

Key SST retrieval concepts Peter Minnett and
Peter Minnett and
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Chris Merchant

Cloud screening (in brief)

Peter Minnett

Clouds from space

Clouds in the visible spectrum - day

Clouds in the infrared spectrum

Clouds in the infrared spectrum

Cloud Screening for SST

- Infrared radiation from the sea surface does not propagate through clouds – similar to visible radiation
Tests should be on a pixel-by-pixel basis.
- Tests should be on a pixel-by-pixel basis.
- Spectral information is be a powerful means for cloud screening.
- Two approaches:
	- Decision trees
	- Bayesian algorithms

To provide operational users and the science community with the SST measured by the satellite constellation

Multi-channel atmospheric correction algorithms

Peter Minnett

Committee on Earth Observation Satellites Sea Surface Temperature Virtual Constellation

- The accuracy target for satellite-derived SST for climate change research is ±0.1K and a decadal stability of better than 0.04K
- It is possible to build self-calibrating infrared radiometers that can meet these target on orbit*.
- But the accuracy of the derived SST is limited by how well the effects of the intervening atmosphere can be corrected.
- Once the satellite data have been successfully screened for the presence of clouds, the effects of the intervening clear atmosphere have to be corrected. This possible to band sen-calibrating illinated radiometers that

can meet these target on orbit*.

• But the accuracy of the derived SST is limited by how well the

effects of the intervening atmosphere can be corrected.

Group for High Resolution Sea Surface Temperature Comparature Committee on Earth Observation Satellites http://www.ghrsst.org Sea Surface Temperature Virtual Constellation Satellite Radiometers, in Experimental Methods in the Physical Sciences, Vol 47, Optical Radiometry for Ocean Climate Measurements, edited by G. Zibordi, C. J. Donlon and A. C. Parr, pp. 201-243, Academic Press, doi:http://dx.doi.org/10.1016/B978-0-12-417011-7.00008-8

Atmospheric transmissivity in the infrared

Spectral dependence of the atmospheric transmission for wavelengths of electro-magnetic radiation from about 1 to 14 µm, for three characteristic atmospheres (above), and (below) the black-body emission for temperatures of $0, 10, 20$ and 30° C, and the relative spectral response functions of the bands MODIS (Flight Model 1) on Aqua used to derive SST.

Atmospheric Transmissivity

Transmission spectra calculated for a moist summer mid-latitude atmosphere, and a very dry winter atmosphere.

Predicted MODIS brightness temperatures at satellite height

Multichannel atmospheric correction

- We use the hypothesis that the difference in the brightness temperatures measured in two spectral channels, i and j, is related to the temperature deficit in one of them. hesis that the difference in the
ratures measured in two spectra
is related to the temperature det
correction algorithm for SST
prmulated:
SST - T_i = f (T_i -T_j)
derived SST, and T_i and T_j the
- The atmospheric correction algorithm for SST retrieval can be formulated:

• where SST is the derived SST, and T_i and T_j the brightness temperatures in channels *i* and *j*.

Linearize Planck Function and Radiative Transfer

- By assuming that the atmospheric attenuation is small in these channels, the radiative transfer can be linearized.
- If the channels are spectrally close Planck's function can also be linearized.
- The algorithm can then be expressed in the very simple form:

$$
SST = a_0 + a_j T_i + a_j T_j
$$

where a_0 , a_i and a_j are coefficients determined by regression analysis either of coincident satellite and in situ measurements, such as from drifting buoys, or of simulated satellite measurements derived by radiative transfer modeling of the propagation of the infrared radiation from the sea surface through a representative set of atmospheric profiles.

MODIS SST atmospheric correction algorithms

The form of the daytime and night-time algorithm for MODIS measurements in the long wave atmospheric window is:

SST = c₁ + c₂ * T₁₁ + c₃ * (T₁₁-T₁₂) *T_{sfc} + c₄ * (sec (θ)-1)* (T₁₁-T₁₂)

- where T_n are brightness temperatures measured in the channels at n µm wavelength, T_{sfc} is a 'climatological' estimate of the SST in the area, and θ is the satellite zenith angle. This is based on the Non-Linear SST algorithm.
- [Walton, C. C., W. G. Pichel, J. F. Sapper and D. A. May (1998). "The development and operational application of nonlinear algorithms for the measurement of sea surface temperatures with the NOAA polar-orbiting environmental satellites." Journal of Geophysical Research 103 27,999- 28,012.]

The MODIS night-time algorithm, using two bands in the 4μ m atmospheric window is:

 $SST4 = c_1 + c_2 * T_{3.9} + c_3 * (T_{3.9} - T_{4.0}) + c_4 * (sec (\theta) - 1)$

Note, the coefficients in each expression are different. They can be derived in three ways:

- empirically by regression against SST values derived from another validated satellite instrument
- empirically by regression against SST values derived surface measurements from ships and buoys
- theoretically by numerical simulations of the infrared radiative transfer through the atmosphere.

Emissivity effects

Figure 6. Observed mean (solid lines) and standard deviation (dashed lines) of sea surface emissivity in 1ms^{-1} wind speed bins for 9um and 11um at 40° and 55° incidence angles (top). Below, the solid lines are the measured 11um emissivity for the 40° and 55° views, the dashed line with triangular markers represents values predicted by [Watts et al., 1996] for 55° at 11 µm (the coefficients given in that paper are valid for 52°-55° viewing angle). The dotted lines are those predicted by [Masuda et al., 1988] for 40° (diamonds), 50° (squares) and 60° (asterisks). From: J.A. Hanafin, Ph.D. Thesis. University of Miami, 2002.

Emission angle dependence

Sea surface emissivities COM COMPOSED SEA SURFACE

Sea surface

emissivities

computed from an

analytical

approach (AN) and

a Monte Carlo ray analytical approach (AN) and a Monte Carlo raytracing method (MC) versus the emission angle. Wind $u_{12} = 5$ ms⁻¹;
λ = 4 μm. computed from an
analytical
approach (AN) and
a Monte Carlo ray-
tracing method
(MC) versus the
emission angle.
Wind $u_{12} = 5 \text{ ms}^{-1}$;
 $\lambda = 4 \mu \text{m}$.
Bourlier, C. (2006), Unpolarized emissivity
with shadow and multiple analytical

approach (AN) and

a Monte Carlo ray-

tracing method

(MC) versus the

emission angle.

Wind $u_{12} = 5 \text{ ms}^{-1}$;
 $\lambda = 4 \mu \text{m}$.

Bourlier, C. (2006), Unpolarized emissivity

with shadow and multiple reflect

with shadow and multiple reflections from random rough surfaces with the geometric optics approximation: application to Gaussian sea surfaces in the infrared band, Appl. Opt., 45(24), 6241-6254.

- Seasonal changes in the atmosphere can be accounted for by having monthly sets of coefficients.
- Regional changes in the atmosphere can be accounted for by having sets of coefficients in zones.

VIIRS Coefficients

Benefits of continuity algorithms

Monthly median bias errors – recent sensors

Monthly median bias errors – recent sensors

Annual median and robust standard deviation for 35 years of satellite IR SSTs. effect (-0.17K) as the satellite SSTs are skin SSTs, whereas the buoy measurements are subsurface.

To provide operational users and the science community with the SST measured by the satellite constellation

SST retrieval using radiative transfer simulations

Chris Merchant

Questions addressed in this part

- What can radiative transfer modelling tell us about SST retrieval?
	- Preview of answer: apparently simple retrieval methods have surprising limitations
- Can radiative transfer modelling help us make better SST retrievals?
	- Preview of answer: yes, at least sometimes

Recap: empirical retrieval coefficients

With RTM, this process can be simulated for a 'perfect data' study

Regional annual biases

Local (mis)behaviour

Algorithm

IRSS1

$$
\hat{x} = a_0 + a_1 y_{11} + (a_2 S + a_3 x_b)(y_{11} - y_{12})
$$

Sensitivity to water vapour, w

Algorithm
\n
$$
\hat{x} = a_0 + a_1 y_{11} + (a_2 S + a_3 x_b)(y_{11} - y_{12})
$$
\n**ensitivity to water vapour,**
$$
\frac{\partial \hat{x}}{\partial w} = (a_1 + a_2 S + a_3 x_b) \frac{\partial y_{11}}{\partial w} + (-a_2 S - a_3 x_b) \frac{\partial y_{12}}{\partial w}
$$

Sensitivity to true SST, x

ensitivity to water vapour,
$$
w
$$

\n
$$
\frac{\partial \hat{x}}{\partial w} = (a_1 + a_2 S + a_3 x_b) \frac{\partial y_{11}}{\partial w} + (-a_2 S - a_3 x_b) \frac{\partial y_{12}}{\partial w}
$$
\n
$$
\text{Sensitivity to true SST, } x
$$
\n
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$$

Sensitivity to water vapour

Imperfect sensitivity to SST

Optimal estimation

- Essentially: calculation local coefficients "on the fly"
- Based on
	- Local atmospheric state
	- Physics of radiative transfer (via the RTM)
- What should OE give us?
	- Minimized random retrieval error
	- No regional biases
	- Reduced (and quantified) sensitivity to water vapour
- But, more complex and any RTM-calibration mismatch can introduce different biases

Optimal Estimation - Equations
Best estimate of the state variables in the vector **x**, given an initial estimate

Best estimate of the state variables in the vector x , given an initial estimate x_a with corresponding (modelled) observations \mathbf{y}_a and new (real) observations y.

$$
\widehat{\mathbf{x}} = \mathbf{x}_a + \mathbf{S}_a \mathbf{K}^T \left[\mathbf{K} \mathbf{S}_a \mathbf{K}^T + \mathbf{S}_\varepsilon \right]^{-1} (\mathbf{y} - \mathbf{y}_a)
$$

 $\boldsymbol{\chi}$ $T\subset V$

State vector

Prior version from NWP Posterior version is retrieved

$$
\mathbf{y} = \begin{pmatrix} BT_1 \\ BT_2 \\ BT_3 \\ \vdots \end{pmatrix}
$$

Observation vector

Prior version from RTM(NWP) Compared to actual observation

Best estimate of the state variables in the vector x , given an initial estimate x_a with corresponding (modelled) observations \mathbf{y}_{a} and new (real) observations y.

$$
\widehat{\mathbf{x}} = \mathbf{x}_a + \mathbf{S}_a \mathbf{K}^T \left[\mathbf{K} \mathbf{S}_a \mathbf{K}^T + \mathbf{S}_\varepsilon \right]^{-1} (\mathbf{y} - \mathbf{y}_a)
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$$

$$
\mathbf{S}_a = \begin{pmatrix}\n\sigma_{SST}^2 & \sigma_{TCWV, SST}^2 & \dots & \dots \\
\sigma_{SST, TCWV}^2 & \sigma_{TCWV}^2 & \dots & \dots \\
\vdots & \vdots & \vdots & \ddots & \vdots\n\end{pmatrix}
$$

Metop-A study

• Showed that potential benefits of OE can largely be obtained in practice

Available online at www.sciencedirect.com

Remote Sensing of Environment 112 (2008) 2469–2484

Remote Sensing Environment

www.elsevier.com/locate/rse

Optimal estimation of sea surface temperature from split-window observations

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Abstract

Optimal estimation (OE) improves sea surface temperature (SST) estimated from satellite infrared imagery in the "split-window", in
comparison to SST retrieved using the usual multi-channel (MCSST) or non-linear (NLSST) est matched in time and space to drifter SSTs collected on the global telecommunications system. There are 32.175 matches. The prior for the OE is

Two main estimators

- Two main estimators

 Maximum a posteriori MAP (equations given)

 Minimizes SST error variance

 Explicitly embeds prior information in result • Maximum a posteriori – MAP (equations given)
• Minimizes SST error variance
• Explicitly embeds prior information in result
• Probably appropriate for NWP, oceanography
• Maximum likelihood – ML
• Minimizes BT residuals
	- Minimizes SST error variance
	- Explicitly embeds prior information in result
	- Probably appropriate for NWP, oceanography
- - Minimizes BT residuals (SST is noisier)
	- "Zero" prior influence in result
	- The only type of SST that should be used in climate reanalyses (if you are a purist)

Reduced SST spread of errors

Reduced regional biases

Coefficients

MAP OE

Reduced sensitivity to water vapour

Coefficients

Retrieval cost: powerful quality indicator

MAP errors by cost l quality indicator

MAP errors by cost

Lowest 44% +0.06 +/- 0.27

Next 36% -0.03 +/- 0.36 1 quality indicator

MAP errors by cost

Lowest 44% +0.06 +/- 0.27

Next 36% -0.03 +/- 0.36

Poorest 19% -0.37 +/- 0.53 MAP errors by cost
Lowest 44% +0.06 +/- 0.27
Next 36% -0.03 +/- 0.36
Poorest 19% -0.37 +/- 0.53

Conclusions

- Coefficient-based retrieval
	- Deceptively simple
	- Built-in biases (bad for everyone)
	- Hidden influence of prior (bad for climate)
	- Very sensitive to water vapour in tropics
- Optimal estimation retrieval
	- Reduced bias, noise and sensitivity to TCWV
	- Cost is a powerful indicator of confidence in result
	- OE involves running a radiative transfer model, which is a lot of effort
	- Calibration of the sensor needs to be good (or estimated)

