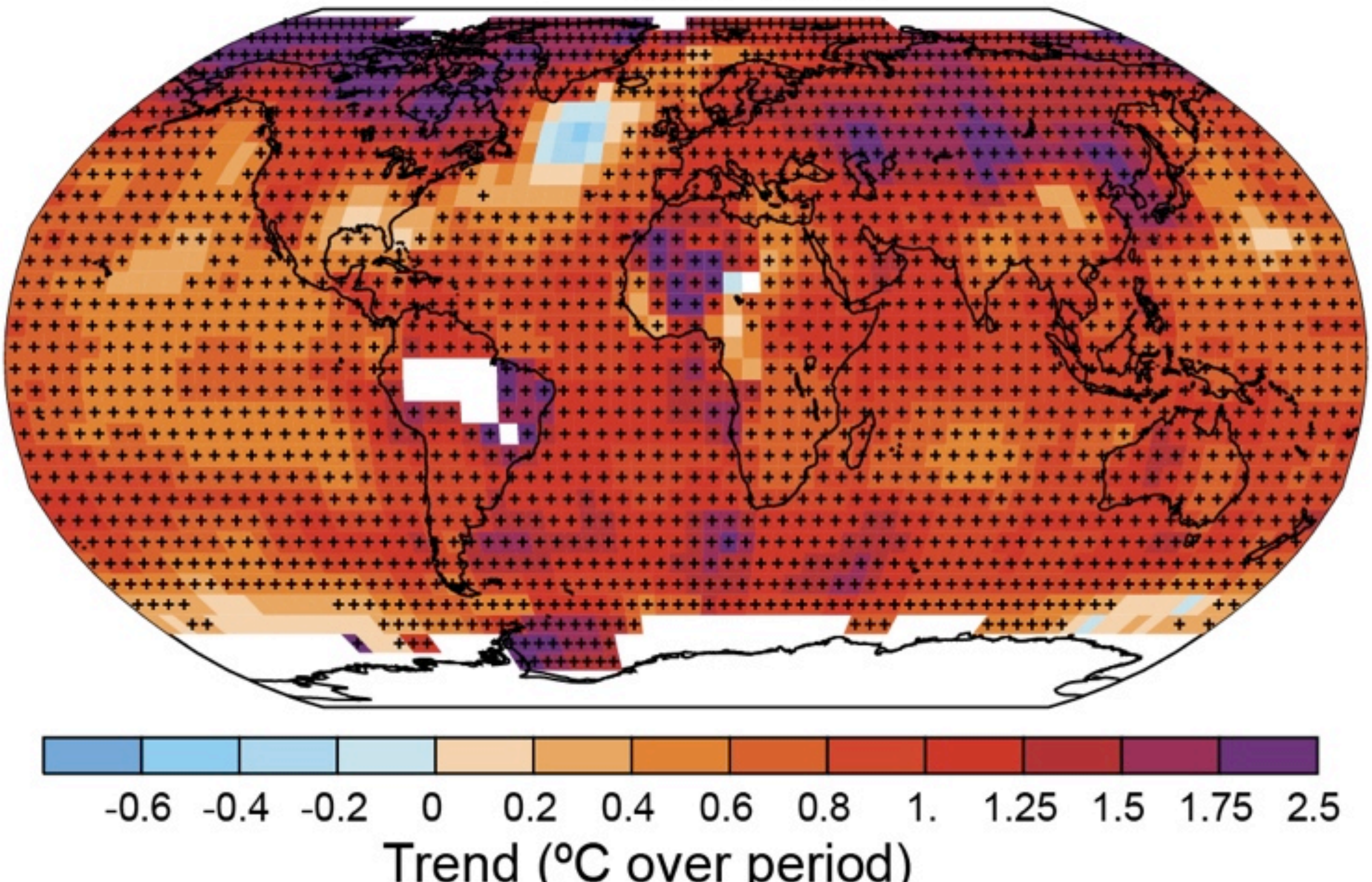
January 2014: Drought, Folsom Lake – California Department of Water Resources

Machine learning can shed light on climate change.

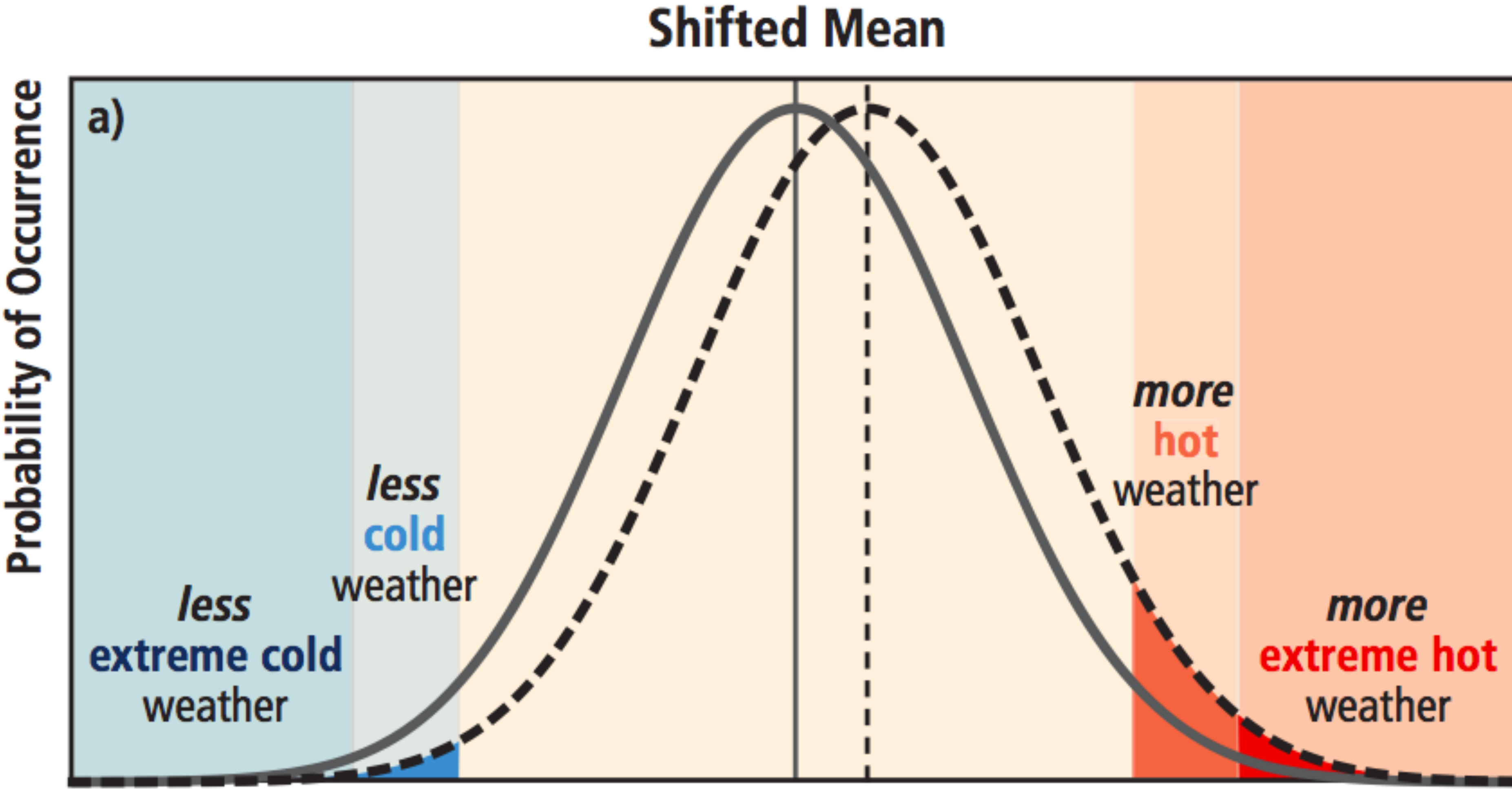
Despite the scientific consensus on climate change, drastic uncertainties remain. For instance:

How does climate change affect extreme events?

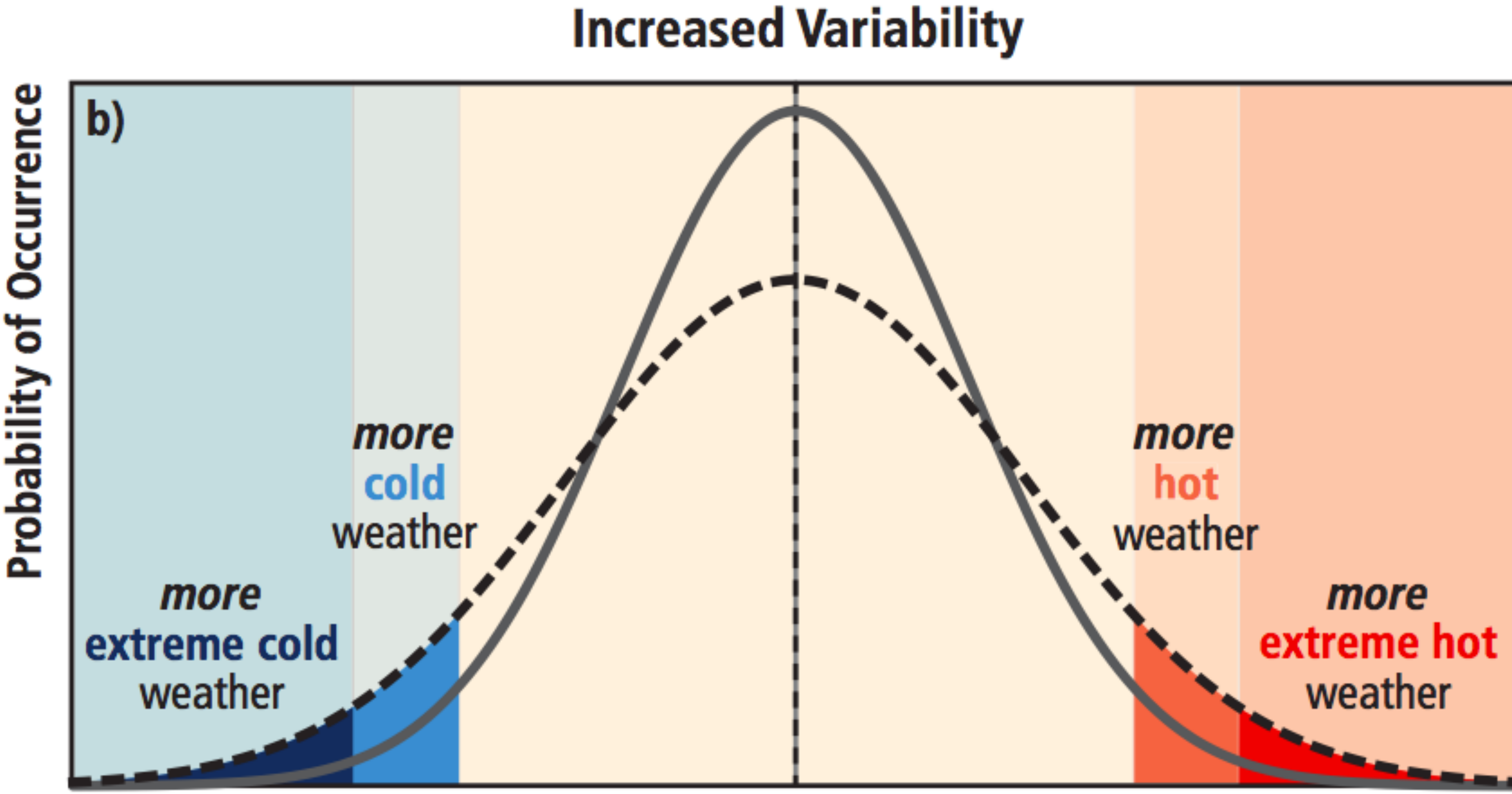
Surface Temperature 1901-2012



Intergovernmental Panel on Climate Change (IPCC), 2013

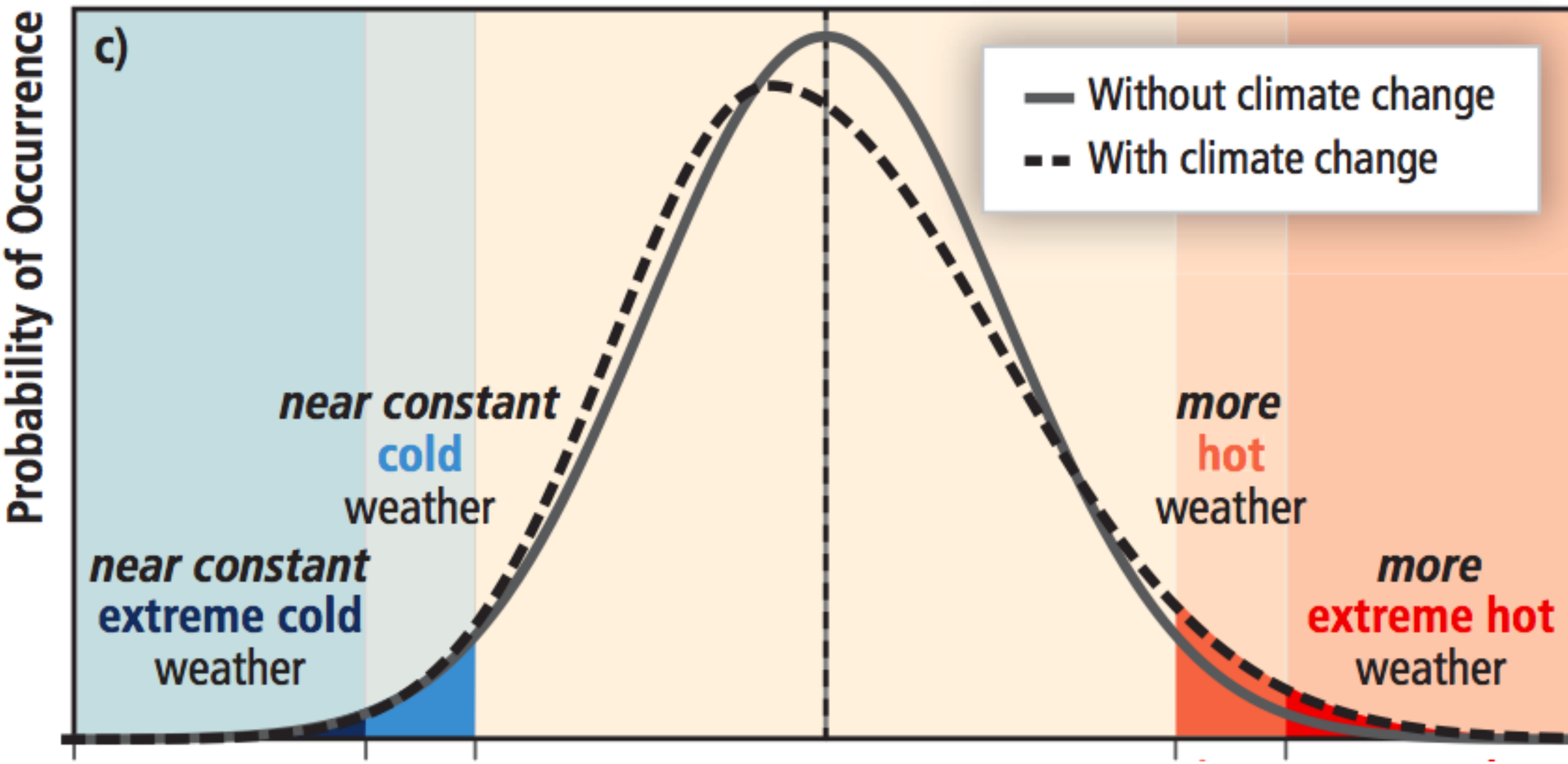


Intergovernmental Panel on Climate Change, 2012



Intergovernmental Panel on Climate Change, 2012

Changed Symmetry



Intergovernmental Panel on Climate Change, 2012

Uncertainty in extremes, especially regional

Warmer atmosphere can hold more water vapor

→ heavier precipitation, storms, flooding

Global warming may increase surface evaporation

→ heat waves, droughts

Possible changes in El Niño-Southern Oscillation

→ changes in floods in some regions, droughts in others

World Climate Research Programme 2013, grand challenge:
understanding and improving predictions of extreme events

Extreme events are rare by definition.

Climate change may affect their distribution.

➔ Past statistics are not sufficient for future prediction.

Augment historical data with climate model simulations.

Massive, high-dimensional, big data.

That’s where machine learning comes in!

Climate Informatics

2011 First International Workshop on Climate Informatics
New York Academy of Sciences
Climate Informatics Wiki launched
2013 "Climate Informatics" book chapter [M et al. 2013]

2015 Please join us in September as Climate Informatics turns 5!
National Center for Atmospheric Research, Boulder CO
In the first 4 years: participants from over 16 countries, 28 states

Climate Data is Big Data

GCMs/ESMs (CMIP3/5) (Tb/day)

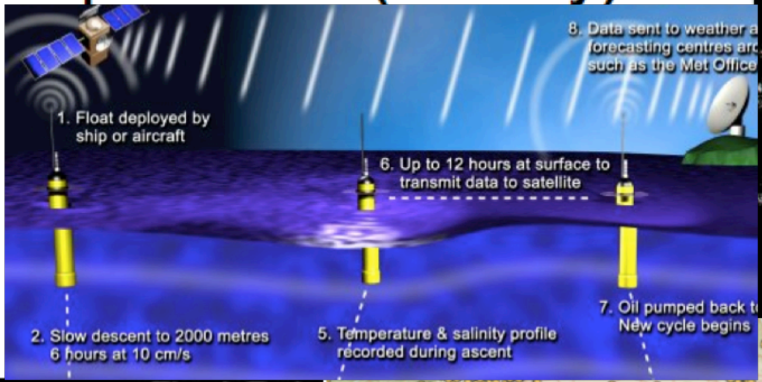
Satellite retrievals (Tb/day)

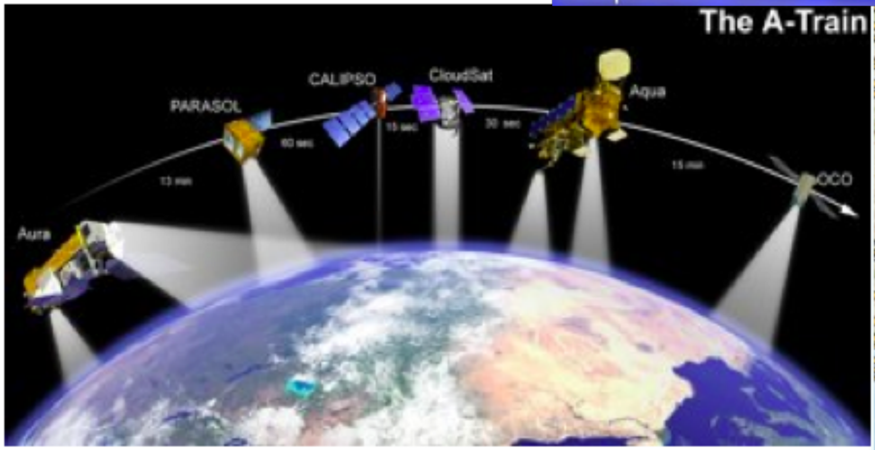
Next-gen reanalysis products (Tb/day)

In-situ data

Paleo-data

Regional models





credit: G. Schmidt/D. Nychka

Main types of climate data

- Past: Historical data
  - Limited amounts
  - Very heterogeneous

- Present: Observation data
  - Increasingly measured. Large quantities for recent times.
  - Can be unlabeled, sparse, measured at higher resolution than relevant information

- Past, Present, Future: Climate model simulations
  - Vast, high-dimensional
  - Encodes scientific domain knowledge
  - Some information is lost in discretizations
  - Future predictions cannot be validated

Challenge problems in climate informatics

1. Past: Paleo-climate reconstruction

   What was the climate before we had thermometers?

2. Local: Climate downscaling

   What climate can I expect in my own backyard?

3. Spatiotemporal: Space and time

   How to capture dependencies over space and time?

4. Future: Climate model ensembles

   How to reduce uncertainty on future predictions?

5. Tails/impacts: Extreme events

   What are extreme events and how will climate change affect them?

6. Other problems

   Data-rich playground with many opportunities for ML to have an impact!

Relevant ML tasks (among others)

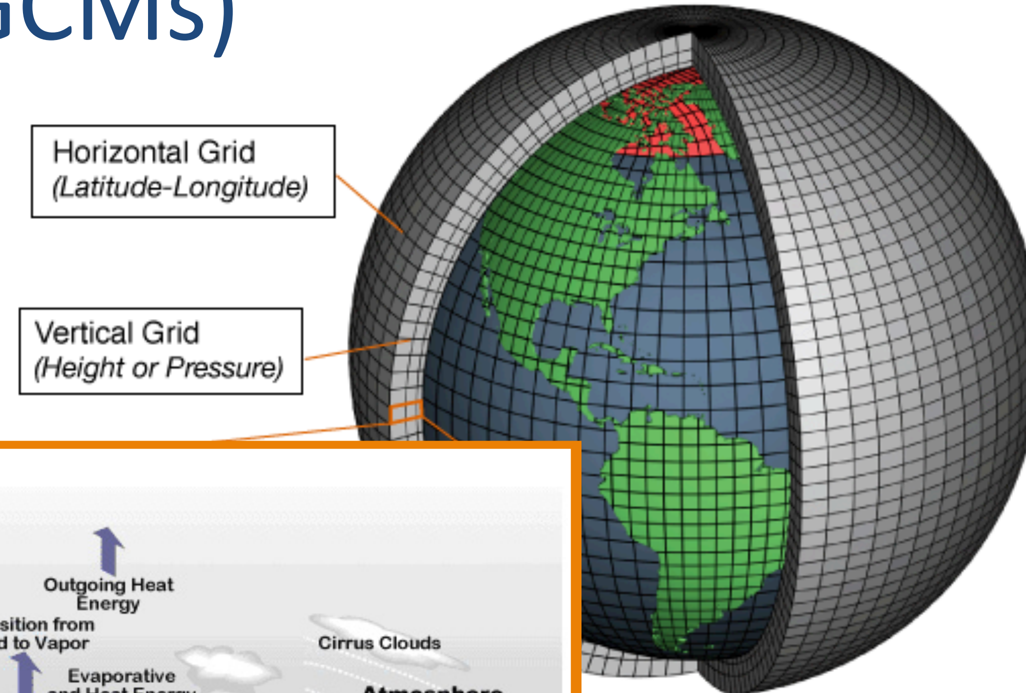
- Graphical models
  - MRF/CRF, topic models, inference, structure learning
- Hierarchical Bayesian models
- Matrix completion
- Sparse representations
- Causality
- Multitask learning
- Unsupervised learning
- Online learning
- Analysis of quantiles and extremes
- Spatial statistics
- Deep learning

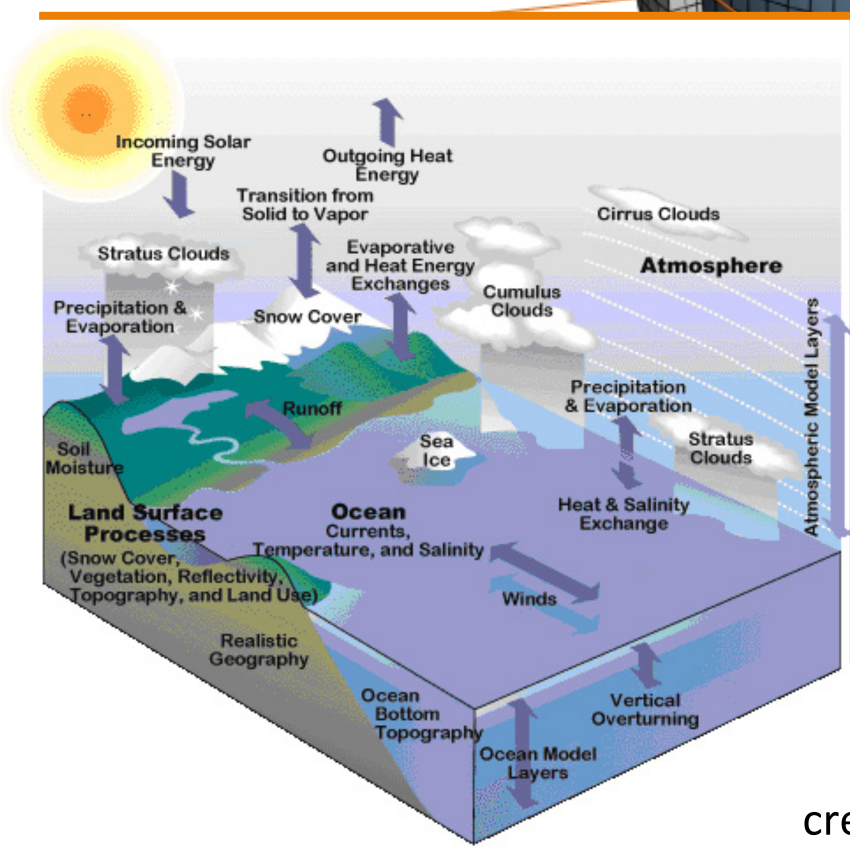
Climate Model Ensembles

Climate models (GCMs)

Climate model: a complex system of interacting mathematical models

- Not data-driven
- Based on scientific first principles
    - Meteorology
    - Oceanography
    - Geophysics
    - …
- Discretization into grid boxes
- Scale resolution differences





credit: UCAR/NCAR, NOAA

Intergovernmental Panel on Climate Change

- IPCC: Intergovernmental Panel on Climate Change
  - Nobel Peace Prize 2007 (shared with Al Gore).
  - Interdisciplinary scientific body, formed by UN in 1988.
  - Fourth Assessment Report, 2007, on global climate change

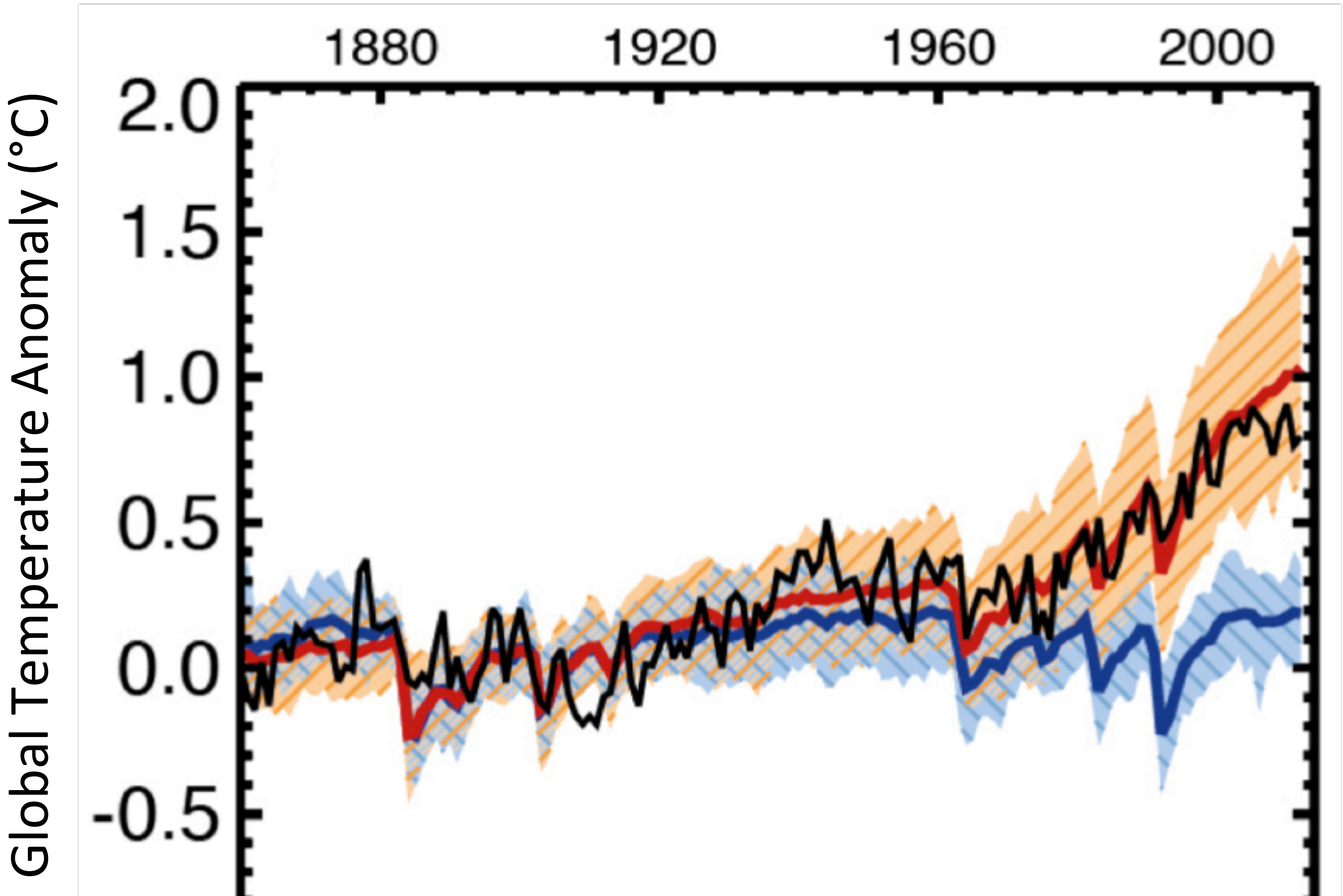
    450 lead authors from 130 countries, 800 contributing authors, over 2,500 reviewers.
  - Fifth Assessment Report, September 2013. Over 830 authors.

- Climate models contributing to IPCC reports include:

  Bjerknes Center for Climate Research (Norway), Canadian Centre for Climate Modelling and Analysis, Centre National de Recherches Météorologiques (France), Commonwealth Scientific and Industrial Research Organisation (Australia), Geophysical Fluid Dynamics Laboratory (Princeton University), Goddard Institute for Space Studies (NASA), Hadley Centre for Climate Change (United Kingdom Meteorology Office), Institute of Atmospheric Physics (Chinese Academy of Sciences), Institute of Numerical Mathematics Climate Model (Russian Academy of Sciences), Istituto Nazionale di Geofisica e Vulcanologia (Italy), Max Planck Institute (Germany), Meteorological Institute at the University of Bonn (Germany), Meteorological Research Institute (Japan), Model for Interdisciplinary Research on Climate (Japan), National Center for Atmospheric Research (Colorado), among others.

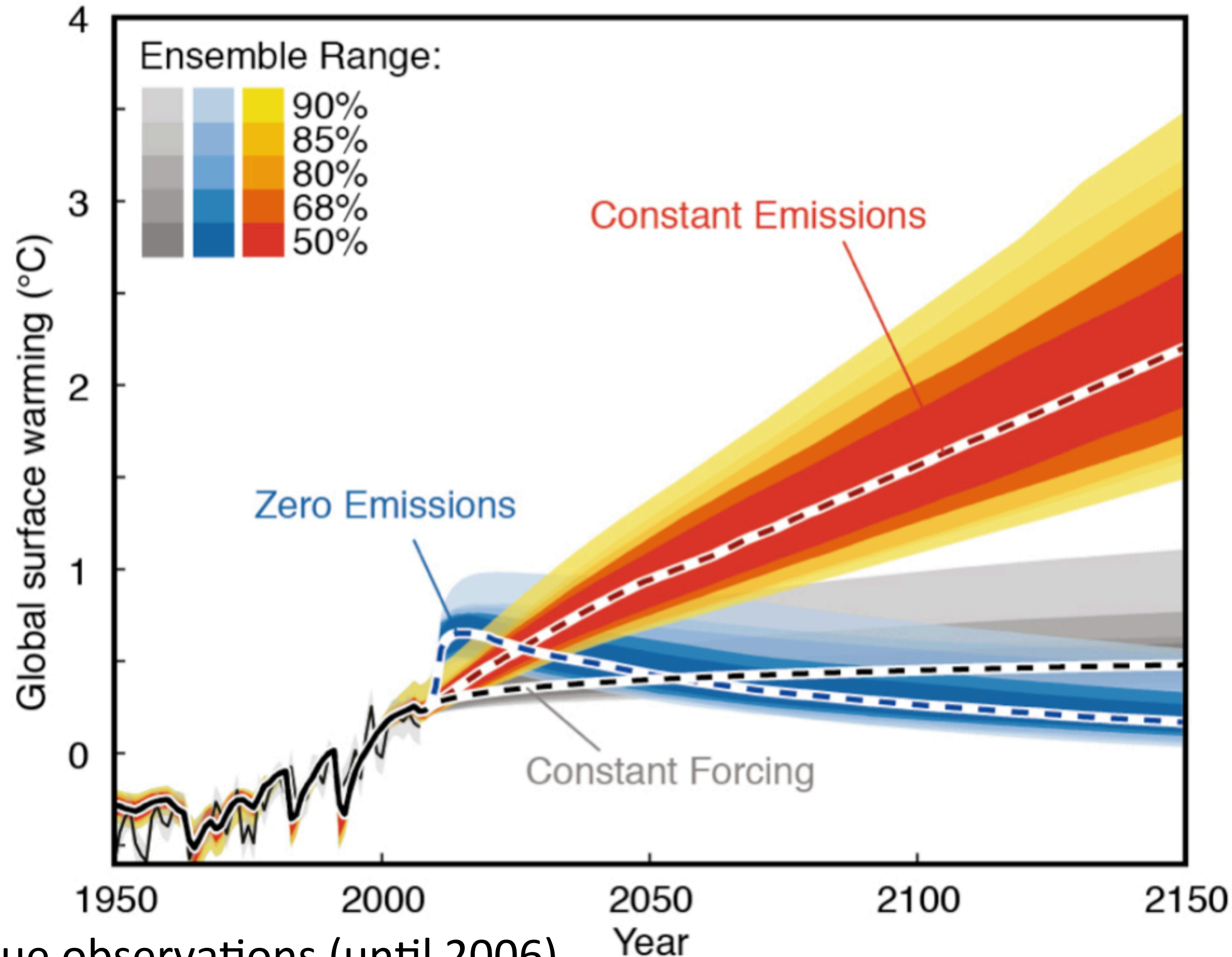
IPCC findings: human influence on climate

Black: true observations.
Orange/red: Climate model simulations with human-induced greenhouse gasses.
Blue: Climate model simulations *without* human-induced greenhouse gasses.



IPCC 2013

Modeling future scenarios



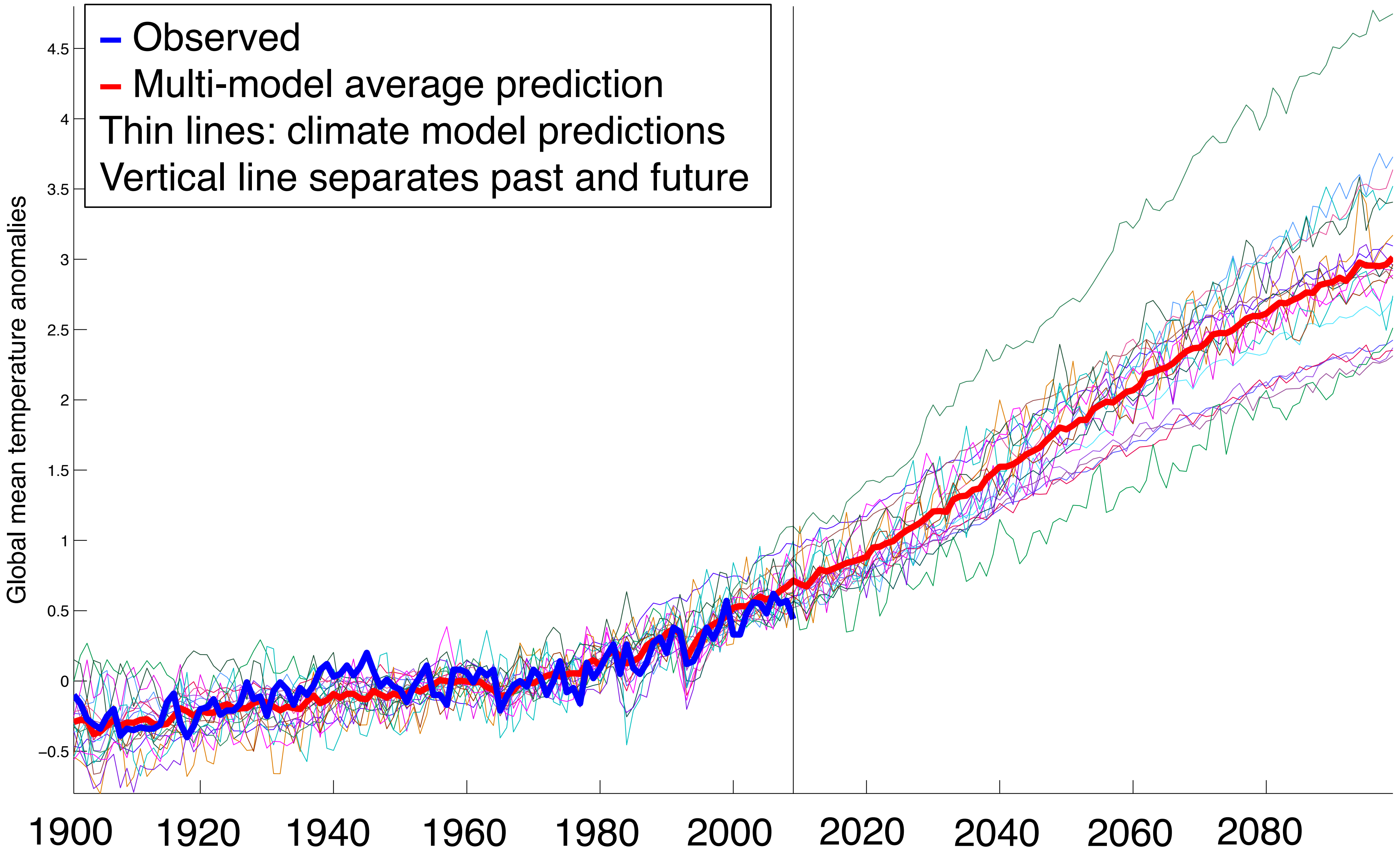
Black: True observations (until 2006).

Orange/red: Constant emissions.

Grey: Constant atmospheric composition (constant forcing).

Blue: Zero emissions starting 2010 (impossible).

credit: IPCC 2013



Future fan-out.

Improving predictions of the IPCC ensemble

- Coupled Model Intercomparison Project (CMIP)

  [Meehl et al., Bull. AMS, ‘00]
- No one model predicts best all the time, for all variables.
- Average prediction over all models is better predictor than any single model. [Reichler & Kim, Bull. AMS ‘08], [Reifen & Toumi, GRL ’09]
- Bayesian approaches in climate science e.g. [Smith et al. JASA ’08]
- IPCC held 2010 Expert Meeting on how to better combine model predictions.

Can we do better, using Machine Learning?

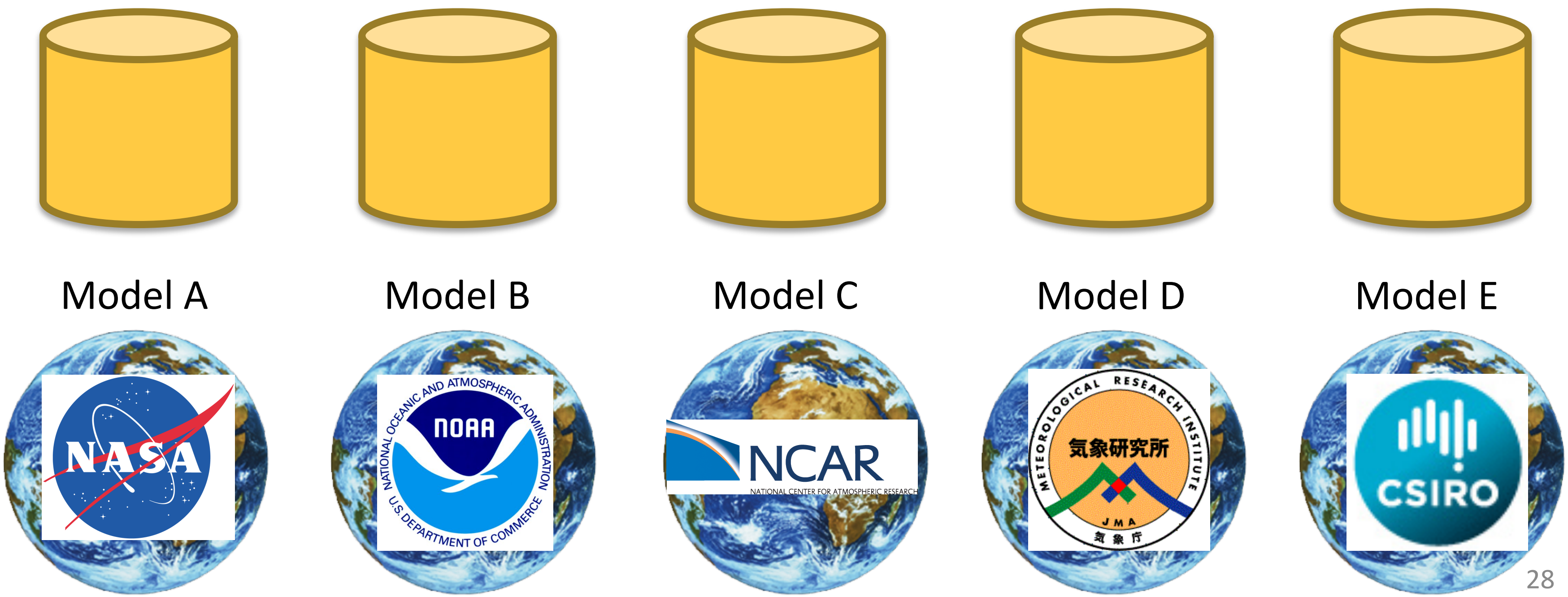
Challenge: How should we predict future climates?

– While taking into account the multi-model ensemble predictions

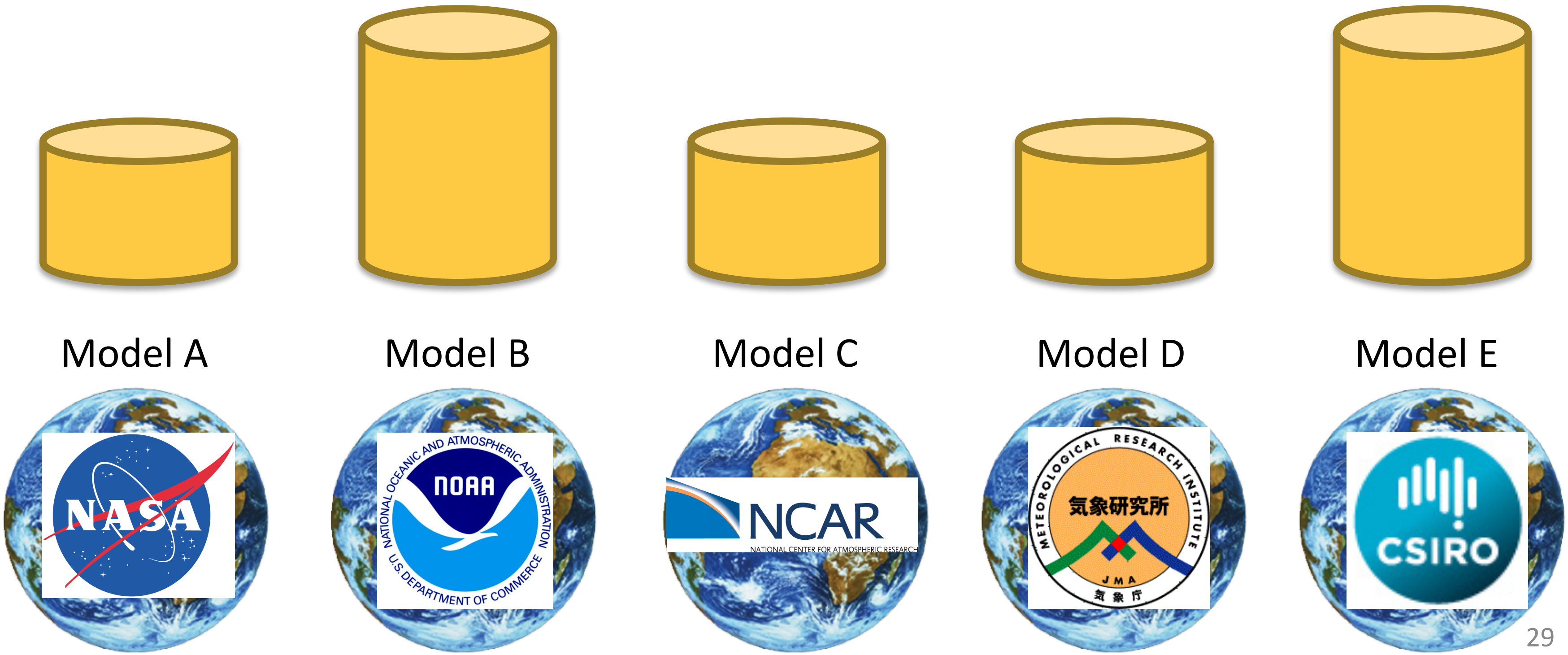
Contributions

- Tracking Climate Models (TCM) [M, Schmidt, Saroha, & Asplund, SAM 2011; NASA CIDU 2010]: Online learning with expert advice.
- Neighborhood-Augmented TCM (NTCM) [McQuade & M, AAAI 2012]: Extend TCM to model geospatial neighborhood influence.
- MRF-based approach [McQuade & M, submitted 2014].
- Climate Prediction via Matrix Completion [Ghafarianzadeh & M, Late-Breaking Paper, AAAI 2013]: use sparse matrix completion.

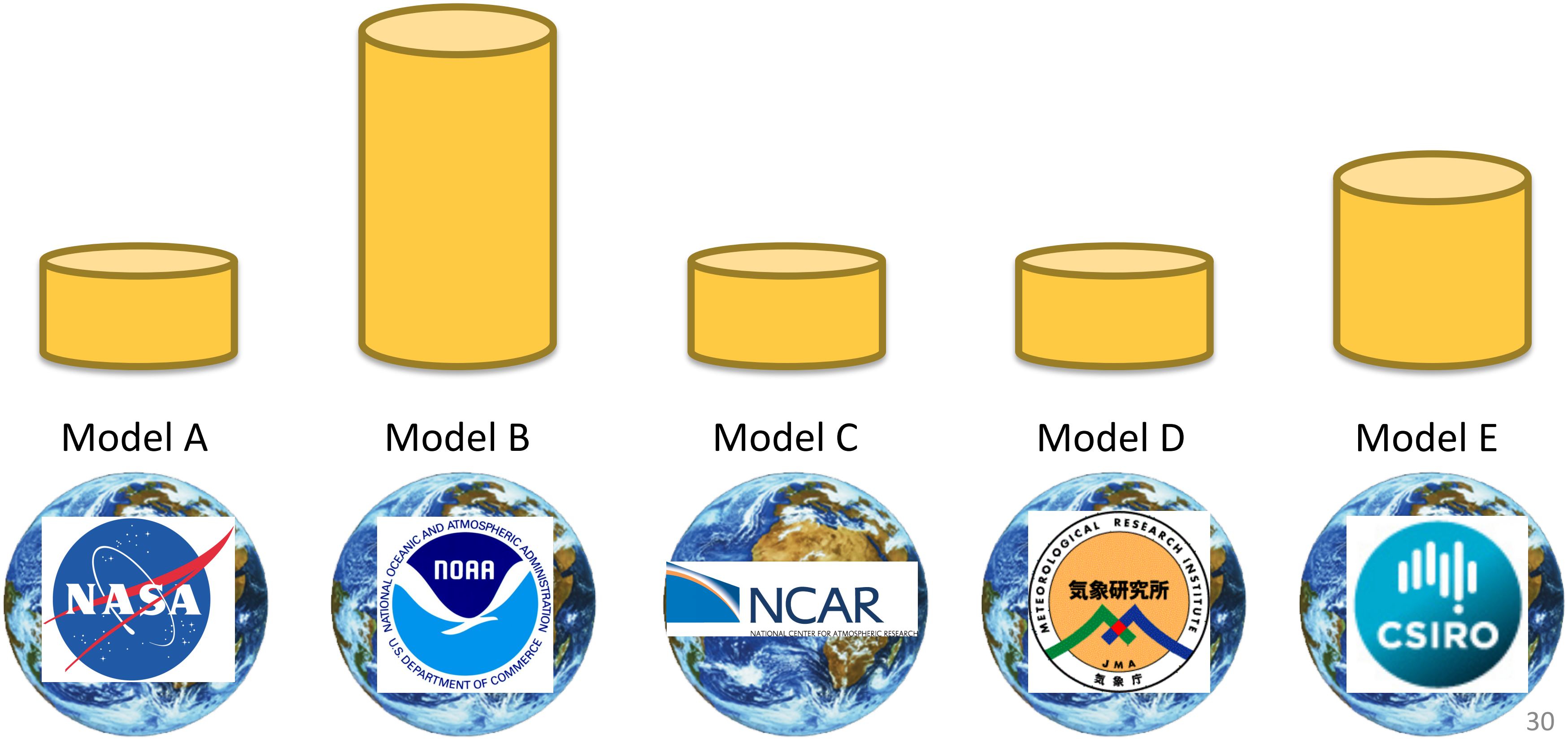
Average prediction



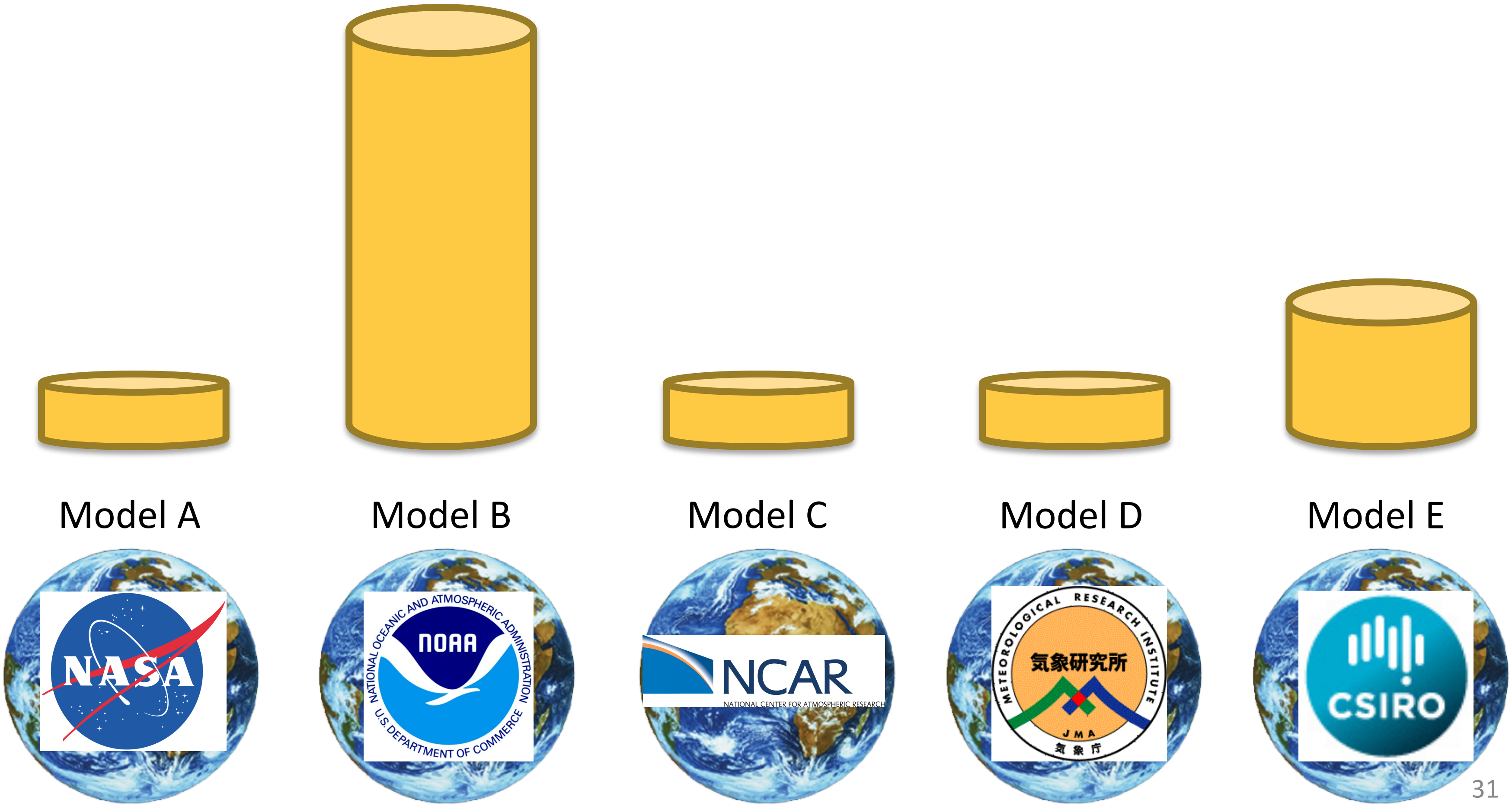
Adaptive, weighted average prediction



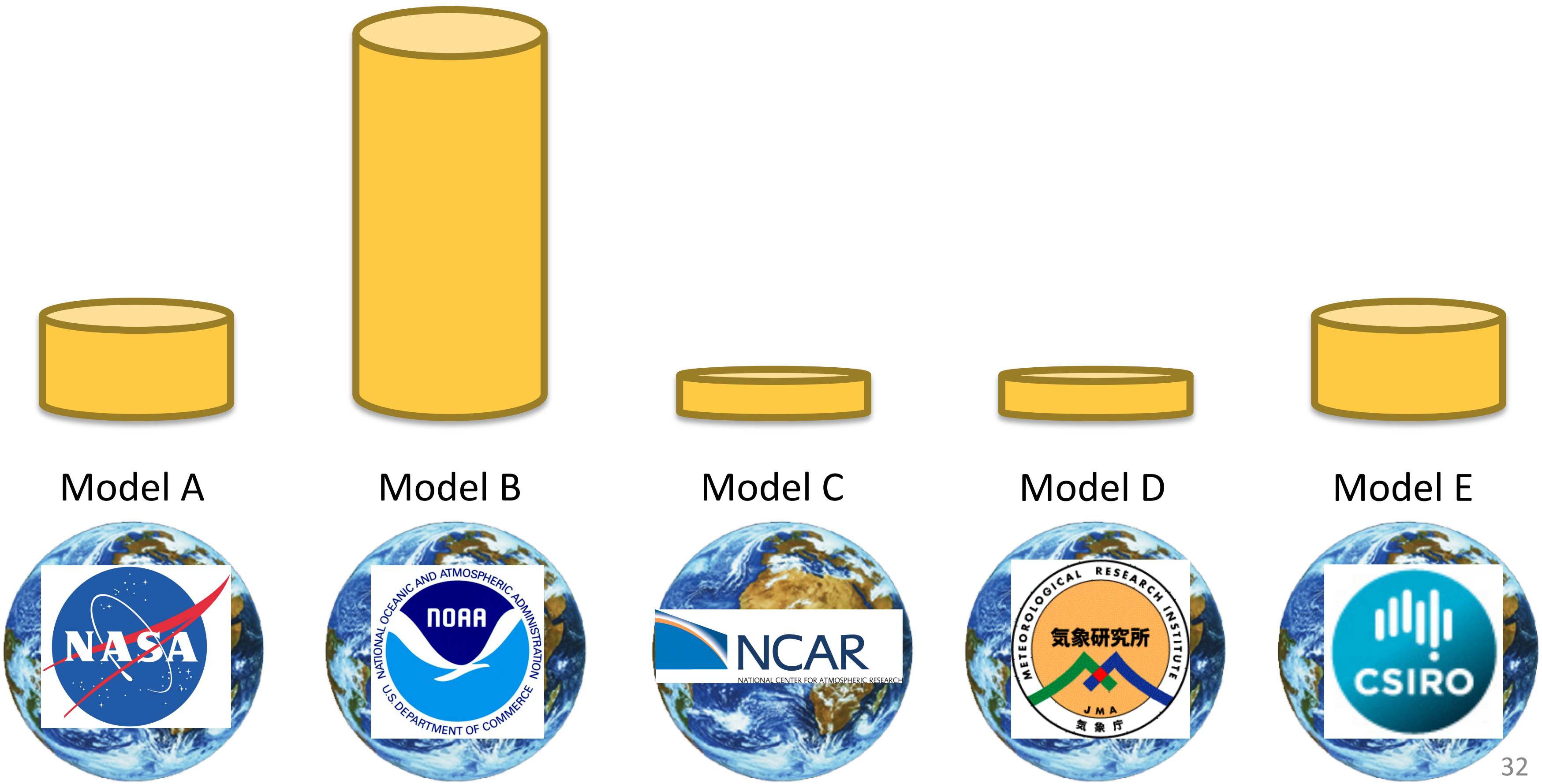
Adaptive, weighted average prediction



Adaptive, weighted average prediction



Adaptive, weighted average prediction

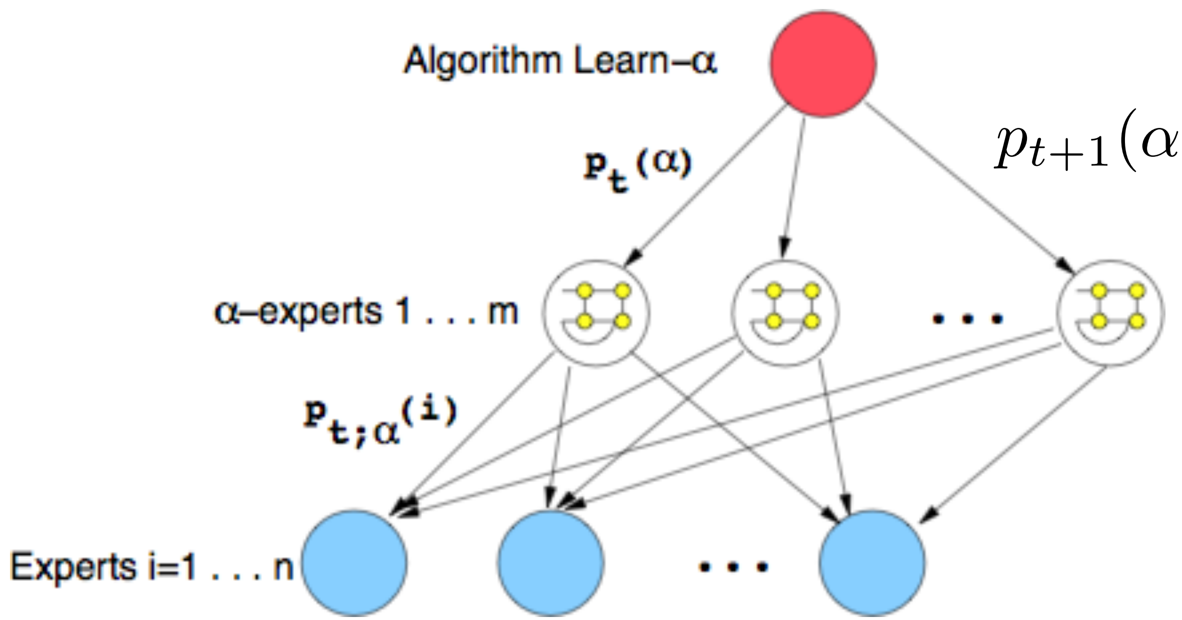


Tradeoff: explore vs. exploit

Tradeoff: Quickly finding current best predicting model vs. being ready to quickly switch to other models.

Tradeoff hinges on how often the identity of the best model switches.

Online learning: non-stationary data

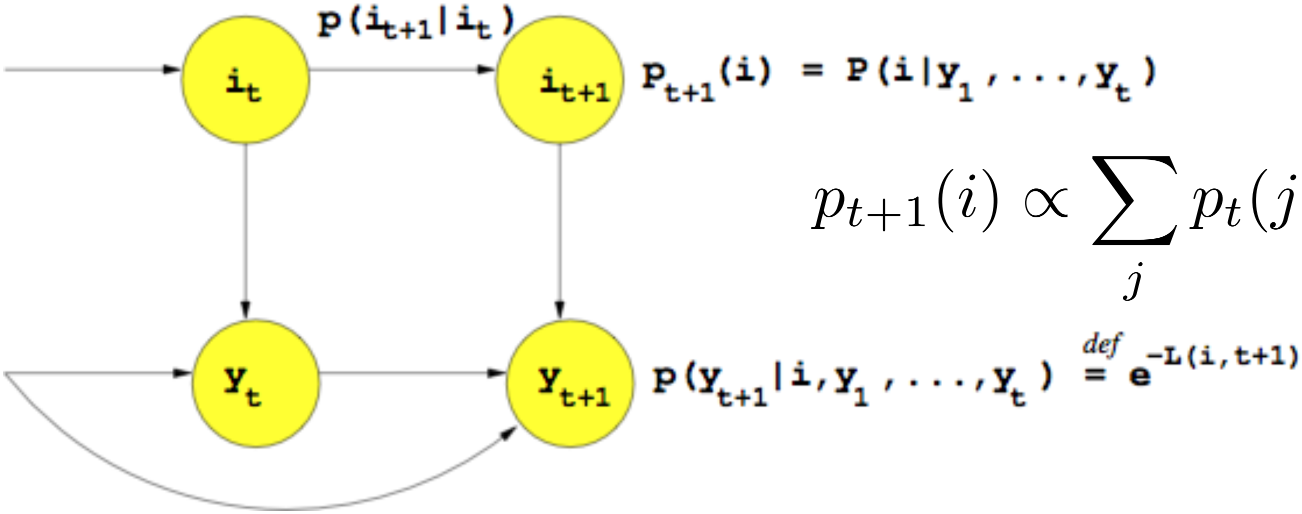


$$p_{t+1}(\alpha) \propto p_t(\alpha) e^{-L(\alpha,t)}$$

Learn-α Algorithm [M & Jaakkola, NIPS 2003]:

- Learns the switching rate: level of non-stationarity: α.
- Tracks a set of meta-experts, online learning algorithms, each with a different value of the α parameter.

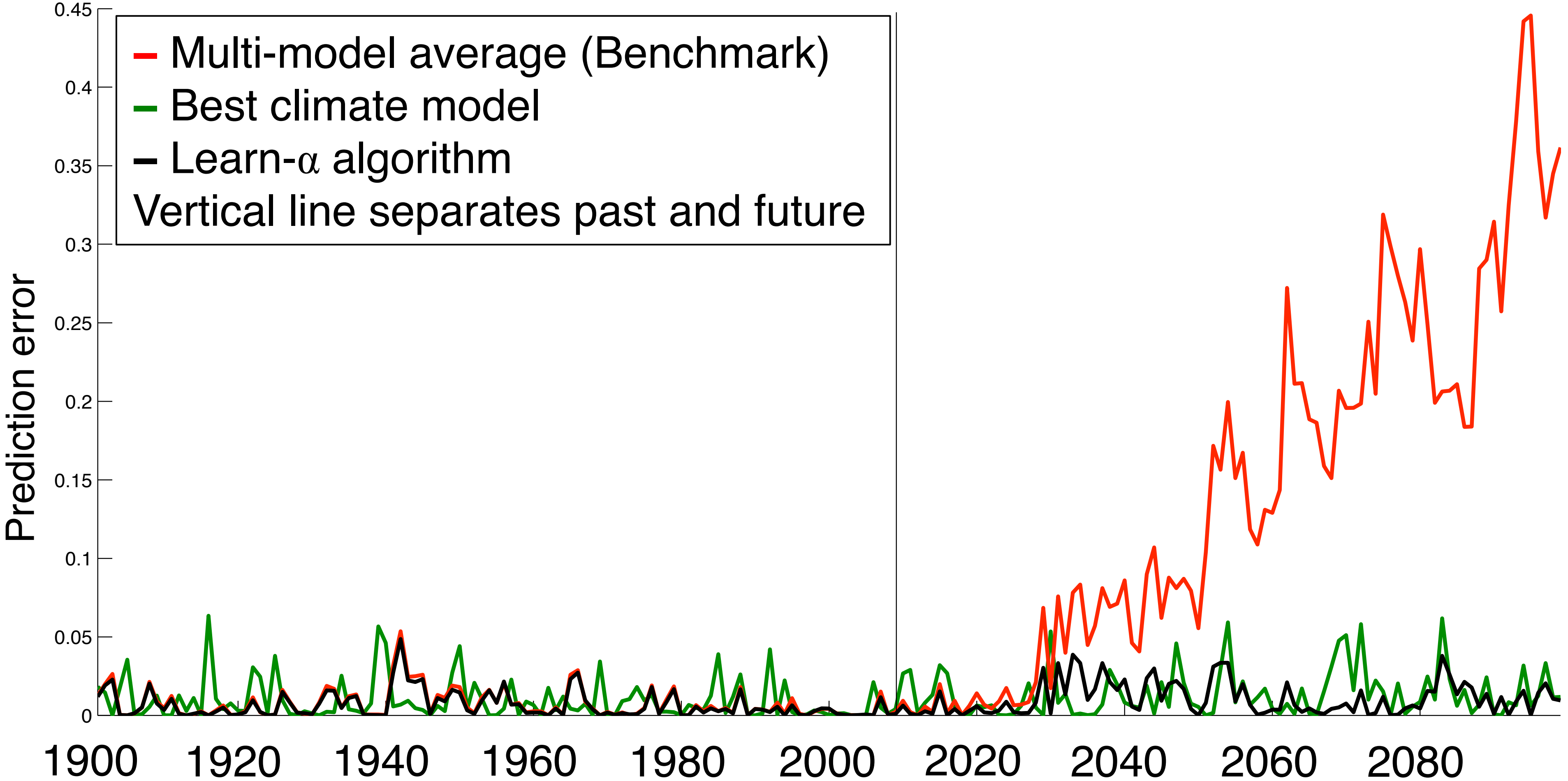
Online learning: non-stationary data



$$p_{t+1}(i) \propto \sum_j p_t(j) e^{-L(j,t)} p(i|j)$$

- [M & Jaakkola, 2003]: In a family of online learning algorithms, weight updates, $p_t(i)$, equivalent to Bayesian updates of a generalized Hidden Markov Model.
  - Hidden variable: identity of "best expert."
  - Transition dynamics, $p(i \mid j)$, model non-stationarity.
- [Herbster & Warmuth, 1998]: Fixed-Share algorithm models switching w.p. α.

$$P(i|j;\alpha) = \begin{cases} (1-\alpha) & i = j \\ \frac{\alpha}{n-1} & i \neq j \end{cases}$$



Learning curves

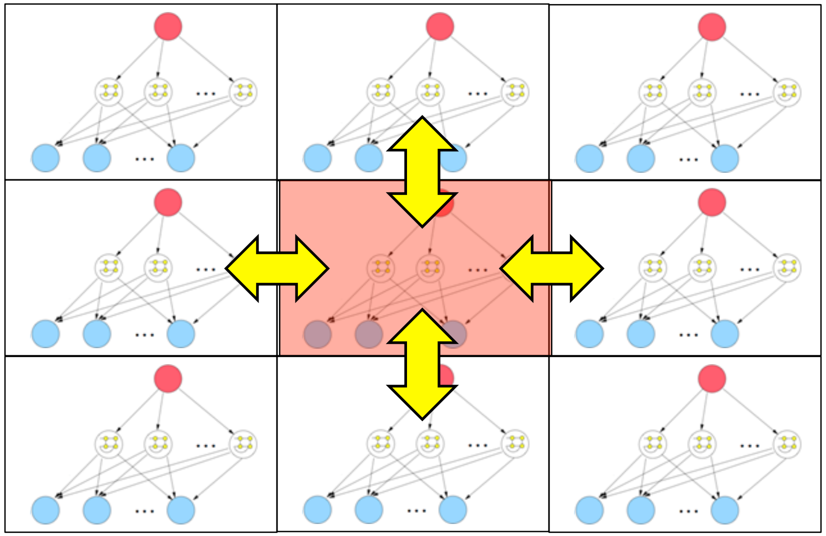
[M, Schmidt, Saroha, & Asplund, SAM 2011; NASA CIDU 2010]

Best Paper Award!

Incorporating neighborhood influence

[McQuade & M, AAAI 2012]

- Climate predictions are made at higher geospatial resolutions.
- Run instances of Learn-α (variant) on multiple sub-regions that partition the globe.
- Model neighborhood influences among geospatial regions.



Incorporating neighborhood influence

Neighborhood-augmented Learn-α.

Non-homogenous HMM transition dynamics:

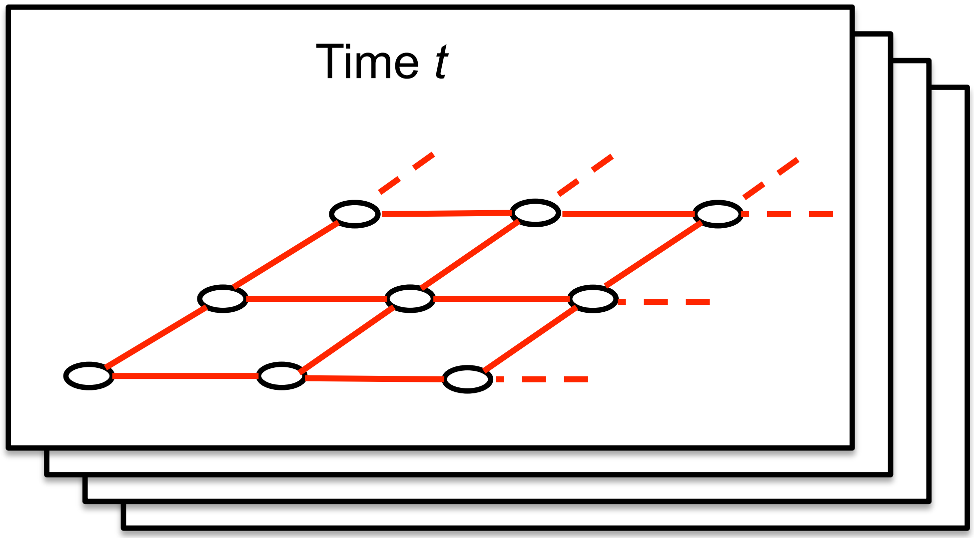
$$P(i \mid k; \alpha) = \begin{cases} (1-\alpha) & \text{if i=k} \\ \frac{\alpha}{Z}\left[(1-\beta) + \beta \frac{1}{|S(r)|} \sum_{s \in S(r)} P_{t,s}(i)\right] & \text{if i}\neq\text{k} \end{cases}$$

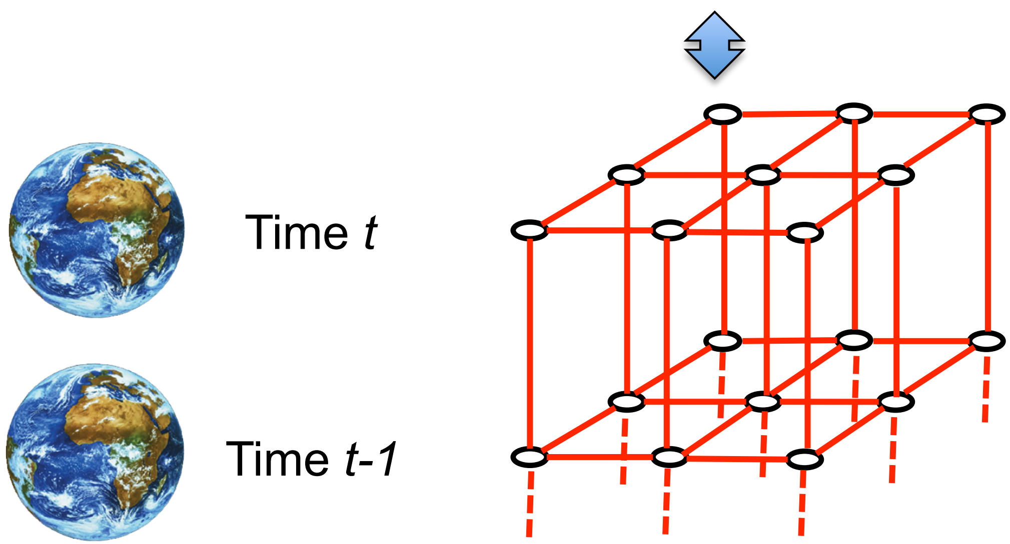
- *S(r)* - neighborhood scheme: set of "neighbors" of region *r*
- $P_{t,s}(i)$ - probability of expert (climate model) *i* in region *s*
- β - regulates geospatial influence
- *Z* - normalization factor

MRF-based approach

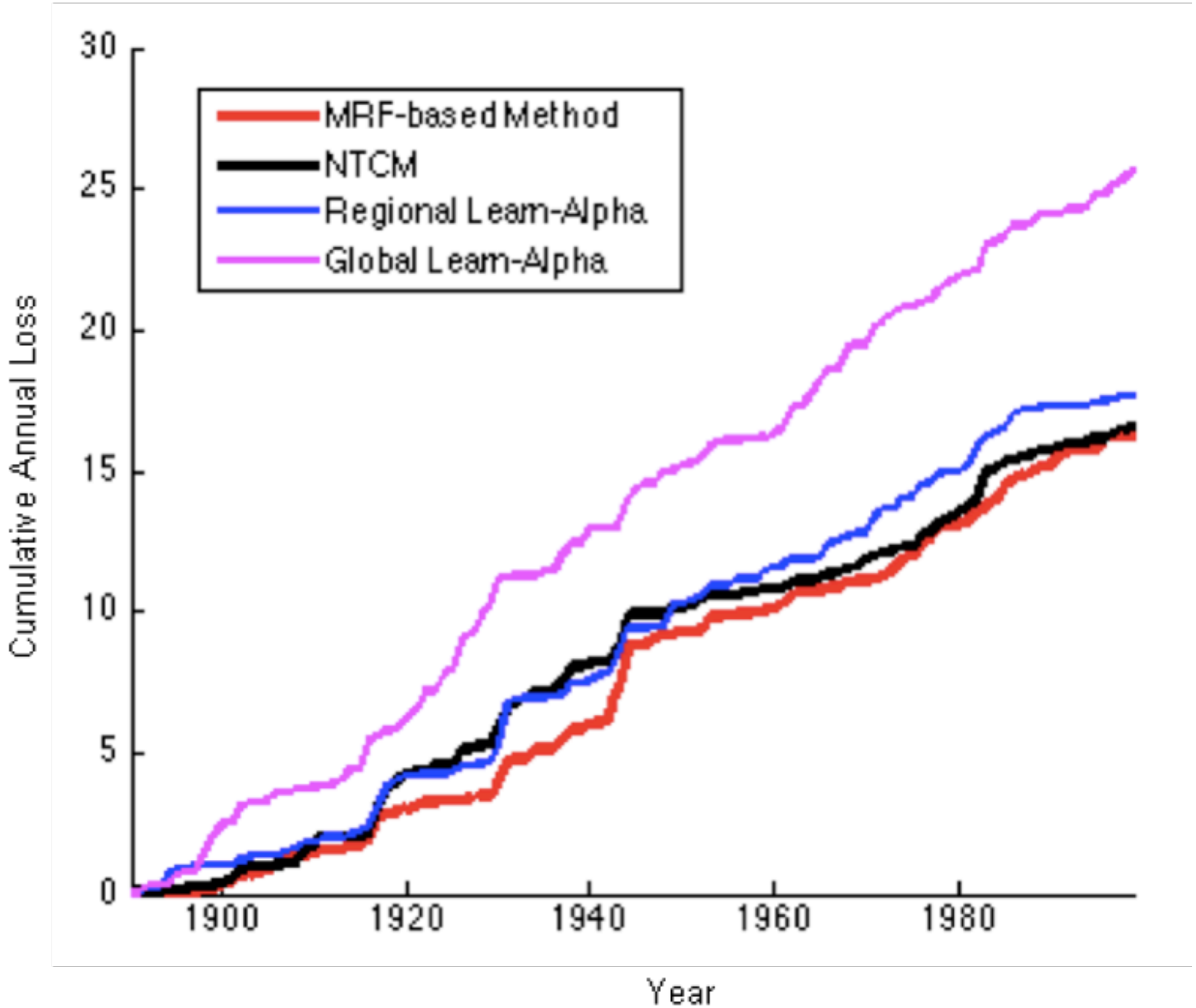
[McQuade & M, submitted]

Geospatial lattice





MRF-based approach



MRF-based approach

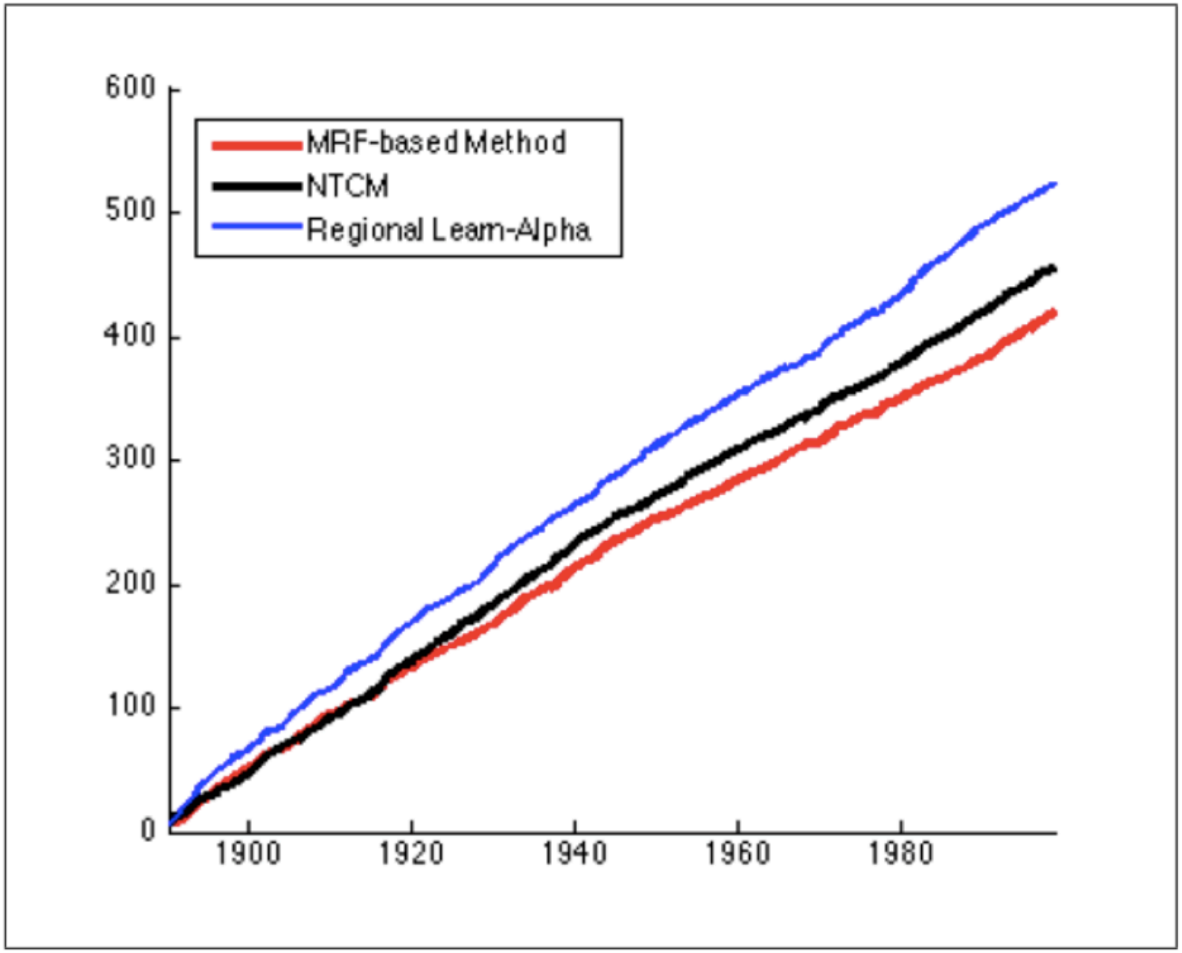


FIGURE 1.11: Cumulative mean regional loss of the hindcast.

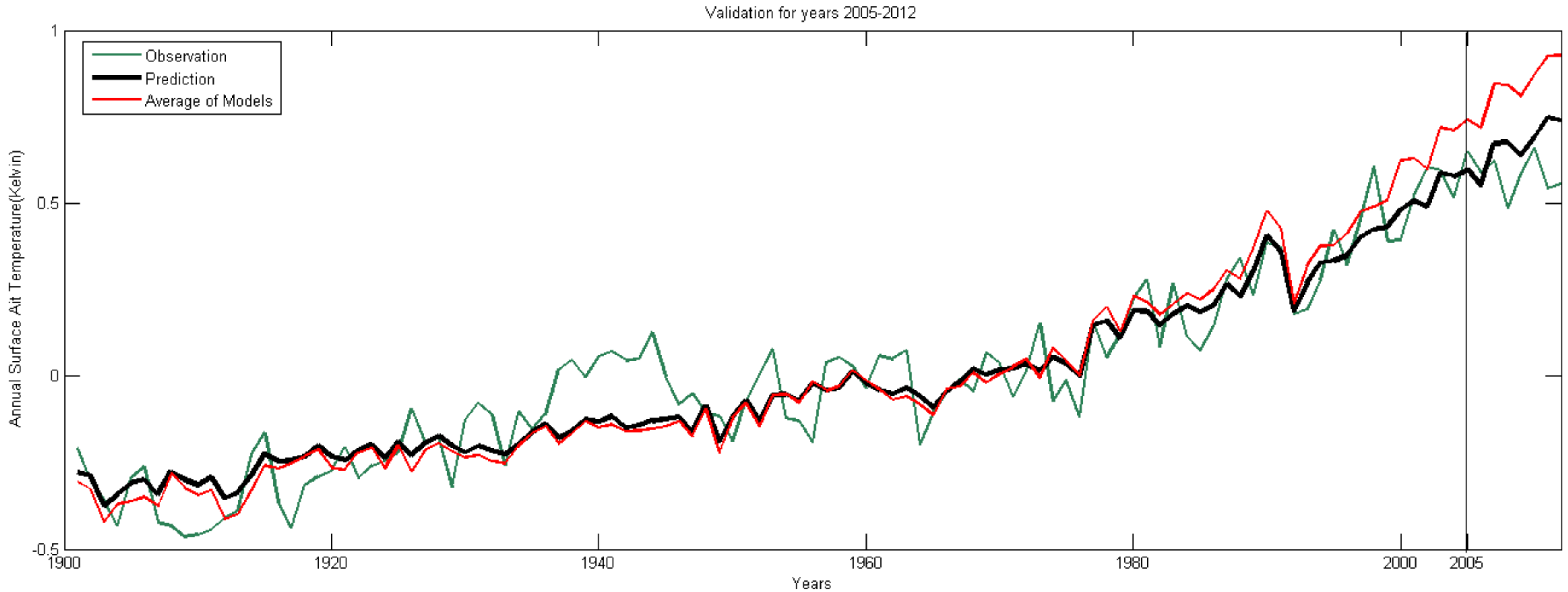
Climate Prediction via Matrix Completion

[Ghafarianzadeh & M, Late-Breaking Paper, AAAI 2013]

- Goal: combine/improve the predictions of the multi-model ensemble of GCMs, using sparse matrix completion.
- Exploits past observations, and the predictions of the multi-model ensemble of GCMs.
- Learning approach is batch, unsupervised.
- Create a sparse (incomplete) matrix from climate model predictions and observed temperature data.
- Apply a matrix completion algorithm to recover it.

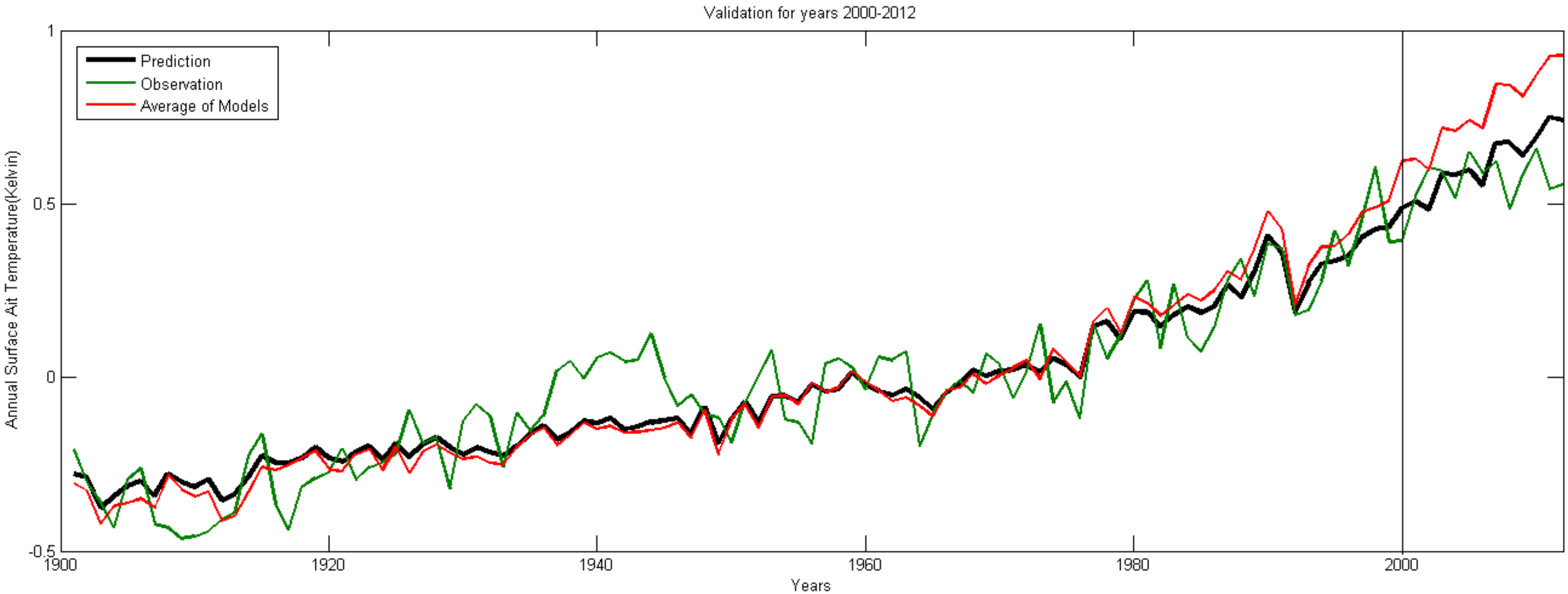
  [Keshavan, Montanari & Oh, JMLR '10] OptSpace algorithm: minimization of nuclear norm; uses spectral techniques and manifold optimization

- Yields predictions of unobserved temperatures.



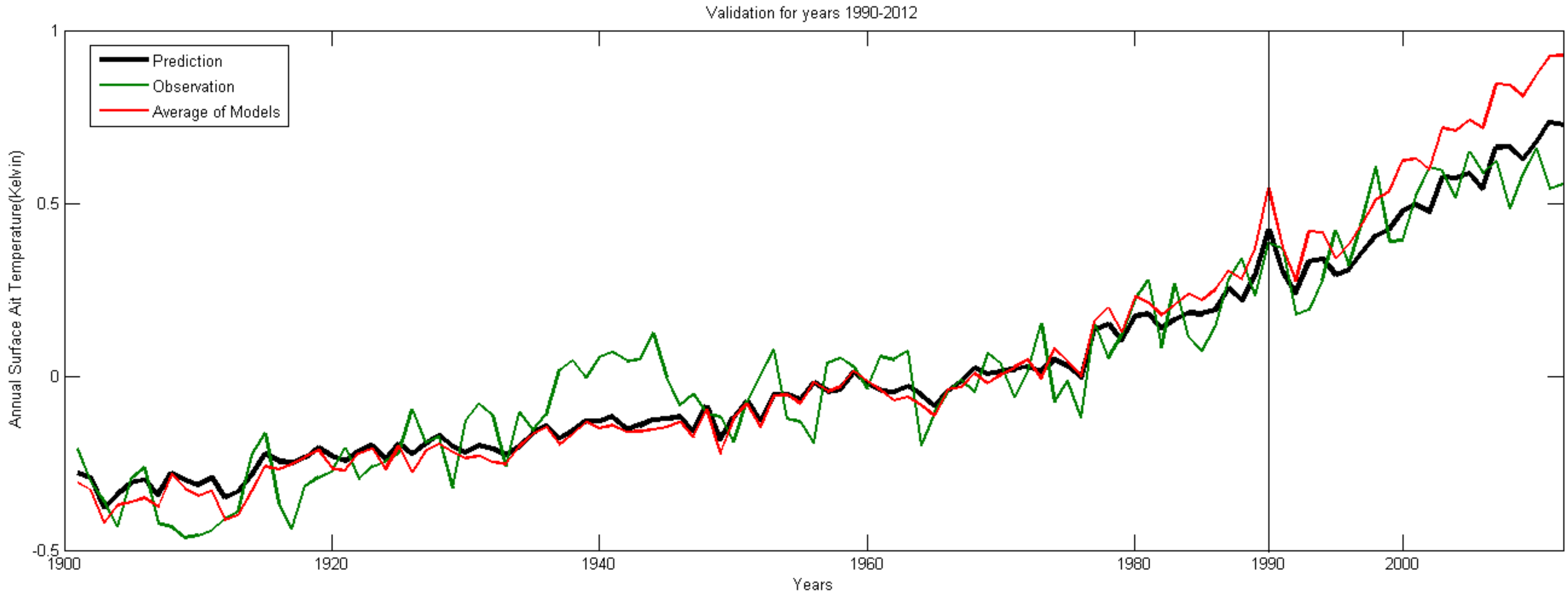
Green: observation, Red: mean prediction of climate models, Black: matrix completion

Validation period: 2005-2012



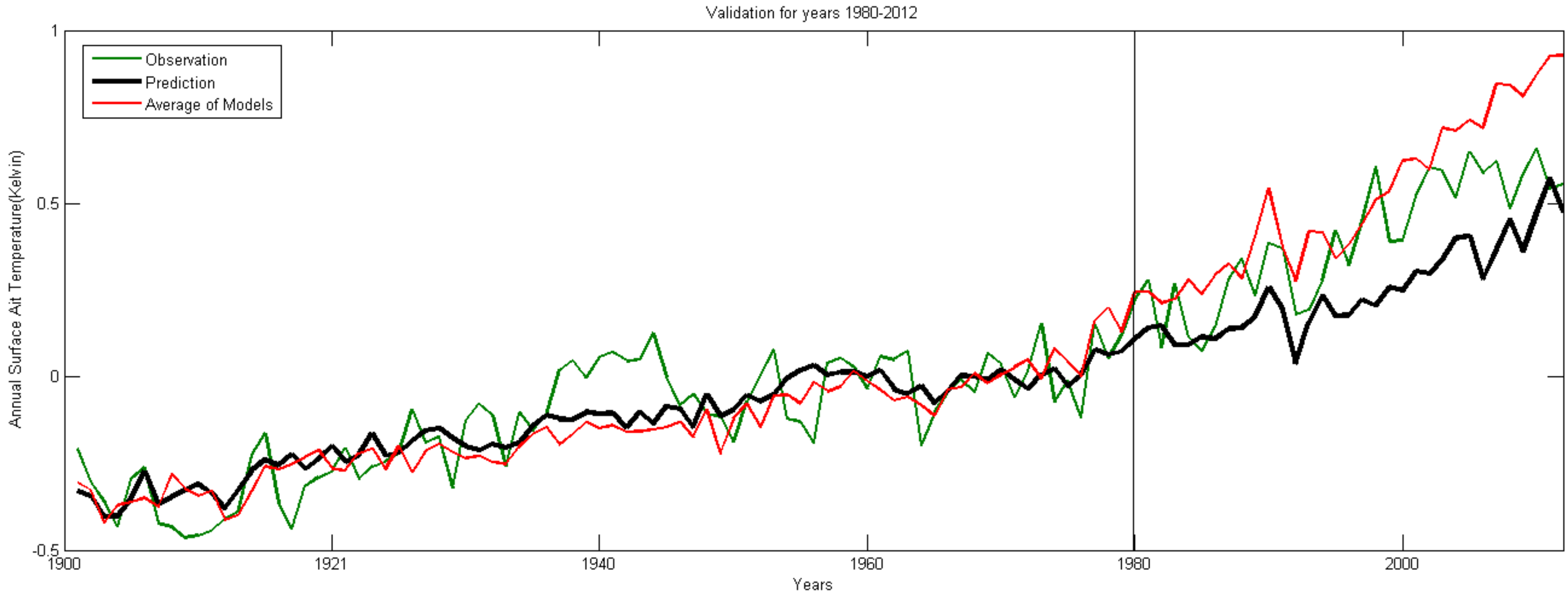
Green: observation, Red: mean prediction of climate models, Black: matrix completion

Validation period: 2000-2012



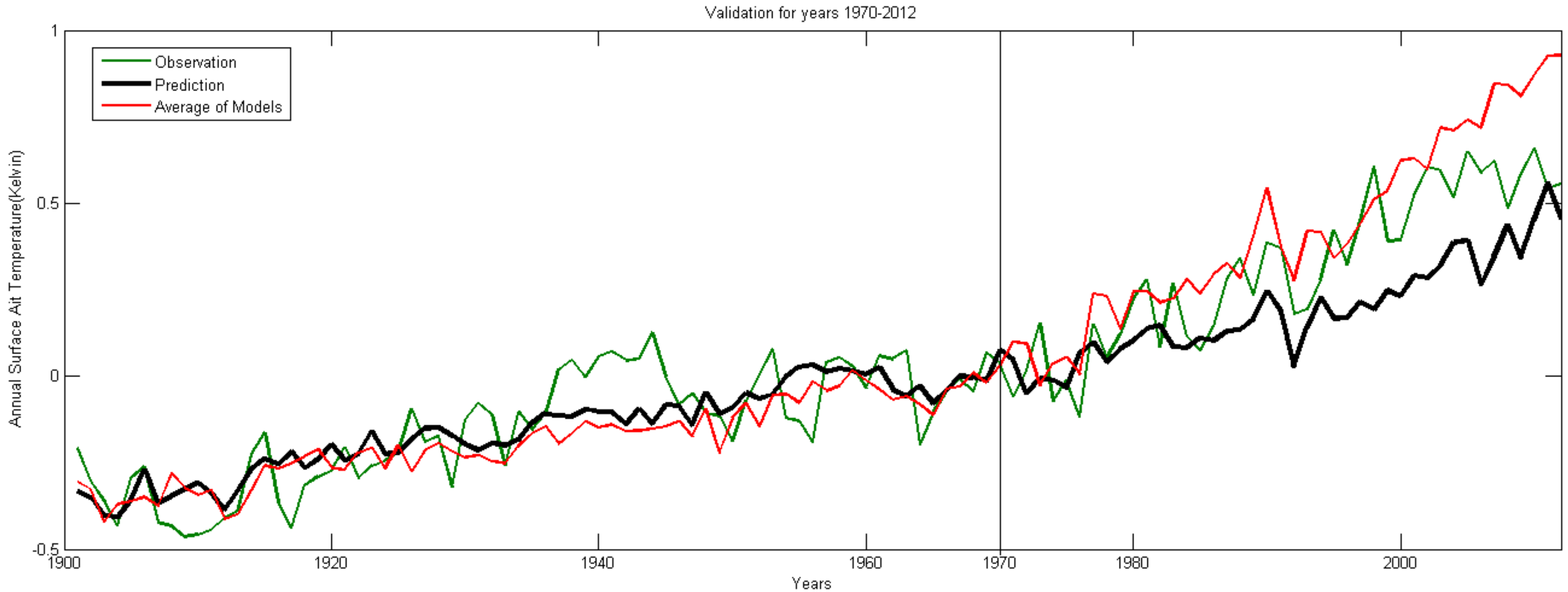
Green: observation, Red: mean prediction of climate models, Black: matrix completion

Validation period: 1990-2012



Green: observation, Red: mean prediction of climate models, Black: matrix completion

Validation period: 1980-2012



Green: observation, Red: mean prediction of climate models, Black: matrix completion

Validation period: 1970-2012

Outlook

- These results suggest some low intrinsic dimensionality.
- We induced some sparsity in the input matrix
  - Need not ensure low intrinsic dimensionality
- [Jia, DelSole & Tippett, J. Climate ‘13] also suggest low intrinsic dimensionality:
  - Only a small number (~2) climatological “predictive components” [DelSole & Tippett, Rev. Geophys. ‘07] determine the predictive “skill” of climate models (measured w.r.t. observations).
    - General warming trend, and El Niño-Southern Oscillation
- GCM ensemble (or subsets) as lower dimensional subspace
  - Can serve as a proxy for the high dimensional, complicated (dependencies, redundancies) space of climatological components in each GCM.
- Suggests future work on tracking a small subset of the ensemble.
  - Subset can change over time and space

Climate Extremes

How to define extremes?

① Threshold in single variable [IPCC special report 2012, p.4]

② Multiple degrees of severity

③ Related to multiple variables (complex extreme events)

④ Accumulation of non-extremes [IPCC 2012, p.6]

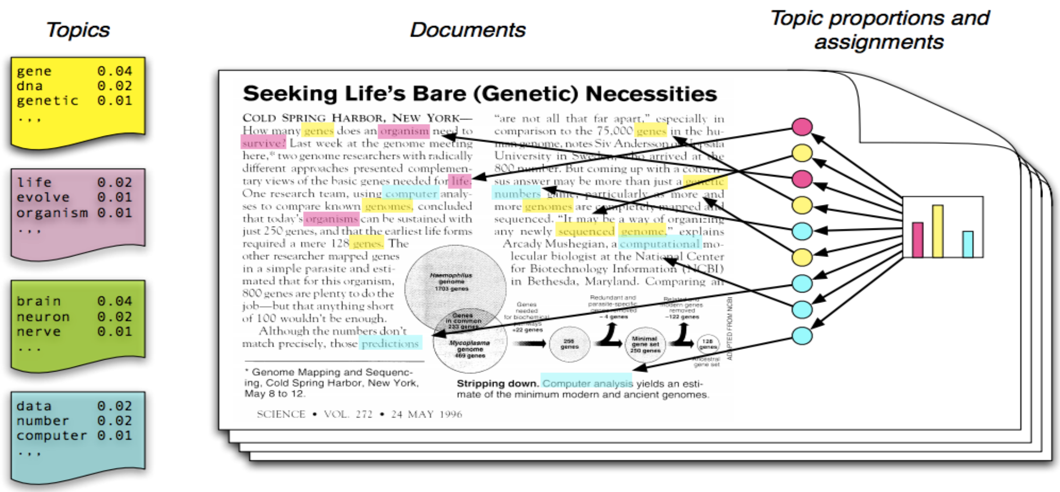
⑤ Subject to local climate characteristics [IPCC 2012, p.7]

Topic modeling approach

[Tang & M, Climate Informatics 2014]

Geophysical Models	$\boxed{\text{Statistical Models}}$	Model
$\boxed{\text{Extreme and Non-extreme values}}$	Extreme values	Data type
Single variable	$\boxed{\text{Multiple variables}}$	Variables
Single event type	$\boxed{\text{Multiple event types}}$	Events

Climate topic modeling



Document
(bag of words)

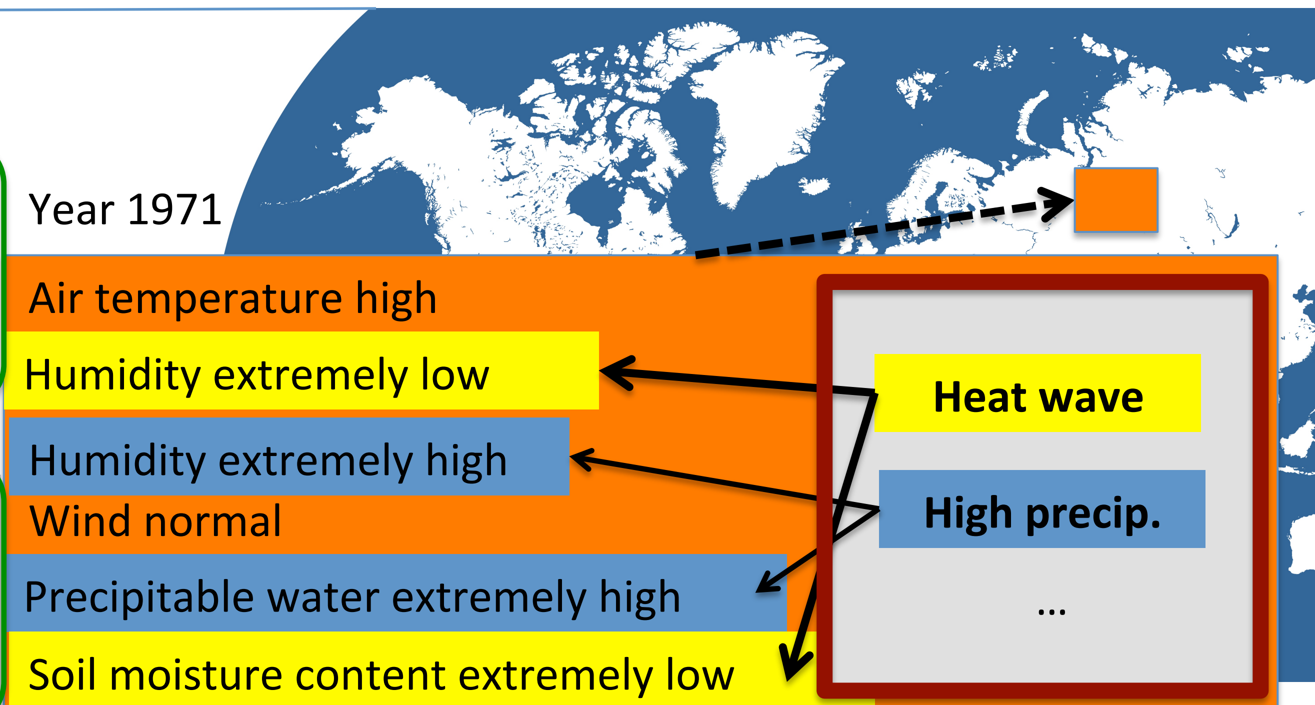
Topics

Words

credit: D. Blei

TOPIC_4	0.25196
shum1	0.18842
pr_wtr1	0.16720
slp5	0.15101
rhum1	0.13596
pres5	0.13455

TOPIC_2	0.24983
rhum5	0.19172
pr_wtr5	0.18384
shum5	0.15476
slp1	0.12487
pres1	0.11816

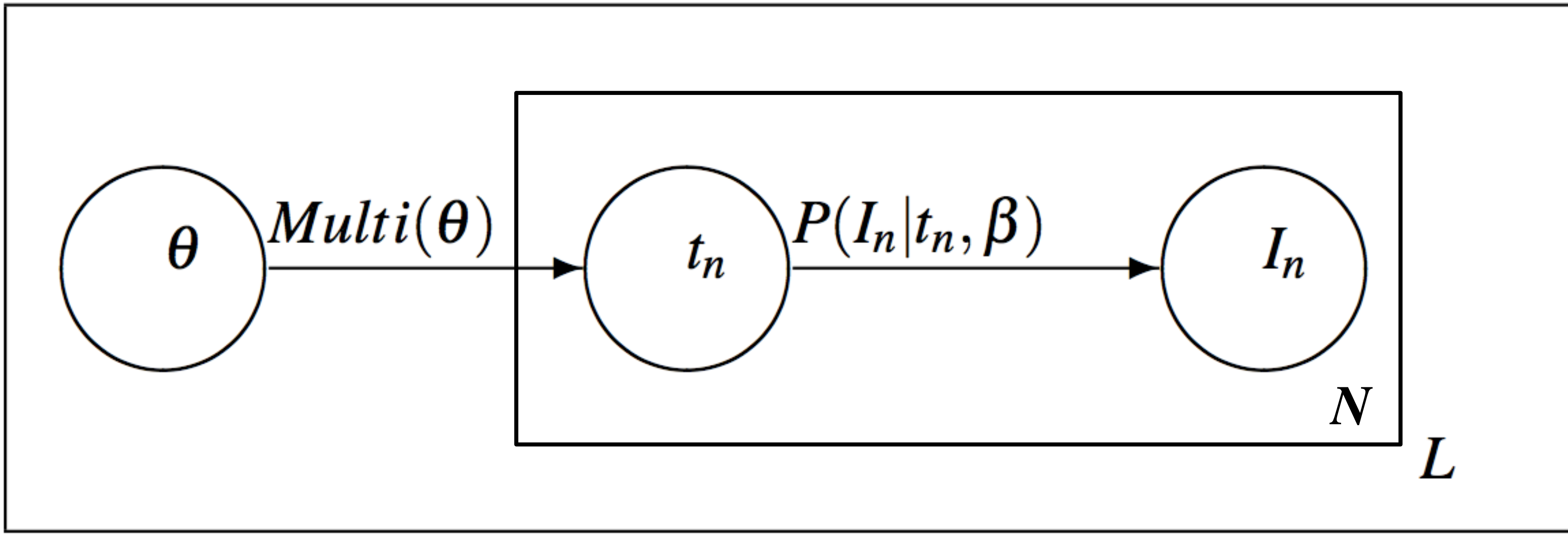


Geo-locations

Climate topics

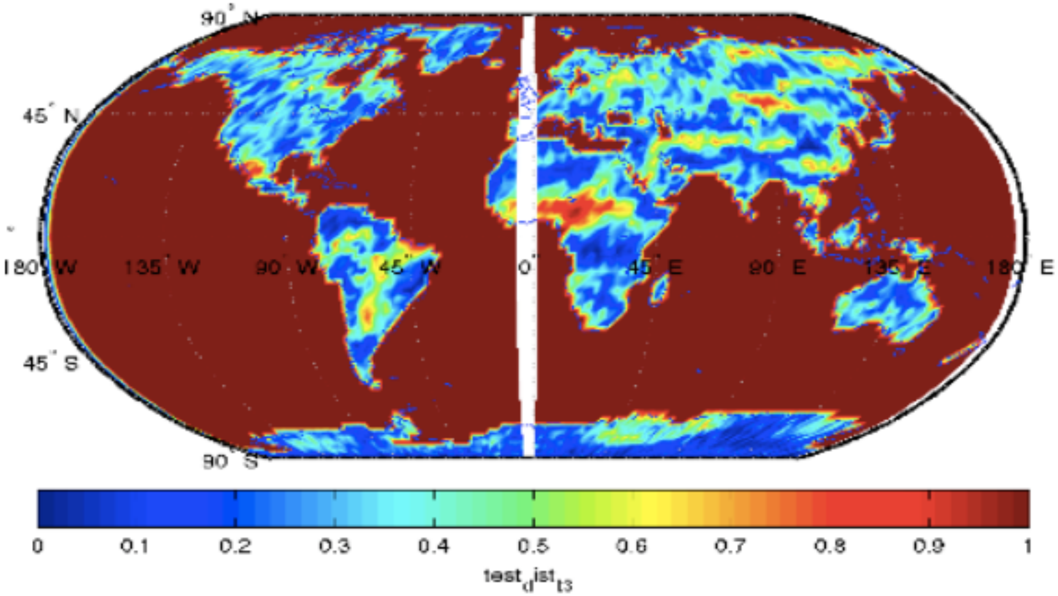
Climate
Descriptors

Climate topic modeling using LDA



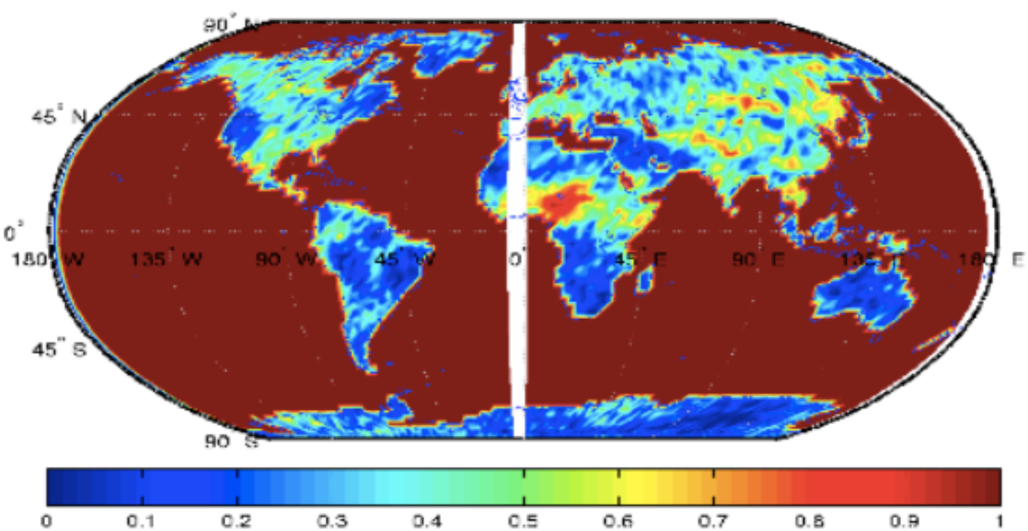
- *L*: number of spatial regions
- *N:* number of observations in region
- t_n: climate topic
- I_n: climate descriptor: discretized observed climate variable
- Dirichlet prior on θ

Qualitative evaluation: Sahel drought



1970

TOPIC_3	0.11299
uwnd1	0.21946
vwnd1	0.18948
shum4	0.10672
shum2	0.08712
rhum1	0.07517
pres4	0.06622
pr_wtr2	0.05297
pres3	0.04640
slp4	0.03748
uwnd2	0.03436



1971

TOPIC_6	0.11236
shum1	0.29531
uwnd1	0.16000
pr_wtr1	0.10355
vwnd1	0.09631
rhum1	0.07629
pr_wtr2	0.05688
pres3	0.05418
slp3	0.04164
uwnd2	0.03991
rhum2	0.03571

Paleo-climate Reconstruction

Paleo-climate reconstruction

Problem:

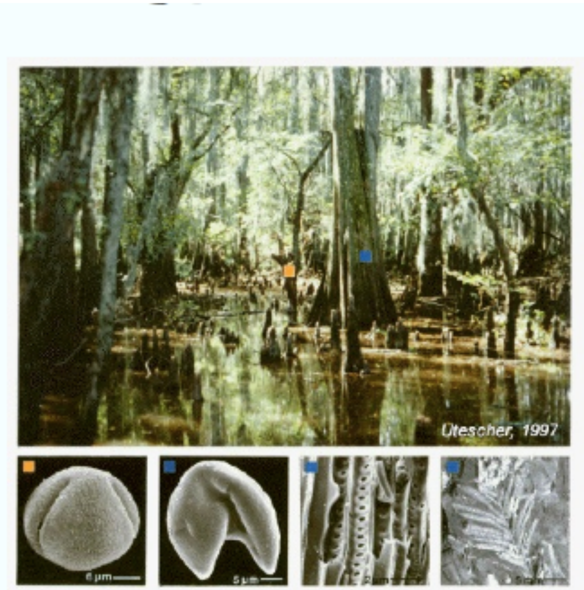
– To understand climate change we need to understand past climates.
– NOTE: climate has fluctuated at much greater scales in the past than in the 20th Century.
– However the variance on measurements is higher in the past.
  • We did not have a global grid of measurements
  • Measurements corrupted or lost

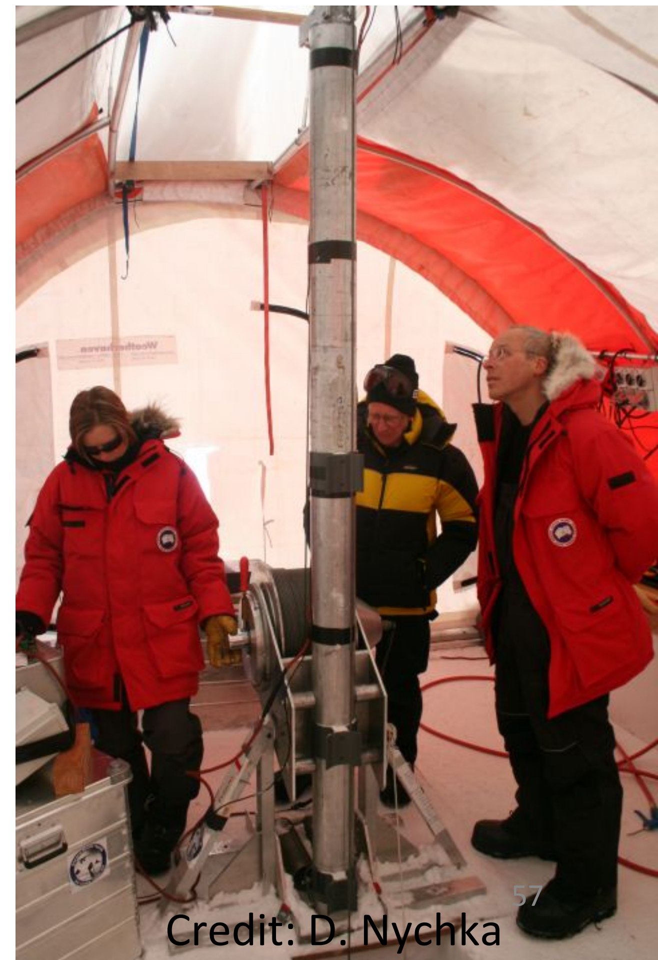
Challenge: use paleo-proxies to reconstruct temperatures, CO_2

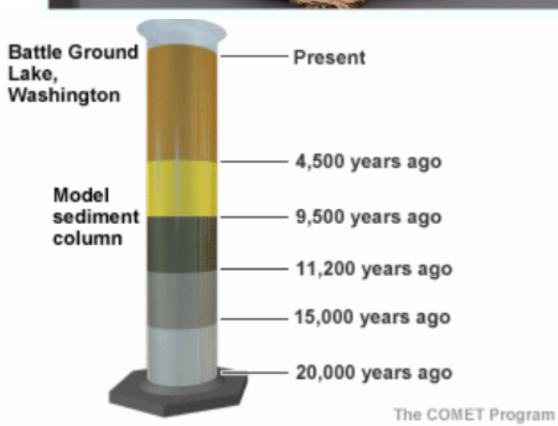
E.g. tree rings, coral, ice cores, lake sediment cores, provide estimates.

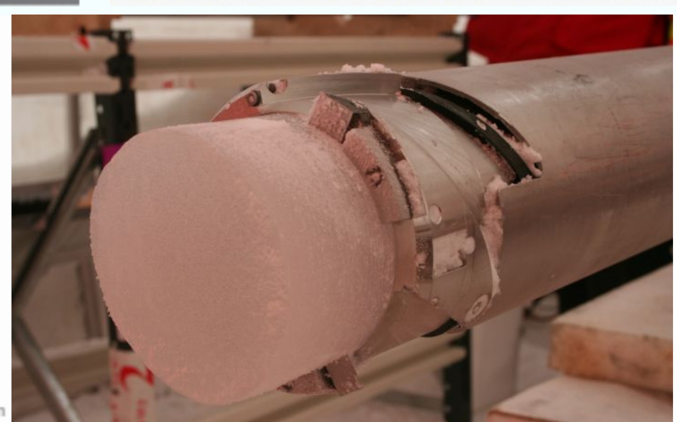
Paleo-climate reconstruction

Challenge: use paleo-proxies to reconstruct temperature, CO_2 concentrations. E.g. tree rings, coral, ice cores, lake sediment cores.









Credit: D. Nychka

Challenge: How how to best harness paleo-proxies to reconstruct past climates?

Possible ML approaches:

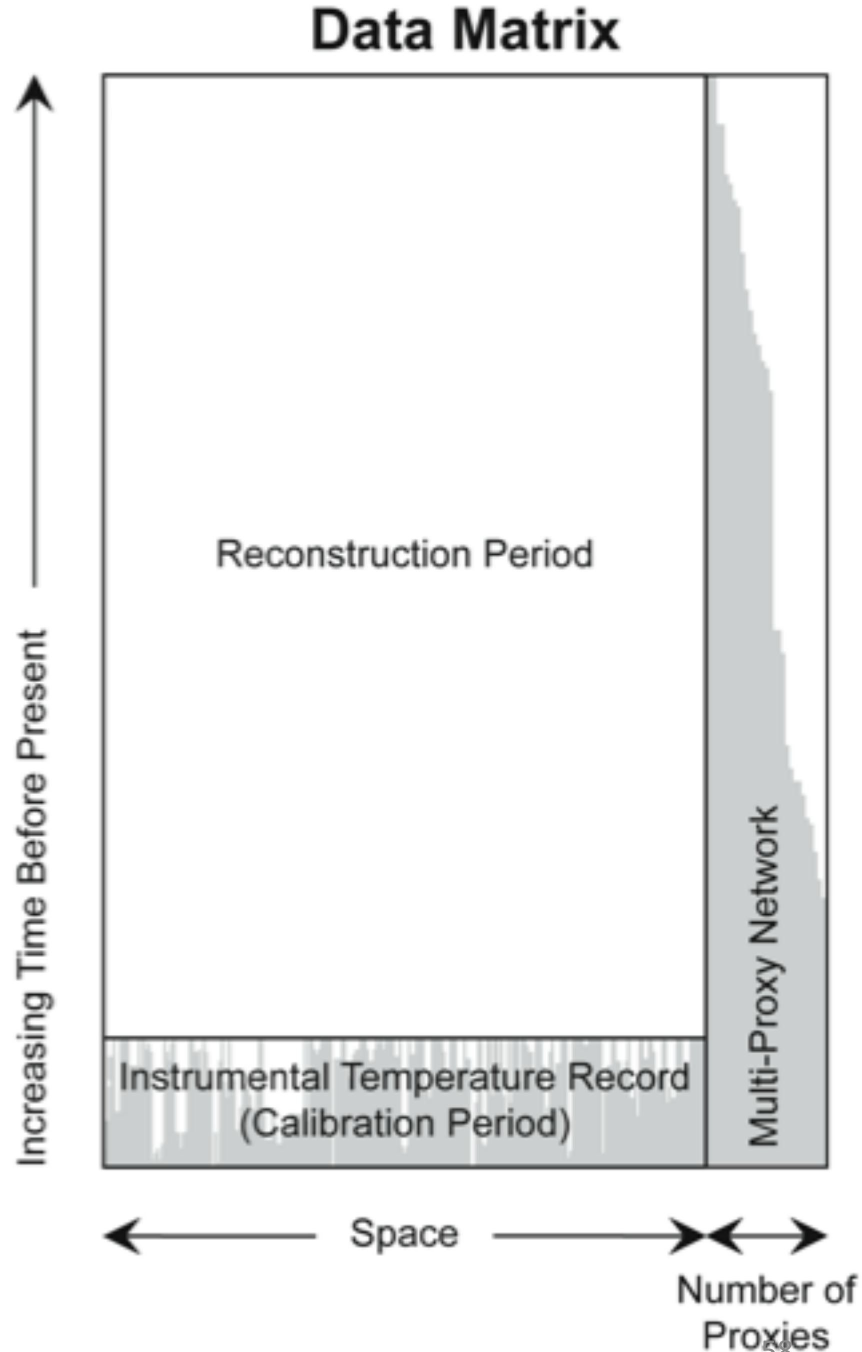
Can sparse matrix completion techniques play a role?

Discover latent structure?

Related ML issues:

Data fusion (many small data sets!)

Multi-view learning



[Smerdon & Kaplan, Journal of Climate, 2007]

Climate Informatics: take-home message

- Very impactful problems for society; climate change mitigation and adaptation. Chance to affect IPCC.
- Data-rich “big data” playground, public data sets
- Largely open field for ML, with many low-hanging fruit
- Climate scientists are already extremely computationally sophisticated, writing massive software, running HPC.
  - Allows for fruitful collaborations focused on the ML value-add.
  - Climate model simulations provide a vast wealth of data/knowledge.
- Physics provides some inertia, predictability!
- Funding opportunities

Thank you! *And thanks to my collaborators:*

Frank Alexander, *Los Alamos National Laboratory*
Eva Asplund, *Barnard College, Columbia University*
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Resources

- Climate Informatics: www.climateinformatics.org
  - Links to resources, Climate Informatics workshops, online community
- Climate Informatics Wiki
  - Data sets here: sites.google.com/site/1stclimateinformatics/materials
- 4th International Workshop on Climate Informatics, 2014
  www2.image.ucar.edu/event/ci2014
- 4th Workshop on Understanding Climate Change from Data, 2014
  www2.image.ucar.edu/event/fourth-climatechange
- IPCC AR5 Report: www.ipcc.ch/report/ar5/
- WCRP Grand Challenges:
  www.wcrp-climate.org/grand-challenges

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