

# Influence of snow and soil moisture initialization on sub-seasonal predictability and forecast skill in CanCM3

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# Outline

- 1 Introduction/Background
- 2 Potential predictability
- 3 Signal-to-Noise Ratio statistics
- 4 Forecast skill
- 5 Summary and concluding remarks

**Aim: examine the influence of snow and soil moisture initialization on sub-seasonal skills of CanCM3 predictions of springtime (April-May) near surface air temperature.**

snow and soil moisture can significantly influence climate on sub-seasonal to seasonal time scales.

### **Snow:**

- ▶ snow cover in the NH has significant impacts on local weather and climate especially during winter season (Cohen and Fletcher [2007, J. Clim.], Orsolini and Kvamstø [2009, JGR] ...).
- ▶ The effects of snow cover on the climate are primarily due to its high albedo and other physical properties

### **Soil Moisture:**

- ▶ the snow cover slows the freezing of the soil due to its low thermal conductivity
- ▶ temporal variability of the snow cover affects infiltration and runoff.  
(Schlosser and Mocko [2003, JGR], Guo et al. [2011, GRL], Koster et al. [2011, J. Hydrometeor.] ...)

### Previous studies:

1. Koster et al. [2011, J. Hydrometeor.] - [GLACE-2] influence of soil moisture on subseasonal air temperature prediction skill
2. Drewitt et al. [2012, Atmos.-Ocean] - influence of soil moisture on boreal summer prediction skill of CanCM3
3. Schlosser and Mocko [2003, JGR] - impact of realistic snow conditions on spring season
4. Jeong et al. [2013, J. Climate], Orsolini et al. [2012, Clim. Dynam.] - impact of snow conditions on cold season/fall-winter season
5. many others

focusing either on the influence of snow for winter season or soil moisture for summer season.

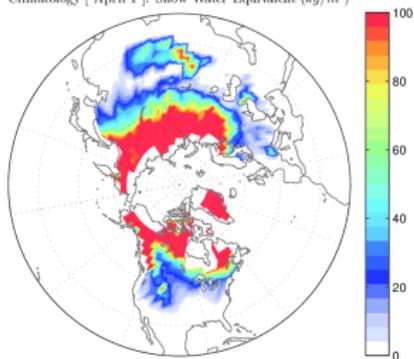
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**Our study focus on the influence of both snow and soil moisture initialization on sub-seasonal predictability during the transition period between cold and warm seasons, which occurs in April-May for much of extra-tropical northern hemisphere (ENH).**

# Observed SWE climatology [1986-2005]

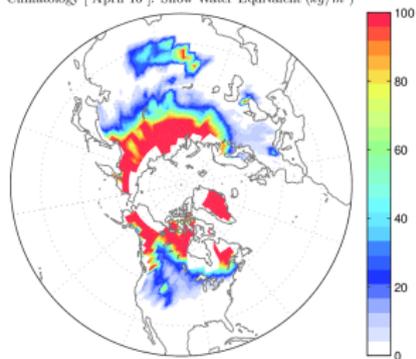
(a) April 1

Climatology [ April 1 ]: Snow Water Equivalent ( $kg/m^2$ )



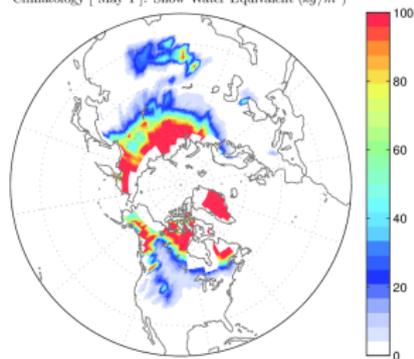
(b) April 16

Climatology [ April 16 ]: Snow Water Equivalent ( $kg/m^2$ )



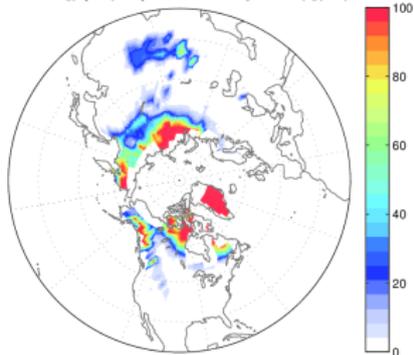
(c) May 1

Climatology [ May 1 ]: Snow Water Equivalent ( $kg/m^2$ )



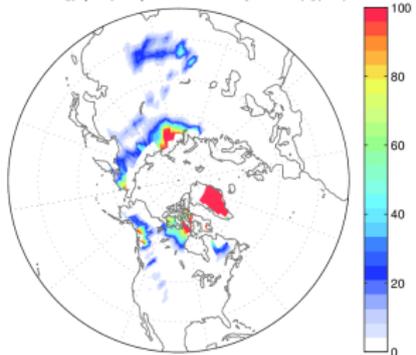
(d) May 16

Climatology [ May 16 ]: Snow Water Equivalent ( $kg/m^2$ )



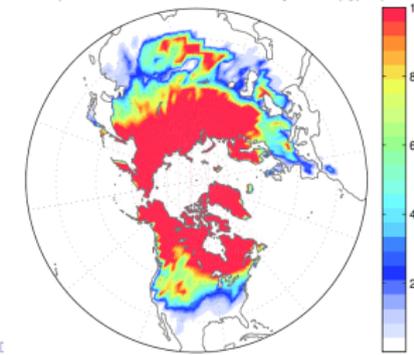
(e) May 31

Climatology [ May 31 ]: Snow Water Equivalent ( $kg/m^2$ )



(f) April anom. st. dev.

Anomaly standard deviation: Snow Water Equivalent ( $kg/m^2$ )



## Data: Land surface initialization strategies

The data used in this study were generated in the framework of the CanSIPS (c.f. Merryfield et al. [2013, Mon. Wea. Rev.]

- ▶ Four series of ten-member ensemble forecasts, initialized on 1<sup>st</sup> April where each series use different land surface initialization, were performed for the 20 year period 1986-2005.

<b>Forecast series</b>	<b>Land surface initial conditions</b>
S1	Off-line forced CLASS values, rescaled to coupled model climatological mean and standard deviation (same for all ensemble members)
S2	Randomized version of S1, i.e., April 1 values from different years assigned to different ensemble members
S1r	Same as S1, except using raw offline forced CLASS values without rescaling (same for all ensemble members)
S1o	Initialization method used in operational CanSIPS, with land state set by coupled model response to assimilation of ERA atmospheric fields (slightly different for all ensemble members)

Two questions are addressed in this study:

1. to what degree initializing the forecasts with realistic land surface conditions can enhance sub-seasonal forecast skill in boreal spring.
2. how forecasts using the three “realistic” formulations (S1, S1r and S1o) of land surface initialization compare.

we focus on the **potential predictability** and **actual forecast skill** of the forecasted 15 day averaged values of temperature initialized on the 1<sup>st</sup> April, at 15 day, 30 day and 45 day lead times.

## Potential predictability

- ▶ *potential* predictability → prediction skill with respect to a model-based *synthetic* truth.
- ▶ actual skill → evaluated using observations.

For a given series, one of the ensemble members is taken as the synthetic truth and is evaluated against the ensemble mean of the remaining ensemble members (c.f. Koster et al. [2011, J. Hydrometeor.])

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**Predictability skill metric:**  $r^2$  = square of the correlation coefficient between the forecast anomaly and observed anomaly. The  $r^2$  value represents the fraction of 'truth' variance explained

The  $r^2$  difference value ( $r_{\text{diff}}^2$ ) between any two series of forecast quantifies the skill difference between them

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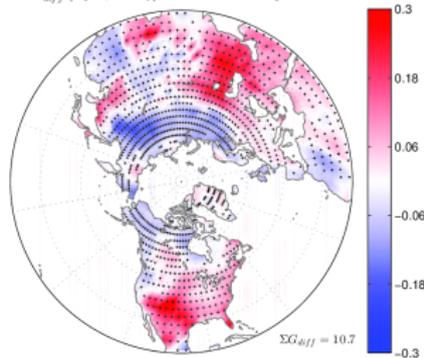
Calculate  $r_{\text{diff}}^2$  for

- ▶ 2m-temperature forecasts ( $T_{2m}$ )
- ▶ cross correlations of  $T_{2m}$  with SWE and (frozen, liquid) soil moisture (WGF, WGL)

## $r_{diff}^2$ potential predictability for S1-S2

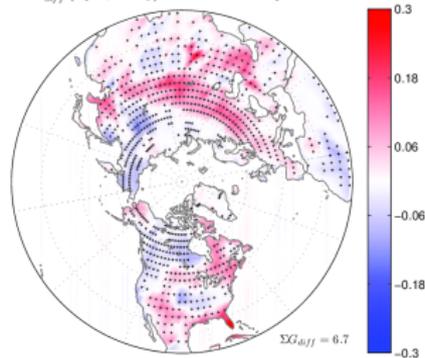
Day 16-30

$r_{diff}^2$  [April, 15 day]: CanCM3 2m-Temperature



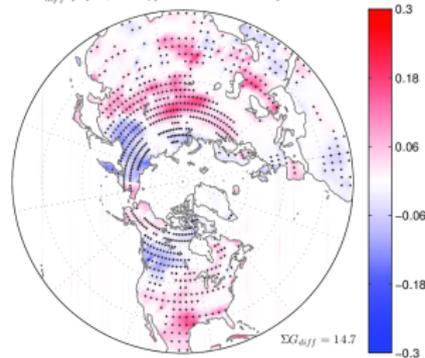
Day 31-45

$r_{diff}^2$  [April, 30 day]: CanCM3 2m-Temperature



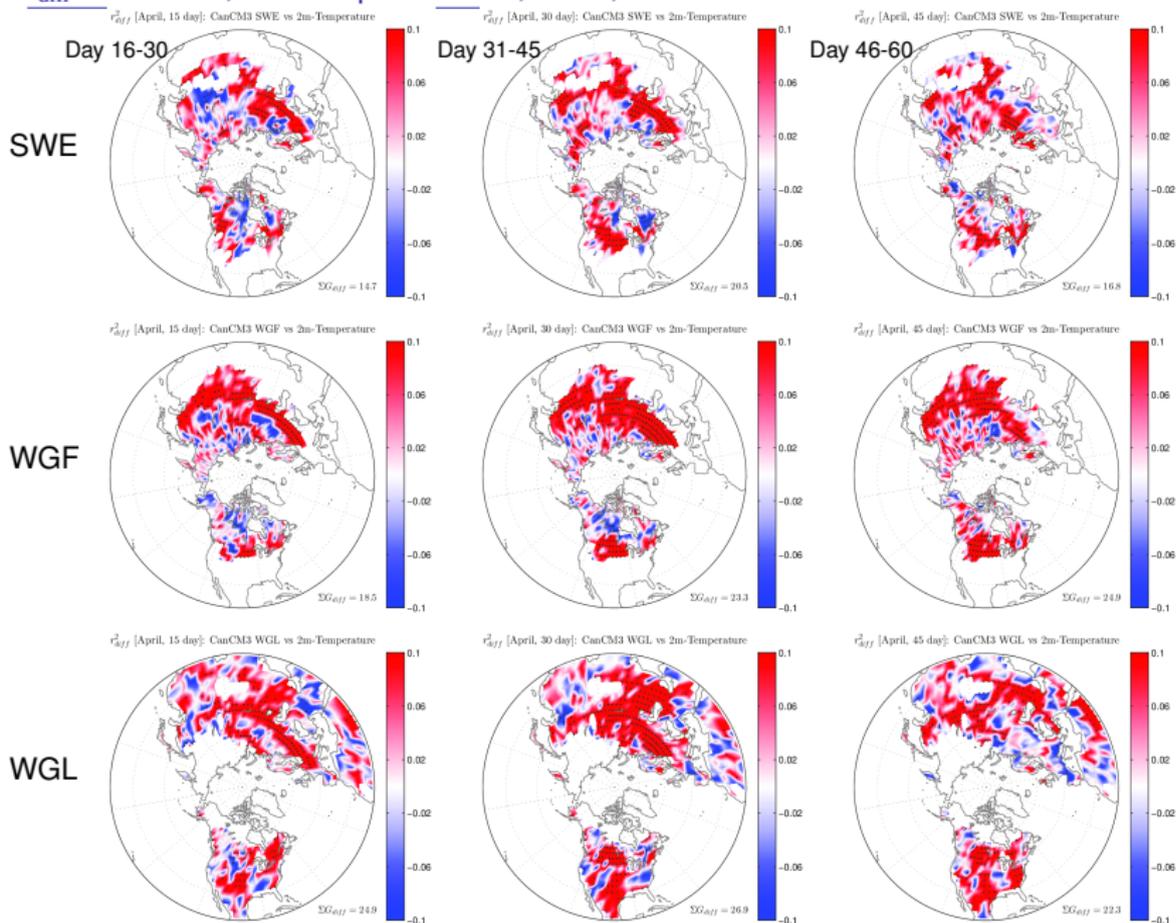
Day 46-60

$r_{diff}^2$  [April, 45 day]: CanCM3 2m-Temperature



The  $\Sigma G_{diff}$  values represent percentage differences between the fraction of ENH land area where  $r_{diff}^2 > 0$  and that the area where  $r_{diff}^2 < 0$ .

# $r_{diff}^2$ for S1-S2; 2m-temp. vs SWE, WGF, WGL



## $r_{\text{diff}}^2$ Pattern correlations for S1-S2

Pattern correlations between S1-S2 potential predictability  $r_{\text{diff}}^2$  and S1-S2  $r_{\text{diff}}^2$  computed from the correlations between forecast 2m-temperature and the indicated land initial conditions.

<b>Land variable/lead time</b>	<b>15 day</b>	<b>30 day</b>	<b>45 day</b>
SWE	0.20	0.30	0.11
WGF	0.44	0.55	0.30
WGL	0.26	0.42	0.33

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This indicates the degree to which  $T_{2m}$  potential predictability is attributable to land surface initial conditions.

SNR is defined as the ratio between signal variance  $\sigma_{\text{signal}}^2$  and the noise variance  $\sigma_{\text{noise}}^2$ .

$$\sigma_{\text{signal}}^2 = \frac{1}{M} \sum_{m=1}^M (\bar{X}_m - \bar{\bar{X}})^2 \quad (1)$$

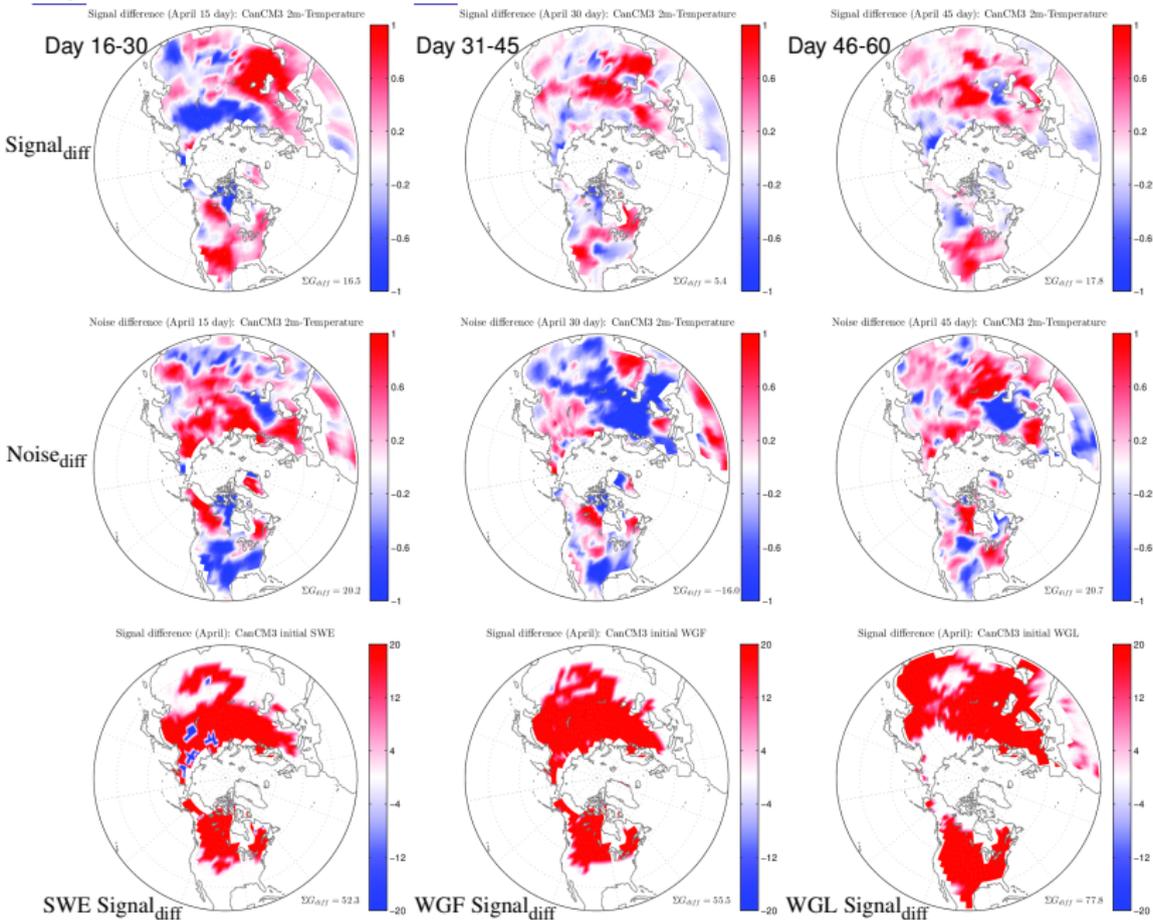
$$\sigma_{\text{noise}}^2 = \frac{1}{MK} \sum_{m=1}^M \sum_{k=1}^K (X_{m,k} - \bar{X}_m)^2 \quad (2)$$

where  $\bar{X}_m$  is the ensemble mean,  $\bar{\bar{X}}$  is the climatological mean,  $K$  is the ensemble size, and  $M$  is the number of predictions.

(c.f. Kumar and Hoerling [1998, J. Climate], Shukla et al. [2000, BAMS], Rowell [1998, J. Climate] ...)

In principle,  $r^2$  and SNR are related by  $r^2 = \text{SNR} / (\text{SNR} + 1)$  when unbiased variance estimates are used.

# Signal, Noise difference statistics based on S1-S2



## Pattern correlations: $r_{\text{diff}}^2$ vs Signal, Noise

Pattern correlations between potential predictability  $r_{\text{diff}}^2$  and **forecast signal difference**.

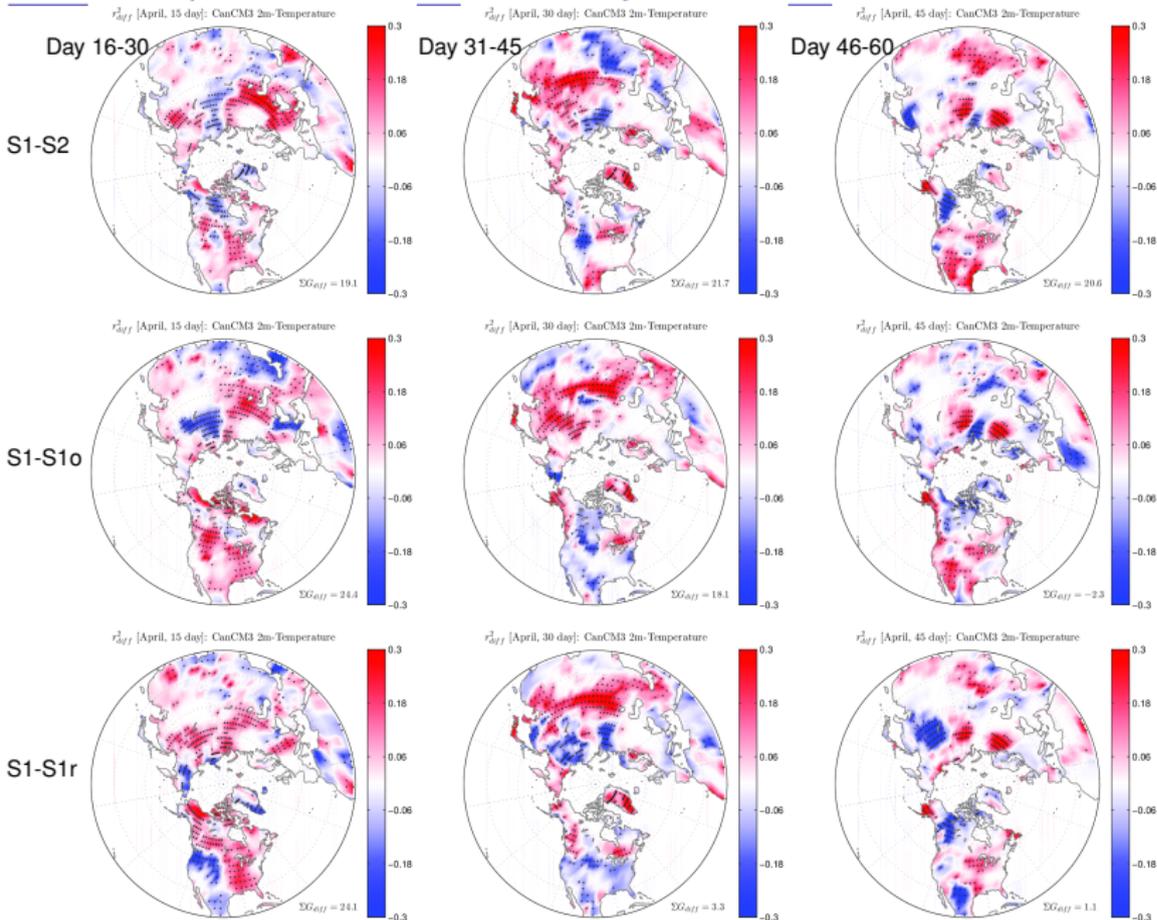
<b>Experiment/lead time</b>	<b>15 day</b>	<b>30 day</b>	<b>45 day</b>
S1-S2	0.84	0.71	0.79
S1-S1o	0.78	0.70	0.70
S1-S1r	0.80	0.73	0.72

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Pattern correlations between potential predictability  $r_{\text{diff}}^2$  and **forecast noise difference**.

<b>Experiment/lead time</b>	<b>15 day</b>	<b>30 day</b>	<b>45 day</b>
S1-S2	-0.37	-0.44	-0.19
S1-S1o	-0.32	-0.35	-0.23
S1-S1r	-0.21	-0.07	0.01

# $r_{diff}^2$ : 2m-temperature forecasts vs Reanalyses = Actual Skill Difference



## Summary and concluding remarks

1. Higher potential predictability over southern part of ENH is attributed to the realistic initialization of liquid soil moisture (WGL)
2. Over northern part of ENH, areas showing higher potential predictability is attributed to accurate representation of interannual SWE variations.
3. spatial pattern correlations indicate frozen soil moisture (WGF) has a stronger influence on the potential predictability than other land surface variables at shorter lead times
4. At longer lead times WGL has the strongest influence likely due to the transformation from frozen to liquid soil moisture that occurs during the spring thaw.
5. SNR analysis indicates that low potential predictability in certain areas is attributable both to low signal and high noise
6. Signal differences play a bigger role in determining potential predictabilities than do noise differences.
7. Overall, land initial conditions obtained from offline-driven CLASS are found to yield more accurate predictions than those obtained from the CanSIPS initialization procedure.



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# Influence of snow and soil moisture initialization on sub-seasonal predictability and forecast skill in CanCM3

## Additional Slides

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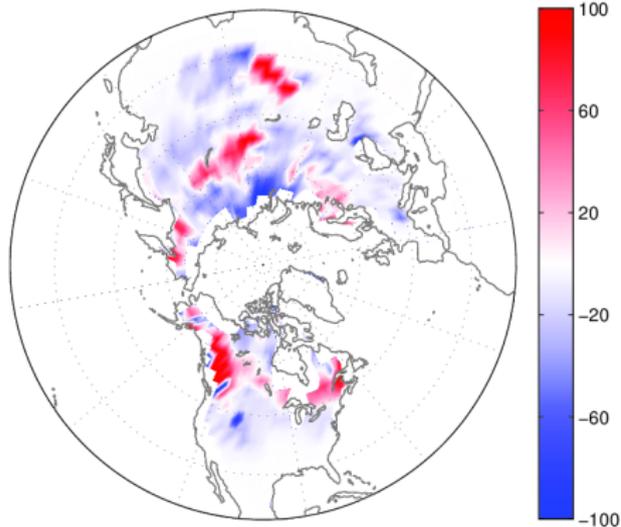
<sup>2</sup>CCCma, Environment Canada

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## April 1<sup>st</sup> initial SWE of S1 vs Observation

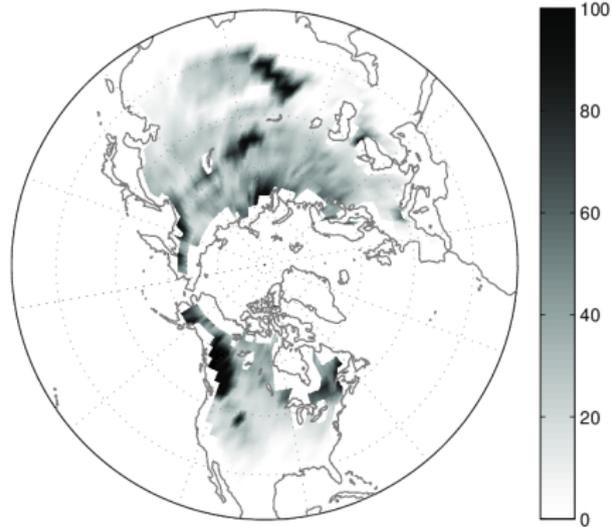
(a)

CanCM3 [ April 1 ] Initial SWE - Reanalysis

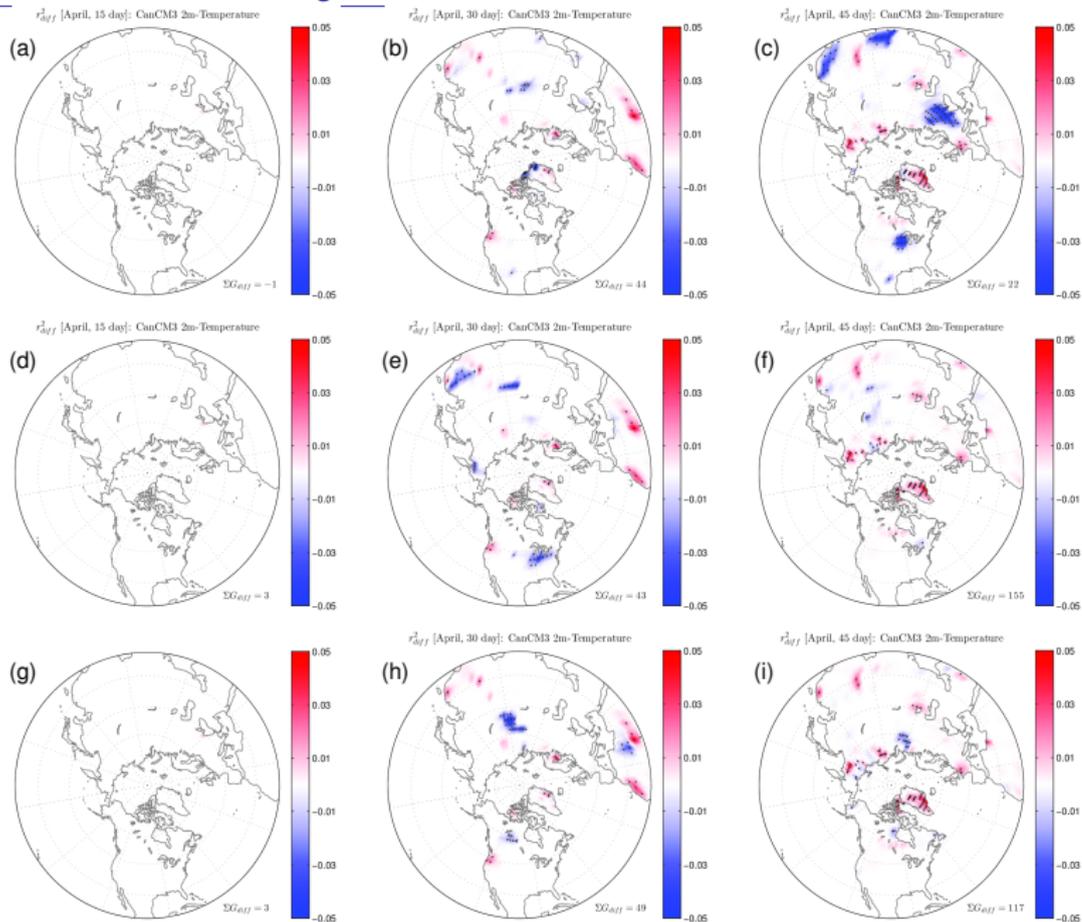


(b)

RMSE: CanCM3 [ April 1 ] Initial SWE vs Reanalysis

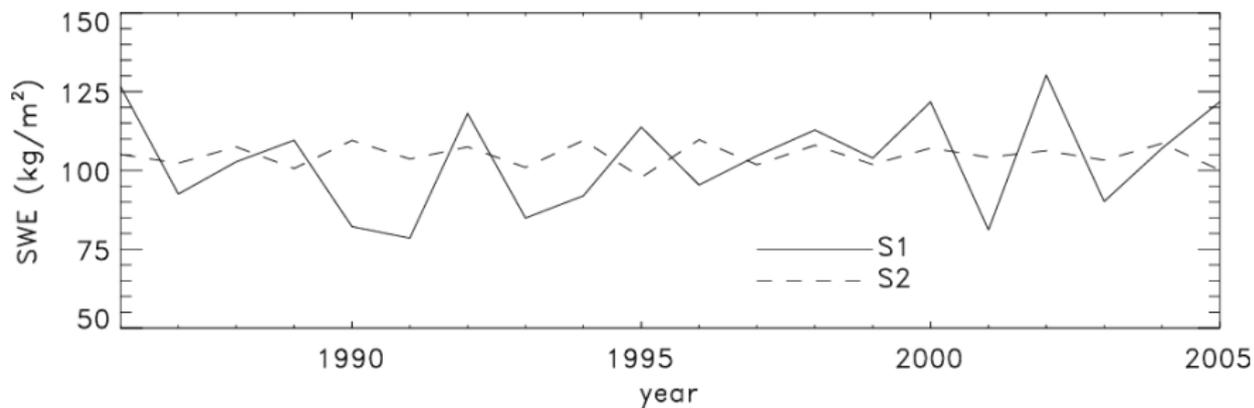


# $r_{diff}^2$ : contributions from negative correlations

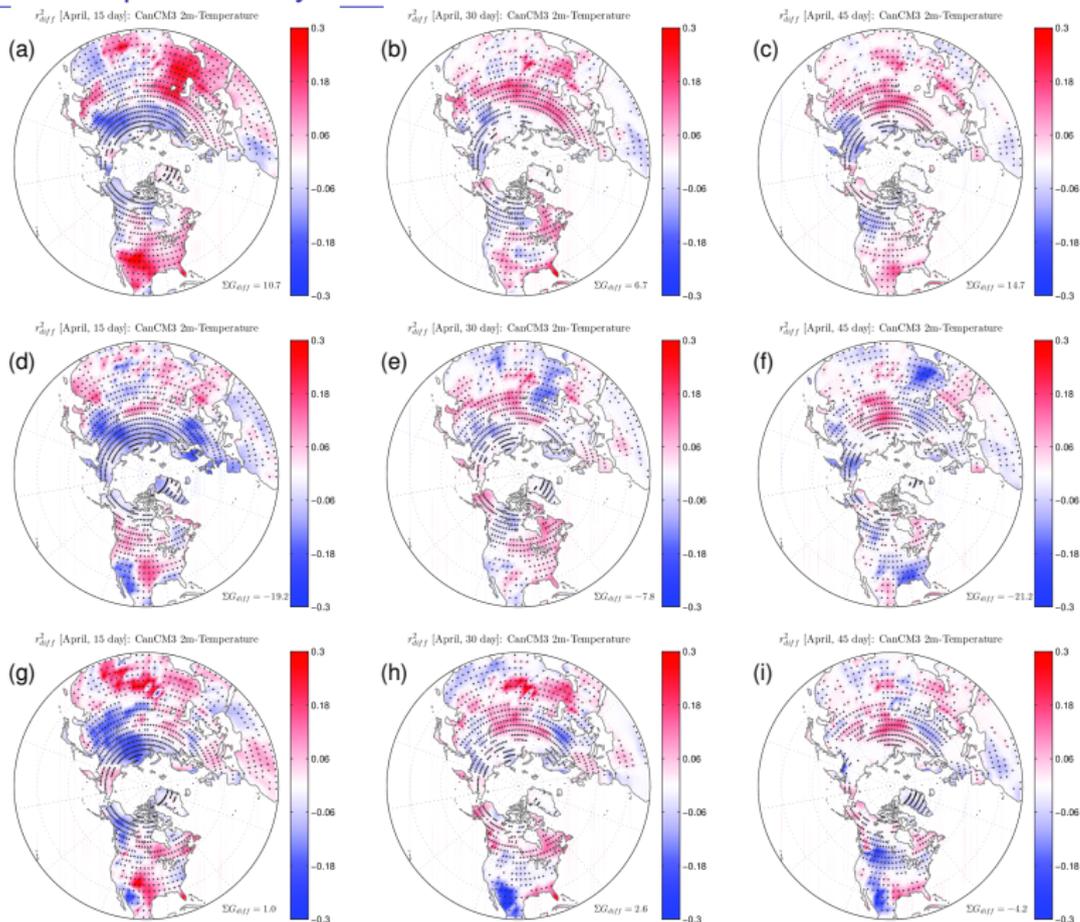


## Time series of ensemble mean initial SWE

Time series of ensemble mean initial SWE for a grid cell near  $120^{\circ}E$ ,  $60^{\circ}N$  for series S1, and S2.

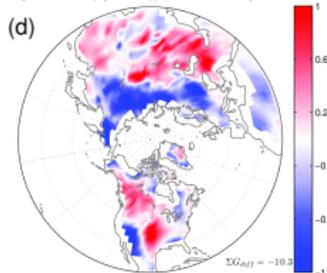


# $r_{diff}^2$ potential predictability for S1-S2

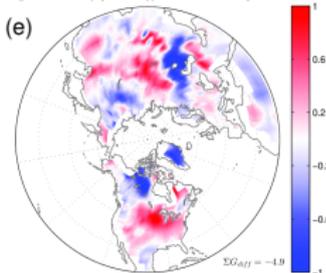


# SNR difference statistics based on S1-S10

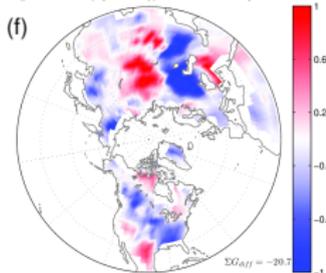
Signal difference (April 15 day): CanCM3 2m-Temperature



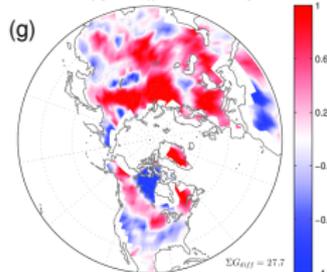
Signal difference (April 30 day): CanCM3 2m-Temperature



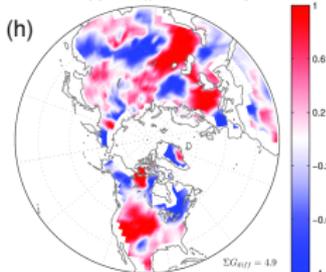
Signal difference (April 45 day): CanCM3 2m-Temperature



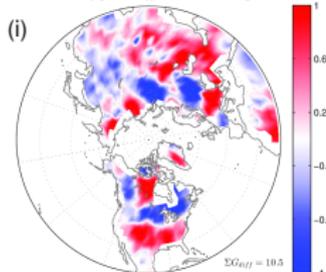
Noise difference (April 15 day): CanCM3 2m-Temperature



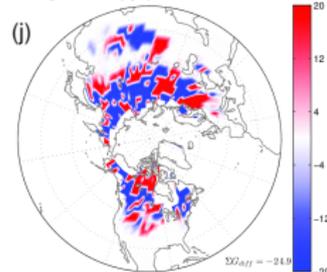
Noise difference (April 30 day): CanCM3 2m-Temperature



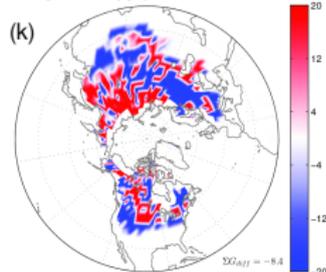
Noise difference (April 45 day): CanCM3 2m-Temperature



Signal difference (April): CanCM3 initial SWE



Signal difference (April): CanCM3 initial WGF



Signal difference (April): CanCM3 initial WGL

