The 20th Century Reanalysis (20CR): Capturing 200 years of weather using surface observations

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SYNOPTIC WEATHER MAP
NORTHERN HEMISPHERE
SEA LEVEL 1300 GMT
AUG 16 1915

CIRES

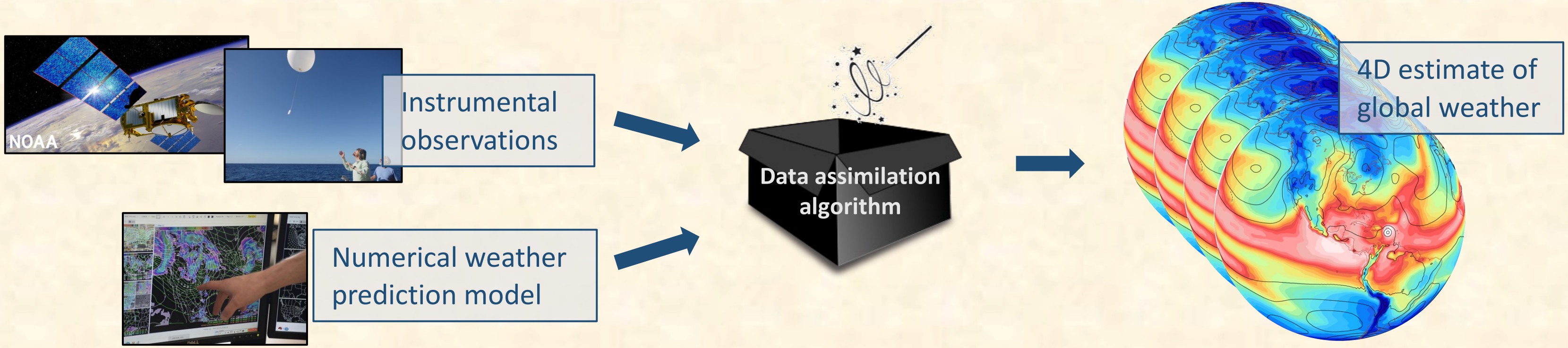
NOAA
NATIONAL OCEANIC AND ATMOSPHERIC ADMINISTRATION
U.S. DEPARTMENT OF COMMERCE

Outline

- Reanalysis fundamentals
- Full input vs sparse input reanalysis
- 20CRv3: methods
- 20CRv3: performance
- Outlook: possibilities for 20CRv4

Reanalysis fundamentals

- Reanalyses provide a consistent, gridded record of weather & climate by assimilating historical observations into a modern weather forecast model (“re-analyzing” the data.)
- To achieve consistency, a single forecast model and single data assimilation method are fixed.
  - To some degree, the observing network may also be fixed.



Full input vs sparse input reanalysis

- **Full input**
  - ERA-interim, ERA5, MERRA, MERRA2
  - Assimilate most observations that are available *(in-situ, satellite, upper-air, aircraft)*
  - Cover latter half of 20th century to avoid spurious trends and signals arising from significant changes in the observing system
  - …Can still be impacted by instruments coming online
- **Sparse input**
  - 20th Century Reanalysis, CERA-20C
  - Assimilate only surface observations (surface pressure, optionally marine winds)
  - Extend 100+ years into the past
  - Less impact from changes in observing network

Image provided by the NOAA-ESRL Physical Sciences Laboratory from their website at https://psl.noaa.gov/data/writ

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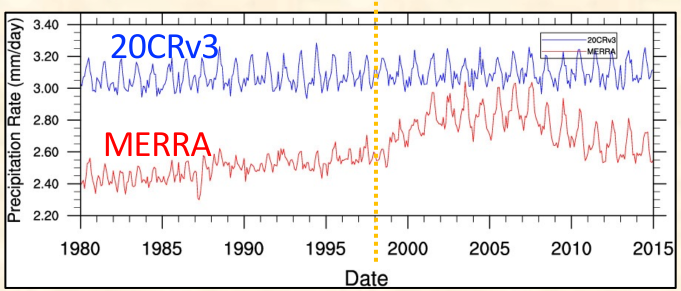
Monthly mean global precipitation



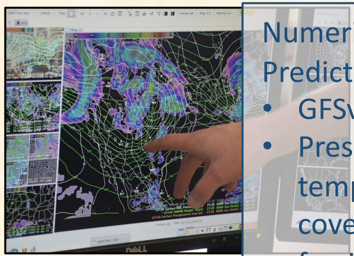
Example: spurious trend in global precipitation from observing network change

- MERRA: model may have dry bias that was corrected by water vapor sensitive radiances from AMSU, which came online in 1998
- 20CRv3 does not assimilate any radiances, therefore does not exhibit this discontinuity

Image provided by the NOAA-ESRL Physical Sciences Laboratory from their website at https://psl.noaa.gov/data/writ

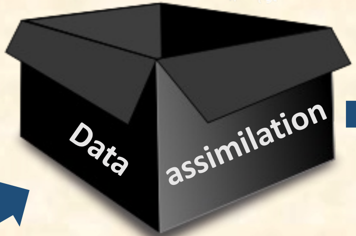
20th Century Reanalysis (20CR)

Only surface pressure observations are assimilated *(other obs necessary for SSTs, ice)*



Numerical Weather Prediction model:

- GFSv14, ~0.75deg
- Prescribed sea surface temperature (SST), ice coverage, and radiative forcings

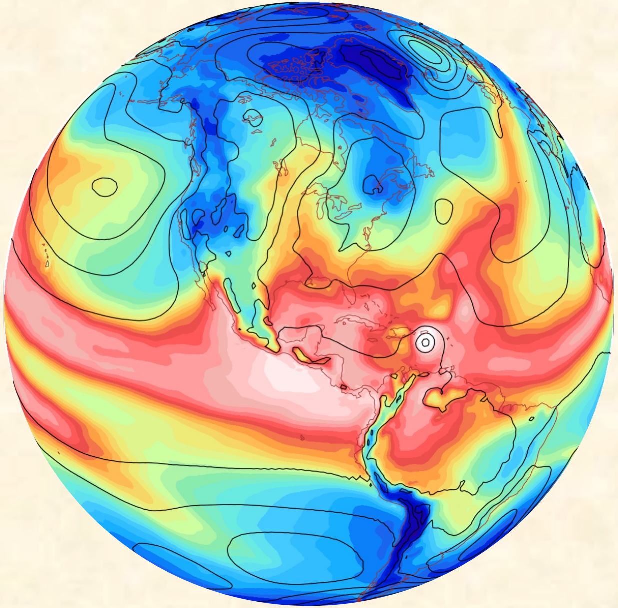


Ensemble Kalman Filter with 80 ensemble members.

➢ EnKF can dynamically move sparse information around via covariances.

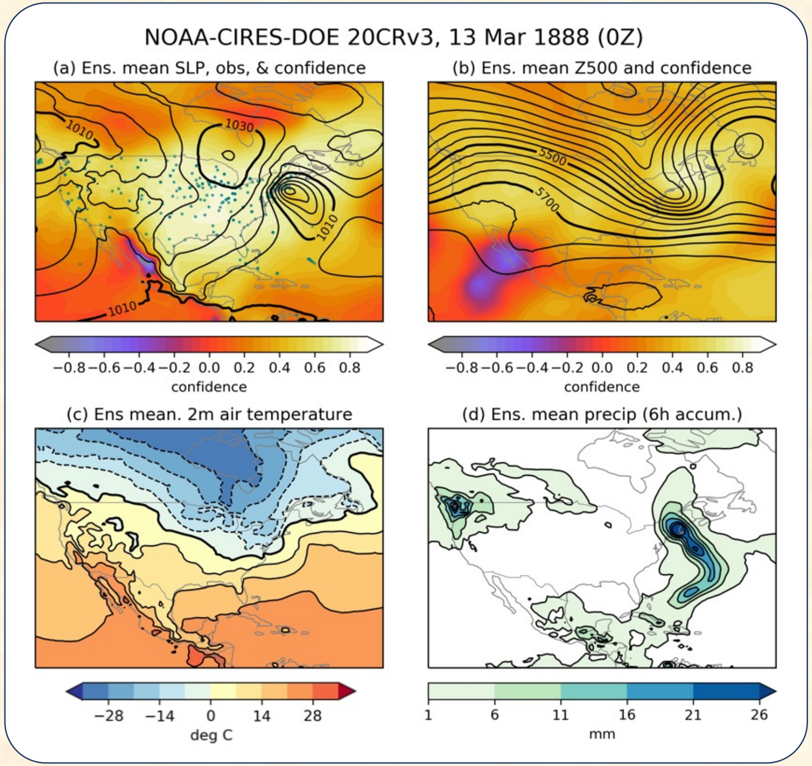
200 years of weather (1806-2015):

20th Century Reanalysis Version 3



The 20th Century Reanalysis (20CR) provides a global, 200-year history of sub-daily weather

by assimilating *only* surface pressure observations into a modern weather model



NOAA-CIRES-DOE 20th Century Reanalysis Version 3

- Estimates temperature, wind, precipitation, pressure, humidity, & other variables, from the ground to the top of the atmosphere
- Prescribed sea surface temperature *(quasi-weakly coupled)*, sea ice concentration, and radiative forcing
- Global 75km grid
- 3-hourly resolution
- Spans 1836-2015 [1806-1835 experimental]
- Data assimilation: Ensemble Kalman Filter with 80 ensemble members to quantify uncertainty

- Publicly available: https://go.usa.gov/XTd

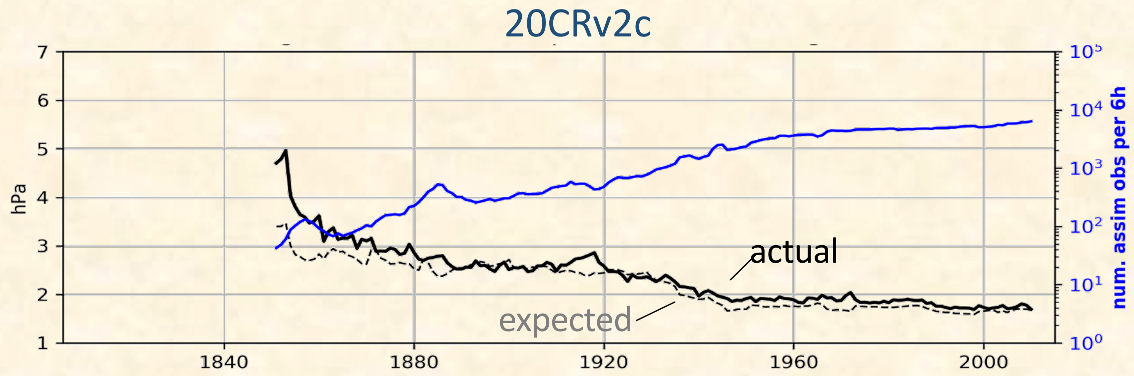
20th Century Reanalysis version 3 (20CRv3)
System improvements over 20CRv2c

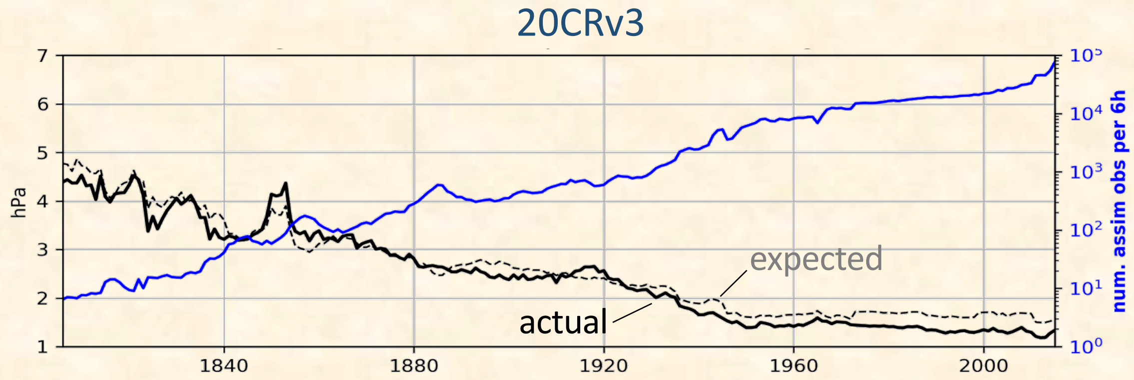
- Newer, higher-resolution forecast model
- Larger available set of observations to be assimilated
- Improved observation quality control methods
- Improved DA methods (4D incremental analysis update, adaptive localization, adaptive inflation)
  - ➢Improved confidence estimates

Slivinski, L.C., et. al. (2019) Towards a more reliable historical reanalysis: Improvements for version 3 of the Twentieth Century Reanalysis system. *Quarterly Journal of the Royal Meteorological Society,* **145**: 2876– 2908. https://doi.org/10.1002/qj.3598

20CRv3 outperforms 20CRv2c:
fit to surface pressure obs

Global annual first-guess root mean squared errors in surface pressure



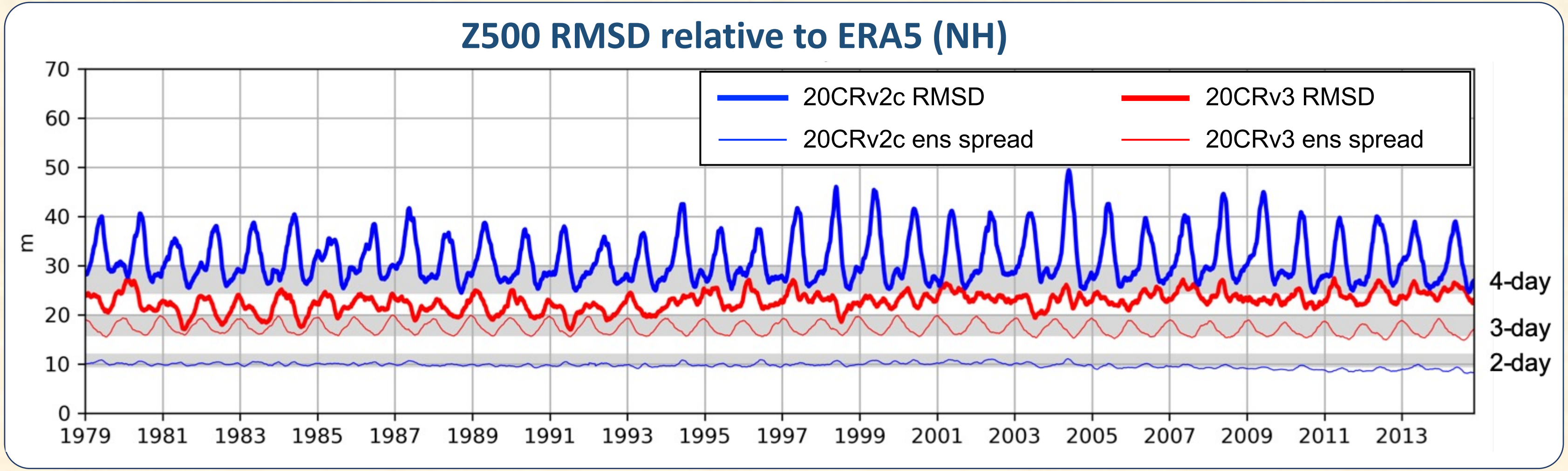


***Actual* error** is the difference between 6-hour forecasts and not-yet-assimilated observations: $\langle (ob - fg)^2 \rangle^{1/2}$

***Expected* error** is the root-mean of the sum of ob error variance and background ensemble covariance at ob time/location: $\left\langle (\sigma^2{}_{ob} + \sigma^2{}_{fg})^2 \right\rangle^{1/2}$

- **20CRv3 errors that are lower and more consistent with ensemble spread than 20CRv2c.**

20CRv3 outperforms 20CRv2c:
500hPa geopot. height agreement with ERA5

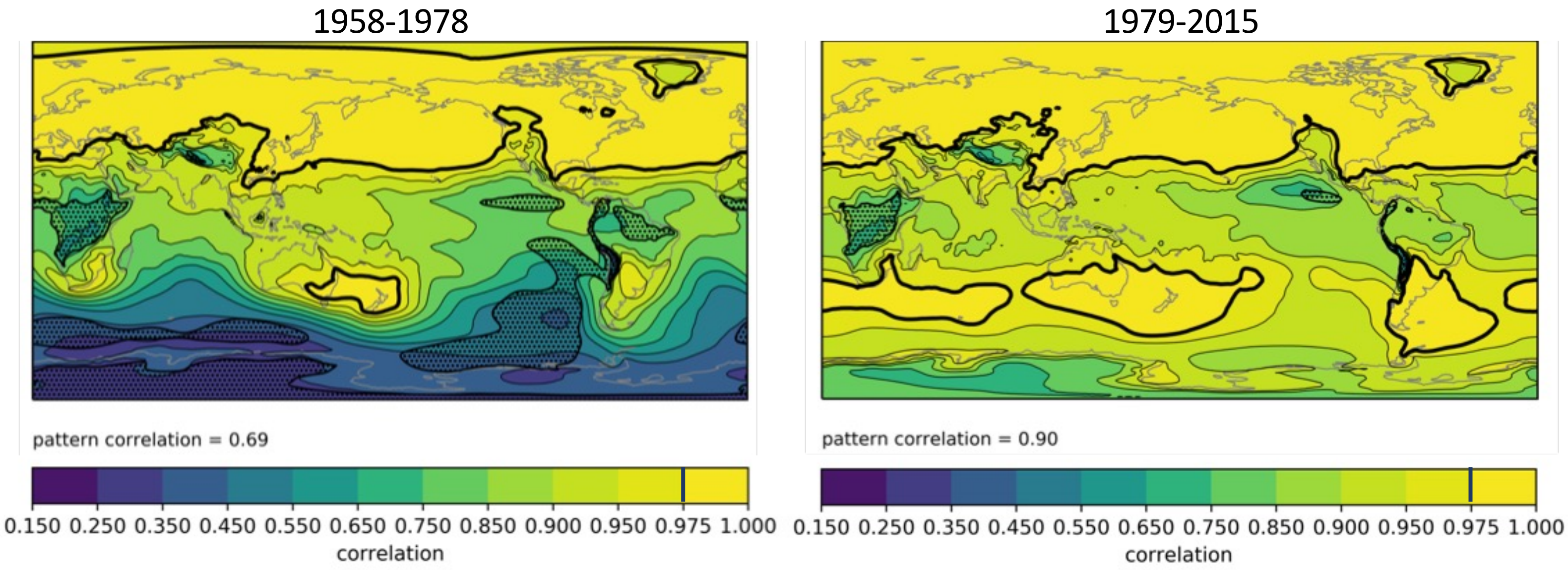


- **20CRv3 Z500 agrees with ERA5 better than 20CRv2c**, and has **more consistent ensemble spread**
- Gray shading shows range of ECMWF and NCEP oper. forecast errors in 2019 for 2-, 3-, 4-day leads
- **20CRv3 Z500 errors are comparable to modern 3-4 day operational forecast skill in the NH** (consistent with earlier predictions by Compo et al, 2006)

Slivinski, L.C., et. al. (2021) An Evaluation of the Performance of the Twentieth Century Reanalysis Version 3. *Journal of Climate,* 34(4): 1417-1438. https://doi.org/10.1175/JCLI-D-20-0505.1

20CRv3 correlates well with other reanalyses, and can "predict" that correlation

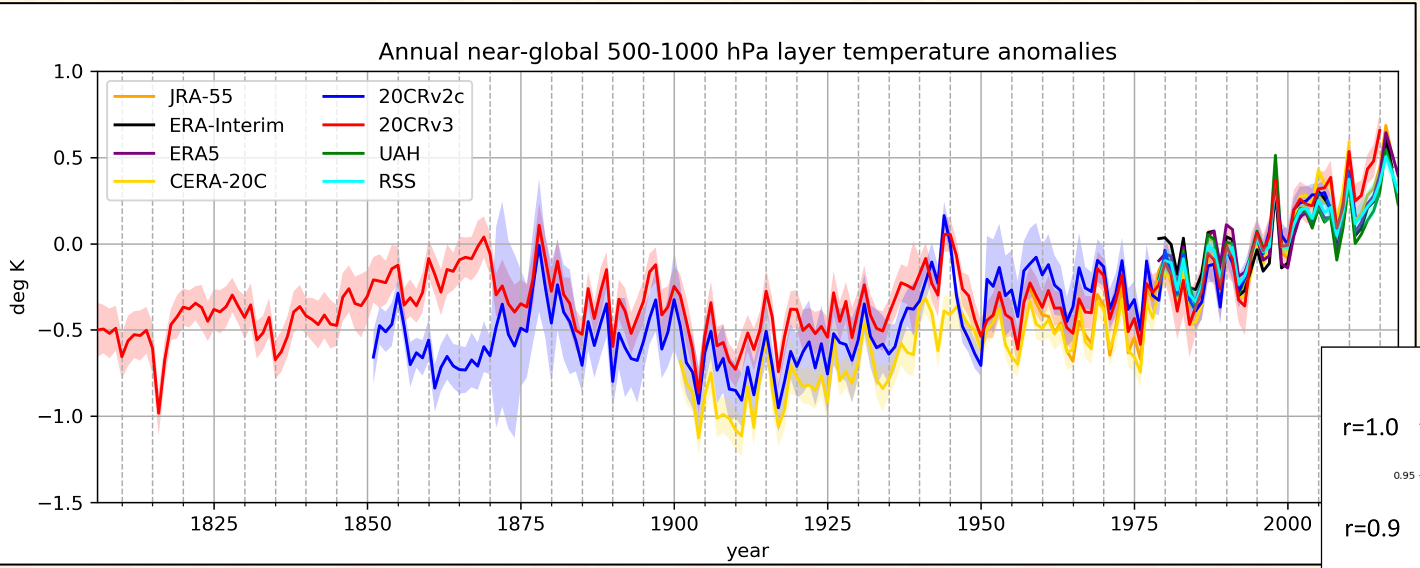
SLP anomaly correlation between JRA-55 and 20CRv3

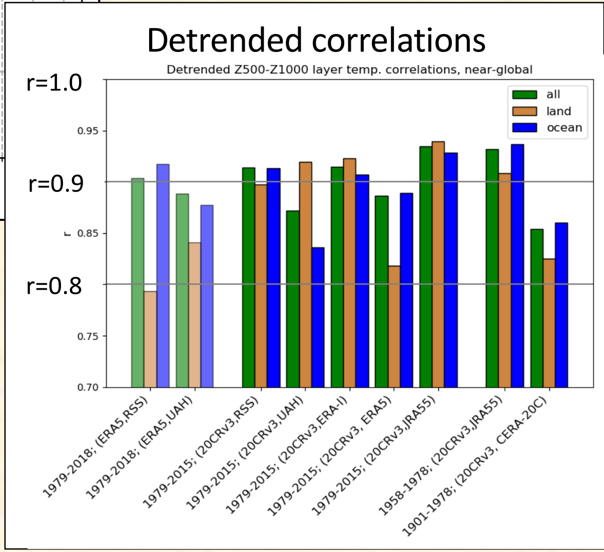


- Stippling indicates regions of low confidence (large ensemble spread) in 20CRv3
- Pattern correlation is given between confidence field and correlation field
- ➢ **20CRv3 uncertainty estimates are a good predictor of skill relative to JRA-55**

Slivinski et. al. (2021)

20CRv3 can capture trends & variability in temperature

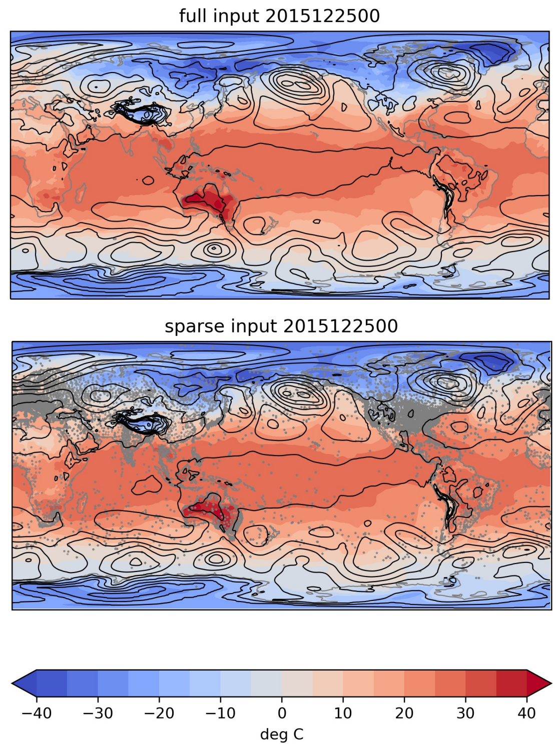


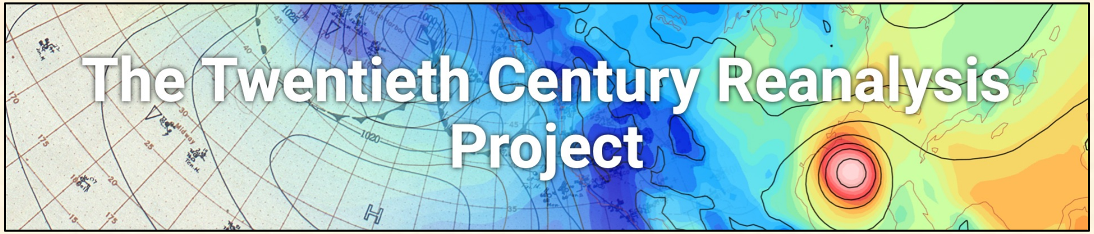


UAH & RSS: two satellite-based temperature reconstructions

Future of 20CR – Possibilities

- ✓ Larger set of available observations *(smaller errors, greater confidence, maybe extend further back in time)*
- ✓ Up-to-date forecast model
- Coupled ocean-atmosphere
- Additional observation types *(SST, wind direction)*
- Data-driven models *(incorporate Linear Inverse Model [LIM] for ocean)*
- No-DA counterpart simulation





- The 20th Century Reanalysis version 3 (20CRv3) *only* assimilates surface pressure observations in order to consistently extend 200 years into the past
- It agrees well with other reanalyses, independent upper-air observations, and station/satellite-based datasets
- Confidence estimates are reliable and 20CRv3 can often predict its own skill
- More information:
  - Compo, G.P., et. al. (2011) The Twentieth Century Reanalysis Project. *Q.J.R. Meteorol. Soc.*, 137: 1-28. https://doi.org/10.1002/qj.776
  - Slivinski, L.C., et. al. (2019) Towards a more reliable historical reanalysis: Improvements for version 3 of the Twentieth Century Reanalysis system. *Quarterly Journal of the Royal Meteorological Society*, 145: 2876–2908. https://doi.org/10.1002/qj.3598
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For data access, visualization tools, and references, please visit https://go.usa.gov/XTd

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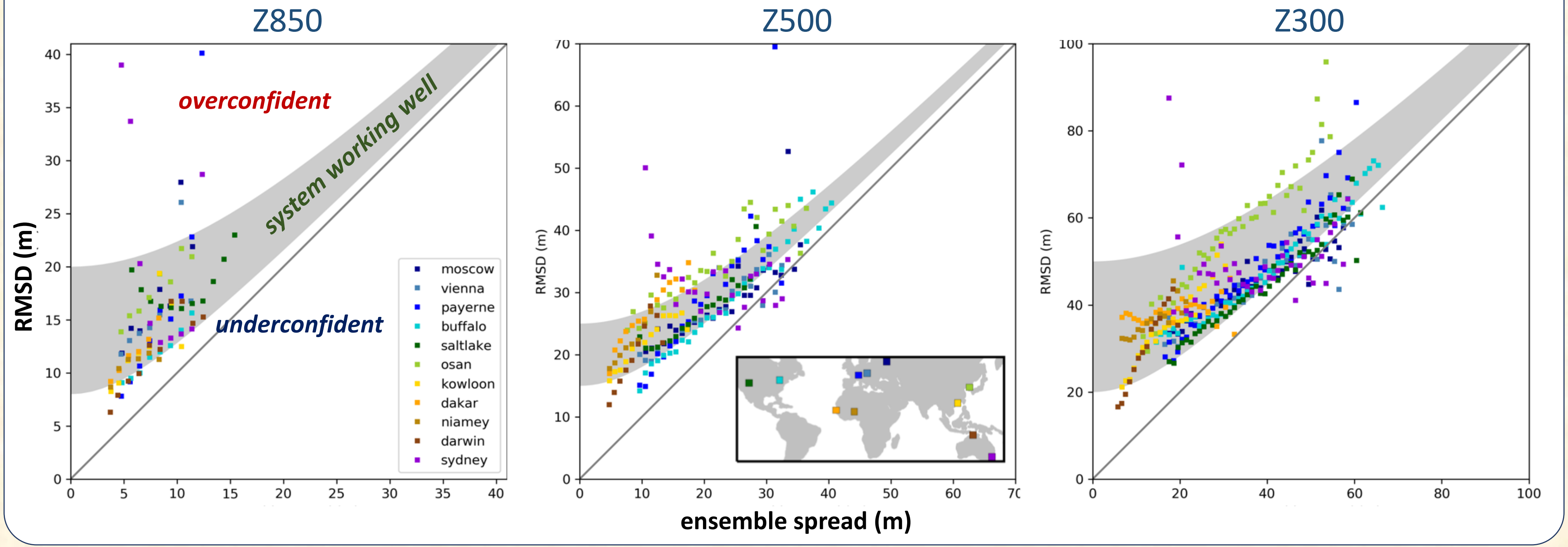
20CRv3 performs well relative to indep. upper air obs

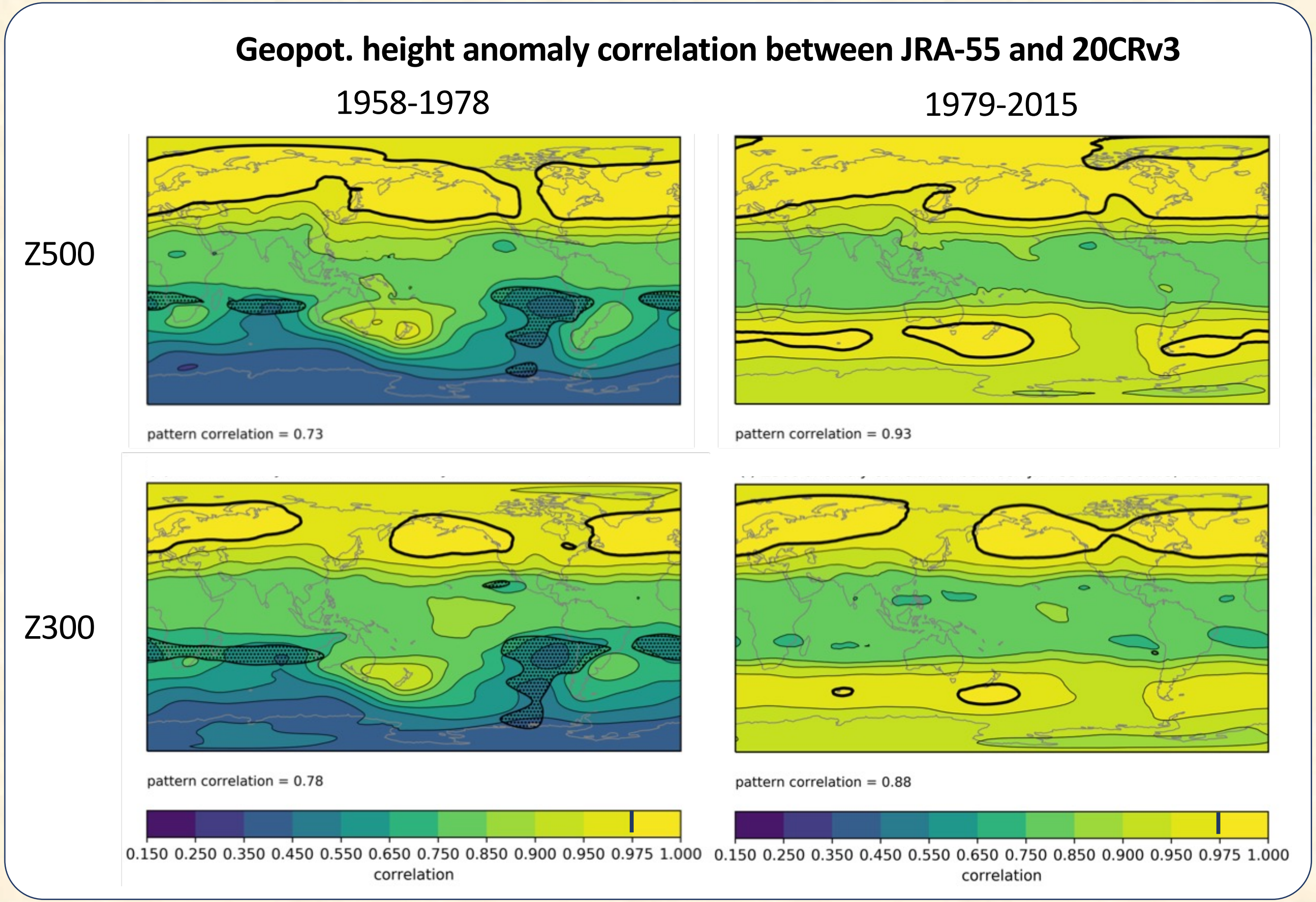
Difference between observed and analyzed values, as function of 20CRv3 ensemble spread; 1943-2015



- If obs were perfect (zero error), then RMSDs should fall on diagonal.
- If ob error range estimated accurately and system works well, RMSDs ideally fall in gray swath.
- Above swath: 20CRv3 is overconfident. Below swath: underconfident.
- **20CRv3 geopot. height analysis performs well globally at several vertical levels**

Slivinski et. al. (2021)

20CRv3 correlates well with other reanalyses, and can "predict" that correlation



(Similar results for 20CRv3/ERA5)

Slivinski et. al. (2021)

Like any EnKF, this system will suffer from filter divergence and/or spurious long-distance correlations without inflation and localization.

- **Inflation**: prevents "ensemble collapse" by artificially spreading out ensemble members.
  - Simple example: multiplying the ensemble covariance by a predefined (often tuned) factor larger than 1
- **Localization**: prevents an observation from incrementing the state at unreasonably long distances.
  - Simple example: Gaspari-Cohn localization, a function applied to the background covariance matrix which smoothly tapers long-distance correlations to zero

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Inflation

- Previous version of reanalysis used **pre-defined multiplicative inflation** factors based on year and location
- Needed larger inflation factors for densely-observed times and places; smaller inflation for sparsely-observed times and places

	Northern Hemisphere	Tropics	Southern Hemisphere
1851 – 1870	1.01	1.01	1.01
1871 – 1890	1.05	1.01	1.01
1891 – 1920	1.09	1.02	1.01
1921 – 1950	1.12	1.03	1.02
1951 – 2012	1.12	1.07	1.07

Simple adaptive inflation

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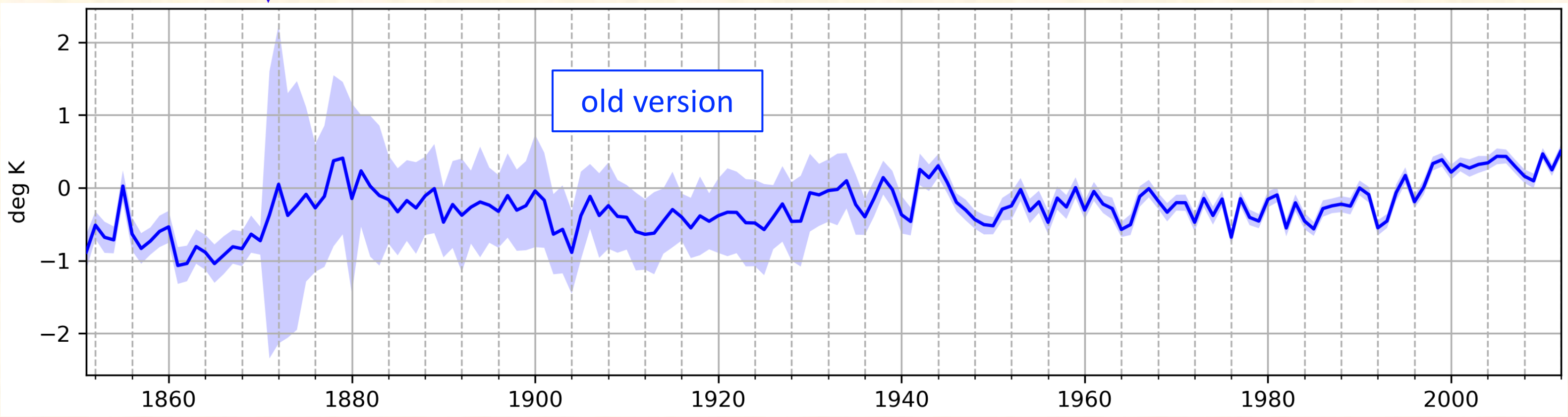
- Unrealistic signals in uncertainty
- Inhibits accurate studies of significance of long-term trends

Atmospheric layer temperature anomalies, Northern Hemisphere



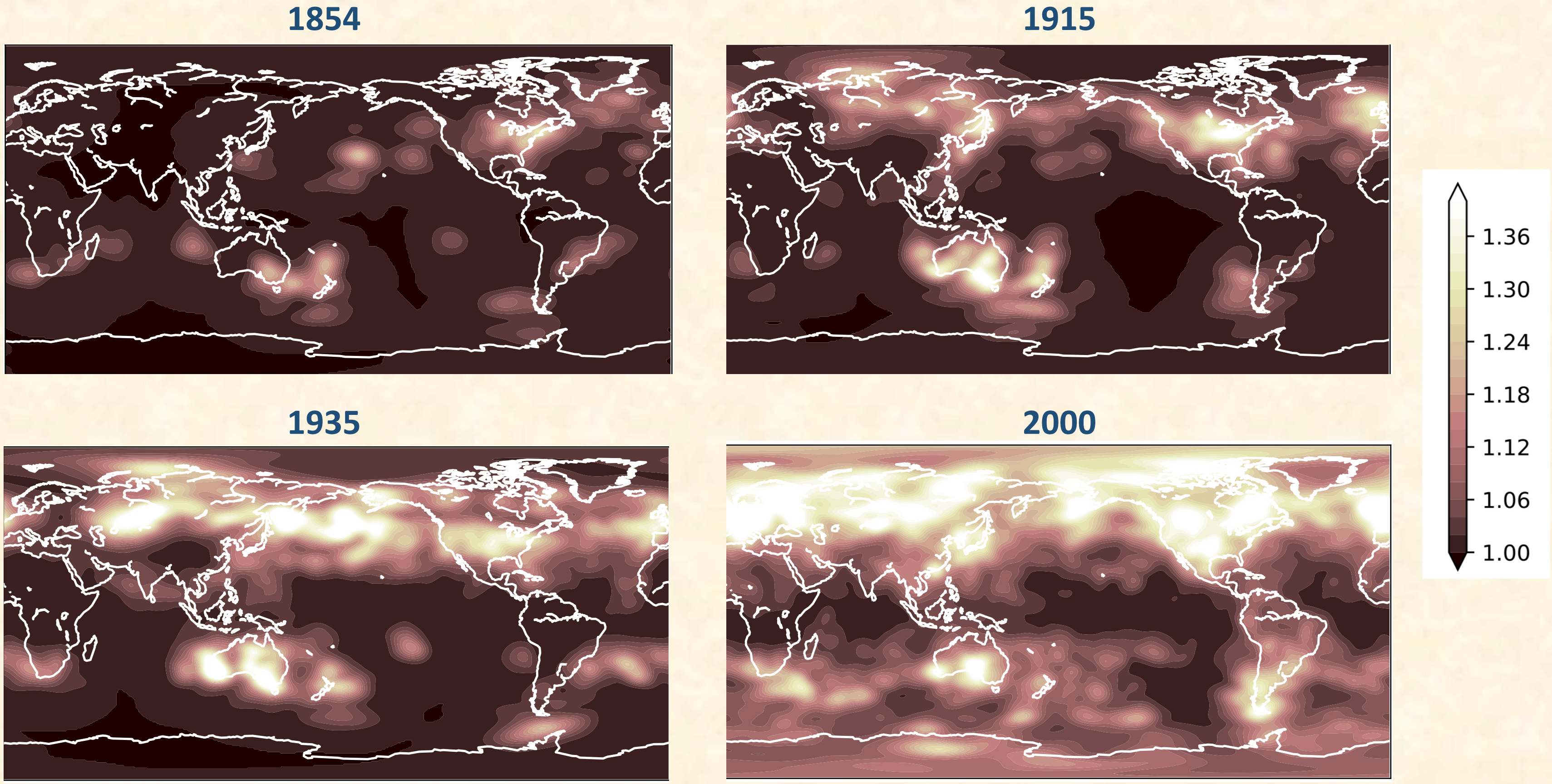
New inflation: relaxation-to-prior-spread

- Adaptive inflation: larger inflation when observations are dense, smaller inflation when observations are sparse
- Inflation parameter λ_{inf} is defined as function of individual gridpoints (x,y) and timesteps (t):

$$\lambda_{inf}(x, y, t) = p_{relax}\left(\frac{\sigma_b(x, y, t) - \sigma_a(x, y, t)}{\sigma_a(x, y, t)}\right) + 1,$$

σ_b is background ensemble standard deviation,
σ_a is analysis ensemble standard deviation, and
p_{relax} is a parameter varying from 0 (no inflation) to 1 (inflate fully to prior spread)

New inflation: relaxation-to-prior-spread



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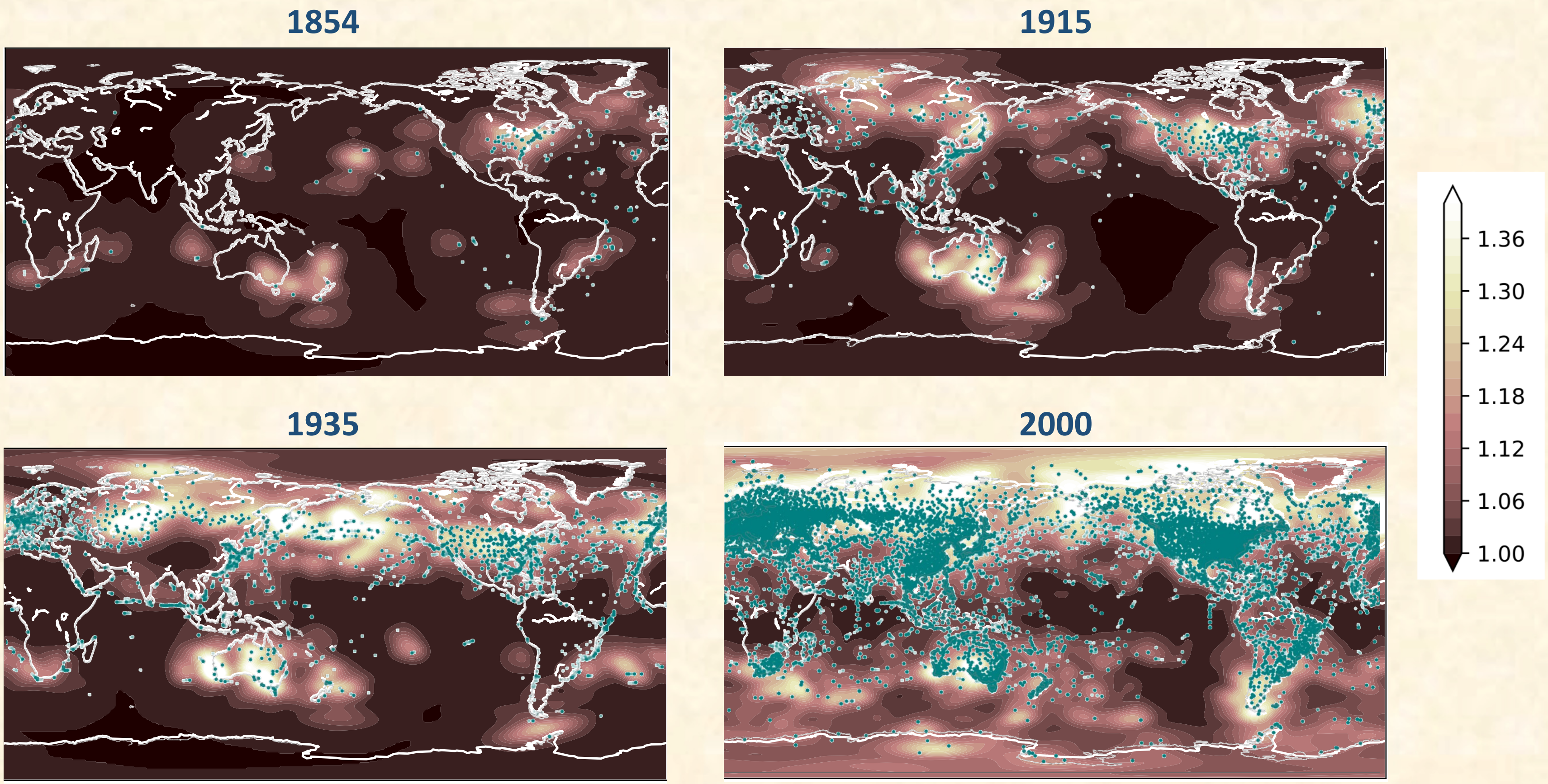
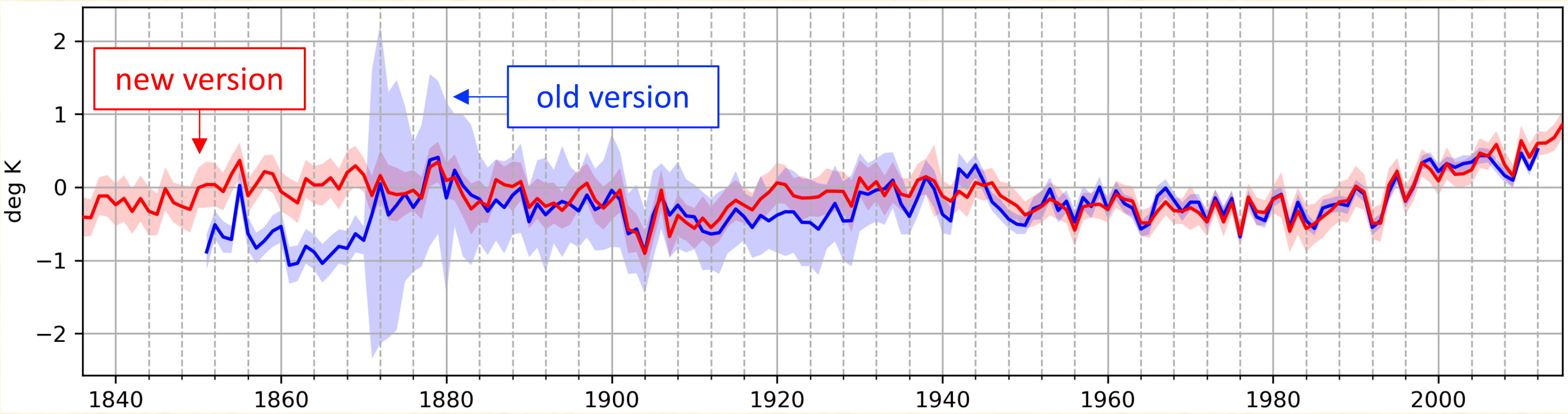


New inflation: relaxation-to-prior-spread

- More accurate, consistent estimates of uncertainty
- Can make stronger statements about trends

Atmospheric layer temperature anomalies, Northern Hemisphere



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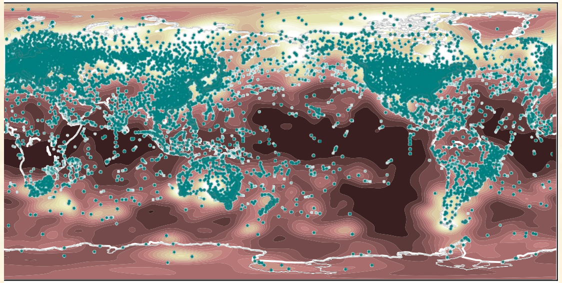
    - "Long-distance" defined in terms of a localization radius (can be fixed)



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  - “Long-distance” defined in terms of a localization radius (can be fixed)
  - **Adaptive localization: allow the localization radius to change for each observation, based on that observation’s expected influence**

Adaptive localization

- **Hypothesis**: for a given single observation, the optimal localization length scale is proportional to the reduction of ensemble variance in observation space
  - In other words, the more a given observation would reduce the analysis covariance, the longer localization length it is given.
- Define ρ as the reduction of ensemble covariance in observation space:

$$\rho = \mathbf{H}\mathbf{P}^a\mathbf{H}^T/\mathbf{H}\mathbf{P}^b\mathbf{H}^T = \mathbf{R}/(\mathbf{H}\mathbf{P}^b\mathbf{H}^T+\mathbf{R})$$

where $\mathbf{H}$ is the linearized observation operator, $\mathbf{P}^a$ is the analysis ensemble covariance, $\mathbf{P}^b$ is the background ensemble covariance, and $\mathbf{R}$ is the observation error covariance

- Small $\rho \longleftrightarrow$ large reduction in variance $\longleftrightarrow$ useful observation $\Rightarrow$ larger optimal localization radius
- Conversely, ρ close to 1 implies a smaller optimal localization radius

Adaptive localization

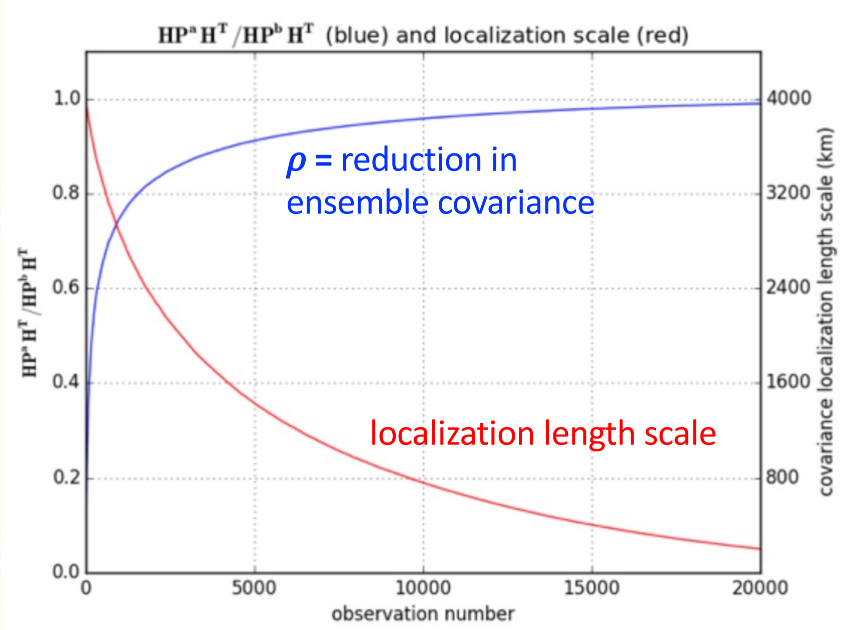
Empirically define

$$L = L_0(1 - e^{-(1-\rho)/r})$$

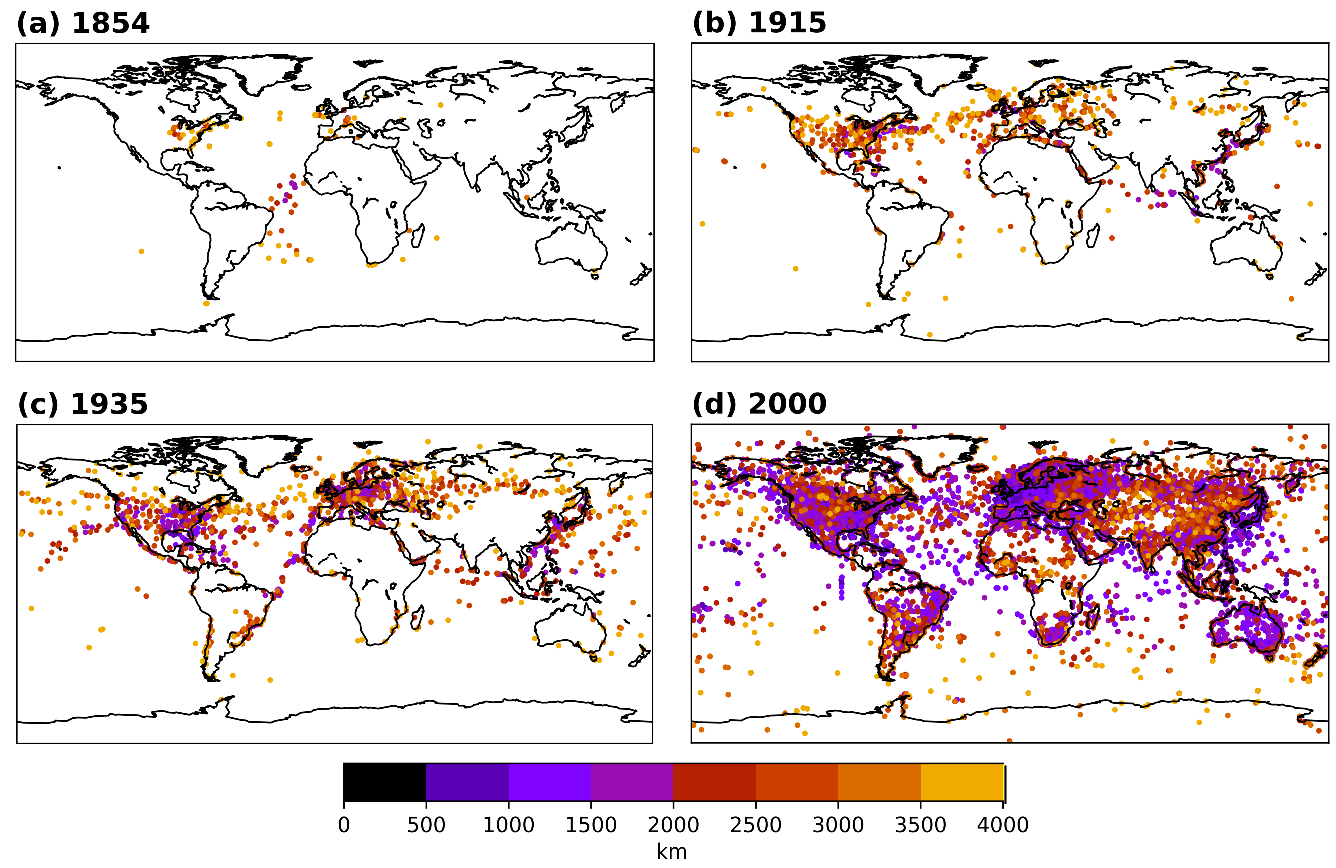
where

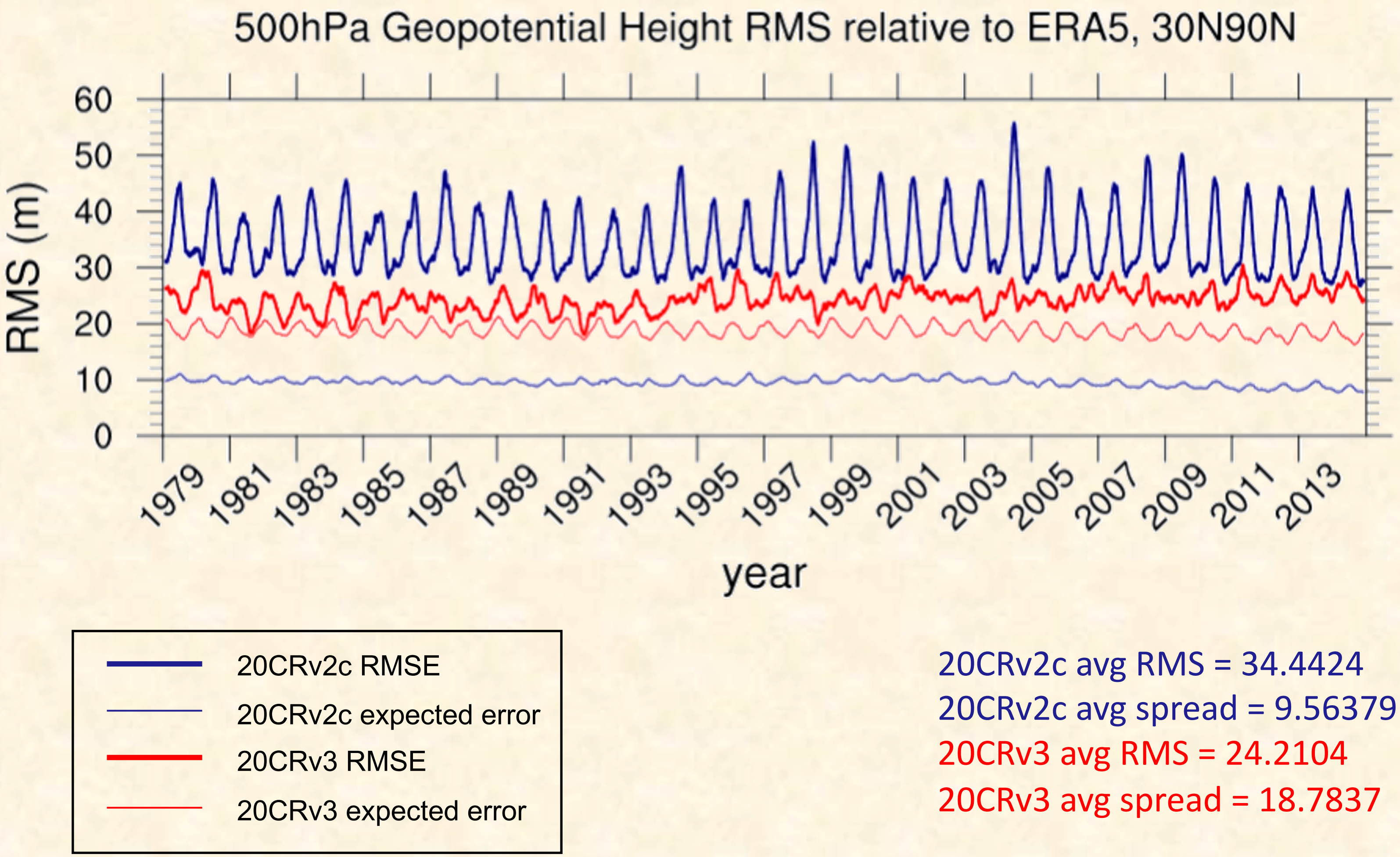
- L is the localization length scale
- L_0 is the maximum allowed localization length scale
- ρ is the reduction of ensemble variance in ob space (prev. slide); $\rho \in (0,1]$
- r is a parameter governing how tight the relationship between ρ and L is

Observations are assimilated serially in order of increasing ρ, and ρ is recomputed after each ob is assimilated.



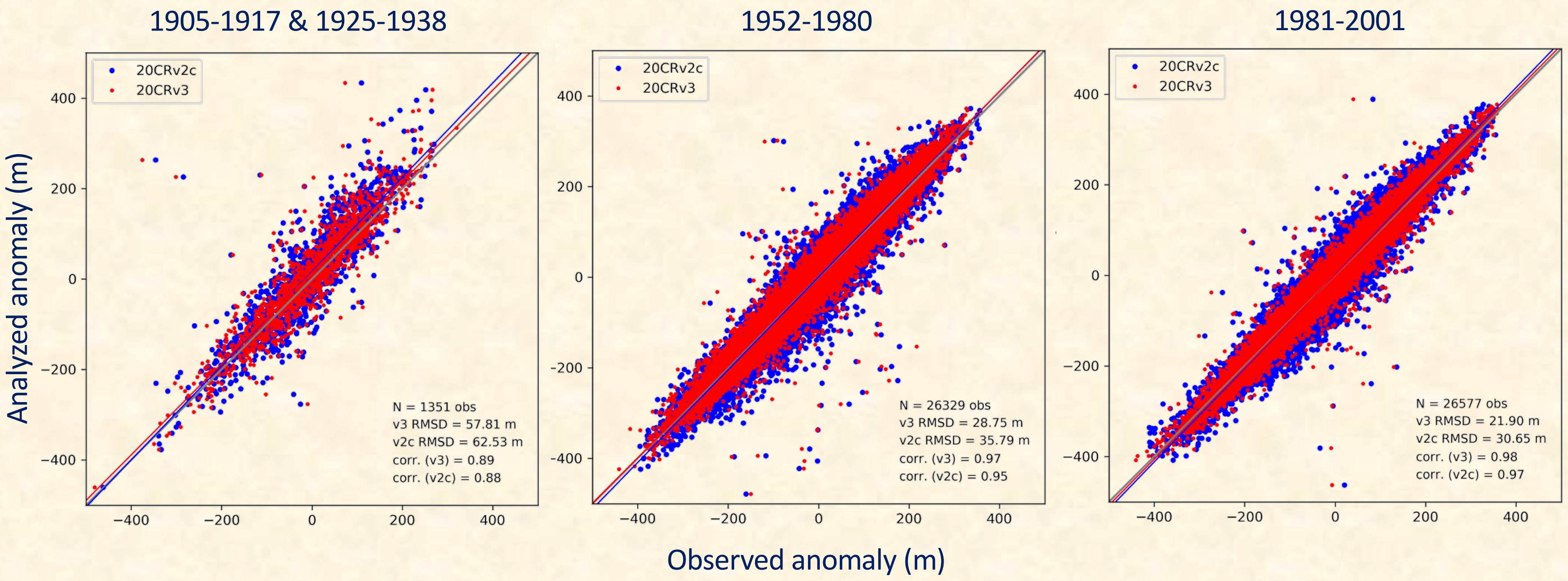
Adaptive localization





20CRv2c avg RMS = 34.4424
20CRv2c avg spread = 9.56379
20CRv3 avg RMS = 24.2104
20CRv3 avg spread = 18.7837

500hPa geopotential height analyzed anomalies versus observed anomalies from upper-air measurements at Lindenberg, Germany



Summary

- The 20th Century Reanalysis version 3 reconstructs nearly 200 years of sub-daily, global weather history by assimilating *only* surface pressure observations
- Reliable confidence and uncertainty estimates provided by 80 ensemble members in EnKF
- Updated inflation algorithm (relaxation-to-prior-spread) yields more consistent estimates of uncertainty
- Adaptively-varying localization makes observation-thinning unnecessary; more observations can be assimilated
- Overall, the 20CRv3 system includes many improvements over the previous 20CRv2c, leading to improved performance of the dataset (Slivinski et al 2019)

References

- 20th Century Reanalysis:
  - Homepage: https://go.usa.gov/XTd
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