

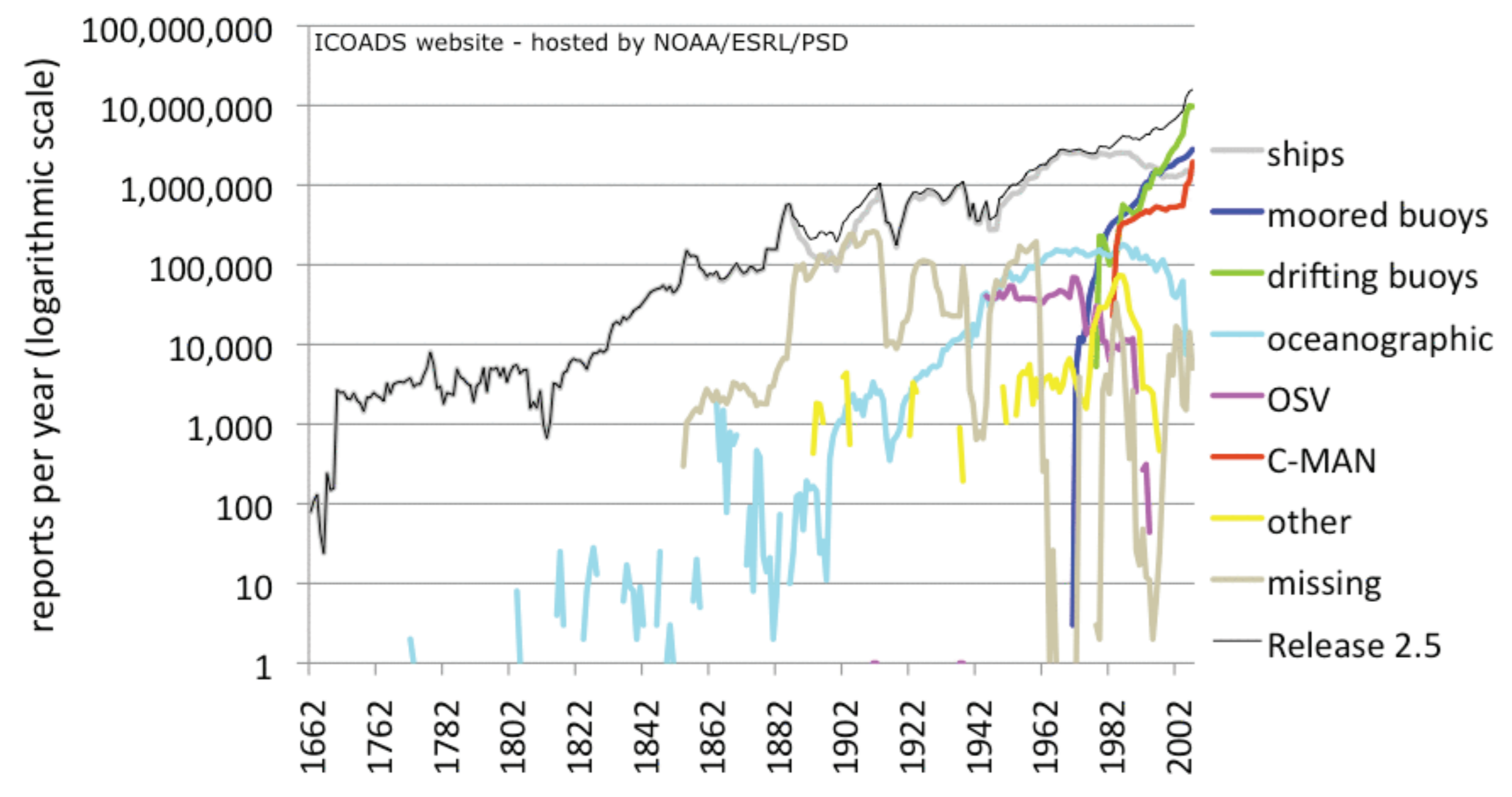
Merging in situ and satellite data for gridded multidecadal analyses of sea surface temperature fields

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Summary

Many climate-related applications require fully interpolated (i.e., with no spatial or temporal gaps) gridded data sets of available observations. Both the content and the uncertainty of such products depend on the error specification for individual observations as well as on the gridding technique. Optimal approaches to the gridding procedures make theoretical estimation of full uncertainty by far more expensive to compute and much more voluminous to report than the calculation of actual gridded fields. Currently popular methods of gridding sea surface temperature (SST) data are different for the satellite era and for the earlier period of sparse historical in situ observations. This difference is also reflected in typical approaches to uncertainty representation for the analyzed SST fields in these periods. Various heuristic approaches are currently used to achieve a measure of coherency when combining gridded fields for such periods of drastically different observational coverage into a single data set. A recently developed approach combines a large-scale low-rank component of the spatial covariance matrix with its high-rank component that represents smaller scales of variability in order to produce high-resolution analyses and to represent their uncertainty by an ensemble of SST fields sampled from their posterior distribution, conditional on the available data. This approach is proposed as a more systematic way to combine SST analyses for the satellite and in situ observational periods.

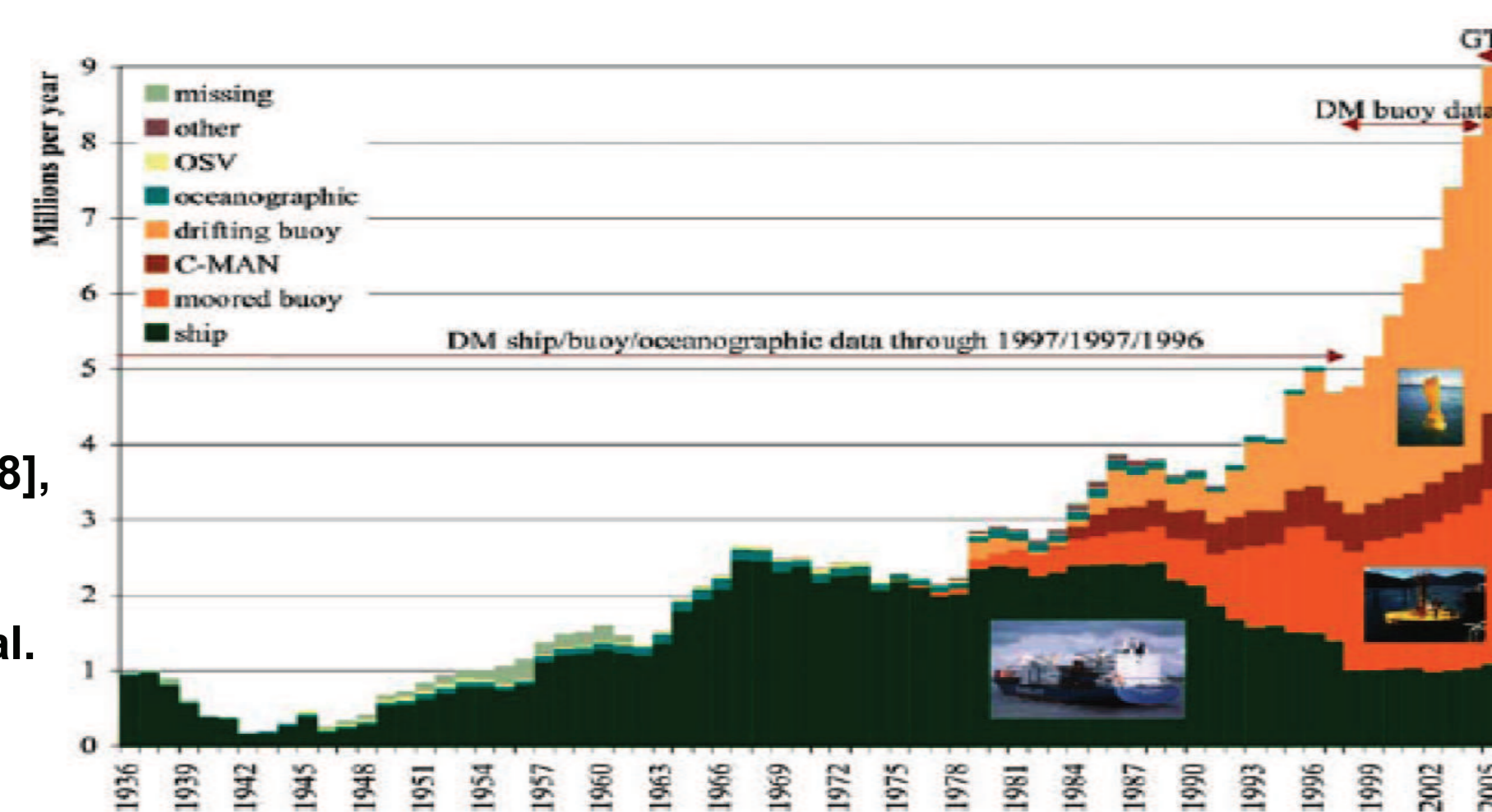
In Situ Observations: ICOADS



http://icoads.noaa.gov/index_fig2.html



Transition to the modern Ocean Observing System



From Woodruff et al. [2008], In Climate Variability and Extremes during the Past 100 Years, Bronniman et al. (eds.)

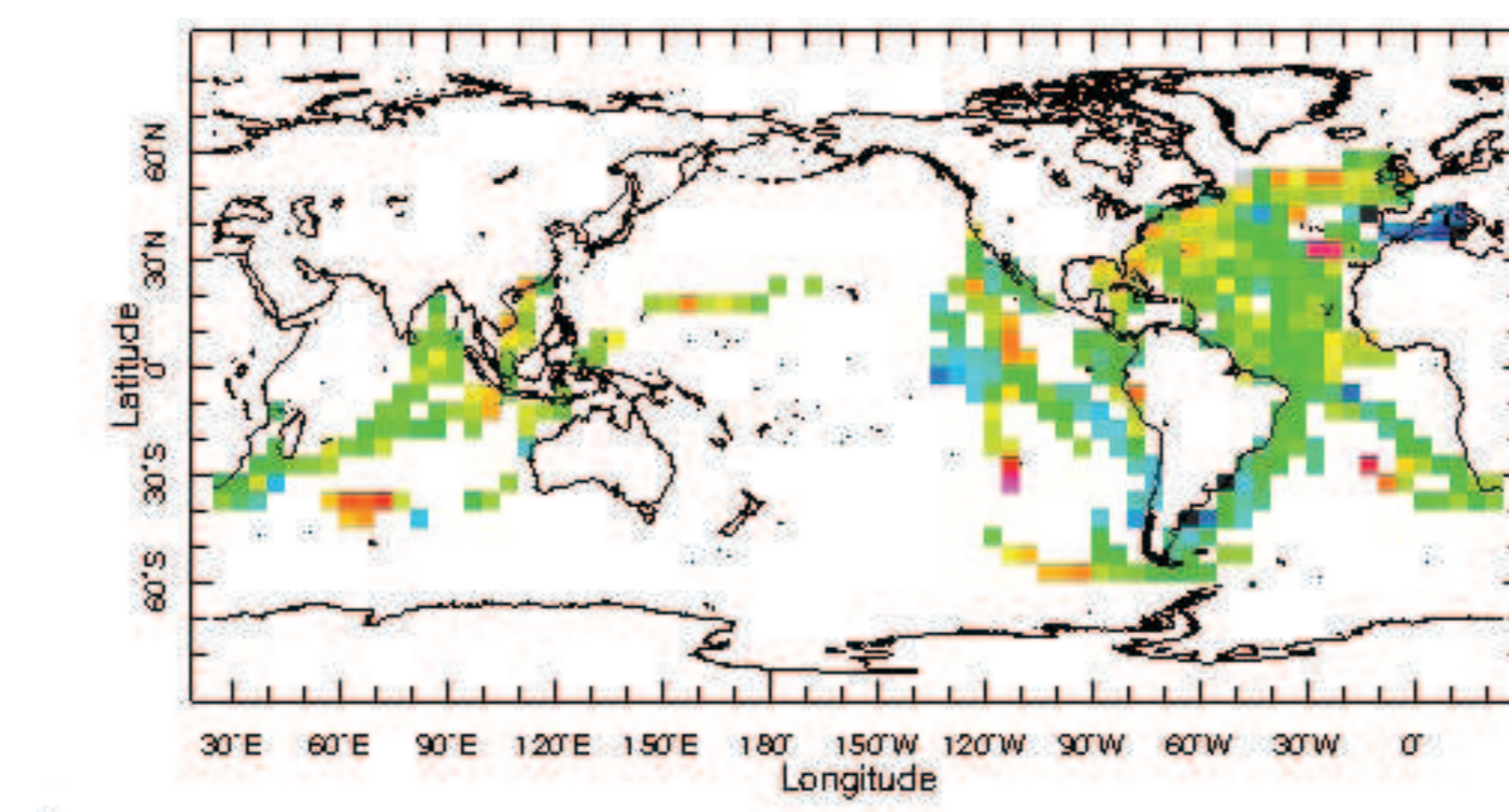
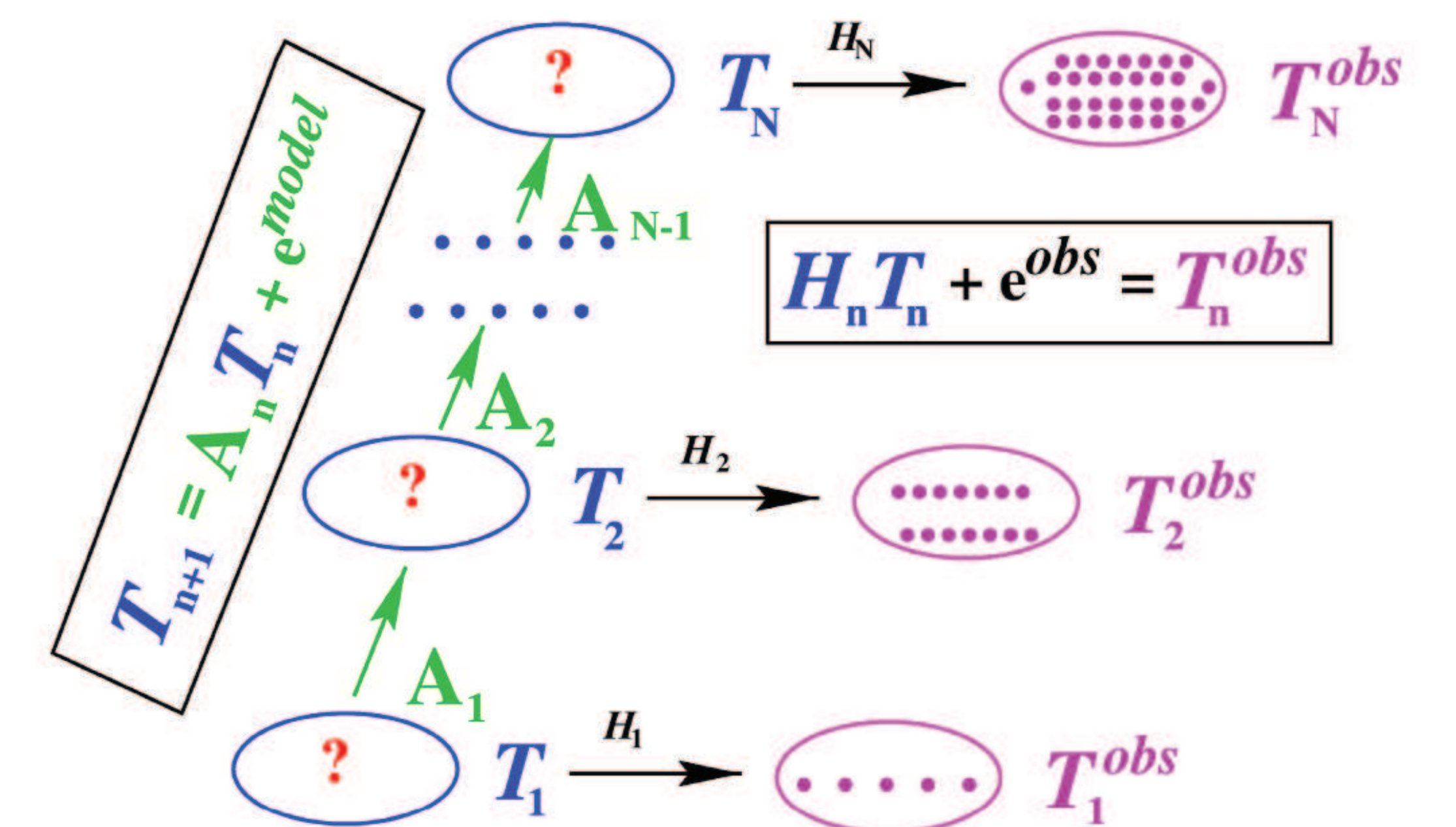
Reduced space approach and modeling observational error

The solution is constrained to the subspace spanned by a few large-scale patterns. This “reduced space” approximation is very different from a more traditional kriging approach which approximates signal covariance with stationary localized correlation structures. Solutions to least squares based objective analyses of spectrally red fields can be efficiently approximated by a few modes, have less variance than the true signal, are redder than the true signal. From Bayesian perspective, the least squares solutions represent only means of the posterior distribution:

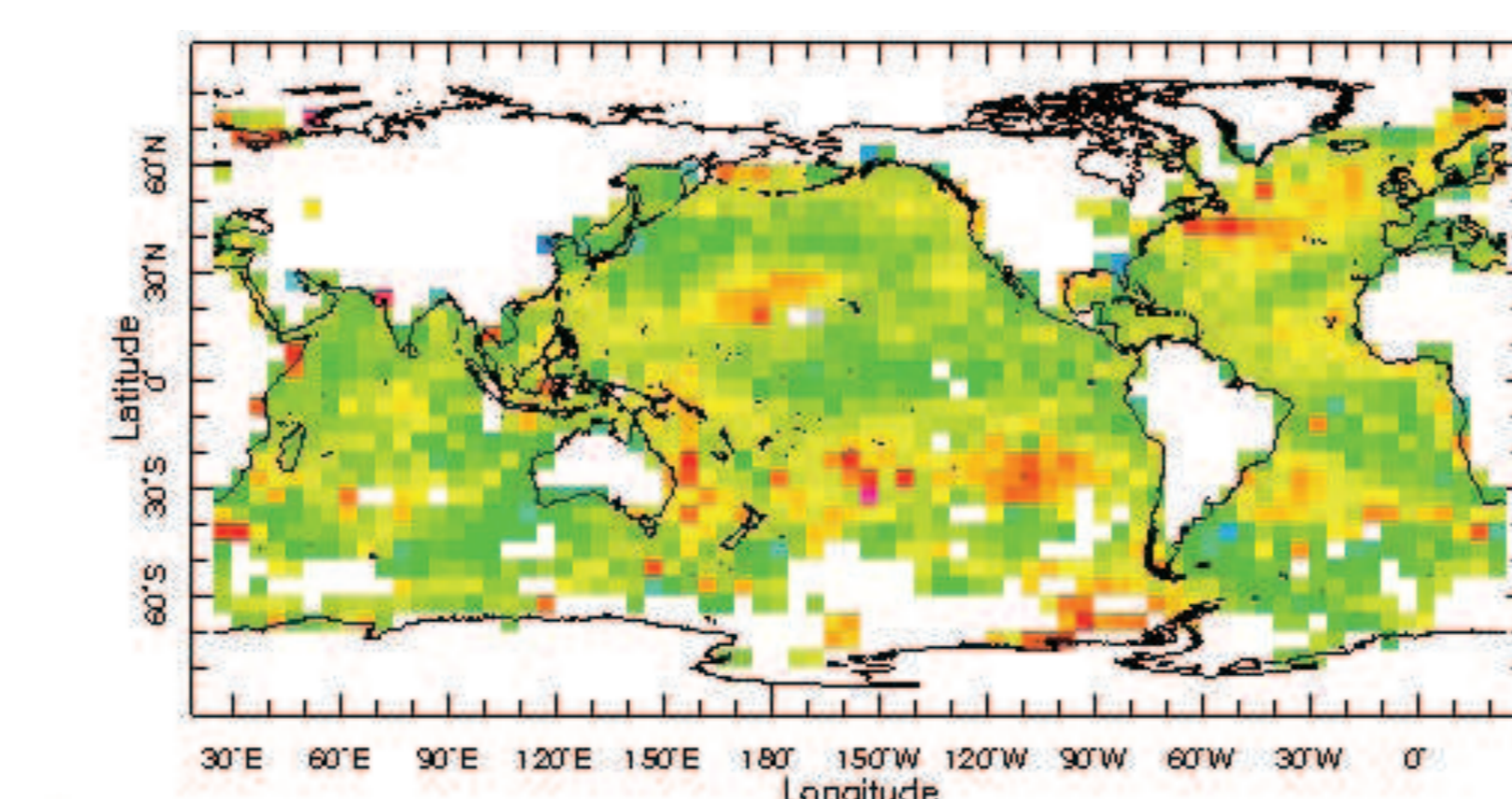
$$P_{OI}(T|T^o, T^B, C) = \mathcal{N}(T^{OI}, P^{OI}) \quad \text{and} \quad C = \langle T^{OI} T^{OI T} \rangle + P^{OI}.$$

Observational error variance in monthly means of binned in situ observations is modeled as $e = \sigma / \sqrt{n_{obs}}$, where σ is the physical variability of the SST within a given bin (estimated using satellite data), while n_{obs} is a number of individual observations inside that bin.

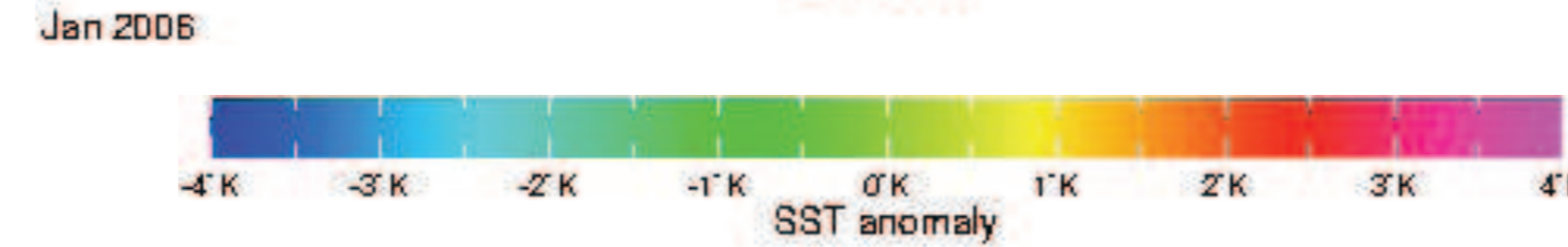
Generic problem of the analysis of time-evolving fields



Jan 1850

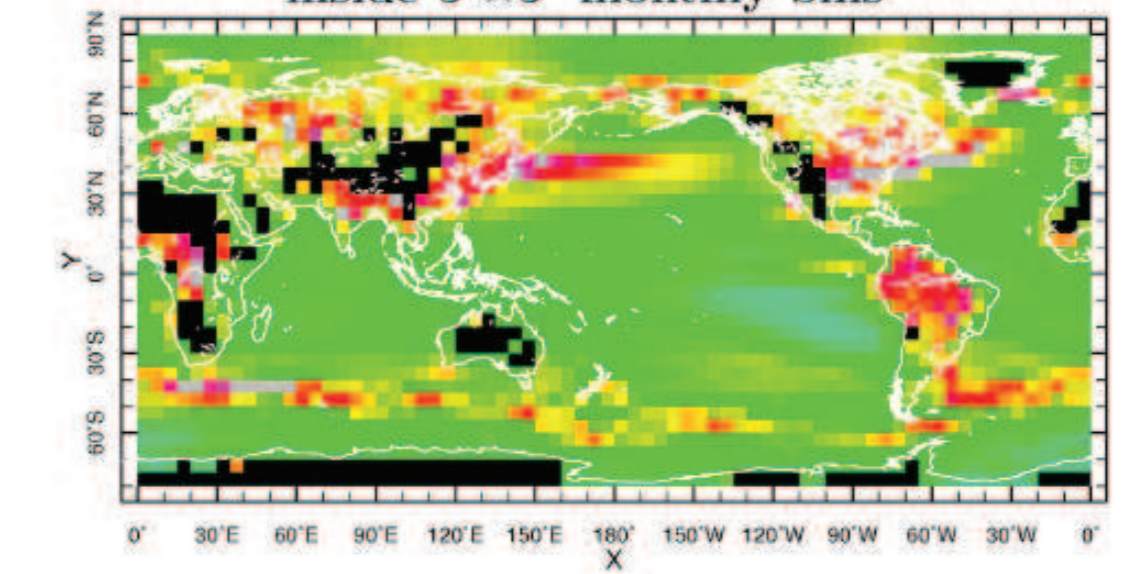


Jan 2006

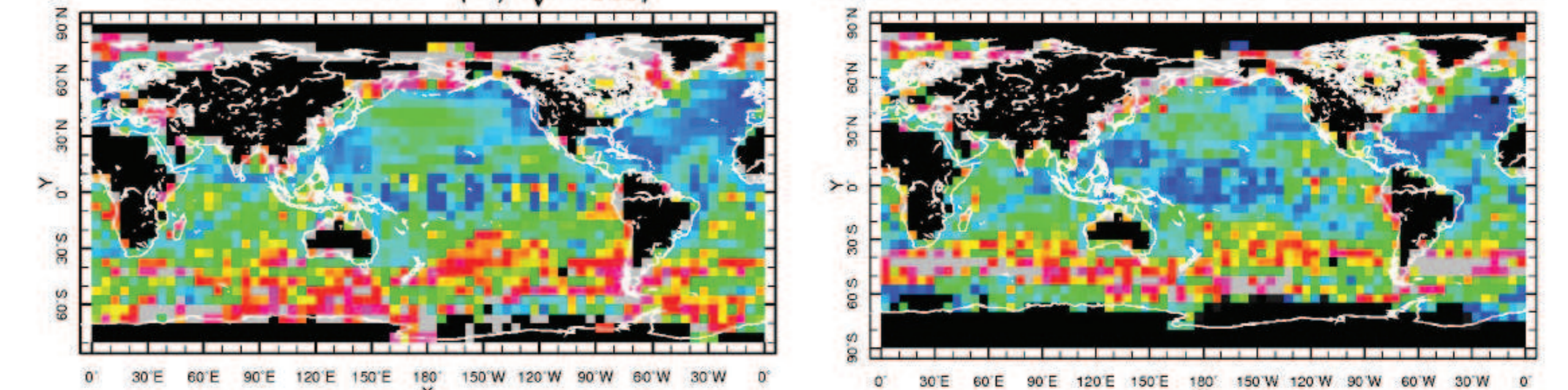


In situ data:
HadSST3
[Kennedy et al., 2011]

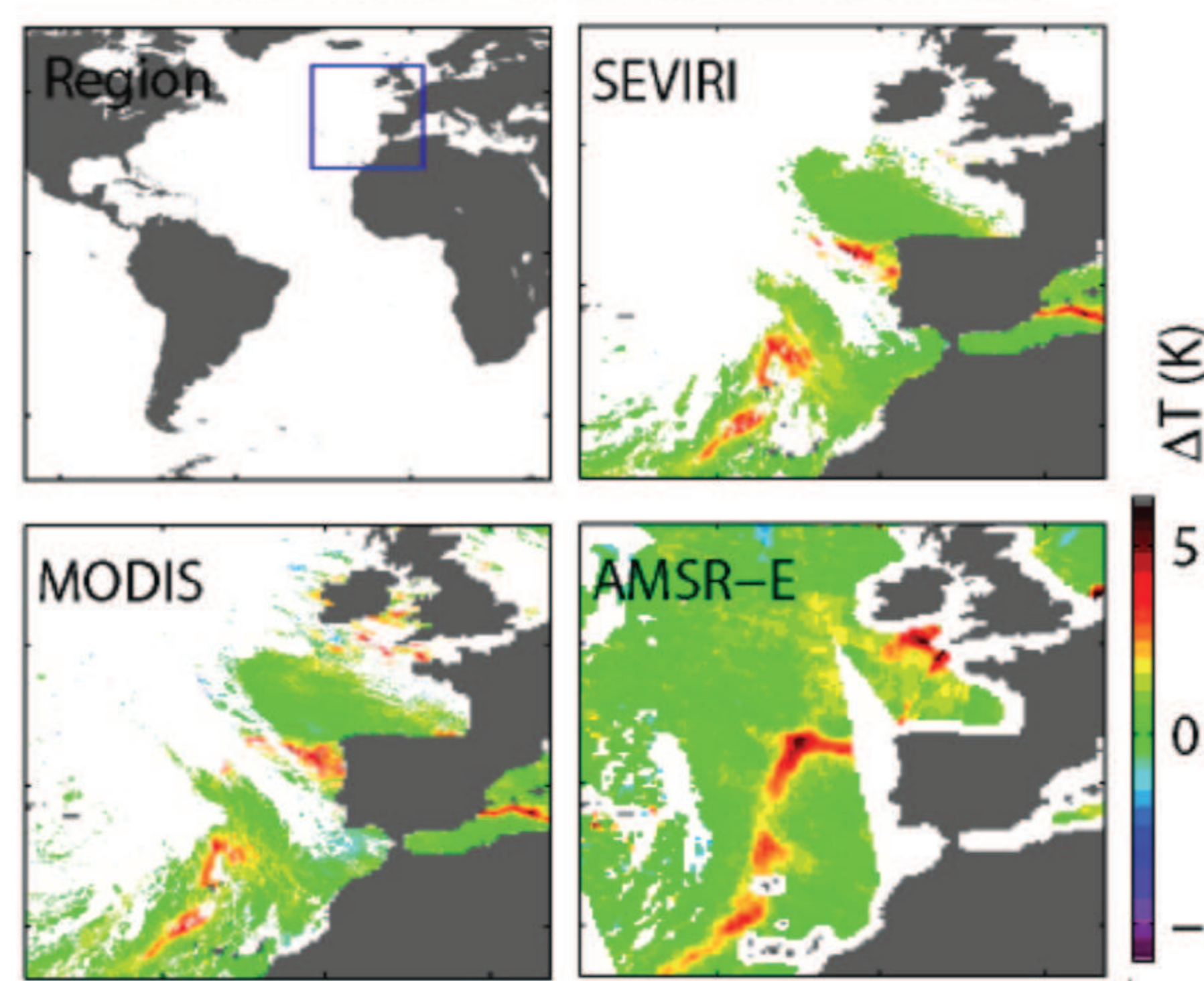
Single observation SST sampling+measurement error, °C, inside 5°x5° monthly bins



Modeling in situ data error for 5° bins
Modeled as $\langle \sigma / \sqrt{n_{obs}} \rangle$ Actual MODIS-ICOADS STD

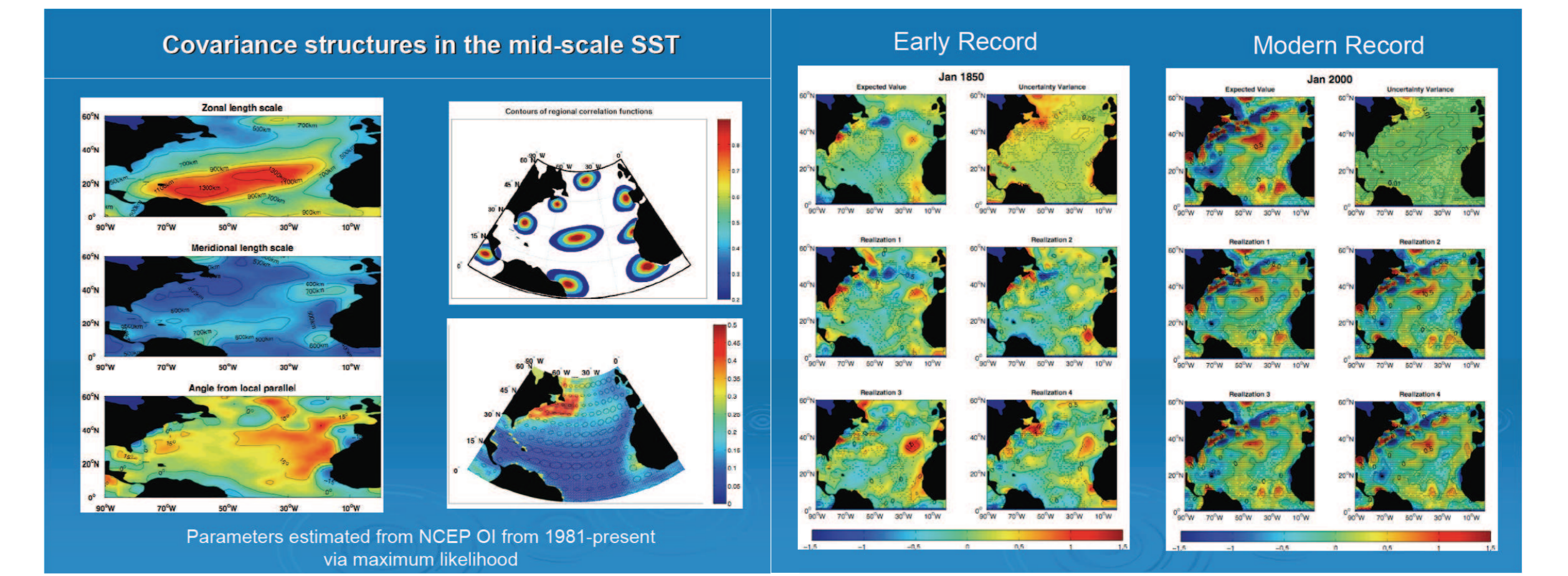


Satellite Observations



Donlon et al., 2010, OceanObs'09, Community White Paper

In analyses of instrumental and satellite data, one direction of work (Karspeck et al., 2012) is to allow non-stationary mid-scale variability into the estimated field, on top of the large-scale “reduced space” variability and to represent uncertainty in interpolated data products via an “ensemble” reconstruction. These issues are currently a subject of active research: e.g., ensemble reconstructions are used by Kennedy et al. (2011), multivariate covariance modeling – by R.W.Reynolds in NCDC (“two-level OI”).



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