Development of NOAA CPC Probabilistic Drought Outlooks

Application of Subseasonal and Seasonal Ensemble Forecasts

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What is drought?

- **Definition**
  - A period of abnormally dry weather sufficiently long enough to cause a shortage of water *(AMS Glossary)*

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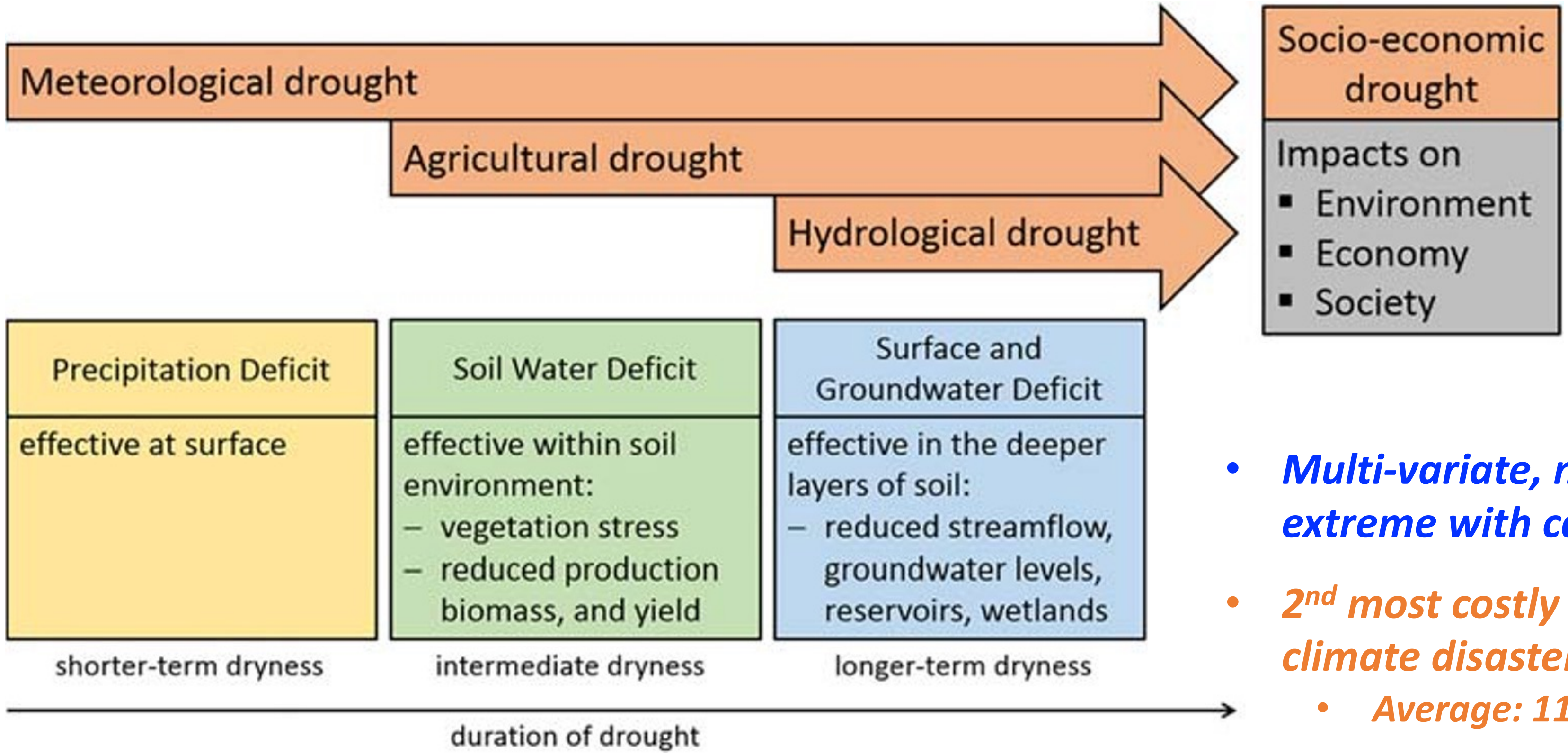
- **Types**

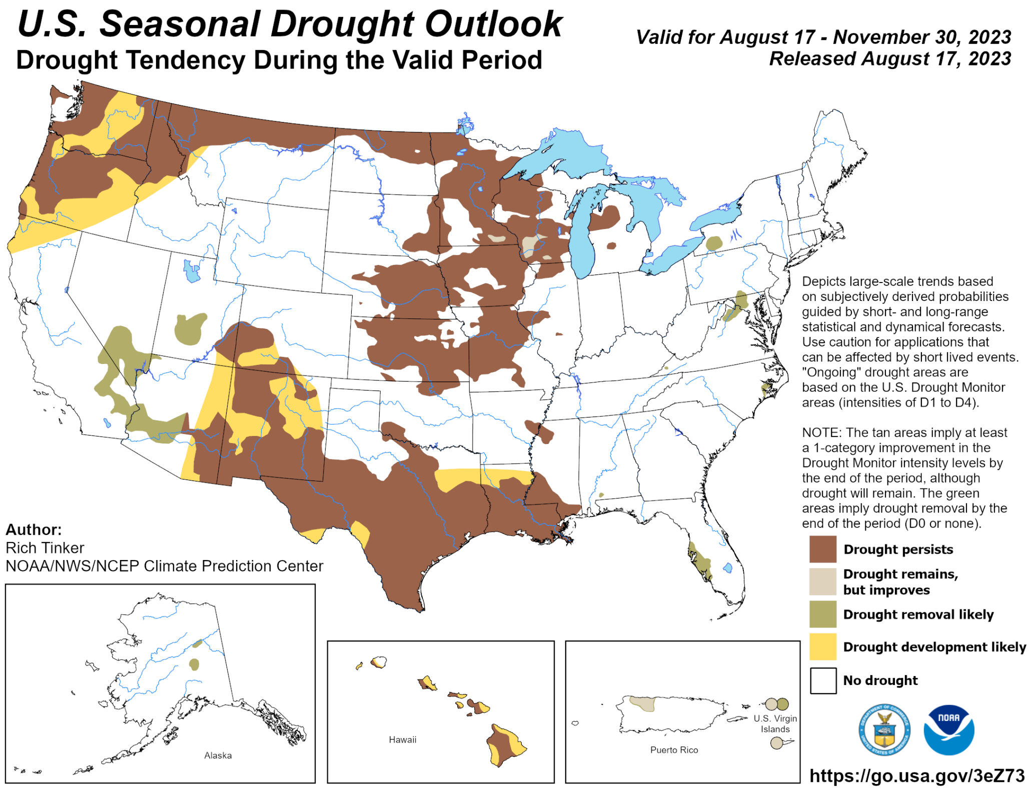


Crocetti et al. 2020

- ***Multi-variate, multi-faceted dry extreme with cascading impacts***
- ***2nd most costly weather and climate disaster in the U.S.***
  - ***Average: 11.2 billon/event***

NOAA CPC Operational Drought Outlooks

- Include monthly and seasonal drought outlooks
- Produced by integrating S2S forecasts, climatologies and analogs, and feedback from stakeholders, using the latest U.S. Drought Monitor as the initial state
- Show drought tendency for four drought categories
    - Development likely
    - Persist
    - Remain but improve
    - Remove likely
- Deterministic, subjective

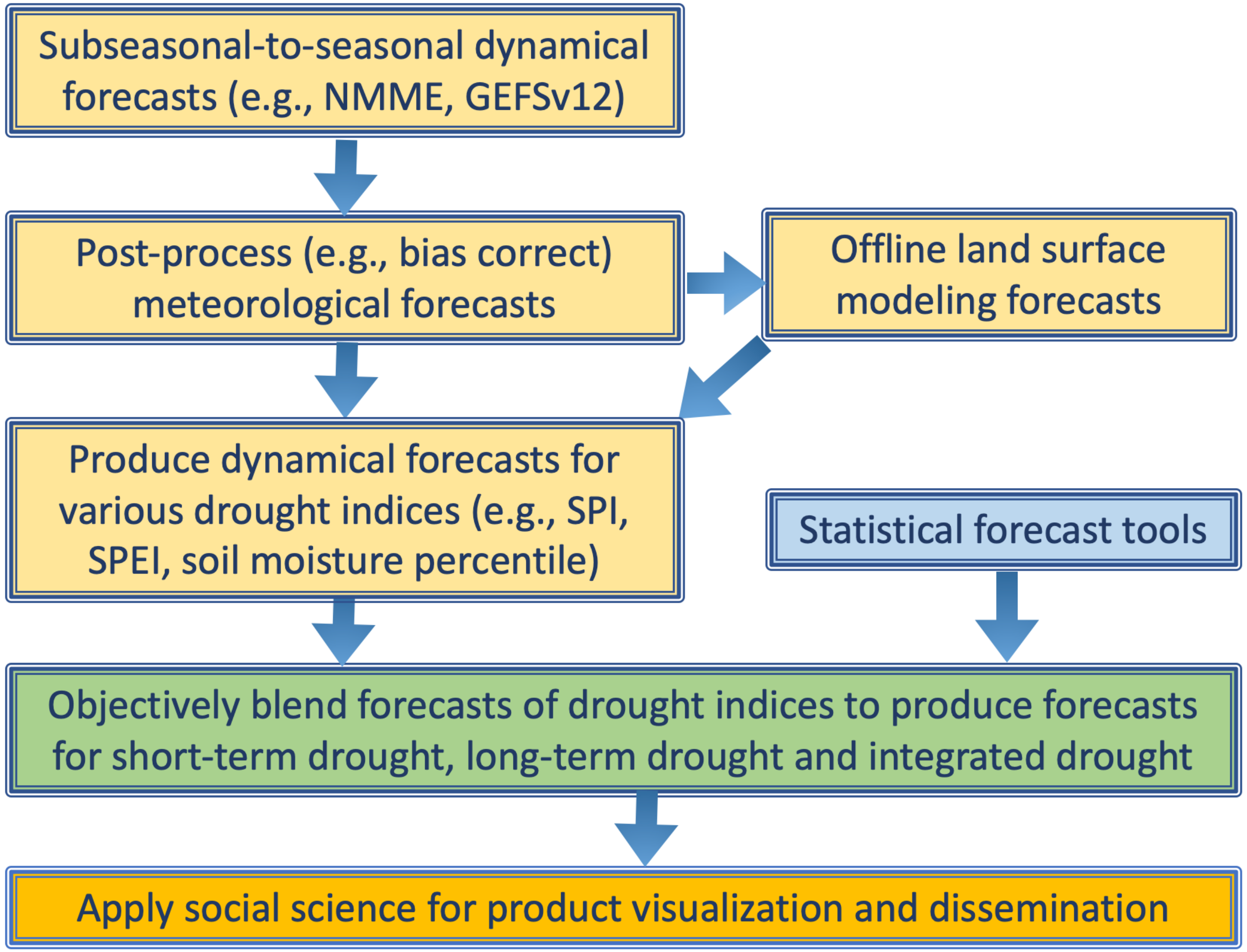


Development of CPC Probabilistic Drought Outlooks

- Address user needs for ***probabilistic*** and ***objective*** drought outlooks
- Complement CPC's deterministic monthly and seasonal drought outlooks

Development of CPC Probabilistic Drought Outlooks

- **Framework**



Sources of probability:

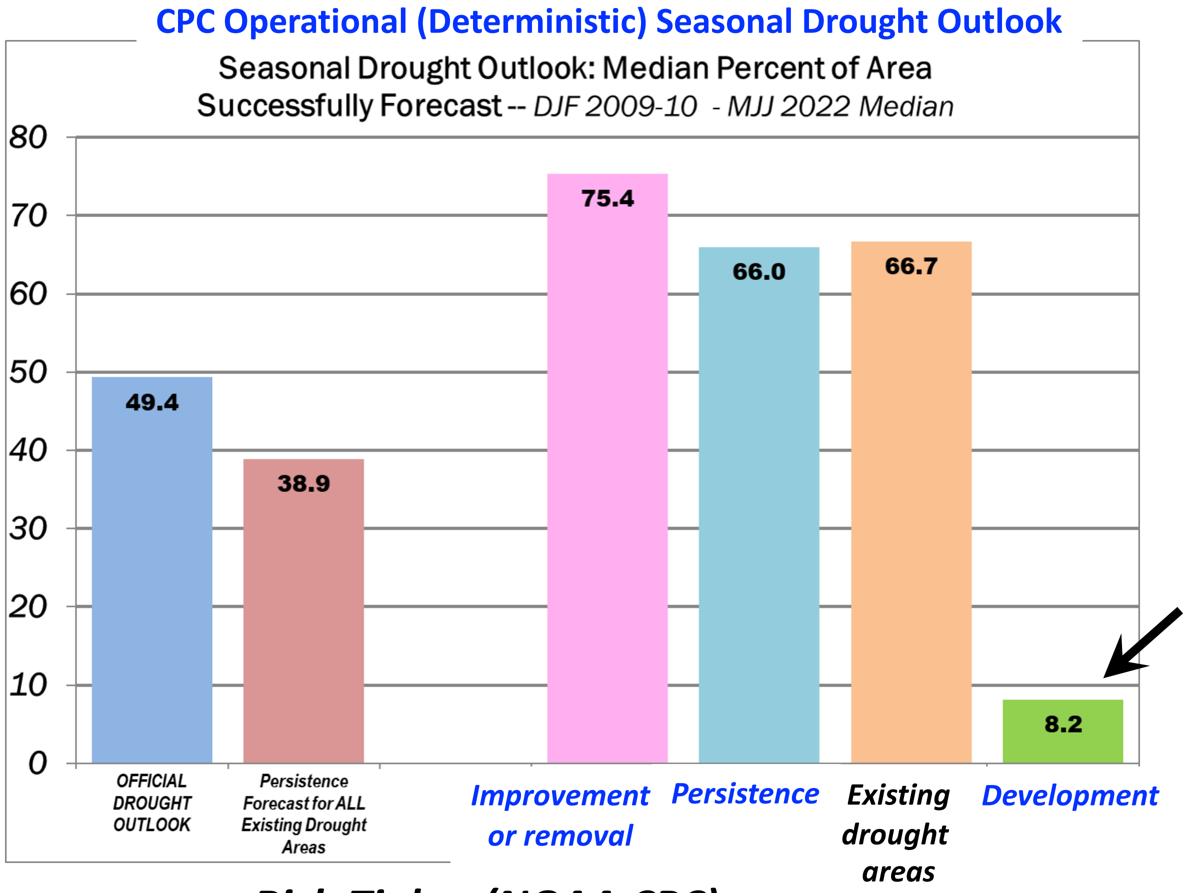
- Chaos of climate system
- Uncertainty of forecast tools

Development of CPC Probabilistic Drought Outlooks

- **Products**
  - Seasonal drought outlook (lead time: 2-6 months)
  - Monthly drought outlook (lead time: 1 month)
  - Flash drought outlook (lead time: 1-5 weeks)

Drought Prediction

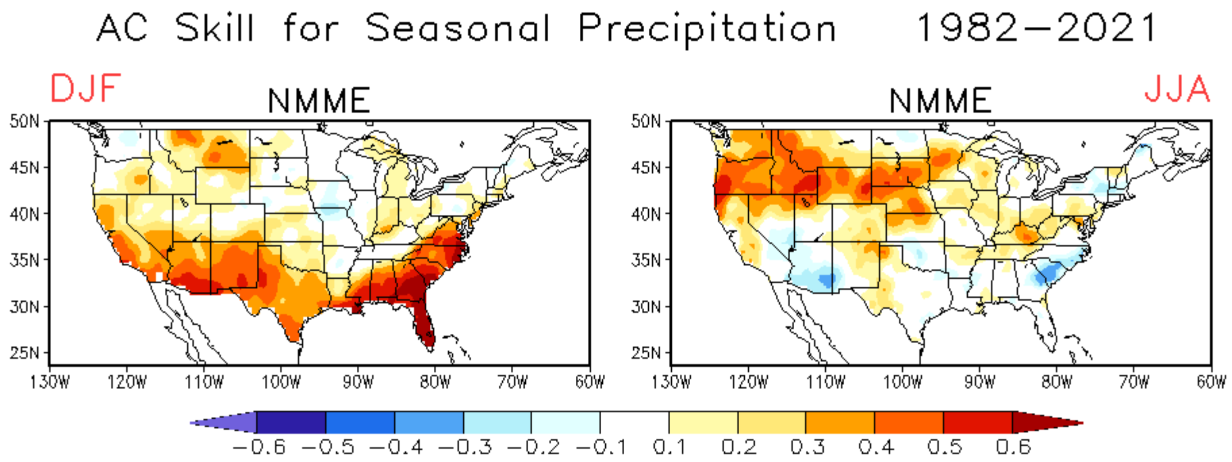
- **Skill influencing factors**
  1. Skill of meteorological drivers (e.g., precipitation, temperature)
  2. Accuracy of land initialization
  3. Seasonal cycle of precipitation climatology
- **Skill dependence on drought phase**
  - Development: ***lowest*** skill (1)
  - Persistence (2, 3)
  - Improvement (1, 2)
  - Removal (1, 2)



Rich Tinker (NOAA CPC)

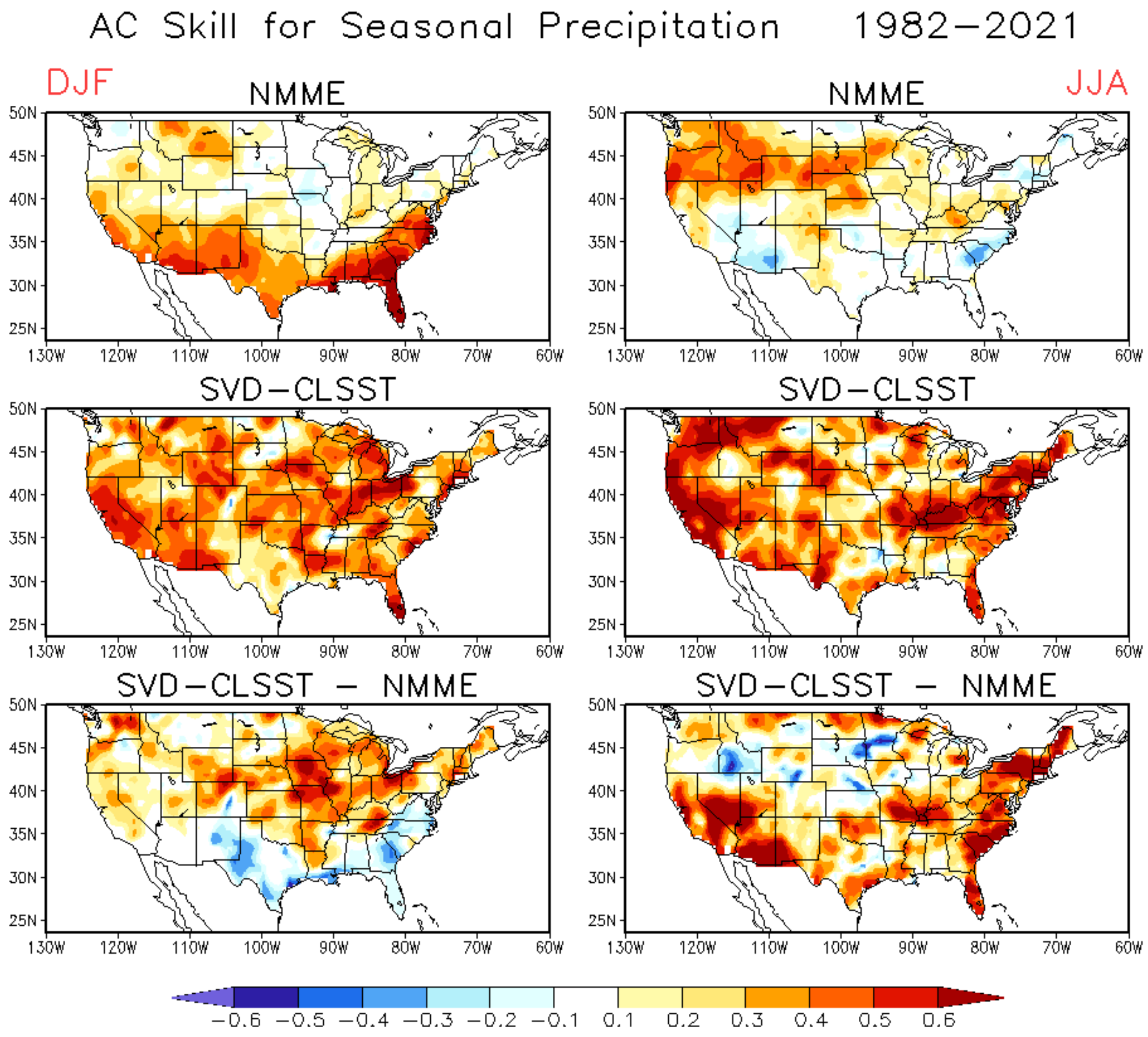
Skill Influencing Factors

1. **Skill of meteorological forecasts (e.g., precipitation, temperature)**
   - Determines the forecast skill for drought development, but is often limited in current dynamical forecast systems



Skill Influencing Factors

1. **Skill of meteorological forecasts (e.g., precipitation, temperature)**
   - To overcome the limited prediction skill in dynamical forecast systems, CPC develops/incorporates statistical prediction models.
   - *Example*: Statistical SVD-CLSST prediction model (Hui Wang/CPC)
     - Based on Switanek *et al*. (2020, CLSST model) and Wang *et al*. (1999, SVD-based forecast).
     - Built on the lag relationships between SST (30°S–60°N, 1–18-month leads) and seasonal P and T2m over CONUS.
     - Complements NMME for regions and seasons that NMME lacks skill.



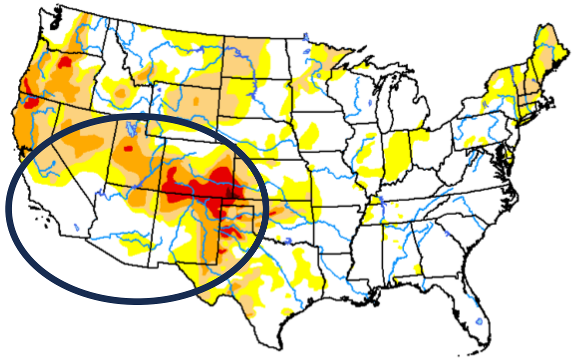
An Example: The 2020-21 Southwestern U.S. Drought

- The southwestern U.S. had a rapid drought development during July-October 2020, due to lack of monsoon rainfall and excessive heat waves.

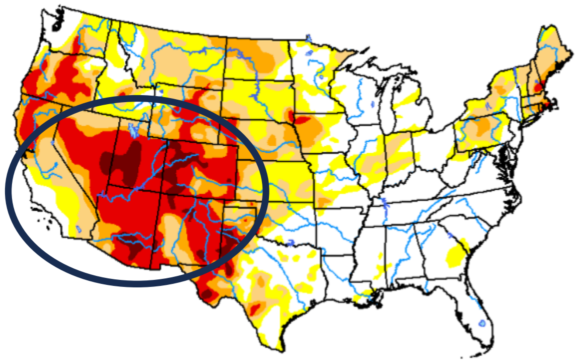
- **Question**: How well can we forecast the drought development?

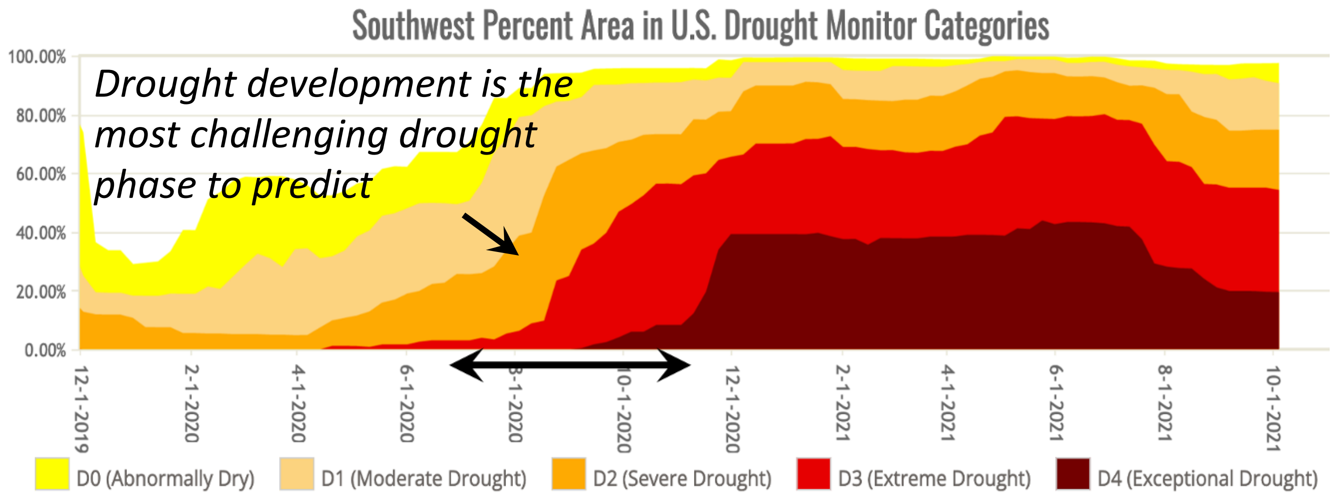
U.S. Drought Monitor

6/30/2020



10/27/2020



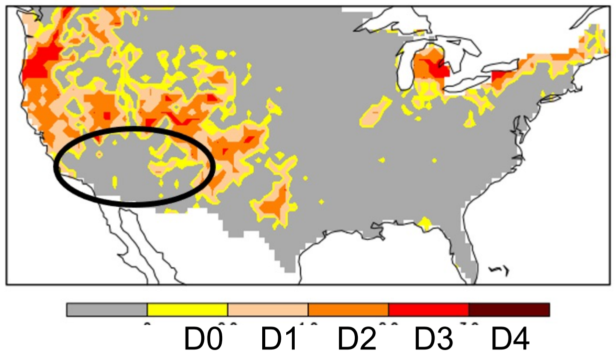


The 2020-21 Southwestern U.S. Drought *Development*

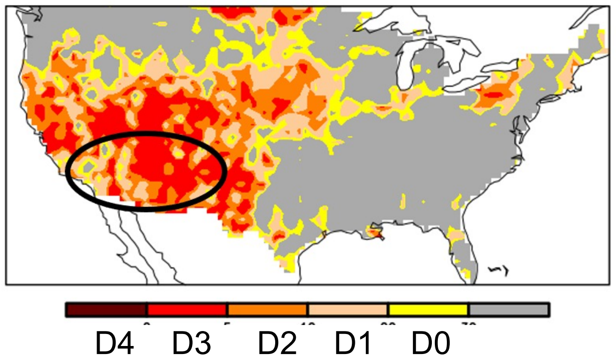
Probabilistic Drought Forecast **Objective Drought Monitor**

Initial Condition: 1Jul2020; **Short-term Drought Forecast** for Oct2020

Ensemble Average



Observation



- **NMME GFDL SPEAR Hindcasts**
  - 15 ensemble members; 1991-2020
- ***Short-term*** drought blend
  - Equal-weighted average of ***SPI3***, ***SMP*** and ***SRI3*** in percentiles
- Ensemble average
  - Equal-weighted average of short-term blend in percentiles across the 15 ensemble members

At 3-month lead time:

- The ensemble average can capture the drought development in much of the W US but not AZ and NM.

The 2020-21 Southwestern U.S. Drought *Development*

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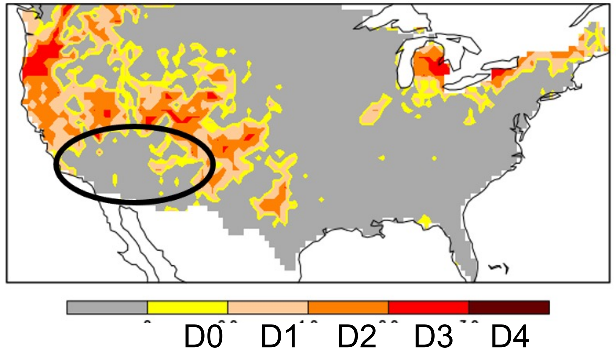

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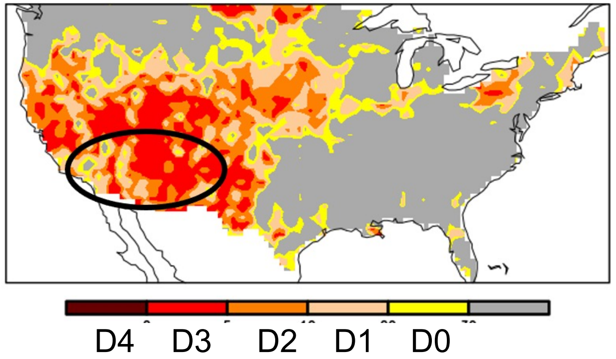

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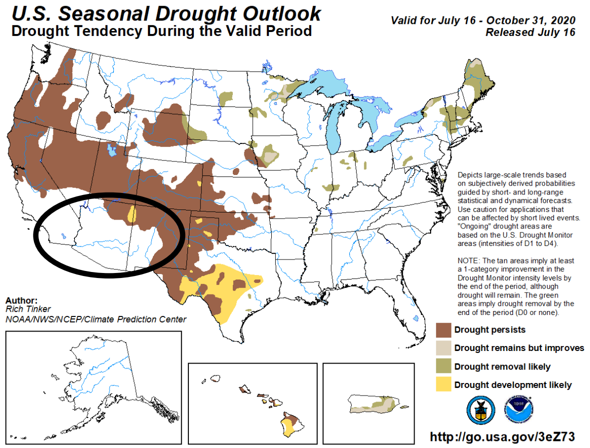
CPC (Deterministic) Seasonal Drought Outlook



U.S. Drought Monitor

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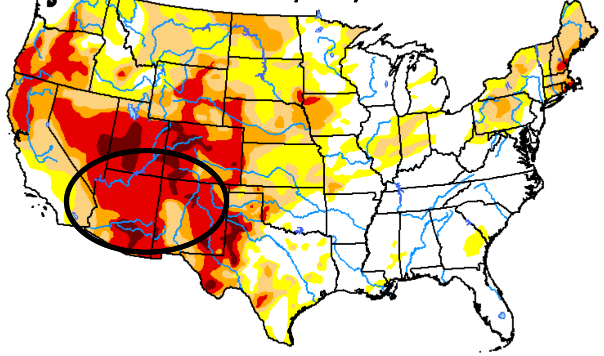


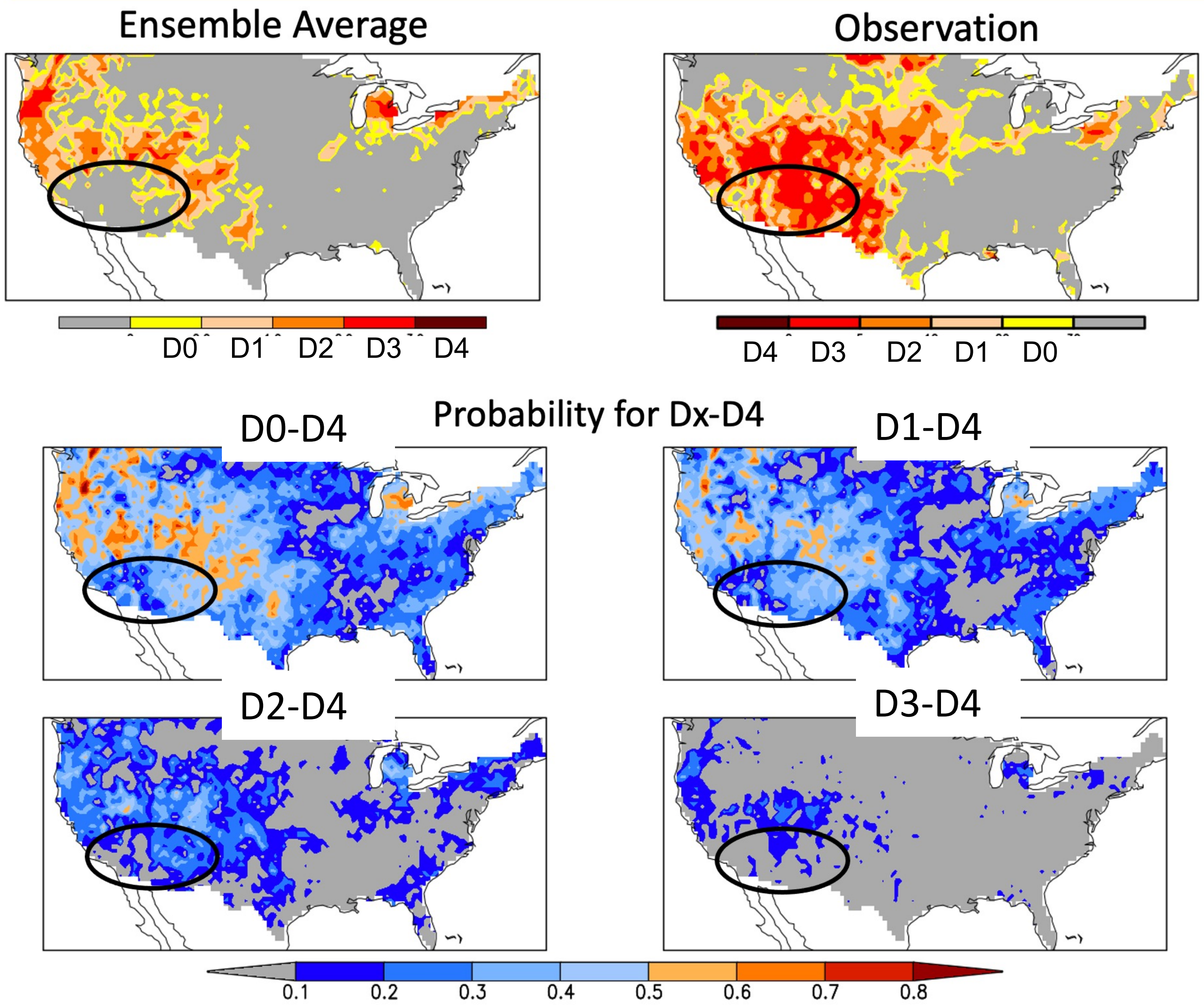
At 3-month lead time:

- The ensemble average can capture the drought development in much of the W US but not AZ and NM, which is similar seen in CPC's operational deterministic Seasonal Drought Outlook (SDO).

The 2020-21 Southwestern U.S. Drought *Development*

Probabilistic Drought Forecast **Objective Drought Monitor**

Initial Condition: 1Jul2020; **Short-term Drought Forecast** for Oct2020



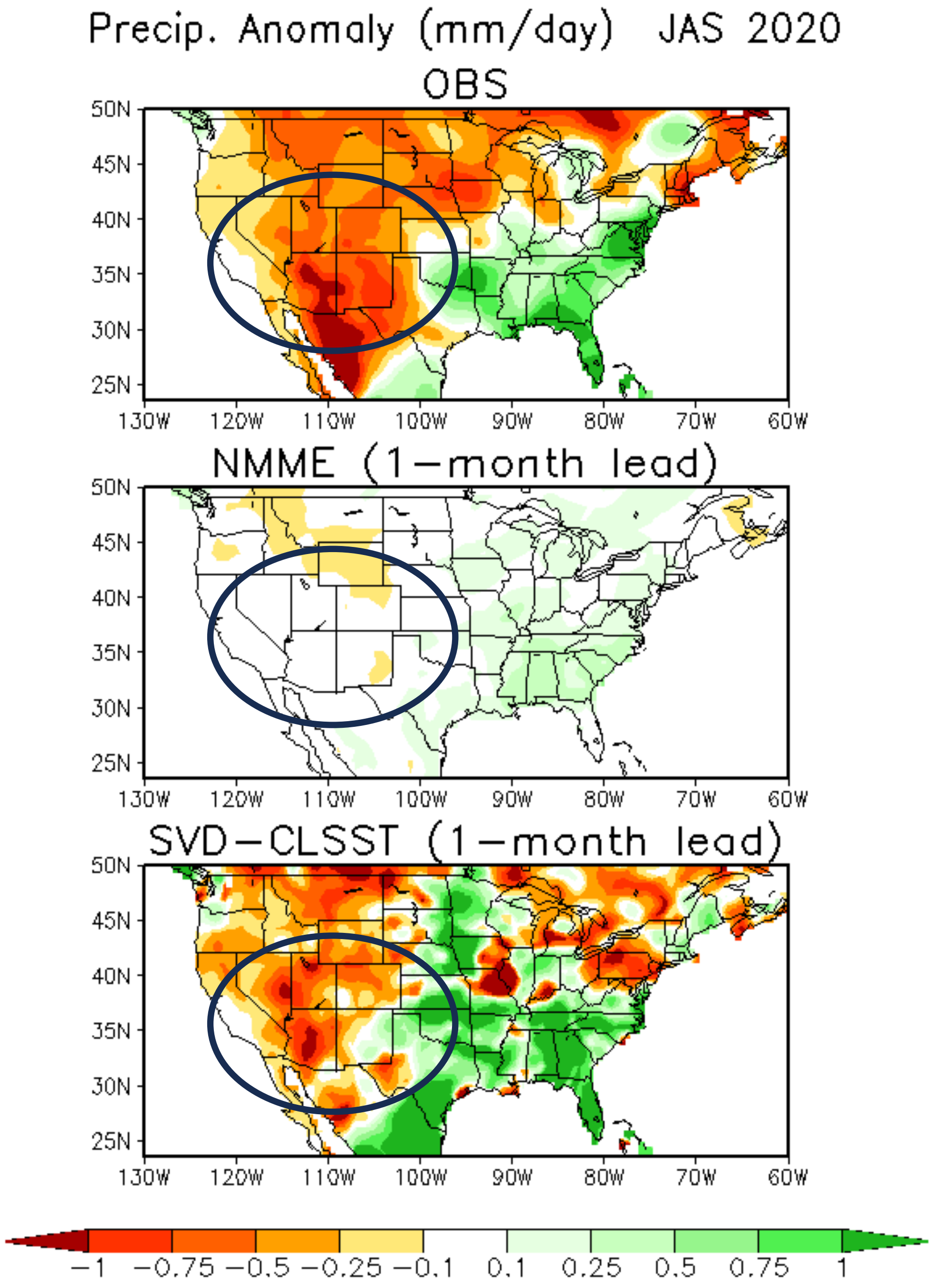
- **NMME GFDL SPEAR Hindcasts**
  - 15 ensemble members; 1991-2020
- ***Short-term*** drought blend
  - Equal-weighted average of ***SPI3***, ***SMP*** and ***SRI3*** in percentiles
- Ensemble average
  - Equal-weighted average of short-term blend in percentiles across the 15 ensemble members
- **Probability**: Percentage of the 15 GFDL SPEAR blended hindcasts that fall in each of the Dx and above categories.

At 3-month lead time:

- The ensemble average can capture the drought development in much of the W US except AZ and NM.
- The probability of predicting the observed drought development in AZ and NM is weak but not zero.

- The JAS2020 precipitation deficit is
  - not predicted by NMME,
  - but well captured by the SVD-CLSST.

- Work is under way to incorporate the SVD-CLSST in the drought outlook development.



Skill Influencing Factors

2. Accuracy of land initialization

- Land initial anomalies can serve as a significant source of S2S drought predictability.

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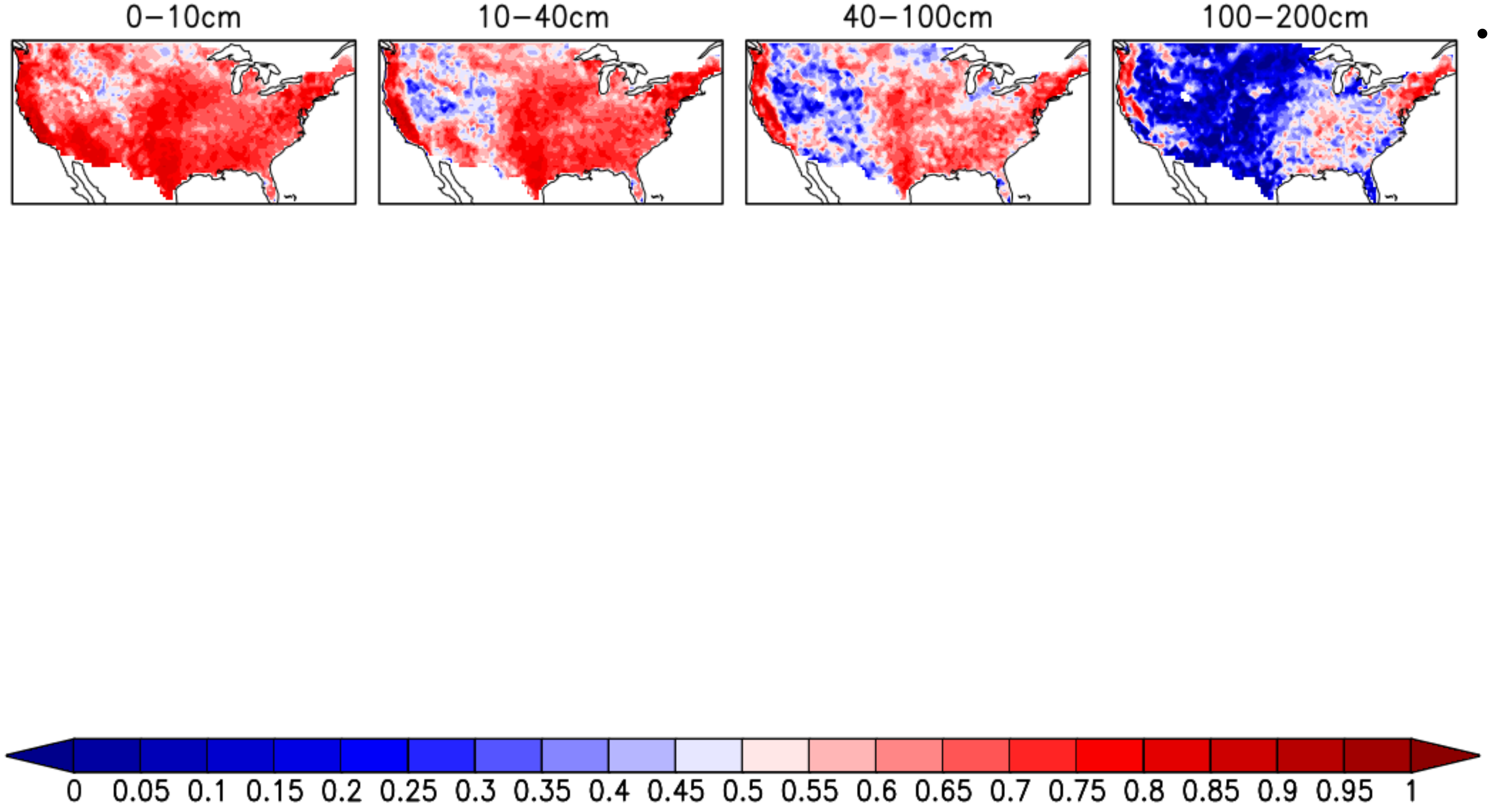
- Land initial anomalies can serve as a significant source of S2S drought predictability.
- We evaluate the accuracy of land initialization in forecast systems, and when necessary, produce land surface forecasts by driving land surface models offline with (post-processed) meteorological forecasts and more accurate land initial conditions.
    - ***Example*: NOAA GEFSv12 forecasts**
        - *Observational reference*: a Noah land analysis (1980-present) produced by driving the EMC Noah with NLDAS-2 atmospheric forcings
        - *Evaluation metric*: Anomaly Correlation Coefficient (ACC)
    - ***Acknowledgment***: Mike Barlage and Helin Wei (NOAA/EMC) provided the EMC Noah and Noah-MP land surface models and consultations.

Skill Influencing Factors

2. Accuracy of land initialization

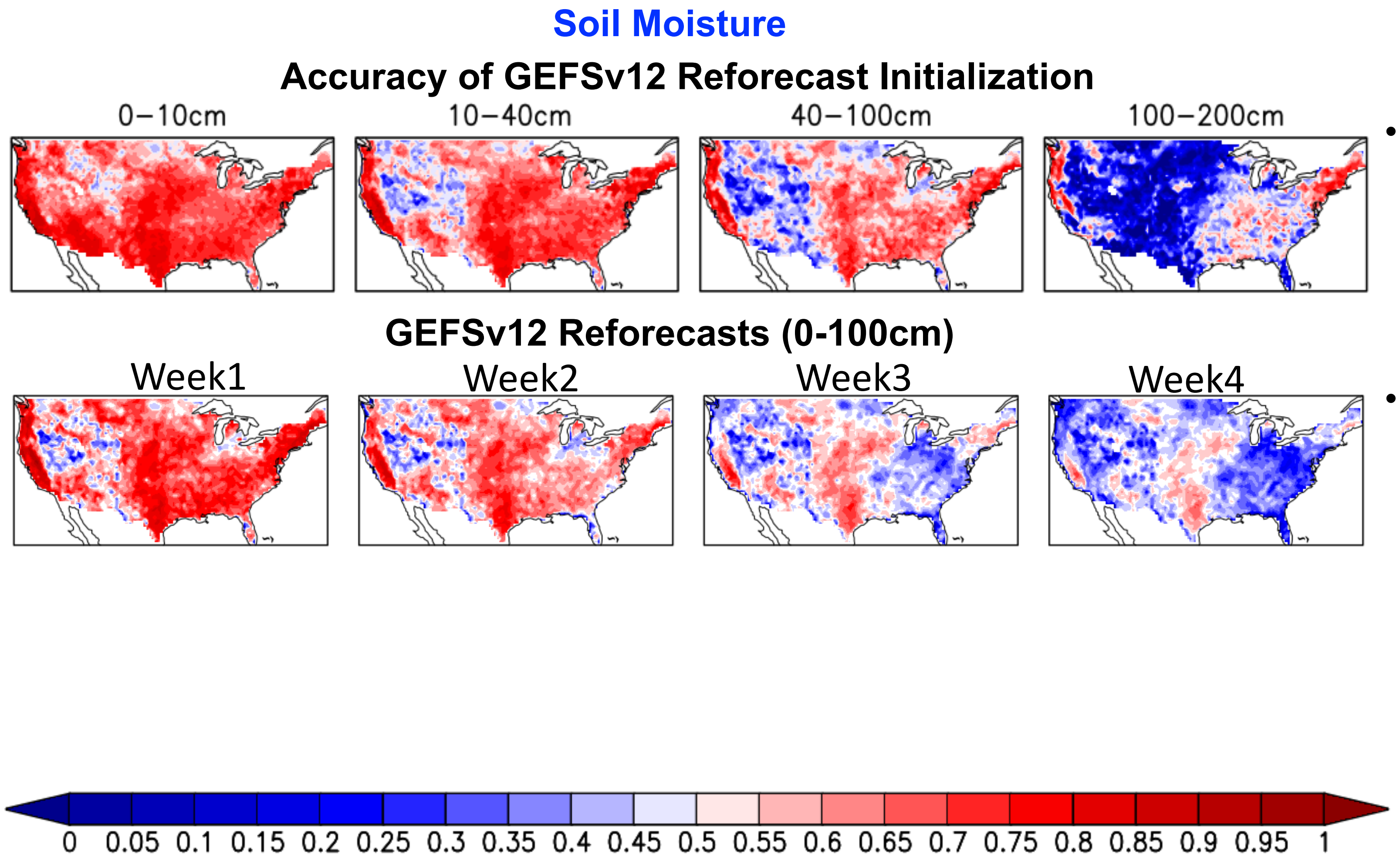
Soil Moisture



- GEFSv12 initial soil moisture shows relatively low accuracy in western interior U.S. and deep soil layers, due to i) precipitation forcing bias in the GEFSv12 reanalysis, and ii) insufficient land surface spin-up in the GEFSv12 reanalysis streams (not shown).

Skill Influencing Factors

2. Accuracy of land initialization



- GEFSv12 initial soil moisture shows relatively low accuracy in western interior U.S. and deep soil layers.
- GEFSv12 forecast skill is strongly influenced by the accuracy of soil moisture initial conditions.

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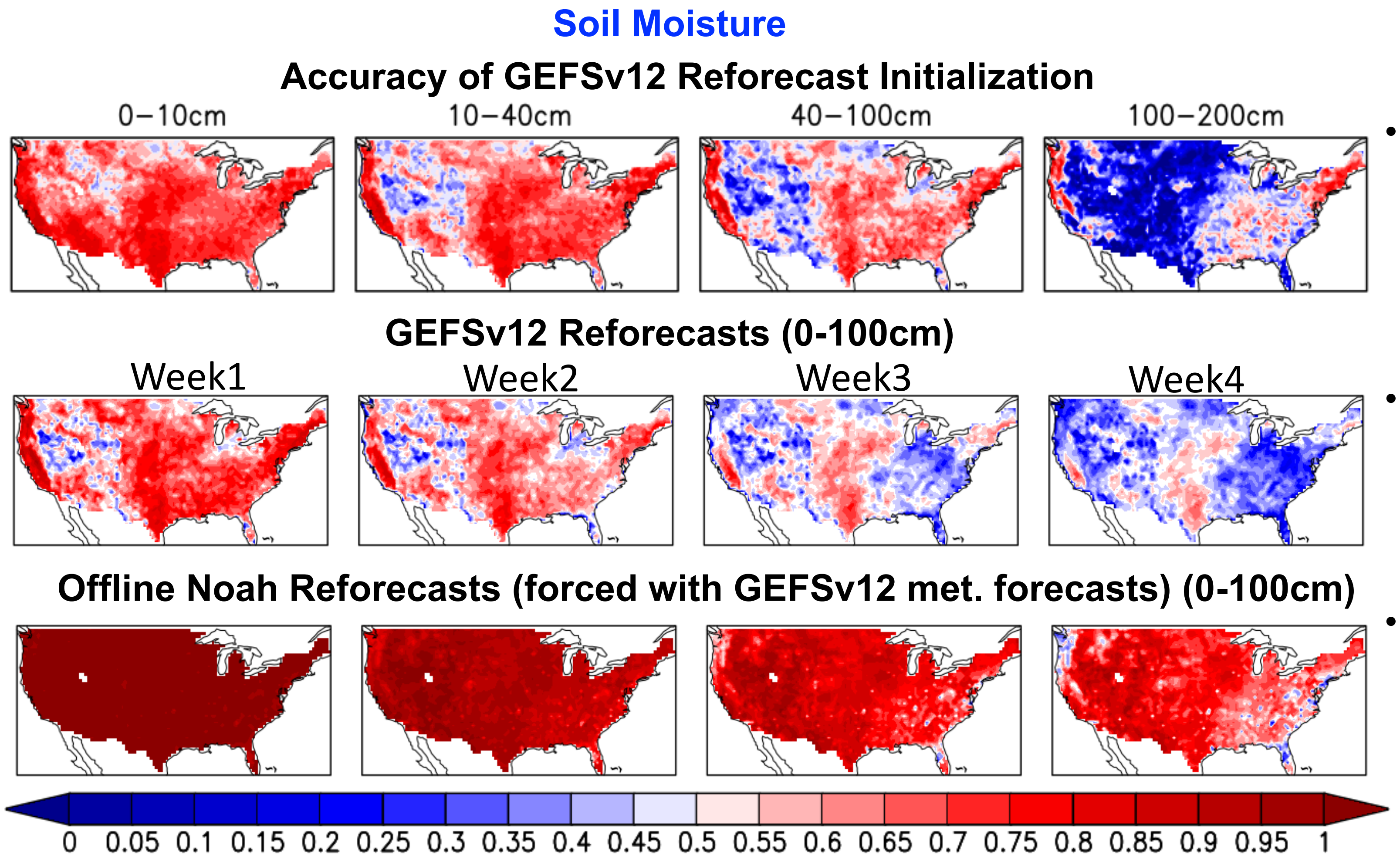

- GEFSv12 initial soil moisture shows relatively low accuracy in western interior U.S. and deep soil layers.
- GEFSv12 forecast skill is strongly influenced by the accuracy of soil moisture initial conditions.
- CPC produces offline Noah land surface forecasts, initialized using the Noah land analysis, which substantially improves the forecasts.

Skill Influencing Factors

2. Accuracy of land initialization

- Land initial anomalies can serve as a significant source of S2S drought predictability.
- The ***offline land surface modeling approach*** allows us to
  - utilize accurate land initial conditions
  - incorporate improved meteorological forecasts via post-processing
  - use more advanced land surface models (e.g., Noah-MP HR1 vs. GEFSv12 Noah)
  - produce forecasts for land surface variables that are needed for producing agricultural and hydrological drought forecasts but are not made publicly available from operational modeling centers (e.g., evapotranspiration, PET)

Summary

- NOAA CPC is developing probabilistic and objective drought outlooks, which consist of seasonal drought outlook, monthly drought outlook and flash drought outlook.
- The probabilistic drought outlooks use S2S dynamical model forecasts (e.g., GEFSv12, NMME) as a key input, with the forecast probability built on forecast ensemble spread and uncertainties of forecast tools.
- The product development involves extensive evaluations of dynamical model forecasts for drought indices, based on which we develop methods to improve drought forecasts.
  - The SVD-CLSST statistical prediction model is developed, to complement dynamical model forecasts.
  - Land surface forecasts are produced by driving land surface models offline with more accurate land initial conditions, postprocessed meteorological forecasts, and advanced land surface models.

Drought Forecasts: Needs

1. **Improved dynamical model forecasts, particularly for precipitation**
   - Improve dynamical model forecasting systems, to properly capture sources of S2S drought predictability
     - Reduce model biases (e.g., atmosphere-ocean-land coupling, convection, jet streams)
     - Improve accuracy of land initialization
   - Improve land surface model processes for drought impact prediction
     - *Example*: Realistic representation of ***dynamic vegetation*** for prediction of vegetation
2. **Improved protocols**
   - Consistent initialization dates
   - More frequent forecasts (e.g., daily or >=2 per week) – *for flash drought prediction*
   - More ensemble members (>=10)
   - More drought-related variables (e.g., land surface variables, PET)