Environment Canada
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McGill Physics

StocSIPS

Stochastic Seasonal to Interannual Prediction System

Apprivoiser les papillons pour de meilleurs prévisions mensuelles, saisonnières et interannuelles

Environnement Canada, **29 April, 2016**

S. Lovejoy, L. Del Rio Amador, **McGill, Montreal**

Forecasts from months to decades:

The unsuspected Elephantine ("long range") memory

StocSIPS* with SLIMM**

10% of the information needed for global seasonal temperature forecasts comes from fluctuations more than 300 years old…

But we can (almost) do it!

*StocSIPS= Stochastic Seasonal and Interannual Prediction System
**SLIMM= ScaLIng Macroweather Model

Statistical Mechanics

Low level (fundamental)

stochastic

Continuum limit

Continuum mechanics

Thermodynamics

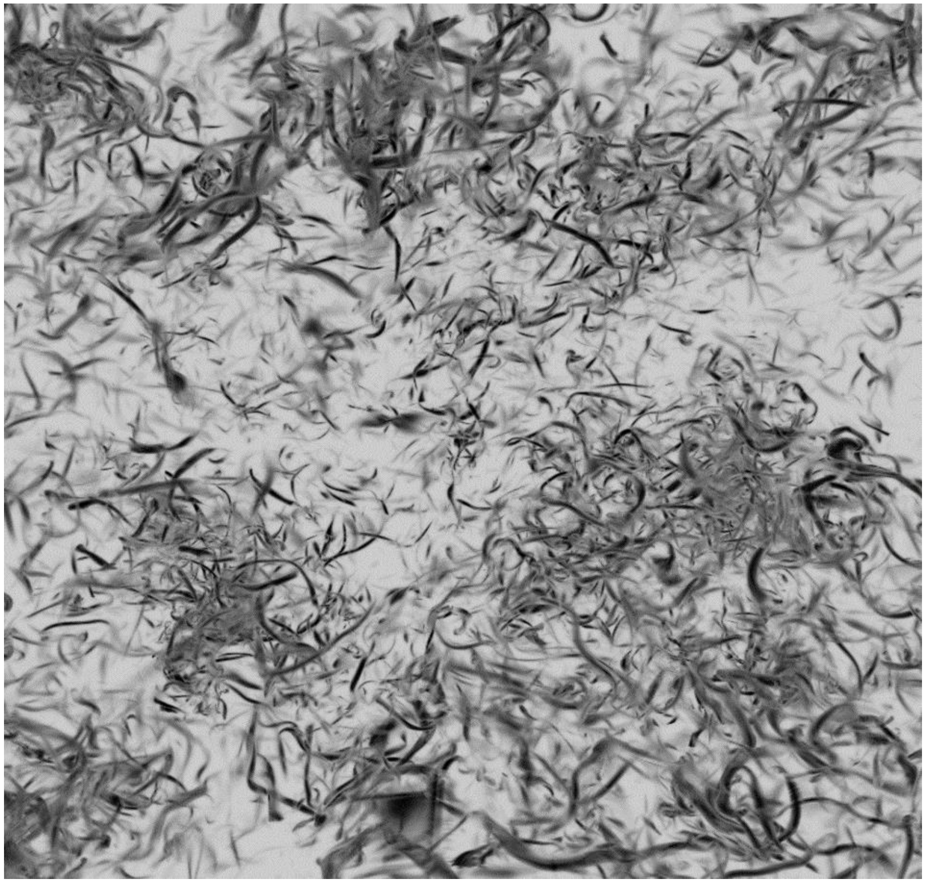
Higher level

deterministic

High Reynolds number limit

Vortices in strongly turbulent fluid

(M. Wiczek, numerical simulation, 2010)



Laws of turbulence

Higher level

Richardson, Kolmogorov, Corrsin, Obukhov, Bolgiano

Fluctuations ≈ (turbulent flux) x (scale)^{H}

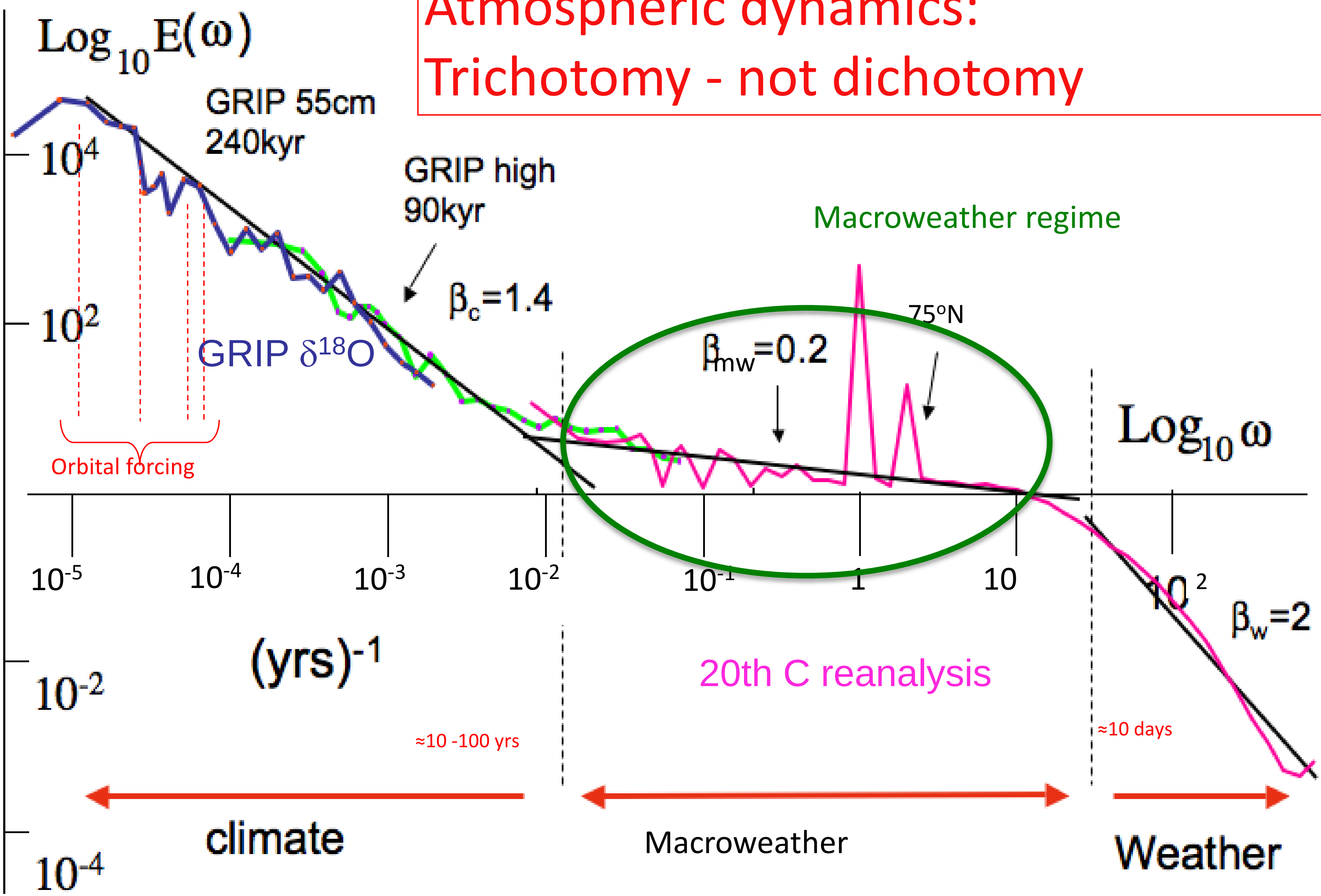
stochastic

Long time limit >10days

Space-time factorization

Macroweather laws

Atmospheric dynamics: Trichotomy - not dichotomy



Two data sources only GRIP, 20CR

Lovejoy and Schertzer 2011

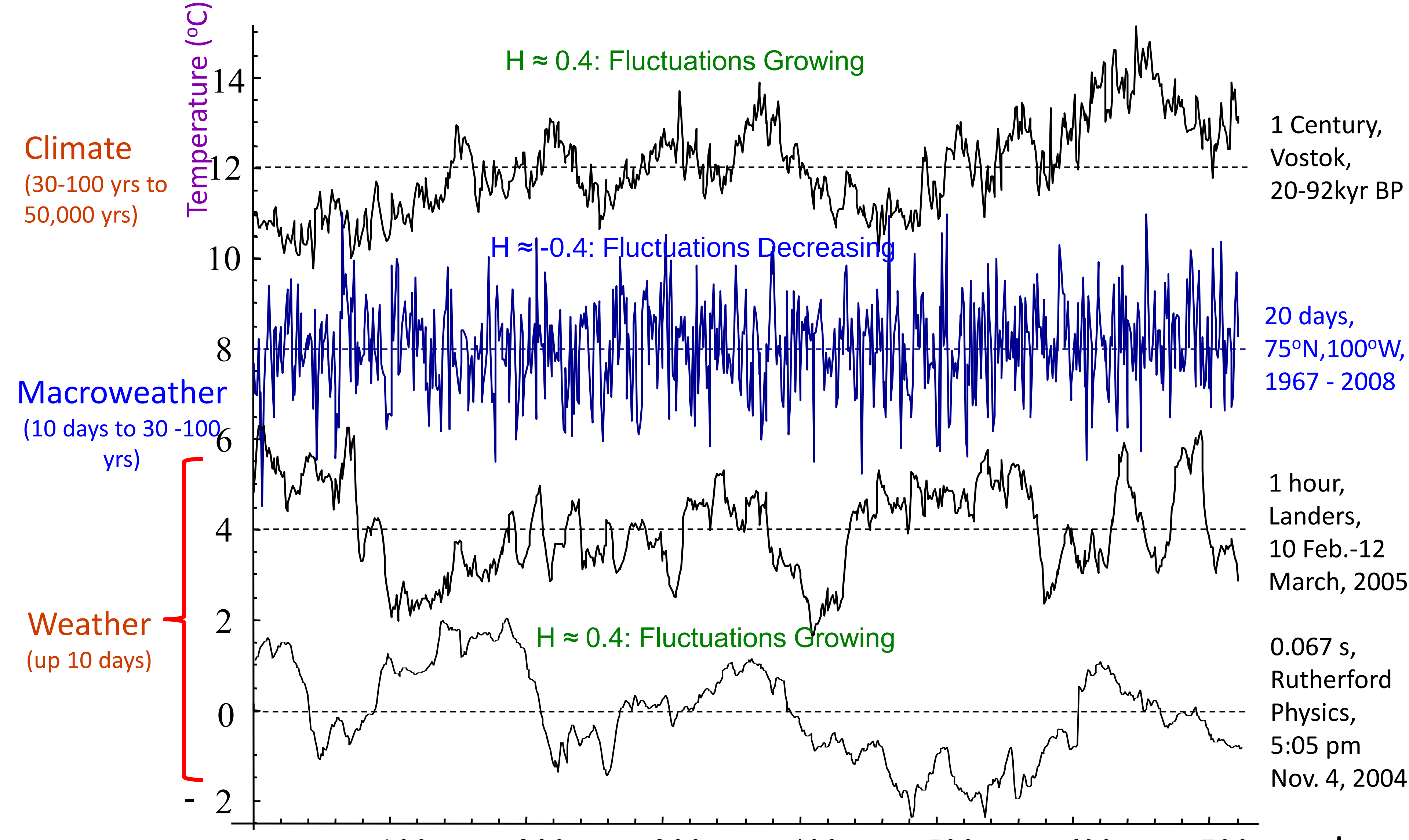
Trichotomy:

Weather – macroweather - climate

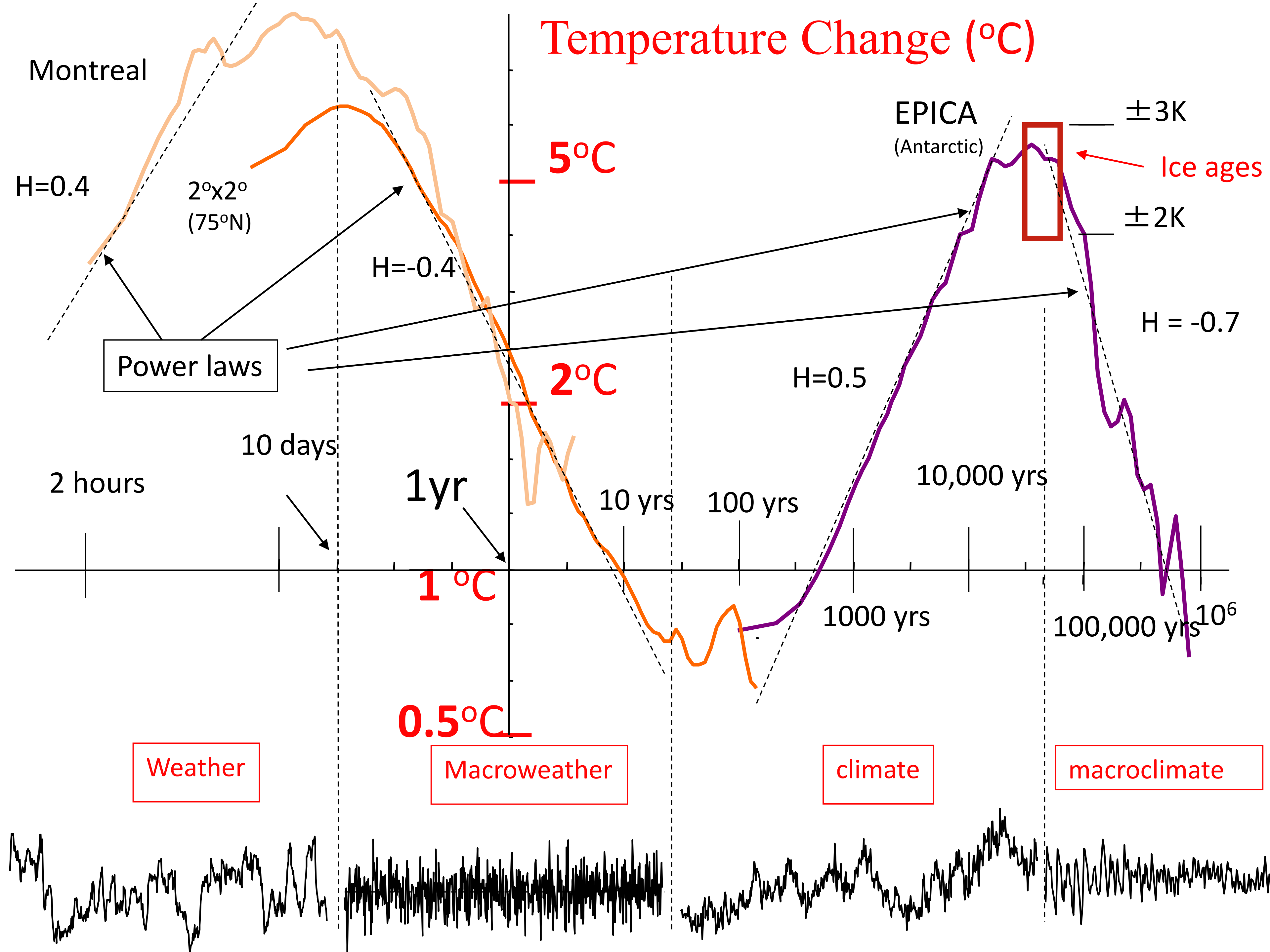
$$\langle \Delta I \rangle = \langle \varphi \rangle \Delta t^H$$

Fluctuation

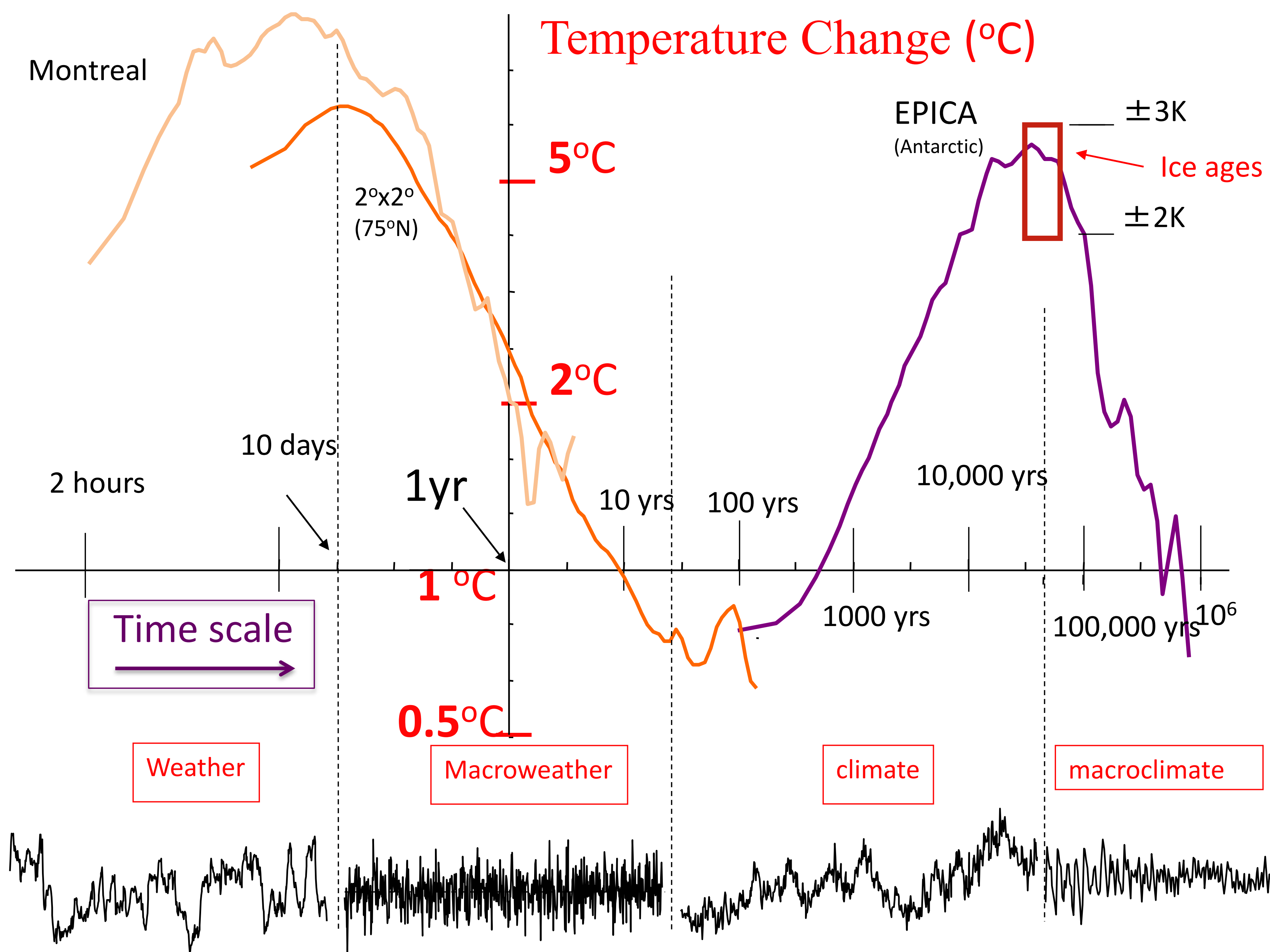
= constant



Lovejoy, 2013, **EOS**



Temperature Change (°C)
Montreal
H=0.4
2°x2°
(75°N)
H=-0.4
Power laws
EPICA
(Antarctic)
±3K
Ice ages
±2K
H = -0.7
H=0.5
5°C
2°C
1 °C
0.5°C
10 days
2 hours
1yr
10 yrs
100 yrs
1000 yrs
10,000 yrs
100,000 yrs
10^6
Weather
Macroweather
climate
macroclimate



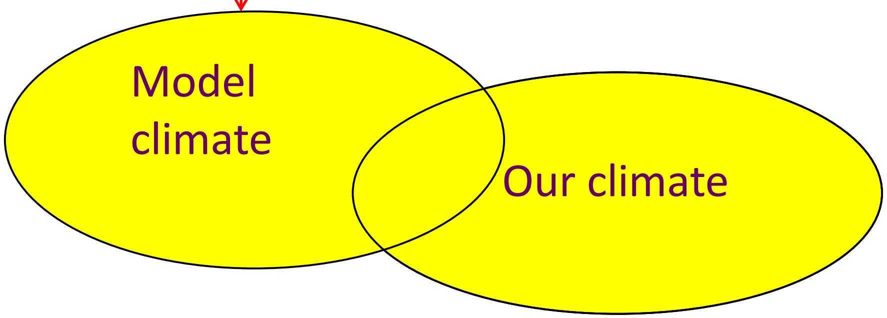
Temperature Change (°C)
Montreal
2°x2°
(75°N)
EPICA
(Antarctic)
±3K
±2K
Ice ages
5°C
2°C
1 °C
0.5°C
2 hours
10 days
1yr
10 yrs
100 yrs
1000 yrs
10,000 yrs
100,000 yrs
10⁶
Time scale
Weather
Macroweather
climate
macroclimate

Beyond their deterministic limit:
GCMs → stochastic

"Brute force"

Weather systems (<10 days) generated by
= random weather noise (statistics)…
but not fully realistic

Averages: slow convergence to



Scaling laws generate realistic (empirically based) statistics (noise)

Potential advantages of direct stochastic macroweather (>1 month) forecasting:

a) More realistic weather "noise" (statistics: based on empirical data, not constrained by model).

b) Ability to use empirical data to force convergence to the real climate.

Statistical characteristics of Macroweather

Temporal domain

- Low intermittency Gaussian theory (except for extremes).

- Scale symmetry ≈ 1 month- >100 years (anthropocene ->30 years) Fluctuations tend to cancel: $H<0$.
- Theoretical stochastic limits to forecast skill: theoretical "benchmark"
- Scale symmetry: huge memory

Spatial domain

- Scale symmetry up to ≈ 4000 km.
- Strong (multifractal) intermittency: climatic zones

Space-time

- Statistical space-time Factorization.

Strong spatial correlations do not give useful information for forecasting: *single grid or single station forecasts close to the theoretical maximum*.

Statistical space-time Factorization

(Ex: factorization of second order statistics)

Spectral densities: $P_{xt}(k,\omega) \propto \left\langle \left| T(k,\omega) \right|^2 \right\rangle$

Macroweather: factorization

$$P_{xt}(k,\omega) = P_t(\omega) P_x(k)$$

Structure Functions: $S_{xt}(\Delta x, \Delta t) = \left\langle \Delta T(\Delta x, \Delta t)^2 \right\rangle$

Macroweather: factorization

$$S_{xt}(\Delta x, \Delta t) = S_t(\Delta t) S_x(\Delta x)$$

No relation between size and lifetime

Weather, no factorization

$$P_{xt}(k,\omega) \approx \quad k,\omega \quad^{-s}$$

$$k,\omega \quad \approx \left(\omega^2 + k^2\right)^{1/2}$$

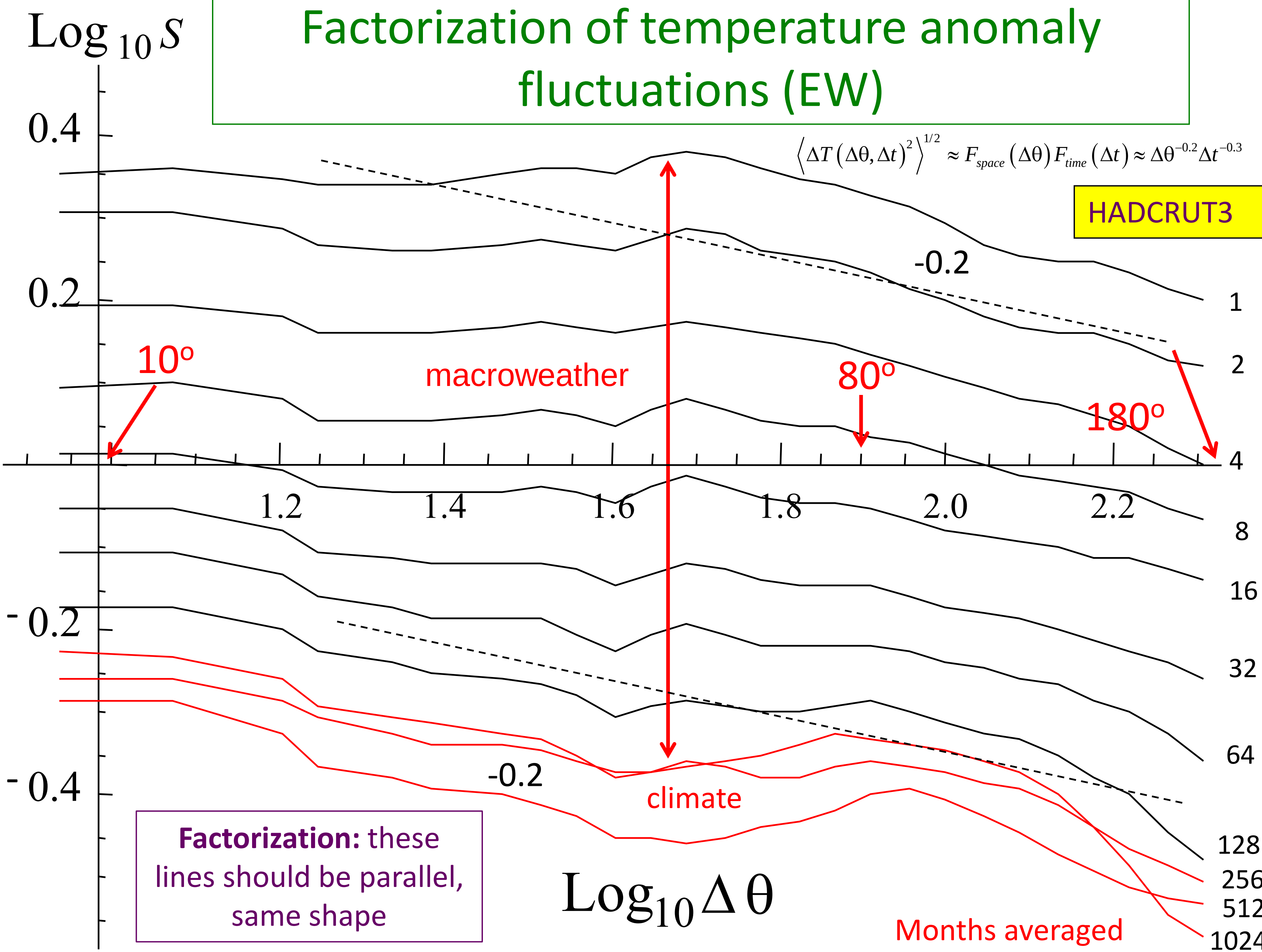
Implies size – lifetime relation

Weather, no factorization

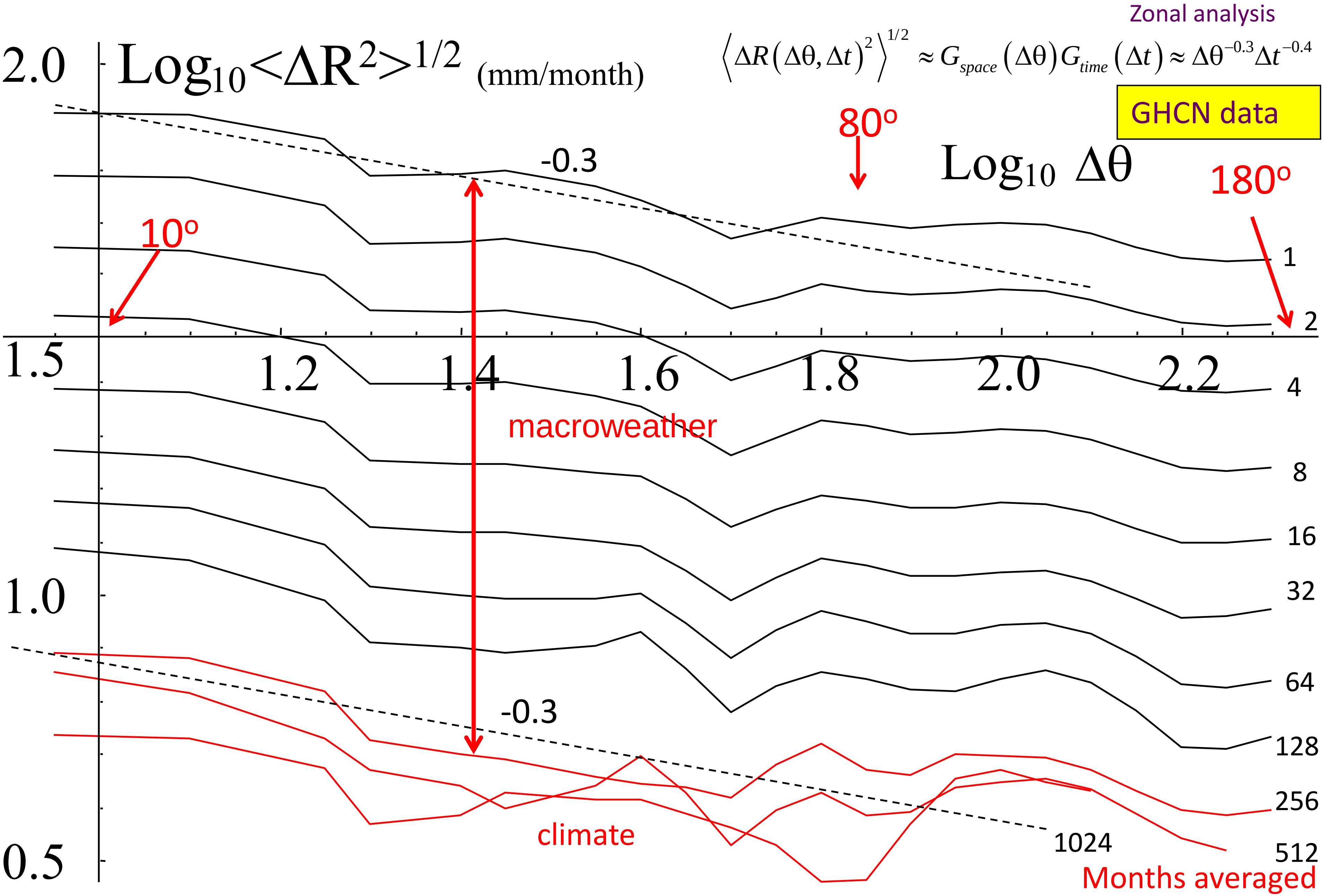
$$S_{xt}(\Delta x, \Delta t) \approx \quad \underbrace{\Delta x, \Delta t}_{\text{Space-time Scale function}} \quad^{\xi(2)}$$

Typical form $\quad \Delta x, \Delta t \quad \approx \left(\Delta x^2 + \Delta t^2\right)^{1/2}$

Factorization of temperature anomaly fluctuations (EW)



Factorization of precipitation anomaly fluctuations



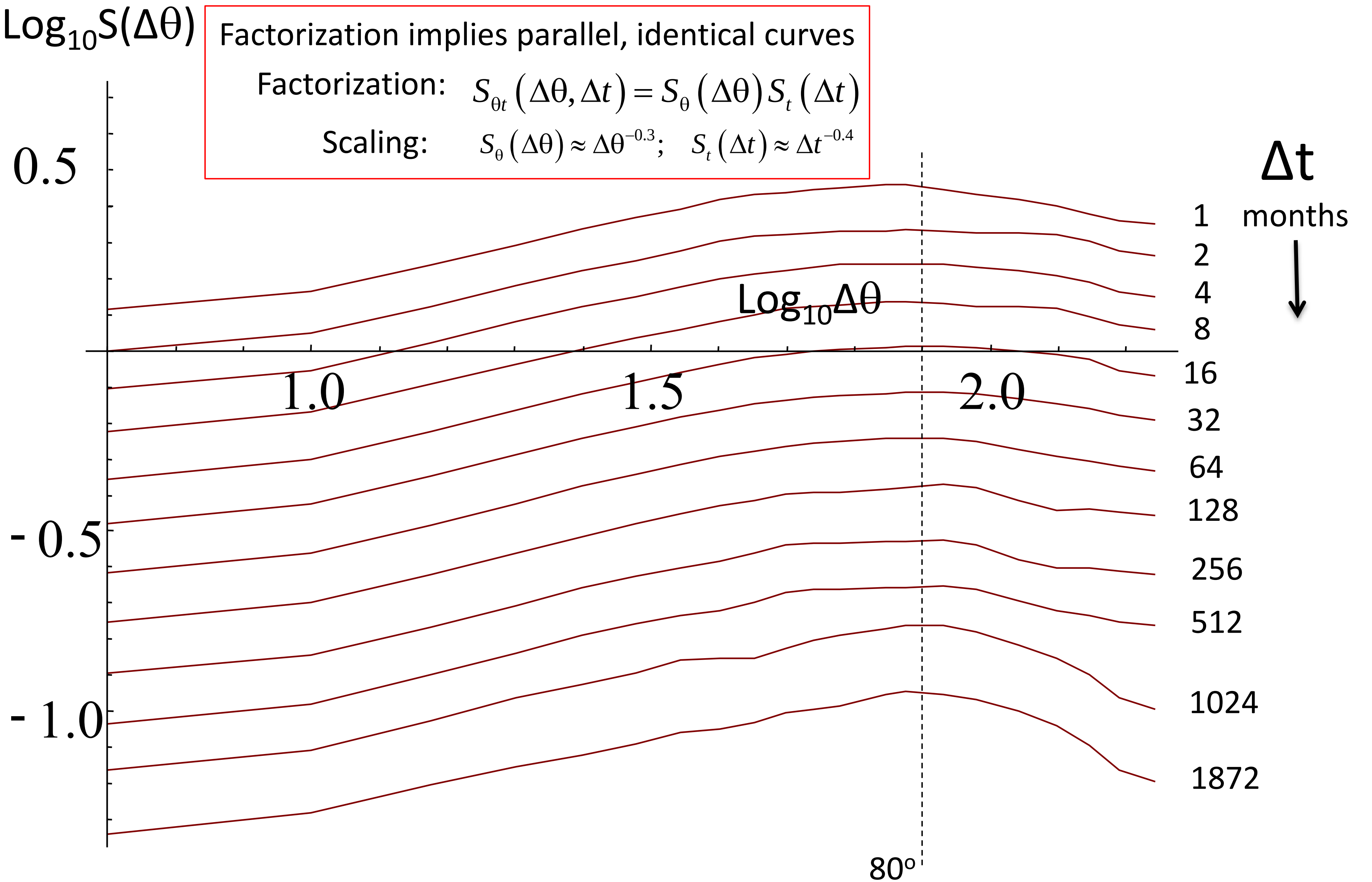
Factorization: GCM's

GISS E2R temperatures (historical run since 1850)

Factorization implies parallel, identical curves

Factorization: $S_{\theta t}(\Delta\theta, \Delta t) = S_{\theta}(\Delta\theta) S_{t}(\Delta t)$

Scaling: $S_{\theta}(\Delta\theta) \approx \Delta\theta^{-0.3}$; $S_{t}(\Delta t) \approx \Delta t^{-0.4}$



Deterministic predictability limits for Weather forecasts

Sensitive dependence on initial conditions leads to limits (“butterfly effect”).

Fundamental limit = error doubling time.

The doubling time increases with the lifetime (hence size).

For planetary structures ≈ 10 days.

Weather forecast skill can be judged by how close the doubling time is to the 10 day limit.

This is the basic benchmark for deterministic weather forecasts

Stochastic predictability limits for Macroweather forecasts

Temporal scaling and statistical space-time factorization imply stochastic predictability limits.

Skill = 1 - (forecast error variance)/(temperature variance)

Theoretical skill = F (lead time, H(x)) ← the exponent H(x) and hence skill varies with position x.

This is the basic benchmark for macroweather forecasts

Comments:

-The skill has only a weak dependence on spatial resolution… hence we can avoid downscaling.

-For 5^{o}x5^{o} resolution monthly and seasonal StocSIPS forecast skill =25%, 18%: theoretical limits = 29%, 21%, respectively.

-StocSIPS forecasts are on average 86% of the theoretical limit.

Can GCM's improve on the theoretical stochastic limits?

Not obvious since the GCM's appear to satisfy space-time factorization and temporal scaling

Earth Syst. Dynam., 6, 637–658, 2015
www.earth-syst-dynam.net/6/637/2015/
doi:10.5194/esd-6-637-2015

Earth System Dynamics
Open Access

The ScaLIng Macroweather Model (SLIMM): using scaling to forecast global-scale macroweather from months to decades

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Revised: 9 July 2015 – Accepted: 22 August 2015 – Published: 29 September 2015

Abstract. On scales of ≈ 10 days (the lifetime of planetary-scale structures), there is a drastic transition from high-frequency weather to low-frequency macroweather. This scale is close to the predictability limits of deterministic atmospheric models; thus, in GCM (gen
a high-frequency noise. However, neither the GC
show how simple stochastic models can be devel
to be realistic so that even a two-parameter mode
forecasts.

AGU PUBLICATIONS

Geophysical Research Letters

RESEARCH LETTER
10.1002/2015GL065665

Key Points:
- The climate system has a huge memory that can be exploited by scaling models
- Fractional Gaussian noise is adequate model for macroweather (10 days–30 years)
- Twentieth century hindcasts (including pause) are accurate with two parameters

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Using scaling for macroweather forecasting including the pause

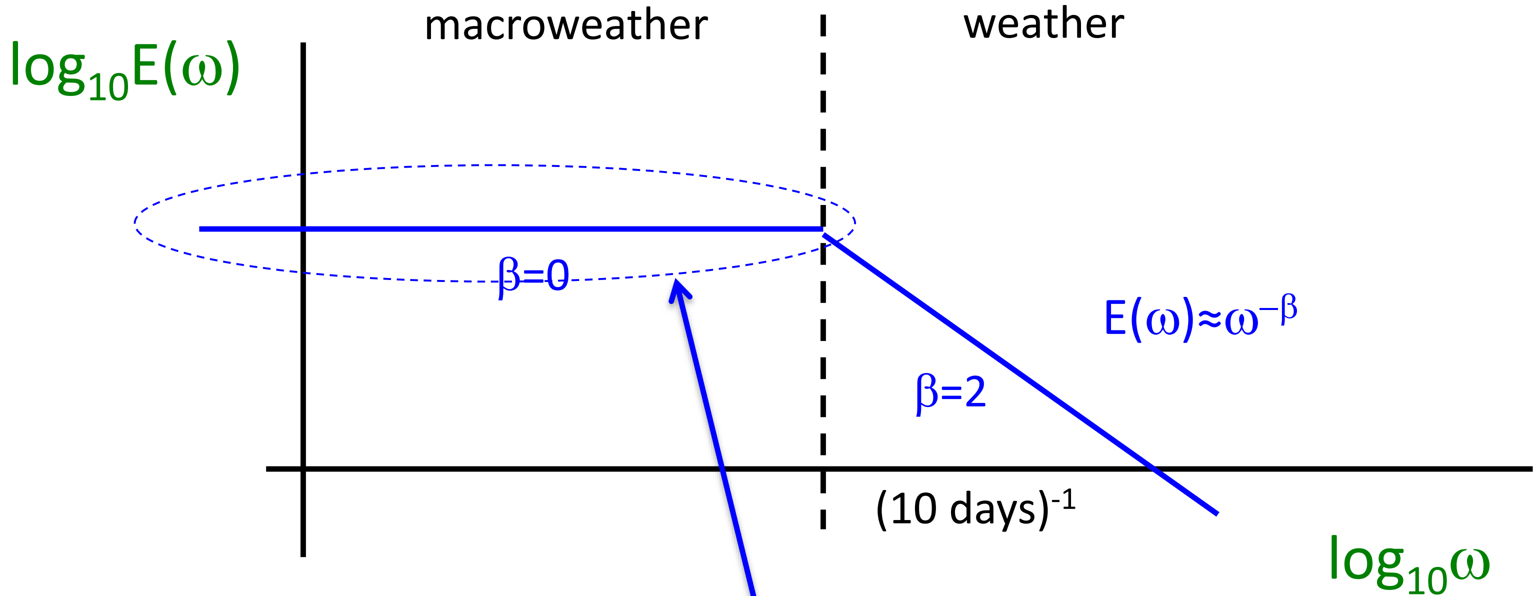
August 2015

S. Lovejoy[1]

[1]Physics Department, McGill University, Montreal, Quebec, Canada

Abstract The ScaLIng Macroweather model (SLIMM) is a new class of stochastic atmospheric model. It exploits the large system memory to overcome the biases of conventional numerical climate models, it makes hindcasts and forecasts over macroweather forecast horizons (≈10 days to decades). Using the simplest (scalar), SLIMM model with only two parameters, we present various twentieth century hindcasts including several of the slowdown ("pause") in the warming since 1998. The 1999–2013 hindcast is accurate to within ±0.11 K, with all the 2002–2013 anomalies hindcast to within ±0.02 K. In comparison, the Climate Model Intercomparison Project Phase 3 hindcasts were on average about 0.2 K too warm.

Hasselman (1976) type stochastic Macroweather processes



The Hasselman (1976) type stochastic approach:

(Orenstein Uhlenbeck processes, Linear Inverse Modelling, Auto Regressive processes)

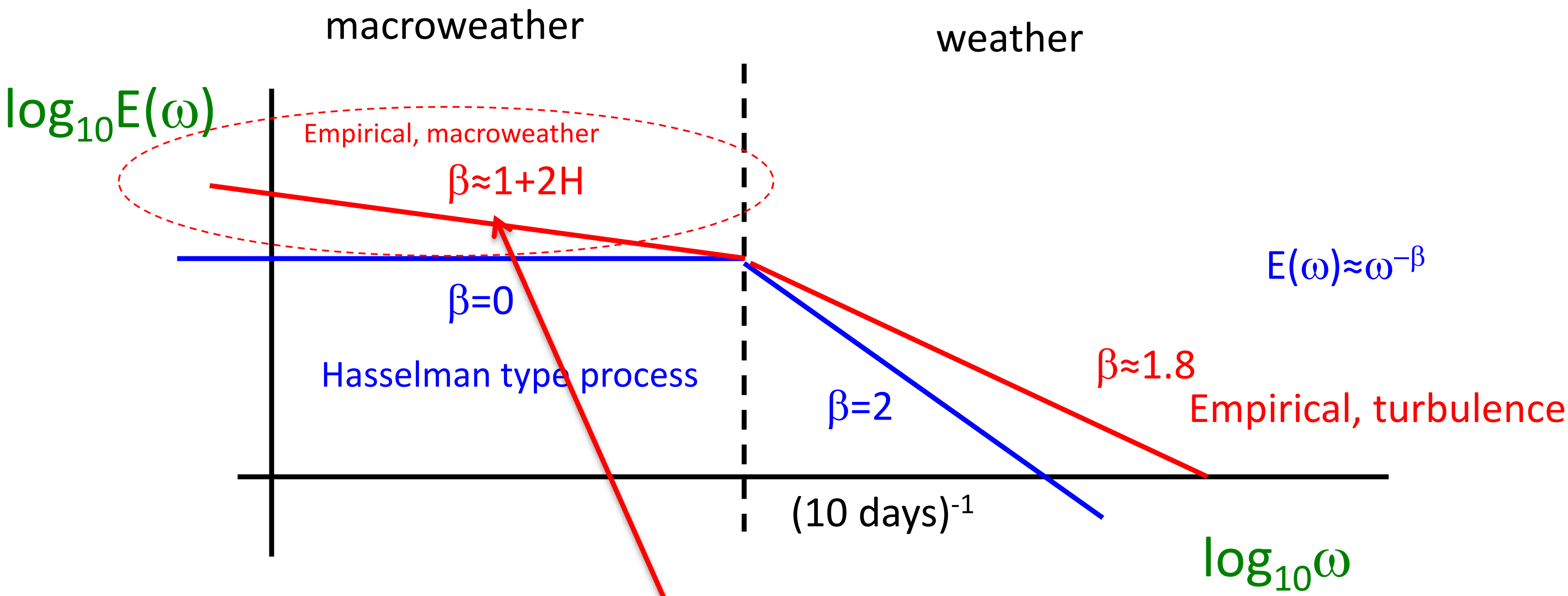
Low frequency ($\beta=0$)

$$T(t) \propto \gamma(t)$$

White noise (no predictability)

White noise

Scaling stochastic Macroweather processes



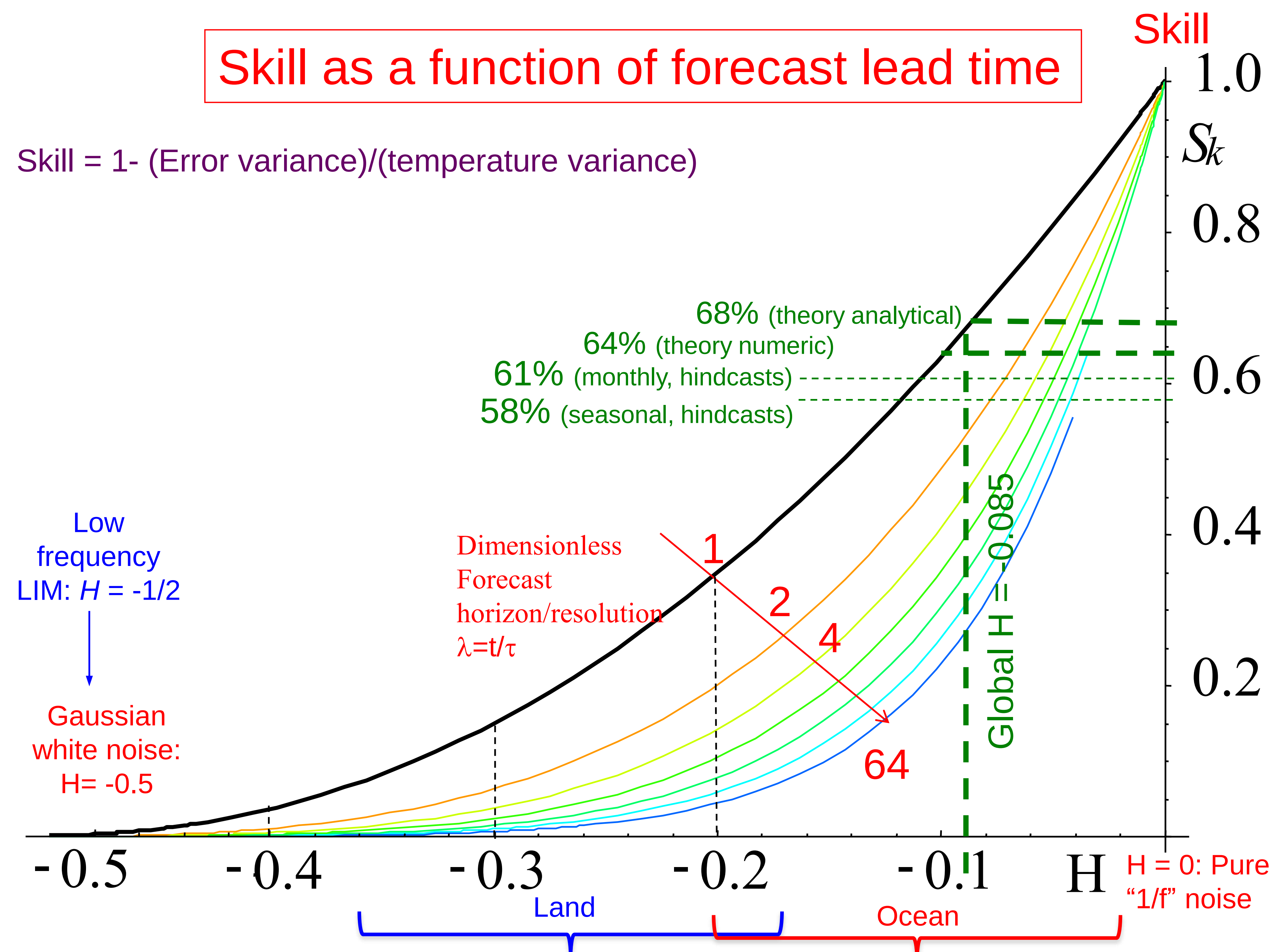
White noise

Scaling, stochastic approach
(Ignoring intermittency)

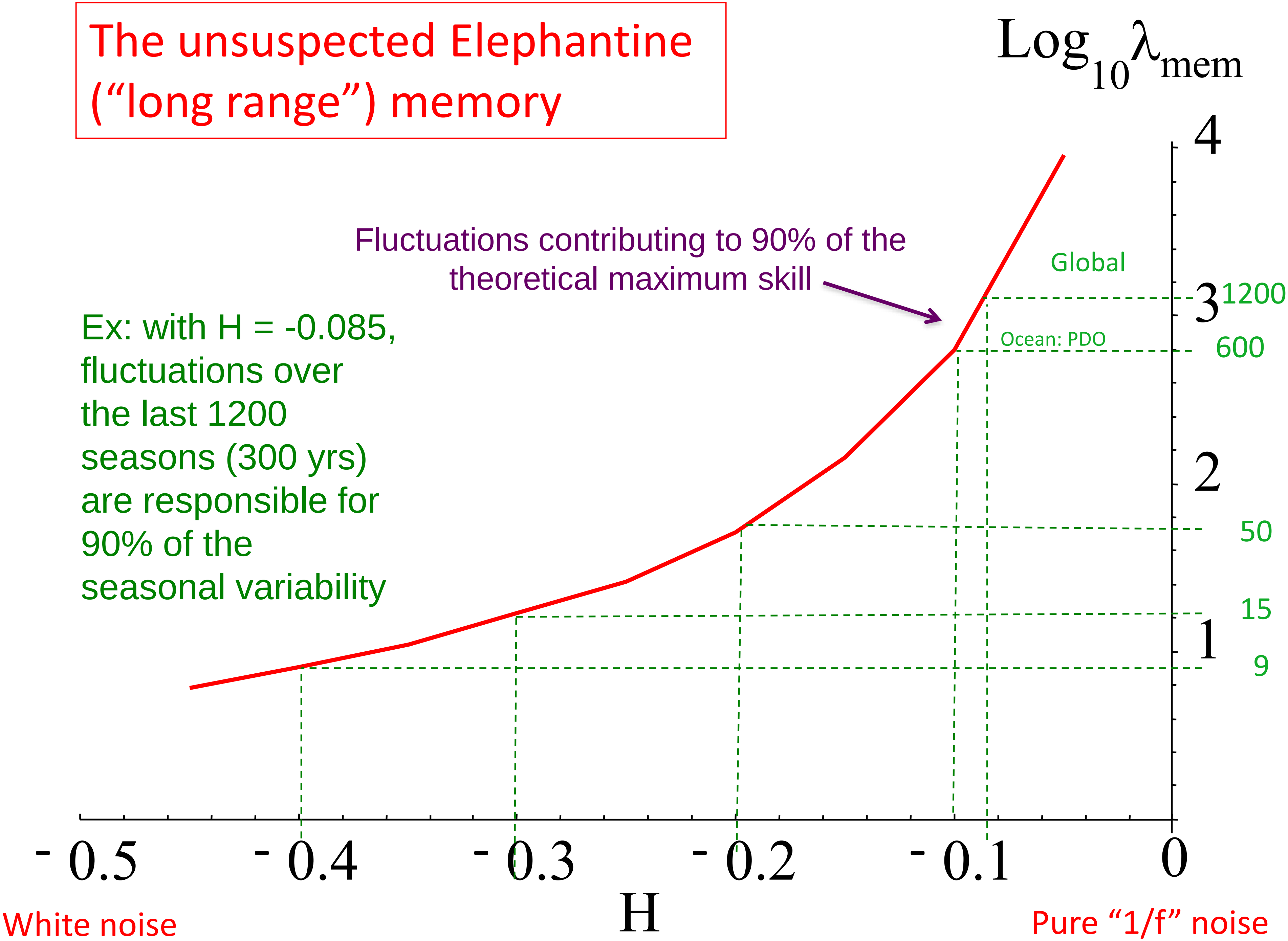
$$T(t)\propto\int_{-\infty}^{t}(t-t')^{-(1/2-H)}\,\gamma(t')\,dt'$$

red noise (potentially huge predictability)

-1/2<H<0 (fluctuation exponent)


Skill as a function of forecast lead time
Skill
1.0
S_k
0.8
0.6
0.4
0.2
Skill = 1- (Error variance)/(temperature variance)
68% (theory analytical)
64% (theory numeric)
61% (monthly, hindcasts)
58% (seasonal, hindcasts)
Low frequency LIM: H = -1/2
Gaussian white noise: H= -0.5
Dimensionless Forecast horizon/resolution λ=t/τ
1
2
4
64
Global H = -0.085
-0.5
-0.4
-0.3
-0.2
-0.1
H
H = 0: Pure "1/f" noise
Land
Ocean

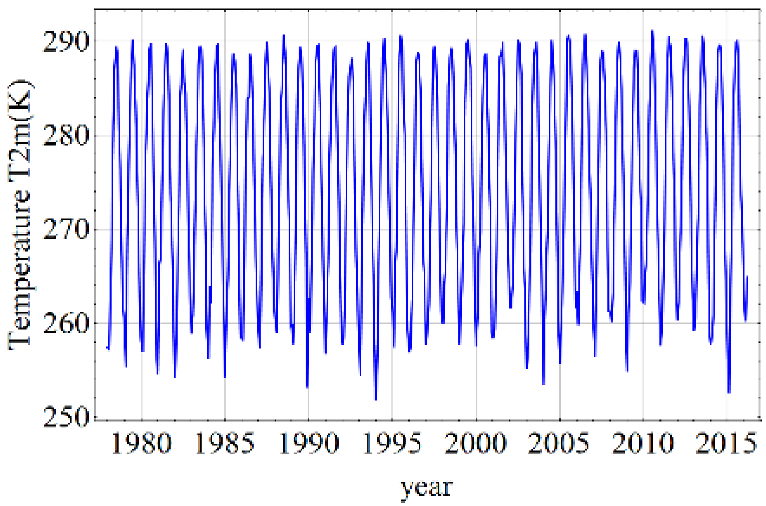
The unsuspected Elephantine ("long range") memory



Preprocessing of the data:

Ref: (NCEP/NCAR) Example for the grid point (-72.5, 47.5), Montreal

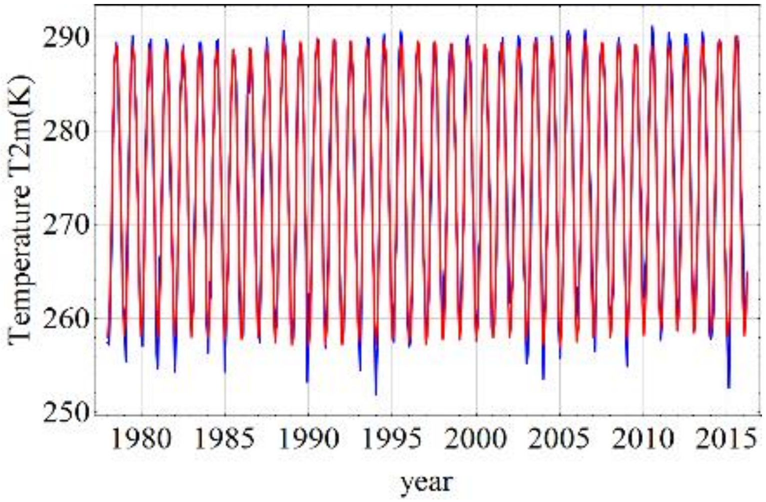
Raw Data



Preprocessing of the data:

Ref: (NCEP/NCAR) Example for the grid point (-72.5, 47.5), Montreal

Raw Data and Annual Cycle



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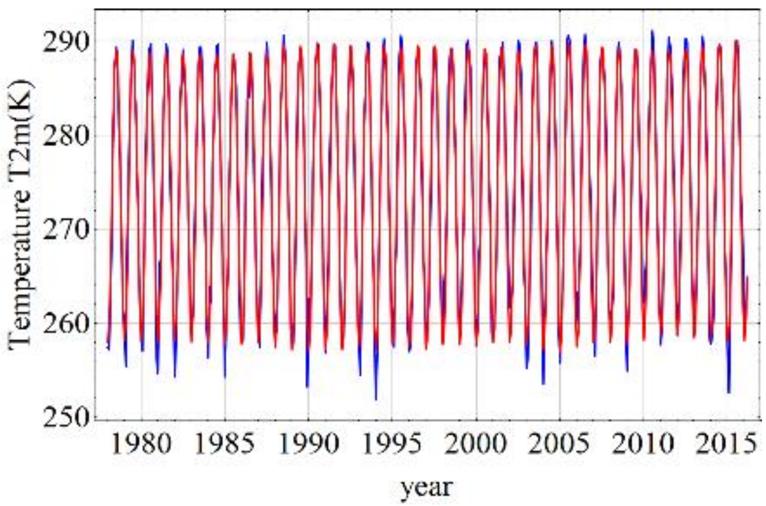
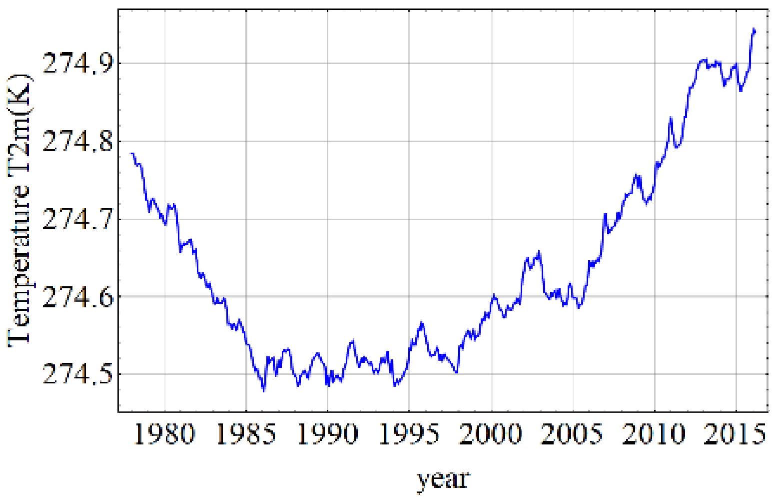
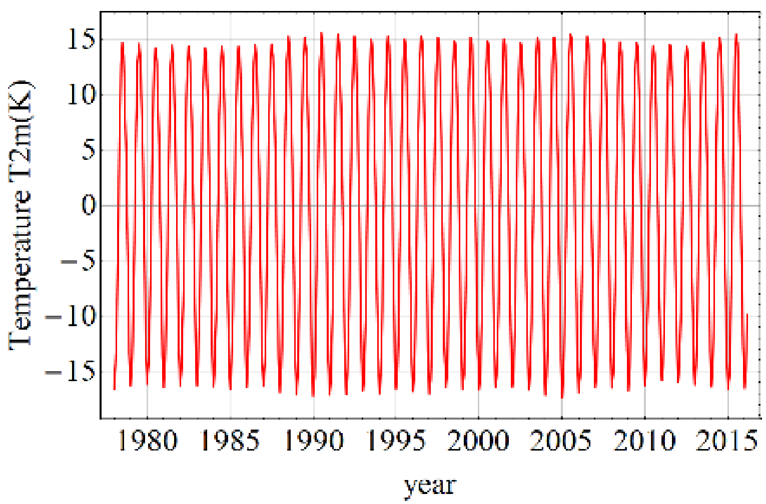
Raw Data and Annual Cycle



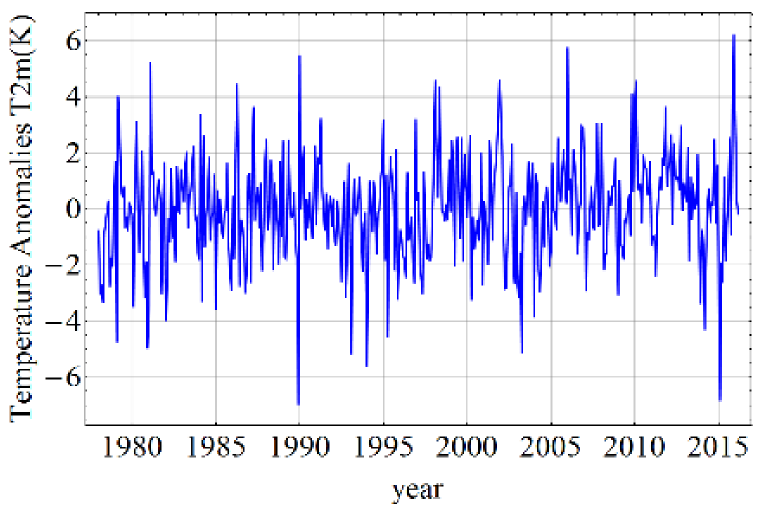
Trend



Annual Cycle



Anomalies



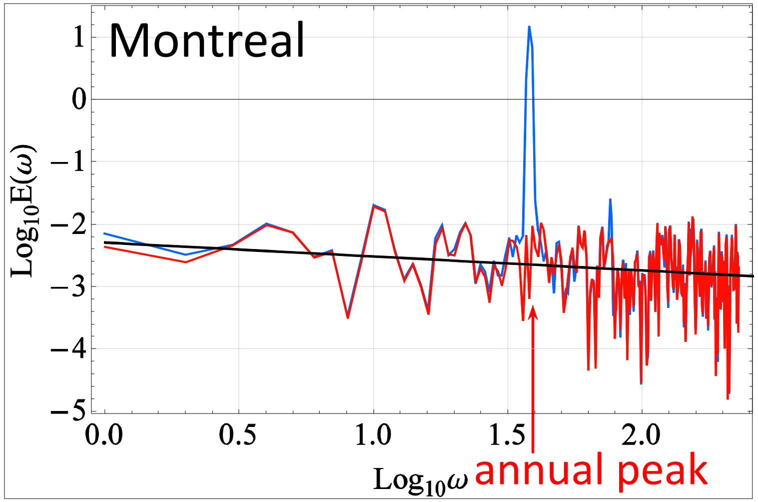
Spectrum and Fluctuation Analysis

Spectra pre and after processing

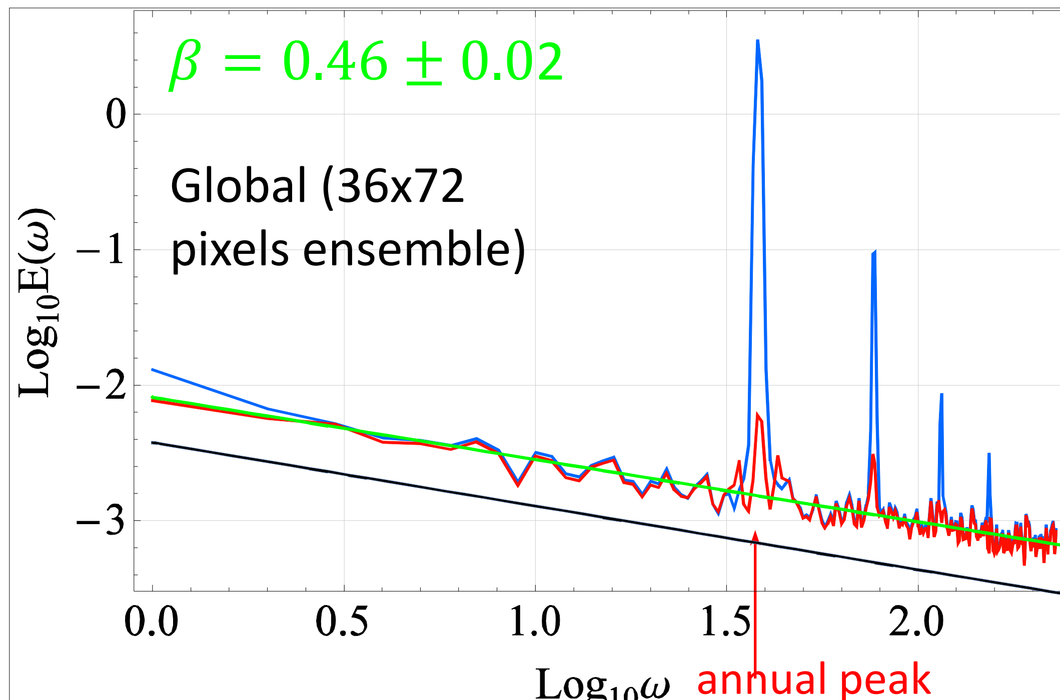
$$E(\omega) \propto \omega^{-\beta}$$

$$S_1(\Delta t) = \langle \Delta T(\Delta t) \rangle \propto \Delta t^{H}$$

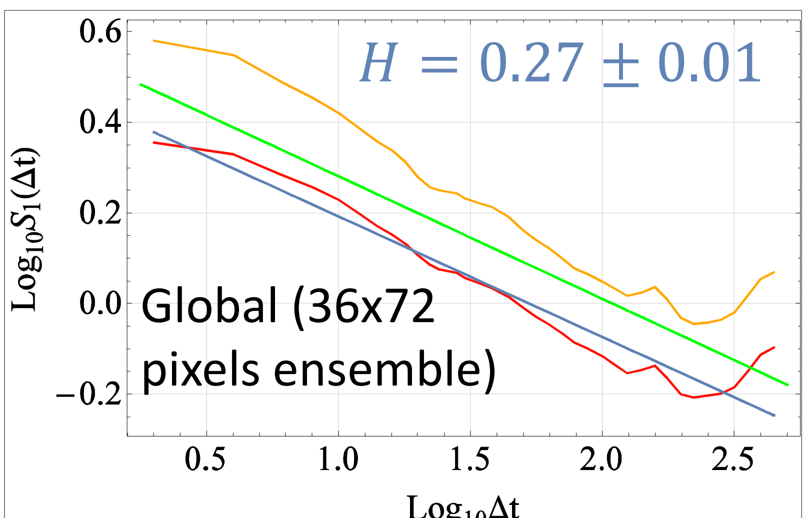
$$\beta = 1 + 2\mathrm{H}$$



Global spectra pre and after processing



Fluctuation Analysis



Scaling LInear Macroweather model (SLIMM) Prediction of fGn

$$T(t) = \sigma_\gamma \int_{-\infty}^{t} (t-t')^{-(1/2-H)} \gamma(t') dt'$$

Gaussian noise

- Power law correlation. Vast memory that can be exploited.
- Predictor for -0.5 < H < 0 based on past data.

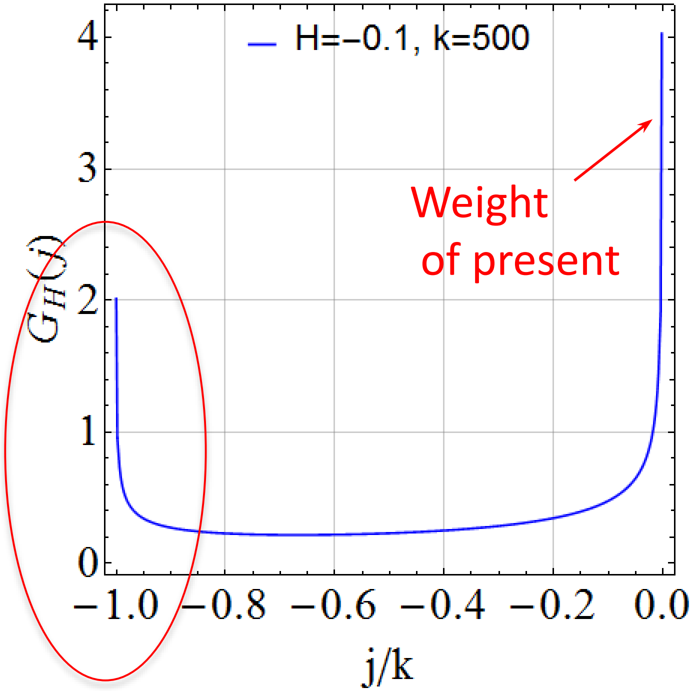
kernel

$$\hat{T}(n+k|n) = \sum_{j=0}^{p} G_H(j) T(n-j)$$

predictor

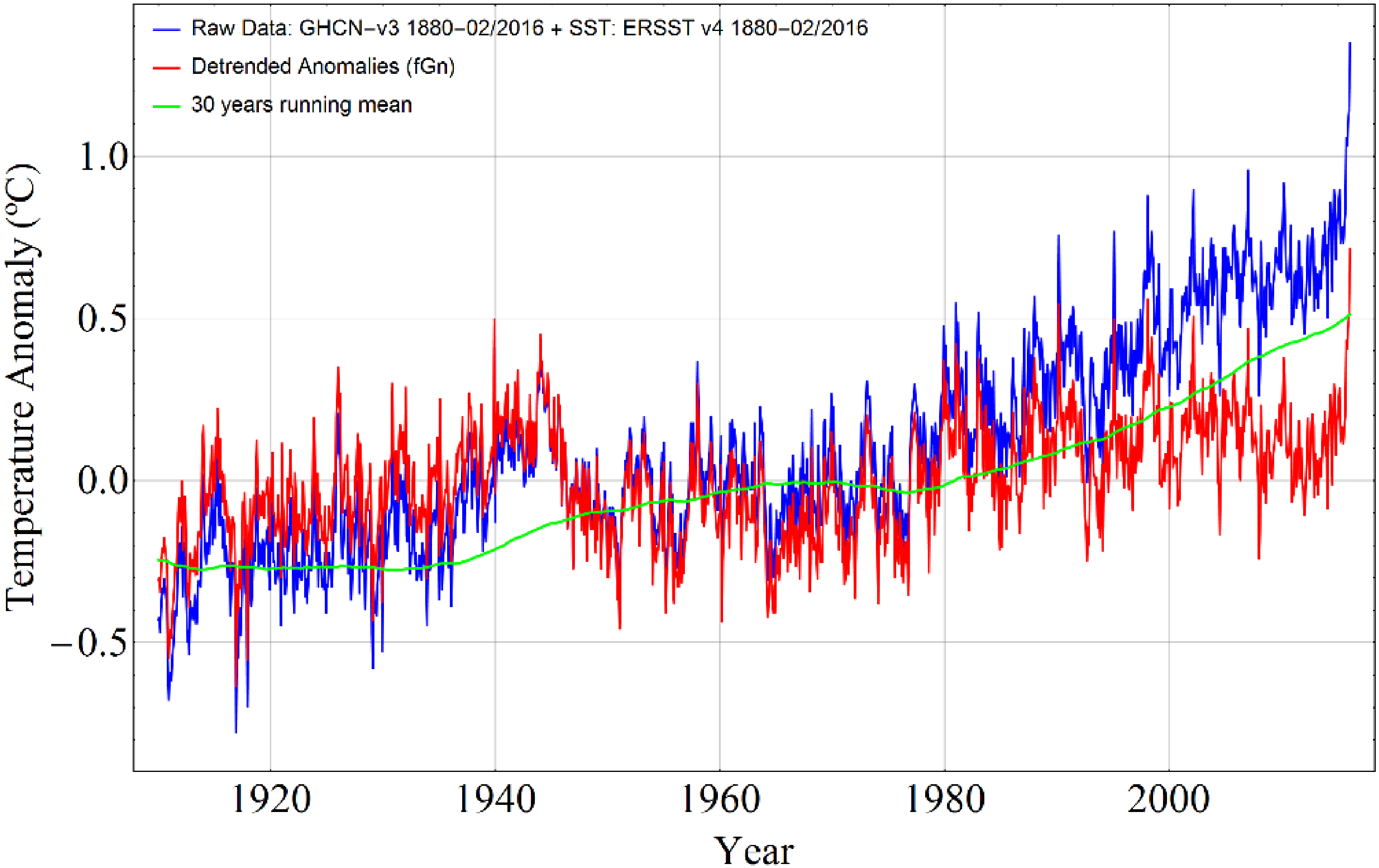
data

Kernel for H = -0,1.

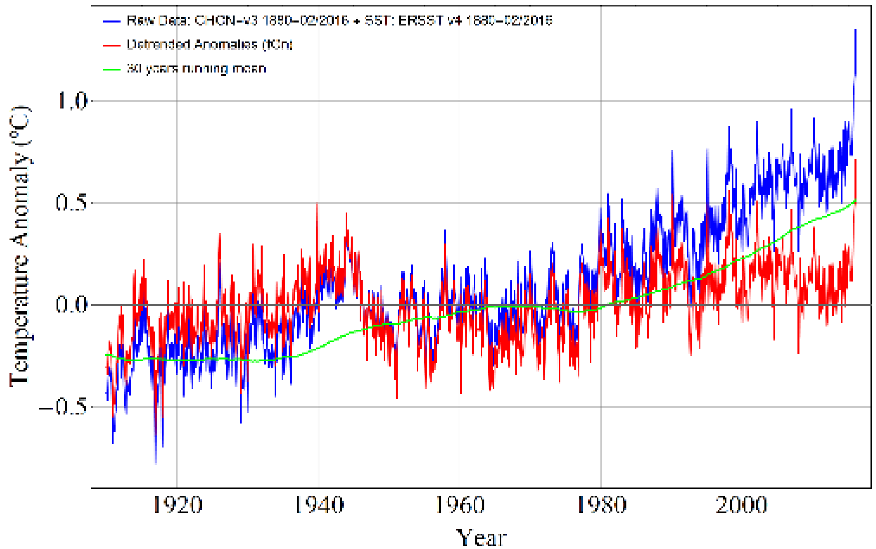


"The 'closest witnesses' to the unobserved past have special weight"

Predicting global series



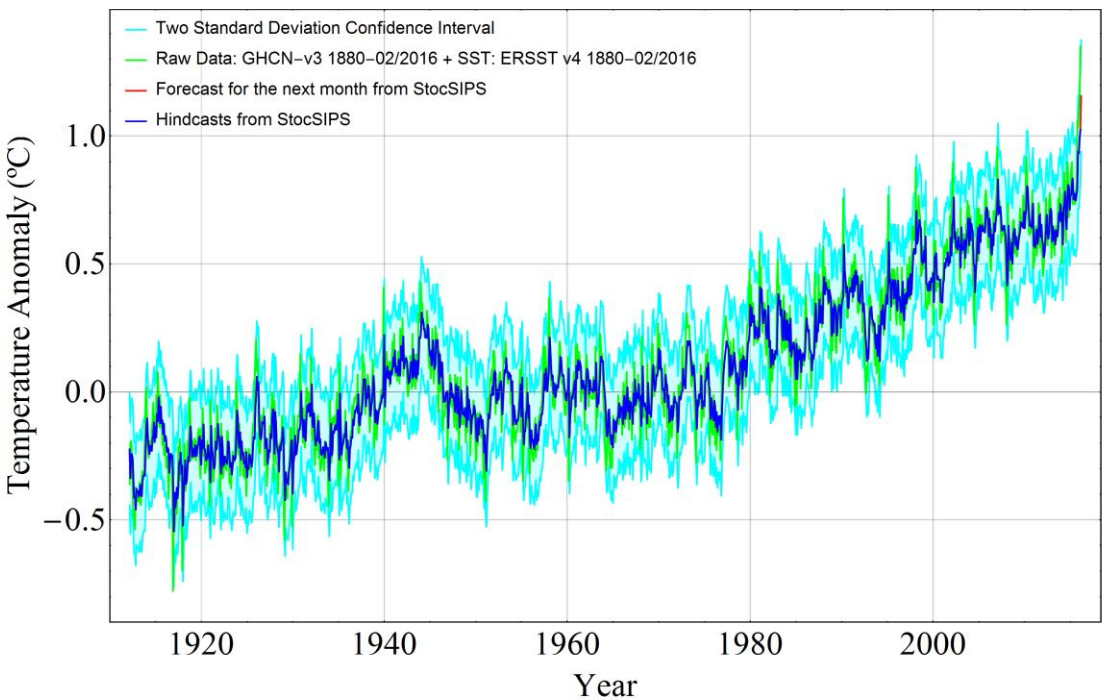
Predicting global series



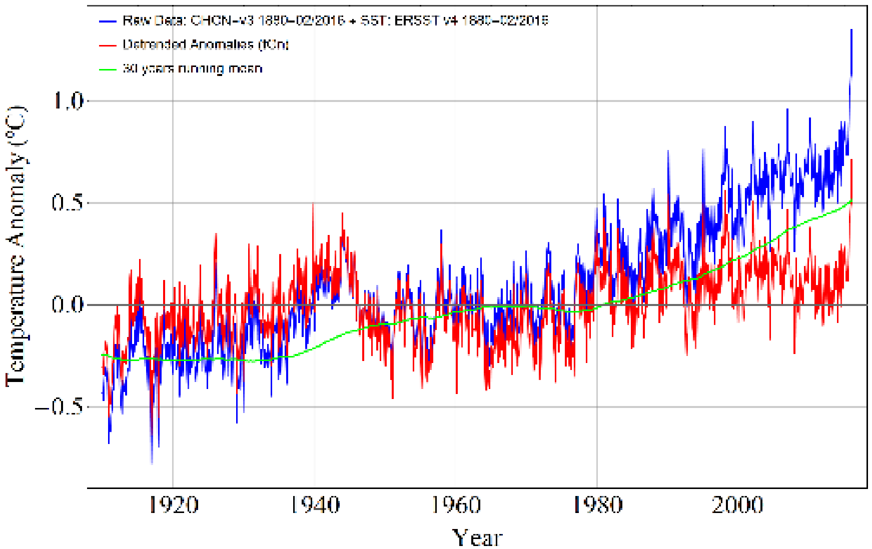
Stochastic Seasonal and Interannual Prediction System (StocSIPS)

Monthly horizon global hindcasts compared to data (since 2006) and a forecast for March 2016.

Reference: NASA, GISS, http://data.giss.nasa.gov/gistemp/



Predicting global series



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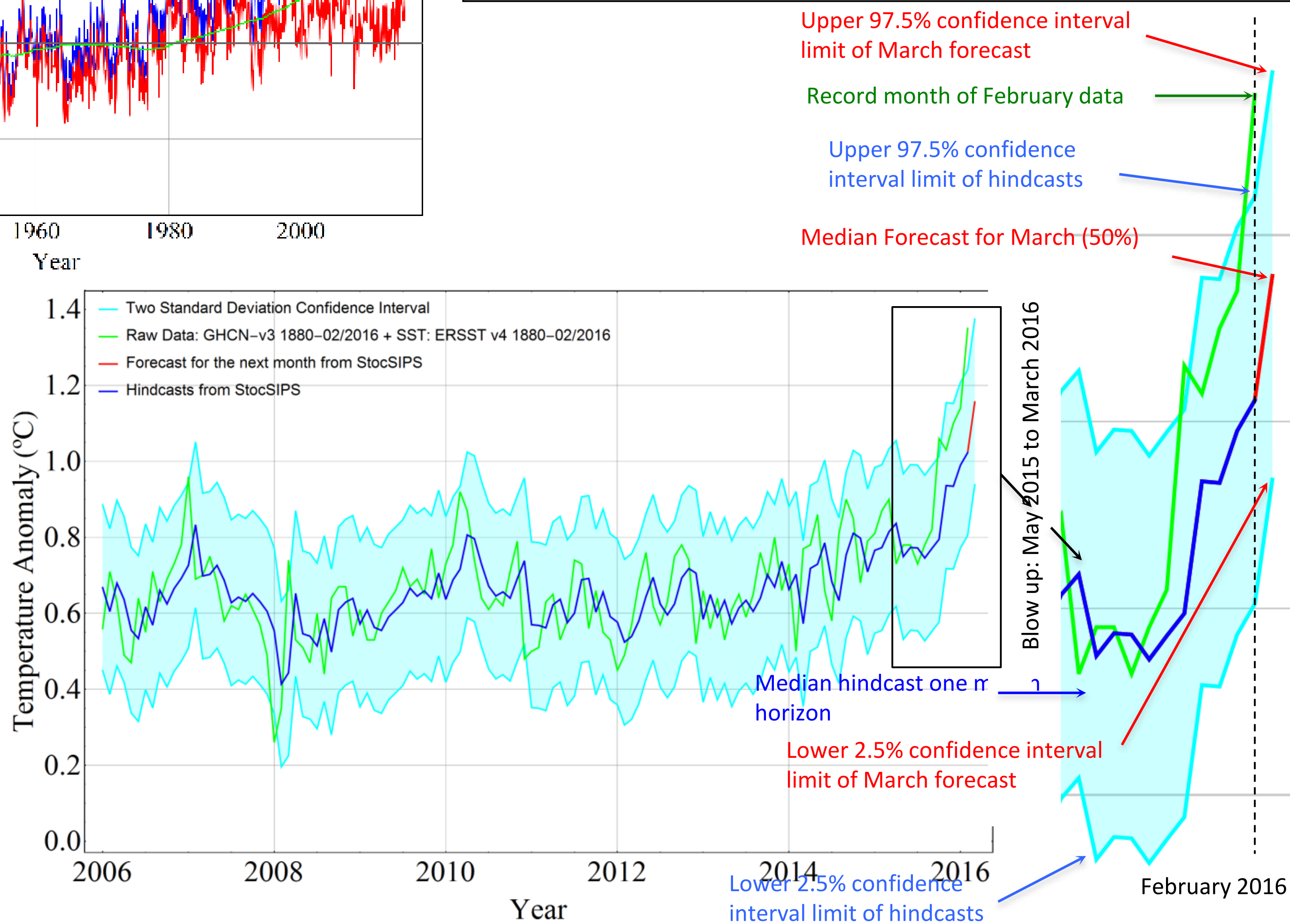
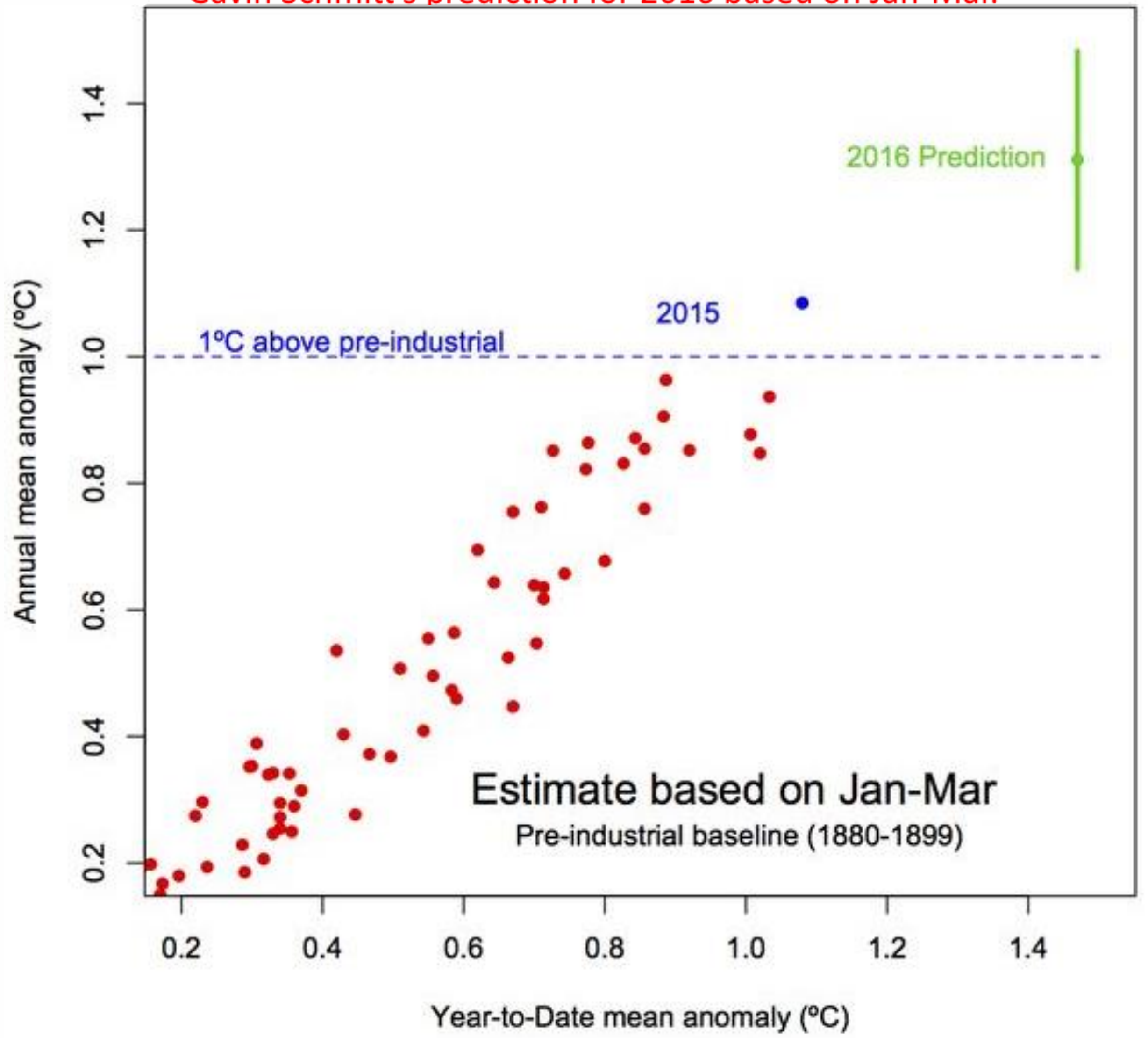


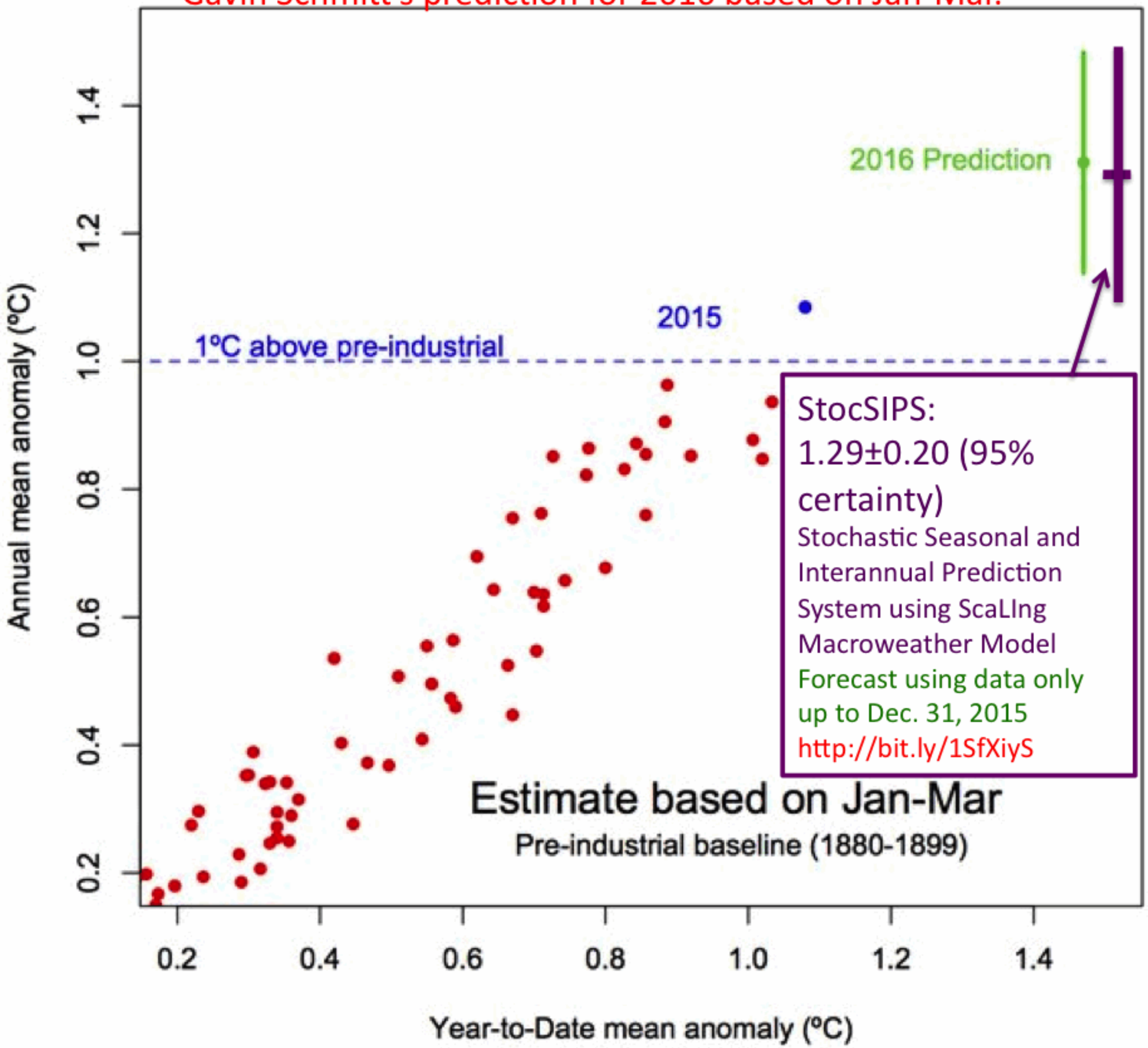
Predicting global series

Gavin Schmitt's prediction for 2016 based on Jan-Mar.

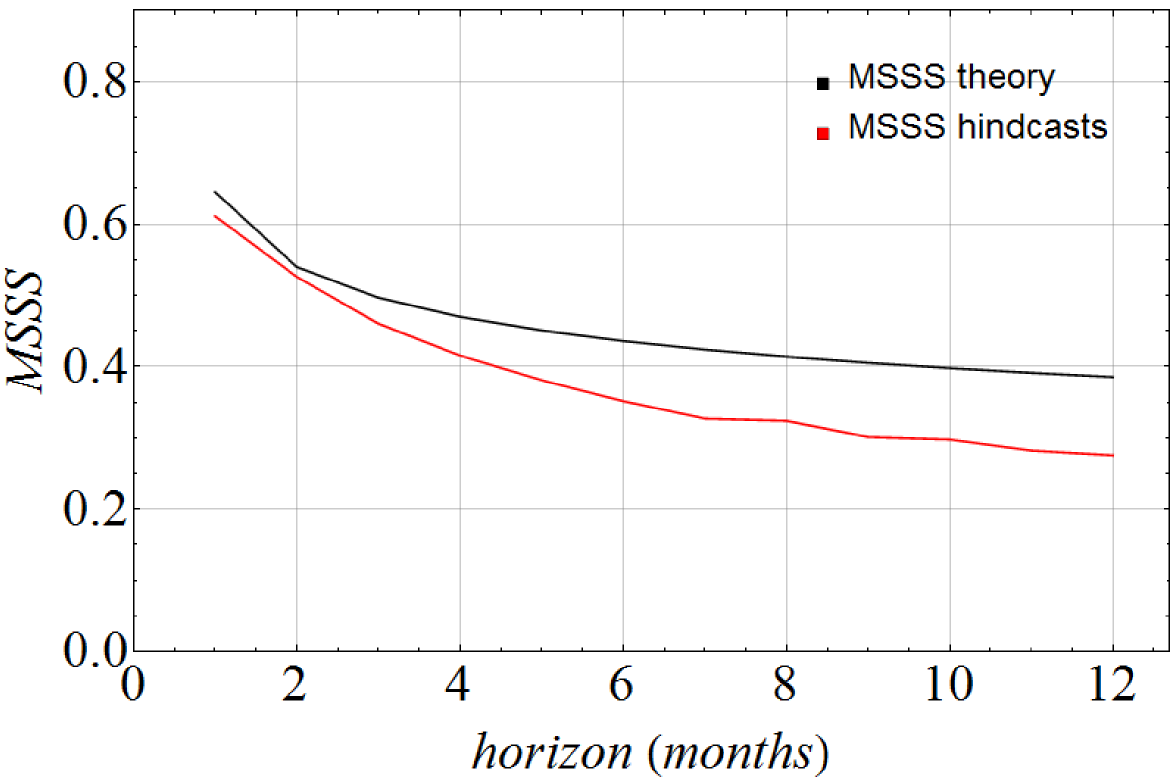


Predicting global series

Gavin Schmitt's prediction for 2016 based on Jan-Mar.



Skill of StocSIPS for global temperature



<u>Mean Square Skill Score (MSSS)</u>

$$MSSS = 1 - \frac{MSE}{Var_{anom}}$$

MSE - Mean Square Errors

Var_{anom} - Variance of anomalies

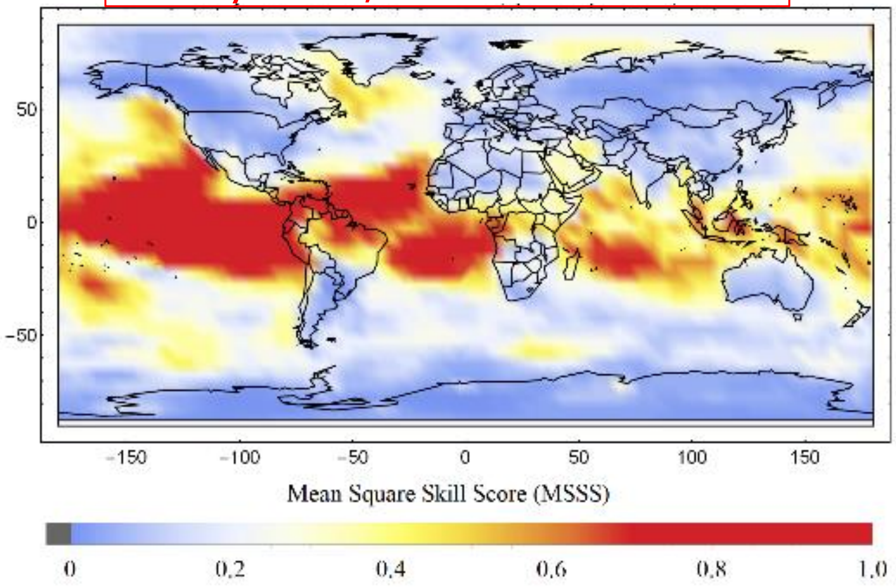
<u>For lead times = 1, 2, 3 months</u>

$$r = \frac{MSSS_{hind}}{MSSS_{theor}} = 95\%, 97\%, 93\%$$

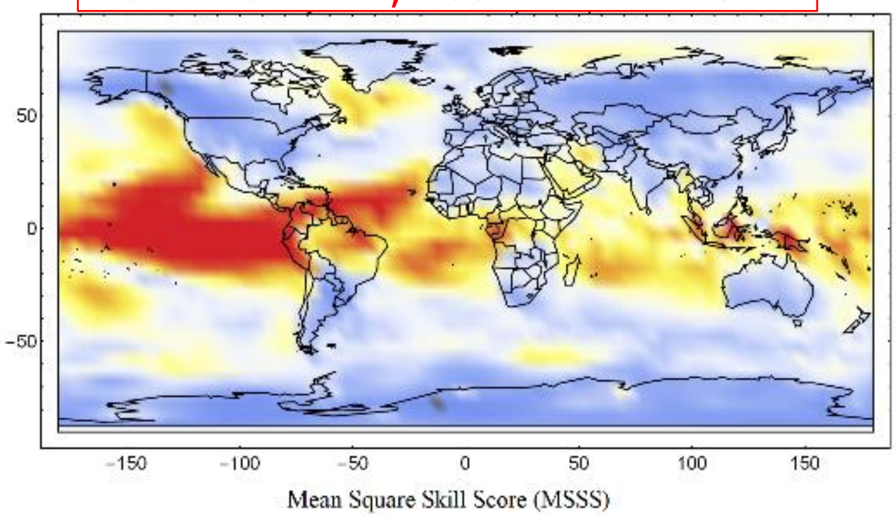
Theoretical and numerical Skills. Monthly resolution.

Period Sep, 1980 - Dec, 2015. Reference: ERA-Interim Reanalysis

Theory MSSS, lead time = 1 month

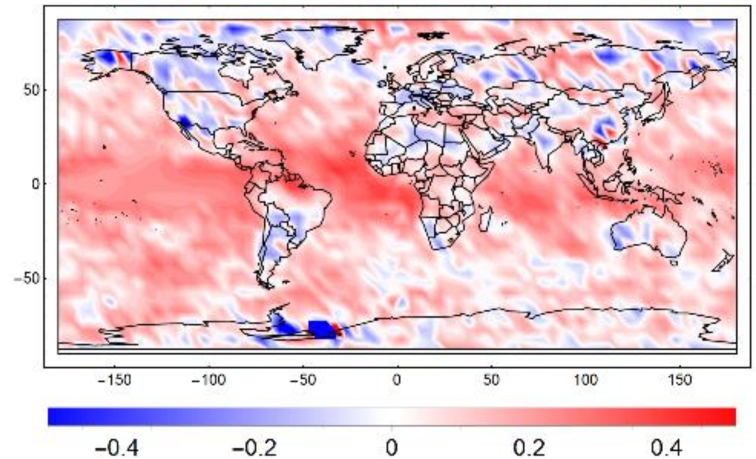


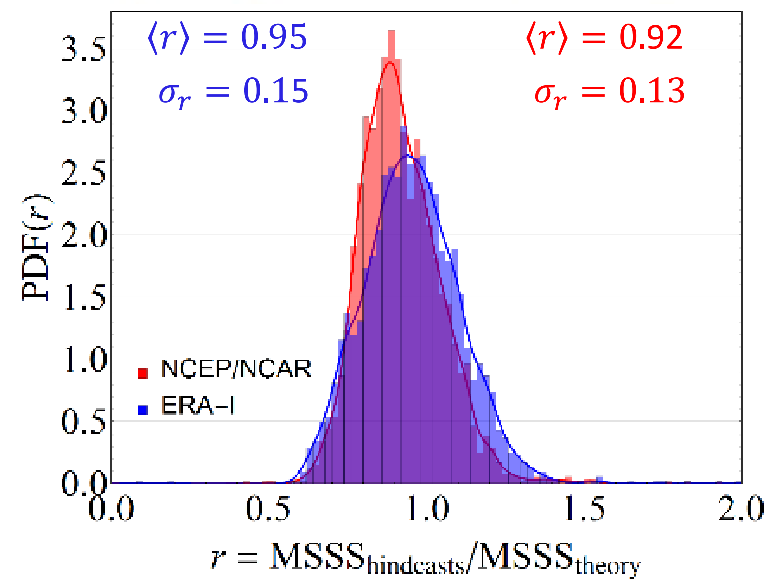
Numerical MSSS, lead time = 1 month



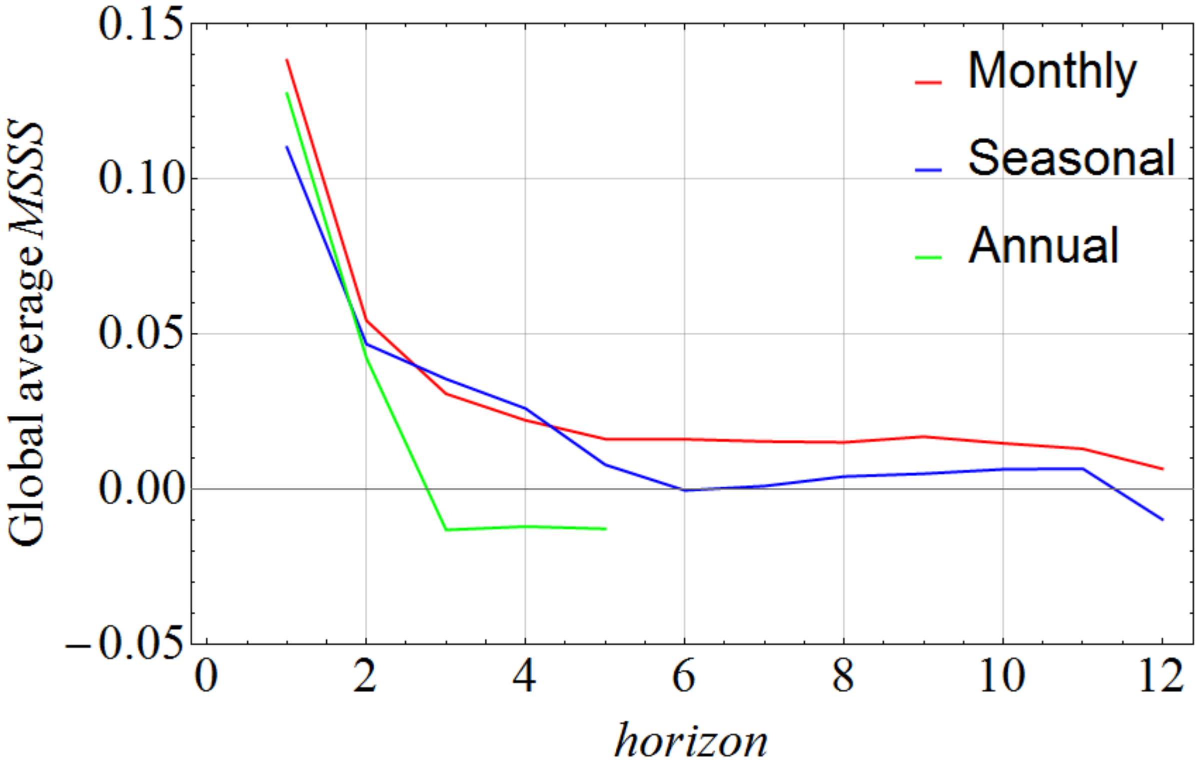
$$r = \frac{MSSS_{hindcasts}}{MSSS_{theory}}$$

$1 - r, \langle r \rangle = 0,95$





Global average Skill



Mean Square Skill Score (MSSS)

$$\langle MSSS \rangle_{global} = 1 - \frac{\langle MSE \rangle}{\langle Var_{anom} \rangle}$$

MSE- Mean Square Errors

Var_{anom}- Variance of anomalies

For lead time = 1 unit

$$r = \frac{MSSS_{hind}}{MSSS_{theor}} \approx 95\%$$

StocSIPS compared with GCM's

World Meteorological Organization
Weather • Climate • Water

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Home

Programmes > World Climate Programme > Climate applications and services > Global Producing Centres of Long-Range Forecasts

Global Producing Centres of Long-Range Forecasts

In 2006, the World Meteorological Organization (WMO) began a process to designate centres making global seasonal forecasts as WMO Global Producing Centres of Long-Range Forecasts (GPCLRFs). This forms an integral part of the WMO Global Data-Processing and Forecasting System (GDPFS).

Through this designation process, GPCLRFs adhere to certain well-defined standards, aiding the consistency and usability of:

- fixed forecast production cycles
- standard sets of forecast products
- WMO-defined verification standards (for retrospective forecasts).

A comprehensive set of standard verification measures has also been defined, and is known as the WMO Standard Verification System for Long-Range Forecasts (SVSLRF).

At minimum, the following are required from GPCLRFs:

- Predictions for averages, accumulations, or frequencies over 1-month periods or longer (typically anomalies in 3-month-averaged quantities is the standard format for seasonal forecasts, and forecasts are usually expressed probabilistically)
- Lead time: between 0 and 4 months
- Issue frequency: monthly or at least quarterly
- Delivery: graphical images on GPCLRF website and/or digital data for download
- Variables: 2m temperature, precipitation, Sea Surface Temperature (SST), Mean Sea-Level Pressure (MSLP), 500hPa height, 850hPa temperature
- Long-term forecast skill assessments, using measures defined by the SVSLRF.

WMO Global Producing Centres of Long-Range Forecasts

WMO has officially designated 12 GPCLRFs:

•Beijing: China Meteorological Administration (CMA) / Bejing Climate Center (BCC)

•Center for Weather Forecasts and Climate Studies (CPTEC) / National Institute for Space Research (INPE), Brazil

•European Centre for Medium-Range Weather Forecasts (ERA-I)

•Exeter: Met Office, United Kingdom

•Melbourne: Bureau of Meteorology (BOM), Australia

•Montreal: Meteorological Service of Canada (MSC)

•Moscow: Hydrometeorological Centre of Russia

•Pretoria: South African Weather Services (SAWS)

•Seoul: Korea Meteorological Administration (KMA)

•Tokyo: Japan Meteorological Agency (JMA) / Tokyo Climate Centre (TCC)

•Toulouse: Météo-France

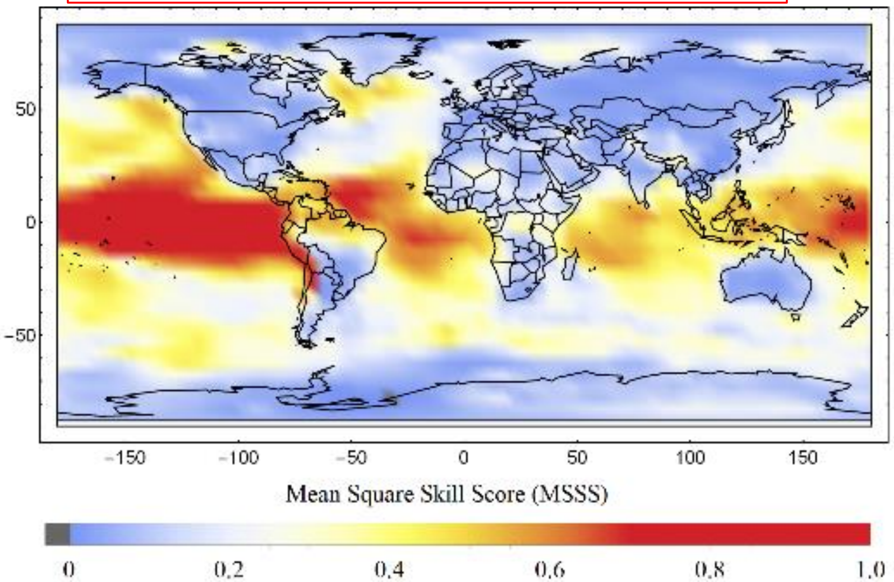
•Washington: Climate Prediction Center (CPC) / National Oceanic and Atmospheric Administration (NOAA), United States of America

Skills StocSIPS and CanSIPS: Comparison

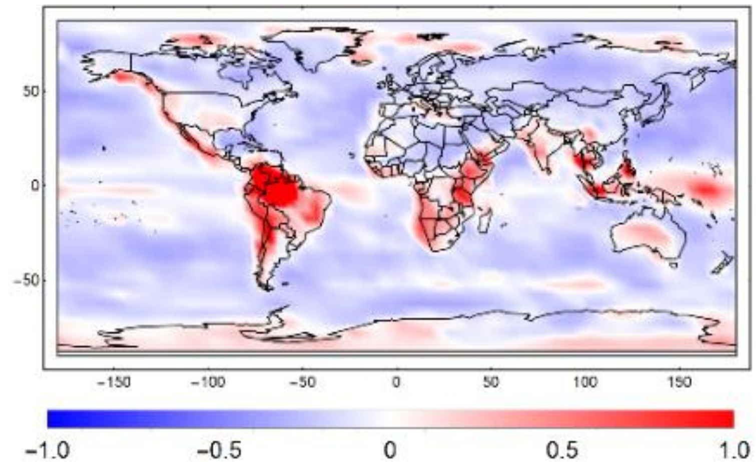
Monthly resolution, lead time = 1 month

$A = \mathbf{26}\%$ - Percentage of the globe where $MSSS_{StocSIPS} > MSSS_{CanSIPS}$

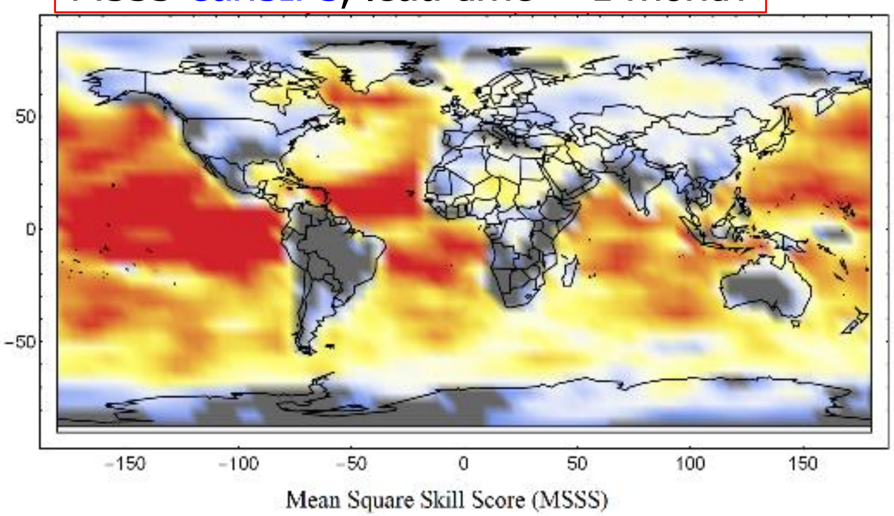
MSSS StocSIPS, lead time = 1 month

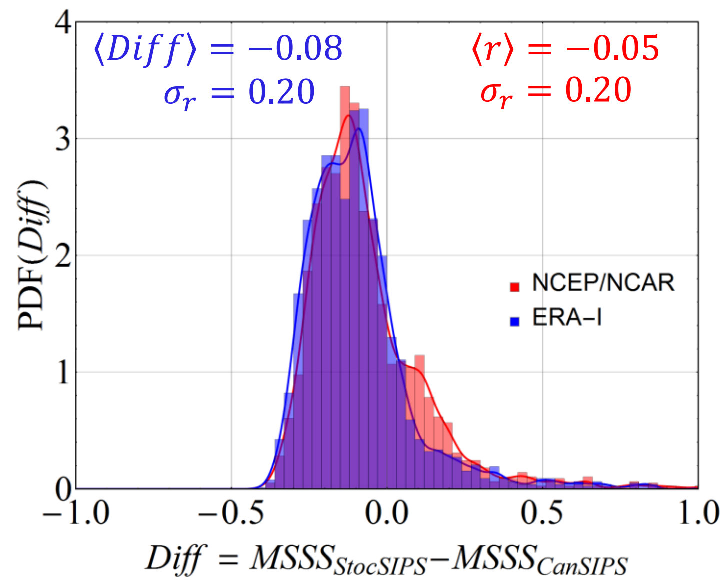


$Diff = MSSS_{StocSIPS} - MSSS_{CanSIPS}$



MSSS CanSIPS, lead time = 1 month



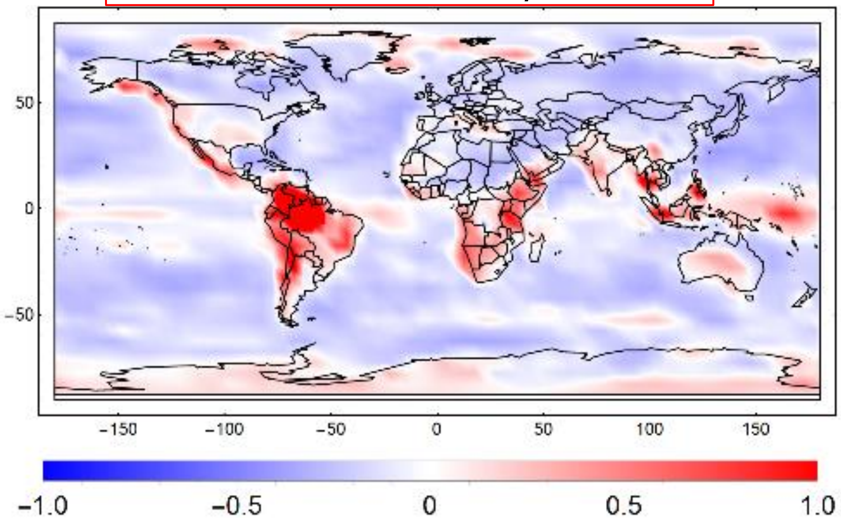


StocSIPS relative advantage increases with lead time

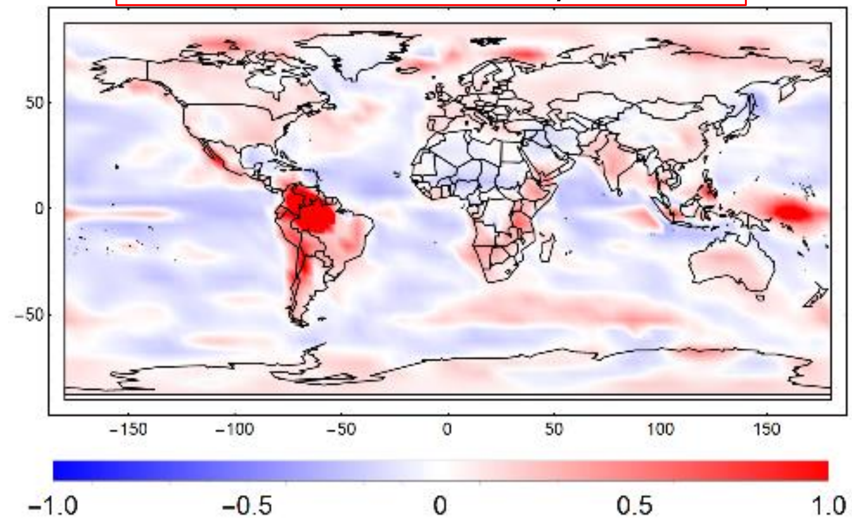
$$Diff = MSSS_{StocSIPS} - MSSS_{CanSIPS}$$

$\boldsymbol{A}$- Percentage of the globe where $MSSS_{StocSIPS} > MSSS_{CanSIPS}$

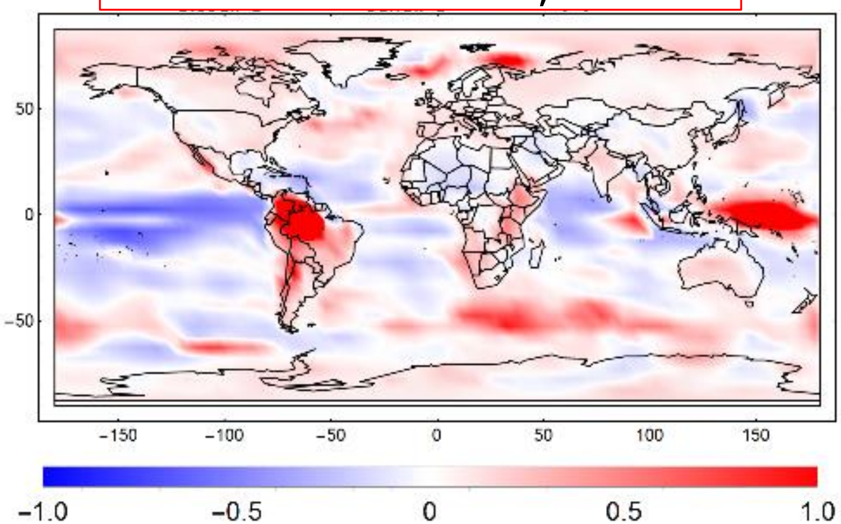
lead time = **1 month**, A=26%



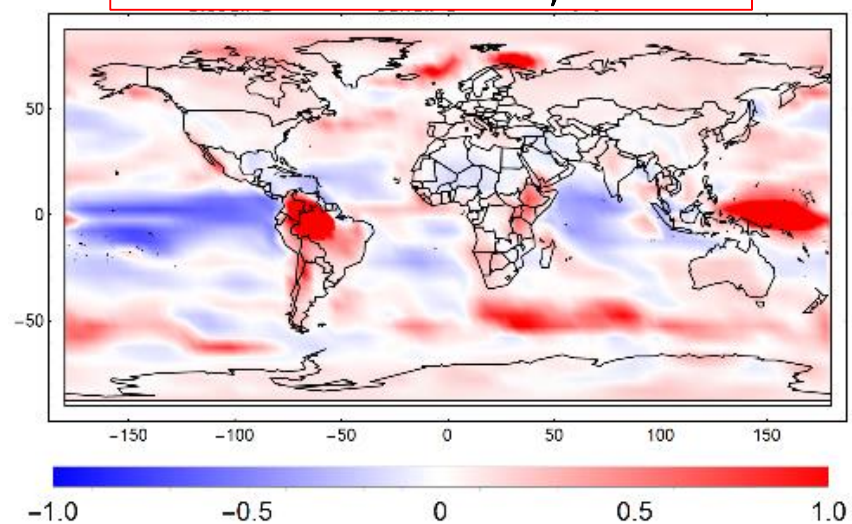
lead time = **2 months**, A=55%



lead time = **6 months**, A=65%



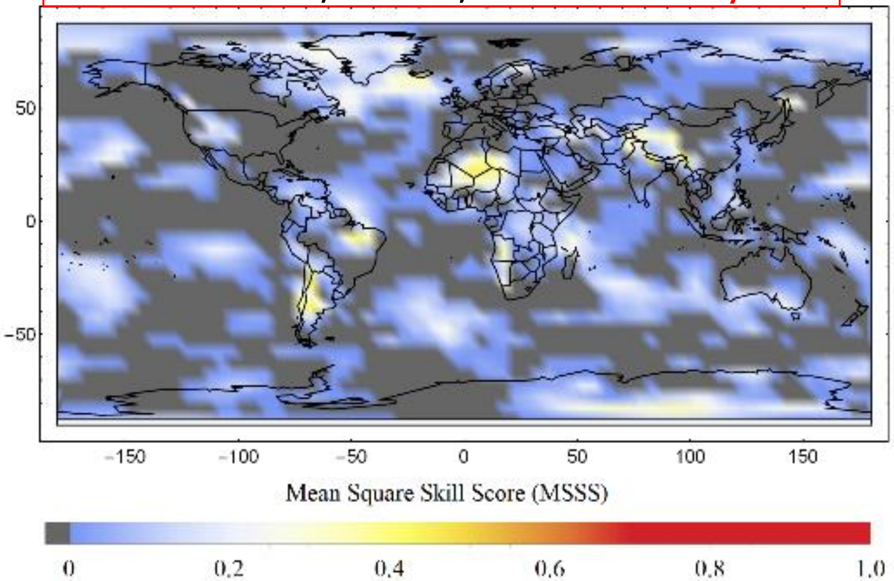
lead time = **9 months**, A=69%



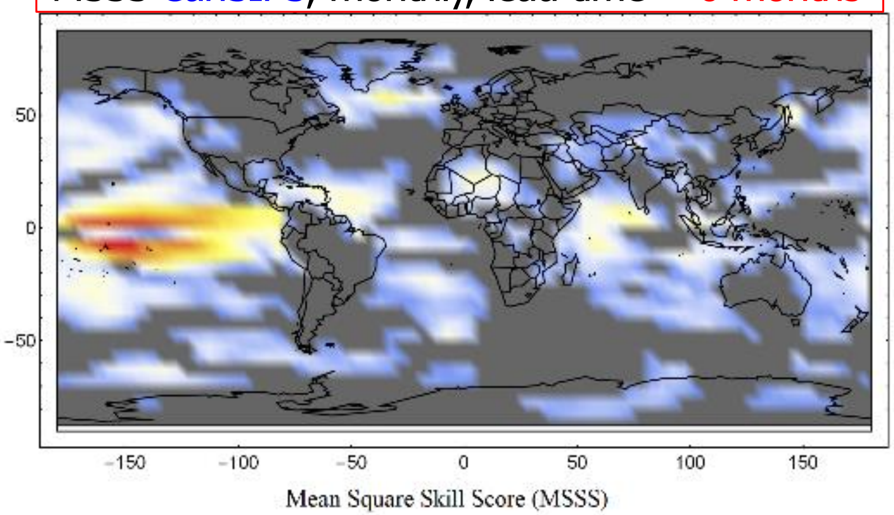
Skills StocSIPS and CanSIPS: Comparison

Annual resolution, lead time = 2 years for StocSIPS. Monthly resolution, lead time = 6 months for CanSIPS

MSSS StocSIPS, annual, lead time = 2 years

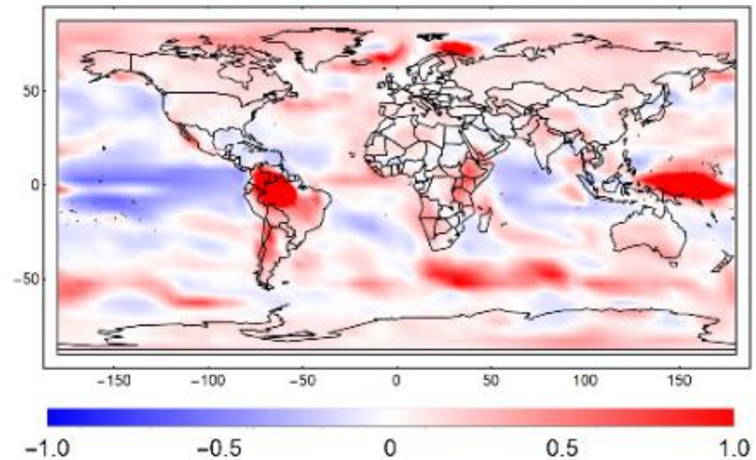


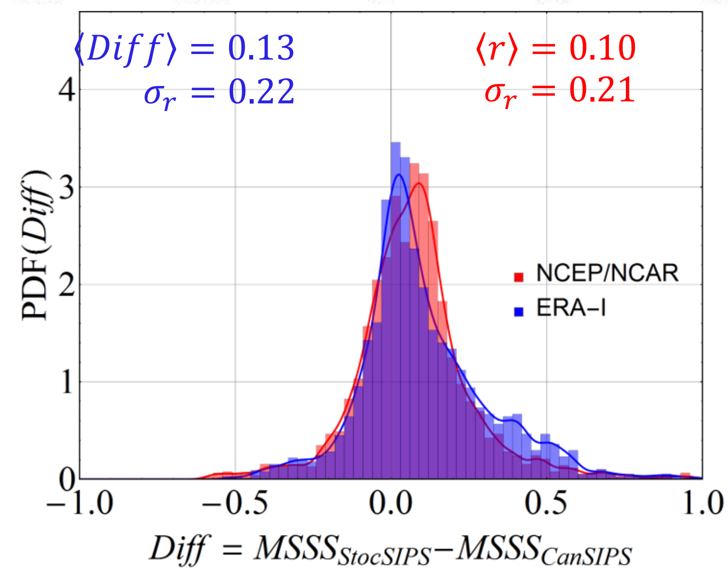
MSSS CanSIPS, monthly, lead time = 6 months



$MSSS_{StocSIPS}(2\,yrs) - MSSS_{CanSIPS}(6\,months)$

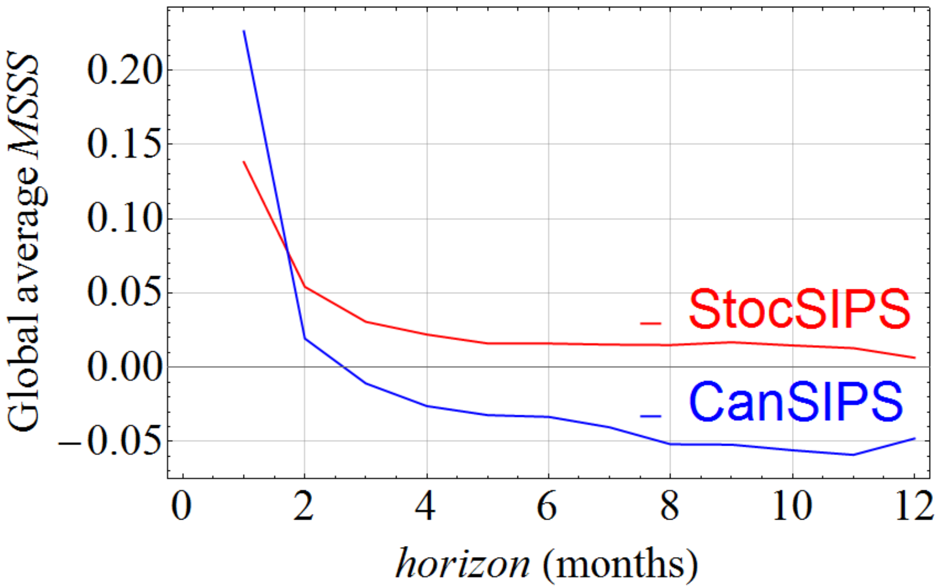
$A = 69\%$

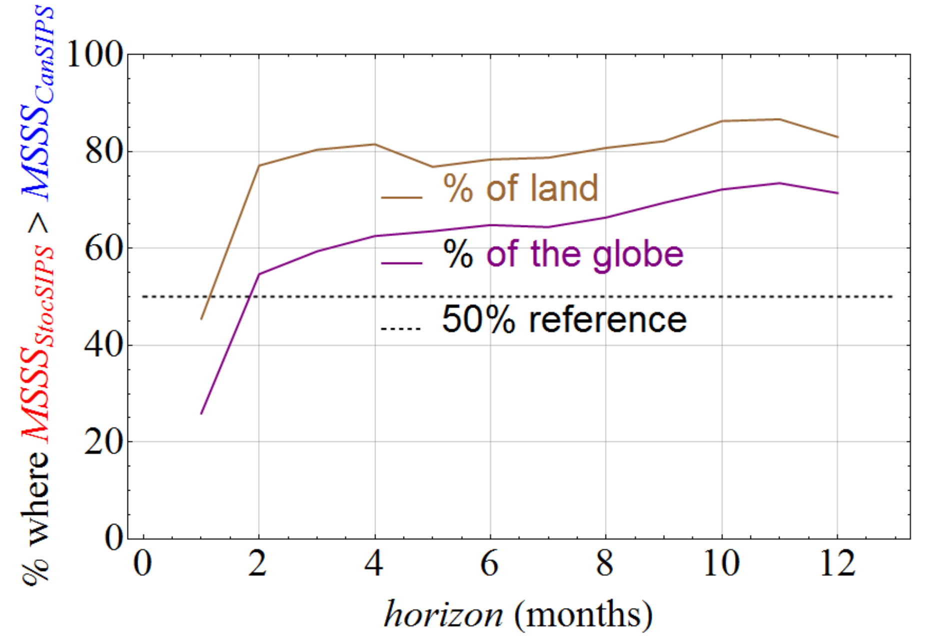




Relative Skill of StocSIPS increases with lead time

$MSSS_{StocSIPS} > MSSS_{CanSIPS}$ for more than one month





$$\langle MSSS \rangle_{global} = 1 - \frac{\langle MSE \rangle}{\langle Var_{anom} \rangle}$$

MSE - Mean Square Error

Var_{anom} - Variance of anomalies

Global Producing Centers: Actuals

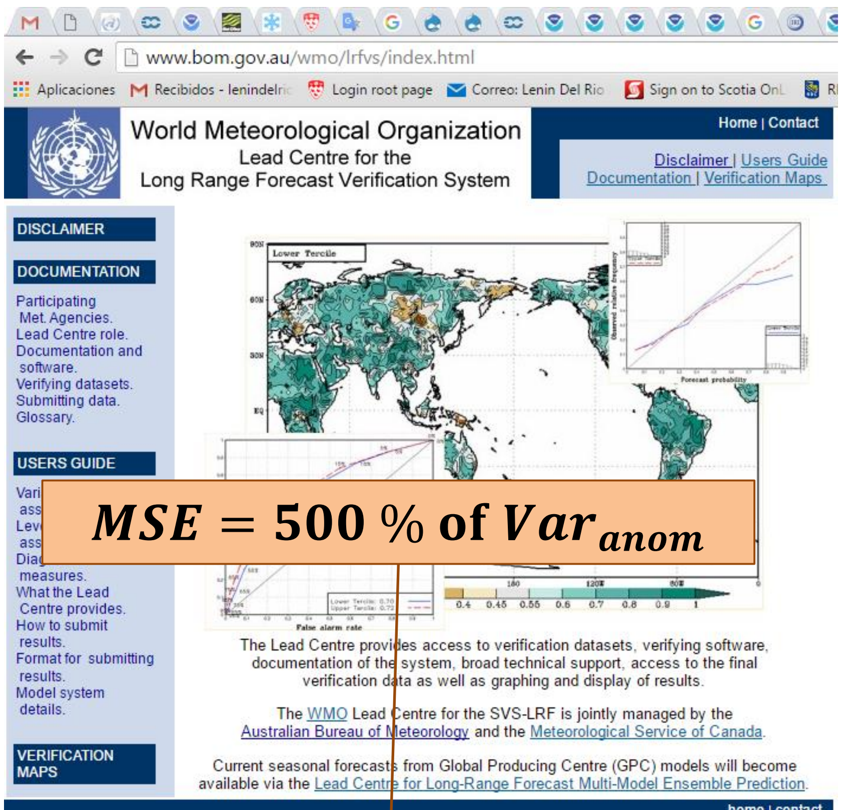
$$T = T_{actuals} = {\color{red}T_{trend}} + {\color{purple}T_{annual\ cycle}} + {\color{blue}T_{anomalies}}$$

Actuals

Anthropogenic

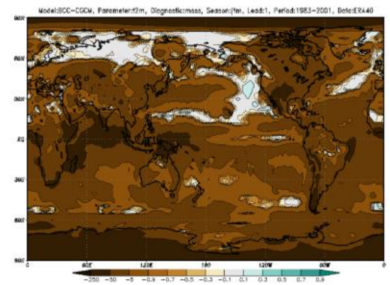
Natural variability

For actuals $MSE > Var_{anom}$ (negative skill)

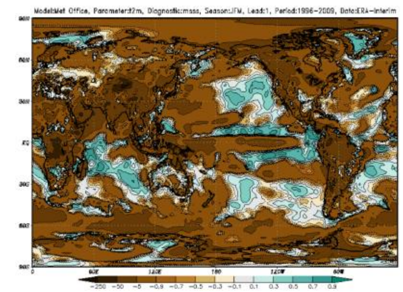


$$MSE = 500\ \%\ \text{of}\ Var_{anom}$$

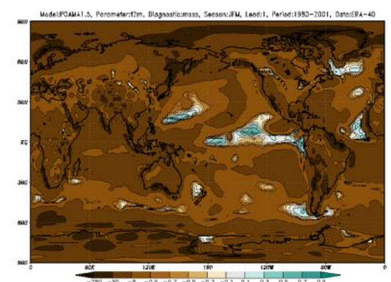
GPC- Beijing, JFM



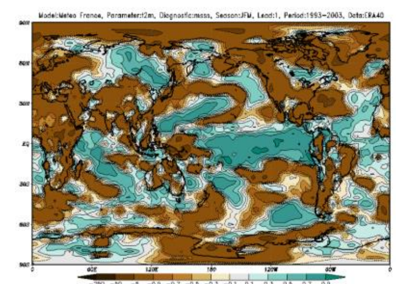
GPC-Exeter



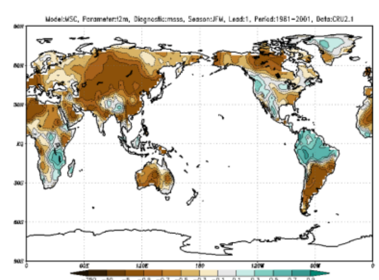
GPC-Melbourne



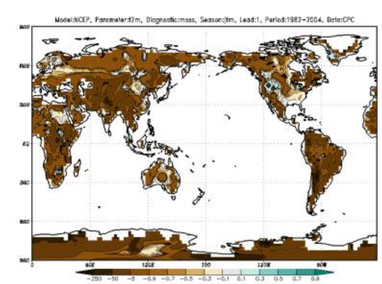
GPC-Toulouse

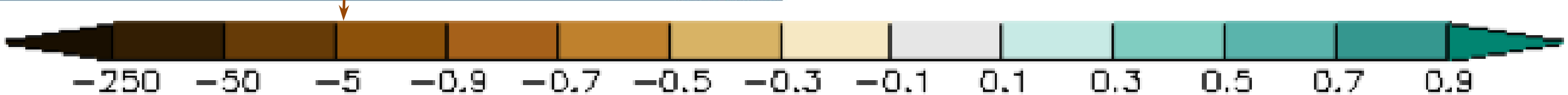


GPC-Montreal



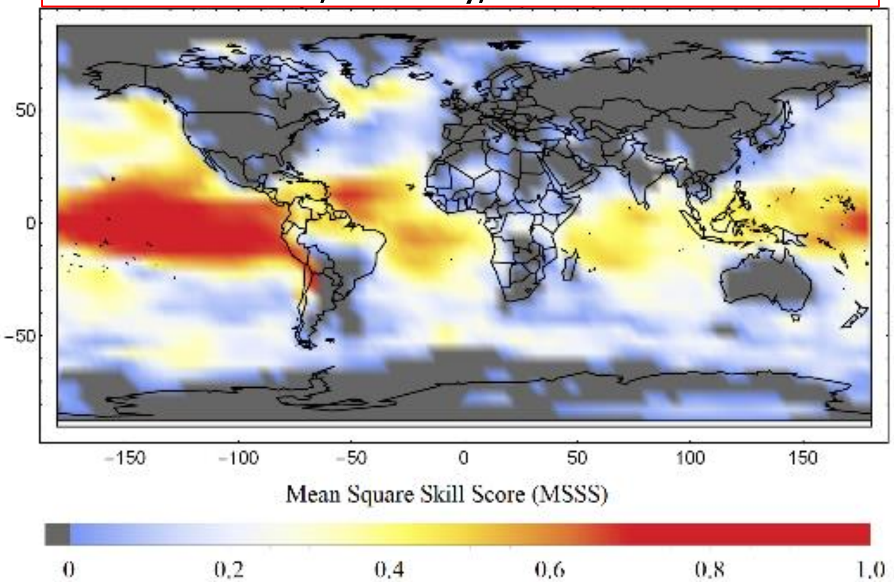
GPC-Washington



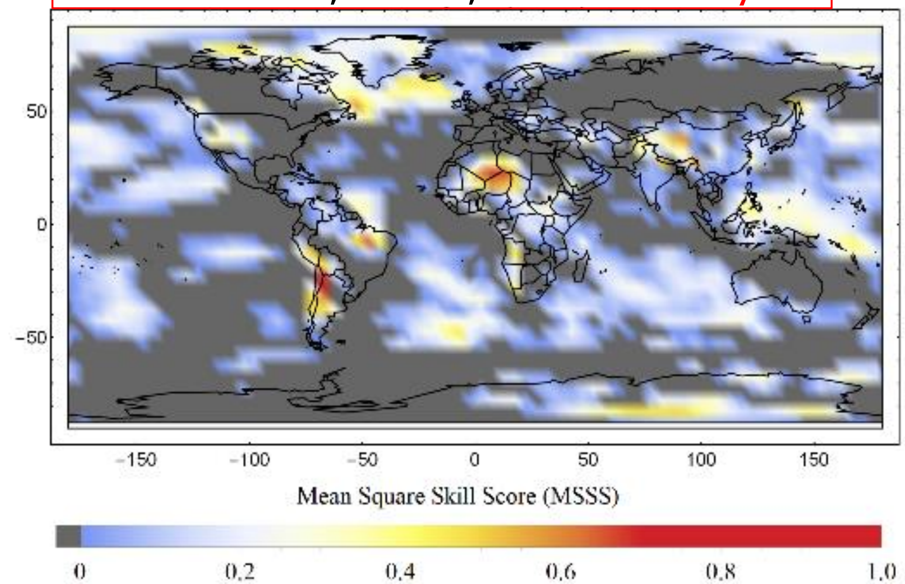


Skills StocSIPS and CanSIPS: Actuals

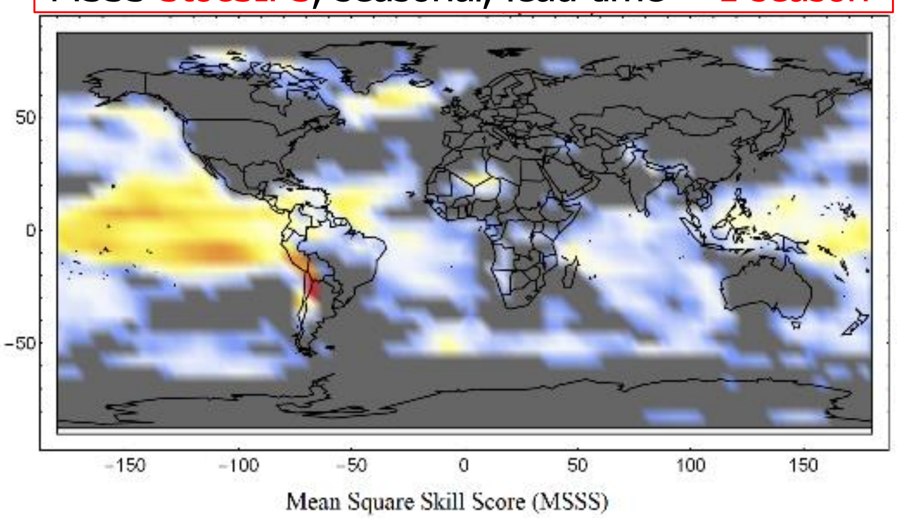
MSSS StocSIPS, monthly, lead time = 1 month



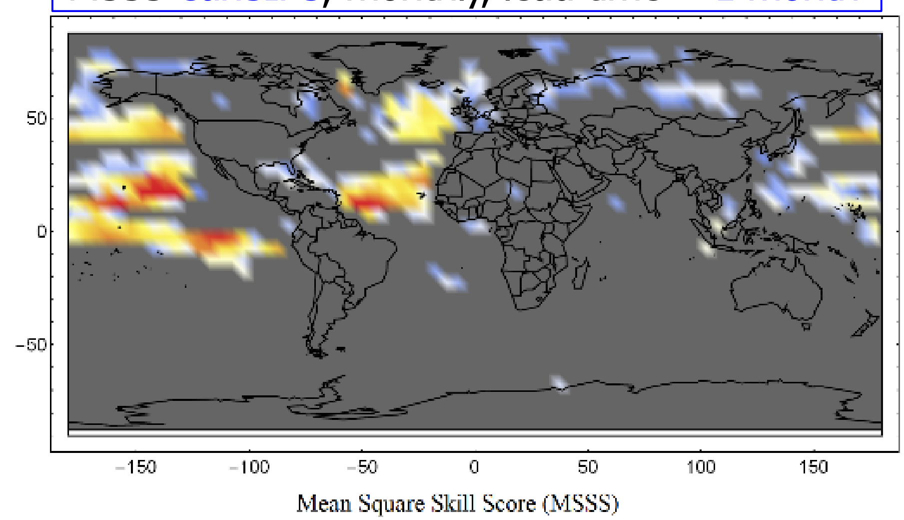
MSSS StocSIPS, annual, lead time = 1 year



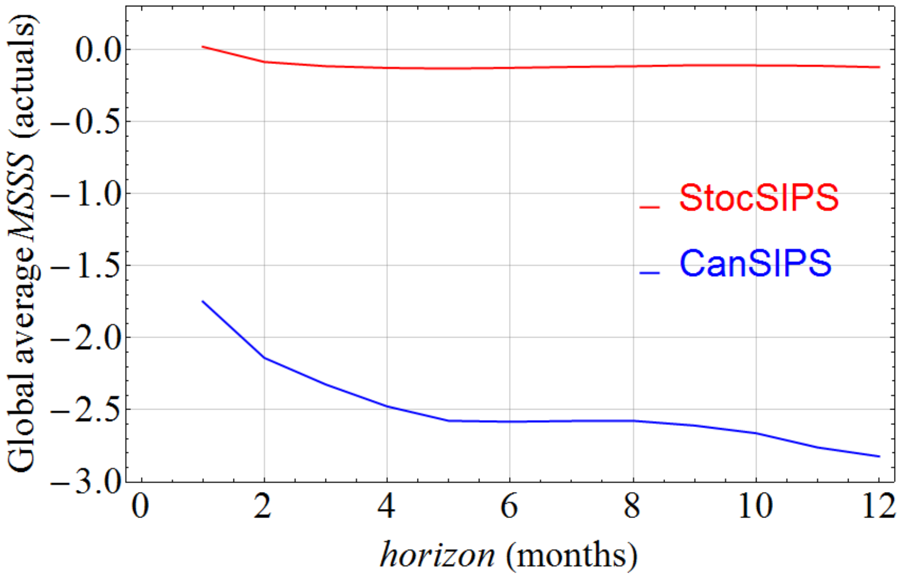
MSSS StocSIPS, seasonal, lead time = 1 season



MSSS CanSIPS, monthly, lead time = 1 month

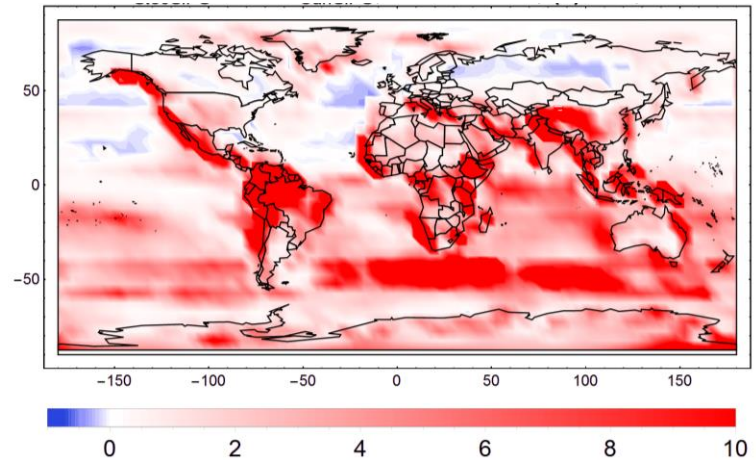


Hindcasts Skill: Actuals



$A = 93\%$

$Diff = MSSS_{StocSIPS} - MSSS_{CanSIPS}$



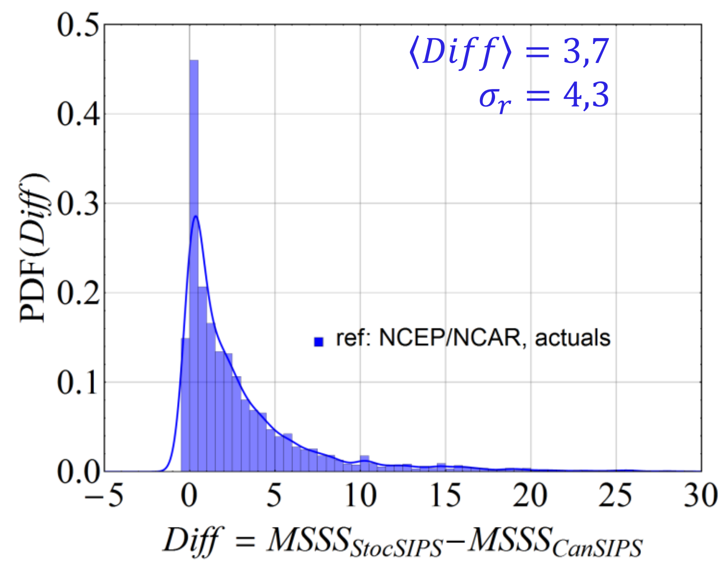
$$\langle MSSS \rangle_{global} = 1 - \frac{\langle MSE \rangle}{\langle Var_{anom} \rangle}$$

$T = T_{actuals} = T_{trend} + T_{annual\ cycle} + T_{anomalies}$

Actuals

Anthropogenic

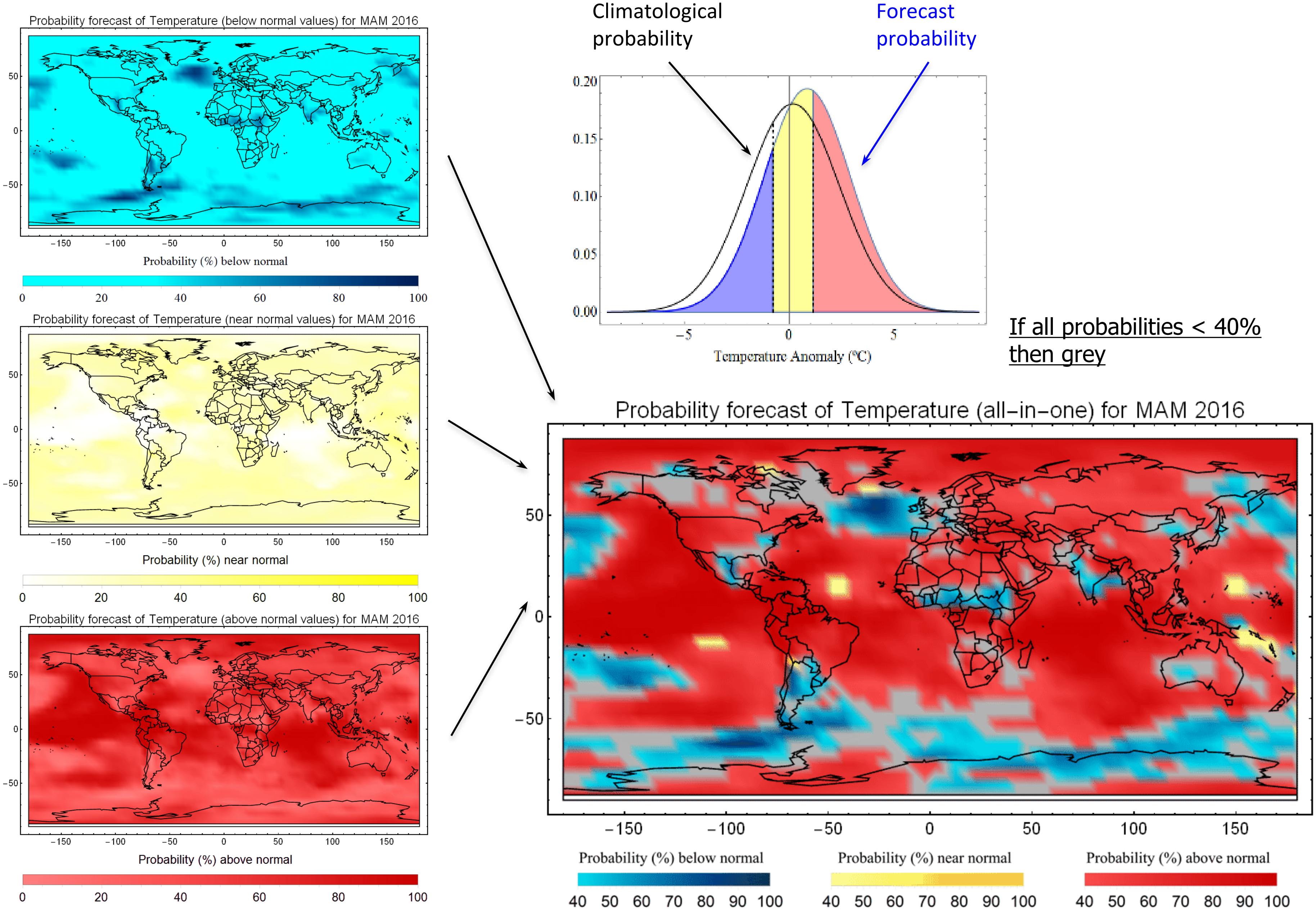
Natural variability



For actuals $MSE > Var_{anom}$

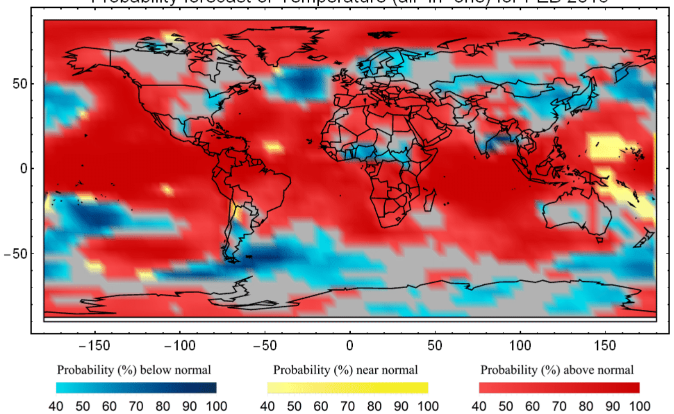
(negative skill)

Probabilistic Forecast

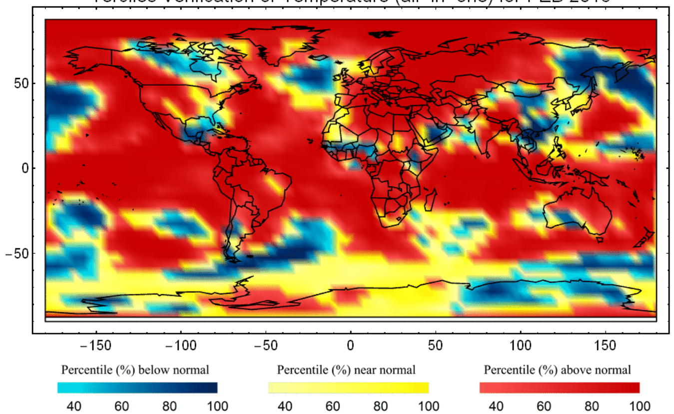


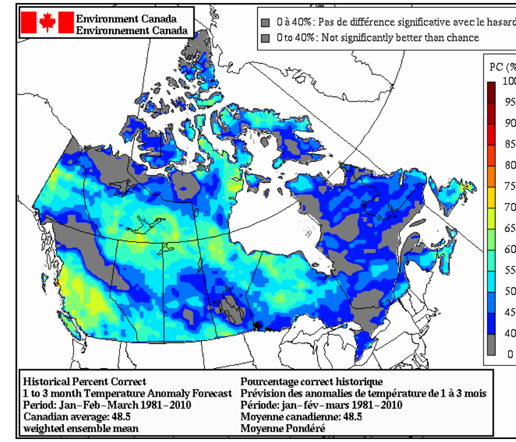
Probabilistic Forecast: verification and validation

Probability forecast of Temperature (all–in–one) for FEB 2016



Terciles Verification of Temperature (all–in–one) for FEB 2016

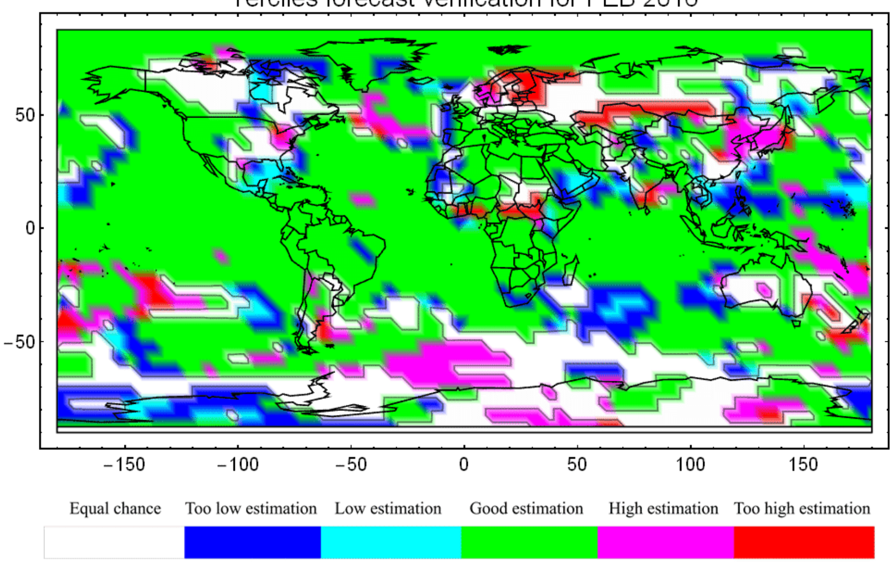




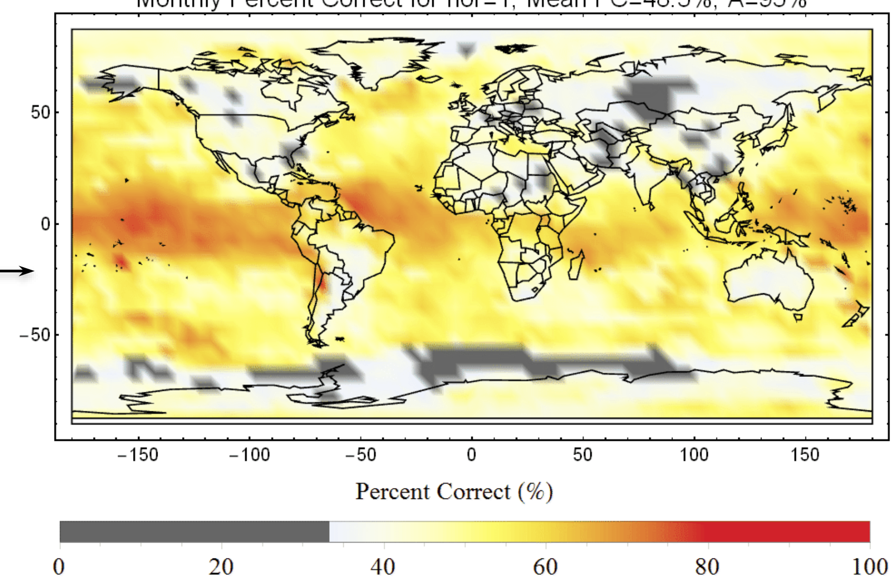
<u>Global average PC = 48,5% (Same as CanSIPS for Canada)</u>

<u>A = 95% of the globe with PC > 33%</u>

Terciles forecast verification for FEB 2016



Monthly Percent Correct for hor=1, Mean PC=48.5%, A=95%



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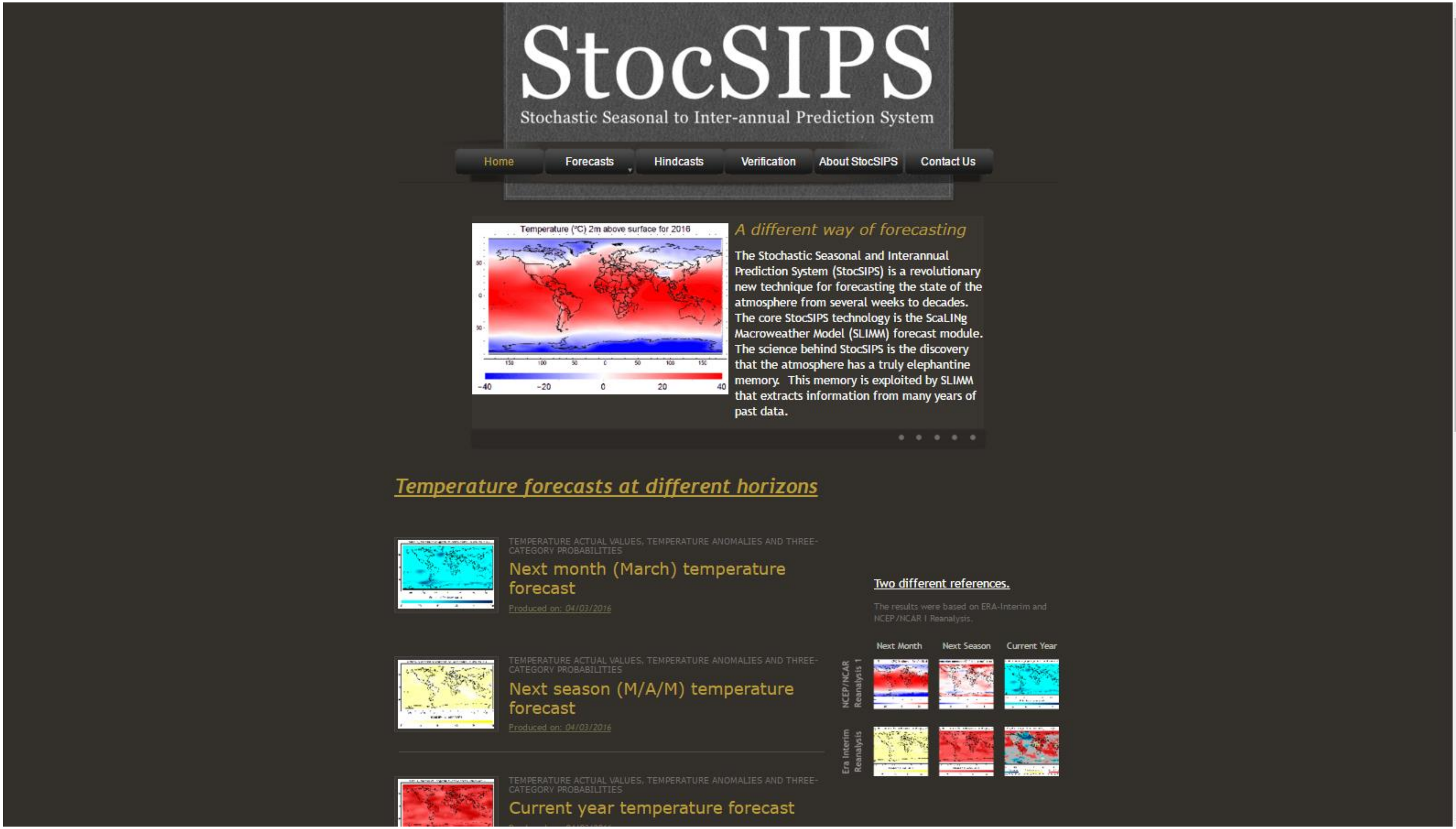

http://www.physics.mcgill.ca/StocSIPS

Conclusions

Theoretical basis of StocSIPS

-Long term memory (scaling, one parameter, H)
-Space-time factorization (space-time prediction decoupling)
-Stochastic predictability limits

StocSIPS performance

-Anomalies: StocSIPS has higher skill than CanSIPS for two months and longer.
-Actuals: Higher skill at all lead times due to direct forecasting of climatology.
-StocSIPS relative advantage: increases with lead time and is higher over land than oceans.

StocSIPS' advantages include

-No data assimilation
-No ad hoc post processing
-No need for downscaling
-Speed: (factor 10^5- 10^6)

Future developments

-Prediction of other fields (precipitation, wind, solar insolation, degree-days, forest fire indices, drought indices).
-Find co-predictors such as El Niño indices.
-Prediction of Extremes

http://www.physics.mcgill.ca/StocSIPS