### High resolution and uncertainties: Combining scales in signal and error

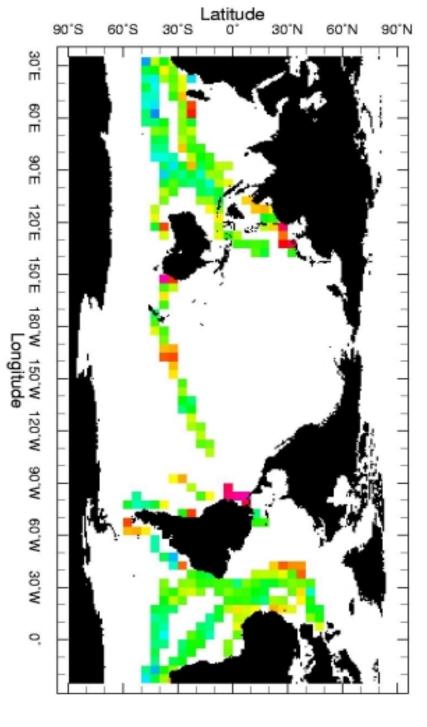
Alexey Kaplan

Lamont-Doherty Observatory of Columbia University
(LDEO)

### In collaboration with:

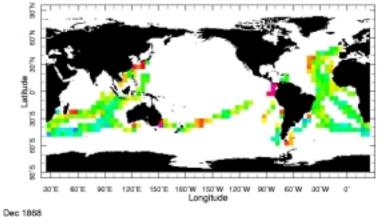
Craig Johns (University of Colorado @ Denver)
Nick Rayner (Hadley Centre)
Mark Cane, Yochanan Kushnir (LDEO)

# Dec 1868: Available observations

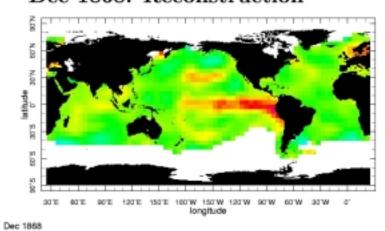


### People prefer right to left

Dec 1868: Available observations



### Dec 1868: Reconstruction



### **Example of Optimal Interpolation**

$$T=T_B+e_B$$

$$HT=T_o+e_o$$

$$===0$$

$$=C$$

$$=R$$

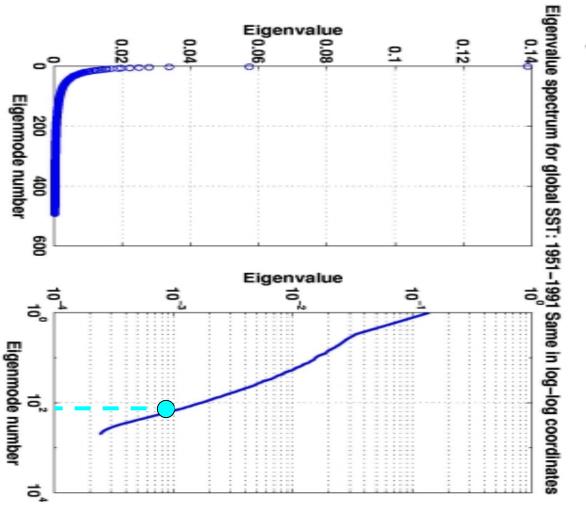
Solution minimizes the cost function  $S[T]=(HT-T_o)^TR^{-1}(HT-T_o)+(T-T_B)^TC^{-1}(T-T_B)$ 

$$T=(H^{T}R^{-1}H+C^{-1})^{-1}(H^{T}R^{-1}T_{o}+C^{-1}T_{B})$$

### Projection of OI solution on eigenvectors

```
C=EDE<sup>T</sup>
T=Ea
For simplicity: H=I, R=rI, T:=T-T_B
Then a=D(D+R)^{-1}E^TT_o
D(D+R)^{-1}=diag[ d_i/(d_i+r) ]
In many applications (for spectrally red signals) diagonal elements of this matrix decrease from ~1 to ~0
```

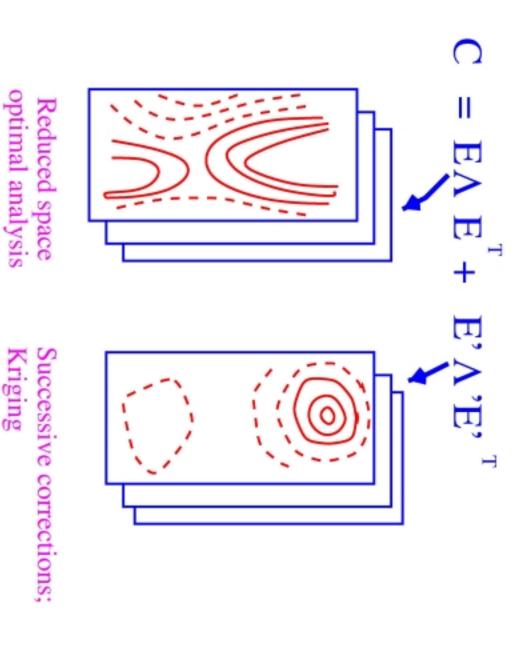




### 3 corollaries:

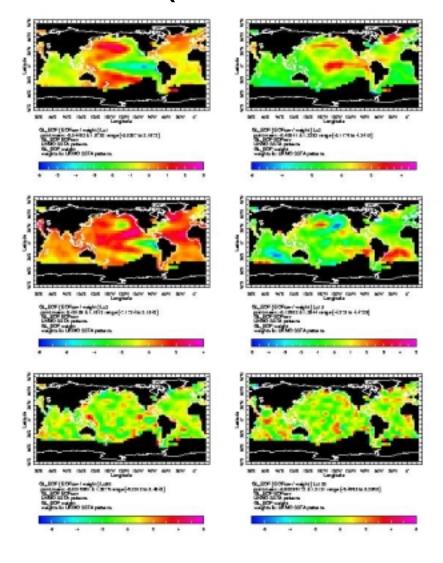
 The first is good: the tail (strongly dampened) modes can be filtered from the solution, i.e. the solution can be effectively approximated by a linear combination of a few leading (only slightly dampened) modes

# APPROXIMATING COVARIANCE



Kriging

### EOFs of SST (#1,2,3,15,80,120)



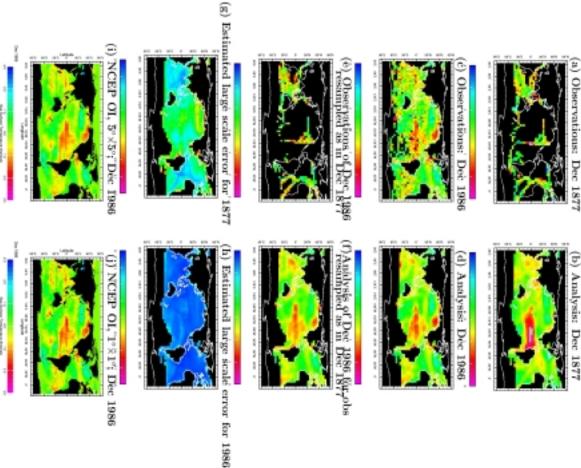


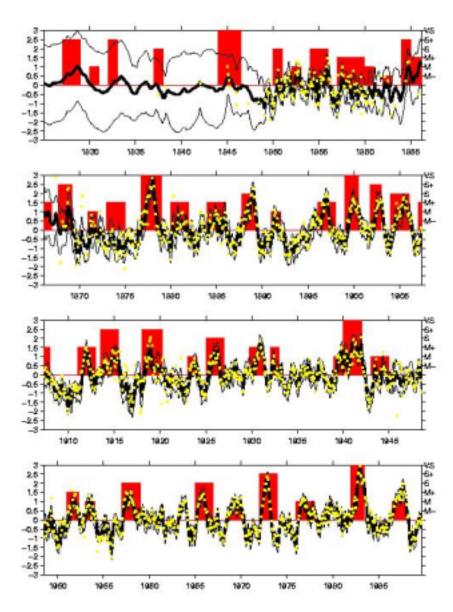
Figure 2: Available SST observations and their RS OS analysis for December 1877 (panels (a) and (b)) with verification through the experiment with 1986 data: simulated OS analysis for December 1986 using the data distribution of 1877 (panels (e) and (f)) versus the standard OS analysis for December 1986 with all available data (panels (c) and (d)). Also shown are large scale errors in the two reconstructions (panels (e) and (f)) and the NCEP OI December 1986 field presented in (f) 5°×5° and (j) 1°×1° resolution. Units are °C.

### 3 corollaries:

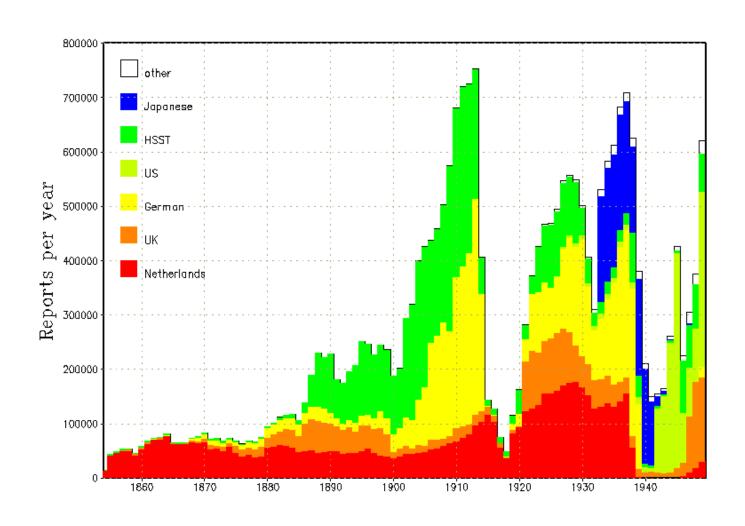
- The first is good: the solution can be effectively approximated by a linear combination of a few leading modes.
- The second is bad: the solution always has less variance than the true field.

In fact, 
$$C = \langle TT^T \rangle + P$$

### SST El Nino indices vs Quinn's historical rankings



### Number of observations in COADS



### 3 corollaries:

- The first is good: the solution can be approximated by a few leading modes.
- The second is bad: the solution always has less variance than the true field.
- The third is ugly: the solution is always redder than the truth (because of predominant dampening of tail modes).

Again, it helps to remember that

$$C = \langle TT^T \rangle + P$$

### Scale separation in a field estimate.

OI problem: estimating a field T from a first-guess (background) solution  $T^{b}$  and an incomplete set of observations  $T^{o}$  is given by:

$$T^b = T + \varepsilon^b$$
,  $\langle \varepsilon^b \rangle = 0$ ,  $\langle \varepsilon^b \varepsilon^{bT} \rangle = C$ , (1)  
 $T^o = HT + \varepsilon^o$ ,  $\langle \varepsilon^o \rangle = 0$ ,  $\langle \varepsilon^o \varepsilon^{oT} \rangle = R$ . (2)

$$T^{o} = HT + \varepsilon^{o}, \langle \varepsilon^{o} \rangle = 0, \langle \varepsilon^{o} \varepsilon^{oT} \rangle = R.$$
 (2)

The solution to this OI problem is a minimizer T of the cost function

$$\mathbf{S}[T] = (HT - T^o)^T R^{-1} (HT - T^o) + (T - T^b)^T C^{-1} (T - T^b).$$

$$\hat{T} = CH^T(R + HCH^T)^{-1}T^o.$$

$$C = E\Lambda E + E'\Lambda'E' = E\Lambda E + C'$$

$$\hat{T} = E\hat{\alpha} + \Delta\hat{T}$$
.

$$T^o = HE\alpha + \tilde{\epsilon}^o$$
,  $\langle \alpha \alpha^T \rangle = C'$ ,  $\langle \tilde{\epsilon}^o \tilde{\epsilon}^o T \rangle = HC'H^T + R$ .

$$\hat{\alpha} = \Lambda E^T H^T (H E \Lambda E^T H^T + H C' H^T + R)^{-1} T^o.$$

Observational residual:  $\Delta T^o = T^o - HE\hat{\alpha}$ 

$$\Delta T^{o} = H\Delta T + \varepsilon^{o}, \quad \langle \Delta T\Delta T^{T} \rangle = C', \quad \langle \varepsilon^{o} \varepsilon^{o} T \rangle = R.$$

$$\Delta T = C'H(HC'H^T + R)^{-1}\Delta T^o$$

### Synthetic example

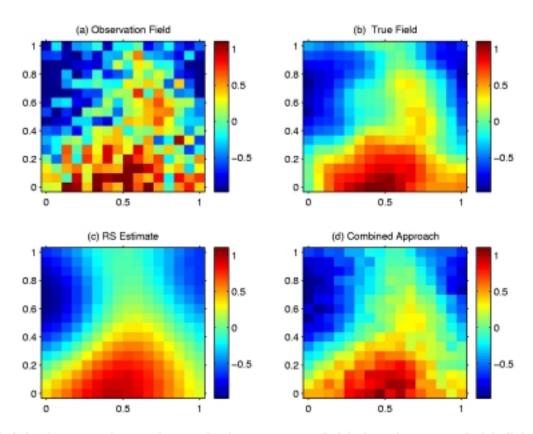
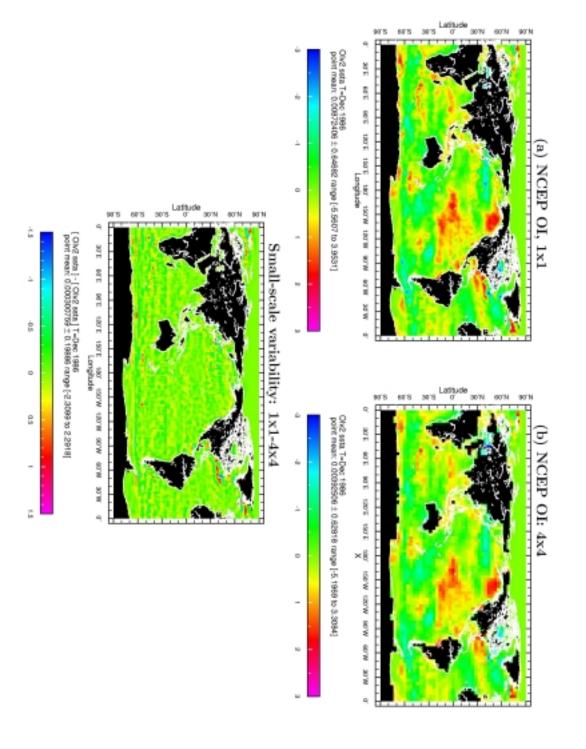
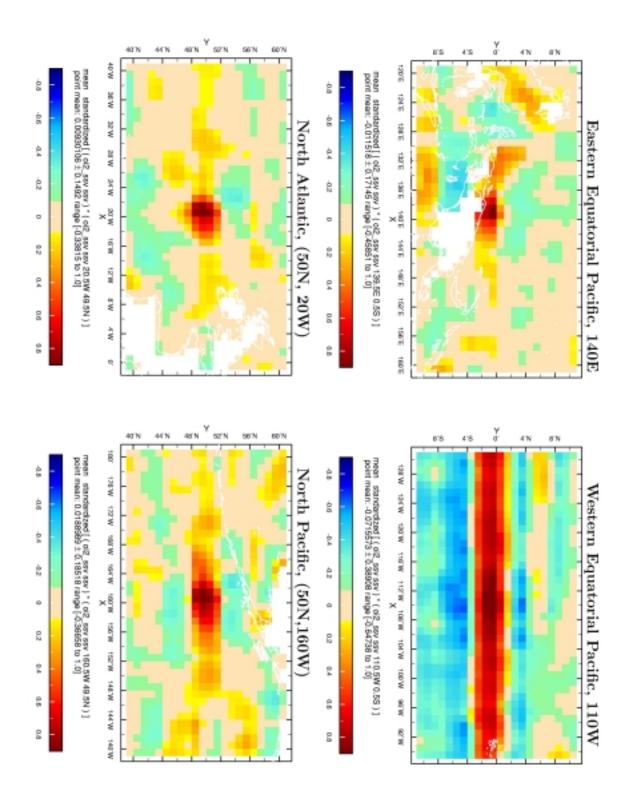


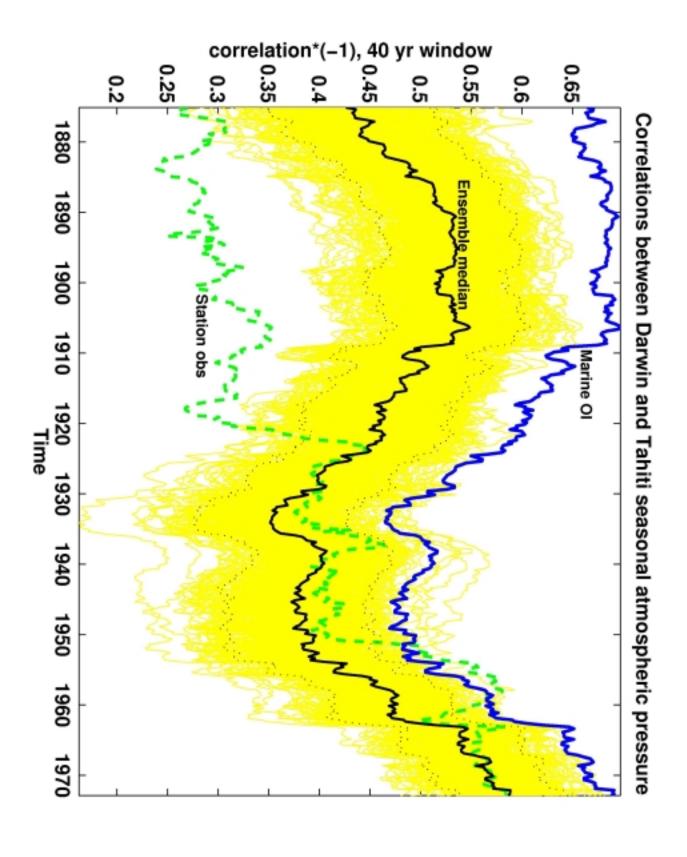
Figure 3: Panel (a) shows a hypothetical observation field for the true field (b). Panel (c) shows the RS part of the solution  $(E\hat{\alpha}$  in terms of equation ()). Panel (d) has the result of approximate Bayesian kriging  $(\Delta \hat{T})$  added

### December 1986



## Small-scale SST variability: spatial autocorrelations





### Take home points

- Spagetti-western properties of least-squares estimates of spectrally red signals: (good) can be approximated by a few modes, (bad) have less variance than the true signal, and (ugly) redder than the true signal.
- Since the effect of these properties is stronger for poor data, and the data quality generally improves with time, use of least-squares analyses at face value, as if they were the truth, poses a threat of misinterpretation.
- A possible way out (however expensive): use of ensembles drawn from the posterior distributions rather than a single ensemble mean.

### **Further Work**

Scale separation approach allows to work towards conceptually uniform globally-complete high-resolution objective analyses of SST according to the following scheme:

- (a) start from the reduced-space analysis (with an assumption of stationary mean and covariance);
- (b) small-scale analysis of observational residuals;
- (c) recomputing non-stationary mean and covariance;
- (d)adding high-resolution corrections, globalization patches, and sea-ice analyzed fields by the same scheme: large-scale prediction from the SST fields + local-scale corrections.