

# Causality in long-term predictions, past-value problems and a stochastic-deterministic combination

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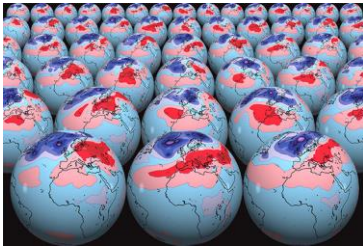
# Motivation

## Seasonal forecast

- The atmosphere is a chaotic system

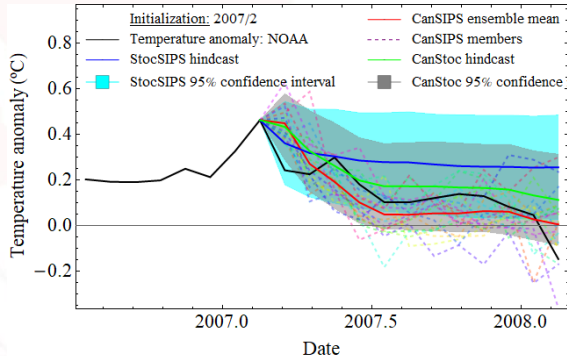


- Conventional ensemble systems



Taken from ECMWF

- Conventional ensemble prediction involves:
  - Many “random” outputs generated with complex deterministic equations
  - Probabilistic interpretation



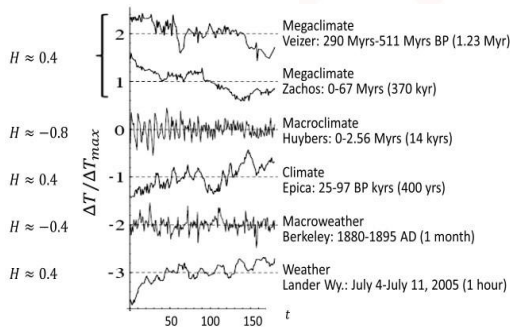
- Why not then directly use a stochastic model?
- Can we combine the two approaches for improving forecasts?

# Motivation

## Scaling

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

Laws of turbulence



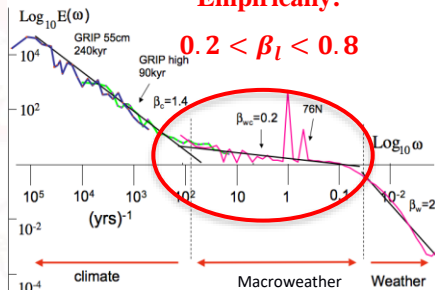
Spectrum:

$$E(\omega) = \langle |\tilde{T}(\omega)|^2 \rangle \propto \omega^{-\beta}$$

$$\beta = 1 + 2H \quad (\text{for mono-fractals})$$

**Empirically:**

$$0.2 < \beta_l < 0.8$$



Lovejoy and Schertzer 2011

multivariate Stochastic Seasonal to Interannual Prediction System:

$$T_i(t) = \sum_j \int_{-\infty}^t \kappa_{ij}(t-t') \gamma_j(t') dt'$$

$\kappa_{ij}(t)$  is a scaling (fractional Gaussian noise) kernel

The innovations,  $\gamma_i(t)$ , are normalized Gaussian white noise processes with cross-correlation matrix:

$$\rho_{ij}(t-t') = \langle \gamma_i(t) \gamma_j(t') \rangle = a_{ij} \delta(t-t')$$

**This implies no Granger causality = past value problem**

A forecast of  $T_i(t > 0)$ , based on its own past  $T_i(s \leq 0)$ , is not worst than a forecast of  $T_i(t)$  based on both  $T_i(s)$  and the information from another pixel,  $T_j(s)$ .

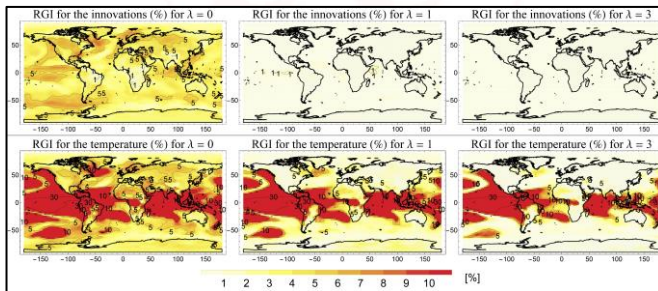
# Correlations and connectivity

$$\rho_{ij}(t-t') = \langle \gamma_i(t) \gamma_j(t') \rangle = a_{ij} \delta(t-t')$$

$$R_{ij}(\Delta t) = \langle T_i(t) T_j(t + \Delta t) \rangle = a_{ij} f_{H_i, H_j}(\Delta t)$$

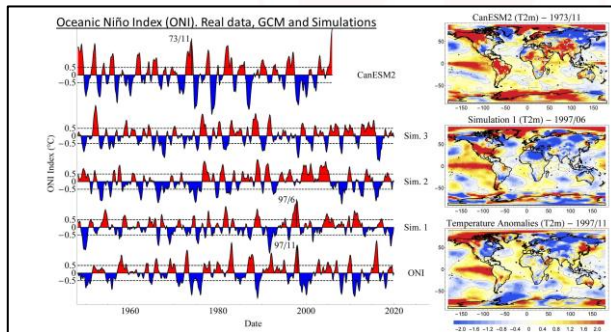
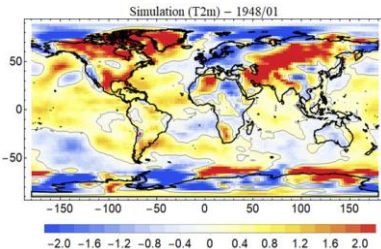
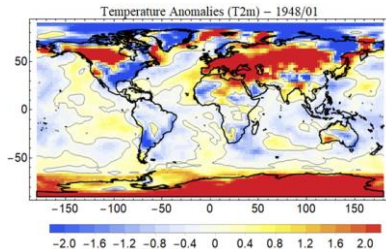
## The Ratio of Global Influence (RGI) or connectivity:

for pixel  $i$  is the fraction of the area of the planet for which  $|R_{ij}(\lambda)| > 0.2$ , averaged over all  $j$  (for innovations  $|\rho_{ij}(\lambda)| > 0.2$ ).



For the innovations, almost all the connectivity is lost for  $\lambda > 0$ .

# Simulations



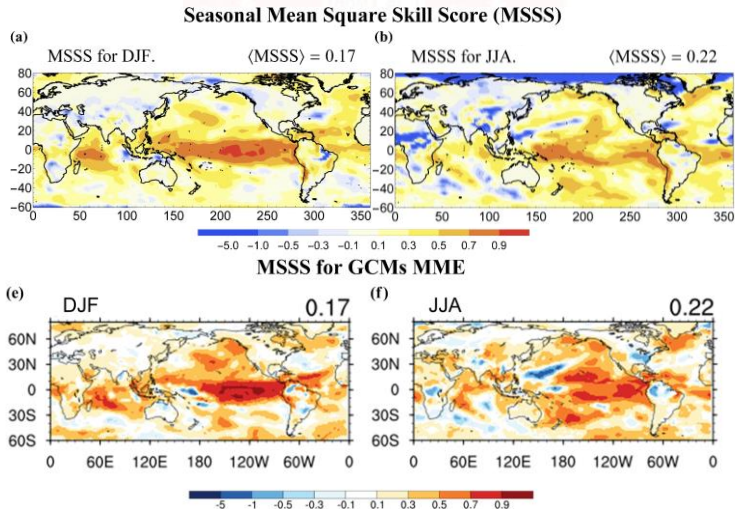
CanESM2 simulation.

StocSIPS simulations.

Observations.

# Predictions and comparison with GCMs

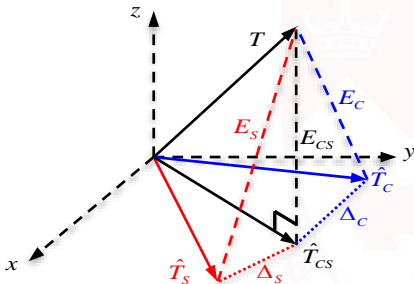
Reference: ERA-Interim; Resolution:  $2.5^\circ \times 2.5^\circ$ ; Period of verification: 1981-2010.



Forecasts from Kim et al. 2020

# Merging CanSIPS and StocSIPS into CanStoc

## Geometric Interpretation



## Errors

$$E_S(t) = T(t) - \hat{T}_S(t)$$

$$E_C(t) = T(t) - \hat{T}_C(t)$$

$$E_{CS}(t) = T(t) - \hat{T}_{CS}(t)$$

$C$  – CanSIPS

$S$  – StocSIPS

$CS$  – CanStoc

## Combined predictor

$$\hat{T}_{CS} = \alpha \hat{T}_S + \beta \hat{T}_C$$

## Minimum Square Framework - Orthogonality Principle

$$\langle \hat{T}_{CS} E_{CS} \rangle = 0$$

## Solving for the coefficients

$$\begin{pmatrix} \langle \hat{T}_S T \rangle \\ \langle \hat{T}_C T \rangle \end{pmatrix} = \begin{pmatrix} \langle \hat{T}_S^2 \rangle & \langle \hat{T}_S \hat{T}_C \rangle \\ \langle \hat{T}_S \hat{T}_C \rangle & \langle \hat{T}_C^2 \rangle \end{pmatrix} \begin{pmatrix} \alpha \\ \beta \end{pmatrix}$$

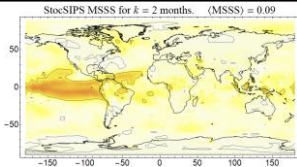


# Mean Square Skill Score comparison

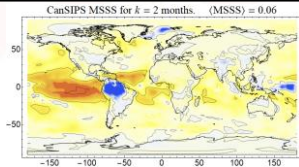
Reference: ERA-Interim; Resolution:  $2.5^\circ \times 2.5^\circ$ ; Period of verification: 1981-2010.

## 1-months lead ( $k = 2$ )

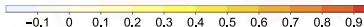
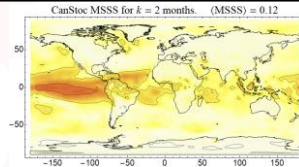
MSSS StocSIPS



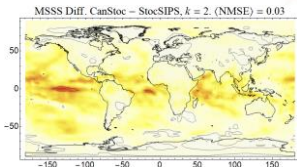
MSSS CanSIPS



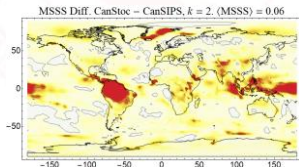
MSSS CanStoc



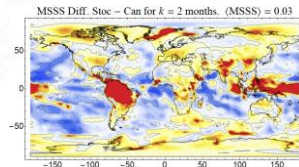
MSSS Diff. CanStoc - StocSIPS



MSSS Diff. CanStoc - CanSIPS

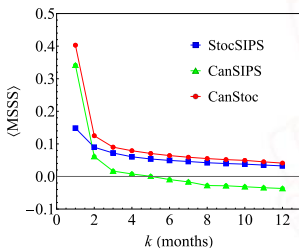


MSSS Diff. StocSIPS - CanSIPS

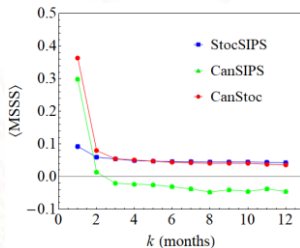


# Average MSSS

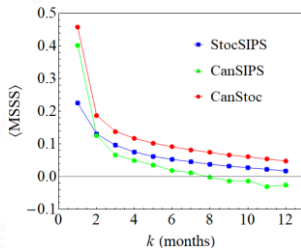
Globally averaged MSSS



Average MSSS over land



Average MSSS over ocean



# Conclusions

- This difference in approach (initial vs. past value problems), opens the possibility of combining the two bringing the best of both worlds.
- The skill on the prediction of temperature was improved at global and regional levels.
- In places where both CanSIPS and StocSIPS show low skill (even negative), its combination in CanStoc could have high quality of prediction.
- The theoretical framework is general and can be used to include other copredictors.
- StocSIPS could be used as an advanced postprocessing technique to improve the skill of GCMs in places where they do not have deterministic predictability.



*Thank You!*

# References

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