SST Retrieval and Assimilation: An Integrated Approach Andy Harris, NOAA/NESDIS/ORA

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- •Why are we looking at this, and why now?
- •What are the main issues?
- ·Possible solutions

The way forward

The technology is in place:

- SST retrievals from polar-orbiting IR, geostationary IR and now MW
- Computing power is sufficient to permit operational application of more sophisticated retrieval methods
- Each data source has its strengths and weaknesses
- An optimally combined product would satisfy many users

"End user" communities that have requirements

- Climate monitoring
- Operational oceanography
- Numerical weather prediction

• Fisheries The requirements are different, but are they mutually exclusive?

Climate monitoring needs observation system
to be stable to better than 0.1 K/decade

 Timeliness for NWP, operational oceanography. Less emphasis on absolute accuracy (±0.5 K)

 Fisheries. Often need fronts, and sometimes absolute temperatures What do we mean by optimal?

Minimize the "cost" of assimilating the data...

$$J = \frac{1}{2} \left(\underline{x} - \underline{x}^{b} \right)^{\mathrm{T}} \mathbf{B}^{-1} \left(\underline{x} - \underline{x}^{b} \right) + \frac{1}{2} \left(\underline{y}^{o} - \mathbf{H}(\underline{x}) \right)^{\mathrm{T}} (\mathbf{E} + \mathbf{F})^{-1} \left(\underline{y}^{o} - \mathbf{H}(\underline{x}) \right)^{\mathrm{T}}$$

An equation of 2 halves: background (or 1st guess) error; observation and forward model error

So, we need to know how good our retrievals are and how good our background value is

SST retrieval has traditionally been performed by direct regression against *in situ*. Is this the best way? What is the main advantage of remote sensing?

 Provides data in remote regions where in situ observation are sparse or non-existent

To utilize remotely-sensed data to an optimum level, we need to be able to specify accuracy in these remote regions

 This requires independent data in order to gain the necessary confidence

Can retrieval accuracy be improved by the addition of other data sources?

 Inclusion of water vapor can probably only be done at a rudimentary level using direct
requestion Studies have demonstrated little The chief advantage of radiative transfer is that it allows specification of the retrieval algorithm without bias towards the data-rich regions

 The in situ data can then act as a random independent sampling of the retrieval conditions.

 If the observed errors agree with the modeled ones, then high confidence can be placed on the modeled errors in data-sparse regions

 Additional advantage is that other sources of error can be accounted for explicitly, and external data (e.g. atmospheric profiles) can be incorporated

This doesn't mean it's easy to do...

Modeling must be accurate:

- Spectroscopy (mainly continuum)
- Representative input data (atmospheric profiles)
- Noise characteristics of real data
- Filter functions

Sensor calibration must be accurate

 However, RT does give rise to possibility of correcting calibration in a more predictable fashion

Cloud masking, aerosols

Surface effects (skin vs. bulk)



Diurnal thermocline is a very non-linear effect:

- Wind mixing energy is proportional to U_*^3
- The heat contained in the upper layer is the same, but the heat capacity is different

 Skin effect is generally a more tractable problem





Diurnal cycle modeling can now be done with reasonable confidence, but solar flux must be accurate and have good time resolution.



Other considerations

- Cloud masking is it time to dispense with thresholds and serial application of tests?
- Should fast-forward RT models be used?
- What about archive data?
- · Aerosols (stratospheric & tropospheric)
- 'Blending' of POES & GOES

Test the schemes - facilitate the feedback loop between validation and algorithm development

Microwave data

Now have the capability to retrieve SSTs from TMI to good accuracy, except in precipitation and "near" land. AMSR will extend coverage

- Spatial resolution is of order 50 km, but oversampled
- Larger errors where emissivity modeling is more difficult (high windspeed)
- Some calibration challenges
- Physically-based retrieval of SST and other parameters (cloud liquid water, TCWV, windspeed)
- Immune to aerosol problems

Errors in IR and MW SST retrievals are essentially

Case study using GOES



TOP

June 27, 1999

18Z

Resolution: 6km at Equator Projection: Geographic

Lat Range: 10 - 40N Long Range: 145 - 180W

Surface Temperature (Degrees Centigrade)

-30
-29
-28
-27
-26
-25
-24
-23
-22
-21
-20
10
-10
-10



Relaxation of cloud masking thresholds has resulted in lower detection rate

З Reynolds TMI SST - IR SST (°C) 2.5 2 1.5 1.5 1.5 0.5 MC SST PF SST GOES SST 0 40 0.2 20 60 0.1 0.3 TMI Cloud Liquid Water (mm) **TMI Water Vapor (mm)**

Mean Differences, 1998

Also some correlation with water vapor

Assimilation techniques

Adaptive, anisotropic analysis structure functions can be developed from study of the observation - background increment field

Where does the 1st guess (background) field come from?

 Previous analysis or predictive model. Some users will want to use their own model

A predictive model can be used



Example of high resolution (9-km) multi-scale OI using night-time AVHRR Pathfinder







Summary

A single, optimal SST product (or methodology) that maximizes the strengths of each input dataset whilst minimizing the impact of the deficiencies requires:

- A common retrieval framework, with known error characteristics (seasonally and geographically varying)
- Modeling of surface effects (accurate fluxes)

 Assimilation methods to take account of characteristics of input data (e.g. non-gaussian)

 This may require a predictive model with appropriate geophysical constraints & forcing