

Stochastic modelling and prediction of monthly surface temperature: StocSIPS



Stochastic Seasonal to Interannual Prediction System

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McGill
Physics

Preprocessing

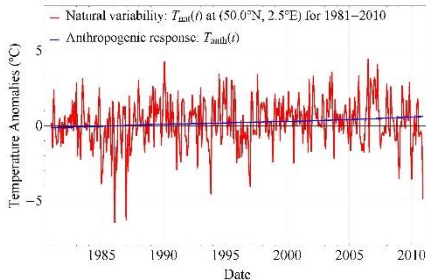
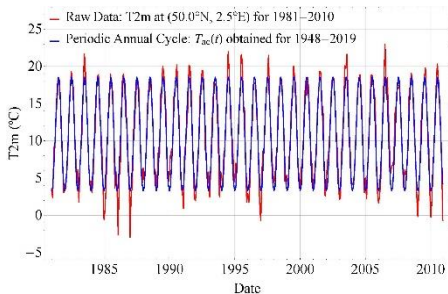
The temperature at every location is:

$$T(x, t) = T_{\text{ac}}(x, t) + T_{\text{anth}}(x, t) + T_{\text{nat}}(x, t)$$

$$T_{\text{anth}}(x, t) = \lambda_{2 \times \text{CO}_2 \text{eq}}(x) \log_2 \left[\rho_{\text{CO}_2 \text{eq}}(t) / \rho_{\text{CO}_2 \text{eq,pre}} \right]$$

$\lambda_{2 \times \text{CO}_2 \text{eq}}(x)$ is the transient climate sensitivity at position x related to the doubling of atmospheric equivalent- CO_2 concentrations.

Example at position (50.0°N, 2.5°E):



Scaling

The fluctuations of the natural variability satisfies:

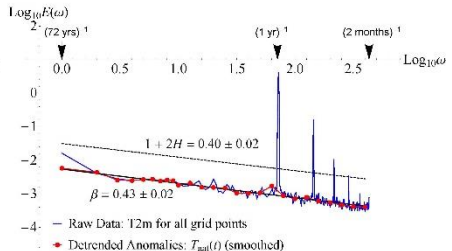
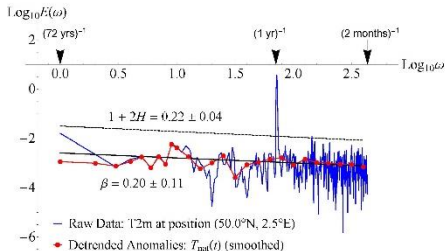
$$\langle |\Delta T(\Delta t)| \rangle \propto \Delta t^H$$

Equivalently for the spectrum:

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

with $\beta = 1 + 2H$

Spectrum:

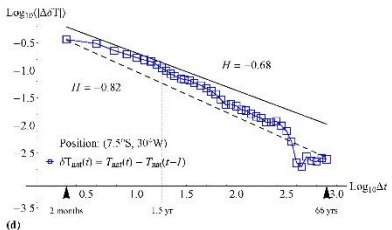
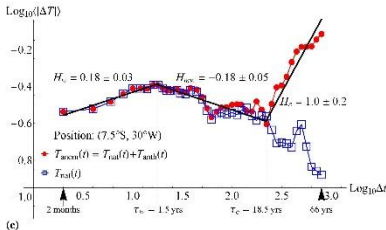
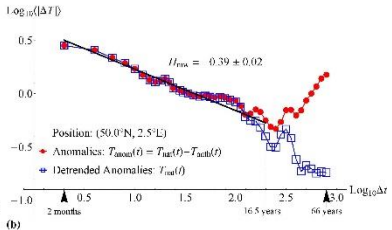
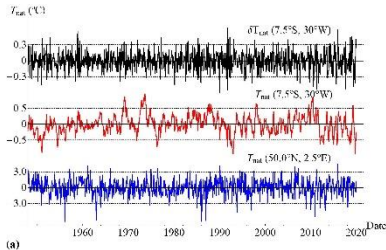


Scaling

Either the detrended anomalies $T_{\text{nat}}(t)$ or its first differences $\delta T_{\text{nat}} = T_{\text{nat}}(t) - T_{\text{nat}}(t-1)$ show a single scaling regime for time scales between one month and many decades with fluctuation exponent:

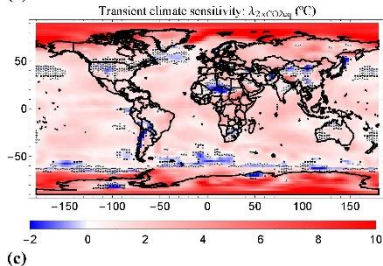
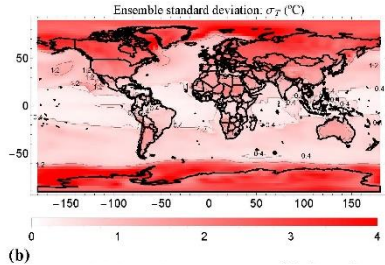
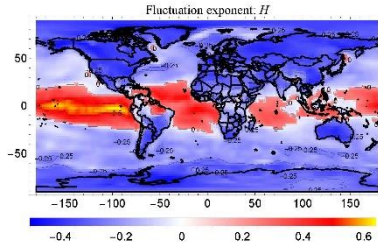
$$-1 < H < 0$$

Examples at (50.0°N, 2.5°E - land) and (7.5°S, 30°W – tropical ocean) :



Stochastic modelling

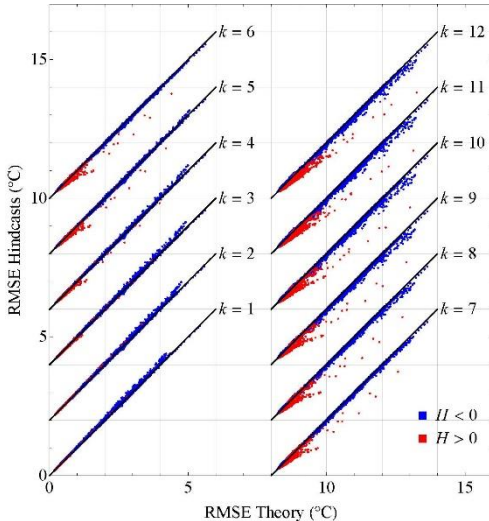
The natural variability, T_{nat} (or its first differences, δT_{nat}) can be modeled by a fractional Gaussian noise (fGn) process with parameters σ (volatility) and H (fluctuation exponent). We assume the series have zero mean. The raw temperature at every location is determined by only 3 parameters (σ , H , $\lambda_{2xCO2eq}$):



In the region with $H > 0$ (tropical ocean), the first differences δT_{nat} are modeled by an fGn process, with fluctuation exponent $H - 1$.

Model validation

We performed monthly hindcasts for the verification period 1951-2019 using as observational reference NCEP/NCAR Reanalysis interpolated to a 2.5° latitude \times 2.5° longitude grid across the globe for a total of $73 \times 144 = 10512$ grid points.

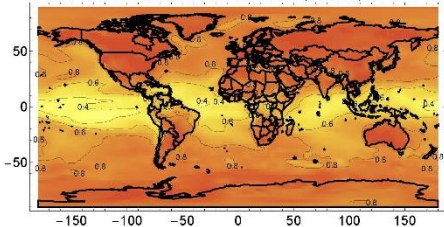


Comparison between the RMSE_{nat} obtained from hindcasts and the theoretical $\text{RMSE}_{\text{nat}}^{\text{theory}}$ predicted by the theory for different forecast horizons, k , from 1 to 12 months. The black line at 45° is a reference indicating perfect agreement between theory and verification results. The blue points represent locations where $H < 0$ and the natural variability is modeled as an fGn process and the red points are for places where $H > 0$ and we have to take the first differences.

Hindcast verification

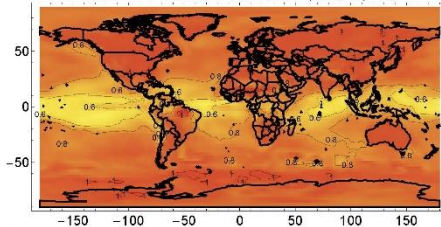
Normalized Root Mean Square Error (NRMSE)

Normalized RMSE for $k = 1$ month. $\langle \text{NRMSE} \rangle = 0.90$



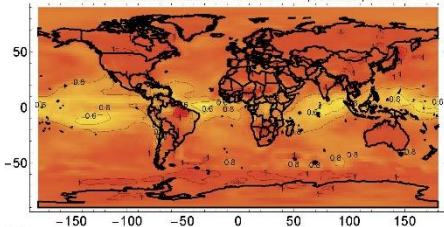
(a)

Normalized RMSE for $k = 2$ months. $\langle \text{NRMSE} \rangle = 0.94$



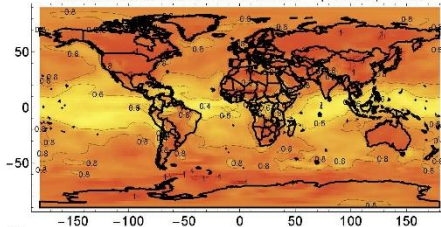
(b)

Normalized RMSE for $k = 3$ months. $\langle \text{NRMSE} \rangle = 0.95$



(c)

Normalized RMSE for $k = 1 - 3$ months. $\langle \text{NRMSE} \rangle = 0.88$



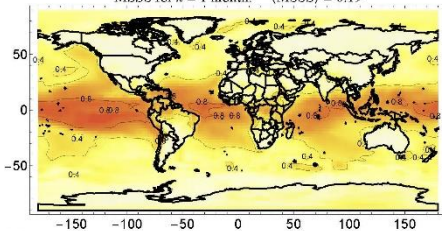
(d)



Hindcast verification

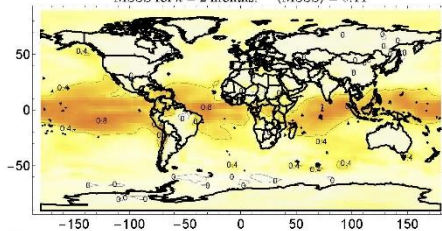
Mean Square Skill Score (MSSS)

MSSS for $k = 1$ month. $\langle \text{MSSS} \rangle = 0.19$



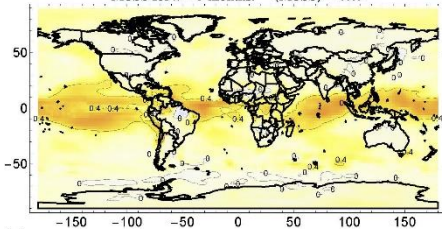
(a)

MSSS for $k = 2$ months. $\langle \text{MSSS} \rangle = 0.11$



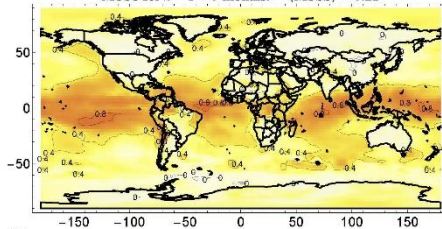
(b)

MSSS for $k = 3$ months. $\langle \text{MSSS} \rangle = 0.09$



(c)

MSSS for $k = 1 - 3$ months. $\langle \text{MSSS} \rangle = 0.22$



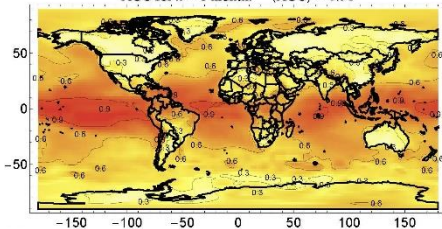
(d)



Hindcast verification

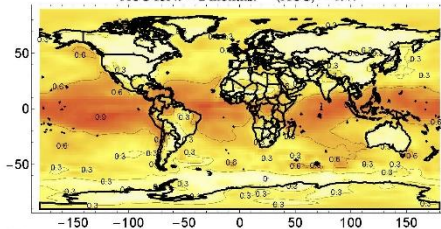
Anomaly Correlation Coefficient (ACC)

ACC for $k = 1$ month. $\langle \text{ACC} \rangle = 0.58$



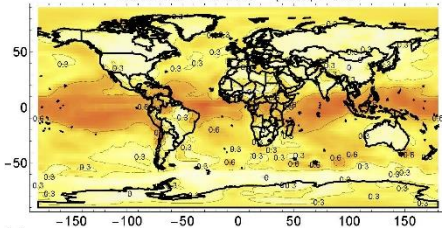
(a)

ACC for $k = 2$ months. $\langle \text{ACC} \rangle = 0.47$



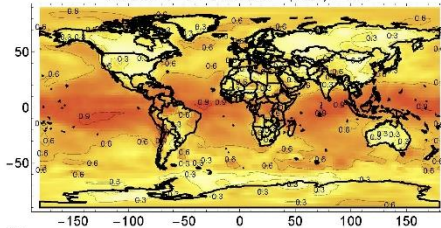
(b)

ACC for $k = 3$ months. $\langle \text{ACC} \rangle = 0.41$



(c)

ACC for $k = 1 - 3$ months. $\langle \text{ACC} \rangle = 0.57$

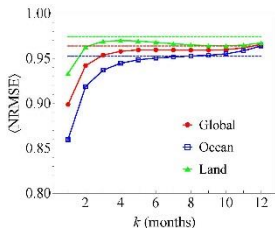


(d)

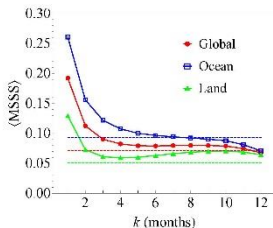


Hindcast verification

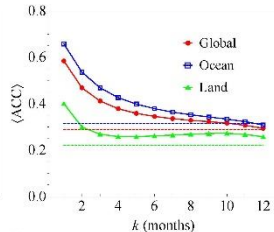
Monthly Average Scores



(a)

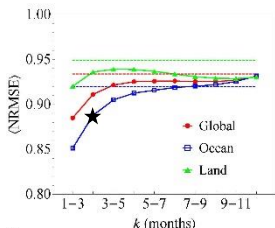


(b)

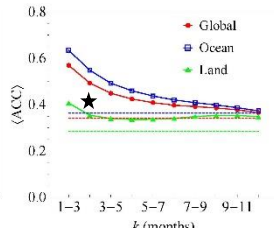
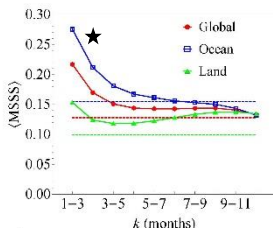


(c)

3-Month Average Scores



(d)



Are results from GCM multi-model ensemble (MME) predictions taken from: Kim G, Ahn J-B, Kryjov VN, et al (2016) Global and regional skill of the seasonal predictions by WMO Lead Centre for Long-Range Forecast Multi-Model Ensemble. Int J Climatol 36:1657–1675. doi: 10.1002/joc.4449

Conclusions

StocSIPS performance

- Anomalies: StocSIPS has higher skill than GCMs for two months and longer.
- Actuals: Higher skill at all lead times due to direct forecasting of real world 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 (for an infinite ensemble): (factor 10^5 - 10^6)

References:

- Del Rio Amador, L. and Lovejoy, S. (2019) *Clim Dyn*, **53**: 4373. <https://doi.org/10.1007/s00382-019-04791-4>
- Lovejoy, S., Del Rio Amador, L., Hébert, R. (2017) In *Nonlinear Advances in Geosciences*, A.A. Tsonis ed. Springer Nature, 305–355 DOI: 10.1007/978-3-319-58895-7