Global Climate Model Tracking using Geospatial Neighborhoods

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Joint work with Scott McQuade

Motivation for Climate Informatics

The threat of climate change:
one of the greatest challenges currently facing society.

We face an explosion in data!
- Climate model outputs
- Satellite measurements
- Environmental sensors
- …

Machine Learning has made profound impacts on:
web search, Bioinformatics, internet advertising, etc.

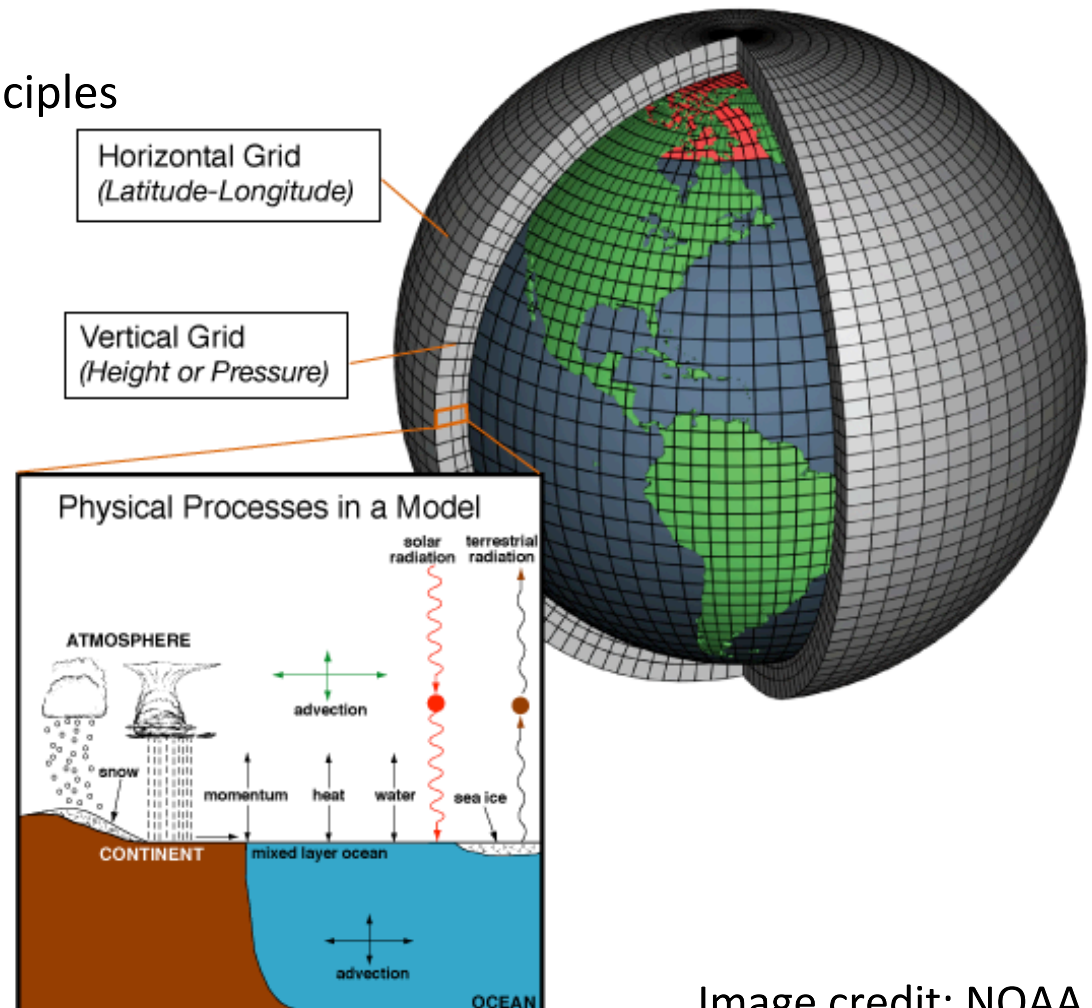
Challenge: accelerate discovery in Climate Science with ML

[“Climate Informatics,” M et al. 2012]

Climate modeling

Climate model: a complex system of interacting mathematical models

- Not data-driven
- Based on scientific first principles
  - Meteorology
  - Oceanography
  - Geophysics
  - …

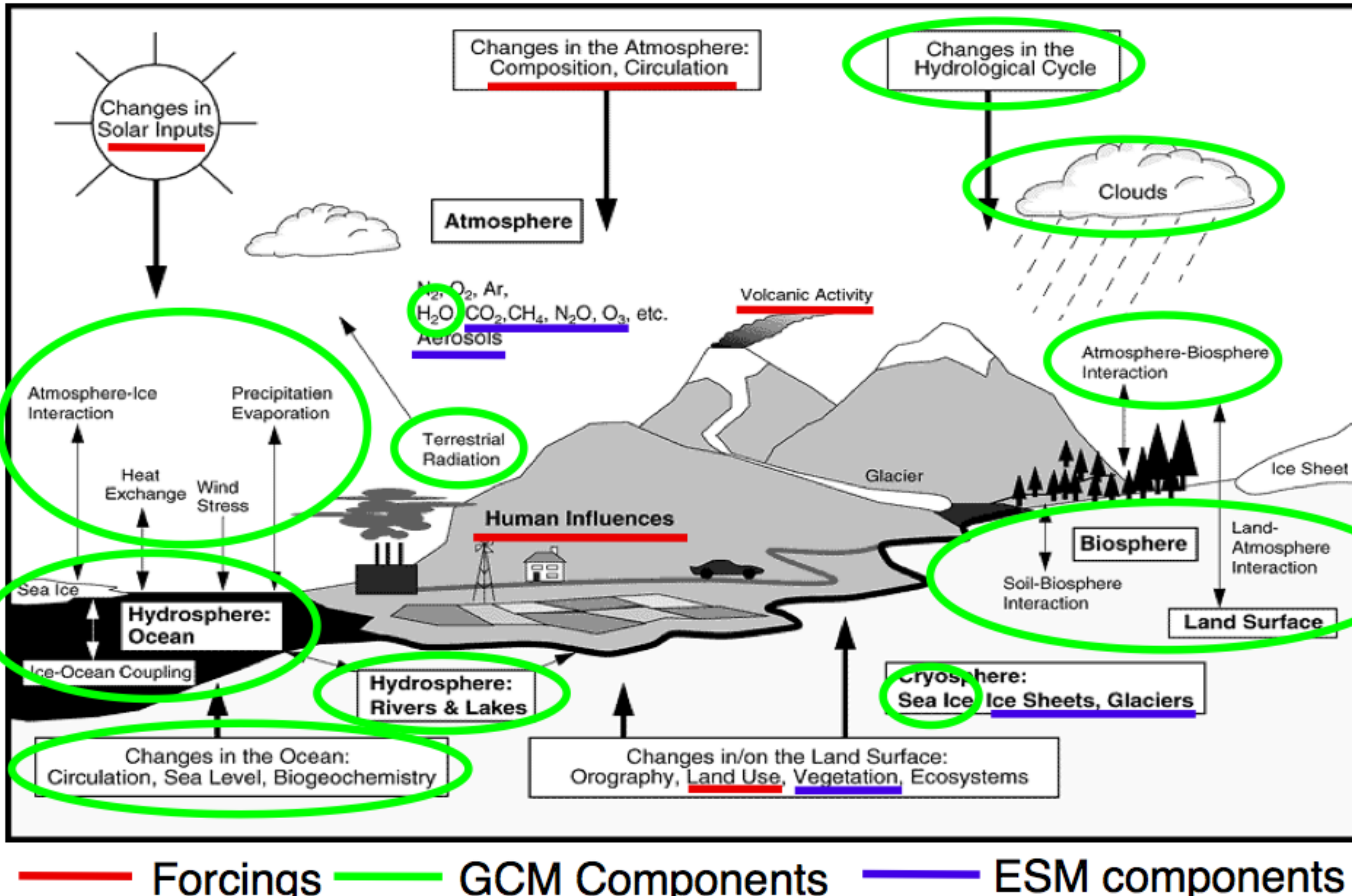


Climate model differences

- Assumptions
- Discretizations
- Scale interactions
  - Micro: rain drop
  - Macro: ocean

Image credit: NOAA

A climate model (image credit: G. Schmidt)



Climate models

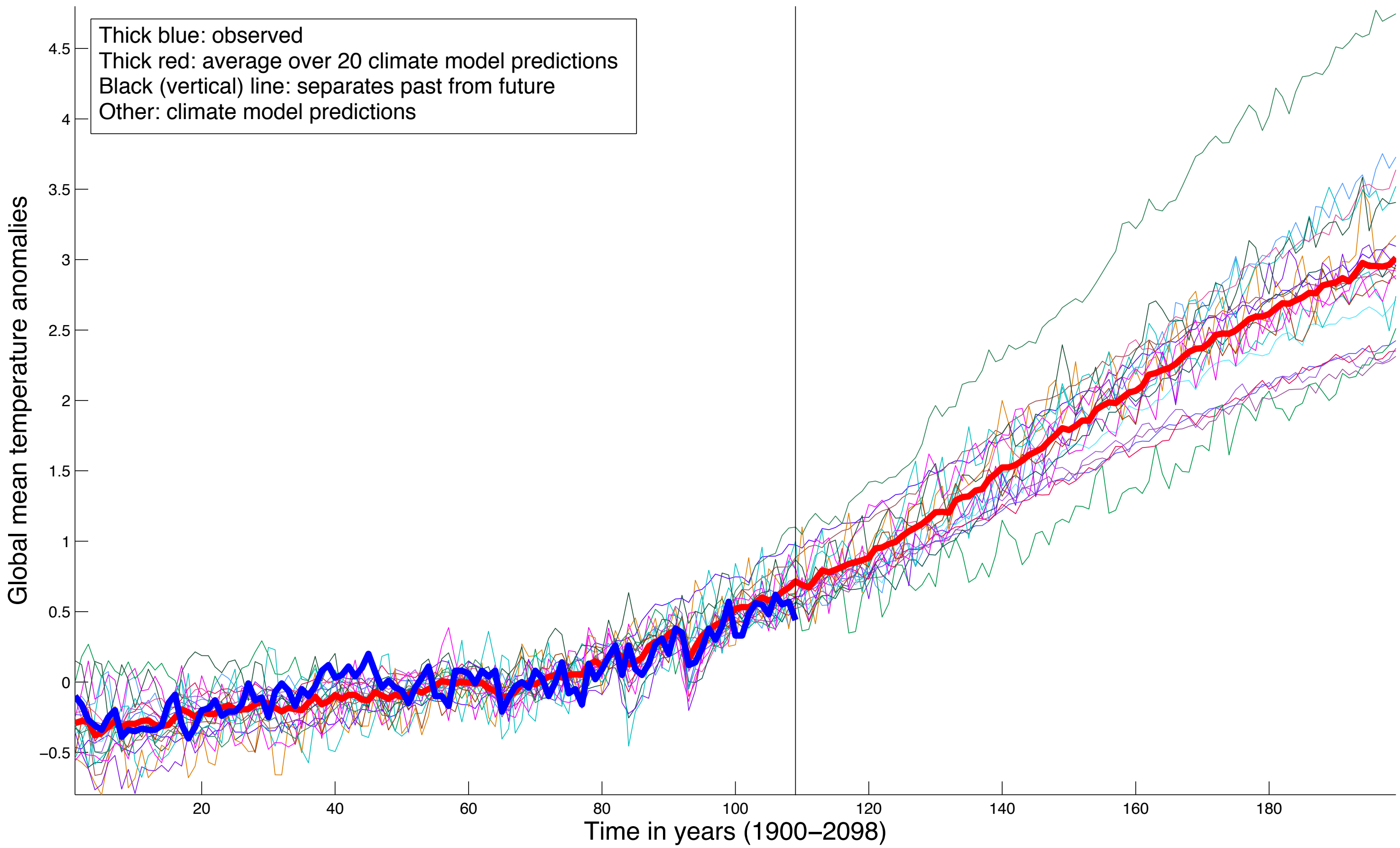
- IPCC: Intergovernmental Panel on Climate Change
  - Nobel Peace Prize 2007 (shared with Al Gore).
  - Interdisciplinary scientific body, formed by UN in 1988.
  - Fourth Assessment Report 2007, on global climate change

    450 lead authors from 130 countries, 800 contributing authors, over 2,500 reviewers.
  - Next Assessment Report is due in 2013.

- 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.

Climate model predictions



- High variance among GCM projections (here: temperature anomalies)
- Future fan-out

Improving predictions of Multi-Model Ensemble of GCMs

- No one model predicts best all the time.
- Average prediction over all models is best predictor over time. [Reichler & Kim, Bull. AMS ‘08], [Reifen & Toumi, GRL ’09]
- 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?

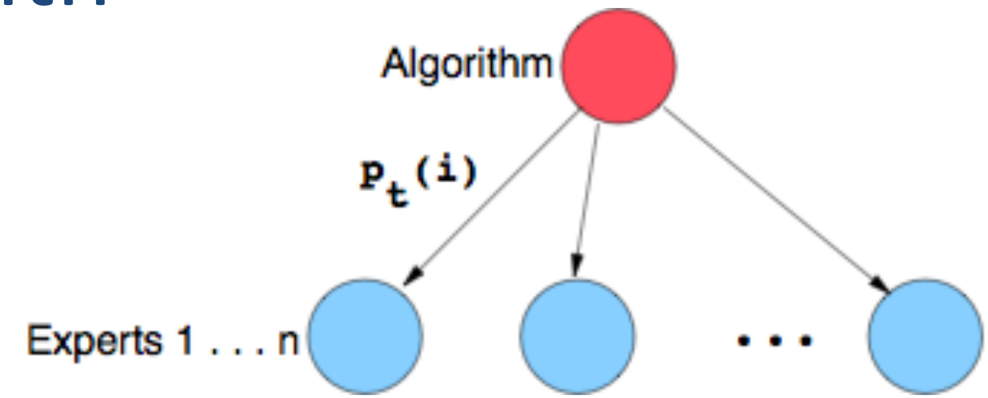
- While taking into account the 20 climate models’ predictions

Contributions

- Tracking climate models (TCM)
  [M, Schmidt, Saroha, & Asplund, SAM 2011 (CIDU 2010)]:
  - Applied online learning with expert advice to track GCMs
  - Considered each geospatial region as a separate problem

- Neighborhood-Augmented TCM (NTCM)
  [McQuade & M, AAAI 2012]:
  - Build a rich modeling framework in which the climate predictions are made at higher geospatial resolutions
  - Model neighborhood influences among geospatial regions

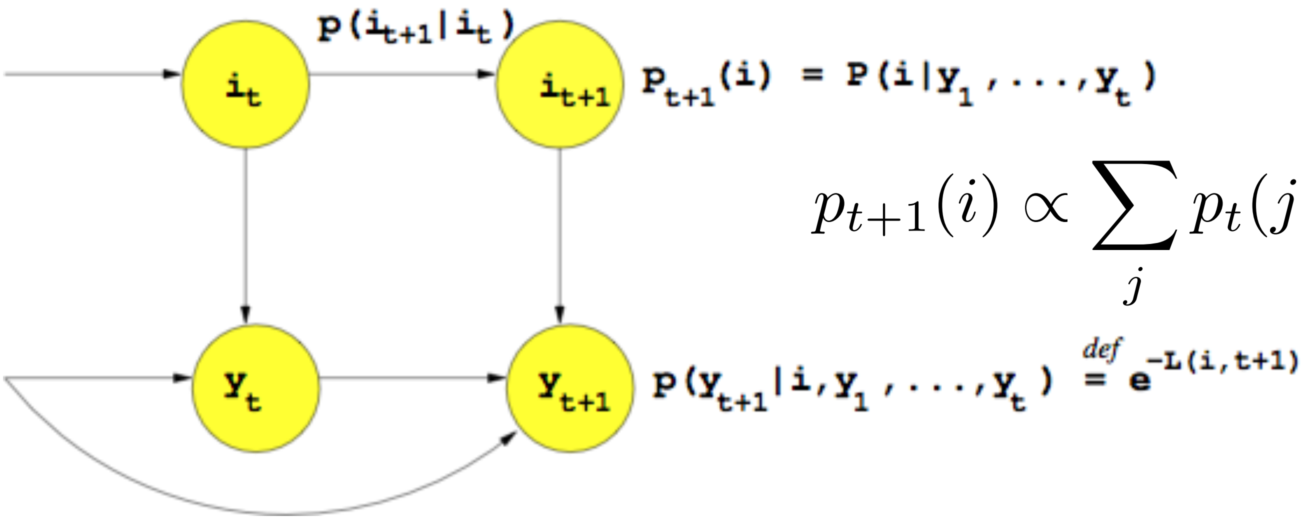
Online learning with expert advice



Learner maintains distribution over *n* "experts."

- Experts are black boxes: need not be good predictors, can vary with time, and depend on one another. We use GCM temp predictions.
- Learner maintains/updates probability distribution $p_t(i)$ over experts, *i*, representing how well each expert has predicted recently.
  - Used to inform learner's prediction.
- *L(i, t)* is prediction loss of expert *i* at time *t*. We use squared loss.
- Family of Multiplicative Updates algorithms (*cf*. "Hedge," "Weighted Majority"), descended from "Winnow," [Littlestone 1988],[Littlestone & Warmuth'89].

Online learning: time-varying data



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

- For a family of these algorithms, [M & Jaakkola, 2003] derived $p_t(i)$ as Bayesian updates of a generalized Hidden Markov Model
- Hidden variable: identity of current "best expert"
- Transition dynamics, *p(i | j)*, model non-stationarity

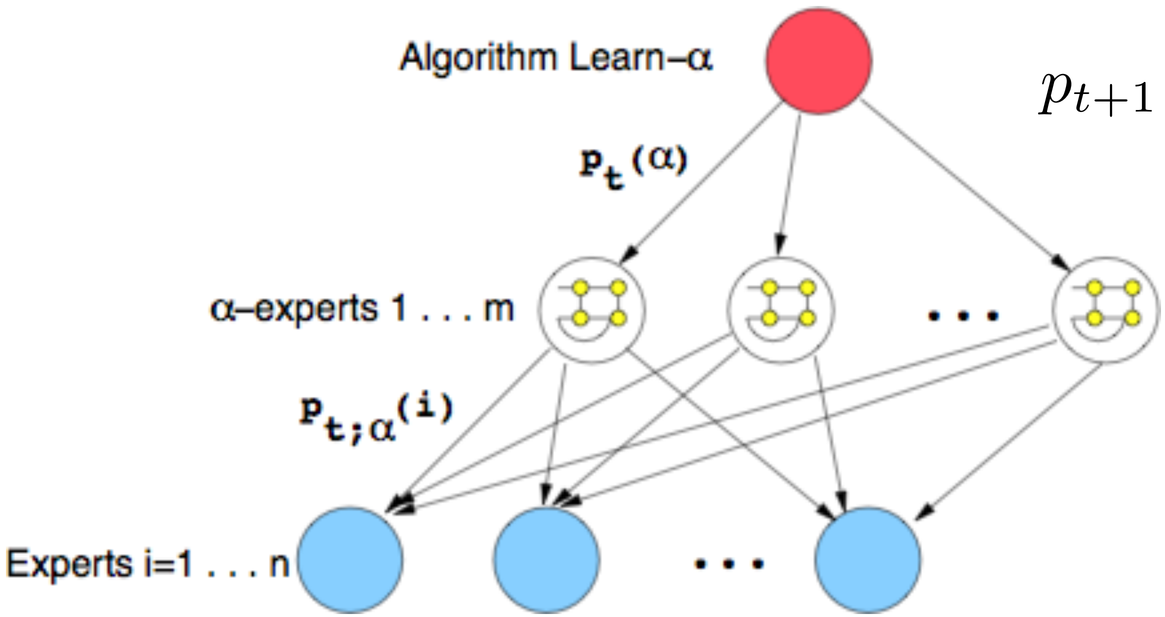
Online learning: time-varying data

Fixed-Share Algorithm [Herbster & Warmuth, 1998]:

- Assumes there is a probability α that the hidden "best expert" switches at each time step

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

Online learning: time-varying data



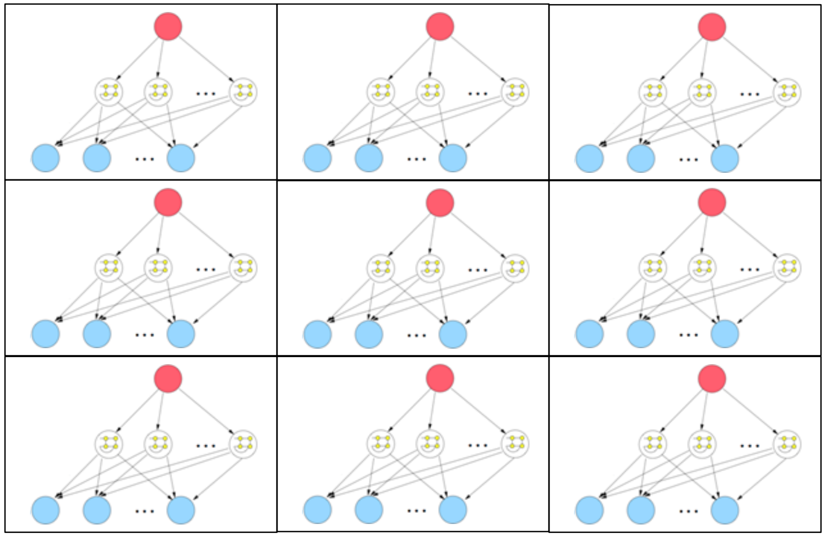
$$p_{t+1}(\alpha) \propto p_t(\alpha)e^{-L(\alpha,t)}$$

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

- Learns the α parameter by tracking a set of meta-experts, Fixed-Share algorithms, each with a different α value

Neighborhood-Augmented TCM (NTCM)

- Run instances of Learn-α (variant) on multiple sub-regions that partition the globe
- Global temperature anomaly computed as mean of sub-region algorithm predictions
- Experiments conducted using several different region sizes



Neighborhood-Augmented TCM (NTCM)

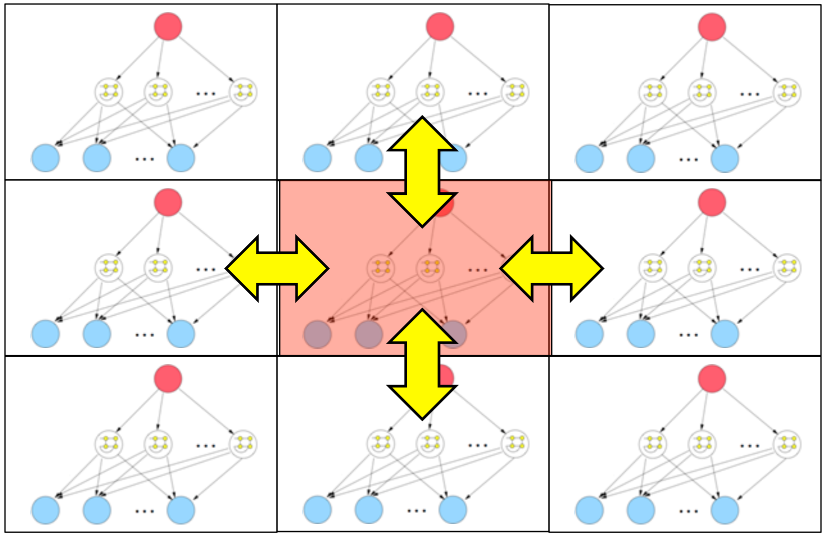
Non-homogenous HMM transition matrix:

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

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

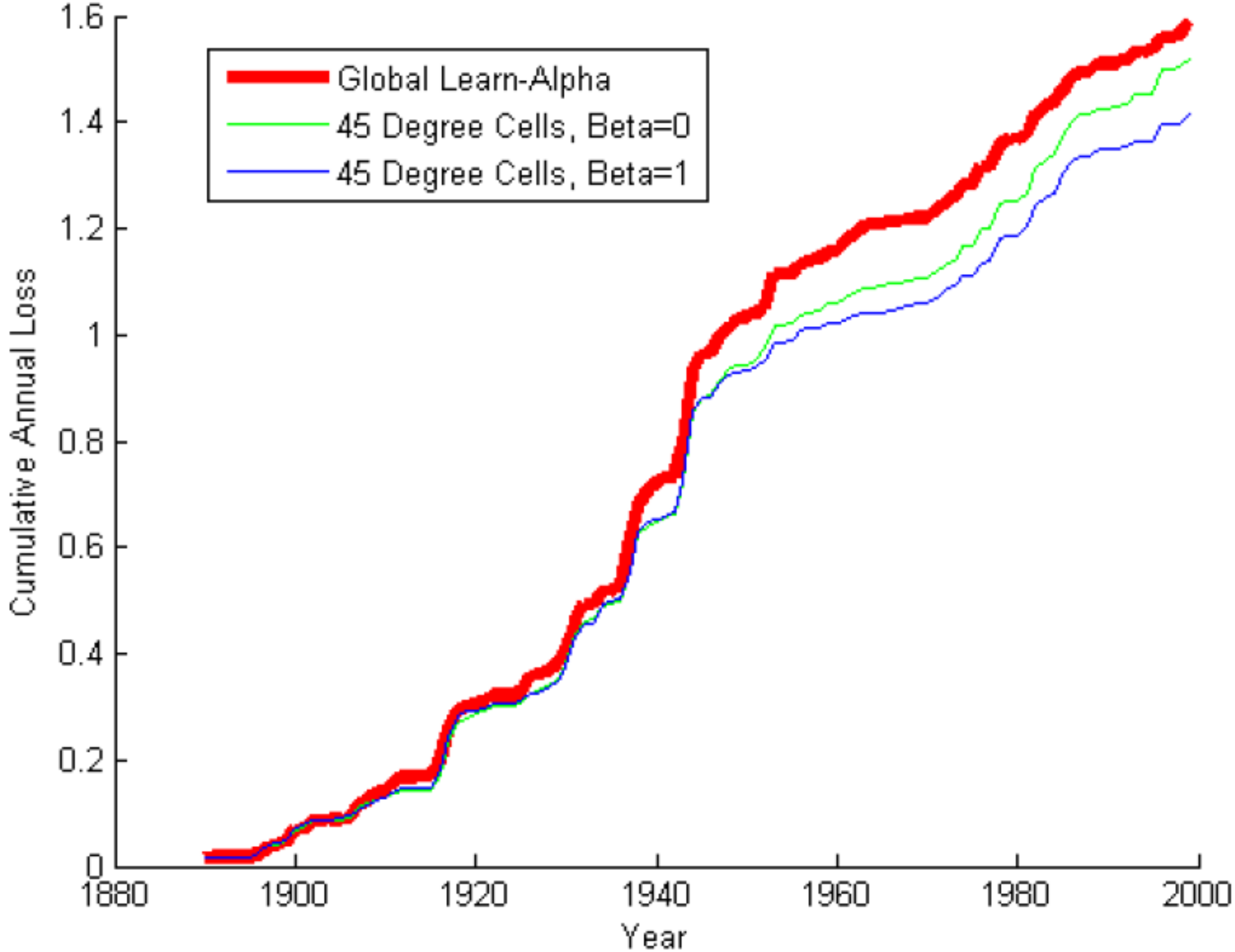
Neighborhood schemes

- Update is modular with respect to neighborhood scheme S(r).
- A possible neighborhood scheme:



Experimental Setup

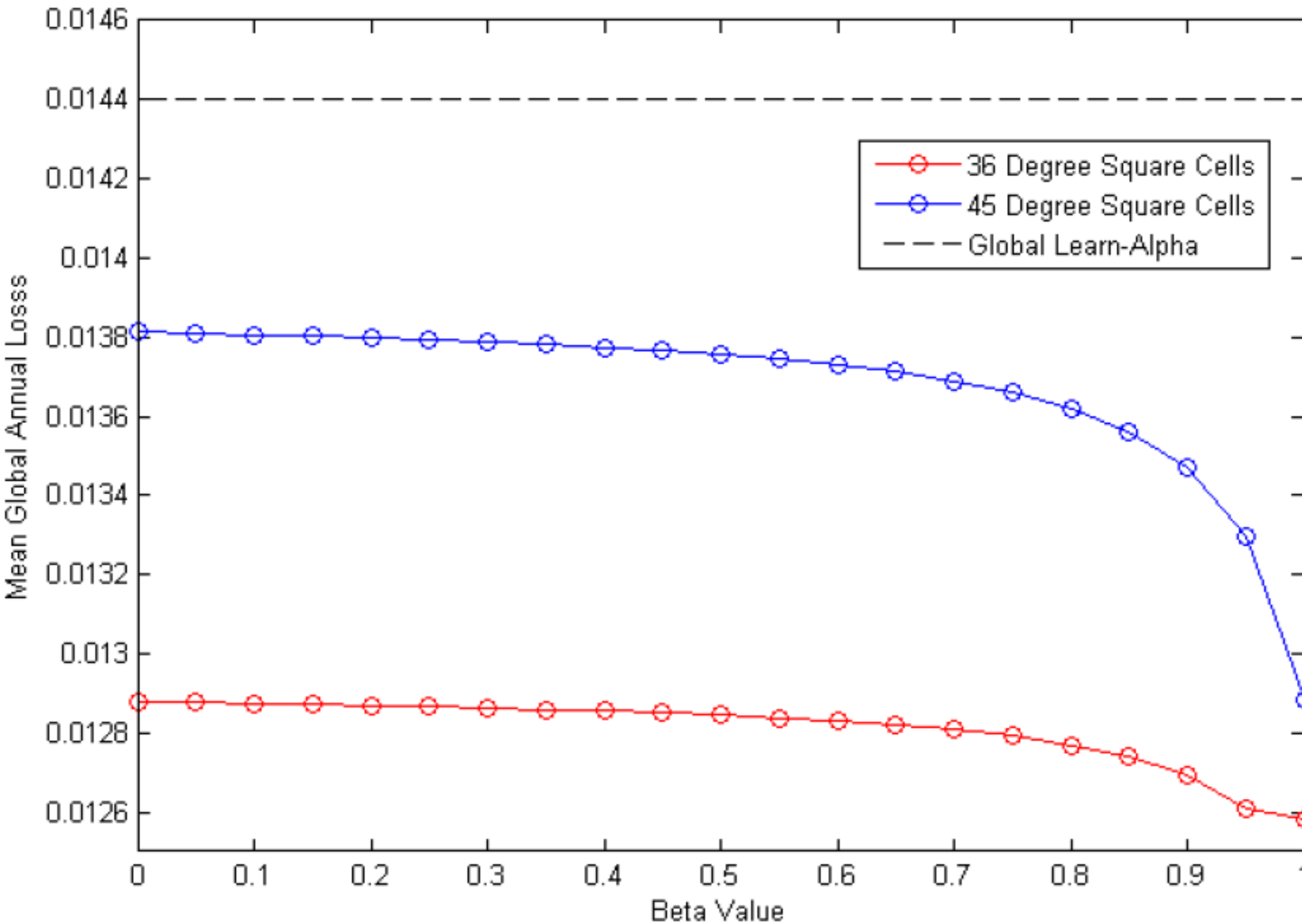
- GCM hindcasts from the years 1890-2000
  - IPCC Phase 3 Coupled Model Intercomparison Project (CMIP3)
  - Climate of the 20th Century Experiment (20C3M)
  - One run from each contributing institution arbitrarily selected
- Observed temperature anomaly data from NASA GISTEMP
- All data converted to temperature anomalies
  - Benchmark period 1951-1980



	Mean Annual Loss	Variance	Cumulative Annual Loss (1890-2000)
Global Learn-α	0.0144	0.0003	1.5879
45 Degree Squares $\beta = 0$	0.0138	0.0004	1.5194
45 Degree Squares $\beta = 1$	0.0129	0.0003	1.4173

Table 1: Cumulative Annual Losses for 45 degree square cells and Global Learn-α.

Results



0.0146
0.0144
0.0142
0.014
0.0138
0.0136
0.0134
0.0132
0.013
0.0128
0.0126
Mean Global Annual Losss
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
Beta Value
36 Degree Square Cells
45 Degree Square Cells
Global Learn-Alpha

Thank You!

And thanks to my coauthors:

"Global Climate Model Tracking Using Geospatial Neighborhoods" AAAI 2012

Scott McQuade, *George Washington University*

"Tracking Climate Models" SAM 2011, CIDU 2010

Gavin Schmidt, *NASA GISS & Columbia University*

Shailesh Saroha, *Amazon.com*

Eva Asplund, *Columbia University*

PLUG: Climate Informatics 2012

The Second International Workshop on Climate Informatics

September 20-21st at the National Center for Atmospheric Research (NCAR), Boulder, CO

http://www2.image.ucar.edu/event/ci2012

Climate Informatics wiki: data, links, and challenge problems:

http://sites.google.com/site/1stclimateinformatics/materials