

Needs for and Scientific Feasibility of Local & Regional Seasonal Precipitation predictions

- Building responsive capabilities with best science
- “The people are local”
- Trustworthiness of information
- Current capabilities
- How to meet needs

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Burlington Inn, destroyed in the floods of August, 1955



NOAA RESEARCH • ESRL • PHYSICAL SCIENCES DIVISION

Panel: Needs for and Scientific Feasibility of Local & Regional Seasonal Precipitation Predictions

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NOAA Climate Prediction
Assessment Workshop
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Burlington, VT



Developing an understanding of user needs

- Ongoing engagement, iteration, with a variety user groups
- Some individual studies focussed on specific groups
- Multiple methods and perspectives
- Quantitative and qualitative & context-sensitive social science methods
- From these efforts, we have identified major classes of users, and the major needs (“EOFs”)
- Need for ongoing social science work to *refine* needs, especially for less studied and under-served
- We know much more about user needs than official products are currently able to serve
- Examples of efforts:

RISAs, DOI CSCs, Dept of Ag Hubs

NOAA/SARP & related grants; River Forecast Center annual user meetings

WWA RISA work with reservoir/water supply managers and the CBRFC

NIDIS regional pilots; Nat’l Drought Mitig. Center

Seasonal Fire Assessments, led by CLIMAS

WHO uses for what:

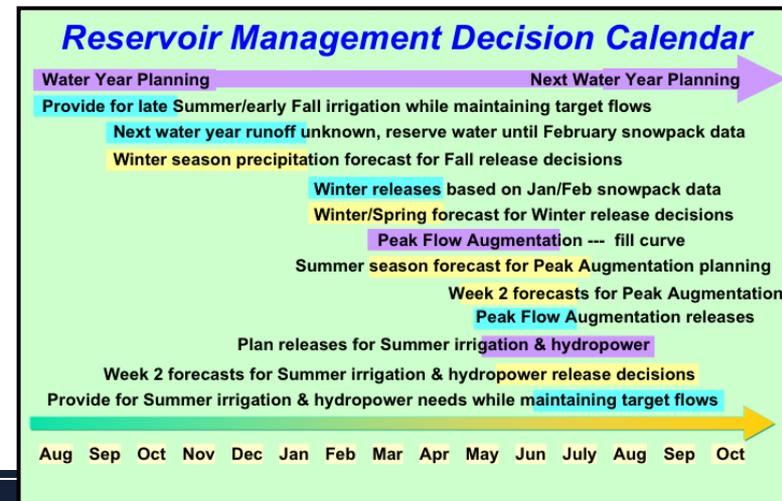
Various user types, major distinction is who's using and what for

- For S2S & precipitation, *a major class of users are intermediaries* who do something with the information to manage the risks for the public
 - often with a preparedness or “ready-set-go” mindset, situational awareness, actions/decisions adjustable thru a season
 - skill needed varies, often changes as they better understand the products
 - for their jobs, have a *vested interest in learning about products*
- Within NWS: Warning Coord. Mets, River Forecast Centers, CSFPs, etc
- Reservoir and water supply managers, Wildfire managers, Public Land managers (grazing, controlling invasive grasses, etc); agriculture
- Many of these *already work with* a variety of uncertain and often probabilistic information

How climate/drought information might be used

- As input to their operational/planning models – but not only
- Mental models of managers for their systems are important *as well as* hydrologic and management models
- Discussions within water management groups & with their management & stakeholders, & w/ scientists
 - “dialogue” about risks, e.g. water supply/drought/flood
- Relationship of climate information to their triggers & thresholds for action – in both ops/planning models *and* mental models
- Many actions/decisions adjustable thru a season/year, responding to updated risk
- As interested in the information behind the Drought Monitor as the DM itself, in order to make their own assessments about the data & products

Ray and Webb 2016, in “Climate in Context” RISA book out in April, AGU/Wiley



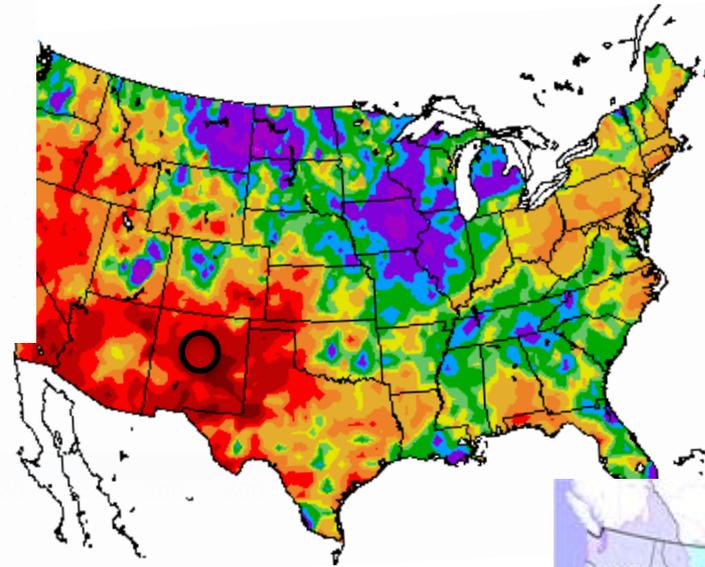
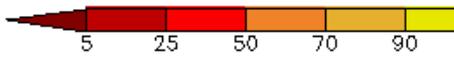
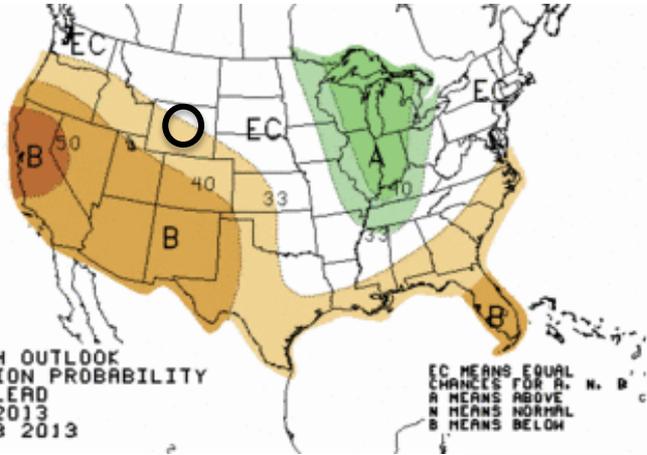
Water management user requirements I

- Seasonal precipitation forecasts targeted at the water resources sector and related sub-seasonal to seasonal information.
 - One of their highest priorities (see WSWC 2014)
- Long range “mainstem” forecasts: precip, temp, wind, soil moisture
 - Different periods, e.g. snow season (Oct-March, Jan-Apr), vs standard 1 & 3 mo
- Skill issue – remember: many users are professionals, already use probabilistic information
 - Need for and ability to use
- *Interpretive or translational information* along with numerical and map products, to inform & educate water management users:
 - Routine interpretation, narratives, product explanations, as well as webinars like those by RISAs or internally for NOAA staff, especially for ensemble streamflow prediction and seasonal outlooks -- Lets them put the information in the context of their triggers, models



Use of CPC Outlooks – from Bob Peters, Denver Water

% Normal
Precip Mar-Apr-
May 2013



Actual



Water management user requirements II

- Knowledge as well as “product” -- Need for synthesis of research knowledge into products & analysis that connect climate impacts to water management impacts
 - Beyond numerical predictions, what more can we say about risks, e.g. given the status of ENSO, certain conditions more/less likely
 - Impacts of temperature --> evaporation, rain/snow mix, urban demand, length of growing season
 - Timing of spring runoff --> water rights, reservoir reliability
 - Key climate features of interest to different regions: monsoon, Ice storms, heavy winter storms in the east coast; Pineapple Express/Atmospheric rivers
 - Seasonal precipitation outlooks will be of more interest if they reflect the risks of these regional concerns
- Simplifying to a two-category product, serves *some* users, but reduces the information available, doesn't meet the needs of many users to support decisions
 - **Keep both??** Let more sophisticated users can drill down
- “Services” includes a network of people who can connect products and knowledge to applications e.g. climate extension agents

Next steps

- We know more about user needs than are currently served
 - 20 years of RISAs; 20+ years of NOAA Climate Program Office “Climate and Society” funded work; other efforts outside these, e.g. NDMC, NIDIS
- Not adequately communicating those to CPC
 - Peer-reviewed papers not usually aimed at CPC communication
 - Presentations/networking at meetings like this aren’t enough
- Need deliberate interaction & engagement with CPC, “co-production” with those who study user needs
 - **Working group?** to work out issues of format, skill, interpretation/translation, integration of research knowledge
- RISA “lessons learned” book: **Climate in Context: Science and Society Partnering for Adaptation**, eds Parris, Garfin, Dow, Meyer, Close; AGU/Wiley

Vermont Weather Analytics Center Motivation

2016

Top 10 risks in terms of

Likelihood

- 1 Large-scale involuntary migration
- 2 Extreme weather events
- 3 Failure of climate-change mitigation and adaptation
- 4 Interstate conflict
- 5 Natural catastrophes
- 6 Failure of national governance
- 7 Unemployment or underemployment
- 8 Data fraud or theft
- 9 Water crises
- 10 Illicit trade

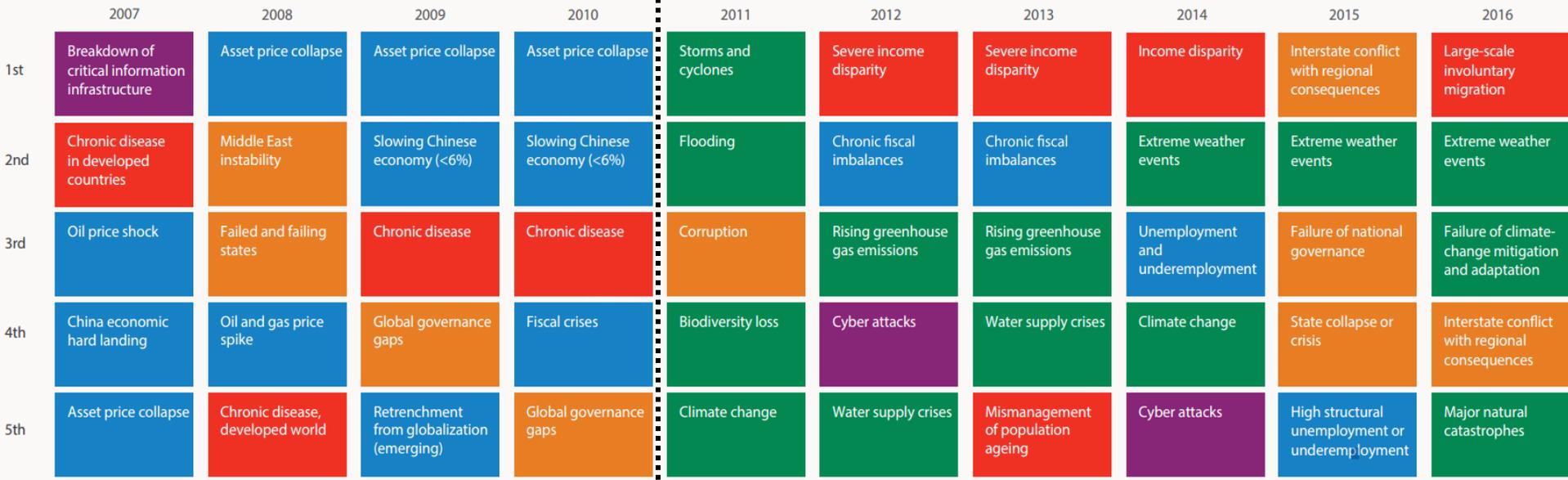
Top 10 risks in terms of

Impact

- 1 Failure of climate-change mitigation and adaptation
- 2 Weapons of mass destruction
- 3 Water crises
- 4 Large-scale involuntary migration
- 5 Energy price shock
- 6 Biodiversity loss and ecosystem collapse
- 7 Fiscal crises
- 8 Spread of infectious diseases
- 9 Asset bubble
- 10 Profound social instability

Sharp increase in environmental risks starting in 2011

Top 5 Global Risks in Terms of Likelihood



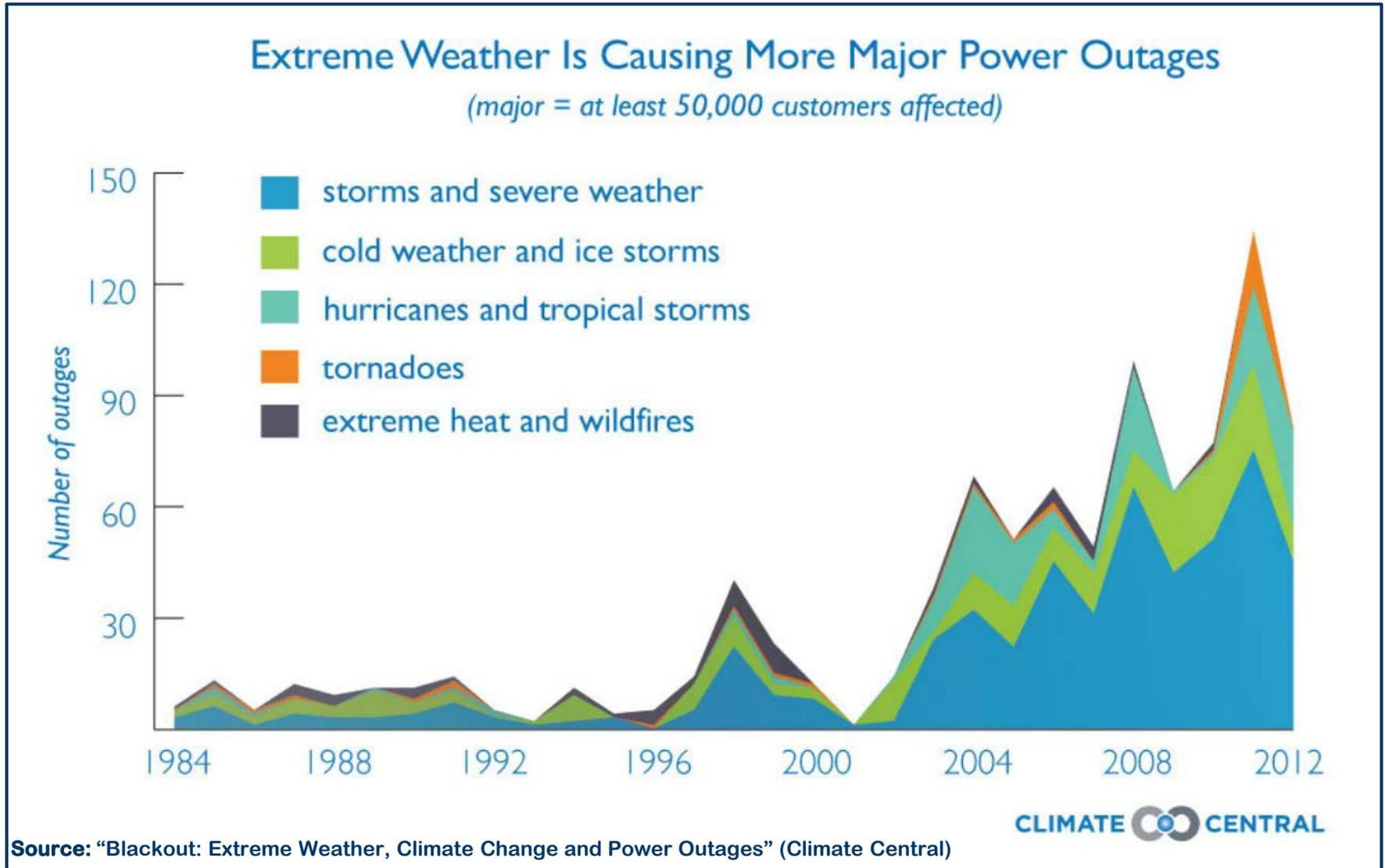
■ Economic ■ Environmental ■ Geopolitical ■ Societal ■ Technological

Source: World Economic Forum



Vermont Weather Analytics Center

Motivation



Vermont Weather Analytics Center

Project Overview

- Two-year, \$16 million research undertaking to develop intellectual property using coupled data models and related software
- 2-year agreement/partnership with IBM
- 3 main goals:



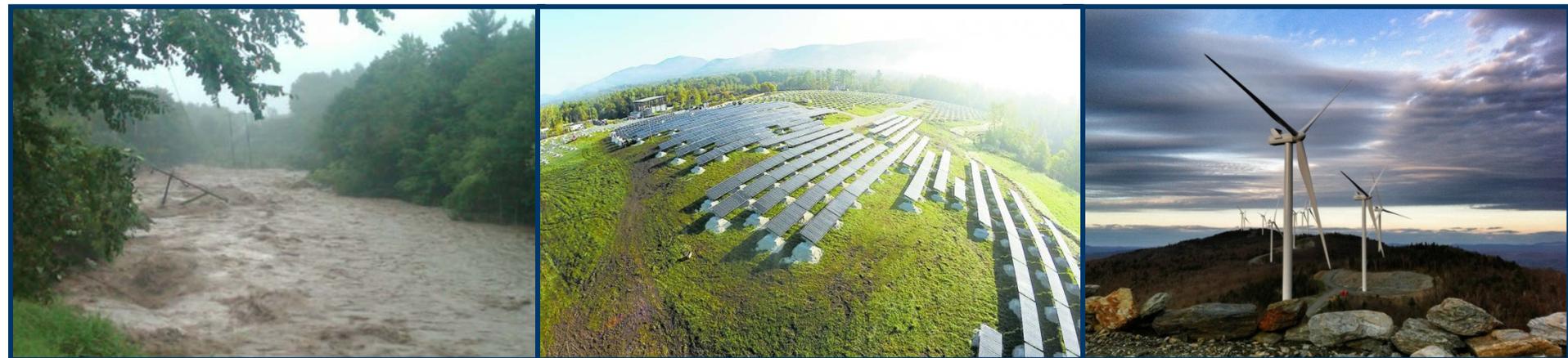
Increase grid reliability



Lower weather event-related operational costs



Optimize utilization of renewable generation resources



Vermont Weather Analytics Center

Models

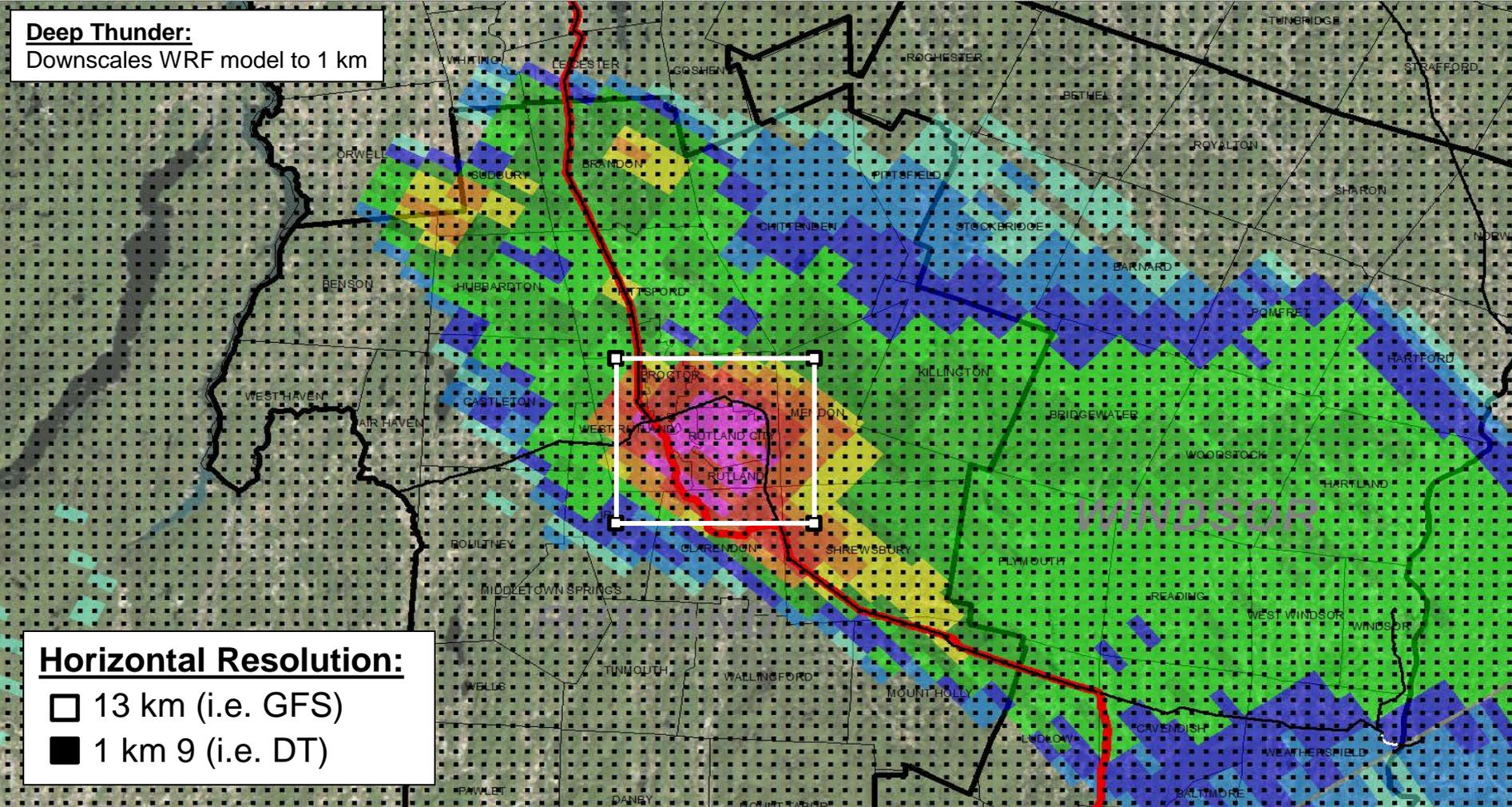


Model	Function
<i>Weather (Deep Thunder)</i>	To produce accurate weather forecasts 72 hours in length down to 1 sq. km → Lower weather event costs
<i>Demand</i>	To increase accuracy of state load forecasts → Better plan for future needs
<i>Renewable</i>	To produce generation forecasts for solar and wind farms → Improve power supply/planning
<i>Renewable Integration Stochastic Engine (RISE)*</i>	To integrate the models' results to optimize the value of Vermont's generation, demand response, and transmission assets

*VELCO Only

IBM Deep Thunder Model Specifications

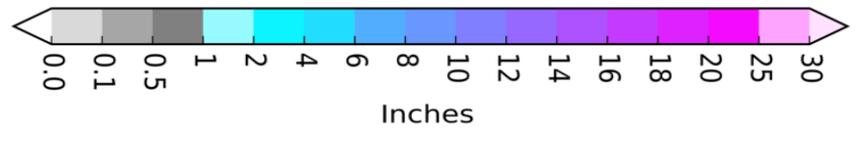
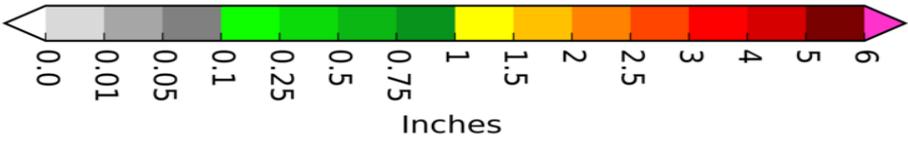
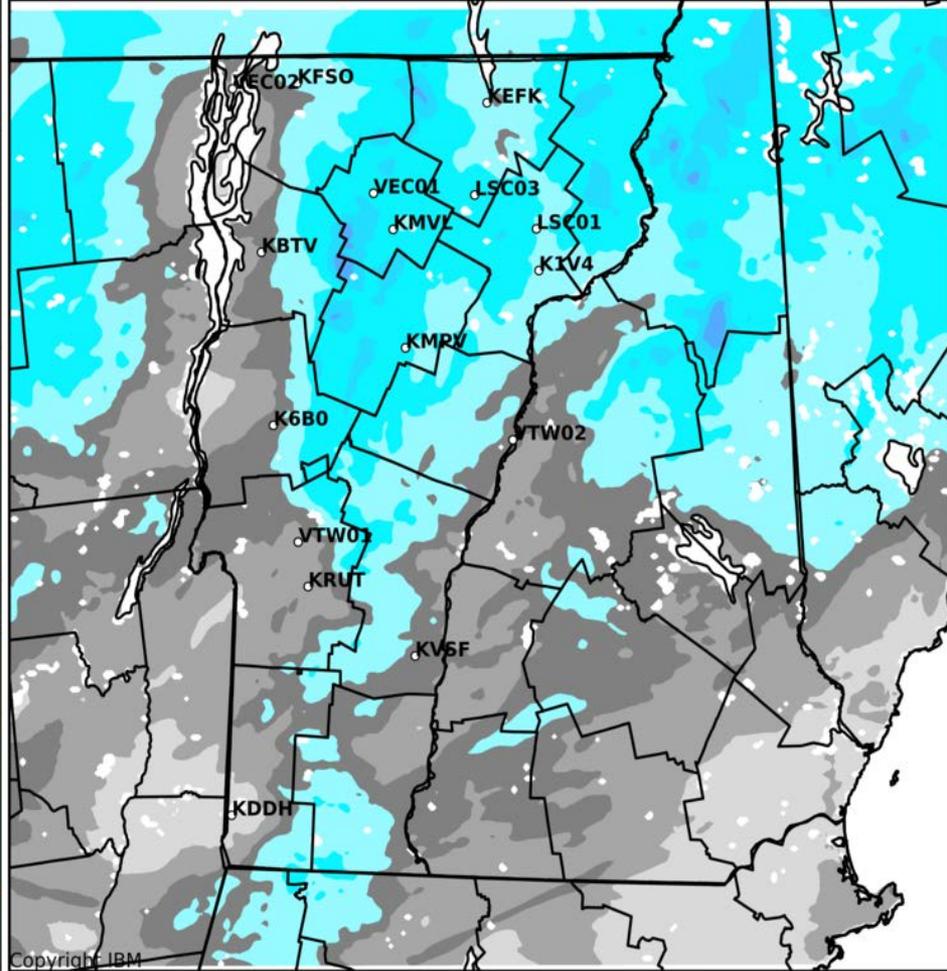
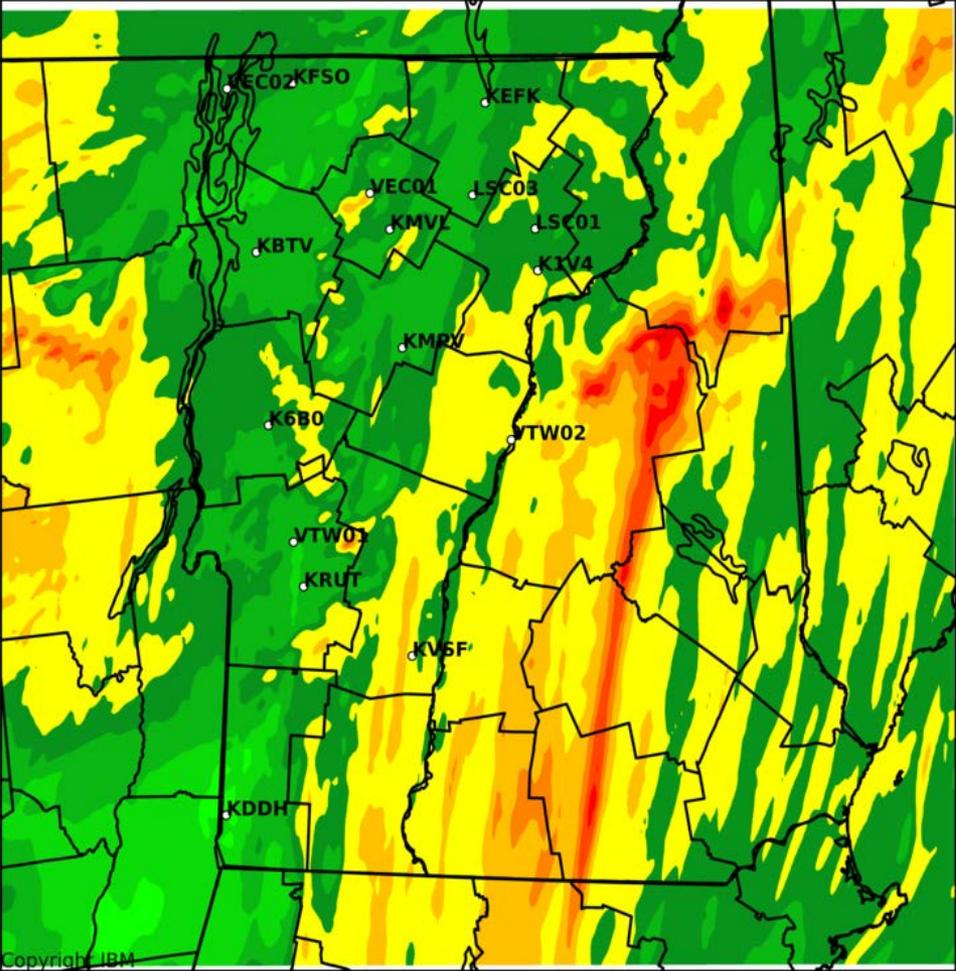
Observed radar on 5/27/14 – Isolated supercell over Rutland that produced golf ball-sized hail, high wind gusts, and flash flooding



Precipitation Forecasts

Accumulated Liquid Precipitation, Forecast Total
Valid: 2016-02-15 07:00:00 - 2016-02-18 07:00:00 LT
DT Forecast: 2016-02-15 07:00:00 LT

Overall Change (+) in Snow Depth
Valid: 2016-01-12 19:00:00 - 2016-01-13 19:00:00 LT
DT Forecast: 2016-01-10 19:00:00 LT



Seasonal precipitation forecast and downscaling

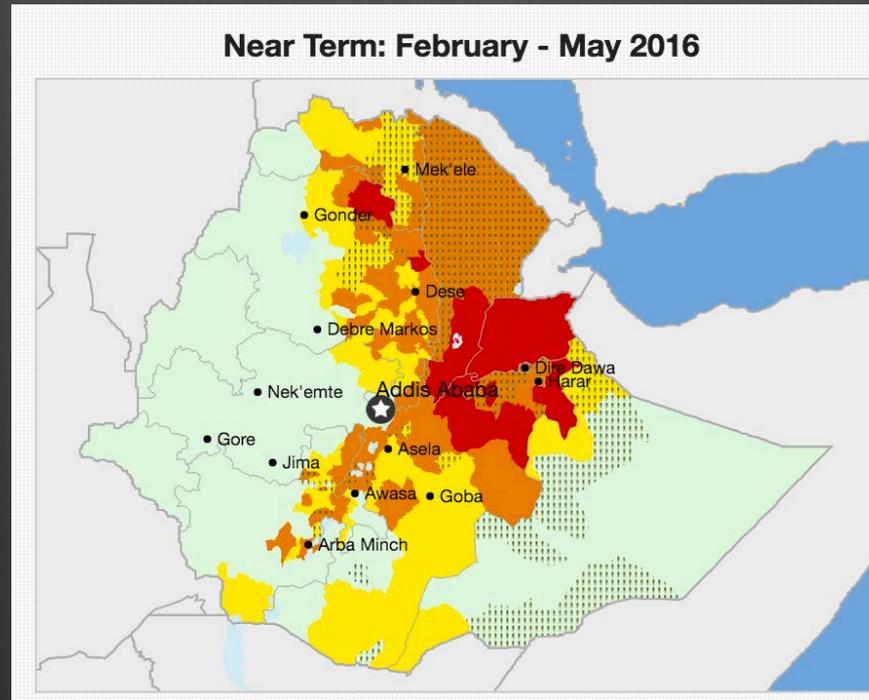
- ⦿ Why?

- ⦿ Issues

- ⦿ Downscaling approaches and evaluation

Why?

To help* provide food security outlook



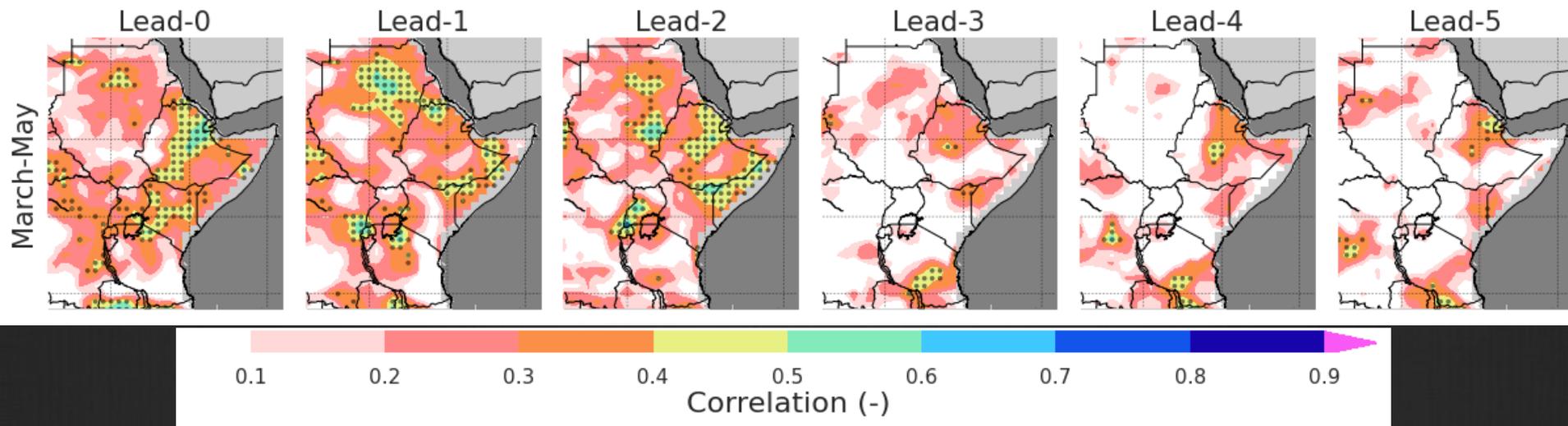
IPC 2.0 Acute Food Insecurity Phase



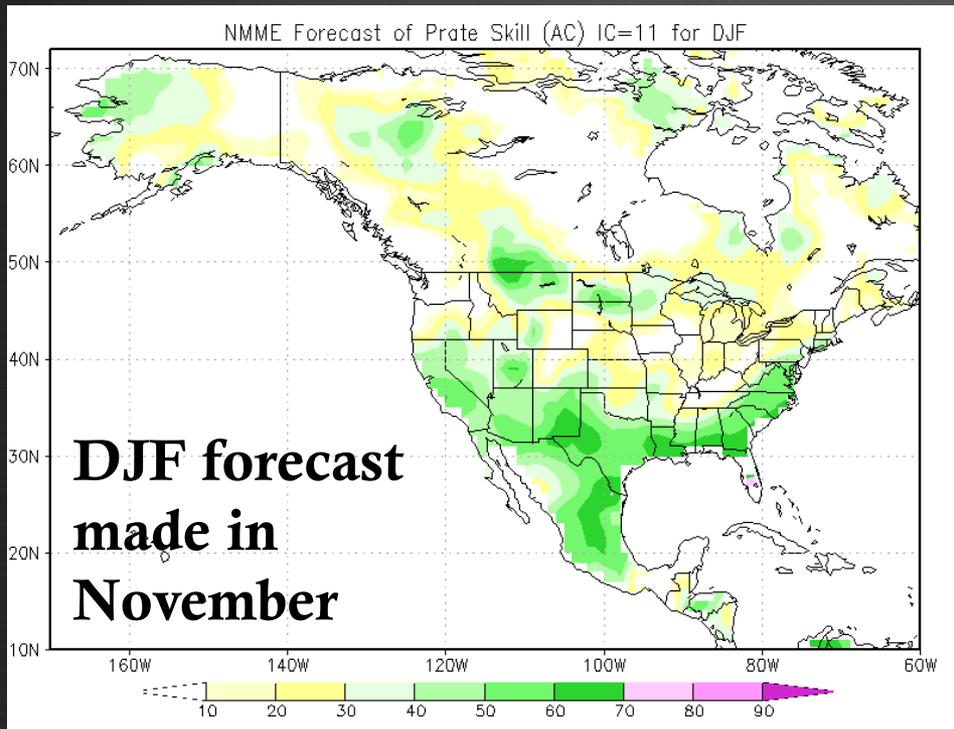
*Other crucial factors include Markets and Trade, Livelihoods and Nutrition information.

Issues

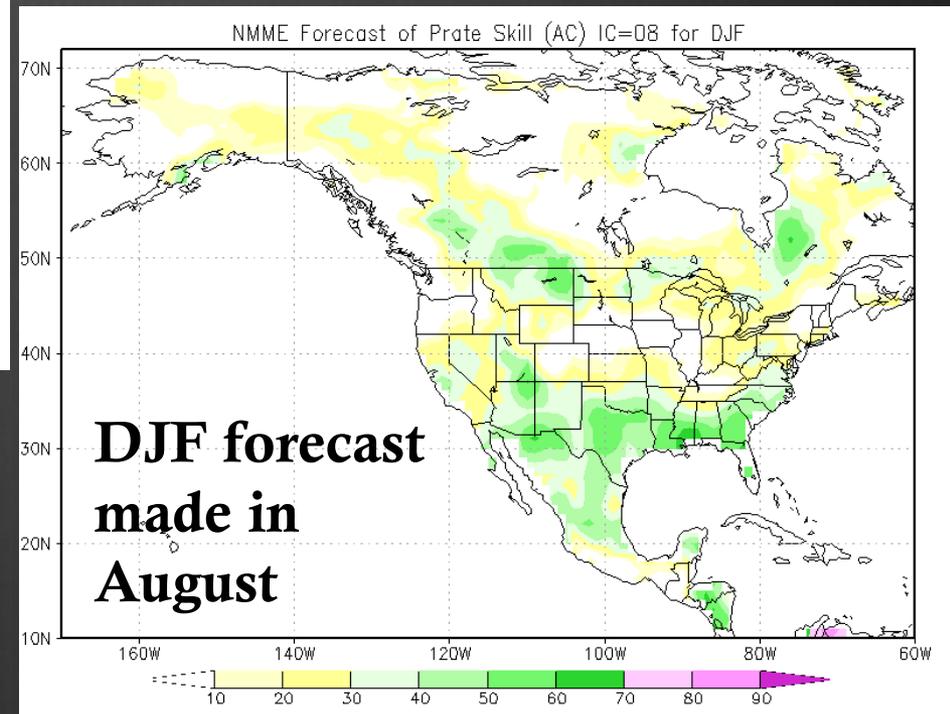
- ❶ Lack of seasonal precipitation forecast skill
- ❷ Uncertainty induced through downscaling methods
- ❸ Lack of long-term observations



Skill of precipitation forecast

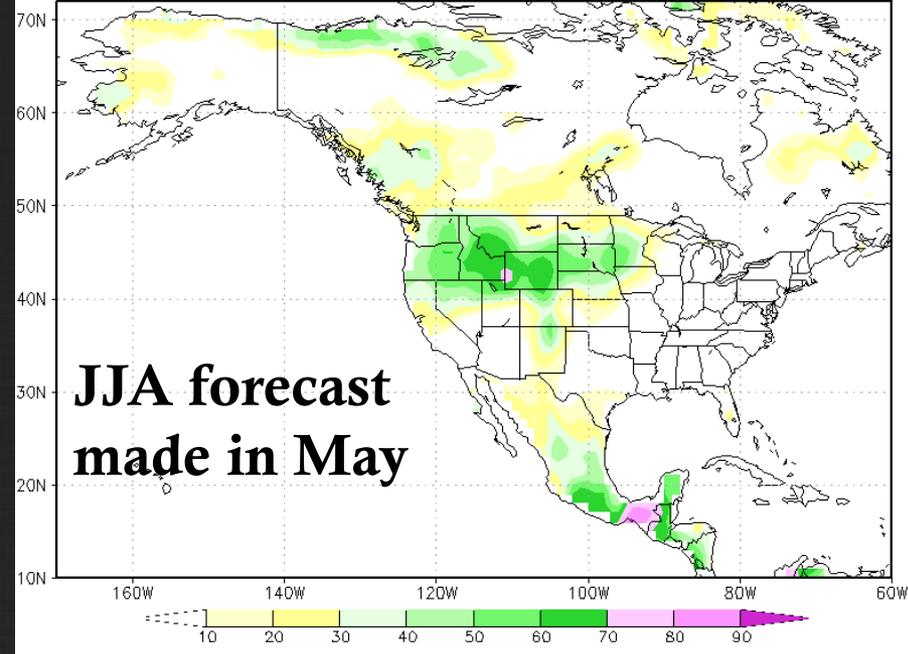


Source: CPC
(<http://www.cpc.ncep.noaa.gov/products/NMME/>)



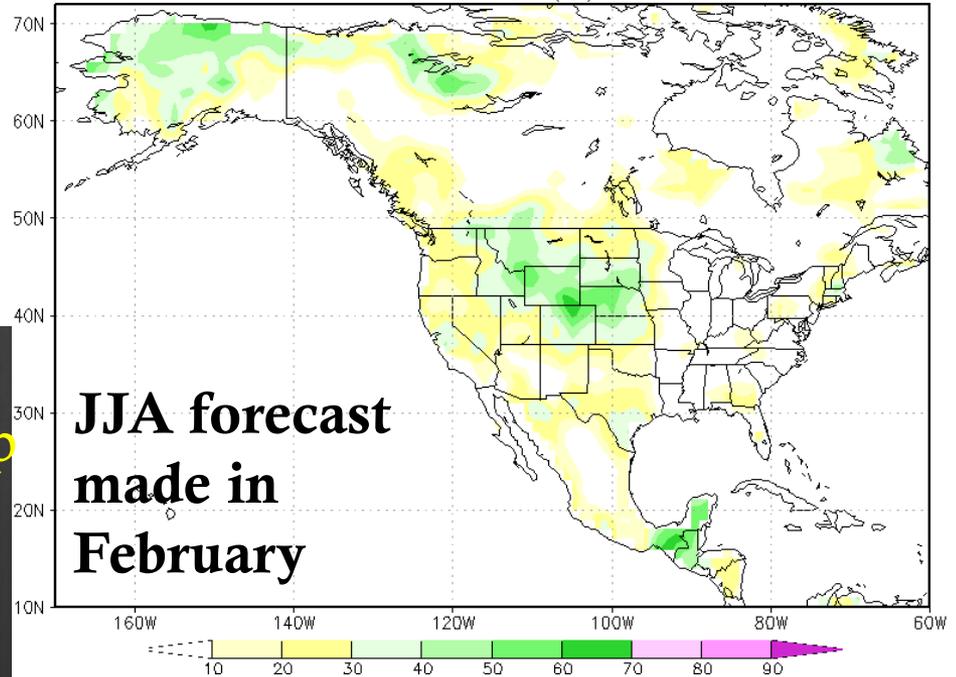
Skill of precipitation forecast

NMME Forecast of Prate Skill (AC) IC=05 for JJA



Source: CPC
(<http://www.cpc.ncep.noaa.gov/products/NMME/>)

NMME Forecast of Prate Skill (AC) IC=02 for JJA

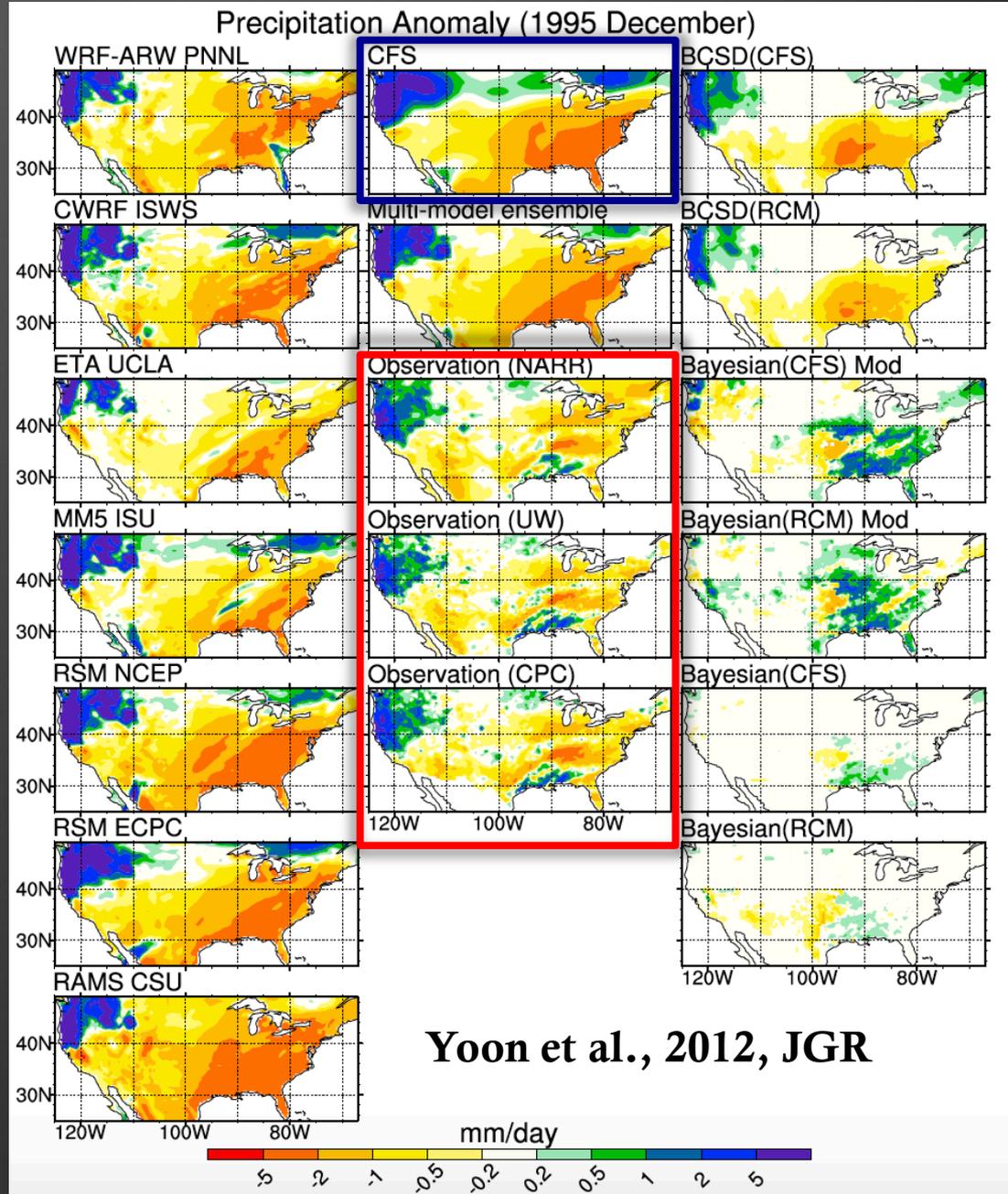


Statistical vs Dynamical Downscaling

- DD by the multiRCM produces finer-scale topographical features.
- However DD outputs suffer from inherent biases in both the global forecast model and the RCMs themselves.
- Statistical bias correction methods needs to be still applied to DD outputs.

Source of DD outputs:
MultiRCM Ensemble
Downscaling (MRED)
Project

Dynamical Downscaling (DD)

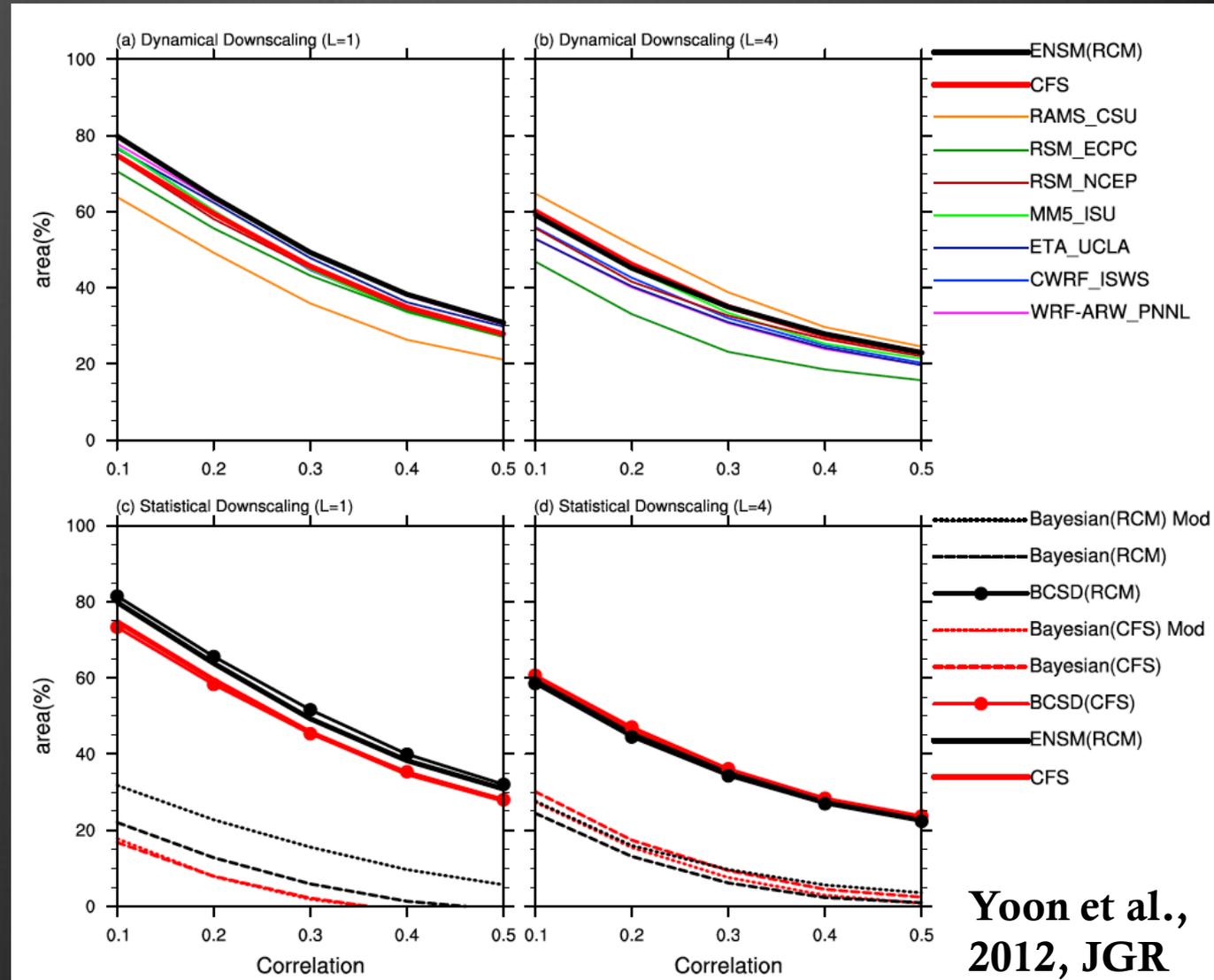


Yoon et al., 2012, JGR

Statistical Downscaling (SD)

Evaluation of downscaling approaches: Statistical vs Dynamical Downscaling

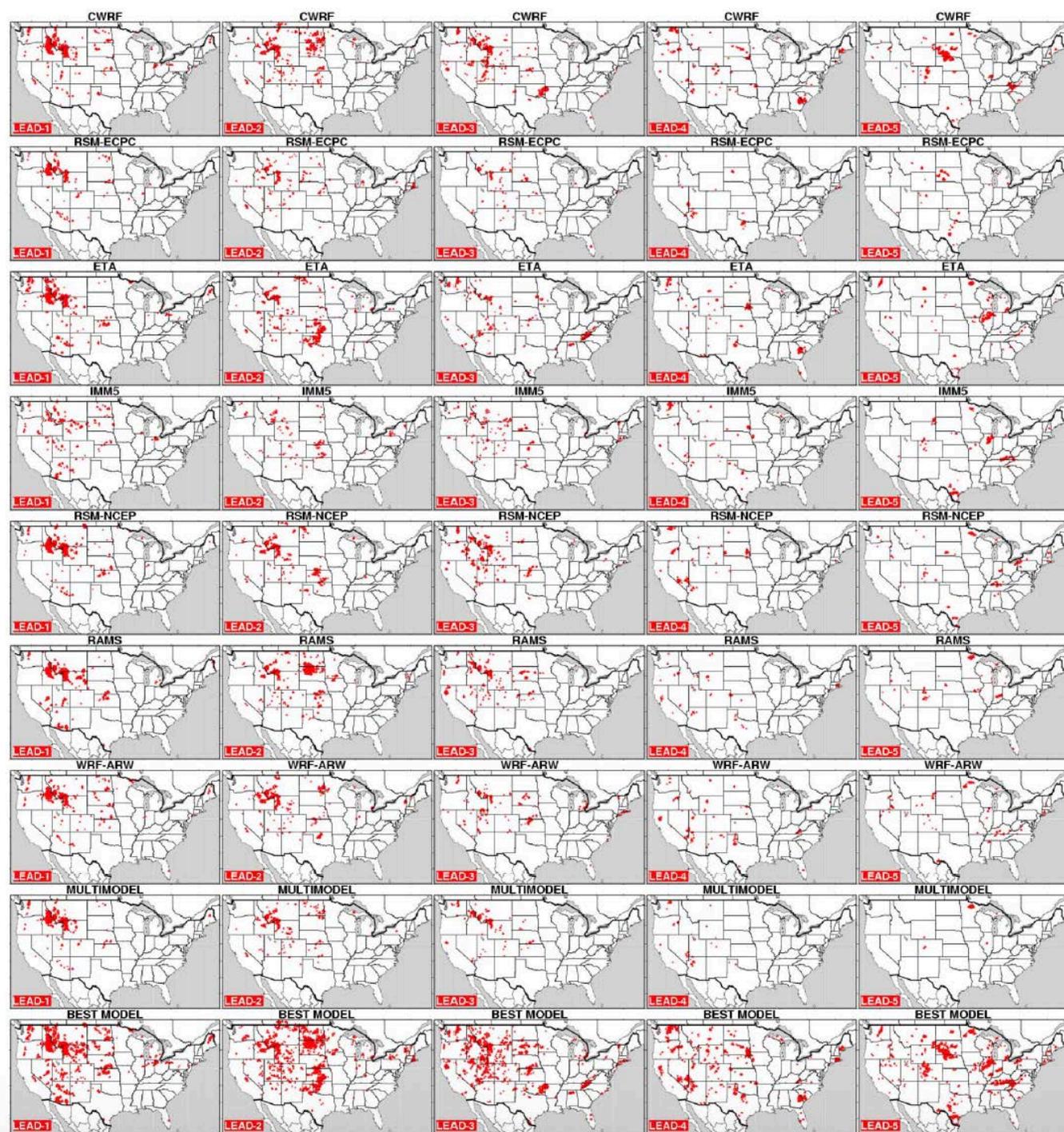
- Forecast skill of the downscaled P and T can vary for different metrics used in the cross validation.
- In terms of temporal AC, it is found that RCMs and statistical downscaling methods generally are somewhat higher than CFS.



Yoon et al.,
2012, JGR

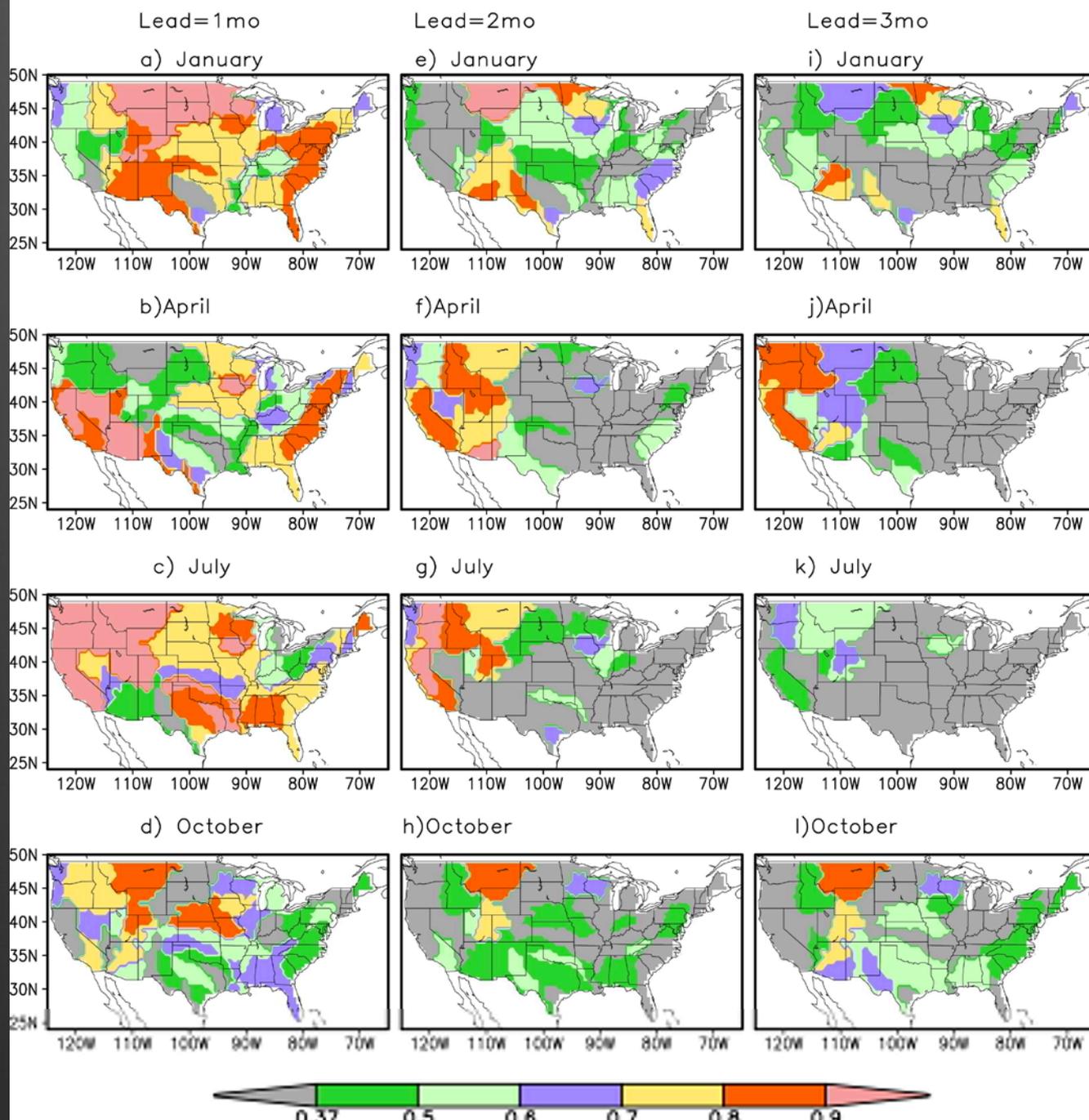
Alternative benchmark for precipitation forecast skill: Streamflow forecast-I

Red dot indicate improvement in runoff forecast by using DD relative to SD
downscaling of CFS climate forecast.



Shukla and
Lettenmaier, 2013,
JGR.

Alternative benchmark for precipitation forecast skill, Streamflow forecast-II



Correlation difference btw NMME and ESP

Runoff Lead=2mo

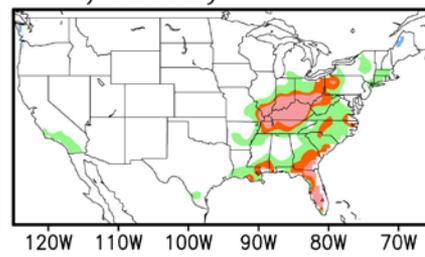
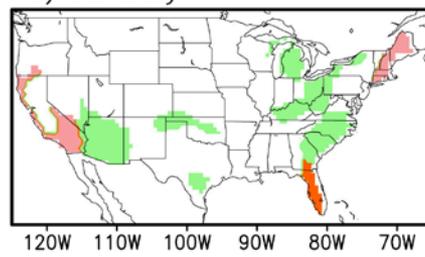
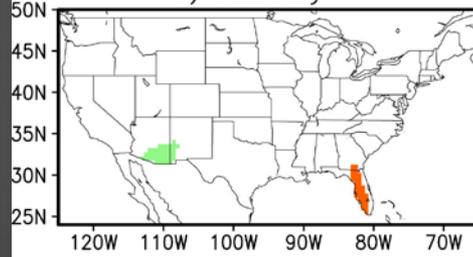
Runoff Lead=3mo

SM Lead=3mo

a) January

e) January

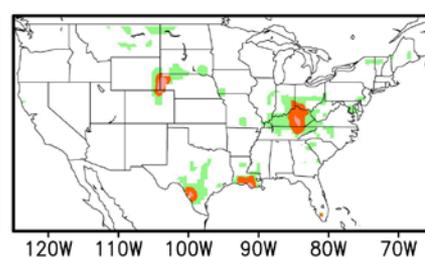
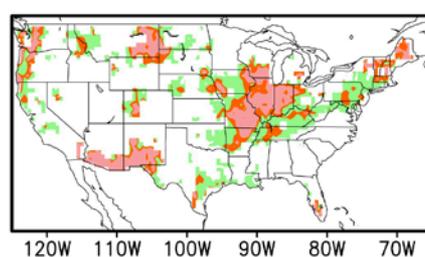
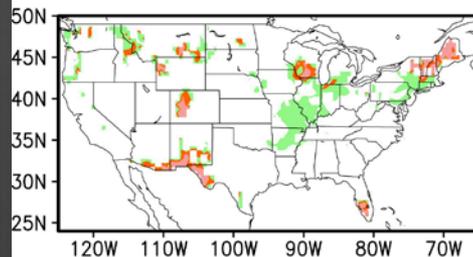
i) January



b) April

f) April

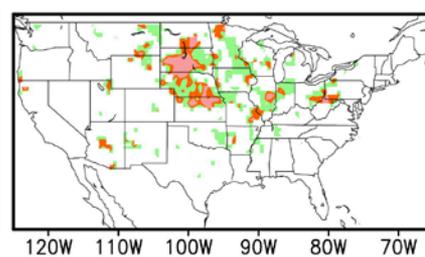
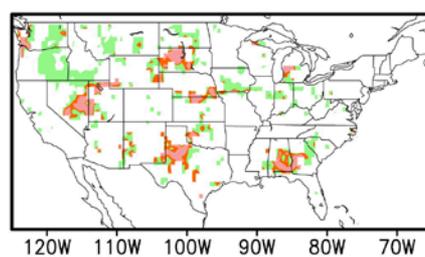
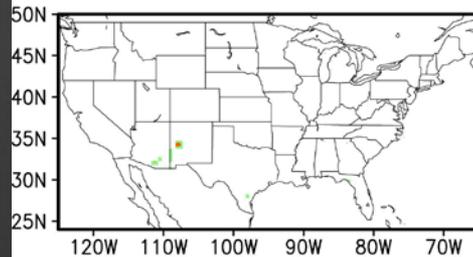
j) April



c) July

g) July

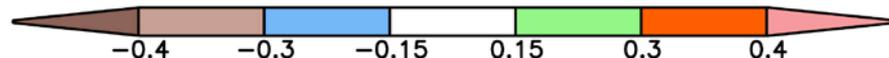
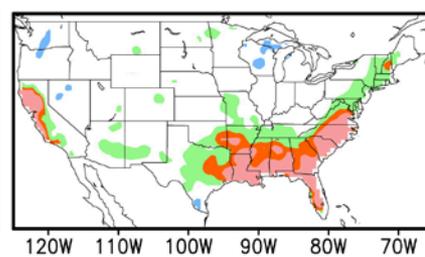
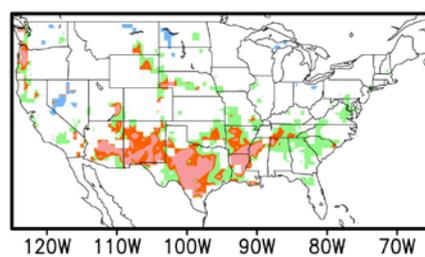
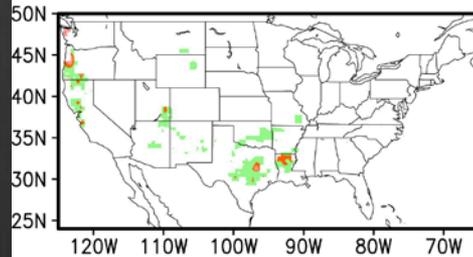
k) July



d) October

h) October

l) October



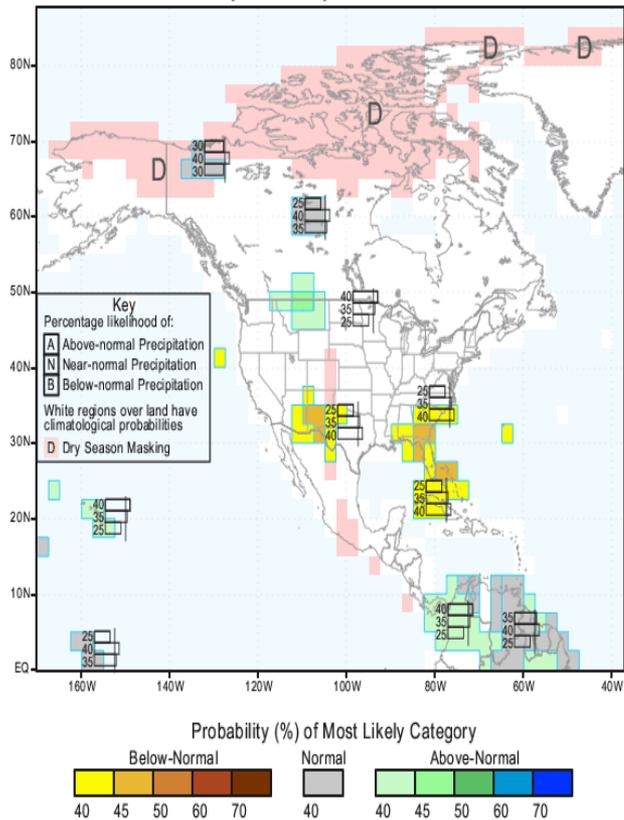
Streamflow forecasting can benefit most by improved precipitation forecast skill at longer lead time (> 1 month).

Verification of US Winter Precipitation Forecasts

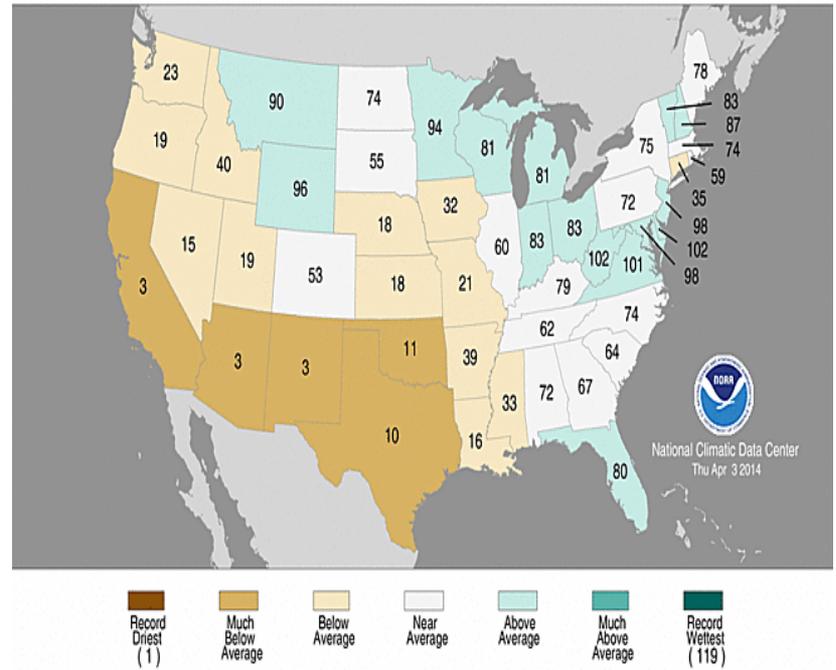
Jason Shafer
Lyndon State College

2013-14

IRI Multi-Model Probability Forecast for Precipitation
for December-January-February 2014, Issued November 2013

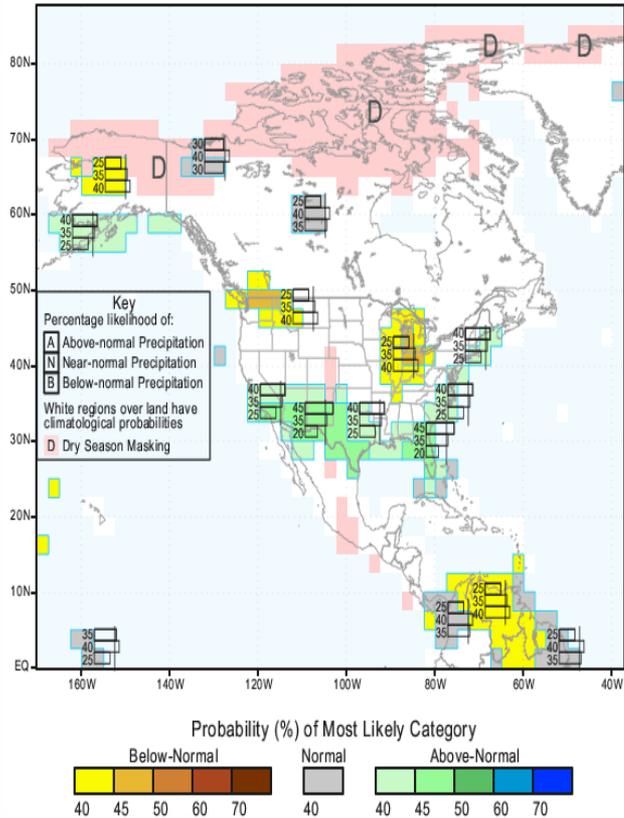


Statewide Precipitation Ranks
December 2013–February 2014
Period: 1895–2014



2014-15

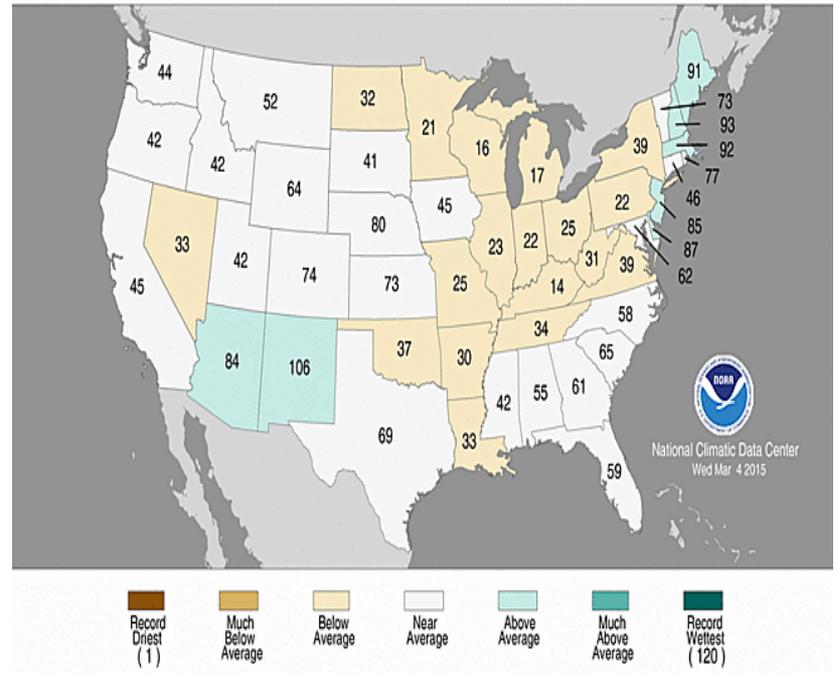
IRI Multi-Model Probability Forecast for Precipitation
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Statewide Precipitation Ranks

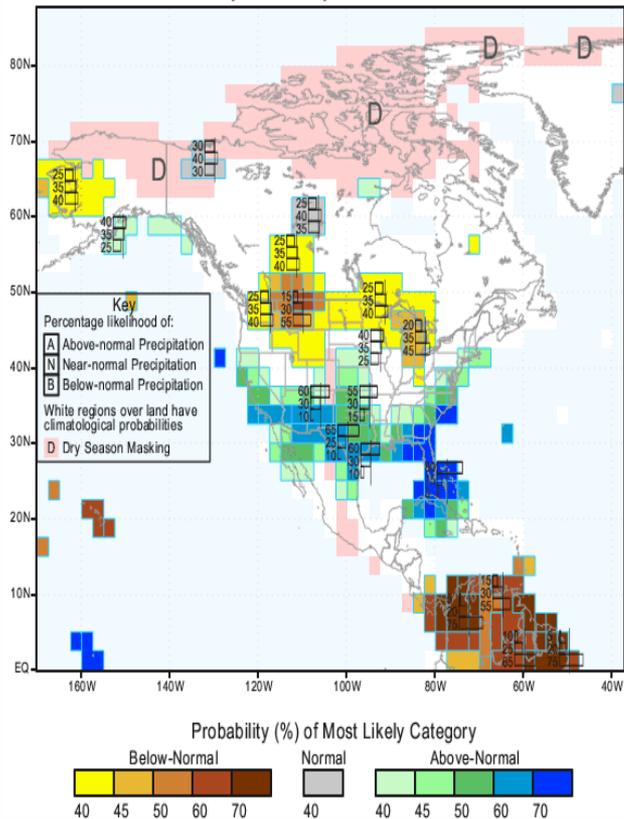
December 2014–February 2015

Period: 1895–2015



2015-16

IRI Multi-Model Probability Forecast for Precipitation
for December-January-February 2016, Issued November 2015



Statewide Precipitation Ranks
December 2015–February 2016
Period: 1895–2016

