Potential and actual predictability of snow in the Canadian Seasonal to Interannual Prediction System (CanSIPS)

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Aim of the talk

- Discuss sources and behaviour of snow predictability in CanSIPS
- Show that CanSIPS is skilful at predicting snow
- Show that (and specifically where) there is room for improvements

Snow Water Equivalent (SWE)

SWE = Depth of water that would result if the mass of snow melted completely

The snow in the rain gauge is melted to determine the liquid water equivalent.

Why is SWE important?

- SWE tells how much **water** is **"sitting on the ground" in frozen form**.
- SWE is **essential to river and flood forecasting** as it can be factored in with expected precipitation **to determine how much runoff might go into rivers and stream**.
- SWE is **useful for climate prediction** as **it contains regional information about previous climate anomalies** (e.g., temperature and precipitation)
- SWE **influences future climate on sub-seasonal to seasonal time scales**.

The Canadian Seasonal to Interannual Prediction System

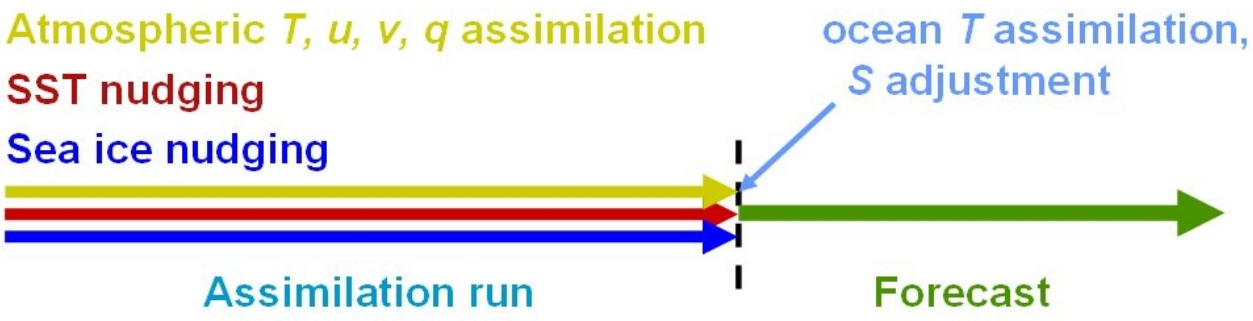
- Operational at CMC since Dec 2011
- Based on two GCMs: CanCM3 and CanCM4

  - **different** Atmosphere
  - **same** Ocean, Land and Sea Ice

- Each model has 10 ensemble members
- Hindcast period: 1981-2010
- Forecast initialized at the start of every month
- Forecast range: 12 months

Merryfield et al., *Mon. Wea. Rev.* (2013)

CanSIPS Initialization: assimilation + ensemble generation



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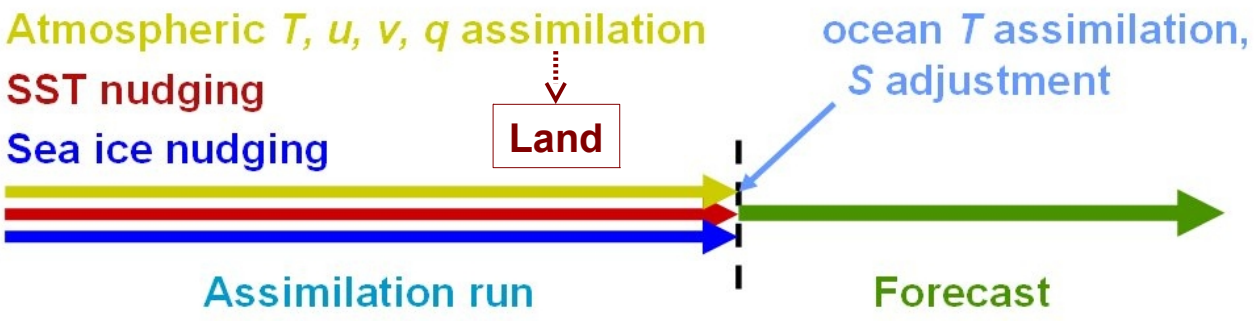
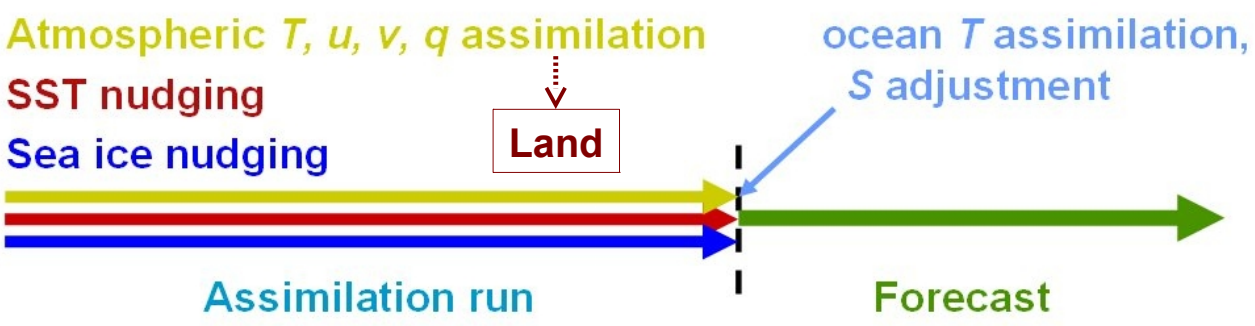


Initialization of land variables

Land variables are initialized from the response of the land component to forcing from atmospheric fields constrained by 6-hourly reanalysis

CanSIPS Initialization: assimilation + ensemble generation



Initial Conditions of Snow Forecast in CanSIPS

- **Agreement** with *in situ* observations comparable to MERRA, GlobSnow and bias-corrected CLASS
- SWE **inter-annual anomaly correlation coefficient** against MERRA is **generally high** (> 0.6)
- SWE and SCE **biased high** relative to MERRA
- **Lower melt and sublimation rates** than MERRA during snow accumulation **despite of higher temperature over snow**

Sospedra-Alfonso et al., *J. Hydrometeorol.* (2015)

Measures of potential and actual skill

Potential skill

- Potential predictability (PP)
- Autocorrelation of forecast anomalies (AC)

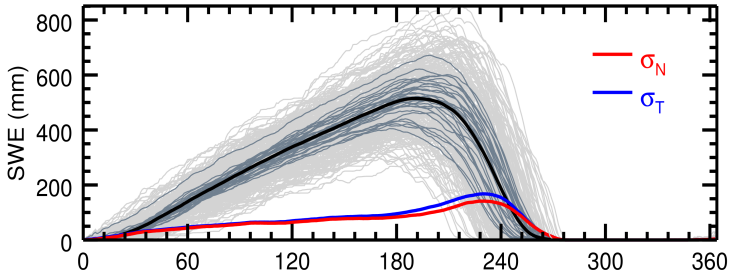
Actual skill

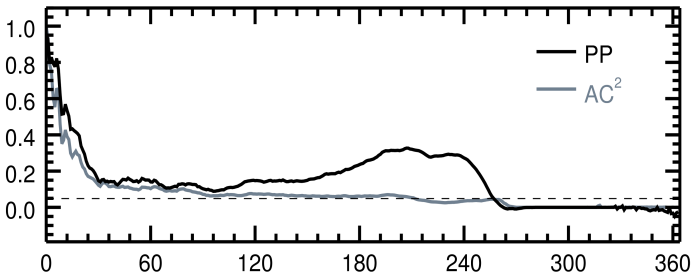
- Anomaly correlation coefficient (ACC)
- Mean Square Skill Score (MSSS)

CanCM4 SWE Hindcasts (1981-2010) for Mission Ridge
10 ensemble members

Initialization at the start of the the month

OCT





Potential Predictability (PP)

$$\sigma_T^2(t) = \frac{Y-1}{YE-1} E\sigma_S^2(t) + \frac{Y(E-1)}{YE-1}\sigma_N^2(t),$$

σ_T^2 = total variance

σ_S^2 = variance **of** the ensemble means

σ_N^2 = variance **about** the ensemble means

t = lead time in days [0,364]

E = number of ensemble members (10)

Y = number of years in hindcast period (30)

$$PP(t) = 1 - \frac{\sigma_N^2(t)}{\sigma_T^2(t)}$$

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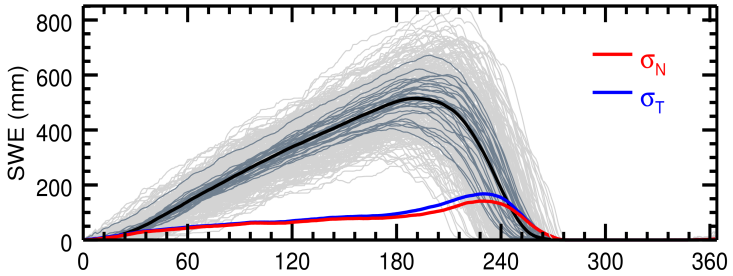
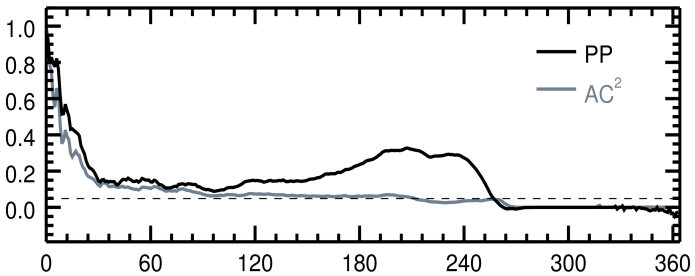
Initialization at the start of the the month

OCT





Autocorrelation (AC) of forecast anomalies

$$AC(t) = \mathbb{EE}\left[\frac{X(0)-\mu(0)}{\sigma(0)} \cdot \frac{X(t)-\mu(t)}{\sigma(t)}\right]$$

X	=	forecast time series
μ	=	forecast climatological mean
σ	=	standard deviation of the forecast time series
$\mathbb{EE}[\cdot]$	=	average over all years and ensemble members
t	=	lead time in days [0, 364]

CanCM4 SWE Hindcasts (1981-2010) for Mission Ridge
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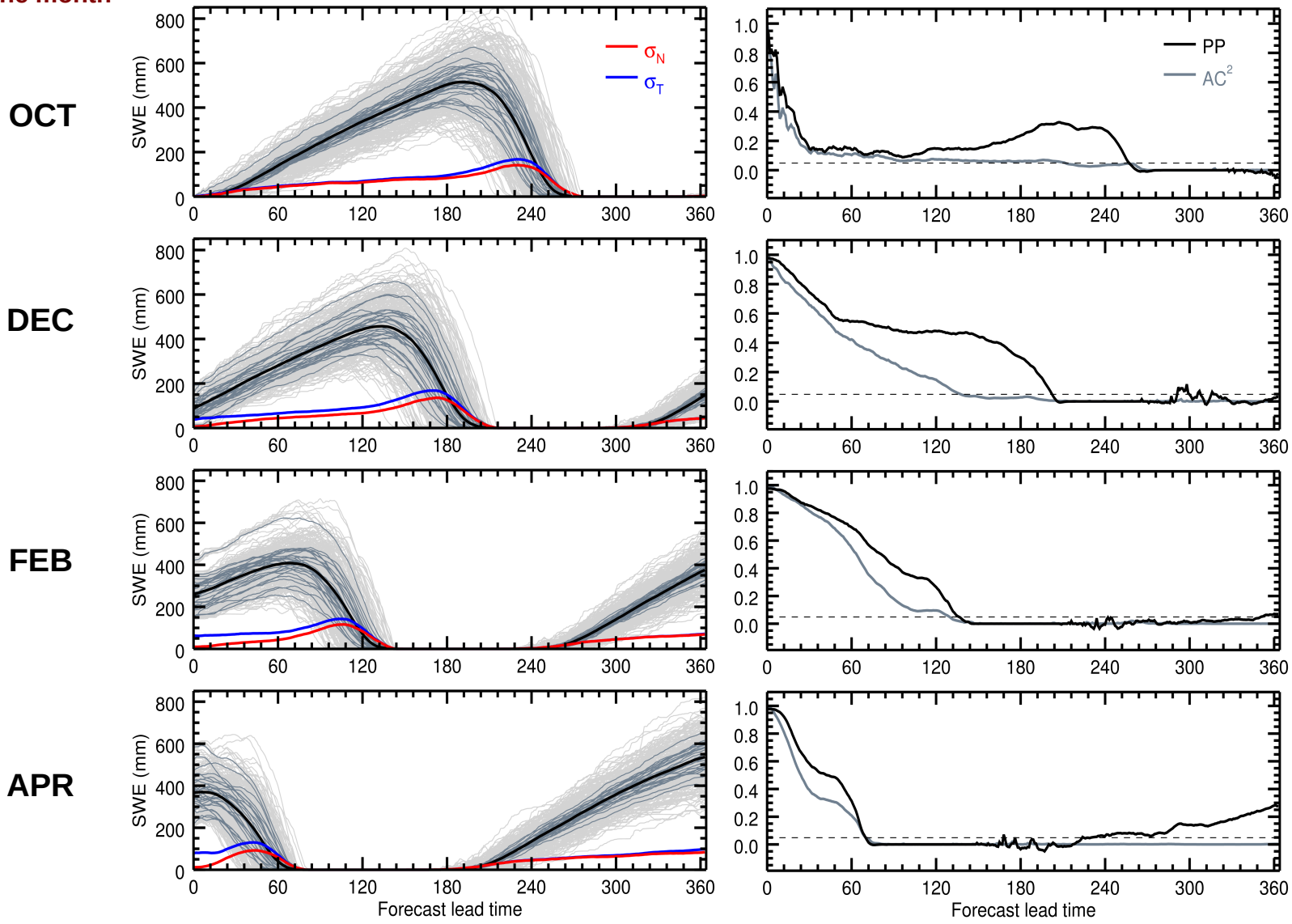
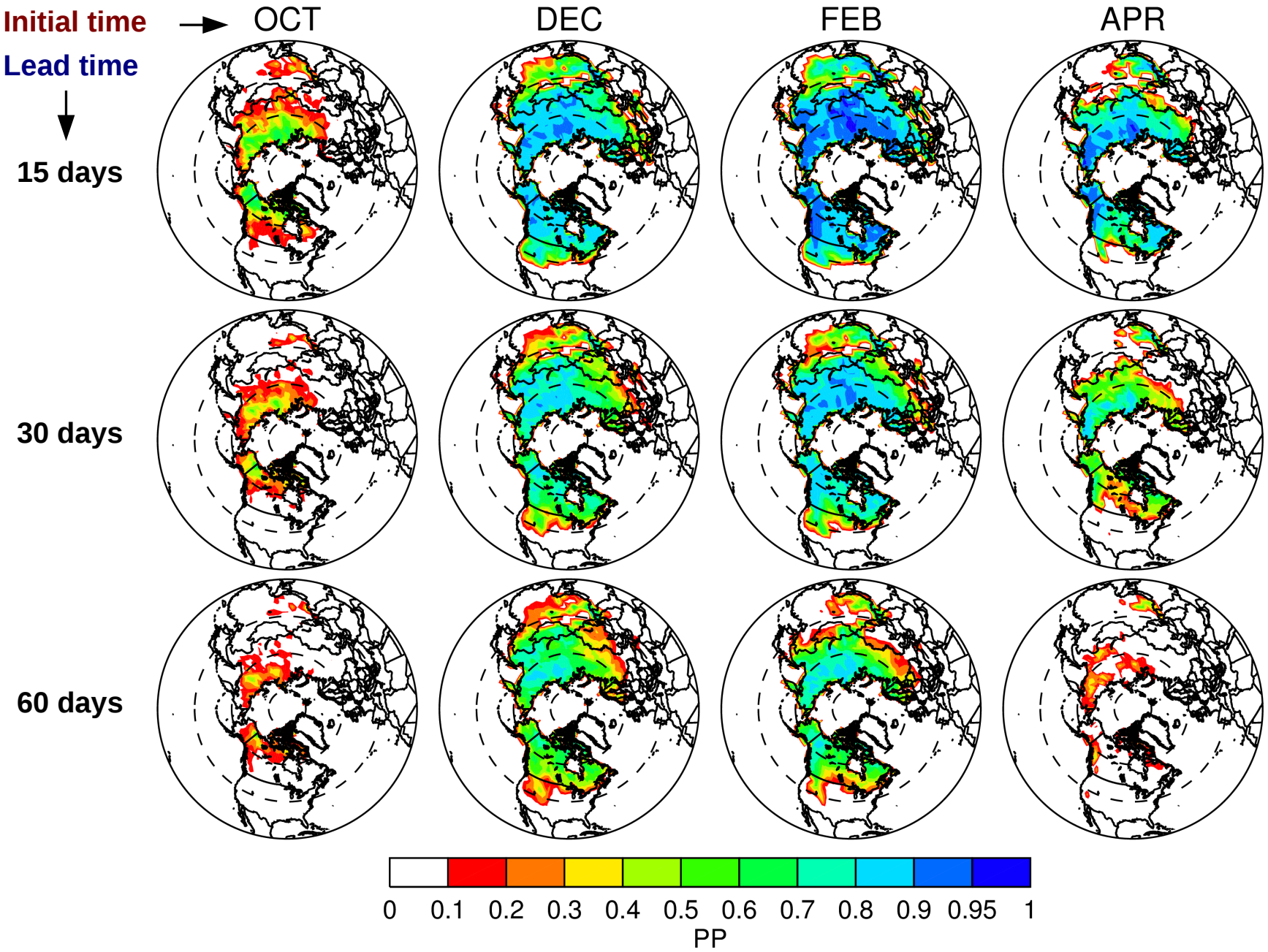
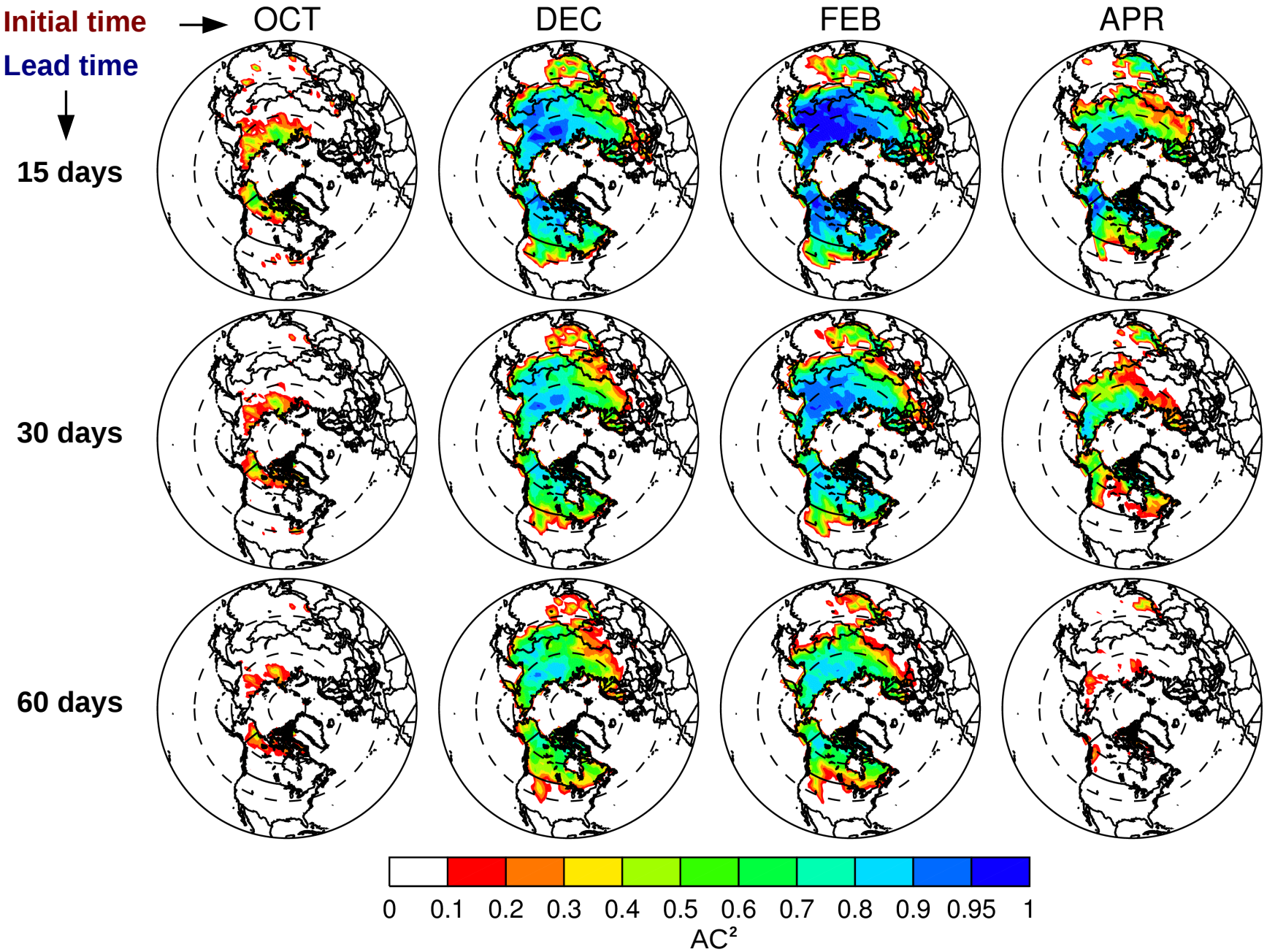
Initialization at the start of the the month




Initial time
Lead time
OCT
DEC
FEB
APR
15 days
30 days
60 days
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
0.95
1
PP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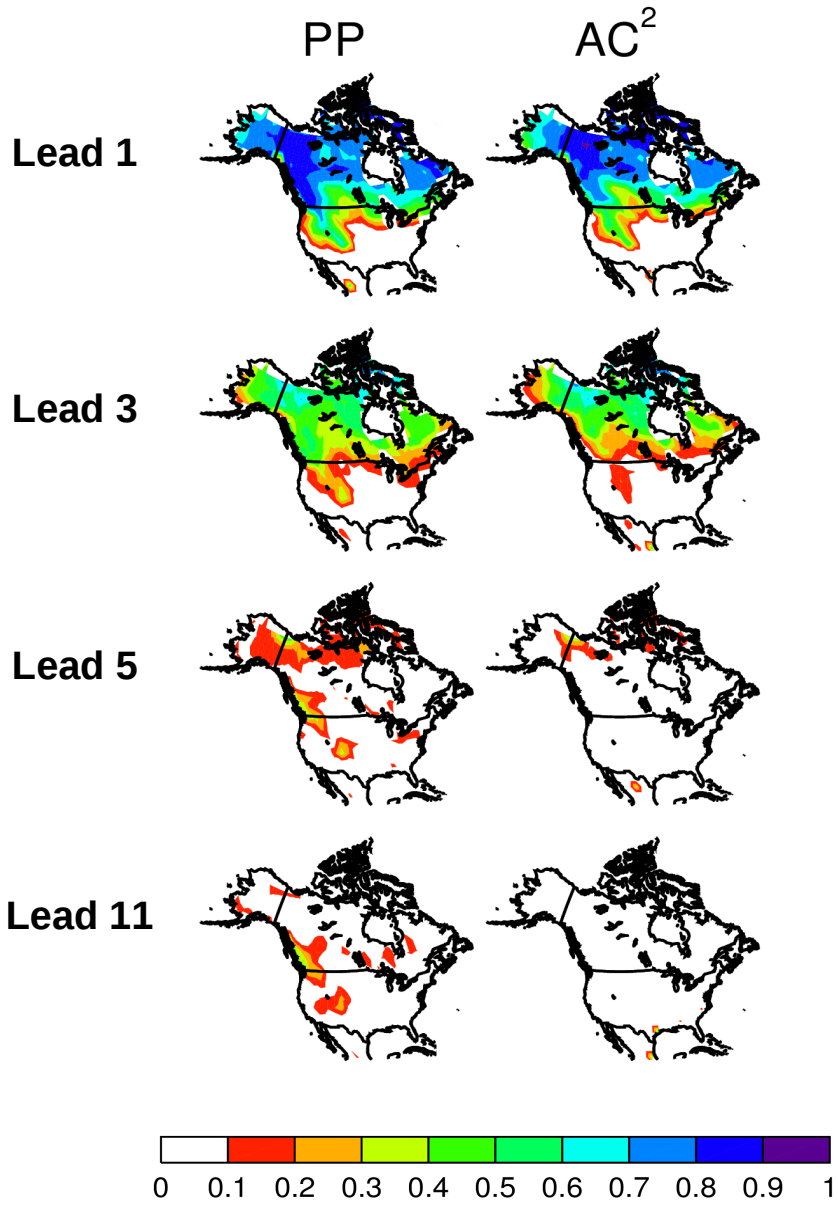
0.5
0.6
0.7
0.8
0.9
0.95
1
AC²

Sources of PP in CanCM4 March SWE



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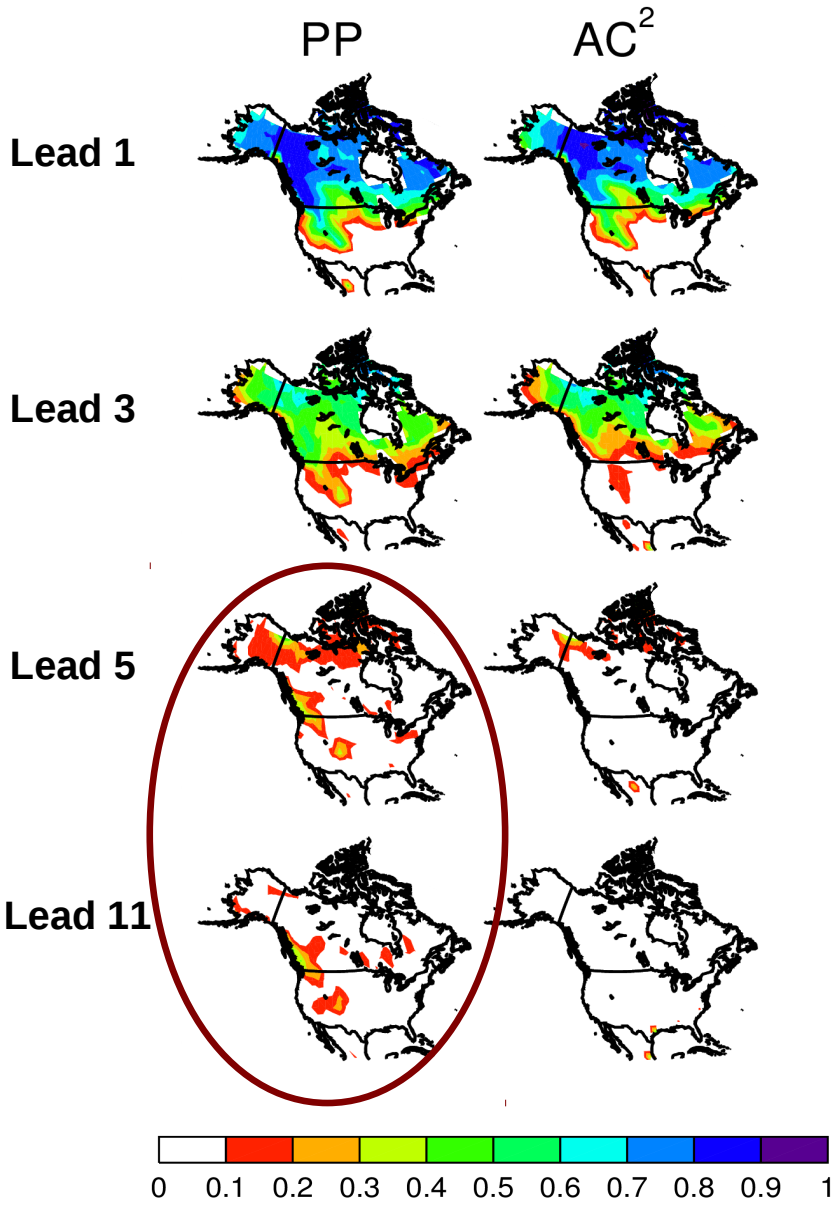
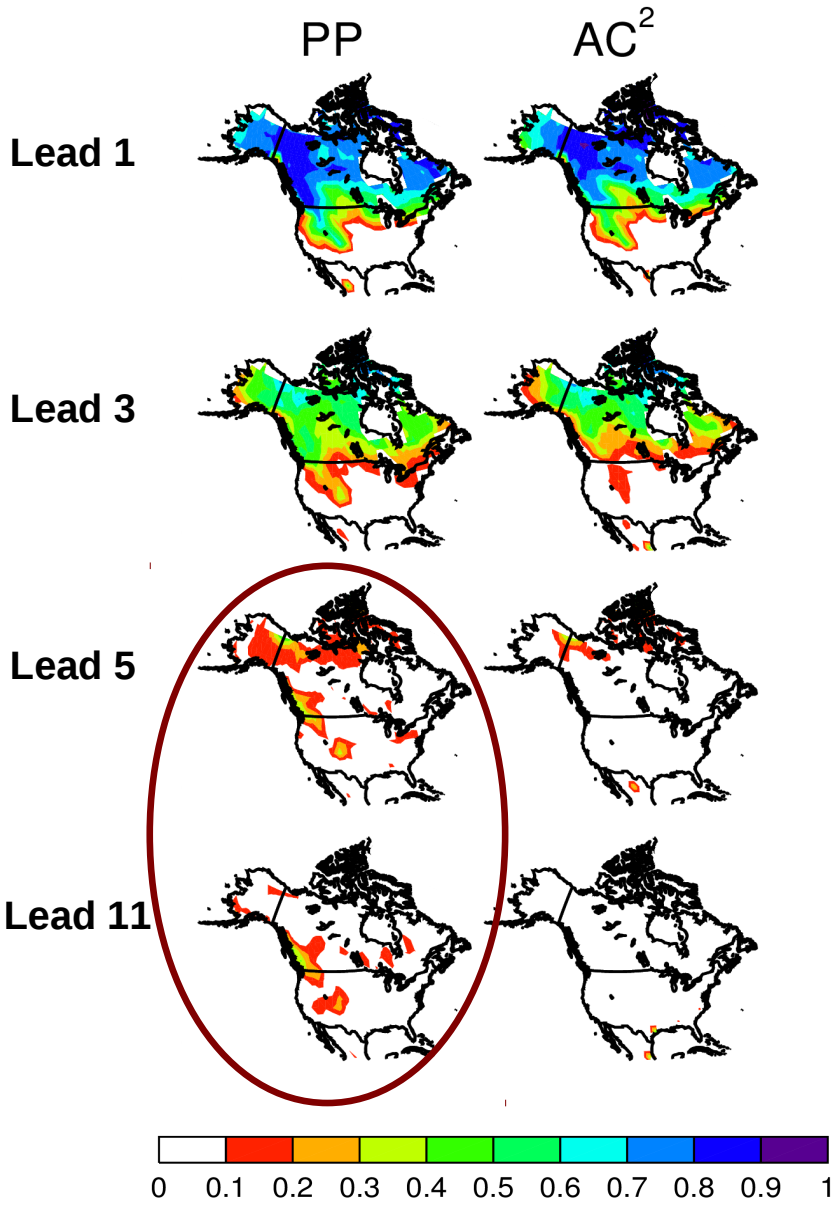
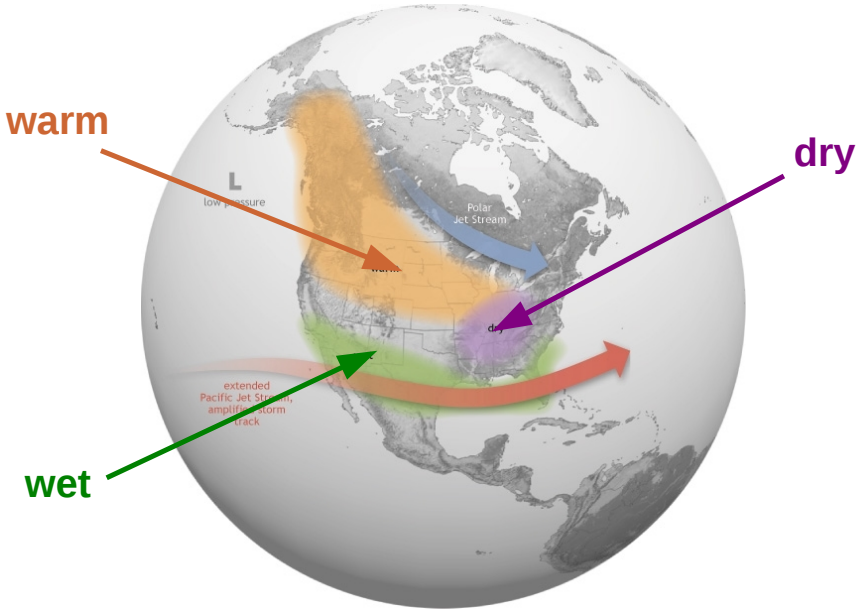


Sources of PP in CanCM4 March SWE

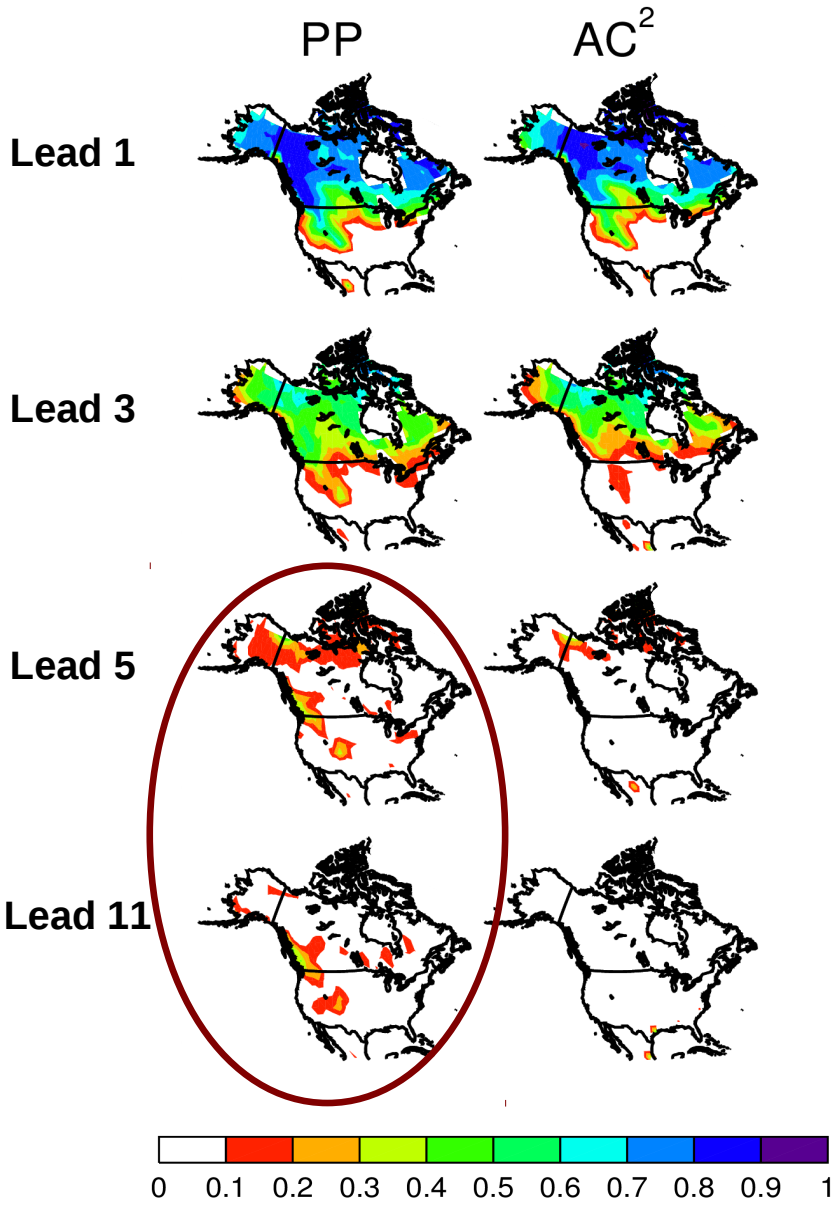


Wintertime El Niño pattern

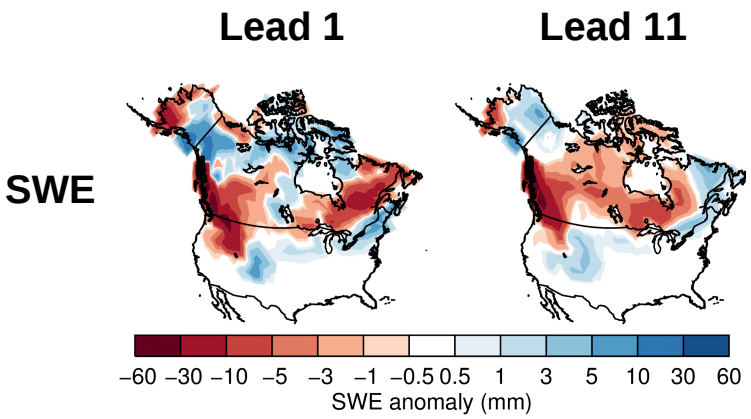


NOAA Climate.gov

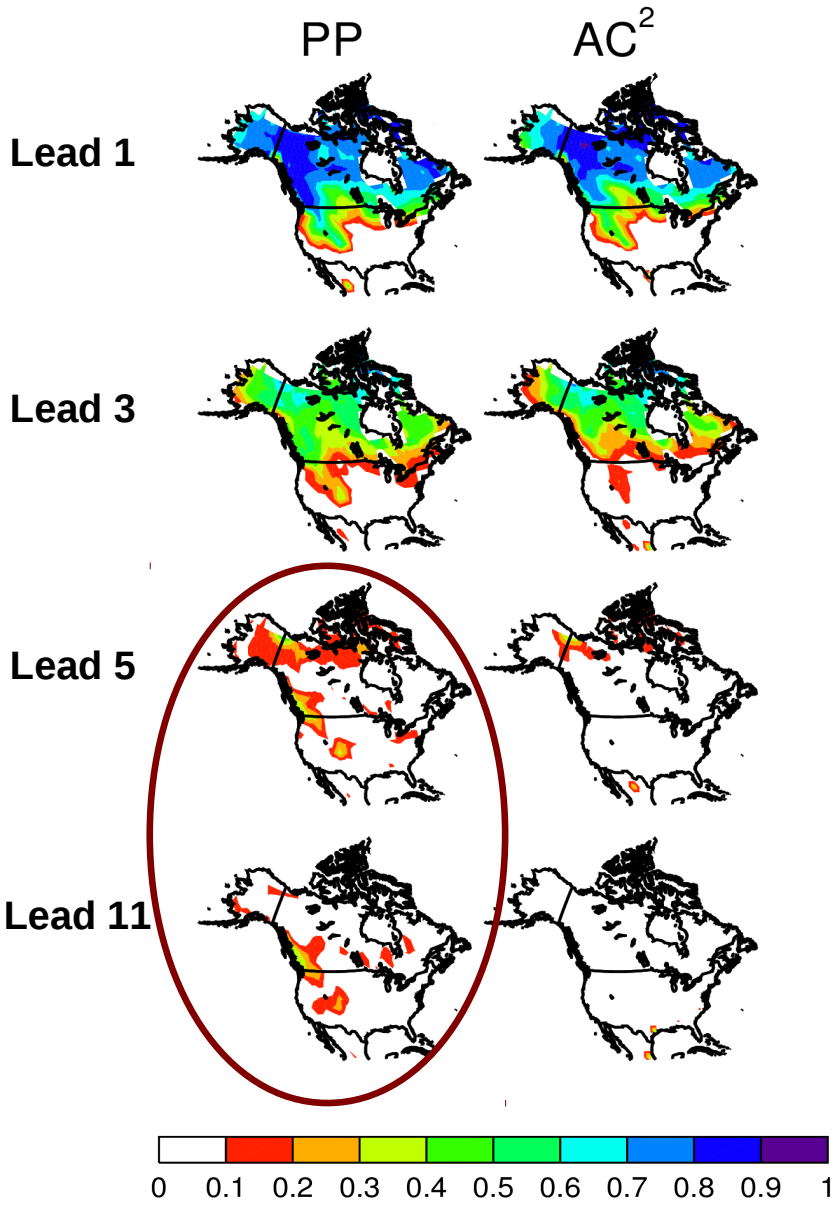
Sources of PP in CanCM4 March SWE



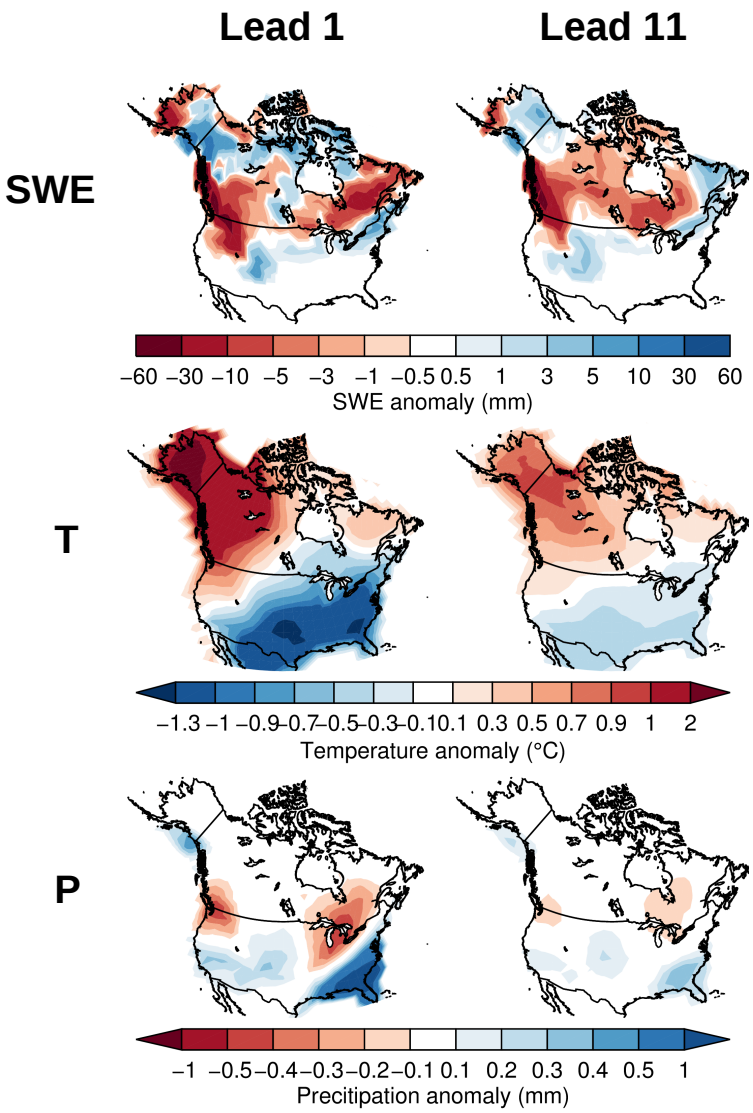
Niño 3.4 index vs SWE



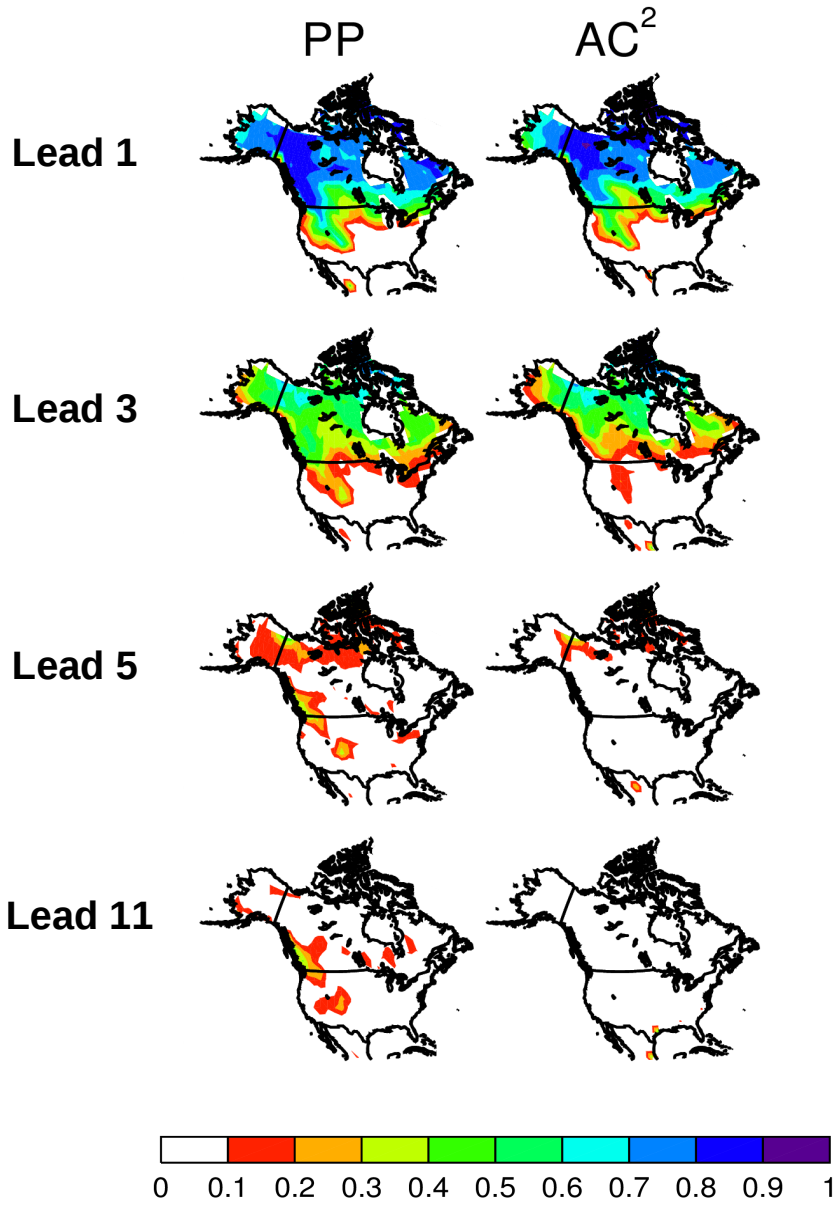
Sources of PP in CanCM4 March SWE



Niño 3.4 index vs SWE or T or P

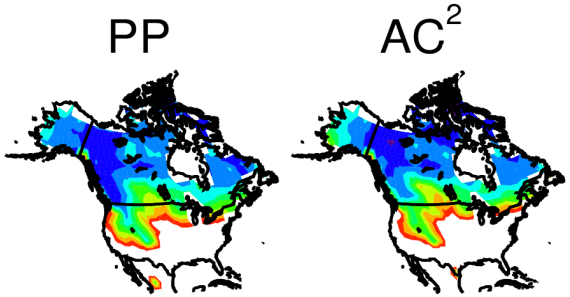


Sources of PP in CanCM4 March SWE



What about actual skill?

Potential and Actual Skill of CanCM4 SWE Forecasts for March



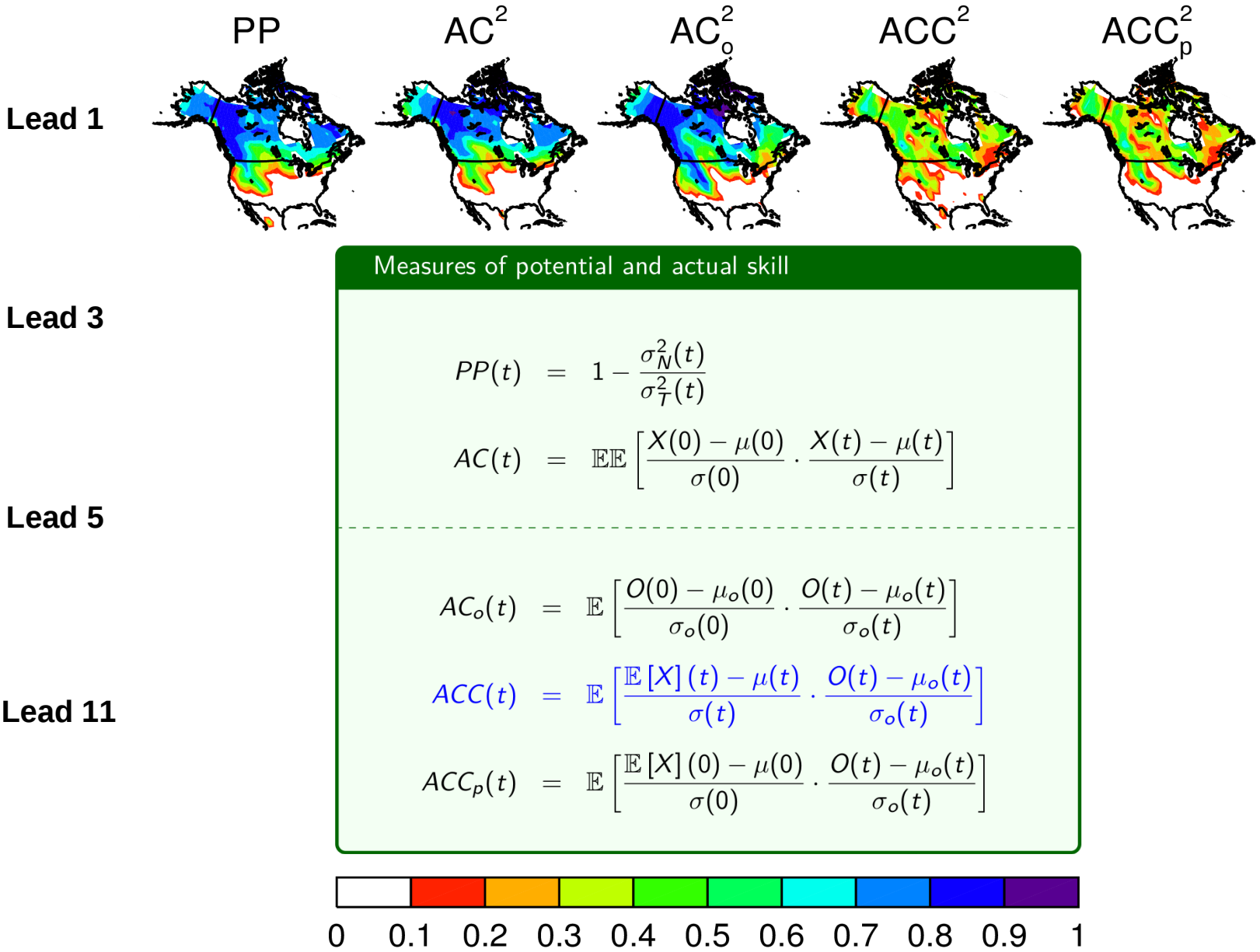
Data products employed as verifying observations

1. MERRA (NASA)
2. ERA-Interim-Land (ECMWF)
3. GlobSnow (ESA)
4. GLDAS-2 (NASA-NCEP)
5. Crocus driven by ERA-Interim (Meteo-France)

OBS = **blended SWE dataset from products 1-5**

Mudryk et al., *J. Climate* (2015)

Potential and Actual Skill of CanCM4 SWE Forecasts for March



Measures of potential and actual skill

$$PP(t) = 1 - \frac{\sigma_N^2(t)}{\sigma_T^2(t)}$$

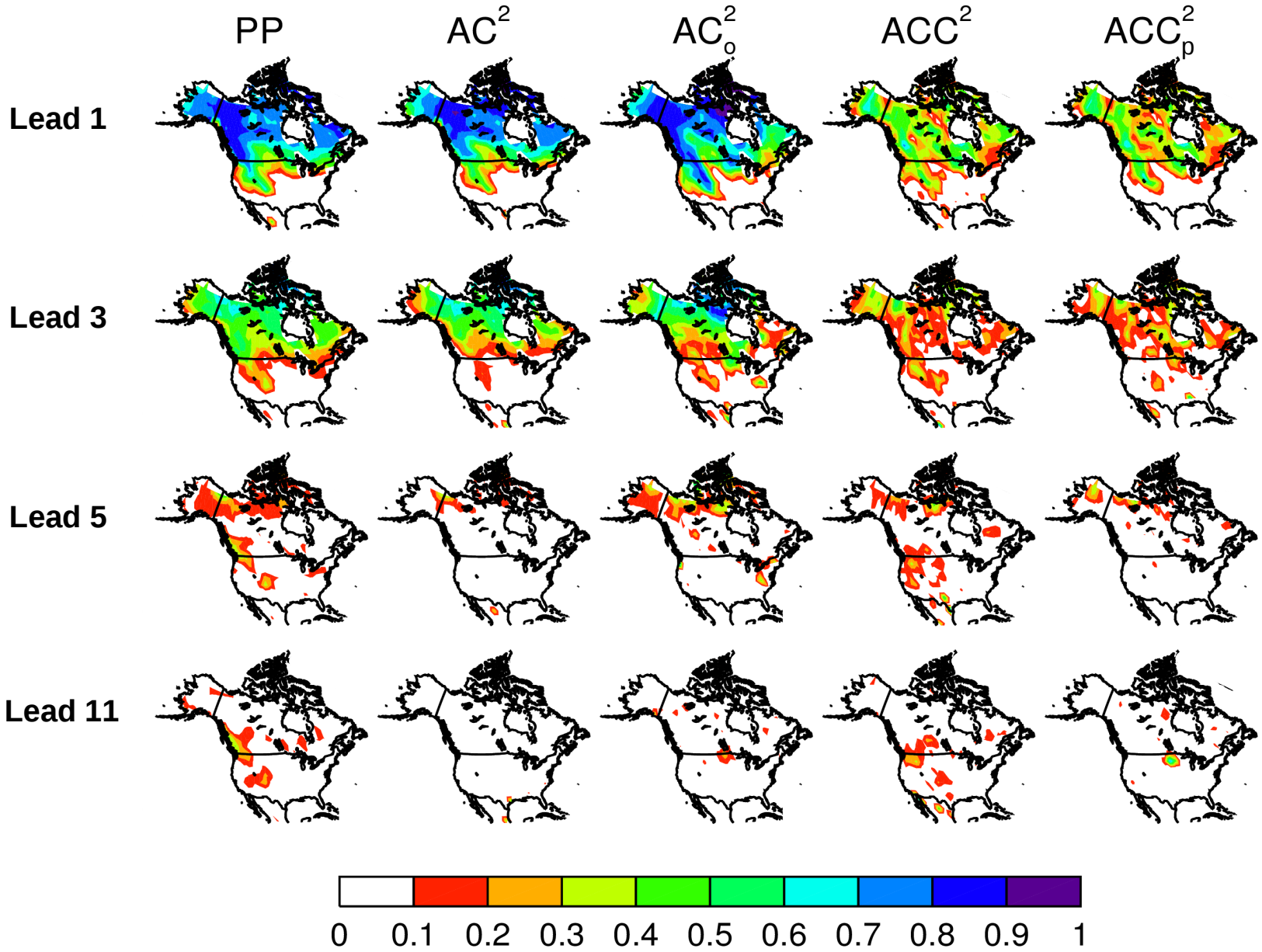
$$AC(t) = \mathbb{E}\mathbb{E}\left[\frac{X(0)-\mu(0)}{\sigma(0)} \cdot \frac{X(t)-\mu(t)}{\sigma(t)}\right]$$

$$AC_o(t) = \mathbb{E}\left[\frac{O(0)-\mu_o(0)}{\sigma_o(0)} \cdot \frac{O(t)-\mu_o(t)}{\sigma_o(t)}\right]$$

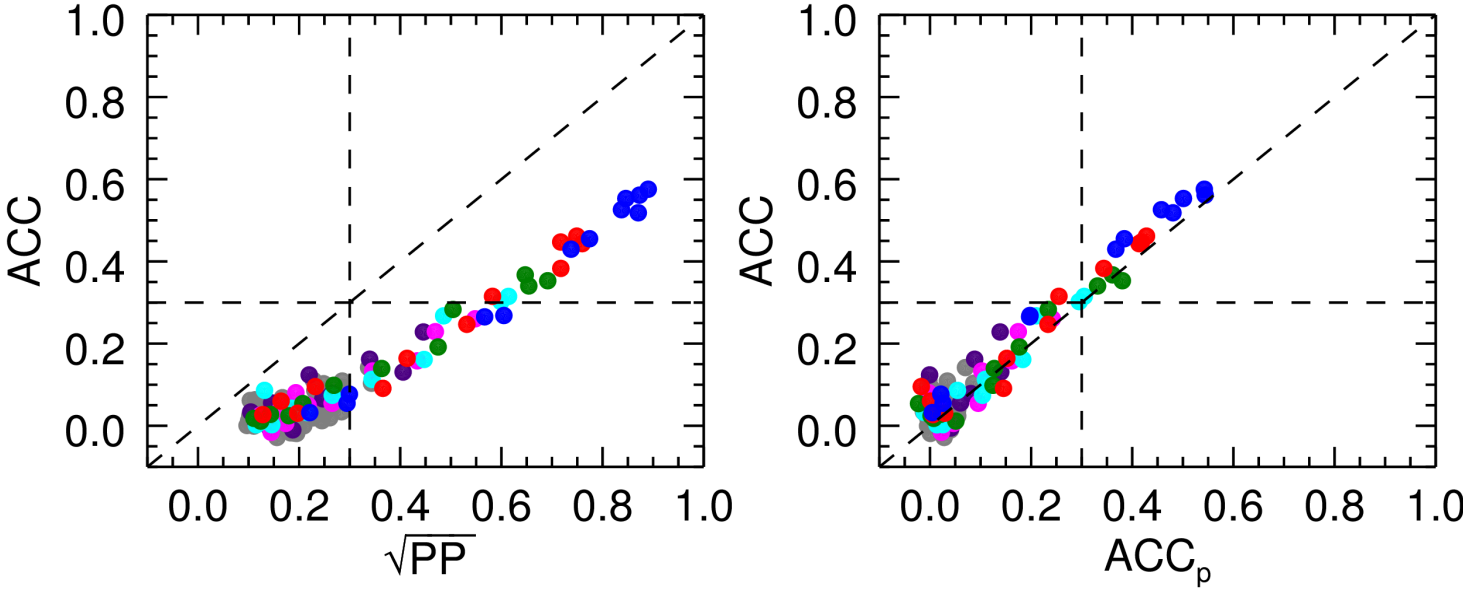
$$ACC(t) = \mathbb{E}\left[\frac{\mathbb{E}[X](t)-\mu(t)}{\sigma(t)} \cdot \frac{O(t)-\mu_o(t)}{\sigma_o(t)}\right]$$

$$ACC_p(t) = \mathbb{E}\left[\frac{\mathbb{E}[X](0)-\mu(0)}{\sigma(0)} \cdot \frac{O(t)-\mu_o(t)}{\sigma_o(t)}\right]$$

Potential and Actual Skill of CanCM4 SWE Forecasts for March

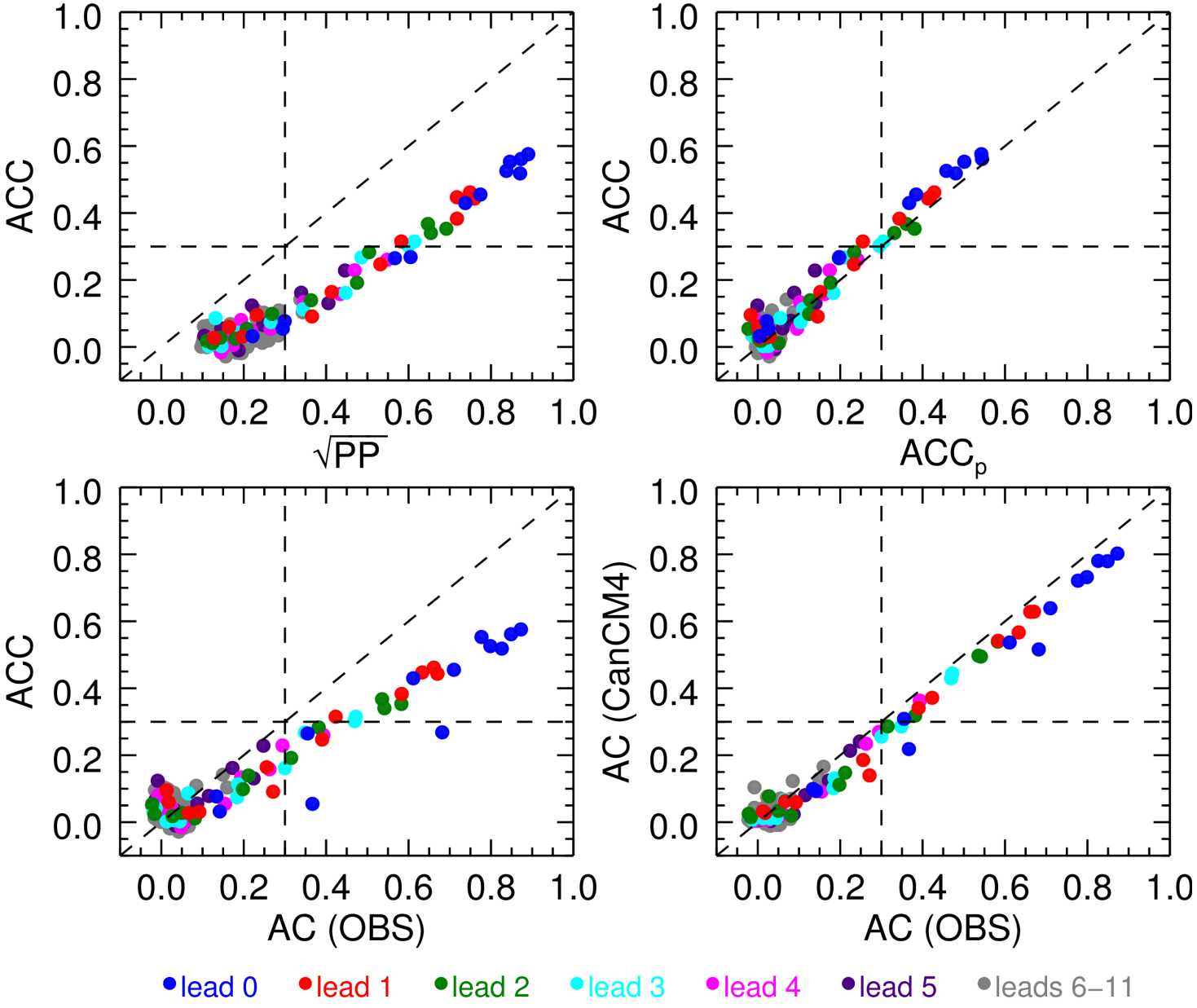


Relationships for area mean skills over North America

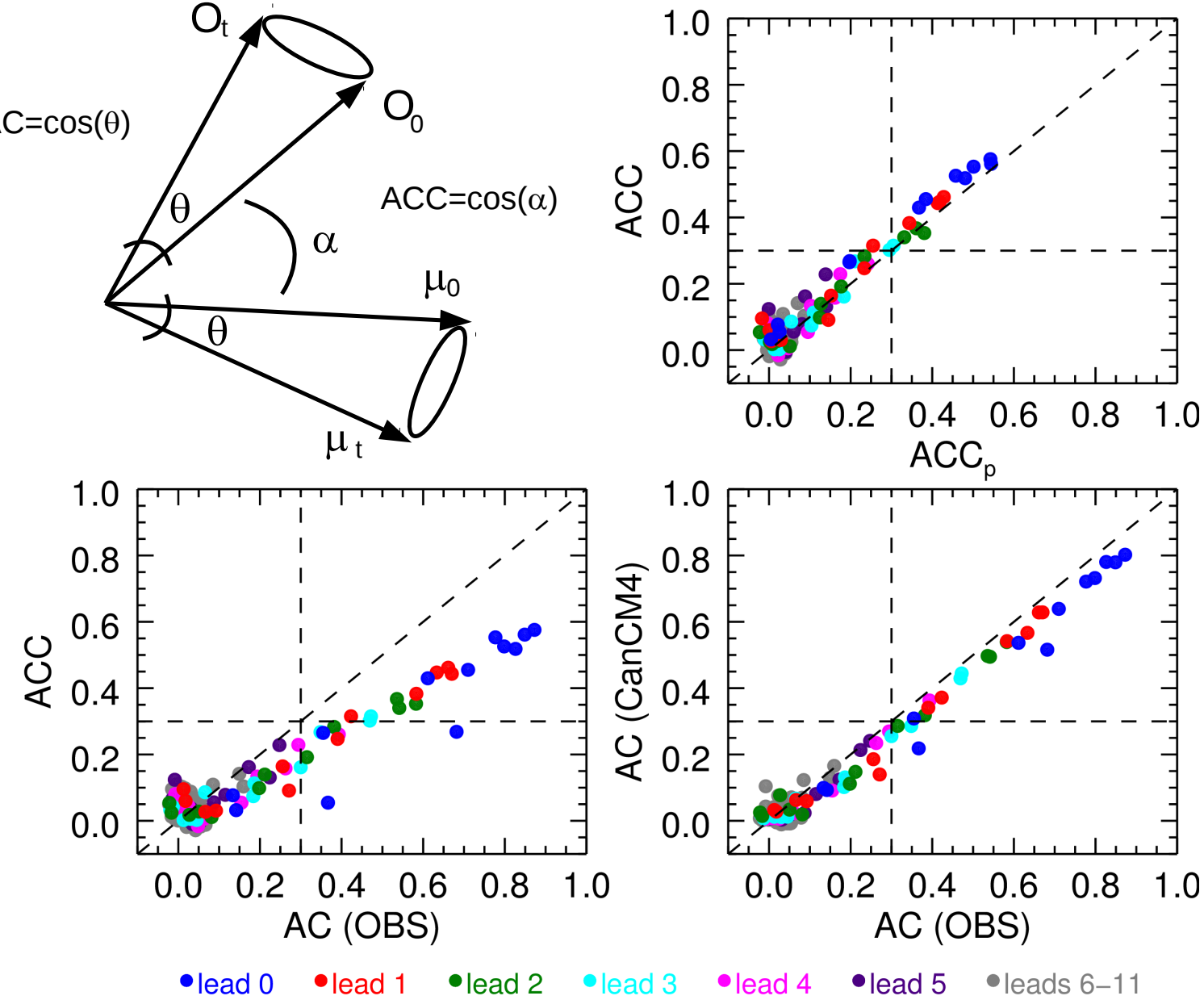


lead 0 lead 1 lead 2 lead 3 lead 4 lead 5 leads 6–11

Relationships for area mean skills over North America



Effects of SWE initialization on actual skill over North America



Conclusions

- **CanSIPS is skilful at forecasting SWE** with actual skill appreciable compared to potential skill. Skills are generally higher in the regions with higher initial S/N variance ratio (typically mature snowpacks).

- **Values and duration of PP depend on the timing of forecast initialization**, e.g., inter-annual variability explains over 50 % of total variance for:
  - ∼1-4 weeks if forecast initialized in OCT
  - ∼1-4 months if forecast initialized in DEC

- **Persistence of initial SWE anomalies explains most of PP during the first weeks/months of the forecast**, e.g., ∼1-3 months for March SWE forecast over NA

Conclusions

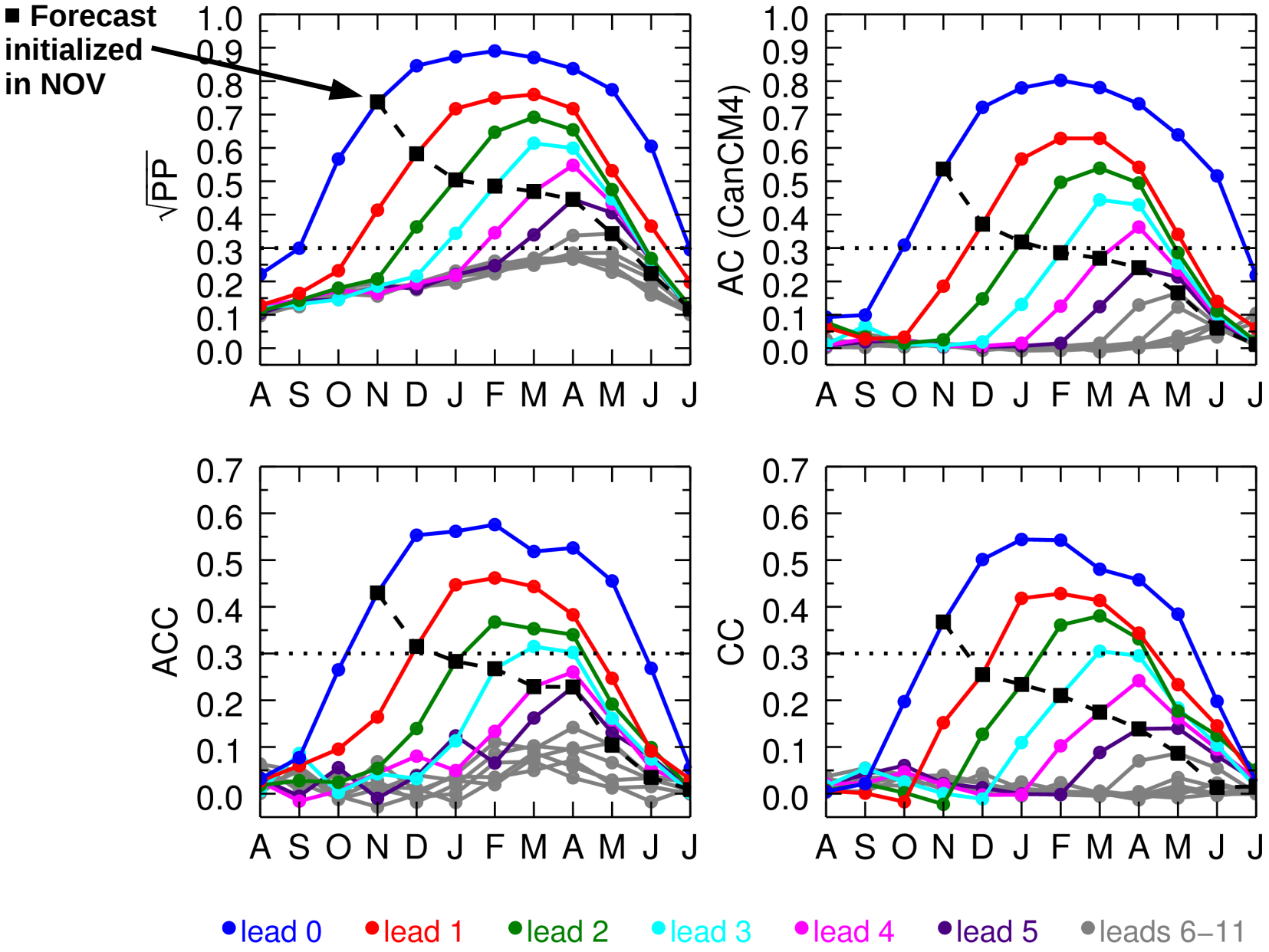
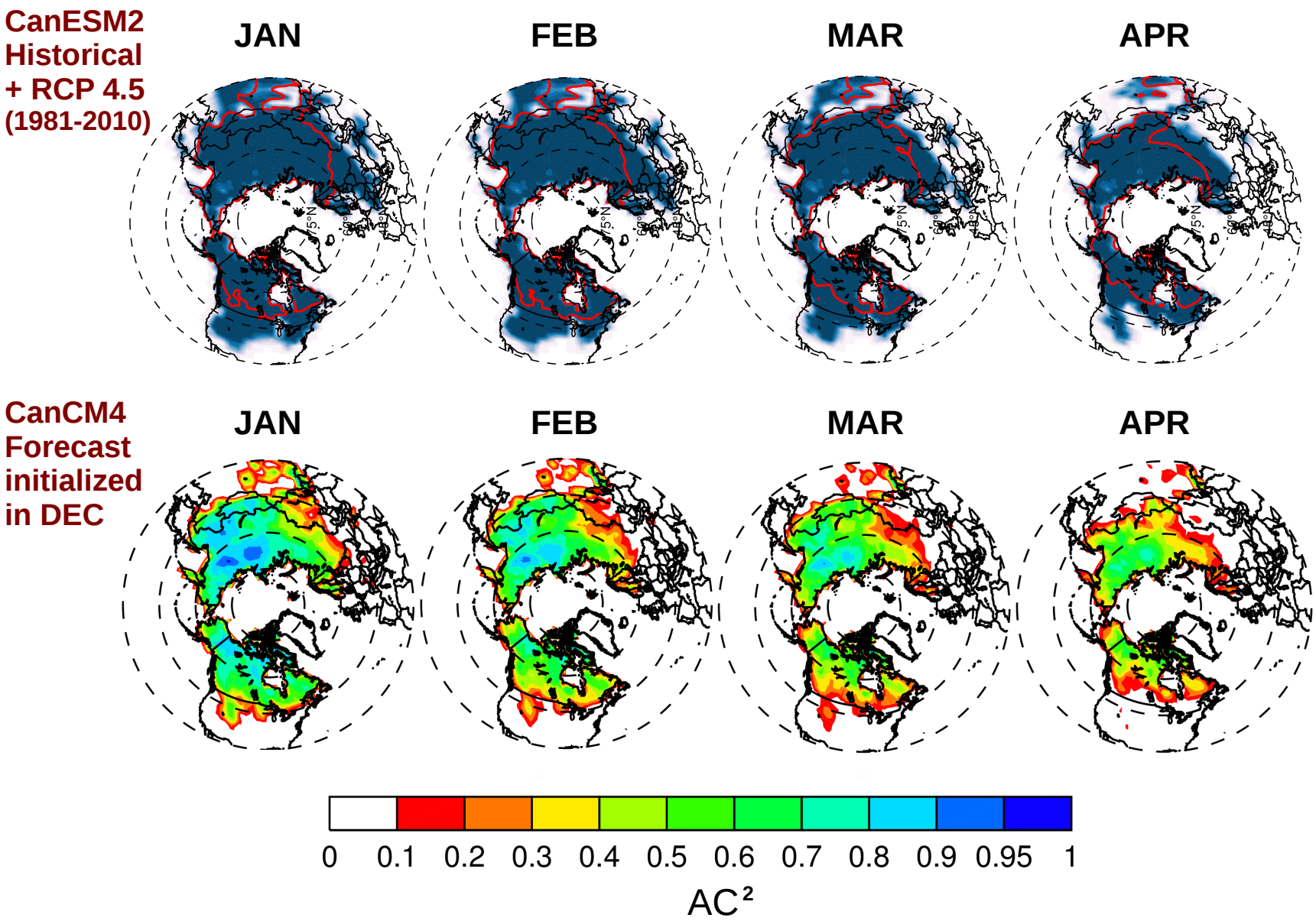
- There are regions, e.g., North-western NA, where **PP is significant across snow seasons** linked to CanSIPS skill in predicting other climate variables (e.g., T and P) with **ENSO teleconnections likely playing a large role**

- **Actual skills are very sensitive to which verifying observation product is used** and are generally highest for a blend of five products developed by Mudryk et al. (2015)

- **Current SWE initialization is reasonably good**, largely contributing to actual skills specially at short range. **Improved SWE initializations** (e.g., initialized directly from an accurate analysis) **would largely improve actual skill**.

Appendix

Area mean skill over North America vs month and lead time



Persistence of initial SWE anomalies is higher for P-driven snowpack