Estimating seasonal streamflow forecast elasticities using a variational ensemble streamflow predictability assessment (VESPA)

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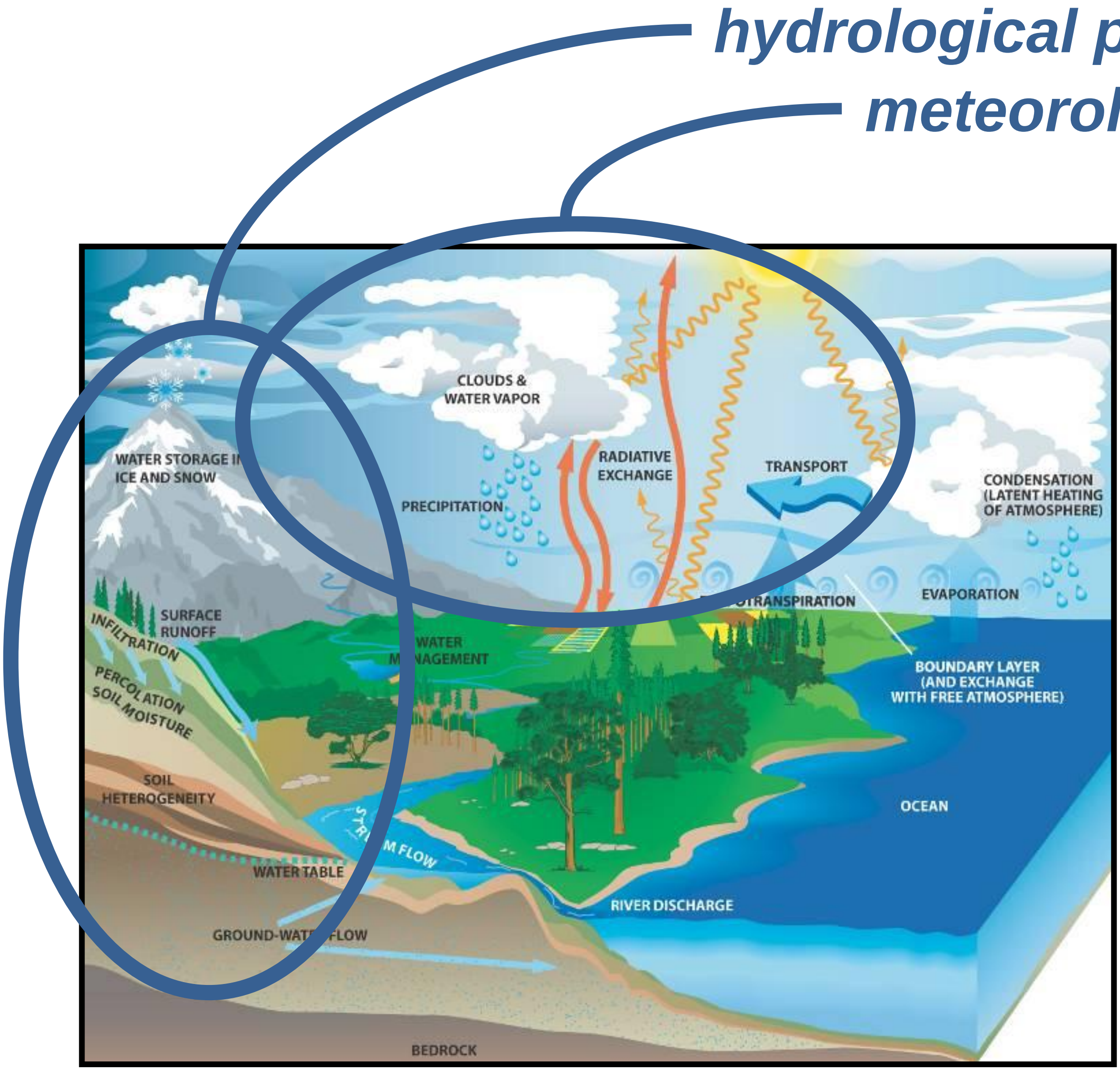
Sources of Streamflow Predictability

hydrological predictability

meteorological predictability



Water Cycle (from NASA)

<u>Hydrological Prediction</u>: How well can we estimate catchment dynamics?

- Accuracy in precipitation and temperature estimates
- Fidelity of hydrology models – process/structure
- Effectiveness of hydrologic data assimilation methods

<u>Atmospheric predictability</u>:

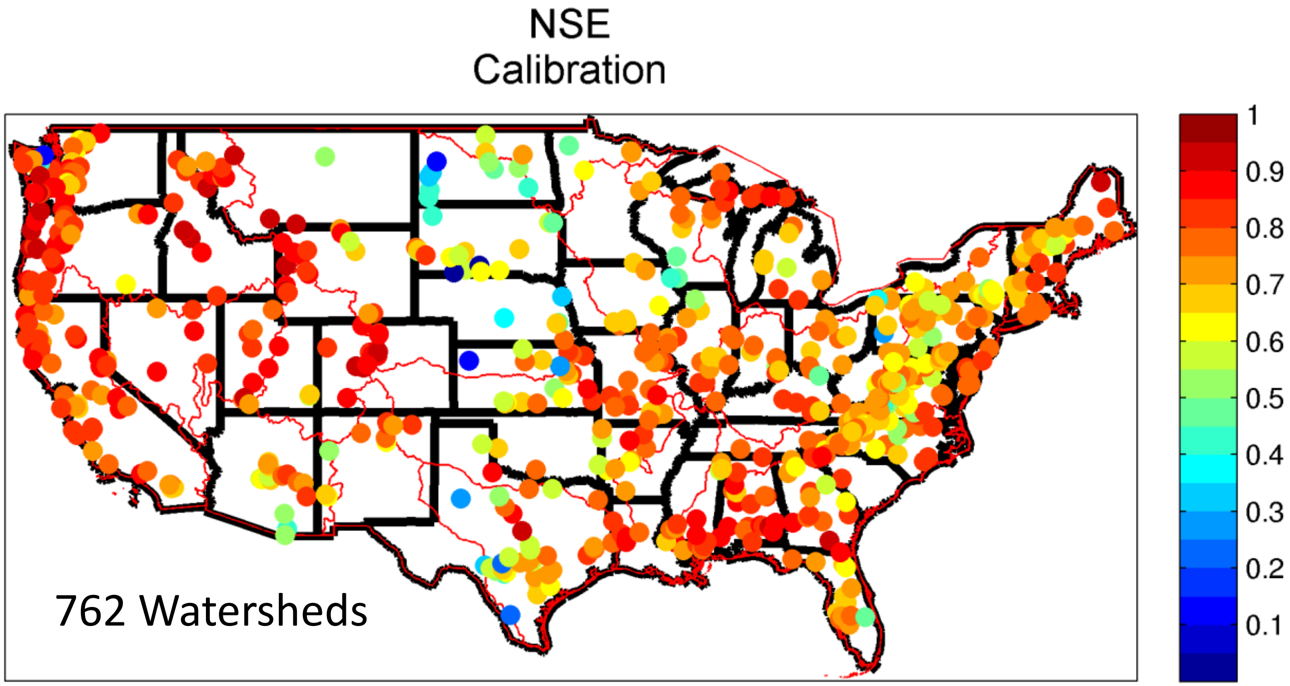
How well can we forecast the weather and climate?

<u>Opportunities</u>: How do these areas influence forecast skill inform different water applications?

Watershed Modeling Dataset

NCAR
RAL/HAP

- Goal: framework for calibrating and running watershed models CONUS-wide
- Basin Selection
  - Used GAGES-II, Hydro-climatic data network (HCDN)-2009
- Initial Data & Models, Calibration Approach
  - Forcing via Daymet (http://daymet.ornl.gov/)
  - NWS operational Snow-17 and Sacramento-soil moisture accounting model (Snow-17/SAC)
  - Shuffled complex evolution (SCE) global optimization routine
  - See http://www.ral.ucar.edu/staff/wood/watersheds/

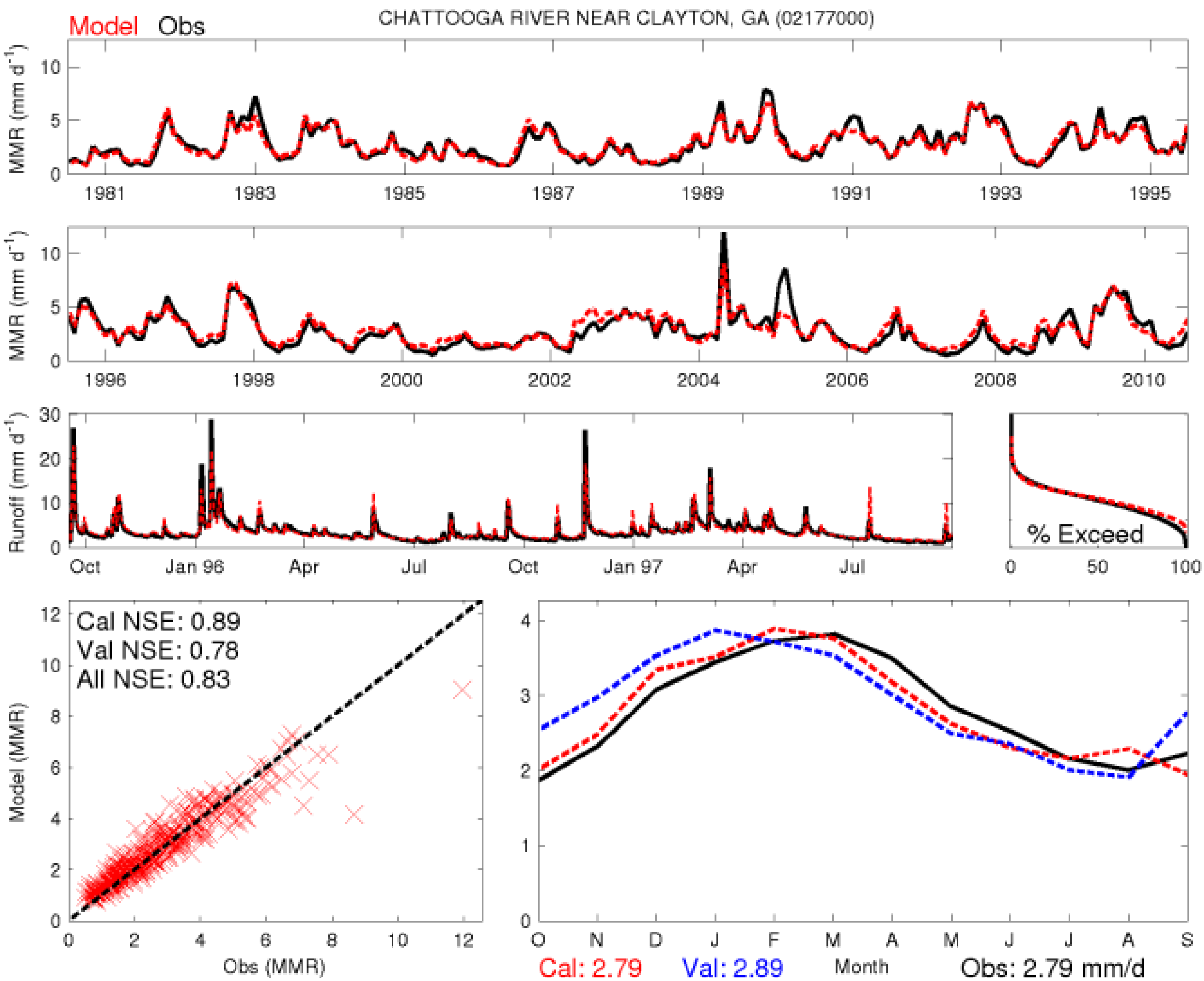


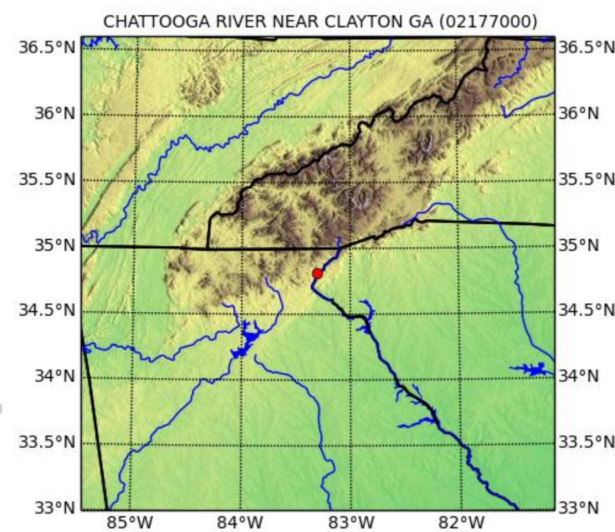
Andy Newman

Hydro-climatic/Seasonal Variation in Watershed Moisture

NCAR RAL/HAP

- Focused on 424 of Sac/Snow17 models for 424 of the Newman et al 762 basins
- Contrasting two today – (1) humid Eastern US basin…

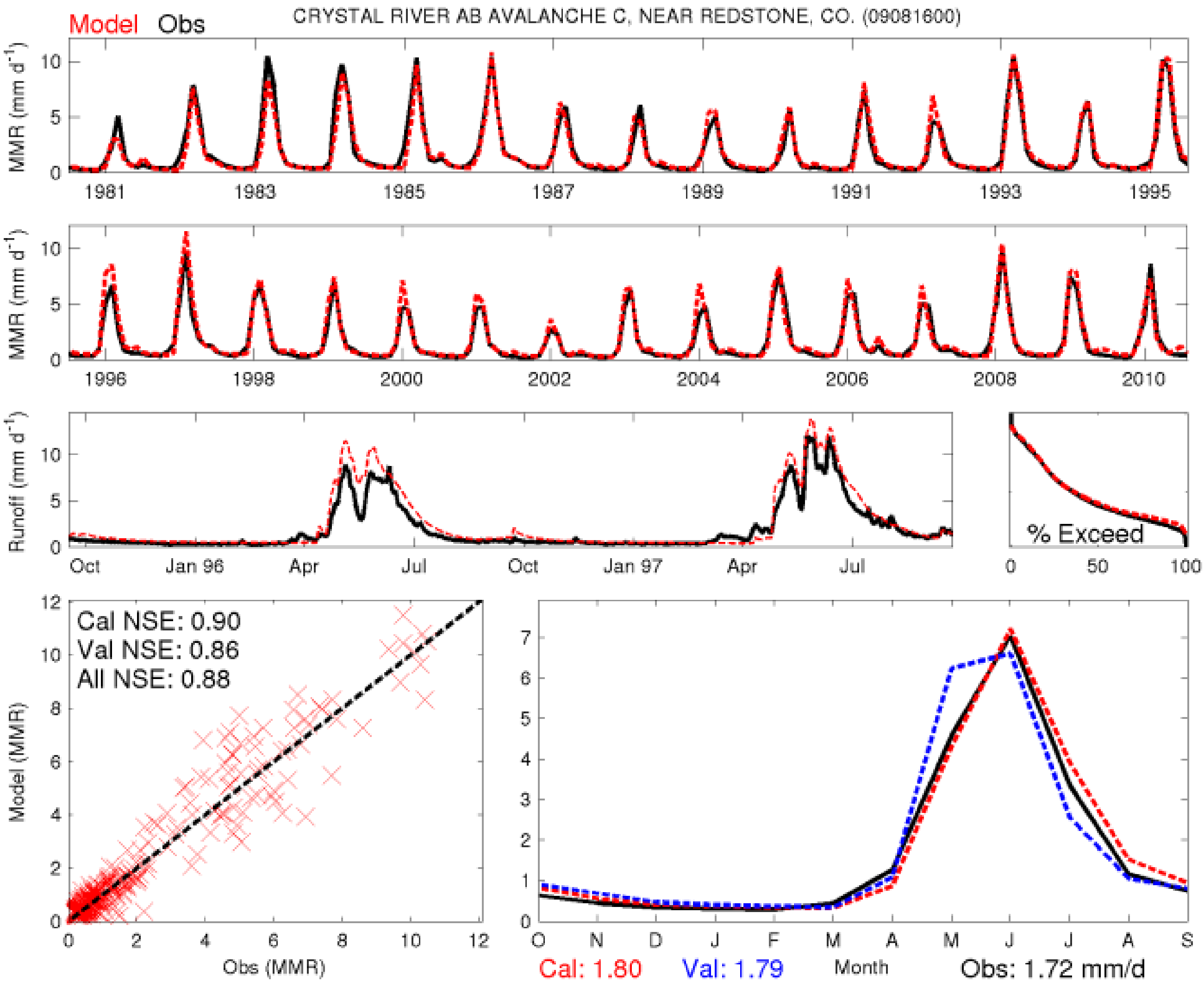


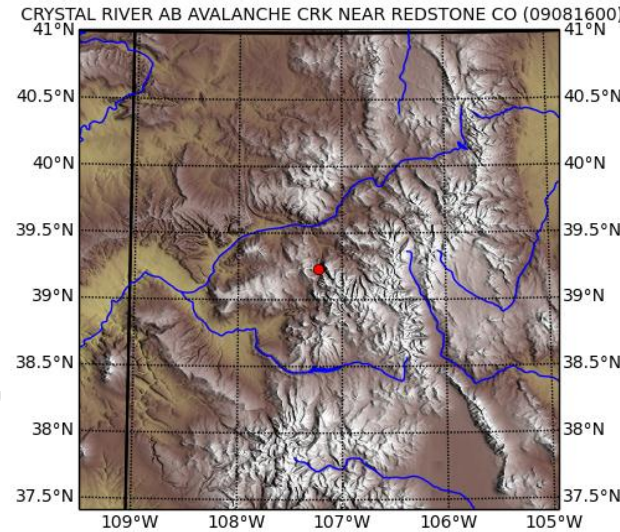


Hydro-climatic/Seasonal Variation in Watershed Moisture

NCAR RAL/HAP

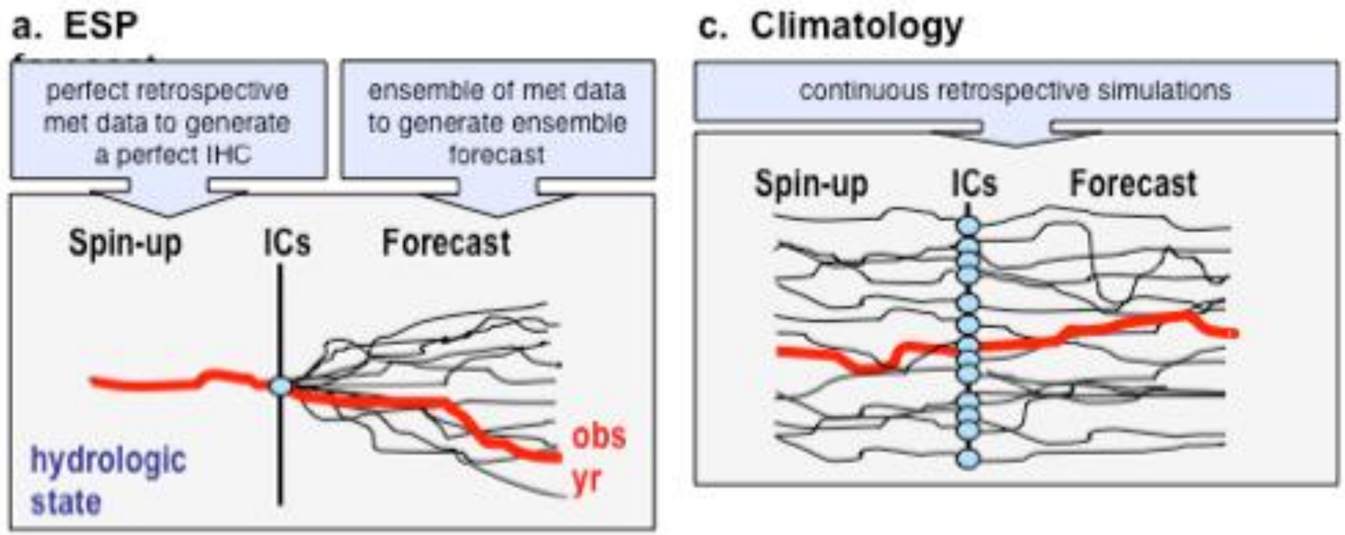
- Focused on 424 of Sac/Snow17 models for 424 of the Newman et al 762 basins
- Contrasting two today – (2) snowy Western US basin…





Assessing the sources of flow forecast skill

vary predictor uncertainty → measure streamflow forecast uncertainty

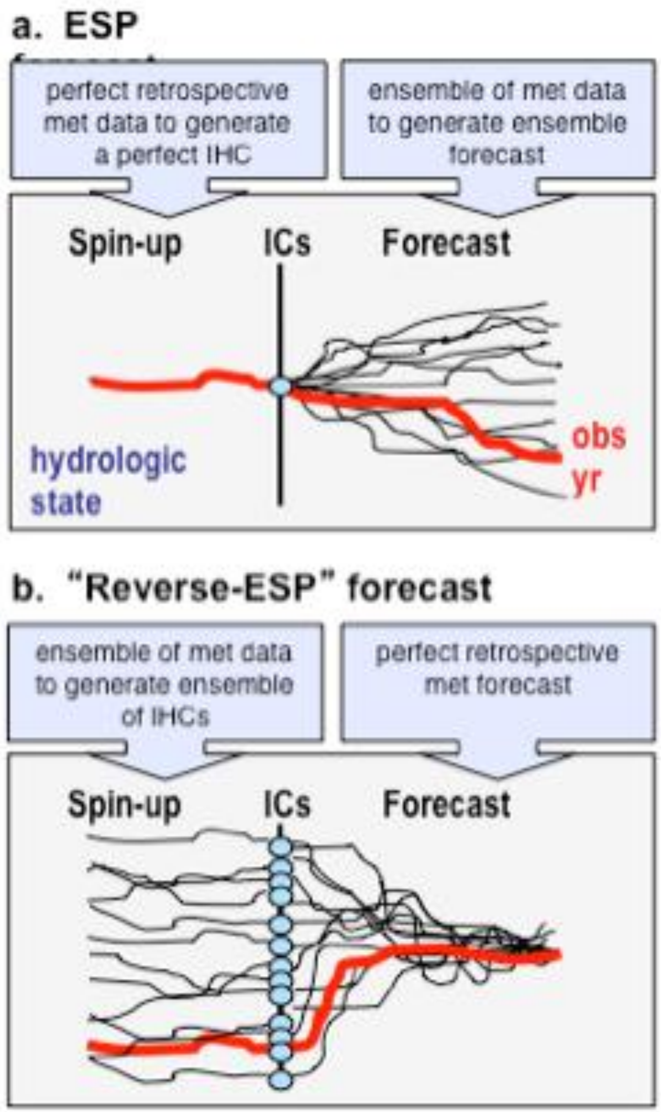


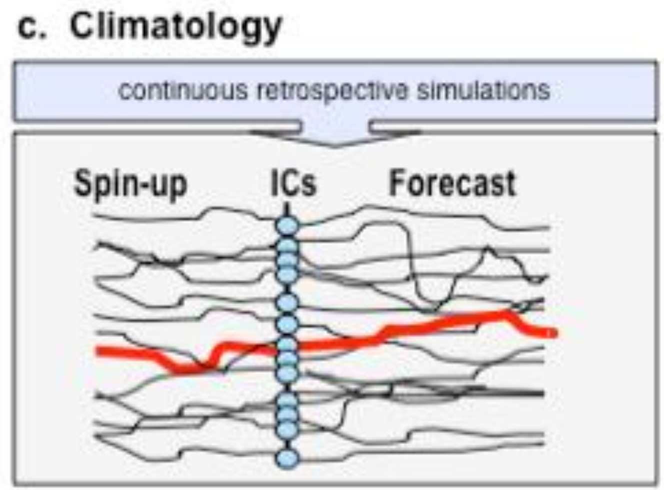
ESP (NWS ensemble streamflow prediction) compared with climatology:

- shows influence of uncertainty in **seasonal climate forecasts (SCFs)** on streamflow forecast uncertainty

Assessing the sources of flow forecast skill

vary predictor uncertainty → measure streamflow forecast uncertainty





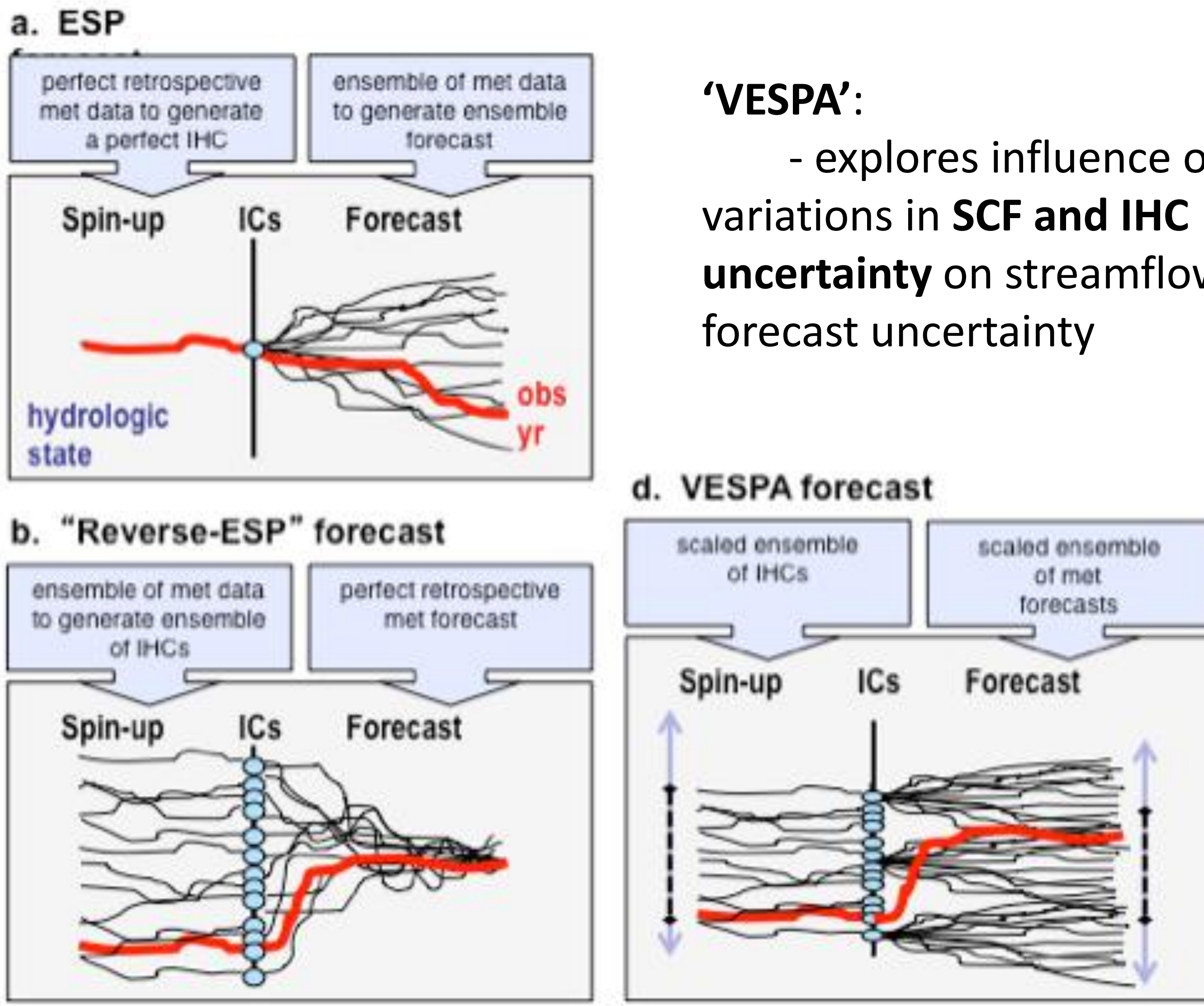
Reverse-ESP:

- shows influence of uncertainty in **initial hydrologic conditions (IHCs)** on streamflow forecast uncertainty

Wood & Lettenmaier, GRL 2008

Assessing the sources of flow forecast skill

vary predictor uncertainty → measure streamflow forecast uncertainty



'VESPA':

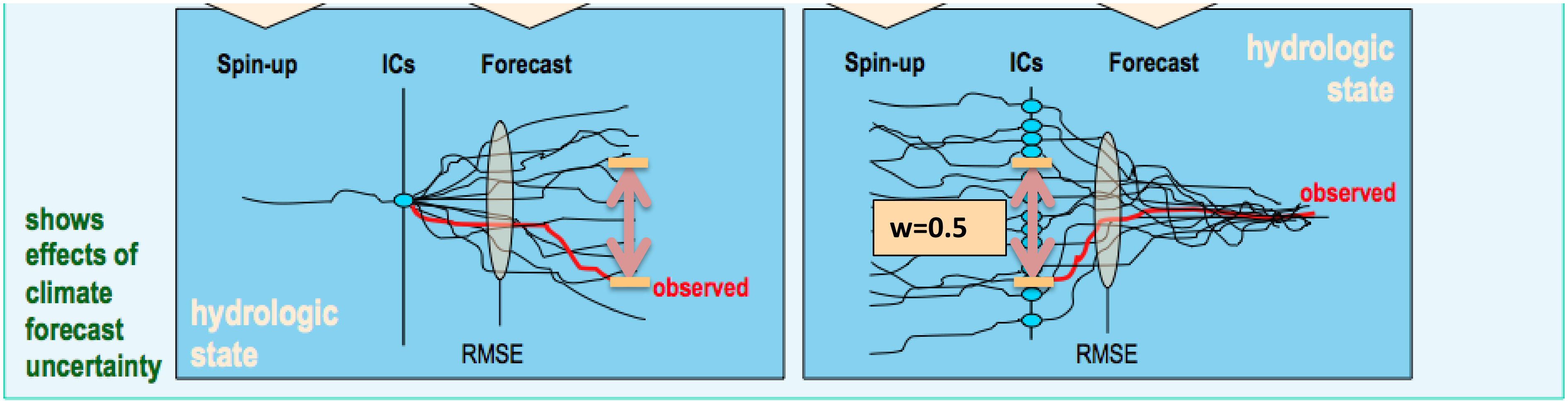
- explores influence of variations in **SCF and IHC uncertainty** on streamflow forecast uncertainty

Wood et al (JHM 2015, in review)

Implementation details

ESP & 'reverse ESP' are end-points – what about realistic/intermediate uncertainties?

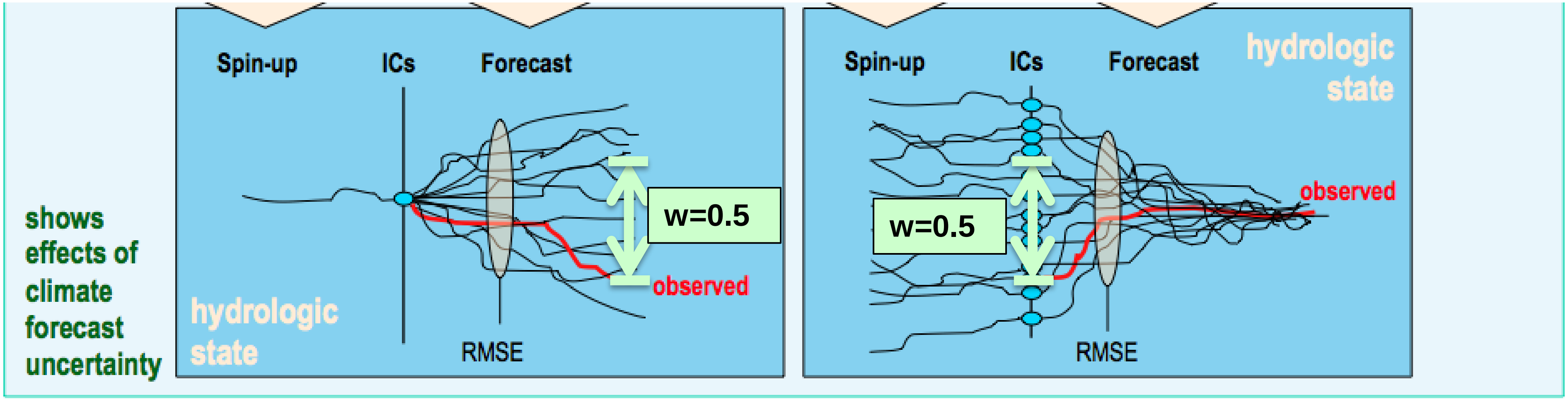
- Define weight ***w*** = fraction between 0 and 1.
  - ***w***=0 means no uncertainty and ***w***=1 means climatological uncertainty
- Modify IHC vector (soil moistures, snow) for each ens. year in climatological period
  - ICmod = ICactual_yr *(1-***w***) + ICens_yr****w***
- Modify SCF met. forcings (precip, temperature) for each year in forecast ensemble
  - SCFmod = SCFactual_yr*(1-***w***) + SCFens_yr****w***
  - weights applied at monthly timestep; actual year daily meteorology scaled to result
- Results in all IHC states initialize all met ensemble members (eg, 30 x 30)
- Assess against model simulations as 'obs' – an idealized 'perfect model' experiment
- Note: w_{ihc} = 0 and w_{scf} = 1 not exactly equal to ESP



Moving beyond the end points

Weights explored:

- Scale IC and Met Forecast variance (uncertainty) between
  - 0 = perfect knowledge & 1 = climatological uncertainty
- Assess flow forecast skill for range of combinations of IHC and SCF weighting:
  - w = 0.00, 0.05, 0.10, 0.25, 0.50, 0.75, 0.90, 0.95, 1.00 (9 weights)
- Given **w,** the resulting variance explained in IHCs or SCFs (monthly) is ~:
  - $(1-\mathbf{w}^2)*100$ = 100, 99.8, 99, 94, 75, 44, 19, 10, 0
  - (in retrospect, the weights could have been better chosen to span this range)



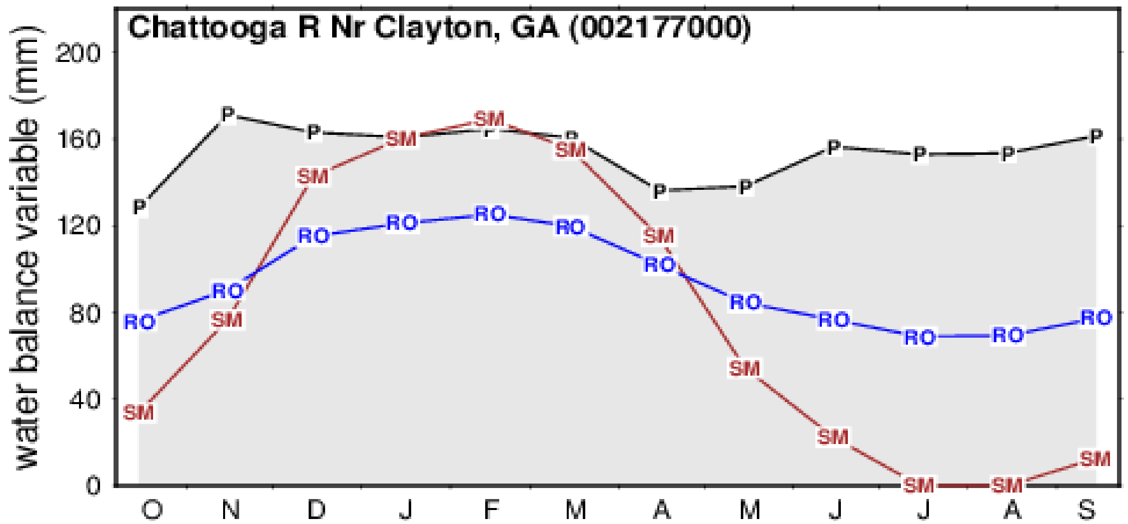
Note: 424 basins * 12 start dates * 81 weight combinations * 30 IHCs * 30 met. traces = 370M simulations

Visualizing predictability

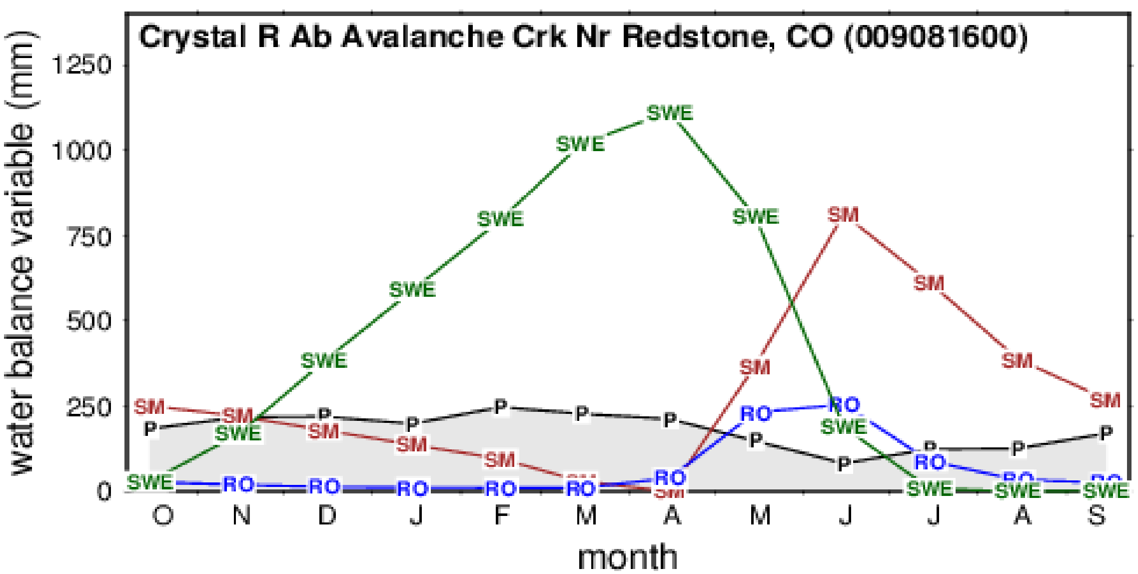
Demo of predictability influences for one location

http://www.ral.ucar.edu/staff/wood/weights/

Seasonal Variation in Watershed Moisture



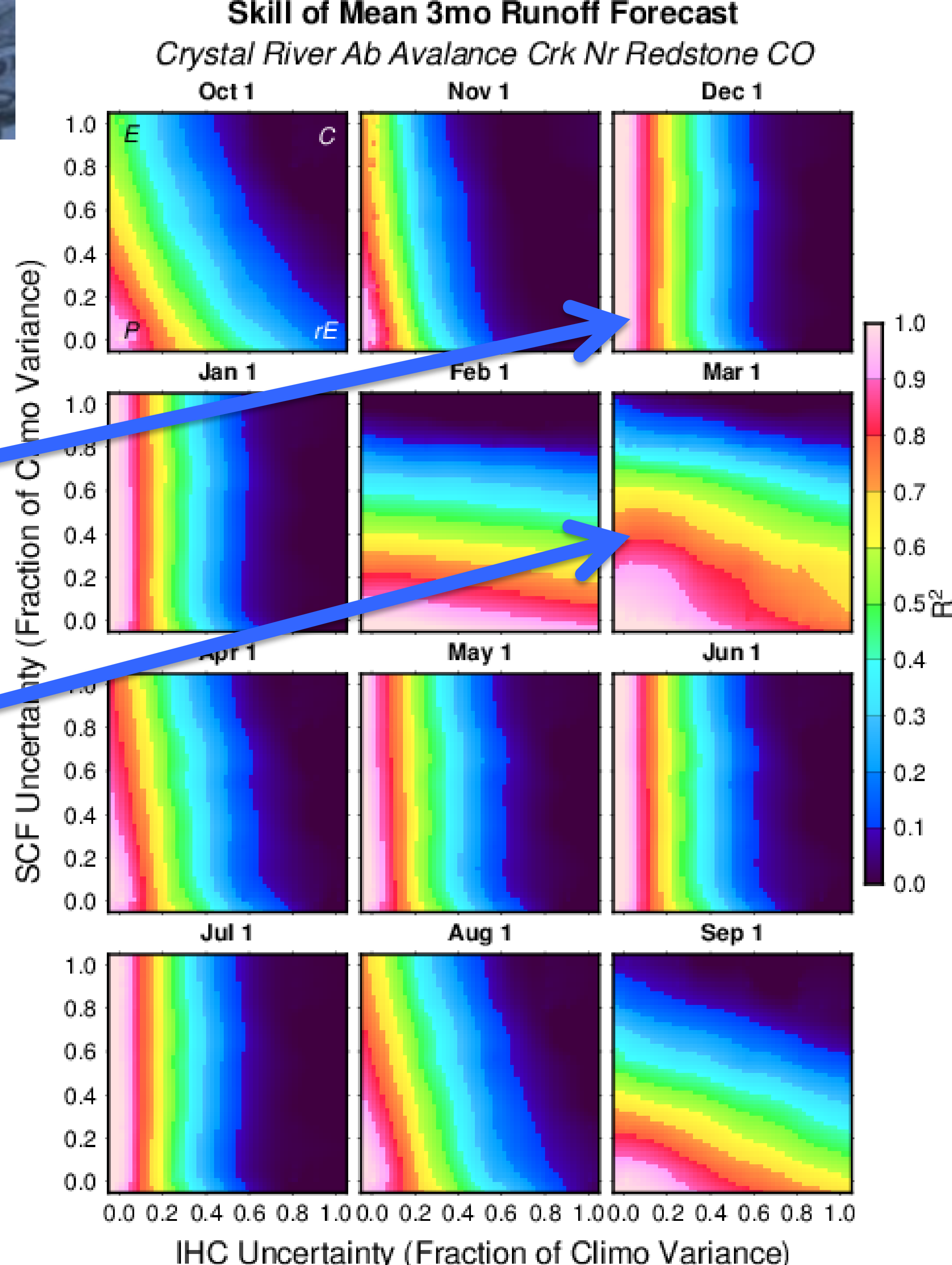
- humid basin
- uniform rainfall
- no snow
- small cycle driven by ET

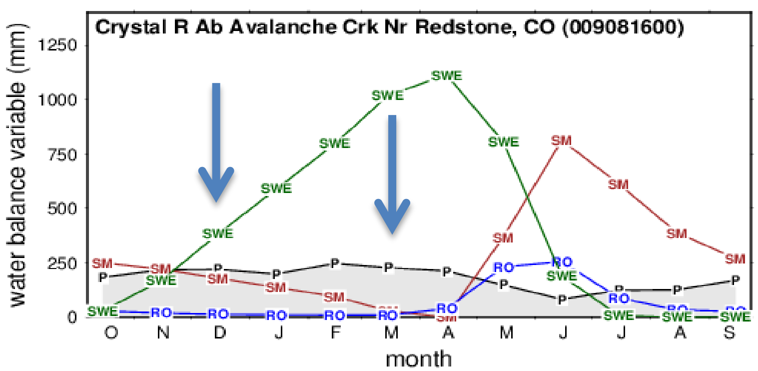


- cold basin
- drier summers
- deep snow
- large seasonal cycle
- April snowmelt dominates May-June runoff

Snow-Driven Basin in the Western US

- Wide seasonal variations in influence of different skill sources
- cold forecast period (Dec-Feb) -- forecast skill depends mainly on initial condition accuracy
- warmer snowmelt forecast period forecast skill depends strongly on met. forecast skill

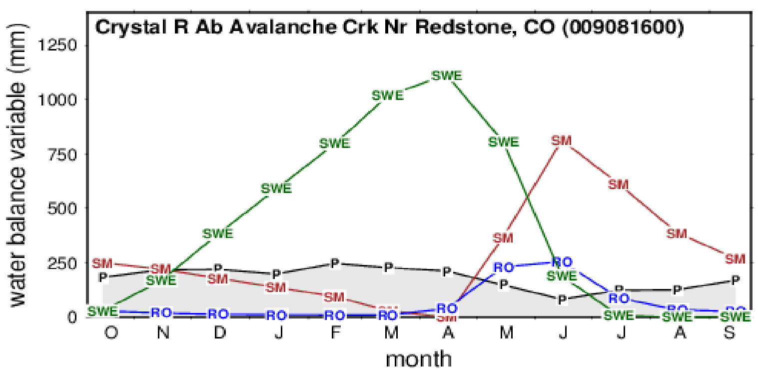




IHC: initial Hydrologic Conditions
SCF: Seasonal Climate Forecasts

Snow-Driven Basin in the Western US

- Sensitivities depend on predictand duration
- For **1 month** runoff (lead 0), IHCs dominate forecast



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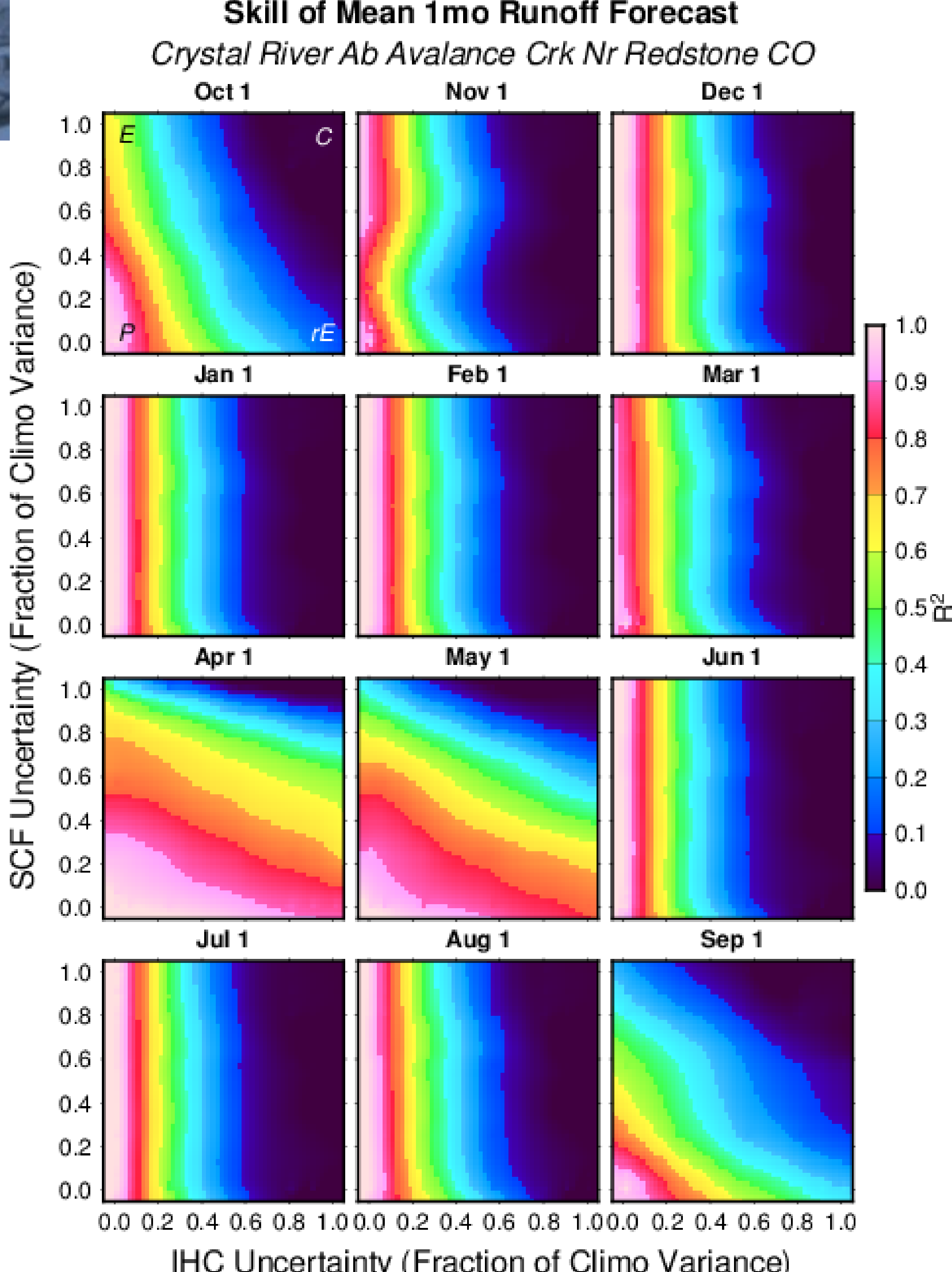
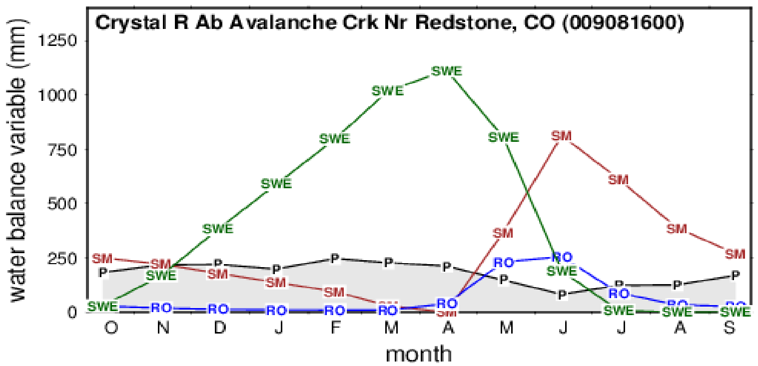


Snow-Driven Basin in the Western US

- Sensitivities depend on predictand duration

- For **6 month** runoff (lead 0), SCFs have more influence than for shorter predictands



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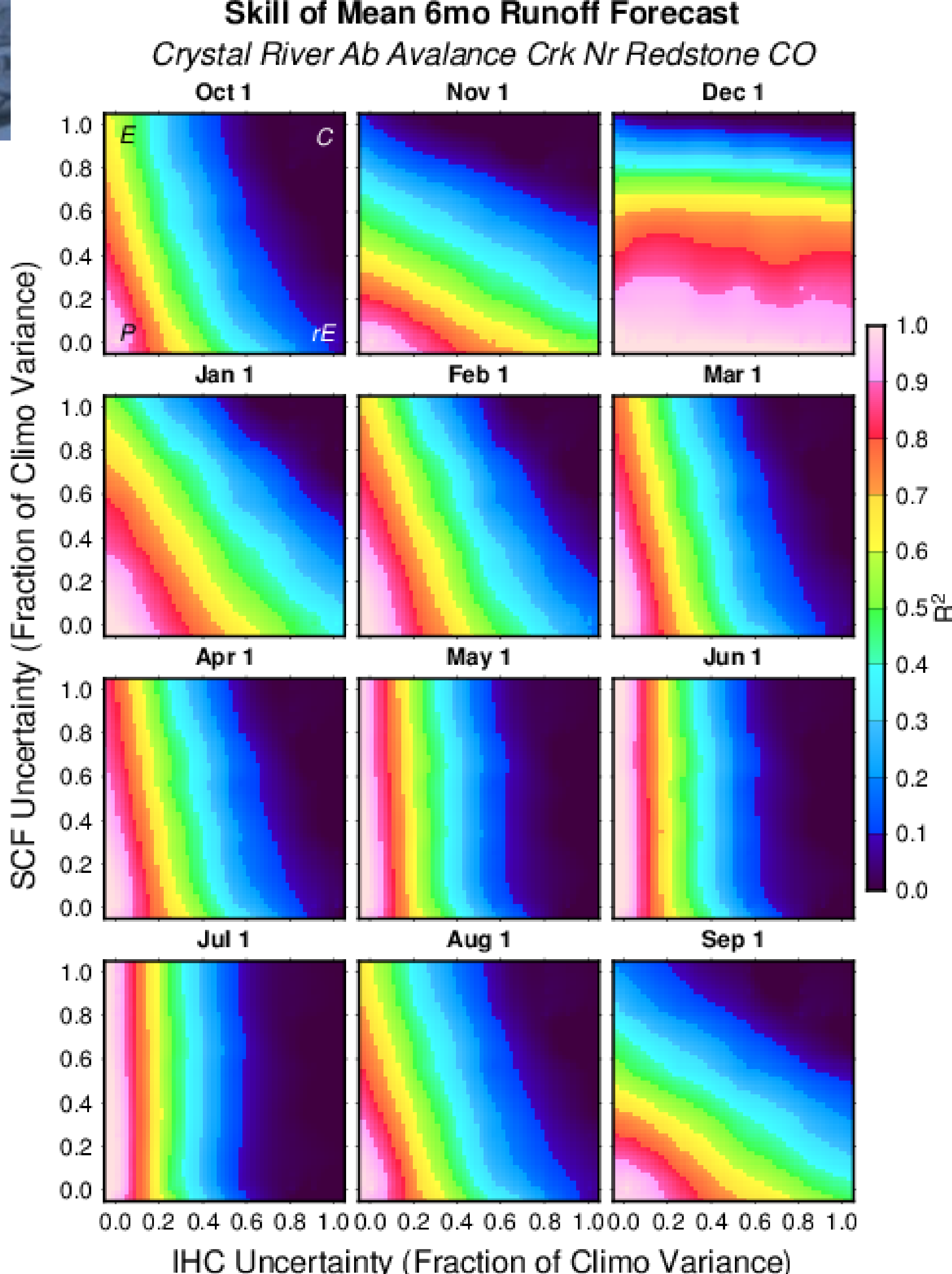
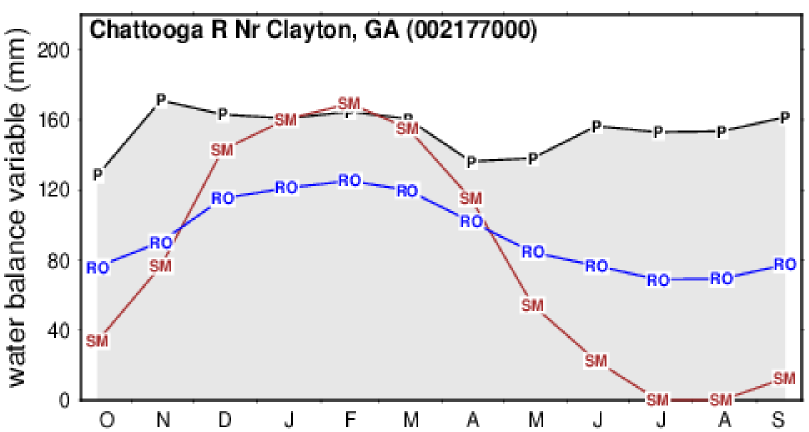


Humid Basin in the Eastern US

- Few seasonal variations in streamflow skill dependence
- Forecast skill (3 months) is always a blend of IHC and SCF influence



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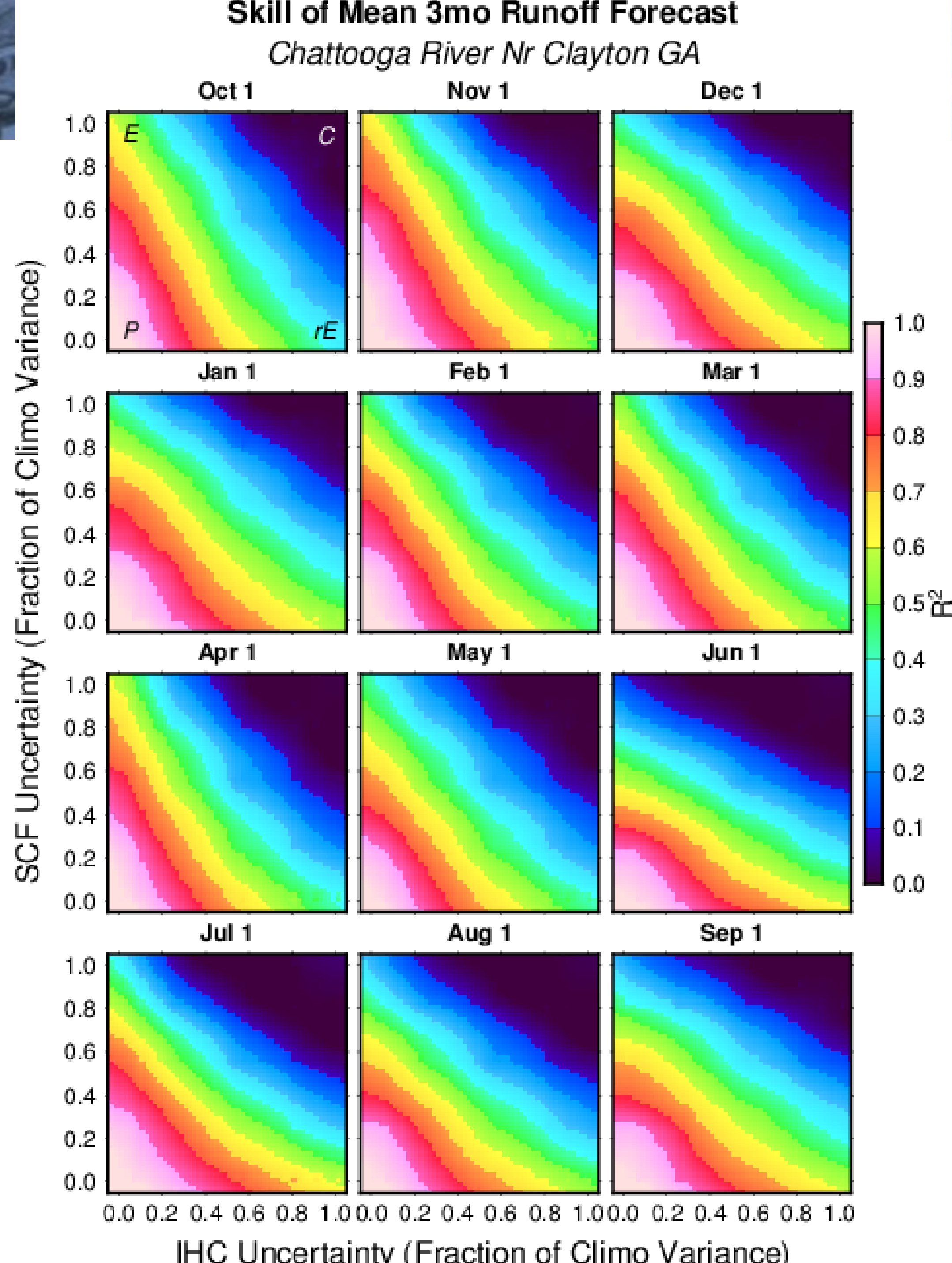

VESPA gradients allow calculation of skill elasticities

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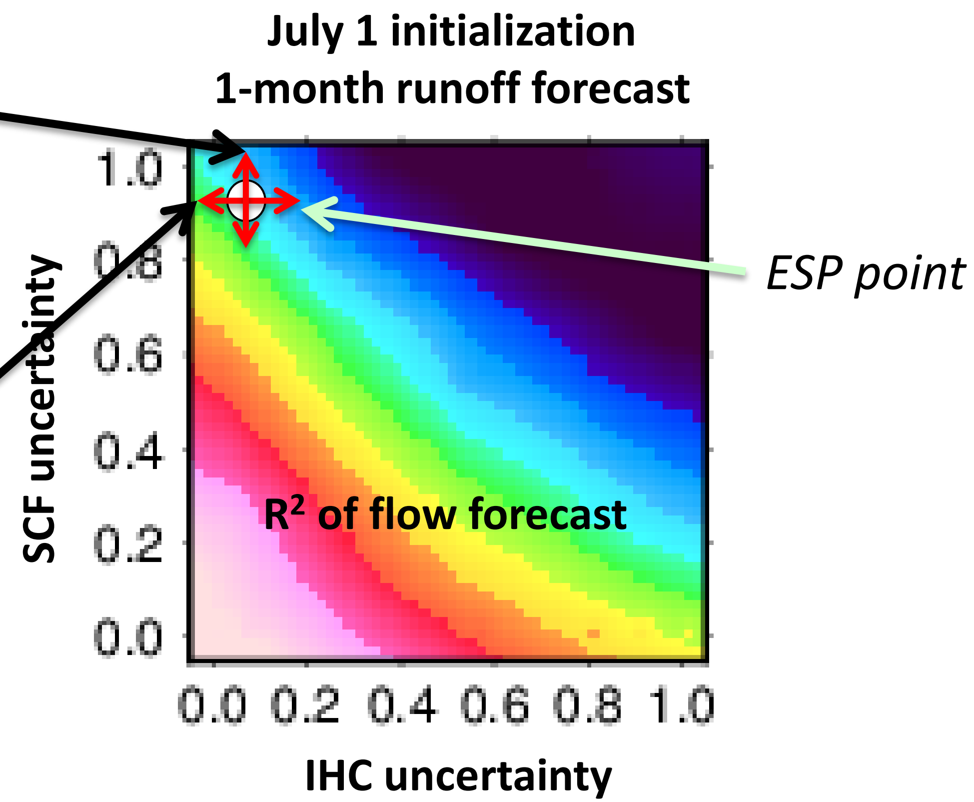
- Elasticity of flow forecast skill elasticity = local derivative of flow skill with respect to IHC skill

  d(flow skill) / *d*(SCF skill)

- Elasticity of flow forecast skill elasticity = local derivative of flow skill with respect to IHC skill

  d(flow skill) / *d*(IHC skill)



We can ask: For a specific flow forecast in a given location, what is the best way to improve the skill?

IHC: initial Hydrologic Conditions
SCF: Seasonal Climate Forecasts

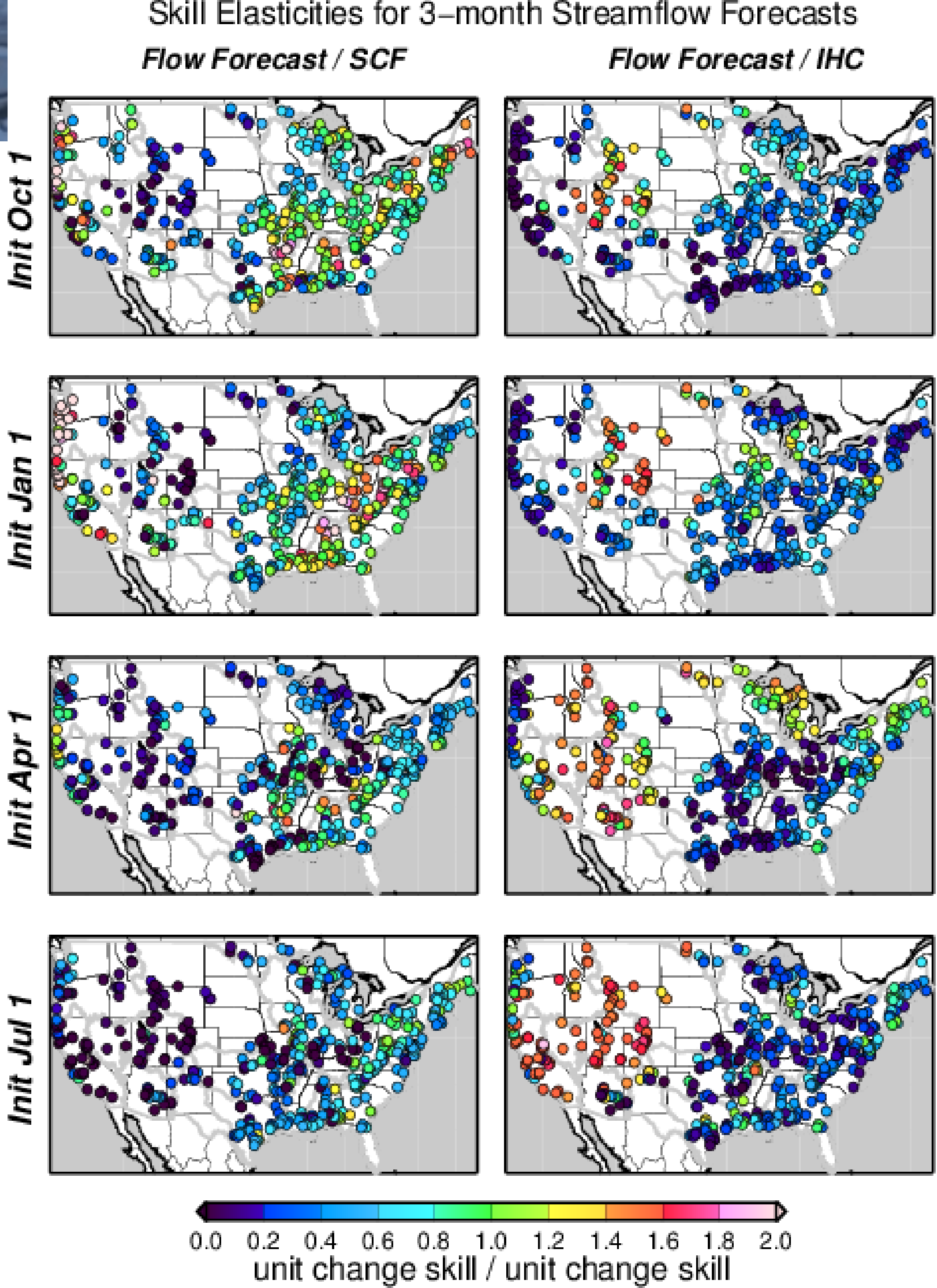
Flow Forecast
Skill Elasticities

- **The % change in flow forecast skill versus per % change in predictor source skill**

- Can help estimate the benefits of investment to improve forecasts in each area (IHC, SCF)
  - for a predictand of interest
  - for a time of interest

- Results emphasize that both SCF skill and IHC skill are important, depending on the forecast being made and the location

- This work is funded by water management agencies – Reclamation and US Army Corps of Engineers



Summary

- VESPA approach provides insight into seasonal and hydroclimatic variations in streamflow forecast skill dependence
  - goes beyond earlier ESP/reverse ESP predictability end-point framework
  - allows calculation of forecast skill elasticities (a new concept)
  - provides a tool for understanding potential benefit of forecast system improvements
- 424-basin assessment provides regional / seasonal view of forecast skill variations
- elasticities > 1 for SCF implies benefits of climate forecasts for hydrology can be more valuable than expected
- Assumes perfect model – model error an area for future exploration

Websites

- http://www.ral.ucar.edu/projects/hap/flowpredict/
- http://www.ral.ucar.edu/staff/wood/weights/

Acknowledge:

- US Army Corps of Engineers
- US Bureau of Reclamation